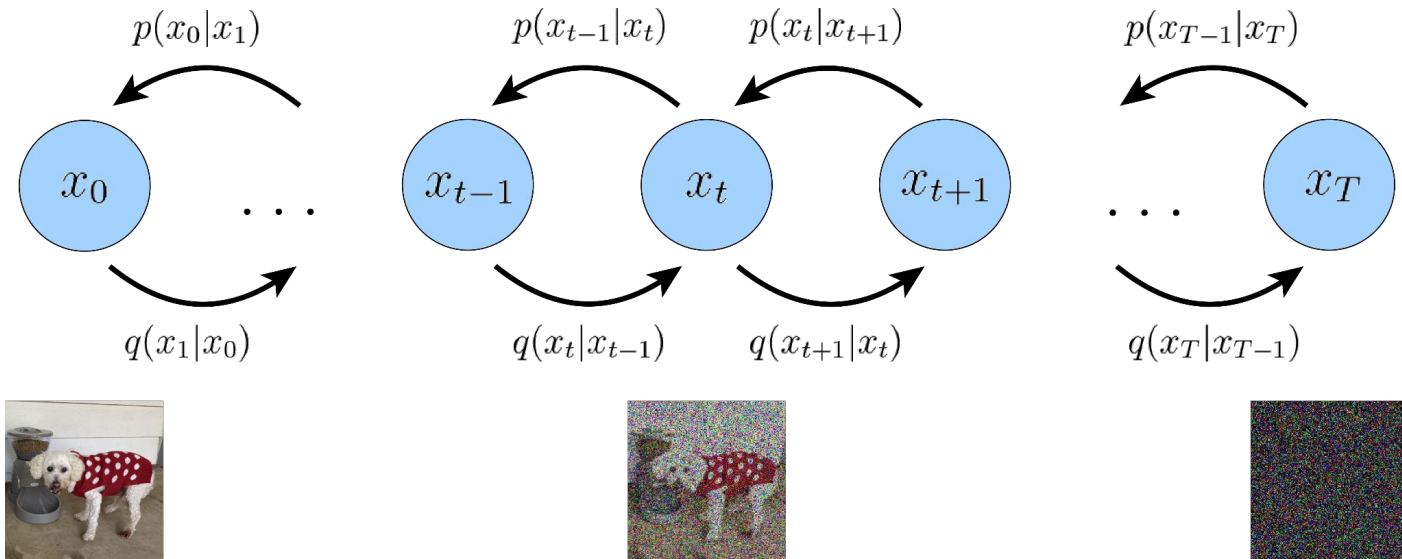


# Image Inpainting with Conditional Diffusion Model

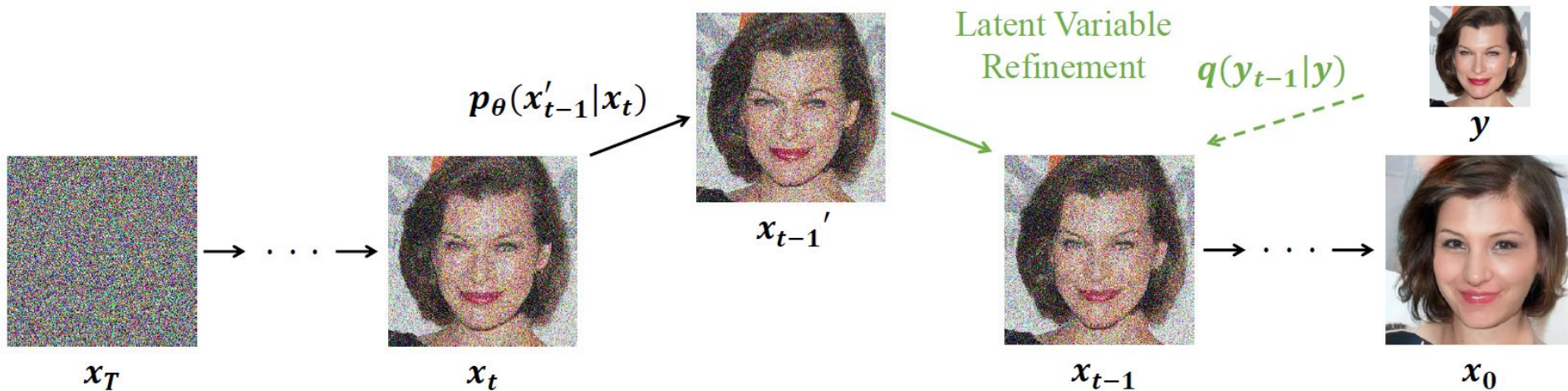
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  - Inpainting (un/blind)
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# Introduction



# Introduction (ILVR)

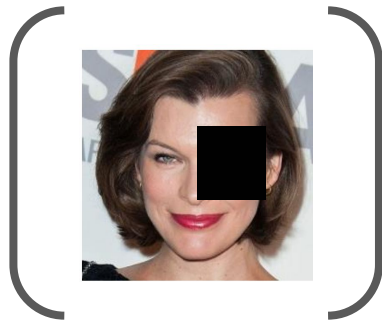


Important params:

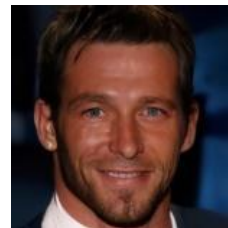
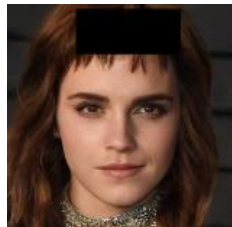
- Diffusion steps
- Timespace-respacing
- Range-t
- Up/Down sampling factor

# Task 1: Blind mask Inpainting

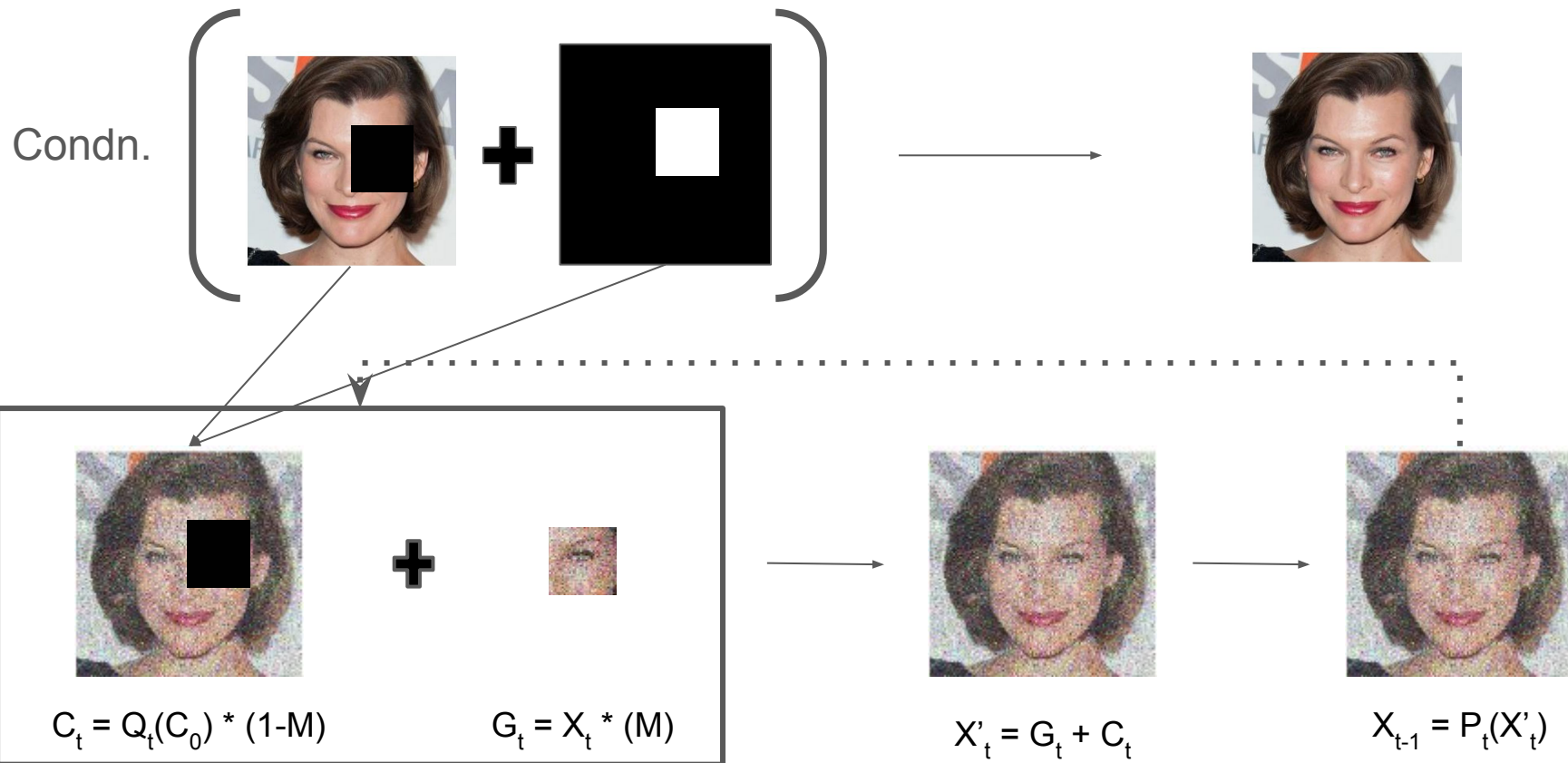
Condn.



# Task 1: Blind mask Inpainting (Outputs)



# Task 1: Known mask Inpainting

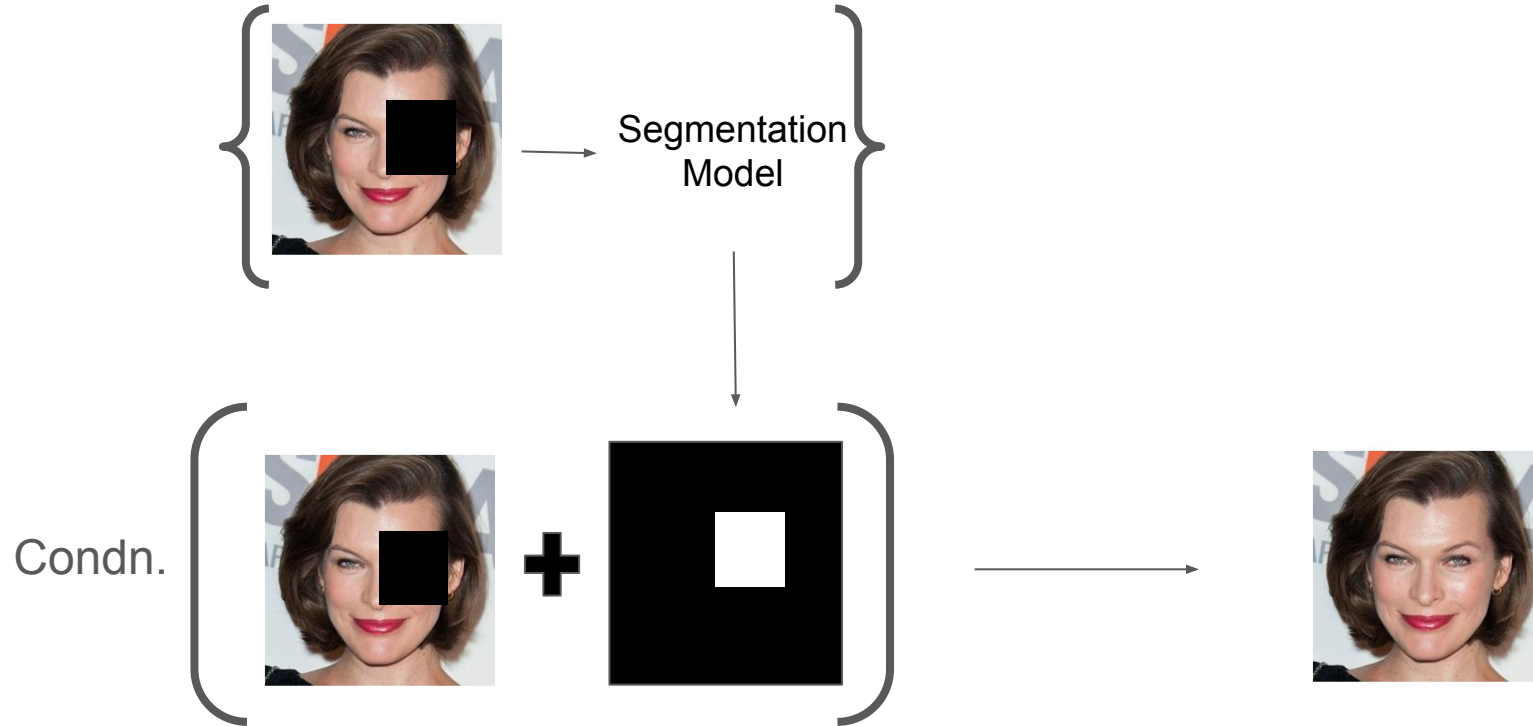


# Task 1: Known mask Inpainting

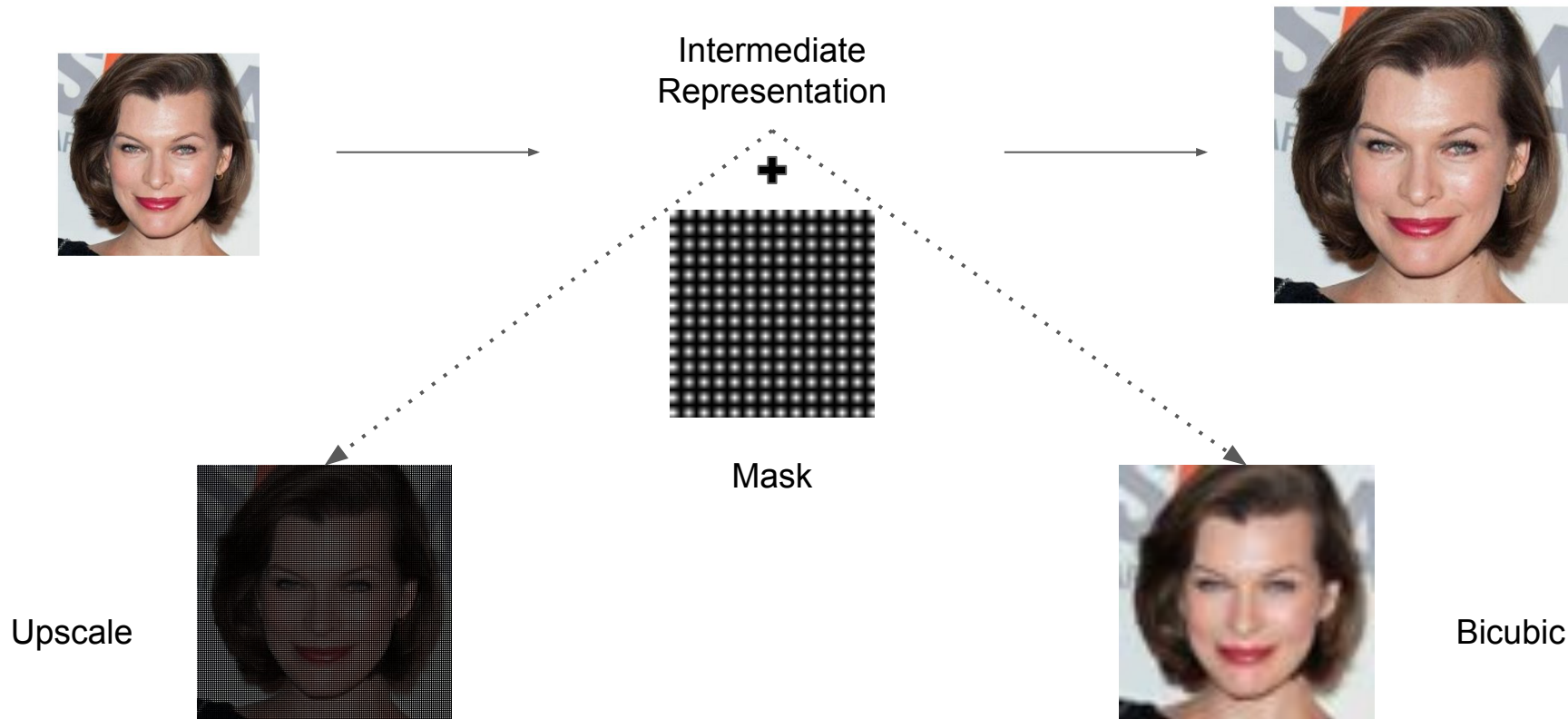




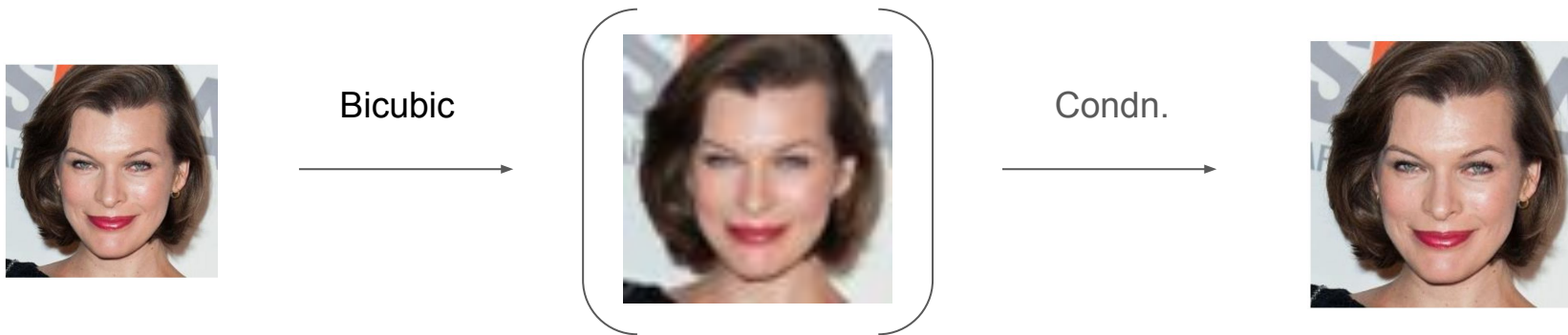
# Task 1: Back to Blind mask Inpainting (+ segmentation)



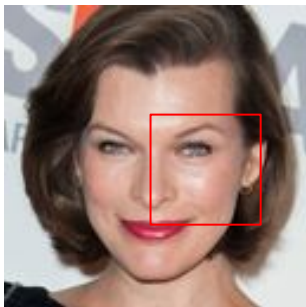
## Task 2: Super resolution (2X)



## Task 2: Super resolution (2X)



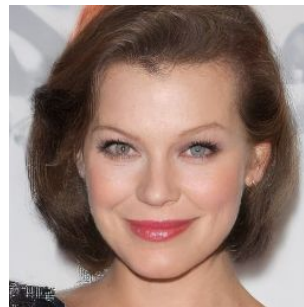
## Task 2: Super resolution (Output)



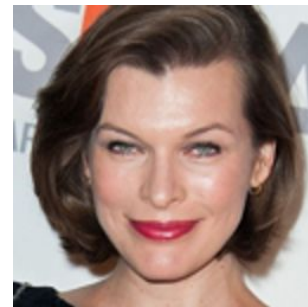
Input



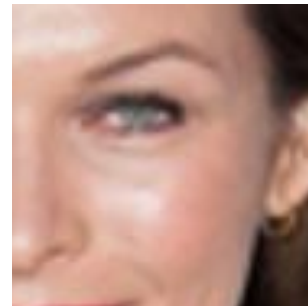
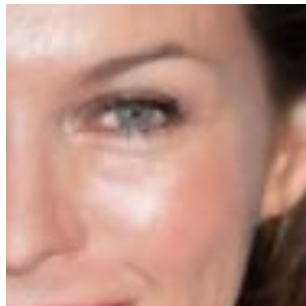
Bicubic cond.



As inpainting



Bicubic extrapolation



# Results (Inpainting)

	Blind	Known Mask (small)	Known Mask (Large)
LPIPS	0.175	0.035	0.115
SSIM	0.802	0.965	0.843

# Results (SR)

	Bi cubic cond.	As Inpainting	Bicubic
PSNR	28.331	22.640	33.747
SSIM	0.984	0.943	0.994

# Conclusion

- Conditional diffusion models are sufficient to inpaint for small masks, but as the mask size increases there occurs an issue of mode-collapse.

This issue could be overcome by providing the mask as an additional channel information to the model.

- Conditional diffusion is capable of generating high resolution outputs given the lower resolution counterparts, but these outputs fare worse on the metric because of some additional variability that creeps in from the generation process. (visually better but worse in metric)

Thank you