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Week 4 Summary

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In the article “KGAT: Knowledge Graph Attention Network for Recommendation”, the authors propose a method named Knowledge Graph Attention Network (KGAT) which can exploit high-order information in Knowledge Graph (KG) in an efficient, explicit, and end-to-end manner. The recent approaches achieved the huge success in recommendation system, but they suffered from the inability of modeling side information. The common solutions are to transform them into a generic feature vector, together with user ID and item ID, and feed them into a supervised learning model to predict the score. However, the drawback is that they model each interaction as independent data instance and don’t consider their relations. The solution for it is to take the graph of item side information (KG) into account to construct the predictive model. The recent efforts have attempted to leverage this structure for recommendation can be categorized into two types which are path-based and regularization-based, but they still need to improve. KGAT is conceptually advantageous to these existing methods in that:

* Compared to path-based methods, it avoids the labor-intensive process of materializing path, thus is more efficient and convenient to use.
* Compared to regularization-based methods, it directly factors high-order relations into the predictive model, thus all related parameters are tailored for optimizing the recommendation objective.

The methodology of KGAT consists of three main components:

* Embedding layer: parameterizing each node as a vector by preserving the structure of CKG.
* Attentive embedding propagation layers: recursively propagating embeddings from node’s neighbors to update its representation and employing knowledge-ware attention mechanism to learn the weight of each neighbor during propagation.
* Prediction layer: aggregating the representations of user and item from all propagation layers and outputting the predicted matching score.

For the experiment and result, KGAT significantly outperforms state-of-art methods like Neural FM and RippleNet on three public benchmark datasets: Amazon-book, Last-FM, and Yelp2018.