Paper self-review

Representation Learning in Heterogeneous Information Networks

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1. Introduction

The interest in Graph Representation Learning (GRL) has been increasing as a research field in recent years. Nowadays, we have a big amount of data that comes in the structure of networks (graphs) where data points (nodes) are connected to each other through some semantic relations (edges). Graph representation learning is a research field that focuses on learning features of nodes, and perhaps edges, in a given graph by exploiting the underlying structure. Most of the research work [4] [5] has focused on homogenous graphs where the nodes and edges are of one type. On the other hand, heterogeneous graphs typically have more than one type of nodes and/or edges. In this review, we choose to address heterogeneous graph representation learning for the rich structure and semantic information they typically have. The next sections will cover the following three research papers:

- “HIN2Vec: Explore Meta-paths in Heterogeneous Information Networks”, CIKM 2017 [1]
- “HAN: Heterogeneous Graph Attention Network”, WWW 2019 [2]
- “MultiSage: Empowering GCN with Contextualized Multi-Embeddings”, KDD 2020 [3]

2. Hin2vec

In Hin2vec [1], the authors focus on learning node and edge representations of real-life heterogeneous graphs. One way to represent information in heterogeneous graphs is via meta-paths. Meta-path is a sequence of node types that are connected through different edge types. Different meta-paths have different semantic meaning; for example in academic graphs, a meta-path of “author-paper-author” could mean two authors who co-authored the same paper, while a meta-path of “author-paper-venue-paper-author” means two authors who published in the same conference. Hin2vec is a two-phase framework for representation learning based on meta-paths. In the first part, pairs of nodes are generated from random walks, and associated with k-length meta-paths. In the second part, a model is trained to predict if a pair of nodes is connected through a given meta-path. Hin2vec soundly outperforms the state-of-the-art models on four datasets and two tasks of link prediction and node classification.

Hin2vec is a promising model with a couple of strength points. First, it leverages the concept of meta-paths allowing modeling richer semantics. And the model is well-designed to handle good learning capacity and scalability. However, there are some gaps that are perhaps worth mentioning. Hin2vec assumes equal importance of meta-paths for nodes; applying attention could be one way to address this. Relying explicitly on meta-paths introduces an issue of having arbitrary meta-paths that can actually hinder the learning process. Finally, there may still be a trade-off between efficiency and scalability of the model depending on the number of meta-paths that are considered.

3. HAN

In HAN [2], the authors seem to address the downside of Hin2vec by introducing a hierarchical attention mechanism. A key difference in HAN is the graph neural network and modelling the learning as a semi-supervised task unlike the random-walk based approach of Hin2vec. HAN has two layers of attention; first, they learn a node-level attention that's specific to a single meta-path/semantic. In this layer, each node gets to learn an embedding that's aggregated from its neighbours per meta-path. The second level is semantic/meta-path, where the final embedding of each node is calculated by aggregating embeddings through each weighted meta-path. Being a graph neural network (GNN) approach, HAN shows including feature information in learning gives better performance. According to the experiments, HAN soundly and consistently outperforms both random-walk based and graph neural network approaches.

HAN is a well-designed GNN for heterogeneity in graphs. They demonstrate good performance and linear complexity given the number of the nodes and meta-path node pairs. Another good aspect of HAN is the interpretability through the learnt attention weights. Analyzing the results of the experiments, it seems that both the heterogeneity-accounted-for design and feature information are the key reasons for the good performance. However, noticeably fewer meta-paths and less-complicated heterogeneous networks are used for evaluation. Also, Hin2vec as the state-of-the-art isn't covered in the experiments. Finally, HAN is a powerful model for semi-supervised tasks, random-walk based approaches such Hin2vec may be more useful in unsupervised settings especially with the absence of features [6].

4. MultiSage

In MultiSage [3], the authors assume a mutli-partite graph of target and context nodes. They introduce a novel idea of CONTEXTUALIZED multi-embeddings where the target node embeddings are first contextualized based on the intermediate context nodes to project their different interactions in multiple embedding spaces. Second they propose a semi-supervised GNN-based approach where embeddings from neighbours are attended and aggregated along different context points. According to the experiments, MultiSage consistently outperforms HAN on two datasets for recommendation.

Similar to [2], MultiSage takes structure and feature information as input, by extending the multi-head attention mechanism proposed in [7] to multi-partite graphs. Although they outperform HAN, the experiments don't seem extensive enough in terms of datasets, tasks and baselines. Also, the design of the model strongly assumes that the input network is k-partite, i.e. most important interactions between target nodes involve context nodes. Assuming minimum expert knowledge is required in MultiSage to define/separate context for target nodes. Finally, the multi-head attention may not be able to scale to many context points at once.

5. Conclusion

Most real-life networks are heterogeneous in nature. Heterogeneous graphs exhibit more complex structure and richer information. Therefore, it is challenging, yet vital, to learn from. In this review, we addressed recent works on heterogeneous graph representation learning. Hin2vec and HAN tried to capture the heterogeneity through meta-paths. MultiSage formulated the problem as contextualized representation learning on k-partite graphs. While Hin2vec is based on random walks, HAN and MultiSage are graph neural network approaches. Finally, the three approaches achieved the-state-of-the-art results. However, they all assumed, as given, information such as well-chosen meta-paths or context nodes, which motivates research for methods with more relaxed assumptions about graphs.

References

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