

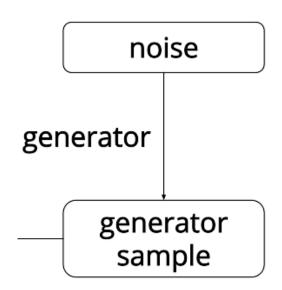


#### Generative Adversarial Networks

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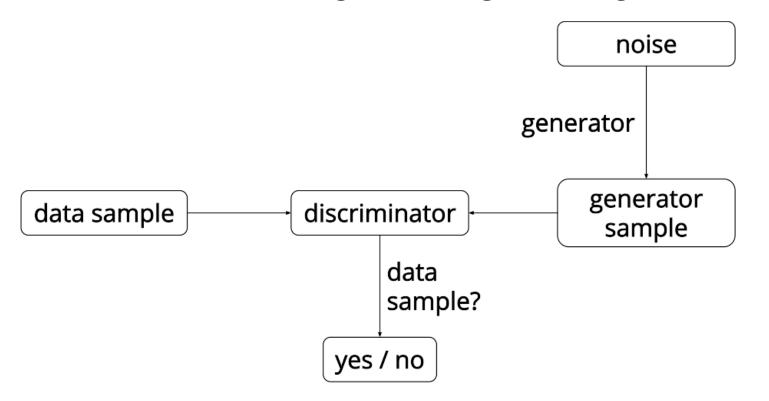
### Generating Data from Random Noise

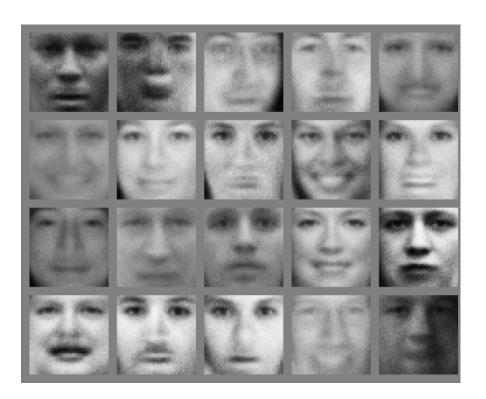
- Variational autoencoders train a network to encode data to a latent space that follows a given distribution and then decode this latent space to match the data
- Instead, we could train a network to map inputs from a given distribution to a distribution that maps that of the data
- We could then generate new data by sampling from our given distribution and obtaining the output of our network
- How can we then enforce that the distribution of that output match the data's distribution?
  - Remember, the distribution of the data may be difficult to formally characterize, especially in high dimensional spaces



# Generative Adversarial Networks (GANs)

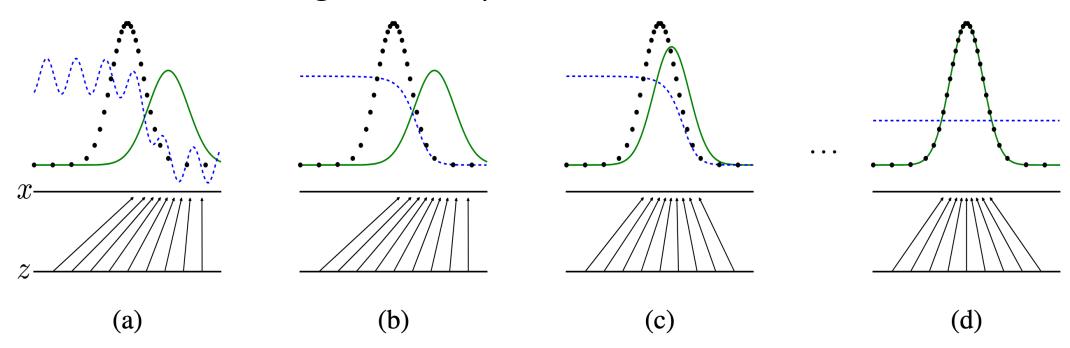
- We can train a discriminator to differentiate between generated data and data from the given dataset
- Will this result in the generator generating realistic data?





## Convergence of GANs

- The distribution of the real data is shown in black
- The distribution the discriminator learns is in blue
- The distribution of the generator is shown in green
- Ideally, the generator converges to the real distribution and the discriminator has no choice but to give an output of 0.5 all the time



# Improvement of GANs

- GANs can be difficult to train, in practice, due to their adversarial nature
  - However, many improvements have been made to stabilize training

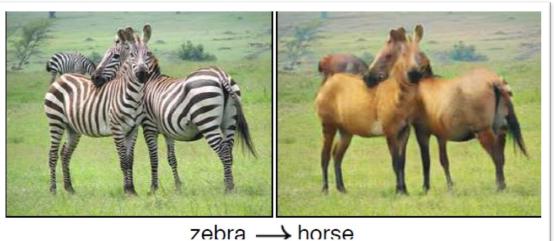


#### Generative Adversarial Networks

#### Unpaired domain transfer



Monet  $\rightarrow$  photo



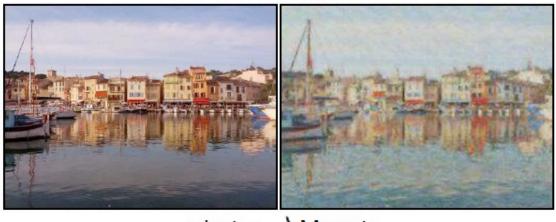


photo  $\rightarrow$  Monet





horse  $\rightarrow$  zebra