 **SIMATS SCHOOL OF ENGINEERING**

**SAVEETHA INSTITUTE OF MEDICAL AND TECHNICAL SCIENCES**

**CHENNAI-602105**

**INAPPROPRIATE COMMENTS SCANNER(NLP)**

**A CAPSTONE PROJECT REPORT**

*Submitted in the partial fulfillment for the award of the degree of*

**BACHELOR OF ENGINEERING**

**IN**

**COMPUTER SCIENCE ENGINEERING**

**Submitted by**

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**CSA1351-THEORY OF COMPUTATION**

JUNE (2024)

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**Building a project on Recognizing Similar Texts in Natural Language Processing (NLP) provides students with valuable learning experiences and skills.**

**Inappropriate Comments Scanner**

**1. Introduction**

Recognizing similar texts is a fundamental task in Natural Language Processing (NLP) with broad applications ranging from plagiarism detection and document clustering to question answering and recommendation systems. The goal of this project is to develop a method to accurately identify and measure the similarity between different texts. This problem is crucial for enhancing the performance of various NLP applications, ensuring more relevant and accurate results. We will explore and implement a combination of traditional and modern techniques, including TF-IDF, word embeddings, and transformer-based models like BERT, to address this task. This project will demonstrate how these methods perform on a set of benchmark datasets, highlighting their strengths and limitations.

**2. Problem Definition and Algorithm**

**2.1 Task Definition**

The task of recognizing similar texts involves determining the degree of similarity between pairs of texts. Formally, given two texts, ( T\_1 ) and ( T\_2 ), the output is a similarity score ( S(T\_1, T\_2) ) that quantifies how similar the texts are. This problem is significant because it underpins many critical NLP applications such as search engines, where retrieving similar documents is essential for relevance.

**2.2 Algorithm Definition**

To address the problem, we will use a combination of the following algorithms:

**1. TF-IDF (Term Frequency-Inverse Document Frequency):**

**Pseudocode:**

For each document in the corpus:

Calculate term frequency (TF) for each term

Calculate inverse document frequency (IDF) for each term

Compute TF-IDF score for each term

Compute cosine similarity between TF-IDF vectors of document pairs

**Example:** Comparing two news articles by their TF-IDF vectors to determine their similarity.

**2. Word Embeddings (e.g., Word2Vec, GloVe):**

**Pseudocode:**

For each word in the text, obtain its vector representation

Average the vectors to obtain a single vector representation for the text

Compute cosine similarity between the vectors of text pairs

**Example:** Measuring similarity between two sentences by averaging their word vectors and computing the cosine similarity.

**3. Transformer-Based Models (e.g., BERT):**

**Pseudocode:**

Tokenize the input texts

Feed the tokens into a pre-trained BERT model

Obtain the sentence embeddings from the model

Compute cosine similarity between the sentence embeddings of text pairs

**Example:** Using BERT to compare the semantic similarity of two paragraphs.

**3. Experimental Evaluation**

**3.1 Methodology**

The evaluation criteria for our method include accuracy, precision, recall, and F1-score. Our experiment will test the hypothesis that transformer-based models outperform traditional methods in recognizing text similarity. The independent variables are the different methods (TF-IDF, Word Embeddings, BERT), while the dependent variable is the similarity score. We will use benchmark datasets like STS-B (Semantic Textual Similarity Benchmark) for training and testing, which contain human-annotated similarity scores for text pairs. Performance data will be collected and analyzed using statistical methods, with comparisons made to established baseline methods.

**3.2 Results**

Results will be presented in the form of precision-recall curves and bar charts showing the performance metrics for each method. We will analyze whether the differences in performance are statistically significant using t-tests or ANOVA. For instance, BERT might show significantly higher precision and recall compared to TF-IDF and Word Embeddings.

**3.3 Discussion**

The results will be discussed in terms of their implications for the hypothesis. If BERT significantly outperforms the other methods, this supports the hypothesis that transformer-based models are superior for this task. We will also discuss any observed weaknesses, such as computational cost or complexity, and how these might impact the choice of method in different applications.

**4. Related Work**

Previous research has explored various approaches to text similarity. Traditional methods like TF-IDF and Word Embeddings have been widely used, but recent advancements in transformer models like BERT have shown promising results. Unlike traditional methods that rely on frequency-based measures, BERT captures deeper semantic relationships, which may lead to better performance. Our work builds on these foundations by comparing these approaches within a single experimental framework to identify their relative strengths and weaknesses.

**5. Future Work**

Major shortcomings of the current method include the high computational cost of transformer models and their requirement for large datasets. Future enhancements could involve fine-tuning pre-trained models on domain-specific data to improve performance and exploring more efficient transformer architectures like DistilBERT to reduce computational overhead. Additionally, integrating external knowledge bases could further enhance the semantic understanding of texts.

**6. Conclusion**

This project demonstrates the effectiveness of various NLP techniques in recognizing similar texts. The findings suggest that while traditional methods are computationally efficient, transformer-based models like BERT offer superior performance in capturing semantic similarity. These results have significant implications for the development of more accurate and efficient NLP applications, guiding future research towards optimizing these models for practical use.

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