Automated Essay Scoring using Transformers

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Abstract—Despite being investigated for over five decades, the task of automated essay scoring continues to draw a lot of attention in the NLP community, in part because of its commercial and educational values as well as the associated research challenges. Large pre-trained models have made remarkable progress in NLP. Data augmentation techniques have also helped build state-of-the-art models for automated essay scoring. Many works in the past have attempted to solve this problem by using RNNs, LSTMs, etc. This work examines the transformer models like BERT, RoBERTa, etc. We empirically demonstrate the effectiveness of transformer models and data augmentation for automated essay grading across many topics using a single model.

Index Terms—Automated System, Transformers, BERT

I. INTRODUCTION

As a result of the COVID-19 pandemic, online schooling system became necessary. Virtually all educational institutions, from elementary schools to universities, have adopted the online education system. The evaluation plays an important part in gauging the student’s learning abilities. The majority of automated evaluations are accessible for multiple-choice questions, but evaluating short and essay responses remains difficult. It is an essential education-related application that employs NLP and machine learning methodologies. It is difficult to evaluate essays using basic computer languages and methods such as pattern matching and language processing.

Among the most important pedagogical uses of natural language processing is automated essay scoring (AES), the technique of using computer technology to score written prose (NLP). Initiated by Page’s [1966] groundbreaking work on the Project Essay Grader system, this area of study has seen continuous activity ever since. The bulk of AES research has been on holistic scoring, which provides a quantitative summary of an essay’s quality in a single number. At least two factors contribute to this concentration of effort. To begin with, learning-based holistic scoring systems may use output of publically accessible corpora that have been manually annotated with holistic scores. Second, there is a market for holistic scoring algorithms because they may streamline the arduous process of manually evaluating the millions of essays submitted each year for standardized aptitude tests like the SAT and GRE.

Past research on automated essay grading has included training models for essays for which training data is available and those models are topic specific. This model is trained on all those topics without training model specific for each topic. This would be useful in the scenario where we did not have enough data to train a model that is specific to a particular topic, but we still needed to evaluate essays on that topic. Therefore, in order to assess them, we may utilize a model that has been trained on essays on a variety of topics and a tiny amount of data on the topic for which we need to develop a model, which will then be fine-tuned using the limited data available on the subject being assessed.

This paper is organized as follows: In Section II, we explore pertinent prior research on automated essay scoring; in Section III, we cover experimental setup; and in Section IV, we describe our methodology for augmenting essay data. In Section V, we give the results and analysis of the automated essay grading model. Section VI comprises of conclusion and future work for Automated Essay Scoring.

II. RELATED WORKS

The AES research started in 1966 with the Project Essay Grader (PEG) by [1]. To score the essay, PEG considers writing qualities such as grammar, vocabulary, composition, etc. Shermis (2001) [2] have produced a modified version of the PEG that focuses on grammatical checking with a connection between human evaluators and the machine. Foltz (1999) [3] developed the Intelligent Essay Assessor (IEA) by analyzing essay content using latent semantic analysis to get an overall score. Powers et al. (2002) [4] presented E-rater and Intellimetric by [5] and Bayesian Essay Test Scoring System (BESTY) by [6]. These systems employ natural language processing (NLP) approaches that concentrate on style and substance to determine an essay’s score.

In the 1990s, the great majority of essay scoring systems used conventional methods like as pattern matching and statistical analysis. Since the turn of the century, essay grading systems have included regression-based and natural language processing algorithms. AES systems produced after 2014, like those by [7] and others, employed deep learning approaches to induce syntactic and semantic characteristics, producing greater outcomes than previous systems.

Multiple studies studied AES systems, from the earliest to the most recent. Wherein the following research on AES systems are presented: Blood (2011) [8] reviewed the PEG literature from 1984 to 2010. Which has discussed just broad features of AES systems, such as ethical considerations and system performance. However, they have not addressed the
implementation aspect, nor has a comparison research been conducted, nor have the real problems of AES systems been highlighted.

Burrows (2015) reviewed AES systems on six dimensions, including datasets, NLP approaches, model construction, model grading, model assessment, and model efficacy. They have not discussed feature extraction approaches and associated difficulties. Only Machine Learning models were discussed, but not in depth. This review does not address the comparative study of AES systems such as feature extraction, model construction, and relevance, cohesion, and coherence.

Ke (2019) offered a state-of-the-art overview of the AES system, but only covered a small number of studies, did not include all obstacles, and did not conduct a comparative analysis of the AES model. On the other hand, Hussein (2019) analyzed two types of AES systems, four papers from handmade features for AES systems and four papers from the neural networks approach, mentioned few issues, and did not elaborate on feature extraction methodologies or the performance of AES models. Klebanov (2020) reviewed 50 years of AES systems, enumerated and classified all significant essay-extractable characteristics. However, no comparative analysis of all work was presented, nor were any problems mentioned.

III. EXPERIMENTAL SETUP

For the purpose of this study, we will constrain the study and experiments to ASAP1 dataset. The Automated Student Assessment Prize (ASAP1) corpus was released as part of a Kaggle competition in 2012. Since then, it has become a widely used corpus for holistic scoring. The corpus is large in terms of not only the total number of essays, but also the number of essays per prompt (with up to 3000 essays per prompt). Since each topic of essay had a different grading method, we firstly normalized score from 0 to 10 so that we could train all the data together.

We run our experiments using the BERT, RoBERTa, ALBERT, DistilBERT, XLM-RoBERTa, implementation available in the Simple Transformers library provided by Thilina Rajapakse. We run our experiment on Google Colab. For baseline trials, we consider the essays which are not supplemented with our data augmentation technique and trained on models based on Transformers.

During training, we additionally fine-tuned our parameters by adjusting the parameters like learning rate, weight decay rate, etc. For the purpose of evaluating our model, we will use the accuracy score measure given by the Scikit library. Since we are approaching our issue as a multi-label classification, the accuracy metric is often used to evaluate multi-label classifications.

IV. METHODOLOGY

A. Large Pre-trained models

The models which we used for training are based on the Transformers architecture introduced by. The Transformer’s architecture follows an encoder-decoder structure. Given below is the brief description of each of the model which we are using for training:

1) BERT: The Bidirectional Encoder Representations (BERT) introduced by is a deep learning model in which every output element is linked to every input element and the weightings between them are dynamically determined depending on their relationship. BERT is pre-trained on two distinct NLP tasks using this bidirectional capability: Masked Language Modeling and Next Sentence Prediction.

2) RoBERTa: Robustly optimized BERT Pre-training Approach (RoBERTa) introduced by builds upon BERT’s language masking method, in which the system learns to anticipate purposely masked bits of text inside unannotated language samples. RoBERTa changes critical hyperparameters in BERT, such as eliminating BERT’s next-sentence pretraining target and training with much bigger mini-batches and learning rates. This enables RoBERTa to outperform BERT at the masked language modeling goal and improves the performance of subsequent tasks.

3) ALBERT: ALBERT, introduced by is an encoder-decoder model with self-attention at the encoder end and attention to encoder outputs at the decoder end. It stands for “A Lite BERT” and is a modified version of the BERT NLP model. It builds on three key points, such as parameter sharing, embedding factorization, and sentence order prediction (SOP).

4) DistilBERT: DistilBERT, introduced by aims to optimize the training by reducing the size of BERT and increasing the speed of BERT—all while trying to retain as much performance as possible. Specifically, DistilBERT is smaller than the original BERT-base model, is faster than it, and retains its functionality.

5) XLM-RoBERTa: XLM-RoBERTa, Unsupervised Cross-lingual Representation Learning at Scale, introduced by is a scaled cross-lingual sentence encoder. It is trained on 2.5 TB of data across 100 languages filtered from Common Crawl. XLM-RoBERTa achieves state-of-the-art results on multiple cross-lingual benchmarks.

B. Data Augmentation

Researchers have attempted to use several RNNs and LSTMs as training models for automated essay scoring. However, the fundamental disadvantage of such models is that they are topic-specific, and we want to construct an automated essay scoring system that can perform well not just on subjects for which we have an abundance of data but also on subjects for which we have a limited amount of data. Now, we want to augment the essay so that it can accurately assess a essay on a different topic for which we have a very small amount of data.

When training a model, we use the accuracy score measure given by the Scikit library. Since we are approaching our issue as a multi-label classification, the accuracy metric is often used to evaluate multi-label classifications.
We conducted extensive data trials by inserting them at different lines should we put the subject for optimum precision? We followed a very simple yet state-of-the-art modeling technique for multi-label classification using transformer models. We bucketed scores into each interval class, resulting in 11 buckets. These 11 classes correspond to a score from 0 to 10. Our methodology assigns each essay to a particular category. If an essay is categorized by my model as being in Bucket 6, then it receives a score of 5. Models like BERT, RoBERTa, ALBERT, DistilBERT, and XLM-RoBERTa were used to teach augmented essays how to recognize multiple labels.

We approached this issue in the same manner as sentiment analysis, which utilizes classification algorithms and yields extremely positive results. We have discovered that using this data augmentation training method contributes to an improvement in accuracy as referenced in Table I. From these results, it is quite evident that BERT and RoBERTa outperform other models, although by a small margin. The analysis of these findings demonstrates that utilizing Transformer-based models is considerably superior than using LSTMs.

When used on top of huge pre-trained classification models, our data augmentation strategies significantly enhance the performance of automated essay grading. The accuracy of all those pre-trained models increases after applying our augmentation technique. We believe this performance is because after mixing a summary of the topic with each essay, it encourages the internal representation of each essay to align with the topic, so that when we test it on a essay with a different topic after fine tuning, it checks for the alignment between the topic and the essay as a result of training and fine-tuning and grades it accordingly.

### V. Results and Analysis

The ASAP1 dataset contains around 17K essays on eight topics. We are using that data for pre-training by augmenting those essays using our technique. For fine tuning For research and testing purposes, we used this dataset. This dataset consists of 1241 essays on four subjects. We fine-tuned and tested our models on each subject individually. We used around two-thirds of the above mentioned dataset for training and fine-tuning, and the remaining one-third for testing.

| Topic | Transformer Models | Unaugmented Data | Augmented Data |
|-------|-------------------|------------------|----------------|
| 1     | LSTM              | 46.6%            | 58.9%          |
|       | XLM-RoBERTa      | 51.3%            | 61.3%          |
|       | RoBERTa          | 49.2%            | 59.9%          |
|       | DistilBERT       | 49.5%            | 58.9%          |
|       | BERT              | 49.3%            | 61.5%          |
| 2     | LSTM              | 50.2%            | 63.7%          |
|       | XLM-RoBERTa      | 57.8%            | 58.6%          |
|       | RoBERTa          | 50.9%            | 60.8%          |
|       | ALBERT            | 49.6%            | 60.2%          |
|       | DistilBERT       | 49.8%            | 58.8%          |
|       | BERT              | 50.2%            | 61.3%          |
| 3     | LSTM              | 42.3%            | 38.1%          |
|       | XLM-RoBERTa      | 46.9%            | 58.9%          |
|       | RoBERTa          | 51.3%            | 61.3%          |
|       | ALBERT            | 49.2%            | 59.9%          |
|       | DistilBERT       | 49.4%            | 58.9%          |
|       | BERT              | 49.3%            | 61.5%          |
| 4     | LSTM              | 40.3%            | 38.1%          |
|       | XLM-RoBERTa      | 46.9%            | 58.9%          |
|       | RoBERTa          | 50.5%            | 61.4%          |
|       | ALBERT            | 47.6%            | 59.3%          |
|       | DistilBERT       | 51.1%            | 58.2%          |
|       | BERT              | 50.3%            | 61.7%          |
Pre-trained transformer-based models BERT, RoBERTa, ALBERT, DistilBERT, and XLM-RoBERTa are very proficient at Automated Essay Scoring.

Data augmentation approaches might further enhance its performance for analyzing lengthier resources such as essays to attain accurate essay scores.

In the future, we’ll come up with a better way to include elements that are relevant to the topic instead of just a summary, so that training with this data will lead to a more accurate model for automatically grading essays.

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