

LLM-Augmented Knowledge-Graph-Based Recommendation System

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Overview

Recommender systems have been widely applied to address the issue of information overload in various internet services, exhibiting promising performance in scenarios such as e-commerce platforms and media recommendations. In the general domain, the traditional knowledge recommendation method is *collaborative filtering (CF)*, which usually suffers from the cold start problem and sparsity of user-item interactions. Knowledge-based recommendation models effectively alleviate the data sparsity issue leveraging the side information in the knowledge graph, and have achieved state of the art performance[1] (e.g. KGAT[6] , LightGCN[2]). However, KGs are difficult to construct and evolve by nature, and existing methods often lack considering textual information. On the other hand, LLMs are black-box models, which often fall short of capturing and accessing factual knowledge. Therefore, it is complementary to unify LLMs and KGs together and simultaneously leverage their advantages (See Figure 1). This project aims to explore areas of improvements in current KG-based recommendation systems and also integrating LLMs to augment them to consider the textual information and improve performance in recommendation.

Objectives

- Investigate the potential of Knowledge Graphs (KGs) in improving the performance of recommendation systems.
- Explore methods to address current limitations e.g. lack of user-personalized recommendations [5] [3] of KG-based recommendation systems.
- Researching combination of those novel methods with the use of LLMs in extracting latent relationships, Knowledge Graph (KG) embedding, KG completion, and KG construction for recommendation in an efficient, explicit, and end-to-end manner.

Datasets

- The proposed system will be extensively compared against state of the art models on popular recommendation datasets (e.g Amazon-book, Last-FM, Yelp2018). More details about the potential datasets can be found in the Figure 2.

Evaluation

- **AUC**, **Recall@K** and **Normalized Discounted Cumulative Gain (NDCG)** are chosen as key metrics to evaluate the performance of the proposed system. These metrics will provide a comprehensive assessment of the system's ability to accurately recommend items that are relevant to users. AUC measures the quality of the overall ranking of items, Recall@K evaluates the model's ability to recommend relevant items within the top K recommendations, and NDCG takes into account both the relevance and the rank of the recommended items.

References

- [1] Qingyu Guo, Fuzhen Zhuang, Chuan Qin, Hengshu Zhu, Xing Xie, Hui Xiong, and Qing He. A survey on knowledge graph-based recommender systems. <https://arxiv.org/abs/2003.00911>, 2020.
- [2] Xiangnan He, Kuan Deng, Xiang Wang, Yan Li, Yongdong Zhang, and Meng Wang. Lightgcn: Simplifying and powering graph convolution network for recommendation. <https://arxiv.org/abs/2002.02126>, 2020.

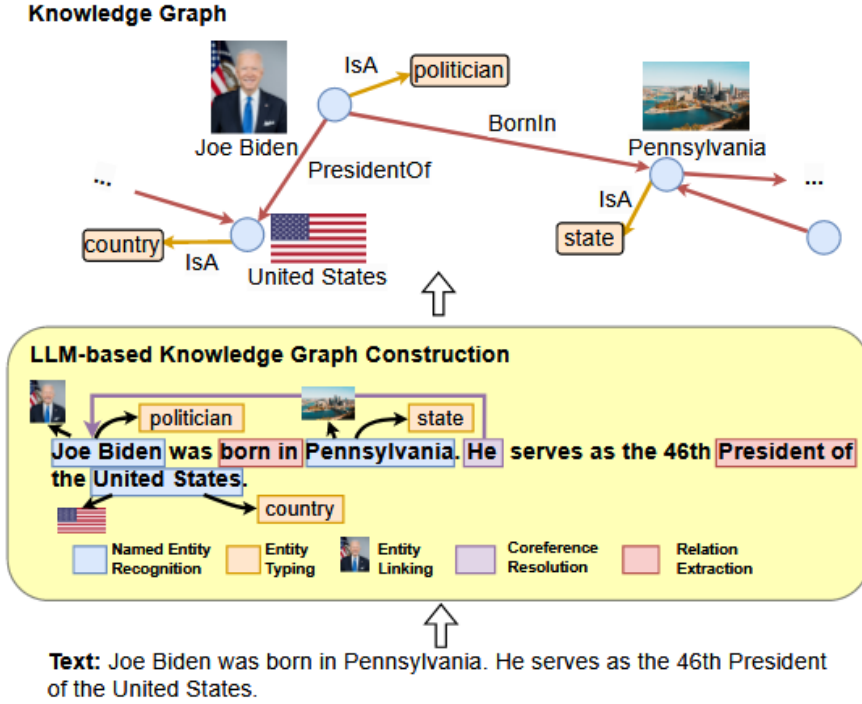


Figure 3: The general framework of LLM-based KG construction. From [4].

Scenario	Dataset
Movie	MovieLens-100K
	MovieLens-1M
	MovieLens-20M
	DoubanMovie
	DBbook2014
Book	Book-Crossing
	Amazon-Book
	IntentBooks
	DoubanBook
News	Bing-News
Product	Amazon Product data
	Alibaba Taobao
POI	Yelp challenge
	Dianping-Food
	CEM
Music	Last.FM
	KKBox
Social Platform	Weibo
	DBLP
	MeetUp

Figure 4: A collection of datasets for different application scenarios. From [1]