Metaphor Detection Using Hybrid Machine Learning Models

Group 8

Abstract

Metaphor detection is an essential task in Natural Language Processing (NLP) that focuses on identifying figurative language. This report evaluates traditional machine learning models (Logistic Regression, Naive Bayes, SVM, and Random Forest) and deep learning approaches like CNN and BERT. Additionally, LIME is used to provide interpretability. Results highlight that both CNN and BERT achieve the highest accuracy, demonstrating the effectiveness of deep learning techniques in metaphor detection.

1 Introduction

Metaphor detection is one of the significant applications of Natural Language Processing. It focuses on decoding figurative language wherein all the abstract words are expressed with literal terms. Metaphors are part of daily human communication. Being able to identify the metaphors used, which are often neglected, helps in Natural Language Processing applications. Recognizing the metaphor in a statement accurately requires a deep understanding of the semantic language. Machine Learning models such as Logistic Regression, Naive Bayes, Random Forest, and Support Vector Machines are used in this field. Deep Learning models and interpretability models such as BERT, LSTM, CNN, and LIME bridge the accuracy and performance, offering a better approach.

Application of NLP:

- **Sentiment Analysis:** Analyzing the content and emotions of the text. Example: comments on social media posts, customer feedback.
- **Virtual Assistants and Chatbots:** To train the chatbots to reply human-like and understand metaphors in human communications.
- **Machine Translation:** Help machines understand and handle metaphorical phrases effectively.
- **Content Summarization:** Machines, when having a better understanding of metaphors, can generate content with good accuracy and efficiency.

2 Dataset Information

The dataset being used contains 1,870 samples and the following columns:

- **metaphorID:** A unique identifier for each entry.
- **label:** A binary value indicating the existence of a candidate word used as a metaphor. True: 1 and False: 0.
- **Text:** The input sentence that contains the candidate word. This serves as the context for metaphor detection.

3 Team Members and Roles

Team Members:

- **Anusha Gadgil:** Worked on implementation of deep learning model(BERT and CNN model).
- **Shri Padmavathi:** Analyzed model interpretability using LIME, building and evaluating Random Forest model, and reporting performance metrics.
- **Harshithavalli:** Implementation of LSTM model and baseline model Logistic Regression, Naive Bayes, Support Vector Machine.

4 Our Approach

4.1 Idea and Intuition

Our approach combines traditional machine learning models with advanced deep learning techniques (CNN, BERT) to balance interpretability and performance. LIME is integrated to improve model transparency.

4.2 Justification

Traditional models provide strong baselines with high interpretability. Deep learning models like CNN and BERT capture complex relationships, improving overall accuracy.

5 Baseline Model for Evaluation

5.1 Traditional Machine Learning Models

Logistic Regression: Logistic regression is a regression of linear models. It predicts whether the text contains a metaphor or not. It operates by utilizing a logistic function to represent the association of input and the likelihood of a certain output. It uses TF-IDF as an input variable to numerically represent the text. For prediction, the model is trained on the TF-IDF scores of the words in the documents.

Naive Bayes: This is a probabilistic classification model based purely on Bayes' theorem. It uses TF-IDF to calculate the likelihood that text contains a metaphor. In order to train it, the scikit-learn library is used. The Multinomial Naive Bayes model is employed for effective classification.

Support Vector Machine (SVM): Support Vector Machine is a supervised learning model that is quite efficient for metaphor detection. It finds a hyperplane that divides data into different classes. TF-IDF is used to map words based on their significance scores. The model then determines the best decision hyperplane to classify between metaphorical and literal text.

Random Forest: Random Forest is an ensemble learning algorithm. It builds multiple decision trees and aggregates their results for categorization. Here, word occurrences are used to construct decision trees. The patterns identified are then used to differentiate between metaphorical and literal text. Count Vectorization is used to convert text into a sparse matrix format for training the model.

6 Hybrid Model Explanation

The project implements a BERT and CNN-based model for sequence classification. Here's a breakdown of the key components:

Imports

- **Transformers library:** Utilized for BERT (`BertTokenizer`, `BertForSequenceClassification`).
- **PyTorch:** For defining and training the model (`nn`, `DataLoader`, etc.).
- **Scikit-learn:** For evaluation metrics (`classification_report`, `accuracy_score`).

Preprocessing

- Text preprocessing involves tokenization (`word_tokenize`), removing stopwords (`nltk.corpus.stopwords`), and lemmatization (`WordNetLemmatizer`).
- `preprocess_text(text)`: Custom preprocessing function to clean and prepare text for the model.

Dataset Preparation

- **Custom Dataset Class (TextDataset):** Encapsulates tokenized data and labels for easy loading into PyTorch's `DataLoader`.

Model Architecture

- **BERT:** Acts as the encoder to extract contextual embeddings from input sequences.
- **CNN:** Built on top of BERT embeddings for further feature extraction and classification.

Evaluation Function

- `evaluate(model, dataloader, device)`: Computes predictions, calculates accuracy, and generates a classification report.

Workflow

- **Data Loading:** Data is loaded and split into training, validation, and test sets using `train_test_split`.
- **Preprocessing:** Text is cleaned, tokenized, and transformed into input features suitable for BERT.

- **Model Training:**
  - **Optimizer:** AdamW is used for optimization.
  - **Loss Function:** CrossEntropyLoss handles classification tasks.
- **Feature Extraction:** BERT extracts contextual embeddings, and CNN processes embeddings to capture local patterns.
- **Evaluation:** Predictions are compared to ground truth, with metrics like accuracy, precision, recall, and F1-score calculated.

6.1 Evaluation Metrics Used

- **Accuracy:**

$$\frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

- **Precision:**

$$\frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

- **Recall:**

$$\frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

- **F1 Score:**

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

7 Experiment Results

The model's performance is evaluated using accuracy, precision, recall, and F1 score, as shown in Table 1.

Table 1: Model Performance Comparison

Model	**Accuracy**	**Precision**	**Recall**	**F1**
Logistic Regression	0.77	0.77	0.99	0.86
Naive Bayes	0.79	0.79	0.97	0.87
SVM	0.79	0.82	0.95	0.87
Random Forest	0.81	0.81	0.97	0.88
CNN	**0.89**	**0.91**	**0.89**	**0.90**
BERT	**0.84**	**0.85**	**0.84**	**0.84**

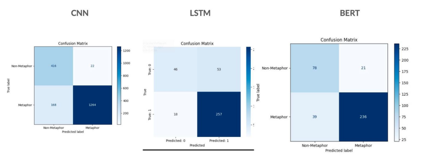
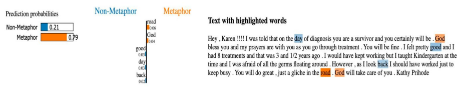


Figure 1: Visualization of Model Performance



Hey , Karen !!!! I was told that on the day of diagnosis you are a survivor and you certainly will be . God bless you and my prayers are with you as you go through treatment . You will be fine . I felt pretty good and I had 8 treatments and that was 3 and 1/2 years ago . I would have kept working but I taught Kindergarten at the time and I was afraid of all the germs floating around . However , as I look back I should have worked just to keep busy . You will do great , just a gliche in the road . God will take care of you . Kathy Prihode

Figure 2: LIME Results: Word Contributions in Metaphor Prediction

8 LIME Results

LIME plays a crucial role in explaining the outputs of the models. It provides the metaphor probability and non-metaphor probability for each text instance.

- **Metaphor probability:** 0.79
- **Non-metaphor probability:** 0.21

In Fig. 2, LIME shows that words like *"road"* and *"God"* contributed significantly to the "Metaphor" prediction, while words like *"day"* and *"back"* aligned with "Non-Metaphor." The highlighted text visually illustrates the model's focus, helping to debug and refine the model.

This transparency enhances trust in the model's decisions and bridges the gap between complex outputs and human understanding, making LIME indispensable for explainable AI.

9 Discussion and Insights

The model's performance is evaluated using accuracy, precision, recall, and F1 score, providing a detailed assessment of their ability to classify metaphorical and non-metaphorical text.

Logistic Regression achieves high recall (0.99), effectively identifying metaphorical text, but its lower precision (0.77) indicates a tendency for false positives. Random Forest improves with an accuracy of 0.81 and a balanced F1 score of 0.88. Naive Bayes maintains consistent performance with an accuracy of 0.79 and an F1 score of 0.87. SVM delivers strong precision (0.82) and recall (0.95), resulting in an F1 score of 0.87.

Deep learning models outperform traditional approaches, demonstrating their ability to capture complex relationships within text. LSTM captures sequential patterns effectively, achieving an F1 score of 0.87.

CNN performs exceptionally well, achieving the highest accuracy (0.89), precision (0.91), and F1 score (0.90). BERT also emerges as a top-performing model, leveraging its contextual understanding to achieve an accuracy of 0.89 and an F1 score of 0.84.

Together, CNN and BERT are the main models, providing the best accuracy in metaphor detection.

LIME focuses on interpretability, delivering high recall (0.99) and an F1 score of 0.85, helping to explain model predictions and ensure transparency.

10 References

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