Attentional Sentiment and Confidence Aware Neural Recommender Model

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Abstract: One of the major problems of recommendation systems is the rating data sparseness and information overload. To address these issues, some studies are leveraging review information to construct an accurate user/item latent factor. We propose in this article a neural hybrid recommender model based on attentional hybrid sentiment analysis, using BERT word embedding and deep learning models. An attention mechanism is used to capture the most relevant information. As reviews may contain misleading information (" fake good reviews / fake bad reviews "), a confidence matrix has been used to measure the relationship between rating outliers and misleading reviews. Then, the sentiment analysis module with fake reviews detection is used to update the user-item rating matrix. Finally, a hybrid recommendation is processed by combining the generalized matrix factorization (GMF) and the multilayer perceptron (MLP). The results of experiments on two datasets from the Amazon database show that our approach significantly outperforms state-of-the-art baselines and related work.

1 INTRODUCTION

Over the past two decades, recommendation systems have been widely employed in many domains. With the information overload problem, finding suitable products on online platforms is increasingly becoming difficult for users. Recommender systems (RSs) are used, for instance, by Amazon to suggest preferred products for customers, by Facebook and LinkedIn to recommend people and webpages to connect and follow, by YouTube to suggest related videos. RSs learn the interests of users through their historical behavior data and predict user preference. Recently, deep learning (DL) techniques have been applied in RSs to solve the cold start and data sparsity problems. To further improve the recommendation effectiveness of traditional algorithms, He et al. (2017) proposed the neural collaborative filtering (NCF) model, which is the widely used model in RSs. They modelled the user-item assessment matrix using a multilayer feedback neural network (MLP) to learn the nonlinear relationship between users and items.

On the other hand, with the considerable development of social media, users often post reviews to express their preferences and feelings about items. These comments are considered reliable indicators that can reflect the overall satisfaction of users, expressing their preferable, non-preferable or neutral opinions. These opinions are very useful for understanding people's references on items (Osman et al., 2021). Several research works are applying sentiment analysis (SA) in RSs (Wankhade et al., 2022; Dang et al., 2021; Berkani and Boudjenah, 2023). However, many malicious users often share misleading information about items in order to manipulate or trap recommendation systems. As reviews often contain fake good or fake bad reviews, Li et al. (2021) leveraged the latent interaction factor between users and items by exploiting the interactivity of review information. To reduce the impact of misleading comments on the model, they used the confidence matrix to measure the relationship between rating outliers and misleading reviews. Birim et al. (2022) explored the most effective feature combination in fake review detection including the features of sentiment scores, topic distributions, cluster distributions and bag of words.

We focus in this article on these same issues and we propose a novel recommender model using a hybrid sentiment-based model and detecting

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fakereviews. We aim to enhance the user-item rating matrix by predicting missing ratings and correcting inconsistent values by matching the users' ratings and their associated comments on the items. Our sentiment model is based on BERT word embedding and several combinations of deep learning models are considered: RNN-LSTM / BiLSTM and CNN-LSTM / BiLSTM. For the detection of fake reviews, we were inspired by the same approach of Li et al. (2022) based on the confidence matrix. By exploiting the enhanced user-item evaluation matrix, our system generates predictions using a hybrid recommendation algorithm using the generalized matrix factorization (GMF) and the MLP models. Extensive experiments conducted on two datasets demonstrated the effectiveness of our model compared to the state-of-the-art approaches and baselines.

The rest of this article is organized as follows: Section 2 provides a literature review about DL and sentiment-based RSs. Section 3 presents our sentiment-based approach for the recommendation of items. The results of experiments are presented and analysed in Section 4. Section 5 concludes this work with some future perspectives.

2 LITERATURE REVIEW

With the latest successes in a variety of domains including computer vision, machine translation, speech recognition and natural language processing, DL models have been exploited, in the last few years, in RSs. Current models mainly use deep neural networks to learn user preferences on items for recommendations. Two categories of models can be distinguished (Ni et al., 2021): (1) recommendation models using a single neural network structure (Zhang et al., 2017), such as Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and its variants Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU); and (2) recommendation models that combine the attention mechanism and neural networks (Hu et al., 2018).

To overcome the rating data sparseness, users' reviews are used for rating prediction. These reviews or comments can express users' overall satisfaction on the items through their preferred, non-preferred or neutral opinions. According to Osman et al. (2021) these opinions will provide a better understanding of user preferences on items. Recently, the application of SA in RSs has been the focus of extensive research. There are currently three approaches to address the SA problem (Bhavitha et al., 2017): (1) lexicon-based techniques, including dictionary-based and corpus-based methods (Salas-Zárate et al., 2017); (2) machine-learning-based techniques (Zhang and Zheng, 2016), including traditional techniques and DL techniques; and (3) hybrid approaches, combining machine learning and lexicon-based approaches (Pandey et al., 2017). Bhattacharya et al. (2022) discussed and analysed recent developments and related works providing an overview of the different aspects of SA. Among these works we reference the following as examples: Diao et al. (2014) integrated two parallel neural networks, and developed DeepCoNN that jointly models users and items through reviews, where the two CNNs are connected by a shared layer facilitated by factorization machines. ConvMF leverages the information in user-contributed reviews and integrates CNN into the matrix factorization (Kim et al., 2016). Chen et al. (2018) developed a neural attentional regression model with review-level explanations (NARRE) taking the review usefulness into consideration.

Furthermore, some approaches combining two models, such as SVM-enhanced CNN (Xue et al., 2016), CNN with RNN (Rehman et al., 2019), have yielded improved results. Dang et al. (2021) applied a SA in RSs based on hybrid DL models and collaborative filtering. According to the authors, the system architecture can integrate a variety of techniques including the pre-processing strategy, hybrid DL models for SA and methods for RSs.

After studying the proposed approaches, we noticed the lack of a neural recommendation model based on hybrid sentiment analysis exploiting both attention mechanisms and fake reviews. Therefore, we are motivated to propose a novel approach that brings these features together, demonstrating the contribution of each component in improving the performance and the quality of recommendation. The following section presents the proposed model.

3 OUR ASCAD-Rec MODEL

The proposed ASCAD-Rec model is summarized as two main modules, as shown in Figure 1: (1) The rating matrix enhancement module, which adjusts the original rating matrix by combining it with our sentiment model, which is based on fake reviews detection; and (2) the recommendation module, which aims to predict the user's rating on a given item using the neural hybrid filtering (NHF) model.

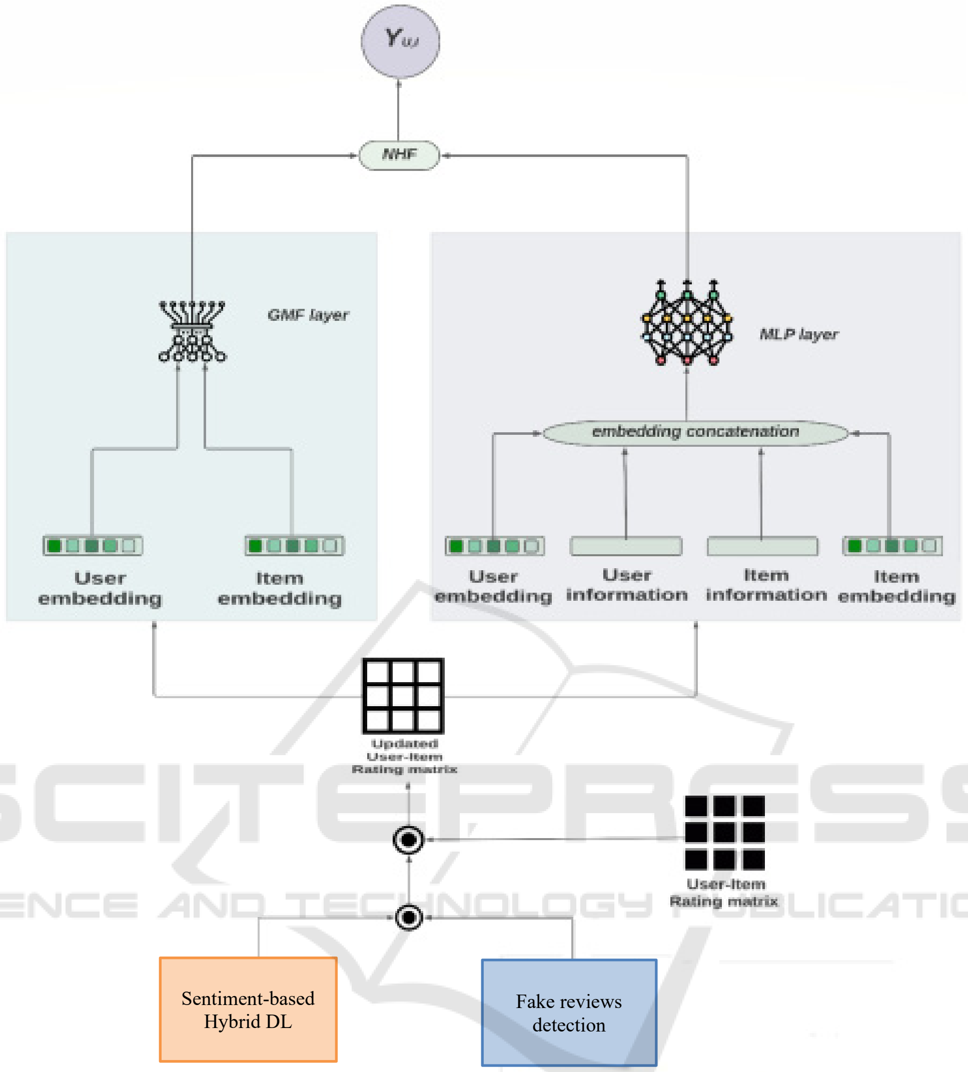

Figure 1: The proposed ASCAD-Rec model.

3.1 Rating Matrix Enhancement

3.1.1 Attentional Sentiment-Based Model

The sentiment module is based on users' reviews on items and ratings assigned on a 1-5 rating scale. Figure 2 illustrates the different steps of this model.

First, we performed a set of pre-processing operations on the data in order to convert it into an interpretable and understandable form by our system. We converted all words to lower case, removed punctuation and stop words, and extracted the stems of the words using the Snowball Stemmer algorithm. Stemming is reducing a word to its base word or stem where the words of similar kind lie under a common stem.

Then, the second step is the embedding layer. Processing textual data requires a conversion to numbers before using any machine learning model. Several methods allow this conversion, including the traditional one-hot encoding on categorical data. Currently, word embedding allows a better representation of textual data. The embedding layer allows converting each word into a fixed length vector of defined size in order to better represent words with reduced dimensions. I can understand the context of a word and thus have similar embeddings for similar words. The output vector represents the input of the neural network's hidden layer. In this work, we used BERT, the Bidirectional Encoder Representations from Transformers proposed by (Devlin et al. 2018).

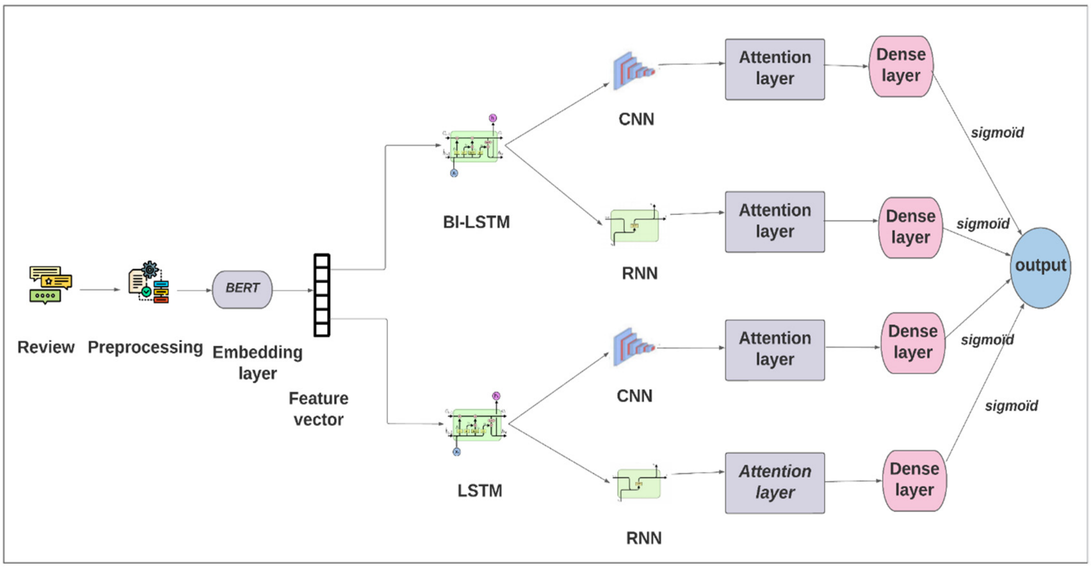

Figure 2: Hybrid sentiment analysis module based on attention mechanism.

BERT is used to transform text data to word embedding. It was used to create the feature vectors.Different combinations of DL models were considered CNN → BiLSTM; and CNN → LSTM; RNN → Bi-LSTM and RNN → LSTM). These models are followed by an attention layer to capture only the most relevant information. The attention mechanism is used to calculate the attention weight for each component of the input sequence. The latter are used to assign weights to the sequence so that the most important components receive a higher weight and therefore have a greater impact on the output.

The attention layer returns the context vector representing the weighted sum of the sequence elements, where the weights are the attention weights. The attention mechanism takes as input the output of the previous model. The result is used to perform the final classification of the comments. It is connected to a dense layer whose activation function is "sigmoid". In order to train and validate the sentiment analysis results, the reviews were labelled with the sentiment score of the review, which can be either positive or negative (value 1 or 0). Finally, the output layer presents the result of the final rating of an item *i* generated from the attentional sentiment model.

3.1.2 Fake Reviews Detection

Misleading reviews are mainly caused by fake good and fake bad reviews. When a user rates an item too low (resp. too high) compared to his/her average low ratings (resp. average high rating) compared to the item's average rating, it will be considered as an outlier value. Therefore, these ratings are given low weights.

The confidence matrix is considered as a regularization that aims to adjust the opinions, taking into account the general opinion. It calculates the difference between the score given by the user to the item and the average of scores given by the user to other items. Then it calculates the difference between the score given by the user to the item and the average of scores given to the item by other users. If the difference is greater than a given threshold (deviation rate), then it will be considered as an outlier. The confidence level function used is the same proposed in (Li et al., 2021).

3.1.3 Sentiment and Fake Reviews Detection

The sentiment score is combined with the fake review detection module. The results obtained from both the sentiment model and the fake reviews detection model will be used to adjust the initial rating matrix. Each initial rating will be combined with the predicted rating using the following weighted formula:

$$\mathrm{Score_F} = \alpha * \mathrm{Score_P} + (1 - \alpha) * \mathrm{Score_R} \qquad (1)$$

where:

- $\mathrm{Score_F}$: is the final score; $\mathrm{Score_P}$: is the predicted score using SA with fake reviews detection;

- $Score_R$: is the real score assigned by the user on the item; and
- α: is a parameter used to adjust the importance of each term of the equation.

3.2 Neural Hybrid Recommendation

The NHF model proposed in a previous work (Berkani et al., 2019) was exploited for the recommendation. NHF is an extension of the very popular NCF model (He et al., 2017), which concatenates the results of the two models GMF and MLP, then passes the result through a dense layer with a "Sigmoid" activation function to obtain the prediction result.

The GMF model considers the latent user and item factors as input, representing the hidden characteristics that determine user preferences and item features. These vectors are given as input to a neural layer which performs the product of the two vectors. The result is then sent to the predictive layer represented by a dense layer with a "sigmoid" activation function. On the other hand, the vectors of the user and item latent factors, concatenated with their respective information, are passed through an MLP network, providing as output the prediction of the evaluation score.

3.3 Training

The data extracted from the datasets must be pre-processed and transformed before passing through the different models. Then, these data are divided into two sets considering 80% of the data for training and the rest for testing in order to evaluate the performance of our models. To guarantee a good performance of our models, we used the "Binary Cross-Entropy" cost function. In order to improve the performance of our models, we use the Adam (Adaptive Moment estimate) algorithm, a stochastic optimization method (Kingma and Ba, 2014). This algorithm will minimize the cost function, as a lower loss means a better performance of our models.

4 EXPERIMENTS

We present in this section the experiments carried out to evaluate the hybrid SA including the contribution of the attention and fake review model. Then we evaluated the hybrid recommender model by comparing its performance with some exiting models. Finally, we compared our approach with the state-of-the art recommender models.

4.1 Datasets and Evaluation Metrics

For the training and evaluation of our sentiment analysis models, we used the IMDB database, which includes 50,000 reviews classified into two categories (positive and negative comments). For our experiments, we used a dataset from the Yelp database, considering the shopping category. This dataset, with a density of 0.25%, comprises 2,472 users, who have carried out 55,738 reviews on 8,785 items.

For the experiments, we used the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) evaluation metrics. MAE and RMSE have been used as they are the most popular predictive metrics to measure the closeness of predictions relative to real scores.

4.2 Evaluation Results

4.2.1 Evaluation of Sentiment Models

To generate the embedding vectors for each comment, we performed the pre-processing of the texts using the Python libraries (tokenization, removal of empty words and punctuation, encoding, padding, etc.). Then we generated the embedding vectors using the BERT model. Next, we varied the hyper-parameter values.

We varied the number of neurons in the last dense layer of our models. We can notice from Table 1 that 128 performed better than the other models, with the exception of the hybrid LSTM-RNN model, which requires 32 neurons.

Table 1: Evaluation of hybrid SA models varying the number of neurons.

NN	LSTM		BiLSTM		LSTM				BiLSTM			
					CNN		RNN		CNN		RNN	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
32	0.2755	0.1375	0.3230	0.1336	0.2640	0.1059	**0.2679**	**0.1135**	0.2659	0.1140	0.2777	0.1110
64	0.2811	0.1354	0.2824	0.1282	0.2777	0.1178	0.2897	0.1217	0.2740	0.1099	0.2707	0.1149
128	**0.2770**	**0.1331**	**0.2746**	**0.1324**	**0.2653**	**0.1029**	0.2708	0.1124	**0.2607**	**0.1074**	**0.2710**	**0.1126**
256	0.2855	0.1448	0.2797	0.1335	0.2649	0.1074	0.2724	0.1174	0.2651	0.1143	0.2835	0.1180

Table 2: Contribution of the attention mechanism on the performance of our models.

Models	Without attention		With attention	
	MAE	RMSE	MAE	RMSE
BiLSTM	0.1307	0.2817	**0.1324**	**0.2746**
BiLSTM-CNN	0.1202	0.2705	**0.1074**	**0.2607**

Table 3: Variations of PF and MLP Layers of the hybrid model.

PF	4		5		6		7	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
8	0.2037	0.1540	0.2042	0.1533	0.2052	0.1523	0.2064	0.1521
12	0.2056	0.1537	0.2051	0.1530	0.2067	0.1538	0.2052	0.1506
16	0.2061	0.1535	**0.2031**	**0.1510**	0.2062	0.1516	0.2052	0.1513
18	0.2050	0.1532	0.2051	0.1522	0.2064	0.1522	0.2065	0.1509

Table 4: Variations of α.

Models		NHF		GMF		PMF		SVD++	
		RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Without SA		0.2031	0.1510	0.2318	**0.1689**	2.1399	1.7754	0.9997	0.7684
With SA	α = 0.3	**0.2012**	**0.1491**	**0.2280**	**0.1785**	2.1136	1.7482	**0.9818**	**0.7632**
	α = 0.4	0.2074	0.1547	0.2335	0.1848	**2.0574**	**1.7207**	1.0085	0.7916
	α = 0.6	0.2327	0.1743	0.2537	0.2053	2.0982	1.7764	1.1116	0.8887
	α = 0.7	0.2501	0.1879	0.2676	0.2182	2.1387	1.8052	1.1929	0.9580

We can observe that the BiLSTM-CNN model performed better than the other models. The BiLSTM network takes into account the context before and after each word in the sequence, providing a better understanding of the overall context. Convolution layers are particularly useful for capturing local features.

We have demonstrated the contribution of the attention mechanism on the performance of the BiLSTM and BiLSTM-CNN models. The results presented in Table 2 show that the attention mechanism considerably improves the predictions of our models.

4.2.2 Recommendation Evaluation

We varied the vector size (T.E) of the hybrid model (NHF), considering T.E equal to 8, 16, 32 and 64. The best results were obtained with a T.E equal to 8 and a performance in terms of MAE equal to 0.1510 and RMSE equal to 0.2031.

Furthermore, as presented in Table 3, we varied the number of MLP layers and the predictive factor (PF) of the MLP network of the NHF model. Given that the PF represents the number of neurons in the last layer.

We can notice that the best results were obtained with PF equal to 16 and a number of layers equal to5. This configuration will be considered in the rest of our experiments. Then, we varied the parameter α, which adjusts the balance between the original and the predicted ratings, of the NHF hybrid model. We compared its performance with three simple matrix factorization models GMF, PMF and SVD++ (see Table 4). We can see from the results that the NHF, GMF and SVD++ models perform better with α=0.3, while the PMF model performed better with α = 0.4. Moreover, the results proved the contribution of SA on NHF compared to the model without SA.

To assess the contribution of fake reviews detection on our model, we have shown in the table a performance comparison between the model with fake reviews (ASCAD-Rec) and the model without fake reviews (ASAD-Rec). We obtained the performance of MAE = 0.1438 and RMSE = 0.1964 with the ASCAD-Rec model, while with the ASAD-Rec model, we obtained the performance of MAE = 0.1491 and RMSE = 0.2012. These results demonstrate that the detection of fake reviews and the regularization of the sentiment score improve the performance of our model and enable more efficient learning.

4.2.3 Comparison with Related Work

We present in this sub-section a comparison of our approach with existing work (see Table 5):

- PMF: is a machine learning model based on probabilistic principles for matrix factorization.
- SVD++: is a matrix factorization technique based on singular value decomposition.

- NCF: is a matrix factorization method based on deep learning techniques for collaborative filtering.
- DeepCoNN: is a deep learning-based approach that exploits user comments to generate recommendations.
- NARRE: exploits user comments by integrating an attention mechanism to create vectors of latent user and item factors.

Table 5: Performance comparison of different models.

Models	MAE	RMSE
PMF	1.7207	2.0574
SVD++	0.7632	0.9818
NCF	0.1689	0.2318
NAREE	0.8767	1.1360
DeepCoNN	0.6370	0.8192
NHF	0.1510	0.2031
ASAD-REC	0.1491	0.2012
ASCAD-Rec	**0.1438**	**0.1964**

The results obtained show the effectiveness of our approach, compared with other state-of-the-art models. Furthermore, the sentiment-based recommender model with fake reviews detection outperformed the model without fake reviews detection.

4.3 Overall Discussion of Our Results

The experiments carried out on our approach using the shopping yelp dataset demonstrated the impact of sentiment analysis and fake review detection on the effectiveness of the recommendation. We obtained an MAE equal to 0.1438, compared with an MAE equal to 0.1491 for the model without fake reviews detection.

Experiments carried out on the sentiment analysis model demonstrated the importance of combining DL models with the significant contribution of the attention mechanism in improving the sentiment predictions. The model with the attention mechanism yielded a MAE equal to 0. 1074, compared with a MAE equal to 0.1202 obtained with the model without the attention mechanism. Furthermore, it should be noted that the hyper-parameter values considerably affect the performance of the models.

5 CONCLUSION

In this article, we have presented a neural hybrid recommendation model that combines the Generalized Matrix Factorization (GMF) and the Multilayer Perceptron (MLP) models to learn respectively the linear and the nonlinear relationship between users and items. This model leverages a user-item rating matrix that has been adjusted by a sentiment model to predict the sentiment scores through users' textual comments on items. To further improve our sentiment model, we used the attention mechanism to capture the most important information, and we identified fake reviews using a confidence matrix. The results of our experiments carried out on the Yelp shopping dataset demonstrated the effectiveness of our model, which outperformed the state-of-the-art models. Our evaluations demonstrated the contribution of the hybrid sentiment model compared to the simple models, and the added value of the attention mechanism and the detection of fake reviews. On the other hand, our hybrid model performs better than several factorization matrix-based models.

In our future work we plan to carry out further experiments on larger datasets with higher density, use multilingual comments and explore other deep learning models such as the transformers.

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