Association of Objects May Engender Stereotypes: Mitigating Association-Engendered Stereotypes in Text-to-Image Generation

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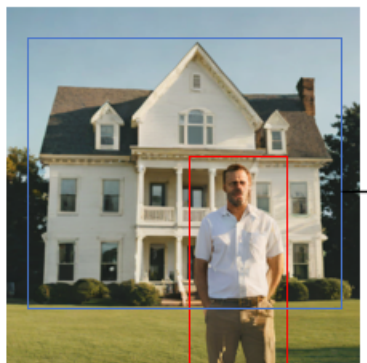
NEURAL INFORMATION PROCESSING SYSTEMS

Association-Engendered Stereotypes

Original T2I models can generate stereotypes when given prompts involving multiple objects; when the prompts are “a photo of black/white people” or “a photo of a house”, they do not engender stereotypes. However, if the prompt is “a photo of black/white people and a house”, the model may engender stereotypes that the white people's house is better than the black people's house.

Modeling Stereotypes in T2I



For the object "x_1=*people*", the sensitive attributes s include gender, race, region, etc.

For the object "x_2=*house*", the sensitive attributes s refers to the description of the house.

For a T2I diffusion model $\mathcal{G}$, which generates images x with a sensitive attribute s. The attribute s can have $\mathcal{Y}$ different categories and needs to align with a target distribution $\mathcal{D}$ that is free of stereotypes. Using a prompt to generate a batch of images, denoted as $I = \{x_i^{v(s)}\}_{i\in\mathbb{N}}$. For the PDF of the snesitive attribute of image x, let $h(x^{v(s)^i}) = p_x^{v(s)^i} = [p_x^{v(s)^1}, p_x^{v(s)^2}, \ldots, p_x^{v(s)^{\mathcal{Y}}}], i \in |\mathcal{Y}|$. Assume another set of stereotype-free images, $\tilde{I} = \{x_i^{u(s)}\}_{i\in\mathbb{N}}$. The probability distribution of its sensitive attribute is $h(x^{u(s)^i}) = p_x^{u(s)^i} = [p_x^{u(s)^1}, p_x^{u(s)^2}, \ldots, p_x^{u(s)^{\mathcal{Y}}}], i \in |\mathcal{Y}|$. The distribution distance between $p_x^{v(s)}$ and $p_x^{u(x)}$:

$$\sigma^* = \arg\min_{\sigma \subseteq S_{\mathcal{Y}}} \sup |\sigma(p_x^{v(s)}) - p_x^{u(s)}|,$$

Modeling Stereotypes in T2I

Non-association-engendered stereotypes	Single Object with a Single Sensitive Attribute		Prompts: "*a photo of a engineer.*" "*a photo of a driver.*" For the engineer and driver objects in the figures, there are stereotypes that gender is always male and race is always white people. Only **one** sensitive attribute can be mitigated at once.
	Single Object with Multiple Sensitive Attributes		Prompts: "*a photo of a farmer.*" "*a photo of a CEO.*" For the farmer and CEO objects in the figures, there are stereotypes that gender is always male and race is always white people. **Multiple** sensitive attributes can be mitigated simultaneously.

For single object with single sensitive attribute.

$$f(x) = P(s_x = v(s_x)|x).$$

For single object with multiple sensitive attributes.

$$f(x) = P(s_x^1 = v(s_x^1), s_x^2 = v(s_x^2), \ldots |x).$$

Modeling Stereotypes in T2I

Association -engendered- stereotypes	Multiple Objects with a Single Sensitive Attribute		Prompts: "*a photo of a boss and a employee.*" "*a photo of a professor and a teacher.*" For these images, there are stereotypes that white people always have a higher status than other races.
	Multiple Objects with Multiple Sensitive Attributes		Prompts: "*a photo of a nurse and a doctor.*" "*a photo of a manager and a secretary.*" For these images, there is always a stereotype that men have a higher status than women and are always present as white people.

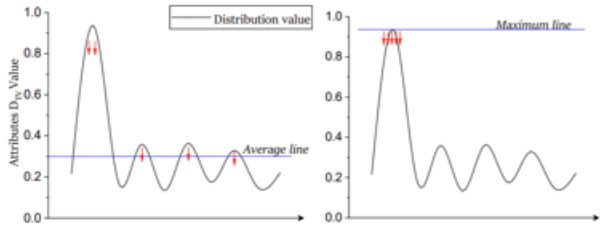
For single object with single sensitive attributes.

$$f(x_1, x_2, \dots) = P\big(s = v(s) | x_1, x_2, \dots\big)$$

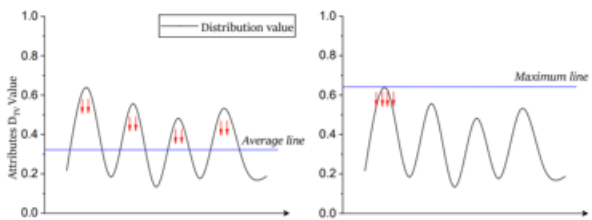
For two object with two sensitive attributes.

$$f(x_1, x_2, \dots) = P\big(s_{x_1} = v(s_{x_1}), s_{x_2} = v(s_{x_2}) | x_1, x_2, \dots\big)$$

Stereotype Distribution Total Variation



(a) The stereotypical extent is described using the maximum and average values when **extreme** attribute values are present in the probability distribution of D_{TV}.



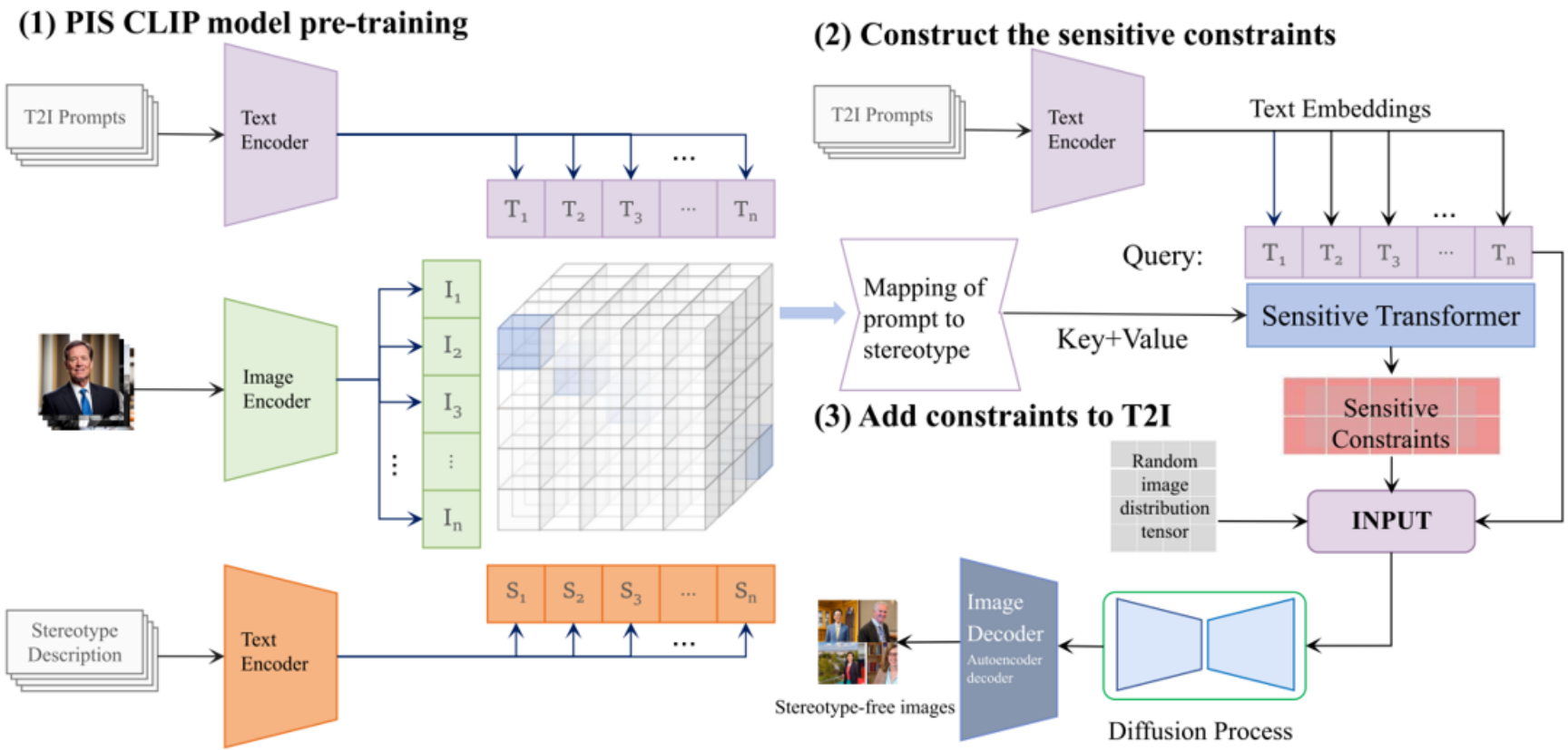
(b) The stereotypical extent is described using the maximum and average values when the attribute values in the probability distribution of D_{TV} are relatively **balanced**.

$$
\begin{aligned}
SDTV(\mathcal{G}) &= \max_{\{i,j\}\subseteq\mathcal{Y}} \left\{ D_{TV}\left(p_\theta(s_x = v(s_x)^i|x), p_\theta(s_x = v(s_x)^j|x) \right) \right\} \\
&= \max_{\{i,j\}\subseteq\mathcal{Y}} \left\{ D_{TV}\left(\int p_\theta(s_x = v(s_x)^i|x,\tau)d\tau - \int p_\theta(s_x = v(s_x)^j|x,\tau)d\tau \right) \right\} \\
&= \max_{\{i,j\}\subseteq\mathcal{Y}} \left\{ D_{TV}\left(\mathbb{E}_{p(s_x=v(s_x)^i|\tau)} p_\theta(s_x = v(s_x)^i|x,\tau) - \mathbb{E}_{p(s_x=v(s_x)^j|\tau)} p_\theta(s_x = v(s_x)^j|x,\tau) \right) \right\} \\
&= \max_{\{i,j\}\subseteq\mathcal{Y}} \left| \left(\mathbb{E}_{p(s_x=v(s_x)^i|\tau)} p_\theta(s_x = v(s_x)^i|x,\tau) - \mathbb{E}_{p(s_x=v(s_x)^j|\tau)} p_\theta(s_x = v(s_x)^j|x,\tau) \right) \right| \\
&= \max_{\{i,j\}\subseteq\mathcal{Y}} \left| \left(p_\theta(\tau^{v(s_x)^i}|x) - p_\theta(x|\tau^{v(s_x)^j}|x) \right) \right|
\end{aligned}
$$

Expanding object and sensitive attributes to multiple simultaneously and define a set $X = \{x_1, x_2, \ldots, x_n\}_{n\in\mathbb{N}}$ and $S = \{s_1, s_2, \ldots, s_n\}_{n\in\mathbb{N}}$ of object and sensitive attributes.

$$
SDTV(\mathcal{G}) = \mathop{\mathbb{E}}_{\substack{s_h\in S_h \\ s'_h\in S'_h}} \left(\max_{\substack{\{i,j\}\subseteq\mathcal{Y}, \\ m\in\mathcal{Z}}} \left| p_\theta(s_h = v(s_h)^i|s'_h = v(s'_h)^m,\tau) - p_\theta(s_h = v(s_h)^j|s'_h = v(s'_h)^m,\tau) \right| \right)
$$

Mitigating Association-Engendered Stereotypes (MAS)



Comparative Experiments

Stereotype mitigation effects in different Stable diffusions.

Model	S-O & S-SA↓			S-O & M-SA↓	M-O&S-SA↓			M-O&M-SA↓
	Gender	Race	Region	G.×R.	Gender	Race	Region	
SD-1.5	.68±.27	.82±.14	.81±.10	.75±.20	.57±.21	.49±.16	.56±.11	.47±.23
MAS(Ours)	.17±.14	.21±.09	.23±.13	.21±.02	.17±.11	.20±.09	.20±.02	.16±.10
SD XL	.84±.14	.40±.29	.59±.20	.61±.12	.74±.13	.83±.11	.87±.08	.73±.15
MAS(Ours)	.15±.12	.16±.05	.13±.04	.19±.09	.16±.10	.20±.11	.21±.07	.15±.05
Lightning	.81±.19	.96±.02	.94±.02	.88±.09	.86±.04	.82±.09	.90±.04	.78±.09
MAS(Ours)	.18±.12	.16±.09	.17±.04	.15±.12	.17±.10	.19±.05	.22±.11	.17±.08
Turbo	.92±.08	.89±.10	.80±.16	.89±.11	.82±.11	.88±.07	.85±.07	.72±.08
MAS(Ours)	.16±.13	.15±.10	.16±.10	.20±.13	.17±.11	.19±.10	.20±.10	.15±.10
Cascade	.96±.02	.90±.07	.87±.09	.93±.05	.90±.05	.88±.07	.89±.06	.81±.04
MAS(Ours)	.17±.15	.17±.09	.19±.08	.17±.08	.17±.08	.21±.07	.23±.09	.16±.04

Comparison results with other SOTA mitigation methods.

approach	S-O&S-SA↓			S-O&M-SA↓	M-O&S-SA↓			M-O&M-SA↓	S.P.↑
	Gender	Race	Region	G.× R.	Gender	Race	Region		CLIP-T2I
SD 1.5	.68±.27	.82±.14	.81±.10	.75±.20	.49±.25	.47±.23	.49±.19	.53±.17	.40±.03
Kim. 2023	.43±.17	.39±.08	-	-	-	-	-	-	.39±.03
Chuang. 2024	.38±.10	.49±.04	-	.24±.02	-	-	-	-	.37±.04
Gandikota. 2024	.49±.33	.43±.06	-	.21±.03	-	-	-	-	.38±.04
Bansal.2022	.46±.32	.37±.08	-	.19±.04	-	-	-	-	.36±.04
Wang. 2023	.47±.23	.40±.05	-	.20±.02	-	-	-	-	.39±.04
Shen. 2024	.22±.13	.42±.05	-	.20±.03	.18±.13	.19±.06	-	-	.39±.04
MAS(Ours)	.17±.14	.21±.09	.23±.13	.21±.02	.17±.11	.20±.09	.20±.02	.16±.10	.39±.04

Generalization Experiments

Semantic preservation experiment.

		SD-1.5	SD XL	Lightning	Turbo	Cascade
CLIP-T2I ↑	Original	.39±.03	.33±.02	.32±.03	.32±.02	.43±.0.4
	Ours	.38±.05	.33±.04	.32±.05	.31±.04	.42±.05
CLIP-I2I ↑	Ours	.80±.11	.78±.13	.84±.07	.76±.12	.89±.02

Stereotype mitigation experiment in complex T2I scenarios.

	S-O&S-SA↓			S-O&M-SA ↓	M-O&S-SA↓	M-O&M-SA ↓	S.P. ↑
	Gender	Race	Region	G.×R.			CLIP-T2I
R-SD	.84±.07	.87±.05	.81±.09	.78±.11	.81±.06	.77±.13	.38±.03
MAS(Ours)	.20±.19	.22±.15	.22±.07	.20±.03	.21±.09	.20±.05	.38±.03
R-SD + LORA	.85±.06	.85±.07	.80±.10	.79±.13	.83±.08	.75±.12	.39±.04
MAS(Ours)	.21±.11	.21±.13	.23±.06	.19±.09	.21±.10	.21±.08	.38±.04
R-SD + ControlNet	.84±.06	.86±.06	.82±.08	.79±.10	.81±.08	.78±.11	.38±.05
MAS(Ours)	.20±.16	.21±.10	.21±.07	.19±.10	.21±.10	.20±.04	.38±.03
R-SD + LORA + Con	.87±.04	.86±.07	.81±.10	.80±.10	.83±.09	.78±.12	.38±.05
MAS(Ours)	.22±.10	.22±.13	.21±.09	.20±.07	.21±.14	.21±.09	.38±.05

Non-template prompts evaluation experiment.

	S-O&S-SA↓			S-O&M-SA ↓	M-O&S-SA↓	M-O&M-SA ↓	S.P. ↑
	Gender	Race	Region	G.×R.			CLIP-T2I
SD-1.5	.69±.24	.84±.10	.82±.11	.73±.16	.48±.21	.52±.17	.40±.05
Kim. 2023	.44±.16	.38±.09	-	-	-	-	.39±.04
Chuang. 2024	.36±.11	.47±.06	-	.24±.04	-	-	.37±.03
Gandikota. 2024	.50±.30	.44±.10	-	.22±.04	-	-	.40±.04
Bansal.2022	.49±.27	.40±.10	-	.18±.04	-	-	.40±.04
Wang. 2023	.49±.18	.43±.10	-	.21±.03	-	-	.39±.03
Shen. 2024	.25±.15	.44±.09	-	.17±.05	-	-	.40±.04
MAS(Ours)	.20±.11	.23±.10	.23±.15	.20±.05	.21±.13	.18±.04	.40±.04

Evaluate the impace of MAS on image quality and efficiency generated by the original T2I model.

	times/(s) ↓				FID ↓
	10	20	50	100	
SD-1.5	25.8±3.00	51.2±5.30	125±9.00	252±19.0	15.5±1.30
MAS(Ours)	29.4±2.80	58.4±4.90	133±11.0	270±23.0	17.2±1.70
SD XL	43.9±2.30	87.6±4.50	219±12.0	429±25.0	16.1±0.90
MAS(Ours)	46.7±3.40	95.4±5.70	230±13.0	443±27.0	16.7±0.80
Lightning	6.39±0.70	12.9±1.93	34.0±3.40	64.5±5.10	22.6±1.20
MAS(Ours)	8.21±0.94	14.7±1.87	39.0±3.21	72.9±5.50	23.1±1.51
Turbo	7.30±1.50	14.5±3.20	35.9±4.20	71.9±5.40	20.6±2.10
MAS(Ours)	10.5±2.10	19.6±3.40	43.1±4.40	88.2±4.90	20.9±3.00
Cascade	25.9±1.30	49.7±3.60	112±7.20	245±17.0	23.6±1.70
MAS(Ours)	29.3±1.90	57.3±3.90	126±8.30	267±17.0	24.0±2.20

Thank you for your attention!