

Uncovering the Disentanglement Capability in Text-to-Image Diffusion Models

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Project



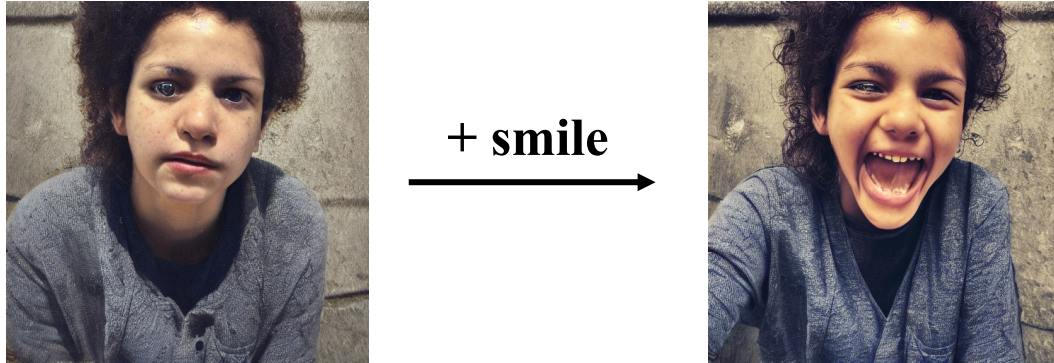
Presenter: Qiucheng Wu

Code



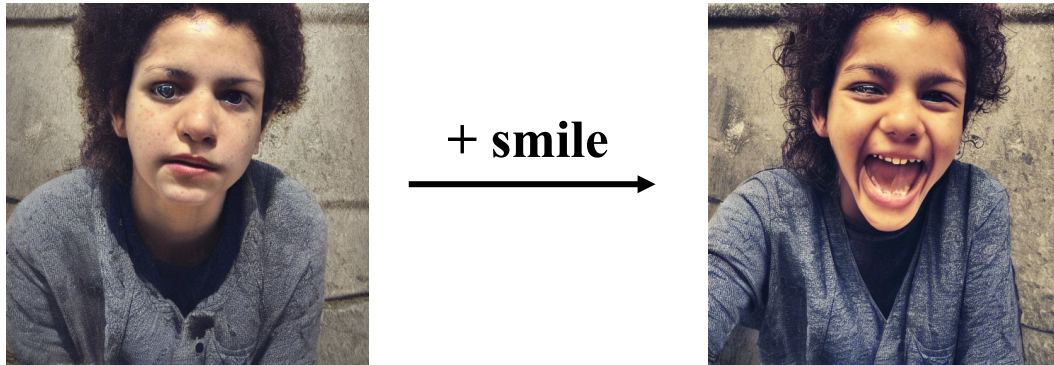
Overview

- **Disentanglement** is a desired property in generative models.
 - E.g., a **disentangled** model can generate a person with **expression changed** but **identity preserved**.



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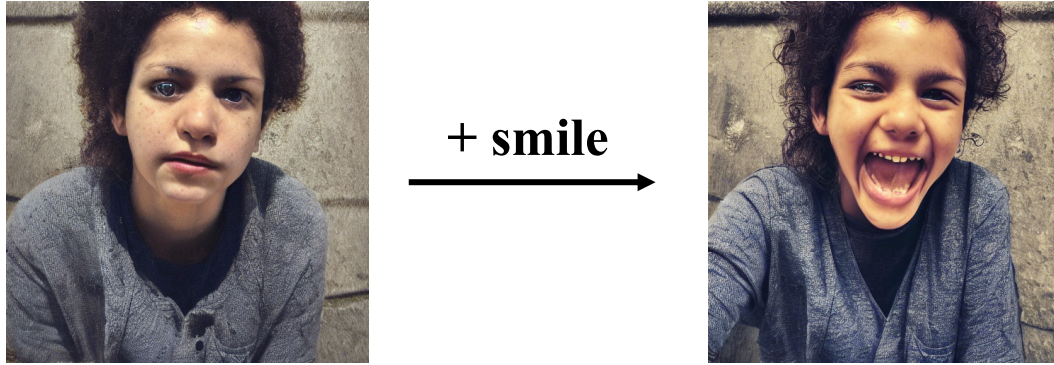


- Many generative models (e.g., GANs) inherently have this disentanglement property.
- Our research question:

*Does a pre-trained **text-to-image model** have the **disentanglement capability**?*

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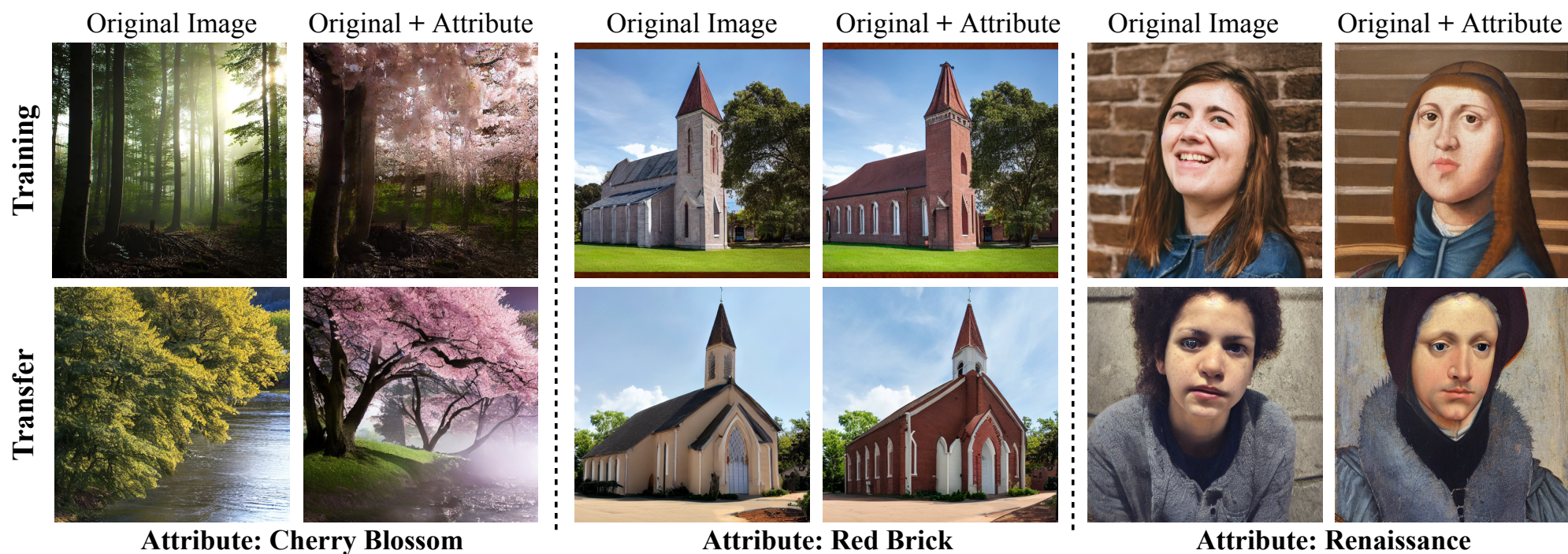
- Many generative models (e.g., GANs) inherently have this property.
- Our research question:

*Does a pre-trained **text-to-image model** have the **disentanglement capability**?*

Yes!

Overview

- In this work, we discover the **disentanglement capability** in **text-to-image diffusion** model.
- Our finding leads to a simple disentangle editing framework.
- The framework can effectively edit a wide range of attributes without changing the contents.



Disentanglement in Diffusion: Preliminary Exploration

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$\mathbf{c}^{(0)}$ (style-neutral): “A photo of person”

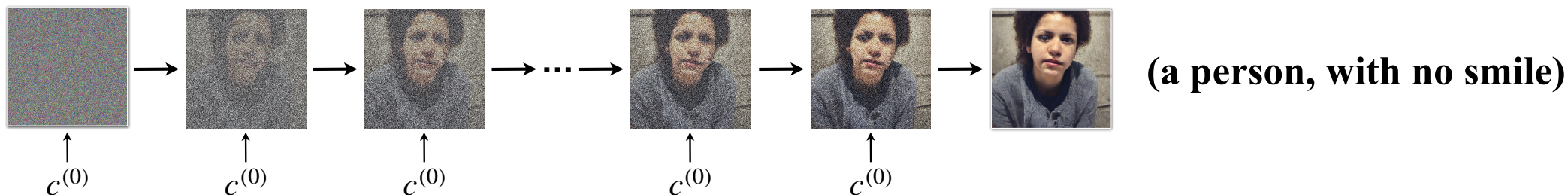
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Disentanglement in Diffusion: Preliminary Exploration

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- **Original: Directly feed $c^{(0)}$.**

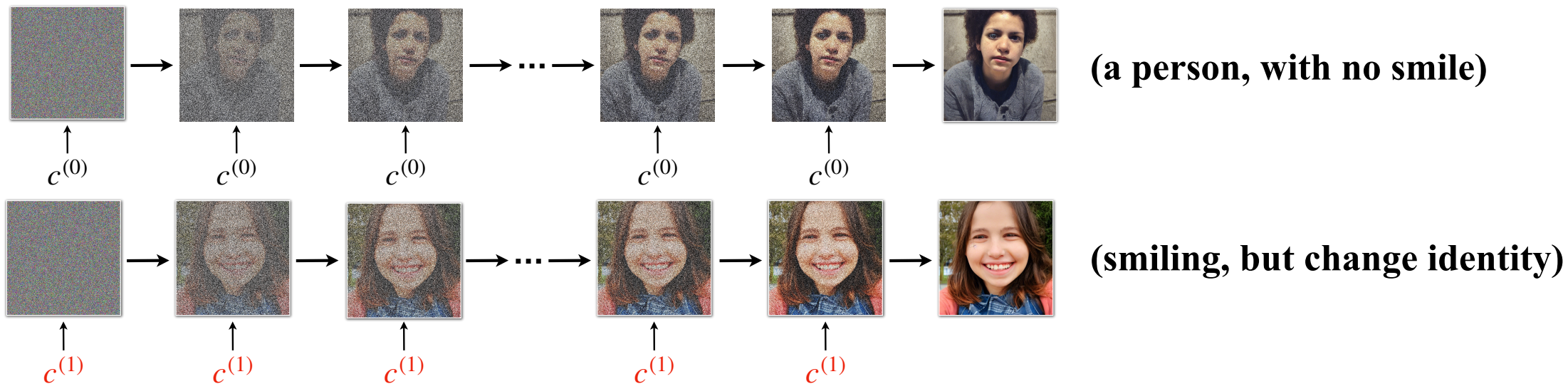


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- **Case 1: Full replacement**

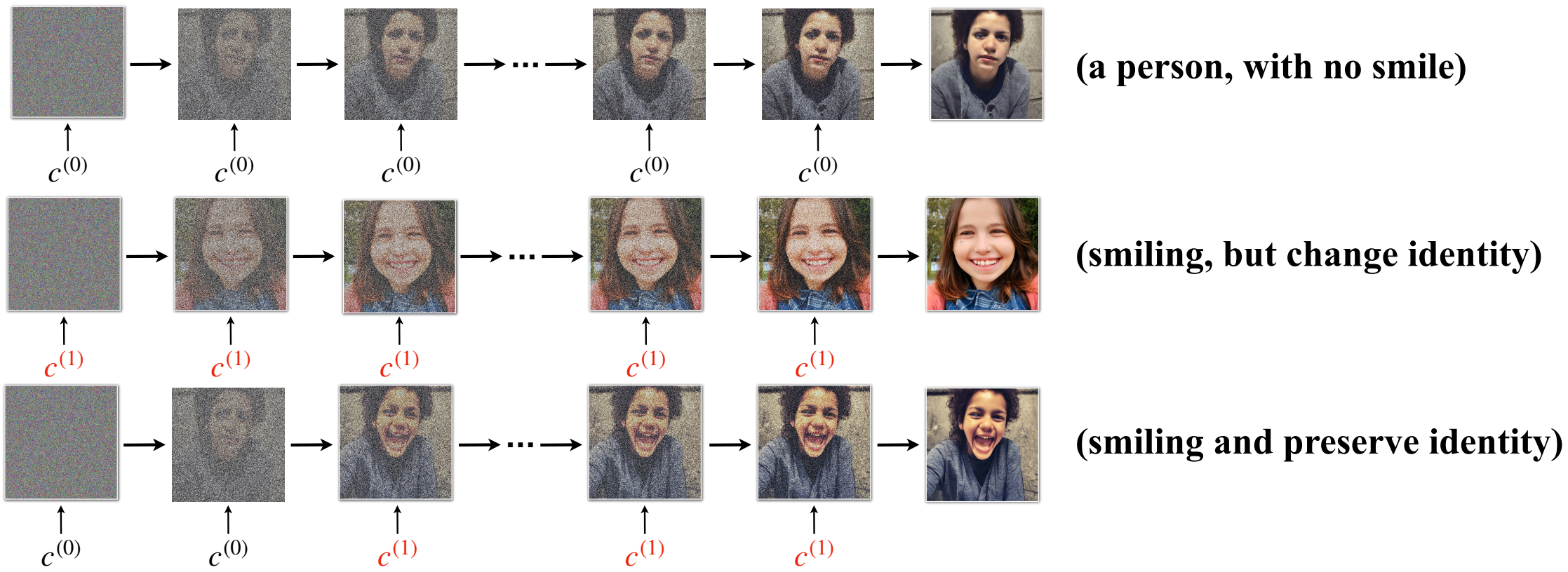


Disentanglement in Diffusion: Preliminary Exploration

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- **Case 2: Partial replacement**

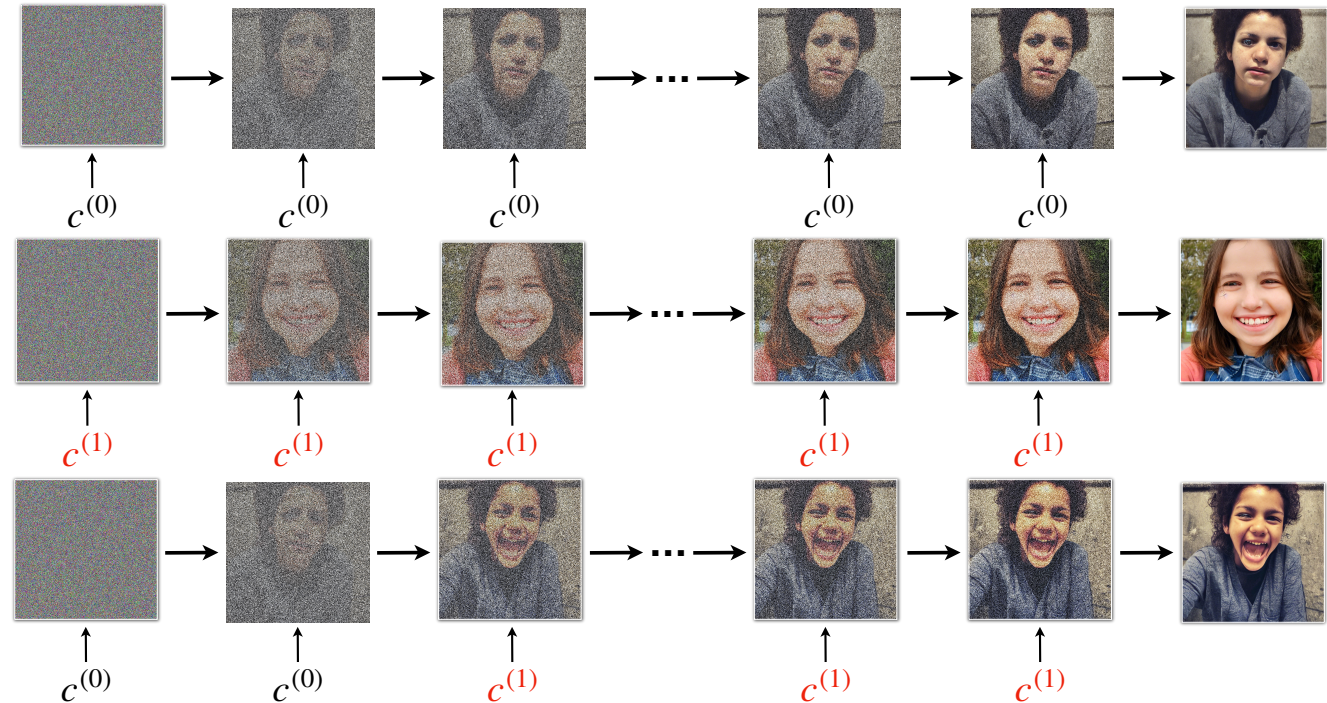


Disentanglement in Diffusion: Preliminary Experiment

- Goal: Generate an image of the **same person** with only **facial expression** changed.
- Consider two text input embeddings:

$c^{(0)}$: “A photo of person”

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- **Conclusion:**

- The stable diffusion model inherently enables disentanglement.
- The disentanglement can be triggered by **partially replacing the text embeddings**.

Optimizing for Disentanglement

- Our method optimizes a soft combination of two text embeddings:

- $\mathbf{c}^{(0)}$: “A castle”
- $\mathbf{c}^{(1)}$: “A children drawing of castle”

$$\left. \begin{array}{l} \mathbf{c}^{(0)} \\ \mathbf{c}^{(1)} \end{array} \right\} \mathbf{c}_t = \lambda_t \mathbf{c}^{(1)} + (1 - \lambda_t) \mathbf{c}^{(0)}$$

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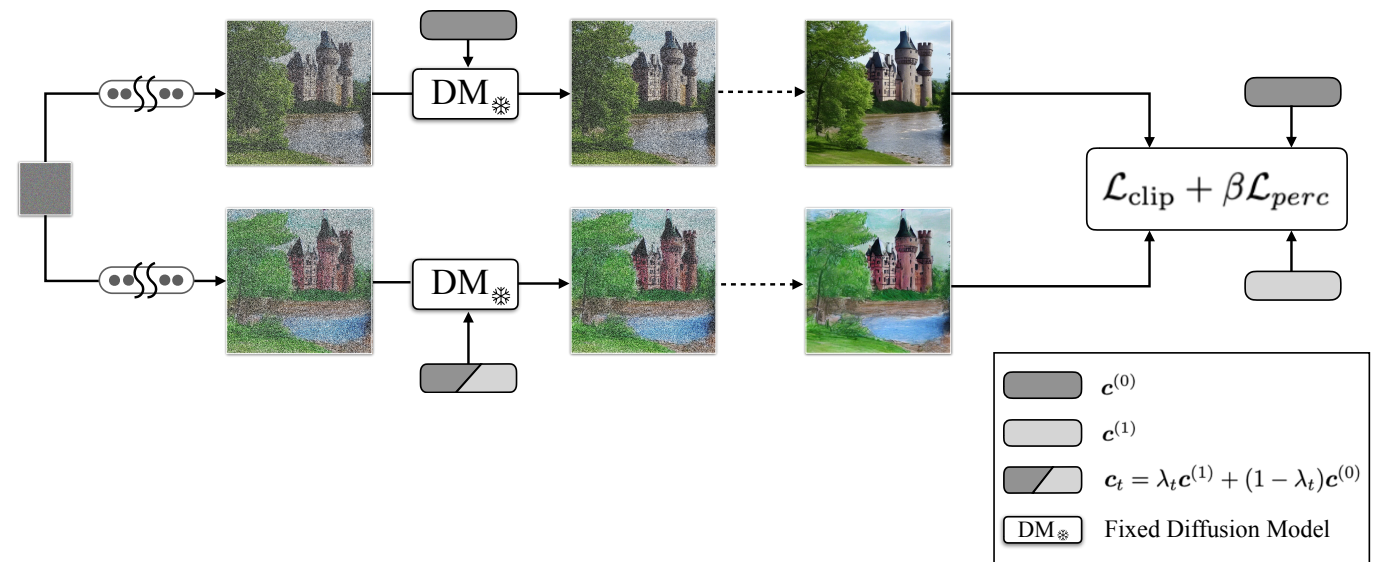
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- The stable diffusion conditions on \mathbf{c}_t to synthesize image with modified style (children drawing).

- λ_t Optimization:

- CLIP loss to control style
- Perceptual loss to preserve content



Optimizing for Disentanglement

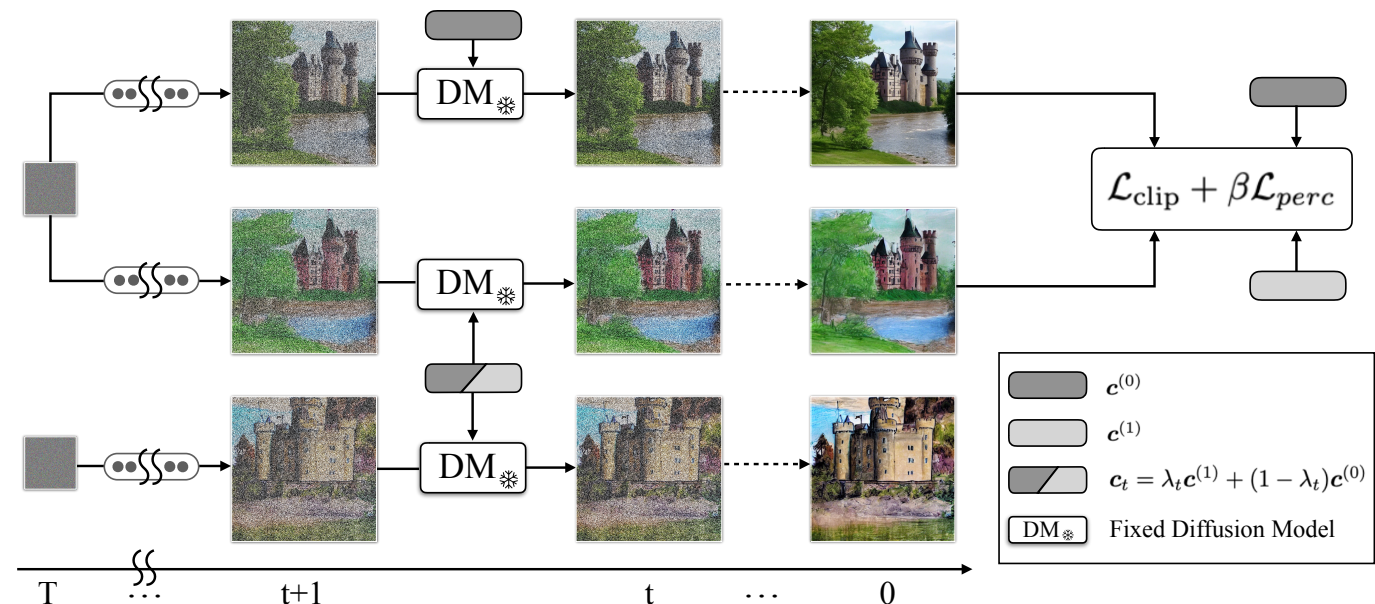
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- λ_t can be transferred to novel images and lead to similar editing effects.



Experiment: Disentanglement Capability

- Our method is able to disentangle a wide range of attributes.
 - Global attributes: scenery styles, architecture materials, etc.
 - Local attributes: facial expressions, etc.

Training

Original Image

Original + Attribute



Original Image

Original + Attribute



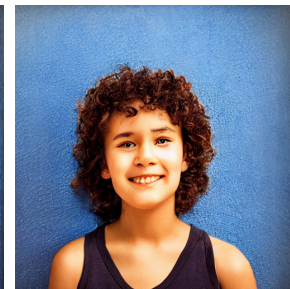
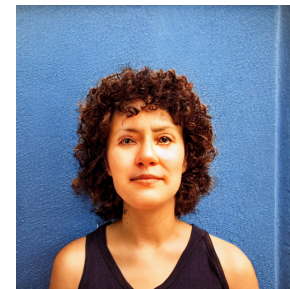
Original Image

Original + Attribute

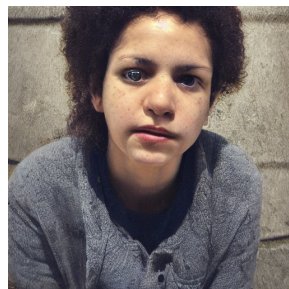


Original Image

Original + Attribute



Transfer



A street view, Cyberpunk style

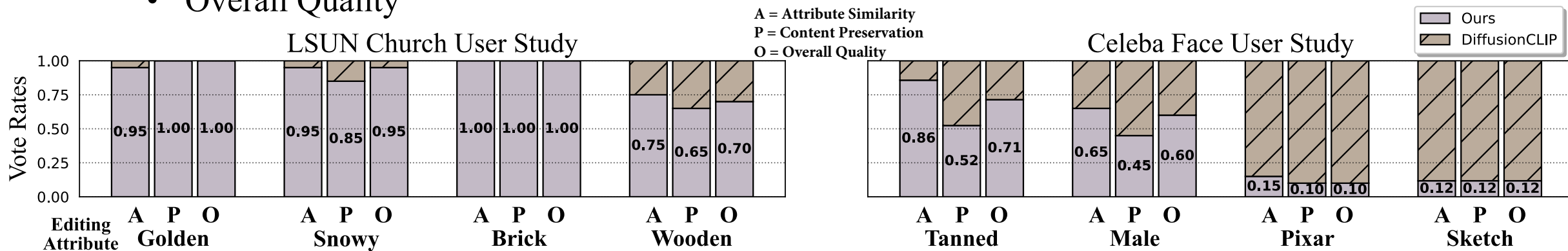
A photo of church exterior, golden

A photo of person, Egyptian mural style

A photo of person, young

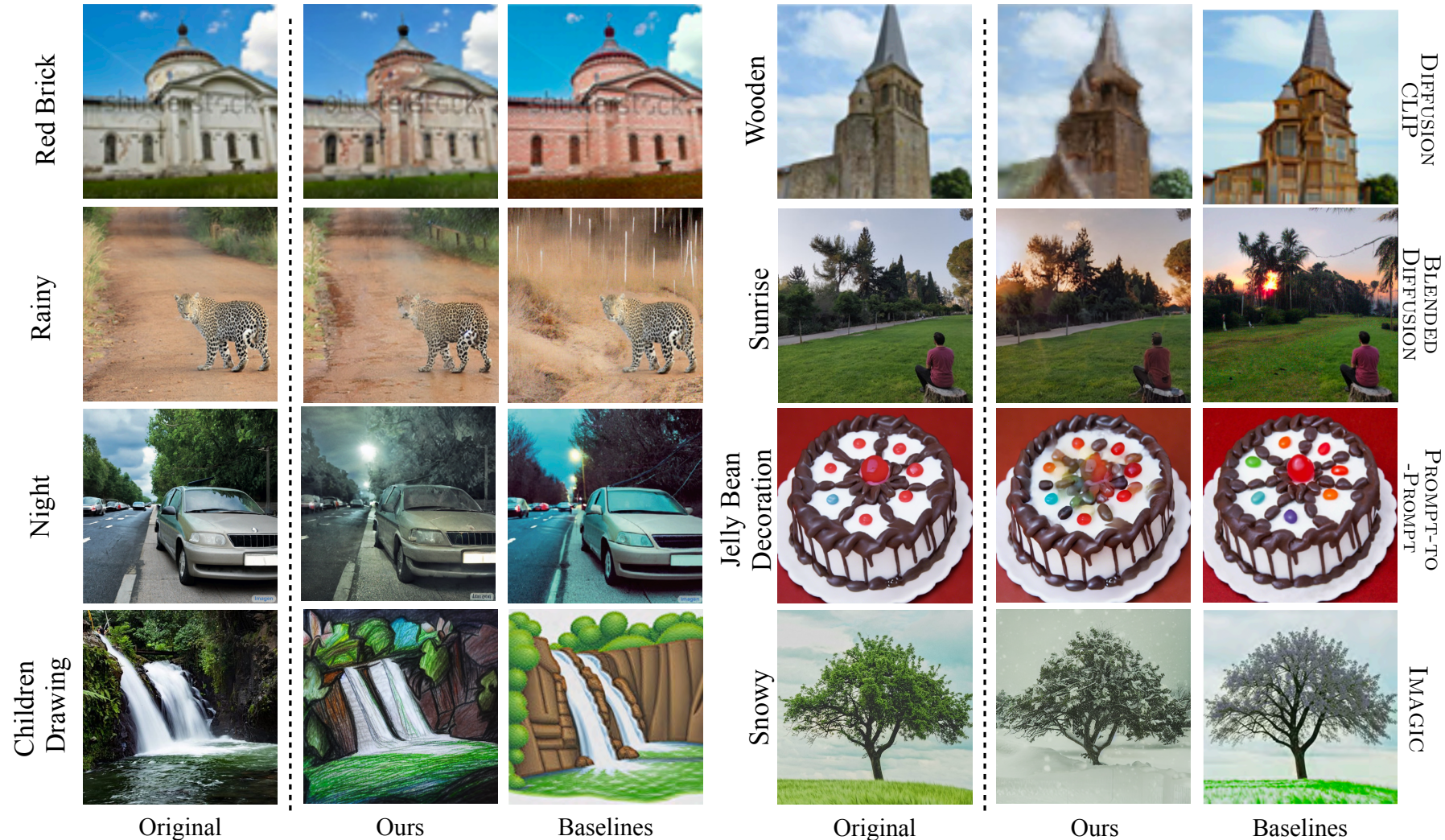
Experiment: Image Editing

- Based on the subjective study, our method shows advantages in image editing.
 - Datasets: LSUN Church (Scene), Celeba Face (Person)
 - Baseline: DiffusionCLIP
 - Our method outperforms DiffusionCLIP in 6 out of 8 attributes with following metrics:
 - Attribute Similarity
 - Content Preservation
 - Overall Quality



Experiment: Image Editing

- Our method shows competitive editing performance compared with strong baselines.



Limitations

	Scenes	Person
✓ Global	Styles (children drawing, cyberpunk, anime), Building appearance (wooden, red brick), Weather & time (sunset, night, snowy)	Styles (renaissance, Egyptian mural, sketch, Pixar) Appearance (young, tanned, male)
Local	Cherry blossom, rainbow, foothills	Expressions (smiling, crying, angry)
✗ Small edits	Cake toppings, remove people on the street	Hats, hair colors, earrings

- We explore a wide range of attributes and find **small edits** are hard to be disentangled.
- Diffusion model has weaker control over these fine-grained details.



A photo of person, wearing hat



A cake, jelly beans decorations

Thank you!

Project



Code

