Discovering Hidden Links and Strength of Relationship using Fuzzy Graph in Facebook

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***Abstract*: The strength of relationship is analysed in social network for asymmetric relationship and predict the hidden links in social network. Using the link prediction concept to calculate the demographic, topological and network transactional data. The fuzzy granular studied to calculate the strength of relationship and differentiate into four granules such as socially close friends, socially near friends, socially far friends, socially very far friends.**

***Keywords*: Fuzzy graph, Fuzzy granular computing, Link prediction, Reciprocity, Social relational networks, strength of relationship.**

1. Introduction

A social network is structures consist of entities which can be individuals, groups or organizations, and the relations or associations among them. With the emergence of the internet, the online social networks have been gained increasing popularity. Online social network has become one of the most influential and the key source of service providing, information or knowledge sharing; and other internet based activities. Social networks are composed of users (nodes) and associations (edges) among them. Granovetter MS gave the concept of the weak ties in 1973. In 1989, Golberg done his work on genetic algorithm for search, optimization and machine learning. Backstrom, gave a details for collect the group information in large social networks, membership, growth and evolution on 2006. In 2007 Liben Nowell et.al. proceeded the solution for the link prediction problem for social network. Viswanath et.al. described the evolution of user interaction in facebook in 2009. In 2014 Bliss et.al. evoluted the algorithm to link prediction in dynamic social network.

2. Preliminaries

2.1 Subset

Let σ be a fuzzy subset of S. Then the set $\sigma^t = \{x \in S : \sigma(x) \geq t\}$ are calld the t-level sets and the set $\sigma^* = \{x \in S : \sigma(x) > 0\}$ is called the support of σ. Here σ^t and σ^* are the crisp set.

2.2 Fuzzy Subset

Let σ and τ be the two fuzzy subset of S. Then

i. $\sigma \subseteq \tau$ if $\sigma(x) \leq \tau(x) \forall x \in S$
ii. $\sigma \subset \tau$ if $\sigma(x) \leq \tau(x) \forall x \in S$ and there exist one $x \in S$ such that $\sigma(x) < \tau(x)$
iii. $\sigma = \tau$ if $\sigma(x) = \tau(x) \forall x \in S$

The restriction $\mu(x, y) \leq \sigma(x) \bigcap \tau(y)$, $\forall x \in S$ and $y \in \tau$ allows $\mu' : \sigma' \to \tau' \forall t \in [0,1]$ and $\mu^* : \sigma^* \to \tau^*$

2.3 Fuzzy Graph

A fuzzy graph G is defined as an ordered pair G=(V,E) where V is the set of vertices and E is the set of edges. An edge which has an membership values and it is denoted by $E : X \times Y \to [0,1]$. The membership values for vertices and edged between [0,1].

2.4 Granular Computing

Granular Computing is a problem solving para diagram with the basic element, called granules. The construction of granules is a crucial process, as their sizes and shapes are responsible for the success of granular computing based models. Further, the inter and intra relationships among granules play an important role. A granules may be defined as the clump of elements that are drawn together, for example, by indiscernibility, similarity and functionality. Each of the granules according to its shape and size, and with a certain level of granularity may reflect a specific aspect of the problem. Granules with different granular levels may represent a system differently. Granulation is the process of construction, representation and interpretation of granules. It involves

the process of forming larger objects into smaller and smaller into larger based on the problem in hand. According to Zadeh, "granulation involves a decomposition of whole into parts. Conversely, organization involves an integration of parts into whole". One of the realizations behind granular computing is that precision is sometimes expensive and not very meaningful in modeling and controlling complex systems. When a problem involves a incomplete, uncertain and vague information, it may sometimes become difficult to differentiate the individual elements, and one may find it convenient to consider granules to represent a structure of patterns evolved by performing operation on the individual patterns. According to granular computing became an effective framework in designing efficient and intelligent information processing systems for various real life decision-making applications. The principles of fuzzy sets, rough sets, neural networks, power algebra, interval analysis for further details on the significance and various applications of granular computing.

2.5 Fuzzy Granular social network

A social network is viewed from the start point of nodes and their relationships. Global phenomenon of a social network always assembles the local behaviors of individuals and their closely related neighborhoods. This motivates us to model the network in terms of granules. Quantifying this vaguely term "closeness" is another concern for modeling the social network in terms of a granular neighborhood system. Fuzzy set comes naturally here to address this issue. Which provides a model to describe a social network in terms of fuzzy granular system, and name it fuzzy granular social network.

2.6 Link Prediction

The relevant problems of link prediction are more concerned to the links that will be formed in the future or findings the missing links in the network. The link prediction is based upon the graphs structure does not take real world factors such as users characteristics and the root of relations into account.

3. Estimation of hidden links

3.1 Algorithm for Hidden link

1] First choose the friendship list from the facebook using demographic , topological and network transactional data.
2] Using supervised learning concept we classified the socially close friends, socially near friends, socially far friends, socially very far friends.
3] Then find the result for strength of relationship.
4] Consider the granular computing to choose the closeness for the far friends.
5] Calculate the number of person accept, not accept, may be by using the nodes.
6] Finally find out the result for link prediction for the given network.

3.2 Supervised Learning

Supervised learning is where you have a input variable (X) and an output variable (Y) and you can use an algorithm to learn the mapping function from the input to output.

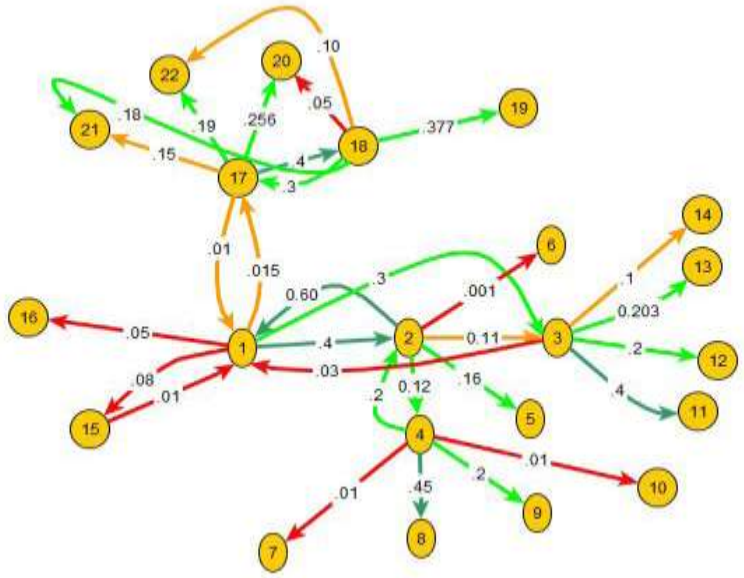
$$y = f(x)$$

The goal is to appropriate the mapping function so well that when you have a new input data (X) that you can predict the output variable (Y) for that data.

It is called the supervised learning because the process of an algorithm learning from the training dataset can be thought of as a teacher supervising the learning process. The algorithm iteratively makes prediction on the training data and is corrected by the teacher. Learning steps when the algorithm achieves an acceptable level of performance. Supervised learning problem is categorized into two types: Classification and Regression. Classification is When output variable is a category such as dark green, light green, orange, red and socially close friends, socially near friends, socially far friends and socially very far friends. Regression is when output variable is a real value such as "dollars" or "weight".

3.3 Estimation of strength of relationship

A small socio-gram for calculate for the data given in below given diagram. The figure is not used to calculate the strength of relationship it gives an idea of different degree or type of relations in the social network. Here calculate the strength between the nodes '1' and node '17' is socially far friends but also for node '17' and node '1' is socially far friends.



A snapshot of different types of friendship and the biased friendship that exists.

Color of edge	Type of friendship	Ratings
Dark Green →	Socially Close Friend	4
Light Green →	Socially Near Friend	3
Orange →	Socially Far Friend	2
Red →	Socially Very Far Friend	1

Results for 'strength of relationship'	
Total Connections	67
True Positive (correctly predicted strengths)	51
Percentage of True Positive	76.1

Nodes Male(M)	Suggested Nodes(M/F)	NA/A/MB	Actual Results (from Participant's response)		
			NA(M/F)	A(M/F)	MB(M/F)
1	5(2/3)	2/2/1	(1/1)	(1/1)	(1/0)
2	1(1/0)	1/0/0	(1/0)	(0/0)	(0/0)
3	2(0/2)	1/0/1	(0/1)	(0/0)	(0/1)
8	1(1/0)	1/0/0	(1/0)	(0/0)	(0/0)
9	2(0/2)	1/1/0	(0/1)	(0/1)	(0/0)
10	1(1/0)	0/0/1	(0/0)	(0/0)	(1/0)
11	1(0/1)	0/1/0	(0/0)	(0/1)	(0/0)
16	2(0/2)	0/0/2	(0/0)	(0/0)	(0/2)
26	1(1/0)	0/1/0	(0/0)	(1/0)	(0/0)
28	1(0/1)	0/1/0	(0/0)	(0/1)	(0/0)
Total	17(6/11)	6/6/5	(3/3)=6	(2/4)=6	(2/3)=5

Nodes Female(F)	Suggested Nodes(M/F)	NA/A/MB	Actual Results (from Participant's response)		
			NA(M/F)	A(M/F)	MB(M/F)
4	1(1/0)	0/1/0	(0/0)	(1/0)	(0/0)
6	1(1/0)	0/0/1	(0/0)	(0/0)	(1/0)
13	1(1/0)	1/0/0	(1/0)	(0/0)	(0/0)
15	1(0/1)	0/1/0	(0/0)	(0/1)	(0/0)
18	1(0/1)	1/0/0	(0/1)	(0/0)	(0/0)
20	2(1/1)	0/1/1	(0/0)	(1/0)	(0/1)
21	1(1/0)	0/0/1	(0/0)	(0/0)	(1/0)
23	1(0/1)	0/0/1	(0/0)	(0/0)	(1/0)
24	1(0/1)	0/1/0	(0/0)	(0/1)	(0/0)
27	1(1/0)	0/0/1	(0/0)	(0/0)	(1/0)
Total	11(6/5)	2/4/5	(1/1)=2	2/2)=4	4/1)=5

Results for Link Prediction based on Data Collected

Results for 'Link Prediction'	
Total Recommendation	28
Rejected Recommendation	8
% of Rejected Recommendation	40%
Error Percentage	60%

Conclusion

The asymmetric social relationship which gives the result for socially far friends when compare to the socially close friends which has an high error in their friendship. Here analyzed the strength of relationship using the supervised learning, granular computing and their networks by using the fuzzy graph and their membership values to calculate the tie strength.

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