Improving Fairness of Large Language Models in Multi-document Summarization

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Abstract

Fairness in multi-document summarization (MDS) is crucial for providing comprehensive views across documents with diverse social attribute values, which can significantly impact decision-making. For example, a summarization system that tends to overrepresent negative reviews of products can mislead customers into disregarding good products. Previous works measure fairness in MDS at two levels: summary-level and corpus-level. While summary-level fairness focuses on individual summaries, corpus-level fairness focuses on a corpus of summaries. Recent methods primarily focus on summary-level fairness. We propose FairPO, a preference tuning method that focuses on both summary-level and corpus-level fairness in MDS. To improve summary-level fairness, we propose to generate preference pairs by perturbing document sets. To improve corpus-level fairness, we propose fairness-aware preference tuning by dynamically adjusting the weights of preference pairs. Our experiments show that FairPO outperforms strong baselines while maintaining the critical qualities of summaries.

1 Introduction

Multi-document summarization (MDS) aims to summarize the salient information from multiple documents about an entity, such as reviews of a product. Each of these documents is generally associated with a *social attributes* such as sentiments in reviews. These documents with different social attribute values e.g. positive sentiment or negative sentiment tend to have diverse information or conflicting opinions. It is crucial that the summary fairly represents conflicting information since it can significantly impact decision-making.

Previous works (Shandilya et al., 2018; Olabisi et al., 2022; Huang et al., 2024) measure fairness in MDS at two levels: summary-level or corpus-level. Summary-level fairness measures how fairly a summary represents documents with different social attribute values. Corpus-level fairness measures how fairly a corpus of summaries as a whole represents different social attribute values.

Recent studies (Zhang et al., 2023; Li et al., 2024) find that modern summarization methods like LLMs struggle with both summary-level and corpus-level fairness. To improve the summary-level fairness, Zhang et al. (2023) prompt LLMs to generate summaries based on the distribution of social attributes among documents. However, it relies on users' prior knowledge of fairness issues and social attributes, limiting its effectiveness in practice. Huang et al. (2024) improve the summary-level fairness of T5 (Raffel et al., 2020) by policy gradient, but their method may not generalize to modern models like LLMs. Furthermore, both methods focus exclusively on summary-level fairness, overlooking the corpus-level fairness.

We propose FairPO (**F**air **P**reference **O**ptimization), a preference tuning (Ziegler et al., 2019) method that focuses on both summary-level and corpus-level fairness of LLMs in MDS. While previous works (Stiennon et al., 2020; Roit et al., 2023) uses preference tuning to improve other qualities of summaries, FairPO is the first to use preference tuning for the fairness in MDS. FairPO is based on Direct Preference Optimization (DPO) (Rafailov et al., 2024). To optimize summary-level fairness, FairPO generates preference pairs given perturbed input document sets by removing a small subset of documents with certain social attribute values. To further improve corpus-level fairness, FairPO performs *fairness-aware preference tuning* by dynamically adjusting the weights of preference pairs.

We conduct an empirical evaluation of FairPO using three LLMs: Llama3.1 (AI@Meta, 2024), Mistral (Jiang et al., 2023), and Gemma2 (Team et al., 2024), on the Amazon (Ni et al., 2019), MITweet (Liu et al., 2023), and SemEval datasets (Mohammad et al., 2016). Our experiments show that FairPO outperforms strong baselines while maintaining other critical qualities of summaries, such as relevance and factuality.

Our contributions are as follows:

- We propose FairPO to improve the fairness of LLMs in MDS;
- We propose to improve summary-level and corpus-level fairness by perturbation-based preference pair generation and fairness-aware preference tuning;
- We perform comprehensive experiments to show the effectiveness of FairPO.

2 Background

In this section, we provide background knowledge on fairness in MDS. Let G denote all document sets in a corpus for MDS. Each document set $D \in G$ contains multiple documents $\{d_1, ..., d_n\}$, where each document d_i is labeled with a social attribute $a_i \in \{1, ..., K\}$. For each document set D, a MDS system is supposed to generate a summary S.

To evaluate fairness in MDS, we use Equal Coverage $EC(D, S)$, a summary-level measure, and Coverage Parity $CP(G)$, a corpus-level measure (Li et al., 2024). The key idea of Equal Coverage $EC(D, S)$ is to examine whether each social attribute value has equal probabilities of being covered by the summary S for a document set D. Specifically, it first defines **coverage probability difference** $c(d_i, S)$ as the difference between the probability of the document d_i being covered by the summary S and the average probability of any document being covered. Then, $EC(D, S)$ is calculated as the average of absolute average coverage probability difference $c(d_i, S)$ for documents with each social attribute value among the document set D. Hence, a lower $EC(D, S)$ indicates a fairer summary. Contrarily, the key idea of Coverage Parity $CP(G)$ is to examine whether certain social attribute values are systematically overrepresented or underrepresented across the corpus G. It is calculated as the average of absolute average coverage probability difference $c(d_i, S)$ for documents with each social attribute value in the corpus G. A lower $CP(G)$ indicates a fairer system. Please refer to App. A.1 and Li et al. (2024) for details.

3 FairPO

In this section, we describe our proposed preference tuning method, FairPO.

3.1 Perturbation-based Preference Pair Generation

In this section, we describe how to generate preference pairs based on perturbation. A preference pair for FairPO contains a chosen summary S_c and a rejected summary S_r for the document set D. Ideally, the chosen and rejected summaries should differ significantly in representing documents with different social attribute values. To this end, FairPO generates summaries for perturbed input document sets, where small subsets ($\alpha\%$) of documents with specific social attribute values are removed.

Specifically, FairPO first generates a summary S for the input document set D and identifies its most overrepresented, k^+, and underrepresented, k^-, social attribute value. For the completeness of information, FairPO only considers social attribute values that appear in more than $\alpha\%$ of the documents (details in App. A.5). These are determined based on the highest or lowest average coverage probability differences, $\mathbb{E}(\{c(d_i, S)|a_i = k\})$. Then, FairPO generates summary S^+ and S^- for the perturbed input document set where $\alpha\%$ of randomly sampled documents with social attribute value a_i of k^+ and k^- are removed. Among summaries S, S^+, S^-, FairPO selects the summary with the lowest Equal Coverage value, indicating the best summary-level fairness, as the chosen summary S_c. The summary with the highest Equal Coverage value is selected as the rejected summary S_r.

3.2 Fairness-aware Preference Tuning

In this section, we describe fairness-aware preference tuning that optimizes summary-level and corpus-level fairness. To achieve this, FairPO dynamically assigns separate weights for the chosen summary S_c and the rejected summary S_r based on estimated corpus-level fairness during training.

FairPO modifies the DPO objective (more explanations in App. A.4) and introduces separate weights, w_c and w_r, for the chosen summary S_c and rejected summary S_r respectively:

$$\sigma(-m)\beta(w_r log\frac{\pi_\theta(S_r|D)}{\pi_{ref}(S_r|D)} - w_c log\frac{\pi_\theta(S_c|D)}{\pi_{ref}(S_c|D)}) \quad (1)$$

where σ is the sigmoid function, π_θ is the policy model, π_{ref} is the reference model, and m is the reward margin as in DPO:

$$m = \beta log\frac{\pi_\theta(S_c|D)}{\pi_{ref}(S_c|D)} - \beta log\frac{\pi_\theta(S_r|D)}{\pi_{ref}(S_r|D)} \quad (2)$$

The term $\sigma(-m)$ in Eq. 1 serves as a scaling factor and FairPO does not consider its gradient.

FairPO assigns weights w_c and w_r to summaries based on their impact on corpus-level fairness. It assigns high weights w_c to chosen summaries that improve corpus-level fairness by balancing the overrepresentation and underrepresentation of social attribute values. Conversely, it assigns high weights w_r to rejected summaries that hurt corpus-level fairness. To estimate corpus-level fairness, FairPO computes the sum of coverage probability differences for documents with social attribute values of k, $C_k(D, S_*) = \sum_{d \in \{d_i | a_i = k\}} c(d, S_*)$ for each chosen or rejected summary, S_*. A summary S_* is considered overrepresenting or underrepresenting the social attribute value k if the sum of coverage probability differences, $C_k(D, S_*)$, is greater or less than zero respectively. In each training step, FairPO estimates the overrepresentation $O(k)$ of social attribute value k:

$$O(k) = \frac{\sum_{(D,S) \in T_k^+} |C_k(D, S)| \cdot \pi_\theta(S|D)/|S|}{\sum_{(D,S) \in T_k^+} \pi_\theta(S|D)/|S|} \tag{3}$$

where T_k^+ is the set of document sets D and corresponding chosen or rejected summaries that over-represent social attribute value k ($C_k(D, S_*) > 0$) in recent training steps. Similarly, FairPO estimates the underrepresentation $U(k)$ using the set T_k^- of document sets and summaries that underrepresent social attribute value k ($C_k(D, S_*) < 0$) as Eq. 3.

Using the overrepresentation $O(k)$ and underrepresentation $U(k)$, FairPO assigns weight w_c and w_r. Chosen summaries that help balance overrepresentation $O(k)$ and underrepresentation $U(k)$ receive higher weights and vice versa for rejected summaries. For example, the weight w_c should be higher if a systematically underrepresented social attribute value k ($U(k) > O(k)$) is overrepresented by the chosen summary S_c ($C_k(D, S_c) > 0$). For social attribute value k, FairPO computes an intermediate weight $w_{c,k}$ for the chosen summary S_c:

$$w_{c,k} = \frac{2}{1 + (O(k)/(U(k))^{C_k(D,S_c)/\tau}} \tag{4}$$

where τ is the temperature. The weight w_c for chosen summaries is the average intermediate weight $w_{c,k}$ across all social attribute values. The weight w_r for the rejected summary S_r is computed similarly with the intermediate weight $w_{r,k}$:

$$w_{r,k} = \frac{2}{1 + (U(k)/(O(k))^{C_k(D,S_r)/\tau}} \tag{5}$$

The design ensures that summaries improving corpus-level fairness are prioritized.

	Domain	Soci. Attr.	Soci. Attr. Val.	Doc. Set Size	Doc. Len
Amazon	Review	Sentiment	negative, neutral, positive	8	40
MiTweet	Tweet	Ideology	left, center, right	20	34
SemEval	Tweet	Stance	support, against	30	17

Table 1: Dataset statistics. Doc. Set Size means size of document sets. Doc. Len. means average length of documents.

4 Experiments

In this section, we describe experiments of finetuning models with FairPO.

4.1 Datasets

We experiment on three datasets: Amazon (Ni et al., 2019), MITweet (Liu et al., 2023), SemEval (Mohammad et al., 2016) datasets. Each dataset includes 1000 samples for training, 300 samples for validation, and 300 samples for testing. The division of training, validation, and testing sets is based on stratified sampling of social attribute values and topics. Tab. 1 shows the statistics of these datasets. The summary length is 50 words. Details of preprocessing are in App. A.2.

4.2 Implementation Details

We perform experiments with three LLMs: Llama3.1-8b-Instruct (AI@Meta, 2024) , Mistral-7B-Instruct-v0.3 (Jiang et al., 2023), Gemma-2-9b-it (Team et al., 2024). Each LLM is trained for 2 epochs using LoRA (Hu et al., 2021) with a learning rate of $5e-5$ and batch size of 16. To generate preference pairs, FairPO removes $\alpha = 10\%$ of documents. The temperature τ is 1 on the MITweet dataset, 2 for Mistral and 1 for other LLMs on the Amazon dataset, 3 for Mistral and 2 for other LLMs on the SemEval dataset. All hyperparameters are tuned on the validation set. More details are in App. A.5.

4.3 Automatic Evaluation of Fairness

We compare FairPO with the following baselines: (i) DPO (Rafailov et al., 2024), where the chosen and rejected summaries are selected among three randomly sampled summaries based on EC values like FairPO; (ii) OPTune (Chen et al., 2024), which weights preference pairs based on EC value differences; (iii) Policy gradients (Lei et al., 2024) and (iv) a prompting method (Zhang et al., 2023). Implementation Details are in App A.6. For evaluation, we consider summary-level and corpus-level

	Amazon		MITweet		SemEval		Overall	
	$EC\downarrow$	$CP\downarrow$	EC	$CP\downarrow$	$EC\downarrow$	$CP\downarrow$	$\overline{EC}\downarrow$	$\overline{CP}\downarrow$
Llama3.1	7.90	1.92	4.43	0.26	2.94	1.33	5.09	1.17
+DPO	6.87	1.04	**4.03**	0.31	2.55	0.91	4.49	0.75
+OPTune	6.58	0.75	4.22	**0.23**	2.50	0.81	4.43	0.60
+Prompt	7.71	1.84	4.33	0.38	2.53	**0.26**	4.86	0.83
+Policy G.	7.71	2.10	4.46	0.31	2.95	1.32	5.04	1.24
+FairPO	**6.57**	**0.37**	4.20	0.26	**2.39**	0.56	**4.39**	**0.39**
Mistral	8.18	2.98	3.98	0.42	2.67	1.07	4.94	1.49
+DPO	7.17	1.55	3.60	0.28	2.21	0.64	4.33	0.82
+OPTune	7.48	1.56	3.60	0.25	2.00	0.67	4.36	0.83
+Prompt	7.67	1.93	4.02	0.23	2.38	0.38	4.69	0.85
+FairPO	**6.98**	**0.89**	**3.56**	**0.21**	**1.97**	**0.36**	**4.17**	**0.49**
Gemma2	8.44	2.75	4.17	0.34	2.74	0.91	5.12	1.33
+DPO	6.87	1.04	4.04	0.29	2.42	0.70	4.44	0.68
+OPTune	6.90	1.15	3.86	0.45	**2.40**	0.65	4.39	0.75
+Prompt	7.21	1.13	4.28	**0.24**	2.62	**0.30**	4.70	0.56
+FairPO	**6.09**	**0.33**	**3.84**	0.47	2.53	0.59	**4.15**	**0.46**

Table 2: Summary-level fairness (EC) and corpus-level fairness (CP) of summaries generated by different methods. The best performing method is in **bold**. The second-best performing method is underlined. FairPO has the best overall performance.

fairness using Equal Coverage (EC) and Coverage Parity (CP) (Li et al., 2024). A lower value is better for these measures. Results are in Tab. 2. We observe that FairPO outperforms other methods for most LLMs on all datasets and yields the best overall performance for all LLMs. The results show that FairPO improves both summary-level and corpus-level fairness. We also report the ablation results in App.A.7 and results using a different splitting of training, validation and testing in App. A.8. The results suggest that FairPO outperforms its ablated versions and its performance is stable on the different dataset splitting.

4.4 Human Evaluation of Fairness

We perform a human evaluation to compare the fairness of summaries generated by LLMs tuned with DPO and FairPO. For each LLM, we randomly select 10 pairs of summaries generated by the LLM tuned with DPO or FairPO, yielding a total of 30 pairs. Each pair is annotated by three annotators recruited from Amazon Mechanical Turk. Annotators are asked to read all corresponding documents and select the fairer summary. We choose the Amazon dataset since each document set only contains eight reviews (Tab. 1) and judging the sentiment of an opinion is relatively easy for common users. The Randolph's Kappa (Randolph, 2005) between annotations of three annotators is 0.40, which shows a moderate correlation. The correlation is expected considering the subjectivity of the task. More details are in App. A.3.

	Llama3.1			Mistral			Gemma2		
	flu.↑	rel.↑	fac.↑	flu.↑	rel.↑	fac.↑	flu.↑	rel.↑	fac.↑
DPO	7.56	8.33	2.78	5.11	11.56	11.56	5.11	1.11	8.67
OPTune	1.00	0.44	-6.89	-0.78	6.78	8.89	7.00	11.67	11.67
Prompt	-15.33	-19.22	-24.44	-0.44	-6.00	-5.56	-42.67	-50.78	-51.44
FairPO	5.78	3.11	2.89	2.11	5.33	9.11	11.44	16.11	9.44

Table 3: Pairwise comparison of quality between summaries generate by LLMs before and after tuning. Statistical significant differences ($p < 0.05$) according to paired bootstrap resampling (Koehn, 2004) are underlined. FairPO does not affect summary quality.

Out of 30 pairs, summaries generated by FairPO-tuned LLMs are fairer in 18 pairs and summaries generated by DPO-tuned LLMs are fairer in 9 pairs.The difference is statistically significant ($p < 0.05$) using bootstrap (Koehn, 2004). The results show that FairPO performs better than DPO in improving fairness. We additionally show example summaries generated by FairPO in App. A.9.

4.5 Evaluation of Summary Quality

To evaluate FairPO's impact on summary quality, we compare summaries generated by LLMs before and after tuning to improve fairness. Specifically, for a pair of summaries, we instruct Prometheus 2 (7B) (Kim et al., 2024) to select the better summary in three dimensions: fluency, relevance, and factuality. To mitigate position bias (Huang et al., 2023), we perform the pairwise comparison twice with different orders of summaries and only consider consistent results. Tab. 3 reports the differences between the winning and losing rates of different methods. A positive value indicates summary quality is better compared to original LLMs.

From the table, we observe that the quaility of summaries generated by LLMs tuned with FairPO is comparable with summaries generated by original LLMs. Contrarily, prompting significantly hurt the quality of summaries. The results show that FairPO improves the fairness of summaries while maintaining their quality.

5 Conclusion

We propose FairPO, a preference tuning method that optimizes summary-level fairness and corpus-level fairness in MDS. Specifically, FairPO generates preference pairs using perturbed document sets to improve summary-level fairness and performs fairness-aware preference tuning to improve corpus-level fairness. Our experiments show that FairPO outperforms strong baselines while maintaining critical qualities of summaries.

6 Limitation

Our experiments demonstrate FairPO's effectiveness in improving both summary-level and corpus-level fairness of summaries within individual domains. While this work focuses on optimizing fairness within a single domain, extending FairPO to improve fairness simultaneously across multiple domains with diverse social attributes presents a promising future direction. Besides, FairPO currently selects the two summaries with the largest fairness differences among the three generated summaries for preference tuning, following commonly used practices of DPO. Exploring approaches to utilize all three summaries generated by FairPO can be another interesting future direction.

7 Ethical Consideration

The datasets we use are all publicly available. We do not annotate any data on our own. All the models used in this paper are publicly accessible. The inference and finetuning of models are performed on one Nvidia A6000 or Nvidia A100 GPU.

We perform human evaluation experiments on Amazon Mechanical Turk. The annotators were compensated at a rate of $20 per hour. During the evaluation, human annotators were not exposed to any sensitive or explicit content.

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A Appendix

A.1 Fairness Measure

In this section, we describe the fairness measure used in this paper. We use Equal Coverage $EC(D, S)$ to evaluate summary-level fairness and Coverage Parity $CP(G)$ to evaluate corpus-level fairness (Li et al., 2024). Below, we summarize these concepts as introduced in the original paper.

Equal Coverage examines whether each social attribute value has equal probabilities of being covered by the summary S for a document set D. Specifically, it first defines **coverage probability difference** $c(d_i, S)$ as the difference between the coverage probability for the document d_i, $p(d_i, s)$, and the average coverage probability across all documents, $p(d, s)$. To estimate the coverage probability for the document d_i, $p(d_i, s)$, FairPO estimates the probability $p(d_i, s_j)$ that a document d_i is covered by a summary sentence s_j. Specifically, the probability $p(d_i, s_j)$ is estimated as the maximum entailment probability $p(d_{i,l}, s_j)$ between any document chunk $d_{i,l}$ of the document d_i and the summary sentence s_j using an entailment model:

$$p(d_i, s_j) = \max\{p(d_{i,l}, s_j)|d_{i,l} \in d_i\}, \quad (6)$$

The coverage probability for the document d_i, $p(d_i, s)$, is then estimated as the average of the probability $p(d_i, s_j)$:

$$p(d_i, s) = \frac{1}{|S|}\sum_{s_j \in S} p(d_i, s_j), \quad (7)$$

The average coverage probability, $p(d, s)$, is then calculated by averaging coverage probability , $p(d_i, s)$, across all documents in the document set D. Using these values, Equal Coverage calculates the coverage probability difference $c(d_i, S) = p(d_i, s) - p(d, s)$. Equal Coverage value $EC(D, S)$ is then calculated as the average of absolute average coverage probability difference $c(d_i, S)$ for documents with each social attribute value:

$$EC(D, S) = \frac{1}{K}\sum_{k=1}^{K} |\mathbb{E}(\{c(d_i, S)|a_i = k\})| \quad (8)$$

A lower $EC(D, S)$ indicates a fairer summary S. To evaluate the fairness of a system, we use the average Equal Coverage value of all examples G.

Coverage Parity examines whether certain social attribute values are systematically overrepresented or underrepresented across the corpus G.

Coverage Parity collects these coverage probabilities differences $c(d_i, S)$ from all input documents of the dataset G whose social attribute value is k into a set C_k. The coverage Parity value $CP(G)$ is then calculated as the average of absolute average coverage probability difference $c(d_i, S)$ for documents with each social attribute value:

$$CP(G) = \frac{1}{K}\sum_{k=1}^{K} |\mathbb{E}(C_k)|, \tag{9}$$

A lower $CP(G)$ indicates a fairer system.

A.2 Datasets

In this section, we describe how we preprocess the datasets.

Amazon (Ni et al., 2019) consists of reviews with labels of their ratings of different products. We filter out reviews that are non-English or without ratings. We obtain the social attribute of each review based on its rating provided in the dataset. The social attribute of a review will be positive if its rating is 4 or 5, neutral if its rating is 3, and negative if its rating is 1 or 2. To construct training, validation and testing sets, we perform stratified sampling based on the distribution of social attribute values among document sets for each set. Therefore, each set has equal proportions of document sets D dominated by each social attribute values. We sample 1000 products and their corresponding reviews for training, 300 products for validation, and 300 products for testing.

MITweet (Liu et al., 2023) consists of tweets with labels of political ideologies on different facets about different topics. The social attribute of a tweet will be left if it is left on most facets, right if it is right on most facets, otherwise neutral. First, we evenly divide all tweets of each topic into two parts so that the distribution of topics is the same between two parts. For each part, we cluster tweets about the same topic based on their TFIDF similarity into clusters. We then divide these clusters into input document sets of 20 tweets about the same topic. We generate 1000 input document sets for training from the first part of the tweets. Similarly, we generate 300 input document sets for validation and 300 input document sets for testing from the second part of the tweets. When generating input document sets of training, validation, and testing sets, we also perform stratified sampling based on the distribution of social attribute values so that each set has equal proportions of document sets D dominated by each social attribute value.

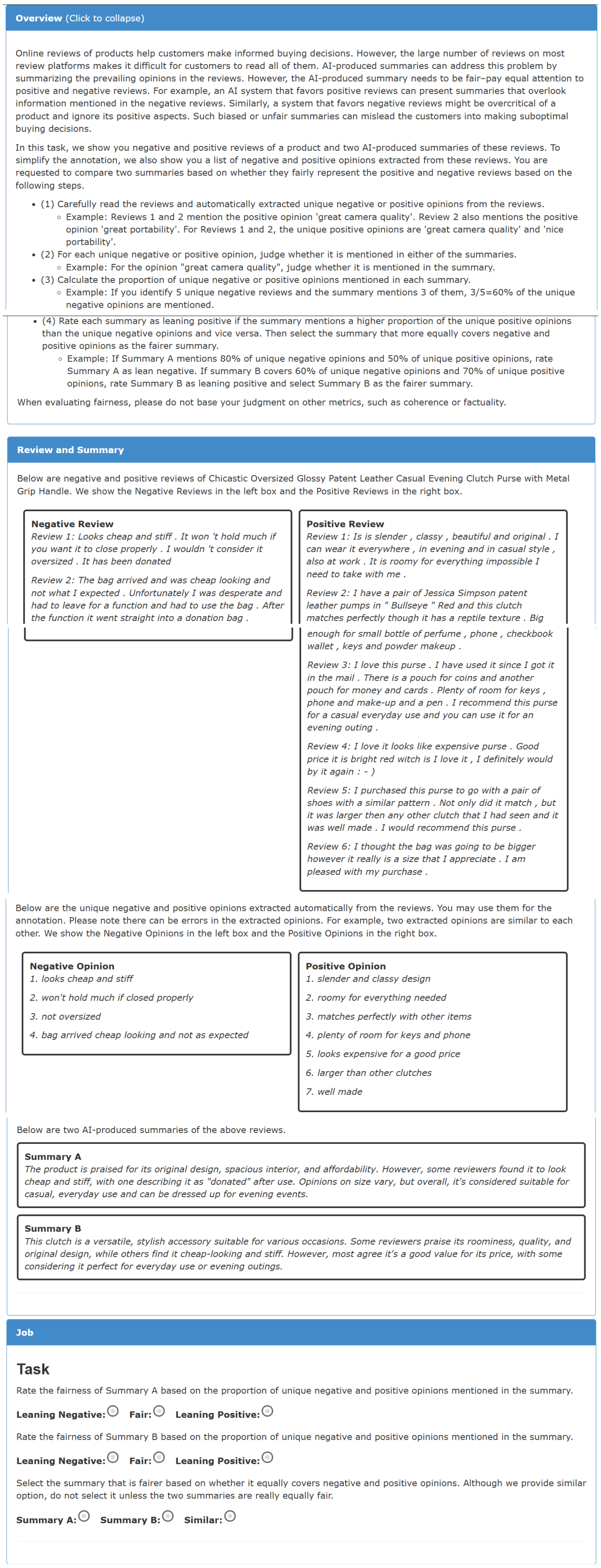
Tweet Stance (Mohammad et al., 2016) consists of tweets with labels of stance toward a target phrase such as Climate Change or Hillary Clinton. First, we evenly divide all tweets of each topic into two parts so that the distribution of target phrase is the same between two parts. We cluster tweets about the same target phrase based on their TFIDF similarity into clusters. We then divide these clusters into input document sets of 30 tweets about the same target phrase. We generate 1000 input document sets for training from the first part of the tweets. Similarly, we generate 300 input document sets for validation and 300 input document sets for testing from the second part of the tweets. When generating input document sets of training, validation, and testing sets, we also perform stratified sampling based on the distribution of social attribute values so that each set has equal proportions of document sets D dominated by each social attribute value.

A.3 Human Evaluation

We perform a human evaluation to compare the fairness of summaries generated by LLMs tuned with DPO and FairPO. For each LLM, we randomly select 10 pairs of summaries generated by the LLM tuned with DPO or FairPO, yielding a total of 30 pairs. To further simplify the evaluation, we consider document sets with only negative and positive reviews. Each pair is annotated by three annotators recruited from Amazon Mechanical Turk. The annotators should be from English-speaking countries and have HIT Approval Rates greater than 98%. For each pair, annotators are first asked to read corresponding reviews and unique opinions automatically extracted by GPT-4o-mini (Ouyang et al., 2022). They then evaluate whether each summary reflects these opinions and classify the summary as leaning negative, fair, or leaning positive. Eventually, they are asked to select the fairer summary in each pair. The interface of human evaluation is shown in Fig. 1.

A.4 Relation between FairPO and DPO

The FairPO objective (Eq. 1) is motivated by the derivate of the DPO objective with respect to the



Overview (Click to collapse)

Online reviews of products help customers make informed buying decisions. However, the large number of reviews on most review platforms makes it difficult for customers to read all of them. AI-produced summaries can address this problem by summarizing the prevailing opinions in the reviews. However, the AI-produced summary needs to be fair–pay equal attention to positive and negative reviews. For example, an AI system that favors positive reviews can present summaries that overlook information mentioned in the negative reviews. Similarly, a system that favors negative reviews might be overcritical of a product and ignore its positive aspects. Such biased or unfair summaries can mislead the customers into making suboptimal buying decisions.

In this task, we show you negative and positive reviews of a product and two AI-produced summaries of these reviews. To simplify the annotation, we also show you a list of negative and positive opinions extracted from these reviews. You are requested to compare two summaries based on whether they fairly represent the positive and negative reviews based on the following steps.

- (1) Carefully read the reviews and automatically extracted unique negative or positive opinions from the reviews.
  - Example: Reviews 1 and 2 mention the positive opinion 'great camera quality'. Review 2 also mentions the positive opinion 'great portability'. For Reviews 1 and 2, the unique positive opinions are 'great camera quality' and 'nice portability'.
- (2) For each unique negative or positive opinion, judge whether it is mentioned in either of the summaries.
  - Example: For the opinion "great camera quality", judge whether it is mentioned in the summary.
- (3) Calculate the proportion of unique negative or positive opinions mentioned in each summary.
  - Example: If you identify 5 unique negative reviews and the summary mentions 3 of them, 3/5=60% of the unique negative opinions are mentioned.
- (4) Rate each summary as leaning positive if the summary mentions a higher proportion of the unique positive opinions than the unique negative opinions and vice versa. Then select the summary that more equally covers negative and positive opinions as the fairer summary.
  - Example: If Summary A mentions 80% of unique negative opinions and 50% of unique positive opinions, rate Summary A as lean negative. If summary B covers 60% of unique negative opinions and 70% of unique positive opinions, rate Summary B as leaning positive and select Summary B as the fairer summary.

When evaluating fairness, please do not base your judgment on other metrics, such as coherence or factuality.

Review and Summary

Below are negative and positive reviews of Chicastic Oversized Glossy Patent Leather Casual Evening Clutch Purse with Metal Grip Handle. We show the Negative Reviews in the left box and the Positive Reviews in the right box.

Negative Review

Review 1: Looks cheap and stiff . It won 't hold much if you want it to close properly . I wouldn 't consider it oversized . It has been donated

Review 2: The bag arrived and was cheap looking and not what I expected . Unfortunately I was desperate and had to leave for a function and had to use the bag . After the function it went straight into a donation bag .

Positive Review

Review 1: Is is slender , classy , beautiful and original . I can wear it everywhere , in evening and in casual style , also at work . It is roomy for everything impossible I need to take with me .

Review 2: I have a pair of Jessica Simpson patent leather pumps in " Bullseye " Red and this clutch matches perfectly though it has a reptile texture . Big enough for small bottle of perfume , phone , checkbook wallet , keys and powder makeup .

Review 3: I love this purse . I have used it since I got it in the mail . There is a pouch for coins and another pouch for money and cards . Plenty of room for keys , phone and make-up and a pen . I recommend this purse for a casual everyday use and you can use it for an evening outing .

Review 4: I love it looks like expensive purse . Good price it is bright red witch is I love it , I definitely would by it again : -)

Review 5: I purchased this purse to go with a pair of shoes with a similar pattern . Not only did it match , but it was larger then any other clutch that I had seen and it was well made . I would recommend this purse .

Review 6: I thought the bag was going to be bigger however it really is a size that I appreciate . I am pleased with my purchase .

Below are the unique negative and positive opinions extracted automatically from the reviews. You may use them for the annotation. Please note there can be errors in the extracted opinions. For example, two extracted opinions are similar to each other. We show the Negative Opinions in the left box and the Positive Opinions in the right box.

Negative Opinion

1. *looks cheap and stiff*
2. *won't hold much if closed properly*
3. *not oversized*
4. *bag arrived cheap looking and not as expected*

Positive Opinion

1. *slender and classy design*
2. *roomy for everything needed*
3. *matches perfectly with other items*
4. *plenty of room for keys and phone*
5. *looks expensive for a good price*
6. *larger than other clutches*
7. *well made*

Below are two AI-produced summaries of the above reviews.

Summary A

The product is praised for its original design, spacious interior, and affordability. However, some reviewers found it to look cheap and stiff, with one describing it as "donated" after use. Opinions on size vary, but overall, it's considered suitable for casual, everyday use and can be dressed up for evening events.

Summary B

This clutch is a versatile, stylish accessory suitable for various occasions. Some reviewers praise its roominess, quality, and original design, while others find it cheap-looking and stiff. However, most agree it's a good value for its price, with some considering it perfect for everyday use or evening outings.

Job

Task

Rate the fairness of Summary A based on the proportion of unique negative and positive opinions mentioned in the summary.

Leaning Negative: ○ **Fair:** ○ **Leaning Positive:** ○

Rate the fairness of Summary B based on the proportion of unique negative and positive opinions mentioned in the summary.

Leaning Negative: ○ **Fair:** ○ **Leaning Positive:** ○

Select the summary that is fairer based on whether it equally covers negative and positive opinions. Although we provide similar option, do not select it unless the two summaries are really equally fair.

Summary A: ○ **Summary B:** ○ **Similar:** ○

Figure 1: Interface for Human Evaluation

Below is a list of product reviews:

1.This is a card reader that does everything I needed it to . My adapters for the micro SD cards were defective so I have no complaints only praise . It reads any Compact Flash , Memory Stick , SD , and XD cards . Well that is all I wanted to say except this is a great product overall , and thank you .

2.The pins in the CF slot are very flimsy and get bent out of alignment easily , making it impossible to insert the card (until you perform delicate surgery on the pins with small tweezers) . Do not buy this product if you will ever use the CompactFlash slot . It will just lead to frustration .

3.So far I only use this for SM and SD cards , but it installed (USB) quickly , easily and reads the cards I need read .

4.Initially it worked great but after the 5th time it stopped working . It also helped fry my SD-card will all my pictures and video clips . Not happy at all with this product .

5.Reads 64 cards is quite deceiving . It only reads four types of cards made by 64 different manufacturers . Also , the connector port is difficult to plug in .

6.good product , reads quite fast. only issue is that the card reader does not have a satisfying ' click ' when the card is inserted. you kinda have to stick the card in the slot and hope it is lodged properly .

7.I can get it to read SD cards , but I bought it to read my CF 's and it won 't read a single one . My experience is in line with others . Go check out similar reviews on newegg.com.

8.The card reader comes in retail packaging and totally lacks instructions on how best to put 68 types of cards into 4 slots . It did read an SD card successfully . The micro usb plug on the usb cord broke after 1 use .

Please write a single summary around 50 words for all the above reviews.

Figure 2: Summarization prompt for the Amazon Dataset.

model parameters θ:

$$\sigma(-m)\beta(\pi_\theta(S_r|D)^{-1}\frac{\partial\pi_\theta(S_r|D)}{\partial\theta} - \pi_\theta(S_c|D)^{-1}\frac{\partial\pi_\theta(S_c|D)}{\partial\theta}) \tag{10}$$

where σ is the sigmoid function, π_θ is the policy model, π_{ref} is the reference model, and m is the reward margin in DPO:

$$\beta log\frac{\pi_\theta(S_c|D)}{\pi_{ref}(S_c|D)} - \beta log\frac{\pi_\theta(S_r|D)}{\pi_{ref}(S_r|D)} \tag{11}$$

The reward margin m can be viewed as a measure of the model's ability to distinguish between the chosen summary S_c and the rejected summary S_r. A larger value of m indicates that the model is already proficient at differentiating S_c from S_r. Consequently, DPO assigns lower weights, $\sigma(-m)$, to chosen and rejected summaries where the model is confident in their differences and higher weights to chosen and rejected summaries where the differences is more challenging. The term $\sigma(-m)$ can help the model focuses more on difficult cases.

The objective of FairPO is designed so that chosen and rejected summaries have separate weight while preserving the effect of the term $\sigma(-m)$ in Eq.10. The derivative of FariPO objective with respect to the model parameters θ is as follows:

$$\sigma(-m)\beta(w_r\pi_\theta(S_r|D)^{-1}\frac{\partial\pi_\theta(S_r|D)}{\partial\theta} - w_c\pi_\theta(S_c|D)^{-1}\frac{\partial\pi_\theta(S_c|D)}{\partial\theta}) \tag{12}$$

Comparing with the derivative of DPO objective (Eq. 10), the term $\sigma(-m)$ remains consistent in the derivative of FairPO objective.

Suppose we directly add seperate weights w_c and w_r for chosen and rejected summaries to DPO objective. The corresponding objective is as follows:

$$-log\sigma(\beta w_c log\frac{\pi_\theta(S_c|D)}{\pi_{ref}(S_c|D)} - \beta w_r log\frac{\pi_\theta(S_r|D)}{\pi_{ref}(S_r|D)}) \tag{13}$$

The corresponding derivative is as follows:

$$\sigma(-m')\beta(w_r\pi_\theta(S_r|D)^{-1}\frac{\partial\pi_\theta(S_r|D)}{\partial\theta} - w_c\pi_\theta(S_c|D)^{-1}\frac{\partial\pi_\theta(S_c|D)}{\partial\theta}) \tag{14}$$

where m' is a weighted reward margin:

$$\beta w_c log\frac{\pi_\theta(S_c|D)}{\pi_{ref}(S_c|D)} - \beta w_r log\frac{\pi_\theta(S_r|D)}{\pi_{ref}(S_r|D)} \tag{15}$$

Comparing with m, m' is less effective as a measure of the model's ability to distinguish between the chosen summary S_c and the rejected summary S_r since the term $log\frac{\pi_\theta(S_c|D)}{\pi_{ref}(S_c|D)}$ and $log\frac{\pi_\theta(S_r|D)}{\pi_{ref}(S_r|D)}$ have different weights. We additionally provide empirical evidences in App.A.7.

A.5 Implementation Details

To reduce training cost, we perform LoRA (Hu et al., 2021) tuning. Specifically, the rank for LoRA tuning is 16 and the scaling factor is also 16. All models are quantized in 8-bit to additionally reducing training cost.

When performing perturbation on each document set to generate preference pairs, we observe that certain social attribute values are extremely rare in some document sets. If FairPO removes α percent of documents with these rare social attribute values, those social attribute values will disappear entirely from the document set. Therefore, when performing perturbation, we only consider social attribute values that appear in more than α percent of the documents. In the most extreme case, if only one social attribute value meets this requirement, FairPO will sample different subsets of α percent of documents with that social attribute value. By doing this, we assure the completeness of social attribute values after perturbation.

We prompt these LLMs to generate summaries for the input document sets of different datasets. The prompt are tuned so that the average length of generated summaries are 50 words. We show the summarization prompts for the Amazon dataset in Fig. 2. The temperature for generation is 0.6 for all LLMs.

The set T_k^+ in Eq.3 is updated so that recent training steps have higher impacts. Specifically, at the end of each training step, the impacts of all the samples already in the set T_k^+ are reduced with a discount factor γ. Then, all the samples that over-represents social attribute value k ($C_k(D, S_*)$>0) in current training steps are added to the set T_k^+. The discount factor γ is 0.75 for Llama3.1 and 0.5 for other LLMs.

The goal of the exponent, $C_k(D, S_*)$, of $O(k)/(U(k)$ or $U(k)/(O(k)$ in Eq. 4 and Eq. 5 is to adjust the weights w_c and w_r such that it more deviates from 1 as $C_k(D, S_*)$ more deviates from 0. Therefore, FairPO does not directly use the raw value of the sum of coverage probability differences $C_k(D, S_*)$ as the exponent. Instead, FairPO separately normalizes $C_k(D, S_*)$ among all training samples where $C_k(D, S_*)$ is greater than zero or less than zero.

A.6 Implementation of Baseline

We implement the policy gradient method proposed by Lei et al. (2024) as a baseline. In the original implementation, there is a loss that maximize the probability for reference summary in addition to the policy gradients. Since datasets used in this paper do not contain reference summary, we only consider the policy gradients. Besides, for a fair comparison with other methods, we implement the policy gradient method in an offline setting. The learning rate for the policy gradeint is $1e-6$ following the original paper. We only implement the policy gradient method for Llama3.1 since the training is very unstable even if we lower the learning rate to $1e-9$ for Mistral and Gemma2. For OPTune and DPO, they use the same hyperparameters as FairPO.

	Amazon		MITweet		SemEval		Overall	
	$EC\downarrow$	$CP\downarrow$	$EC\downarrow$	$CP\downarrow$	$EC\downarrow$	$CP\downarrow$	$\overline{EC}\downarrow$	$\overline{CP}\downarrow$
				Llama3.1				
FariPO	6.57	**0.37**	4.20	**0.26**	2.39	**0.56**	**4.39**	**0.39**
w/o pert.	7.01	0.48	**4.07**	0.34	2.54	0.81	4.54	0.54
w/o fair.	6.70	0.95	4.26	0.31	**2.29**	0.65	4.42	0.64
w/o rew	**6.48**	0.79	4.19	0.27	2.60	0.86	4.42	0.64
				Mistral				
FariPO	**6.98**	**0.89**	**3.56**	0.21	**1.97**	**0.36**	**4.17**	**0.49**
w/o pert.	7.29	1.64	3.81	0.21	2.30	0.26	4.47	0.71
w/o fair.	7.31	1.36	3.57	0.25	2.21	0.66	4.37	0.76
w/o rew	7.05	1.26	3.65	**0.14**	2.06	0.55	4.25	0.65
				Gemma2				
FariPO	**6.09**	**0.33**	**3.84**	0.47	2.53	0.59	**4.15**	0.46
w/o pert.	6.18	0.19	4.17	**0.21**	2.43	0.53	4.26	**0.31**
w/o fair.	6.77	1.11	3.84	0.51	**2.39**	0.59	4.34	0.74
w/o rew	6.89	0.90	3.94	0.40	2.49	**0.44**	4.44	0.58

Table 4: Summary-level fairness (EC) and corpus-level fairness (CP) of summaries generated by ablated versions of FairPO. The best performing method is in **bold**. FairPO has the best overall performance.

A.7 Ablation Study

We compare FairPO with its ablated versions. We consider FairPO without perturbation-based preference generation (w/o pert.). For this version, the chosen and rejected summaries are selected among three randomly sampled summaries based on Equal coverage values. We consider FairPO without fairness-aware preference tuning (w/o fair.). For this version, FairPO uses DPO objective for preference tuning. We also consider FairPO without reward margin (w/o rew.). For this version, FairPO uses the objective function described in Eq. 13. Tab.4 reports the average measures from three runs for each dataset, and *Overall* scores, which is the average across all datasets. A lower value indicates better fairness.

From the table, we observe that FairPO yields the best overall performance compared to its ablated versions. The results show the effectiveness of perturbation-based preference pair generation and fairness-aware preference tuning. It also provides empirical evidences for the choice of objective of FairPO.

A.8 Results using Different Dataset Splitting

To validate the stability of FairPO on different splittings of datasets, we generate the training, valida-

	Amazon		MITweet		SemEval		Overall	
	$EC\downarrow$	$CP\downarrow$	EC	$CP\downarrow$	$EC\downarrow$	$CP\downarrow$	$\overline{EC}\downarrow$	$\overline{CP}\downarrow$
Llama3.1	7.90	2.05	4.50	0.63	2.90	1.41	5.10	1.36
+DPO	7.27	1.37	4.30	0.37	2.70	1.12	4.76	0.95
+OPTune	**6.92**	**0.40**	4.30	0.52	2.82	1.00	4.68	0.64
+Prompt	7.28	1.67	4.41	0.44	2.74	**0.51**	4.81	0.87
+Policy G.	7.75	1.85	4.47	0.48	2.80	1.30	5.02	1.21
+FairPO	6.96	0.44	**4.26**	**0.29**	**2.69**	0.59	**4.64**	**0.44**
Mistral	8.60	2.74	4.18	0.73	2.91	1.28	5.23	1.58
+DPO	7.24	1.79	**3.39**	**0.26**	2.70	1.15	4.44	1.07
+OPTune	6.59	0.52	**3.57**	0.53	**2.04**	0.58	4.07	0.54
+Prompt	7.90	1.76	3.74	0.51	2.43	0.52	4.69	0.93
+FairPO	**6.06**	**0.11**	3.83	0.39	2.13	**0.33**	**4.01**	**0.28**
Gemma2	8.31	2.33	4.30	0.80	2.97	1.03	5.19	1.38
+DPO	7.04	0.98	4.07	0.44	2.43	0.48	4.51	0.63
+OPTune	6.91	0.56	3.94	0.86	**2.35**	0.56	4.40	0.66
+Prompt	7.33	1.26	4.49	**0.44**	2.91	0.85	4.91	0.85
+FairPO	**6.09**	**0.44**	**3.82**	0.65	2.70	**0.32**	**4.20**	**0.47**

Table 5: Summary-level fairness (EC) and corpus-level fairness (CP) of summaries generated by different methods. The best performing method is in **bold**. The second-best performing method is underlined. FairPO has the best overall performance with different splitting of datasets.

tion and testing set using different random seeds and run the automatic evaluation on the new splitting. The results are shown in Tab. 5. From the table, we observe that FairPO still shows the best overall performance, which shows the stability of FairPO on different splittings of datasets.

A.9 Qualiative Example

We show sample summaries generated by LLMs tuned with DPO and FairPO on the Amazon dataset in Fig. 3. From the figure, we observe that summaries generated by LLMs tuned FairPO tend to more balancely present negative and positive information.

Llama3.1	Mistral	Gemma2
DPO: The product reviews are mixed, with some customers expressing satisfaction with the quality and price, while others find it flimsy, useless, and painful to use. Issues include bending, crookedness, and difficulty with hair removal, leading to disappointment and a recommendation to avoid the product.	**DPO:** This tablet receives generally positive reviews, praised for its portability, picture quality, speed, and features like USB and HDMI ports. Some users found the battery life lacking, while one experienced a defective product. Overall, it's considered a good value for the price and user-friendly, with a few noting its similarity to Android phones.	**DPO:** This plush bed topper is generally well-received for its comfort and ability to stay in place thanks to its straps. Many users praise its cloud-like softness and how it elevates their sleep quality. However, some users found it loses its fluffiness over time and requires manual plumping.
FairPO: The product reviews are mixed, with some users praising its availability and quality, while others criticize its flimsiness, uselessness, and high price. Some users find the tips too long, weak, or hard to use, while others appreciate its effectiveness, but note that it may not be suitable for all purposes.	**FairPO:** This Toshiba tablet receives mixed reviews. Users praise its lightweight design, fast speed, great picture quality, and affordability. Some highlight its functionality similar to laptops and its ease of use. However, concerns arise regarding battery life and a negative experience with a damaged, non-functional product.	**FairPO:** This plush bed topper receives rave reviews for its comfort, fluffiness, and stay-in-place straps. Some users find it a dream come true, while others experience flattening over time. It's praised for its luxurious feel, comparable to a feather bed without the prickliness. While some find it ideal for air mattresses and adding height, others note back pain issues.

Figure 3: Sample summaries generated by DPO and FairPO.