

# Perceptrons

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Based on lecture slides by Jerry Zhu

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# Recall From Previous Lecture

## Supervised Learning

- Supervised learning:

Data	Features (Input)	Output	-
Sample	$\{(x_{i1}, \dots, x_{iD})\}_{i=1}^N$	$\{y_i\}_{i=1}^N$	find "best" $\hat{f}$
-	observable	known	-
New	$\{(x'_1, \dots, x'_D)\}_{i=1}^N$	$y'$	guess $\hat{y} = \hat{f}(x')$
-	observable	unknown	-

# Recall From Previous Lecture

## Training and Test Sets

- Supervised learning:

Data	Features (Input)	Output	-
Train	$\{(x_{i1}, \dots, x_{iD})\}_{i=1}^{N_T}$	$\{y_i\}_{i=1}^N$	find many $\hat{f}$
-	observable	known	-
Test	$\{(x_{i1}, \dots, x_{iD})\}_{i=1}^{N-N_T}$	$\{y_i\}_{i=1}^N$	find "best" $\hat{f}$
-	observable	known	-
New	$\{(x'_1, \dots, x'_D)\}_{i=1}^N$	$y'$	guess $\hat{y} = \hat{f}(x')$
-	observable	unknown	-

# Recall From Previous Lecture

## Real Life Examples

- Examples of supervised learning:

Data	Features (Input)	Output
Images	$x_{i1} = \text{How much red?}$	$y_i \in \{0, 1\}$
-	$x_{i2} = \text{How many circles?}$	0 = cat,
-	...	1 = dog
Sentences	$x_{i1} = \text{Length?}$	$y_i \in \{0, 1\}$
-	$x_{i2} = \text{How many verbs?}$	0 = bad news
-	...	1 = good news
Medical	$x_{i1} = \text{Age}$	$y_i \in \{0, 1\}$
-	$x_{i2} = \text{Height}$	0 = not sick
-	...	1 = sick
Grades	$x_{i1} = \text{Midterm?}$	$y_i \in \{0, 1\}$
-	$x_{i2} = \text{Average homework?}$	0 = fail
-	...	1 = pass

# Recall From Previous Lecture

## Objective Function

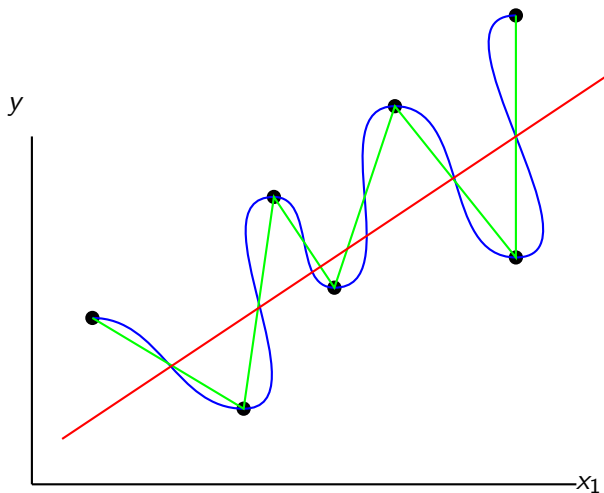
- How to select  $\hat{f}$ ? Need an objective function

$$\hat{f} = \arg \min_{f \in \text{all functions}} \frac{1}{2} \sum_{i=1}^N (f(x_i) - y_i)^2$$

- Problem: too many functions to choose from

# Recall From Previous Lecture

## Function Space Diagram



# Recall From Previous Lecture

## Hypothesis Space

- How to select  $\hat{f}$ ? Need a hypothesis space

$$\hat{f} = \arg \min_{f \in \text{all linear functions}} \frac{1}{2} \sum_{i=1}^N (f(x_i) - y_i)^2$$

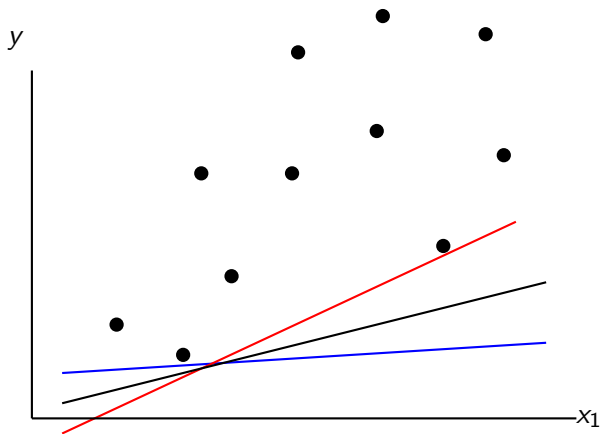
$$(\hat{w}_0, \hat{w}_1, \dots, \hat{w}_D) = \arg \min_{(w_0, w_1, \dots, w_D) \in \mathbb{R}^D} \frac{1}{2} \sum_{i=1}^N (a_i - y_i)^2$$

$$\text{where } a_i = w_0 + w_1 x_{i1} + w_2 x_{i1} + \dots + w_D x_{iD}$$

- Problem: need an algorithm to solve the minimization problem

# Recall From Previous Lecture

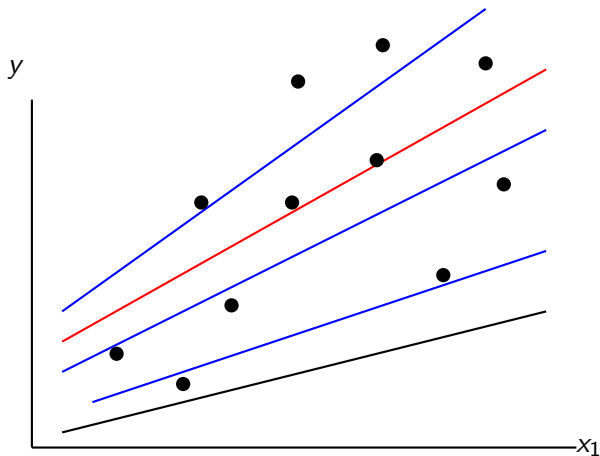
## Optimization Diagram





# Recall From Previous Lecture

## Optimization Diagram, Converge



# Recall From Previous Lecture

## Optimization Intuition

- If a small increase in  $w_d$  causes the distances from the points to the regression line to decrease: increase  $w_d$
- If a small increase in  $w_d$  causes the distances from the points to the regression line to increase: decrease  $w_d$
- Change in distance due to change in  $w_d$  is the derivative
- Change in distance due to change in  $w$  is the gradient

# Recall From Previous Lecture

## Gradient Descent

- How to select  $\hat{f}$ ? Need gradient descent

$$(\hat{w}_0, \hat{w}_1, \dots, \hat{w}_D) = \arg \min_{(w_0, w_1, \dots, w_D) \in \mathbb{R}^D} \frac{1}{2} \sum_{i=1}^N (a_i - y_i)^2$$

where  $a_i = w_0 + w_1 x_{i1} + w_2 x_{i1} + \dots + w_D x_{iD}$

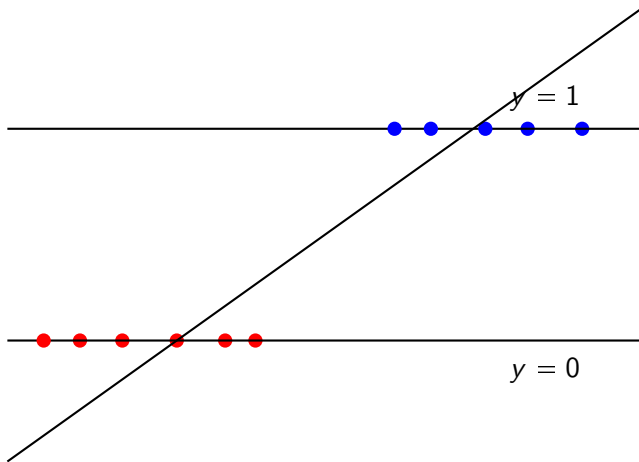
$$w_d = w_d - \alpha \sum_{i=1}^N (a_i - y_i) x_{id},$$

for  $d = 0, 1, \dots, D, x_{i0} := 1$

- Problem: not for binary classification

# This Lecture

## Binary Classification Diagram



# This Lecture

## Binary Classification Intuition

- The prediction  $\hat{y}$  is not between 0 and 1
- Large  $x_i$  are classified correctly but have large distances from the regression line

# This Lecture

## Activation Function

- How to select  $\hat{f}$  for binary classification? Need an activation function.

$$\hat{f} = \arg \min_{f=g(w_0+w_1x_{i1}+w_2x_{i1}+\dots+w_Dx_{iD})} \frac{1}{2} \sum_{i=1}^N (a_i - y_i)^2$$

where  $a_i = g(w_0 + w_1x_{i1} + w_2x_{i1} + \dots + w_Dx_{iD})$

- Obvious choice: step function

# Non-linear Activation Function

## Step Function

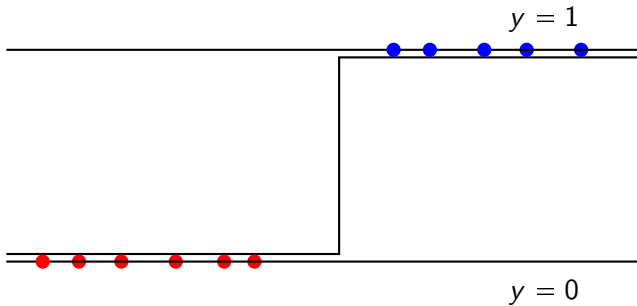
- Activation function: step function  $g(\boxed{\cdot}) = \mathbb{1}_{\boxed{\cdot} \geq 0}$

$$\mathbb{1}_{\boxed{\cdot} > 0} = \begin{cases} 1 & \text{if } \boxed{\cdot} \geq 0 \\ 0 & \text{if } \boxed{\cdot} < 0 \end{cases}$$

- Derivative:  $g'(\boxed{\cdot}) = 0$  but undefined at  $\boxed{\cdot} = 0$
- Problem: discontinuous, cannot use gradient

# Non-linear Activation Function

## Step Function Diagram





# Another Non-linear Activation Function

## Sigmoid Function

- Activation function: sigmoid function  $g(\boxed{\cdot}) = \frac{1}{1 + \exp(-\boxed{\cdot})}$
- Derivative:  $g'(\boxed{\cdot}) = g(\boxed{\cdot}) (1 - g(\boxed{\cdot}))$
- Gradient descent step:

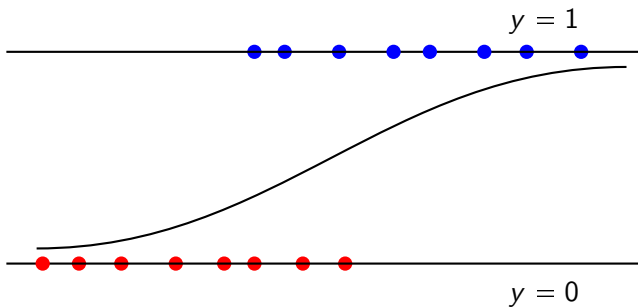
$$w_d = w_d - \alpha \sum_{i=1}^N (a_i - y_i) a_i (1 - a_i) x_{id}$$

where  $a_i = g(w_0 + w_1 x_{i1} + w_2 x_{i1} + \dots + w_D x_{iD})$

for  $d = 0, 1, \dots, D, x_{i0} := 1$

# Non-linear Activation Function

## Sigmoid Function Diagram



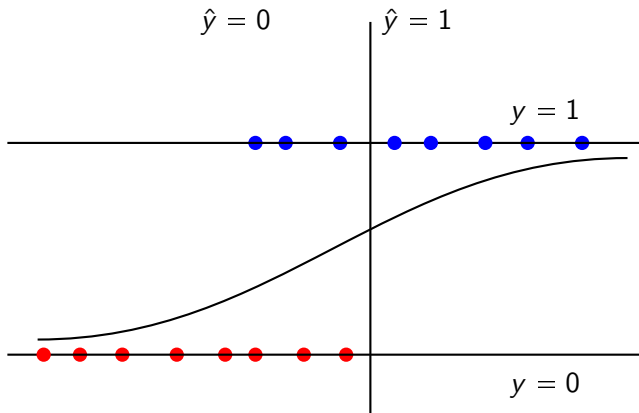
# Other Non-linear Activation Function

Tanh, Acrtan and ReLu

- Activation function:  $g(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
- Activation function:  $g(x) = \arctan(x)$
- Activation function (rectified linear unit):  $g(x) = x \mathbb{1}_{x \geq 0}$
- Gradient descent: all convex and differentiable.
- Problem: decision boundary is still step function

# Other Non-linear Activation Function

Decision Boundary



# Multi-layer Neural Network

## Intuition

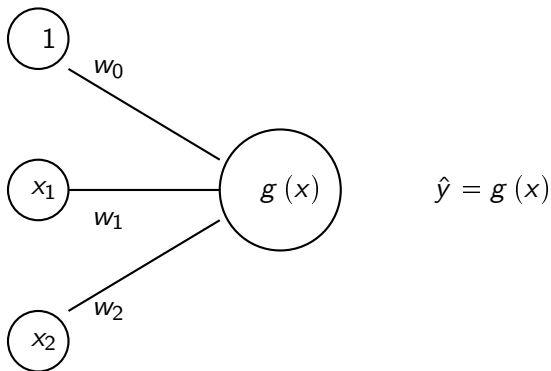
- $f(x_i) = g(w_0 + w_1x_{i1} + w_2x_{i2} + \dots w_Dx_{iD})$  is called a perceptron model
- Connect perceptrons into a network

# Multi-layer Neural Network

## Single Layer Diagram

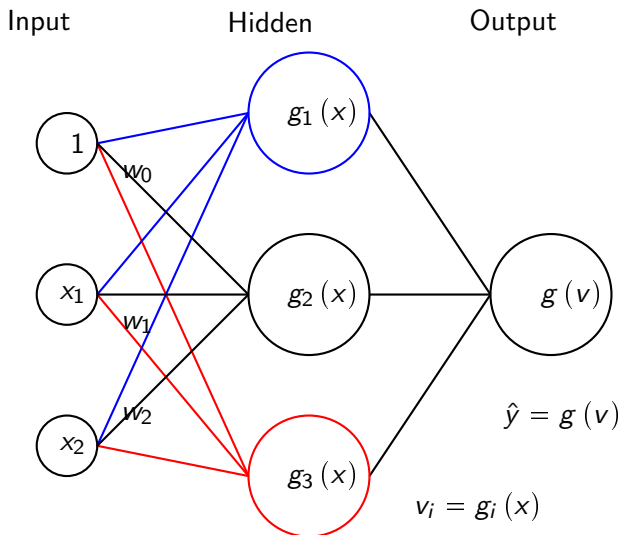
Input

Output



# Multi-layer Neural Network

## Multi Layer Diagram



# Multi-layer Neural Network

## Power

- In theory:
  - ① 1 Hidden-layer with enough hidden units can represent any continuous function of the inputs with arbitrary accuracy
  - ② 2 Hidden-layer can represent discontinuous functions
- In practice:
  - ① AlexNet: 8 layers
  - ② GoogLeNet: 27 layers
  - ③ ResNet: 152 layers



# Multi-layer Neural Network

## Multi-class Classification

- Encode  $y \in \{1, 2, 3, \dots, K\}$  by using  $K$  output units
- ① Class 1 =  $(1, 0, 0, \dots, 0, 0)$
- ② Class 2 =  $(0, 1, 0, \dots, 0, 0)$
- ③ ...
- ④ Class  $K = (0, 0, 0, \dots, 0, 1)$
- Decode by choosing the class corresponding to the largest output unit

# Next Lecture

## Training Neural Network

- Derivatives are difficult to compute: use chain rule
- Backpropagation