A Feature Based Model for Negative Sign Prediction in Signed Social Networks

by

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Declaration of Co-Authorship/Previous Publication

I. Co-Authorship

I hereby declare that this thesis incorporates material that is a result of research conducted under the supervision of Dr. Ziad Kobti (Advisor), Dr. Jianguo Lu and Dr. Mohammed Fazel Baki contributed in revising the publication. In all cases, the key ideas, primary contributions, experimental designs, data analysis and interpretation, were performed by the author, and the contribution of co-authors was primarily through the proofreading of the published manuscripts.

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Abstract

People hold all kinds of positive and negative feelings for one another. Social networking online serves as a platform for showcasing such relationships, whether friendly or unfriendly, like or dislike, trust or distrust, cooperation or dissension. These types of interactions result in the creation of signed social networks (SSNs). The sentiments among social individuals are complexity and diversity, and the relationships between them include being friendly and hostile. The positive ("friendly", "like" or "trust") or negative ("hostile", "dislike" or "distrust") sentiments in the relations can be modeled as signed connections or links. The missing relations or sentiments between individuals are always worthy of speculation. Hence, we need to predict negative sign prediction. Although negative signs typically dominate the positive signs in various analytical decisions in most real applications, it cannot be directly propagated between users like positive signs. The study on negative sign prediction is still in its early stages. There is a difference between the value of negative signs and the availability of these links in real data sets. It is therefore normal to analyze whether one can automatically predict negative signs from the widely available social network data. In this thesis, we propose a novel negative sign prediction model which includes negative sign related features from various categories to predict negative sign in signed social network. An extensive set of experiments is carried out on real-world social network datasets which demonstrate that the proposed model outperforms the existing method in predicting negative signs in terms of accuracy and F1 score(is a measure of a test's accuracy) by $3\% \sim 4\%$ and $5\% \sim 15\%$ respectively.

Dedication

I would like to dedicate this thesis to my parents, Ashish Sanghvi and Richa Sanghvi without their support I would not have made it this far, my loving brother Jash Sanghvi, my family and friends.

Acknowledgements

I would like to acknowledge the enormous support I have been given by my parents and family members Ashish Sanghvi and Richa Sanghvi to conduct this research.

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Background

One of the inherent possible advantages of social media is that one can take a deep insight into one's life because people use it as a platform to open up on different opinions on social media with their views, feelings, thoughts and their beliefs. They may express their opinions in different ways by liking or disliking because different people have different opinions on a particular topic. Social networks that have information about this type of relations (positive or negative) between users are called Signed Social Networks (SSNs). In real-world applications, many social networks are signed social networks, i.e. relations between nodes of such social networks having positive or negative signs. A positive sign means that two end nodes of the network are linked positively, such as trusting each other, becoming friends or agreeing with each other. Whereas, negative sign means that two end nodes of the network are linked negatively, e.g. they dislike each other, they are rivals, or they disagree [39].

The increasing availability of large-scale signed social networks can be widely used in many applications such as link prediction[32], community detection[35], recommender system[11]. The vast majority of current research has centered on social networks with only positive links. That is because positive signs are easier to predict than negative signs[41]. Also, positive signs can be propagated among social network users. For example, if A trusts B and B trusts C, A would somehow trust C. The specification of negative sign is interesting in its own way. While negative signs can not be propagated among social network users, which makes the prediction of negative signs more complex. For example, if A distrusts B and B distrust C, it is difficult to explicitly determine the ties between A and C. Hence, it is necessary and interesting to know more about negative sign prediction. Secondly, the number of datasets available to the public for negative sign prediction research is limited[43].

From recent research, it is evident that in various analytical tasks negative links have substantial added benefit over positive links. For example, Guha et al. tried to improve positive link prediction using small amount of negative links[18]. Victor et al. also attempted to improve the performance of the recommender system in social media using negative signs[42]. Similarly, trust and distrust relations in Epinions can help users find high-quality and reliable reviews[18]. In addition, the specification of negative links is interesting by itself.

Previous work [15] [22] [50] [47] [3] of negative sign prediction is based on two theories i.e. Social status theory[33], Structural Balanced theory[10], or both. Social status theory and Structural balance theory analyze the triad relationship between network nodes, including positive relationships and negative relationships. The social status theory is based on the assumption that a positive link from source node to destination node means that the source node believes it has a lower status than the destination node, and a negative relation from source to target suggests that the source node believes it has a higher status than the target node. Therefore it defines eight balanced triad relationships in signed networks. Whereas, the Structural Balance Theory regards the enemy of enemy as a friend, and considers the enemy of friend as an enemy. It considers four potential triad relationships in signed networks, with positive and/or negative relationships. Two of these triad relationships are called balanced[33]. However, the features developed in current works only represent partial knowledge related to negative signs, leading to limited predictive accuracy of negative signs. Although this issue is very challenging, the effects of such an approach have the potential to increase the efficiency of a wide variety of applications arising from it by considering various features in different aspects of signs to achieve better predictive results in negative sign prediction problems.

1.2 Problem Definition

Researchers predicted signs by using negative triad features like Structural Balance Theory[10], Status Theory[33], or both. But they only involve partial information related to negative signs, which leads to the limited prediction accuracy. To solve the issues, we propose a novel negative sign prediction model which includes negative sign related features from various categories to predict negative sign in signed social network. The proposed model is aimed to predict negative sign from negative sign related features of different categories.

Formally, we define our problem as follows:
Let G=(V,E) where V is set of nodes presenting users of signed social networks and E is set of edges presenting connections between nodes of signed social network. e_{uv} is the edge pointing from node u to node v, $e_{uv} \epsilon E$. e_{uv} does not necessarily mean equal to e_{vu}, i.e. edges have directions in the signed social networks and G is a directed

graph. e_{uv} has three possible values, which is described as follows:

$$e_{uv} = \begin{cases} 1, & u \text{ likes/trusts/agrees } v \\ 0, & \text{no relationship between } u \text{ and } v \\ -1, & u \text{ dislikes/distrusts/disagrees } v. \end{cases}$$

In first condition, $e_{uv} = 1$ represents the positive sign link from u to v. In second, $e_{uv} = 0$ represents there is no relationship or linkage between two nodes. i.e. u and v. In last, e_{uv} = -1 represents the negative sign link from u to v. Our goal of negative sign prediction is to predict the sign in last case e_{uv} = -1.

The negative link prediction problem in this paper is unique and much more complex than the current positive/ negative sign prediction existing methods [26], and the sign prediction problem[45].

1.3 Motivation

In social networks, relations among members not only exhibit friendship and cooperation, but also hostility and competition. Positive and negative links were used to describe cooperative (friendly/trustful) and competitive (hostile/distrustful) relationships, respectively. Assigning signs to links were a significant way of including additional information to networks than traditional binary or weighted approaches. One of the challenges in signed networks is inferring the signs of unknown relations that is often referred to as sign prediction, which reveals the underlying relationships between social members. Therefore, it can be widely used in many applications such as recommendation systems and abnormal user detections etc.

Sign prediction is the problem of inferring those hidden signs using the information provided by the rest of the network. It is similar to link prediction, which is a well-studied problem in traditional unsigned social network analysis. However, compared with link prediction, sign prediction is still in its beginning stage due to the following difficulties:

- Positive signs are easier to predict than negative signs. As Positive signs can be propagated between members of social networks while negative signs cannot. For example, A trusts B and B trusts C, A will trust C to some extent, while A distrusts B and B distrusts C, it is hard to judge the relationships between A and C directly.

- The number of publicly accessible databases for research into negative sign prediction is limited because members of social networks rarely express their antipathy to others for fear of being retaliated.

So the negative sign prediction became a difficult problem in the field of sign prediction. Therefore, it motivates us to do in-depth study and mining of the formation mechanism of social network which is the key to improve the accuracy of negative sign prediction.

1.4 Thesis Statement

The majority of research is done using the information that has been derived from Structural Balance Theory[10], Status Theory[33], or both, but it is not sufficient, so it is necessary to consider both triad features from the previous and the optimized features that we get on basis of weight matrix and time complexity for better prediction performance. Though existing model performs well in predicting negative sign, they only involve partial information related to negative signs, which leads to the limited prediction accuracy.

So we hypothesize that if we include negative sign related features, other than triad features from various categories, we expect to see better negative sign prediction accuracy. Also, we believe that an important step in developing predictive models is determining the best features to be used for building the models but for that we need to find optimal features so as to see the reduction in cost and also making it more efficient.

To solve such issues, we designed a new negative sign prediction system that consists of two components with one components that extract the optimized features on basis of time complexity and weight matrix and the other component that can more reliably predict the negative signs from signed social network.

1.5 Thesis Contribution

The main contributions of this research can be summarized as follows:

- We design a negative sign prediction framework for predicting negative sign in signed social networks. The proposed model is aimed to predict negative sign from negative sign related features of different categories.

- We have taken into consideration some of the optimized negative sign related features from various categories based on the weight matrix and time complexity to get the better prediction performance.

- Our proposed architecture provides a general idea of how the prediction process works in a network for predicting negative signs.

- We experimentally demonstrate that the proposed model can efficiently predict negative sign in a network and outperform existing state-of-the-art methods on few standard datasets.

1.6 Thesis Organization

The rest of the thesis / research work is structured as follows.

In chapter II, we introduce background knowledge of Signed Social Networks and its various perspective. We also discuss its characterization, feature extraction, and model construction.

In chapter III, we discuss the related work/literature review in the field of Negative sign prediction using different features.

In chapter IV, we explain the detailed description of the proposed method and introduced our architecture model for Negative Sign prediction.

In chapter V, we present the experimental setup and statistical analysis of different types of data set used for the experiment with its assumptions.

In chapter VI, we compare our work with other state-of-the-art methods and a detailed analysis of the observations is done.

In chapter VII, concludes the research, explaining the insights received during the work and setting up a wide range of opportunities for the future work.

Chapter 2

Online Social Networks

2.1 What are online social networks?

We begin by describing online social networks, offering a brief overview of their rise in popularity, and explaining the tools that today's online social networks offer for users to communicate and exchange information.

2.1.1 Definition and purpose

We describe an online social network as a platform where (a) users are first class individuals with a semi-public identity, (b) users are able to create an online social network and express links to other users or content items, and (c) users can navigate the social network by browsing the links and profiles of other users. This definition is consistent with the description used in previous studies[7].

Online social networks have a variety of functions, but three main tasks are consistent to all pages. First, online media networks are used to preserve and improve established social connections or to build new social relations. Sites encourage users to "articulate and make accessible their social networks" and thereby "communicate with others who are already part of their expanded social network"[7]. Second, online social networks are used by each user to post their own content. Notice that information posted also varies from site to site, and is often just the user's own profile. Third, online social networks are used to find new and interesting content by filtering, recommending, and organizing the content submitted to consumers.

2.1.2 A brief history

We are now offering a short overview of online social networks. Classmates.com[] is known to be the first website to allow people to link to other people. It launched in 1995 as a forum for users to communicate with former classmates and is now closed. There are 40 million registered users. However, Classmates.com did not allow users to link to other users; rather, it allowed users to link to each other only through the schools they attended. SixDegrees.com was created in 1997 as the first social networking platform to enable users to connect directly to other users. As such, SixDegrees.com is the first site to follow the concept of an online social network mentioned above.

Online social networks have started to rise in popularity as more people have become linked to the Internet. A variety of general-purpose sites for finding friends have been developed in the early 2000s, the most prominent of which is Friendster. Friendster was based on encouraging friends-of-friends to connect, beginning as a counterpart to the Match.com online dating platform. Other, related sites produced in the same time frame shall include CyWorld, Ryze, LinkedIn.

MySpace was founded in 2003 as an alternative to Friendster and the others. MySpace has allowed users to heavily customize the appearance of their profile, which has proven to be very common with users , making MySpace quickly the largest online social network. As of this writing, MySpace has 247 million user accounts, more than twice as many as the second most popular network, Facebook. For a more detailed history as well as an study of the evolution of online social networks, the reader is directed to various papers by boyd [8], [4], [7], [6].

With the increase in popularity of online social networks, many other types of sites have begun to include social networking features. Types include digital web sharing platforms like Flickr, YouTube, and Zoomr, blogging sites and BlogSpot. social networking sites like LinkedIn and Ryze, and news aggregations Digg, Reddit, and del.icio.us. Each of these sites have different purposes, but use a similar technique to leverage the social network and enhance their sites. The list above is not intended to be complete, since new pages are being developed on a regular basis. For a more comprehensive and up-to - date list of big online social networking sites, please direct the reader to Wikipedia[44].

Sociological implications of exponential development and proliferation of social networking sites are now the focus of a great deal of scholarship. One of the main reasons for the success of social networking sites is their user-centric nature. Content shared on social networking sites is often information about users themselves, such as their status, photos, and so on. For more info , please refer to boyd, reader of the work[5].

2.1.3 Mechanisms and policies

We are now giving a short summary of the processes and practices that most online social networks have.

Users

Active involvement in online social networks requires users to register their (pseudo) identity with the network, although some sites do allow public data to be browsed without an explicit sign-on. Users can include voluntarily details about themselves (e.g., their birthday, place of residence, preferences, etc.), all of which shape the profile of the consumer.

The social network itself is made up of connections between members. Some sites allow users to link to any other user (without the consent of the link recipient), while other sites follow a two-phase procedure that only allows a link to be established if both parties agree. Some sites, such as Flickr, have social networks with a direct link (i.e. a link from A to B does not imply the presence of a reverse link) while others have a direct link. Some, such as Orkut, have undirected social networks.

Users are connected to other users for a variety of reasons. The purpose of a connection could be a real-world relationship, a business contact, a virtual relationship, someone who has the same passions, someone who uploads fascinating content and so on. In fact, some users even consider the acquisition of many links to be an end in itself[36]. Compared to web links, links in online social networks combine the functionality of both hyperlinks and bookmarks.

Links to the consumer, along with their profile, are typically available to anyone who access the user's site. Users are therefore able to navigate the social network by following user-to - user links, browsing the profile information and any content contributed by the users visited as they go. Such platforms, like LinkedIn, allow for the viewing of accounts within the user's own neighborhood (i.e. the user can only access all users within two hops), whereas other platforms, such as Flickr, allow users to view any other user on the network.

Groups

Most sites often allow users to build special interest groups similar to Usenet[127] newsgroups. Users will add comments to groups (visible to all members of the community) and also upload shared material to the community. Some groups are moderated, and access to the party is regulated by a single community maintainer, while other groups are available to any member to participate. All pages today require specific user group declaration; users must manually set up classes, designate administrators (if necessary) to announce which classes they are part of. Many platforms (such as Facebook) build a few pre-populated groups based on the email address domain of members, but most groups do not fall under this category.

The predominant use of communities in today's networks is either to communicate access management strategies or to provide a platform for shared information. Definitions of the former include sites such as Twitter, which by necessity only require people living in the same geographical area or company to access their profiles. Examples of these are more general, including Flickr 's collaborative photo groups and Orkut 's community apps.

Content

Once an identity is established, users of file-sharing sites will add content to their account. Many such sites require users to label content as public (visible to anyone) or private (visible only to their immediate "friends") and mark content. Many platforms, such as YouTube, encourage users to upload unlimited content, whereas other platforms, such as Flickr, ask users to either pay for a subscription fee or be subject to a upload limit. Usually, the content is immediately stored and, if publicly available, made accessible via a text search. An example of this is the Flickr Photo Search, which allows users to locate photos by searching for tags and comments.

When on the web, users can send their posted content to communities that they are part of. Privacy settings also require material to be available only to members of the community. In addition, sites generally allow users to browse content uploaded to groups of which they are members.

Users are also often allowed to create favorite lists that link to the user's favorite content uploaded by other users. These favorite lists are also generally publicly available on the user's profile page. Similarly, most platforms require users to vote on material, just like a Usenet forum, and comments appear alongside the material itself.

Finally, other pages include the most popular content charts, which include the most popular content items (in terms of the amount of downloads, reviews, or ratings) that have recently been posted. Users can browse these lists to find new content for viewing. A noteworthy example of this is YouTube 's top 100 charts, where visibility is dependent on the amount of likes, reviews, or recommendations the video has recently got.

2.2 Types of online social networks

An online social network is a network where nodes represent individuals and lines between nodes, called edges, represent mutual ties between them, such as friendship or collaborating together on a project. Such networks can be either undirected or guided, signed or unsigned and positvely or negatively signed networks.

2.2.1 Directed and undirected social network

The network is a constellation of nodes connected by a link. These links are naturally mutual in many social networks. For example, if Jon and Jane are friends, this connection or connection has no path. Jon is a colleague of Jane's, and vice versa. Such a network of friendships would be known as an undirected network. Many interactions go in a course. Jon will ask for Jane 's advice, but Jane does not ask for Jon's advice. The connection has a path, from Jon to Jane. As a result, a network of advisory bodies seeking advice is made up of a directed network. Communication via social media produces both directed and undirected networks. In social media, threaded discussion forums are guided, as Bob might respond to Ron's post, but Ron doesn't have to respond. Danielle will follow Michelle on Twitter, providing a directed link from Danielle to Michelle. A connection does not always be mutual, because Michelle is not expected to follow Danielle's Twitter account in order to create a bond between them. When forming a follow-up relationship on Twitter , users form directed networks. The Facebook network of friends, on the other hand, has no direction. One must accept a motion for friendship to form a bond. Bob and Ron are friends on Facebook, and there's no direction to this connection. The Facebook network of friends is thus an undirected one.

Therefore, the directionality of the network is defined by the concept of connections, not nodes. Users in a social media environment that have a variety of networks, some focused and others not. For example , Facebook users form an undirected network by making friends with each other. The same users also form directed networks when they like, comment or share a friend's post, as these activities are forms of directed ties. Hyperlinks sent from one blog to another are directed links on the blogosphere, and therefore the network of blogs connected via hyperlinks is a directed network. Blogs may also be connected by a common tag (e.g. SNA), generating an undirected network of blogs.

The importance of the direction of connections and networks is both methodological and analytical. Conceptually, a direct link defines the direction of the flow (e.g. information, power, social capital, web traffic).Methodologically, as mentioned at length later, certain social network measurement metrics are best adapted to capture key users and connection patterns in directed networks, while others are better suited to undirected networks.

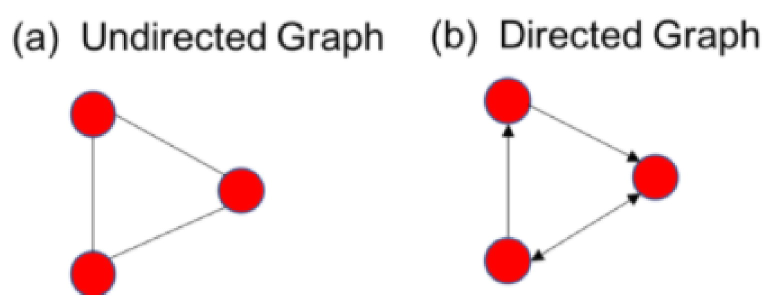


Figure 2.1: Undirected graph v/s Directed graph

2.2.2 Signed and Unsigned social networks

An unsigned social network can be modeled as a guided chart, G=(V,E,A) where V the nodes are set and E is the set of edges. The nodes and edges in the diagram correspond to users and to user relations on social networks. A is an adjacence matrix with $A_{u,v} > 0$ that has a non-negative weighted weight with only if and when the edge $(u, v) \in E$, with $A_(u, v)$ is weight.

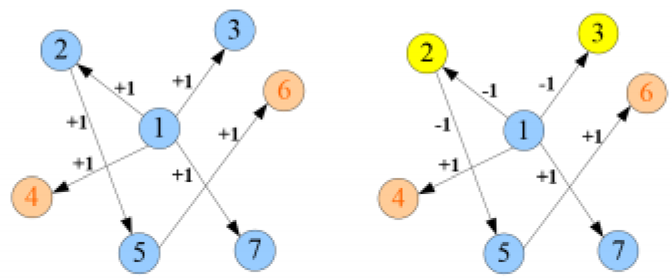
Traditionally, [32], [37], [34], [16] analyzes relationships unsigned by propagating observations via net topology and estimates the link strength of two people. Link analyzes have been thoroughly studied in unsigned social networks (or networks with only positive links). For example , consumers prefer to create positive connections with other people who have such characteristics (Homophilia) or are more likely to become friends with two people physical closer (Confounding). Nevertheless, both positive and negative links can be seen in social media networks. For example, the Epinions with trust / distrust links and Slashdot with friend / foe links are signed social networks. There are a variety of the current principles and properties of unsigned networks in the sense of negative links in signed networks.

There has been growing exposure to the signed social networks for both constructive and negative relations. The aim is to predict the results of group votes rather than the wider organization of the social network. BrzoZowski et al.[9] examined positively or negatively the links between ideologically-based sites like Essembly. Kunegis et al.[24] have researched Slashdot friend and foe relations and calculated global network properties. Signed spectral clustering methods, signed graphic kernels and visualization methods for the network in signed graphs[25] were also studied. Their research was associated with hypotheses of signed social psychological networks[27]. Leskovec et al. Another research by Leskovec et al. used signature triads for the estimation of positive and negative ties, and developed a logistic regression model[26]. In order to use the border sign Information from the source network to predict positive or negative links, Yeet al. adopted the transfer learning approach[46]. Yang et al. also discussed the issue of turning an unsigned information network into a signed trust-discrimination network[45] (e.g. Twitter, Myspace). The structural balance of large signed networks was studied by Facchetti et al. They concluded that the structural balance is now present in most online networks available[13]. None of the above works, however, address the issue of negative signed social networks prediction.

Here, Blue is positive node, yellow is negative, and red is inactive nodes, which can be considered as promoting, opposing for marketing example which will be discussed at last. Unsigned networks are the networks where individuals adopt the opinion of their neighbors with certain probability. According to social theory, people tend to have similar opinions to their friends but opposite of their foes. That is why all the relations between users in this network are considered to be positive[31].

In signed networks, there are both positive and negative relationships. The initially selected nodes in (b) can activate other nodes to be either positive state or negative state, and thus have positive and negative relation simultaneously. Also, if a signed social network is roughly treated as an unsigned social network, both the positive and negative relation will be mistakenly counted as positive[31].

For example: As shown in (a), the number of nodes positively influenced by selecting node 1 will be estimated to be 5 while the actual number is 3 in (b). In this way, in the marketing, if we select the users who have large negative influence (mistaken as large positive influence) to promote the product, as a result, a lot of users will be influenced to dislike and oppose the product[31].



(a) A graph of an unsigned social network (b) A graph of a signed social network

Figure 2.2: Unsigned v/s signed social network[31]

2.2.3 Positive and Negative Signed social networks

There are distinct properties for positive and negative links. When we find positive and negative links together, they pose mutual properties, which can be explained by two important social theories in the signed networks , i.e. equilibrium theory[10] and rank theory [18], [27]. First, we address these mutual properties by incorporating these two social hypotheses, which have been seen to be very beneficial in the mining of signed social networks [27], [45], [52], [23]. For example, the signed cluster coefficient and the relative signed cluster coefficient [24] are defined on the basis of the assumption that "the enemy of my enemy is my friend" is inferred by the balance theory. Remember that balance theory is being formulated for undirected signed social networks, while status theory is being formulated for directed signed social networks.

Balance Theory

This was first developed at the individual level in [20] and expanded by Cartwright and Harary et al.[10]. When the signed network is not limited to complete, the network would be balanced if any of the loops have an equal number of negative connections. Using this definition, it is defined in Harary et al. [19] that "a signed graph is balanced if and only if nodes can be divided into two mutually exclusive subsets, so that each positive link joins two nodes of the same subset and each negative link joins nodes of different subsets." It is difficult to describe a balanced network of real-world signed networks. Davis et al. [12] therefore introduced the notion of clusterizable Graph.

Status Theory

While balance theory is naturally defined for undirected networks, status theory [18], [27] is relevant for directed networks. Social status can be expressed in a number of ways, such as the ranking of nodes in social networks, which represents the prestige of nodes. In proposed method, both balanced and status theory is used.

2.3 Application of social networks

There are many applications of social networks such as Link prediction, community detection, Recommender system, Trust, Distrust and Reputation in Community Detection.

2.3.1 Link prediction

Traditional link prediction approaches used for social networks are massively based on the concept of "friendship". Users in these networks find it difficult to decide among the people they trust from those they do not. Thus, they find it confusing to distinguish between a friend and an enemy. These approaches are therefore not well suited for analyzing and predicting links in SSNs[17].

Scientists have recently begun to examine how to turn an unofficial network of associates into a signed trust / distrust network. A number of accessible networks, such as Epinions, Slashdot, Wikipedia, etc., have now begun to mark connections directly either as a friend / foe or as trust / distrust. A variety of studies in sociology offer a greater glimpse into the basic concepts that describe how cycles of negative and positive links have contributed to various kinds of relationships. According to structural balance theory people in signed networks appear to adopt the notion of FOAF, while status theory is based on the idea of social status that people have throughout a community[17].

Thus, the problem of sign inference, which aims to infer an unknown relationship between two entities, can be achieved by learning from the balance or status information of the signed networks.

2.3.2 Community Detection

Community detection (CD) in a social network is the recognition of a group of nodes that are more closely related to each other than to the rest of the network[17].

Various methods in the literature are presented to address the issue of group identification in social networks. Some conventional clustering algorithms consider communities as a disjointed structure, where as other methods consider communities as interacting systems in real-world networks. Graph partitioning algorithms, hierarchical clustering algorithms have also been used for CDs on social networks, etc. As the CD in the signed social networks is a bit different from the CD in the social networks, its meaning should take into account additional details on the type of connections between members[17], in addition to the links itself, as follows:

Group detection in SSNs aims to partition the network in such a way that each partition will have thick positive intra-connections and sparsely negative intra-connections. One way to do so is to use the modularity principle proposed by Newman[17].

2.3.3 Trust, Distrust and Reputation in Community Detection

A lot of research has been done in recent years on trust and credibility. Trust and mistrust are personal characteristics, while credibility is a public characteristic of a individual or institution. Trust and credibility are important elements of real-world social networks incorporated in most areas, such as preferred systems, e-learning, e-commerce, semantic web, and so on[17].

Researchers have recently started to investigate how to turn the unsigned social network into a signed trust / distrust network. A number of existing networks have already begun to mark connections directly either as friends / foe or as trust / distrust (like Epinions, Slashdot, Wikipedia). To get every web platform or network closer to the real world , it is necessary that trust and integrity must be built into it[17].

2.3.4 Social Recommender Systems

The main objective of Social Recommender Systems (SRSs) is to ease the overload of information on social media users by delivering the most attractive and relevant content / items they are looking for. SRSs that suggest content, people and communities often use customization techniques to adapt the needs and interests of individual users or groups of users[17].

In SSNs, not only are the relationship specifics given, but also the kind of relationship that can be used to make proposed programs easier than current ones, because it would be easy to recommend items to a group of people who have common interests[17].

Chapter 3

Literature Review

3.1 Theories of Signed social network

There are two basic theories in the field of sign prediction. Existing works followed one of those ideas, both of them or expanded them. Those two main theories are:

3.1.1 Structural Balanced Theory

In general, the concept of balance theory[10] is based on the assumption that "Friend-of-a-Friend"(FOAF) and "the enemy of my enemy is my friend", this theory is a notion of understanding the structure, causes of tensions and disputes in the network of users between the two sentiments (positive and negative). There are four configurations possible to label the three edges among three nodes with positive and negative signs. These theory relates the theory of balance of signs on triad which includes three users in a signed social network with positive and negative links. Three nodes named u,v and w are given[26].

(i) Seeing three positive signs from fig 3.1(a), we can say that such nodes are reciprocal of each other.

(ii) Getting a single positive sign and two negative signs as shown in the Fig 3.1(b).It means that two of the three nodes are friends, and in the third node, they have mutual enemy.

(iii) Getting two positive signs and one negative sign as shown in Fig 3.1(c) means that one node is a friend with each of the other two nodes, but these two nodes aren't getting along. There will be implied factors in this situation pushing one negative sign to be positive, or pushing one positive sign to be negative.

(iv) Getting three signs as negative, as shown in Fig 3.1(d). It means the three nodes are enemies of one another. In this case, factors will inspire two of the three nodes to team up to the third (turning one of the three edges to be positive). On the basis of the above logic, triangles with one or three positive signs are considered balanced (i and ii), while triangles with zero or two positive signs are considered unbalanced (iii and iv).

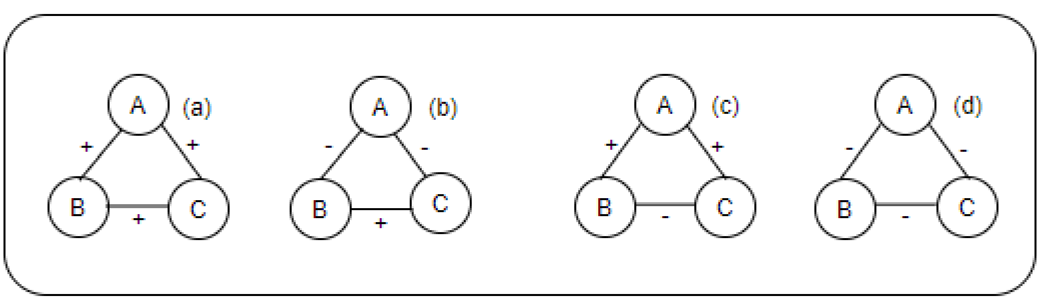


Figure 3.1: Triad relationship for Structural Balanced Theory[10]

3.1.2 Social Status Theory

The Social Status Theory suggested by Guha et al.[18] and developed by Leskovec et al.[27] suggests using a person's status as a factor in determining if a individual should make a link (positive or negative) with another person on the network. Status may be social or it may be economic status.

According to this theory, if a positive link between individual A (creator) and individual B (recipient) is created, then A assumes that B has a higher status than him/her, while a negative link between individual A and B suggests that A considers B to be lower than him/her. It is clear that the status theory is best suited to directed networks[17]. Fig 3.2 gives Status Theory permissible triad relations. Fig 3.2(a), (d), (e) and (h) are similar to the Structural Balance Theory based balanced triad relations, as shown in Fig 3.1(a) and (b). The other four relationships to the triads Fig. 2(b), (c), (f) and (g) are also appropriate triad relationships that have already been validated statistically in the real applications.

Balance Theory vs Status Theory: In order to discern the discrepancy between balance theory and status theory, assume that node A connects negatively to node B, and that node B connects negatively to node C. Now, what would be the sign of a relation between node A and node C? Using the structure of the balance theory, "My enemy's enemy is my friend," the sign of the link between A and C is predicted as positive, while the status theory predicts the sign of the link between A and C as negative. In other words, the outcome of the balance theory in this case differs from the results of the status theory.

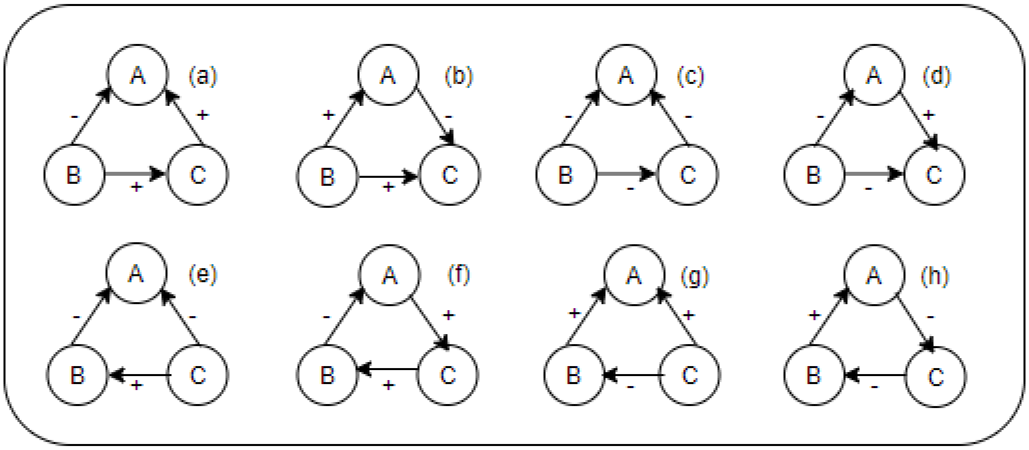


Figure 3.2: Triad relationship for Status Theory[18]

3.2 Related work of Signed social network

Many social media platforms offer unsigned social networks, such as the Facebook Friendship Network and the accompanying Twitter network, although only a few providers offer signed social networks. The role of the sign prediction is to infer the signs of the current connections in the unsigned network. It is difficult , if not impossible, to predict the signs of existing links by using only the unsigned network[45]. As a result, most existing signal predictors use additional sources of information. App engagement information and cross-media information are the most commonly cited outlets.

3.2.1 Sign Prediction with Interaction Data

In this, we are likely to follow the opinions of our friends while battling against the opinions of our enemies. As a result, the choices of users with positive links are more likely to agree, while for users with negative links, the likelihood of conflict will be significantly greater. Users may participate in positive or negative experiences with other people of social media. Positive interactions indicate consensus and encouragement, while negative interactions show differences and antagonism, too. There are strong correlations between positive (or negative) and positive (or negative) interactions[45]. Tang et al. suggest a simple sign prediction algorithm based on the correlation between interactions and linkages. The first step is to initialize interaction-based link signs. Positive signs are used for positive interactions, whereas negative signs are used for negative interactions. First, the link signs are optimized by status theory or balance theory[40]. More advanced algorithms incorporate relation and connection knowledge into coherent frameworks. In[45], a framework with a set of latent factor models is proposed to infer signs of unsigned links that capture the behavior of users, social relations and their interactions. It also sets out the principles of balance and status theories for signed networks. A single-dimensional latent factor i is introduced for u_i, and then we model the sign between u_i and u_j as $Si, j = {}_{ij}$, which can capture balance theory. The vector parameter is introduced to allow users to capture their partial order, and then the status I of ui is modeled as I = i, where i is the u_i's latent factor vector. Status Theory characterizes the u_i to u_j symbol as their relative rank difference I_j = I j. Yu and Xie can consider important similarities and reciprocal effects between user experiences and indicators of ties. We suggest a latent, random graph system for robust simulation of user interface proof and Signs, sir. This technique is used to simulcast user interaction and sign prediction[48][49].

3.2.2 Sign Prediction with Cross-Media Data

In the form of link prediction in signed networks, Leskovec et al.[26] find that the studied link predictors have very high generalization ability across social networking sites. This observation indicates the general guideline that may be rules for sign inference through various networks, including when links have different semantic meanings in different networks[26]. Cross-media knowledge is another valuable source of sign prediction. The goal is to forecast the signals of a reference network using a source-signed network. The general method is to gain information or trends from a source-signed network and use it to forecast linkages signs on the goal network. The vast majority of algorithms in this family are using transfer learning to achieve this goal. One representative way is to build generalizable features that can transfer patterns from the source network to the target network for sign prediction. Because some social theories, such as status and balance theories, are common to all signed networks, it is possible to derive generalizable features proposed by social theories, such as balance and position theory. A factor-graph in [38] Model is trained with the characteristics of the source network to predict the signals of the target network.

3.3 Related works of Negative signed social network

Existing negative sign prediction works [3], [14], [22], [47] to adopt or extend these theories. We train their models on the basis of various features extracted from signed social networks, including triad features originating from Structural Stability Theory or Rank Theory. While various researchers have suggested different methods of negative sign prediction, the method proposed by Leskovec et al.[26] is by far the most common method of negative sign prediction. This approach is used as the basis for the negative sign estimation, and the performance of the new method is compared with the performance of this method.

Chapter 4

Proposed Methodology

In this chapter, we will provide a brief summary and a detailed description of the two main components of the proposed model: Sign predictor Feature extractor and Sign predictor. Subsections below describe the importance of these two components for the prediction of negative signs in a network.

4.1 Proposed Architecture

Here we introduce our model for predicting negative sign in signed social networks. The architecture of the proposed negative sign prediction method is shown in fig 4.1. The basic idea behind our model is to predict negative sign in a network using feature extraction.

4.2 Proposed model overview

The main contribution of the paper is to design a negative sign prediction framework. The proposed model is aimed to predict negative sign related features of different

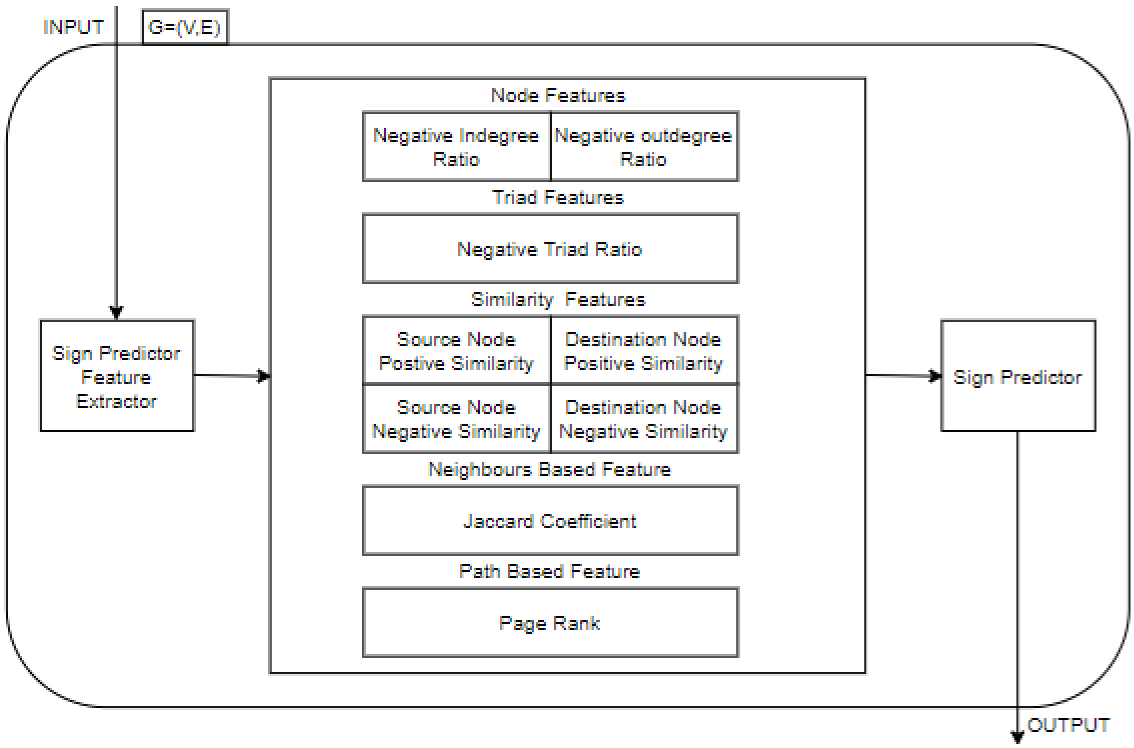


Figure 4.1: Architecture of proposed model

categories. The proposed model contributes to generalize five main categories: Nodes features, triad features, similarity features, Neighbor based features, and Distance-based features. Feature representation from all these is finally used for negative sign prediction.

We divided our model into two main components:

- First, Sign Predictor Feature extractor and Sign Predictor. Sign predictor feature extractor is used to extract five category based features from signed social network. It extracts features from source node and destination node of the link.

- Second, Sign predictor is used to predict negative signs based on the features extracted from signed Predictor feature extractor component from signed social network

4.3 Sign Predictor Feature extractor

We extract five types of features corresponding to node features, triad features, User-Similarity features, neighbour based features and distance based features. The extracted features are described as follows:

4.3.1 Node features

Node features reflects the characteristics of source node and destination node. They are extracted from each node including nodes Indegree or outdegree. Negative Indegree Ratio is defined as ratio of nodes negative indegree to its total indegree. Whereas, negative outdegree ratio is the ratio of nodes negative outdegree to its total outdegree[51]. To evaluate the sign of link from node(u, v), we calculate $NOR(u)$ and $NIR(v)$ as follows:

$$NOR(u) = \frac{d^-_{out}(u)}{d^+_{out}(u) + d^-_{out}(u)}$$

$$NIR(v) = \frac{d^-_{in}(v)}{d^+_{in}(v) + d^-_{in}(v)}$$

Since we are interested in estimating the sign of the edges from u to v, we call outgoing edges from u and incoming edges to v. In particular we use $d^+_{out}(u)$ and $d^-_{out}(u)$ to represent the number of outgoing positive and negative edges from u respectively. And similarly, we use $d^+_{in}(v)$ to denote the number of incoming positive and $d^-_{in}(v)$ incoming negative edges to v.

Outdegree of a user means the number of other users that the active user has trust or distrust in. The higher the negative outdegree ratio of a user, the more likely he is to mistrust other users.An indegree of a user corresponds to the number of trust or mistrust of other users directed to the active user. The higher the negative indegree ratio for a user, the more people appear to be distrustful of that user. For a node u to node v, the more negative ties u give out, or v gets, the more likely the sign of the relation from u to node v is negative.

4.3.2 Triad features

Triad features express the characteristics of nodes according to social status theory and structural theory. The structural details of the links affects the sign prediction in signed social networks according to both Structural Balance Theory and Status Theory. Hence, we use the negative triad ratio to reflect the link's structural details.

Two heuristic optimisation approaches are used to determine the degree to which each of the three networks has global balance and status properties which is describe in [26] work.The signed social network includes two kinds of negative triads. The negative triad ratio of (u, v) means the ratio of negative triads between node u, node v and their common neighbours over all triads between node u, node v and their common neighbours. The higher the negative triad ratio (u, v) gets, the more often it is the negative sign of the relation between (u, v).

$$NTR(u,v) = \frac{\sum_{w \epsilon W} I(Sign(u,w) \times Sign(v,w))}{|W|}$$

where W denotes the neighbours of node u and node v, —W—represents number of common neighbours u and v, and (I) represents the number of negative triads needed to be unique from Sign(u, w) and Sign(v, w).

4.3.3 User-Similarity based features

User-similarity based features is used to express the similarity between user(source node) receiving or giving negative signs from/to the another user(destination node). It include source node positive and negative similarity and destination node positive and negative similarity respectively. The principal concept in these features is to evaluate a score for each connection pair (u,v) in the graph.To predict the sign from user u pointing the link toward user v, four neighbour similarities are considered in this work[51].

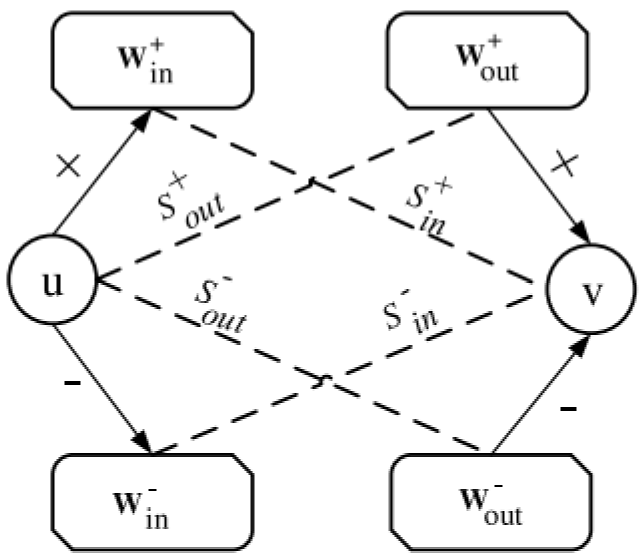


Figure 4.2: Neighbour similarity between users.

Source node positive similarity $S^+_{out}(u, v)$ is the average similarity of u to nodes that provide positive links to v.

$$S_{out}^{+}(u,v) = \frac{\sum_{w \in W_{out}^{+}} \mathrm{sim}_{out}(u,w)}{\left|W_{\mathrm{out}}^{+}\right|}$$

$$Sim_{out}(u,w) = \frac{\sum_{i \in I_{out}} r_{u,i} r_{w,i}}{\sqrt{\sum_{i \in I_{out}} r_{u,i}^2 \sum_{i \in I_{out}} r_{w,i}^2}}$$

For $S_{out}^{+}(u,v)$, where W_{out}^{+} is the set of nodes which give positive links to v, $Sim_{out}(u,w)$ is the similarity between node u and node w, which is a neighbor of node v. This work uses cosine similarity to calculate the user similarity between users. For $Sim_{out}(u,w)$, where $r_{u,i}$ and $r_{w,i}$ are the sign of the link pointing from node w and node u to node i respectively, and I_{out} is the set of nodes which u and v both gives link to.

Source node negative similarity $S_{out}^{-}(u,v)$ is the average similarity of u to nodes that provide negative links to v.

$$S_{\mathrm{out}}^{-}(u,v) = \frac{\sum_{w \in W_{\mathrm{out}}^{-}} \mathrm{Sim}_{\mathrm{out}}(u,w)}{\left|W_{\mathrm{out}}^{-}\right|}$$

where W^{out} is the set of nodes which give negative links to v, and $Sim_out(u,w)$ is the similarity between node u and node w, which is calculated by[21].

Destination node positive similarity $S_{in}^{+}(v,u)$ is the average similarity of v and the nodes that receive positive links from u.

$$S^{+}_{in}(v,u) = \frac{\sum_{w \in W^{+}_{in}} \mathrm{Sim}_{in}(v,w)}{|W^{+}_{in}|}$$

For $S^{+}_{in}(v,u)$, where W^{+} in is the set of nodes u gives positive links to and $Sim_{in}(v,w)$ is the similarity between node v and node w, which is a neighbor of node u.

$$\mathrm{Sim}_{in}(v,w) = \frac{\sum_{i \in I_{in}} r_{i,v} r_{i,w}}{\sqrt{\sum_{i \in I_{in}} r^2_{i,v} \sum_{i \in I_{in}} r^2_{i,w}}}$$

For $Sim_{in}(v,w)$, where $r_{i,v}$ and $r_{i,w}$ are the signs of the links pointing from node I to node v and node w respectively, and I_{in} is the set of nodes which v and w both receive link from.

Destination node negative similarity $S^{-}_{in}(v,u)$ is the average similarity of v and the nodes that receive negative links from u.

$$S^{-}_{in}(v,u) = \frac{\sum_{w \in W^{-}_{in}} \mathrm{Sim}_{in}(v,w)}{|W^{-}_{in}|}$$

For $S^{-}_{in}(v,u)$, where W in is the set of nodes u gives negative links to and $Sim_{in}(v,w)$ is the similarity between node v and node w.

$$P(+ \mid \mathbf{x}) = \frac{1}{1 + e^{-(\mathbf{w}^T \mathbf{x} + b)}}$$

For prediction of sign P(+—x), where x is the vector of features, including $NOR(u)$, $NIR(v)$, $S^+_{out}(u,v)$, $S^-_{out}(u,v)$, $S^+_{in}(v,u)$ and $S^-_{in}(v,u)$, w is the vector of weight assigned to each feature, and b is a constant number.

4.3.4 Neighbour based features

Neighbour based feature is used to collect information from the interactions of two nodes with neighbours for each edge in E which connects u and v. Here we have used Jaccard coefficient to evaluate common neighbours. It is evaluated as the ratio of common neighbours by the total nodes of combined neighbours[2].

$$JC(u,v) = \frac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u) \cap \Gamma(v)|}$$

4.3.5 Path based features

Within a social network a path between two users has useful information about their relation, such as closeness or friendship. We have evaluated the page rank of each node using the centrality function which is the ratio of time spent at a particular node while randomly traversing the graph. There are three distinct factors which decide a Page Rank of the node: (i) the number of links it receives, (ii) the linker tendency to link and (iii) the linker's centrality[2].

Page Rank describes the possibility of using a random walk across the graph to reach a node.

$$P(u) = (1 - d) + d \sum_{z \epsilon \Gamma(u)} \frac{P(z)}{|\Gamma(z)|}$$

where d is depreciation factor, the probability of reaching neighbouring nodes rather than restarting the initial node u is indicated.

4.4 Sign Predictor

This model extract features for the particular node and the target node of the link. It predicts the negative sign on basis of feature extracted using using Sign prediction feature extractor from signed social networks. On the basis of above mentioned features belonging from 5 different categories, sign predictor component uses Support Vector Machine(SVM) classifier to classify the sign between links from source node to destination node into two classes.i.e.Positive and Negative.

Support Vector Machine (SVM) was introduced in 1979 (Vapnik, 1982). This algorithm has been shown to support both classification and regression tasks and has therefore grown in popularity over the years. The basic concept of this algorithm is as follows: in the context of an input vector, find a hyperplane (boundary) that separates a set of objects that have memberships of the class. This raises the question of how do we find a good hyperplane that not only separates the training data but also generalizes well-as not only will all the hyperplanes that separate the training data automatically separate the test data[42]. The optimal hyperplane for this work can be defined as a decision function with a maximum margin between positively signed

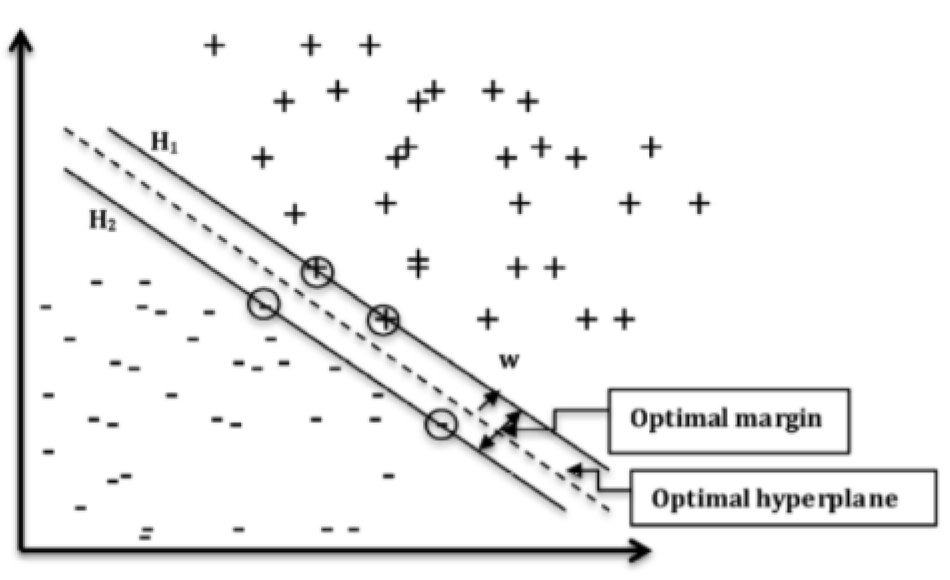


Figure 4.3: Support vector(circled) shows the margin of maximal separation between two classes

vectors and negatively signed vectors[1].

In this Algorithm 1, it states that when we input the data, we expect to get the outcome in terms of prediction of signs. First, we load the dataset N on which we did the preprocessing step where we filtered our data like cleaning, normalization etc. to get the new matrix after the preprocessing step. Here, we extract the feature matrix and will wait till we extract all the efficient features and we get the create a feature matrix on basis of weighted matrix, time complexity and similarity features where we set the ratio of negative triad between 0 and 1. Again we get a new matrix where we apply SVM classifier in which we divide and train our model with 80% of knowledge and test it on 20% and we get a new matrix on which classification of sign is done in terms of positive and negative signs.

Inputs : Load dataset N
Output: Prediction of sign
begin
Load dataset N.
Apply preprocessing step on N matrix $(N_1, ..., N_{n-1})$.
Create new matrix M, where $M = (N - (preprocess))$.
Extract feature matrix P(M,N) and create feature $P(M_i, N_j)$.
Wait();
Create feature matrix based on $P(M_i, N_j)$ and similarity features.
Set Negative triad ratio between 0 to 1.
New feature matrix $Q(M_i, N_j)$.
Apply SVM on feature matrix.
Divide data in training and testing (8:2), where
Training set $(x_i, y_j, i, j = 1, 2, ...)$
Weights $(q_i, i = 1, 2, ...)$
New matrix $C = (X_c, Y_c)$ and classify sign.
end

Algorithm 1: Pseudocode of proposed method

4.5 Case scenario

Different case scenarios are considered when evaluating the features.

4.5.1 Scenario 1 using Triad features

First, we consider a scenario in an ideal signed social network. As shown in Figure 4.4, there are five users ($u1 \sim u5$) who are connected by a social network. The label of each social tie represents positive semantic (denoted as '+') or negative semantic (denoted as '-'). The ideal signed social network means that most edges in the network have been labeled. So we can acquire abundant evidence to predict new signed links (denoted as dashed). Here we can use social psychology theories, such as balance theory and status theory, to infer some new links. For example, we can infer a link labeled as "negative" from u1 to u3. It is consistent with the intuition that "the enemy of my friend is my enemy". Besides the tie from u1 to u3, lots of new links can be inferred as positive or negative. Therefore, by using the traditional techniques for sign prediction, we can acquire a better result for the ideal signed social networks.

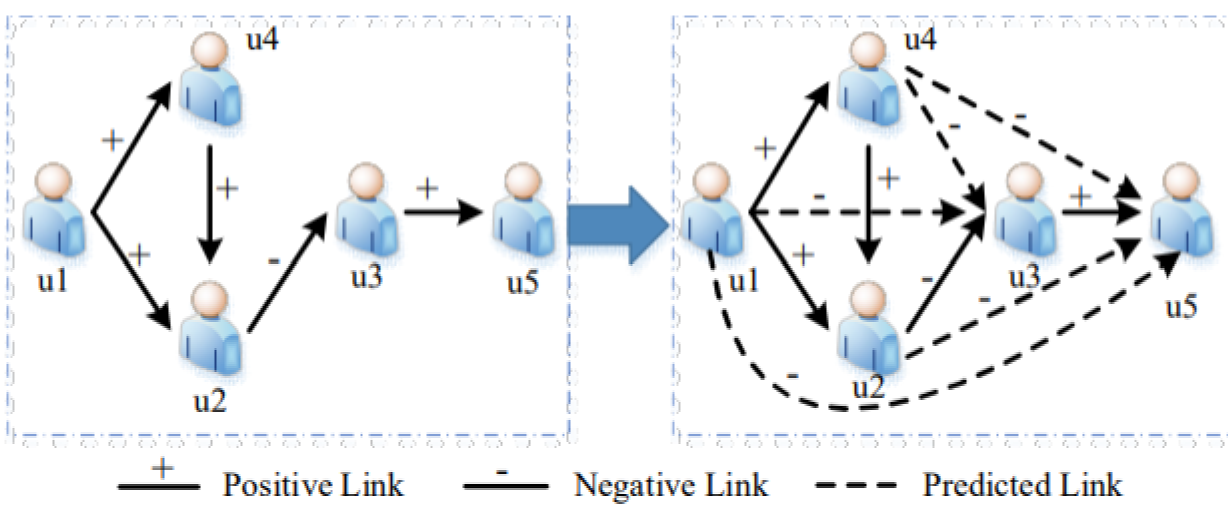


Figure 4.4: Scenario 1[30]

4.5.2 Scenario 2 using Neighbor based features

Now we consider the case of sign prediction in incomplete (i.e. non-ideal) signed social networks (shown in Figure 4.5). Here an incomplete network means that only a small fraction (e.g. lower than 10%) of the signed links is given. Most links are unlabeled in an incomplete network. In fact, there are usually less explicit signed links in mainstream online social networks. We focus on the question whether the traditional sign prediction approaches are still effective to infer signed ties in the absence of many labels, especially in the case that most of the labels are missed. However, most existing methods for sign prediction tend to rely on the features of labeled ties. Due to scarce labeled links in incomplete networks, there is inadequate evidence for them to make prediction. Similar to Scenario 1, we also use social psychology theories to predict links. As shown in Figure 4.5, only one link labeled as “positive” from u4 to u2 can be predicted.

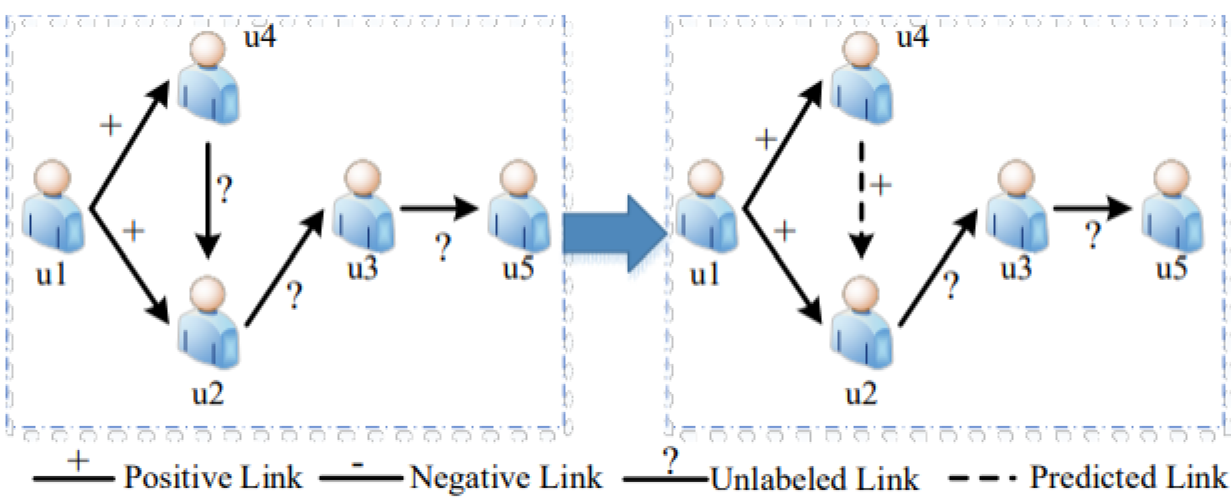


Figure 4.5: Scenario 2[30]

4.5.3 Scenario 3 using user behaviour features

Now let us see what will happen to sign prediction if we consider users' behavior. Based on Figure 4.5, suppose the heterogeneous information network after adding users' behavior (items and ratings) is shown in Figure 4.6. It includes not only the labeled (or unlabeled) social ties between users, but also the ratings which users express on some items. For example, u2 expresses ratings (3, 4, 5) on items I1, I2 and I3 respectively. For example, If statistics indicated that the majority (almost 90%) of positive links indeed show positive behavioral correlations. Also, almost 40% of the negative links, the signs of relations are consistent with the signs of behavioral correlations. Therefore, we can use behavioral correlations to infer the signs of links between users. Due to negative behavioral correlation between u2 and u3, there is a higher probability that u2 distrusts u3 as well. On the contrary, due to positive behavioral correlation between u3 and u5, it is more likely to lead to a positive link from u3 to u5. Further, based on the social psychology theories, we can acquire the same result as Scenario 1.

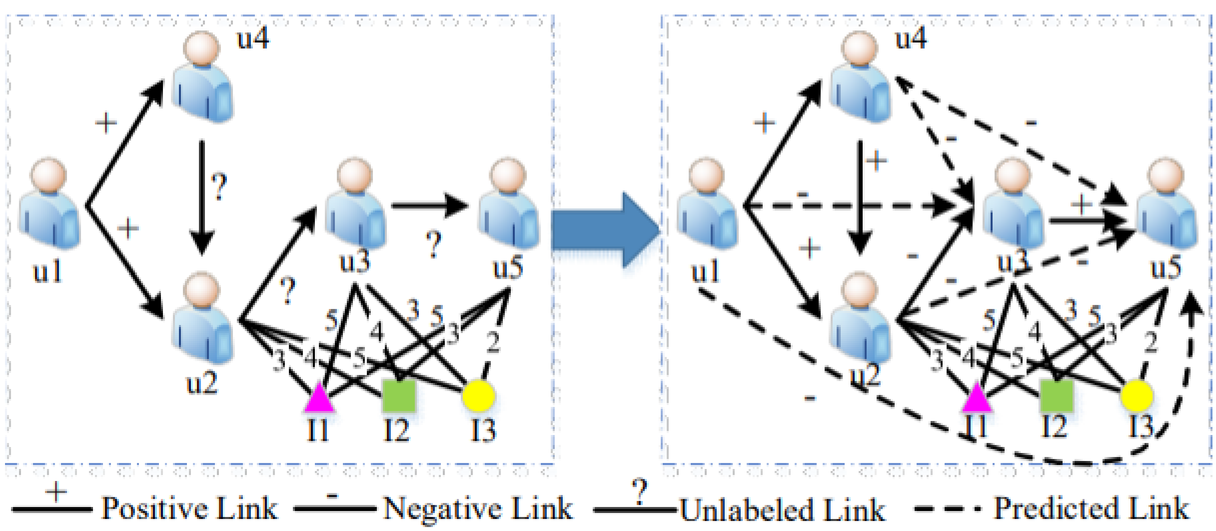


Figure 4.6: Scenario 3[30]

In this scenario, let us see what links' signs do to users' behavior prediction. Based on Figure 4.6, suppose we want to infer the behavior of u4. If we only consider the acquaintance relationship between users rather than links' signs (as is the case with most recommendation technologies in social networks), u2, u3 and u5 will be used to infer u4's behavior due to their adjacency to u4. But in fact, only u2 is the user whom u4 trusts and has the similar behavior with u4. While u3 and u5 will not promote the behavior prediction of u4, even though they will have a negative effect on it. Therefore, the behavior of one user is only similar with the users whom he trusts rather than whom he knows.

Path based features works on whole network and node features are individual to each node. At last, considering all this scenarios for each features we extracted feature vector which is passed for sign classification.

Chapter 5

Experiments

In this section we explain all the six real world datasets on which we performed our experiments. We then briefly discuss the state-of-the-art approaches to fake news detection. We are also exploring various training variants of our proposed model. Finally we are demonstrating the effectiveness of our proposed model. Comprehensive data-set statistics are provided in Table 5.1.

5.1 Dataset Collection

The datasets used for this study comprise of papers delivered at two main conferences: the International Semantic Web Conference (ISWC) and the Neural Information Processing Systems (NIPS). This was pulled from the computer science archive platform between 2007 and 2014. The main data includes the number of nodes, number of edges, number of positive and negative links. Throughout our research, we divide up the connections to prove that they have positive and negative links in a network in order to utilize this dataset effectively.

5.2 Dataset description

We consider six real world online social network datasets to verify the performance of our proposed method. Here each link is explicitly labeled as positive or negative: Epinions, Slashdot, Wikipedia, Wiki-vote, Gplus and Twitter. The datasets are publicly available at[36].

- **Epinions**

  Epinions is a Web site for product review with a very active user group. Users are linked to a trust (positive) and distrust (negative) network, which is then paired with assessment scores to assess which reviews are most authoritative. They can write reviews on specific products and other users can share their feedback on these reviews using 'helpfulness' scores 1 to 6. The data spans from the site's launch in 1999 until 12 August 2003[28].

- **Slashdot**

  Slashdot is a Web site with topics relating to technology. In 2002 Slashdot launched the Slashdot Zoo which allows users to tag each other as 'friends' or 'foes.' A signed link's semantics is identical to Epinions, because a friendly relationship means a user likes comments from another user, whereas a foe relationship means a user considers comments from another user uninteresting[28].

- **Wikipedia**

  Wikipedia is an encyclopedia freely written, with an involved user base. The network we are researching correlates to votes casted in elections by Wikipedia users to appoint individuals to the position of administrator. A signed relation shows a positive or negative vote on the advancement of another by one person (positive for a vote in favor and negative for a vote in opposition). Using the new full Wikipedia page edit history dump (as of January 2008) we extracted all data on administrator preference and voting history[28].

Total number of content	**Nodes**	**Edges**
Epinions	131828	841372
Slashdot	82168	948464
Wikipedia	7115	103689
Twitter	81306	1768149
Gplus	107614	13673453
Facebook	4039	88234

Table 5.1: Statistics of data

- **Twitter**

  From Twitter, we have gathered data from 1,000 ego-networks, comprising of 4,869 circles and 81,362 users. The ego-networks we have built vary in scale from 10 to 4,964 nodes. Also, twitter data is classified only in part, in the sense that we only have access to popular circles[29].

- **Gplus**

  We received data from Google+ from 133 ego-networks, consisting of 479 circles and 106,674 users; The 133 ego-networks represent all 133 Google+ users who had shared at least two circles at the time of our crawl, and whose network information was available to the public. The Google+ circles are very different from those of Facebook, in the sense that their developers have opted to release them publicly, and as Google+ is a network that is driven. For example, one circle involves candidates from the 2012 Republican Party. Primary, who are not likely to follow their followers or follow each other[29].

- **Facebook**

  Facebook is an online social networking website from where we have received profile and network data from 10 ego-networks, consisting of 193 circles and 4,039 people. To do this we developed our own Facebook application and carried out a survey of ten users asked to manually label all the groups their peers belonged to. Users have identified on average 19 circles in their ego-networks, with an average circle size of 22 friends. Types of these groups include common university graduates, sporting teams, relatives etc[29].

  Originally,Epinion dataset is based on reviews where 0 to 6 points. We divide into positive label (0-3) and negative label (4-6). Slashdot is label as friends and foes. Wikipedia is label as positive ties and negative ties. A class of social networks is those with both positive (friendship or trust) and negative (enmity or distrust) links. Other datasets are unlabeled and were extract features by unsupervised method.

5.3 Evaluation functions

The accuracy of the negative sign prediction and the F1 Score are examined to evaluate the efficiency for the proposed model. Predictive accuracy of the negative sign is defined as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

where TP, FP, TN, FN are shown in table II.

where F1, Precision and recall are defined as follows:

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall}$$

	Positive	**Negative**
Predicted class (Positive)	TP (True Positive)	FP (False Positive)
Predicted class (Negative)	FN (False Negative)	TN (True Negative)

Table 5.2: Parameters used for calculating F1 and accuracy

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

To get better performance of F1, recall and precision of the negative sign prediction shall be maximized, i.e., to maximize the true positive cases and minimize false positive cases. Since the proposed model predicts negative signs for the signed social networks, we regard negative signs as positive cases to get the F1 score. To achieve the performance of parameters of negative sign prediction the true positive cases should be maximized while false positive cases should be minimized[51].

Chapter 6

Results and Analysis

We will discuss the toolkit and the conditions in which the tests are conducted in this chapter. We then compare and examine the results from the previous research and our proposed methods by carrying out various experiments.

6.1 Implementation environment

The environmental details and toolkit used for the implementation are outlined in this section.

6.1.1 Software and Hardware configuration

The implementation of proposed methodology was performed on Processor: Intel(R) Core(TM) i3 and 8 GB RAM, running under Windows 10 operating system. The experiments were performed in MATLAB 2018R.

Item	Detail
OS	Windows 10 (64-bit)
Processor and storage	Core i3 ,8 GB
Language	MATLAB
IDE	MATLAB R2018a

Table 6.1: Implementation environment

6.2 Performance Comparison

In this section, we have compared our results with that of Leskovec et al[26] and Yuan et al.[51] methods to prove the efficiency of our model in predicting negative sign for a given network in signed social networks.

6.2.1 Performance comparison on Epinions dataset

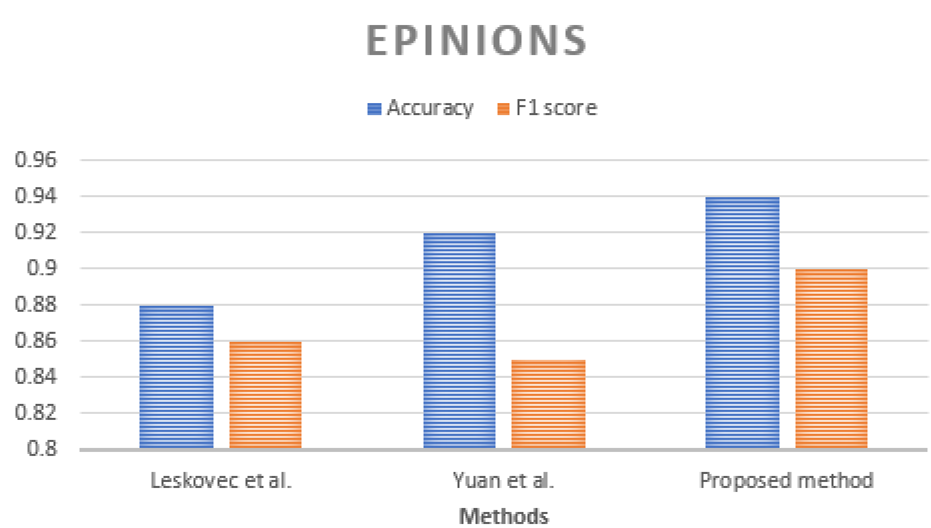


Figure 6.1: Comparison between existing methods[51] [26] and proposed method

Epinions is a website for product review dataset with 131828 nodes and 841372 edges. Existing methods are compared with our proposed method which shows that results that we achieved showed efficient result which help in predicting negative sign for a given signed network in terms of Accuracy and F1 score. Other latent methods are showing lower performance than most of the heuristic methods for prediction purposes. The State-of-the-art sign prediction methods are showing similar results as most heuristics. Our proposed method outperforms all methods compared and showing efficient prediction performance than other heuristics methods.

6.2.2 Performance comparison on Slashdot dataset

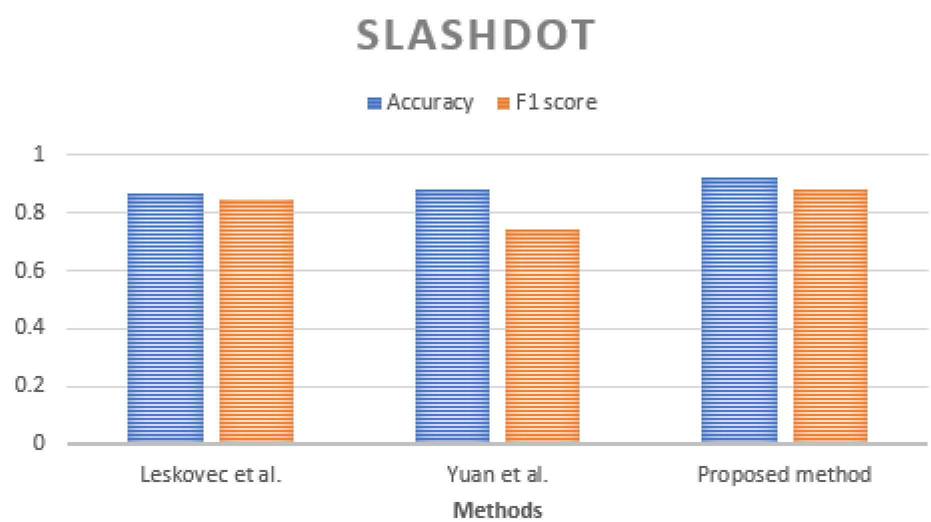


Figure 6.2: Comparison between existing methods[51] [26] and proposed method

Slashdot is a website with topics related to technology with 82168 nodes and 948464 edges. Existing methods are compared with our proposed method which shows that results that we achieved showed efficient result which help in predicting negative sign for a given signed network in terms of Accuracy and F1 score. Other latent methods are showing lower performance than most of the heuristic methods for prediction purposes. The State-of-the-art sign prediction methods are showing similar results as most heuristics. Our proposed method outperforms all methods compared and showing efficient prediction performance than other heuristics methods.

6.2.3 Performance comparison on Wikipedia dataset

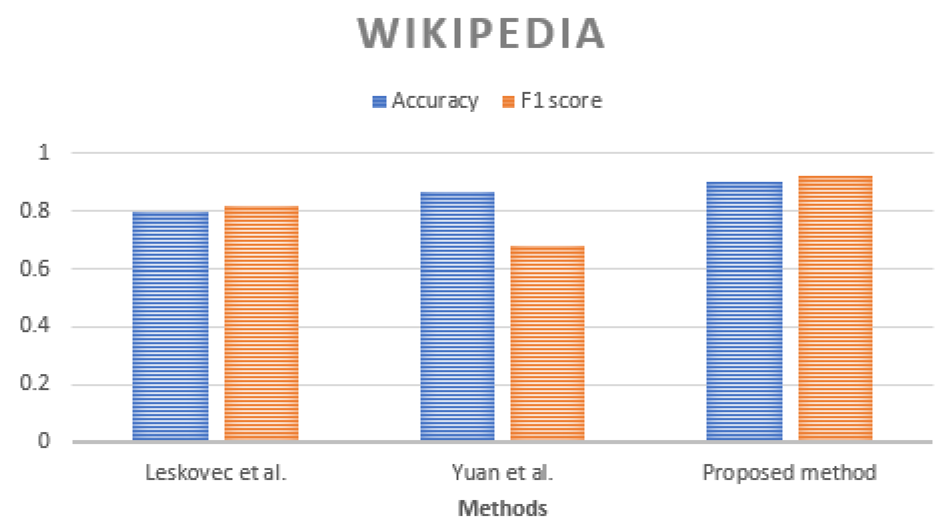


Figure 6.3: Comparison between existing methods[51] [26] and proposed method

Wikipedia is an encyclopedia freely written, with an involved user base with 7115 nodes and 103689 edges. Existing methods are compared with our proposed method which shows that results that we achieved showed efficient result which help in predicting negative sign for a given signed network in terms of Accuracy and F1 score. Other latent methods are showing lower performance than most of the heuristic methods for prediction purposes. The State-of-the-art sign prediction methods are showing similar results as most heuristics. Our proposed method outperforms all methods compared and showing efficient prediction performance than other heuristics methods.

6.2.4 Performance on Gplus, twitter and facebook dataset

We also performed our model on three additional datasets like Gplus, twitter and facebook. Table 6.2 shows the performance with accuracy and F1 on these datasets. We can observe that overall performance on the proposed method is consistent with the current method in terms of accuracy and F1 score as shown in table 6.2.

Dataset	Method	Accuracy	F1 score
Gplus	Leskovec et al[26].	0.87	0.84
	Yuan et al[51].	0.90	0.87
	Proposed method	0.94	0.92
Twitter	Leskovec et al[26].	0.88	0.87
	Yuan et al[51].	0.89	0.85
	Proposed method	0.92	0.90
Facebook	Leskovec et al[26].	0.84	0.86
	Yuan et al[51].	0.87	0.85
	Proposed method	0.92	0.89

Table 6.2: performance of proposed model on 3 different datasets

6.3 Performance Analysis

In this subsection, we compare the proposed framework with baseline method and also evaluate it in terms of evaluation matrix. The method in [26] is by far the most common method used in the prediction of negative signs. While researchers have suggested various methods of improvement[26], these methods typically require additional information, such as context information, not always available in general applications. However, these method is not including all the features related to negative sign prediction, so [51] proposed a new method which consist of other additional features and can predict signs more accurately. We have extended the previous researchers work [[26][51]] by adding new optimized features and able to predict negative sign more accurately then existing methods.

As shown in figures above, we can see that on all six datasets the negative sign prediction accuracy and F1 score of the proposed model are higher than existing method. It gives the improvement on negative sign prediction accuracy of around $3\% \sim 4\%$. The increase in negative sign prediction F1 score is very significant relative to F1 by using the existing methods, negative sign prediction F1 score will increase by $5\% \sim 14\%$ percent for Epinions, Slashdot, Wikipedia, Gplus, Twitter, Facebook dataset by using the proposed method.

6.4 Statistical Analysis

Computational complexity

The proposed method will determine the evaluation of feature matrix for the training section K, the general term for feature matrix is $K(x_i, x_j)$. I propose upper limits here if the data is dense (as the realization of this limit is described).

Calling n, the number of samples in training, p the number of features, n_{sv} ,the number of support vectors, we have the following approximations where training complexity is $O(n^2 p, n^3)$ and prediction complexity is $O(n_{sv} p)$. It took approx 16 hours to run our program on Intel(R) Core(TM) i3-3227U CPU @ 1.90GHz (4 CPUs), 1.9GHz.

Error analysis

These experiments have been performed five times and the best results have been reported. The five results did not, however, vary a lot. For each run of the algorithm there was less than 1 difference in the error observed. The standard error is 0.02.

This shows that we obtained consistent results from the experiments. Below we show margin of error, where five iterations where taken into consideration.

Dataset	**Margin of Error**
Twitter	0.9136 $\pm$0.008($\pm$0.94%)
	0.9136 $\pm$0.014($\pm$1.54%)
	0.9136 $\pm$0.016($\pm$1.83%)
	0.9136 $\pm$0.022($\pm$2.41%)
	0.9136 $\pm$0.028($\pm$3.08%)

Table 6.3: Error analysis

Chapter 7

Conclusion and Future Work

7.1 Conclusion

Negative sign prediction for signed social networks predicts the existence of negative signs for the links. While the number of negative signs is much smaller than the number of positive signs in signed social networks, negative signs are much more important to user action. Negative signs can not be propagated by users as positive signs. Negative signs are generally expected according to the Structural and/or Social Balance Concept. Existing negative sign prediction models prediction performance is reduced because they only involve partial information related to negative sign properties. The proposed work analyses the characteristics of negative signs in the signed social network and also categorises the relevant features into five groups: features of nodes, features of triads, feature of user-similarities, neighbour based features and path based features. The suggested approach has superior negative sign prediction performance then existing works by combining features from these groups. In fact, the new model is also more stable than existing works. Social networks are scale free networks, meaning that their degree distributions obey the power theorem, i.e. that only a very small number of nodes have large relations to other nodes, whereas other nodes in the signed social networks have very limited relations to other nodes. The data sparseness problem may be much more severe with the negative sign prediction issue as opposed to the positive sign prediction. This is because negative signs in the signed social networks are often much fewer than positive signs.

7.2 Future work

Our future work will concentrate mainly on the issue of negative sign estimation with little knowledge about signals. It can also be called the negative sign prediction 's data sparseness problem. The social networks are scale-free and thus their ranking distribution is based on power law,i.e there is only a very small number of nodes with large links to other nodes, while other nodes in the social networks which are signed have very minimal links to other nodes. The data sparseness problem could be much more severe with the negative sign prediction issue in contrast with the positive sign prediction. That is why negative signs in the signed social networks are often much lower than positive signals. It is not easy to extract sufficient effective features for some nodes with the limited information available. We also plan to make or keep looking for newer datasets to work on in this field of sign prediction.

Also, we will concentrate mainly on negative sign prediction concern with limited sign dependent information. It can also be considered the negative sign prediction data sparseness problem. We expect to find more information available from the limited node links in signed social networks, and use that information to enhance the efficiency of negative sign prediction.

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Appendix A

All the experiments were performed using Matlab library. To develop the predictive models for research purposes I strongly suggest using Matlab.

All the source code for this thesis is available at (`https://github.com/Shikhar2012/A-feature-based-model-for-negative-sign-prediction-in-signed-social-network.git`).You may need to adjust the parameters, elements, or even code mentioned above to best suit the dataset and tests.

The code was executed on NVIDIA GeForceGTX with dedicated GPU memory of 8 GB. The code was executed on an Intel(R) Core(TM) i3-3227U CPU @ 1.90GHz (4 CPUs), 1.9GHz. The runtime can be increased by increasing the GPU memory for each experiment that lasted around 16 hours.

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