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Week 6 Summary

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In the article “Dynamic Graph Neural Networks for Sequential Recommendation”, the authors point out one of the core problems of sequential recommendation, which is modeling user preference from his historical sequences. More precisely, most of existing methods only model users’ interests within their own sequences and ignore the dynamic collaborative signals among different user sequences. Thus, they cannot efficiently explore users’ preferences. To deal this problem, there are two importance need to be solved:

* How to dynamically represent user-item interactions with a graph: Most existing methods represent user-item interactions as a static bipartite graph, and this results in the failure of recording the interaction order of the user-item pair.
* How to explicitly encode the dynamic collaborative signal for each user sequence: For each user sequence, its dynamic associated items and users form a graph structure, which contains more time/order information than conventional static graph.

Thus, the authors propose a novel method named Dynamic Graph Neural Network for Sequential Recommendation (DGSR) as the solution. This method will explore interactive behaviors between users and items through dynamic graph. For the methodology of DGSR, there are four components as follows:

* Dynamic Graph Construction: convert all user sequences into a dynamic graph annotated with time and order information on edges. For the edge representation, when user acts on the item at time , the edge is established between and can be represented by the tuple . is the timestamp when interaction occurred. is the order of - interaction – the position of item in all items that has interacted with. vice versa.
* Sub-graph Sampling: devise a sub-graph sampling strategy to dynamically extract sub-graphs containing user’s sequence and associated sequences. Therefore, reduce the computational cost.
* Dynamic Graph Recommendation Networks: encode user’s preference from the sub-graph. It consists of message propagation and node updating components and takes the and from previous step as inputs. Each input contains two types of information which are long-term and short-term. For item to user, long-term reflects user’s inherent characteristics and general preference induced from user’s all historical items and short-term reflects user’s latest interest. For user to item, long-term reflects general characters of the item and short-term reflects newest property of item. Message propagation will encode long-term and short-term information, and node updating will aggregate the long-term embedding, short-term embedding, and the previous layer embedding to update the node’s representation.
* Prediction Layer: convert the next-item prediction task into a link prediction task for user nodes.

For the experiment and result, the authors use three public benchmark datasets verify the effectiveness of DGSR method, and DGSR achieves the state-of-the-art performance.