How I met Your Bias: Investigating Bias Amplification in Diffusion Models

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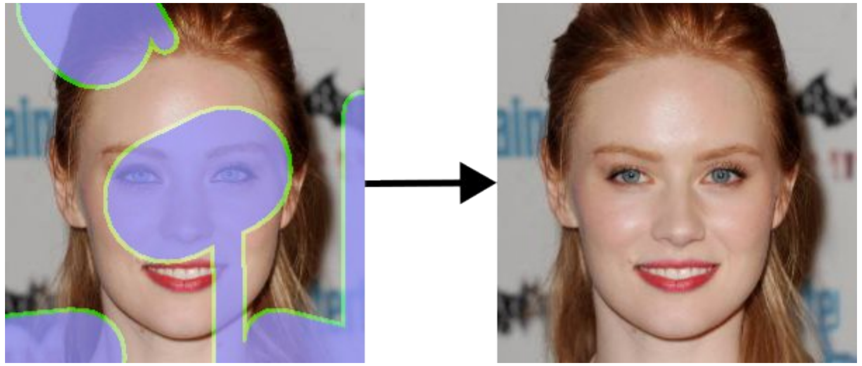
Introduction



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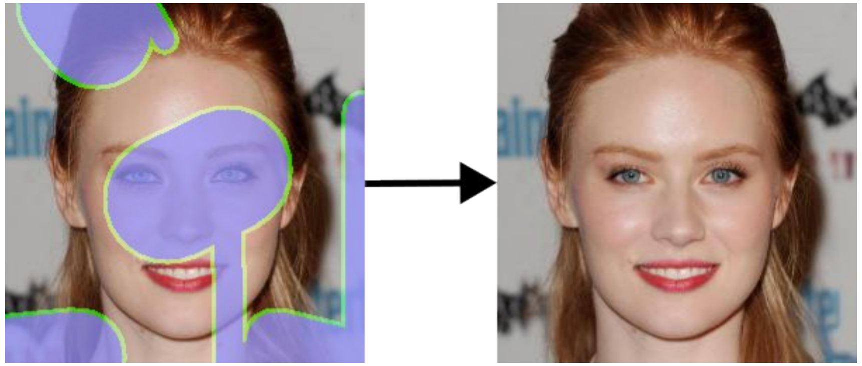

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Insertion of this video at editing :
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Sora 2, OpenAI (2025)

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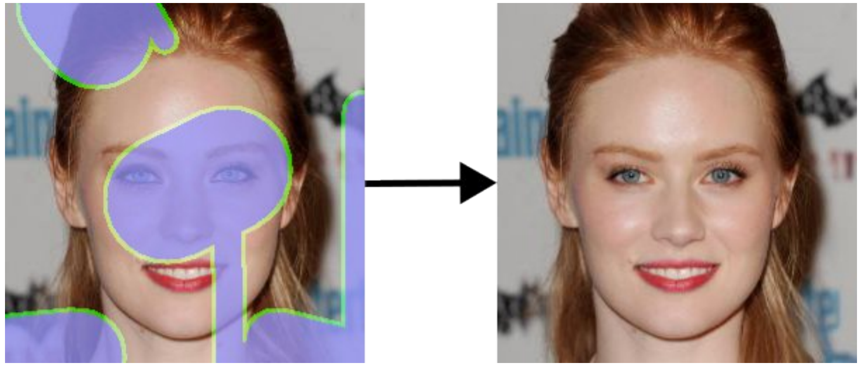

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Sora 2, OpenAI (2025)

Prompt: “A portrait photo of a lawyer”

StableDiffusion v2.1-base

DDIM sampling with 50 steps

Generated images

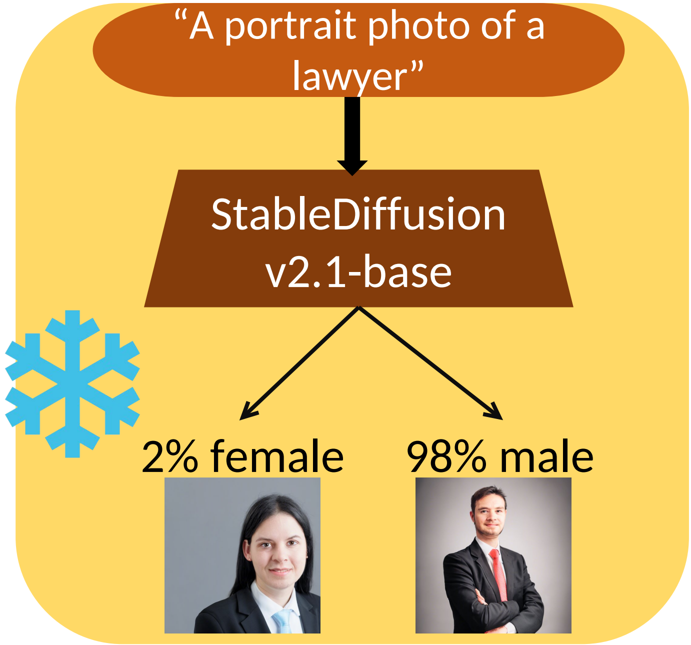
2% female lawyers

98% male lawyers

Research Motivation

Previous works:

- bias amplification is **a fixed, intrinsic feature of the model** [2, 3, 4]



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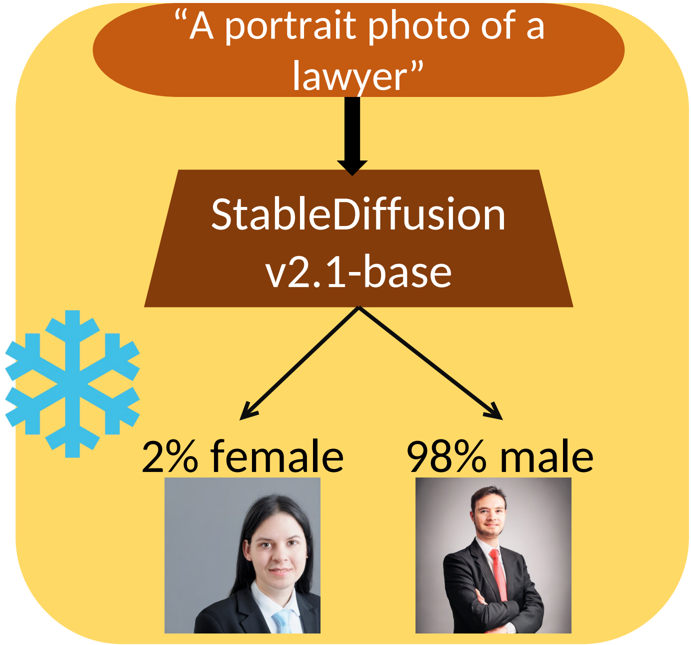

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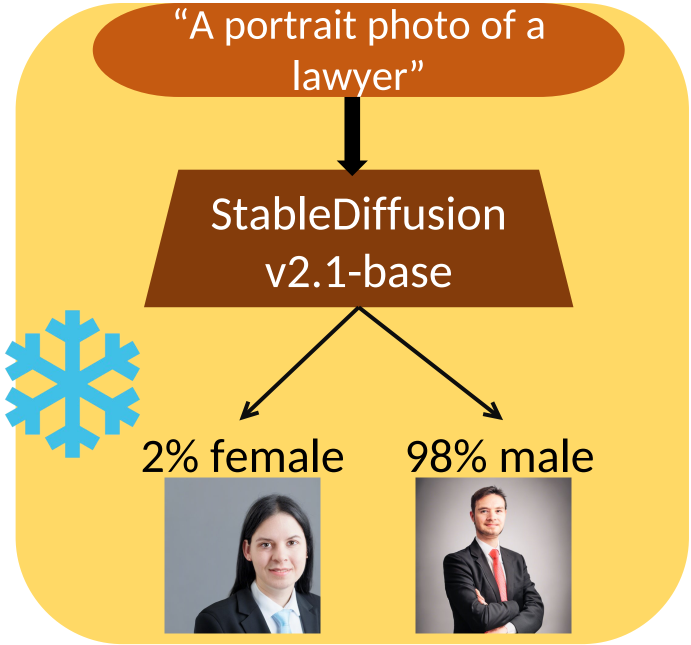
- no systematic analysis of how the sampling process itself affects bias amplification



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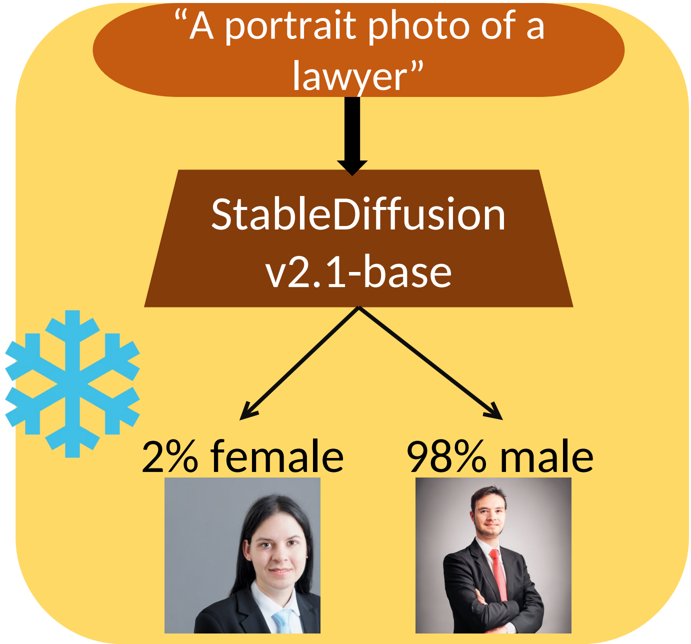
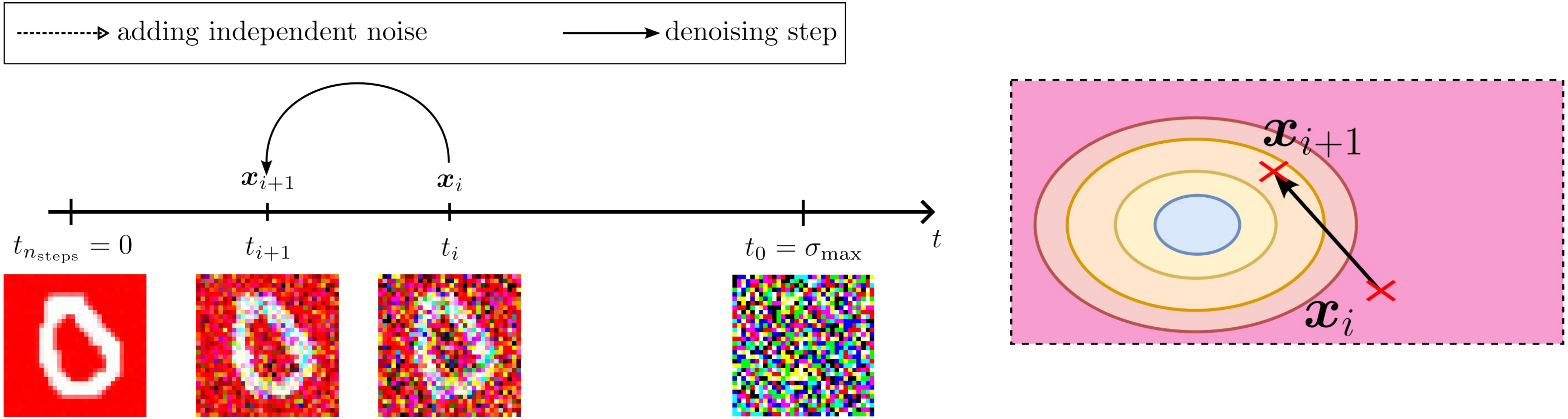


<u>Research question:</u>

Does the choice of sampling hyperparameters influence the level of bias in images generated by Diffusion Models?

Background: Diffusion Models

Deterministic sampling



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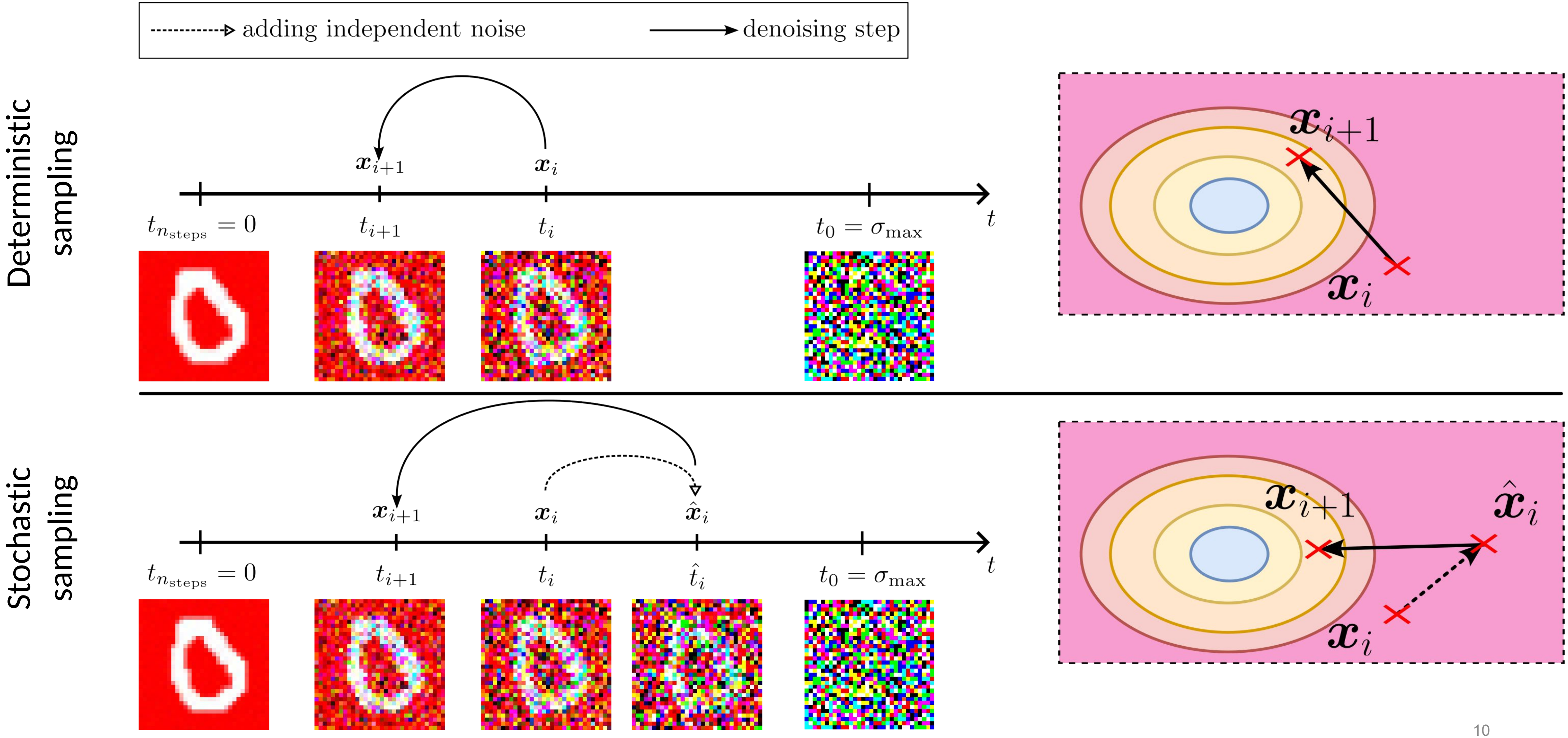

Method (1/3): definition of bias

The level of bias is measured by ρ the ratio of bias-aligned samples in the generated images or in the dataset:

$$\rho = P(\text{"bias-aligned"} \mid \text{target attribute})$$

$\rho_{model} > \rho_{dataset}$: bias amplification

$\rho_{model} < \rho_{dataset}$: bias reduction

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target attribute: “lawyer”

Both images were generated using StableDiffusion v2.1-base with the prompt *“A portrait photo of a lawyer”*

bias attribute: “gender”

“male”
bias-aligned sample

“female”
bias-conflicting sample

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Method (2/3): selecting hyperparameters

Relevant groups of hyperparameters:

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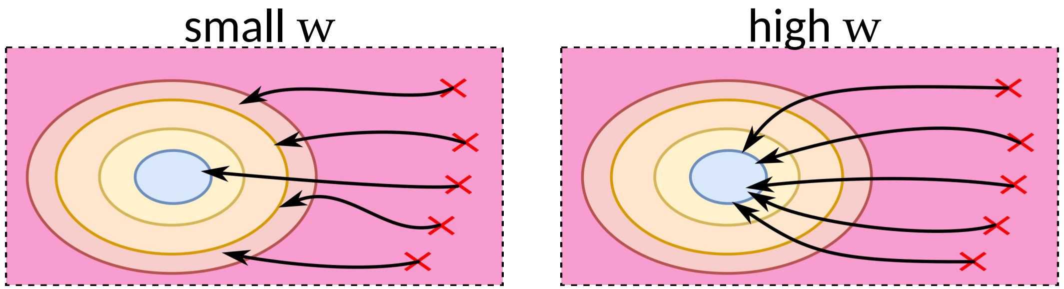
- **Conditioning strength**:
  - guidance scale w of CFG



Method (2/3): selecting hyperparameters

Relevant groups of hyperparameters:

- **Conditioning strength**:
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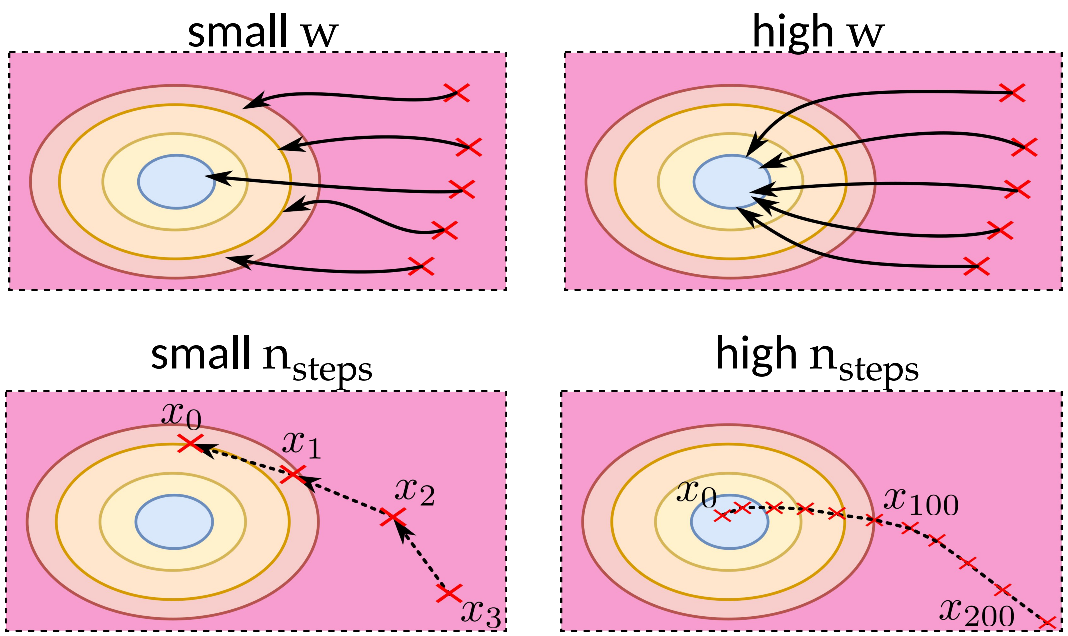
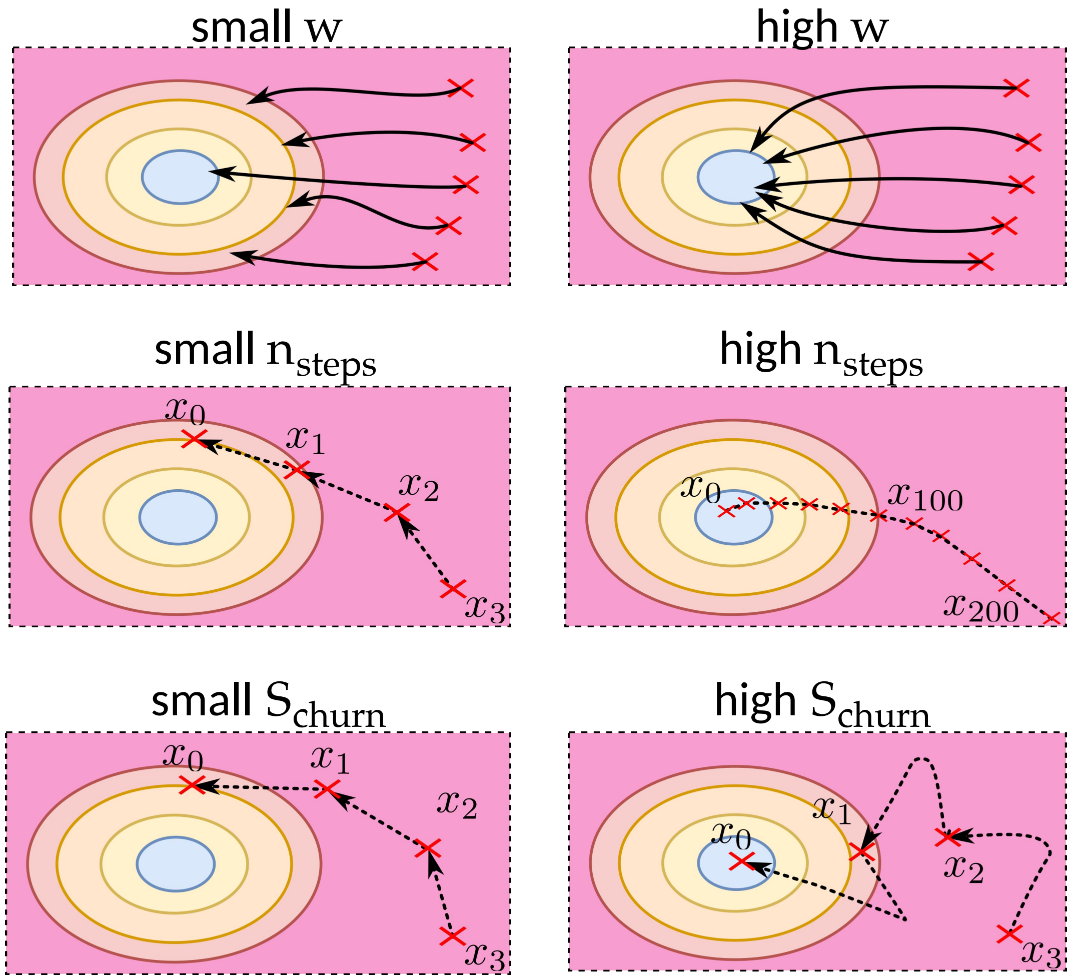
- **Computational cost**:
  - number of sampling steps $\mathrm{n}_{\mathrm{steps}}$
  - type of integration scheme



Method (2/3): selecting hyperparameters

Relevant groups of hyperparameters:

- **Conditioning strength**:
  - guidance scale w of CFG
- **Computational cost**:
  - number of sampling steps n_{steps}
  - type of integration scheme
- **Amount of stochasticity**:
  - η or S_{churn}: variance of added noise
  - $S_{t,min}$, $S_{t,\,max}$: time window with noise

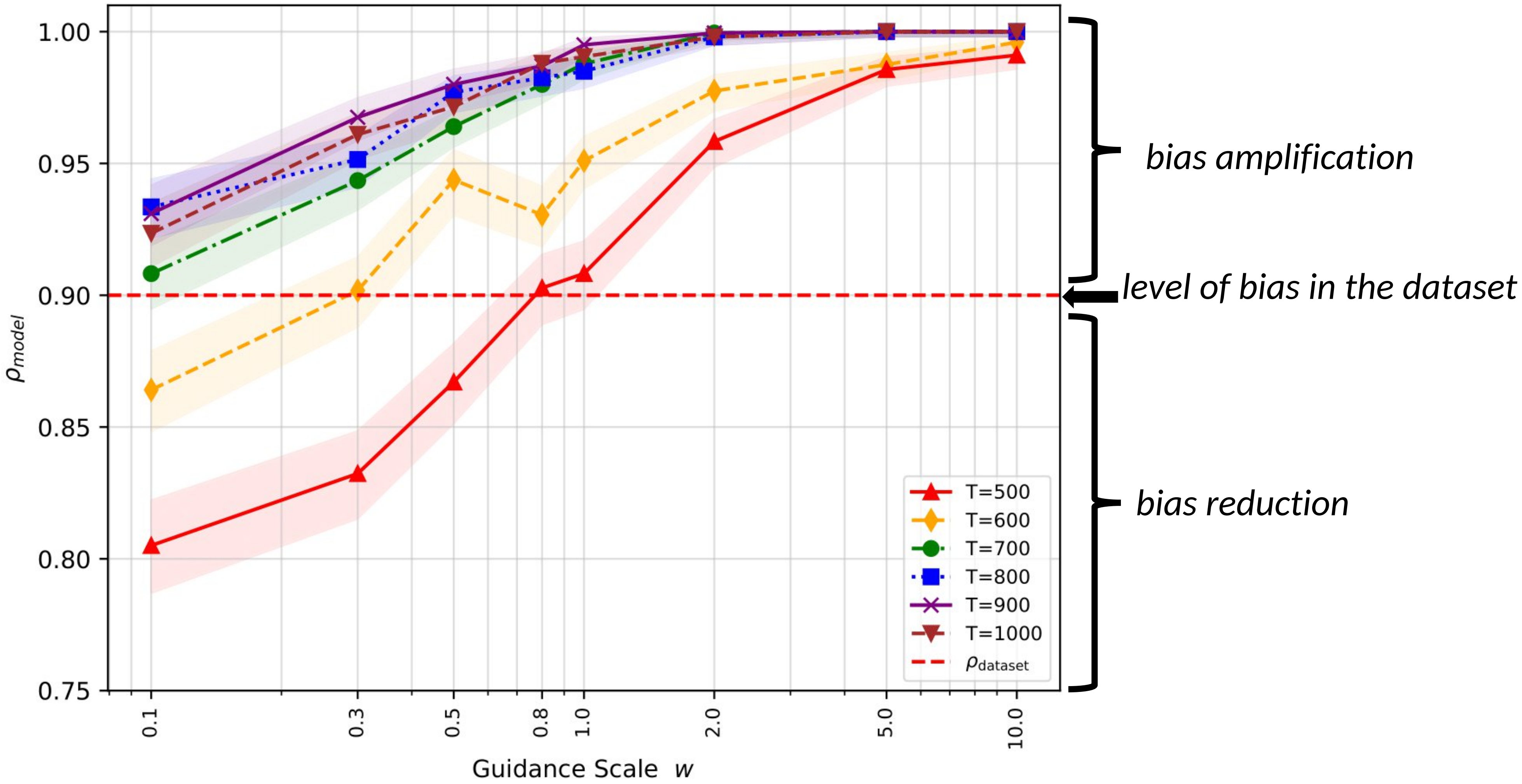


Method (3/3): experiments

Assess the impact of the hyperparameters on ρ_{model} across several models, samplers and datasets:

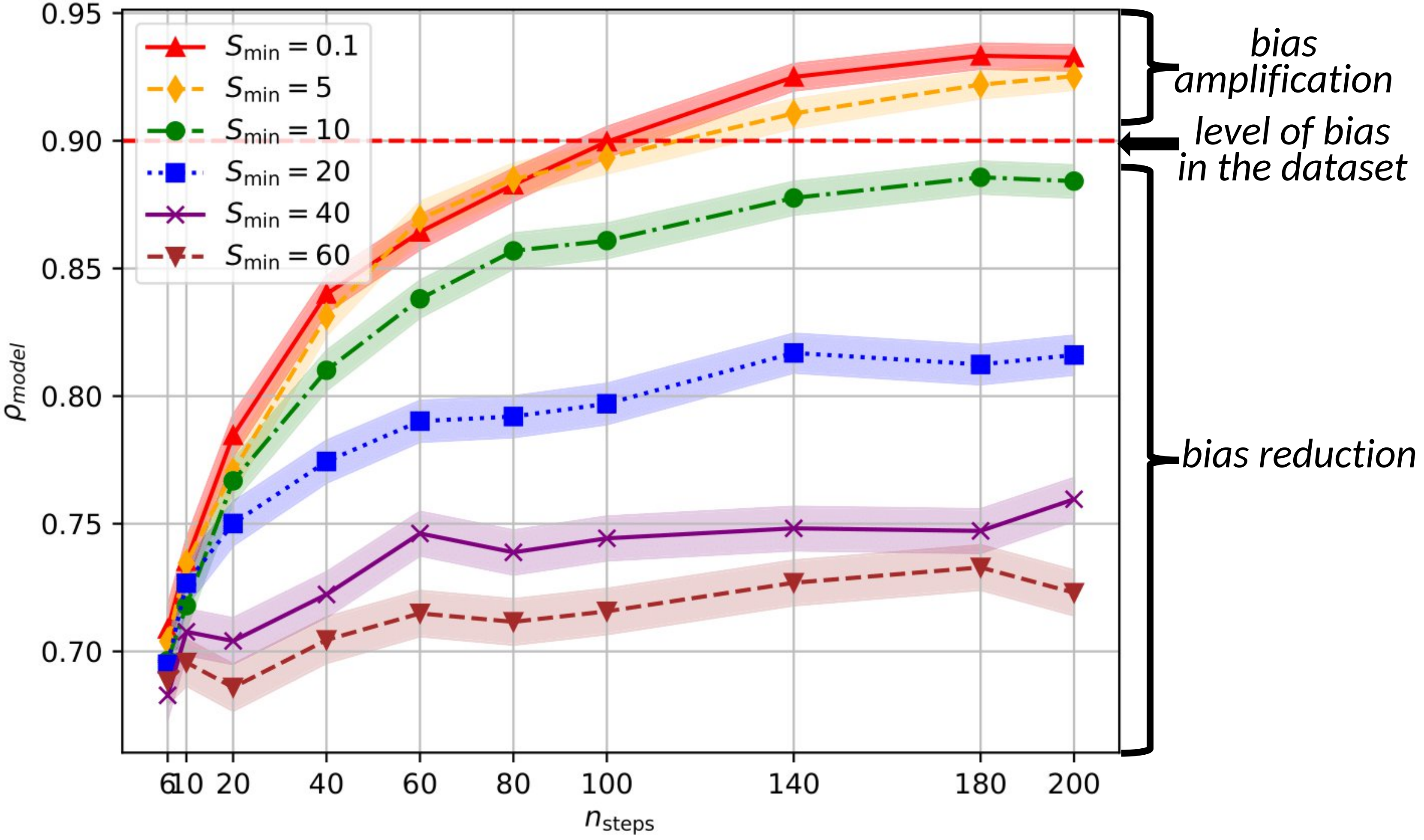
Model	Sampler	Datasets
DDPM [8], CDPM	DDPM, DDIM [9]	Biased MNIST [10], BFFHQ [11]
Continuous framework of [12]	EDM-Sampler, VP-Sampler [13], DPM-Solver [14]	Biased MNIST, Multi-color MNIST [15]
Stable Diffusion [16]	DDIM	Laion-5B [17]

Results: effect of the conditioning strength



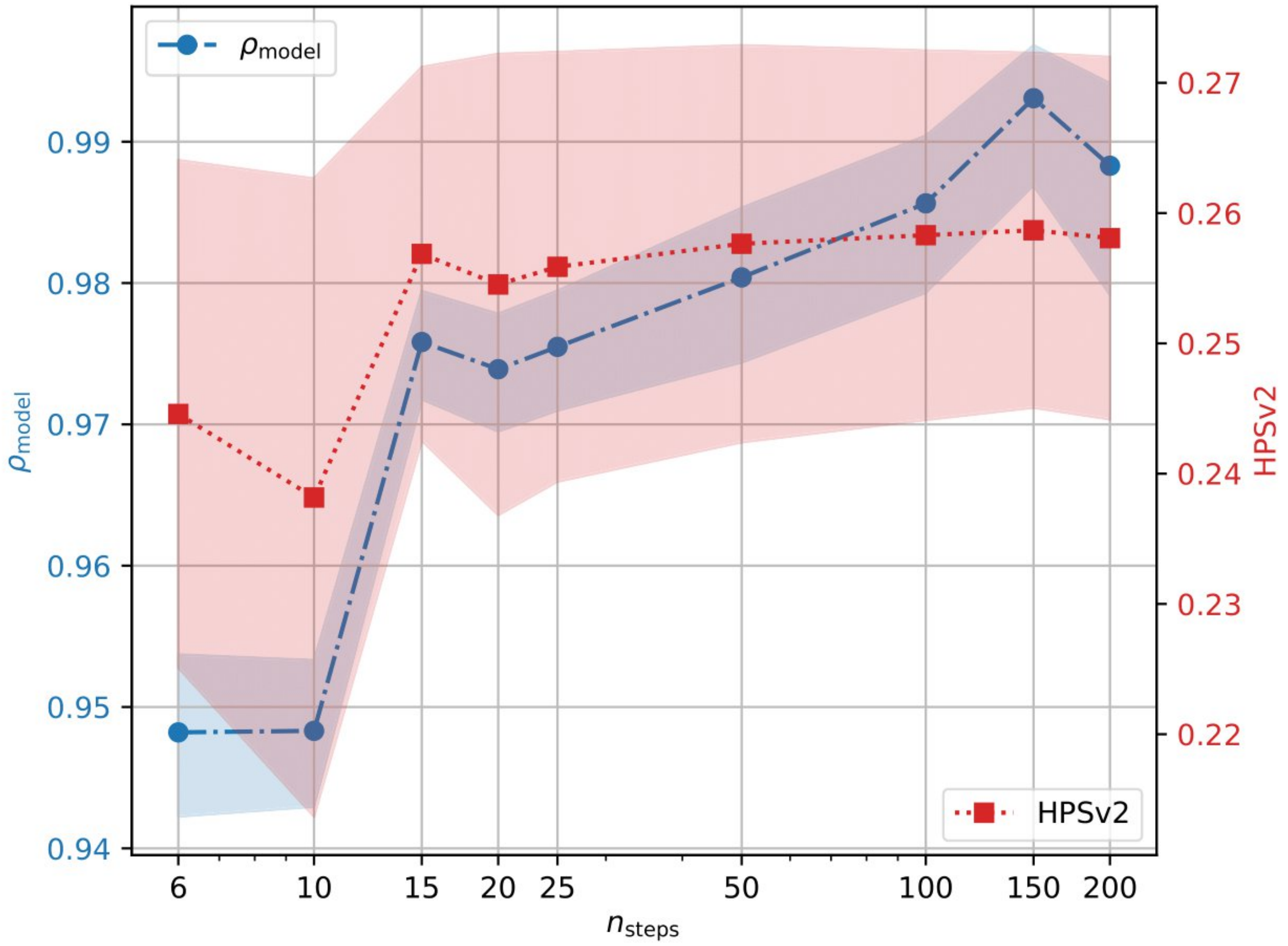
ρ_{model} vs guidance scale of CFG for various T for a fixed model trained on 2-classes Biased MNIST ($\rho_{dataset} = 0.9$), standard DDPM sampler

Results: effect of the computational cost (1/2)



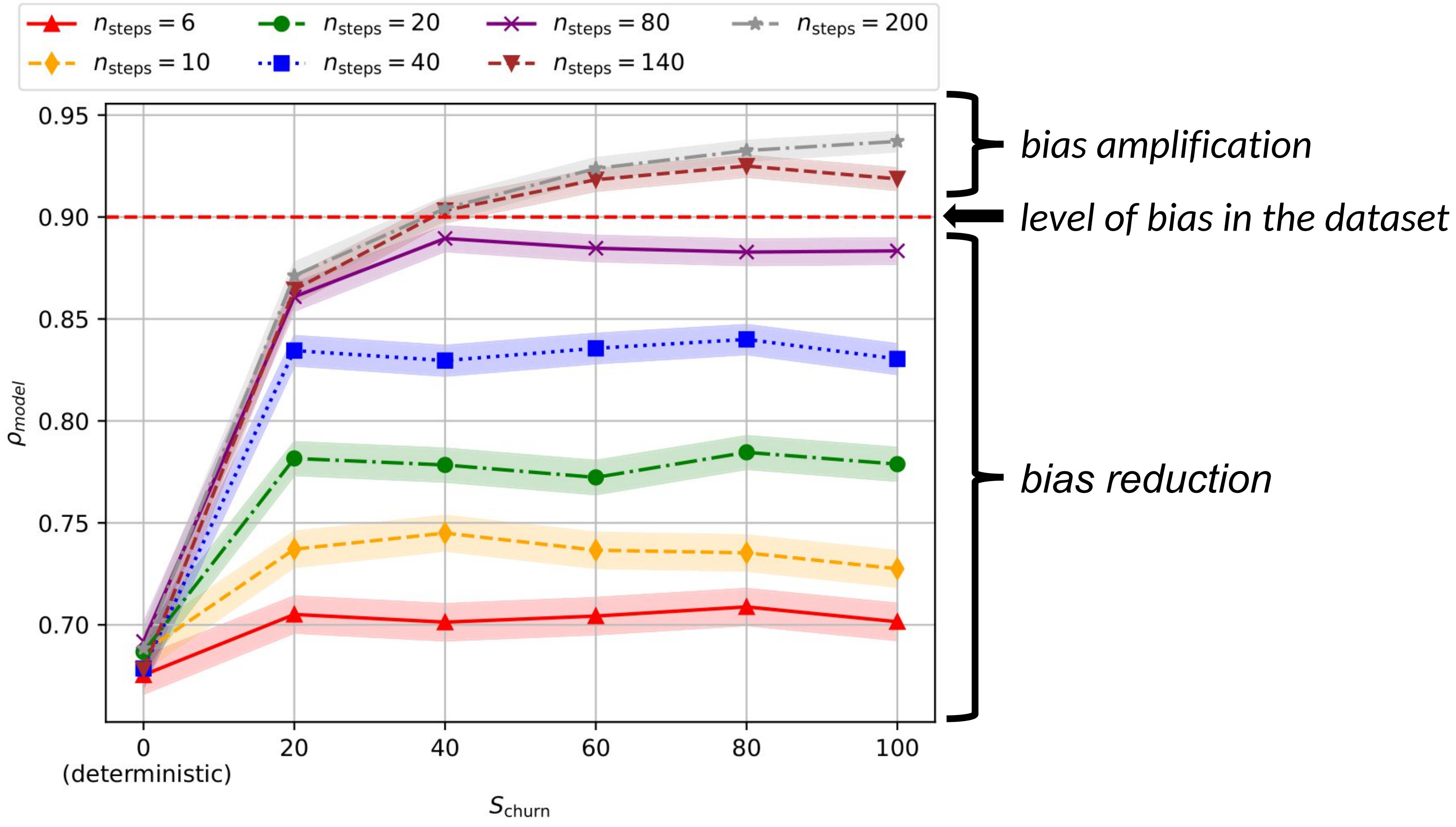
ρ_{model} vs $\mathrm{n_{steps}}$ for a fixed model trained on 10-classes Biased MNIST, EDM-Sampler

Results: effect of the computational cost (2/2)



ρ_{model} and HPSv2 vs $\mathrm{n_{steps}}$ for Stable Diffusion, DDIM sampler

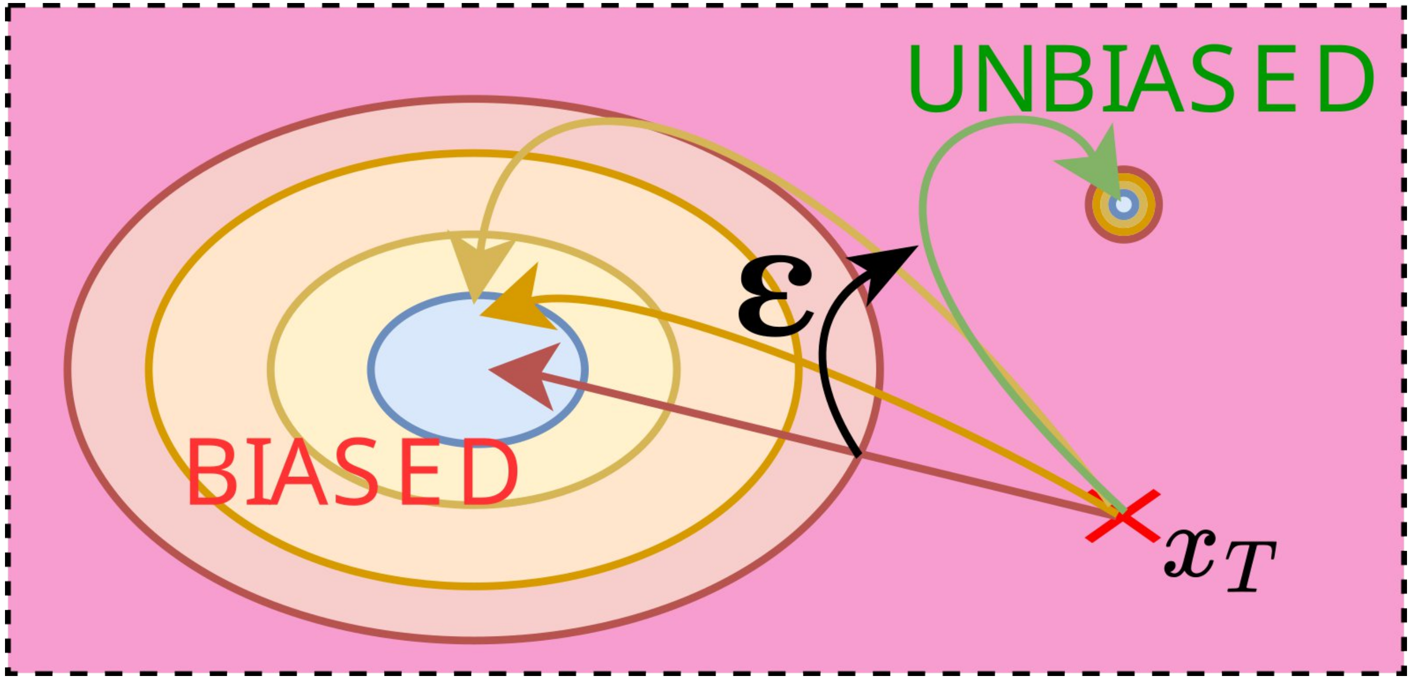
Results: effect of the amount of stochasticity



ρ_{model} vs S_{churn} with various n_{steps} for a fixed model trained on 10-classes Biased MNIST, EDM-Sampler

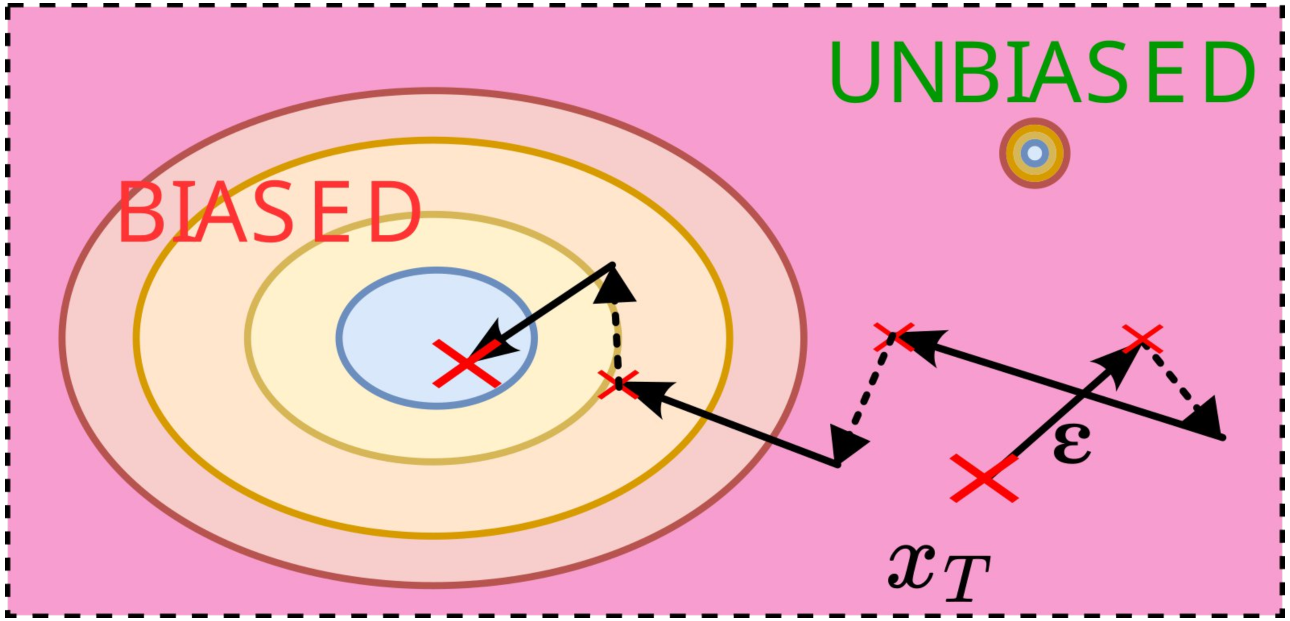
Discussion (1/2)

- Low number of sampling steps →numerical errors → sampling trajectory deviates from biased data distribution



Discussion (2/2)

- Surprisingly, the noise of stochastic sampling does not help in debiasing, but the opposite → correction of early numerical errors?



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$\longrightarrow$YES

Consequences:

- Careful constructions of vanilla baselines for comparison with debiasing methods
- Possible to design a debiasing strategy by tuning the sampling hyperparameters

Thank you for your attention !

ArXiv Paper

Source code of the experiments

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