

Improve LLM-based Automatic Essay Scoring with Linguistic Features

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Abstract

Automatic Essay Scoring (AES) assigns scores to student essays, reducing the grading workload for instructors. Developing a scoring system capable of handling essays across diverse prompts is challenging due to the flexibility and diverse nature of the writing task. Previous work has shown promising results in AES by prompting large language models (LLMs). While prompting LLM is data efficient, it does not surpass supervised methods trained with extracted linguistic features [Li and Ng \(2024\)](#). In this paper, we combine both approaches by incorporating linguistic features into LLM-based scoring. Experiments show promising results from this hybrid method for both in-domain and out-of-domain essay prompts¹.

Keywords: Automatic Essay Evaluation, Large Language Model, Zero shot Learning, LLM as Evaluator, Linguistic Features

1. Introduction

Research in Automatic Essay Scoring (AES), the task of automatically assessing the quality of an essay, dates back to over five decades ago [Page \(1968\)](#). Since then, researchers in this domain have taken various perspectives; some focus on building hand-crafted features [Chen and He \(2013\)](#) [Uto et al. \(2020\)](#), some leverage the computational power of neural-network to learn effective representation of essays [Dong et al. \(2017\)](#) [Ridley et al. \(2020a\)](#) [Jin et al. \(2018\)](#), and some adapt pre-trained language models for fine-tuning or prompting [Wang et al. \(2022\)](#); [Xue et al. \(2021\)](#).

However, as much of the research above has shown, AES remains an open question. The main challenge of this task is the models’ ability to generalize across different essay prompts: ideally, the method should be applicable to any grading scenario given a concrete grading rubric. Yet, numerous factors, including but not limited to instructors, education institutions, the essay’s purpose, and the type of the essay (from the literature point of view) make essay grading context-specific. To this end, the cross-prompt AES system, which aims to work similarly well for different essay prompts and scoring rubrics, has been an important direction that draws much attention [Ridley et al. \(2020a\)](#) [Jin et al. \(2018\)](#) [Li and Ng \(2024\)](#) [Phandi et al. \(2015\)](#) [Ridley et al. \(2021a\)](#).

Creating cross-prompt AES systems with sufficient capabilities requires the system to examine more than just simple word surface forms and incorporate more linguistically motivated features [Burststein et al. \(1998\)](#). Recent work [Ridley et al. \(2020b\)](#) [Uto et al. \(2020\)](#)

1. Codebase: https://github.com/JoeyHou/essay_eval

pairs linguistic features with supervised methods to boost AES quality. However, there is little work on exploring linguistic features in the context of instruction-based large language models (LLMs). Most work with LLMs explores other aspects such as rubric-incorporation Hashemi et al. (2024) and prompting techniques Liu et al. (2023) Chiang and Lee (2023). To bridge the gap, we explore adding linguistic features to the LLM prompt. We conduct experiments in the cross-prompt AES setting with both open- (Mistral) and closed-source (GPT-4) large language models and find that, in most cases, LLMs align better with human judgments when given linguistic features.

Our main contribution can be summarized as follows: 1) through prompt tuning and feature engineering, we have shown incorporating linguistic features into existing zero-shot prompting methods can improve the overall score prediction; 2) even for out-of-distribution data (i.e., essay from an different dataset), the improvement holds; 3) we have shown that there is still notable headroom for open-source LLM to automatically evaluate student essay, compared to their closed-source counterparts and smaller, supervised language models.

2. Related Works

2.1. Automatic Essay Scoring

Feature Engineering approaches leverage various features to predict essay scores, including linguistic features, e.g., readability metrics and word length Ridley et al. (2020a); Uto et al. (2020); Jin et al. (2018); Foltz et al. (1999); Chen and He (2013), and content features, e.g., content quality and organization Mathias and Bhattacharyya (2018); Crossley et al. (2023). Models that utilize these features range from simple logistic regression models Chen and He (2013) to deep neural networks Uto et al. (2020). These approaches assess the quality of essays in an interpretable manner with well-defined features.

Language-model-based approaches emerge with the rising popularity of Transformer architecture, including BERT-based methods that require supervised fine-tuning Wang et al. (2022); Chen et al. (2024); Xue et al. (2021) and LLM-based methods that focus on prompt-engineering Mansour et al. (2024); Stahl et al. (2024). In particular, Stahl et al. (2024) explores zero-shot prompting with persona prompts and analysis instructions. Building on this, our work aims to utilize linguistic features in LLM prompting.

2.2. LLM as Evaluator

Given the increasing capability of LLMs and their scalable nature, researchers in various domains have explored how to use them for the automatic evaluation of text content Zubiaga et al. (2024); Alhafni et al. (2024); Gao et al. (2024); Fu et al. (2024). Although some research has shown proper prompt tuning, such as explanation-guided generation, clear rubric guidance, and chain-of-thought (COT) could improve the alignment between human and LLMs Chiang and Lee (2023); Liu et al. (2023); Hashemi et al. (2024), the LLM-based evaluators still perform underwhelming in more complex tasks, such as reviewing papers Zhou et al. (2024) and scoring students essay Mansour et al. (2024); Stahl et al. (2024). In this work, we specifically focus on improving LLMs as student essay graders by incorporating the linguistic features of essays. Additionally, we examine the transferability

of the prompts, i.e., how a prompt that is tuned in the in-distribution data would perform out-of-distribution in the same task.

3. Methods

3.1. Zero-shot Prompts with LLM

We build on top of the prompt template and instruction strategy by [Stahl et al. \(2024\)](#) for our zero-shot prompt design. Each prompt follows the following structure: **persona pattern**, **essay prompt**, **analysis task**, **student’s essay**, **additional information**, and **format instruction**. We adopt the best-performing combination of each component based on [Stahl et al. \(2024\)](#), i.e., *educational researcher* as the prompt template, *Explanation → Scoring* as the analysis instruction. We also add the **additional information** to incorporate linguistic features of the essay (see Sec. 3.2). Below is the prompt template we use. More details about the prompt structure and examples can be found in Appendix C.

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You are part of an educational research team analyzing the writing skills of students in grades
7 to 10. You have been given a student’s essay and the prompt they responded to.
### Essay Prompt: { essay prompt }
### Analysis Task: { analysis instruction }
### Analyzed Student Essay: { essay }
### Additional Information: Studies show that the following features are highly, positively
correlated with the grade of the essay (i.e., higher features typically mean higher end score):
{ linguistic features }
### Analysis: Conclude your analysis with a grade and comments in the following format:
{ format instruction }
    
```

3.2. Linguistic Features

In addition to the naive zero-shot baseline, we experimented with incorporating linguistic features into the prompts. We base our model’s linguistic features off of [Ridley et al. \(2020b\)](#), which were additionally used by [Li and Ng \(2024\)](#). These features are cited as being some of the most impactful features in essay grading, having a Pearson’s correlation score of 0.6 or above with the essay’s score. While the original works contain more linguistic features, we limit the number linguistic features to be include in the prompt to avoid overly long prompts, which could negatively impact LLM performance [Hilgert et al. \(2024\)](#). The linguistic features we used are listed below.

Unique Words refers to the number of single-instance words in the essay. For **essay character length**, we only count the number of non-space, non-punctuation characters². **Word/Sentence counts** are the total number of words/sentences in a given essay. We get the **individual counts for the total number of lemmas, nouns, and stop-words**. Finally, we get the essay’s **Dale-Chall** ([Dale and Chall \(1948\)](#)) word count, **total character count** (all characters) and **long word count**.

During prompt construction, the linguistic features are formatted as an unordered list of a short feature description followed by feature value. The formatted text containing all linguistic features is inserted into the prompt as **additional information**.

2. Words are not normalized as in the original paper.

3.3. Output Parsing via LLM

The output format varies across essay sets since each essay set has its own scoring schema. To make the pipeline generic to any input, we implement a few-shot parsing module powered by a stand-alone LLM. More details can be found in Appendix E.

4. Experiments

4.1. Datasets & Linguistic Features

We conduct our experiments on two widely used essay-grading datasets:

ASAP ASAP Hamner et al. (2012) is one of the most widely used evaluation datasets for AES, with 12,980 essays written by students in grades 7 through 10. It is divided into 8 subsets based on the formulation of essay prompts, including argumentative (1, 2), source-dependent (3, 4, 5, 6), and narrative (7, 8) essay prompts. The scores are annotated by at least two graders to ensure validity. We split the ASAP dataset into 5 equally sized folds. We use 3 folds for training (BERT baseline fine-tuning), 1 fold for validation (BERT baseline model selection and prompt tuning for prompting method), and 1 fold for evaluation.

ELLIPSE *English Language Learners Insight, Proficiency and Skills Evaluation (ELLIPSE)* by Crossley (2024) is composed of 6483 essays from English language learners in the United States educational system’s grades 8-12 get from an unnamed standardized test. The dataset features the full essay of each student and demographic information such as race/ethnicity and income background. There are 29 different argumentative essay prompts covering topics such as cell phones in school and community service. Each essay includes an overall holistic score as well as six rubric-based scores, all scored from one to five (in intervals of 0.5) by one of two annotators (see Appendix A for the full rubric). Note that we do not split the data since we want to treat this dataset as an entirely out-of-distribution dataset to examine the generalizability of our method across different essay prompts and contents.

Linguistic Features We use the linguistic features for the ASAP dataset as they are reported in Li and Ng (2024); Ridley et al. (2021b). We extract the features from the ELLIPSE dataset by following the same procedure as exactly as possible to recreate the features from Section 3.2. See Appendix D for the implementation details.

4.2. Evaluation Metrics

For both ASAP and ELLIPSE, the task is to predict the overall scoring. We follow the Kaggle competition evaluation metric of Hamner et al. (2012) and use Quadratic Weighted Kappa (QWK) to measure the agreement between the predicted and annotated overall scores.

4.3. Models and Experiment Setup

Our Pipeline As mentioned in Sec. 3, our main method consists of a prompt construction module and a zero-shot prompting module with an LLM followed by a parsing module powered by another LLM. For prompt construction, we include three setups to integrate linguis-

tic features: the most correlated feature (i.e., unique word count), the top 3 correlated features (i.e., unique word count, lemma count, and complex word count), and all 10 features, described in Sec. 4.1. For prompting and parsing, we use `Mistral-7B-Instruct-v0.2` Jiang et al. (2023) for all LLM-related jobs. We use 0 temperature and 4096 max token length, following Stahl et al. (2024)³. We use default sampling parameters in `vllm` framework during decoding⁴. All experiments are conducted with the VLLM⁵ Kwon et al. (2023) on a single-card NVIDIA L40S device.

Unsupervised Baseline (GPT-4) We also include one of the most capable models available to us, GPT-4 (`gpt-4-0613`), as the strong, unsupervised baseline. The experiment setup is exactly the same as in our pipeline above, with two differences, both due to the limited budget: 1) we only experiment with no more than 500 randomly sampled essays per essay set in ASAP (some essay sets have less than 500 essays in the test set) and 500 randomly sampled essays in ELLIPSE; 2) we only experiment with no linguistic feature and the best-performing linguistic feature setup (i.e., all top 10 features) based on the performance on the `dev` set of ASAP. We also set the temperature to 0 and leave all other parameters at the default values.

Supervised Baseline (BERT) We also experimented with a supervised method on ASAP to establish a performance upper bound. Our supervised baseline is a BERT-based architecture utilizing three main feature classes: document-, token- and segment-scale features Wang et al. (2022). We base our fine-tuning on the authors’ available code. The authors only released the fine-tuned model for ASAP prompt 8, therefore, to obtain models for all prompts, we fine-tuned `bert-base-uncased` as they did in the original paper. We used our splits of the ASAP dataset for fine-tuning, validation, and testing (see 4.1). More details about fine-tuning is in Appendix B.

5. Result and Discussion

5.1. Cross-dataset Performances

The experimental results are summarized in Table 1. For ASAP, the BERT-based supervised baseline achieved the highest average QWK, aligning with our expectation that AES remains a challenging task for naive LLMs prompting. When comparing cross LLMs, the performance between GPT-4 and Mistral showed mixed results across the two datasets. We suspect this is due to the differences in the essay type. ELLIPSE essays are argumentative, similar to essay sets 1 and 2 in ASAP. Additionally, the grading rubric for ASAP essay set 2 is more specific (focusing on "Writing Application" and "Language Conventions") compared to the broader "Overall" quality criteria used for ELLIPSE and ASAP essay set 1. These observations suggest that LLM performance on ELLIPSE is more comparable to ASAP essay set 1 rather than the entire ASAP dataset, a pattern confirmed by the results

3. We also tried Llama 3 in early experiments, but the results were significantly worse than the ones from Mistral, so we dropped it and kept only Mistral.

4. https://docs.vllm.ai/en/v0.6.1.post1/dev/sampling_params.html

5. <https://docs.vllm.ai/en/v0.6.1.post1/index.html>

Model	Linguistic Features	ASAP									ELLIPSE
		Avg.	1	2	3	4	5	6	7	8	
BERT	None	.545	.741	.447	.331	.430	.734	.552	.715	.413	N/A
GPT-4	None	.499	.221	.581	.514	.631	.561	.686	.250	.553	.307
	Top 10	.488	.285	.592	.444	.578	.620	.645	.251	.491	.345
Mistral 7B	None	.454	.254	.474	.526	.549	.506	.567	.388	.367	.454
	Unique Word	.458	.362	.516	.454	.552	.492	.539	.438	.313	.475
	Top 3	.461	.383	.516	.453	.567	.503	.542	.409	.318	.481
	Top 10	.492	.423	.483	.493	.623	.511	.537	.508	.360	.468

Table 1: Results of our experiments; BERT model is trained on ASAP training set and not applicable to ELLIPSE; **Bold** numbers are best-performing setups of the model; Examples of output scores and explanations can be found in App. F

in Table 1. Another research Chen et al. (2024) that conducted a zero-shot prompting experiment on ELLIPSE with ChatGPT ⁶ also got similar results (QWK = 0.29).

5.2. Benefit of Linguistic Features

As shown in Table 1, the prompts with linguistic features almost always perform better than the ones without – with the exception of GPT-4. This trend holds even for out-of-distribution data (ELLIPSE). When it comes to Mistral 7B, for ASAP, *Top-10* features are the most effective by both average and subset QWK measurement; for ELLIPSE, the best performing linguistic feature choice is only *Top-3* feature, while the difference is marginal. In addition, the improvement brought by the linguistic features even pushes the Mistral performance on ASAP close to GPT-4 performance. Based on these observations, we can conclude that including linguistic features can benefit LLM-based zero-shot AES.

6. Conclusion

In this work, we explore the combination of linguistic features and zero-shot prompting with SoTA LLMs in the task of automatic essay scoring. Empirical experiments show performance improvement when linguistic features are integrated into the zero-shot prompt. However, the performance improvement varies depending on the type of the essay, proving the challenging nature of generalizability in AES systems. We hope our work can serve as a starting point for the research in more interpretable and more generalizable LLM-based AES methods.

7. Limitations

During our experiments, we noted several limitations that future work could expand upon and resolve. Firstly, there is only one open-source and one close-source model. Future work could look at including more LLMs for comparison. Secondly, the prediction target, holistic

6. <https://chatgpt.com/>

score, is still hard to interpret, whereas some subsets (7 and 8) of ASAP and the entire set of ELLIPSE do have fine-grained essay score annotations (see examples in Appendix A). Incorporating them into the overall score prediction process would make the overall score more transparent. Thirdly, the persona section of the prompt template mentions “grade 7 to 10,” which is the age range for students in ASAP; however, the students in the ELLIPSE dataset are from grades 8 to 12, which might lead to performance differences among those two datasets. Lastly, our datasets have a clear Western bias, especially ELLIPSE, which focuses on ESL students in the United States. We believe the community would benefit from more diverse and inclusive datasets.

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Appendix A. ELLIPSE Rubric

Score Category	5	4	3	2	1
Overall	Native-like facility in the use of language with syntactic variety, Appropriate word choice and phrases; well-controlled text organization; precise use of grammar and conventions; rare language inaccuracies that do not impede communication.	Facility in the use of language with syntactic variety and range of words and phrases; controlled organization; accuracy in grammar and conventions; occasional language inaccuracies that rarely impede communication.	Facility limited to the use of common structures and generic vocabulary; organization generally controlled although connection sometimes absent or unsuccessful; errors in grammar and syntax and usage. Communication is impeded by language inaccuracies in some cases.	Inconsistent facility in sentence formation, word choice, and mechanics; organization partially developed but may be missing or unsuccessful. Communication impeded in many instances by language inaccuracies.	A limited range of familiar words or phrases loosely strung together; frequent errors in grammar (including syntax) and usage. Communication impeded in most cases by language inaccuracies.
Cohesion	Text or organization consistently using a variety of effective linguistic features such as reference and transitional words and phrases to connect ideas across sentences and paragraphs; appropriate overlap of ideas.	Organization generally well controlled; a range of cohesive devices used appropriately such as reference and transitional words and phrases to connect ideas; generally appropriate overlap of ideas	Organization generally controlled; cohesive devices used but limited in type; Some repetitive, mechanical, or faulty use of cohesion use within and/or between sentences and paragraphs.	Organization only partially developed with a lack of logical sequencing of ideas; some basic cohesive devices used but with inaccuracy or repetition.	No clear control of organization; cohesive devices not present or unsuccessfully used; presentation of ideas unclear.

Syntax	Flexible and effective use of a full range of syntactic structures including simple, compound, and complex sentences; There may be rare minor and negligible errors in sentence formation.	Appropriate use of a variety of syntactic structures, such as simple, compound, and complex sentences; occasional errors or inappropriateness in sentence formation.	Simple, compound, and complex syntactic structures present although the range may be limited; some apparent errors in sentence formation, especially in more complex sentences.	Some sentence variation used; many sentence structure problems.	Pervasive and basic errors in sentence structure and word order that cause confusion; basic sentences errors common.
Vocabulary	Wide range of vocabulary flexibly and effectively used to convey precise meanings; skillful use of topic-related terms and less common words; rare negligible inaccuracies in word use.	Sufficient range of vocabulary to allow flexibility and precision; appropriate use of topic-related terms and less common lexical items	Minimally adequate range of vocabulary for the topic; no precise use of subtle word meanings; topic related terms only used occasionally; attempts to use less common vocabulary but with some inaccuracy	Narrow range of vocabulary to convey basic and elementary meaning; topic related terms used inappropriately; errors in word formation and word choice that may distort meanings	Limited vocabulary often inappropriately used; limited control of word choice and word forms; little attempt to use topic-related terms
Phraseology	Flexible and effective use of a variety of phrases, such as idioms, collocations, and lexical bundles, to convey precise and subtle meanings; rare minor inaccuracies that are negligible.	Appropriate use of a variety of phrases, such as idioms, collocations, and lexical bundles; occasional inaccuracies and colloquialisms.	Evident use of phrases such as idioms, collocations, and lexical bundles but without much variety; some noticeable repetitions and misuses.	Narrow range of phrases, such as collocations and lexical bundles, used to convey basic and elementary meaning; many repetitions and/or misuses of phrases.	Memorized chunks of language, or simple phrasal patterns predominate; many repetitions and misuses of phrases.
Grammar	Command of grammar and usage with few or no errors.	Minimal errors in grammar and usage.	Some errors in grammar and usage.	Many errors in grammar and usage.	Errors in grammar and usage throughout.

Conventions	Consistent use of appropriate conventions to convey meaning; spelling, capitalization, and punctuation errors nonexistent or negligible.	Generally consistent use of appropriate conventions to convey meaning; spelling, capitalization, and punctuation errors few and not distracting.	Developing use of conventions to convey meaning; errors in spelling, capitalization, and punctuation that are sometimes distracting.	Variable use of conventions; spelling, capitalization, and punctuation errors frequent and distracting.	Minimal use of conventions; spelling, capitalization, and punctuation errors throughout.
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Table 2: The ELLIPSE rubric, gotten directly from the original paper.

Appendix B. Supervised Baseline Details

Our supervised baseline Wang et al. (2022)⁷ is a BERT-based architecture comprised of two sub-components—each pretrained BERT models (Devlin et al.)—which analyze three main feature classes: document-, token- and segment-scale features. The first sub-component receives the document- and token-scale features. It is fine-tuned to learn the document-scale feature representation through the [CLS] (start) token⁸ and the token-scale features through the BERT word embeddings. Its output goes through a final max pooling layer to represent the sub-component’s score. The segment-scale features are received by the second sub-component, which takes in an essay as a series of segments each of size k (except the last segment, which is smaller). A list of these segment series of varying sizes k_i are input into the model sequentially, and a final LSTM and attention and dense pooling layer is used to output the sub-component’s score. Lastly, the output from the two sub-components are added together to produce the final holistic score. The model’s loss function is additive between mean squared error (MSE), cosine similarity (CS) and margin ranking loss (MLR): $\mathcal{L}_{\text{Total}}(\mathbf{x}, \mathbf{y}) = \alpha \mathcal{L}_{MSE}(\mathbf{x}, \mathbf{y}) + \beta \mathcal{L}_{CS}(\mathbf{x}, \mathbf{y}) + \gamma \mathcal{L}_{MLR}(\mathbf{x}, \mathbf{y})$.

We base our fine-tuning on the authors’ available code⁹. The authors only released their fine-tuned model for ASAP prompt 8, so—to obtain models for all prompts—we fine-tuned **bert-base-uncased** as they did in the original paper. We used our splits of the ASAP dataset for fine-tuning, validation and testing (see 4.1). We fine-tune for 80 epochs, our hyperparameters for α , β and γ were all set to 0.5 and with cosine similarity `dim=1` and margin ranking loss `margin=0`. Everything is implemented in PyTorch (Paszke et al. (2019)) and HuggingFace (Wolf et al. (2019)) using `google-bert/bert-base-uncased`. We run the test set on the prompt’s model with the best loss.

7. <https://github.com/lingochamp/Multi-Scale-BERT-AES>

8. There can be multiple text segments per essay as their input length is set to 510.

9. Available upon acceptance.

Appendix C. Zero-shot Essay Scoring Prompts

Here are some examples of zero-shot essay scoring prompts. Note that the exact phrasing and wording are not exactly the same as [Stahl et al. \(2024\)](#) paper. That is because we have failed to reproduce the exact same results in their paper, motivating us to conduct a limited prompt tuning in the `dev` set of ASAP. To reduce complexity, the tuning is done only in phrasing and formatting, without changing the overall structure of the prompt compared to the original design.

C.0.1. NO LINGUISTIC FEATURE

You are part of an educational research team analyzing the writing skills of students in grades 7 to 10. You have been given a student’s essay and the prompt they responded to.

Essay Prompt: More and more people use computers, but not everyone agrees that this benefits society. Those who support advances in technology believe that computers have a positive effect on people. They teach hand-eye coordination, give people the ability to learn about faraway places and people, and even allow people to talk online with other people. Others have different ideas. Some experts are concerned that people are spending too much time on their computers and less time exercising, enjoying nature, and interacting with family and friends. Write a letter to your local newspaper in which you state your opinion on the effects computers have on people. Persuade the readers to agree with you.

Analysis Task: Grade the given essay with the following requirements:

- Use those score ranges: Overall: from 1 to 6.*
- Provide an explanation for your score as well.*

Analyzed Student Essay: Dear, @CAPS1 @CAPS2 @CAPS3 More and more people use computers, but not everyone agrees that this benefits society. Those who support advances in technology believe that computers have a positive effect on people. Others have different ideas. A great amount in the world today are using computers, some for work and spme for the fun of it. Computers is one of mans greatest accomplishments. Computers are helpful in so many ways, @CAPS4, news, and live streams. Don’t get me wrong way to much people spend time on the computer and they should be out interacting with others but who are we to tell them what to do. When I grow up I want to be a author or a journalist and I know for a fact that both of those jobs involve lots of time on time on the computer, one @MONTH1 spend more time then the other but you know exactly what @CAPS5 getting at. So what if some expert think people are spending to much time on the computer and not exercising, enjoying natures and interacting with family and friends. For all the expert knows that its how must people make a living and we don’t know why people choose to use the computer for a great amount of time and to be honest it’s non of my concern and it shouldn’t be the so called experts concern. People interact a thousand times a day on the computers. Computers keep lots of kids of the streets instead of being out and causing trouble. Computers helps the @ORGANIZATION1 locate most wanted criminals. As you can see computers are more useful to society then you think, computers benefit society.

Analysis: Conclude your analysis with a grade and comments in the following format:

Explanation:

Score:

- Overall:*

C.0.2. TOP-10 FEATURES

You are part of an educational research team analyzing the writing skills of students in grades 7 to 10. You have been given a student's essay and the prompt they responded to.

Essay Prompt: More and more people use computers, but not everyone agrees that this benefits society. Those who support advances in technology believe that computers have a positive effect on people. They teach hand-eye coordination, give people the ability to learn about faraway places and people, and even allow people to talk online with other people. Others have different ideas. Some experts are concerned that people are spending too much time on their computers and less time exercising, enjoying nature, and interacting with family and friends. Write a letter to your local newspaper in which you state your opinion on the effects computers have on people. Persuade the readers to agree with you.

Analysis Task: Grade the given essay with the following requirements:

- Use those score ranges: Overall: from 1 to 6.
- Provide an explanation for your score as well.

Analyzed Student Essay: Dear, @CAPS1 @CAPS2 @CAPS3 More and more people use computers, but not everyone agrees that this benefits society. Those who support advances in technology believe that computers have a positive effect on people. Others have different ideas. A great amount in the world today are using computers, some for work and spme for the fun of it. Computers is one of mans greatest accomplishments. Computers are helpful in so many ways, @CAPS4, news, and live streams. Don't get me wrong way to much people spend time on the computer and they should be out interacting with others but who are we to tell them what to do. When I grow up I want to be a author or a journalist and I know for a fact that both of those jobs involve lots of time on time on the computer, one @MONTH1 spend more time then the other but you know exactly what @CAPS5 getting at. So what if some expert think people are spending to much time on the computer and not exercising, enjoying natures and interacting with family and friends. For all the expert knows that its how must people make a living and we don't know why people choose to use the computer for a great amount of time and to be honest it's non of my concern and it shouldn't be the so called experts concern. People interact a thousand times a day on the computers. Computers keep lots of kids of the streets instead of being out and causing trouble. Computers helps the @ORGANIZATION1 locate most wanted criminals. As you can see computers are more useful to society then you think, computers benefit society.

Additional Information: Studies show that the following features are highly, positively correlated with the grade of the essay (i.e., higher features typically means higher end score)

- total number of unique words in the essay: 113
- total number of words in the essay.: 279
- total number of sentences present: 14
- total number of characters: 279
- total number of lemma: 133
- total number of nouns: 50
- total number of stopwords: 71
- total number of words that are not in the Dale-Chall word list of 3000 words recognized by 80% of fifth graders: 80
- total number of characters: 1229

Analysis: Conclude your analysis with a grade and comments in the following format:
 ### Explanation:
 ### Score:
 - Overall:

Appendix D. Linguistic Features

Unique words refers to the number of single-instance words in the essay. For **essay character length**, we only count the number of non-space, non-punctuation characters. Words are not normalized before these metrics as in the original paper. **Total word count** and **total sentence count** per essay are gotten via `nltk` (Loper and Bird (2002)) tokenizers. We additionally utilize the `en_core_web_sm` in `spaCy` (Honnibal et al. (2020)) to get **separate counts for lemma, noun, and stop-words**. Finally, we get **the Dale-Chall (Dale and Chall (1948)) word count, total character count and long word count** with the `readability`¹⁰ Python package.

Our implementation is based on the code¹¹ from the original paper Ridley et al. (2021b). Our implementation will be made available upon acceptance.

Appendix E. Parsing Module

E.1. Configurations

- Model: Mistral-7B (the same configuration as the scoring model)
- Overall parsing error is less than 7%.

E.2. Few-shot Output Parsing

You are an AI agent that specialized in converting text input into JSON format.

Instruction:

- *Input: text with one or more score and some other relevant information (e.g., explanation, feedbacks, etc.)*
 - *Output: JSON text with ‘Score’ as a mandatory key and other information organized by their field names*
 - *Make sure ONLY return the VALID JSON data, without any additional text or characters.*
- Here are some examples*

Example Input:

Explanation: The student’s essay demonstrates a limited understanding of the topic and a lack of cohesion. The essay jumps from one idea to another without a clear connection between them. The writing is also filled with numerous grammatical errors, misspellings, and inconsistent capitalization.

Score:

- Overall: 1 The essay demonstrates a very limited understanding of the topic and contains

10. <https://pypi.org/project/readability/>

11. <https://github.com/robert1ridley/cross-prompt-trait-scoring/blob/main/features.py>

numerous errors in grammar, spelling, and capitalization. The writing lacks cohesion and a clear thesis statement, and the arguments are not well-supported with evidence or examples.

Example Output:

{ "Score": { "Overall": 1 }, "Explanation": "The student's essay demonstrates a limited understanding of the topic and a lack of cohesion. The essay jumps from one idea to another without a clear connection between them. The writing is also filled with numerous grammatical errors, misspellings, and inconsistent capitalization." }

Example Input:

Explanation: The student's essay demonstrates a basic understanding of the topic and presents a clear position, but the writing is disorganized and contains numerous errors in language conventions. The essay jumps between discussing censorship in libraries and specific examples of offensive music, making it difficult to follow the main argument.

Score:

- Writing Applications: 2 The essay presents a viewpoint on the issue of censorship, but the argument is not well-developed or clearly stated. The student uses personal experiences and examples. - Language Conventions: 1 The essay contains numerous errors in language conventions, including incorrect capitalization, punctuation, and sentence structure.

Example Output:

{ "Score": { "Writing Applications": 2, "Language Conventions": 1 } "Explanation": "The student's essay demonstrates a basic understanding of the topic and presents a clear position, but the writing is disorganized and contains numerous errors in language conventions. The essay jumps between discussing censorship in libraries and specific examples of offensive music, making it difficult to follow the main argument." }

Example Input:

Explanation: The student's essay demonstrates a moderate level of awareness of the audience, as they address the readers directly and use a conversational tone.

Feedbacks: the essay could have been more effective if the student had used more formal language and addressed specific concerns of the local community regarding the overuse of computers.

Score:

- Overall: 3 The student's essay shows some awareness of the audience, but there is room for improvement in terms of language and organization. The essay could benefit from more specific examples and a clearer, more focused argument.

Example Output: { "Score": { "Overall": 3 }, "Explanation": "The student's essay demonstrates a moderate level of awareness of the audience, as they address the readers directly and use a conversational tone.", "Feedbacks": "the essay could have been more effective if the student had used more formal language and addressed specific concerns of the local community regarding the overuse of computers." }

Now work on the following input:

Input:

{LLM OUTPUT}

Output:

Appendix F. Output Examples

Note Red text refers to incorrect reason(s); Green text refers to correct reason(s) ; Blue text mentions linguistic feature(s).

F.1. Example 1 (from essay set 1 in ASAP)

Student’s Essay *instructor score: 9 (range: 2-12)*

Dear @CAPS1 @CAPS2, I’m writing you today so you can see why advanced technology is a positive effect on people. My reasons for writint this is because computers allow people to talk online to others people learn about faraway places, and finally it teacher hand-eye coordination. As you read my letter I hope you fell the same way. First of all computers allow you to talk to other people online. The reason I feel this way is what if you can’t fond your fone in your hose or even your cell phone, you could see if they were online. Also its the same thing as texting, but with a bigger keyboard/screen I can relate to this because I was texting someone and went online to find whtm on too, so we sent aims to each other instead. I hope you can see why computers can be good for people. Secondly not a lot of people will go to the library to look up information for a paper for a school. The reason I feel this way is a computer has google to make finding things easier. Another reason is going to the library @MONTH1 cause you send more money to fill up your gas tanks. I can relate this because everytim my family goes to the library we have to fill the car up after we go. This is another reasons why computers a good. Finally the computers can teach hand-eye coordination. The reason for this is because if your writing an email then you should know the keys that your fingers touch. Another reasons why computers are hand-eye coordination is because if your kid take karayta then might have learned to move there hands that fast from somewhere. I can relate ti this because when I was in the first grade there was a guy that you told me and my friends that be need us to get in the truck to help him find his lost puppy, and he tried grabbing me but I pulled my hard away before I became pinned. I hope you can see why we need computers. I would like to that the I for sitting and reading my essay. Once again my reasons for writing where people can talk to other people online, learn about faraway places, and finally hand-eye coordination. I hpoe you will rethink why we should have computers in school.

Mistral + None Linguistic Feature *Score: 8*

The student’s essay effectively addresses the given prompt by stating their opinion on the positive effects computers have on people and persuading the readers to agree. The essay is well-structured and presents several arguments to support the main idea.

The student **uses statistics and examples** to strengthen their arguments, making the essay more persuasive and engaging. The use of contractions and colloquial

language adds a conversational tone, making the essay more accessible to a general audience.

However, there are some areas for improvement. The essay contains several grammatical errors, such as missing articles, incorrect verb tenses, and inconsistent capitalization. The student also repeats some ideas and could benefit from more varied sentence structures.

Mistral + Full Linguistic Feature *Score: 10*

The student’s essay effectively addresses the given prompt by stating their opinion on the positive effects computers have on people and persuading the readers to agree. The essay includes several reasons to support the argument, such as the ability to get updated on important issues, contact people, and learn new information. The student also provides examples and statistics to strengthen their argument.

In terms of the rubric, the essay demonstrates a clear and coherent argument with a logical flow of ideas. The student uses a variety of sentence structures and vocabulary, which shows a good command of language. The essay also includes some use of transitional words and phrases to connect ideas.

The essay contains a good number of unique words and lemmas, indicating a strong vocabulary and use of varied sentence structures. The number of words not in the Dale-Chall word list is also relatively low, suggesting that the student has a good command of grade-level vocabulary.

Summary Under both settings, the Mistral model predicts closely compared to the instruction score. Including the linguistic features makes the predicted score increase by 2.

F.2. Example 2 (from essay set 3)

Student’s Essay *Instructor Score: 3 (range: 0-3)*

The setting of this story is very rigorous. At the begining of the story the boy was fine. He had a bottle of water with him so that he didn’t get dehydrated. When he was riding he started to feel the sun get higher into the sky, though he could barely feel. It because of the pines that caused the road, and the cool feel of the river. The cyclist got to the second town on his journey and he had been drinking his water all day and was about out. He had found a water pump. He got down on his knees and palled with his night hot all that came but was blackish water. He just feared the water and stated that it tasted like battery acid. He began to ride again. Not two miles up the road the terrain changed. Not only was it rolling hills, it was also getting hotter. He was majorly dehydrated because he was out of water except nor a few tantalizing sips. Dry sweat circled his shirt and he was afraid he could froz up heatstrokes. Where he was at was in the middle of no where, with no buildings, cars or structures in sight. Over were of the hills he saw a building came in no view. He wiped

the sweat off his eyes so makee sure it was not a malinge, By the lols of it had been a Welch @CAPS1 @CAPS2 Factory. He is a dehydrated and tired that he could see a Young boy pouring a refreshing glass of juice in his mouth. There is only the problems it is abandoned. This person was imagining things. He got back on his bike and stuck pebbles into mouth. This was to help tabe his mind off being thirst.

Mistral + None Ling. Feat. *Score: 1*

The student’s essay demonstrates an attempt to understand the role of the setting in the cyclist’s experience, but it falls short in providing a clear and detailed analysis. **The essay includes some relevant details from the text**, such as the changing terrain and the cyclist’s increasing dehydration, but it lacks cohesion and organization. The student’s use of grammar and sentence structure is also inconsistent, making it difficult to follow their ideas.

Mistral + Full Ling. Feat. *Score: 1*

The student’s essay demonstrates an attempt to summarize the main points of the given text, focusing on the effects of the setting on the cyclist. **However, the essay contains several errors in grammar, capitalization, and word usage that hinder the clarity and coherence of the ideas.** The essay also lacks a clear introduction and conclusion, making it difficult to assess the depth of understanding.

GPT-4 + None Ling. Feat. *Score: 1*

The student’s essay does attempt to address the prompt by discussing how the setting affects the cyclist. The student provides examples from the text to support their points, such as the cyclist’s dehydration due to the hot weather and the lack of water, the change in terrain, and the cyclist’s hallucinations due to exhaustion and dehydration. **However, the essay is riddled with spelling and grammatical errors**, which make it difficult to understand in places. **The student also fails to fully explain how these aspects of the setting affect the cyclist beyond causing physical discomfort.** For example, they could have discussed how the isolation of the setting contributes to the cyclist’s desperation and fear.

GPT-4 + Full Ling. Feat. *Score: 2*

The student’s essay does a decent job of summarizing the events of the story and how the setting affected the cyclist. The student mentions the heat, the lack of water, the changing terrain, and the isolation of the cyclist. However, the essay lacks depth in its analysis of how these elements of the setting affected the cyclist beyond causing physical discomfort. The student could have delved deeper into how the setting contributed to the cyclist’s mental state, his hallucinations, and his desperation. **The essay also contains several grammatical errors and awkward phrasing**, which detracts from its overall clarity and coherence.

The student’s use of unique words and sentences is commendable, but the high number of words not recognized by fifth graders suggests that the student may be

using complex vocabulary without fully understanding it. This could contribute to the essay’s lack of clarity. The student also uses a significant number of stopwords, which could indicate a lack of precision in their language use.

Summary Only GPT-4 is able to identify the linguistic features presented and it was helped by those features to get a closer score. All models are able to identify grammatical errors in the essay. However, grammatical correctness is not explicitly mentioned in the rubric and this miss match between the focus of the rubric and the focus of the models might be the reason that all models predict incorrectly.

F.3. Example 3 (from essay set 4)

Student’s Essay *Instructor Score: 2*

In the story the author concludes with, When they come back, Saeng vowed silently to herself, in the spring, when the snows melt and the geese return and this hibiscus is budding, then I will take that test again. I think she did that to say that you shouldn’t give up. In the story Saeng goes to the store and touched a petal. She buys the plant in an attempt to get a reminder of her old home. In this way it seems Saeng is willing to give up her memories of her past. When she brings home the plant and her mom and her plant it in the garden. I think Saeng is trying to make her new home like her old.

Mistral + None Ling. Feat. *Score: 1*

The student’s essay provides a reasonable interpretation of the story’s conclusion, but it lacks sufficient detail and specific examples to fully support their ideas. The student correctly identifies that Saeng’s vow to retake the test in the spring when the hibiscus is budding is a symbol of not giving up, but they do not provide enough evidence from the text to back up this claim. The student mentions that Saeng touches a petal and buys the plant as an attempt to hold on to her memories, but they do not connect this action to the vow she makes at the end of the story. Additionally, the student suggests that Saeng is trying to make her new home like her old one by planting the hibiscus, but this idea is not explicitly stated in the text.

Based on the given rubric, I would give the student a score of 1 for this essay. The student demonstrates an understanding of the text, but their analysis is not fully developed and lacks specific examples and evidence to support their ideas.

Mistral + Full Ling. Feat. *Score: 2*

The student’s essay provides a clear and accurate summary of the story’s conclusion and offers an interpretation of Saeng’s actions. The student identifies the significance of Saeng’s vow to retake the test in the spring and connects it to her purchase of the hibiscus plant. The student also offers an explanation for why Saeng might be trying to make her new home like her old one.

However, the essay **could benefit from more specific details and examples from the text to support the interpretation.** For instance, the student could have quoted or paraphrased Saeng’s thoughts or actions to illustrate her determination to overcome her failure and create a sense of familiarity in her new environment.

Additionally, **the essay could be more polished in terms of grammar and sentence structure.** For example, the student could revise the sentence ”In this way it seems Saeng is willing to give up her memories of her past” to ”In this way, Saeng’s purchase of the hibiscus plant suggests that she is willing to let go of her memories of her past.”

GPT-4 + None Ling. Feat. *Score: 2*

The student’s essay shows a basic understanding of the story and the author’s intent in the concluding paragraph. The student correctly identifies the theme of not giving up and Saeng’s attempt to connect her new home with her old one through the hibiscus plant. **However, the essay lacks depth and does not fully explain why the author concludes the story with Saeng’s vow to retake the test.** The student does not provide enough details and examples from the story to support their ideas. The essay could be improved by discussing the symbolism of the hibiscus plant and the returning geese, and how these elements relate to Saeng’s determination to adapt to her new life and overcome her challenges.

GPT-4 + Full Ling. Feat. *Score: 2*

The student’s essay demonstrates a basic understanding of the story and the significance of the concluding paragraph. The student correctly identifies the theme of not giving up and the symbolism of the hibiscus plant as a connection to Saeng’s past. **However, the essay lacks depth in its analysis and does not provide sufficient evidence from the text to support its claims.** The student’s interpretation that Saeng is ”willing to give up her memories of her past” is not fully explained or supported by the text. **The essay could be improved by providing more detailed examples from the story and by further exploring the significance of the hibiscus plant and Saeng’s decision to retake the test.** **The essay is also relatively short and could benefit from a more thorough exploration of the story’s themes and symbols.**

Summary As shown above, Mistral model generally perform worse than GPT4 due to incorrect analysis of the essay text. Also, GPT4 is able to correctly identify the linguistic features in the reasoning text, although it does not need those features to improve its prediction as the non-linguistic setting already gets the prediction correct.

F.4. Example 4 (from essay set 6 in ASAP)

Student’s Essay *instructor score: 3 (range: 0-4)*

When Designing the dock for dirigibles on the top of the empire state Building there were @CAPS1 oBstacles that the @CAPS2 and the @CAPS3 were faced

with. One problem was they couldn't @CAPS4 drop the mooring mast on top of the empire state Building Because it was too @CAPS5 for the frame of the Building. So Because of that problem The @CAPS2 and @CAPS3 had to come up with a way to modify the frame of the Building so that the Building could put up with the added stress of the mooring mast. Another problem that they were faced with was that it was @CAPS4 too dangerous. I was deemed dangerous Because most dirigibles were filled with Hydrogen which was extremely flammable and they couldn't @CAPS8 having @CAPS9 happen to the Hindenburg happen 102 floors above city streets that were crowded with people. So those were @CAPS4 a few obstacles that @CAPS2 were faced with when building the mooring mast on top of the empire state Building

Mistral + None Linguistic Feature *Score: 1*

The student's essay provides a brief summary of the obstacles faced by the builders of the Empire State Building when attempting to allow dirigibles to dock there. However, the essay contains **several errors in grammar, capitalization, and word choice** that make it difficult to fully understand the intended meaning.

Mistral + Top 3 Linguistic Feature *Score: 2*

The essay demonstrates an understanding of the main ideas presented in the text, but the **errors in grammar, capitalization, and word choice** detract from the clarity and coherence of the writing. **The essay contains only 50 unique words and 76 lemmas, which is below the expected range for a grade 7-10 essay. Additionally, 45 of the words used in the essay are not in the Dale-Chall word list, which is a concern for a student at this level.**

To improve the essay, the student should focus on using proper grammar, capitalization, and word choice to ensure that the meaning of the essay is clear and concise. **The student should also aim to use a wider range of vocabulary and increase the total number of words in the essay to meet the expected grade level requirements.**

Summary In this case, the Mistral model is able to identify linguistic features embedded in the prompt and analyze them. Including the linguistic features also improves the final prediction.

F.5. Example 5 (from essay set 6 in ASAP)

Student's Essay *instructor score: 2 (range: 0-4)*

The builders of the empire state building faced many obstacles to have dirigibles dock there. First off, it was a huge safety issue; "most dirigibles from outside the United States used hydrogen... hydrogen is highly flammable" (paragraph @NUM1) if an accident happened (lets say to the magnitude of the Hindenburg) over New York City, thousands of people could die because of this highly flammable

substance. Secondly a very large problem was to successfully use the mooring mast. "The winds at the top of the building work constantly shifting due to air currents" (paragraph @NUM2). If the wind was out of controll and the dirigible wasn't tied down right, the harsh winds could be dangerously dangeling over the people of New York. Amongst many other reasons and the use of common sense, it is clear that the construction of this mooring mast should never have ever been thought of as a reality.

Mistral + None Linguistic Feature *Score: 3*

The student's essay provides a clear and concise summary of the two main obstacles that prevented dirigibles from docking at the Empire State Building: safety concerns due to the use of hydrogen and the difficulty of mooring in the windy conditions at the building's height. The student effectively references the text by using specific quotes and paraphrasing information to support their points.

However, the essay could be improved by providing more detail about the specific challenges of mooring in the wind and how it differed from mooring in open landing fields. Additionally, the student could have mentioned the existence and failure of attempts to moor dirigibles at the building, as this information is also provided in the text.

Mistral + Unique Word *Score: 2*

The student's essay provides a clear and concise explanation of the two main obstacles the builders of the Empire State Building faced in attempting to allow dirigibles to dock there: safety concerns due to the use of hydrogen and the difficulty of mooring in the windy conditions. The essay references the text directly and uses specific details to support each point. However, the essay could benefit from more development and elaboration on each point to increase the total number of unique words and improve the overall grade.

Summary In this example, Mistral, with the top linguistic feature (unique words), is able to make correct suggestions about how to improve the essay and make a closer score prediction.