relations and knowledge-graph relations. Zheng *et al.* [43] considered items' category and price as nodes in the graph, built a graph consisting of four types of nodes, and then applied GCN for the price-aware recommendation.

In our work, we build a heterogeneous graph based on users' multi-feedback and rely on the strong ability of graph convolutional networks in learning representation of users' and items' embedding vectors for recommendation.

6 CONCLUSIONS AND FUTURE WORK

In this work, we study the problem of multi-behavior recommendation that considers multiple types of user-item interactions. To fully model the different preference strengths reflected by different behaviors and various behavioral semantics, we propose a graph-based solution that re-constructs the multiple user-item interaction matrices into the unified graph. We then propose an MBGCN model that takes advantage of graph convolutional network's ability in learning node representations from complex graph structure. Extensive experimental results on real-world datasets demonstrate the superiority of our MBGCN model. Further ablation studies verify the effectiveness of modeling preference strength and behavioral semantics, respectively. We also evaluate the performance of cold-start users, and results confirm the applicability of MBGCN in real-world applications.

For future work, we plan to conduct experiments on online systems with A/B testing to evaluate the recommendation performance of our proposed solution. We also plan to explore the fine-grained multiple interactions in session level, which is also known as multiple micro-behaviors.

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