Measure User Intimacy by Mining Maximum Information Transmission Paths

Lin Guo1 and Dongliang Zhang2

1School of Economics and Management, Changchun University of Science and Technology, Changchun, Jilin 130022, China
2Institution of Technical Science, Fudan University, Shanghai 200000, China

Correspondence should be addressed to Lin Guo; guolin@cust.edu.cn

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The Internet has become an important carrier of information. Its data contain abundant information about hot events, user relations and attitudes, and so on. Many enterprises use high-impact Internet users to promote products, so it is very important to understand the mechanism of information transmission. Mining social network data can help people analyze the complex and changing relationships between users. The traditional method for doing this is to analyze information such as common interests and common friends, but this data cannot truly describe the degree of intimacy between users. What really connects different users on the Internet is the delivery of information. The algorithm proposed in this paper considers the dynamic characteristics of information transmission, finds maximum transmission paths from information transmission results, and finally calculates the intimacy degrees between users according to all the maximum information transmission paths within a certain period.

1. Introduction

Social network data contains a wealth of information about events, relationships, and attitudes. On the basis of fully understanding and analyzing the data, a series of technologies, such as text mining, statistical theory, association analysis, and visualization technologies, are adopted to realize emotional orientation analysis, information extraction, user influence analysis, and so on. Many current methods of computing user intimacy can be applied to static networks. However, users might unfollow certain friends and their interests might shift to new and different topics. In other words, the tie strengths between different users change over time. The algorithm proposed in this paper takes the dynamic nature of data into account to improve information transmission analysis in social networks. After that maximum transmission paths are identified in the information transmission results, and then the intimacy degrees between nodes can be computed according to multiple groups of maximum transmission paths.

The remainder of this paper is organized as follows: Section 2 introduces the related work of this paper. Section 3 proposes the concept of the information transmission matrix. Section 4 introduces the computational process of tie strength. Section 5 states the experimental results. Section 6 introduces the conclusions.

2. Related Works

Many enterprises use influential users to promote new products, but the mechanism of how information spreads through the network still needs to be further studied. It is very important to understand the communication mechanism of information, which can be applied in many fields, such as viral marketing, social behavior prediction, social recommendation, and community detection. These problems attract the attention of researchers from different fields, such as epidemiology, computer science, and sociology, who propose different information diffusion models to describe and simulate the process of information transmission, such as the independent cascade model, linear threshold model, and epidemic model. These models are mainly applied to influence evaluation, influence maximization, and information source detection. Most models recognize that
information is transmitted from a source node set and other
nodes can only obtain information from the nodes that
neighbor the source node set.

Social networking service providers, such as Twitter and
Facebook, have grown rapidly in recent years, with in-
creasing number of users sharing information with their
friends. There are more than 2 million active users on
Facebook every month from all over the world and about 5
billion new tweets on Twitter every day. Social network
analysis can be divided into the following aspects [1, 2]: (a)
studying the network structure and trends [3], (b) online
learning of complex networks [4], (c) comparing different
models, and (d) predicting node status [1, 5]. The focus of
social influence study is to investigate neighbors and asso-
ciates to predict the impact and influence of the occur-
rence of an action [2, 6].

Researchers have examined information transfers, in-
cluding the analysis of relationships [7], social action
tracking [1], and other types of relationship transfer [8]. The
algorithm proposed in this paper constructs a matrix based
on the information transmission between users to describe
the complex correlation relations. By making certain
changes to the matrix, information transmission paths can
be identified and the tie strengths between nodes can be
calculated. Due to the small computational difficulty in-
volvied in constructing a matrix, the algorithm proposed in
this paper performs more efficiently than other algorithms.

3. Information Transmission Matrix

A piece of information is very valuable at one time, but after
that it may be worthless. From the perspective of infor-
mation transmission, the degree of interaction between users
can be calculated. By analyzing information transmission
paths, an information transmission tree can be generated to
describe the information transmission rules and be used to
analyze the dynamic changes of the correlations between
users.

Definition 1. Let G be a graph with n nodes and e edges. If
\[ a_{ij} = \begin{cases} 
1, & \text{if } e_j \text{ is associated with } v_i, \\
0, & \text{if } e_j \text{ is not associated with } v_i,
\end{cases} \] 
(1)
then the \( n \times e \) matrix composed of element \( a_{ij} (1 \leq i \leq n, 1 \leq j \leq e) \) is constructed. \( M = (a_{ij})_{n \times e} \) is the complete inci-
dence matrix of graph G, namely, the information trans-
mission matrix.

In this paper, information transmission data is used to
construct and update M. The construction process of M is
given below.

Figure 1 depicts the information transmission rela-
tionships between nodes. If there is an edge between nodes,
then it means that information has been successfully passed
between them. Otherwise, no information has been passed.
We construct matrix M according to Figure 1, which de-
scribes the mapping relationship between nodes and edges.
If there is an association between \( N_x \) and \( e_j \), then \( a_{xy} = 1 \).
Otherwise, \( a_{xy} = 0 \).

Because there is a large number of inactive nodes, most
of the actions of the nodes on the Internet are from browsing
information while actions such as commenting and for-
warding are rare. Therefore, matrix M is a sparse matrix. To
reduce the negative impact of a large number of meaningless
zeros in the matrix on subsequent calculations, further
analysis of M is required to delete redundant nodes. In
Section 3.1, we describe a quick and effective way to remove
redundant nodes.

3.1. Isolated Nodes

Definition 2. If the determinant of nth order matrix M is not
zero, that is, \( |M| \neq 0 \), then M is called a nonsingular matrix or
full rank matrix. Otherwise, M is called a singular matrix or
reduced-rank matrix.

Definition 3. Nodes in graph G are connected if and only if
the rank of the complete incidence matrix is \( n - 1 \). The
matrix whose order is \( \min \{ p, q \} \) is called a large submatrix of
the \( p \times q \) matrix.

By calculating whether \( |M| \) is 0, we can judge whether the
nodes in G are connected or not. A reduced matrix D can be
achieved by deleting redundant nodes in M. D is a full rank
matrix, that is, \( |D| \neq 0 \). At this time, D is the maximum
complete incidence matrix. That is, all the nodes in the new
graph G that are formed by D are reachable, and there are no
isolated nodes for information transmission.

Take matrix M in Figure 2 as an example to illustrate
the process of removing isolated nodes. The rank of M is ob-
tained by calculating the maximum number of linearly-
independent crossings (that is, the maximum order of the
nonzero submatrix):
According to the abovementioned calculation results, \( R(\mathbf{M}) = 6 \). This indicates the existence of isolated nodes in \( \mathbf{M} \). It can be seen that rows \( N_5 \) and \( N_8 \) are \( \vec{0} \), so \( N_5 \) and \( N_8 \) are redundant, isolated nodes. Because the original data in line \( N_6 \) and \( N_7 \) are same and \( N_7 \) was determined to be an isolated node to be deleted, \( N_6 \) is also an isolated node. In conclusion, \( N_6, N_7, \) and \( N_8 \) are isolated nodes. After removing redundant nodes, it is necessary to determine whether there are redundant edges in the matrix. Because column \( e_6 \) is \( \vec{0} \) after the redundant nodes are deleted, \( e_6 \) is a redundant edge that needs to be deleted.

Matrix \( \mathbf{D} \) is obtained after deleting the redundant nodes in \( \mathbf{M} \). Next, whether the nodes in \( \mathbf{D} \) are connected must be calculated as follows:

![Matrix D](image)

The result is \( R(\mathbf{D}) = 5 \). That is, \(|\mathbf{D}| \neq 0\), so \( \mathbf{D} \) is a full rank matrix. The conclusion is that all nodes in \( \mathbf{D} \) are connected. In other words, there are no isolated nodes of information transmission.

To discover all information transmission paths in \( \mathbf{M} \), it is necessary to further determine which nodes can be tentatively considered to be redundant. The deleted redundant nodes are reconstituted into a new matrix \( \mathbf{M} \) and the abovementioned operations are repeated to obtain a matrix \( \mathbf{D} \). Finally, multiple matrix \( \mathbf{D}s \) are obtained.

3.2. Information Transmission Path. To study the information transmission mechanism, it is necessary to identify all the information transmission paths from the information matrix. Therefore, further processing of the set of \( \mathbf{D}s \) is required.

![Definition 4](image)
first combination, edges \((e_1, e_2, e_3, e_4, e_5)\) are selected. It is found that in the matrix \(M_{N_1,e_1}, M_{N_1,e_2}, M_{N_1,e_3}, M_{N_2,e_4}, M_{N_2,e_5}\) are all 0, so this path does not contain \(N_5\). That is, it is not a maximum information transmission path, so the combination of \((e_1, e_2, e_3, e_4, e_5)\) is deleted and the calculation is stopped. Similarly, in the second combination, \(M_{N_1,e_1}, M_{N_1,e_2}, M_{N_1,e_3}, M_{N_1,e_4}, M_{N_2,e_5}\) is 0, so the calculation result obtained by this structure does not include \(N_6\), that is, it is not a maximum information transmission path. The ranks of the third, fourth, and fifth matrices are all 4, so they are full rank matrices that satisfy the condition of generating maximum information transmission paths. The fourth column in rows 3, 4, and 5 in Table 1 show the row transformation process. Number 1 is the lowest in the transformed matrix, so the matrix does not have redundant edges. Column 5 shows the graph structure of the matrix obtained after eliminating the redundant edges. It can be seen from the graphs that the method proposed in this paper can be used to identify all maximum information transmission paths.

4. Tie Strength between Nodes

According to the characteristics of information transmission, it is reasonable to assume that there must be some association between the nodes in the same transmission path. Here, it is assumed that if information is transmitted frequently between two nodes, then the degree of intimacy between these two nodes is high. After a period of data accumulation, data about maximum information transmission paths is added to the correlation strength matrix (denoted as \(T\)). Because the construction of \(T\) is executed according to information transmission flows, matrix \(T\) also keeps changing with the change of information transmission state. In matrix \(T\), \(T_{i,j}\) represents the occurrence number of node \(i\) in the process of information transmission and \(T_{i,j}\) represents the information transfer times between nodes \(i\) and \(j\).

The following is the formula for calculating the weight of node \(i\):

\[
\text{node}_i = \frac{T_{i,i}}{\sum_{x=1}^{n} T_{x,x}}
\]  

(5)

The following is the formula for calculating the ties between node \(a\) and \(b\):

\[
\text{edge}_{a,b} = \frac{\sum_{x=1}^{n} T_{a,x} - \frac{T_{a,a}}{x\neq a}}{n} \quad (a > 1).
\]  

(6)

According to formulas (5) and (6), the degree of intimacy between different users is calculated. The specific algorithm is shown in Algorithm 1.

5. Experiments

Five datasets are used in this paper. For detailed information about the datasets, please refer to our paper [2] published earlier.
Table 1: The process of mining maximum information transmission paths.

| Matrix | Result | Reasons for failure to meet the criteria/matrix transformation process/the structure corresponding to the calculation result |
|--------|--------|------------------------------------------------------------------------------------------------------------------|
| 1 \((e_1, e_2, e_3, e_4)\) | Not satisfied | Reason: \(M_{N_1,e_1}, M_{N_2,e_2}, M_{N_3,e_3}, \) and \(M_{N_4,e_4}\) in \(M\) are 0; therefore, \(N_5\) is excluded, and it is not a maximum information transmission path |
| 2 \((e_1, e_2, e_3, e_3)\) | Not satisfied | Reason: \(M_{N_1,e_1}, M_{N_2,e_2}, M_{N_3,e_3}, \) and \(M_{N_4,e_4}\) in \(M\) are 0; therefore, \(N_4\) is excluded, and it is not a maximum information transmission path |
| 3 \((e_1, e_2, e_4, e_3)\) | \(R = 4;\) full rank matrix | 

\[
\begin{pmatrix}
N_1 & 1 & 1 & 0 & 0 \\
N_2 & 1 & 0 & 0 & 0 \\
N_3 & 0 & 1 & 1 & 1 \\
N_4 & 0 & 0 & 1 & 0
\end{pmatrix} \Rightarrow \begin{pmatrix}
N_1 & 0 & 1 & 0 & 0 \\
N_2 & 1 & 0 & 0 & 0 \\
N_3 & 0 & 0 & 0 & 0 \\
N_4 & 0 & 0 & 1 & 0
\end{pmatrix}
\]

| 4 \((e_1, e_3, e_4, e_3)\) | \(R = 4;\) full rank matrix | 

\[
\begin{pmatrix}
N_1 & 1 & 0 & 0 & 0 \\
N_2 & 1 & 1 & 0 & 0 \\
N_3 & 0 & 1 & 1 & 1 \\
N_4 & 0 & 0 & 1 & 0
\end{pmatrix} \Rightarrow \begin{pmatrix}
N_1 & 1 & 0 & 0 & 0 \\
N_2 & 0 & 1 & 0 & 0 \\
N_3 & 0 & 0 & 0 & 1 \\
N_4 & 0 & 0 & 1 & 0
\end{pmatrix}
\]

| 5 \((e_2, e_3, e_4, e_3)\) | \(R = 4;\) full rank matrix | 

\[
\begin{pmatrix}
N_1 & 1 & 0 & 0 & 0 \\
N_2 & 0 & 1 & 0 & 0 \\
N_3 & 1 & 1 & 1 & 1 \\
N_4 & 0 & 0 & 1 & 0
\end{pmatrix} \Rightarrow \begin{pmatrix}
N_1 & 1 & 0 & 0 & 0 \\
N_2 & 0 & 1 & 0 & 0 \\
N_3 & 0 & 0 & 0 & 1 \\
N_4 & 0 & 0 & 1 & 0
\end{pmatrix}
\]

Algorithm 1: TieCP.

1. Coauthor (https://www.aminer.cn/data): a dynamic coauthor network from ArnetMiner (http://www.aminer.cn/). We collected publications published from 2010 to 2016 by 100,000 authors.
2. DBLP (http://www.vldb.org/dblp/): the dataset is derived from a snapshot of the bibliography for 10 years, where each vertex represents a scientist and two vertices are connected if they work together on an article.
3. Twitter (https://twitter.com): we crawled the following links between 19,000,00 users from Twitter at 10 different time stamps from October to December 2017.
4. Weibo (http://code.google.com/p/weibo4j/): the most popular Chinese microblogging site. The data are crawled from March 8, 2014 when the crash of MH370 happened to April 8, 2014.
Dolphin’s Associations (http://www-personal.umich.edu/~mejn/netdata/): this dataset is an undirected social network of frequent associations between 62 dolphins, which has 62 nodes and 159 edges.

Three sets of baseline approaches are chosen for the experiments:

1. **PTPMF [9]**: this method uses neighborhood overlap to approximate tie strength and extend the popular Bayesian Personalized Ranking (BPR) model to incorporate the distinction of strong and weak ties.

2. **TrustMF [10]**: this is a model-based method that adopts matrix factorization technique that maps users into low-dimensional latent feature spaces in terms of their trust relationship and aims to more accurately reflect the users’ reciprocal influence on the formation of their own opinions and to learn better preferential patterns of users for high-quality recommendations.

3. **SBPR**: this method presents a generic optimization criterion BPR-Opt for personalized ranking, that is,
the maximum posterior estimator derived from a Bayesian analysis of the problem.

Figure 3 shows the information transmission graph without data processing. It contains 38,501 nodes and 20,354 edges. If all nodes in the Coauthor dataset were displayed in Figure 3, then the picture would be black and the structure would not be visible. Therefore, only some of the nodes in the Coauthor dataset are shown in this figure. As can be seen in Figure 3, it is very difficult to process network data.

In the Coauthor dataset, the lengths of most information transmission paths are 2 or 3. Figure 4 shows the path with the maximum length in the Coauthor dataset.

By constructing a matrix according to the structure in Figure 4 and executing the algorithm proposed in this paper on this matrix, it can be found that several groups of the largest and nonsegmented information transmission paths can be found, as shown in Figure 5. As can be seen from Figure 5, all the paths are loop free and achieve the maximum coverage of all nodes. Therefore, Figure 5 verifies the accuracy of the algorithm from the perspective of visualization.

Figure 6 depicts the degree of all nodes in the maximum information propagation path. It is found that the degree of most nodes is 1, the degree of a few nodes is greater than or equal to 2, and the highest degree value is 13. Figure 6 illustrates that the algorithm achieves the maximum removal of redundant edges.

The tie coefficients between different nodes are calculated according to information transmission paths. Figure 7
shows the tie coefficient of nodes. In it, the darkness of the edges represents the correlation strengths between the node and the ego node. The darker the color is, the stronger the correlation is and vice versa. The number in the edge represents the tie strength between two connected nodes, which is the final result obtained by fusing multiple sets of maximum information transmission paths.

In order to analyze the experimental results, we use the following measurement parameters [10]: Precision calculated by $P = \frac{tp}{tp + fp}$, Recall by $R = \frac{tp}{tp + fn}$, and $F1$-score by $F = \frac{P \times R}{P + R}$. $tp$ is the number of correctly identified examples, $tn$ is the number of correctly identified nonrelated examples, $fn$ is the number of not correctly identified related examples, and $fp$ is the number of not correctly identified nonrelated examples. Table 2 shows a comparison of the performances of different clustering algorithms on different datasets. It displays performance comparisons of SBPR, TrustMF, PTPMF, and TieCP using different datasets. According to Table 2, we can conclude that TieCP has the most stable execution effect and the best result regarding $F$-Score.
6. Conclusion

The algorithm proposed in this paper calculates the intimacy degrees between users according to the information transmission matrix. Compared to some mainstream methods, our method is simple and able to identify all the maximum information transmission paths. Beyond that our algorithm is relatively more stable when dealing with different kinds of data. Due to the small computational difficulty of constructing a matrix, the algorithm proposed in this paper performs more efficiently than other algorithms.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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