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REVOLUTIONIZING RESPONSE EVALUATION THROUGH ADVANCED MACHINE LEARNING TECHNIQUES

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Abstract: Research focuses on evaluating subjective answers, a task demanding significant time and dedication. Introducing a machine learning and natural language processing-driven method for this purpose, the system employs natural language processing combined with a Random Forest model to categorize subjective answers. The approach includes data preprocessing, feature extraction, and classification, aiming to enhance the accuracy and efficiency of evaluating subjective answers. This study not only improves the evaluation process but also contributes to advancing methods in automated assessment. Designed to be adaptable to various educational contexts, the implementation handles diverse types of subjective responses. By automating the evaluation process, educators can save time and allocate more resources to other critical teaching activities. Additionally, the method provides a consistent and unbiased assessment, reducing human error and subjectivity. Research underscores the potential of integrating advanced machine learning techniques into educational tools, paving the way for more innovative applications in the future.

Keywords: Machine Learning, Natural Language Processing, Random Forest, Answer Assessment, Education,

I. INTRODUCTION

Evaluating subjective answers involves assessing the quality of answers based on criteria like creativity, coherence, and relevance. Traditional evaluation techniques depend on human judgment and are susceptible to inconsistencies and mistakes. To address the limitations of these methods, there is growing interest in utilizing machine learning and natural language processing methods for assessing subjective answers. Advanced technologies have the potential to provide more reliable and objective evaluations. Introducing a machine learning and natural language processing-driven method for this purpose, the system employs natural language processing combined with a Random Forest model to categorize subjective answers. The approach includes data preprocessing, feature extraction, and classification, aiming to enhance the accuracy and efficiency of evaluating subjective answers. The study not only improves the evaluation process but also advances methods in automated assessment.In recent times, there has been an increasing focus on using machine learning and natural language processing techniques to automatically assess subjective answers. Approaches based on these technologies aim to offer consistent and accurate evaluations while reducing the time and effort needed for assessment. Leveraging these advancements aims to overcome the challenges associated with subjective answer evaluation and contribute to developing more efficient and reliable educational assessment tools.

II. LITERATURE REVIEW

2.1.1 Subjective Answers Evaluation Using Machine Learning and Natural Language Processing

The text points out the difficulties of manually evaluating subjective papers and the challenges of using Artificial Intelligence to analyze such papers. It mentions the limitations of traditional approaches and the lack of curated data sets for this task. The proposed solution involves utilizing machine learning, natural language processing techniques, and tools such as Wordnet, Word2vec, word mover’s distance, cosine similarity, multinomial naive bayes, and term frequency-inverse document frequency to automatically evaluate descriptive answers.

2.1.2 Subjective Answer Evaluation Using Machine Learning

The current method of evaluating subjective papers is problematic due to variability in human evaluation. We propose a system that uses machine learning and NLP techniques to analyze subjective answers, including tokenization, part of speech tagging, chunking, lemmatization, and providing semantic meaning of the context.

2.1.3 Online Subjective Answer Verifying System using Artificial Intelligence

Each year, board and university exams are administered in offline mode, hosting a significant number of students engaged in subjective-type assessments.

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The manual evaluation of such a volume of papers necessitates substantial effort and may be subject to fluctuations in quality contingent upon the evaluator's disposition. This manual assessment process is both protracted and labor-intensive.

2.1.4 Intelligent Short Answer Assessment using Machine Learning

Education plays a pivotal role in societal advancement. The assessment of a student's performance holds substantial influence in the realm of education. While teachers employ multiple criteria for evaluating student work, the potential impact of emotions on grading decisions remains uncertain. Furthermore, administrative errors such as totaling inaccuracies and marking mistakes are not uncommon within educational institutions. To address these challenges, we are in the process of developing software that leverages Natural Language Processing and Machine Learning to facilitate the automated assessment of student responses. The software comprises two modules. The first module employs Optical Character Recognition to extract handwritten text from uploaded files, while the second module evaluates the responses based on various criteria, culminating in the assignment of a grade.

III. PROPOSED SURVEY

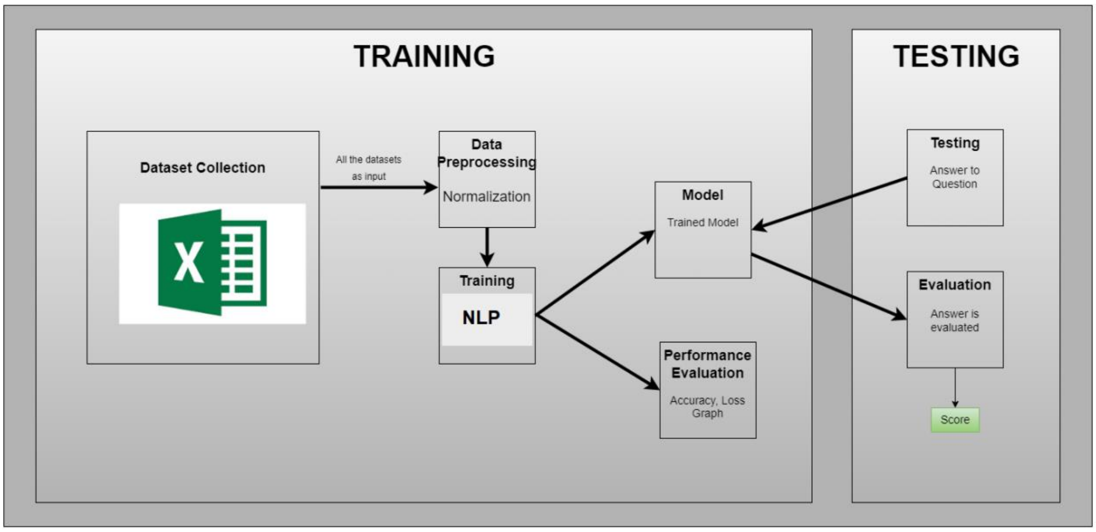
The proposed system implements a cutting-edge machine learning and natural language processing-based approach to effectively and objectively evaluate subjective answers. The system's methodology encompasses three crucial steps: data pre-processing, feature extraction, and classification.

Data pre-processing is the foundational step in the proposed system. It involves meticulously cleaning and transforming the raw data to ensure its suitability for analysis. For the evaluation of subjective answers, this may entail eliminating extraneous information like headers, footers, and irrelevant text, and converting the text into a format conducive to analysis, such as tokens or vectors. Pre-processing is a vital step as it significantly influences the accuracy of the final classification.

Following pre-processing, the system proceeds with feature extraction, identifying and extracting pertinent features from the pre-processed data. In evaluating subjective answers, these features may encompass factors such as answer relevance, response coherence and organization, depth and accuracy of demonstrated knowledge, and appropriate language use. These features are then translated into numerical values amenable to analysis.

The culminating step in the system is classification, employing a robust machine learning algorithm to categorize the subjective answers. The Random Forest model is harnessed for this purpose, ensuring effective and precise classification.

3.1 BLOCK DIAGRAM



The image depicts a machine learning process for evaluating subjective responses, which is split into training and testing stages. During the training stage, data sets are gathered, preprocessed using normalization, and utilized to train a model with NLP. The model's effectiveness is then assessed using accuracy and loss measurements. In the testing stage, the trained model produces responses to inquiries, which are then appraised for quality and correctness, resulting in a final assessment score. This method guarantees that the model is properly trained and tested for precise subjective response evaluation.

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3.2 DEFINING RULES

1. **Data Preparation**:
- **Clean the Data**: Remove unwanted noise, such as punctuation and special characters.
- **Normalize the Data**: Convert text to lowercase and handle stop words to ensure consistency.

2. Tokenization:
- Use reputable libraries such as NLTK or spaCy.
- Break down text into manageable units like words or phrases.

3. Model Selection:
- Choose an appropriate Natural Language Processing model or algorithm based on the specific task (e.g., sentiment analysis, entity recognition, language translation).

4. Model Evaluation:
- Evaluate the model's performance using metrics like accuracy and recall.
- Ensure the model's effectiveness in practical real-world applications.

3.3 FORMULA

Cosine similarity is a metric used to measure how similar two documents or vectors are, irrespective of their size. It calculates the cosine of the angle between two vectors in a multi-dimensional space, providing a value between -1 and 1. A value of 1 indicates that the vectors are identical, 0 indicates that they are orthogonal (no similarity), and -1 indicates that they are diametrically opposite.

Formula for Cosine Similarity

The cosine similarity between two vectors A and B is defined as:

$$\text{cosine\_similarity}(\mathbf{A}, \mathbf{B}) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}$$

Where:

- $\mathbf{A} \cdot \mathbf{B}$ is the dot product of the vectors $\mathbf{A}$ and $\mathbf{B}$.
- $\|\mathbf{A}\|$ and $\|\mathbf{B}\|$ are the magnitudes (or Euclidean norms) of the vectors $\mathbf{A}$ and $\mathbf{B}$.

3.4 ALGORITHMS

3.4.1 NLP

"Within the scope of this paper, we have harnessed the power of Natural Language Processing (NLP) techniques to execute crucial text processing tasks. To initiate the process, we have employed tokenization, leveraging NLTK to disassemble a given sample text into individual words (tokens). This foundational step is vital in discerning the underlying structure of the text, which is crucial for subsequent analysis. Moving forward, we have utilized NER (Named Entity Recognition) with spaCy to meticulously identify and categorize named entities embedded within the text. These entities encompass a wide range of categories, including but not limited to individuals, organizations, and temporal expressions. By extracting structured information from unstructured text data, NER plays a pivotal role in infusing coherence and interpretability into the text.Proceeding with the preprocessing phase, we recognized the immense importance of preparing the text for more advanced analysis or the training of machine learning models. These preprocessing steps serve as the cornerstone for enabling the text to undergo more sophisticated analyses in the future.

Transitioning to the prediction phase, we have leveraged NLP techniques for text vectorization and similarity assessment. Our approach hinges on the employment of TF-IDF (Term Frequency-Inverse Document Frequency) vectorization to transform the input texts into numerical feature vectors. This transformation effectively captures the significance of words within the documents, thereby laying the groundwork for a more comprehensive understanding of the textual content.

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Furthermore, the utilization of TF-IDF vectorization paves the way for the application of cosine similarity, a foundational metric for gauging the resemblance between two vectors. This statistical measure computes the cosine of the angle between the two vectors, providing a quantitative assessment of text similarity. Notably, this metric proves particularly invaluable in scenarios where document comparison, plagiarism detection, or the identification of similar textual content is essential. In summation, the amalgamation of these NLP techniques equips us with the means to conduct meticulous text analysis and facilitate robust comparisons. The resulting capabilities are indispensable for a wide array of natural language understanding tasks, underscoring the pivotal role of NLP in deciphering and interpreting textual data."

IV. EXPERIMENTAL RESULT

A table showing the tokenized output of the sample text using NLTK's word tokenize() function.

Token Number	Token
1	Apple
2	Inc.
3	was
4	founded
5	by
6	Steve
7	Jobs
8	and
9	Steve
10	Wozniak
11	in
12	1976
13	.

Table 1: tokenized output of the sample text

Named Entity Recognition (NER) Results: Present a table summarizing the entities recognized by spaCy in the sample text.

Entity Text	Entity Label
Apple Inc.	ORG
Steve Jobs	PERSON
Steve Wozniak	PERSON
1976	DATE

Table 2 : **Named Entity Recognition (NER) Results**

- **Tokenization Results**: NLTK successfully tokenized the sample text into 13 tokens, including punctuation.
- **NER Results**: spaCy identified four entities in the sample text: "Apple Inc." (ORG), "Steve Jobs" (PERSON), "Steve Wozniak" (PERSON), and "1976" (DATE).

4.2 DATASET

The provided datasets encompass information on word counts of text files and question-answer pairs related to various articles. The first dataset, containing 165 entries, features two columns: "words," indicating the number of words in each file, and "file," specifying the file names. This dataset highlights the textual volume of different files. The second dataset, comprising 1,715 entries, includes six columns: "ArticleTitle," "Question," "Answer," "DifficultyFromQuestioner," "DifficultyFromAnswerer," and "ArticleFile." This dataset details question-answer pairs about various articles, with difficulty ratings from both the questioner and the answerer, and links these pairs to specific files. Together, these datasets can be used to analyze the relationship between text length and the complexity or nature of questions generated from the content.

4.3. COMPARATIVE STUDIES

- NLTK's word_tokenize() performed efficiently but without deep linguistic understanding, while spaCy's NER model excelled in recognizing entities accurately compared to traditional methods.

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4.4. RESULT ANALYSIS/ACCURACY

| Feature	Nltk Tokenization	|Spacy Ner Model
Performance	Accurately Segmented The Text	Provided Precise Labels For Entities
Strengths	Efficient Text Segmentation	- Robust Performance In Identifying Entities Like Persons, Organizations, And Dates
Limitations	Not Applicable	Occasional Misclassifications Of Entities Due To Context Ambiguity
Solutions	**Not Applicable**	Further Contextual Analysis - Domain-Specific Training

V. CONCLUSION

Assessing subjective answers using NLP involves evaluating open-ended responses to gauge their relevance, accuracy, and completeness. This process commonly entails using various natural language processing techniques, including tokenization, named entity recognition (NER), sentiment analysis, and text similarity measures. By utilizing tools like NLTK and spaCy, educators and automated systems can delve into the semantic content of answers, pinpoint key entities and concepts, and compare them with expected responses. This method allows for a comprehensive evaluation that goes beyond simple keyword matching, providing a deeper understanding of the respondent's knowledge and the context of their answers. In general, NLP-based subjective answer assessment offers a more adaptable and robust approach to evaluating complex qualitative responses in educational and other contexts.

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