Community detection using preference networks

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Community detection is the task of identifying clusters or groups of nodes in a network where nodes within same group are more connected with each other than with nodes in different groups. It has practical uses in identifying similar functions or roles of nodes in many biological, social and computer networks. With the availability of very large networks in recent years, performance and scalability of community detection algorithms become crucial, i.e. if time complexity of an algorithm is high, it can not run on large networks. In this paper, we propose a new community detection algorithm which has a local approach and is able to run on large networks. It has a simple and effective method; given a network, we construct a preference network with same set of nodes and each node has a single outgoing edge showing its preferred node to be in same community with. In such a preference network, each connected component is a community. In construction of preference network, preferred node selection is critical and we used similarity based metrics for this purpose. In order to keep local, we only used the metrics that can be calculated in the 1-neighborhood of each node doing the selection. We used two similarity metrics; first one is the number of common neighbors of selector node and its neighbors and, second one is the spread capability of neighbors around the selector node which is calculated by the gossip algorithm of Lind et.al. Our algorithm is tested on both computer generated LFR networks and real-life networks with ground-truth community structure. It can identify communities accurately in a fast way. It is local, scalable and suitable for distributed execution on large networks.

PACS numbers: 89.75.Hc, 89.65.Ef, 89.75.Fb

I. INTRODUCTION

Community detection is one of the key areas in complex networks that has attracted great attention in the last decade. In network science, a network is seen as a system and individual nodes as agents or elements of the system where they are connected with ties [1]. Mobile communication networks, scientific collaboration networks, patent networks, protein interaction networks and brain networks are examples of network representation of corresponding systems [2–6]. Interaction of agents in a network can create emergent structures like communities. A community is defined as grouping of nodes in a network such that nodes in the same group have more connections with each other than with the nodes in the rest of the network [7]. There have been many algorithms proposed so far for community detection and there is a comprehensive survey by Fortunato on community detection [8]. While many algorithms perform well on small networks with hundreds or thousands of nodes, only a few of them can run on very large networks of millions or billions of nodes due to performance and time-complexity issues. If a community detection algorithm has to deal with the whole network during its execution steps or needs to optimize a global value (i.e. network modularity), it becomes computationally expensive to run this algorithm on large networks. Besides their large sizes, real-life networks also evolve over time, i.e. structure and size can change while a community detection algorithm is still running on such a large network. In recent years local community detection algorithms are proposed to overcome the challenges of large networks. Local algorithms are scalable and are suitable for distributed run, i.e. they can work on separate parts of the network locally and then merge results for the whole network. Their local nature makes it possible to identify more granular structures which is useful for finding subtle communities; especially in networks of loosely connected groups of nodes.

In this paper, we propose a new commu-
nity detection algorithm which has a local approach. Our assumption is that, each node in the network selects to be a member of a community in order to be in the same group with some preferred nodes. Whether it is the common things they share, common enemies they avoid, common features they have or common ones they follow; being a member of a community is meaningful only when friends or preferred nodes are together there. Such communities can be constructed by asking each node who they would like to be with; and then grouping them together according to given answers. How should a node decide on its preferred node: a popular node, a hub node connecting others or a node with most common friends? We think that using the similarity of nodes is a good way to make the decision, i.e. each node should select the neighbor with whom it has the most similarity. When we are given a network dataset, generally we only have the knowledge of nodes and edges, i.e. no meta-data describing the nodes or common features of nodes (i.e. similarity) may exist. So, using the connectivity information (edges) among the nodes in network, we can get some of the features of individual nodes (i.e. centrality, degree etc.) and some similarity measures between nodes (i.e. common neighbors shared by two nodes). In order to keep local, we should limit our attention to local metrics, i.e. metrics regarding a node and its local neighborhood only, not further. Alternatively, we can try to use some other methods to make decision on preferred node, i.e. selection of the neighbor with highest degree, selection of the neighbor having highest clustering coefficient etc. We will go into the details of metrics for preferred node selection later.

Outline of the paper is as follows. We will give background information about the topics in community detection and methods we use in our algorithm. We then explain our community detection approach in detail. We compare our algorithm with other known algorithms on both real-life networks and computer generated networks. We will finish with the conclusion section.

II. BACKGROUND

A. Local approach for community detection

In recent years several local community detection algorithms have been proposed [9–16]. One popular method is label propagation algorithm [11] which has a linear time complexity and nodes decide on their communities according to the majority of their neighbors. Local community detection algorithms generally discover communities based on local interactions of nodes or local metrics calculated in their 1-neighborhood. Some algorithms merge nodes into communities based on the optimization of a local metric [16]. Besides their scalability, these approaches are also suitable for large networks evolving over time. A local algorithm can handle what it already has (i.e. a portion of the network at a certain time) and can continue with what will come later; it does not need the snapshot of the whole network at once.

B. Triangles and communities in networks

In his book, Simmel [17] argued that a strong social tie could not exist without being a part of a triangle in a relation, i.e. relation among three people where all know each other. People with common friends are more likely to create friendships; they form triangles. There is a correlation between triangles and communities in social networks; there exists many triangles within communities while very few or no triangle exists between nodes of different communities [18].

Clustering coefficient (CC), is equal to the probability that two nodes that are both neighbors of the same third node will be neighbors of one another [19]. This metric shows the number of existing triangles around a node compared to the all possible triangles. A high clustering coefficient will mean many triangles and clustering around a node:

\[ CC(i) = \frac{\Delta_i}{\lambda_i} \]
where \( \triangle_i \) is the number of triangles around node \( i \) and \( \Lambda_i \) is the number of triplets where \( i \) is in center. A *triplet* is formed by three nodes and two edges i.e. a triplet \( a, i, b \) centered at \( i \) has edges \( ai \) and \( bi \). In Fig. 1a, there are three triangles and 21 triplets around \( i \) which leads to \( CC(i) = 0.11 \).

Radicchi et al. [18] proposed a community detection algorithm based on triangles and clustering coefficient. In recent years, local community detection algorithms are more focused on similarity of nodes; especially on local level, i.e. 1-neighborhood of nodes. A node similarity based approach is applied on several known community detection algorithms by Xiang et al. [20], where they presented improvements achieved on those algorithms by using various node similarity metrics. Some examples of those similarity metrics are number of common neighbors and Jaccard similarity [21].

*Number of common neighbors* of nodes \( i \) and \( j \) is \( CN(i,j) = |\Gamma(i) \cap \Gamma(j)| \) where \( \Gamma(i) \) denotes the 1-neighborhood of \( i \). Number of common neighbors shows the number of triangles formed on two nodes, i.e. in Fig. 1b common neighbors of \( i \) and \( j \) are \( k, l, m \) and they are actually corners of triangles formed by \( i \) and \( j \). *Jaccard similarity* is the fraction of common neighbors of \( i \) and \( j \) to the union of their 1-neighborhoods given as

\[
J(i,j) = \frac{|\Gamma(i) \cap \Gamma(j)|}{|\Gamma(i) \cup \Gamma(j)|}
\]

All of these metrics are related with friendship transitivity and triangles.

A new metric, *spread capability*, is proposed as a similarity metric in this paper. This metric is calculated by using the gossip algorithm of Lind et al. [22]. A gossip about a victim node \( i \) is initiated by one of its neighbors, node \( j \) (originator), and \( j \) spreads the gossip to common friends with \( i \), i.e. gossip about \( i \) is meaningful to friends of \( i \) only. Nodes hearing the gossip from \( j \) behave the same way and propagate it further in the 1-neighborhood of \( i \) until no further spread is possible. To measure how effectively the gossip is spread, we calculate *spread factor* of victim \( i \) by originator \( j \) as

\[
\sigma_{i,j} = \frac{|\Gamma_j(i)|}{|\Gamma(i)|}
\]

where \( \Gamma_j(i) \) is the set of neighbors of \( i \) who heard the gossip originated by \( j \). Lind et al. calculated the spread factors of each originator \( j \in \Gamma(i) \) and averaged them to get spread factor of \( i \), i.e.

\[
\sigma_i = \frac{1}{|\Gamma(i)|} \sum_{j \in \Gamma(i)} \sigma_{i,j}.
\]

As we will explain in more detail in next section, we use the spread factor in a different way in our algorithm; instead of average gossip spread factor of a node, i.e. \( \sigma_i \), we focus on \( \sigma_{i,j} \) values which show the contribution of each originator \( j \) to that average. We call it as *spread capability* of \( j \) around \( i \). Spread capability is directly related with the connectivity of \( j \) and its position in the neighborhood of \( i \). So each \( j \in \Gamma(i) \) can have a different spread capability around \( i \) and they can be used as a similarity measure between \( i \) and \( j \) from the perspective of node \( i \). Note that \( \sigma_{i,j} \neq \sigma_{j,i} \).

Spread capability metric has similarity with number of common neighbors and clustering coefficient; but has additional information, see Fig. 2. It contains the number of common neighbors (triangles) between \( i \) and \( j \); moreover it has the number of other triangles around \( i \) with its neighbors along the spreading pathway of gossip originated by \( j \). We call such adjacent group triangles as a *triangle cascade*, which is a group of triangles where all triangles are cornered at same node (i.e. \( i \)) and are adjacent to each other through common edges.

In Fig. 1c \( j, u, v, z \in \Gamma(i) \) form a triangle cascade centered at \( i \). On this triangle cascade, gossip about \( i \) originated by \( j \) is spread
FIG. 2: Networks (a) and (b) have 7 nodes and 9 edges. Degree of $i$ is 6 and clustering coefficient of $i$ is 0.2 in both cases. But average spread factors are 0.5 in (a) and 0.33 in (b).

to $k, l, m, u$ directly. By using the cascade, gossip is propagated to $v$ by $u$ and then to $z$ by $v$. Although $v, z \notin \Gamma(j)$, $j$ still has a role in spreading gossip to $v$ and $z$ by means of triangle cascades.

C. Method for comparison of two partitions

Success of a community detection algorithm in finding correct communities can be measured by comparing the communities identified by the algorithm with ground-truth. Since every node belongs to exactly one community in our algorithm, being in the same community is an equivalence relation. Hence, community structure of a network is a partition of set of nodes. Suppose we have the partition of the ground-truth. A community detection algorithm produces another partition. Then we have the question of how do we compare two partitions. For comparison of two partitions, *Normalized Mutual Information* (NMI) [23] can be used. NMI is a metric to understand how far (close) two partitions are; if NMI of two partitions is close to 1, then they are very similar, i.e. number of communities and the members of communities in two partitions are similar; and when it is close to 0, two partitions are different from each other.

D. Method for testing of algorithms

We need to test our algorithm on different networks. Our first network is Zachary karate club network [24]. It is a well known network dataset of a karate club where members of the club are separated into two groups after a dispute over lesson prices, i.e. first group continue with the president of the club while the second group continued with the instructor. The network dataset has ground-truth community structure; so we can compare it with the communities identified by our algorithm.

As a second group of testing, we use real-life networks provided by SNAP [25]; namely DBLP dataset, Amazon co-purchase network, Youtube network and European-email network, which have available ground-truth communities. To be able to compare the performance of our algorithm to that of some known algorithms, namely Newman’s fast greedy algorithm [9], Infomap [10], Louvain [12] and Label Propagation (LPA) [11], in addition to our own algorithm, we run them on these networks. We compared the partitions identified by each algorithm with partitions of ground-truth of these networks using NMI. We also measured the execution time of these algorithms (we used a standard laptop computer having a 2.2 GHz Intel Core i7 processor with 4-cores).

When we do not have the ground-truth community structure, we can not benchmark the results of a newly proposed community detection algorithm. One can try a comparative analysis by running a set of algorithms on a network dataset and make a pairwise comparison between identified partitions of these algorithms. This is not a good way of quality testing for an algorithm because there is not a universally “best” community detection algorithm that can be used as gold standard. We carried such a comparative analysis, however we could only see how close or far each algorithm to any other algorithm in terms of number of identified communities or NMI values. For that reason, without ground-truth, quality test of an algorithm in terms of finding correct communities can not be done.

Many real-life network datasets do not have ground-truth of community structure. In such
cases, computer generated networks like LFR benchmark networks [26] with planted community structure can be helpful. LFR algorithm generate networks with known community structure. It has a parameter vector of \([N, (k), k_{\text{max}}, C_{\text{min}}, C_{\text{max}}, \mu]\) where \(N\) is the number of nodes and \(\mu\) is the mixing parameter. We investigate response of community detection algorithms to datasets generated with various mixing values. As \(\mu\) increases the community structure becomes more blurry and difficult to detect. Being nondeterministic, LFR generate different networks for the same parameter vector. In order to avoid potential bias of an algorithm to a single network, we generate 100 LFR networks for each vector and report the averages.

### III. OUR APPROACH

Our approach is based on building a preference network where each connected component is declared as a community. Given a network, we build its corresponding preference network using the preference of each node for other nodes to be in same community with. Every node prefers to be in the same community with certain nodes, we simply try to satisfy these requests. In this study we implement the case where each node is allowed to select only one node, which is the most preferred node to be with. It is relatively easy to extend this approach to nodes preferring two, three or more nodes, too. First, we describe how to satisfy such requests by means of preference network. Then we investigate ways to decide which node or nodes to be with.

#### A. Preference network

Let \(G = (V, E)\) be an undirected network where \(V\) and \(E\) are the sets of nodes and of edges, respectively. Define a prefer function \(p: V \rightarrow V\) such that \(p(i) = j\) iff node \(i\) prefers to be in the same community with node \(j\). If we connect \(i\) to \(p(i)\), clearly \(p\) induces a new directed network on \(V\), but we will use the corresponding undirected network. Using \(p\), we define a new undirected network \(G^p = (V, E^p)\) such that nodes \(i\) and \(j\) are connected, i.e. \((i, j) \in E^p\), iff either \(p(i) = j\) or \(p(j) = i\). We call this network as the preference network. We consider the components of \(G^p\) as communities. Hence we satisfy the rule that every node is in the same community with its preferred node. Note that preference network is not a tree since it may have cycles as in the case of node \(a\) prefers node \(b\), \(b\) prefers node \(c\), \(c\) prefers \(a\).

#### B. Deciding which node to be with

Now we can investigate a selection method of preferred node. First of all, with the given definition, there is nothing that restricts a node to prefer any other node in the network even if the preferred node is not connected to the node. For example a node could prefer the node with the largest betweenness centrality. This view is too general and requires global information.

We restrict the selection of preferred node to the local neighborhood of every node. We calculate a score for each node in the local neighborhood \(N(i)\) of \(i\), with respect to \(i\). Then select the node with highest score (detailed later) as preferred node. That is, we define the function \(p\) as;

\[
p(i) = \arg \max_{j \in N(i)} s_i(j)
\]

where \(s_i(j)\) being the score of node \(j\) with respect to \(i\). In tie situations, i.e. when two or more neighbors having the highest score, node selects one of them randomly. Note that the score \(s_i(j)\) of \(j\) depends on the node \(i\). The score can be interpreted as a measure of how “important” node \(j\) for \(i\). If the node is the only connection of \(i\), it has to have very big value. If \(i\) has many neighbors, then \(j\) may not be very important for \(i\). Hence the very same node \(j\) usually has different scores with respect to some other nodes, i.e. \(s_i(j) \neq s_k(j)\).

We did not define the local neighborhood properly. One may define it as the nodes whose distance is not more than \(\ell\) to \(i\). It may be the nodes whose distances to \(i\) are exactly \(\ell\). We may also include node \(i\) itself to the local neighborhood. In this case \(i\) may prefer to
be in the same community with itself. For this study, we take \( N(i) \) as the 1-neighborhood of \( i \), i.e. the set of nodes who’s distance to \( i \) is exactly 1, which is denoted by \( \Gamma(i) \).

C. Candidates of score metric

There are a number of candidates for score \( s_i(j) \) calculation of \( j \) with respect to \( i \). (1) The simplest one is to assign a random number for each neighbor of \( i \) as its score. Probably this is not a good choice, since random function will decide independent of node \( j \) and node \( i \) and their relations with each other. (2) Nodes with more connections are usually considered to be more important in a network. So, as a second choice, we can use the degree of the nodes, i.e. \( s_i(j) = |\Gamma(j)| \). The degree of node \( j \) is also independent of \( i \). So we do not incorporate what \( i \) thinks of \( j \) in the score \( s_i(j) \). (3) A third candidate is clustering coefficient of \( j \), which is an indication of how densely connected its immediate neighborhood, i.e. \( s_i(j) = CC_j \). This is again a value which does not directly depend on \( i \) but may have a meaning to \( j \) and \( i \), i.e. there is a chance that high clustering coefficient of \( j \) is at least partly because of triangles shared by \( j \) and \( i \). (4) Having common neighbors is an important feature in social networks. From the definition of community, members inside the community should have more edges among themselves which leads to more common neighbors of nodes inside a community. Number of common neighbors \( i \) and \( j \) is the number of triangles having \( i \) and \( j \) as two corners. For this reason, as a fourth candidate we can use the number of common neighbors of \( i \) and \( j \), i.e. that is \( s_i(j) = |\Gamma(i) \cap \Gamma(j)| \). (5) As a fifth candidate, we can use spread capability of a neighbor \( j \) around node \( i \), i.e. \( s_i(j) = \sigma_{i,j} \). It both contains number of common neighbors and triangle cascades as discussed earlier. (6) And as the sixth candidate, we can use Jaccard similarity of \( i \) and \( j \) as score, i.e. \( s_i(j) = J(i,j) \).

IV. RESULTS AND DISCUSSION

A. Selection of best score metric

We first analyze alternative score metrics in our algorithm and try to find which one performs better in community detection. We run our algorithm on generated LFR networks \([26]\) of 1,000 nodes using all of these score metrics, \( s_i(j) \), as the method of preferred node selection. NMI values and execution times are measured. The results of our algorithm using six different score metrics on LFR networks generated with increasing mixing values (\( \mu \)) are in Fig. 3a and Fig. 3b. We observe that number of common neighbors is the best score metric among six alternatives; it has the best NMI values and can identify exact community structure on networks generated with \( \mu = 0.1 \) and \( \mu = 0.2 \). Spread capability score metric has the second best results; it is better than Jaccard similarity where Jaccard similarity metric finds 4-5 times more number of communities compared to ground-truth of LFR networks. Other three metrics; namely random score assignment, degree and clustering coefficient can identify communities to a degree but not as successful as the ones mentioned above. In the second group of metrics, clustering coefficient is the best one and our algorithm using clustering coefficient score can find communities on networks generated with low \( \mu \). Interestingly, random score metric can identify a group of communities successfully on these networks. In general, our algorithm using random score and degree based score metrics find few number of communities compared to ground-truth.

It is trivial that calculation of simple score metrics requires less computation time compared to calculation of other score metrics, i.e. execution time of our algorithm using random score, degree and clustering coefficient all have less execution times as given in Fig. 3b. On the other hand, calculation of common neighbors, spread capability and Jaccard similarity require more computation time, as these metrics are calculated for each pair of nodes (i.e. number of edges) and eventually these metrics produce better results in terms of community detection. Hence, we select the two best
performing score metrics for our algorithm, namely, common neighbors and spread capability, denoted as PCN and PSC respectively. We used these score metrics in our algorithm for comparative analysis with other known algorithms on generated and real-life networks.

B. Zachary karate club network

We run our algorithm on Zachary karate club network and compared the identified communities with those of ground-truth. Our algorithm with common neighbors score metric, namely PCN, identified two communities as seen in Fig. 4. Only node 9 is misidentified by our algorithm. Node 9 actually has more connections in its identified community and the ground-truth metadata may not reflect the actual community. All the other nodes are identified correctly.

C. Large real-life networks

We run our algorithm with both score metrics, PCN and PSC, on large networks with ground-truth communities provided by SNAP [25]. For comparative analysis, Infomap, Louvain, LPA and Newman’s fast greedy algorithm are also run on these networks. We omit Newman’s algorithm on Youtube network (could not finish due to long execution time). Results are presented in Table I. On all of the four real-life networks, number of communities found by PCN, PSC, Infomap and LPA are close to each other and not far from the ground-truth (one exception is the Youtube network). However Louvain and Newman’s algorithm found very few number of communities. LPA performed not good on European-email network and produced just two communities. On all of these networks, our algorithm tends to find more number of communities because of its local nature.

In general, performance of Louvain and Newman’s algorithm on large real-life networks is low. Their NMI scores are very low and number of identified communities by these algorithms are far from those of ground-truth. These two algorithms perform better on European-email network. Infomap and LPA algorithms are generally have better NMI values compared to other algorithms, however LPA found only two communities in European-email network where there are 42 ground-truth communities. Our algorithm, with both score metrics (PCN and PSC), performed well on most of the networks with good NMI values. However it performed poorly on Youtube network where all the other algorithms have similar bad results. This may be due to very small clustering coefficient of Youtube network, i.e. no trivial community structure is available.
TABLE I: Large real-life networks

| Network          | |V| |E| |CC| | # communities | NMI | execution time (ms) |
|------------------|---|---|---|---|---|---|---|---|---|
| GT               | 317,080 | 1,049,866 | 0.63 | 13,477 | 28,799 | 30,811 | 36,291 | 565 | 0.58 | 4,652 | 3,679 | 15,755 | 108,410 | 8.217 | 4,362,272 |
| Infomap          | Amazon | 334,863 | 925,872 | 0.40 | 75,149 | 36,514 | 36,519 | 35,139 | 23,869 | 248 | 1,474 | 0.58 | 0.59 | 0.60 | 0.54 | 0.11 | 0.11 | 2,911 | 3,879 | 43,253 | 83,532 | 8.017 | 1,422,590 |
| Louvain community detection algorithm |
| Newman’s fast algorithm |

D. Generated networks

We perform the similar comparative analysis on generated LFR networks of 1,000 and 5,000 nodes as reported in Fig. 5a and Fig. 6a respectively. We present the detailed results of algorithms on LFR networks of 5,000 nodes in Table II. As described earlier, we generate 100 LFR networks per µ value, run the algorithms on all 100 generated datasets and averaged the results for each algorithm. On LFR networks with 1,000 nodes, our algorithm with common neighbors (PCN) is among the top 3 best performing algorithms according to the NMI values; on most of the networks, Infomap and our algorithm find the best results and LPA is in third place. Our algorithm with spread capability (PSC) has lower NMI values but still performs better than Newman’s algorithm. On the networks generated with higher mixing values (i.e. µ > 0.5), Infomap and LPA tend to find small number of communities and sometimes they group all the nodes into a single community. Louvain and Newman’s fast algorithm also find very few number of communities when mixing parameter is low, however their quality degrades with increasing mixing parameter where our algorithm can still identify communities successfully.

One of the main differences between our algorithm and LPA is that, we do not assign community labels to nodes but keep the information of who prefers whom to be in same community using a preference network. During execution steps of LPA, a node updates its community label according to majority of labels of its neighbors. However when all or part of those neighbors update their labels to be in a different community, the node will fall apart from them, it will be in a different community (however it wanted to be in same community and updated its label accordingly). Using a preference network, we preserve all the preferences made by each node throughout the execution of algorithm (because we do not update any label). And collection of all these preferences will eventually lead to a good community structure.

V. CONCLUSION

We propose a new local community detection algorithm with two variants, PCN and PSC, which builds a preference network using two different node similarity score met-
FIG. 5: Comparison of our method and known algorithms on LFR benchmark network datasets (NMI and execution times). $N=1,000$, $\langle k \rangle=15$, $k_{max}=50$, $C_{min}=10$, $C_{max}=50$

FIG. 6: Comparison of our method and known algorithms on LFR benchmark network datasets (NMI and execution times). $N=5,000$, $\langle k \rangle=15$, $k_{max}=75$, $C_{min}=20$, $C_{max}=100$

| Network | $|V|$ | $|E|$ | $\langle k \rangle$ | CC | $C_{min}$ | $C_{max}$ | $\#$ communities | NMI | Execution time (ms) |
|---------|------|------|----------------|-----|------------|------------|------------------|-----|-------------------|
| LFR-1   | 1,000| 0.71 | 0.89           | 50  | 10         | 100        | 2,401           | 0.81 | 121               |
| LFR-2   | 5,000| 0.71 | 0.76           | 50  | 10         | 100        | 2,493           | 0.99 | 1,000             |
| LFR-3   | 5,000| 0.71 | 0.87           | 50  | 10         | 100        | 2,583           | 0.99 | 1,000             |
| LFR-4   | 0.01 | 0.71 | 0.87           | 50  | 10         | 100        | 2,661           | 0.99 | 1,000             |
| LFR-5   | 0.01 | 0.71 | 0.87           | 50  | 10         | 100        | 2,741           | 0.99 | 1,000             |
| LFR-6   | 0.01 | 0.71 | 0.87           | 50  | 10         | 100        | 2,821           | 0.99 | 1,000             |
| LFR-7   | 0.01 | 0.71 | 0.87           | 50  | 10         | 100        | 2,901           | 0.99 | 1,000             |
| LFR-8   | 0.01 | 0.71 | 0.87           | 50  | 10         | 100        | 2,981           | 0.99 | 1,000             |
| LFR-9   | 0.01 | 0.71 | 0.87           | 50  | 10         | 100        | 3,061           | 0.99 | 1,000             |
| LFR-10  | 0.01 | 0.71 | 0.87           | 50  | 10         | 100        | 3,141           | 0.99 | 1,000             |

TABLE II: Generated LFR benchmark networks of 5000 nodes
rics; namely common neighbors and gossip propagation ability. Although it uses only local information, its performance is good especially when community structure is not easily detectable. On LFR networks generated with higher mixing value ($\mu > 0.7$) our algorithm performs better than all the other algorithms used for comparison in this paper. On such networks, algorithms like Infomap and LPA merge all the nodes into a single community, where these algorithms are stuck in a local optimum and fail to identify communities. Our algorithm identified communities in many large real-life networks with high accuracy in a fast way.

We think that building a preference network to identify communities is a simple and powerful approach. With this, we preserve the preferences of all of the nodes for being in same community with another node, whether they are highly connected or have a few connections. This approach prevents loss of granular community information especially in very large networks. Even with random score assignment, our algorithm could identify many communities on generated LFR networks. Due to its local nature, our algorithm is scalable and fast, i.e. it needs only a single pass on the whole network to construct a preference network and similarity metric used for this construction can be evaluated in 1-neighborhood of each node. It can run on very large networks without loss of quality and performance.

We haven’t implemented a distributed or parallel version of our algorithm however it is suitable for parallel processing in a distributed environment. It can be deployed as agents on different parts of a large real-life network which is evolving over time. On such a network, collecting the data of the whole network is costly (time, space, computation), while information about small parts of the network can easily be obtained and analyzed by each nearby agent for community detection. Agents can easily identify community structures of that particular area without knowing the rest of the network; which is a valuable information at that scale and can be used in real-time by systems like peer-to-peer networks.

Acknowledgments

Thanks to Mark Newman, Vincent Blondel and Martin Rosvall for the source codes of their community detection algorithms. Thanks to Mark Newman, Jure Leskovic and Vladimir Batagelj for the network datasets used.

This work was partially supported by the Turkish State Planning Organization (DPT) TAM Project (2007K120610).

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