Artificial Intelligence (CS303)

Lecture 10: Perceptron & Neural Networks

感知器

Credit: Ansaf Salleb-Aouissi and "Artificial Intelligence, A Modern Approach" Stuart Russell and Peter Norvig. Third Edition. Pearson Education.

Perceptron

Classification

Given: Training data: $(x_1, y_1), \dots, (x_n, y_n)$, $x_i \in \mathbb{R}^d$ and y_i is discrete (categorical/qualitative), $y_i \in Y$.

Example $Y = \{-1, +1\}$, $Y = \{0, 1\}$

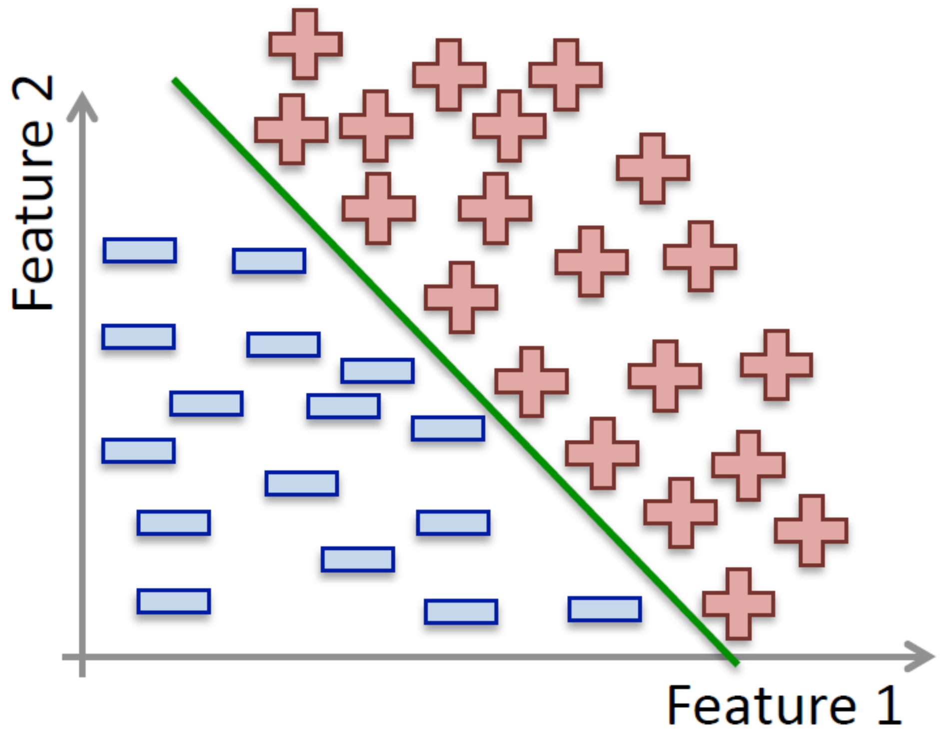
Task: Learn a classification function, $f\colon \mathbb{R}^d \to Y$

Linear Classification: A classification model is said to be linear if it is represented by a linear function f (linear hyperplane)

Perceptron

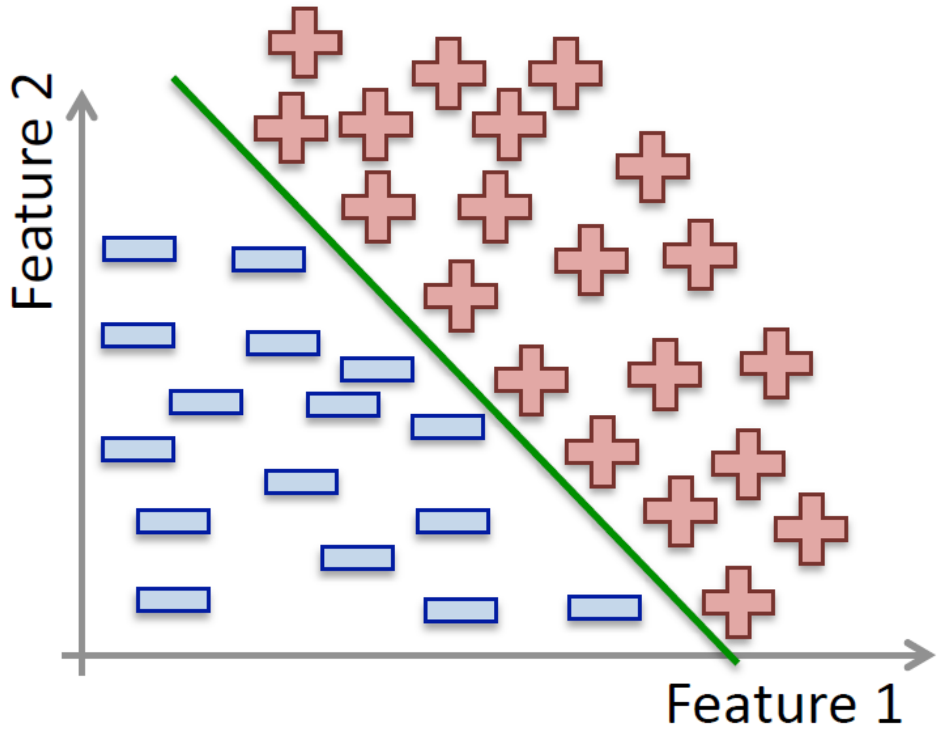
- Belongs to Neural Networks class of algorithms (algorithms that try to mimic how the brain functions).
- The first algorithm used was the Perceptron (Resenblatt 1959).
- Worked extremely well to recognize:
    1. handwritten characters (LeCun et a. 1989),
    2. spoken words (Lang et al. 1990),
    3. faces (Cottrel 1990)
- NN were popular in the 90' s but then lost some of its popularity.
- Now NN back with deep learning.

Perfectly separable data

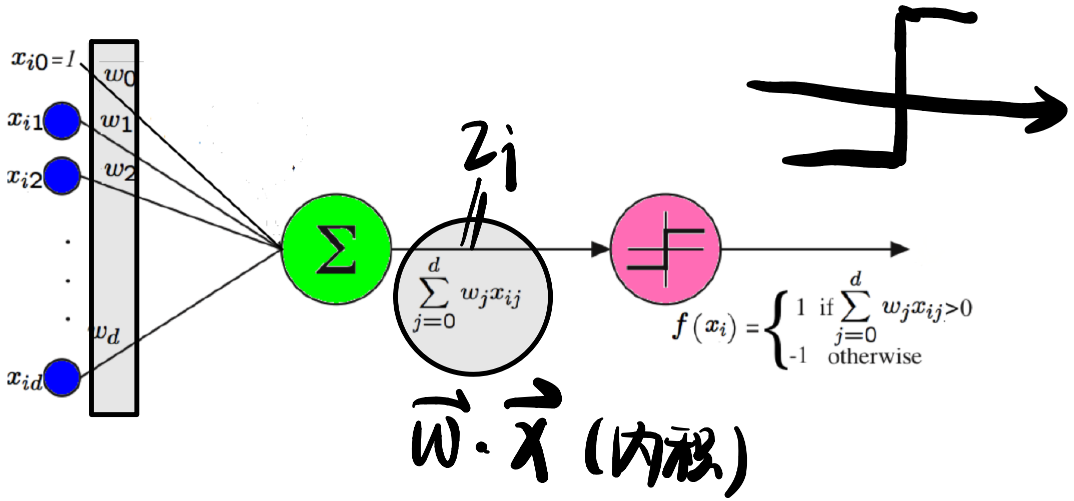


Perceptron

- Linear classification method.
- Simplest classification method.
- Simplest neural network.
- For perfectly separated data.



Perceptron



Given *n* examples and *d* features.

$$f(x_i) = sign(\sum_{j=0}^{d} w_j x_{ij})$$ 针对一个样本

Perceptron

- Works perfectly if data is linearly separable. If not, it will not converge.
- Idea: Start with a random hyperplane and adjust it using your training data.
- Iterative method.

Perceptron

Perceptron Algorithm

Input: A set of examples, $(x_1, y_1), \cdots, (x_n, y_n)$
Output: A perceptron defined by $(w_0, w_1, \cdots, w_d)$

Begin

2. Initialize the weights w_j to 0 $\forall j \in \{0, \cdots, d\}$
3. Repeat until convergence
    4. For each example x_i $\forall i \in \{1, \cdots, n\}$
    5. if $y_i f(x_i) \leq 0$ #an error?
    6. update all w_j with $w_j := w_j + y_i x_{ij}$ #adjust the weights

End

$\{-1, 1\}$

Perceptron

Some observations:

- The weights $w_1, \ldots, w_d$ determine the slope of the decision boundary.
- w_0 determines the offset of the decision boundary (sometimes noted b).
- Line 6 corresponds to:

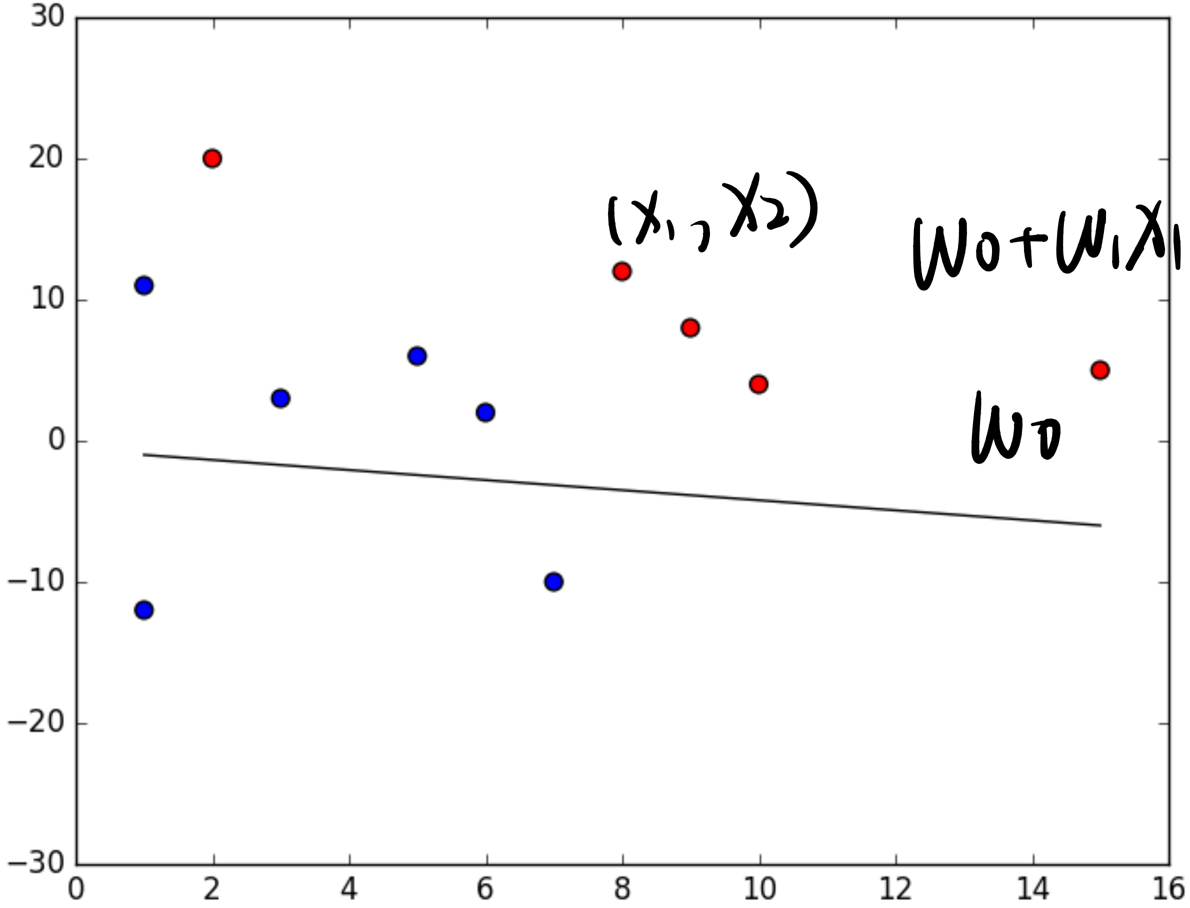
  Mistake on positive: $\boxed{\text{add}}$ x to weight vector.

  Mistake on negative: $\boxed{\text{subtract}}$ x from weight vector.

  Some other variants of the algorithm add or subtract 1.
- Convergence happen when the weights do not change anymore (difference between the last two weight vectors is 0).

Perceptron: Example

(with coordinaite as x, color as lable)

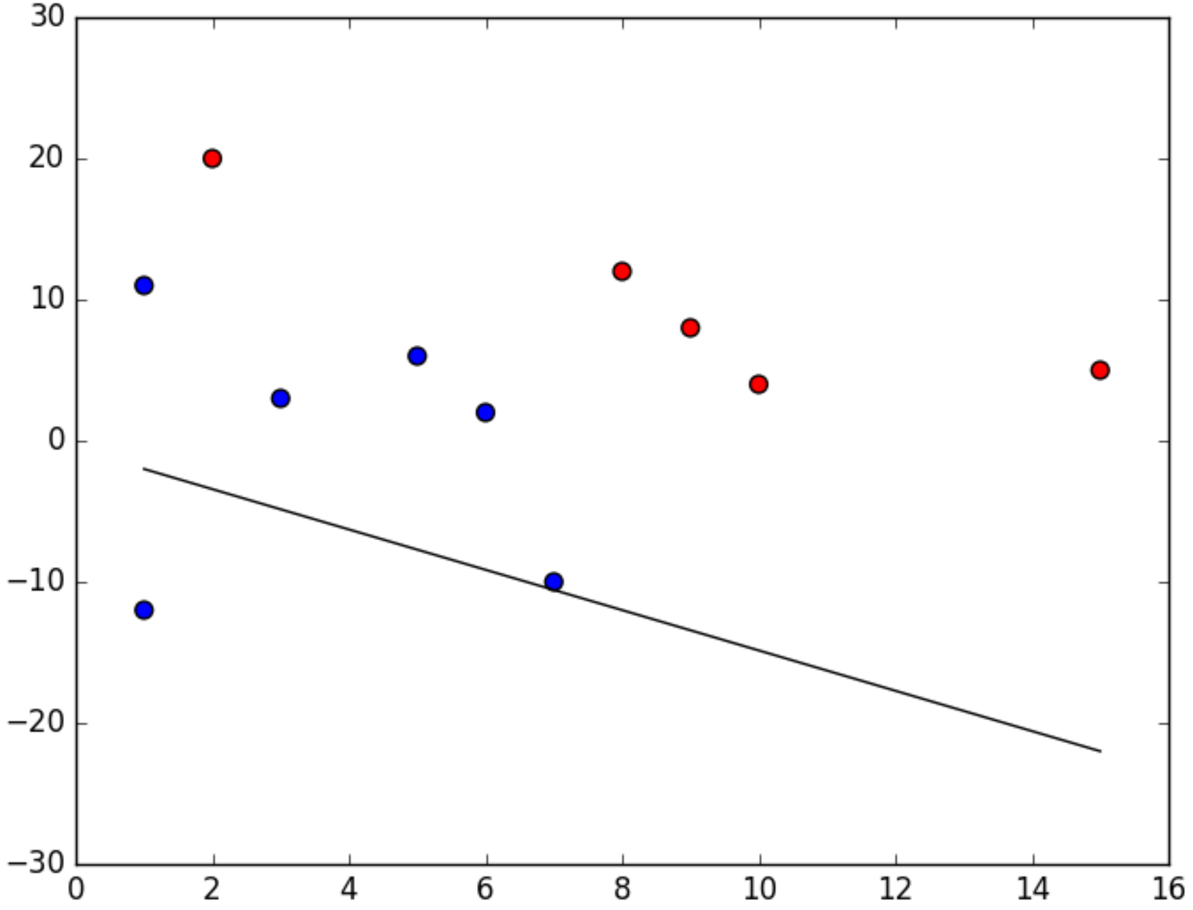


(x_1, x_2)

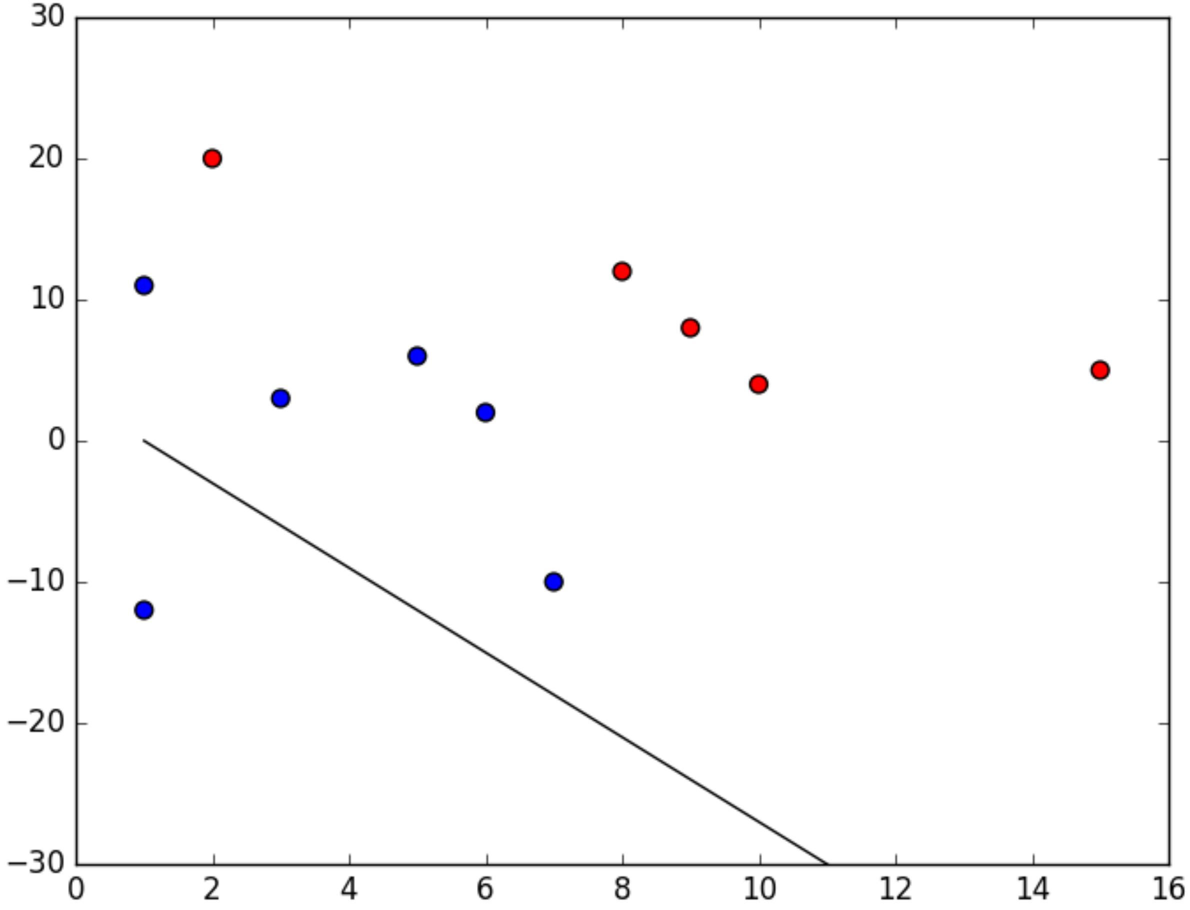
$w_0 + w_1 x_1 + w_2 x_2 = \square$

w_0

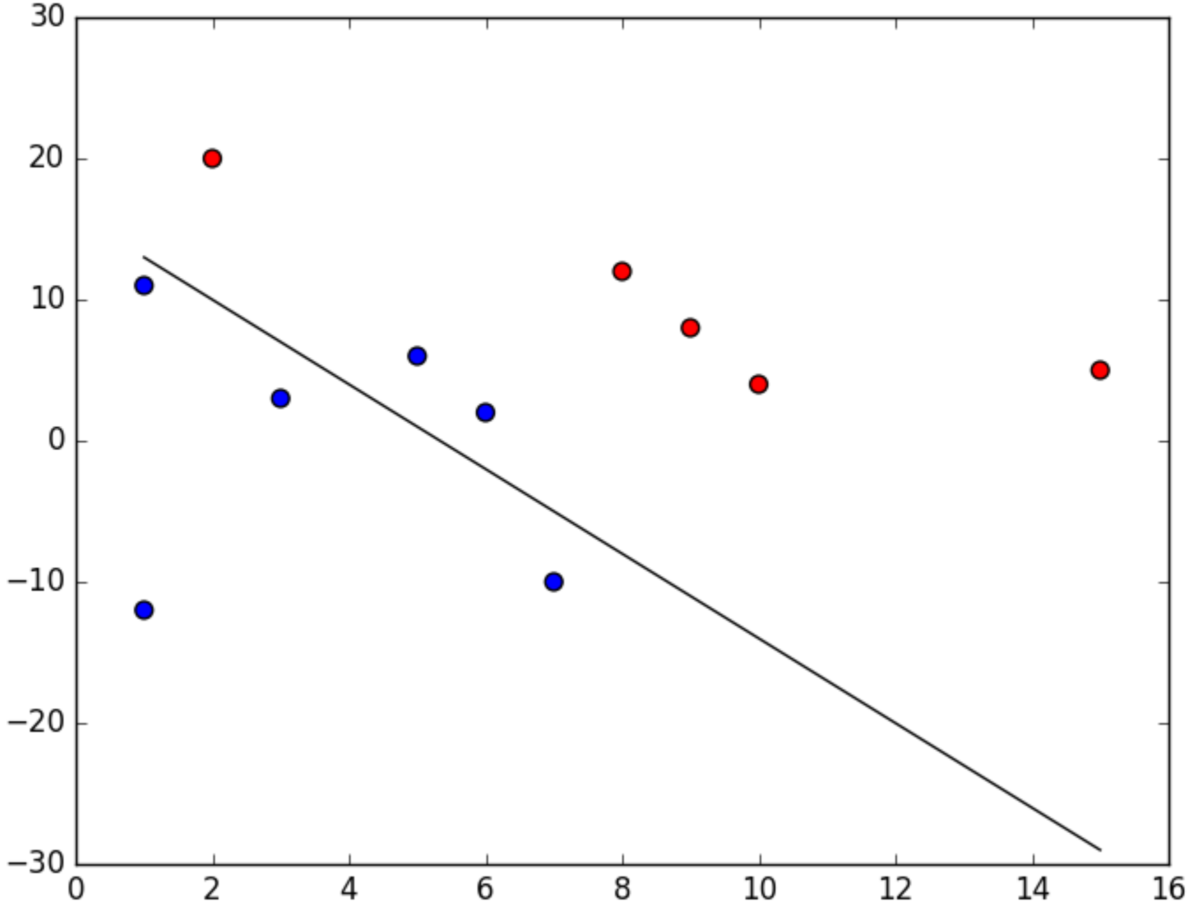
Perceptron: Example



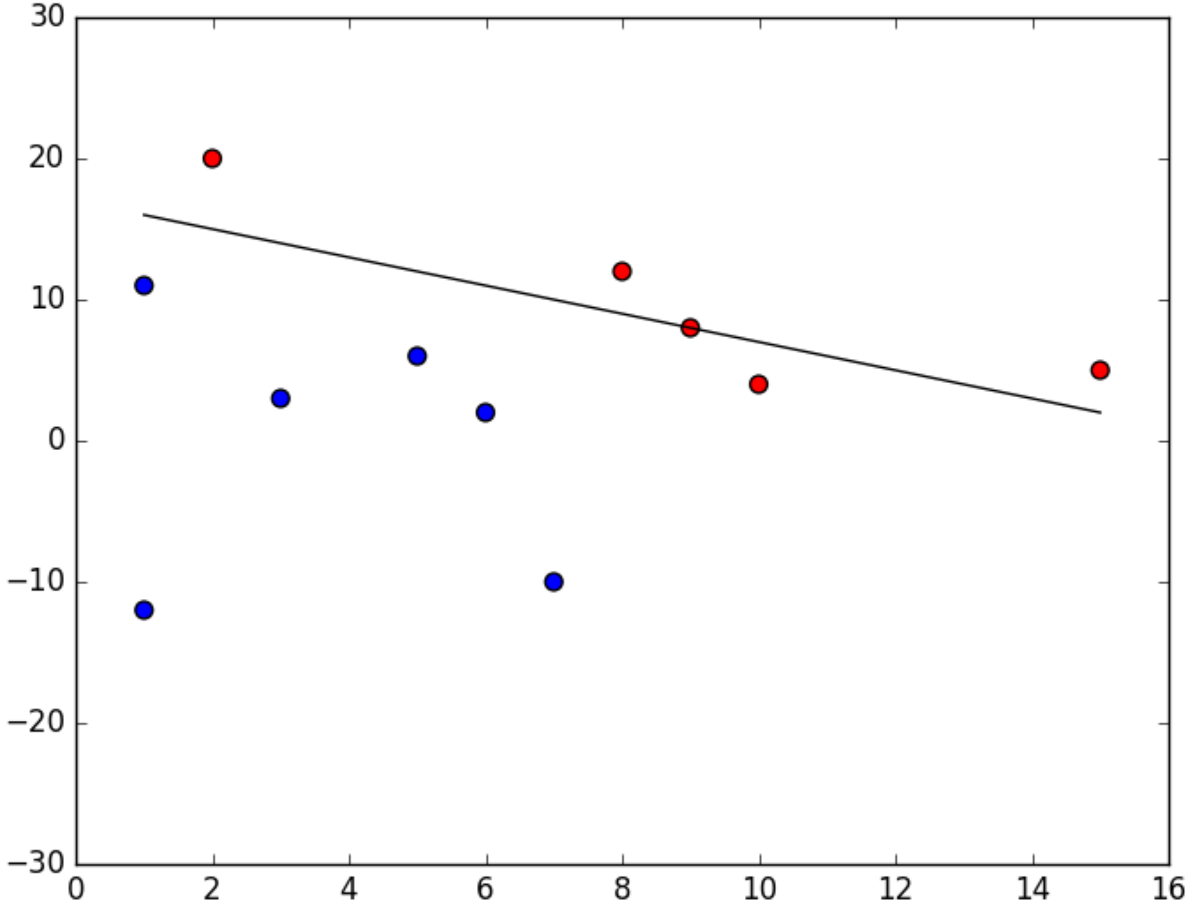
Perceptron: Example



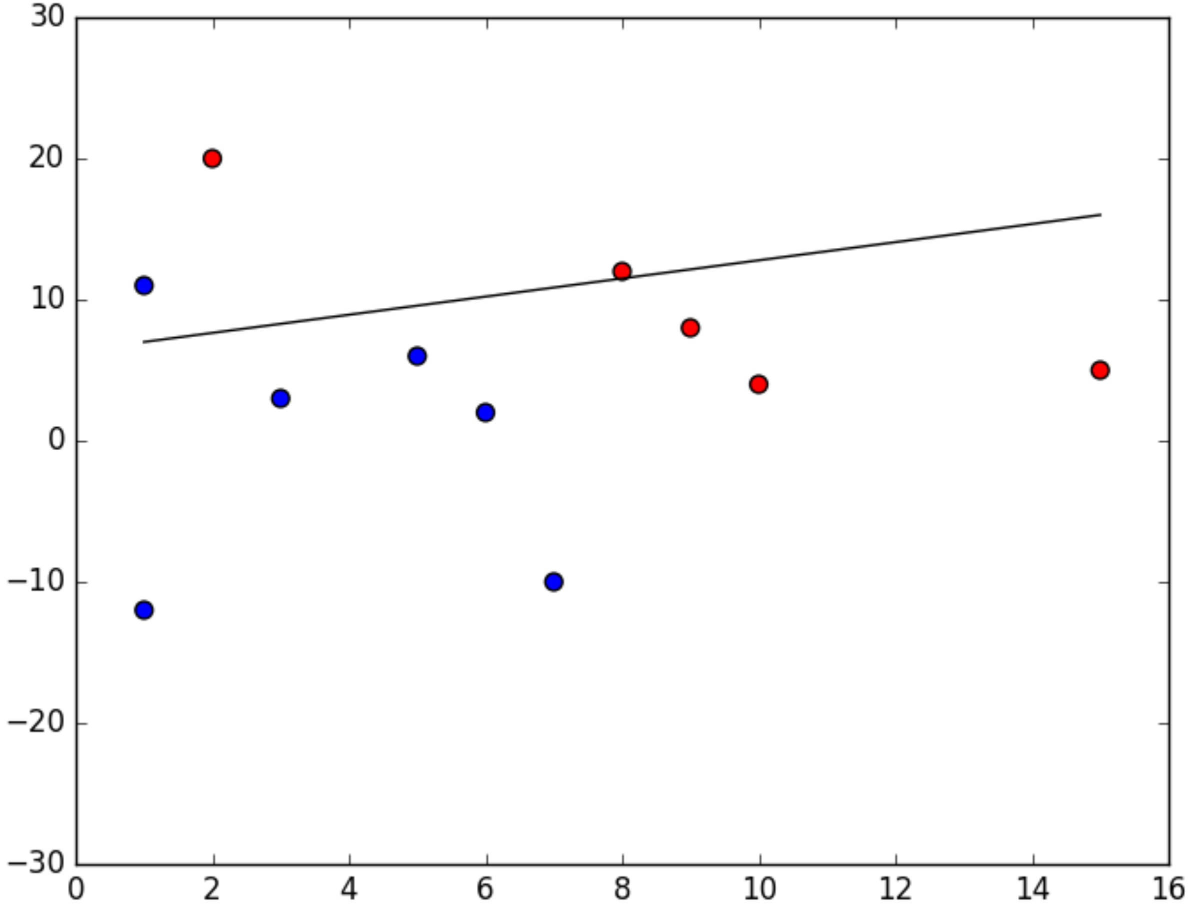
Perceptron: Example



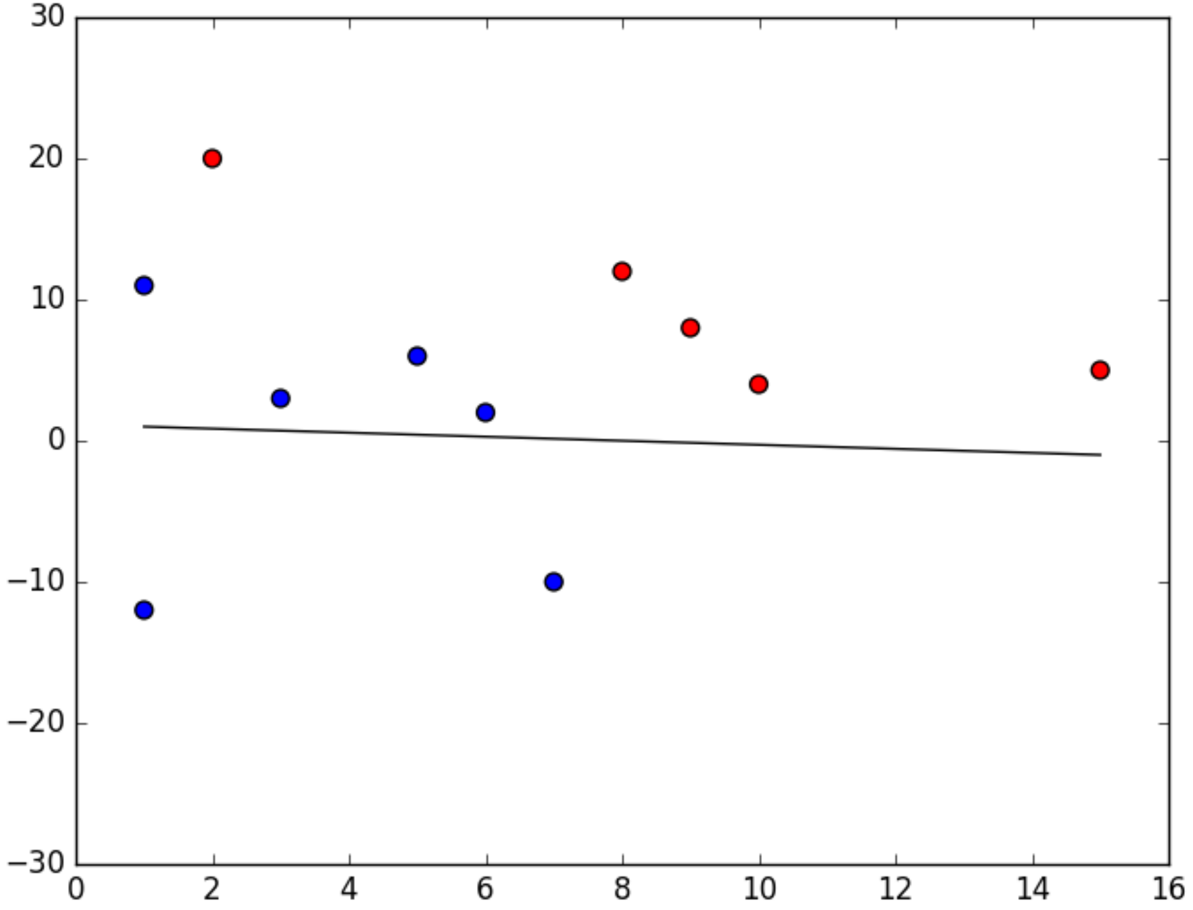
Perceptron: Example



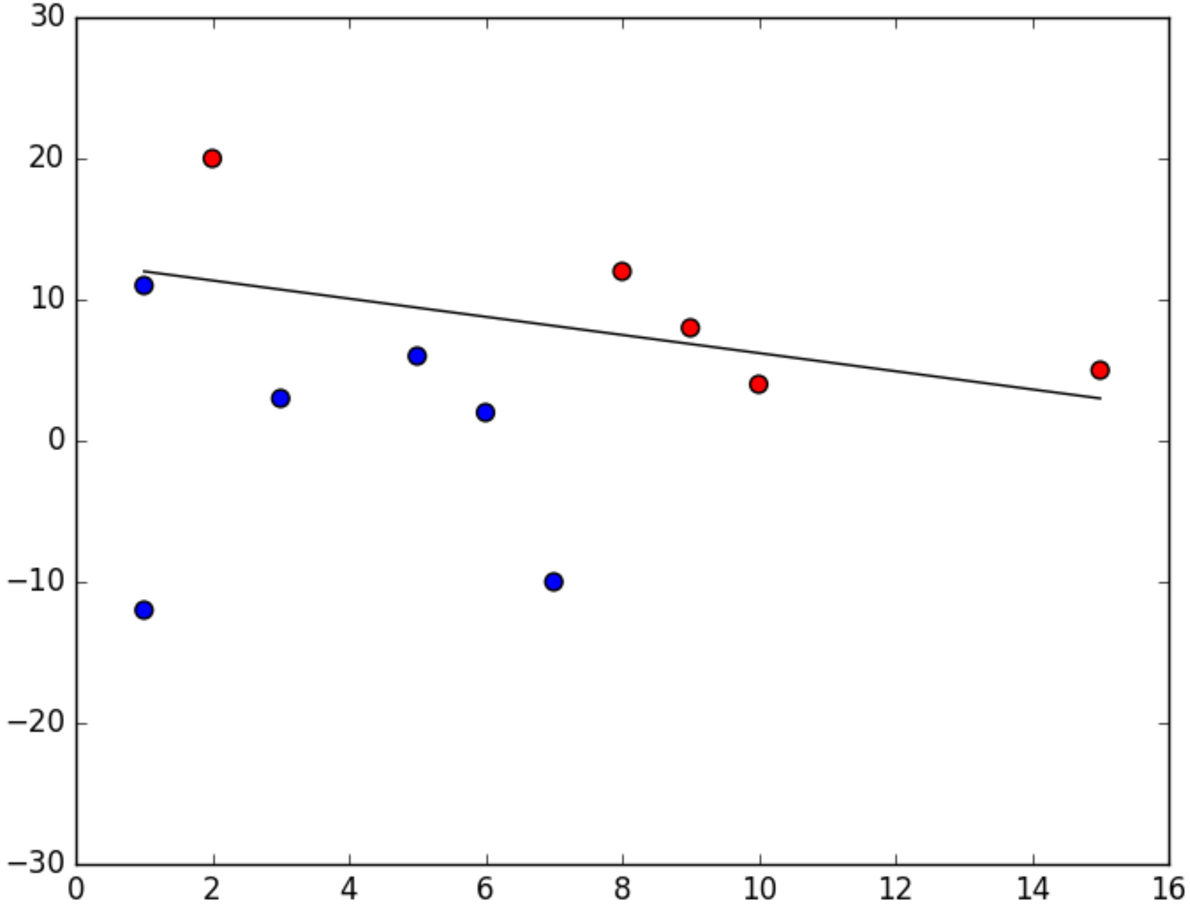
Perceptron: Example



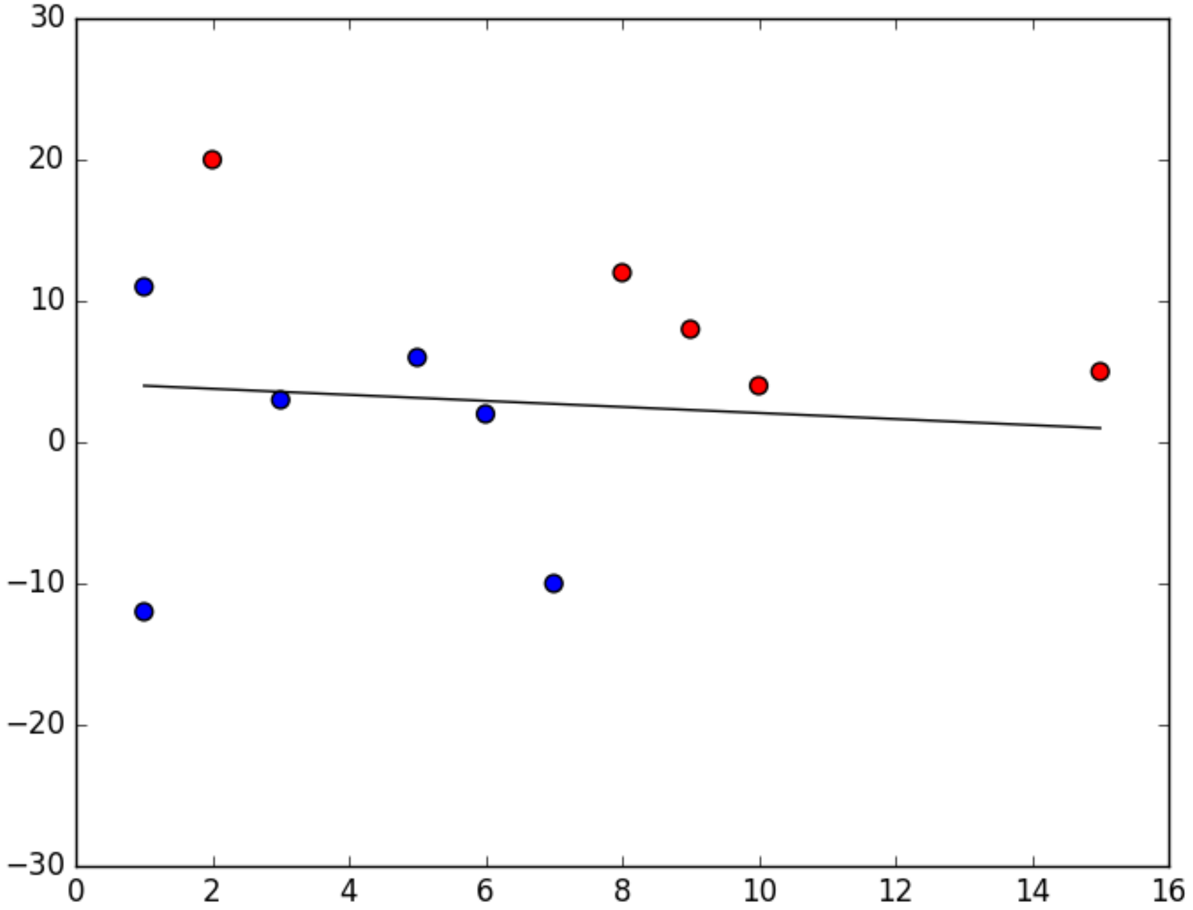
Perceptron: Example



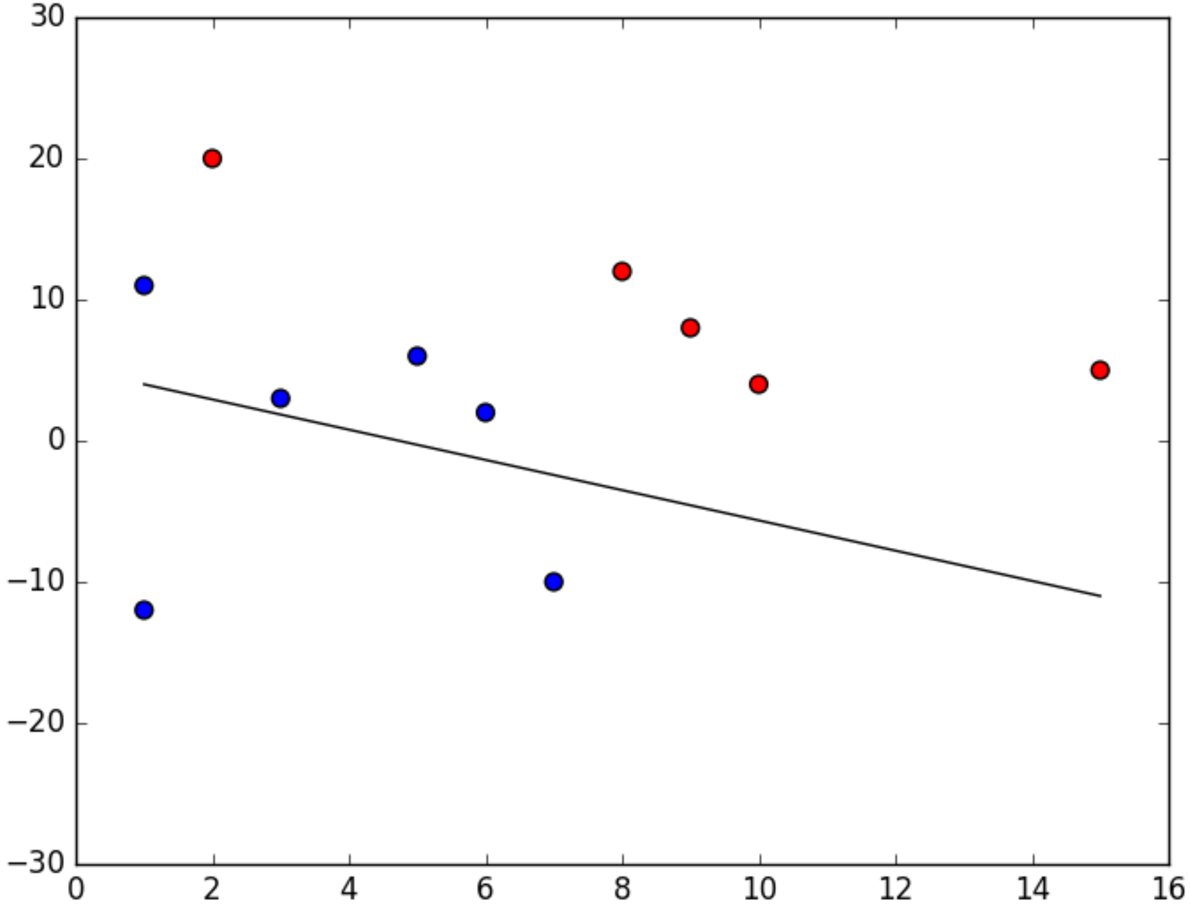
Perceptron: Example



Perceptron: Example

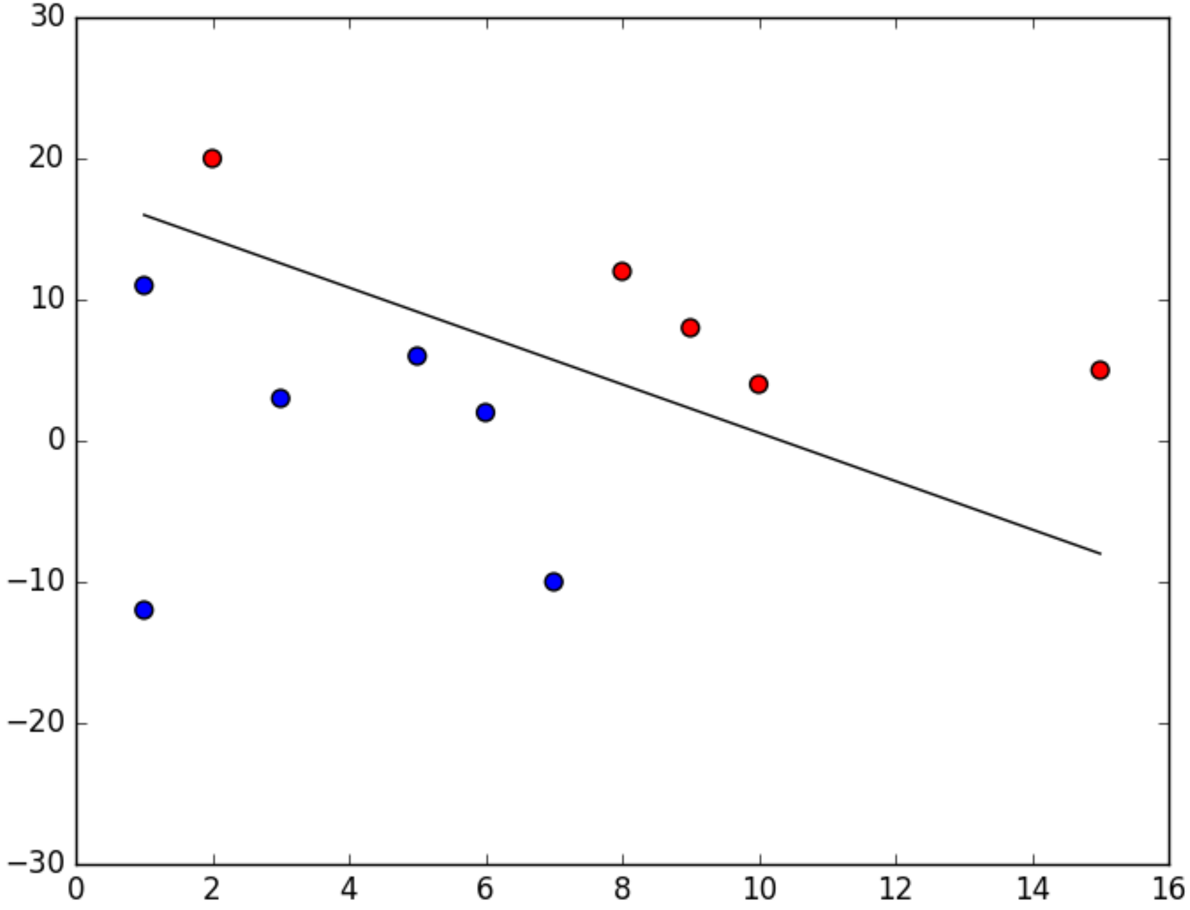


Perceptron: Example



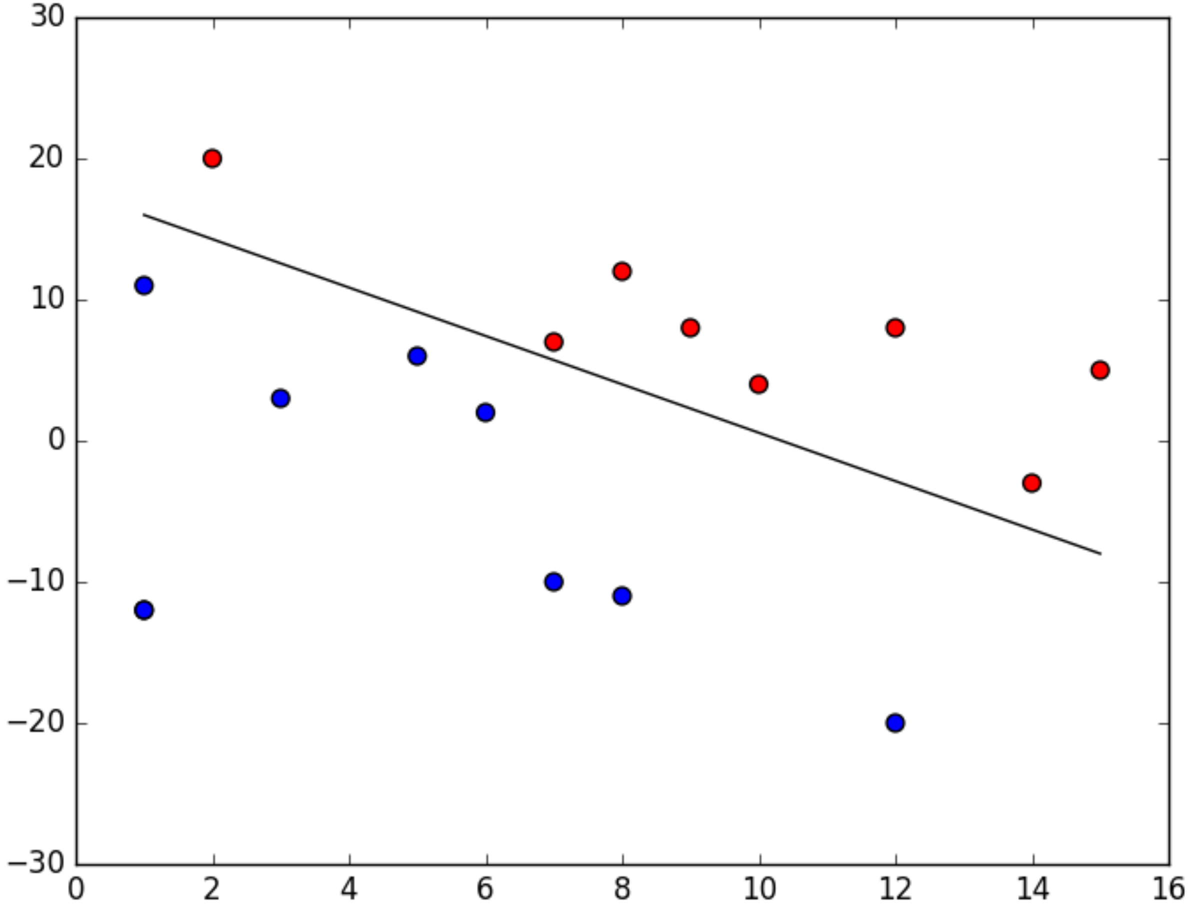
Perceptron: Example

Finally converged!



Perceptron: Example

With some test data:



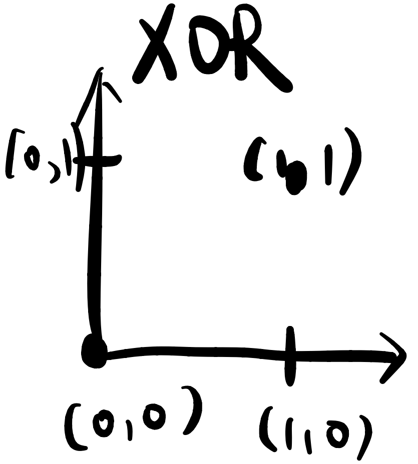
Perceptron

- The w_j determine the contribution of x_j to the label.
- $-w_0$ is a quantity that $\sum_{j=1}^{d} w_j x_j$ needs to exceed for the perceptron to output 1.

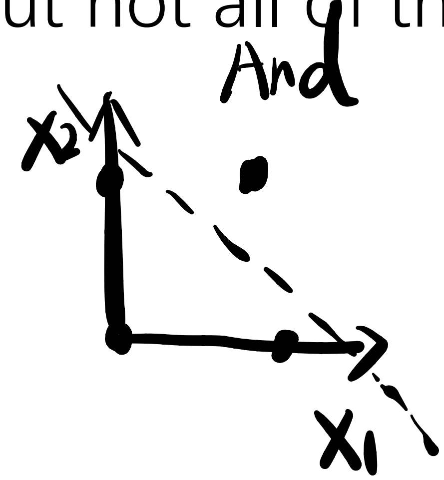
θ

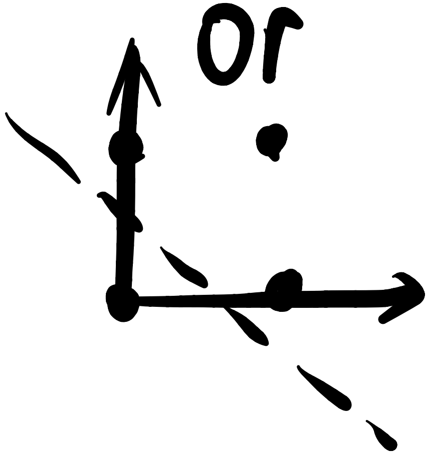
阈值

- Can be used to represent many Boolean functions: AND, OR, NAND, NOR, NOT but not all of them (e.g., XOR).

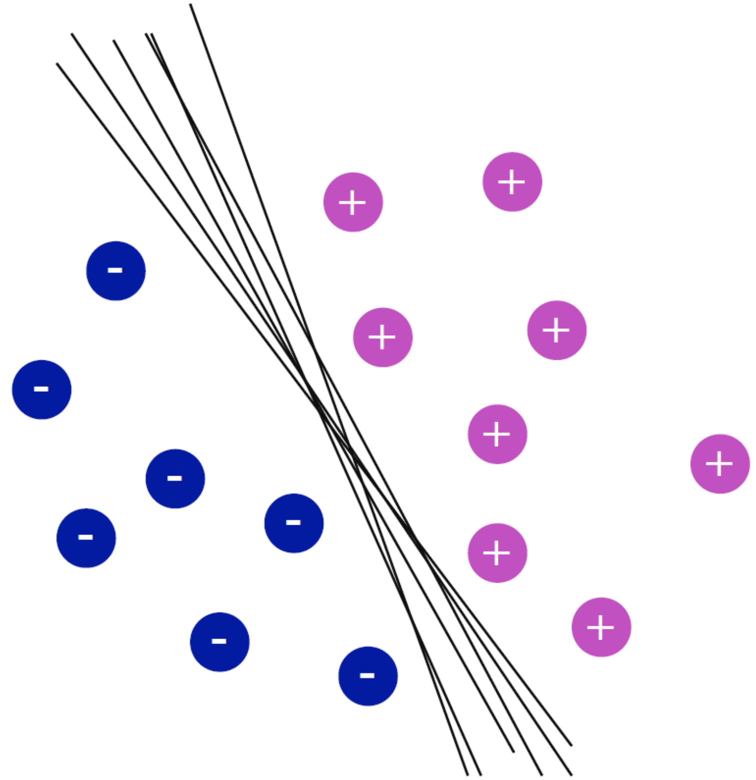


不是线性可分的





Choice of the hyperplane



Lots of possible solutions! (与初始状态.节点训练顺序有关)

: Idea of SVM is to find the optimal solution.

Neural Networks

From perceptron to NN

- Neural networks use the ability of the Perceptrons to represent elementary functions and combine them in a network of layers.
- However, a cascade of linear functions is still linear!
- And we want networks that represent highly non-linear functions.

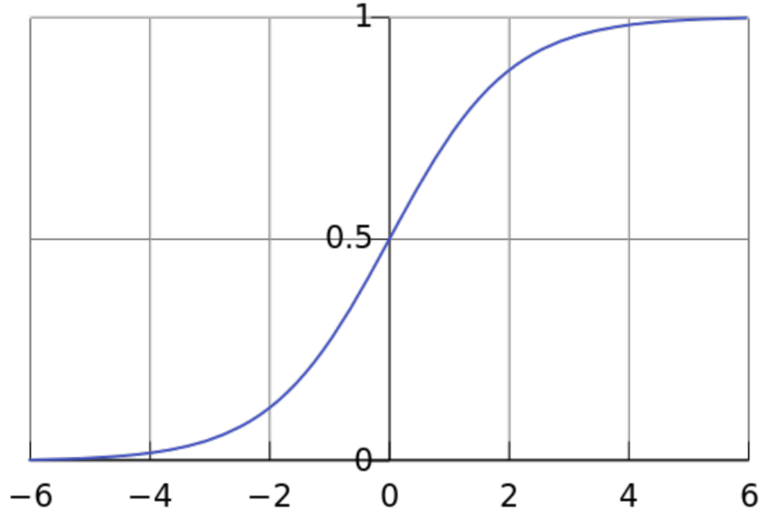
From perceptron to NN

- Also, perceptron used a **step function**, which is non-differentiable and not suitable for gradient descent in case data is not linearly separable.
- We want a function whose output is a differentiable function of the inputs. One possibility is to use the **sigmoid function**:

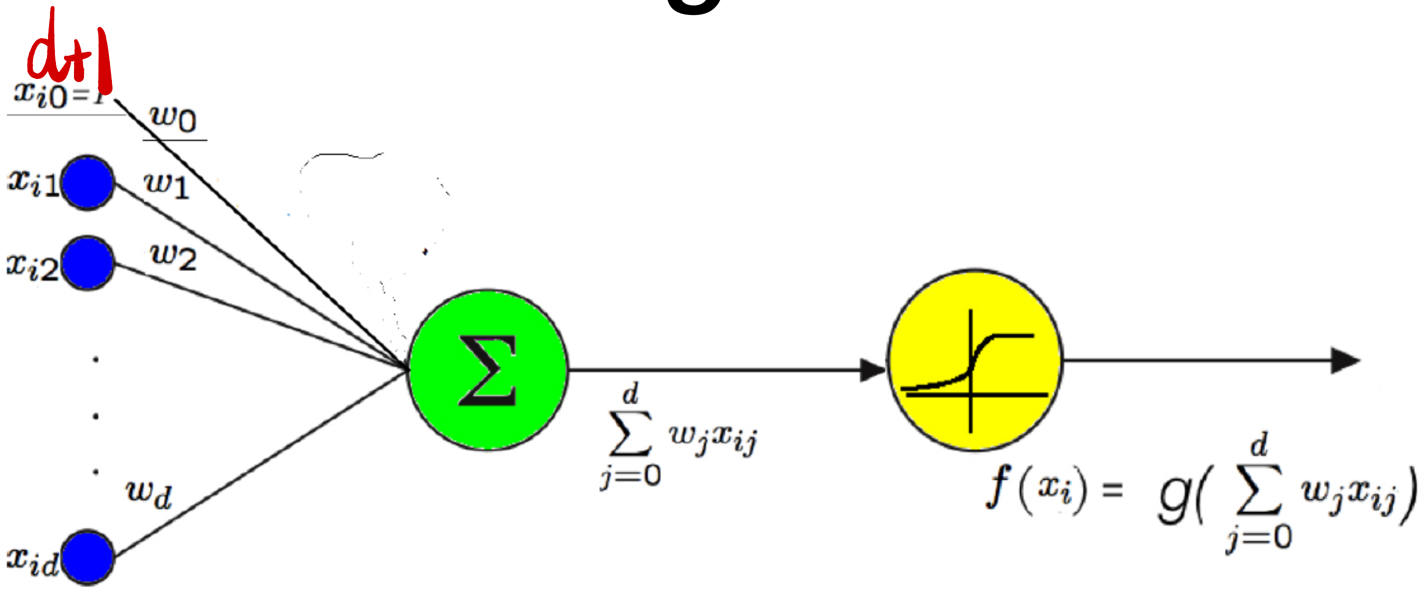
$$g(z) = \frac{e^z}{1+e^z} = \frac{1}{1+e^{-z}}$$

$g(z) \rightarrow 1$ when $z \rightarrow +\infty$

$g(z) \rightarrow 0$ when $z \rightarrow -\infty$



Perceptron with Sigmoid



Given n examples and d features.

For an example x_i (the i^{th} line in the matrix of examples)

$$f(x_i) = \frac{1}{1 + e^{-\sum_{j=0}^{d} w_j x_{ij}}}$$

The XOR example

Let' s try to create a MLP/NN for the XOR function using elementary perceptrons.

First observe:

$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g(10) = 0.99995$$

$$g(-10) = 0.00004$$

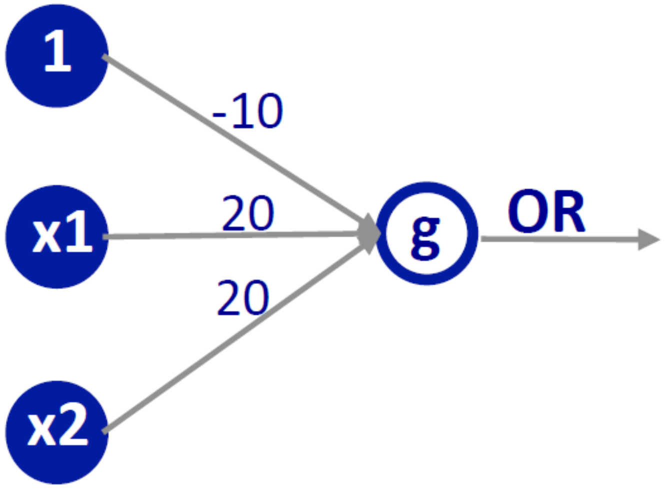
Let' s consider that: For $z \geq 10$, $g(z) \rightarrow 1$. For $z \leq -10$, $g(z) \rightarrow 0$.

The XOR example

First what is the perceptron of the OR?

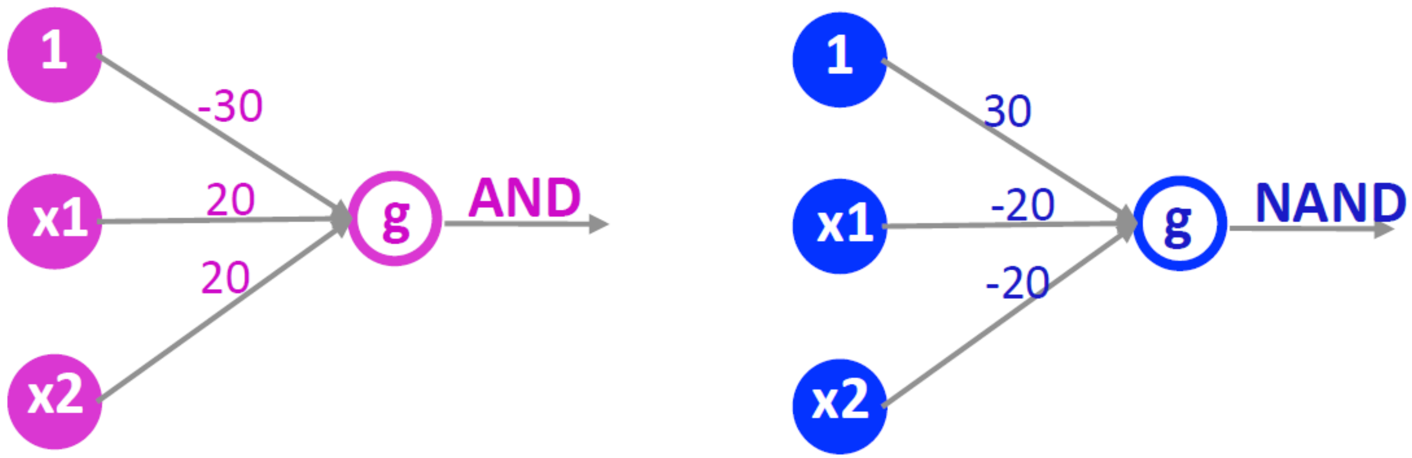
The XOR example

x_1	x_2	x_1 OR x_2	$g(z)$
0	0	0	$g(w_0 + w_1 x_1 + w_2 x_2) = g(-10)$
0	1	1	$g(10)$
1	0	1	$g(10)$
1	1	1	$g(30)$



The XOR example

Similarly, we obtain the perceptrons for the AND and NAND:



Note: how the weights in the NAND are the inverse weights of the AND.

The XOR example

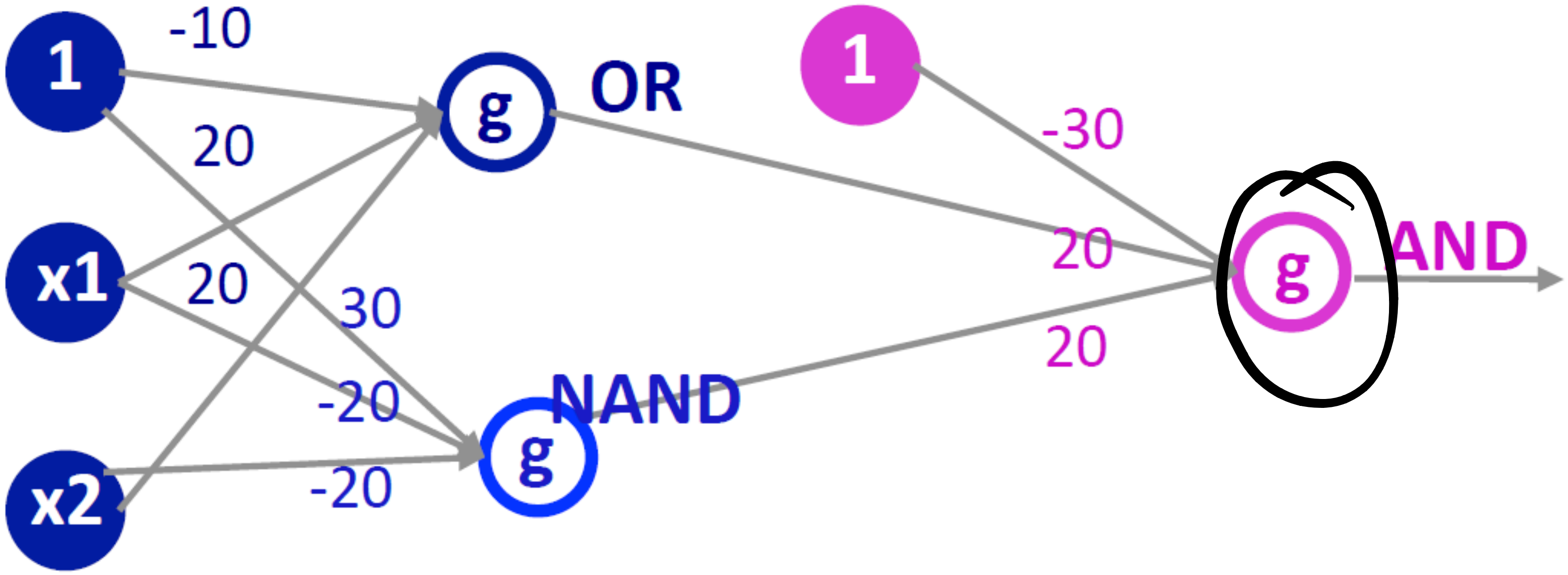
Let' s try to create a NN for the XOR function using elementary perceptrons.

x_1	x_2	x_1 **XOR** x_2	$(x_1$ **OR** $x_2)$ **AND** $(x_1$ **NAND** $x_2)$
0	0	0	0
0	1	1	1
1	0	1	1
1	1	0	0

The XOR example

实现线性可分

Let' s put them together...

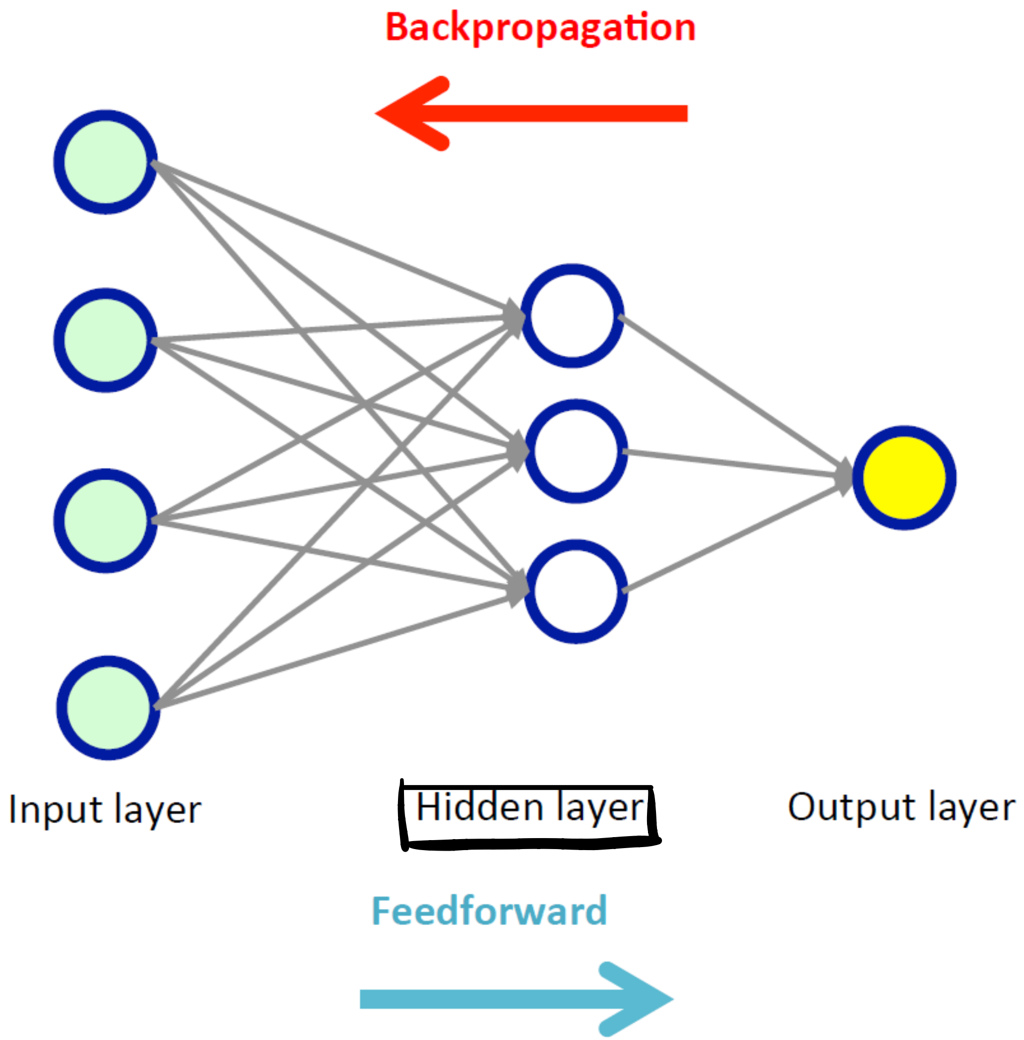


XOR as a combination of 3 basic perceptrons.

Backpropagation algorithm 反向传播

- Note: Feedforward NN 神经网络 (as opposed to recurrent networks) have no connections that loop.
- Learn the weights for a multilayer network.
- Backpropagation stands for "backward propagation of errors".
- Given a network with a fixed architecture (neurons and interconnections).
- Use Gradient descent to minimize the squared error between the network output value *o* and the ground truth *y*.
- We suppose multiple output *k*.
- Challenge: Search in all possible weight values for all neurons in the network.

Feedforward-Backpropagation前馈



Backpropagation rules

- We consider *k* outputs
- For an example *e* defined by (*x*, *y*), the error on training example *e*, summed over all output neurons in the network is:

$$E_e(w) = \frac{1}{2}\sum_k (y_k - o_k)^2$$

- Remember, gradient descent iterates through all the training examples one at a time, descending the gradient of the error w.r.t. this example.

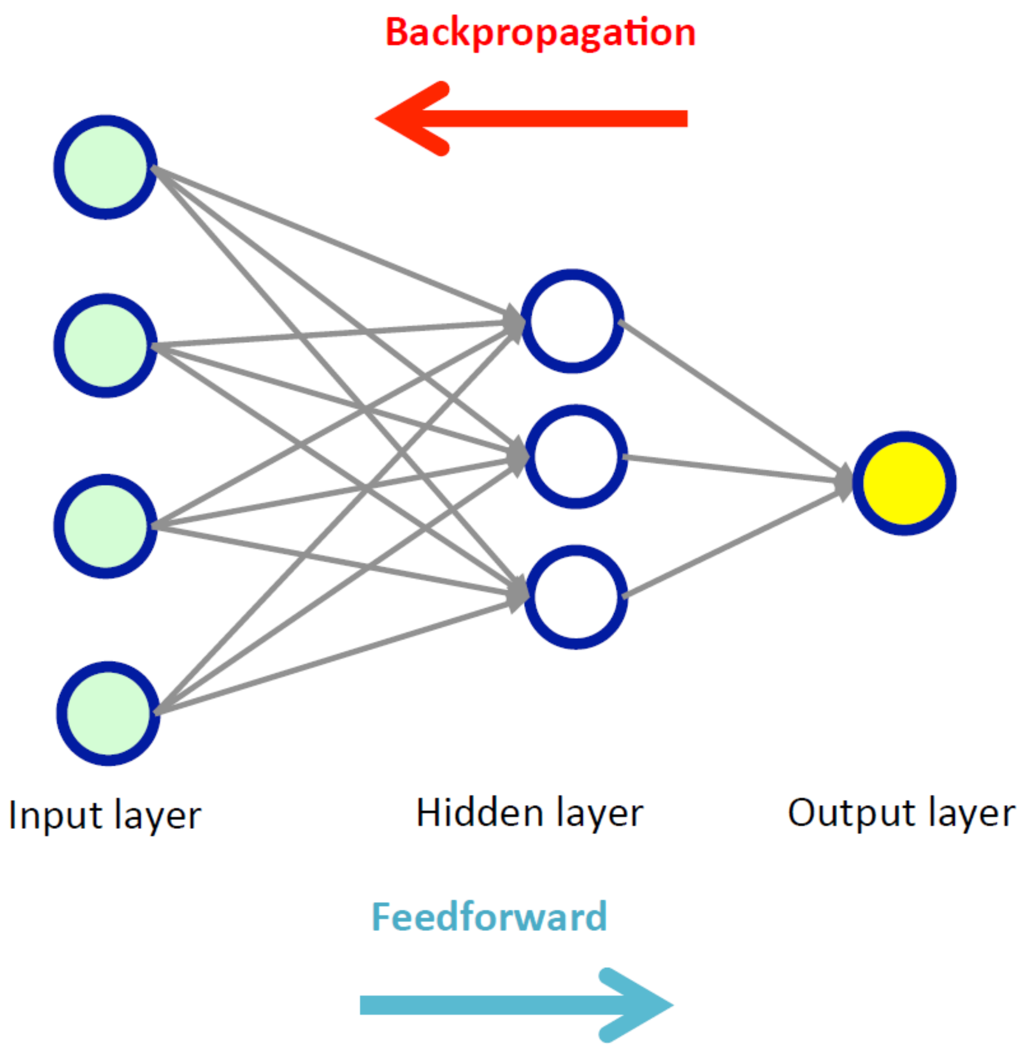
$$\Delta w_{ij} = -\alpha \frac{\partial E_e(w)}{\partial w_{ij}}$$

Backpropagation notations

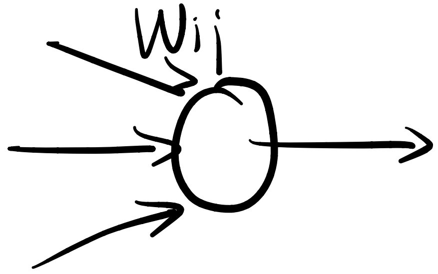
Notations:

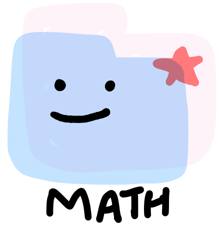
- x_{ij}: the i^{th} input to neuron j.
- w_{ij}: the weight associated with the i^{th} input to neuron j.
- $z_j = \Sigma w_{ij} x_{ij}$, weighted sum of inputs for neuron j. 求和项的输出
- o_j: output computed by neuron j. $g(z_j)$
- g is the sigmoid function.
- *outputs*: the set of neurons in the output layer.
- $Succ(j)$: the set of neurons whose immediate inputs include the output of neuron j.

Backpropagation notations



Backpropagation rules





$$\frac{\partial E_e}{\partial w_{ij}} = \frac{\partial E_e}{\partial z_j}\frac{\partial z_j}{\partial w_{ij}} = \frac{\partial \mathbf{E_e}}{\partial \mathbf{z_j}} x_{ij}$$

$z_j = \sum w_i x_i$

$$\Delta w_{ij} = -\alpha \frac{\partial \mathbf{E_e}}{\partial \mathbf{z_j}} x_{ij}$$

We consider two cases in calculating $\boxed{\frac{\partial E_e}{\partial z_j}}$ (let' s abandon the index *e*):

- **Case 1: Neuron *j* is an output neuron**
- **Case 2: Neuron *j* is a hidden neuron**

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial z_j} \cdot \frac{\partial z_j}{\partial w_{ij}}$$

Backpropagation rules

- Case 1: Neuron j is an output neuron

$$\frac{\partial E}{\partial z_j} = \frac{\partial E}{\partial o_j} \frac{\partial o_j}{\partial z_j}$$

$$\frac{\partial E}{\partial o_j} = \frac{\partial}{\partial o_j} \boxed{\frac{1}{2}\sum_k (y_k - o_k)^2}$$

其余项对j求导为0

$$\frac{\partial E}{\partial o_j} = \frac{\partial}{\partial o_j} \frac{1}{2}(y_j - o_j)^2$$

$$\frac{\partial E}{\partial o_j} = \frac{1}{2}\, 2\, (y_j - o_j) \frac{\partial (y_j - o_j)}{\partial o_j}$$

$$\frac{\partial E}{\partial o_j} = -(y_j - o_j)$$

We have: $o_j = g(z_j)$

$$\frac{\partial o_j}{\partial z_j} = \frac{\partial g(z_j)}{\partial z_j}$$

sigmod函数求导

$$\frac{\partial o_j}{\partial z_j} = o_j(1 - o_j)$$

Backpropagation rules

$$\frac{\partial E}{\partial z_j} = -(y_j - o_j)o_j(1 - o_j)$$

$$\Delta w_{ij} = \alpha(y_j - o_j)o_j(1 - o_j)x_{ij}$$

We will note

$$\delta_j = -\frac{\partial E}{\partial z_j}$$

$$\Delta w_{ij} = \alpha \ \delta_j \ x_{ij}$$

Backpropagation rules

- Case 2: Neuron *j* is a hidden neuron

$$\frac{\partial E}{\partial z_j} = \sum_{k \in succ\{j\}} \frac{\partial E}{\partial z_k} \frac{\partial z_k}{\partial z_j} = \sum_{k \in succ\{j\}} -\delta_k \frac{\partial z_k}{\partial z_j}$$

$$\frac{\partial E}{\partial z_j} = \sum_{k \in succ\{j\}} -\delta_k \frac{\partial z_k}{\partial o_j} \frac{\partial o_j}{\partial z_j}$$

$$\frac{\partial E}{\partial z_j} = \sum_{k \in succ\{j\}} -\delta_k \, w_{jk} \frac{\partial o_j}{\partial z_j}$$

$$\frac{\partial E}{\partial z_j} = \sum_{k \in succ\{j\}} -\delta_k \, w_{jk} \, o_j \, (1 - o_j)$$

$$\delta_j = -\frac{\partial E}{\partial z_j} = \boxed{o_j \, (1 - o_j) \sum_{k \in succ\{j\}} \delta_k \, w_{jk}}$$

Backpropagation algorithm (BP)

- **Input:** training examples (x, y), learning rate α (e.g., α = 0.1), n_i, n_h and n_o.
- **Output:** a neural network with one input layer, one hidden layer and one output layer with n_i, n_h and n_o number of neurons respectively and all its weights.

范化能力 max weight 成反比.

1. Create feedforward network (n_i, n_h, n_o)
2. Initialize all weights to a small random number (e.g., in [–0.2, 0.2])
3. Repeat until convergence

   For each training example (x, y)

   I. Feed forward: Propagate example x through the network and compute the output o_j from every neuron.

   II. Propagate backward: Propagate the errors backward.

   Case 1 For each output neuron k, calculate its error

   $$\delta_k = o_k(1 - o_k)(y_k - o_k)$$

   最小为 $\frac{1}{4}$

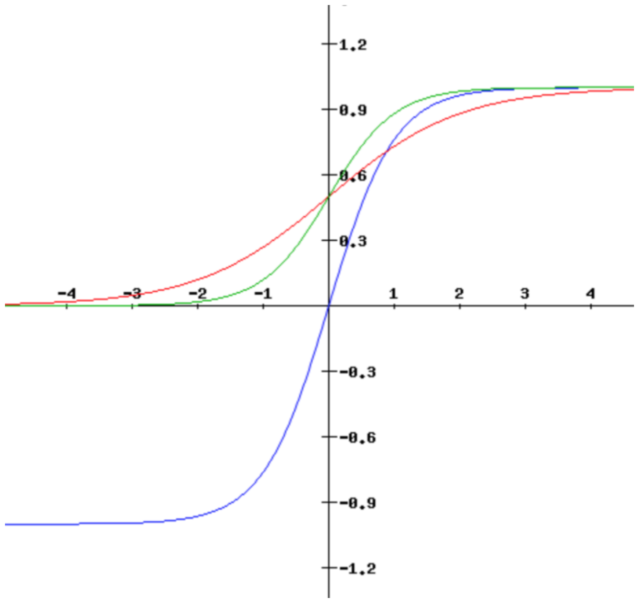
   Case 2 For each hidden neuron h, calculate its error

   $$\delta_h = o_h(1 - o_h)\sum_{k \in Succ(h)} w_{hk}\delta_k$$

   III. Update each weight: $w_{ij} \leftarrow w_{ij} + \alpha \delta j x_{ij}$

Observations

- Convergence: small changes in the weights
- There are other activation functions. Hyperbolic tangent function, is practically better for NN as its outputs range from -1 to 1.



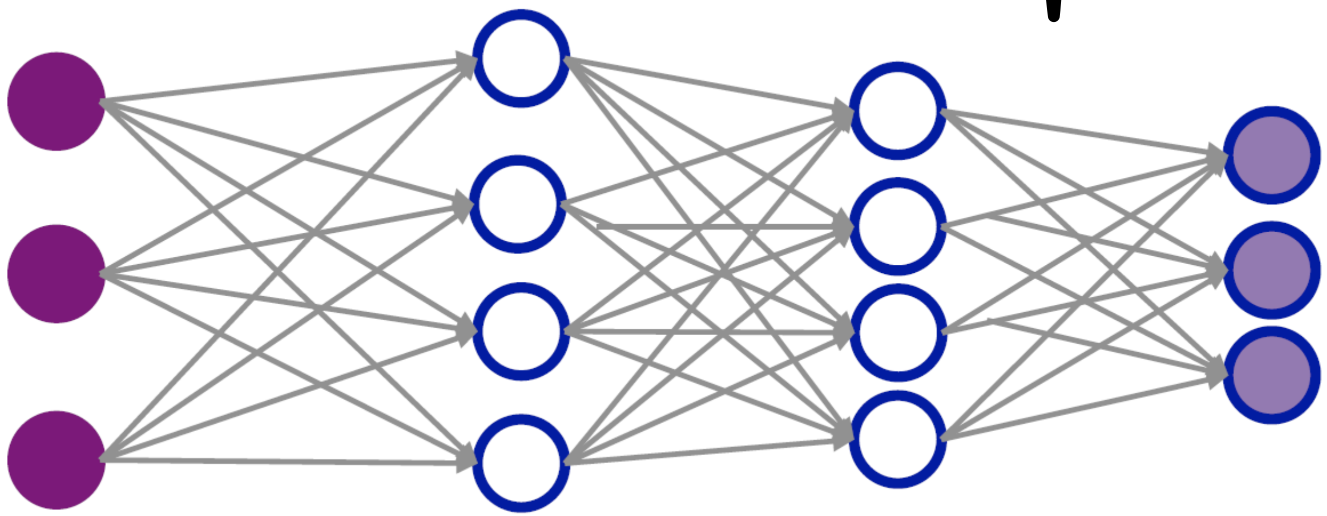
$$g(x) = sigmoid(x) = \frac{e^{kx}}{1+e^{kx}}$$ for $k = 1$, $k = 2$, etc.

$$g(x) = tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$$ (It is a rescaling of the logistic/sigmoid function!)

Multi-class case etc.

| vs the others

1 vs 1



- Nowadays, networks with more than two layers, a.k.a. deep networks, have proven to be very effective in many domains.
- Examples of deep networks: restricted Boltzman machines, convolutional NN, auto encoders, etc.

MNIST database

- The MNIST database of handwritten digits
- Training set of 60,000 examples, test set of 10,000 examples
- Vectors in $\mathbb{R}^{784}$ (28x28 images)
- Labels are the digits they represent
- Various methods have been tested with this training set and test set
- Linear models: 7% - 12% error
- KNN: 0.5%- 5% error
- Neural networks: 0.35% - 4.7% error
- Convolutional NN: 0.23% - 1.7% error

To be continued