Fast and Accurate Knowledge-Aware Document Representation Enhancement for News Recommendations

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ABSTRACT

Knowledge graph contains well-structured external information and has shown to be useful for recommender systems. Most existing knowledge-aware methods assume that the item from recommender systems can be linked to an entity in a knowledge graph, thus item embeddings can be better learned by jointly modeling of both recommender systems and a knowledge graph. However, this is not the situation for news recommendation, where items, namely news articles, are in fact related to a collection of knowledge entities. The importance score and semantic information of entities in one article differ from each other, which depend on the topic of the article and relations among co-occurred entities. How to fully utilize these entities for better news recommendation service is non-trivial.

In this paper, we propose a fast and effective knowledge-aware representation enhancement model for improving news document understanding. The model, named KRED, consists of three layers: (1) an entity representation layer; (2) a context embedding layer; and (3) an information distillation layer. An entity is represented by the embeddings of itself and its surrounding entities. The context embedding layer is designed to distinguish dynamic context of different entities such as frequency, category and position. The information distillation layer will aggregate the entity embeddings under the guidance of the original document vector, transforming the document vector into a new one. We have conduct extensive experiments on a real-world news reading dataset. The results demonstrate that our proposed model greatly benefits a variety of news recommendation tasks, including personalized news recommendation, article category classification, article popularity prediction and local news detection.

KEYWORDS

news recommendations, knowledge graph, document representation

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1 INTRODUCTION

With the vigorous development of the Internet, online news has become an increasingly important source of daily news consumption for users. It enriches user experience tremendously by providing various services such as news browsing, sharing and commenting. According to the 2019 News Consumption in the UK1 reported by Jigsaw Research, the Internet is the most-used platform for news consumption in the United Kingdom among young people aged 16-24, and the ratio of all adults who use social media for news reaches 49%. Meanwhile, Reuters Institute Digital News Report 20192 points out that online news has overtaken TV as the biggest part of news sources, with a coverage up to 75%.

Considering that hundreds of thousands of news articles can be produced every day, recommendation systems become critical for news service providers to improve user experience. Distinguished from other recommendation domains such as movies, music and restaurants, news recommendation has three characteristics. First, news articles are highly time sensitive. As revealed in [19], about 90% of news expire within just two days. Classical ID-based collaborative filtering methods are therefore less effective in this situation. A deep understanding of news content is necessary. Second, news articles possess the accuracy, brevity and clarity characteristics, thus natural language understanding (NLU) models can be more easily applied to produce high-quality document representations for user interest capturing, compared with other complex textual messages such as unstructured webpage or abstruse poetry. Third, news articles may contain a few entities, e.g., celebrities, cities, companies or products. These entities are usually the key message conveyed by the article. Meanwhile, entities are not isolated, they can be linked by various relationships and organized as a graph. Figure 1 shows a piece of real news, where multiple entities are mentioned in the article (for the sake of brevity, some of entities

1https://www.ofcom.org.uk/research-and-data/tv-radio-and-on-demand/news-media/news-consumption
2https://reutersinstitute.politics.ox.ac.uk/sites/default/files/2019-06/DNR_2019_FINAL_1.pdf
Tom Brady fans into a frenzy last week when he listed his mansion for sale, but the future Hall of Famer cautioned against reading too much into that decision to make predictions about his playing career, and his wife Gisele has been house hunting in the New York area, and the Brookline mansion they are selling is currently their only home in Massachusetts. When Brady was asked about it during an appearance on WEEI’s ‘The Greg Hill Morning Show’ on Monday, he said he hopes selling the house doesn’t mean his Patriots career is close to ending.

A precise understanding of textual content is the key to news recommendations. Several previous works in news recommendation focus on exploring manual features from news items [13], or extracting latent features via NLU models [15]. These approaches ignore the importance of entities in an article. Recently, a few research works [23] have revealed that traditional models assume that user-item interactions are independent instances for supervised learning, while leveraging a knowledge graph can break this limitation and interactions instances can be connected via high-order relations. However, they assume that items in recommendation service are entities and can be linked to a node in the knowledge graph. E.g., a movie or a song is an entity in knowledge graph. While this is not true for news recommendations, where a news article usually carries a set of entities, including informative and non-informative ones. The work most related to this paper is DKN [19], which is a content-based model incorporating knowledge graph representation into news recommendation. The key component of DKN is the knowledge-aware convolutional neural network (KCNN). We observe that there are mainly three weaknesses in DKN: (1) It only takes news title as input. While extending to incorporate news body is possible, it will lead to inefficiency problems; (2) It ignores the dynamic context of entities and relations among entities co-occurring in one article; (3) It uses a Kim-CNN [11] framework to fuse words and associated entities, which is not flexible and many more sophisticated models such as Transformers [17] cannot be applied.

In this paper, we aim to fully utilize entity information to improve news understanding in a fast, elastic, accurate manner. To this end, we propose KRED, which represents Knowledge-aware Representation Enhancement for news Documents. Given a document vector which can be produced by any type of NLU model (such as BERT [5]), KRED effectively fuses knowledge entities included in the article and produces a new representation vector. The document vector can be consumed by many downstream tasks, such as related article retrieval, Click-Through Rate (CTR) prediction, article classification and news popularity prediction. Specifically, there are three layers in our proposed model, i.e., an entity representation layer, a context embedding layer, and an information distillation layer. The original entity embedding is trained based on a knowledge graph using TransE [2]. Motivated by the recent progress of the Knowledge Graph Attention network (KGAT) [23], we aggregate an entity’s surrounding entities with an attention mechanism as its new representation. Considering that the context of entities can be complex and dynamic, we then design a context embedding layer to incorporate different contextual information such as position, category and frequency. Lastly, since the importance of different entities depends on entities themselves, co-occurrence of entities, and topics in the current article, we design an attentive mechanism to merge all entities into one fixed-length embedding vector, which can be concatenated with the original document vector and then be transformed into a new document vector. We conduct extensive experiments a real-world news reading dataset. We observe that our proposed model significantly benefits many tasks related to news recommendations, including personalized article recommendation, article category classification, article popularity prediction and local news detection. To summarize, we make the following contributions:

- We highlight the importance of leveraging knowledge graph for news recommendations and demonstrate the usefulness in four related applications. To the best of our knowledge, we are the first to propose a knowledge-aware model to serve various news recommendation applications.
- We propose a novel knowledge-enhanced document representation model, named KRED, which contains an entity representation layer, a context embedding layer, and an information distillation layer. The proposed model can fully utilized knowledge information in a fast, elastic, accurate manner.
- We conduct extensive experiments on a real-world dataset. Results demonstrate that our model significantly and consistently benefits multiple news recommendation applications.

2 RELATED WORK

2.1 Recommender Systems Overview

Matrix factorization (MF) [12] is one of the most popular and successful methods for recommender systems. It is a model-based collaborative filtering (CF) method and it reconstructs the sparse user-item interaction matrix based on two low-rank and dense matrices. Factorization machine (FM) [16] is also widely applied in both academia and industry, due to its superiority of combing IDs and features compared with MF. Recommendation systems have a wide-spread applications, such as restaurant recommendations [28], online shopping [?] and news reading service [13]. The key point for most of these systems is to precisely catch the collaborative user behaviors and to effectively leverage the content information in different scenarios. In the past few years, deep learning techniques
have been intensively studied in recommender systems for addressing various challenges, such as replacing the simple inner product in MF [8], modeling sequential behaviors [9], and fusing auxiliary information [4, 7]. More recently, graph convolutional networks (GCN) [22, 26] have become a research hotspot due to its strengths in learning higher-order information and combing collaborative behaviors with auxiliary information.

2.2 News Recommender Systems

[15] argues that ID-based methods are not suitable for news recommendations because candidate news articles expire quickly. The authors exploit a denoising autoencoder to generate representation vectors for news articles. [13] explores how to effectively leverage categories of NLU models.

There are quite a few document representation methods in literature, such as bag of words, LDA [1], denoising autoencoder [15], DSSM [10], Kim-CNN [11], HAN [25] and BERT [5]. To stay concise we discuss three of them which stand for different categories of NLU models.

3 PRELIMINARIES

3.1 Document Representation

Precise document representation is the key to the success of news recommendations. There are quite a few document representation methods in literature, such as bag of words, LDA [1], denoising autoencoder [15], DSSM [10], Kim-CNN [11], HAN [25] and BERT [5]. To stay concise we discuss three of them which stand for different categories of NLU models.

3.1.1 LDA. Latent Dirichlet allocation (LDA) [1] is a generative statistical model which can discover the abstract “topics” of a document. It assumes that each document is a mixture of a set of topics and each word’s presence is attributable to one of these topics. LDA is an unsupervised learning model and is not a neural model. Given a document, LDA can associate it to a topic vector \( v_d = (s_1, s_2, ..., s_n) \), where \( s_j (j \in [1, n]) \) means the probability of topic \( j \) occurring in the document, and \( n \) indicates the number of topics.

3.1.2 DSSM. Deep Structured Semantic Model (DSSM) [10] is a deep neural network modeling technique for representing raw text into a continuous latent space and modeling semantic similarity between text strings. It is a supervised learning model with the label being users’ responses. It has been successfully applied in many web applications such as web search ranking and ads selection. Given a document, DSSM performs several non-linear projection and finally transforms it into a latent vector \( v_d \in \mathbb{R}^n \) in a low-dimensional semantic feature space.

3.1.3 BERT. Pre-training has proven effective for improving language models. BERT [5], which stands for Bidirectional Encoder Representations from Transformers, presents a deep bidirectional pre-training model for language representation and advances state-of-the-art methods for a suite of NLU tasks. We adopt the feature-based strategy to apply representations from BERT, namely to compute the latent vector \( v_d \in \mathbb{R}^n \) as input features for downstream tasks without fine-tuning BERT layers.

3.2 Knowledge Graph

A knowledge graph contains enriched and structured side information and has shown to be helpful for recommendation systems. Here we formulate a knowledge graph as a collection of entity-relation-entity triples: \( G = \{(h, r, t) | h, t \in E, r \in R\} \), where \( E \) and \( R \) represent the set of entities and relations respectively, \( (h, r, t) \) represents that there is a relation \( r \) from \( h \) to \( t \). We assume that entities which appear in one news article can be linked to the corresponding entities in the knowledge graph.

In order to utilize information from the knowledge graph, we resort to a knowledge graph embedding technique which can learn a low-dimensional representation vector for entities and relations. In practice any kind of graph embedding method can be used here, while for simplicity purpose we introduce TransE [2] in this paper. TransE learns embedding vectors \( e \in \mathbb{R}^d \) for each entity and relation, so that \( e_h + e_r = e_t \) when \( (h, r, t) \) holds. The learning process minimizes the following margin-based ranking criterion over the training triplets:

\[
L = \sum_{(h, r, t) \in \Delta} \sum_{(h', r', t') \in \Delta'} \max(0, f_d(e_h + e_r - e_t) + \gamma - f_d(e_{h'} + e_{r'} - e_{t'}))
\]

(1)

where \( \gamma > 0 \) is a margin hyperparameter, \( f_d \) is a dissimilarity measure such as the L1 and the L2-norm, and \( \Delta, \Delta' \) are the set of correct triplets and incorrect triplets.

3.3 News Recommendation Applications

Different from most existing works which study only item recommendations, we study four applications in news recommendations.
3.3.1 Item Recommendation. This is the most widely studied application. Given a user $i$, let $\{d_{i1}, d_{i2}, ..., d_{it}\}$ denotes his/her click history, where $d_{ij}$ denotes the $j$-th news article clicked by the user. We want to recommend personalized new articles to him/her in the future based on the click history.

3.3.2 News Popularity Prediction. New popularity prediction application is important in several aspects. First, in the candidate retrieval layer of an industrial recommender system, usually there are various recall methods including personalized and non-personalized methods. Retrieving popular items is one of the most commonly used non-personalized methods. Second, a precise forecasting of news popularity can help editors select high-quality articles especially in the headline channel. Third, for personalized ranking models, the popularity level of an item is an important feature. We take this task as a multi-class classification problem.

3.3.3 Local News Detection. In this application, we want to predict whether a news article reports an event that happens in a local context that would not be an interest of another locality. This is a binary classification problem.

3.3.4 News Category Classification. This application predicts the category label that a news article belongs to. We have 15 top-level categories in the news corpus, thus this is a multi-class classification problem.

Figure 2: An overview of the proposed KRED model.

4 THE PROPOSED METHOD

We propose a Knowledge-aware Representation Enhancement model for Document (KRED), which is illustrated in Figure 2. Given an arbitrary document vector (such as LDA vector or DSSM vector), our model produces a new Knowledge-enhanced Document Vector (KDV). The benefits of this design are three-fold. First, unlike DKN which relies on Kim-CNN, it has no constrain on which specific document representation method should be used. Second, it can utilize all the data included in the news document, e.g., title, body and meta-data. Third, it is fast because it does not take the whole text strings as model’s input data. It is also accurate because it fuses both the original document vector and knowledge entities.

4.1 Entity Representation Layer

We exploit the idea of Knowledge Graph Attention (KGAT) Network [23] to generate entity representation. The motivation is that, an entity is not only represented by its own embeddings, but also partially represented by its neighbors. Let $\mathcal{N}_h$ denote the set of triplets where $h$ is the head entity. Then an entity is represented by:

$$e_{\mathcal{N}_h} = ReLU \left( W_0 (e_h \oplus \sum_{(h, r, t) \in \mathcal{N}_h} \pi(h, r, t)e_t) \right)$$

(2)

where $\oplus$ denotes the vector concatenation, $e_h$ and $e_t$ are the entity vectors defined in Section 3.2. $\pi(h, r, t)$ is the attention weight that
controls how much information the neighbor node need to propagate to the current entity, and it is calculated via a two-layer fully connected neural network:

\[ p_0(h, r, t) = w_2 \text{ReLU}(W_2(e_h \oplus e_r \oplus e_t) + b_1) + b_2 \]  

\[ p(h, r, t) = \frac{\exp(p_0(h, r, t))}{\sum_{(h', r', t') \in N_h} \exp(p_0(h', r', t'))} \]  

Here we use a softmax function to normalize the coefficients. We can take the idea of graph neural networks \cite{27} to train the model with higher-order information propagation, where neighborhood aggregation is stacked for multiple iterations. However, it comes with heavy computational costs and the performance gain is insignificant considering the accompanying model complexity. Therefore we only enable one-hop graph neighborhood, the TransE embedding vector \( e \) is taken as node features and the trainable parameters are \( \{W_0, W_1, w_2, b_1, b_2\} \).

4.2 Context Embedding Layer

To reduce computational cost, we avoid taking the whole original document as model’s input. An efficient way is to extract entities’ conclusive information from the document. We observe that an entity may appear in different documents with various ways, such as position and frequency. The dynamic context heavily influences the importance and relevance of the entity. To tackle this problem, we design three context embedding features:

4.2.1 Position Encoding. The position where the entity appear in the news article matters. For instance, in most cases, entities in news titles are more important than those only appear in news body. To inject some information about the position, we add a position bias vector \( e_p \) to the entity embeddings, where \( p_i \) indicate the position type of entity \( i \).

4.2.2 Frequency Encoding. We assume that if an entity is mentioned many times in the document, then it is more important than other entities which are only mentioned once. In order to inject frequency information, we create another encoding matrix \( C^{(2)} \). We count the occurrence frequency \( f_i \) of each entity, use it as a discrete index to look up a frequency encoding vector \( C^{(2)}_{f_i} \), then add it to the entity embedding vector. The upper bound of \( f_i \) is set to 20.

4.2.3 Category Encoding. Entities belong to different categories, e.g., Donald Trump is a person, Microsoft is a company, WDSM is a conference. Explicitly revealing the category of entities helps the model understand context more easily and more accurately. Thus we maintain a category encoding matrix \( C^{(3)} \). For each entity \( i \) with type \( t_i \), we add a category encoding vector \( C^{(3)}_{t_i} \) to its embedding vector.

After the context embedding layer, for each entity \( h \), its embedding vector as input for the next layer is a compound vector:

\[ e_{f_h} = e_N_h + C^{(1)}_{p_h} + C^{(2)}_{f_h} + C^{(3)}_{t_h} \]  

where + indicates the element-wise addition of vectors.

4.3 Information Distillation Layer

After the Entity Representation Layer and the Context Embedding Layer, for each entity we have its informative representation which is particularly tuned for the current context. The final importance of an entity is not only determined by its own message, but also influenced by the other entities co-occurring in the article and the topics of the article. For instance, suppose there are two news articles related to a city A. The first article reports that a famous music star is playing concerts in city A, while the second news reports a strong earthquake happened in city A. Obviously, the key entity in the former article is the celebrity, while in the latter it is the location. We exploit the Transformer \cite{17} architecture, which describes an attention function in forms of a query and a set of key-value pairs, to merge all entities’ information into one output vector. Specifically, in our model, query is the original document vector \( v_d \) (which serves as the context information), both key and value are entity representation \( e_{f_h} \). The attention weight is computed as:

\[ p_0(h, v) = w_2 \text{ReLU}(W_2(e_{f_h} \oplus v_d) + b_1) + b_2 \]  

\[ p(h, v) = \frac{\exp(p_0(h, v))}{\sum_{i \in E_v} \exp(p_0(i, v))} \]  

\[ e_{O_h} = \sum_{(h, v) \in E_v} p(h, v)e_{f_h} \]  

Then the entity vector and the original document vector is concatenated and goes through one fully-connected feed-forward network:

\[ v_k = \text{Tanh}(W_3(e_{O_h} \oplus v_d) + b_1) \]  

\( v_k \) is the Knowledge-aware Document Vector (KDV). It is interesting to point out that we omit the self-attention encoder and multi-head attention mechanism in the Transformer architecture, because via experiments we observe that, (1) adding multi-head attention does not lead to an improvement in our applications, and (2) adding self-attention encoding layers even makes the performance worse. The reason may be that relationships between entities in one news document are not as complex as raw text in NLU, so adding complex layers is useless and even makes the model hard to train.

4.4 Learning

4.4.1 Prediction. We use a fully-connected neural network as the prediction model due to its effectiveness and efficiency, while other models such as factorization machines \cite{16} can also been applied. The running architectures can be found in Figure 3. For item recommendations, the input vectors include a user vector \( u_j \) and a document vector \( v_j \) (for brevity we remove the knowledge-aware subscript \( k \)), the predictive score is:

\[ \hat{y}(i, j) = g(u_i \oplus v_j) \]  

where \( g \) denotes the predictive function of one-layer neural network as depicted in Figure 3(b). For all other tasks, the input vector is only a document vector \( v_j \), so the predictive score is \( \hat{y}(j) = g(v_j) \) as illustrated in Figure 3(e).

\(^3\)For simplicity of notation, we reuse some notations in Section 4.1. Please note that they are different parameters.
User-item model. KRED on Item model. KRED on item side. Figure 3: Architectures for different models and different tasks. (a): Item recommendation model without KRED, DV are enhanced by the KRED module. (b): Item recommendation model, both UV and DV are enhanced by the KRED module. (c): Item recommendation model, UV are enhanced by the KRED module. (d): Document classification model, DV are enhanced by the KRED module. (e): Document classification model, DV are enhanced by the KRED module.

4.4.2 Training. For item recommendation task, we exploit a ranking-based loss function for optimization. Given a (positive) user-item pair \((i, j)\) in the training set, we randomly sample 5 items to compose negative user-item pairs \((i, j')\). The training process maximizes the probability of positive instance:

\[
P(j|i) = \frac{\exp(y\hat{y}(i, j))}{\sum_{j' \in J} \exp(y\hat{y}(i, j'))}
\]

where \(J\) denotes the candidate set which contains one positive item and five negative items, \(y\) is a smoothing factor for softmax function, which is set to 10 according to a held-out validation dataset. Thus the loss function we need to minimize becomes:

\[
L = -\log \prod_{(i, j) \in H} P(j|i) + \lambda \||\Theta||
\]

where \(H\) denotes the set of user-item click history, \(\Theta\) denotes the set of trainable parameters, and \(\lambda\) is the regularization coefficient.

For all other tasks, since they belong to multi-class classification or binary classification problems, we take cross entropy as the objective function:

\[
L = \sum_{c=1}^{M} y_{j,c} \log(\hat{y}(j, c)) + \lambda \||\Theta||
\]

where \(y_{j,c} = 1\) when the label of \(y(i)\) is \(c\), otherwise \(y_{j,c} = 0\). \(M\) denotes the maximum number of labels. Note that binary classification problem can be regarded as a special case of a multi-class classification problem.

5 EXPERIMENTS

5.1 Dataset and Settings

We use a real-world industrial dataset from Microsoft News 4 (previously known as MSN News). We collect impression logs during Jan 15, 2019 to Jan 28, 2019, with the first week used for the training and validation set and the latter week being the test set. In order to build user profiles, we collect another two weeks of impression logs prior to the training date and aggregate each user’s behaviors for user modeling. We filter out users who clicked on less than 5 articles in the profile building period. After filtering, in the instance set \((\text{training + valid + test set})\) there are in total 665,034 users, 24,542 news articles, 1,590,092 interactions. Note that these impressions are from default homepage, on which the news are mostly hot news and all of them are reviewed manually by professional editors, the number of articles therefore is not very large. The average word number in the document is 701. We use Microsoft Satori [6] to link entities in a news document to the knowledge graph. We only keep the entities whose linking confidence score are higher than 0.9. Under this configuration, on average one document contains 24 entities, news entities and their 1-hop neighborhood cover 3,314,628 entities, 1,006 relations and 71,727,874 triples in Satori.

To demonstrate the effectiveness of our KRED, we choose baselines for comparison from two orthogonal bases:

- Knowledge fusion methods. We compare with 1) without entity, 2) entity with attentive fusion, 3) DKN, and 4) our KRED to test different approaches of knowledge fusion. The architectures are shown in Figure 3. Entity with attention indicates a simple approach to fuse entities by weighted average, and the weights are computed by a one-layer fully-connected neural network (128 ReLU) followed by the softmax normalization. The core component in DKN is KCNN, which is a multi-channel and word-entity-aligned fusion approach. For our model, we also test some variants which remove one of the layers in KRED.
- Document embedding methods. As introduced in Section 3.1, the original document vector (DV) we use are from three different models, including LDA, DSSM and BERT. We want to verify whether our KRED can benefit various kinds of DV,
and when the DV is sophisticated enough (such as a compound of several DVs), whether our KRED can still improve the representation.

Model architectures are illustrated in Figure 3, where EV represents entity vector, which is a 90-dimension dense vector from TransE. UV represents user vector, DV represents document vector. Note that we not compare against other recommendation models from literature such as [14, 29] simply because that the focus of this paper is not on user modeling or user-item feature interactions. Instead, our enhanced document representations can be consumed by these models as features. In summary, we would like to explore the following questions:

- Q1: How does our KRED model perform compared with competitive baselines in knowledge fusion?
- Q2: How can our KRED model benefit different kinds of document representations?
- Q3: How does each layer in KRED contribute to the model?
- Q4: Can the representation generated by KRED used as static features for downstream models?
- Q5: How does KRED perform across different tasks?
- Q6: How about the efficiency of KRED compared with the DKN?

For item recommendations, we exploit AUC\(^3\) and NDCG@$10$\(^6\) as the evaluation metrics. For news popularity prediction and news accuracy as the evaluation metrics. For news popularity prediction and news body information together with title for DKN. As shown in Table 1, DKN with title performs worst among all models, which demonstrates that full text contains much important information for news recommendation.

Knowledge entities are very important for news recommendation. Starting from the original setting $DV+UV$, we compare the performance of adding entities via naive attention network ($DV+entity_{att}+UV$) and via our KRED model ($KDV+UV$). Both methods outperform the model without entities, while our proposed model perform much better.

Adding more sophisticated document representation (+BERT) can lift the performance, and our method can still enhance the model and further improve the accuracy event when the document representation is very strong (i.e., a compound vector of LDA, DSSM and BERT).

$KDV_{att}$ means that we enable KRED module in user side and use an attentive pooling to merge user’s history for user modeling, as depicted in Figure 3(c). Row $KDV+UV+KDV_{att}$ and $KDV(+BERT)+UV(+BERT)+KDV_{att}$ demonstrate that the time-decaying average user modeling method can be improved by the attentive user modeling. However, because the focus of this paper is document representation enhancement, we just conduct moderate experiments on user modeling part.

The improvement of the proposed model is consistently across different days, which makes the result convincing, significant and meaningful.

### 5.2 Item Recommendation

We compare several different methods of knowledge entities fusion: 1) without entities; 2) DKN; 3) an attentive pooling of entity embeddings as illustrated in Figure 3(a); and 4) our proposed method as illustrated in Figure 3(b). In the production setting of the Microsoft News dataset, there is a pre-built document vector (DV) and user vector (UV), where the DV is a 90-dimensional dense vector combining LDA and DSSM, and UV is a time-decay average of DV of documents he/she has clicked in the past. Therefore, we take LDA+DSSM as a unit configuration for DV. In order to test the performance on latest NLU techniques, we further add the representation from BERT (with 1024 dimension). Since there are 7 days in the test set, to demonstrate the results in a finer granularity, we report the daily performance, and the last column overall means the overall results for the whole week.

| Model                     | day1 | day2 | day3 | day4 | day5 | day6 | day7 | overall | day1 | day2 | day3 | day4 | day5 | day6 | day7 | overall | NDCG@$10$ |
|---------------------------|------|------|------|------|------|------|------|---------|------|------|------|------|------|------|------|---------|-----------|
| DKN(title)                | 0.6446 | 0.6521 | 0.6294 | 0.6393 | 0.6572 | 0.6321 | 0.6351 | 0.6382 | 0.2409 | 0.2492 | 0.2357 | 0.2327 | 0.2289 | 0.2254 | 0.2351 | 0.2389 |
| DKN(title + body)         | 0.6752 | 0.6812 | 0.6709 | 0.6723 | 0.6730 | 0.6740 | 0.6747 | 0.6734 | 0.2092 | 0.2437 | 0.2502 | 0.2523 | 0.2324 | 0.2437 | 0.2453 | 0.2382 |
| DV + UV                  | 0.6691 | 0.6882 | 0.6741 | 0.6792 | 0.6695 | 0.6535 | 0.6793 | 0.6724 | 0.2687 | 0.2732 | 0.2590 | 0.2572 | 0.2528 | 0.2467 | 0.2701 | 0.2628 |
| DV + entity$_{raw}$ + UV | 0.6722 | 0.6725 | 0.6765 | 0.6845 | 0.6757 | 0.6639 | 0.6879 | 0.6784 | 0.2643 | 0.2642 | 0.2562 | 0.2749 | 0.2688 | 0.2547 | 0.2749 | 0.2678 |
| KDV + UV                 | 0.6144 | 0.6958 | 0.6778 | 0.6942 | 0.6580 | 0.6797 | 0.6905 | 0.6865 | 0.2218 | 0.2753 | 0.2394 | 0.2765 | 0.2679 | 0.2875 | 0.2785 | 0.2448 |
| KDV + UV + KDV$_{att}$   | 0.6077 | 0.7081 | 0.7062 | 0.7145 | 0.6994 | 0.6896 | 0.7089 | 0.7045 | 0.2097 | 0.2419 | 0.2501 | 0.2566 | 0.2709 | 0.2693 | 0.2777 | 0.2845 |
| DV(+BERT) + UV(+BERT)    | 0.6784 | 0.6922 | 0.6763 | 0.6887 | 0.6773 | 0.6822 | 0.6879 | 0.6844 | 0.2498 | 0.2715 | 0.2488 | 0.2315 | 0.2639 | 0.2754 | 0.2702 | 0.2731 |
| DV(+BERT) + entity$_{att}$(+BERT) | 0.6789 | 0.6935 | 0.6838 | 0.6963 | 0.6914 | 0.6891 | 0.6906 | 0.6905 | 0.2754 | 0.2702 | 0.2568 | 0.2850 | 0.2902 | 0.2672 | 0.2706 | 0.2739 |
| KDV(+BERT) + UV(+BERT)   | 0.6970 | 0.7078 | 0.6858 | 0.7028 | 0.6886 | 0.6895 | 0.7023 | 0.6992 | 0.2667 | 0.2849 | 0.2587 | 0.2797 | 0.2763 | 0.2762 | 0.2839 | 0.2629 |
| KDV(+BERT) + UV(+BERT) + KDV$_{att}$ | 0.7022 | 0.7089 | 0.7044 | 0.7130 | 0.6978 | 0.6948 | 0.7100 | 0.7064 | 0.3076 | 0.2799 | 0.2772 | 0.2935 | 0.2841 | 0.2788 | 0.2873 | 0.2858 |

1. https://en.wikipedia.org/wiki/Receiver_operating_characteristic
2. https://en.wikipedia.org/wiki/Discounted_cumulative_gain
3. https://en.wikipedia.org/wiki/F1_score
4. https://pytorch.org/
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Table 2: Performance evaluation of variants of the KRED model. Removing any of the layers in KRED leads to a significant (p-value<0.01) performance drop.

| Model            | AUC       | ACC       | NDCG@10   |
|------------------|-----------|-----------|-----------|
| KRED             | 0.6867    | 0.2748    |           |
| w/o KGAT         | 0.6824\(\uparrow0.63\)% | 0.2704 \(\uparrow1.60\)% |           |
| w/o Context      | 0.6821\(\uparrow0.67\)% | 0.2721 \(\uparrow0.98\)% |           |
| w/o Distillation | 0.6818\(\uparrow0.71\)% | 0.2688 \(\uparrow2.25\)% |           |

5.2.2 Study of Layers in KRED. Next we investigate whether every layer contributes to KRED. Since there are three layers in KRED, we remove one layer each time and test if the performance is influenced. Table 2 shows the results. We observe that removing either one layer will cause consistent performance drop (due to space limit, we omit the daily performance henceforth), which indicates that all layers are necessary for the model.

Table 3: KDV as features for downstream models.

| Model   | AUC   | p-value | NDCG@10 | p-value |
|---------|-------|---------|---------|---------|
| FM      |       |         |         |         |
| DM+entity| 0.6518 | 0.2405  | 0.2421  | 0.124  |
| KDV     | 0.6539 | 0.238   | 0.2421  | 0.124  |
| DNN     |       |         |         |         |
| DM+entity|        |         | 0.2627  |         |
| KDV     | 0.6853 | 1.01e-8 | 0.2680  | 1.62e-7|

5.2.3 KDV Used as Features. In production, a common practice is to pre-infer the embedding of documents and users, and downstream modules will consume them as features. We want to verify whether KRED can produce useful features for other models. Different from the previous experiments, in this setting, KDV is inferred from a fixed KRED model, and parameters are not trainable. We adopt factorization machine (FM) and deep neural network (DNN) as the downstream benchmark models. Table 3 reports the results. The KDV indeed is very helpful when used as features for DNN, but for FM the performance improvement is not significant (p-value>0.05). The results are in line with expectations. FM is good at handle categorical features (which are high-dimensional and sparse), however, the features here (such as KDV and UV) and dense continuous features from a neural model. So intuitively the features are better consumed by a neural model.

5.3 Local News Detection

For the rest of tasks, because they are not related to users, the model input is only the content of documents. To demonstrate the effectiveness of our model, we compare four models: DV, DV with entities (as depicted in Figure 3(d)), KDV and finetuned KDV. KDV indicates a static feature vector, which is trained based on item recommendation tasks. Considering that the number of documents is limited in our dataset, directly training a KRED model from instances set \([\text{documents}_i, \text{label}_i]\) is sub-optimal. Therefore we first train a KRED model based on a large volume of user-item interactions, then finetune the model using task-specific instances.

The total number of local news is 2945, which leads to an imbalanced positive label ratio 12%. When computing the accuracy (ACC) metrics, the threshold for positive class is set to 0.2. Table 4 demonstrates the overall results of local news detection application. Averaging the embeddings of entities in the document to augment the features is better that merely using DV, but it not as good as using our KDV. Finetuning the KRED module indeed improves the performance.

Table 4: AUC, ACC and F1-score for local news detection.

| Model          | AUC   | ACC   | F1   |
|----------------|-------|-------|------|
| 1 DV           | 0.8143 | 0.9036 | 0.6242 |
| 2 DV+entity    | 0.8179 | 0.9080 | 0.6272 |
| 3 KDV          | 0.8282 | 0.9143 | 0.6409 |
| 4 KDV(finetuned)| 0.8324 | 0.9263 | 0.6452 |

Figure 4: ACC and F1-score for news popularity prediction.

5.4 News Popularity Prediction

We split the news documents into four equal-size groups according to their click volume, so each group indicates a certain level of popularity (mediocre, popular, super popular and viral). We train a multi-class classifier based on different document representations. The results are shown in Figure 4. Again, KDV and finetuned KDV perform very well in this application.

5.5 News Category Classification

We have a total of 15 (top level) categories for news documents, including US News, Entertainment, Sports, Lifestyle, Money, Celebrities and Royals News, World News, Travel, Autos, Politics, Health and Fitness, and Food and Drink. Obviously, entities are very informative for article category classification, e.g., the entity Toyota can strongly suggest that the document is related to the Autos category, while the entity Robert Downey can indicate that the document may be related to the Entertainment category. Figure 5 shows the results of different models. The fine-tuned KDV performs the best.
We prepare 100 thousand documents and count the average time to evaluate the efficiency. We compare the computational cost of our Knowledge-aware Representation Enhancement (KREU) model consistently and significantly outperforms baseline models. Extensive experiments demonstrate that our proposed news detection, news category classification and new popularity prediction. Different from most existing works that only focus on item representation, our model can leverage both news title and body and is much faster than the KCNN module.

6 CONCLUSIONS
In this paper, we propose the KRED model, which can enhance the representation of news articles with entity information from a knowledge graph in a fast, elastic, accurate manner. There are three core components in KRED, namely the entity representation layer, the context embedding layer and the information distillation layer. Different from most existing works that only focus on item recommendations, we study four important applications for news recommendation service, including item recommendations, local news detection, news category classification and new popularity prediction. Extensive experiments demonstrate that our proposed model consistently and significantly outperforms baseline models. For future work, we will study a KRED model, which means a Knowledge-aware Representation Enhancement model for Users.

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