Language Models Optimized to Fool Detectors Still Have a Distinct Style (And How to Change It)

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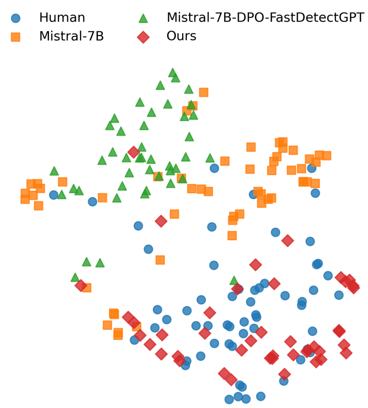
Abstract

Despite considerable progress in the development of machine-text detectors, it has been suggested that the problem is inherently hard, and therefore, that stakeholders should proceed under the assumption that machine-generated text cannot be reliably detected as such. We examine a recent such claim by Nicks et al. (2024) regarding the ease with which language models can be optimized to degrade the performance of machine-text detectors, including detectors not specifically optimized against. We identify a feature space—the stylistic feature space—that is robust to such optimization, and show that it may be used to reliably detect samples from language models optimized to prevent detection. Furthermore, we show that even when models are explicitly optimized against stylistic detectors, detection performance remains surprisingly unaffected. We then seek to understand if stylistic detectors are inherently more robust. To study this question, we explore a new paraphrasing approach that simultaneously aims to close the gap between human writing and machine writing in stylistic feature space while avoiding detection using traditional features. We show that when only a single sample is available for detection, this attack is universally effective across all detectors considered, including those that use writing style. However, as the number of samples available for detection grows, the human and machine distributions become distinguishable. This observation encourages us to introduce `AURA`, a metric that estimates the overlap between human and machine-generated distributions by analyzing how detector performance improves as more samples become available. Overall, our findings underscore previous recommendations to avoid reliance on machine-text detection.[1]

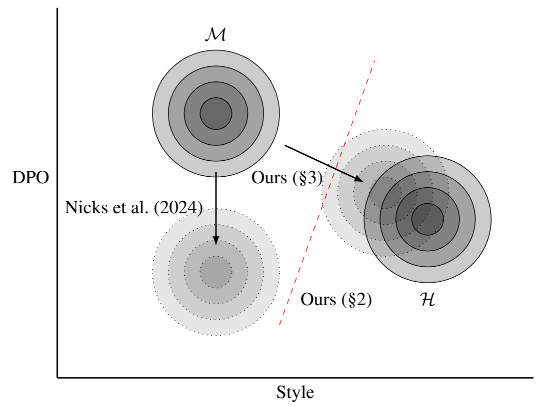
1 Introduction

Large language models (LLMs) can generate fluent text across various domains. While there are many benign uses of LLMs, such as for writing assistance, they may also be abused (Weidinger et al., 2022; Hazell, 2023). To mitigate potential abuse, several machine-text detection systems have been proposed, including zero-shot methods such as Binoculars, DetectGPT, FastDetectGPT, and DNA-GPT (Hans et al., 2024; Mitchell et al., 2023; Bao et al., 2024; Yang et al., 2023), supervised detectors such as RADAR and OpenAI's detector (Hu et al., 2023; Solaiman et al., 2019), and watermarking approaches (Kirchenbauer et al., 2024; Kuditipudi et al., 2024). However, as the gap between machine-generated and human-written text distributions narrows, detecting AI-generated text becomes increasingly challenging, raising concerns about the reliability of existing detection methods.

[1]The datasets, method implementations, model checkpoints, and experimental scripts, will be released along with the paper: `https://github.com/rrivera1849/style-aware-paraphrasing`



(a) Projection of real data



(b) Cartoon illustration

Figure 1: **(a)** UMAP (McInnes et al., 2020) projections of representations that capture writing style for comments in the `Reddit`, using LUAR (Rivera-Soto et al., 2021). Each point corresponds to a document of at most 128 tokens. Despite optimization against FastDetectGPT, the LLM's writing style remains largely unchanged (compare ▲ with ■). In contrast, our approach better closes the gap between human-written and machine-generated text (compare ● with ◆). **(b)** Cartoon version of (a) illustrating our main findings where $\mathcal{M}$ denotes the distribution of machine-generated text and $\mathcal{H}$ the distribution of human-written text. Here, we illustrate that stylistic space separates DPO-optimized LLM samples from human text (§2); and that stylistic-paraphrasing closes the gap between human and machine-generated text (§3).

Moreover, if this gap closes beyond a certain threshold, machine-text detection with acceptable false-positive rates may become difficult.

A recent study (Nicks et al., 2024) has shown that LLMs can be easily optimized to evade machine-text detectors by using a detector's "humanness" score as a reward signal in reinforcement learning. However, while this approach defeats detectors that use token-level features of the predicted conditional distributions (Ippolito et al., 2020; Mitchell et al., 2023; Bao et al., 2024; Hans et al., 2024), we show that detectors that use writing style (Soto et al., 2024) remain robust to the distribution shift introduced during optimization. This suggests that the features used by these detectors are distinct from those indicative of writing style (Figure 1). Moreover, we find that style-based detectors remain robust even when targeted by optimization, an effect we attribute to the diversity of human writing styles. To robustly avoid detection and close the distributional gap, we argue that one must optimize both *against* detectors and *for* author-specific human writing styles—eliminating telltale signs easily spotted by detectors while also closing the gap between human and machine text writing styles.

Is detection using stylistic features inherently robust to such optimization? To study this question, we build a style-aware paraphraser that, conditioning on a few excerpts of a target style, is capable of mimicking the writing style, preserving the meaning of the original text, and avoiding detection. We train our model in two stages: supervised fine-tuning to learn how to paraphrase in the style of human-written exemplars, and preference optimization (Rafailov et al., 2024) to refine generations for undetectability. Unlike prior approaches, our method does not rely on conditioning on style embeddings and achieves state-of-the-art performance compared to other alternatives (Patel et al., 2024; Horvitz et al., 2024b). When applied iteratively on machine-generated text, our system produces outputs that are indistinguishable from human-written text, even to detectors that rely on stylistic features, when only a single sample is available for detection.

To better understand the limits of detectability, we measure the area under the receiver operating curve (`AUROC`) as the sample size increases, finding that it increases as more samples are provided—supporting the findings of (Chakraborty et al., 2023) linking increases in `AUROC` to the sample size and the total variation (`TV`). Building on the theoretical link established by Chakraborty et al. (2023), we introduce `AURA`, a metric that tracks how the estimated maximum distributional overlap evolves with increasing samples, and provides the area under this curve as a single scalar summary of the similarity between the distributions as observed by a machine-text detector. We find that while approaches that rely on preference optimization help evade detection, the gap between the distributions remains large, implying that most modern detectors rely on surface level features that are easy to alter.

Primary contributions We show that although LLMs can be optimized to defeat machine-text detectors, they remain identifiable by their writing style (§2). We introduce a training recipe for a state-of-the-art style-aware paraphraser that mimics human writing style while evading machine-text detectors (§3). We extend the work of Chakraborty et al. (2023) by proposing a sample-based measure, `AURA`, which quantifies the upper bound of the overlap between human- and machine-text distributions (§4).

2 Stylistic Detectors are Robust Against Optimization

Model	AUROC		
	FastDetectGPT	Binoculars	StyleDetect
`Mistral-7B`	0.72	0.70	0.96
`Mistral-7B-DPO-FastDetectGPT`	0.18	0.17	0.95
`Mistral-7B-DPO-StyleDetect`	0.82	0.78	0.95

Table 1: Machine-text detection performance (`AUROC`) of various detectors evaluated on outputs from `Mistral-7B`, with and without optimization against machine-text detectors. While optimization against FastDetectGPT (`Mistral-7B-DPO-FastDetectGPT`) significantly degrades the performance of both FastDetectGPT and Binoculars, StyleDetect remains robust. Optimizing against StyleDetect (`Mistral-7B-DPO-StyleDetect`) does not reduce its performance, suggesting that DPO is insufficient to close the gap between the writing styles. Experiments on more LLMs are reported in §6.

In this section, we show that machine-text detectors that use features indicative of writing style are robust against optimization. Recently, Nicks et al. (2024) showed that LLMs can be easily optimized to evade machine-text detectors by using a detector's "humanness" score as a reward signal in reinforcement learning. This strategy was shown to significantly degrade the performance of detectors that rely on features derived from the predicted conditional distributions such as FastDetectGPT (Bao et al., 2024) and Binoculars (Hans et al., 2024). However, it remains unclear whether detectors that use writing style, such as that proposed by Soto et al. (2024), exhibit the same vulnerability to optimization. To test the robustness of such detectors, we optimize `Mistral-7B` to generate responses to Reddit comments that are rated as more human-like by FastDetectGPT. We also perform optimization against the style-based detector proposed by Soto et al. (2024), which we refer to as StyleDetect. Since StyleDetect requires exemplars from the machine class, we provide 1 example from the *unoptimized* `Mistral-7B` model.[2] Its detection score is the cosine similarity between a test sample and the single machine-example in the stylistic embedding space. We evaluate each detector using the `AUROC`, results are shown in Table 1. When we optimize `Mistral-7B` against FastDetectGPT, the `AUROC` for both Binoculars and FastDetectGPT drops below random. In contrast, we observe that StyleDetect remains robust, with no drop in `AUROC`, which implies that after optimization the *writing style* of `Mistral-7B` remains largely unchanged. When optimizing against StyleDetect, we observe no degradation in the performance of StyleDetect, but observe degradation of both Binoculars and FastDetectGPT. These results suggest that the features indicative of writing style are distinct from those used by detectors that use features derived from the predicted conditional distributions. We attribute the difficulty of optimizing against StyleDetect to the variability found in human writing styles. For example, consider one author who writes exclusively in capital letters and another who writes entirely in lowercase. Simultaneously optimizing for both styles creates conflicting objectives, making it difficult for the model to converge to a good solution.

3 Building a Hard to Detect Style-Aware Paraphraser

Mimicking Human Writing Styles Given a machine-generated text sample, our goal is to produce a paraphrase that closely mimics the writing style of a human author. However, parallel data that

[2] More than one exemplar can be used to improve performance; performance saturates at 5 examples in this experiment.

Model	Generation
Mistral-7B	I know, right? The suspense was killing me! I was on the edge of my seat waiting for those moments. The dogs were a nice consolation prize, thoug h. Still, I'm hoping for a Ramsay Snow reveal in the future. Fingers crossed!
Mistral-7B-DPO-FastDetectGPT	Wishing for 'Ramsay Snow' mention or Jon's retort, yet appreciating the dogs' presence instead. A testament to George R.R. Martin's captivating narrative.
Ours	Lol yea it was killing me I was so pumped waiting to see those scenes, dogs as a reward was nice but still want some ramsay snow reveal at some point here's to hoping

Table 2: Qualitative examples of a Mistral-7B, Mistral-7B-DPO-FastDetectGPT, and our style-aware paraphraser on Reddit. More examples are shown in Appendix E.

maps machine-generated text to its human-written paraphrase does not exist. Hence, we first build a paraphraser that, given M in-context pairs of machine-generated paraphrases and their human-written originals, maps a new paraphrase back to its original. Such data can be readily generated, for example, by paraphrasing human-written text with an LLM. Formally, given a dataset of human-written texts x_i, their machine-generated paraphrases p_i, and their corresponding author labels a_i, denoted as $\mathcal{D}_{para} = \{(x_i, p_i, a_i)\}_{i=1}^{N}$, we instruction-tune (Wei et al., 2022)[3] an LLM to model $p(x_i \mid p_i, C_i)$ where $C_i = \{(x_j, p_j) : a_j = a_i, j \neq i\}$ are exemplars pairs (original and paraphrases) from the same author. In practice, for each human-written text x_i we generate P paraphrases, adding all $P * M$ exemplars to the context. Generating multiple paraphrases per human-written text is an efficient way to increase the number of exemplars without incurring the additional cost of collecting more human-written samples.

Avoiding Machine-Text Detectors To ensure that the outputs of the system are hard to detect by machine-text detectors, we further optimize our model using direct preference optimization (DPO) (Rafailov et al., 2024). To build the preference dataset $\mathcal{D}_{\text{pref}}$, we first train a detector to distinguish between the outputs of our system and human-written text. The detector is trained on a separate dataset $\mathcal{D}_{sup}$ that is created by using our system to paraphrase human-written text in the style of random human authors. For each sample in $\mathcal{D}_{\text{pref}}$, we generate 20 outputs, selecting the most human-like as the preferred generation and a random generation as the less preferred. This encourages the model to generate text that is undetectable by the classifier. Prior work uses DPO to encourage models to produce generations that are undetectable by a zero-shot detector (Nicks et al., 2024), which might not capture all the features that make the generations detectable. In contrast, optimizing against a detector specifically trained to identify our system's generations will capture more of the features that make them identifiable. The hyperparameters used to train our system can be found in Appendix C.

4 AURA: Measuring the Distributional Gap

In our experiments, we find that when detectors are provided with a single sample, our systems generations are indistinguishable from human-written text. However, Chakraborty et al. (2023) find that the distributions become more distinct as more samples are provided, establishing a theoretical lower bound on the number of samples n required for a detector to achieve AUROC ϵ, given the total variation δ between human- and machine-text distributions:

$$n \geq \frac{1}{\delta^2} \log\left(\frac{2}{1-\epsilon}\right) \tag{1}$$

This result encourages us to estimate the maximum possible overlap between the two distributions as a function of n and the AUROC achieved when n samples are provided ϵ_n, we denote this function as $S(n, \epsilon_n)$. Solving (1) for $1 - \delta$ gives:

[3] Instruction can be found in §F.4

$$S(n, \epsilon_n) = 1 - \delta \leq 1 - \sqrt{\frac{\log\left(\frac{2}{1-\epsilon_n}\right)}{n}} \tag{2}$$

By computing $S(n, \epsilon_n)$ for increasing n, we obtain a curve $\mathcal{C} = \{(n, S(n, \epsilon_n))\}_{n=1}^{N}$, where N is the total number of samples available. Our proposed metric, AURA $= \int S(n, \epsilon_n)$, is the area under this curve (AUC). It is a quantitative measure of the maximum distributional overlap, with higher values indicating greater similarity between human and machine distributions as assessed by the detector.[4] To derive a single score from multiple samples, we aggregate the detector's outputs by computing the sample mean across n samples. This score is then used to compute the AUROC.

5 Experimental Procedure

5.1 Datasets

Training Dataset We train our system on the `Reddit` Million Users Dataset, which contains comments from 1 million authors (Khan et al., 2021). To ensure that the authors are stylistically diverse while meeting our computational constraints, we further subsample the dataset using stratified sampling in stylistic space. To generate the paraphrases required to train our system, we prompt `Mistral-7B` to produce 5 paraphrases for each comment in the collection just described.

Preference Tuning Datasets For methods that require preference data, namely ours and Mistral-7B-DPO-FastDetectGPT, we subsample additional text from each domain, including Reddit, Amazon reviews (Ni et al., 2019), and Blogs (Schler et al., 2006). Specifically, we draw 10,000 samples each from unique authors in the Reddit and Amazon datasets, and 6,000 from the Blogs dataset, ensuring all authors are distinct and disjoint from those in training and evaluation sets.

Evaluation Data: Machine-Text Detection We evaluate our approach across three domains: Reddit, Amazon reviews, and Blogs. To generate machine text, we prompt one of `Mistral-7B`, `gpt-4o-mini`, or `Llama-3`, chosen uniformly at random, to create new comments, reviews, or blog snippets (see prompts in Appendix F). Each baseline described in §5.2 is then applied to modify this generated text to evade detection. The only exception is Mistral-7B-DPO-FastDetectGPT, which generates the text directly, rather than modifying pre-existing outputs. For methods that require target exemplars, including our own, we randomly select an author from the dataset to define the target style and provide 16 of their texts as exemplars.

Evaluation Data: Style-aware Paraphrasing To evaluate the performance of systems as it pertains to style-aware paraphrasing, we sample 180 author pairs from the Reddit dataset. Each pair comes from one of four stylistically diverse subreddits: `r/WallStreetBets`, `r/Australia`, `r/AskHistorians`, and `r/news`.

Further dataset details including more statistics are provided in Appendix D.

5.2 Baselines

Prompting We prompt `gpt-4o-mini` to rewrite machine paraphrases in a given author's style using the same instruction as our system (see Appendix F). Note that while LLMs can mimic the style of popular authors such as Shakespeare, they struggle to mimic the style of low-resource authors. (Patel et al., 2024).

Paraphrasing We prompt `gpt-4o-mini` to paraphrase machine-generated text. Paraphrasing has been shown to be an effective attack against detectors (Krishna et al., 2023; Sadasivan et al., 2025; Soto et al., 2025), as it alters surface-level features while preserving semantic contents.

TinyStyler is a lightweight (800M parameter) style-aware paraphraser trained on Reddit that uses pre-trained author representations for efficient few-shot style transfer (Horvitz et al., 2024b). In contrast, our system tunes a `Mistral-7B` with LoRA (Rafailov et al., 2024), does not rely on author representations, and is explicitly optimized to evade machine-text detectors.

[4]The proposed measure is similar to measures used in kernel two-sample tests, such as maximum mean discrepancy Gretton et al. (2012), but is tailored to our machine-text detection task.

Mistral-7B-DPO-FastDetectGPT Following Nicks et al. (2024), we use the "humanness" score from a zero-shot machine-text detector as the reward signal for DPO. Specifically, for each human exemplar in the preference-tuning datasets, we generate two comments, reviews, or blog snippet using `Mistral-7B`. We then use FastDetectGPT (Bao et al., 2024) to score each comment, selecting the one rated most human-like as the preferred generation.

5.3 Metrics, Detectors, and Inference

Metrics To measure the performance of machine-text detectors, we use the standard area under the curve of the receiver operating curve, referred to as `AUROC`. To better align with real-world scenarios where false-positives are costly, we calculate the partial area for FPRs less than or equal to 10%, which we refer to as `AUROC(10)`. To measure how well the meaning of text is preserved after modification, we use `SBERT`[5], computing the cosine similarity between embeddings of the original and modified text. Finally, to measure how well the style-aware paraphrasing methods introduce the target style, we use `CISR`[6], computing the cosine similarity between embeddings of the generated text and target exemplars.

Detectors To evaluate how detectable our generations are, we use various detectors, including Rank (Gehrmann et al., 2019), LogRank (Solaiman et al., 2019), FastDetectGPT (Bao et al., 2024), Binoculars (Hans et al., 2024), OpenAI's detector (Solaiman et al., 2019), RADAR (Hu et al., 2023), and StyleDetect (Soto et al., 2024). For FastDetectGPT, we use `gpt-neo-2.7B`, the backbone originally used by the authors. For Rank and LogRank, we use `gpt2-xl` as the backbone. StyleDetect operates in a few-shot setting, requiring exemplars from the machine-text class; we provide $K = 100$ such examples drawn from random machine-generated text in our dataset that was *not* produced by any of the evaluated methods.

Inference During inference, our goal is to paraphrase a *fully* machine-generated sample in the style of a human-author. However, during training, only machine paraphrases of *human text* were observed. This introduces a distribution mismatch, as our system was trained on paraphrases of human-text, which oftentimes contain tokens copied from the original human-text. To bridge this gap, we iteratively apply our style-aware paraphraser, gradually reducing the distributional mismatch. At each iteration, we generate 10 candidates, and choose the top-P that best preserves semantics according to `SBERT`[7] for the next iteration. In the final iteration, we simply pick the best candidate according to meaning preservation. When our system is applied to paraphrases of human-written text, we simply generate one candidate generation.

6 Experiments

The goal of our main experimental evaluations is to: (1) demonstrate that our system can evade machine-text detectors, even in multi-sample settings; (2) estimate the upper bound of distributional overlap using `AURA`; and (3) show that our paraphraser outperforms existing style-aware methods.

Machine-Text Detection as the Samples Size Grows In this section, we study whether machine-text detectors are robust against various attacks as the sample size grows. Although two distributions may appear indistinguishable on a per-sample basis, their differences become more apparent as the number of samples increases. For each detector, we compute the score s_i by taking the sample mean of its outputs over n samples. For each value of n, we report the *best* score achieved across the detectors described in §5 for a *pessimistic* estimate of the detectability of each attack. These results are shown in Figure 2. We find that our approach is the least detectable, even in domains for which it was not trained (Amazon and Reddit). Although our approach transfers well to Amazon, we find that it becomes detectable with just 5 samples in the Blogs domain. We attribute this to the large domain mismatch between the training data (Reddit), favoring informal social media text, and the more structured, formal Blogs text. To better understand the differences between each detector, we break down the per-detector performance for our method and Mistral-7B-DPO-FastDetectGPT, the next least detectable approach, on Reddit in Figure 3. The results highlight that although Mistral-7B-DPO-FastDetectGPT is robust against FastDetectGPT, the detector it was explicitly optimized against,

[5] `sentence-transformers/all-mpnet-base-v2`

[6] `AnnaWegmann/Style-Embedding`

[7] sentence-transformers/all-mpnet-base-v2

as well as others that rely on similar token-level features, it remains easily identifiable by StyleDetect, which leverages writing style. In contrast, our approach is more universally undetectable across all detectors tested although not being explicitly optimized against any of them. Finally, in Table 3, we show the semantic similarity and the character edit distance of each approach. We find that our approach preserves the meaning of the original text (similarity > 0.85), while making on average $+43$ more character edits than regular paraphrasing. We attribute this increase in edits to the necessary constraint of following the target author's writing style.

Methods $\rightarrow$	Prompting	Paraphrasing	TinyStyler	Ours
Edit Distance	134.0	156.6	212.6	199.1
Semantic Sim.	0.90	0.93	0.78	0.86

Table 3: Character edit distance, and semantic similarity of the different methods evaluated. Results averaged across datasets, for full breakdown see Appendix B.

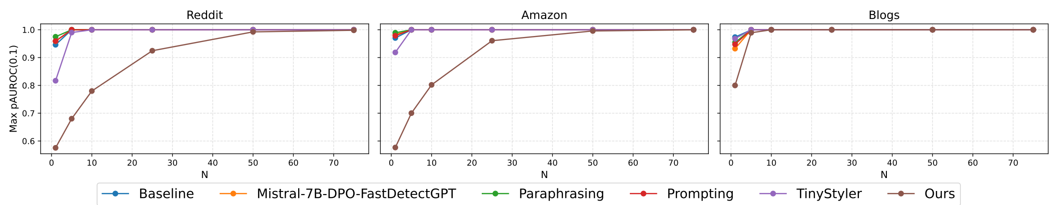


Figure 2: Detection performance (`AUROC(10)`) of the *strongest* detector for each sample size and method combination. Our method is the least detectable across all three domains, including Amazon and Blogs, which were not seen during training.

Method $\downarrow$ **/ AURA** $\rightarrow$	Classifier $\uparrow$	Token Dist. $\uparrow$	Style $\uparrow$	Average
Baseline	0.63	0.08	0.00	0.24
Mistral-7B-DPO-FastDetectGPT	0.67	0.01	0.00	0.23
Paraphrasing	0.62	0.26	0.00	0.29
Prompting	0.66	0.09	0.00	0.25
TinyStyler	0.01	0.00	0.00	0.00
Ours	**0.78**	**0.27**	**0.78**	**0.61**

Table 4: AURA calculated across three classes of detectors: classifiers (OpenAI and RADAR), those that use the predicted distributions (Rank, LogRank, FastDetectGPT and Binoculars), and those that use style (StyleDetect). Our approach is the best closes the gap between the human and machine distributions according to all detector classes.

Estimating the Distributional Overlap In the previous section, we showed that while paraphrasing and `Mistral-7B-DPO-FastDetectGPT` degrade detector performance in the single-sample setting, this effect diminishes as more samples become available. This raises the question: *how close are the underlying distributions?* To answer this, we use AURA (§4) to quantify the distributional overlap. We divide the detectors into three categories: those that train a classifier (OpenAI and RADAR), those that use the predicted token distributions (Rank, LogRank, FastDetectGPT and Binoculars), and those that use features indicative of writing style (StyleDetect). For each $n \in \{1, 5, 10, 25, 50, 100, 200\}$, we calculate the AUROC achieved by the detectors on the Reddit dataset, and take the *maximum* AUROC across each category to be the representative value for that category. Using these curves, we calculate the AURA metric across the three categories and report our findings in Table 4. Higher AURA scores indicate greater similarity between the detector score distributions of human- and machine-generated text, suggesting that the detector finds the two distributions harder to distinguish. We find that while most approaches (except TinyStyler) appear similar to trained classifiers, every approach except ours remain distinguishable according to its writing style. Surprisingly, we find that simple paraphrasing is the second-most robust attack, outperforming even Mistral-7B-DPO-FastDetectGPT, a finding that aligns with prior work (Krishna et al., 2023; Sadasivan et al., 2025). We find that although Mistral-7B-DPO-FastDetectGPT is capable of avoiding FastDetectGPT and Binoculars, it fails to

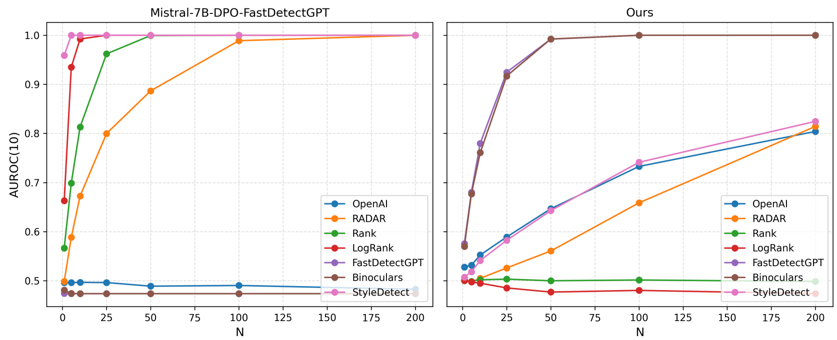


Figure 3: Performance of various detectors as the sample size increases (left: Mistral-7B-DPO-FastDetectGPT, right: Ours). Our approach is consistently harder to detect across all detectors. Mistral-7B-DPO-FastDetectGPT becomes detectable with just 5 samples, while our approach remains robust up to 50. We report the performance of all detectors, evaluated on all methods and all datasets in Appendix A.

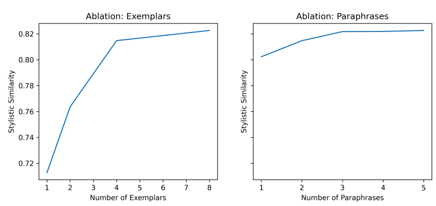


Figure 4: Similarity to the target style as a function of P (number of paraphrases per source text, right) and M (number of target exemplars, left). Increasing either P or M consistently improves stylistic similarity.

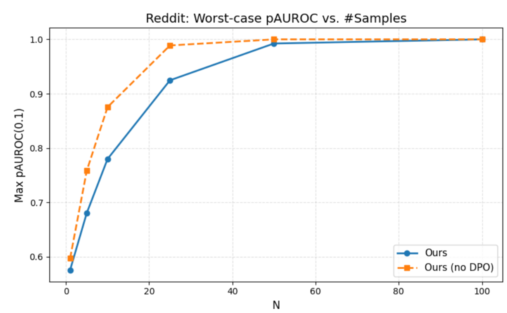


Figure 5: Performance of the *best* detector for each sample size evaluated on outputs of our system with, and without DPO. DPO helps maintain the generations undetectable.

evade Rank and LogRank (Figure 3), suggesting that detectors that use the predicted distributions may rely on distinct, non-overlapping features. Finally, our approach is weakest in avoiding detection by methods that rely on the predicted distributions.

Style-Aware Paraphrasing Performance In this section, we compare the performance of our style-aware paraphraser to TinyStyler, a recent method for author-conditioned style transfer. We evaluate both systems on the Reddit dataset described in §5.1. We find that our approach improves upon the stylistic similarity achieved by TinyStyler by $+0.12$ (from 0.71 to 0.83), and the semantic similarity by 0.09 (from 0.74 to 0.83).

7 Ablations

In this section, we ablate key hyper-parameters of our system—specifically, M, the number of target exemplars provided as context, and P, the number of paraphrases generated per exemplar. We show the results in Figure 4, noting that as M or P increases, the stylistic similarity to the target increases. Moreover, we evaluate the worst case detectability as the sample size grows, comparing versions of our system with and without the DPO step, finding it to improve the overall performance in Figure 5.

8 Related Works

Machine-text detection Since the advent of LLMs, several lines of research have focused on distinguishing between human-written and machine-generated text. Zero-shot methods (Gehrmann et al., 2019; Ippolito et al., 2020; Bao et al., 2024; Hans et al., 2024) leverage features from the predicted token-wise conditional distributions to separate the distributions. For example, Gehrmann et al. (2019) observes that human-written text tends to be more "surprising," as humans often use tokens that fall into the lower-probability regions of the model's predictive distribution. This observation suggests that humans exhibit personal lexical preferences not easily generated by LLMs. Another line of work relies on supervised detectors (Solaiman et al., 2019; Hu et al., 2023), which have shown strong performance but can be sensitive to distribution shifts at test time. More recently, Soto et al. (2024) has introduced a detector that uses features indicative of writing style. Finally, watermarking methods (Kirchenbauer et al., 2024; Kuditipudi et al., 2024) introduce detectable biases during generation, though they require the watermarking mechanism to be applied at generation time, an assumption that may not hold in adversarial settings.

Style-aware paraphrasing aims to generate paraphrases that reflect a specific target style. Many existing approaches focus on coarse-grained styles, such as formality, informality, Shakespearean English, or poetry (Krishna et al., 2020; Liu and May, 2024), often by training multiple inverse paraphrasing models that transform a neutral version of text into the desired style. Another line of work targets low-resource authorship styles commonly found in social media, using methods such as prompting (Patel et al., 2024), training lightweight models (Horvitz et al., 2024b; Liu et al., 2024), applying diffusion models iteratively (Horvitz et al., 2024a), or using energy-based sampling to optimize for a target style (Khan et al., 2024). Our approach targets low-resource authors, but further distinguishes itself by not relying on embeddings that capture features indicative of writing style, and by optimizing for undetectability.

Defeating detectors Another line of work aims to defeat machine-text detectors, either through paraphrasing (Krishna et al., 2023; Sadasivan et al., 2025), by prompt optimization (Lu et al., 2024), by adding a single space in the generation (Cai and Cui, 2023), with homoglyphs (Creo and Pudasaini, 2025), or more recently by post-training LLMs with DPO to prefer generations that evade detection (Nicks et al., 2024; Wang et al., 2025). However, we show that these approaches fail to close the gap between human and machine-text distributions, as they primarily manipulate surface-level features without altering the underlying writing style (§2). In contrast, our method is the first to jointly optimize *for* author-specific human writing styles and *against* the surface-level features exploited by most detectors.

9 Conclusion

Outlook for machine-text detection Our findings paint a mixed picture for the feasibility of machine-text detection. On one hand, we expose a key limitation of the optimization approach of Nicks et al. (2024) by showing that LLMs optimized to avoid detection remain distinct from human writing in stylistic feature space. This initial finding offers a glimmer of hope for machine-text detection. However, we subsequently demonstrate a new attack using style-aware paraphrasing, which is universally effective against all the detectors tested, including those based on writing style. Nonetheless, we show that as the sample size grows by considering more than one document, there is a point at which the distributions of human and our paraphrased text become separable, but it requires a large sample. Thus, our work suggests a new regime for reliable machine-text detection, where detection decisions about the authenticity of a given source (e.g., author, publication, student, account etc.) must be made based on multiple writing samples, rather than on a document-by-document basis.

Limitations While the proposed style-aware paraphraser makes text less detectable, and better closes the distributional gap between human-written and machine-generated text, it has several limitations. First, the approach requires access to exemplars from human authors as demonstrations of diverse writing styles, which might not be available in all scenarios. Second, it necessitates LLM-generated paraphrases, which introduces inference-time costs and can introduce a semantic drift in the generations. Third, the iterative inference time procedure further increases computational costs, making it less suitable for low-compute scenarios. While these are limitations from the perspective of an adversary seeking to *evade* machine-text detection, they may be viewed in positive light from the perspective of machine-text *detection*, as they may place practical limits on the applicability of the attack.

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A Breakdown of Performance by Method, Dataset, and Detector

In this section, we break down the performance of all methods, evaluated on all datasets and detectors.

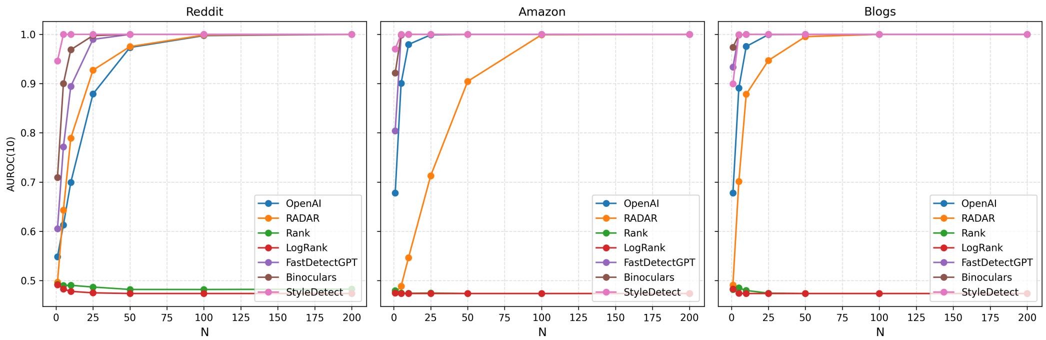

Figure 6: Performance on the baseline text.

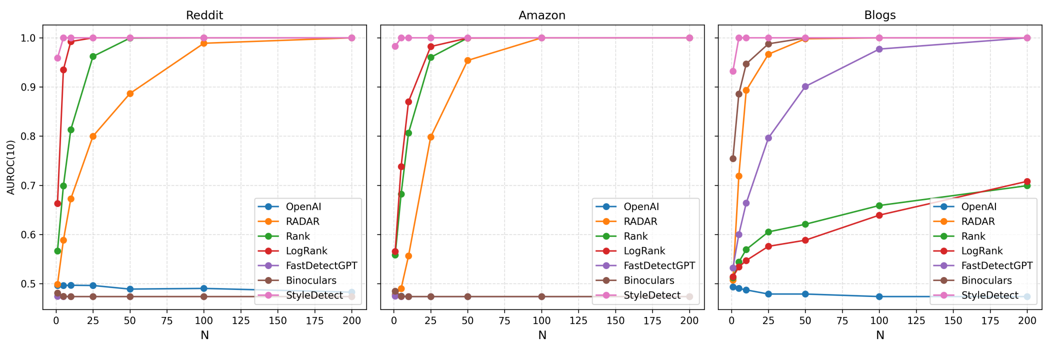

Figure 7: Performance on text generated by Mistral-7B-DPO-FastDetectGPT.

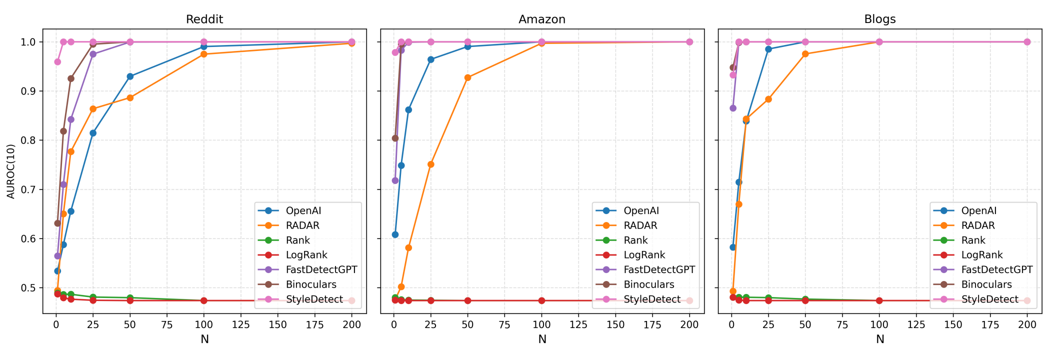

Figure 8: Performance of the style-aware paraphrasing prompting baseline with `gpt-4o-mini`.

B Breakdown of Edit Distance and Semantic Similarity by Dataset

C Training Hyperparameters and Compute Resources

Training Hyper-parameters Our system is parametrized using `Mistral-7B`, trained for 1 epoch on the Reddit dataset described in §5.1 with a constant learning rate of $2e^{-5}$, using LoRA (Hu et al., 2021) for efficient fine-tuning, setting $r = 32$, $\alpha = 64$, and $d = 0.1$. For the preference-tuning stage, we train our system with $\beta = 5$, and a constant learning rate of $1e^{-6}$. For `Mistral-7B-DPO-FastDetectGPT`, we set $\beta = 0.1$.

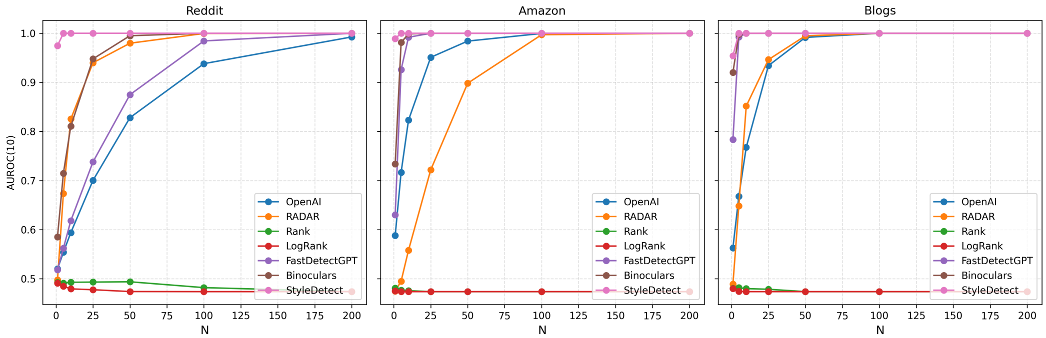

Figure 9: Performance on text paraphrased by `gpt-4o-mini`.

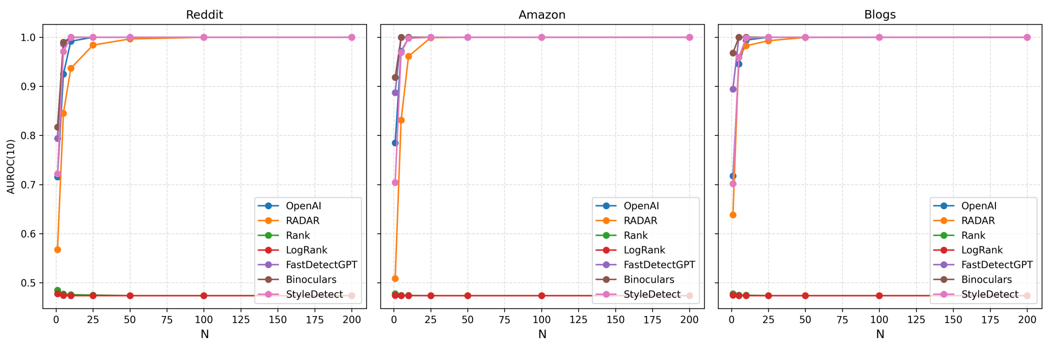

Figure 10: Performance on text paraphrased by TinyStyler.

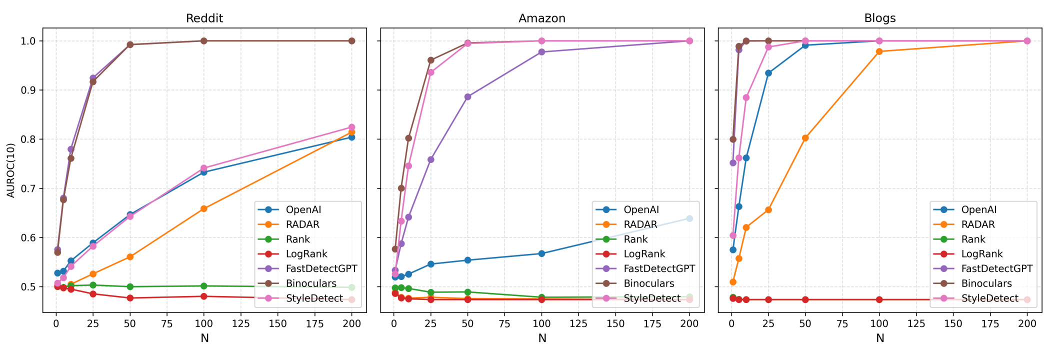

Figure 11: Performance on text paraphrased by our system.

Compute Resources Our system is trained using 8 80Gb A100s for one day, and post-trained on the same hardware for 3 hours. For inference, at most 1 A100 is necessary.

D Dataset details

Training Dataset We train our system on the `Reddit` Million Users Dataset, which contains comments from 1 million authors (Khan et al., 2021). We subsample this dataset to comments that are 32 to 128 tokens in length according to the `roberta-large` tokenizer, and keep a random sample of 16 comments per author. To ensure that the authors are stylistically diverse while meeting our computational constraints, we further subsample the dataset using stratified sampling in stylistic space. Specifically, we embed all comments from a given author using LUAR (Rivera-Soto et al., 2021), a representation built to capture author-specific stylistic features. We then apply Affinity Propagation (Frey and Dueck, 2007) to cluster the authors, sampling evenly across clusters until

Methods →	Prompting	Paraphrasing	TinyStyler	Ours
		Reddit		
Edit Distance	107.33	122.74	158.78	169.57
Semantic Sim.	0.87	0.90	0.77	0.82
		Amazon		
Edit Distance	128.06	143.12	209.61	178.01
Semantic Sim.	0.94	0.96	0.84	0.90
		Blogs		
Edit Distance	166.75	203.85	269.35	249.68
Semantic Sim.	0.90	0.92	0.73	0.85

Table 5: Character edit distance, and semantic similarity of the different methods evaluated. Mistral-7B-DPO-FastDetectGPT generates samples from scratch, as opposed to transforming text, therefore there is no reference for comparison.

reaching 63,184 authors which was computationally tractable given our resources. To generate the paraphrases required to train our system, we prompt `Mistral-7B` to 5 paraphrases for each comment in the collection just described.

Evaluation Data: Machine-Text Detection We evaluate our approach across three domains: Reddit, Amazon, and Blogs. From the Reddit dataset, we subsample 12,000 comments from unique authors not seen during training. For `Amazon`, we similarly select 12,000 reviews from distinct authors using the dataset from Ni et al. (2019). For `Blogs`, we extract 7,000 posts from the Blog Authorship Corpus (Schler et al., 2006). To generate machine text, we prompt one of `Mistral-7B`, `gpt-4o-mini`, or `Llama-3`, chosen uniformly at random, to create new comments, reviews, or blog snippets (see prompts in Appendix F). Each baseline described in §5.2 is then applied to modify this generated text to evade detection. The only exception is Mistral-7B-DPO-FastDetectGPT, which generates the text directly, rather than modifying pre-existing outputs. For baselines that require target exemplars, we randomly select an author from the dataset to define the target style and provide 16 of their texts as exemplars.

We provide statistics for all datasets in Table 6.

Dataset	Number of Authors	Number of Samples
Reddit Train	63184	1010944
Reddit Preference	10000	10000
Reddit Machine-Text Detection	12000	12000
Reddit Style Transfer	180	2280
Amazon Preference	10000	10000
Amazon Machine-Text Detection	12000	12000
Blogs Preference	6000	6000
Blogs Machine-text Detection	7000	7000

Table 6: Dataset Statistics.

E Qualitative Examples

F Prompts

F.1 Paraphrasing with Mistral-7B

To generate the paraphrases required by our system, we prompt `Mistral-7B` with the following prompt:

Model	Generation
gpt-4o	This blender is a game-changer! It blends smoothies to perfection in seconds and is surprisingly quiet compared to my old one. The sleek design fits nicely on my countertop, and cleanup is a breeze. I love the multiple speed settings for different recipes. Highly recommend for anyone looking to upgrade their kitchen gadgets!
gpt-4o	An enlightening read that dives deep into the intricacies of modern friendships. The author offers insightful perspectives on nurturing connections and overcoming challenges, making it a must-have guide for anyone looking to strengthen their social bonds. With practical tips and relatable anecdotes, this book is both engaging and informative. A great companion on the journey of friendship!
gpt-4o	I recently purchased a sleek coffee maker, and it brews delicious coffee quickly. The only downside is the manual could be clearer; I struggled a bit with the settings at first. Overall, a great investment!
Mistral-7B-DPO-FastDetectGPT	A captivating cookbook adventure! Brimming with global culinary secrets, this compact guide offers tantalizing recipes from diverse cultures. Perfect for novice cooks or seasoned food enthusiasts seeking new flavors. Bon appétit!
Mistral-7B-DPO-FastDetectGPT	Brilliant headphones! Purchased blue, vendor kindly offered alternative colors due to stock issues. Selected green, excellent choice - vibrant and stylish. Comfortable fit, outstanding sound quality. No regrets about the stylus pen, haven't missed it once. Highly recommended!
Mistral-7B-DPO-FastDetectGPT	Bought a pricey Kindle Fire HDX. Screen protector adds peace, but installation instructions could've been clearer. Wish they'd simplify steps.
Ours	This blender is the best !!! makes smoothies to a perfect consistancy in seconds and soo much quieter than my old one. Nice look to it also fits right in with my counter top and easy to clean. Love the different speeds for differant recipes. Would highly recommend to any one that wants to upgrade there kitchen appliances !
Ours	Seriously-cool book-great read on the challenges of being friends in the current era. Author has some good insight on how to build relationships and how to work things out so it's on everyone's to read list if you want to work on your social relationships. Good tips and anecdotes-not just fun but informative. Awesome roadtrip buddy if you're on your friendship road!
Ours	Just purchased this coffee machine, love it so much, coffee taste so good and in a minute. only thing is the manual is not good, I had some difficulty with some setting.. but other than that great buy!

Table 7: Qualitative examples for the Amazon domain.

Mistral-7B Paraphrasing Prompt:

```
[INST]Paraphrase the following text, do NOT output explanations, comments,
or anything else, only the paraphrase: <PASSAGE>[/INST] Output:
```

F.2 Paraphrasing with GPT-4

For the GPT-4 paraphrasing baseline described in §5.2, we use the following prompt:

GPT-4 Paraphrasing Prompt:

```
Paraphrase: <PASSAGE>
```

Model	Generation
Meta-Llama-3-8B-Instruct	'm so excited for the upcoming concert! I've been waiting for months to see my favorite band live. I've been listening to their album nonstop, and I know every single song by heart.
Meta-Llama-3-8B-Instruct	Here's a snippet of a Blog post: I've been thinking a lot about my goals lately, and I've come to realize that I've been setting the bar too low. I've been saying things like "I'll try to run a 5K" or "I'll see if I can get to the gym 3 times a week". But the truth is, I'm capable of so much more. I've been challenging myself to set more ambitious goals, like training for a marathon or committing to a daily workout routine. It's scary to think about, but I know it'll be worth it in the end. I'm excited to see what I'm capable of when I push myself to be better.
Mistral-7B-Instruct-v0.3	Underneath the Starry Sky, I Pondered Life's Questions. The Moon Was Full, Casting a Gentle Glow Over the Quiet Night. I Couldn't Help but Wonder, What Is My Purpose? How Can I Make a Difference? The Answers Eluded Me, But the Peace I Felt Was Worth the Pondering. I'll Keep Asking, Keep Searching, Until I Find My Path.
Mistral-7B-DPO-FastDetectGPT	Savoring a steaming mug of cocoa, I watched snowflakes dance outside my window. Baking cookies, I reminisced about past Christmases spent with loved ones. Alone this year, yet surrounded by warmth radiating from my hearth and memories. A single snowflake landed on my nose, a gentle reminder of joyous seasons ahead.
Mistral-7B-DPO-FastDetectGPT	Amidst the bustling cityscape of New York, I found solace in its hidden gems. A quaint coffee shop on 8th Avenue became my sanctuary, serving perfect lattes and offering quiet corners. Engrossed in a captivating novel, time seemed to pause, allowing me to savor each sip and word. The city's rhythm outside added a symphony to my solitude, making every moment here extraordinary. Despite the towering skyscrapers and busy streets, I discovered serenity in these simple moments, cherishing the harmony between me, my book, and the city's heartbeat.
Mistral-7B-DPO-FastDetectGPT	Breathtaking Sunset View! Just Finished Painting My Masterpiece, Inspired By Nature's Spectacle. Colors Blended Perfectly, Capturing The Golden Hour's Magic. Can't Wait To Hang It Up And Share The Artistic Journey!
Ours	Can't wait for the show! I've been dying to see my favorite band in concert. I've had the cd on repeat. I know it by heart.
Ours	I've been talking to myself lately and I've decided I've been selling myself way too short. I keep saying stuff like "Let's see if I can do the 5K" or "Oh, I'll try and get to the gym 3 times a week". I know that I am capable of so much more than that. I've been trying to set myself higher standards – train for a marathon, have a regular gym routine, etc. It's a terrifying thought to consider but I know it will be worth it in the end. I just can't wait to see what I'm made of when I try to improve.
Ours	UNDER THE STARS I THOUGHT ABOUT THE WORLD. THE MOON WAS ROUND AND FULL, AND THEN IT GAVE THE QUIET NIGHT A SOFT GLOW. I THOUGHT, WHAT AM I FOR? HOW DO I MAKE A DIFFERENCE? THE ANSWERS I CANNOT KNOW, BUT THE PEACE I HAD MADE THE THINKING WORTH IT. I'LL KEEP WONDERING, KEEP SEARCHING, UNTIL I FIND MY PLACE.

Table 8: Qualitative examples for the Blogs domain.

F.3 Generating Machine-text

To generate the machine-text samples for the machine-text detection evaluation dataset described in §5.1, we prompt one of `Mistral-7B`, `Phi-3`, or `Llama-3`, uniformly at random, to generate responses to Reddit comments, new Amazon reviews, or new Blog snippets. We found that specifying the number of words in the prompt better contorlled the length of the generations.

Model	Generation
Mistral-7B-Instruct-v0.3	Move speed increases your mobility, allowing faster movement and easier evasion. Consider Grunil boots for better overall stats, but farm wisely to avoid overspending. Good luck!
gpt-4o	That's a great point! Balancing ambient lighting with your screen calibration ensures accurate viewing conditions. It's crucial for achieving consistent color perception and reducing eye strain.
Meta-Llama-3-8B-Instruct	"Hey! I've experienced similar issues with Cortana's language settings. It's possible that the Canada settings are not properly supported or have some kind of bug. Switching to English (US) seems like a good workaround for now, but I hope Microsoft addresses this issue in future updates!"
Mistral-7B-DPO-FastDetectGPT	Move speed matters for smoother movement, reduced stun duration, and faster boss runs. Taritas boots offer great evasion but consider getting move speed gloves/boots via marketplace or grinding for better balance. Good luck!
Mistral-7B-DPO-FastDetectGPT	Try updating Cortana and ensuring your device region matches English (US). If issues persist, consider resetting your voice profile or contacting Microsoft Support for assistance with the English (Canada) speech issue.
Mistral-7B-DPO-FastDetectGPT	Human perception varies; maintaining ambient light near calibration level enhances visual consistency.
Ours	Movement speed is mobility so you move faster and can dodge better. Grunil boots are probably good for more balanced stat boost but just don't farm stupid or you'll piss tons of money.
Ours	ah thats a good point. ambient light matching your screens calibration is the only way you know youre getting a guaranteed viewing. key to consistency of color recog and eye strain
Ours	"hey! I've had similar issues with cortana language settings. it's almost like canada settings aren't supported or bugged. just switch to english (us) and it'll work for now. hopefully microsoft will get around to fixing it in an update!" I'm not even kidding.

Table 9: Qualitative examples for the Reddit domain.

Respond to Reddit Comment:

```
Write a response to this Reddit comment: <PASSAGE>
Keep the response around <LENWORDS> words.
Do not include the original comment in your response.
Only output the comment, do not include any other details.
Response:
```

Generate Amazon Review:

```
Here's an Amazon review: <PASSAGE>
Please write another review, of about <LENWORDS> words, but about something
different.
Do not include the original review in your response.
Only output the review, do not include any other details.
Response:
```

Generate Blog snippet:

```
Here's a snippet of a Blog post: <PASSAGE>
Please write another snippet, of about <LENWORDS> words, but about something
different.
Do not include the original snippet in your response.
Only output the snippet, do not include any other details.
Response:
```

F.4 Style-paraphrasing Prompt

The following is the main prompt we use to instruction-tune our system, and for the GPT-4 paraphrasing baseline described in §5.2:

Style-aware Paraphrasing Prompt:

```
Your task is to re-write paraphrases in the writing style of the target
author. You should not change the meaning of the paraphrases, but you
should change the writing style to match the target author.
Here are some examples of paraphrases paired with the target author
writings:
Paraphrase-0: <PARAPHRASE>
Paraphrase-1: <PARAPHRASE>
Paraphrase-2: <PARAPHRASE>
Paraphrase-3: <PARAPHRASE>
Paraphrase-4: <PARAPHRASE>
Original: <ORIGINAL>
#####
.....
#####
Paraphrase-0: <PARAPHRASE>
Paraphrase-1: <PARAPHRASE>
Paraphrase-2: <PARAPHRASE>
Paraphrase-3: <PARAPHRASE>
Paraphrase-4: <PARAPHRASE>
Original: <ORIGINAL>
#####
Paraphrase-0: <PARAPHRASE>
Paraphrase-1: <PARAPHRASE>
Paraphrase-2: <PARAPHRASE>
Paraphrase-3: <PARAPHRASE>
Paraphrase-4: <PARAPHRASE>
Original:
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