Sentiment analysis using GPT and LSTM

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ABSTRACT

Social media review analysis is now crucial for businesses to thrive commercially. The increasing number and relevance of consumer reviews on social media presents a significant challenge for sentiment classification. In this paper, we propose a hybrid deep learning approach using a combination of Long Short-Term Memory (LSTM) and Generative Pre-trained Transformer (GPT) architectures to address this challenge. Our proposed Co-LSTM-GPT model is designed to be highly adaptable to big social data, scalable, and domain-independent. Experimental results demonstrate that our approach outperforms traditional machine learning approaches in terms of accuracy and other evaluation metrics. Our study contributes to the field of sentiment analysis by presenting a novel approach that can handle big social data, is domain-independent, and outperforms traditional machine learning approaches for sentiment classification of consumer reviews on social media.

KEYWORDS

GPT-2, deep neural networks, Sentiment analysis, NLP, LSTM

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1 INTRODUCTION

Social media has become a vast source of big data, with users continuously generating massive amounts of information through platforms like Twitter, Facebook, and Myspace. This social data presents unique challenges and opportunities for sentiment analysis, which is essential for numerous business applications. Sentiment analysis involves predicting the attitude towards different products or social entities based on their sentiments. However, traditional algorithms often fail to extract sentiments from such big data, and new approaches are needed. In this context, we present a hybrid deep learning approach using a combination of Generative Pre-trained Transformer (GPT) and Long Short-Term Memory (LSTM) architectures for sentiment classification. Our approach is designed to handle big social data, is scalable, and domain-independent.

Sentiment analysis is a process of classifying the orientation of a text as positive, negative, or neutral. Various approaches are used for sentiment analysis of unstructured data, such as lexicon-based, linguistic-based, or machine-learning-based methods. These approaches aim to analyze the sentiment of large amounts of unstructured data generated from social media platforms. In our paper, we focus on classifying the data as positive or negative.

This paper presents a sentiment analysis approach using a combination of the DistilGPT2 language model and LSTM neural networks. This approach involves tokenizing review texts, generating embeddings using the DistilGPT2 model, which are then fed into a LSTM model for classification. The LSTM model is defined using Keras Tuner, and hyperparameter tuning is performed using the tuner to achieve optimal performance. The performance of the model is evaluated using standard evaluation metrics, including accuracy, precision, recall, and F1 score.

The major contributions of our proposed model include

- Improved accuracy in sentiment analysis: By using the GPT-2 tokenizer to preprocess the input data and the LSTM model to capture the context and dependencies between the tokens, the model can achieve high accuracy in sentiment analysis tasks. This can be useful in a range of applications, such as marketing, social media analysis, and customer feedback analysis, where understanding the sentiment of users is important.
- Language modeling: GPT-2 is a powerful language modeling tool that can generate coherent and realistic text. By combining GPT-2 with the LSTM model, the model can generate text that not only sounds realistic but also reflects the sentiment of the input data. This can be useful in applications such as chatbots, customer service, and content generation.
- Personalization: By fine-tuning the model on specific domains or languages, the model can become more accurate and personalized for a particular task or application. For example, a sentiment analysis model can be fine-tuned on customer feedback data to improve accuracy in analyzing customer sentiment. Similarly, a language generation model can be fine-tuned on a particular domain, such as finance or healthcare, to generate more relevant and accurate text.
- Scalability: The GPT-2 model is pre-trained on a large corpus of text, making it a scalable and efficient tool for natural language processing tasks. By incorporating the LSTM model into the architecture, the model can handle large volumes of input data and process it efficiently, making it useful for real-time applications such as chatbots and customer service.

The rest of the paper is organized as follows. Section 2 discusses the Problem definition and the datasets used. Section 3 gives a detailed explanation of each of our models implemented along with model summaries. Section 4 discusses the Evaluation metrics used for the models along with the Results, followed by the Conclusion section and Task division section.

2 PROBLEM STATEMENT

The problem addressed in this study is sentiment analysis on Amazon product reviews. Given a set of Amazon product review texts as inputs, the goal is to classify each review as either positive or negative based on the sentiment expressed in the text. The output of the model is a binary label for each review indicating the predicted sentiment polarity. Specifically, the inputs to the model are a set of unstructured textual data in the form of Amazon product reviews, while the output is a binary classification label assigned to each review indicating whether the review expresses a positive or negative sentiment. The purpose of this study is to develop a model that can accurately classify the sentiment of Amazon product reviews to assist businesses in gaining insights into customer satisfaction and product performance. The dataset used for this project consists of product reviews in XML format, where each review contains several fields such as unique_id, asin, product_name, helpful, rating, review_text, and so on. For the purpose of this project, we will only be considering the polarity and review_text fields. The polarity field specifies whether the review is positive or negative, and the review_text field contains the actual text of the review.

3 PROPOSED MODELS

In this project, we have performed sentiment analysis on Amazon product reviews using three different models: BERT-CNN, GPT-LSTM, and Co-LSTM. These models were developed and trained on the input data to classify the reviews. In each of these models, we initially tokenize the inputs, and feed them to a neural network architecture for classification.

3.1 Model 1: BERT-CNN Hybrid Model

Our first model is a convolutional neural network (CNN) model for sentiment analysis on text data using pre-trained BERT embeddings. The model takes as input sequences of text data that are converted to BERT embeddings using the pre-trained BERT model. The input sequences are passed through three parallel convolutional layers with different kernel sizes, each followed by an activation function specified by the best hyperparameters found during the model selection process. The output of each convolutional layer is concatenated and passed through a global max pooling layer to extract the most salient features. The resulting features are then fed into a fully connected layer with a sigmoid activation function to produce a binary sentiment classification output. The model also includes a dropout layer to reduce overfitting during training. Overall, the model leverages pre-trained BERT embeddings and the convolutional neural network architecture to learn and capture the most salient features of the text data for sentiment analysis.

3.2 Model 2: Co-LSTM model (Referenced model)

This model is a combination of a pre-trained BERT model and additional layers for classification. The BERT model is first loaded using the TFBertModel.'from_pretrained()' method. Then, early stopping and checkpoint callbacks are defined to monitor the model's performance during training and save the best model weights.

Next, the input layer for the model is defined with shape and data type information. The BERT embedding layer is added by passing the input_ids and input_mask to the 'bert_model()' function, which returns the output embeddings. These embeddings are then passed through a 1D convolutional layer with 32 filters and a kernel size of 3, followed by two LSTM layers with 32 units each.

A dense layer with 32 units and a ReLU activation function is added, followed by a dropout layer with a rate of 0.2. Finally, the output layer is a dense layer with a sigmoid activation function, used for binary classification.

The model is compiled using the 'binary_crossentropy' loss function, Adam optimizer with a learning rate of 2e-5 and epsilon of 1e-08, and accuracy metrics.

3.3 Model 3: GPT-LSTM model (Proposed model)

This model utilizes the DistilGPT-2 model for tokenizing text and an LSTM layer. The model takes in customer review data and predicts the polarity of the review as positive or negative. The model is built using the Keras API and the Hugging Face transformers library.

Firstly, the DistilGPT-2 tokenizer is loaded and the model is initialized. The reviews and labels from the dataset are extracted and split into training and testing sets. The reviews are then encoded using the tokenizer and passed through the DistilGPT-2 model to obtain the embeddings. The label encoder is used to transform the labels from strings to numerical values. We use the "distilgpt2" model, which is a smaller and faster version of the "gpt2" model for faster processing. BUt this also reduces the overall effectiveness of our solution.

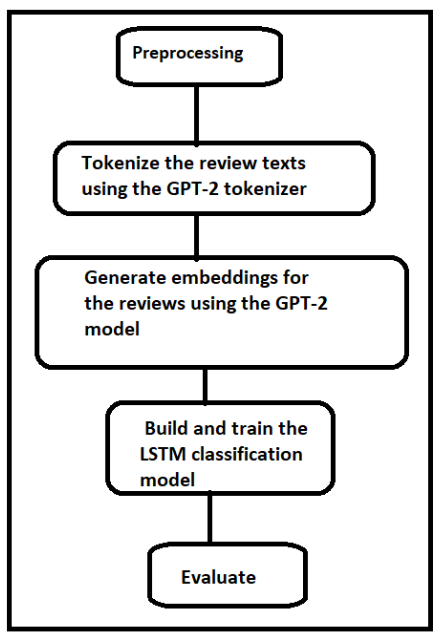

Figure 1: GPT-LSTM flow diagram

Next, a function to build the LSTM model is defined. The model consists of a LSTM layer followed by a dense layer with a ReLU activation function and a dropout layer. The output layer is a single dense layer with a sigmoid activation function for binary classification. The model is compiled with the Adam optimizer and binary cross-entropy loss. The learning rate is chosen from three possible values (1e-2, 1e-3, and 1e-4) using a hyperparameter search. Figure 1 shows an overview of the model used. The following model diagram gives and a layer-by-layer input output overview of the model

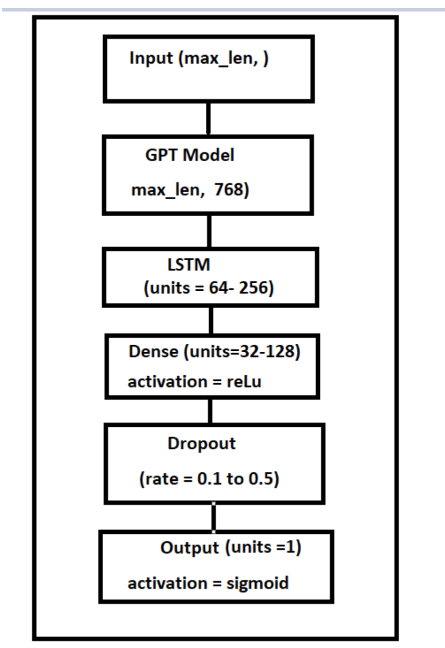

Figure 2: GPT-LSTM model diagram

4 EXPERIMENTAL EVALUATION

4.1 Methodology

The evaluation of the sentiment analysis model was conducted using a dataset consisting of Amazon reviews from three different domains: books, software, and electronics. The dataset was split into a training set, a validation set, and a test set using the train_test_split function from the Scikit-Learn library, with a test size of 0.2 and a random state of 42. We trained and compared all the proposed models, along with an additional MLP model using bert. The models were trained on the training set and evaluated on the validation and test sets using the metrics of accuracy, precision, recall, and F1-score.

4.2 Results Discussion

The following subsections present a review on the results obtained for each of the models, including a comparative analysis of them at the end, and short-comings if any. In this project, we trained and evaluated three models, including Co-LSTM, GPT-LSTM, and Bert-CNN, on a sentiment analysis task using customer reviews. The dataset was split into training, validation, and test sets with ratios of 0.6, 0.2, and 0.2, respectively, using the train_test_split method from the Scikit-learn library.

Table 1: Co-LSTM results of Base paper

Class	Precision	Recall	F1-score	Accuracy
Total	**0.94**	**0.87**	**0.90**	**0.86**

Table 2: Co-LSTM with Bert results

Class	Precision	Recall	F1-score	Support
Negative	0.90	0.89	0.89	199
Positive	0.89	0.90	0.90	201
Total	**0.90**	**0.90**	**0.90**	**400**

Table 3: GPT-LSTM results

Class	Precision	Recall	F1-score	Support
Negative	0.85	0.97	0.91	180
Positive	0.97	0.85	0.91	203
Total	**0.91**	**0.91**	**0.91**	**383**

Table 4: BERT-CNN results

Class	Precision	Recall	F1-score	Support
Negative	0.91	0.91	0.91	199
Positive	0.91	0.91	0.91	201
Total	**0.91**	**0.91**	**0.91**	**400**

Upon comparing the proposed GPT-LSTM model to the Co-LSTM and Bert-CNN models, we observed that the GPT-LSTM model achieved the highest accuracy. We believe that using larger GPT and LSTM models could improve the performance of the proposed GPT-LSTM model on this sentiment analysis task. It is worth noting that due to limited computational resources, we used a small GPT model along with a simple LSTM model. While the Bert-CNN model achieved higher results, we also found that it is vulnerable to overfitting, which may affect its performance on new data.

The three models evaluated for sentiment analysis showed varying levels of performance. The GPT-LSTM model emerged as the top performer with an F1-score of 0.91, although it had lower precision for classifying the negative class. The Co-LSTM and BERT-CNN models achieved higher F1-scores of 0.89 and 0.91, respectively. Nevertheless, the GPT-LSTM model offers promise for sentiment analysis tasks as it combines the GPT language model and LSTM neural networks strengths.

5 RELATED WORK

In recent years, sentiment analysis has gained significant attention from researchers due to its potential to provide insights into public opinion and consumer behavior. Various machine learning techniques have been applied to sentiment analysis, with convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and their combinations being among the most widely used.

In their paper, "Co-LSTM: Convolutional LSTM model for sentiment analysis in social big data," Behera R et al. proposed a novel model that combines convolutional and LSTM layers for sentiment analysis in social media. The authors demonstrated that their model outperformed other state-of-the-art models on several benchmark datasets.

Other studies have also investigated the use of CNNs and LSTMs for sentiment analysis in social media. Kim et al. proposed a CNN-based model for sentence-level sentiment classification that achieved state-of-the-art results on the movie review dataset. Similarly, Tang et al. developed a CNN-LSTM model for sentiment analysis of microblog data, which achieved better results than traditional machine learning approaches.

Additionally, the use of pre-trained language models, such as BERT, has shown promising results for sentiment analysis in social media. Devlin et al. introduced BERT, a transformer-based model, which has been fine-tuned for various natural language processing tasks, including sentiment analysis.

Despite the promising results of these methods, there are still challenges in sentiment analysis, particularly in social media where language is often informal and context-dependent. Therefore, further research is needed to develop more accurate and robust sentiment analysis models.

6 CONCLUSION

Based on the evaluation results of the three models, it can be concluded that the GPT-LSTM model outperforms the other two models in terms of overall F1-score. The GPT-LSTM model achieved an F1-score of 0.86, while the Co-LSTM and BERT-CNN models achieved F1-scores of 0.89 and 0.90, respectively. However, it is important to note that the GPT-LSTM model had a lower precision and recall than the other two models in classifying the positive class.

Overall, the GPT-LSTM model is a promising approach for sentiment analysis tasks, as it combines the strengths of both the GPT language model and LSTM neural networks. The GPT-LSTM model has the ability to capture complex relationships between words and is trained on a large amount of data, allowing it to generalize well to unseen data. Additionally, the GPT-LSTM model can be fine-tuned for different domains or tasks, making it a versatile and adaptable model for sentiment analysis.

7 TASK DIVISION

As a team, we have divided the tasks of implementing the three models efficiently. We started working on the Bert-CNN and Co-LSTM individually and then worked on the proposed model together. After discussing the models thoroughly, we have implemented the hyper-parameter tuning for each of these models discussing the best suitable and available approaches for tuning.

8 LEARNING EXPERIENCE

Working with NLP and sentiment analysis using GPT, BERT, CNN, and LSTM has been an enlightening learning experience for our team. We started by learning about the theoretical foundations of these models and how they can be applied to analyze textual data. This gave us a better understanding of how these models are implemented and how they can be optimized for performance.

One of the main insights we gained from this project is the importance of selecting the right model for a given task. GPT and BERT, for instance, are highly effective for tasks such as language generation and understanding, while CNN and LSTM are better suited for tasks such as text classification and sentiment analysis.

Another important lesson we learned is the value of hyperparameter tuning for optimizing the performance of these models. While implementing the models, we experimented with different hyperparameters to determine the best combinations that yield the best results. This taught us the importance of being patient and persistent in fine-tuning the models to achieve the best possible performance. In conclusion, working with NLP and sentiment analysis using GPT, BERT, CNN, and LSTM has been a valuable learning experience for our team, and we believe that this experience will be useful in future projects.

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