

# Lecture 4

## Perceptron

Rui Xia

School of Computer Science & Engineering  
Nanjing University of Science & Technology

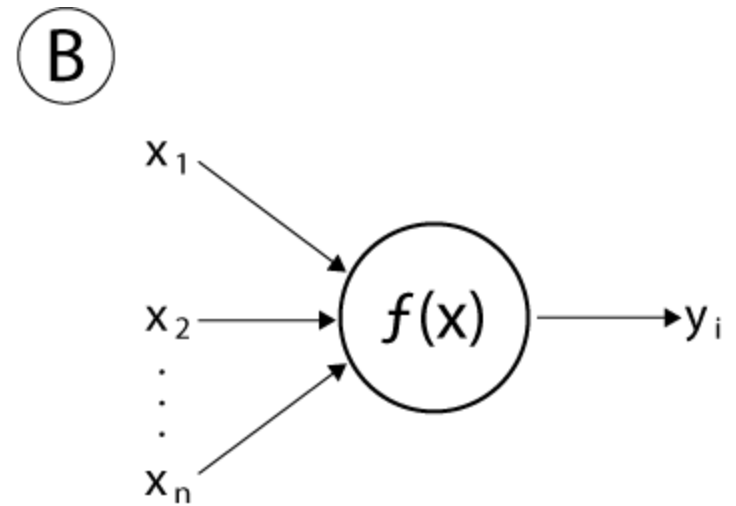
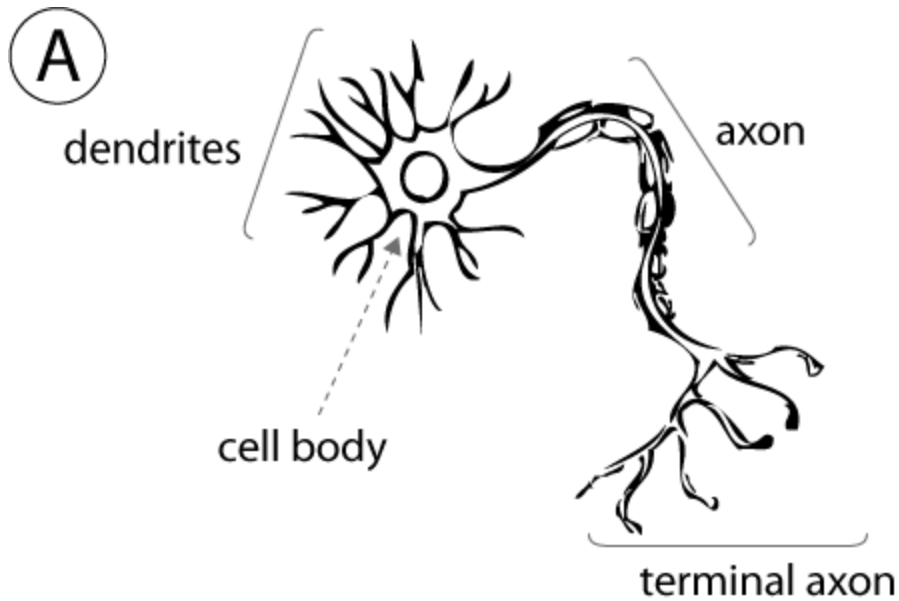
<http://www.nustm.cn/~rxia>

# Perceptron



- The perceptron algorithm was invented in 1957 at the Cornell Aeronautical Laboratory by Frank Rosenblatt.
- Perceptron is an algorithm for supervised classification.
- It is a type of linear classifier.
- It lays the foundation of artificial neural networks (ANN).

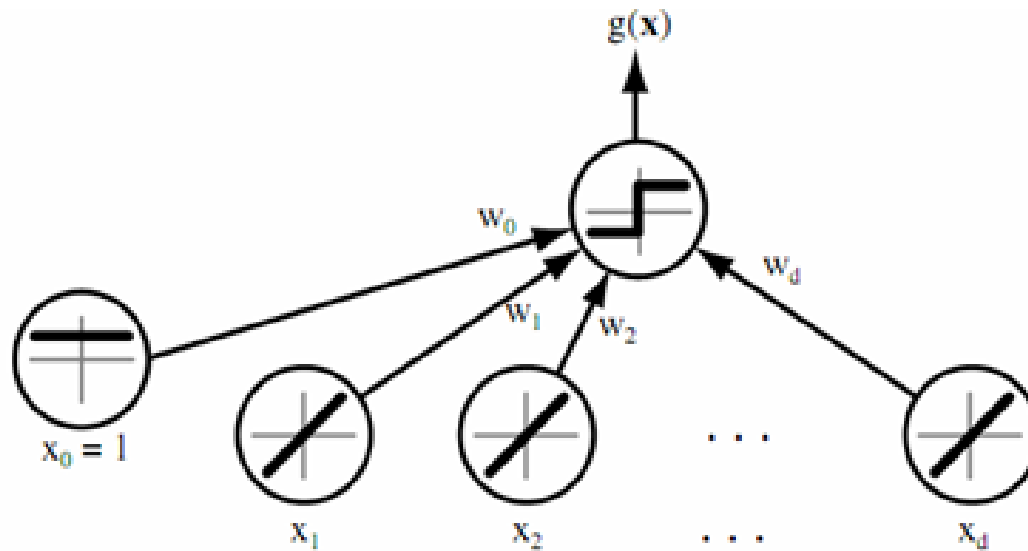
# Inspired from Neural Networks



# Hypothesis

- Model hypothesis

$$h_{\mathbf{w}}(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{w}^T \mathbf{x} \geq 0 \\ 0 & \text{if } \mathbf{w}^T \mathbf{x} < 0 \end{cases}$$



# Learning

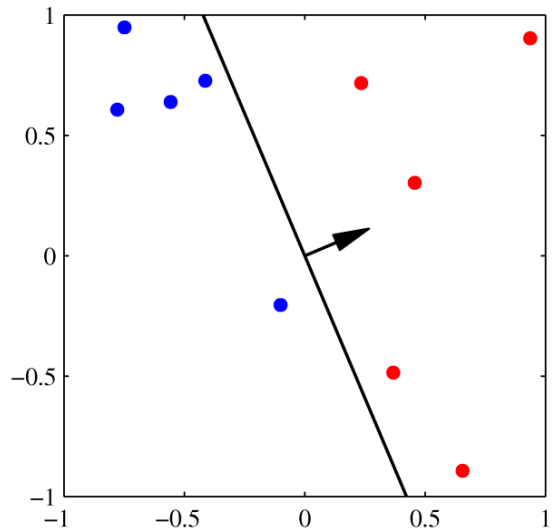
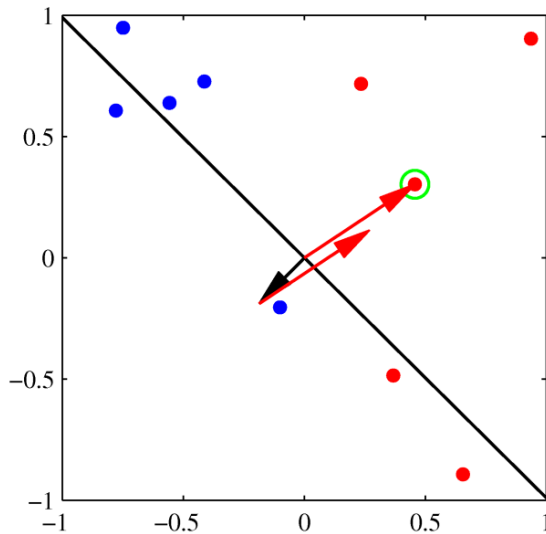
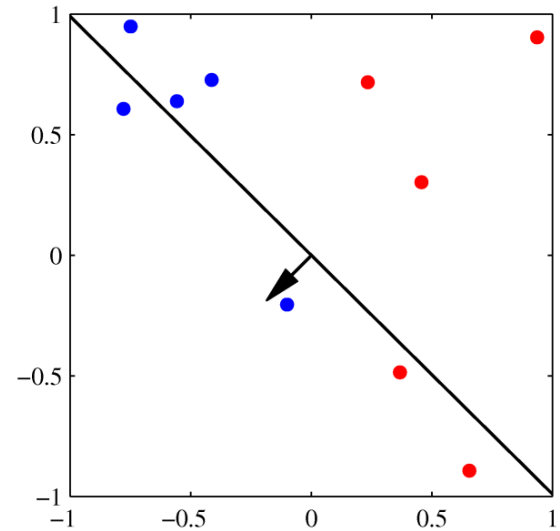
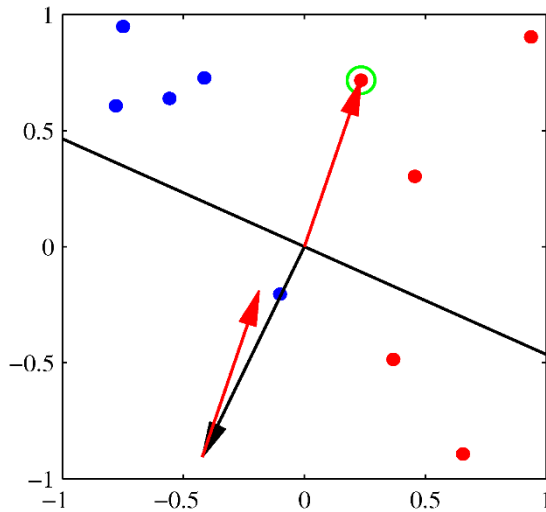
- Perceptron cost function

$$\begin{aligned} J_P(\mathbf{x}) &= \sum_{\mathbf{x}^{(i)} \in M_0} \mathbf{w}^T \mathbf{x}^{(i)} - \sum_{\mathbf{x}^{(j)} \in M_1} \mathbf{w}^T \mathbf{x}^{(j)} \\ &= \sum_{i=1}^N \left( (1 - y^{(i)}) h_{\mathbf{w}}(\mathbf{x}^{(i)}) - y^{(i)} (1 - h_{\mathbf{w}}(\mathbf{x}^{(i)})) \right) \mathbf{w}^T \mathbf{x}^{(i)} \\ &= \sum_{i=1}^N (h_{\mathbf{w}}(\mathbf{x}^{(i)}) - y^{(i)}) \mathbf{w}^T \mathbf{x}^{(i)} \end{aligned}$$

- Perceptron updating rule (by applying SGD)

$$\begin{aligned} \mathbf{w} &= \mathbf{w} + \alpha (y - h_{\mathbf{w}}(\mathbf{x})) \mathbf{x} \quad \text{Error} \times \text{Feature} \\ &= \begin{cases} \mathbf{w} + \alpha \mathbf{x}, & \text{if } y = 1 \text{ and } h_{\mathbf{w}}(\mathbf{x}) = 0 \\ \mathbf{w} - \alpha \mathbf{x}, & \text{if } y = 0 \text{ and } h_{\mathbf{w}}(\mathbf{x}) = 1 \\ \mathbf{w}, & \text{otherwise} \end{cases} \end{aligned}$$

# An Illustration



# A Simple Python Code

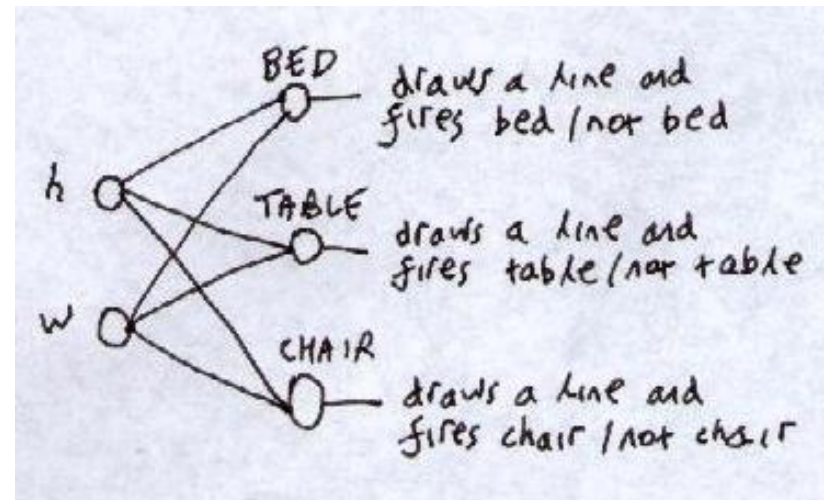
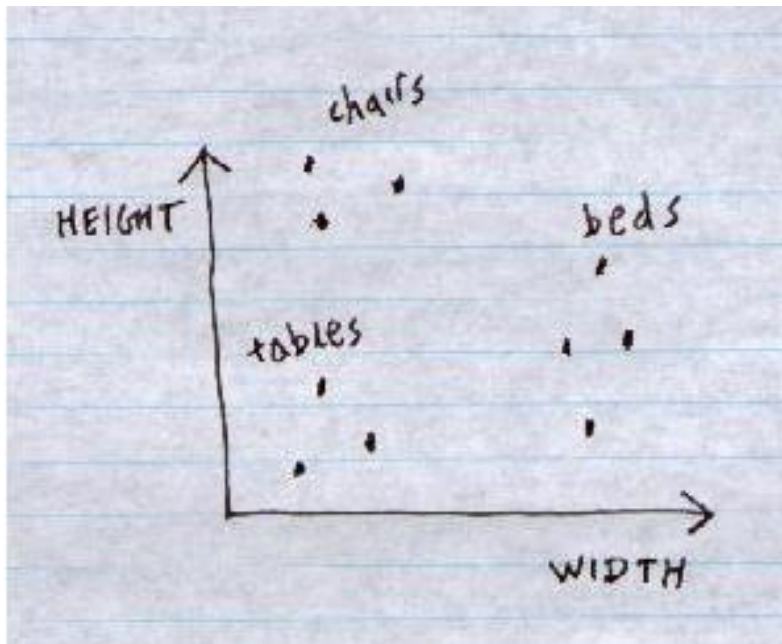
```
threshold = 0.5
learning_rate = 0.1
weights = [0, 0, 0]
training_set = [((1, 0, 0), 1), ((1, 0, 1), 1), ((1, 1, 0), 1), ((1, 1, 1), 0)]

def dot_product(values, weights):
    return sum(value * weight for value, weight in zip(values, weights))

while True:
    print('-' * 60)
    error_count = 0
    for input_vector, desired_output in training_set:
        print(weights)
        result = dot_product(input_vector, weights) > threshold
        error = desired_output - result
        if error != 0:
            error_count += 1
            for index, value in enumerate(input_vector):
                weights[index] += learning_rate * error * value
    if error_count == 0:
        break
```

# Multi-class Perceptron

- Multi-class perceptron is an extension of standard perceptron to solve multi-class classification problems;
- Multi-class perceptron is widely used in NLP.





# Hypothesis and Learning

- Hypothesis

$$C^* = \arg \max_{j=1,\dots,C} \mathbf{w}_j^T \mathbf{x}$$

- Cost function

$$J_p(\mathbf{w}) = \sum_{k=1}^N \left( \max_{j=1,\dots,C} \mathbf{w}_j^T \mathbf{x}^{(k)} - \mathbf{w}_{y^{(k)}}^T \mathbf{x}^{(k)} \right)$$

- Parameter update rule

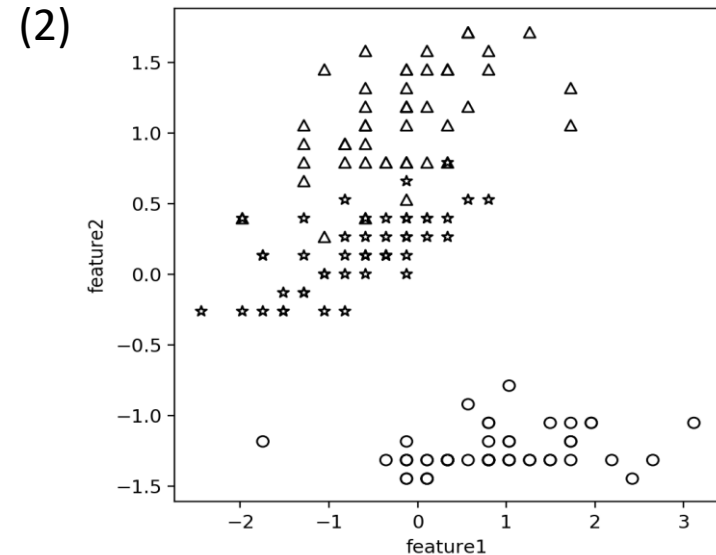
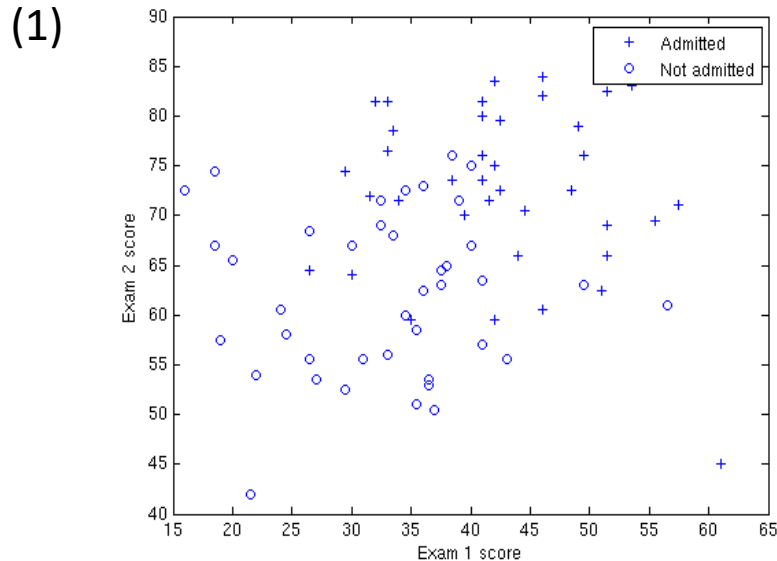
$$\mathbf{w}_j := \mathbf{w}_j - \alpha (1\{j = c^{(k)}\} - 1\{j = y^{(k)}\}) \mathbf{x}^{(k)}$$

$$= \begin{cases} \mathbf{w}_j - \alpha \mathbf{x}^{(k)}, & \text{if } j = c^{(k)} \neq y^{(k)} \\ \mathbf{w}_j + \alpha \mathbf{x}^{(k)}, & \text{if } j = y^{(k)} \neq c^{(k)} \\ \mathbf{w}_j, & \text{otherwise} \end{cases}$$

$$\text{where } c^{(k)} = \arg \max_{j=1,\dots,C} \mathbf{w}_j^T \mathbf{x}^{(k)}$$

# Practice 4: Perceptron

- Given the following training data sets:



- (1) <http://openclassroom.stanford.edu/MainFolder/DocumentPage.php?course=DeepLearning&doc=exercises/ex4/ex4.html>  
(2) <https://pan.baidu.com/s/1gU81bKslj8cRokOYEK1Jzw> password: w2a8

- For data set (1), implement perceptron algorithm and compare it with logistic regression (SGD);
- For data set (1), implement multi-class perceptron algorithm and compare it with standard perceptron (SGD);
- For data set (2), implement multi-class perceptron algorithm and compare it with softmax regression (SGD).



**Any Questions?**