YASCA: A collective intelligence approach for community detection in complex networks

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1. INTRODUCTION

Complex networks are frequently used for modeling interactions in real-world systems in diverse areas, such as sociology, biology, information spreading and exchanging, scientometrics and many other different areas. One key topological feature of real-world complex networks is that nodes are arranged in tightly knit groups that are loosely connected one to each other. Such groups are called communities. Nodes composing a community are generally admitted to share common propeties and/or be involved in a same function and/or having a same role. Hence, unfolding the community structure of a network could give us much insights about the overall structure a complex network.

We distinguish between two different problems: partitioning the whole graph into (eventually overlapping) communities [Fortunato 2010] and identifying ego-centered communities for a given query node [Kanawati 2014a]. In this work we propose a new algorithm, YASCA, that use local community identification in order to compute a global graph partition into communities. The algorithm belongs to the seed centric algorithms family [Kanawati 2014b]. The basic idea of seed centric algorithms is to select a set of nodes (i.e. seeds) around which communities are constructed. Being based on local computations, these approaches are very attractive to deal with large-scale and/or dynamic networks. Different algorithms apply different policies for seed selection and for community construction around seeds. The number of seed nodes can be pre-determined [Khorasgani et al. 2010] or computed by the approach itself [Kanawati 2011]. The seed selection process can be : random [Khorasgani et al. 2010] or informed [Kanawati 2011]. The community construction can be made applying consensus techniques, expansion techniques or agglomeration techniques [Kanawati 2011]. Next we propose an original seed centric approach that apply an ensemble clustering approach [Strehl and Ghosh 2003] to different network partitions derived from ego-centered communities computed for each selected seed.

2. YASCA: THE PROPOSED ALGORITHM

The YASCA\footnote{Yet Another Seed-centric Community detection Algorithm} algorithm is structured into three main steps:

(1) First, we select a subset of nodes acting as seed nodes. Let $S \subset V$ denotes the set of selected seed nodes. Different selection strategies can be applied as mentioned in previous section. A detailed discussion of selection strategies can also be found in [Kanawati 2014b].

(2) For each selected node, we compute an ego-centered community using a recently proposed ensemble ranking based greedy optimisation algorithm described in [Kanawati 2014a]. This ensemble ranking based approach allows combining efficiently different local modularities generally used for identifying local communities [Chen et al. 2009]. Let $C_v$ be the computed local community of seed node $v \in V$. The set of vertices $V$ can then be partitioned into two disjoint sets : $P_v = \{C_v, \overline{C_v}\}$ where $\overline{C_v}$ denotes the complement of set $C_v$. 
(3) We merge the set of obtained partitions $P_v, v \in S$ by applying a cluster ensemble method. The output of this process is the taken to be the final decomposition of the shoe graph into communities.

The goal of an ensemble clustering approach is to compute a clustering (here a partition) that combine the different obtained partitions. One widely applied method is based on constructing a consensus graph out of the set of partitions to be combined [Fern and Brodley 2004; Strehl and Ghosh 2003]. The consensus graph $G_{cons}$ is defined over the same set of nodes of the initial graph $G$. Two nodes $v_i, v_j \in V$ are linked in $G_{cons}$ if there is at least one partition $P_y$, where both nodes are in a same cluster. Each link $(v_i, v_j)$ is weighted by the frequency of instances that nodes $v_i, v_j$ are placed in the same cluster. Different approaches has been proposed to detect communities in the consensus graph [Strehl and Ghosh 2003; Dahlin and Svenson 2013]. In this work we propose applying to the consensus graph a community detection algorithm that can handle unconnected, weighted graphs. The Louvain algorithm [Blondel et al. 2008] is one good option.

3. EXPERIMENTS

In order to quantitatively analyse and compare performances of the different proposed approaches we have applied these to networks whose community structure is already known. Performance of the proposed algorithms are evaluated in function of the similarity of the obtained clustering with the ground truth known clustering as measured by the normalized mutual information (NMI) index [Strehl and Ghosh 2003]. We compare the performances of the YASCA algorithm on three well known benchmark networks: the Zachary Karate Club network [Zachary. 1977], the dolphins social network [Lusseau et al. 2003], and the political books network [Girvan and Newman 2002]. We have configured YASCA as follows : Seed nodes are composed of the 25% of top high degree nodes and 25% of low degree nodes. For the consensus graph we keep a link is the associated frequency if equal of greater than 0.5 (these are the best parameters when using the degree centrality for selecting seeds). Figure 3 shows the obtained results on the three datasets compared to state of the art algorithms : Louvain [Blondel et al. 2008], Infomap [M. Rosvall and . 2009], Walktrap [Pons and Latapy 2006] and edge-betweenness based modularity optimisation algorithm [Girvan and Newman 2002].

4. CONCLUSION

A new seed centric algorithm for community detection is proposed. First results on small networks show the potential of this algorithm compared to the state of the art algorithms. Further investigations about the effects of different parameters of the algorithm are considered (seed selection strategy, the
local community algorithm to be used, etc.). Validations on large-scale graphs are also scheduled. This requires to parallelise the step of local community identification of each seed node.

REFERENCES

Vincent D Blondel, Jean-loup Guillaume, and Etienne Lefebvre. 2008. Fast unfolding of communities in large networks. (2008), 1–12.

Jiyang Chen, Osmar R. Zaiane, and Randy Goebel. 2009. Local Community Identification in Social Networks. In ASONAM. 237–242.

Johan Dahlin and Pontus Svensson. 2013. Ensemble approaches for improving community detection methods. CoRR abs/1309.0242 (2013).

Xiaoli Zhang Fern and Carla E. Brodley. 2004. Solving cluster ensemble problems by bipartite graph partitioning. In ICML (ACM International Conference Proceeding Series), Carla E. Brodley (Ed.), Vol. 69. ACM.

S. Fortunato. 2010. Community detection in graphs. Physics Reports 486, 3-5 (2010), 75–174.

M. Girvan and M. E. J. Newman. 2002. Community structure in social and biological networks. PNAS 99, 12 (2002), 78217826.

Rushed Kanawati. 2011. LICOD: Leaders Identification for Community Detection in Complex Networks. In Social-Com/PASSAT. IEEE, 577–582.

Rushed Kanawati. 2014a. Combinaison de modularités locales pour l'identification de communautés échelle-centrées , 28/01/2014 Rennes. In Actes de 2ième atelier de fouille de grands graphes - EGC’14, Lydia Boudjeloud, Benédicte Le Grand, and Rushed Kanawati (Eds.). Rennes.

Rushed Kanawati. 2014b. Seed-centric approaches for community detection in complex networks. In 6th international conference on Social Computing and Social Media, Gabriele Meiselwitz (Ed.), Vol. LNCS. Springer, Crete, Greece.

Reihaneh Rabbany Khorasgani, Jiyang Chen, and Osmar R Zaiane. 2010. Top leaders Community Detection Approach in Information Networks. In 4th SNA-KDD Workshop on Social Network Mining and Analysis. Washington D.C.

D. Lusseau, K. Schneider, O. J. Boisseau, P. Haase, E. Slooten, and S. M. Dawson. 2003. The bottlenose dolphin community of Doubtful Sound features a large proportion of long-lasting associations. Behavioral Ecology and Sociobiology 54 (2003), 396–405.

D. Axelsson M. Rosvall and C. T. Bergström . 2009. The map equation. Eur. Phys. J. Special Topics 13 (2009), 178.

Pascal Pons and Matthieu Latapy. 2006. Computing Communities in Large Networks Using Random Walks. J. Graph Algorithms Appl. 10, 2 (2006), 191–218.

A. Strehl and J. Ghosh. 2003. Cluster ensembles: a knowledge reuse framework for combining multiple partitions. The Journal of Machine Learning Research 3 (2003), 583–617.

W W Zachary. 1977. An information flow model for conflict and fission in small groups. Journal of Anthropological Research 33 (1977), 452–473.