

Graph Contrastive Pre-Training for Few-Shot Node Classification in Heterogeneous Networks Under Adversarial Attacks

Assignee Research

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Abstract

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: Do graph contrastive pre-training methods improve few-shot node classification accuracy on heterogeneous information networks compared to traditional supervised fine-tuning under adversarial attacks. The text-attributed graph (TAG) is one kind of important real-world graph-structured data with each node associated with raw texts. For TAGs, traditional few-shot node classification methods directly conduct training on the pre-processed node features and do not consider the raw. 15 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 2.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Pre-Training and Prompting for Few-Shot Node Classification on Text-Attributed Graphs. Research question: Do graph contrastive pre-training methods improve few-shot node classification accuracy on heterogeneous information networks compared to traditional supervised fine-tuning under adversarial attacks?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 2.5/10.

3 Results

16 papers retrieved. 15 claims extracted; 0 independently verified. Quality review score: 2.5/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The model adopts masked language modeling (MLM) as the self-supervised training objective.	×	0.13
In the training stage, a predefined portion of tokens is randomly masked by replacing them with a special token named [M]	×	0.02
The probability of a token being masked is denoted by the hyper-parameter p , where p is in the range $(0, 1)$.	×	0.02
For BERT-like language models, a starting token [CLS] and an ending token [SEP] are added to the sequence.	×	0.03
The first hidden vector o_0 corresponding to the [CLS] token is treated as the summary representation of the whole text s	×	0.03
The input of node v_i for the GNN is the first hidden vector o_0 of the text sequence.	×	0.07
Node representations after passing a GNN encoder are denoted as $H = f_{\text{GNN}}(G, X)$.	×	0.12
For each node, the hidden representation h_i is concatenated with the output vector o_t of each token and fed to an MLP.	×	0.03
The objective of the masked language model is to predict the masked tokens in the original text sequence.	×	0.09
On the ogbn-arxiv dataset with OGB features in a 5-way 3-shot setting, the TENT method achieved an accuracy of $53.24\% \pm 0.7$	×	0.03
On the ogbn-arxiv dataset with OGB features in a 5-way 5-shot setting, the G2P2 method achieved an accuracy of $78.18\% \pm 1.2$	×	0.03
On the ogbn-products dataset with GIANT features in a 5-way 3-shot setting, the G2P2 method achieved an accuracy of 60.0	×	0.03
On the Children dataset with node features in a 3-way 3-shot setting, the P2TAG (LM) method achieved an accuracy of 73.6	×	0.07
On the Children dataset with node features in a 3-way 10-shot setting, the P2TAG (GNN) method achieved an accuracy of 80	×	0.07
On the History dataset with node features in a 3-way 3-shot setting, the G2P2 method achieved an accuracy of $54.77\% \pm 0.42$.	×	0.04

References

- <http://arxiv.org/abs/2008.11416v3>
- <http://arxiv.org/abs/2407.15431v1>
- <http://arxiv.org/abs/2311.17853v2>