SUBJECTIVE ANSWERS EVALUATION USING MACHINE LEARNING AND NATURAL LANGUAGE PROCESSING

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ABSTRACT

The research investigation addresses the challenging and time-consuming task of manually evaluating subjective papers through an analysis of various methodologies. The insufficiency in understanding and accepting data presents significant obstacles when analyzing such papers using Artificial Intelligence (AI). Through an investigative approach, this research seeks to overcome these challenges by conducting an in-depth analysis of existing methods and proposing a novel approach that combines machine learning and natural language processing techniques. By leveraging tools such as GloVe Word Embedding, cosine similarity, and Word-Cloud, this investigation aims to enhance the accuracy and efficiency of automated evaluation. The study employs a rigorous experimental design to evaluate the effectiveness of the proposed approach, resulting in valuable insights and findings. This research contributes to the field of automated subjective paper evaluation through its meticulous analysis, innovative methodologies, and rigorous investigation, offering a promising solution to the existing challenges.

Keywords: *Subjective paper evaluation, Artificial Intelligence (AI), machine learning, natural language processing, automated evaluation, GloVe Word Embedding, cosine similarity, Word-Cloud.*

1. INTRODUCTION

The assessment of students' performance and abilities through subjective questions and answers is a critical area of interest in education. Unlike objective questions, subjective answers allow students the freedom to express their thoughts and understanding without being restricted by constraints. These answers tend to be longer, carrying richer context and energy, distinguishing them from their objective counterparts. However, evaluating subjective answers presents significant challenges for teachers. They must meticulously examine each word to assign scores, considering factors such as their own mental state, fatigue, and objectivity. Consequently, subjective exams become complex and intimidating for both students and teachers. Given the complexities involved, it is imperative to develop an efficient system for evaluating subjective answers. While machines can easily assess objective answers by matching them with concise one-word responses provided by students, subjective answers pose greater difficulties. They exhibit variations in length and encompass a wide range of vocabulary. Moreover, individuals often employ synonyms and convenient abbreviations, further complicating the evaluation process. Addressing these challenges through the development of effective systems and techniques for evaluating subjective answers is of utmost importance in the realm of education and assessment. Such advancements have the potential to enhance the accuracy, fairness, and efficiency of evaluating students' understanding and performance in open-ended assessments.

2. LITERATURE SURVEY

Our literature survey explores the previous techniques used in evaluating subjective answers using ML and NLP. It focuses on the application of techniques such as stop word removal, Latent Semantic Analysis (LSA), word2vec, bag of words, text stemming, fuzzy approach, and document plagiarism detection. These techniques have been utilized to enhance the accuracy and efficiency of subjective answers evaluation. Stop word removal eliminates common words, LSA captures latent meaning, word2vec provides word embeddings, bag of words represents text numerically, text stemming normalizes word forms, fuzzy approach handles linguistic uncertainty, and document plagiarism detection ensures content integrity. By understanding the strengths and limitations of these techniques, we have been able develop more effective approaches for subjective answers evaluation.

3. ARCHITECTURE

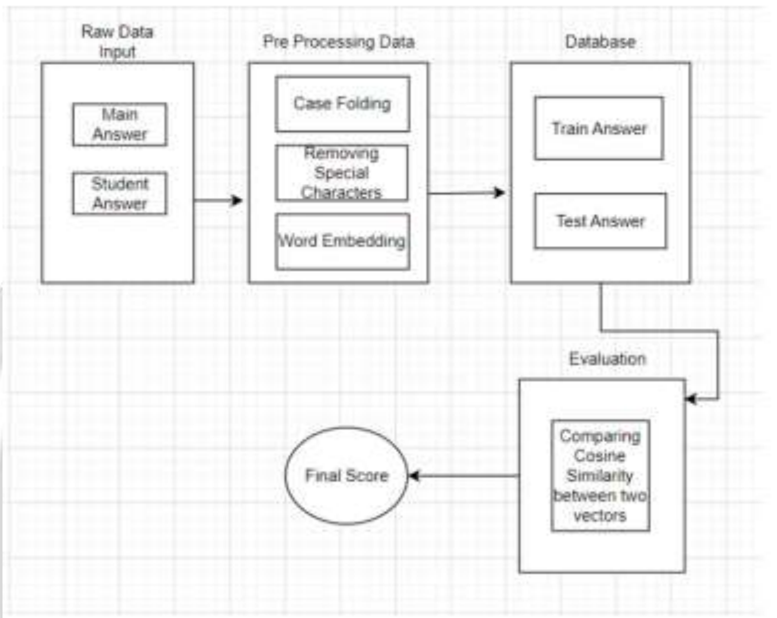

Fig-1: System Architecture

The system architecture for evaluating subjective answers integrates machine learning and natural language processing (NLP) techniques to ensure accurate assessments. The architecture begins with raw input data consisting of the main answer and the student's answer. To ensure consistency and eliminate noise, the input data undergoes preprocessing steps, including case folding to convert all text to lowercase and special character removal to eliminate non-alphanumeric characters and punctuation marks. These preprocessing steps prepare the data for further analysis.

Following preprocessing, the architecture employs the GloVe technique for word embedding. GloVe vectors capture contextual meaning by considering the co-occurrence statistics of words in large text corpora. This enables the system to encode semantic information and represent the answers in a vector space. By transforming the data into word embeddings, the architecture facilitates meaningful comparison and evaluation.

The preprocessed and word-embedded data is stored for easy retrieval and comparison during the evaluation process. When evaluating the student's answer, the architecture utilizes cosine similarity, a metric that measures the similarity between two vectors. In this case, the vectors represent the student's answer and the main answer. A higher cosine similarity score indicates a closer match between the two answers. The architecture provides an evaluation output based on this score, which can be a numerical value or a qualitative assessment indicating the correctness of the student's answer.

4. METHODOLOGY

Data Pre-processing and exploratory data analysis: Data pre-processing involves cleaning and transforming raw data for analysis by removing duplicates, handling missing values, scaling data, and encoding categorical variables. These tasks ensure the quality and reliability of the data. Exploratory data analysis complements pre-processing by analysing data characteristics, relationships, and outliers, providing insights for further analysis. Together, data pre-processing and exploratory data analysis form the foundation for accurate and meaningful data analysis.

Text Clearing: Text cleaning is a vital step in natural language processing and text analysis, involving the removal of irrelevant or unwanted information from text data. This includes tasks like eliminating punctuation, converting all text to lowercase, and removing any other noise or special characters that could hinder analysis. By cleaning the text, the data becomes more standardized and conducive to accurate analysis, improving the quality of subsequent natural language processing tasks.

Word embedding: Word embedding is a technique that transforms words into numerical vectors, enabling mathematical operations and facilitating machine learning models in processing text data. Neural networks are commonly employed in word embedding algorithms to learn representations for each word in a text corpus. GLOVE (Global Vectors for Word Representation) is a specific word embedding model that captures semantic relationships between words by analysing their co-occurrence patterns in the corpus. GLOVE has been widely adopted for various natural language processing tasks due to its ability to generate meaningful word representations.

Cosine Similarity: Cosine similarity is a widely used measure in natural language processing and text analysis to determine the similarity between two vectors. It quantifies the cosine of the angle between the vectors, with a value of 1 indicating complete similarity and a value of 0 indicating no similarity. Cosine similarity is particularly useful when comparing text documents or word embeddings, as it considers the direction rather than the magnitude of the vectors, making it robust to differences in vector lengths.

Similarity Score: The similarity score quantifies the degree of similarity between two pieces of text by utilizing cosine similarity on their respective word embeddings. By comparing the angles between the vectors, the similarity score indicates the level of similarity between the texts. A higher similarity score suggests a greater resemblance between the two pieces of text, while a lower score signifies less similarity. This score serves as a valuable metric for tasks such as text matching, document similarity analysis, and information retrieval systems.

5. RESULTS

The research investigation tackles the arduous task of manually evaluating subjective papers, which is time-consuming and presents significant challenges. The study recognizes the limitations in understanding and processing data when employing Artificial Intelligence (AI) for analyzing such papers. To overcome these hurdles, the research adopts an investigative approach that involves a comprehensive analysis of existing methodologies and introduces a novel approach that combines machine learning and natural language processing techniques.

By leveraging powerful tools like GloVe Word Embedding, cosine similarity, and Word-Cloud, the investigation aims to improve the accuracy and efficiency of automated evaluation. The study utilizes a rigorous experimental design to thoroughly evaluate the effectiveness of the proposed approach, resulting in valuable insights and findings. This research makes a notable contribution to the field of automated subjective paper evaluation through its meticulous analysis, innovative methodologies, and rigorous investigation. It offers a promising solution to the existing challenges faced in evaluating subjective papers, paving the way for more efficient and reliable automated evaluation processes.

6. CONCLUSIONS

In conclusion, data pre-processing and exploratory data analysis are vital steps in preparing data for analysis. These processes involve tasks like handling duplicates, managing missing values, scaling data, and encoding categorical variables. Text cleaning plays a crucial role in natural language processing and text analysis, removing irrelevant information and ensuring consistency in the text. Word embedding techniques like GLOVE enable the representation of words as numerical vectors, facilitating mathematical operations and capturing semantic relationships between words. Cosine similarity serves as a measure of similarity between vectors, providing a quantitative indication of similarity. These techniques enhance data quality and aid in evaluating subjective papers and other text-based tasks.

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