

Tutorials: part I

# Fun with Neural Network

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程嵩

2016/11

**CS:**

Network structure

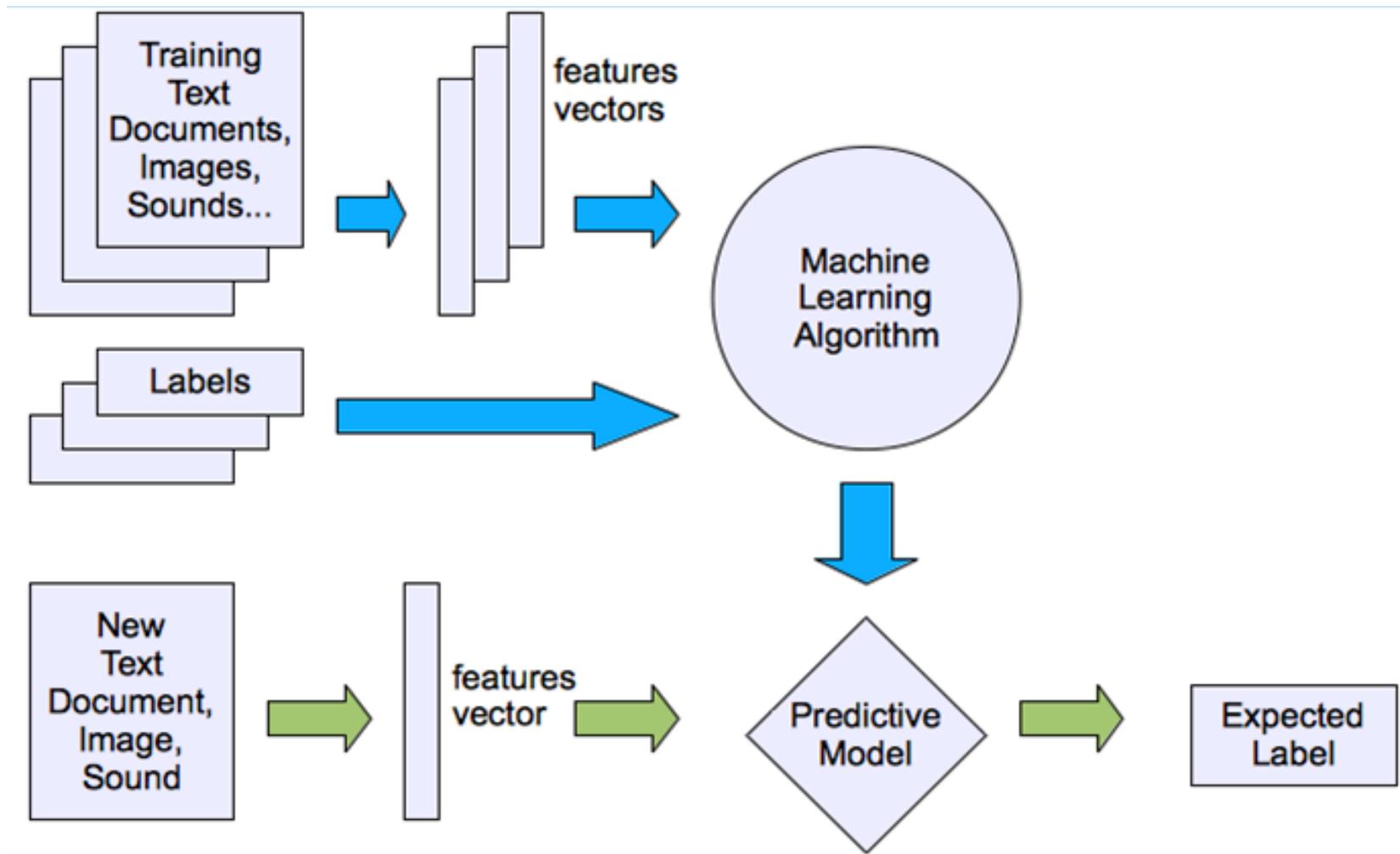
Back propagation algorithm

**honghao:**

Tensorflow

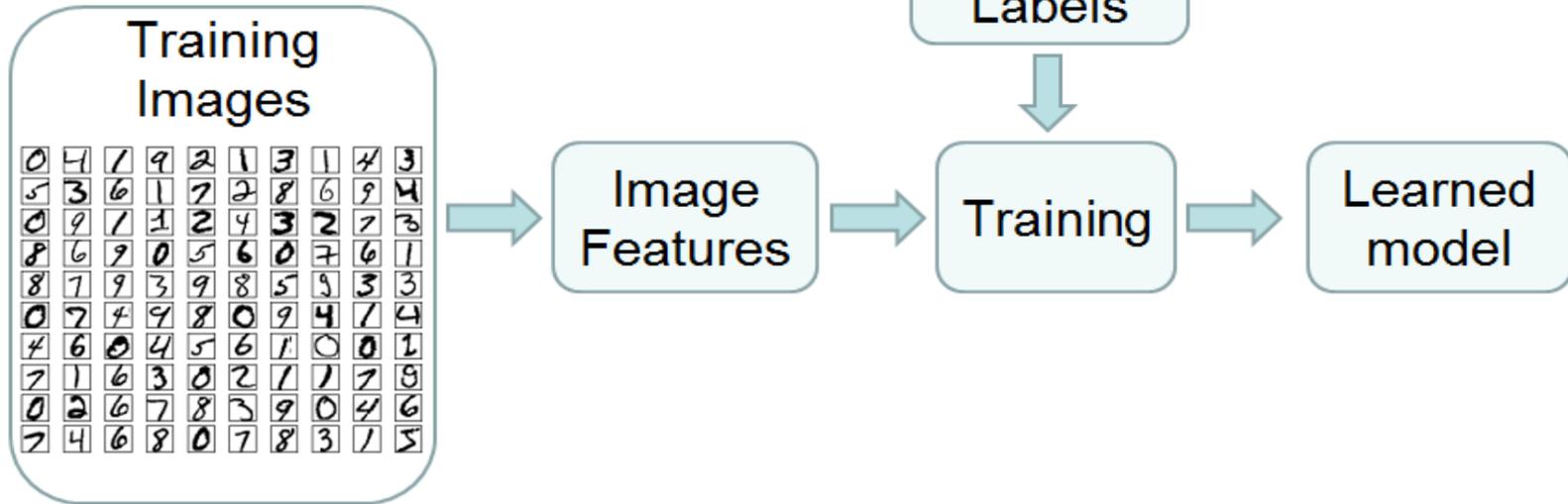
Tensorboard

# Supervised learning

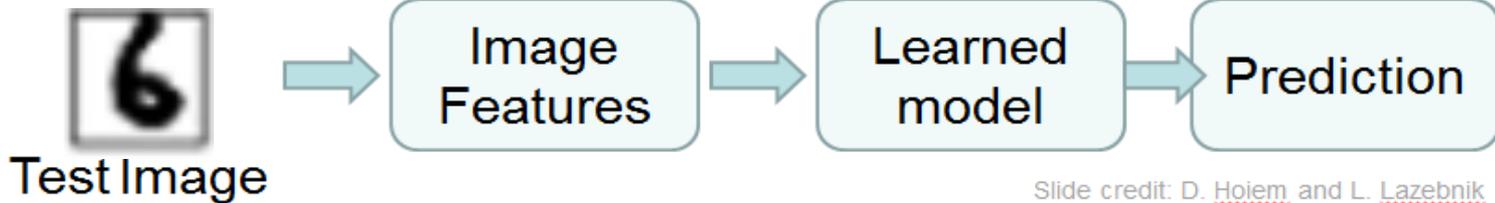


# Steps

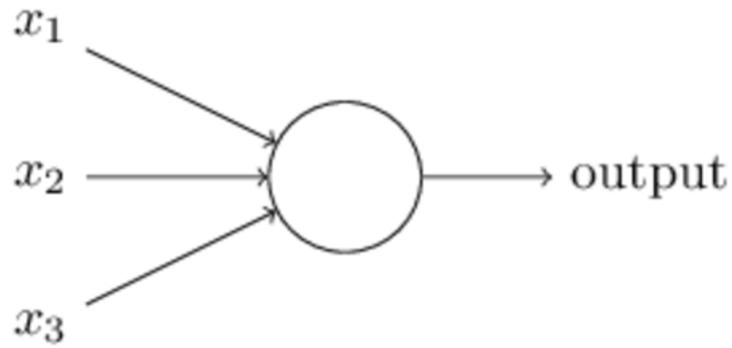
## Training



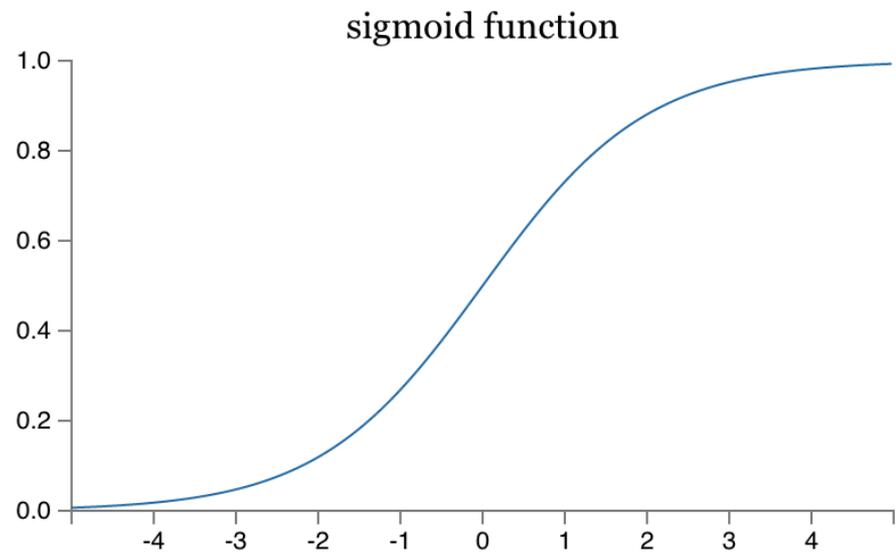
## Testing

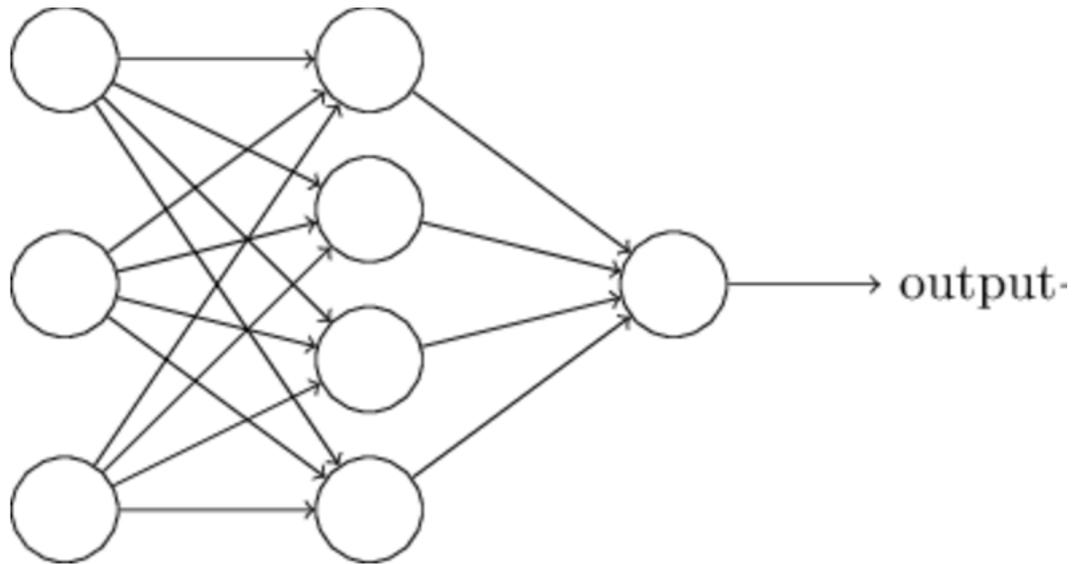


Slide credit: D. Hoiem and L. Lazebnik



$$\text{output} = \frac{1}{1 + \exp(-\sum_j w_j x_j - b)}$$



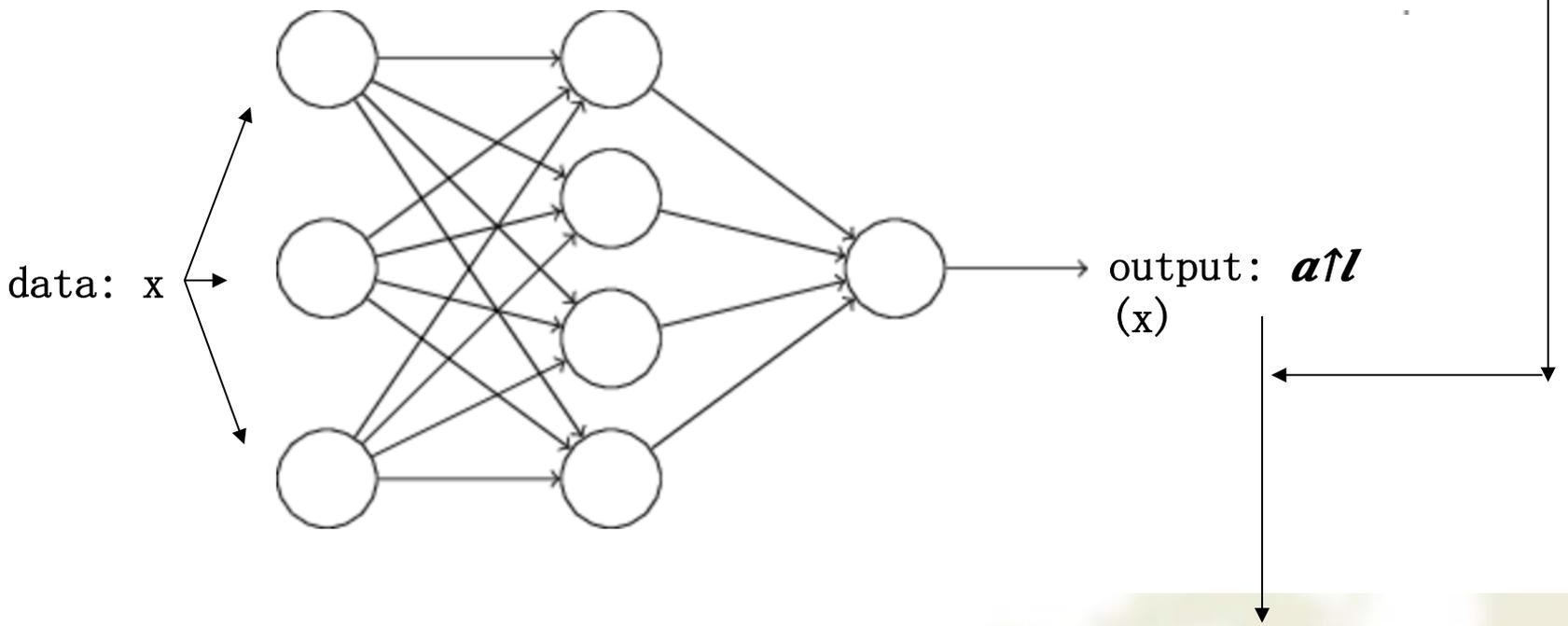


$$z = w x + b$$

$$a = \sigma(z) = 1 / (1 + e^{-z})$$

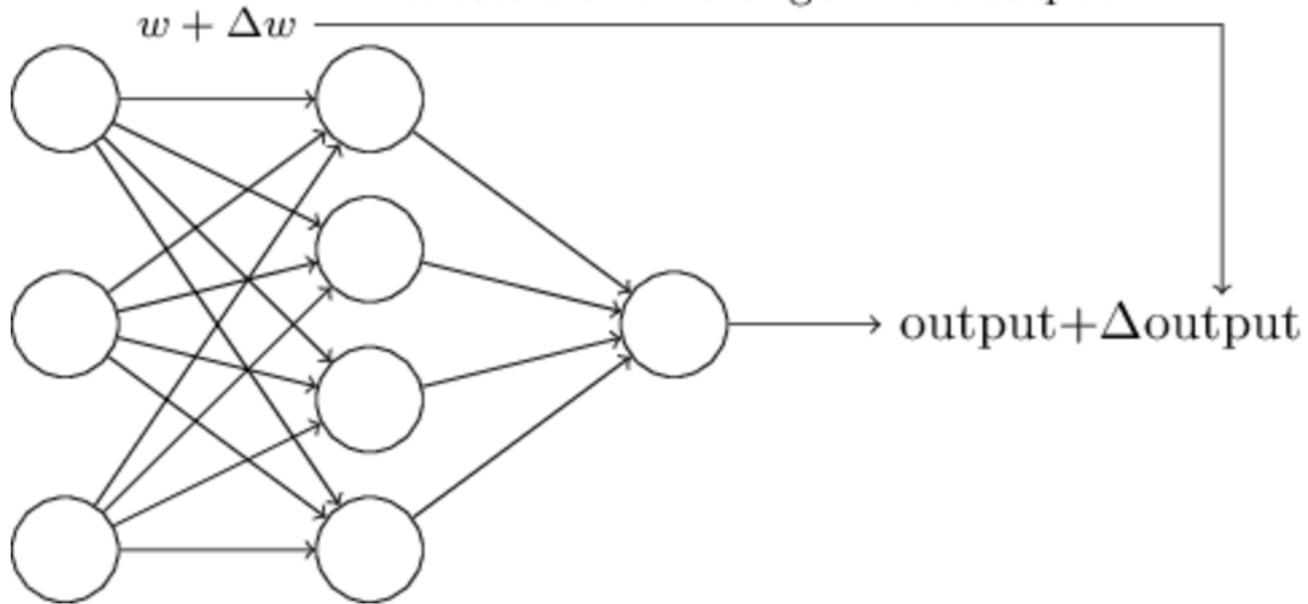
$$[z_1 \ z_2 \ z_3 \ z_4] = [w_{11} \ w_{12} \ w_{13} \ w_{21} \ w_{22} \ w_{23} \ w_{31} \ w_{32} \ w_{33}]$$

data\_label:  $y(x)$



Cost function: 
$$C = \frac{1}{2n} \sum_x \|y(x) - a^L(x)\|^2$$

small change in any weight (or bias)  
causes a small change in the output



$$\Delta \text{output} \approx \sum_j \frac{\partial \text{output}}{\partial w_j} \Delta w_j + \frac{\partial \text{output}}{\partial b} \Delta b$$

# Optimization

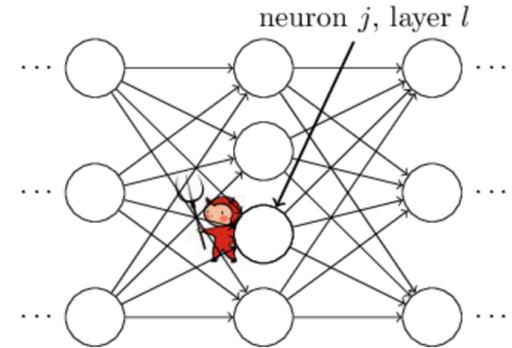
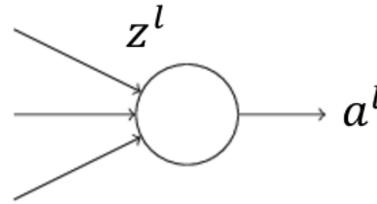
## Backpropagation algorithm

Def:  $z^l = w^l a^{l-1} + b^l$

Def:  $a^l = \sigma(z^l)$

Def:  $\delta_j^l = \partial C / \partial z_j^l$

Def: hadamard product  $\odot$ :  $a = [1, 2], b = [3, 4], a \odot b = [1*3, 2*4] = [3, 8]$

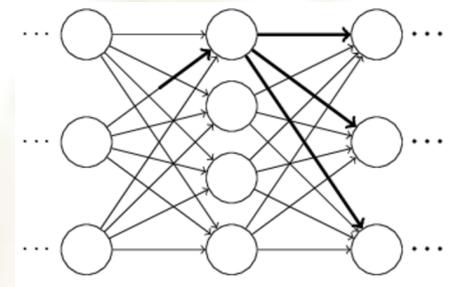


$$\delta_j^l = \partial C / \partial z_j^l = \sum_j \sigma'(z_j^l) \delta_j^{l+1}$$

$$\delta^l = \nabla_a C \odot \sigma'(z^l)$$

$$\delta_j^l = \left( \sum_i w_{ji}^{l+1} \delta_i^{l+1} \right) \sigma'(z_j^l)$$

$$\delta^l = ((w^{l+1})^T \delta^{l+1}) \odot \sigma'(z^l)$$



$$\frac{\partial C}{\partial b_j^l} = \delta_j^l$$

$$\frac{\partial C}{\partial w_{jk}^l} = a_k^{l-1} \delta_j^l$$

# Optimization

## Backpropagation algorithm

1. **Input  $x$ :** Set the corresponding activation  $a^1$  for the input layer.
2. **Feedforward:** For each  $l = 2, 3, \dots, L$  compute  $z^l = w^l a^{l-1} + b^l$  and  $a^l = \sigma(z^l)$ .
3. **Output error  $\delta^L$ :** Compute the vector  $\delta^L = \nabla_a C \odot \sigma'(z^L)$ .
4. **Backpropagate the error:** For each  $l = L - 1, L - 2, \dots, 2$  compute  $\delta^l = ((w^{l+1})^T \delta^{l+1}) \odot \sigma'(z^l)$ .
5. **Output:** The gradient of the cost function is given by  $\frac{\partial C}{\partial w_{jk}^l} = a_k^{l-1} \delta_j^l$  and  $\frac{\partial C}{\partial b_j^l} = \delta_j^l$ .

# Stochastic gradient descent

## Optimization

### 1. Input a set of training examples

### 2. For each training example $x$ : Set the corresponding input activation $a^{x,1}$ , and perform the following steps:

- **Feedforward:** For each  $l = 2, 3, \dots, L$  compute

$$z^{x,l} = w^l a^{x,l-1} + b^l \text{ and } a^{x,l} = \sigma(z^{x,l}).$$

- **Output error  $\delta^{x,L}$ :** Compute the vector

$$\delta^{x,L} = \nabla_a C_x \odot \sigma'(z^{x,L}).$$

- **Backpropagate the error:** For each

$$l = L - 1, L - 2, \dots, 2 \text{ compute } \delta^{x,l} = ((w^{l+1})^T \delta^{x,l+1}) \odot \sigma'(z^{x,l})$$

.

### 3. Gradient descent: For each $l = L, L - 1, \dots, 2$ update the weights according to the rule $w^l \rightarrow w^l - \frac{\eta}{m} \sum_x \delta^{x,l} (a^{x,l-1})^T$ , and the biases according to the rule $b^l \rightarrow b^l - \frac{\eta}{m} \sum_x \delta^{x,l}$ .

Andrew Ng 百度首席科学家

<https://www.coursera.org/learn/machine-learning>

Hinton 是deep learning的大牛

<https://www.coursera.org/course/neuralnets>

比较详尽的概览

<https://www.udacity.com/course/machine-learning--ud262>

极好的网络教程(Michael Nielsen)

<http://neuralnetworksanddeeplearning.com/index.html>

Deep learning 专著

<http://www.deeplearningbook.org/>

MNIST DEMO:

<http://myselfph.de/neuralNet.html>

**Thanks!**