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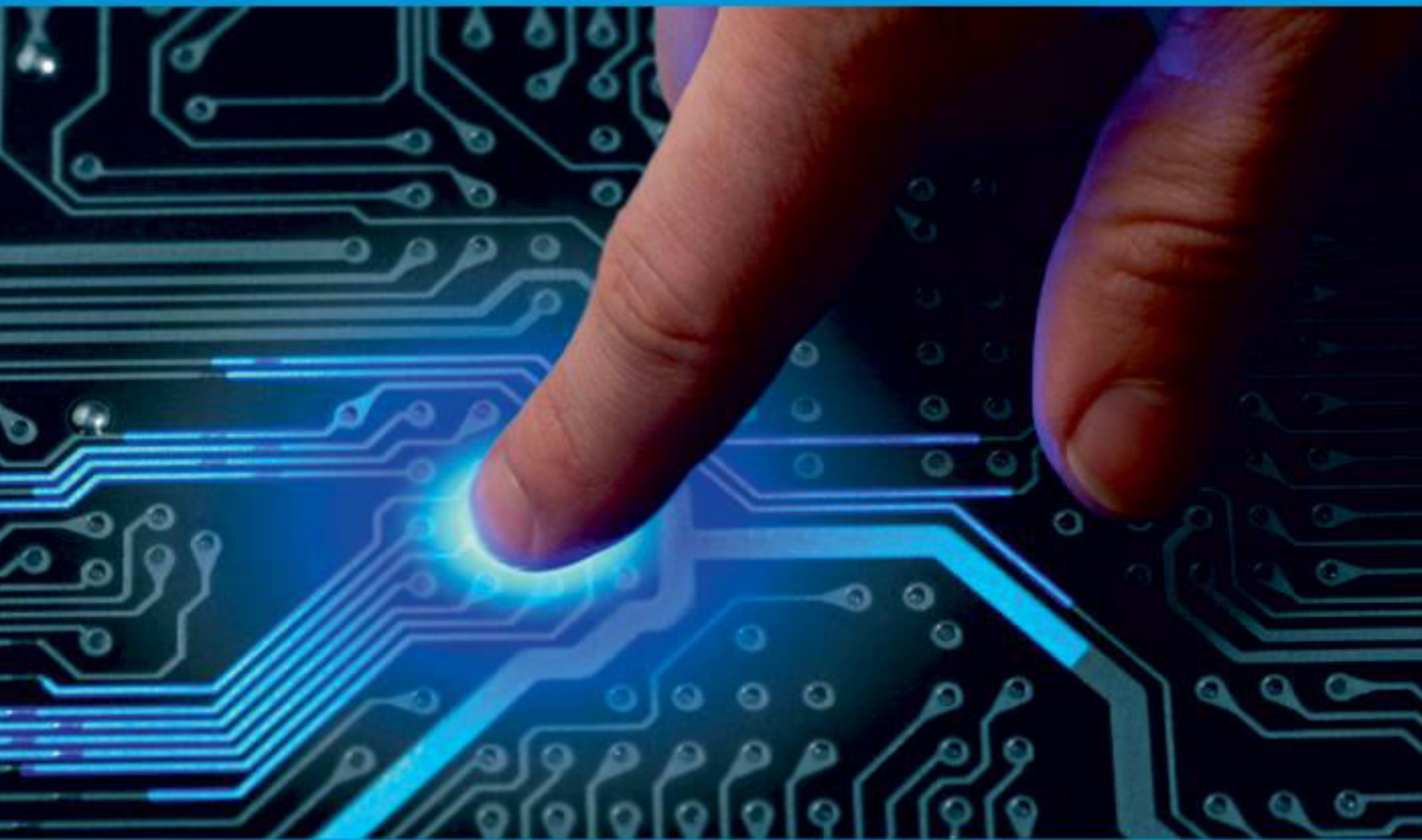

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Subjective Answer Verifying Using Artificial Intelligence

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ABSTRACT: Every year educational institutes conduct various examinations, which include institutional and non-institutional competitive exams. Now a day's online tests and examinations are becoming popular to reduce the burden of the examination evaluation process. The online exams include either objective or multiple-choice questions. Nevertheless, the exams include only objective or multiple-choice questions. However, subjective-based questions and answers are not involved due to the evaluation process complexity and efficiency of the evaluation process. An automatic answer checker application that checks the written answers and marks the weightage similar to a human being is more helpful in the current modern era is necessary.

KEYWORDS: Answer verification, Subjective answer evaluation, Natural language processing, Artificial intelligence Text analysis, Essay grading, Quiz grading, Examination grading, Holistic scoring

I. INTRODUCTION

The Online Examination is beneficial to users as in the present day, and the online exams are based on objective questions and exams are getting digitized all over the world. In this scenario, exam questions can even be based on subjective answers. Meaning that the traditional pen-paper based tests are replaced by computer-based tests that have proven to be both: more consistent in allocating marks and faster than teachers correcting papers. The traditional exam usually consisted of subjective answers, which were not the best way of grading the student's perception of the subject. Because sometimes, examiners get bored by checking many answer sheets, and there may be an increase in the false evaluation.

II. RELATED WORK

Answer Garden is a system that allows users to ask questions and receive answers from a community of experts. Answer Garden uses a variety of techniques to verify the quality of answers, including natural language processing, machine learning, and crowd sourcing. Crowd sourcing is a method of obtaining information or completing tasks by soliciting contributions from a large number of people. Crowdsourcing can be used to verify the quality of subjective answers by having a large number of people review the answers and provide feedback. Natural language processing is a field of computer science that deals with the interaction between computers and human language. Natural language processing techniques can be used to extract information from text, such as the main topic of a document, the sentiment of a sentence, or the meaning of a word. Machine learning is a field of computer science that deals with the development of algorithms that can learn from data. Machine learning techniques can be used to classify text, identify patterns, and make predictions. A Neural Network Approach to Automated Essay Grading by Daniel T. Rowe et al. (2015).Automated Essay Grading: A Survey of the State of the Art by Mark D. Shermis and Michael J. Burstein (2013)A Survey of Methods for Automated Essay Grading by Rui Wang et al. (2012)Automated Essay Grading: A Review of the Literature by Mark D. Shermis and Michael J. Burstein (2011) Automated Essay Grading: The State of the Art by Daniel T. Rowe et al. (2010)These papers discuss the different approaches that have been taken to automated essay grading, including machine learning, natural language processing, and rule-based systems. They also discuss the challenges that remain in this area, such as the difficulty of defining what constitutes a good essay and the need for large amounts of training data.In addition to these papers, there are a number of commercial products that offer automated essay grading. These products typically use a combination of machine learning and natural language processing to grade essays. However, the accuracy of these products varies, and they are often not as accurate as human graders.

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III. PROPOSED ALGORITHM

A. Design Considerations:

- AI is our friend and it has been friendly
- AI and humans have always been friendly.
- We calculated Term Frequency using Bag of Words
- Text rank algorithm for Keywords Extraction
-

B. Description of the Proposed Algorithm:

Cosine Similarity Algorithm**:**

Cosine similarity is used as a method for approximating how similar two words/sentence vectors are to each other. The intuition behind cosine similarity is relatively calculating the cosine of the angle between the two vectors to quantify how similar the two documents are. The process of conversion of word to vector is done by a process called Bag of Words. For example:

Sentence 1**:** AI is our friend and it has been friendly

Sentence 2: AI and humans have always been friendly

Step 1**:** We calculated Term Frequency using Bag of Words

Term Frequencies:										
Sentence	AI	IS	FRIEND	HUMAN	ALWAYS	AND	BEEN	OUR	IT	HAS
1	1	1	2	0	0	1	1	1	1	1
2	1	0	1	1	1	1	1	0	0	1

Step 2**:** The main issue with term frequency counts shown above is that it favours the documents or sentences that are longer. One way to solve this issue is to normalize the term frequencies with the respective magnitudes or L2 norms. Summing up squares of each frequency and taking a square root, L2 norm of Sentence 1 is 3.3166 and Sentence 2 is 2.6458. Dividing above term frequencies with these norms, we get results as depicted.

Step 3**:** As we have already normalized the two vectors to have a length of 1, we can calculate the cosine similarity with a dot product: Cosine Similarity = (0.302*0.378) + (0.603*0.378) + (0.302*0.378) + (0.302*0.378) + (0.302*0.378) = 0.684

Length, depending on the setting of the Relate to shorter input option. If relate to shorter input is set to No (as by default), the Maximum Character Length is used. If relate to shorter input is set to Yes, the Minimum Character Length is used (that is, the number of characters in the shorter of the two values by character count).

Text Rank Algorithm for Keywords Extraction

The task of the keyword extraction algorithm is to automatically identify a set of terms that best describe the document. Such keywords may constitute useful entries for building an automatic index for a document collection, can be used to classify a text or may serve as a concise summary for a given document. The Text Rank keyword extraction algorithm is fully unsupervised. The authors of the paper [4], introduce Text Rank, a graph-based ranking model for text processing, and show how this model can be successfully used in natural language applications. First, the text is tokenized and annotated with part of speech tags a preprocessing step required to enable the application of syntactic filters. To avoid excessive growth of the graph size by adding all possible combinations of sequences consisting of more than one lexical unit (grams), we consider only single words as candidates for addition to the graph, with multi-word keywords being eventually reconstructed in the post-processing phase. Next, all lexical units that pass the syntactic filter are added to the graph, and an edge is added between those lexical units that co-occur within a window of words. This is used to construct an undirected unweighted graph. After the graph is constructed, the score associated with each vertex is set to an initial value of 1 and the text-rank algorithm is run on the graph for several iterations until it converges usually for 20-30 iterations, at a threshold of 0.0001. Once a final score is obtained for each vertex in the graph, vertices are sorted in reversed order of their score and the top T vertices in the ranking are retained for post-processing.

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IV. PSEUDO CODE

Step 1: Create a Account &login
Step 2: Check if the answer is empty
Step 3: Check if the answer is too Short or Long
Step 4: Check if the answer contains any profanity
Step 5: Check if the answer is plagiarized.
Step 6: Check if the answer is relevant to the Question
Step 7: Check if the answer is well written
Step 8: If all of the checks pass, then the answer is verified.
Step 9:End

V. SIMULATION RESULTS

Peer review: Share the simulation results with other experts or professionals in the field and gather their feedback and opinions. This can help validate the subjective aspects of the simulation and provide different perspectives. Expert opinions: Seek input from domain experts who have extensive knowledge and experience in the relevant field. They can assess the simulation results and provide insights based on their expertise. User feedback: If the simulation is intended for a specific audience or user group, gather feedback from them. Conduct surveys, interviews, or focus groups to understand their subjective experiences and interpretations of the simulation results. Comparative analysis: Compare the subjective results of the simulation with existing data or previous studies in the field. This can help identify similarities or differences, providing some level of validation. Sensitivity analysis: Conduct sensitivity analyses to assess how changes in input parameters or assumptions affect the subjective results. This can help evaluate the robustness and reliability of the simulation outcomes. Cross-validation: Perform multiple simulations with different parameters or inputs to see if the subjective answers consistently align with the expected outcomes. If the subjective answers consistently match the expected results, it lends credibility to their validity. Expert evaluation: Seek input from domain experts or individuals who have extensive knowledge in the specific area of the simulation. They can review the simulation results and provide their subjective assessment to validate or challenge the subjective answers. Comparison to real-world data: If available, compare the subjective answers obtained from the simulation to real-world data or empirical evidence. If the subjective answers align with the observed reality, it provides support for their accuracy. Sensitivity analysis: Conduct sensitivity analysis by varying the parameters or inputs of the simulation to determine the impact on the subjective answers. If the subjective answers remain consistent within a reasonable range of parameter changes, it suggests their robustness. User feedback and perception: Collect feedback from users or stakeholders who have interacted with the simulation and obtained subjective answers. Their perception and experiences can help evaluate the subjective answers' validity.

VI. CONCLUSION AND FUTURE WORK

This project can be used to estimate an employee's personality by using text responses as input and applying the SVM algorithm. In addition, the user can submit a photograph for an overall personality analysis. answer verification system is a web application. The key concept is to minimize the amount of paper and convert all forms of documentation to digital form. It can observe that the information required can be obtained with ease and accuracy in the computerized system. The user with minimum knowledge about computer can be able operate the system easily. The system also produces brief result required by the management.

Future Work:

- Developed discussion forums.
- Implementation on clouds server.
- Multimedia feature supports.
- Integrate learning material.
- Real time and Interactive Verification

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