# Machine Learning

#### Lecture 2

#### Perceptron

### Perceptron - Basic

 Perceptron is a type of artificial neural network (ANN)



### Perceptron - Operation

 It takes a vector of real-valued inputs, calculates a linear combination of these inputs, then output 1 if the result is greater than some threshold and -1 otherwise

$$R = w_0 + w_1 x_1 + w_2 x_2, \cdots, w_n x_n = w_0 + \sum_{i=1}^n w_i x_i$$

$$Y = sign(R) = \begin{cases} +1; & \text{if } R > 0\\ \\ -1, & \text{otherwise} \end{cases}$$



# Perceptron – Decision Surface

- Perceptron can be regarded as representing a hyperplane decision surface in the n-dimensional **feature space** of instances.
- The perceptron outputs a 1 for instances lying on one side of the hyperplane and a -1 for instances lying on the other side.
- This hyperplane is called the **Decision Surface**

### Perceptron – Decision Surface

• In 2-dimensional space



- The Decision Surface is linear
- Perceptron can only solve Linearly Separable Problems



 Can represent many boolean functions: Assume boolean values of 1 (true) and -1 (false)



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• Separate the objects from the rest



**Decision Surface:** 

• Some problems are linearly non-separable



• Separate the — objects from the rest





 $w_0 + w_1 x_1 + w_2 x_2 = 0$ 

We are given the training sample (experience ) pairs (X, D), how can we determine the weights that will produce the correct +1 and -1 outputs for the given training samples?

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 $\mathbf{x}_1$ 

• Training sample pairs (X, d), where X is the input vector, d is the input vector's classification (+1 or -1) is iteratively presented to the network for training, *one at a time*, until the process converges

- The Procedure is as follows
  - 1. Set the weights to small random values, e.g., in the range (-1, 1)
  - 2. Present X, and calculate

$$R = w_0 + \sum_{i=1}^n w_i x_i \quad Y = sign(R) = \begin{cases} +1; & \text{if } R > 0\\ -1, & \text{otherwise} \end{cases}$$

3. Update the weights

$$w_i \leftarrow w_i + \eta (d - y) x_i, i = 1, 2, \dots, n$$
  
 $0 < \eta < 1$  is the training rate  $x_0 = 1$  (constant)

4. Repeat by going to step 2

• Example





$$w_i \leftarrow w_i + \eta (d - y) x_i, i = 1, 2, \cdots, n$$

- Convergence Theorem
  - The perceptron training rule will converge (finding a weight vector correctly classifies all training samples) within a finite number of iterations, provided the training examples are linearly separable and provided a sufficiently small η is used.

## **Further Reading**

• T. M. Mitchell, Machine Learning, McGraw-Hill International Edition, 1997

Chapter 4

# Tutorial/Exercise Questions

1. What is the weight values of a perceptron having the following decision surfaces



2. Design two-input perceptrons for implementing the following boolean functions

AND, OR, NAND, NOR

3. A single layer perceptron is incapable of learning simple functions such as XOR (exclusive OR). Explain why this is the case (hint: use the decision boundary)

# Tutorial/Exercise Questions

4. A single layer Perceptron is as follows



- a) Write down and plot the equation of the decision boundary of this device
- b) Change the values of w1 and w2 so that the Perceptron can separate following two-class patterns

Class 1 Patterns: (1, 2), (1.5. 2.5), (1, 3) Class 2 Patterns: (2, 1.5), (2, 1)