Generative models

AE, VAE, GAN

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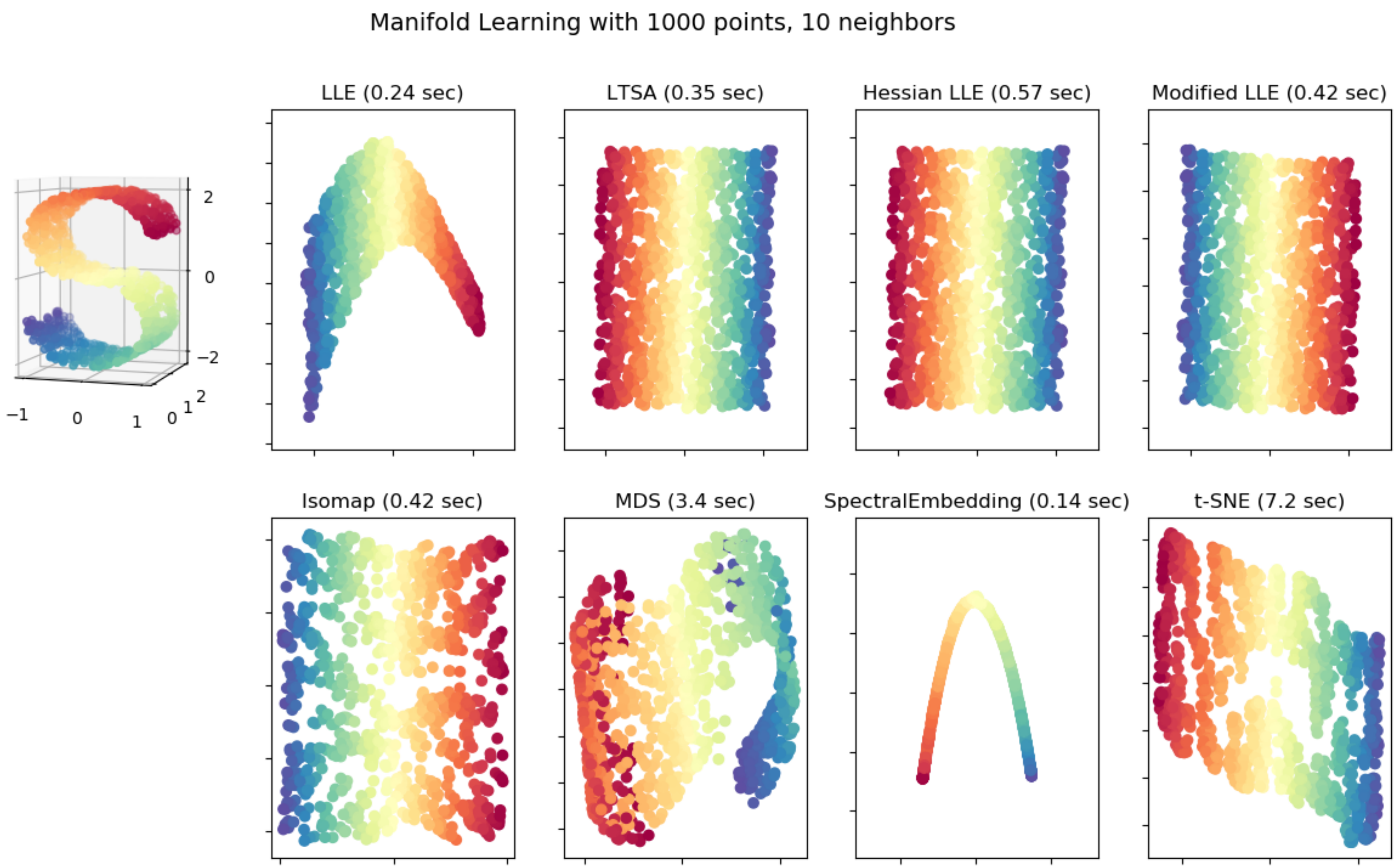
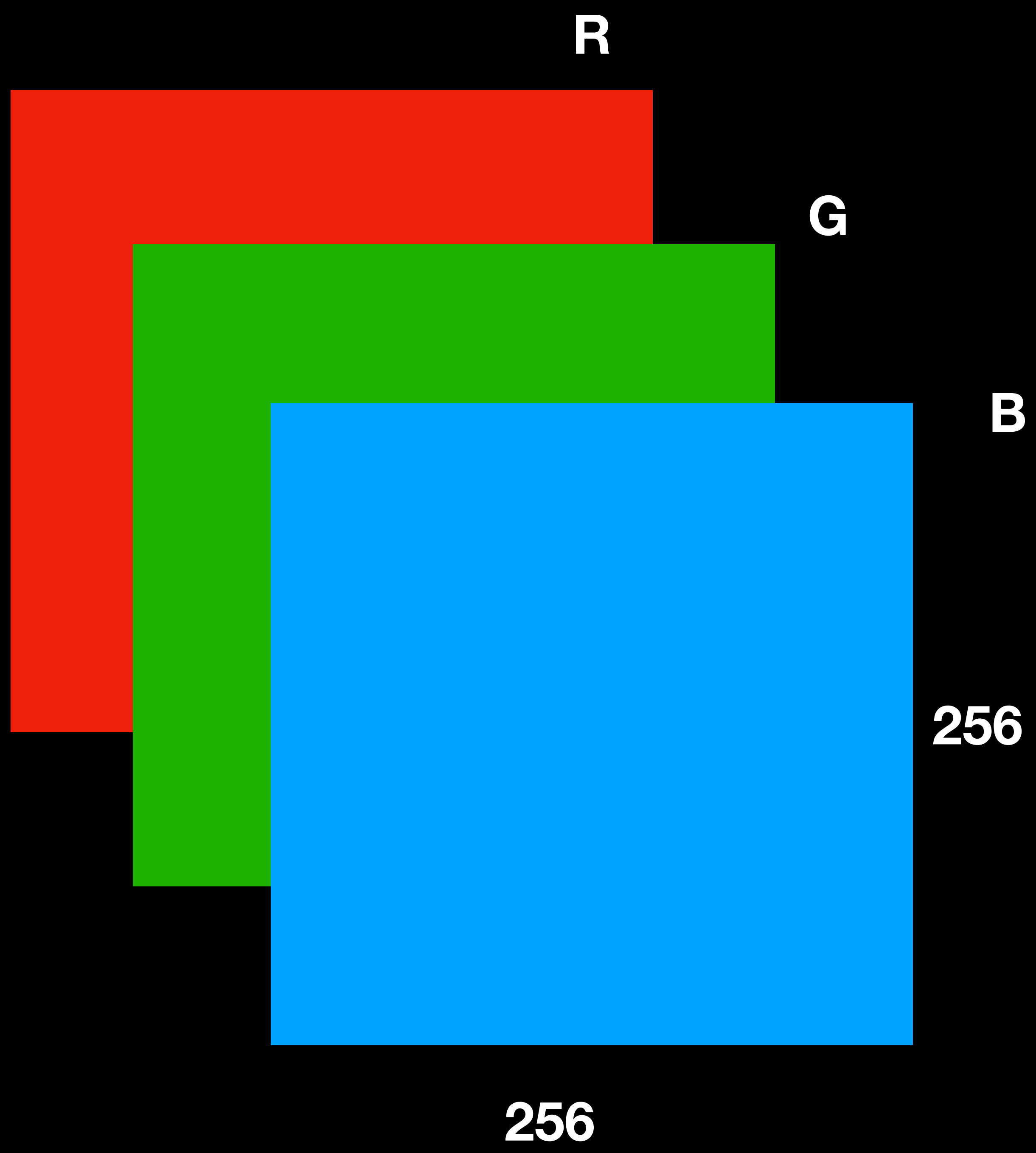
19.10.2018

The manifold hypothesis



Data in theory



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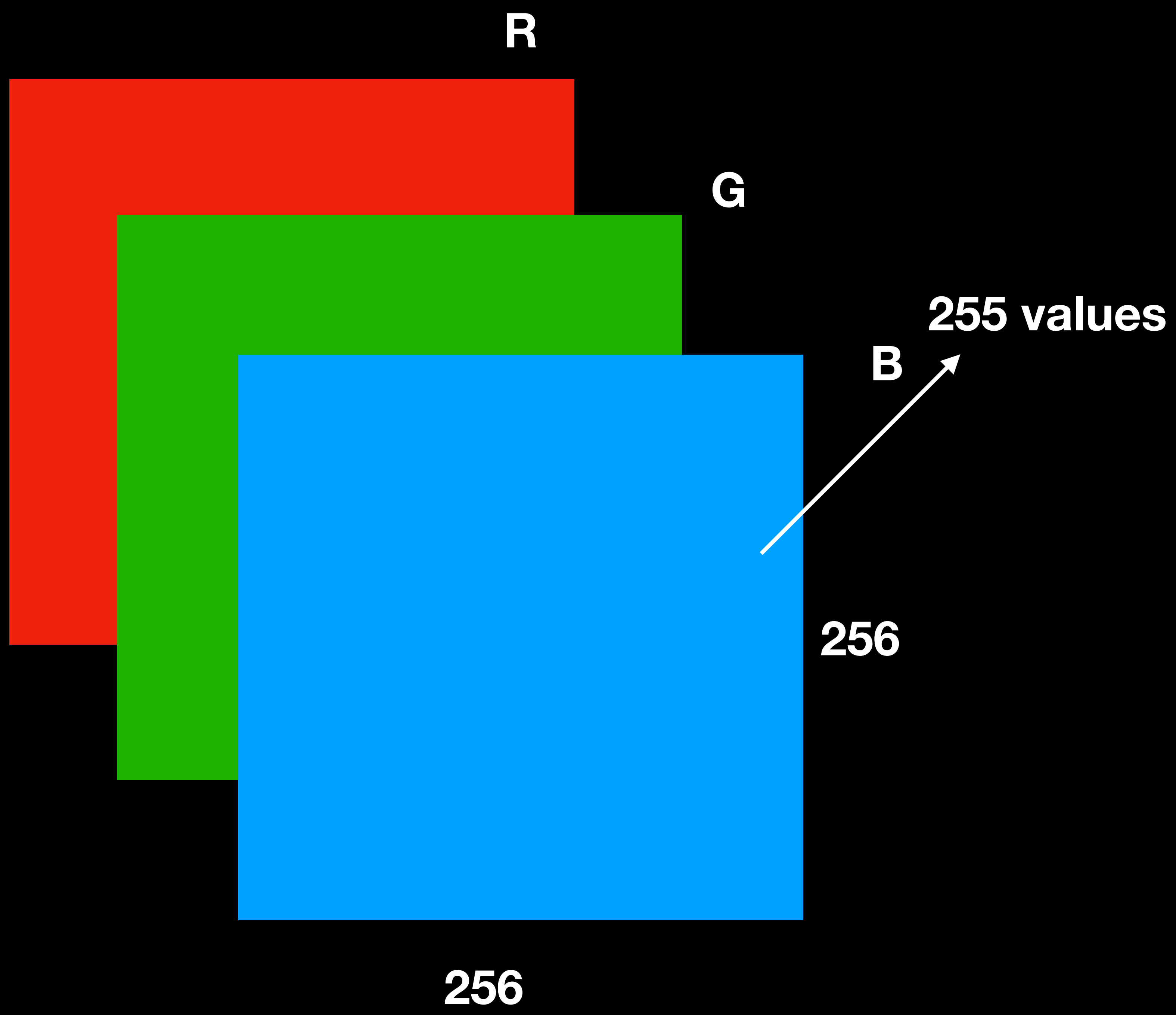

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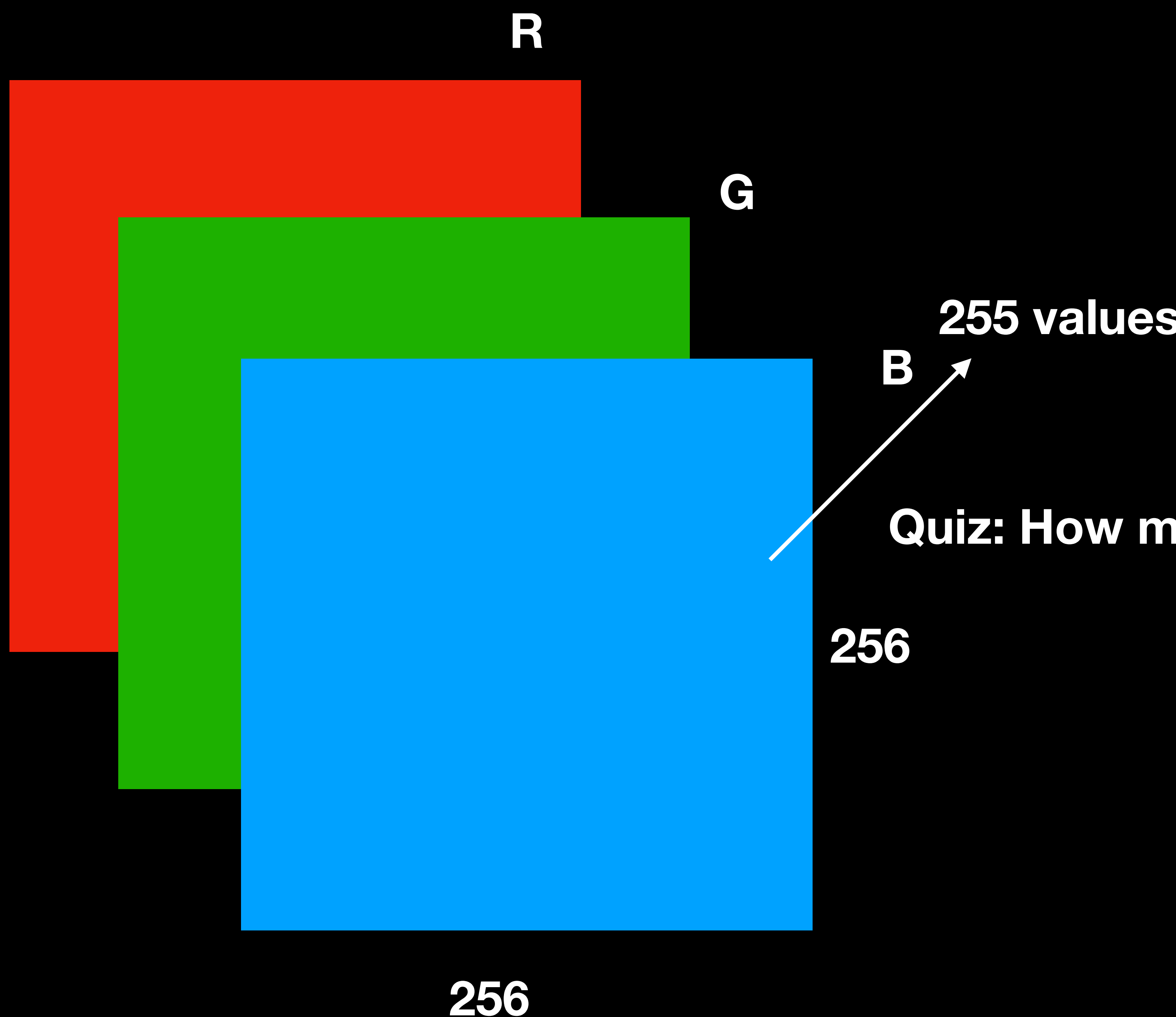
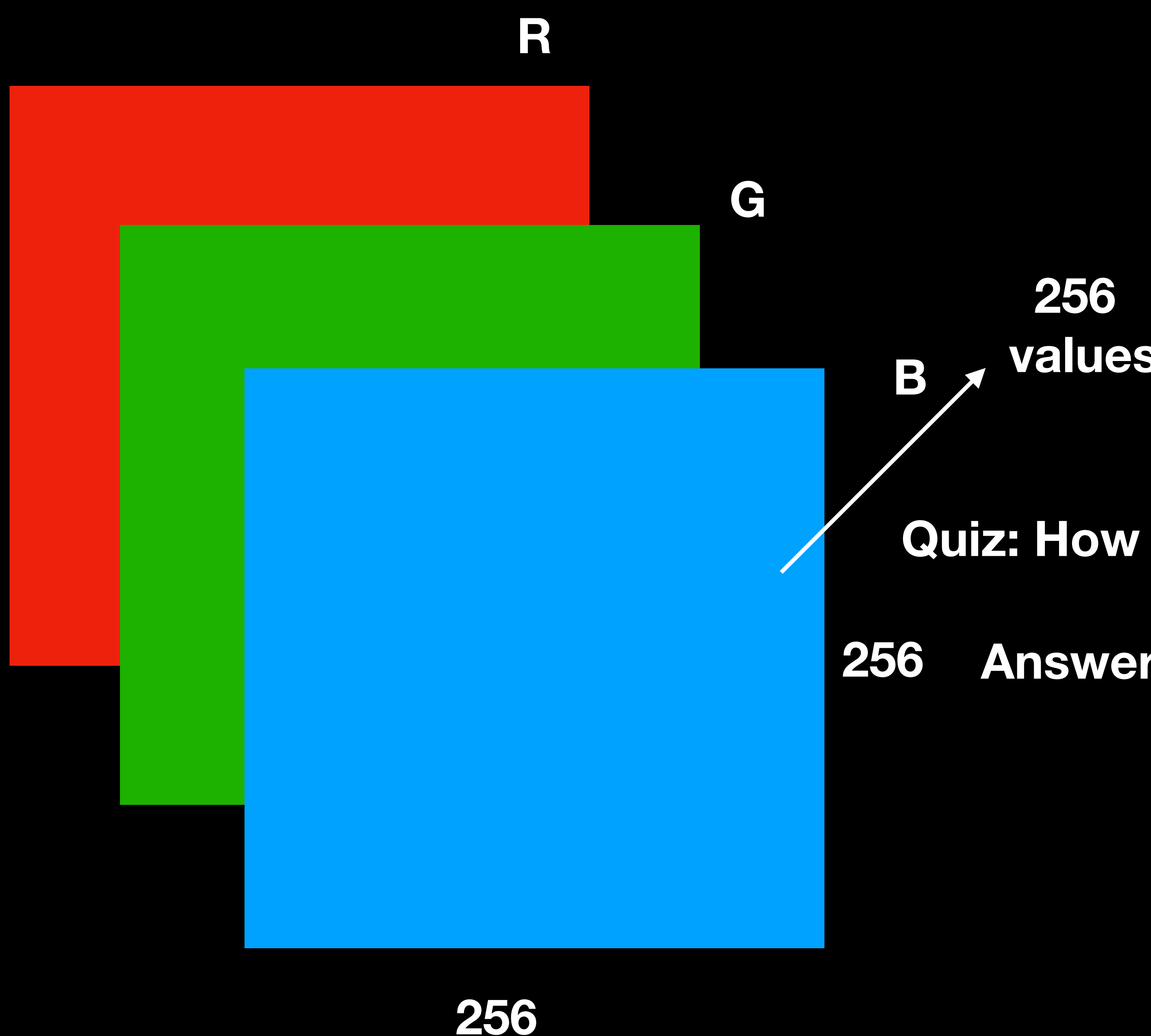


Quiz: How many unique image might exist?

Data in theory

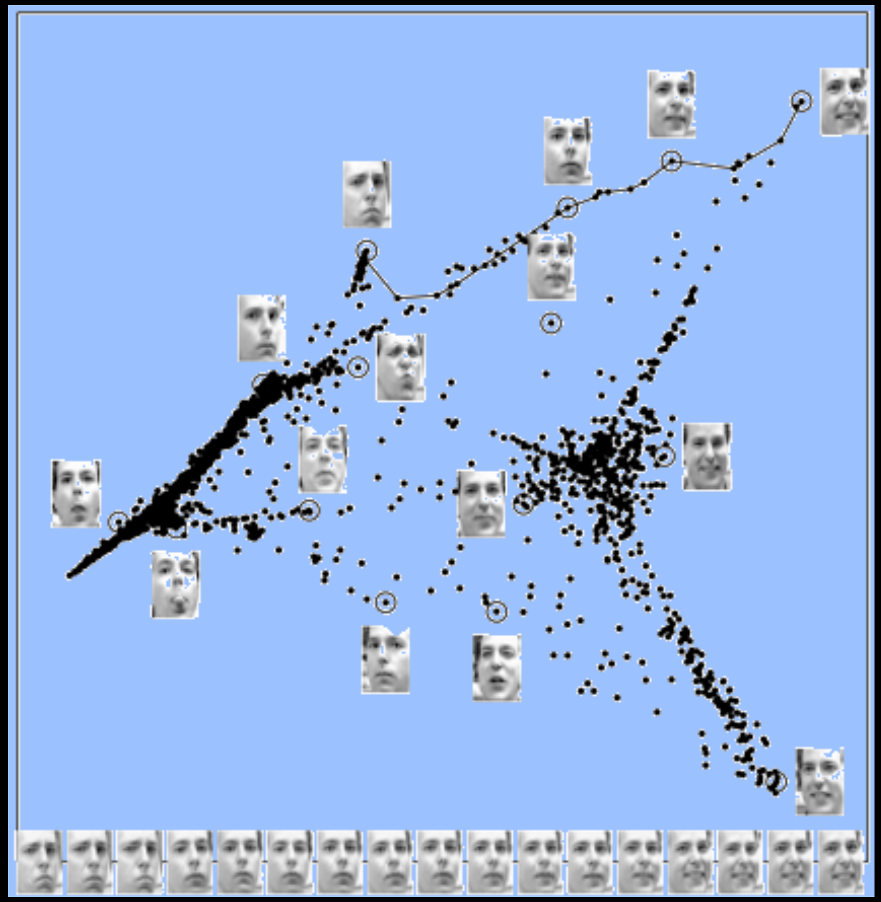


Quiz: How many unique image might exist?

Answer: $256^{256\times256\times3}$

Data in reality: manifold hypothesis

- Data live in manifolds
- dim(manifold) << dim(data)



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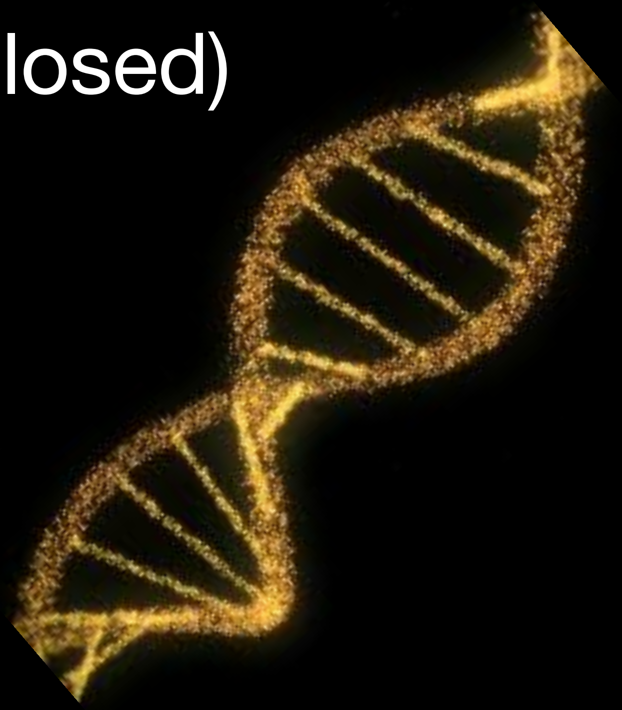

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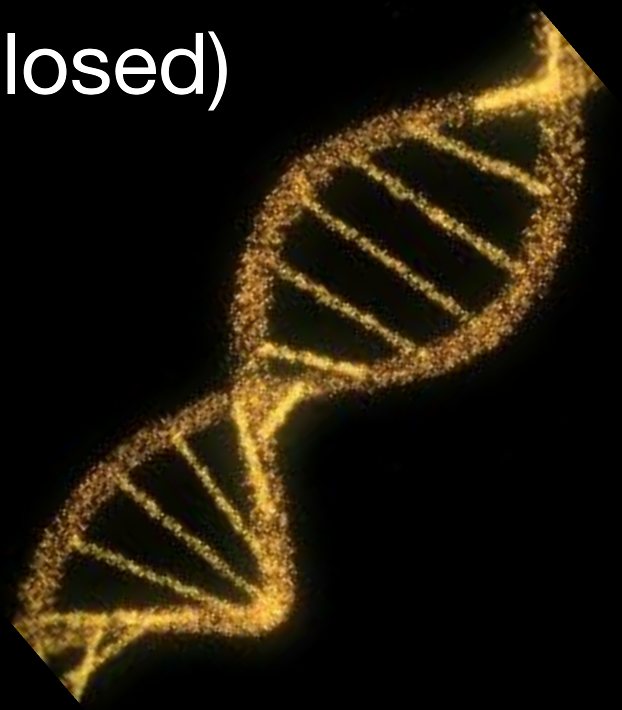
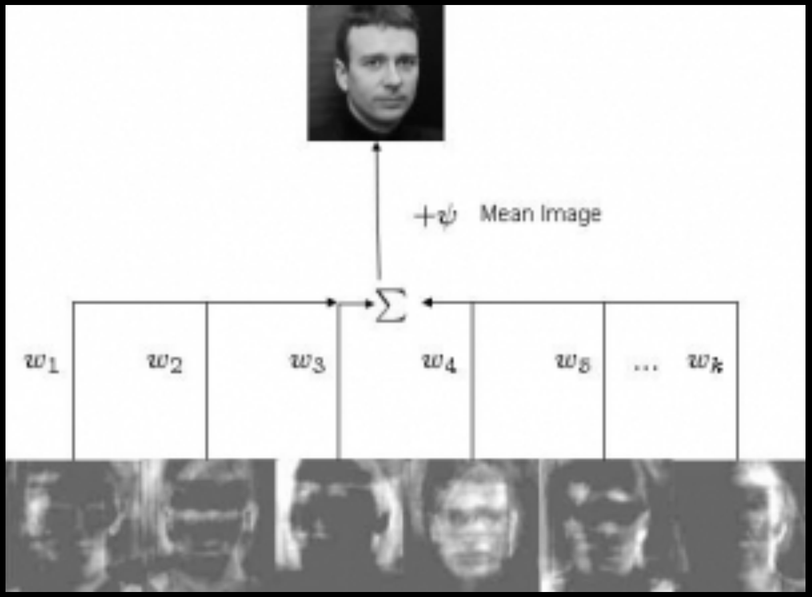


Data in reality: manifold hypothesis

- One can define image as a vector in the space of images [N, M, 3]

- Or given the embedding, much smaller vector in intrinsic manifold coordinates



So what ?

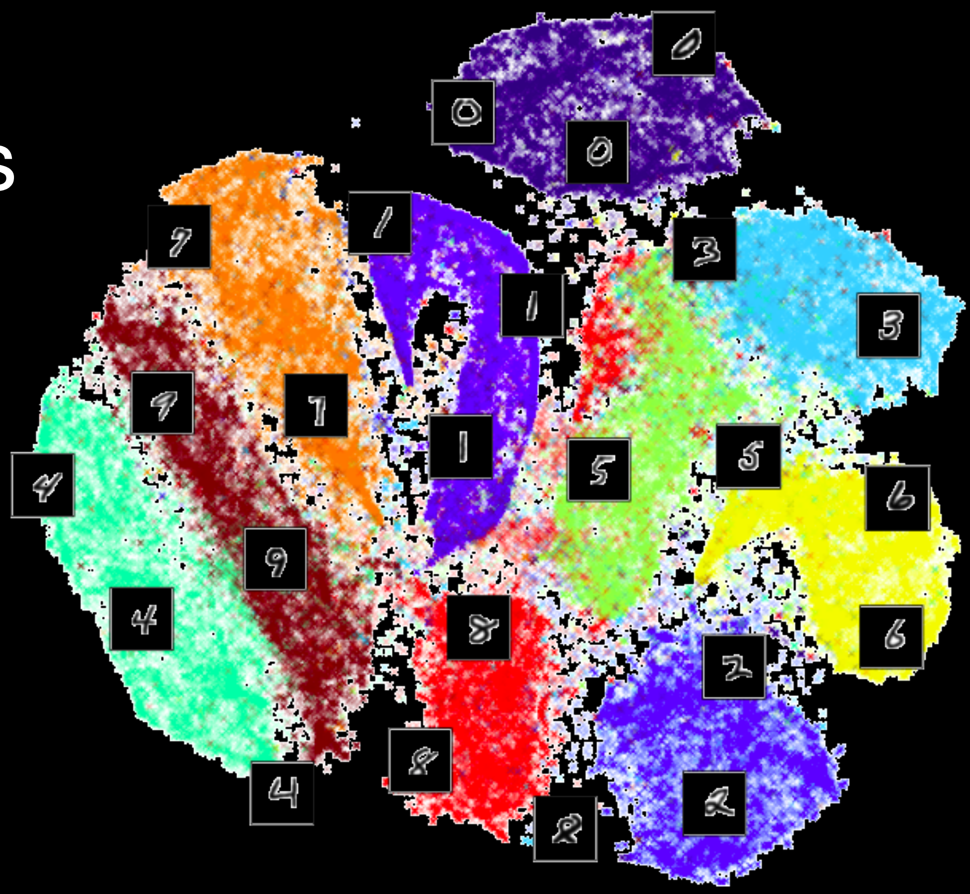
- Manifold -> data distribution
- Learning manifold -> learning data distributions and variances
- How to learn the variances automatically ?
- Unsupervised and/or generative learning

Unsupervised learning. What ?

- Latent space manifolds
- AE / VAE
- Adversarial Networks (GANs)

Unsupervised learning. Why ?

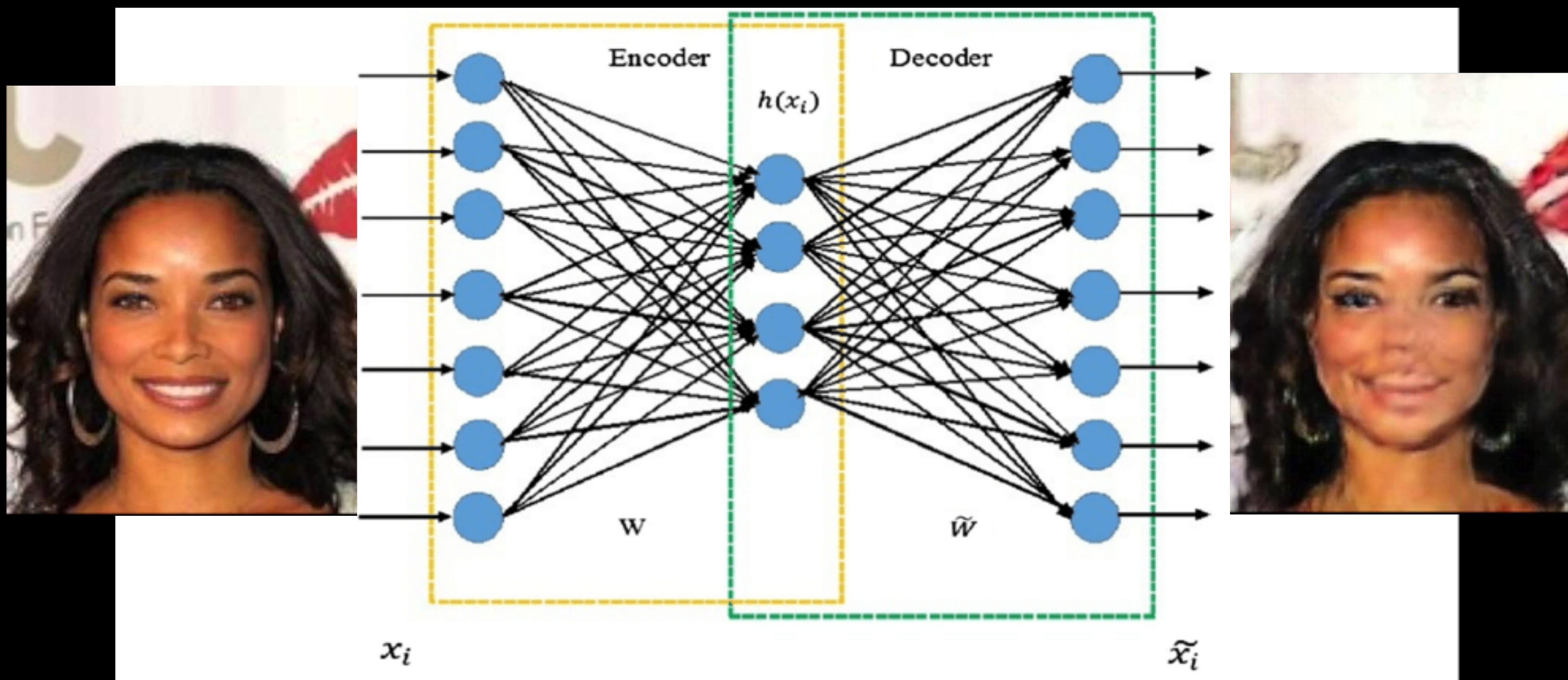
- More data for free
- How to annotate distribution parameters ?
- Discovering structure
    - Important and redundant features



Why generative ?

- Latent space manifolds
- AE / VAE
- Adversarial Networks (GANs)

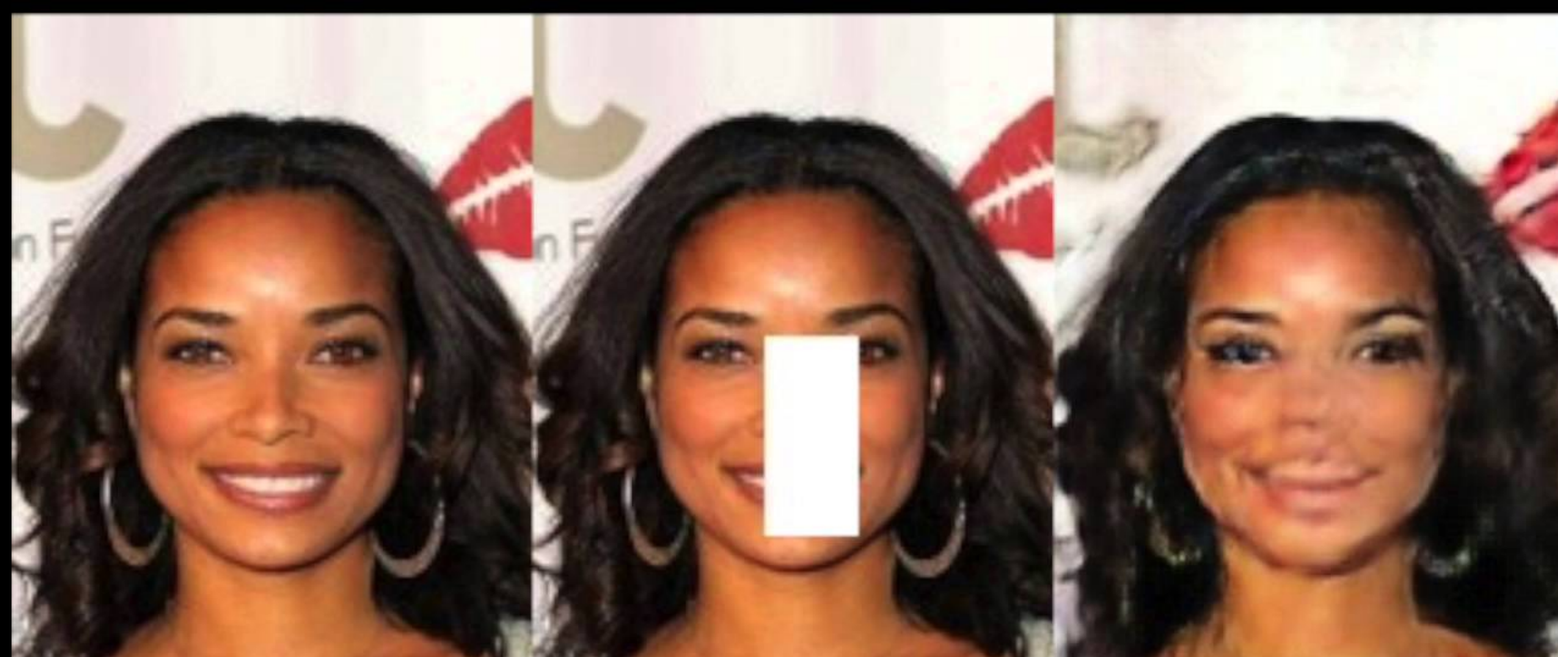
Autoencoders



Autoencoders

- Latent space is lower than input (otherwise -> Identity)
- If Z is linear -> PCA
- Usually MSE loss -> blur

Denoising AE



Denoising AE

- Add random noise to input
  - Dropout
  - Gaussian
- Loss includes expectation over noise distribution

Noise: $\epsilon : q(\hat{x} \,|\, x, \epsilon)$

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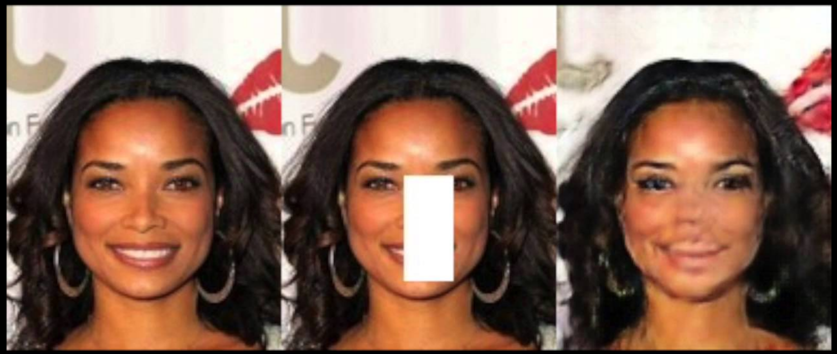
Noise: $\epsilon : q(\hat{x} \,|\, x, \epsilon)$

- No over-learn, might even complete



Variational AE

We want to model the data distribution

$$p(x) = \int p_\theta(z) p_\theta(x \mid z) dz$$

Posterior $p(x) = p_\theta(x \mid z)$ **is intractable for complicated likelihood functions**

Variational AE

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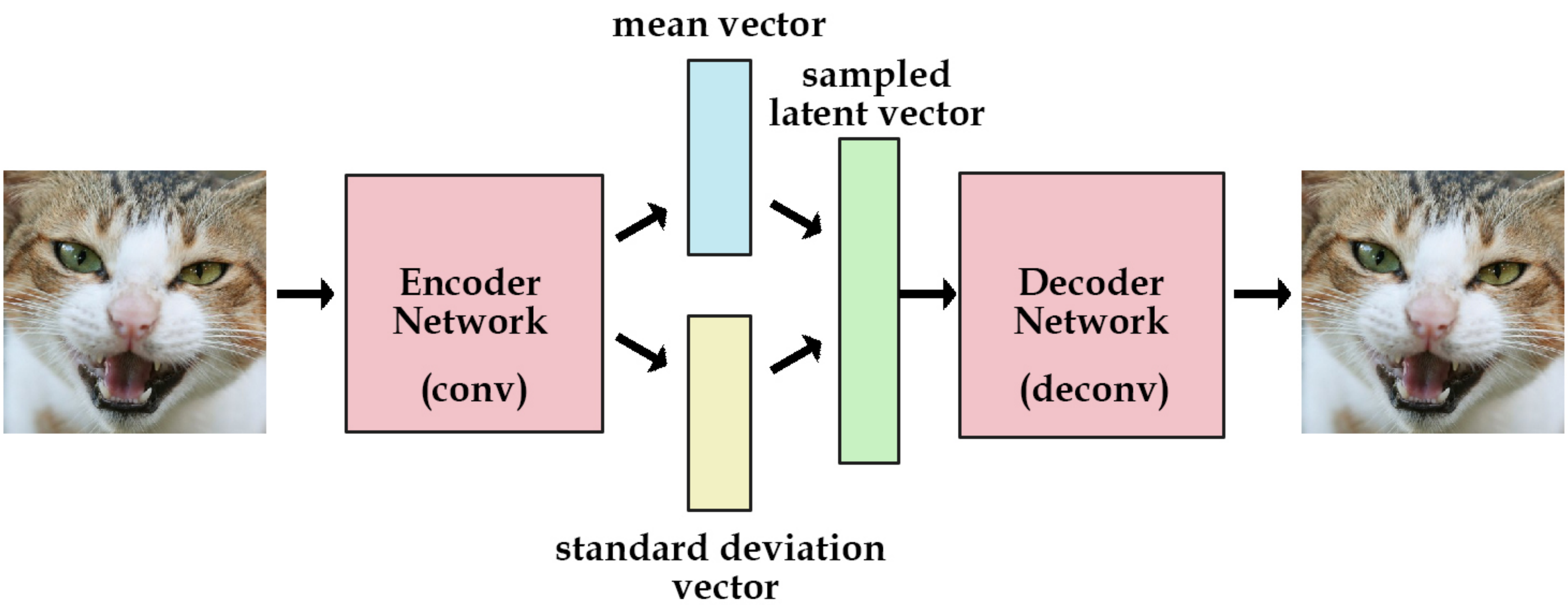
$$p(x) = \int p_\theta(z) p_\theta(x \mid z) dz$$

Posterior $p_\theta(z \mid x)$ **is intractable for complicated likelihood functions**

Instead learn $q_\phi(z \mid x)$ **e.g. another NN, which learns to approximate posterior**

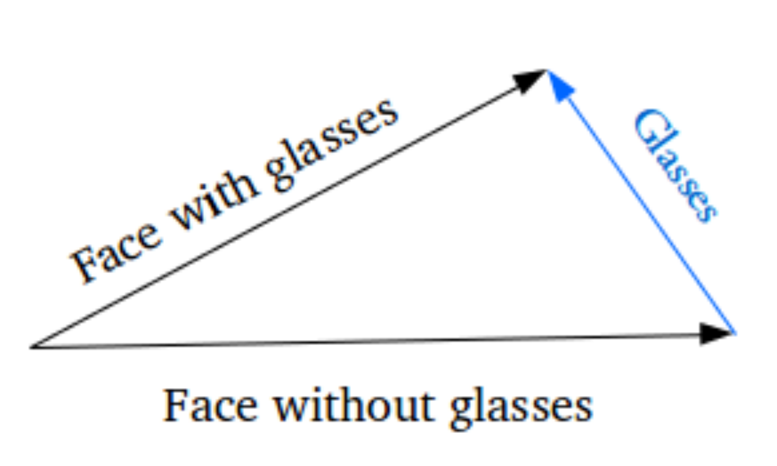
ELBO(evidence lower bound) $\ln p(x) \geq E_{q_\theta(z|x)}[\ln(p(x \mid z))] - D_{KL}[q(z \mid x) \mid\mid p(z)]$

Variational AE



Variational AE

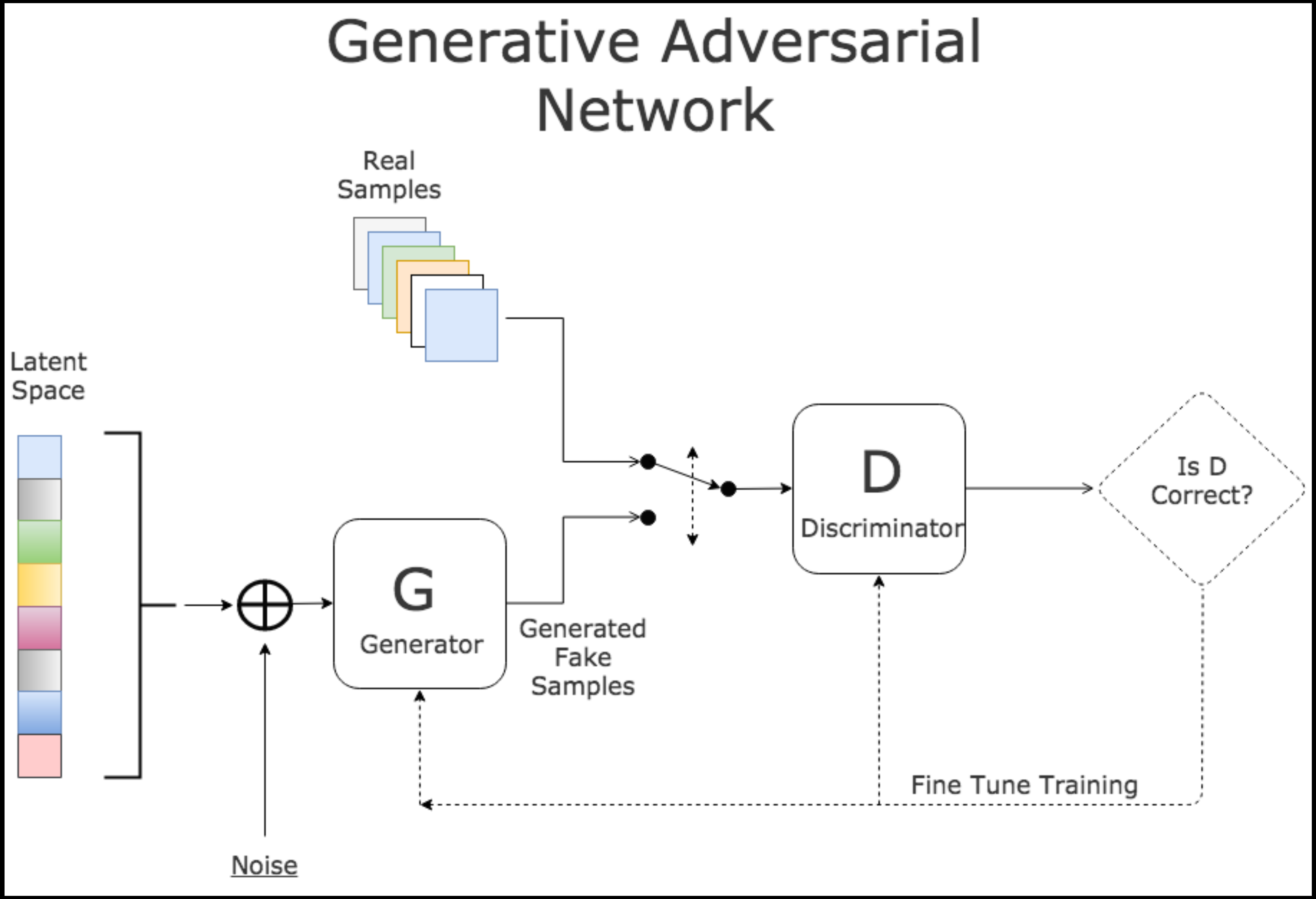
"Image arithmetics"



GANs

- So far we were trying to learn data distribution $p(x)$
- Do we need that really ? Isn't it limiting ?
- Can we model directly from samples ?

GANs



$$min_G max_D V(G,D) = E_{x \sim p_{data}(x)} \log(D(x)) + E_{z \sim p_z(z)} \log(1 - D(G(z)))$$

GANs problems

- Optimum exists, but it is a saddle point
- GANs are unstable
- Very fresh