Deep Learning

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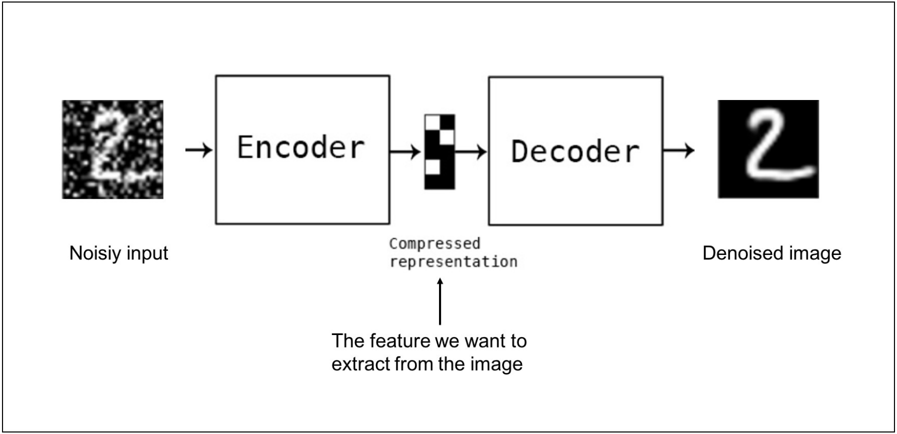
Outline

1. Autoencoders

2. Generative Adversarial Networks

Denoising Autoencoders



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- Minimizes the loss function between the output node and the corrupted input.

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- Variational autoencoder can be defined as being an autoencoder whose training is regularised to avoid overfitting and ensure that the latent space has good properties that enable generative process.
- Instead of encoding an input as a single point, we encode it as a distribution over the latent space.

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- Let minimize the function

$$L(w) = KL(q_w(z|x) || p(z|x)).$$

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Note that

$$KL\left(q_w\left(z|x\right)||p\left(z|x\right)\right) = \mathbb{E}_{q_w(z|x)}\left[\log \frac{q_w\left(z|x\right)}{p\left(z|x\right)}\right]$$

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$$\underset{w,w'}{\operatorname{argmin}}\left(KL\left(q_w\left(z|x\right)||p\left(z\right)\right) + \mathbb{E}_{q_w(z|x)}\left[\|x - f_{w'}\left(z\right)\|^2\right]\right)$$

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Solution: we will assume that $q_w = \mathcal{N}\left(\mu, \Sigma\right)$ and $p = \mathcal{N}\left(0, I\right)$.

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Assumptions

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Assumptions

- In practice, the encoded distributions are chosen to be normal so that the encoder can be trained to return the mean and the covariance matrix that describe these Gaussians.
- The distributions returned by the encoder are enforced to be close to a standard normal distribution.

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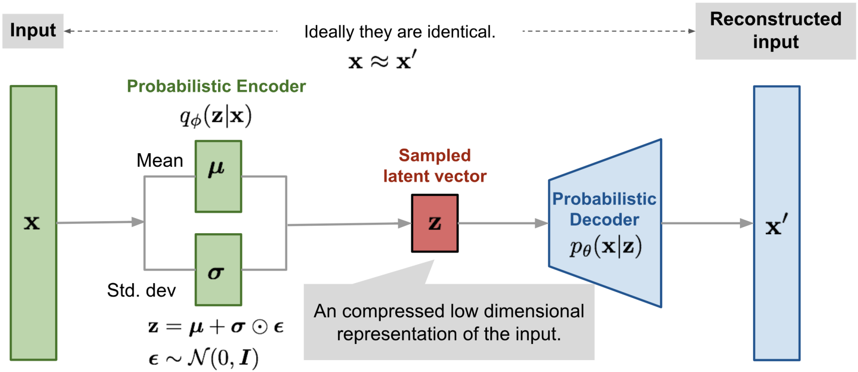

Variational Autoencoders

Let f is our encoder, g is the decoder and D is our training dataset. In this case we will minimize the following loss function

$$\sum_{x \in D} L\left(x, g\left(f\left(x\right)\right)\right) + \lambda KL\left(N\left(\mu, \Sigma\right) || N\left(0, I\right)\right).$$

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- GANs consist of two models:
    - **Discriminator**
      takes samples of true and generated data and that try to classify them as well as possible.
    - **Generator**
      trained to fool the discriminator as much as possible by generating fake data.

Different types of GANs

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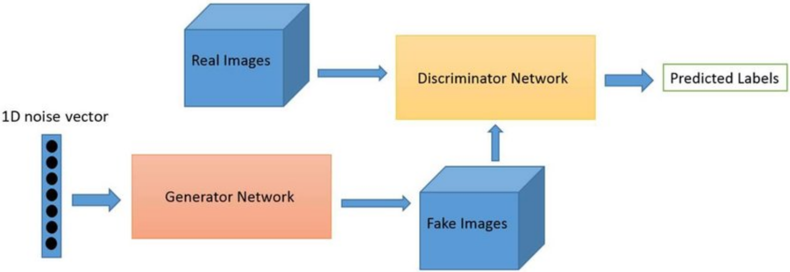
- Wasserstein GANs (WGANs)
- Discover Cross-Domain Relations with Generative Adversarial Networks (Disco GANs)

Simple GANs


Real Images
Discriminator Network
Predicted Labels
1D noise vector
Generator Network
Fake Images

The Loss Function

Let p_z and p_{data} be respectively the distributions of input noise and our data and let D and G be respectively discriminator and generator.

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Let p_z and p_{data} be respectively the distributions of input noise and our data and let D and G be respectively discriminator and generator. We will do the following optimization

$$\min_G \max_D \left(\mathbb{E}_{x \sim p_{data}} \left[\log D\left(x\right) \right] + \mathbb{E}_{z \sim p_z} \left[\log\left(1 - D\left(G\left(z\right)\right)\right) \right] \right)$$

Optimization Algorithm for GANs

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

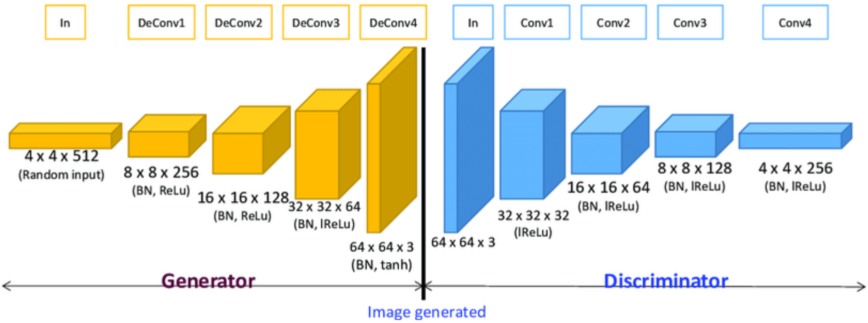
end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

DCGANs



In
DeConv1
DeConv2
DeConv3
DeConv4
In
Conv1
Conv2
Conv3
Conv4
4 x 4 x 512
(Random input)
8 x 8 x 256
(BN, ReLu)
16 x 16 x 128
(BN, ReLu)
32 x 32 x 64
(BN, lReLu)
64 x 64 x 3
(BN, tanh)
64 x 64 x 3
32 x 32 x 32
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Generator
Discriminator
Image generated

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cGANs