# Heterogeneous Network Analysis on Academic Collaboration Networks

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By

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The undersigned hereby certify that they have read this thesis entitled "**Heterogeneous Network Analysis on Academic Collaboration Networks**" by **Qinxue Meng** and that in their opinions it is fully adequate, in scope and in quality, as a thesis for the degree of **Doctor of Philosophy**.

Dated: July 2014

Research Supervisors: _____
Paul J. Kennedy

# CERTIFICATE

Date: **July 2014**

Author: **Qinxue Meng**

Title: **Heterogeneous Network Analysis on Academic Collaboration Networks**

Degree: **Ph.D.**

I certify that this thesis has not already been submitted for any degree and is not being submitted as part of candidature for any other degree.

I also certify that the thesis has been written by me and that any help that I have received in preparing this thesis, and all sources used, have been acknowledged in this thesis.

Signature of Author

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# Table of Contents

# List of Figures

# List of Tables

# Abstract

Heterogeneous networks are a type of complex network model which can have multi-type objects and relationships. Nowadays, research on heterogeneous networks has been increasingly attracting interest because these networks are more advantageous in modeling real-world situations than traditional networks, that is homogenous networks, that can only have one type of object and relationship. For example, the network of Facebook has vertices including photographs, companies, movies, news and messages and different relationships among these objects. Besides that, heterogeneous networks are especially useful for representing complex abstract concepts, such as friendship and academic collaboration. Because these concepts are hard to measure directly, heterogeneous networks are able to represent these abstract concepts by concrete and measurable objects and relationships. Because of these features, heterogeneous networks are applied in many areas including social networks, the World Wide Web, research publication networks and so on. This motivates the thesis to work on network analysis in the context of heterogeneous networks.

In the past, homogeneous networks were the research focus of network analysis and therefore many methods proposed by previous studies for social network analysis were designed for homogenous networks. Although heterogeneous networks can be considered as an extension of homogenous networks, most of these methods are

not applicable on heterogeneous networks because these methods can only address one type of object and relationships instead of dealing with multi-type ones. In network analysis, there are three basic problems including community detection, link prediction and object ranking. These three questions are the basis of many practical questions, such as network structure extraction, recommendation systems and search engines. Community detection, also called clustering, aims to find the community structure of a network including subgroups of vertices that are closely related, which can facilitate people to understand the structure of networks. Link prediction is a task for finding links which are currently non-existent in networks but may appear in the future. Object ranking can be viewed as an object evaluation task which aims to order a set of objects based on their importance, relevance, or other user defined criteria. In addition to these three research issues, approaches for determining the number of clusters *a priori* is also important because it can improve the quality of community detection significantly. This thesis works on heterogeneous network and proposes a set of methods to address the four main research problems in network analysis including community detection, determining the number of clusters, link prediction and object ranking.

There are four contributions in this thesis. Contribution 1 proposes a Multiple Semantic-path Clustering method which can facilitate users to achieve a desired clustering in heterogeneous networks. Contribution 2 develops a Leader Detection and Grouping Clustering method which can determine the number of clusters *a priori*, thereby improving the quality of clustering. Contribution 3 introduces a Network Evolution-based Link Prediction method which can improve link prediction accuracy by modeling evolution patterns of objects. Contribution 4 proposes a co-ranking

method which can work on complex bipartite heterogeneous networks where one type of vertex can connect to themselves directly and indirectly.

The performance of all developed methods in the thesis in terms of clustering quality, link prediction accuracy and ranking effectiveness, is evaluated in the context of a research management dataset of University of Technology, Sydney (UTS) and public bibliographic DBLP (DataBase systems and Logic Programming) dataset. Moreover, all the results of the proposed methods in this thesis are compared with state-of-the-art methods and these experimental results suggest that the proposed methods outperform these state-of-the-art methods in quantitative and qualitative analysis.

# Publications

Below is the list of the journal and conference papers associated with my PhD research:

1. Meng, Q., Tafavogh, S. & Kennedy, P. J. (2014), 'Community Detection on Heterogeneous Networks by Multiple Semantic-Path Clustering', *in* 'Proceedings of the 6th International Conference on Computational Aspects of Social Networks (CASoN)', IEEE.

2. Tafavogh, S., Meng, Q., Catchpoole, D. R., Kennedy, P. J. (2014), 'Automated quantitative and qualitative analysis of the whole slide images of neuroblastoma tumor for making a prognosis decision', *in* 'Proceedings of The 11th IASTED International Conference on Biomedical Engineering (BioMed 2014)', IEEE.

3. Asabere, N. Y., Xia, F., Meng, Q., Li, F. & Liua, H. (2014), 'Scholarly paper recommendation based on social awareness and folksonomy', *International Journal of Parallel, Emergent and Distributed Systems*.

4. Meng, Q. & Kennedy, P. J. (2013b), 'Survey on spectral clustering and its applications in social networks', *Computer Engineering and Applications* **49**(3), 213–221.

5. Meng, Q. & Kennedy, P. J. (2013a), 'Discovering influential authors in heterogeneous academic networks by a co-ranking method', *in* 'Proceedings of the 22nd ACM International Conference on Information & Knowledge Management', ACM, pp. 1029–1036.

6. Meng, Q. & Kennedy, P. J. (2012c), 'Using network evolution theory and singular value decomposition method to improve accuracy of link prediction in social networks', *in* 'Proceedings of the Tenth Australasian Data Mining Conference',Volume 134, Australian Computer Society, Inc., pp. 175–181.

7. Meng, Q. & Kennedy, P. J. (2012b), 'Using field of research codes to discover research groups from co-authorship networks', *in* 'Proceedings of the 2012 International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2012)', IEEE Computer Society, pp. 289–293.

8. Meng, Q. & Kennedy, P. J. (2012a), 'Determining the number of clusters in co-authorship networks using social network theory', *in* '2012 Second International Conference on Social Computing and Its Applications (SCA 2012)', IEEE, pp. 337–343.

# Table of Symbols

| Symbols | Description |
|---|---|
| $G$ | Networks or graphs |
| $V$ | Vertex set |
| $\|V\|$ | the number of vertices |
| $E$ | Edge set |
| $\|E\|$ | the number of edges |
| $P$ | Semantic path set |
| $\|P\|$ | the number of semantic paths |
| $V_n$ | The set of vertices in type $n$ |
| $E_m$ | The set of edges in type $m$ |
| $v, u$ | vertices |
| $e_{uv}$ | The edge from vertex $u$ to $v$ |
| $A$ | Adjacency matrix |
| $a_{uv}$ | An element of adjacency matrix $A$. |
| | If $a_{uv} = 1$, there is an edge from $u$ and $v$; |
| | If $a_{uv} = 0$, vertex $u$ and $v$ are not connected. |

| **Symbols** | **Description** |
|---|---|
| $W$ | Weighted adjacency matrix |
| $w_{uv}$ | the weight of edge $e_{uv}$ |
| $d_v$ | Degree of vertex $v$, $d_v = \sum_{i=1}^{\|V\|} w_{vi}$ |
| $D$ | Degree matrix which is a diagonal matrix |
| | with the degrees $d_1, \ldots, d_{\|V\|}$ |
| $L$ | Laplacian matrix |
| $l_i$ | $i$th eigenvalue of Laplacian matrix |
| $I$ | Identify matrix |
| $S$ | Similarity matrix |
| $s_{uv}$ | The similarity beween vertex $u$ and $v$ |
| $C$ | Cluster indicator matrix |
| $k$ | Number of clusters |
| $W^{V_iV_j}$ | The weight adjacency matrix |
| | between object type $V_i$ and $V_j$ |
| $w_{uv}^{V_iV_j}$ | $w_{uv}^{V_iV_j} = w_{uv}$ where $u \in V_i$ and $v \in V_j$ |
| $C_D$ | Vertex degree centrality |
| $C_B$ | Vertex betweenness centrality |
| $LG_i$ | $i$th leader group |

| **Symbols** | **Description** |
|---|---|
| $N_{uv}(i)$ | The number of paths between vertex $u$ and $v$ and that belong to semantic path $i$ |
| $len(i)$ | The length of semantic path $i$ |
| $X, Y$ | Network partitions |
| $T(u, v)$ | Time of randomly moving agent from starting vertex $u$ to the end vertex $v$ |
| $\Omega$ | Network evolution |
| $neighor(v, t)$ | The neighborhood set of vertex $v$ in timeslot $t$ |
| $rank(v, i)$ | The ranking scores of vertex $v$ in $i$th iteration |
| $Diff(i, i+1)$ | The difference of vertex ranking scores between $i$th iteration and $(i+1)$th iteration |

# Chapter 1

# Introduction

The world where we are living is interconnected and interrelated: most data such as objects, groups or components link or interact with each other, thereby forming numerous, large, interconnected and complex networks. As a result, the analysis of large-scale, complex networks has gained wide attention nowadays from researchers in computer science, social science, physics, economics, biology, and so on. This is not only because network analysis can facilitate people to understand how current networks are formed but also because the research can forecast the direction of network evolution and identify the roles networked objects play.

Recently the advent of Web 2.0 and advances in mobile technologies have accelerated information publishing, sharing, interaction and collaboration across the world, making the process of collecting, integrating and organising data much easier than ever before. This drives the emergence and rapid growth of many successful online social, academic, and information sharing networks. Most of those real-world networks are heterogeneous, where vertices and relations are of different types (Sun & Han 2012). For example, in academic networks, vertices can be researchers, publications,

venues, and so on. Clearly, treating all the vertices as the same type is unreasonable as different vertices have different patterns in forming networks and in network evolution. Thus heterogeneous network modelling is needed to capture the essential information of those networks.

Till now the theories and methods related to network analysis have been well researched via both theoretical and experimental studies. However, most current network analysis research (Scott & Carrington 2011) is based on homogeneous networks where vertices are objects of the same entity type (e.g., authors) and links are relationships from the same relation type (e.g., co-authorship). Most famous and widely applied network analysis methods are based on homogeneous networks, such as neighbourhood theory (Lü & Zhou 2011), Katz similarity (Katz 1953), random walk (Spitzer 2001), spectral clustering (von Luxburg 2007) and the well-known PageRank algorithm (Page et al. 1999) as well as many other community detection (Fortunato 2010) and link prediction (Liben-Nowell & Kleinberg 2007) methods.

This thesis addresses some typical questions of network analysis on heterogeneous networks in the context of academic collaboration. This is not only because academic collaboration is a typical social phenomenon but also because available datasets are open, standard and well-organised thereby providing a benchmark to verify the effectiveness and efficiency of the proposed methods. Those questions covers community detection, link prediction and ranking objects. Community detection looks for cohesive groups which are also called communities, clusters, cohesive subgroups or modules in different contexts. Individuals interact more frequently with members within groups than those outside the group. Link prediction is the problem of predicting the existence of a link between two entities, based on attributes of the objects and other

observed links. Examples include predicting links among actors in social networks, such as predicting friendships, predicting the participation of actors in events and so on. The objective of ranking objects is to find "important" objects in a given network by exploiting the structure of the network to order or prioritize the set of objects.

## 1.1 What are heterogeneous networks?

Traditional networks, also called homogeneous networks, are appropriate and applicable for representing an abstraction of the real world, focusing both on objects and the interactions between objects. This model cannot only represent and store essential information about the real world, but also provides a useful tool for mining knowledge from it.

The concept of heterogeneous networks derives from the concept of homogeneous networks. The major difference between these types of networks is the types of vertices and relations. Homogeneous networks can only have one type of vertex and one typed relation, while heterogeneous networks have no such constraint and are allowed to have multi-typed vertices, or multi-typed relations or both. On the other hand, heterogeneous networks inherit most characteristics of homogeneous networks. These networks can have directed, undirected, weighted or unweighted links, and different attributes can be attached to vertices.

However, it is challenging to understand the global structure of heterogeneous networks, because they may have many vertices and edges of different types. In the literature review, network schemas are often applied to denote heterogeneous networks. The schema can specify typed constraints on the sets of objects and relationships between objects. These constraints make a heterogeneous information

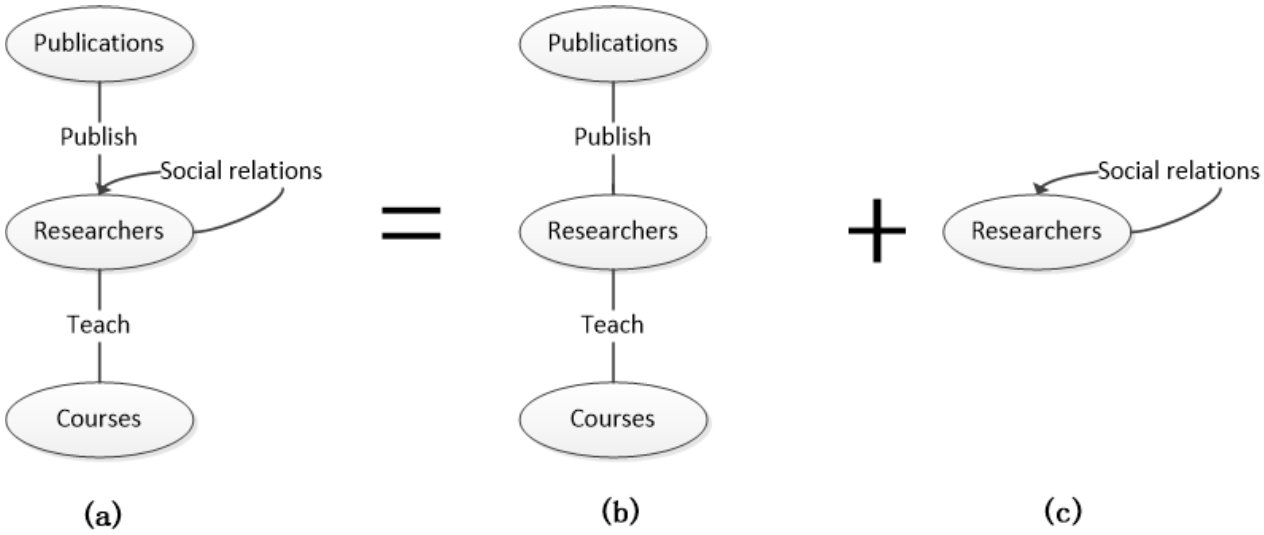



Figure 1.1: An example of how to decompose complex heterogeneous networks

network semi-structured, guiding the exploration of the semantics of networks.

Although heterogeneous network schemas are useful for presenting and understanding the global structure of heterogeneous, it is still hard to explore the hidden patterns of heterogeneous networks based on them due to their complex topological structures. As objects of different types have different importance, this thesis decomposes complex schemas further. For example, Figure 1.1a is the schema of a complex heterogeneous network, representing academic collaboration where researchers are connected to each other by social relations or are connected to publications and courses by publishing and teaching relationships respectively.

The complexity of the heterogeneous network is that one type of object can be connected directly or indirectly via other objects of different types. In the network, for example, researchers can be connected by social relations directly and linked to each other indirectly by teaching courses or publishing publications. For this example, the object type, researchers, is the major study focus and then it is called

the target object in the thesis. Once the target object type is determined, schemas of heterogeneous networks can be further divided into combination of multipartite heterogeneous networks and homogeneous networks. Multipartite heterogeneous networks refer to networks where objects are linked if and only if they are from different types and there is no link among the same type of objects. The complex heterogeneous network (Figure 1.1a) is divided into a multipartite heterogeneous network ( Figure 1.1b) and a homogeneous network (Figure 1.1c). Thus, the research focus of this thesis lies in multipartite heterogeneous networks.

In the real world, heterogeneous networks are ubiquitous, ranging from social, scientific, to business applications. Here are a few examples of such networks.

1. **Facebook network**

   Currently, Facebook, as the most successful social media, can also be considered as a heterogeneous network. This website contains many different types of objects such as users, companies/organizations, topics, messages and news. These objects are connected by different relationships. Users can post their status and send messages. Companies and organizations can release news and users can share news with their friends.

2. **Wikipedia network**

   The knowledge sharing website Wikipedia can be viewed as a heterogeneous network, containing a set of object types: articles, key words, users and references, and a set of relation types including editing between users and articles, links between articles and key words, citations between articles, authorship between users and articles and so on.

3. **Bibliographic information network**

   Another example of heterogeneous networks is bibliographic information networks. These networks normally have four types of object: publications, venues (i.e., conference/journal), authors, and terms (key words of publications). Each publication has links to a set of authors, a venue, and a set of terms, belonging to a set of link types. It may also contain citation information for some publications. That is, these papers have links to cited papers as well as a set of papers citing the paper. Examples of bibliographic information networks are DBLP [1] and CiteSeer [2]. Both of them are online public bibliography websites and have been major dataset sources of many network analysis experiments.

Heterogeneous networks can be constructed in almost any domain, such as social networks (e.g., Twitter, Myspace), e-commerce (e.g., Amazon and eBay), online movie databases (e.g., IMDB), and numerous database applications. Heterogeneous networks can also be constructed from text data, such as news collections, by entity and relationship extraction using natural language processing and other advanced techniques. This thesis validates methods for heterogeneous networks in the domain of academic collaboration.

Sun & Han (2012) gives a general definition of heterogeneous network: they can be denoted as $G = (V, E; \alpha, \beta)$, where $V$ is the vertex set, $E \subseteq V \times V$ is the link set, $\alpha$ is the set of object types, and $\beta : V \mapsto \alpha$ is the mapping function from each vertex to its type. Each object $v$ ($v \in V$) belongs to and can only belong to one type of objects while each link $e$ ($e \in E$) belongs to a particular relation. If two links belong to the same relation type, the two links cannot have the same starting point and

[1] http://dblp.uni-trier.de/
[2] http://citeseer.ist.psu.edu/

ending point simultaneously. Unlike homogeneous networks, heterogeneous networks are presented by the network schema which describes the specified type constraints on the sets of objects and relations between the objects.

## 1.2 Significance of mining heterogeneous networks

Mining heterogeneous networks is of great importance and necessity. Compared with homogeneous networks, heterogeneous networks are better for modeling some complex phenomena without much loss of information. Modeling entertainment activities has to include many different types of object such as concerts, theaters, cinemas, shopping malls, beaches and so on. In this case, homogeneous networks are insufficient to cover all the information. Another application of heterogeneous networks is for representing abstract concepts such as friendship and academic collaboration.

A difficulty of analyzing those concepts is how to measure relationships of objects quantitatively. People have to face this difficulty when using homogeneous networks to model these concepts. By contrary, heterogeneous networks are able to use concrete and measurable concepts to represent abstract ones. For example, friendship is hard to measure directly, but in heterogeneous networks, friendship can be represented by easily measureable concepts such as common hobbies, classmates in primary, secondary or tertiary schools, times of meeting per week, and so on. Using a heterogeneous network to represent friendship, thus, can reflect the real situation better.

Many methods have been developed for the analysis of homogeneous networks, especially on social networks, such as ranking, community detection, link prediction, and object influence analysis. However, most of these methods cannot be directly

applied to mining heterogeneous networks. This is not only because heterogeneous relations across entities of different types may carry rather different semantic meaning but also because a heterogeneous network in general captures much richer information than homogeneous networks.

Network analysis of homogeneous networks is a mature field and network analysis research has transferred from homogeneous networks to heterogeneous networks in recent years. Research of heterogeneous network analysis is becoming a hot topic in network analysis. The methods developed in this thesis for heterogeneous network analysis have the potential to be directly applied on homogeneous networks.

## 1.3 Why study academic collaboration?

Academic collaboration (Katz & Martin 1997) is a prevalent and typical social phenomenon with a long history. Research interest in academic collaboration has much significance in many aspects.

Investigation into academic collaboration focuses on practical questions. The study of detecting communities (Xu et al. 2012) and investigating evolutionary process of individual communities or whole networks (Lin et al. 2013) are beneficial for understanding collaboration in academia and for predicting new research directions. This information is a key for universities and research institutions for setting their future strategies. Ranking (Zhou et al. 2007) in academic collaboration refers to evaluating researcher' contributions quantitatively. Ranking results are often viewed as an important index in promotion or research funding allocation.

The research and proposed methods of academic collaboration network analysis

and theories can easily be applied to other social networks (Sun & Han 2012). Academic collaboration networks are a type of social networks which are large-scaled, complex, relatively sparse and change rapidly over time. As a result the experimental processes and developed techniques are easily applied on social networks in other domains.

Another important aspect of studying academic collaboration is that datasets of academic collaboration networks have their own advantages and are more suitable than those of other domains. Although many famous social websites such as Facebook and Twitter provide Application Program Interface (API) functions for researchers to acquire data, the resulting datasets are always different because of choosing different attributes or time period. By constrast, the data of academic collaboration networks is public, well-organised and standardised by online bibliographic websites (e.g. DBLP and CiteSeer) which constitutes the primary reason that so many experiments (Sun, Yu & Han 2009, Abbasi et al. 2011, Yu et al. 2011, Lu & Feng 2009, Pilkington & Meredith 2009) verify the effectiveness and efficiency of their proposed methodologies and theories based on academic collaboration datasets.

Finally, in contemporary society, an increasing number of new products and projects are the result of academic collaboration, crossing several different disciplines. The motivation of collaborative research is that it enables humans to gain capability in solving complex problems, especially, when facing huge and complicated projects over multiple discipline domains. Meanwhile, academic collaboration improves the quality of our solutions by analyzing and approaching problems from different aspects. The ideas and opinions from these aspects, undoubtedly, make our research

outputs robust. Furthermore, collaborative research boosts the development of disciplines as some methodologies generated in one discipline can be applied in others. In addition, collaborative research provides a platform to share academic methods and achievement, thereby avoiding repeated work and then saving labor and budgets. Due to these advantages, academic collaboration analysis becomes an interesting topic nowadays.

## 1.4 Research questions

Mining heterogeneous networks is a new emerging research field with many detailed questions and this thesis aims to answer the following questions with validation in the context of academic collaboration:

RQ 1: **How to acquire a desired clustering when using heterogenous networks to model abstract concepts?**

Abstract concepts, such as academic collaboration, friendship and love relationship, are hard to be measured directly which is a reason why it becomes a hot research topic. Heterogeneous networks are advantaged to model these concepts by decomposing them into detailed, concrete objects and relationships. For example, academic collaboration can be represented by co-teaching subjects, co-authoring publications, co-supervising students and co-working in labs. However, a difficulty is how to combine the different contributions of relationships for these abstract concepts.

RQ 2: **How to determine the number of clusters *a priori*?**

One notable difference between classification and clustering is that in classification, people have prior knowledge about the labels of clusters and how many groups they want. By contrast, for clustering, it is often impossible to know the number of clusters beforehand. However, the quality of clustering highly depends on whether the chosen number of clusters is appropriate. This needs to be investigated in both homogenous and heterogeneous networks.

RQ 3: **Should objects be treated individually in link prediction so as to improve the accuracy?**

From observations and experiences, individual objects in networks, especially humans, show different patterns of connections as networks evolve. Some change their connections rapidly while others tend to maintain their existing connections. This interesting phenomenon provides a new aspect to improve the accuracy of link prediction.

RQ 4: **How to rank objects in complex bipartite heterogeneous networks?**

Object ranking in complex bipartite heterogeneous networks is not well-investigated due to their complex topological features. Unlike bipartite heterogeneous networks where one-type of objects are connected indirectly by the other type of objects, complex ones allow one-type of objects connected to themselves directly or indirectly by the other type of objects. The feature of complex bipartite heterogeneous extends their applications.

## 1.5 Contributions to knowledge

By investigating the above research questions and comparing the results of the proposed methods with state-of-the-art methods, this thesis identifies four main contributions to knowledge:

**Contribution 1. Multiple semantic-path clustering on heterogeneous networks.** Chapter 3 proposes a Multiple Semantic-path Clustering method to address RQ 1 which is based on the idea that similarities between objects of abstract concepts are collective similarities from the combination of all possible semantic paths. The proposed multiple semantic-path clustering decomposes relations into a set of semantic paths which are a sequence of object types to represent a meaningful relationship. For example, schoolmate relationship can be represented by a semantic path (*People-School-People*) and co-working relationship can be represented by semantic path (*People-Company-People*). Indeed, different weights and combinations of semantic paths generate different clustering results (Sun et al. 2012). In order to generate a desired clustering, this thesis assesses the weights of semantic paths, that is, their contributions to the collective similarity by a few examples provided by users to specify their clustering preference. Through experimental verification, this proposed method outperforms spectral clustering with random walk (von Luxburg 2007) and semantic-path selection clustering (Sun et al. 2013).

**Contribution 2. Determining the number of clusters based on leader's topological features.** To answer the second research question, this thesis proposes a novel way of determining the number of clusters based on topological

features of the network. This method is inspired by a perspective in social theory that a cohesive community is generally constituted by one or several leaders and their followers (Scott 2012). Then the main idea of the proposed method is to differentiate leaders from their followers by their topological features. As leaders may come from the same communities, the method also combines those nearby leaders based on their semantic paths to form leader groups. Then the number of clusters is determined by the number of leader groups. Chapter 4 describes the algorithm for segmenting leaders and their followers and verifies it on a real life university academic collaboration heterogeneous networks. The performance of the proposed method is compared with another two commonly used methods for determining the number of clusters based on the structure of eigenvalues, and it acquires better results.

**Contribution 3. Network evolution-based link prediction.** The thesis answers RQ 3 by developing a link prediction method based on object activeness. Dynamic networks by definition change over time, but at a given time point, they are stable. More specifically, the evolution of a dynamic network can be considered as a continuous function $G = f(t)$ where $G$ stands for the network and $t$ is time. This function suggests that the network changes as time changes. At a time point $t = t_0$, the network is determined, $G = f(t_0)$. Then the evolutionary process of a network can be represented by a sequence of networks at different time points. The closer two time points are, the more accurate the evolutionary process is modeled. Based on this, the proposed object activeness based link prediction method collects a series of snapshots of a dynamic network at different time points to represent the evolutionary process of the

network. The pattern of how an object evolves is captured from differences of their local connectivity among each two adjacent time points and these evolving patterns of evolution are considered when predicting future connections. The proposed method achieves higher accuracy of link prediction on a real life university academic collaboration heterogeneous networks compared with other robust state-of-the-art link prediction methods in Chapter 5.

**Contribution 4. A co–ranking method on complex bipartite heterogeneous networks.** How to rank different objects simultaneously in a complex bipartite heterogeneous network is the biggest motivation for proposing the co-ranking framework in Chapter 6. This novel approach is a flexible framework based on a set of customized rules, taking into account both directed and undirected relationships. The thesis verifies the proposed method on the DBLP bibliographic dataset. The approach ranks authors and publications iteratively and uses the ranking scores of each round to reinforce the ranks of authors and publications. Unlike traditional approaches for assessing publications based on a large number of citations, the proposed approach can make a correct ranking based on a very small set of citations. The method is validated by comparing the ranking results with another two commonly used methods, PageRank (Fiala 2012) and Hyperlink-Induced Topic Search (HITS) (Berendt et al. 2002) on DBLP dataset.

## 1.6 Organisation of contents

The thesis is organised as follows:

**Chapter 1** outlines the general context of this thesis including research aims, problems and corresponding contributions to knowledge.

**Chapter 2** surveys the recent researches of social network analysis related to the thesis, covering studies of similarity measures, community detection, link prediction and ranking on both homogeneous networks and heterogeneous networks because many heterogeneous network algorithms and methods derive from those of homogeneous networks. It also highlights the research gaps to motivate the research in this thesis.

**Chapter 3** presents the principles and implementations of the proposed multi-path clustering to detect communities on the University of Technology, Sydney (UTS) academic collaboration heterogeneous networks. The experiment verifies the effectiveness and efficiency of the proposed multi-path clustering by comparing it with spectral clustering and semantic-path selection clustering. The multi-path clustering can generate better clustering results than the other two methods.

**Chapter 4** presents an experiment in the academic collaboration domain to determine the number of clusters before clustering. To determine the accurate number of clusters, this study takes both social theory and network topological structure into consideration. The experimental results show that the proposed method is effective and can facilitate most clustering methods such as spectral clustering to achieve better clusters by comparing with two eigenvalue-based methods of determining the number of clusters.

**Chapter 5** describes a study to improve the accuracy of link prediction in the context of heterogeneous networks by involving the process of network evolution. In social theory, people have different levels of activity in developing or enhancing

the links over time. Compared with a single snapshot of networks, an historical dataset is able to provide such information and helpful to capture the evolutionary patterns of individuals. This chapter applies the proposed method to predict links on the University of Technology, Sydney (UTS) academic collaboration heterogeneous networks, showing that the accuracy of considering activeness is much higher than treating objects equally.

**Chapter 6** proposes a co-ranking method for ranking objects in complex bipartite heterogeneous networks where objects can be connected to themselves directly or connected via other types of objects indirectly. This novel ranking approach is a potential flexible because it allows users to define their own rules which are extracted from topological features. The method is validated by comparing the ranking results of PageRank and HITs on DBLP and CiteSeer datasets. The co-ranking method ranks authors and publications iteratively and uses the results of each round to reinforce the ranking scores of authors and publications.

**Chapter 7** concludes the research work presented in this thesis and provides discussions, lists the strengths and weaknesses of the contributions, and proffers some further research directions.

# Chapter 2

# Literature review

Network analysis, a class of data mining, is the analysis of objects and their relationships within networks. It views objects and their relationships based on networks where vertices represent individual objects and edges denote relationships or interactions between them, such as friendship, kinship, organizations and so on. Compared with traditional ways of organizing data (objects attached with attributes), networks can describe social phenomena, biological functions and information systems better. In recent years, public and academic interest in network analysis has been growing rapidly (Brandes & Erlebach 2005).

Network analysis has three fundamental research areas including community detection (Lancichinetti & Fortunato 2009), link prediction (Zhang & Philip 2014) and object ranking (Berendt et al. 2002) which are the basis for many practical questions, such as network structure extraction, recommendation systems and searching engines.

Many networks of various kinds, especially social networks, demonstrate a strong community effect in that objects tend to communicate or interact with objects in the same community frequently while seldom communicate or interact with those in different communities. Community detection aims to find the community structure

of a network, which can facilitate people to understand the structure of networks.

Link prediction is a task for finding links which are currently non-existent in networks but may appear in the future. As many networks are dynamic, predicting links is a key to understanding network evolution. In some cases, not all links in networks are observable and they can be hidden due to personal privacy security or be incorrect due to mistakes in data collection, integration and transmission. Link prediction can help to fix these issues.

Object ranking can be viewed as an object evaluation task which aims to order a set of objects based on their importance, relevance, or other user defined criteria. The most important application of object ranking is in Internet searching engines, such as Google which ranks webpages by the relevance with user inputs.

In addition to these three research issues, how to determine the number of clusters beforehand is also important because it can improve the clustering quality significantly.

However, most studies of network analysis over these issues (Lancichinetti & Fortunato 2009, Zhang & Philip 2014, Tsai et al. 2014) focus on homogenous networks rather than heterogeneous networks. Indeed, heterogeneous networks have a much more flexible structure and are more appropriate in modelling real-world situations. This constitutes the major motivation of the thesis.

The major difference between these two types of networks is that homogenous networks can only have one type of object and relationship while heterogeneous ones can have many types. The formal definitions (Sun & Han 2012) are given below:

**Definition 1** (Homogeneous Networks): For a given network $G = (V, E)$, where $V$ is the vertex set and $E$ is the edge set. If all vertices in $V$ are identical and all

links in $E$ are of the same type, then $G$ is defined to be a homogenous network.

**Definition 2** (Heterogeneous Networks): A network is heterogeneous if it contains multiple types of vertices and edges. Heterogeneous networks can be represented as $G = (V, E)$, where $V = (V_1 \cup V_2 \cdots \cup V_n)$ is the union of vertice sets of different types and $E = (E_1 \cup E_2 \ldots \cup E_m)$ is the union of heterogeneous edge sets. Value $n$ and $m$ are the numbers of object types and relationship types respectively.

Both homogenous networks and heterogeneous networks can be directed, undirected, weighted and unweighted networks. In directed networks, edges have a direction associated with them while in undirected networks, edges have no directions. For example, considering two vertices $v$ and $u$, the edge from $v$ to $u$ is represented by $e_{vu}$ and the edge from $u$ to $v$ is represented by $e_{uv}$. In directed networks, $e_{vu} \neq e_{uv}$ because edges have directions while in directed networks, $e_{vu} = e_{uv}$. Weighted networks mean edges have weights to stand for the distances between vertices and the weights of edge $e_{vu}$ is generally labelled as $w_{vu}$.

This review of the literature will group and discuss existing work in the fields of community detection (Section 2.2), determining the number of clusters (Section 2.3), link prediction (Section 2.4) and object ranking (Section 2.5) in network analysis. Before reviewing these topics, this chapter firstly reviews the similarity measures in networks (Section 2.1) because they are the basis of network analysis research. This literature review also covers some state-of-the-art methods and validations which are used to test the effectiveness and efficiency of the proposed methods in this thesis.

## 2.1 Similarity measures in networks

Similarity is a very abstract and general concept with different meanings in different domains, so that there are various similarity measures in different contexts. Traditionally, the level of object similarity is roughly determined by commonalities of object attributes but vertex similarity represents how close two vertices are (Brandes & Erlebach 2005).

Measuring similarities among vertices in networks plays a fundamental role in network analysis because many methods or algorithms for community detection, link prediction and ranking are based on it. For instance, it is natural to see that communities are groups of objects which are similar to each other; in link prediction, the more similar two objects are, the higher the possibility that those two vertices will link to each other in the future; top ranked objects always contain the same attributes or topological features.

This section reviews three main approaches for measuring similarity between vertices in homogeneous networks: distance-based similarity measures, neighborhood-based similarity measures and probability-based similarity measures.

### 2.1.1 Distance-based similarity measures

In a given network, it is intuitive to measure the similarity between vertices by distances. The most widely applied one is shortest-path which calculates a path between two vertices such that the sum of the edge weights or the edge number of this path is minimized. The major algorithms for calculating shortest paths are the Bellman (1956) algorithm and Dijkstra (1959) algorithm with time complexity $O(|V||E|)$ and $O(|V|^2)$ respectively where $|V|$ is the number of vertices and $|E|$ is the number of

edges. A social network study on personal data privacy (Bonneau et al. 2009) applies shortest-path to measure the similarities among users in Facebook and then detects community structure based on user similarities to suggest that leaking personal information enables transitive privacy loss. The study confirms that shortest-path is an effective similarity measure and the experimental results show that if two Facebook users have a short shortest-path, they tend to have similar profiles. If one of them leaks his/her profile, the profile of the other user is insecure.

However, a major drawback of shortest-path is that it just focuses on one path. In fact, for many networks, especially dense networks where the number of edges is far more than the number of vertices, paths between vertices are often more than one. Shortest-path just focuses on the shortest one which is sometimes hard to reflect distances between vertices. This inspires people to consider all paths between vertices instead of one of them. A typical similarity measure based on this idea is max-flow (Ahuja et al. 1993) which counts the number of paths between two vertices. But for this method, there may be a problem that if a network contains a cycle, the total number of paths between two vertices is infinite because max-flow repeats to count edges in the cycle. However this problem can be avoided if the weighted sum or the length of paths is constrained (Even 2011). A study by Newman (2001) on collaboration networks shows that there is a positive correlation between the number of all paths and the probability that two scientists will collaborate in the future and max-flow works better than shortest-path in predicting co-authorship.

Time complexity of distance-based similarity measures are proportionable with the number of edges in networks which means the computational process takes a long time in dense networks. This drawback of distance-based similarity measures gives

rise to the research of neighborhood-based similarity measures.

### 2.1.2 Neighborhood-based similarity measures

Neighborhood is another important topological feature in networks. The general idea of these similarity measures is that vertex similarity is reflected by the levels of their neighborhood overlap. Two vertices are considered to be similar if they have common neighbors, even if they are not adjacent themselves. Vertices without common neighbors are considered "far" from each other. Consider two vertices $v$ and $u$ in a network, the similarity of these two vertices is determined by the overlap of their neighborhood sets which are represented by $\Gamma(v)$ and $\Gamma(u)$. $|\Gamma(v)|$ is the number of neighbors of vertex $v$ and $|\Gamma(u)|$ represents the number of neighbors of vertex $u$. $d_v$ is the degree of vertex $v$. Several most widely applied neighborhood-based similarity measures are given below.

Table 2.1: Summarization of Neighborhood-based similarity measures

| **Neighborhood-based similarity measures** | **Definition** |
|---|---|
| Common Neighbours (CN) | $sim_{CN}(v,u) = \lvert\Gamma(v) \cap \Gamma(u)\rvert$ |
| Jaccard Coefficient | $sim_{Jaccard}(v,u) = \frac{\lvert\Gamma(v)\cap\Gamma(u)\rvert}{\lvert\Gamma(v)\cup\Gamma(u)\rvert}$ |
| Adamic-Adar (AA) | $sim_{AA}(v,u) = \sum_{i\in\Gamma(v)\cap\Gamma(u)} \frac{1}{\log d_i}$ |
| Preferential Attachment (PA) | $sim_{AA}(v,u) = \sum_{i\in\Gamma(v)\cap\Gamma(u)} \frac{1}{\log d_i}$ |
| Katz | $sim_{Katz}(v,u) = \sum_{l=1}^{\infty} \beta^l \cdot \lvert paths^l_{v,u}\rvert$ |

(1) Common Neighbours (CN) (Caplow & Forman 1950) is the simplest neighborhood-based similarity. It simply measures the number of shared neighbors.

$$sim_{CN}(v,u) = |\Gamma(v) \cap \Gamma(u)| \tag{2.1.1}$$

(2) Jaccard Coefficient (Cheetham & Hazel 1969) emphasizes the shared neighbors and different neighbors simultaneously. For two vertices, it calculates the proportion of their shared neighbors and all their neighbors.

$$sim_{Jaccard}(v,u) = \frac{|\Gamma(v) \cap \Gamma(u)|}{|\Gamma(v) \cup \Gamma(u)|} \tag{2.1.2}$$

(3) Adamic-Adar (AA) (Adamic & Adar 2003) refines the simple counting of common neighbors by assigning the less-connected neighbors more weight.

$$sim_{AA}(v,u) = \sum_{i \in \Gamma(v) \cap \Gamma(u)} \frac{1}{\log d_i} \tag{2.1.3}$$

(4) Preferential Attachment (PA) (Barabási & Albert 1999) is commonly used in evolving scale-free networks where the probability that a new edge is connected to vertex $v$ is proportional to $d_v$. Then the probability that a new link will connect $v$ and $u$ is proportional to $d_v \times d_u$.

$$sim_{PA}(v,u) = \frac{|\Gamma(v) \cap \Gamma(u)|}{d_v \times d_u} \tag{2.1.4}$$

(5) Katz (1953) is a very interesting similarity measure considering both neighbourhood and distance between vertices.

$$sim_{Katz}(v,u) = \sum_{l=1}^{\infty} \beta^l \cdot \left|paths^l_{v,u}\right| \tag{2.1.5}$$

where $paths^l_{x,y}$ is the set of all $l$-length paths from $v$ to $u$ and $\beta > 0$ is a scale parameter for the function. Parameter $\beta$ can be regarded as a radius around the target vertex and predictors can only fetch neighbors from inside the circle formed by this radius. A very small $\beta$ yields predictions much like common neighbors as the long paths contribute very little to the sum. Due to the fact

that a network without node attributes can be represented by its adjacency matrix $A$, the corresponding matrix for Katz's similarity is defined, using the approach in (Liben-Nowell & Kleinberg 2007), as

$$P = (I - \beta A)^{-1} - I \tag{2.1.6}$$

where $A$ is the adjacency matrix $I$ is the identity matrix.

These similarity measures are effective in both community detection and link prediction. For community detection, a comparative study by Fortunato (2010) investigates the effectiveness and efficiency of CN, AA, Jaccard Coefficient, PA and Katz on two community detection benchmark datasets: GN benchmark dataset (proposed by Girvan & Newman (2002)) and LFR benchmark dataset (proposed by Lancichinetti & Fortunato (2009)). The quality of clustering is evaluated by normalized mutual information (NMI) (Lancichinetti et al. 2008) which computes the agreement between two given partitions or between a partition and the ground truth. The experimental results suggest that both AA and Katz good performance in community detection followed by Jaccard Coefficient, PA and CN. Katz has the longest CPU time. For link prediction, Liben-Nowell Liben-Nowell & Kleinberg (2007) systematically compared a number of neighborhood-based similarity measures on a social collaboration network. The experimental results shows Katz and RA outperform AA and CN in terms of link prediction accuracy, the computational complexity of Katz is still higher than others though.

From the above studies, Katz similarity measure is effective in community detection and link prediction. An important feature in this similarity measure is to take all paths between vertices into consideration and assigns paths different weights

according to their length. Inspired by this idea, this thesis proposes a semantic-path based similarity measure in Chapter 4.

### 2.1.3 Probability-based similarity measures

Another category of similarity measures in networks are probability-based similarity measures. The main idea behind them is that: given a network, there is an agent walking around on it and if two vertices are similar, the agent can travel from one to the other in a short time.

(1) Random Walk (RW) (Pearson 1905) counts the number of edges, weighted sum or time of randomly moving agent from the starting vertex $u$ to the end vertex $v$. This count is marked as $T(u, v)$.

(2) Average Commute Time (ACT) (Yen et al. 2009) counts the average number of edges, weighted sum or time of randomly moving agent from the starting vertex $u$ to the end vertex $v$ and back to $u$.

$$sim_{ACT}(u, v) = \frac{T(u, v) + T(v, u)}{2} \tag{2.1.7}$$

This similarity is designed for undirected networks where the travelling time from one vertex to the other sometimes may be quite different from the time of the reverse trip.

Probability-based similarity measures are effective in finding clusters and predicting links in directed networks compared with neighborhood-based similarity measures (Liu & Lü 2010). This feature enables probability-based similarity measures to be applied more in heterogeneous networks because those networks often contain

directed and undirected edges simultaneously (Noh & Rieger 2004, Vishnumurthy & Francis 2006, Zhou et al. 2007, Chen et al. 2012).

This thesis applies random walk to measure vertex similarity on heterogeneous networks in Chapter 3 and Chapter 4 for validating the effectiveness of the proposed methods.

## 2.2 Community detection

Many biological, social, technological and information networks are inhomogeneous, revealing a high level of order and organization. Specifically the attributes of different vertices may differ so that some vertices are similar while others are dissimilar. Meanwhile the degree distribution is broad, with a tail that often follows a power law. Therefore most vertices have low degrees while some vertices have high degrees. The unbalanced distribution of edges of networks gives rise to a feature: high concentration of vertices and edges within some groups and low concentrations between these groups. This inhomogeneity is named as *community structure* (Figure 2.1).

The aim of community detection in networks is to identify clusters and, possibly, the hierarchical organization, by only using the information encoded in networks including the attributes of vertices and topological features. Communities are also called *groups*, *clusters*, *cohesive subgroups*, or *modules* in different contexts. Community detection is one of the fundamental tasks in both homogeneous and heterogeneous network analysis. Actually, many social and academic phenomena are to be found by groups instead of individuals. Finding a community requires identifying a set of vertices such that they interact with each other more frequently than with those vertices outside the group. A simple example of detecting communities is illustrated in

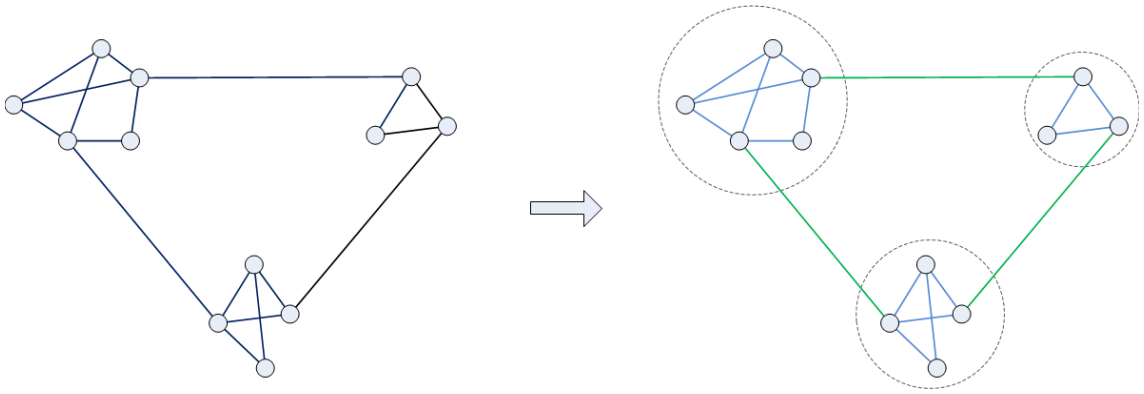


Figure 2.1: A simple example of community detection to show that three communities have been found.

Figure 2.1 where there is a clear community structure with three cohesive groups.

The research on community detection has a long history and it has been well discussed in different areas. Early research on community detection can be traced back to the late 1950s and early 1960s. Rice (1928) identified political groups in a small area based on their voting patterns. This starts to measure how close two people are in a quantitative way. Although people began to focus on community detection, without the modern technologies of computers and the Internet, most researches (Morse & Weiss 1955, Sprott 1958) were done manually.

From the 1970s, work on community detection accelerated with the increasing availability of computers and large-scale network datasets. Since then, many community detection methods have been proposed and developed including similarity-based community detection (Stull 1988), hierarchical clustering (Scott & Carrington 2011), spectral clustering-based algorithms (Fiedler 1973, Donath & Hoffman 1973), modularity partitioning (Newman 2006) and other community detection methods on heterogeneous networks (Sun et al. 2013). Similarity-based community detection, hierarchical clustering and spectral clustering-based algorithms were initially proposed

for homogenous networks and later are extended to heterogeneous networks. This section reviews these methods and describes how they apply on heterogeneous networks.

### 2.2.1 Similarity-based community detection

In the early stages of community detection research for large-scale networks, most community detection methods are based on the natural idea that vertices which are close to each other should be allocated to the same community while those who are far from each other should be put into different communities. Then many similarity measures are proposed based on topological features for homogeneous networks, including distance-based similarity (Bozkaya & Ozsoyoglu 1997) which measures the closeness of two vertices by the number of paths or the sum of path weights between them such as shortest-path, neighborhood-based similarity (Jarvis & Patrick 1973) which measures the closeness of vertices by their shared neighbors in networks such as common-neighborhood, and probability-based similarity (Spitzer 2001) which measure the closeness of two vertices based on how long an agent takes to travel between them, such as random-walk. A comprehensive literature review of similarity measures can be found in Lü & Zhou (2011).

These similarity measures are effective in dealing with different types of networks. A recent study by Pan et al. (2010) comprehensively compared these three kinds of similarity measures on a set of benchmark datasets, such as Zachary's karate club network (Zachary 1977), American college football network (Girvan & Newman 2002), the dolphin association network (Lusseau 2003) and computer-generated networks introduced by Lancichinetti et al. (2008). The study demonstrates that for sparse

networks where the ratio of edge number and vertex number is low, distance-based similarity works better than neighborhood-based similarity while for dense networks where the ratio of edge number and vertex number is high, neighborhood-based similarity is more efficient. This is because the computational complexity of distance-based similarity is sensitive to the number of edges and the large number of edges in dense networks increases the computational complexity of distance-based similarity dramatically. Probability-based similarity performs better than the other two similarity measures in networks with a clear community structure and works effectively to find large communities but is weak to find small ones because random travelling agents are more likely to stay in large communities and seldom travel to smaller ones.

Recently, research of community detection focuses on probability-based and distance-based similarity measures. This is because as heterogeneous networks have multi-typed objects and relations, neighborhood-based similarity measures are not valid. Random walk, one of the famous probability-based similarity measures is applied to detection communities on heterogeneous networks (Chen et al. 2012, Li & Li 2012, Zoia et al. 2010). These studies impose no constraints when an agent is moving from one type of vertice to the others, which means different types of vertices and edges are treated equally. Wang et al. (2013) takes its drawback into consideration and proposes NEIWalk in their study to overcome it. To capture the differences of edge types, NEIWalk assigns transition probability to different types of vertices and the cost of moving from one type of object to the other depends on how often an agent moves between them. If the frequency is high meaning this these two types of objects are closely related to each other (e.g. authors and publications in co-authorship), the cost is low. The method is tested on DBLP dataset and it achieves a high accuracy

(0.537) in finding communities.

Based on distance-based similarity measures, Sun et al. (2011) propose a novel similarity measure, PathSim, designed for heterogeneous networks. Given a heterogeneous network $G$, the similarity of two vertices $u$ and $v$ of the same type is defined as

$$sim(u, v) = \frac{2path(u, v)}{path(u, u) + path(v, v)} \tag{2.2.1}$$

where $path(u, v)$ is the number of paths between $u$ and $v$, $path(u, u)$ is the number of paths between $u$ and $u$ and $path(v, v)$ is the number of paths between $v$ and $v$.

They fully tested the effectiveness and efficiency of SimPath on Facebook dataset, Flickr dataset, DBLP dataset and Twitter dataset in the book (Sun & Han 2012). The experimental results demonstrate that for heterogeneous networks, SimPath performances better in both community detection and link prediction than random walk and pairwise random walk.

In fact, the major objective of similarity-based community detection methods on heterogeneous networks is to find accurate similarities among objects. Given a heterogeneous network, once similarities of target-type vertices are determined, this heterogeneous network can be transferred into a homogeneous network where vertices are connected by their similarities. As a result, for the problem of community detection on heterogeneous networks, these methods often work with hierarchical clustering and spectral clustering-based algorithms (von Luxburg 2007) to improve the quality of clusters such as balancing detected communities or achieving global optimal solutions.

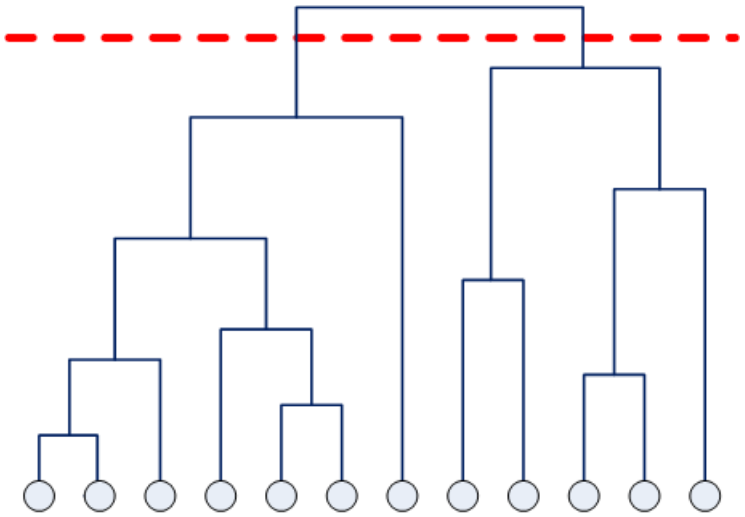


Figure 2.2: An example of hierarchical tree. Horizontal cuts correspond to partitions of a network in communities from Newman & Girvan (2004).

### 2.2.2 Hierarchical clustering

Many networks, especially social networks, display a clear hierarchical structure (Scott & Carrington 2011). Close vertices tend to form small communities while small communities are joined into large ones (illustrated in Figure 2.2). Compared with similarity-based community detection, utilizing this feature is able to acquire more balanced and globally optimal clustering.

The general process of hierarchical clustering algorithms starts with the calculation of similarities of vertices and then groups the similar ones. These techniques can be classified into two categories:

1. *Agglomerative algorithms*, where clusters are iteratively merged if their similarity is sufficiently high;

2. *Divisive algorithms*, where clusters are iteratively split by removing edges connecting vertices with low similarity.

Both categories of algorithm are based on an iterative process but refer to opposite directions. Agglomerative algorithms are bottom-up starting from vertices in a network as separate clusters and ending one cluster. Divisive algorithms are top-down, the opposite direction. They assume the whole network is one cluster and repetitively splits large clusters into smaller ones until the smaller clusters are cohesive enough. Both ways involve a stopping condition such as satisfying a special criterion like a pre-assigned number of clusters or optimization of a quality function which is used to measure the quality of clusters (e.g. their modularity).

Since clusters are merged or split based on their mutual similarity, it is essential to define a measure that estimates how similar clusters are. The general idea for comparing the similarity of two clusters is based on their distances. For example, given two clusters $C_1$ and $C_2$, the similarity between two groups is defined as

$$sim(C_1, C_2) = \sum_{x \in C_1, y \in C_2} sim(x, y) \tag{2.2.2}$$

where $x$ is an element of cluster $C_1$ and element $y$ belongs to $C_2$. Function $sim(x, y)$ is the similarity between $x$ and $y$.

Hierarchical clustering has many advantages. It has a low requirement *a prior* knowledge on the number and size of the clusters and it is compatible with different similarity measures thereby increasing its feasibility in different domains. There are many studies of applying hierarchical clustering on homogeneous networks. A typical study of community detection by hierarchical clustering can be found in Gulbahce & Lehmann (2008) which aims to detect communities on a set of computer-generated datasets to verify their proposed method. The method first measures common-neighbor similarity between vertices and then derives the hierarchical structure of the network by a top-down approach. After every split, the proposed method checks

the average modularity of the partition so as to achieve an optimal clustering. Hierarchical clustering can also achieve good results on many real-world networks, like the world airport network (Guimera & Amaral 2004), email exchange networks (Barrat et al. 2004) and metabolic networks (Sales-Pardo et al. 2007).

Although hierarchical clustering for community detection on homogenous networks has worked well, it is seldom applied on heterogeneous networks. This is because the results of hierarchical clustering highly depend on which similarity measures are chosen and whether networks have a clear hierarchical structure. On the one hand, similarity measures in heterogeneous networks are not well researched and this is a motivation of this thesis to propose a user-guided collective similarity in Chapter 3. On the other hand, heterogeneous networks are complex and it is hard to know whether it has a clear hierarchical structure beforehand. If there is no clear structure, the clustering results are different when choosing different starting vertices. Another problem is that vertices with just one neighbor are often classified as separate clusters. These limit the application of hierarchical clustering to detect communities on heterogeneous networks. However, spectral-based clustering algorithms do not have these limitations.

### 2.2.3 Spectral-based clustering algorithms

As the research on topology of networks progressed, it was realized that community detection on networks can be cast into a graph partitioning problem. This aims to divide vertices in a given network into $k$ groups of predefined size so that the number of edges lying between the groups is minimal. Figure 2.3 presents the solution of the problem for a graph with twelve vertices and the communities are found if those three

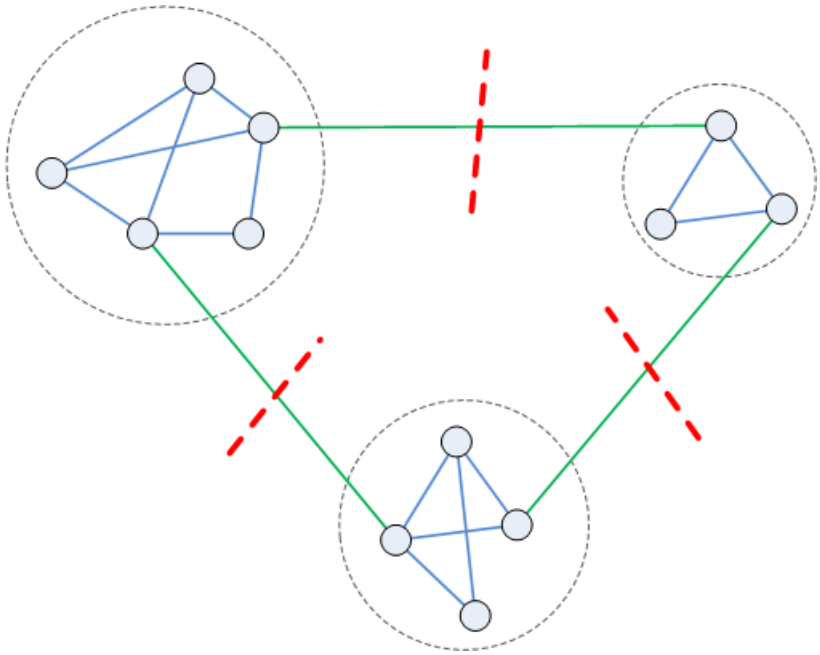


Figure 2.3: An example of graph partitioning.

edges are removed.

Spectral-based clustering methods are based on the idea of graph partitioning. The focus is on finding the best cuts of a graph that optimize a certain predefined criterion function. The first contribution on spectral clustering was a paper by Donath & Hoffman (1973) who applied the eigenvectors of the adjacency matrix for graph partitions. In the same year, Fiedler (1973) realized the importance of the eigenvector of the second smallest eigenvalue of the Laplacian matrix which could be used to cluster bipartite networks. Since then, spectral clustering has been discovered, re-discovered and extended many times in different communities (Pothen et al. 1990, Hagen & Kahng 1992, Shi & Malik 2000, Meila & Shi 2001) and a detailed description about the historical development of spectral clustering is in von Luxburg (2007).

The core step of spectral-based clustering methods is to build network Laplacian

Table 2.2: Laplacian matrices

| **Laplacian matrix** | **Definition** |
|---|---|
| Minimum cut Laplacian matrix | $L_u = D - A$ |
| Ratio cut Laplacian matrix | $L_r = D^T(D - A)D$ |
| Normalized cut Laplacian matrix | $L_n = I - D^{-1/2}AD{-}1/2$ |
| Random-walk Laplacian matrix | $L_{rw} = I - D^{-1}A$ |

matrices. Different studies can have different ways to define and build their own Laplacian matrices. There is a review to summarize different ways of matrices (Chung 1997) and this section describes three major methods. Given a network $G$ with adjacency matrix $A$, the three commonly used Laplacian matrices are defined in Table 2.2 where matrix $D$ is the degree matrix defined as the diagonal matrix with values $d_1, d_2, \ldots, d_n$ on the diagonal, $d_i = \sum_{j=1}^{n} a_{ij}$ and $a_{ij}$ is the element of $A$ in row $i$ and column $j$. Matrix $I$ is the identify matrix.

Different Laplacian matrices represent networks in different ways. The minimum cut Laplacian matrix (also named unnormalized Laplacian matrix) (Stoer & Wagner 1997) is the simplest and most direct way to construct a partition of the network for solving the minimum cut problem. However in practice it often does not lead to satisfactory partitions. The problem is that in many cases, the solution of minimum cut simply separates one individual vertex from the rest of the graph. Of course this is not what we want to achieve in clustering, as clusters should be reasonably large groups of points. One way to circumvent this problem is to explicitly request that the clusters should be "reasonably large". The two most common objective functions to encode this are ratio cut (Hagen & Kahng 1992) and normalized cut (Shi & Malik 2000). In ratio cut, the size of a cluster is measured by its number of vertices, while

in normalized cut the size is measured by the weights of its edges. The random walk Laplacian matrix (Meila & Shi 2001) is based on random walks over the network. The random walk Laplacian matrix can be interpreted as trying to find a partition of the network such that the random walk stays for long within the same cluster and seldomly jumps between clusters. It seems that there is no universal Laplacian matrix and its definition can be tailored user requirements and similarity measures.

The success of spectral clustering is mainly based on the fact that it does not make strong assumptions on the form of the clusters. As opposed to hierarchical clustering where the resulting clusters form convex clusters, spectral clustering can solve very general problems like intertwined spirals. Moreover, spectral clustering can be implemented efficiently even for large data sets because the major calculation is concentrated on a matrix calculation which is compatible with parallel computation in distributed systems (Chen et al. 2011). This algorithm is not dependant on the initialization and there are no issues of getting stuck in local minima or restarting the algorithm for several times with different initializations.

Recently, spectral clustering-based studies have covered many areas in both homogeneous and heterogeneous networks. For homogeneous networks, Thurlow et al. (2010) identified functionally related prognostic gene sets for head and neck squamous cell carcinoma by applying spectral clustering on microarray data and found gene sets highly significant for predicting patient outcome by grouping patients and their genes into different clusters. Krzakala et al. (2013) compared spectral clustering with different Laplacian matrices in some real world datasets and they found random walk based spectral clustering outperformed others. Another study (van Gennip et al. 2013) applied spectral clustering on a dataset combining social and geographical

data together and investigated the limitations of this method in the circumstance of missing social data.

For heterogeneous networks, spectral clustering was firstly applied to bipartite networks such as word-document data (Dhillon 2001, Ding et al. 2001). These algorithms formulate the data matrix as a bipartite network and seek to find the optimal normalized cut for networks. However, the clusters generated by these methods contain vertices of both types. The following research aims at clustering different types of objects into different clusters instead of mixing them. This type of spectral-based clustering (called co-clustering or bi-clustering) is based on matrix factorization. Studies (Dhillon et al. 2003, Long et al. 2005, Li 2005) model the co-clustering as an optimization problem involving a triple matrix factorization. In their experiments, they build a set of clusters for each type of object and recursively maximize the mutual information between clusters with the same type of objects. A more generalized co-clustering framework is presented by Zhong & Ghosh (2005) which can combine with different optimization functions such as modularity and information entropy.

Later spectral-based clustering methods are extended to networks with more than two types of data objects. Gao et al. (2005) formulated star-structured relational data as star-structured multi-partite networks and this method allows users to define their own optimization functions. Another important study was done by Long et al. (2006). The study proposes a general model of clustering multi-type interrelated data object simultaneously and the model is applicable to heterogeneous networks with various structures. The method iteratively clusters each type of data objects and reinforces the clustering quality of each type by the interactions among objects in different types until convergence. This method also considers both object attributes and topological

features at the same time which extends its usage. However, there is no convergence analysis, such as what kind of networks converge and how fast they will converge.

Till now, spectral-based clustering has become the major and most widely applied community detection method for both homogenous and heterogeneous networks. A drawback of recent spectral-based methods for heterogeneous networks which reduces the efficiency is to cluster different types of objects simultaneously. The multiple semantic-path clustering proposed in this thesis aims to cluster target object type instead of all types of vertices. This improves the clustering efficiency significantly.

### 2.2.4 Modularity partitioning

Modularity partitioning is another class of community detection methods on networks. The concept of modularity is proposed by Newman (2004) and it was initially introduced as a optimal function to define a stopping criterion for hierarchical clustering. In other words, modularity is the goal of community detection. Of course in different situations the definition of modularity can be different and modularity-based clustering is an optimal function to maximize values of predefined modularity. In the survey paper, Newman (2006) summarized and explained different definitions of modularity and how they affect the clustering results.

The first algorithm developed for maximizing modularity is based on greedy algorithms (Newman 2004). This algorithm is an agglomerative hierarchical clustering method where vertices with high similarities are joined into small groups and then small groups are connected to form large ones, thereby increasing the modularity. The process of modularity maximization is this: it starts from $|C|$ clusters where $|V|$ is the number of vetices and each cluster has one vertex and edges are not added one

by one during the procedure. Adding the first edge to the set of disconnected vertices reduces the number of groups from $n$ to $n-1$, so it generates a new partition of the network. The edge is chosen such that this partition gives the maximum increase of modularity with respect to the previous configuration. All other edges are added based on the same principle. If the insertion of an edge does not change the partition, i.e. the edge is internal to one of the clusters previously formed, modularity stays the same. A later paper (Clauset et al. 2004) improves the efficiency of Newman's method. The previous approach involves a large number of useless operations due to the sparse adjacency matrix and the revised method is more efficient when using data structures for sparse matrices.

Although this approach to optimization of modularity tends to form large communities quickly, it often yields low values of maximum modularity. A study by Danon et al. (2005) modifies the modularity to this: the merger of two communities depends on the edge fraction of two communities so as to favor small ones. This trick leads to a better modularity optima as compared to Newmans original approach.

Currently, modularity works mainly as an index to estimate the quality of clustering in both homogeneous and heterogeneous networks instead of a community detection method (Dhillon 2001, Dhillon et al. 2003, Long et al. 2005, 2006, Thurlow et al. 2010, Meng & Kennedy 2012*b*, Wang et al. 2013). This thesis also applies Newman's modularity to evaluate the results of community detection in Chapter 3 and Chapter 4.

### 2.2.5 Other community detection methods on heterogeneous networks

As community detection on heterogeneous networks has become a topic of huge interests in network analysis, there are many new approaches developed for heterogeneous networks.

The work starts from developing new similarity measures based on semantic paths. Jeh & Widom (2002) proposed a similarity measure, SimRank, to calculate pairwise similarity between objects in heterogeneous networks. This method is quite similar to common neighbor similarity measures in homogenous networks and it counts path numbers of each semantic path between two vertices. Although this similarity measure treats the contribution of different semantic paths in the same way, it is still applied by many studies (Jeh & Widom 2004, Fogaras & Rácz 2005, Lin et al. 2006, Tian et al. 2008, Li et al. 2010). A study by Lizorkin et al. (2010) combines SimRank with optimization functions so as to improve the quality of clustering. He et al. (2010) parallelize SimRank to improve its capability of processing large-scale datasets.

Another similarity measures, PathSim, is proposed by Sun et al. (2011). This method involves a mechanism of semantic path selection through which this method can choose semantic paths with high contributions. However, PathSim is not applicable to asymmetric paths.

Sun & Han (2013) proposed a novel way to deal with the community detection problem by combining clustering and ranking approaches. The method is based on the idea that ranking and clustering can mutually enhance each other because objects highly ranked in each cluster may contribute more towards an unambiguous clustering. If an object is ranked high by one cluster, the object is more likely belong

to this cluster. Their experimental results demonstrate that the accuracy of clustering results can be significantly enhanced. However, the scale of experimental data is too small and covers the bibliography of only two areas (Data mining and database) in the DBLP dataset.

Although there are many community detection methods proposed for heterogeneous networks, few of them consider that different users may have different purposes for clustering. This thesis proposes a multiple semantic-path clustering in Chapter 3 which can select and estimate semantic paths with user guidance in order to achieve user-desired clustering results.

### 2.2.6 Community detection validation

As reviewed in the previous sections, there are many algorithms to detect communities in networks and this requires a comprehensive set of ways to compare or evaluate them. This section briefly reviews some state-of-the-art approaches for evaluating community detection methods covering statistical indices, modularity and information theoretic-based agreement measures. In this thesis, these approaches are applied to assess the clustering results in Chapter 3 and Chapter 4.

In community detection, a community is roughly defined as "densely connected" objects that are "loosely connected" to others. Whether a clustering is "good" or not is determined by whether the detected communities follow this rule and how closely. Many evaluation methods are proposed in accordance to this idea but with different explanations of "internal density" and "external looseness". For example, "density" can either be the number of edges, the number of $n$-cliques or even the total number of shared neighbors.

The most straightforward approach to validation is statistical analysis. The quality of clustering is evaluated by one or several indices. In this way, two independent functions $f$ and $g$ are introduced, where $f$ is used to measure the "density" inside the clusters while $g$ indicates the "looseness" among clusters. Till now, many different indices are proposed based on different definitions of "internal density" and "external looseness". Among them, coverage and performance (Scott & Carrington 2011) are two widely applied indices for evaluating the quality of community detection results. This thesis applies them to evaluate the community detection results in Chapter 3 and Chapter 4.

1. **Coverage** is a common index in evaluating quality of clustering and the function $f$ refers to the proportion of numbers of intra-cluster edges to all edges. After clustering, every vertice must be allocated into clusters but edges may exist among clusters. In order to achieve the purpose that edges are dense in clusters and sparse among clusters, this proportion should be large. In weighted graphs, this proportion represents the ratio of the sum of edge weights in clusters to the sum of all edge weights. In unweighted graphs, it is the number of edges. The function $g$ is always zero in this approach.

2. **Performance** first defines a "correct" and "incorrect" clustering which refers to the connectivity of vertices. If two vertices are in the same cluster and there is an edge between them or they are in different clusters and there is no edge between them, they are labeled as a "correct" clustering. Otherwise, they are "incorrect". Based on this, function $f$ is defined as counting the number of edges in clusters whereas $g$ counts the number of nonexistent edges between clusters.

However, the values of these indices are influenced by the number and the size of communities. A slight difference in the number of communities and sizes may give rise to a huge differences in indice values. For example, a good division of a network into communities is not merely one in which there are few edges between communities; it is one in which there are fewer than expected edges between communities. If the number of edges between two groups is significantly less than expected, this means that the division is effective as it shows meaningful community structure. This idea, that the true community structure in a network corresponds to a statistically surprising arrangement of edges, can be quantified by using the measure known as modularity (Newman & Girvan 2004) which is roughly the number of edges within communities minus the expected number in an equivalent network with edges placed at random. Indeed, modularity has multiple usages: it was initially proposed to be a clustering method (Clauset et al. 2004); later it also served as an optimization approach to improve clustering results by other methods (Newman 2006); and recently it is often adopted as a evaluation of clustering quality (Shen et al. 2009).

The approach for calculating modularity follows Newman's formula which was proposed to work on unweighted networks. Consider a network $G = (V, E)$, the modularity of this network is

$$Q = \frac{1}{4|E|} C^T B C \tag{2.2.3}$$

where matrix $C$ is a cluster indicator matrix of the network and $C_{i,j} = 1$ denotes that the $i$th vertex belongs to the $j$th community. Matrix $B$ is the modularity matrix and it is defined as

$$B_{uv} = A_{uv} - \frac{d_u d_v}{2|E|} \tag{2.2.4}$$

where $A$ is the association matrix and $d_u$ and $d_v$ are the degrees of vertex $u$ and $v$

respectively.

The modularity can be either positive or negative, with positive values indicating the possible presence of community structure. Thus, one can search for community structure precisely by looking for the divisions of a network that have positive and preferably large, values of the modularity.

Another way to evaluate clusters involved in this thesis is the information theoretic agreement measure, Normalized Mutual Information (NMI) (Batina et al. 2011) which computes the agreement between two given partitions or between a partition and the ground truth. This evaluation is applied in Chapter 3 for verifying how to acquire a desired clustering.

Given a network with $n$ vertices, there are two partitions $X$ and $Y$ with $x$ and $y$ clusters respectively. For partition $X$, the clusters are labeled as $1, 2, \ldots, x$ while for partition $Y$ the clusters are labeled as $1, 2, \ldots, y$. In NMI, partitions are regarded as the different distributions of vertices. As a result, the normalized mutual information $I_{norm}(X, Y)$ is defined as

$$\begin{aligned} I_{norm}(X,Y) &= \frac{2I(X,Y)}{H(X)+H(Y)} \\ I(X,Y) &= \sum_{i=1}^{x}\sum_{j=1}^{y} P_{XY}(i,j)\log\frac{P_X(i,j)}{P_Y(i)P(j)} \\ H(X) &= -\sum_{i=1}^{x} P_X(i)\log P_Y(i) \\ H(Y) &= -\sum_{j=1}^{y} P_Y(j)\log P_Y(j) \end{aligned} \tag{2.2.5}$$

where $P_X(i)$ stands for the probability of objects belonging to Cluster $i$ in partition $X$ and $P_Y(j)$ stands for the probability of objects belonging to cluster $j$ in partition $Y$.

$P_{XY}(i, j)$ is a joint probability, denoting the probability of objects belonging to both cluster $i$ in partition $X$ and cluster $j$ in partition $Y$. The measure $I(X, Y)$ tells how similar partition $X$ and $Y$ are. The value of NMI is zero when two distributions are independent and one when they are identical.

Normalized Mutual Information, which is derived from probability theory and information theory, is a reliable method for measuring the mutual dependence of two random variables (Paninski 2003). It is applied in many papers (Lancichinetti et al. 2008, Lancichinetti & Fortunato 2009, Blondel et al. 2008) for comparing clustering quality among different community detection algorithms because of its sound theoretical basis and easy implementation.

## 2.3 Determining the number of clusters

In networks, choosing the number of clusters $k$ in advance is a general problem for nearly all clustering algorithms and the choice of "right" number of clusters can improve the quality of clustering substantially because the number of clusters is a mandatory input parameter of many state-of-the-art and widely applied clustering methods such as $K$-means and spectral clustering. There are two main families of approaches: clustering result-based methods and topological feature-based methods.

### 2.3.1 Clustering result-based methods

In a real dataset, the number of clusters is often unknown. The simplest method of choosing the number of clusters is to try different values, and cluster validation techniques are used to measure the clustering results and determine the best

value of $k$ (Caliński & Harabasz 1974, Hartigan 1975). These approaches where the clustering algorithms are repeatedly executed are computationally expensive and time-consuming. To extend the availability of this idea, Kryszczuk & Hurley (2010) integrate the process of multiple execution of clustering algorithms and clustering comparison into a standard, general framework where the framework is compatible with different clustering validity indices (Maulik & Bandyopadhyay 2002) including modularity, performance and coverage. These are a group of functions measuring the clustering quality. Although this proposed method is very effective in finding the correct number of clusters in benchmark datasets, it is still confined to small datasets.

### 2.3.2 Topological feature-based methods

Recently with the emergence and rapid expansion of social, biological and bibliographic networks, the problem of determining the number of clusters becomes more challenging because the traditional approach to repeatedly execute the clustering algorithms is impractical with these large-scale datasets. Then the problem has been reconsidered from the aspect of the clustering algorithms based on topological features. As presented in the previous section, topological features and community structures of networks can be understood to some extent through the analysis of their corresponding matrices such as adjacency or Laplacian matrices. From this idea, the number of clusters is determined by how many eigenvalues are chosen and therefore the methods in this area are usually based on the eigenvalue structure (Fraley & Raftery 2002).

**Cumulative percentage variance** (Abdi & Williams 2010) is an accurate method for determining the number of clusters based on matrices built from networks. As different eigenvalues contribute differently to the network partition, an intuitive idea

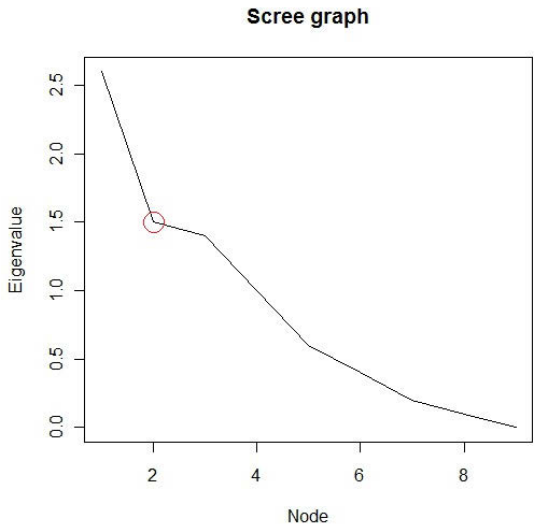



Figure 2.4: Scree graph

is to choose those important eigenvalues. In spectral-based clustering, smaller eigenvalues are more important than larger ones in terms of network partitioning. Assume that there are $m$ eigenvalues and the first $k$ smallest eigenvalues are chosen. The cumulative percentage variance is defined as

$$C = 1 - \frac{\sum_{i=1}^{k} l_i}{\sum_{j=1}^{m} l_j} \tag{2.3.1}$$

where $l_i$ is the $i$th smallest eigenvalue of the Laplacian matrix. However, this method does not solve the problem completely but transfers it to a new question on how to choose $C$.

Another better way to choose $k$ is with a scree graph (Jolliffe 2005). A scree graph, shown in Figure 2.4, is a plot of eigenvalues associated with vertex indices. In general, the "elbow point" is the separation and the eigenvalues which are less than it are chosen. For example, in Figure 2.4, eigenvalues with index 2 should be chosen. One way to find the "elbow point" is to compare the slope between both sides of

eigenvalues with the "elbow point" having the maximum value. The slope value is defined as

$$S(k) = (l_{k-1} - l_k) - (l_k - l_{k+1}) \tag{2.3.2}$$

where $l_k$ is the $k$th smallest eigenvalue of the Laplacian matrix.

There are many similar methods and examples include *ad hoc* measures such as the ratio of within-cluster and between-cluster similarities (Chiang & Mirkin 2010), information-theoretic criteria (Still & Bialek 2004), the gap statistic (Tibshirani et al. 2001) and stability approaches (Lange et al. 2004).

Although many methods are proposed, it is still hard to give a general answer to the question of how many eigenvalues to choose as different methods have their own advantages in different types of networks. For example, the methods based on the ratio of within-cluster to between-cluster similarities perform better on networks with a clear community structure. Lange et al. (2004) comprehensively describes the above methods and explains the different usages of them. The study applies $K$-means on 20 randomly generated datasets with different numbers of clusters determined by different approaches. The performances of the different methods vary when the generated networks show different topological features like density.

Indeed, choosing which approach is suitable for determining the number of clusters requires a deep understanding of networks and indeed this information is hard to retrieve before clustering. However the current researches confirm that determining the number of clusters from topological features is feasible.

This thesis is inspired to continue to address the problem by considering network topology and finds that social network theory proposes a completely new idea. In social science, the reason why social networks tend to have a community structure

is because different individuals play different roles and roles are reflected through their topological features (Scott & Carrington 2011). More specifically, some objects are considered to be more important in terms of topological features than others as they are the core of groups and the regular members are linked to each other via them. Those objects with high ranks in significance are defined as "group leaders" and the number of clusters is highly related to the number of those leaders. The early research (Sparrowe et al. 2001, Mehra et al. 2006) attempted to detect leaders via degree centrality as they believed that leaders should have more links with others. However, they ignored an important fact that in the real world, core members sometimes have a high degree-centrality (Abbasi et al. 2011) as well. As a result, the number of detected leaders is often more than the real number of leaders.

This thesis (Chapter 4), therefore, involves betweenness-centrality (Baglioni et al. 2012) to remedy the methods for searching for leaders because leaders not only have more connections in clusters but they also often relate with individuals in other clusters and betweenness centrality, that quantifies the number of times a vertex acts as a bridge along the shortest path between two other vertices, can reflect this characteristic. Meanwhile, considering the case that sometimes there are two or more leaders in one potential group, this thesis devises an algorithm to combine leaders when they are close enough. Beside "group leaders", this thesis defines "group coordinators" who mainly take responsibility to connect groups together. For example, in academic collaboration network, directors of research centers are the coordinators of research labs. Removing the edges between "group coordinators" in advance may make the work of community detection much easier. Finally a novel community detection approach based on the concept of "roles" is proposed. Because leaders are detected

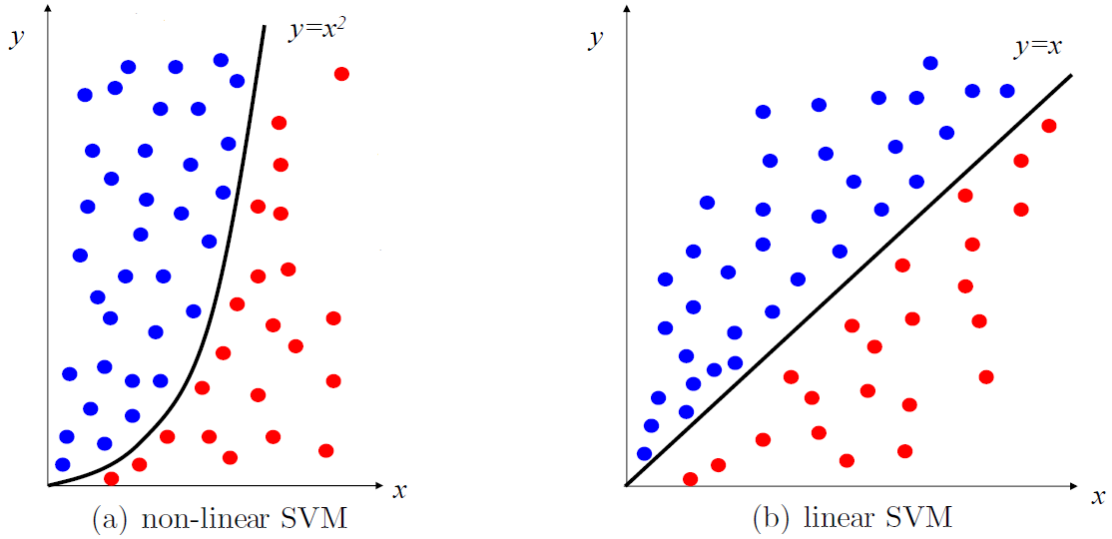



Figure 2.5: SVM aims to draw a boundary among objects and those objects in the same side are classified into one cluster (Cortes & Vapnik 1995).

by Support Vector Machine (SVM) based on training datasets, next section briefly reviews SVM methods.

### 2.3.3 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a kind of binary classification method (Moya & Hush 1996). This classification method tries to identify objects belonging to two classes amongst all objects, by learning from a training set containing positive and negative examples of objects. According to the problem of determining the number of clusters, this thesis applies SVM to find leaders from all objects.

In binary classification methods, Support Vector Machine (Cortes & Vapnik 1995) of them outperform others in terms of generalization. This method was initially proposed in 1995 but the concept could be traced back to 1979 (Cortes & Vapnik 1995).

Support Vector Machine aims to find the optimal boundaries between two groups of objects and these optimal boundaries are decided by involving different kernel functions. Unlike traditional methods which minimize the empirical training error, Support Vector Machine minimizes an upper bound of the generalization error through maximizing the margin between the separating hyperplane and the data. Another attractive aspect is that it can be compatible with different kinds of kernel functions (a distance measure between objects). Therefore it can be linear or non-linear.

In the thesis, Support Vector Machine with Gaussian kernel function is applied to find leaders in a heterogeneous co-authorship network and the followed procedure of non-linear SVM refers to Burges (1998).

## 2.4 Link prediction

The link-prediction problem for social networks can be described from the point of view of data mining in the following way: given a snapshot of a social network at time $t$, the goal is to predict new links that will be added to the network during the interval from time $t$ to a given future time $t'$.

This problem can be viewed as a simple binary classification problem. That is, for any two potentially linked objects $o_i$ and $o_j$, predict whether $l_{ij}$ is 1 or 0. Current research aims to measure the degree of similarity and closeness between two target nodes. In network terms this means not only that they should be similar to each other, but also that they must also be reachable through the network. In other words, the closer and more similar are they, the higher possibility they have to be connected in the future. Generally, approaches to address this problem come from two aspects: the attribute information of nodes and the structural properties of social networks.

In the first of these kinds of approach, attribute information is used for link prediction. Popescul & Ungar (2003) introduces a structured logistic regression model that can make use of relational features to predict the existence of links on citation datasets from CiteSeer. In that experiment, link prediction on citation networks is cast into a citation recommendation system by gauging similarities between target publications and existing publications. However, those methods have limitations in that the attributes of nodes can only reveal similarity with others, but fail to take the concept of "distance" into consideration. For instance, two people may be quite similar to each other in terms of habits, interests and backgrounds. However, they cannot be friends if they are located far from each other in geography as they have no chance to meet.

Links are predicted on the basis of different graph proximity measures. Among the selection of proximity measures, nearest neighbourhood algorithms are quite famous and have been widely applied. In the experiment of Murata & Moriyasu (2008), they introduced a weighted common neighbour approach and compared its prediction results with common neighbour and Jaccard's coefficient method. Unfortunately, their experimental results have accuracies that are all lower than 50%.

The reason for this is because neighbourhood algorithms can make correct prediction when two nodes are quite close to each other. In fact, some relationships such as friendship, co-authorship and citation relationships are transitive: nodes may be connected in the future if there is a path among them, but those methods may ignore this situation.

The second approach takes into account the structural properties of social networks, namely "distance" between nodes, when devising measures of closeness. One

famous approach is the Katz measure (Katz et al. 1997) which defines a measure that directly sums over the collection of paths, exponentially damped by their length so as to count short paths more heavily. Another approach uses random walk (Rudnick & Gaspari 2004), to calculate the moving time or number of steps of an agent from a start point $s$ to the end point $e$. Because the time to arrive is not in general symmetric, a common way to detect closeness from this probabilistic approach is to consider the commute time $C_{s,e} = T_{s,e} + T_{e,s}$, where $T_{s,e}$ and $T_{e,s}$ are times to move from start to end and end to start respectively. Liben-Nowell & Kleinberg (2007) present an experiment comparing predictors on large co-authorship networks. Their work suggests that information about future interactions can be extracted from the network topology alone and that subtle measures for detecting node proximity can outperform more direct measures. However, the results show that among all predictors, Katz, the method combining neighbourhood and distance concepts, is the best. However, the accuracy they found of 16% is still quite low.

The above research confirms that current methods of link prediction have a large room for improvement. In this thesis, information concerning the evolution of a co-authorship network is collected so as to treat vertices differently. Through observing their past actions, vertices are labeled by their activities and those vertices with high values in activity have a high possibility to connect with others. In order to improve the accuracy further, matrix theory is applied to detect the main patterns of predicting results.

## 2.5 Ranking

Early stages of ranking objects in networks focused on object connectivity. The initial research on ranking vertices in networks is inspired by the voting mechanism that highly ranked objects are those who get more votes from others. Based on this idea, highly ranked vertices in networks should have more connections from others. For this reason, Brin & Page (1998) proposed the famous PageRank algorithm to rank web pages based on keywords that user input and webpage connectivity. Till now this idea is still the core algorithm of Google search engine. Since then, many studies have been devoted to this area and have proposed many customized PageRank algorithms (a comprehensive review about PageRank algorithms and their applications can be found in Berkhin (2005)).

Kleinberg (1999) first extended the ranking work from homogeneous networks to heterogeneous networks. His famous method, the Hyperlink Induced Topic Search (HITS), confirms that ranking can be reinforced through interactions between nodes of various types. As a result, many famous papers with a few citations can be assigned high ranks. Since then, numerous papers on link analysis–based ranking based on PageRank or HITS have appeared (Ahmedi 2012, Fiala 2012).

Recent advances in graph theory and corresponding methods have enriched ranking methods by incorporating topological features. It is believed that in networks, an object is ranked high, if it is located in an important position. Many centralities (Scott 2012) are proposed to achieve this purpose. Liu et al. (2005) compared the rankings of scientists by PageRank with three other rankings using degree, betweenness centrality and closeness centrality. The results confirmed that centrality

measures are effective each with their own advantages and that without considering citations, famous but not so highly cited papers are ranked very high. Another work (Chiang et al. 2012) exploits social links and uses local information only to find the top-$k$ users in a co-authorship network based on a probabilistic model using random walks.

Soon, the research focus of ranking moves to heterogeneous networks. Deng et al. (2012) proposed a joint regularization framework to model heterogeneous networks and treated multi-typed linking edges differently, which is effective to ranking objects in heterogeneous networks. Sun & Han (2012) proposed a new ranking approach called Authority Ranking for heterogeneous networks. The main idea is that the rank of an object in a heterogeneous network is determined by its authority and that authors can be clustered by authority. For example, highly ranked authors tend to attend highly ranked venues and highly ranked venues attract highly ranked authors. The approach is applied to co-ranking authors and venues on the DBLP dataset and the experimental results are very effective. However, this method can only work for bipartite networks.

Inspired by the previous work, this thesis develops a co-ranking method based on both object connectivity and topological features for heterogeneous network. The proposed method can rank objects in complex heterogeneous networks where one-type of objects can connect to other types of objects or themselves. For testing the effectiveness and efficiency, two state-of-the-art ranking methods, PageRank and Hyperlink-Induced Topic Search (HITS), are involved for comparison.

## 2.6 Research gaps

In summary, this chapter reviews current research on four basic network analysis questions: detecting communities, determining the number of clusters, predicting links and ranking vertices in both homogenous and heterogeneous networks. The major identified research gaps are listed below.

The complex topological features of heterogeneous networks give rise to one major issue in community detection: how to estimate the contributions of different relationships, especially for abstract concepts. The current community detection methods on heterogeneous networks (reviewed in Section 2.2) fail to provide an applicable way for users to estimate contributions to relationships and ignore that different users may have different purposes for clustering. This thesis proposes a multiple semantic-path clustering method which can achieve a desired clustering with user-guided information.

The major way of determining the number of clusters is via eigenvalue structures of networks. Different eigenvalues are of different importance for having network topological information. In spectral-based clustering algorithms, smaller ones are more important than larger ones. However, the number of leading smallest eigenvalues to choose is hard to determine. This thesis addresses the problem by considering network topology. The proposed method in Chapter 4 determines the number of clusters by finding cores of communities which are labeled as leader groups.

For link prediction, the major issue is that the link prediction accuracy is still low and there is a large room to improve. The current methods predict links via vertex similarities. If two vertices are similar, they are likely to connect; otherwise, they have a small possibility to connect in the future. In fact, there are often some

exceptions that dissimilar vertices are connected while similar ones are not connected and this is the major reason why link prediction accuracy is low. This thesis proposes a network evolution-based link prediction method which can capture these exceptions based on vertex evolving patterns.

For vertex ranking, the current studies of ranking vertices in heterogeneous networks focus on bipartite networks where there are two types of vertices and one type of vertex is not connected directly but connect to each other indirectly via the other type of vertex. The proposed co-ranking method in Chapter 6 can work on complex bipartite networks where one type of vertex can connect directly or indirectly.

# Chapter 3

# Community detection on heterogeneous networks

In the real world, there are many abstract social phenomena like academic collaboration which are hard to measure directly. An approach to solving this problem is to decompose abstract concepts into a set of concrete and measurable ones. For example, academic collaboration can be represented by co-authorship and co-work relationship. This practice gives rise to heterogeneous networks.

Compared with homogeneous networks, heterogeneous networks always contain different types of objects which are connected by different types of relations. Because of this topological complexity, many traditional ways of community detection designed for homogeneous networks are not feasible. To solve this problem, this chapter proposes a Multiple Semantic-path Clustering method which is a general approach of community detection on heterogeneous networks based on paths and matrix factorization (Tang & Liu 2010). This method can also achieve a desired clustering based on user-guided information.

This chapter validates this measurement by investigating academic collaboration at the University of Technology, Sydney (UTS). The experimental results confirm that the proposed method outperforms the combination of random-walk similarity measurement and spectral clustering (von Luxburg 2007) in identifying research groups.

This chapter encapsulating **Contribution 1** of the thesis, is an extended description of my publications (Meng & Kennedy 2012*b*, 2013*b*, Meng et al. 2014).

## 3.1 Methodology

This part covers the theory and implementation of Multiple Semantic-path Clustering in details followed by path assessment.

### 3.1.1 Multiple semantic-path clustering

In this section, a general method, named Multiple Semantic-path Clustering, of community detection on heterogeneous networks is proposed based on semantic paths and matrix factorization.

To derive a general model, the process of calculating the similarity of semantic paths is formulated as a matrix calculation and the start and end type of object of those paths should be the same as the target object type.

Figure 3.1 shows three examples of heterogeneous networks with an assumption that object type $A$ is the target research object. Example (a) refers to basic bi-type relational data such as word-document with one semantic path $A - B - A$. The similarity of objects in type $A$ can be calculated by $M_{AB}M_{AB}^T$ where $M_{AB}$ is the association matrix. Example (b) represents tri-type data such as web pages,

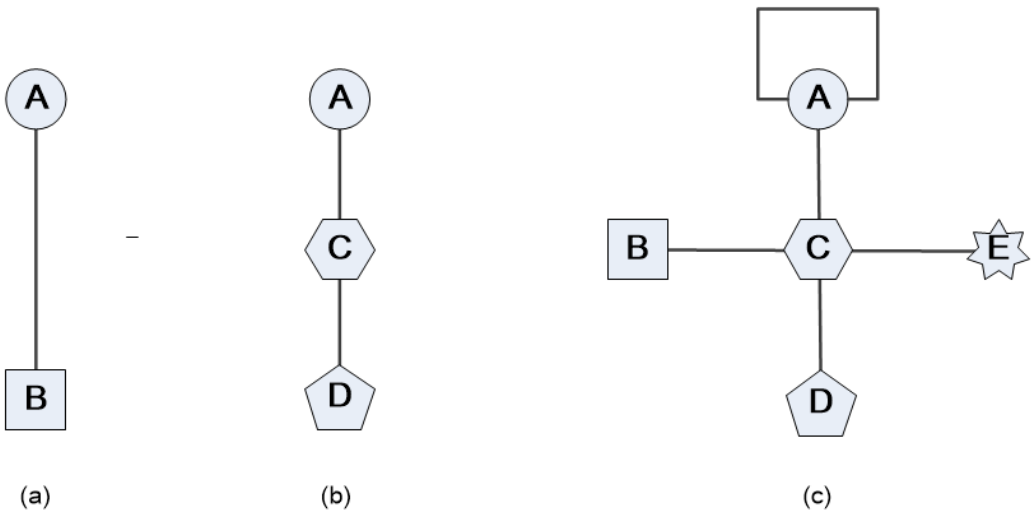



Figure 3.1: Examples of semantic paths.

web users and search queries in web search engines with two paths $A-C-A$ and $A-C-D-C-A$. There are two association matrices $M_{AC}$ and $M_{CD}$ and therefore the similarity of objects in type $A$ can be represented by the combined similarity of two paths. The similarities of these paths can be calculated by $M_{AC}M_{AC}^T$ and $M_{AC}M_{CD}M_{CD}^TM_{AC}^T$ respectively. Example (c) is a much more complex homogeneous networks with five object types and objects $A$ are linked both directly and indirectly. The possible paths are $A-A$, $A-C-A$, $A-C-B-C-A$, $A-C-D-C-A$ and $A-C-E-C-A$. In this case, the similarity of $A$-type objects is the collective similarities of all these paths.

**Definition 3.1**. Given a heterogeneous network $G=(V,E)$, there are $m$ different types of object $(V_1,\ldots,V_m)$ and $n$ types of relation $(E_1,\ldots,E_n)$. Each type of object may contain different number of vertices. If the target object type is $V_t$ with $|V_t|$ vertices $(1\leq t\leq m)$. The corresponding semantic path set of this target object type

is $P_t$, the collective similarity of objects in type $V_t$ is defined as

$$S_{V_t} = \sum_{i=1}^{|P_t|} a_i S_i \quad s.t. \quad \sum_{i=1}^{|P_t|} a_i = 1 \tag{3.1.1}$$

where $S_{V_t}$ is the collective similarity matrix of target objects $V_t$ while matrix $S_i$ is the similarity matrix of target objects $V_t$ in terms of path $i$. There is scale parameter $a_i$ which indicates the contribution of semantic path $i$ to the collective similarity $S_{V_t}$.

It has been shown that the hidden structure of a data matrix can be explored by matrix factorization (Tang & Liu 2010). Motivated by this finding, the clustering process of multiple semantic-path clustering is based on matrix factorization because the cluster structure for a type of objects $V_t$ is embedded in the collective similarity matrix $S_{V_t}$ and the cluster structure of $V_t$ is revealed by the triple factorization,

$$R_{V_t} \approx C_{V_t} S_{V_t} C_{V_t}^T = C_{V_t} \left( \sum_{i=1}^{|P_t|} a_i S_i \right) C_{V_t}^T \tag{3.1.2}$$

where $C_{V_t} \in \{0,1\}^{|V_t| \times k}$ is a cluster indicator matrix for target object $V_t$ and $k$ is the number of clusters such that $C_{V_t}(p,q) = 1$ denotes that the $p$th object in $V_t$ is associated with the $q$th cluster and $\sum_{q=1}^{k} C_{V_t}(p,q) = 1$.

Based on the above discussions, the task of Multiple Semantic-path Clustering on heterogeneous networks can be formally defined as the following optimization problem and the optimization function below is the objective function of the proposed Multiple Semantic-path Clustering method.

$$\min F(C_{V_t}) = \left( R_{V_t} - C_{V_t} \left( \sum_{i=1}^{|P_t|} a_i S_i \right) C_{V_t}^T \right) \tag{3.1.3}$$

The minimization in Equation (3.1.3) is equivalent to the maximization in Equation (3.1.4). An iterative algorithm is proposed to determine the optimal solution to

the maximization problem.

$$\max G(C_{V_t}) = \left( C_{V_t} \left( \sum_{i=1}^{|P_t|} a_i S_i \right) C_{V_t}^T \right) \tag{3.1.4}$$

Although the maximization problem in Equation (3.1.4) is NP-hard, the solution of which cannot be found in polynomial time, an approximate solution can be achieved by a relaxation by converting the cluster indicators from discrete ones to continuous values using spectral graph partitioning (Ding et al. 2010).

Multiple Semantic-path Clustering clusters multi-type interrelated data objects based on their relations by exploiting both direct and indirect interactions between the hidden structures of different types of objects via semantic paths and matrix factorization. The proposed Multiple Semantic-path Clustering method is an extension of traditional spectral graph partitioning for community detection. As a result, it inherits many advantages such as achieving a global solution, having a theoretical support and easy implementation.

### 3.1.2 Semantic path assessment

In the previous section, all paths in multiple semantic-path clustering have scalars that denote their relative importance when clustering target objects. However, heterogeneous networks, especially complex ones, always have a large set of semantic paths. Consequently, the corresponding similarity calculations will be time and labor intensive. It is necessary to know which semantic paths are important and the value of their weights before clustering. This section explains how to choose scalars for different semantic paths.

In fact, semantic paths can be considered as features and path assessment is a process of feature selection and estimation. Given a heterogonous network with $p$ semantic paths, there is a training dataset where users label the objects with cluster indictors. The correlations between semantic paths and cluster indictors are $b_1$, $b_2$, ..., $b_l$ from largest to smallest. If the first $l$ ($l \leq p$) paths are chosen, the weights of paths are defined as

$$a_i = \frac{b_i}{\sum_{i=1}^{l} b_i} \quad s.t. \quad \sum_{i=1}^{l} a_i = 1 \tag{3.1.5}$$

In the experiment, academic collaboration at University of Technology, Sydney is considered as a ground truth. Based on this, a sample is formed where researchers are labeled with their laboratories. The weight of a path is represented by the correlation between the path and cluster labels and paths with the leading closest correlations are chosen as the main features.

## 3.2 Clustering evaluation

The proposed multiple semantic-path clustering method to detect communities on heterogeneous networks is validated from the following two aspects: cluster comparison and cluster validation.

### 3.2.1 Cluster comparison

To verify the effectiveness and efficiency of multi-path clustering, a well known community detection method, spectral clustering (a comprehensive description about this method can be found in literature review, Section 2.2.3.) is involved for comparison. However, spectral clustering cannot be applied on heterogeneous networks directly.

To overcome this, a random-walk similarity measure is applied to build a similarity matrix which spectral clustering can work on. In the experiment, as the current laboratory setting of UTS is regarded as a ground truth, the clustering results generated by multi-path clustering and spectral clustering are compared with the UTS laboratory settings.

The first approach for cluster comparison refers to vector comparison. It is apparent that clustering results can be represented by an indicator matrix and the element of the matrix indicates whether two data points are in the same cluster or not. Given two partitions $X$ and $Y$ with $n$ data points, there are two matrices $M_X$ and $M_Y$ built from these two partitions respectively. For partition $X$, if object $i$ and $j$ are in the same clusters, $M_X(i,j) = 1$; otherwise $M_X(i,j) = 0$. The similarity between partition $X$ and $Y$ is well defined as

$$\begin{aligned} Similarity(X,Y) &= \frac{1}{n}\sum_{i=1}^{n}\frac{V_i \cdot U_i}{||V_i|| \cdot ||U_i||} \\ V_i \in M_X \quad s.t. \quad M_X &= (V_1, \ldots, V_n) \\ U_i \in M_Y \quad s.t. \quad M_Y &= (U_1, \ldots, U_n) \end{aligned} \tag{3.2.1}$$

where $V_i$ and $U_i$ are the vectors belonging to matrices $M_X$ and $M_Y$ respectively.

Another comparison approach is Normalized Mutual Information (NMI) 2.2.6 which computes the agreement between two given partitions or between a partition and the ground truth. This chapter regards the UTS laboratory settings as a ground truth and it compares the clustering results by the proposed method and spectral clustering with the ground truth.

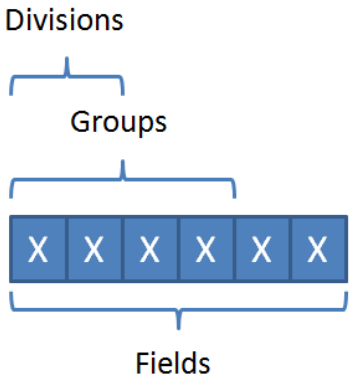



Figure 3.2: The constitution of Field of Research (FoR) codes

### 3.2.2 Cluster validation

Besides that, the clusters generated by multi-path clustering and spectral clustering are also verified and compared by a set of clustering validation methods including Coverage, Performance (Scott & Carrington 2011) and Modularity (Newman 2006). The detailed descriptions about them are included in literature review (Section 2.2.6).

## 3.3 Experimental dataset

The dataset used for analysis and visualization is from the University of Technology, Sydney (UTS) research master enterprise (RME) database, which is a collection of over 60000 records, covering all the faculties and schools in UTS. Information on all publications of UTS during the recent six years ($2006 - 2011$) was selected including journals, conference papers and proceedings, chapters and books of all faculties.

The distinctive advantage of this data source over other scientific bibliographic databases like CiteSeer and computer sciences bibliographic data source DBLP is its integrity. Although the number of records from this data source is relatively small

compared to those scientific bibliographic databases, it contains more types of publications, research fields and researchers. Due to its integrity, it is easier to understand academic collaboration in this closed environment. The data for verification such as the configuration of laboratory settings and research leaders is easily accessed.

Besides researchers, faculties, roles and papers, another important object is introduced to build the academic collaboration and it is Field of Research (FoR) codes. They are used by Australia and New Zealand to indicate which research field publications belong to. Field of Research (FoR) codes are a system with 6 digits containing three hierarchical levels: divisions (first 2 digits), groups (first 4 digits) and fields (all 6 digits) with divisions at the highest level. For example, the FoR code for Pattern Recognition and Data Mining is 080109 while 08 is for Information and Computing Sciences and 0801 stands for Artificial Intelligence and Image Processing. How one publication belongs to different research fields is represented by percentages with each publication having at most three FoR codes. For example, the journal article "Genetic algorithm-based strategy for identifying association rules without specifying actual minimum support" (Yan et al. 2009) is attached to three FoR codes: 080100 Artificial Intelligence and Image Processing (50%), 080604 Database Management (30%) and 010200 Applied Mathematics (20%).

After data cleaning, integration, transformation and reduction (Han & Kamber 2006), the number of remaining records are stored in nine files: researcher file, publication file, FoR code file, faculty file, role file, researcher-publication relationship file, publication-FoR codes relationship file, researcher-faculty relationship file and researcher-role relationship file (See Table 3.1). Researchers file, publication file, FoR

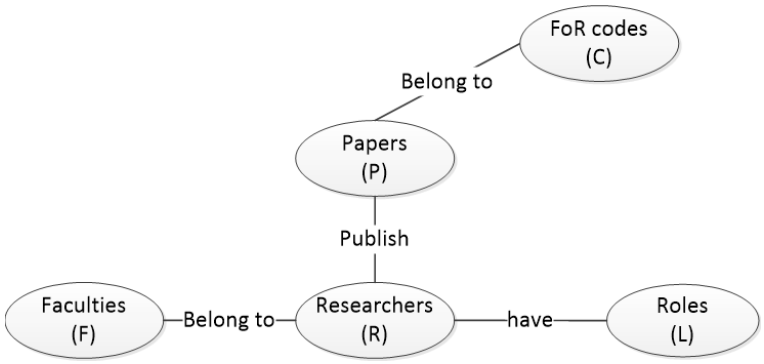



Figure 3.3: The schema of the network presenting the academic collaboration at UTS

codes file, faculty file and role file contain five types of nodes: researchers, publications, FoR codes, faculties and roles respectively, while the relationship files are used to add links among the nodes.

Table 3.1: The number of records in files from 2009 to 2011

| **File name** | **Number of records** |
|---|---|
| Researcher file | 5621 |
| Publication file | 3737 |
| FoR code file | 585 |
| Faculty file | 13 |
| Role file | 5 |
| Researcher-Publication relationship file | 12105 |
| Publication-FoR codes relationship file | 4576 |
| Researcher-Faculty relationship file | 5621 |
| Researcher-Role relationship file | 5621 |

The schema of the heterogeneous UTS academic collaboration networks is illustrated in Figure 3.3. It shows that researchers ($R$) are the core research objects. Researchers are not linked to each other directly but through other objects (Faculties ($F$), Roles ($L$), Papers ($P$) and FoR codes ($C$)). To be specific, researchers ($R$)

can have different roles ($L$) such as professors, associate professors, senior lecturers, lecturers and research followers. Different researchers ($R$) may belong to different faculties ($F$) while researchers ($R$) publish papers ($P$) which belong to FoR codes ($C$).

Finally, the information about the research organizational structure of UTS is collected as the ground truth of academic collaboration. This information includes researchers ($R$), laboratories ($B$) and working relationships ($R - B - R$).

## 3.4 Experimental results

This section evaluates the performance of the proposed multiple semantic-path clustering on achieving a user desired community detection covering collective similarity calculation, path assessment and cluster validation. The proposed method is applied on the heterogeneous UTS academic collaboration network which involves multi-typed objects and relationships to represent an abstract concept: academic collaboration. Multiple semantic-path clustering can integrate different types of relationships by assigning scalars to these relationships with user-guided information.

### 3.4.1 Collective similarity calculation

This section investigates the schema of the heterogeneous networks from UTS, describes the process of collective similarity calculation and explains that different weights of semantic paths influence the collective similarities among researchers significantly.

The experimental object is the UTS academic collaboration network. According to the collected dataset in Section 3.3, it is a heterogeneous network with five object

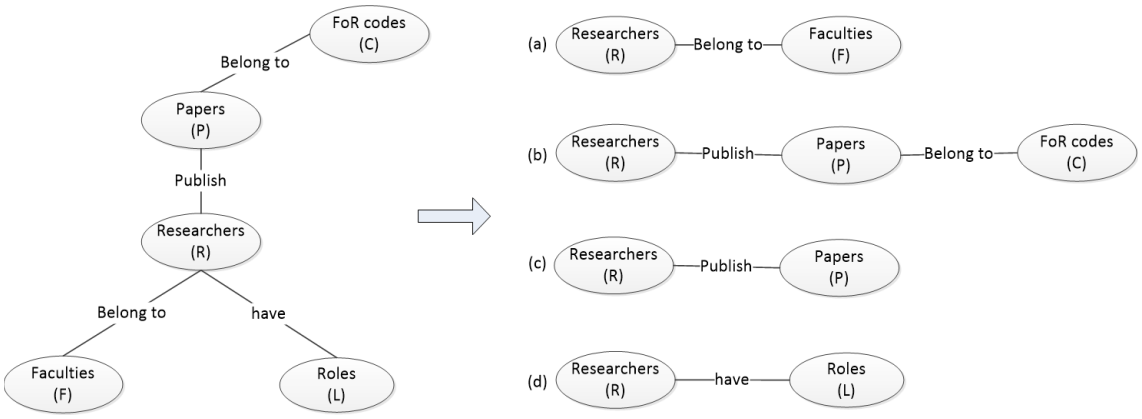



Figure 3.4: Semantic paths derived from the academic collaboration heterogeneous networks.

types (Researchers ($R$), Faculties ($F$), Roles ($L$), Papers ($P$) and FoR codes ($C$)) and the 4 types of relation. In this experiment, researchers ($R$) are the target objects and Figure 3.4 illustrates all semantic paths related to researchers ($R$).

Table 3.2: Similarity calculation of all semantic paths related to researchers.

| **Path** | **Similarity calculation** |
|---|---|
| $R-F-R$ | $M_{RF}M_{RF}^T$ |
| $R-P-C-P-R$ | $M_{RP}M_{PC}M_{PC}^TM_{RP}^T$ |
| $R-P-R$ | $M_{RP}M_{RP}^T$ |
| $R-L-R$ | $M_{RL}M_{RL}^T$ |

The similarity of researchers ($R$) in each path can be calculated through matrix computation. Given a path $R-P-C-P-R$ where $R$ is the set of target objects, the similarity of $R$ in the path is marked as $M_{RP}M_{PC}M_{PC}^TM_{RP}^T$ where $M_{RP}$ and $M_{PC}$ are the adjacency matrices between object types $R$ and $P$ and between object types $P$ and $C$ respectively. $M_{RP}^T$ is the transposed matrix of $M_{RP}$ and $M_{PC}^T$ is the transposed matrix of $M_{PC}$. The collective similarities between researchers are

measured by the similarities of those paths. The ways of calculating similarities of each path is presented in Table 3.2 and the collective similarities of researchers ($R$) are the combinations of these similarities.

### 3.4.2 Path assessment

If different weights are assigned to the paths, collective similarities of researchers ($R$) may be fairly different. That is why different types of objects and relations must be involved so as to reflect real situations in this domain.

Table 3.3: The paths and their corresponding scalars

| **Path** | **Scenario I** | **Scenario II** | **Scenario III** |
|---|---|---|---|
| $R-F-R$ | 0.97 | 0.01 | 0.05 |
| $R-P-C-P-R$ | 0.01 | 0.01 | 0.28 |
| $R-P-R$ | 0.01 | 0.97 | 0.62 |
| $R-L-R$ | 0.01 | 0.01 | 0.05 |

To clarify this point further, this chapter designs three scenarios (Table 3.3) and these scenarios have different scalar combinations. To be specific, Scenario I and Scenario II overly emphasizes paths $R-F-R$ and $R-P-R$ respectively but put very small weights (0.01) on the other paths. By contrast, the weight combination in Scenario III are based on *Pearson correlations* (Kantardzic 2011). The weights of each path are determined by this way (refer to Section 3.1.2): a random sample dataset is built with 200 researchers and they are labeled with their laboratories; then the similarities of each path are normalized and the weights of paths are represented by the correlation between each path and the laboratory labels.

In this chapter, researcher similarity networks are built based on each of these

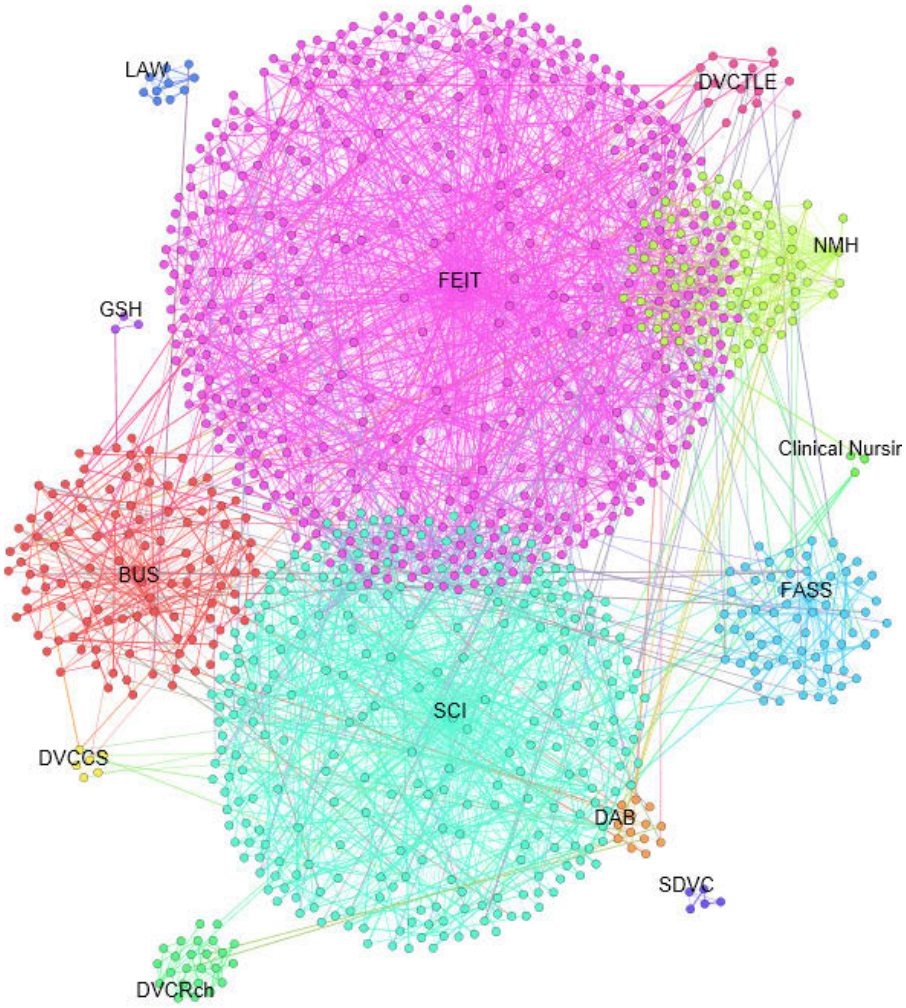



Figure 3.5: The similarity graph of researchers in Scenario I

scenarios.

In Scenario I, faculties ($F$) and the "belonging to" relation between researchers ($R$) and faculties ($F$) are emphasized to a large extent. The weight of this path is 0.97 while the remaining three paths are 0.01 respectively. The similarity graph of researchers ($R$) is illustrated in Figure 3.5 which shows that researchers ($R$) are grouped by the faculties.

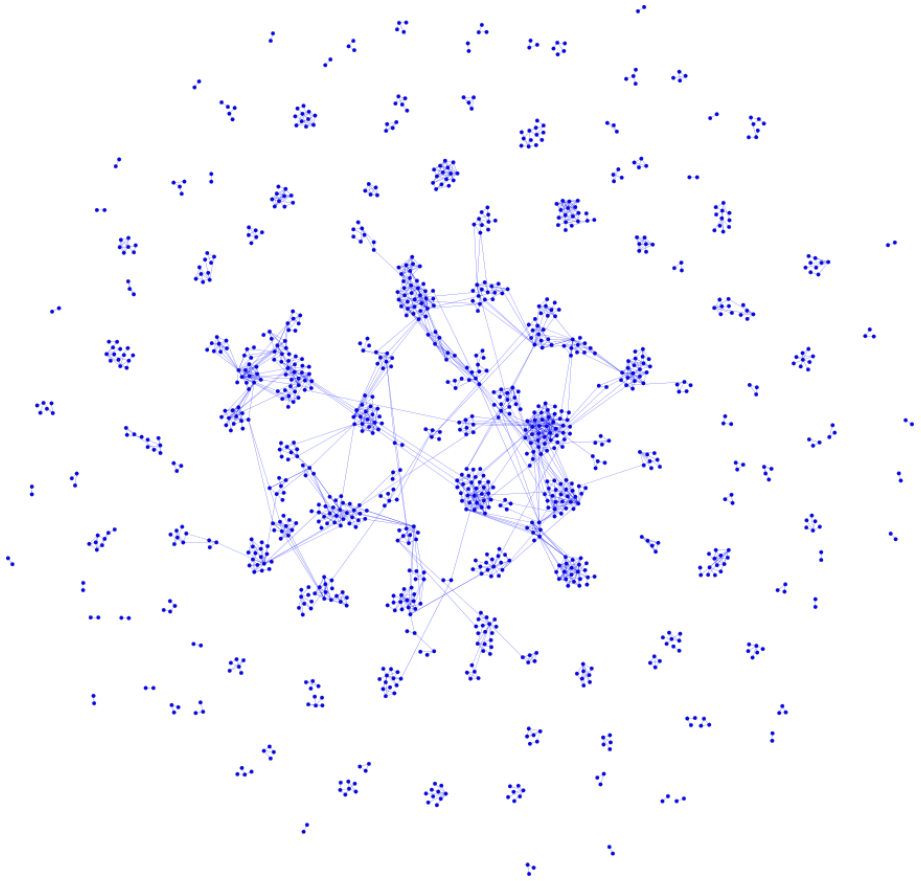


Figure 3.6: The similarity graph of researchers in Scenario II

Scenario II lays emphasis on co-authorship (0.97). This relationship connects two authors together if they coauthored papers and the more papers they worked on, the larger the weight of the connection. Co-authorship is also a widely used relation in terms of academic collaboration research. However the detected groups (Figure 3.6) are relatively small and meaningless because each author's number of papers is limited, normally ranging from three to five. Thus it is necessary to consider other types of objects and relations such as faculties ($F$) and field of research codes ($C$).

Similarly if the other two paths are overemphasized, it is also difficult to understand the real academic collaboration. Path $R-P-C-P-R$ groups researchers ($R$)

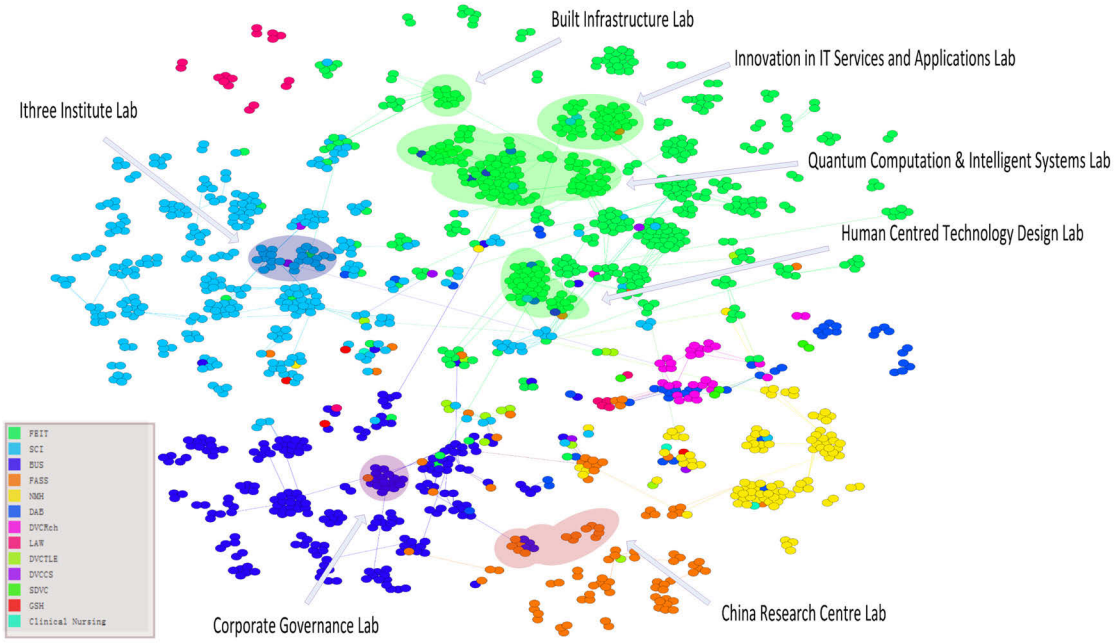



Figure 3.7: Some laboratories are labeled in the researcher similarity network of Scenario III.

with same or similar research fields together while Path $R - L - R$ categories researchers ($R$) by roles ($L$). Thus it is reasonable to consider all types of objects and relations simultaneously.

In Scenario III, path $R - P - R$, the co-authorship, is regarded to contribute to the academic collaboration the most and its weight is 0.62 followed by the path $R - P - C - P - R$. Field of research codes ($C$) which tend to link small research groups together and then to form relatively larger ones, must be involved. From this, it can be found that longer paths with three or more types of objects, like $R-P-C-P-R$, are interesting and using them properly is a good way of building a more realistic network. On the one hand, they are useful for finding some relatively large and meaningful communities. On the other hand, just because of this, they

cannot have a large weight; otherwise all objects are linked together. This conclusion is also supported by the theory in Sun & Han (2012).

The other two paths ($R - F - R$ and $R - L - R$) are of little importance and can be ignored in the further research. The situation of academic collaboration at UTS is better revealed by this scalar combination. Figure 3.7 is the researcher ($R$) similarity network where researchers are colored by their faculties. The edge weights between researchers are the collective similarities. It can be seen that the academic collaboration groups are relatively larger than those in Scenario II. Meanwhile these groups are meaningful. They are matched with the current laboratory setting of UTS and some of them are labeled.

From the analysis above, it can be seen that it is necessary to consider multi-typed relations and objects in investigating abstract concepts and the single relationships and objects are insufficient for revealing the real situation. On the other hand, relationships (represented by semantic paths) have varying levels of importance. Therefore, assessing them before clustering is of great necessity and the proposed method for evaluating paths based on correlations is effective.

### 3.4.3 Community detection and validation

In this section, both Multiple Semantic-path Clustering and spectral clustering are applied to detect communities on the heterogeneous UTS academic collaboration network. Spectral clustering works on the researcher similarity matrix built by random-walk. For Multiple Semantic-path Clustering, the researcher similarities are based on the collective similarity which is from Scenario III and communities are detected by the method proposed in Section 3.1.1. This chapter considers the UTS laboratory

setting as a partition where laboratories are clusters and researchers who work in these laboratories are objects in these clusters.

The clustering results generated by these methods are compared with the ground truth, the UTS laboratory setting by Vector-Based Comparison (V-B Comparision) and Normalized Mutual Information (NMI).

Table 3.4: Clustering validation

| **Comparative methods** | **V-B Comparison** | **NMI** |
|---|---|---|
| Multi-path clustering vs. the lab setting | 0.932 | 0.916 |
| Spectral clustering vs. the lab setting | 0.762 | 0.658 |

The comparative results are listed in Table 3.4 which shows that the clusters generated by multi-path clustering are more similar to the laboratory setting than spectral clustering as evidenced by the relatively high values in V-B Comparison and NMI. This result also confirms that random-walk is not suitable to apply on heterogeneous networks. The possible reasons for this are that 1) random-walk is advantaged in finding large communities but weak in finding small communities where vertices have fewer edges because the random moving decisions are made based on probability; and 2) in heterogeneous networks, the probabilities of an agent moving from one type of object to the other type objects should be different. Indeed, these probabilities are often hard to measure or estimate.

This suggests that taking multi-typed relationships and objects into consideration is necessary to analyze some abstract and hard-to-be-measured social phenomena.

This section also compares the quality of clusters of both methods by clustering quality indices: Coverage, Performance and Modularity.

Table 3.5: Clustering quality validation

| **Methods** | **Coverage** | **Performance** | **Modularity** |
|---|---|---|---|
| Multi-path clustering | 0.865 | 0.792 | 0.783 |
| Spectral clustering | 0.812 | 0.723 | 0.792 |

According to Table 3.5, both Multiple Semantic-path Clustering and spectral clustering perform well in community detection, achieving similar values of quality indices. This suggests that compared with spectral clustering, the proposed Multiple Semantic-path Clustering method is also an effective community detection method.

The reason why these methods get similar results in clustering quality indices is that these quality indices evaluate clustering based on different researcher similarity networks instead of the heterogeneous UTS academic collaboration network. The network used in spectral clustering is built by random-walk while that used in the proposed Multiple Semantic-path Clustering method is from the collective similarity. Currently, these clustering quality indices are only applicable in homogenous networks. Thus, it is unreasonable to estimate the quality of community detection by clustering quality indices alone and this is why this thesis involves a ground truth to verify the effectiveness of the proposed multiple semantic-path clustering.

## 3.5 Contribution and discussion

Heterogeneous networks are a model to represent abstract social phenomena for covering multi-typed objects and relations. Use of multi-typed objects and relationships results in the fact that detecting communities on heterogeneous networks must consider objects and relations of different types simultaneously and also needs to assess

the contributions of different relations to the abstract concepts accurately.

This chapter addresses **Contribution 1** of this thesis as listed in Section 1.5 by proposing a general model to identify communities on heterogeneous networks based on semantic paths and matrix factorization.

Contribution 1, a novel community detection method, named Multiple Semantic-path Clustering is proposed in Section 3.1. In the proposed method, relations are represented by semantic paths and the weights of semantic paths are assessed by correlations between each semantic path and a ground truth situation. Then a collective similarity is calculated based on the combination of semantic paths and the community structure can be identified by using matrix factorization theory.

The outcomes of the above stated method are compared with another robust state-of-the-art method, spectral clustering. The results of the proposed method are superior to that in terms of revealing the academic collaboration more accurately and the quality of clusters is also very high in three indices: coverage, performance and modularity.

The main issue with the results of the proposed Multiple Semantic-path Clustering is that this method is applied on the academic collaboration at UTS which is a relatively small dataset. Its effectiveness and efficiency should be tested in a large dataset further in the future. Another limitation is that this method just finds communities for the target object instead of all types, which means if users want to find communities for all types of objects, this method will need to be executed many times. Therefore, one research direction is to extend this method to find communities for all types of objects in the same time.

# Chapter 4

# Determine the number of clusters by leaders

As is explained in the literature review (Sec. 2.2), determining the correct number of clusters functions as an effective way of finding high-quality clusters. Although there are many ways of achieving this (Fraley & Raftery 2002, Chiang & Mirkin 2010, Maulik & Bandyopadhyay 2002, Lange et al. 2004), they are sensitive to the topological features of networks. This chapter aims to overcome this weakness by proposing a Leader Detection and Grouping Clustering (LDGC) method. The proposed method is designed for both homogenous and heterogeneous networks to determine the number of clusters beforehand based on network topological features. This can support **Contribution 2** of this thesis which is to propose a method to determine the number of clusters in both homogeneous and heterogeneous networks.

In social networks, communities are generally constituted by leaders and community members simultaneously. Leaders are often regarded as more important than others in terms of network connectivity because they are the core of communities and the other objects are connected to each other via them. This phenomenon is also seen in social science (Parkin 2013) in that a networked community is always formed by

one or several leaders and their followers. These leaders often have many connections with community members while community members are often connected via the leaders. This gives rise to a close correlation between the number of community leaders and the number of clusters. As long as leaders and their similarities are identified, it is possible to know the number of clusters.

The proposed Leader Detection and Grouping Clustering method can distinguish leaders from all objects based on their different topological features. Leaders not only have more connections in clusters but also have a relationship to individuals in other clusters. Degree-centrality and betweenness-centrality can reflect this characteristic. Meanwhile, considering the situation that sometimes there are two or more leaders in one potential group, this thesis proposes an algorithm to combine leaders when they are close enough. Leaders who are similar should be grouped to form leader groups. The number of leader groups is the number of communities. The proposed Leader Detection and Grouping Clustering method can also detect communities in both heterogeneous and homogeneous networks. After determining leader groups, the remaining vertices are allocated into those groups which they are close to.

Finally, the proposed Leader Detection and Grouping Clustering method is validated on the UTS heterogeneous academic collaboration network for determining the number of clusters and detecting communities. To illustrate its effectiveness, this chapter involves spectral clustering in a comparative experiment.

The rest of this chapter is organized as follows: Section 4.1 describes the proposed Leader Detection and Grouping Clustering method followed by the experimental dataset in Section 4.3 and results in Section 4.4. The contribution and discussion of the proposed method is given in Section 4.5.

This chapter with **Contribution 2** is an extended description of my publications (Meng & Kennedy 2012*a*, 2013*b*).

## 4.1 Leader detection and grouping clustering

The section describes the principles, algorithms and implementation of the proposed Leader Detection and Grouping Clustering method. It contains three phases: leader identification, leader group formation and community detection.

### 4.1.1 Leader identification

This phase aims to identify leaders in networks based on their topological features by centrality calculations and support vector machine (SVM) classification.

There are many potential centrality measures, but most of them may not be suitable. Closeness-centrality (Okamoto et al. 2008) based on distance measures is defined so that the lower the sum of distances of a vertex to the others is, the more central this vertex is. This centrality measure is generally used for finding the center of a network, but leaders may be spread loosely across the entire network. Eigenvector-centrality and Katz-centrality (Grindrod et al. 2011) are measures of vertex influence in a network and the values of these centralities are largely determined by the number of vertex neighbors. As a result, the influence of vertices varies greatly when they are from different communities. The influence of leaders in large communities often far exceeds those of leaders from small communities.

However, degree centrality and betweenness centrality can show the importance of objects in clusters while betweenness centrality can reflect the importance of them

out of clusters. For example, in a company, managers can be naturally considered as leaders. They not only need to communicate with his or her team members but also need to talk to other managers. For team members, they generally interact with their managers or other members in the same team instead of communicating with other managers. Degree-centrality and betweenness-centrality can capture this feature accurately. As a result, they are empirically considered as major indices to reflect the topological features of networked objects in both local and global levels. The following are the definitions of these centralities which are reviewed in Section 2.3.

1. **Degree centrality** is the simplest centrality which counts the number of links from one node, say $v$ to the others.

$$C_D(v) = degree(v) \tag{4.1.1}$$

2. **Betweenness centrality** describes that the more central one vertex is, the more edges and vertices are joined by it. It is the ratio between the number of short paths from starting point $s$ to ending point $e$ passing through $v$ to not passing through $v$.

$$C_B(v) = \sum \frac{p_{se}(v)}{p_{se}} \tag{4.1.2}$$

The calculation of betweenness-centrality in this chapter refers to the approach in Brandes (2001). It is a well-known algorithm requiring $O(|V||E|)$ time for unweighted networks and $O(|V||E| + |V|^2 \log |V|)$ time for weighted graphs, where $|V|$ is the number of vertices and $|E|$ is the number of edges in the network.

Values of degree-centrality and betweenness-centrality often have different ranges. For classification and visualization, the values of these two centralities are normalized into the same range by two different ways. For degree-centrality, values are linearly scaled into [0, 1] because the ranges of degree-centrality values is narrow. For betweenness-centrality, values of this centrality have a wide range and the distribution of these values are not even with a long tail. This chapter applies log function to scale these values into a small range and then linearly normalized these processed values into [0, 1].

Table 4.1: A sample of new built dataset

| **VertexID** | **Degree centrality** | **Betweenness-centrality** |
|---|---|---|
| 10001 | 0.0417 | 0 |
| 10002 | 0.0833 | 0 |
| 10003 | 0.1251 | 0.0084 |

Leaders are identified through their special topological features which are revealed by the combination of degree-centrality and betweenness-centrality. Leader identification can be viewed as a binary classification problem (refer to Section 2.3.3) because there are just two classes: leaders and community members. In this chapter, this binary classification problem is addressed by Support Vector Machine (Chang & Lin 2011) which is a widely applied binary classification and the kernel function is chosen as Gaussian kernel function which can detect clusters with an irregular boundary.

$$K_G(v_i, v_j) = \exp\left(-\frac{||v_i - v_j||^2}{\sigma^2}\right) \tag{4.1.3}$$

After the degree-centrality and betweenness-centrality calculations, this chapter builds a new dataset which contains vertexID, degree-centrality and betweenness-centrality. The dataset is randomly divided into three sub datasets: a training dataset

(300 researchers), a cross validation dataset (300 researchers) and a test dataset (835 researchers). In the training dataset, vertices are labeled as leaders or not. The reason for setting up relatively small training and a cross validation datasets is to evaluate the effectiveness of the proposed method in detecting leaders. The cross validation dataset is for determining the parameters of the Gaussian kernel function based on the error rate.

### 4.1.2 Leader group formation

It is noticeable that the number of leaders is often not the number of clusters unless the aim is to find small, cohesive cliques. In most cases, the number of leaders outnumbers the number of clusters because one community is very likely to have more than one leader, especially in large communities. For acquiring the "correct" number of clusters, leaders with a close relationship should be grouped and then the number of leader groups is the number of clusters. As is shown in the example in Figure 4.1, there are three communities: group A, group B and group C. Based on the values of degree-centrality and betweenness centrality, leader 1 and leader 2 in group A have the same importance. Consequently, the number of leaders is four because leader 1 and leader 2 are very close and they have 6 common neighbors. So after leaders are found, the next step is to look into their similarities. In this phase, similar leaders are allocated to the same leader group; otherwise they are put into different leader groups.

Another usage of leader groups is to control the size of clusters. For example, in order to achieve balanced clusters which means clusters having similar numbers of objects, large leader groups can be separated into small ones while small groups

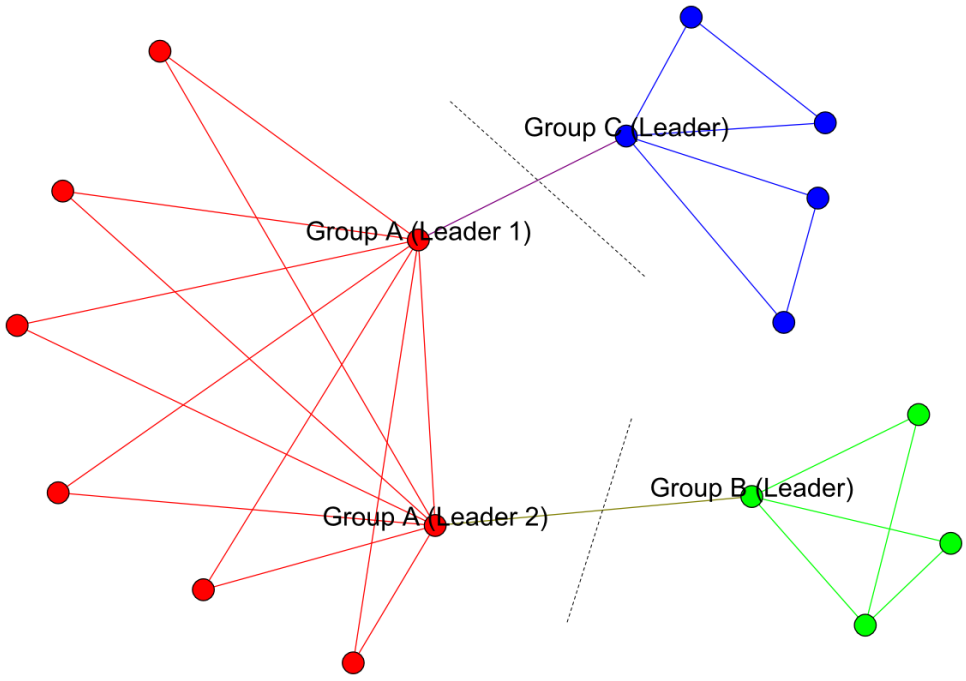



Figure 4.1: An example of why leaders should be grouped

can be integrated into a larger one. This allows LDGC to satisfy more complex user requirements on the size of clusters.

Leader groups are built based on their similarities. This chapter proposes a heterogeneous network oriented similarity measure which is designed to make full use of topological features of heterogeneous networks. The similarities among objects are acquired based on the number and the length of semantic paths, and the number of paths in each semantic path. Given vertices $x$ and $y$ in a heterogeneous network $G$, their semantic paths are represented by set $P_{xy}$. The similarity between them is defined as

$$Sim(x, y) = \frac{1}{|P_{xy}|} \sum_{i \in P_{xy}} \frac{1}{len(i)} \frac{2N_{xy}(i)}{N_x(i) + N_y(i)} \tag{4.1.4}$$

where $|P_{xy}|$ is the number of elements in set $P_{xy}$. For a semantic path $i$, $N_{xy}(i)$ is the number of paths in this type between $x$ and $y$. $N_x(i)$ and $N_y(i)$ are the number of paths

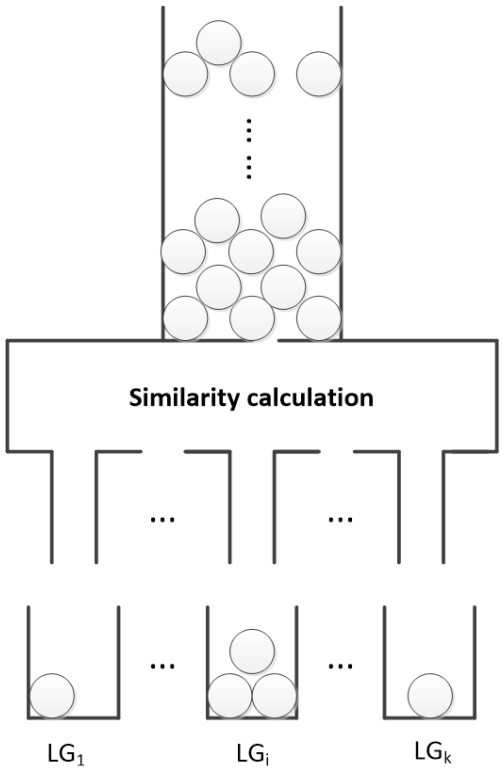



Figure 4.2: The working process of community detection by Leader Detection and Grouping Clustering. Circles are vertices and $LG_i$ refers to leader groups. The similarity between vertices and leader groups are calculated and vertices are allocated to those leader groups with highest similarity.

in semantic path $i$. The length of semantic path $i$ is marked as $len(i)$. For example, the length of semantic path $A - B - C - B - A$ is four. In heterogeneous networks, length is an important topological features of a semantic path. Long semantic paths mean far distances between objects and should be assigned small weights (Sun & Han 2012). This is the reason why length is taken into account.

### 4.1.3 Community detection

After building leader groups, the proposed Leader Detection and Grouping Clustering method can detect communities in heterogeneous networks based on these groups. Given a heterogeneous network $G = (V, E)$, there are $k$ leader groups $(LG_1, \ldots, LG_k)$. The remaining vertices are allocated to leader groups based on their similarities with leader groups. Figure 4.2 illustrates the working process of the proposed Leader Detection and Grouping Clustering method in community detection. It can be seen that similarities between the rest vertices and leader groups are calculated and then these vertices are allocated to these most similar ones. The ways of measuring similarities between vertices and leader groups are many. In this chapter, the similarity measure is based on shortest-path. Vertex $v$ $(v \in V)$ is allocated to leader group $LG_i$, if the average shortest-path distance of $v$ to the leaders in $LG_i$ is shorter than to the leaders in the other leader groups.

**Algorithm 4.1** Algorithm for community detection by Leader Detection and Grouping Clustering

**Initialization:**

Set $LG_1, \ldots, LG_k$ as array;
Set $CLS_1, \ldots, CLS_k$ as array;

**Iteration:**

```
for v = 1; v <= |V|; v++ do
    t = 1;
    for i = 1; i <= k; i++ do
        if AvgShortPath(v, LG_i) < AvgShortPath(v, LG_t) then
            t = i;
        end if
    end for
    put(v, CLS_t);
end for
```

Algorithm 4.1 describes the method for community detection by the proposed

Leader Detection and Grouping Clustering method. $LG_1, \ldots, LG_k$ are leader groups which are declared as arrays, containing identified leaders. Arrays $CLS_1, \ldots, CLS_k$ represent clusters and $k$ is the number of leader groups. Function $AvgShortPath(v, LG_i)$ is to calculate the average shortest-path between vertex $v$ and leader group $LG_i$. Function $put(v, LG_t)$ puts vertex $v$ into leader group $LG_t$. $|V|$ is the number of vertices. The algorithm works in this way: for each vertex $v$, it is initially allocated to leader group $LG_1$ by $t = 1$. Then the algorithm calculates the average shortest-path between the vertex and each leader group and keeps updated $t$ until to find the leader group with shortest average shortest-path. Finally the vertex is allocated to the leader group with the minimum average shortest-path. The running time of this algorithm is related to $|V|$ and $|k|$ and then its complexity is $O(|V||k|)$.

## 4.2 Clustering validation

In this chapter the proposed Leader Detection and Grouping Clustering method is validated on the UTS heterogeneous academic collaboration network in two ways.

The first one is to evaluate the effectiveness of LDGC in determining the number of clusters. To verify this, another two widely used methods of determining the number of clusters are involved: cumulative percentage variance (Abdi & Williams 2010) and scree graph (Jolliffe 2005) which are reviewed in Section 2.3. This chapter applies these three methods to determine the number of clusters and their results are the input of spectral clustering (refer to Section 2.2.3) which is a-state-of-art method of finding communities in networks. For this method, the number of clusters is a mandatory input parameter and it highly affects the clustering quality.

The second validation is to evaluate the effectiveness of LDGC in community detection. This chapter compares the clustering results generated by the proposed Leader Detection and Grouping Clustering method and spectral clustering. These two methods have the same input and their clustering results are evaluated by a set of clustering validation indices, including Coverage, Performance (Scott & Carrington 2011) and Modularity (Newman 2006) . The detailed descriptions about these indices are included in the literature review (Section 2.2.6).

## 4.3 Experimental dataset

The heterogeneous network used for analysis, visualization and explaining the proposed method of clustering is based on the UTS academic collaboration phenomenon. This heterogeneous network has four types of objects: researchers ($R$), publications ($P$) and research labs ($B$) and the schema is illustrated in Figure 4.3. There are two semantic paths regarding to researchers ($R$): $R-P-R$ and $R-B-R$. Path $R-P-R$ stands for co-authorships. If two researchers work in the same lab, their co-working relationships are represented by $R-B-R$. The detailed information about the dataset is shown in Table 4.2.

Table 4.2: The number of records in files from 2009 to 2011

| **Name** | **Number of records** |
|---|---|
| Researcher ($R$) | 5621 |
| Publication ($P$) | 3737 |
| Labs ($B$) | 54 |
| Co-authorships ($R-P$) | 12105 |
| Co-working relationships ($R-B$) | 5621 |

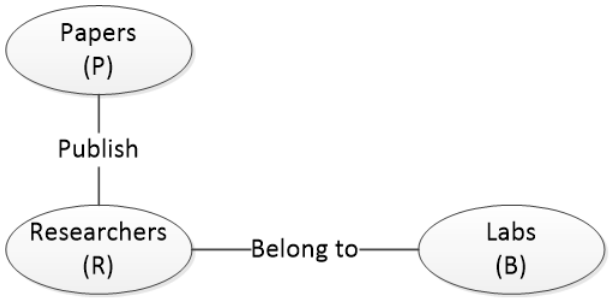



Figure 4.3: The schema of the experimental heterogeneous network.

## 4.4 Experiment

This section validates the effectiveness of the proposed Leader Detection and Grouping Clustering method on the UTS heterogeneous academic collaboration network in determining the number of clusters and community detection respectively. The network contains three types of vertices: Researchers ($R$), Papers ($P$) and Labs ($L$) and two types of edges: publishing and belonging to. The weight of edges is 1.

### 4.4.1 Leader identification

The experimental heterogeneous network is the UTS heterogeneous academic collaboration network (Figure 4.3). The degree and betweenness centrality of researchers in the UTS heterogeneous academic collaboration network is calculated by referring to the Equations (4.1.4) and (4.1.2) respectively. In the experiment, degree and betweenness centrality have different value ranges. Degree centrality ranges from 1 to 24 and betweenness centrality from 0 to 95127.57. For adjusting these values into the same range, values of both centralities are rescaled into [0, 1] (refer to Section 4.1.1).

After normalization, the distributions of degree and betweenness centrality of

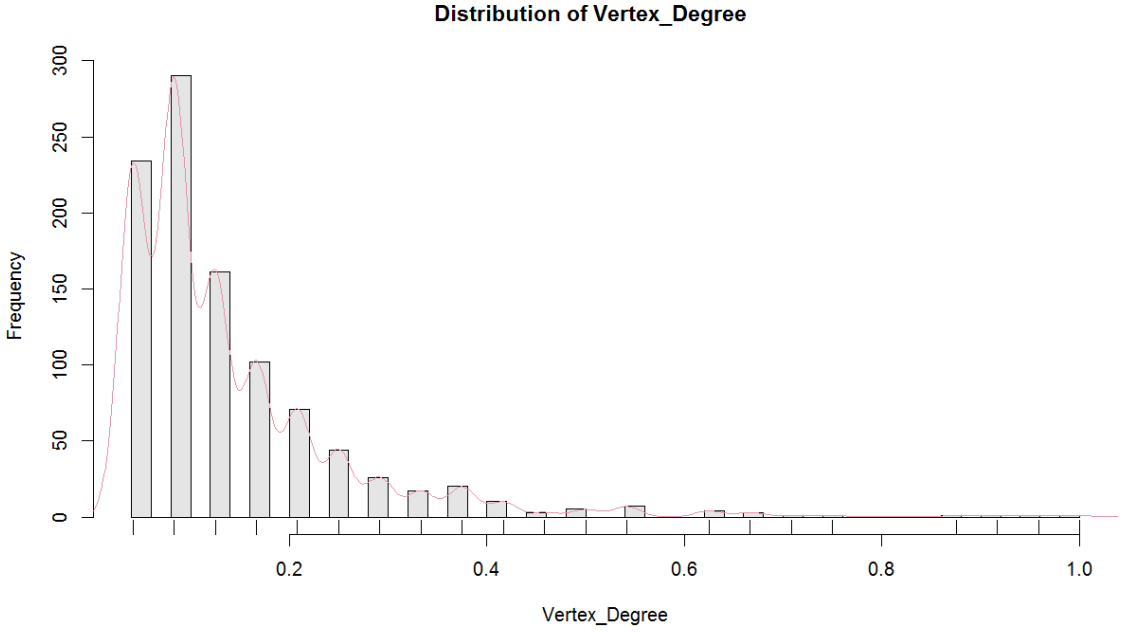



Figure 4.4: The distribution of researcher degree centrality

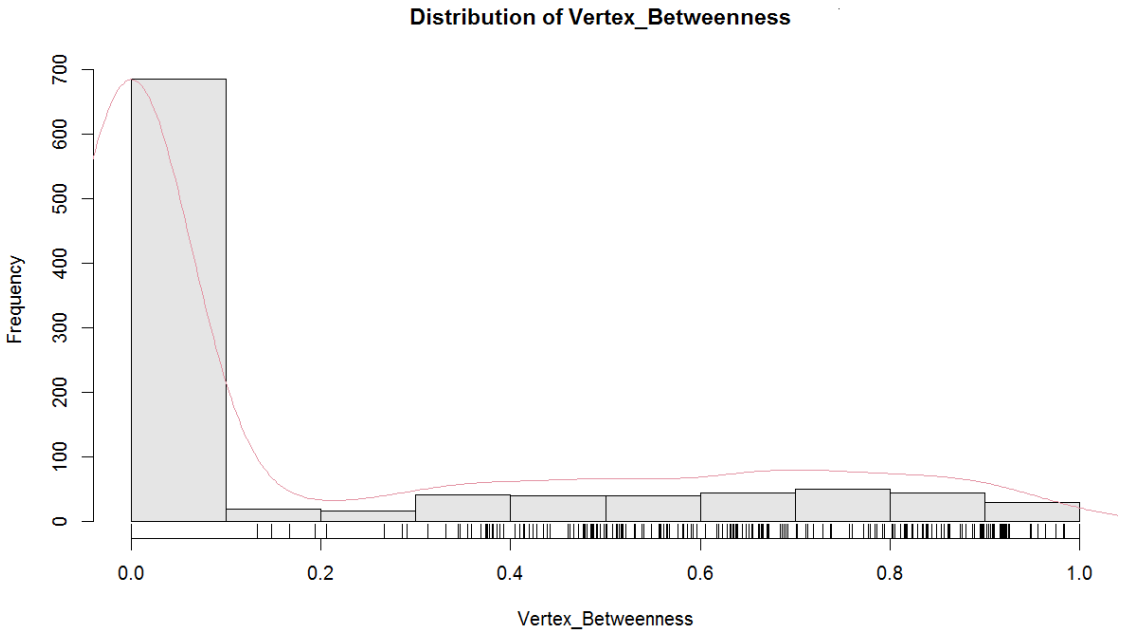



Figure 4.5: The distribution of researcher betweenness centrality

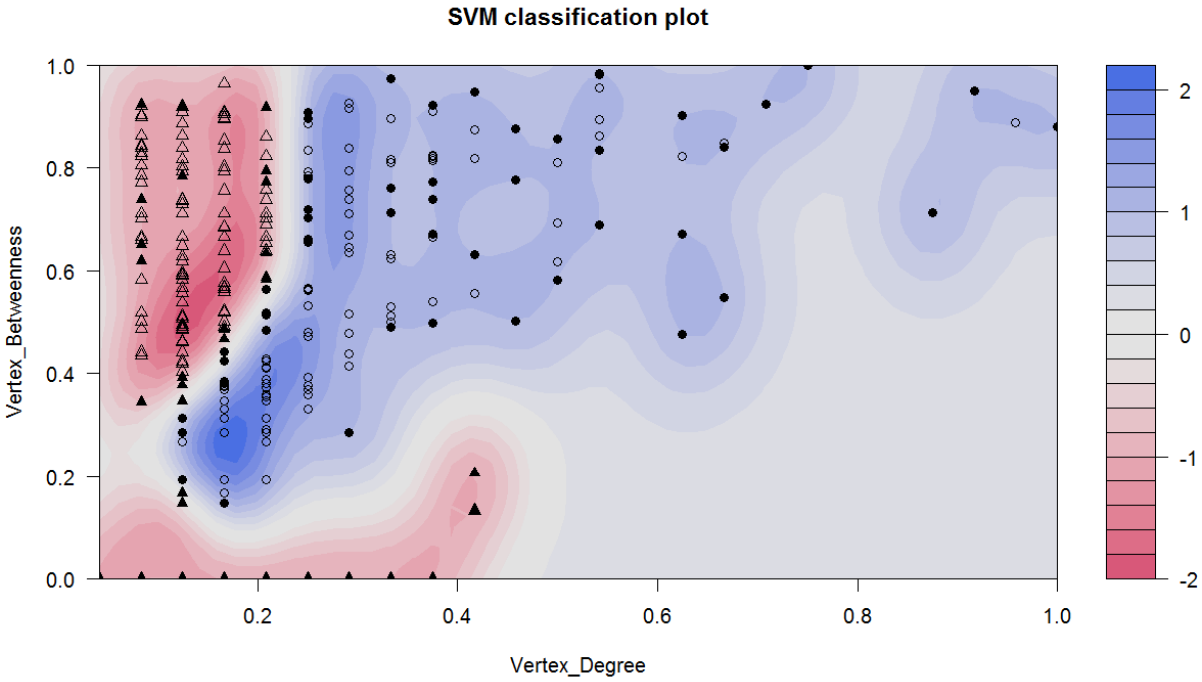



Figure 4.6: The result of leader detection by SVM in R. Triangles and circles are data points from two clusters. Circles stand for leaders and triangles are community members. Solid triangles and circles are support vectors of these two clusters respectively.

researchers ($R$) are shown in Figure 4.4 and Figure 4.5 respectively. It can be seen from these two figures that these two distributions display a long tail. This means these two distributions are uneven: most researchers ($R$) have very small values of degree and betweenness centrality and the gap between small values and large values are very huge.

Leader detection in this chapter is a binary classification problem which is addressed by Support Vector Machine (SVM). This experiment builds a new dataset which contains vertexID, degree-centrality and betweenness-centrality. The dataset is randomly divided into three sub datasets: a training dataset (300 researchers), a

cross validation dataset (300 researchers) and a test dataset (835 researchers). In the training dataset, laboratory directors are considered as leaders and they are labeled as 1 while the other researchers ($R$) are labeled as 0. The scale parameter $\sigma$ of Gaussian kernel function (Equation (4.1.3)) is set as 0.45 based on the cross validation dataset through error rate. After classification with a training error rate as 0.330865 and 94 support vectors, leaders with high similarities are combined into leader groups. This experiment calculated the similarities between leaders referring to Equation (4.1.4). Leaders are connected to their most similar neighbors to build a similarity network if they are connected in both semantic paths, $R - B - R$ and $R - P - R$. The unconnected sub networks are leader groups. After leader combination, there are 206 leader groups and this is the number of clusters of this heterogeneous network.

### 4.4.2 Community detection

This section verifies the effectiveness of the proposed leader based community detection method in determining the number of clusters and in community detection.

In determining the number of clusters, the verifying process is based on the idea that an accurate number of clusters can give rise to a high quality clustering. In this chapter, the number of clusters of the heterogeneous networks is determined by three approaches: cumulative percentage variance, scree graph and the proposed Leader Detection and Grouping Clustering method. For cumulative percentage variance, the threshold is chosen as 98% empirically. For scree graph the biggest slop is chosen as the separating pointing of selected and unselected eigenvalues. Section 4.4.1 has explained the way of determining the number of clusters by LDGC. The other two methods determine the number of clusters through the structure of the researcher

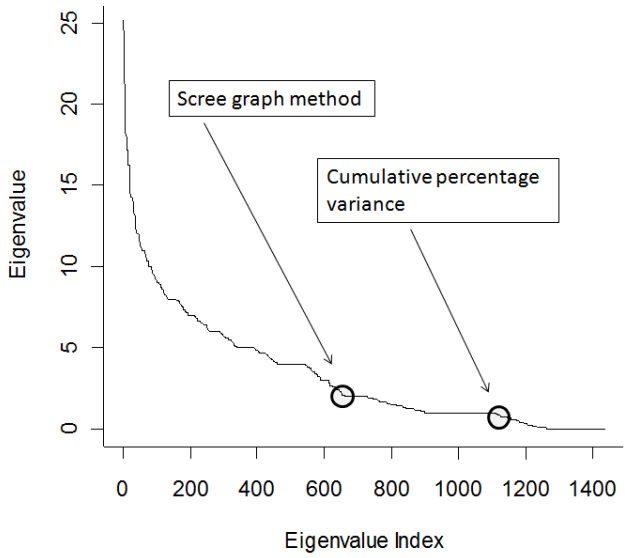



Figure 4.7: The eigenvalues of the random-walk Laplacian matrix.

similarity matrix which is generated by random walk. For The numbers of clusters determined by these three methods are 206, 298 and 812 respectively. Spectral clustering is applied with these three numbers of clusters and the clustering results are shown in Table 4.3.

Table 4.3: Clustering results by spectral clustering

| **Methods** | **Cumulative percentage variance** | **Scree graph** | **LDGC** |
|---|---|---|---|
| **Clusters** | 298 | 812 | 206 |
| **Modularity** | 0.803 | 0.771 | 0.884 |
| **Coverage** | 0.822 | 0.803 | 0.876 |
| **Performance** | 0.784 | 0.782 | 0.889 |

It can be seen that the number of clusters determined by LDGC results in the

best clustering quality and it achieve highest values in Modularity (0.884), Coverage (0.876) and Performance (0.889) followed by Cumulative percentage variance (Modularity (0.803), Coverage (0.822) and Performance (0.784)) and Scree graph (Modularity (0.771), Coverage (0.803) and Performance (0.782)).

Table 4.4: Clustering results by spectral clustering and LDGC

| **Methods** | **Spectral clustering** | **LDGC** |
|---|---|---|
| **Clusters** | 206 | 206 |
| **Modularity** | 0.884 | 0.912 |
| **Coverage** | 0.876 | 0.908 |
| **Performance** | 0.889 | 0.932 |

In validating the effectiveness of Leader Detection and Grouping Clustering method in community detection, both spectral clustering and LDGC have the same number of clusters as an input which is determined by the proposed method in this chapter. The clustering results generated by these two methods are compared by three community detection indices: Modularity, Coverage and Performance in Table 4.4. It can seen from this table that the proposed LDGC method outperform spectral clustering because it achieves higher values in these three indices than spectral clustering.

## 4.5 Contribution and discussion

The literature review of community detection shows that for most clustering methods, accurate cluster numbers are of great importance to achieve a high-quality clustering. However, determining the number of clusters before clustering is a challenge for both homogeneous and heterogeneous network analysis.

This chapter addresses **Contribution 2** of this thesis as listed in Section 1.5 by

proposing a Leader Detection and Grouping Clustering to address this problem and it is applicable for both homogeneous and heterogeneous networks. This method is based on the social theory that a close connected community is constituted by one or several leaders and their followers to investigate the different topological features of group leaders and members in networks.

The proposed Leader Detection and Grouping Clustering method can distinguish leaders from all objects based on their different topological features. Leaders not only have more connections in clusters but also have a relationship to individuals in other clusters. Degree-centrality and betweenness-centrality can reflect this characteristic. Meanwhile, considering the situation that sometimes there are two or more leaders in one potential group, this thesis proposes an algorithm to combine leaders when they are close enough. Leaders who are similar should be grouped to form leader groups. The number of leader groups is the number of communities. The proposed Leader Detection and Grouping Clustering method can also detect communities in both heterogeneous and homogeneous networks. After determining leader groups, the remaining vertices are allocated into those groups which they are close to.

The proposed LDGC method is verified in two aspects: determining the number of clusters and detecting communities. In the former aspect, the number of clusters determined by LDGC is more accurate than cumulative percentage variance and scree graph because spectral clustering with the number of clusters from LDGC can achieve better clustering. In the latter aspect, LDGC is more effective than spectral clustering in community detection. The clustering result of LDGC is better than spectral clustering with accurate number of clusters determined by LDGC in terms of Modularity, Coverage and Performance.

For the proposed Leader Detection and Grouping Clustering method, the strategy of identifying leaders can be improved. The experiment suggests that the error rate of identifying leaders is high because the proposed method just applies degree-centrality and betweenness-centrality to distinguish leaders and community members. It could be possible that these two centralities may be insufficient to achieve this and other topological features should be involved. Another limitation of this chapter is that the laboratory directors are considered as leaders of communities and the SVM classifier is trained based on this. In fact, some managers in companies or universities are not leaders of communities. For example, department managers may have a close connection with project managers rather than all the staffs that they supervise. Training the classifier by managers may give rise to biased results.

# Chapter 5

# Network evolution-based link prediction

Link prediction is a fundamental question of heterogeneous network analysis. This chapter aims to address it by proposing a novel link prediction method named Network Evolution-based Link Prediction (NELP) which is designed for heterogeneous networks. The major innovation of this method is to model vertex activeness by their evolving patterns shown in network evolution so as to improve link prediction accuracy.

Predicting whether two vertices in networks will develop a new connection or maintain their current connection is mainly based on their "distance". This means the closer two vertices are, the higher possibility they will be connected in the future. However, there are some exceptions that some vertices with a far distance may develop a connection among them while some vertices with a close distance may not be connected in the future. These exceptions are the main reason for failing to achieve high link prediction accuracy.

Through observations and social theory (Carrington et al. 2005), different objects,

particularly humans, displayed different tendency towards developing their connections. Active ones tend to have more new connections or strengthen their current connections in a short timeslot while stable ones prefer to maintain their existing connections. Another interesting phenomenon is that objects have different capacities of connections. For examples, extroverted people generally have more friends than the introvert. All these features can be acknowledged and extracted from network evolutionary process which means that treating objects individually and capturing their own evolutionary tendency are necessary to improve the accuracy of link prediction. This is the reason why this chapter considers network evolution instead of a single network snapshot for making link prediction.

Traditional link prediction methods are based on similarity measures. The principle of these methods is that they use similarity measures to calculate the similarities between vertices and predict that those links of $r$ leading highest similarities will appear in the future. Indeed, it is hard to determine the value of $r$. The proposed can overcome this by involving matrix decomposition theory to exclude noisy data.

The chapter is organized as follows: Section 5.1 describes the proposed Network Evolution-based Link Prediction method followed by the experimental dataset and results in Sections 5.2 and 5.3. Section 5.4 presents the contribution and discussion of this chapter.

This chapter, describing **Contribution 3**, is an extended description of my publication (Meng & Kennedy n.d.).

## 5.1 Methodology

This section describes how to model vertex activeness followed by the descriptions about the proposed Network Evolution-based Link Prediction method and evaluation.

### 5.1.1 Modeling vertex activeness

This section first describes how to model network evolution followed by determining vertex activeness. Most social networks keep changing due to their dynamic nature. But in a particular time point, these networks are static. From this perspective, it is reasonable to model the evolutionary process of a dynamic network by using a set of static networks captured at different time points to represent the network evolutionary process. The closer the time points are, the more accurate the network evolution can be modeled.

**Definition 5.1**. Given a heterogeneous network $G = (V, E)$, there are $n$ types of object ($V = \{V_1, \ldots, V_n\}$) and $m$ types of edges ($E = \{E_1, \ldots, E_m\}$). The process of the network evolution can be represented by a series of snapshots of this network, $\Omega = (G_{t_1}, \ldots, G_{t_n})$. These snapshots are captured at different time points, $t_1, \ldots, t_n$. Among them, $G_{t_i} = (V_{t_i}, E_{t_i})$ represents the network at $t_i$. Then the link prediction problem is to predict $G_{t_{n+1}}$ based on these networks $(G_{t_1}, \ldots, G_{t_n})$.

This chapter determines vertex activeness based on their evolving patterns which measures how fast vertices change their connections. Two speed indices are proposed in this chapter to capture vertex evolving patterns on heterogeneous networks and they are *Neighborhood Changing Velocity* (NCVelocity) and *Neighborhood Changing Accelerated Velocity* (NCAVelocity). *Neighborhood Changing Velocity* (NCVelocity) refers to a vertex speed of changing neighbors and the NCVelocity of vertex $v$ ($v \in V$)

at $t_i$ is defined as

$$NCVelocity(v, t_i) = \frac{1}{t_i - t_{i-1}} \cdot \frac{|neighbor(v, t_i) \cap neighbor(v, t_{i-1})|}{|neighbor(v, t_i) \cup neighbor(v, t_{i-1})|} \tag{5.1.1}$$

where $neighbor(v, t_i)$ represents the neighbor set of vertex $v$ at $t_i$ and $|neighbor(v, t_i) \cap neighor(v, t_{i-1})|$ is the number of common neighbors of vertex $v$ at times $t_i$ and $t_{i-1}$. *Neighborhood Changing Accelerated Velocity* (NCAVelocity), the accelerated speed of NCVelocity, represents the changes of NCVelocity over time and NCAVelocity of vertex $v$ at $t_i$ is defined as

$$NCAVelocity(v, t_i) = \frac{NCVelocity(v, t_i) - NCVelocity(v, t_{i-1})}{t_i - t_{i-1}} \tag{5.1.2}$$

With these two indices, it is possible to investigate into how vertices evolve over time. These evolving patterns are about vertex preference of developing new connections or maintaining their existing connections. Through observations, the changing patterns can be categorized into four groups: guest vertices, active vertices, stable vertices and regular vertices and in terms of behaviors and activeness. Followings are the detailed descriptions about these four groups.

**Guest vertices**

Guest vertices means those vertices that fail to stay in networks permanently. They may stay in networks for a short time and then disappear or they jump in and out networks from time to time. In link prediction, these vertices can be considered as noise data as their behaviors are hard to be predicted. In this chapter, those vertices who fail to appear in one or more collected snapshots of networks are considered as guest vertices.

**Active vertices**

Vertices in this group are very vigorous and they are the main contributors to make networks keep changing. During network evolution, their connections are growing fast and they also can maintain a large number of connections. Meanwhile a connection of two isolated groups may often start from them. This chapter regards these vertices that have positive NCAVelocity at every time point as active vertices. This means these vertices not only have more connections with others but also their speeds of having new connections are increasing.

**Stable vertices**

Stable vertices tend to maintain their existing relationships ($NCVelocity(v, t_i) = 1, i \in (1, \ldots, n)$) as time goes. They may be viewed as inactive vertices because they contribute little to the network evolution.

**Regular vertices**

The remaining vertices are defined as regular vertices. These vertices with moderate speeds of changing connections are allocated in this category. In fact, most vertices are in this category.

Due to the fact that vertices have different evolving preferences, it is necessary to classify them before predicting links. In the task of link prediction, adopting different strategies to handle vertices in different groups can not only increase the accuracy of link prediction but can also improve the efficiency. For two active vertices, even though they are far from each other, the possibility of them to develop a new link

is high. For two stable vertices, even if they are near to each other, they are very unlikely to develop a connection. The evolving patterns of guest vertices are often unpredictable. This thesis treats them as noisy data and excludes them from link prediction.

### 5.1.2 Network Evolution-based link prediction

Most link prediction methods in networks are based on distances which are calculated by similarity measures. Generally, if two vertices are close in networks, they have a higher possibility of developing a connection between them in the future. If they are far apart, the possibility of developing a connection between them is low. However, when the process of network evolution is considered, it can be seen that vertices have different velocities of changing their connections. Some of them are fast while some of them are low. The proposed Network Evolution-based Link Prediction method is designed to consider vertex evolving patterns to improve link prediction accuracy and is compatible with different heterogeneous network similarity measures.

The proposed Network Evolution-based Link Prediction method is designed to work on a similarity matrix of heterogeneous networks which can be built by different heterogeneous similarity measures. This means the proposed link prediction method can improve accuracies of link prediction methods based on different similarity measures. Consider a similarity matrix $S$, $s_{ij}$ is the similarity between vertex $i$ and $j$. The proposed Network Evolution-based Link Prediction method integrates similarity matrix $S$ with vertex involving patterns and redefines it as

$$P = ZSZ^T \tag{5.1.3}$$

where $Z = (z_1, \ldots, z_{|V|})^T$ is a vector containing vertex Neighborhood Changing Velocity where $|V|$ is the number of vertices, $z_i = NCVelocity(i, t_n)$ and $1 \leq i \leq |V|$. Then the link prediction matrix $P$ can be written as $P = UDV^T$ by the singular value decomposition (SVD). Matrices $U$ and $V$ are orthogonal matrices and $D$ is a diagonal matrix of singular values $\sigma_1 > \sigma_2 > \ldots > \sigma_R > 0$. According to truncated matrix theory,

$$P \approx U_k D_k V_k^T \tag{5.1.4}$$

where $U_k$ and $V_k$ comprise the first $k$ columns of $U$ and $V$, and $D$ is the $k \times k$ principal submatrix of $D$. As a result, a matrix of predicted links can be written as $P' = U_k D_k V_k^T$ which contains the main features of matrix $P$. For link prediction, if $p_{uv} > 0$ where $p_{uv}$ is an element in link prediction matrix $P$, there will be a connection between vertices $u$ and $v$; otherwise, vertices $u$ and $v$ will not be connected in the future.

There are two types of link prediction: new-link prediction and all-link prediction. The problem of new-link prediction aims to find those links that do not exist in current networks but will appear in the future. For example, in a friendship network, predicting new links means whether two persons will become friends in the future. For link prediction matrix $P$, if $p_{uv} > 0$ and vertices $u$ and $v$ are not connected in the current network, it is predicted to develop a new link between them in the future. The problem of all link prediction aims not only to find new links but also to predict whether two vertices will maintain their existing links. For example, in a co-authorship network, all link prediction aims to not only find links that do not exist in the current network and will appear in the future, but also predicts whether current links will be maintained in the future. For link prediction matrix $P$, if $p_{uv} > 0$,

it is predicted to have a link between them in the future. The propose Network Evolution-based Link Prediction method in this chapter can work on both of them. According to the vertex evolving analysis in the previous section, it can be seen that both active and regular vertices tend to have new connections. Stable ones keep their existing connections and guest ones are noise. In this way, when predicting new links by Equation (5.1.4), $k$ is the number of active vertices plus the number of regular vertices. When predicting all links, $k$ is the total number of active, regular and stable vertices. The complexity of the proposed Network Evolution-based link prediction method is constituted by vertex activeness calculation $O(|V||t|)$ and SVD based link prediction $O(|V|^3)$ (Skillicorn (2007)) where $|V|$ is the number of vertices and $|t|$ is the number of time slots. Thus the overall complexity is $O(|V|^3)$.

### 5.1.3 Evaluation

This chapter evaluates the proposed Network Evolution-based Link Prediction method on the UTS heterogeneous academic collaboration network for predicting new links and all links. This chapter applies three similarity-based link prediction methods: random-walk, SimPath (the descriptions about these two similarity measures can be found in the literature review of this thesis) and the proposed semantic-path similarity (Section 4.1.2) of this thesis. Then the proposed link prediction method works on the link prediction matrices generated by these three methods for improving link prediction accuracy.


Figure 5.1: The schema of the heterogeneous academic collaboration network at UTS.

## 5.2 Experimental dataset

The experimental network of link prediction is a heterogeneous academic collaboration network at UTS. In this network there are three types of objects: researchers ($R$), publications ($P$) and FoR codes ($C$). Researchers ($R$) are connected to their publications ($P$) while publications ($P$) are linked to research domains ($C$). The schema of this heterogeneous network is illustrated in Figure 5.1.

Table 5.1: The experimental dataset from UTS

| **Year** | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 |
|---|---|---|---|---|---|---|
| **Researchers** | 2763 | 2972 | 3148 | 3231 | 3548 | 3592 |
| **Publications** | 1941 | 1971 | 2010 | 1985 | 2047 | 2052 |
| **FoR Codes** | 584 | 584 | 584 | 584 | 584 | 584 |
| **Res-Pub links** | 5389 | 5739 | 5981 | 5893 | 6336 | 6963 |
| **Pub-FoR links** | 4562 | 4279 | 4632 | 4341 | 5457 | 5358 |

The datasets contains researcher ($R$), publication ($P$), FoR codes ($C$), researcher-publication links and publication-FoR codes links of each year from 2006 to 2011 (Table 5.1). In the chapter, datasets from 2006 to 2010 are used to summarize the evolution of the heterogeneous academic collaboration network which link prediction is based on and the 2011 data is used to estimate the link prediction accuracies.

## 5.3 Experimental results

This section describes the application of proposed Network Evolution-based Link Prediction method on a real-world dataset. This method is applied to predict links of UTS academic collaboration in 2011 based on the data from 2006 to 2010 and the real situation in 2011 is used to verify the accuracy of the proposed link prediction method.

### 5.3.1 Modeling vertex activeness evolution

As discussed in the previous section, network evolution can be represented by a set of network snapshots. This chapter models the process of network evolution from 2006 to 2010 and builds one network for each year. The summary information of these networks are listed in Tab. 5.2. It clearly illustrates that the academic collaboration network is a mature network. The numbers of vertices and edges grow annually, but the density of network ($|E|/|V|^2$) keeps almost the same. Meanwhile, the network is quite sparse because its density is very low.

Table 5.2: Statistics of the academic collaboration network from 2006 to 2011

| **Year** | **Vertices** | **Edges** | **Density of Networks** |
|---|---|---|---|
| 2006 | 5288 | 9951 | 0.00035 |
| 2007 | 5527 | 9658 | 0.00032 |
| 2008 | 5742 | 10613 | 0.00032 |
| 2009 | 5800 | 10234 | 0.00031 |
| 2010 | 6159 | 11793 | 0.00031 |
| 2011 | 6228 | 12321 | 0.00032 |

### 5.3.2 Determining vertex evolving patterns

The core step of increasing the accuracy of link prediction is to capture vertex evolving patterns. These patterns are based on their activeness which are measured by two proposed evolving speeds: NCVelocity and NCAVelocity. According to Equations (5.1.1) and (5.1.2), these two speeds of researchers in the UTS heterogeneous academic collaboration are calculated at years 2007, 2008, 2009 and 2010. Then researchers are categorized into four groups: guest, active, regular and stable vertices based on the definitions in Section 5.1.1. It can be seen in Table 5.3 that most vertices are regular vertices, followed by stable vertices, guest vertices and active vertices.

Table 5.3: Categories of vertices

| **Category** | **Vertex numbers** | **Percentage** |
|---|---|---|
| Active vertices | 359 | 10.4% |
| Regular vertices | 1713 | 49.6% |
| Stable vertices | 854 | 24.7% |
| Guest vertices | 526 | 15.3% |

### 5.3.3 Link prediction

This section evaluates the proposed link prediction method on the UTS academic collaboration network. The target object type is researchers ($R$) and the relationship between them is co-authorship. The proposed Network Evolution-based Link Prediction is applied to predict new links and all links respectively in 2011 based on the network evolution from 2006 to 2010.

This experiment applies random walk and PathSim to predict links respectively. These two methods calculate similarities of researchers ($R$) and the $r$ leading highest

similarities are predicted to happen in the future. As is shown in Table 5.1, the number of edges grows steadily during the five years. There are 6336 edges in 2010 and then it can be safely assumed that there are 6800 edges in 2011. As a result, for predicting all links, the first leading 6800 largest similarities of researchers are predicted to appear while for predicting new links, the first leading 464 (6800 - 6336) largest similarities of researchers who are not connected before are predicted to connect.

This experiment compares the accuracies of random-walk, SimPath and the proposed semantic-path similarity with and without the proposed link prediction method and the comparative results are listed in Table 5.4. It can be seen that the proposed semantic-path similarity measure outperforms random walk and SimPath in both types of link prediction. For predicting new links, the accuracy of the proposed semantic-path similarity is 0.62 followed by Simpath (0.51) and random walk (0.26). For predicting all links, the accuracy of the proposed semantic-path similarity is 0.71 followed by SimPath (0.53) and random walk (0.34). This demonstrates that the proposed semantic-path based similarity measure works better to measure the similarities on heterogeneous networks than random walk and SimPath.

Table 5.4: Link prediction accuracy comparison.

| **Link prediction methods** | **New Link prediction accuracy** | **All Link prediction accuracy** |
|---|---|---|
| Random-walk | 0.26 | 0.34 |
| Random-walk with NELP | 0.31 | 0.45 |
| SimPath | 0.51 | 0.53 |
| SimPath with NELP | 0.54 | 0.63 |
| Semantic-path similarity | 0.62 | 0.71 |
| Semantic-path similarity with NELP | 0.69 | 0.82 |

When integrating the proposed link prediction method with these three similarity measures, the accuracies of new-link prediction and all-link prediction are improved significantly. For predicting new links, the accuracies of random walk, SimPath and the proposed semantic-path similarity increases from 0.26 to 0.31, from 0.51 to 0.54 and from 0.62 to 0.69 respectively. For predicting all links, the accuracy of random walk increases from 0.34 to 0.45, accuracy of SimPath increases from 0.53 to 0.63, and accuracy of the proposed semantic-path similarity increases from 0.71 to 0.82. This suggests that the proposed link prediction method is effective for integrating with different similarity measures and it can improve their accuracies in both new-link prediction and all-link prediction. These accuracies illustrate the proposed link prediction works better in improving the accuracy of all-link prediction than it of new-link prediction.

## 5.4 Contribution and discussion

Making an accurate link prediction requires including network evolution instead of working on a single snapshot of networks. This is because vertices display varying levels of activeness in network evolution. Active vertices tend to build and strengthen their connections often while stable ones tend to maintain their existing connections. Regular vertices expand their connections gradually. This chapter aims to improve the accuracy of link prediction by developing a Network Evolution-based Link Prediction method which can consider vertex evolving patterns, supporting **Contribution 3** of the thesis.

The proposed Network Evolution-based Link Prediction determines vertex activeness by two velocities: Neighborhood Changing Velocity (NCVelocity) and Neighborhood Changing Accelerated Velocity (NCAVelocity). The former velocity represents the vertex speed of changing neighbors and the latter velocity the changes of NCVelocity over time. Then the method categories vertices into four categories and treat them differently in link prediction. The experimental results illustrate that the proposed link prediction method can be integrated with existing similarity-based link prediction methods and improve their accuracies in link prediction, especially all-link prediction.

There are two major issues about the proposed link prediction method. It can be seen from the experimental results that the proposed link prediction method performs better in all-link prediction than new-link prediction. This may be because of the loose definition about guest vertices. The definition of guest vertices in this chapter is that if vertices fail to stay in networks from years 2006 to 2010, they are guest vertices. This definition may exclude active and regular vertices which joined the networks after year 2006. Another issue is that the proposed link prediction method is evaluated on a sparse heterogeneous network in the domain of academic collaboration. The effectiveness of the proposed link prediction method on heterogeneous networks is not clear and should be tested further.

# Chapter 6

# Co-ranking on complex bipartite heterogeneous networks

This chapter aims to address the last research question of this thesis: how to rank objects in complex bipartite heterogeneous networks where one type of object can be connected directly or indirectly. This chapter proposes a novel co-ranking method which can iteratively evaluate both types of object in complex bipartite heterogeneous networks and describes supporting experimental results. This addresses **Contribution 4** of the thesis.

The proposed co-ranking method is based on a set of customized rules which are extracted from relationships among objects. According to these rules, the co-ranking method ranks two types of object iteratively and uses the ranking result of each iteration to reinforce the object ranking scores. The proposed co-ranking method is potentially flexible because it is based on a set of user-defined rules and because it is also applicable on both directed and undirected relationships.

This co-ranking method has been validated on a dataset collected from DBLP and CiteSeer, and the results suggest that it is effective and efficient in ranking authors and publications simultaneously in academic collaboration heterogeneous networks

with fast convergence.

This chapter has five sections, Section 6.1 defines the data and matrix model used in the proposed co-ranking method. Section 6.2 describes the principles and working process of the co-ranking method followed by experimental dataset in Section 6.3 and experimental results in Section 6.4. The conclusions and discussions about co-ranking methods are listed in Section 6.5.

This chapter is an extended report of a published paper of the author of this thesis (Meng & Kennedy 2013*a*).

## 6.1 Data model

This section describes the data model that co-ranking methods is based on, including the network and matrix models.

### 6.1.1 Network model

The proposed co-ranking method is designed for ranking objects on complex bipartite heterogeneous networks and the definition of complex bipartite heterogeneous networks is given below:

**Definition 6.1** Consider a complex bipartite heterogeneous network (Figure 6.1), there are two types of object ($A$ and $B$) and multiple typed relationships ($R_1$, $R_2$ and $R_3$). Relationship $R_1$ connects two types of object together. Relationship $R_2$ and $R_3$ connect $A$-type objects and $B$-type objects together respectively.

It can be seen that the complex bipartite heterogeneous network $G$ can be divided into three sub networks: $G_{AA}$, $G_{AB}$ and $G_{BB}$. $G_{AA}$ is a homogenous network with

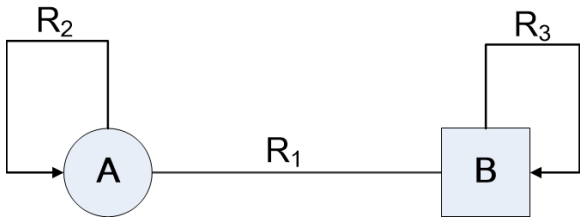



Figure 6.1: An example of a complex bipartite heterogeneous network is used for co-ranking.

type-$A$ objects and the objects are connected by $R_2$. $G_{AB}$ is a simple bipartite heterogeneous networks with two types of objects, and objects in the same type are not connected directly but connected indirectly by the other type of objects via $R_1$. $G_{BB}$ is also a homogenous network with type-$B$ objects and the objects are connected by $R_3$

### 6.1.2 Matrix model

For the purpose of storing and calculating easily, a matrix is used to represent complex bipartite heterogeneous networks. For the complex bipartite heterogeneous network $G$, it can be represented as

$$M = \begin{pmatrix} M_{AA} & M_{AB} \\ M_{BA} & M_{BB} \end{pmatrix} \tag{6.1.1}$$

where $M$ is the adjacency matrix of the network $G$, and $M_{AA}$, $M_{AB}$, $M_{BA}$ and $M_{BB}$ each denote a type of relationship between object type $A$ and object type $B$. Relationships $R_1$, $R_2$ and $R_3$ are represented by adjacency matrices $M_{AB}$, $M_{AA}$ and $M_{BB}$ respectively. $M_{AB}$ is the transposed matrix of $M_{BA}$.

## 6.2 Methodology

In this section, a ranking method based on rules are described followed by the co-ranking working process and finally evaluation of this ranking method.

### 6.2.1 Ranking based on rules

Like many state-of-the-art ranking methods in networks, such as PageRank, the proposed co-ranking method is also inspired by a voting mechanism so that the rank of a vertex in a network is determined by its incoming connections. The more incoming connections a vertex receives, the higher it is ranked. For example, in an email sending/receiving network, a person is important if he/she receives many emails from others. Meanwhile the proposed co-ranking method takes weights of objects into consideration. If an object is considered to have a high rank, its neighbors should also be ranked highly (Sun & Han 2012).

Unlike these approaches which only work in homogeneous networks, the proposed co-ranking method ranks objects in a complex bipartite heterogeneous network by a set of rules and reinforces ranking results by an iterative ranking process. The rules, given below, have parameters $(\alpha_{aa}, \alpha_{ab}, \alpha_{bb}, \alpha_{ba})$ taking values ranging from 0 to 1, which determine how much weight to put on each rule. The values for these parameters can be assigned based on experience, special requirements or experimental datasets. The experiment assigns them to be 1, which means they are considered equally.

The four rules are:

Rule 1: Type-$A$ objects are ranked by type-$A$ objects.

$$Rank_{AA}(j) = \alpha_{aa} \sum_{k=1}^{|V_A|} M_{AA}(j,k) Rank_A(k) \tag{6.2.1}$$

Rule 2: Type-$B$ objects are ranked by type-$A$ objects.

$$Rank_{AB}(i) = \alpha_{ab} \sum_{j=1}^{|V_A|} M_{AB}(i,j) Rank_A(j) \tag{6.2.2}$$

Rule 3: Type-$B$ objects are ranked by type-$B$ objects.

$$Rank_{BB}(i) = \alpha_{bb} \sum_{l=1}^{|V_B|} M_{BB}(i,l) Rank_B(l) \tag{6.2.3}$$

Rule 4: Type-$A$ objects are ranked by type-$B$ objects.

$$Rank_{BA}(j) = \alpha_{ba} \sum_{r=1}^{|V_B|} M_{BA}(j,r) Rank_B(r) \tag{6.2.4}$$

where $|V_A|$ is the number of type-$A$ objects and $|V_B|$ is the number of type-$B$ objects.

For these four rules, rules 1 and 3 are designed to rank both types of object respectively while rules 2 and 4 are designed to rank one type of object by the other type.

### 6.2.2 The co-ranking framework

The developed ranking rules show that the co-ranking method ranks both types of objects in complex bipartite heterogeneous networks repeatedly and the ranking result of former iteration becomes the input of next one. Thus the co-ranking framework is a mutual reinforcement ranking method.

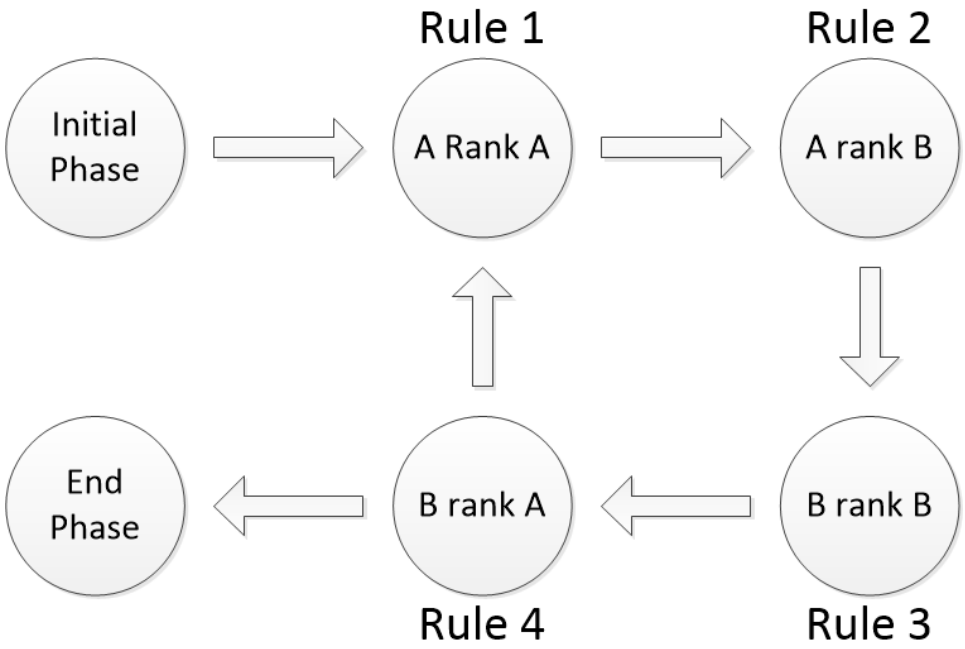



Figure 6.2: The working flow between different rules in the co-ranking method.

Figure 6.2 illustrates the working process of the proposed co-ranking method. It shows that apart from application of the four ranking rules, there is a starting point and an end point to this co-ranking framework. The main task of the initial phase is to assign initial ranking scores to type-$A$ objects before starting the process. Actually, the co-ranking method can start from any one of rules because the choice does not strongly affect the ranking results and the mutually ranking process stably converges to the primary eigenvector of $M_{AA}$, $M_{AB}$, $M_{BA}$ and $M_{BB}$ respectively (Sun, Han, Zhao, Yin, Cheng & Wu 2009). There are many approaches ranging from basic in-degree counting, through to random walk or the advanced PageRank in the initial phase.

For the question of when to stop repetition, one way is that users can choose the number of iterations. Another way of controlling the number of iterations is to

terminate when the ranking stops changing between iterations. That is,

$$Diff(t, t+1) = \frac{\sum_{i=1}^{|V|} |rank(i, t+1) - rank(i, t)|}{|V|} \tag{6.2.5}$$

where $|V|$ is the number of vertices of network $G$ and function $rank(i, t+1)$ is the ranking score of vertex $i$ in the $t+1$th iteration.

Another key point in this framework is normalization. After each round of co–ranking, the elements in matrices $M_{AA}$, $M_{AB}$, $M_{BA}$ and $M_{BB}$ are linearly scaled into [0, 1] respectively. Although this does not change the ranking position of objects, it gives a relative importance score to each object.

The time complexity of the proposed co-ranking framework is $O(t|2(|V_A|+|V_B|)|)$, where $t$ is the number of iterations through the framework and $|V_A|$ is the number of type-$A$ objects and $|V_B|$ is the number of type-$B$ objects. This is because for each round of ranking, the proposed co-ranking method applied these four rules once. The computational complexities of rules 1 and 2 are determined by $|V_A|$ and The computational complexities of rules 3 and 4 are determined by $|V_B|$. The proposed ranking method in this thesis gives an importance measure to each type of objects based on the whole network, rather than its local neighbourhood.

### 6.2.3 Evaluation

This section evaluates the proposed co-ranking method in a heterogeneous academic collaboration network built from the DBLP and CiteSeer bibliographic datasets. The co-ranking method is applied to rank authors and publications simultaneously and the ranking results are compared with two state-of-the-art ranking methods: PageRank and Hyperlink-Induced Topic Search (HITS) (a review of these two methods can

be found in Section 2.4). However, PageRank and HITS cannot work on complex bipartite heterogeneous networks. Because of this, this chapter sets up two citations: a small citation set and a complete citation set. For the proposed co-ranking method, the experiment in this chapter collects a small citation set which contains citation relationships among selected publications. For PageRank and HITS, the experiment in this chapter collects a complete citation set to have all citations that the selected publications have. The ranking results generated by these three ranking methods are compared in Jaccard similarity and object ranks comparison.

Jaccard similarity (Lü & Zhou 2011) evaluates the ranking results of different ranking methods by their correlation. Ranking results can be regarded as object sets and Jaccard's similarity is efficient to compare the similarity between sets. Considering two ranking approaches $a$ and $b$, $r_w(a)$ and $r_w(b)$ are two sets containing the top $w$ ranked objects on a dataset. The correlation of two ranking methods can be defined as

$$C(a,b) = \frac{|r_w(a) \cap r_w(b)|}{|r_w(a) \cup r_w(b)|} \tag{6.2.6}$$

If the ranks of elements in $r_w(a)$ and $r_w(b)$ are taken into consideration, the correlation of the two methods $a$ and $b$ is computed as

$$CP(a,b) = 1 - \frac{\sum_{i=1}^{|r_w(a) \cup r_w(b)|} |F(r_w(a),i) - F(r_w(b),i)|}{w(w+1)} \tag{6.2.7}$$

where function $F(r_w(a),i)$ returns the rank of element $i$ in ranking method $a$. If $F(r_w(a),i) = 5$, the rank of element $i$ in method $a$ is 5 and if $i \notin r_a(w)$, $F(r_a(w),i) = 0$.

The main reason for this evaluation is to evaluate the effectiveness of the proposed co-ranking methods, as it provides a way to compare new approaches with existing ones.

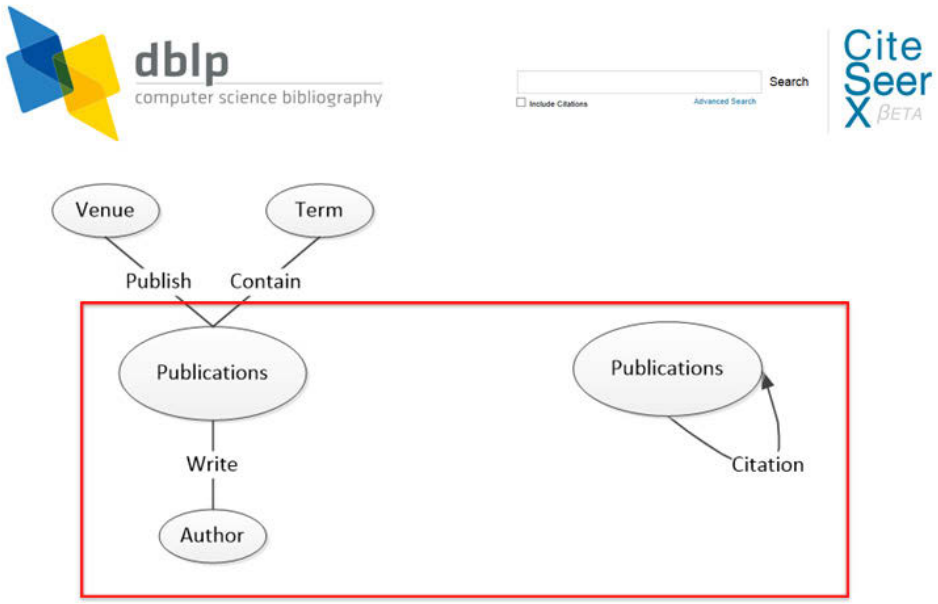



Figure 6.3: The data sources of the experimental dataset.

## 6.3 Experimental dataset

The dataset depicting the heterogeneous network used in the experiment is built from the DBLP digital library (Ley 2009) and website (Giles et al. 1998). The version (downloaded on 2011-10-18) of the DBLP[1] dataset includes more than 1.8 million publications by 0.8 million authors. Those records provide a way to trace the work of researchers and to retrieve bibliographic details when composing lists of references for new papers. However, it fails to provide citation relations among publications and this is the reason why the CiteSeer[2] database is used. CiteSeer website is a popular search engine and digital library with a collection of 1.2 million scientific documents.

[1] http://dblp.uni-trier.de/
[2] http://citeseer.ist.psu.edu/

Table 6.1: Statistics of the academic network used to validate the proposed co-ranking approach

| | |
|---|---|
| Number of Authors | 34,342 |
| Number of Papers | 17,786 |
| Number of co-authorships | 87,384 |
| Number of authorships | 62,251 |
| Number of citations | 34,265 |
| Time Interval | 2006 — 2010 |
| Selected Conferences | SIGMOD, ICDE, PODS, KDD, SSDBM ICDM, VLDB, EDBT, SDM, DASFAA |

In the experiment, data from DBLP is regarded as the main information as it has a clear and effective mechanism to disambiguate names. CiteSeer mainly provides information about citations. In the formed heterogeneous academic network, each vertex represents an author who published at least one paper in one of the major venues for the data mining and database communities between 2006 and 2010. Each edge links two authors who co-authored at least one paper. The vertex properties are the number of publications in each of the 10 selected conferences, which are highly ranked conferences. The reason for choosing these conferences cover frequently cited papers and famous authors that people are familar, and therefore readers are able to understand the experimental results clearly.

Two different citation sets are gathered to test the effectiveness and efficiency of the proposed co-ranking method: a small citation set and a complete citation set. For the proposed co-ranking method, the experiment in this chapter collects a small citation set which contains 34,265 citation relationships between selected publications from 10 venues. For PageRank and HITS, the experiment in this chapter collects a complete citation set to have all citations that the selected publications have. The

complete citation set has 67,258 references and 282,463 citation relationships which is much larger and more complex than the small citation set. The configuration of this is to verify that compared with PageRank and HITS, the proposed co-ranking method is effective to rank authors and publications with a small citation set in the domain of academic collaboration.

## 6.4 Experiment

This section evaluates the performance of the proposed co-ranking method on ranking authors and publications in a complex bipartite heterogeneous academic collaboration network built from the DBLP dataset. It includes extracting ranking rules, co-ranking authors and publications, ranking-result evaluation and divergence analysis.

### 6.4.1 Extracting ranking rules

The considered complex bipartite heterogeneous network contains two types of objects (authors and publications) and three types of relations (social relationship, authorship and citation). However, the social ties among researchers are hard to fetch and measure. The experiment adopts co-authorship to represent the social relationship based on an assumption that the more publications two researchers coauthored, the closer their social relations are. Based on the dataset collected from the DBLP website, the experiment firstly builds a complex bipartite heterogeneous network $G = (V, E)$ which has researchers, publications and the relationships among them. The schema of the experimental complex bipartite heterogeneous network is illustrated in Figure 6.4. From this network schema, it can be seen that the network $G$ consists of

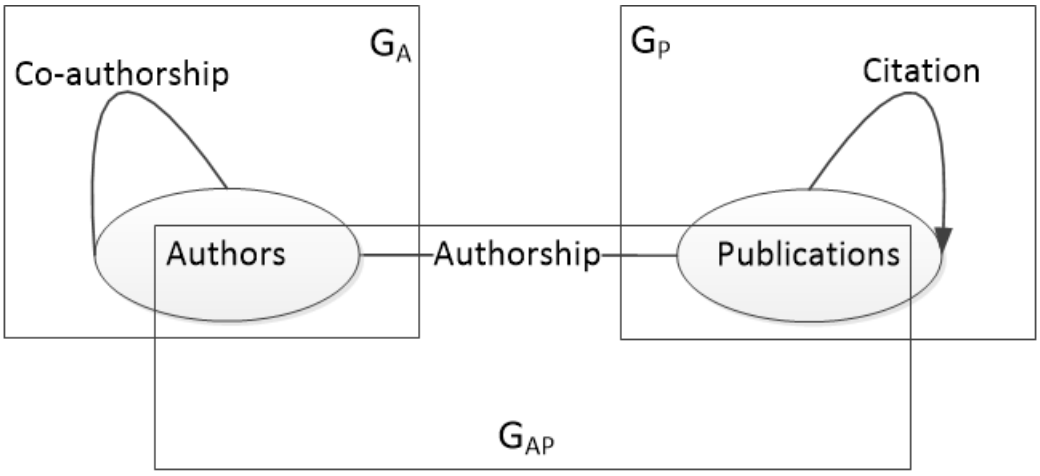



Figure 6.4: The schema of the experimental complex bipartite heterogeneous network built from the DBLP website.

three sub-networks: the co-authorship network $G_A$, the citation network $G_P$ and the authorship network $G_{AP}$.

$G_A = (V_A, E_A)$ is the weighted undirected graph (co-authorship network) of authors. $V_A$ is the set of authors, while $E_A$ is the set of edges, representing co-authorships. The number of authors is $n = |V_A|$ and the set of authors is $V_A = (a_1, \cdots, a_n)$. Weights of the edges are the number of publications two authors coauthored.

$G_P = (V_P, E_P)$ is the unweighted directed graph (citation network) of publications, where $V_P$ is the publication set, $E_P$ is the set of links, representing citations between publications. The number of publications is $m = |V_P|$. Individual documents are denoted as $V_P = (p_1, \cdots, p_m)$

$G_{AP} = (V_{AP}, E_{AP})$ is the weighted bipartite graph representing authorship. $V_{AP} = V_A \cup V_P$. Edges in $E_{AP}$ connect each publication with all of its authors. In the authorship network the order of authors is considered. It is assumed that given a

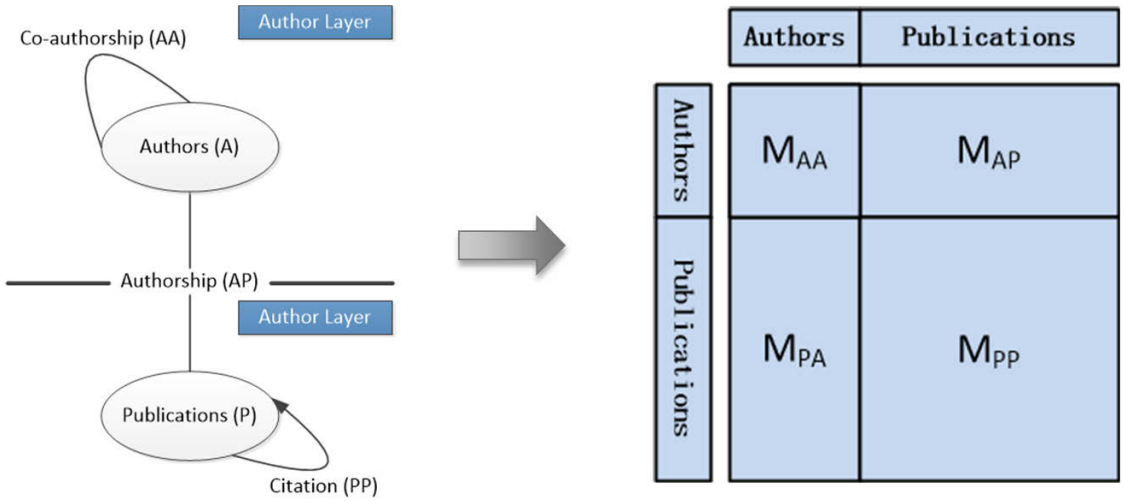



Figure 6.5: The academic collaboration network is represented by a matrix for further computation.

publication in the author list, the earlier listed authors contribute more to the publication than the later authors and that the first author has the highest weight. Then the weight of author $a_i$ to publication $p_j$ is defined as $w_{AP}(a_i, p_j) = 1/order(a_i, p_j)$, where $order(a_i, p_j)$ is a function to retrieve the position of author $a_i$ in the naming list of publication $p_j$. For example, the weight of first author is 1, and that of $n$th author is $1/n$.

The corresponding adjacency matrices of the networks $G$, $G_A$, $G_{AP}$ and $G_P$ are $M_{AA}$, $M_{AP}$, $M_{PP}$. The weight of author–author ($M_{AA}$) edges is the number of co-authored papers. $M_{AP}$ indicates the number of papers that an author has published taking into consideration the order of the author lists. The citation relationships are described in $M_{PP}$. $M_{PA}$ is the transposed matrix of $M_{AP}$.

With the network built, the ranking rules of the network is given below:

Rule 1: Highly ranked papers tend to cite other highly ranked papers.

$$Rank_{PP}(j) = \sum_{k=1}^{m} M_{PP}(j,k) Rank_P(k) \tag{6.4.1}$$

In this equation, a publication $j$ is ranked highly if the $m$ papers which refer to it, indexed by $k$, have high ranking scores.

Rule 2: Highly ranked authors publish many highly ranked papers.

$$Rank_{AP}(i) = \sum_{j=1}^{m} M_{AP}(i,j) Rank_P(j) \tag{6.4.2}$$

The above equation describes that author ranking scores are determined by the quantity and quality of papers they publish. A high rank publication $j$ with rank $Rank_P(j)$ can increase the ranking score of author $i$.

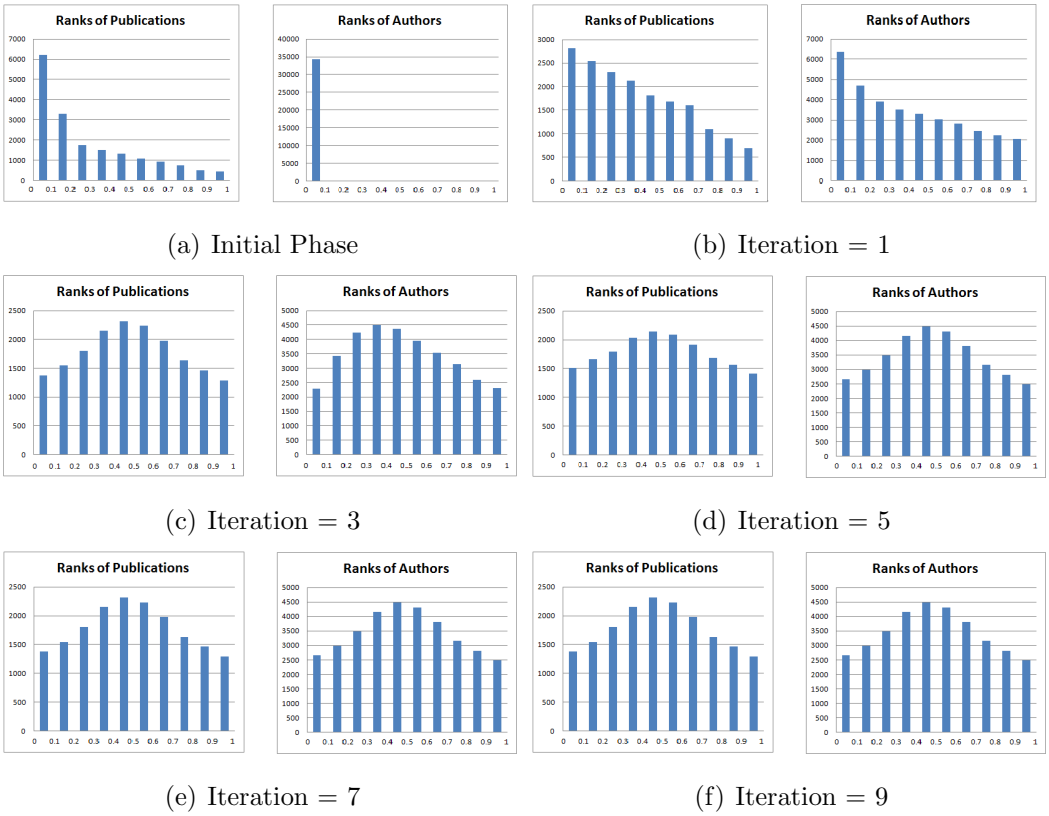
Rule 3: Highly ranked authors tend to co-author with other highly ranked authors.

$$Rank_{AA}(i) = \sum_{l=1}^{n} M_{AA}(i,l) Rank_A(l) \tag{6.4.3}$$

Rule 4: Highly ranked authors generally publish highly ranked papers.

$$Rank_{PA}(j) = \sum_{r=1}^{n} M_{PA}(j,r) Rank_A(r) \tag{6.4.4}$$

The above ranking rules show that publications are ranked through other publications and authors and those authors are also ranked through publications and other authors. Thus the co–ranking framework is based on mutual reinforcement by repeatedly ranking authors and publications.




(a) Initial Phase (b) Iteration = 1

(c) Iteration = 3 (d) Iteration = 5

(e) Iteration = 7 (f) Iteration = 9

Figure 6.6: Mutual improvement of co–ranking publications and authors through iterations. Each of the six pairs of graphs shows the distributions of publication and author ranks. The $x$ axis in each diagram is ranking score and the $y$ axis is the frequency of objects.

### 6.4.2 Co-ranking authors and publications

The experiment starts from ranking publications by citations because the number of citations is an indispensable index to rank the papers and assessment of publications before co–ranking can accelerate the rate of convergence. In this phase, the importance of papers is estimated by applying a citation count on network $G_P$.

The iterative process of co–ranking is shown in Figure 6.6. In the initial phase, citation count is applied to rank publications and authors have no ranks. However,

due to the limited number of citations, most publications have a very low value (from 0 to 0.1) except for some widely cited papers such as (Lee et al. 2007) and (Backstrom et al. 2006). Highly ranked papers in this phase have the common feature that they are very general and therefore receive many citations. After the first iteration, more than 50% of publications are assigned relatively large ranks ranging from 0.2 to 1 and authors are ranked based on co–authorship, authorship and ranking scores of publications. After the third iteration, the distributions of both publication and author ranks show a similar pattern. Nevertheless, most authors have low ranks. From iteration 5 on, distributions of both papers and authors are becoming consistent and stable, showing a Gaussian distribution. It is interesting to see that most low ranked authors are students or junior researchers with a few papers such as the first authors of the papers (Henderson et al. 2010, Dourado et al. 2009, Poelmans et al. 2009).

The top 10 papers and authors is listed by the co–ranking approach (Table 6.2). It is pleasing to see that the researchers and papers are all highly ranked in CiteSeer (Table 6.3). CiteSeer provides the ranking scores of authors by *h-index* which is an index that measures both the productivity and impact of the published work of scholars and this index takes all publications of an author and all received citations of these publications. The reason why the last two authors of Table 6.2 receive high ranking scores by h-index but relatively low ranks by co-ranking is because the collected publications in the experiment are from 2006 to 2010. This means the approach is effective in ranking authors and papers with limited citations. The paper "Mondrian multidimensional $k$-anonymity" (LeFevre et al. 2006) is the highest ranked paper as it is coauthored by two top 10 ranked authors: David J. DeWitt and Raghu

Table 6.2: Top 10 authors and publications by co–ranking

| **Rank** | **Top 10 Authors** | **Top 10 Publications** |
|---|---|---|
| 1 | H. V. Jagadish | Mondrian multidimensional $k$-anonymity (LeFevre et al. 2006) |
| 2 | Jiawei Han | Frequent pattern mining: current status and future directions (Han et al. 2007) |
| 3 | Surajit Chaudhuri | A comparison of approaches to large-scale data analysis (Pavlo et al. 2009) |
| 4 | Divesh Srivastava | PNUTS: Yahoo!'s hosted data serving platform (Cooper et al. 2008) |
| 5 | David J. DeWitt | Materialization strategies in a column-oriented DBMS (Abadi et al. 2007) |
| 6 | Jeffrey F. Naughton | Trajectory clustering: a partition-and-group framework (Lee et al. 2007) |
| 7 | Michael Stonebraker | Finding $k$-dominant skylines in high dimensional space (Chan et al. 2006) |
| 8 | Raghu Ramakrishnan | A primitive operator for similarity joins in data cleaning (Chaudhuri et al. 2006) |
| 9 | Hector Garcia-Molina | Aggregate query answering on anonymized tables Zhang et al. (2007) |
| 10 | Rakesh Agrawal | Declarative information extraction using datalog with embedded extraction predicates (Shen et al. 2007) |

Ramakrishnan. Han is usually ranked after Srivastava in many experiments (Zhou et al. 2007, Sun & Han 2012) as Srivastava has co–authored more papers. In fact, when considering the order of authors in papers, Han outperforms Srivastava as he is often the first or second author. Another interesting finding is that the top 10 ranked papers are from three conferences: ACM Special Interest Group on Management of Data Conference (SIGMOD) (accounting for 4 of the top 10 papers), IEEE International Conference on Data Engineering (ICDE) (4) and International Conference on

Table 6.3: Top 10 authors by co–ranking and their H-index scores by CiteSeer

| **Rank by co-ranking method** | **Top 10 Authors** | **H-index scores by CiteSeer** |
|---|---|---|
| 1 | H. V. Jagadish | 32 |
| 2 | Jiawei Han | 39 |
| 3 | Surajit Chaudhuri | 24 |
| 4 | Divesh Srivastava | 31 |
| 5 | David J. DeWitt | 39 |
| 6 | Jeffrey F. Naughton | 31 |
| 7 | Michael Stonebraker | 28 |
| 8 | Raghu Ramakrishnan | 34 |
| 9 | Hector Garcia-Molina | 56 |
| 10 | Rakesh Agrawal | 42 |

Very Large Databases (VLDB) (2), which implies that these three venues have higher ranks than others. This result is also confirmed by Han's experiment (Sun & Han 2012) ranking venues using a combined ranking and clustering framework.

### 6.4.3 Evaluation

This experiment evaluates the effectiveness of the proposed co-ranking method by comparing its ranking results with these of PageRank and HITS. The proposed co-ranking method is applied on the small citation set to rank authors and publications simultaneously. PageRank is applied on the citation network with the small and complete citation sets to rank publications. HITS is applied to rank authors through publications based on the results of PageRank on the small and complete citation sets. The top 100 ranked authors and publications of these three ranking methods are chosen to form ranking sets for comparison and the similarities of these ranking sets are listed in Table 6.4. The most interesting finding is that the ranking results of the

Table 6.4: Evaluation of ranking results by co–ranking, PageRank and HITS

| **Object** | **Citation set** | **Evaluation** | **Result** |
|---|---|---|---|
| Publications | small | $C(PageRank, Co-ranking)$ | 0.62 |
| | | $CP(PageRank, Co-ranking)$ | 0.54 |
| | complete | $C(PageRank, Co-ranking)$ | 0.92 |
| | | $CP(PageRank, Co-ranking)$ | 0.88 |
| Authors | small | $C(HITS, Co-ranking)$ | 0.82 |
| | | $CP(HITS, Co-ranking)$ | 0.76 |
| | complete | $C(HITS, Co-ranking)$ | 0.94 |
| | | $CP(HITS, Co-ranking)$ | 0.91 |

co–ranking method with the small citation set are similar to those of PageRank and HITS with the complete citation set. For publication ranking, the similarities of the ranking sets are 0.92 and 0.88 when considering element orders. For author ranking, the similarities of the ranking sets are 0.94 and 0.91 when considering element orders. The results of PageRank and HITS using a small citation set are not satisfactory, giving the low correlation values of 0.62 for publications and 0.82 for authors. The less the number of citations, undoubtedly, decreases the cost of computation. As a result, it can be safely concluded that the proposed co–ranking method is effective as it can achieve good results via the small citation set.

### 6.4.4 Divergence analysis

All three ranking methods are based on a repetitive process and each of them runs for twenty times. Figure 6.7 illustrates how these methods converge when ranking authors and publications. From the diagram, the differences of iterations is calculated (refer to Equation (6.2.5)) and it is clear that the differences for co-ranking become small and stable at iteration 6 which means the ranking results have converged while the

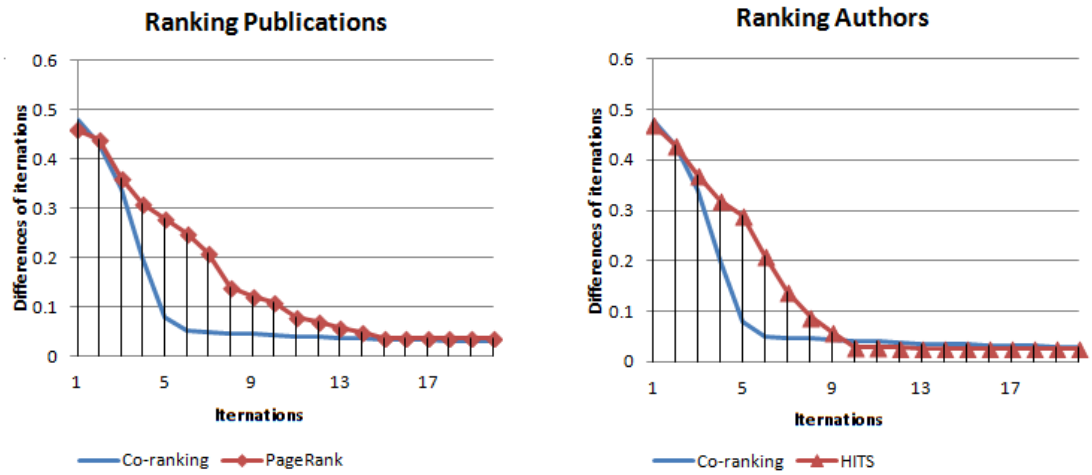



Figure 6.7: Convergence analysis: the rates of convergence from the proposed co–ranking method, PageRank and HITS are illustrated: (a) describes the process of publication ranking by co–ranking and PageRank; (b) compares the converge rate between coranking and HITS for author ranking.

other two only become stable later in iterations 15 and 10 respectively. This is partly because they work on the complete set of citations. HITS converges more quickly than PageRank in the experiment because HITS is applied to rank authors by publications and their ranks, which are determined by PageRank on the complete set of citations. This means that the proposed co-ranking method is efficient because it has a fast convergence rate.

## 6.5 Contribution and discussion

Almost all ways of ranking objects are based on the voting mechanism that the neighbors of highly ranked objects should have a high ranking score. The major problem of ranking objects in heterogeneous networks is that different types of objects

are influenced by others in terms of ranks and it is unreasonable to consider only one type but ignore others.

This chapter addresses Contribution 4 as listed in Section 1.5 by proposing and verifying a new co–ranking method. The proposed co-ranking method is based on a set of customized rules which are extracted from relationships among objects. According to these rules, the co-ranking method ranks two types of objects iteratively and uses the ranking result of each iteration to reinforce the object ranks. The proposed ranking approach is potentially flexible because it is based on a set of customized rules taking into account topological features and because it is also applicable on both directed and undirected relationships.

The developed approach is a flexible framework based on a set of customized rules taking into account both topological features of networks and the included citations. In academic networks, the approach ranks authors and publications iteratively and uses the ranking scores of each round to reinforce the ranks of authors and publications. Unlike traditional approaches to assess publication based on a great number of citations, this approach can make a correct ranking based on a very small set of citations.

In this chapter, the experiment on the DBLP dataset suggests that the proposed co–ranking approach is effective in ranking authors and publications in heterogeneous academic networks via a small citation set because it can achieve similarity results with PageRank and HITS which have to work on a complete citation set. The proposed co-ranking method is efficient with a fast convergence rate. Experimental results illustrate that the rules can be customized easily, for example to consider the order of authors on publications, and that this has a strong effect on the results.

A major issue of the proposed co-ranking methods is that it works in heterogeneous networks with two types of object and cannot applied to those heterogeneous networks with more than two types of object.

# Chapter 7

# Conclusions

Conventional networks, also named as homogenous networks have not scaled to model complex social phenomena, especially those with more than one relationship type and/or object type. This is because they are limited to one type of relationship and object. Relaxing this limitation gives rise to heterogeneous networks. These networks are complex, having multi-type relationships and objects. Because of this feature, heterogeneous networks have been becoming a more widely used network model than homogenous networks. However, current research on heterogeneous network analysis are insufficient because the complex topological features make many state-of-the-art methods proposed for homogenous networks not applicable in the heterogeneous context. Thus, there is an urgent demand for researching on heterogeneous networks.

The research in this thesis is motivated to work on heterogeneous network analysis for the following reasons:

1. Although heterogeneous networks are advantaged in modeling general and abstract concepts via involving multi-type relationships and objects, it is challenging to estimate the contributions of relationships to these concepts.

2. Determining an accurate number of clusters beforehand is important for community detection methods, because the quality of clustering highly depends on whether the chosen number of clusters is appropriate. However, there is no a universal method for determining the number of clusters in both homogeneous and heterogeneous networks.

3. Link prediction accuracy is low. The reason for this is that most current link prediction methods are based on vertex similarity in both homogenous and heterogeneous networks. They believe similar vertices have a higher possibility to connect than dissimilar ones. However, there are some exceptions that sometimes dissimilar vertices can develop a new connection while similar ones cannot because of their activeness. This interesting phenomenon provides an insight into improving the accuracy of link prediction by investigating and modeling vertex activeness based on network evolution.

4. Current ranking studies in heterogeneous networks mainly focus on bipartite heterogeneous networks where one type of objects are connected indirectly by the other type of objects, and ignore the research on complex bipartite heterogeneous network which allow one-type of objects connected to themselves directly and indirectly.

In light of these issues, this research makes the following main contributions:

**Contribution 1** describes a Multiple Semantic-path Clustering method proposed in Chapter 3, which is designed for achieving a user-desired clustering in heterogeneous networks. This proposed method uses semantic paths to represent object relationships. The selection and the contributions of the semantic paths are assessed by their

correlations to user-guided information. The proposed method can build a collective similarity matrix of target vertices based on the combination of the semantic paths and their weights and then can detect community structure in heterogeneous networks. The experiment in Chapter 3 compares the clustering results of the proposed Multiple Semantic-path Clustering method with spectral clustering. The results illustrate that the proposed method outperforms spectral clustering in terms of achieving a user-desired clustering. The results also suggest that the Multiple Semantic-path Clustering method is effective in community detection, achieving high values in coverage, performance and modularity. A major issue of the proposed Multiple Semantic-path Clustering method is that it clusters just one-type of object (target objects) in heterogeneous networks instead of all types of object. This limits the efficiency of the proposed method.

**Contribution 2** in Chapter 4, develops a Leader Detection and Grouping Clustering (LDGC) method for determining the number of clusters in heterogeneous networks. The proposed method determines the number of clusters based on the social theory that communities are generally formed by leaders and group members. Leaders are the core of communities, keeping close connections with members in the community, while members have fewer connections and are often connected to each other via leaders. The proposed Leader Detection and Grouping Clustering method identifies leaders by capturing the topological differences between leaders and members and combines leaders when they are close enough to form leader groups. Then, the number of clusters is the number of leader groups.

The experimental results in Chapter 4 illustrate that the proposed Leader Detection and Grouping Clustering method outperforms cumulative percentage variance

and scree graph in determining the number of clusters because the clustering result generated by spectral clustering with the number of clusters from LDGC achieves higher values than these with the number of clusters from cumulative percentage variance and scree graph. The experimental results also suggest that the proposed Leader Detection and Grouping Clustering method is effective in community detection and it can achieve high values in performance, modularity and coverage.

The possible issues of the proposed Leader Detection and Grouping Clustering method are these: 1) This method identifies leaders by degree-centrality and betweenness-centrality and this practice gives rise to a relatively low accuracy of leader identification. This means that depending on these two centrality measures may be insufficient to identify leaders accurately. 2) Another limitation is that the laboratory directors are considered as leaders of communities in the experiment and the SVM classifier is trained based on this. In fact, many managers in companies or universities are not leaders of communities. For example, department managers may keep a tide connection with project managers instead of staffs in terms of emails or face-to-face talks. Training the classifier with managers may give rise to biased results.

**Contribution 3** in Chapter 5, introduces a Network Evolution-based Link Prediction (NELP) method for improving the link prediction accuracy further in heterogeneous networks. The proposed method models the evolutionary process of a network by a set of its continuous snapshots and captures vertex activeness by two proposed indices: Neighborhood Changing Velocity (NCVelocity) and Neighborhood Changing Accelerated Velocity (NCAVelocity). The former velocity represents the vertex speed of changing neighbors and the latter velocity the changes of NCVelocity

over time. Then vertices are categorized into four categories based on their activeness: guest, active, regular and stable vertices. For link prediction, the link prediction matrices generated by similarity measures are adjusted by vertex activeness. The experimental results in Chapter 5 illustrate that the proposed link prediction method can be integrated with existing similarity-based link prediction methods and improve their accuracies in link prediction, especially all-link prediction.

There are two major issues with the proposed link prediction method. The first one is that the proposed link prediction method can significantly improve the accuracy in all-link prediction but little in new-link prediction. This may be because of the loose definition of guest vertices. The definition of guest vertices in this chapter is that if vertices fail to stay in networks from years 2006 to 2010, they are guest vertices. This definition may exclude active and regular vertices which joined the networks after year 2006. The second issue is that the proposed link prediction method is evaluated on a sparse heterogeneous network. The effectiveness of the proposed link prediction method in dense heterogeneous networks is not clear and should be tested further.

**Contribution 4** in Chapter 6, develops a co–ranking method for ranking objects in complex bipartite heterogeneous networks. This proposed method is a flexible framework based on a set of customized rules which are defined via topological features and user requirements. Chapter 6 evaluates the proposed co-ranking method on the DBLP dataset to rank authors and publications simultaneously. The experiment sets up two citation sets: a small citation set and a complete citation set. The small citation set contains citation relationships between selected publications. The complete citation set has all citations that the selected publications have. The experimental results verify that the proposed co-ranking method with the small citation

set can obtain similar ranking results as with PageRank and HITS with the complete citation set in author ranking and publication ranking. The small citation set can alleviate the computational complexity of the proposed co-ranking method so as to achieve a high efficiency. A possible issue of the proposed co-ranking method is that it can only work on bipartite heterogeneous networks, which limits its applications on heterogeneous networks with more than two types of object.

To sum up, the proposed methods of addressing heterogeneous network problems have potential benefits for understanding academic collaboration and for heterogeneous network analysis. The proposed methods are applicable on other real-world heterogeneous networks. Compared with the proposed co-ranking method which can only work on complex and simple bipartite networks, the Multiple Semantic-path Clustering method, the Leader Detection and Grouping Clustering method and the Network Evolution-based Link Prediction method have relatively loose requirements to networks. These three networks can work on multipartite heterogeneous networks. The latter two methods can work on homogenous networks as well because they focus on one-type of objects and their topological features. Thus, this research has a broad, promising vision to be applied on real world networks.

## 7.1 Future research directions

This thesis focuses on solving a series of heterogeneous network analysis problems from Chapter 3 to 6 including community detection, determining the number of clusters, link prediction and object ranking. The following research plans to focus on extending the applications of the proposed methods in this thesis, overcoming limitations of the

methods and investigating other topological features of heterogeneous networks.

One potential research direction is to test and evaluate the proposed methods further. The experimental heterogeneous networks in this thesis are from the UTS research datasets and the DBLP dataset. As these two datasets are in the domain of academic collaboration, the built heterogeneous networks display some special topological features: 1) these heterogeneous networks are relatively sparse; 2) academic collaboration heterogeneous networks often display a strong community structure and it can be seen via the terms of their research areas and venues; 3) these networks contains little missing and noisy information because the collected information is complete. In fact, many heterogeneous networks have no such features. For example, online social networks like Facebook, may have many missing or incorrect connections. Users may have a friendship connection with others that they do not know. Meanwhile, different ratios of the number of edges and the number of vertices can affect the computational complexity of the proposed methods significantly. As a result, it is necessary to test the effectiveness and efficiency of these methods in other domains so as to guarantee their robustness.

Another research direction is to investigate the use of other topological features of networks. The methods proposed in the thesis are based on two topological features: paths and centralities. In potential future research, it is reasonable to evaluate the contributions of different topological features and to cover more important features to enhance the performance of these methods. For example, neighborhood is one important topological feature and it is widely applied in homogeneous networks. The usage and advantages of this feature are not well investigated and exploited in the context

of heterogeneous networks. This is because vertices in heterogeneous networks are often connected to vertices in other types. For example, in bibliographic heterogeneous networks, authors are connected to each other via publications. Other topological features can be considered as degree distributions of different types of vertices, clustering coefficients, the hierarchical structure of communities, correlations of edges, multiplex patterns with nested structures, or strong and weak ties, cores, islands, rings and cliques.

The current research in this thesis mainly focuses on observed academic collaboration network but ignores the investigation of unobserved networks (also marked as hidden networks) such as emerging research areas and researcher friendship networks. Detecting unobserved networks from observed academic collaboration will be a promising research direction.

This thesis measures the academic collaboration relationship based on the combined effects of different measurable collaborating relationships such as co-working and co-authoring. But it is often observed that people have different levels of closeness to others in terms of relationships. For example, two lecturers may work together closely in teaching but may not be co-authors on publications. This phenomenon is marked as dynamics heterogeneity. Detecting this phenomenon and investigating why it happens on some people but not on the others will be another important research direction.

The research in this thesis on network evolution just considers one type of object in heterogeneous networks and further research is planned to focus on co-evolving phenomenon of all types of object. For example, in a heterogeneous network with

researchers and their topics, as time goes, researchers may change their topics and research topics can be combined or split into new ones. For addressing this problem, it is necessary to model the evolution patterns both in one type of objects and among different types of object.

The proposed co-ranking method in this thesis can only applied on bipartite networks and extending it to be applicable on multipartite networks may be an interesting direction.

This thesis only considers the topological features of vertices and fails to consider vertex attributes in addressing heterogeneous network analysis problems. This practice constrains the applications to those heterogeneous networks where vertices have no attributes. Proposed future work should focus on this limitation and get vertex attributes involved because vertex attributes work well in distinguishing vertices. For predicting friendship in a social network, taking gender, age and interests and occupations into consideration could be a way to improve the link prediction accuracy.

Finally, heterogeneous network analysis has becoming a major research area of data mining because it can help us to model and understand the informative, universal connected world better. This thesis developed a set of methods to address a series of fundamental problems in heterogeneous networks and innovations of these proposed methods have the potential to provide people with new methods for addressing these problems.

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