Multi-Relational Graph Generation

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Abstract

Graphs are a fundamental structure to model relational data including text, images, knowledge bases, etc. Recent research efforts have shown that graph neural networks are powerful for representing graph-structured data as well as learning deep generative models for graphs. However, there are few works in generative models for multi-relational graphs. We first review the prior works in deep generative models for plain graphs and then show the potential applications of generative models for multi-relational graphs.

1 Related Work

1.1 Representation Learning on Graphs

Graphs are a fundamental abstraction for modeling relational data (Grover et al., 2018). Matrix factorization, random walk are all used for graph representation. Recently, researchers have raised interests on using neural networks to embed the graph information. The idea behind these representation learning approaches is to learn a mapping that embeds nodes, or entire (sub)graphs as points in a low-dimensional vector space (Hamilton et al., 2017). There are lots of graph neural networks operate over graphs using message passing.

Kipf and Welling (2016) developed an efficient variant of convolutional neural network with a layer-wise propagation rule to pass messages. It encodes the information from both the graph structure and node features. Authors demonstrate the efficiency with semi-supervised classification tasks. There are some other similar works to GCN (Li et al., 2016; Battaglia et al., 2016).

Veličković et al. (2017) propose graph attention networks GAT leveraging masked self-attention layers to address the shortcomings of the previous graph convolutional neural networks. It provides more modeling power than its ancestors.

Grover et al. (2018) propose a latent variable generative model for graphs based on variational autoencoding (Kingma and Welling, 2013). It uses graph neural networks for both the inference and generation.

Li et al. (2018) propose to use graph neural networks to express probabilistic dependencies among a graph's nodes and edges. It claims that the networks can learn distributions over any arbitrary graph.

Based on the deep understanding of the graph structure and node information, researchers also use deep neural networks to generate graphs. You et al. (2018) propose GraphRNN to both model distributions over graphs and sample from these distributions. It decomposes the graph generation process into node sequences and edge formation. Researchers also adopt the idea of GAN (Goodfellow et al., 2014) to the graph generation domain. NetGAN (Bojchevski et al., 2018) learns the distribution by random walks over the graph and mimic the original input.

1.2 Relation Modeling

Researchers used to create auxiliary triples and add to the learning objective factorization model to model the relation (Guu et al., 2015; García-Durán et al., 2015).

Schlichtkrull et al. (2017) introduce R-GCNs, first showing that GCN frames can be used to model relational data and proves the efficiency with link prediction and entity classification tasks.

Knowledge graphs are widely used in lots of domains. Extracting the information among entities in the knowledge base has recently received considerable attention. In the recommendation field, Wang et al. (2019) propose KGNN-LS, which transform the knowledge graph into a user-specific weighted graph and apply a graph neural network. The biggest difference of between this work and other works is that KGNN-LS is designed for heterogeneous knowledge graphs, while others are designed for homogeneous bipartite graphs.

1.3 Text Generation with Graph Neural Networks

Although lots of current works deal with both the graph representation, graph generation and relation modeling, there are fewer works in the natural language processing domain, which can combine the relation extraction and graph representation together.

Researchers have some attempts about extracting the graph structure from the text information. Abstract Meaning Representation (AMR) graph generation was one of the popular methods. Bojchevski et al. (2018) first applies the neural network to parse and generate text using AMR. However, they model the AMR structure with sequence encoding instead of operating on the graph structure, which may lose some information.

The most recent work is GraphWriter (Koncel-Kedziorski et al., 2019). Instead of using AMR, authors use a title and a transformed knowledge graph as input, encodes them respectively and generates text using GAT (Veličković et al., 2017) as we mentioned in Section 1.1.

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