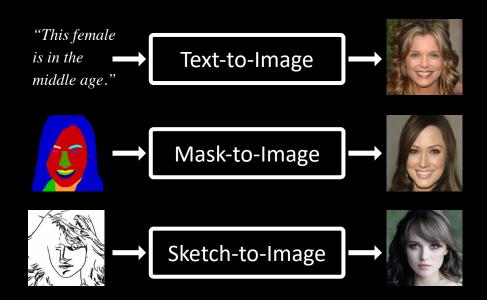


#### Motivation

Existing diffusion models are mainly uni-modal, that is., driven by only one modality of condition.



. . . . . .

However, in real applications, users want multi-modal control. See examples next slide.

## Task Highlight

### (A) Multi-Modal Face Generation

given multi-modal controls

"This female is in the middle age."

synthesize high-quality image consistent with the controls



## Task Highlight

### (B) Multi-Modal Face Editing

given input image

and target multi-modal conditions

edit the image to 1) satisfy the target conditions while 2) preserving the facial identity





"This man has beard of medium length. He is in his thirties."

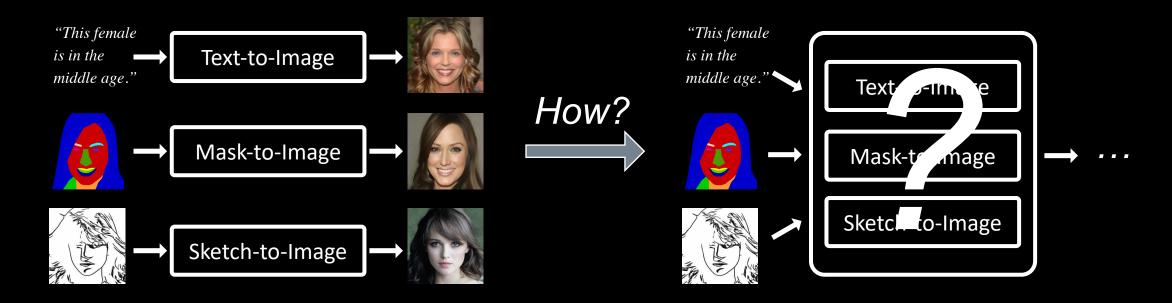
. . . . . .



### Motivation

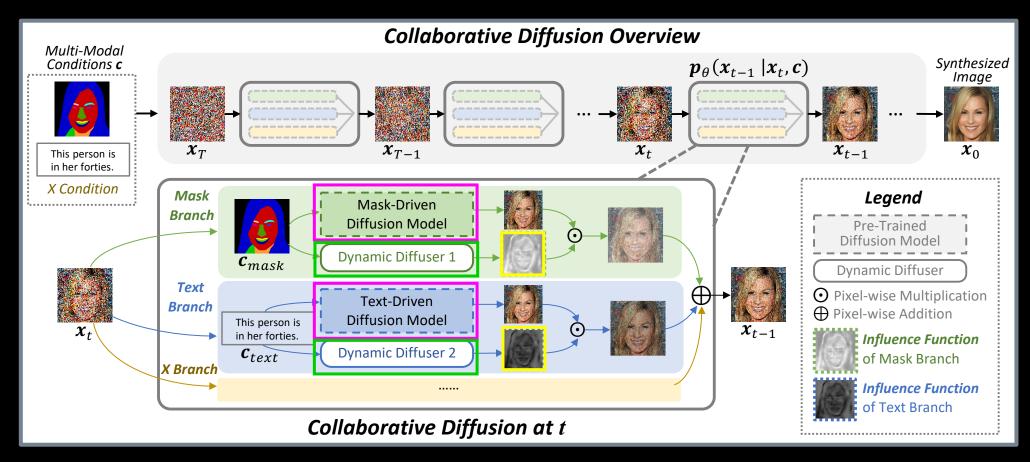
#### **Uni-Modal Diffusion Models**

#### **Multi-Modal Control**



.....

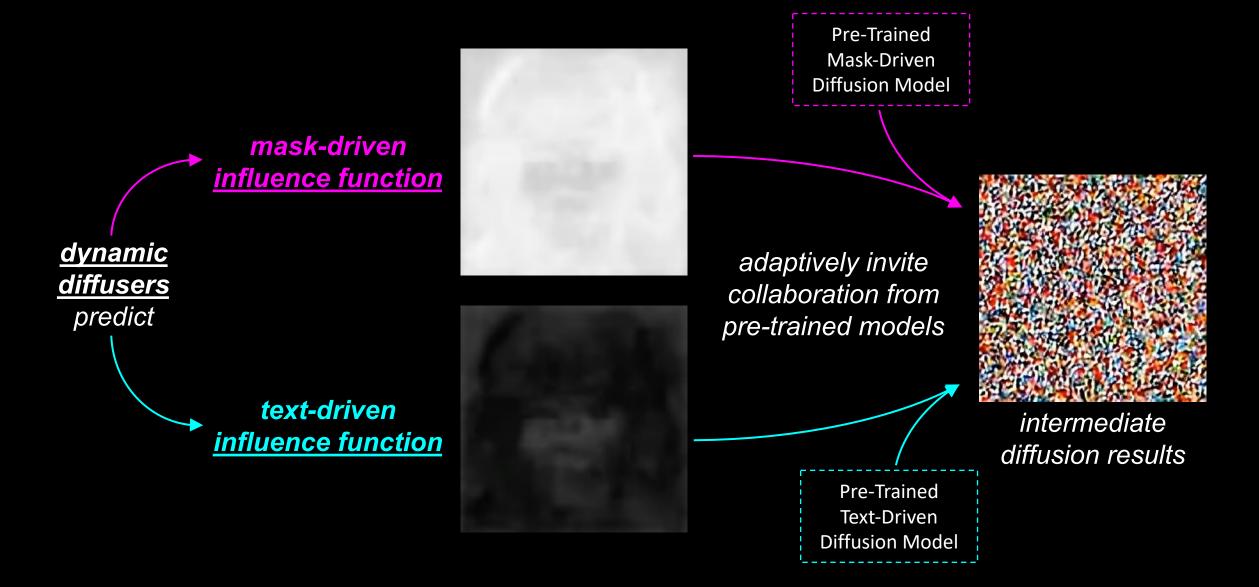
### Collaborative Diffusion Framework



During the reverse process of diffusion models:

- Pre-trained uni-modal diffusion models collaborate to achieve multi-modal control without being re-trained
- Dynamic diffusers predict spatial-temporal influence functions to enhance or suppress contributions from each pre-trained model

# **Dynamic Diffusers** predict **Influence Functions**



## Visual Results: Generation

Mask Condition Generated Images Text Condition This man has beard of medium length. He is in his thirties. This woman looks very old. She is a teenager. This female is in the middle age.

## Visual Results: Editing

Input Image





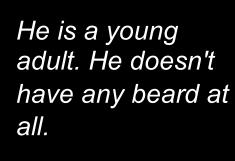
Target Mask





Target Text





Edited Image













### Summary

- We exploit pre-trained uni-modal diffusion models. They can collaborate to achieve multi-modal control without being re-trained.
- Collaborative Diffusion can be used to extend arbitrary uni-modal approach (e.g. face generation, face editing, motion generation, 3D generation) to the multi-modal paradigm.



Project Page



Code