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Week 8 Summary

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In the article “Self-supervised Graph Learning for Recommendation”, the authors point out the challenge behind the success of graph coevolution network for recommendations. Representation learning on user-item graph for recommendation has evolved from using single ID or interaction history to exploiting higher-order neighbors, and the recent approaches already achieved state-of-the-art performance. However, these methods suffer from some limitations which are Sparse Supervision Signal, Skewed Data Distribution, and Noises in interactions. To solve these limitations, the authors focus on exploring self-supervised learning (SSL) in recommendations. Therefore, improving the accuracy and robustness of GCN for recommendations. The man idea is to supplement the classical supervised task of recommendation with an auxiliary self-supervised task, which reinforces node representation learning via self-discrimination. Specifically, it will generate multiple views of a node, maximizing the agreement between different views of the same node compared to that of other nodes. According to this, the authors propose a new learning paradigm named Self-supervised Graph Learning (SGL). Conceptually, SGL supplements existing GCN-based recommendation models in following aspects:

* node self-discrimination offers auxiliary supervision signal, which is complementary to the classical supervisions from observed interactions only.
* the augmentation operators help to mitigate the degree biases by intentionally reducing the influence of high-degree nodes.
* the multiple views for nodes regarding different local structures and neighborhoods enhance the model robustness against interaction noises.

SGL mainly consists of three components as follow:

* Data Augmentation on Graph Structure: To mining the inherent patterns in graph structure, there are three operators devised, which are node dropout, edge dropout, and random walk, to create different views of nodes. The operators can be uniformly expressed as follow:

The augmentation operators should be same as follow:

* Node Dropout:
* Edge Dropout:
* Random Walk:

These augmentations are applied on graph structure per epoch for simplicity — that is, generating two different views of each node at the beginning of a new training epoch.

* Contrastive Learning: To maximize the agreement of positive pairs and minimize the negative pairs, the authors follow SimCLR and adopt the contrastive loss. The formula is the same as follow:

Analogously, loss of the item side also can be obtained. And by combining these two losses, objective function of self -supervised task can be calculated.

* Muti-task Training: To improve recommendation with the SSL task, the authors leverage a multi-task training strategy to jointly optimize the classic recommendation task and the self-supervised learning task.

For the experiment and result, the studies on three benchmark datasets demonstrate the effectiveness of SGL, which significantly improves the recommendation accuracy, especially on long-tail items, and enhance the robustness against interaction noises.