

First Perspectives on Explanation in Complex Network Analysis

(Extended Abstract)

Spyroula Masiala and Martin Atzmueller

Tilburg University, CSAI
{s.masiala,m.atzmuller}@uvt.nl

Abstract. Over the past decades, the study of complex interaction networks has emerged as a prominent research direction. With complex ubiquitous and social environments, e. g., due to the emergence of the Internet of Things and complex social networks, explainable analysis and mining methods are required in order to make the involved models more understandable and acceptable. In this work, we sketch perspectives on explanation methods, goals and exemplary results in complex network analysis.

1 Introduction

Social network analysis reveals what is hidden in plain sight and provides explanations of different social phenomena in a variety of fields from economics to communication studies [6]. Moreover, social network analysis focuses on investigating social (interaction) structures, shaped as networks[4,1]. Over the last years, the scientific research has focused more and more on the study of complex networks obtained from real data. Current scientific interest has moved not only on applying the developed concepts of graph theory, but also on studying the dynamical evolution of network topology, pattern recognition, representation of the structure and analysis of the given topological features [5]. Moreover, the Internet of Things (IoT) supported by ubiquitous devices offers multi-modal social interaction data sets which can be described as networks. Given the (large) data sets, appropriate data mining techniques are commonly applied, in order to discover novel and useful knowledge and gain a better understanding of the complex network structures. For instance, the analysis and mining of social interaction patterns are important tasks as they require appropriate explanation techniques e.g. for increasing the acceptance of the patterns and their evaluation [2]. Indeed, a good machine learned model is often not good enough if the domain experts want to understand why the model behaves the way it behaves, or if the produced patterns are expected, based on their knowledge of the application domain [5].

2 Overview: Explanation Goals and Methods

In particular in the scope of black box methods, further explanation and interpretation are required to enable domain experts and users to understand, trust, and transform the novel and useful model into a real-world application [11][8]. Explicative data mining, as introduced by [2], aims to describe and explain the underline

structure of the data, by using explanation-aware methods, e.g. data summarization and visualization and pattern-based data mining. In the case of community detection, for example, traditional approaches aim at partitioning the social network graph. The richer available data in complex networks, i.e. additional information of each user e.g., demographics, interests, help us develop mining methods which can take advantage them and detect good communities, associated with good descriptions in terms of user information [9]. In case of the link prediction, the prediction of the topological evolution of a network over time is concerned. Previous work focused on finding a “perfect” set of features capable of predicting the formation of a link, most of the times with a black box type of approach. However, grouping the features on their topological scope [7] leads to a efficient and explainable set of features, capturing the essential network properties. An exemplary major social network analysis application is the development of recommendation systems[10]. Explainable recommendation method that not only predicts a numerical rating for a recommended product, but also generate explanations for users preferences, improve effectiveness, transparency, scrutability and user trust [10].

3 Explanation Examples on Social Interaction Networks

As examples, we investigate distinctive structural patterns, e.g., connectivity and association between face-to-face interaction networks obtained by surveys and wearable sensors. Our preliminary results indicate interesting insights into human behavior, where we focus on the structural analysis and association between the networks utilizing visual and pattern-based approaches, e. g., [3].

References

1. Atzmueller, M.: Data Mining on Social Interaction Networks. *JDMDH* **1** (June 2014)
2. Atzmueller, M.: Onto Explicative Data Mining: Exploratory, Interpretable and Explainable Analysis. In: *Proc. Dutch-Belgian Database Day*. TU Eindhoven (2017)
3. Atzmueller, M.: Compositional Subgroup Discovery on Attributed Social Interaction Networks. In: *Proc. Discovery Science*. Springer, Springer (2018)
4. Borgatti, S.P., Mehra, A., Brass, D.J., Labianca, G.: Network Analysis in the Social Sciences. *Science* **323**(5916), 892–895 (Feb 2009)
5. Costa, L.d.F., Rodrigues, F.A., Travieso, G., Villas Boas, P.R.: Characterization of Complex Networks: A Survey of Measurements. *Adv. Phys.* **56**(1), 167–242 (2007)
6. Du, Z., Hu, L., Fu, X., Liu, Y.: Scalable and Explainable Friend Recommendation in Campus Social Network System. In: *Frontier and Future Development of Information Technology in Medicine and Education*. pp. 457–466. Springer (2014)
7. van Engelen, J.E., Boekhout, H.D., Takes, F.W.: Explainable and efficient link prediction in real-world network data. In: *Proc. IDA*. pp. 295–307. Springer (2016)
8. Liu, S., Wang, X., Liu, M., Zhu, J.: Towards Better Analysis of Machine Learning Models: A Visual Analytics Perspective. *Visual Informatics* **1**(1), 48–56 (2017)
9. Pool, S., Bonchi, F., Leeuwen, M.v.: Description-Driven Community Detection. *ACM Transactions on Intelligent Systems and Technology (TIST)* **5**(2), 28 (2014)
10. Ren, Z., Liang, S., Li, P., Wang, S., de Rijke, M.: Social Collaborative Viewpoint Regression with Explainable Recommendations. In: *Proceedings of the tenth ACM international conference on web search and data mining*. pp. 485–494. ACM (2017)
11. Samek, W., Wiegand, T., Müller, K.R.: Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models. *arXiv preprint arXiv:1708.08296* (2017)