Team 28

Unpaired style-transfer with diffusion models by distilling discrete batched entropy optimal transport (EOT)

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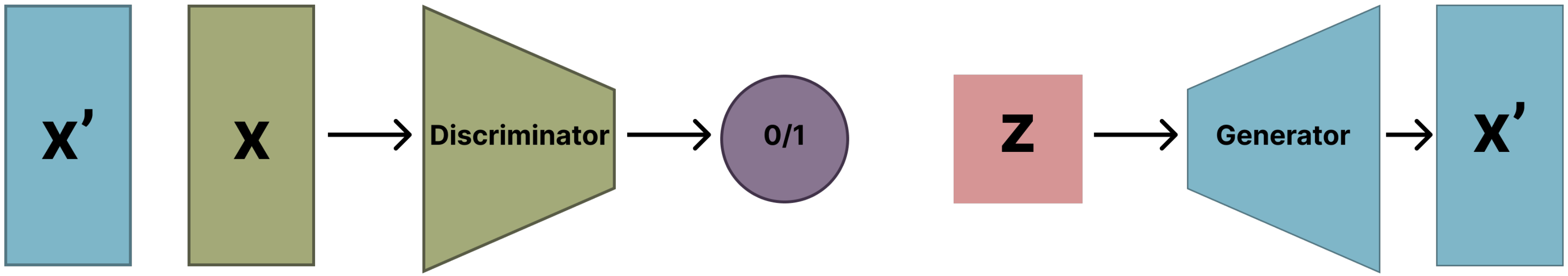
Main goal

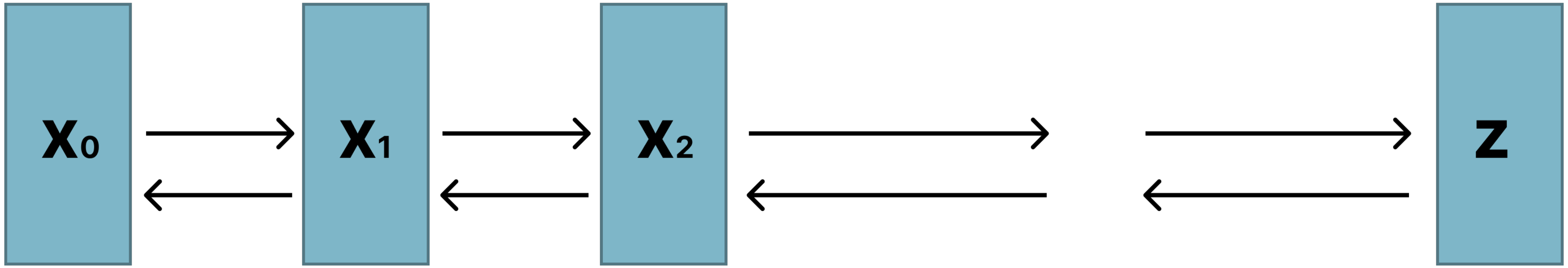
- **Diffusion probabilistic model:** generative modeling task (goal: generate new samples that have similar statistical properties to the original data; use: tasks such as data augmentation or generating synthetic data for training other ma models)
- **Optimal Transport:** optimization problem (goal: measure the distance or dissimilarity between probability distributions; use: image processing)

Generative models

GAN



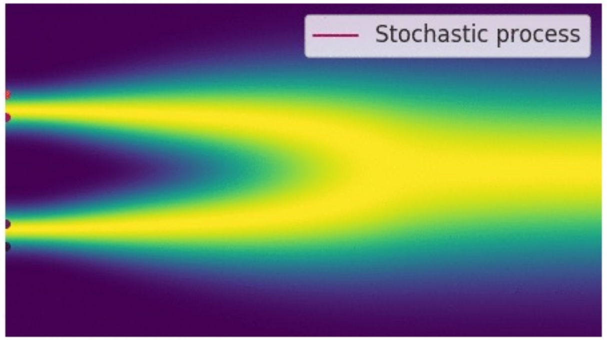
Diffusion models



Denoising Diffusion Probabilistic models

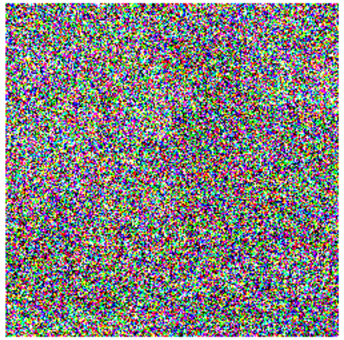
Forward process or diffusion process

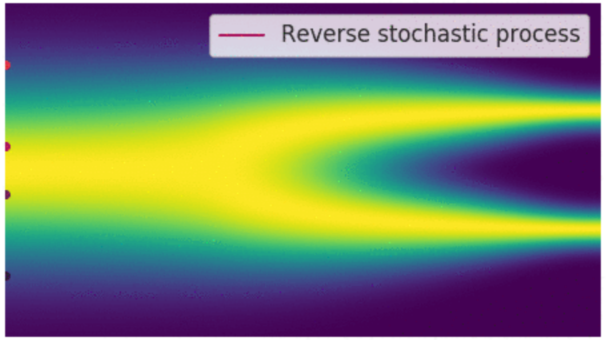
(fixed to a Markov chain that gradually adds Gaussian noise)

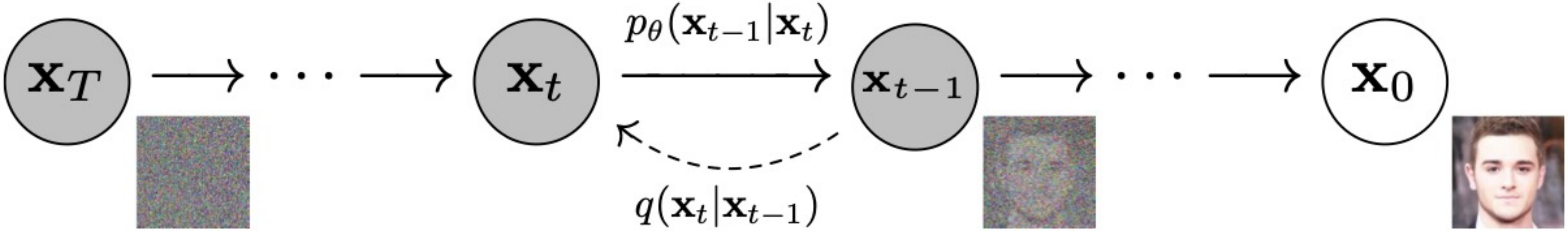


Reverse process

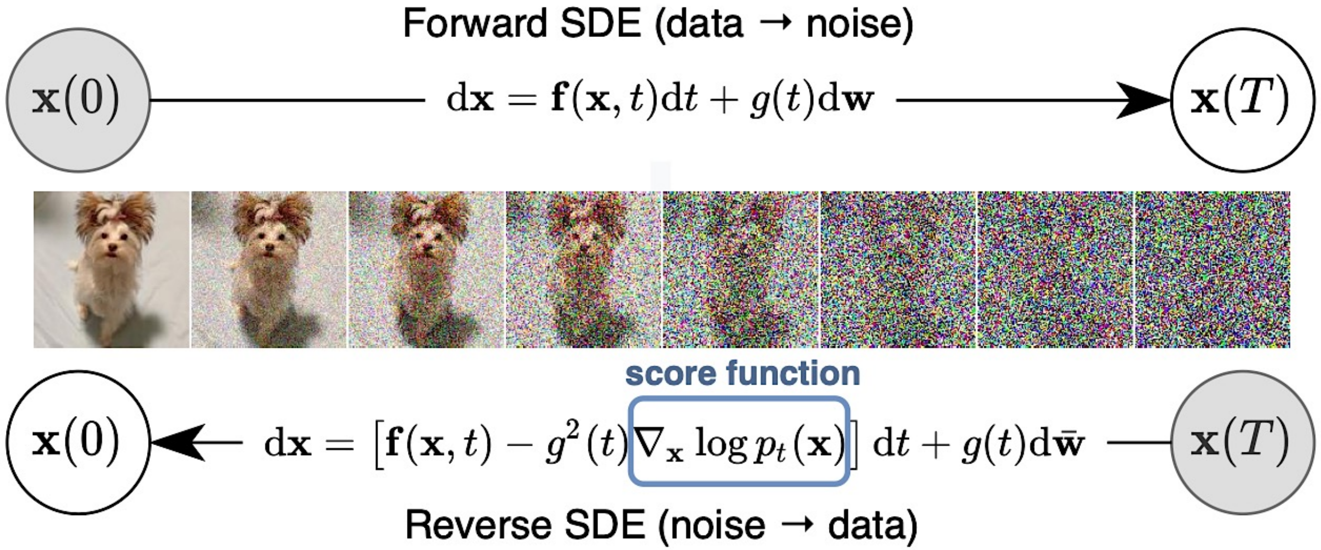
(defined as a Markov chain with learned Gaussian transitions)







Conditional diffusion models

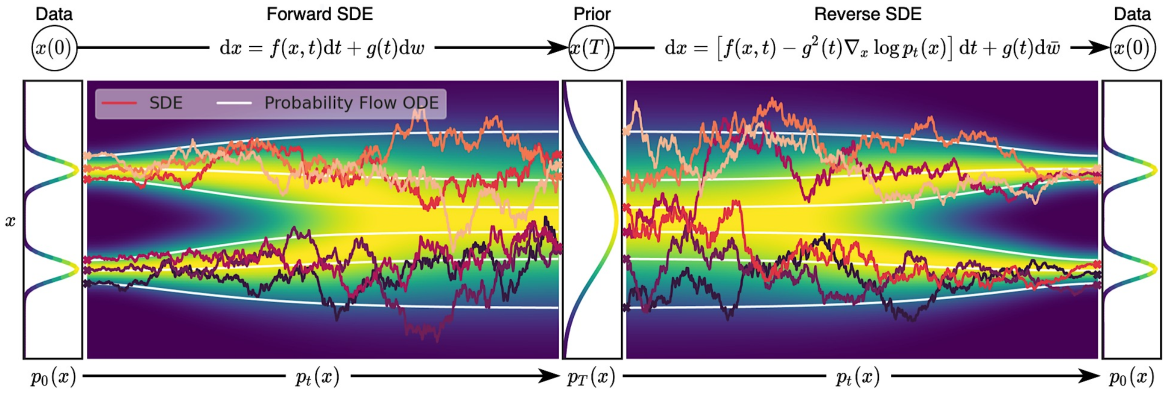


Unconditional diffusion model

- forward SDE that noises the sample;
- there is a reversed process that denoises the sample if the gradient of the logarithm of density at intermediate time points ($\nabla_x \log p_t(x)$) is known;
- this logarithm is learnt with neural networks;

Conditional diffusion model

- diffusing both the input x and condition y, and then learning $\nabla_x \log p(x_t|y_t)$



Discrete optimal transport

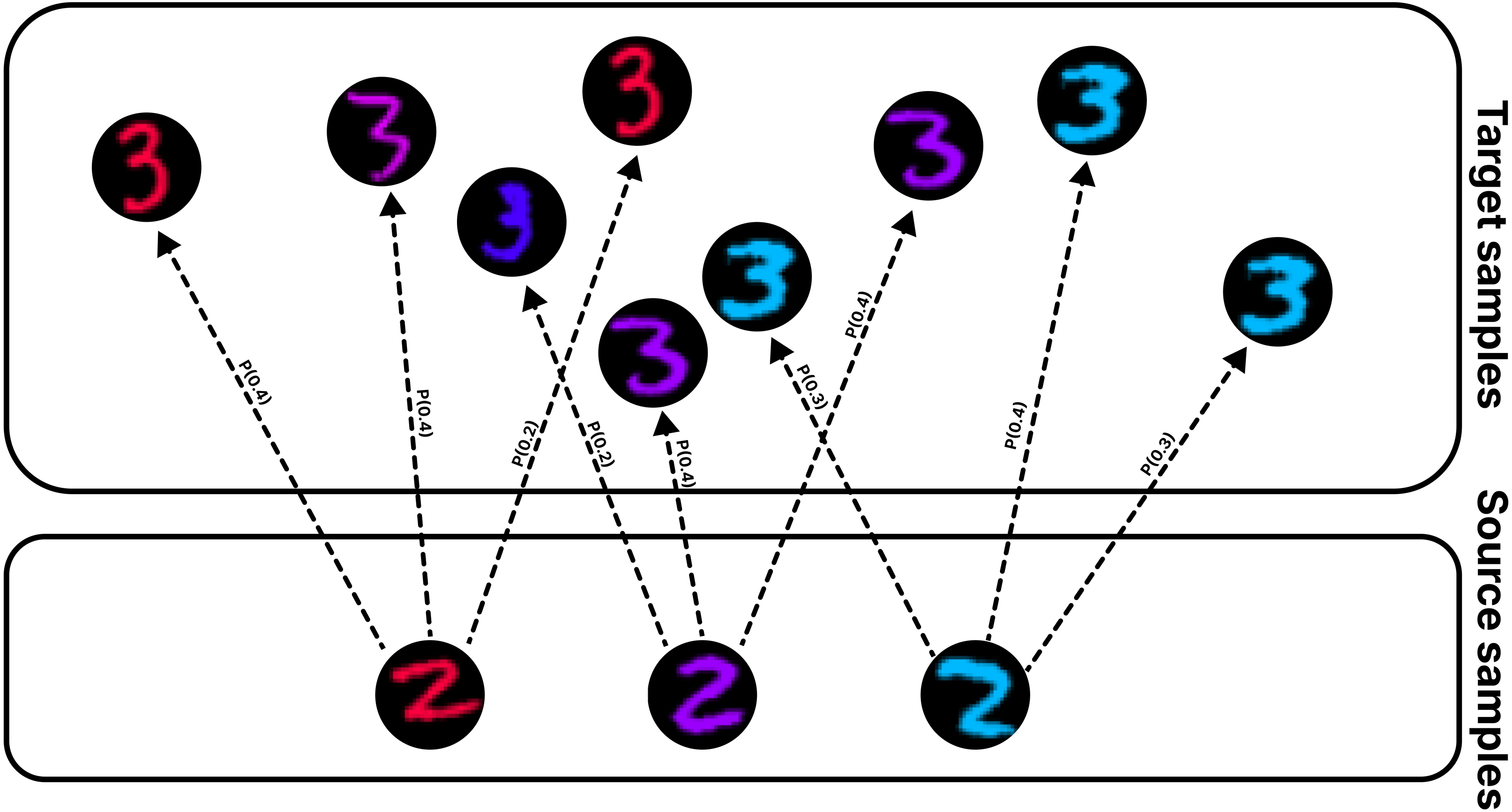
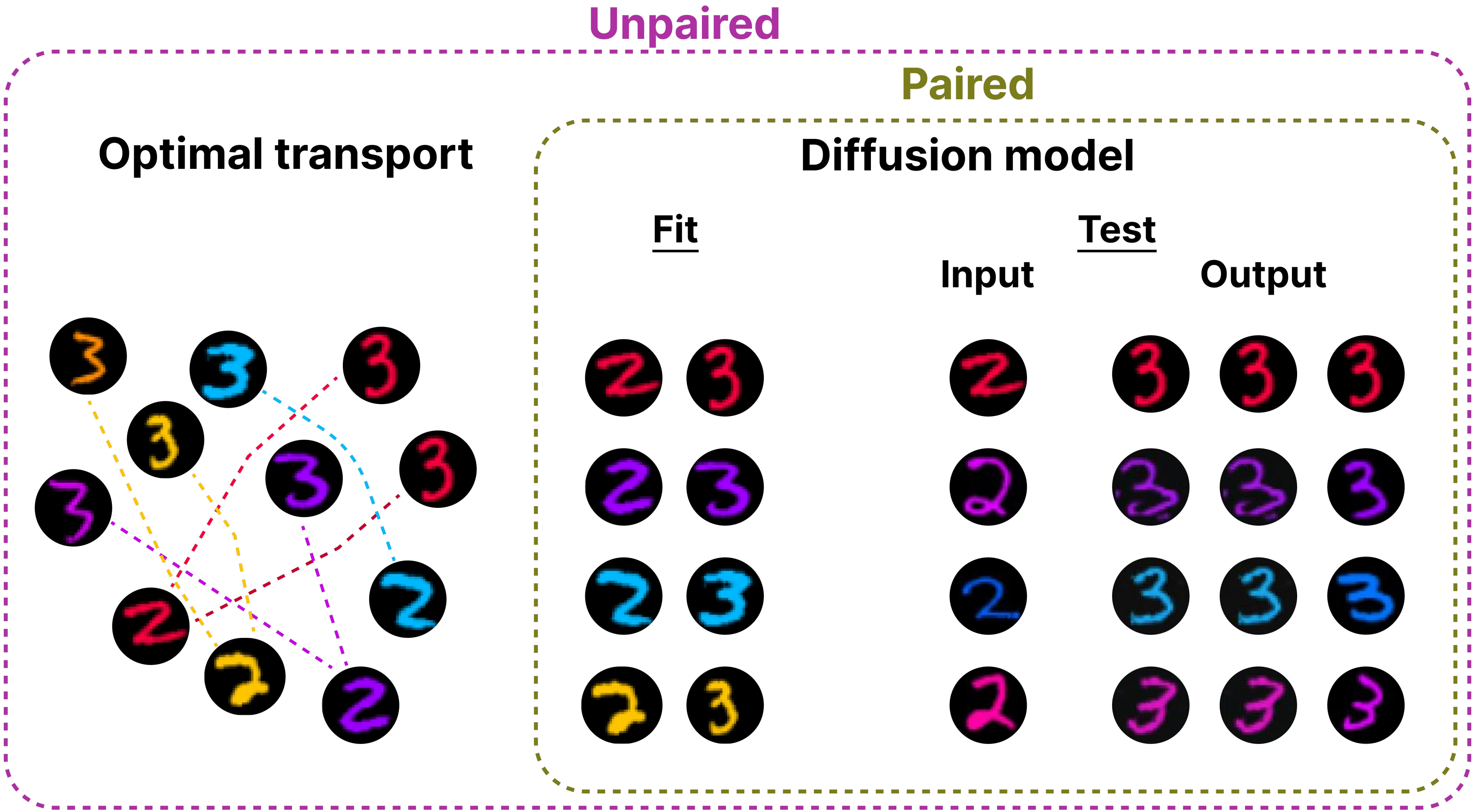
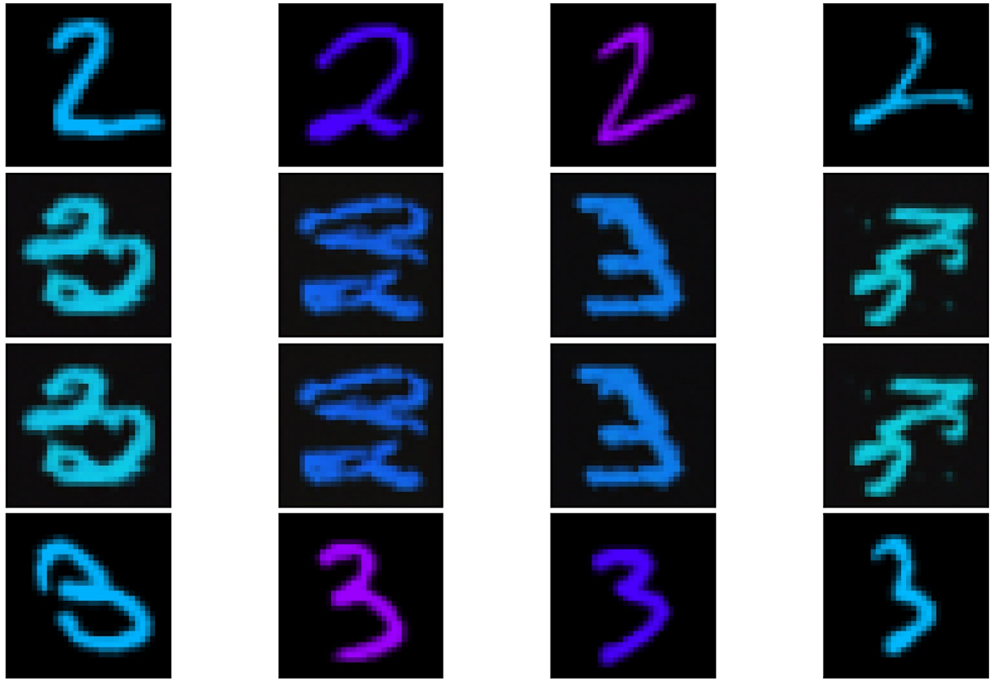


Image-to-image translation



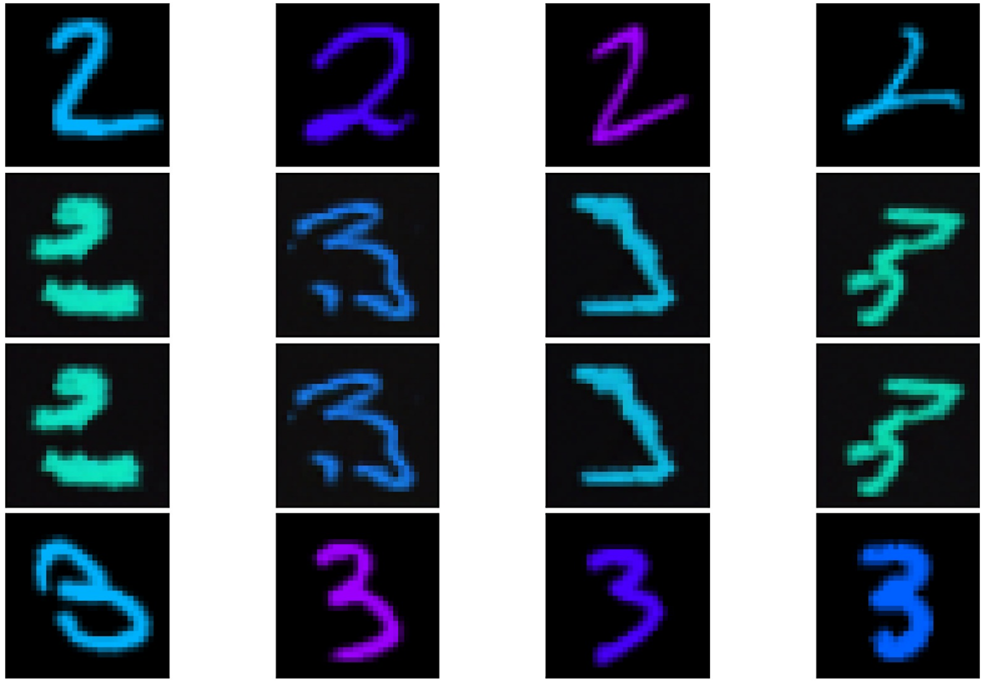
Through iterations

Input
Y
Y_ema
Optimal target



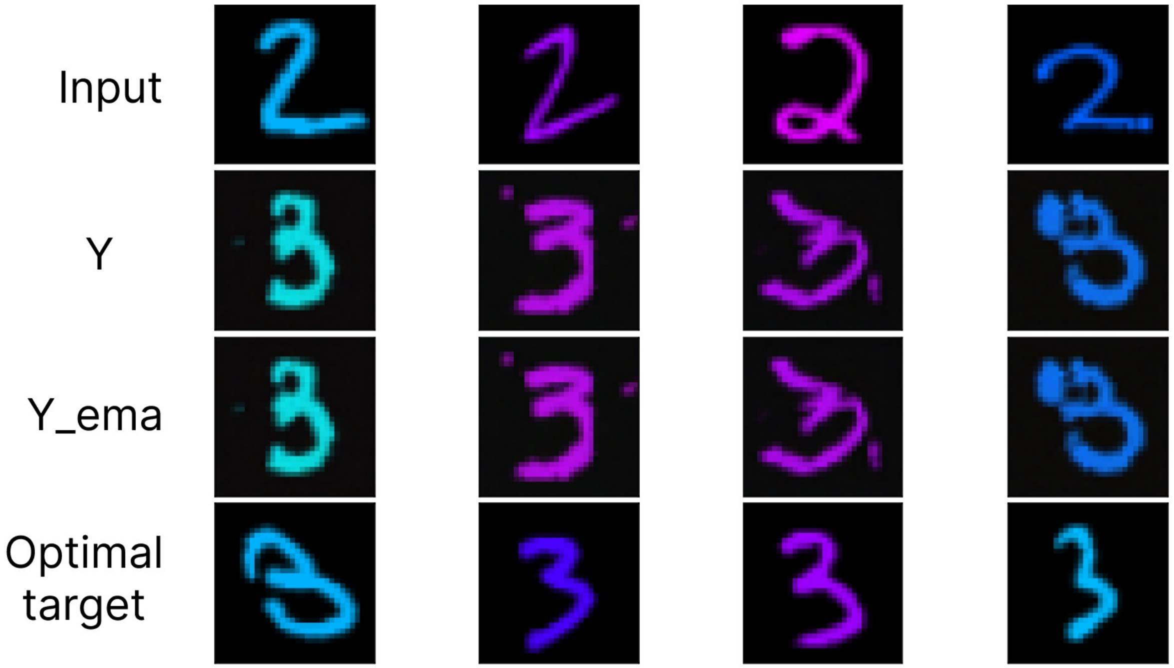
unregularized OT

Input
Y
Y_ema
Optimal target

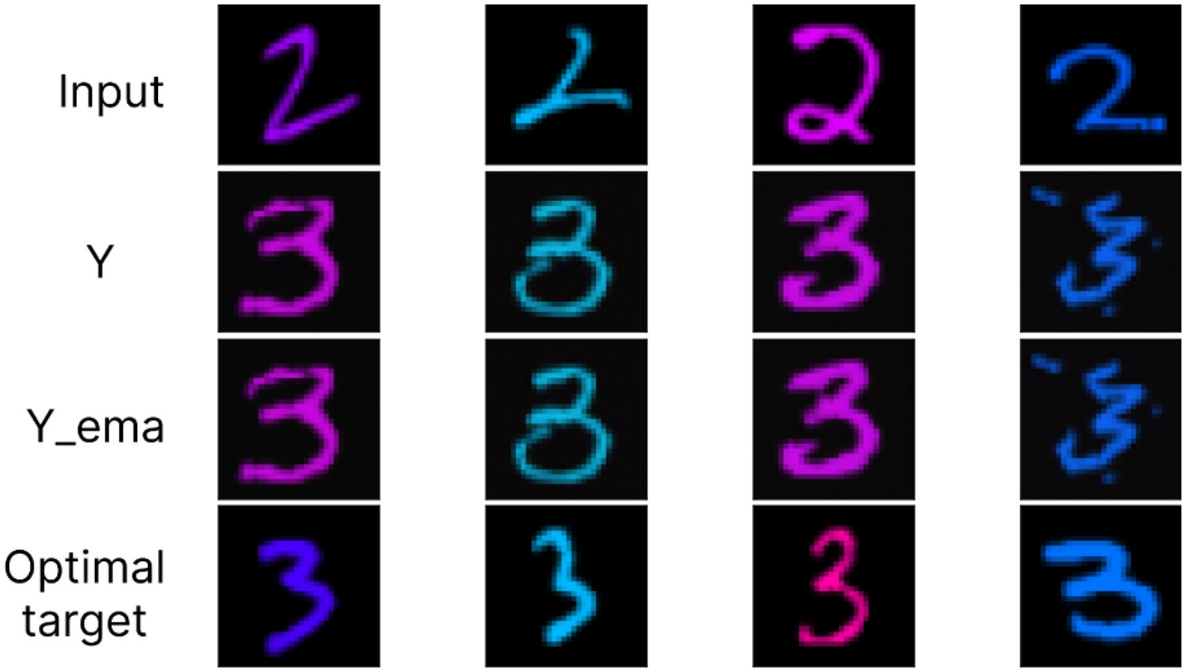


regularized OT

Final Results



unregularized OT



regularized OT

GPU is all you need?