FUM: Fine-grained and Fast User Modeling for News Recommendation

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ABSTRACT
User modeling is important for news recommendation. Existing methods usually first encode user’s clicked news into news embeddings independently and then aggregate them into user embedding. However, the word-level interactions across different clicked news from the same user, which contain rich detailed clues to infer user interest, are ignored by these methods. In this paper, we propose a fine-grained and fast user modeling framework (FUM) to model user interest from fine-grained behavior interactions for news recommendation. The core idea of FUM is to concatenate the clicked news into a long document and transform user modeling into a document modeling task with both intra-news and inter-news word-level interactions. Since vanilla transformer cannot efficiently handle long document, we apply an efficient transformer named Fastformer to model fine-grained behavior interactions. Extensive experiments on two real-world datasets verify that FUM can effectively and efficiently model user interest for news recommendation.

CCS CONCEPTS
• Information systems → Recommender systems.

KEYWORDS
News Recommendation, Fine-Grained User Modeling, Efficient User Modeling

1 INTRODUCTION
News recommendation methods can alleviate the information overload, which are important for improving user experience and developing smart cities [3, 7, 8, 15]. A critical step of news recommendation is to accurately model the interest of a target user [12, 23, 33]. Existing methods usually first independently encode user’s clicked news into news embeddings and then aggregate them to build user embedding [13, 14, 16, 26, 31, 34]. For example, Wu et al. [25] first employ the self-attention mechanism to learn news embeddings into news embeddings and then aggregate them to build user embedding [13, 14, 16, 26, 31, 34]. For example, Wu et al. [25] first employ the self-attention mechanism to learn news embeddings into news embeddings and then aggregate them to build user embedding [13, 14, 16, 26, 31, 34]. For example, Wu et al. [25] first employ the self-attention mechanism to learn news embeddings into news embeddings and then aggregate them to build user embedding [13, 14, 16, 26, 31, 34]. For example, Wu et al. [25] first employ the self-attention mechanism to learn news embeddings into news embeddings and then aggregate them to build user embedding [13, 14, 16, 26, 31, 34].
We assume that a news article composed of a fine-grained user model and a coarse-grained user model. The fine-grained user model is used to capture user interest from word-level behavior interactions. Its core is to concatenate user’s clicked news as a long document and capture inter- and intra-news word-level interactions to model user interest. Specifically, we first encode the i-th genre of news text \( T_i \) into a text embedding sequence \( \mathbf{T}_i \in \mathbb{R}^{L 	imes d} \) via a genre-specific embedding layer, where \( d \) is embedding dimension. Then we concatenate texts sequences of user’s reading history into a long sequence \( \mathbf{T} \in \mathbb{R}^{L \times m \times k \times d} \).

\[
\mathbf{T} = [\mathbf{T}_1^1; \ldots ; \mathbf{T}_1^m; \ldots ; \mathbf{T}_k^1; \ldots ; \mathbf{T}_k^m],
\]

where \( \mathbf{T}_i^j \) is the j-th text embedding sequence of the i-th clicked news \( h_i \) and ; is the concatenation operation. Besides, different genres of news texts usually have different semantic characteristics and meanwhile the positional information of texts are also important for semantic understanding. Thus, to further enrich the embedding sequence of the user document, we concatenate text embeddings of each token with its genre and position embeddings and build a behavior embedding sequence \( \mathbf{H} \in \mathbb{R}^{L \times g} \), where \( g \) is dimension of the concatenated token embedding, and \( L \) denotes the total length (i.e., \( mkl \)) of the behavior embedding sequence.

The transformer network \([18]\) is an effective technique for document modeling. However, due to its quadratic complexity, the vanilla transformer network cannot efficiently model long documents. Fortunately, some efficient transformer methods have been proposed. To model fine-grained behavior interactions across the long user document, we employ a SOTA efficient transformer network named Fastformer \([29]\). Take an arbitrary attention head as example, the core idea of Fastformer is to first summarize global contexts into an embedding \( \mathbf{q} \) and then transform embeddings of each token based on their relatedness with global contexts:

\[
\mathbf{q} = \text{Att}(\mathbf{q}_1; \ldots ; \mathbf{q}_L), \quad \mathbf{q}_i = \mathbf{W}_q \mathbf{h}_i.
\]

\[
\mathbf{k} = \text{Att}(\mathbf{q} * \mathbf{k}_1; \ldots ; \mathbf{q} * \mathbf{k}_L), \quad \mathbf{k}_i = \mathbf{W}_k \mathbf{h}_i.
\]

\[
\hat{\mathbf{h}}_i = \mathbf{W}_o (\mathbf{k} * \mathbf{v}_i), \quad \mathbf{v}_i = \mathbf{W}_v \mathbf{h}_i,
\]

where \( \mathbf{h}_i \) and \( \hat{\mathbf{h}}_i \) denote the input and output of the i-th token in the behavior embedding sequence, \( \text{Att}(\cdot) \) denotes the attention pooling network and \( \mathbf{W}_q, \mathbf{W}_k, \mathbf{W}_o \) and \( \mathbf{W}_v \) denote trainable projection parameters. We remark that
Fe \[65.47\pm0.18\] 65.21 64.02 65.02 AUC \[64.83\] 66.93 64.92 65.31

We first apply a news encoder to transform user’s clicked news training data set, scores \(r_n\) candidate news \(n\) for the former and an attention network. Then, we attentively aggregate learn a genre-specific news embedding \(FUM_i\). For the 2.3 News Encoder

\[f_i = \text{Att}(g_{(i-1)k+1}, g_{(i-1)k+2}, \ldots, g_{ik}).\] (5)

where \(f_i\) represents the \(i\)-th clicked news. Finally, we pooling them to build the user embedding \(u^f = \text{Att}(f_1, \ldots, f_m)\). In this way, we can efficiently and effectively model and encode user interest from word-level fine-grained behavior interactions.

Besides, we also adopt a coarse-grained user model to better summarize user interest from news-level behavior interactions. We first apply a news encoder to transform user’s clicked news into embeddings. Details of the news encoder is introduced in Sec. 2.3. Then we apply a transformer network to model news-level behavior interactions across user’s clicked news, where \(e_i\) is the contextualized embedding of \(h_i\). Finally, we build a user embedding \(u^f = \text{Att}(e_1, \ldots, e_m)\) from news-level behavior interactions and aggregate it with \(u^f\) to form a unified user embedding \(u = u^f + u^r\).

2.3 News Encoder

Next, we briefly introduce the architecture of the news encoder in FUM. For the \(i\)-th genre of news text, we apply a text encoder to learn a genre-specific news embedding \(f_i\) from \(T_i\). Motivated by Ge et al. [4], the text encoder is implemented by the stack of a transformer and an attention network. Then, we attentively aggregate genre-specific news embeddings to learn the news embedding \(n\).

2.4 News Recommendation

Following Wu et al. [24, 27], we match the target user \(u\) and the candidate news \(n\) based on the inner product of their embeddings \(r = u^r n\). Then candidate news are ranked based on their matching scores \(r\) for news recommendation. Besides, we train models based on the BPR loss [17]: \(\mathcal{L} = -\frac{1}{|D|} \sum_{(i, j) \in D} \sigma(r_i - r_j)\), where \(D\) is the training data set, \(\sigma\) is the sigmoid function, \(r_i^u\) and \(r_j^u\) are matching scores for the \(i\)-th clicked and non-clicked news.

3 EXPERIMENT

3.1 Dataset and Experimental Settings

We conduct experiments on two real-world datasets: MIND and Feeds. MIND is a public dataset based on user data sampled from Microsoft News [30]. Feeds is based on user data sampled from the news feeds platform of Microsoft during Jan. 23 to Apr. 01, 2020 (13 weeks). We select 200,000 news impressions in the first ten weeks for training and validation, and 100,000 impressions in the last three weeks for evaluation. Codes are in https://github.com/taoj98/FUM.

In experiments, we utilize news topic labels, description texts of entities, titles, and abstracts for news modeling. Their embeddings are initialized by 300-dimensional glove embeddings [11] and fine-tuned in experiments. Besides, we adopt users’ recent 50 clicked news to model interest. In FUM, the transformer and Fastformer networks are set to 20 heads, and each head outputs 20-dimensional vectors. The attention networks are implemented by MLP networks. We adopt Adam [6] with 0.0001 learning rate to train models for 2 epoch. We tune hyper-parameters based on the validation set.

3.2 Performance Evaluation

We compare FUM with several SOTA news recommendation methods: (1) GRU [10]: propose to build user embeddings via a GRU network. (2) DKN [20]: propose an attentive memory network to learn user embeddings. (3) NPA [22]: propose a personalized attention mechanism to learn news and user embeddings. (4) KRED [9]: propose a knowledge-aware graph network to learn news embeddings from news titles and entities. (5) GNewsRec [5]: model user interest from user-news graph via a GRU and GNN network. (6) NAML [21]: learn user embeddings via an attention network. (7) LSTUR [1]: model long- and short-term user interest via GRU network and user IDs. (8) NRMS [25]: learn user embeddings via self-attention networks. (9) FIM [19]: model user interest in news from the matching of news texts and reading history via CNN network.

We repeat experiments of different methods 5 times and show average results and standard deviations in Table 1. Results show that FUM can achieve much better performance than baseline methods, e.g., LSTUR and NRMS. This is because baseline methods can only capture news-level behavior interactions to model user interest.
Table 2: Efficiency comparison of user modeling methods on both model training and inference based on 1k samples.

| Method         | GRU | DKN | NAML | NPA | KRED | GNewsRec | LSTUR | NRMS | FIM | FUM |
|----------------|-----|-----|------|-----|------|----------|-------|------|-----|-----|
| Training Time  | 11.46s | 8.19s | 7.98s | 8.10s | 10.40s | 10.72s | 11.53s | 11.39s | 15.85s | 13.21s |
| Inference Time | 2.41s | 44.90s | 1.23s | 1.15s | 1.24s | 86.90s | 2.43s | 2.16s | 350.38s | 2.75s |
| Cacheable      | ✓   | ✗   | ✓    | ✓   | ✓    | ✗       | ✓     | ✓    | ✗   | ✓   |

Figure 3: Ablation study of our FUM approach.

This is because fine-grained behavior interactions across user’s clicked news at word-level contain rich detailed clues to understand user interest. However, baseline methods usually neglect the fine-grained behavior interactions and thereby only achieve inferior performance. Different from these methods, in FUM we concatenate texts of user’s reading history as a long document and apply an efficient transformer network to capture the fine-grained behavior interactions. Thus, our FUM approach can more accurately model user interest from fine-grained behavior interactions and achieve more effective news recommendation performance.

3.3 Efficiency Comparison

Next, we compare the efficiency of different methods on both model training and inference. In Table 2, we first summarize the average time of different methods for training and inferring 1000 samples. Due to the space limitation, we only show results on MIND in the following sections. According to Table 2, FUM achieves comparable or better efficiency than methods that neglects fine-grained behavior interactions. This is because in FUM we adopt a SOTA transformer network proposed for efficient long document modeling to capture fine-grained behavior interactions. Thus FUM can efficiently model fine-grained interactions of the long user document to mine user interest. Besides, real-world systems usually have strict online latency constraints [28]. Thus, in the practice on real-world systems, news and user representations are expected to be offline computed and cached in the platform to improve online efficiency. Like some baseline methods, news and user representations of FUM are also cacheable, which further verify the feasibility of FUM in practice.

3.4 Ablation Study

Next, we conduct an ablation study to verify the effectiveness of the fine- and coarse-grained user model in FUM (Fig. 3). First, after removing the fine-grained user model, the performance of FUM seriously declines. This is because fine-grained interactions across different clicked news from the same user usually contain rich clues to understand user interest. The fine-grained user model can effectively capture word-level interactions and better model user interest. Second, removing the coarse-grained user model also hurts performance. This is because intra-news behavior interactions are also important for user modeling, which can be effectively captured by the coarse-grained user model in FUM. Besides, the coarse-grained user model also outperforms the fine-grained user model, which may be because intra-news interactions cannot be effectively exploited by the fine-grained model.

3.5 FUM with Different Efficient Transformers

Next, we apply different efficient transformers to FUM to verify their impacts. Besides FastFormer, we apply two other SOTA efficient transformers, i.e., LongFormer [2] and PoolingFormer [32] in FUM (Fig. 4). We first find FUM with various transformers can consistently outperform baselines, which verifies the importance of fine-grained user modeling. Second, Fastformer significantly improves efficiency of FUM than other transformers. Thus, we choose FastFormer for the fine-grained user modeling in FUM.

4 CONCLUSION

In this paper, we propose a fine-grained and fast user modeling framework for news recommendation (named FUM), which can understand user interest from fine-grained behavior interactions. In FUM, we first concatenate user’s clicked news as a long document. Then we employ an efficient transformer network named Fastformer to capture fine-grained behavior interactions from word-level to target user interest more accurately. Extensive experiments on two real-world datasets verify that FUM can outperform many news recommendation methods and meanwhile efficiently model user interest from fine-grained behavior interactions.
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