John (Ziyuan) Zhou

Week 9 Summary

UW ID: 2150115

In the article “Continuous-Time Sequential Recommendation with Temporal Graph Collaborative Transformer”, the authors point out the problem of the most existing sequential recommendation methods. Since the most existing works ignore the crucial temporal collaborative signals, they only leverage the sequential patterns to model the item transitions within sequences, which is still insufficient to yield satisfactory results. To incorporate the temporal collaborative signals is SR, there are two challenges need to be solved. The first challenge is that it is hard to simultaneously encode collaborative signals and sequential patterns, and the second one is that it is hard to express the temporal effects of collaborative signals. Therefore, the authors propose a new model named Temporal Graph Sequential Recommender (TGSRec), which consists of two novel components – Temporal Collaborative Transformer (TCT) layer and graph information propagation. In the methodology, there are three major components as follows:

* Embedding layer: The goal of this component is to encode nodes and timestamps in a consistent way to connect the SR problem with graph embedding method. There are two types of embeddings in this paper, one being the long-term embeddings of nodes, and the other being the continuous-time embeddings of timestamps on edges.
  + Long-term User/Item embeddings: The user/item node is parameterized by a vector . Since the embeddings for node should be learned in the CTBG, the authors retrieve the embedding of a node by indexing an embedding table , where .
  + Continuous-Time embedding: The continuous time encoding behaves as a function that maps scalar timestamps into vectors. The authors define the temporal effects as a function of time span in continuous time space. Given a pair of interactions and of the same user, the temporal effect is defined as , where .
* Temporal Collaborative Transformer: There are two sections in TCT layer – information construction and collaborative attention module.
  + Information Construction: The authors construct input information of each TCT layer as the combination of long-term node embeddings and time embeddings. The query input information at the 𝑙-th layer for user 𝑢 at time 𝑡 is: .The input information at the -th layer for each pair can be calculated by: .
  + Information Propagation: After constructing the information, the authors propagate the information of sampled neighbors to infer the temporal embeddings. They compute the linear combination of the information from all sampled interactions as: .
  + Temporal Collaborative Attention: The attention weight is formulated as follows: . According to the previous equations in the information construction, the authors normalize the attention weights across all sampled interactions by: . Moreover, for simplicity and without ambiguity, they ignore the superscripts and time and combine the above equation. Then, rewriting the equation for linear combination of the information as: .
  + Information Aggregation: To output the temporal node embedding, the final step of a TCT layer is to aggregate the query information by: .
  + Generalization to items: Alternating the user query information to the item query information and changing the neighbor information. Then, making an inference of the temporal embedding of item 𝑖 at time 𝑡 as , which is sent to the next layer.
* Model Prediction: The prediction scores of all candidate items are calculated by: .

For the experiments and results, the empirical results on five datasets show that TGSRec significantly outperforms other baselines, in average up to 22.5% and 22.1% absolute improvements in Recall@10 and MRR, respectively.