Generative Neural Networks

CS 6384 Computer Vision
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Supervised Learning

\[ f(x) \]

Training Data \[ \{x_i, y_i\}_{i=1}^{N} \]
Unsupervised Learning

• Training data $\left\{ x_i \right\}_{i=1}^{N}$ No label

• Goal: discover some underlying hidden structure of the data

• Examples
  • Dimension reduction
  • Clustering
  • Probability density estimation
Dimension Reduction

• Map data from a high-dimension space to a low-dimension space

\[ \mathbf{x} \in \mathbb{R}^n \rightarrow \mathbf{y} \in \mathbb{R}^m \quad m < n \]

• The low-dimensional representation maintains meaningful properties of the original data
  • E.g., can be used to reconstruct the original data

• Applications
  • Data compression, data visualization, data representation learning
Principal Component Analysis (PCA)

- Linear mapping

\[ y = Px \]

Rows of \( P \), principal components
Principal Component Analysis (PCA)

• Change of basis

\[ y = \begin{bmatrix} p_1 \cdot x \\ p_2 \cdot x \\ \vdots \\ p_m \cdot x \end{bmatrix} \]

\[ a \cdot b = ||a|| \cdot ||b|| \cdot \cos \theta \]

\[ a_1 = ||a|| \cdot \cos \theta = \frac{a \cdot b}{||b||} \]

If \( ||b|| = 1 \)

\[ a_1 = a \cdot b \]
Principal Component Analysis (PCA)

- Given a set of data points:
  \[ Y = PX \]

- Covariance matrix:
  \[ X = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} \]
  \[ C_X \equiv \frac{1}{n} XX^T \]
  \[ C_Y \]

\[ X \in \mathcal{R}^{m \times n} \]

- Dimension: \( m \)
- # Data points: \( n \)
Principal Component Analysis (PCA)

• The goal of PCA
  • All off-diagonal terms in $C_Y$ should be zero ($Y$ is decorrelated)
  • Each successive dimension of $Y$ should be rank-ordered according to variance

• Solution

$$C_Y = \frac{1}{n} YY^T$$
$$= \frac{1}{n} (PX)(PX)^T$$
$$= \frac{1}{n} PXX^T P^T$$
$$= P \left( \frac{1}{n} XX^T \right) P^T$$
$$= PC_X P^T$$

$$C_Y = PC_X P^T = P(E^T DE) P^T = P(P^T DP) P^T = (PP^T) D(PP^T) = (PP^{-1}) D(PP^{-1}) = D$$

The principal components $P$ is the eigenvectors of

$$C_X = \frac{1}{n} XX^T$$

A Tutorial on Principal Component Analysis. Jonathon Shlens, 2014
Principal Component Analysis (PCA)

- Dimension reduction

\[ y = Px \]

\[ \begin{align*}
  y &= \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_L \end{bmatrix} \\
  x &= \begin{bmatrix} \end{bmatrix}
\end{align*} \]

Use \( L < m \) principal components
Autoencoder

• Use a neural network for dimension reduction

$z = f(x)$ \quad \hat{x} = g(z)$

Reconstruction loss function

$L_2 = \|x - \hat{x}\|^2$
Augmented Autoencoders: Implicit 3D Orientation Learning for 6D Object Detection. Sundermeyer et al., IJCV’20
Case Study: Augmented Autoencoder

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Case Study: Denoising Autoencoder

Content Generation

• Given a dataset \( \{ x_i \}_{i=1}^{N} \)
• How to generate new content from the underlying distribution \( P(x) \)?
• Autoencoder is not suitable for content generation

The latent space is not regularized. Some latent vectors may generate meaningless content.
Variational Autoencoder

• Introduce regularization to the latent space
• Probabilistic formulation

\[ p(z|x) = \mathcal{N}(\mu_x, \sigma_x) \quad \leftrightarrow \quad \mathcal{N}(0, I) \]

Prior distribution
Variational Autoencoder

• Latent space
  • Continuity (close points in latent space decode similar outputs)
  • Completeness (a sampled latent should generate meaningful output)

https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73
Variational Autoencoder

- Encoder

\[ \mu_x \rightarrow z \sim \mathcal{N}(\mu_x, \sigma_x) \]

Sampling

Not differentiable

Reparameterization

\[ \zeta \sim \mathcal{N}(0, I) \]

No gradient

\[ z = \sigma_x \zeta + \mu_x \]
Variational Autoencoder

- Encoder-Decoder

\[ \zeta \sim \mathcal{N}(0, \mathbf{I}) \]

\[ \mu_x \]

\[ \sigma_x \]

\[ z = \sigma_x \zeta + \mu_x \]

- Loss function

\[ L = C \| \mathbf{x} - \hat{\mathbf{x}} \|^2 + \text{KL}(\mathcal{N}(\mu_x, \sigma_x), \mathcal{N}(0, \mathbf{I})) \]

Reconstruction loss

Prior loss

\[ D_{\text{KL}}(P \parallel Q) = \int_{-\infty}^{\infty} p(x) \log \left( \frac{p(x)}{q(x)} \right) dx \]
Variational Autoencoder

• Generating data

\[ z \sim \mathcal{N}(0, I) \]

• Diagonal prior on \( z \rightarrow \) independent latent variables

• Different dimensions of \( z \) encode interpretable factors of variation

2D latent space

Direct Content Generation

• VAE models the density as

\[ p_\theta(x) = \int p_\theta(z)p_\theta(x|z)dz \]

• Directly sample from the training distribution without modeling the probability density

• Generative Adversarial Networks (GANs) can generate better samples compared to VAEs
Generative Adversarial Network (GAN)

• Goal: sample examples from training distribution \( P(x) \)
• Solution
  • First sample from a simple distribution (e.g., uniform distribution)
  • Learn transformation to the training distribution

Input: random noise

Output: sample from the training distribution

How to train the generator?
  • We do not know the mapping from \( z \) to training data
Generative Adversarial Network (GAN)

- Generator-Discriminator
Training GAN: Two-player Game

- Discriminator: try to distinguish between real image and fake images (generated images from the generator)
- Generator: try to fool the discriminator by generating real-look images
Training GAN: Two-player Game

- Minmax objective function

$$\min_{\theta_g} \max_{\theta_d} \left[ \mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

- Discriminator: maximize the objective such that $D(x)$ is close to 1 and $D(G(z))$ is close to 0
- Generator: minimize the objective such that $D(G(z))$ is close too 1 (fool the discriminator)

Generative Adversarial Nets. Goodfellow et al. NeurIPS’14
Training GAN: Two-player Game

• Minmax objective function

\[
\min_{\theta_g} \max_{\theta_d} \left[ \mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]
\]

• Alternate between
  • Gradient ascent on discriminator

\[
\max_{\theta_d} \left[ \mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]
\]
  • Gradient descent on generator

\[
\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))
\]

Generative Adversarial Nets. Goodfellow et al. NeurIPS’14

Gradient is relative flat
Training GAN: Two-player Game

• Minmax objective function

$$\min_{\theta_g} \max_{\theta_d} \left[ \mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

• Alternate between
  • Gradient ascent on discriminator

$$\max_{\theta_d} \left[ \mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

  • Gradient ascent on generator

$$\max_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(D_{\theta_d}(G_{\theta_g}(z)))$$

Generative Adversarial Nets. Goodfellow et al. NeurIPS’14
Training GAN: Two-player Game

for number of training iterations do
    for \( k \) steps do
        • Sample minibatch of \( m \) noise samples \( \{z^{(1)}, \ldots, z^{(m)}\} \) from noise prior \( p_g(z) \).
        • Sample minibatch of \( m \) examples \( \{x^{(1)}, \ldots, x^{(m)}\} \) from data generating distribution \( p_{data}(x) \).
        • Update the discriminator by ascending its stochastic gradient:
          \[
          \nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[ \log D(x^{(i)}) + \log \left( 1 - D \left( G \left( z^{(i)} \right) \right) \right) \right].
          \n          \]
    end for
    • Sample minibatch of \( m \) noise samples \( \{z^{(1)}, \ldots, z^{(m)}\} \) from noise prior \( p_g(z) \).
    • Update the generator by descending its stochastic gradient:
      \[
      \nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log \left( 1 - D \left( G \left( z^{(i)} \right) \right) \right). \]
end for

Generative Adversarial Nets. Goodfellow et al. NeurIPS’14
Generative Adversarial Network (GAN)

Visualization of samples from the model

Nearest neighbor from training set

Generative Adversarial Nets. Goodfellow et al. NeurIPS’14
Deep Convolutional GANs (DCGANs)

- Use CNNs for generator and discriminator

*Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks.* Radford et al., ICLR’16
Deep Convolutional GANs (DCGANs)

UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS. Radford et al., ICLR'16
Summary

• Autoencoder
  • Good for dimension reduction, cannot generate new data

• Variational autoencoder
  • Probabilistic formulation
  • Regularized latent space, can be used to generate new data

• Generative Adversarial Network
  • Directly sample training distribution to generate data
  • Better samples compared VAEs
Further Reading


• UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS. Radford et al., ICLR’16. https://arxiv.org/abs/1511.06434