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GReS: Workshop on Graph Neural Networks for Recommendation and Search

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Graph neural networks (GNNs) have recently gained significant momentum in the recommendation community, demonstrating state-of-the-art performance in top-k recommendation and next-item recommendation. Despite promising results on GNN-based recommendation and search, most of the current GNN research remains essentially concentrated on more traditional tasks such as classification or regression. The GReS workshop on Graph Neural Networks for Recommendation and Search is then a first endeavor to bridge the gap between the RecSys and GNN communities, and promote recommendation and search problems amongst GNN practitioners.

Additional Key Words and Phrases: recommendation, graph neural networks, information retrieval

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1 DESCRIPTION

1.1 Motivation

The longstanding paradigm of collaborative filtering in recommender systems posits that users with similar behavior tend to exhibit similar preferences. A graph formulation naturally arises from this view: the user-item interactions form a bipartite graph, which can be leveraged to refine recommendations by integrating similarities in users' historical preferences. This perspective inspired numerous graph-based recommendation approaches in the past [3, 5, 10, 12, 21, 23].

Recently, the success brought about by deep learning led to the development of graph neural networks (GNNs) [1, 4, 9, 14, 16]. The key idea of GNNs is to propagate high-order information in the graph so as to learn representations which are similar for a node and its neighborhood. GNNs were initially applied to traditional machine learning problems such as classification [9] or regression [8], and later to recommendation [6, 7, 15, 18, 19, 22] and search [2, 11, 13]. GNNs have in particular led to a new state of the art in top-k recommendation [6] and next-item recommendation [17]. A more comprehensive review of the GNN-based recommendation literature can be found in [20].

Despite promising results on GNN-based recommendation and search, most of the fundamental GNN research remains essentially focused on the more traditional tasks of node/graph classification and regression. Bringing together the RecSys and GNN communities for discussion would prove beneficial on both sides. For the RecSys community this could be a path to discovering possible connections between GNNs and traditional methods for recommendation and search that can lead to improved performance on those tasks, while for GNN researchers it can be a venue to discover new challenges specific to recommendation and search. The GReS workshop on Graph Neural Networks for Recommendation and Search is then a first endeavor to bridge the gap between these two communities and foster inter-collaborations, creating a more attractive and dedicated space to foster contributions that could be seen as too GNN-specific for RecSys or that do not have sufficient emphasis on recommendation for the conference.

1.2 Topics

The topics relevant to the GReS workshop include (but are not limited to):

- Top-k recommendation and matrix completion approaches based on GNNs;
- Session-based and next-item recommendation via GNNs and dynamic graphs;
- Knowledge graph and social network-enhanced recommendation models;
- Multimodal recommendation and search approaches based on GNNs;
- Explainability, fairness, accountability, transparency, and privacy issues in GNN-based recommendation;
- GNN-based result diversification in recommendation or search;
- Hypergraph neural networks for recommendation or search;
- GNNs for personalized recommendation via link prediction in multipartite or heterogeneous graphs;
- Temporal and Dynamic GNNs or applications of GNNs to next-item recommendation and dynamic environments;
- Graph topology inference for recommendation and search;
- Challenges, pitfalls, and negative results in applying GNNs to recommendation or search;
- Libraries, benchmarks, and datasets for GNN-based recommendation or search;
- Industrial applications and scalability of GNNs for recommendation or search.

The selected topics complement the RecSys themes in two ways: they give a special focus on GNN-based approaches for recommendation and search, and extend to more fundamental subjects relevant for both RecSys and GNN practitioners.

2 WORKSHOP ORGANIZATION

2.1 Format

The submissions to the workshop were evaluated through double-blind peer review. Each submission was assigned to 2 to 3 reviewers. The submissions with the highest ratings were accepted as papers with oral presentation and the other ones as posters. Papers were limited to 14 pages excluding references following the standard single-column ACM RecSys template.

2.2 Program Committee

The workshop benefitted from a program committee composed of experts in the domain and that was diverse in institution, country, gender, domain expertise (RecSys/Search or GNNs), and seniority level. In addition to the organizers, the following invited researchers participated in the program committee:

- Devanshu Arya (University of Amsterdam)
- Evgeny Burnaev (Skoltech)

- Fei Cai (National University of Defense Technology)
- Mark Coates (McGill University)
- Fernando Gama (University of California, Berkeley)
- Chen Gao (Tsinghua University)
- Vincent Gripon (IMT Atlantique)
- Stephan Günnemann (Technical University of Munich)
- Ruining He (Google)
- Vassilis Ioannidis (University of Minnesota)
- Alexandros Karatzoglou (Google Research)
- Irwin King (The Chinese University of Hong Kong)
- Ira Ktena (DeepMind)
- Muyang Ma (Shandong University)
- Jose Moreno (University of Toulouse)
- Athanasios Nikolakopoulos (Amazon)
- Xia Ning (Ohio State University)
- Chanyoung Park (KAIST)
- Rajesh Piryani (SAU, Delhi)
- Benjamin Piwowarski (Sorbonne Université)
- Emanuele Rossi (Twitter)
- Luana Ruiz (University of Pennsylvania)
- Neil Shah (Snap Inc.)
- Julien Velcin (University of Lyon 2)
- Hongwei Wang (Stanford University)
- Marcel Worring (University of Amsterdam)

2.3 Dissemination

As a follow-up of the workshop, the co-chairs will write a report summing up the main themes and discussions during the workshop.

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