




ECE 599/692 – Deep Learning

Lecture 9 – Autoencoder (AE)

Hairong Qi, Gonzalez Family Professor
 Electrical Engineering and Computer Science
 University of Tennessee, Knoxville
<http://www.eecs.utk.edu/faculty/qi>
 Email: hqi@utk.edu

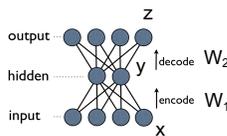



Outline

- Lecture 9: Points crossed
 - General structure of AE
 - Unsupervised
 - Generative model?
 - The representative power
 - Basic structure of a linear autoencoder
 - Denoising autoencoder (DAE)
 - AE in solving overfitting problem
- Lecture 10: Variational autoencoder
- Lecture 11: Case study




General structure



$$y = f_{\theta_1}(W_1x + b_1)$$

$$z = g_{\theta_2}(W_2y + b_2)$$

$$\theta_1 = \{W_1, b_1\}, \theta_2 = \{W_2, b_2\}$$

$$\theta_1^*, \theta_2^* = \arg \min_{\theta_1, \theta_2} \frac{1}{n} \sum_{i=1}^n L(x^{(i)}, z^{(i)}) = \arg \min_{\theta_1, \theta_2} \frac{1}{n} \sum_{i=1}^n L(x^{(i)}, g_{\theta_2}(f_{\theta_1}(x^{(i)})))$$

$$L(x, z) = \frac{1}{2} \|x - z\|_2^2$$

$$L_H(x, z) = - \sum_{i=1}^n [x_i \log z_i + (1 - x_i) \log(1 - z_i)]$$

$$\theta_1^*, \theta_2^* = \arg \min_{\theta_1, \theta_2} E_{q(X)}[L_H(X, g_{\theta_2}(f_{\theta_1}(X)))]$$

Generative Model

- The goal is to learn a model P which we can sample from, such that P is as similar as possible to P_{gt} , where P_{gt} is some unknown distribution that had generated examples X
- The ingredients
 - Explicit estimate of the density
 - Ability to sample directly

Discrimination vs. Representation of Data

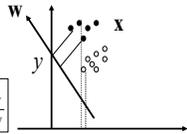
- Best discriminating the data

- Fisher's linear discriminant (FLD)

- NN

- CNN

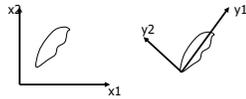
$$J(\mathbf{w}) = \frac{|\tilde{m}_1 - \tilde{m}_2|^2}{\tilde{s}_1^2 + \tilde{s}_2^2} = \frac{|\mathbf{w}^T(\mathbf{m}_1 - \mathbf{m}_2)|^2}{\mathbf{w}^T \mathbf{S}_D \mathbf{w}} = \frac{\mathbf{w}^T \mathbf{S}_B \mathbf{w}}{\mathbf{w}^T \mathbf{S}_W \mathbf{w}}$$



- Best representing the data

- Principal component analysis (PCA)

$$\mathbf{x} = \sum_{i=1}^m y_i \mathbf{b}_i + \sum_{i=m+1}^d y_i \mathbf{b}_i \approx \sum_{i=1}^m y_i \mathbf{b}_i + \sum_{i=m+1}^d \alpha_i \mathbf{b}_i$$



Error: $\Delta \mathbf{x} = \sum_{i=m+1}^d (y_i - \alpha_i) \mathbf{b}_i$

PCA as Linear Autoencoder

Raw data ($X_{n \times d}$) \rightarrow covariance matrix (Σ_x) \rightarrow eigenvalue decomposition (λ_{dx1} and E_{dx1}) \rightarrow principal component ($P_{d \times m}$) $\rightarrow Y_{n \times m} = X_{n \times d} * P_{d \times m}$

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Denoising Autoencoder (DAE)

$$\theta_1^*, \theta_2^* = \arg \min_{\theta_1, \theta_2} E_{q(X, \tilde{X})} [L_H(X, g_{\theta_2}(f_{\theta_1}(\tilde{X})))]$$

[DAE:2008]

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The Two Papers in 2006

- [Hinton:2006a] G.E. Hinton, S. Osindero, Y.W. Teh, "A fast learning algorithm for deep belief nets," *Neural Computation*, 18(7):1527-1554, 2006.
- [Hinton:2006b] G.E. Hinton, R.R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," *Science*, 313:504-507, July 2006.

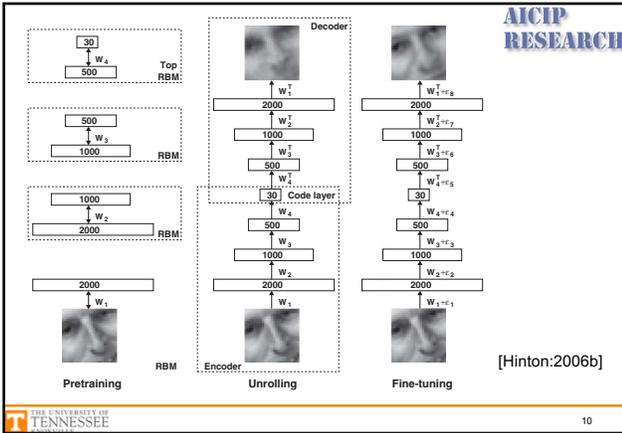
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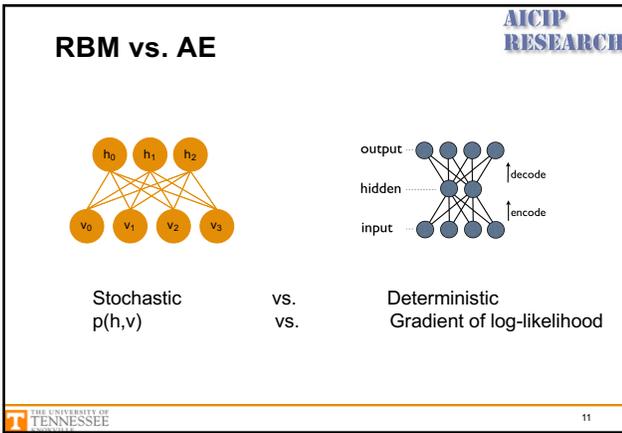
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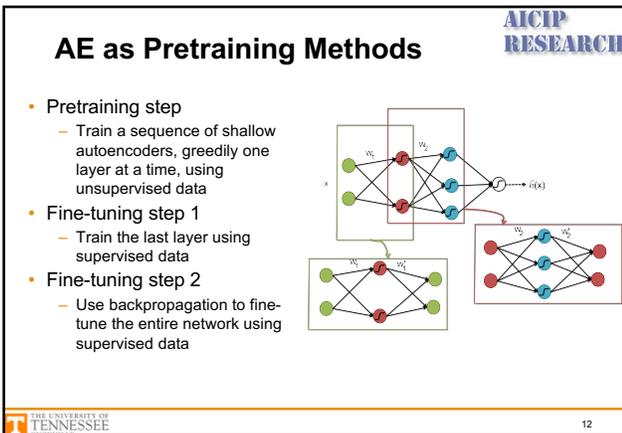
Techniques to Avoid Overfitting

- Regularization
 - Weight decay or L1/L2 normalization
 - Use dropout
 - Data augmentation
- Use unlabeled data to train a different network and then use the weight to initialize our network
 - Deep belief networks (based on restricted Boltzmann Machine or RBM)
 - **Deep autoencoders (based on autoencoder)**

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Recap

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