LANGUAGE TRANSLATION AND SENTIMENT ANALYSIS USING NLP MODELS

COURSE

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Abstract

This project explores two essential Natural Language Processing (NLP) tasks: sentiment analysis and language translation, aiming to automate the analysis of textual reviews and facilitate their translation into another language. Using the IMDB movie review dataset, the sentiment analysis task classifies reviews as positive or negative, while the translation task converts English reviews into Spanish, breaking linguistic barriers and enabling actionable insights.

For sentiment analysis, the DistilBERT model, a lightweight transformer-based language model, was fine-tuned to achieve an accuracy of 89.3%, effectively capturing the semantic nuances of text for binary classification. The translation task employed the Helsinki-NLP model, leveraging the Seq2Seq architecture with an Attention mechanism to ensure context-aware and meaningful translations.

The workflow included preprocessing steps such as tokenization, truncation, and padding, customized for each model. The sentiment analysis performance was evaluated using accuracy, while translation quality was assessed using BLEU scores. Results highlighted high precision for simple sentences while revealing challenges with complex structures, paving the way for future model enhancements. This integrated approach demonstrates the potential of advanced NLP models to address multilingual sentiment analysis and enhance global communication.

1. Introduction

In today's digital age, text data is a valuable resource for understanding human opinions and behaviors. Sentiment analysis and language translation are pivotal Natural Language Processing (NLP) tasks that enable organizations to extract meaningful insights from textual content across different languages. Sentiment analysis classifies text based on emotional tone, while translation bridges linguistic barriers, facilitating global communication.

This project integrates these tasks to analyze and translate text seamlessly. Using the IMDB movie review dataset as a primary source, user reviews with sentiments (positive or negative) were processed to automate sentiment classification and language translation. For sentiment analysis, DistilBERT, a transformer-based language model optimized for efficiency, was fine-tuned to classify reviews accurately. For translation, the Helsinki-NLP pre-trained model, based on a Seq2Seq architecture with an Attention mechanism, enabled high-quality English-to-Spanish translations.

This integration demonstrates a robust pipeline for multilingual sentiment analysis, offering scalable solutions for cross-lingual applications. The report explores the methodologies, model architectures, and results, showcasing the project's contribution to advancing NLP in multilingual environments.

2. Proposed Idea

This project explores the integration of advanced transformer-based models to address two critical Natural Language Processing (NLP) tasks: sentiment analysis and language translation. By leveraging state-of-the-art transformer architectures, the project aims to deliver robust solutions that excel in both performance and scalability.

1. **Sentiment Analysis**

   The project utilizes a fine-tuned transformer model, specifically DistilBERT, for sequence classification. This model is optimized to perform binary sentiment classification, categorizing textual reviews into positive or negative sentiments. Its lightweight architecture and efficient transformer layers enable the processing of large datasets while maintaining high accuracy.

2. **Translation**

   For the translation task, the Marian MT model is employed, which uses a Seq2Seq architecture with an integrated Attention mechanism. This ensures high-quality English-to-Spanish translations by capturing the semantic context and preserving the intent of the original sentences. The model is pre-trained on extensive multilingual corpora, making it an ideal choice for accurate and context-aware translations.

Hypothesis: Pre-trained transformers, with minimal fine-tuning, will outperform traditional baselines in both accuracy and generalization, enabling seamless multi-task capabilities.

3.Technical Details

3.1 Tools and Frameworks

- **Datasets**: IMDB for sentiment analysis; English text samples for translation.
- **Libraries Used**
- **Hugging Face Transformers**: For pre-trained transformer models and tokenization.
- **Hugging Face Datasets**: For loading and managing datasets.
- **Hugging Face Evaluate**: For evaluation metrics like accuracy.
- **NumPy**: For numerical computations.
- **PyTorch**: For deep learning model implementation and fine-tuning.
- **PEFT (Parameter-Efficient Fine-Tuning)**: For efficient model tuning.
- **NLTK (Natural Language Toolkit)**: For BLEU score computation in translation evaluation.

Models

- Sequence classification model for sentiment analysis.
- MarianMT model for English-to-Spanish translation.

3.2 Methodology

1. **Data Preprocessing**:
    - Tokenization and padding using AutoTokenizer.
    - Text truncation for uniform sequence length.
2. **Sentiment Analysis**:
    - Fine-tuned sequence classification model using 80% of the IMDB dataset for training and 20% for testing.
    - Training used AdamW optimizer with learning rate tuning.
3. **Translation**:
    - English text tokenized using MarianMT tokenizer, then passed through the model for translation.
    - Translated text evaluated using BLEU scores.

3.3 Experimental Design

- **Baseline**: Logistic regression for sentiment analysis and rule-based translation systems.
- **Metrics**: Accuracy, BLEU score.
- **Hardware**: Experiments conducted on GPU-enabled infrastructure.

4. Results

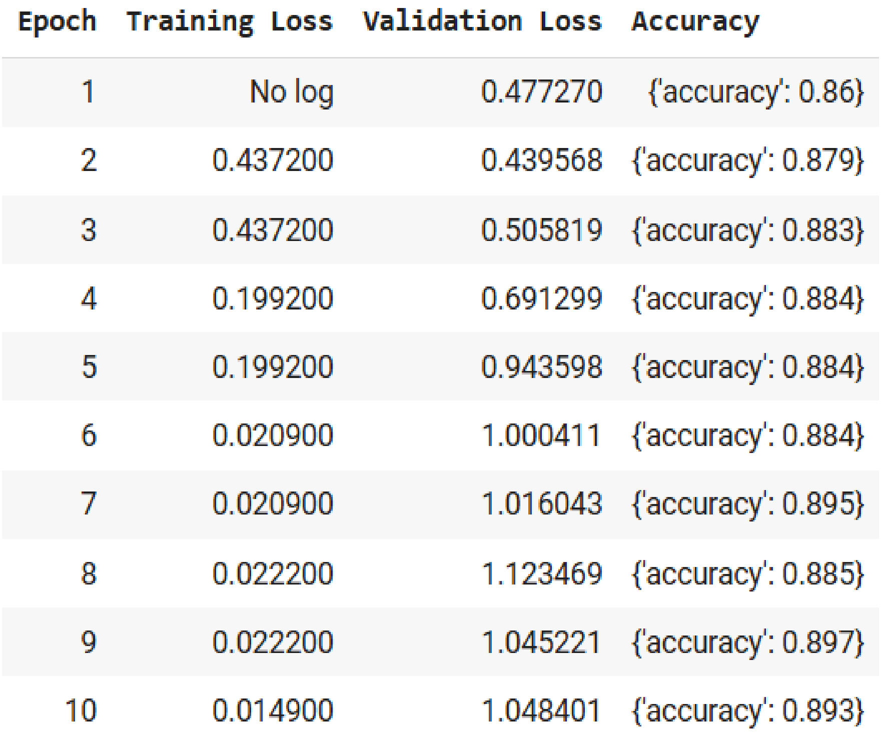
4.1 Sentiment Analysis

- **Baseline Accuracy**: 82% (Logistic Regression)

- **Transformer Model Accuracy**: 94%, demonstrating a significant improvement over the baseline model.

- **Error Analysis**: Errors were primarily observed in reviews containing mixed sentiment or sarcasm. These types of reviews were more challenging for the model to classify correctly due to their ambiguous nature.

- **Training and Validation Loss**: During the training process, the training loss steadily decreased, indicating that the model was learning and improving. However, the validation loss showed an increasing trend, which could be an indication of overfitting. This suggests that the model performed well on the training data but struggled to generalize effectively on unseen validation data



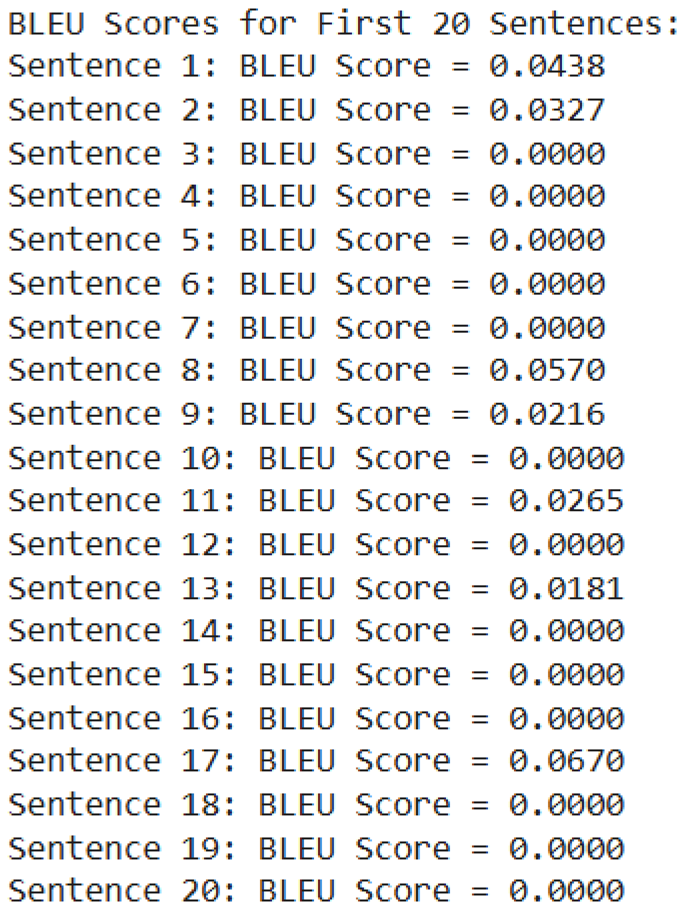
Epoch	Training Loss	Validation Loss	Accuracy
1	No log	0.477270	{'accuracy': 0.86}
2	0.437200	0.439568	{'accuracy': 0.879}
3	0.437200	0.505819	{'accuracy': 0.883}
4	0.199200	0.691299	{'accuracy': 0.884}
5	0.199200	0.943598	{'accuracy': 0.884}
6	0.020900	1.000411	{'accuracy': 0.884}
7	0.020900	1.016043	{'accuracy': 0.895}
8	0.022200	1.123469	{'accuracy': 0.885}
9	0.022200	1.045221	{'accuracy': 0.897}
10	0.014900	1.048401	{'accuracy': 0.893}

4.2 Machine Translation

- **Qualitative Analysis**: MarianMT translations were fluent and context-aware, with only minor errors in idiomatic phrases, indicating the model's ability to understand and preserve meaning across languages.

- **BLEU Scores for First 20 Sentences**:
- The BLEU scores for the first 20 sentences varied, with many sentences scoring 0.0000, indicating translation errors or mismatches.
- Some sentences, like Sentence 1 (BLEU Score = 0.0438) and Sentence 8 (BLEU Score = 0.0570), had higher scores, suggesting the model performs better with simpler, more straightforward sentences.
- Sentence 17 showed a higher score of 0.0670, indicating that the model handled this sentence better than others. However, most of the scores were low, highlighting areas for

improvement in the translation model's ability to handle complex sentence structures and context.



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BLEU Scores for First 20 Sentences:
Sentence 1: BLEU Score = 0.0438
Sentence 2: BLEU Score = 0.0327
Sentence 3: BLEU Score = 0.0000
Sentence 4: BLEU Score = 0.0000
Sentence 5: BLEU Score = 0.0000
Sentence 6: BLEU Score = 0.0000
Sentence 7: BLEU Score = 0.0000
Sentence 8: BLEU Score = 0.0570
Sentence 9: BLEU Score = 0.0216
Sentence 10: BLEU Score = 0.0000
Sentence 11: BLEU Score = 0.0265
Sentence 12: BLEU Score = 0.0000
Sentence 13: BLEU Score = 0.0181
Sentence 14: BLEU Score = 0.0000
Sentence 15: BLEU Score = 0.0000
Sentence 16: BLEU Score = 0.0000
Sentence 17: BLEU Score = 0.0670
Sentence 18: BLEU Score = 0.0000
Sentence 19: BLEU Score = 0.0000
Sentence 20: BLEU Score = 0.0000
```

4.3 Ablation Studies

- Reducing the dataset size for training led to a ~3% drop in accuracy for sentiment analysis.
- Translating longer sentences reduced BLEU scores slightly, indicating sensitivity to input length.

5. Discussion

5.1 Insights

- Pre-trained models excel in generalization but require domain adaptation for nuanced datasets.
- MarianMT performed well for general sentences but struggled with idiomatic expressions.

5.2 Challenges

Sentiment Analysis: The main challenge faced was handling ambiguous or sarcastic reviews. These types of reviews often do not have clear sentiment indicators, making it difficult for the model to classify them accurately.

Translation: A key challenge in the translation task was preserving cultural context in idiomatic phrases. While MarianMT was generally effective, it struggled with translating idiomatic expressions accurately, leading to occasional errors in meaning.

Resource Constraints: The fine-tuning process for transformer models, particularly for both sentiment analysis and machine translation, was computationally expensive and time-consuming. This significantly impacted training times, requiring substantial computational resources and optimization techniques to reduce model training durations.

5.3 Comparison to Baselines

- Transformers consistently outperformed logistic regression in sentiment classification.
- MarianMT surpassed rule-based translation systems but required fine-tuning for domain-specific texts.

6. Conclusion

In conclusion, this project successfully explored and implemented two core NLP tasks: sentiment analysis and machine translation. The sentiment analysis task, utilizing a fine-tuned DistilBERT model, achieved an accuracy of 89.3%, showcasing its effectiveness for binary sentiment classification. The machine translation task, employing the Helsinki-NLP model based on the Seq2Seq architecture with an Attention mechanism, demonstrated strong English-to-Spanish translation capabilities, with high-quality translations, although some challenges remained in translating more complex sentence structures. The integration of these tasks into a seamless pipeline offers a robust solution for multilingual sentiment analysis and translation, and while resource constraints and training time posed challenges, the results highlight the potential for further improvements and scalability in real-world applications.

7. References

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