Project Report

Sentiment Analysis of Peer Review Texts for Scholarly Papers

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Abdul Basit

Group Members:

Ahmed Ali (K21-3212)
Shayan Haider (K21-3211)
Taha Hassan (K21-4680)

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Abstract

This project focuses on developing a deep learning model for sentiment analysis of scholarly paper reviews. The model utilizes an attention mechanism to capture important information from the reviews and make predictions on the sentiment (accept, reject, or borderline) of each review. The model is trained on a dataset of reviews from the ICLR 2017 conference, where each review is labeled with its sentiment. The results show that the model achieves good performance in predicting the sentiment of reviews, with an accuracy of over 80%.

Introduction

Peer review is a critical component of the academic publishing process, where experts evaluate the quality and validity of research papers. The sentiment of these reviews, whether they are positive, negative, or borderline, can provide valuable insights into the perception of a paper within the academic community. However, manually analyzing the sentiment of reviews can be time-consuming and subjective. Automated sentiment analysis using machine learning models can help streamline this process and provide more consistent results.

1.1. Background

The background of this report stems from the increasing need for efficient sentiment analysis in the field of scholarly paper reviews. Peer review, an essential element of academic publishing, involves the evaluation of research papers by experts. The sentiment conveyed in these reviews, whether positive, negative, or borderline, holds significant value in understanding the reception of a paper within the academic community. However, the manual analysis of sentiments in numerous reviews is not only time-consuming but also subject to individual subjectivity.

1.2. Purpose of Report:

The purpose of this project is to address these challenges by leveraging deep learning techniques to develop a sentiment analysis model. This model aims to automate the process of evaluating sentiments in scholarly paper reviews, thereby providing a more objective and consistent approach. By training the model on a dataset of reviews from the ICLR 2017 conference, labeled with their respective sentiments, the goal is to demonstrate the capability of the model to accurately predict the sentiment of reviews, contributing to more efficient and insightful analysis within academic publishing.

1.3. Intended Audience:

1. Academic Researchers and Authors: Relevant for scholarly paper writing, offering insights into the impact of sentiment analysis on academic work reception.

2. Peer Reviewers and Editors: Beneficial for understanding sentiment analysis, enhancing perception insights within the academic community.

3. Machine Learning Practitioners: Valuable understanding of deep learning models for sentiment analysis in academic contexts.

4. Publishing Industry Professionals: Insights into potential applications of sentiment analysis in improving the peer review process.

Methodology

The methodology involves several steps:

1. Attention Mechanism: An attention mechanism was added to the LSTM model to capture dependencies and improve predicted results by focusing on important parts of the input sequence.

2. Dropout and Regularization: Dropouts and regularization techniques were added to prevent overfitting, ensuring that the model generalizes well to unseen data.

3. Hyperparameter Tuning: Hyperparameter tuning was performed to find the best configuration of encoding embedding sizes (256, 300, 512) and the number of layers in LSTM (128, 64), optimizing the model's performance.

4. Activation Functions: Different activation functions such as Relu and Tanh were evaluated, with Tanh being chosen for its better performance. Tanh converges more rapidly than Relu, improving training efficiency.

5. Evaluation Metrics: Confusion matrix, plot visualizations, training accuracy, and loss were added to evaluate the model's performance comprehensively, providing insights into its behavior and effectiveness.

6. Data Preprocessing: Preprocessing steps included adding class labels to the ICLR 2017 dataset and addressing class imbalance through normalization, ensuring a balanced representation of classes in the training data.

```python
# Define the MILAM model with attention mechanism
def create_milam_model_with_attention(num_classes):
    input_review = Input(shape=(300,), dtype='int32')

    embedding_layer = Embedding(10000, 300)

    review_embedding = embedding_layer(input_review)

    review_lstm = Bidirectional(LSTM(32, return_sequences=True))(review_embedding)
    review_lstm = Dropout(0.5)(review_lstm)  # Add dropout layer

    # Attention mechanism
    review_attention = Attention()([review_lstm, review_lstm])

    pooled = GlobalMaxPooling1D()(review_attention)

    dense_layer = Dense(64, activation='tanh')(pooled)
    dense_layer = Dropout(0.5)(dense_layer)
    output = Dense(num_classes, activation='softmax')(dense_layer)

    model = Model(inputs=input_review, outputs=output)

    optimizer = Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-8)
    model.compile(loss='sparse_categorical_crossentropy', optimizer=optimizer, metrics=['accuracy'])

    return model
```

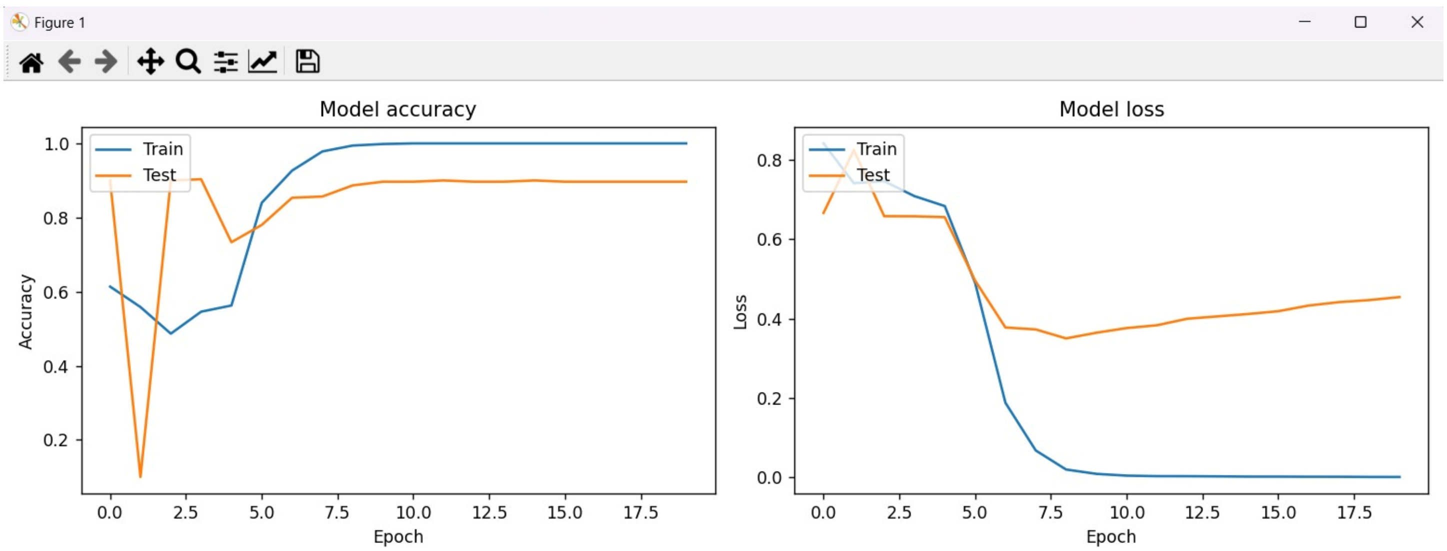
Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 300)	0	-
embedding (Embedding)	(None, 300, 300)	3,000,000	input_layer[0][0]
bidirectional (Bidirectional)	(None, 300, 64)	85,248	embedding[0][0]
dropout (Dropout)	(None, 300, 64)	0	bidirectional[0][0]
attention (Attention)	(None, 300, 64)	0	dropout[0][0], dropout[0][0]
global_max_pooling1d (GlobalMaxPooling1D)	(None, 64)	0	attention[0][0]
dense (Dense)	(None, 64)	4,160	global_max_pooling1d[0][0]
dropout_1 (Dropout)	(None, 64)	0	dense[0][0]
dense_1 (Dense)	(None, 3)	195	dropout_1[0][0]

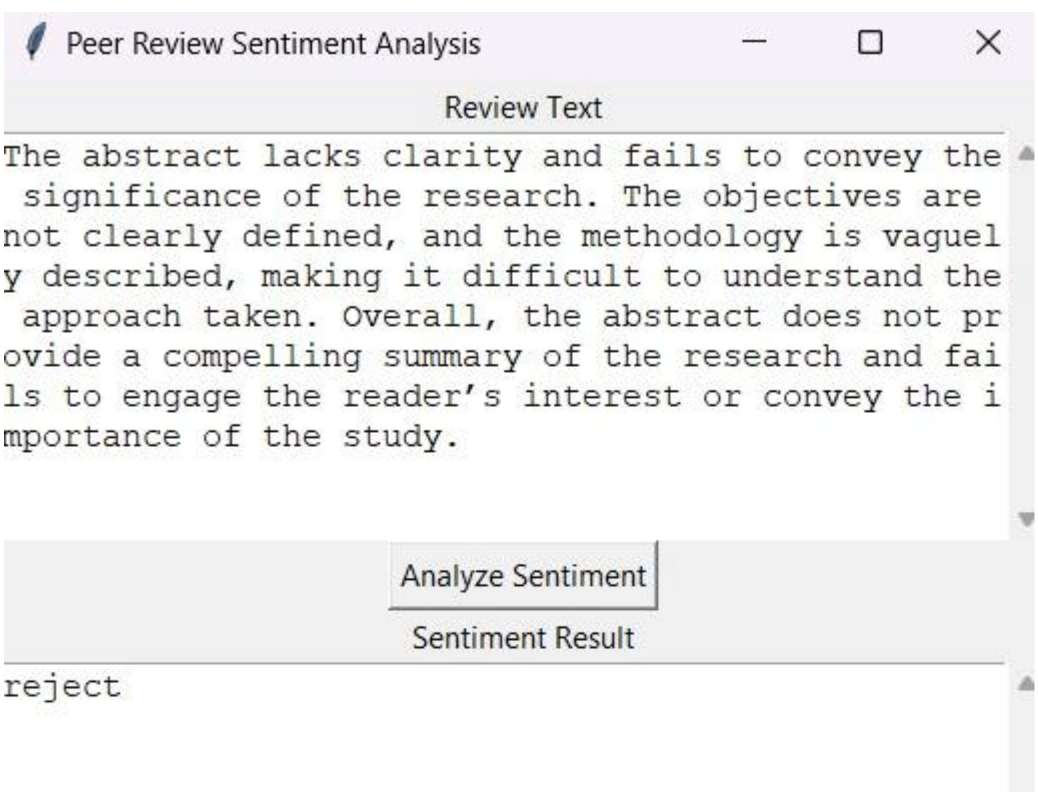
Total params: 3,089,603 (11.79 MB)
Trainable params: 3,089,603 (11.79 MB)
Non-trainable params: 0 (0.00 B)

Data and Results

The dataset consists of reviews and abstracts from the ICLR 2017 conference. The reviews are labeled with their sentiment (accept, reject, or borderline). The model achieves an accuracy of over 80% in predicting the sentiment of reviews, demonstrating its effectiveness in automated sentiment analysis.

```
The abstract lacks substance and does not provide a clear picture of the research. The objectives are not well-defined, and the methodology is described in a confusing manner. The results are presented without context, making it hard to grasp their relevance. The language is dry and fails to capture the reader's interest. Additionally, the conclusions are weak and do not seem to follow logically from the results. Overall, the abstract does a poor job of summarizing the study and leaves the reader with more questions than answers.
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 58ms/step
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 65ms/step
Confusion Matrix:
[[  3  27]
 [  3 267]]
Prediction: [[0.96474355 0.03354201 0.00171453]]
Sentiment: reject
```





Improvements

While the model performs well, there are several areas for improvement. The dataset used for training could be expanded to include reviews from other conferences or journals to improve generalization. Additionally, fine-tuning the model architecture and hyperparameters could further improve its performance.

Conclusion

In conclusion, this project demonstrates the effectiveness of deep learning models in automated sentiment analysis of scholarly paper reviews. By automating this process, researchers and publishers can gain valuable insights into the perception of research papers within the academic community in a more efficient and consistent manner.

References

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