Subjective Answer Evaluation Using Machine Learning

Final Presentation

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Problem Statement

- Subjective questions are capable of examining the adopting ability of knowledge of a student.
- However correctly evaluating this answers is a complex and time consuming process.
- Hence an efficient mechanism is needed to tackle this challenge by not only reducing human errors but also providing a quicker and faster output.

Scope and Objectives

- The goal of this project is to develop a software to ease the burden on evaluators.
- The answers will be typed by students and various NLP techniques will be applied.
- Model answer sets will be provided by the evaluator.
- Compare the model answer with the student answer based on QST, grammar and keywords.
- Answers will be graded and results will be displayed accordingly.

- System is used only for evaluating short subjective answers.
- Answer scripts are supposed to be in digital format.
- Algorithm will evaluate only theoretical answers.
- The answers consisting of non textual data like equations, diagrams etc. will not be processed through the system.

- Difference in the answer structure of student and model answer.
- There is enormous ambiguity that exists while processing Natural Language.

- The proposed sequential model consists of LSTM-RNN layer which sequentially takes the glove vector representation in a sentence of each word and converts to embedding vector representation.
- The sequential model consists of embedding layer, Long Short Term Memory layer, dropout layer and dense layer.

- The motivation behind Text Mining is to process unstructured (textual) data, remove significant numeric files from the content, and, along these lines,make the data contained in the content open to the different information mining (statistical and machine learning calculations)
- Content mining is utilised to separate vital data or information or example or learning from the test proprietors and applicant's answers which are in the unstructured frame.

- Two different approaches (feature-based and fine-tuning-based) for answer selection are being used.
- Based on the experiments, it finds that the fine-tuning approach outperforms the feature-based approach on all of them.
- Among the fine-tuning-based models, the Robustly Optimised BERT Pre Training Approach (RoBERTa) model results in new state-of-the-art performance.

- The BERT model was significantly undertrained.
- The RoBERTa model was proposed by modifying different hyperparameters in BERT along with new design choices.
- These new parameter settings and objectives showed significant improvements in the BERT model in different NLP tasks.

- The naive Bayes classifier greatly simplifies learning by assuming that features are independent.
- It analyses the impact of the distribution entropy on the classification error, showing that low-entropy feature distributions yield good performance of naive Bayes.

Proposed Solution

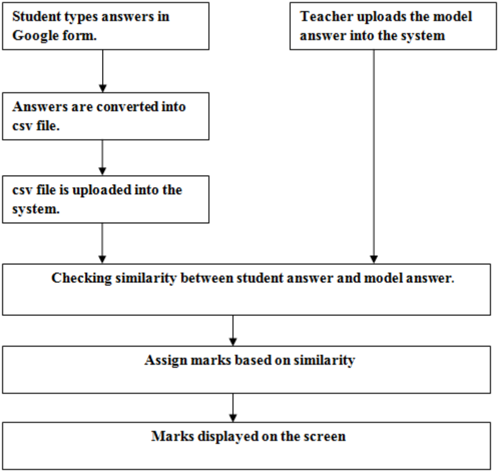

Figure: Proposed Solution

System Overview

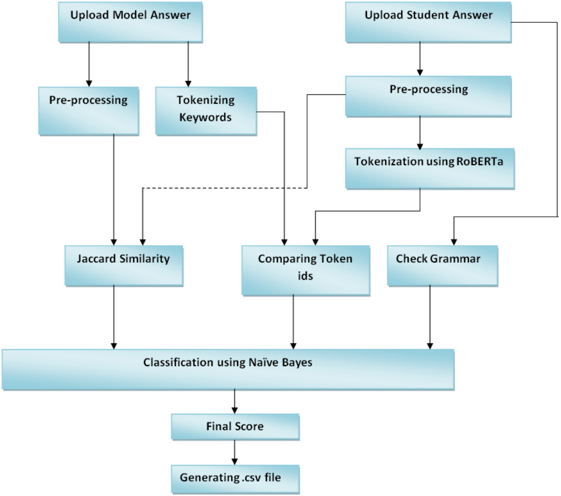

Figure: System Overview

Functional requirements

- Student enters answers into the google form.
- Student answers are combined into a csv file.
- Teacher writes the model answers and corresponding keywords into a csv file.
- Student answers are compared with the model answers.
- Final scores are predicted and the results are generated and converted into a csv file.

- Processor : Intel core i5 or i7
- Clock speed : 1.8 GHz or more
- RAM : Minimum 8 GB
- Hard disk space : 50GB or more

Software Requirements

- Operating System : Windows 7 or later
- Python version 3 or later
- Anaconda
- Google Colab

System Design

Use Case Diagram

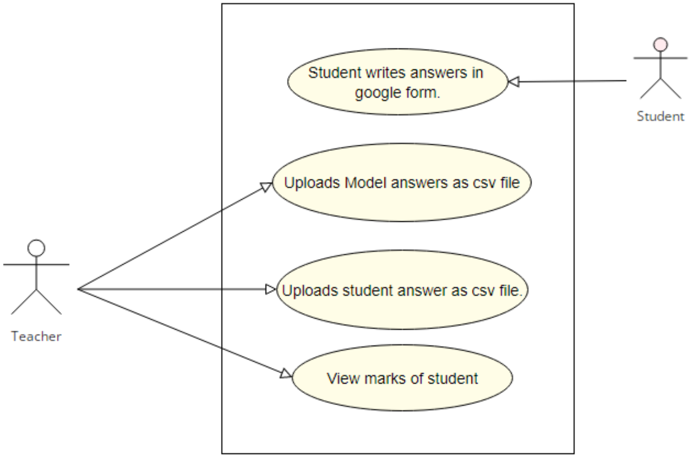

Figure: Use Case Diagram

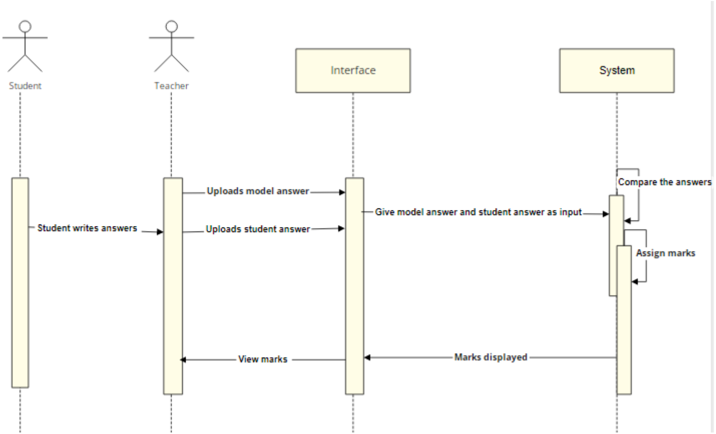

Figure: Sequence Diagram

Module Division

1. Preprocessing
2. Tokenization using RoBERTa
3. Grammar Checking Module
4. QST Evaluation Module
5. Classification
6. GUI

Module 1-Preprocessing

- Converting the text to lowercase.
- Removing special characters using regular expression.
- Removing Punctuations.
- Removing whitespaces.

Module 2-Tokenization using RoBERTa

- Tokenization is done using RoBERTa model(Robustly Optimized BERT model).
- It is based on Google's BERT model.
- It is a pretrained model.
- It has the same architecture as BERT model.

Module 3-Grammar Checking

- This is done using language tool python.
- It is an open source grammar tool.
- It allows you to detect grammar errors and spelling errors

Module 4-QST Evaluation

- QST is evaluated using Jaccard similarity
- Jaccard similarity is used to check the similarity between two documents.
- Text distance, a python library, compares the distance between two documents.

- Naive Bayes model is used to classify data points into specific labels.
- These labels are used to predict the scores.
- This is based on Bayes theorem.

- Tkinter is used to create GUI.
- It is a standard library in python.
- Text alignments can be easily done using Tkinter.

Dataset

- We had developed a data set which consists of 50 students and 20 questions.
- Each student enters answers for these 20 questions.

Results

- There are a total of 50 students. We have given 20 questions to each student.
- Each student enters answers for these 20 questions.
- Our model evaluates each answer and generates a list which consists of the answers of 50 students for the first question, similarly the second question and so on.
- The model also calculates the total marks obtained by each student by adding the marks assigned for each answer.

Results

	precision	recall	f1-score	support
1	1.00	1.00	1.00	1
5	1.00	1.00	1.00	1
7	0.50	1.00	0.67	1
8	1.00	0.50	0.67	4
9	0.50	1.00	0.67	1
accuracy			0.75	8
macro avg	0.80	0.90	0.80	8
weighted avg	0.88	0.75	0.75	8

Figure: Result

References

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Thank You!