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Sentiment Analysis on Reviews of E-commerce Sites Using BERT

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Abstract

The Internet's widespread use has had a significant impact on electronic commerce. The trend of review-oriented consumption, where consumers rely on customer reviews of a film, is gaining popularity in the market. E-commerce platforms face a significant challenge in accurately interpreting user sentiments from the large volume of customer evaluations. This research suggests a BERT-based ecommerce reviews sentiment analysis algorithm to address the aforementioned issues[3]. Our approach to researching sentiment analysis involves analysing annotated data and labelling entities using the BIO (B-begin, I-inside, O-outside) data labelling pattern. By utilizing this method, we are able to accurately identify and classify entities within the data, and determine their sentiment. Based on experimental findings on the Taobao cosmetics review datasets, our approach has demonstrated significant improvements in both accuracy rate and F1 score when compared to conventional deep learning methods.

Keywords: e-commerce reviews; sentiment analysis; BERT.

Introduction

Sentiment analysis, which utilizes natural language processing to classify emotions expressed in text, has gained popularity across various industries, including ecommerce. The expansion of the internet has brought about significant changes in the customer experience, with the growth of e-commerce challenging traditional business models and altering people's purchasing habits and lifestyles. As a result, understanding the sentiments and thoughts of target customers through sentiment analysis of e-commerce reviews has become increasingly important. By analyzing e-commerce reviews, businesses can quickly pinpoint essential customer demands, aiding in the study of consumer demand and management of public opinion. With a substantial amount of reviews posted on e-commerce platforms, businesses can efficiently analyze public opinion, user comprehension, product

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optimization, and make informed marketing decisions. The analysis of ecommerce reviews has practical applications and economic value, making it a valuable tool for businesses.

E-commerce reviews often lack specificity and are often vague, repetitive, and brief, making sentiment analysis and entity detection challenging despite having a defined entity and emotional polarity.

Deep learning models, such as BERT, have been shown to outperform traditional machine learning methods and sentiment dictionaries in sentiment analysis tasks, particularly in the aspect-based sentiment analysis. These models can not only identify the overall sentiment of a text but also extract and classify sentiment associated with specific aspects of the text, such as product features or customer service. This level of granularity can provide businesses with more detailed insights into customer preferences and satisfaction, allowing them to make targeted improvements to their products and services. Overall, sentiment analysis, especially when combined with NER techniques and deep learning models, is a valuable tool for businesses in understanding and responding to customer feedback in the e-commerce industry. As significant datasets of labelled e-commerce reviews are not widely available, employing neural networks for sentiment analysis can be a difficult task. Therefore, in this paper, we aim to address this challenge by leveraging the advanced pre-training language model, RoBERTa (Robustly Optimized BERT Pretraining Approach), to refine the concept of transfer learning for sentiment analysis. RoBERTa is an enhanced version of BERT that achieves state-of-the-art results by improving the training task and the data generation method, training for longer periods, repeating training more frequently, and utilizing more data. By utilizing RoBERTa, we can overcome the limitations of limited labelled data and still obtain accurate sentiment analysis results.

Literature Survey:

[1] “Fine-grained Sentiment Analysis Of Online Reviews by Yan Wan, Hongzhurui Nie, Tianguang Lan.

This study concentrates on conducting a more detailed sentiment analysis by analyzing the sentiment of text words and phrases, which is narrower in scope than traditional sentiment analysis performed at the sentence or chapter level. The primary objective is to perform fine-grained sentiment analysis by identifying product attributes, also known as aspects or features, such as the properties or functions of a product. The proposed method, which is based on POS rules, achieved an accuracy of 84.4%. [1]

[2] “Sentiment Analysis of Chinese Ecommerce Reviews Based on BERT by Song Xie,Jingjing Cao.

That sounds like an interesting approach to ABSA using BERT and the BIO data labeling pattern. It's impressive to achieve an accuracy of 89.4%, which indicates the effectiveness of

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the proposed method in addressing the challenges associated with e-commerce reviews. The use of MLM for pre-training BERT is also a common approach for improving performance in natural language processing tasks. [3]

[3] "Sentiment Analysis on Reviews of Ecommerce Sites Using Machine Learning Algorithms by Md.Jahed Hossain,Dabasish Das Joy.

The study successfully developed a labeled dataset for sentiment analysis in Bangla, English, and Romanized Bangla reviews, and trained a machine learning model to classify reviews into different sentiment categories. The researchers employed various techniques such as cross-validation and feature extraction to enhance the model's accuracy, and determined that Support Vector Machine was the most effective algorithm for English language datasets, achieving an accuracy of 88.81%. The primary objective of the study was to aid businesses in making informed decisions by efficiently analysing customer sentiment in their reviews.[4]

Problem Identification

The e-commerce industry heavily relies on customer reviews and feedback to understand their interests and make informed business decisions. However, analysing these reviews can be a challenging task. To address this challenge, sentiment analysis is widely used in the industry to improve efficiency and gain better understanding of customer

Preferences[2]. By leveraging sentiment analysis techniques, businesses can gain insights into customer sentiments and use this information to develop strategies for improving customer satisfaction and loyalty in a competitive marketplace.

Methodology

Sentiment analysis can help businesses in the e-commerce industry to gain valuable insights from customer feedback and make data-driven decisions. It can also help them to identify potential issues or concerns and address them quickly, improving customer satisfaction and loyalty. The methodology for conducting sentiment analysis in the ecommerce industry typically involves several steps:

Data Collection: The first step is to collect data from customer reviews and feedback on the e-commerce platform. This data can be collected manually or through automated web scraping techniques.

Text pre-processing is an important step in the sentiment analysis pipeline, which involves cleaning and transforming raw text data to a more structured and standardized format that can be further analysed. This step may include various techniques such as tokenization, stop-word removal, stemming/lemmatization, and normalization. By removing irrelevant

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information and standardizing the text data, we can improve the accuracy and efficiency of the sentiment analysis model.

Yes, that's correct. Sentiment analysis uses NLP techniques to analyze the text and determine the sentiment expressed in it. The sentiment can be classified as positive, negative, or neutral, and the sentiment scores can be calculated to give a quantitative measure of the sentiment expressed in the text.

Data visualization is an important step in sentiment analysis as it helps to present the sentiment scores in a more understandable and actionable format. Histograms can show the distribution of sentiment scores, word clouds can highlight the most frequently used positive and negative words, and scatter plots can show the relationship between different variables such as sentiment and product ratings. These visualizations can help businesses make informed decisions and improve their products or services based on customer feedback.

Overall, sentiment analysis is a valuable tool for e-commerce platforms to understand customer sentiment and preferences, which can help them make data-driven decisions to improve their products and services and ultimately increase customer satisfaction and loyalty.

System Implementation

BERT is a state-of-the-art pre-trained NLP model that can be finetuned for various downstream tasks such as sentiment analysis, named entity recognition, and question answering. The transformer architecture used in BERT allows it to capture long-term dependencies in the input text, making it highly effective for language understanding tasks. Additionally, BERT is bidirectional, meaning it can understand the context of a word by looking at both the preceding and following words, making it more effective than traditional models that only consider the context of a word in one direction.

The working of the BERT algorithm can be divided into two phases:

During the pre-training phase, the BERT model is trained on a vast amount of text data through an unsupervised process. This phase aims to help the model understand the structure and context of language without a particular task. BERT is trained on two tasks during this phase: masked language modeling and next sentence prediction.

To develop a contextual understanding of language that can be fine-tuned for various downstream NLP tasks, BERT uses two pre-training tasks - masked language modeling and next sentence prediction. Through predicting masked words and consecutive sentences, BERT can learn and comprehend the relationships between words and sentences. These

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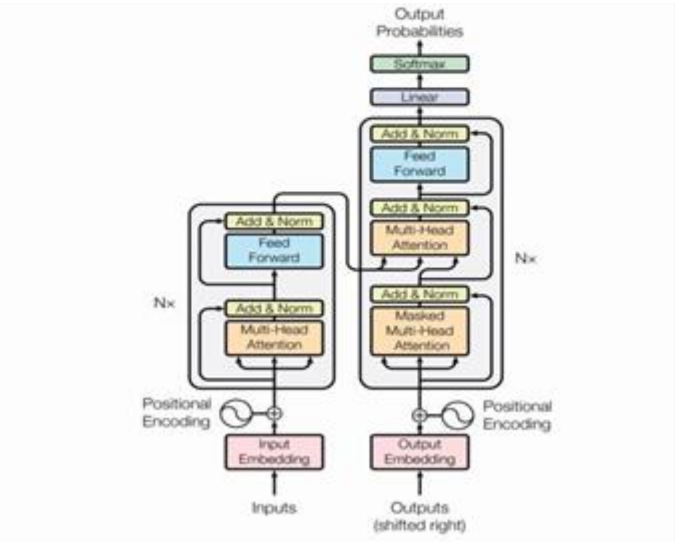
pre-training tasks help BERT to understand language contextually, which can be utilized for various NLP tasks in the future.

During fine-tuning, the model is fed with the task-specific dataset and trained to predict the output for each input, based on the pre-trained weights of the model. This process is supervised, as the model is trained on a labeled dataset, and the output is compared to the ground truth. The fine-tuning phase is crucial in adapting the pre-trained BERT model to a specific task and achieving high accuracy.



In summary, the BERT algorithm follows a two-step process of pre-training and fine-tuning to gain a deep understanding of natural language. During the pre-training phase, the model learns language structure and context through unsupervised training. The fine-tuning phase enables the model to be tailored to specific NLP tasks. Consequently, BERT is capable of performing sentiment analysis, text classification, and other NLP tasks with impressive accuracy, making it a powerful tool for language analysis.

BERT is a part of the transformer architecture, specifically the encoder portion. BERT-base has a smaller encoder with 12 layers, while BERT-large has a larger encoder with 24 layers. The decoder part of the transformer architecture is not used in BERT as it is a pre-trained language model for various NLP tasks.

BERT was trained on a sizable text corpus, which offers the architecture/model the capacity to learn variability in data patterns, better grasp the language, and generalise well on a number of NLP tasks. Bidirectional means that during the training phase, BERT gathers data from both the left and right sides of the context of a token.

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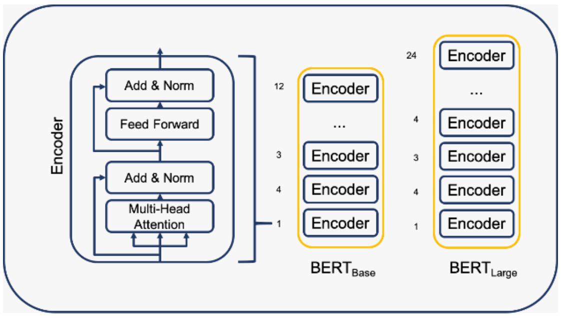

Working of BERT Algorithm

Training an NLP model such as BERT requires a significant amount of labeled data to learn and generalize well. Labeling data is often a time-consuming and expensive task that requires human annotation. In the case of BERT, it was trained on a massive amount of text data, including web pages and books, to learn the relationships between words and phrases in natural language. This pretraining process allows the model to be fine-tuned on a smaller set of labeled data for specific NLP tasks.

Training an NLP model such as BERT requires a significant amount of labeled data to learn and generalize well. Labeling data is often a time-consuming and expensive task that requires human annotation. In the case of BERT, it was trained on a massive amount of text data, including web pages and books, to learn the relationships between words and phrases in natural language. This pretraining process allows the model to be fine-tuned on a smaller set of labeled data for specific NLP tasks.

In order to train an NLP model like BERT, a large amount of labeled data is required, which is a time-consuming and expensive process. This labeled data is used to teach the model to understand the relationships between words and to recognize patterns in the language. However, once a model like BERT is trained, it can be fine-tuned for specific tasks with much less labeled data, which makes it a powerful tool for NLP applications.

The transformer architecture in BERT allows for a deep understanding of the context of each word by analyzing its relationship to every other word in the sentence, instead of processing each word

individually. This helps BERT to comprehend the meaning of the sentence as a whole and provide more accurate results by taking into account the surrounding terms and the searcher's intent.

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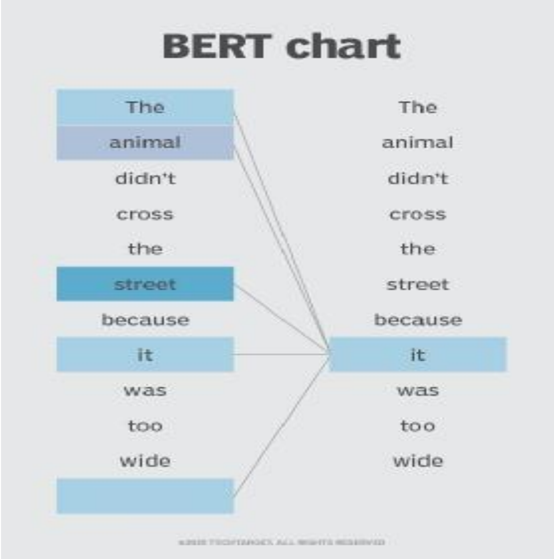
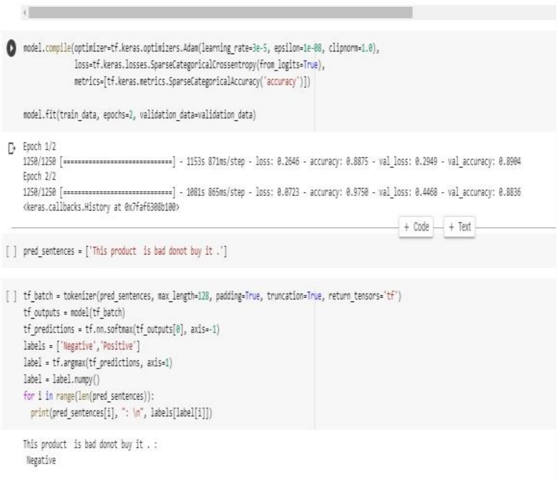


BERT's bidirectional self-attention mechanism enables it to capture the context of a word within a sentence, as well as the relationship between words within the same sentence. By considering both the left and right context of a word, BERT can better understand how the meaning of a word evolves as the sentence progresses, which helps to improve its overall language understanding capabilities.

BERT's ability to use its attention mechanism to consider all other words in a sentence or phrase helps it to accurately determine the context and meaning of each word. This results in more nuanced and accurate search results for search queries or more precise language understanding for other NLP tasks.

Results

Our model gives us the following results for each of the comment



```
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=3e-5, epsilon=1e-08, clipnorm=1.0),
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=[tf.keras.metrics.SparseCategoricalAccuracy('accuracy')])

model.fit(train_data, epochs=2, validation_data=validation_data)

Epoch 1/2
1250/1250 [==============================] - 1153s 871ms/step - loss: 0.2646 - accuracy: 0.8875 - val_loss: 0.2949 - val_accuracy: 0.8904
Epoch 2/2
1250/1250 [==============================] - 1081s 865ms/step - loss: 0.0723 - accuracy: 0.9750 - val_loss: 0.4468 - val_accuracy: 0.8836
<keras.callbacks.History at 0x7faf6308b100>

pred_sentences = ['This product  is bad donot buy it .']

tf_batch = tokenizer(pred_sentences, max_length=128, padding=True, truncation=True, return_tensors='tf')
tf_outputs = model(tf_batch)
tf_predictions = tf.nn.softmax(tf_outputs[0], axis=-1)
labels = ['Negative','Positive']
label = tf.argmax(tf_predictions, axis=1)
label = label.numpy()
for i in range(len(pred_sentences)):
  print(pred_sentences[i], ": \n", labels[label[i]])

This product  is bad donot buy it . :
 Negative
```

This picture tells about that the product is bad don't buy it. Indicates Negative.

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```
[13] model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=3e-5, epsilon=1e-08, clipnorm=1.0),
               loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
               metrics=[tf.keras.metrics.SparseCategoricalAccuracy('accuracy')])

     model.fit(train_data, epochs=2, validation_data=validation_data)

     Epoch 1/2
     1250/1250 [==============================] - 1127s 848ms/step - loss: 0.2674 - accuracy: 0.8845 - val_loss: 0.2971 - val_accuracy: 0.8836
     Epoch 2/2
     1250/1250 [==============================] - 1045s 836ms/step - loss: 0.0742 - accuracy: 0.9746 - val_loss: 0.4773 - val_accuracy: 0.8826
     <keras.callbacks.History at 0x7f15d61e63a0>

[14] pred_sentences = ['This product  is good and is at affordable price .']

[15] tf_batch = tokenizer(pred_sentences, max_length=128, padding=True, truncation=True, return_tensors='tf')
     tf_outputs = model(tf_batch)
     tf_predictions = tf.nn.softmax(tf_outputs[0], axis=-1)
     labels = ['Negative','Positive']
     label = tf.argmax(tf_predictions, axis=1)
     label = label.numpy()
     for i in range(len(pred_sentences)):
       print(pred_sentences[i], ": \n", labels[label[i]])

     This product  is good and is at affordable price . :
      Positive
```

This picture tells about that the product is Good do not buy it. Indicates Positive.

Evaluation Measure

The accuracy of trained model is calculated using formula

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Percentage	Accuracy	Loss
Training	97.5	7.2
Testing	88.3	44.6

Table-I: Accuracy and loss percentages

Conclusion

Sentiment analysis using BERT and can provide valuable insights for businesses in the e-commerce industry. By analyzing customer feedback and reviews, businesses can identify common themes, detect sentiment trends, and take actionable steps to improve their products and services. Additionally, sentiment analysis can help businesses identify their strengths and weaknesses, stay ahead of their competitors, and ultimately increase customer satisfaction and loyalty.

Although sentiment analysis has some limitations, such as data quality and language barriers, ongoing research is addressing these challenges and improving the accuracy of sentiment analysis models. With the potential for future advancements in areas such as multilingual sentiment analysis, aspect-based sentiment analysis, real-time sentiment analysis, and transfer learning, sentiment analysis will continue to be a valuable tool for

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businesses seeking to improve customer satisfaction and stay competitive in the e-commerce industry.

Limitations

Data Quality: The accuracy of sentiment analysis depends largely on the quality of the data. If the data contains a lot of noise, inaccuracies, or biases, then the results of sentiment analysis may not be reliable.

Language: Sentiment analysis tools may not work well with languages other than English, as they are often trained on

Context: Sentiment analysis tools may not be able to capture the nuances of language and context. For example, sarcasm, irony, and humor can be difficult to detect, and sentiment may change depending on the context of the text.

Domain-specific language: Sentiment analysis models may not perform well on domain-specific language, such as technical or medical jargon, which may require domain-specific knowledge.

Future Scope

Multilingual Sentiment Analysis: One of the major challenges in sentiment analysis is handling multiple languages. Future work could involve developing models that can effectively analyze sentiments in different languages.

Aspect-based sentiment analysis involves analyzing the sentiment of different aspects or features of a product or service mentioned in a piece of text, such as customer reviews. By identifying the sentiment associated with specific aspects, businesses can gain a more granular understanding of customer feedback and use it to make targeted improvements. This can provide more granular insights into customer feedback and help businesses improve specific aspects of their products or services.

Real-time sentiment analysis involves analyzing and processing customer feedback and reviews as they are posted in real-time. This can help businesses stay on top of customer sentiment and respond promptly to any negative feedback or issues. Real-time sentiment analysis can also be used for monitoring brand reputation and tracking the success of marketing campaigns.

Transfer Learning: Transfer learning involves using pre-trained models to train new models on specific tasks with limited amounts of labeled data. This approach can help improve the accuracy of sentiment analysis models on domain specific data.

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