TRUST MINING AND ANALYSIS IN COMPLEX SYSTEMS

A THESIS SUBMITTED TO AUCKLAND UNIVERSITY OF TECHNOLOGY
IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF PHILOSOPHY

July 2014

By
Jing Jiang
School of Computer and Mathematical Sciences

Copyright

Declaration

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the qualification of any other degree or diploma of a university or other institution of higher learning.

Signature of candidate

Acknowledgements

MPhil study is a challenging journey that could only have been completed with the help of many people.

First and foremost, I would like to express my sincere gratitude to my supervisor, Dr. Quan Bai, for his continuous support of my MPhil study and research, for his patience, motivation, enthusiasm, and immense knowledge and for opening the door to academic research for me. Over almost a year of development, Dr. Quan Bai helped provided guidance and he helped me select my thesis topic. He also provided encouragement, moral support and the freedom I needed to carry on, during the most challenging times while I was writing this thesis.

My thanks also go to Dr. Jiamou Liu. I am extremely grateful to him for his expert, sincere and valuable guidance and encouragement. I also thank my parents for their unceasing encouragement and support.

My thanks also go to all the faculty members of the Department of Computer and Mathematical Sciences for their help and encouragement. I am very grateful to Annie for proofreading and providing me with useful comments and suggestions.

And thanks go to Auckland University of Technology for providing me with all the necessary facilities as well as to the School of Computer and Mathematical Sciences for all of the funding they were able to provide me with in order to make this thesis possible.

Finally, I also place on record, my sense of gratitude and appreciation to one and all who, directly or indirectly, have lent their helping hand in this venture.

Abstract

A complex system, as a collection of loosely coupled interacting components, can group and create functioning units together. Complex systems have become a powerful framework for describing, analysing, modelling systems in nature and society. Trust among components, established by considering past interactions, represents a subjective expectation which a component has about another's future behaviour to perform given activities dependably, securely, and reliably. Hence, trust is essential to effectively reduce the perceived risks of transactions and guide future interactions. It is applied to quantify the performance of both individual component behaviours and the correlations among interdependent components in a complex system.

With regard to certain challenges in the current complex system research, this thesis deeply investigates trust relationships among components within two different types of complex systems, i.e., the collaborative complex system and the preference system, and proposes three trust estimation approaches. Firstly, collaborative complex systems consist of loosely coupled autonomous and adaptive components. In order to address complicated problems which usually require multiple skills and functions, components are grouped as composite teams and collaborate by providing different knowledge, resource and skill. Two types of team formation strategies for collaborative complex systems are proposed for scenarios of team formation without predefined workflow structures, and team formation with predefined workflow structures, respectively. Hence,

the *Correlated Contribution* trust evaluation model is proposed to explore the compositional trust through considering correlations and dependencies among both skills required by tasks and individual components within collaborative composite teams. Furthermore, we propose an automatic approach, i.e., the Same Edge Contribution trust evaluation model, to estimate the trustworthiness of proposed candidate composite teams by analysing historical provenance graphs which are adopted to capture predefined workflow structures. Finally, preference systems mainly focus on the entities with similar preferences and group them into various communities. However, in the real world, a particular entity usually places its trust differently from other social entities, because of their multi-faceted interests and preferences. In this thesis, a *Community-Based* trust estimation approach is proposed to explore the similarity of criteria or preference among entities within the same community in relation to a certain context. It automatically infers trust relationships among entities from previous entity-generated feedback, and predict a particular entity's potential feedback for items which the entity does not have previous experience with.

Publications

The followings are a list of my research papers that have been published during my MPhil study that is to end by the completion of this thesis.

1. Jing Jiang, Quan Bai, Minjie Zhang and Shaojie Yuan (2014). Community discovery for knowledge collaborations in collective intelligence systems. *Journal of Information Processing*, 22 (2), 243-252.

2. Jing Jiang and Quan Bai (2013), Provenance-Based Trust Estimation for Service Composition. In *26th Australasian Joint Conference on Artificial Intelligence: Advances in Artificial Intelligence* (pp. 68-73). Springer International Publishing, Dec 2013, Dunedin.

3. Jing Jiang and Quan Bai (2013), Correlated Contribution Analysis for Service Composition in Dynamic Environments, *2013 IEEE International Conference on Services Computing (SCC)*, pp.113-119, June 28 2013-July 3 2013, Santa Clara, CA.

Contents

Copyright **ii**

Declaration **iii**

Acknowledgements **iv**

Abstract **vi**

Publications **viii**

1 Introduction **1**

1.1 Complex Systems 2

1.1.1 Emergent Complexity 2

1.1.2 Characteristics of Complex Systems 4

1.1.3 Collaborative Complex Systems and Preference Systems . . . 6

1.2 Trust and Trust Mining in Complex Systems 7

1.3 Research Methodology 10

1.4 Research Objectives and Major Contributions of the Thesis 11

1.4.1 Compositional Trust in Collaborative Complex Systems 11

1.4.2 Context-Specific Inter-Personalised Trust in Preference Systems 12

1.5 Thesis Organisation 13

2 Literature Review **14**

2.1 Introduction 14

2.2 Direct Trust Evaluation Models 15

2.3 Reputation-Based Trust Evaluation Models 18

2.3.1 Trust Evidence Aggregation Approaches 19

2.3.2 Testimony Filtering Approaches 21

2.3.3 Socio-Cognitive Trust Evaluation Models 23

2.3.4 Organizational Trust Evaluation Models 24

2.4 Trust-Aware Interaction Decision-Making 25

2.5 Community-Based Trust Evaluation Models 27

2.5.1 Community Analysis and Mining 27

2.5.2 Community Detection Algorithms 29

2.6 Summary of Literature Review 32

3 Compositional Trust in Collaborative Complex Systems **34**
3.1 Introduction 34
3.2 Team Formation without Predefined Workflow Structure 36
3.2.1 Problem Definition and Assumption 37
3.2.2 Analysis of Correlated Contribution 39
3.2.3 Experiments 46
3.3 Team Formation with Predefined Workflow Structure 50
3.3.1 Problem Definition and Assumption 52
3.3.2 The Provenance-Based Trust Estimation Approach 53
3.3.3 Experiments 58
3.4 Summary 62

4 Context-Specific Inter-Personalised Trust in Preference Systems **64**
4.1 Introduction 64
4.2 Problem Definition 67
4.3 Trust Estimation Protocol 70
4.4 Hierarchical Community Structure 71
4.4.1 User Community 72
4.4.2 Object Community 76
4.4.3 Facet Object Set 82
4.4.4 Context-Specific Inter-Personalised Trust Calculation 85
4.5 Experiments 91
4.5.1 Experiment Setup 91
4.5.2 Comparison Method 92
4.5.3 Experimental Results 94
4.6 Summary 97

5 Conclusion **98**
5.1 Summary of Major Contributions 99
5.2 Future Works 101

References **102**

List of Tables

3.1 Setup of the three Experiments 59
3.2 Confusion Matrices for the *SEC* model and the *J48* model 61
3.3 Experimental Results 62

4.1 Fuzzy Rule Base Matrix 90

List of Figures

1.1 Diagram: Research Methodology 10

3.1 *Correlated Contribution* among Skill Types and Quality Contribution among Individual Services 38
3.2 Composition protocol 44
3.3 Changing Trend of Performance Quality of Composite Team by Using *Correlated Contribution* Model 48
3.4 The *Correlated Contribution* Model 48
3.5 The *Reputation-Based* Model 49
3.6 Comparison of QoS Distribution by using the *Correlated Contribution* Model, the *Reputation-Based* Model and the *Random* Model 50
3.7 Average QoS Level for *Correlated Contribution* Model vs *Reputation-Based* Model vs *Random* Model 51
3.8 Performance Quality distribution of Composite Team by Using the *Correlated Contribution* Model 51
3.9 Provenance Compositional Trust Estimation Protocol 54
3.10 Proposal Graph PRG 55
3.11 Provenance Graph PVG 55

4.1 Community-Based Trust Estimation Protocol 71
4.2 Distance Membership 87
4.3 Support Membership 88
4.4 Confidence Membership 90
4.5 Numbers of Reviews Rated by Users with Cold Start Users 92
4.6 Accuracy for Dataset with Cold Start Users 94
4.7 Accuracy for Cold Start Users 95
4.8 Difference for Dataset with Cold Start Users 95
4.9 Difference for Cold Start Users 96

Chapter 1

Introduction

Traditionally, the view of science holds knowledge to be specific and, thus, most knowledge may usually be gained by studying more details of certain systems. Once the view has led to professional specialization, the individual disciplines have progressively become more and more isolated from one another. Therefore, nowadays, scientific research is becoming increasingly universal and holistic, more emphasized on system-level behaviour rather than system constituents, but also increasingly multidisciplinary as the existence of potential synergies across different fields in being acknowledged (Bar-Yam, 1997).

Recently, the study of complex systems in a common framework has become recognized as a new discipline, breaking barriers to a wide range of domains, such as social network, scientific collaboration network, biology, economics, service-oriented systems, e-commerce, and psychology (Newman, 2003). There are three primary reasons for the emergence of the complex systems research. Firstly, the large increasing amount of data on diverse systems become available. Secondly, more sophisticated mathematical machineries and approaches are developed for tracking these problems. Thirdly, the advances in computing technologies and computational capacity enable simulations and analysis of these systems.

Complex systems have become a powerful framework for describing, analysing, modelling systems in nature and society. In this framework we learn about a system by studying its network representation. The network represents a complex system by focusing mainly on the essentials and elements denoted by nodes (vertices), and interactions among the elements denoted by edges. For example, a scientific collaboration system can be described as a complex network of diverse domain experts connected by cross-domain problems. The approach is possible because the interaction topology of the underlying system, captured by the network, is related to its function and dynamics. Therefore, in this thesis we also learn about a complex system by studying its network representation.

1.1 Complex Systems

A complex system contains a number of loosely coupled interacting components. The components may flexibly group together toward achieving different incoming tasks. The system become complex due to a characteristic set of evolving behaviours in both system and subsystem levels, and the dynamic relationships among system components. In order to understand a complex system well, we need to analyse the behaviour of individual components and also the interrelationships among components in different levels. Moreover, identifying and describing a system or hierarchies in a system requires certain levels of abstractions (Bar-Yam, 1997; Mitchell & Newman, 2002).

1.1.1 Emergent Complexity

The emergent complexity is defined as the behaviours of a number of components interacting in a way that the behaviour of the whole is complex (Bar-Yam, 1997). Components are those parts of a complex system that may be considered simple when describing the behaviour of the whole. Simple systems may also consist of parts, yet their behaviours usually are predictable and understandable. However, a complex system may consist of a large number of components whose behaviours are emergent. Namely, the behaviour of a complex system cannot be simply inferred from the behaviours of its components. The amount of information necessary to describe the behaviour of such a system is a measure of its complexity. In addition, the term "interconnected" are essential to distinguish a simple system and a complex system. In a complex system, each component must be described in relation to other interacted components.

Connectivity and interaction are necessary elements of the emergence of complexity. Interactions among individual components in a complex system often lead to "large-scale behaviours" that are not easy to predict only from the knowledge of the individuals. Such collective effects are called "emergent" complexity. Namely, the behaviour of many simple components interact in such a way that the behaviours of the whole is complex (Bar-Yam, 1997). Examples of emergent complexity include short and long-term climate changes, price fluctuations in markets, and so forth.

A complex system is identified with a global emergent property which is being formed out of interdependent components. In contrast to "interacting", "interdependent" not only demonstrates strong interactions among components, it also implies that each of the components may have an influence on the others (Bar-Yam, 1997). Therefore, the interdependent property may lead to unintended and unanticipated output for a complex system. For example, in an ecosystem, which is another typical complex system, the increase of temperature can be caused by the composition of the atmosphere, the solar radiation budget, the Earth's albedo, or a combination of all of these factors. Moreover, these factors are also dependent on one another. Changes in atmospheric composition can lead to changes in precipitation rates, which can lead to changes in the percentages of land covered by snow and ice, thus changing the Earth's albedo. Finally, human activities also result in the change of global climate. In this case, it is obviously hard to know exactly which and how these factors contribute to the observed output.

1.1.2 Characteristics of Complex Systems

The complex system is a model for thinking about the real world around us, and for understanding universal laws and phenomena in relation to the great complexity and variety of systems. The main purpose of studying the complex system is to extract general principles and the complexity which usually exhibits the following important characteristics.

- Interacting components in the complex system can be organised into nested groups which are represented as organisational hierarchies. Low level components are joined into subsystems, and these groups are joined into higher level margaropus or whole system. For example, if we make a graph of social interactions of "who talks to whom", the clusters of dense interaction in the graph will identify a hierarchical structure. The group detection process in this structure may be defined operationally by some measure of frequency of interaction in the sociometric matrix (Garud, Kumaraswamy & Langlois, 2009).

- A complex system becomes complex because of a characteristic set of evolutionary process. Evolution is a general approach to the formation of complex organisms from simple parts through incremental change. Hierarchic systems evolve more quickly than non-hierarchical ones of comparable size (Jennings, 2001).

- A complex system can be decomposed as a set of more manageable interrelated subsystems, each of which is in turn hierarchical in structure, until the lowest level of elementary subsystem is reached. Each subsystem can be dealt with in relative insolation to help reduce complexity. However, the appropriate coarseness on which to ground a model is determined by the function task of interest, because the complex system is differentiated in interlinked levels of organisation without preferred granularity level. The structure of a complex system consists in the patterns that are caused by particular objects and the interactions among components.

- Relationship between components and subsystems are dynamic and vary over time in a complex system. This is because that the selection of system components are primitive and relatively arbitrary. It is defined by the observer's aims and objectives (Jennings, 2001). The ability to specify and enact organisational relationships is helpful for tackling complexity by not only enabling a number of basic components to be grouped together and treated as a higher-level unit for analysis, and it also helps by providing the meanings of describing high-level relationships among the various parts. Therefore, to analyse the behaviour of a complex system, the relationships among the components can be more important than their individual characteristics.

- In complex systems, interactions within subsystems are more frequent and predictable than those among subsystems. Therefore, it raises the decomposable attribute of a complex system and some of these interactions are predictable. Rich interactions among complex systems and their environments also connect different domains in various ways. The effects of those changes might propagate through a system and into other domains (Chu, Strand & Fjelland, 2003).

- Feedback mechanism is a threshold concept for understanding complex systems, which is difficult to learn yet transformative once mastered (Kastens et al., 2009). A feedback loop is the update of a feedback value (either increasing or decreasing). After feedback loops a few times, small changes in the initial conditions of the system can have significant effects after they have passed through the emergence. Therefore, feedback provides complex systems with a contextual dementedness that makes system boundaries fuzzy and difficult to demarcate.

1.1.3 Collaborative Complex Systems and Preference Systems

As mentioned in Subsection 1.1.2, a complex system contains a number of loosely coupled interactive components with dynamic behaviours. Many existing systems with such features can be considered as complex systems. This thesis mainly focuses on two types of complex systems, i.e., collaborative complex systems and preference systems, which commonly occur in many real world applications. Both of these two types of complex systems can be thought of as social systems which consist of social entities or groups of social entities (components) with some pattern of contacts or interactions between them (Newman, 2003). Social networking service is a platform to build social relations and interactions among entities. Moreover, in this thesis, the feedback is represented as a numeric rating value. However, as the social entities and feedback generation mechanism have different meanings in different system, we will describe them in detail in this subsection.

Collaborative Complex Systems

Collaborative complex systems are typically affiliation networks in which participants with different knowledge, resource and skill collaborate in groups of one kind or another for diverse complex problems, and links between pairs of individuals are established by common group membership (Newman, 2003). The collaboration of actors and directors is a classic example of collaborative systems, which is published in the online *Internet Movie Database* (*IMDb*) [1] and each movie has a rated value. In this example, actors and directors collaborate in movies and pairs of actors/directors are connected if they have appeared in a movie together. Co-authorship among academics is another example of collaborative complex systems, where researchers, who have coauthored papers, are linked. Moreover, in collaborative systems, trust feedback is normally generated

[1] http://www.imdb.com

by using unified assessment standards. Hence, according to the same standard, each composite team will be evaluated and given feedback related to the interaction between entities.

Preference Systems

Preference systems mainly focus on the entities with similar preferences and group them into various communities. There are two popular community detection approaches, i.e., topological and topical. The topological-based community detection approach considers the graph structure of a network. On the other side, the topic-based community detection approach mainly focuses on the analysis of the textual information of network nodes. In both of these two approaches, the edge linking a pair of entities can be weighted by the strength of preference similarity (Ding, 2011).

Usually, a preference system consists of two kinds of nodes representing individuals and the objects of their preference. For example, customers are connected with the books they bought with rating values. Therefore, a preference network also can be represented as a bipartite network. The *EachMovie* dataset [2] of movie preferences is a particular examples of a preference system. In order to predict users' preference similarity of movies, the collaborative filtering algorithms and recommendation systems are widely applied based on comparisons of individuals' rating histories (feedback).

1.2 Trust and Trust Mining in Complex Systems

Components in complex systems interact with each other, and trust is a subjective expectation a component has about another's future behaviour to perform given activities dependably, securely, and reliably based on experiences collected from previous interactions (Skopik, Truong & Dustdar, 2009). In a complex system, trust among

[2] http://research.compaq.com/SRC/eachmovie

components is established by considering past interactions in particular situations. By representing a complex system as a network, entities (components) can be denoted as vertices and interactions among them can be denoted as edges, and the feedback of component interactions can be represented as edge weights.

As previously discussed, the complex system is identified by the significant correlations among interdependent components (Maturana, 1980). Trust is essential to effectively reduce the perceived risks of transactions and guide social interactions (Metzger, 2004). We apply trust to quantify the performance of both individual component behaviours and the collaborative relationships among components in a complex system.

There are three main characteristics of a foundational trust model (Skopik, Schall & Dustdar, 2010), as follows:

- Trust is extracted from previous interactions and supports the inference about a prediction of components' future performance
- Trust is influenced by subjective perceptions of the involved components, so it cannot be expressed objectively.
- Trust is context dependent and is basically valid within a particular facet only, such as the interest and criterion of a book about a certain domain.

There are five popular interaction metrics translating the feedback to trust values in particular situations (Skopik et al., 2010).

- Background metrics: an entity's expertise and knowledge degree in distinct domains.
- Similarity metrics: entities' criteria and interests similarities in certain domains.
- Trust Metrics: the trust relationship among entities in particular domains which are interpreted from the background metrics and similarity metrics.

- Collaboration metrics: the reliability of the collaboration between two social entities.
- Group metrics: the reliability of the service group composition

As trust value cannot be obtained directly and the main process is to interpret feedback from previous interactions in a complex system through different approaches. Based on previously mentioned characteristics and metrics, in this thesis, we intend to mine different trust from collaborative complex systems and preference systems through analysing historical collaboration records and the similarity of dynamically adapting interests and opinions among social entities, respectively.

Firstly, for collaborative systems, interactions among components signifies that, according to the complexity of the problem, a group of skill providers collaborate together by providing particular skills to satisfy the function requirements. Trust relationships among skill providers indicate whether they are willing to collaborate or not, and how confident they are in predicting others' future performances. Therefore, we consider trust in a collaborative system as **compositional trust**, which exists within groups consisting of more than two components. Due to the emergent complexity and characteristics of the complex system, it is hard to know exactly which and how these individual components contribute to the observed output. Hence, it is challenging to have an accurate trust evaluation without analysing the inter-relationships among the different components in a collaborative system.

Secondly, in terms of preference systems, two different kinds of interactions exist, i.e., "user-object" interaction and "user-user" interaction. Moreover, these two types of interactions reveal different types of trust relationships. The "user-object" interaction indicates the trust relationships between users and objects. Furthermore, it reveals which kinds of preference and criteria the user holds in relation to particular items. The "user-user" interaction reveals the trust relationship between users. It indicates whether a user trusts the feedback from other users on particular items or not. As the characteristic of trust, the feedback which users give on different items is not always objective, and, furthermore, social entities have different criteria to establish trust with others. Hence, trust interpreted from such user-generated feedback is influenced by subjective perceptions of the users involved. Therefore, trust relationships among users are context dependent and basically valid within a particular facet only. According to interactions and trust relationships types, we want to mine, from preference, context-specific inter-personal trust which combines both personalised feedback and the multi-faceted trust. Context-specific inter-personal trust is based on the diversity of trust by enabling the flexible aggregation of various interaction metrics that are determined by observing ongoing collaboration.

1.3 Research Methodology

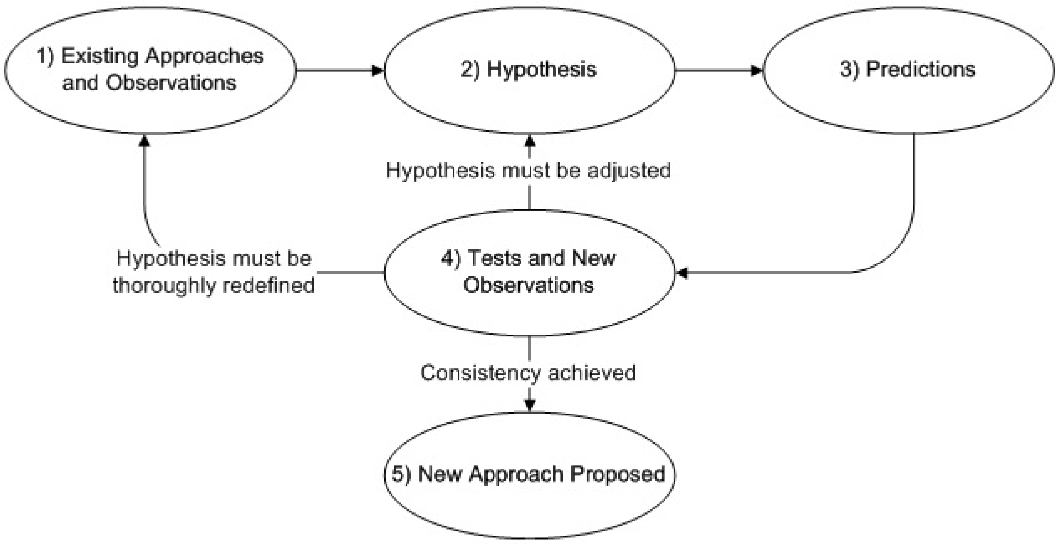

Figure 1.1: Diagram: Research Methodology

Research is a systematic and methodical process of enquiry and investigation. The research methodology is a standard on how to do research that aims to discover new knowledge. The steps of research by the research method can be summarized into five steps and shown in Figure 1.1. In the first step, we review the existing approaches and observations with regard to what has already been researched related to complex systems. This is in order to clearly define our research questions. In the second step, according to each defined research question, we formulate a hypothesis as a tentative answer. Thirdly, we can deduce consequences and make predictions regarding potential outcomes. Fourthly, the hypothesis is tested in a specific experiment field. We construct experiments to collect and analyse data to see whether it supports or rejects our hypothesis. The new hypothesis has to prove and offer considerable advantages, in order to replace the existing approaches and observations. Then step 2 through 4 is repeated with modifications of the hypothesis until agreement is obtained. Finally, at the time consistency is obtained, the hypothesis becomes a theory and new approaches are proposed (Dodig-Crnkovic, 2002).

1.4 Research Objectives and Major Contributions of the Thesis

Due to the characteristics of different types of complex systems, different trust management approaches can be applied in different complex systems. In this thesis, we propose three approaches for two different complex systems.

1.4.1 Compositional Trust in Collaborative Complex Systems

As previously mentioned, a collaborative complex system consists of a number of loosely coupled autonomous and adaptive components. In such systems, a unified assessment standard is normally predefined. The performance of all composite teams for completing different tasks can be evaluated based on the unified assessment standard.

Furthermore, a composite group can only obtain an overall rating for the completion of each task. It is hard to know exactly which and how these team members contribute to the observed output feedback value.

In this thesis, we intend to mine the compositional trust of each of the candidate components for a certain complex problem request. As the emergent complexity and characteristics of the complex system, in order to understand and predict the behaviour of a composite team, it is necessary to analyse the behaviour of components, and it is also necessary to investigate how they work together to form the behaviour of the whole is also need to be investigated. Compositional trust is evaluated from a dynamic point of view, whereby entities select interaction partners flexibly in a complex system.

1.4.2 Context-Specific Inter-Personalised Trust in Preference Systems

According to the decomposable characteristic of complex systems, we consider a preference system as a set of manageable interrelated subsystems, and manage them in relative insolation to help reduce complexity. However, most existing trust mining approaches for preference systems mainly focuses on the analysis of preference similarity among individual entities (Luo, Niu, Shen & Ullrich, 2008). In this thesis, we want to propose a rational approach which combines user criteria clustering and link analysis for objects to group entities into various subsystems. The combination is based on a subsystem (community) structure to model and analyse the massive dataset with interactions in preference systems.

The context-specific inter-personalised trust is considered as the similarity of criteria or preference among users within the same community in relation to a certain context. As the users within one community are closely connected, meanwhile they have the same criteria for certain groups of items. The proposed approach can make more accurate context-specific inter-personal prediction for users' expectation.

1.5 Thesis Organisation

The remainder of this thesis is organised as follows.

In Chapter 2, we classify current trust evaluation models into four types in terms of the different risk estimation techniques that are employed. Then, different trust evaluation models are reviewed and discussed from different perspectives.

In Chapter 3, we propose two trust evaluation approaches, i.e., the *Correlated Contribution* model and the *Same Edge Contribution* model, to explore compositional trust in terms of different composite team execution mechanisms in collaborative complex systems. In addition, we define team formation strategies into two categories, i.e., team formation without predefined workflow structures, and team formation with predefined workflow structures. Experimental comparisons between two proposed models and traditional approaches are also introduced.

Chapter 4 presents a community based approach for modelling and analysing context-specific inter-personalised trust in preference systems. The proposed approach combines the idea of traditional recommendation systems and identification of cluster structures to explore heterogeneous trust relationships among diverse components. The experimental results validate the effectiveness of the community based approach comparing it with the traditional user-based collaborative filtering algorithm, the item-based collaborative filtering algorithm, and the K Nearest Neighbour (*KNN*) algorithm.

Finally, the contribution of this thesis and future work related to this research are presented in Chapter 5.

Chapter 2

Literature Review

2.1 Introduction

In a complex system, components interact with others to achieve their goals. In this process, components are exposed to the risk of being exploited by others. In recent years, researchers from various fields with different viewpoints have developed diverse trust evaluation models for different complex systems with different characteristics. In this chapter, some existing related research work and important techniques of trust evaluation are reviewed.

In this thesis, we categorised trust evaluation models into four types in terms of the diverse potential risk estimation techniques employed: (1) direct trust evaluation models which rely on historical observed direct experience; (2) reputation-based trust evaluation models which depend on third party (indirect) testimonies from other components in the same environment; (3) trust-aware interaction decision-making models which select interaction partners based on candidate components' trust values evaluated by different algorithms; and (4) community-based trust evaluation models which cluster components into tightly knit groups with density of internal interactions through interpreting past interactive behaviours and communication via direct or indirect connections in social media (Girvan & Newman, 2002).

We analyse and review these existing trust evaluation models from different perspectives: the problems these approaches attempt to address, the suitable operating situations, the advantages and limitation of these approaches. In additional, we also discuss whether these approaches can be adopted to mine compositional trust and context-specific inter-personalised trust in collaborative and preference complex systems.

In Section 2.2, we review a number of direct trust evaluation models, and the reputation-based trust evaluation model is mentioned in Section 2.3. In contrast to the direct trust evaluation model, reputation-based trust evaluation models help a truster build its trust model of a potential trustee by requesting indirect trust evidence from third-party. In terms of different sources of trust evidence and filtering out biased testimonies, reputation-based evaluation models can be classified into four categories: trust evidence aggregation approaches (Section 2.3.1), testimony filtering approaches (Section 2.3.2), socio-cognitive trust evaluation model (Section 2.3.3) and organizational trust evaluation models (Section 2.3.4). In Section 2.4, in terms of receiving a cross domain task, trust-aware interaction decision-making approaches are proposed to help a truster to decide how to select a potential trustee to collaborate with. Finally, we review community-based trust evaluation models in Section 2.5 to analyse how to mine trust information from social media in regard to user-generated content.

2.2 Direct Trust Evaluation Models

Direct trust evaluation models establish trust among components within complex systems through observing the outcomes of a truster's previous interactions with a trustee to estimate that trustee's future behaviour. Hence, the historical interaction outcomes serves as the direct evidence available for trustees' trustworthiness evaluation (Yu, Shen, Leung, Miao & Lesser, 2013). The risk of interactions is considered as the probability of being cheated by the interaction partner based on the outcomes of previous interactions. The direct trust evaluation model is advantageous when components have opportunities for numerous and frequent interactions. When the outcomes of interactions are observable, transaction experiences provide a candidate truster with trustworthiness feedback that is certain (Fullam & Barber, 2007).

The Beta Reputation System (*BRS*), proposed by Jsang and Ismail (2002), is inspired by the Beta distribution to project past interaction experience with a trustee entity into its possible future behaviour and provide a measure of its trustworthiness prediction (Jsang & Ismail, 2002). The reputation of a trustee is defined as the probability expectation value of a distribution that consists of the positive and negative feedback about it and the *BRS* estimates the trustworthiness of a trustee by calculating its reputation. Due to the belief, disbelief and uncertainty with respect to the truthfulness of the feedback, the *BRS* may discount the expectation value of candidate trustees' future behaviour and then introduce a time decay factor to allow past evidence to gradually diminish. However, the *BRS* can only generate a binary value (i.e. successful/unsuccessful) for the predictive outcome of an interaction between the truster and trustee.

In contrast to the *BRS*, the Dirichlet Reputation System (*DRS*) is proposed to handle cases where the interaction outcomes are rated on a multinomial scale by Jsang and Haller (2007) (Jøsang & Haller, 2007). In terms of a finely grained rating value, the *DRS* introduces several approaches to derive the reputation of candidate trustees, such as an evidence representation, a density representation, a multinomial probability representation, and a point estimate representation. The basic principle underlying the *DRS* model is similar to that in the *BRS*, even so previous two representation are still difficult for human interpretation.

Furthermore, in a complex system, there are multiple factors that may affect the performance of a trustee, so a several multi-dimensional trust model is proposed. An experience-based multi-dimensional trust evaluation approach is proposed by Griffiths (2005) which models the trustworthiness of candidate trustees to minimize the risk associated with cooperation. It mainly assesses the trustworthiness of a trustee along four dimensions: 1) the likelihood that it can successfully generate an interaction result; 2) the likelihood of delivering an interaction output within the expected budget; 3) the likelihood of completing the task within the specific deadline; 4) the likelihood that the quality of the result meets the expectation (Yu et al., 2013). Based on the truster's personal preference with respect to these four dimensions, a weighted average approach is applied to calculate the trustworthiness of candidate trustees. However, the experience-based multi-dimensional trust evaluation approach can only predict the component's future behaviour according to its previous individual performance.

The Priority-Based Trust Model (*PBTrust*) is proposed by Su, Zhang and Mu for selection of candidate service providers (trustees) in general service-oriented environments, according to the priority distribution on attributes (multi-dimensional factors) from the perspective of the consumer (truster). The *PBTrust* model evaluates the reputation for a candidate trustee from four perspectives: 1) the trustee's historical interaction experience; 2) the similarity of priorities distributions on attributes between the referenced experience and the request; 3) the suitability of the candidate trustee for the request and the time effectiveness of ratings from third parties (Su, Zhang, Mu & Sim, 2010). The *PBTrust* model evaluates the component's historical performance and weights rating from a third party reference based on time stamps. However, it still cannot be applied to predict the performance of a trustee group.

In 2011, Su et al. introduce a *GTrust* model for group services selection for a multi-dimensional service request. There are four merits being employed: 1) the functionalities coverage which a potential service group can provide corresponding to the request from the consumer; (2) the dependency degree among trustee service providers in a service group; (3) the historical performance of candidate trustee service providers; and (4) the similarity in terms of priority distributions on attributes between historical services of group members and requested services. The *GTrust* model adopts the group's overall performance as the reference report for each of the members of the group during the updating of their historical records. However, the dependency degree among group members is needed to be predefined and it ignores many other factors such as the uncertainty of the environment and the correlation among the truster and candidate trustees (Su, Zhang, Mu & Bai, 2011).

The evidence-based trust model introduced by Wang and Singh (2007) quantifies the uncertainty of trust evaluation evidence for two crucial characteristics, i.e., dynamism and composition. It not only considers the challenge that trust evolves over time, it also combines trust reports which cannot themselves be perfectly trusted, possibly because of their provenance or the way in which they are obtained. The evidence-based trust model satisfies two main insights. Firstly, if the amount of trust evidence is large, the certainty is high; secondly, if the conflict among the feedback is low, the certainty is high. Even though the evidence-based trust model takes the dynamic characteristic of complex systems into account, it is only effective to predict the future behaviour of individual candidate trustees. Another significant drawback of approaches reviewed in this section is that they evaluate the trustworthiness of candidate without considering the context. However, trust is context dependent and only valid within a particular facet only.

2.3 Reputation-Based Trust Evaluation Models

Reputation can be defined as the opinion or view about someone on something and it is useful for quickly learning trustworthiness characteristics of potential trustees without previous direct interactive experience (Ramchurn, Huynh & Jennings, 2004) (Fullam & Barber, 2007). Reputation can be evaluated based on two kinds of evidence, i.e., the direct interaction experience, and 2) the information provided by other members of the society about experiences they have had in the past (Sabater & Sierra, 2001). Even though direct evidence usually is the most relevant and reliable sources for the trustee evaluation, but it may not always be available, because if a large number of components exist within a complex system, the interaction among them is rare. Hence, reputation-based trust evaluation models adopt indirect evidence from the third party to complement direct experience for estimating a candidate trustee's trustworthiness (Yu et al., 2013).

Through reputation-based trust modelling, a truster establishes its trust of a potential trustee by requesting indirect trust evidence from a third-party (Fullam & Barber, 2007). Such indirect trust evidences can be classified as three types, i.e., 1) witness reputation: based on the information about the target components coming from others, 2) system reputation: it is a default reputation value based on the role that the target component played in the complex system, 3) neighborhood reputation: in terms of the social environment of the target component, that is, the neighbours of the target and their relations with it (Simmhan, Plale & Gannon, 2005). In terms of the indirect trust evidence, the possibility of receiving biased testimonies exists which can negatively influence the trust-aware interaction decisions. Therefore, the main purpose of the reputation-based trust evaluation model research is to mitigate the adverse effects of biased testimonies and aggregate trust evidence from diverse sources.

2.3.1 Trust Evidence Aggregation Approaches

As previously mentioned, there are two kinds of trust evidence: direct trust evidence and indirect trust evidence. Many existing trust reputation-based approaches adopt a weighted average method for aggregating these direct and indirect trust evidences. For example, the direct trust evidence is assigned with a weight of γ, $(0 \leq \gamma \leq 1)$, and the indirect trust evidence is assigned with $(1 - \gamma)$ (Yu et al., 2013). There are two trust aggregating categories, i.e., static approaches which predefine the value of of γ, and in dynamic approaches, the value of γ can be adjusted.

The direct trust revision is a static trust aggregation approach based on multi-agent belief revision (Barber & Kim, 2003). In this approach, direct trust is aggregated through dissimilarity measurements. On the other side, indirect trust evidences retrieved from communication between components gives an accurate picture more quickly, that is, assuming the reputation information from third-party is accurate. However, some existing static approaches exclusively use only one source of trust information, so advantages of trust source previously mentioned are missed (Jonker & Treur, 1999; Schillo, Funk & Rovatsos, 2000). Therefore, a predefined static value of γ usually is not a good trust evaluation strategy for dynamic environments (Yu et al., 2013).

Mui, Mohtashemi and Halberstadt (2002) proposed an dynamic trust aggregation model by increasing the value of γ with the changing number of direct interactive candidate trustees. It is supposed that the amount of direct trust evidence of trustees is accumulated gradually from no prior interaction experience. The advantage of this model is that it proposes a probabilistic mechanism for inference among direct trust and indirect trust evidence, and level of reciprocity. At the beginning, the direct trust evidence is zero (i.e. $\gamma = 0$), so the truster completely relies on the indirect trust evidence to select potential trustees. With the increasing number of interactions, the value of γ also rises (Mui et al., 2002). However, once the value of γ reaching to 1, the approach implicitly assumes that behaviors of the potential trustee do not change with time and ignore most dynamic scenarios.

Fullam and Barber (2007) demonstrate Q-learning method for identifying the best γ value (combination of direct trust evidence and reputation-based models). Based on the reward accumulated by a truster agent under different γ values, the method selects the value of γ associated with the highest accumulated reward. This research approach assumes consistent reputation errors and ignores the problem of identifying the most reliable third-parties, who provide reputation information. Furthermore, a truster has to learn separate γ values for each candidate trustee since interactions frequency, accuracy of reputations, and trustee trustworthiness characteristics may be diverse (Fullam & Barber, 2007).

2.3.2 Testimony Filtering Approaches

As previously mentioned, the reliability and accuracy of third-party also influences the quality of trust evaluation. In this section, we mainly discuss some representative models for filtering potentially biased third-party testimonies. Most of these models assume some infrastructure support or special characteristics exist in the environment, so each of them has different limitations.

The Regret system presents how the social relationships among the components of a complex system can be used in a reputation system that takes into account the social dimension of reputation (Sabater & Sierra, 2001, 2002). Based on the combination of complementary methods which utilize various aspects of the interaction and social relations, the Regret system enables the component to calculate reputation values at different stages of its knowledge of the society (Sabater & Sierra, 2002). It predefines fuzzy rules to estimate the credibility of each witness which is then used as the weight of third-party testimony for a trustee component when aggregating all the testimonies. Therefore, this model relies on the availability of social network information among components.

Weng, Miao, and Goh (2006) proposed an entropy-based approach to measure how much a testimony deviates from the current belief of the truster before deciding whether to incorporate it into the current belief. Unlike some other existing methods, the proposed method does not require the assumption regarding the rating distribution to carry out the testimony filtering. For example, the approach introduced by Whitby, Jøsang and Jadwigato (2004) assumes that the majority opinion is always correct and records testimonies in the form of counts of successful and unsuccessful interactions with potential trustees. In contrast, the entropy-based approach scales linearly with the increase of the testimony number. Even so, in terms of entropy-based approaches, sufficient direct interaction experience with a trustee is required, even though it conflicts with the purpose of the reputation-based trust modelling which is to help truster make reliable decisions when trusters lack of direct trust evidences.

An integrated clustering-based approach (*iCLUB*) proposed by Liu et al. (2011) filters unfair testimonies for reputation systems using multi-nominal testimonies. It adopts two rounds of clustering of the received testimonies to identify testimonies which are extremely positive or extremely negative about a trustee. However, due to the iterative nature of *iCLUB*, the computational complexity of this approach is high. Furthermore, like the approach introduced by Whitby, Jøsang and Jadwigato (2004), the *iCLUB* is also not robust in most hostile environments where the majority of the witnesses are malicious.

In practice, the information about prior experience of witness components usually is obtained piecemeal and is required to be maintained over time. A probabilistic approach introduced by Wang, Hang and Singh (2011) assist a truster to update its trust on a potential trustee on an ongoing basis and allow both trust and certainty measures to vary incrementally when new trust evidence is available. However, the probabilistic approach does not accommodate either multi-valued events or distinct events whether a referral overestimates or underestimates the quality of the potential trustee.

2.3.3 Socio-Cognitive Trust Evaluation Models

In terms of the socio-cognitive trust evaluation models, when there is a lack of sufficient evidence to make a trust decision, it analyses the intrinsic properties of the trustee agents and the external factors as a complement to the evidence for inferring candidate trustees' future behaviors in interactions.

Castelfranchi, Falcone and Pezzulo developed a socio-cognitive trust model to distinguish internal and external attributions by using Fuzzy Cognitive Maps (*FCM*) (Castelfranchi, Falcone & Pezzulo, 2003). They introduced a degree of trust derived from the credibility of the trust beliefs, while the credibility of the beliefs depend on their sources and the sources' number, convergence/divergence and reliability. The main purpose of this approach is to capture trust variations instead of assigning absolute values to the trustee. However, belief source variations and the variations in value selection for causal links may dramatically influence the performance of the model, and it is difficult to verify the validity of the models produced.

Whereas the *SUNNY* model presented by Kuter and Golbeck (2007) provides an explicit probabilistic interpretation for confidence in social networks and produces a Bayesian Network suited for approximate probabilistic reasoning, confidence is used as heuristics to calculate the most accurate estimations of the trustworthiness of potential trustees in the Bayesian Network (Yu et al., 2013). The model developed by Ashri et al. (2005) builds up relationships between entities in an electronic marketplace and adopts this information to reason regarding the trustworthiness of candidate trustees. Then although these relationships are analyzed by an ontology-based framework to provide a realistic application of semantic web technologies, it is difficult to explore complex combinations of relationships (i.e., more than 3 entities in all relationships).

In complex systems, even though the short-term and temporal groups are formed to meet some specific goals, it is difficult to gain necessary information, with regard to prior interactive experience and social relationship information, to make an accurate trust evaluation. Therefore, the bootstrapping trust evaluations model introduced by Burnett, Norman and Sycara (2010) generates stereotypes with known partners and adopts these to form behavioral expectations about newcomer potential trustees. Such stereotypes are learned based on some visible features in existing trustees' profiles through a decision tree based technique. Even so, how to obtain reliable and enough visible features in trustees' profiles is also a challenge in the complex system.

The model proposed by Noorian, Marsh and Fleming (2011) contains a two-layer filtering algorithm that cognitively elicits the behavioral characteristics of the participating components in an e-marketplace. In the first layer, the competency of the truster's neighbours is measured according to the required experience and reliability. Afterwards, the second layer measures the similarity for opinions received from competent witness neighbours and the current belief by the truster self. This approach enriches the trustworthiness evaluation process by incorporating social entities' dispositions, such as optimism, pessimism and realism. As previously mentioned, as the notion of unfairness does not exclusively refer to deception, it can also imply differences in dispositions and criteria of social entities. Nevertheless, it only explores the personal disposition of social entity in the single world fact without considering the context-specific inter-personalised trust.

2.3.4 Organizational Trust Evaluation Models

If there exists at least one trusted third-party who can act as a supervising entity for the transactions among others in a complex system, an organizational structure can be introduced for trust management. The supervised interaction model, introduced by Kollingbaum and Norman (2002), is one of the earliest research works in this area. The supervised interaction consists of three elements, i.e., an organizational framework, a contract specification language, and a contract management process. Furthermore, three essential roles in the organizational framework are: the addressee, the counter-party, and the authority as a "trusted third party". In order to conduct transactions, an entity needs to register with the authority, negotiate with other entities to set up the terms in the contracts, and carry out the work required by the contracts under the supervision of the trusted third party.

The Certified Reputation (*CR*) model introduced by Huynh, Jennings and Shadbolt (Huynh, Jennings & Shadbolt, 2006a) allows entities to actively provide third-party references with certified ratings about their historical performances. In this way, trusters build up trust with their potential interaction partners, and the certified ratings are adopted as a standard part of setting up a transaction between a truster and trustee. Therefore, in terms of trusters, it is unnecessary to solicit third-party testimonies and then filter these testimonies. Furthermore, all available third-party references are sent to a truster directly, thus making the *CR* model suitable for distributed environments.

A role-evolution-based trust model introduced by Hermoso, Billhardt, Ossowski (2010) assigns components to different roles based on their observed performance in diverse types of interactions. Based on the descriptive features of roles, the model can identify potential trustees who are competent for a particular task. In complex systems, the role of each system component may gradually evolve, and, thus, dynamically change the organizational structure with the evolution of an organizational taxonomy.

2.4 Trust-Aware Interaction Decision-Making

The goal of trust-aware interaction decision-making is to help a truster decide which candidate trustee(s) is to be selected to perform a given task. The greedy and dynamic approaches are two popular trust-aware interaction decision making categories to help trusters to select potential trustees for interactions. The greedy approach tends to use simple rules to explore candidate trustees with a desired reputation standing through either some supporting infrastructure (e.g. peer recommendation, social network analysis, etc.) or random exploration. From an individual truster's point of view, the greedy approach is to select the best available option and help the truster achieve maximum long term wellbeing. Therefore, the reputation values of the candidate trustees are calculated using a choice evaluation model and the potential trustee with the highest reputation value is selected for interaction (Yu et al., 2013).

The aim of dynamic approaches is to balance the exploitation of known trustworthy candidate trustees with the exploration for potentially better alternatives by assessing the changing situation in the operating environment. In current computational trust literature, reinforcement learning is one of the most popular dynamic approaches. A computationally tractable Bayesian reinforcement learning algorithm introduced by Teacy et al. (2008) selects each trustee component for further interaction according to the Q-value from Q-learning as well as the expected value of perfect information of an entity's actions. At each time stamp, a truster entity selects an action sequentially to maximize its gain by assessing different conditions.

An adaptive trust-based sequential decision making model, introduced by Hoogendoorn, Jaffry and Treur (2010), dynamically determines the amount of exploration and exploitation the potential trustee performs. In this approach, each truster keeps the value of candidate trustees' both the long term trust based on experiences over a longer time period, and the short term trust based on the most recent set of experiences. The average absolute difference between long term and short term trust is used to estimate the collective degree of changes in trustees' behaviours. When the collective degree is equal to 0, the trustee with the highest reputation evaluation is always selected for interaction.

In highly dynamic complex systems, if it is hard for components to form stable trust relationships necessary for confident interactions, the system may break down, because the trust between components is too low to motivate interactions. Therefore, except for decisions in regard to the balance of exploration and exploitation, Burnett, Norman and Sycara also introduced additional mechanisms to induce the desired behaviour from candidate trustees (Burnett, Norman & Sycara, 2011). There are three kinds of controls which permit interactions when trust is low, i.e., explicit, monitoring, and reputational incentives. By employing such controls in addition to trust, the truster can be motivated to provide some crucial initial interactions which is necessary to bootstrap trust.

The trust-related decision is not only related to whom to trust and how trustworthy to be, it is also relative to which reputation information to believe and how truthful to be when exchanging reputation information with others. As previously mentioned, most trust evaluation models are designed to help trusters select potential trustees. In contrast, Fullam and Barber (Fullam & Barber, 2006) introduced an interesting model, which can help candidate trustees to explain the interdependencies between decisions which a truster may face in systems with reputation exchange and correlate rewards to each decision. Based on a case study of the Agent Reputation and Trust (*ART*) Testbed, the interdependencies, rewards and complexities of these decisions are explained. Then, a Q-learning approach is employed to help trusters determine the factors relating to the trust-related decision.

2.5 Community-Based Trust Evaluation Models

2.5.1 Community Analysis and Mining

In terms of social media, it can be defined as a group of web-based applications that allow the creation and exchanges of user-generated content. The main purpose of social media gives entities an easy way to communicate and network with each other. Social trust among social entities refers to interpretation of previous interactive behaviors and communication in social media. In most situations, previously mentioned trust evaluation models are suitable for the social network trust evaluation. For example, in scientific collaboration systems, once a cross-domain problem is proposed, based on the feedback of previous social interaction, candidate experts are evaluated and compose a group to complete the request, by using direct trust evaluation models, reputation-based trust evaluation models, or trust-aware interaction decision-making approaches.

However, in some social complex systems, social entities are indirectly connected via interacting with same intermediate entities. Social media, such as opinion, reviews and ratings, enables people to connect friends and find new users with similar interests. Therefore, the trust between social entities may be interpreted from the similarity between the feedback they previously gave to the same intermediate entities. The more similar the feedback distributions are, the stronger the trust relationship between the pair of social entities could be. In terms of such a social system, the network is a powerful framework for describing, analyzing and modelling complex systems, where the elementary components of a system and their mutual interactions are represented as nodes and links, respectively.

Complex systems are usually organized in compartments with their own role and/or function. As the property of complex systems, the nodes are not uniformly distributed, rather they are clustered together into some small groups. Therefore, finding compartments sheds light on the organization and decomposition property of complex systems, as well as the community structure is one of the most important properties in network systems. For network representation, such compartments appear as sets of nodes which are joined together in tightly knit groups with density of internal interaction, whereas links between compartments are comparatively looser (Girvan & Newman, 2002). In terms of the community structure of complex systems, individual components within a group interact with each other more frequently than with those outside the group. Hence, communities can be observed via connections in social media, because social media allows entities to expand their networks (Gundecha & Liu, 2012).

2.5.2 Community Detection Algorithms

In a complex system, the communities implicitly emerge naturally through interactions, so the definition of a community is subjective for specific context. Therefore, the community detection approach can help mine context-specific inter-personalised trust in preference systems. Most current community detection algorithms are based on following four categories of principle, but not exclusive (L. Tang & Liu, 2010).

- Node-centric community detection: each node in a group satisfies certain properties, such as node degrees, frequency of within and outside ties, and so forth.
- Group-centric community detection: considering the connections within a group as a whole, a group needs to satisfy certain properties without zooming into node-level.
- Network-centric community detection: groups are formed based on partition of network into disjoint sets through diverse approaches, such as clustering based on vertex similarity, modularity maximization, and spectral clustering, and so forth.
- Hierarchy-centric community detection: based on the network topology, the complex system can be decomposed into a hierarchical structure of communities. Divisive clustering and agglomerative clustering are the two main approaches in hierarchy-centric community detection.

Newman (2006) proposes a quality function Q to evaluate the goodness of a particular partition of the network into groups as follows:

$$Q = \sum_i (e_{ii} - a_i^2), \tag{2.1}$$

where e_{ii} is the number of edges within the same community connecting the nodes and a_i^2 is the sum of edges from vertices in the ith community to anther jth communities. This quality function is called modularity. The modularity can be either positive or negative, with positive values indicating the possible presence of community structure, with larger values indicating stronger community structure. In order to improve the effectiveness and reduce complexity, Clauset and Newman (2004) introduced the fast greedy modularity optimization approach based on the modularity technique. It is a hierarchical divisive algorithm whereby links are iteratively removed/added. The procedure of link removal/addition ends when the modularity of the resulting partition reaches a maximum.

The fast modularity optimization approach, introduced by Blondel, et al. (2008), is a heuristic method based on local optimization. There are two iterative phases in the approach. Firstly, each node of a network is assigned as a community, so the initial number of communities is as many as the number of nodes. Then, for each node i, the gain of modularity that would take place by removing i from its community and by placing it in its neighbors' community j is evaluated. Subsequently, the node i is then placed in the community for which this gain is maximum. If no positive gain is possible, i stays in its original community. This process is adopted repeatedly for all nodes until no further improvement can be achieved. Secondly, after a partition is identified in the first phase, communities are replaced by supernodes, yielding a smaller weighted network. Nevertheless, the order of nodes selection influence the computation time.

Radicchi et al. (2004) proposed a hierarchical method by removing links iteratively based on the value of their edge clustering coefficient. The edge clustering coefficient is a local measurement, which is defined as the ratio between the number of loops based on the link and the largest possible number of loops based on the link. So its computation is not as heavy as that of the edge "betweenness" mentioned proposed by Newman, thereby significantly reducing the complexity of the algorithm. In contrast to Newman's algorithm, the stopping criterion of this approach is dependent on the properties inherent in the communities instead of the modularity.

In the above approaches, the community detection is regarded as a single-objective optimization problem and different algorithms vary in optimization technique and criterion. Moreover, such algorithms are not suitable for the complex networks with multiple potential structures (e.g., hierarchical or overlapping). Hence, Rosvall and Bergstrom (2007) proposed a multi-objective community detection (*MOCD*) algorithm for finding efficient solutions under a multi-objective framework for community detection. The *MOCD* algorithm includes two phases, i.e., community detection phase and model selection phase. Firstly, the *MOCD* simultaneously optimizes two conflicting objective functions with evolutionary algorithm (EA) and returns a set of solutions which are optimal in terms of optimization objectives. Secondly, one recommendation solution will be selected from the solution set returned by two model selection methods, i.e., *Max Q* and *Max-Min Distance*. Compared with the single-objective community detection problem, the *MOCD* can deliver a more comprehensive community structure.

Nevertheless, the approaches mentioned above only detect communities through analyzing the linkage in a network, but cannot reflect the semantics such as the interesting topics shared by social entities of the community. As previously mentioned, except for nodes and links, the social media also allow for the creation and exchange of user-generated content, and a lot of information is encoded in the content of the interaction among entities in the complex systems. For example, participants with similar content of communication are much more likely to belong to the same community than those who do not. Taking *Flickr* as another example, users may tag an image with keywords. Such keywords, which are kinds of edge content, not only help to construct a network of both people and images, they also provide knowledge about the nature of the underlying community. Therefore, the context, such as interests and expertise, of the community can be identified based on the internal edges which are associated with similar content. In addition, the edge content is also useful to analyse subject matter that is most relevant to the particular community. Although it is possible to mine the context-specific inter-personalised trust from the edge content of the particular community, how to extract and model accurate and relevant edge content is still a challenging problem.

Qi, Aggarwal and Huang (2012) introduced a community detection algorithm by tightly integrating the structural and content aspects of the network with the use of a matrix-factorization approach. Edge content models the characteristics of pairwise interactions to provide better supervision to enable the community detection process. The content from social media, such as interested topics, expertise, keywords etc., is represented as social objects in the topic oriented community detection approach proposed by Zhao et al. (2012). Firstly, it groups all social objects into topics via a subspace clustering algorithm. Secondly, social entities which are involved in those social objects are divided into topical clusters corresponding to a distinct topic. A link analysis on each topical cluster is adopted to detect the topic communities by differentiating the strength of connections. However, both of the two approaches require preliminary text-content preparation to transform the initial content from social media in a structural format. In additional, they fail to extract opinions expressed in the user-generated content without sentiment analysis and opinion mining, which directly influence the context-specific inter-personalised trust in the preference network.

2.6 Summary of Literature Review

Trust is an integrated topic that involves diverse techniques in a number of research areas. In this thesis, we classified trust evaluation models into four categories, i.e., direct trust evaluation models, reputation-based trust evaluation models, trust-aware interaction decision-making models, and community-based trust evaluation models, in different complex system operating environments.

Firstly, multiple direct trust evaluation models were reviewed. Such approaches are appropriate for some complex systems when numerous and frequent interactions among components exist. Outcomes of historical interactions serve as the direct trust evidence available for trustees' further trustworthiness evaluation. Secondly, in terms of complex systems without sufficient interactions among various components, reputation-based trust evaluation models predict the future performance of a potential trustee by requesting information about reputation from third-party. There are four main approaches for the reputation-based trust evaluation, i.e., trust evidence aggregation approaches, testimony filter approaches, socio-cognitive trust evaluation models, and organization trust evaluation models. Thirdly, by virtual of the trust-aware interaction decision-making approach, once given a multi-skill task, the truster can select candidate trustees to collaborate and deliver desirable outcome. Fourthly, community-based trust evaluation models mine trust from various user-generated content from social media in terms of social complex systems. The communities implicitly emerge naturally through interactions among components. There are two main community detection approaches, i.e., the topological and topical approaches. The topology-based community detection approach considers the graph structure of the complex network. On the other hand, the topic-based community approach reflects the semantics from user-generated contents which provide knowledge about the nature of the underlying community.

Chapter 3

Compositional Trust in Collaborative Complex Systems

3.1 Introduction

Collaboration is a critical issue in complex systems. For most complex systems, it is difficult for an individual component to provide solutions and resources necessary for addressing complex problems which usually require multiple skills and functions. Meanwhile, a collaborative complex system normally consists of a number of loosely coupled autonomous and adaptive components for handling these problems. Namely, tasks in a complex system are achieved through collaborations in composite teams. Interactions between pairs of components are established by common composite team experiences. Even though components in collaborative systems are usually heterogeneous in terms of their operating environments, behaving roles and goals, they collaborate together as a composite team to achieve common or compatible goals. Hence, the aim of compositional trust evaluation in collaborative systems is to focus on the structure, behaviour, and evolving dynamics of systems of autonomous components that collaborate to achieve goals better and more effectively by supporting interactions among them

(Camarinha-Matos & Afsarmanesh, 2005).

There are two kinds of general social entity in collaborative complex systems: skill and skill provider. Firstly, skill denotes the provision of a discrete function within a certain system environment. For example, a complex problem request may contain a particular set of different functions, so the skill denotes a certain function type. Secondly, the skill provider decides which skills to expose in collaborative environment. Once a request is generated, a set of skill providers who can satisfy the function requirements are selected and comprise a composite team to complete the request.

Traditionally, a naive scheme to form teams would be to identify and group components with required functions for achieving tasks. Obvious refinements of such strategies would be to define some ways to rank candidate composite teams, for example, based on the degree of competence of the team members (Rodrigues, Oliveira & de Souza, 2005). However, due to the emergent complexity and characteristics of the complex system, another important factor determining the quality of a composite team is how well team members can collaborate together. This depends on the degree of cohesiveness, correlation and dependency among the team members (Hupa, Rzadca, Wierzbicki & Datta, 2010).

There are two major challenges for team composition and selection in collaborative complex systems. Firstly, most collaborative complex systems employ predefined and unified assessment standards to evaluate the performance of composite teams in different task executions. A composite team can only obtain an overall feedback for a particular accomplished task. According to the characteristics of complex systems, it is hard to know exactly which and how individual team members contribute to the observed performance of the whole team. Secondly, the performance of composite teams depend not only on historical experience for each team member, it can also be influenced by other factors, such as uncertainty of the environment and the correlation among different components.

As previously mentioned, trust is the subjective expectation a component has about others' future behaviours to perform a given task. In terms of team performance, trust reflects interrelationships among team members. It discovers that, in addition to the skill competence of individual components, the soft skills, such as the effectiveness and efficiency of information exchange, the distances among individual goals and so forth, are at least equally important (Skopik et al., 2009).

In this chapter, according to the availability of execution related information, we classify team formation strategies into two categories, i.e., team formation without predefined workflow structures, and team formation with predefined workflow structures. Firstly, without a predefined workflow structure, we assume each individual component in a team operates independently without relying on any prerequisite actions of other team members. On the other hand, with a predefined workflow structure, the collaboration among components is based on an event-triggered mechanism. According to this classification, we propose two different automatic trust mining approaches to recommend the most trustable and reliable candidate composite teams by evaluating the compositional trust relationship among team members in Section 3.2 and Section 3.3, respectively.

3.2 Team Formation without Predefined Workflow Structure

In this section, we propose a *Correlated Contribution* trust evaluation model to explore the compositional trust within collaborative composite teams without predefined workflow structure. During task executions, each component may have chances to directly interact with other team members, so the correlations and dependencies among both skills required by tasks and individual components are considered in this model. The remainder of this section is organised as follows. First, the description of the problems we want to handle, and some assumptions are presented in Subsection 3.2.1. The details of the *Correlated Contribution* model are described in Subsection 3.2.2. Finally, we evaluate the performance and effectiveness of the *Correlated Contribution* model by conducting some experiments, and the experimental results are explained and discussed in Subsection 3.2.3.

3.2.1 Problem Definition and Assumption

In the *Correlated Contribution* trust evaluation model, we suppose there is a universe of n predefined abstract skill types $ST = \{ST_1, ST_2, ST_3, ..., ST_n\}$ in a collaborative complex system. If a skill provider can provide a particular type of skill, e.g., ST_i, it can register as a concrete individual service s_i^l, where i is the skill type ID, and l is an unique ID of the provider.

A collaborative complex system receives tasks which require multiple skills. The task requirements are specified as multi-skill problem requests (see Definition 3.1).

Definition 3.1: A multi-skill problem request R is defined as a 2-tuple, i.e., $R =< RequestID; ReqSkillTypeSet = \{STi; STj; STk; ...\} >$. ***RequestID*** is the unique identifier of R, and ***ReqSkillTypeSet*** is a finite set of skill types required for achieving the functional requirement of R.

In order to complete a specific task in systems, a set of skill types are required. The system will select individual services for each required skill type and form a composite team for the task. After the completion of a task, the system generates feedback RF (see Definition 3.2) for the composite team which indicates the quality of team performance, and also contains team composition information.

Definition 3.2: A request feedback RF is defined as a 3-tuple, $RF =< RequestID, GS, Q >$. Based on a predefined team performance assessment standard, a composite team obtains an overall rating Q for the task completion quality. GS describes a set of selected individual services for satisfying $ReqSkillTypeSet$ in R:

$$GS = \begin{pmatrix} ST_i & ST_j & ST_k \\ s_i^l & s_j^m & s_k^n \end{pmatrix}$$

Definition 3.3: A *Correlated Contribution* CR is defined as the correlation among a pair of skill types or individual services in contributing to the deduction of team performance uncertainty.

Correlated Contributions (CRs) to composite team performance are existing in two levels, i.e. the abstract skill type level, and the concrete individual service level. CRs can be represented as an undirected weighted graph, which is shown in Figure 3.1.

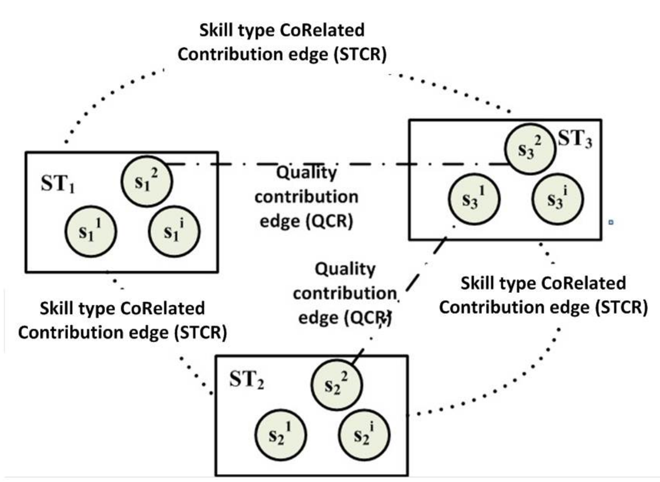

Figure 3.1: *Correlated Contribution* among Skill Types and Quality Contribution among Individual Services

Definition 3.4: A correlated contribution edge $STCE_{ij}$ links two skill types ST_i and ST_j. The Skill Type Correlated Contribution, $STCR_{ij}$ ($0 \leq STCR_{ij} \leq 1$) is the weight of $STCE_{ij}$.

Once given a cross-domain task, the system will generate a request R and define a finite set of skill types to meet the functional requirement. In terms of diverse tasks, the same skill type may enjoy different importance, so the compositional trust contribution of skill types in a specific composite team will be calculated based on the value of $STCR_{ij}$ and the required skill type set in R. Since no predefined workflow structure exists, all team members can potentially collaborate with others during task executions. Therefore, after the required skill types are fixed, all possible compositions of individual services can be taken into account for compositional trust evaluation. In order to calculate the compositional trust value for the possible compositions, it is necessary for us to determine the correlated edge between individual services.

Definition 3.5: A Quality Contribution edge $ISCE_{il,jm}$ is the link between two individual services s_i^l and s_j^m. The individual service quality contribution $QCRil, jm$, is defined as the weight of $ISCE_{il,jm}$, $-1 \leq QCRil, jm \leq 1$.

Different with $STCR_{ij}$, the value of $QCR_{il,jm}$ is determined by the correlation degree between the two individual services, and also the historical performance of the composite teams which used to contain both s_i^l and s_j^m. Therefore, $QCR_{il,jm}$ can have a negative value, which means the coexistence of individual service s_i^l and s_j^m can cause poor performance in composite teams. The equations for calculating $STCR_{ij}$ and $QCR_{il,jm}$ will be introduced in Subsection 3.2.2.

3.2.2 Analysis of Correlated Contribution

Due to the dynamic nature of operating environments, uncertainties are unavoidable and need to be considered in forming composite team in complex systems. Modeling of uncertainty and dynamics has been investigated in many fields, especially information theory (Cover & Thomas, 2012; Garg, Konugurthi & Buyya, 2011). In particular, probability is a tool for dealing with uncertainty, which represents the likelihood of the occurrence of an event based on knowledge of physical law and historical records (Cover & Thomas, 2012). Probability is the ratio of the number of favorable cases to the number of possible cases. It is a theoretical expectation of occurrence frequency (Garg et al., 2011). In addition, Entropy $H(X)$ and Mutual Information $I(X;Y)$ can also be used for calculating the uncertainty level of random behaviors (Garg et al., 2011). In this thesis, these methods are used to measure the correlations of skill types/components and the quality of composite team performance in collaborative complex systems.

In this research, the quality of a composite team performance (Q) is assumed as a random behaviour. The uncertainty degrees of such random behaviors are related with the required skill types in the request, and can be reduced by the existence of particular skill types and individual service compositions. Therefore, we firstly calculate the Quality Entropy ($H(Q)$) by using Equation 3.1 to measure the average uncertainty of the quality of composite team performance (Cover & Thomas, 2012). Then, mutual information (i.e., $I(Q;X)$) is used to measure how much reduction a particular skill type ST_i or individual service s_i^k can make to the performance uncertainty (Renner & Maurer, 2000). Finally, the conditional mutual information (i.e., $I(Q;X|Y)$) is calculated by using Equation 3.2 to measure the uncertainty reduction due to the existence of a skill type or individual service (X in Equation 3.2) when another skill type or individual service (Y in Equation 3.2) is given (Qu, Hariri & Yousif, 2005).

$$H(Q) = -\sum p(Q)\log_2 p(Q) \tag{3.1}$$

$$\begin{aligned} I(Q;X,Y) &= I(Q;X) + I(Q;Y|X) \\ &= I(Q;Y) + I(Q;X|Y) \end{aligned} \tag{3.2}$$

$I(Q;X)$ is smaller than $I(Q;X|Y)$, if a pair of skill types (or individual services) X and Y are strongly correlated. Furthermore, when a skill type ST_j or individual service s_j^l is given, the reduction of quality uncertainty due to the existence of another skill type ST_i or individual service s_i^k is larger than the reduction caused by ST_i or s_i^k. If a skill type or individual service (i.e., X) is totally independent with the QoS value, $I(Q; X) = 0$. If a skill type ST_j or individual service s_j^l (i.e., X) is independent in relation to the existence of the quality value and another skill type or individual service (i.e., Y), then $I(Q; X|Y) = 0$.

Calculation of Skill Type Correlated Contribution

Mutual information and conditional mutual information are used to calculate correlated contribution ($STCR$) of pairs of skill types within different requests. The "decision" of Q is set to the selection of individual services in order to achieve the expected quality. The correlation measurement is to quantify the information redundancy between ST_i and ST_j with respect to Q in all previous request feedback. It can be calculated by using Equations 3.3 and 3.4.

$$STCR_{ij} = \frac{I(Q; ST_i, ST_j)}{H(Q)} \tag{3.3}$$

$$WST_{ij} = \frac{STCR_{ij}}{STCR_{ij} + STCR_{ik} + STCR_{jk}} \tag{3.4}$$

In Equation 3.4, WST_{ij} is the correlated contribution of ST_i and ST_j for the required types in request R. The larger $STCR_ij$ is, the closer interrelationship between skill types ST_i and ST_j is, and the less uncertainty the Q (quality) value is. When skill types ST_i and ST_j are completely correlated, they contribute 100 percent in determining Q, i.e., $STCR_{ij}$=1.

Calculation of Joint Individual Service Quality Contribution

The correlation between pairs of individual services may also be impacted by the skill types they belong to. Hence, we also use service quality contribution edge to decide the optimal route for the final component composition. However, the correlation values may have two different meanings, i.e., complementariness or exclusion. Complementariness means that two individual services, e.g., s_i^l and s_j^m, are positively correlated with the performance quality of composite teams they participate in. Namely, high quality is more likely to be achieved. Exclusion means that s_i^m and s_j^n are negatively correlated with respect to the performance quality of composite teams they participate in. Namely, a low performance quality value is more likely to be obtained. Therefore, in our approach, the performance quality values of previous composite teams participated by these two individual services are also taken into account for potential team performance evaluation by using Equation 3.5.

$$p(Q^{th}) = \frac{count(Q_i \geq th)}{\sum_{q=1}^{n} count(Q_i)} \tag{3.5}$$

In Equation 3.5, $p(Q^{th})$ represents the proportion of previous compositions where both s_i^l and s_j^m are involved, and with performance quality value greater than a required quality threshold *th*. In addition, users can also define their quality weight assignment functions $W_{Q_q} = f(Q_q)$ ($-1 \leq W_{Qq} \leq 1$), where Q_q is a QoS value and W_{Q_i} represents the assigned weight value of Q. For example, if "level 1" and "level 4" represent the highest and lowest quality levels, respectively, the system will have the following quality weight assignment function: $W_{level1} = 1$ and $W_{level4} = -1$.

The weight of the quality contribution (QCR) between two joint individual services s_i^l and s_j^m can be calculated by using the following two equations.

$$CR(s_i^l, s_j^m) = \frac{I(Q; s_i^l, s_j^m)}{H(Q)} \tag{3.6}$$

$$QCR_{il,jm} = CR(s_i^l, s_j^m) * \sum_{q=1}^{n} p(Q^{th}) * W_{Q_q} \tag{3.7}$$

When individual services s_i^l and s_j^m are positively correlated with respect to the quality of composite team performance, the quality contribution edge will range from 0 to 1, which means complementariness correlation between these two individual services exists. On the other hand, if exclusion correlation exists between s_i^l and s_j^m, the quality contribution edge will range from 0 to -1. Moreover, if they contribute 100 percent information in determine the decision of Q, the absolute value of $QCR_{il,jm}$ is equal to 1. This means that s_i^l and s_j^m are completely correlated and all previous composite team performance records including these two individual services reaches to the same quality level. According to the weighted skill type correlated contribution edge WST_{ij} with respect to a particular request, we can get different correlations between different pairs of skill types required to achieve a particular task by using Equation 3.8:

$$rST_{i,j} = WST_{ij} * STCR_{ij} \tag{3.8}$$

The trust value for possible group composition can be calculated by summing all edge value within the path. Then, the best composition is those nodes (individual services) in the path with the highest sum value by using the following equation.

$$\begin{aligned} Trust &= rST_{i,j} * QCR_{il,jm} \\ &\quad + rST_{i,k} * QCR_{il,kn} \\ &\quad + rST_{j,k} * QCR_{jm,kn} \end{aligned} \tag{3.9}$$

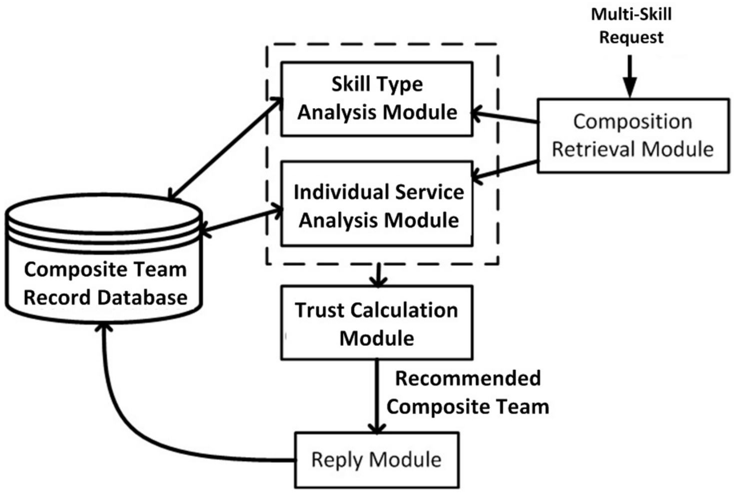

Figure 3.2: Composition protocol

Correlated Contribution Trust Evaluation Protocol

In the *Correlated Contribution* trust evaluation approach, the component composition is generated from the protocol in Figure 3.2. There are six major components in the protocol and each module is introduced in detail, as follows:

1. **Composition Retrieval Module:** Based on the functional requirements of a cross-domain task, a multi-skill request R will be generated. Then R will be sent to the Composition Retrieval Module. The Composition Retrieval Module then searches for all candidate composite teams which can satisfy R, and the number of potential teams is based on the number of required skill types in R and the number of available individual services in these skill types.

2. **Composition Team Record Database:** All team composite records are stored in the Composition Record Database. Based on these records, the Skill Type Analysis Module and the Individual Service Analysis Module update the correlated contributions between skill types, and the quality contributions between individual services.

3. **Reply Module:** The function of the Reply Module is to generate feedback RF for composite teams. After each task, the Reply Module evaluates the performance quality Q for the composite team in this execution, and stores the feedback RF, which contains the composition details (selected individual services) and Q into the Composition Record Database for future evaluations.

4. **Skill Type Analysis Module:** The Skill Type Analysis Module is for evaluating the Request-Oriented trust relationships between different skill types. According to a skill request R, the Skill Type Analysis Module weighs the $STCR_{ij}$ and return rST_{ij} (refer to Definition 3.4 and Equation 3.3 and 3.8) to the Trust Calculation Module. The default value for each $STCR_{ij}$ is 1.0, which will not be updated until all $STCR_{ij}$ values are calculated. Therefore, at the beginning, all skill types are given the same weight within the request.

5. **Individual Service Analysis Module:** The Individual Service Analysis Module is for evaluating the compositional trust relationship based on the correlation between pairs of individual services within candidate composite teams. According to each candidate group composition, the Individual Service Analysis Module returns $QCR_{il,jm}$ (refer to Equation 3.7) to the Trust Calculation Module. Since the default value for each $QCR_{il,jm}$ is set to 0.0, we intend to give each individual service the same chance to be selected.

6. **Trust Calculation Module:** Based on the outputs from the previous two analysis modules, the Trust Calculation Module is for estimating the compositional $Trust$ value for each potential group, and select the composite team (*GS*) with the highest trust value. Then, GS is returned to the Reply Module. If more than one team obtains the highest trust value, the Trust Calculation Module will randomly pick a service group within these alternatives.

3.2.3 Experiments

In this research, we evaluated the performance of the *Correlated Contribution* model on a set of synthetic data. In the experiments, the *Correlated Contribution* model was compared with the *Reputation-Based* model and *Random* model. According to the Definition 3.2, the dataset for experiments need to contain both team composition details and team performance information. However, there is no such desirable dataset available in any of the recent research. Therefore, we have to generate a dataset to simulate the collaboration complex system operation environments.

Experiment Setup

In the experiments, we included four skill types, i.e., $\{ST_0$,ST_1,ST_2,ST_3 $\}$, in a simulative collaborative complex system. Each skill type contains five registered individual services, i.e., ST_0 = $\{s_0^0, s_0^1, s_0^2, s_0^3, s_0^4\}$, ST_1 = $\{s_1^0, s_1^1, s_1^2, s_1^3, s_1^4\}$, ST_2 = $\{s_2^0, s_2^1, s_2^2, s_2^3, s_2^4\}$, ST_3 = $\{s_3^0, s_3^1, s_3^2, s_3^3, s_3^4\}$. Each request R requires three different skill types to meet its functional requirements of multi-domain skills task. Therefore, we can have at most four different kinds of requests: $\{ST_0, ST_1, ST_2\}$, $\{ST_0, ST_1, ST_3\}$, $\{ST_0, ST_2, ST_3\}$ and $\{ST_1, ST_2, ST_3\}$, and there are six skill type correlated contribution edges among the four skill types, which are $STCR_{01}$, $STCR_{02}$, $STCR_{03}$, $STCR_{12}$, $STCR_{13}$ and $STCR_{23}$. Four quality-level classes are adopted to represent team performances, i.e., Level 1, 2, 3 and 4. Level 1 stands for the highest quality level and Level 4 stands for the lowest level. As previously mentioned, a unified assessment standard is applied to evaluate the performance of composite teams. In order to find high quality compositions, we set four different quality weights for the above four classes: W_1 = 1, W_2 = -0.1,W_3 = -0.5 and W_4 = -1.

Firstly, we predefined six pairs of individual services with high correlations. Four of them have exclusion correlation, i.e., they have high possibility (over 90%) to generate low performance quality values (e.g., Level=4). We also include two pairs of individual services with complementariness correlations, which means they have high possibility (over 90%) to generate high performance (e.g., Level=1). Secondly, we established a true value table by predefining all classification level for each candidate composite team for each kind of request. There are 500 possible team compositions in the true value table, 78 for Level 1 (high quality), 111 for Level 2, 140 for Level 3 and 171 for Level 4 (low quality). Thirdly, based on our algorithms we randomly generated 100 requests and calculated the trust value for each alternative composite team. We then choose the most trustable team composition. If the highest trust value equal to 0.0 (initial value), all the recommended group service will be randomly chosen from those compositions whose trust value is equal to the highest trust value. This is because we want to give the same chance for different team composition. Fourthly, in terms of each selected composite team, we get the predefined quality level GP for the true value table and then place it with the composite team member information GS into the feedback RF. All RFs will be stored in the Composite Team Record Database for further calculations.

Experimental Results

We conducted the experiments by using the *Correlated Contribution* model for three times, and, in each experiment, 100 compositions were conducted. The experimental results are demonstrated in Figure 3.3. Each line in Figure 3.3 represents the changing trend of team performance. It can be seen that in Experiment 1, all teams maintain at high quality since the 32th request. The Experiment 2 has the poorest performance. However, it also can be found that the best group composition can be discovered since the 65th request. According to the Figure 3.4, in terms of a particular request, the *Correlated Contribution* model randomly pick potential team, when there is no enough knowledge to make prediction at the beginning, until the team with the highest quality appears. Once the high quality composition has been selected, the following quality

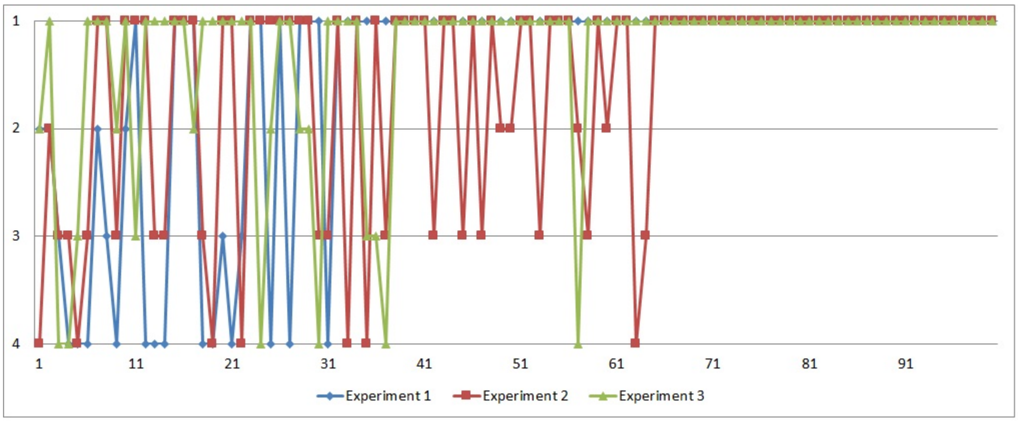

Figure 3.3: Changing Trend of Performance Quality of Composite Team by Using *Correlated Contribution* Model

of composite team for such request will stand at highest level and maintain. In Figure 3.8, the proportion of high quality performance of teams which are selected by the *Correlated Contribution* model occupies at more than 70%, and even it reaches 84% in Experiment 3.

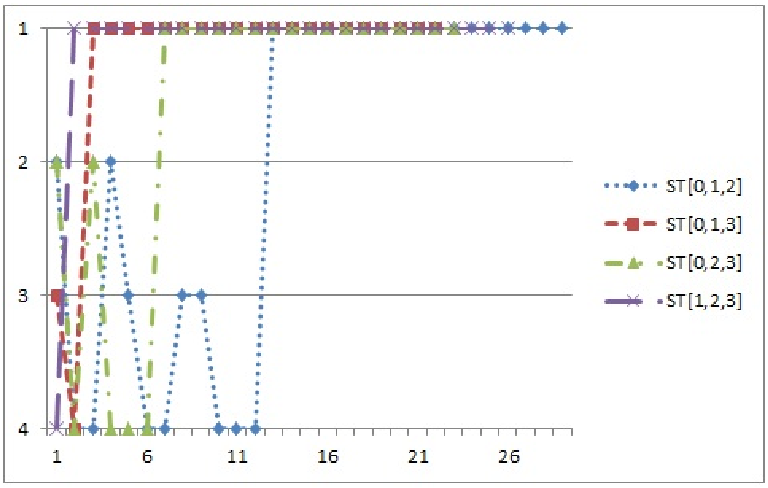

Figure 3.4: The *Correlated Contribution* Model

In order to compare the performance of the *Correlated Contribution* model, we applied the same dataset on the *Reputation-Based* model and the *Random* model, and then compared their performances. Usually, the Reputation-Based models are

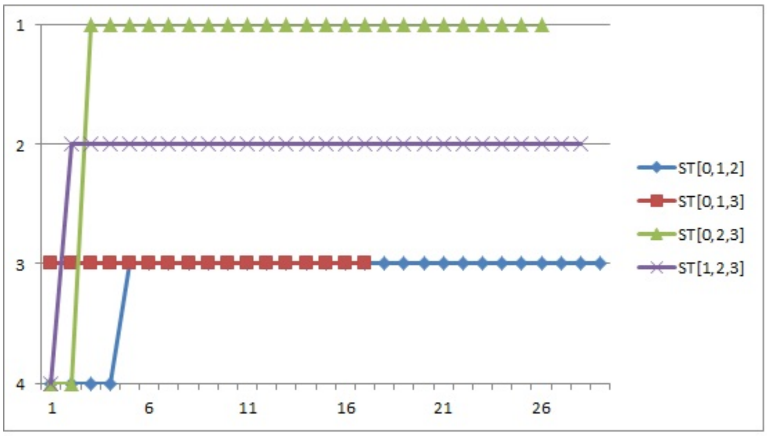

Figure 3.5: The *Reputation-Based* Model

implemented as a centralized rating system so that clients can report about the quality of the composite team in previous transactions via ratings (Huynh, Jennings & Shadbolt, 2006b). The reputation of an individual service is based on the average quality of the previous composite team which the individual service participated.

With the same setting, each model has been repeated a total of three times. It has been found that neither the *Reputation-Based* model nor the *Random* model could perform stably. From Figure 3.5, it can be found that the *Reputation-Based* model can only figure out the highest quality (Level =1) composite team for one kind of multi-domain request (i.e., $ST[0, 2, 3]$). In terms of the other three kinds of requests, once the model picked a potential composite team whose performance is better than previous, the quality may maintain at a local optimal value, even if it has not reached at the highest level. We also compared the performance quality of composite team distribution of three models in Figure 3.6. From this figure, it can be seen that the *Correlated Contribution* model performs significantly better than the other two, as it generates more than 80% high performance composite teams and low quality teams are less than 10%. In terms of the average performance quality of composite team (see Figure 3.7), the *Correlated Contribution* model performed better than the *Reputation-Based* model and the *Random*

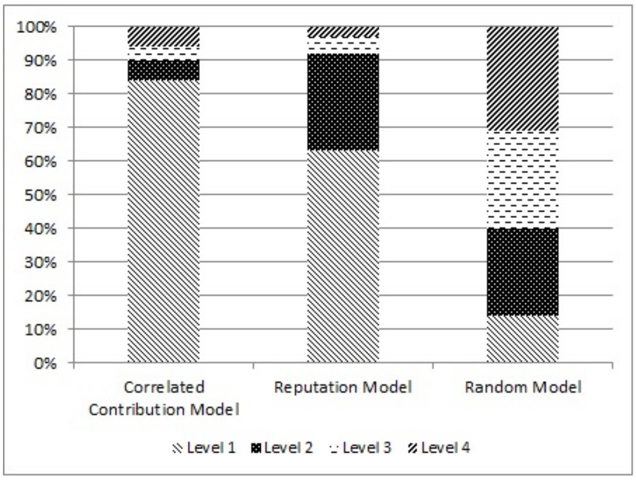

Figure 3.6: Comparison of QoS Distribution by using the *Correlated Contribution* Model, the *Reputation-Based* Model and the *Random* Model

model, could also increasingly improve the performance.

3.3 Team Formation with Predefined Workflow Structure

Nowadays, with the development of provenance technologies, information about workflow structures and task executions can be tracked and recorded. Provenance describes the origins and processes related to the generation of service or data products in a standard format (Moreau et al., 2008). Furthermore, it can also be used to capture workflow structures of composite teams in complex systems. Hence, with the availability of provenance information, workflow structures of composite teams in complex systems can also contribute to trust mining.

The analysis of provenance information is a complex process which normally requires rich domain knowledge and expertise (Bai et al., 2011). In this section, we propose an automatic approach, i.e., the Same Edge Contribution trust evaluation (*SEC*) model, to estimate the trustworthiness of proposed composite teams by analysing

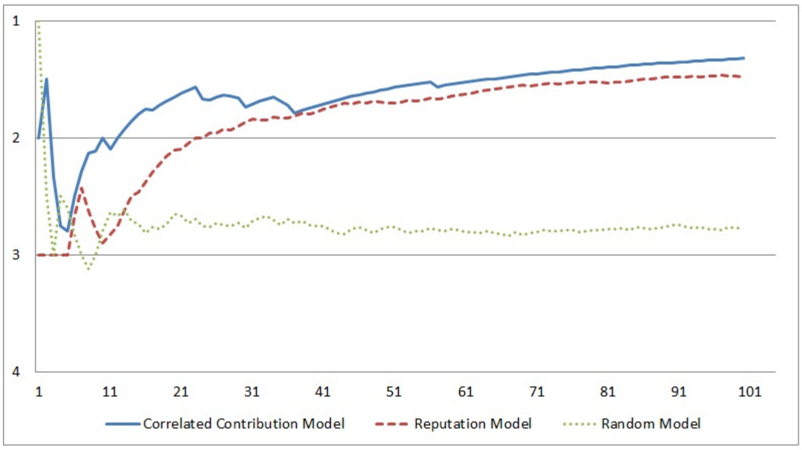

Figure 3.7: Average QoS Level for *Correlated Contribution* Model vs *Reputation-Based* Model vs *Random* Model

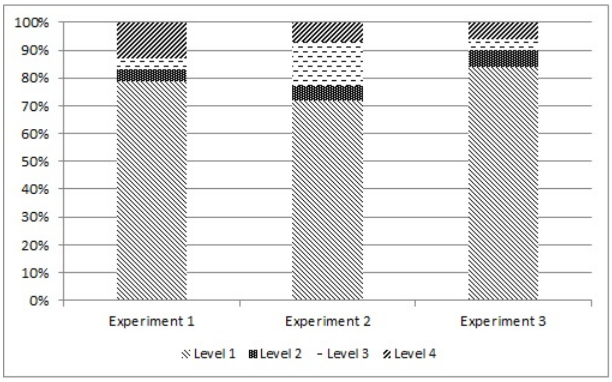

Figure 3.8: Performance Quality distribution of Composite Team by Using the *Correlated Contribution* Model

historical provenance data. In the *SEC* model, provenance information of a composite team is represented as a provenance graph (Moreau et al., 2008), and is then based on graph similarities and correlation to trust values, the *SEC* model can predict the future performance of a candidate composite team. The rest of this section is organised as follows. We define the problem and introduce some assumptions in Section 3.3.1. Section 3.3.2 presents the *SEC* model, and how to derive trust support values from provenance graph. In Section 3.3.3, some experimental results are given to demonstrate the performance of the *SEC* model by comparing it with decision tree *J48*.

3.3.1 Problem Definition and Assumption

A number of graph-based provenance models have been developed to represent provenance information (Moreau et al., 2008). These models normally define a number of nodes and links to represent different concepts in provenance, and the generation process of a composite service can then be represented as a provenance graph. In this research, we describe the workflow of a composite team in its provenance graph. It identifies data passed among components, interactions involved in the generation of results, component members in the composite team and so forth (Freire, Koop, Santos & Silva, 2008) (Simmhan et al., 2005). We try to analyse provenance information based on the features of provenance graphs. Hence, some graph analysis methods (Sanfeliu & Fu, 1983) are used to measure the similarities of provenance graphs.

Given a multi-skill request R, workflows with detailed team composition information, which can satisfy R, will be proposed by different skill providers. The system will estimate each proposed workflow based on the analysis of historical provenance data (graphs). We suppose that there is a universe of n skill components $S = \{S_1, S_2, ..., S_i, ..., S_n\}$, where S_1 to S_n are loosely coupled to satisfy the requirement of multi-skill requests R in a collaborative complex system. $E_x(S_i, S_j)$ represents an interaction leads from S_i to S_j. Suppose S_j is a successor of S_i and reachable from S_i, and S_i is a predecessor of S_j. Proposals from different providers are encoded as *proposal graph* (see Definition 3.6).

Definition 3.6: A *proposal graph* PRG is a 2-tuple $PRG = (V_{PRG}, E_{PRG})$, where

- $V_{PRG} = v_{S_1}, v_{S_2}, v_{S_3}, ..., v_{S_n}$ is a finite set of nodes
- $E_{PRG} \subseteq V \times V$ is the finite set of edges
- $\mid PRG \mid = \mid V_{PRG} \mid + \mid E_{PRG} \mid$ denote the size of composite team

PRG is the proposal graph from providers that describes a finite set of service components $V_{PRG} = \{S_1, S_2, S_3, ..., S_n\}$ and a finite set of edges $E_{PRG} = \{E_1(S_1, S_2), E_2(S_1, S_3), ..., E_n(S_{n-1}, S_n)\}$. The skill components in V_{PRG} are required to achieve the functional requirement of R, and E_{PRG} indicates the process of a composite team. Though compositional trust evaluation, the most trustable proposal graph PRG will be selected to complete R. After the request completion, the system will generate feedback RF contains both the provenance graph PVG and performance quality of composite team for achieving R.

Definition 3.7: A *provenance graph* PVG is defined as 2-tuple, i.e., $PVG =< ReqestID, PRG = (V_{PRG}, E_{PRG}) >$. $ReqestID$ is the unique identifier for each multi-domain skill request, and proposal graph PRG describes concrete skill components and processes of task execution.

Definition 3.8: A *feedback* RF is defined as a 2-tuple, $RF =< PVG, Q >$. Q represents the performance quality of composite team.

Definition 3.9: $g = (V_g, E_g)$ is a subgraph of a graph PRG or PVG, denoted by $g \subseteq PRG/PVG$, if $V_g \subseteq V_{PRG}/V_{PVG}$ and $E_g \subseteq E_{PRG}/E_{PVG}$.

Definition 3.10: A common subgraph cg of PVG and PRG is a subgraph of PVG and PRG, and there exist subgraph isomorphisms from cg to PVG and from cg to PRG (Bunke & Kandel, 2000). A *Maximum Common Edge Subgraph* (*MCES*) is a common subgraph consisting of the largest number of edges common to both PVG and PRG (Raymond, Gardiner & Willett, 2002).

3.3.2 The Provenance-Based Trust Estimation Approach

In this approach, compositional trust estimation is achieved via two steps. Firstly, we adopt tier screening procedure to calculate an upper bound on the size of a *MCES* between candidate proposal graph PRG and provenance graph PVG in the knowledge

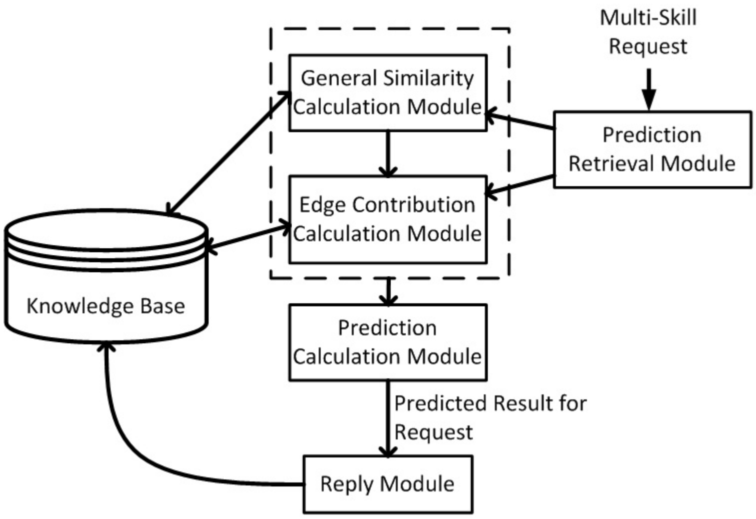

Figure 3.9: Provenance Compositional Trust Estimation Protocol

base. Secondly, if the similarity between PRG and PVG reach a minimum acceptable value, we calculate the exact edge-based edit operation cost of each PVG to get the support trust value for the class of target graph.

Trust Estimation Protocol

In our approach, compositional trust prediction is conducted by following the protocol in Figure 3.9. Firstly, after the system generates a multi-skill request, proposal graphs PRG based on the functional requirements of requests will be generated. Then the proposal graphs will be sent to the Prediction Retrieval Module. The Prediction Retrieval Module will search the knowledge base for all possible provenance graphs PVGs, which are similar to PRG. Then, based on the previous provenance graphs PVG in the knowledge base, the Edge Contribution Module updates the edge contribution value for total available edges. At the beginning, all edges are given the same weight within the request. The General Similarity Calculation Module calculates the similarity between proposal graphs PRG and provenance graph PVG based on the common skill components and edges in graphs, and then passes the most similar provenance graphs

PVGs to the Prediction Calculation Module. Comparing the same edges in proposal graph PRG and provenance graphs PVG, the Prediction Calculation Module will use the edge contribution value to give each provenance graph PVG a support value. The system will then send the performance quality value of the provenance graph PVG for the composite team which obtains the highest support value to the Reply Module.

General Similarity Calculation

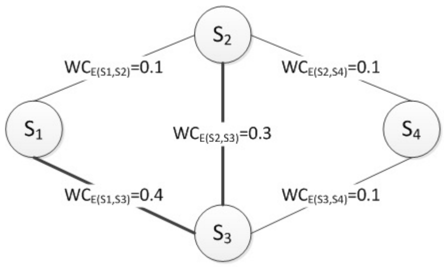

Figure 3.10: Proposal Graph PRG

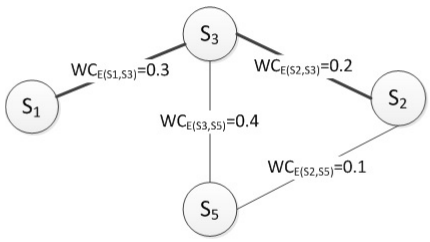

Figure 3.11: Provenance Graph PVG

The general similarity between potential proposal graphs PRGs and previous provenance graphs PVGs in the knowledge base is decided by an upper bound on the size of the ***MCES***. First, according to skill components S in each graph, the set of vertices is partitioned into l partitions. Let cg_i^{PRG} and cg_i^{PVG} denote the sub-graph in the i^{th} partition in graph PRG and PVG, respectively (Raymond et al., 2002). An upper-bound on the similarity between provenance graph PRG and PVG, i.e., $sim(PRG, PVG)$, can be calculated as follows:

$$V(PRG,PVG)=\sum_{i=1}^{l} min\{|cg_i^{PRG}|,|cg_i^{PVG}|\} \tag{3.10}$$

$$E(PRG,PVG)=\lfloor\sum_{i=1}^{cg}\sum_{j=1}^{max\{|cg_i^{PRG}|,|cg_i^{PVG}|\}}\frac{min\{d(cg_j^{PRG}),d(cg_j^{PVG})\}}{2}\rfloor \tag{3.11}$$

$$sim(PRG,PVG)=\frac{[V(PRG,PVG)+E(PRG,PVG)]^2}{[|V(PRG)|+|E(PRG)|]\times[|V(PVG)|+|E(PVG)|]} \tag{3.12}$$

A higher $sim(PRG,PVG)$ value means more common edges and nodes are shared between PRG and PVG. For example, based on Figure 3.10 and 3.11, $V(PVG,PRG)=3$, $E(PVG,PRG)=\frac{1+2+3}{2}=3$, $sim(PVG,PRG)=\frac{(3+3)^2}{(4+5)(4+4)}=0.5$. Therefore, the general similarity between PVG and PRG is 0.5. In order to reduce the calculation complexity, we set a minimum acceptable value sim^{th} for general similarity measurements. If $sim(PVG,PRG)\le sim^{th}$, a candidate provenance graph PVG will be ignored.

Edge Contribution Calculation

In our approach, the composite team performance is assumed as a random behaviour and we intend to adopt the *Edge Contribution* to quantify the edit operation cost of each edge $E(S_i,S_j)$. The uncertainty of such a random behaviour is related to the required edges $E_G^x(S_i,S_j)$ in the process of a multi-skill request. It can be reduced with the existence of a particular edge. Therefore, we firstly calculate the Quality Entropy ($H(Q)$) by using Equation 3.13 to measure the average uncertainty of performance quality values of a composite team (Cover & Thomas, 2012). Then, mutual information $I(Q;E_G^x)$ (Renner & Maurer, 2000) is used to measure how much reduction a particular edge E_G^x can make to the uncertainty of the performance quality value.

$$H(Q) = -\sum p(Q)\log_2 p(Q) \tag{3.13}$$

$$C_{E_G^x(S_i,S_j)} = \frac{I(Q; E_G^x(S_i,S_j))}{H(Q)} \tag{3.14}$$

$$WC_{E_G^x} = \frac{C_{E_G^x}}{\sum\limits_{E_x \in E_G} C_{E_G^x}} \tag{3.15}$$

In Equation 3.14 and 3.15, G represents PRG or PVG in different situations, and $WC_{E_G^x}$ is the contribution of edge E_G^x for PRG or PVG. The larger the $WC_{E_G^x}$ is, the more contribution the edge E_G^x makes in the process. If E_G^x is the only path in the process, it contributes 100 percent in determining Q, i.e., $WC_{E_G^x} = 1$.

Comparing a candidate proposal graph PRG and previous provenance graphs PVGs passed from the General Similarity Calculation step, we can get a particular same edge set between PRG and each PVG (see Equation 3.16).

$$\{E^i_{sameSet}\} = Same(E_{PRG}, E_{PVG}) = \{E_i, E_j, E_k, ...\} \tag{3.16}$$

where all edges $\{E_i, E_j, E_k, ...\}$ in $\{E^i_{sameSet}\}$ occur in both PRG and PVG. For example, according to Figure 3.10 and 3.11, $\{E_{sameSet}\} = \{E(S_1, S_3), E(S_2, S_3)\}$.

Then, we can calculate the Same Edge Contribution rate (*SEC*) on a proposal graph PRG and a particular provenance graph PVG as follows (see Equation 3.17 and 3.18):

$$SEC_{PRG} = \frac{\sum\limits_{E_x \in E^i_{sameSet}} WC_{E^x_{PRG}}}{\sum\limits_{E_x \in E_{PRG}} WC_{E^x_{PRG}}} \tag{3.17}$$

$$SEC_{PVG} = \frac{\sum\limits_{E_x \in E^i_{sameSet}} WC_{E^x_{PVG}}}{\sum\limits_{E_x \in E_{PVG}} WC_{E^x_{PVG}}} \tag{3.18}$$

Due to different edge compositions in different graphs, edge contributions $WC_{E^x_G}$ in different graphs are different. For example, according to Figures 3.10 and 3.11, $SEC_{PRG} = 0.4 + 0.3 = 0.7$ and $SEC_{PVG} = 0.3 + 0.2 = 0.5$. In order to compare the contribution of the same edge set which occurs in both PRG and PVG, we calculate the *Support* value of each provenance graph PVG for a particular proposal graph SEC_{PVG}, as follows (see Equation 3.19):

$$Support = SEC_{PRG} \times SEC_{PVG} \tag{3.19}$$

The *Support* value ranges from 0 to 1. In order to get a high *Support* value for a certain provenance graph PVG, Same Edge Contribution rate for proposal graph (SEC_{PVG}) and provenance graph (SEC_{PVG}) should be as high as possible, and as close as possible. For example, according to Figures 3.10 and 3.11, $Support = SEC_{G_1} \times SEC_{G_2} = 0.7 \times 0.5 = 0.35$. The class which the proposal graph PRG should be classified into is dependent on the support value of each provenance graph PVG. Finally, the Reply Module generates a feedback RF for the selected proposal PRG after the execution, and store RF which contains both the provenance information of composite team and preformation quality into the knowledge base for further compositional trust evaluation.

3.3.3 Experiments

In order to compare the performance of the Same Edge Contribution (*SEC*) model, we compare it with the decision tree (*J48*) model with the same synthetic dataset, and then get the result will be discussed together with *SEC* model in the following part. Decision tree algorithm is a divide-and conquer approach to the problem of learning from a set of instances by offering a genuine simplicity of interpreting models, which helps to consider the most important factors in a dataset first by placing them at the top of the tree (Xhemali, Hinde & Stone, 2009). The unknown instance is classified by being routed down the tree according to the values of the attributes tested in successive nodes until the instance encounters a leaf which indicates a specific class (Witten & Frank, 2005). In this experiment, we adopt C4.5 decision tree revision 8 (*J48*) to execute the experiment.

Table 3.1: Setup of the three Experiments

		Number of Skill Components	Number of Edges	Dataset Size
Experiment 1	Training Dataset	10	45	500
	Test Dataset	10	45	100
Experiment 2	Training Dataset	10	45	500
	Test Dataset	10+2(New)	66	100
Experiment 3	Training Dataset	10+2	45+12	500+100
	Test Dataset	12	66	100

Experiment Setup

As mentioned in section 3.3.1, the dataset for experiments should contain information related to the quality of team performance, and also provide provenance information in relation to each composite team for each particular task. However, there is no such desirable dataset available in recent research. Therefore, it is necessary for us to generate a synthetic dataset to simulate the collaboration complex system operation environments.

In the experiments, we included 10 skill components, i.e., $\{S_0, S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9\}$ and 45 kinds of edges $E(S_i, S_j)$. In order to represent performance quality, two kinds of classes are adopted, namely, successful and unsuccessful. As previously mentioned, a unified assessment standard is applied to evaluate the performance of composite team as feedback for future consultation. In our experiments, we consider it as a classification problem with two class values, i.e., Successful and Unsuccessful.

Firstly, we predefined 8 high contribution edges among the total 45 edges with high contribution to the successful class. The probability of successful class is dependent on high contribution edge included in the proposal/provenance graph, ranging from 50% to 100%. Secondly, if a proposal/provenance graphs does not include any high contribution edges, the class value is assigned randomly. Namely, in the scenario, we assume that the performance quality of a composite team is a random behaviour. Thirdly, based on the result of General Similarity Calculation $sim(PRG, PVG)$, the ten most similar provenance graphs PVG will be selected and be calculated. Finally, the class with the highest support value of provenance graph PVG will be assigned to the proposal graph PRG as the predicted performance.

Experimental Results

In view of the characteristics of the dataset, we mainly expect two standard classification metrics, i.e., accuracy and precision for successful class. Firstly, except for 8 high contribution edges, most class values for composite teams are assigned randomly (50% to 50%). Therefore, if the accuracy of classifier is higher than 0.5, we consider that the classification model has already been improved. Secondly, the precision for successful class means the proportion of the predicted successful class for provenance graph that were correct. In terms of composition recommendation issue, the success rate of predicting high performance composite team should be as high as possible to avoid poor performance of recommended composite team. We conducted three experiments under different situations by comparing the result from the *SEC* model and the *J48* model.

Experiment 1

In Experiment 1, all graphs in the knowledge base and requests can be composed by the same 10 skill components and 45 edges. We have 500 provenance graphs in the knowledge base and submit 100 proposal graphs for prediction (see Table 3.1). According to Confusion Matrix for the two models (see Table 3.2), the accuracies

Table 3.2: Confusion Matrices for the *SEC* model and the *J48* model

				ACTUAL	
				Successful	Unsuccessful
Experiment 1	***SEC***	PREDICTED	Successful	51	12
			Unsuccessful	20	17
	J48	PREDICTED	Successful	60	24
			Unsuccessful	11	5
Experiment 2	***SEC***	PREDICTED	Successful	58	11
			Unsuccessful	22	7
	J48	PREDICTED	Successful	NaN	NaN
			Unsuccessful	NaN	NaN
Experiment 3	***SEC***	PREDICTED	Successful	64	12
			Unsuccessful	18	6
	J48	PREDICTED	Successful	70	14
			Unsuccessful	12	4

from the *SEC* model and the *J48* model are similar. The *SEC* model achieved a higher precision (0.810) than the *J48* model (0.714) (see Table 3.3).

Experiment 2

Table 3.2 and Table 3.3 show the result of Experiment 2. In this experiment, although two new skill components emerged with 21 new edges from the proposed graphs, the knowledge base will still be the same as the first experiment (10 skill components and 45 edges within 500 provenance graphs, see Table 3.1). The *SEC* model still achieved the similar performance of Experiment 1 with higher precision (0.841). The *J48* decision tree model cannot work in such a situation as the condition for training dataset and testing dataset is not compatible. Therefore, once new skill components and edges appear, the decision tree model has to be rebuilt.

Experiment 3

In Experiment 3, we added the test dataset in Experiment 2 into the original knowledge base (see Table 3.1). Therefore, the current knowledge has been enlarged to 600 provenance graphs PVG with 12 skill components and 66 edges. Reviewing Table 3.2 and Table 3.3, even though it can be seen that the accuracies of the *SEC* model and the *J48* model are similar, the *SEC* model still achieved a higher precision (0.842) than the *J48* model (0.833).

Table 3.3: Experimental Results

	Model	Accuracy	Precision
Experiment 1	SEC	0.68	0.810
	J48	0.65	0.714
Experiment 2	SEC	0.65	0.841
	J48	NaN	NaN
Experiment 3	SEC	0.7	0.842
	J48	0.74	0.833

Result Analysis

Experiments 1 to 3 compare the performance of the *SEC* model and decision tree *J48* model in three different scenarios. In Experiment 1, all training dataset and test dataset share the same set of skill components and edges. Although new skill components and edges appear in the test in Experiment 2, they cannot be found in the knowledge base. In Experiment 3, provenance graphs PVG with new service components and edges are added into the knowledge base.

From the three experiments, the following characteristics of the *SEC* model can be demonstrated. Firstly, even if new skill components and edges appear in *proposal graph* PRG, the *SEC* model still can work and perform better in precision for predicting successful performance of composite team. Secondly, according to the experimental results, the precision for the *SEC* model in three experiments seems to be similar, because they share the same high contribution edge set. Thirdly, once a new edge is included into the knowledge base, if it contributes greatly to the class value, its $WC^{x}_{E_G}$ will immediately influence the prediction ability of the *SEC* model.

3.4 Summary

In this chapter, we propose two compositional trust evaluation approaches, i.e., the *Correlated Contribution* model and the *Same Edge Contribution* model for the collaborative complex system without or with workflow structure, respectively. The *Correlated*

Contribution model evaluates both skill types and individual services, which have directly contributed to the performance quality value of composite teams. Experimental results have shown that the performance of the *Correlated Contribution* model is better than the traditional *Reputation-Based* models, which are widely applied in complex systems. Especially, the *Correlated Contribution* model has demonstrated a significant improvement in the performance quality value of composite teams when receiving dynamic multi-skill requests.

With the workflow structure information, we investigated the possibility of using provenance graphs in trust estimation, and proposed a compositional trust estimation model, named the *SEC* model. The *SEC* model can predict the trustworthiness of a composite team based on related provenance information. The proposed approach can work effectively to facilitate systems to analyse huge amounts of provenance data, and derive trust information from the provenance data automatically. Through a comparison with the *J48* model, which is a well known classification approach, it can be found that the *SEC* model has better performances in relation to compositional trust estimation, especially when new skill components and composition relationships occur in a complex system randomly. Therefore, we claim that our approach is more suitable for dynamic working environments, and can be applied for component composition in open systems.

Chapter 4

Context-Specific Inter-Personalised Trust in Preference Systems

4.1 Introduction

In terms of the decomposable characteristic of the complex system, the preference system can also be classified as one kind of complex system. Research in preference systems mainly focus on the analysis of preference similarity among entities (Newman, 2003). In this research, we consider the preference system as a set of manageable interrelated subsystems and each of them is in turn in a hierarchical structure. As mentioned in Chapter 1, a preference system contains three kinds of social entities, i.e., users, items and objects. An item denotes an objective article or unit in the system. Users are able to provide feedback to items based on their interactive experience with them. An object is a 2-tuple which represents an item with a particular feedback rating value. E-Commerce system is a good example of the preference system. In an E-Commerce system, customers can be modeled as users. They can have a particular preference and opinions on a list of products, i.e., items, which they have previous experience. Rating values of items provided by users imply the preferences of these users. The detailed definition will be given in Section 4.2.

The aim of this chapter is to explore context-specific inter-personalised trust from the preference complex system. As previous mentioned, trust, as a social concept, has many facets (Golbeck, 2009). So, the context-specific inter-personalised trust indicates multiple and heterogeneous trust relationships between social entities in terms of different contextual situations. In other words, a particular social entity may place its trust differently to different social entities in terms of their multi-faceted interests and opinions of different types. Therefore, the trust relationship between a pair of users is context dependent and is basically valid within a particular facet only. In contrast to the unified assessment standard in collaborative complex systems, the feedback for a particular item from different users is not objective and each user may have a particular preference. Hence, the process of interpreting the context-specific inter-personalised trust from such entity-generated feedback is influenced by subjective perceptions of users.

The aim of trust mining in preference systems is to track the context-specific inter-personalised trust in preference complex systems based on various activities and relationships from huge archives of data, such as transaction records from social media. In a preference complex system with network structures, the users and objects are not uniformly distributed, rather they are clustered into some small groups. Namely, the network has some dense subnetworks, which are called communities. A community is formed by individuals who more frequently interact with each other within a group than with others outer-side the group. The discovery of inherent community structures for both the user community and object community can help us understand the networks more deeply and reveal interesting properties shared by the community members (Zhao et al., 2012). Therefore, in order to explore multi-facet and heterogeneous trust relationships among users, items and objects need to be organised into nested groups which are represented as organisational hierarchies. Furthermore, based on the decomposable and organisational characteristic of preference systems, a set of more manageable interrelated subsystems can help to reduce complexity of analysis and trust evaluation by dealing them in relative isolation.

In this chapter, we proposed a community based approach for modelling and analysing massive transactional data in preference systems by analysing the network structure. The proposed approach reveals potential trust relationships among entities of a preference system, and these relationships are not usually readily discernible (Mao, 2012). Furthermore, the approach predicts a user's potential feedback for particular items corresponding to his/her preference in terms of the user's previous interaction experience. In the approach, we combine the idea of traditional recommendation systems and identification of network structures to explore context-specific inter-personalised trust relationships in preference complex systems.

Our approach is motivated by the intuition that , according to the rating history of users, a group of users share the similar feedback records for same items, as they have similar preference and criteria for items. The proposed approach is based on the hypothesis that users who are socially connected are more likely to share the same or similar preferences and criteria for a particular group of items. Hence, recommendations from the members of the community that a user belongs to are more suitable for the user's preference.

The rest of this chapter is arranged as follows. Firstly, the detailed problem definition and some assumptions in this research are presented in Section 4.2. Secondly, the general protocol of the proposed community-based trust evaluation model is introduced in Section 4.3, and then the detailed algorithm analysis will be discussed in Section 4.4. Thirdly, in Section 4.5, some experimental results are given to demonstrate the performance of the community-based model by comparing it with a user-based collaborative filtering algorithm, an item-based collaborative filtering algorithm, and the *KNN* algorithm. Finally, the summary of this chapter is presented in Section 4.6.

4.2 Problem Definition

In this section, we give some definitions which are used in the *Community-Based* approach. We consider a preference complex system which consists of an item set, i.e., $I = \{item_1, item_2, item_3, ..., item_n\}$, and a user set, i.e., $U = \{u_1, u_2, u_3, ..., u_m\}$. Many to many relationships among users and items exist, namely, a group of users can collect many different items, and a set of items can be collected by many different users.

Given a preference complex system consisting of m users and n items, there is a $m \times n$ user-item rating matrix R. Each entry $r_{m,n}$ in R represents the feedback rating of item $item_n$ provided by user u_m. The default value of $r_{m,n}$ is 0, which means that u_m does not have any previous interactive experience with $item_n$. The user-item rating matrix R can be decomposed into row vectors:

$$R = [R_{u_1}, R_{u_2}, R_{u_3}, ..., R_{u_m}]^T, R_{u_m} = [r_{m,1}, r_{m,2}, r_{m,3}, ..., r_{m,n}], \tag{4.1}$$

where each row vector R_{u_m} represents the ratings of all items given by u_m. Alternatively, the matrix can also be represented by its column vectors:

$$R = [R_{item_1}, R_{item_2}, R_{item_3}, ..., R_{item_n}]^T, R_{item_n} = [r_{1,n}, r_{2,n}, r_{3,n}, ..., r_{m,n}], \tag{4.2}$$

where a column vector R_{item_n} represents the ratings of $item_n$ given by different users.

In our approach, an item with a particular non-zero rating value is regarded as an distinct object, and a preference system can have an object set.

Definition 4.1: The object set O in a preference system is a set of objects. Each object $o^{\tau}_{item_n} =< item_i, \tau_x >$, where $item_n \in I$, and τ_x denotes the particular rating value for each $item_n$.

As mentioned in Chapter 1, network is a useful tool for reasoning about the structure and dynamics of complex systems by mainly focusing on the essentials and elements denoted by nodes (vertices), and the interaction between the elements denoted by edges. Once a pair of users, e.g., u_j and u_k, provide a same rating τ_x for an item $item_n$, the object $o^{\tau_x}_{item_n}$ is connected to both u_j and u_k. In other words, the edges between users are constructed by objects, vice versa. Hence, we can model a preference complex system as a bipartite network consisting of two exclusive kinds of vertices representing users and their objects, and in addition, edges which link vertices belonging to different sets, i.e., U, O, respectively. Therefore, we can have the following formal definition for a preference complex system.

Definition 4.2: A preference complex system is represented as a bipartite network with three-tuple: $CG =< U, O, E >$, where

- U is the user vertex set involved in the preference complex network CG.
- O is the set of object vertex set that users have usually interacted with particular items by giving particular feedback ratings.
- E is the edge set representing interactions that exist in CG. $E = E_{UO}$, where $E_{UO} = \{(u_j, o^{\tau_x}_{item_k}) | u_j \in U, o^{\tau_x}_{item_k} \in O\}$.

In terms of edges linking two vertices from different vertex sets, there is no connection among vertices in the same vertex set. One of the basic approaches for transforming bipartite networks into unipartite networks is projection (Guimerà, Sales-Pardo & Amaral, 2007). In order to get single vertices set, projection transforms such $u_j - o^{\tau_x}_{item_k} - u_l$ or $o^{\tau_x}_{item_j} - u_l - o^{\tau_y}_{item_k}$ connection into $u_j - u_l$ or $o^{\tau_x}_{item_j} - o^{\tau_y}_{item_k}$ connection. However, such projection transformation cause the loss of information about the edge-content between user-object interactions, which is valuable for characterizing the preference complex system. If there is one-to-one correspondence between an object set and a user set, it shows that one particular group of objects only attracts one particular group of users. On the other hand, if there is many-to-many correspondence between an object group and some user groups, it shows that some objects may attract several different groups of users, as well as objects preferred by difference users may have overlaps.

In traditional bipartite network based on community detection approaches, several real-world relations are represented as bipartite graphs composed on two types of vertices, such as actor-event network, product-customer networks (E-Commerce systems) and book-reader networks (J. G. Liu, Zhou, Che, Wang & Zhang, 2010; Guimerà et al., 2007). The communities reflect topological relationships between elements of the underlying system and represent functional entities (Lancichinetti, Fortunato & Kertész, 2009). However, most of researches do not take the available feedback rating in the system into consideration to improve the community detection process. Actually, feedback ratings, which are one kind of user-generated content, are critical for perceiving item opinions according to users' preferences through sentiment analysis and opinion mining (Gundecha & Liu, 2012). Therefore, in our approach, we take feedback ratings into account which will provide better supervision to the community detection process in the preference complex systems by providing rich context information.

Once a particular interaction has been completed, the system will update the interaction record IR related with the user, item and object information.

Definition 4.3: The interaction record IR is defined as a 3-tuple, $IR =< u_i, item_j, o^{\tau_x}_{item_j} >$. τ_x represents the feedback rating which user u_i gives to item $item_j$.

If u_i inquires the potential quality of $item_j$, and u_i lacks of previous interaction experience with $item_j$, the system will generate an item enquiry IE containing the information of u_i and $item_j$, i.e., $IE =< u_i, item_j >$. $IE.item_j$ represents which item a user $IE.u_i$ enquires about.

4.3 Trust Estimation Protocol

The protocol for community-based trust estimation approach is illustrated in Figure 4.1. There are six modules in the protocol, including, the Reply Module, the Interaction Record Database, the User Criteria Clustering Module, the Facet Object Set Generation Module, the Prediction Retrieval Module and the Trust Calculation Module. In this section, we will introduce the overall process in detail.

Firstly, once a user u_i completes an interaction between an item $item_j$, the Reply Module updates the interaction record IR related with u_i, $item_j$ and $o^{\tau_x}_{item_j}$. Then, the feedback ratings on diverse items given by users are stored as interaction records and sent to the Interaction Record Database. Then, based on the records in the Interaction Record Database, the User Criteria Clustering Module and the Facet Object Set Generation Module will detect user communities and object communities, respectively.

The objective of the User Criteria Clustering Module is to cluster users into hierarchical communities according to the user-generated ratings of items. The user criteria clusters generation is based on hierarchical clustering organises users as a hierarchy of nested partitions. The lower the level of communities the users belong to, the more same ratings for particular items users gave.

Similarly, the purpose of the Facet Object Set Generation Module is to generate object communities based on the hierarchical user criteria clustering tree from the User Criteria Clustering Module. This module transforms the item with specific rating values to objects. Based on the rating interactions between users and items, objects are partitioned into communities on different levels corresponding to a user criteria clustering tree in an optimization phase by link analysis.

If a user inquires about particular items that the user does not have previous interactions with, the enquiry will be sent to the Prediction Retrieval Module. The Prediction Retrieval Module will search for all facet object sets which include objects related to the required item $IE.item_j$. Then, the Facet Object Set Generation Module will pass the facet object sets which satisfies the item enquiry IE to the Trust Calculation Module.

The objective of this module is to generate a quality prediction for the required item $IE.item_j$ based on the preference of required user $IE.u_i$. Therefore, in terms of each related facet object set passed from the previous module, the Trust Calculation Module will compare the objects with the enquirer's previous interaction records. The more similar objects between the related facet object set and the enquirer's previous interaction records, the more confident it is that the objects in the particular facet object set will match the preference of user $IE.u_i$. Finally, the Trust Calculation Module will return the rating value of the object regarding to the required item $IE.item_j$ in the facet object set which obtained the most confidence to user $IE.u_i$.

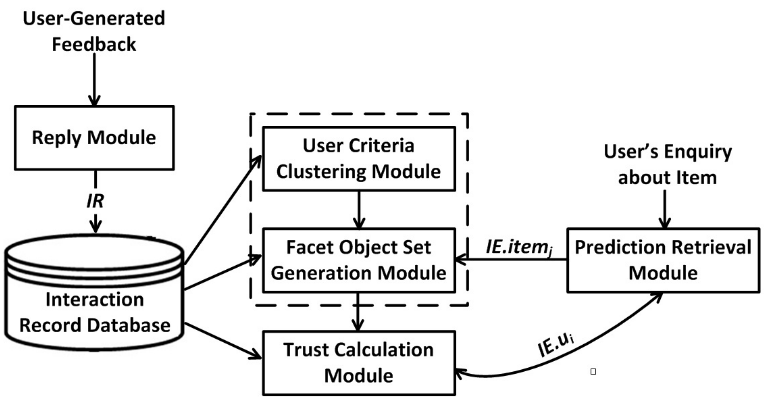

Figure 4.1: Community-Based Trust Estimation Protocol

4.4 Hierarchical Community Structure

As mentioned in the previous section, a preference complex system can be represented as a bipartite network, which contains three kinds of elements, including, users, items and objects. In this section, a four-step trust mining algorithm is proposed to partition theses three kinds of elements into different community (subnetwork) structures, called user criteria cluster, object community and facet object set, respectively. A community detection approach is also introduced in this section, which combines user criteria clustering and link analysis for objects. In terms of the hierarchical organisation of a preference complex system, the lower-level communities are embedded within other higher-level communities and vertices can be shared between different communities (Lancichinetti et al., 2009). Discovering inherent structures for both user communities and object communities can help us understand a preference complex system better and reveal interesting hidden patterns (Zhao et al., 2012). Whereas users within one communities are closely connected, they have the similar preference for certain groups of items.

4.4.1 User Community

The goal of user criteria clustering is the separation of users into groups based on user-item rating matrix R. The user community evolution is based on the idea that two users should have more chances to be in the same community when they share more similar ratings for different items. Meanwhile, as users in the same community are more likely to have common preferences, they are more likely to have similar expectations about a certain group of items. In this thesis, we cluster user criteria based on hierarchical clustering (*HC*) and organise users as a hierarchy of nested partitions. By using *HC*, partitions can be obtained through "horizontal" cuts. This enables us to see how users are being merged into clusters. Therefore, according to the user-item rating matrix R, we utilise agglomerative hierarchical clustering to build user criteria clusters by joining users with the most similar rating history into pairs, and then evolve groups (Kraskov & Grassberger, 2009).

In this approach, items are regarded as random variables and mutual information is capable of measuring general dependence among them. The entropy of a user rating pattern is a measurement of the uncertainty in the feedback value given on items. It can be calculated by using Equation 4.3 (Cover & Thomas, 2012):

$$H(u_j) = -\sum_{i=1}^{n} P(R_{u_j} = r_{j,i}) \log P(R_{u_j} = r_{j,i}), \tag{4.3}$$

where n is the number of possible items which u_m can rate. Higher entropy of users for item variables means that their selection and rating pattern levels are more randomly distributed (Zhou, Wang, Dougherty, Russ & Suh, 2004). Mutual information describes the amount of common feedback rating given by both users. Thus, it can be used to derive distance measure quantifying the similarity of pairs of user selection and rating pattern. The mutual information between user u_j and u_k is defined by Equation 4.4 (Cover & Thomas, 2012):

$$I(u_j, u_k) = H(u_j) + H(u_k) - H(u_j, u_k). \tag{4.4}$$

The smaller values of mutual information $I(u_j, u_k)$ is, the larger difference between pair of user selection and rating patterns. Another feature of mutual information which is essential for the hierarchical cluster analysis is its grouping property. It means that the mutual information can be decomposed into hierarchical levels. For example, the mutual information between three users u_i, u_j and u_k is equal to the sum of the mutual information between u_i and u_j, plus the mutual information between u_k and the combined variable $(u_i\ u_j)$ (see Equation 4.5) (Cover & Thomas, 2012):

$$I(u_i, u_j, u_k) = I(u_i, u_j) + I((u_i u_j), u_k). \tag{4.5}$$

It means that the mutual information can be decomposed into hierarchical levels of preference complex system. By iterating it, we can decompose $I(u_1 u_2 u_3 ... u_m)$ $(m > 2)$ for any partitioning of the user set $(u_1 u_2 u_3 ... u_m)$ into the mutual information between elements within one cluster (Kraskov & Grassberger, 2009).

However, mutual information is not bounded, so it would not be a suitable distance measurement for itself. Therefore, we transform the mutual information into a bounded mutual-information-based distance by normalizing it (see Equation 4.6).

$$D(u_j, u_k) = 1 - \frac{I(u_j, u_k)}{\max(H(u_j), H(u_k))}. \tag{4.6}$$

In Equation 4.6, $D(u_j, u_k)$ denotes the preference similarity between a pair of users. It is equal to zero, when identical users have maximum possible selection and rating patterns and have identical entropies, i.e., $H(u_j) = H(u_k) = I(u_j, u_k)$ (Dawy, Hagenauer, Hanus & Mueller, 2005). Hence, given a user set with m users, an $m \times m$ mutual-information-based distance matrix can be calculated by using Equation (4.6).

Internal nodes of the ***HC*** tree $T.Node$ correspond to subsets of the set of all leaves, and the root represents all user sets, i.e., the joint variables $(u_1 u_2 u_3 ... u_m)$. Therefore, we define that there is a user set $T.Node.U$ at each cluster, which contains all leaves of the node. When presenting the mutual-information-based clustering tree, the leaf nodes are user instances group $u_1, u_2, u_3, ..., u_m$ and the height of the leaf nodes is zero. We put the leaf nodes on the x-axis and use the value of the distance/similarity to control the height of the tree. Let's assume that an internal node Φ has two child nodes X and Y, i.e. Φ =(X Y). X and Y themselves might be either leaves or internal nodes. Therefore, the user set U^Φ and the height of the parent node Φ can be defined as Equations 4.7 and 4.8.

$$U^\Phi = \{U^X \cup U^Y | U^X \cap U^Y = \phi\}, \tag{4.7}$$

$$height(\Phi) = D(X, Y). \tag{4.8}$$

The user criteria clustering analysis algorithm is shown in Algorithm 1. In the

Algorithm 1 The User Criteria Clustering Analysis

Input: U, R
Output: T
1: $K_C = K_T = |U|$, $c_i.ID = i$, $c_i \leftarrow u_i$, $c_i.rating \leftarrow R_{u_i}$, $T.Node_i \leftarrow c_i$, $T.Node_i.left = T.Node_i.right = Null$
2: **while** $K_C > 1$ **do**
3:     **for** $\forall c_i \in C$ **do**
4:         **for** $\forall c_j \in C \wedge i \neq j$ **do**
5:             $M_{i*j} = D(c_i.rating, c_j.rating)$
6:             $(c_i, c_j) \leftarrow argmin(D(c_i.rating, c_j.rating))$
7:         **end for**
8:     **end for**
9:     $K_C = K_C - 1$, $K_T = K_T + 1$, $c_{temp} \leftarrow merge(c_i, c_j)$, $c_{temp}.U \leftarrow merge(c_i.U, c_j.U)$, $T.Node_{K_T} \leftarrow c_{temp}$, $T.Node_{K_T}.U \leftarrow c_{temp}.U$, $T.Node_{K_T}.left \leftarrow c_i$, $T.Node_{K_T}.right \leftarrow c_j$, $T.Node_{c_i.ID}.parent = T.Node_{c_j.ID}.parent = T.Node_{K_T}$, $c_i \leftarrow c_{temp}$, $C.remove(c_j)$, $c_i.ID = K_T$
10: **end while**
11: **return** T

algorithm, there are two input variables, i.e., U denoting user set, and R denoting user-item rating matrix. T is the output variable in the algorithm. It denotes the hierarchical user criteria tree. Furthermore, $c_i.rating$ denotes the rating matrix for each cluster, and M_{i*j} denotes the entry of the mutual-information-based distance proximity matrix. $M_{|U|*|U|}$ is symmetric and the diagonal is zero. A more detailed explanation of the algorithm is given below.

- Line 1: Initialize the leaf nodes of the user criteria cluster tree T by assigning each user into a cluster.
- Line 2 - Line 8: If the number of clusters is still more than 1, the mutual-information-based distances between the each pair of clusters are calculated. The proximity matrix M is updated and the minimum distance for the pair of clusters (c_i, c_j) are found.
- Line 9: The closest pair of clusters are merged as a new cluster c_{temp} and a new cluster user set $c_{temp}.U$. c_{temp} and $c_{temp}.U$ are assigned as the latest internal

node $T.Node_{K_T}$ and $T.Node_{K_T}.U$, respectively $T.Node_{c_i.ID}$ and $T.Node_{c_j.ID}$ are assigned as the left/right child node of the $T.Node_{K_T}$. Meanwhile, $T.Node_{K_T}$ is the parent node for these two nodes.

- Line 10-11: If the size of the cluster set is equal to 1, the construction of the user criteria cluster tree is completed.

4.4.2 Object Community

As previously mentioned, users with similar preference usually give same feedback value for a certain group of items, so we intend to figure out such groups of items with particular feedback values based on the user criteria tree. In our approach, each item with particular feedback rating, except for 0, are regarded as objects. Therefore, the object community implies the preference and criterion of particular user group for certain items. In order to make an accurate prediction for a user's item enquiry, we need to find out what the preference and criterion the enquirer holds for a certain groups items related to enquired items $IE.item_j$ based on the enquirer's previous feedback rating experience.

Although the contents of item description may often imply some common interests of users who used to collect them, such information only represents a simplistic world view and may still contain weak connections between members within user communities (Zhao et al., 2012). In this section, we perform a link-based community detection approach to differentiate the strength of connections between users and objects. An object $o^{\tau_x}_{item_i}$ is connected to both u_j and u_k between these two vertices set and models the characteristics of pairwise interactions rather than individual users. Hence, the object as one of the end points of the edges, not only represents the linkages of the community, it also indicates the edge-content which provides an idea of the nature of the interactions (Qi et al., 2012). Two edges sharing a same end point clearly have a higher similarity degree than those without a common end point.

Based on the user criteria cluster tree, the user community has already emerged at each level of the tree. In terms of each node of the tree, the edge set E are partitioned into object communities in a principle way with the use of linkage and edge-content information. However, the common endpoints of edges are unable to provide sufficient information for the similarity measurement. Hence, the higher degree of an object is within the current level user community than without the community, the more significant correlation between objects within the community.

The aim of partitioning a set of objects into different communities is to ensure that intra-interactions within communities are dense and inter-interactions between the communities are sparse. In most uniqartite network research, modularity maximization is the most popular approach for community identification. Modularity Q uses the denseness and sparsity of the communities' intra-connections and inter-connections to quantify the quality of community structure (Mao, 2012). Here, we modify the previous modularity functions that, upon optimization, yield a partition of the objects in a bipartite network into community at each node of the cluster tree.

Definition 4.4: An object community is defined as a 3 tuple, i.e., $OC = < U, O, E >$, where

- $OC.U \leftarrow T.Node.U$
- $OC.O \leftarrow T.Node.parent.O$
- $OC.E = \{(u_i, o_{item_j}^{\tau_k}) | u_i \in OC.U, o_{item_j}^{\tau_k} \in OC.O\}$

A preference complex system with $m \times n \times l$ edges can be represented as an adjacency matrix $E_{(u_i, o_{item_j}^{\tau_k})}$, where m represents (see Equation 4.9 and Equation 4.10). The entry in the ith row and $[(j-1) \times l + k]$th column, (i.e., $e_{(u_i, o_j^{\tau_k})}$) is referred as the edge between user u_i and object $o_{item_j}^{\tau_k}$. $e_{(u_i, o_{item_j}^{\tau_k})}$ equals to 1 if the rating value of $item_j$

given by u_i is τ_k, and equals to 0 otherwise. Then, a weight $w_{o^{\tau_k}_{item_j}}$ can be assigned for each edge linking to the object $o^{\tau_k}_{item_j}$. $w_{o^{\tau_k}_{item_j}}$ can be calculated according to the edge degree of an object vertex $o^{\tau_k}_{item_j}$ which is denoted as $\deg(o^{\tau_k}_{item_j})$ by using Equation 4.11.

$$E_{(u_i, o^{\tau_k}_{item_j})} = \begin{pmatrix} e_{(u_1, o^{\tau_1}_{item_1})} & \cdots & e_{(u_1, o^{\tau_l}_{item_n})} \\ \vdots & \ddots & \vdots \\ e_{(u_m, o^{\tau_1}_{item_1})} & \cdots & e_{(u_m, o^{\tau_l}_{item_n})} \end{pmatrix} \tag{4.9}$$

$$e_{(u_i, o^{\tau_k}_{item_j})} = \begin{cases} 1 & \text{if the rating value which user } u_i \text{ gives item } item_j \text{ equals to } \tau_k \\ 0 & \text{otherwise} \end{cases} \tag{4.10}$$

$$w_{o^{\tau_k}_{item_j}} = \frac{1}{\deg(o^{\tau_k}_{item_j})} \tag{4.11}$$

The traditional modularity method starts off with each vertex representing a community which contains only one member, and then it calculates the changes of modularity to choose the largest of them (Zhao et al., 2012). In terms of each node $T.Node$ of the user criteria cluster tree T, the gain of modularity ΔQ is obtained by removing an isolated object $o^{\tau_k}_{item_j}$ from the object community of its parent node $T.Node.parent.O$ in the optimization phase. This process is applied repeatedly and sequentially for all object vertices until a local maximum modularity is achieved, i.e. when no object vertex removal can improve the modularity. It is noted that the result of the algorithm is influenced by the order in which the objects are considered. Although the ordering of the objects may not exert significant influence on the modularity, it still can dramatically affect the computation time and efficiency (Blondel et al., 2008). In this approach, we calculate the distance value $dv_{o^{\tau_k}_{item_j} \in T.Node.parent.O}$ for each object $o^{\tau_k}_{item_j}$ belonging to the object community of its parent node $T.Node.parent.O$ by using Equation 4.12. Therefore, the gain of the modularity $\Delta Q_{o^{\tau_k}_{item_j}}$ is calculated in the decreasing order of the $dv_{o^{\tau_k}_{item_j} \in T.Node.parent.O}$ (see Equation 4.13).

$$dv_{o^{\tau_k}_{item_j} \in T.Node.parent.O} = \left(\sum_{u_i \in T.Node.parent.U}^{T.Node.parent} e_{(u_i, o^{\tau_k}_{item_j})} - \sum_{u_i \in T.Node.U}^{T.Node} e_{(u_i, o^{\tau_k}_{item_j})} \right) \times w_{o^{\tau_k}_{item_j}} \tag{4.12}$$

$$\Delta Q_{o^{\tau_k}_{item_j}} = \left[\frac{\sum_{in \setminus o^{\tau_k}_{item_j}} + 2 l_{o^{\tau_k}_{item_j}, in}}{2m} - \left(\frac{\sum_{tot \setminus o^{\tau_k}_{item_j}} + l_{o^{\tau_k}_{item_j}}}{2m} \right)^2 \right] - \left[\frac{\sum_{in \setminus o^{\tau_k}_{item_j}}}{2m} - \left(\frac{\sum_{tot \setminus o^{\tau_k}_{item_j}}}{2m} \right)^2 - \left(\frac{l_{o^{\tau_k}_{item_j}}}{2m} \right)^2 \right] \tag{4.13}$$

In Equation 4.13, m is the sum of the weights of all the edges in the preference complex system CG; $\sum_{in \setminus o^{\tau_k}_{item_j}}$ denotes the sum of the weights of the edges inside OC except for inside edges linking object $o^{\tau_k}_{item_j}$; $\sum_{tot \setminus o^{\tau_k}_{item_j}}$ denotes the sum of the weights of the edges incident to objects in OC except for object $o^{\tau_k}_{item_j}$; $l_{o^{\tau_k}_{item_j}}$ denotes the sum of the weights of the edges connecting to object $o^{\tau_k}_{item_j}$ in the whole network CG; $l_{o^{\tau_k}_{item_j}, in}$ denotes the sum of the weights of the edges from object $o^{\tau_k}_{item_j}$ to users belonging to the current node of the user criteria cluster tree. The values of these parameters can be calculated from Equations 4.14 to 4.18, respectively.

$$m = \sum_{o^{\tau_x}_{item_j} \in CG.O}^{CG} \sum_{u_i \in CG.U}^{CG} e_{(u_i, o^{\tau_x}_{item_j})} \times w_{o^{\tau_x}_{item_j}} \tag{4.14}$$

$$\sum_{in \setminus o^{\tau_k}_{item_j}} = \sum_{o^{\tau_x}_{item_j} \in OC.O, o^{\tau_x}_{item_j} \neq o^{\tau_k}_{item_j}}^{OC} \sum_{u_i \in OC.U}^{OC} e_{(u_i, o^{\tau_x}_{item_j})} \times w_{o^{\tau_x}_{item_j}} \tag{4.15}$$

$$\sum_{tot \setminus o^{\tau_k}_{item_j}} = \sum_{o^{\tau_x}_{item_j} \in OC.O, o^{\tau_x}_{item_j} \neq o^{\tau_k}_{item_j}}^{OC} \sum_{u_i \in CG.U}^{CG} e_{(u_i, o^{\tau_x}_{item_j})} \times w_{o^{\tau_x}_{item_j}} \tag{4.16}$$

$$l_{o^{\tau_k}_{item_j}} = \sum_{u_i \in CG.U}^{CG} e_{(u_i, o^{\tau_k}_{item_j})} \times w_{o^{\tau_k}_{item_j}} \tag{4.17}$$

$$l_{o^{\tau_k}_{item_j}, in} = \sum_{u_i \in OC.U}^{OC} e_{(u_i, o^{\tau_k}_{item_j})} \times w_{o^{\tau_k}_{item_j}} \tag{4.18}$$

If $\Delta Q_{o^{\tau_k}_{item_j}}$ is positive, the object vertex $o^{\tau_k}_{item_j}$ is then added into the object community of the current node of the tree $T.Node.O$ for which its gain is maximum. If no positive gain can be found, the object $o^{\tau_k}_{item_j}$ only stays in the $T.Node.parent.O$. The discrepancy of the modularity $\Delta Q_{o^{\tau_k}_{item_j}}$ is expected to be as large as possible so that $item_j$ is more likely to be rated as τ_k by users in the user community of the current node of the user criteria tree $T.Node.U$ than users from outside. Furthermore, some objects are connected with limited users. If it is randomly distributed, these objects will be removed from higher object communities. On the other hand, such objects may be connected with particular user groups. So, they will always be maintained in some object communities.

The hierarchical object community generation algorithm is shown in Algorithm 2. In the algorithm, Line 1 to Line 11 are to initialize the top object community based on the user criteria clustering tree. Line 12 to Line 31 are to generate the object community OC for each node of the user criteria cluster tree T. The output of the algorithm is the object community OC set and each OC is assigned to the related node of the user criteria clustering tree T. A more detailed explanation of the algorithm is given below.

- Line 1 - Line 2: The top node of the hierarchical object community OC is initialised. The ID of each object community OC is same as the ID of the node of the user criteria cluster tree T. The user set of the object community OC is the corresponding node of the user criteria cluster tree T;

- Line 3: A temporal object set $tempO1$ is generated. Due to the top node of the user criteria cluster tree T without parent node, the $tempO1$ is assigned to the top object community and is equal to the object set of the bipartite subnetwork $CG.O$;

- Line 4 -Line11: All objects which are not rated by any users are removed from the $tempO1$;

- Line 12: The updated $tempO1$ is assigned to the top object community OC and the object set of the top node of the user criteria clustering tree T;

- Line 13 to Line 14: $T.Node_{index}.parent.O$ is the object set belongs to the parent node of corresponding node of the user criteria clustering tree T. For each object community OC, a temporal object set $tempO2$ is generated and assigned as the object set of its parent node.

- Line 15 to Line 25: The difference amounts ($distanceValue$) of user rating for each object in the $tempO2$ between the user set of node $T.Node_{index}.U$ and its parent node $T.Node_{index}.parent.U$ are checked. All $distanceValue$ are sorted in decreasing order and stored in the queue $distanceQue[]$;

- Line 26 to Line 31: According to the order of $distanceQue[]$, $\Delta Q_{o_j^{\tau_k}}$ for each object in $tempO2$ is calculated. If $\Delta Q_{o_{item_j}^{\tau_k}}$ is less than zero, object $o_{item_j}^{\tau_k}$ is removed from the $tempO2$.

- Line 32: The updated $tempO2$ are assigned to the object community $OC.O$ and the object set $T.Node.O$ of the node of the user criteria cluster tree. Furthermore, the user set $T.Node.U$ is assigned to the corresponding user set $OC.U$ of the object community OC.

Algorithm 2 The Hierarchical Object Community Generation Algorithm

Input: $T, CG =< U, O, E >$
Output: $T, \{OC\}$

$index = T.Node.size() - 1$
$OC_{index}.U \leftarrow T.Node_{index}.U$
$tempO1 \leftarrow CG.O$
for $\forall o_j^{\tau_x} \in tempO$ **do**
  for $\forall u_i \in OC_{index}.U$ **do**
    $sum = sum + e_{(u_i, o_j^{\tau_x})}$
  end for
  if $(sum == 0)$ **then**
    $tempO1.remove(o_j^{\tau_x})$
  end if
end for
$OC_{index}.O \leftarrow tempO1, T.Node_{index}.O \leftarrow OC_{index}.O$
for $\forall T.Node_{index} \in T \wedge T.Node_{index} \neq Null$ **do**
  $tempO2 \leftarrow T.Node_{index}.parent.O$
  for $\forall o_j^{\tau_x} \in tempO2$ **do**
    $tP = tC = 0$
    for $\forall u_i \in T.Node_{index}.parent.U$ **do**
      $tP = tP + e_{(u_i, o_j^{\tau_x})}$
    end for
    for $\forall u_i \in T.Node_{index}.U$ **do**
      $tC = tC + e_{(u_i, o_j^{\tau_x})}$
    end for
    $distanceValue_{o_j^{\tau_x}} = (tP - tC) * w_{o_j^{\tau_x}}$
    $distanceQue[].add(distanceValue_{o_j^{\tau_x}}), sort(distanceQue[])$
  end for
  for $\forall distanceValue_{o_j^{\tau_k}} \in distanceQue[]$ **do**
    calculate $\Delta Q_{o_j^{\tau_k}}$
    if $(\Delta Q_{o_j^{\tau_k}} < 0)$ **then**
      tempO2.remove($o_{item_j}^{\tau_k}$)
    end if
  end for
  $OC_{index}.O \leftarrow tempO2$, $T.Node_{index}.O \leftarrow OC_{index}.O$, $OC_{index}.U \leftarrow T.Node_{index}.U$
end for
return OC, T

4.4.3 Facet Object Set

In terms of the emergent complexity defined in Chapter 1, we can characterise a preference complex system through removing part of the system, because the properties of the rest are affected by the removal of a part. Such a complex system has a collective behaviour that is dependent on the behaviours of all of the components in the system. Therefore, this concept becomes more precise when we connect it to a quantitative measurement of complexity (Bar-Yam, 1997).

Trust is considered as the level of belief established between two entities in relation to a certain context (Pitsilis & Marshall, 2005). In our approach, such belief is interpreted as the user criteria for certain items. Most of the recommended algorithms only assume a single type of trust between users. The main idea is to suggest items to users or give predictions on ratings of item based on who provided previous rating experience. However, the characteristics of a user have many aspects. If we try to characterize a user by one aspect only, the rest will be disregarded. Trust, as a social concept, naturally has multiple facets, indicating different aspects of character and heterogeneous trust relationships between users (Gundecha & Liu, 2012). Therefore, users' multifaceted interests and criteria of different items suggest that user may place trust differently to different interaction partners (J. Tang, Gao & Liu, 2012).

In the previous two steps, i.e. user criteria clustering and object community detection, for each node of the user criteria clustering tree, both user community and object community have been figured out. At each node of user criteria clustering tree, the user community not only shares a common preference, it also accepts a similar criteria of items. Hence, the object community of this level implies a particular facet of the real-world. One important feature for hierarchical object community is that the lower level an object community is, the more significant a correlativeness exists among objects. However, too low levels of object community cannot include all relevant objects, and too high levels of object community may consist of too many noisy objects. Therefore, we narrow the scope of the object community to generate the corresponding facet object set which imply the preference of a certain user community.

Let $FO = \{o_i | o_i \in O\}$ denote the facet object. The objects in a particular facet object not only have correlation among each others, yet are also evaluated under the same criteria by certain group of users. In terms of each internal node $T.Node$ with child nodes $T.Node.left$/$T.Node.right$, users in the user community of left child node $T.Node.left.U$ should also have interactions with part of objects belonging to the object community of right child node $T.Node.right.O$, and vice versa. Equation 4.19 defines the distance between two child nodes of current internal node. The community distance value $CDist(T.Node)$ is smaller if two objects in object communities of child nodes are more frequently and evenly connected with users in both two child user communities. It is necessary to specify a minimum acceptable threshold value, i.e. δ. The facet object set generation algorithm is shown in Algorithm 3. There are two input variables, i.e., user criteria clustering tree T, and predefined threshold δ. The output of the algorithm is a set of facet objects $\{FO\}$. If $CDist(T.Node) \geq \delta$, the contraction of facet object set will be terminated.

$$CDist(T.Node) = \sqrt{\sum_{o^{\tau_k}_{item_j} \in T.Node.O}^{T.Node} \left(\frac{\frac{\sum_{u_i \in T.Node.left.U}^{T.Node.left.U} e_{(u_i, o^{\tau_k}_{item_j})}}{|T.Node.left.U|}}{\frac{\sum_{u_i \in T.Node.U}^{T.Node.U} e_{(u_i, o^{\tau_k}_{item_j})}}{|T.Node.U|}} - \frac{\frac{\sum_{u_i \in T.Node.right.U}^{T.Node.right.U} e_{(u_i, o^{\tau_k}_{item_j})}}{|T.Node.right.U|}}{\frac{\sum_{u_i \in T.Node.U}^{T.Node.U} e_{(u_i, o^{\tau_k}_{item_j})}}{|T.Node.U|}} \right)^2} \tag{4.19}$$

Algorithm 3 The Facet Generation Analysis

Input: T, δ
Output: $\{FO\}$

```
for ∀T.Node_i ∈ T ∧ T.Node_i.left ≠ Null ∧ T.Node_i.right ≠ Null do
    if (ComDependency(T.Node_i) ≤ δ) then
        {FO}.add(T.Node_i.O)
    end if
end for
return {FO}
```

4.4.4 Context-Specific Inter-Personalised Trust Calculation

In terms of the inquired item in particular enquirer IE, more than one facet object sets which include the item $IE.item_j$ usually exists. Therefore, in order to make a more accurate prediction of inquired item $IE.item_j$ potential performance corresponding to the preference of the enquirer $IE.u_i$, the system will compare the user's previous interaction records with the particular facet object sets related to inquired item, and then figure out the most trustable facet object set. Finally, the feedback rating of the object about the required item $IE.item_j$ in the most trustable facet object set which obtained the most confidence will be returned to the user $IE.u_i$ as a prediction result.

In this section, we define two factors: Distance and Support, which influence the confidence of candidate facet object sets.

Definition 4.5: Distance represents the divergence between user's preference, R_{u_i} and the certain facet of the world implied by the facet object set, FO. It can be calculated by using Equation 4.20.

$$Dist(u_i, FO_j) = \frac{\sum_{R_{u_i}.r_{i,k} \neq 0, o_k^{\tau_x} \in FO_j}^{R_{u_i}, FO_j} \sqrt{(R_{u_i}.r_{i,k} - \tau_x)^2}}{|u_i.ratedItemSet \cap FO_j.ItemSet|} \tag{4.20}$$

, where $|u_i.ratedItemSet \cap FO_j.ItemSet|$ denotes how many items that user u_i used to rate are also covered in the item-set of facet object set $FO_j.ItemSet$. In terms of $item_k$, $(R_{u_i}.r_{i,k} - \tau_x)$ calculates the difference between the rating given by u_i and τ_x implied by the object $o_{item_k}^{\tau_x}$ in facet object FO_j. $Dist(u_i, FO_j)$ (in our dataset, the value of $Dist(u_i, FO_j)$ ranges from 0 to 5) and will be smaller if objects in the facet object set FO_j are more appropriate for user's criteria about inquiry $item_k$.

Definition 4.6: Support is the ratio that each facet object set FO_j supports the rating history of user u_i. It can be calculated by using Equation 4.21. K_{con} in a normalized constant, which can be calculated by using Equation 4.22, and $Support(u_i, FO_j)$

ranges from 0 to 1.

$$Support(u_i, FO_j) = \frac{|u_i.ratedItemSet \cap FO_j.ItemSet|}{K_{con}} \tag{4.21}$$

$$K_{con} = max(Support(u_i, FO_j)) \tag{4.22}$$

As both *Distance* and *Support* occur by degrees, it is challenging to establish a mathematic model to define the membership function. Therefore, we adopt fuzzy solution to assign degrees (Eberhart, Simpson & Dobbins, 1996; Skopik et al., 2010). A fuzzy method is applied to determine the confidence degree for each candidate facet set, FO. $Dist(u_i, FO_j)$ and $Support(u_i, FO_j)$ are two input parameters in the fuzzy method. The output parameter is confidence which represent the personal trust value for particular facet object set, ranging from 0 to 1. By calculating the *Distance* and *Support* between enquirers' rating experience and rating value of items in the different facet object sets, the system can produce the most trustable and suitable quality prediction of particular item $IE.item_j$ required by the user $IE.u_i$. The detailed trust calculation process will be introduced in the following paragraphs.

Membership Functions for Input Parameter

For *Distance*, three linguistic states are defined and expressed by appropriate fuzzy sets. They are *Similar*, *Medium* and *Different*. The membership functions for *Distance* are defined from Formulae 4.23 to 4.25, and depicted in Figure 4.2.

$$F_{DistanceSimilar}(x) = \begin{cases} 1 & x \in [0, 0.8] \\ -\frac{10}{7}x + \frac{15}{7} & x \in (0.8, 1.5) \end{cases} \tag{4.23}$$

$$F_{DistanceMedium}(x) = \begin{cases} \frac{10}{7}x - \frac{8}{7} & x \in (0.8, 1.5] \\ 1 & x \in (1.5, 2] \\ -2x + 5 & x \in (2, 2.5) \end{cases} \tag{4.24}$$

$$F_{DistanceDifferent}(x) = \begin{cases} 2x - 4 & x \in (2, 2.5) \\ 1 & x \in [2.5, 5] \end{cases} \tag{4.25}$$

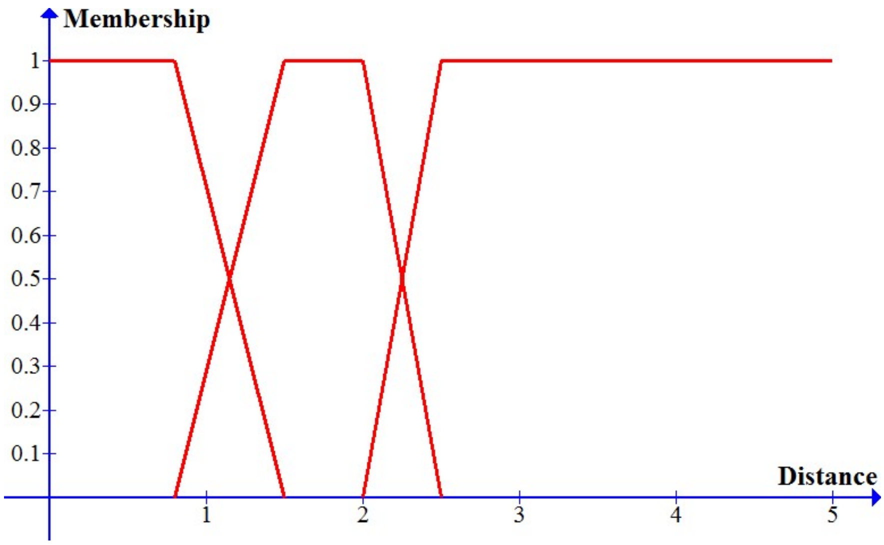

Figure 4.2: Distance Membership

For *Support*, three linguistic states are defined, which are *Low*, *Medium*, *High*. The membership functions for these three fuzzy sets are defined from Equations 4.26 to 4.28, respectively. They are also depicted in Figure 4.3.

$$F_{SupportLow}(x) = \begin{cases} 1 & x \in [0, 0.1] \\ -5x + \frac{3}{2} & x \in (0.1, 0.3) \end{cases} \tag{4.26}$$

$$F_{SupportMedium}(x) = \begin{cases} 5x - \frac{1}{2} & x \in (0.1, 0.3] \\ 1 & x \in [0.3, 0.5] \\ -\frac{10}{3}x + \frac{8}{3} & x \in (0.5, 0.8) \end{cases} \tag{4.27}$$

$$F_{SupportHigh}(x) = \begin{cases} \frac{10}{3}x - \frac{5}{3} & x \in (0.5, 0.8) \\ 1 & x \in [0.8, 1] \end{cases} \tag{4.28}$$

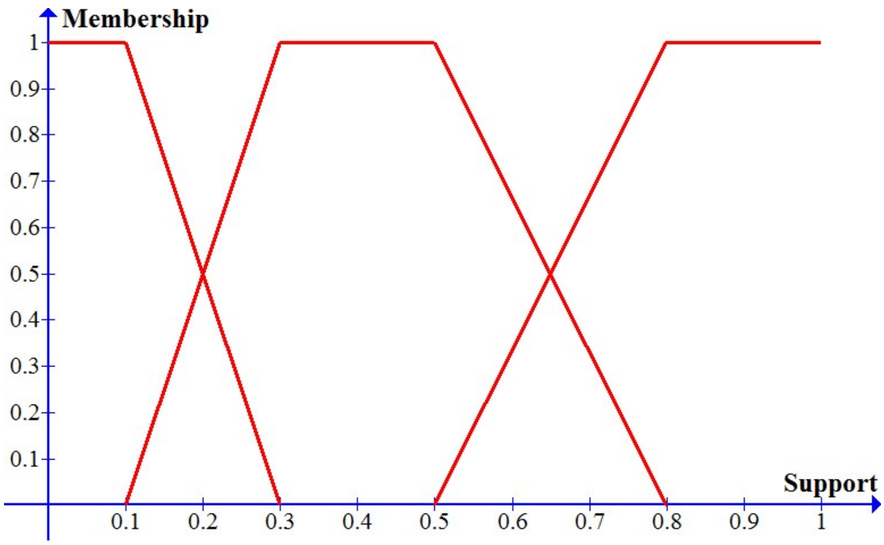

Figure 4.3: Support Membership

Membership Functions for Output Parameter

Confidence is the output parameter in the fuzzy method. It has five linguistic states, which are *Very Low*, *Low*, *Medium*, *High* and *Very High*. The more confidence the facet object set is, the more trustable the rating value of the object about the enquired item $IE.item_j$ in the facet object set is, corresponding to the preference of the enquirer $IE.u_i$. Fuzzy membership functions of these fuzzy sets are defined from Formulae 4.29 to 4.33 and described in Figure 4.4.

$$F_{ConfidenceVeryLow}(x) = \begin{cases} 1 & x \in [0, 0.1] \\ -10x + 2 & x \in (0.1, 0.2) \end{cases} \tag{4.29}$$

$$F_{ConfidenceLow}(x) = \begin{cases} 10x - 1 & x \in (0.1, 0.2] \\ 1 & x \in [0.2, 0.3] \\ -10x + 4 & x \in (0.3, 0.4) \end{cases} \tag{4.30}$$

$$F_{ConfidenceMedium}(x) = \begin{cases} 10x - 3 & x \in (0.3, 0.4] \\ 1 & x \in [0.4, 0.6] \\ -10x + 7 & x \in (0.6, 0.7) \end{cases} \tag{4.31}$$

$$F_{ConfidenceHigh}(x) = \begin{cases} 10x - 6 & x \in (0.6, 0.7] \\ 1 & x \in [0.7, 0.8] \\ -10x + 9 & x \in (0.8, 0.9) \end{cases} \tag{4.32}$$

$$F_{SupportVeryHigh}(x) = \begin{cases} 10x - 8 & x \in (0.8, 0.9) \\ 1 & x \in [0.9, 1] \end{cases} \tag{4.33}$$

Fuzzy Rule Base

A fuzzy rule base is represented as a matrix of combinations of each of the input parameters. Each matrix position is corresponding to one value of the output parameter (Eberhart et al., 1996). The rule base matrix is shown Table 4.1. It contains nine rules that describe the interaction between inputs and output. The columns are *Support* ranges and the rows are *Distance* ranges.

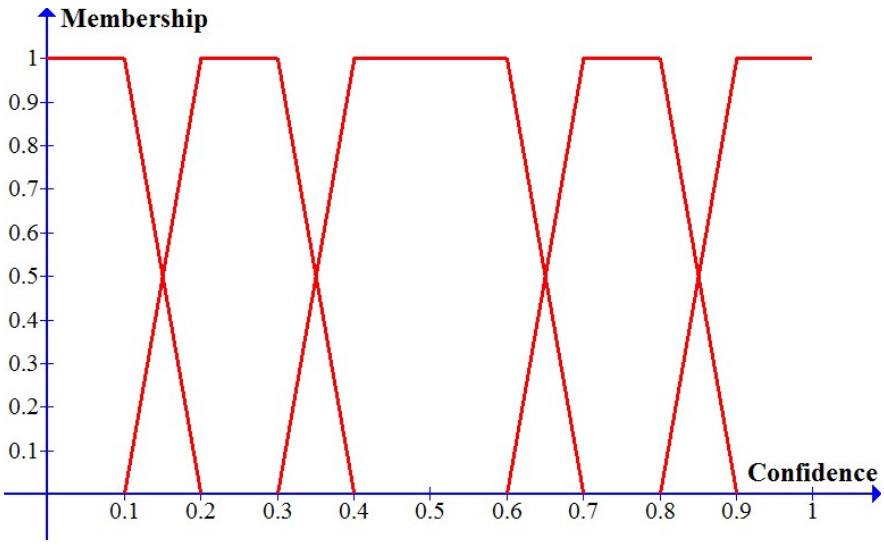

Figure 4.4: Confidence Membership

Table 4.1: Fuzzy Rule Base Matrix

Support \ Distance	Similar	Medium	Different
Low	Low Confidence	Low Confidence	Very Low Confidence
Medium	Medium Confidence	Low Confidence	Very Low Confidence
High	Very High Confidence	High Confidence	Very Low Confidence

Determination of Output membership Values and Defuzzification

Each entry in the rule base is defined by *ANDing* two linguistic parameters to produce individual output response, in the form of: IF *(F(Distance)=α AND F(Support)=β)* THEN *(F(Confidence)=γ)*, where $\alpha \in$ (*Similar*, *Medium*, *Different*), $\beta \in$ (*Low*, *Medium*, *High*), and $\gamma \in$ (*Very Low*, *Low*, *Medium*, *High*, *Very High*). In this mechanism, *AND/MIN* operator is used to combine the membership values together, i.e. the weakest membership determines the degree of membership in the interaction of fuzzy sets (Eberhart et al., 1996). Hence, the output membership value $\mu_\gamma(Confidence)$ can be calculated by using Equation 4.34.

$$\mu_\gamma(v) = MIN(\mu_\alpha(Distance), \mu_\beta(Support)) \tag{4.34}$$

With the output membership, the output values can be determined by tracing the membership values for each rule back through the output membership functions. Finally, the *centroid* defuzzification method (Eberhart et al., 1996) is used to determine the output value. In *centroid* defuzzification, the output value is calculated by using Equation 4.35, where $\mu(v_i)$ is the i^{th} output value, v_i is its corresponding output value, and k is the number of activated fuzzy rules.

$$DF = \frac{\sum_{i=1}^{k}(v_i * \mu(v_i))}{\sum_{i=1}^{k}\mu(v_i)} \tag{4.35}$$

4.5 Experiments

4.5.1 Experiment Setup

To analyse the performance of the community-based trust estimation approach, some experiments have been conducted. In the experiments, we compare the proposed approach with two memory-based collaborative filtering approaches, i.e. the user-based approaches and the item-based approach, and one traditional data mining algorithm, i.e. the *KNN* algorithm. In the experiments, we used the real world dataset collected by Paolo Massa. The dataset were collected via a five-week crawl from (November/December 2003) *epinions* [1], which is a consumer opinion website containing users' reviews of various items (cars, books, music, etc.). Numeric ratings, ranging from 1 to 5, are used in each review. The dataset consists of 195 users who rated a total of 200 different items. There are in total 5035 reviews.

A realistic collaborative filtering matrix may contain millions of users and millions of items. In practice, users only rate a few of the entire set of items, which results in a sparse matrix. The "sparseness" of a collaborative filtering matrix is the percentage

[1] www.epinions.com/

of empty cells (Massa & Bhattacharjee, 2004). Figure 4.5 shows the number of users who created reviews. The X axis in Figure 4.5 represents the user ID, while the Y axis indicates the item rating amount of each user. The sparseness of the dataset is around 87.1%. There are more than 17% users providing no more than five rating records, while the maximum number of rating given by one user is 121. The mean number of created reviews is 25.82 with a standard deviation of 24.40, and the median is 19.

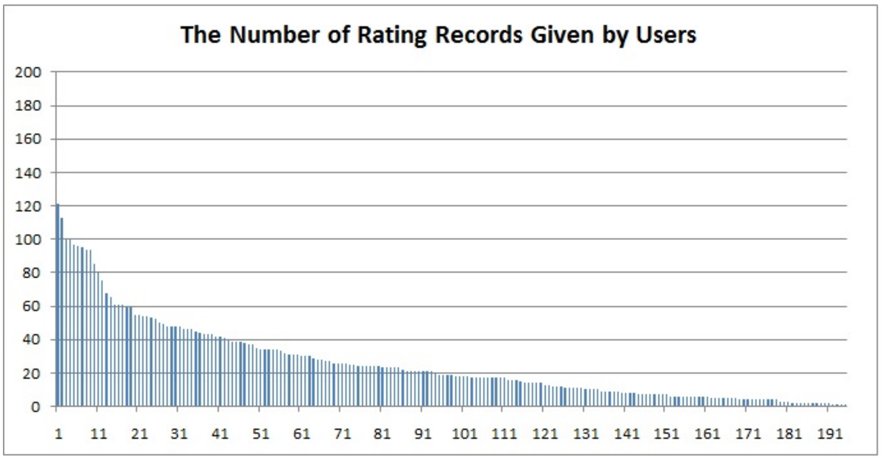

Figure 4.5: Numbers of Reviews Rated by Users with Cold Start Users

4.5.2 Comparison Method

There are two major categories of collaborative filtering approaches, including the memory-based and the model-based approaches. In terms of the memory-based algorithm, it provides recommendations based on the entire user profile database. In contrast, the model-based approach applies a compact model, which is previously learned from the user profile database, to generate recommendations.

- **User-Based Collaborative Filtering Algorithm** User-based collaborative filtering predicts an active user's evaluation criteria for a particular item based on rating records from users with similar profiles. Firstly, it calculates all similarities of any two row vectors of the user-item matrix. With regarding to the prediction for a target user's rating of a particular item, a set of most similar users can be identified. Those similar users' ratings for an item will be averaged by weights. Equation 4.36 computes the similarity between the test user u_a and his/her neighbours. The predicted rating $r_{u_a,\hat{item_y}}$ of the test item y of u_a is computed by using Equation 4.37

$$w_{u_a,u_b} = \frac{\sum\limits_{i|r_{u_a,i},r_{u_b,i}\neq 0} (r_{u_a,i} - \overline{r_{u_a}})(r_{u_b,i} - \overline{r_{u_b}})}{\sqrt{\sum\limits_{i|r_{u_a,i},r_{u_b,i}\neq 0} (r_{u_a,i} - \overline{r_{u_a}})^2} \times \sqrt{\sum\limits_{i|r_{u_a,i},r_{u_b,i}\neq 0} (r_{u_b,i} - \overline{r_{u_b}})^2}} \tag{4.36}$$

$$r_{u_a,\hat{item_y}} = \overline{r_{u_a}} + \frac{\sum\limits_{k=1}^{K} w_{u_a,u_k} \times (r_{u_k,item_y} - \overline{r_{u_k}})}{\sum\limits_{k=1}^{K} |w_{u_a,u_k}|} \tag{4.37}$$

- **Item-Based Collaborative Filtering Algorithm** Item-based recommendation algorithms use the similarity between items instead of users. Firstly, the similarity of items can be calculated from Equation 4.38 to 4.40. Then unknown ratings can be predicted by averaging the ratings for other similar items generated by the test user (see Equation 4.41).

$$d_{item_a} = \sqrt{\sum\limits_{i|r_{u_i,item_a},r_{u_i,item_b}\neq 0} (r_{u_i,item_a} - \overline{r_{item_a}})^2} \tag{4.38}$$

$$d_{item_b} = \sqrt{\sum\limits_{i|r_{u_i,item_a},r_{u_i,item_b}\neq 0} (r_{u_i,item_b} - \overline{r_{item_b}})^2} \tag{4.39}$$

$$w_{item_a,item_b} = \frac{\sum\limits_{i|r_{u_i,item_a},r_{u_i,item_b}\neq 0} (r_{u_i,item_a} - \overline{r_{item_a}})(r_{u_i,item_b} - \overline{r_{item_b}})}{d_{item_a} \times d_{item_b}} \tag{4.40}$$

$$\hat{r_{u_a,item_y}} = \overline{r_{item_y}} + \frac{\sum_{k=1}^{K} w_{item_y,item_k} \times (r_{u_a,item_k} - \overline{r_{item_k}})}{\sum_{k=1}^{K} |w_{item_y,item_k}|} \tag{4.41}$$

- ***KNN*** In many recommendation systems, correlation and similarity between items or users are utilized as measurements of proximity to form a neighborhood scheme. The best-k-neighbours algorithm (Larose, 2005) selects k most similar neighbours to be considered in the prediction algorithm.

4.5.3 Experimental Results

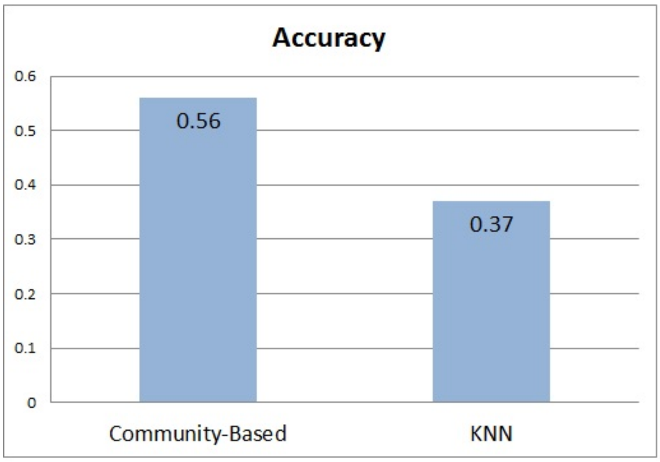

Figure 4.6: Accuracy for Dataset with Cold Start Users

When a new user enters the system without any rating history, it is hard to predict her preference as the user has never left any ratings before. We consider users with less than five rating records as "cold start users". In terms of "cold start users", traditional collaborative filtering algorithms are usually unable to provide high quality recommendations. Moreover, accurate predictions also create an incentive for such users to continue using the system. Therefore, in our experiments, we also compare algorithms' performances for "cold start users".

In the experiment, we mainly apply two metrics, i.e., accuracy and difference,

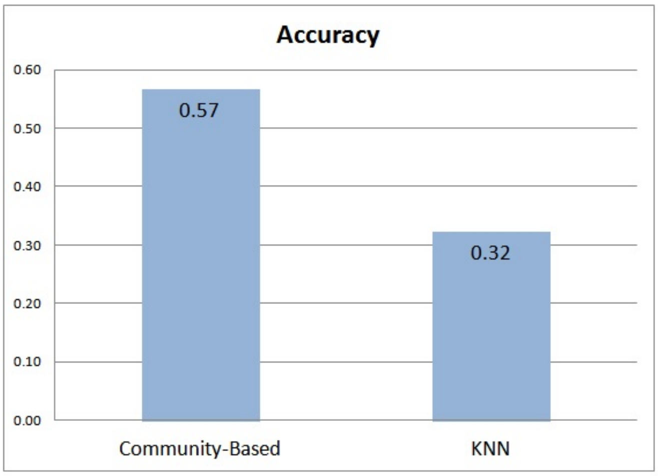

Figure 4.7: Accuracy for Cold Start Users

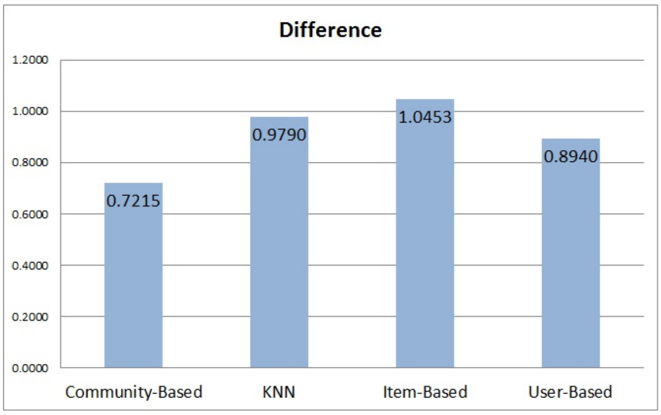

Figure 4.8: Difference for Dataset with Cold Start Users

to compare the performance of the community-based trust estimation algorithm and the other three algorithms. The accuracy of an algorithm denotes the percentages of potential quality prediction of items which are equal to the actual feedback rating values given by enquirers. However, neither user-based collaborative filtering algorithm nor item-based collaborative filtering algorithm can predict exact rating values for required items. Hence, *difference* is adopted as another comparison metric. It measures the average distance between actual (true) values and predicted rating values.

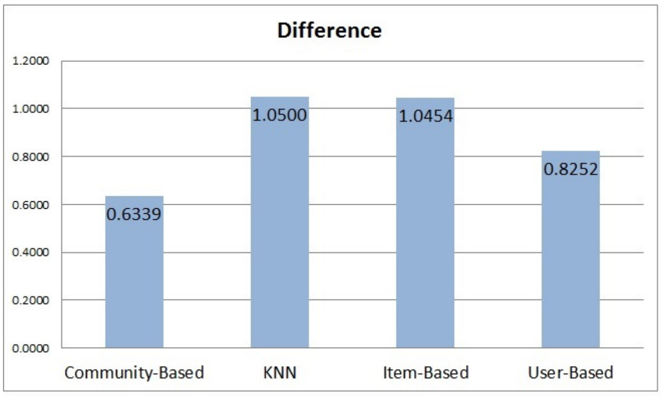

Figure 4.9: Difference for Cold Start Users

Comparison of Accuracy

Figure 4.6 illustrates the comparison of the accuracy of both the community-based algorithm and the *KNN* algorithm. The accuracy of proposed algorithm reaches 0.56, which is much higher than the accuracy of *KNN* at 0.37. In terms of the "cold start users" (see Figure 4.7), the accuracy of community-based algorithm increased by 0.01 which is significantly higher than the performance of *KNN* at 0.32. Therefore, once a new comer user has rating experience, the community-based recommendation algorithm still can provide trustable suggestions to users.

Comparison of Difference

Figure 4.8 compares the difference values of the four algorithms. The community-based algorithm performed better than the other three algorithms, where the difference is around 0.72. Furthermore, from Figure 4.9, it can be seen that, the difference of the community-based approach narrowed to 0.6339 in terms of the "cold start users". However, the difference of the *KNN* and item-based algorithm increased to above 1. Although the performance of the user-based recommendation algorithm improved, the difference (0.8252) is still larger than the community-based trust estimation algorithm.

From the experimental results, it can be seen that the performance of the community-based approach can perform better than the other three approaches in terms of both difference and accuracy, under the "cold start users" situation.

4.6 Summary

In this chapter, we proposed a community-based trust estimation approach to mine context-specific inter-personalised trust within the preference complex system. In terms of the decomposable characteristic of the complex system, we organise the preference system as a set of more manageable interrelated communities, each of which is in turn hierarchical in structure. The approach mainly focuses on the user-to-user with similar preference and groups them into various user communities. Furthermore, the object community implies the interest and criterion of particular user community for certain items. Finally, the fuzzy logic membership function is applied to ascertain the most confident facet object set and make the trustable quality prediction based on the rating value of the object about the enquired item $IE.item_j$ in this facet object set.

Chapter 5

Conclusion

Trust evaluation is an important topic in complex system research. A complex system is a collection of interacting components which can group and create functioning units together (Mitchell & Newman, 2002). The trust among these components is derived from interactions. It represents a subjective expectation which a component has about another's future behaviour to perform given activities dependably, securely, and reliably. For many complex systems, the generalisable methods and measures for characterisation are required. These measures cannot be too application specific and need to be transferred to disparate complex systems.

Collaborative and preference complex systems are two major types of complex systems, and can be applied in many potential applications. In this thesis, we proposed several trust evaluation approaches by targeting the characteristics of these two types of complex systems. In this chapter, the major contributions and conclusion of this thesis are summarised and the future work of this research is outlined.

5.1 Summary of Major Contributions

In this thesis, we proposed three trust estimation approaches to explore trust relationships among components within the collaborative complex system and the preference system. A collaborative complex system consists of a number of loosely coupled autonomous and adaptive components, and diverse composite teams are formed to address complicated problems which usually require multiple skills and functions. Solutions for such problems are achieved through collaborations in composite teams. Hence, interactions between pairs of components are established by common composite team experiences. In this thesis, we assume that a unified assessment standard is adopted to generate feedback value for the performance of a composite team. However, due to the emergent complexity and characteristics of the complex system, it is difficult to know exactly which and how each team member contributes to the observed output. Therefore, in order to understand and predict the behaviour of a composite team, it is necessary to analyse the behaviour of the components, and it is also necessary to analyse how they work together to form the behaviour of the whole.

Two types of team formation strategies for collaborative complex systems were proposed for scenarios of team formation without predefined workflow structures, and team formation with predefined workflow structures, respectively. In terms of team formation without predefined workflow structure, each individual component in a team operates independently without relying on any prerequisite actions of other team members. During task executions, individual components may have chances to directly interact with other team members, so the relationships between the components are generally more important than their characteristics.

Hence, we propose the *Correlated Contribution* trust evaluation model to explore the compositional trust through considering correlations and dependencies among both skills required by tasks and individual components within collaborative composite teams.

On the other hand, in terms of a composite team with a particular pre-defined workflow, the coordination between components and the implementation of the workflow are all based on an event-triggered mechanism. When a particular event occurs, the workflow system will let components execute according to pre-defined workflow. Therefore, we should not only consider the correlation between pairs of components, we should also take the workflow structure into account. Provenance information is adopted to capture the workflow structure of composite teams in a standard format. However, the analysis of provenance information is a complex process which requires rich domain knowledge and expertise. Hence, we propose an automatic approach, i.e., the *SEC* model, to estimate the trustworthiness of proposed candidate composite teams by analysing historical provenance graph. Based on graph similarities and correlation to compositional trust values, the *SEC* model can predict future performance of a proposed composite team.

For preference systems, we proposed the *Community-Based* trust estimation approach to explore the context-specific inter-personalised trust. According to the decomposable characteristic of complex systems, we organise the preference complex system as a set of more manageable interrelated subsystems (communities) based on the density of internal interactions to discover the multi-facet and heterogeneous trust relationships among users, items and objects in terms of different contextual situations. In the real world, a particular social entity usually places its trust differently from other social entities, because of their multi-faceted interests and preferences. Therefore, a user intends to trust another user's feedback with respect to one specific item, whilst not necessarily to another. The *Community-Based* trust estimation approach can automatically infer such trust relationships from previous user-generated feedback, and predict a particular user's potential feedback for items which the user does not have previous experience with.

5.2 Future Works

This research can be extended by engaging in investigations focussing on the following two directions.

Firstly, future exploration of trust evaluation for collaborative complex systems can be conducted by focusing on multi-dimensional trust evaluation. Usually, there are several attributes to adopt to evaluate the performance of a composite team. Furthermore, with regard to different attributes, in terms of different tasks, the user also has different priorities. Therefore, multi-dimensional trust evaluation will improve the prediction accuracy of the potential quality of task completion.

Secondly, in this thesis, the *Community-Based* trust estimation model is proposed to explore context-specific inter-personalised trust in the preference complex system. However, the proposed approach still manages trust information in a centralized manner. Therefore, future work related to this research could focus on extending the community-based mechanism to include distributed environments.

References

Ashri, R., Ramchurn, S. D., Sabater, J., Luck, M. & Jennings, N. R. (2005). Trust evaluation through relationship analysis. In *Proceedings of the 4th International Joint Conference on Autonomous Agents and Multiagent Systems* (pp. 1005–1011).

Bai, Q., Su, X., Liu, Q., Terhorst, A., Zhang, M. & Mu, Y. (2011). Case-based trust evaluation from provenance information. In *Proceedings of 2011 IEEE 10th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom)* (p. 336-343). doi: 10.1109/TrustCom.2011.44

Barber, K. S. & Kim, J. (2003). Soft security: Isolating unreliable agents from society. In *Trust, Reputation, and Security: Theories and Practice* (pp. 224–233). Springer.

Bar-Yam, Y. (1997). *Dynamics of complex systems* (Vol. 213). Addison-Wesley Reading, MA.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R. & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*(10), P10008.

Bunke, H. & Kandel, A. (2000). Mean and maximum common subgraph of two graphs. *Pattern Recognition Letters*, *21*(2), 163–168.

Burnett, C., Norman, T. J. & Sycara, K. (2010). Bootstrapping trust evaluations through stereotypes. In *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems-Volume 1* (pp. 241–248).

Burnett, C., Norman, T. J. & Sycara, K. (2011). Trust decision-making in multi-agent systems. In *Proceedings of the 22nd International Joint Conference on Artificial Intelligence-Volume 1* (pp. 115–120).

Camarinha-Matos, L. M. & Afsarmanesh, H. (2005). Collaborative networks: a new scientific discipline. *Journal of Intelligent Manufacturing*, *16*(4-5), 439–452.

Castelfranchi, C., Falcone, R. & Pezzulo, G. (2003). Trust in information sources as a source for trust: a fuzzy approach. In *Proceedings of the Second International Joint Conference on Autonomous Agents and Multiagent Systems* (pp. 89–96).

Chu, D., Strand, R. & Fjelland, R. (2003). Theories of complexity. *Complexity*, *8*(3), 19–30.

Clauset, A., Newman, M. E. & Moore, C. (2004). Finding community structure in very large networks. *Physical Review E*, *70*(6), 066111.

Cover, T. M. & Thomas, J. A. (2012). *Elements of information theory*. John Wiley &

Sons.

Dawy, Z., Hagenauer, J., Hanus, P. & Mueller, J. C. (2005). Mutual information based distance measures for classification and content recognition with applications to genetics. In *Proceedings of 2005 IEEE International Conference on Communications* (Vol. 2, pp. 820–824).

Ding, Y. (2011). Community detection: Topological vs. topical. *Journal of Informetrics*, *5*(4), 498–514.

Dodig-Crnkovic, G. (2002). Scientific methods in computer science. In *Proceedings of the Conference for the Promotion of Research in IT at New Universities and at University Colleges in Sweden, Skövde, Suecia* (pp. 126–130).

Eberhart, R., Simpson, P. & Dobbins, R. (1996). *Computational intelligence pc tools*. Academic Press Professional, Inc.

Freire, J., Koop, D., Santos, E. & Silva, C. T. (2008). Provenance for computational tasks: A survey. *Computing in Science & Engineering*, *10*(3), 11–21.

Fullam, K. K. & Barber, K. S. (2006). Learning trust strategies in reputation exchange networks. In *Proceedings of the 5th International Joint Conference on Autonomous Agents and Multiagent Systems* (pp. 1241–1248).

Fullam, K. K. & Barber, K. S. (2007). Dynamically learning sources of trust information: experience vs. reputation. In *Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems* (pp. 1055–1062).

Garg, S. K., Konugurthi, P. & Buyya, R. (2011). A linear programming-driven genetic algorithm for meta-scheduling on utility grids. *International Journal of Parallel, Emergent and Distributed Systems*, *26*(6), 493–517.

Garud, R., Kumaraswamy, A. & Langlois, R. (2009). *Managing in the modular age: architectures, networks, and organizations*. John Wiley & Sons.

Girvan, M. & Newman, M. E. (2002). Community structure in social and biological networks. *Proceedings of the National Academy of Sciences*, *99*(12), 7821–7826.

Golbeck, J. (2009). Trust and nuanced profile similarity in online social networks. *ACM Transactions on the Web (TWEB)*, *3*(4), 12.

Griffiths, N. (2005). Task delegation using experience-based multi-dimensional trust. In *Proceedings of the 4th International Joint Conference on Autonomous Agents and Multiagent Systems* (pp. 489–496).

Guimerà, R., Sales-Pardo, M. & Amaral, L. A. N. (2007). Module identification in bipartite and directed networks. *Physical Review E*, *76*(3), 036102.

Gundecha, P. & Liu, H. (2012). Mining social media: A brief introduction. *Tutorials in Operations Research*, *1*(4).

Hermoso, R., Billhardt, H. & Ossowski, S. (2010). Role evolution in open multi-agent systems as an information source for trust. In *Proceedings of the 9th International Conference on Autonomous Agents and Multiagent Systems: Volume 1* (pp. 217–224).

Hoogendoorn, M., Jaffry, S. W. & Treur, J. (2010). Exploration and exploitation in adaptive trust-based decision making in dynamic environments. In *Proceedings of 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)* (Vol. 2, pp. 256–260).

Hupa, A., Rzadca, K., Wierzbicki, A. & Datta, A. (2010). Interdisciplinary matchmaking: Choosing collaborators by skill, acquaintance and trust. In *Computational Social Network Analysis* (pp. 319–347). Springer.

Huynh, T. D., Jennings, N. R. & Shadbolt, N. R. (2006a). Certified reputation: how an agent can trust a stranger. In *Proceedings of the 5th International Joint Conference on Autonomous Agents and Multiagent Systems* (pp. 1217–1224).

Huynh, T. D., Jennings, N. R. & Shadbolt, N. R. (2006b). An integrated trust and reputation model for open multi-agent systems. *Journal of Autonomous Agents and Multi-Agent Systems*, *13*(2), 119–154.

Jennings, N. R. (2001). An agent-based approach for building complex software systems. *Communications of the ACM*, *44*(4), 35–41.

Jianshu, W., Chunyan, M. & Angela, G. (2006). An entropy-based approach to protecting rating systems from unfair testimonies. *IEICE TRANSACTIONS on Information and Systems*, *89*(9), 2502–2511.

Jonker, C. M. & Treur, J. (1999). Formal analysis of models for the dynamics of trust based on experiences. In *Multi-Agent Formal Analysis of Models for the Dynamics of trust based on experiencesSystem Engineering* (pp. 221–231). Springer.

Jøsang, A. & Haller, J. (2007). Dirichlet reputation systems. In *Proceedings of the Second International Conference on Availability, Reliability and Security, 2007* (pp. 112–119).

Jsang, A. & Ismail, R. (2002). The beta reputation system. In *Proceedings of the 15th Bled Electronic Commerce Conference* (pp. 41–55).

Kastens, K. A., Manduca, C. A., Cervato, C., Frodeman, R., Goodwin, C., Liben, L. S., ... Titus, S. (2009). How geoscientists think and learn. *Eos, Transactions American Geophysical Union*, *90*(31), 265–266.

Kollingbaum, M. J. & Norman, T. J. (2002). Supervised interaction: creating a web of trust for contracting agents in electronic environments. In *Proceedings of the first International Joint Conference on Autonomous Agents and Multiagent Systems: Part 1* (pp. 272–279).

Kraskov, A. & Grassberger, P. (2009). MIC: mutual information based hierarchical clustering. In *Information theory and statistical learning* (pp. 101–123). Springer.

Kuter, U. & Golbeck, J. (2007). Sunny: A new algorithm for trust inference in social networks using probabilistic confidence models. In *Proceedings of the Twenty-second AAAI Conference on Artificial Intelligence* (Vol. 7, pp. 1377–1382).

Lancichinetti, A., Fortunato, S. & Kertész, J. (2009). Detecting the overlapping and hierarchical community structure in complex networks. *New Journal of Physics*, *11*(3), 033015.

Larose, D. T. (2005). K-Nearest Neighbor Algorithm. *Discovering Knowledge in Data: An Introduction to Data Mining*, 90–106.

Liu, J. G., Zhou, T., Che, H. A., Wang, B. H. & Zhang, Y. C. (2010). Effects of high-order correlations on personalized recommendations for bipartite networks. *Physica A: Statistical Mechanics and its Applications*, *389*(4), 881–886.

Liu, S., Zhang, J., Miao, C., Theng, Y.-L. & Kot, A. C. (2011). iCLUB: an integrated clustering-based approach to improve the robustness of reputation systems. In

Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 3 (pp. 1151–1152).

Luo, H., Niu, C., Shen, R. & Ullrich, C. (2008). A collaborative filtering framework based on both local user similarity and global user similarity. *Machine Learning*, *72*(3), 231–245.

Mao, C. (2012). A heuristic algorithm for bipartite community detection in social networks. *Journal of Software*, *7*(1), 204–211.

Massa, P. & Bhattacharjee, B. (2004). Using trust in recommender systems: an experimental analysis. In *Trust Management* (pp. 221–235). Springer.

Maturana, H. R. (1980). *Autopoiesis and cognition: The realization of the living* (No. 42). Springer.

Metzger, M. J. (2004). Privacy, trust, and disclosure: Exploring barriers to electronic commerce. *Journal of Computer-Mediated Communication*, *9*(4), 00–00.

Mitchell, M. & Newman, M. (2002). Complex systems theory and evolution. *Encyclopedia of Evolution*, 1–5.

Moreau, L., Freire, J., Futrelle, J., McGrath, R. E., Myers, J. & Paulson, P. (2008). The open provenance model: An overview. In *Provenance and Annotation of Data and Processes* (pp. 323–326). Springer.

Mui, L., Mohtashemi, M. & Halberstadt, A. (2002). A computational model of trust and reputation. In *Proceedings of the 35th Annual Hawaii International Conference on System Sciences, 2002. HICSS* (pp. 2431–2439).

Newman, M. E. (2003). The structure and function of complex networks. *SIAM Review*, *45*(2), 167–256.

Newman, M. E. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences*, *103*(23), 8577–8582.

Noorian, Z., Marsh, S. & Fleming, M. (2011). Multi-layer cognitive filtering by behavioral modeling. In *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 2* (pp. 871–878).

Pitsilis, G. & Marshall, L. (2005). *Trust as a key to improving recommendation systems*. Springer.

Qi, G.-J., Aggarwal, C. C. & Huang, T. (2012). Community detection with edge content in social media networks. In *Proceedings of 2012 IEEE 28th International Conference on Data Engineering (ICDE)* (pp. 534–545).

Qu, G., Hariri, S. & Yousif, M. (2005). A new dependency and correlation analysis for features. *IEEE Transactions on Knowledge and Data Engineering*, *17*(9), 1199–1207.

Radicchi, F., Castellano, C., Cecconi, F., Loreto, V. & Parisi, D. (2004). Defining and identifying communities in networks. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(9), 2658–2663.

Ramchurn, S. D., Huynh, D. & Jennings, N. R. (2004). Trust in multi-agent systems. *The Knowledge Engineering Review*, *19*(01), 1–25.

Raymond, J. W., Gardiner, E. J. & Willett, P. (2002). Rascal: Calculation of graph similarity using maximum common edge subgraphs. *The Computer Journal*, *45*(6), 631–644.

Renner, R. & Maurer, U. (2000). About the mutual (conditional) information. *Designs, Codes, and Cryptography*.

Rodrigues, S., Oliveira, J. & de Souza, J. M. (2005). Competence mining for team formation and virtual community recommendation. In *Proceedings of the 9th International Conference on Computer Supported Cooperative Work in Design, 2005* (Vol. 1, pp. 44–49).

Rosvall, M. & Bergstrom, C. T. (2007). An information-theoretic framework for resolving community structure in complex networks. *Proceedings of the National Academy of Sciences*, *104*(18), 7327–7331.

Sabater, J. & Sierra, C. (2001). Regret: A reputation model for gregarious societies. In *Proceedings of 4th Workshop on Deception Fraud and Trust in Agent Societies* (Vol. 70).

Sabater, J. & Sierra, C. (2002). Reputation and social network analysis in multi-agent systems. In *Proceedings of the 1st International Joint Conference on Autonomous Agents and Multiagent Systems: Part 1* (pp. 475–482).

Sanfeliu, A. & Fu, K.-S. (1983). A distance measure between attributed relational graphs for pattern recognition. *IEEE Transactions on Systems, Man and Cybernetics*(3), 353–362.

Schillo, M., Funk, P. & Rovatsos, M. (2000). Using trust for detecting deceitful agents in artificial societies. *Applied Artificial Intelligence*, *14*(8), 825–848.

Simmhan, Y. L., Plale, B. & Gannon, D. (2005). A survey of data provenance in e-science. *ACM Sigmod Record*, *34*(3), 31–36.

Skopik, F., Schall, D. & Dustdar, S. (2010). Modeling and mining of dynamic trust in complex service-oriented systems. *Information Systems*, *35*(7), 735–757.

Skopik, F., Truong, H.-L. & Dustdar, S. (2009). Trust and reputation mining in professional virtual communities. In *Web Engineering* (pp. 76–90). Springer.

Su, X., Zhang, M., Mu, Y. & Bai, Q. (2011). GTrust: An innovated trust model for group services selection in web-based service-oriented environments. In *Web Information System Engineering* (pp. 306–313). Springer.

Su, X., Zhang, M., Mu, Y. & Sim, K. M. (2010). PBtrust: A priority-based trust model for service selection in general service-oriented environments. In *Proceedings of 2010 IEEE/IFIP 8th International Conference on Embedded and Ubiquitous Computing* (pp. 841–848).

Tang, J., Gao, H. & Liu, H. (2012). mTrust: discerning multi-faceted trust in a connected world. In *Proceedings of the 5th ACM International Conference on Web Search and Data Mining* (pp. 93–102).

Tang, L. & Liu, H. (2010). Community detection and mining in social media. *Synthesis Lectures on Data Mining and Knowledge Discovery*, *2*(1), 1–137.

Teacy, W., Chalkiadakis, G., Rogers, A. & Jennings, N. R. (2008). Sequential decision making with untrustworthy service providers. In *Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 2* (pp. 755–762).

Wang, Y., Hang, C.-W. & Singh, M. P. (2011). A probabilistic approach for maintaining trust based on evidence. *Journal of Artificial Intelligence Research*, *40*(1), 221–267.

Wang, Y. & Singh, M. P. (2007). Formal trust model for multiagent systems. In *Proceedings of the 23rd International Joint Conference on Artificial Intelligence* (Vol. 7, pp. 1551–1556).

Whitby, A., Jøsang, A. & Indulska, J. (2004). Filtering out unfair ratings in bayesian reputation systems. In *Proceedings 7th International Workshop on Trust in Agent Societies.*

Witten, I. H. & Frank, E. (2005). *Data mining: Practical machine learning tools and techniques*. Morgan Kaufmann.

Xhemali, D., Hinde, C. J. & Stone, R. G. (2009). Naïve bayes vs. decision trees vs. neural networks in the classification of training web pages. *International Journal of Computer Science Issues*, *4*(1), 16-23.

Yu, H., Shen, Z., Leung, C., Miao, C. & Lesser, V. (2013). A survey of multi-agent trust management systems. *IEEE Access*, *1*, 35-50. doi: 10.1109/ACCESS.2013.2259892

Zhao, Z., Feng, S., Wang, Q., Huang, J. Z., Williams, G. J. & Fan, J. (2012). Topic oriented community detection through social objects and link analysis in social networks. *Knowledge-Based Systems*, *26*, 164–173.

Zhou, X., Wang, X., Dougherty, E. R., Russ, D. & Suh, E. (2004). Gene clustering based on clusterwide mutual information. *Journal of Computational Biology*, *11*(1), 147–161.