Autoencoders

Lecture slides for Chapter 14 of *Deep Learning* www.deeplearningbook.org Ian Goodfellow 2016-09-30

Structure of an Autoencoder

Hidden layer (code) \boldsymbol{h} gf \boldsymbol{x} r Input Reconstruction Figure 14.1

Stochastic Autoencoders



Figure 14.2

Avoiding Trivial Identity

- Undercomplete autoencoders
 - h has lower dimension than x
 - f or g has low capacity (e.g., linear g)
 - Must discard some information in h
- Overcomplete autoencoders
 - h has higher dimension than x
 - Must be regularized

Regularized Autoencoders

- Sparse autoencoders
- Denoising autoencoders
- Autoencoders with dropout on the hidden layer
- Contractive autoencoders

Sparse Autoencoders

- Limit capacity of autoencoder by adding a term to the cost function penalizing the code for being larger
- Special case of variational autoencoder
 - Probabilistic model
 - Laplace prior corresponds to L1 sparsity penalty
 - Dirac variational posterior



C: corruption proce (introduce noise)

$$L = -\log p_{\text{decoder}}(\boldsymbol{x} \mid \boldsymbol{h} = f(\tilde{\boldsymbol{x}}))$$

Denoising Autoencoders Learn a Manifold



Score Matching

- Score: $\nabla_{\boldsymbol{x}} \log p(\boldsymbol{x})$. (14.15)
- Fit a density model by matching score of model to score of data
- Some denoising autoencoders are equivalent to score matching applied to some density models



Tangent Hyperplane of a Manifold



Figure 14.6

Learning a Collection of 0-D Manifolds by Resisting Perturbation



Non-Parametric Manifold Learning with Nearest-Neighbor Graphs



Tiling a Manifold with Local Coordinate Systems



Contractive Autoencoders

$$\Omega(\boldsymbol{h}) = \lambda \left\| \frac{\partial f(\boldsymbol{x})}{\partial \boldsymbol{x}} \right\|_{F}^{2}$$



 $(Goodfellow \ 2016)$

(14.18)