5.7 Offline and Online A/B Testing (RQ5)

For the offline A/B testing, we compare PolyGCN, GATNE-I and DecGCN on the large-scale industrial JD.com dataset. As shown in Table 1, the JD.com dataset contains over 4 million items, 84 million substitute relations and 51 million complement relations. The parameters are set the same as in Section 5.1. The results in Table 6 show that DecGCN outperform the two baselines on both inference tasks. Compared with GATNE-I, DecGCN is able to achieve better performance by 0.9%–5.6% and 0.5%–6.1% for inferring substitutes and complements, respectively, w.r.t. all evaluation metrics.

For the online A/B testing, we deploy DecGCN and the strongest baseline GATNE-I in the Candidate Generation module in the online Recommender System in JD.com for one month (from June 2020 to July 2020). For each request, we use the model to generate candidates, and merge them with other candidate generation sources for re-ranking. Online experiments show that our method DecGCN significantly outperforms the strongest baseline method GATNE-I by 3.6% (p-value < 0.01) in Click-Through Rate. In addition, we observe 0.3% improvement on browsing depth (i.e., the depth of scrolling recommendation lists).

6 CONCLUSION

In this paper, we propose an effective decoupled Graph Convolutional Network for the task of inferring substitutable and complementary items. The propose DecGCN is able to learn item substitutability and complementarity as separated embeddings vectors, where mutual influence between different graph structures and item semantics are further captured. Experiments on three public datasets and A/B testing on a real-world industrial recommender system demonstrate the remarkable performance of our solution.

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