Scientific and Technological News Recommendation Based on Knowledge Graph with User Perception

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Abstract: Existing research usually utilizes side information such as social network or item attributes to improve the performance of collaborative filtering-based recommender systems. In this paper, the knowledge graph with user perception is used to acquire the source of side information. We proposed KGUPN to address the limitations of existing embedding-based and path-based knowledge graph-aware recommendation methods, an end-to-end framework that integrates knowledge graph and user awareness into scientific and technological news recommendation systems. KGUPN contains three main layers, which are the propagation representation layer, the contextual information layer and collaborative relation layer. The propagation representation layer improves the representation of an entity by recursively propagating embeddings from its neighbors (which can be users, news, or relationships) in the knowledge graph. The contextual information layer improves the representation of entities by encoding the behavioral information of entities appearing in the news. The collaborative relation layer complements the relationship between entities in the news knowledge graph. Experimental results on real-world datasets show that KGUPN significantly outperforms state-of-the-art baselines in scientific and technological news recommendation.

Keywords: Recommendation; Knowledge graph; User perception

1 Introduction

With the development of the World Wide Web, online news platforms such as Bing News, microblogs [1] and Microsoft News emerge one after another. Due to the convenience and speed of online news, the Internet has gradually replaced traditional media like newspapers and TV as the preferred source for news consumption. Tech News follows the latest developments in technology. The latest scientific and technological information [2] is reported in real time, which makes technology news a popular and indispensable type of news. News websites collect news from various sources, which makes the number of news articles grow exponentially. At the same time, because of its rich semantics, short timeliness, and many types of technology news, it leads to problems such as user information overload. In order to assist users quickly read the scientific news they like and enhance the browsing inspect; personalized news recommendation technology came into being.

Traditional news recommendation methods include methods based on collaborative filtering [3-7], content-based methods [8][9], and hybrid methods [10][11], which generate user and item features from interaction matrices. For example, in scoring-related recommender systems, the interaction between users and items usually adopts collaborative filtering [12][13]. However, the special challenges faced by technology news recommendation make traditional recommendation algorithms less effective.

To solve the existing challenges of technology news recommendation mentioned above, in this paper, we propose a new framework for technology news recommendation using knowledge graphs and user portraits, namely the knowledge graph user perception network (KGUPN).

To summarize, the following are the primary contributions of our work::

- We propose KGUPN, an end-to-end framework that utilizes knowledge graphs with user perception to assist scientific and technological news recommend systems. KGUPN utilizes collaborative relations and iteratively propagates user interests in the KG to find consumers' potential preferences.
- We suggest three crucial layers in KGUPN to fully exploit knowledge information., including a collaborative relations layer, a propagation representation layer, and a contextual information layer. By doing ablation investigations, we confirm that each element does, in fact, contribute to the model.
- We test our algorithms on two actual news recommend scenarios, and a benchmark dataset widely used for general recommendation, and the outcomes show that KGUPN is effective on a number of cutting-edge baselines.

2 Related Work

2.1 News Recommendation System

Traditional news recommendation methods include methods based on collaborative filtering [3][4][5], content-based methods [8][9] and hybrid methods [10][11]. As a result of the frequent replacement of news items, however, collaborative filtering-based approaches frequently experience cold-start issues. Content-based

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methods can solve the cold-start issue through analyzing the content of the news users browse to recommend similar news to users.

However, these methods ignore the sequential information in the user's browsing history, making it difficult to learn users' changing interests.

Previous news recommendation works extract features from news items manually[12] or extract latent representations through neural models[14]. DKN is the study that is most pertinent to the topic of integrating knowledge graphs for news recommendation.[15][16]. But DKN only accepts input in the form of news headlines. It is conceivable to grow to include news organizations, this would lead to inefficiencies.

2.2 Graph Based Recommendation System

Path-based approach combined with knowledge graph in the field of recommendation is mainly to select and construct paths of different patterns between entities by defining meta-paths on the knowledge graph [17][18] or a path selection algorithm [19][20], to mine various associations in the knowledge graph, between users and items, and then realize recommendation prediction. Embedding-based schemes [21][22] and tracking algorithms [23] are mostly based on knowledge graph embedding algorithm. With the development of graph convolutional network [24][25], researchers try to use it to the topological structure information realizes modeling [26][27][28], takes the knowledge graph topology and recommendation prediction as multiple learning objectives, and utilizes the attention mechanism [29][30] to acquire the neighborhood weights to obtain the embedded representation of users and items.

Existing works usually directly use general knowledge graphs [31-34]. In this work, the knowledge graph we build is more specialized and incorporates user news interaction information.

3 Knowledge Graph User Perception Network

We propose a Knowledge Graph User Perception Network model for news (KGUPN), which can be used for science and technology news recommendation. Figure 1 shows the overall KGUPN framework, which consists of three key layers: a collaborative relations layer, a propagation representation layer and a contextual information layer.

3.1 Collaborative Relations Layer.

In this paper, we mine the correlation of entities contained in news content and user clicks as supplementary knowledge of the KG. Based on the KG we built with Microsoft Satori; we supplement the correlation between entities in the knowledge graph. The correlation of newly added entities in KG includes two types.

From the same scientific news. When two entities continually appear in the same news, it often represents that there is deep mutual correlation between the two. Invariably appearing in the same scientific news can be used for the mining and representation of deep relations in KG. Therefore, we add this relation to the KG as a complementary relation.

Same user browsed the news. Entities that have been watched by the same user can represent the interest correlation between entities. If multiple users have clicked on two entities at the same time, there may be some potential connection between the two entities. Therefore, we also add this relation to the KG as a supplementary relation.

3.2 Propagation Representation Layer

Entities from science and technology news and user-news interactions can be linked to a knowledge graph. A knowledge graph consists of a series of triples, which can be expressed as $G = \{ (u, r, n) \mid u \in U, r \in R, n \in N \}$. 

Figure 1 An overview of the proposed KGUPN mode
In addition, the entities and related users in the news article are represented as embedding vectors. A news entity $n$ is represented as an embedding vector $e_n \in \mathbb{R}^d$, and a user $u$ is represented as $e_u \in \mathbb{R}^d$, where $d$ represents the embedding size.

We use $e_u^{(k)}$ to represent the K-hop propagation of embedding of user $u$. Users (and news) can receive messages transmitted from their k-hop neighbors.

$$ e_u^{(k)} = \text{LeakyReLU}(t_u^{(k)} + \sum_{n \in A_u} l_{u-n}^{(k)}) $$

After K-hops of propagation, a set of representations for user $u$ can be obtained, namely $\{e_u^{(1)}, ..., e_u^{(K)}, e_u^{(K)}\}$. We integrate them into the final embedding representation of the user $e_u^{(p)}$. The final embedding of the news $e_n^{(p)}$ is also obtained in the same way:

$$ e_u^{(p)} = e_u^{(0)} \odot ... \odot e_u^{(K-1)} \odot e_u^{(K)} $$

$$ e_n^{(p)} = e_n^{(0)} \odot ... \odot e_n^{(K-1)} \odot e_n^{(K)} $$

Where $\odot$ is the concatenation operation. In addition to enhancing the embeddings, we provide K-adjustable propagation range control by doing this.

3.3 Contextual Information Layer

Eventually, we conduct inner product of news and user embeddings, so the matching score is predicted as:

$$ \hat{y}_{(u,n)} = (e_u^{(p)})^T e_n^{(p)} $$

We use the pairwise BPR [35] loss to improve the recommendation model.

4 Experiment

4.1 Datasets

We employ the processed Microsoft news recommendation dataset MIND, as well as a benchmark dataset frequently used in recommender systems: MovieLens, which is publicly accessible and differs in domain, size, and sparsity, to thoroughly assess the efficacy of the suggested algorithm above.

MIND[36]: This data set was gathered from the Microsoft news website's anonymized usage records. It includes click statistics and behavioral diaries from users who clicked on at least five news stories during the six-week period. We took the 61,013 technical news and the associated user activity data from the dataset.

MovieLens[37]: This benchmark dataset for recommendations is frequently utilized. On a scale of 1 to 5, it contains roughly 1 million explicit ratings for movies from the MovieLens website. We translate ratings into implicit feedback, where each item is marked either with 1 or 0.

4.2 Baselines

To verify the effectiveness of our proposed method KGUPN, we use the following methods as baselines:

• FM[38] is a benchmark decomposition model in which second-order feature interactions between inputs are considered.

• DKN[39] takes entity and word embeddings as channels and combines them in CNN for prediction.

• CKE[40] is a representative regularization-based method.

• CFKG[41] transforms recommendation tasks into reasonable predictions of triplets.

• LibFM[42] is a popular feature-based decomposition model in CTR scenarios.

• RippleNet[43] combines regularization based and pathbased methods.

4.3 Performance Comparison

Table I reports the experimental results on KGUPN and other baselines.

• On all datasets, KGUPN consistently produces the best results. Over the best baselines, KGUPN improves as recall@20 by 4.6%, 4.69% in Mind and MovieLens, respectively.

• KGUPN effectively increases the recommendation accuracy by adding supplementary knowledge, user interaction information, and higher-order reasoning connectivity.

• The fact that FM and DKN outperform CFKG and CKE shows that the decomposition model can more effectively use item knowledge than regularization-based approaches.

• CFKG and CKE only use the embeddings of their aligned entities, while FM and DKN use the embeddings of connected entities to enrich the representation of items. In addition, CFKG and CKE keep high-order connections unchanged, while FM and DKN take their cross features as second-order connections between users and entities.

Figure 2 present the Recall and Hit Ratio with K on KGUPN and other baselines, such as FM, CFKG, RippleNet. As K increases, we can see that the KGUPN curve constantly exceeds the baselines, which amply supports KGUPN’s performance is competitiveness.

![Figure 2 Recall with top K on MIND dataset](image)

5 Conclusions

In this paper, we proposed KGUPN, an end-to-end framework that incorporates knowledge graph and user awareness into scientific and technological news systems,
solves the shortcomings of previous embedding-based and path-based knowledge graph-aware recommendation approaches. The propagation representation layer, the contextual information layer, and the collaborative relation layer are the three key layers that make up KGUPN. On two recommendation datasets, we run in-depth tests. The findings demonstrate that KGUPN performs much better than the other baselines.

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