Carnegie Mellon University

Generative Visual Prompt:

Unifying Distributional Control of Pre-Trained Generative Models

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Presented @NeurIPS 2022
https://chenwu98.github.io/PromptGen/

What is a good generative model?

Faithfully modeling the data distribution?

Uncurated samples from StyleGAN2

Things not in data…

Controllability (hard to label all concepts, e.g., “baby”)

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Controllability (hard to label all concepts, e.g., "baby")

Fairness (hard to build a truly fair training set, e.g., across races)

PromptGen is a remedy!

A **feed-forward** neural network to model desired distributions in latent space

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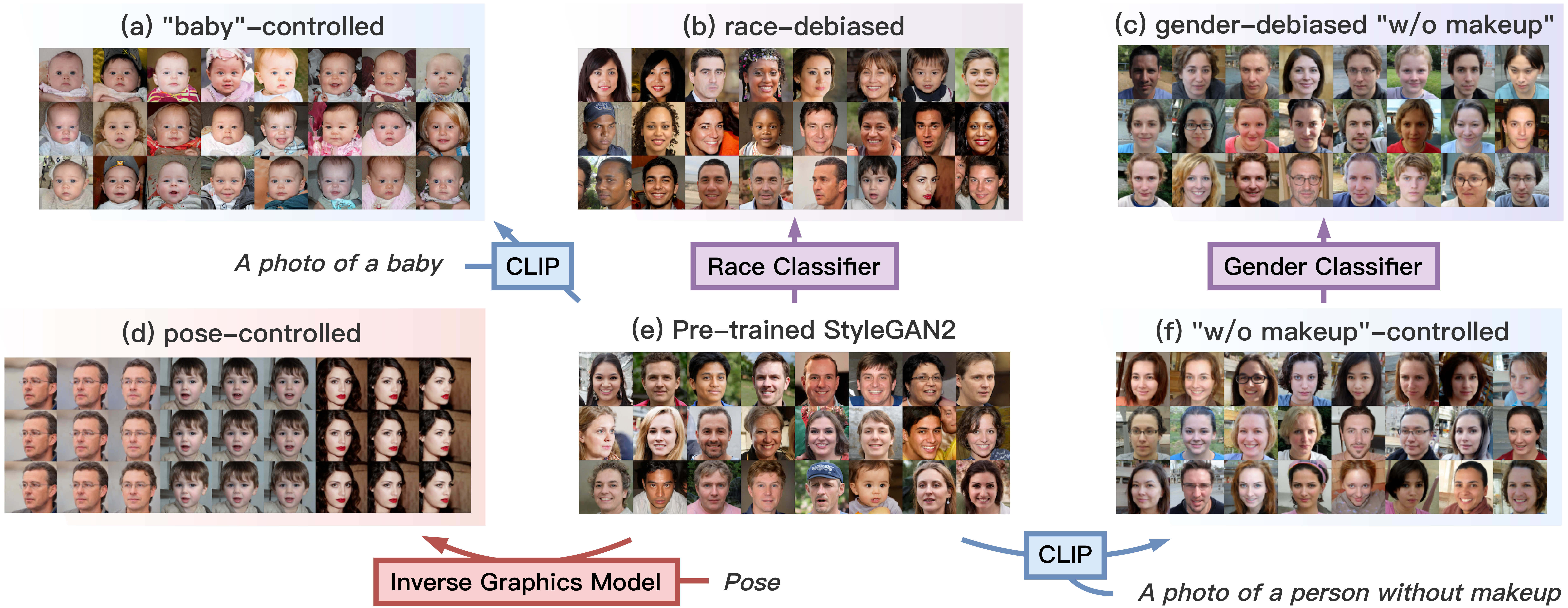

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(e) Pre–trained StyleGAN2

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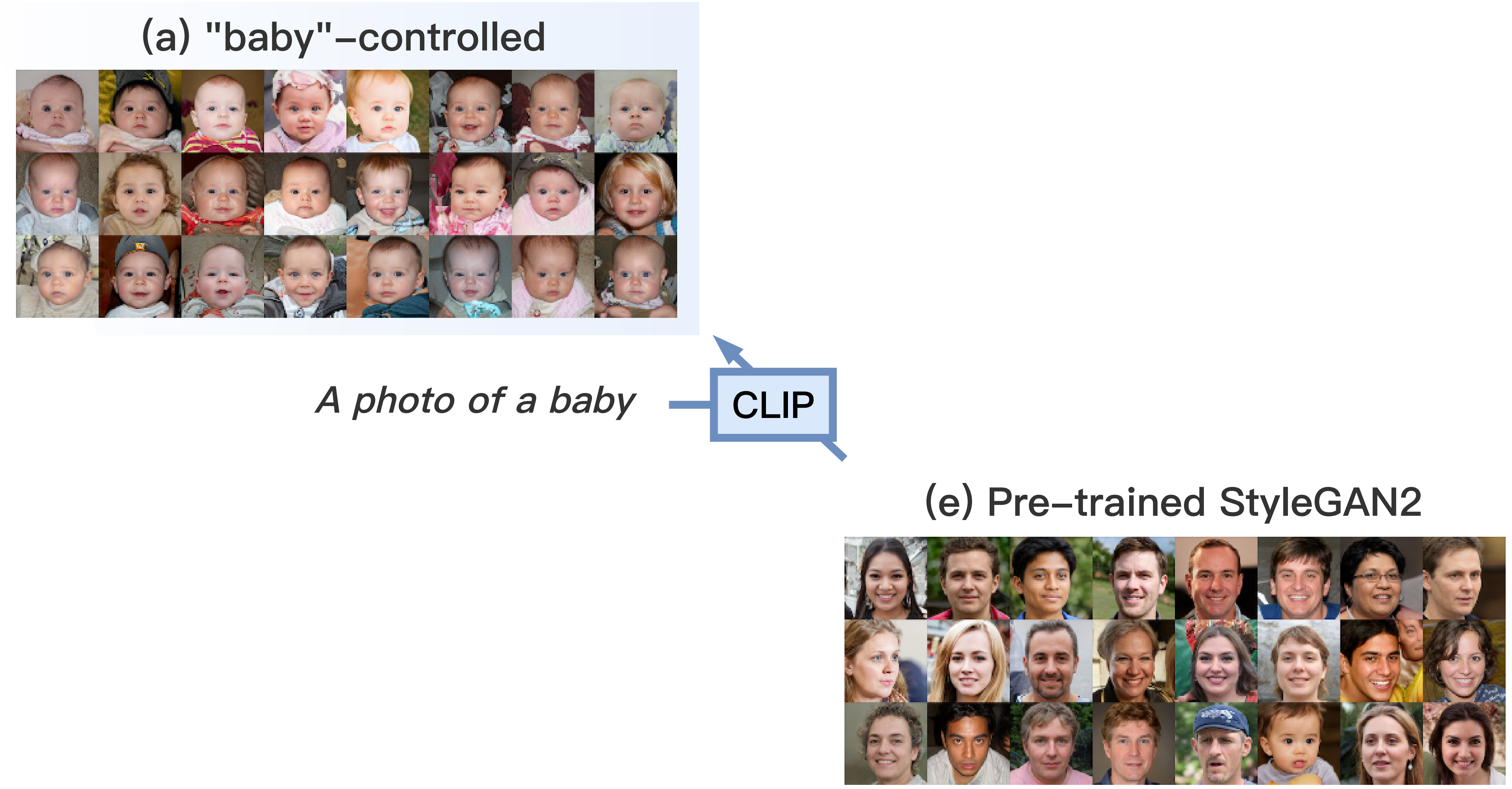

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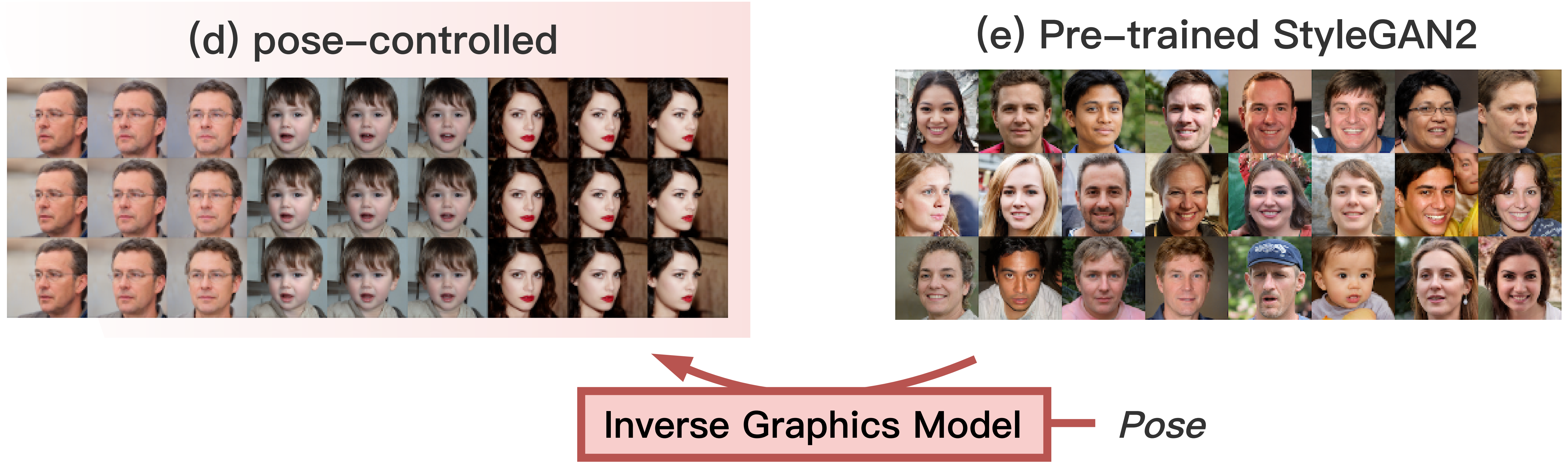

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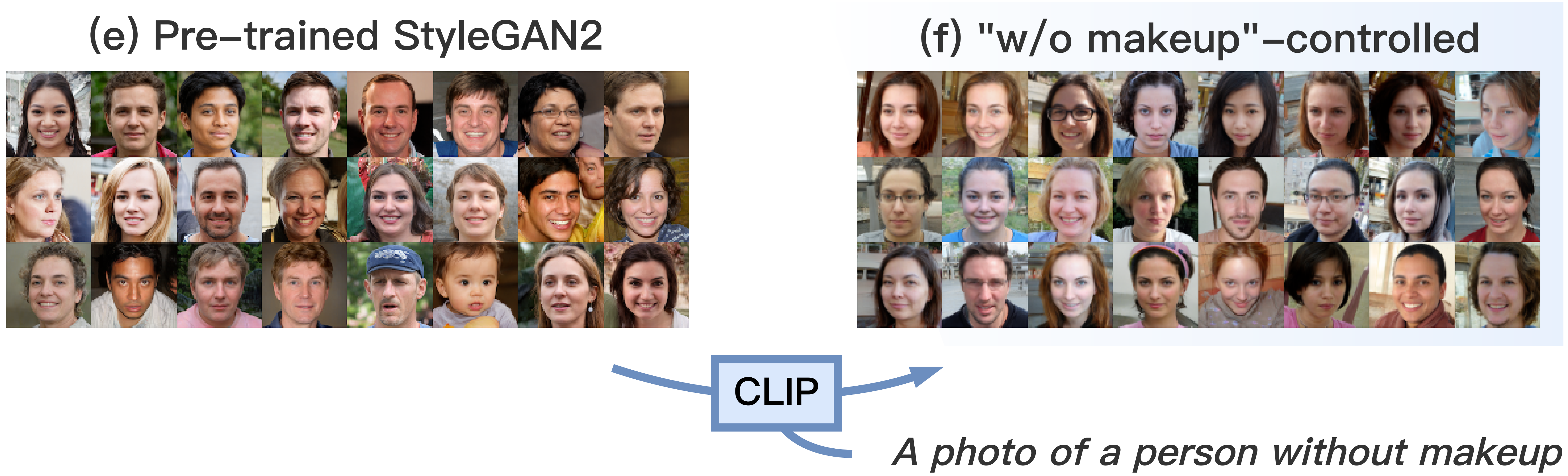

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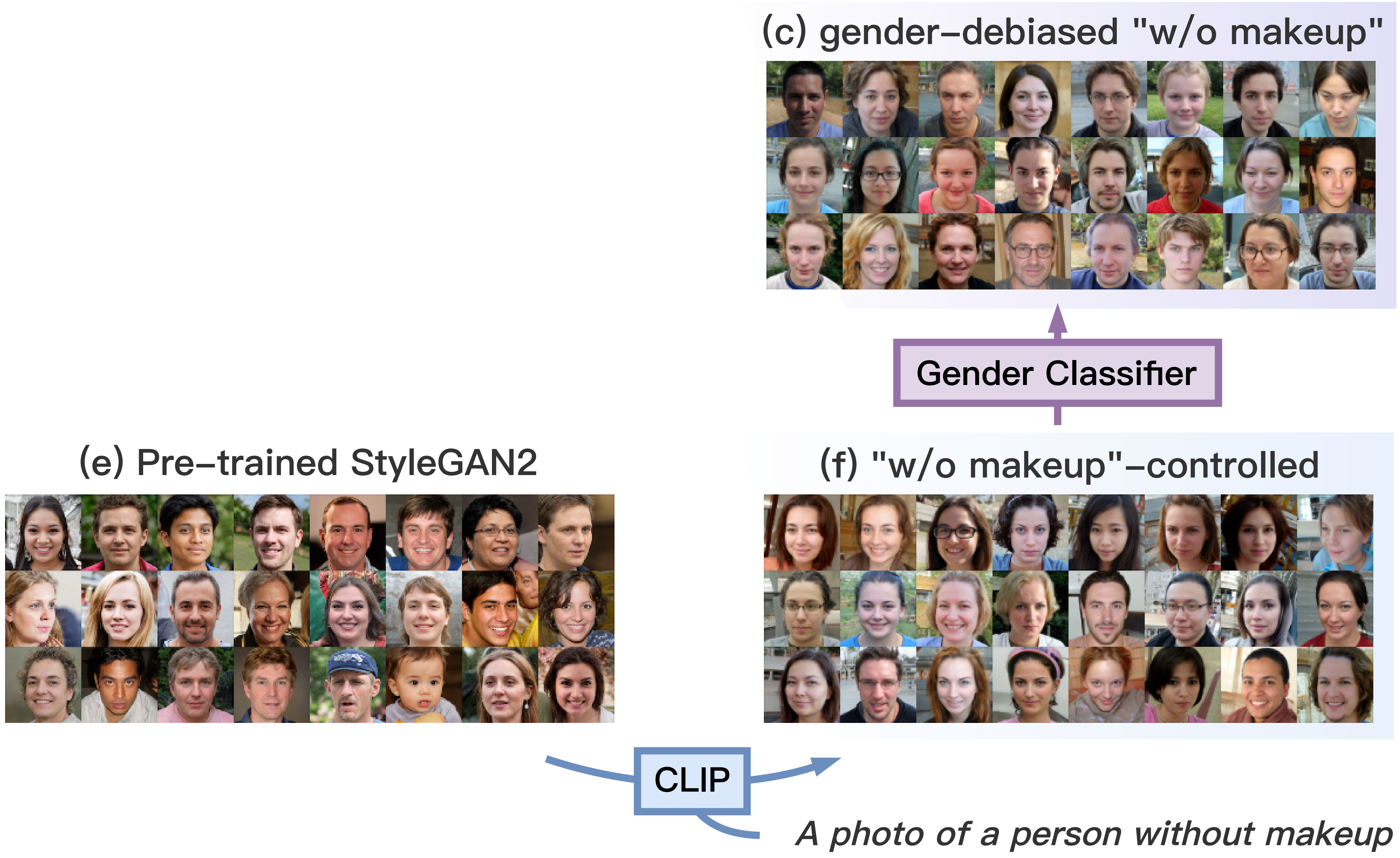

Framework overview

1. User specifies a generative model;

$$\boxed{G} \in \left\{ \begin{array}{c} \text{StyleGAN2} \\ \text{StyleNeRF} \\ \text{Diffusion AE} \\ \text{NVAE} \\ \cdots \end{array} \right\}$$

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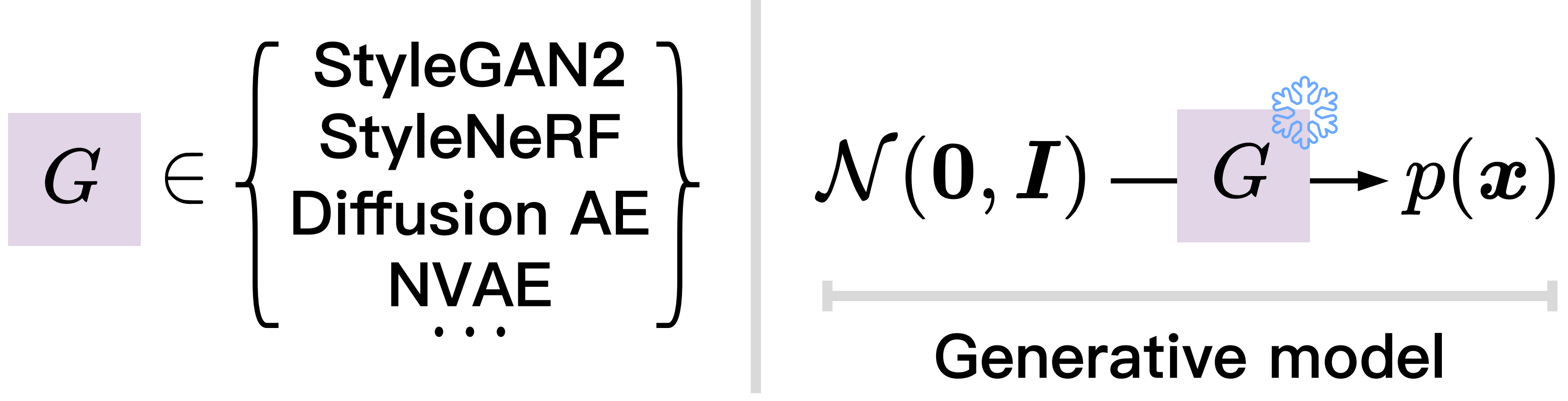
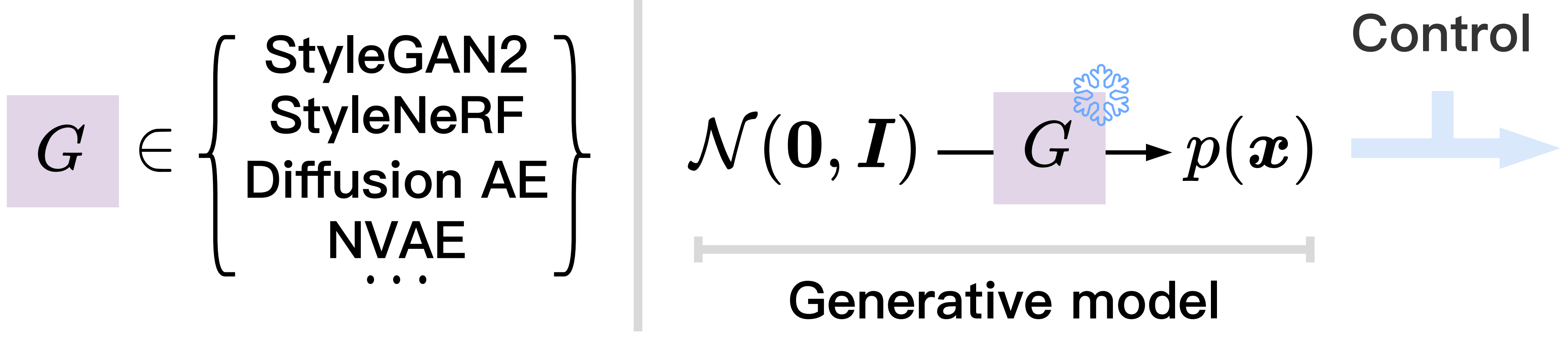


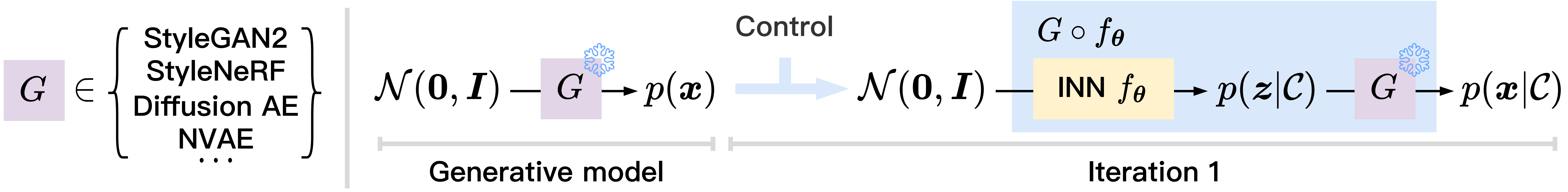
Framework overview

1. User specifies a generative model;
2. User specifies a control;



Framework overview

1. User specifies a generative model;
2. User specifies a control;
3. Approximates the control with an invertible neural network;



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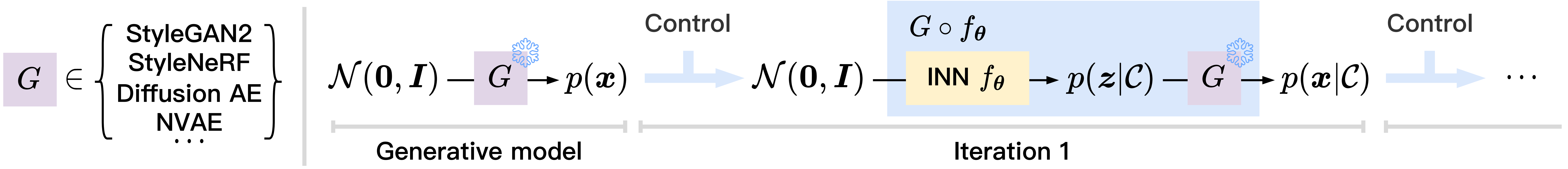

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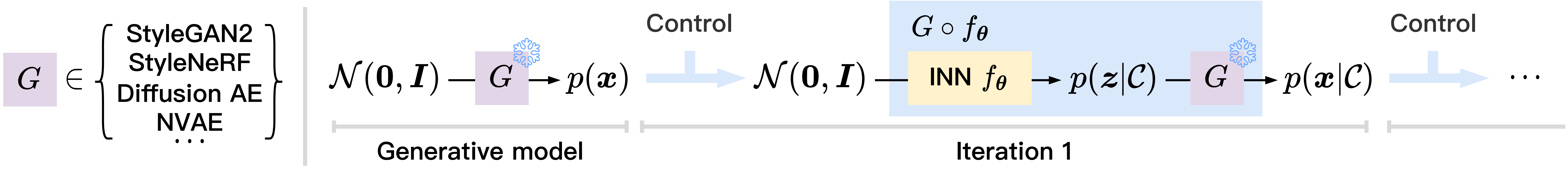


How to specify a control?

Image-space energy (lower is better)

Inverse graphics energy

$$E_{\text{inv-graphics}}(\boldsymbol{x}, \boldsymbol{\rho}) = d\langle f_{\mathcal{X}\to\mathcal{P}}(\boldsymbol{x}), \boldsymbol{\rho}\rangle^2$$

Classifier energy

$$E_{\text{classifier}}(\boldsymbol{x}, a) = -\log P(a|\boldsymbol{x})$$

CLIP energy

$$E_{\text{CLIP}}(\boldsymbol{x}, \boldsymbol{t}) = \frac{1}{L}\sum_{l=1}^{L}\left(1 - \cos\left\langle \text{CLIP}_{\text{img}}(\text{DiffAug}_l(\boldsymbol{x})), \text{CLIP}_{\text{text}}(\boldsymbol{t})\right\rangle\right)$$

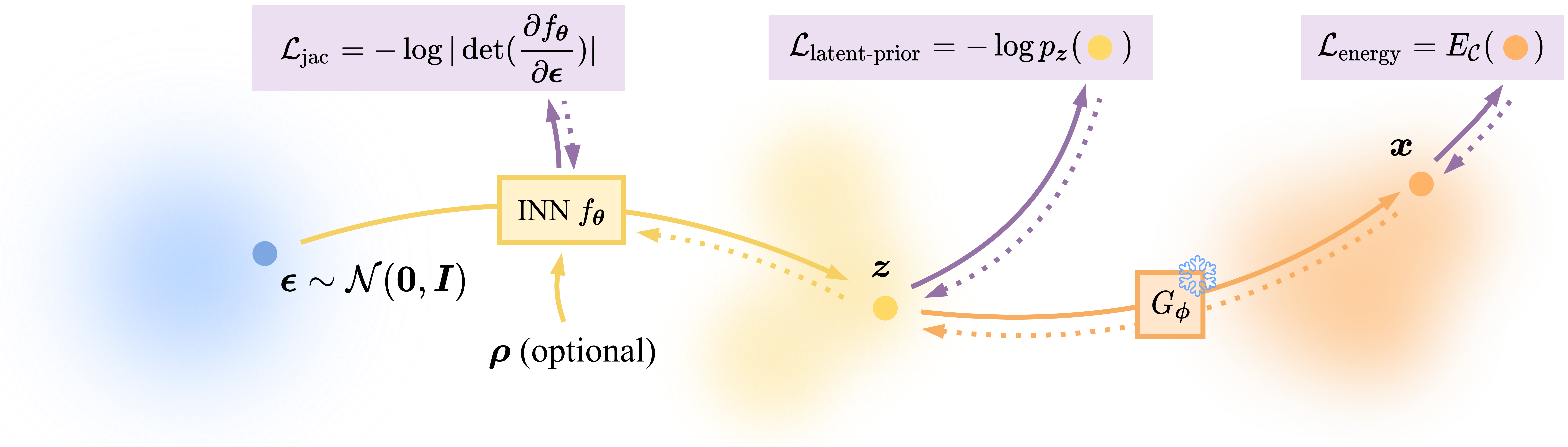
Moment constraint

$$p(\boldsymbol{x}|\mathcal{C}) = \underbrace{\arg\min_{p(\boldsymbol{x}|\mathcal{C})} \mathbb{D}_{\text{KL}}(p(\boldsymbol{x}|\mathcal{C})\|p_{\boldsymbol{x}}(\boldsymbol{x}))}_{\text{Deviation from the pre-trained distribution}}, \quad \text{s.t. } \underbrace{\mathbb{E}_{\boldsymbol{x}\sim p(\boldsymbol{x}|\mathcal{C})}[\boldsymbol{\gamma}(\boldsymbol{x})] = \boldsymbol{\mu}}_{\text{Moment constraint}}$$

How to approximate the control?

Optimize $\mathbb{D}_{\mathsf{KL}}(p_{\boldsymbol{\theta}}(\boldsymbol{z}) \| p(\boldsymbol{z}|\mathcal{C}))$ with a normalizing flow in the latent space

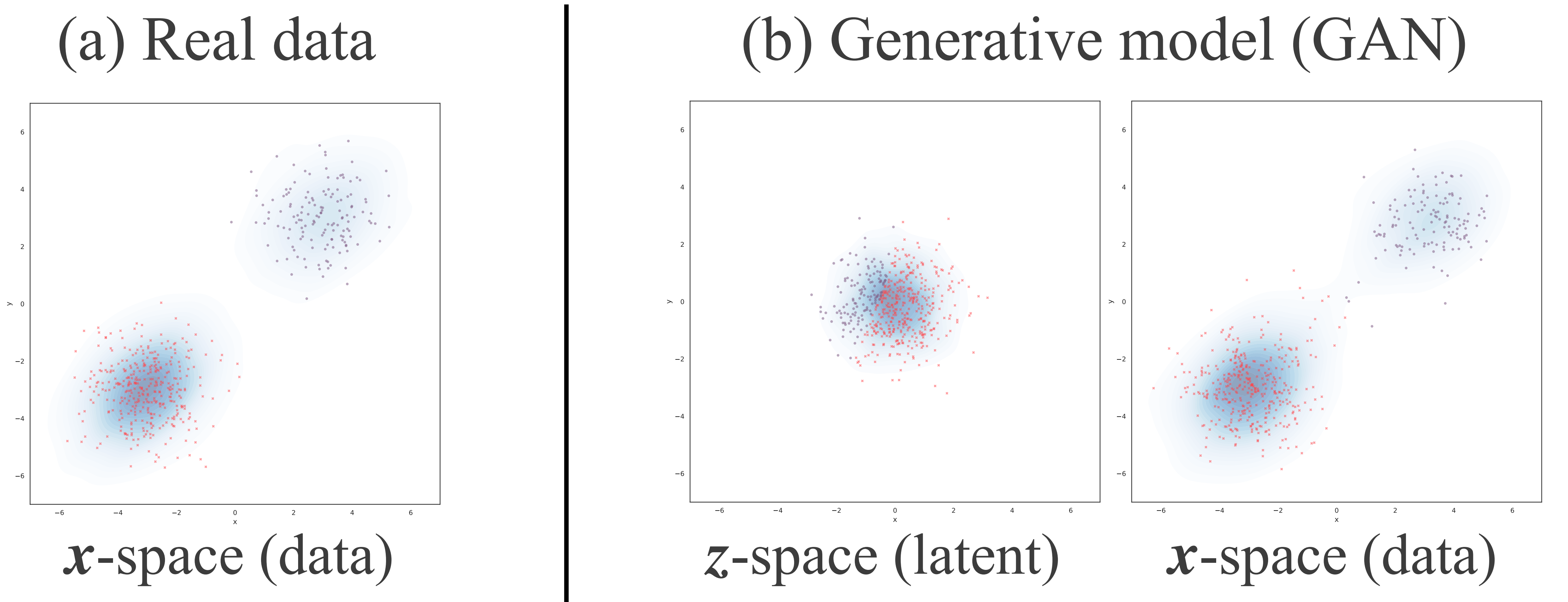
Training algorithm and objective:

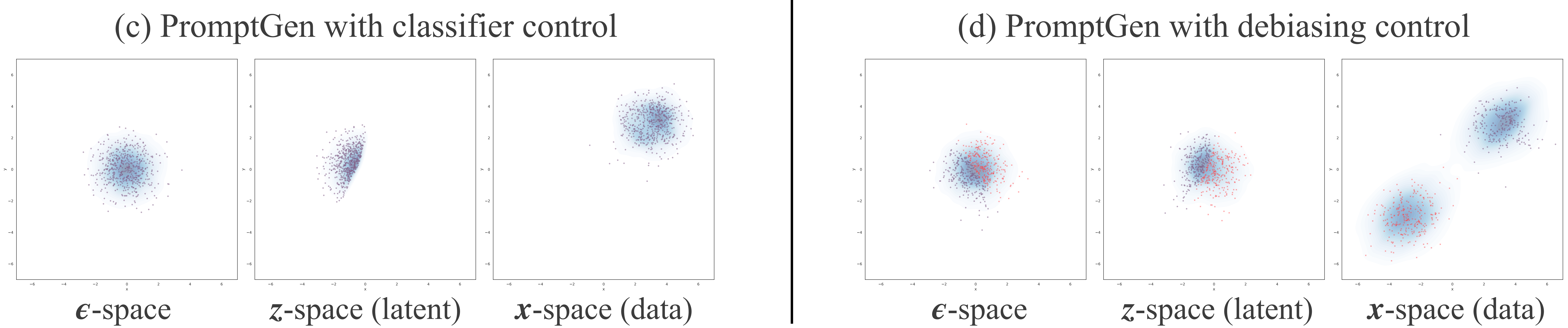


A synthetic 2D example

Real dist.
$$\begin{cases} p(\boldsymbol{x}) = 0.3 \cdot p(\boldsymbol{x} \mid a_1) + 0.7 \cdot p(\boldsymbol{x} \mid a_2) \\ p(\boldsymbol{x} \mid a_1) = N\left(\boldsymbol{x} \,\middle|\, (3,3)^\top, \boldsymbol{I}\right) \\ p(\boldsymbol{x} \mid a_2) = N\left(\boldsymbol{x} \,\middle|\, (-3,-3)^\top, \boldsymbol{I}\right) \end{cases}$$

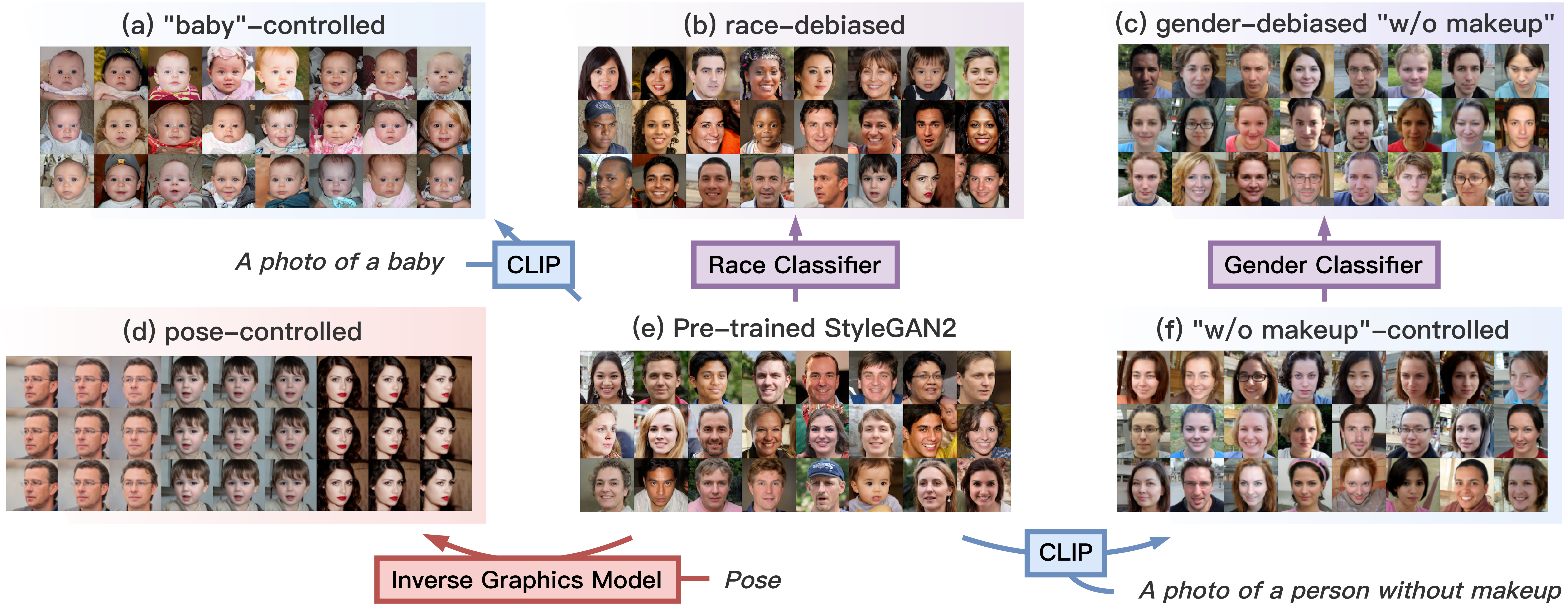
Fair classifier
$$p(a_i \mid \boldsymbol{x}) = \frac{p(\boldsymbol{x} \mid a_i)}{p(\boldsymbol{x} \mid a_1) + p(\boldsymbol{x} \mid a_2)}$$





Real data experiments

Check our paper for details



Code available