Financial Sentiment Analysis using LSTM

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1. Introduction

Sentiment analysis has become a key tool in financial markets for predicting market movements, understanding investor behavior, and enhancing decision-making processes. By analyzing financial texts—such as news articles, social media posts, and corporate reports—sentiment analysis can classify the sentiment expressed in the text as positive, negative, or neutral, providing insights into how the market might react. Research has demonstrated that sentiment analysis can provide valuable predictions in stock market trends and investor behavior [1], with financial news content playing a significant role in price movements [2]. This report presents a system that uses deep learning techniques, specifically an LSTM (Long Short-Term Memory) network, to perform sentiment analysis on financial data.

2. Objective and Problem Statement

2.1 Objective

The objective of this study is to build and evaluate an LSTM-based model to classify financial texts into sentiment categories (positive, neutral, and negative). By using a deep learning approach, the model aims to accurately predict sentiment from financial text data, helping financial analysts and investors gauge market sentiment more effectively. The ultimate goal is to enhance financial decision-making and contribute to better market predictions by leveraging sentiment data.

2.2 Problem Statement

In the rapidly changing financial markets, the need for timely and accurate sentiment analysis is critical. Many existing sentiment analysis models rely on traditional machine learning techniques, which can be limited by their ability to capture the complex temporal dependencies present in text data. This limitation is particularly apparent when processing financial data, which is often jargon-heavy, context-sensitive, and subject to rapid changes in sentiment. While LSTM models have shown promise in capturing these complex patterns due to their ability to remember long-term dependencies, there remains a challenge in accurately classifying negative sentiment in financial text. The problem addressed in this report is to build an LSTM-based model that can classify financial sentiment accurately, particularly focusing on improving the classification of negative sentiment, which often gets overshadowed by more frequent neutral and positive sentiments.

3. Methodology

The methodology for this sentiment analysis system involves several key steps:

1. **Data Loading and Preprocessing**
    - Load dataset from CSV file containing text and sentiment labels.
    - Clean text by removing special characters, converting to lowercase, and trimming extra spaces.
2. **Text Tokenization and Padding**
    - Use Keras' `Tokenizer` to convert text into integer sequences.
    - Pad sequences to ensure uniform input length for the LSTM model.
3. **Sentiment Encoding**
    - Encode labels ("positive", "neutral", "negative") into numerical form using Scikit-learn's `LabelEncoder`.
4. **Model Architecture**
    - **Embedding Layer:** Converts tokenized sequences into dense vectors.
    - **LSTM Layers:** Two stacked LSTM layers to capture temporal dependencies.
    - **Dropout Layer:** Reduces overfitting.
    - **Dense Output Layer:** Softmax activation to predict one of three sentiment classes.
5. **Training and Evaluation**
    - Train for 5 epochs using the Adam optimizer and sparse categorical cross-entropy loss.
    - Evaluate using accuracy, precision, recall, F1-score, and confusion matrix.

4. Results

- **Validation Accuracy:** 69.97%
- **Classification Report:**
    - **Negative (Class 0):** Precision 0.35, Recall 0.22, F1-score 0.27
    - **Neutral (Class 1):** Precision 0.73, Recall 0.82, F1-score 0.77
    - **Positive (Class 2):** Precision 0.75, Recall 0.73, F1-score 0.74
- **Weighted Avg F1-score:** 0.69
- **Confusion Matrix:** Model struggles to classify negative sentiment accurately, leading to lower performance for Class 0.

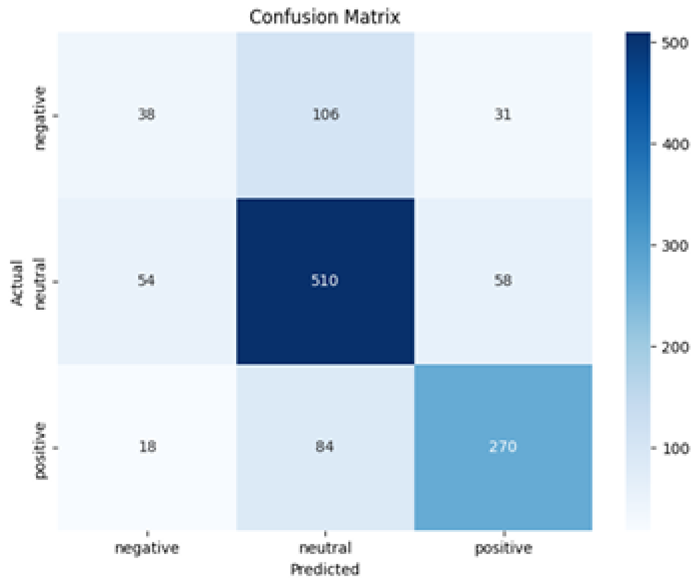

Figure 1: Confusion Matrix of the Sentiment Analysis Model

5. Model Performance Analysis

The model performed well in classifying neutral and positive sentiments, demonstrated by high precision and recall. However, it faced challenges accurately classifying negative sentiment, likely due to class imbalance in the dataset. Negative examples are less frequent than neutral and positive ones, which may have hindered the model's ability to learn their patterns effectively.