

# GRASPE: An Adaptive Grading Support for Persuasive English Essays

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*Master Semester Project, Fall 2022*

**Abstract – The purpose of this work is to design and implement a tool to help English teachers with grading persuasive essays. We present the user stories on which we based the design of our tool as well as the different techniques used for the implementation. Our tool uses three Machine Learning language models to detect spelling mistakes, grammar incoherence, and claim and premises in arguments. This report presents the first version of the tool as it is still under construction and needs further insights from English teachers in order to improve it and have it tested.**

## I. INTRODUCTION

Among all ways of language evaluations, writing assignments remain one of the most effective and reliable ways to capture the student's skills or, for the matter, lack of them. In fact, writing demonstrates not only the student's level of mastering the language, but also their critical thinking and their abilities to express themselves and explain their opinions. To the present, the evaluation of writing skills is being done only manually. Even though the task of manually grading writing essays takes between 20 to 30 minutes per assignment in the best scenario leading to a total of 40 hours per class per academic year at minimum<sup>1</sup>, teachers cannot give up this exercise. Fortunately, Natural Language Processing (NLP) advances come in handy to read and understand text content and can be leveraged to automate the scoring of essays. However, automatic scoring techniques are still not showing promising results and cannot totally replace the teacher because they can be biased and not scalable. In this work, we propose GRASPE, an IT tool to help teachers with grading argumentative essays by automating certain steps of this task. The tool is aimed to be tailored to the teachers' needs and to be adaptive accordingly offering them the space to give the feedback and the final grade.

<sup>1</sup>20 students per class, 6 assignments per year.

## II. RELATED WORK

Multiple papers investigate the different NLP-based approaches to improve automated corrections. Yuan et al. in [8] propose a context-aware grammatical error correction (GEC) system outperforming previous GEC systems. Wang et al. on the other hand suggest a novel representation for BERT that improves its performance and outperforms other deep learning models such as LSTM [6]. These are two of many examples of projects working towards making automated scoring faster and more accurate.

As examples of applications that use these state of the art NLP models, AL [5] and ALEN [4] are both IT tools designed to help English learners to improve their writing skills by giving them feedback on the quality of their argument structures. By leveraging argumentation mining techniques, these tools detect the claims and premises in the text and the links between them as a primary feature to judge the quality of the arguments.

Sevcikova in [2] makes the comparison between human and automated scoring. She shows that, even though the computerized feedback is fast and efficient in large classes, it lacks the ability to evaluate abstract features like comprehensibility, content and aesthetic style. Also, automated scoring techniques cannot give a feedback focusing on a specific grade range that is associated with a specific set of tasks and a specific rubric as most human raters are trained to do. Sevcikova suggests that these technologies should be used carefully to contribute to the efficient delivery of essay scoring and ease the burden of the grading task but not to entirely replace the student-instructor interaction.

Thus far, we have available various technologies capable of detecting grammar, spelling, and argumentation errors with very high performances that have been used in applications to give automated feedbacks to students. However, for what we know, these techniques have never been used in applications to help the teachers with

the grading task. Additionally, along with Sevcikova's critique, the tool we propose in the aim of filling this gap, is intended to be an automated support for the teachers to make parts of grading faster and easier but still provide them enough space to give their personal feedback.

### III. USER STORIES

To design a tool as tailored to the user's needs as possible, we intended to interview 12-to-15 English teachers from schools in Switzerland. The first interviews were designed to extract the user stories based on which we choose the different features of the tool. Our plan was then to have another one or two interviews with each teacher to try the tool and give us feedbacks to improve it. The last step of our plan was to evaluate the tool through a real-life experiment where the teachers would use the eventual final version of the tool to grade the assignments of their students. Unfortunately things did not go as planned. We managed to interview only three teachers who then did not follow-up for a second interview. These are the few stories we could draw from the interviews:

- I would like to be able to see two assignments of two different students on the same view for comparison.
- I would like to be able to deactivate the options (i.e. automatic checks) when I do not need them because otherwise the interface becomes cumbersome.
- I would like to know the percentage of faulty words in the text.
- I would like to see which assignments were already graded to keep track of my work.
- I would like to have access to the student's past assignments and feedbacks to see if they overcame their past mistakes.
- I would like to have key words highlighted in the text to see how well did the student stick to the topic, and how rich is the lexicon they are using.

As you would notice from the description of the tool, we tried to rely as much as possible on these stories to design our tool, but also used literature. We would like to insist here on the importance of running the planned experiment even at a late stage of the development of

the tool because from the three interviews we had, we could already see a number of differences between the teachers' needs and ways of doing when it comes to grading. For example, one interviewed teacher considers identifying the content and ideas in the text to be the most important part of grading, whereas another teacher thinks that, depending on the level of the student, grammar is sometimes more important than content. Also, one teacher would like to use past assignments of a student to check whether or not they are making the same mistakes, while another teacher would grade each assignment individually and would not penalize more a student for making the same mistake again. Such differences between the teachers can be linked to their experiences, to the levels of their students, or to their workload (number of students and writing assignments per year). This kind of hypothesis and other can only be validated or rejected when conducting the experiment with more teachers.

### IV. IMPLEMENTATION

We decided for GRASPE to be a simple web interface for the ease of testing and also to save the teachers the struggle of a software installation. To design the interface, we relied on the few user stories that we collected from the interviews we had with the teachers, and mostly on literature and common sense. The interface consists of a main view used for the grading task, presented in Fig. 1, and two other views for statistic and final grade formula described later. All the features related to the task of grading are contented in the main "grading view" on purpose to provide more flexibility and less going back and forth between pages for different small tasks.

The grading view contains three main correction tools: detection of spelling mistakes, detection of grammar incoherence, detection of claims and premises for argumentation. The three tasks rely on three different language models listed below. As the main purpose of the project is the design of the tool, we decided to leverage the variety of existing language models rather than build ones ourselves. The grammar and argumentation models have been pushed to the Hugging Face Hub <sup>2</sup> after training to avoid local storage of heavy files and speed up the loading time.

<sup>2</sup><https://huggingface.co/docs/hub/index>

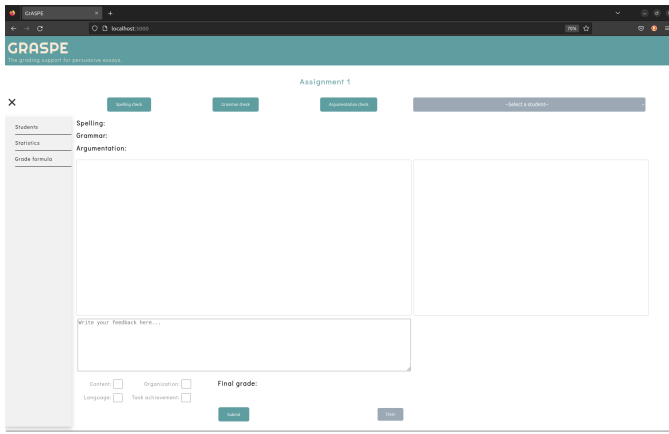


Fig. 1: Screenshot of the main grading view of GRASPE.

### A. Language models

**Spelling.** For the detection of spelling mistakes, we used NeuSpell - A Neural Spelling Correction Toolkit<sup>3</sup>. It comprises several neural models such as BERT and ELMo that accurately capture context around the misspellings [1]. The final model was trained on 1.6M sentences with spelling mistakes injected synthetically and tested against 63K sentences extracted from real students' written essays. Details of the remarkable accuracy and correction rates of the toolkit are represented in the paper.

These strengths of NeuSpell are well confirmed when used on our test examples and compared to other models. It however doesn't seem to take into account punctuation mistakes. Even though it takes 2 to 3 seconds to generate the corrected text when run on an average long text, NeuSpell is by far faster than other pre-trained models that we tested.

When the spelling check is activated, the metrics area above the text shows the percentage of correct words of the total number of words in the text.

**Grammar.** For the grammar check, we used BertForSequenceClassification<sup>4</sup> from the Hugging Face Transformers package<sup>5</sup>. For the training of the model, we used 8,551 sentences from The Corpus of Linguistic Acceptability (CoLA) dataset [7] which is a set of sentences labeled as grammatically correct or incorrect.

<sup>3</sup><https://github.com/neuspell/neuspell>

<sup>4</sup>[https://huggingface.co/transformers/v3.0.2/model\\_doc/bert.html#transformers.BertForSequenceClassification](https://huggingface.co/transformers/v3.0.2/model_doc/bert.html#transformers.BertForSequenceClassification)

<sup>5</sup><https://huggingface.co/docs/transformers/index>

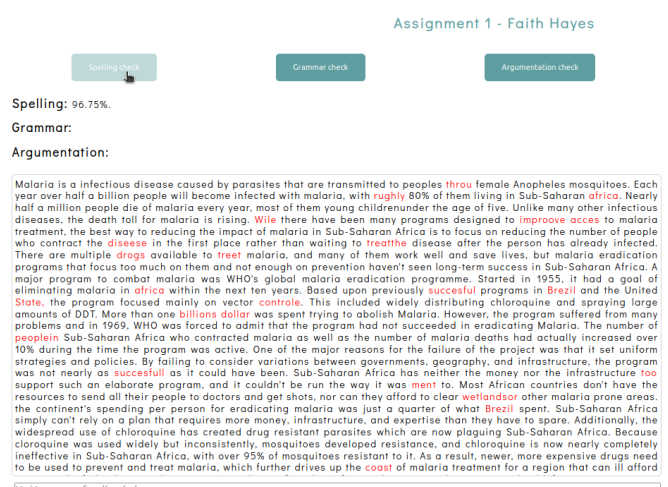


Fig. 2: Screenshot of GRASPE showing the spelling check feature.

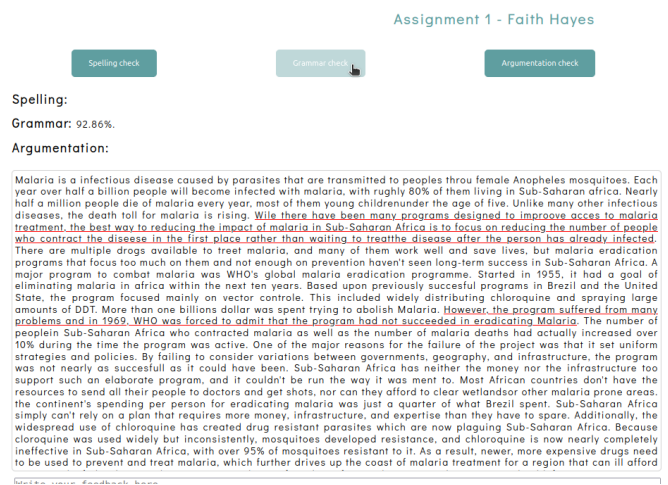


Fig. 3: Screenshot of GRASPE showing the grammar check feature.

To evaluate the model on the test set, we used the "Matthews correlation coefficient" (MCC) metric because the classes are imbalanced. We got an MCC of 68.60% on 516 sentences. The model works well on the examples given in our interface. The output seems however to be impacted by the spelling mistakes; i.e. a grammatically correct sentence can be marked as incorrect when it contains a spelling mistake even if the overall structure is correct.

The percentage shown in the metrics area is output after the grammar check completes running and it represents the percentage of grammatically correct sentences from the total number of sentences in the text.

**Argumentation.** For the argumentation check, we used the `AutoModelForSequenceClassification` model class from the `Transformers` package to instantiate a sequence classification model class from a pre-trained configuration of the `DistilBERT` model. We chose `DistilBERT` over `BERT` mainly for it being lighter and faster. We trained our text classification model on the Feedback Prize dataset from Kaggle. It is the biggest dataset of student writing ever released containing over 144K annotated sentences extracted from argumentative essays written by U.S. students in grades 6-12. The essays were annotated by expert raters for elements commonly found in argumentative writing. The labels originally stated in the dataset are: Lead, Position, Claim, Counterclaim, Rebuttal, Evidence, and Concluding Statement. To make things easier for a starter we narrowed the list down to 2 labels by considering both "Claim" and "Counterclaim" as Claim, and the remainder as Premise. This choice was made for the first, rather simple, version of the interface but we intend to implement the 7-label-classification if it is more appealing to the teachers.

When the "Argumentation check" button is clicked, claims are highlighted in yellow and premises in orange, and the number of each is displayed in the metrics area above the text. We assume that this quantitative representation of the output can be helpful to the teacher to give them an idea on how dense or scarce is the argumentation, and the highlighting is more of a qualitative representation to show how balanced are the claims with respect to the premises and how well are they distributed through the text.

The model is accurate to 87%.

### B. Other features

**Feedback.** As stated previously, this tool is not an automated scoring tool. It is a support that would help the teachers speed up the grading of essays while giving them enough space to accomplish their task in the ways they are used to. One of the most important parts of grading is the teacher's feedback. They precisely highlight the strengths and weaknesses of the student's writing, and can give them ways to improve. For these and other reasons, it only makes sense to provide a space on the interface for the teachers to type a personalized feedback.

**Grade attribution.** Under the span for the feedback, we put a section to give a grade. This section was mostly inspired from the analytic scoring method described in

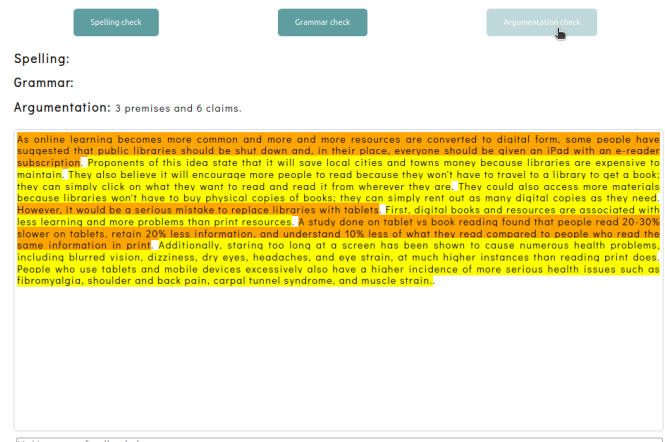


Fig. 4: Screenshot of GRASPE showing the argumentation check feature.

[3]. In this paper, Veloo et al. state that this type of scoring offers more detailed explanation on the writer's performance than one single score done in a holistic scoring. Even though Veloo et al. consider this method to be consisted of five different ratings (content, organization, vocabulary, language use and mechanics), we are here considering four categories only based on the needs of the teachers we interviewed: content, organization, language, task achievement. As a reminder, this is only the first version of the tool; and because of the lack of teachers' feedbacks, this version is prone to modifications. To make our tool as adaptive as possible, we can make this section to be adjustable to the user's will. I.e. we can implement a feature allowing the teacher to add, remove or edit the categories of sub-grades; or to remove the section completely if for example they are used to the holistic method of scoring which consists of giving a single and integrated score based on a general impression of writing [3]. In order to help the teacher save more time, and in case they are using the analytic method, we provide a separate view where they can define the formula to compute the final grade automatically based on the sub-grades of the different categories.

**Statistics.** Also inspired from the paper by Veloo et al., we thought of adding a second view to our tool where we would display statistics on the overall level of the class or on students individually. This feature goes along with the analytic method of grading because it would help the teachers to discriminate the students' weak and strong aspects of their writing performance from one test to another, and based on that they would adjust the

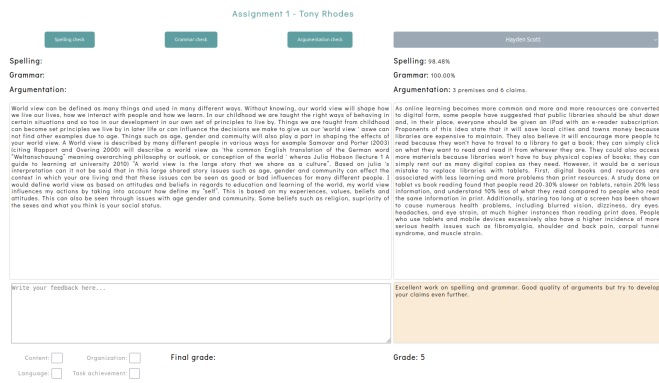


Fig. 5: Screenshot of GRASPE showing the comparison feature.

follow-up activities of consolidation after the tests [3]. The statistics view is still not implemented in this version of the interface mainly because we need more insights on what to include in it and how to measure certain writing skills and plot them on charts especially that the teachers we interviewed do not all agree on the idea as a whole.

**Comparison.** A major preoccupation of teachers when grading essays is to guarantee the fairness between the students when attributing the grades. 2 of the 3 teachers we interviewed use the comparison between different texts of students to decide whether the grades they have given are fair enough or need to be adjusted; and they expressed their will to have this feature implemented in the tool. One of the two teachers also uses the comparison between the student’s actual work and their past assignments to check if they keep making the same mistakes in which case they might get more penalized.

To use this feature, the teacher simply needs to select a student’s name from the dropdown list on the right-hand side of the interface to have their essay, feedback, grade and the different metrics of the spelling, grammar and argumentation checks displayed next to the essay they are currently grading.

## V. CONCLUSION

Through this work, we have presented a first version of GRASPE, an adaptive grading support for persuasive English essays. We used three main language models to detect spelling mistakes, grammatically incorrect sentences, and the argumentation structure in students’ writing essays. They all present high levels of accuracy. The tool also includes various other features based on user stories extracted from interviews with teachers. These features are meant to speed up the process of grading

and make it easier on the teachers. The tool is currently still under construction and it would be useful to have further insights from teachers to continue the next steps of implementation and evaluation. As our aim is to make GRASPE as tailored as possible to the teachers’ needs, existing literature in this case is not enough, and running the experiment with multiple interviews as planned would be the best way to finish the work. This process however might need more time than we think mainly due to the teachers’ lack of free time during working periods of the year.

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