Sentiment Analysis of Hotpot Reviews with LSTM Based on Keras Framework

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Abstract. Natural language processing as a domain of artificial intelligence has gotten a lot of interest in recent years, thanks to the fast growth of the Internet sector, and sentiment analysis has become one of the hottest study fields in natural language processing. Based on the study findings, this article analyzes sentiment analysis of Chongqing and Chengdu hotpot reviews using a Keras-based long and short-term memory neural network model, and offers ideas for merchants as well as a means for potential customers to rapidly comprehend merchant information. The model obtains a 79 percent accuracy on the test set, according to the results. Taste, service attitude, environmental hygiene, and pot base were judged to be deficient in both cities, notably in Chongqing, where tripe, duck intestine, and crispy pork were the key causes for unfavorable ratings; in Chengdu, portion size and hygiene were the main complaint areas.

Keywords: Natural language processing · Keras · long and short-term memory neural network · hotpot

1 Introduction

With the rapid development of the Internet industry, natural language processing as a subfield of artificial intelligence has received much attention in recent years, and sentiment analysis has become one of the hottest research areas in natural language processing (NLP) [1]. In recent years, users have created a large amount of valuable information while accessing information on the Internet [2]. And these subjective texts often have potential value and are important for consumers' choices and business organisations' decisions [3]. Scholars at home and abroad have applied different sentiment analysis methods to study the sentiment tendencies of text reviews in different fields. Zhang Brawn analysed online reviews of VW Dianping and Meituan Takeaway based on methods such as sentiment dictionary [4]. Ahmad et al. used SVM to analyse self-driving car and Apple product review datasets respectively [5]. Wang Shengying analysed reviews of Meituan takeaway Pizza Hut and other shops in different cities based on Baidu AI (combining sentiment dictionary and machine learning) and re-studied the results to provide suggestions to users and merchants [3]. In order to make building neural networks more modular and easier to debug and extend, Longwen Liu et al. built: a Keras-bert

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model and an RNN (LSTM) network based on the Keras framework, respectively, to achieve sentiment analysis of user review information on Taobao [6, 7].

Nowadays, there is relatively little research on text sentiment analysis in food and beverage, resulting in a lack of analysis of different types of single cuisines on Meituan; most of it is still research on the effect of sentiment analysis models or text mining techniques. Therefore, this paper proposes an LSTM model based on the Keras framework to classify the sentiment of Chengdu and Chongqing hotpot review sets and compare the results in an in-depth study to provide suggestions for merchants; and to improve the efficiency of consumers' understanding of merchants.

2 Material and Methods

2.1 Data Collection and Pre-processing for Comments

2.1.1 Data Design and Acquisition

The Octopus collector was used to collect all of the Meituan.com review training datasets in this study, with shop detail information (shop name, link address, rating, and total number of reviews) collected first, followed by stratified sampling by Meituan.com shop rating: five shops each with 3.5–4, 4–4.5, and 4.5–5 scores. After de duplication, reviews were collected from fifteen hotpot shops in Chongqing and Chengdu, for a total of 30 stores. Each shop averaged 350 articles, for a total of 11,556 pieces of reviews. I structured each layer of the research to have one hotpot shop of the same brand scattered in a different region for the following stage [8, 9].

2.1.2 Data Pre-processing

Using the Pytorch-based Bert model [10] for sentiment propensity annotation, it was expected that the annotation of a total of 11,556 comment data would take about 40–60 min. In this study, the maximum vector dimension of words is 250, and if the input sequence is insufficient for 250, it is filled with zeros using Keras' pad sequences function. The training set's preparation is then complete based on this. A remark is translated into a series of numerous integer values that are used as a tensor for the next input model training phase since each word in the training corpus text corresponds to a unique index.

2.2 LSTM Model Construction Based on Keras Framework

2.2.1 Keras Framework

Keras is a Python-based high-level neural network application programming interface for defining and training practically any form of deep learning model [11]. Keras is the key to good research [12], with its development focus on efficiently translating users' ideas into experimental results. It has four characteristics that make it popular [13].

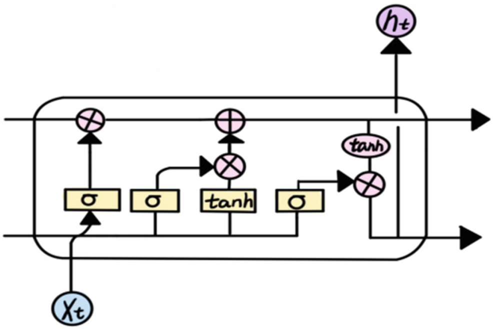

Fig. 1: Cell structure of the LSTM

2.2.2 Creating a Long-Term and Short-Term Memory Neural Network Model

Hochreiter & Schmidhuber suggested the long short-term memory (LSTM) as a particular form of RNN in 1997 to overcome the gradient disappearance and gradient explosion difficulties during long sequence training [14]. To put it another way, LSTMs outperform standard RNNs on longer sequences since they are gated to regulate the discarding or addition of information to accomplish forgetting or memory [15]. This gating mechanism lets it to choose whether to replace, update, or forget the information held in each neuron with a unit state, preserving long-term interdependence.

The unit state (long-term memory) lies at the heart of the LSTM's algorithmic framework [16]. The forgetting gate, the input gate, and the output gate are the three gates of the neuron that update the unit state. Through the calculation of the hidden state h^t (short-term memory) and the h^{t-1} transmitted down from the previous state with the current input x^t REF_Ref106219101\r\h [17], the LSTM regulates selective memory. The LSTM's unit structure is seen in Fig. 1.

The Keras-based Sequential model [18] was created in two parts: (1) feature extraction and vectorisation from comment sentences, and (2) classification model using LSTM. In the data pre-processing section, the feature extraction and vectorization procedure was finished. The dimensionality diagram of each layer is depicted in Fig. 2 in the LSTM classification model in this work. The first of these layers is the embedding layer [19], which is used to transform the word embeddings generated by the previous text preprocessing step into a sequence vector matrix; the second layer is composed of 100 LSTM units to extract and learn features from the input text; the third layer is the dropout layer to prevent overfitting during training; and the last layer is the fully connected layer Dense to map the feature representation to the sample token space to achieve the function of triple classification.

Table 1 shows the parameters of the LSTM model used in this paper: Select the Adam optimiser and use the loss function:categorical crossentropy.

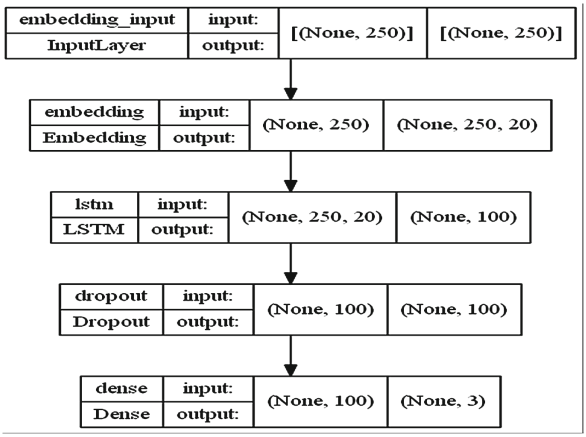

Fig. 2: Neural network layer diagram

Table 1: LSTM model parameter settings

Insert Embedding	n_units	batch_size	epochs	output_dim	Dropout
250	100	32	9	20	0.5

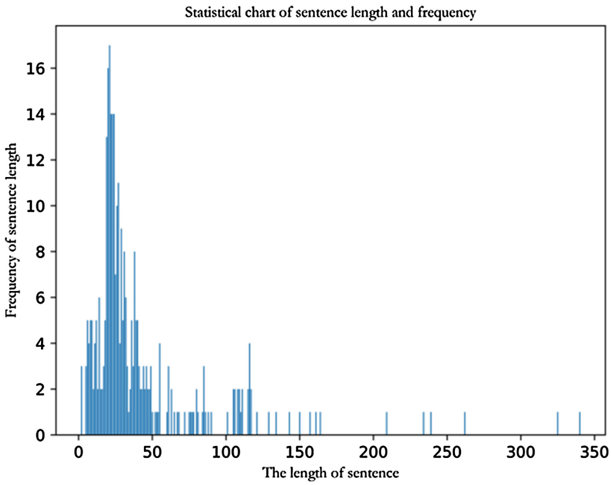

Fig. 3: Sentence length and frequency of occurrence

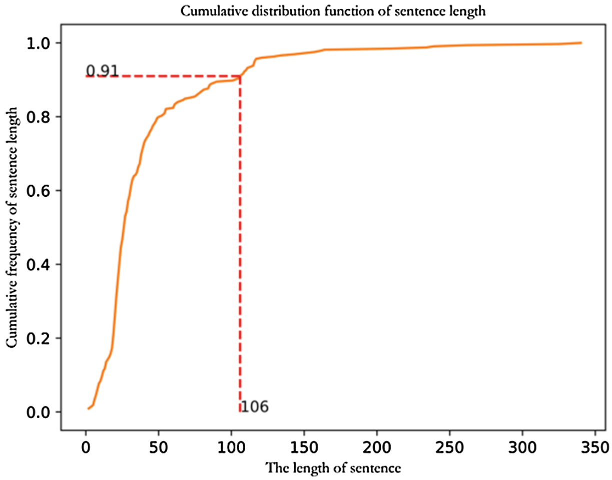

Fig. 4: Cumulative distribution function of sentence length

3 Results and Discussion

3.1 Sentence Length Frequency Statistics, Cumulative Distribution Chart

The whole comment data set's sentence lengths are primarily in the range of 40–50 characters, with no more than 1500 comments in the range of 100–150 characters and no more than 500 comments in the range of more than 150 characters, as shown in Fig. 3.

Figure 4: The quantile is drawn at the 105th character with a probability value of 0.91 in the CDF probability distribution. This picture shows that 91 percent of the remarks in the sentence have a likelihood of being less than 105, 9% have a probability of being greater than 105, and 1% have a probability of being greater than 250. According to this probability distribution, practically all of the samples are distributed in the interval up to sentence length 105, and the analysis makes it easier to choose input shape to unify the input sequence size.

3.2 Comparison of Emotional Tendencies in Chengdu and Chongqing

As shown in Fig. 5, there were 5744 Chongqing hot pot reviews analyzed, with 2902 good ratings, 704 negative reviews, and 2138 neutral opinions. There were 5807 Chengdu hot pot reviews processed, including 2921 good ratings, 732 bad reviews, and 2154 neutral opinions.

3.3 Comparison of Negative Reasons Between Chongqing and Chengdu

3.3.1 Comparison of Reviews of Shops of the Same Brand in Different Areas of the Same City

Because shops with a rating of 4–4.5 are more common in Chengdu and Chongqing, this study compares and analyzes the negative word cloud map of the same brand of hotpot category by selecting shops with a rating of 4–4.5 in both cities.

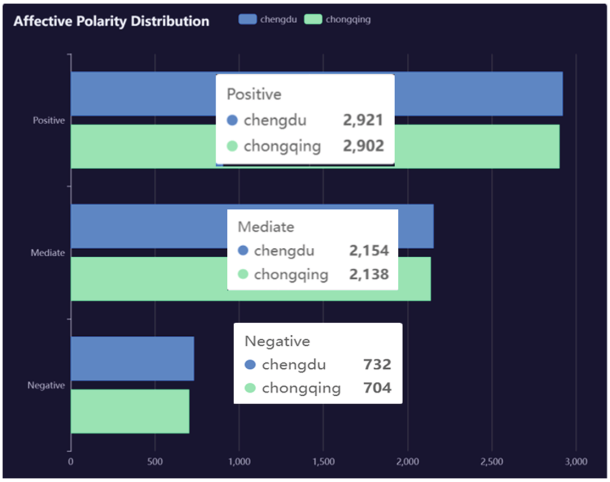

Fig. 5: Distribution of emotional dispositions

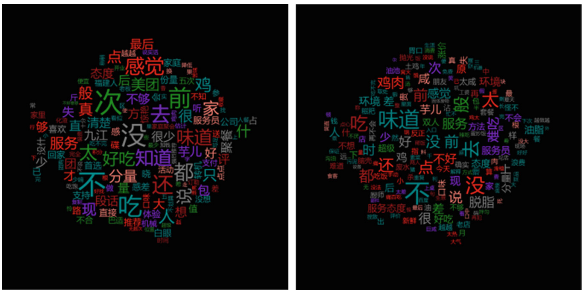

Fig. 6. Chengdu Yuerji poorly reviewed word cloud. Yingchunqiao Branch(left), Xiangyang Street Main Branch(right).

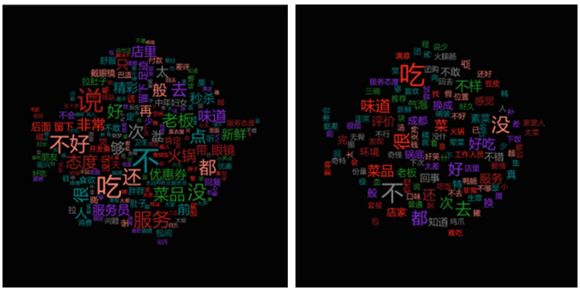

Fig. 7. Chongqing Huoyanyan Old Hot Pot poorly rated word cloud. Crystal Li City Branch(left), Tongliang Branch(right)

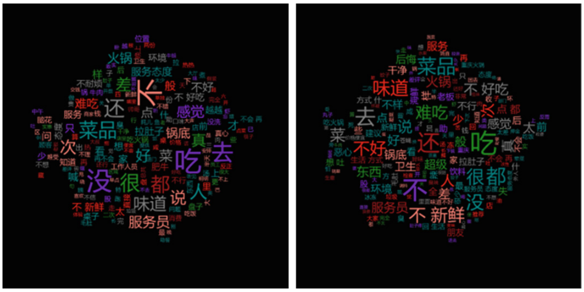

Fig. 8. Chengdu Chuanjiangdabazi Hot Pot Buffet Shuang Hua Qiao Main Store(left), Chongqing Jiangcheng Seafood Hotpot Buffet(right) Negative word cloud.

The keywords “portion size,” “service,” and “taste” are more prominent, as shown in Fig. 6. Customers have usually given the Yingchunqiao restaurant (left) bad evaluations due to the taste of the hotpot items, the portion size, and the service attitude, as seen by these keywords. The main Xiangyang Street restaurant (right) has the same prominent typeface as the Yingchunqiao restaurant, and the term “environment” is prominent as well. Customers of the Xiangyang Street restaurant frequently submit negative evaluations owing to the restaurant’s dining environment, as evidenced by this.

The concerns of “coupons,” “dish taste,” “service,” and “not fresh” are the primary reasons why users of the crystal Licheng store (left) leave negative remarks, as shown in Fig. 7. The usage of coupons without invoicing and the consumption of meals without taking advantage of concessions have gotten a lot of attention. Consumers of Tongliang shop (right) also mentioned concerns with duck sausage, chicken feet, ham sausage, and soup, in addition to the conspicuous typeface like crystal Licheng store (left).

The stratified sample and analysis method described above can be utilised in the hotel and home accommodation industries, where businesses can use the results to make targeted modifications to improve the service industry’s overall brand image.

3.3.2 Analysis of the Reasons for Shops with a Negative Emotional Disposition

As shown in Fig. 8, the main reasons for negative sentiment in the Chengdu restaurant (left) are “dishes,” “waiters,” and “bottom of the pot,” while some users give low ratings to “service attitude” and “taste,” and the words that stand out in the Chongqing restaurant (right) are “dishes,” “taste,” “difficult to eat,” and “fresh,” with secondary reasons being “hygiene,” “bottom of the pot,” and “seafood”.

The restaurant business holds a significant market share, and the introduction of more and more online stores is reducing the income of some of the more conventional stores. The so-called keeping up with the times, which entails locating and listening to the disgruntled voices of today’s consumers, and then developing answers to specific problems. Negative sentiment accounts for 1/3 of the overall sentiment value at two shops in Chengdu (Fig. 8 (left)) and Chongqing (Fig. 8 (right)). (i.e. the shop has a negative sentiment bias).

In short, the majority of the reasons for poor hot pot reviews in Chongqing and Chengdu point to “quality of food” and “service attitude,” but due to differences in the two cities, Chengdu users are more concerned with environmental hygiene, while Chongqing users are more concerned with group purchase vouchers.

Because of the differences in flavors, ingredients, eating methods, practices, and the subdivision of different kinds of emotions created in each location, different cities have the same subjective emotions for the same type of food. Similarly, different franchises under the same brand will still differ in the emotions expressed by consumers, not only in the catering industry, but also in the hospitality industry, e-commerce sector, even if the signage is the same, but their consumer user expressed emotional tendencies are also affected by many factors, such as geographical, epidemic, or even environmental, weather, and so on, even if the signage is the same.

As a result, text sentiment analysis must be used to precisely detect the linkages and differences between them, as well as to devise ways to improve user happiness and hence raise income for the state.

3.4 Emotional Classification

In this work, the training model predicts the sentiment of a total of 4000 review texts from Chengdu and Chongqing by inputting statements, and then classifies the positive and poor reviews with an accuracy of up to 79 percent on the test set. In the future, this service might be evolved into a prediction and classification system, with merchants simply uploading a CSV file with review text to receive a file with sentiment annotations and classifying good and negative reviews based on this.

4 Conclusion

In this study, we employ an LSTM model built on the Keras framework to identify text sentiment for reviews of two types of hotpot in Chengdu and Chongqing, and our trained model achieves a test set accuracy of up to 79 percent. Both parallels and differences emerged from a comparison of the whole investigation of the causes of negative sentiment in the two locations. The quality and quantity of the food, as well as the service attitude, are comparable; the distinctions are that Chengdu customers are more concerned with environmental hygiene, while Chongqing users are more concerned with group buy coupons.

The findings of this study will not only provide advice to merchants on how to improve user satisfaction and the overall brand image of the shop, but will also help potential customers quickly understand the shop's characteristics after an in-depth study of the results of a stratified sampling of shops with a rating of 4–4.5 and shops with a negative sentiment rating of 3.5.

(1) In light of the preceding results, the following suggestions can be made.
(2) Ensure that the contents in the meals are fresh, and that the quality and the size of the ingredients are accurately controlled.
(3) The restaurant's surroundings should be monitored on a regular basis, especially during epidemics, when restaurant decontamination is more necessary.

(4) Businesses may use market research to enhance the Hot pot bottom to solve the issue of pot bases.
(5) Improve waiter training and create a system of incentives and penalties for waiters.
(6) Make it easier for consumers to use online coupons by improving the regulations.

References

1. Liu, R., Shi, Y., Ji, C., et al. (2019). A survey of sentiment analysis based on transfer learning. IEEE Access, 7, 85401-85412.
2. Wei Wei, Xiang Yang & Chen Qian. (2011). A review of Chinese text sentiment analysis. Computer Applications (12), 3321-3323.
3. Wang Shengying. (2018). Research on sentiment analysis based on online reviews of Meituan takeaway users. Modern Trade Industry (23), 67-69. doi:https://doi.org/10.19311/j.cnki.1672-3198.2018.23.030.
4. Zhang Brawn. (2016). Analysis of emotional disposition based on restaurant reviews. Master's thesis, Kunming University of Technology, 2: 73.
5. Ahmad, M., Aftab, S., & Ali, I. (2017). Sentiment analysis of tweets using svm. Int. J. Comput. Appl, 177(5), 25-29.
6. Liu, Longwen, Dan, Zhiping & Namgyel Aung Mao. (2022). Text sentiment analysis based on Keras framework. Changjiang Information Communication (02), 81-83.
7. Shiyaojia, Wu, Fei, Zhu, Hai, et al. (2020). Convective layer delay prediction by LSTM model based on Keras platform. Global Positioning System (06), 115-122. https://doi.org/10.13442/j.gnss.1008-9268.2020.06.017.
8. Tao Meng Jun. (2020) Merchant information in Meituan.com and review collection tutorial. https://www.bilibili.com/video/BV1Af4y1m78K?spm_id_from=333.337.search-card.all.click
9. Ba Zhua Yu. (2017) Meituan merchant review data collection method. https://www.bazhuayu.com/tutorial/meituansjpl
10. Devlin, J., Chang, M. W., Lee, K., et al. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.
11. Shiyaojia, Wu, Fei, Zhu, Hai & Han, Xuefa. (2020). Convective layer delay prediction by LSTM model based on Keras platform. Global Positioning System (06), 115–122. https://doi.org/10.13442/j.gnss.1008-9268.2020.06.017
12. Huan, J., Li, H., Li, M., et al. (2020). Prediction of dissolved oxygen in aquaculture based on gradient boosting decision tree and long short-term memory network: A study of Chang Zhou fishery demonstration base, China. Computers and Electronics in Agriculture, 175, 105530.
13. XiaoJinZi De XiaTian. (2019)Introduction to Keras. https://blog.csdn.net/WangYouJin321/article/details/97414439?spm=1001.2101.3001.6650.4
14. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-1780.
15. ChongShiJiuShiGuang. (2020) LSTM neural network. https://blog.csdn.net/qq_38376616/article/details/107674344?spm=1001.2101.3001.6650.1
16. Fu, L.F. & Zhao, F.F.. (2021). Prediction and analysis of agricultural public opinion based on attention mechanism LSTM model. Mathematical Practice and Understanding (17), 64-76.
17. lijfrank. (2019) What is GRU and what are RNN and LSTM respectively? https://blog.csdn.net/Frank_LJiang/article/details/103142557
18. newnahnaiq.(2020)Two ways of building models for Keras. https://zhuanlan.zhihu.com/p/150697902
19. YJango. (2018) What is word embedding? https://zhuanlan.zhihu.com/p/27830489