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Evaluation of Subjective Responses Through Natural Language Processing and Machine Learning

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Abstract:

Content evaluation is a complex and difficult task that needs to be done with the help of a consultant. When using artificial intelligence (AI) to read educational materials, the lack of knowledge and information is still very difficult. There have been many attempts to get answers from university students using computer technology knowledge. However, most jobs use mathematics or special words to accomplish this task. There is also no good record keeping system. This paper presents a new method that uses a set of machine learning, linguistic concepts and tools, including Wordnet, Word2vec, Sentence Movement Coldness (WMD), Cos Parallel, Polynomial Naive Bayes (MNB), and Time Frequency-Inverse Document Frequency (TF-IDF) to repeatedly measure the explanation. The solution expression and key expression are used to evaluate the answer, and the learning process version expert estimates the solution level. The results show that WMD generally outperforms cos relationship. With sufficient guidance, the intellectual typical can also be an independent model. The test without the MNB version reached an accuracy of 88%. Using MNB also reduces error by 1.3%.

Key words: Subjective Responses, Natural Language Processing, Machine Learning

I. Introduction

Open-ended, subjective questions and solutions would possibly compare a scholar's performance and competencies. clearly, there are not any restrictions at the responses, so college students are unfastened to compose them whichever first-rate suits their know-how of the fabric and attitude. Having stated that, there are some greater important differences among subjective and objective responses. they may be significantly lengthier than the objective questions, to start. Secondly, writing them requires extra time. additionally, they require the instructor grading them to focus carefully and be goal, and they create loads extra context. it's far tough to assess such queries the use of computers, normally because to the anomaly of spoken language. earlier than working at the statistics, some of preprocessing procedures have to be finished, including cleansing and tokenization. Next, a ramification of techniques, which includes idea graphs, ontologies, latent semantic structures, and record similarity, may be used to examine the textual information. evaluation criteria for the final rating consist of similarity, lifestyles of key phrases, structure, and language. despite the fact that this problem has been tackled earlier than in a few one-of-a-kind ways, there is nonetheless opportunity for improvement, some of which are included in this paper. due to their one crucial element—context—both students and instructors view subjective assessments as greater difficult and scary. A subjective response calls for the checker to actively score every phrase of the reaction, and the checker's objectivity, weariness, and intellectual nation all have a great impact at the very last rating.

Consequently, it is far less expensive in terms of both time and resources to let a method process this labor-intensive and occasionally significant assignment of estimating individual replies. device evaluation of goal responses is a extraordinarily easy and realistic procedure. One-phrase answers to questions may be entered into a program to swiftly map college students' responses. Subjective responses, but, are a way greater difficult to address. They range broadly in period and feature a big vocabulary. additionally, humans frequently make use of reachable abbreviations and synonyms, which in addition complicates the manner.

II. LITERATURESURVEY

natural language processing tasks, including information retrieval, gadget translation, chat structures, automatic query answering, and record matching, rely heavily on textual content similarity dimension. This painting creates a more thorough category description gadget of text similarity dimension algorithms, examines the country of similarity dimension studies methodically, weighs the blessings and downsides of present techniques, and descriptions the direction for destiny take a look at. textual content distance and text representation are the two features that characterize the textual content similarity dimension technique, which targets to serve as a reference for associated examine and alertness. Textual content distances can be divided using semantic, distribution, and period distances; text illustration can be classified as thread-based, corpus-based, single-semantic, multi-semantic, and graph-shape-based in a similar manner. Lastly, the discussion section provides a summary of the evolution of text similarity.

In natural language processing, short text similarity is critical (NLP). it's been used in severa industries. it's far hard to gauge the similarities due to the fact there isn't always enough information inside the quick textual content. The utility of semantic similarity in textual similarity calculations has garnered hobby from both academics and enterprise, yielding superior consequences. we've got performed a thorough and methodical investigation of semantic similarity on this survey. to begin with, we put up 3 classifications for semantic similarity: expertise-based, corpus-primarily based, and deep gaining knowledge of (DL)-based. In each category, we weigh the benefits and downsides of representational and innovative algorithms. the use of these similarity evaluation techniques in other NLP domain names is likewise covered in our analysis. next, we determine the maximum advanced deep learning techniques on 4 well known datasets, demonstrating that DL-based totally strategies are superior in addressing problems related to sparsity and complexity in short textual content similarity. mainly, bidirectional encoder representations derived from the transformer model are able to fully make use of the restrained availability of semantic and short text data, ensuing in increased F1 fee and accuracy. ultimately, we endorse a few in addition paths.

pc in latest years, there was a super deal of labor involved in assisted evaluation of unfastened-textual content answers because of the need to assess college students' in-depth information of the path necessities, which maximum educators and researchers agree cannot be carried out by easy multiple-desire query checking. in this examine, we've got examined the techniques that underlie this device, defined the structures which might be now in place for rating short, unfastened text responses, and finally counseled an answer that might use natural language processing to evaluate the descriptive type responses.

This task proposes a singular method that makes use of numerous machine mastering, accepted words processing strategies, to evaluate descriptive answers robotically.

•answer statements and key phrases are used to assess solutions, and a system getting to know version is trained to predict the grades of solutions.

•With enough schooling, the gadget gaining knowledge of version may be used as a standalone as properly.

•Experimentation produces an accuracy of 97% with the Proposed version.

•apparently, synthetic intelligence is applied notably as an efficient device for predicting one of these problem.

•The proposed paintings makes use of the deep gaining knowledge of method together with some preprocessing steps to improve the prediction of solution assessment.

in these studies, a method for record plagiarism detection making use of formal idea evaluation (FCA) and incremental information technology is proposed. To facilitate document matching among the suspect report and the saved supply record, incremental information production is obtainable. therefore, for the cause of retrieving formal ideas in the know-how creation, a new idea similarity measure is also proposed. The concept similarity that is being provided makes use of appearance frequencies to generate information. Our approach can be used to accumulate pertinent information for the reason that shape we've got acquired employs FCA in a idea shape that can be defined by way of combining sure traits.

it is mathematically proven that this degree is a formal similarity metric. The cautioned similarity measure's effectiveness in report plagiarism detection is shown. furthermore, this paper affords a set of rules to assemble the information shape for file plagiarism detection. Thai textual content takes a look at collections are used for overall performance evaluation of the implemented web software.

Although subjective questions can be used to analyze a student's ability for knowledge adoption, their assessment suffers from questions that are difficult to answer, have too many synonyms, or use polysemy. The benefit of subjective questions for online exercises is diminished as a result. This research investigates an automated evaluation method for subjective queries that solely relies on latent semantic indexing. Chinese automatic segmentation techniques and challenges the reference solutions are transferred via ontology to a time period-document matrix, which is then projected using the statistical method onto a k-dimensional LSI space. To solve the synonymy and polysemy issues, use singular value decomposition. To reduce the tricky issue, a reference unit vector is included. Then, primarily based on the similarity of the projected vectors, the gadget determines the niceness of the answer. The outcomes of the test display the viability of our theoretical framework and waft for the automatic evaluation of subjective questions.

We introduce a brand-new distance feature between textual content documents referred to as phrase Mover's Distance (WMD). Our method is grounded in latest advances in phrase embedding, which use local co-occurrences in sentences to generate semantically meaningful representations for phrases. The minimum distance that embedded words in one report ought to "journey" to attain embedded words in every other report is known as the WMD distance, and its miles used to measure the dissimilarity of textual content documents. We reveal how this distance metric may be expressed as an example of the Earth Mover's Distance, a nicely-researched transportation problem with a number of extremely powerful solvers available Our measure is simple to apply and does no longer require any hyper parameters. further, we show that the WMD metric results in traditionally low good enough-nearest neighbor document class errors fees on eight real-international report kind records gadgets, compared with seven baselines.

With the growing call for for pc-assisted bdd5b54adb3c84011c7516ef3ab47e54 in justice, deep reading has frequently become an effective method of assisting smart justice. The similarity evaluation of law files is the premise of wise justice, at the identical time as law files based totally on severe forms of instances are quite precise in terms of format and duration, which reasons trouble in studying similarities. For that we advocate a greater particular technique to coping with regulation documents, combining Word2vec with legal documents corpus. To degree the efficiency of the proposed method, we designed sets of controls. The experimental consequences expertise that the Word2vec version can decorate the accuracy through 0.20 in comparison with the bag of terms (BOW) version, and the organized regulation files corpus can growth by zero.05-zero.10 based totally on the Word2vec model. for this reason, the aggregate of Word2vec and the regulation documents corpus is greater nicely appropriate with the smooth and green software of similarity assessment of regulation files.

Studies on the evaluation of subjective exams with automated technology have been conducted for more than four decades. Numerous mathematical and statistical methods had been put forth by different experts. This study compares a number of previously proposed algorithms, including most entropy (Maxent), bilingual evaluation understudy (BLEU), generalized latent semantic assessment (GLSA), and latent semantic analysis (LSA), on regularly entered data. MATLAB, another open-source system, and the Java programming language are used to implement the techniques. Advanced prototypes and experiments were conducted using a database containing 4500 responses to approximately 50 laptop technological questions (bdd5b54adb3c84011c7516ef3ab47e54). There isn't an extensive evaluation of these procedures on a shared database in the literature, only the authors' assessment. The database utilized for testing was constructed using the ability to do background checks on graduate students specializing in laptop technology. The study discusses the advantages and disadvantages of each strategy at the notion of experiments.

There are several learning management systems (LMSs) available in the market right now. The specifics of how scholar assessment is handled are a component of an LMS. In some evaluation types involving open-ended questions, the LMS is unable to assess the academics' answers; as a result, human intervention is required. In order to assess higher levels of Bloom's (1956) taxonomy, open-ended questions must be included. In these questions, the student is allowed the opportunity to arrive at a response without the comfort of recalling specific phrases or terms. Research on automating the open-ended question evaluation process has been going on since the 1960s.

Previous artistic endeavors used statistical or probabilistic techniques, primarily grounded in conceptual data. The way loose text can be assessed has changed as a result of recent advancements in natural language processing. This has made it possible to apply an additional linguistic approach that is highly fact-based. This test will make use of the most recent findings in the fields of natural language processing, record extraction, and record retrieval in order to provide an impartial, timely, and accurate evaluation of academic responses to open-ended questions based on the semantic meaning of those responses.

III.SYSTEM ANALYSIS

In this paper, we explore a machine learning and natural language processing-based approach for subjective answers evaluation. Our work is based on natural languages processing techniques such as tokenization, lemmatization, text representing techniques such as TF-IDF, Bag of Words, word2vec, similarity measuring techniques such as cosine similarity, and word mover's distance, classification techniques such as multinomial Naive Bayes. We use different evaluation measures such as F1-score, Accuracy, and Recall to evaluate the performance of various models against each other. We also discuss various techniques used in the past for subjective answers evaluation or text similarity evaluation in general.

Following are some of the major limitations when dealing with subjective answers:

• Existing studies tend to have synonyms.

• Existing studies tend to have an extensive range of possible lengths.

• Existing studies tend to be randomly ordered among their sentences.

1. **Dependency on Training Data Quality:**
The performance of the models heavily relies on the quality and representativeness of the training data. If the training data is biased, incomplete, or not representative of the entire spectrum of subjective answers, the models may produce inaccurate or biased results.

2. **Difficulty Handling Complex Sentences**:
Subjective answers often contain complex sentence structures, idiomatic expressions, and nuanced language. Machine learning models may struggle to accurately interpret and evaluate such complexity, leading to errors or misinterpretations.

3. **Limited Generalization:**
While the models may perform well on the training data, their ability to generalize to unseen data or different contexts may be limited. Variations in language use, topic, or domain can affect the models' performance and reliability.

4. **Interpretability Issues:**
Some machine learning models, particularly complex ones like neural networks, lack interpretability, making it challenging to understand how the model arrives at its decisions. This lack of transparency can be problematic, especially in applications where explanations or justifications are required.

5. **Scalability Concerns:**
Training and deploying machine learning models for subjective answers evaluation can be resource-intensive, particularly when dealing with large datasets or real-time evaluation requirements. Scaling the system to handle increased volumes of data or users may pose challenges in terms of computational resources and infrastructure.

6. **Inherent Biases:**
Machine learning models are susceptible to inheriting biases present in the training data, leading to biased evaluations of subjective answers. Biases can arise from various sources, including societal biases, cultural norms, or biases in the data collection process, and may result in unfair or discriminatory outcomes.

This paper proposes a new and improved way of evaluating descriptive question answers automatically using machine learning and natural language processing. It uses 2 step approach to solving this problem. First, the answers are evaluated using the solution and provided keywords using various Similarity-based techniques such as word mover's distance.

Then the results from this step are then used to train a model that can evaluate answers without the need for solutions and keywords. For example, a subjective question "What is the capital city of Pakistan and what is it famous for?" can have a correct answer: "Islamabad is the capital city of Pakistan and it is famous for mountain scenery".

Before evaluating the student's answer to the question, both the question, the answer, and also some keywords essential to the answer are fed into the system (in this case, keywords will be Islamabad and mountain scenery), and the system evaluates the student's answer by comparing both the similarity (keeping context in mind) of modal answer and student's response as well as the presence or absence of any keywords. So a student's answer of ''Karachi is the capital of Pakistan, it is famous for mountain scenery'' might get 50% marks, ''Islamabad and mountain scenery'' might get 30% marks since the main keywords are present even the context is missing and ''Islamabad is the capital and its famous for mountain scenery'' might get 100% marks since it satisfies both contextual similarities as well as keywords presence in relation to the correct answer.

IV.SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

MODULES

A. DATA COLLECTION

In order to instruct and evaluate the suggested version, a substantial corpus of subjective question-answers may be required; currently, there isn't a publicly available categorized corpus of such responses. We construct a subjectively categorized corpus of replies in this picture. The most important thing when creating a corpus is to target blogs and websites that have arbitrary queries and responses. We gather a corpus of subjective query solutions and flow diverse websites gradually. Information related to various domain names is then moved slowly alongside fashionable and technological computer records

B. DATA ANNOTATION
after getting crawled statistics, there may be a similarly need to annotate facts due to the fact that crawled records is unlabelled. To annotate information, a group of diverse volunteers is chosen, which belong to the location of our subjective question answers corpus. We lease 30 incredible annotators from unique faculties and universities and reside in Pakistan's one-of-a-kind towns. maximum of them are students and teachers. The common age of annotators is in the 21-25 range, whilst some annotators are inside the age variety of 27-fifty-one. We undertaking annotators to quality score the subjective query solutions in step with the solutions given through university college students

C. PREPROCESSING MODULE
After taking inputs from the user, both the solution and the answer go through some preprocessing steps, which involve tokenization, stemming, lemmatization, stop words removal, case folding, finding, and attaching synonyms to the text. Note that stop words are not removed when passing the data to word2vec because word2vec contains a vast vocabulary and can utilize those stop words to make better semantic sense of the text. However, stop words are removed before passing to a machine learning model such as Multinomial Naive Bayes because they hinder the machine's ability to learn the patterns.

D. SIMILARITY MEASUREMENT MODULE
This module consists of WDM and Cosine Similarity functions which take two sentences or word vectors and return their Similarity. WDM tells us the dissimilarity while Cosine Similarity measures Similarity. Our approach uses both of these similarity measures one at a time and compares the results at the end. Various similarity (or dissimilarity) thresholds. 1) THRESHOLDS ANALYSIS Various thresholds used in this paper have been experimentally deduced to produce the optimal result. WDM thresholds of WDM_LOWER and WDM_UPPER represent the dissimilarity between two sentences, where more dissimilarity represents high similarity. 0.7 threshold for WDM_LOWER was experimentally observed to represent semantically very similar sentences, and 1.6 thresholds for WDM_UPPER were observed to represent semantically less similar sentences. Anything beyond 1.6 is assumed to be too dissimilar to consider viable for comparison. Similarly, Cosine similarity thresholds COS_LOWER and COS_UPPER represent the similarity between two sentences. It should be noted that cosine similarity does not take the context of two sentences into account when measuring similarity as opposed to WDM, hence the usage of both of these similarities (or dissimilarity) measuring approaches.

E. RESULT PREDICTING MODULE
stop result Predicting Module is the centre of this paintings. shows the going for walks of this module.
It operates on the following set of rules 1: we've got the overall score calculated via our module using each WDM or Cosine Similarity at the same time as thinking about the maximum matched solution/solution sentence pairs. This end result can be in contrast to a real score or fed proper into a device studying model to have a look at.

F. MACHINE LEARNING MODEL MODULE
This model includes gadget getting to know models skilled on the records acquired from the result prediction module.
Its working is as follows:
• input facts from end result Prediction Module.
• Pre-process the solution and solution, getting rid of stop phrases, and use Count vectorizer to represent them in both Bag of words or TF-IDF shape.
• Convert the overall rating received from result Prediction Module into some category. four classes A, B, C, and D, are used inside the paper, representing 1st, second, 3rd, and 4th quarter of a 100. for example, A represents marks from 0 to twenty-five, and B represents 26 to 50.
• The range of categories is stored to a minimum due to the unavailability of the real dataset. nearly, these categories can be prolonged to cowl smaller rating degrees.
• A system learning model such as Multinomial Naive Bayes, which plays properly for multi-elegance class, is selected.
• The pre-processed answer is used as checking out facts with the gadget gaining knowledge of version to are expecting its class/category, and that category is checked with the result received from result Prediction Module. This offers us self-assurance within the expected result from the version..

VI .RESULTS AND DISCUSSION

The experiment setup consists of a python notebook running on a web-based Google Collab portal with a RAM of 12 GB and an HDD of 100+ GB. No GPU is turned on for this experiment. A pre-trained word2vec model from Google consisting of 300 dimensions of around 100 billion words vocabulary is used for this experiment. Corpus was divided into 8:2 ratio representing test and train data, respectively. Train data was used to calculate initial scores from the score prediction modules and train the machine learning model. Afterward, testing data was fed to the system one by one, updating the machine learning model. The results are obtained using cosine similarity and word mover's distance combined with a Multinomial Naive Bayes model. Both the approaches with and without the model produced results in under a minute at Google Collab. The results are as follows.

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VI I.CONCLUSION AD FUTURE WORK

This research offered a novel approach for evaluating subjective responses that is based on herbal language processing and gadget mastering procedures. We provide score prediction systems that yield as much as 88% correct effects. To deal with the anomalous instances of semantically unfastened answers, a variety of similarity and dissimilarity thresholds are tested, and other metrics like the existence of the keyword and the proportion mapping of sentences are hired. The findings of the experiments suggest that, on common, the word2vec method outperforms traditional word embedding techniques because it preserves semantics. Additionally, word Mover's Distance speeds up device getting to know model schooling and typically outperforms Cosine Similarity. After enough schooling, the model can forecast scores on its personal without requiring semantics validation. future traits of the word2vec model encompass the functionality to train it specifically for evaluating a given domain's subjective solutions and the capacity to substantially amplify the variety of schooling or grades it includes thru the use of massive statistics sets. The evaluation of subjective responses remains a charming problem to take a look at, and we expect to discover extra effective solutions inside the destiny.

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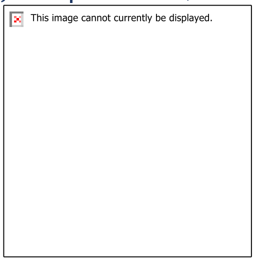

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