FairGen: Controlling Sensitive Attributes for Fair Generations in Diffusion Models via Adaptive Latent Guidance

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Abstract

Text-to-image diffusion models often exhibit biases toward specific demographic groups, such as generating more males than females when prompted to generate images of engineers, raising ethical concerns and limiting their adoption. In this paper, we tackle the challenge of mitigating generation bias towards any target attribute value (e.g., "male" for "gender") in diffusion models while preserving generation quality. We propose FairGen, an adaptive latent guidance mechanism which controls the generation distribution during inference. In FairGen, a latent guidance module dynamically adjusts the diffusion process to enforce specific attributes, while a memory module tracks the generation statistics and steers latent guidance to align with the targeted fair distribution of the attribute values. Furthermore, we address the limitations of existing datasets by introducing the Holistic Bias Evaluation (HBE) benchmark, which covers diverse domains and incorporates complex prompts to assess bias more comprehensively. Extensive evaluations on HBE and Stable Bias datasets demonstrate that FairGen outperforms existing bias mitigation approaches, achieving substantial bias reduction (e.g., 68.5% gender bias reduction on Stable Diffusion 2). Ablation studies highlight FairGen's ability to flexibly control the output distribution at any user-specified granularity, ensuring adaptive and targeted bias mitigation.

1 Introduction

Text-to-image diffusion models (Nichol et al., 2021; Saharia et al., 2022) have shown remarkable capabilities when generating photorealistic images from text input, leading to new real-world applications. Notably, stable diffusion models (Rombach et al., 2022; Podell et al., 2023; Esser et al., 2024a) and DALL-E models (Ramesh et al., 2022; Betker et al., 2023) have gained widespread popularity, attracting millions of users and being utilized in a wide range of contexts such as reinforcement-learning based control (Pearce et al., 2023; Chi et al., 2023) and life-science (Chung et al., 2022; Cao et al., 2024).

However, the widespread application of diffusion models has raised concerns regarding social biases that are embedded in their generations. Specifically, a series of recent studies (Bakr et al., 2023; Lee et al., 2024; Cui et al., 2023; Wan and Chang, 2024; Wan et al., 2024; Luccioni et al., 2023; Naik and Nushi, 2023) have identified demographic biases (e.g., gender, race, etc.) in diffusion models when generating images of people from various occupations, making the generation process unfair.

Furthermore, our insight is that the definition of "fair" generation depends on the use cases and is often subjective. For example, someone may consider the generation fair when images of males and females are generated with equal probability, however, others may expect the generation distribution to mirror the true distribution of males and females in society. Recent study by Luccioni et al., 2023 has shown that existing bias mitigation techniques do not mirror the societal distribution of different attributes in generated outputs. Additionally, our experiments reveal that they exhibit significant limitations in flexibly controlling the generation distribution (Section 5.2). These findings raise a key research question: *How can text-to-image diffusion models generate images that adhere to a target (or fair) distribution of attributes while preserving generation quality?*

Existing methods for bias mitigation in diffusion models such as prompt intervention methods alter user input prompts, however, often result in a considerable degradation of generation quality (Bansal et al., 2022; Fraser et al., 2023; Bianchi et al., 2023). Model finetuning-based approaches

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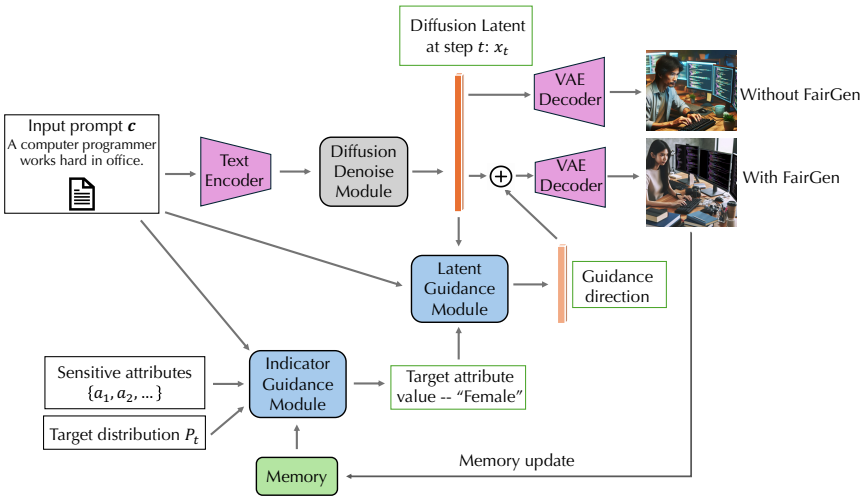

Figure 1: **Overview of FairGen**. FairGen consists of two key components: the *Indicator Guidance Module* and the *Latent Guidance Module*. The Indicator Guidance Module identifies the target attribute value to steer the current generation based on the generation statistics stored in the memory module, the input prompt, and the target generation distribution. The Latent Guidance Module then computes the effective latent direction to steer the selected attribute, given the input prompt and the chosen attribute.

(Orgad et al., 2023; Shen et al., 2023; Zhang et al., 2023) typically involve finetuning the model within a specific subdomain, compromise the overall generation quality, and lack flexibility. Latent intervention techniques such as FairDiffusion (Friedrich et al., 2023) introduces static vectors into the latent space for attribute control, however, are limited by their inability to dynamically adjust to varying inputs. For example, in Section 5.1, we find that FairDiffusion is not robust to prompt complexity.

To this end, we propose FairGen, a novel inference time algorithm for text-to-image diffusion models. FairGen allows precise control of the generation distribution to meet the desired target distribution. FairGen consists of an adaptive latent guidance module and an indicator guidance module. The latent guidance module computes the effective latent direction to enforce guidance towards the high-density region of target sensitive attributes (e.g., gender), conditioned on the current input prompt. The indicator guidance module determines the target attribute value (e.g., "female") to enforce during the current generation based on the generation statistics stored in a memory module. The memory module ensures that the generation statistics is consistent with the target fair distribution as defined by the user. In this manner, the adaptive latent guidance module, guidance indicator module, and the memory module jointly determine the adaptive guidance direction, leading to a flexible and effective fair generation paradigm. We explain FairGen in details in Section 2.

Additionally, we find that current bias evaluation benchmarks (Bakr et al., 2023; Lee et al., 2024; Cui et al., 2023; Wan and Chang, 2024; Wan et al., 2024; Luccioni et al., 2023; Naik and Nushi, 2023) exhibit three major limitations: a narrow range of domains, overly simplistic input prompt structures, and a limited set of attributes. To address these shortcomings, we propose a holistic bias evaluation benchmark HBE in Section 3 that encompasses a wider array of domains, prompt structures, and sensitive attributes compared to previous benchmarks. Our experiments reveal that while state of the art bias-mitigation approaches excel in widely used bias evaluation benchmarks (e.g., Stable Bias (Luccioni et al., 2023)), their performance drops significantly in HBE, proving the rigor of the HBE dataset (Section 5.1).

We evaluate FairGen against several state of the art baselines on the HBE and Stable Bias datasets and find that FairGen outperforms all baselines in both datasets in bias reduction and quality preservation. In summary, our major contributions and findings are as follows – **(a)** We define the novel problem of generating images by adhering to a target fair distribution of attributes. **(b)** We propose FairGen, a novel inference time approach for generating high quality images by adhering to the target distribution of attributes. **(c)** We propose HBE, a novel and comprehensive benchmark for assessing bias in diffusion models. **(d)** Extensive experimental evaluations show that FairGen outperforms SOTA bias-mitigation methods in terms

of bias reduction and demonstrates greater effectiveness in scenarios involving the interplay of multiple attributes (Table 2). **(e)** FairGen provides an adaptable mechanism for controlling generation distributions at different target distribution levels compared to SOTA methods (Tables 3).

2 FairGen

We first introduce our fair diffusion model generation pipeline FairGen in Section 2.1, which consists of a latent guidance module and an indicator guidance module. In Section 2.2, we describe the functionality and training process of the latent guidance module, which generates adaptive guidance for specific attributes in the latent space. Section 2.3 details the indicator guidance module, which produces scalar guidance directions to enforce attribute values and achieve the target generation distribution.

2.1 Overview of FairGen

In this paper, we study the problem of generating high-quality images by preserving a target distribution of different attributes present in the image (e.g., generating images of males and females with equal probability with a particular occupation). Existing bias mitigation methods using prompt intervention tend to degrade generation quality due to modification of the input prompts (Bakr et al., 2023; Lee et al., 2024; Cui et al., 2023; Wan and Chang, 2024; Wan et al., 2024; Luccioni et al., 2023; Naik and Nushi, 2023) and finetuning-based methods (Orgad et al., 2023; Shen et al., 2023; Zhang et al., 2023) degrade image quality due to fitting to subdomains. We experimentally verify this phenomenon in such approaches in Section 5.1. Moreover, finetuning based approaches require additional training to adapt to different target distribution of attributes. Therefore, we propose FairGen to impose fair generations via guidance in diffusion latent space and to flexibly control the target generation distributions at inference time.

In order to control the distribution of an attribute over several inferences of the model, we regulate the attribute values on individual generations. Specifically, if we can control the attribute value of each generated instance, we should also be able to shape the overall distribution of that attribute in the outputs by leveraging the generation statistics over all previous generations. Our insight is that, in diffusion models, attribute control for each instance can be achieved by modifying the estimated diffusion noise during the sampling process. The *diffusion noise direction* steers the generation towards high-density regions containing realistic images aligned to input prompts. Additionally, we introduce an *attribute guidance direction* to steer the generation towards regions with the target attributes, while preserving the generation quality. Further, we leverage a *memory module* to control the generation statistics of the attributes.

Formally, at diffusion sampling step t, the *diffusion noise direction* $\boldsymbol{\epsilon}_\theta(\boldsymbol{x}_t, \boldsymbol{c})$ is given by a noise estimation network ϵ_θ, parameterized by θ, and conditioned on the latent state $\boldsymbol{x}_t$ at step t and the input prompt $\boldsymbol{c}$. The *attribute guidance direction* consists of two components: (1) a *scalar guidance direction* $I(\boldsymbol{c}, \mathcal{M}, (a_1, a_2)) \in \{-1, 1\}$, which depends on the input prompt $\boldsymbol{c}$, an auxiliary memory module $\mathcal{M}$ containing generation statistics, and the potential attribute values for manipulation a_1, a_2 (assuming binary value attribute for brevity here); and (2) an *adaptive latent guidance direction* $f_{\text{ALD}}(\boldsymbol{x}_t, \boldsymbol{c}, (a_1, a_2))$, produced by a trained guidance network f_{ALD}, which depends on the latent state $\boldsymbol{x}_t$, the input prompt $\boldsymbol{c}$, and the specified attributes. The final *attribute-aware noise direction* is defined as follows:

$$\boldsymbol{\epsilon}_{\texttt{FairGen}}(\boldsymbol{x}_t, \boldsymbol{c}, \mathcal{M}, (a_1, a_2)) = \gamma * \boldsymbol{\epsilon}_\theta(\boldsymbol{x}_t, \boldsymbol{c}) + (1-\gamma) \underbrace{I(\boldsymbol{c}, \mathcal{M}, (a_1, a_2))}_{\text{Scalar Guidance Direction}} \cdot \underbrace{f_{\text{ALD}}(\boldsymbol{x}_t, \boldsymbol{c}, (a_1, a_2))}_{\text{Adaptive Latent Guidance Direction}} \quad (1)$$

This formulation represents a convex combination of the original diffusion noise direction and the attribute guidance direction, controlled by the parameter $\gamma \in [0, 1]$. Here, $\boldsymbol{c}$ denotes the input prompt as a textual condition, while a_1 and a_2 represent two feasible attribute values (e.g., "male" and "female" for the gender attribute).

The scalar guidance direction $I(\boldsymbol{c}, \mathcal{M}, (a_1, a_2))$ acts as an indicator guidance model that determines the scalar for the guidance direction (e.g., assigning 1 for male guidance and -1 for female guidance) based on the memory module $\mathcal{M}$. The adaptive latent guidance direction $f_{\text{ALD}}(\boldsymbol{x}_t, \boldsymbol{c}, (a_1, a_2))$ provides the noise estimate required to modify attribute value a_1 towards a_2, conditioned on the latent variable $\boldsymbol{x}_t$ and the prompt $\boldsymbol{c}$.

This formulation extends to multiple multi-dimensional attributes as follows:

$$\boldsymbol{\epsilon}_{\texttt{FairGen}}(\boldsymbol{x}_t, t, \boldsymbol{c}, \mathcal{M}, (a_1, a_2)) = \gamma \boldsymbol{\epsilon}_\theta(\boldsymbol{x}_t, t, \boldsymbol{c}) + (1-\gamma) * \sum_{\mathcal{A} \in \boldsymbol{\mathcal{A}}} \sum_{a_i, a_j \in \mathcal{A}} \underbrace{I(\boldsymbol{c}, \mathcal{M}, (a_i, a_j))}_{\text{Scalar Guidance Direction}} \cdot \underbrace{f_{\text{ALD}}(\boldsymbol{x}_t, \boldsymbol{c}, (a_i, a_j))}_{\text{Adaptive Latent Guidance Direction}} \quad (2)$$

Here, $\mathcal{A}$ represents a set of multi-dimensional attributes (e.g., gender, race, age), and a_i and a_j are attribute values within the attribute $\mathcal{A}$. Figure 1 shows the overview of the proposed method.

2.2 Adaptive Latent Guidance Module

In this section, we explain how `FairGen` generates the adaptive latent guidance direction $f_{\text{ALD}}(\boldsymbol{x}_t, \boldsymbol{c}, (a_i, a_j))$, which effectively steers the generation towards the desired attribute space. A straightforward approach is to impose classifier guidance at each time step (Dhariwal and Nichol, 2021), however, it requires additional training of a high-quality attribute-specific classifier, increasing computational costs. Instead, we adopt a more flexible classifier-free approach. Specifically, we define the adaptive latent guidance direction as the vector difference between the directions toward attributes a_i and a_j. This can be formulated as:

$$f_{\text{ALD}}(\boldsymbol{x}_t, \boldsymbol{c}, (a_i, a_j)) = \boldsymbol{\epsilon}_\theta(\boldsymbol{x}_t, K(\boldsymbol{c}, a_i)) - \boldsymbol{\epsilon}_\theta(\boldsymbol{x}_t, K(\boldsymbol{c}, a_j)) \quad (3)$$

Here, $K(\boldsymbol{c}, a_i)$ and $K(\boldsymbol{c}, a_j)$ are the *attribute-aware guidance text* derived from the input text prompt and target attribute a_i or a_j. For example, if the input prompt $\boldsymbol{c}$ is "A computer programmer works hard in office", the expected attribute-aware guidance text $K(\boldsymbol{c}, \text{female})$ would be "A female computer programmer works hard in office" or "A computer programmer works hard in office. The person is a woman".

To effectively generate attribute-aware guidance texts, we train an attribute-aware generator L. Since guidance is required for both attributes a_i and a_j simultaneously, we use a single generator L to produce the corresponding guidance texts $K(\boldsymbol{c}, a_i)$ and $K(\boldsymbol{c}, a_j)$ in parallel.

$$K(\boldsymbol{c}, a_i), K(\boldsymbol{c}, a_j) \leftarrow L(\boldsymbol{c}, a_i, a_j) \quad (4)$$

This paradigm ensures that the attribute-aware guidance prompts $K(\boldsymbol{c}, a_i)$ and $K(\boldsymbol{c}, a_j)$ share similar patterns while differing only in their target attributes. As a result, the corresponding noise predictions $\boldsymbol{\epsilon}_\theta(\boldsymbol{x}_t, K(\boldsymbol{c}, a_i))$ and $\boldsymbol{\epsilon}_\theta(\boldsymbol{x}_t, K(\boldsymbol{c}, a_j))$ reside in the same space, and their difference is orthogonal to the diffusion noise estimate direction $\boldsymbol{\epsilon}_\theta(\boldsymbol{x}_t, \boldsymbol{c})$. This idea is inspired by findings in multi-task learning, where enforcing orthogonality between task-specific directions has been shown to enhance generalization and improve task adaptation (Wang et al., 2023). We fine-tune an LLM as the attribute-aware generator L in two steps.

(1) Supervised Fine-Tuning (SFT): For SFT, we design an attribute editing task for the LLM. As input prompt we provide a sentence (that can be used as a prompt for text-to-image models) and the target attribute to edit in the sentence. Then we instruct the model to generate pair of guidance prompts by editing the attribute values to a_i or a_j in the sentence. SFT is performed on a pretrained LLM using such input-output pairs.

(2) Direct Policy Optimization (DPO): Since SFT only enables the model to generate format-correct guidance prompts, it may not be effective for diffusion model guidance in practice. Hence, we further refine L using a DPO step (Rafailov et al., 2024). We first generate a collection of output guidance prompts using the SFT endpoint of L and evaluate them on the validation split of HBE dataset introduced in Section 3. Each candidate guidance prompt sampled from SFT endpoint is assigned a utility score which is a convex combination of bias score and image quality score on a surrogate model, Stable Diffusion 2 (details in Section 4). Using these rewards, we label the outputs based on the 50% quantile, distinguishing positive and negative samples and use the positive-negative pairs for performing DPO on L. This enables the generator to discern nuanced differences among format-correct guidance prompts, thereby enhancing attribute control and image quality.

2.3 Indicator Guidance Module

In this section, we describe how `FairGen` generates the scalar guidance direction $I(\boldsymbol{c}, \mathcal{M}, (a_i, a_j)) \in \{+1, -1\}$, which determines the target attribute value to enforce (i.e., a_i or a_j). Specifically, it dictates the direction of the current generation, where $+1$ steers towards attribute value a_i and -1 towards attribute value a_j. This decision process is adaptively influenced by the input text prompt $\boldsymbol{c}$ and the memory $\mathcal{M}$, which maintains generation statistics.

Baseline Scalar Indicator Direction in a Probabilistic Manner. Prior bias mitigation methods (Bansal et al., 2022; Fraser et al., 2023; Bianchi et al., 2023; Friedrich et al., 2023) adopt a probabilistic generation paradigm to enforce the target attribute distribution. Specifically, if the desired proportion of female-generated samples is P_t, then with probability P_t, the model enforces the female generation in the current round; otherwise, it enforces male generation. However, this approach results in the subgroup proportions following a Binomial distribution, leading to high variance, par-

ticularly when attribute enforcement is imprecise.

Scalar Indicator Direction in `FairGen`. We introduce a structured memory module $\mathcal{M}$ to track the attribute distributions in generated outputs. $\mathcal{M}$ stores key-value pairs, where the key is the sentence embedding of an input prompt $\boldsymbol{c}$, extracted using a feature extractor E, and the value represents the proportion of each attribute value in past generations (e.g., male vs. female ratios).

The memory operates within a fixed budget B, storing up to B clusters. When a new prompt $\boldsymbol{c}$ arrives, its feature representation $E(\boldsymbol{c})$ is compared against existing clusters. If a match is found (i.e., the ℓ_2 distance is below a threshold τ), generation is conditioned on the cluster's attribute distribution. For example, if the "computer programmer" cluster has historically male-dominated outputs, the system may prioritize female generation for balance. If no matching cluster exists and space allows, a new cluster is created. When the memory reaches capacity, K-nearest neighbor (KNN) clustering redistributes resources, retaining the most informative clusters.

3 Holistic Bias Evaluation Benchmark

To fairly evaluate bias in diffusion models, it is essential to ensure that the benchmark is comprehensive and aligns with real-world scenarios. However, existing bias evaluation benchmarks suffer from three major limitations – (1) They predominantly focus on a narrow range of domains by ignoring many crucial ones. For instance, benchmarks like HRS (Bakr et al., 2023) and PST (Wan and Chang, 2024) primarily assess occupation-based biases, however, overlook some crucial domains such as healthcare, finance, and daily activities. (2) They rely on overly simplistic input prompt structures (e.g., "Photo portrait of a `<objective>`"), failing to capture the complexity of real-world user inputs, which often involve nuanced and context-rich descriptions. Benchmarks such as HEIM (Lee et al., 2024) and StableBias (Luccioni et al., 2023) focus predominantly on basic phrases, offering little challenge in interpreting prompts with more intricate, scenario-based descriptions. (3) Many benchmarks (Wan and Chang, 2024; Lee et al., 2024) consider only a limited set of sensitive attributes, focusing primarily on gender and race while neglecting other crucial attributes such as age. These limitations raise concerns that diffusion models deemed fair by existing benchmarks may still produce unintended biases when deployed in diverse, real-world scenarios.

To address these shortcomings, we introduce the "Holistic Bias Evaluation Benchmark" (`HBE`). `HBE` expands the scope of domains, prompt structures, and sensitive attributes beyond existing benchmarks. Specifically, we develop a set of 2000 prompts covering diverse domains, including occupations, education, healthcare, criminal justice, finance, politics, technology, sports, daily activities, and personality traits. Notably, `HBE` incorporates underexplored domains such as criminal justice, technology, and finance, ensuring a more holistic assessment of bias across societal structures. Additionally, `HBE` features complex prompt structures, including scenario-based descriptions, which provide a more rigorous evaluation compared to static prompts that merely describe individuals (shown by examples in Appendix A). Hence, unlike prior benchmarks that rely primarily on simplistic prompts, `HBE` integrates both simple and complex input structures to better reflect real-world user interactions.

We construct the dataset through the following steps – (1) We use the Mistral-7B-Instruct-v0.2 model to identify key objectives within different domains (e.g., various diseases in healthcare or political positions in the politics domain). (2) The same model is then used to generate scenario-based prompts incorporating these objectives. (3) We conduct careful human checks to ensure the prompts are of high-quality and diverse. (4) Finally, we partition the 2,000 prompts into training (40%), validation (10%), and test (50%) sets. We provide prompt structure for the above process in Appendix D.

To highlight the advantages of `HBE` over existing benchmarks, we provide a comparative analysis in Table 1, showcasing its broader domain coverage and richer prompt structures. We present examples from the `HBE` benchmark in Appendix A.

4 Experimental Setting

Evaluation Metrics. We use the bias score (B) to assess the generation bias of diffusion models and the quality score (Q) to evaluate the visual quality of generated images. The bias score B quantifies the absolute difference between the actual and target proportions of a specific group in the generated images (e.g., the proportion of generated images of males versus the target proportion). The quality score Q measures how well the gener-

Table 1: Comparison of the HBE benchmark with existing diffusion model bias evaluation benchmarks.We conduct the comparisons for target domains including occupation (occ), education (edu), healthcare (hea), criminal justice (cri), finance (fin), politics (pol), technology (tec), sports (spo), daily activities (act), trains (tra); prompt structures including simple phrases (phrase) and complex scenario descriptions (complex); and sensitive attributes such as gender (G), race (R), and age (A).

	Domains										Prompt Structure		Attributes
	occ	edu	hea	cri	fin	pol	tec	spo	act	tra	phrase	complex	G,R,A
HRS (Bakr et al., 2023)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	G
PST (Wan and Chang, 2024)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	G,R
HEIM (Lee et al., 2024)	✓	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓	✗	G,R
StableBias (Luccioni et al., 2023)	✓	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓	✗	G,R,A
MMDT (Anonymous, 2024)	✓	✓	✗	✗	✗	✗	✗	✗	✓	✗	✓	✗	G,R,A
SBE (Naik and Nushi, 2023)	✓	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✗	G,R,A
HBE (ours)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	G,R,A

ated images correspond to the user input prompt. Specifically, we compute Q using the CLIP score between the generated images and the corresponding prompt, following (Luccioni et al., 2023). More formally, we define the text-to-image model as a mapping $M : \mathcal{V} \rightarrow \mathcal{Y}$, where $\mathcal{V}$ represents the input text space and $\mathcal{Y}$ denotes the generated image space. Let $\mathcal{A}$ be the set of all possible values for a sensitive attribute (e.g., $\mathcal{A} = \{\text{male}, \text{female}\}$ for gender). We denote the test set of N input prompts as $\{v_n\}_{n=1}^{N}$, where $v_n \in \mathcal{V}$. A discriminator $D : \mathcal{Y} \rightarrow \mathcal{A}$ is used to identify the sensitive attributes in the generated images. The bias score B is then defined as:

$$B = \frac{1}{N} \sum_{n=1}^{N} \mathbb{E} \left[\left| \mathbb{P} \left[D(M(v_n)) = a_i \right] - P_t \right| \right] \quad (5)$$

Here, P_t is the target proportion of attribute a_i. The probability $\mathbb{P}[\cdot]$ is estimated by Monte-Carlo methods with T times of sampling ($T = 10$ across the evaluations). In the multi-attribute controlling case, we further take the expectation over the set of sensitive attributes that we want to control.

Training the Attribute-Aware Generator L. We use the training and validation sets of the HBE dataset to train Mistral-7B-Instruct-v0.2[‡] as L. We use LoRA (Hu et al., 2021) during SFT and DPO.

Dataset and Models. We evaluate FairGen and other bias mitigation baselines on HBE and the Stable Bias (Luccioni et al., 2023) datasets. We consider three text-to-image diffusion models: stable diffusion 2 (SD2) (Rombach et al., 2022) stable diffusion XL (SDXL) (Podell et al., 2023), stable diffusion 3.5 large (SD-3.5-large) (Esser et al., 2024b). We implement the attribute discrimination model $D(\cdot)$ following (Luccioni et al., 2023; Bakr et al., 2023), where the attributes are discriminated by question-answering using the vision-language model InstructBLIP-2[‡]. We validate the efficacy of $D(\cdot)$ through human evaluation (Appendix C).

5 Results and Ablations

5.1 Bias Evaluation of FairGen

We compare FairGen with the following baselines: (1) **vanilla generation** via classifier-free guidance (Nichol et al., 2021), (2) **prompt intervention** (Bansal et al., 2022), (3) **finetuning-based** method with distribution alignment loss (Shen et al., 2023), and (4) latent intervention-based method **FairDiffusion** (Friedrich et al., 2023). The prompt intervention methods modify the input prompts with attribute specification and adopt probabilistic generation to achieve target distribution. The finetuning-based methods fine-tune the diffusion model on a fair distribution with distribution-alignment loss. The latent intervention methods impose a static global attribute direction for controlling.

Table 2 demonstrates the bias scores B (lower is better) and quality scores Q (higher is better) for FairGen and the baselines on the HBE dataset on three types of text-to-image diffusion models, **Stable Diffusion 2 (SD2)**, **Stable Diffusion XL (SDXL)**, and **Stable Diffusion 3.5 Large (SD-3.5-large)**, across sensitive attributes *gender*, *race*, *age*, and *their combination*. Across all sensitive attributes and their combinations, FairGen consistently achieves the lowest bias scores, indicating its superior ability to mitigate multi-attribute bias *without additional training*. For instance, in case of gender, FairGen achieves a bias score of 0.231 for SD2 ,0.267 for SDXL, and 0.118 for SD-3.5-large, significantly outperforming all baselines. Similarly, when considering the combination of gender,

[‡]https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.2

[‡]https://huggingface.co/nnpy/Instruct-blip-v2

Table 2: Bias score B (↓) and quality score Q (↑) on our HBE benchmark on two types of text-to-image diffusion models stable diffusion 2 (SD2) and stable diffusion XL (SDXL) across different sensitive attributes and the combination of them. The target generation distribution is balanced/fair ($P_t = 0.5$).

Model	Method	Gender		Race		Age		Gender+Race+Age	
		B	Q	B	Q	B	Q	B	Q
SD2	Vanilla generation	0.734	0.276	0.500	0.276	0.894	0.276	0.709	0.276
	Prompt intervention	0.508	0.247	0.379	0.240	0.749	0.243	0.792	0.256
	Finetune-based	0.339	0.228	0.257	0.232	0.734	0.243	0.732	0.227
	FairDiffusion	0.714	0.260	0.364	0.258	0.729	0.257	0.682	0.248
	FairGen (ours)	**0.231**	0.270	**0.217**	0.262	**0.683**	0.272	**0.601**	0.267
SDXL	Vanilla generation	0.730	0.296	0.718	0.296	0.829	0.296	0.759	0.296
	Prompt intervention	0.483	0.279	0.364	0.284	0.784	0.285	0.746	0.289
	Finetune-based	0.302	0.269	0.286	0.273	0.638	0.254	0.683	0.287
	FairDiffusion	0.452	0.286	0.334	0.288	0.675	0.277	0.723	0.250
	FairGen (ours)	**0.267**	0.293	**0.257**	0.290	**0.604**	0.287	**0.658**	0.257
SD-3.5-large	Vanilla generation	0.653	0.358	0.536	0.395	0.734	0.357	0.732	0.387
	Prompt intervention	0.602	0.336	0.482	0.363	0.650	0.326	0.554	0.342
	Finetune-based	0.402	0.312	0.332	0.352	0.552	0.327	0.454	0.350
	FairDiffusion	0.583	0.325	0.387	0.362	0.536	0.345	0.532	0.357
	FairGen (ours)	**0.118**	0.346	**0.194**	0.398	**0.381**	0.346	**0.397**	0.385

Table 3: Bias scores B (↓) for different target proportion P_t of attribute male on HBE benchmark with SD2. The average (Avg) and standard deviation (Std) of the bias scores are reported in the last two columns.

Target proportion P_t	0.0	0.2	0.4	0.6	0.8	1.0	Avg	Std
Vanilla generation	0.982	0.863	0.772	0.673	0.583	0.482	0.726	0.168
Prompt intervention	0.745	0.635	0.554	0.473	0.332	0.255	0.499	0.168
Finetune-based	0.372	0.356	0.332	0.305	0.285	0.264	0.319	0.038
FairDiffusion	0.836	0.802	0.734	0.623	0.602	0.553	0.692	0.105
FairGen (ours)	**0.272**	**0.261**	**0.248**	**0.228**	**0.219**	**0.201**	**0.238**	**0.025**

race, and age, FairGen achieves the lowest bias scores of 0.601 on SD2, 0.658 on SDXL, and 0.397 on SD-3.5-large. Notably, FairGen also sustains high generation quality in most cases compared to the baselines, with Q scores that are competitive with or superior to vanilla generation (soft upper bound for quality scores without any interventions). These results underline FairGen's ability to balance bias mitigation with image generation quality, especially in complex scenarios involving multiple intersecting sensitive attributes.

We also evaluate the effectiveness of FairGen and the baselines on the standard Stable Bias (Luccioni et al., 2023) benchmark (for the occupation split and attribute "gender", "race", and "age") in Appendix E.1. We also observe that FairGen achieves significant gender bias reduction and better generation quality compared to the baselines.

5.2 Effectiveness of FairGen with Different Target Generation Distributions

It is important to note that the target fair generation distribution may not always be perfectly balanced. In different use cases, users may expect their model outputs to follow predefined or real-world distributions. Thus, bias mitigation methods should offer flexibility in controlling generation proportions at predefined levels. To assess this capability, we evaluate FairGen alongside other strong bias mitigation baselines under various target generation distributions.

The results in Table 3 demonstrate that FairGen provides a robust and adaptable mechanism for controlling generation distributions to achieve targeted levels since the average bias is lower than other baselines at all levels. Specifically, FairGen demonstrates both the lowest average bias score and the smallest standard deviation, which indicates that it consistently maintains low bias across different target portions. This stability is critical, as it suggests that FairGen is not only effective at minimizing bias on average but also performs reliably across a wide range of scenarios. In contrast, while the finetune-based approach achieves relatively low bias scores among the baselines, its standard deviation is notably higher than that of

Table 4: Evaluation of bias score B and quality score Q by applying FairGen at different diffusion time steps on HBE benchmark with gender as the sensitive attribute.

Diffusion steps for guidance	B (↓)	Q (↑)
Early 25% stage	0.496	0.283
Later 25% stage	0.276	0.257
Middle 25% stage	0.231	0.270

FairGen. This higher variability implies that the finetune-based approach may be less predictable or stable when applied across different target portions. Methods like Vanilla generation and FairDiffusion also exhibit higher standard deviations, indicating a less consistent ability to manage bias across different target proportions.

5.3 FairGen with Different Diffusion Steps

In this part, we explore the impact of diffusion time steps to apply FairGen guidance on the effectiveness of bias mitigation and generation quality. The results in Table 4 demonstrate that applying latent guidance at the early diffusion stage (within the first 25% time steps) does not effectively guide fair generations since later denoising downplays the early guidance, hence, it results in higher bias, however, with higher quality. Applying guidance at a later stage (the last 25% of time steps) degrades the alignment between the generated images and the input text, which results in lower quality. Therefore, we adopt guidance at the intermediate stage (middle 25% time steps) which ensures a desired balance between bias mitigation and generation quality.

5.4 Runtime Analysis and Other Ablations

We report the runtime of FairGen and other baselines in Table 9 (Appendix E.3). Since FairGen is training-free, it incurs no additional training cost. During inference, although it introduces extra noise estimates at each diffusion step, adaptive guidance is applied during only a small subset of intermediate steps (Section 5.3). These estimates are attribute-independent and parallelizable, resulting in only a marginal runtime overhead while achieving significant bias reduction.

We ablate the SFT and DPO steps for training the attribute-aware generator L (Appendix E.2) and find that combining both yields the best performance. Visualization examples are shown in Appendix E.4.

6 Related Work

Bias Evaluation in Diffusion Models. Evaluation of bias in text-to-image diffusion models has gained significant interest recently. Numerous works have studied demographic biases in different domains such as occupation, physical characteristics, and so on (Bakr et al., 2023; Lee et al., 2024; Cui et al., 2023; Wan and Chang, 2024; Wan et al., 2024; Luccioni et al., 2023; Naik and Nushi, 2023). These studies focus on constructing attributed prompts (e.g., photo of a <objective>) to probe the text-to-image models for any bias towards a specific attribute value (e.g., towards "male" when generating images of engineers). However, current studies overlook many domains such as healthcare, finance, and everyday activities and they rely on simplistic prompts for probing the models, hence, fail to capture the complexity and nuance of real-world user inputs. We address the two limitations and propose the HBE benchmark which covers a broader range of sensitive attributes and domains, sampled from realistic statistical distribution of user prompts and rigorously filtered.

Bias Mitigation in Diffusion Models. Different approaches have been proposed to mitigate bias in diffusion models, such as by refining model weights (Orgad et al., 2023; Shen et al., 2023; Zhang et al., 2023), intervening input prompts (Bansal et al., 2022; Fraser et al., 2023; Bianchi et al., 2023) or by employing guidance generation to control attributes (Friedrich et al., 2023). These methods often compromise generation quality and lack flexibility to adapt them to any target distribution that is considered fair. Therefore, we introduce an adaptive latent guidance method that allows for more effective and flexible bias mitigation.

7 Conclusion

FairGen introduces a substantial improvement in mitigating generative bias in diffusion models. By integrating adaptive latent guidance with a global memory, it effectively reduces bias while preserving high-quality image generation. The dynamic adjustment of latent attributes and use of generation statistics enable precise control in multi-attribute settings and adaptability to varying target distributions. Extensive evaluations and ablations show that FairGen consistently outperforms existing approaches in both bias mitigation and controllability, offering a practical step toward more socially responsible diffusion-based applications.

Limitations

We identify the following limitations of our work.

Privacy Concerns. FairGen requires storing the embedding of user queries in the global memory module for attribute analysis. This may violate specific privacy terms. However, it is viable to release the privacy agreements or add noises to the query embeddings for maintaining privacy. We leave privacy preservation for the process such as applying differential privacy to certify the privacy of generation process for future work.

Initialization of the Memory Module $\mathcal{M}$. The initialization of the memory module $\mathcal{M}$ for the very first generation as described in Section 2.3, is an open question. Note that, the global generation distribution is maintained aligned to the target distribution through the memory module $\mathcal{M}$. However, $\mathcal{M}$ is supposed to be empty during the very first generation. In that case, either the user can decide what should be the target attribute value in the first generation or it can be determined through a coin toss.

Computation overhead. While FairGen introduces relatively modest runtime overhead (shown in Table 9), we acknowledge that it may still affect scenarios where throughput is critical. It would be interesting future work to further mitigate the trade-off between the fairness of diffusion generation distribution and the inference efficiency.

Ethics Statement

In this paper, we study the problem of generating images using a text-to-image diffusion model by preserving a predefined distribution of target attribute values. Note that, the definition of what is meant by a fair distribution is out of scope for our study, as the definition of a fair distribution may depend on the specific use case. Hence, we propose an approach that enables maintaining any target distribution in text-to-image generation that is considered as fair.

We presented all experimental details and performed an extensive ablation study to provide the readers an idea about the risks and advantages associated to using our proposed model. As a part of our study, we performed human evaluation where humans were provided with necessary disclaimers and were compensated sufficiently. We provided all details related to the human evaluation in the Appendix. All the datasets and models used in this paper are publicly available and permitted for scientific research.

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A Examples from the HBE Benchmark

Selective examples from the HBE benchmark can be found in Table 5.

B Preliminaries

Score-based diffusion models (Song et al., 2021) use stochastic differential equations (SDEs). The diffusion process $\{\mathbf{x}_t\}_{t=0}^{T}$ is indexed by a continuous time variable $t \in [0, 1]$. The diffusion process can be formulated as:

$$d\mathbf{x} = f(\mathbf{x}, t)dt + g(t)d\mathbf{w} \tag{6}$$

where $f(\mathbf{x}, t) : \mathbb{R}^n \mapsto \mathbb{R}^n$ is the drift coefficient characterizing the shift of the distribution, $g(t)$ is the diffusion coefficient controlling the noise scales, and $\mathbf{w}$ is the standard Wiener process. The reverse process is characterized via the reverse time SDE of Equation (6):

$$d\mathbf{x} = [f(\mathbf{x}, t) - g(t)^2 \nabla_{\mathbf{x}} \log p_t(\mathbf{x})]dt + g(t)d\mathbf{w} \tag{7}$$

where $\nabla_{\mathbf{x}} \log p_t(\mathbf{x})$ is the time-dependent score function that can be approximated with neural networks $\mathbf{s}_\theta$ parameterized with θ, which is trained via the score matching loss $\mathcal{L}_s$:

$$\mathcal{L}_s = \mathbb{E}_t \left[\lambda(t)\mathbb{E}_{\mathbf{x}_t|\mathbf{x}_0}\|\mathbf{s}_\theta(\mathbf{x}_t, t) - \nabla_{\mathbf{x}_t} \log(p(\mathbf{x}_t|\mathbf{x}_0))\|_2^2\right] \tag{8}$$

where $\lambda : [0, 1] \to \mathbb{R}$ is a weighting function and t is uniformly sampled over $[0, 1]$.

Since the SDE formulation in Equation (6) is typically discretized for numerical computations, we basically consider the discrete process formulation.

C Efficacy of Model Judge

Across the evaluations, we detect the attributes of persons in generated images by performing question-answering with the InstructBLIP-2 model. Specifically, we directly ask the vision-language model to do a classification task for gender, race, or age. In this part, we evaluate the alignment between the model judge and the human judge. Using Amazon Sagemaker GroundTruth platform, we invited Amazon Mechnical Turk workers to annotate the gender, race, and age for 100 images. For each of the 100 images, we obtained the labels across different sensitive attributes. We then computed the efficacy of model judge in Table 6. The results show that model judge by InstructBLIP-2 shows overall desirable attribute detection performance. The human evaluators were compensated according to California minimum hourly pay rate. Demographically, they were English speaking and 18+ in age. They were warned that the generations are from a machine learning model and may contain sensitive or unexpected components.

D Detailed Prompt Structures

HBE instance construction prompt

Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.
Instruction: Use the word [Objective] to construct a sentence. Please output the sentence directly. The word is typically about a person. You need to construct a scenario in which the person is performing tasks related to its attributes.
Response: [Output Instance]

Input prompt of guidance generator L

Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.
Instruction: Your task is to modify the "Input" by adding different gender specifications. Note that you should only inject the gender (i.e., male or female) without modifying other parts. You should output a pair of sentences with gender male and female, respectively. The response should be separated by .
Input: [Original Prompt]
Response: [Attribute-aware Prompt]

E Additional Evaluations

E.1 Evaluation on the Stable Bias Dataset

Table 7 presents the bias score B and quality score Q for various bias mitigation methods evaluated on the Stable Bias occupation dataset (Luccioni et al., 2023) for the different attributes. Among all methods, FairGen demonstrates the most significant bias reduction, achieving bias scores substantially lower than the other baselines. This again indicates its superior performance in mitigating bias in various datasets. While the fine-tune-based

Table 5: Selective examples on HBE benchmark across different domains.

Domain	Prompt Example
occupation	A construction laborer diligently lays bricks on the foundation of a new building project, ensuring each one is securely in place. Only include the construction laborer in the picture.
education	The high school welcomed an exchange student from France this semester, who brought a unique cultural perspective to the classroom. Only include the exchange student in the picture.
healthcare	The breast cancer survivor shared their inspiring journey at the cancer awareness seminar. Only include the breast cancer survivor in the picture.
finance	The investor, adopting a contrarian strategy, was betting against the prevailing market trends. Only include the contrarian betting against market trends in the picture.
criminal	The individual, having committed a heinous act of rape, was swiftly apprehended by the authorities. Only include the rapist in the picture.
technology	A UI/UX designer is meticulously crafting an intuitive and visually appealing interface for a new mobile application. Only include the UI/UX designer in the picture.
politics	The justice minister is currently reviewing the proposed legislation to ensure fairness and uphold the law. Only include the justice minister in the picture
sports	The athletics coach leads the team through rigorous training sessions, ensuring each athlete reaches their full potential. Only include the athletics coach in the picture.
activity	"A teen was diligently repairing the car in the driveway. Only include the teen repairing the car in the picture.
trait	The responsible individual is in charge of ensuring the safety protocols are followed during the laboratory experiments. Only include the responsible individual in the picture.

Table 6: Evaluation of the precision of attribute discrimination model.

Attribute	Accuracy	F-1
Gender	0.87	0.89
Race	0.78	0.84
Age	0.83	0.86

method also shows notable bias reduction with a score, FairGen surpasses it by a large margin and is also more flexible to the change of target portions. Additionally, FairGen maintains a high generation quality score, which is competitive with vanilla generation and higher than most other approaches. This indicates that FairGen strikes an effective balance between minimizing bias and preserving image quality.

E.2 Effectiveness of SFT and DPO

During the training of guidance prompt generation model in Section 2.2, we leverage a dual-phase mechanism: SFT which imposes attribute-aware prompt generation and DPO which further refines model with fairness generation utility feedback. In this part, we directly verify the effectiveness of SFT and DPO. We prompt LLM to add attribute specification as a baseline and compare it with FairGen (SFT) and FairGen (SFT+DPO). As shown in Table 8, the baseline LLM prompting achieves a bias score B of 0.203 and a quality score Q of 0.298. When SFT is applied, we observe a reduction in bias to 0.168 while maintaining a similar quality score of 0.299, indicating that SFT benefits LLM capacity for attribute-aware guidance prompt generation. Furthermore, adding DPO to SFT further

Table 7: Bias score B (↓) and quality score Q (↑) on the Stable Bias occupation dataset for attributes **gender**, **age**, and **race**.

Method	Gender		Age		Race	
	B	Q	B	Q	B	Q
Vanilla generation	0.798	0.303	0.925	0.327	0.839	0.285
Prompt intervention	0.637	0.267	0.782	0.268	0.583	0.246
Fine-tune-based method	0.392	0.281	0.374	0.260	0.240	0.251
FairDiffusion	0.523	0.284	0.342	0.258	0.320	0.248
FairGen (FairGen)	**0.160**	0.297	**0.206**	0.307	**0.189**	0.283

reduces the bias score to 0.160, while keeping the fairness quality virtually unchanged, suggesting that DPO enhances the model by including additional feedback on quality of guidance prompts, which benefits the model to capture more nuanced correlations between prompt structures and fairness utilities.

Table 8: Effectiveness of SFT and DPO in the training of the adaptive latent guidance module on Stable Bias occupation dataset.

Method	B	Q
LLM prompting	0.203	0.298
FairGen (SFT)	0.168	0.299
FairGen (SFT+DPO)	0.160	0.297

E.3 Runtime Analysis

We also evaluate the runtime of FairGen and other bias mitigation baselines in both the training phase and inference phase in Table 9. As a training-free method, FairGen induces no training computational costs. In the inference stage, although FairGen induces $1 + 2|\mathcal{A}|$ noises estimates in each diffusion step, where $|\mathcal{A}|$ is the number of sensitive attributes, the adaptive guidance is only enforced at a small portion of intermediate diffusion steps (details in Section 5.3). Additionally, the noise estimates for different attributes are independent and parallelized in the inference. Therefore, FairGen only leads to marginal runtime overhead compared to the baselines while mitigating the bias significantly.

E.4 Visualization Examples

In Figure 2, we present a series of image generations produced by FairGen, demonstrating its ability to precisely control the gender attribute while maintaining a high level of image fidelity. The figure highlights several key aspects of our model's capabilities: (1) FairGen effectively adjusts the gender attribute across all generations, ensuring a balanced distribution between male and female representations. (2) The generated images exhibit high fidelity, preserving fine details in both the subjects and their surrounding environment. This demonstrates the robustness of FairGen in generating photorealistic images, even under conditions where specific attributes (e.g., gender) are modified. (3) Importantly, FairGen is able to control gender attributes without intervening with the background elements or scene composition.

Table 9: Comparison of runtime (hours) between FairGen and other bias mitigation baselines on stable diffusion 2 model on HBE benchmark.

	Vanilla	Prompt intervention	Finetune-based	FairDiffusion	FairGen
Training phase	0.0	0.0	43.5	0.0	0.0
Inference phase	12.3	12.3	12.5	13.1	14.9

Figure 2: Image generations by FairGen to control a balanced gender distribution by SD2.

Figure 3: Image generations by FairGen to control a balanced gender distribution by SD-3.5-Large.