Multi-modal Network Representation Learning

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ABSTRACT

In today's information and computational society, complex systems are often modeled as multi-modal networks associated with heterogeneous structural relation, unstructured attribute/content, temporal context, or their combinations. The abundant information in multi-modal network requires both a domain understanding and large exploratory search space when doing feature engineering for building customized intelligent solutions in response to different purposes. Therefore, automating the feature discovery through representation learning in multi-modal networks has become essential for many applications. In this tutorial, we systematically review the area of multi-modal network representation learning, including a series of recent methods and applications. These methods will be categorized and introduced in the perspectives of unsupervised, semi-supervised and supervised learning, with corresponding real applications respectively. In the end, we conclude the tutorial and raise open discussions. The authors of this tutorial are active and productive researchers in this area.

KEYWORDS

Multi-modal networks, Network representation learning, Deep learning

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1 INTRODUCTION

Complex systems such as social media, cybersecurity system, or chemical synthesis, are often modeled as multi-modal networks. Different from the general homogeneous networks (e.g., social network), they are associated with complexity in heterogeneous structural relation (e.g., heterogeneous network with multi-typed nodes and relations), unstructured attribute/content (e.g., attributed network with node/edge attributes), temporal context (e.g., dynamic network), or their combination (e.g., attributed heterogeneous network). Automating the feature discovery through representation learning can largely reduce labor-consuming feature engineering activity which requires both domain understanding and large exploratory search when addressing various problems in those complex data. In recent years, representation learning in multi-modal networks has been a popular research topic with practical significance in many applications such as recommendation/search, behavior prediction, anomaly detection, etc. Therefore, we are motivated to organize this tutorial to review the state-of-the-art work for multi-modal network representation learning and illustrate how they can tackle real-world problems. Aligned with machine learning strategies, representation learning for multi-modal networks can be categorized as supervised, semi-supervised, and unsupervised learning methods, according to the usage of available supervisory information. In this tutorial, we systematically review recent studies in these directions and introduce corresponding applications.

- **Supervised methods and applications**. Supervisory information (e.g., relation pairs, node class labels) is extremely helpful on guiding the representation learning in multi-modal networks. The supervised approaches use ground-truth labeled information to develop task guided models and learn customized node representations for specific tasks in multi-modal networks. The related work brings impact to various applications including relevance search [21, 25], recommender systems [2, 4, 19, 20, 24], user profiling [12], event detection [8], behavior prediction [11, 15, 16], and malware and anomaly detection [6, 7, 9, 18].
- **Semi-supervised methods and applications**. Supervising information is often expensive to collect. Therefore, semi-supervised representation learning for multi-model networks becomes a highly demanding, while barely explored technique. It is expected that the model is trained with a small portion of labeled nodes and plenty of unlabeled nodes. The learned node representation naturally serves well for node classification [1], multi-label classification [1], graph alignment [13, 14], and so on.
- **Unsupervised methods and applications**. Without any supervised information, the unsupervised models aim to learn task independent node representations (without ground-truth label) for different tasks (e.g., node classification) in multi-modal networks. The related work includes heterogeneous network embedding [3, 5, 10, 23], heterogeneous graph neural network [22], temporal/dynamic/evolutionary graph neural network [17], and graph neural networks for unsupervised anomaly detection [26].

The intended audiences are students, researchers, and practitioners who are new to this topic or who already have some experience in data mining, machine learning, and network science.

2 SIMILAR EVENTS AND SOCIETAL IMPACTS

Several similar tutorials have been given at related conferences: (i) Peng Cui et al., Modeling Data With Networks + Network Embedding: Problems, Methodologies and Frontiers, at KDD 2018; (ii) Jian Tang and William L. Hamilton, Graph Representation Learning, at

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AAAI 2019; (iii) Jie Tang and Yuxiao Dong, Representation Learning on Networks, at WWW 2019. This tutorial is different from them in two main aspects: (1) it focuses on the study for representation learning in multi-modal networks with complexity in structure, content, dynamics, or their combinations, while the previous tutorials review work for general networks; (2) it covers the most recently techniques, many of which are not included in previous tutorials. This tutorial will provide a good resource and inspirations for researchers and practitioners.

3 OUTLINE

The outline and schedule of the 3-hour tutorial is as follows.

1. Introduction and Overview (20 mins) 1.1 Multi-modal network representation learning 1.2 Tutorial organization
2. Supervised Methods and Applications (60 mins) 2.1 Task-guided relation learning 2.2 User and behavior context learning 2.3 Malware detection 2.4 Abnormal user identification
3. Semi-supervised Methods and Applications (30 mins) 3.1 Semi-supervised attributed network embedding 3.2 Semi-supervised graph alignment
4. Unsupervised Methods and Applications (50 mins) 4.1 Heterogeneous network embedding 4.2 Heterogeneous graph neural network 4.3 Temporal/dynamic/evolutionary graph neural network 4.4 Graph neural network for unsupervised anomaly detection
5. Conclusions and Discussions (20 mins)

4 TUTORS' BIOGRAPHY

Chuxu Zhang is an Assistant Professor in the Department of Computer Science at the Brandeis University. His research interests are data mining, machine learning, and their applications in graph/network mining, recommendation/user modeling, natural language processing and science domains (e.g., chemistry). His work have appeared in KDD, WWW, AAAI, IJCAI, and so on.

Meng Jiang is an Assistant Professor in the Department of Computer Science and Engineering at the University of Notre Dame. His research interests include data mining, machine learning, and information extraction. His research work focuses on computational behavior modeling. He has published over 50 conference and journal papers of the topics. His work was recognized as ACM SIGKDD 2014 Best Paper Finalist. He has delivered six tutorials in conferences such as KDD, SIGMOD, WWW, CIKM, and ICDM. He is the recipient of Notre Dame Global Gateway Faculty Award.

Xiangliang Zhang is an Associate Professor of Computer Science and directs the Machine Intelligence and Knowledge Engineering (http://mine.kaust.edu.sa) group at KAUST, Saudi Arabia. Her research mainly focuses on learning from complex and large-scale streaming and graph data. She has published over 130 research papers in referred international journals and conference proceedings, including TKDE, SIGKDD, AAAI, IJCAI, ICDM, VLDB J, ICDE etc. She is selected and invited to deliver an Early Career Spotlight talk at IJCAI-ECAI 2018.

Yanfang (Fanny) Ye is the Theodore L. and Dana J. Schroeder Associate Professor in the Department of Computer and Data Sciences (CDS) at Case Western Reserve University (CWRU). Her research mainly focuses on data mining, machine learning, cybersecurity and health intelligence. She recently received the prestigious NSF Career Award (2019) and IJCAI Early Career Spotlight (2019), the AICS 2019 Challenge Problem Winner, the ACM SIGKDD 2017 Best Paper Award and ACM SIGKDD 2017 Best Student Paper Award (Applied Data Science Track), and so on.

Nitesh V. Chawla is the Frank M. Freimann Professor in the Department of Computer Science and Engineering at the University of Notre Dame and the Director of the Center for Network and Data Science (CNDS) at Notre Dame. His research focuses on machine learning, AI and network science fundamentals and interdisciplinary applications. His papers have received several best paper nominations and awards. He is also the recipient of several awards and honors including IEEE CIS Outstanding Early Career Award, the IBM Watson Faculty Award, and so on.

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