Metropolis-Hastings Generative Adversarial Networks

Ryan Turner, Jane Hung, Eric Frank, Yunus Saatci, Jason Yosinski

Poster #201

Uber AI

Typical GAN training

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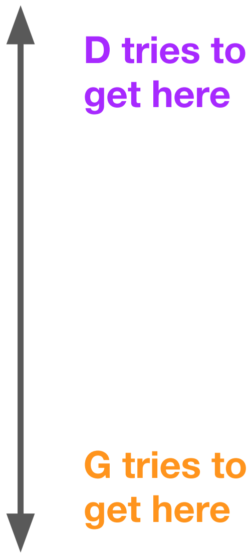

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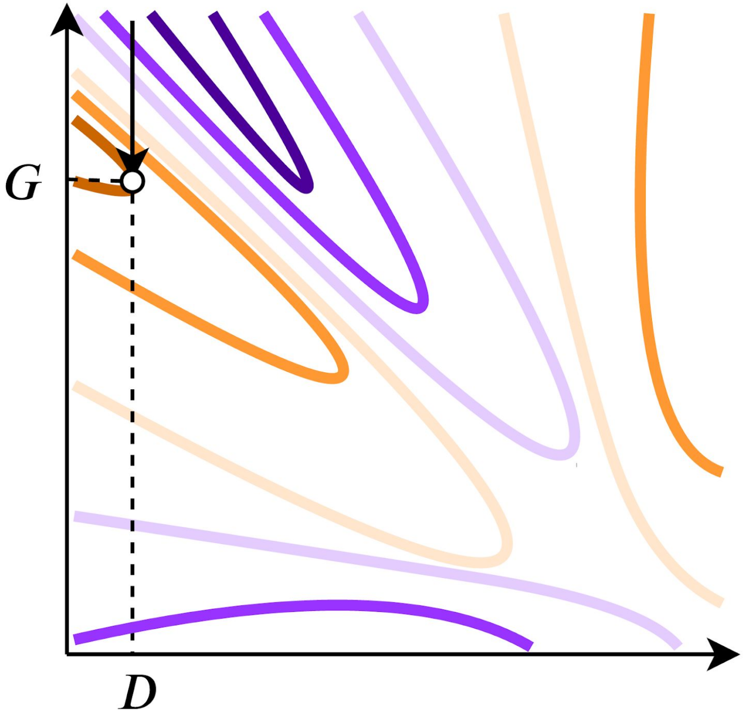
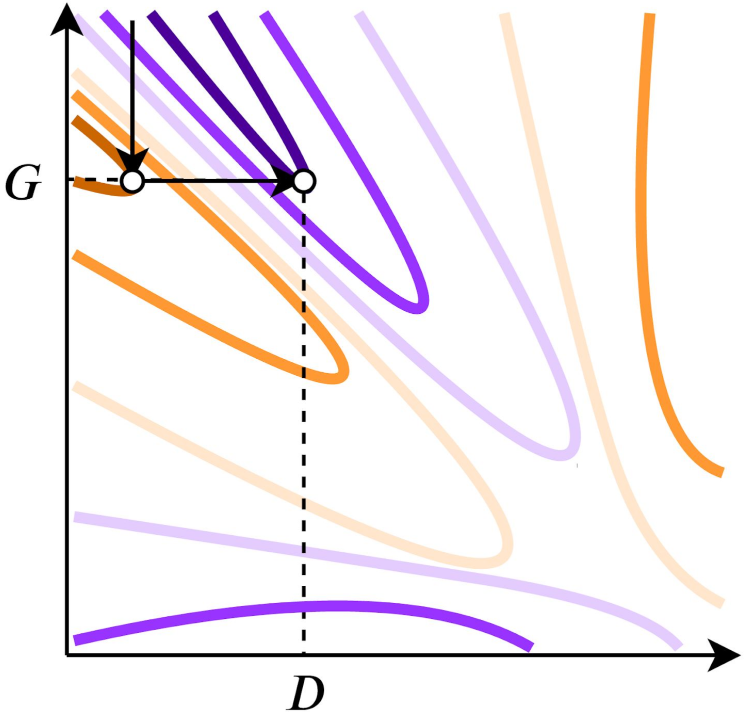
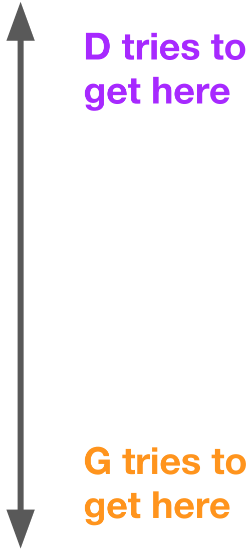


D tries to get here

G tries to get here

Typical GAN training





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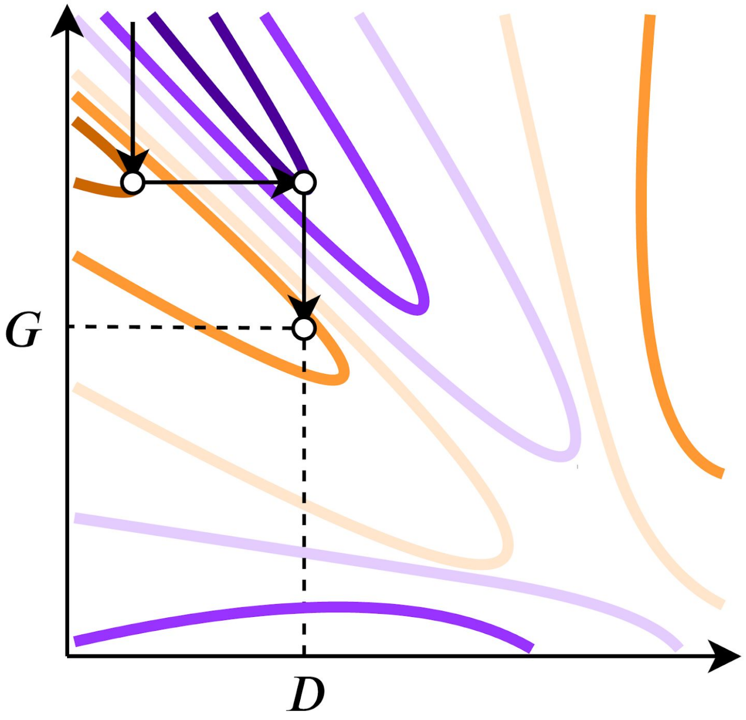

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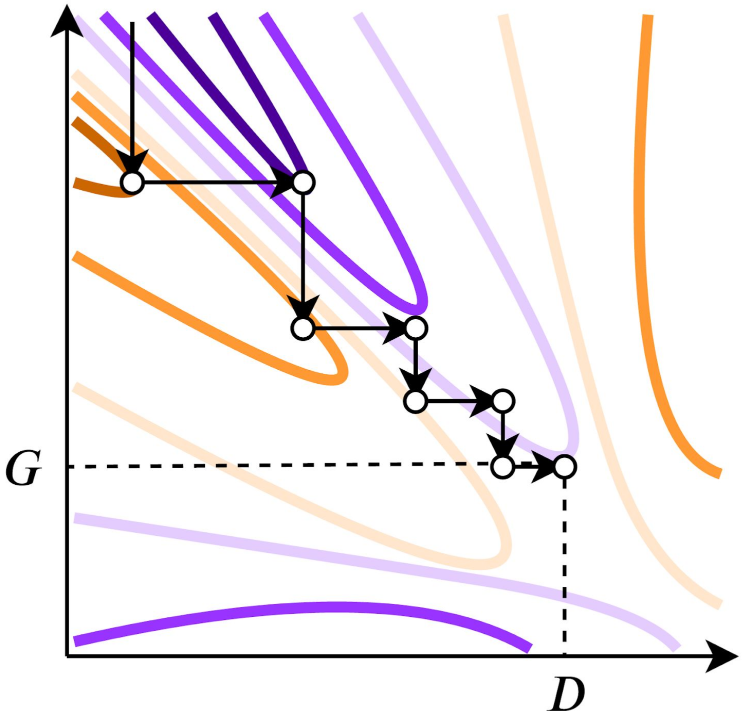
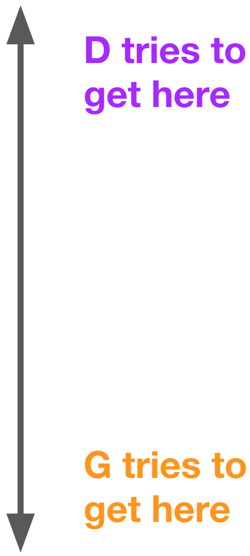
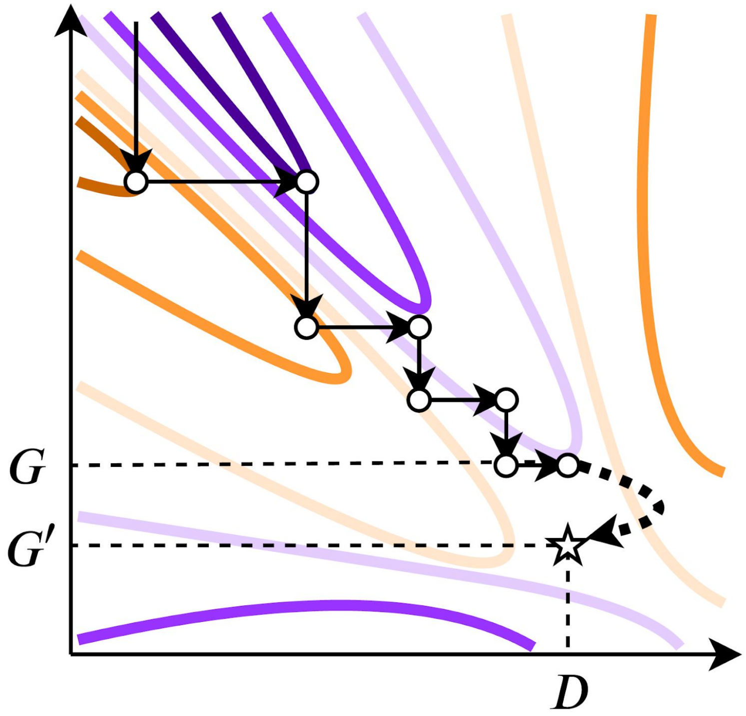
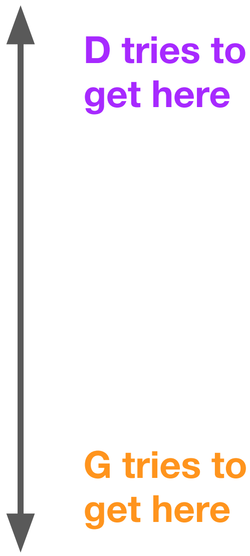
Typical GAN training … gets stuck





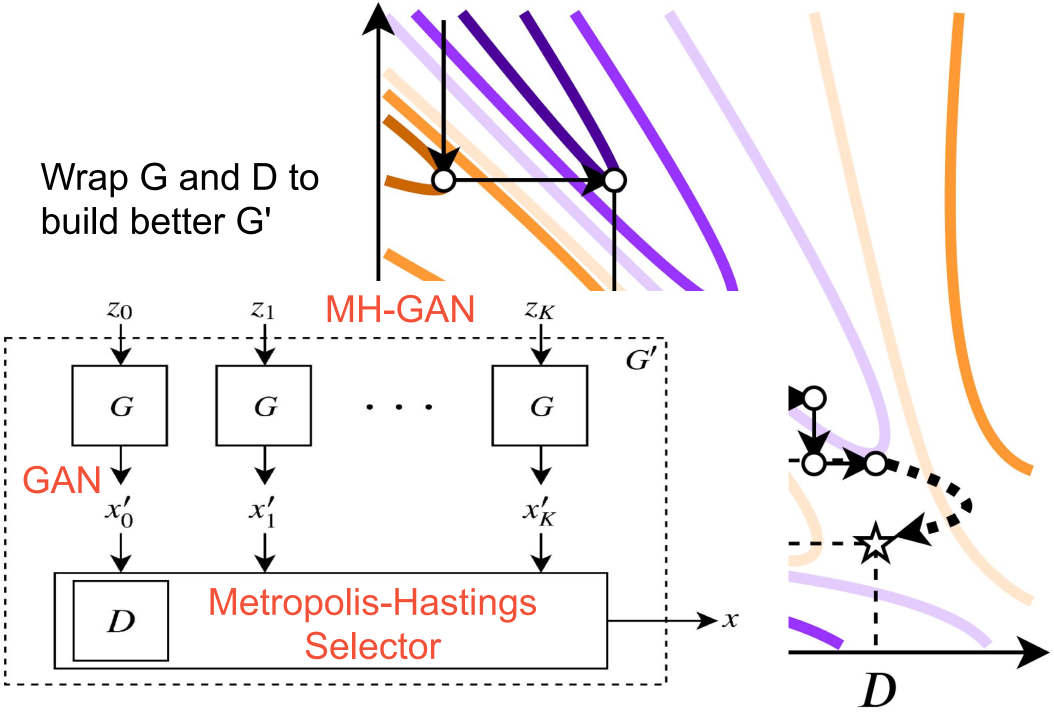
MH-GAN helps you reach the star

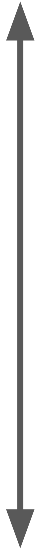




MH-GAN helps you reach the star

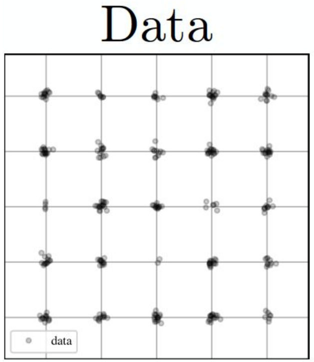
- Wrap G and D to build better G'





MH recovers the true data distribution

"Mixture of Gaussians" dataset [1]



[1] Azadi et al. ICLR 2019.

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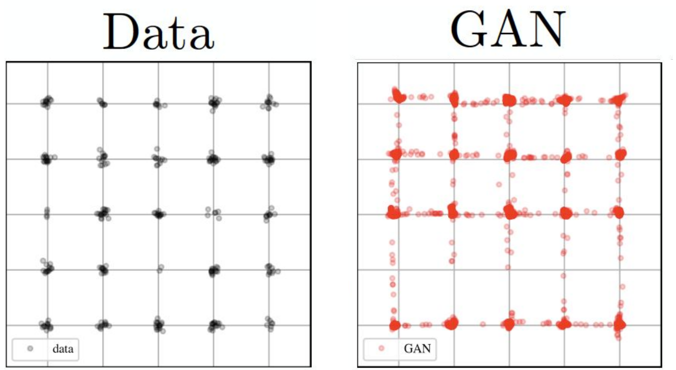

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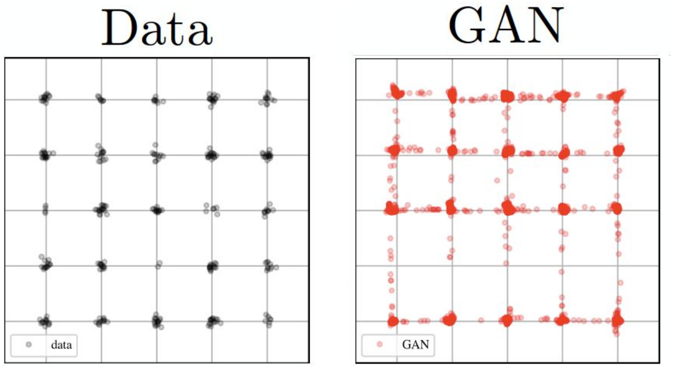

Dropped modes!

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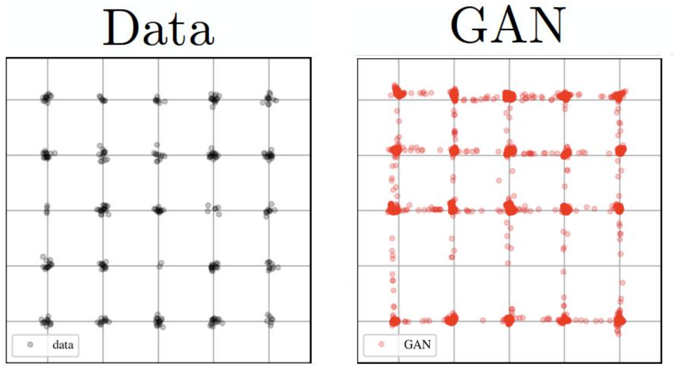

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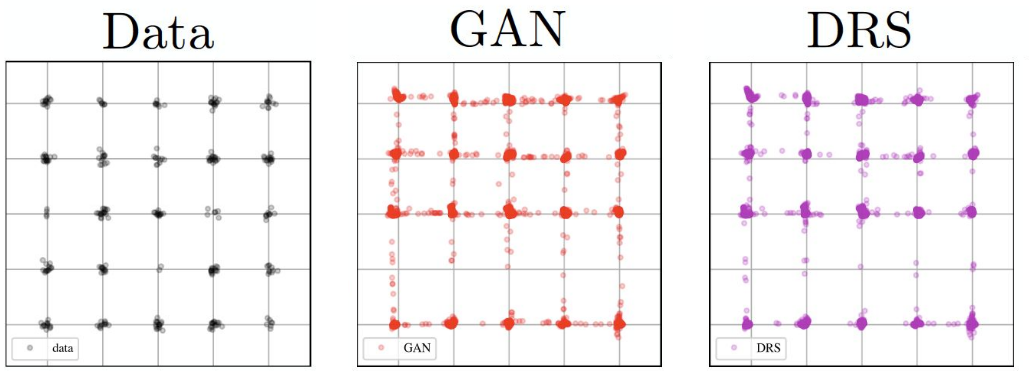

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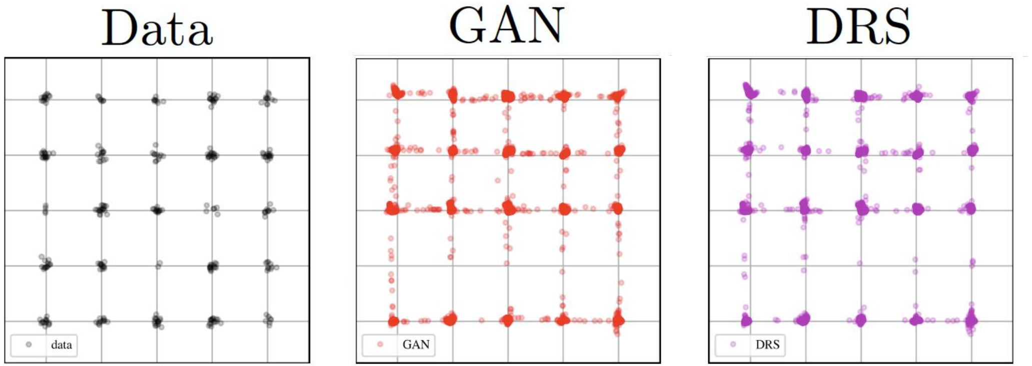

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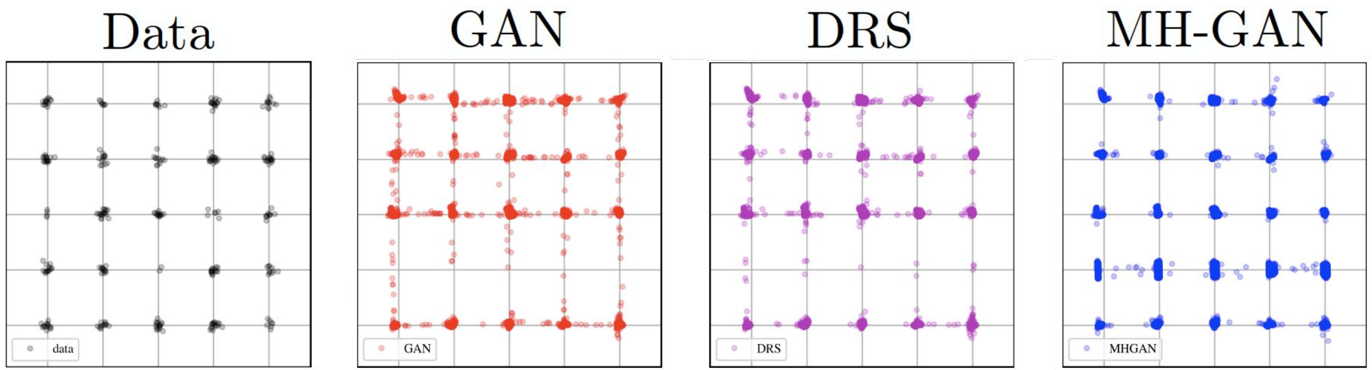

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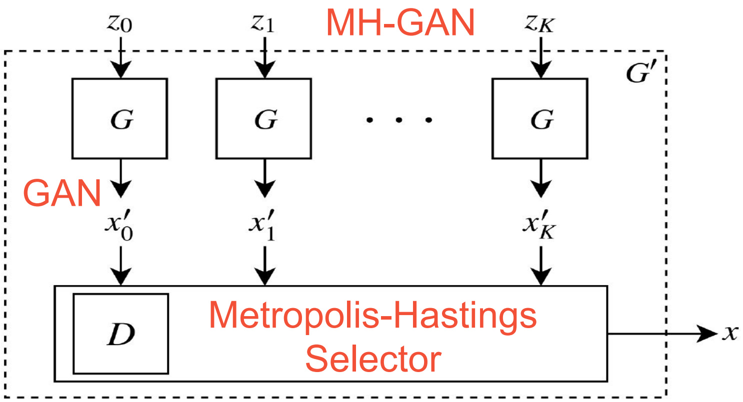
Motivation for Metropolis-Hastings

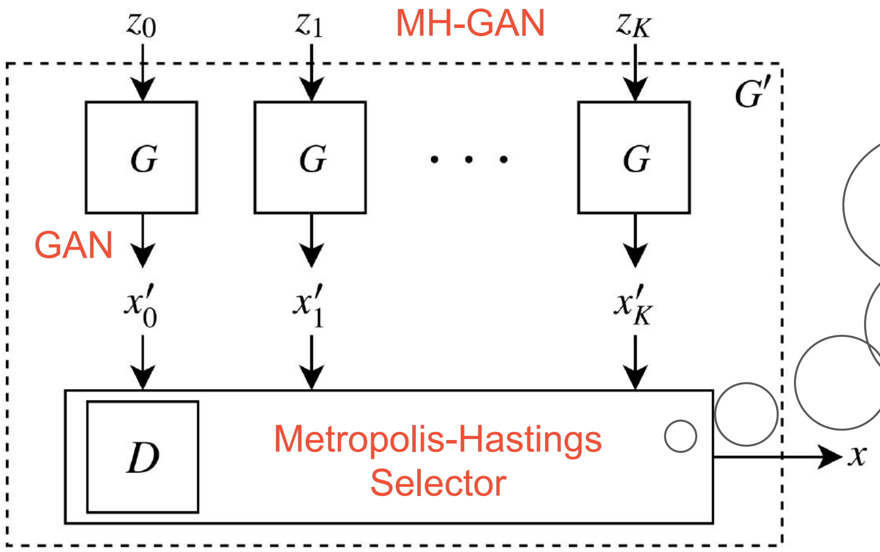
- Use MCMC *independence sampler*: sample p_D from G
- Given a perfect D and imperfect G, still obtain exact samples from true data distribution!
- Avoid densities in MCMC, just need *density ratios*:



$$D(\mathbf{x}) = \frac{p_D(\mathbf{x})}{p_D(\mathbf{x}) + p_G(\mathbf{x})}$$

$$\frac{p_D(\mathbf{x})}{p_G(\mathbf{x})} = \frac{D(\mathbf{x})}{1 - D(\mathbf{x})}$$

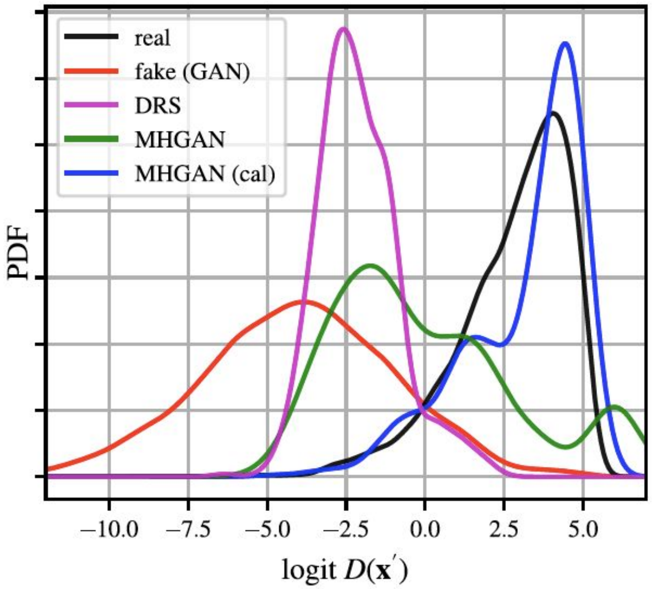
Metropolis-Hastings as a post-processing step for generators



$$\frac{p_D}{p_G} = \frac{1}{D^{-1} - 1}$$

$$\implies \alpha(\mathbf{x}', \mathbf{x}_k) = \min\left(1, \frac{D(\mathbf{x}_k)^{-1} - 1}{D(\mathbf{x}')^{-1} - 1}\right)$$

MH recovers the correct score distribution



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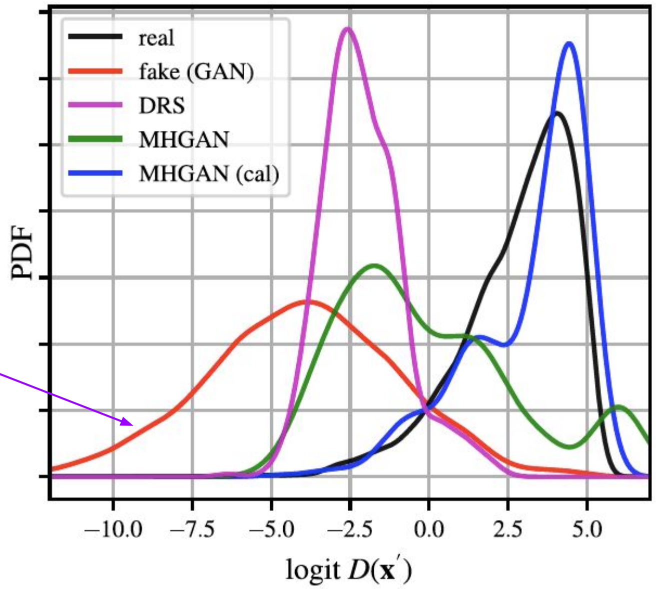
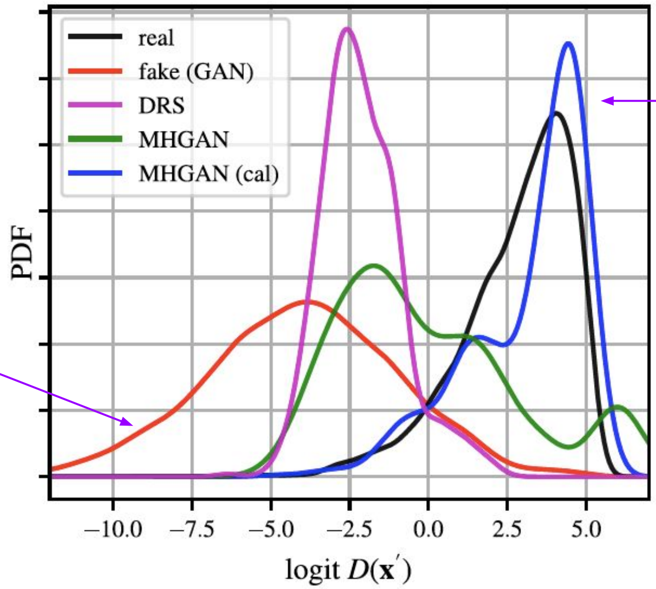


Discriminator gives different scores to fakes

MH recovers the correct score distribution



Discriminator gives different scores to fakes

Score distribution now matches real data

Also… sample images

Progressive GAN (base)

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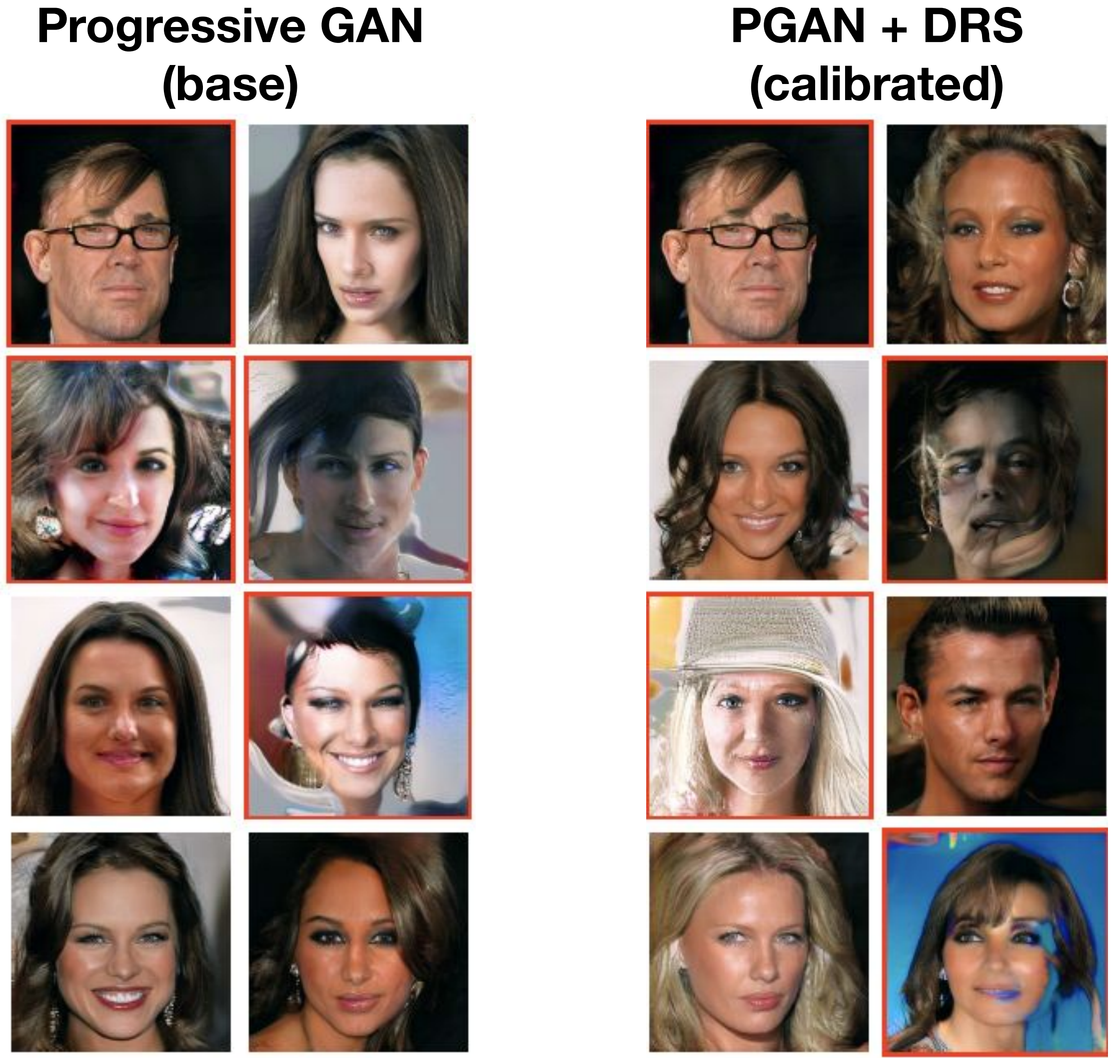
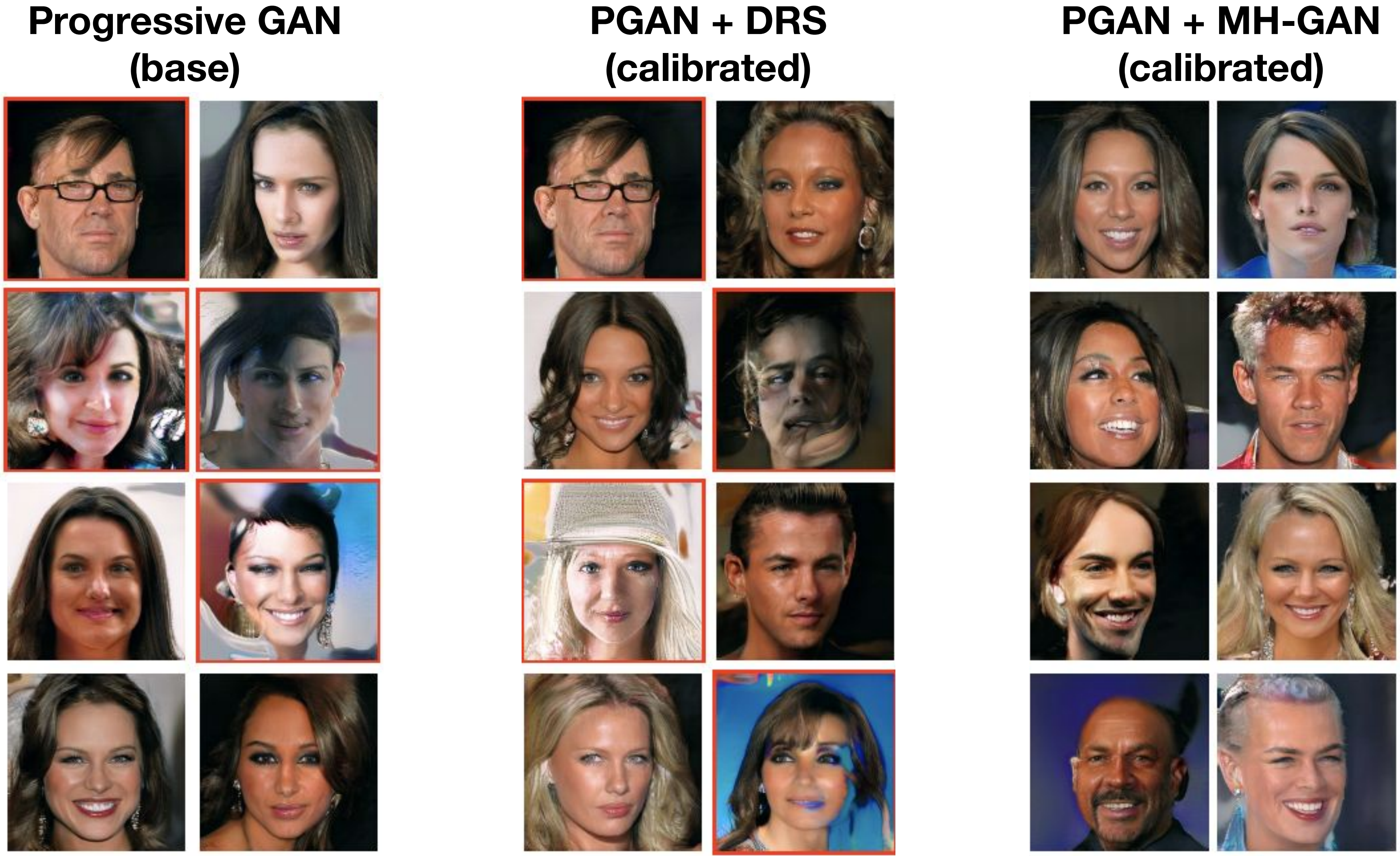

Progressive GAN
(base)
PGAN + DRS
(calibrated)


Progressive GAN
(base)
PGAN + DRS
(calibrated)
PGAN + MH-GAN
(calibrated)

Metropolis-Hastings GAN

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https://github.com/uber-research/metropolis-hastings-gans

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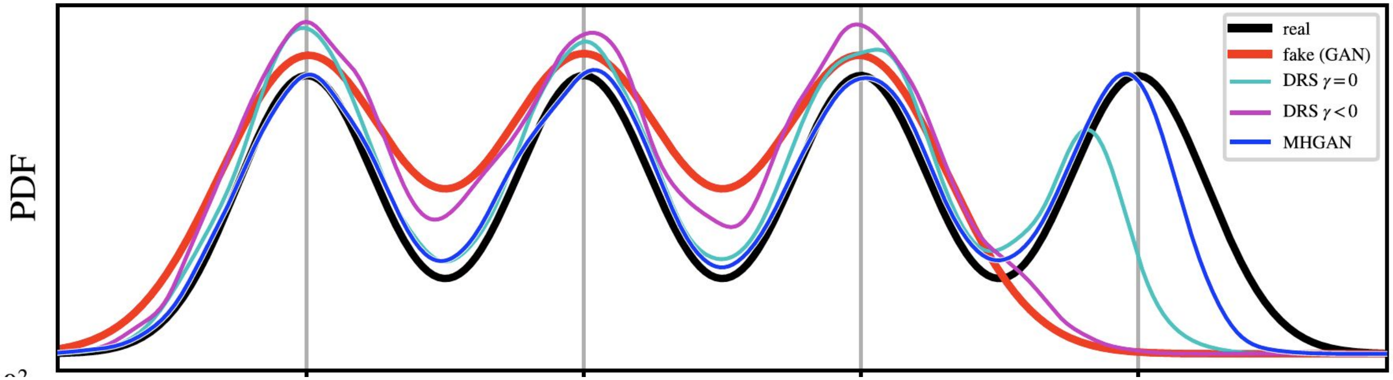

1) 1D mixture of 4 Gaussians, missing one mixture