Project Title: *Exploit the interpretability in network representation learning methods*

Introduction

Recent years, network representation learning(denoted as NRL later), which is also called Graph embedding, is really a hot topic. Effective representation for nodes make network analysis tasks, such as nodes classification[1], link prediction[2] and even recommendation based users' interests[3], give outstanding performance. There are truly some great works proposed and exploiting different kind of networks like social networks, collaboration networks and biology related networks. At the same time, there is going to be more methods put up. However, almost all the methods only work best on specific datasets or specific tasks. Thus, it is really a problem about choosing methods while targeting specific datasets and tasks, which means that interpretability of these methods are critical. Interpretability shows people theoretical relation about the methods and their result. In this way, the interpretability will direct people about choosing proper methods for their tasks. What's more, interpretability will also contribute to the birth of better NRL methods in that solid theoretical background gives more specific direction to researchers to develop their new models.

Literature Review

Interpretability of Network representation learning

Network representation learning(NRL) methods are distributive. One node's vector representation contributes to few phenomena in the network and a phenomenon is composed by a few nodes. Embedding of nodes in the network contains structure information of the network and other information like labels, texts and communities can be also integrated. To exploit the interpretability of network representation learning methods, NRL methods are divided into three parts.

Matrix Factorization methods

Matrix factorization series methods in NRL area, like LE[4], GNMF[5], GraRep[6], directly get low dimensional representations of nodes in networks. There is not clear theoretical relation between method and their performance. On the other hand, some methods leverage specific information in their process for matrix factorization. MMDW[1] integrates information of distances between nodes and a selected hyperplane, like Support Virtual Machine, to get representations for nodes classification. CPNE[7] combine the modularity information of network to persist community information in node embeddings. Recommendation system also can be improved by proper NLR method [3]. The algorithms only focus on specific tasks and get nodes embeddings and none of them point out the interpretability of the matrix factorization methods on networks. Thus a unified framework for task-oriented network representation learning methods by matrix factorization should be proposed, in which basic structure information like adjacent matrix or laplacian matrix is involved and position for task-related information like classification or community is also integrated optionally. In this way, we can get theoretical foundations for network representations gotten by matrix factorization.

Random walk based methods

Random-walk is used for distributed node representation by DeepWalk[8] for the first time, motivated by language models. Generating “corpus” for network representation learning using random-walk in networks truly captures pairwise structure information od nodes. The nodes also follow a power-law by their degrees like words in documents corpus. Though DeepWalk was proved to be equal with Matrix Factorization in TADW[9], but it is a special case of random walk generating process. Variation of random-walk like restart random walk[10], absorbing random walk and partly absorbing random walk can also improve the performance for NRL, and restart-walk is already used for uncertain network embedding. As for interpretability, how to choose a specific random-walk method to generate the “corpus” for NRL is not exploited. A principle should be proposed and can be interpreted to decide how to generate the training “corpus” for specific networks and tasks, which is the interpretability of network representation learning.

Deep learning methods

Representation learning means learn the features of datasets instead of human engineering. Deep learning method for NRL like SDNE[11] and DNGR[12], which use autoencoder and variation of autoencoder distinctly, exploit representation learning of sparse networks efficiently. But they are uninterpretable, and thus it is too difficult to integrate other information like labels and attributes of nodes into their representations if we don’t know the meaning of the outputs of neural network layers. It is critical to make the process interpretable, in which deep learning methods are used for NRL, to integrate other kinds of information of nodes into the embedding results.

Methodology

Anticipated aims and expected outcome

The goal is to exploit the interpretability of network representation learning methods. Four papers are expected to published by top conference like AAAI, ICML, IJCAI and etc.

Experiment equipment and software

Sloid mathematics and programing skills, which I have always been working on, are necessary. Servers for huge quantity of computing are needed.

Datasets

Almost all of the datasets related to the project are network related. First, open sources datasets related to co-authorization networks, biology protein networks and language networks can be obtained from websites of various universities and labs in this area. Second, some datasets can be built up by crawler and pre-processing. Building datasets can also be regarded as a part of the contribution of my thesis.

TimeLine

First Year

In my first year, a paper named “***Interpretability of matrix factorization on network representation learning***” should be published, in which a unified framework about how to get node embeddings in network integrating other information will be proposed.

Second Year

In this year, a paper “***How to choose a random walk method for network representation learning***” should be accepted to conference. On the other hand, it should be half on the way of my third paper.

Third Year

Finish third my journal or conference paper and pre-defense.

Fourth Year

In the last, the thesis should be finished and I would be ready for final defense.

References

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