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THESIS

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OPTION : Artificial Intelligence

By: **Marwa MEISSA**

Composition de services basée sur les relations sociales entre objets dans l'IoT

Service composition based on social relations between things in IoT

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BISKRA, ALGERIA. May 2022

بسم الله الرحمن الرحيم

﴿ وَٱبۡتَغِ فِيمَآ ءَاتَىٰكَ ٱللَّهُ ٱلدَّارَ ٱلۡأٓخِرَةَۖ
وَلَا تَنسَ نَصِيبَكَ مِنَ ٱلدُّنۡيَاۖ وَأَحۡسِن
كَمَآ أَحۡسَنَ ٱللَّهُ إِلَيۡكَۖ وَلَا تَبۡغِ ٱلۡفَسَادَ فِي
ٱلۡأَرۡضِۖ إِنَّ ٱللَّهَ لَا يُحِبُّ ٱلۡمُفۡسِدِينَ ٧٧ ﴾

Dedication

This humble effort is dedicated to my parents,

*A special feeling of gratitude to my loving parents, **Ahmed** and **Zineb** whose have taught me to work hard for the things that I aspire to achieve and their words of encouragement for tenacity still ringing in my ears.*

Marwa

Contents

"When we give cheerfully and accept gratefully, everyone is blessed."

Maya Angelou

Acknowledgement

In the name of **Allah**, the most gracious, the most merciful. All thanks to **Allah**, the lord of both worlds, and may prayers and peace be upon our prophet, **Muhammad** and, upon his companions.

The past few years have been an incredible journey. This page is about the people that have supported me throughout this journey.
First of all, I would like to thank Professor Saber BENHARZALLAH , my supervisor, for giving me the opportunity to pursue a PhD. He is open minded, thoughtful, humorous. Doing research under his guidance gives me the feeling of “free to fly”. His support and guidance enabled me to complete this work .I am very fortunate to have had the opportunity to work under his supervision. Then, I would like to thank Professor Laid KAHLOUL, my co-supervisor for his assistance and cooperation. Additional gratitude goes to Professor Okba KAZAR for introducing me to the wonderful field of artificial intelligence and to be a member in LINFI Laboratory. I thank also my co-author Professor Reinhardt EULER for his productive and enjoyable collaboration. I owe my deepest gratitude and warmest affection to Dr. Khadija ABID, Dr. Mounir BEGGAS and PhD. Med Nadhir ABID who have been advising and supporting me during my doctoral research. I would like also to express my gratitude to Jury Members: Professor Hammadi BENNOUI from Biskra University and Doctor Mohammed Charef Eddine MEFTAH from El Oued University for kindly agreeing to be the examiners of my thesis and for their helpful comments, their insightful discussion and intellectual contributions to this work.
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Marwa MEISSA
Biskra, Algeria, May 2022.

Abstract

With the rapid development of service-oriented computing applications and social Internet of things (SIoT), it is becoming more and more difficult for end-users to find relevant services to create value-added composite services in this big data environment. Therefore, this work proposes S-SCORE (Social Service Composition based on Recommendation), an approach for interactive web services composition in SIoT ecosystem for end-users. The main contribution of this work is providing a novel recommendation approach, which enables to discover and suggest trustworthy and personalized web services that are suitable for composition. The first proposed model of recommendation aims to face the problem of information overload, which enables to discover services and provide personalized suggestions for users without sacrificing the recommendation accuracy. To validate the performance of our approach, seven variant algorithms of different approaches (popularity-based, user-based and item-based) are compared using MovieLens 20M dataset. The experiments show that our model improves the recommendation accuracy by 12% increase with the highest score among compared methods. Additionally it outperforms the compared models in diversity over all lengths of recommendation lists. The second proposed approach is a novel recommendation mechanism for service composition, which enables to suggest trustworthy and personalized web services that are suitable for composition. The process of recommendation consists of online and offline stages. In the offline stage, two models of similarity computation are presented. Firstly, an improved users' similarity model is provided to filter the set of advisors for an active user. Then, a new service collaboration model is proposed that based on functional and non-functional features of services, which allows providing a set of collaborators for the active service. The online phase makes rating prediction of candidate services based on a hybrid algorithm that based on collaborative filtering technique. The proposed method gives considerable improvement on the prediction accuracy. Firstly, it achieves the lowest value in MAE (Mean Absolute Error) metric and the highest coverage values than other compared traditional collaborative filtering-based prediction approaches.

Keywords:

Service composition , Recommendation ,Social Internet of Things, Social relations, Trust.

ملــخــص

مع التطور السريع لتطبيقات الحوسبة الموجهة نحو الخدمة، وكذلك الشبكة الاجتماعية لإنترنت الأشياء، أصبح من الصعب على المستخدمين العثور على خدمات مناسبة لإنشاء خدمات مركبة ذات قيمة مضافة في هذه البيئة ذات البيانات الضخمة. لذلك، يقترح هذا العمل مقاربة تعمل على تكوين خدمات الويب من قبل المستخدمين بشكل تفاعلي داخل بيئة اجتماعية لإنترنت الأشياء. تتمثل المساهمة الرئيسية لهذا العمل في توفير نهج جديد للتوصية، والذي يمكّن من اكتشاف واقتراح خدمات الويب موثوقة وموجهة بشكل شخصي للمستخدم وفي نفس الوقت تكون مناسبة لعملية التكوين. يهدف نموذج التوصية الأول إلى مواجهة مشكلة التحميل الزائد للمعلومات، بحيث يسمح باكتشاف الخدمات وتقديمها بشكل اقتراحات تكون شخصية للمستخدمين دون التضحية بدقة التوصيات. للتحقق من صحة أداء نهجنا، تمت مقارنة سبع خوارزميات مختلفة من مناهج مختلفة (قائمة على الشعبية، وقائمة على المستخدم، وقائمة على العناصر) باستخدام مجموعة بيانات حقيقية. تُظهر التجارب أن نموذجنا حسّن دقة التوصية بنسبة 12٪ زيادة مع أعلى نسبة تم تسجيلها من بين الطرق التي تمت مقارنتها. بالإضافة إلى أنه تفوق في مختلف أطوال قوائم التوصيات. النهج الثاني المقترح هو آلية توصية جديدة لتكوين الخدمة، والتي تقترح خدمات ويب موثوقة وذات طابع شخصي تكون مناسبة للتكوين. تتكون عملية التوصية من مرحلتين أونلاين وأوف لاين. في المرحلة الأولى، تم تصميم نموذجان لقياس التشابه. نموذج التشابه الأول المحسّن خاص بالمستخدمين يعمل على تصفية مجموعة المستشارين للمستخدم النشط. النموذج الثاني خاص بالخدمات مبني على نهج تعاوني يجمع بين الميزات الوظيفية وغير الوظيفية للخدمات، مما يتيح توفير مجموعة من المتعاونين للخدمة النشطة. في مرحلة الأون لاين، يتم التنبؤ بتصنيف الخدمات المرشحة بالاعتماد على خوارزمية هجينة تعتمد على تقنية التصفية التعاونية. الطريقة المقترحة تعطي تحسنا كبيرا في دقة التنبؤ بحيث حقق أقل قيمة في معامل (متوسط الخطأ المطلق) وأعلى قيم تغطية مقارنة بالطرق التقليدية الأخرى التي تعتمد على التنبؤ بواسطة التصفية التعاونية.

الكلمات المفتاحية: تركيب الخدمات، التوصية، انترنت الأشياء الاجتماعي، العلاقات الاجتماعية، الثقة

Résumé

Avec le développement rapide des applications informatiques orientées services et de l'Internet social des objets (SIoT), il devient de plus en plus difficile pour les utilisateurs de trouver des services pertinents pour créer des services composites à valeur ajoutée dans cet environnement de big data. Par conséquent, ce travail propose S-SCORE (Social Service Composition based on Recommendation), une approche pour la composition interactive de services Web dans l'écosystème SIoT pour les utilisateurs. La principale contribution de ce travail est de fournir une nouvelle approche de recommandation, qui permet de découvrir et de proposer des services web fiables et personnalisés adaptés à la composition. Le premier modèle de recommandation proposé vise à faire face au problème de la surcharge d'informations, ce qui permet de découvrir des services et de fournir des suggestions personnalisées aux utilisateurs sans sacrifier la précision de la recommandation. Pour valider les performances de notre approche, sept variantes d'algorithmes de différentes approches (basées sur la popularité, basées sur les utilisateurs et basées sur les items) sont comparées à l'aide de dataset MovieLens 20M. Les expérimentes indiquent que notre modèle améliore la précision de recommandation de 12% d'augmentation avec le score le plus élevé parmi les méthodes comparées. De plus, il surpasse les modèles comparés en diversité sur toutes les longueurs de listes de recommandations. La deuxième approche proposée est un nouveau mécanisme de recommandation pour la composition de services, qui permet de suggérer des services Web fiables et personnalisés adaptés à la composition. Le processus de recommandation comprend des étapes en ligne et hors ligne. Dans l'étape hors ligne, deux modèles de calcul de similarité sont présentés. Premièrement, un modèle de similarité des utilisateurs amélioré est fourni pour filtrer l'ensemble de conseillers pour un utilisateur actif. Ensuite, un nouveau modèle de collaboration de service est proposé, basé sur des caractéristiques fonctionnelles et non fonctionnelles des services, qui permet de fournir un ensemble de collaborateurs pour le service actif. La phase en ligne permet de prédire la notation des services candidats sur la base d'un algorithme hybride basé sur une technique de filtrage collaboratif. La méthode proposée améliore considérablement la précision de la prédiction. Premièrement, il atteint la valeur la plus faible de la métrique MAE (erreur absolue moyenne) et les valeurs de couverture les plus élevées par rapport aux autres approches de prédiction basées sur le filtrage collaboratif traditionnelles comparées.

Mots clés Composition des services , Recommendation , Intenet des objets sociale , Relations sociales ,Confiance.

List of Abbreviations and Acronyms

AP	*Affinity Propagation*
API	*Application Programming Interface*
CB	*Content-based Filtering*
CF	*Collaborative Filtering*
CoAP	*Constrained Application Protocol*
FOAF	*Friend Of A Friend*
HOSVD	*Higher Order Singular Value Decomposition*
HTTP	*Hypertext Transfer Protocol*
IoT	*Internet of Things*
IbCF	*Item-based Collaborative Filtering*
JSON	*JavaScript Object Notation*
KNN	*K-Nearest Neighbors*
MAE	*Mean Absolute Error*
MF	*Matrix Factorization*
OGC	*Open Geospatial Consortium*
PARFAC	*PARAllel FACtor analysis*
PCA	*Principle Component Analysis*
PCC	*Pearson' correlation coefficient*
PMF	*Probabilistic Matrix Factorization*
PITF	*Pairwise Interaction Tensor Factorization*
QoS	*Quality of Service*
REST	*Representational State Transfer*
ROC	*Receiver Operating Characteristic*
RS	*Recommender System*
SC	*Service Composition*
SIoT	*Social Internet of Things*
SN	*Social Network*
SNA	*Social Network Analysis*
SOA	*Service oriented Architecture*
SoC	*Service oriented Computing*
SOM	*Service oriented Middleware*
SVD	*Singular Value Decomposition*
SWoT	*Social Web of Things*
TD	*Tucker Decomposition*
TF	*Tensor Factorization*
UbCF	*User-based Collaborative Filtering*
WoT	*Web of Things*
WS	*Web Service*
WSRec	*Web Service Recommendation*

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"A story has no beginning or end: arbitrarily one chooses that moment of experience from which to look back or from which to look ahead."

Graham Greene

Introduction

Research Scope

In recent years, the Internet has been enriched by a huge amount of data. Especially, with the growing mass movement of connected devices in what is known as Internet of Things (IoT). The emergence of IoT contributes to massively inflated data, where, more than 38 billion connected devices in 2025 and is estimated to reach 50 billion by 2030[1], which each person in the world projected to have six connected devices. This transformation from real-world functionalities of devices to the digital world has essentially led up to the emergence of a new generation of software and web applications, which is developed to be consumed by these things and allows them to integrate and to communicate with various other entities on the web.

Furthermore, the explosive growth of the web is fundamentally leading also to information inflation and diversity, especially with the development of the social web (web 2.0), its related technologies, and the emergence of the web of things (web 4.0). Moreover, there is a convergence of social technologies and the Internet of Things (IoT) to what is known as Social Internet of Things (SIoT), where every object can establish social relations with other objects. SIoT contributes in turn to massively inflated data due to data generated by social objects (2.5 quintillion bytes per day)[2]. This makes us inevitably talk about a 'big data' environment.

In the service oriented computing (SoC)-based SIoT environment, the pressing need to create new services and to offer new functionalities that none of the services can provide individually, confronts the user with the crucial challenge to choose the most appropriate services to be composite services. Furthermore, there are a huge number of web services that offer similar functionalities, which makes the user confused in choosing services that suits his requirements and meets his needs. Additionally, it is a key challenge to understand how to exploit and to process these big data provided by SIoT to compose service accurately and efficiently.

Recently, with the proliferation of web services, developing a web service recommendation system has become trend and directive research [84], [181], [159], [131], [146], due to the efficiency of this technology, especially in the big data environment, with a huge number of candidate services having similar functionalities. Additionally, with the evolution of the social web (web 2.0) there

[1] https://www.statista.com/statistics/802690/worldwideconnected-devices-by-access-technology/ (Accessed January 30, 2021)

[2] https://alln-extcloud-storage.cisco.com/ciscoblogs/GITR-2014-Cisco-Chapter.pdf

are a huge number of social media users (about half of the internet users), i.e., 3.72 billion active users on social media out of 4.54 billion users on the internet[3]. Employing social information in service recommendation is becoming more prevalent, because it has proved its effectiveness to fulfill end-user needs [172], [30], [63]. In front of this tremendous growth of web connectors and web services, building recommendation engines for WS composition has become of paramount importance on one side. On the other side, involving those end-users in composition tasks has become an imperative, allowing them to find relevant results that meet their needs, especially, with the appearance of what is known as Mashup, an end-user oriented tool that enables to compose services and web APIs easily and efficiently.

Research Problems and Challenges

Developing Web service Recommendation (WSRec) approaches has emerged as a promising way to solve service proliferation problems. In the context of service composition, there remains a paucity of WSRec models in literature despite the driven force to build up WSRec engines. Most of the existing models are focused on functional features of service, that are based on content-based filtering techniques [17], [3], [182] that matches service description with mashup requirement, while other works [153] take into consideration non-functional attributes of service by predicting Quality of Service (QoS) values. However, the main shortcome of those service-centric approaches is the lack of attention on users' preferences, which reduce the accuracy and exclude the personalized recommendation. In contrast to the previous service-centric approaches, some researchers pay more attention to the user side [8]. Collaborative Filtering (CF) is proposed in [133], [69], on the basis of users' history and feedbacks. Recently, with the advances of social networks, several studies have switched their attention to employ social information to enhance recommendation [96], [158]. Despite all of their advantages and opportunities to personalized recommendation, CF-based and social-aware solutions for service composition ignore the trust issue in their models. However, the notion of trust among users is widely investigated in other individual service recommendation models [131], [30], [63].

Through the analysis of the proposed works on classical WSRec, and in spite of their efforts, most of the existing models cannot always be applied to recommend services in web-based SIoT ecosystems in an appropriate manner due to some constraints. (i) Unlike traditional web services, IoT services cannot be recommended based on description matching [181], [3], [69], because there is no standard representation on IoT services offered by heterogeneous devices. (ii) SIoT is a highly dynamic environment, which led QoS prediction-based approaches [153], [4], [39] to suffer from some obstacles, such as the difficulty of collecting QoS values, high dynamicity and instability of QoS information due to network and resource constraints. This leads to a strong decrease of the accuracy of prediction. (iii) In an open SIoT environment, trustworthiness of services is a crucial issue to avoid recommending harmful services that are provided by misbehaving devices and misbehaving providers, which effects disastrously on the recommendation performance.

[3]https://www.brandwatch.com/blog/amazing-social-media-statistics-and-facts/

Dissertation Aims and Contributions

This dissertation aims to investigate novel approaches in response to the challenges in developing service composition platform in social IoT environment. More specifically:

> The main objective of this thesis is designing, building and evaluating a recommendation system that discovers and recommends personalized services for service composition to end-users in social IoT ecosystem.

In order to achieve this objective, the major contributions of this dissertation are as follows:

- **The theoretical contributions**
  - A comprehensive survey on service composition: overviews and analyzes more than 20 representative research efforts. This study traces the contribution of the social computing to improve traditional service composition in order to investigate the possibility of applying classical solutions on IoT environment.
  - An exploratory review: offers a reference value to understanding the exploitation of different data sources to solve and to meet the recommendation challenges.
  - A novel approach for service composition (S-SCORE) in social IoT ecosystem: suggests and recommends to an end-user trustworthy and personalized web services.
- **The practical contributions**
  - *A new service discovery model (PWR):* accurately finds and suggests to users personalized web services that meet their needs. The presented model combined user-based CF and item-based CF techniques to predict the missing ratings. Then it ranks the candidates services according to their final score.
  - An original service recommendation mechanism: provides trustworthy and personalized services for composition. This mechanism is based on three sub-contributions:
    - *An enhanced model for user similarity computation (UMM):* promotes the quality of neighbor selection. The proposed model combines contextual, social and historical information to overcome the cold start problem.
    - *A novel service collaboration measurement model (SCC):* selects service based on functional and non-functional features of services
    - *A hybrid algorithm for rating prediction (HCCF):* based on collaborative filtering technique and clustering, which simultaneously clusters similar users of a user by applying K-mean clustering, and clusters collaborator services according to their collaboration degree.
  - Implementation and evaluation: we implemented our different models and algorithms and, we validate their performance by experiments that tested on real datasets.

Scenario Examples in E-Health

Social networks have become an important area for E-health applications [128], in which healthcare actors (e.g., physicians, health organizations, and healthcare centers) and healthcare consumers (e.g., patients) connect and collaborate. Moreover, the empowering of E-health with IoT objects and medical devices [130] imposes new challenges and an urgent need to develop new applications [35]. The current trend in dealing with the intermingling of SIoT in E-health is offering different functionalities of devices; this leads to the necessity of providing standardized mechanisms to healthcare organizations that allow these heterogeneous entities to exchange data and allowing them to expose their functionalities on the web. The ideal choice to be used for this purpose is the web service model, which due to its features is very suitable for high heterogeneous and dynamic environments such as SIoT [42]. Thus, we introduce the concept of S-SCORE into the E-Health environment as shown in Figure 1, where there is a high number of services proposed by various E-health providers such as emergency, pharmacies, hospitals and clinics etc. The end-user is an E-Health consumer who needs to compose services, and this consumer may be a doctor, physician, or a patient who sends a request to the system, which in turn makes suggestions to him.

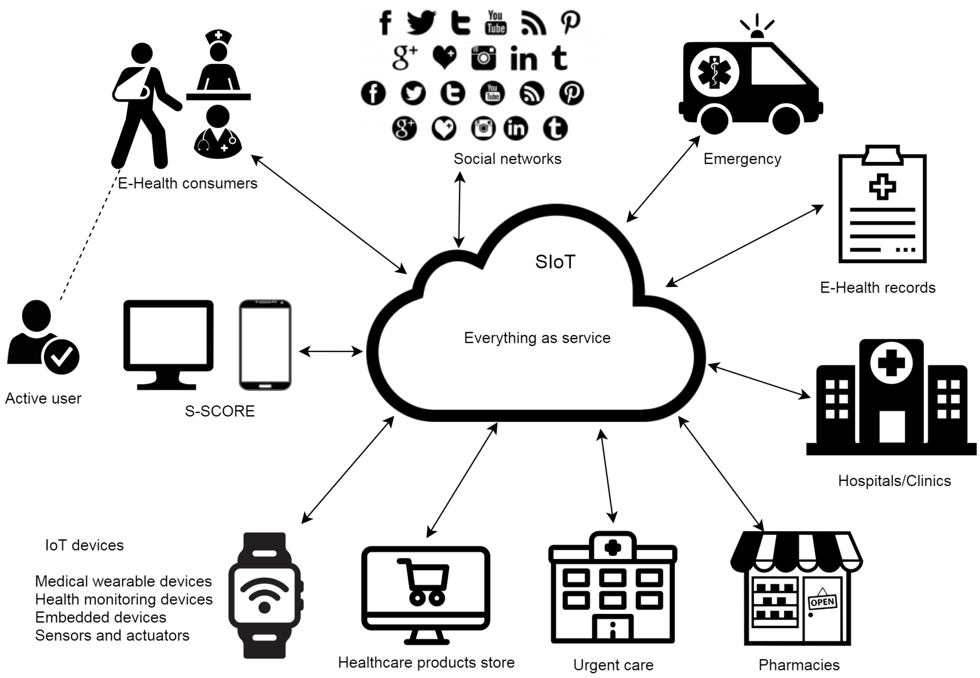

Figure 1: Concept of S-SCORE in a social IoT environment for E-Health.

To motivate our S-SCORE approach, we present the following E-health scenarios:

Scenario of service discovery

To motivate our approach, we present running scenario in E-Health-based IoT ecosystem as shown in Figure 1. The scenario is as follow: "Alice has diabetes; she got an electronic Glucose meter. She is looking for an services that can be used for her device (e.g., service that enables her to send her Glucose measurement to her doctor). Firstly, she connect her device via mobile phone, and then send a request to the recommender system. Here, recommendation engine searches for similar users to Alice (e.g., are also diabetic) who have been used the same kind of device before. Then, it chooses the services that have been invoked by those users (Sophia, Emma, James). Typically, there are a huge amount of services, thus, recommender engine uses rating values of services to select the highest ones and recommend the Top-K services to Alice."

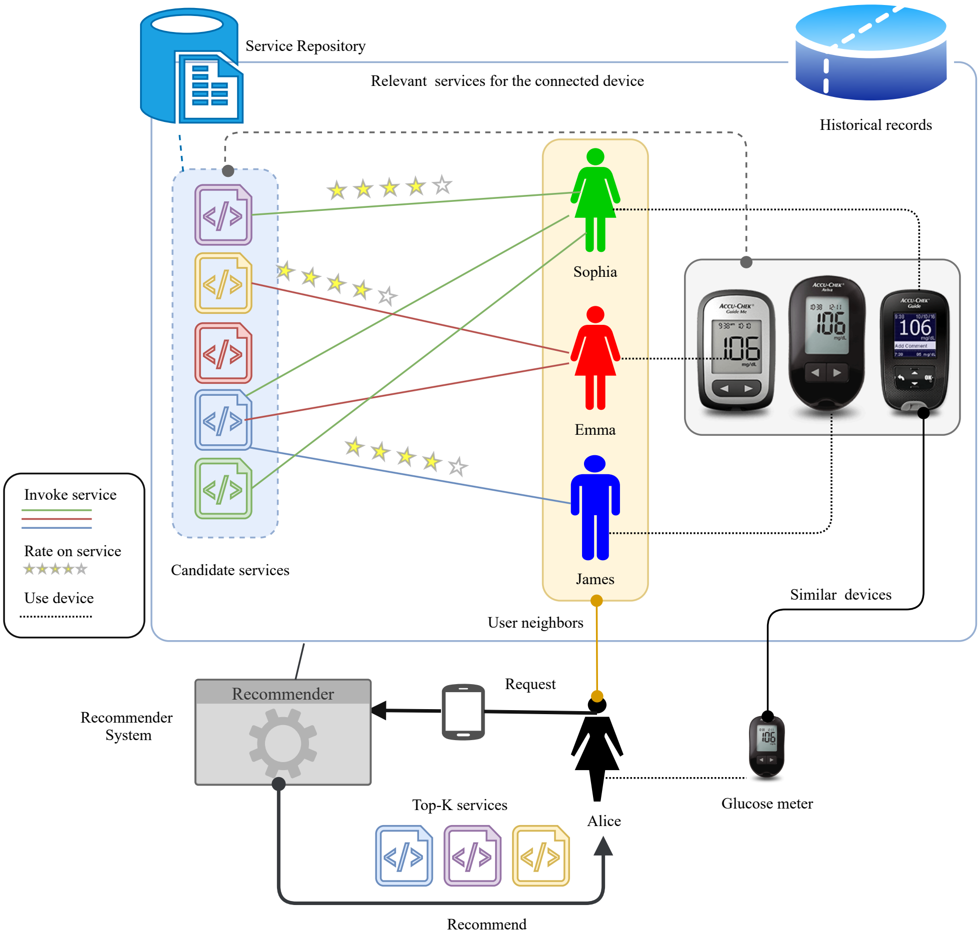

Figure 2: Running scenario in E-health-based IoT system

Scenarios of service recommendation

- Scenario 1: How do end-users work on the platform to get what they want easily and smoothly?

  "In the Tele-healthcare context, Sami is a physician who wants to follow up on the health status of one of his patients. First, Sami logs on to the platform and determines the "patient monitoring" service by dragging it into GUI of S-SCORE. Thus, the recommendation engine suggests a list of services to Sami, who uses the "drag and drop" actions several times until he gets the suitable composite service that fulfills his needs.”

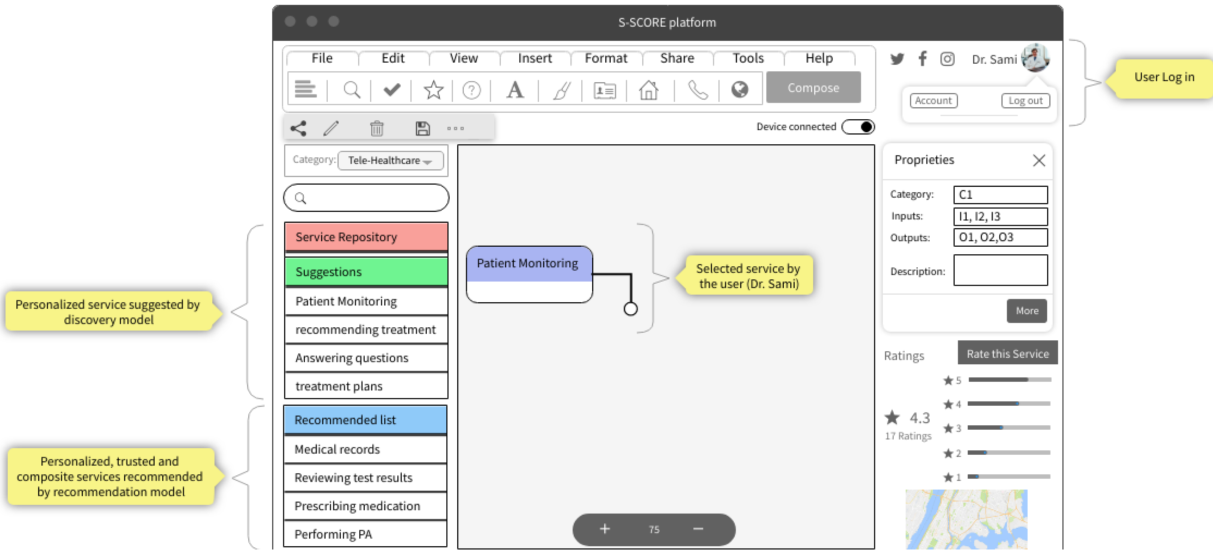

Figure 3: A scenario in the contexte of Tele-health

- Scenario 2: What is the mechanism in which WSRec in S-SCORE works to provide appropriate, trustworthy and personalized suggestions to end-users?

“In the context of E-commerce in the healthcare industry, Matilda is a buyer who wants to purchase a medical device from an online healthcare products store. She chooses the "search online store" service from the list of standard services in S-SCORE. The recommendation engine determines the services that will be recommended. Then the engine sets up the list of collaborator services of the target service (i.e., services that can be composed with the active service). Simultaneously, it selects a list of users to Matilda who have similar characteristics (advisors). Afterwards, the system creates a user-service rating matrix. Then it predicts the missing rates based on the proposed rating prediction algorithm (HCCF). Next, it calculates the final score of the candidate services, to finally make suggestions to Matilda.”

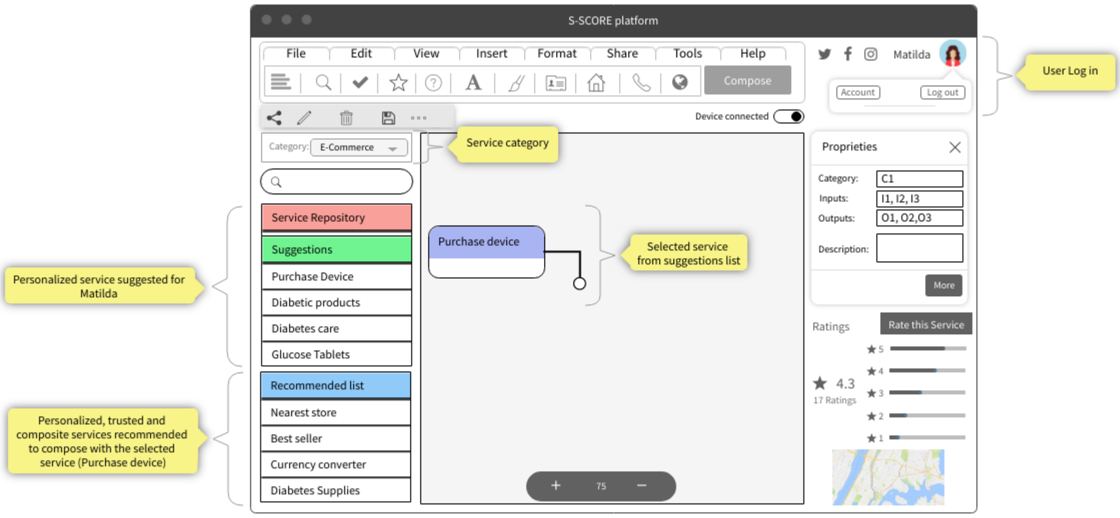

Figure 4: A scenario in the contexte of E-commerce

Thesis Outline

The remainder of this thesis is structured in three parts as following:

Part I: State of the art

In this part, we provide the context of this work:

- **Chapter 1:** presents some preliminary knowledge and basic concepts used throughout the thesis. We show the evolution of the web and definitions of web of things and social internet of things.
- **Chapter 2:** presents a literature overview of the related research topics to this thesis, including service composition and recommender systems.

Part II: Related works

In this part, we analyze the related works in search for related models and technologies that can be used to bring about service composition and in IoT ecosystem.

- **Chapter 3:** In this chapter, we survey and discuss this chapter the efforts on service composition in literature. We give an overview about efforts to integrate social knowledge in classical service composition. We also give an overview about the different approaches of service composition in web-based IoT environment

- **Chapter 4:** we surveys and summarizes the literature on web service recommendation models. We also analyze existing approaches in search for related models and technologies that can be used to bring about service recommendation.

Part III: Contributions

This part represent the core of our thesis, which elaborate our approach for service composition problems. We present the design of service composition platform, the implementation and the evaluation of the proposed models for service discovery and recommendation .

- **Chapter 5:** we introduce our proposed platform for service composition, and the proposed models and solutions for service discovery.
- **Chapter 6:** we present our novel solution for service composition that based on recommendation. Afterwards, the conducted experimentation is presented in order to evaluate the proposed ideas.

Finally, summary marks, perspectives and future directions are given in conclusion.

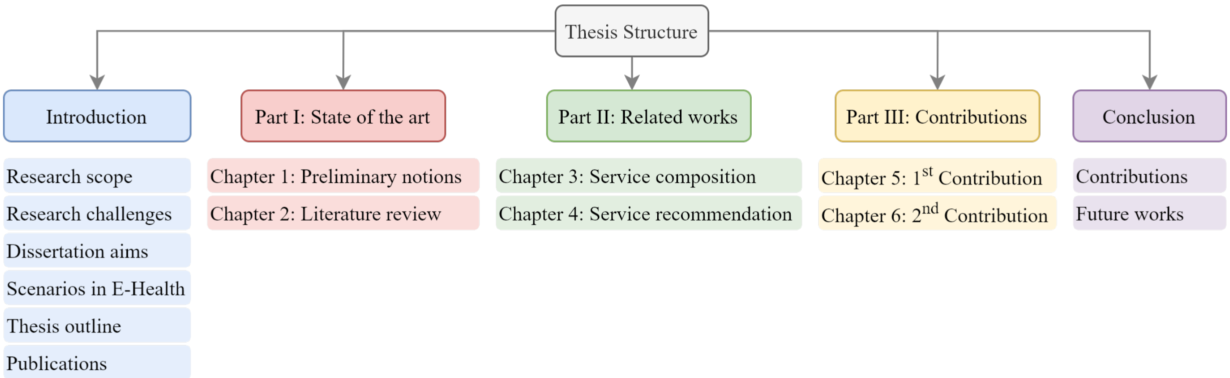

Figure 5: Thesis outline

Publications and Communications

- **Marwa MEISSA**, Saber BENHARZALLAH, Laid KAHLOUL, Okba KAZAR, A Personalized Recommendation for Web API Discovery in Social Web of Things, International Arab Journal of Information Technology, 2021 (A class)
- **Marwa MEISSA**, Saber BENHARZALLAH, Laid KAHLOUL, O.KAZAR, Social-aware Web API Recommendation in IoT, the 20 th international Arab conference on information technology, (ACIT'2020), City 6 of October, Egypt, November 2020.
- **Marwa MEISSA**, Saber BENHARZALLAH, Laid KAHLOUL, Towards Employing Social Information for Web services Management in SoC-based IoT Ecosystem, International Pluridisciplinary PhD Meeting (IPPM'2020), El Oued, Algeria, February 2020.
- **Marwa MEISSA**, Saber BENHARZALLAH, Laid KAHLOULL, Service composition based on the social relations in the Internet of things, the 18 th international Arab conference on information technology, (ACIT'2017), Yassmine Hammamet, Tunisia, December 2017.
- **Marwa MEISSA**, Saber BENHARZALLAH, Laid KAHLOUL, Social Service Composition in the Internet of Things,1 ^{ère} Journées Doctoriales Informatique, Théorique et Appliquée (JDITA'2018), Biskra,Algeria, January 2018.
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- **Marwa MEISSA**, Saber BENHARZALLAH, Laid KAHLOUL, Service composition oriented social recommendation in IoT, the 7th international conference on smart communications in networks technologies (SaCoNet'18) autumn school, El Oued, Algeria, October 2018.

Part I: State of the Art

“ If the facts don’t fit the theory, change the facts.”

Albert Einstein

1

Preliminary Notions

Sommaire

1.1 Introduction

Tim Berners-Lee introduced the web (World Wide Web, as it has been referred to) in early 1990s. It is defined as an information sharing system where web resources are identified, interlinked and are accessible over the Internet. The prevalence of social networks and related technologies led up to new generation of web (web 2.0). Additionally, the emergence of the interconnected networks of physical objects contributed to the emergence of the last generation of the web (web 4.0). In this chapter, we present the different generation of web evolution. Then, we define and describe the web of thing and its architecture in the third section. Finally, we provide an overview on the social aspect of IoT by defining social thing term, social-awareness in SoC-based IoT ecosystem and social IoT model [62] .

1.2 The Evolution of the Web

Over the past two decades, we have seen changes in the using of web and much progress has been made about his related technologies. Four generations of web were defined, namely web 1.0 as traditional web, web 2.0 as social web, web 3.0 as semantic web and web 4.0 as intelligent web. To better understand the different phases of web evolution, we have undertaken a summary table 1.1, which is by no means exhaustive, but which should provide with the most important keys to understanding the difference among web generations.

1.3 Web of Things

The basic idea of Internet of Things (IoT) is the connectivity of real-world things to the Internet [156] so that they can be discovered, managed, monitored or communicated with. However, on the one hand, while things become connected at the network layer, they stay isolated at the application layer. On the other hand, there is an urgent need to enabling people and devices to have access to information. Thus, The Web of Things (WoT) concept envisions an interoperable middleware for allowing physical devices to interact and data access to create future IoT applications through web-based technologies.

1.3.1 WoT Architecture and Platforms

The interoperability problems is one of the key challenges that faced by IoT due to the heterogeneity of protocols, devices and frameworks. WoT is an architectural solution that meets this issue based on web standards to ensure interoperability. This section presents the different proposed WoT architectures in literature. The proposed REST-based architecture of[27] is one of the first preliminary works in WoT architecture, this proposal is detailed as a four layered architecture for the WoT in Guinard's Ph.D. dissertation [41] as shown in figure 1.1. *Accessibility* layer enables to integrate IoT devices to the Internet and the web by applying RESTFul principals. Then, *Findability* layer is designed to expose the functionalities of IoT devices as RESTful

	Web 1.0 Classical web	**Web 2.0 Social web**	**Web 3.0 Semantic web**	**Web 4.0 Smart web**
Emergence	1990	2000	2010	2020
Internet generation	Internet of content	Internet of services	Internet of people	Internet of things
User role	Passive consumer Read-only	Consumer and actor read-write-share	User increasingly active, mobile, always connected read-write-execute	The user becomes a creator, in constant symbiosis with his environment
Oriented	Enterprise and institution	Community	People context	Objects
Business	Catalog forms	Social commerce, auctions, E-commerce	Smart search and advertising, virtual shopping	AI robots, voice processing, personal assistants
Contents	Static contents hosted on web servers	Dynamic contents	Semantic web , web services	Electronic Agents, ubiquitous web
Interaction		Ability to interact with web users	App to app interactions	Human to machine interactions
Communication tools	E-mail, forum	Social networks, blogs, collaborative platforms	Previous tools adapted to the mobile internet and cross media tools	Connected space, wearable technologies

Table 1.1: Summary of web evolution

services. By this means, people, other devices and web applications can discover and invoke these services. The *Sharing* layer provides to web connectors platforms that allow them to access to IoT services. Finally, *Composition* layer deals with supporting composite WoT applications and physical mashups, which empowering developers and end-users to create applications and services tailored to their needs.

The authors in [166] proposed WISE a WoT architecture on fog computing ecosystem, which enables to create new services and mashups for smart home and providing things-oriented web services and applications. Similarly, in fog computing environment, WOTPY [103] is an experimental framework that based on the reference architectural designs of the WoT servient provided by the W3C WoT specifications[1]. SeCoS [66] is also a WoT platform that supports time-awareness, it consists of three parts, micro-services, an API façade and the client interfaces,

[1]https://w3c.github.io/wot-architecture/

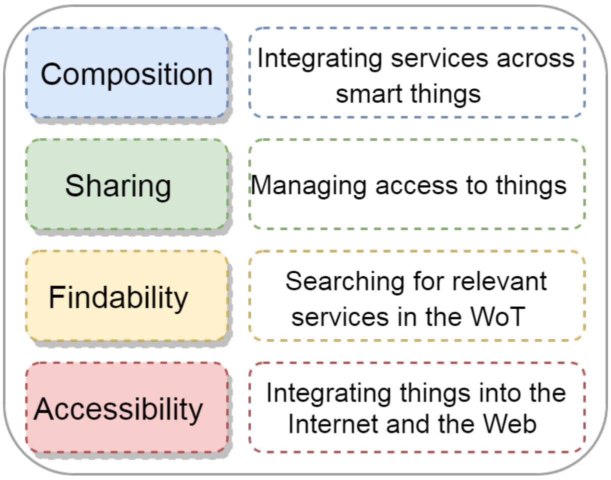

Figure 1.1: Layred architecture of Web of Thing

each of micro-services operate independently of one another such as authorization, storage, data processing visualization…etc. Avatar is yet another platform for WoT provided by [111], the authors define an avatar as virtual extension of physical objects on web. Avatars expose the capabilities and the functionalities of cyber-physical objects as RESTful services and communicate with each other via HTTP and COAP protocols. A more comprehensive approach to semantic interoperability in IoT ecosystem is proposed by [26], a SPARQL-based mechanism is provided that enables accessing and discovering heterogeneous IoT devices. Besides, other WoT-related initiatives have been undertaken by several organizations. In 2014, the World Wide Web Consortium (W3C) has created a WoT Interest Group[2] , which aims to provide an abstarct architecture for WoT, technical requirements, use cases and guidelines for WoT. Open Geospatial Consortium (OGC)[3] is also focus on this field by providing SensorThings API wich deals with the integration of IoT devices to the web. Likewise, Mozilla[4] proposes data model and API to expose IoT devices in the web, by defining JSON serialisation of a Thing Description and a HTTP and WebSockets protocols.

1.3.2 Abstracting Things as Services

After the efforts made to achieve the integration of physical things into the internet, it was imperative to extend the IoT to the World Wide Web. Connecting real-world things with the web enables the web connectors to access and exchange the various data provided by IoT devices and allowing them to interoperate. It is widely acknowledged that Service-oriented Computing (SoC) paradigm [117] is promising way for IoT in order to supporting the interoperability and consistency across the heterogeneous devices, and allowing to abstract device functionalities and capabilities in services delivered and consumed on demand. Thus, in this section we wanted to

[2] https://www.w3.org/2014/09/wot-ig-charter.html, Accessed: 08.07.2020
[3] http://docs.opengeospatial.org/is/15-078r6/15-078r6.html, Accessed: 08.07.2020
[4] https://iot.mozilla.org/wot/, Accessed: 08.08.2020

answer some research questions in order to conduct on the usage of SOC concept within IoT. Then, we discuss each question trying to seek answers to them.

1.3.2.1 How IoT meets SOA architecture?

SOA (Service-Oriented Architecture) [34] is considered as the typical embodiment of SOC that provides an architecture aiming to set up an information system made up of services independent and interconnected applications. SOA revolves around three fundamental concepts namely registry, service consumer and service provider (Fig 1.2). Service provider means a person or organization that publishes the service on a server and generates its description containing the necessary information in order to use it, as well as the available operations and how they are invoked. Registry is a service description directory. It represents also a mediator between consumers and service providers. In fact, the directory automates communications between the latter two by providing consumers with technical and semantic information on the operation of the service. Service consumer they rely on the services offered by the providers.They can be either client applications or services that rely on the functionality of another service provider service. A well-constructed, standards-based SOA can empower IoT due to following main reasons:

- Interoperability: The heterogeneity in IoT devices, network protocols and hardware platforms is one of the most important features of the IoT. This heterogeneity also carries over to the software level, where IoT provides various data formats, services and applications. This makes building IoT applications more challenging and requires providing an infrastructure that guarantee the interoperability among IoT entities. In fact, SOA provides exactly that.

- Reusability: SOA architecture allows the reuse of existing applications and services, so new services can be created from existing ones. In other words, SOA enables businesses to leverage existing investments by enabling them to reuse existing applications, by offering them interoperability between heterogeneous applications and technologies.

- Scalability: By the end of 2025, there will be an estimated 38.6 billion IoT connected devices in use around the world [5]. This ultra-large scale IoT will make service and thing discovery a cumbersome process. Loosely-coupled services vision in SOA allows IoT to be scalable, where there are few dependencies between the requesting application and the services it uses.

Despite the huge advantages that SOA provided to IoT [42], there is an urgent need to improve SOA-based models to comply with all IoT requirements. Numerous Service-oriented Middlewares (SOMs) are proposed in literature to deal with IoT issues such as high dynamicity, deep heterogeneity, flexibility and scalability...etc. Thing-based SOA (Fig 1.3) is a SOM solution for IoT systems that have developed within the MiMove team at Inria Paris [56]. The proposed SOA-based architecture MobIoT aims to address the scalability, the heterogeneity and the dynamicity

[5]https://www.statista.com/statistics/802690/worldwide-connected-devices-by-access-technology/, Accessed: 08.15.2020

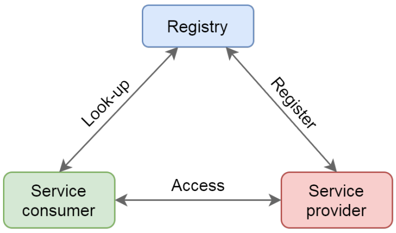

Figure 1.2: Classical SOA model

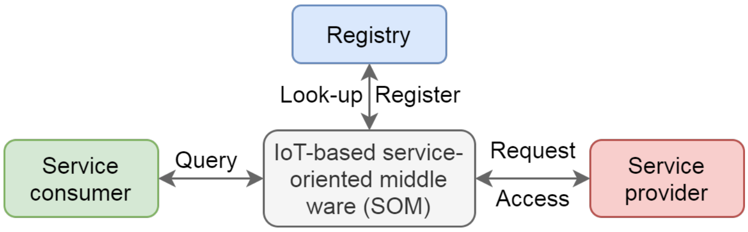

Figure 1.3: Thing-based SOA [56]

of IoT environment. MARINE [29] is also a service-oriented middleware for IoT-based systems, where the authors focus on heterogeneous WSNs and extends their research by proposing SACHSEN [151] a heuristic algorithm for resource allocation. AUSOM [14] is another SOM for IoT sensors and actuators based on context. Similarly, MSOAH-IoT [106] is middleware solution based on REST API . SmartCityWare is also SOM solution proposed by [109] in order to resolve the accessibility and flexibility of smart city services and applications by exploiting cloud and fog computing technologies in IoT ecosystem.

1.3.2.2 What is IoT service?

In the context of Internet of Things, The ubiquitous environment requires integration between heterogeneous devices. Extending IoT with the web Services technology is a promising way to enable these devices to provide their functionalities on the web, and to achieve interoperable interaction and communication to other entities. Those services that were provided by IoT devices (sensors, actuators, domestic appliances...etc.) were called real-world services or IoT service. In [138], the authors have conducted on the term of IoT service and have defined IoT service as follows:

> “ An IoT-Service is a transaction between two parties, the service provider and the service consumer. It causes a prescribed function enabling the interaction with the physical world by measuring the state of entities or by initiating actions, which will cause a change to the entities.”

In order to apply the concept of IoT into the web, REST and SOAP are two most known architectural styles for the development of IoT services. SOAP fits better for the requirements of business applications; while REST is suited for IoT applications, comprising mobile and embedded devices [6]. A comparison between SOAP and REST is given by [102].

1.4 Social Aspect of IoT

The social aspect of IoT has little been exploited in service composition. In this section, we attempt to draws the barest outline of the social relations among IoT components could be

[6]https://www.linkedin.com/pulse/web-services-iot-shayani-chakraborty

exploited. Moreover, we mention few research studies conducted on this topic.

1.4.1 Social Thing

A Social Internet of Thing (SIoT) is a novel paradigm of "social network of intelligent objects", based on the notion of social relationships among Objects [6]. In this reference, the authors identified the social relationships among things and they classified it into five types as following:

- *Ownership Object Relationship (OOR): two things had the same owner.*
- Parental Object Relationship (POR): refers to the similar things created by the same producer.
- *Co-work Object Relationship (CWOR): defined among cooperated things offer a common functionality.*
- Co-location Object Relationship (CLOR): tow objects located in the same place.
- *Social Object Relationship (SOR): when objects established companionship with each other.*

The authors in [150] proposed a new vision of social relations among physical things. They categorized the social relationships according spatial and temporal attributes, which divided the social relationships into four kinds:

- *Spatial: when objects situated in the same special position.*
- Temporal: refers to the social relations that change with time, or relations that effected with time factor.
- *Spatial-Temporal: expresses the type of relations that related to the time and position simultaneously.*
- Nor Spatial-Temporal: refers to unchangeable relations with temporal and spatial features of physical objects.

1.4.2 Social-awareness in SoC-based IoT Ecosystem

In SOC-based IoT applications, exploiting the social aspect is still in its infancy with limited works reported in the literature to date. The exploitation of SIoT addressed in service recommendation [160][22][55]. To assuring network navigability and environment scalability and the possibility to support interaction level among things by using the trustworthiness. Some recent researches highlight on the trust management in SIoT. [148][115][22]. Using the classical social networks platforms for IoT applications is proposed in this work [46]; when the authors chosen twitter as platform to enable the interaction between entities (human/thing/ service) and to facilitate the integration of objects into the web. [44] proposed system allows to the owners of things to share them via traditional social network (Twitter, Facebook. . . etc.) taking in the consideration some metrics as the energy consumption, also the authors mentioned web of things constraints like the addressability, uniform interface. For Social service composition in IoT, [43] proposed an approach based on social network concept to IoT service composition and device management, which addressed relationships between things and services.

1.4.3 Social Web of Things Model

In this sub-section, we present the social aspects of the web 4.0 by proposing a novel model that based on graph representation of SWoT. the model is based on two basic components: nodes, and social links, we visualize SWoT as multilayer network [119], where there are various types of nodes(objects, users, services), and multirelationships between them as shown in table 1.2 . We can categorize the social links in SWoT as follownig:

- *Asymmetric/Symmetric*: in social web of thing network, the social links could be among symmetric entities such as user-to-user, service-to-service and object-to-object relationships. In addition, the links could be among asymmetric items as user-to-service, user-to-object or service-to-object relations.
- *Direct/Indirect:* direct relations refer to directly linked entities such as friendship relation between two users or correlation between two services. The indirect link among entities can be defined as the existence of an intermediate entity between two entities, for example, friend of a friend FOAF relationship.
- *Explicit/Implicit:* implicit links between social nodes represent the hidden relation among them, such as co-invoked services relation between two service consumers, common interest between users...etc. The explicit relations refers to relation that entity have initiated with another one. Such as trust, social reputation . . . etc.

Relationships in SWoT					
Symmetric			Asymmetric		
(service,service)	(user,user)	(object,object)	(service,user)	(service,object)	(user,object)
Collaboration Replacement Correlation Competition	Friendships Co-invocation Co-rating	Co-location Friends Co-work Ownership	Invocation Rating Composing Consuming	Providing Invocation	Ownership Usage

Table 1.2: Example of relationships in SWoT environment

Graph $G = (V_m, E_m, N, L)$ is given as illustrated in figure 1.4 , where $N = U \cup S \cup O$ is the set of nodes, and $L = l_1, l_2, l_3$ is the set of elementry layers, where 3 is the number of aspects (users, services , objects). V_m is the set of state nodes, where $V_m \subseteq V \times L_1 \times L_2 \times L_3$. E_m is the set of multilayer edges, where $E_m \subseteq V_m \times V_m$. The edge $((x, L_i), (y, L_j)) \in E_m$ represent the edge from node x on layer L_i to the node y on layer L_j. We define $R = R_1, R_2, ..., R_n$ set of diffrent relationships in SWoT network, where the function that weights the edges $f : E_m \rightarrow R$.

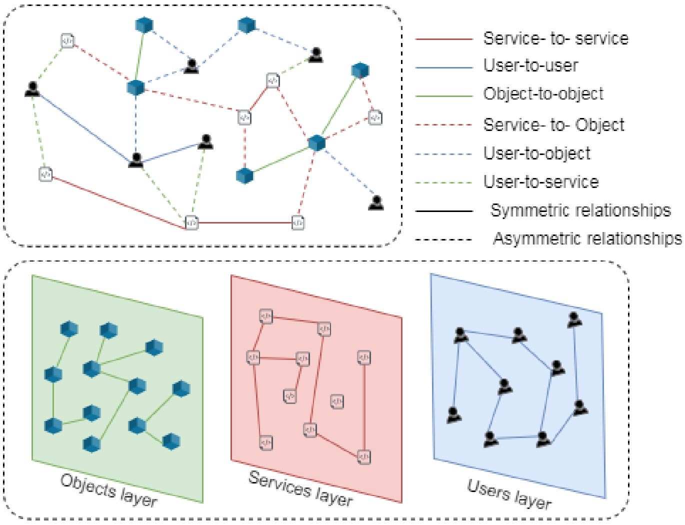

Figure 1.4: A multilayer network model for SWoT

1.5 Summary

In this chapter, we have introduced the evolution phases of the web and we describe in details the key differences of its four generations. Then, we have also presented the preliminary concepts of web of things. In addition, we have provide insights on social aspect of IoT and we have analyzed the existing efforts in this area of research in order to understand the basic concepts that we will discuss in the following chapters.

"Troubles are often the tools by which God fashions us for better things."

Henry Ward Beecher

2

Literature Review

Sommaire

2.1 Introduction

In service oriented computing , service composition is one of the hot issues for its necessity; it promotes the creation of complex applications by aggregating atomic services to provide new functionalities that none of the services could provide individually [79]. This pressing need to create new services and to offer new functionalities confronts the user with the crucial challenge to choose the most appropriate services to be composite services. Thus developing web service recommendation approaches has emerged as a promising way to solve the aforementioned problem.

This chapter provides an overview on service composition and recommendation systems in order to advance the understanding of this area of research. Service composition taxonomy is proposed in the second section, which sheds new light on the classification of service composition approaches. The third section presents a background on recommender systems and draws the barest outline of their challenges.

2.2 Service Composition Taxonomy

Typically, web service composition approaches can be classified according to different criteria. In this section, we propose a frame of reference that allows to analyzing them. This frame of reference addresses five questions to help in understanding the concept of service composition and also categorizes the approaches of WS composition as illustrated in Figure 2.1.

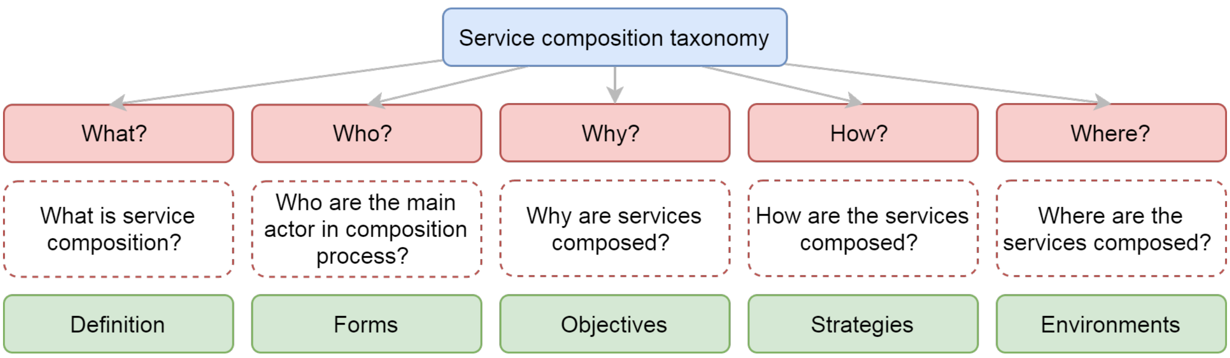

Figure 2.1: Service composition taxonomy

2.2.1 Definition and Objectives

S. Dustdar and W. Schreiner [32] defined service composition as:

> “ *The basic infrastructure of web services is sufficient for the implementation of simple interactions between a client and a web service. If the implementation of a business application involves the invocation of other services web, it is therefore necessary to combine the functionalities of several web services. In this case, we are talking about a composition of web services* .”

According to L. Ling et al. [79]:

> “ *Service composition promotes the creation of complex applications by aggregating atomic service to provide new functionalities that none of the services could provide individually.*”

Generally, in service-oriented computing, the term service composition refers to the technique of combining web services in order to build new applications, mashups and services. Those services called composite services are normally a collection of two or more atomic or component services as illustrated in Figure 2.2.

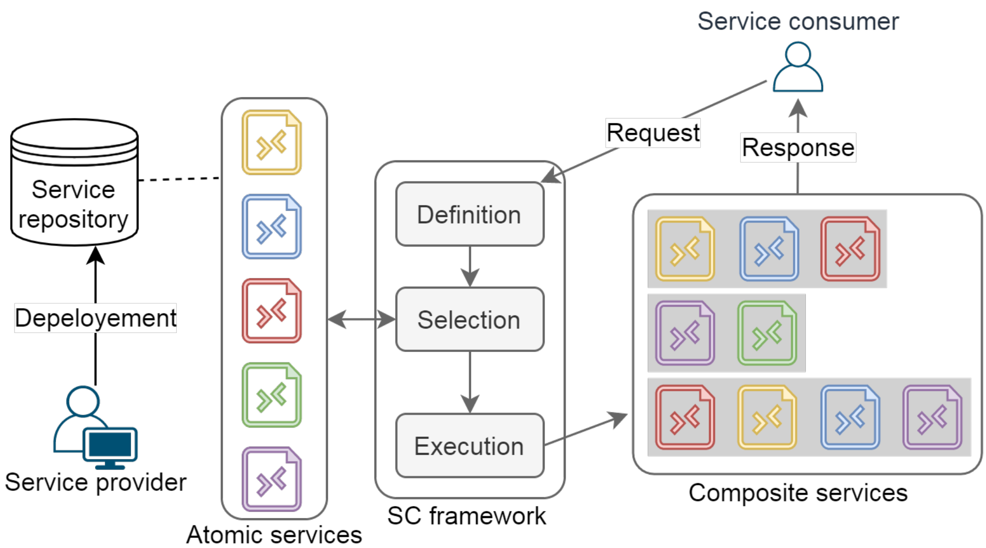

Figure 2.2: An overview on service composition process

Typically, the exploiting of the open standards of the web and by ensuring a weak coupling of the components, the web service paradigm presents a flexible and promising technique for the interoperability of heterogeneous systems. Moreover, it is allowing a faster, cheaper and more cost-effective integration of applications. Hence, composing web services also has many benefits, which are summarized in the following:

- Providing new functionalities by combining already existing services.
- Reducing costs, effort and development time for new applications.

- Satisfy the user requirements and fullfil his needs by optimizing and improving an existing functionalities.
- Improving the efficiency of software development and solving unsolved complex problems.
- Enabling to differ and various enterprises to collaborate.

2.2.2 Forms of Service Composition

In this section, we classify web service composition in three main fashions:

- *Automatic/Semi-automatic:*

  Typically, the automated composition produces a composite service by aggregating atomic services, without user intervention. However, the semi-automatic composition refers to the composition process that based on series of interactions with user. Recent researches dedicate to make composition process much more user oriented. Specifically, with the emergence of web 2.0, where the users have the ability to participate in producing contents. The mashup editors are one of the most familiar tools to the concept of semi-automated composition, which enables involving users into composition process in easy way even with their limited programming skills.

- *Orchestration/Choreography:*

  Web services orchestration consists of programming an engine, which invokes a set of web services according to a predefined process. This orchestration engine is a software entity, which acts as an intermediary between the services by invoking them according to the orchestration script. It defines the process as a whole and invokes web services (both internal and external to the organization) in the order execution tasks. The choreography is the internal behavior of the service. It describes the different interactions (collaborations) that the customer of this service must respect in order to consume the functionalities of the latter. It is a way to achieve a common goal using a set of web services (components). The collaboration between each web service in this collection is described by floods of control. The illustration of two types as follows:

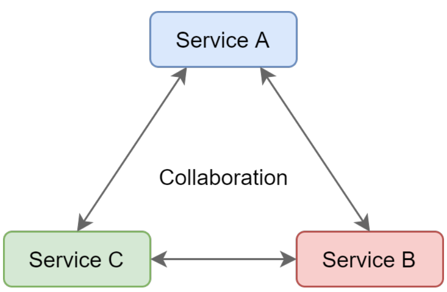

Figure 2.3: Choreography

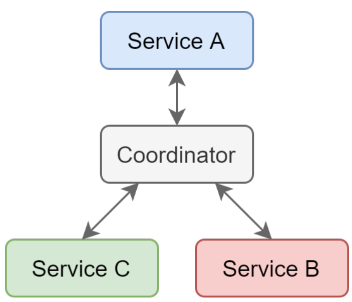

Figure 2.4: Orchestration

- *Dynamic/Static*

  A composition is known as static if to the combination of two or more services at the design time and an expert previously determines the composition scheme. The term “static” implies that once a service is created, it cannot be modified by users any more. This kind of service composition generally targets the developers. In dynamic composition, no composition scheme is defined in the query user. It is post-compiled or even reactive. It refers to the selection of basic services "on the fly". In other words, the selection of basic services cannot be predefined to in advance but it will be done at runtime depending on the constraints imposed by the user. This makes it possible to develop different composition scenarios which offer the same functionalities and which take into account the dynamics of the user’s situation. The main shortcomings of static composition is: since the services to be composed are pre-selected and the control flow is previously specified then if one of the services participating in the composition are not available, the composition scheme is no longer valid. In addition, user needs in this type of approach are defined in advance. However, the user may also need to issue custom requests. and completely unpredictable by an expert. Dynamic approaches take into account this need.

2.2.3 Service Composition Strategies

During recent years, a considerable number of strategies and mechanisms have been proposed to solve service composition issue in literature. In this section, we provide a classification of composition solutions from a specific point of view, which is the following directions of solving the service composing issue:

2.2.3.1 Pattern oriented approaches

In this category of solutions, researchers have devoted their energy to focus on the workflow and on the design of composition process and . Two main categories have been defined:

- *Horizontal/Vertical:*

  The task of service composition includes two main composition processes: Vertical and Horizontal. Horizontal composition consists of determining the most appropriate service, from among a set of alternative services, which provide equivalent functions. Vertical composition consists of defining an appropriate combination of simple processes to perform a composition task by extending the web services functionality as illustrated in Figure 2.5.

- *Sequential /Parallel* In sequential patterns, the workflow of composite services is obtained by a sequence combination of services (i.e., serial). While, the workflow of composition in parallel pattern is obtained by invoking multiple component services where all services parallelly participate in this composition. In order to distinguish between the two styles of composition, we define a service as: A service S from input type X to output type Y is a binary relation: $S \subseteq X \times Y$. Figure 2.6 illustrates those patterns of composition as follows:

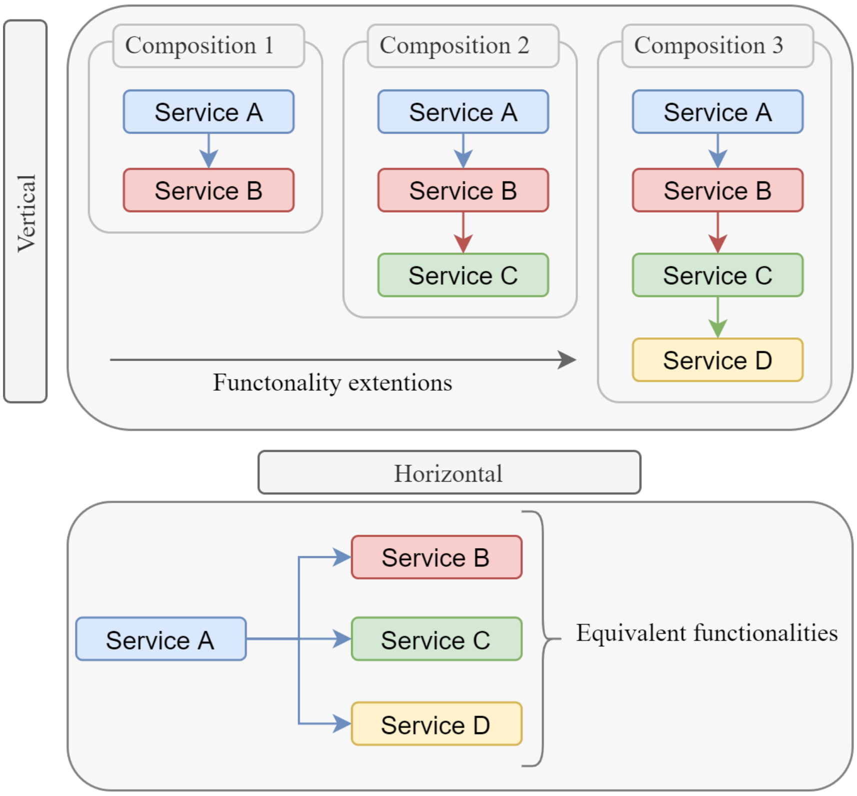

Figure 2.5: Illustration of horizontal and vertical styles of service composition

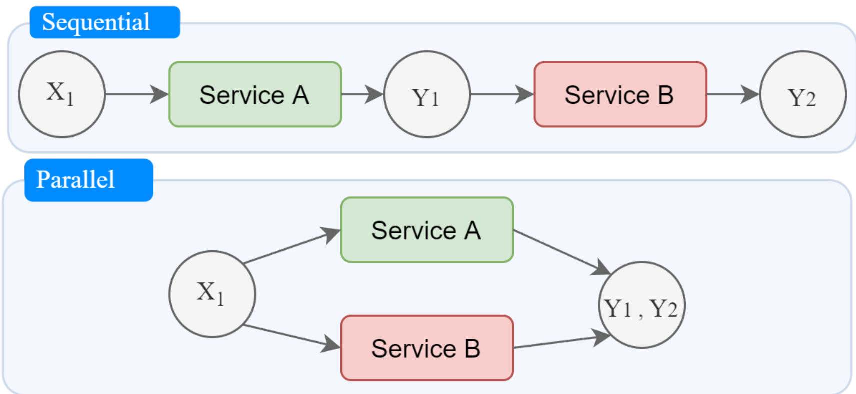

Figure 2.6: Illustration of sequential and parallel patterns of service composition

2.2.3.2 Life cycle oriented approaches

The majority of efforts made to resolve service composition issues have been directed towards life cycle of service composition such as discovery, selection, palnning...etc. By analyzing service composition approaches in chapter 3, we noticed that most of studies focus on service discovery and selection as shown the following chart:

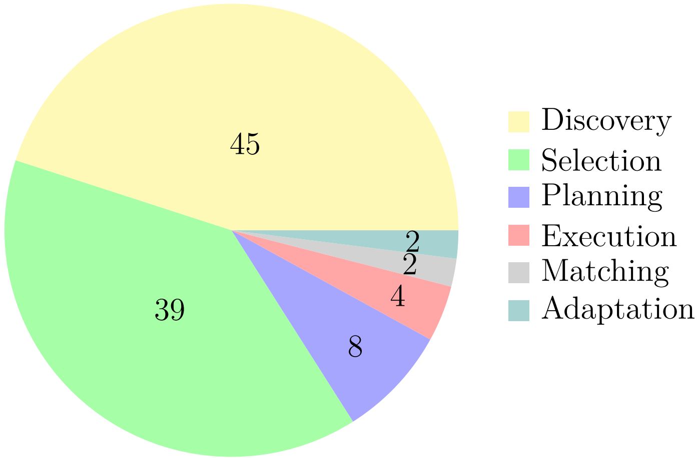

Figure 2.7: Research focus in life cycle oriented approaches

2.2.3.3 Model oriented approaches

Web services composition approaches range from those that that exploit resources on classical web to those that exploit various resources found in next generations of the web. In this context, we identify four non-exclusive approaches: formal, structural, semantic and social- aware approaches. Formal approaches provide tools and mathematical tools for testing, verification and validation in order to check the correctness and the reliability of the service composition implementation. Structural approaches aim to provide techniques and formalisms to describe services, how and in what order services can be composed, and what conditions should be satisfied. Semantic approaches harness the potential of the semantic web such as ontologies in order to enable the automation of composition tasks. Social approaches brings social knowledge provided by social web to improve and optimize the quality of service composition.

2.2.4 Environments

The Service-oriented architecture (SOA) provides the opportunity of the reuse of existing applications and services, by offering them interoperability between heterogeneous applications and technologies, which facilitates rapid system deployment. Thus, service composition can be widely performed under several environments. These environments have different characteristics and have many different features such as scalability, heterogeneity, dynamicity. . . etc. In literature, web services have been composed in different environments and various ecosystems as IoT, Clouds, wireless sensor network (WSN), social networks...etc.

2.3 Recommender System Background

2.3.1 Definition

Numerous authors have implemented several definitions of recommender systems. Below, we quote a definition generally accepted and provided by [98]:

> "*Recommender systems are intelligent applications, which assist users in their information-seeking tasks, by suggesting those items (products, services, information) that best suit their needs and preferences.* "

In other words, recommender system is a software tool that suggest relevant items to users based on recommendations from other people. Helping users to discover and to choose resources in big data environment is still remains an important challenge today. Thus, several famous websites use recommendation engine in their systems, such as Facebook[1] by recommending friends, pages, groups, Netflix[2] (movies), YouTube[3] (videos)...etc.

2.3.2 Recommendation Strategies

The core idea of RSs is to reduce the problem information overload. Additionally, data analysis techniques are widely applied in recommender engines in order to improve their performance and help users to find suitable items. We divide the strategies of recommendation into three parts: filtering techniques, dimensionality reduction techniques and similarity measurements.

2.3.2.1 Filtering Techniques

Filtering techniques are classified into two main categories: collaborative filtering (CF) and content-based strategies (CB).

2.3.2.1.1 Collaborative Filtering (CF)

Collaborative filtering technique is widely used in RS, which is mainly based on historical information of users such as user behavior or user ratings. the concept of CF is illstrated in figure 2.8. CF-based recommendation is dependent on the relations among users and items to show up new hidden. Fundamentally, collaborative recommender systems can be categorized into two types: memory-based and model-based CF.

[1] www.facebook.com
[2] www.netflix.com
[3] www.youtube.com

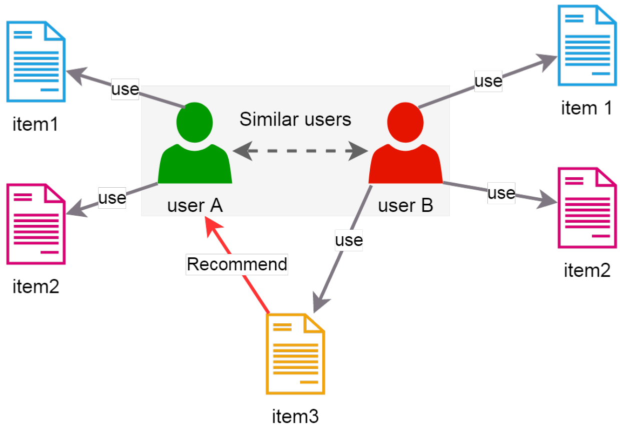

Figure 2.8: The concept of CF-based recommendation

The model-based CF approach enables to alleviate the problem of data sparsity by building prediction models that based on statistical [114] and machine learning [5] and deep learning [85] methods [73]. The main purpose of this approach is handle of extraction of specific data from the dataset and utilize them as a model to predict the missing value in rating matrix without using the whole matrix each time. Numerous techniques are proposed in literature; the most popular ones are: matrix factorization [74] [91], neural networks [37], clustering [33], fuzzy systems [162] [175], Bayesian classifiers [142]...etc.

Memory-based CF (is also known as neighborhood-based) is mainly based on K-Nearest Neighbors algorithm (KNN), it employs user and/or item correlations to predict missing values in order to make recommendation for user on future items. The recommendation in memory-based is based on similarity measures (see 2.3.2.3). Neighborhood-based approach is devided into two methods: user-based (UbCF) and item-based filtering (IbCF) [31]. The difference between UbCF and IbCF algorithms is illustrated in the following example:

Example 1. Given set of users $U = \{u_1, u_2, u_3, u_4, u_5, u_6\}$ and set of items $I = \{A, B, C, D, E, F, G\}$. User-item rating matrix is given as show in figure 2.9. In order to predict the rating value of the active user u_2 on the item F, we can use two methods: IbCF or UbCF.

User-based CF prediction: the prediction of missing ratings in UbCF is based on the ratings given on a specifc item by his neighbors (similar users with same taste). The rating prediction in UbCF is given by the following equation:

$$Pred(u_2, F) = \frac{1}{n} \sum_{u_i \in Neighbors(u_2)} (Sim(u_2, u_i) \times r(u_i, F)) \tag{2.1}$$

Where the predicted rating of user u_2 on item F is equal to the rating values of his neighbors $Neighbors(u_2)$ on item F multiplied by their degree of similarity with him $Sim(u_2, u_i)/u_i \in Neighbors(u_2)$ that given by user-user similarity matrix. According the example illustrated in 2.9, the neighbors of u_2 is $Neighbors(u_2) = \{u_1, u_3, u_6\}$. So, the predcited rating is calculated as follows:

$$
\begin{aligned}
Pred(u_2, F) &= \frac{1}{3} \times [\, Sim(u_2, u_1) r(u_1, F) + Sim(u_2, u_3) r(u_3, F) + Sim(u_2, u_6) r(u_6, F)] \\
&= \frac{1}{3} \times [\, (0.8 \times 3) + (0.9 \times 2) + (0.7 \times 3)] \\
&= 0.33 \times [\, 2.4 + 1.8 + 2.1] \\
&= 2.1
\end{aligned}
$$

Item-based CF prediction: in UbCF the prediction is computed by collecting the ratings of similar items to item F that are rated by the same user u_2 as the next equation:

$$
Pred(u_2, F) = \frac{1}{m} \sum_{K \in Neighbors(F)} (Sim(F, K) \times r(u_2, K)) \tag{2.2}
$$

The simialr items of item F are $Neighbors(F) = \{C, D, G\}$, the predicted rating is calculated as follows:

$$
\begin{aligned}
Pred(u_2, F) &= \frac{1}{2} \times [\, Sim(F, G) r(u_2, G) + Sim(F, C) r(u_2, C)] \\
&= 0.5 \times [\, (0.9 \times 3) + (0.6 \times 5)] \\
&= 0.5 \times [\, 2.7 + 3] \\
&= 2.85
\end{aligned}
$$

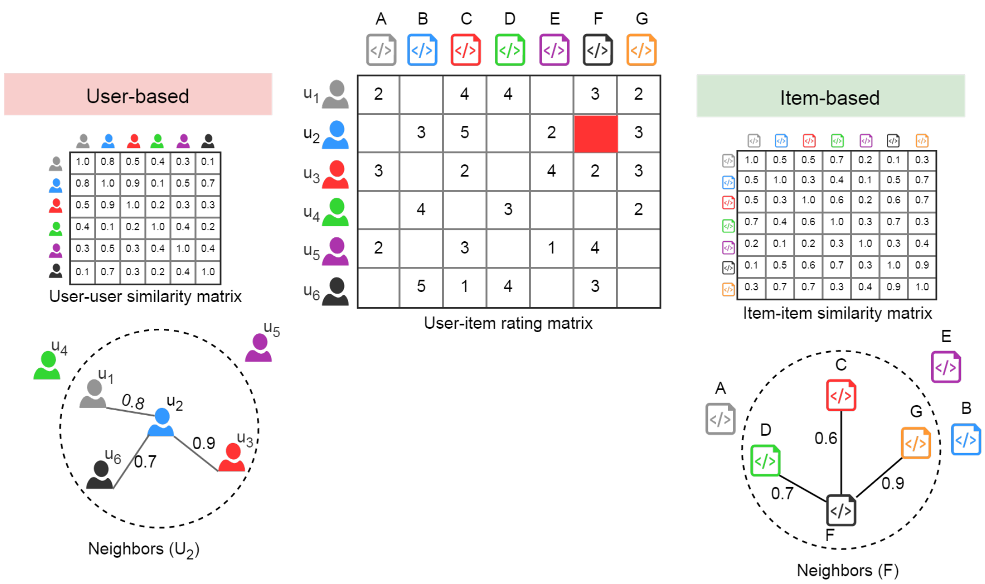

Figure 2.9: Example of rating prediction in IbCF and UbCF

2.3.2.1.2 Content-based Filtering (CB)

The main idea behind CB filtering is to recommend items to an active user that are similar to items he has already consumed in the past based on item description rather than similarity of other users.In this approach, the recommendation engine first builds item descriptions of those items that the user has liked. Then, user profiles are built inferring from those item descriptions. Finally, the recommendation is made by matching the user's attributes with items' features. For example in content-based recommendation system for books, the recommendation engine find out the set of rated books by the active user. Then by analyzing their contents, it characterizes the user's preferences on books such as title, authors, publisher, year, type...etc. Then, it matches the user's preferences with books' features, resulting in a score of how interesting this book to the active user to finally recommend the high similar books with his preferences.

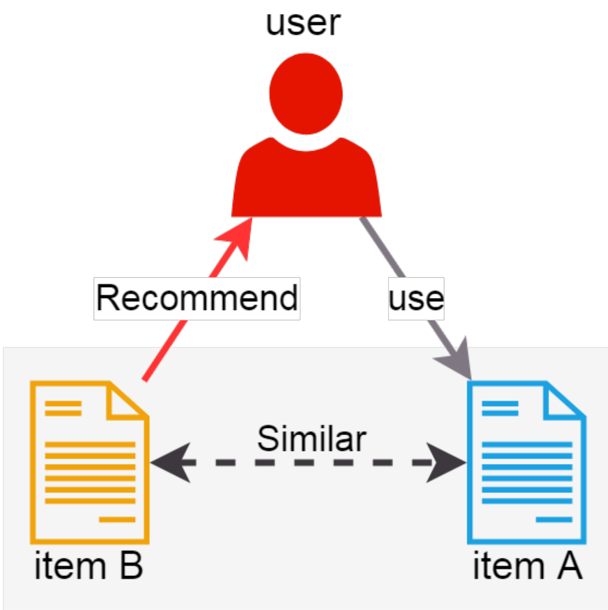

Figure 2.10: The concept of Content-based recommendation

Fundamentally, the global architecture of a content-based recommendation system revolves around three main modules [123] as illustrated in figure 2.11 :

- Content analyzer: represents the pre-processing phase for building item descriptions and extracting their features. This module aims to transform items from unstructured text to a structured representation.
- Profile learner: the aim of this module is generalizing the preferences into a user profile based on his historical interaction with items using machine learning techniques [1] [116].
- Filtering module: in this phase, a set of items is selected by using the similarity measures and matching user profile with item features. Then, applying ranking techniques [2] in order to recommend the most relevant items.

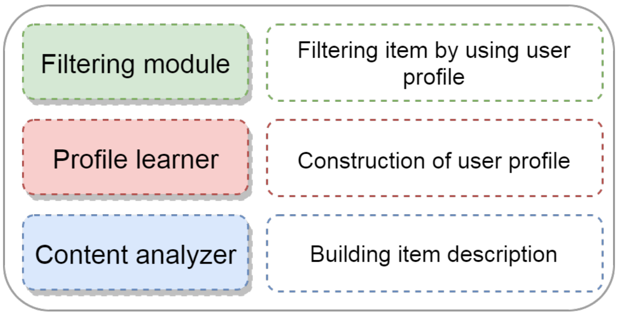

Figure 2.11: The architecture of Content-based recommendation system

2.3.2.2 Dimensionality Reduction Techniques

It is common in rating matrix to have the number of rated items is much lower than the number of total items (i.e., the number of data points is much lower than the number of dimensions); this problem is known as the curse of dimensionality. The notions of data sparsity and density, which are critical for classification and clustering, become more meaningful in recommendation accuracy. In order to overcome this problem, dimensionality reduction approaches have been proposed in literature. The purpose of dimensionality reduction techniques is to break the rating matrix into the product of smaller matrices to estimating the blank ratings in this sparse matrix. In this section, we summarize the most relevant techniques to manage the curse of dimensionality in the context of recommendation systems into matrix factorization (MF) and tensor factorization (TF).

2.3.2.2.1 Matrix Factorization (MF)

Data sparsity and the large size of rating matrix or similarity matrix are the most important problems in rating prediction, which causes a decrease in recommendation performance. Thus, the technique of matrix factorization [74] aim to eliminate insignificant rows or columns from a matrix by factorizing this matrix R into two matrices U and V such that their product approximates $R \approx U \times V^T$. Where each row of U represents the strength of the association between user and k latent features. Similarly, each column of V represents the strength of the association between an item and the latent features as shown in figure 2.12.

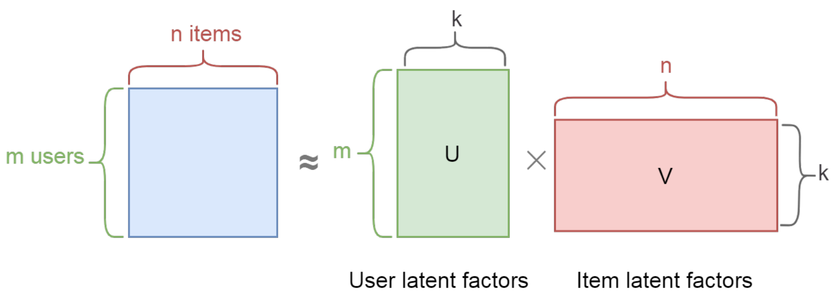

Figure 2.12: The concept of matrix factorization

In the context of collaborative filtering, there are various models of MF such as Singular Value Decomposition (SVD) [125], Principle Component Analysis (PCA) [40] , Probabilistic Matrix Factorization (PMF) [108], and cure decomposition (CUR) [100]...etc. The benefit of CUR decomposition over other decomposition models such as SVD is that rows of the matrix R and columns of the matrix C are expressed in terms of a small number of columns and rows of the rating matrix A as shown in figure 2.13. This would give more interpretable results on what features or rows in the data are most significant. Therefore, in this thesis, we use CUR decomposition technique to decompose the rating matrix A into three matrices: C, U and R, the second matrix of which (the selected rating matrix) is dense, even when the main matrix is sparse. We employ the LeverageScoreCUR (LSCUR) algorithm [100] which is a low-rank matrix decomposition that enables to reduce rows or/and columns.

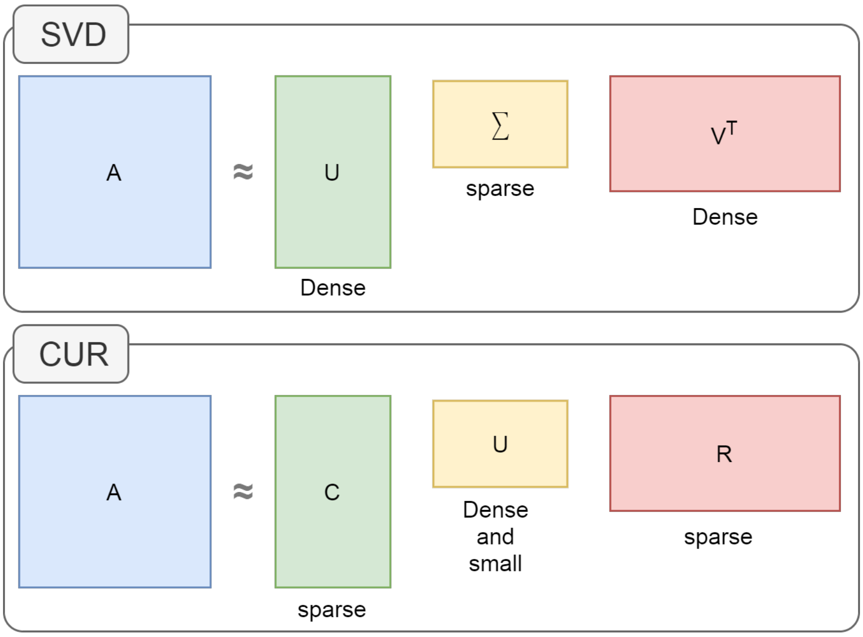

Figure 2.13: Diagramatic representation of SVD and CUR decomposition

2.3.2.2.2 Tensor Factorization (TF)

The core deficiency in MF techniques is that they only take on consideration the standard profile of users and items. Despite, recommender systems still need to involve more kinds of information such as context and social knowledge to improve the prediction accuracy in the face of data sparsity. Various models of TF are proposed in literature such as Tucker Decomposition method (TD) [139], PARAFAC method (PARAllel FACtor analysis) [164] and PITF method (Pairwise Interaction Tensor Factorization) [126]. Moreover, other extended methods from MF techniques such as Higher order Singular Value Decomposition (HOSVD)[28] and tensor CUR decomposition [101]. The main purpose of tensor factorization method is handling three-dimensional user-item-criterion rating data, which allows employing additional context as shown in figure 2.14. The three dimensions of the tensor known as modes M, N and D. Additionally, fibers are higher order analogues of matrix rows and columns. A fiber is secured by fixing all but one of the indices of the tensor. Similarly, slices are obtained by fixing all but two of the indices of the tensor. For example, in social-aware recommendation, the ternary relation of (user, item, tag) can be represented as a third-order tensor $T = (a_{i,j,t}) \in \mathbb{R}^{M \times N \times D}$, where dimension 1 has M users, dimension 2 has N items, dimension 3 has D tags, and $a_{i,j,t}$ means that user i tagged the item j with the tag t. The fibers are given by $a(:,j,t)$ (column fiber), $a(i,:,t)$ (row fiber), and $a(i,j,:)$ (tube fiber). The slices are also given by $a(i,:,:)$ for horizontal slice, the lateral slice as $a(:,j,:)$ and the frontal slice as $a(:,:,t)$.

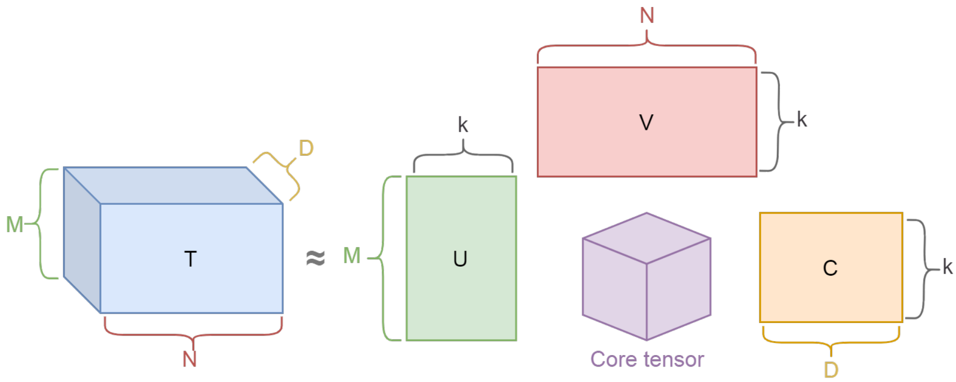

Figure 2.14: The concept of tensor factorization

2.3.2.3 Similarity Measurements

Similarity measures are widely used in CF-based approaches in order to find k-neighbors to a target user (the most similar users) or similar items for a target item (relevant ones). Typically, the similarity between users is based on their ratings on items. Likewise, the similarity between two items is also based on their ratings given by users whom rated both of them. In literature, various similarity measures have been applied to identify the set of similar users/items. This section mentions the most used similarity measurement for user similarity and consequently, it is easily to infer item similarity because they have the same principle. The equations and the definitions of similarity measures that have been used for neighborhood based CF are detailed in the following:

Jaccard index

Jaccard coefficient is based on the idea of intersection of sets. Formally, it is defined as the size of the intersection divided by the size of the union of the sample sets. In CF context [9], this index is used to measure the similarity among two users u and v by counting common feauters I_u and I_v (i.e., consumed items, co-ratings or preferences...etc). The mathematical representation of this coefficient is as following:

$$Jaccard(u,v) = \frac{|I_u \cap I_v|}{|I_u| \cup |I_v|} \tag{2.3}$$

Cosine similarity

Cosine similarity is applied to compute the distance between two vectors by calculate the cosine of the angle between them. This metric of similarity is widely used in CF-based approaches. For example, for users u and v, the sets of their rated items are R_u, R_v (i.e., rating vetors), respectively. The cosine similarity is given as follows:

$$Cosine(u,v) = \frac{\vec{R_u} \bullet \vec{R_v}}{|\vec{R_u}| \cdot |\vec{R_v}|} \tag{2.4}$$

Pearson' correlation coefficient

Pearson' correlation coefficient is one of the best and the most used metrics to measure the statistical association between two continuous variables. It is based on the covariance to find how strong a relationship is between variables. In CF, for two users u and v, the set of items I is the set ofitems that have been rated by both of users. $r_{u,i}$ and $r_{v,i}$ denote the ratings of user u and v on item i, respectively. $\bar{r}_u$ and $\bar{r}_v$ are the average of ratings provided by user u and user v, respectively. The following equation gives the formula of the Pearson correlation coefficient between user u and v:

$$PCC(u,v) \frac{\sum_{i \in I}(r_{u,i} - \bar{r}_u)(r_{v,i} - \bar{r}_v)}{\sum_{i \in I}(r_{u,i} - \bar{r}_u)^2 \sum_{i \in I}(r_{v,i} - \bar{r}_v)^2} \tag{2.5}$$

2.4 Summary

In this chapter, we have explained in details the notion of web service composition and the types of composition inspired by existing works. In the area of recommendation systems, our exploration of this domain gave birth to a frame of reference, which highlights: filtering techniques, dimensionality reduction and similarity measurements. In the next part, we will analyze and discuss the related works in this field.

Part II: Related work

" There is a powerful driving force inside every human being that, once unleashed, can make any vision, dream, or desire a reality. "

Anthony Robbins

3

Service Composition: From Web 2.0 to Web 4.0

Sommaire

3.1 Introduction

With the evolution of social web, service composition based on social relationships has become an active area of research, due to the benefits of employing the social knowledge that extracted from social networks to enhance different composition tasks such as service recommendation, selection and discovery. Additionally, the emergence of web of things, where, real-world objects can be expose their functionalities in service style, led up to new technical challenges that need to be addressed, especially in the issue of IoT service composition. We survey in this chapter the efforts on service composition. Before introducing the different approaches, we first give an overview about efforts to integrate social knowledge in classical service composition. While section 3.3 gives an overview about the different approaches of service composition in web-based IoT environment. Finally, section 3.4 describes service composition challenges in IoT environment[61].

3.2 Social Service Composition in Classical Web

This section presents an overview on the approaches based on social relations in traditional SC; numerous researchers have proposed mechanisms and methods to solve SC problems. Many of the suggested contributions are concerned of the employing of the social knowledge into composition process, where the definition of sociability varies from one search to another, in this section; we survey SC solutions that have exploited social knowledge into SC.

[78] proposed planning algorithm called Trusty for semantic SC using user's ratings to find the trustworthy services in social environment, they computed the social trust value base on similarity measures over users' rating about their experiences with the service by considering some behavioural characteristics of service. [12] proposed a framework for a trust based dynamic SC, the authors calculated the trust rating of service provider based on centrality measures of social network of service providers instead similarity between users as in [78]. The paper of [97] presented a framework called SoCo (social composer) for service discovery and selection in social network, which was defined as a graph representation of all the interactions that occur between people and services in a composition environment. The links in the social graph are used to calculate social proximity between users to build services recommendation system.[90] presented the trustworthiness of agents in social network. They considered the social network as a general kind of complex networks, the multi-relation social network (MRSN) which takes into account the semantic aspect of the relationship linking two nodes (two agents), they propose three trust measures : i)- Trust in sociability, ii)- Trust in expertise, iii)- Trust in recommendation. [113] exploited the sociability in a collaborative service network, which the nodes are service instances, two social connections are considered between services: positives links such as correlation and negatives links like competition. Similarly, [144] used the collaborative service network to provide trustworthy web service selection by considering not only the individual reputation but also the collaboration reputation of web services. [49] presented a social network to facilitate the negotiation (SNRNeg), and they exploited the trust relationships between nodes to extract recommended services in selection process.

The previous works are analyzed in Table 3.1 . We emphasize on the social network definition, and we take on consideration the various relationships that have been exploited in SC process, in additionally the social network analysis (SNA) have been used and which measures have been used. We describe the social environment by three elements, which are the nature of the social environment, the social entities and the links among these entities. In addition, we define the process of social composition by dividing into three stages as shown in Figure 3.1.

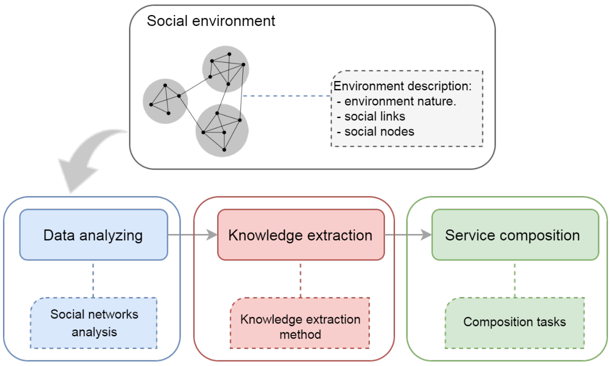

Figure 3.1: Social service composition phases.

Sociologists define the concept of social network in 1960s as a network of people [149] . In computing, the social network is a set of entities denote users that communicate each other and share their interests and activities easily, in web-based social networks the nodes could represent people, groups, organizations, computers, or any knowledge entity. A social network in composition environment is a graph representation of all interactions that occur between people and services [96], so we distinct two types of sociality are utilized in traditional web service composition: user sociality and service sociality.

- *User Sociality:* refers to different links between people are common interests or activities, where each one has his own profile such as in traditional social networks (Facebook, Twitter...etc.), in the context of SC, user may be a web service provider or web service consumer. The possible relationships of type (user- user), that can be exploit are friendship, communities, family, knowledge exchange, cooperation . . . etc.

- *Service Sociality:* refers to different types of social connections between services, the conversion from isolated service to social service presented in [23], where using social service network to improve composition task. Replacement, collaboration, fellowship and competition are some interactions that can connect web services together. In literature, the most researches use the links between services to calculate individual or collaborative reputation or trust for service recommendation such in references [113], [144].

approches		Social Environment Description			Social Composition Phases		
		Social Environment nature	Social Nodes	Social Links	Analysing phase	Extraction phase	Composition stage
User sociality	[78]	App store	consumers	Correlation	Similarity between users	Trust of services	Automatic planning
	[12]	Social network of providers	providers	Closeness betweeness	Centrality degree of providers	Trust of services	Planning
	[97]	Users social network	users	Friendship Community of interests	Social proximity between users	Trust of users'	recommendation and selection
	[90]	Users social network (Multi-Agent-based SN)	users	Friendships Partner Relationship	Sociability Expertise Recommendation	Trust of services	Selection
	[49]	Classical social networks	users	Neighborhood	Similarity Expertise	Trust of services	Automatic negotiation
Service sociality	[113]	Web services collaborative network	services	Interaction Collaboration	Services' past usage	To predict composition pattern	Recommendation
	[144]	services collaborative network	services	Invoking Invoked	Reputation Neighborhood	Trust of services	Selection
	[95]	Social network of services	services	Partnership Robustness Collaboration	Recommendation Collaboration	To weight web services	Discovery
	[94]	Social network of services	services	Collaboration Competition Substitution	Similarity among web services	To weight web services for selection	Discovery

Table 3.1: Analysis of social-aware approaches in classical service composition.

The social network analysis allows analysing information from data sources by using different measures like (centrality, similarity ...etc.) as used in [78], [12]. The extracted knowledge from SN are divided into two types: micro level and macro level. Micro level knowledge means the individual information of social entity such as user interest, experience and personal characteristics...etc. The macro level knowledge refers to the social behaviours and the public information in the SN such as the global reputation, trust values, ratings on services or users, tags, topics and all the different relationships among social nodes. Most of the previous studies focus on service recommendation and using the social network analysis measures to extract social knowledge such as trust value of services or service consumers. The above approaches imposing the social aspect to improve SC, Figure 3.2 illustrates the classification of social composition approaches in classical web, by defining the social environment that represents data source for composition platforms. On the other hand, we have explained the most important advantages and benefits of the use of social knowledge in each class.

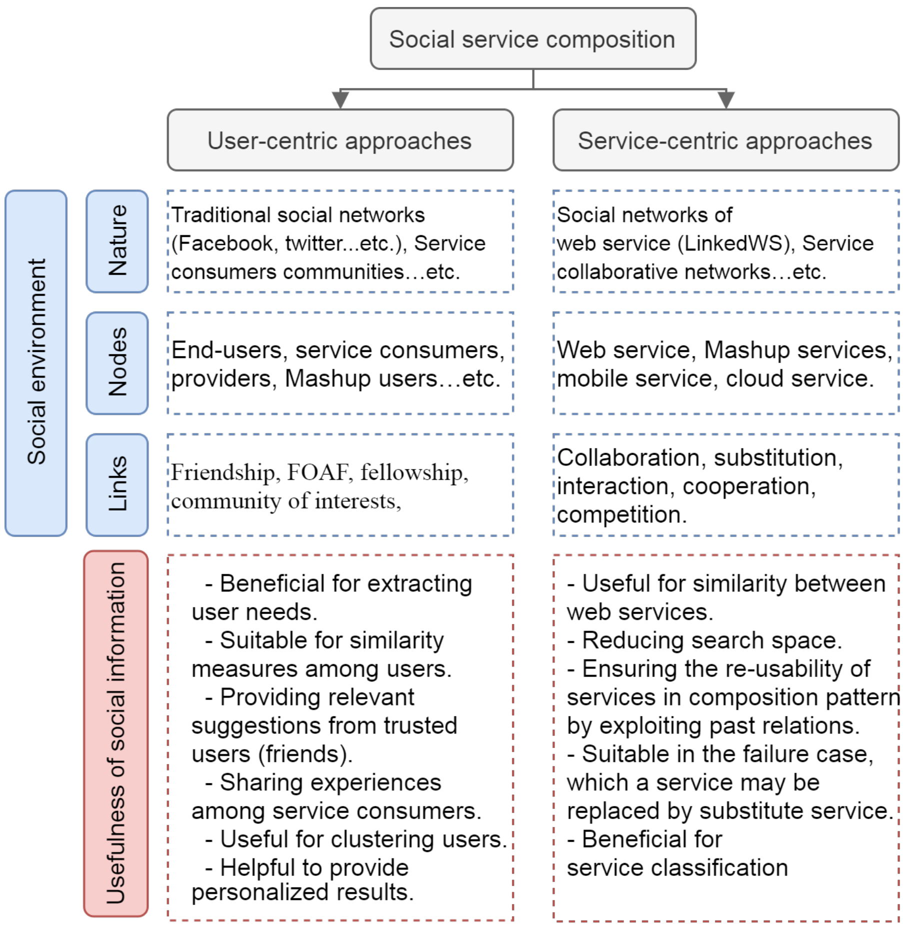

Figure 3.2: Classification of Social Service composition approaches in classical web

3.3 Service Composition in Web-based IoT Environment

In this section, we review some of the key concepts in the areas of IoT and SC. Specifically, we define IoT environment in the context of SC in Sub-section 3.3.1.Then, in order to give the basis criteria to discuss existing approaches, we define the process of SC in IoT environment as presented in Sub-section 3.3.2. Finally, in Sub-section 3.3.3, we summarize and analyze the different proposed works on SC in IoT in literature.

3.3.1 Web-based IoT Environment

In this sub-section, we present a model for IoT architecture in the context of service composition; the proposed model based on three primary abstractions: user, service, and thing, which represent the key elements in SoC-based IoT applications. So far,we define IoT environment as multi-layer architecture, which are physical, application and end-user layer as shown in Figure 3.3.

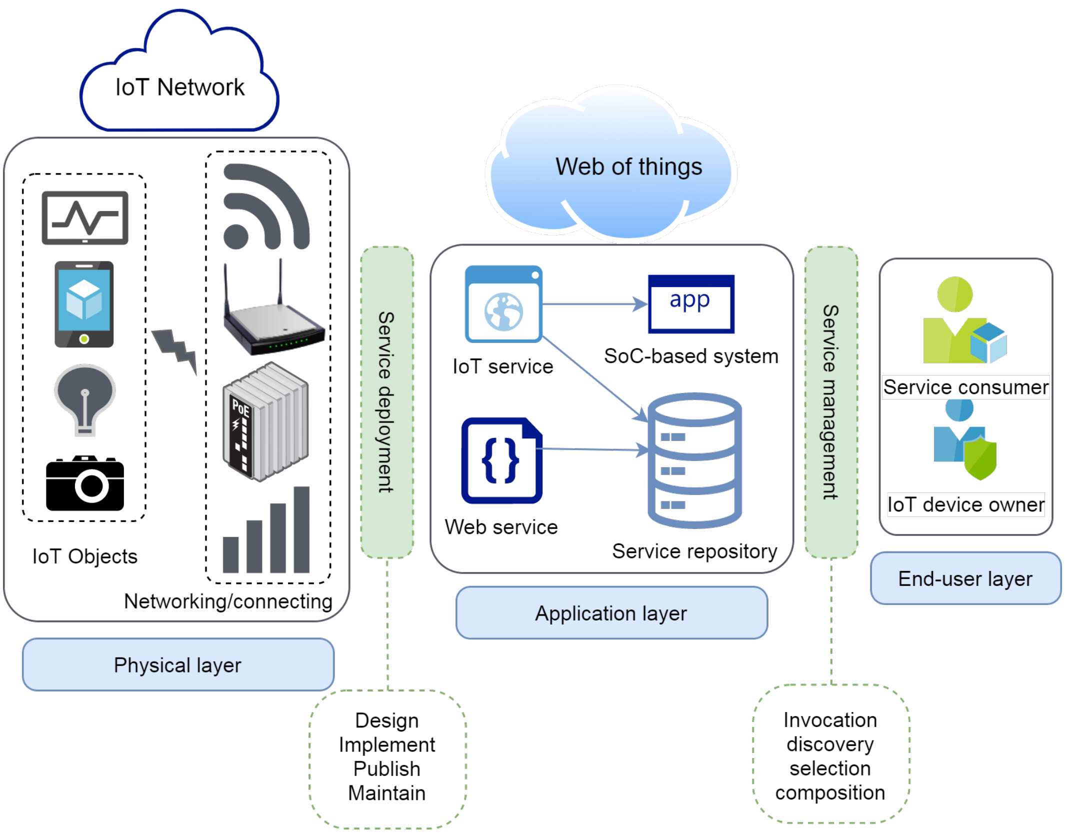

Figure 3.3: Web-based IoT environment layers in the context of Service composition

3.3.2 IoT Service Composition Phases

Typically, service composition process is a multi-stage task. Various strategies and mechanisms are proposed in literature to tackle this problem. In this sub-section, we propose a general process to enable classifying and summarizing the available methods as shown in Figure 3.4. Most precisely, the main phases of service composition in IoT are the following:

- Gathering information: this phase refers to the tasks of analyzing user request, and collecting necessary data, that enable to filter candidate services and selecting which are the optimal for execution. Furthermore, choosing optimal plans for composition or optimal sets of services is closely related to this phase. Consequently, the stage of gathering information directly affects the performance of composition process.
- Filtering services: this process aims to choose the most appropriate services that meet user needs. Moreover, it is closely associated with the previous phase. Service filtering is multistage process, which consists of many tasks, such as planning, selection, optimization, recommendation ...etc. This phase greatly affects the accuracy of composition result, because the filtered services will be within the composed services
- Execution: this last phase aims to come up with the composite service that achieve user's request through the services are provided from the previous phase. This is a very critical stage because service composition in IoT will be in a very changeable and dynamic environment. Therefore, this should be taken into consideration during execution.

3.3.3 Overview of Major Researches

IoT service composition has become a critical topic in web of things; various notable contributions have been proposed to solve this problem. In this sub-section, we sketch the outline of this stream, and we surveyed and classified related research efforts. Here seven categories of composition mechanisms have been identified based on the techniques that were used: context aware composition, QoS aware composition, Energy aware composition, Petri Nets based composition, BPEL based composition, Social networks-aware approaches and Bio-inspired technique based.

- **Context aware service composition :** In [92], the authors divided the context ontology into upper ontology and domain specific ontology; upper ontology is a high-level ontology which captures general knowledge and is divided into four categories (user context, computation context, physics context, time context), and low-level ontology which defines details of concepts. As the previous work [170] taken context information in consideration to guide real-world service composition, the authors proposed an ontology model for context; the ontology is divided into two levels: top level captures all common knowledge for the IoT (computing, environment, user) and low level defines concepts and properties for each subdomain. They divided the composition process into two sub processes; firstly, they used device context to filter the appropriate services. Then, they selected the best service that satisfies user's needs according to user's expectation to the quality of service. A similar

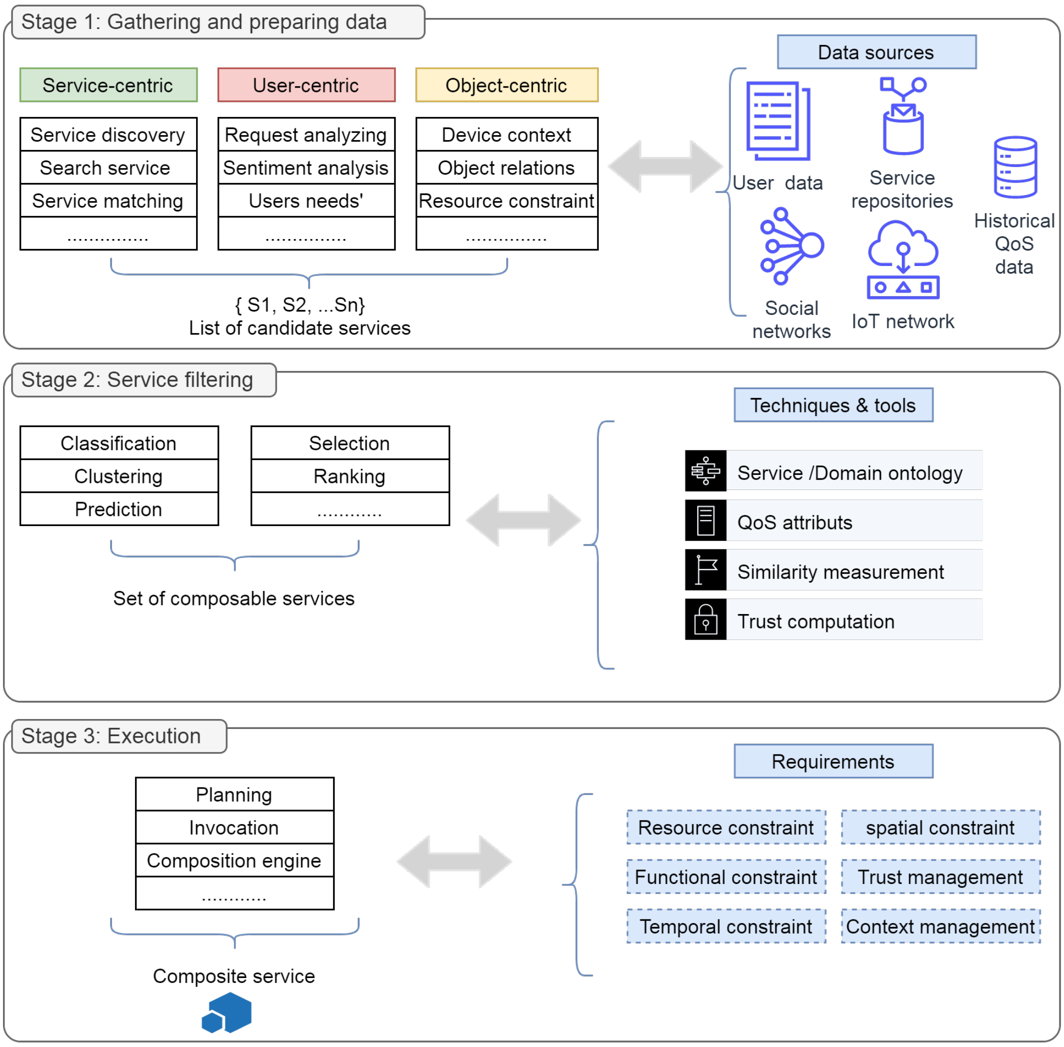

Figure 3.4: Service composition process in IoT environment

approach [141] presented a composition framework for smart cities based on context. In addition, [148] addressed discovery of IoT service problem as a contextual bandit problem.

- **QoS aware service composition:** Various research contributions addressed the issue of QoS reasoning in IoT services composition. [107] proposed QoS computational method to find selection algorithm for IoT composite service and make comparison with genetic algorithm, [137] provided model for QoS parameters, which divided the attributes into dynamic (response time, energy level, availability, and Reliability) and static(price, security level). In addition, the authors tackled the problem of optimal service selection using distributed optimization approach in the three patterns of composition (sequential, loop, parallel). [11] taken into account not only QoS factors but also QoUE, when the key contribution was designing a middleware based on QoS requirements (reliability and availability) and QoUE constraints (execution time, response time, latency time, throughput, capacity). Moreover, the composition of the service is modelled as a DAG (Directed Acyclic Graph).

- **Service composition based on BPEL:** [174] gave the extensions of BPEL language to composition of IoT RESTFUL service, with similar purpose [104] used BPEL extensions in his service composition framework. Moreover, designed an activity description model by using ontology to construct a semantic extension of a business activity in BPEL and a logical composition model to express the composition of the services that match the business functionalities in an activity.

- **Bio-inspired based approach's:**several work takes advantage of the coordination mechanisms of biological societies and use the bio-inspired technique. [120] proposed a bio-inspired decentralized service discovery and selection model, which it is inspired from the Response Threshold Model (RTM). [11] used Particle Swarm Optimization (PSO) for ideal service selection. Also [169] formulated the problem of composition as a multi-objective optimization problem, which it can be solved through particle swarm optimization or genetic algorithms.

- **Social Network aware Service composition:** [44] provided a web platform called SAC (Social Access Controller), which use the existing social network (Twitter, Facebook. . . etc.). To enable owners of smart things to connect and share them on the web with his trusted connections; the advantage of using RESTful interface makes SAC an integral part of web and its API can be used to create a physical Mashups to compose physical and virtual services. [21] proposed trust management to support service composition in IoT system based on SOA architecture, the nodes of the social network are devices and its owners, the considered relationships among users are: friendship(the intimacy), social contact (physical proximity), community of interest (knowledge on the subject matter). In similar social interests of users, used distributed collaborating filtering technique to select trust feedback for recommendation. [43] proposed an approach based on social network concept to IoT service composition and device management, which addressed relationships between things and services.

- **Petri Nets based approach's:** [163] proposed an algorithm to find the optimal composition path using Petri Nets in order to fulfil user requests. Which uses a comprehensive performance function "rtc" (the sum of three items; reliability, response time and cost) to evaluate the cost-effectiveness.

- **Energy aware service composition:** [10] developed an algorithm that searching for and selecting the minimum number of IoT service in an energy-aware service composition, to satisfy user's requirements. [169] proposed a mechanism for WSN (wireless sensor network) services composition, which consider three factors (spatial and temporal constraints, and energy-efficiency).

This sub-section discusses the above-mentioned researches in the last sub-section; we will evaluate these approaches by the previous criteria that mentioned in Sub-sections 3.3.1 and 3.3.2. As illustrate in Table 3.2. The first column is clarifying research orientation by answering the three following questions:

- **Q1:** What is the problem have been addressed? (Purpose)
- **Q2:** What is the mechanism used? (Technique)
- **Q3:** What outcomes have been found? (Contribution)

The second criteria of evaluation is the existence of the validation phase in these works, in the third column, we evaluate the proposed solutions by the main layers of IoT are considered in composition process. The last factor of evaluation is defined the composition stage that the researchers have been treated.

After analysing current efforts that tackle service composition in IoT environment,we noticed that most of studies focus on service selection. Because the number of devices is increasing and the number of services is also increasing, so there is an urgent need for effective selection methods. Social knowledge has proved his effectiveness in the traditional web in reducing search space; so, considerable attention should be taken to including this kind of information into SC in web of things, especially with the emergence of SIoT. We also noticed that there are a few contributions handled execution phase, which is one of the most important stages of SC, as any failure may occur will cost a lot, so this phase must be taken into account while respecting the environmental features of IoT such as dynamicity, heterogeneity...etc.

works	Research Orientation			Considered Layers in Composition			Composition phases addressed			validation
	Composition problem	Techniques used	Research outcomes	End user	Application	Physical	Gathering	Filtering	Execution	
[44]	Service deployment	Social Networks	platform	✓	✓	x	✓	N/A	N/A	No
[92]	Describing composition scenario	Context ontology	Context ontology	✓	✓	✓	✓	N/A	N/A	No
[170]	Service selection	Context information	Context Model, algorithm	✓	✓	x	✓	✓	N/A	No
[82]	Composition Evaluation	Combining PSO And GA	Algorithm	x	✓	x	N/A	N/A	✓	Yes
[107]	Service Selection	QoS computation	Algorithm	x	✓	✓	N/A	✓	✓	Yes
[174]	Combine asynchronous IoT services	BPEL extension	Architecture of IoT service	x	✓	x	N/A	N/A	✓	Yes
[163]	Finding optimal path	Petri Net	Composition Model	x	x	✓	N/A	N/A	✓	Yes
[21]	Trust management	Bayesian	Trust protocol design	✓	✓	x	✓	N/A	N/A	Yes
[75]	Service selection and planning	Multi Agents Heuristic planning	platform	x	✓	✓	✓	✓	N/A	Yes
[43]	Services description and selection	Social Networks theory	Algorithms	✓	✓	✓	✓	✓	N/A	Yes
[104]	Service Matching	BPEL extension	Framework	x	✓	✓	N/A	N/A	✓	No
[141]	composition adaptation	Data flow Context flow	Framework	✓	✓	x	N/A	✓	N/A	Yes
[137]	Service Selection	DCoP	Algorithm	x	✓	✓	N/A	✓	N/A	Yes
[11]	Service Selection	Fuzzy inference PSO	Algorithm	✓	✓	x	N/A	✓	N/A	Yes
[120]	Service discovery and selection	Response Threshold Model Agents	Algorithm	x	✓	✓	✓	✓	N/A	Yes
[148]	Service discovery	Contextual bandit	Prototype system	✓	✓	x	✓	N/A	N/A	Yes
[72]	Service selection	Pareto dominance	Algorithm	✓	✓	✓	✓	✓	N/A	Yes
[161]	Service discovery and selection	Dynamic QoS estimation	Framework	✓	✓	✓	N/A	✓	N/A	Yes
[140]	Service selection	Ontology Service and resource Models	platform	✓	✓	✓	✓	✓	N/A	No
[169]	Service classification	GA PSO	Framework	✓	✓	✓	✓	✓	N/A	Yes
[10]	Planning	Energy efficiency	Algorithm	✓	✓	✓	✓	N/A	N/A	Yes

Table 3.2: IoT service composition approaches analysis.

3.4 Service Composition Challenges in IoT

In SOC-based IoT environment, each device provides one or more services that offer their capabilities on web, the composition of this type of services involve new challenges. Moreover, the above surveys assert that it is hard to apply directly existing service composition technologies into web of things. This section draws the barest outline of service composition requirements in IoT. We distinguish the challenges according IoT layers that mentioned in the Sub-section 3.3.1 .

3.4.1 Enironment Requirement

IoT as environment has many characteristics, which make challenges cropped up. This subsection highlights the core features of IoT.

- Heterogeneity: one of the most attributes of IoT is the heterogeneity of devices (tagging, sensing, and thinking things...etc.) that have different performances and capabilities. Moreover, various producers that do not necessarily follow the same standards could produce objects. For service composition in IoT, some approaches took on consideration these features such as energy consumption, energy conservation, data storage, processing capacity...etc.
- Scalability: the huge and growing number of connected devices considers the scalability in composition task as one of the critical issue, that leads to the necessity of composition platforms must be capable of supporting those requirements, such as managing and monitoring the large silos of devices and the increasing numbers of their services without QoS fluctuation.
- Dynamicity: due the high distribution of devices, IoT is a highly flexible changeable and dynamic environment. The context-aware approaches meet this challenge and make service composition more efficiency.
- Safety: assuring privacy and security in IoT is paramount issue; Trust management research efforts try to meet these two requirements by proposing approaches to enhance level of trustworthiness of service composition by including the trust computing of IoT devices.

3.4.2 Service Requirement

The challenges that IoT presents in this layer in service composition context are related to two kinds of services, which are atomic services offered by real-world devices and composite services in IoT environment.

- Atomic services: the atomic services obtained from discovery process are further used; in order to get the best result required new considerations and QoS measures rather than traditional services, such as availability and accessibility, which must ensure timely access to IoT services. Because it is a bridge to interact with the physical world. In addition, the interoperability of IoT services that provided by heterogeneous devices, and implementing by different standards is core factors in composition.

- Composite services: the reliability of the composite service is one of the critical factors in the service composition, [107] proposes computational model based on QoS for IoT composite service, author requirements and challenges face IoT service composition as reusability, correctness, trustworthiness, sociability. . . etc.

3.4.3 User Requirement

The crux of service composition in IoT is to satisfy users' requirements; the user requirements is set of user preferences, may be temporal (response time), spatial (location), financial (price). . . etc. Besides, the imposing of human social networks in IoT applications and multidimensional social networks are very useful to improve service composition and to provide personalized results that meet users' needs. Moreover, the adaptability of IoT service to users' context must be take on consideration during the implementation of service composition platforms.

3.5 Summary

This chapter offers some important insights into social service composition in web of things. An objective of this chapter was to trace the contribution of the social computing to improve traditional service composition; the purpose of this investigation is to know the possibility of applying the traditional solutions on IoT environment. Furthermore, this chapter presented a comprehensive survey on service composition in IoT by overviewing and analyzing more than 20 representative research efforts in this field, in which we abstracted a model for service composition and IoT environment. In addition, we highlighted on the social aspect of IoT that far too little attention has been paid in this field. Finally, we identify the greatest challenges and the major considerations that must be addressed in composition as the IoT environment requirements, IoT service requirements and user requirements. From this exploratory study, we can make the following observations and recommendations in the field of web service composition under IoT environment:

- The proposed solutions must be ensure the three levels of requirements of IoT environment.
- Intensive research are needed to support data collection and processing in gathering information and execution phases.
- An enhancement of social-aware methods is recommended due to the importance of using social networks concept in the issue of trustworthiness and credibility, in order to make trustworthy results.
- The application of the social relationships among things may be considered into service composition, in order to leverage the cooperation and substitution between objects and services offered by them.

- The need of effective services selection and planning methods that capable of facing IoT services challenges.
- The employing of social knowledge allows to understanding user preferences and interests and making composition results more suitable and personalized.
- The proliferation of web services and devices envisioned by IoT is one of the most challenging topic that a service composition solution must address, the composition oriented recommendation enable to reduce the space of research to face the scalability challenge. The most challenging problems in SC in IoT are the increasing number of services and the high dynamicity of this environment, our research into solving those problems is already underway, which we aim to develop a framework for SC in IoT environment based on social relations among things, which enhances cooperation among devices and services. As well, our future work will concentrate on composition-oriented recommendation that help overcome a part of these problems.

"Success seems to be connected with action. Successful people keep moving. They make mistakes, but they don't quit."

Conrad Hilton

4

Web service Recommendation Models

Sommaire

4.1 Introduction

Web service recommender system is used to suggest web services and has the effect of guiding users to useful and relevant services, which meets their needs in large space of available web services. Service recommender systems as information processing systems gather data from different sources to make recommendation. Many previous works are limited with techniques and strategies of recommending services, regardless the problem of overload information and locating relevant inputs for accurate and effective recommendation. In order to bridge this gap, we aim to highlight information source types that are used to enhance recommendation performance, which are not extensively covered by most of previous works. In this chapter, we will classify the proposed approaches in literature according information-awareness, and we will present the main sources of information, that have been described in the recent works in this field.

4.2 Classification of Web Service Recommender Systems

The crux of WSRec systems is to match the user preferences with the features of services or user with similar users that have same taste to recommend relevant services. To achieve this goal many approaches and researches have been proposed. In this section, we represent our original classification of WSRec approaches. This classification based on the kind of information that are taken on consideration in recommendation process. Furthermore, in this section, we explore the ways in which are employed to enhance recommendation.

4.2.1 QoS aware approaches

QoS aware approaches exploited Quality of Service information in recommendation, in order to predict QoS value. In this subsection, we present QoS aware approachesand we provide an analysis of the previous studies. The authors in [57] proposed tow algorithms for bidirectional recommendation using hybrid collaborative filtering technique. They provided a three-dimensional model for QoS parameters. The recommender system exploited the different relationships among (service, consumer, and provider) to recommend not only web service for consumers, but also to recommend consumers for providers (people recommendation). The process of web service recommendation is divided into three steps: i) Similarity computation, ii) K-nearst neighbors selection, iii) prediction of missing QoS vectors. Paper [25] presented a recommender system which exploit the users' physical location to employ this correlation in the QoS prediction. The clustering of users by region enables to predict the relevant service to active user from his neighbors' experience whose belong to the same region. As the previous works, the authors in [168] proposed a QoS prediction approach. They provided a hybrid method based on user-item collaborative filtering and they conducted Large-scale real-world experiments. Reference [184] tackled the problem of QoS prediction by using a hybrid collaborative filtering algorithm includes a user contribution for QoS information collection. Moreover, the authors conducted a real large-scale experimental analysis for verifying the proposed algorithm. Likewise, the authors in [135] focused on the QoS prediction; the prediction method is based on active user region's using the similarity measures between the active user and the region center.

4.2.2 Context aware approaches

The contextual information is kind of information are used to prediction strategies for service recommendation, in reference [152], the authors proposed a personalized service recommendation based on user's context in mobile environment; they modeled the context information with symbolic model and used by the probability mode to predict user's next state. In paper [159] the contextual information is employed to predict QoS values; the web service recommendation mechanism is based on both user and service context, which the user context is the geographical information, and the affiliation information is used as service context. Numerous researchers have proposed approaches related to location aware WSRec. There are several approaches take on consideration the user's locations, other works have considered services' locations or both services and users. In papers [25] and [135], the authors used the user's location in QoS values predicting. Clustering users in regions enables to improve the recommendation accuracy and to employ the correlation between users' locations. In addition, user location information are used in [77] in order to satisfy user needs in mobile environment (M-commerce). Furthermore, employing location information from user-service pairs to improve prediction performance is addressed in reference [93]; which the authors' defined models to represent location information and stored them in a hash table. As in work [93], the prediction of QoS values in [84] is based on both locations of users and web services taking into account the personalized deviation of them.

4.2.3 Social aware approaches

The imposition of the social information in WSRec making it more accurate and effective, numerous studies have been exploited the social relationships among users and services. For instance, paper [171] proposed a hybrid method based on collaborative filtering for manufacturing service recommendation employing both calculation global reputation and similarity between consumer enterprises in the social network. The recommended service is the service with higher ratings value through selection, optimization and evaluation phases. The social relations among services are mined in [158] to construct recommender system for Mashup services discovery. Reference [30] proposed a method for web service recommendation to predict ratings by considering of both trust, and similarity between users in the social network. The authors in [158] exploited the social relations between users, and the interactions among services to create a Mashup.

4.2.4 Trust based approaches

Many research studies has been conducted on this topic, which trust definition differ from study to other. In paper [30], the authors calculated the trust of users by combining the similarity between neighbors and the degree of trust among users in social network. With similar purpose, reference [132] exploited the neighborhood relation to calculate the similarity between users. Moreover, they combined the user similarity with the user reputation to assess trust value. Paper

[63] computed the trust level between friends according the similarity level and interaction level taking on consideration the time factor. The recommendation in papers [48] and [87] based on the trust of service; which computed in [48] by the trust degree of service provider taking into account the current time, likewise [87] assessed the trust value of service for recommendation; which they proposed distributed model based on trusted third party model. Reference [112] proposed reputation model based on Bayesian Network; which derived the trust value by taking three kinds of trust in consideration: direct trust i.e. direct experience opinion, recommendation trust i.e. the recommendation from other consumer, and conformance trust i.e. the QoS monitoring information.

4.2.5 Time aware approaches

In literature, the temporal information are exploited in different ways to enhance WSRec. In this sub-section, we sketch the outline of the time aware WSRec. The approach [176] presented triadic relations among users, services and temporal information to QoS value prediction taking on consideration the service invocation time. The authors in [183] proposed a time aware WSRec for Mashup creation; which the temporal information is the sequence of timestamps of service invocation time by Mashup, in order to achieve services ranking. In paper [76], for measuring the similarity between users, the time was used as contextual information, where it was presented in QoS properties as time response, and in the user context as the time when the consumer requests a service. Reference [147] employed the temporal information from both users and services to improve QoS prediction for the current time slot. In the aim of services raking, paper [59] proposed a temporal, tag and social (TTS) based algorithm for WSRec, where it added the temporal modeling into tag and social recommendation to calculate the users' preference value by time decay function. In addition, reference [54] integrated the time information into the similarity measures among users and services to predict QoS value, compared between tow time factors according to the timespan between the invocation time and the current moment, in order to determine the QoS prediction method (user-based or service-based)

4.2.6 User aware approaches

Several researchers focused on the user side, and they employed the user information to enhance WSRec (e.g., users' preferences, interests and their experience). Reference [86] provided an approach of clustering users in 'preference lattice' based on multi criteria preference, which the ranking of service is based on the past feedback of neighbors (users in the same cluster). In paper [16], the authors proposed an approach to extracting user's interest form Mashup service recommendation. The user interests are inferred from his usage history. In order to enhance user experiment in recommender system, the authors in paper [51] proposed a method to guide users to understand their interests and preference by presenting user profile. In this work [13], the authors presented an approach to modeling user preferences using type2 fuzzy set. Paper [173] is seminal work to reference [13]; where it focused on user modeling. The proposed approach is based on Bayesian model to construct a profile for new user or for user with few feedbacks. In paper [105], a personalized recommendation method is proposed; where the user preference is captured by keyword extraction. Applying the past usage information in turn the rating data is more effective to enhance the recommendation performance, thence several works proposed usage-based recommendation. In references [64], [53] and [65], the users' usage history employed to infer user's interest and preferences. In order to make a personalized recommendation, a usage history based approach is proposed in paper [47]; which the users of the system shared their experiences. The authors in [18] used the usage information to analyze users' query for the sake of helping user to discover web services.

- Discussion

In a large space of web services, a recommender system is an effective tool to help users to find relevant services that meet their preferences and interests. With The emergence of social web (web 2.0), semantic web (web 3.0) and smart web (web 4.0), recommender systems aggregate data from diverse sources, and impose various information to recommendation and filtering process. This section discusses the above-mentioned works, we will organize the information are used for web services recommendation into three categories: contextual information, personal information, and social information, in addition, we present the different knowledge resources that are used in research literature as shown in Tabel 4.1.

From the previous approaches and the research papers, we can make the following observations and requirements in the field of WSRec:

- Most of previous works are based on collaborative filtering technique, which recommending to users a service with similar taste liked in the past. The similarity among users and/or web services are widely applied in WSRec, especially in the social web, where the users and/or services are linked by social relationships. The social information is very useful for similarity calculations.

- The information offered by the social networks can help collaborative filtering techniques to find accurate WSRec and to face scalability problem. However, it is very critical in the issue of credibility, which it is very important to ensure the reliability and the trustworthiness of recommended services by employing trust and reputation measures.

- Prediction of user preferences and using his consuming or navigation history help WSRec to suggest relevant services by computing the utility of services for the given users.

- Using personal information of users in QoS-based approaches is helpful to provide a personalized recommendation, especially, in the case when the system apply the knowledge-based technique.

- Few approaches take in to account the temporal information into WSRec. Although, the time context information help recommender systems to provide an effective recommendation in high dynamic environment.

– Imposing the location attribute in recommendation process allows cost reduction and it is so beneficial to reduce research domain.

Finally, it is obvious that the majority of approaches that applied the collaborative filtering suffer from the cold start and data sparsity problems, which need to consider various inputs and to use hybrid methods. Due to the requirements of web services, combining QoS information with available information is so beneficial. In addition, the consideration of time dimension and trust levels makes recommended services reliable and trustworthy.

	Representative works	Data source	Merits	Demerits
Contextual	Temporal - timestamps of services invocation [183] - response time [76] - request time [76] - tagging time [59] - timespan between invocation and current moment [54] Geographical - User's location [25][135][77][152] - Service's location [93] - Both of them [84][159]	-log analysis -Queries analysis -Historical QoS analysis	-Geographical information is helpful for clustering and neighborhood techniques. -Taking into account temporal features ensure the reliability of recommended services and face data dynamicity problem.	-Need constant updating. -Lack of availability of data due to the privacy issues.
Social	-Reputation among service consumers [171][112]. -Social relations among services [158] -Trust among users [30][132] -Interaction among services [158] -Trust between friends [63] -Trust degree of services providers [48] -Service feedbacks [87]	-Social networks of customers. -Social networks among providers -Web services collaborative networks. -Tag analysis	-Suitable for collaborative filtering -Useful for classification phase and similarity measures.	-Useless in the case of cold start (new service or new user)
Personal	-Users' interests and preferences [16][51][13][173][105][64][53][65] -Users' usage information[18] -Users' experiences[47]	-User profile -User reviews and feedbacks -Historic invocation -Navigation history	-Ensure the personalization of recommendation results. -Suitable for knowledge-based and content-based techniques. -Beneficial for similarity computations	-Difficulty of extract users' needs. -Need a representation and modeling of users profiles

Table 4.1: Data sources of web service recommendation

4.3 Service Recommendation for Composition Models

Despite the numerous WSRec approaches that have been proposed in literature, there is little models are built for service composition task. In this section, we summarize the different proposed recommendation engines for service composition and mashup creation. Then, we provide a comparative evaluation of the proposed solutions (as shown in Table 4.2) according the following criteria:

- *Composition environment:* It is refers to the environment in where are done the different processes for services such as discovery, invocation, selection and composition...etc.
- *Involved information:* This criterion refers to information types that used as input for recommender engine. We classify the information into three main categories: contextual which describes temporal, geographical and personal data that can be aggregated from users and/or web services. Historical information that expresses the usage history of users, their past feedbacks on services, or QoS records of services...etc. Finally, social information, which refers to the social knowledge that used in recommendation as social relations among users, or/and services and mashups. . . etc.
- *Oriented user:* It refers to the target user of the applications.
- *Personalization:* It expresses the personalization level of recommendation results, and to which extent to match users' interests.
- *Interactivity:* We talk about a high level of interactivity between users and recommendation framework if recommendation engine offers new suggestions to the user each time he chooses a service, so that recommended services are made each time based on the active service as in [96]. While, when the user is slightly involved in composition task, here the level of interactivity is low.
- *Credibility:* This criterion describes the trustworthiness and reputation considerations in recommended results, such trust degree of services.

We symbolize the possible cases by (-), (+) and (++), which means low, medium and high level, respectively.

Although, almost all of the proposed solutions are user-centered platforms, they are with low interactivity level with end-users, which need to more user involvement in composition tasks. Because building a recommendation engine that allows to end-user to interact with application is a promising way that enables to facilitate the complexity of composition process and increase his cognition to face the problem of web services proliferation. Recommending appropriate services for a selected service, which are suitable for the users and meets their needs among the huge number of functionally equivalent services is a critical issue in composition-oriented recommendation. Additionally, the E-health applications deal with information about users and their activities, which means that it should be personalized with consideration to users' context. Therefore, involving contextual information can help to achieve the aim of providing personalized results. A neglected area in this field is services' credibility; Recommending untrustworthy services for composition may be disastrous and costly, especially in IoT-based environment, thus, there is an urgent need to making trustworthy and reputed recommendation.

The employing of usage history and past historical data into recommendation process is widely used, especially in prediction phase and similarity computations. Nevertheless, recommender systems still need to involve more kinds of information such as context and social knowledge to improve prediction accuracy and face data sparsity and cold start problems. In this context, social-aware recommendation models proved their efficiency to improve the quality of recommendation [63], [158]. Simultaneously, with the prevalence of IoT and SIoT, Recommender system for IoT-based applications has attracted the attention of several researchers [165], [110]. However, few works that are carried out on service recommendation in SIoT. The authors in [160] highlighted on the exploitation of social aspect of IoT for service recommendation, similarly, in [24], the authors investigated on service recommendation in SIoT by proposing a dynamic access service recommendation scheme. In the view of the previous limitations and deficiencies in WSRec models for composition, we propose a social collaborative recommendation model that ensures the interactivity between end-users and composition system and provides personalized and trustworthy services. Additionally, we benefit the richness of SIoT and his related technologies to enhance service recommendation quality.

		Evaluation metrics							
		Oriented		Involved Information					
Composition Environment	Model	Developer	End-user	Contextual	Historical	Social	Personalization	Interactivity	Credibility
Web of things	[7]	✓			✓		-	+	-
	[83]		✓	✓	✓		++	+	-
	[154]		✓	✓	✓		-	-	-
Social web	[96]		✓	✓	✓	✓	++	++	-
	[158]		✓		✓	✓	++	+	-
Traditional web	[3]	✓		✓	✓		-	+	-
	[36]		✓	✓	✓		++	-	-
	[134]		✓	✓	✓		++	+	++
	[8]		✓	✓			++	-	-
	[68]	✓	✓	✓	✓		++	++	-
	[38]		✓	✓	✓		++	+	-
	[129]	✓		✓	✓		-	-	-
	[155]	✓		✓			-	-	-
	[180]		✓	✓	✓		-	-	-
	[181]	✓		✓	✓		-	-	-

Table 4.2: Comparative evaluation of service recommendation models for composition.

4.4 Filtering Techniques for WSRec Models

The purpose of developing recommendation engines is to address the information overload issue. Numerous methods have been applied for filtering data and refining data sets for WSRec. In this section, we summarize the different methods and algorithms have been proposed in literature, we classify those approaches into two categories: User-centric and Service-centric approaches.

4.4.1 User-centric approaches

In user-centric approaches, the focus is mainly on user side, which selecting highly relevant users enables to achieve higher prediction accuracy. This idea is supported by study in [88], which the proposed model LoNMF is based on QoS prediction strategy for recommending personalized web services, the main purpose of this work is providing a novel neighborhood selection mechanism for target user that based on historical and geographical information. Similarly, LoRec [25] and NIMF [177] models employed location and historical QoS information for neighbors' selection and clustering. The key benefit of those works is taking past usage experiences of other users whom are nearly located with the target user, which allows to tackle cold start problem. However, they still suffer from trustworthiness and data sparsity problems, where the selected neighbors might be untrustworthy advisors with fake feedbacks or with few rated services. Hence, In view of these shortcomings, trust-based methods are proposed [132], [30], [179]. Meanwhile, the emergence of social web and social network paradigm, social information and relationships of users are widely exploited to enhance neighbors' selection and users filtering. In the same context, social-aware approaches are proposed [63], [143], [80]. Although, social-aware recommendation approaches improve traditional users filtering and selection methods, they still have some drawbacks; when the target user have a too few trusted users or a little number of friends which leads to the shortage in neighbors set. In addition, where the active user have invoked or have rated a few number of web services as in [177], [146]. That is what leads to include dissimilar users into neighbors set by combining past usage similarity with location distance as in [88], [21], or with trust value as in [30], [58].

4.4.2 Service-centric approaches

In the context of service-oriented computing, recommendation engine aims to find relevant and reliable services to an active user. Typically, in order to service selection or discovery, recommended services have similar functionalities, which leads up to the need of considering non-functional features of services into filtering stage. On the contrary, in WSRec for composition, the recommended services are functionally different services. For example, in a WSRec for service discovery or selection, services with the highest score are recommended based on user feedback (ratings) or previous usage information (QoS values). This method is useless for WSRec for composition, where the services that are recommended for composition must be correlated and cooperative with the active service on the one hand, and have the highest values in their non-functional attributes among the set of services. In light of this conclusion, we classify service-filtering approaches into two category: functional and non-functional filtering.

4.4.2.1 Non-functional filtering

In non-functional filtering based WSRec, QoS records of services is widely used in prediction phase [159], [132], [7], [177], [88], [159], [25], [168]. Recently, with the convergence of social networks and SoC-based systems, the rating of consumers on services is beneficial to empowering the personalized recommendation and to be used as non-functional characteristics of services [30], [63], [167], especially, in similarity computation and prediction tasks. Despite, QoS-aware approaches has received abundant attention in classical WSRec, it is hard for recommendation oriented composition in IoT to employ QoS data due to several challenges. Firstly, the most QoS values are usually subjective depending on client-side such as response time, reliability and availability...etc., which make it unstable according the dynamicity of IoT environment and depending on the context of users and their connection conditions. Additionally, the integrating of QoS properties in prediction phase is impractical in the case of WSRec for composition due to time constraint and resource constraint of this online stage. Conversely, users' ratings evaluation is suitable for online prediction, which each entry of user-service matrix represents one value in the range of [1,5], unlike QoS based prediction, where there is a certain user-service matrixes according QoS features that are taken on consideration. Moreover, from the perspective of end-users is more easy and practical to evaluate services by giving them a number from 1 to 5 than evaluating services by different QoS properties and high various values ranges.

4.4.2.2 Functional filtering

Functional aspect has been paid a little attention in service selection or discovery oriented WSRec, because service-scoring task is often based on non-functional factors (e.g. QoS values, rating score, trust level...etc.). Conversely, in service composition approaches, this concept has grown in importance in light of recent development of web generations such as social web, semantic web and finally yet importantly web of things. In [121], the authors provide a model for service composition based on service social network (SSN) in IoT environment. The proposed selection method based on multi social relationships that have been computed to evaluate the collaboration capacity of services. Although this study has been provided new insights into employing social relations to measure collaboration capacity by focusing on the behavioral aspect of services, it is still insufficient to be used in recommendation engine for composition, because it will face the problem of cold Start, when a service is a new comer. In order to build up a framework for service composition, a discovering mechanism is presented in [124], where the authors propose two processing modules for services and queries, then matching service and query by measuring the similarity between input/output vectors of both. Commonly, using the previous syntactic measurement of input/output vector between services will be useful for WSRec, which allows to the new services to be in candidate set. Unfortunately, it is not enough to recommend suitable services, because if two services are syntactically compatible, this does not necessarily mean that composing them together may be meaningful. Therefore, there is a driven force to combine syntactic and semantic measurement to evaluate collaboration level among services.

4.5 Recommender System Challenges and Solutions

Recommendation systems face many challenges in term of scalability, cold start problem, credibility and data sparsity. These requirements should be considered when implementing an efficient recommendation engine. This section represents the keys challenges and the different approaches that meet those requirements.

- **Cold Start:** the cold start problem is a key challenge in recommendation systems; it refers to the case of a new user in the system provided no ratings or users only have a few. Thus, The lack of usage history of users prevents systems to provide personalized suggestions to users. It also describes new item has no ratings or has not enough ratings (i.e., less than a specific threshold number), which makes those items isolated and are not likely to be recommended. This problem is a continuous challenge because new items and users appear daily. Combining the collaborative filtering and the content-based filtering approaches [15], using users description and semantic information turn into the best choice to solve user cold start problem. User profile construction [105], preference modeling [13][173] and users' demographic features-based approaches [185][50] aim also to overcome user cold start problem. In addition clustering techniques [25][135] are used to reduce the cold start problem. For instance, with the emergence of the social networks, the explicit and implicit relations among users and users' influence on others are employed to make useful and personalized recommendation [171]. In contrast to the new user problem, there is far too little attention in the literature to the new item problem, because it have less impact on recommendation quality while existing similar items in the system.
- **Data Sparsity** :data sparseness is one of the most frequently stated problems in recommender systems; where the users do not rate most of the existing items and the available ratings are very sparse, which makes the feedback data insufficient for the similarity computation. The widespread trend in solving data sparsity is the prediction strategies. Two prediction approaches are proposed in literature: user-oriented and item based. User-oriented approach [168][184] is employed the usage history of user or similar user experiences to predict the missing values (i.e., ratings). In item-oriented approach [57][25][135], past ratings of items, queries and log analysis and historical QoS records is widely used to predict missing values for web service recommendation. Certain studies have used extracting user's interest paradigm, in order to reduce the data sparsity problem; the usage information as individual behavior is exploited to infer user's interest [53][67] and it helps users to understand their interests [19]. In addition, with the prevalence of the social networks, the social behavior of users is employed to mine user's interest. Additionally, the reduction strategies are also used to overcome data sparsity problem by using matrix factorization methods [159][30][158].
- **Credibility:** trustworthiness problem represents one of the great difficulties faced by recommender systems. The employing of trust and reputation information allow recommendation engine to provide reliable and relevant results. Several researchers ensure the trustworthiness of recommendation by finding the trustworthy users. In [132], the trustworthy

users are defined as the similar users with reputation value more than 0.5, this value is given according to his past feedbacks. This technique helps users to make the right decision and solve the problem of the fake feedbacks. In [63], a trustworthy user is a close friend in social network; the trusted friend is a person with similar interest and with high social interactions. In the other side, finding the trustworthy services in large space of services has become one of the major challenges in service recommendation. The problem of malicious services is tackled by considering the honesty of service providers [48][87]. In order to determine the trustworthy services and to solve the fake rating problem. The authors in [112] combined the user ratings with QoS monitoring in both subjective and objective dimensions.

- **Scalability** the information overload problem is one of the main reason that triggering the construction of recommender systems. In turn, the number of both users and items is increasing, thus it makes a great challenge in which known as the scalability problem. A personalized recommender system [77] enables to handle the large scale of services. Furthermore, the location-aware recommendation [25][135] allows to reduce the search space. Besides, clustering-based approaches [93][77] enables to employ the correlation between users and items. In addition, the employing of the social information and social network analysis enable to refine user and item sets [171][16][158].

4.6 Summary

In this chapter, we proposed an original taxonomy for WSRec. We presented different existing approaches for service recommendation and it discussed the necessity of considering various information in recommendation process. In addition, we underlined the different sources of implicit and explicit information that can be used into service recommendation process. We have identified three main classes of information sources: contextual, social and personal information, besides the exploiting of user and service data. Furthermore, we offered reference value to understand of the using different inputs to solve and to meet recommendation challenges.

Part III: Contributions

"The secret to success is to know something nobody else knows."

Aristotle Onassis

5

First Contribution: Recommendation Approach for Service Discovery

Sommaire

5.1 Introduction

With the explosive growth of web of things and social web, it is becoming hard for device owners and users to find suitable web services that meet their needs among a large amount of web services. Social-aware and collaborative filtering-based recommender systems are widely applied to recommend personalized web services to users and to face the problem of information overload [71]. However, most of the current solutions suffer from the dilemma of accuracy-diversity [52] where the prediction accuracy gains are typically accompanied by losses in the diversity of the recommended services due to the influence of popularity factor on the final score of services (e.g., high rated or high-invoked services). To address this problem, the purpose of this chapter is developing an improved recommendation model called PWR [70], which enables to discover services and provide personalized suggestions for users without sacrificing the recommendation accuracy.

5.2 Service Composition Platfrom

In this section, we describe the global architecture of service composition framework. The main purpose of our approach is allowing user to compose new services by linking existing ones, and give him an effective suggestions by recommending relevant services. The following figure shows a screenshot of the framework. This framework provides a graphical user interface (GUI) to compose services. The repository of services is displayed on the left side. Then, the personalized and ranked list of services (suggestions) below the reduced list of service that can be composed with the selected services (recommended list). On the right side, the framework displays the properties of selected service and shows his rating information. The space in the middle represents a graphical environment for user to compose services by in mashup style by drag and drop actions several times until he gets the suitable composite service that fulfills his needs.

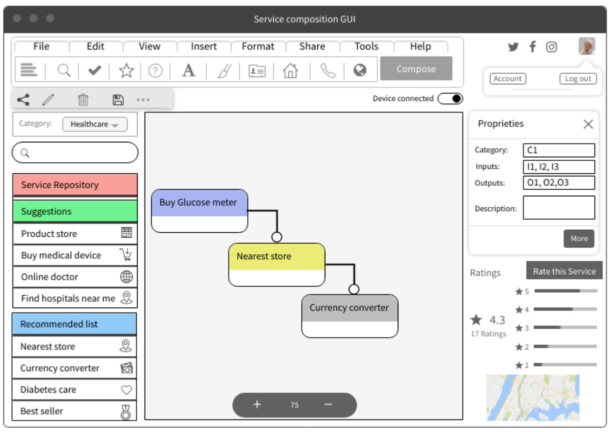

Figure 5.1: A screenshot of service composition framework GUI

5.3 Framework Components

In our proposed approach, the user chooses a service from list of suggestions, which represents user request. The system helps user to find suitable services for composition by recommending a list of services (recommended list). The composition framework consists of four principal modules: graphic user interface, recommendation engine (recommender), social analyzer and classifier.

- Graphic user interface(GUI): represents the interface between the user and the system. It is the composition editor where the user chooses service and compose them in mashup style.
- Recommender: Refers to the recommendation engine that discovers and filters services. The recommender filters and ranks services based on the knowledge given by the social analyzer and classifier as shown in 5.4 and 6.2 .
- Social analyzer: crawling the social IoT network to collect data in order to find similar users. The similarity computation among user is based on User similarity Measurement Model (UMM) that presented in 6.2.1.1
- Classifier: establishes a catalog of services by classifying them into categories and filtering them according their social functional and non-functional features in order to find set of service collaborators by using a Service Collaboration Model (SCC) that presented in 6.2.1.2.

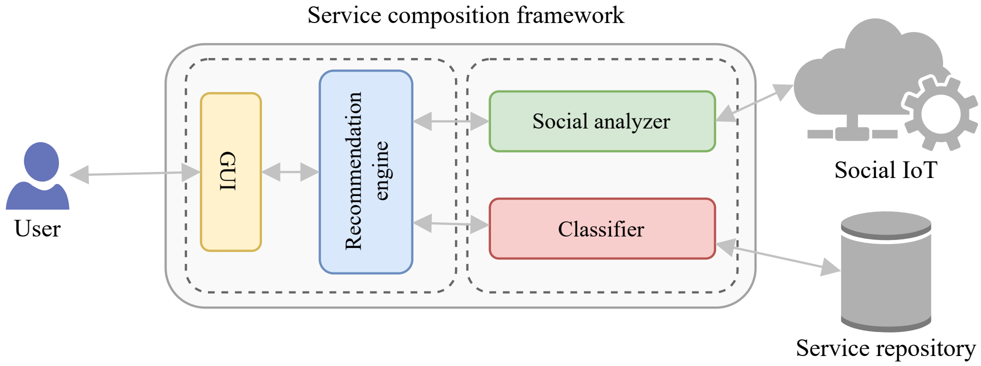

Figure 5.2: The global architecture of composition framework

In order to clarify the interactions among the different modules in the composition platform, we present the following sequence diagram 5.3.

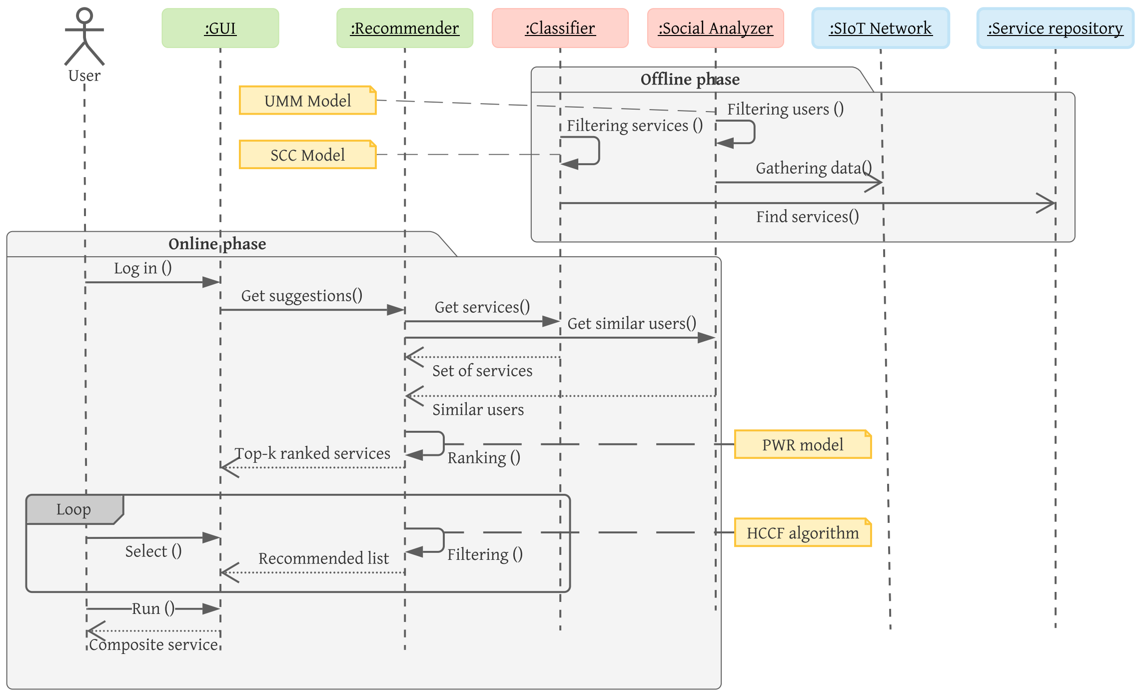

Figure 5.3: The structure of the vertical recommendation model

5.4 Discovery Process

In this section, we present our recommendation approach. The core idea of the proposed model is to provide relevant and personalized suggestions of services for WoT users. The structure of recommendation model is illustrated in Figure 5.4. Recommendation process is divided into two phases: online and offline. In the offline phase, there are two main stages, which are device similarity computation and k-nearest neighbours' selection for user. The online phase includes two main tasks: rating prediction and service ranking.

5.4.1 Offline phase

This phase consists of two models: user similarity and device similarity. The aim of user similarity model is to select neighbors of the target user in SWoT. The purpose of device similarity model is to find similar devices of the target device. These models are adopted in offline to reduce the time cost of recommendation due the requirement of IoT environment such as resource constraint of IoT device.

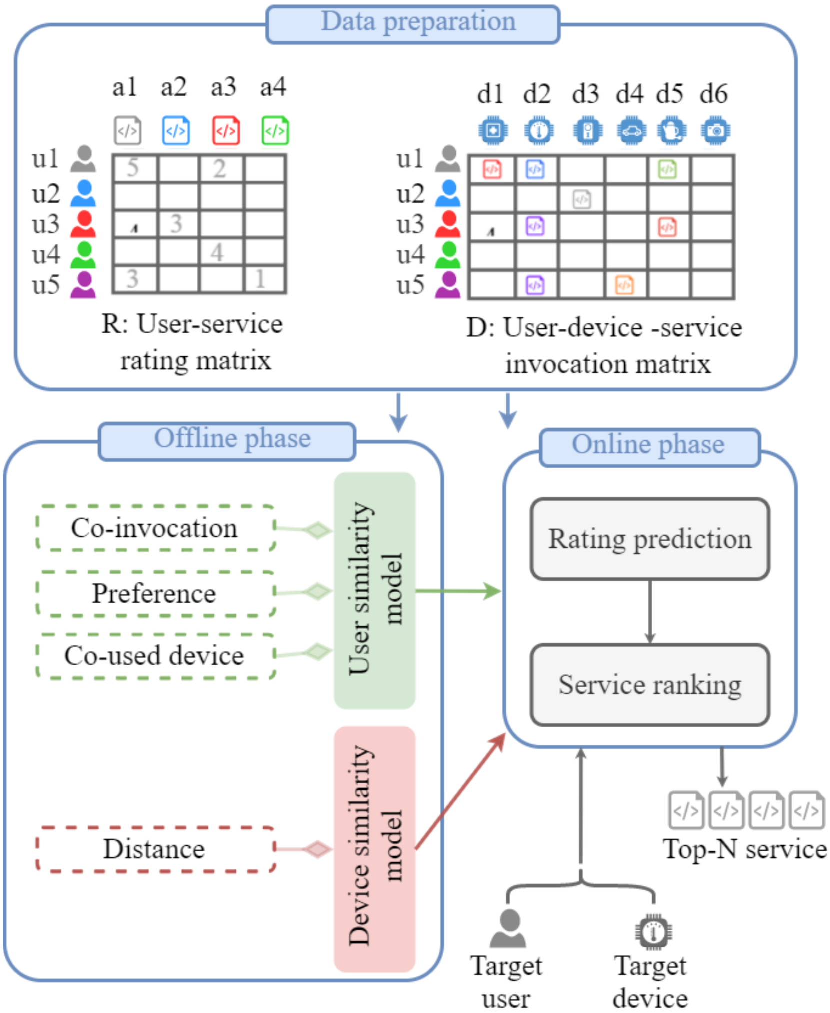

Figure 5.4: The structure of the vertical recommendation model

5.4.1.1 User Similarity

In order to measure the similarity level between users, we propose a similarity module that calculates the similarity degree. This module is based on three factors as shown in the next equations:

- Preference similarity refers the similarity of user preferences. It is calculate by Jaccard distance as follows:

$$sim_p(u,v) = \frac{|P_u \cap P_v|}{|P_u| \cup |P_v|} \tag{5.1}$$

  Where $sim_p(u,v)$ denotes the degree of similarity between user u and user$v$, P_u and P_v refers to the set of preferences of user u and v, respectively.

- Co-used devices similarity is computed the similarity of device using between users. It is measured as follows:

$$sim_D(u, v) = \frac{|D_u \cap D_v|}{|D_u| \cup |D_v|} \tag{5.2}$$

Where $sim_D(u, v)$ is the similarity degree between user u and user$v$, D_u and D_v refers to the set of used devices by user u and v, respectively.

- Invocation similarity represents the similarity of invocation behavior among two users a and b , it is computed by *Pearson correlation coefficient (PCC)* of both user ratings $r_{u,s}$ and $r_{v,s}$ on service s as follows:

$$sim_s(u, v) = \frac{\sum_{s \in S}(r_{u,s} - \bar{r}_s)(r_{v,s} - \bar{r}_s)}{\sum_{s \in S}(r_{u,s} - \bar{r}_s)^2 \sum_{s \in S}(r_{v,s} - \bar{r}_s)^2} \tag{5.3}$$

The set of similar users is defined as $neighborhs(u) = \{v|sim(u, v) > 0\}$, where the final similarity degree $sim(u, v)$ is given by the following formula:

$$sim(u, v) = \frac{sim_p(u, v) + sim_D(u, v) + sim_s(u, v)}{3} \tag{5.4}$$

5.4.1.2 Device Similarity

The similarity $Dis(x, y)$ between two devices x and y is computed by the Euclidean distance as in equation (5), where the Fi represent the features of device such as device type, availability time, location, mobility...etc. Here, we used device profile model that proposed in [60]:

$$Dis(x, y) = \sqrt{\sum_{i \in N}[F_i(x) - F_i(y)]^2} \tag{5.5}$$

5.4.2 Online phase

This section presents the online phase of our recommendation model. Two stages are proposed: rating prediction and service ranking.

5.4.2.1 Rating Prediction

In this sub-section, we present our rating prediction approach. The service have been invoked by similar users of the target user and have been consumed by similar devices to target device are selected as candidate services. The aim of this stage of recommendation is to predicting rating values of the candidate services. The proposed method is combined user-based CF and item-based CF technique to predict the missing ratings and to score the services via employing user similarity. Then, it is polymerizing the results returned from every iterations. Finally, the K-largest score of services are selected for the next stage. We have used the following equation to predict the rating value.

$$Pred(u,s) = \frac{\bar{R}(s)}{R(u,s) - \bar{R}(s)} \times \frac{sim(u,v)}{max \sum_{u' \in U} sim(v,u')} \tag{5.6}$$

Where $Pred(u,s)$ is the predicted rating of service s by the user u, $\bar{R}(s)$ is the average ratings values of serice s and finally, $sim(u,v)$ is the similarity degree among user v and the active user u .

5.4.2.2 Service Ranking

From the previous stage, for each service a in the set of candidate services, Equation 5.7 is applied to calculate the relevancy degree. Where N_u is the number of similar users whom invoked service, N_o is the number of similar devices that have consumed this service. U; O are cardinalities of total users and devices, respectively.

$$Relevancy(s) = \frac{N_u}{U} + \frac{N_o}{O} \tag{5.7}$$

The predicted rating score that given for each service in prediction stage is adjusted by relevancy degree. Then the services have been ranked according to their final adjusted scores as shows in the following algorithm:

Algorithm Hybrid CF-based Rating prediction

Input
M User-service rating matrix
R Relevancy vector
$neighbors$ Set of neighbors
Method
for each service $s_i \in Candidateservices$ do
  for each user $u_j \in neighbors$ do
    $P[i][j] \leftarrow Pred(u_j, s_i)$
  End for
  $S(a_i) \leftarrow \frac{1}{N} \sum_{u_j \in U}^{N} P[i][j] \times Relevancy(s_i)$
End for
$recommended_{list} \leftarrow s_j/Top - K[S(s_j)]$
Output $recommended_{list}$

5.5 Experimental Evaluation

For experimental evaluation, due the lack of real-world dataset that meets our benchmark to validate the performance of our proposed approach, we select MovieLens 20M dataset from Group lens Research Project. This dataset consists of 138,000 users, 27,000 different movies and 465,000 tag applications; the total number of rating is 20 million ratings. In this experiments, we consider the movies as services and tags as IoT devices. We filtered the dataset so that only the users who had tags were selected, meaning that the ratings for users who own devices was taken only. We define two matrices R and D; R is the user-service rating matrix and D is the user-device-service invocation matrix. The filtered dataset statistics shown in the Table 5.1.

Ratings	4601
Users	321
Services	2307
Devices	747
Range of Rating	[0.5,5]
R-density	0.62 %
D-density	1.17 %

Table 5.1: Statistics of the filtered dataset

5.5.1 Compared Methods

To verify the performance of our PWR model, we selected seven baseline models to compare with the proposed approach. These are:

1. UPCC is the traditional user-based collaborative filtering method, which exploiting the historical behavior of users to compute users similarity by Pearson Correlation Coefficient for making prediction [127],[136], [178].
2. IPCC is adopting Pearson Correlation Coefficient, which gets the predicted rating based only on the similarity between items [81],[122], [157].
3. UC-KNN employs similar user attribute information for service recommendation based on Cosine similarity and k-nearest neighbor algorithm [118].
4. IC-KNN the item based collaborative filtering model for rating perdition using KNN algorithm based on the Cosine similarity measure.
5. PHR is a popularity-based recommendation baseline. We define popularity of an service as the high rated services in rating matrix (i.e., the average rating of service).
6. PMI refers to the recommendation of services based on their invocation frequency by IoT devices.
7. PHS is a variation of the popularity-based model that defines the popularity of service by the high-scored services.

Among the above, 1 and 3 are user-based CF methods, 2 and 4 are item-based CF methods, and 5, 6 and 7 are popularity-based models. For the experiments, the dataset is divided into two parts: 20% were randomly selected to represent the test data and 80% constitutes the training set. Our experiment is implemented on a PC with Intel Core i5 CPU and 4 GB RAM under windows 7 using Python 3.7.

5.5.2 Evaluation Metrics

To evaluate the quality of recommendation in our PWR model, firstly, we use the personalization metric that asses if a recommendation model suggests the same items to different users. It is employed to measure the personalization degree of our recommendation model in comparison with other models. Personalization PER is defined by the dissimilarity between user lists of recommendation as following:

$$PER@N = 1 - Cos(L_u, L_v) \tag{5.8}$$

Where N is the number of top-N recommended services. $Cos(L_u, L_v)$ denotes the Cosine similarity between the recommended service list of user u and the recommended list of user v.

To evaluate the prediction accuracy of the proposed model, we use the Receiver Operating Characteristic ROC metric, which indicates to the quality of recommended services. The ROC metric is defined as following:

$$ROC = \frac{\sum_{i=1}^{n} d_i}{\sum_{i=1}^{n} a_i} \tag{5.9}$$

Where d_i and a_i refer to the probability of detection and the probability of false alarm, respectively. In our experiments, for the predicted ratings $\{p_1, p_2, p_3...p_n\}$ and real ratings $\{r_1, r_2, r_3...r_n\}$, we use two thresholds T_1,T_2, and we also define d_i and a_i as following:

$$d_i = \begin{cases} 1 & \text{if} \quad p_i \geq T_1 \quad and \quad r_i \geq T_2 \\ 0 & \text{else} \end{cases} \tag{5.10}$$

$$a_i = \begin{cases} 1 & \text{if} \quad p_i \geq T_1 \\ 0 & \text{else} \end{cases} \tag{5.11}$$

5.6 Results and Discussion

In the following, we present the results of the experiments in order to highlight how the proposed model PWR outperforms the other compared models by the prediction accuracy and personalization performance

5.6.1 Prediction Accuracy Performance

We compare our prediction model PWR with other compared methods in *ROC* metric. We set the thres hold for real ratings. We set T_1 equals to the median $T_2 = 4$ between the highest predicted score and the lower predicted score in each service for all models. Figure 4 shows the results of the comparison.

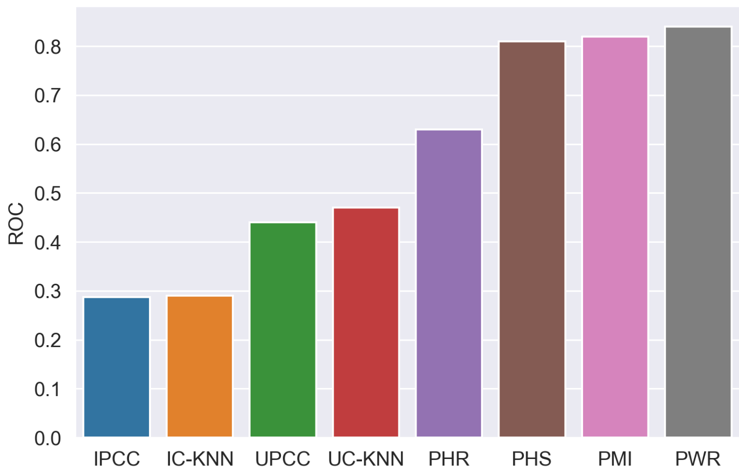

Figure 5.5: The comparison of ROC metric between the compared models.

The results show that under all ROC values of the compared algorithms our model PWR achieves the highest value. That means that the prediction in our model is more accurate than other models. Additionally, we observe that the lower score in ROC is obtained in item-based algorithms, we also observe that the popularity- based models (PMI, PHS and PHR) achieve a higher ROC values than the baseline userbased and item-based approaches. The superiority our PWR model over all the compared algorithms is confirmed by a 12% increase in the recommendation quality with popularity-based approaches.

5.6.2 Personalization Evaluation

Table 5.2 shows the results of obtained personalization degree over different Top-N recommendation (5, 7, 10 and 15) in order to see how our model improves the diversity of recommendation results.

From the results in Table 5.2. We can make the following observations:

- Under all personalization values, PWR achieved the largest values even by varying the length N of recommended lists. It is a significant that our model PWR recommends higher personalized results than the other baselines.

- User-based models outperformed the other models (popularity and item-based algorithms). That indicates that employing user similarity is beneficial in personalized recommendation.
- Popularity-based and item-based models achieved the lower score. That means that these models recommend the same services for different users which is the opposite of what should be in personalized recommendation oriented users in IoT environment.

Model		Top N =			
		Per@5	Per@7	Per@10	Per@15
User-based models	UPCC	0.0009	0.24	0.05	0.0002
	UC-KNN	0.0002	0.12	0.003	0.00001
Popularity-based algorithms		0.00	0.00	0.00	0.00
Item-based algorithms		0.00	0.00	0.00	0.00
Our Model PWR		0.29	0.86	0.38	0.39

Table 5.2: Comparison results of personalization values by varying N recommended services

5.7 Summary

This chapter presented a personalized service recommendation model in social WoT environment. The basic idea is to predict rating values and recommend the top-k services, based on their adjusted rating score that is computed based on their relevancy degree and their predicted rating that is weighted by similarity values between users and the target user. Additionally, a similarity measurement model is proposed that based on three factors, which are coinvocation, co-used and preference. The rating prediction method is combined item-based and user-based CF techniques in order to enhance prediction accuracy. The experimental results demonstrate that the performance of our recommendation system outperforms the other compared methods in both prediction accuracy and diversity of recommended lists.

"Success is no accident. It is hard work, perseverance, learning, studying, sacrifice and most of all, love of what you are doing or learning to do."

Pele

6 Second Contribution: Recommendation Approach for Service Composition

Sommaire

6.1 Introduction

With the rapid development of service-oriented computing applications and social internet of things (SIoT), it is becoming more and more difficult for an end-user to find relevant services to create value-added composite services in this big data environment. Therefore, this chapter proposes Social Service Composition based on Recommendation (S-SCORE), an approach for recommending web services to users for interactive composition in SIoT ecosystems. The main contribution of this chapter is to provide a novel recommendation mechanism for service composition, which enables to suggest trustworthy and personalized web services that are suitable for composition. The proposed mechanism consists of online and offline stages. In the offline stage, two models of similarity computation are presented. The first is an improved user similarity model that incorporates contextual, social and historical information, which enables to select user neighbors. Then a new service collaboration model is provided that allows service selection based on functional and non-functional features of services. In the online phase, a Hybrid Clustering-based Collaborative Filtering algorithm (HCCF) is proposed for rating prediction.

6.2 Recommendation Process

This section introduces the recommendation mechanism in detail. The process of recommendation is divided into two phases: offline and online. In offline phase, the system gathers and analyzes the social information in order to reduce time complexity of recommendation. In online phase, the system uses a hybrid algorithm to predict rating and recommend top-k services. Figure 6.1 illustrates the different stages of recommendation.

6.2.1 Offline phase

This sub-section describes the offline phase of recommendation. This phase consists of two models namely user similarity measurement model (UMM)and service collaboration computation model (SCC).

6.2.1.1 User similarity measurement Model (UMM)

In this sub-section, we present the proposed model for user similarity computation. We give an explanation on the mechanism of finding the set of neighbors and introduce the different attributes that used in similarity measurement. In collaborative filtering-based approaches, the similarity measurements between users are so critical, which effect on the accuracy of recommendation. Moreover, with the emergence of SIoT and the growing number of users and service consumers, SIoT richness can be employed to get the set of similar users. In the context of E-health, a person with diabetes would be useful to take the feedbacks on services from people with the same disease who have tried these services before. This is better than asking his friends who are not interested in diabetes or didn't consume those services before to make recommendations for him. The best case is when the advisor (similar user) has the same interests, and has actually consumed

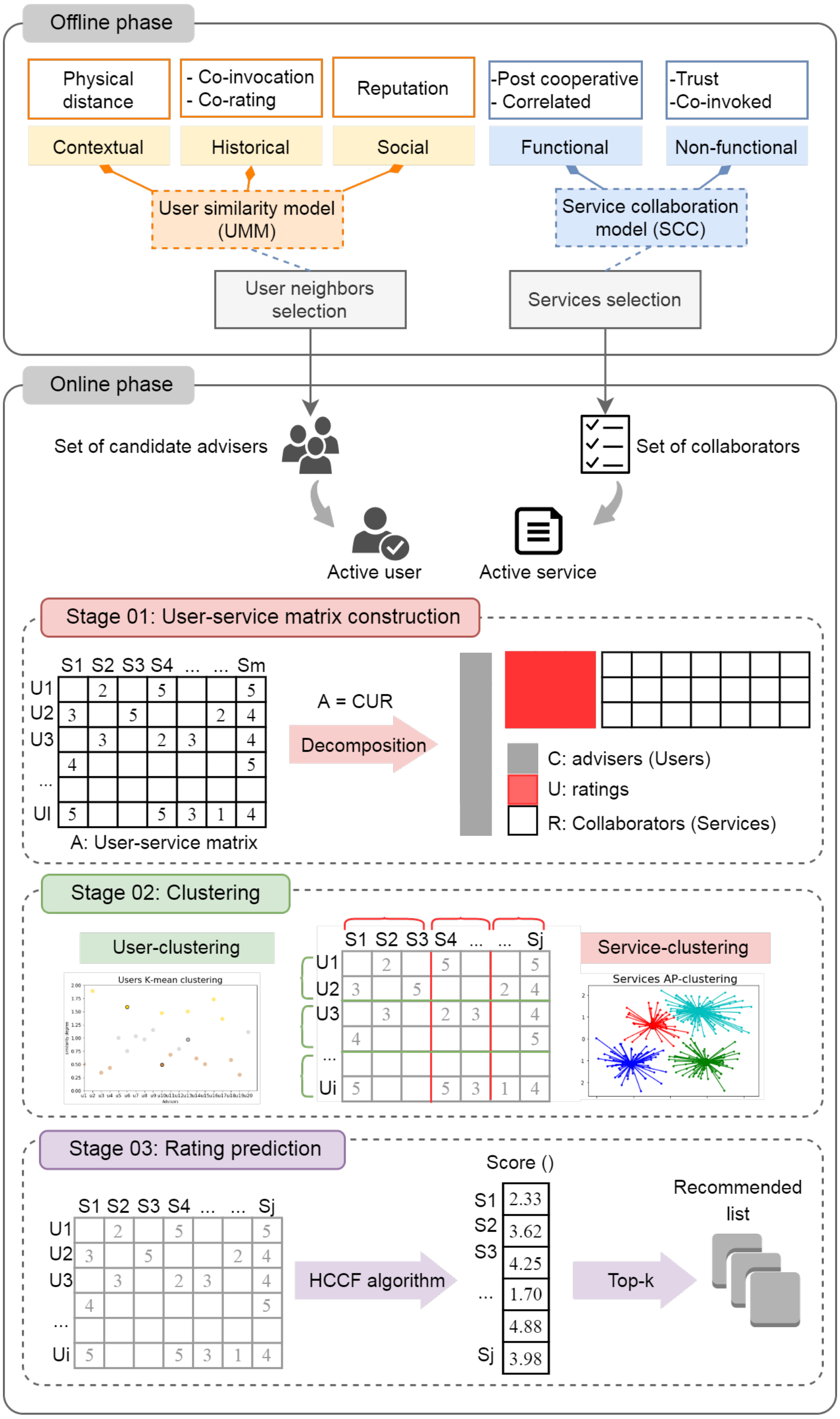

Figure 6.1: Overall S-SCORE recommendation process

and rated services that could eventually be used by the active user. From this point, we define the similarity degree among users by four factors: $co-invocation$, $co-rating$, $reputation$ and $distance$.

- Co-invocation: represents the degree of similarity between the sets of commonly-invoked services, where similarity degree of co-invocation relation among user u and user v is measured by Jaccard distance as follows:

$$Coi(u,v) = \frac{|I_u \cap I_v|}{|I_u| \cup |I_v|} \tag{6.1}$$

  Where $Coi(u,v)$ denotes the degree of similarity between user u and user$v$, I_u and I_v refers to the set of invoked services by user u and the set of invoked services by user v, respectively.

- Co-rating: computes the similarity between two users according to their ratings on common set of services, it is measured by *Pearson correlation coefficient (PCC)* as follows:

$$Cor(u,v) = \frac{\sum_{s \in S}(r_{u,s} - \bar{r}_s)(r_{v,s} - \bar{r}_s)}{\sum_{s \in S}(r_{u,s} - \bar{r}_s)^2 \sum_{s \in S}(r_{v,s} - \bar{r}_s)^2} \tag{6.2}$$

  $Cor(u,v)$: similarity degree between user u ratings' and users v ratings' on the set of services S.

  s: common rated service, where $s \in I_u \cap I_v$.

  $r_{u,s}$: rating value of service s is given by user u.

  $r_{v,s}$: rating value of service s is given by user v.

- Reputation degree: refers to the global reputation degree of a user in the social network, it is calculated using the following equation, where the rating values of a user on set of services is considered as an n-dimensional vector space:

$$Rep(u) = \frac{m}{n} + \frac{R_u \bar{R}_s}{\|R_u\| \|\bar{R}_s\|} \tag{6.3}$$

  N: the cardinality of the set of total rated services.

  s: set of rated services by user u, and m is the cardinality of s.

  R_u: Vector of ratings values are given to S by user u.

  $\bar{R}_s$: Vector of the average ratings values of S.

- Physical Distance [159] : is computed by the *Euclidean distance* between two users as follows:

$$Dis(u,v) = \sqrt{(lon_u - lon_v)^2 + (lat_u - lat_v)^2} \tag{6.4}$$

  Where lon_u and lon_v are the longitude coordinates of user u and user v respectively. lat_u, lat_v are the latitude in location of u and v respectively.

Inspired by [25] that combined co-invocation and co-rated similarities values into one adjusted value to alleviate overestimation problem when two users have very similar ratings but not similar co-invoked services. We define the similarity as:

$$Sim_{L1}(u,v) = \frac{Rep(v)}{Coi(u,v) \times Cor(u,v)} \tag{6.5}$$

To avoid the shortage of neighbors' number and to ensure that there is no dissimilar users in set of neighbors, we define the second metric of similarity as follows:

$$Sim_{L2}(u,v) = \frac{Rep(v)}{Dis(u,v)} \tag{6.6}$$

In order to select the most relevant similar users, we employ our proposed similarity measurement into the hybrid strategy of *top-k algorithm* that is proposed in [89]. Neighborhood selection mechanism is based on two similarity levels as shown in Figure 6.2. Here, the first level of neighbors are users with positive similarity value $Sim_{L1}(u,v) > 0$, if the cardinality of set of similar users less than K, the number of users is completed by the set of highest reputed geographical neighbors number. In cold start case, the neighbors of the new user are the highest reputed users in his geographical region $Top - k(Sim_{L2}(u,v))$.

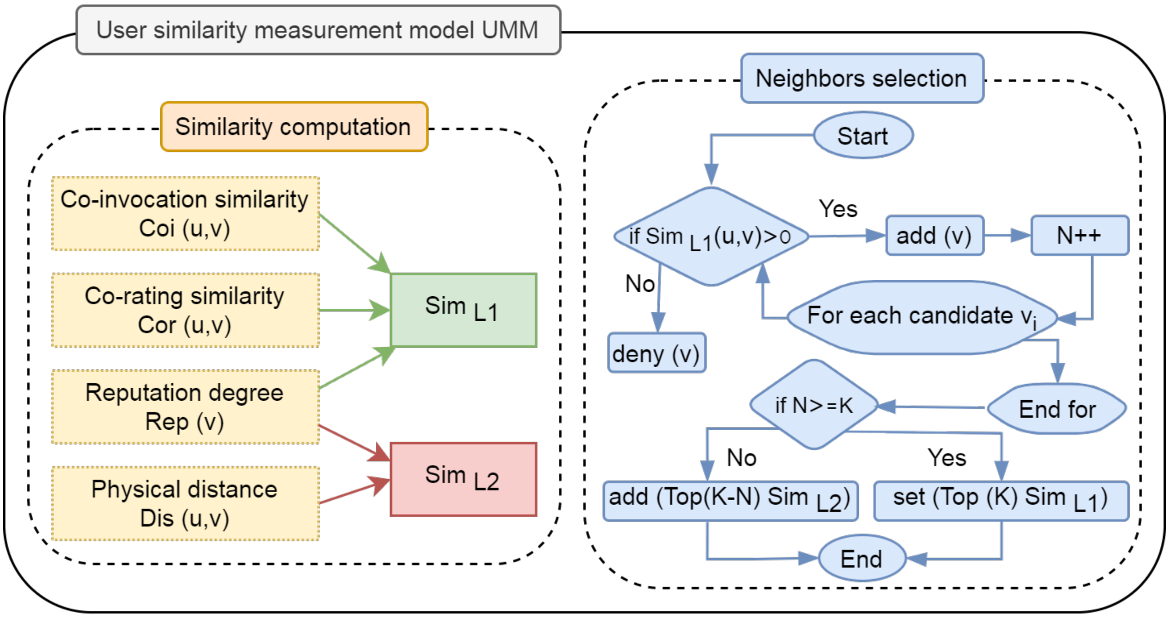

Figure 6.2: The mechanism of neighbors' selection in UMM model

6.2.1.2 Service collaboration computation model (SCC)

Unlike WSRec models for discovery or selection process, web service recommendation engine for composition does not need to find similar services to target service but it needs to search for services closely related to the active service (i.e. collaborators) that could be composed with the active service. Furthermore, matching between services must consider not only the non-functional features of service, but also the functional aspect must be taken into consideration. Consequently, we propose a collaboration model, which enables to select the set of the admissible services to compose with the active service. Let us suppose that the service pool is category-based registry, in which services are classified into categories. In order to select highly relevant neighbors of target service Si, we propose two stages of selection. Firstly, we select the functional correlated services set of target service from the services space. Then, we purify services inside the previous (i.e., correlated services) according their non-functional features.

6.2.1.2.1 Functional selection

In the context of service composition, the candidate services are *post-cooperative services (PCS)* of the target service. Thus, we defined the set of cooperative services by the following formula:

$$PCS(S_i) = \{S_j | O(S_i) \subseteq I(S_j)\} \tag{6.7}$$

Where $O(S_i)$ denotes the set of the parameters of S_i output, and $I(S_j)$ denotes the set of the parameters of S_j input. Finally, the set of correlated services is presented as follows:

$$Correlated(S_i) = \{S_j | S_j \in PCS(S_i) \quad \text{and} \quad corr[C(S_i), C(S_j)] > 0\} \tag{6.8}$$

Where the correlation degree among two categories is calculated by the following equation:

$$corr(C_a, C_b) = \frac{f(C_a, C_b)}{\max\{f(C_a, C_i) : i..n \wedge i \neq a\}} \tag{6.9}$$

The function f is defined as follows:

$$f : (X, Y) \mapsto \sum_{S_i \in X, S_j \in Y} \parallel \overrightarrow{\mathrm{S_i S_j}} \parallel \tag{6.10}$$

X , Y are service categories, and $\parallel \overrightarrow{\mathrm{S_i S_j}} \parallel$ refers to service s_i invocation towards service s_j.

Example 1. Given four categories of services: C_1,C_2,C_3 and C_T (category of target service). Through our selection mechanism, a set of post cooperative service is selected from each category (blue, green and red highlights in Figure 6.3). Then correlation degree among target category and other categories is calculated according equation 6.9,which gives the following results $Corr(C_T, C_1) = 0$, $Corr(C_T, C_2) = 0.75$, $Corr(C_T, C_3) = 1$. Finally, correlated services list is given as defined in equation 6.8.

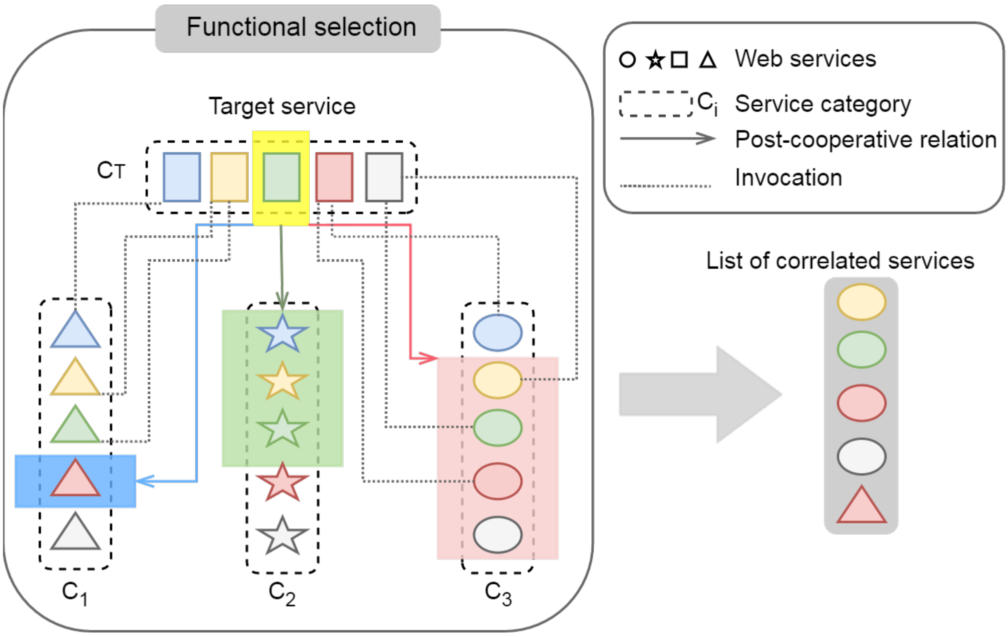

Figure 6.3: An example of functional selection of candidate services.

6.2.1.2.2 Non-functional selection

The second task of service selection is to filter the highest services from the list of correlated services according to their non-functional characteristics. We use trust relationship of services, where trust degree $trust(S_i)$ is defined in the following formula:

$$Trust(S_i) = \begin{cases} Trust(p) & \text{if} \quad S_i \in AS \\ Trust(o) & \text{if} \quad S_i \in CS \end{cases} \tag{6.11}$$

Where, $Trust(p)$ denotes the trust degree of service provider, and $Trust(o)$ is the trust value of the physical object in SIoT network. We define two set of services; AS : set of abstract services (i.e. classical services), and CS : set of concrete services (IoT services) that offered by physical devices. The trust degree of service provider is computed by one of the proposed models of trust in the literature such as [12], [145]. For IoT services or in what is known as Device Profile web services (DPWS), the trust level of services is measured by the trust degree of the physical device offered by this service. Hence, we used trust model proposed in [20]. It is defined by three factors in SIoT environment: honesty, cooperativeness and community-interest.

The final collaboration score $Coll(S_j)$ for each service is given by the following adjusted value:

$$Coll(S_j) = 2 \times \frac{Trust(S_j) \times Corr[C(S_i), C(S_j)]}{Trust(S_j) + Corr[C(S_i), C(S_j)]} + Coin(S_i, S_j) \tag{6.12}$$

The *coin* metric refers to the times that S_i and S_j are both co-invoked in the same mashups, PCC is employed to measure the similarity between two services a and b using the following equation:

$$Coin(a,b) = \frac{\sum_{m=1}^{M}(I_m(a) - \bar{I}(a)) \times (I_m(b) - \bar{I}(b))}{\sqrt{\sum_{m=1}^{M}(I_m(a) - \bar{I}(a))^2} \times \sqrt{\sum_{m=1}^{M}(I_m(b) - \bar{I}(b))^2}} \tag{6.13}$$

Where M denotes the number of mashups where a and b services are co-invoked;$I_m(a)$ and $I_m(b)$ denote the number of times that a and b are both invoked in mashup, respectively; $\bar{I}(a)$ and $\bar{I}(b)$ denote the average of times that a and b invoked in mashups, respectively. The value of co-invoked is in the range $[-1, 1]$. Finally, the set of collaborators services of target service S_i is presented as follows:

$$Collaborators(S_i) = \{S_j | S_j \in correlated(S_i) \quad \text{and} \quad Coll(S_j) > 0\} \tag{6.14}$$

Example 2. Given ten correlated services (rows) with *trust*, *corr* and *coinv* values (columns) in matrix S, respectively. Then, collaboration degree is given in vector $Coll$, where the collaboration value of each service is calculated by applying equation 6.12. Finally a set of collaborators is selected for the next stage, where their collaboration value is positive as defined in formula 6.14.

$$S = \begin{bmatrix} 0.50 & 0.75 & -1.00 \\ 0.40 & 0.50 & -0.60 \\ 0.39 & 0.63 & 0.95 \\ 0.61 & 0.30 & -0.56 \\ 0.15 & 0.23 & 0.73 \\ 0.26 & 1.00 & 0.32 \\ 0.59 & 0.75 & 1.00 \\ 0.74 & 0.83 & 0.74 \\ 0.00 & 0.63 & -0.80 \\ 0.48 & 0.12 & 0.14 \end{bmatrix} \quad Coll = \begin{bmatrix} -0.40 \\ -0.16 \\ 1.43 \\ -0.16 \\ 0.91 \\ 0.73 \\ 1.66 \\ 1.52 \\ -0.80 \\ 0.33 \end{bmatrix} \quad Collaborators = \begin{bmatrix} -0.40 \\ -0.16 \\ \boxed{1.43} \\ -0.16 \\ \boxed{0.91} \\ \boxed{0.73} \\ \boxed{1.66} \\ \boxed{1.52} \\ -0.80 \\ \boxed{0.33} \end{bmatrix}$$

6.2.2 Online phase

This sub-section presents the online phase of recommendation. Firstly, sets of advisors and collaborators are selected based on UMM and SCC models that described in Sub-sections 6.2.1.1 and 6.2.1.2, respectively. Three main stages are proposed in online phase; the preliminary stage is the construction of user-service rating matrix. Then, clustering users and services, which is the pre-processing task of next stage inputs. Finally, HCCF algorithm is applied to predict the missing values of rating and to provide a list of candidate composite services.

6.2.2.1 User-Service rating matrix construction

For the active user u a set of candidate advisors is given, and for active service s a set of collaborators services is given. User-service rating matrix A is with dimension $l \times m$, where l is the number of candidate advisors, and m the cardinality of collaborators set, the entry $r_{i,j}$ is the rating value of service S_j given by user U_i. Rating matrix will be sparse because most of advisors do not rate most services. We decompose rating matrix A based on *CUR decomposition* due to its advantages which the middle matrix (selected rating matrix) is dense, even the main matrix is sparse. We employ *LeverageScoreCUR (LSCUR)* algorithm [99] which is low-rank matrix decomposition that enables to reduce rows or/and columns. In this paper, we aim to reduce rows (advisors in rating matrix), according their importance in rating matrix, i.e. the most influential in the prediction. Thus, rating matrix A is approximately decomposed into three matrices C, U and R as follows:

$$A = \begin{pmatrix} r_{11} & .. & r_{i,m} \\ .. & .. & .. \\ r_{lj} & .. & r_{lm} \end{pmatrix} \approx CUR \tag{6.15}$$

Where:

C: the most important users, $C \in R^{n \times m}$

U: reduced matrix, $U \in R^{n \times m}$

R: contains the services, $R \in R^{l \times m}$

We define leverage scores of *i-th* row as the following equation:

$$Score(A_{i,:}) = \frac{1}{m} \sum_{j=1}^{m} \parallel r_{i,j} \parallel \tag{6.16}$$

Finally, the list of advisors is presented as follows $Advisors = \{u | score(u) > T\}$. Where T is the threshold, which equals to K-largest score value, where K refers to the cardinality of set of advisors having larger score than others.

6.2.2.2 Clustering stage

After decomposing rating matrix, we propose a hybrid clustering method for advisors and services, which enables the system to address data sparsity problem. The proposed method is employed to enhance prediction accuracy and it is divided into two steps: service clustering and users clustering.

6.2.2.2.1 User clustering

For n advisors (users) in R matrix and their similarity degrees with the active user a: $sim(u_i)/i \in n$, a k-mean algorithm is applied to cluster the set of advisors into three classes: *Platinum*, *Gold*, and *Silver* advisors, according their similarity degree with the active user and the ratio of rated services among collaborators services as shown in the algorithm 1. The distance function among users is defined as follows:

$$F(u_i) = Sim(u_i) \times \frac{r}{m} \tag{6.17}$$

where $sim(u_i)$ is the similarity degree with the active user, r is the number of rated services by user u_i in rating matrix R, and u_i is the total number of services in rating matrix R.

For each user in advisors set, the similar users are users having the identical degree of similarity with him, and his neighbors are users that situated in the same cluster that he belongs to.

Algorithm 1 Users K-mean clustering

Input
$Advisors(a) = \{u_1, u_2, ...u_n\}$ — set of users to be clustered
Cluster= { *Platinum*, *Gold*, *silver* } — Cluster labels
Initialization
$K \leftarrow 3$ — number of clusters
$C \leftarrow c1, c2, c3$ — initial centroids
$c1 \leftarrow maxSim(u_i)$
$c2 \leftarrow minSim(u_i)$
$c3 \leftarrow (maxSim(u_i) + minSim(u_i))/2$
Method
Repeat
  For $i \in 1..n$ do:
    $Platinum(u_i) \leftarrow argmin_i f \parallel u_i - c_1 \parallel^2$
    $Gold(u_i) \leftarrow argmin_i f \parallel u_i - c_2 \parallel^2$
    $Silver(u_i) \leftarrow argmin_i f \parallel u_i - c_3 \parallel^2$
  End For
  For $i \in 1..3$ do:
    $c_j \leftarrow \frac{\sum_i I(cluster(u_i)=j)u_i}{\sum_i I(cluster(u_i)=j)u_i}$
  End For
Until convergence
Output Cluster, C

6.2.2.2.2 Service clustering

For a given set of services collaborators for the active service: $Collaborators = s_1..s_m$, we aim to cluster the set of services into sub groups according their rating weights. K-mean clustering is unemployable because the number of cluster is not previously known. Therefore, we employ *affinity propagation (AP)* algorithm for service clustering due to its advantages, it does not require user to determine the number of clusters. Firstly, we construct a matrix S, it is $m \times m$ matrix. $Sim^s(i, j)$ represents the similarity between service s_i and service s_j. The similarity between services is computed by the negative squared distance among them by the following equation:

$$Sim^s(i, j) = - \parallel s_i - s_j \parallel^2 = -[(\overrightarrow{r_i} - \overrightarrow{r_j})^2 + (R_i - R_j)^2] \tag{6.18}$$

where $Sim^s(i, j)$ is the similarity between service i and service j, $\overrightarrow{r_i}$,$\overrightarrow{r_j}$ are vectors of i and j ratings' in the rating matrix, and R_i,R_j are number of raters of services i , j respectively. In order to alleviate numerical oscillations in the proposed algorithm, a damping Where n refers to iterations times, and $0.5 \leq \lambda < 1$.

Algorithm 2 Services AP-based clustering

Input

$Collaborators = \{s_1, s_2 ... s_m\}$ Data points

$P(j) = [\overrightarrow{r_i}, R_i]$ Preferences

P_max Maximum number of iterations

Initialisation

0 Similarity matrix construction S: $S(i, k) \leftarrow sim^s(i, k)$

1 Update similarity matrix (diagonal elements): $S(k, k) \leftarrow min(S)$

2 Availability matrix initialization a: $a(i, k) \leftarrow 0$

Method

Repeat

3 Responsibility matrix update r

$r(i, k) \leftarrow S(i, k) - max_{k'|k' \neq k}\{a(i, k'), r(i, k')\}$

4 Availability matrix update (off-diagonal elements)

$a(i, k) \leftarrow min\{0, r(k, k) + \sum_{i'|i' \in \{i,k\}} r(i', k)\}$

5 Self-Availability matrix update (diagonal elements) S

$a(k, k) \leftarrow \sum_{i'|i' \in k} max\{0, r(i', k)\}$

6 Exemplar decision

$Exp(i) \leftarrow max_{j=\{1..m\}}(r(i, j) + a(i, j))$

$P \leftarrow P + 1$

Until convergence or $P > P_max$

Output Clusters

6.2.2.3 Rating prediction stage

This section introduces the proposed hybrid filtering technique. Table 6.1 gives the variables definition used in the algorithm. The purpose of our Hybrid-based Clustering Collaborative Filtering (HCCF) algorithm is to give a score for each service Sj in set of collaborators services $Collaborators(s)$ of active service s based on users' ratings, by predicting a rating for each user in a set of advisors $Advisors(u)$ of the active user u. Then, HCCF algorithm attains predicted ratings for each service by all users through multiple iterations. The final score is obtained by polymerizing the results returned from every iterations. Finally, the K-largest score of services are recommended. Rating prediction in HCCF is illustrated in Figure 6.4. HCCF outeperforms the other baseline algorithms as shown in next section.

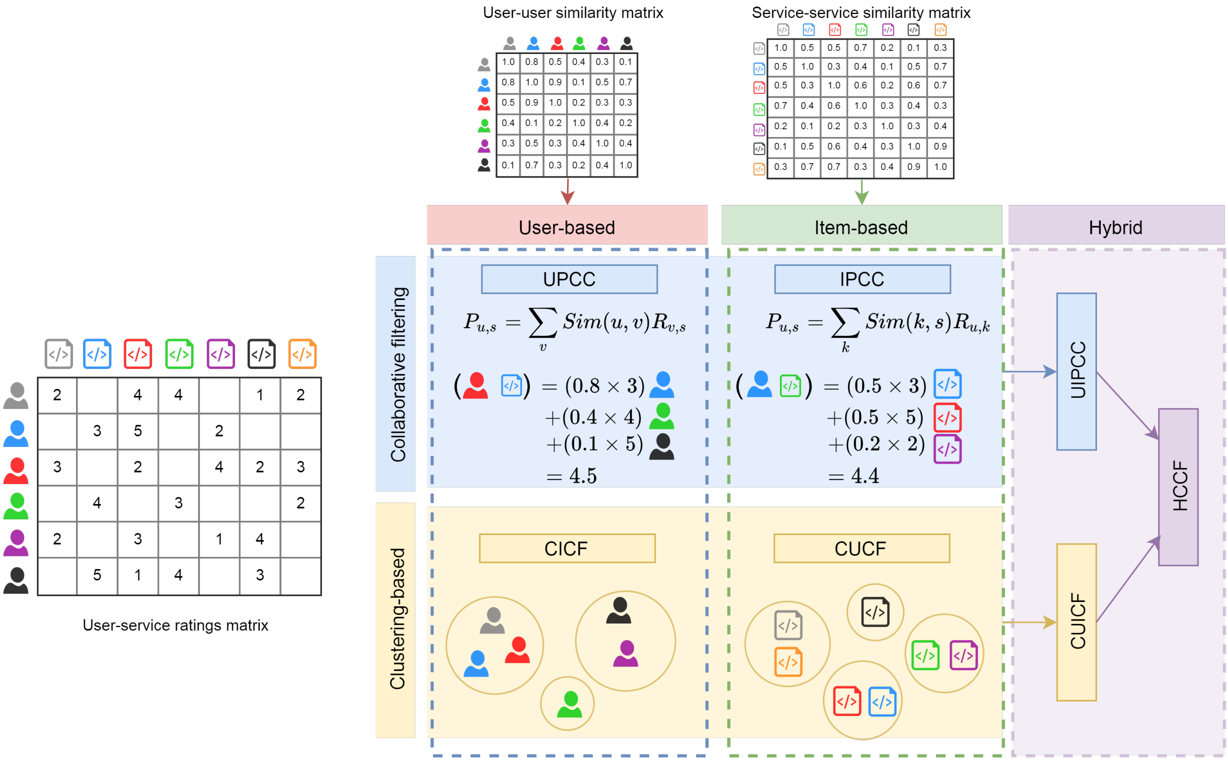

Figure 6.4: Rating prediction in hybrid CF-based clustering algorithm HCCF.

Variables	Description
$Collaborators(s)$	Set of collaborators services of active service s
$Advisors(u)$	Set of advisors of active user u
R	User-service ratings matrix
$Sim(u)$	Similarity degree of users u
$Col(s)$	Collaboration degree of service s
$R(u, s)$	Rating value of user u on service s
$P[i][j]$	Predicted rating value of user i on service j
$L^s(s)$	Set of neighbors of service s
$L^u(u)$	Set of neighbors of user u
$Score(S)$	Score of service S
I^s	Set of recommended services

Table 6.1: Variables definition of HCCF algorithm

Algorithm 3 HCCF-based prediction

Input
$Collaborators(s)$, $Advisors(u)$, R
Method
for each service $S_j \in Collaborators(s)$ do
  for each user $U_j \in Advisors(u)$ do
    If (U_i has rated S_j)
      $P[i][j] = R(U_i, S_j) \times Col(S_j) \times Sim(U_i)$
    Else
      If (S_j has similar services that rated by user U_i)
        $P[i][j] = \frac{1}{|L^s|} \sum_{S_s \in L^s(S_j)} R(U_i, S_s) \times Sim(U_i)$
      Else
        If (S_j has neighbors services that rated by user U_i)
          $P[i][j] = \frac{1}{|L^n|} \sum_{S_n \in L^n(S_j)} R(U_i, S_n) \times Sim(U_i)$
        Else
          If (U_i has similar users rated on S_j)
            $P[i][j] = \frac{1}{|L^u|} \sum_{U_k \in L^u(U_i)} R(U_k, S_j) \times Sim(U_k)$
          Else
            If (U_i has neighbors users rated on S_j)
              $P[i][j] = \frac{1}{|L^b|} \sum_{U_b \in L^b(U_i)} R(U_b, S_j) \times Sim(U_b)$
            Else
              If (S_j has been rated on R)
                $P[i][j] = \frac{1}{n} \sum_{k \in S^s(S_j)} R(U_k, S_j) \times Sim(U_k)$
              Else
                $P[i][j] = \frac{1}{n+m} \sum_{S_y \in L^s(S_j)}^{y=n} \sum_{U_x \in L^u(U_i)}^{x=m} R(U_x, S_y) \times Sim(U_i)$
  End for
End for
$Score(S_j) = \frac{1}{M} \sum_{i=1}^{M} P[i][j] \times Col(S_j)$
$I^s \leftarrow Sj, Score(S_j)$
Output I^s

6.3 Dataset and Experimental Setup

In this section, we conduct experiments to evaluate our proposed model and compare it with other CF-based prediction methods. Our experiment is dedicated to answer the main following questions:

- How does our hybrid-filtering algorithm HCCF compare with other well-known collaborative filtering algorithms in prediction accuracy and quality?

- How the density of matrix affects the performance?

For experimental evaluation, MovieLens data set form Grouplens Research Project is used. We select the MovieLens 100k (ml-100k) dataset [1] focusing on rating matrix. Table 6.2 presents the statistics of the used data source. This data set consists of 943 users and 1682 different movies; in this paper, we consider the movies as services. The total number of rating is 100000 in range of [1-5], with density of user-item rating matrix equal to 6.30 %.

Users	943
Items	1682
Ratings	100000
R-density	6.30 %
Range of Rating	[1-5]
Avg. rated items per user	106.04
Max rated items per user	737
Avg. raters on item	59.45
Max raters on item	583

Table 6.2: Statistics of MovieLens dataset

Six filtering methods are selected to make comparison with the proposed filtering algorithm. These are:

- UPCC: this method is the traditional user-based collaborative filtering method, which exploiting the historical behavior of users to compute users similarity by Pearson correlation coefficient and make prediction [178].
- IPCC: this method is the classical item-based filtering, which gets the predicted rating based only on the similarity between items [157].
- UIPCC: this approach is combines the results obtained from user-based and item-based collaborative approach [45].
- CUCF: this approach tries to involve clustering algorithms to enhance collaborative filtering methods, which employ users' clusters in prediction.
- CICF: this approach is an extension of IPCC, which integrates item clustering in prediction.
- CUICF: this approach is a hybrid between CICF and CUCF.

[1] https://grouplens.org/datasets/movielens/100k/

6.4 Evaluation Metrics

Our experiments are implemented using Python 3.7 on Spyder, they are conducted on a PC with Intel Core i5 CPU, 4 GB RAM under Windows 7.

To evaluate the prediction accuracy of the proposed algorithms, we use: Mean absolute error (MAE) metric, which refers to the average absolute deviation of the predicted rating and the actual rating, it is employed to measure the accuracy of prediction of our filtering algorithm HCCF in comparison with other algorithms. MAE is defined as follows:

$$MAE = \frac{1}{T}\sum_{u,s}|R^p_{u,s} - R^a_{u,s}| \tag{6.19}$$

Where T is the number of tested ratings, and $R^p_{u,s}$, $R^a_{u,s}$ denote the predicted and the actual rating, respectively. Coverage metric is used to measure the percentage of predicted ratings in the total missing ratings.

$$Coverage = \frac{|\sum_{u,s} R^p_{u,s}|}{T} \tag{6.20}$$

Where T refers to the number of missing values, and $|\sum_{u,s} R^p_{u,s}|$ denotes the number of predicted ratings. To measure the performance of the proposed algorithm compared with other approaches, we use F-score metrics based on harmonic mean. Firstly, F1-score measures the balance between MAE and coverage, then, we use F2-score between F1-score and time to ensure that there is no improvement in accuracy at the expense of time. F1-score, F2-score are defined as follows:

$$F1 - score = 2 \times \frac{MAE \times Coverage}{MAE + Coverage} \tag{6.21}$$

$$F2 - score = 2 \times \frac{Time \times F1 - score}{Time + F1 - score} \tag{6.22}$$

6.5 Results and Discussion

In this section, we present the results of several experiments in order to represent the accuracy of the proposed algorithm, called the HCCF.

Tables 6.3 and 6.4, and Figures 6.5 and 6.6 show the results of methods comparison in coverage metric, the data set is divided into two parts; 20% were randomly selected to represent testing data and the rest to be the training set. We can observe that:

- HCCF obtains highest coverage values among all aproaches. Additionally, the coverage ratio extensively stationary during all cases and densitie unlike the other algorithms, where we observed fluctuation in coverage values; this reflects that our proposed method improves the coverage value and did not change by the increase in the size of services/users. Which means that, no matter how many services and users, and whatever the density changes, the algorithm HCCF is able to predict all the missing values in user-service matrix. Because, HCCF adopt the clustering of users and services to avoid the failures prediction due to the lack of information.

- The employment of clustering algorithms in CF contributed to higher coverage value (CICF > IPCC), (CUCF > UPCC), (CUICF > UIPCC), which proves the effectiveness of our proposed approach based on clustering.
- The combination of item-based and user-based approaches significantly outperforms the coverage under all the density values, this is due to the fact that, the fusion of two approaches takes the advantage of both item-based and user-based to achieve a superior coverage than each single one, This involves in the improvement of the quality of recommendation.
- The impact of user and service sizes on coverage is obvious, when the number of services increase, user-based approaches (UPPC,CUCF) coverage values decrease. Likewise, when the number of users increase , item-based approaches (IPPC, CICF) coverage values decrease, That is why our algorithm has been built based on the merging of those two approaches with the application of clustering method to solve the problem of vulnerability in coverage due to the expansion of users and services, which ensures the scalability.

S=	HCCF	CUCF	CICF	UPCC	IPCC	UIPCC	CUICF
100	100%	**58%**	49%	**15%**	14%	19%	54%
200	100%	49%	48%	12%	15%	19%	58%
300	100%	47%	53%	10%	16%	21%	61%
400	100%	46%	63%	10%	18%	21%	70%
500	**100%**	45%	**68%**	10%	**20%**	**24%**	**74%**

Table 6.3: Coverage results per service neighbors

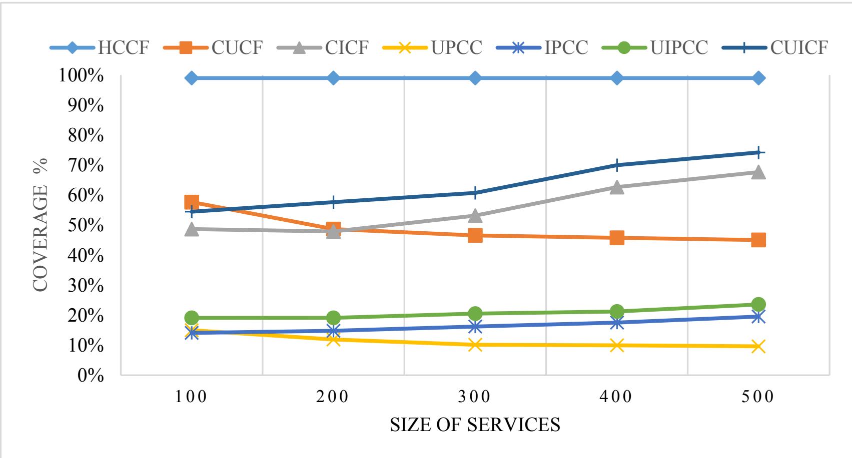

Figure 6.5: Coverage results per service neighbors

U=	HCCF	CUCF	CICF	UPCC	IPCC	UIPCC	CUICF
100	100%	15%	**43%**	15%	**14%**	19%	54%
200	100%	14%	35%	14%	11%	18%	46%
300	100%	14%	38%	14%	10%	18%	48%
400	100%	18%	42%	18%	12%	23%	55%
500	**100%**	**19%**	43%	**19%**	12%	**24%**	**56%**

Table 6.4: Coverage results per user neighbors

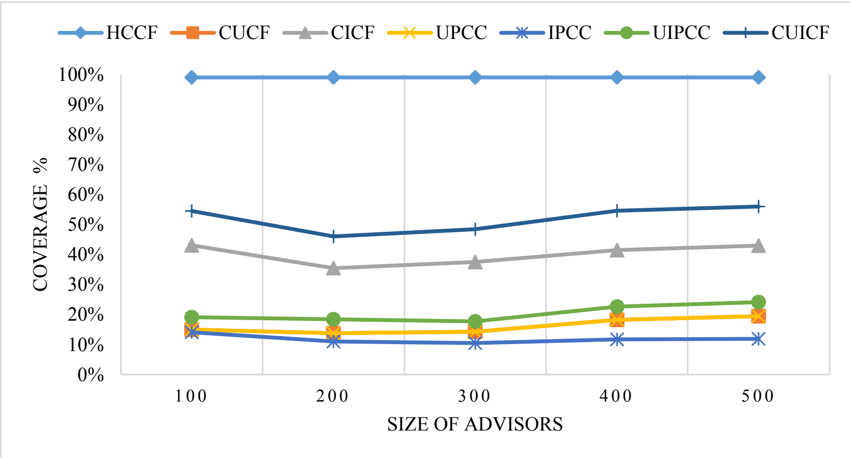

Figure 6.6: Coverage results per user neighbors

Table 6.5 shows the results of MAE, Coverage, Time, F1-score and F2-socre over three densities (30%, 50%, and 80%). From experimental results shown in Table **??** and Figure 6.7, we can deduce the following observations:

- Under all MAE values, HCCF achieves smallest values than other approaches, indicating that HCCF is more accurate than other methods. This observation occurs because HCCF can predict more precisely.
- The MAE of almost approaches increase with the increase of density, this means that performance of the prediction method is weakened by increasing the density. On the contrary; MAE values in HCCF and CICF algorithms are decreasing despite the increase in density.
- We note that HCCF has the highest F1-score and F2-score which means that it is more accurate than other algorithms.
- We can observe that hybrid based CF approaches has the highest F1-score values (UIPCC > { IPCC, UPPC } and CUICF > { CUCF,CICF }), which means that the combination on item-based and user-based improves the accuracy of prediction.

- The time cost of IPCC, UPCC and IUPCC are the smallest, because the other methods based on clustering, that led to increase the computation cost. Therefore, F2-score is balancing between the prediction accuracy and time cost, which proves that our proposed algorithm HCCF outperforms the compared algorithms over all the three densities as shown in Figure 6.3.

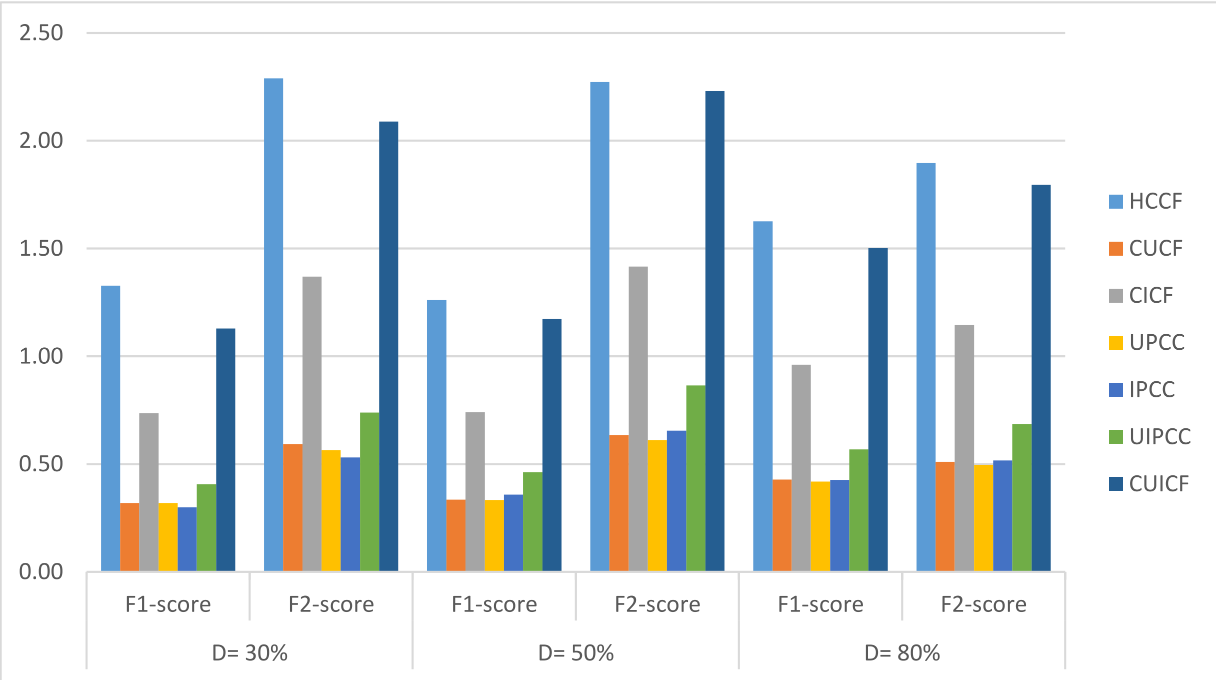

Figure 6.7: F-score metrics comparison

	Density														
	D= 30%					D= 50%					D= 80%				
	MAE	Cov	Time	F1	F2	MAE	Cov	Time	F1	F2	MAE	Cov	Time	F1	F2
CUCF	2.00	0.17	4.08	0.32	0.59	2.35	0.18	6.16	0.33	0.63	3.08	0.26	6.13	0.48	0.89
CICF	2.01	0.45	9.99	0.74	1.37	1.89	0.46	16.57	0.74	1.42	1.67	0.49	17.37	0.76	1.45
UPCC	2.00	0.17	2.45	0.32	0.57	2.23	0.18	**3.67**	0.33	0.61	3.08	0.26	**3.78**	0.49	0.86
IPCC	2.01	0.16	**2.32**	0.30	0.53	2.30	0.19	3.91	0.36	0.66	2.53	0.28	4.03	0.50	0.89
UIPCC	2.42	0.22	4.13	0.41	0.74	3.26	0.25	6.78	0.46	0.87	4.81	0.35	6.79	0.65	1.18
CUICF	16.86	0.58	13.88	1.13	2.09	24.90	0.60	22.60	1.17	2.23	27.7	0.57	18.00	1.12	2.10
HCCF	**1.98**	**1.00**	8.29	**1.33**	**2.29**	**1.71**	**1.00**	11.46	**1.26**	**2.27**	**1.38**	**1.00**	12.60	**1.16**	**2.12**

Table 6.5: Comparison results of MAE, Coverage , F1, F2 and time metrics

6.6 Summary

In order to build an interactive service composition framework for end-users in an SIoT environment, the main purpose of this chapter is to develop a service recommendation approach S-SCORE that helps to suggest personalized and trustworthy results for users. In summary, the proposed model addresses the following: (i) problems of cold start and data sparsity in the selection of neighbors, (ii) the use of social knowledge mined from SIoT networks to ensure personalization and credibility of recommendation results, and (iii) an improvement of classical CF-based algorithms in the aim to increase prediction accuracy. Furthermore, and for this model, (1) we have presented a model for user similarity computation (UMM) that allows to improve the quality of user neighbors, (2) we have proposed a novel collaboration measurement among services (SCC), (3) we have developed a hybrid algorithm HCCF which is based on clustering techniques applied to user and service sets. The evaluation of the proposed algorithm was realized on real-world data of MovieLens. Through comparisons with six baseline collaborative filtering-based prediction algorithms, the experiments have shown that the proposed algorithm HCCF outperforms the reference methods without compromising time cost. Moreover, the F-score of HCCF is the highest and his MAE value is the lowest even with varying rating matrix density which means that HCCF has a prediction accuracy superior to the compared methods. This is very meaningful and beneficial for the recommendation efficiency and, consequently, composition quality. Despite the fact that the clustering phase improves the accuracy of rating prediction, it requires an increase in computation time cost. However, we note that the time cost of HCCF is still acceptable compared to other algorithms.

"Success belongs to those who believe in the power of their ideas."

Michael Irwin

Conclusion

Contributions

Recently, with the proliferation of web services, developing a web service recommendation system has become trend and directive research, due to the efficiency of this technology, especially in the big data environment, with a huge number of candidate services having similar functionalities. Additionally, with the evolution of the social web, there are a huge number of social media users (about half of the internet users), i.e., 3.72 billion active users of social media out of 4.54 billion users on the internet [2]. In front of this tremendous growth of web connectors and web services, building recommendation engines for WS composition has become of paramount importance on one side. On the other side, involving those end-users in composition tasks has become an imperative, allowing them to find relevant results that meet their needs, especially, with the appearance of what is known as Mashup, an end-user oriented tool that enables to compose services and web APIs easily and efficiently.

Employing social information in service recommendation is becoming more prevalent, because it has proved its effectiveness to fulfill end-user needs. Specifically, the overlap between IoT and social networks led up to the emergence of SIoT. The upcoming movement of SIoT is more than just being a tool for sharing things and building relationships among them. Instead of that, the scalability of SIoT networks enables various entities (e.g., service consumers, device owners, web services…etc.) to establish social interactions with many connectivity options. Additionally, the potentialities of SIoT guarantee the navigability among various nodes based on different social links such as trust, co-invocation, co-location…etc. In the context of WSRec, SIoT networks will be able to provide some of the most vital benefits: (1) Social relationships among physical objects could be exploited to enhance recommendation results (e.g., trust value of objects could be used to evaluate trustworthiness of IoT services). (2) The understanding of service consumers' behavior could provide them suitable services that meet their needs. (3) A collaboration among users, services and objects, by collecting historical records (co-rated services, co-invoke users…etc.) could allow to analyze user feedbacks on services, to make decisions and to share experience with others.

In this dissertation, we investigated and launched a novel research direction and a unique view on

[2]https://www.brandwatch.com/blog/amazing-social-media-statistics-and-facts/. Accessed January 30, 2020.

the problem of service composition oriented end users in SIoT environment. In order to build an interactive service composition platform (S-SCORE), we proposed approaches for (1) discovering web services and suggesting personalized ones for end users, and (2) recommending trustworthy, personalized and suitable web services for users, and helps them to find relevant services for composition. The proposed approaches address the following: (i) problems of cold start and data sparsity in the selection of neighbors, (ii) the use of social knowledge mined from SIoT networks to ensure personalization and credibility of recommendation results, and (iii) an improvement of classical CF-based algorithms in the aim to increase prediction accuracy.

In this dissertation, we focused on the following key points:

For the theoretical aspects, in order to illustrate the basic concepts, we present an in-depth literature review and background in Part I, which is on the crossroads of four fields of research: the web and its related technologies, the Internet of Things, service composition and recommender systems. Those fields represent the perimeter of this thesis as shown in the following figure:

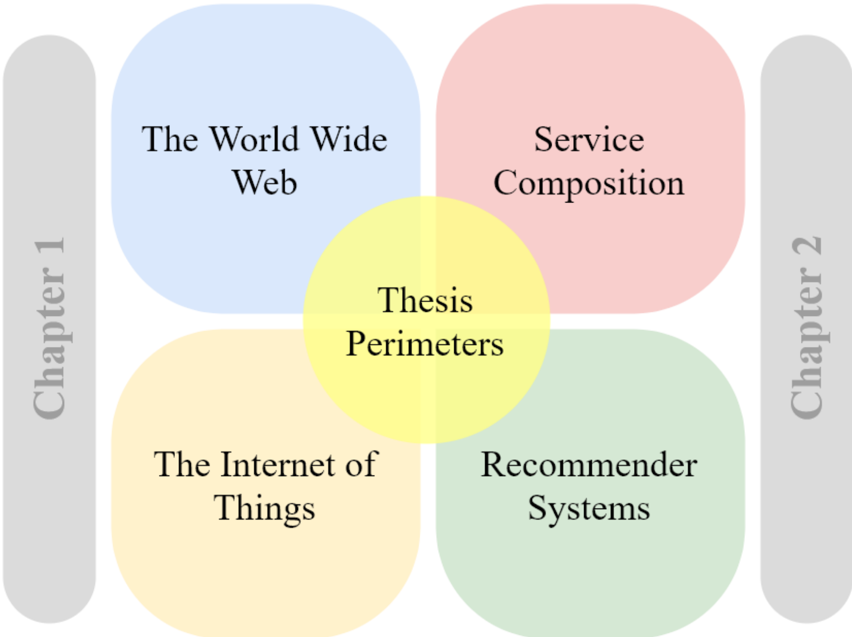

Figure 6.8: The perimeters of this thesis have presented in Part I.

In order to draw the main requirements and then to address them in the fields of service composition in social IoT environment, we have studied and analyzed the proposed approaches in social web and web of things environments in Chapter 3. Additionally, we surveyed the proposed solutions for WSRec by analyzing the classical models and the models that have been developed for SC. The aim of this review is to address the challenges of service recommendation in IoT-based environment in Chapter 4. By that, the research gaps have been identified from the proposed solutions and the challenges that need to be handled, which also presented the motivation of this thesis as shown in Figure 6.9 below.

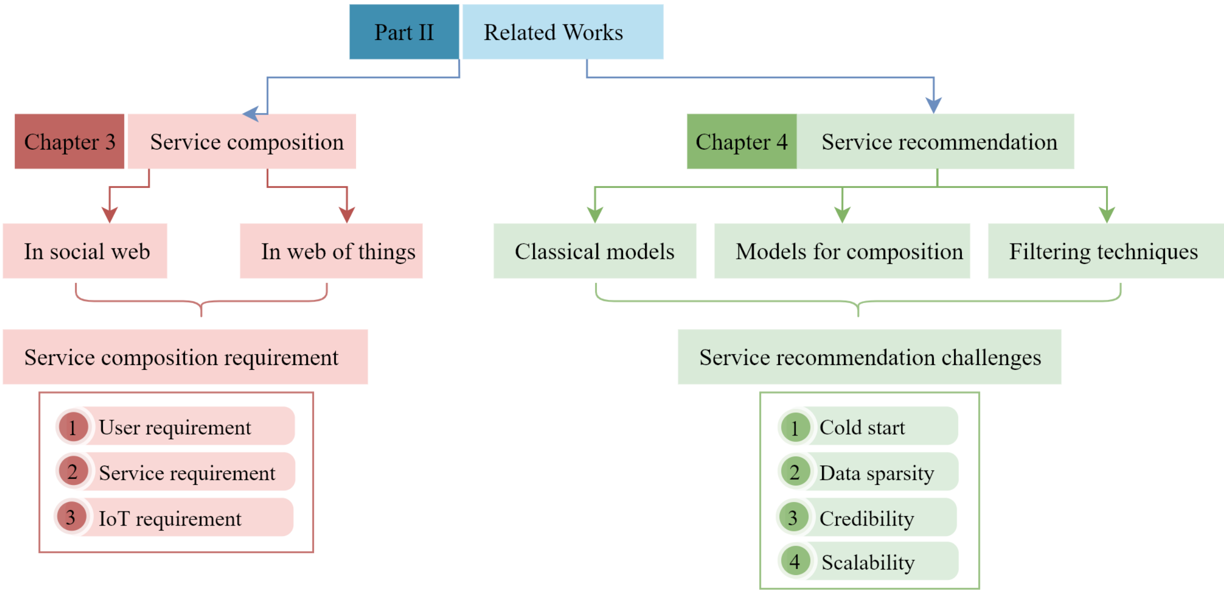

Figure 6.9: The summary and the synopsis of related work (Part II)

For the practical aspects, throughout the third part, we deal with the challenges and cover the different aspects of the above requirements. In this aim, the core contributions of this thesis are as follows:

- **A recommendation approach for service discovery (PWR):** that suggests to end-users personalized web services that meet their needs. The experimental results proved the improvement in prediction accuracy and diversity by our approach compared with seven methods.

- Service recommendation approach for composition: provides trustworthy and personalized services for composition. This mechanism is based on three sub-contributions:
  - **Model for user similarity computation (UMM):** a model for user similarity computation that allows to improve the quality of user neighbors. The proposed model combines contextual, social and historical information to overcome the cold start problem.
  - **Service collaboration measurement model (SCC):** a novel model for collaboration measurement among services
  - **Algorithm for rating prediction (HCCF):** based on collaborative filtering technique and clustering, it has been compared with the basic CF algorithms, and other extended methods of CF. The experimental results proved that our algorithm HCCF generates better performance within the metrics of MAE, coverage, F1-score and F2-score, compared with six baseline algorithms.

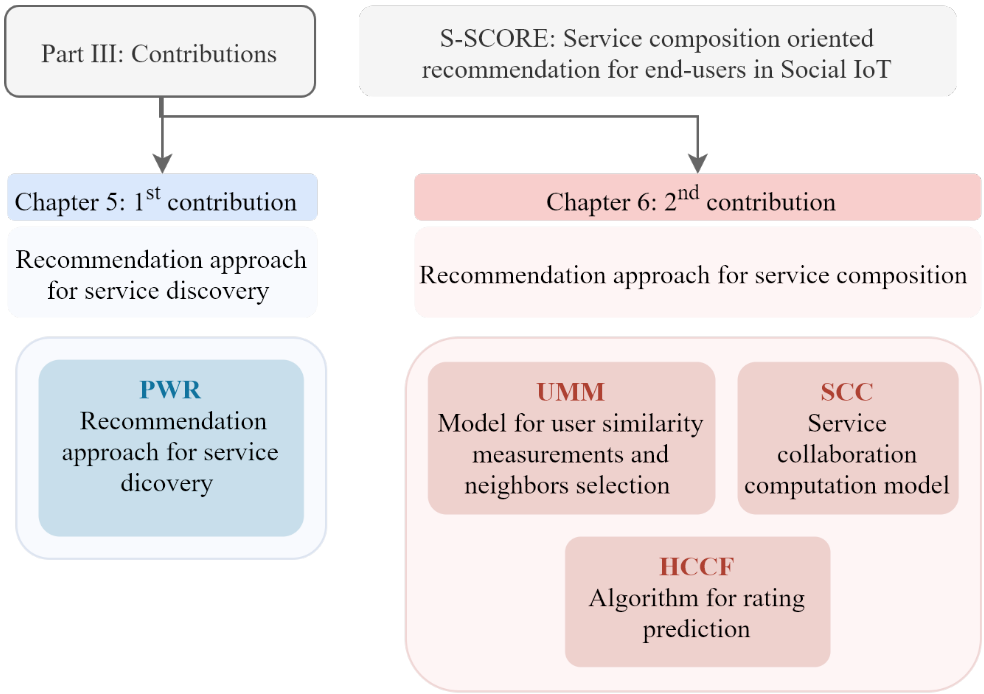

Figure 6.10: The summary of contributions of this thesis (Part III)

Future Works

As a matter of fact, within this thesis we could not handle every single issue related to the topic of service composition in IoT. Thus, In the future work, we have identified a set of research axes on:

- **Service composition in IoT:** extending the proposed approach of composition by adding another components to platform in order to meet the IoT challenges as execution module, adaptation module and device management. . . etc.
- **Social service Recommendation:** investigating and exploring other social relations among objects in SIoT (e.g., co-collaboration, co-location, co-ownership etc. [6]) that might be used to measure collaboration capability among services to further enhance the quality of recommendation.
- **Experiments:** while our solutions have been extensively evaluated by two datasets compared to numerous state-of-the-art methods, Developing extensive experiments on further datasets in order to expand the prediction quality is required for a better improvement.

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