Title: Sentiment Analysis of Airline Tweets Using LSTM and Deployment with Streamlit

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Abstract

This project aims to analyze the sentiment of airline-related tweets using a Long Short-Term Memory (LSTM) neural network model. The data, extracted from a publicly available dataset, contains user tweets labeled as positive, neutral, or negative. Preprocessing techniques such as text cleaning, tokenization, and padding were applied to prepare the data for the LSTM model. The trained model achieved high accuracy in sentiment classification and was subsequently deployed as an interactive web application using Streamlit. The deployment allows users to input tweets and receive real-time sentiment predictions. This study demonstrates the effective use of deep learning models for text analysis and user-friendly deployment tools for real-world applications.

Introduction

In the digital age, social media platforms like Twitter provide a valuable source of public opinion on various topics, including airline services. Analyzing customer feedback through sentiment analysis allows businesses to understand user experiences, improve their services, and resolve issues proactively. This project focuses on building an end-to-end pipeline for sentiment analysis of airline tweets. Using an LSTM model, known for its ability to capture sequential data patterns, this project explores how to classify sentiments effectively. The deployment of the model as a web application ensures accessibility for both technical and non-technical users.

Literature Review

Sentiment analysis is a widely researched area in natural language processing (NLP). Earlier methods relied on rule-based approaches and traditional machine learning algorithms such as Naive Bayes and Support Vector Machines (SVM). However, these techniques often failed to capture contextual information. With the advent of deep learning, models like Recurrent Neural Networks (RNNs) and LSTMs have proven to be highly effective in text-based tasks. LSTMs, in particular, address the vanishing gradient problem in RNNs, enabling better handling of long-term dependencies in text. Deployment of sentiment analysis models has also gained attention with frameworks like Streamlit, which provide a straightforward method for creating interactive user interfaces.

Proposed Methodology

The methodology for this project consists of the following steps:

1. **Data Collection**:
    - Dataset containing airline tweets and corresponding sentiment labels (positive, neutral, negative).

2. **Data Preprocessing**:
    - Cleaning text by removing URLs, mentions, hashtags, special characters, and emojis.
    - Tokenizing text to convert words into numerical sequences.
    - Padding sequences to ensure uniform input length for the LSTM model.
3. **Model Development**:
    - Building an LSTM-based neural network.
    - Including embedding layers to learn word representations.
    - Using dropout layers to prevent overfitting.
    - Training the model with sparse categorical cross-entropy loss and Adam optimizer.
4. **Evaluation**:
    - Splitting the dataset into training and testing sets.
    - Evaluating model performance using accuracy, loss, and confusion matrix.
5. **Deployment**:
    - Developing an interactive web application using Streamlit.
    - Allowing users to input tweets and receive sentiment predictions.

Experimental Setup

1. **Hardware and Software**:
    - Google Colab for training the LSTM model.
    - Streamlit for deployment.
    - Python libraries: TensorFlow, Keras, Numpy, Pandas, Matplotlib, and Scikit-learn.
2. **Dataset**:
    - Publicly available dataset containing 14,640 tweets labeled with sentiments (positive, neutral, negative).
3. **LSTM Model Architecture**:
    - Input: Tokenized and padded tweet sequences.
    - Embedding layer: Dimension of 128.
    - Two LSTM layers with 128 and 64 units, respectively.

- Dropout layers with a rate of 0.2 to prevent overfitting.
- Dense output layer with a softmax activation function for multi-class classification.

4. **Hyperparameters**:
   - Maximum sequence length: 50.
   - Batch size: 32.
   - Epochs: 100 (with early stopping to prevent overtraining).

Findings

The LSTM model achieved an accuracy of 87% on the test dataset, demonstrating its ability to classify sentiments effectively. The confusion matrix revealed that the model performed well in distinguishing between positive, neutral, and negative sentiments, though minor misclassifications occurred between neutral and positive tweets.

The deployment via Streamlit resulted in a user-friendly interface, enabling real-time sentiment predictions. Users can input tweets and receive sentiment classifications with confidence scores.

Discussion

The project highlights the importance of robust preprocessing and model selection in achieving high-performance sentiment analysis. LSTMs effectively captured the sequential nature of text data, making them suitable for this task. However, challenges remain in handling ambiguous tweets, where sentiment is not explicitly clear.

Hyperparameter tuning played a significant role in optimizing model performance. Early stopping prevented overfitting, and the embedding layer improved word representation quality. The Streamlit deployment demonstrated how deep learning models could be integrated into accessible applications for real-world use.

Conclusion

This project successfully built and deployed a sentiment analysis model for airline tweets. By leveraging an LSTM model, it achieved high accuracy in classifying sentiments and demonstrated practical applicability through Streamlit deployment. Future work could focus on improving the model by using pre-trained embeddings such as GloVe or BERT, handling multilingual tweets, and integrating additional features like user demographics.

This project showcases the potential of combining deep learning with user-friendly deployment frameworks to address business challenges and enhance customer insights.