Proceedings of the 2023 International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/8/20230283

False comment detection based on BERT and long short-term memory

Qingyang Chen

Beijing Information Science and Technology University, Beijing, 100101, China

2020011170@bistu.edu.cn

Abstract. In the beginning and ending of an article of the rapid development of e-commerce, almost all e-commerce websites support consumers to rate and comment on the workmanship, express delivery, and price of products. Publishing many messages and comments on the network platform has become a popular form of the Internet. Nowadays, online paid Internet platforms are also in the process of continuous evolution. The comments written are more and more authentic and highly misleading. It is a waste of time and easy to be confused to distinguish by the naked eye alone. This article manually annotates a valid dataset containing 4000 snack product reviews and proposes a false review detection model based on Bidirectional Encoder Representation from Transformers (BERT) and Long Short-Term Memory (LSTM). The experimental results show that the accuracy of the BERT and LSTM false comment detection model and BERT false comment detection model is above 50% and effective. The BERT and LSTM model is slightly better than the BERT model regarding loss rate and accuracy. The experiments were scientific and effective, and the data provided by the two experimental models are of the reference value.

Keywords: natural language process, text classification, deep learning, BERT, LSTM.

1. Introduction

With the rapid development and popularization of Internet information technology, e-commerce has been continuously expanded, as well as the promotion of e-commerce network platform applied by various enterprises and the importance of relevant policies and regulations on the development of e-commerce industry market, e-commerce has begun to gradually change people's daily life concept and gradually affect the consumption concept of Chinese people [1, 2]. According to statistics from the investigation report published by the China E-Commerce Research Centre in 2021, the volume of e-commerce transactions in China reached 42.3 trillion yuan, an increase of 19.6% compared to the previous year; Online retail sales reached 13.1 trillion yuan, up 14.1% year on year; Online retail sales of physical goods amounted to 10.8 trillion yuan, accounting for 24.5% of the total retail sales of social consumer goods; The volume of cross-border e-commerce imports and exports reached 1.92 trillion yuan, almost a 10-fold increase in five years; E-commerce related industries absorb and promote employment of more than 67 million people; China has maintained its position as the largest online retail market in the world for 9 consecutive years. Chinese e-commerce enterprises have obtained unprecedented development opportunities and challenges. The continuous acceleration of the pace of world economic globalization and the accelerated evolution and development of science and technology and information technology have led e-commerce enterprises into a new era of economic activity. At the same time, the competition in e-commerce industry has become increasingly fierce. For example, the benign competition between enterprises has changed significantly, the increase and elimination of e-commerce websites have accelerated, and the customer turnover rate is high.

The biggest advantage of e-commerce is that it is easy to obtain large-scale customer behavior data, and this data information is growing tens of millions of times every day. If the data of users' browsing behavior and purchasing behavior on the website are integrated and processed, massive and complex customer shopping behavior information can be collected. If these customer behavior information data can be effectively used, e-commerce enterprises can carry out corresponding marketing adjustment strategies and constantly obtain new customer resources. In short, taking customer behavior analysis seriously will enable e-commerce enterprises to grasp the important means of leading other competitors, and also means that enterprises will win more market share. Fully screening effective information and finding the pain points of commodities have become essential to obtaining new customer resources. Since the advent of Alibaba Taobao, e-commerce has been a concept that has been introduced previously. Because of the rapid growth of e-commerce in China over the last ten years, many large and medium-sized enterprises have already laid out e-commerce sales models and carried out many e-commerce activities. However, behind its development, there are also various problems, such as the existing judicial system is not perfect for the e-commerce model; The vicious competition of e-commerce products leading to the expulsion of good coins by bad ones; Early e-commerce giants monopolizing the market, etc.

The prevalence of false comments is also one of the problems. The study of automatic detection models for false comments can help users quickly screen out effective information and help users understand the true positive feedback rate of products. It can assist buyers and effectively resist the generation of false comments.

Bidirectional Encoder Representation from Transformers (BERT) has gained great attention. And then, many training models such as "BERT" have emerged, including the generalized autoregressive model Generalized Autoregressive Pretraining for Language Understanding (XLNet), which introduces two-way beginning and ending of an article information in BERT, A Robustly Optimized BERT Pretraining Approach (RoBERTa), and SpanBERT, which improve BERT training methods and objectives, and Multi-Task Deep Neural Networks (MT-DNN), which combines multi-task and knowledge distillation to strengthen BERT [3-6]. In recent years, the Long Short-Term Memory (LSTM) and BERT models have achieved remarkable results in natural language processing.

As with Recurrent Neural Networks (RNN), LSTM can better manage time series tasks than Convolutional Neural Networks (CNN); At the same time, LSTM resolves the problem of long-term dependence of the RNN and alleviates the problem of "gradient disappearance" caused by the RNN's rear drive during training [7].

The BERT model has also brought new insights into the Natural Language Processing (NLP) field. Multiple attention mechanisms and bidirectional coding can greatly improve the efficiency of BERT's unsupervised training, helping BERT build many extensive depth models. Moreover, if conditions permit the provision of suitable pre training models for BERT, using some simple logical regression can also yield satisfactory models. The unsupervised (self-supervised) pre training method of BERT provides a good solution for solving continuous and massive data processing problems in the field of NLP.

This paper has labeled 4000 comments from Taobao and Tmall, with 2000 life and 2000 false comments each. Based on BERT and LSTM, a false comment analysis model is established. In the experiment, the BERT false comment analysis model will be used as a control group, and the BERT and LSTM false comment analysis model will be used to analyze ten datasets each. The experimental results of the two models will be compared, and the advantages of BERT and LSTM compared to the BERT model will be judged based on the results.

2. Method

This paper uses the BERT and LSTM methods to construct an experimental model. The following introduces the principles of BERT and LSTM, respectively.

2.1. Long short-term memory

LSTM is an abbreviation for short - and long-term memory. The LSTM can determine the state of transmission with the aid of the state of gating. LSTM can actively leave important and long-term valid information in the model and forget unnecessary information. LSTM training models with many long-term and high-frequency information are very effective. However, compared to RNN, due to the introduction of a lot of content and the addition of many parameters, it is much more difficult for LSTM to train a large amount of data.

2.2. Bidirectional encoder representations from transformer

The complete name of the BERT model is Bidirectional Encoder Representations from Transformer. The original intention of BERT is to train a model using an unmarked, huge amount of text to attain a semantic space of words that contains rich semantic text information. Under certain conditions, BERT will fine-tune the semantic representation of the text input to Natural Language Process (NLP) tasks, and then apply the resulting output to the tasks that need to be completed. The main modules of BERT include Multi head Self Attention and Transformer Encoder [8-10].

Attention mechanism. The basic function of the attention mechanism is to allow neuronal networks to concentrate their analysis on the part of the input, concentrate on the distinction between the different output outcomes that are affected by the different parts of the input. Consequently, if user wish to improve the semantic representation, the effect of the various words in the beginning and ending of an article on the results cannot be ignored. In summary, the scenario for using the attention mechanism is to improve the semantic representation of the target words by using textual information from top to bottom.

In the example of highlighting the semantic representation of the text depicted above, the keywords and the beginning and ending of an article have themselves initial status. The Attention treats the keywords as a search target, sets keywords in the beginning and ending of an article of the keywords as aim, and queries the similarity from each keyword as a weight.

The result of each semantic text in the beginning and ending of an article is submitted to the initial state of the keyword. The attention mechanism takes as an entry the vector semantic representation of keywords and each word at the beginning and end of an article. Vectorial representation of the query of the search target, the key vector representation of the text at the beginning and end of an article, and the initial value of the keywords and each word at the beginning and end of an article can be changed in a linear way to achieve the desired results. The weight is obtained by calculating the similarity between the Query vector and each Key vector. After weighting and merging the text value vectors of keywords and every start and end of an article, it is used as the output result of Attention.

Self-Attention. The template must improve the semantic vector representation of each word to assist with text entry. Therefore, self-attention regards each word as a keyword, weighting the semantic information of the text, and may interrogate the improved semantic vector of every texts. According to the attachment mechanism described above, if you want the vector representation results of Query, Key, and Value to be accurate enough, the information of the input text must also be accurate. Consequently, the attention mechanism is also known as attention to oneself.

Multi-head Self-Attention. If there is a need to strengthen the diversity of focus, it is necessary to introduce different self-attention modules to achieve improved semantic text vectors under different conditions. After linearly combining multiple enhancement semantic vectors of a text, a final refinement semantic vector of the same length as the started word vector can be obtained. The purpose of mindfulness is to improve the semantic representation of keywords and non-mots. In different environments, attention should be focused on different keywords. Therefore, Multi-head Self-Attention

DOI: 10.54254/2755-2721/8/20230283

can be understood as a non-conventional fusion method that considers the semantic vectors of keywords and other words in words under various semantic scenarios.

Transformer Encoder. The transformer encoder is made from multi-head self-attention. Transformer Encoder adds three operations based on multi header self-attention. Remaining connections: Module inputs and outputs are immediately added as final outputs. The main idea behind this operation is that it is much easier to change the input value than to reconstruction the global output. This can greatly reduce the difficulty of network training. Layer normalization: normalize the 0 mean and 1 variance of a layer of neural network nodes. Linear Transformation: Perform two additional linear transformations on each word's enhanced semantic vector to improve the entire model's ability to express. Here, the modified vector keeps the same length as the original vector.

3. Data collection

The data set used in this experiment contains 4000 snack reviews. Comments were all from Taobao and Tmall Supermarket. Among them, 2000 comments were from real people, and Paid Internet trolls wrote the other 2000. Mark the real person's comments in the data as "1", and the paid Internet trolls swipe the screen to mark them as "0". By removing duplicates, duplicate comments in the data set are removed. The author also deleted the Yan characters and emoji in the comments to alleviate the burden of later model training.

When selecting data, the author found that the same account often posts lengthy comments on a product multiple times, and this account is usually a paid Internet troll; In long reviews, those with multiple emoji or yam characters are usually paid Internet trolls reviews; When describing the advantages of food, comments that avoid discussing the taste are usually water reviews; Comments on any product with more images (three or more) are usually navy comments; Comments that refer to the name of the store multiple times are usually paid Internet trolls reviews; The negative comment rate is probably not paid Internet trolls.

4. Experimental results and analysis

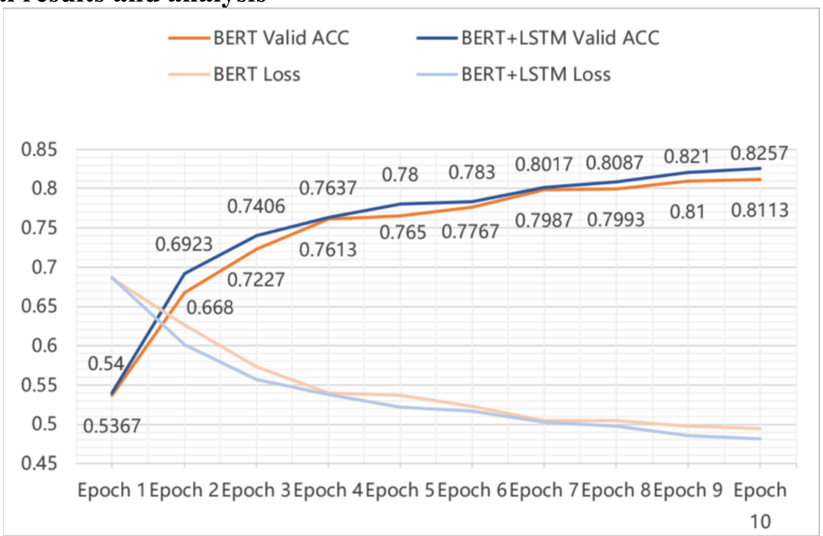

Figure 1. Line chart of experimental results.

Table 1. Data sheet of experimental results.

Project	BERT		BERT + LSTM	
	Valid ACC	**Loss**	**Valid ACC**	**Loss**
Epoch 1	0.5367	0.6862	0.5400	0.6868
Epoch 2	0.6680	0.6259	0.6923	0.6008
Epoch 3	0.7227	0.5730	0.7406	0.5569

DOI: 10.54254/2755-2721/8/20230283

Table 1. (continued).

Epoch 4	0.7613	0.5400	0.7637	0.5383
Epoch 5	0.7650	0.5372	0.7800	0.5222
Epoch 6	0.7767	0.5231	0.7830	0.5165
Epoch 7	0.7987	0.5041	0.8017	0.5028
Epoch 8	0.7993	0.5049	0.8087	0.4971
Epoch 9	0.8100	0.4980	0.8210	0.4854
Epoch 10	0.8113	0.4940	0.8257	0.4816
Average Value	0.7627	0.5383	0.7739	0.5275

The average value is the average of eight data after removing the highest and lowest values from 10 experiments.

As shown in Table 1 and Figure 1, in experiments, the accuracy of both models is higher than 0.5, indicating that both models are effective. The experimental results show that the BERT + LSTM experimental model is superior to the BERT experimental model in accuracy, and the loss is also smaller than the BERT model. In ten experiments, the average accuracy and loss rate of BERT and LSTM were still superior to BERT's experimental model after removing their highest and lowest values. According to the optimal model of both, the loss rate is between 0.52 and 0.54.

The experimental verification results show that the BERT and LSTM model does not have significant advantages for the following four reasons. The first reason may be that the difference between true and false comment data is insignificant, making it difficult for machines to distinguish them in detail. Many keywords have appeared in real-person and navy reviews, and the model cannot accurately distinguish between them. The second reason may be that the accuracy of manually created datasets needs to be higher. Even if the dataset has been checked in the experiment, there are still errors in labeling, which can cause certain errors in the experimental results. The third reason may be that the dataset's data needs to be bigger. Need help to train a model that can perform accurate analysis. The LSTM model is good at processing large amounts of data, but the data set used in the experiment needs to be bigger to exert the full power of the model. The fourth reason may be that the parameters needed to be carefully adjusted, causing some errors in the experimental results. In summary, this experiment is challenging for machine learning.

5. Conclusion

With the rapid development and popularization of Internet information technology, e-commerce continues to expand. Still, behind its development, there are also many problems, such as the proliferation of false comments in product reviews on e-commerce platforms. In mixed reviews, it is easier for buyers to quickly obtain true, accurate, and effective information from the reviews. Therefore, this paper proposes establishing a BERT and LSTM false comment analysis model using BERT and LSTM methods. This paper manually annotates a valid dataset containing 4000 snack product reviews and proposes a false review detection model based on BERT and LSTM. Using the BERT false comment analysis model as a control group, the BERT and LSTM false comment analysis model and the BERT and LSTM false comment analysis model were analyzed ten times each, and the experimental results were compared. The experimental results showed that the accuracy of the BERT and LSTM false comment detection model and BERT false comment detection model was above 50%, and both models were effective. However, the BERT and LSTM model has a few advantages for the following four reasons. The first reason may be that the difference between true and false comment data is insignificant, making it difficult for machines to distinguish them in detail. Many keywords have appeared in real-person and navy reviews, and the model cannot accurately distinguish between them. The second reason may be that the accuracy of manually created datasets needs to be higher. Even if the dataset has been checked in the experiment, there are still errors in labeling, which can cause certain errors in the experimental results. The third reason may be that the dataset's data needs to be bigger. Need help to train a model that can perform accurate analysis. The fourth reason may be that the parameters were not

DOI: 10.54254/2755-2721/8/20230283

carefully adjusted, causing some errors in the experimental results. In summary, this experiment is challenging for deep learning.

References

[1] Kedah, Z. (2023). Use of E-Commerce in The World of Business. Startupreneur Bisnis Digital (SABDA Journal), 2(1), 51-60.

[2] Chong, H. X., Hashim, A. H., Osman, S., Lau, J. L., & Aw, E. C. X. (2023). The future of e-commerce? Understanding livestreaming commerce continuance usage. International Journal of Retail & Distribution Management, 51(1), 1-20.

[3] Choi, H., Kim, J., Joe, S., & Gwon, Y. (2021, January). Evaluation of bert and albert sentence embedding performance on downstream nlp tasks. In 2020 25th International conference on pattern recognition (ICPR) (pp. 5482-5487). IEEE.

[4] Yan, R., Jiang, X., & Dang, D. (2021). Named entity recognition by using XLNet-BiLSTM-CRF. Neural Processing Letters, 53(5), 3339-3356.

[5] Timmapathini, H., Nayak, A., Mandadi, S., Sangada, S., Kesri, V., Ponnalagu, K., & Venkoparao, V. G. (2021). Probing the SpanBERT Architecture to interpret Scientific Domain Adaptation Challenges for Coreference Resolution. In SDU@ AAAI.

[6] Chi, H. V. T., Anh, D. L., Thanh, N. L., & Dinh, D. (2021). English-Vietnamese Cross-Lingual Paraphrase Identification Using MT-DNN. Engineering, Technology & Applied Science Research, 11(5), 7598-7604.

[7] Karaman, Y., Akdeniz, F., Savaş, B. K., & Becerikli, Y. (2023, March). A Comparative Analysis of SVM, LSTM and CNN-RNN Models for the BBC News Classification. In Innovations in Smart Cities Applications Volume 6: The Proceedings of the 7th International Conference on Smart City Applications (pp. 473-483). Cham: Springer International Publishing.s

[8] Zhu, W., Wang, Z., Wang, X., Hu, R., Liu, H., Liu, C., ... & Li, D. (2023). A Dual Self-Attention mechanism for vehicle re-Identification. Pattern Recognition, 137, 109258.

[9] Rahali, A., & Akhloufi, M. A. (2023). End-to-End Transformer-Based Models in Textual-Based NLP. AI, 4(1), 54-110.

[10] Wang, Y., Cheng, X., & Meng, X. (2023). Sentiment Analysis with An Integrated Model of BERT and Bi-LSTM Based on Multi-Head Attention Mechanism. IAENG International Journal of Computer Science, 50(1).