

Group-Adaptive Threshold Optimization for Robust AI-Generated Text Detection

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Abstract

The advancement of large language models (LLMs) has made it difficult to differentiate human-written text from AI-generated text. Several AI-text detectors have been developed in response, which typically utilize a fixed global threshold (e.g., $\theta = 0.5$) to classify machine-generated text. However, we find that one universal threshold can fail to account for subgroup-specific distributional variations. For example, when using a fixed threshold, detectors make more false positive errors on shorter human-written text than longer, and more positive classifications on neurotic writing styles than open among long text. These discrepancies can lead to misclassification that disproportionately affects certain groups. We address this critical limitation by introducing *FairOPT*, an algorithm for group-specific threshold optimization in AI-generated content classifiers. Our approach partitions data into subgroups based on attributes (e.g., text length and writing style) and learns decision thresholds for each group, which enables careful balancing of performance and fairness metrics within each subgroup. In experiments with four AI text classifiers on three datasets, FairOPT enhances overall F1 score and decreases balanced error rate (BER) discrepancy across subgroups. Our framework paves the way for more robust and fair classification criteria in AI-generated output detection. We will release our code and data at URL upon publication.

1. Introduction

The large-scale adoption of large language models (LLMs) has led to the widespread dissemination of AI-generated text that is challenging to differentiate from human-written content (Wu et al., 2025). This has raised concerns around

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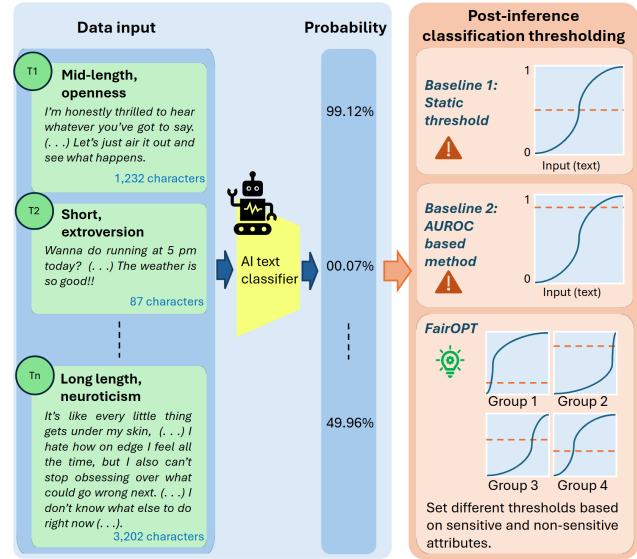


Figure 1. We find that using one universal probability threshold (often $\theta > 0.5$) to classify AI and human-generated text can fail to account for subgroup-specific distributional variations, such as text length or writing style, leading to higher errors for certain demographics. We propose *FairOPT* to learn multiple decision thresholds tailored to each subgroup, which leads to more robust AI-text detection.

the spread of misinformation (Chen & Shu, 2024), the degradation of publication standards (Wu et al., 2023), potential cybersecurity threats (Yao et al., 2024), and breaches of academic integrity (Perkins, 2023). As a result, effective AI content detection systems are essential for mitigating the risks from generative models. Recently, there has been substantial development in AI text detection tools, such as RoBERTa-based models (Solaiman et al., 2019), DetectGPT (Mitchell et al., 2023), Fast-DetectGPT (Bao et al., 2023), GLTR (Gehrmann et al., 2019), RADAR (Hu et al., 2023), and efforts to use LLMs as detectors (Bhattacharjee & Liu, 2024). Generally, these methods estimate a probability p that the text is generated by AI by comparing the patterns (e.g., token probabilities or logits) of the given text against AI-generated text, and use a single universal threshold of $p > 0.5$ for classification (Freeman & Moisen, 2008).

However, a single universal threshold for AI content classification fails to account for text with different characteristics,

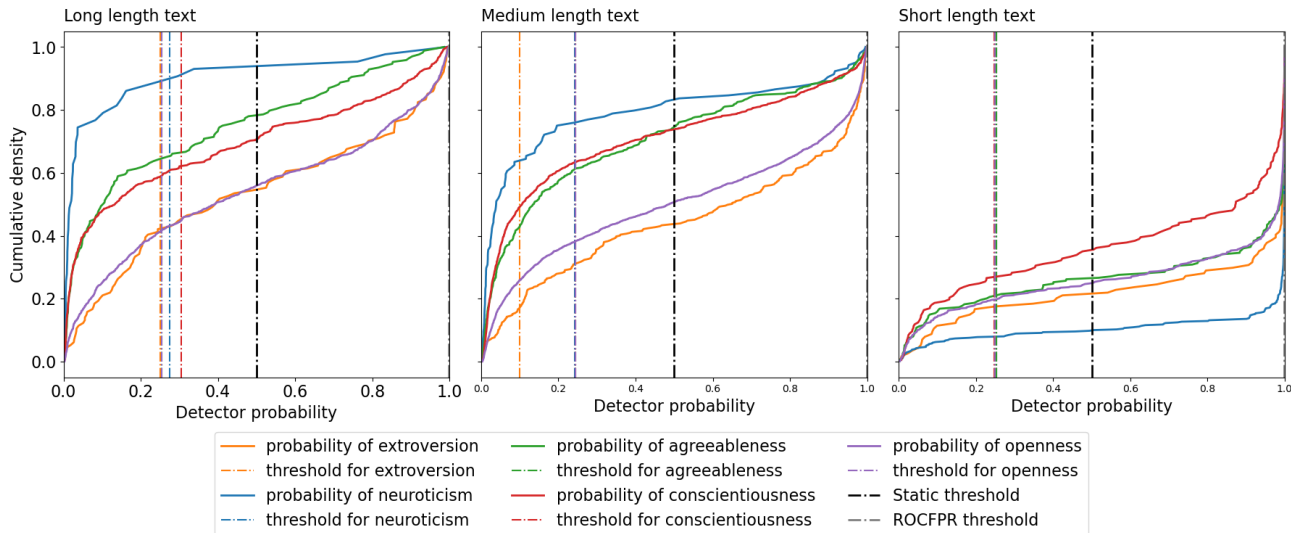


Figure 2. Applying adaptive thresholds to different probability distributions by subgroup, as seen through cumulative density functions (CDFs). We partition texts by three length categories (short, medium, long) and five personality traits (extroversion, neuroticism, agreeableness, conscientiousness, openness), and use RADAR (Hu et al., 2023) to infer AI-generated probabilities on the test dataset. Observe that a static classification threshold (0.5, in black) and a single optimized threshold (in gray at the right end side) does not account for subgroup-specific distributional variations. We used the thresholds in Appendix C. The static threshold followed conventional 0.5, AUROC method is noted in Appendix B.

such as length or writing style, which can have very different probability distributions. That is to say, one fixed threshold does not consider the variation of the probability. For example, when using a fixed threshold of 0.5, a writing style characterized by openness and positivity is more likely to be identified as AI-generated than one characterized by neuroticism, as illustrated in Figure 2. This can lead to misclassification and disproportionately affect certain groups. Similar concerns were raised regarding race (Alghamdi et al., 2022; Bendekgey & Sudderth, 2021) and gender (Weber et al., 2020; Jang et al., 2022; Bendekgey & Sudderth, 2021).

To address these limitations, we propose *FairOPT* to learn decision thresholds for distinct subgroups rather than using a standard threshold (see Figure 1). Our method balances performance (e.g., ACC, F1, precision) and fairness metrics (e.g., demographic parity, equality of odds, equal opportunity) in learning these thresholds, ensuring that predefined fairness criteria are met across all subgroups in question. In experiments with four AI text classifiers on three datasets, FairOPT increases overall F1 score and decreases balanced error rate (BER) discrepancy across subgroups, yielding better overall tradeoffs between performance and fairness. To summarize, our main contributions are: (a) identifying discrepancies in AI-generated text classifiers based on length and stylistic characteristics, (b) developing FairOPT, a group-adaptive decision threshold method to enhance group performance and fairness, and (c) developing a

model with a rule-based relaxed fairness criteria to achieve fast convergence even when perfect fairness is not possible.

2. Related Work

We review work in AI-generated text detection and methods to threshold probability distributions into classifier labels.

AI text detectors AI text detectors have been developed to flag AI-generated text. RADAR utilizes adversarial learning techniques (Hu et al., 2023), GLTR employs statistical metrics, including entropy, distributions, and ranks, to discern anomalies suggestive of AI content (Gehrmann et al., 2019), DetectGPT examines the curvature of log probability distributions, concentrating on local likelihood curvature to detect AI-generated text (Mitchell et al., 2023), and RoBERTa-based detectors fine-tune pretrained language models to proficiently categorize text as either human-produced or AI-generated (Solaiman et al., 2019). We employed *probabilistic classifiers* among them which require a threshold-based decision mechanism. Unlike direct discrimination methods, thresholding enables post-processing for the balancing of performance and fairness.

Fixed universal thresholds for classification: The most prevalent approach for making decision thresholds in classification involves employing a fixed universal threshold of 0.5 to map predicted probabilities to class labels (Freeman & Moisen, 2008). It is commonly used in many fields

like photogrammetry (Shao et al., 2016), ecology (Manel et al., 1999; Hanberry & He, 2013) and computer science (Lu et al., 2024). Nevertheless, as highlighted by Freeman & Moisen (2008), the dependence on $\theta = 0.5$ as a default threshold, merely due to its general acceptance, is frequently unreliable owing to variations in data distributions.

Universal thresholds with optimization: Threshold optimization techniques have been formulated to learn optimal thresholds across entire datasets. These methods optimize metrics such as the area under the receiver operating characteristic curve (AUROC) (Bradley, 1997) and derive optimized decision thresholds under constraints such as the false positive rate (FPR) (Krishna et al., 2024; Lipton et al., 2014). These approaches find applications across disciplines, including econometrics (Staňková, 2023), statistics (Esposito et al., 2021), and machine learning (OpenAI, 2023). While these methods yield a globally optimized threshold tailored to the chosen model, they can fail to adapt to the characteristics of individual instances, which can compromise the robustness of detection systems, particularly in significantly divergent data distributions.

Adaptive thresholds across groups: Recent work has highlighted the necessity for adaptive thresholds across groups (Jang et al., 2022; Bakker et al., 2021). Menon & Williamson (2018) propose instance-dependent thresholds for inferred probabilities, resulting in optimal classifiers under cost-sensitive fairness objectives and enhancing overall performance. Similarly, Corbett-Davies et al. (2017) demonstrate that group-specific thresholds, informed by group-level statistics, can facilitate fairness-aware classification. Canetti et al. (2019) investigate thresholds differentiated by race and proved that adaptive thresholds reduce performance disparity. Jang et al. (2022) present threshold-adaptation methods to ensure fair classification, and Bakker et al. (2021) explore threshold tuning to maintain stable classification performance across subgroups. Our method, *FairOPT* is grounded in the aforementioned principles and introduce a novel approach of adaptive thresholding.

3. Conceptual Framework and Methodology

This section outlines our method for adaptive thresholds in AI-generated text detection, *FairOPT*, which iteratively adjusts classification thresholds for different subgroups to balance performance with inter-group fairness.

3.1. Objective

Considering a set of subgroups G_1, \dots, G_i characterized by attributes (e.g., length and style) and acknowledging that texts with varying characteristics shows discrepancies in probability distributions, our objective is to refine the binary

classification thresholds $\{\theta(G_1), \dots, \theta(G_i)\}$ applicable to G_1, \dots, G_i . By accounting for subgroup-specific variations, these tailored thresholds ensure that decision boundaries accurately reflect the specific probability distributions.

3.1.1. PRELIMINARIES OF AI TEXT DETECTION

The detection of AI-generated text is commonly formulated as a binary classification task, where the input space \mathcal{X} consists of the sequence of tokenized indices derived from a given text, and the label space $\mathcal{Y} = \{0, 1\}$ denotes the two distinct classes of 0 for human-written text and 1 for AI-generated text. To address this task, existing work primarily utilizes a pretrained neural network as a probabilistic classifier $M_\theta : \mathcal{X} \rightarrow [0, 1]$, which assigns a probability p to the input reflecting the likelihood of it being AI-generated (Solaiman et al., 2019; Hu et al., 2023). This probability is then converted into a predicted label by applying a threshold, typically set at 0.5. Thus, the final predicted label $\hat{Y} \in \{0, 1\}$ is determined as follows:

$$\hat{Y} = \begin{cases} 1, & \text{if } M_\theta(x) \geq \text{threshold}, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

3.1.2. PERFORMANCE METRICS

After inferring \hat{Y} , we can compare Y and \hat{Y} . Correctly classifying AI-generated content as AI constitutes a true positive (TP). If human text is not classified as AI, it is true negative (TN). Flagging human text as AI is a false positive (FP), and flagging AI text as human is a false negative (FN). Details about the classification matrix and performance metrics are in Appendix A.1.

3.1.3. FAIRNESS METRICS

The objective of fair classification is to mitigate disparities while preserving performance. To quantify fair performance, we focus on *Demographic Parity (DP)* (Kim et al., 2020), a fairness criterion measuring whether a classifier’s predictions \hat{Y} are statistically independent across attributes S : $\hat{Y} \perp\!\!\!\perp S$. This condition mandates that the probability of assigning a positive outcome is equitable across all groups, regardless of the true class labels Y . To measure the extent of disparity, we define the DP metric:

$$\Delta_{\text{DP}} = \left| P(\hat{Y} = 1 \mid S = a) - P(\hat{Y} = 1 \mid S = b) \right| \quad (2)$$

By addressing an overall equal rate of positive predictions across groups, DP seeks to measure *disparate impact*, where one group receives a disproportionate share of positive or negative outcomes due to biases in the classifier model (Feldman et al., 2015). In applying DP, the perfect fairness is $\Delta_{\text{DP}} = 0$, which means that there is no difference in positive rates between groups. Details about fairness and performance metrics are noted in Appendix A.2.

3.2. Relaxed Fairness

While achieving 100% fairness across groups is theoretically ideal, it is often impractical due to computational constraints and the difficulty of ensuring model convergence under strict fairness criteria (Dwork et al., 2012). The 80% fairness rule, often called relaxed fairness, offers a pragmatic approach to balance reasonable fairness and performance (Feldman et al., 2015), and can also mitigate overfitting risks and ensure convergence based on the rule-based constraints.

We formalize a relaxed fairness criterion requiring that the ratio of minimum to maximum value of each fairness metric across all subgroups does not fall below a specified threshold τ , set to 0.8. It can be mathematically represented as:

$$\frac{\min_{i \in \mathcal{S}} c_i^{(k)}(\theta)}{\max_{i \in \mathcal{S}} c_i^{(k)}(\theta)} \geq \tau, \quad \forall k \in \mathcal{K}, \quad (3)$$

where:

- \mathcal{S} denotes the set of attributes (e.g. *length, writing style, etc.*)
- \mathcal{M} represents the set of fairness metrics (e.g., *demographic parity, equalized odds, etc.*).
- $c_i^{(k)}(\theta)$ computes the k -th metric in \mathcal{K} for each group using classifier parameters θ .
- $\tau \in [0, 1]$ is the fairness criteria, with $\tau = 0.8$ reflecting the 80% rule and $\tau = 1$ reflects 100% fairness.

Note that we should consider limiting the number of fairness metrics because of the *impossibility theorem* (Dwork et al., 2012) as it is computationally impractical to satisfy all fairness criteria simultaneously. The generated thresholds for subgroups based on the training dataset is used for the classification criteria in the test dataset that has same subgroups.

3.3. Group-Adaptive Threshold Optimization

Process Given these preliminaries, we now introduce our FairOPT algorithm, which is summarized in Algorithm 1. At a high level, FairOPT uses a gradient-based subgroup threshold update to jointly optimize classification performance (ACC and F1) and group-level fairness.

Formally, we partition the dataset D into subgroups $\{G_1, \dots, G_i\}$ based on features $\{S_1, \dots, S_n\}$. Each subgroup G_i is assigned an initial threshold θ_{init} (e.g., 0.5 to all groups).

During each iteration, we compute predictions for each sample $x_n \in G_i$ by binarizing the predicted probability

Algorithm 1 FairOPT: Group-Specific Thresholding

- 1: **Input:** D dataset, S_n features, predicted probabilities p , performance targets (α, β) , fairness gap limit δ_{fair} , max iterations, step size η .
 - 2: Split D into sub-datasets D_1, \dots, D_j by S_n .
 - 3: **for** iteration = 1 to max iterations **do**
 - 4: **for** each subgroup G_i **do**
 - 5: Convert p in G_i to binary predictions using $\theta(G_i)$ and compute confusion matrix.
 - 6: **if** $(\text{ACC}_i \geq \alpha$ and $\text{F1}_i \geq \beta$ for all i) **and** (fairness gap $\leq \delta_{\text{fair}}$) **then**
 - 7: **return** $\{\theta(G_1), \dots, \theta(G_j)\}$.
 - 8: **else**
 - 9: Adjust $\theta(G_i)$
 - 10: **Output:** $\{\theta(G_1), \dots, \theta(G_j)\}$.
-

p_n using the current threshold $\theta(G_i)$. The model derives a contingency matrix based on the predictions \hat{y}_n and actual values y_n .

For each subgroup G_i , we define a loss function that penalizes both low accuracy and insufficient F1 score:

$$L_i(\theta) = -\text{ACC}_i(\theta) + \kappa [\beta - \text{F1}_i(\theta)]_+, \quad (4)$$

where β is a minimum F1 threshold, $\kappa > 0$ is a penalty weight, α is also given for the minimum ACC, and $[\cdot]_+$ denotes the positive part that only positive values are retained, turning negative numbers to zero. The minimum thresholds are essential for ensuring stable convergence and preventing degenerate outcomes across all subgroups.

To optimize each $\theta(G_i)$, we employ a *finite-difference approximation* of the gradient:

$$\nabla L_i(\theta(G_i)) \approx \frac{L_i(\theta(G_i) + \delta) - L_i(\theta(G_i) - \delta)}{2\delta}. \quad (5)$$

The finite-difference approximation estimates the gradient of each subgroup’s threshold-based loss function by computing the difference between the loss values at $\theta(G_i) + \delta$ and $\theta(G_i) - \delta$, then dividing by 2δ (Liu et al., 2020). This method is employed for an effective interaction with the discrete contingency matrix, as it allows gradient estimation without requiring an explicit analytic form of the loss function’s derivative.

We then perform a gradient descent step for each subgroup:

$$\theta(G_i) \leftarrow \theta(G_i) - \eta \nabla L_i(\theta(G_i)), \quad (6)$$

followed by clipping to the allowable interval $[a, b] \subseteq [0, 1]$ to make sure it is a valid probability.

Finally, the model calculates domain-relevant fairness metrics $\{M_1, \dots, M_k\}$ across all subgroups by measuring the

maximum inter-group disparity:

$$\Delta_k = \max_i M_k(G_i) - \min_i M_k(G_i), \quad (7)$$

and verifies whether $\Delta_k \leq \delta_{\text{fair}}$ for each metric M_k . If any disparity exceeds δ_{fair} , it is considered unfair. The evaluation for fairness is not included in the loss function because it assesses performance in a binary manner, fair or unfair (e.g., pass or fail), similar to *zero-one loss*, rather than providing a continuous gradient that can guide optimization.

To determine termination, we monitor the largest threshold change among all groups,

$$\Delta_\theta = \max_{G_i} |\theta_{\text{new}}(G_i) - \theta_{\text{old}}(G_i)|. \quad (8)$$

If Δ_θ falls below a tolerance ϵ_{tol} and all groups meet the performance criterion ($\text{Acc}_i \geq \alpha$, $\text{F1}_i \geq \beta$) and fairness disparities ($\Delta_k \leq \delta_{\text{fair}}$) hold, the algorithm terminates.

Outcome By iterating this process, the algorithm 1 produces an optimized set of subgroup thresholds $\{\theta(G_1), \dots, \theta(G_i)\}$ that strike a balance between high classification performance and bounded inter-group fairness disparities. This adaptive thresholding method is particularly effective when probability distributions differ significantly across subgroups, as it tailors the decision boundary to each subgroup’s characteristics rather than relying on a single global threshold. Additional details about the algorithm, including learning and implementation details, are included in Appendix F.1.

4. Experiments

Our experiments aim to assess the performance of FairOPT in comparison to a static threshold and a single universally optimized threshold. For training, we use the RAID and MAGE datasets, and for testing, we utilized SemEval24, MAGE, and Human v. AI 500K dataset.

4.1. Datasets

4.1.1. TRAIN DATASET

The RAID dataset (Dugan et al., 2024) encompasses text samples generated by a wide array of language models, including GPT-4, GPT-3, Llama 2 70B, Cohere, MPT-30B, and Mistral 7B. These models produced text across diverse domains such as abstracts, recipes, reddit posts, book summaries, news articles, and poetry. MAGE (Li et al., 2024) includes human-written text covering opinion statements, news articles, question answering, stories, and scientific writing, with machine-generated texts produced by 27 LLMs, including OpenAI’s GPT variants, LLaMA series, FLAN-T5, and EleutherAI models. We randomly extracted 10,000 samples from each of these two datasets.

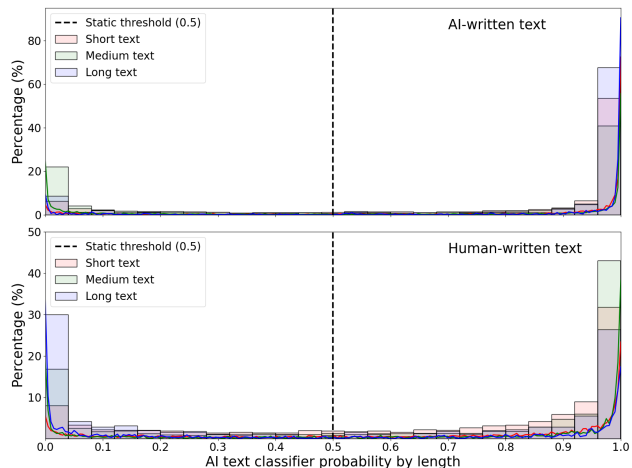


Figure 3. Histograms show how AI-generated probability distributions differ by text length (Short in red, Medium in green, Long in blue). If we use the threshold of 0.5 (black dash line), human-written medium-length text shows higher error rate than other lengths. Each kernel density estimation (KDE) curve reflects the probability scores assigned by RoBERTa-large on the training dataset.

4.1.2. TEST DATASET

We also use three datasets for test: SemEval24, MAGE, and Human v. AI 500K. The SemEval24 dataset (Wang et al., 2024) was employed for its diverse representation of commonly used AI text generators balanced with human-written texts across various topics such as news, social media posts, and creative writing, from which we extracted 3,000 samples. We also extracted random 3,000 writings from the MAGE dataset except for the instances that used in the training, and randomly selected 2,000 samples from the Human v. AI 500K dataset, the most widely used dataset for AI text detection on Kaggle.

4.2. AI-Generated Text Classifiers

To detect AI-generated text, we employed a combination of openly accessible classifiers, RoBERTa-base (Solaiman et al., 2019), RoBERTa-large (Solaiman et al., 2019), and RADAR (Hu et al., 2023). These classifiers were selected based on their open-source availability and the ability to produce unified probabilistic outputs ranging from 0 to 1 with seven decimal points. GPT4o-mini was incorporated for its promising application in AI content detection tasks (Bhattacharjee & Liu, 2024). Unlike binary classification approaches, these models assign a probability score indicating the likelihood that a given text was generated by AI rather than directly making a discrimination. To maintain uniformity in our evaluation, GPT4o-mini was explicitly prompted to return probability scores within the same range as other detectors.

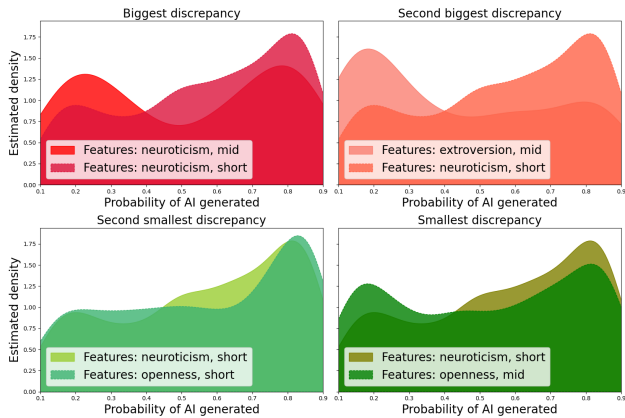


Figure 4. Top two highest and lowest distributional differences using Kolmogorov-Smirnoff (KS) test on RoBERTa-large detector probabilities. The visualization is based on KDE. The biggest discrepancy is observed with a KS statistic of 0.2078 ($p < 0.01$), while the smallest is 0.1001 ($p < 0.01$). These discrepancies indicate varying levels of divergence between groups based on the characteristics of the given text.

4.3. Subgroup Attributes

We extracted subgroup attributes from each dataset to uncover the potential disparities present in AI classifiers. These attributes are shown in Table 1 and include both non-sensitive attributes like text length and sensitive attributes inferred from stylistic traits.

Attribute	Characteristics	Labels
Text Length	Number of characters in a text	Short, medium, long ($n = 3$)
Stylistic personality	Inferred Big Five personality traits.	Openness, conscientiousness, extroversion, agreeableness, neuroticism ($n = 5$)

Table 1. The subgroup attributes studied in our experiments.

Text length measures the number of characters in a text. OpenAI’s evaluations (OpenAI, 2023) revealed performance disparities between short (under 1,000 characters) and long text when using their AI classifier. Building on this and using exploratory data analysis, we refined the thresholds to 1,000 and 2,500 characters, categorizing texts as short (up to 1,000), mid-length (1,000 to 2,500), or long (over 2,500).

The **stylistic personality** attribute includes five traits: extroversion, neuroticism, agreeableness, conscientiousness, and openness (Minej, 2023). We determine the personality trait by selecting the one with the highest probability among the five using a BERT-based personality prediction model (Minej, 2023), which is fine-tuned from BERT-base-uncased (Devlin et al., 2018). Details are noted in Appendix D.

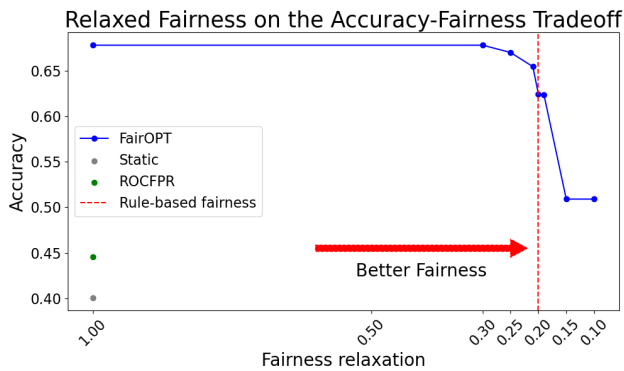


Figure 5. RoBERTa-large

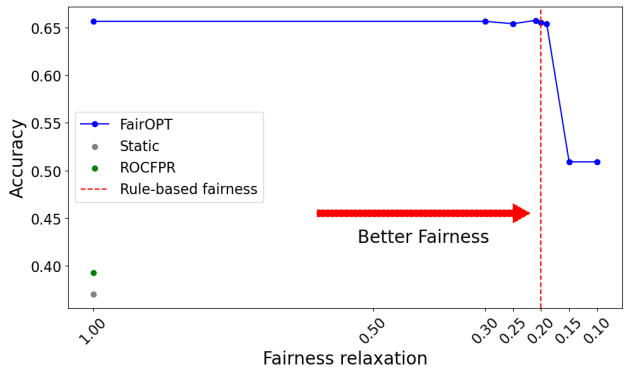


Figure 6. RoBERTa-base

Figure 7. The FairOPT algorithm enables us to obtain a balanced tradeoff between performance and fairness, through a relaxed fairness criterion specified by a given fairness threshold. We improve the Pareto frontier of performance and fairness compared to static and ROCFPR baselines.

4.4. Discovery of Subgroup Bias in Text Detection

Our first experimental analysis uncovers many discrepancies in AI-text detection performance with respect to different text lengths and writing styles. For example, as shown in Figure 3, medium-length human-written text is more likely to be flagged as AI-generated than short-length human-written text. Similarly, in Figure 2, long text with a neurotic style is also more likely to be detected as AI-generated.

To obtain a holistic view of these biases, we used the Kolmogorov-Smirnov (KS) test to evaluate distributional discrepancies across various text groups under the assumption of a non-parametric distribution. As shown in Figure 4, there are notable differences between certain subgroup pairs. For instance, the comparison between texts characterized by *neuroticism and medium-length* versus those with *neuroticism and short-length* yielded a KS statistic of 0.2078 ($p < 0.01$). *Extroversion and mid-length* and *neuroticism and short length*, showed a KS statistic of 0.1959 ($p < 0.01$). On the other hand, relatively smaller discrepancies were ob-

served between groups such as *neuroticism and short length* versus *openness and short length*, with a KS statistic of 0.1155 ($p < 0.001$), and between *neuroticism and short length* versus *openness and mid-length*, with a KS statistic of 0.1001 ($p < 0.01$). These observed discrepancies show that varying subgroup characteristics can lead to diverging outcomes when using a fixed threshold for classification. Addressing these discrepancies through tailored threshold adjustments or other interventions is crucial to ensuring equitable treatment across all subgroups.

4.5. Mitigating Subgroup Bias using FairOPT

Given these findings, we now describe the experimental setup using FairOPT for more robust AI-text detection across subgroups. We extracted the text length and personality features from every item in the dataset, which enabled the partition of 15 subgroups with different characteristics. For the training dataset, the AI text classifiers RoBERTa-base, RoBERTa-large, and RADAR were employed to generate predicted probabilities indicating the likelihood that a given text was AI-generated. These probabilities ranged from 0 to 1, with no direct classification decisions made at this stage. For the test dataset, additional predictions were generated using the GPT4o-mini API.

We used FairOPT to get adaptive thresholds $\{\theta(G_1), \dots, \theta(G_j)\}$ for each subgroup. We include all hyperparameters and training details in Appendix F.3. Threshold optimization was performed on the training dataset based on the results only from RoBERTa-large rather than averaging the probabilities of three detectors. The relaxed fairness criteria in 3.2 is employed to encourage earlier convergence and minimize the sacrifice of overall performance while pursuing group fairness. The RoBERTa-large model was also used to implement the AUROC-based approach (Method based on ROC curve B) with $FPR < 0.1$ constraint for comparison, and the static threshold 2 does not need a model for training in generating a decision threshold.

The optimized thresholds were then applied to the test dataset. Performance was evaluated using F1, ACC, BER, and BER calculated per subgroup. FairLen and FairPer metrics were utilized to quantify the maximum discrepancies in BER across groups defined by text length and personality traits. These metrics are defined as follows:

$$\text{FairLen} = \max_{a \in L} \text{BER}(a) - \min_{a \in L} \text{BER}(a) \quad (9)$$

$$\text{FairPer} = \max_{b \in P} \text{BER}(b) - \min_{b \in P} \text{BER}(b) \quad (10)$$

where L includes three groups based on text length, P includes five groups based on big five personality traits, and BER denotes the balanced error rate for each group. A higher value of FairLen or FairPer indicates a greater dispar-

ity in classification performance across subgroups.

4.6. Results with FairOPT for AI-Text Detection

Table 2 presents a comprehensive comparison of three thresholding methodologies—**Static**, **ROCFPR**, and **FairOPT**—applied to four AI text detectors (**RoBERTa-base**, **RoBERTa-large**, **RADAR**, **GPT4o-mini**) across three distinct datasets (**MAGE**, **Kaggle**, **SemEval**). The evaluation metrics include F1, ACC, FairLen (maximum BER discrepancy for text length), FairPer (maximum BER discrepancy for personality traits), and FPR. Overall across all datasets and tasks tested, using FairOPT yields an average increase of 2.91% in F1 Score and a decrease of 1.77% in FairPer, thereby strictly improving the performance-fairness tradeoff. Overall accuracy was only reduced by a marginal 0.58%, indicating that FairOPT does not affect performance accuracy. These results indicate that FairOPT effectively enhances the overall classification performance and reduces fairness disparities across subgroups, outperforming the **Static** threshold approach by achieving higher F1 scores and lower BER discrepancies related to stylistic features.

We now analyze the results of FairOPT on each specific dataset. On the SemEval task, overall F1 scores show significant improvement, with RADAR achieving a notable increase of 7% after running our FairOPT algorithm. These findings imply that environments exhibiting patterns similar to SemEval can greatly benefit from this method. Additionally, the RoBERTa-large model exhibits a substantial reduction in discrepancy across all datasets that it was tested on - in the MAGE dataset, the discrepancy related to writing style based on personality decreases by 5%. This implies that models that work similarly to RoBERTa-large can pursue better fairness through our method. For example, RoBERTa-based models also exhibit reduced disparities in text length and style. These results provide strong evidence to support the future application of FairOPT to other models, particularly detectors currently under development, as outlined in OpenAI (2023).

4.7. Tradeoff Analysis between Performance and Fairness

Figure 7 illustrates the accuracy-fairness tradeoffs achieved by our proposed FairOPT algorithm compared to the Static and ROCFPR baselines. The relaxed fairness criterion from Section 3.2 effectively navigates the trade-off space, enhancing the Pareto frontier between classification performance and fairness metrics. Especially, the relaxed fairness criterion leads to early termination of the algorithm before overly sacrificing ACC while still satisfying a reasonable level of fairness. In contrast, the ROCFPR baseline, while achieving lower FPRs as noted in Table 2, significantly compromises

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Detector	Method	SemEval					Kaggle					MAGE				
		F1	ACC	FairLen	FairPer	FPR	F1	ACC	FairLen	FairPer	FPR	F1	ACC	FairLen	FairPer	FPR
RoBERTa-large	Static	0.4382	0.2847	0.1444	0.1377	0.9892	0.4309	0.2823	0.0607	0.1161	0.9830	0.7147	0.6360	0.1817	0.1760	0.6464
	ROCFPR	0.0740	0.2990	0.2197	0.1792	0.4854	0.3469	0.3900	0.1490	0.5782	0.6364	0.5201	0.6475	0.3471	0.2777	0.1031
	FairOPT	0.4849	0.3223	0.1347	0.1075	0.9892	0.4542	0.2973	0.0291	0.0755	0.9835	0.7088	0.6080	0.1749	0.1209	0.6473
RADAR	Static	0.5592	0.6373	0.3826	0.3399	0.2266	0.7097	0.7373	0.3088	0.2876	0.3360	0.4364	0.3930	0.5979	0.4599	0.6896
	ROCFPR	0.0153	0.5293	0.1162	0.0475	0.0019	0.0351	0.6333	0.1199	0.1412	0.0005	0.3215	0.4935	0.4102	0.4811	0.2662
	FairOPT	0.6307	0.6620	0.3536	0.4939	0.2228	0.6445	0.6183	0.2269	0.1566	0.3732	0.4541	0.3820	0.5705	0.4140	0.6965
RoBERTa-base	Static	0.3345	0.2133	0.0976	0.0978	0.9703	0.3659	0.2457	0.0950	0.1294	0.9553	0.7020	0.6515	0.2023	0.2124	0.5265
	ROCFPR	0.0740	0.2253	0.2463	0.1428	0.7633	0.3374	0.2943	0.0876	0.1276	0.8171	0.5814	0.6580	0.4275	0.3666	0.1739
	FairOPT	0.3548	0.2253	0.1072	0.0866	0.9696	0.3706	0.2447	0.0876	0.1234	0.9553	0.7122	0.6485	0.1966	0.1517	0.5265
GPT4o-mini	Static	0.3737	0.5497	0.1806	0.3137	0.2114	0.2949	0.3083	0.1042	0.2494	0.7390	0.2017	0.4340	0.2921	0.1990	0.2878
	ROCFPR	0.0004	0.5247	0.0053	0.0130	0.0057	0.0000	0.6267	0.0005	0.0020	0.0005	0.0000	0.5080	0.0064	0.0039	0.0020
	FairOPT	0.4371	0.5553	0.1907	0.6844	0.2139	0.3792	0.3223	0.1279	0.3471	0.7459	0.2802	0.4170	0.2578	0.1697	0.3006

Table 2. Comparison of three thresholding methods (Static, ROCFPR, FairOPT) across four probabilistic AI text classifiers (RoBERTa-large, RoBERTa-base, RADAR, GPT4o-mini) and three data sources (SemEval, Kaggle, MAGE). Metrics include F1, ACC, FairLen (BER discrepancy for Length), FairPer (BER discrepancy for Personality), and FPR. Compared to the Static method, FairOPT results in an average increase of 2.91% in F1 score and decrease of 1.77% in FairPer, while causing a decrease of 0.58% in ACC and an increase of 1.59% in FairLen., demonstrating its effectiveness in enhancing specific aspect of performance and fairness with minimal trade-offs in classifier performance. Although ROCFPR method showed the best result in decreasing the FPR of the model, it overly sacrificed performance.

TPR thus harming overall ACC, highlighting the superiority of FairOPT in maintaining a harmonious balance between constraints and model performance.

The ROCFPR method demonstrates a notable ability to minimize the FPR across various classifiers and datasets. However, this reduction in FPR comes at a significant cost to the TPR, leading to a sacrifice of ACC as illustrated in Appendix B. This trade-off is particularly problematic as it diminishes the detector’s reliability in correctly identifying AI-generated text.

Conversely, the adaptive thresholding approach employed by FairOPT offers advantages in F1 and group fairness over both static and ROCFPR methods by tailoring decision boundaries to subgroup-specific probability distributions. This strategy ensures that each subgroup, characterized by attributes such as text length and personality traits, is evaluated with an appropriate threshold, thereby balancing the trade-off between fairness and performance. FairOPT achieves this balance by improving F1 scores and reducing FairPer discrepancies without substantially sacrificing ACC, thereby enhancing the classifier’s overall performance and addressing fairness.

5. Conclusion

This paper proposed FairOPT, based on the observation that there is a statistically significant difference in AI-generated text classifier outputs across subgroups of text (e.g. length and personality) and that this discrepancy can lead to notably higher error rates in specific groups. To address this problem, we proposed FairOPT, a new method for group-specific threshold optimization in AI-generated content classifiers without sacrificing performance. Unlike a universal thresh-

old, which presumes well-calibrated probabilities across varied text distributions, our method effectively captures the variations of the probability distribution across different subgroups, leading to a more robust and fair classification.

While our work focuses primarily on text classifiers, the FairOPT framework can naturally extend to other modalities where detecting AI-generated content is critical for safety and copyright (e.g., image, video, and audio). This method will be highly beneficial in post-processing, guiding the model toward enhanced performance or increased fairness, contingent upon the specific requirements and deployment context. Furthermore, while our primary focus has been on improving fairness in the post-training stage, we hypothesize that the proposed method can also be integrated as an in-training fairness enhancement mechanism. Finally, other approaches for threshold optimization, including Bayesian methods and convex optimization, can also be studied in future research.

Impact Statement

This paper introduces novel theoretical frameworks and methodologies to enhance the robustness of AI-generated text detection systems. By extracting and using features for subgroups such as text length and stylistic traits, our approach addresses disparity in classification outcomes. This technology can play a crucial role in AI detection for identifying misinformation (Chen & Shu, 2024), safeguarding the integrity of publication and academic organizations (Wu et al., 2023; Perkins, 2023), and countering potential cybersecurity threats (Yao et al., 2024). Since it is crucial for these AI-content detection methods to be robust and fair across many potential users, our method takes a major step in this direction by formulating the problem setting and

developing a new algorithm.

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A. Performance and fairness metrics

A.1. Contingency table

The model can make not only true positive (TP) and true negative (TN) cases but also false positive (FP) and false negative (FN):

	Classified as AI (\hat{Y}_1)	Classified as non-AI (\hat{Y}_0)
AI-generated (Y_1)	TP: Correct identification	FN: Failed to detect AI and misidentified as human
Human-developed (Y_0)	FP: Incorrectly marked human work as AI	TN: Correctly identified by not classifying human work as AI

Table 3. Confusion matrix for the four possible outcomes when an AI detection system classifies either AI-generated or human-developed content.

A.2. Notation and Metrics

Given the table A.1 that denotes the outcomes in a binary classification task, we can mathematically express the performance and fairness metrics like below:

- **Accuracy (ACC).**

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}.$$

- **F1 Score.** Given Precision and Recall below,

$$F1 = 2 \times \frac{(\text{Precision}) \times (\text{Recall})}{\text{Precision} + \text{Recall}}.$$

F1 matters because it balances Precision and Recall into a single measure, making it especially useful when the class distribution is imbalanced or when both metrics are important.

- **Precision.**

$$\text{Precision} = \frac{TP}{TP + FP}$$

Precision measures the fraction of predicted positives that are actually correct, focusing on how often the model is right when it predicts a positive.

- **Recall.** (Recall is also referred to as TPR in some contexts.)

$$\text{Recall} = \text{TPR} = \frac{TP}{TP + FN}$$

Recall measures the fraction of actual positives that are correctly identified by the model, capturing how many real positives are detected.

- **Demographic Parity (DP).** Suppose we have a protected attribute $A \in \{0, 1\}$. Demographic Parity requires $P(\hat{Y} = 1 | A = 0) = P(\hat{Y} = 1 | A = 1)$, or $P(\hat{Y} = 1 | A = 0) \approx P(\hat{Y} = 1 | A = 1)$. A common metric is the disparity:

$$\Delta_{DP} = |P(\hat{Y} = 1 | A = 0) - P(\hat{Y} = 1 | A = 1)|.$$

- **Equalized Odds (EO).** Equalized Odds requires equal *true positive rates* and *false positive rates* across groups. One way to measure the gap is:

$$\Delta_{EO} = |P(\hat{Y} = 1 | Y = 1, A = 0) - P(\hat{Y} = 1 | Y = 1, A = 1)| + |P(\hat{Y} = 1 | Y = 0, A = 0) - P(\hat{Y} = 1 | Y = 0, A = 1)|.$$

Under the strictest notion of fairness, one requires

$$\Delta_{EO} = 0,$$

implying no disparity in true or false positive rates across groups.

Relaxation in fairness allows

$$\Delta_{EO} \geq 0,$$

for feasibility.

- **False Positive Rate (FPR).**

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

- **Balanced Error Rate (BER).**

$$\text{BER} = \frac{1}{2} \left(\frac{\text{FP}}{\text{FP} + \text{TN}} + \frac{\text{FN}}{\text{TP} + \text{FN}} \right) = \frac{\text{FPR} + (\text{FNR})}{2} = \frac{\text{FPR} + (1 - \text{TPR})}{2}$$

Balanced Error Rate (BER) averages the error rates across both classes, providing a metric that is insensitive to class imbalance. By considering both the False Positive Rate and the False Negative Rate, BER ensures that the classifier performs equally well on both classes. The concept is especially well-introduced in (Ferrer, 2022)

- **Specificity.**

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Specificity measures the proportion of actual negative cases correctly identified by the model, reflecting its ability to detect true negatives. It is also known as true negative rate (TNR).

A.3. Impossibility theorem

The impossibility theorem typically refers to the result that no single classifier can satisfy all common fairness metrics (e.g., demographic parity, equalized odds, predictive parity) simultaneously, except in trivial cases. This arises because different fairness definitions can be mathematically incompatible when the base rates (prevalences) differ across groups. This research used one fairness metrics in the processing to address this issue.

B. AUROC

B.1. Static threshold and AUROC-based approach

In this research, the AUROC-based approach is employed to optimize the classification threshold while balancing model performance and fairness constraints. This method evaluates the trade-off between the TPR and FPR, as visualized by the ROC curve shown in Figure 8. The optimal threshold is determined under a specified FPR constraint, $\text{FPR} \leq 0.1$, ensuring that the selected threshold aligns with a predefined ethical constraint.

C. Applied Thresholds

Figure 2 uses thresholds that is noted on Table 4.

D. Feature Engineering

In order to mitigate disparities within AI classifiers, a thorough feature engineering process was undertaken. Features were systematically extracted to characterize each text within the dataset. The table 5 includes all extraced features for this research. The primary focus of the experiment encompassed text length and anticipated personality traits. Although formality and sentiment were also extracted, these attributes are utilized to expedite processing, as the computational time increases exponentially with the inclusion of additional features. The subsequent table illustrates the features primarily extracted for the experiment, with an emphasis solely on the utilization of length and personality traits.

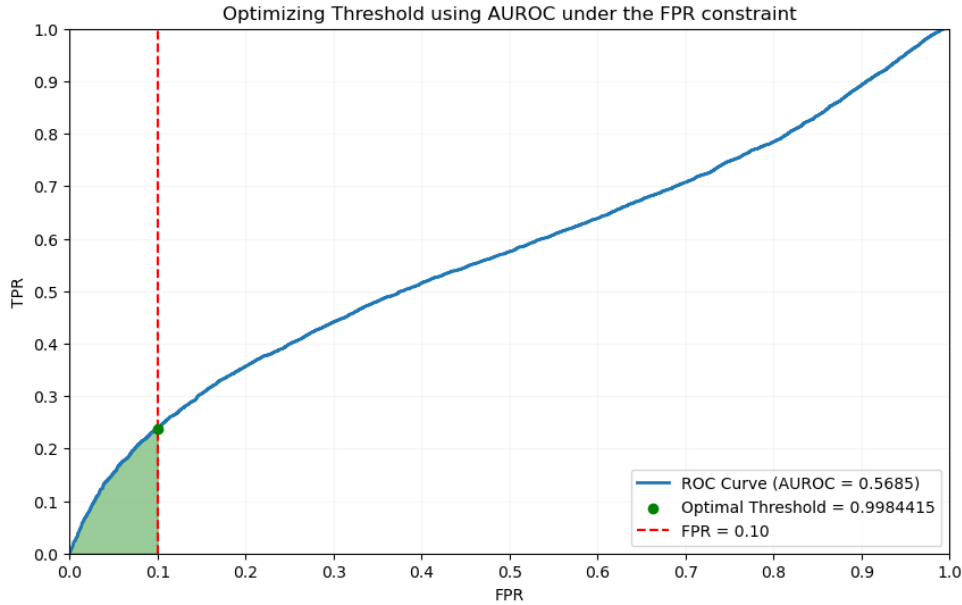


Figure 8. Threshold optimization process using the AUROC-based approach with an FPR constraint of 0.1. The ROC curve (blue line) demonstrates the trade-off between TPR and FPR. The optimal threshold (green marker) is selected to maximize performance under the specified FPR constraint.

Threshold Type	Value
Static	0.5
ROCFPR	0.9984415
Adaptive Thresholds (n=15)	
Group	Threshold
long_agreeableness	0.2545000
long_conscientiousness	0.3055681
long_extroversion	0.2500000
long_neuroticism	0.2748645
long_openness	0.2549773
medium_agreeableness	0.2445749
medium_conscientiousness	0.2448965
medium_extroversion	0.1000000
medium_neuroticism	0.2429920
medium_openness	0.2436330
short_agreeableness	0.2529650
short_conscientiousness	0.2480741
short_extroversion	0.2528146
short_neuroticism	0.2528743
short_openness	0.2489719

Table 4. Thresholds that used in the study

This research mainly used **length** and **personality** as a main feature in using FairOPT.

The **text length** attribute measures the number of characters in a text. OpenAI’s evaluations (OpenAI, 2023) revealed performance disparities between short (under 1,000 characters) and long texts when using their AI classifier. While their global threshold approach failed to address group-specific differences, it provided a valuable benchmark. Building on this and using exploratory data analysis (EDA), we refined the thresholds to 1,000 and 2,500 characters, categorizing texts as short (up to 1,000), mid-length (1,000–2,500), or long (over 2,500).

The **personality** attribute includes five traits: extroversion, neuroticism, agreeableness, conscientiousness, and openness. This attribute contributes to the enforcement of fairness metrics, such as demographic parity and equality of odds. For this

feature, we determine the personality trait by selecting the one with the highest probability among the five using the (Minej, 2023) model, which is fine-tuned from BERT-base-uncased (Devlin et al., 2018).

Attribute	Characteristics	Labels
Text Length	Measures the number of characters in a text	short, medium, long (n = 3)
Formality	Indicates the level of formality in the language	formal, informal (n = 2)
Sentiment	Reflects the emotional tone.	positive, negative (n= 2)
Personality	Represents the inferred Big Five personality traits.	Openness, Conscientiousness, Extroversion, Agreeableness, Neuroticism (n = 5)

Table 5. Characteristics and labels of each attribute

Outside of the **length** and **sentiment**, the **formality** attribute measures a text’s formality by analyzing the frequency of specific parts of speech. According to (Heylighen & Dewaele, 2002), with formal texts typically containing a higher proportion of nouns, adjectives, articles, and prepositions, whereas informal texts tend to have a greater frequency of pronouns, adverbs, verbs, and interjections. As general rule, we set a threshold of 50 to distinguish between formal (scores above 50) and informal texts.

The **sentiment** attribute allows for the assessment of emotional tone and attitudes within content. AI-generated texts may display distinct sentiment patterns due to the differences in their underlying algorithms compared to human expression. To classify texts as positive or negative, we used the label output from the (DistilBERT-community) model, which is a fine-tuned version of DistilBERT-base-uncased (Sanh et al., 2019), specifically trained on the SST-2 dataset(Socher et al., 2013).

E. Discrepancies by classifiers with additional features

E.1. Discrepancy of Probability in Subgroups

E.1.1. DISCREPANCY IN ROBERTA-LARGE DETECTOR

The analysis revealed significant variability in the probability distributions between subgroup pairs, as depicted in Figure 9. Employing two-sample Kolmogorov-Smirnov (KS) statistic for two-sided tests, we assessed distributional discrepancies across various text groups characterized by distinct feature combinations, under the assumption of a non-parametric distribution. Significant differences were identified in certain subgroup comparisons, indicating notable discrepancies in their probability distributions. For example, comparing texts characterized by *conscientiousness, positive sentiment, formal style, and long length* with those exhibiting *extroversion, negative sentiment, formal style, and long length* resulted in a KS statistic of 0.7286 ($p < 0.05$). Similarly, evaluating *agreeableness, positive sentiment, formal style, and mid-length* against *conscientiousness, positive sentiment, formal style, and long length* yielded a KS statistic of 0.7143 ($p < 0.01$).

Conversely, smaller discrepancies were observed between *neuroticism, positive sentiment, formal style, and short length* versus *openness, positive sentiment, formal style, and mid-length* ($KS = 0.2706, p < 0.05$) and *neuroticism, negative sentiment, formal style, and short length* versus *openness, positive sentiment, formal style, and mid-length* ($KS = 0.2323, p < 0.05$).

E.1.2. DISCREPANCY IN ROBERTA-BASE DETECTOR

The analysis revealed a substantial variation in the probability distributions among pairs of subgroups, as shown in Figure 10. The KS test was applied to assess distributional differences across diverse text groupings defined by multiple feature sets, under the assumption of a non-parametric distribution. Specific subgroup comparisons highlighted significant differences, pointing to noticeable disparities in their probability distributions. For example, contrasting texts defined by *agreeableness, positive sentiment, formal style, and mid-length* with those featuring *neuroticism, negative sentiment, informal style, and short length* produced a KS statistic of 0.9 ($p < 0.01$). Furthermore, the comparison between *conscientiousness, negative sentiment, formal style, and long length* and *neuroticism, negative sentiment, informal style, and short length* resulted in a KS statistic of 0.7750 ($p < 0.01$).

Lesser discrepancies were noted between *neuroticism, negative sentiment, informal style, and short length* versus *openness, positive sentiment, formal style, and long length* ($KS = 0.5522, p < 0.05$) and *neuroticism, negative sentiment, informal*

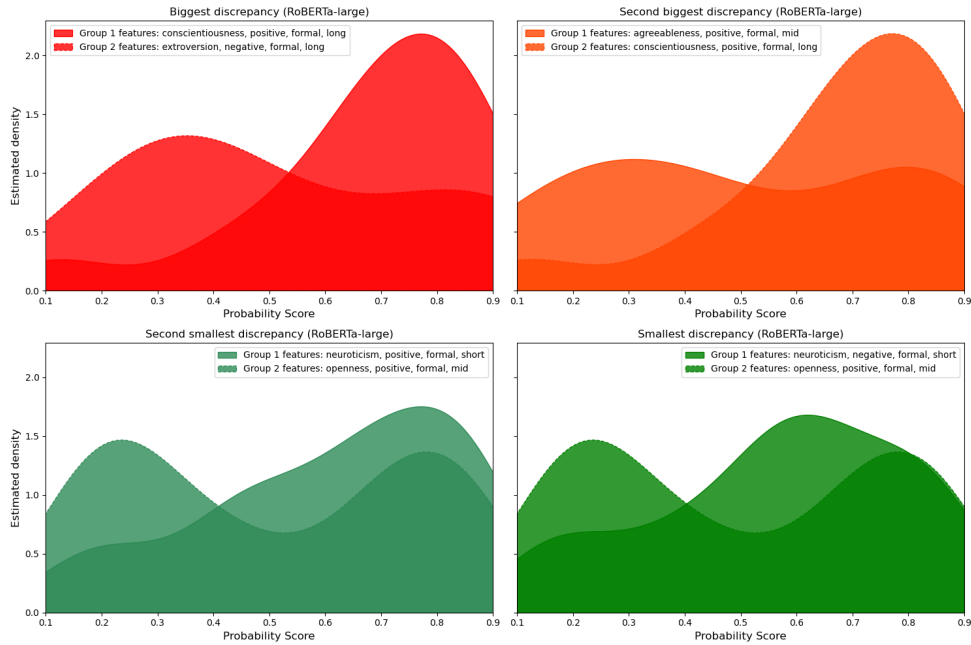


Figure 9. Kernel Density Estimation (KDE) plots comparing probability distributions for subgroup pairs with the top two highest and lowest discrepancies based on the K-S test with statistical validity. The largest discrepancy is observed with a KS statistic of 0.7286, while the smallest discrepancy has a KS statistic of 0.2323.

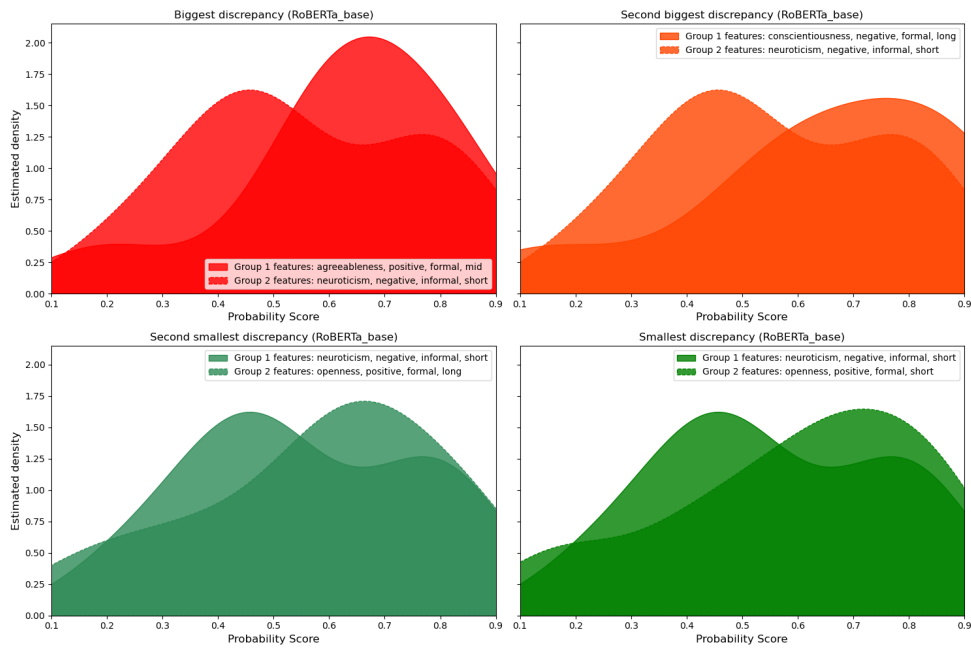


Figure 10. KDE plots comparing probability distributions for subgroup pairs with the highest and lowest discrepancies based on the K-S test with statistical validity. The largest discrepancy is observed with a KS statistic of 0.9, while the smallest discrepancy has a KS statistic of 0.5071. These discrepancies indicate varying levels of divergence between groups based on their characteristics.

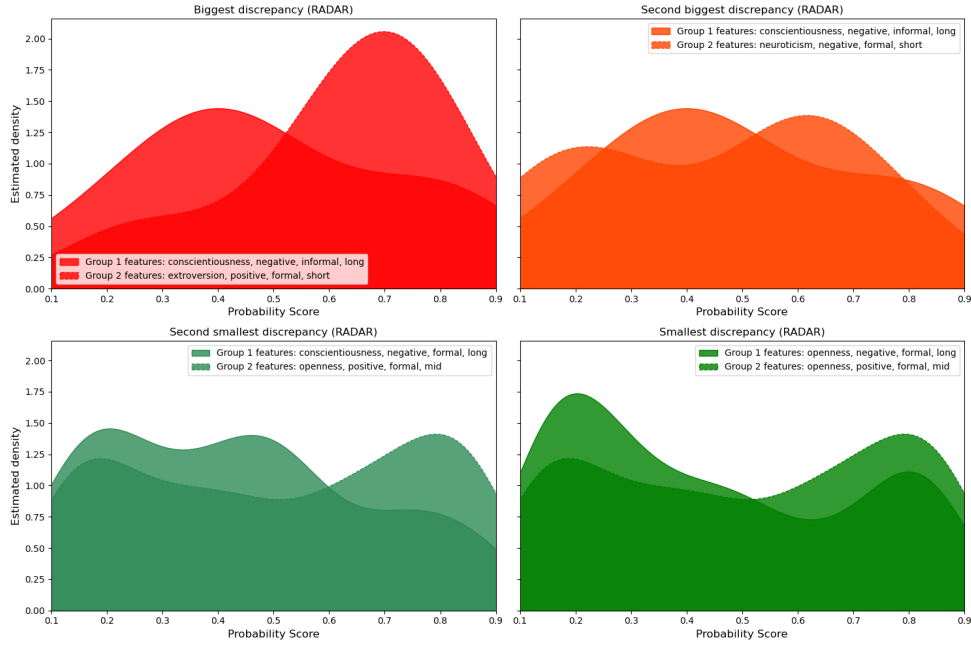


Figure 11. KDE plots comparing probability distributions for subgroup pairs with the highest and lowest discrepancies based on the K-S test with statistical validity. The largest discrepancy is observed with a KS statistic of 0.8, while the smallest discrepancy has a KS statistic of 0.1830.

style, and short length versus openness, positive sentiment, formal style, and short length (KS = 0.5071, $p < 0.05$).

E.1.3. DISCREPANCY IN RADAR DETECTOR

The investigation disclosed considerable variability in the probability distributions across subgroup pairs, as illustrated in Figure 11. Through the application of the KS test, we evaluated distributional discrepancies among various text groups defined by distinct feature combinations, operating under the premise of a non-parametric distribution. Significant differences were discerned in particular subgroup comparisons, which highlight notable discrepancies in their probability distributions. For instance, the comparison between texts characterized by *conscientiousness, negative sentiment, informal style, and long length* and those exhibiting *extroversion, positive sentiment, formal style, and short length* yielded a KS statistic of 0.8 ($p < 0.05$).

Similarly, the examination of *conscientiousness, negative sentiment, informal style, and long length* against *neuroticism, negative sentiment, formal style, and short length* resulted in a KS statistic of 0.6667 ($p < 0.05$). In contrast, smaller discrepancies were detected between *conscientiousness, negative sentiment, formal style, and long length* versus *openness, positive sentiment, formal style, and mid-length* (KS = 0.2110, $p < 0.01$) and *openness, negative sentiment, formal style, and long length* versus *openness, positive sentiment, formal style, and mid-length* (KS = 0.1830, $p < 0.01$).

E.1.4. DISCREPANCY IN GPT4O-MINI DETECTOR

The analysis revealed substantial variability in the probability distributions among subgroup pairs, as depicted in Figure 12. Using the KS test, we assessed distributional discrepancies across various text groups defined by distinct feature combinations, assuming a non-parametric distribution. Significant differences were detected in particular subgroup comparisons, suggesting notable divergences in their probability distributions. For example, the comparison between texts characterized by *openness, negative sentiment, informal style, and mid-length* and those exhibiting *openness, positive sentiment, informal style, and mid-length* resulted in a KS statistic of 0.6667 ($p < 0.001$). Similarly, the evaluation of *extroversion, negative sentiment, formal style, and mid-length* versus *openness, positive sentiment, informal style, and mid-length* produced a KS statistic of 0.6522 ($p < 0.001$). Conversely, smaller discrepancies were noted between *neuroticism, positive sentiment, formal style, and short length* versus *openness, negative sentiment, formal style, and long length* (KS = 0.2853, $p < 0.05$) and

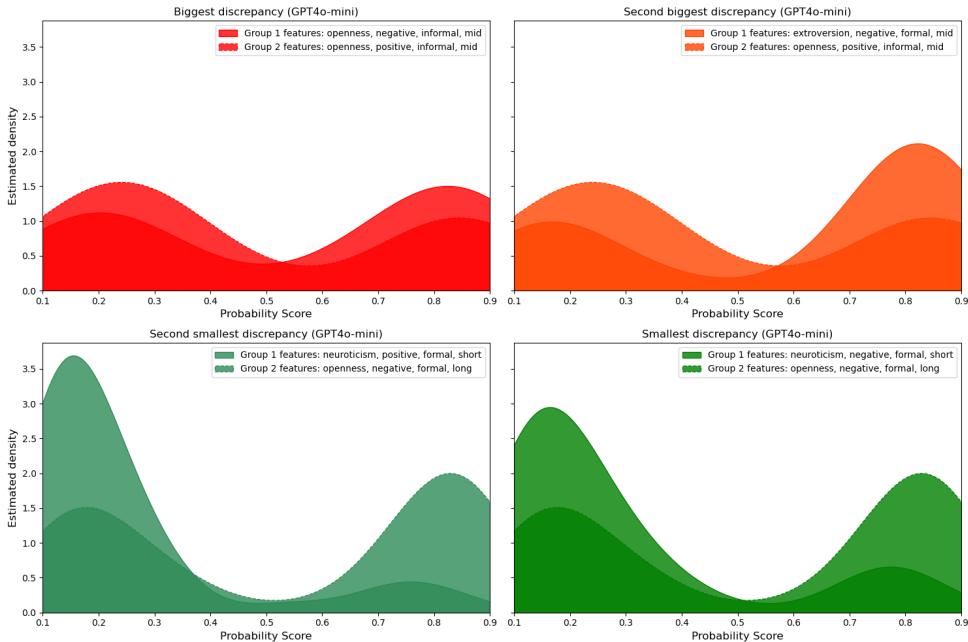


Figure 12. KDE plots comparing probability distributions for subgroup pairs with the highest and lowest discrepancies based on the K-S test with statistical validity. The largest discrepancy is observed with a KS statistic of 0.6667, while the smallest discrepancy has a KS statistic of 0.2560.

neuroticism, negative sentiment, formal style, and short length versus openness, negative sentiment, formal style, and long length (KS = 0.2560, $p < 0.05$).

F. Operationalizing FairOPT

F.1. Algorithmic description

F.2. Early stopping method for the tradeoff curve

An optimization algorithm was implemented using a function from the `scipy.optimize` library, aiming to determine probability thresholds that satisfy specific fairness constraints (`acceptable_disparity = [1.00, 0.30, 0.25, 0.21, 0.20, 0.19, 0.15, 0.10]`) while ensuring minimum performance thresholds for both performance criteria (ACC and F1). The optimization in the `minimize` function was performed using the `L-BFGS-B` method. Early stopping is facilitated by the default values of `ftol` and `gtol` in `L-BFGS-B`. Additionally, the `learning_rate` was set to 10^{-3} to enable controlled and stable updates during optimization, and a `penalty` parameter was set to 10 to strengthen the L2 penalty in the loss function. Furthermore, minimum performance thresholds for accuracy and F1-score were enforced based on the performance observed for each group when applying a static threshold of 0.5 and a ROC-based threshold. As stricter fairness constraints are imposed, these minimum thresholds are gradually relaxed.

F.3. Hyperparameter settings for the FairOPT

The application of the FairOPT is configured with a set of hyperparameters designed to ensure a balance between fairness and performance during the threshold optimization process. The `learning_rate` is set to 10^{-3} to enable controlled and stable updates during optimization. The maximum number of iterations is specified as 10^5 to provide sufficient time for the optimization algorithm to converge. An acceptable disparity of 0.2 is defined to regulate subgroup fairness, ensuring that performance differences across subgroups remain within an acceptable range through the relaxed fairness. Minimum thresholds for accuracy (0.25) and F1-score (0.25) are enforced to maintain baseline model performance and stability, particularly in cases of imbalanced datasets. A tolerance level of 10^{-2} is introduced to impose convergence criteria, ensuring the optimization process halts only when the changes in the objective function are negligible. Furthermore, a `penalty` parameter of 20 is applied to enforce performance

Algorithm 2 FairOPT: Gradient-based adaptive threshold optimization with fairness for subgroups

1: **Input:** Labeled dataset $D = \{(x_n, y_n)\}$, predicted probabilities $\{p_n\}$, subgroup labels $\{g_n\}$ with possible groups G_1, \dots, G_j , features $\{S_1, \dots, S_n\}$, initial thresholds θ_{init} , fairness metrics $\{M_1, \dots, M_k\}$ with acceptable disparity δ_{fair} , minimum performance thresholds: α (ACC) and β (F1), penalty weight κ , learning rate η , tolerance ϵ_{tol} , maximum iterations, finite-difference step δ , minimum probability for threshold a , maximum probability for threshold b

2: **Output:** Subgroup thresholds $\{\theta^*(G_1), \dots, \theta^*(G_j)\}$

3: **Initialization:**

4: split D to $(G_1), \dots, (G_j)$ by S

5: **while** iteration < maximum iterations **do**

6: **for** each group G_j **do**

7: $\mathcal{I}_i \leftarrow \{n \mid g_n = G_j\}$ // all samples in group G_j

8: $\hat{y}_n \leftarrow [p_n \geq \theta(G_j)]$, $\forall n \in \mathcal{I}_i$

9: Store contingency table for G_i using \hat{y}_n and y_n

10: $\Omega \leftarrow \min_i \{\text{ACC}(G_j)\} \geq \alpha \wedge \min_i \{\text{F1}(G_j)\} \geq \beta$ // boolean output

11: **for** each fairness metric M_k **do**

12: Compute $\{M_k(G_1), \dots, M_k(G_j)\}$

13: $\Delta_k \leftarrow \max_i (M_k(G_j)) - \min_i (M_k(G_j))$

14: $\Psi \leftarrow [\max_k \Delta_k \leq \delta_{fair}]$ // boolean output

15: **for** each group G_j **do**

16: $L_i(\theta) = -\text{Acc}_j(\theta) + \kappa [\beta - \text{F1}_j(\theta)]_+$

17:
$$\nabla L_i(\theta(G_j)) \approx \frac{L_i(\theta(G_j) + \delta) - L_i(\theta(G_j) - \delta)}{2\delta}.$$

18:
$$\theta(G_j) \leftarrow \theta(G_j) - \eta \nabla L_i(\theta(G_j)).$$

19: Clip $\theta(G_j)$ to stay within $[a, b]$

20: $\Delta_\theta \leftarrow \max_{G_j} |\theta(G_j) - \text{previousThresholds}[G_j]|$

21: **if** $(\Delta_\theta < \epsilon_{tol} \wedge \Omega \wedge \Psi)$ **then**

22: **break**

23: previousThresholds $\leftarrow \theta(\cdot)$

24: iteration \leftarrow iteration + 1

25: **return** $\{\theta(G_1), \dots, \theta(G_j)\}$

constraints by penalizing significant performance disparities across subgroups. For fairness criteria, Demographic Parity (DP) was employed to test whether the generated thresholds meets the expected fairness. Also, this experiment used early stopping method for effective processing. The early stopping check through the change of the ACC, F1, and maximum DP discrepancy of each group, and terminates if all of them shows minimal change based on predefined patience.