Appendix: Assessing LLM Text Detection in Educational Contexts: Does Human Contribution Affect Detection?

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1 Dataset Statistics

1.1 Text Corpora Analysis

In the following, we provide detailed statistics of the subdatasets AAE [6, 5] (Fig. 1), BAWE [4] (Fig. 2), and PERSUADE [2] (Fig. 3). Note that we compare essays from *Task* contribution level with *Human* contribution level.
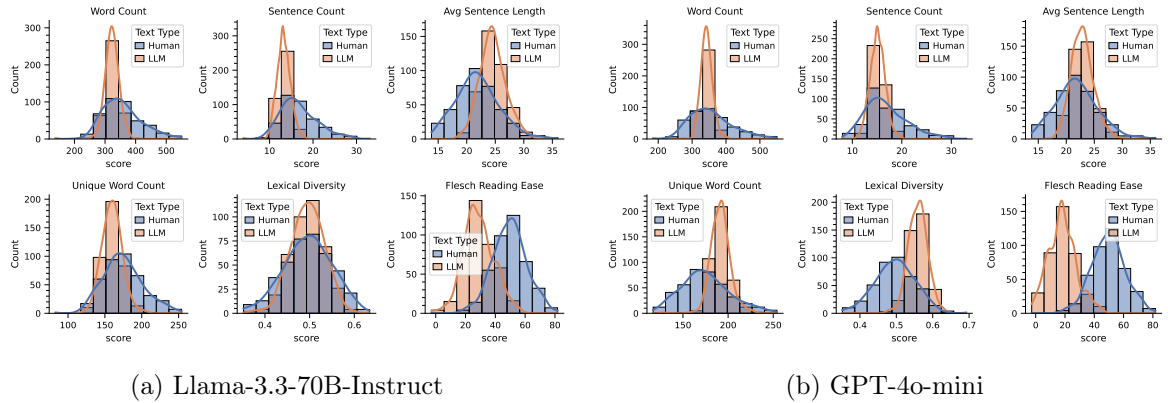

(a) Llama-3.3-70B-Instruct   (b) GPT-4o-mini

Figure 1: AAE *Task* vs *Human* statistics

(a) Llama-3.3-70B-Instruct   (b) GPT-4o-mini
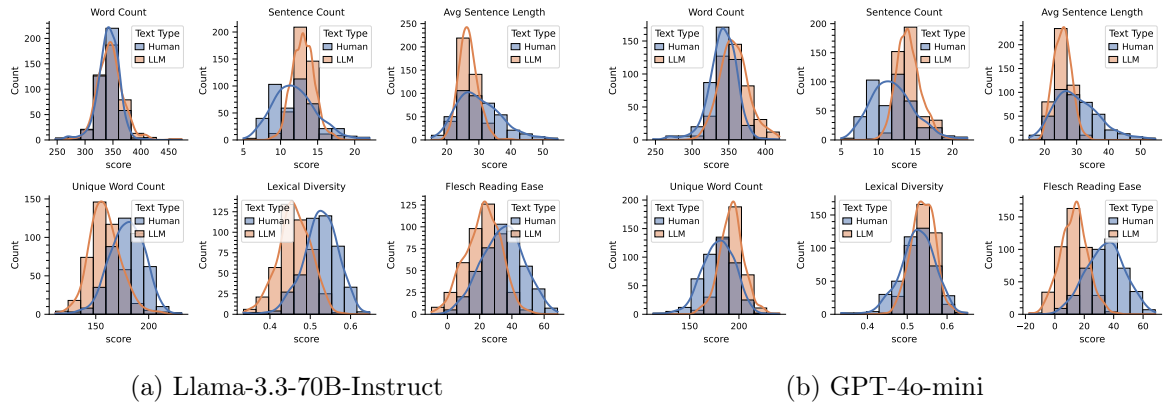
Figure 2: BAWE *Task* vs *Human* statistics

(a) Llama-3.3-70B-Instruct   (b) GPT-4o-mini
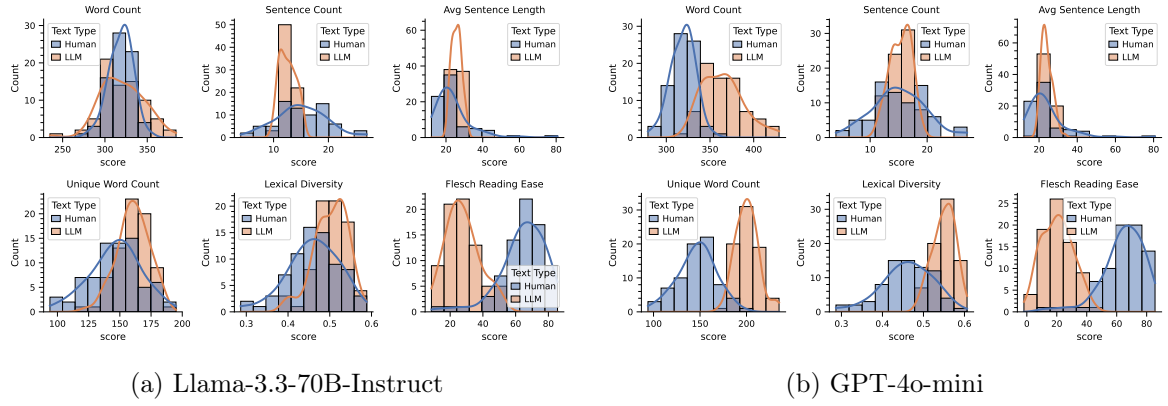
Figure 3: PERSUADE *Task* vs *Human* statistics

1.2 BAWE Disciplines

Table 1 provides an overview of the disciplinary groups included in the BAWE corpus and their respective frequencies and the mean ROC-AUC scores across all detectors.

Table 1: Discipline ROC-AUC comparison

Discipline Group	Group Mean ± Std	Group Count	Discipline	ROC-AUC (Mean ± Std)	Discipline Count
AH	0.812 ± 0.11	197	History	0.841 ± 0.09	25
			Comparative American Studies	0.841 ± 0.09	25
			Other	0.841 ± 0.08	22
			Archaeology	0.829 ± 0.13	25
			English	0.823 ± 0.10	25
			Classics	0.804 ± 0.11	25
			Linguistics	0.793 ± 0.15	24
			OTHER	0.786 ± 0.17	1
			Philosophy	0.753 ± 0.15	25
LS	0.823 ± 0.14	57	Medicine	0.868 ± 0.10	4
			Biological Sciences	0.864 ± 0.07	4
			Agriculture	0.823 ± 0.18	11
			Psychology	0.805 ± 0.17	25
			Health	0.802 ± 0.15	10
			Food Sciences	0.775 ± 0.15	3
PS	0.830 ± 0.13	16	Chemistry	0.910 ± 0.06	1
			Computer Science	0.880 ± 0.09	3
			Architecture	0.816 ± 0.14	3
			Planning	0.812 ± 0.13	6
			Physics	0.731 ± 0.16	3
SS	0.828 ± 0.12	169	Publishing	0.859 ± 0.08	2
			HLTM	0.858 ± 0.11	17
			Business	0.829 ± 0.16	25
			Anthropology	0.828 ± 0.15	22
			Sociology	0.826 ± 0.14	25
			Law	0.819 ± 0.10	25
			Other	0.815 ± 0.15	3
			Economics	0.814 ± 0.13	25
			Politics	0.804 ± 0.14	25

2 Changes to the Human-Written Text in the *Improve-Human* and *Rewrite-Human* Contribution Level

Figure 4a shows an excerpt from a randomly selected human-written text from the BAWE corpus, improved by GPT-4o-mini for the *Improve-Human* contribution level. Text passages highlighted from orange to blue represent changes made by the model to the existing text,

while red indicates removed words and green newly added ones. Although the model made some changes to the text, the meaning remains the same. When comparing the improvements made by GPT to Llama-3.3 in Figure 4b, we can observe that Llama makes fewer changes to the original text. However, both LLMs show similar patterns like correcting '*changes*' to '*shift*' or '*In order to*' to '*to*'.

Furthermore, we compute the cosine similarity between the original human-written text and the corresponding improved/rewritten text from *Improve-Human* and *Rewrite-Human* contribution levels. Figure 5 shows that texts from the *Improve-Human* category are closer to the original texts than the ones from *Rewrite-Human*.

The present study aims to discuss the implications for extension practice of changes → resulting from a shift in thinking about extension from 'transfer of technology' to 'communication to support innovation'. In order to discuss → innovation.' To explore this topic, this → the study will present → provide an overview of what innovation is, what → entails, the focus of technology transfer, and the reasons for transitioning from a technology transfer of technology focus, and the reasons why there is a need to shift from transfer of technology → model to an innovative approach in the extension practices context. In → within the context of extension practices. For this study, rural extension is defined as assistance provided to individuals living in rural areas (farmers → (whether farmers or not) in helping → to help them to identify and analyse → analyze their problems, and → problems while also being aware of opportunities for improvement (see Adams, 1982). Extension was usually → Traditionally, extension has been associated with increasing food production and encouraging → promoting economic development, having the function of promoting → functioning as a means of disseminating knowledge and transferring technology between farmers and researchers (or among farmers to farmers) → themselves) (Leeuwis, 2004:17). ...

(a) Visualization of the changes made by GPT-4o-mini.

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(b) Visualization of the changes made by Llama-3.3-70b-Instruct.

Figure 4: Visualization of the changes made by both LLMs to a human-written text from the BAWE subset, belonging to the *Improve-Human* contribution level.
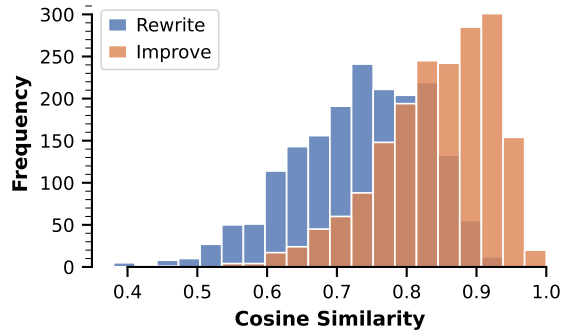
Figure 5: Cosine Similarity between Improve-Human and Rewrite-Human texts.

3 Contribution Level Prompts

Table 2 shows all prompts used to create the LLM-generated essays. The *Human* and *Humanize* levels are included in this table for completeness, although they are not created using system and user prompts.

Table 2: System and User Prompt for each contribution level.

Contribution Level	System Prompt	User Prompt
Human	-	-
Improve-Human	Your task is to improve a given text. Structure and content of the text should be retained and you should only make small improvements to the grammar and language.	Rewrite this text: {`human-text`}
Rewrite-Human	-	Rewrite this text: {`human-text`}
Summary	You are a student writing an essay on a given topic. Write around 300 words.	Write an essay with the following information: {`summary`}
Summary+Task	You are a student writing an essay on a given topic. Write around 300 words.	Write an essay for this task: {`task`} Please include the following information: {`summary`}
Task	You are a student writing an essay on a given topic. Write around 300 words.	Write an essay for this task: {`task`}
Rewrite-LLM	-	Rewrite this text: {`llm-text`}
Humanize	-	-

4 RoBERTa Fine-Tuning

We fine-tune the RoBERTa model using the HuggingFace *roberta-base* model[1] on each of the three text corpora. Table 3 shows the hyperparameters we used for fine-tuning RoBERTa on

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[1]https://huggingface.co/FacebookAI/roberta-base

the different subsets. We chose the best epoch based on the evaluation cross-entropy loss.

Table 3: Hyperparameter of RoBERTa fine-tuning on the different text corpora subsets.

Subset	Batch Size	Test Size	Epochs	Best Epoch
AAE	32	0.2	5	3
BAWE	32	0.2	5	2
PERSUADE	32	0.2	8	3

5 Contribution Level Performance

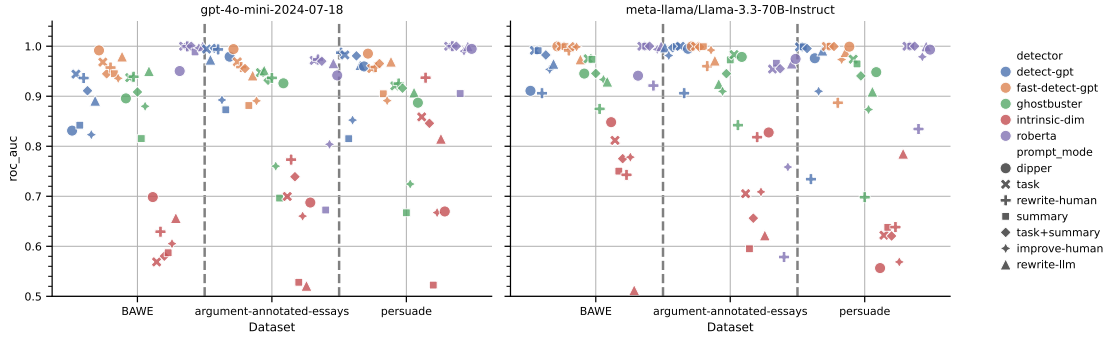Figure 6 shows the performance of all detectors on a single contribution level, corpus, and generative model.

Figure 6: Violin plot of the ROC-AUC over all prompt modes for all detectors on all datasets and generative models.

6 ROC-Curve of Varying Label Boundaries

Figure 7 shows the ROC curves of the different detectors for varying label boundaries. Due to its weak performance on our dataset, IntrinsicDim [7] shows no real difference between the different label boundaries. The RoBERTa [9] model shows multiple inflection points in the ROC curve. This is likely caused by many samples receiving the same prediction score, leading to abrupt changes in the true positive and false positive rates at some thresholds.
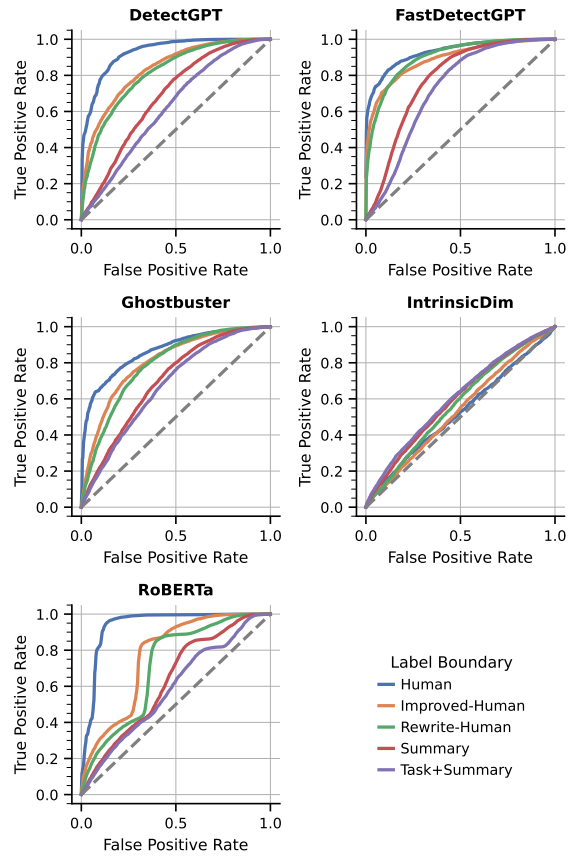
Figure 7: ROC Curve of different detectors at varying human label boundaries.

7 Threshold Optimization

Table 4 provides detailed values for the threshold optimization methods shown in Fig. 3a of the paper.

Table 4: Comparison of different threshold computation methods

Detector	Method	Threshold	Accuracy	Specificity	F1 Score
DetectGPT [3]	F1 Score	0.51	0.76	0.65	0.73
DetectGPT	FPR-based	1.09	0.53	0.95	0.53
DetectGPT	J-Index	0.60	0.74	0.72	0.72
Fast-DetectGPT [1]	F1 Score	2.08	0.84	0.73	0.82
Fast-DetectGPT	FPR-based	3.39	0.69	0.95	0.69
Fast-DetectGPT	J-Index	2.51	0.81	0.83	0.80
Ghostbuster [8]	F1 Score	0.22	0.75	0.62	0.72
Ghostbuster	FPR-based	0.78	0.47	0.95	0.45
Ghostbuster	J-Index	0.27	0.74	0.68	0.72
Ghostbuster	static	0.50	0.63	0.84	0.63
RoBERTa [9]	F1 Score	1.00	0.77	0.59	0.73
RoBERTa	FPR-based	1.00	0.42	0.95	0.40
RoBERTa	J-Index	1.00	0.77	0.60	0.73
RoBERTa	static	0.50	0.72	0.20	0.58

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