Correlation Management and Search for the Internet of Things

Ali Shemshadi

School of Computer Science

The University of Adelaide

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Supervisors: Prof. Michael Sheng

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To my mother and father,

my wife and my two little princes,

my brother and sister,

who made all of this possible,

for their endless encouragement and patience.

Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree. I give consent to this copy of my thesis, when deposited in the University Library, being made available for loan and photocopying, subject to the provisions of the Copyright Act 1968. I also give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library Search and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

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Abstract

The Internet of Things (IoT) is a compelling paradigm, which aims to enable everyday physical things embedded with electronics, software, sensors, and network connectivity to collect and exchange data on the Internet. It is anticipated that by 2020, billions of things get connected to the Internet. Creating future IoT search engines is a key step towards unlocking answering the above question. Future search engines can potentially in revolutionise various applications in different domains. Existing approaches for searching the IoT use simple techniques to obtain a list of things for a query. The state of the art needs to be improved in different aspects. For instance, it is often disregarded that in the context of IoT, we have two types of users including machines and human users. In addition, many have complained about the absence of the real-world IoT data. Unsurprisingly, a common question that arises regularly nowadays is "Does the IoT already exist?". So far, little has been known about the real-world situation on IoT, its attributes, the presentation of data and user interests. Moreover, existing approaches also disregard the attribute based correlations between things in the real-world. In this dissertation, we review the state of the art in IoT search domain and propose a novel framework to collect and analyse IoT data. Our system is also able to resolve IoT queries based on the knowledge that is acquired from the IoT data sources. Furthermore, we introduce a novel technique to extract the correlations between things. Our framework is capable of using the correlations to improve the quality of search results for both types of users. We investigate the scalability and the effectiveness of our approach using large scale and real-world datasets. Moreover, we investigate two case studies in transport systems in

our research. The first case study, challenges the complex problem of taxi ridesharing in the context of smart cities. The second case study, involves a real-time prediction method for flight delays based on the IoT sourced data.

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Chapter 1

Introduction

The Internet of Things (IoT) is a novel paradigm which escalates the data transfer on the Internet by interconnecting the sensors and actuators of physical things in a global scale. The IoT has progressively evolved over recent years in terms of enabling technologies, applications, architectures and scope. Due to its broad spectrum of applications, there are many visions for the IoT paradigm in the literature. Kevin Ashton, a co-founder of MIT Auto-ID Center, coined the name IoT by imagining on extension of the Internet to the physical world [1]. In the last decade, a variety of novel visions have been depicted for IoT applications [2]. Atzori et al. [3] distinguish three types of categories for IoT visions including *things oriented*, *Internet oriented* and *semantic oriented* approaches. As reviewed by other surveys in this area, the IoT concept definition revolves around its two main keywords, *Things* and the *Internet* [4–6, 2]. Thus, overall, we view the IoT concept as Internet connected swarm of uniquely identifiable virtual and physical sensors, where each sensor belongs to a physical object.

Observations and predictions demonstrate promising growth for IoT in the near future. In 2015, Gartner placed IoT on the peak of its Hype Cycle [7], predicting that it will reach the Plateau of Productivity of the cycle within 5-10 years. McKinsey Global Institute identifies IoT as one of the top twelve technologies whose solid disruptive economic impact will trigger

profound changes in our daily lives, as well as the global economy [8]. Nowadays, IoT is growing at a dazzling speed, as predictions show that billions of devices will become connected to the Internet by 2020 [9, 10]. Progressively, IoT is gaining attention in many application domains such as the *Industrial Internet* [11–15], *Environmental Monitoring* [16, 17], *Smart Cities* [18–20] and *Health Management* [21].

Given the accelerated adoption of the IoT, effective searching is still considered as one of the key challenges for the deployment of IoT in real-world application domains. Efficient and effective discovery of things is described as one of the main challenges in the establishment of the IoT [22, 2]. The heterogeneity of the things, highly dynamic environment and the lack of standards increase the complexity of IoT search. Based on Chen et al. [23], with the emergence of IoT, people will no longer be the only producers and consumers of the big data on the Internet. As a result, current online platforms must transform to effectively and efficiently support the emerging network of heterogeneous network of people and things. In particular, a number of important strategies need to be devised to provide useful results from searching the IoT. According to Yao et al. [24] the traditional postactive search paradigms would no longer be sufficiently effective to fully utilize the potential of the IoT to extract useful information from sensory data. Thus, rather than traditional postactive approaches, a proactive approach will be more suitable. Due to the scale, heterogeneity and the complexity of IoT, devising effective proactive discovery strategies requires enormous computing infrastructure in addition to significant user contribution, which cannot be justified in terms of costs and benefits. Ultimately, the goal is to enable machines to seamlessly facilitate the so called self adaptable *zero-touch* management and analysis of the streaming IoT data [25].

An efficient and effective platform for crawling, processing and searching the IoT data should: (i) extract data from heterogeneous sensory data sources on the Internet; (ii) load, transform and interpret the data according to its context [26]; (iii) extract and manipulate

correlations between things [27]; and (iv) be scalable to enable real-time processing of IoT data.

This chapter is organized as follows. In Section 1.1, we illustrate a motivating scenario, from which we will draw sub-scenarios as examples throughout this dissertation. In Section 1.2, we outline research issues that are tackled in our dissertation. In Section 1.3, we summarize our contributions in addressing the research issues and in Section 1.4, we enumerate the publications by the author that are related to this work. Finally, in Section 1.5, we describe the structure of this dissertation.

1.1 Motivating Scenario

In this dissertation, we work on tackling a number of research issues in searching and management of IoT with focus on transport systems and environmental monitoring. Although different parts of our approach are deployed for different scenarios and case studies in our work, we use this motivating scenario as a generic example, from which we define sub-scenarios in each chapter of this dissertation.

Figure 1.1 illustrates our motivating scenario. In our scenario, we focus on two types of users including *smart devices* and *human users*. Specifically, two types of search queries can be identified in this scenario, which are described as follows:

- **Correlation based search**: based on Yao et al. [24], searching and recommending things using heterogeneous correlations is a promising and interesting trend in IoT research. This type of search queries can be used by both smart devices and human clients to find the things of interest.

- **Intent based search**: another trend in IoT research emphasizes the role of the knowledge that is acquired from things in real-world applications. Ragget proposes intent based search as a promising research opportunity for IoT search [28]. Accordingly, this

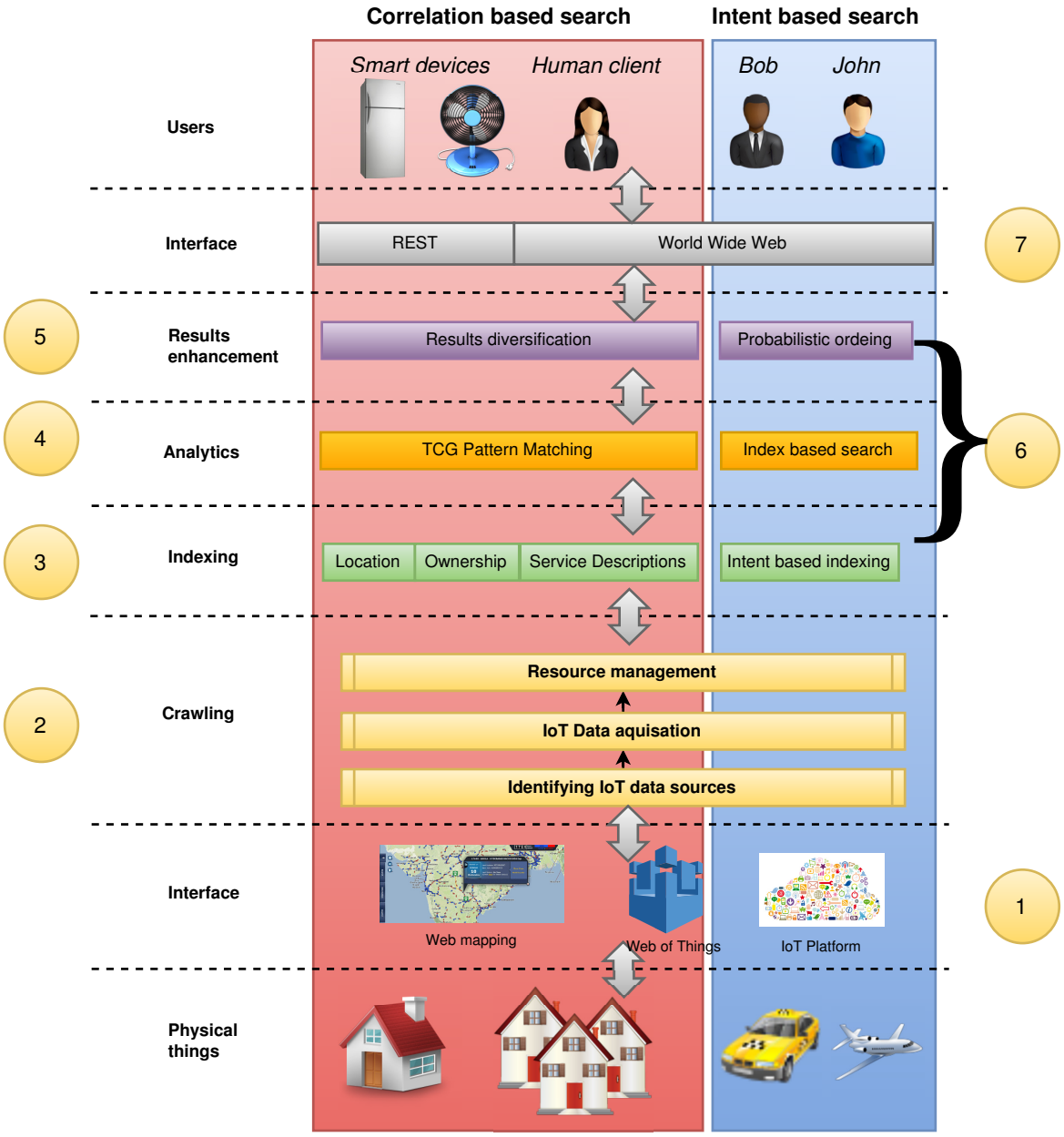


Fig. 1.1 Motivating scenario for IoT search

would provide the footpath for smarter search in IoT. Thus, application specific search queries can be manipulated to improve the effectiveness of IoT search in application. Yet, this type of query is mainly useful for human clients only as the knowledge or domain specific applications cannot be easily deployed by things.

We describe each part of the motivating scenario of Figure 1.1 as follows:

1. Initially, sensor enabled physical things propagate their data such as sensor readings and meta-data through different mediums on the Internet. This includes, real-time maps, real time Web pages which use Web of Things (WoT) technology and IoT platforms such as Xively [29]. A crawler engine in the next level would only have access to the visible IoT data sources on the Internet. The following steps are all activated by a user's request, which is submitted to the system as a search query. The format of the search query can be different based on the particular application.

2. A crawler engine identifies IoT data sources and crawls them based on a pre-constructed crawling pattern. The purpose of the crawling pattern is to specify the amount of resources required to crawl the data. In addition, due to the heterogeneity of the data sources and deployed technologies, the crawler must be tuned to support, then integrate the used data formats.

3. Due to the lack of interconnection between IoT data sources on the Internet, heterogeneous correlations are identified and used to construct networks of things. The key elements in the data, which enable us to create edges, are location, ownership meta-data and descriptive tags.

4. Pattern matching is the core of our analytic engine. It has a number of applications in our scenario. For example, it can be used to find matches for complex queries on correlation graphs. Furthermore, given the Things Correlations Graphs (TCG) from

the previous steps, pattern matching can be applied to identify matching nodes from different data sources to form a larger enterprise TCG.

5. Smart devices have limited resources in terms of processing power and memory. In addition, providing unprocessed sets of all existing things that match a query, is not useful for human clients. Thus, in our scenario, the size of the search result is limited to contain k things only. Due to the ambiguity in the purpose of the search, we can select either a set of k closest things, k things with closest owners, k things that have the closest set of tags or a diversified result set. Results diversification can improve the quality of results in this stage, before they are presented to the users.

6. Alternatively, human users may use the search engine to either find things or search the knowledge that is acquired by the sensory data over the Internet. In this scenario, considering a case where a client is looking for things, a human user (John) searches for the nearest booked taxi to get a rideshare instead of booking a separate taxi. However, the ridesharing request must be agreed by Bob who has previously booked the same taxi. A sub-set of processing steps needs to be redesigned to serve the desired purpose in this scenario. In this case, we focus on getting the best taxi which is not only the closest, has the highest opportunity of success in the process of booking the request.

7. Final results can be tailored and presented to the users based on their type. For instance, a smart device receives a message that contains the list of top k things and a human client can receive a visualized result set instead.

This motivating scenario poses several major concerns including: (i) due to the limited capacity of machine users, the size of the response should be limited to k and thus, preparing the best response may require finding the most relevant and/or diversifying the things in the result set; (ii) based on the previous issue, given that the IoT resources are presented in singular form and are not correlated to each other, we are interested in digging the correlations

and establishing a heterogeneous network of things using a scalable approach; and (iii) we are specifically interested to deploy the role of the IoT search engine in two use cases including taxi ridesharing and flight delay analysis.

1.2 Research Issues

Based on the observation in the aforementioned motivating scenario, correlation based search for IoT search and data management services should tackle the following issues:

- **Discovery.** Indeed, there is no universal directory of IoT connected devices due to a number of reasons. Firstly, IoT is not a unified network or platform as heterogeneous types of sensory data are publicized using a variety of technologies and thus, it is not straightforward to identify IoT data sources on the Internet. Secondly, most works on IoT search have used simulated or small scale datasets and, as yet, the current status of IoT is not investigated by other works [30]. Thirdly, given the security and privacy concerns of the IoT, the majority of sensory data sources are kept private and not revealed to the public, making it impossible to collect and process that data.

- **Correlation extraction.** The heterogeneity of the nodes of the IoT network implies a variety of correlations which can be defined across those nodes. However, unlike the traditional Web documents, which are correlated using hyperlinks, all of the correlations in IoT are implicit and none is explicitly demonstrated. Given the scale of the streaming sensory data in IoT, it would be very complex to capture all types of correlations on the fly. Moreover, in correlation based IoT search the correlation of the querying user with other nodes is required to provide the best results.

- **Network matching.** It is defined as finding the top-k matches in a data graph for a given subgraph. Network matching is a core function that lies at the heart of IoT data management and querying due to a number of reasons. Firstly, open linked data

and service descriptions are widely deployed for Wireless Sensor Network as well as the IoT [31, 32]. Resource Description Framework (RDF) descriptions are useful in providing semantic foundations for the dynamic networks of things, where each node is provided with a set of descriptions [33]. Secondly, merging different networks to create an enterprise correlation graph is a challenging task. Having the network of networks where each sub-network is a collection of things in IoT, finding the best matches to integrate all networks is NP-Hard. Thirdly, in the IoT, things may have more than one service description and very often, different things can share the same description. Thus, assigning unique labels to things based on their service description in a semantic network is not viable in the real-world.

- **Query resolution for smart machines.** Due to the limits in the processing power and memory of the smart machines, the size of the response to the query made by a smart machine should be limited. Thus, only a subset of the result set should be returned to the machine user. In this case, as well as other scenarios when the user is a human being, a good result subset is a subset of correlated things. One example is the search locality concept where only things in the same area are returned as a result. However, due to the heterogeneity of the correlations in the IoT, a combination of the correlations can be selected to prepare the result set. In this case, rather than returning the things that are locally correlated with the query maker, we need to balance the correlations in order to get the best result set. However, due to the lack of IoT data, this problem yet has not been studied in detail.

- **Intent based search.** Intent based search is proposed as one of the strong application areas for searching the IoT [28]. It is difficult to identify the users' search intention only by using the query keywords and the ambiguity can cause high degree of fuzziness in the result set [34]. Modelling the user's intention can vary significantly across different applications. Given a sub-scenario of taxi ridesharing, taxi search engines, which are

equivalent to ridesharing applications, are designed to find the nearest taxi. However, the intention of users in this case is not only to find the nearest taxi, but rather find the most economical taxi which can be booked conveniently, while traditionally it is assumed that when the nearest taxi is found, it is then booked. Considering the consequences of selecting taxis that cannot be easily booked can change the solution fundamentally and thus, increase the complexity of finding the optimal taxi.

- **Knowledge acquisition from IoT data.** In addition to acquiring the most relevant things in query results or finding the most optimal solution for an intention search, from the motivating scenario we know that users are more interested in acquiring knowledge from sensory data. In the case of flight tracking and management, one of the major intentions of flight data analysis is to understand the parameters that affect flight delays in order to predict flight delays beforehand. However, previous work in this area either consider only one dataset and/or rely on using historical data [35]. Nowadays there are a variety of online tools available. For instance, flight tracking software such as the website FlightRadar24 [36] are currently very popular. Using the real-time sensory data from heterogeneous data sources requires more complex and deeper analysis of the parameters that affect flight delays.

1.3 Contributions Overview

We propose a framework for collecting, managing correlations and querying the IoT data according to the set of edges between heterogeneous things. We also provide an implementation of our approach in the *ThingSeek* prototype [37]. In ThingSeek, we identify and crawl publicly available IoT data sources with millions of objects. Correlations are extracted and used for query resolution to limit the size of the response to k most correlated objects. We propose a novel framework for identifying correlations and diversify the result set based on

different types of correlations. Finally, we consider query handling in two sub-scenarios of IoT in application. The first sub-scenario, aims at benefit maximisation in taxi ridesharing applications. We use a novel approach to extend traditional models by considering new decision parameters such as companion users' decisions. This implies intent based IoT search, where the search result is presented based on the users' intentions (finding the best taxi to get a rideshare) rather than aimlessly querying them (finding local taxis). We also propose a novel model for the analysis of the features that affect flight delays. In particular, our main contributions in this work are focused on the following:

1.3.1 Data Collection

IoT is increasingly gaining popularity amongst the industry and academia. Yet, due to security and privacy concerns, the majority of the sensory data on the Web is not accessible to the public. Thus, research on the real-world applications of IoT remains limited in terms of scope and effectiveness. In our study, we include IoT data from different resources that are already available on the Internet. We collect a real-world dataset of publicly available IoT data for millions of things. We analyse the collected IoT data to gain some insights on the patterns and changes in the IoT data over a 24 hour timeframe. Furthermore, we present our findings from the analysis of real-world queries from a popular IoT search engine to get some insights about user interests in IoT. Based on the results of the analyses, we discuss the future challenges and opportunities for research in IoT search. We provide the evidence of return cycles in sensor readings, which significantly improves our ability to archive and analyse IoT data.

1.3.2 Correlation Discovery

In order to address the heterogeneity of the correlations between things, we propose a novel approach to identify three types of correlations including Object Ownership Relationship

(OOR), Category Based Object Relationship (CBOR) and Co-Location Object Relationship (CLOR). We conduct experiments on real-world data and demonstrate the performance of our approach. Our approach automates the process of extracting correlations from IoT data.

1.3.3 Diversified Query Resolution

The diversity of the correlations between things can result in the ambiguity of the search queries where the type of the desired correlation is not normally stated in the query. Moreover, given the limitations in the processing power and the memory of the smart IoT connected things and considering the fact that the user may not need all of the result set, we propose to limit the size of the response to include only k-most correlated things. Thus, a challenging issue is how to prepare the best results for a given IoT search query. We propose a novel approach which identifies correlations and forms multiple Things Correlation Graphs (TCG), integrates the TCGs and and diversifies the selection of the objects in the response. We define and use a measure to estimate the quality of the result. Moreover, we conduct experiments using real-world and synthetic datasets and demonstrate the effectiveness and efficiency of our approach [38].

1.3.4 Pattern Matching for Correlation Graphs

Digging further into TCG analysis and also given that the Open Linked Data is popular for representing the dynamic IoT data, a core process is subgraph pattern matching. Furthermore, with the emergence of the Social Internet of Things (SIoT) [39–41], the significance of the application of graph pattern matching for IoT increases. In particular, we target integrating TCGs and matching patterns for owners in the graph heterogeneous things and users. We redefine the pattern matching problem (*MULTIMATCH*) to be used for IoT data. We use multiple labels for nodes instead of the traditional single label. We propose a novel approach for identifying top-k patterns in the data graph with vertices with multiple labels. Moreover,

we conduct experiments using both real-world and synthetic patterns and data graphs and analyse the time and space complexity of our approach.

1.3.5 Intent-Oriented Search:Taxi Ridesharing

In order to address intent based search, we focus on a specific application scenario where a user shares a ride with companion users to reduce the cost of the ride. Considering the intention of users in a taxi ridesharing scenario, we redefine the purpose of the taxi search in order to find the “nearest and the easiest-to-book taxi". Due to the complexity of the new problem, we propose a novel and scalable approach. We conduct extensive experiments using real-world data and demonstrate the efficiency and the effectiveness of our approach to find the best taxi.

1.3.6 A Crawling and Search Engine

Building future generation of crawlers and search engines is critical for research on IoT. We demonstrate our implementation of ThingSeek, a search engine with a crawler to hunt for IoT data on the Web. We mainly focus on the sensor data that is disseminated through Web Mapping. Our ThingSeek framework contains a crawler and two querying interfaces to cover both human and machine users, e.g., smart devices. We crawl IoT data and demonstrate two types of outputs: knowledge and things for each type of user. We use a flight delay analysis scenario as our case study.

1.4 Dissertation Publications

In the following, we include the papers from my work related to this dissertation. The list of the papers, including all accepted, revised and submitted manuscripts is a follows:

Journals

1. Shemshadi, A., Sheng, Q.Z., Zhang, W. E., Sun, A., Qin, Y., Yao, L. (2016) *Personal and Ubiquitous Computing*, to appear.**[Impact:1.498]**

2. Shemshadi, A., Sheng, Q.Z., Qin, Y. (2016) Efficient Pattern Matching for Graphs with Multi-Labeled Nodes. *Knowledge Based Systems*, 38(10), 12160-12167. **[ISI, Impact:3.32]**

3. Shemshadi, A., Sheng, Q. Z., Zhang, E. W. TRIPS: Scalable and Dynamic Taxi Ridesharing with Uncertain Data. Under review by IEEE Computer.

4. Shemshadi, A., Sheng, Q. Z., Qin, Y., Dustdar, S. An Empirical Investigation of the Internet of Things on the Web. Under preparation.

5. Zhang, W. E., Sheng, Q. Z., Taylor, K., Shemshadi, A., Qin, Y. A Learning Based Caching Framework for Enhanced SPARQL Endpoint Query Answering. Revision under review by Information Systems. **[CORE A* Rank, Impact:1.832]**

Conferences

1. Shemshadi, A., Sheng, Q. Z., Qin, Y., Alzubaidi, A. CEIoT: A Framework for Interlinking Things in the Internet of Things. Submitted to the 12th International Conference on Advanced Data Mining and Applications (ADMA), 2016.

2. Shemshadi, A., Aljubairy, A., Sheng, Q. Z. An Analytical Investigation of Flight Delays Based on the Internet of Things. Submitted to the 12th International Conference on Advanced Data Mining and Applications (ADMA), 2016.

3. Shemshadi, A., Sheng, Q. Z., Qin, Y. ThingSeek: A Framework for Crawling and Searching the Internet of Things. In Proceedings of the 39th ACM SIGIR Conference

on Research and Development in Information Retrieval (SIGIR 2016), 2016. to appear. [demo - **CORE rank: A*- top 3 downloaded papers from SIGIR 2016**]

4. Zhang, WE, Sheng, QZ, Qin, Y, Yao, L, Shemshadi, A, Taylor, K. (2016) SECF: improving SPARQL querying performance with proactive fetching and caching. *Proceedings of the 31st Annual ACM Symposium on Applied Computing*, 362-367. [Full paper - **CORE rank: B**]

5. Shemshadi, A., Yao, L., Qin, Y., Sheng, Q. Z., and Zhang, Y. ECS: A Framework for Diversified and Relevant Searching for the Internet of Things. In Proceedings of the 16th International Conference on Web Information System Engineering (WISE 2015), 2015. to appear. [Full paper - **CORE rank: A**]

6. Yao, L., Sheng, Q. Z., Qin, Y., Wang, X., Shemshadi, A., and He, Q. Context-aware Point-of-Interest Recommendation Using Tensor Factorization with Social Regularization. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2015), 2015. pp. 1007-1010. ACM. [**CORE rank: A***]

7. Qin, Y., Sheng, Q. Z., Falkner, N. J., Shemshadi, A., and Curry, E. Batch matching of conjunctive triple patterns over linked data streams in the internet of things. In Proceedings of the 27th International Conference on Scientific and Statistical Database Management (SSDBM 2015), 2015. pp. 41. ACM. [**CORE rank: A**]

8. Qin, Y., Sheng, Q. Z., Falkner, N., Shemshadi, A. and Curry, E. Towards Efficient Dissemination of Linked Data in the Internet of Things. The 23rd ACM Conference on Information and Knowledge Management (CIKM 2014). Shanghai, China, November 3-7, 2014. [**CORE rank: A**]

9. Shemshadi, A., Sheng, Q. Z., Zhang, E. W. (2014) A Decremental Search Approach for Large Scale Dynamic Ridesharing. *15th International Conference on Web Information Systems Engineering (WISE)*. [full paper - **CORE rank: A**]

10. Ma, J., Sheng, Q. Z., Yao, L., Xu, Y. and Shemshadi, A. (2014) Keyword Search over Web Documents based on Earth Mover's Distance, *The 15th International Conference on Web Information Systems Engineering (WISE)*. Thessaloniki, Greece, October 12-14. [**CORE rank: A**]

11. Peng, Y., Xie, D., & Shemshadi, A. (2013). A Network Storage Framework for Internet of Things. *The 3rd International Symposium on Internet of Ubiquitous and Pervasive Things, 2013. IUPT 2013*, 1136-1141.

1.5 Dissertation Organization

The remainder of this dissertation is organized as follows.

Chapter 2 corresponds to steps 1 and 2 in the motivating scenario. In this chapter, we identify and crawl IoT data sources on the Internet. We analyse the critical characteristics of IoT data including its volume, dynamics, formats and used technologies. We provide the details of our findings based on an empirical analysis of the the IoT data.

Chapter 3 provides the details of our approach, namely CEIoT, for automated interlinking of things in IoT. Based on the set of features that are obtained from the real-world IoT data in the previous section, our approach focuses on three types of correlations including *Co-location Object Relationship*, *Ownership Object Relationship* and *Category Based Object Relationship*. We use Open Linked Data to Represent Correlations. We use autonomous agents in our agent-based architecture to enable smart objects and IoT platforms to identify and represent their correlations without external intervention. This is a novel approach for

constructing the TCGs in step 3 of the motivating scenario, where TCGs of different types are constructed. Finally, we evaluate our approach using a real-world IoT data set.

Chapter 4 covers further TCG processing in our research. It corresponds to step 4 in the aforementioned scenario. Graph pattern matching is core to a number of purposes which involve TCG processing including (i) knowledge processing; and (ii) merging information from different data sources. However, due to the complexity of the sub-graph matching problem, accommodating nodes with a single label is applied to enable pattern matching in polynomial time. However, based on our observation, due to the lack of standards for service description which leads to the huge overlap between the nodes' meta-data, we cannot define single labels for the nodes in TCGs. Thus, we propose a new approach for approximating the top-k matches of a query node in query graph Q from a given data graph G. We evaluate our approach using real-world datasets and show that our approach can perform more efficiently than existing approaches in terms of processing time and memory use.

In Chapter 5 we address the problem of search query ambiguity when the type of correlations are not specified in the search query. Based on our dataset of IoT query logs, we observe that this problem is common in real world scenarios. In addition, we address the needs of users by limiting the size of the result set to include k objects. Moreover, we need to integrate the TCGs of different types to be able to process the queries. Thus, we propose a framework that consists of an integration mechanism of TCGs of different types and a search diversification that improves the quality of search results by diversifying the query results. Chapter 5 addresses step 5 in the aforementioned scenario. We use a number of real-world datasets to evaluate the effectiveness of our approach.

We focus on an intent based IoT search scenario in Chapter 6. In this chapter, we target taxi ridesharing, which is an application of IoT in the context of urban areas. We propose a novel indexing, searching and ranking approach, namely TRIPS, for the taxi ridesharing problem which improves the probability of ridesharing request acceptance by companion

passengers. While existing solutions focus on finding the nearest taxi, our approach improves the effectiveness of the search by considering new parameters. In addition, using an intent oriented search limit, we improve the performance of the search algorithm significantly. Finally, we use a real-world dataset consisting of taxi trajectories to validate our approach. This chapter corresponds to step 6 in our motivating scenario.

We demonstrate the details of our ThingSeek implementation in Chapter 7. This chapter mainly addresses step 7 of the aforementioned scenario, where the search results are presented to the final user. More specifically, in this chapter we focus on a flight data analysis and show a number of search results that enable value added search experience in IoT.

We conclude this dissertation in Chapter 8. We summarize the key points of each chapter of this dissertation, then describe their relationship with the publications from this thesis. Finally, we finish this dissertation by discussing the directions for future research.

Chapter 2

Crawling the IoT Data

Finding, crawling and knowing the IoT data sources over the Web is the first step in our research. IoT is a generic concept while as an emerging paradigm, it can be applied a variety of applications including but not limited to healthcare, mining industry, environmental sensing, transportation and logistics, and etc [42, 43]. For instance, through the use of an IoT infrastructure, in-home healthcare terminals can be developed to continuously check a patient's heart rate [43]. Various definitions of the IoT are traceable within the research community, and each of them targets at some strong interest to a specific type of applications or technologies. The very first definitions of IoT consider simple objects and RFID technology only. Later, IoT definitions broaden the purpose, perspective and the enabling technologies [3]. In a broader sense, it is hard to limit the boundaries of IoT to specific applications or specific technologies. Thus, we envisage IoT as the set of initiations that publish the data generated by embedded and non-embedded sensors that are publicly available on the Web.

The status of IoT is indeed similar to an iceberg as only a small part of it is visible to the public. Due to its novelty, its visibility is still very limited to the extent that a common question for many people is that *"Does the IoT already exist?"* [44]. Crawling and analyzing real-world IoT data may help to answer this question. In the context of World Wide Web, this is usually carried out by existing search engines such as Google. However, in the context

of IoT, very little work has been carried out in this regard. To the best of our knowledge, the only working example of the IoT search engine is *Thingful* [45] and none of the IoT search engines in the literature have been deployed for real-world or large-scale data. Furthermore, the Thingful initiation itself is still limited and significant progress is needed to expand this area. One instance of such limitations is the public availability of the collected data. For example, Thingful provides access to its data only via a dedicated User Interface. Another example of the limitations is the fast expiration of the data due to the highly dynamic nature of the IoT [46, 47]. *Graph of Things* [48] is another interesting project which aims to provide live IoT data in real-time, which is still limited and can be potentially expanded in terms of scope and capabilities.

There is another search engine, namely Shodan [49] which also claims to be a search engine for IoT. The main difference between Shodan and IoT search engines such as Thingful, is that Shodan is basically designed as a search engine for hackers. It identifies and hacks into password protected devices connected to the Internet. Servers and routers as well as other Internet-connected devices have been archived with their IP addresses in its database. The website itself does not process sensor outputs. Due to its large and broad scope, catching everyday objects on this website is still difficult while servers and network devices constitute the majority of the things in its database. Due to ethical issues and scope matters, we do not include Shodan in our study.

Given the lack of powerful IoT search engines and the unavailability of large-scale IoT data, the visibility of IoT and its data is far from satisfying. This creates notable gaps in the IoT research and development [44] and still leaves many questions without answers. We list some of them as follows:

1. Does IoT already exist on the Web?

2. What technologies are used to make IoT visible?

3. Which aspects of IoT are more interesting to users?

4. What are the characteristics of the large-scale IoT data?

In this chapter, we conduct an extensive study on publicly available IoT data sources and the current status of the real-world IoT. Studying the characteristics of IoT data is crucial for designing a proper crawling and analysis strategy. Our main contributions are summarized as follows:

- We identify and classify IoT data sources into three categorizations, including *Cloud based IoT platforms*, *Web of Things enabled platforms*, and *Web Mapping*. Our practical experience provides strong evidence that IoT does exist on the Web nowadays and we suggest that more IoT research efforts are needed to take advantage of this availability.

- We design and implement a novel IoT crawling platform, to collect and analyze IoT data. Using our crawler, we capture publicly available data from the major IoT data sources that we identify over the Web. We make the collected IoT dataset available to the public in order to boost the research related to IoT.

- We study the general user interests on IoT data by using a real world query log dataset from an IoT search engine. We also analyze the characteristics of the collected IoT data including spatio-temporal distributions of things, data dynamics, and data quality.

- Based on the collected real-world IoT data and our analysis, we discuss future research challenges and identify open research problems to shed light on the future IoT research and development.

The rest of this chapter is organized as follows. We discuss the potential places to look for IoT over the Web in Section 2.1. In Section 2.2, we discuss the best practices that we learn in IoT data acquisition. Then in Section 2.3, we present the analytical results of the collected IoT data and search logs. We discuss some of the observed opportunities for IoT research in

Section 2.4. In Section 2.5, we overview the related works and Section 2.6 summarizes this chapter.

2.1 Where is the IoT?

The interactions with IoT can be realized in Machine-to-Machine (M2M) as well as Machine-to-Human (M2H) [50]. The M2M approach is mainly used for smart things and enabled by predefined APIs, e.g., RESTful APIs [51, 52]. In contrast, M2H can include almost every object that are connected to the Internet and enabled using current Web protocols and existing IoT middleware. Pioneering IoT cloud services such as Xively [29], Paraimpu [53], ThingSpeak [54] and Sen.se [55] are some of the examples of IoT dedicated cloud services which provide infrastructure to store and share things data for various types of sensors. Nowadays, there are numerous examples of websites which focus on a specific type of applications such as tracking aircrafts [36], marine traffic [56], traffic jams [57] or Raspberry Pi board [58] In the rest of this chapter, we refer to these two types of IoT services as general and niche IoT services, respectively.

In our work, we categorize IoT data sources into three groups, namely the *cloud based IoT platforms*, the *WoT enabled platforms*, and the *Web Mapping enabled data sources*.

2.1.1 Cloud Based IoT Platforms

Cloud computing is a very popular demand-based Internet computing paradigm in which, shared resources, data and information are provided to computers and other devices on-demand. Since the introduction of the concept, numerous cloud services have been launched where each service is designed specifically for certain applications such as web hosting, file sharing, programming and etc.

With the growth of the idea of connecting things to the Internet, one of the dominant visions for developing the IoT is to use cloud computing technologies to develop cloud services which facilitate the utilities for storing, sharing and visualizing IoT data through the conventional tools of the World Wide Web [10, 59]. For this purpose, many services have been developed where Table 2.1 enlists some of them.

One of the main features of this category, is that the platforms have been designed with the idea of enabling any object of any kind to be connected to the IoT rather than being a solution designed specifically for a certain application. Furthermore, the service model of the cloud platforms, can provide more details about cloud based platforms for IoT. Infrastructure as a Service (Iaas), Platform as a Service (Paas) and Software as a Service (SaaS) are the prevalent service models for cloud services. These models provide services at different levels from basic access to infrastructure to complete service via online application software and database, respectively. IoT cloud platforms in this category, such as the services in Table 2.1, may follow a SaaS model for connecting devices to IoT. All of the mentioned services provide dashboard, API, M2M communication, middleware and the infrastructure to facilitate the IoT connection of the devices. In addition, many of the popular cloud services which follow other models, such as Amazon Web Services and Google Cloud, have recently provided tools for IoT integration.

Basically, cloud platforms for heterogeneous IoT devices are considered as the primary means of sharing IoT data [10]. The data ownership policy of these platforms is typically set to be private with a few exceptions such as Xively that provides a public sharing option. Public IoT data, if available, can be generally retrieved through a pre-designed API such as Xively API [60].

Table 2.1 Examples of IoT cloud services

Platform	Description
Xively	Popular IoT cloud with open data
Paraimpu	Social network with IoT cloud
TheThings.io	IoT cloud with open data
Ayla Networks	IoT cloud with smartphone app
Jasper	Scalable IoT cloud with predefined business applications
Cloud Plugs	IoT cloud with variety of development libraries
ThingSpeak	One of the earliest IoT clouds
Covisint	Enterprise purpose built IoT cloud
particle.io	IoT cloud with hardware development kits
ThingWorx	IoT cloud with machine learning

2.1.2 WoT Enabled Platforms

The WoT concept describes approaches, frameworks and programming patterns that allow things to share their data through the World Wide Web. Currently, WoT is an active research area with a range of challenges and opportunities including security, resilience, intent oriented search, legal implications and so on [28]. Backed by existing WoT packages [61], these data sources create mashups to publish IoT data. One of the most popular WoT packages is the WoTKit [62]. Although some WoT packages have been used by IoT cloud services, we distinguish them from other cloud services (e.g., Xively) that are not developed based on the WoT. WoT can be applied in both of the traditional server (such as WeIO examples [63]) and the cloud based (such as SenseTecnic [64]) environments.

2.1.3 Web Mapping Enabled Data Sources

Web Mapping is the process of using online maps to browse and visualize geospatial data in a Web environment (e.g., Google Maps) [65]. Web Mapping is more than just Web cartography. There exist a wide variety of use cases for Web Mapping presentation of the data. In fact, we realize that a considerable number of Web pages with maps are providing IoT data and

thus, include them in our list of data sources. The main categories of such data sources are as follows:

- *Real-time Transportation Information Services*: Real-time tracking services (e.g., FlightRadar24 [36] and Arrivebus [66]) are designed to process and share the coordination of public transport services generated by embedded GPS devices. Unlike IoT cloud platforms, these services are often publicly available and data is visualized via Web Mapping. The most dynamic attributes of the objects in these networks are location-related including latitude and longitude.

- *Urban Crowdsensing Services*: Urban crowdsourcing services provide a platform for people to report and share their observations of things around them. For example, Waze [57] provides a mobile phone application for users to report their locations, traffic jams, roadworks or police attendances. Although the collected data from this type of platforms is not originated from embedded physical sensors, the information is still related to physical or virtual things that people observe around themselves. Most often, the data is available through a Web based map.

- *Public Environmental Sensing Services*: These services include platforms that share the data originated by environmental sensors such as weather stations and pollution metrics. The data is available through a Web based map interface available to public.

2.2 IoT Data Acquisition

In this section we provide details on identifying the data sources of things and collecting the things dataset. We focus on the general idea of the IoT which is composed of two main words: *Internet* and *Things*. As every object occupies a space and the location is one of the key features of things, we limit the scope of our search to the sources which necessarily contain, or at least consider, the location data. The location data is usually represented as a unique

tuple $(latitude, longitude)$ such that $latitude \in [-90, 90]$ and $longitude \in [-180, 180]$. On top of the location information, we also need to focus on specific features to identify the relevant sources of things data. We include some of the available WoT and IoT platforms to our search queries to cover popular IoT implementation techniques. We also consider Web Mapping as an IoT data sharing interface to identify more IoT data sources. Thus, we limit our search scope to the sources which contain a map.

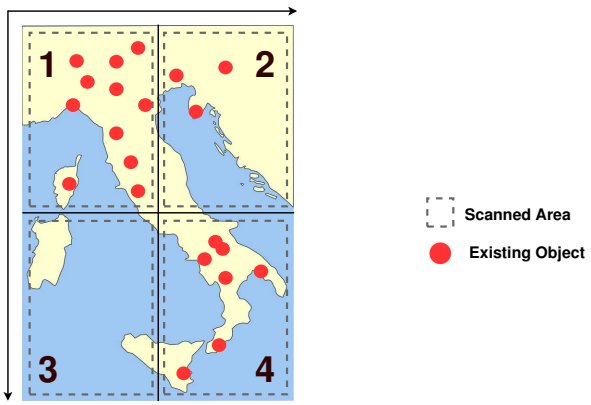


Fig. 2.1 Illustration of the sequential-spatial access to things data

Due to the size and dynamics of the sensor-generated data, IoT data sources often provide a subset of their data with a call to their API. Thus, pagination techniques such as location-based queries are deployed to present the data. We use the same mechanism through implementing the URL generator. The URL generator plays a key role in adjusting the workload on the data source. It converts a set of spatial segments to a sequence of queries which can be submitted via the API of the data source. Thus, a highly populated area can be placed multiple times in the processing queue while an empty area may appear only once (or not appear) in the queue.

Specifically, the procedure of our research consists of: 1) building a database for the available data sources which share sensor generated data over the Web; 2) building the necessary tools to automatically crawl IoT data from the set of maps specified in the previous step; 3) creating a Web based interface to visualize and analyze the collected data in real-time;

4) analyzing the data sources based on their architecture, reliability and technologies used; 5) analyzing the retrieved IoT data based on key attributes such as location, volume, redundancy and distribution; and 6) identifying and overcoming the challenges in data collection step.

2.2.1 Identification of Data Sources

The number of cloud IoT platforms with open access data is limited and thus, identifying them is not difficult. For WoT enabled data sources, one can check the traces of existing WoT packages such as the ones from WeIO [67], WoT Code Forge [61] and WoT Project Directory [68].

In principle, not all IoT data appears in the form of Web Mapping and not every Web based map is related to IoT data. Web based maps have been used for a variety of purposes including presenting IoT data. From our experience, those Web pages that visualize IoT data have the following requirements: 1) containing an interactive map; 2) being publicly available; 3) being real-time; 4) being real-world; and 5) being within valid ranges.

Relying on the spatial characteristics of things, we observe that Web based maps are key features to discover IoT data. Interactive Web based maps often contain a RESTful back end [51, 52] and a script on the front end, thus the RESTful API can be used to collect the data. If a map is not interactive, then no general approach can be found to collect the data. If the map is not publicly available, then the access to the data will be restricted.

IoT is usually updated in real-time and vintage maps are not very useful in this case. The real-world data is a key to find real physical things, thus, maps of virtual worlds such as game maps do not provide IoT data. Finally, key features of the data should contain proper values. Maps with encrypted data cannot be very useful for IoT data collection.

Based on the features of IoT data, which are mentioned above, we use the following procedure to identify the data sources: 1) the Web page should contain an interactive map; 2) data is presented inside the XMLHttpRequest (XHR) response of the requests that the

page makes; 3) the response in the XHR may continuously be updated; and 4) data contains coordinates which are within the valid boundaries.

2.2.2 IoT Data Collection

We design a distributed crawler which can automate the process of IoT data collection. Firstly, we identify a set of potential sources and categorize them based on the pre-specified features and criteria. Then from the result set, we use around 20 data sources from which many are partially included in Thingsful as well. The datasets include Xively, Air Quality Egg, Raspberri Pi, Air Quality Index, ThingSpeak, Flight tracking (three different sources), Ocean (underwater) things tracking, WUnderground (weather stations), Weatherlink, Waze (three different datasets for traffic jams, users and alerts), University buses (4 universities), London subway tracking, Bus tracking in UK, Vessel tracking and Cruise ship tracking.

As we need to further process Thingful queries with our crawled things dataset, the sources are selected to represent the Thingful data. We crawl the selected data sources in two hour intervals for a period of one week between 25/8/2015 and 1/9/2015. In this study, our goal is to monitor daily changes and patterns in the IoT data sources. As we use the whole dataset, no bias can be involved. Wherever a selection is made, it is done randomly, which alleviates the bias in data sampling [69]. The crawling resulted in two million things from the selected IoT data sources. We distribute the crawler over 4 machines where each machine has the maximum of 2.5 GHz Intel core-i5 CPU, 8 GB memory.

We observe that the majority of data sources use pagination to limit the output size. Thus, capturing the whole dataset through a single request using API would be impractical. For example, the length of the resultset of a query from a Web Mapping enabled website such as a flight tracker would be limited to a few hundred aircrafts. For this reason, we need to construct a spacial or paginated query and process it through the API. As shown in Figure 2.1, a larger area will be segmented into a grid of smaller segments and then we capture things

data in a sub-area of each segment. In this regards, small margin will be considered to avoid capturing duplicate things. Duplicate things will be created if a single object is captured twice as it is moving from one segment to its neighbour. However, using the above technique will result in sequential access to the whole data. In the example shown in Figure 2.1, Segment 4 may only be accessed after screening the other segments such as 1,2 and 3. Considering the high rate of updates as well as the size of data, this could make a problem as other segments such as 2 and 3 are not as populated as Segment 4. Thus, a considerable amount of resources is not used properly and a long delay in data refreshing is triggered by this mechanism.

Due to the frequent sensor reading updates, the volume of IoT data can be huge. Based on our observation, storing IoT data requires more than 0.25 GB of space per second. Thus, we can estimate that to store the data in 24 hours, we need approximately 21 TB of space. Obtaining this amount of information from a data source can be time consuming and bear a high cost. However, in order to save the processing cost and reduce the distortion of the captured things dataset, one option is to analyze the density of things in each area and put more effort on the areas with more things. For instance, in Figure 2.1, Segment 3 on average has the least density of things, thus it can be removed from the queue. Another option, which can be taken at the same time, is to consider the distribution of the retrieval queries. For instance in Figure 2.1, if user queries specify the Segment 2 more than Segment 4, more resources can be devoted to scan Segment 2 data.

In our dataset, we have identified nearly two million objects. The number of records for each object deviates between 10 and 1,933 based on the fact that the time for scanning different data sources varies between 30 seconds to more than 50 minutes. In average, the readings per object in our data set are 32. On top of the crawled things dataset, we use a real-world query set consisting of 136,746 queries between 12/2/2014 to 27/1/2015 from the Thingful search engine. We use the query set to investigate user interests. A query in our query set is structured as follows: `{"timestamp":"2015-01-27T09:33:06+00:00",`

"query":{"lat":"51.55", "lng":".03", "zoom":"8", "what":"speed camera"}}

2.3 IoT Data Analysis

In this section, we present the result and statistical analysis of IoT data and queries collected during multiple routine crawling rounds. We investigate the results from user-related and things-related points of view and then we compare the distribution of IoT and queries data.

2.3.1 User Interests

We investigate user interests from different angles including *Popularity Trends*, *Search Queries Statistics* and comparing the *Things vs Query Distribution*.

Popularity Trends

A glimpse into IoT keyword trends over Google Trends [70], suggests that the public interest towards IoT with its most popular abbreviations has been steadily increasing over the past few years.

To further understand this trend, we select some of the most cited IoT platforms (i.e., Xively, ThingSpeak, sensetecnic.com, and Thingful) from the literature and compare their popularity using Alexa Web Ranking [71]. Figure 2.2 shows the results for the selected websites during six months from 16 Apr., 2015 to 15 Oct., 2015. Accordingly, the popularity of cloud based IoT platforms (e.g., Xively) have been gradually decreasing throughout the last six months while the popularity of Thingful search engine has been increasing during the same period. Clearly, a powerful search engine for IoT can help attract users' interests.

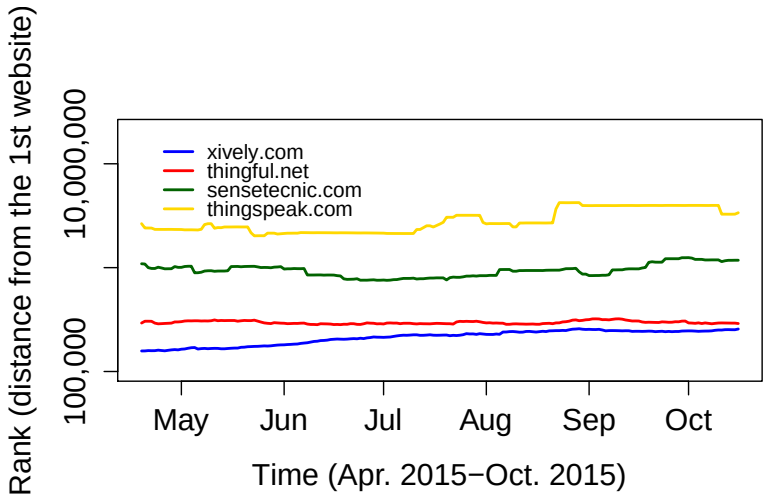


Fig. 2.2 Ranking of the popular IoT services

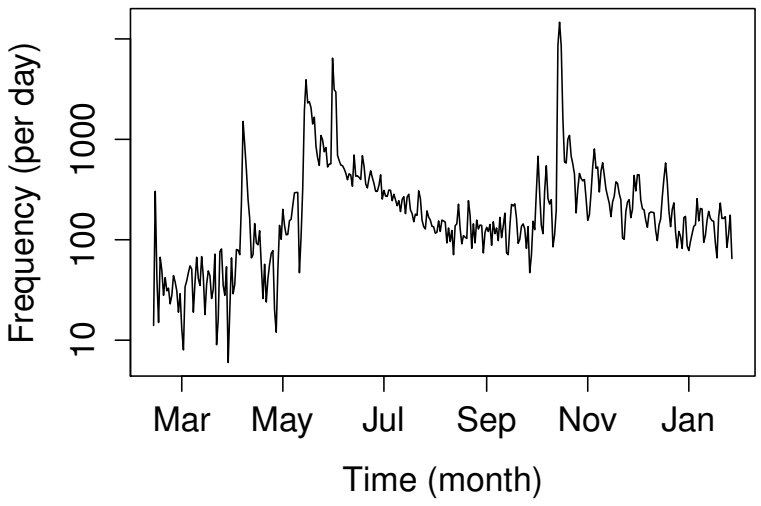


Fig. 2.3 Query frequency per day in Thingful

Search Queries Statistics

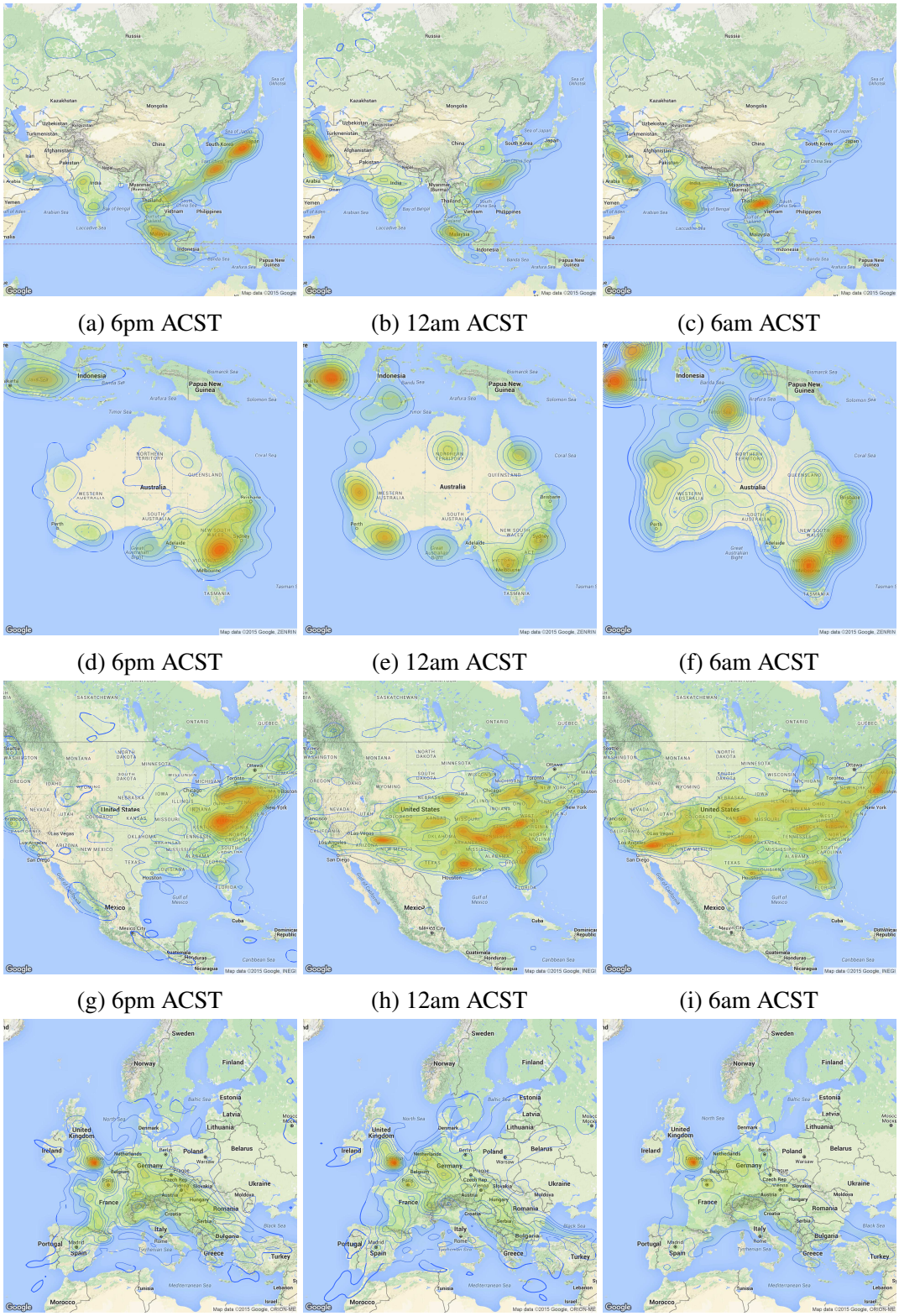
Analyzing real-world IoT search queries can provide valuable insights for the design and development of future IoT search engines. To get the statistics, we use a dataset of search queries from the Thingful search engine. Figure 2.3 shows the number of IoT search queries per day. It has been gradually increasing through the time and the average number of queries have been tripled since the beginning. However, in three points of time, during May, June and October, 2014, an abrupt increase in the number of queries per day can be observed. One of the reasons for such increase can be the introduction of new features by the search engine such as embedding and the release of the beta version. This also denotes that any novel improvement in this area can attract many users in a relatively short period of time.

According to the query logs, 84.9% of queries are associated with keywords. An investigation over the popular keywords yields Table 2.2. The category is selected from Thingful's predefined categories including Energy, Home, Health, Environment, Flora and Fauna, Transport, Experiment, Miscellaneous. Apparently, environmental sensing related keywords such as “air quality" and “radiation" have been very popular amongst users.

The category analysis in Table 2.2 shows that for the majority of the queries, transportation related keywords constitute less than 3% of the search queries. On the other hand, keywords that are related to the environmental scanning, constitute more than 67% of the search queries. Thus, in assigning computing resources, environmental data sources should receive more attention. That is, more effort is needed to make the environmental data sources updated and in this way, we can use our computing resources more efficiently.

2.3.2 IoT Data Characteristics

IoT data is semi-structured as the popular format in IoT data transmission is JSON. To provide a more detailed vision over IoT data characteristics, we investigate *data source types* and the *dynamics* and the *quality* of IoT data.



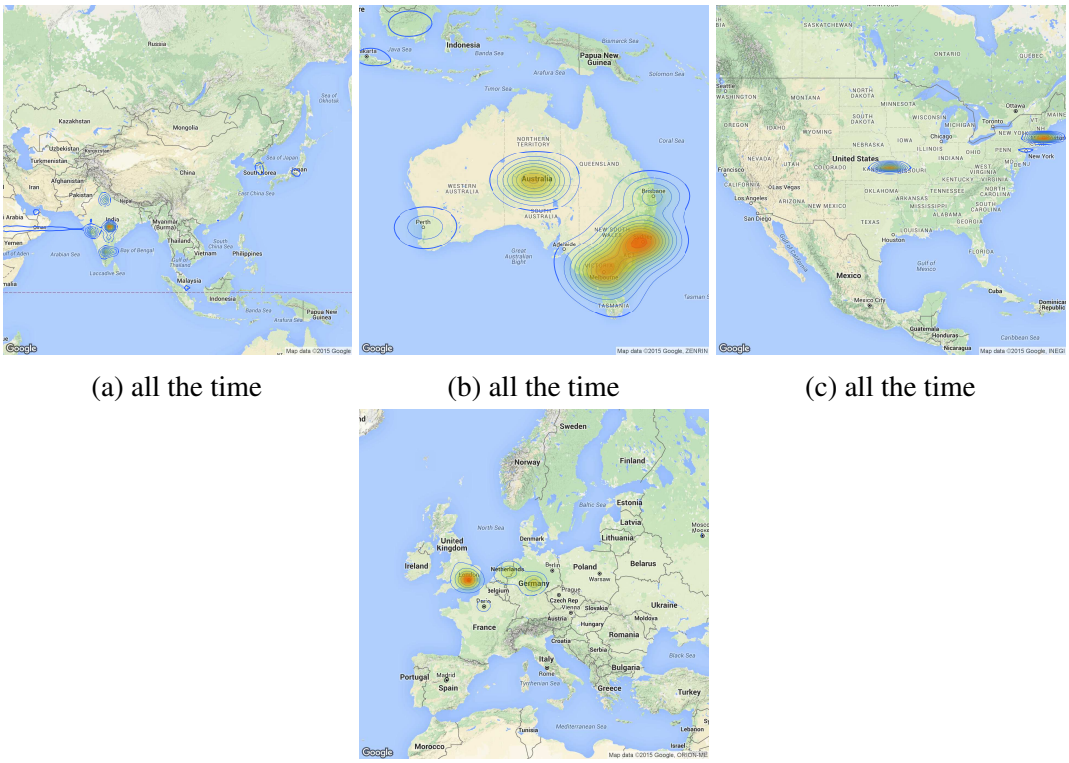
(a) 6pm ACST (b) 12am ACST (c) 6am ACST

(d) 6pm ACST (e) 12am ACST (f) 6am ACST

(g) 6pm ACST (h) 12am ACST (i) 6am ACST

(j) 6pm ACST (k) 12am ACST (l) 6am ACST

Fig. 2.4 The distribution of things trajectories on a map



(a) all the time (b) all the time (c) all the time

(d) all the time

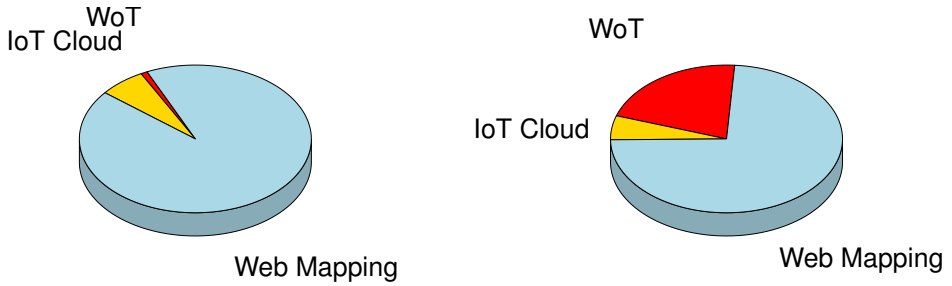
Fig. 2.5 The distribution of IoT queries on a map

Table 2.2 Most popular keywords and their categories

	keyword	**freq**	**category**	**%**
1	air quality	71,700	environment	61.7
2	sensor	3,348	misc.	2.8
3	ship	1,851	transport	1.6
4	radiation	1,825	environment	1.5
5	earthquake	1,601	environment	1.4
6	gamma	1,131	environment	1.0
7	weather	876	environment	0.8
8	shark	851	flora and fauna	0.7
9	temperature	581	environment	0.5
10	camera	397	home	0.3
11	car	392	transport	0.3
12	iphone	271	home	0.2
13	fridge	259	home	0.2
14	webcam	255	home	0.2
15	aircraft	247	transport	0.2
16	sharks	245	flora and fauna	0.2
17	energy	242	energy	0.2
18	food	239	home	0.2
19	netatmo	216	environment	0.2
20	coffee	177	home	0.2
21	traffic	168	transport	0.1
22	transport	166	transport	0.1
23	cars	163	transport	0.1
24	raspberry pi	159	experiment	0.1
-	other keywords	28,771	-	24.6
-	Total	116,131	-	100

Data Source Types

As Figure 2.6a suggests, amongst the publicly available data sources, Web Mapping serves the majority of things (88%), which is followed by IoT Cloud services (7%) and WoT (1%). However, in exchange we observe that a larger number of data sources use WoT to share IoT data on the Web (Figure 2.6b) while most of the IoT cloud platforms do not provide access to any public data.



(a) Number of things by each technology (b) Number of websites by each technology

Fig. 2.6 Major provider technologies for public IoT data

Table 2.3 WoT vs. IoT cloud services

Data Source	**Public Sensors (Things)**	**Type**
Xively	~67,000	IoT Cloud
WoTkit	4,065	WoT
ThingSpeak	3,571	WoT
WikiBeacon	30,052	WoT
ISMN*	2,080	WoT

*International Soil Moisture Network

To grasp a more detailed image of IoT clouds and WoT, Table 2.3 shows WoT and IoT clouds and the number of non-private things which use these technologies.

Spatial and Temporal Distribution of Things

Understanding the spatial and temporal distribution of IoT and query updates is valuable for identifying the existing gaps, which can help in predicting the trends of searches and updates. To model the spatial gaps between IoT and queries, we use the Earth Mover's Distance (EMD) measure. EMD describes the normalized minimum amount of work required to transform one distribution to the other. In our case, given the two distributions matrices of things, d_1 and d_i, which have been taken in timestamps t_1 and t_i respectively, we want to measure the amount of changes in the latter distribution (d_i) from the initial distribution d_1 using $EMD(d_1, d_i)$ measure. Therefore, we can monitor the changes in distribution over the time.

We summarized the two datasets into a list of density indices shown in Figure 2.7. The length and width of each record density index is 5 degrees of longitude and 5 degrees of latitude, respectively. The EMD yields 0.4338619 for an image of IoT data and the whole queries dataset.

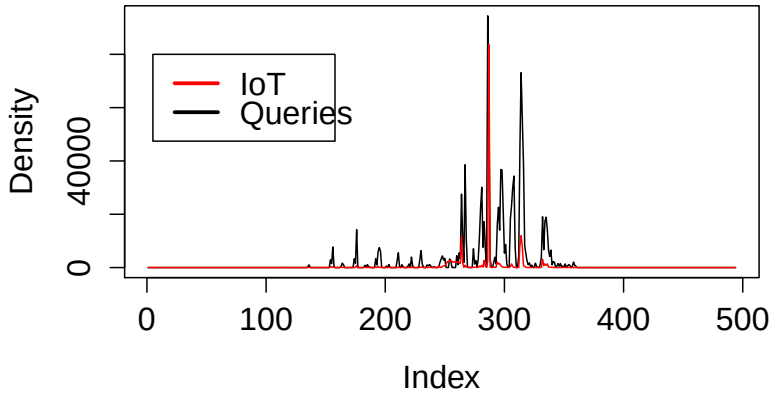


Fig. 2.7 Comparison of the densities of the query logs and IoT data

In the next step, we want to know whether the patterns in Figure 2.5 and changes in the distribution of things recur over the time. Thus, we perform the same analysis over a period of time on how the spatial distribution of things changes through the time. In particular, we use the emdist [72] implementation to approximate the EMD score for each transition. Figure 2.8 shows the EMD score for a given period of time in 48 timetamps which we have collected within 48 hours. The curve shows that in each given timestamp t_i, the value of $EMD(t_1,t_i) \in [0,1]$. Thus, the EMD score for t_1 is 0 since there is no difference between the distribution matrix in t_1 and itself.

Shortly, a huge amount of change is observed between t_2 to t_5 and later the EMD score continuously decreases as the distribution returns to its initial status. The very same pattern recurs on the next period of time. As a result, we understand that the geospatial distribution of things goes back to its original state over a period of time (in this case, after 24 hours). This

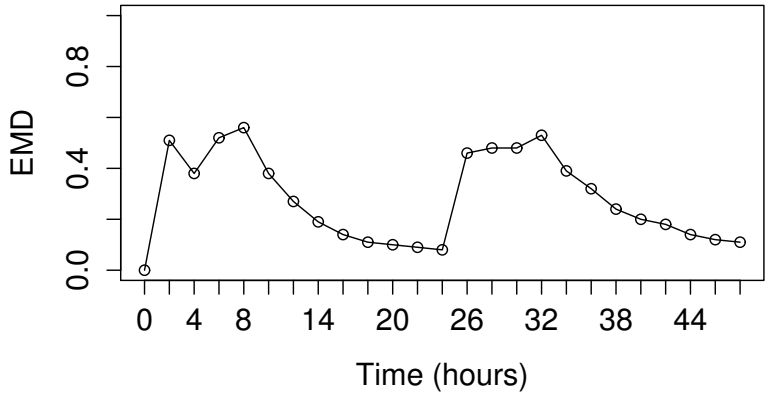


Fig. 2.8 EMD score for things data during 48 hours

result can assist in setting up new strategies for saving computing resources when updating the things dataset. For example, during an update process, we can scan the areas with higher densities more often than the lesser dense areas.

Table 2.4 Example of selected parameters from a set of readings of a specific sensor in Xively

	id	title	private	status	updated	Created	value	Symbol
1	1213	house	false	public	2015-06-10T13:01:59.997058Z	2008-11-27T18:20:25.169483Z	77.46	F
2	1213	house	false	public	2015-06-10T20:31:00.777699Z	2008-11-27T18:20:25.169483Z	78.56	F
3	1213	house	false	public	2015-06-11T03:50:00.136106Z	2008-11-27T18:20:25.169483Z	79.5	F

Data Dynamics

IoT data are widely regarded as highly dynamic and volatile [46]. Although several approaches have been proposed to tackle various problems caused by the dynamic nature of IoT, no other work investigates the real-world IoT data on their dynamics. With our first-hand dataset collected, we observe the following interesting aspects on IoT data:

- Only a small portion of IoT data changes frequently. This finding can be easily checked by measuring the number of things and the amount of data that is being updated (new sensor reading during the next IoT scan). For instance, Figure 2.9 shows the ratio of things which have updated their previous readings from nearly 70,000 objects on the Xively network, which is a part of our things dataset. The ratio of updated rows $r \in [0,1]$, is obtained from the following equation:

$$r(i,j) = \frac{|diff(d_i, d_j)|}{max(|d_i|, |d_j|)} \tag{2.1}$$

  where if D is the domain of sensor readings, $d_i \in D$ denotes sensor readings in timestamp i, $diff : D \times D \rightarrow N^+$ is a function which returns the new rows in d_j and also $j > i$. Here, the time difference between each $j-1$ and j is 6 hours. As shown, up to 23% of objects have new sensor outputs during the experiment. Furthermore, only a small part of each tuple gets updated each time. Table 2.4 shows an example from the Xively platform. We only select a small subset of the attributes (77 attributes in the original version) for the illustration purpose. As it shows, only the *value* attributed is being updated every time.

- Frequencies of updates for the same object from different data sources can be highly variant. For instance, with every flight tracker website the sensor readings for flights are updated several times per second, while in MarineTraffic the sensor readings for ships and vessels are updated every three minutes.

- Similar to the geographical distribution of objects, IoT dynamics may follow patterns over the time. As Figure 2.9 shows, the ratio of updated values decreases when increasing the number of steps. This indicates that many of the updated tuples return to their initial values after a while. For example, an air quality egg, which is an egg shaped device to measure indoor temperature and air quality, may report the similar temperature in 24 hours.

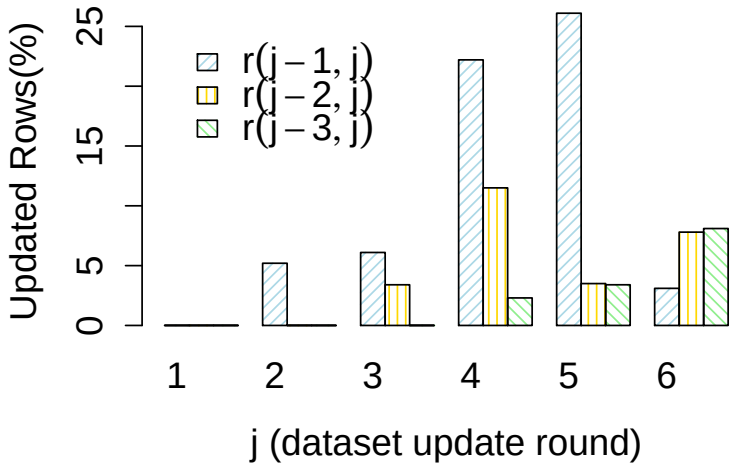


Fig. 2.9 Ratio of the rows with new sensor outputs

Data Quality

We observe that different data sources, may share the data that is being generated by the same sensors. One of the interesting points in the integration of IoT data would be knowing the redundancy. Also consistency of the redundant data will be an interesting topic for researchers.

Table 2.5 shows a list of redundant sources of IoT data and the type of the things that they cover. We select a few data sources which seem to be more popular from three different

categories: *flight tracking* and *marine traffic tracking*. Every object from these sources is associated with an identifier which can distinguish it from other objects. We merge the data from all websites in each category to get the ratio of inclusiveness. This measure denotes the rate of the objects which exist in the data source and the union set of objects for the corresponding category.

For the captured flight data, the objects information from different sources is quite different. There are two main reasons associated with this issue. The first reason is the delay in updating the information. The second reason is the loss of some values for some flights. For example, the flight registration is provided by a data source while the same attribute for the same flight is not set in other websites. For the marine traffic tracking websites, we observe that the majority of niche websites are using the same techniques and data as the source website. No delay is observed while the ratio of overlapped data is higher than flight trackers.

Table 2.5 Transportation data sources with overlapping set of objects

Application	URL	Scope	Novel Data	Inclusiveness	Delay
Flight tracking	http://www.flightradar24.com	Worldwide	✓	99.99%	-
	https://flightaware.com/live/		✓	0.01%	✓
	https://planefinder.net		✓	0.01%	✓
	http://www.radarbox24.com		✓	0.01%	✓
	http://www.radarvirtuel.com		✓	0.01%	✓
	http://tinyurl.com/klmliv	Airline	✓	0.01%	✓
	http://tinyurl.com/perthliv	Airport	✓	0.01%	✓
Marine traffic tracking	http://www.marinetraffic.com	Worldwide	✓	100%	-
	http://www.shipspotting.com/ais/		✓	0.01%	✓
	http://ship.gr/map/index.htm		×	100%	×
	http://www.cruisemapper.com	Cruise	✓	0.01%	×
	http://www.cruisin.me/cruise-ship-tracker/		×	100%	×

2.3.3 IoT vs. User Interests

As mentioned, the analysis of the distribution of things and queries can lead to finding more efficient strategies for storing and retrieving IoT data.

Our observation shows that in many cases, there is a huge difference between the distribution of the queries and the distribution of the things data. Figures 2.5a, 2.5b and 2.5d show the local distribution of the queries from Thingful in Asia, Australia and the Europe, respectively. We do not include other continents such as the Americas and the Africa as their results do not add new information on top of the selected regions. As the figures show, in each region most of the queries are focused on specific regions such as India, East Coast of Australia and London.

We also investigate the distribution of the things and its changes over the time in each region separately. We randomly pick a 12-hour time frame and conduct the analysis over three snapshots all over the world. Due to the space limit, we select three snapshots and investigate the distribution of the things in each region. The first snapshot is during evening, the second is during early morning and the third is around noon. The snapshots are all based on the Australian Central Standard Time (ACST). In Asia, during the afternoon most of the things are concentrated on East Asia (Figure 2.4a) while later in the morning the concentration of the things transfers to the South West Asia (Figure 2.4b). In the next snapshot, the concentration moves towards South East Asia again (Figure 2.4c). A large part of this change is due to the existing large ratio of flight data comparing to the other types of things data in Asia. However, in Asia, no record demonstrates a good match between the distribution of things and the distribution of the queries, while most queries are concentrated on India (see Figure 2.5a).

In Australia, things are mostly concentrated on the east coast of Australia during evening time (Figure 2.4d) which is a good match for the distribution of the queries (Figure 2.5b). Later as Figures 2.4e and 2.4f show, many things are present in other places as well as around

the capital cities of Sydney and Melbourne. Thus, a huge gap exists between the distribution of things and queries in this region. However, unlike Asia, the distribution of the things partially matches with the distribution of the queries over the two cities.

In the US, the snapshots demonstrate the change of distribution throughout the time during daylight. The distribution of things continuously spreads from the east coast to the west coast as Figures 2.4g, 2.4h and 2.4i illustrate. However, there is a loose connection between the queries distribution 2.5c and things distribution over the New York.

The situation is quite different in Europe. As Figures 2.4j, 2.4k and 2.4l show, a large number of things are constantly concentrated over London area and partially over Germany which is a very good match with the distribution of the queries in this part of the world (Figure 2.5d).

2.4 Discussions

In this section, we provide further discussions on the challenges and opportunities for IoT research and development.

2.4.1 Challenges in IoT Data Discovery

IoT data discovery is important towards establishing the next step in the life of the Internet. Since the early days of IoT, several technologies have been specifically proposed to share IoT data. There have been several successful stories for cloud based IoT platforms such as Xively and Paraimpu. They are often designed to provide global support for almost any type of sensors or actuators.

However, the community of users does not restrict themselves to what these IoT platforms provide. An increasing number of techniques are being used to publish sensory data on the Web. The number of sensors, various types of applications and the increasing demand

for real time data have driven to reinvent various techniques which are previously used for other purposes (e.g., Web Mapping). In this case, a large number of niche websites have been developed to publish the data that are generated by specific sensors or for specific applications. In fact, the volume of the publicly available information provided by these websites is much more than the general purpose IoT cloud platforms. However, identifying these websites is similar to finding a needle in haystack as there is no comprehensive list of such websites, many of which have been created recently after the success of similar applications such as the flight trackers.

Another challenge is the structure of the data that is provided on the Web. For a large portion of the websites, the data should be collected from the deep Web. For example, to obtain the results from a flight tracker website, several parameters need to be set and passed. Otherwise, a small subset of the data or an empty set will be provided by the server. In some cases, authentication may also be required as a part of the process when accessing the data.

Unlike other types of the information on the Web, IoT data mostly are presented in a structured or semi-structured format. The structure of the data widely varies from one website to another. In addition, in many cases, the parameter names are not self descriptive and these parameters need to be demystified manually.

2.4.2 Information Retrieval in IoT

Currently, IoT search is quickly evolving to address the needs of users and leverage the benefits of deploying IoT. This includes preserving accuracy, speed, consistency and ease of use for IoT search engines in future. Thus, new search forms such as searching the retrieving knowledge from things data, intent-based search are emerging which in turn require proper data source selection, tackling query ambiguity [38].

We consider a simple example to further explain this point. For example, a user may search for air quality in a specific area rather than a specific air sensor. To answer her query,

firstly, the documents containing air quality sensors in that area should be retrieved. Secondly, sensors which also provide contextual information about the air quality should be retrieved as well. Thirdly, knowledge about air quality can be extracted from the selected documents. We should note that due to the high uncertainty in IoT data, some estimation or prediction (in case of data unavailability) techniques may be used to fill the empty pieces of the puzzle. Finally, result diversification would be very important to address issues such as query ambiguity.

Due to the highly dynamic nature of IoT, documents containing IoT information can change drastically from the time when they are crawled to the time when their data are presented. Thus, effective and efficient indexing techniques would be required to retrieve information from IoT data.

Furthermore, IoT will leverage *Temporal Information Retrieval* more [73]. We observe that the content of a large number of documents as well as the data sources, may variate between 1% to 100% in a very short period of time. With the high rate of changes in IoT data sources, document selection as well as the user query results will require novel temporal techniques to tackle the issues.

2.4.3 Other Challenges

Our dataset can be used for a variety of purposes in the IoT research and development, including correlation discovery between things [74], IoT data storage [75, 59], context aware computing for IoT [76] by merging sensor readings from different sources such as environmental and transportation sensors, point of interest recommendation [77] and other active IoT research areas which may need real-world data.

Data Integration

Continuous retrieval of IoT data is very challenging. Some of the sources demand authentication before providing the access. In many cases, data for the same object (e.g., an aircraft)

is being broadcasted by different data sources. Furthermore, in some cases, each available source may only provide partial information for an object. The similar issue affects merging data for the same resource. For example, the results of parsing objects data for a single resource have different length and parameters which need to be integrated at the end. Lastly, many data sources limit their response length due to load balancing concerns. We do not fully resolve all challenges in the integration but rather, we use an efficient approach to integrate the data from different sources for the purpose of our research. However, the integration of IoT data is more challenging than what is believed and more research in this area is required in the future.

Scalability

Collecting, processing and storing IoT data can be a time consuming procedure, particularly if the size of the dataset is large. As the number of sources and objects increases, which might count in billions, using one instance of the crawler would be very inefficient. In particular, dramatic difference between the update rate of different data sources which also partially depends on their size, can be challenging. Furthermore, technical failures of one resource may affect collecting data from other data sources in the same chain. Thus, we use a distribution strategy to coordinate different instances of the crawler running on different machines.

Archiving IoT Data

IoT fully interprets the Big Data. The volume, velocity and the variety of the data generated by things are enormous. The amount of the data that is already being published from 20 IoT data sources on the Web, which we estimate to be more than 100 TB a day, is already comparable to the amount of data that is being generated by users on social networks. With

the rapid growth of the IoT, in the near future, new techniques will be required to effectively and efficiently process and store IoT data.

Currently, to the best of our knowledge, there is no popular website for archiving the publicly available IoT data. In this regard, the traditional approaches need to be revised for the new era of the IoT. The result can be valuable to many core applications such as IoT search while we compromise on some issues to make the impossibles possible. For instance, we discover that based on the changes in the geographical distribution of objects, a crawling strategy can be issued to capture the most updated data in the least amount of time. Through creating spatial and per resource indexes, the process can also become more optimized.

2.5 Related Work

Over the past few years, the IoT has received increasing attention from researchers and practitioners. In the earlier days, Atzori et al.[3] offers an initial survey on the IoT research. Accordingly, there exist manifold definitions of the IoT paradigm within the research community. Each definition may view this paradigm from a specific angle including things oriented, Internet oriented and semantic oriented definitions. More specifically, based on all these definitions, a wide variety of networking and sharing technologies have been used to enable the future IoT including but not limited to the Web of Things (WoT) [28], RFID, Near-Field Communication (NFC), middleware and the Wireless Identification and Sensing Platform (WISP) [78].

Some researchers have claimed that the IoT is implemented with the technologies specifically designed for the purpose of being deployed in IoT [44]. Thus, it is argued that the IoT already exists but only a small number of experiments and as a result, yet many researchers consider as inaccessible [44]. Restricting IoT with this point of view is contrary to the spirit of open systems at the heart of the original Internet standards. Moreover, within the technologies which have been applied to facilitate IoT, open Web technologies including

HTML, Ajax, HTTPS, OpenID and structured data apply equally well to IoT. However, yet there is no advanced mechanism to be able to effectively search and retrieve things from the Web.

The very diverse range of the objects, approaches and technologies used to implement IoT have contributed in broadening the definition of this paradigm. For instance, the IoT can be realized through deploying an RFID ecosystem consisting of objects tagged with numerous RFID labels [79]. Another option is to build the IoT using smart objects [80] which in turn can be divided into activity-aware, policy-aware and process-aware smart objects.

Cloud based platforms such as Paraimpu [53, 81] and Xively provide environments which have been considerably discussed in the literature. In the literature, WoT is not the only, but is one of the mostly adopted technologies to facilitate the future IoT. The WoT concept describes approaches, software architectures, frameworks and programming patterns that allow things to share their data with human beings through the World Wide Web. Currently, WoT is an active research area with a wide range of challenges and opportunities including security, resilience, intent oriented search, legal implications and so on [28].

Currently IoT search is a trending research direction [82] with stress over some major goals such as real-time search [83], context-awareness [76] and relationship support [84].

Researchers have complained about the lack of real-world IoT data in the past [74]. Although some of the previous works have claimed testing their proposed solutions for large scale IoT data, such as meta-heuristic [85] or context aware sensor search [76], all these previous works mainly deal with small or simulated datasets. To the best of our knowledge, no work has ever collected or analyzed large scale things data. In addition, none of the existing works use real IoT search query dataset. Moreover, we could not find any other work that has deployed or analyzed a large real-world IoT query dataset for mining user interests in the IoT domain. By combining the user interests and the IoT data, we can analyze the gap of what people look for and what currently the IoT presents on the Web. Our work is the

very first that investigates IoT in large scale and the dataset released from our study is the first real-life, large IoT dataset that is publicly available for the research community.

2.6 Summary

The unique characteristics of IoT require that the future search engines provide support for a variety of new requirements. Firstly, IoT is no longer solely attached to the public cloud based solutions, and IoT indeed has been spreading by all means throughout the World Wide Web. Secondly, due to the dynamics of IoT, future search engines need to provide real-time results. In this work, we conduct an in-depth analytical investigation on IoT data that exists on the Web. Based on our real-life IoT data, we investigate the current status of the IoT and identify open research and development issues. Our findings show that conventional geospatial data presentation techniques such as Web Mapping play an important role in disseminating IoT data. We also discover that the environmental scanning is the most popular application of IoT followed by transportation while transportation data sources require the majority of the resources. We also show that we can find patterns on the updates and the distribution of things. Moreover, our observation shows that the presentation of things data is limited and very isolated. Thus, in the next chapter, we focus on correlating things from a bottom-up perspective. In a bottom up perspective, data sources can process the data of the things which belong to them then extract and present the correlations to an external viewer such as a search engine.

Chapter 3

Interlinking IoT Resources

Our observation in the previous chapter shows that IoT data is widely visualized and presented through Web mashups. For instance, Figure 3.1 shows an example of Web of Things mashup from the ThingSpeak platform [86]. As shown, none of the parts of the present mashup is referring to other mashups or correlated things on the Web. As a result, correlations remain implicit and IoT resources may remain isolated from each other. Interlinking relevant smart things will trigger improved user navigation as well as providing a solid foundation for crawling WoT. This is a very critical issue which resembles the role of hyperlinks in the traditional Web.

A hyperlink is a reference to Web resources that the reader can directly follow either by clicking or by hovering. Usually, hyperlinks are associated with a textual description about their target, which is called hypertext. Hyperlinks play a key role in interlinking Web resources and provide navigation between different Web pages for users. Web crawlers which are deployed by search engines are navigated based on the existing hyperlinks in a Web-based document [87].

To enable the interlinking between resources in the context of interconnected networks of things, one eminent issue is that the traditional approach of interlinking Web documents, cannot fully unravel the benefits of interlinking IoT. In this regard, IoT-specific requirements

Fig. 3.1 Example of Web mashup from ThingSpeak platform

Table 3.1 Requirements of traditional WWW hyperlinks vs. novel IoT-links

	Hyperlinks	**IoT-Links**
Establishment	manual	automatic
Term	long-lasting and fixed	short term and highly dynamic
Connection Types	simple (single type)	various types
Weighted	No	Yes
Node Types	web pages	heterogeneous resources
Users	human users and crawlers	smart things, human users and crawlers

must be taken into account. Table 3.1 summarizes the differences between interlinking IoT resources vs. hyperlinks in the traditional Web.

Due to the highly dynamic and heterogeneous nature of IoT, correlations between entities may quickly outdated due to the frequent changes in the status of things. Thus, one eminent issue is how to effectively and efficiently establish and maintain the links to the correlated resources. As the Table denotes, IoT-links have different requirements from hyperlinks in the traditional Web. Automatic maintenance of IoT-links require a solid understanding of the implicit correlations between IoT resources in the physical world.

Although every pair of smart things around the world could potentially be correlated, in the context of IoT, correlations may not necessarily share the same type or the same weight.Thus, several types of correlations can be identified between interconnected things [40]. For instance, the type of the correlation that exists between two things that belong to the same person (`owned by` correlation) can be different from the correlation between two objects that are present in the same physical area (`co-located` correlation). Moreover, correlations of the same type, may not necessarily have the same weight. For example, the weight of co-located things may vary based on their distance from each other.

In this chapter we propose the CEIoT (**C**orrelations **E**xtractor for **IoT**), a framework to facilitate automated correlation extraction for smart things in IoT. We use Multi-Agent System (MAS) architecture to design and implement our approach in order to be able to simulate the behaviours of smart things in real-world. Our framework regulates the extraction of different types of correlations. The correlation types that we cover in this chapter are defined as follows [40]:

- Ownership object relationship (OOR): correlates objects with the same owner.

- Co-location object relationship (CLOR): correlates objects that are physically close to each other.

- Category based object relationship (CBOR): correlates objects which have the same describing tags.

In our CEIoT framework, we provide correlations with normalized weights to enable our model to represent more details from the real-world. Thus, our approach employs a weighted undirected graph to model the heterogeneous network of things. In this chapter, we assume that each thing is registered only to one network and belongs only to maximum of one user. We only focus on the publicly available things. We design a distributed and scalable

framework to support the correlation extraction and use Open Linked Data to present the extracted correlations. Our contributions are summarized as follows:

- We propose our CEIoT framework to extract things correlations in IoT. Our approach can support correlations with different types including CBOR, CLOR and OOR. We use a distributed architecture to enable our CEIoT framework to estimate the weights of the correlations. To the best of our knowledge, other approaches focus on one type correlation or have only been deployed in small scales.

- We define the process of correlation discovery for IoT. We propose two novel algorithms for extracting and one algorithm for integrating the extracted correlations. In the CEIoT framework, we localize CBORs and estimate the weights of correlations for CLORs to increase the efficiency of the correlation extraction process. We increase the efficiency of correlation extraction and integration using a distributed architecture.

- We conduct extensive experiments to evaluate our approach. We use both synthetic and real-world datasets to and demonstrate the efficiency and effectiveness of our framework based on measures including system performance and number of messages.

The remainder of this chapter is organized as follows. We describe the CEIoT framework in Section 3.1. We present the results from the implementation of the framework in Section 3.2. Section 3.3 reviews the research activities that are relevant to our work. Finally, we summarize the chapter in Section 3.4.

3.1 The CEIoT Approach

In this section, we present the details of our CEIoT architecture for automated extraction and representation of the correlations between things in IoT.

3.1.1 Correlation Discovery Process

Today, there are many online IoT platforms such as Xively [29] and Paraimpu [53, 81]. Despite of their large scale and complexity, no means has been deployed to analyze or present the correlations between things. This includes the correlations of things of both inter and intra data sources.

We define correlation discovery as the process of extraction and representation of correlations of any types that exist between the resources in the IoT. Figure 3.2 illustrates the process of correlation discovery for the IoT consisting of four different phases: *Collection*, *Extraction*, *Integration* and *Presentation*. In the first phase, things' data is collected via RESTful application interfaces and maintained on a server. In the next step, *Extraction*, the similarity of given object pairs is examined based on different measures and criteria to extract the correlations. During the *Integration* phase, all of the extracted correlations are integrated to form a *Things Correlations Graph* (*TCG*) [38], which resembles the graphs in the traditional social networks. Finally, in the last phase, the edges of the TCG are converted into IoT hyperlinks.

3.1.2 Framework Architecture and System Entities

Our CEIoT framework architecture is inspired by MAS framework. We design and implement a set of agent classes with built-in behaviors which facilitate the simulation of important entity types and their interactions in IoT correlation extraction problem. In the next step, agents are instantiated and deploy pre-designed communication protocols to interact and submit/receive messages. An overview of the CEIoT framework is shown in Figure 3.3. Each platform in our framework operates independently from other platforms as IoT platforms operate in the real-world. The figure shows the main types of agents in each platform and how their instances interact with other parts of the system such as smart things, database and other platforms. Each platform maintains its own correlation database and Data Facilitator

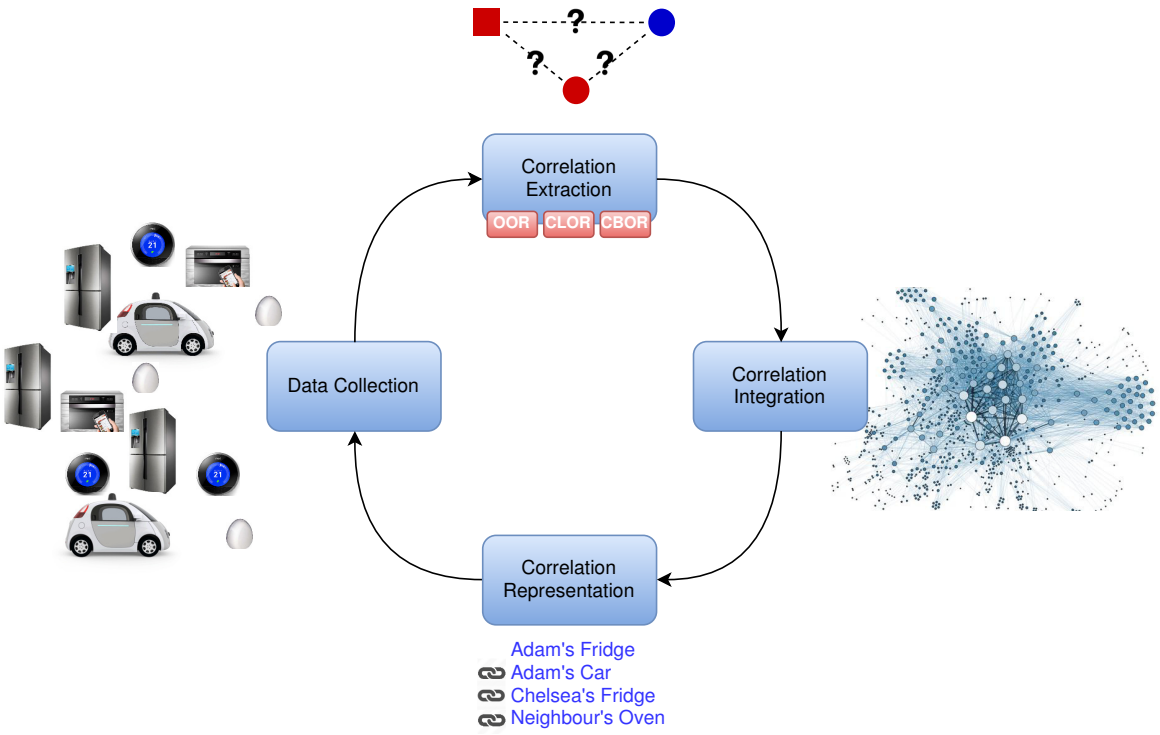


Fig. 3.2 Different phases of the correlation discovery process in IoT

(DF) Service. As shown, agent classes include Service Agent, Object Agent and DF Agent. Due to the huge complexity of the nature of human user behaviors, we do not simulate them in our system and leave it for future works in this area. Existing agent classes and their roles are described in the following.

Object Agent.

Object Agents are the main building block of the system; the smart things. These agents maintain the characteristics of the “things" that are connected to IoT and contain necessary behaviors to facilitate interconnections with other agents such as updating characteristics/readings and service registration. These agents constitute the largest number of agents in the system as each Object Agent is launched for one “thing" only. Each Object Agent models $A_i^o = (t, dt, lat, lon, u)$ such that $t \subset T$, $dt \in \mathbb{R}$, $lat \in \lfloor -90, 90 \rceil$ and $lon \in \lfloor -180, 180 \rceil$, $u \in U$ where T is the set of descriptive tags, dt is the latest datastream reading, u is the owner of the

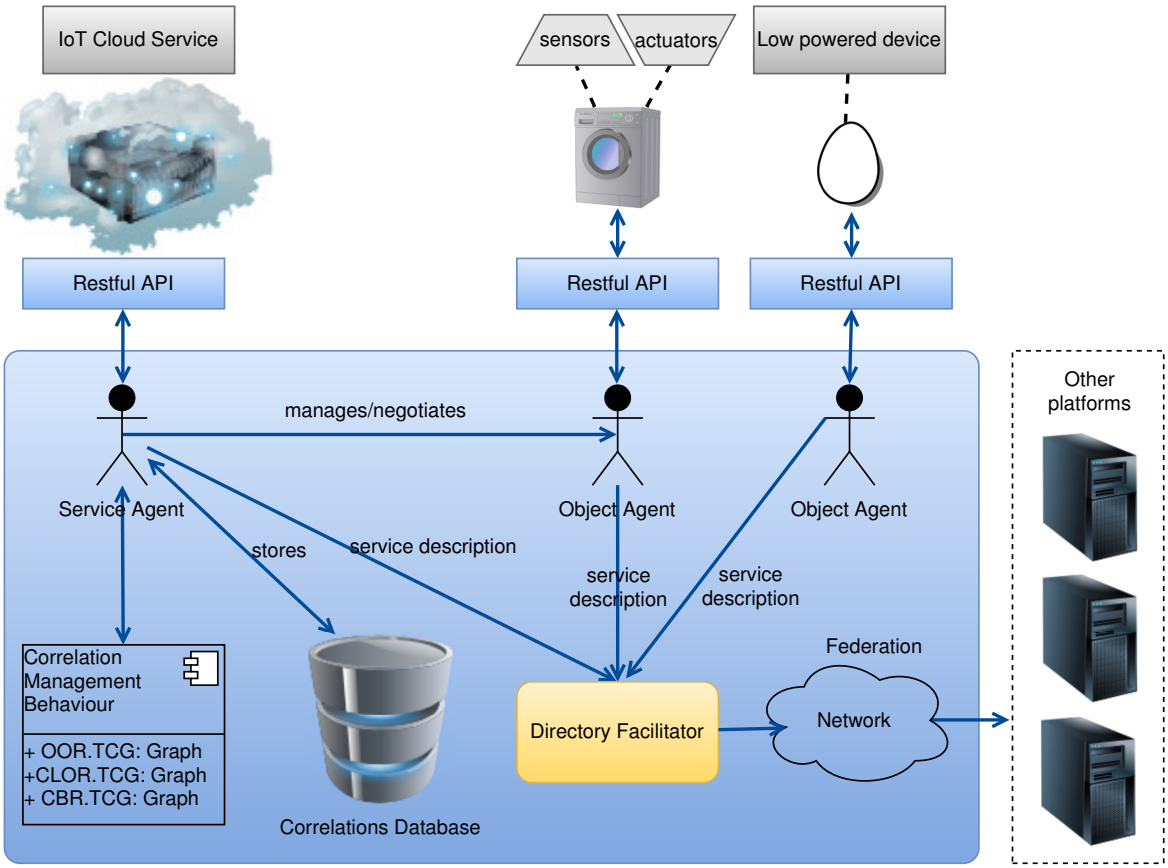


Fig. 3.3 A general overview of the CEIoT framework

smart thing and lat, lon are the latitude and longitude of the object, respectively. Also, the Object Agent contains at least three default behaviors. One is to register their descriptive tags (t) into DF service. Two other behaviors are for updating location and other characteristics.

Service Agent.

A Service Agent represents an IoT service provider (IoT platform) which facilitates the management of Object Agents. There is only one service agent per platform. It is responsible for coordinating and managing all agents present in its container as well as correlation discovery. These agents maintain all of the necessary information about their corresponding IoT platform. This includes host URL, port, Agent Communication Channel's address, platform ID and the DF Agent. Moreover, the Service Agent can launch, suspend or destroy Object Agents if required. It can directly communicate with the IoT cloud and transfer data when required. However, the main responsibility of the Service Agent is to enquire other agents and update the correlation database frequently.

DF Agent.

DF service facilitates the address book of each platform. Intra-platform agents can enquire the DF service to find agents with the specified services. The DF Agent stores tuples of services and agent URIs in the form of $\{(t,a)\}$ such that $t \in T$ and $a \in A$ where T is the set of descriptive tags and A is the set of all agents in the platform. Usually, DF service is provided only for the platform agents internally and is not designed to be shared across multiple platforms. Hence, inter-platform agent communication cannot be established in this situation. To avoid having a number of isolated MAS platforms, we devise a medium to share DF data across authorized platforms.

3.1.3 Correlation Extraction

Correlation extraction is the key step in the IoT correlation discovery process. In this step, our aim is to set up an efficient approach to extract the three types of correlations discussed earlier. As each type of correlation is discovered independently, firstly, we propose a separate approach for each correlation type. Then secondly, we investigate how we can integrate the process and the results.

CLOR.

Given a pair of Object Agents (A_i^o, A_j^o) and a threshold $t \in [0,1]$, CLOR can be defined as follows:

$$\texttt{clor}(A_i^o, A_j^o) = \begin{cases} \frac{\Delta(A_i^o.l, A_j^o.l)}{max\{\Delta(A^o.l, A^o.l)\}} & if\ \Delta(A_i^o.l, A_j^o.l) \geq t; \\ 0 \qquad otherwise \end{cases}$$

where $\Delta : (latitude, longitude)^2 \rightarrow R$ returns the distance between two points (Manhattan, Euclidean, Haversine and etc.).

Unlike OOR, extracting CLORs among objects can be very complex if a naive approach is used. A naive approach would require mutual comparison between every pair of things. Thus, at least two for loops are required to trace all pairs of Object Agents. Therefore, the complexity for extracting the CLORs for N things using a naive approach is $\mathbf{O}(N^2)$, which is not suitable for a large number of things as in IoT.

To overcome the complexity of naive approach, we introduce a weight estimation strategy for CLORs. Our estimation strategy uses R-Tree data structure along with capping the distance granularity to construct weighted CLOR edges between a number of Object Agents. To describe the idea of limiting distance granularity, consider the area of the parent rectangle (T) with a diagonal length $\texttt{D}(T)$. Any given pair of objects in this rectangular area will have a distance $0 \geq d \leq \texttt{D}(T)$. In this case, if we limit the granularity of the distance to $\texttt{D}(T)$ (means that the distance can only be 0 or $\texttt{D}(T)$), then the CLOR between all objects located in T

forms a complete graph $G_T = (V, E, w)$ where V is the set of objects, $E = V \times V$ is the set of edges defined between all objects in T and $w = \mathtt{D}(T)$. In order to increase the precision of the correlation weights w, we can fragment the rectangular area T and strengthen the weights of the correlations between objects in the same sub-areas. This initiates a new level with higher precision. In this case, objects in the same sub-area $t \in T'$, will have a maximum distance of $\mathtt{D}(t)$ yielding a correlation which is $\frac{\mathtt{D}(T)}{\mathtt{D}(t)}$ stronger than the previous step. For example, objects surrounded by a rectangle with $1km$ diagonal have a correlation twice stronger than objects surrounded by a larger rectangle with a $2km$ diagonal. Figure 3.4 depicts this idea.

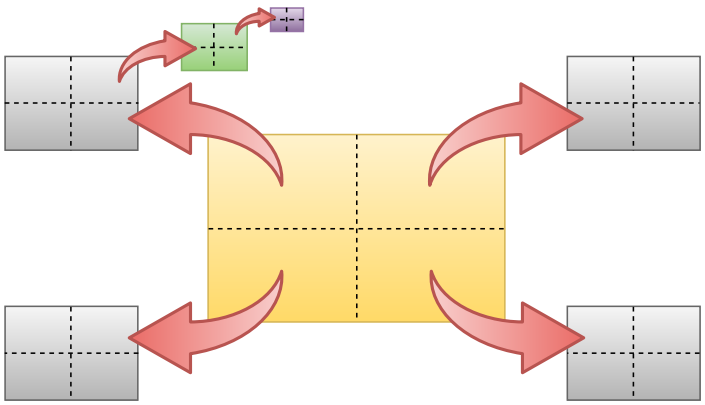


Fig. 3.4 The surrounding rectangular area recursively breaks down into smaller sub areas

Algorithm 1 describes our approach in further details. The `Extract_CLOR` is a recursive algorithm to estimate the strength of correlations between object agents. In the first level, the algorithm is launched with initial adjacency matrix $M = \{0\}_{m,m}$ where m is the number of object agents. In each recursion round (level l), the algorithm assigns correlation weights to all object agents included in the target area T. Thereafter, the algorithm would stop recursion for empty areas or if it reaches to the maximum level of granularity. The order of the algorithm would mainly depend on the distance granularity level rather than the number of object agents.

Algorithm 1 EXTRACT-CLOR

Require: Granularity level l, max level l_m, current sub-tree rectangle$T$, *global* adjacency matrix M, set of object agents A
Ensure: Set of CLORs

```
1: if |A^o ∈ T| ≥ 2 : M(A_i^o, A_j^o) = M(A_i^o, A_j^o) + 2^{l_m} / D(t) then
2:   for all (A_i^o, A_j^o) ∈ T do
3:     if l ≤ l_m then
4:       T' = subtrees(T)
5:       for all t ∈ T' do
6:         if |A^o ∈ t| ≥ 2 then
7:           call EXTRACT − CLOR(l + 1, l_m, M)
```

OOR.

OOR is defined as the correlation between objects which belong to the same person. For a given pair of object agents (A_i^o, A_j^o), they have an OOR if and only if

$$\texttt{oor}(A_i^o, A_j^o) = \begin{cases} 1 & if\ A_i^o.u = A_j^o.o; \\ 0 & otherwise \end{cases}$$

where $\texttt{oor} : A^o \times A^o \rightarrow [0,1]$ is the function that returns the OOR score.

To obtain the correlation defined above, each Service Agent can reach the federated DFs and enquire the existing agents as well as their owners. The result set can be sorted based on the owners using a quick sort algorithm. As a result, OORs can be constructed for agents with the same owners which are in the same group. The order of such algorithm would be $\mathcal{O}(n.log(n))$. The results will be indexed by the Service Agent to accelerate the retrieval of the correlations.

CBOR.

As defined earlier, each Object Agent A^o be assigned a set of textual tags $A^o.t = \{t_1, t_2, ..., t_k\}$ where each tag denotes a descriptive feature of the object such as its functionality or datastream unit. For instance, an Air Quality Egg which is designed to measures the indoor air quality and temperature, can be assigned textual tags such as "^oC", "air quality" and "indoor".

The tags are assigned by the users of the IoT platform and thus, can vary significantly based on their count, keyword selection, dictation and used symbols. We assume that the tag set for each object can be used for the purpose of categorization. For a given pair of Object Agents (A_i^o, A_j^o), a text similarity function $\sigma : T^2 \rightarrow [0,1]$ and a similarity threshold $\tau \in [0,1]$ we define the CBOR as follows:

$$\texttt{cbor}(A_i^o, A_j^o) = \begin{cases} \prod \sigma(A_i^o.t, A_j^o.t) & if\ \sigma(A_i^o.t, A_j^o.t) > \tau; \\ 0 \qquad otherwise \end{cases}$$

where $\texttt{cbor} : A^2 \rightarrow [0,1]$ is the weight function of the CBOR correlation between (A_i^o, A_j^o).

Algorithm 2 shows our approach to identify and extract CBORs amongst a set of given Object Agents. Using a naive approach for finding the similarity between all pairs of object agents is time consuming and complex. Thereupon, the three scenarios of searching for similar objects using CBOR are:

- There is no matching result and a Null value returned.
- The number of objects in the list $\leq$ *Max_results*. Thus, all objects in the list are returned.
- The number of objects exceeds the max criterion. Provided that the list is descendingly sorted, a sub list with size of *Max_results* is cut from the first element and retrieved as an answer for the query indicating that there is high potentiality to connect, correlate, cooperate, and any action can be taken with these objects.

3.1.4 Correlation Representation

Correlation representation is a part of correlation discovery process in which all of the extracted correlations are presented based on a standard format. We use RDF to represent correlations in IoT. Thus, we can maintain the connections between things while a large

Algorithm 2 EXTRACTCBOR

Require: Requester ID, Type, Sensor_ set, Actuators_ set, Max_ results
Ensure: resultsList : List of relevant objects agents

if $Results \neq \emptyset$ **then**
  for all $Object \in result$ **do**
    if $Sensors \neq \emptyset \,||\, Actuators \neq \emptyset$ **then**
      $S = \{Sensors\}$
      $A = \{Actuators\}$
      $S\_SIM(Sensor\_set, S) = \lceil Sensor\_set \cap S \rceil / \lceil Sensor\_set \cup S \rceil$
      $A\_SIM(Actuators\_set, A) = \lceil Actuators\_set \cap A \rceil / \lceil Actuators\_set \cup A \rceil$
      $Similarity = SIM.S + SIM.A$
      Assign Similarity to Object
      Add Object to resultsList
  Sort resultsList descendingly
  if $\{Results - list\} \geq Max\_results$ **then**
    Shrink the result by excluding elements from *Max_ results* until the end of the list
return resultsList

portion of them are quickly evolving. Through the use of specifically designed ontologies along with RDF correlations, our approach can be deployed to empower pattern queries for IoT search engines. In this regard, we use triple space computing (TSC) to facilitate the communication and store relationships triples.

Figure 3.5 depicts an example of how things can be correlated using RDF triples, where each object is considered as a resource. Each statement is identified via a unique URI. A statement consists of three elements: *subject*, *predicate*, and *object*. A *subject* (a thing) is linked with an *object* (another thing). The connection between two *objects* is called a *predicate*. The *predicate* explains the relationship between the *subject* and the *object* of the statement.

Two objects will have OOR if and only if they have the same owner. In this type of relationships, we point out the possibility of connecting objects under different regimes based on a criterion such as a common owner. The result is retrieved from federated DFs as graph of RDF triples similar to the following.

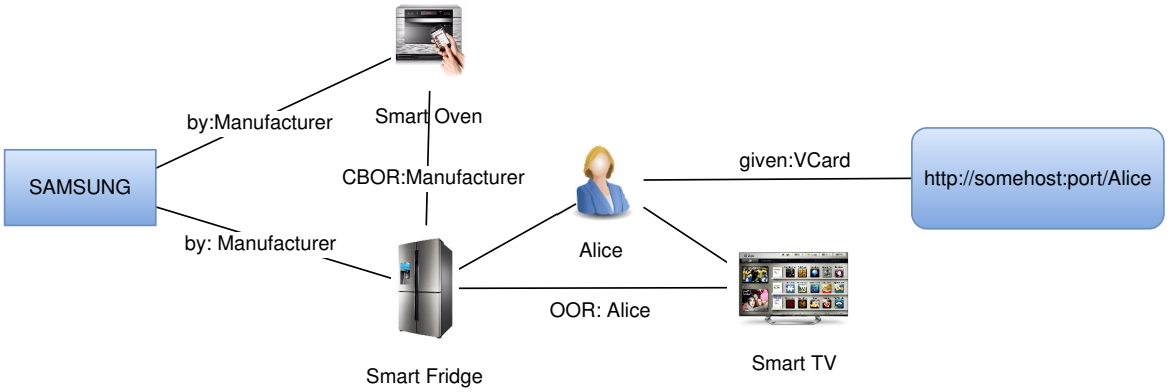


Fig. 3.5 An example of 2 types of relationships established among objects A, B, and C based on their common owners (OOR) and common tags for production batch (CBOR)

Listing 3.1 Example of OOR correlated object agents

```
<rdf:RDF
    xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
    xmlns:RT="http://uqucs.com/RT"
    xmlns:vcard="http://www.w3.org/2001/vcard-rdf/3.0#"
    xmlns:dc="http://purl.org/dc/elements/1.1/" >
  <rdf:Description rdf:about="http://uqucs.com/objectAgent10@Platform2">
    <RT:OOR>objectAgent43@Platform2</RT:OOR>
    <RT:OOR>objectAgent18@Platform2</RT:OOR>
    <RT:OOR>objectAgent5@Platform1</RT:OOR>
    <RT:OOR>objectAgent61@Platform2</RT:OOR>
    <RT:OOR>objectAgent42@Platform2</RT:OOR>
    <RT:OOR>objectAgent29@Platform1</RT:OOR>
    <RT:OOR>objectAgent48@Platform2</RT:OOR>
    <vcard:N>Tahani</vcard:N>
  </rdf:Description>
</rdf:RDF>
```

3.2 Experimental Results

In this section, we present the evaluation results for the proposed CEIoT framework. We conducted the experiments on a PC with a Core i7 2.20 GHz, 4 GB memory and Windows 7 64-bit.

We used a synthetic simulation and a real-world IoT dataset to evaluate our framework. The details of the used datasets are as follows:

1. Synthetic dataset: we simulated a set of four IoT service providers where each service provider is supplied with one Service Agents and 1,000 Object Agents. Furthermore, each service provider was initialized on a separate platform, which can run on an independent machine or share the same machine with other service providers. We use this simulation to evaluate the framework on a distributed infrastructure and for multiple service providers. Figure 3.6a shows four RMA GUIs visualizing all four platform and their agents. We used this dataset only for the purpose of examining the effect of decentralization of our approach. As all other characteristics are already featured in the real-world dataset, there is no merit in reporting the results on the synthetic approach, separately. Thus, the rest of the results are acquired from the experiment on the real-world dataset as described below.

2. Real-world dataset: we used our dataset from the previous chapter. We randomly picked the data from one of the crawling rounds from Xively [29]. The dataset contains around 67,000 things and their most recent sensor readings. However, after filtering records with incomplete data, only 11,894 records remain in our dataset. A primary analysis of the tag sets reveals that the tags are scattered (Figure 3.7a) but densely focused on some tags (Figure 3.7b). Moreover, only less than 10% of the tags have been assigned to more than 60% of things (Figure 3.7c). Thus, a single label based without considering location based correlations will not be helpful in application.

We used tools provided by *RMA GUI* such as *Sniffer* and *Dummy* for debugging and testing purposes. Dummy agent is used to communicate with agents in the platform and command them to execute specific behaviors. We prepared the agents with *Cyclic behaviors* that are responsible for receiving these commands and their execution. Otherwise, these behaviors are blocked until a command is received to prevent infinite loop. Blocking the behaviors in agents does not block the entire agent. Additional aim of implementing agents behaviors and communication is to use them as self-explained examples of how agents can

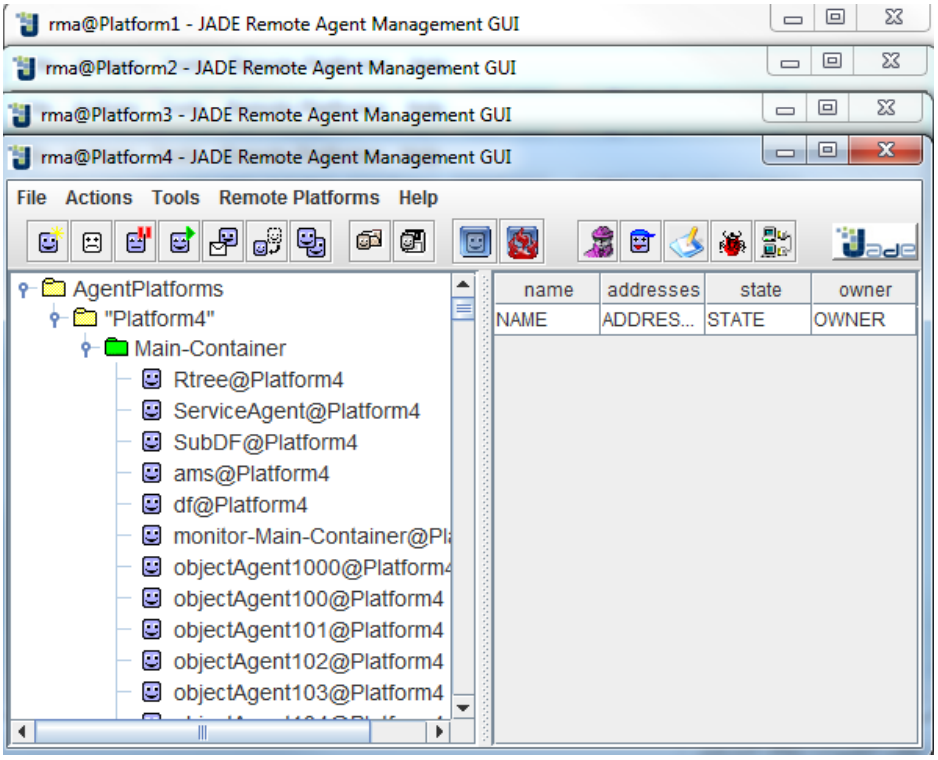
be communicated and commanded by end users of the framework using third-party agent such as *Dummy* agent.

3.2.1 System Performance

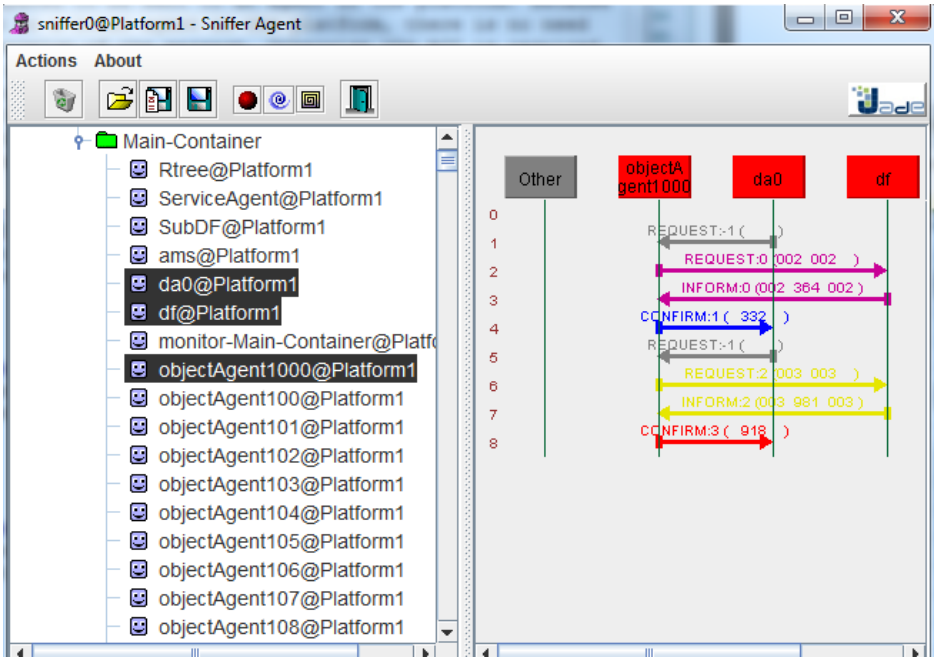
One concern is the overall performance of the framework including all aspects discussed except the relationships extraction and establishment. Mainly, the framework does the following: i) launches all independent platforms; ii) launches all agents mentioned above; iii) federates DF service; iv) communication for exchanging stetting information; v) generating RDFs and message de/serialization; and vi) R-tree insertion. Using the fixed parameters with an RMA launched for each platform, it takes the system roughly 25 seconds to perform all the mentioned key tasks. This is due to that each *Service Agent* waits for about 10 seconds to ensure all platforms are established, as well as additional 10 seconds for federation. These 20 seconds were introduced to avoid racing conditions.

The experiment was conducted on 4,000 object agents which were distributed over four independent platforms. In the worst scenario, for all objects agents, we took them under the same owner, the same sensors, the same actuators. These values were set to make them all similar in order to be able to observe the performance. Thus, when an object searches for other objects, all other 3,999 should be retrieved from the DF to an object agent requesting OOR relationships. For the experiment, each object agent has a cycle behavior that receives a message with a *Request* per-formative act. It recognizes commands OOR, and CBOR. Otherwise, it responses with a *non-understood* message associated with which commands it can understand. If the commands are understood, it complies with them to search for other agents matching the type in the command.

The communication with Object Agent was performed as expected (Figure 3.6b). The figure shows the UML sequence for sending relationship requests by the dummy agent (d0) to an object agent. Agent d0 was used in our experiment for requesting object agents to

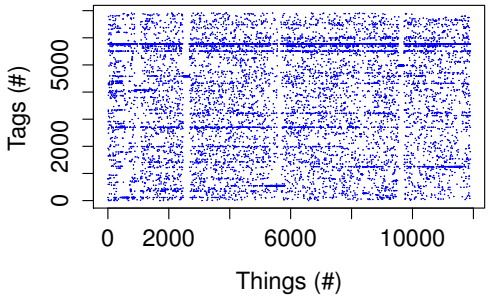


(a) RMA view of launched platforms for each service agent

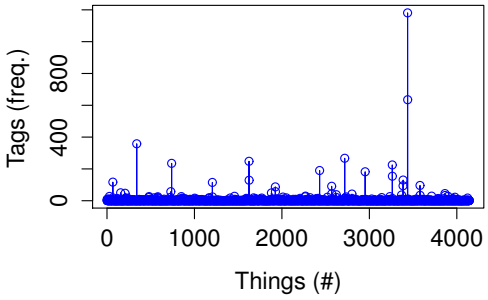


(b) Sniffed communications between two object agents

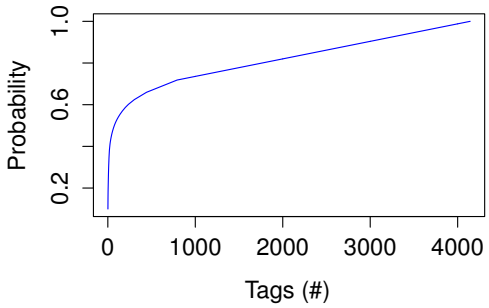
Fig. 3.6 CEIoT System View



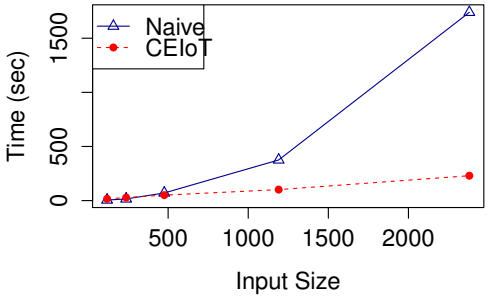
(a) Scatter plot for things and tags



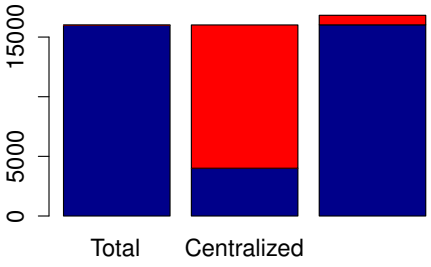
(b) Tags frequency



(c) Tags reusing probability

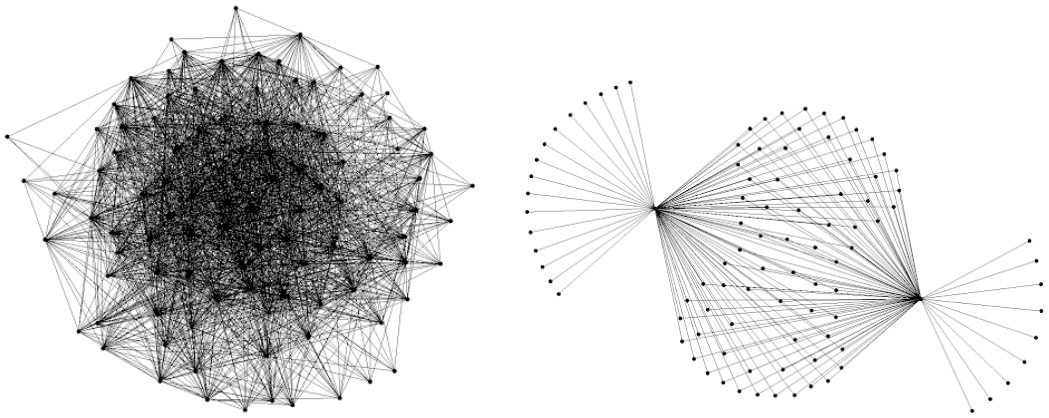


(d) Runtime for each method



(e) Message count

Fig. 3.7 Characteristics of the data set and the final results



(a) Reduced threshold (b) Increased threshold

Fig. 3.8 CLOR graphs for connections with different thresholds

perform a relationship on demand which are OOR or CBOR. Lines 1-4 shows that sending the OOR request, the agent received the request, then it searches the DF in Line 2, and DF returns the results to the agent in Line 3. Finally, the agent confirms to the dummy agent the success of the relationship establishment. Additionally, there should appear the RDF description for the relationships of the object agent. The same process is done with CBOR in lines 5-8. In OOR relationships extraction, it took 200 *milliseconds* on average to retrieve the results and correlate them with the requester object as an RDF triple. However, in the CBOR it took approximately 1,300 *milliseconds*. For CLOR correlation, we observed the proposed system's response under a varying number of input sizes to ensure the system's scalability. We compare our approach with the naive method. As Figure 3.7d shows, the naive approach may take less time for results with small sizes. However, as the size of the input increases, for inputs with 500 or more things, our algorithm's runtime outperforms the naive approach. We found out that using the naive approach for an input size with the real-world dataset would be impractical, particularly when we consider the size and the dynamic nature of the IoT.

3.2.2 Things Correlation Graph

For Algorithm 1, we applied different thresholds to simulate a search engine harvesting the graph. For example, it can be interesting in relationship matching a certain criteria. Thus, the threshold was used to reduce the search space and to limit it to connections with values equal or larger than the threshold. We visualized this by passing the symmetric weighted graph to the *GraphVis class*. The graph is the file holding all CLOR relationships among the Object Agents resulted from Algorithm 1. The higher the value of a threshold, the smaller search space is. Figures 3.8a and 3.8b illustrate the samples of graphs produced based on different thresholds, respectively.

3.2.3 Message Volume

One of the key factors is to minimize the number of transacted messages between the machines. In our CEIoT framework, the messages that should be transacted between different platforms are summarized. Thus, we expect a dramatic reduction in the number of transacted messaged compare to a centralized scenario. Figure 3.7e shows the number of both internal and external messages which were transacted between agents during the experiment on the synthetic dataset. In this Figure, the As it is shown, although the red stack (top) shows the number of inter-platform messages and the blue (bottom) shows the number of intra-platform messages in our experiment. As shown, despite the fact that using the CEIoT approach in a distributed mode increases the number of transacted messages by a small amount, it may enhance the total throughput of the system by reducing the ratio of inter-platform messages which are quite expensive. Moreover, in the distributed mode the messages are being processed by a larger number of machines than the centralized approach.

3.3 Related Work

There are some studies which promote that the IoT can be implemented as the Internet of agents [88]. This is due to the ability of agents to mimic human activities such as willingness to achieve certain goals, and the social ability to interact with each other and with human as well. In a proposal by Fortino et al [89], MAS is also considered to perfectly help developing a smart environment for objects without direct human intervention. The heterogeneity and disparity can intensify the problem of dealing with smart things in an effective way. Things data is never under centralized control. Hence, datasets are usually stored in distributed locations. Using central location for data storage is an obstacle for materializing an effective solution. The diversity of sensors infrastructures means that, data are structured and documented in different ways, which complicates combining their datasets in an easy way. Thus, one of the solutions called *Concinnity* [90] takes the advantage of Semantic Web technologies such as RDF, Ontology, and SPARQL.

There is an interesting paradigm called *Triple Space Computing* [91] that has the potential to facilitate storage and communication in the Internet of Things context. It is basically a dedicated Web for machines, which is combined of space-based computing and the Semantic Web. It uses RDF triples for data representation to exchange knowledge using shared space, just like HTML representation in human-driven Web [92]. TSC provides asynchronous communication such that consumers neither need to recognize each other through identifiers, nor need to concurrently consume data.

A provisional approach is the Social Internet of Things (SIoT) [40, 39, 93]. To socialize things in the IoT, unlike the solutions for socializing smart things that depend totally on their owners' relationships, this approach seeks a solution to enable smart things to be interlinked by themselves. Objects have their own profiles and IDs, so they can discover other objects of interest and establish a friendship with each other according to their owners' constraints. Additionally, this approach defines some types of relationships established among objects.

For instance, *Parental Object Relationship* (*POR*), *Co-Location Object relationship* (*CLOR*), *Co-work Object Relationship* (*C-WOR*), and *Social Object Relationship* (*SOR*). However, no realistic and scalable solution given on how to identify and extract these relationships. Correlating things in IoT has various benefits such as better navigability experience, query result diversification and matters of an interest can be effectively discovered with the least effort possible [38]. As discussed before, Atzori et al. [40] discuss the characteristics of *Social Internet of Things* and define polices for relationships establishment among connected things. Unlike the approaches that socializes things according to what relationships their owners [93, 94], this approach is more focused on things as key players in relationships establishment, which limits the roles of their owners to managing them and setting appropriate rules for their relationships. However, to the best of our knowledge, this vision has not been implemented yet. Additionally, currently no technical details have been given on how to automate the establishment of relationships between objects when they are aware of each other. Automated correlation extraction is limited to one type of correlation for a small number of objects [27, 74].

3.4 Summary

One of the missing components in the IoT is something similar to hyperlinks in the World Wide Web. Unlike the traditional Web, establishing correlations in IoT can be challenging as it must be automated. In this chapter, we have proposed the CEIoT framework for extraction and representation of correlations between things in the IoT. We have used a distributed architecture and local correlation filtering to stabilize the performance of the library in different conditions. Our framework can be used in parallel with the crawler and enable it to improve its navigation through the WoT resources.

However, given the pool of correlations and/or sensor data in the form of Open Linked Data (using RDF), there are a number of challenges that need to be tackled. Firstly, to

merge/integrate the networks of things that are acquired from multiple data sources, we need to find the matches of the given nodes in different graphs. Secondly, it is crucial to an IoT search engine to be able to process subgraph queries. To identify the answers to a given query, it is critical to find the best matches for a given pattern that is extracted from the query, similar to the Graph Search in Facebook [95]. We address this key function in the next chapter and tackle the associated technical challenges of pattern matching by proposing a novel approach that can address the requirements of the IoT data.

Chapter 4

Pattern Matching for Things Correlation Graphs

Graph pattern matching is already a fundamental method for various applications in many domains including, but not limited to, social computing [96], computer vision [97] and computational chemistry[98]. Existing variations of this method is extensively studied in different contexts in the past few years. Given the Things Correlation Graphs (TCGs) from correlating the objects, we can apply pattern matching for the following purposes:

- Knowledge processing: linked sensor data is a popular format for presenting and modeling IoT data on the Web [99–105]. Due to the fundamental role of pattern matching in processing sensor data in RDF format [106, 107], it is necessary to develop efficient approaches.

- TCG merging: Sensors can provide data on different networks simultaneously. The analysis of IoT data in Chapter 2 confirms this claim by showing that in some cases, the ratio of the overlapping things between different networks are high. Given the distributed bottom-up interlinking approach from Chapter 3, a number of distinct TCGs

are extracted from different networks. Thus, a pattern matching approach is required to process the data for a given node from a TCG and find the matches in the other TCGs.

Assorted types of conditions and requirements impose different constraints on pattern matching techniques. In general, pattern matching aims to solve the problem of finding subgraphs of a given data graph G, which match a given pattern graph Q. One of the particular conditions, i.e., processing graphs with labeled nodes [108], is increasingly receiving attention.

The existing approaches for labeled graph pattern matching use a particular definition of labeled nodes where each node is associated with a single label [96]. Thus, for the pattern Q and the data graph G, the nodes of G can be categorized based on the set of labels of nodes in Q without any conflict. This approach is useful for many applications in social computing but does not cover some of the new domains, such as the IoT [3], and some sophisticated problems in social networks, i.e., when the labels are uncertain or when the data is incomplete. In any of these cases, assigning a single label to each node could be unrealistic and we need to define graphs with *multi-labeled* nodes. However, using multi-labeled graphs compared to the single-labeled graphs can potentially increase the complexity of the problem. In this case, revising the current pattern matching approaches for multi-labeled graphs is beneficial.

Example 1. *To provide a clear image of the problem, in this chapter we explain an application in the context of the Internet of Things. For example, a search service extracts the pattern graph from one network of things and the data graph from another. Figure 4.1 illustrates two graphs that are obtained from these two networks. Each edge represents a relationship between two nodes in the same network.*

Each node (i.e., a thing) is described with a set of metadata about its sensors and actuators. We can take each tag as a label due to some reasons including (1) there is not universal description for things connected to the network, and (2) each node can be

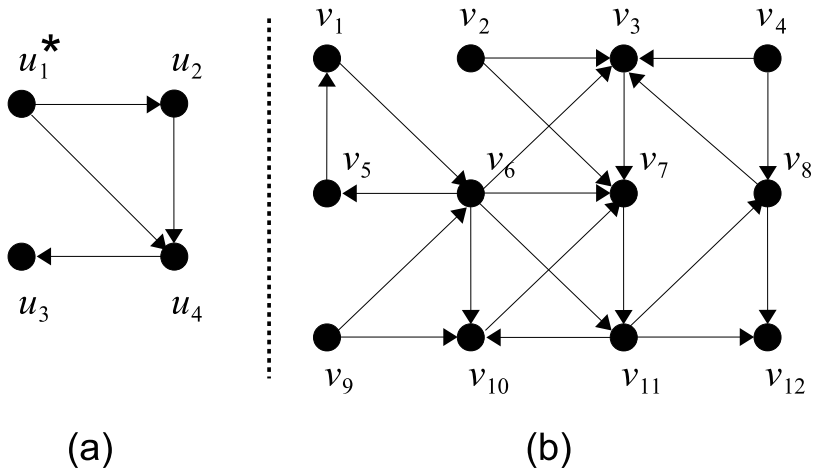


Fig. 4.1 Querying two networks of things (a) the pattern graph, (b) the data graph

Table 4.1 The set of label assignments

Node	**Labels**
u_1	$l.s_0, l.s_1, l.a_0, l.a_3$
u_2	$l.s_2, l.s_3, l.a_1, l.a_3$
u_3	$l.s_1, l.s_3, l.a_2, l.a_3$
u_4	$l.s_0, l.s_1, l.a_0, l.a_1$
v_1	$l.s_2, l.s_3, l.a_1, l.a_3$
v_2	$l.s_0, l.s_1, l.a_0, l.a_2$
v_3	$l.s_1, l.s_2, l.s_3, l.a_1, l.a_2$
v_4	$l.s_2, l.a_0, l.a_1, l.a_2$
v_5	$l.s_3, l.a_0, l.a_1, l.a_3$
v_6	$l.s_0, l.s_1, l.a_0, l.a_1$
v_7	$l.s_1, l.s_2, l.s_3, l.a_3$
v_8	$l.s_0, l.s_2, l.a_0, l.a_1$
v_9	$l.s_1, l.s_2, l.s_3, l.a_0$
v_{10}	$l.s_0, l.s_2, l.a_0, l.a_1, l.a_2$
v_{11}	$l.s_1, l.s_2, l.a_1, l.a_2$
v_{12}	$l.s_0, l.s_1$

registered partially on different networks. The labels are selected from a language $\Sigma.s =$ {*sensor/thermal, sensor/weather, sensor/signal, sensor/current, sensor/motion*} *and* $\Sigma.a =$

{*actuator/screen, actuator/switch, actuator/fan, actuator/speaker, actuator/alarm*}. *Table 4.1 shows the labels assigned to each node.*

To examine the similarity between two nodes, we use a similarity ratio as follows:

$$s(v_i, v_j) = \frac{|L(v_i) \cap L(v_j)|}{|L(v_i) \cup L(v_j)|} \tag{4.1}$$

where $|L(v_i) \cap Ł(v_j)|$ *denotes the number of common labels between two nodes and* $|L(v_i)|$ *denotes the number of the labels of* v_i*. We can compare the similarity score with a threshold* t.

Based on the present model, if we set the similarity threshold as 0.5, for each node $u_i \in Q$*, Table 4.2 lists the nodes* $v_i \in G$ *that can be a match. All of the nodes from the data graph appear more than once in the set of similarity lists. Due to this conflict, no unique label can be associated with any of the nodes. For instance, although* v_2 *is specified a match of the query node (*u_1*), it can match node* u_4 *as well. The set of similarity lists is more complex than the case when each node is assigned only one table. This is because in that case, each node of the data graph would appear only once in the final list. Therefore, the pattern matching process can be more complex and new situations must be considered.*

Table 4.2 Nodes with label similarity above threshold

Query Graph Node	**Similar Data Graph Node**
u_1	v_2, v_6, v_{12}
u_2	v_1, v_3, v_5, v_7
u_3	v_3, v_7
u_4	$v_2, v_6, v_8, v_{10}, v_{12}$

With the increasing complexity and volume of graphs in new contexts such as social networks and the Internet of Things, performance will be the main issue that we should tackle when we revise graph pattern matching for multi-labeled graphs. The typical definitions of

graph simulation are generally too restrictive to be applied for this purpose. Nonetheless, computing all of the possible simulations will result in the inefficiency of any solution. In order to tackle these challenges, we propose a novel approach for graph pattern matching for multi-labeled graphs. Our contributions in this chapter are as follows:

- We introduce the concept of *surjective simulation*, which is more flexible than graph simulation and bounded simulation. Through the use of surjective simulation, the proposed approach can notably reduce the complexity of simulation creation step to $|V_p||V|$. With this concept, we can optimize the process via removing the simulations that do not contain any match of the query nodes.

- To avoid going through the computation of each simulation to get its size, we propose an approximation procedure based on the Metropolis-Hastings Algorithm. We also devise an early stop mechanism when (1) we have at least k nodes in the results and (2) the size of the smallest simulation is equal to or greater than the rest of surjective simulations.

- We evaluate the proposed approach via extensive experimental studies. The results show the efficiency of our approach and verify the superiority of our approach over existing approaches.

The rest of this chapter is organized as follows. In Section 4.1 we define the problem. A naive approach based on a very recent work is provided in Section 4.2. We provide necessary background in Section 4.3. Then in Section 4.4 we show how we can compute the set of the top-k results using the proposed concept of surjective simulation with the Metropolis-Hastings algorithm. Section 4.5 presents the experimental results. Finally, Section 4.6 reviews the related works and Section 4.7 provides some concluding remarks.

4.1 Problem Formulation

Before presenting our approach for graph pattern matching, we first formally define the problem that we are going to investigate. Multi-labeled graph pattern matching is the task of matching the nodes of a given pattern graph Q with a data graph G based on structural similarity, where each node is given a set of labels.

Definition 1 (*Graph*). A graph is represented as $G = (V, E, L)$ where (1) $V = \{v_1, v_2, ..., v_n\}$ is a set of nodes; (2) $E \subseteq V \times V$ is a set of edges; and (3) $L = \{l_i : l_i \in V \times \Sigma\}$ is a mapping that relates each node to a set of assigned labels from language Σ. □

Definition 2 (*Pattern Graph [109, 108]*). A pattern graph is a directed and connected graph $Q = (V_p, E_p, L_p, u^*)$, where (1) V_p is a set of query nodes; (2) E_p is a set of query edges; (3) $L_p \subseteq V_p \times \Sigma$ is a mapping that links every node $u \in V_p$ to a set of labels in $\Sigma_p \subseteq \Sigma$; and (4) $u^* \in V_p$ that specifies the query node. □

Definition 3 (*Graph Simulation [109]*). A graph G matches a pattern Q iff there exists a binary relation $S \subseteq V_p \times V$ such that (1) for each node $u \in V_p$, there exists a node $v \in V$ such that $(u, v) \in S$, referred to as a match of u; (2) for each pair $(u, v) \in S$, $L(u) = L(v)$, and for each edge (u, u') in E_p, there exists an edge (v, v') in G such that $(u', v') \in S$. □

A top-k problem can be defined in the following. Given a surface $\Gamma(x, y)$, a function $f(x, y) : x, y \rightarrow D$, a scoring function $\delta(f)$, and a positive integer k, it is to find a subset $\phi \subseteq D$, such that $|\phi| = k$ and

$$\phi = \underset{\phi \subseteq \Gamma, |\phi| = k}{\operatorname{argmax}} \sum_{x,y \in \Gamma} \delta(f) \tag{4.2}$$

In the rest of this chapter, we refer to the following problem as *MULTIMATCH*. Given a data graph G and a query graph Q with the query node u^*, assuming that there are at least k subgraphs in G that match the query graph (i.e., containing the nodes, edges and labels in Q), we want to find the top-k matches $M_k = \{m_1, m_2, ..., m_k\}$ of u^* in G such that (1) for

every $m_i \in M$, there exists at least one simulation S_i that contains (u^*, m_i), and (2) $i < j$ iff $|S_i| \geq |S_j|$ and S_i, S_j represent the largest simulations containing (u^*, m_i) and (u^*, m_j), respectively. In the case that we do not have k matches of the query graph in the subsets of the data graph, we look for all matches instead. In other words, we want to compute the following equation:

$$M = \underset{M \subseteq V, |M|=k}{\operatorname{argmax}} \sum_{v \in V} |S = (V_s, E_s, L_s, M_s)| \tag{4.3}$$

where S denotes a simulation of pattern $Q = (V_p, E_p, L_p)$ in data graph $G = (V, E, L)$ and $|(V_s, E_s, L_s, M_s)|$ denotes the size of the simulation.

Example 2. *For the pattern Q and the data graph G in Figure 4.1, we can retrieve simulation* $S = \{(u_1, v_6), (u_2, v_{11}), (u_3, v_7), (u_4, v_{10})\}$. *S is one of the possible simulations. Definition 3 is strict and does not include other subsets of S.*

4.2 The Naive Approach

The naive approach explores the whole set of possible permutations for the answers. To the best of our knowledge, one of the closest efforts that only works for single-labeled nodes is the *diversified graph pattern matching* in [110].

As mentioned, high complexity is the first critical issue that we encounter when employing the graph simulation to deal with graphs containing multi-labeled nodes. This is mainly the result of the restrictions imposed by the graph simulation definition. A more flexible definition that is used in naive approaches is the *bounded simulation*.

Definition 4 (*Strong (Bounded) Simulation [111]*). A pattern graph Q matches a data graph G via strong simulation, denoted by $Q \prec_D^L G$, if there exists a node v in G and a connected subgraph G_s of G such that (1) $Q \prec_D G_s$, with the maximum match relation S; (2) G_s is exactly

the match graph w.r.t. S; and (3) G_s is contained in the ball $\widehat{G}[v, d(Q)]$, where $d(Q)$ is the diameter of Q. □

We take the gist of this work (which work? Any reference?) to develop a naive approach. We use two algorithms for both Directed Acyclic Graphs (Algorithm 3) but modify them to support the possible worlds of multi-labeled nodes.

Algorithm 3 works as follows. The underlying idea of this algorithm is to execute TopKDAG [110] for all possible label assignments of the both graphs (i.e., Q and G). We first compute the possible worlds for label assignment with $\prod_i L(v_i)$ for G in line 1 and $\prod_j L_p(u_j)$ for Q in line 2. Then, for every possible combination, we use the following process to get the biggest possible simulation S^*. We initialize the min-heap S that is used to store the simulation and the $termination$ variable (line 5). The topological rank $r(u)$ is used to keep track of the distance from the starting point. We define $r(u)$ for $u \in G$ as (a) $r(u) = 0$ if the mapped node of u is a leaf in G_{SCC}; and otherwise (b) $r(u) = max\{(1 + r(u'))|(u_{SCC}, u'_{SCC}) \in E_{SCC}\}$. This algorithm dynamically maintains a vector $v.T$, which contains (1) a Boolean equation $v.bf$ of the form $X_v = f$, where f is a Boolean formula that indicates whether v is a match of u; (2) a subset $v.R$ of its relevant set $R(u, v)$; and (3) integers $v.l$ and $v.h$ to estimate the lower and upper bounds of $\delta_r(u, v)$, respectively. The algorithm iteratively computes the set of matches and updates the vectors of other candidates by "propagating" the partially evaluated results.

Algorithm 3 supports directed acyclic graphs (DAGs) only. For other types of graphs that contain cyclic paths, the complexity of the solution could rise and naive approaches could be developed based on running the SccProcess [110] for all label permutations. Otherwise, we can convert the graph with cyclic paths to a set of DAGs [112] and use Algorithm 3 for all subgraphs. However, due to the complexity and poor connection with our contribution, in this chapter we do not cover this situation and leave it for future research.

Theorem 4.2.1. *Given a pattern graph $P(V_P, E_P, L_P)$ and a data graph $G(V, E, L)$, the complexity of the naive approach for computing the top-k matches for $u^* \in Q$ is $O(|V|^{|V_p|}|E||E_P|)$.*

Proof. We can prove the complexity of the given problem via computing the upper and the lower bounds for the complexity. To compute the upper bound, we suppose that for each node $v \in G$, $|\Sigma| = |V|$ and $|V|$ different labels have been assigned. In other words, all of the nodes have the same set of assigned labels. Respectively, let us suppose $|\Sigma_p| = |V_p|$ and for each node $u \in Q$, $|V_p|$ labels have been assigned.

This means that in the worst case, we have to go through a search space of all possible matches. In the ith iteration for matching u_i and v_j, $|V|$ possible cases are available. Thus, by the last iteration, $|V_p|^{|V|}$ matches have been traced.

On the other hand, the lower bound for the complexity of the mentioned problem occurs when each node in G is assigned with only one label. All of the nodes $u \in Q$ except one (e.g., u^*) are assigned with only one label while u^* owns n labels. Therefore, by running the TopKDAG [110] for the two possible cases, we end up with $O(n*(|Q||G|+|V|(|V|+|E|)+|V|\log(k)))$ time to compute the top-k matches where $|G| = |V|+|E|$ and $|Q| = |V_P|+|E_P|$. Thus, the time order of the NAIVE-DAG approach is $O(V^2V_P)$. □

4.3 Background

In this section, we review some of the necessary background materials before we propose our approach in the next section.

4.3.1 Markov Chains

Here we provide a concise description of the theory of Markov chains. Interested readers may refer to [113] for more details. Briefly, a Markov chain is a sequence of random variables $x_1, x_2, x_3, \ldots, x_n$ with the Markov property, namely that, given the present state, the future and past states are independent.

Algorithm 3 NAIVE-DAG

Require: $Q = (V_p, E_p, L_p, u^*)$ the DAG pattern, G the data graph, t node similarity threshold
Ensure: S^* the biggest set of simulations

Let $\mathscr{L} \subseteq \prod_i L(v_i)$ and $\mathscr{L}_p \subseteq \prod_j L_p(u_j)$ be the set of possible permutations of the labels of G and Q
for all $l \in \mathscr{L}$ **do**
  for all $l_p \in \mathscr{L}_p$ **do**
    Let `min-heap` $S \leftarrow \varnothing$ and $termination \leftarrow false$
    for all $u \in V_p$ **do**
      get topological rank $r(u)$ and initialize $can(u)$
      for all $v \in can(u)$ **do**
        initialize v.T
    while $termination = false$ **do**
      select a set of unvisited candidates $S_c \subseteq can(u)$ of query nodes u in Q, where $r(u) = 0$
      if $S_c \neq \varnothing$ **then**
        Let $\langle G, S \rangle \leftarrow$ `AcyclicProp`(Q, S_c, G, S)
        check the termination condition and update $termination$
      else
        $termination \leftarrow true$
    Update S^*
return S^*

To be more specific, let x be a random variable, where $x(t)$ denotes the value of x at time t. Let $S = \{s_1, \ldots, s_n\}$ be the set of possible x values, denoted the state space of x. If x moves from the current state to a next state based only on its current state, then x follows a Markov process. That is, $Pr(x(t+1) = s_i | x(0) = s_m, \ldots, x(t) = s_j) = Pr(x(t+1) = s_i | x(t) = s_j)$, here s_m is the initial state. The process starts in one of these states s_m and moves successively from one state to another. Each move is called a *step*. A Markov chain is a state sequence generated by a Markov process. The *transition probability* between a pair of states s_i and s_j can be denoted by $Pr(s_i \rightarrow s_j)$. If the chain is currently in state s_i, then it moves to state s_j at the next step with a probability specified by $Pr(s_i \rightarrow s_j)$.

A Markov chain may reach a stationary distribution π over its state space S, where the probability of being at a particular state is independent from the initial state of the chain. There are two conditions of reaching a stationary distribution, including (1) irreducibility (i.e., any state is reachable from any other state), and (2) aperiodicity (i.e., the chain does not cycle between states in a deterministic number of steps). A unique stationary distribution is reachable if the following balance equation holds for every pair of states s_i and s_j :

$$Pr(s_i \rightarrow s_j)\pi(s_i) = Pr(s_j \rightarrow s_i)\pi(s_j) \tag{4.4}$$

4.3.2 Markov Chain Monte-Carlo

The concepts of Monte-Carlo method and Markov chains are combined in the Markov Chain Monte-Carlo (MCMC) method [113] to simulate a complex distribution using a Markovian sampling process, where each sample depends only on the previous sample. A Markov chain is normally to start with some transition distribution (a transition matrix in the discrete case) modelling some process of interest, to determine conditions under which there is an invariant or stationary distribution and then to identify the form of that limiting distribution. By contrast, MCMC methods involve the solution of the inverse of this problem whereby the

stationary distribution is known, and it is the transition distribution that needs to be identified, though in practice there may be many distributions to choose from.

A standard MCMC algorithm is the Metropolis-Hastings (M-H) sampling algorithm [114]. Suppose that we are interested in drawing samples from a target distribution $\pi(x)$. The (M-H) algorithm generates a sequence of random draws of samples that follow $\pi(x)$. A more detailed process is shown as follows: (1) start from an initial sample x_0, (2) generate a candidate sample x_1 from an arbitrary proposal distribution $q(x_1|x_0)$, (3) accept the new sample x_1 with probability $\alpha = min\left(\frac{\pi(x_1)\cdot q(x_0|x_1)}{\pi(x_0)\cdot q(x_1|x_0)}, 1\right)$, (4) if x_1 is accepted, then set $x_0 = x_1$, and (5) repeat from step (2).

The (M-H) algorithm draws samples biased by their probabilities. At each step, a candidate sample x_1 is generated given the current sample x_0. The ratio α compares $\pi(x_1)$ and $\pi(x_0)$ to decide on accepting x_1. The (M-H) algorithm satisfies the balance condition (Eq. 4.4) with arbitrary proposal distributions [114]. Hence, the algorithm converges to the target distribution π. The number of times a sample is visited is proportional to its probability, and hence the relative frequency of visiting a sample x is an estimate of $\pi(x)$. The (M-H) algorithm is typically used to compute distribution summaries (e.g., average) or estimate a function of interest on π.

4.4 Pattern Matching

The high complexity of the naive approach affects the performance of the solution, particularly when the graphs become large. In this section, we describe the details of our approach to resolve the mentioned problem, which consists of two steps: *identifying matches* and *ranking matches*.

4.4.1 Identifying Matches

Bounded simulation has shown to be useful for graphs containing nodes with single label assigned. But when it comes to multiple labels, the use of bounded simulation does not scale well. Thus, we need to define a more flexible definition of graph simulation. In addition, the main criteria that can be used in ranking matches is the number of connected nodes in the simulation. A graph simulation by definition demands that the nodes in the generated simulation remain connected if the nodes in the pattern graph are already connected. Regarding the fact that a bounded simulation does not ensure the connectivity of nodes of the simulation, it increases the complexity of estimating the mentioned criteria. Furthermore, this can increase the complexity of the pattern matching step. Thus, in this chapter we use a more flexible definition of graph simulation as follows:

Definition 5 (*Surjective Simulation*). For a pattern graph $Q = (V_p, E_p, L_p, u^*)$ and a data graph $G = (V, E, L)$, a surjective simulation $S = (V_s, E_s, L_s, M_s)$ is defined as a graph with the following conditions: (1) $\forall v_s \in V_s \Rightarrow \exists (v \in G)$ such that $v = v_s$ and there exists a nonempty path ρ in G which connects every pair of nodes in V_s; (2) $E_s = \{(v_s, v'_s) | v_s, v'_s \in V_s\}$ and for all of its edges there exists a $(v_p, v'_p) \in E_p$ s.t. $s(v_p, v_s) \geq t$ and $s(v'_p, v'_s) \geq t$; (3) Labels L_s are the set of common labels from (2); (4)$M_s = \{(u, v) \subseteq V_p \times V_s \wedge s(u, v) \geq t\}$ where t is a threshold for the degree of labels similarity; and (5) S is connected and $\mathtt{d}(S) \leq \mathtt{d}(P)$ where $\mathtt{d}$ denotes diameter. □

We call our proposed graph simulation *surjective* since it covers any part of bounded simulations that exists in a strongly connected component after mapping edges of the pattern and the data graphs. One important difference between the proposed surjective simulation and the graph simulation is that it does not oblige the neighbors' nodes to remain as neighbors after being simulated. Very similar to the bounded simulation, for every neighbor nodes u_m and u_n, it is sufficient to remain connected after being simulated. The idea behind introducing the concept of surjective simulation is to reduce the complexity of finding simulation stage.

Based on the Lemma 1, it is possible to use the concept of surjective simulation in domains where simulation has been adopted.

Example 3. *Based on the given graphs Q and G in example 1, a surjective simulation can be obtained as shown in Figure 4.2. The surjective simulation can be shown as a graph and each node is mapped to a set of nodes in Q. It is composed of several simulations and all of the nodes similar to the query node can be identified with "*" sign.*

Lemma 1. *If $\mathscr{S}$ denotes the set of all possible surjective simulations and S_B denotes the set of all bounded simulations for data graph G and pattern Q, for every $\{s \in S_B | s = (V_s, E_s)\}$ there exists a set of surjective simulations $S_s = \{s_1, s_2, ..., s_n | s_i = (V'_s, E'_s) \in \mathscr{S}, \sum_i V'_s = V_s \wedge \sum_i E'_s = E_s\}$.*

Theorem 4.4.1. *The MULTIMATCH problem is NP-Hard.*

Proof. We prove the above theorem as follows. First, we show that any solution to this problem can be verified in polynomial time. In order to verify an answer consisting of k given subgraphs, we show that all of the steps can be accomplished in polynomial time and space. For verifying each given subgraph, the set of nodes and edges could be sorted and matched against the pattern graph in polynomial time. In addition, to verify that the subgraphs are maximal, we can verify the extensions of each subgraph by matching the added node against the pattern. In this regards, to generate each extension, a new edge from the original graph is added to the subgraph. This part of the process can also be done in polynomial time, either.

Second, we show that this problem is a reduction of a NP problem. Since in the least complex form, where all nodes in the data graph have unqiue labels, e.g., each node $v \in V$ has only one label but there does not exist a $u \in V$ where $L(u) \neq L(v)$, the *MULTIMATCH* problem is similar to *topKDP* problem[110] that is shown to be NP-Hard. If we increase the number of labels for all nodes v and assume that for all nodes $v \in V$ the labels are the same s.t. $\forall u \in V$ and $u \neq v$, $L(u) = L(v)$, the *MULTIMATCH* problem is a reduction of

subgraph isomorphism [115] which is NP-complete. Graph pattern matching is very costly. It is NP-complete for subgraph isomorphism [115], cubic-time for bounded simulation [96], and quadratic-time for simulation [109]. □

Taking the advantage of the surjective simulation, we can avoid processing the nodes which may not be a part of the maximum unique simulation and will be eliminated from the pool of alternatives for further processing. To achieve this goal, we propose an index for surjective simulation with a simple structure in the following: $\mathscr{I}_u = \{(u,v)|u \in Q, v \in G \wedge \sigma(L_p(u), L(v)) \geq t\}$.

Algorithm 4 provides the steps to create and maintain the set of surjective simulations. The algorithm returns a set of surjective simulations $\mathscr{S}$ based on the given data graph G, the given pattern graph Q and a given threshold for node similarity t. At the first step, matrix $\mathscr{M} = \{(\mathscr{M}_V, \mathscr{M}_E)|u \in Q, v \in G\}$ denotes a mapping from Q to G. For every edge $e_p \in Q$ and $e \in G$, we iteratively (1) compare all labels and compute the corresponding degree of similarity based on the number of common labels, and (2) add the new nodes and the new edge to $\mathscr{M}$. In the next step, we update the indexes including the set of query nodes ($s.q$), the size of connected component ($s.s$). The new surjective simulation is then added to $\mathscr{S}$.

One strength of Algorithm 4 is its *low complexity* without losing too much matching quality. In the proposed algorithm, for the two **for** loops in steps 2-7, if we use an index to get the mapped nodes in G, the complexity will be $O(|E||E_p|)$. Based on the fact that getting the connected components in step 8 is performed in a polynomial time $O(|G|)$, the whole process runs in $O(|V||V_p| + |G|)$ time.

Example 4. *Figure 4.2 shows the outcome of passing parameters Q, G, and the threshold from previous example to the Algorithm 4. The set of mappings of the edges is shown in Table 4.3. During the edge matching procedure, some of the edges in the data graph are omitted when no corresponding edge is found in the query graph for them. Thus, one of the first things that can be observed is that the data graph is divided into multiple connected*

Algorithm 4 GET-SURJECTIVE-SIMULATIONS

Require: Q the pattern graph, G the data graph, t node similarity threshold
Ensure: $\mathscr{S}$ the set of surjective simulations
1: Let $\mathscr{M}$ be the set mapped nodes in G
2: **for all** $e_p = (u_p, v_p) \in Q$ **do**
3: **for all** $e = (u, v) \in G$ **do**
4: Let sim_u be the degree similarity of u and u_p based on the set of their labels
5: Let sim_v be the degree similarity of v and v_p based on the set of their labels
6: **if** $sim_u > t$ **and** $sim_v > t$ **then**
7: Add (u, v) to $\mathscr{M}$
8: **for all** Connected component $C \in \mathscr{M}$ **do**
9: Let $s.q$ point to the set of query nodes in C
10: Let $s.s$ point to the size of C
11: **if** $|s.q| > 0$ **and** $\mathtt{d}(S) \geq \mathtt{d}(Q)$ **then**
12: Add surjective simulation S with specifications $s.s$ and $s.q$ to the $\mathscr{S}$
13: Sort $\mathscr{S}$ based on $s.s$ value for each set
14: **return** $\mathscr{S}$

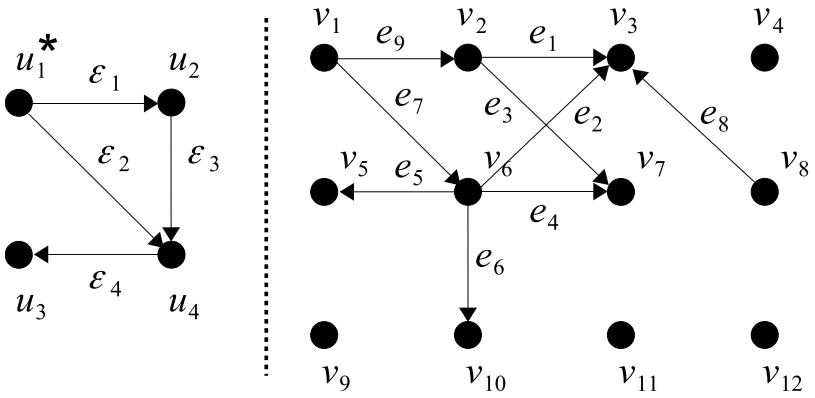


Fig. 4.2 The query and data graphs after removing non-matching edges

components as shown. Thus, connected components with lesser nodes than the query graph can be removed from the result set. As a result, in the next step, we can limit our search only to the connected components with greater number of nodes. In this example, we have only one large connected component and other nodes including v_4, v_9, v_{11} *and* v_12 *will no longer be considered to match any node in the query graph. In the next step, we observe that each query edges* ε_2 *and* ε_3 *are mapped to only one corresponding data edge each. On the other hand, there are multiple data graph nodes that match query nodes* ε_1 *and* ε_4*. Based on*

*this example, no match can be retrieved using simulation and strong simulation definitions. However, based on the surjective simulation definition, different subgraphs exist in the main connected component which contain nodes and edges that match nodes and edges in the Q. These surjective matches include any connected subgraph with diameter 3 that contains e*6 *and* e_7.

Table 4.3 Mapping of the edges of G to edges in the query graph Q

Query Graph Edge	**Matching Data Graph Edge**
ε_1	$e_1, e_2, e_3, e_4, e_5, e_9$
ε_2	e_6
ε_3	e_7
ε_4	e_1, e_2, e_3, e_4, e_8

4.4.2 Top-k Matches

We propose a new approach, which approximates the maximum-sized match so as to reduce the complexity introduced by the naive approach. The main idea is to employ the set of surjective simulations to start the ranking procedure with an inter-simulations approach that first gets sufficient candidates. Then it further ranks and sorts the intra-simulations. To provide an efficient solution for finding top-k matches, we divide this step into two sub-problems. In the first step, we look for the suitable surjective simulations within the identified set of surjective simulations from Algorithm 4. In the second step, we approximate the scores and rank of each match of the query node until we obtain the top-k nodes.

Algorithm 5 details the second step to obtain the top-k results. Unlike Algorithms 3, we can process the both kinds of input (directed acyclic graphs and graphs with cycles) using the same procedure. In this algorithm, similar to TopKDAG and SccProcss[110], we use an *early termination* strategy by employing a termination variable. This variable gets updated after each iteration by checking the conditions where (1) we still have more simulations in the $\mathscr{S}$ to process, and (2) if the top k list is filled, the approximation of the size of the smallest

Algorithm 5 GET-TOP-K

Require: $\mathscr{S}$ the set of simulations, Q the pattern graph, G the data graph, t node similarity threshold, k
Ensure: V' the list of top-k nodes

```
1: Let termination ← false
2: while termination = false do
3:    Let S ∈ 𝒮 be the next member of simulation set
4:    for all u ∈ S.u* do
5:       Let x0 ← {u}
6:       for all u' ∈ S.U do
7:          if u' ≠ u then
8:             Initialize π(u')
9:             Add none state to π(u')
10:            Add a random member from π(u') + 1 to x0
11:      Let terminate_s ← false
12:      while terminate_s = false do
13:         Let x1 ← {u}
14:         for all u' ∈ S.U do
15:            if u' ≠ u then
16:               Add a random member from π(u') + 1 to x1
17:         Compute the transition probability p
18:         Accept the new state x1 by probability p
19:         Update terminate_s
20:      if |V'| < k then
21:         Add M to V'
22:      else if |M| > |V'_k| then
23:         Let V'_k ← M
24:   Update terminattion
25: return V'
```

simulation is equal to or less than the size of the next surjective simulation in the ordered set $\mathscr{S}$, which is obtained from the previous step.

The rest of Algorithm 5 is designed based on the Metropolis-Hastings (M-H) Algorithm. For each match of query node in each simulation ($u \in S.u^*$), we perform matching in the following order. We generate the initial state x_0 in steps 5-10 by parsing every node u' in the set of nodes of the surjective simulation ($S.U$). The set $\pi(u')$ is initialized with the all of the labels l_i of node u' in step 8. Also there is a possibility that the node u' does not appear in a simulation. Thus we generate (step 9) and add (step 10) a *nil* state to the $\pi(u')$. We also use

a termination mechanism for the next steps by using the $termination_s$ variable. The variable can be changed to true (step 19) after we get a certain number of iterations with no change in the approximate size of simulation S. In steps 14-16 we generate a new random state x_1 in a process similar to x_0 initiation. In the next steps (steps 17,18), we compute the probability of accepting the new state x_1 by the following equation:

$$p = min(\frac{\pi(x_1).q(x_0|x_1)}{\pi(x_0).q(x_1|x_0}) \tag{4.5}$$

The early termination strategy is implemented afterwards in steps 20-23. Finally, the top k matches are returned in step 25.

To calculate the values of $\pi(x_n)$ and $q(x_m|x_n)$, we can use the following approach: Supposing that to create $\pi(x_n)$ a procedure f in $i = 1,...,N$ steps is executed. In each step, a new node is selected and added to the graph simulation. Based on the fact that the probability of state x_{i+1} in the step $i+1$ is independent from the states $1,2,...,i-1$ and only depends on the state i, we assume that the sequence is a Markov chain. Thus, for the step $i+1$, we have:

$$\pi(x_{i+1}) = \frac{1}{P(x_{i+1})} \tag{4.6}$$

Similarly, to calculate $q(x_m|x_n)$, we can compute the cost of converting x_n to x_m. In step i, we can convert x_n to x_m by converting the selected element to the new selection. In other words, to make it simple, we can use the following equation:

$$q(x_m|x_n) = \frac{\pi(x_m \cap x_n)}{\pi(x_m - x_n)} \tag{4.7}$$

where $x_m \cap x_n$ denotes the sequence of common selections between x_m and x_n and $x_m - x_n$ denotes the sequence of difference of selections in x_m.

4.5 Experimental Evaluation

We have implemented the proposed approach and conducted extensive experiments to study its performance.

4.5.1 Experimental Setting

We used Java 1.6 and graphstream [116] 1.2 in the implementation. The experiments were conducted on a computer with a 3.4 GHz Intel Core i7 processor and 8 GB of memory running Ubuntu 14.04. We used the following datasets:

- Facebook dataset [117]: an anonymized social circles graph from Facebook with 4,039 nodes and 88,234 edges. Each node is associated with a set of features which are dynamically defined and mapped.

- Twitter dataset [117]: an anonymized social circles graph from Twitter with 81,306 nodes and 1,768,149 edges. Each node is associated with a set of features which are dynamically defined and mapped.

- Two synthetic datasets: we created a graph generator which takes the size of the nodes and the size of the edges, and then generates a graph with randomly selected labels for its nodes. We generated two graphs: one with 1,000 nodes and 10,000 edges and the other with 1,000 nodes and 100,000 edges. Each node is associated with a set of features which are randomly selected from a set of 40 labels similarly defined as the ones in Example 1.

Although the main topic of this research is focused on IoT, due to the wide application of pattern matching, the application of the proposed work in this chapter is not limited to IoT. Thus, the main reason for selecting a social network graph is due to the lack of existing established graphs in the domain of IoT. In other words, to avoid the questionableness of the

proposed approach, we use datasets from a well established area, which is social networks. However, in the context of IoT, we need to process social graphs in processing correlations that are related to social networks.

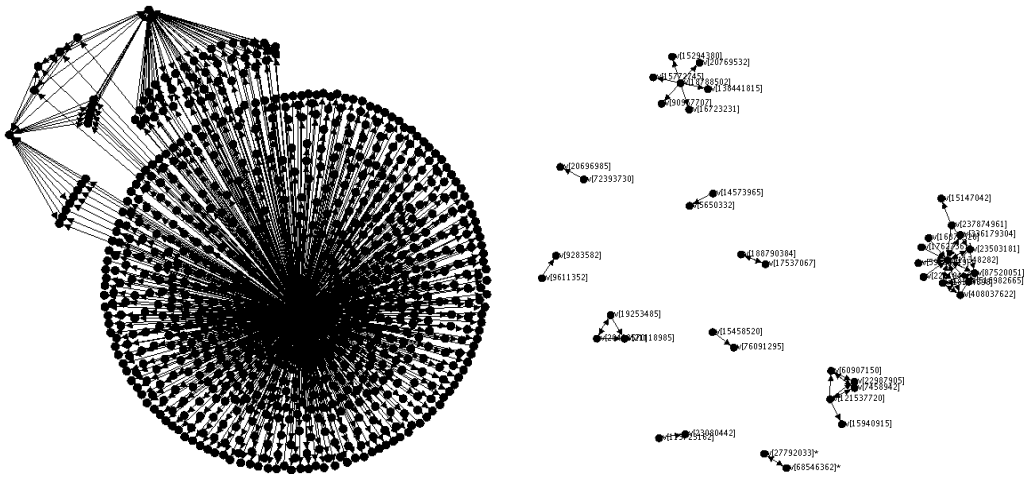
We also implemented a pattern generator for generating the graph $Q = (V_p, E_p, L_p, u^*)$ based on a given set of parameters such as graph $G_p = (V, E, L)$, which is the source graph for generating patterns, and an integer number r, which is the Euclidean radius of the pattern graph starting from the query node.

The pattern's label assignment process is carried out in the same way as for data graphs label assignment. For this purpose, to maintain the closeness of the problem with reality, we used the set of tags and features for each node provided by each dataset. At the beginning, each node is associated with the set of its own labels. To compare the similarity of the labels of two nodes, we used the Jaro Winkler method [118]. To optimize the proficiency of the solution, we developed an index which stores the nodes that have similar labels for a given node u_i using the process shown in Algorithm 6.

To generate the pattern, a random node from Q_s is picked as the query node u^* and for the rest of the nodes, only nodes within a certain distance from u^* ($\leq r$), are picked out with related edges and added to form Q. Jaro-Winkler is a measure of similarity between two string based on the Jaro distance metric. The Jaro-Winkler score is normalized in the range of $[0, 1]$ as the higher score denotes the higher similarity between strings. It is well suited for short strings and a good option for comparing features of different nodes.

Algorithm 6 INITIALIZE-INDEX

Require: Q_s the source graph for pattern, G the data graph, t node similarity threshold
Ensure: $\mathscr{I}$ nodes similarity index
1: **for all** Node $u \in Q_s$ and $v \in G$ **do**
2: Let $s_{u,v} \leftarrow$ `Jaro-Winkler`$(L(u), L(v))$ be the similarity score of u and v
3: **if** $s_{u,v} \geq t$ **then**
4: Add v to $\mathscr{I}_u$
5: **return** $\mathscr{I}$



(a) Example of larger pattern (b) Example of smaller pattern

Fig. 4.3 Visualization of pattern graphs

Table 4.4 provides a summary for the construction of the proposed index for each pair of used datasets. Technically, the amount of time and the size of index highly depend on the similarity threshold, or the degree of similarity for the set of nodes, in each test case.

Table 4.4 Index construction summary for different datasets

First Dataset	Second Dataset	Threshold	Time (s)	Comparisons	Entries	Size (MB)
Synthetic	Synthetic	0.7	1,472.296	10,000,000	236,491	1.5
Facebook	Facebook	0.998	2,426.721	16,000,000	330,739	1.6
Facebook	Twitter	0.7	7,832.821	324,000,000	4,585,485	21.7
Twitter	Twitter	0.75	19,397.461	6,561,000,000	9,562,748	89.1

However, the results show that although the amount of time and space are still high, using the proposed index can significantly decrease the query processing time (see Figure 4.4).

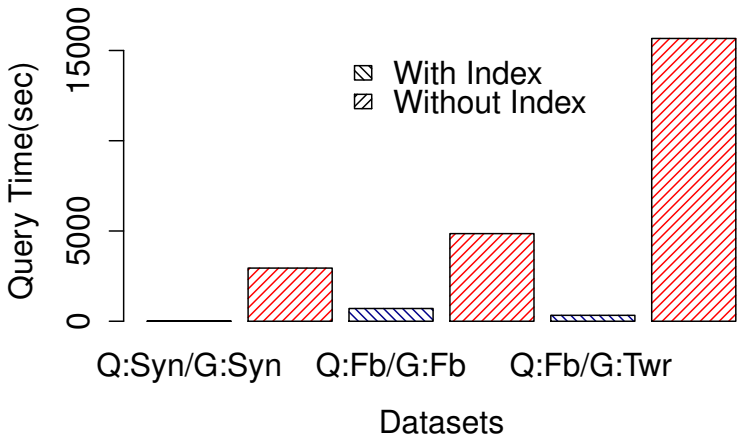


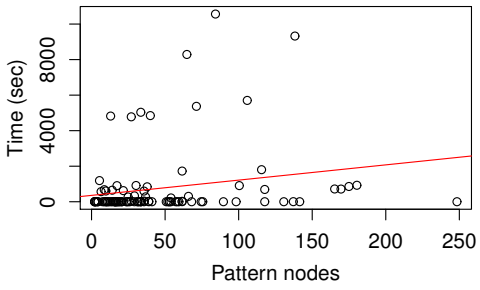
Fig. 4.4 Results for the total runtime

4.5.2 Efficiency

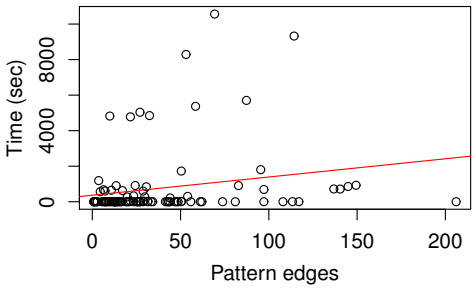
To assure the efficiency of our approach, we performed several tests using each of the datasets mentioned above. Each efficiency test requires a pattern source graph Q_s and a data graph G. In the following figures, the efficiency test results are depicted as scatter plots along with their regression (red) lines. From all datasets, we use a number of scenarios, which are presented in the following.

Facebook as both the pattern source and the data graph

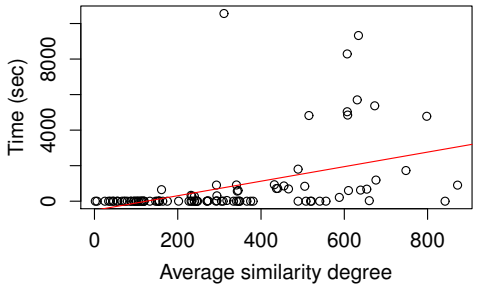
In this scenario, we used the node similarity threshold $t = 0.97$ due to the high similarity of the metadata of features. The pattern was generated randomly by the Elucidian radius $r = 2$. The size of the set of matching nodes for a given node deviates between 0 and 3,500 (Figure 4.5c). We ran this test 100 times with 100 M-H iterations. The results are shown in



(a) Varying nodes count



(b) Varying number of edges



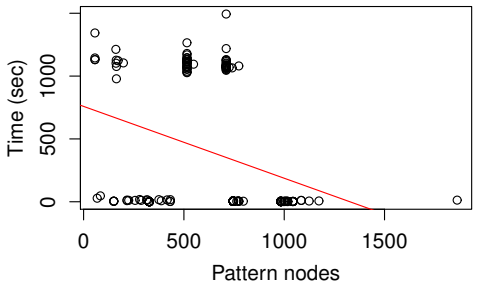
(c) Varying average similarity

Fig. 4.5 The results for Q_s :Facebook and G :Facebook

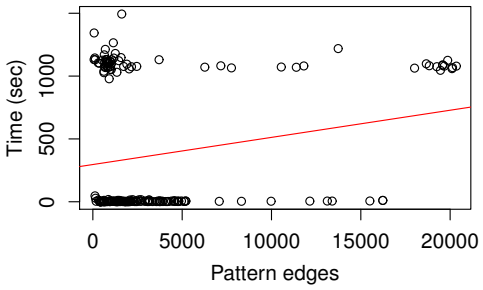
Figure 4.5a and 4.5b. Regression lines show the linear increment in the average processing time as the number of pattern nodes, pattern edges and the average similarity degree increase.

Facebook as the pattern source and Twitter as the data graph

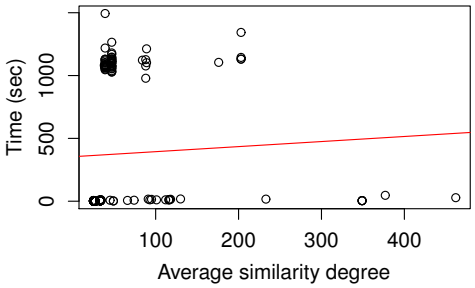
In this scenario, we used the node similarity threshold $t = 0.7$. The pattern was generated randomly by the Elucidian radius $r = 2$. The average size of the set of matching nodes for a given node deviates between 25 to 462 (Figure 4.6c). We ran this test 200 times. The results are shown in Figures 4.6a and 4.6b. Figure 4.3a shows an example of a large pattern graph generated from the Facebook dataset and Figure 4.3b smaller patterns through breaking down larger patterns. The decreasing regression line in the pattern nodes increment is due to the



(a) Varying nodes count



(b) Varying edges count



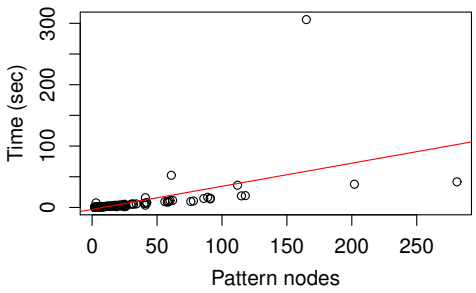
(c) Varying average similarity

Fig. 4.6 The results for Q_s :Facebook and G :Twitter

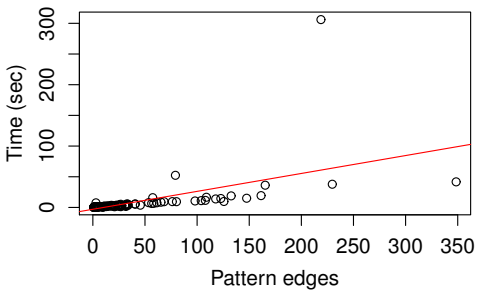
special nature of the patterns extracted from Facebook dataset and the cross domain pattern matching.

Twitter as both the pattern source and the data graph

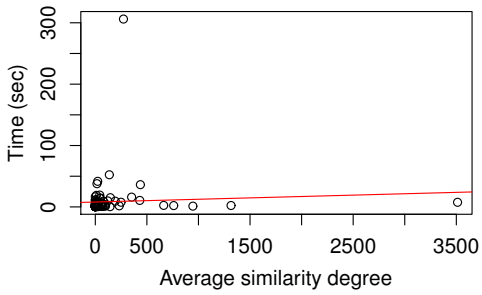
In this scenario, we used the node similarity threshold $t = 0.75$. The pattern was generated randomly by the Elucidian radius $r = 1$. The average size of the set of matching nodes for a given node deviates between 0 and 3,512 (Figure 4.7c). We ran this test 100 times with 100 M-H iterations. The results are shown in Figures 4.7b and 4.7a. As the Figures show, there is a linear increment in processing time as the number of edges and nodes increase. However, the average similarity degree does not show a strong impact on the processing time.



(a) Varying nodes count

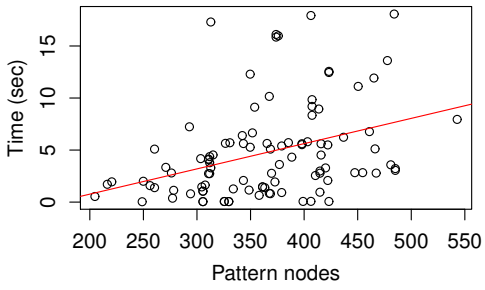


(b) Varying edges count

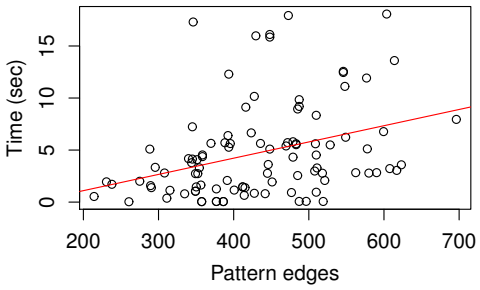


(c) Varying average similarity

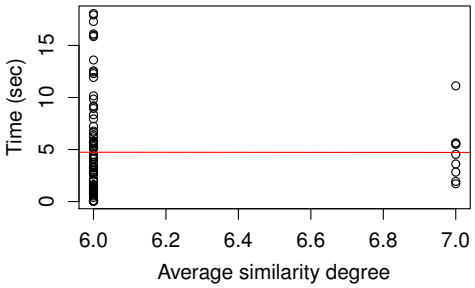
Fig. 4.7 The results for Q_s :Twitter and G :Twitter



(a) Q_s :Synthetic 1 and G :Synthetic 2



(b) Q_s :Synthetic 1 and G :Synthetic 2



(c) Q_s :Synthetic 1 and G :Synthetic 2

Fig. 4.8 The results for synthetic Q_s and G

Two synthetic graphs

The pattern source graph Q_s contains 1,000 nodes and 10,000 edges. The pattern was generated randomly by the Elucidian radius $r = 2$. We used threshold $t = 0.9$ to compare the similarity of labels. The size of the set of matching nodes for a given node deviates between 6 and 7 matches per node (Figure 4.8c). We ran this test 100 times with 100 M-H iterations. The results are shown in Figures 4.8b and 4.8a. Same as the above case, there is a linear increment in processing time as the number of edges and nodes increase while, the average similarity degree does not show a strong impact on the processing time.

From the results, we understand that for more than 90% of the queries, the result can be prepared in a short time. Based on the input graphs, the portion of the short process time may

vary, but it deviates in a limited interval for the social networks datasets. To have a better estimation of the impact of the proposed approach, we can estimate the time required by the naive approach based on Theorem 4.2.1.

4.5.3 Discussion

To examine our approach, we used a different mix of the datasets. We designed a new test, in which we take the same dataset as the pattern source Q_s and data graph G with the same label setting. In other words, we selected the following dataset matches for this test:

- *Facebook as both the pattern source and the data graph*: In this scenario, we used the node similarity threshold $t = 0.97$ for Jaro-Winkler label similarity due to the high similarity of the metadata of features.

- *Twitter as both the pattern source and the data graph*: In this scenario, we used the node similarity threshold $t = 0.75$ for Jaro-Winkler label similarity.

Time Complexity

The reduced complexity of relaxed pattern matching and the proposed approximation technique does not come without any price. The precision of the estimated scores for each match depends on the ratio of the explored possible worlds in the universal set of possible matchings.

The range of approximation error can change from 1.0, which results in low precision, to very small values based on the traversed portion of possible worlds. With fixed number of iterations for Metropolis Hastings, the accuracy of the result depends on the nature of the problem. For example, for an extreme case in which all nodes have similar labels, the result from our approach will be approximated by a relatively low precision while finding a precise answer will be Np-Complete.

Comparison with Baseline

To assure the improvement from existing works, we compare the total runtime our approach with the naive execution of the existing works. We use the synthetic dataset and use a query pattern with 20 nodes. The naive approach is based on the *SccProces* and *TopKDAG* algorithms [110]. As Figure 4.9 shows, in spite of the heavy indexing, our approach outperforms the baseline as the average degree of similarity (average number of labels for each node) increases.

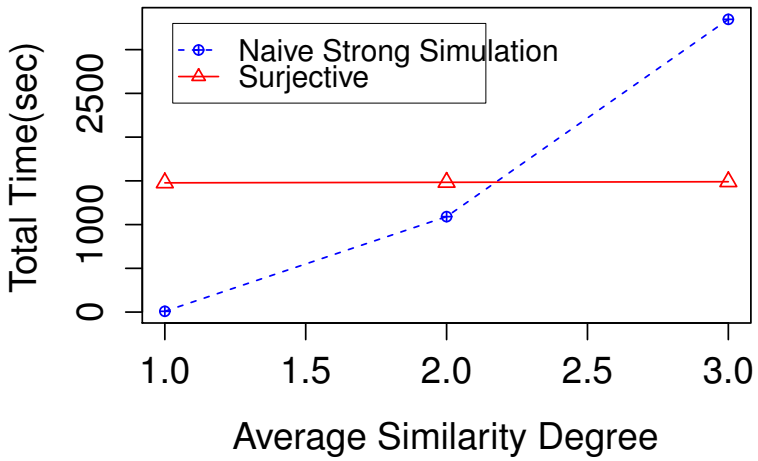


Fig. 4.9 Comparison with the baseline

Graph Representation and Space Complexity

Graph representation can affect space complexity. The space complexity in our approach can be divided into three major parts including graph representation, runtime space and index storage. However, unlike the Algorithm 3 which is not scalable due to the large space that is required to store all permutations of the labels, our approach only records trees of parsed nodes in connected components which do not highly exceed the size of the given query graph.

There are two different approaches to store graph data including *Adjacency List* and *Matrix* representation. The first approach normally reduces the file size while the second approach can potentially reduce the runtime of the process. The original version of the real-world data sets that we have used, are stored using adjacency list format. However, due to the heavy processing workload in our experiment, we convert the graphs to adjacency matrices as we import them into our application. Through the use of scalable libraries, our approach can handle graphs with millions of nodes on one machine.

As Table 4.4 shows, the size of the index increases when we process larger graphs or use smaller thresholds. As shown, the size of the index can take up 1.6 MB for around 330,000 entries or up to 89.1 MB for 9.5 million entries. Thus, our approach is scalable in terms of space and time.

4.6 Related Work

Graph pattern matching has been extensively studied and employed in various domains. Typically, two main approaches are often used for this purpose: subgraph isomorphism [119–122] and graph simulation [123–125]. When it comes to new applications such as social computing, none of these approaches can meet the applications' requirements. Recently, there has been a trend towards revising pattern matching for new domains, e.g., social networks [108]. The main problem in deploying the mentioned approaches is their too much restrictive definition. This reduces the efficiency and scalability of matching process. In addition, in the case of social networks analysis, these approaches will fail to obtain many useful and meaningful solutions [108].

One of the problems which recently has been discussed along with graph pattern matching is querying top-k nodes in a data graph by matching a query node from a pattern graph [110]. In the previous works both of the pattern graph and data graph use a single tag for each node [108]. The top-k query processing is challenging and an ongoing issue particularly under

special conditions such as uncertainty. For instance, in a distinct approach, given a noisy or uncertain dataset, Song et al. propose to return *Top-k Oracle* instead of returning only k tuples [126]. Users can later sub-query the results oracle to get the best answers based on their choice. However, so far this approach has not been examined for graphs, thus this approach needs further investigations to be applied on graph shaped data. In more graph oriented applications, Top-k exploration has been applied to efficient graph search on RDF data, which is represented using basic graph patterns [127].

Due to the frequently changing nature of social networks, it is often too costly to recompute all of the matches of a given pattern starting from scratch. To respond to this issue, the incremental graph pattern matching [128] can be adopted in many cases [129]. This approach identifies the changes in the data graph once they are made and corrects the pre-computed match set regardless of the complexity of batch algorithms.

The trend towards reforming the concept of graph simulation and graph isomorphism has continued to form new definitions such as bounded graph simulation [96], edges relationship simulation [130], strong simulation [111, 131] and strict simulation [132]. The strict simulation has been accompanied with distributed computing to tackle the performance obstacle. Using on-the-fly ranked lists and spanning trees is another approach that can optimize the solution [133]. One of the most important factors in this evolution process is the specifications of the application context. However, none of these efforts has applied graphs with multi-labeled nodes. Nonetheless, the size of pattern in most cases is very small. Efficient processing of probabilistic graphs has also been discussed by previous works [134]. Although dealing with probabilistic graphs to some extent can have similarities with analyzing graphs with multiple node labels, their purpose and definition are quite different.

4.7 Summary

Graph matching is a fundamental method which is applied in many important areas, such as social computing, image processing and computational chemistry. In IoT search, graph pattern matching can be applied for many purposes including RDF sensor data processing and correlation graph merge. Considering the results of the previous chapters, we identify that each node in TCGs can carry multiple labels based on the specifications of their sensors and actuators.

In this chapter, we propose a novel approach to efficiently match graphs with nodes that can take multiple labels. The aspects of the novelty of our approach include: (1) we address pattern graphs that are much larger than pattern graphs used by previous approaches, (2) in our approach each node can be associated with multiple labels while previous approaches only accept one label for each node, (3) we propose the concept of surjective simulation that is more flexible than graph simulation and strong simulations, and we have shown how it can greatly improve the efficiency of the graph matching process. We conduct several experiments to examine the efficiency of our approach and demonstrate the superiority of our approach over existing methods.

For the future research, we plan to extend our approach to support several new specifications, such as matching probabilistic graphs with multi-labeled and graph based processing for large-scale distributed pattern matching.

However, finding the best matches for a given user query is a different process. Based on the intention of search, users may look for things that are either locally, semantically or socially correlated with them. Thus, different TCGs are produced in correlation extraction. Unfortunately, in most cases the desired type of correlation is not reflected in the query and remains implicit. Thus, on challenge is how to integrate the TCGs of different types. On the other hand, presenting all of the matching results is not a suitable approach due to the interests of human users and the limitations of the machine users of an IoT search engine.

Thus, we cannot use the approach presented in this chapter for the purpose of user query processing. In Chapter 5, we propose a novel approach to address the above challenges. We use diversification the address the different needs/intentions of the users by diversifying the search results of the query.

Chapter 5

Diversifying Top-k Query Matches

The formation of Social IoT [40] and the Semantic IoT [135] triggered the idea of establishing correlation graphs for things similar to social networks analysis. Technically, it bears a good potential to support more complex queries and design more effective search approaches by adopting the correlation graphs between things. Although this idea may seem similar to making connections between people through social networks, correlations in IoT are not established in the same way. In Chapter 3, we proposed a novel approach, namely CEIoT, for extracting and presenting the correlations graphs (TCGs). As we show, in IoT, correlations are extracted based on the attributes of things while in social networks users contribute in establishing their relationships. Different correlations between things are expressed and understood differently and thus, can fall into different categories based on their definition and scope. For example, a correlation that is defined based on location attributes is different than a correlation which is defined based on ownership attributes. In the CEIoT approach, IoT services collaborate to establish the TCGs with minimized human intervention.

We consider TCGs to represent things correlation networks. Each vertex in a TCG represents a thing in IoT and each pair of vertices may be connected through an edge of a specific type, which represents a correlation of that type. Establishing correlations of different types can improve the depth of our model from the real world. It becomes possible

to apply more filters to get the related things from the huge pool of things. Each type of edge is formed based on a specific type of correlation. A non-exhaustive list of correlation types include Co-location Object Relationship, Parental Object Relationship, Social Object Relationship, Co-Working Object Relationship and Ownership Object Relationship [40]. However, in the last step for preparing the query results, a challenging problem is to find an approach to integrate TCGs of different types. Furthermore, given the limitations of smart devices and the interests human users demand that the length of the result set should be limited and maintain high quality.

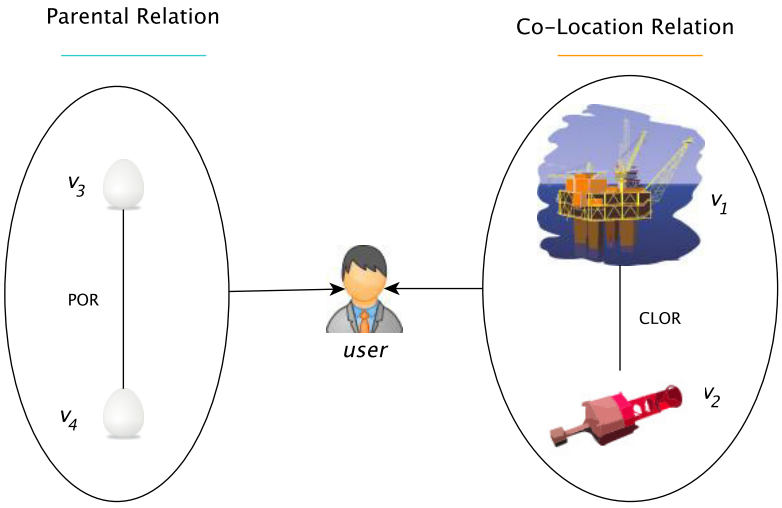


Fig. 5.1 Example of various relationships between things and users in IoT

An important problem is how we can effectively manipulate correlations in the IoT to obtain better search results when it is not clear that what kind of correlations are more important for users' search? If we pick only one type of correlation, would it harm the *diversity* of the search results? Example 5 describes this in more details.

Example 5. *Assume a user simply enters a query such as* `<"air", "USA">`*. As shown in Figure 5.1, keyword filtering can yield four different types of things such as an oil rig (v_1) and a Buoy (v_2) close to each other in the gulf of the Mexico as well as two air quality eggs (v_3 and v_4) in two different places. We can see that v_1 and v_2 are almost in the same location*

and thus they are connected through a co-location edge. This indicates a CLOR relationship between them. Meanwhile, v_3 and v_4 belong to same type of sensors, and thus they are connected through a parental relationship edge. This indicates a POR relationship between them. Now, if we want to limit the number of things in the result to two items only, how can we select them to best balance coherence and diversity? A selection of $\{v_3, v_4\}$ or $\{v_1, v_2\}$ will improve the coherence, but the search result is limited to just one type of correlation, leading to less diversity. In contrast, the selection of $\{v_1, v_3\}$ or other similar combinations will increase the diversity of the final result but with less coherence. Thus, there will be a tradeoff between coherence and diversity in the selection process.

In response to the above challenge, we propose a novel framework to answer search queries by maintaining different types of correlations. Our main contributions are as follows:

- We formally define the characteristics of search results (coherence and diversity) and use them to increase the quality of search in IoT. To the best of our knowledge, our work is the first piece of research that investigates and formulates different types of relationships.
- We propose a new framework, the ECS (Extract, Cluster, Select) framework, to manage the coherence and diversity of search results. Our framework contains a novel approach to extract and integrate different types of correlation graphs with a spectral clustering method and a selection method to improve the coherence and the diversity of top-k results for a given search query.
- We conduct extensive experiments to validate the effectiveness of our approach using real-world datasets.

The rest of this chapter is organized as follows: In Section 5.1 we use a graph based data structure to formally define the problem and provide an overview of our methodology. Section 5.2 presents the technical details for our ECS approach. We describe the results of

experimental evaluation in Section 5.3. In Section 5.4 we review the related works. Finally, we summarize the chapter in Section 5.5.

5.1 Problem Statement

5.1.1 Problem Formulation

In this section we formally define various types of correlations and then the problem. In this chapter we focus mainly on two types of correlations: *Co-Location Object Relationship* (*CLOR*) and *Parental Object Relationship* (*POR*).

Definition 6 (*Thing*). Suppose that V is the universal set of things and a thing $v \in V$ is an object connected to IoT where (1) $(v.lat, v.lon) = v.l$ denotes the location of the object composed of latitude $v.lat$ and longitude $v.lon$; (2) $v.dt = \{dt_i\}_{i=1}^{m}$ and $dt_i \in T_d$ denotes a set of descriptive tags about v, where T_d is an alphabet consisting of descriptive tags; (3) $v.lt = \{lt_i\}_{i=1}^{n}$ and $lt_i \in T_l$ where T_l is an alphabet consisting of location tags such as road and/or grid cell IDs. □

Definition 7 (*Parental Object Relationship – POR*). For every given pair of objects $v, v' \in V$, they have a *POR* if the following equation is satisfied:

$$\sigma^P(v, v') = \frac{|v.dt \cap v'.dt|}{|v.dt \cup v'.dt|} \geq \tau \tag{5.1}$$

where $\sigma^P(v, v') \in [0, 1]$ denotes the strength of *POR* and $\tau \in [0, 1]$ is the similarity threshold. □

Definition 8 (*Co-Location Object Relationship – CLOR*). For every given pair of objects $o, o' \in V$, they have a *CLOR* if the following equation is satisfied:

$$\sigma^L(v, v') = \frac{|v.lt \cap v'.lt|}{|v.lt \cup v'.lt|} \geq \tau \tag{5.2}$$

where $\sigma^L(v,v') \in [0,1]$ denotes the strength of *CLOR* and τ is the similarity threshold. □

Definition 9 (*Things Correlation Graph (TCG)*). A *TCG* is an undirected graph denoted as $G = (V,E,w)$ where (1) V is the universal set of things; (2) $E \subseteq V \times V$ is the set of edges and each edge $(v_1,v_2) \in E$ indicates a correlation (either POR or CLOR) between v_1 and v_2; and (3) $w : E \rightarrow [0,1]$ is the weight function and $w(v_1,v_2)$ represents the weight of relationship of edge (v_1,v_2). □

Our goal is that given the set of *TCG*s for two types of relationships (*POR* and *CLOR*), retrieve the most coherent and diverse results for a search query issued by a user. The problem is formally defined as:

For a given query $Q =$<keyword,location>, we need to select the ordered set of *Things* ($\mathscr{V} \subseteq V$) with highest *coherence* and *diversity* which are ordered non decreasingly by their *matching scores*. We compute the matching score from the following:

$$\mu(Q,v) = w_1 \frac{|Q.dt \cap v.dt|}{|Q.dt \cup v.dt|} + w_2 \frac{|Q.lt \cap v.lt|}{|Q.lt \cup v.lt|} \tag{5.3}$$

where $Q.dt$ and $Q.lt$ refer to the descriptive and location tags, respectively.

We obtain the coherence of the result set from the following equation:

$$\phi(\mathscr{V}) = \frac{1}{|\mathscr{V}|^2} \sum_{v,v' \in \mathscr{V}} w_1 \sigma^L(v,v') + w_2 \sigma^P(v,v') \tag{5.4}$$

We define search results diversity based on the selection size as follows:

$$\delta(\mathscr{V}) = \frac{k \times |C^*|}{n \times |C|} \tag{5.5}$$

where C^* denotes the clusters with selected nodes, C denotes the set of all clusters and n denotes the number of selected nodes.

The objective function is defined as follows:

$$f = \alpha \times \phi(\mathcal{V}) + \beta \times \delta(\mathcal{V}) \tag{5.6}$$

where $\alpha, \beta \in [0,1]$.

5.1.2 Methodology

We design a novel framework to answer search queries based on the correlations between things. Figure 5.2 shows the general structure of our framework and how it is evolved from the traditional approach.

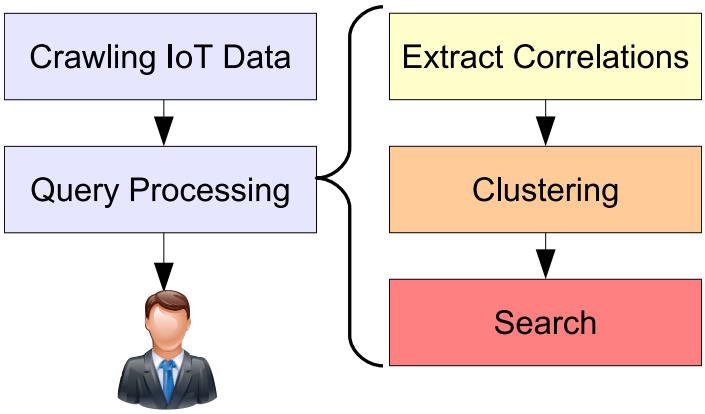


Fig. 5.2 Components of the ECS framework

As mentioned, current IoT search engines deploy a simple keyword based search strategy based on the crawled data from the IoT. The initial steps are *TCG Construction* and then *Clustering*. The next step is *Selection* which is performed on clusters. In our framework, we integrate different types of *TCG*s and cluster the vertices into a set of different clusters. Then, in the next step, we prepare the top-k results for a given search query.

5.2 ECS Approach

In this section, we introduce the details of our approach. The *TCG* construction covers *Extracting Correlations* in ECS framework followed by *Clustering* and *Selection*.

5.2.1 TCG Construction

Given a set of things represented by $\mathscr{V} = \{v_{i=1}^n\} \in \mathbb{R}^m$, their correlation graph TCG (Definition 5) is an undirected weighted graph $TCG =< V, E, \mathbf{W} >$, where V denotes all the things, $E \subseteq V \times V$ is the edges of TCG, the weighted matrix $\mathbf{W}$ can be obtained using ℓ_1-based one-to-all sparse graph based reconstruction, in which each thing can be considered as a linear span of other things in the dataset.

Given a set of things $\mathscr{V} = \{v_{i=1}^n\} \in \mathbb{R}^m$, for each thing v_i, its similarity/affinity with other things can be obtained by $\mathbf{v}_i = \mathscr{V}_i\mathbf{w}$, where $\mathbf{v}_i \in \mathbb{R}^m$ is the sample to be reconstructed, $\mathbf{w} \in \mathbb{R}^n$ is the reconstruction coefficients, $\mathscr{V}_i = \mathscr{V} \backslash v_i = [v_1, ..., v_{i-1}, v_{i+1}, ..., v_n] \in \mathbb{R}^{m \times (n-1)}$, which is formed by other objects in the dataset except for object v_i. The reconstruction coefficients of v_i can be computed using the objective function:

$$\min_{\hat{\mathbf{w}}} ||\hat{\mathbf{w}}||_1, \qquad s.t. \quad v_i = \mathscr{V}_i\mathbf{w} \tag{5.7}$$

where $||\cdot||_1$ is the ℓ_1 norm, tending to minimize the ℓ_1 norm of reconstruction error. Since the relations of nodes on a graph is supposed to be non-negative, we impose an extra constraints on Equation 5.7, which is formulated as:

$$\min_{\hat{\mathbf{w}}} ||\hat{\mathbf{w}}||_1, \qquad , s.t. \quad v_i = \mathscr{V}_i\mathbf{w}, \quad \mathbf{w}_i^j \geq 0 \tag{5.8}$$

The construction process is summarized in Algorithm 7. Algorithm 8 summarizes the clustering process using the weighted matrix generated by Algorithm 7. Under this way, the

algorithm can adaptively select the neighbors for each data point, and at the same time the similarity matrix indicating pointwise similarity is automatically derived from the calculation of these sparse representations. It automatically leads to a sparse solutions, which means the thing correlation graph would be a sparse graph.

Algorithm 7 ℓ_1-based Thing Correlation Graph Construction

Require: A collection of feature vectors of things $\mathscr{V} = \{v_1, .., v_n\}, v_i \in \mathbb{R}^m$
Ensure: Similarity matrix $\mathbf{W} \in \mathbb{R}^{n \times n}$

Each v_i is normalized to be $v_i = \frac{v_i}{||v||_2^2}$
for $i = 1 \rightarrow n$ **do**
  $\mathscr{V}_i = [\mathscr{V} \backslash v_i | \mathbf{I}] \in \mathbb{R}^{m \times (m+(n-1))}$
  $\min_{\hat{\mathbf{w}}_i} ||\mathbf{w}||_1$ s.t., $||v_i - \mathbf{B}\mathbf{w}_i||_2 = 0$, $\mathbf{w} \geq 0$
  for $j = 1 \rightarrow i-1$ **do**
    if $1 \leq j \leq i-1$ **then**
      $\mathbf{W}(i, j) = \mathbf{w}_i^j$
    if $i+1 \leq j \leq n$ **then**
      $\mathbf{W}(i, j) = \mathbf{w}_i^{j-1}$
return $\mathbf{W}$

5.2.2 Clustering

After solving the proposed optimization program in Equation 5.8, we obtain a sparse representation for each data points whose nonzero elements ideally correspond to points from the same subspace. To infer the cluster of each data points on TCG into different subspaces using the sparse coefficients $\hat{\mathbf{w}} \in \mathbf{W}$, we first employ spectral clustering techniques to extract more informative structures by computing the first K eigenvectors of graph Laplacian of $\mathbf{W}$, the graph Laplacian can be computed as

$$\mathbf{L} = \mathbf{I} - \mathbf{D}^{-1/2}\mathbf{W}\mathbf{D}^{-1/2} \tag{5.9}$$

where $\mathbf{D} = [\mathbf{d}_{ij}]$ is a diagonal matrix with $\mathbf{d}_{ii} = \sum_j w_{ij}$. $\mathbf{D}^{-1/2}$ indicates the inverse square root of $\mathbf{D}$. The Laplacian is symmetric positive semidefinite, and its first K eigenvectors

corresponding to K smallest eigenvalues can be computed. Thus, we can perform $k$means to cluster all the data points.

Algorithm 8 Subspace Clustering on Weighted Matrix $\mathbf{W}$ of TCG

Require: Weighted matrix $\mathbf{W}$ of TCG
Ensure: Clustering membership for each data point v_i

1: Normalizing columns of $\mathbf{W}$ as $\mathbf{W}(:,i) \leftarrow \frac{\mathbf{W}(:,i)}{||\mathbf{W}(:,i)||_\infty}$
2: Symmetrizing $\mathbf{W} = \frac{1}{2}(\mathbf{W} + \mathbf{W}^T)$
3: Computing graph Laplacian matrix $\mathbf{L} = \mathbf{I} - \mathbf{D}^{-1/2}\mathbf{W}\mathbf{D}^{-1/2}$, where $\mathbf{D} = [\mathbf{d}_{ij}]$ is a diagonal matrix with $\mathbf{d}_{ii} = \sum_j w_{ij}$
4: Computing K eigenvectors of $\mathbf{L}$ corresponding to K largest eigenvalues, and form the matrix $\mathbf{C} = [\mathbf{c}_1, ..., \mathbf{c}_K]$
5: Performing K-means using $\mathbf{C}$
6: Assign each data point v_i to cluster j if the i-th row of the matrix $\mathbf{C}$ is assigned to the cluster j
7: **return** the set of clusters

Time Complexity Analysis. Sparse similarity $\mathbf{W}$ construction and k-means based spectral clustering would be two main stages of consuming computational resource. As we know, efficiency is crucial, especially we will deal with a large amount of ubiquitous things. We briefly draw some analysis of time complexity of our method and how to adapt our proposed approach in a scalable way to match the needs of IoT.

We adopt the ℓ_1 sparse representation to decode the similarity of queries and the training dataset, which is the most expensive part of our proposed method. Given a collection of data points (i.e., each object can be considered as a virtual data point), ℓ_1-graph finds a sparse representation for the object using all other objects in the dataset and builds a similarity graph using the representation coefficients. Although the sparse similarity graph performs well, it needs an iterative optimization process for respective objective function, and has no closed form like ℓ_2 norm. In our implementation, we adopt Homotopy algorithm based fast solver, where each step of the algorithm involves the rank-one update of a linear system. If the whole procedure stops in K steps, yielding a solution with K nonzeros, its overall complexity

is bounded by $4Kd'^2/3 + Kd'n + \mathcal{O}(Kn)$, where d' is the dimension of the reduced features and n is the number of the training samples. To further reduce the computational cost, we can sparsely reconstruct each data point from its k nearest neighbors in feature space instead of using all the other samples to improve the efficiency while maintaining its effectiveness. In this way, the searching space of constructing TCG will be reduced from $n-1$ to k ($k < n$).

On the other hand, k-means algorithm employs an iterative procedure. At each iteration, one finds each data point's nearest center and assigns it to the corresponding cluster. Cluster centers are then recalculated. The procedure stops after reaching a stable error function value. Since the algorithm evaluates the distances between any point and the current k cluster centers, the time complexity of k-means is $\mathcal{O}(nk^2)$, where n is the number of data points and k number of clusters. However, since its weight matrix $\mathbf{W}$ is a sparse similarity matrix as well, we can use sparse eigensolvers to accelerate the computation of top K eigenvectors from Laplacian matrix $\mathbf{L}$, e.g., ARPACK [136], which can reduce the time complexity of computing eigenvectors from $\mathcal{O}(m^3)$ to $\sim \mathcal{O}(nm)$.

5.2.3 Selection

To make this selection, we can pick a single node from each cluster and add it to the result set. We can use different strategies in the selection step. For example, one can choose elements based on their similarity values, or the medoid element of each cluster. However, the quality of the final results highly depends on the quality of the selection strategy [137]. We propose an approach to implement a selection strategy in such a way that can satisfy the following conditions:

1. The set of things in each cluster have the most similarity to each other while the inter-cluster similarity is minimized; and

2. The returned results maximize the objective function which aggregates the *coherence* and the *diversity* of the result set. We select the nodes with maximum similarity index to intra-cluster nodes.

Algorithm 9 Node Selection

Require: A collection of Clusters $C = \{C_i\}_{i=0}^{N}$; k the size of the result set; Query Q; and α, β
Ensure: An ordered set of things $\mathscr{V}$ for which $|\mathscr{V}| = k$
1: Filter the nodes in clusters set C based on the features specified in the query Q
2: **for** $i = 1 \rightarrow |C|$ **do**
3: $m = \mathsf{random}(v_x) \in C_i$
4: **for** $v_z \in C_i$ **do**
5: **if** $\sum_{v_y \in C_i} \mathbf{W}(z,y) > \sum_{v_y \in C_i} \mathbf{W}(z,y)$ **then**
6: $m = v$
7: $\mathscr{V} \leftarrow \mathscr{V} + m$
8: $C_i \leftarrow C_i \backslash m$
9: **if** $|\mathscr{V}| < k$ **then**
10: Add $\mathsf{select}(\text{updated } C, k - |\mathscr{V}|, Q, \alpha, \beta)$ to $\mathscr{V}$
11: **return** $\mathscr{V}$

Algorithm 9 summarizes the steps of our selection strategy. The algorithm takes a set of parameters including the clusters from the clustering step, the expected size of the result k, the query Q and the *tradeoff* coefficients α and β. The algorithm initializes $\mathscr{V}$ in the first turn (Lines 1-8) to cover conditions (1) and (2). First, the set of nodes are filtered based on the keywords from the query (line 1). Then the algorithm iterates through all of the clusters with a for loop (line 2), picks a random node from the cluster C_i as its medoid (line 3), and iterates through the remaining nodes in the cluster (line 4) to find nodes which have less intra-cluster dissimilarity with other nodes. Once a new optimal node is found, it is replaced by the selected medoid (lines 5-8). Later the medoid is added to $\mathscr{V}$ and removed from C_i(lines 9, 10). The algorithm recursively calls itself with subtracted $\mathscr{V}$ from the clusters k is greater than k in lines 12-14. Finally, set $\mathscr{V}$ is returned. The order of execution for the Algorithm 9 for a small k is $n + \frac{K\mathscr{O}(kn)}{k}$ as it is mainly composed of keyword based filtering,

a loop through all clusters and their nodes and a recursive call. This order for the case of $K = k$ is reduced to $n + \mathcal{O}(kn)$ as the need for a recursive call is removed.

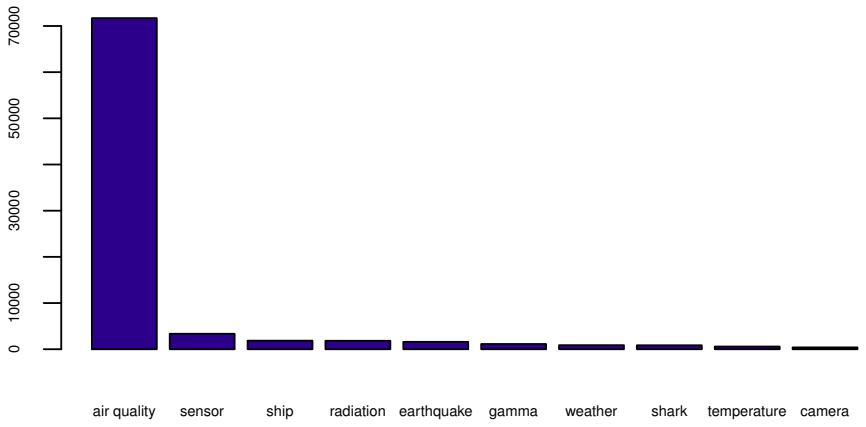


Fig. 5.3 Distribution of query keywords from *Thingful* dataset

5.3 Experimental Results

We perform extensive experiments to evaluate the effectiveness of our approach. We use real-world datasets to ensure that the proposed approach works under different conditions. We implemented our framework and experiments in R programming language with *ggmap* [138]. The experiments were performed on a computer with 2.5GHz core-i5 processor and 8GB of RAM. In this section we first describe the characteristics of datasets we used, and then present the results from experimental evaluation and discuss the findings of our research.

5.3.1 Datasets

Nowadays, many of IoT applications such as smart cities, intelligent transport systems, environmental sensing and etc. are publishing their data on the Internet. IoT search engines such as *Thingful*, rely on this type of data. We take this opportunity to create a large scale dataset of IoT data.

We use the following real-world datasets to evaluate our work:

1. Vehicle Trajectory Data: It contains nearly 16,000,000 trajectories for 10,357 taxicabs in the city of Beijing in a one week period [139]. The sampling frequency for each taxi differs from a few seconds to a couple of hours. In order to prepare the data to be used in the experiment, we performed some preprocessing. We first divided the city into 76 parts in length and 76 parts in height, which means that we have 5,776 segments. We specified the average speed between each pair of subsequent records to find the vehicle's status.

2. Weather Sensor Data: We also used a dataset known as LinkedSensorData [99, 140], which is an RDF dataset containing expressive descriptions of nearly 10,000 weather stations in the United States. The data originated at MesoWest, a project within the Department of Meterology at the University of Utah that has been aggregating weather data since 2002 [141]. It contains the observations from weather sensor measurements of phenomena such as temperature, visibility, precipitation, pressure, wind speed, humidity, etc. The dataset includes observations during the time periods that several major storms were active. This includes Hurricane Katrina, Ike, Bill, Bertha, Wilma, Charley, Gustav, and a major blizzard in Nevada in 2003. The dataset contains 1,730,284,735 triples from 159,460,500 observations. We accompanied every sensor's data with location tags from GeoNames [142].

3. Query Data: we used a real-world dataset consisting of 136,746 queries between Feb, 2014 to Feb, 2015 from Thingful search engine. This dataset is not IoT data, but we used it for query generation and analysis. We random selections from key features such as location, related keywords and timestamp to generate the queries for each of the above datasets. Figure 5.3 shows distribution of most popular keywords in the queries dataset.

Table 5.1 describes the thing data structure and the dimensionality of each category of properties for the taxis dataset. Furthermore, Table 5.2 describes the thing data structure and the dimensionality of each category of properties for the weather dataset.

Table 5.1 Object data structure for taxi trajectories dataset

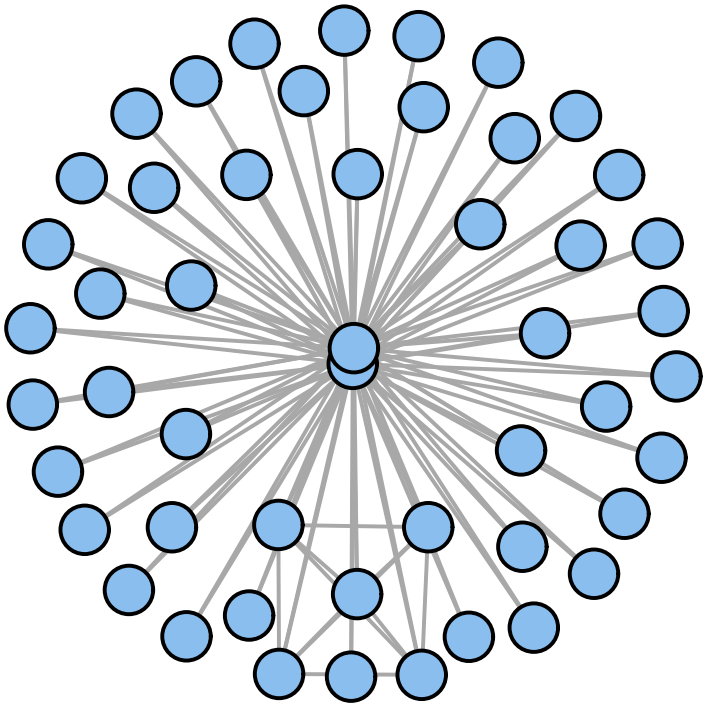
Category	**Dim.**	**Structure**
Location	2	$v.lat$, $v.lon$
Descriptive tags	2	$v.type \in$ {taxi,ordinary,bus}, $v.status \in$ {moving,stopped}
Location tags	2	$v.cell = (s_i, s_j)$ and $s_i, s_j \in [0,76]$, $v.rd$ the road id
Owner	1	$v.u$

Table 5.2 Object data structure for weather stations dataset

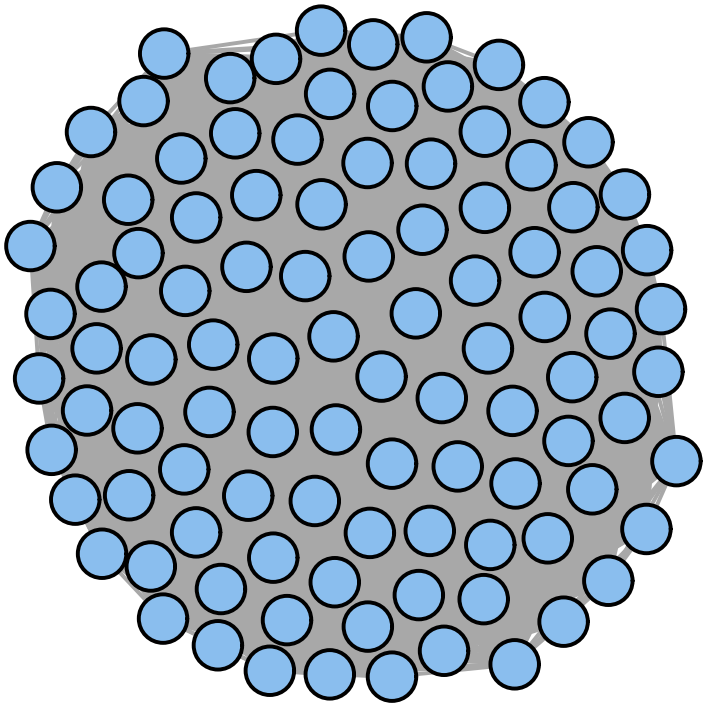
Category	**Dim.**	**Structure**
Location	3	$v.lat$, $v.lon$, $v.alt$
Descriptive tags	16	$v.feat \subseteq D$ where D is the universal set of feature tags
Location tags	2	$v.state$ and $v.county$ which refer to the name of the state and the name of the county in which the weather station is located, respectively

First we perform a dataset analysis on each dataset we have used. After computing the weights matrix $\mathbf{W}$, we normalized the matrices and obtained the graph for the two real-world datasets. Figure 5.4a shows a partition of the integrated *TCG* for the vehicles trajectory

dataset. Comparing with Figure 5.4b which shows a partition from weather stations dataset, the graph of the first dataset is far more scarce than the graph for the first dataset.

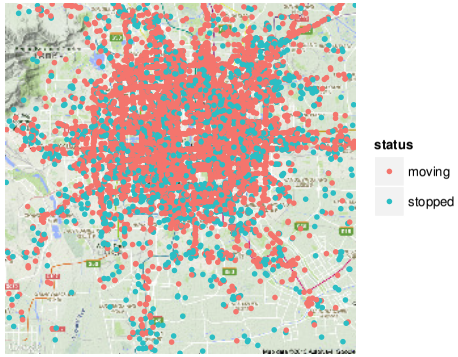


(a) The trajectory dataset

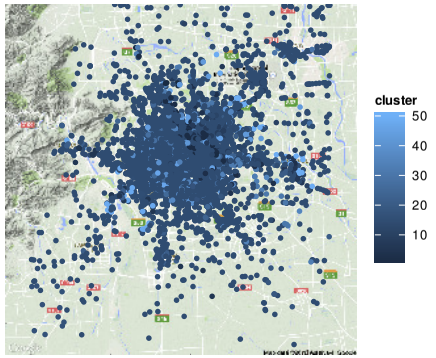


(b) The weather stations dataset

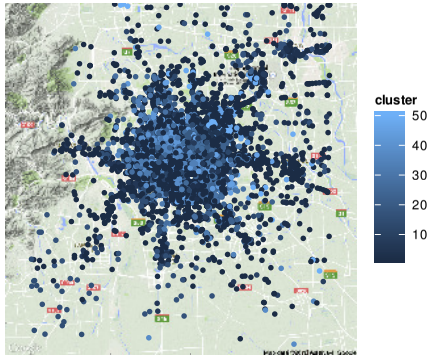
Fig. 5.4 Visualization of two TCGs



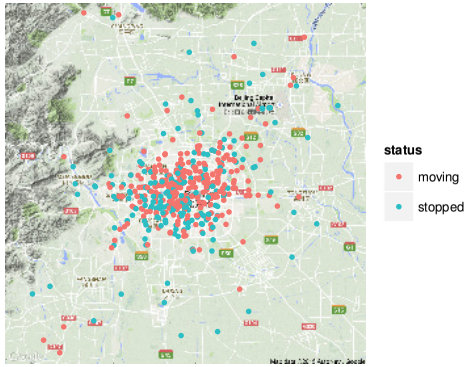
(a) Trajectory dataset mapped onto Beijing area



(b) Results of clustering with 10 nearest neighbors

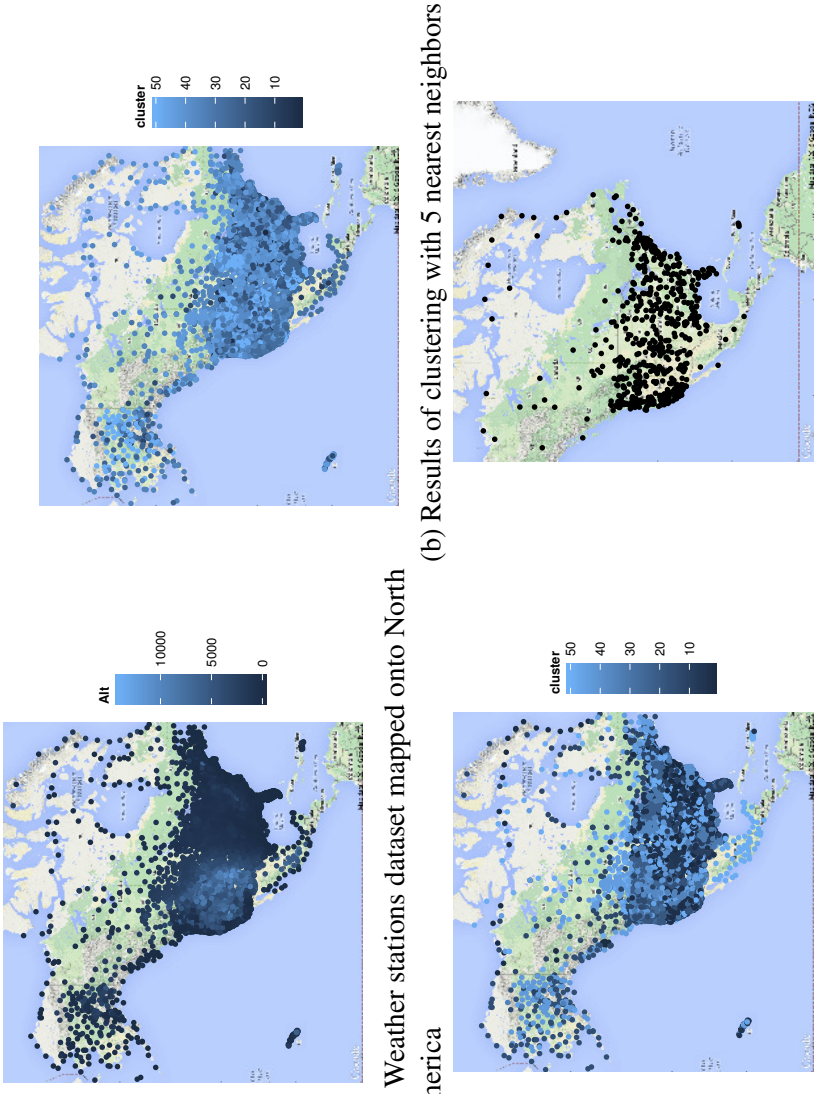


(c) Results of clustering with 30 nearest neighbors



(d) Selection results from the trajectory dataset

Fig. 5.5 Visualization of different selection methods on the trajectory dataset



(a) Weather stations dataset mapped onto North America

(b) Results of clustering with 5 nearest neighbors

(c) Results of clustering with 200 nearest neighbors

(d) Selection result from the weather stations dataset

Fig. 5.6 Visualization of different selection methods on the weather stations dataset

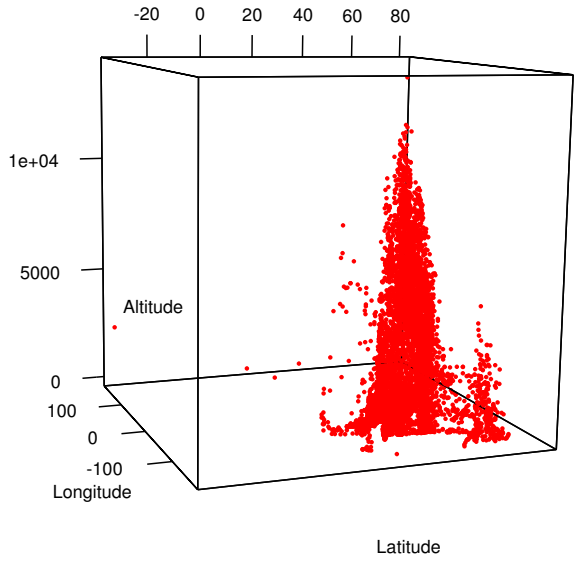


Fig. 5.7 Distribution of 3D location data for weather stations

Figure 5.5a depicts a map of Beijing and the trajectory data along with the status of the vehicles. Figure 5.5b shows the result of clustering using 10 nearest neighbors and can be compared to Figure 5.5c which depicts the same dataset clustered with 30 nearest neighbors. As the figures show, we end up with a less number of same color patches in the second figure.

For the weather station dataset, Figure 5.6a depicts the location and altitude of weather station across North America. Clustering this dataset is more challenging as things have more common features and as Figure 5.7 shows, the density of 3D location distribution for a large part of the data is concentrated around two points. Figure 5.6b shows the result of clustering using 5 nearest neighbors and can be compared to Figure 5.6c which depicts the same dataset clustered with 200 nearest neighbors. We observed that the geographical distribution of the clusters increases when we increase the number of nearest neighbors in our clustering algorithm.

5.3.2 Results

In our experiments, our target is to investigate the answers to the following questions: (i) How do different methods react to different ratios between α and β? (ii) What would be the outcome for different amount of k in the initial clustering? (iii) Which selection approach would be more effective?

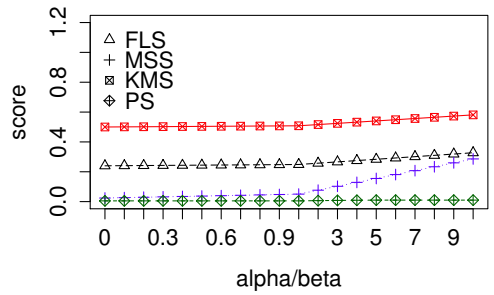
In the following we present the experimental results from our work. We compare our approach with other thing selection approaches including *Fixed Length Selection* (**FLS** - selecting random k nodes), *Maximum Similarity Selection* (**MSS** - selecting things with highest augmented μ), *k-Medoids Selection* (**KMS** - our approach) and *Plain Selection*(**PS**) which is the current approach used by *Thingful* and other works.

Varying α and β

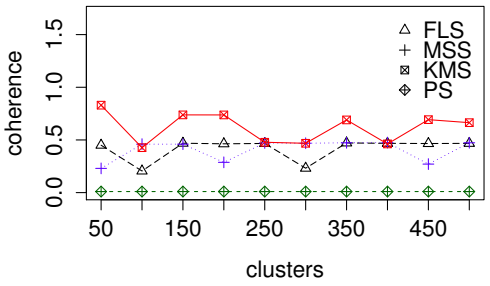
In Figure 5.8a, we compare the final ranking scores for different ratios of α and β between different other selection approaches. As we increase the ratio from 1 to 10, the final score for *MSS* approach increases to meet *FLS* score. As *FLS* and *KMS* strategies both experience a slight increase in their final scores for greater amounts of α, it shows that the *MSS* is better in providing more coherent results but the *KMS* performs stronger in overall distribution of diversity and coherence.

Varying k

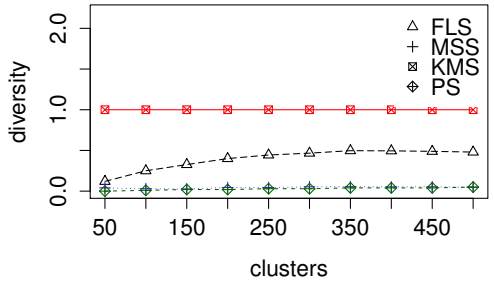
To answer the last question, we investigate the coherence and diversity of results for each one of the object selection strategies. Figure 5.8b compares the coherence of the outcomes for varying k. As shown, the *KMS* method outperforms other methods in terms of results coherence. While the coherence scores of PS are quite steady, *MSS* and *FLS* methods fluctuate dramatically.



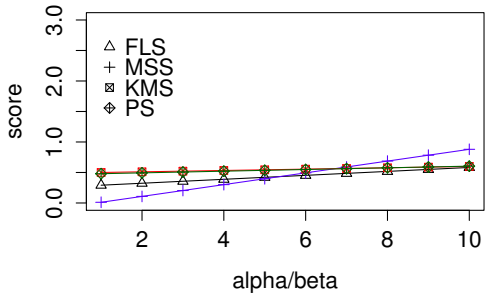
(a) Trajectory dataset selection score analysis for different ratios of α and β



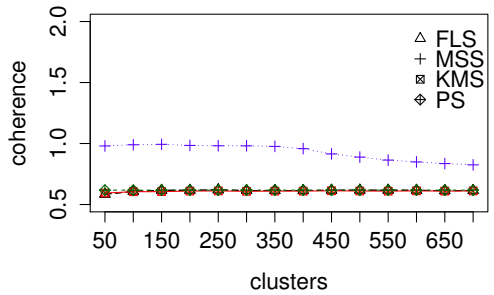
(b) Trajectory dataset coherence for different amounts of k



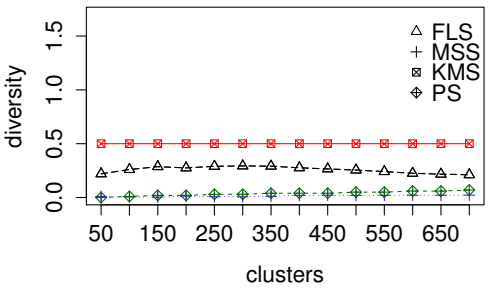
(c) Trajectory dataset diversity for different amounts of k



(d) Weather stations dataset selection score analysis for different ratios of α and β



(e) Weather stations dataset coherence for different amounts of k



(f) Weather stations dataset diversity for different amounts of k

Fig. 5.8 Experimental results for IoT search results diversification

Finally, Figure 5.8c compares the diversity of the outcomes for different methods. The diversity index for the results of *KMS* method constantly remains as 1.00 for varying amounts of k as one vertex is selected from each cluster. For *MMS* method, the diversity of results improves to a limit as k is increased. As the figure shows, both of the *PS* and *FLS* methods perform very poor in terms of diversity.

Due to the fact that the weather sensors dataset generates a much denser graph than the trajectory dataset, it is more challenging for our approach to improve the *coherence*, the *diversity* and as a result the overall score of the selected k things. However, as Figure 5.8d shows, the *KMS* method outperforms other methods when the coherence has a higher weight ($\geq 1/7\beta$). For higher values of α, the *MSS* method outperforms *KMS* as the graph is very dense and its nodes have a very strong correlation.

Figure 5.8e compares the coherence of the results for a varying amount of k. As shown, the *MSS* approach outperforms other approaches in terms of coherence but their difference decreases as as k is increased. Figure 5.8e compares the diversity of the outcomes for different methods. The diversity index for the results of *KMS* method remains 1.00 for varying amounts of k as one vertex is selected from each cluster.

Methods Analysis

To conclude, the experimental results show that our approach improves the *coherence* and *diversity* compared to the current and baseline approaches. Our findings show that our approach performs better on sparse graphs although it improves the overall results score from dense graphs as well.

In our design, we feature the nodes along with filtering criteria based on different types of correlations to simplify the final filtering for users (Figures 5.5d and 5.6d).

5.4 Related Work

As the idea of WoT implementation in large scale keeps flourishing and gains more popularity everyday, provisioning of its future structure, components, functionality and challenges becomes clearer. As a matter of fact, the implementation of IoT, in the first place does not require unknown technologies that are still unborn, as numerous academic and non-academic initiations have been carried out in this area. In advance, search engines in the context of IoT will play a significant part as they are doing today. Accordingly, the current structure will no longer support large scale IoT implementation sufficiently. Major technical challenges and changes in needs of users will require search engines to undertake new approaches for their query processes. To illustrate the future of search engines, [143] identified some of the challenging issues for searching within IoT as search locality and real-time search. Furthermore, based on IoT characteristics such as networked interconnection, real-time, semantic coherence and spontaneous interaction will result in raising issues such as architectural design, search locality, scalability and real-time for designing and implementing IoT search engines [144]. However, due to the existing differences in the nature of WoT with the IoT, WoT may even strike additional different challenges.

5.4.1 Search Based on Social Relationships

Some of the notable works in this area are as follows [30]: (1) Snoogle/Microsearch [145, 146]; (2) Dyser [83]; and (3) SPITFIRE [147]. Current search engines perform the search using keyword based filtering. This kind of approaches have limited applications in the context of the IoT due to the dynamic nature of IoT. Some other recent approaches such as Context Aware Search [76] and Sensor Similarity Search [148] provide more functionality to search in the IoT. However, a glimpse into IoT applications reveals that supporting the correlations between things yet remains undiscovered in the IoT search.

The *library paradigm* constitutes the basis of traditional information retrieval and based on this paradigm, traditional search engines perform search and rank results using keywords. Another approach that is so called the *library paradigm* [144] in which knowledge dissemination is achieved socially and the search should aim finding the right person rather than finding the right document.

In [144] the details of anatomy of a social search engine, namely Aardvark, have been discussed. The search process in Aardvark is based on the village search paradigm in which people use natural language to ask questions and answers are generated in real-time by someone from the village and trust is based on intimacy. Main components of Aardvark are as follows: Crawler and indexer, Query analyzer, Ranking function, UI. To index the relationships and affiliation of users, social graph structure has been deployed. Aardvark is a social search engine designed to index people and propose the best users to answer a question given by a user and the results are ranked based on factors such as topic expertise, intimacy (connectedness) and activity (availability).

5.4.2 IoT Search Engines

Microsoft SensorMap [149] and linked sensor middleware [150] support search for sensors based on textual metadata that describes the sensors (e.g., type and location of a sensor, measurement unit, object to which the sensor is attached). Such metadata is often manually entered by the person who deploy the sensors. Other users can then search for sensors with certain metadata by entering appropriate keywords. There are efforts to provide a standardized vocabulary to describe sensors and their properties such as SensorML [151] or the Semantic Sensor Network Ontology (SSN) [152]. Unfortunately, these ontologies and their use are rather complex. It is problematic that end users are able to provide correct descriptions of sensors and their deployment context without the help from experts. In other words, this type of solutions require the time-consuming prior and expertise knowledge, e.g.,

define the descriptions of things and their corresponding characteristics under a uniform format such as Resource Description Framework (RDF). Furthermore, these solutions do not exploit the rich information about user's historical interactions with things, containing implicit relations of different entities, e.g., if some users have the similar usage pattern on some things, which may indicate close connection of these things.

Another alternative approach for searching things is based on search-by-example. The work in [148] adopts this approach to sensors, i.e., a user provides a sensor, respectively a fraction of its past output as an example, and requests sensors that produced similar output in the past. Ostermaier et al. [83] propose a real-time search engine for Web of Things, which allows searching real-world entities having certain properties. They associate a Web page to a real-world entity (e.g., a meeting room) containing additional structured metadata about the sensors connected to it. This method takes care of the valuable information of historical data, but misses the relations among contextual information. Maekawa et al. [153] propose a context-aware web search in ubiquitous sensor environments, Brown and Jones [154] explore a new environment for information retrieval and information filtering, and Yao et al. [155, 156] construct the models that captures the pairwise relations between things via mapping the contextual information into separate graphs. However, more complex relations between heterogeneous objects can not be captured in these works. In addition, some useful information and structure might be lost when flating the multi-dimensional information into graphs. [157] propose a hypergraph-based model to capture the high-order and complex relations among things, however it suffers from the scalability issue and heavy computational cost resulted from hypergraph calculations.

5.5 Summary

Building enterprise search services is considered as one of the most significant steps in IoT research area. Being inspired by social networks, in this chapter we proposed a framework for diversified query result preparation for IoT.

TCGs of different types are generated by the CEIoT framework in Chapter 3. In Chapter 4, we merged those TCGs by using a novel approach to find the top matches for the given nodes in the TCGs. In this chapter, we focus on integrating the merged TCGs of different types. Furthermore, we propose a diversification method for search results. Our aim is to maintain the quality of the search results whilst we limit the size of the search results. We measure the quality in terms of *coherence* and *diversity*. We use a number of techniques including k-Nearest Neighbors, Spectral Clustering and k-Medoids Clustering for query results preparation. We assess our approach using real-world datasets and show that our approach can improve the coherence and diversity compared to the current and possible substitute approaches.

One of the future directions for this research is to extend the framework to support other types of correlations such as *Social Object Relationship*. We also target to extend the solution over time series and uncertain IoT data to provide more accurate search results.

The work presented in this chapter, is the final step before presenting the raw results that include a list of things to the user(s). However, the results can be further enriched using further analytical plots when they are presented. We present details and a showcase in aviation industry in Chapter 7. However, query resolution for intent-based search can be customized if the intention of the search is already known. Instances of customized systems in different fields of application can serve as examples for intention-oriented IoT search. In particular, we use a taxi ridesharing example in Chapter 6. In order to maintain the flow of the motivating scenario in Chapter 1, we present the taxi ridesharing case study first.

Chapter 6

Intent Based Search: A Case Study in Taxi Ridesharing

Automated dynamic ridesharing is a promising approach to relieve the problem of traffic lines which are overwhelmingly growing in our cities. In general, ridesharing provides us with various benefits such as economical (e.g., reduced total mileage and fuel consumption), environmental (e.g., less air pollution) and social benefits (e.g., passenger waiting time) [158, 159]. With the growth of newly introduced networking paradigms such as the IoT, nowadays we are able to derive knowledge in real-time from large and heterogeneous data collected by sensors from urban spaces [160]. In the recent years, various propositions have been made to facilitate ridesharing where each proposition focuses on particular types of results. For instance, a ridesharing application designed to minimize the effect of stochastic time frames (delays) [161] has different effects than a solution that is designed to minimize the mileage of the vehicles [159, 162].

Given the above details, taxi ridesharing can serve as a suitable example of intention-oriented search in IoT. In particular, a search query that is issued by the end user of the system is not issued to find the list of the taxis that are spatially or semantically correlated, but rather to find a convenient and economic taxicab for a shared ride. Thus, the architecture

of an intention-oriented IoT search engine in this case will be affected by the intention of the search. As a result, to provide an effective solution, a common instance of the search scenario along with the participating users and their interactions should be considered in the search engine design and implementation.

Taxi ridesharing is a complex problem. Most often, it is no possible to find a taxi which travels at exactly the same itineraries and the same time. Thus, we need to find nearby taxis by extending the search areas around the origin and the destination points. Existing solutions on ridesharing typically exploit an *Incremental Search* (*IS*) strategy in which the search area gradually increases until a compromise match is found [159, 162]. A *Decremental Search* (DS) approach has been proposed to increase the performance of search to some extent [163]. However, the success of a dynamic ridesharing application is affected by a variety of factors, where the vehicle mileage is only one of them.

Some of the existing ridesharing applications are designed to focus on only one factor [159, 164] while some other works address a set of different factors [165]. Moreover, existing works focus on minimizing the vehicle mileage [159, 162], but optimize ridesharing benefits can also be achieved through maximizing the number of participants [158]. However, due to the complexity of the human decision making, further advances are required to maximize user participation. It requires considering related constraints such as schedules and preferences [166, 167]. Unfortunately, in spite of its importance, the acceptance rate of ridesharing requests has merely been addressed by other works [168].

There are three types of different users, which are involved in a typical dynamic ridesharing scenario. This includes *seeker users* who have not secured a taxi, *companion users* who are already on the taxi or scheduled a trip with a taxi which will take place shortly, and finally the *taxi driver*. For the sake of simplicity, we exclude taxi drivers from our study and only focus on the mutual interaction of the first two types of users. Typically, in a ridesharing scenario, a seeker user uses an application to get a shared ride with a number of

companion passengers or passengers who may have already booked the taxi [159]. In the real world, the companion passengers may accept or reject the ridesharing request based on their desired criteria. If the seeker users cannot efficiently and effectively find a good match for ridesharing, they might no longer continue to use the system. Thus, considering companion users is crucial for the success of the ridesharing application. For instance, unaccompanied female travelers may reject the requests made by stranger male travelers. However, due to the complexity in the nature of human decision making, it is too difficult to predict the outcome of this decision at this stage. Thus, in this study we focus only the economical criterion and leave the rest of criteria for future research. We rely on the *mutual benefit principle*, which is a basic concept that demands almost anyone who is participating in the ridesharing process, mainly is looking for financial benefits.

We particularly consider three scenarios in dynamic ridesharing context, which are related to the outcome of the decisions of companion travelers. Those scenarios are explained in the following.

(a) Companion passenger's phone (b) Ordered by proximity (c) Ordered by accepting chance

Fig. 6.1 Intent-based search in ridesharing scenario

Firstly, as the Figure 6.1a shows the list of rideshare requests on the screen of the mobile device of a companion passenger. Based on the savings from each request, the user may pick the second request and reject the first as the second option provides better savings. However, in many cases, if the amount of savings is very low compared to the total cost of the private ride, the companion passenger may reject all requests and accept none of them as well.

Secondly, Figure 6.1b shows an example of the results of an existing ridesharing application on the seeker passenger's mobile device. The application orders the results based their from the seeker user's pickup point. As shown, it is not far from reality if several attempts by the seeker user get declined due to the preferences of the companion passengers. Only after several attempts the user have found a shared ride with $taxi_8$ successfully while the taxi is not very far from the first (nearest) taxi. If the users of the ridesharing application need to make numerous retries to get a taxi, they may cease using the application due to the hassle it takes.

Thirdly, along with the second scenario, we suggest to develop a new application or extend the existing solutions to consider the probability of accepting the user's rideshare request. As shown in Figure 6.1c, this time the list is ordered by a score that includes the probability of request acceptance. As a result, the $taxi_8$ which had the most opportunity and savings, will sit on the top of the list.

In this chapter, we propose the TRIPS framework which maximizes the real-world savings from dynamic ridesharing by combining two important parameters: vehicle mileage and users' acceptance. Unlike current works which suppose that the ridesharing request gets accepted and select the nearest taxi, we consider the probability of rejection in our design and propose a new search approach. We design a framework, named TRIPS, which provides a layered architecture with modules to provide support for handling the uncertainty of end users' decisions. Our framework is based on *search-once-and-rank* strategy rather than *extending* [162] or *shrinking* [163] the search area in each step. For the search step, by extending the decremental search idea, we propose a fixed search approach which runs only

one time per each user query. We further optimize our search using an indexing approach. For the ranking step, we propose a ranking algorithm which exploits probabilistic partial orders. Finally, the sorted result set will be ordered by the combination of extra mileage and acceptance probability.

A review by [169] divides the paradigm of trajectory data mining into sub-areas with different directions. Our work in this chapter uses *segmentation* in preprocessing as a part of its model. We also target the uncertainty in ridesharing problem, which is different from trajectory uncertainty in [169]. The main contributions of our work are as follows:

- We propose a novel scalable approach which improves the query results considering the uncertainty in the decisions made by companion passengers. We propose a new search algorithm which utilizes a *search-once-and-rank* strategy instead of IS [162, 159] and DS [163] approaches. The new approach facilitates the support for criteria that is associated with probability such as companion passengers decisions. To the best of our knowledge, our work is the first that incorporates the rideshare request acceptance possibility into the dynamic ridesharing problem.

- We develop an indexing scheme based on scheduled trips and their corresponding segments. Through incorporating interval estimates instead of crisp values, our approach is able to respond to the queries where no historical estimates are available. Our system can also incorporate *travel time estimation* and *routes prediction*, which have been addressed elsewhere [170–172], to improve the accuracy of time and cost estimation.

- We conduct extensive experimental studies to examine the effectiveness and the efficiency of our approach and we compare it with other approaches using a real-world dataset which includes 15,784,344 trajectories of 10,357 taxis in Beijing.

The remainder of the chapter is organized as follows. Section 6.1 defines the problem and basic concepts that we use to develop our solution. Section 6.3 presents the technical details

of TRIPS framework which includes our algorithms for search (Fixed Search and Index Powered Fixed Search) and ranking (based on Probabilistic Partial Orders). In Section 6.2, we formulate two existing search approaches, including IS and DS. Section 6.4 reports the experimental results. Finally, Section 6.5 reviews the related works and Section 6.6 provides some summary remarks.

6.1 Preliminaries

In this section, we define the notations and concepts which we use in this chapter.

6.1.1 Problem Definition

As mentioned in the use case scenario, our ridesharing application continuously perceives the status of each taxi within the boundaries of the Area of Interest (AOI). Taxi status can be defined as follows:

Definition 10 (*Taxi Status*). A taxi status V represents the instantaneous state of a taxi and is comprised of a taxi ID $V.id$, a geographical location $V.l$, a list of companion passengers $V.p$, and the set of travel schedules $V.S = \{\sigma_1, \sigma_2, ...\}$ where each σ_i denotes a scheduled trip and contains an origin, destination and time windows to be at each spot. The structure of each schedule is similar to the structure of a query. □

Ridesharing requests (queries) are generated by seeker users. We define query as follows:

Definition 11 (*Query*). A query Q is a seeker passenger's request to find a rideshare. It includes a timestamp $Q.t$ indicating when the query is submitted, a pickup point (*latitude*,*longitude*) $Q.o$, a delivery point (*latitude*,*longitude*) $Q.d$, a time window $Q.wp$ defining the time period when the passenger needs to be picked up at $Q.o$, and a time window $Q.wd$ defining the time period when the passenger needs to be dropped off at $Q.d$. The early and late bounds of a pickup window are denoted by $\underline{Q.wp}$ and $\overline{Q.wp}$. Likewise, $\underline{Q.wd}$ and $\overline{Q.wd}$

denote the bounds of the delivery window. Also $Q.u$ represents the user u who have made the query. For the sake of simplicity, each query indicates one passenger's request, but the approach can readily support multi-passengers' requests. □

Given a query Q, we would like to find the alternatives which can satisfy Q such that they can maximize the benefits for both companion and seeker users while the effort to get a rideshare is minimized. A taxi, with the corresponding status V, satisfies Q if and only if (i) $size(V.p)$ is smaller than the seat capacity of the taxi; (ii) the taxi can pick up the passenger of Q at $Q.o$ within $Q.wp$ and delivers her at $Q.d$ within $Q.wd$; (iii) the taxi can pick up and drop off the existing passengers in $V.s$ no later than the late bound of their corresponding pickup and delivery time windows.

In this chapter we use a *cost* function which depends on three main parameters: distance, time and taxi fares. The fee that is paid for the distance roughly is a constant number while the time variable is accountable for the extra costs that are incurred in during the waits in traffic or similar reasons. We define these two variables first and then we define the cost function. The distance between two points o and d is denoted as $\delta_{od} \in \mathtt{R}^+$, which refers to the length of the shortest path in the roads network between the two points. The travel time estimate for the same points is denoted as $\theta_{od} \in \mathtt{R}^+$, which is a measure in seconds that approximates the time required to travel from o to d. Taxi fares are positive real numbers f_c, f_d and f_t that are used to calculate the final cost. Thus, we define the cost function as follows:

Definition 12 (*Cost Function*). Cost function $cost(\delta, \theta)$ approximates the cost of a taxi based on the distance δ_{od} and the trip time estimate θ_{od} using:

$$\overline{cost(\delta_{od}, \theta_{od})} = f_c + \delta_{od} f_d + \theta_{od} f_t \tag{6.1}$$

$$\underline{cost(\delta_{od}, \theta_{od})} = f_c + \delta_{od} f_d \tag{6.2}$$

Where o and d denote the origin and destination of a trip, f_c is a constant pickup fee, f_d denotes the constant distance rate and f_t denotes traffic and waiting rate. □

We also consider the decisions of the companion users to minimize the effort for users by reducing the number of attempts needed to get a rideshare. We suppose that every user makes decision based on their own savings from the rideshare. Thus, for a new passenger u and every companion passenger u', the following statement should be true:

$$\begin{aligned} &u.cost < u.SRcost; and \\ &u'.cost < u'.SRcost \end{aligned} \tag{6.3}$$

Table 6.1 summarizes the most important notations that we use in this chapter. Other notations will be covered in the rest of the chapter.

6.1.2 Design Basics

In the following, we illustrate some of the basic concepts for designing the search approach.

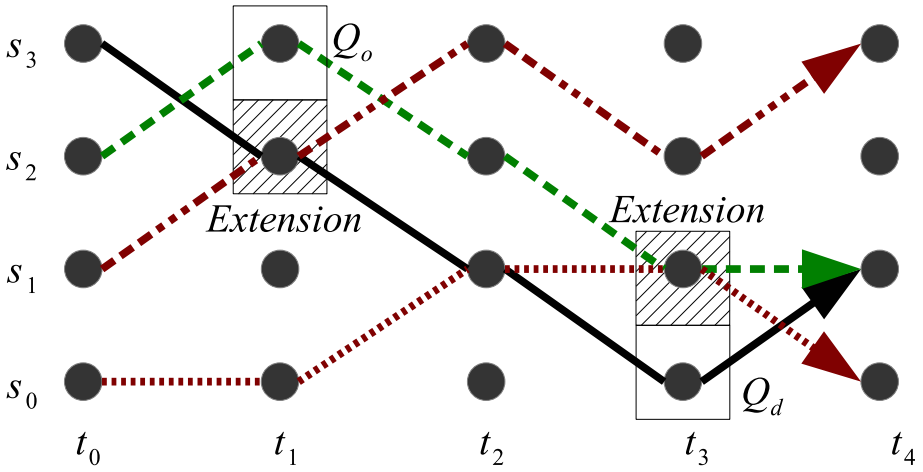


Fig. 6.2 Extended search areas for a query

Figure 6.2 shows the transition of four taxis (specified with four different colors) on four points during the time window t_0 to t_4. A given query Q, specifies p_3 in t_1 for the pickup and p_0 in t_3 for the drop off. As shown, the taxi in the origin (green) is not found in the destination

Table 6.1 List of important notations

Notation	Definition
AOI	The area of interest
p_i	Point i in AOI
$\delta_{p_i p_j}$	The distance between points p_i and p_j
$[\underline{i}, \bar{i}]$	Any interval value i with the minimum bound $\underline{i}$ and maximum bound $\bar{i}$
$\theta_{p_i p_j}$	The trip time estimate between points p_i and p_j at time t
$cost(\delta, \theta)$	Travel cost estimation function
Q	A query made by the seeker users
$Q.o$	The pickup point (*latitude*,*longitude*) of query Q
$Q.d$	The delivery point (*latitude*,*longitude*) of query Q
$Q.wp$	The pickup time window of query Q
$Q.wd$	The delivery time window of query Q
$Q.dur$	Defined as $[\underline{Q.wp}, \overline{Q.wd}]$ is the duration of a trip for Q
V	Taxi status
$V.S$	Set of scheduled trips for the given taxi V
σ	A scheduled trip
A	The set of alternatives which are displayed to the user
R^*	Maximum range of economically justifiable alternatives
idx	The segments index
u	User
$u.cost$	Ridesharing cost for user u
$u.SRcost$	Sole ride cost for user u
$\mathscr{V}$	Any set of taxi trajectories
$P(u', Q)$	The probability of user u' accepting a rideshare offer based on Q

(only the black taxi is there), if the exact points in the query are used. In this situation, to find a compromise solution, we need to apply some extension to the search area to find the nearest taxi that satisfies the query. Only after extending the origin and/or destination, two taxis are found. The IS approach [159, 162] proposes applying extension after each unsuccessful search. For the given example in the figure, after applying two extensions taxis starting from p_2 and p_3 are found as the closest alternatives. Following the IS approach, one of the taxis will be selected based on the extra distance required by taxis to get to the points $Q.o$ and $Q.d$. Previous works aim at finding the nearest taxi while it may not necessarily be the best

alternative. Each ridesharing request needs to be evaluated by the companion passengers and can be either accepted or rejected finally. Thus, the nearest taxi will not necessarily be the best alternative.

We identify two main steps in preparing the results for an incoming query Q. The first step is to find the alternatives, which can satisfy the query. If an alternative has other passengers who have already booked the taxi, it will be considered only if these passengers would like to share the ride. In the second step, we can rank and sort the alternatives based on economical merits to benefit users with less effort. In order to establish a search and rank strategy, we analyze the possible sequences of the schedules.

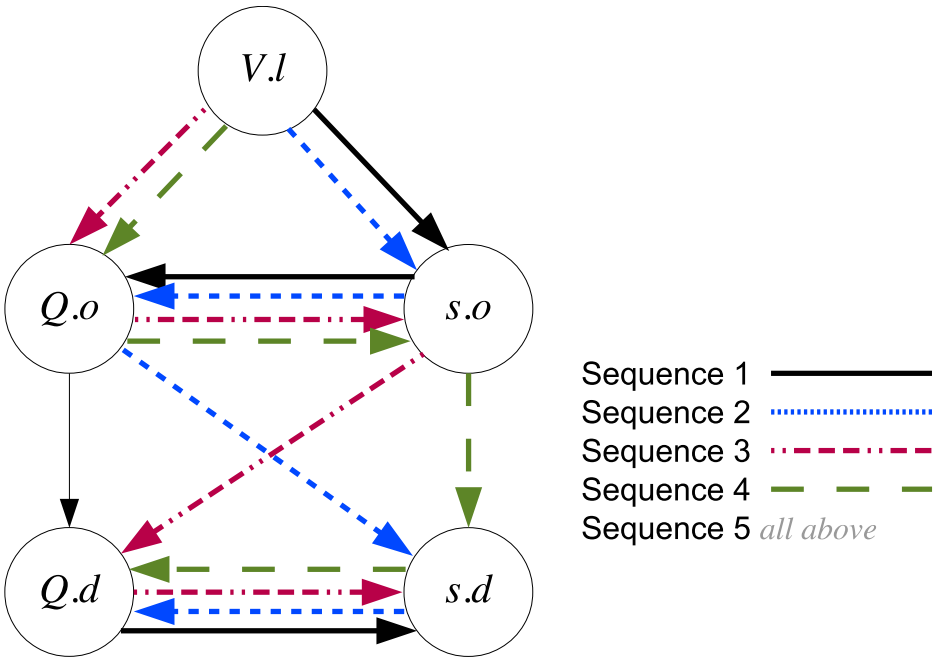


Fig. 6.3 Possible schedule sequences for a query

Let $Q.o$ and $Q.d$ respectively denote the origin and the destination of a query, and $p.o$ and $p.d$ denote a scheduled trip's origin and destination[1]. There are 5 possible travel sequences for the ridesharing as shown in Figure 6.3: (1)$\{V.l, p.o, Q.o, Q.d, p.d\}$; (2)$\{V.l, p.o, Q.o, p.d, Q.d\}$; (3)$\{V.l, Q.o,\ p.o, Q.d, p.d\}$; (4)$\{V.l, Q.o, p.o, p.d, Q.d\}$; (5) if one or more time windows

[1]For the sake of simplicity, we only consider one travel schedule for existing passengers.

overlap, any order for pick up/delivery is possible; and (6) if the companion traveler is already on the taxi.

For the sake of simplicity, we consider two sets of users but the approach can be generalized to support sequences with multiple pickup/drops. The following sequences are possible for the taxi (see Figure 6.3):

Sequence 1: Respectively, pre-scheduled pickup, new user pickup, new user delivery, pre-scheduled delivery. The riding cost can be formulated as follows:

$$u.cost = \frac{cost(\delta_{od}, \theta_{od})}{(m+1)} \tag{6.4}$$

$$u'.cost = \frac{cost(\delta_{io}, \theta_{io})}{m} + \frac{cost(\delta_{od}, \theta_{od})}{m+1} + \frac{cost(\delta_{dj}, \theta_{dj})}{m} \tag{6.5}$$

Sequence 2: Respectively, pre-scheduled pickup, new user pickup, pre-scheduled delivery, new user delivery. The riding cost can be formulated as follows:

$$u.cost = \frac{cost(\delta_{oj}, \theta_{oj})}{m+1} + cost(\delta_{jd}, \theta_{jd}) \tag{6.6}$$

$$u'.cost = \frac{cost(\delta_{io}, \theta_{io})}{m} + \frac{cost(\delta_{oj}, \theta_{oj})}{m+1} \tag{6.7}$$

Sequence 3: Respectively, new user pickup, pre-scheduled pickup, new user delivery, pre-scheduled delivery. The riding cost can be formulated as follows:

$$u.cost = cost(\delta_{oi}, \theta_{oi}) + \frac{cost(\delta_{id}, \theta_{id})}{m+1} \tag{6.8}$$

$$u'.cost = \frac{cost(\delta_{id}, \theta_{id})}{m+1} + \frac{cost(\delta_{dj}, \theta_{dj})}{m} \tag{6.9}$$

Sequence 4: Respectively, new user pickup, pre-scheduled pickup, pre-scheduled delivery, new user delivery. The riding cost can be formulated as follows:

$$u.cost = cost(\delta_{oi}, \theta_{oi}) + \frac{cost(\delta_{ij}, \theta_{ij})}{m+1} + cost(\delta_{jd}, \theta_{jd}) \tag{6.10}$$

$$u'.cost = \frac{cost(\delta_{ij}, \theta_{ij})}{m+1} \tag{6.11}$$

Sequence 5: One or more overlapping schedules. In this case, we cannot find a deterministic order for pickups and deliveries as the taxi driver may pick any order in advance. Thus, as the level of uncertainty is higher in this case, the estimated cost of each ride can be formulated as follows:

$$\underline{u.cost} = \frac{\underline{cost}(\delta_{od}, \theta_{od})}{(m+1)} \tag{6.12}$$

$$\overline{u.cost} = \overline{cost}(\delta_{oi}, \theta_{oi}) + \frac{\overline{cost}(\delta_{ij}, \theta_{ij})}{m+1} + \overline{cost}(\delta_{jd}, \theta_{jd}) \tag{6.13}$$

$$\underline{u'.cost} = \frac{\underline{cost}(\delta_{ij}, \theta_{ij})}{m+1} \tag{6.14}$$

$$\overline{u'.cost} = \frac{\overline{cost}(\delta_{io}, \theta_{io})}{m} + \frac{\overline{cost}(\delta_{od}, \theta_{od})}{m+1} + \frac{\overline{cost}(\delta_{dj}, \theta_{dj})}{m} \tag{6.15}$$

Sequence 6: If the companion passenger has already started his/her trip and is already on the taxi then the taxi will not get to the $p.o$ and the sequence starts with $V.l$. In this case, depending on the order of the destinations of the schedules, the estimated cost of each ride can be formulated similar to the Sequences 1 and 2. However, in both cases the $V.l$ will replace $p.o$.

Economic Search Margin

One of the problems that is associated with the IS approach is that the search area is gradually extended until the nearest taxi with enough space is found. Thus, it is possible that for a number of searches, we get results which should travel a long distance to reach the seeker user making it is not efficient for the companion passengers. We use the following theorem to set up this concept.

Theorem 6.1.1. *Given the Query Q, where the user intends to travel from o to d, a taxi that can pick the user iff it does not have any other trip with the origin and destination further than the following distance from the points o and d:*

$$R^* = \delta_{od} \tag{6.16}$$

where δ_{od} denotes the distance that the user wants to travel and R^* is the economically justifiable radius. A taxi with scheduled trips further this distance is not within the economically justifiable range.

Proof. We can prove the above theorem by using costs and benefits analysis for all possible schedule sequences. Based on the mutual benefit principle, by summing up the total cost for all users (e.g., all passengers), we have:

$$u.cost + m * u'.cost < u.SRcost + m * u'.SRcost \tag{6.17}$$

This statement holds for all of the possible schedule sequences. For instance, for Sequence 1, we have:

$$u.cost + m * u'.cost = cost(\delta_{oi}, \theta_{oi}) + cost(\delta_{ij}, \theta_{ij}) + cost(\delta_{jd}, \theta_{jd}) \tag{6.18}$$

If we make a false assumption that $R^* > \delta_{od}$, we will have the following:

$$u.cost + m * u'.cost \geq SRcost \tag{6.19}$$

where $SRcost$ denotes $u.SRcost + m * u'.SRcost$. Equation (6.19) in fact contradicts the mutual benefit principle and cannot be correct. Theorem 1 is therefore proved. □

6.2 Background: IS vs. DS Approach

Area extensions are applied to the origin and destination areas in order to find the taxis with the least extra distance for taxis because for most of the queries no taxi is found to exactly match the specified requirements. As mentioned before, one of the recent taxi search approaches is exploiting an *incremental* search approach. Using the R^* concept, instead of increasing the search area, we can decrease the search area in each step. This will lead to the decremental search approach. The details of each approach are as follows.

Incremental Search (IS)

It has been used in designing dynamic ridesharing applications such as T-Share [159]. Algorithm 10 shows a procedure based on this approach.

The steps of the Algorithm 10 take place in the following order. The input of the algorithm is the given query Q and the extended areas of origin and destination, which in the first round would be equal to $Q.o$ and $Q.d$. First, the taxis at extended origin area and extended destination area are queried and stored in T_1 and T_2 respectively (lines 1-2). The `getTaxis` function loops through all taxis to find the right ones. The list of the common taxis in the two sets are stored in the T set (lines 3-5). Then, if T is empty (lines 6-9), the area is expanded and search is recursively called with the expanded origin and/or destination areas and the

Algorithm 10 INCREMENTAL-SEARCH

Require: $Q, origin, dest$
Ensure: T set of taxis which satisfy the query
1: Let $T_1 \leftarrow$`getTaxis(`$origin, Q.wp$`)`
2: Let $T_2 \leftarrow$`getTaxis(`$dest, Q.wd$`)`
3: **for all** $taxi \in T_1$ **do**
4: **if** $taxi \in T_2$ **then**
5: Let $T \leftarrow T \cup taxi$ add taxi to output list.
6: **if** T is empty **then**
7: Let $origin \leftarrow$`expand(`$origin, Q.o$`)` extending the search area.
8: Let $dest \leftarrow$`expand(`$dest, Q.d$`)` extending the search area.
9: **return** `INCREMENTAL-SEARCH(`$Q, origin, dest$`)`
10: **else**
11: **return** T

same query. Otherwise, if a common taxi is found in the same area, it is returned (lines 10-11).

The complexity of this algorithm depends mainly on three factors: the number of segments ($|AOI|$) in AOI, the number of taxis ($|taxis|$), and the number of scheduled trips n. Thus the order is $\mathbf{O}(n.|AOI|.|taxis|^2)$.

The IS approach, as proposed [159], does not support the economical search margin and continues extension until the first taxi is found. However, if this approach is extended to support this margin, it still will continue to expand to fill the whole area within the boundaries of the margin even if no taxi is found. Thus, a decremental strategy can be developed [163] to fill this gap.

Decremental Search (DS)

The decremental search approach is proposed to decrease the cost of the search procedure [163]. The details of this approach are shown in Algorithm 11. To initialize, the decremental search requires the total extended area that includes all of the economically justifiable taxis. We call it *Economic Search Margin* and denote the radius with R^* (Figure 6.5).

The inputs to the algorithm are the given query Q and the extended areas of origin and destination. In the first step of this algorithm, we check if each of the origin and destination areas are limited to only their initial values or in other words, none of them is an extended area. In this case, we cannot split them further and the set of common taxis in the specified time windows is returned (lines 1-2). The `getTaxis` function is similar to the same function in the incremental approach. If the search areas are already extended, the rest of the process is applied as follows. We search the areas with the given timeframes for the taxis and store them in T_1 and T_2 (lines 3-4). The set of common taxis which appear at both T_1 and T_2 are stored in T (lines 5-7). Next, if T is not empty, which means that some taxis can be found, we shrink the search areas and recursively call the decremental search with the new parameters and then store them in T' (lines 8-11). If no common taxi is found, the taxi search algorithm can stop the further recursion. The results of recursion will replace current set of T only if they are not empty (lines 12-13) and finally T is returned.

In general, the order of the decremental approach is the same as the incremental approach. However, the IS approach does not consider a limit for expansion of the search area, which can make it inefficient if no suitable taxi is found in a close distance. Even if we fix this problem, when no suitable taxi is found in a search round, we have to repeat the search on previously search areas, which in turn can be solved by introducing incremental indexing [159]. Moreover, due to the early stop feature, it can potentially increase the speed of the search process by stopping further recursion when no suitable taxi is found in the economically justifiable range. As a result, to some extent, the decremental approach can increase the efficiency of IS approach.

6.3 The TRIPS Framework

Our TRIPS framework (see Figure 6.4) adopts a layered architecture that consists of the *User Interface* layer, the *TRIPS Application* layer, the *Traffic Modeling* layer, the *Distribution*

Algorithm 11 DECREMENTAL-SEARCH

Require: $Q, origin, dest$
Ensure: T set of taxis which satisfy the query
1: **if** *origin* equals $Q.o$ **and** *dest* equals $Q.d$ **then**
2: **return** $T \leftarrow$ `getTaxis(`$origin, dest, Q.wp, Q.wd$`)`
3: Let $T_1 \leftarrow$`getTaxis(`$origin, Q.wp$`)`
4: Let $T_2 \leftarrow$`getTaxis(`$dest, Q.wd$`)`
5: **for all** $taxi \in T_1$ **do**
6: **if** $taxi \in T_2$ **then**
7: Let $T \leftarrow T \cup taxi$ add taxi to output list.
8: **if** T is **not** empty **then**
9: Let *origin* $\leftarrow$`shrink(`$origin, Q.o$`)` shrinking the search area.
10: Let *dest* $\leftarrow$`shrink(`$dest, Q.d$`)` shrinking the search area.
11: Let $T' \leftarrow$`DECREMENTAL-SEARCH(`$Q, origin, dest$`)`
12: **if** T' is **not** empty **then**
13: Let $T \leftarrow T'$
14: **return** T

Management layer, and the *Data Storage* layer. The data storage layer facilitates the storage and retrieval of TRIPS data, including the *spatio-temporal index* of taxis, the *routes index*, and the *traffic data*. Parts of the work in previous section can be reused in this section. Accordingly, we use the *design basics* for limiting the search area. Also, The search algorithms in previous section can be used for comparison and the application layer. In the following, we focus on the technical details of the other layers in the TRIPS framework.

Our framework supports a novel combination of functional factors as follows:

1. Minimizing the end user's attempt to get a rideshare: The preferences of the companion passenger(s) is an important factor for the success of ridesharing. For instance, some studies suggest that behavioral parameters—such as the low rate of acceptance to the requests from male strangers by female participants who travel alone [173] and issues related with e.g., smoking [168] can affect the final decision of other riders on the same taxi. However, in this chapter we do not aim to address all behavioral factors. In our model, we assume that users only decide based on their own economical benefits.

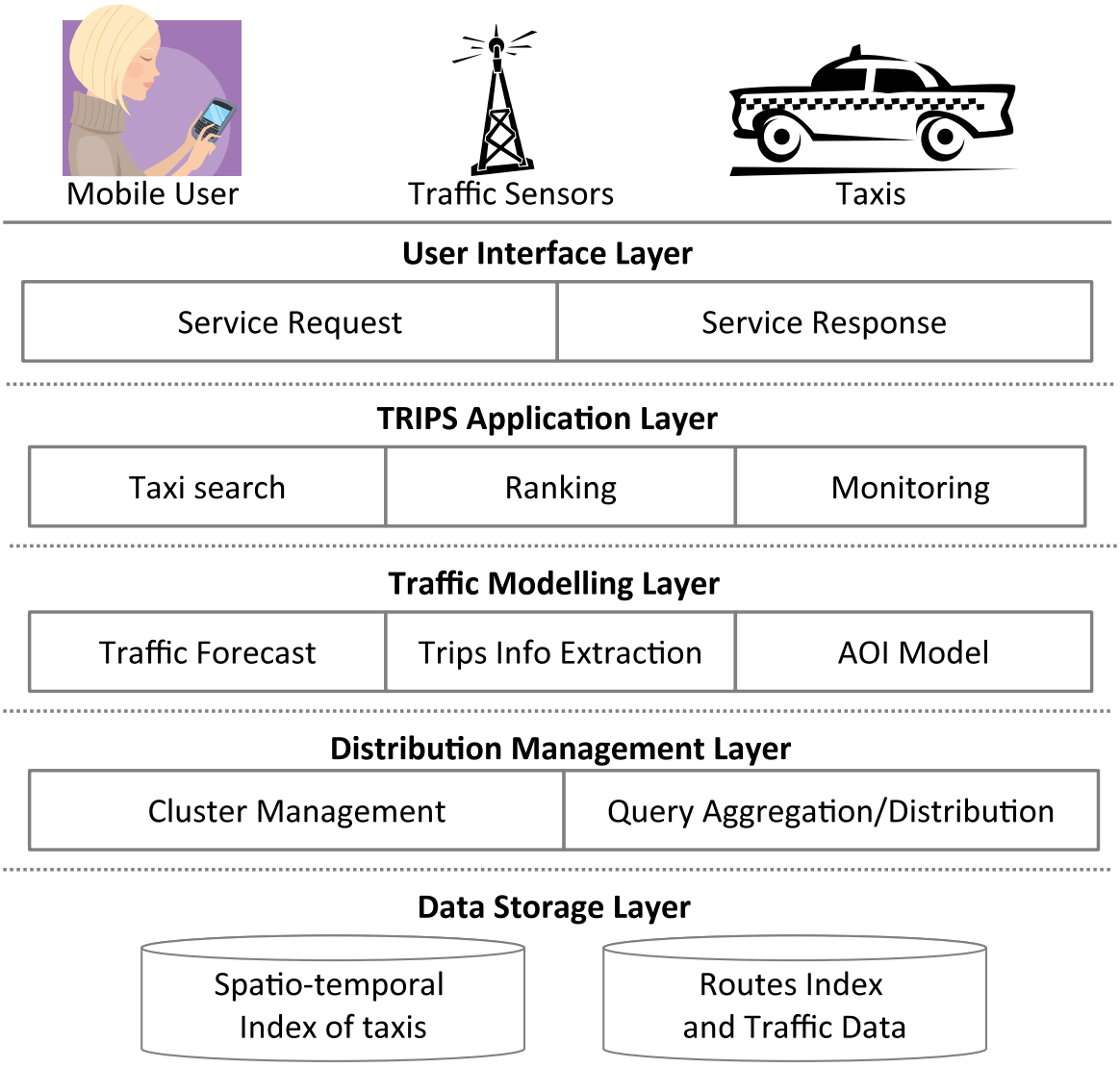


Fig. 6.4 TRIPS framework for taxi ridesharing service

2. Maximizing the performance of the application: Computationally, matching finding the best taxi is a complex problem. In Moreover, in particular, including uncertain user decisions and processing the distances of all taxis from all users are complex processes. In this chapter, we particularly focus on the uncertain end users decisions and avoid duplicate rounds for performing the search when the ridesharing requests get rejected.

3. Maximizing overall savings from using the application: The savings from ridesharing is the primary goal of users when they use a the application. To maximize the savings, we improve the rate of accepted requests and the amount of savings (by reducing vehicle mileage) for the accepted queries.

6.3.1 Traffic Modeling Layer

The traffic modeling layer operates in parallel to the TRIPS application layer (details in Section 6.3.2) in order to provide the application layer with the needed traffic forecasts and identified common trips model. The *AOI model, the* trips information extraction, and the *traffic forecast* are the three main modules of this layer.

AOI Model: The underlying roads network can be modeled via different approaches such as *R-tree* and partitioning using a grid network. In our work, a grid partitioning system similar to [159] is developed in order to avoid high cost indexing level. However, the indexing system can easily be upgraded if needed.

Trips Information Extraction: Trips information extraction module is designed to obtain the regular trips that taxis undertake within different locations in a certain period of time. For this purpose, we use the same algorithm as in [163] which provides the actual upper and lower bounds from the historical data. In our study we use these results to avoid dealing with technical complexity over the accuracy of predicted travel times. However, in application it can simply be replaced by prediction algorithms such as [172].

Traffic Forecast: The traffic forecast module can exploit several techniques to forecast traffic because many approaches have been proposed for this task in the literature [174, 175]. Although the traffic forecast model is not the focus of this study, we briefly discuss in the following on how traffic index is generated in our work.

To generate a traffic index, the speed of taxis moving along a specified trip is taken as an index. The traffic load in a route between two points can have direct relationship with the speed of cars passing over that route if they are moving. A query over historical data record can easily provide the margins of each entry in traffic index and trip time matrices. Thus $\overline{\theta_{p_i p_j}} = max\{\theta_{p_i,p_j}\}$, $\underline{\theta_{p_i,p_j}} = min\{\theta_{p_i,p_j}\}$.

6.3.2 TRIPS Application Layer

In the proposed framework, TRIPS application layer runs on top of the traffic modeling layer, facilitating modules for responding user queries, ranking and monitoring the successful requests.

Taxi Search: Upon receiving a query from a user, the taxi search module returns all possible taxis which can satisfy the query by considering uncertainty. Since every taxi that can satisfy user's query could be an option for the user, instead of gradually increasing search area (IS) such as T-Share [159, 162] or gradually decreasing it (DS approach), in TRIPS we develop a new strategy, namely Fixed Search (FS), to perform *search once* to get all of the available taxis.

Based on the FS approach, to find the alternatives we calculate all taxis' locations at the pickup and delivery time windows specified by the user's query. However, this approach requires traversing all scheduled trips for all taxis which makes it very inefficient for large scale applications. In order to increase the efficiency, the search area can be limited to R^* (Figure 6.5). In Theorem 1, we have showed that any taxi beyond the economic search

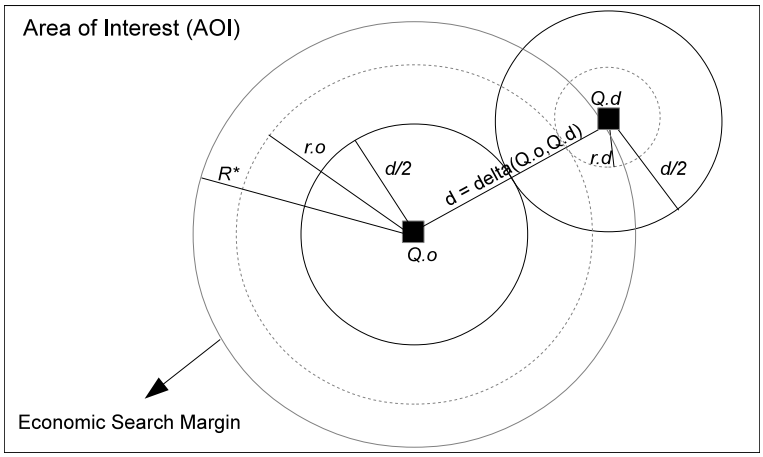


Fig. 6.5 Symmetric (solid) and asymmetric (dashed) extended search areas

margin will not be suitable. As Figure 6.5 shows, the margins can grow symmetrically or in an asymmetric manner. However, the total added distance should exceed the R^* limit.

Based on this approach, we propose a novel search algorithm (see Algorithm 12). The algorithm has several steps as follows. First, R^* is initialized to prevent searching unnecessary locations (line 1). Then the algorithm loops through every scheduled trip of each taxi (lines 2-3) and checks if the duration of trips overlap at pickup point, the taxi is added to T_1 . Also, if they overlap at destination, it is added to the T_2 set (lines 4-7). Later, common taxis in T_1 and T_2 are added to the set of alternatives (lines 8-10). As a result set consisting of numerous taxis is not suitable for users, due to the fact that only one needs to be selected, the taxis in the result set need to be ranked and sorted based on the gain and the possible acceptance rate by other users to get the best result. Thus, we call the RANK function and return the best taxi as a result (lines 11-12). The details of RANK algorithm will be discussed later in this section.

The complexity of the FS algorithm depends on two factors the number of taxis ($|taxis|$) and the number of scheduled trips (n). Thus the order of FS approach is $\mathbf{O}(|taxis|.n)$. As a result, with the growth of the number of taxi schedules, the FS approach will become inefficient as it is shown by our experiments (Section 6.4).

Algorithm 12 FIXED-SEARCH

Require: Q user's query
Ensure: T set of available taxis
1: Let $R^* \leftarrow \delta_{od}$ Setting the R^* to avoid searching the unnecessary area
2: **for all** $taxi \in taxis$ **do**
3: **for all** $\sigma \in taxi.V.S$ **do**
4: **if** $i = \sigma.pickup$ and $\delta_{io} \leq R^*$ **and** $Q.dur$ overlaps$(\sigma.dur)$ **then**
5: Add $taxi$ to T_1
6: **if** $j = \sigma.destination$ and $\delta_{jd} \leq R^*$ **and** $Q.dur$ overlaps$(\sigma.dur)$ **then**
7: Add $taxi$ to T_2
8: **for all** $taxi \in T_1$ **do**
9: **if** $taxi \in T_2$ **then**
10: Add $taxi$ to T
11: $T \leftarrow RANK(T)$
12: **return** $T.first$

We also design a new algorithm, namely Index Powered Fixed Search (IPFS), to use the index in the search procedure.

First, we set up the indexing scheme and then we present the new algorithm. For creating the index, similar to T-Share [159], we divide the spatial domain of moving taxis, which we refer to as the AOI, into a finite set of rectangular cells. Each cell is called a segment and is denoted by s. The number of segments in an AOI is often limited and constant. Also, the number of scheduled trips which begin from or end to a segment are limited as well. Therefore, we introduce a segment based index denoted by $s.idx$, which keeps the set of schedules relevant (pick up or delivery) to s.

The index contains two sets of entries. The first set is the scheduled trips from the segment and the second contains the scheduled trips to the segment. The records in the index are updated whenever a new trip is scheduled and removed whenever a trip is finished. Thus, the index is updated during schedule set up and schedule removal steps without notable extra workload on the system. The complexity order of the index update algorithm, if implemented separately, is $O(\sum |V.S)$.

The new search approach is presented in Algorithm 13. Similar to the FS algorithm, the IPFS algorithm starts with initializing R^* (line 1). The algorithm loops through the index entries for each segment within the range of $R*$ instead of the schedules of each taxi (lines 2-4). Then for each segment within the *economical search margin* (i.e., the area that includes all of the economically justifiable taxis), if a scheduled trip is found in the segment index entry, the corresponding taxi will be added to the set of found taxis at origin denoted by T_1 and/or destination denoted by T_2 (lines 5-8). Only taxis appearing in both sets (T_1 and T_2) are included in the output (T), ranked similar to the FS algorithm and finally returned (lines 9-13).

The complexity of the IPFS algorithm depends on two factors: the number of index entries (n) and the number of segments ($|AOI|$). Thus the order of FS approach however depends on the number of taxis as well. However, the execution cost of this algorithm will be lower than the FS algorithm due to the fact that only a small portion of the scheduled trips are processed in each round.

Algorithm 13 INDEX-POWERED-FIXED-SEARCH

Require: Q user's query, AOI list of segments in AOI
Ensure: T set of available alternatives
1: Let $R^* \leftarrow \delta_{od}$ Initializing the R^* to avoid searching the unnecessary area
2: **for all** segment $s \in AOI$ **do**
3: **if** $\delta_{seg,o} \leq R^*$ **then**
4: **for all** $trip \in s.idx$ **do**
5: **if** $\delta_{seg,o} \leq R^*$ **and** $Q.dur$ overlaps$(trip.dur)$ **then**
6: Add $idx.taxi$ to T_1
7: **if** $\delta_{seg,d} \leq R^*$ **and** $Q.dur$ overlaps$(trip.dur)$ **then**
8: Add $idx.taxi$ to T_2
9: **for all** $taxi \in T_1$ **do**
10: **if** $taxi \in T_2$ **then**
11: Add $taxi$ to T
12: $T \leftarrow RANK(T)$
13: **return** $T.first$

Ranking: Ranking can be challenging when it comes to uncertain data. The score for each alternative will be represented as an interval. Hence, to rank and sort them, different possible orders must be considered. We propose the RANK algorithm (see Algorithm 14) which works in the following order: 1) the algorithm starts by calculating the score for each alternative. For each active scheduled trip (line 2) of each alternative (line 1) we determine the sequence (*seq*) of the new user's trip and the previously scheduled trip (see Figure 6.3) in line 3 and update users sole ride cost ($u.SRcost$), shared ride cost ($u.cost$), the amount of saving ($u.saving$) and the possibility of accepting the rideshare request ($P(u,Q)$) based on the savings in lines 4-9; 2) In the next step (line 10), we pass the query (Q) and the set of scored alternatives (A) to BUILD-TREE algorithm (Algorithm 15) which updates the global tree of possible worlds; 3) Then, the alternatives will be sorted based on the tree of possible worlds and the result will be returned (lines 11 and 12).

The complexity of RANK algorithm in the worst case is $\mathbf{O}(|taxis|.n)$ if $|taxis|$ and n represent the number of the taxis and the number of scheduled trips. However, due to the fact that usually only a small subset of the taxis set is received from the search algorithm, the runtime and order of RANK algorithm are negligible. Moreover, using segment schedules index can also improve this algorithm by reducing the number of accessed schedules.

We design the BUILD-TREE using the *probabilistic partial order* as follows.

Definition 13 (*Probabilistic Partial Order [176]*). Let $A = \{a_1, ..., a_n\}$ be the set of the alternatives with their scores, and O be the set of orders of alternatives. The probabilistic partial order PPO(A,O) is a set with $(a_i, a_j) \in O$ iff a_i precedes a_j. □

Algorithm BUILD-TREE recursively builds the tree of possible worlds, which is a globally defined variable, and can stop at the specified level (if any) in line 1. Building each level starts by finding sources (lines 2-4), which are alternatives that dominate others by their scores, and ends up with passing the generated probabilistic partial order to the next level (line 5). The complexity of this algorithm only depends on the number of taxis received from

Algorithm 14 RANK

Require: Q user's query, T the set of taxis
Ensure: A_r ranked list of alternatives
1: **for all** $taxi \in T$ **do**
2: **for all** $\sigma \in taxi.V.S$ **do**
3: Let *seq* be the sequence of $Q.wp$ and $Q.wd$ comparing with $\sigma.wp$ and $\sigma.wd$
4: Calculate $Q.u.SRcost$, $Q.u.cost$, $Q.u.saving$ based on *seq*
5: Calculate $\sigma.u.SRcost$, $\sigma.u.cost$, $\sigma.u.saving$ based on *seq*
6: Update $P(\sigma.u, Q)$ based on *seq*
7: Update $Q.u.totalSRcost$, $Q.u.totalCost$ and $Q.u.totalSaving$
8: Update $\sigma.SRcost$, $\sigma.cost$ and $\sigma.saving$
9: Set the saving and possibility to *taxi*
10: Update global tree of possibilities T by BUILD-TREE(Q,A,*nil*,*nil*,0)
11: Let $A_r \leftarrow$ `sort(` A, T `)` be the set of sorted alternatives
12: **return** A_r

the RANK algorithm, and as there are usually a small number of taxis, we expect that the complexity and runtime of the BUILD-TREE algorithm would be negligible.

Algorithm 15 BUILD-TREE

Require: PPO(A, O), Treenode n, *level*
1: **if** $level \leq max - level$ **then**
2: **for all** sources $taxi \in A$ **do**
3: Add *taxi* as a new *child* to children
4: Let $PPO \leftarrow PPO(A, O)$ after removing *taxi*
5: BUILD-TREE(Q,A,PPO,*child*,$level + 1$)

6.3.3 Distribution Management Layer

The distribution management layer handles two main tasks: the *cluster management* and the *query distribution/aggregation*.

The cluster management module maintains taxis in a set of object clusters. Formally, an object cluster is defined in the following:

Definition 14 (*Object Cluster*). Object cluster is a set of tables containing the data of moving objects (taxis) $\{taxis_i | i \in D(taxis)\}$, where the member items share one or more common values in their status V such as their location or corresponding ID. The set of clusters can be

defined as: $C = \{c_i | i = 1,2,...,X\}$, where X is the number of clusters and each cluster can be shown as $c_i = \{o_j | j = 1,2,...,Y\}$, where Y is the size of the cluster. □

The query distribution and aggregation module is responsible for dividing an incoming query, denoted as $Q = \{q_i | i = 1,2,...,X\}$ in which each q_i is submitted to the corresponding cluster c_i for further query processing (see Section 6.3.2). Later, the returned results are aggregated to compose the final result set.

6.4 Experiment

We implement the proposed TRIPS framework and conduct extensive experiments using a real world dataset to study its effectiveness and efficiency.

6.4.1 The Dataset

We use a real world dataset which contains the records of raw GPS trajectories for 10,357 taxis in the city of Beijing, China [170, 139]. In addition to raw trajectories data, we need the details of previous trips in order to generate the indexes and prepare traffic forecast data. To prepare the data to be used in our experiments, we apply a number of data refinement steps.

First, to create the index, we divide the AOI into a 76×76 segments grid and map each GPS reading to its corresponding segment. Next, we remove the records that are located outside of the AOI. Then, for every record we use the distance and the time elapsed from the last record to calculate the minimum speed of a taxi. Since we do not have the details of previous trips for the taxis, for every taxi trajectory we calculated the permutations of successor records. Each permutation can be considered as a possible trip unless it represents a trip to the initial origin point. To have a set of permutations with a reasonable size, we dismiss the records with speeds less than 1 km/h (i.e., taxi stops or traffic jams).

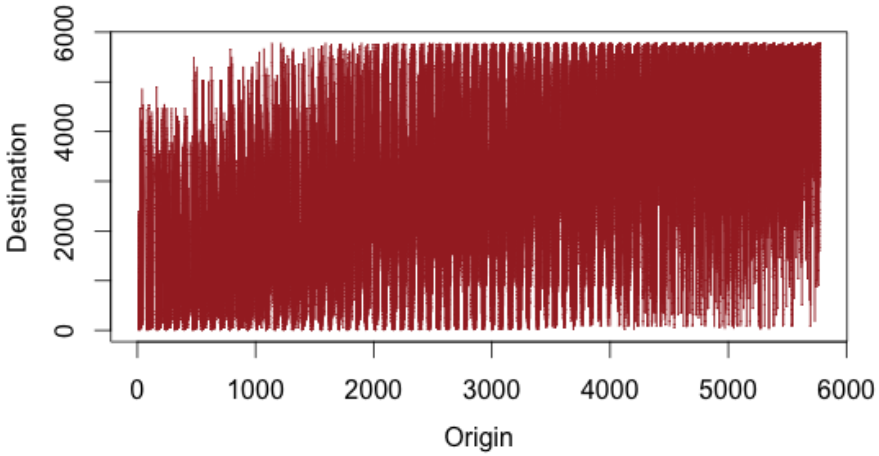


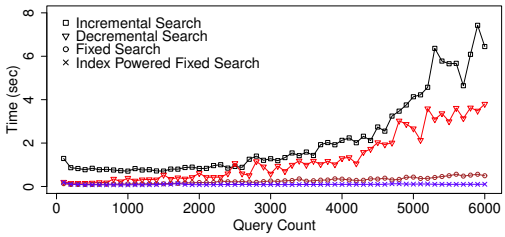
Fig. 6.6 Availability of the index for all origins and destinations

Figure 6.6 shows the index availability for all origins and destinations in the *AOI*. Each dark point indicates that the time estimation for the corresponding segments pair is existing. The density in the central areas is higher than the density of indexed data in the surrounding areas while some of the segment pairs have no data.

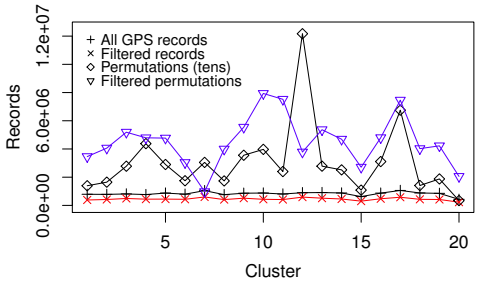
Then, we conduct two separate experiments to examine the effect of the proposed approach on efficiency (performance) and effectiveness (cost saving).

6.4.2 Performance

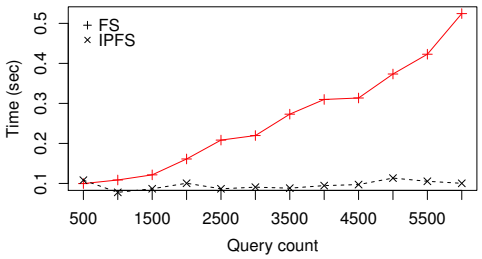
We analyze two measures for the performance and the scalability of our system: i) search space, and ii) its ability to respond to a heavy workload. The size of search space can greatly affect the performance of a search procedure. One of the advantages of using segments index is that it fixes the maximum size of search space. For any number of given trips data in the input, the size of trip information index is equal to or less than $|AOI|^2$ (e.g., 33,362,176 records). Figure 6.7b shows the size of the dataset in each step of the dataset preparation.



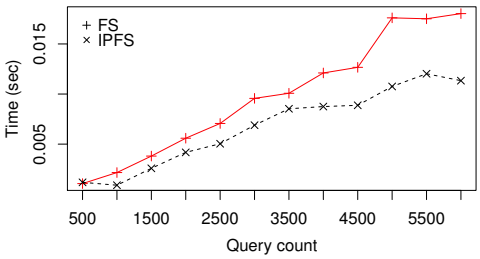
(a) Index availability



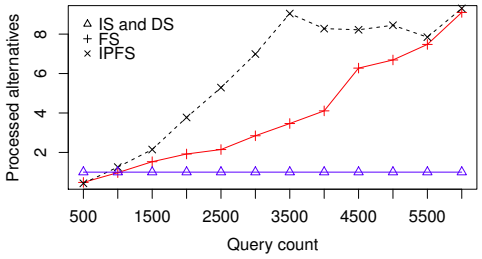
(b) Processing time



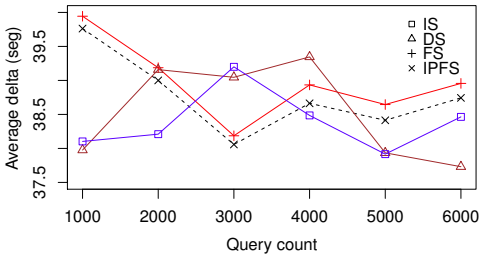
(c) Dataset size



(d) Search time



(e) Rank time



(f) Average delta

Fig. 6.7 The results of the experimental evaluation

For the second indicator, we implement a simulation, in which we use a set of entities such as a 76×76 grid of segments (same as AOI), using key parts of a random taxi query generator [159]. We also use 10,000 taxis with limited capacity (up to 4 people) to represent a realistic scenario.

In our experiments, we use 6,000 queries which are processed by the system. For the baseline, we use an improved version of T-Share which uses the IS approach. The improved version applies extension to the search area by adding all the surrounding segments (instead of one by one segment strategy used by e.g., T-Share) in each iteration. Figure 6.7a compares the total query processing time among IS, DS, FS and IPFS approaches. As the Figure shows, the IFPS algorithm is the most efficient one. We also measure the amount of time spent on *search* and *rank* stages separately and for each of them, we compare the runtime between using and not using the segments index. Figure 6.7c compares the average search time between FS and IPFS for the same number of queries. As it shows, while the IPFS takes less than 0.1 second until the end of the experiment, the FS search time gradually increases and reaches to 1.4 seconds. This is mainly due to the constant size of the search space in the IPFS algorithm.

The RANK function can benefit from the segments index as well. Figure 6.7d compares the execution time for two versions of the RANK function. The use of segments index reduces the increment in average ranking time by nearly 50%. The average ranking time for index powered approach is nearly 15 milliseconds per query where without using the index, it can take up nearly 30 milliseconds for the last set of queries.

Another interesting feature found in our performance analysis is the number of index access times. While in the incremental approaches same segments may be accessed several times [159, 162], in our TRIPS framework, the same segment index is accessed only twice in maximum.

To have a deeper analysis of the changes in conditions between the two experiments (index-powered and FS approach), we deploy two more parameters. The first parameter is the *average number of alternatives* found by the FS algorithm. This can be useful to assure that the two ranking approaches have not been affected by the number of their input (processed alternatives). Figure 6.7e shows that the enhanced RANK algorithm has processed more alternatives while it has a better performance. Except a slight difference for a number of queries, the number of processed alternatives is almost the same.

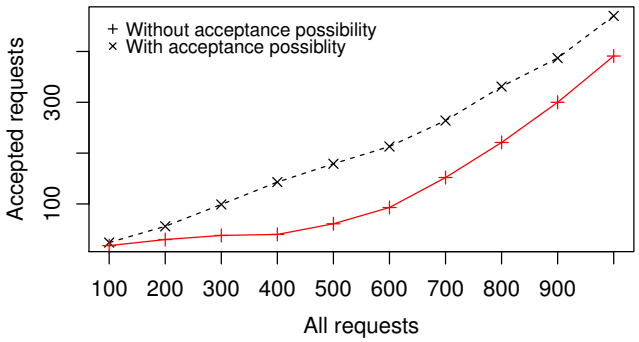
The second parameter is δ_{od}, which also can affect the performance of the search step. As shown in Figure 6.7f, the average amount of δ_{od} from the two experiments are very close to each other most of the time. As a result, we have a good evidence that the IPFS and FS approaches have been examined in a fairly comparable condition. However the index powered approach shows to be more efficient.

6.4.3 Cost Savings

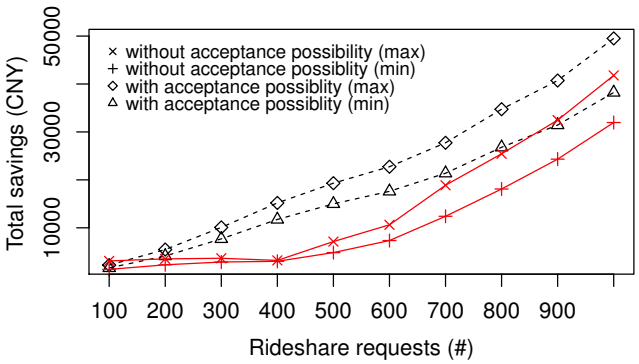
The second experiment investigates the effect of considering uncertainty in the total savings of the ridesharing process. In this experiment, we enable the riders who have booked earlier to accept or reject the incoming ridesharing requests. The decision is made based on the ratio of their own savings from the rideshare to their initial cost:

$$P(u', Q) \propto \frac{u'.SRcost - u'.cost}{u'.SRcost} \tag{6.20}$$

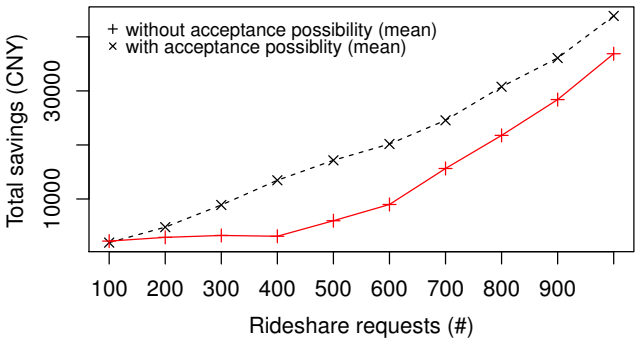
Where u' is a user who has previously booked the taxi for a time which overlaps with $[Q.wp, Q.wd]$, $possibility$ is the possibility of accepting the new user, $u'.cost$ is the cost after accepting the rideshare and $u'.SRcost$ denotes the sole ride cost for u' before accepting the rideshare.



(a) Accepted requests



(b) Bounds of savings



(c) Mean Savings

Fig. 6.8 Effectiveness results

In a similar setting to the previous experiments, we develop two implementations of the RANK algorithm to the same number of ridesharing requests. Nearly 1,000 ridesharing requests were successful in finding a set of suitable alternatives. The result (see Figure 6.8a) shows that considering the companion passenger decision factor increases the acceptance rate of the companion users. To assess the amount of financial benefits for users, we use the following formula to calculate the taxi fares in Chinese Yuan (CNY)[2]:

$$\begin{aligned} \overline{cost(\delta,\theta)} &= 12+\delta*(2.2)+(\overline{\theta}-\underline{\theta})*(0.01) \\ \underline{cost(\delta,\theta)} &= 12+\delta*(2.2) \end{aligned} \tag{6.21}$$

Figure 6.8b shows the upper and lower bounds for the estimated cumulative savings. The possible amount of savings increases due to the increment in acceptance rate. As the amount of uncertainty increases throughout the time, the upper and lower bounds of the two estimations may interfere. Figure 6.8c shows the average amount of cumulative savings for users in each approach. From the experimental results, we conclude that the total savings remarkably increase by using our TRIPS framework. This is due to the reason that our approach considers the most probable and most efficient alternatives rather than the most efficient ones only.

6.4.4 Comparison with Other Solutions

In this section, we compare our approach with other existing approaches. T-Share's search approach [159, 162] is the main work comparable with our search approach. It is not designed to support the effect of users' decisions, it does not have any component similar to the taxi ranking part of our framework. Thus, we can only compare the searching part. After customizing the approach to find all possible taxis, the customized code does not stop with finding the first taxi. We realize that in this case, the performance of this approach is

[2]http://www.numbeo.com

Table 6.2 Taxi speed estimation based on GPS reading analysis

All	Stopped $v < 1\ km/h$	High Probability $1 \leq v < 90\ km/h$	Low Probability $90 \leq v < 200\ km/h$	Impossible $v \geq 200\ km/h$
15,784,344	6,419,947	9,280,967	32,283	51,147

almost the same as IS approach. In addition, with returning the whole set of available taxis, ranking and sorting taxis will become complex and more time consuming as it depends on the number of taxis.

Moreover, Sharek [177] is another candidate which can be compared to our search approach. The main purpose of Sharek is to design a scalable dynamic ridesharing system for dynamic ridesharing which allows riders requesting the ridesharing service to indicate the maximum price they are willing to pay and the maximum waiting time before being picked up. However, it does not take the response time and other scheduled trips into account. This approach also uses an IS based search approach without indexing. Thus, this approach can be less efficient than the IS approach as shown Figure 6.7c.

6.5 Related Work

In this section, we overview the research activities that are related to the research work presented in this chapter. We cover the literature related to dynamic ridesharing, travel time estimation and more generally, the uncertainty in spatio-temporal data.

6.5.1 Dynamic Ridesharing

The ridesharing problem has been actively studied in past few years. The problem has been considered in various forms such as Carpooling/Vanpooling, Hitchhiking, Mass Transit Systems, Dial A Ride, Web-based Shared Ride Systems (e.g., *Google ride finder* that was later replaced by *Google Transit* which in turn was integrated into *Google maps*).

Dynamic ridesharing is generally described as an automated system that facilitates drivers and riders to share one-time trips close to their departure times/places and can be characterized with features like dynamic, independent, cost-sharing, non-recurring trips, prearranged and automated matching [158]. A survey over Trajectory Data Mining [169], which is a more comprehensive research area, divides this paradigm into different sub-paradigms including trajectory preprocessing, trajectory indexing and retrieval, trajectory pattern mining, trajectory classification, trajectory outlier/anomaly detection and uncertainty. However, the uncertainty sub-paradigm is more focused on the uncertainty of the trajectory data rather than the uncertainty in the application context. The use of contextual information and user centered trajectory data mining, which is the main direction of this chapter, have been mentioned as the areas of future research in the same survey. Inferring gas consumption and pollution emission from the trajectory data is an example of contextual information processing in this paradigm [178].

Most of the proposed applications have not been examined for either real-life and/or large-scale datasets. These solutions are developed based on a variety of techniques and approaches such as auction negotiation [179, 164], analyzing social connections in SRSS [180], and multi source-destination path planning [181].

Some other recent solutions such as T-Share [159, 162], Noah [182] and kinetic tree algorithm [183] treat dynamic taxi ridesharing as finding k-nearest neighbors (kNN) problem although it does not cover the whole challenges and minimizing the system wide travel time and travel distance. However, although using this approach can enormously reduce the complexity of the problem, using kNN for dynamic ridesharing is not a suitable approach as k is unclear. CallCab [184] deploys a generic *MapreduceMeasure* to tackle the raw dataset of 14,000 taxis efficiently. However, the dominating approach is the IS approach while in real world scenarios, this approach does not find all suitable taxis and leaves search iterations right after finding the first taxi.

Some of the related works such as [164] take companion users willingness for ridesharing into account and develop a multi-agent system to support dynamic ridehsaring in real-time. However, the scalability of the framework has not been evaluated for real-world or large scale data. The proposed approach is still too simplistic. Other works in this area often focus on different criteria and do not address uncertainty or scalability. For instance, [165] propose a solution based on genetic algorithms to achieve the following goals:

1. Minimize the total distance of vehicles' trips
2. Minimize the total time of vehicles' trips
3. Minimize the total time to successfully get a ride
4. Maximize the number of accepted (served) requests

The work by [161] considers time window restrictions and models them as a soft constraint, where for instance, a reasonable delay might be acceptable. They consider the problem as an on-line continual planning problem, in which additional ride requests may arrive while plans for previous ride-matching are being executed. The success of this model depends on other uncertain parameters such as routes selected by drivers and travel time estimate.

6.5.2 Travel Time Estimation

In addition, estimating the travel time is a sub-problem of dynamic taxi ridesharing. It is a highly challenging problem because it deals with different factors such as traffic fluctuations, demand and supply, traffic signals, weather conditions and seasonal changes [139, 170]. One of the existing approaches proposes a real-time travel time estimation using sparse trajectories [172]. The requirements for this method is knowing the path for which a part of the path is not associated with previous values. One of the recent works proposes an approach for travel

time estimation using large-scale taxi data with partial information [185]. The proposed model focuses on uncertainty in path choices. It infers the possible paths for each trip and then estimates the link travel times by minimizing the error between the expected path travel times and the observed path travel times. This model uses only the current time data and does not support historical data.

6.5.3 Uncertainty in Spatio-Temporal Data

Many applications such as monitoring and querying moving objects over traceability networks, querying and searching objects in the IoT, and querying uncertain and incomplete spatio-temporal data. In many cases, these applications deploy the RFID technology to identify and locate the moving objects. The main characteristics of RFID data are simplicity [186, 187], large volumes [188, 189], uncertainty and inaccuracy [190, 191], spatial, temporality and distribution [192].

Another example for static uncertain data [193] makes use of a method called *probabilistic inverse ranking*. In the proposed model, a *probabilistic threshold top k query* is used to find the set of records in which, each one takes a probability of at least p, a given probability threshold, to appear in the top k lists in the possible worlds. Uncertain spatial data also has been discussed in the literature.

Many studies discuss spatial data in a time snapshot [194–196]. Thus, the spatial data is treated as static data while it can easily change in the matter of time especially in the case of enterprise traceability networks. On the other hand, several studies focus on temporal data. For instance, [197] discusses the problem of ranking top-k query results of temporal data in an instance of time and develop a SEB-Tree, which is more efficient than R-Tree indexing scheme.

In spite of its applicability, the problem of uncertain spatio-temporal data has been rarely discussed. One of the studies that takes this type of data into account is [198]. In that study,

the problem of analyzing a moving object's data has been modeled as a Markovian chain and impossible states are pruned based on previous status of that object. Hence, the search area is reduced to possible states.

Uncertain data streams also have attracted researchers recently. For instance, Tran et al. [199] discuss conditioning and aggregation operations on uncertain data streams. Furthermore, some studies consider high-volume uncertain streams specifically. In [200], the proposed system employs probabilistic inference to generate uncertainty description for its input (raw data), then a set of statistical methods are deployed to capture changes of uncertainty as data propagates through query operators. The proposed system is inspired by two case studies, namely i) object tracking and monitoring using RFID and ii) hazardous weather monitoring using radar networks.

6.6 Summary

Taxi ridesharing is an interesting example of intention-oriented search in IoT. The intention of using a search engine in this case is to find a convenient and economic option for a shared ride rather than finding a list of correlated taxis. In this chapter, we present the details of the TRIPS, an intention-oriented search engine for taxi ridesharing. We use this example to emphasize the impacts of the search intention on query resolution in IoT search. Our approach improves the results by considering the probability of users decisions, which is not previously addressed by the proposed systems in this area. We describe the details of three novel approaches including the DS, FS and IPFS, to search for the suitable alternatives.

Unlike other state-of-the-art ridesharing solutions which use the IS approach, our approach focuses on finding the maximum number of taxis that match the query and then rank them based on certainty and closeness (i.e., the search once and rank strategy). We also reformulate the criteria for searching and ranking ridesharing alternatives to optimize the process. We conduct extensive experiments using a real-world dataset of taxi trajectories

collected in Beijing, China to evaluate the proposed search approach. The experimental results show not only the efficiency and scalability of the proposed approach, but also the financial benefits brought by the approach.

There are several interesting directions for the future research. First, the nature of uncertainty in dynamic ridesharing is very complex. We plan to further investigate the modeling of different sources of uncertainty and analyze their impacts on taxi ridesharing. For instance, our observation of the real-world dataset shows that the validity of sensor readings are contaminated with a high level of uncertainty. Table 6.2 shows the speeds of taxis in the dataset that we have used. There are 51,147 records showing taxis traveling with high speed of 200 km/h or more, which are most likely due to errors in GPS readings for some taxis. Sensor uncertainty, which is likely to increase during the operation of the system, can result in incorrect and non optimal query results. Therefore, extending uncertainty factor is one of our future research directions. Finally, we also will target automating decision making and optimized stochastic planning for the cases in which, taxi or passenger(s) get missed due to the external factors such as predictable delays and traffic.

In Chapter 7, we present the final stage of the query resolution process for our IoT search engine. Independently from how the query results have been prepared, the interface of our IoT search engine can prepare the results for the users. Considering the requirements of different groups of users, the results can be presented in different ways. Furthermore, the results can be enriched through the use of additional analytical plots particularly for human users.

Chapter 7

ThingSeek: An Enriched Interface for IoT Search Engine

IoT is a generic paradigm that can be deployed in various sectors of our society. Some interesting examples are smart cities, smart homes, healthcare, security and surveillance [201]. Web services are now mature enough to enable sensors to automatically publish their data on the Internet. Unfortunately, traditional Web search engines currently do not cover existing IoT data on the Web. Therefore, a major milestone in boosting this area is to create tools to search IoT.

Given the variety of the IoT systems and their purposes, we provide a number of approaches for query result resolution in previous chapters. In this chapter, we focus on our points of contact with the users and the data sources. This includes the crawling engine and the user interface. Some of the notable works in this area are as follows [30]: (1) Snoogle/Microsearch [145, 146]; (2) Dyser [83]; and (3) SPITFIRE [147]. Currently, to the best of our knowledge, all of the existing search engines have been examined only for small and/or unreal data. Furthermore, all of these search engines have been designed for human users only and it is neglected that smart objects may also require this service.

There are a number of tangible results of initiations for IoT search such as *Thingful* project [45] and the *Graph of Things* [48]. Thingful is a search engine for the IoT, providing a geographical index of connected objects around the world, including energy, radiation, weather, and air quality devices as well as seismographs, beacons, ships, aircraft and even wildlife trackers. The search engine indexes the data which is generated by publicly available sensors from different data sources. However, handling the data that should be indexed is a huge technical problem and the data on Thingful is mostly outdated. Moreover, the data collected by Thingful cannot be extracted by any means and the interface of the website presents raw data only. Thus, further improvements are required to convert the existing work to a good infrastructure for future works in this area. On the other hand, Graph of Things, which originally launched in 2015, is designed to provide a visualization of sensor readings in real-time for its users. Quite recently, the interface was improved to add a map of things distribution. However, it cannot be regarded as a search engine due to its limited functionality and no further analytical results are used to enrich the search experience.

Meanwhile, there is another search engine, namely *Shodan* [49] which also claims to be a search engine for IoT. Shodan is basically designed as a search engine for hackers as it identifies and hacks password protected devices such as servers and routers as well as any other object that is connected to the Internet. Shodan itself does not process sensor outputs and despite the size of its dataset, catching everyday objects on Shodan is still not straightforward as servers, routers and network devices constitute the majority of devices on its database.

We develop a data discovery engine to extract, analyze, visualize and export IoT data from publicly available data sources on the Internet. In our design, we focus on collecting publicly available real-time IoT data. The result of our work includes integrated tools for managing IoT data sources, a crawler engine to collect highly dynamic IoT data and two novel user interfaces to serve both human and machine users.

7.1 ThingSeek: An Overview

In this section, we present the framework of the ThingSeek crawler engine and specifications of the collected dataset.

7.1.1 ThingSeek Crawler Engine

ThingSeek Framework

To minimize the required amount of work when collecting data from a new source, we have broken down the crawling procedure into a certain set of steps in a unified framework.

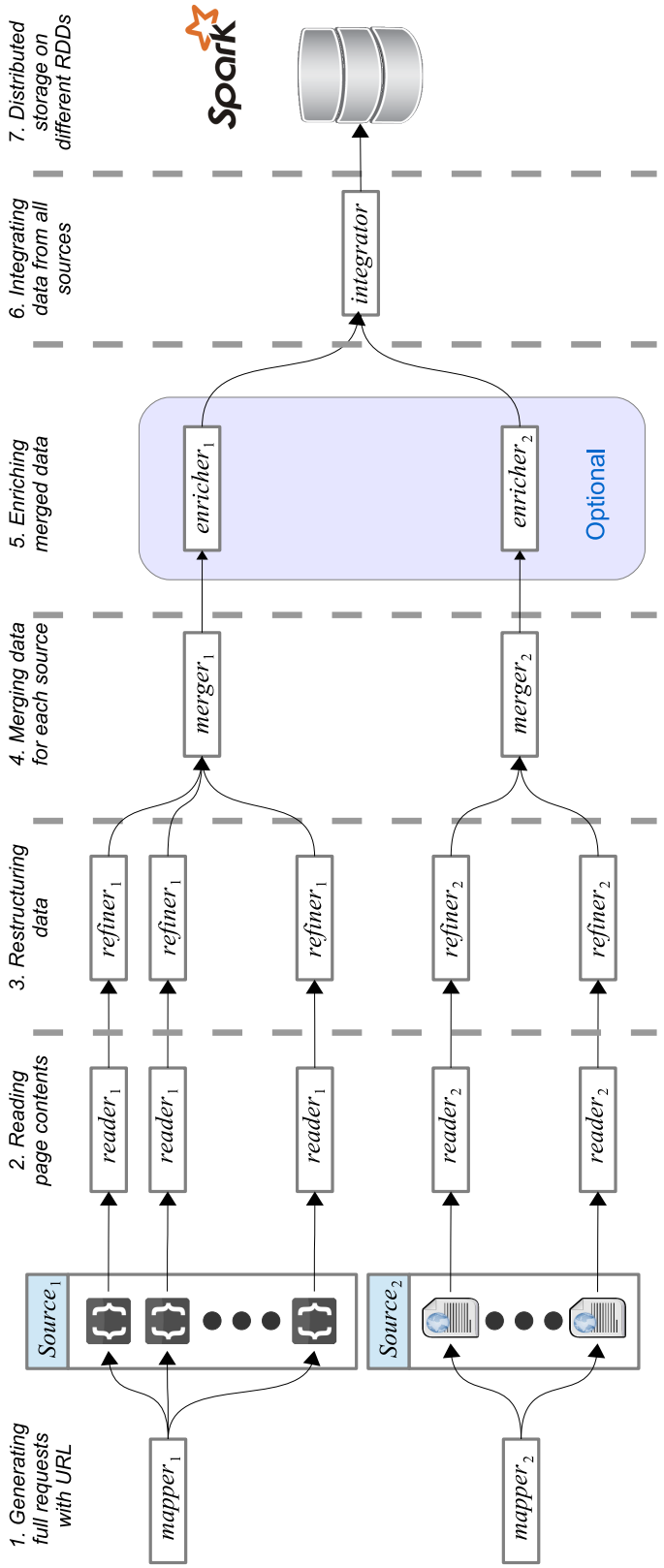


Fig. 7.1 Architecture of the ThingSeek crawler engine

Figure 7.1 illustrates the main features of the ThingSeek crawler engine. In the first step, a URL generator initializes the queue of queries. Each entry in the queue is supplied with certain parameters to construct a query to a page or a specific location. The parameters can be the time window, the boundaries of the querying region and/or other parameters. Then for each entity in the queue, a reader function reads the selected part of the page, and the contents are converted to a set of vectors and refined using a refiner. The data for each subset is separately held until all subsets are refined where we merge all of the subsets of the resource's data. In this step, a specific enricher can be used to collect the missing information, if any, from other sources. This can, for example, fill the incomplete fields such as IP address by acquiring them from Shodan. Finally, the collected data from different sources are integrated and stored on a distributed backend.

Due to the size and dynamics of the sensor-generated data, IoT data sources often provide a subset of their data with a call to their API. Thus, pagination techniques such as location-based queries are deployed to present the data. We use the same mechanism through implementing the URL generator. The URL generator plays a key role in adjusting the workload on the data source. It converts a set of spatial segments to a sequence of queries which can be submitted via the API of the data source. Thus, a highly populated area can be placed multiple times in the processing queue while an empty area may appear only once (or not appear) in the queue. For example, through a URL generator, URL b will be repeated three times for others during a scan as it contains more dynamic objects than others:

$$\begin{bmatrix} a:1 & b:3 \\ c:1 & d:1 \end{bmatrix} \Longrightarrow [a,b,c,b,d,b] \tag{7.1}$$

We have developed ThingSeek using a set of tools to collect, process and visualize the dataset. Some of the tools we used are as follows: R programming language, SparkR, Apache Spark 1.4.1 and Rails framework.

Adding IoT data sources

We leverage Web Mapping such as Google Maps which is the most dominant way of visualizing spatial data on the Web, to achieve the goal. Thus, we limit our search scope to the sources which contain a map. We use a set of keywords to narrow our search results to find such sources such as "*real-time map of [application]*", "*live map of [application]*" and "*tracker map of [application]*". In the search query, the term "application" can be replaced with any application of IoT such as *flight*. We also include some of the available IoT platforms such as Xively[1] to the initial set of data sources.

7.1.2 Query Results Preparation

Human User

In this section, we propose our approach for query resolution and the indexing approach to enable large-scale search for IoT. Figure 7.2 shows the procedure of retrieving query results in ThingSeek. As the figure shows, the query processing workflow works as follows.

1. Queries, which are formed as pairs of keywords and locations, are fed into the system. The query structure is inspired from the Thingful search engine.

2. The Queries are processed in two steps: location based filtering and keyword based filtering and finally the results are updated with the most recent values before being presented to the user.

3. We use approximate values based on indexed data in the location filtering step. The location filtering is facilitated using the R-Tree data structure to enhance the flexibility and the performance of the system.

[1] https://xively.com/

4. In the keyword filtering, the results of location filtering are processed for each given keyword accordingly.

5. Before presenting the results to the user, we update the results with the most recent values using the data source index for each object in the result set. After preparing the final result set, we update the result continuously when presenting to the user. This would provide a better user experience of real-time data.

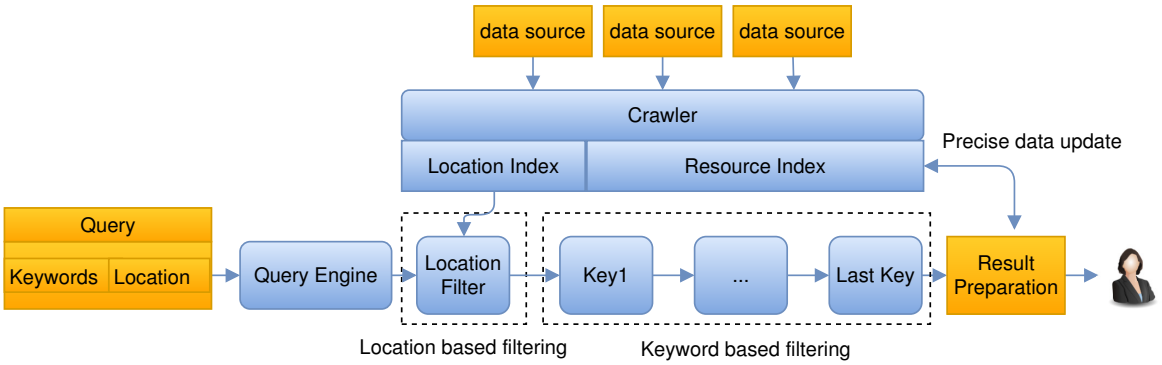


Fig. 7.2 Query resolution and indexing in ThingSeek framework

Due to the highly dynamic nature of the IoT data, analytical result may change promptly. In addition, raw IoT data are often meaningless and not very useful by themselves. Thus, we also designed a Web-based interface to visualize the IoT data as well as query the IoT data.

Smart Objects Interface

As objects are becoming smarter, they become the main producers and consumers of information. Thus, we created an interface for smart objects to enable them to query the dataset. To cope with the existing standards, we used Constrained Application Protocol (CoAP), which is a protocol for simple electronic devices to allow them to communicate interactively over the Internet. We initialize a CoAP based RESTful interface for smart objects to search for things in our database. Although CoAP contains a discovery tool, its scope is limited and lacks flexibility.

Figure 7.3 compares our architecture with CoAP discovery and illustrates how the ThingSeek's machine interface serves queries. For example, a smart air conditioning system searches objects related to air or weather to plan its cooling strategy. As shown, with the use of CoAP, a querying object can only enquire objects on the same network via distributing discovery messages to all objects on the network. Following this, the issuer gets objects' responses if they match to the query. However, this approach can limit the scope and effectiveness of the search. To resolve this issue, in our ThingSeek architecture, the smart object uses a service to send its query directly to the search engine with a POST or GET message. Due to the power, network and computing limits of things, ThingSeek should respond the query with a number of messages containing only a small number of results. In this regard, we use the *ECS* approach [38] (Extract-Cluster-Select) to provide the best response with limited size. The ECS approach extracts co-location (objects in the same location or very close to each other) and co-owned (objects with the same owner) correlations between things and forms a unified Things Correlation Graph. Then, the nodes are clustered into k groups and finally a number of things from each cluster are selected and returned. It is designed to rank objects based on their correlations and responds the query with a limited number of the top-k results based on the weight of their correlations with the query issuer. Finally, the URI of the corresponding data source is located and crawled to get the latest sensor readings. If the object is not found in the index, the latest cached records will be supplied.

7.2 Demonstration

In this section, we demonstrate the functionality of the proposed ThingSeek framework. ThingSeek can extract IoT data from desired data sources by providing separate simple interfaces and effective search algorithms for users and machines. In particular, we demonstrate

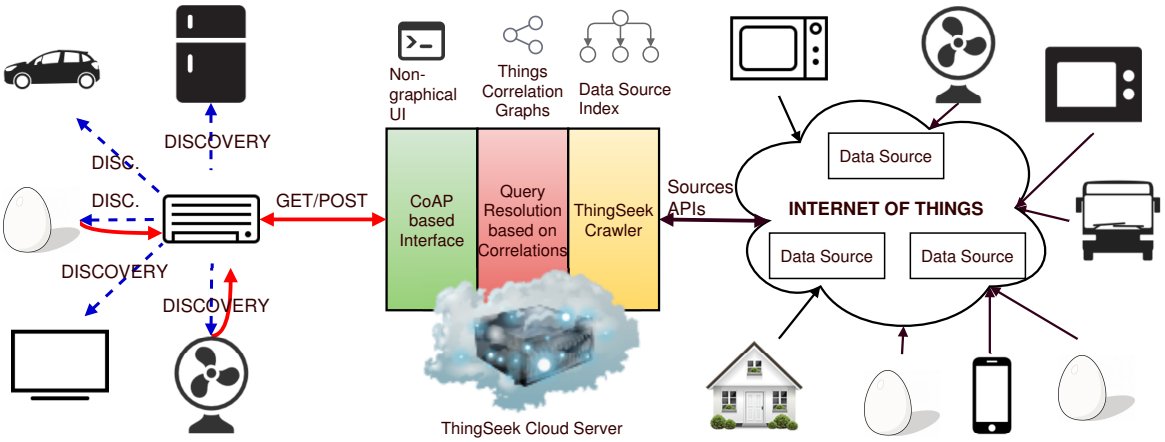


Fig. 7.3 Query resolution for smart things in ThingSeek framework

main functions through three main search scenarios: crawling an IoT data source, a human user searching IoT and a smart machine user searching IoT.

7.2.1 Crawling an IoT Data Source

Adding and removing data sources is a key to preserving the quality of the crawled data. To add a new data source, a new crawling procedure should be created in the system. Defining a new crawling procedure starts by initializing the link of the data source. Then, the following steps of the crawling procedure should be specified according to the steps in Figure 7.1. We have defined a universal module for each step which by default will be used. Otherwise, the user can introduce her own modules by defining new ones. Finally, a strategic crawling queue for the new data source will be specified by the user. For example, users can choose to crawl the new data source hourly and only update certain parts of the data.

7.2.2 IoT Search by Human Users

Through a Web-based user interface, a human user uses the search engine to acquire information from sensors. For example, a user would like to get information from nearby weather sensors. Figure 7.4 shows a screen shot of our Web-based interface where each red spot

denotes an object in the result set. Users can use the query panel to generate new queries and the result can be shown as a list of sensors or through an interactive map as shown. However, users would be more interested in acquiring knowledge from the data streams rather than finding the sensors. Thus, we added an interactive plot maker to generate real-time plots.

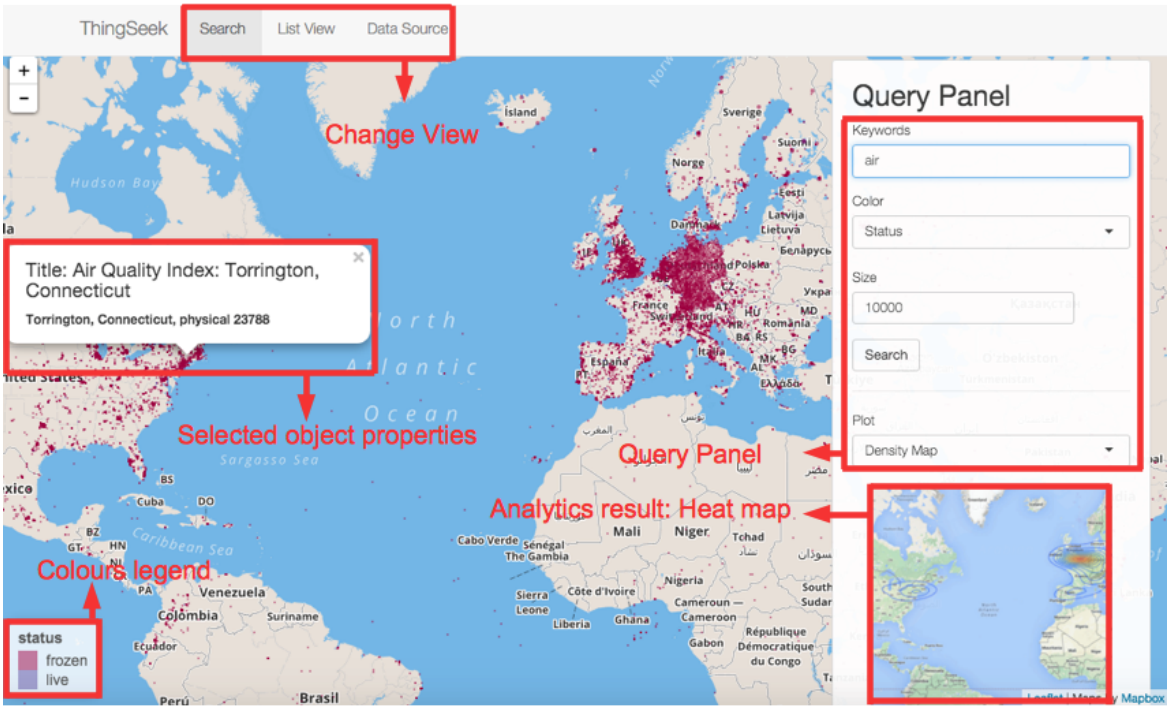


Fig. 7.4 ThingSeek Web based visualization

7.2.3 IoT Search by Smart Machines

In this scenario, we consider a smart object querying our search engine. We developed a Machine-to-Machine (M2M) interface based on the architecture in Figure 7.3 to enable things to use CoAP to connect to our server and submit their queries. To use the interface, on the client side, users can use any of CoAP implementations on CoAP website[2] to send a GET or POST message to our server. The message payload contains keywords followed the desired number of the result set at the end. The server would provide the results in response.

[2]http://coap.technology/

7.3 ThingSeek in Application: Flight Delay Analysis

In the previous chapters we already presented a number of examples of the search results for searching things. In this chapter, we present results for a novel application in the aviation industry. Specifically we focus on flight delay analysis. For our case study, we use three different data sources including a real-time flight data, air quality index and real-time weather data. While finding the trajectories of aeroplanes in real-time can be interesting for aviation professional, value added results such as flight delay predictions can be widely used.

The results of our study fall into two categories. First, a search result can provide the list of contextual features that can be identified based on the selected IoT data sources. Secondly, additional results can precisely show that the extent of effectiveness for a given feature such as *temperature*. We briefly present the results as follows.

7.3.1 Model Features

Due to the heterogeneity of IoT data, the semi-structured or unstructured sensor reading data that is provided by different data sources can widely vary based on our selection of the dataset. An intra-source feature model is an interesting showcase to demonstrate the correlation between different data sources. Accordingly, Figure 7.5 shows the list of the features that we have extracted from our case study.

In order to provide a clearer image, we describe the characteristics of each feature in Table 7.1.

7.3.2 Feature Analysis Results

For this case study, we select seven airports from the largest cities of China. The cities are: Beijing (PEK), Shanghai (SHA), Guangzhou (CAN), Wuhan (WUH), Chengdu (CTU), Harbin (HRB), and Dalian (DLC). In our case study, we collect the data of all flights between

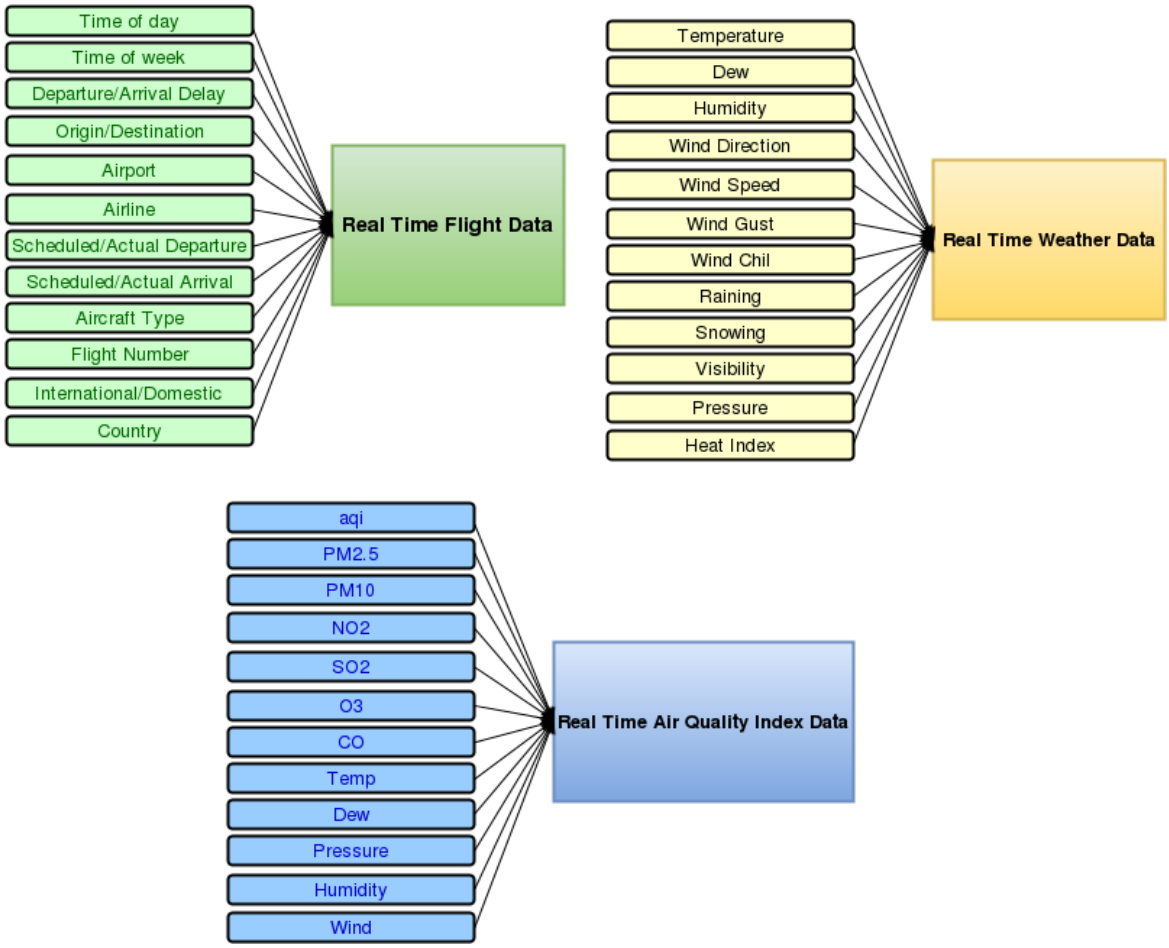


Fig. 7.5 Features affecting flight delays from each source

Table 7.1 Feature description for flight delay search

Source	Feature	Description
Flight	Time of day	Represents the time of the flight during the day.
	Day of week	Represents the day of the flight during the week.
	Departure/Arrival Delay	Represents the departure delay and the arrival delay of the flight in minutes.
	Origin/Destination	Represents the origin airport, city, country of the flight.
	Airport	Represents the airport where the flight departs or arrives.
	Airline	Represents the airline that operates the flight.
	Scheduled/Actual Departure	Represents the scheduled/actual departure time of the flight.
	Scheduled/Actual Arrival	Represents the scheduled/actual arrival time of the flight.
	Aircraft Type	Represents the airplane type of the flight.
	Flight Number	Represents the flight number.
	International/Domestic	Represents if the flight domestic or international.
Weather	Temperature	Represents the current temperature of the weather at the airport where the flight departs or arrive.
	Dew	Represents the dew at the airport.
	Humidity	Represents the Humidity at the airport.
	Wind Direction	Represents the Wind Direction at the airport.
	Wind Speed	Represents the Wind Speed at the airport.
	Wind Gust	Represents the Wind Gust at the airport.
	Wind Chill	Represents the Wind Chill at the airport.
	Raining	Represents the Raining at the airport.
	Snowing	Represents the Snowing at the airport.
	Visibility	Represents the Visibility at the airport.
	Pressure	Represents the Pressure at the airport.
	Heat Index	Represents the Heat Index at the airport.
Air Quality	aqi	Represents the air quality index at the airport.
	PM2.5	Represents Particulate Matter 2.5 micrometers. It is a for particles found in the air, including dust, dirt, smoke, etc.
	PM10	Represents particulate matter 10 micrometers or less in diameter
	NO2	Represents the chemical compound Nitrogen dioxide.
	SO2	Represents the chemical compound Sulfur dioxide.
	O3	Represents the Ozone.
	CO	Represents the Carbon monoxide.

these cities. The distribution of the number of flights varies according to the city size and the population number. The airlines operate the flight between these cities are: China Air (CA), Shanghai Airlines (FM), China Eastern Airlines (MU), China Southern Airlines (CZ), Juneyao Airlines (HO), Hainan Airlines (HU), Xiamen Airlines (MF), Sichuan Airlines (3U), Shandong Airlines (SC), Chongqing Airlines(OQ), Grand China Air (CN), Shenzhen Airlines (ZH), Spring Airlines (9C), Tibet Airlines (TV), Beijing Capital Airlines (JD), Chengdu Airlines (EU).

In our study we focus on China, where environmental factors can be concerning due to the industrial development. We get around 14,000 records for more than 800 flights between the selected cities. Figure 7.6 shows a screenshot of a few records from the flights dataset.

identification.row	identification.number.default	identification.number.alternative	status.live	status.text
2938392811	CA1855	CA1855	FALSE	Scheduled
2934625405	CA1855	CA1855	FALSE	Scheduled
2930890219	CA1855	CA1855	FALSE	Scheduled
2930890220	CA1855	CA1855	FALSE	Scheduled
2920607116	CA1855	CA1855	FALSE	Scheduled
2916225693	CA1855	CA1855	FALSE	Scheduled
2912409039	CA1855	CA1855	FALSE	Scheduled
2908630624	CA1855	CA1855	FALSE	Scheduled
2904833455	CA1855	CA1855	FALSE	Scheduled

Fig. 7.6 Example of the flight records

We also crawl 2,091 records for weather data from public and private weather stations. Figure 7.7 shows a screenshot from a number of records in our dataset.

We also collect 3,084 records for air quality data near the airports. Figure 7.8 shows a screenshot from a number of records.

The following results would be shown to the user after a search for the flights data. Figure 7.9 compares the delay at departure for different airlines. Therefore, the user can easily identify the airlines which have the least and the most delay in real-time.

winddir	windspeedmph	humidity	tempf	rainin	baromin	dewptf	weather
-999	0.0	72	87	-999	29.85	79	Partly Cloudy
290	2.3	75	88	-999	29.82	81	Partly Cloudy
230	5.8	72	80	-999	29.80	72	Partly Cloudy
270	9.2	73	86	-999	29.79	78	Scattered Clouds
270	5.8	42	93	-999	29.71	72	Scattered Clouds
230	2.3	43	93	-999	29.71	73	Scattered Clouds
230	17.3	77	89	-999	29.72	83	Mostly Cloudy
-999	0.0	71	83	-999	29.77	75	Mist

Fig. 7.7 Example of the weather records

lat	lon	aqi	utime	sutime	stamp
14.349366683822	100.56853549578	21	Friday 28th August 08:00	2015-08-28 06:00:00	1440716400
14.683085094818	100.87513981078	49	Friday 28th August 08:00	2015-08-28 06:00:00	1440716400
14.523536277394	100.92917127159	17	Friday 28th August 09:00	2015-08-28 07:00:00	1440720000
14.040299305494	100.60873959621	-	Sunday 16th August 21:00	2015-08-16 19:00:00	1439726400
14.976785802969	102.10219652705	-	Thursday 27th August 10:00	2015-08-27 08:00:00	1440637200
14.5995124	120.9842195	108	Friday 28th August 08:00	2015-08-28 07:00:00	1440716400
14.6714904	120.93984669999998	166	Friday 28th August 08:00	2015-08-28 07:00:00	1440716400
14.65	120.96666700000003	98	Friday 28th August 09:00	2015-08-28 08:00:00	1440720000
14.554729	121.02444519999995	-	Tuesday 25th August 14:00	2015-08-25 13:00:00	1440478800

Fig. 7.8 Example of the air quality records

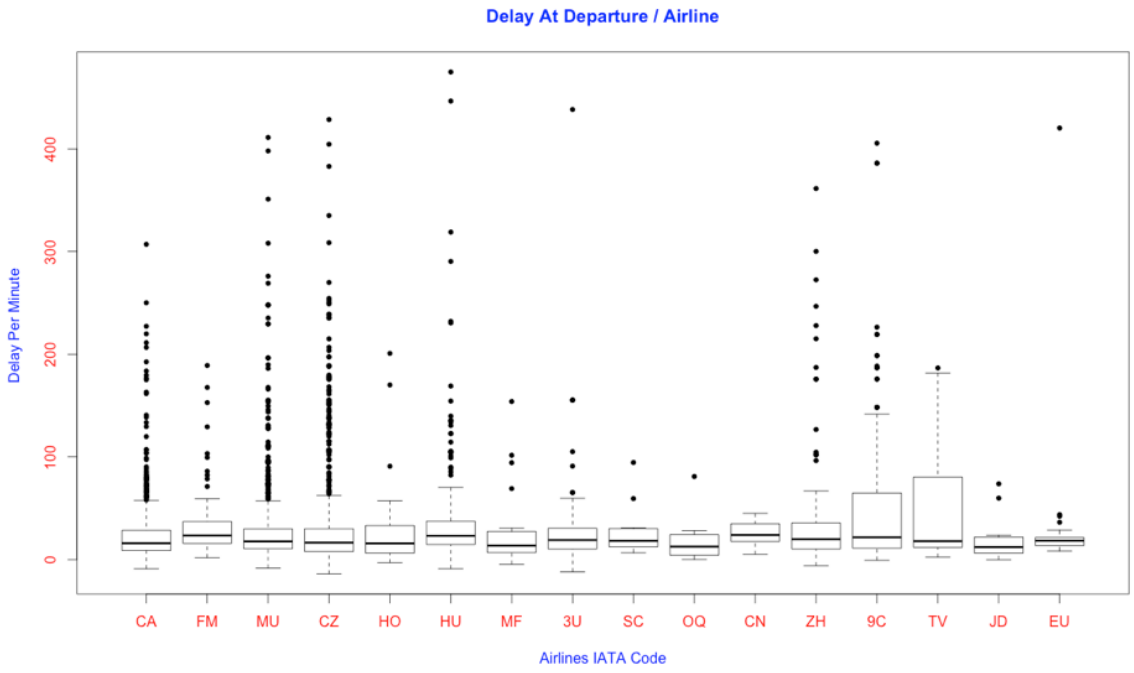


Fig. 7.9 Delay at departure performance for airlines

Another interesting output from this case study is shown in Figure 7.10, which can be used by the user to identify the airports which have the least and the most amount of delay for the flights departing from them.

Finally, Figure 7.11 shows the results of a multiple linear regression analysis which shows the identified features and the extent that each feature contributes towards the delay at departure from the our dataset. These results are prepared and displayed in almost real-time and would enable the users to not only find things from performing search in IoT, but also acquire more knowledge and deploying it for their application.

7.4 Related Work

To illustrate the future of search engines, [143] identified some of the challenging issues for searching within IoT as search locality and real-time search. Furthermore, based on IoT characteristics such as networked interconnection, real-time, semantic coherence and

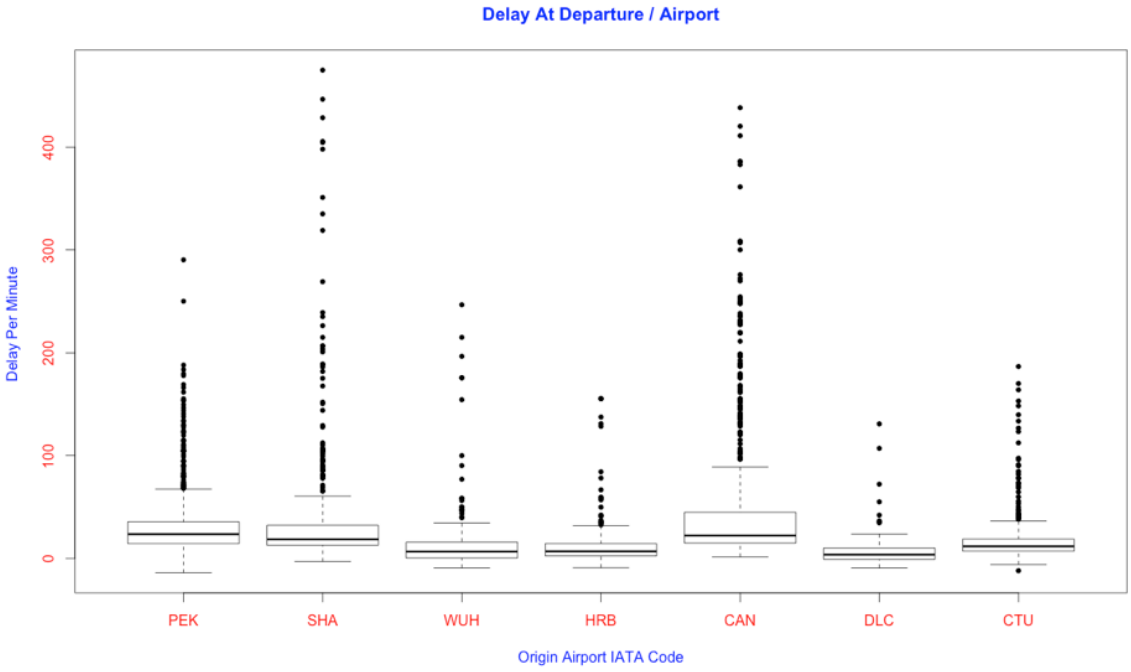


Fig. 7.10 Delay at departure performance for airports

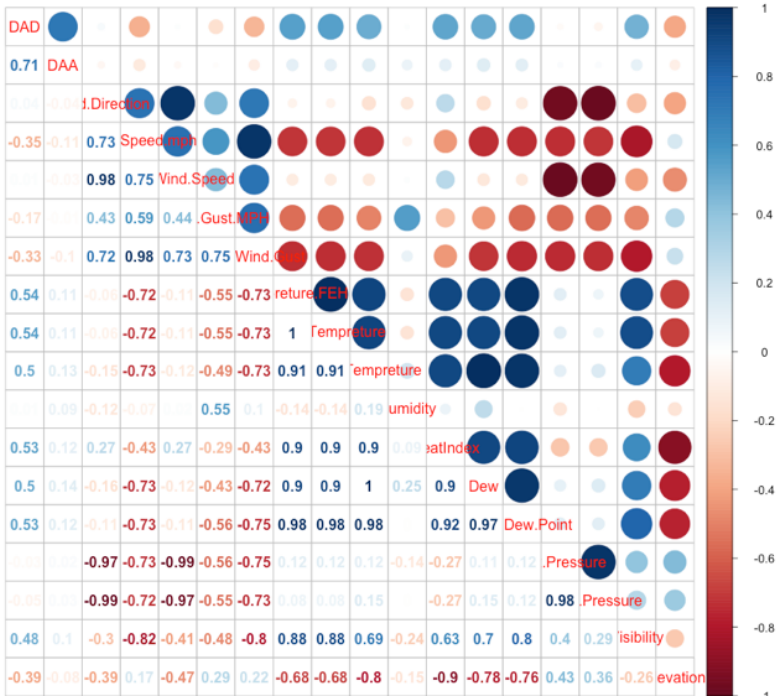


Fig. 7.11 Results of the correlation analysis

spontaneous interaction will result in raising issues such as architectural design, search locality, scalability and real-time for designing and implementing IoT search engines [144]. However, due to the existing differences in the nature of Web of Things (WoT) with the IoT, WoT may even strike additional different challenges.

In order to design the next generation of search engines, many components of current search engines from data collection methods to user experience and semantics should be redesigned. In this section, some of the previous initiations in this area are categorized and reviewed. MAX [202], Microsearch [203] and Snoogle [146] are developed based on this idea. In keyword search approach, keywords are extracted from a given term and top query results are ranked based on a score derived from the percentage of similarity between the given query term and the keyword-based description on sensors. The result is a list of sensors and thus, it might not be very useful particularly for human users.

In the following, we also address the works that are related to flight delay analysis. Flight delay is not a new problem, and it has been considered by many researchers. In [204] the authors analyzed the time factor influence of the flight delay in twenty airports in the US. They observed the changes of the delay rate using historical data. Their investigation aim was to predict the delay of each period based on their mode. They used ANOVA and k-means clustering model in order to demonstrate the periodic of the delay rate. After that they applied the Fast Furious Transform to find the period of the delay. Although their model was able to predict accurately for the first airport they were studying, they found out that their model should be improved in order to be applied to the other 19 airports. However, they did not consider the airline influence.

Liu and Yang studied in [205] the flight delay propagation in the flight chain. So they proposed a new algorithm that could estimate the delay from the beginning in order to to determine how much time the flights in chain could be delayed. Authors of [205] did not

focus on the potential causes of the delay. They only modelled the problem utilizing the Bayesian Network.

Liu and Ma (2009) [206] analyzed how flight delay is influenced by delay propagation using Bayesian Network. First, they investigated the correlation between the departure delay and the arrival delay at a particular airport. They found that the majority of delays happens in the period between 8 am and 9 pm. They measured the delays as light, medium, or heavy. They proposed that cancelling flights when there is a heavy delay in the chin will relief the problem. Even though cancelling the flights will definitely help other subsequent flights in the chain to be on-time, other factors that may cause the flight delay should be taken in account.

In the study in [35], authors studied the major factors that contribute to flight delay. They developed a model to predict the flight delay using historical records of Denver International Airport. Basically, their model considers two types of delays. First is daily propagation patterns that might be caused by crew connection problems, propagated delay from previous flights, or other factors. Second is seasonal trend where weather or seasonal demand have impact on it. However, as in [204] predicting the status of the flight in the future would require additional dynamic resources that could enrich the model.

In [207] the authors looked at how the arrival delay could be propagated and impact the other subsequent flights in the stream. They believe all these types of delay only happen in busy hub-airports. They created three models. First, they had a propagation model after they investigated the relationships among flights. After that, they came up with an arrival delay model using Bayesian Network. Then they discussed the propagation delay in the hub-airport. They claim that the arrival delay is the source that mainly cause the departure delay.

Geng in his paper [208] provided statistical analysis of the flight delay. He listed all potential factors that may cause the flight delay. Some of these factors are airports, airlines,

passengers, public safety, weather, fuel, departure control system, and air force. All these factors are actually play a role on the flight delay. Then he discussed some countermeasures in order to deal with the flight delay.

Another study [209] focused on study the flight delay problem based on the random flight point delays. They used series analysis on airline data and presented an influence factor model of the random flight points. The basic idea of this model is to combine the Bayesian Network with the Gaussian Matrix Model using expectation maximization algorithm. This model can predict the delay of the downstream.

As the best of our knowledge, there is no study has considered the real-time data to investigate the flight delay. In [204] the authors recommend for the future work to combine the analysis of historical data with real time data. That would predict the on-time performance of any airport. Our work will consider the real time data to predict the performance of individual flights.

Rebollo and Balakrishnan [210] presented a new model to predict the flight delay. They consider the temporal and the spatial delay states as explanatory variables. Their approach is to predict the delay sometime in the future between 2 to 24 hours. They use the Random Forest algorithm to do so. Although this model predicts the flight status in the future, the aforementioned interval seems too short because people require time more than that when they book their flights.

7.5 Summary

In this paper, we demonstrate ThingSeek, a search interface with a crawler to hunt IoT data on the Web. We mainly focus on the sensor data that is published through Web Mapping. Our ThingSeek framework contains a crawler and two querying interfaces to cover both human and machine users, e.g., smart things. In our crawler engine, we deploy a number of technologies and a multi-layered approach to prepare the data for correlation analysis. In

our search interface, we demonstrate the details of the two interfaces, which are develop to serve different groups of users. The machines interface of our engine complies with COAP technology that is developed for machine-to-machine interaction.

Furthermore, we showcase an application of our search engine in the aviation industry. In particular, we target flight delay analysis, which has a significant impact and depends on a variety of environmental and operational factors that change in real time. Specifically, in our showcase, we use two other data sets for assessing the air quality and weather data from the identified data sources using our crawler engine. We use the real-time data of seven cities in China, mainly due to the environmental circumstances, which affect flight schedules in many cases. We initiate our model based on our data then investigate the correlation between the collected datasets and the delay at departure. We use multiple linear regression analysis to assess the weight of each feature and attach the final results to the search results for flights data. In this case, our records show a relatively effective correlation between the delay at departure and some features including dew and altitude. However, we hope thatr further development of our method can lead to precise flight delay prediction, which can enrich the experience of IoT search in future.

We conclude the dissertation in Chapter 8 and discuss some of the possible directions for our research in future.

Chapter 8

Conclusion

In this chapter, we summarize the contributions of this dissertation and propose the directions for future research in intent oriented and correlation aware IoT search.

8.1 Summary

The IoT paradigm is increasingly attracting a wide spectrum of researchers and professionals, mainly due to its tremendous potential in impacting on our daily lives in the near future. IoT search and related topics have attracted a large number of researchers in the last few years. However, in IoT, with the highly dynamic, large volume and loosely interconnected data sources, correlation based and intent oriented search have not been sufficiently developed. Further research on application oriented interconnection of IoT resources is essential for establishing the future search engines and recommender systems for IoT.

In this dissertation, we propose a novel framework for a context aware and correlation based IoT discovery service. We also provide an implementation of our approach in the *ThingSeek* prototype. Our framework incorporates a number of subcomponents where each is devised to serve a specific purpose in the steps of the given motivating scenario. In the ThingSeek architecture, we consider two types of users including human clients and smart

devices. We enable correlation based search for finding things and intent oriented search for domain specific applications. Our ThingSeek framework provides the foundation that is required by higher level IoT search and analytic engines. Furthermore, we propose novel approaches for analytical steps in the higher levels of application, including correlation extraction, graph pattern matching, search results diversification and intent oriented search. Our approach exploits some techniques in high levels of application to enhance the quality of search results while the size of the result set is limited. In particular, we summarize our main research contributions in the following:

- IoT Crawler Engine: We propose and implement our ThingSeek [211] framework, which is a crawler and a search engine for the IoT. Our search engine handles results presentation for its users and is able to support different types of users. In addition to searching for things, our ThingSeek framework provides analytical and visualized knowledge to the human users. We demonstrate a showcase in the field of flight delay analysis. In our case study, we collect the real time data of domestic flights as well as weather and air quality data across the seven largest cities in China. From our dataset, we identify the existing feature that affect flight at departure. We analyse the correlations between the extracted features using multiple linear regression and show that there is a correlation between the different data sources.

- IoT data analysis: We collect and analyse IoT data for millions of objects worldwide. In our study, we focus on identifying IoT data sources and analysing the most popular technologies that are being used. We also identify research opportunities in crawling and archiving IoT data. We compare the distribution and focus areas of the IoT data and search query logs using real world datasets. The gap analysis shows that a significant gap exists between the supply and the demand of data. Moreover, we analyse the evolution of the gap and IoT data over the time. We use Earth Mover's Distance to improve keyword based document retrieval from the Web [212]. We conduct the same

analysis over IoT data and identify the patterns of the recurring sensory data around the world. Our results show that traditional technologies are a trend in sensor data dissemination and Web mapping is playing a key role in IoT [213].

- Automatic correlation extraction: We propose a novel framework, namely CEIoT, for extracting correlations from IoT data. Specifically, we focus on three types of correlations between objects, based on the features that we extract from IoT data. In particular we focus on the location based correlations. Our framework represents correlations using RDF triples and R-Tree to extract the co-location correlations. We use a Multi Agent System architecture to implement our approach and use a real world dataset to verify its efficiency [214]. Moreover, we provide a novel method for batch matching of conjunctive triple patterns over linked data streams, which can be used by the Service Agents in our architecture to match the features of sensory data [106].

- Pattern matching for IoT data: We provide an efficient approach for integrating Linked Data streams from various data collectors. Our approach disseminates matched data to relevant data consumers based on conjunctive triple pattern queries registered in the system by the consumers [106, 107]. Moreover, we redefine the graph pattern matching problem for the context of IoT and form the *MULTIMATCH* problem, which increases the cardinality of the labels that are assigned to each node compared with the previous work. We use Monte Carlo Markov Chain to approximate the matches in polynomial time. We validate all of the proposed methods and show that our approach is efficient in terms of processing time and space allocation [215].

- High quality query results: Given the limits of end users, in particular, smart devices with limited processing power and memory, we propose a novel solution to select the top-k results from the things dataset [38]. Our proposed method constitutes three different layers to Extract correlations, Cluster objects and Select the results (ECS)

to derive the top-k records based on the correlations between things. We analyse the effect of different parameters and use real world IoT datasets to identify the correlation between the parameters and the *coherence* and the *diversity* of results.

- Intent oriented search for taxi ridesharing: We focus on an application of IoT in the context of Urban Computing, which is a subdomain of IoT, concentrating on the requirements of urban environments. Firstly, we improve the efficiency of the existing approaches by proposing a decremental search approach [163]. Furthermore, we repurpose the whole system to improve the actual profits of the application via improved ridesharing request acceptance rates. To address the scalability requirements, we improve our approach by changing the strategy and reducing the number of recursions in the search algorithm. Moreover, we validate the results using a real world dataset of taxi trajectories in Beijing, China.

8.2 Future Research

Although research on the discovery and application of IoT has already attracted many researchers, there are still many issues that need to be addressed. In particular, we identify the following directions for research in IoT search and analysis:

- Dataset extension: We are planning to extend the range of our dataset by including new IoT data sources in our system. A fully automated IoT data source identification and selection is required to extend our dataset. Moreover, nowadays, numerous services are being provided by the applications on smart phones, which are left out from our study.

- Advanced correlation extraction on the data streams: Correlation extraction for IoT is in its infancy. Some of the major challenging issues are related to the characteristics of the sensory data, which include but are not limited to uncertainty, inaccuracy, location,

dynamics and security. Further developments are required in order to provide a solid basis for correlation analysis on IoT. Deployment of the existing approaches in the existing applications can escalate the amount of knowledge that is acquired from the worldwide sensory data of IoT.

- Enhanced intent based search: We plan to develop the intent based search further in two areas. Firstly, we will develop our progress on flight delay analysis to enable the prediction of flight delays in real time. Furthermore, we can build up a context aware real time flight recommender system which can potentially reduce the amount of the losses that are caused by flight delays. Secondly, we plan to improve the current search experience of taxi ridesharing to include more contextual features based on the historical social and sensory data in the city.

- Dynamic graph pattern matching: Graph pattern matching is key to many applications including IoT sensory data analysis. We plan to develop our method further in two directions. Firstly, given the high dynamics of the IoT, we will revise the graph pattern matching analysis problem to include dynamic data graphs with dynamic patterns. Considering the fact that the pattern matching has relied on the static pattern graphs so far, dynamic patterns can extend the range and applications of graph based queries significantly. Secondly, we are planning to introduce context aware pattern matching with a focus on the applications in IoT. The context of a given pattern matching problem may vary widely, based on the intent of the search. However, this is not covered in the existing pattern matching approaches which return the same set of patterns for all contexts.

- Archiving IoT data: Nowadays existing WWW archives are playing significant roles both in research and application. The recording of the contents of the documents on the Internet started shortly after the emergence of the WWW. However, due to

the technical challenges of handling sensory data in its current form, to the best of our knowledge, there is no initiative on archiving the IoT data. We are planning to introduce an archival service for IoT by tackling these challenges based on our results and observations. For instance, through a thorough pattern analysis, we can reduce the size of the data significantly.

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Appendix A

Curriculum Vitae

Personal Information

Name:	Ali Shemshadi
Tel:	+61 41 081 0378
Email:	ali.shemshadi@adelaide.edu.au
Homepage:	http://cs.adelaide.edu.au/∼ali/
Visa status:	Permanent Resident of Australia

Research Interests

Internet of Things, Industrial Internet, Big Data, Cloud Computing, Parallel Graph Processing, Multi-Agent Systems, Machine Learning, Supply Chain Management, Urban Computing

	Ph.D. in Computer Science
	The University of Adelaide, Adelaide, Australia[1]
2012-2016	Supervisors: Michael Sheng
	Hong Shen
	Zbigniew Michalewicz
	M.Sc. in I.T. engineering - E-commerce
	K. N. Toosi University of Technology, Tehran, Iran[2]
2009-2011	Dissertation: A Supplier Selection Approach for Real-time Supply Chain Coordination System
	Supervisor: M. J. Tarokh
	GPA: 3.7/4 (top 10%)
	B.Sc. in I.T. engineering
	Shiraz University of Technology, Shiraz, Iran[3]
2004-2008	Dissertation: A Multi-Agent System for Real-time Supply Chain Coordination
	Supervisor: Javad Soroor
	GPA: 3.4/4 (top 5%)

Education

Honours and Awards

Author of one of the top 1% papers

2016

Identified as the author of one of the top 1% most highly cited papers in my field by the *Council of Canadian Academics*.

Higher Degree Research Fellows for Computer Science PhD Candidates

2014

Offered by the *University of Adelaide*. Fellows will be involved in a range of academic experiences to complement the research training provided as part of the School of Computer Science HDR program. The salary can be up to A$61,880 p.a. + superannuation.

Adelaide Scholarship International

2012-2015

Awarded by the *University of Adelaide* in midyear round. This award for midyear round is highly competitive and only 9 applications were successful. The award covers tuition fees ($\sim$ A$28,000 p.a.), living stipend ($\sim$ A$24,000 p.a.) for three years and the total amount of required Overseas Students Healthcare insurance.

Commended Research Poster Award, ADC PhD School

2014

Selected by the committee during the PhD school, Australian Database Conference 2014, Brisbane, Australia.

International Postgraduate Research Scholarship

2012

I got offers from some other universities such as the *University of New South Wales*. The amount of award was equal to *ASI*.

DR Stranks Travel Fellowship

2014

Was offered by the *University of Adelaide*. The amount of award was equal to A$5,000.

International Khwarizmi Award

2008

Ranked 3rd among more than 2,500 proposals in the 10th Khwarizmi Awards for Youth in Tehran, Iran. This is a very prestigious science and technology award offered by http:

//www.irost.org/en/IROST that provides the winners with highly regarded merits including but not limited to membership in the National Elite Foundation, a research grant equal to $3,000, several loans and supports from the foundation and exemption from the compulsory military service. My bachelors research project had to compete with many PhD proposals to win this prize.

Tuition Waiver

2004-2008 Based on the academic excellence, several tuition waivers and prizes were offered by *Shiraz University of Technology* in Shiraz, Iran. The total amount of the awards was more than $2,000.

Excellence in Academic Records

I was the top %10 student in Masters and top %5 student in my undergraduate studies. The track of academic excellence even goes back to my high school when I was the only student in my city and one of very few students in Fars province for National Physics Olympiad.

Publications

Book Chapter

- Soroor, J. Tarokh, M. J., Shemshadi, A., & Shemshadi, J. (2009). Decentralized Manufacturing via Autonomous Multi-Agent Modules: Case of a Distributed Control Architecture in a Real-time Coordinated Supply Chain. *Supply Chain Performance Management Current Approaches, Part IV: Supply chain optimization*, 217-238. **[citation:5]**

Journal

- Shemshadi, A., Sheng, Q.Z., Zhang, W. E., Sun, A., Qin, Y., Yao, L. (2016) *Personal and Ubiquitous Computing*, to appear.

- Shemshadi, A., Sheng, Q.Z., Qin, Y. (2016) Efficient Pattern Matching for Graphs with Multi-Labeled Nodes. *Knowledge Based Systems*, 38(10), 12160-12167. **[ISI, Impact:3.32]**

- Shemshadi, A., Shirazi, H., Toreihi, M., & Tarokh, M. J. (2011). A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting. *Expert Systems with Applications*, 38(10), 12160-12167. **[ISI, Impact:1.85, citation:143]**

- Soroor, J., Tarokh, M. J., & Shemshadi, A. (2009). Initiating a state of the art system for real-time supply chain coordination. *European Journal of Operational Research*, 196(2), 635-650. **[ISI, Impact:2, citation:46]**

- Ali Shemshadi, M. Toreihi, H. Shirazi, & M. J. Tarokh. (2011). Supplier Selection Based on Supplier Risk: An ANP and Fuzzy TOPSIS Approach. *The Journal of Mathematics and Computer Science*, 2(1), 111-121. **[citation:9]**

- Ali. Shemshadi, H. Shirazi, M. J. Tarokh. (2010). Simulating A State of the Art Agent Based System with Fuzzy Reasoning for Supply Chain Coordination. *The Journal of Mathematics and Computer Science*, 1(4), 293-30.

Conference

- Shemshadi, A.; Sheng, Q. Z.; Qin, Y. ThingSeek: A Framework for Crawling and Searching the Internet of Things. In Proceedings of the 39th ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2016), 2016. to appear. [demo - **CORE rank: A*- top 3 downloaded papers from SIGIR 2016**]

- Zhang, WE, Sheng, QZ, Qin, Y, Yao, L, Shemshadi, A, Taylor, K. (2016) SECF: improving SPARQL querying performance with proactive fetching and caching. *Proceedings of the 31st Annual ACM Symposium on Applied Computing*, 362-367. [Full paper - **CORE rank: B**]

- Shemshadi, A.; Yao, L.; Qin, Y.; Sheng, Q. Z.; and Zhang, Y. ECS: A Framework for Diversified and Relevant Searching for the Internet of Things. In Proceedings of the 16th International Conference on Web Information System Engineering (WISE 2015), 2015. to appear. [Full paper - **CORE rank: A**]

- Yao, L., Sheng, Q. Z., Qin, Y., Wang, X., Shemshadi, A., and He, Q. Context-aware Point-of-Interest Recommendation Using Tensor Factorization with Social Regularization. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2015), 2015. pp. 1007-1010. ACM. [poster - **CORE rank: A***]

- Qin, Y., Sheng, Q. Z., Falkner, N. J., Shemshadi, A., and Curry, E. Batch matching of conjunctive triple patterns over linked data streams in the internet of things. In Proceedings of the 27th International Conference on Scientific and Statistical Database Management (SSDBM 2015), 2015. pp. 41. ACM. [poster - **CORE rank: A**]

- Qin, Y., Sheng, Q. Z., Falkner, N., Shemshadi, A. and Curry, E. Towards Efficient Dissemination of Linked Data in the Internet of Things. The 23rd ACM Conference on Information and Knowledge Management (CIKM 2014). Shanghai, China, November 3-7, 2014. [poster - **CORE rank: A**]

- Shemshadi, A., Sheng, Q. Z., Zhang, E. W. (2014) A Decremental Search Approach for Large Scale Dynamic Ridesharing. *15th International Conference on Web Information Systems Engineering (WISE)*. [full paper - **CORE rank: A**]

- Ma, J., Sheng, Q. Z., Yao, L., Xu, Y. and Shemshadi, A. (2014) Keyword Search over Web Documents based on Earth Mover's Distance, *The 15th International Conference on Web Information Systems Engineering (WISE)*. Thessaloniki, Greece, October 12-14. [poster - **CORE rank: A**]

- Peng, Y., Xie, D., & Shemshadi, A. (2013). A Network Storage Framework for Internet of Things. *The 3rd International Symposium on Internet of Ubiquitous and Pervasive Things, 2013. IUPT 2013*, 1136-1141.

- Shemshadi, A., Soroor, J., & Tarokh, M. J. (2008, June). Implementing a multi-agent system for the real-time coordination of a typical supply chain based on the JADE technology. *In Proc. of IEEE International Conference on System of Systems Engineering, 2008. SoSE'08.* (pp. 1-6). **[citation:17]**

- Shemshadi, A., Soroor, J., & Tarokh, M. J. (2008, April). An Innovative Framework for the New Generation of SCORM 2004 Conformant E-Learning Systems. *In Proc. of Fifth International Conference on Information Technology: New Generations, 2008. ITNG 2008.* (pp. 949-954). **[citation:7]**

Under review

- Shemshadi, A., Sheng, Q. Z., & Zhang, E. W. TRIPS: Scalable and Dynamic Taxi Ridesharing with Uncertain Data. Under review by a top tier journal.

- Co-authored 3 other works which are under review.

Teaching Experience

- Associate lecturer at the University of Adelaide, Australia. (2016)

- Casual lecturer and Course Coordinator at the University of Adelaide, Australia. (2016)

- Teacher at the College of Bradford, Australia. (2016)
- Tutor and casual Lecturer at the University of Adelaide, Australia. (2016)
- Supervised *two* master students project in the University of Adelaide, Australia. (2014)
- Tutoring Introduction to Programming (Python) in Adelaide University, Australia. (2014)
- Practical supervision for Object Oriented Programming (C++) in Adelaide University, Australia. (2013)
- Practical supervision for Internet Computing (PHP) in Adelaide University, Australia. (2013)
- Teaching assistance for Data Structure (in Java) in Shiraz University of Technology, Iran.

Work Experience

Bradford College

ADELAIDE, AUSTRALIA

Tutor/Lecturer

Feb '16 – Jun'16

Responsible for lecturing and tutoring for several courses such as Programming and Object Oriented Programming.

The University of Adelaide

ADELAIDE, AUSTRALIA

Associate Lecturer/Course Cooriator

Jun '16 – Nov '16

Responsible for lecturing and coordinating a number of courses including Introduction to Programming for Engineers, Algorithm and Data Structure Analysis and Small Group Discovery Experience.

HDR Teaching Fellow/Lecturer

Feb '14 – '16

Responsible for lecturing and tutoring for a number of courses including Introduction to Programming and Object Oriented Programming.

Senior Developer

Sep '12-Feb '16

Designed and developed a number of software projects for different customers in the University. These projects include a data sharing website for geological data, an integration software for large scale data.

Architects of Communication Age co.

TEHRAN, IRAN

Programmer Developer

Sep '10 – Sep '12

Architects of Communication Age is a software development company which has been operating for 15 years with focus on enterprise software for universities, news agencies and foreign industries such as *Renault*. I was included developer teams for several web-based and

application projects for companies such as *Renault Iran*, organizations such as *Geological Survey of Iran*. Following the successes as a developer and I was called in to solve several technical design and implementation challenges and assist in proposing new solutions for businesses. The most common challenges were information security, data consistency and DBMS performance. Used multiple approaches from architectural corrections to deploying NoSQL for addressing these challenges.

Tejarat Bank

TEHRAN, IRAN

Researcher and Data Analyst

Sep '09 – Sep '10

One of the largest banks in Iran with more than 3,000 branches. Researching into a proper model for assessment of the bank's software systems which were already more than 300. Later, using PHP (Joomla) and MySQL, developed a website (which is only accessible from Intranet) which implements intelligent and real time handling of the assessment procedure.

Shiraz City Council

SHIRAZ, IRAN

IT Consultant

Sep '07 – Sep '8

Researching for proper system design and implementation of Automated Vehicle Location (AVL) system for Shiraz public transport. After the success of the first project, finished

working on two other contracts for the same organisation. The first was related to the intelligent traffic cameras and the second was related to e-learning for physicians across the Fars province.

Skills

Programming:

Java (Spring, Maven, JBeans), C++, Ruby on Rails, Python, PHP, Scala, R

Starting with Java and C++ more than 10 years ago, I have always enthusiastically worked on a variety of programming projects both in academia and industry. I have worked with PHP and Ruby on Rails as a professional Web developer and am able to provide a number of professional work examples in my portfolio. During my PhD, I gained extensive experience with Scala and R in developing a number of innovative projects including a real-time crawler and search engine for the Internet of Things.

Data Analytics: Hadoop, Giraph, Spark, MLib, R, SparkR

I have extensively used Big Data technologies for analysing large scale sensor data from the Internet of Things and large scale graphs from social networks (twitter). However, I have used Spark with SparkR (development phase) and physical machines (configured Hadoop and Spark myself) but am very confident in using the Scala based Spark shell in production mode and on a cloud infrastructure if required. I have extensively used R for my research and data analysis. Shortly, I will be able to provide certificates for any of above.

Cloud: Heroku, Digital Ocean, AWS

I have used a number of academic cloud services (ERSA) and popular cloud services such as Heroku and Digital Ocean. I am familiar with SOA and RESTful Web services and have

some working examples on each cloud service. Also, I have some familiarity with AWS but have not used it so far. Furthermore, I have also worked with lots of dedicated servers which were mainly Linux (Ubuntu, Red Hat and Cent OS) but also have some experience with Windows based servers, as well.

IDEs and Build Tools and Development Management: Eclipse, NetBeans, Aptana, IntelliJ, TypeSafe stack, Ardunio IDE, SBT, ANT, Maven, Git

I have worked with variety of IDEs such as Eclipse, Aptana and NetBeans for Java, Python, RoR and C++. I have worked with variety of add-ons and plug-ins for those. Am very interested in Typesafe stack despite its limitations. Moreover, I am also experienced very fond of using Linux/Mac shell and simple editors for development. Am also experienced in using Git. Furthermore, I am also experienced in using package managers along with IDEs to deploy TDD.

Design and Documentation: MS Visio, Enterprise Architect, MS Project, IBM Rational Rose

As an analyst developer and a solution designer, I have designed the architecture of many projects from scratch for international and local clients using the above software. I have experience in UML, UI, DFD, Database Schema and Project Management Charts and many other designs for different projects.

Natural languages:

Farsi *(mother tongue)*, English *(fluent)*, Arabic *(fluent)*.

Services

- Program Co-Chair in the 7th International Symposium on Internet of Ubiquitous and Pervasive Things (IUPT 2017)
- Program Co-Chair in the 6th International Symposium on Internet of Ubiquitous and Pervasive Things (IUPT 2016), Madrid, Spain
- Program Co-Chair in the 5th International Symposium on Internet of Ubiquitous and Pervasive Things (IUPT 2015), London, UK
- Reviewer for IEEE Transactions on Emerging Topics in Computing
- Reviewer for Information Systems Frontiers
- Reviewer for Journal of Computer and System Sciences
- Reviewer for International Journal of Production Research
- Reviewer for World Wide Web Journal
- Reviewer for Journal of Ambient Intelligence and Humanized Computing
- Reviewer for IEEE International Conf. on Service Oriented Computing and Applications (SOCA 2014)
- Reviewer for the 10th International Conf. on Advanced Data Mining and Applications (ADMA 2014)

Membership

- Australian Computer Society

- Iranian National Elite Foundation[4]
- Honorary member of BPJ (Young Researchers Club)
- ACM
- IEEE

References

Available upon request.

[4]Only a small number of people (less than 3,000 in more than 3,000,000 uni students to the date) are accepted based on the academic merits.