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Extracting Aspect Sentiment from Users' Book Reviews for Recommendation

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***Abstract*—When shopping for books on e-commerce platforms, other users' evaluations of books contain a large number of users' intuitive feelings, from which useful information can be mined to provide buyers with ideas for shopping. In terms of recommendation algorithms, although the existing research work can use various methods to model fine-grained user preferences to improve the recommendation effect. However, we believe there are still shortcomings. First, existing methods are overly dependent on the accuracy of external sentiment analysis tools and are not necessarily applicable to the recommendation domain. Second, the features extracted from reviews are still potential features when incorporated into recommendation algorithms, and they cannot be fully utilized to characterize user embeddings. For this reason, this paper proposes a new user comment extraction scheme for personalized recommendation. We first use text summarization techniques in the field of NLP to preprocess and refine the comment text to reduce data noise and obtain high-quality text information. Subsequently, in order to more accurately characterize user embeddings and item features, we use advanced aspect-based sentiment analysis techniques to extract fine-grained aspectual items and corresponding sentiment polarity from the review text. Finally, experimental validation on a real book dataset is conducted to demonstrate the effectiveness of our model.**

***Keywords*—recommendation algorithms, sentiment analysis, aspect sentiment, review extraction**

I. Introduction

Online review texts contain a large amount of users' intuitive feelings, and analyzing these reviews can more comprehensively mine reviewers' interest preferences. Based on these preferences, recommender systems can be provided with more accurate recommendation results. Therefore, many researchers have tried to use user comments to improve recommendation performance. Previous work has typically modeled topics from comments, or used deep learning methods to model user preferences and thus learn the user's embedded representation. While these approaches have made good progress, the granularity is too coarse to model fine-grained user preferences. In order to model fine-grained user preferences, the researcher attempted to extract aspectual items in the reviews as well as the corresponding opinion words. For example, TriRank [1] extracts aspects from reviews and constructs user-item-aspect ternary relationships. It explores the evidence of each aspect to make the recommender system better interpretable. UPCF [2] is a collaborative filtering method based on user preferences. This method can extract important aspects of user concerns from reviews in order to provide recommendations that meet the user's personalized needs. Huang et al [3] proposed a personalized review recommendation model based on aspect sentiment similarity. It improves user similarity by analyzing users' aspect preferences from reviews and utilizing their fine-grained aspect sentiment and product similarity.

However, we believe that these approaches still suffer from the following shortcomings: on the one hand, the reliance on external sentiment analysis tools. Moreover, the extracted features are still latent features and cannot be fully utilized to characterize user embedding. To address the above problems, we propose the method in this paper. It extracts aspect terms and sentiment polarity using aspect-based sentiment analysis. Before that, in order to remove the noise from the text, we preprocess the text using text summarization techniques and, at the same time, extract the important information. Based on this, we processed the sentences into single sentences and then extracted the aspect terms and corresponding sentiment using the well-established ABSA algorithm. Finally, the extracted results are applied to the recommendation algorithm. We conducted experiments on the Amazon book dataset, and the experimental results proved that our approach is more effective than the baseline model. To summarize, our main contributions are:

- Applying aspect-based sentiment analysis and text summarization techniques from the field of natural language processing to the recommendation domain.
- Extracting fine-grained user sentiment preference information from reviews.
- Experiments on the book dataset validate the state-of-the-art of the proposed model.

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II. Related Work

A. Aspect-based Sentiment Analysis

Aspect-Based Sentiment Analysis (ABSA) is a fine-grained approach to sentiment analysis that has greater significance for practical applications. The literature [4] differs from ordinary sentiment analysis in that ABSA addresses an entity or an aspect of an entity in a sentence, rather than the entire sentence. ABSA is categorized into single and composite tasks, with more researchers focusing primarily on ABSA for composite tasks. In this regard, pre-training based ABSA models have become more popular in recent years. Earlier work [5, 6] simply utilized the contextual embedding of PLMs to get a big performance boost. To better adapt PLMs to ABSA tasks, the literature [7, 8] uses the MRC modeling paradigm to decompose ABSA tasks to naturally capture pairwise relationships. Literature [9, 10] uses pre-trained generative models to transform tasks into Seq2Seq problems.

B. Text Summary

Text summarization is the extraction and summarization of lengthy document information through various techniques to distill important information [11]. In short, it is an important means to solve the information overload. It is mainly divided into extractive text summarization and generative text summarization. The representative work of extractive text summarization [12] proposes a data-driven approach based on neural networks and continuous sentence features. It can propose sentences and words from a large number of documents, and still achieves good results without any linguistic annotations. The classic work on generative modeling [13] proposes a data-driven based approach to generate sentence summaries using the ATTENTION mechanism.

III. The Proposed Model

In this section, we describe our approach in detail. We describe a review document as a set $\{(p,b,t)|\ p \in P, b \in B, t \in T\}$, where p denotes the reviewer, b denotes the book being reviewed, and t denotes a specific review. P is the set of reviewers, B is the set of books, and T is the set of reviews. As shown in Fig. 1, we first preprocess the review text using an extractive text summarization technique[14], and after compression and condensation, we obtain a streamlined set of sentence documents $\{(p,b,t')|\ p \in P, b \in B,\ t' \in T'\}$, t' is the preprocessed reviews, and T' is the preprocessed set of reviews. Subsequently, we use the classic ABSA algorithm in PyABSA [15] to extract the aspect terms of books and the corresponding sentiment polarity in the sentence. We describe the extraction results as $\{(p,b,a,s)|p \in P, b \in B, a \in A, s \in S\}$, where a is the aspect term associated with the book and s is the sentiment polarity (1 for positive sentiment, -1 for negative sentiment, and 0 for neutral sentiment). Finally, we apply the extraction results to a recommendation algorithm to predict the probability of a user's preference for a particular book.

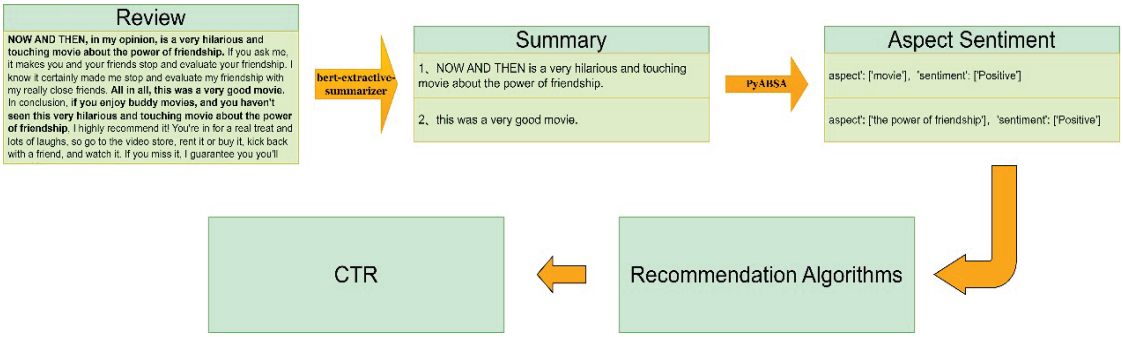

Fig.1. The figure of our proposed model.

IV. Experiments

In this section, we conduct experiments on user review data from the Amazon book dataset, extract the aspect terms and the corresponding sentiment polarity of the users, and validate our approach on a baseline model. Our experimental environment uses transformers=4.34.0, spacy=3.7.1 and python version 3.8. Also install bert-extractive-summarizer and pyabsa packages. cuda version is 12.1.

A. Data Sets

The Amazon book dataset is a commonly used dataset in recommendation algorithms [16, 17]. To ensure the quality of the dataset, we use the 10-core setting for our dataset, i.e., we ensure that both the user and the book have more than 10 pieces of interaction data respectively. The specifics of the dataset are shown in Table 1.

TABLE I. Data statistics table for the book dataset

Users	Books	Reviews	Train	Test
14762	24915	311887	243397	68490

B. Baselines

To validate the effectiveness of our proposed approach, we conducted comparative experiments on the classical recommendation algorithm KGAT [18], a recommendation model that explores user preferences on a collaborative knowledge graph using the graph attention mechanism.

C. Results

We perform experimental validation in two recommendation scenarios, click-through prediction and top-k recommendation. Recall and ndcg are used to evaluate the

prediction results in click-through prediction, and recall@k is used to evaluate the recommendation results in top-k recommendation. The experimental results are shown in Table 2 and Figure 2. We observe the following conclusions from them:

TABLE II. CTR PREDICTED RECALL AND NDCG RESULTS

MODEL	RECALL	NDCG
KGAT	0.0939	0.0934
OURS	0.1059	0.1036

- Overall, our model outperforms KGAT on the book dataset, indicating that our proposed method for extracting aspect terms and sentiment polarity from reviews is effective.
- Recall has more boosts than ndcg, and we speculate that perhaps our model is better able to incorporate information of interest to the user.

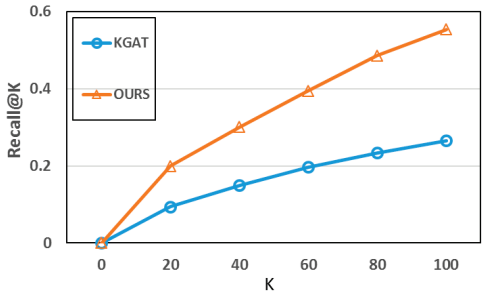

Fig.2. Top-k recommended results for Recall@k.

V. CONCLUSION

In this paper, we extract a new approach to extract fine-grained aspect terms and sentiment from user review documents of books and apply the approach to the recommendation domain. Processing the review text using important techniques such as text summarization and ABSA in the field of NLP and using the results in the recommendation domain provides a new perspective on recommendation algorithms. Experiments on a real book dataset initially show the effectiveness of our approach. However, there are still some shortcomings, for example, although it is convenient to use unsupervised methods when we process reviews using ABSA advanced methods, there may be a compatibility problem of pre-trained models on the dataset. In the future, we will further investigate the use of ABSA techniques to extract review information for better compatibility with recommendation domain datasets. In the meantime, we will validate the sophistication of our model with more comparative experiments.

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