

Decoding Weibo Sentiments: Unveiling Nuanced Emotions with Bidirectional LSTM Analysis

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Abstract: This study highlights the critical role that deep learning plays in deciphering the complex emotional subtleties prevalent in social media interactions via sentiment analysis of Weibo comments. The primary goal is to deploy a bidirectional Long Short-Term Memory (LSTM) model that is intended to thoroughly analyze and understand user attitudes, providing priceless information for improving marketing tactics and gauging public opinion. Utilizing character-level segmentation and Tencent Artificial Intelligence (AI) Lab's pre-trained word embeddings, the study advances sentiment analysis by enhancing sensitivity to contextual subtleties within textual data. The study, which used a dataset of Weibo comments with sentiment annotations, demonstrates the remarkable 96% accuracy with which the bidirectional LSTM model can categorize sentiments. This result demonstrates how well the model captures complex emotional expressions, outperforming both other deep learning methods and conventional machine learning techniques in sentiment analysis tasks. The novel elements of the model's architecture, such character-level analysis and the intelligent use of pre-trained embeddings, improve its classification accuracy and contextual comprehension. These aspects represent significant advancements in sentiment analysis, with broad implications for both academic research and practical applications in understanding social media discourse.

1 INTRODUCTION

The Weibo comment is the text content that users reply and discuss the content on the Weibo platform, covering rich emotions, attitudes, and views. The significance of analyzing Weibo comments is that being able to understand the emotional relationships, attitudes, and views of users in social media. This is of great significance for enterprises to formulate accurate marketing strategies for public opinion (Chen, 2022; Yuan, 2019), government understanding of the people's conditions, and academic research on social public opinion. Therefore, this paper aims to use deep learning technology, especially the text classification model based on technologies based on long-term memory (LSTM) to help reveal the motivation and factors behind user behavior, and provide strong support for decision-making in related fields (Li, 2019; Halawani, 2023). Scholars in the discipline of analysis of sentiment have put forth a number of approaches to handle text data and propel technological progress.

Deep learning-based techniques have advanced substantially in the past few years in sentiment analysis tasks. Among them, for text classification tasks, recurrent neural network, or Recurrent Neural Network (RNN), models like LSTM, or long-short-term memory, are used extensively, particularly in sentiment analysis (Khan, 2022; Wu, 2023). Through these models, researchers are able to effectively capture the semantic and contextual information in written content, strengthening sentiment analysis's precision and effectiveness (Yang, 2022). Furthermore, sentiment analysis tasks have also been handled by convolutional neural networks (CNNs). Convolutional and pooling processes are used by CNN models to extract features from text, which are subsequently used for sentiment categorization. Compared to traditional methods based on bag-of-words models, CNNs can more effectively convey local information through text, improving the functionality of sentiment analysis (Kaur, 2023). Moreover, sentiment analysis heavily relies on traditional machine learning methods like Naive

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Bayes and Support Vector Machines (SVM). These methods typically rely on manually designed features and statistical models for text classification. Although these methods can achieve the goal of sentiment analysis to some extent, they often perform poorly in handling complex text data and struggle to capture deep semantic information in text. In conclusion, Deep learning-based techniques are gradually gaining popularity in the past decade and become mainstream in the field of sentiment analysis, especially LSTM and CNN models have achieved significant results in sentiment classification tasks. These methods can better understand the semantic and contextual information of text data, therefore raising sentiment analysis's precision and effectiveness (Alsini, 2023; Contreras, 2023).

The project's objective is to use LSTMs to develop a sentiment analysis model for Weibo comments. By breaking down remarks into individual characters, it preprocesses the material and improves comprehension of linguistic subtleties. Leveraging pre-trained word embeddings from Tencent Artificial Intelligence (AI) Lab enriches the model's comprehension of context and sentiment. A bidirectional LSTM architecture is employed to capture both past and future context, improving sentiment classification accuracy. The predictive performance of the model is contrasted with different deep learning architectures and conventional machine learning techniques. The experiment demonstrates the LSTM model's effectiveness in analyzing Weibo comments' sentiment, underscoring its robust support for social sentiment analysis and decision-making.

2 METHODOLOGIES

2.1 Dataset Description and Preprocessing

The study utilizes a dataset comprising Weibo comments, aiming to analyze sentiment through an LSTM-based model. The dataset consists of text comments which have been annotated for sentiment, with the intention of facilitating a comprehensive understanding of public sentiment on various topics discussed on Weibo (ChineseNlpCorpus, 2018). The dataset is a collection of Weibo comments, each associated with a sentiment label indicating the comment's overall sentiment (positive or negative). These comments have been meticulously collected to ensure a diverse representation of topics, linguistic styles, and sentiments, providing a robust foundation for analyzing sentiment nuances in social media text.

The preprocessing of the dataset is a critical step to prepare the raw text data for the LSTM model. The paper preprocessing pipeline involves several key stages: Character Segmentation: Given the nature of the Chinese language, which does not use spaces to separate words, this paper adopts a character-level segmentation approach. This method involves breaking down each comment into individual characters, thereby capturing the linguistic features more effectively. Vocabulary Construction: A vocabulary index is created from the segmented dataset, with a maximum size set to 10,000 unique tokens. Special tokens such as <UNK> for unknown characters and <PAD> for padding are included to handle out-of-vocabulary words and maintain uniform comment lengths, respectively. Sequence Padding and Truncation: To ensure uniform input sizes for the LSTM model, comments are either padded or truncated to a fixed length of 50 characters, as defined by the `pad_size` parameter. This step ensures that each input tensor to the model maintains a consistent shape. Tokenization and Indexing: Each character in a comment is replaced with its corresponding index from the vocabulary, converting the textual data into a numerical format that can be processed by the model. Characters not found in the vocabulary are replaced with the index for <UNK>. Training, validation, and test sets are separated from the pre-processed dataset with a distribution of sixty percent, twenty percent, and twenty percent, accordingly. By splitting the data this way, the model can be trained on an important part of the data, refined and confirmed on another portion, and then tested for generalization on unseen data.

2.2 Proposed Approach

This study explores the sentiment orientation in Weibo comments by leveraging a model based on LSTM networks. LSTM, recognized for its capacity to effectively process sequential data and model long-term dependencies, emerges as an optimal tool for addressing Natural Language Processing (NLP) tasks, especially emotion analysis. The methodology unfolds in several pivotal phases: data preprocessing, involving character-level segmentation and sequence normalization; model construction, which incorporates pre-trained word embeddings to bolster the understanding of textual sentiment; and a series of training, fine-tuning, and evaluation steps, employing diverse performance metrics such as F1 scores and accuracy to ascertain the efficacy of the model. Aimed at conducting a thorough analysis of sentiment orientations in Weibo comments, the research



Figure 1: The pipeline of this study (Photo/Picture credit: Original).

employs deep learning technologies to delve into public emotions. The approach not only seeks to improve the precision of sentiment analysis but also to introduce new angles and methods for examining sentiment on social media platforms. The process is shown in the Figure 1.

2.2.1 LSTM

The core of the proposed approach is an LSTM-based model for sentiment analysis. LSTM networks, a special kind of RNN, are made to teach sequence prediction problems about order dependence. Unlike traditional feedforward neural networks, LSTM can handle complete data sequences in addition to individual data points since it contains feedback connections. This feature is notably helpful for applications involving natural language processing, because sentiment interpretation depends heavily on word order and context. The sentiment analysis model based on the LSTM forms the basis of the suggested methodology. An advanced kind of RNN called LSTM networks is developed specifically to identify order dependency in sequence prediction issues. Because LSTM incorporates feedback connections, it can handle complete data sequences in addition to individual data points, unlike traditional feedforward neural networks. This characteristic is especially beneficial for natural language processing tasks where context and order of words play a crucial role in understanding sentiment. The LSTM model's defining feature is its ability to remember and utilize past information through its internal state, commonly referred to as the cell state, to make informed predictions. This is particularly important in sentiment analysis where the sentiment conveyed by a sentence can be heavily dependent on the context provided by preceding words or phrases. The use of LSTM in sentiment analysis of Weibo comments allows for a more nuanced understanding of user sentiment, which can be leveraged for market analysis, public opinion monitoring, or even for sociological research. In this experiment, the implementation process begins with data preprocessing, involving character-level segmentation, vocabulary construction, sequence padding and truncation, and tokenization and indexing. The LSTM model is then initialized with

pre-trained embeddings and configured with hyperparameters such as hidden layer size quantity of layers and rate of learning. Cross-entropy loss and the Adam optimizer are used to train the pre-processed data, and performance is measured using metrics like accuracy, precision, recall, and F1 scores. There are three main parts to the suggested model architecture: the Embedding Layer, which uses word embeddings that have already been trained to convert vocabulary indices into vector representations; the LSTM Layer, which uses bidirectional LSTM units to gather information from both previous and subsequent contexts, making it easier to learn long-term dependencies from sequential data and the Fully Connected Layer, which translates abstract features learned by the LSTM into predictive outputs for sentiment classification, typically through the modelling of sentiment scores and conversion into a probability distribution using the SoftMax function.

2.2.2 Model Configuration

A model architecture is crafted with a careful balance between complexity and computational efficiency, selecting 128 units for the size of the hidden layers. A dual-layer LSTM structure is used to improve sentiment context recognition and to further comprehend text sequences. Furthermore, as part of a regularization strategy to mitigate model overfitting, a dropout rate of 0.5 is set, randomly ignoring a fraction of the network's nodes during training. Additionally, the batch size is determined to be 128, based on a trade-off consideration between memory demands and gradient estimation stability during the model training process.

2.2.3 Loss Function

The Adam optimizer is the optimization function used in this model. Adam, which stands for Adaptive Moment Estimation, is based on the idea of combining the advantages of Momentum and RMSProp, two additional optimization techniques. Adam records each weight in the neural network's first moment vector (m) and second moment vector (v). The first moment (the mean) and the second moment (the uncentered variance) of the gradients are estimated by the parameters m and v , respectively.

The squared gradient and the gradient's exponential moving average are calculated mathematically. The parameters updating guidelines with Adam are as follows:

$$m_t = \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t \quad (1)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) \cdot g_t^2 \quad (2)$$

$$\hat{m}_t = m_t \cdot (1 - \beta_1^t) \quad (3)$$

$$\hat{v}_t = v_t \cdot (1 - \beta_2^t) \quad (4)$$

$$\theta_{t+1} = \theta_t - \eta \cdot (\frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}) \cdot m_t \quad (5)$$

The gradient and the decay rates for the moment estimates, which are typically set to 0.9 and 0.999, respectively, indicate the parameters of the model at time step t . The rate of learning is denoted by η , and the tiny scalar, ϵ , is used to avoid dividing by zero, usually around 10^{-8} .

The advantage of Adam is its adaptive learning rate capability, which allows for individual learning rates for each parameter. This adaptive mechanism often leads to faster convergence and has proven to be effective in various contexts, particularly in complex tasks such as sentiment analysis with large datasets and models with a significant number of parameters.

2.3 Implementation Details

The LSTM-based sentiment analysis model was implemented in the research using Python 3.9 and the integrated programming environment PyCharm 2023.3.3. For development, a Microsoft Windows 11 Home Edition system with an RTX 3070 graphics card and a 12th generation Intel(R) Core (TM) i7-12700H processor operating at the frequencies of 2.30 megahertz frequencies was employed. Data augmentation techniques were applied to enrich the dataset and mitigate overfitting issues, ensuring a robust model training process.

3 RESULTS AND DISCUSSION

In the conducted study, the analysis succinctly evaluates the model's performance through three crucial visual representations: an ascending training accuracy curve indicating swift initial learning, a descending loss graph signifying effective optimization, and a confusion matrix that highlights competent classification with an imbalance in false negatives, suggesting potential areas for refinement.

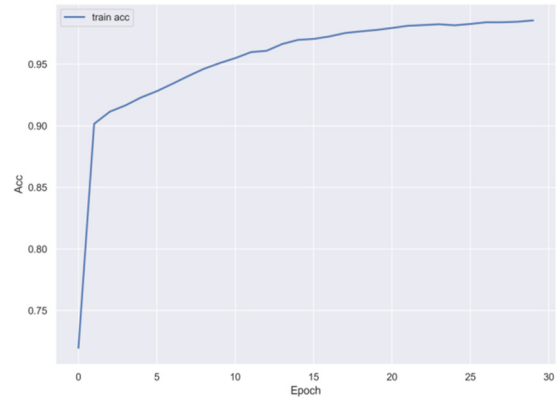


Figure 2: The training accuracy of a model over epochs (Photo/Picture credit: Original).

As depicted in Figure 2, the model's training accuracy incrementally increases with the progression of epochs. The accuracy exhibits a precipitous climb from approximately 75% to over 85% within the initial epochs, signalling the model's rapid learning from the training data. Subsequently, the increment in accuracy decelerates, yet it continues to demonstrate a slow and steady enhancement until it plateaus around 96% at the 30-epoch mark. This pattern indicates that after a period of swift learning, the model begins to converge, and the stability of accuracy suggests that it has reached its performance potential given the current architecture and dataset. Although the high accuracy denotes strong model performance on the training set, the absence of validation or test accuracy precludes a full assessment of overfitting. Without appropriate regularization, there is a potential for the model to overfit the training data, diminishing its generalizability to new data.

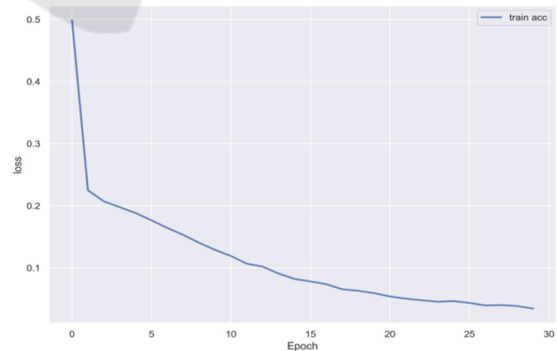


Figure 3: The training loss of a model over epochs (Photo/Picture credit: Original).

Figure 3 portrays the fluctuation in the model's loss during the training process. The loss markedly decreases in the initial epochs, which indicates that

the model rapidly reduces error, effectively optimizing towards a superior direction. In subsequent epochs, the decline in loss decelerates, suggesting that the model is entering a phase of fine-tuning and plateaus after 30 epochs. This descending and stabilization of loss reflect the model's approach to optimal performance; concurrently, vigilance is warranted against the risk of overfitting associated with excessively low loss. Ideally, the decrease in loss should coincide with the model's enhanced understanding of data representation, yet an overly complex model might learn noise rather than underlying useful patterns.

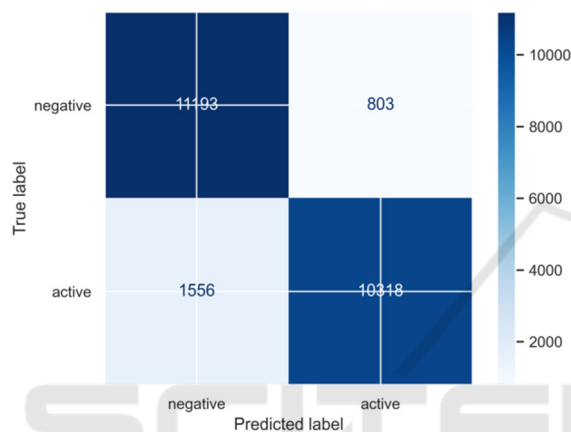


Figure 4: The predictions of the model's confusion matrix (Photo/Picture credit: Original).

The confusion matrix, shown in Figure 4, offers an intuitive perspective of the model's predictive performance. The matrix reveals that 11,193 negative samples and 10,418 active samples were correctly classified, signifying a strong predictive accuracy for both classes. However, there were also 803 false positives where negative samples were incorrectly labeled as active, and 1,556 false negatives where active samples were mistakenly labeled as negative. The relative abundance of false negatives suggests a propensity of the model to misclassify active samples as negative, which may be attributable to dataset imbalance or improper threshold settings in the classifier. This imbalance in error distribution could impact the model's utility in practical applications, especially if accurate identification of one class is paramount. Further refinement of the model may necessitate adjustments in data preprocessing strategies or further tuning of the model parameters.

In conclusion, the comprehensive experiments conducted in this chapter have significantly illuminated both the capabilities and areas of improvement for the machine learning model under

scrutiny. Through detailed analyses encompassing training accuracy, loss patterns, and confusion matrix insights, the experiments have elucidated a trajectory of rapid learning and convergence, while also cautioning against the potential for overfitting due to high training accuracy without corresponding validation. Furthermore, the analysis of predictive accuracy through the confusion matrix has highlighted challenges related to class imbalance and classification thresholds, underscoring the necessity for ongoing model refinement. Collectively, these findings not only validate the significance of the experimental efforts undertaken but also pave the way for future enhancements to optimize model performance.

4 CONCLUSIONS

This study presents a groundbreaking approach to sentiment analysis within the realm of Weibo comments, harnessing the power of a bidirectional LSTM model. By intricately combining character-level segmentation and pre-trained word embeddings, this innovative methodology delves deep into the intricate emotional fabric woven within social media discourse. Through meticulous experimentation, the model exhibits remarkable proficiency, achieving a commendable accuracy plateau of 96% in sentiment classification, thus solidifying its status as a formidable tool in the realm of sentiment analysis.

Looking forward, the scope of exploration extends to the dynamic nature of sentiment within Weibo comments, with a particular emphasis on understanding how sentiments evolve over time in response to various social, political, and cultural stimuli. It is believed that a deeper analysis of sentiment fluctuations holds the key to unveiling invaluable insights into collective social behavior, thereby informing decision-making processes across diverse domains. This study demonstrates the effectiveness of the bidirectional LSTM model and represents a major advancement in the area of sentiment evaluation in deciphering the nuanced emotional undertones embedded within Weibo comments. As the journey of exploration continues, the commitment remains unwavering in further refining the model's sensitivity and applicability, thereby contributing meaningfully to the ongoing discourse surrounding sentiment analysis in the digital age.

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