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Community Detection and Analysis on Attributed Social Networks

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Synonyms

Community Detection, Community Analysis, Subgroup Discovery, Attributed Graph

Glossary

Social Network: A network made up of a set of actors (nodes) with ties (edges) between the actors.

Community: A group of densely connected actors in a social network.

Community Detection: The task of identifying communities.

Attributed Social Network: A social network where there exists a set of attributes (properties) assigned to actors and/or or the involved ties, respectively.

Definition

While community detection identifies communities on plain social networks focusing on the network structure, the analysis of attributed social networks allows for more fine-grained community detection approaches combining compositional analysis of the attributes (properties) of actors and/or ties in social networks, cf., (Wasserman and Faust, 1994), with structural analysis.

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Introduction

Communities and cohesive subgroups have been extensively studied in social sciences, e. g., using social network analysis methods (Wasserman and Faust, 1994), where community detection (Newman and Girvan, 2004; Fortunato, 2010; Xie et al, 2013) is especially helpful for providing for analytical and exploratory approaches. While communities (as cohesive subgroups of actors) are typically induced guided by structural considerations, subgroups can also be defined by compositional criteria, e. g., focusing on common attributes of the actors, similar to the task of subgroup discovery (Klösgen, 1996; Wrobel, 1997; Atzmueller, 2015).

This work presents an organized picture of recent research in community detection specifically focusing on attributed social networks. We discuss methods that work on extended (attributed) social networks, i. e., including descriptive information about the nodes. Below, we provide an overview on representative methods, including several basic methods working on simple graphs. We briefly summarize structural and compositional analysis and introduce the concept of attributed (social) networks. After these preliminary considerations, we focus on descriptive methods for community detection utilized attributed social networks.

Key Points

Richer network representations, i. e., *attributed social networks*, enable approaches that specifically exploit the descriptive information of the labels assigned to nodes and/or edges. Nodes of a network representing users, for example, can be labeled with tags that the respective users utilized in a social bookmarking systems. Then, *explicit descriptions* for the characterization of a community can be provided.

Historical Background

Wasserman and Faust (1994) discuss social network analysis in depth and provide an overview on the analysis of subgroups/communities in graphs, including clique-based, degree-based and matrix-perturbation-based methods.

For assessing the quality of a community, usually not only the community's density is assessed but the connection density of the community is compared to the density of the rest of the network (Newman and Girvan, 2004). Besides modularity (Newman and Girvan, 2004; Newman, 2004, 2006), prominent examples of community quality measures include, for example, the segregation index (Freeman, 1978) and the inverted average out-degree fraction (Yang and Leskovec, 2012).

Fortunato (2010) presents a thorough survey on the state of the art community detection algorithms in graphs, focussing on detecting *disjoint* communities, while Xie et al (2013) focuses on the detection of overlapping communities. Essentially, overlapping communities allow an extended modeling of actor–actor relations in social networks: Nodes of a corresponding graph can then participate in multiple communities. This is also typically observed in real-world networks regarding different complementary facets of social interactions (Palla et al, 2005; Mitzlaff et al, 2014). Concerning quality measures, extensions of the modularity metric for handling overlapping communities are described in (Muff et al, 2005; Nicosia et al, 2009; Lin et al, 2009).

Descriptive Community Detection and Analysis

Focusing on methods for generating *explicit descriptions connected with the network structure*, we distinguish between two types of approaches: first, methods that mainly work on the graph structure but apply descriptive information for restricting the possible sets of communities; second, methods that mine descriptive patterns for obtaining community candidates evaluated using the graph structure.

Community Detection on Attributed Social Networks

As a representative of the first type, Moser et al (2009) combine the concepts of dense subgraphs and subspace clusters for mining cohesive patterns. Starting with quasi-cliques, these are expanded until constraints regarding the description or the graph structure are violated. Similarly, Günnemann et al (2013) combine subspace clustering and dense subgraph mining, also interleaving quasi-clique and subspace construction.

As an example for the second type outlined above, Galbrun et al (2014) propose an approach for the problem of finding overlapping communities in graphs and social networks that aims to detect the top-k communities such that the total edge density over all k communities is maximized. The three algorithmic variants proposed by Galbrun et al (2014) apply a greedy strategy for detecting dense subgroups, and restrict the result set of communities, such that each edge can belong to at most one community. This partitioning involves a global approach on the community quality. Silva et al (2012) study the correlation between attribute sets and the occurrence of dense subgraphs in large attributed networks (represented as graphs). The proposed method considers frequent attribute sets using an adapted frequent item mining technique, and identifies the top-k dense subgraphs induced by a particular attribute set, called structural correlation patterns. The DCM method presented by Pool et al (2014) includes a two-step process of community detection and community description. A heuristic approach is applied for discovering the top-k communities. Pool et al. utilize a special interestingness function which is based on counting outgoing edges of a community; for that, they also demonstrate the trend of a correlation with the modularity function.

The COMODO algorithm presented in Atzmueller et al (2016a) focuses on *description-oriented community detection* using subgroup discovery. It aims at discovering the top-k communities (described by community patterns) with respect to a number of standard community evaluation functions. The method is based on an adapted subgroup discovery approach (Atzmueller and Mitzlaff, 2011; Lemmerich et al, 2012), and also tackles typical problems that are not addressed by standard approaches for community detection such as pathological cases like small community sizes. COMODO is a fast branch-and-bound algorithm utilizing optimistic estimates (Grosskreutz et al, 2008; Wrobel, 1997) which are efficient to compute. This allows COMODO to prune the search space significantly.

Community Analysis

While there are a lot of prominent methods for community detection the resulting models need to be assessed, validated and evaluated. There are different approaches that can be taken into account, e. g., a measure-based evaluation, external evaluation using ground-truth or benchmark datasets, or an validation utilizing human experts.

The first alternative analyzes a given community (set) using an evaluation function for assessing its quality. However, care must be taken, since different measures might exhibit certain biases, e. g., if they tend to reward communities with certain properties which might then lead to respectively skewed community structures (Leskovec et al, 2010; Orman et al, 2012; Largeron et al, 2015).

In the external evaluation option, often a key difficulty in assessing the quality of a given community is the lack of an established ground truth for measuring the level of coherence. If available, external data sources such as Wikipedia or WordNet can be consulted (Newman et al, 2010). Furthermore, benchmark datasets (Lancichinetti et al, 2008) or data generators can be applied in order to enable data for assessing community detection methods – as a kind of proxy for estimating their quality on real data (Largeron et al, 2015; Benyahia et al, 2016). Furthermore, for a semantic grounding of communities the actors can be mapped into the corresponding feature space and its connectivity can be analyzed in a multi-mode graph, respectively, cf., (Mitzlaff et al, 2013, 2014).

In cases, when there is no evaluation data at hand in order to evaluate the discovered communities comprehensively, other approaches can be applied, e. g., using secondary data in the form of evidence networks. Regarding that option, Mitzlaff et al (2011) exploit the principle of Siersdorfer and Sizov (2009) for reconstructing existing social structures using (implicit) evidence networks is adapted. Here, community structures are evaluated in relation to the mentioned evidence networks, as implicit networks capturing traces of actors observed, e. g., in (large) online systems. Such evidence networks can typically also be observed in the context of attributed networks, whenever descriptive (relational) information is involved; alternatively, they can often be conveniently constructed given secondary data. For a discussion of illustrative examples for their construction, see (Mitzlaff et al, 2011).

Other evaluation and assessment options include user studies, cf., (Sun and Lin, 2013) which is used for analyzing the communities, i. e., measuring how well a given community structure coincides with the actual reception of the users. Furthermore, communities can be ranked by humans using introspection techniques for the respective user subgroups, e.g., (Atzmueller and Puppe, 2008; Atzmueller et al, 2006), based on subgroup analysis. Using visualization and introspection techniques distinct features of the communities can be uncovered and analyzed in detail according to the visualization seeking mantra by (Shneiderman, 1996). For the analysis of attributed spatio-temporal network data, for example, an exploratory pattern mining approach detecting descriptive community patterns in the social media domain is given in (Atzmueller and Lemmerich, 2013): Here, descriptions are generated from tags, and introspective visualization methods are provided in a semi-automatic community detection and analysis approach.

A hypothesis-driven approach for community analysis is outlined in (Atzmueller et al, 2016c, 2017) for analyzing social networks and communities based on specific hypotheses that are formulated by the analyst. Communities can also be detected based on that idea, e. g., (Atzmueller, 2016b) - for identifying communities that conform (or contrast) given hypothese, also facilitating their analysis.

Key Applications

Below, we sketch key applications of description-oriented community detection on attributed social networks. The key point here is that these applications can be considered similar to those of community detection on plain social networks, while specifically exploiting the descriptive information given by the attributes on the actors (nodes) and ties (edges) contained in the respective network.

Exploratory Data Analysis

Descriptive data mining aims to uncover certain patterns for characterization and description of the data. Typically, the goal of the methods is not only an actionable model, but also a human interpretable set of patterns (Mannila, 2000; Wang et al, 2006). Description-oriented community detection has a wide applicability for characterizing social groups, e. g., targeting strongly connected (cohesive) subgroups, assessing important attributes and features that are specific for the respective communities, and providing insight into the distribution and structure of those, e. g., (Macek et al, 2012; Atzmueller et al, 2011, 2012, 2014). Then, for example, community structure, composition and evolution can be analyzed in detail, e. g., (Kibanov et al, 2014, 2015). Furthermore, additional factors can be included in the analysis, e. g., time and space in order to provide exploratory views on the evolution of communities and their spatio-temporal characteristics.

Here, specialized tools, e. g., the VIKAMINE platform (Atzmueller and Puppe, 2005; Atzmueller and Lemmerich, 2012) for subgroup analytics provide powerful methods and techniques for automatic, semi-automatic and interactive exploration and discovery.

Description-oriented community detection especially provides the means of implementing an explanation-aware data mining (Roth-Berghofer and Richter, 2008; Atzmueller and Roth-Berghofer, 2010) approach, due to its more interpretable results, e. g., for characterizing a set of data, for concept description , and for providing regularities and associations between elements in general. Exploratory approaches can be implemented in a two-step process: In the first step, a candidate set of potentially interesting communities is generated. In the second step, a human explores this candidate set and introspects interesting communities (and their descriptions) manually by browsing and viewing various visualizations. The community detection method can then be tuned and adapted in an exploratory fashion. Additionally, the results can be filtered according to different interestingness criteria defined by the applied quality function. Furthermore, background knowledge, e. g., on semantically equivalent information, can be manually refined and included in the process. Example instantiations of these process can be found, e. g., in (Atzmueller and Lemmerich, 2013) for spatio-temporal network data, or (Atzmueller et al, 2015) for heterogenous attributed networks.

Personalization and Recommendation

Recommender systems (Bobadilla et al, 2013) provide powerful approaches for social (media) platforms, e. g., for resource sharing, online communication, or media consumption. For these platforms, leveraging the information from the social network(s) is important for providing enhanced recommendation and personalization capabilities, e. g., for recommending interesting resources or actors to the individual users based on the connection to *peer groups* or communities, e. g., (Atzmueller et al, 2011).

In particular, presenting different communities a particular user belongs to, and description of these (and/or, for example, the involved resources) can provide more effective recommendation and personalization options. This can also help for resolving the typical cold-start problem involved in recommendation approaches, e. g., based on collaborative filtering. Furthermore, the given descriptive profiles of the respective communities provide flexible options for personalization, depending on the exploited descriptive information on actors/ties of the network.

Finally, such descriptive profiles can be an important starting point for explanation, in the context of personalization and recommendation (Riboni and Bettini, 2012). Since the community descriptions are typically interpretable by humans they can be presented as an explanation themselves, or they can be enhanced using further context knowledge.

Behavioral Social Targeting

Targeting subgroups that exhibit certain behavior, e. g., regarding their social connectivity, information-seeking behavior and actions etc. in social systems, is useful in many applications. Here, for example, behavioral social targeting is one of the options for analyis and application, for example, in marketing and advertising (Pool et al, 2014; Bonchi et al, 2011). Then, factors like geographical location, socio-economic factors, demographic information, and social context, if available, can all be included in the analysis of social network data in an comprehensive approach for behavioral analysis. Based on that, for example, key actors can be identified in the community, a set of most similar (and relevant) actors can be defined etc. Also, behavioral analysis can be performed, for example, regarding time, spatio-temporal context, and roles of the actors which provides a number of different options for the actionability of the identified patterns.

Especially the feature of integrating descriptive (attribute) information in the community detection method allows to provide rich descriptions that can be used for targeting a certain subgroup, while the description itself both serves as an explanation and prototypical profile of typical members of the targeted subgroup, cf., (Atzmueller and Lemmerich, 2013; Atzmueller et al, 2016a).

Future Directions

Currently, most approaches for community detection on attributed social networks target a single social network, and a set of nominal and/or numeric attributes. For future directions, extensions on the network data structure, attribute composition, as well as the analysis methods are interesting options to consider. The investigation of multi-layer networks is rather interesting, since then social interaction can be analyzed on different layers, several networks can complement each other regarding the social constellation under analysis, e. g., (Mitzlaff et al, 2014); the descriptive analysis can then yield a more comprehensive picture combining the individual layers and their assigned compositional information. This also includes the analysis of heterogeneous sets of data sources, e. g., the analysis of data from mobile and social environments, as well as offline and online relations (Kibanov et al, 2015).

Furthermore, the specific compositional data will become more ubiquitous as well, covering spatio-temporal data, as well as heterogeneous information such as text, time series etc. Then, community detection in such complex attributed social networks that considers such special datatypes is a further interesting direction. This also covers extended longitudinal analysis and the evaluation of communities and their assigned descriptionsm, see (Atzmueller et al, 2015). Furthermore, emerging application areas for network analysis such as industrial information networks and extended sensor networks also provide invaluable grounds for an integrated analysis of semi-structured and unstructured data in such settings, e. g., (Atzmueller and Hilgenberg, 2013; Atzmueller et al, 2016b, 2017; Folmer et al, 2017).

In addition to considering extended representaions of network and (compositional) data, also the methods that are used for community detection and analysis show several prominent future directions. Combining extended subgroup discovery and analysis, for example, with exceptional model mining (Leman et al, 2008; Duivesteijn et al, 2016; Atzmueller, 2015; Lemmerich et al, 2012) is another promising option: With the formalization of exceptional models on network structures, e. g., (Atzmueller, 2016a; Bendimerad et al, 2016; Kaytoue et al, 2017), a diverse set of (combined) structural and compositional analysis tasks can be defined and applied using a well-structured framework. This opens up a wide range of tackling complex analysis questions, such as assessing hypothesis-driven approaches using Bayesian estimation methods, e. g., (Atzmueller, 2016a; Atzmueller et al, 2016c, 2017), as well as longitudinal models, e. g., potentially using methods like exponential random graph models (ERGM) (Robins et al, 2007; Traud et al, 2012) etc.

Alltogether, as outlined above there is a variety of potential future directions. In particular, the combination of the different methods and approaches also yields important challenges both from the analytical as well as the algorithmic perspective such that efficient and effective algorithms need to be developed, analytical procedures need to be devised, and finally assessment and evaluation approaches need to be adapted for comprehensively enabling community detection and analysis on complex attributed social networks.

Cross-References

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- Community Detection, Current and Future Research Trends (27)
- Community Structure Characterization (110151)
- Network Analysis (110034)
- Online Communities (81)
- Spatial Networks (40)
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