Title	グラフニューラルネットワークを用いた知識グラフ表現学習に関する研究
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ABSTRACT

Graph Neural Networks have emerged as the standard paradigm for representation learning on graph date. However, the practical application to real-world, large-scale graphs faces three main challenges: (1) noisy or uninformative graph topologies, (2) the prohibitive cost of generating high-quality node features, and (3) the difficulty of scaling to massive, heterogeneous graphs. This dissertation attempts to investigates structured models that are able to systematically addresses these challenges.

First, we address the challenge of learning on noisy topologies by proposing SSDA Framework, a differentiable, self-supervised data augmentation framework. SSDA jointly learns optimal policies for both structural and attribute augmentation in an end-to-end manner, enhancing the robustness of GNN models.

Second, we propose the LME framework to achieve a balance in the quality of LLM generated features and the computational cost. We conduct an analysis of feature engineering strategies for Text-Attributed Graphs. Our proposed LME pipeline, which utilizes an LLM as an intelligent keyword extractor to generate sparse features for the nodes, achieves over 90% of SOTA performance while being 2.4× smaller in storage and enabling 3.7× faster downstream GNN training.

Finally, to apply on massive heterogeneous graphs, we introduce the LME-Prop model. This scalable framework propagates the efficient LME sparse features from a 10% anchor set to the entire graph. The core innovation is a Dual-Channel Prop-GNN that fuses signals from the original topology (Structural Channel) and a new, efficiently-constructed k-NN graph (Semantic Channel). We demonstrate on the large-scale ogbn-mag benchmark that LME-Prop recovers over 80% of the full-graph SOTA performance while reducing total featurization time by 4.3×.

In conclusion, this dissertation establishes a complete, efficient, and scalable methodology for deploying semantically-aware GNNs on real-world, industrial scale graphs.

Keywords: Graph neural network, Graph representation learning, Data augmentation, Large language models, Heterogeneous graph, Computational efficiency.