Identifying emerging influential nodes in evolving networks: Exploiting strength of weak nodes

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Abstract

Identifying emerging influential or popular node/item in future on network is a current interest of the researchers. Most of previous works focus on identifying leaders in time evolving networks on the basis of network structure or node's activity separate way. In this paper, we have proposed a hybrid model which considers both, node's structural centrality and recent activity of nodes together. We consider that the node is active when it is receiving more links in a given recent time window, rather than in the whole past life of the node. Furthermore our model is flexible to implement structural rank such as PageRank and webpage click information as activity of the node. For testing the performance of our model, we adopt the PageRank algorithm and linear preferential attachment based model as the baseline methods. Experiments on three real data sets (i.e Movielens, Netflix and Facebook wall post data set), we found that our model shows better performance in terms of finding the emerging influential nodes that were not popular in past.

1. Introduction

The influence analysis problem was initiated since the introduction of the viral marketing phenomena [42]. Finding influencers is considered as many body problem in which topological features play a very important role [4]. In general topologically centralized nodes plays an important role as influencer [2], [40] but influential phenomena is not always depends on structural centrality of the node. Sometimes weakly connected nodes can be influential node. Since considering the collective influence effect top influencers are low degree nodes as compare to hubs in the network [38]. Activity of the node plays a very important role in influential processes, i.e., if the nodes are hub but not active, it cannot help in spreading processes. Activity of the node can be quantified as many ways such as rate of in degree or out degree formation and so on. Here we have considered in degree formation with temporal effect. Activity of the node can also be considered how fast the node is making links with other nodes such as in case of social network how actively user is involved in commenting, liking and creating posts. Activity of the node can also be considered as how many friends or followers the user is able to make in recent past. To contain this information we have made network that contains both characteristics; such as if user A comment or like on user B’s posts then there is a directed link from A to B. In the same manner if user C followed user A then there is also a link from C to A, although our data set lacks this full information. So we have created only activity based network. If we are able to identify the critical node having specific characteristics in dynamically evolving network, it will help us in solving many problems from our daily life such as epidemics outbreak [39], advertisement [26], precluding failure of grids or internet[1], managing transport problem [50] , telecommunication network and so on. Preferential attachment explains effectively growth of time evolving real time system. Most recently researchers have found that the popularity of online contents like news, blog posts, videos, mobile

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Preprint submitted to Elsevier
app download [22] in online discussion forums and product reviews exhibits temporal dynamics. [52], [27] has also discussed how content popularity fluctuate with time. Some items grow ones while some items can again gain popularity after decay [8]. In these cases when items can gain popularity multiple times considering recent popularity will give benefit. In other way in cases when content gain popularity many times the whole item or node degree will not be a good predictor, although recent popularity gain may help as it is found in predicting future popularity gain [37], [10], [41], [37]. In some network such as paper citation the rate of attracting new node decays due to aging factor [41], [37]. Therefore we can say for making prediction aging factor also matters. Although in some network such as citation network the new link formation will also matter on the fact that this node has been linked with which node. In other words if a paper has been cited by a popular scientist then it’s probability increases that other will cite or make link with this node.

Problem of finding influential user or node in network is being studied for quite long time such as [28], [13], [38]. They have considered static network and did not taken into consideration temporal dynamics of the node. Since we know by time how network structure are changing there for its node centrality also get affected so to consider only static view of the network is not good in knowledge discovery. Node centrality may vary from network to network especially when we consider the dynamics of the node. Some researchers have solved this problem using supervised classification problem such as [45]. Authors in reference [5] have proposed Popularity based predictors(PBP) for predicting popular item or node using bipartite network. It is “preferential attachment” theory based model; they show that instead of whole degree of the node recent degree gain is a good predictor. In addition they also proposed the novel entries in the top list those were not in past time window. Further ([22]) also came up that recent degree of the node is a good predictor for future popularity of the node. Some researchers have found the aging or decay factor also in the time evolving node’s degree [41], [51], [15], [12], [30]. PageRank based metrics has also been exploited by many researchers. The authors in [29] applied PageRank algorithm on twitter conversational network, they have considered metrics such as acceleration of the graph also. Similarly authors in [36] have proposed userRank based on the tweet relevance for user influence. [16] came up diversity-dependent influence score (DIS) in tweeter conversational graph for user influence by exploiting the social diversity and influence propagation phenomena. It has also employed the PageRank philosophy. The authors in reference [14] have proposed “Influence Rank” based recursive concept of user influence. Authors in [33] have proposed tweet correlation based financial users prediction, they supposed if user A does similar tweet than user B then they will influence each other. Although this method will not apply in macro level analysis, such as if we are interested in viral node. [21] proposed three algorithm based on PageRank namely “InfRank”, “LeadRank” and “DiscussRank”. InfRank is the ability of a user to spread information and to be re tweeted by other influential users. LeadRank quantifies the ability of user to stimulate other user to re tweet and mention from other user. DiscussRank identifies the active users who initiate discussion and involved others in discussion by replying and initiating tweets. [7], [31] has applied PageRank algorithm on citation data sets, they have found Google PageRank and citation positively correlated. [48] has proposed ‘TwitterRank’ algorithm extension of PageRank algorithm for identifying topic based influential users in micro blogging network such as twitter.[43] has considered recent citation with Google PageRank to predict the future citation gain of the paper. A recent work by [46] has solved this problem by considering information flow pattern in the network. Authors in reference [47] have solved this problem considering static network and exploiting k-core decomposition method.

2. Preliminaries

2.1 Problem definition

In this script we have given a model to find top-k emerging influential nodes in evolving network. We have modeled the problem by taking snapshot of the network at different time. Snap shot contains all the information of the link before time \( t \) only. The prediction problem is, considering node \( n \) in any system at time \( t \) and past time window \( T_P \), predicting the ranking of the node after future time window \( T_F \) on the basis of number of links it has received in past time window \( T_P \). So in case of user item bipartite network [31], [44], [17] we can consider how many user have bought/rated as receiving link of the node \( n \). In case of other directed network, how many link node \( n \) has received. So the prediction problem can be defined as given snap shot of the network at time \( t \) and past time window \( T_P \) we have to predict node’s ranking in future at \( t + T_F \) time on the basis of links
received during \((t, T_F)\), where \(T_F\) is future time window. Second we have to predict the novel entries or emerging influential node that were not in top \(N\) list before time \(t - T_p\).

2.2 Baseline method

PageRank

PageRank given by [6] was developed to rank webpages on internet for Google search engine optimization purpose. It can be applied in other networks also where structural property of the node plays an important role such as information diffusion [48], scientific paper/author ranking [43] etc. PageRank has also been applied on bipartite network [3], [19] PageRank algorithm can be given as follows:- If site \(n_i\) have link to site \(n_j\) there will be a directed link between node \(n_i\) and node \(n_j\) \((n_i > n_j)\). If page/node \(n_j\) has \(S_i\) set of link to other pages/nodes then page will distribute its importance in \(|l_j|\) (number of nodes in set \(S_i\)) nodes equally. The transition matrix of a graph \(A\) can be given as follows-

\[
A_{ij} = \begin{cases} 1/|l_j| & \text{if } n_j \in S_i \\ 0 & \text{Otherwise} \end{cases}
\]

Since there can be pages that do not have link to other pages although they are being pointed by other page, also known as dangling nodes, so new transformed matrix can be given as-

\[
S = A + N_{cd}
\]

where \(N_{cd}\) matrix have all the elements zero except for dangling nodes’ column which are 1/\(N\) where \(N\) is the number of rows or nodes in matrix. Easy to find that those columns are normalized that sums to one for making column stochastic matrix. Now the PageRank of dangling nodes will not be zero. Since random surfer will follow the link from one page to another, suppose that random surfer follows the PageRank (follows \(S\)) with probability \((\alpha)\) then there is \((1 - \alpha)\) probability that he will choose a random page. So now PageRank matrix also known as Google matrix \(M\) can be given as-

\[
M = \alpha S + \frac{(1 - \alpha)}{n} I_n
\]

where \(I_n\) is matrix of size \(n \times n\), it’s every element as one. Since Google Matrix \(M\) is combination of stochastic matrix and all the entries are positive which implies that \(M\) is primitive and irreducible. So PageRank vector \(PR\) can be calculated using power method as \(PR^k = M.PR^{k-1}\) it will eventually converge to a static vector which is PageRank.

3. Model

Importance of node depends on structural position as well as activity (e.g rate of link formation) of the node. If node is not active in current recent time it’s structural centrality have no value in some context such as information spread. A webpage might be ranked high due to other important webpages are pointing to it but if people are not clicking on the link after recommendation it means it is not an important page at least in temporal sense. So to develop a good model for predicting influential node we have considered both characteristics in our model.

\[
s_n(t, T_P) \propto s_c(n, t) * d_c(n, t, T_P)
\]  

Where \(s_n(t, T_P)\) predicted rating score of node \(n\) at time \(t\) given past time window \(T_P\), \(s_c(n, t)\) structural centrality metric of node such as degree, closeness, PageRank at time \(t\) etc and \(d_c(n, t, T_P)\) is dynamic centrality of the node at time \(t\) given some past time window \(T_P\) such as [51], [5], [32] has given model considering node’s activity.
$d_c(n, t, T_p)$ can vary according to need such as in webpage ranking structural property can be PageRank while dynamic centrality can be a score based on it’s click over time. PageRank is one of the best model that considers structural feature of the network so we have considered PageRank as structural centrality metric. The PageRank code is given by [34]. The original PageRank algorithm was given by [6]. The dynamic metric we have considered given by [51]. Although the generic model above can be implemented according to need of the problem such as if we care about a critical node to prevent the node damage, we can use Betweenness centrality as a structural centrality and dynamic centrality as it’s ‘work done’ such as in case of Internet router network and power grid network. Here we are considering PageRank as structural metric since it’s wide application in different areas such as academic articles and authors [7], [11], [49], image ranking [24], urban road ranking [23], protein interaction network [20], software ranking on the basis of Procedure Call Network (PCN), since large software contains many procedures that call to each other [9] So our one of specific model is as following we name it m1.

$$s_n(t, T_p) = K \sum_{n', t_n > = T_p} PR_n(t) \times \exp(\gamma(t_n - t))$$

Where K is a normalization constant which normalizes the score of all node which sums to 1. Here $t_n$ is the time when node $n$ received link, $T_p$ is the past time window. $\gamma$ is decay rate, $PR_n(t)$ is PageRank score of the node $n$, $n'$ is the set of rest of the node from which $n$ has received link. $t_n > = T_p$ condition tells that we consider only link that is formed after $t - T_p$ time. Considering only recent activity ($T_p$) of the node saves computation cost since in real time network size is very large. We are considering in degree of the node one can consider out degree also if activity of the node is based on out degree.

When there are only few active nodes in a system

Since from the above model if the node is not receiving any link after time ($t - T_p$), its score will be zero. To overcome this weakness we assume even if node has not received any link during past time window $T_p$ there is a probability of getting new link in future according to its structural centrality. Suppose probability of a node for getting in-links depends on recent gain in new links then we can say probability ($P_{n/t, T_p}$) given past time window $T_p$ of node $n$ at time $t$ of getting links in future is -

$$P_{n/t, T_p} \propto \sum_{n', t_n < = T_p} \exp(\gamma(t_n - t))$$

So predicted rating score $s_n(t, T_p)$ of a node can be given as follows-

$$s_n(t, T_p) = L \times PR_n(t)(1 + P_{n/t, T_p})$$

Where L is a normalization constant which normalizes the score of all node which sums to 1. The above predictor makes sure that even if node has not received any link in recent past it will be ranked according to its structural centrality. Although nodes which are more structurally central, and also active in recent past will be given more score. In addition if node’s structural centrality is not high but recently it is very active then score will also be high which is why we call it “strength of a weak node”. Such as in case of web page ranking if we want to consider both the centrality.

When system contains, recent activity as well as total popularity followers.

If in any system people follows rich get richer phenomena as well as recent behavior. Then we can model as follows, suppose with probability $\delta$ they follow already popular node or item and with probability ($1 - \delta$) they will follow recent behaviors of their peers. Such as in case of author citation network people do care about scientists’ popularity and also if any new scientist does a potential discovery. In a system where people follow recent behaviors of their peers the model in equation (4) will be a good predictor for future popularity gain of the node. Although it can be modeled as recent degree gain also, since if people follow recent behavior then recent degree gain “must” be a good predictor for future popularity or link gain of the node. We have considered decay
effect because nodes in most of the time evolving systems show competition for getting links which causes aging effect in other nodes. Introduction of aging phenomena helps in identifying emerging influential nodes.

\[ s_n(t, T_p) = M(\delta P R_n(t) + (1 - \delta)P_{n/t, T_p}) \]  

(5)

Where M is a normalization constant which normalizes the score of all node which sums to 1.

4. Experiment and Results

About Dataset

We have used Netflix data set the original Netflix data has 480189 users, 100480507 ratings and 17770 objects. The original Facebook data set have 42390, 39986 objects and 876993 links. While data preparation we have sampled small subset from each by randomly choosing users who have rated at least 20 movies. The original rating was in the form of numerical 1 – 5, we have considered the link between the user and object which object have received higher than two ratings. For all the three data sets Facebook, Movielens and Netflix the time is considered in days. In case of Facebook if user has posted/like or commented on other user’s wall there will be a link between the user and the wall. The link between user and its own wall post have not been considered to avoid self-influence. The data description after cleaning process -

- **Netflix** data contains 4960 users, 16599 movies and 1249058 links, data was collected during (1st Jan 2000 – 31st Dec 2005).

- **MovieLens** data set contains 7533 movies, 864581 links and 5000 users and data was collected during (1st Jan 2002 – 1st Jan 2005).

- **Facebook** data contains 40981 set of users and their 38143 wall post activity and 855542 links, during period of (14 Sep 2004 – 22nd Jan 2009).

Evaluation metrics

Following evaluation metrics are adopted to measure the accuracy of the proposed model including precision \((P_n)\), novelty \((Q_n)\), Area Under Recieving Operating Characteristic \((AUC)\) and Kendall’s Tau \((\tau)\).

- **Precision** is defined as the fraction of objects that are predicted also lie in the top \(N\) object of true ranking [25].

\[ p_n = \frac{D_n}{n} \]

Where \(D_n\) is the number of common objects between predicted and real ranking. \(n\) is the size of list to be ranked. It’s value ranges in \([0,1]\), higher value of \((P_n)\) is better.

- **Novelty\((Q_n)\)** is a metric to measure the ability of a predictor to rank the items in top \(n\) position that was not in top \(n\) position in previous time window. We call these new entries as “potential items” or emerging leaders throughout the script. If we denote the predicted object as \((P_{po})\) and potential true object as \(P_{ro}\) , then the novelty of a model is given by [5]-

\[ Q_n = P_{po}/P_{ro} \]
• **AUC** measures the relative position of the predicted item and true ranked items. Suppose predicted item list is \((L_{pn})\) and real item list is \((L_{rn})\). if \(s_{op} \in L_{pn}\) and \(s_{rp} \in L_{rn}\) is score of object in predicted then **AUC** is given by -

\[
AUC = \frac{\sum_{op \in L_{pn}} \sum_{rp \in L_{rn}} I(s_{op}, s_{rp})}{|L_{pn}| |L_{rn}|}
\]

where,

\[
I(s_{op}, s_{rp}) = \begin{cases} 
0 & \text{if } s_{op} < s_{rp} \\
0.5 & \text{if } s_{op} = s_{rp} \\
1 & \text{if } s_{op} > s_{rp}
\end{cases}
\]

• **Kendal’s Tau** measures the correlation between predicted and actual ratings. It varies between −1 and +1. \(\tau = 1\) when predicted and actual are identical, \(\tau = 0\) when both ranking is independent and \(\tau = −1\) shows they perfectly disagree. It can be given as-

\[
\tau = \frac{C - D}{C + D}
\]

Where \(C\) is the number of concordant pairs and \(D\) is the number of discordant pairs.

**Results and discussion**

**Popularity-based predictor**

The authors in [5] came up with Popularity based predictor (PBP). It exploit the *preferential attachment* theory, which states that popularity increases cumulatively; the rate of new link (Either item receives rating in case of Movielens, or a friend like or comments in case of Facebook wall post activity) formation for any node is proportional to the observed number of links which node has received in past. If an item is popular at time \(t\), then it will probably become popular due to the condition that current degree of an item \(k_o(t)\) is a good predictor of its future popularity. Further ([22], [5]) have found that current degree is a good predictor of items’ future popularity.

[5] proposes to calculate the prediction score of an item at time \(t\) can be given as follows-

\[
s_o(t, T_p) = k_o(t) - \lambda k_o(t, T_P)
\]

Where \(\Delta k_o(t, T_P)\) is the rating/links received in past time window \(T_P\) from \(t\). \(\lambda \in [0, 1]\), note that \(\lambda = 0\) gives the total popularity and for \(\lambda = 1\) it gives recent popularity. Throughout the script we mean number of ratings or links received by item or node.

To check the accuracy and robustness of our proposed model we have considered various data sets such as MovieLens, Netflix and Facebook wall post activity. Our method out performs specially in predicting emerging entries. While performing experiments we have selected 10 random time and constructed network on the basis of prior link formation. From randomly chosen point we measure the past time window \(T_P\) and future time window \(T_F\). We have constructed the network up-to the randomly selected time and calculated PageRank score of the nodes. In case of our proposed hybrid PageRank we have considered how many ratings the node has received in the past time window. We took average of 10 results to make sure robustness of our model.
**Relationship between decay rate (γ) and teleportation parameter (α)**

Below are the empirical results on relationship between PageRank teleportation parameter (α) and decay rate (γ). We have considered different values of both parameters to find that best fit with the data. In all the data sets we have found the optimal value of γ and α is 0.1. Decay rate more affect novelty prediction γ. Although the optimal value is around 0.1 which maximizes the precision for these data sets. In manual parameter setting one can choose higher value of γ to recommend more novel items.

![Diagram](image)

Figure 1: Effect of both the parameters on our model and, on accuracy. Here we have consider TP and TF both as 30 days. The Rank correlation is for whole data while other metrics is for top 100 items.

In figure [Figure 2] we have compared the result with baseline methods. We have considered the future and past time window TF, TP respectively same. We can see our model have better prediction accuracy for novel or emerging node prediction. Our model has better precision accuracy with respect to PageRank. AUC metric also shows better performance over PageRank while with respect to PBP it is not very low. It shows our predictors robustness since it shows better performance for top items means it support preferential attachment theory therefore it can be applied in scale free networks. It’s rank correlation is also considerable means it’s performance will not go down no matter how big the recommendation list size is. From [Figure 2] we can see the correlation coefficient is not better than the other two the reason the other metrics only considers top 100 items while correlation is for whole nodes. We put τ here to show the robustness of our model that it’s performance not much affected in digging novel entries.
Figure 2: The above figure shows the performance of the predictor for different values on future time window $T_F$. Red line shows the performance of our proposed predictor while blue shows the base predictor PBP and green line PageRank predictor. $T_F$ and $T_P$ are considered same upto 200 days. This is result of model m1.

Results using equation (4)

The above results are obtained using equation (2). But as we see some times we need equation(4) to rank the nodes. In [Figure 3] we have considered past and future time window as 30 days for all the data sets. For evaluating Precision ($P_n$), Novelty($Q_n$) and AUC we have considered top 100 elements. While Tau is ranking correlation which works on the whole data.
Figure 3: The above figure shows the comparison with different predictors. The read color bars m1, m2, m3 are for our proposed model in equation 2, 4, 5 from left to right respectively. These results are for different data sets such as MovieLens(A), Netflix(B) and Facebook(C). The blue color bar is for Popularity Based Predictor and green one is for PageRank. Past and future time window is considered as 30 days.

Results using equation (5) when people follows popularity as well as recent activity of the node.

The model given in equation (5) considers both the phenomena. If in some system people follows popularity as well as recent activity of the node then this model will work. We have considered the node attracts new link in a system with probability $\delta$ according to its structural or topological centrality and with probability $(1 - \delta)$ according to recent activity of the node. The results on three data sets are as follows-
From the [Figure 4] we can find that lower value of $\delta$ gives better results. Lower value of delta gives higher weight to dynamic centrality in eq.(5). In other words on these data sets we can say people follow recent activity of the node.

5. Conclusion

User attention can be seen as a scarce and valuable resource and its aggregation as “attention economy” [18]. As user have limited time and energy therefore they cannot give their full resource to dig quality items in this universe of online web. It is like searching for the star without any tool. Although Recommender system helps user to find items of their interest. But whether Recommender system is able to identify all the quality items, is a quest. Being a machine judging quality items is not possible for the Recommender system without any prior history of the item. Recommending novel item at random can cause “shock” to user, which can cost revenue of the enterprise. On the other hand appropriate novel items can help in getting user attention therefore revenue generation. As novelty and popularity are two main causes found for getting user attention [18]. To overcome the “novelty-shock” problem content provider selects many strategies one of them is promoting their products using social media as a “word-of-mouth” or “viral marketing” strategy. To implement these strategy they select the leader or popular user to promote their product. In this work we have given solution to identifying those influential node. Although our model can be applied any time evolving network. Here we have used structural information on the basis of user activity (Facebook case). The best result will come when we have topological (friendship network) as well as user activity of the node such as (wall post, liking and sharing etc). In this paper we have given model that identifies emerging influential node in time evolving network. To find the leader node or
items on social media, we have considered both temporally evolving dynamics as well as structural characteristics of the network. We have found that if we consider recent temporal effects of the node with PageRank then future popularity prediction accuracy improves. Our model predicts the emerging influential nodes, that were not in past popular list without any significant cost of accuracy. We have considered PageRank algorithm for ranking nodes on the basis of structural or topological characteristics. We have also considered the temporal dynamics of the node to consider recent activity of the node.

Acknowledgement

This work is done under NSFC project grant no:61673086.

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