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Alleviating the User Cold-Start Problem in Recommendation Systems Based on Textual Reviews Using Deep Learning

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Abstract

The main objective of recommender systems is to assist users in overcoming the issue of information overload by providing them with a carefully selected list of items that they are likely to find useful or relevant. Recommender systems may face many limitations and challenges, such as the cold start problem, which occurs when there is insufficient or no information about a new user or item. This leads to a decline in the performance of the recommender system. In this paper, we propose a recommendation system based on textual reviews and the deep learning method (RS-TRDL) to alleviate the user cold-start problem. Our RS-TRDL model can extract the important aspects and underlying sentiment polarity classification from the review text using NLP techniques and a deep learning method. These are then fused into collaborative filtering techniques to improve the RS and alleviate the user cold-start problem. The proposed method consists of two components: (i) An aspect-based sentiment analysis module that aims to extract aspects from the review text with its polarity; (ii) A recommendation generation component that uses the aspects as additional information with the numeric ratings. It also employs an important feature in the dataset, namely, the helpfulness to finally infer the overall rating prediction. Extensive experiments were conducted by the proposed system on two Amazon datasets. The experimental results show that the proposed RS-TRDL model exceeded all literature-reviewed comparison methods in the cold-start problem alleviation task.

Keywords: Recommender System, Cold-start problem, User reviews, Opinion Mining, LSTM.

تخفيف مشكلة البداية الباردة للمستخدم في أنظمة التوصية بناء على المراجعات النصية باستعمال التعلم العميق

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الخلاصة

الهدف الاساسي لأنظمة التوصية هو مساعدة المستخدمين في التغلب على مشكلة الحمل الزائد للمعلومات من خلال تزويدهم بقائمة مختارة بعناية من العناصر التي من المحتمل أن يجدوها مفيدة أو ذات صلة. قد تواجه أنظمة التوصية الكثير من القيود والتحديات مثل مشكلة البداية الباردة التي تحدث عندما لا تتوفر معلومات كافية

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أو تكاد تكون معدومة حول مستخدم جديد أو عنصر جديد. وهذا يؤدي إلى انخفاض في أداء نظام التوصية. نقترح في هذا البحث نظام التوصية القائم على المراجعات النصية واستعمال طريقة التعلم العميق (RS−TRDL) للتخفيف من مشكلة البداية الباردة للمستخدم حيث يمكن لنموذج (RS−TRDL) استخراج الجوانب المهمة وتصنيف قطبية المشاعر الأساسية من نص المراجعة باستعمال تقنيات البرمجة اللغوية العصبية وطريقة التعلم العميق. يتم بعد ذلك دمجها في تقنيات التصفية التعاونية لتحسين نظام التوصية وتخفيف مشكلة البداية الباردة للمستخدم. تتكون الطريقة المقترحة من عنصرين: (1) وحدة تحليل المشاعر القائمة على الجوانب والتي تهدف إلى استخراج الجوانب من نص المراجعة مع قطبيتها (2) مكون توليد التوصيات الذي يستعمل الجوانب كمعلومات إضافية مع التصنيفات الرقمية. حيث يتم استعمال صفة (helpfulness) الموجودة ضمن البيانات في تنبؤ القيمة النهائية للتقييم . تم إجراء تجارب واسعة النطاق بواسطة النظام المقترح على مجموعتي بيانات أمازون. أظهرت النتائج التجريبية أن نموذج RS−TRDL المقترح تجاوز جميع طرق المقارنة التي راجعتها الأدبيات في مهمة التخفيف من مشكلة البداية الباردة.

1. Introduction

The Internet and the Web have allowed a vast amount of information to be shared and accessed by large numbers of people [1]. This has led to a problem called information overload, which is the challenge of making decisions when faced with too much information.
A recommendation system (RS) is a software tool that suggests products or services to users based on their past behavior, interests, and preferences. RS can offer suggestions for items that the users might be interested in. The suggestions made by a recommender system are intended to assist users in different processes of decision-making, such as what products to buy, what articles to read, what songs to listen to, or what films to watch, by analyzing their past behavior. This can save users time as well as their efforts and help them deal with the problem of information overload [2].

Recommender systems have evolved to become an essential part of our digital lives, helping users navigate the vast number of options available and personalize their online experiences [3]. They are commonly used in several types of online services and platforms, including social media platforms, e-commerce sites (such as Amazon, eBay, and E-shops Taobao), content platforms, and streaming services (such as Netflix and Spotify).

Recommender systems analyze user data, item characteristics, and user-item interactions using several kinds of techniques and algorithms, including machine learning, data mining, and statistical modeling. These technologies learn and improve their recommendations iteratively over time by incorporating updated data and feedback from users [4].

In general, there are three main types of recommendation approaches: collaborative filtering (CF), content-based filtering (CB), and hybrid strategies. CF is the most popular approach to recommender systems as it is simple to implement and can be used with a wide range of items, including non-textual data [5].

Traditional collaborative filtering recommendation system algorithms rely primarily on user suggestions based on historical numerical ratings. However, for new users (known as cold-start users) who lack historical rates, these strategies lose some of their effectiveness. The cold start problem affects both new users and new items in the system [6]. This issue appears because traditional recommendation algorithms make predictions based mainly on user preferences gained from historical data. When the system encounters a new user who has not provided much information or a new item that has not been used by many users, it lacks the essential information needed to produce useful recommendations [7]. Addressing the cold start problem is critical for providing a positive experience to new users and ensuring that the recommendation system remains efficient as new items are encountered.

To alleviate this issue, some researchers have suggested using textual information published by new users on social networks as additional information. To make reliable recommendations, a recommendation system must be able to recognize the valence of sentiments precisely [8].

The textual reviews served as a dataset, and then several analysis techniques were performed in the first step, including text analysis and opinion mining. Later, the system uses text analysis and opinion mining to understand each user's preferences. These visions are then used to suggest relevant items for each user. In the textual datasets, an important feature that has been used in this work is helpfulness. This feature usually indicates a numeric value or rating that indicates how useful or helpful a particular review is to other users. It is a way to evaluate the quality and importance of reviews provided by individuals who have tried a product, service, or content.

Opinion mining, also referred to as sentiment analysis (SA), is a technique for extracting irrational information or opinions from textual data [9]. SA is the process of identifying the sentiment or feelings expressed in a piece of text. This could be positive, negative, neutral, or even more subtle. It involves using text analytics, machine learning, and natural language processing tools to analyze texts and recognize emotions. Different techniques, such as lexicon-based techniques, machine learning techniques, and deep learning algorithms, are utilized to perform sentiment analysis, providing state-of-the-art performance in various opinion mining tasks. Deep learning methods, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown significant improvements in opinion mining. RNNs, like Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU), can detect contextual dependencies and sequential information in textual data. LSTM is a type of recurrent neural network (RNN) architecture that is commonly used for sentiment analysis tasks due to its ability to capture sequential dependencies in text data [10].

One new technique in opinion mining that has gained a lot of attention recently is aspect-based opinion mining, also known as aspect-based sentiment analysis (ABSA). It's a natural language processing (NLP) technique used to analyze text and extract opinions about certain aspects of a product or service [11]. These aspects can be attributes, features, or components about which people may express their opinions. ABSA is a more precise approach to sentiment analysis than traditional sentiment analysis approaches, which only take into account the general sentiment of a text [9]. It provides a more accurate understanding of sentiments. Instead of simply determining whether the text is positive or negative, it provides information about the specific aspects the user cares about. When buying a phone, one user may prioritize camera quality, while another may prioritize battery life. Depending on a specific phone's 4-star rating, no one may decide to buy it without reading additional reviews.
ABSA involves two major tasks: The first is to extract important aspects of an item from user reviews, and the second task is to predict the user's rating of each aspect based on the sentiments described in their reviews. Reviews typically mention aspects, which are features or elements of an item, to describe its quality [12]. For example, some of the restaurants' aspects include service, food, and staff. Reviewers describe the quality of each aspect using sentiments, which are mostly adjectives, such as good service, delicious food, and uncooperative staff. These sentiments reflect the level of satisfaction customers have with the quality of each aspect. In this paper, we attempted to alleviate the problem of new users, or the so-called Cold Start problem, by proposing a novel recommendation method. This method is based on opinion-mining techniques, specifically on aspect-based opinion mining. We also used the Long Short-

Term Memory (LSTM) algorithm, which has certain contributions in the field of review-based recommender systems, to obtain superior results.

This paper is structured as follows: In Section 2, a literature review is presented. Section 3 will then detail our proposed method. Then, Section 4 presents and discusses the experimental results on two real-world datasets to verify the accuracy of our rating prediction approach. Section 5 finally presents the conclusion.

2. Related Work

Over many years, several works have been introduced to alleviate the cold start problem and improve the performance of RSs. For instance, in [13], the researchers proposed a review and content-based deep fusion model named RC-DFM for a cross-domain recommendation. First, they extended Stacked Denoising Autoencoders (SDAE) to successfully fuse review texts and item contents with the rating matrix in both the auxiliary and target domains. As a result, the learned latent factors of users and items across both domains preserve more semantic information for recommendation. Once user latent factors had been transferred between the two domains, they used a multi-layer perceptron to produce predictions in order to address the data sparsity and cold start problems. They used Amazon to assess their model's efficiency. The experimental results showed that their model was superior.

In their work [14], the researchers developed a system that combines an online shopping domain with information from an advertising platform. Their methodology used deep learning to build a cross-domain recommender system based on shared users in these two domains. This improved recommendation performance and alleviated the cold-start issue. Word2Vec was used to convert textual information about users and items into latent vectors as their representations. Then, various collaborative filtering models were applied to build a cross-domain recommender system. In addition, extensive experiments (on a real-world dataset that combines data from advertisements and online shopping) were carried out to evaluate the performance of recommendations for new users. The authors of [15] presented an approach for using social media data to generate a behavioral profile to classify users. Based on this classification, predictions will be created via machine learning techniques such as classification trees and random forests. The system will utilize this data to create user profiles, which will serve as input for recommender system engines. Hence, the user would not have to actively provide any kind of explicit data other than their social media source. This eventually alleviated the cold start problem. The researchers evaluated prediction accuracy using precision, RMSE, and F-measure.

In [16], the researchers proposed an ontology-based (OB) content recommender system to address the cold-start problem for new users. The proposed model uses ontology to model the learner and learning objects, taking into account their attributes. The recommendation model incorporated collaborative and content-based filtering techniques to generate the top N recommendations based on learner ratings. Experiments were carried out on a real-world dataset containing the data of 300 students to evaluate the performance and prediction accuracy of the proposed model under cold-start conditions using the evaluation metrics of mean absolute error (MAE), precision, and recall. The experimental results showed that the performance and accuracy of the proposed algorithms are better in cold-start situations. Additionally, the proposed approach provides more personalized and reliable recommendations using historical learner ratings in the recommender system and ontological domain knowledge.

In [17], the authors presented a novel ranking model, RBPR, which integrated explicit ratings and implicit feedback into a single model. First, the proposed method employed the

Singular Value Decomposition (SVD) model for pre-processing to increase the density of explicit ratings. After that, probabilistic matrix factorization (PMF) and Bayesian personalized ranking (BPR) were unified jointly. BPR was used to reconnoiter the implicit features of users and items from implicit feedback data. On the other hand, PMF was employed to recognize the explicit features of users and items based on explicit ratings. Lastly, the final features of users and items were determined by taking the shared latent features of users and items that were extracted from both models. Four original datasets were used to test this model. They are Movielens 100k, Movielens 1M, FilmTrust, and Ciao artificially. According to experimental results, the proposed approach, RBPR, performs well in terms of different evaluation metrics.

The work in [18] proposed a framework named MetaTL to enhance sequential recommendations for cold-start users. MetaTL learns a model in a meta-learning manner, adapting it for new users with just a few interactions. Based on experiments on three real-world datasets and the evaluation metric mean reciprocal rank (MRR), the proposed MetaTL can deliver significant improvements. They also evaluate the hit rate (hit) for the top-1 prediction.

3. Methodology

In general, the objective of our proposed RS-TRDL model is to develop a hybrid system by fusing recommender systems with sentiment analysis ones. It predicts the ratings by employing the polarity of the aspects extracted from user textual reviews as additional information to alleviate the cold start problem and improve the performance of the recommendation system. This section will present the system's major phases and components. Figure 1 illustrates the entire RS-TRDL architecture.

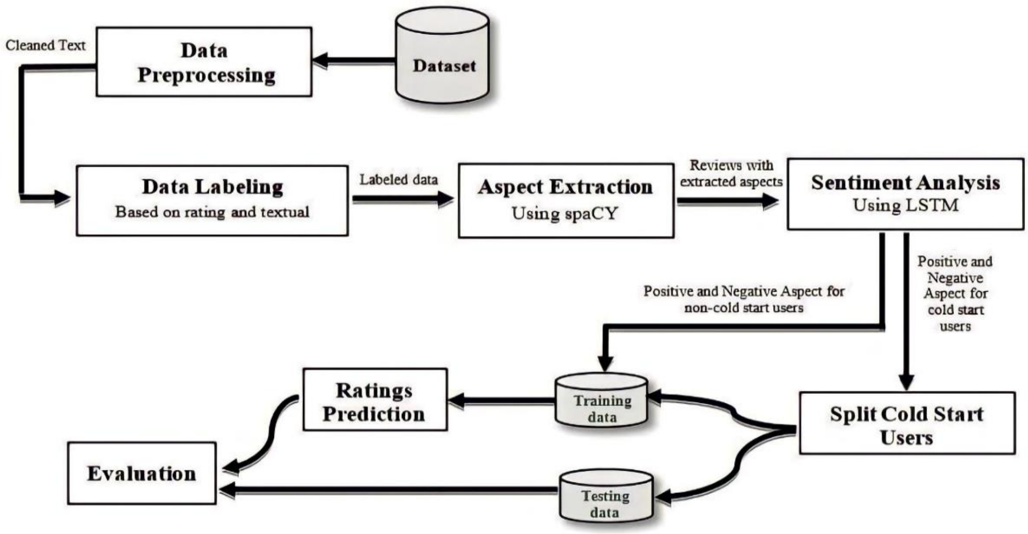


Figure 1: The Architecture of the proposed RS-TRDL model

3.1 Data Preprocessing

Typically, NLP projects involve a modeling phase where we train the model to handle real-world data. This model requires numerical data, but our data is textual, so we must go through several stages of text preprocessing. In our work, we have implemented three distinct stages. The first one is the Handling Missing Values stage. These can be handled using lots of techniques. In our work, we removed the rows with missing values in the ratings column. The next step is text cleaning, which is the process of extracting the raw text from the input data and converting it to the desired encoding format by removing all non-textual elements like markups and metadata. This stage involves three operations. Initially, we eliminate URLs that lack contextual significance and could potentially confuse the NLP model. The second step is Unicode Normalization, which entails addressing equivalency issues and managing emojis. The third step is to correct spelling using the Python library pyspellchecker. Finally, there is the text preprocessing stage, which includes several tasks (tokenization, removing stop words, lowercasing, stemming, and lemmatization).

3.2 Data Labeling

Data labeling is the process of assigning relevant and informative tags or labels to raw data (such as text, images, audio, or video) to make it accessible and usable by machine learning algorithms. In our work, we labeled our data based on textual reviews and numerical ratings. We also labeled the user's training data with a rating greater than 3 as positive, and the remainder with a rating less than 3 as negative reviews. Simultaneously, we used the TextBlob Python library to extract the sentiment of the user's textual reviews (positive or negative reviews). The two results were then fused to get one label for each user's training.

3.3 Aspect Extraction

This phase incorporates two operations, namely, noun extraction and topic modeling. First of all, we have the segmentation process. It is the process of dividing a continuous stream of text into meaningful sentences or segments. The textual review is divided into sentences, and each sentence proceeds separately. As we were looking for the significant aspects of the user (which are usually expressed as nouns in textual user reviews), the words that had the noun tag were extracted using the spaCY package, which extracts nouns.

Bidirectional encoder representations from Transformers Topic (BER Topic) filter unrelated nouns due to their potentially large total number. BERTopic is an open-source library that uses a BERT model to do topic detection with a class-based TF-IDF procedure. TF-IDF (Term Frequency-Inverse Document Frequency) is an algorithm that weights the importance of words in a corpus, exactly as the name implies. How often a word appears in a document is a useful indicator of its importance, but the more often it appears in different documents, the less important it becomes.

3.4 Sentiment Analysis

Now, having extracted the aspect, we can proceed to the sentiment analysis (SA) phase. In this phase, we need to extract and classify the polarity of the extracted aspects based on the sentiment of the sentence in which they appear. To do this process accurately, we utilized the LSTM algorithm, which is one of the deep learning algorithms commonly used in the NLP field. Additionally, LSTM has feedback connections in contrast to standard feedforward neural networks [19]. As is well known in the basics of deep learning, the model was built based on the labeled dataset to learn and train the classifier. Then, this model was used to classify the extracted aspects.

3.5 Splitting the cold start users

First, to deal with the cold start problem, the cold start users should be selected. Therefore, the users have been divided into two groups based on their rating history. The first group comprises users who have provided ratings exceeding a predefined threshold (namely the non-cold start group). Conversely, the second group, often referred to as the (Cold Start group), consists of users with a rating history equal to or less than the established threshold. After extensive experimentation and data analysis, a threshold value of 5 was selected for identifying cold start users. So each group was split into its positive and negative extracted aspects (the cold start group with its aspect and the non-cold start group with its aspect). Next, the process of train-test data splitting was done to assess the performance of the trained model. Our work involves splitting the cold start group dataset into two sub-datasets. 80% of the entire data is used for training, and 20% of it is used for testing.

3.6 Rating prediction

For each new user in the cold start group, the ratings have been predicted depending on the similarity in the aspects preferred by the user. These aspects are extracted from the text reviews they publish about a specific item. Therefore, instead of relying solely on default criteria such as item and user information for prediction, we strive to incorporate two additional crucial features. These are the aspects that the user cared about in his text reviews, in addition to the helpfulness of the review. The latter refers to how helpful a particular review is to other users in making decisions. This could be indicated through ratings, upvotes, or other mechanisms. For each new user in the cold-start group, all users who belong to the non-cold-start group and share the same aspects of the same item as this user are determined. Then, these users are ranked in descending order based on their helpfulness. Next, the formula, which represents the average user's rating, selects ten users with the highest values to proceed with the rating prediction process.

$$P = \left(\sum_{u=1}^{n} R_u\right)/n \tag{1}$$

Where P is the predicted rating value, R_u is the rating of the selected users, and n is the number of selected users, which equals 10 in this case, where many experiments and data analysis led to choosing the number 10 to select the users with the highest helpfulness values. Having applied this formula, we get the final value of the predicted rating.

3.7 Evaluation

We use root mean square error (RMSE) and mean absolute error (MAE) to measure how well the recommendation model works. These errors are found by looking at the average distances between an item's actual rating and its predicted rating made by the recommendation model. The smaller the value, the better the performance. RMSE represents the sample standard deviation of the differences between predicted and actual ratings. MAE, on the other hand, calculates the absolute differences between predicted and actual ratings of test items. These metrics are given as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left| p_{u,i} - r_{u,i} \right| \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(p_{u,i} - r_{u,i})^2}{n}} \tag{3}$$

Where, $p_{u,i}$ is the predicted rating of user u to item i, $r_{u,i}$ is the real rating, and n is the number of all ratings in the test set.

4. Experiment

This study aims to use sentiment analysis in the rating prediction process. Several experiments were conducted to verify the outputs of our model on two Amazon datasets. These are Amazon Fine Food Reviews (AFF) and Amazon Electronics (AE). The MAE and RMSE metrics were employed to evaluate the results of our model, RS-TRDL, against other methods. It is important to note that, due to the local machine's memory limitations, a representative sample is picked from both extensive datasets. We randomly selected 9,621 users who have provided 37,527 ratings and textual reviews on 16,330 items for the Amazon Electronics dataset and 8,489 users who have provided 67,814 ratings and textual reviews on 20,678 items for the Amazon Fine Food Reviews dataset, as demonstrated in Table 1 below:

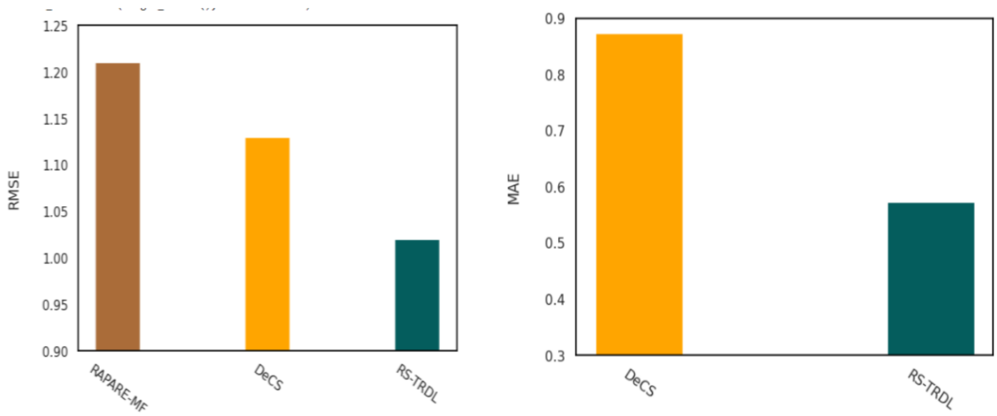
Table 1: Datasets information.

Datasets	#Users	#Cold start users	#Items	#Ratings	#Reviews
Amazon Electronics	9621	8173	16330	37527	37527
Amazon Fine Food	8489	5490	20678	67814	67814

For the AE dataset, two previous studies that had used the same dataset were selected to compare with our RS-TRDL model. Table 2 and Figure -2 below display the results.

Table 2: RS-TRDL results on AE dataset.

Methods	MAE	RMSE
RAPARE-MF	N/A	1.21
DeCS	0.874	1.13
RS-TRDL	*0.574*	*1.02*



(a) **(b)**

Figure 2: The results of RS-TRDL model against the comparison methods on AE dataset.

Regarding the baseline models, it can be seen from Table 2 and Figure 2 that the RAPARE-MF method [20], which is mainly based on user ratings for predictive performance, achieves relatively the lowest performances on the RMSE metric compared to other baseline models. On the other hand, compared to the DeCS model [21], our method, RS-TRDL, achieves huge gains with a significant margin in terms of both RMSE and MAE. This appears to indicate the impact of incorporating user textual feedback into RS's CF approach.

Our method demonstrably outperforms previous models in terms of RMSE, achieving a value of 1.02 compared to the DeCS model's value of 1.13. This translates to a 9.73% improvement in metric performance. Furthermore, our model enhances metric performance by 15.7% in comparison to the RAPARE-MF model, which attained a score of 1.21. Further, in terms of MAE, our model outperforms existing methods, attaining a value of 0.574 compared to the value of 0.874 observed in the DeCS model. Thus, the proposed RS-TRDL model demonstrates a 34.32% improvement in predicting the target metric compared to the previous method.

Our approach has a significant benefit over baselines in that it considers the user's opinions on several aspects of the item. This is in addition to the effective aspect extraction technique utilized to generate quality aspect terms required to improve RS performance. This clearly illustrates that a better aspect extraction technique can generally lead to improved recommendation system performance.

In our literature review, we didn’t find any research in the cold start problem field that used the AFF dataset in its work. Consequently, we compared our RS-TRDL model with the baseline method. We assumed that the baseline is an RS based on sentiment analysis using the TextBlob library, without resorting to deep learning methods or utilizing the helpfulness feature in the recommendation process.

Table 3: RS-TRDL results on AFF dataset.

Methods	MAE	RMSE
Baseline	0.882	1.261
RS-TRDL	0.855	1.258

As illustrated in Table 3, the results showed that the recommender system's accuracy improved because the RS-TRDL model relied on deep learning methods in the sentiment analysis process. As previously proven, deep learning models have achieved state-of-the-art performance in various sentiment analysis tasks. In addition to relying on the helpfulness feature (which is an important feature in the dataset that identifies trust users) in the recommendation process, the focus was on the opinions of the users who had the greatest value for helpfulness. This means that many users benefited from their text reviews.
Compared to the baseline method, with MAE achieving the value of 0.882, our model demonstrably improves this measure by reaching up to 0.855. This means reducing the error rate and improving performance by 3.06%. In terms of the RMSE value, the baseline method achieved a value of 1.261, compared to the value of 1.258 observed in our proposed model. This indicates a 0.24% performance improvement. We can confidently state that our RS-TRDL model has great accuracy, which confirms the use of deep learning algorithms in applying sentiment analysis to recommendation systems. It also demonstrates that using the helpfulness feature significantly improves the quality of the recommendations.

5. Conclusions

In this paper, we introduced a recommendation model that utilizes aspect-based sentiment analysis and the LSTM algorithm, known as RS-TRDL, to address the issue of user cold start. This method relies on the application of Natural Language Processing (NLP) techniques to process the user's textual review and then extract the key aspects. To obtain the opinion of each aspect mentioned in the user’s textual comment, aspect-based sentiment analysis has been performed, making use of one of the most important deep learning algorithms employed in the NLP field, LSTM, to indicate whether their opinion in a specific aspect is positive or negative. Depending on the similarity between cold-start users and other users in the aspects extracted from the textual reviews, it was possible to help the former users. Therefore, predicting the overall rating could alleviate this problem. Several experiments were conducted on two Amazon datasets to show the efficiency of the proposed method (RS-TRDL) compared to other recommendation methods. The results of the experiments showed that the proposed method outperformed other recommendation approaches by a significant margin. Our experiments supported the idea that integrating recommender systems and sentiment analysis would have significant advantages.

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