

Reproducing FastText Sentiment Analysis

Using VADER Sentiment

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Introduction

In this presentation, we describe the sentiment analysis project using FastText. The tasks involved include:

- Preprocessing and cleaning the BBC news dataset.
- Applying VADER sentiment analysis.
- Training a FastText model.
- Improving model performance with hyperparameter tuning.
- Balancing the dataset and re-evaluating the model.

Replication of Original Work

In this project, we replicated the original work on sentiment analysis using the fastText library developed by Facebook AI Re-search team.

Data Preprocessing

The preprocessing steps applied to the dataset were as follows:

- Lowercasing and removing special characters.
- Removing stop words using the NLTK library.
- Lemmatizing text to its root form.

The cleaned data columns include:

- Title cleaned.
- Description cleaned.
- Combined sentiment (using VADER analysis).

Model Training and Evaluation

We utilized FastText for the training and evaluation process:

- **Training Parameters:**

```
model = fasttext.train_supervised(  
    input = 'bbc_news_train_combined.txt',  
    l.r=1.0, epoch=25, wordNgram=2,  
    minCount=1, verbose=2)
```

- **Evaluation Result:**

- ▶ Precision: 73.68%
- ▶ Recall: 73.68%
- ▶ Confusion Matrix: Highlighted True Positive and False Negative.

Hyperparameter Tuning

A grid search approach was employed for hyperparameter tuning:

- Learning rates: 0.01, 0.05, 0.1
- Epochs: 25, 50
- WordNgrams: 1, 2
- Embedding Dimensions: 50, 100

The best model achieved a precision of 0.733 using:

- Learning rates: 0.01
- Epochs: 50
- WordNgrams: 2
- Embedding dimension: 100

The result of the best model is lower than the official model.

Dataset Balancing

Oversampling techniques were applied to balance the neutral class, avoid bias in model training. Class distribution after oversampling:

- Negative: 17801
- Positive: 14401
- Neutral: 14401

Model trained on the balanced dataset achieved a precision of 98.1%.

Comparison of Model Results

We compared the results of our trained model with the official fastText models using **precision** as the evaluation metric:

```
test\_data['balanced\_predictions'] = test\_data['  
text\_only'].apply(lambda x: balanced\_model.  
predict(x)[0][0])
```

- **Our Model:** Precision = 98.1%
- **Official Model:** Precision = 73.68%
- **Official Model with hyperparameter:** Precision = 73.39%

Precision was chosen as it measures the proportion of correctly identified languages out of the total predicted. It is a crucial metric when accuracy alone doesn't capture performance in multi-class classification.

Model Utilities

The FastText-based sentiment analysis model offers several key utilities:

- **Efficient Sentiment Analysis:** Automates the classification of news articles, providing quick and scalable sentiment analysis for large datasets.
- **Real-Time Classification:** FastText allows for real-time sentiment detection, which is crucial for media monitoring platforms and sentiment-based recommendations.
- **Balanced Dataset Approach:** By employing oversampling, the model handles underrepresented classes effectively, ensuring reliable results across sentiment categories.
- **Generalizability Across Topics:** Demonstrates effective sentiment classification across diverse news topics, useful for media analysts and researchers.
- **Practical Applications for Media Organizations:** Helps automate content tagging, monitor sentiment trends, and analyze public opinion in real-time.

Model Limitations and Future Improvements

Despite achieving high accuracy, the model exhibits several limitations:

- **Overfitting Risk:** High accuracy on the test set could indicate overfitting, especially when the training and testing datasets are closely related.
- **Imbalance in Sentiment Classes:** Although oversampling was employed, the model may still face challenges in identifying minority classes like neutral sentiments.
- **Handling Ambiguous Sentiments:** The model struggles with articles that have mixed or subtle sentiments, leading to misclassification in cases where sentiments are not clear-cut.
- **VADER Limitations:** Using VADER as the sentiment analysis base might be insufficient for complex language structures, leading to inaccuracies in cases involving nuanced language.

Incorporating Techniques and Tools

This project effectively utilized various techniques and tools to accomplish sentiment analysis on the BBC news dataset:

- **FastText for Text Classification:** Leveraged the FastText library for efficient model training and hyperparameter tuning to perform text classification tasks.
- **Data Cleaning and Preprocessing:** Employed regular expressions, NLTK's stopwords, and VADER sentiment analysis to clean and preprocess text data effectively.
- **LaTeX for Presentation:** The entire presentation, including code listings, was written using LaTeX.
- **Google Colab for Execution:** Leveraged Google Colab's cloud-based environment for running and testing large-scale experiments conveniently.

Conclusion

Key Takeaways:

- ▶ **Improved Sentiment Classification:** Achieved high precision through effective preprocessing and FastText training.
- ▶ **Class Imbalance Addressed:** Applied oversampling to enhance model accuracy, particularly for neutral sentiments.
- ▶ **Thorough Data Cleaning:** Used stopwords removal, lemmatization, and filtering to refine sentiment predictions.

GitHub Repository: The repository contains:

- Python scripts for data cleaning and model training, training on balanced datasets and tuning hyperparameters.
- Instructions on reproducing results and applying improvements.