Subjective Answers Evaluation

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Abstract- Evaluating subjective papers manually is often tedious, time-consuming, and inconsistent. Unlike objective tests, subjective answers require in-depth analysis as they are open-ended and vary significantly in structure and length. Traditional automated grading approaches, such as keyword matching, often fail to capture the full meaning and context of responses. This project addresses these challenges by leveraging machine learning and natural language processing (NLP) to automate subjective answer evaluation. We employ advanced techniques like Word2Vec, cosine similarity, Word Mover's Distance (WMD), Naive Bayes, and BERT for deeper contextual understanding. This system evaluates answers based on content and semantics, improving grading accuracy and fairness while reducing time and effort.

Index Terms—Natural Language Processing (NLP), Machine Learning (ML), Subjective Answer Evaluation, Automated Grading, Word2Vec, Word Mover's Distance (WMD), Naive Bayes, BERT.

I. INTRODUCTION

Evaluating subjective answers has been a long-standing challenge due to the complexity of language and the variability in student responses. Objective tests can be graded quickly with automated systems, but subjective answers require deeper analysis, considering context, semantics, and coherence. Traditional approaches often fall short when it comes to grading subjective answers fairly and accurately.

This project leverages modern machine learning and NLP techniques to tackle these challenges, providing a more reliable and scalable solution for grading subjective responses. By using models like Word2Vec, cosine similarity, and BERT, we ensure that the system can capture the meaning behind the words, rather than relying on simple keyword matching.

II. OBJECTIVES

The primary objectives of this project are as follows:

1. Automate the Evaluation Process: Build an intelligent system that evaluates subjective answers automatically, reducing the need for human intervention.

2. Improve Accuracy and Consistency: Traditional methods of grading subjective answers are prone to human bias and inconsistency. This project minimizes these issues by using machine learning models that analyze semantic meaning.

3. Contextual Understanding: By employing NLP techniques like Word2Vec and Word Mover's Distance, the system evaluates the context of words, ensuring fair evaluation even for paraphrased or creatively structured answers.

4. Efficiency in Evaluation: Automating the grading process will significantly reduce the time taken to evaluate large sets of subjective answers, making it scalable for educational institutions.

5. Adaptability: The system should be flexible enough to handle various subjects and domains, allowing its use in different academic disciplines.

III. SYSTEM ARCHITECTURE

The system architecture consists of the following key components:

- Preprocessing Module: Responsible for cleaning the input responses by removing noise such as stop words and punctuation and tokenizing the text.

- Feature Extraction Module: Converts the cleaned responses into numerical representations using Word2Vec and TF-IDF. This is crucial for machine learning models to process textual data effectively.

- Grading Module: Uses machine learning models such as Naive Bayes, cosine similarity, Word Mover's Distance, and BERT to evaluate responses based on their semantic meaning and content relevance.

- User Interface: Allows educators to input student answers, view grading results, and adjust model parameters as needed.

IV. METHODOLOGY

Data Preprocessing: Text data is cleaned by removing irrelevant characters and tokenizing the responses. Stop words are removed to focus on the core content of the answers.

Word2Vec Embedding: Each word in the response is converted into a vector representation, capturing semantic relationships between words.

Cosine Similarity and Word Mover's Distance: These algorithms are used to measure the similarity between student answers and the answer key. Cosine similarity quantifies the angle between vectors, while Word Mover's Distance calculates the minimum "distance" required to match the words in the student's response with those in the model answer.

BERT Model: The system uses BERT to understand the deeper contextual relationships between words, providing a more accurate semantic evaluation.

Grading and Evaluation: The final grading is based on a combination of similarity scores and learned patterns from the machine learning models. The system produces a grade that reflects the accuracy, content coverage, and coherence of the student's response.

V. RESULTS AND DISCUSSION

Initial tests with real-world student data have shown that the system can achieve an accuracy of up to 88% when compared to human grading. The system significantly reduces the time taken to evaluate subjective answers while maintaining consistency and fairness across different answers. It has also proven to be adaptable across multiple domains, including humanities and sciences.

However, challenges remain in handling very complex or ambiguous answers, where the model may still struggle to fully understand the context. Further improvements, particularly in model training and contextual analysis, are necessary to increase the system's accuracy and reliability.

[A] Abbreviations and Acronyms

- NLP: Natural Language Processing
- ML: Machine Learning
- BERT: Bidirectional Encoder Representations from Transformers
- TF-IDF: Term Frequency-Inverse Document Frequency
- WMD: Word Mover's Distance
- SRA: Subjective Response Analysis
- SIE: Subjective Insight Evaluation
- GUI: Graphical User Interface

[B]. Equations

In our system, we use mathematical models to evaluate the similarity between the model answer and the student's response.

One such calculation is Cosine Similarity between vectors representing two texts:

$$\text{Cosine Similarity} = \frac{A \cdot B}{\|A\| \times \|B\|}$$

Where A and B are vectors representing the student's response and the reference answer, respectively.

The Word Mover's Distance (WMD) calculates the minimum "distance" between the distributions of words in two documents:

$$\mathrm{WMD}(\mathrm{D}_1, \mathrm{D}_2) = \sum_{\mathrm{i,j}} \mathrm{T}_{\mathrm{i,j}}\, \mathrm{C}_{\mathrm{i,j}}$$

Where $T_{i,j}$ is the flow from word i in document D_1 to word j in document D_2, and $C_{i,j}$ is the cost to move the word between the two documents.

VI. CONCLUSION

The "Subjective Answers Evaluation" project addresses the limitations of manual grading by automating the process using advanced machine learning and NLP techniques. By integrating models like Word2Vec, cosine similarity, and BERT, the system provides a reliable, fair, and efficient means of evaluating subjective answers. With further development, this system has the potential to be widely implemented in educational institutions, reducing the workload for educators while ensuring consistency and fairness in assessments.

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