GNN for RecSys & Knowledge Graphs

I. Makarov & V. Pozdnyakov & D. Kiselev

BigData Academy MADE from Mail.ru Group

Graph Neural Networks and Applications

Topics

1. Large-Scale Rec Sys (PinSAGE recap)
2. GNN & RecSys
3. Adding Knowledge Graphs

PinSAGE

Large Scale RecSys: PinSAGE

- Pinterest: 3 billion pins and boards; 16 billion interactions; label, text and image features

from Leskovec et al., 2018

Large Scale RecSys: PinSAGE

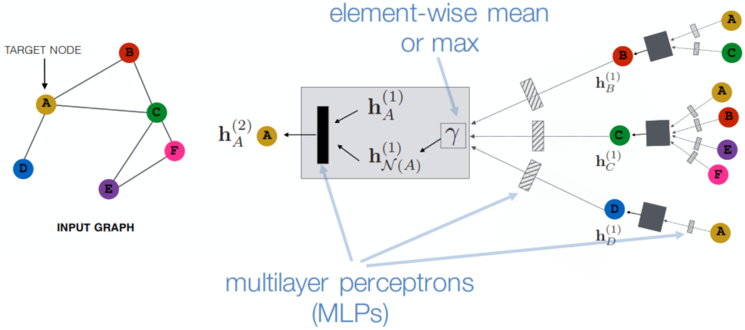
Recommendations pipeline:

- Collect consequent clicks
- Train system using metric learning approach
- Generate embeddings
- Recommend via k-NN

Key advances:

- Sub-sample neighborhoods for efficient GPU batching
- Producer-consumer training pipeline
- Curriculum learning for negative samples
- MapReduce for efficient inference

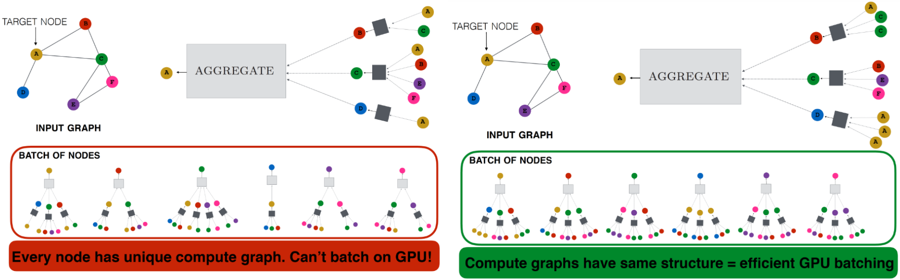
- Train so that pins that are consecutively clicked have similar embeddings, use smart negative sampling



from Leskovec et al., 2018

Large Scale RecSys: Batch Sampling

- Use one computation graph, sample nodes according top-PPR among neighbors



from Leskovec et al., 2018

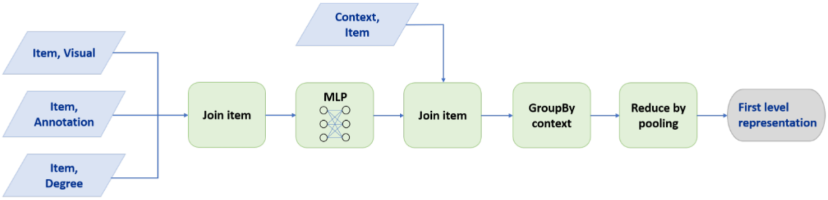
Large Scale RecSys: Training

CPU (producer):

- Select a batch of pins
- Run random walks (for PPR approximation)
- Construct their computation graphs

GPU (consumer):

- Multi-layer aggregations
- Loss computation
- Backprop



from Leskovec et al., 2018

- Include more and more hard negative samples for each epoch

$$\mathcal{L} = \sum_{(u,v)\in \boxed{\mathcal{D}}} \max(0, -\boxed{\mathbf{z}_u^\top \mathbf{z}_v} + \mathbf{z}_u^\top \boxed{\mathbf{z}_n} + \boxed{\Delta})$$

set of training pairs from user logs

"positive"/true training pair

"negative" sample

"margin" (i.e., how much larger positive pair similarity should be compared to negative)

Source pin

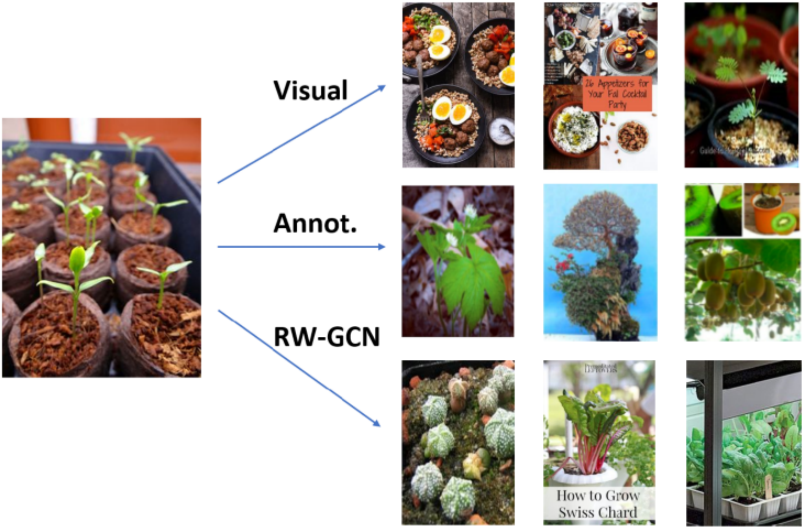
Positive

Easy negative

Hard negative

from Leskovec et al., 2018

Large Scale RecSys: Visual Comparison



PinnerSAGE: 2020

1. Take users' action pins from the last 90 days and cluster them into a small number of clusters.
2. Compute a medoid based representation for each cluster.
3. Compute an importance score of each cluster to the user.

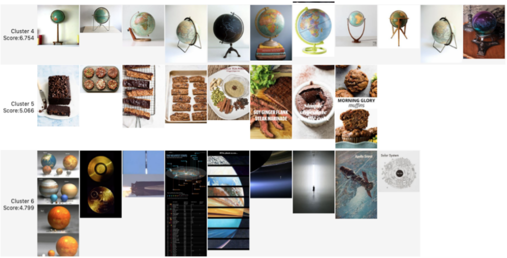


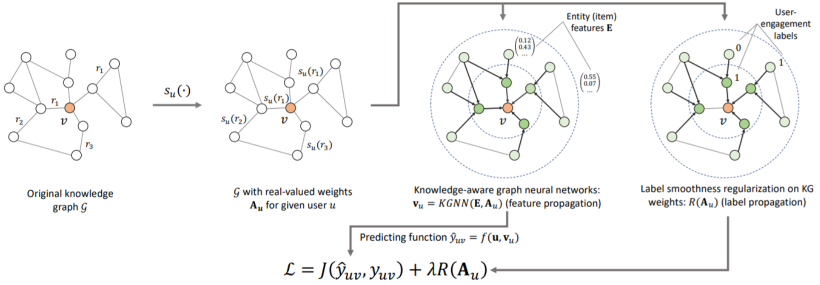
Figure 5: PinnerSage clusters of an anonymous user.

Figure 6: Sample recommendations generated by PinnerSage for the top 3 clusters 5.

from Leskovec et al., 2020

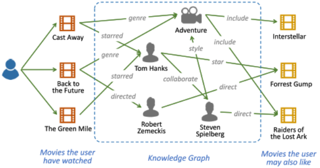
Knowledge-aware Graph Neural Networks with Label Smoothness Regularization for Recommender Systems

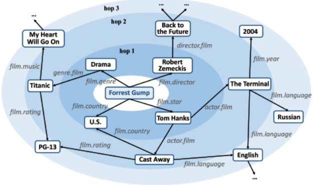
1. Proposed KGNN-LS model takes original KG and transform it into a user-specific weighted graph
2. Feature propagation using GNN with feature smoothness

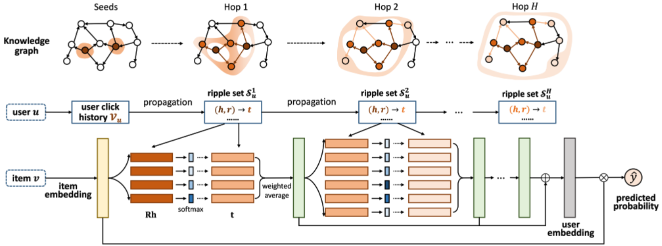


from Wang et al., 2019

RippleNet: KG-to-RecSys



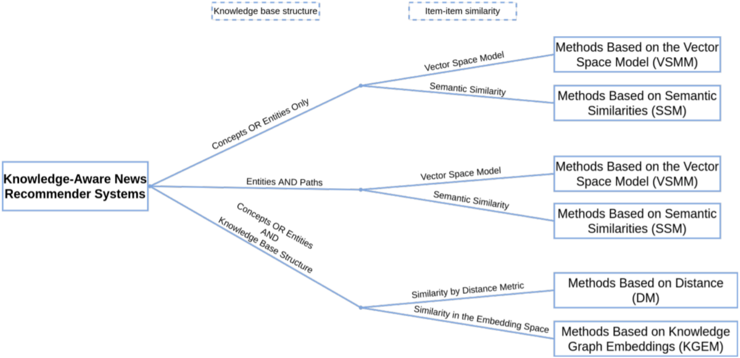




from Guo et al., 2018

A Survey On Knowledge-Aware News Recommender Systems

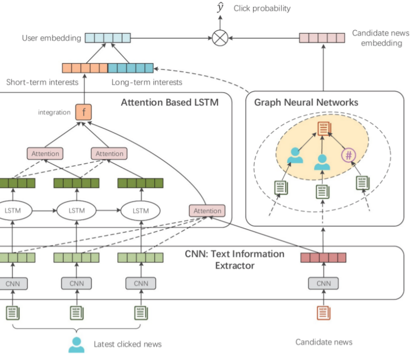
1. The categorization of knowledge-aware news recommender systems.
2. Taxonomy based on the type of knowledge base structure utilized and the way of computing item-item similarity



from Paulheim et al., 2021

Graph neural news recommendation with long-term and short-term interest modeling

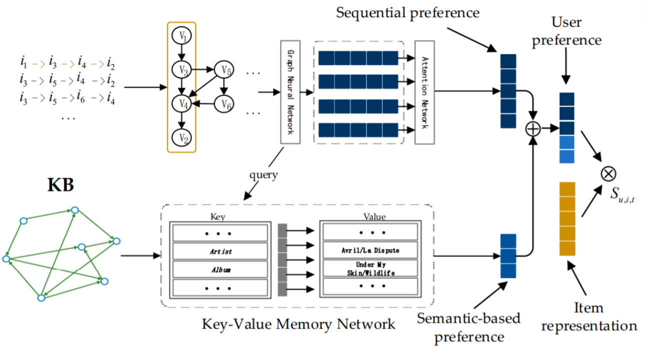
1. heterogeneous graph for interactions of users, news and latent topics
2. topic information alleviate the sparsity of user-item interactions
3. graph neural networks to learn user and news representations



from Shao et al., 2020

Knowledge-Enhanced Graph Neural Networks for Sequential Recommendation

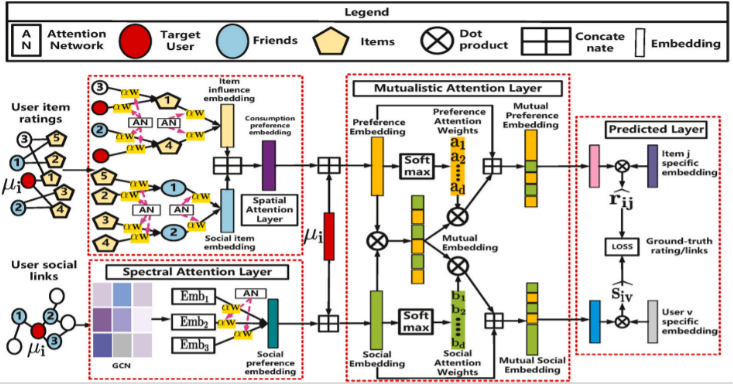
1. Linking existing external knowledge base entities with items in recommender systems,
2. Key-value memory networks are able to incorporate KB knowledge,
3. GNN component is used to capture complex transitions.



from Cai et al., 2020

MutualRec: Joint friend and item recommendations with mutualistic attentional graph neural networks

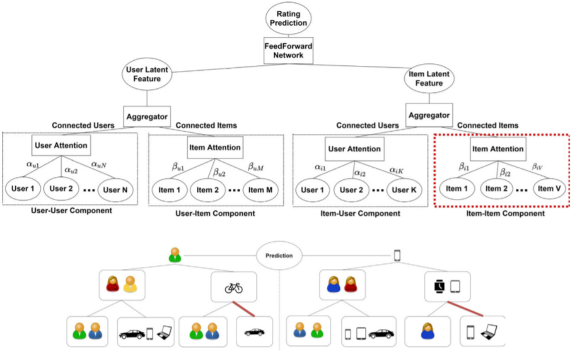
1. Spatial attention layer, spectral attention layer, mutualistic attention layer and predicted layers



from Liu et al., 2021

HeteroGraphRec: A heterogeneous graph-based neural networks for social recommendations

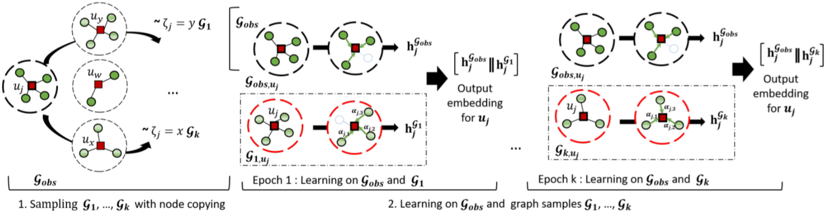
1. social recommendations by modeling the social network as a heterogeneous graph,
2. utilizing GNNs with attentions to aggregate information for building the connections between user to user, item to item, and user to item.



from Jafari et al., 2021

Framework for recommending accurate and diverse items using bayesian graph convolutional neural networks

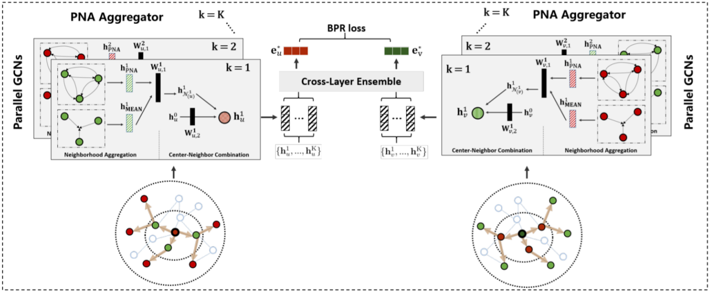
1. There are missing links that represent a user's future actions. In addition, there may be spurious or misleading positive interactions.
2. Model the uncertainty in the user-item interaction graph using the Bayesian Graph Convolutional Neural Network framework via Bayesian Probabilistic Ranking training loss.



from Coates et al., 2020

Neighbor Interaction Aware Graph Convolution Networks for Recommendation

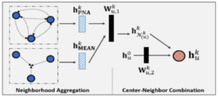
1. NIA-GCN framework. Arrowed lines present the flow of information. Solid black rectangular boxes denote densely-connected MLPs.
2. Cross-hatched blue rectangles denote embeddings learned from the neighborhood.
3. Rectangles with black slash denote central node embeddings.

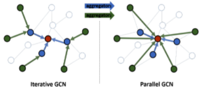


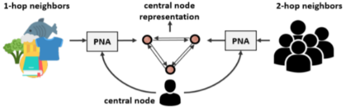
from Coates et al., 2020

Neighbor Interaction Aware Graph Convolution Networks for Recommendation

1. PNA layer. A user node as the central node is assumed. The case of item node as central node is symmetric.
2. Difference between proposed Parallel-GCN and Iterative GCN. Arrowed lines present the flow of aggregation.
3. Cross-Depth Ensemble for better node aggregation.





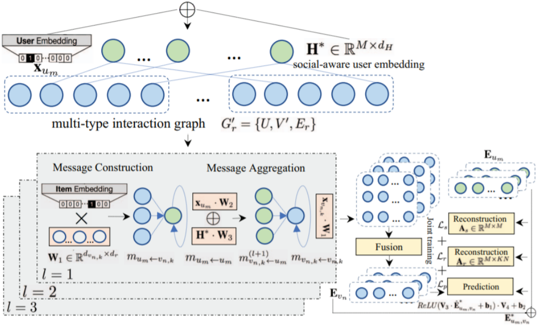


from Coates et al., 2020

see also Zhang et al., 2020

Global Context Enhanced Social Recommendation with Hierarchical Graph Neural Networks

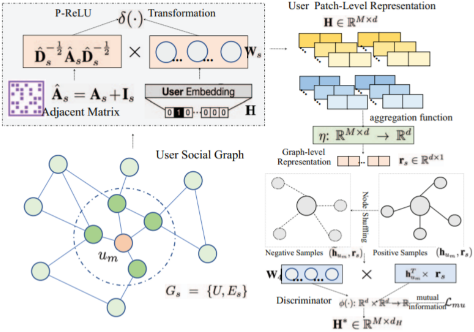
1. Social Recommendation framework with Hierarchical Graph Neural Networks (SR-HGNN).
2. Relation-aware reconstructed graph neural network to inject the cross-type collaborative semantics.



from Yin et al., 2020

Global Context Enhanced Social Recommendation with Hierarchical Graph Neural Networks

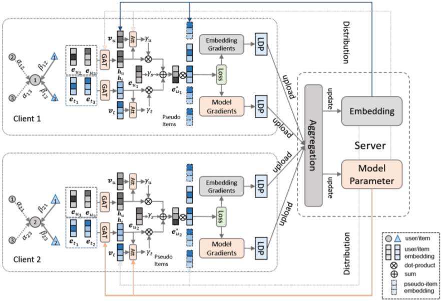
1. Augmentation of SR-HGNN with a social relation encoder based on the mutual information learning paradigm
2. SR-HGNN captures the global social contextual signals



from Yin et al., 2020

Federated Social Recommendation with Graph Neural Network

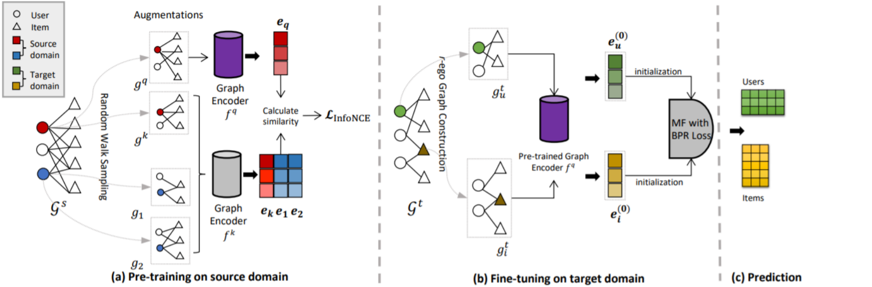
1. FeSoG uses the local GAT layer to infer node embeddings and adopt the attention layer to aggregate social neighbors and item neighbors.
2. Sampling a set of pseudo items bundled with local data.
3. Both the embedding gradients and model gradients are uploaded to the server for aggregation after LDP operation.



from Yu et al., 2021

Pre-training Graph Neural Network for Cross Domain Recommendation

1. PCRec model pretrains with the structural learning of nodes' embedding
2. Target domain is put into the pre-trained model to initialize nodes' embedding and fine-tune by a bipartite recommendation system
3. Finally, applied fine-tuned embedding is used to predict.



from Yu et al., 2021

References

- Hamilton, W.L., Ying, R. and Leskovec, J., 2017, December. Inductive representation learning on large graphs. In Proceedings of the 31st International Conference on NIPS (pp. 1025-1035).
- Ying, R., He, R., Chen, K., Eksombatchai, P., Hamilton, W.L. and Leskovec, J., 2018, July. Graph convolutional neural networks for web-scale recommender systems. In Proceedings of the 24th ACM SIGKDD International Conference (pp. 974-983).
- Pal, A., Eksombatchai, C., Zhou, Y., Zhao, B., Rosenberg, C. and Leskovec, J., 2020, August. PinnerSage: multi-modal user embedding framework for recommendations at pinterest. In Proceedings of the 26th ACM SIGKDD International Conference (pp. 2311-2320).
- Wang, H., Zhang, F., Wang, J., Zhao, M., Li, W., Xie, X. and Guo, M., 2018, October. Ripplenet: Propagating user preferences on the knowledge graph for recommender systems. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management (pp. 417-426).

References

- Wang, H., Zhang, F., Zhang, M., Leskovec, J., Zhao, M., Li, W. and Wang, Z., 2019, July. Knowledge-aware graph neural networks with label smoothness regularization for recommender systems. In Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining (pp. 968-977).
- Wang, B. and Cai, W., 2020. Knowledge-enhanced graph neural networks for sequential recommendation. Information, 11(8), p.388.
- Xiao, Y., Pei, Q., Xiao, T., Yao, L. and Liu, H., 2021. MutualRec: Joint friend and item recommendations with mutualistic attentional graph neural networks. Journal of Network and Computer Applications, 177, p.102954.
- Hu, L., Li, C., Shi, C., Yang, C. and Shao, C., 2020. Graph neural news recommendation with long-term and short-term interest modeling. Information Processing & Management, 57(2), p.102142.

References

- Salamat, A., Luo, X. and Jafari, A., 2021. HeteroGraphRec: A heterogeneous graph-based neural networks for social recommendations. Knowledge-Based Systems, 217, p.106817.
- Sun, J., Guo, W., Zhang, D., Zhang, Y., Regol, F., Hu, Y., Guo, H., Tang, R., Yuan, H., He, X. and Coates, M., 2020, August. A framework for recommending accurate and diverse items using bayesian graph convolutional neural networks. In Proceedings of the 26th ACM SIGKDD International Conference (pp. 2030-2039).
- Sun, J., Zhang, Y., Guo, W., Guo, H., Tang, R., He, X., Ma, C. and Coates, M., 2020, July. Neighbor interaction aware graph convolution networks for recommendation. In Proceedings of the 43rd International ACM SIGIR Conference (pp. 1289-1298).
- Wang, Y., Tang, S., Lei, Y., Song, W., Wang, S. and Zhang, M., 2020, October. DisenHAN: Disentangled Heterogeneous Graph Attention Network for Recommendation. In Proceedings of the 29th ACM International Conference on CIKM (pp. 1605-1614).

References

- Xu, H., Huang, C., Xu, Y., Xia, L., Xing, H. and Yin, D., 2020, November. Global context enhanced social recommendation with hierarchical graph neural networks. In 2020 IEEE International Conference on Data Mining (ICDM) (pp. 701-710). IEEE.
- Federated Social Recommendation with Graph Neural Network Zhiwei Liu, Liangwei Yang, Ziwei Fan, Hao Peng, Philip S. Yu. https://arxiv.org/pdf/2111.10778.pdf
- Wang, C., Liang, Y., Liu, Z., Zhang, T. and Yu, P.S., 2021. Pre-training Graph Neural Network for Cross Domain Recommendation. arXiv preprint arXiv:2111.08268.
- Iana, A., Alam, M. and Paulheim, H., 2021. A Survey On Knowledge-Aware News Recommender Systems.