Yapay Sinir Ağları

Sınıflandırma Teknikleri

- Uzaklık Temelli (Nearest-Neighbor) yöntemler
- Karar Ağacı(Decision Tree) yöntemleri
- Olasılık temelli yöntemler (Naïve Bayes)
- Support Vector Machines
- **Yapay Sinir Ağları (Artificial Neural Networks)**
- Ensemle Yöntemler (Bagging - Boosting)
  - Rastgele Ormanlar (Random Forest)
  - AdaBoost ve XGBoost(eXtreme Gradient Boosting)

Artificial Neural Networks/Deep Learning

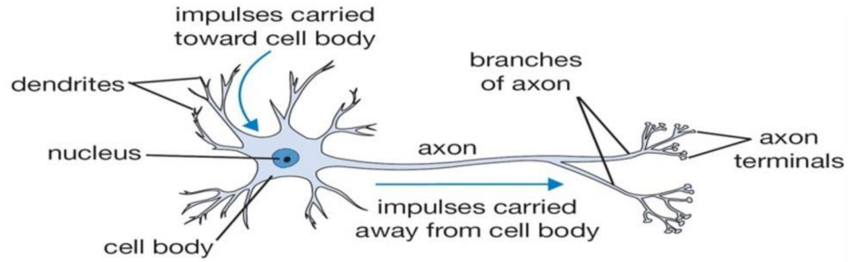
Neural Network Türleri

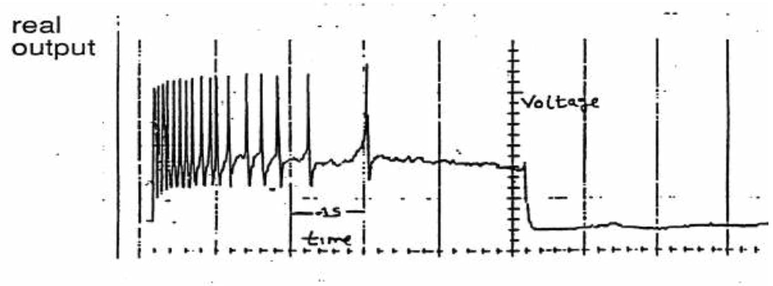
- Multi Layer Perceptron
- Recurrent neural network
- Convolutional neural network

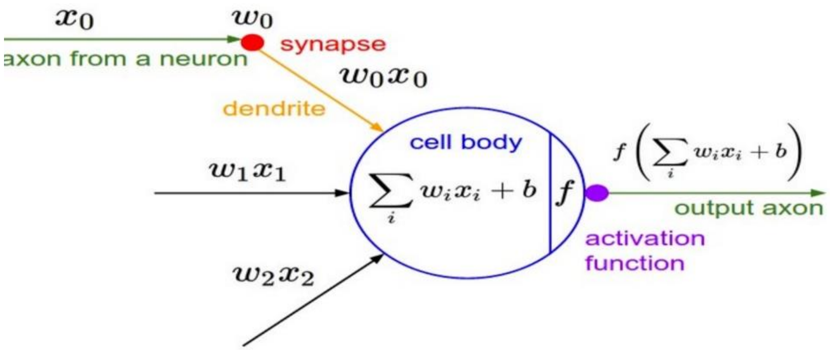
Neural Networks Uygulamaları

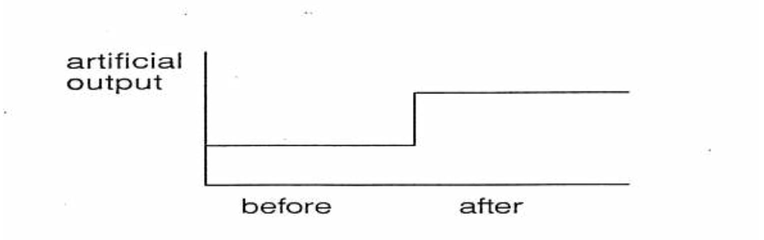
- El yazısı karakter tanımlama.
- Görüntü işleme.
- Borsa stok tahmini
- ve binlerce farklı uygulama

“Gerçek” ve Yapay Nöron



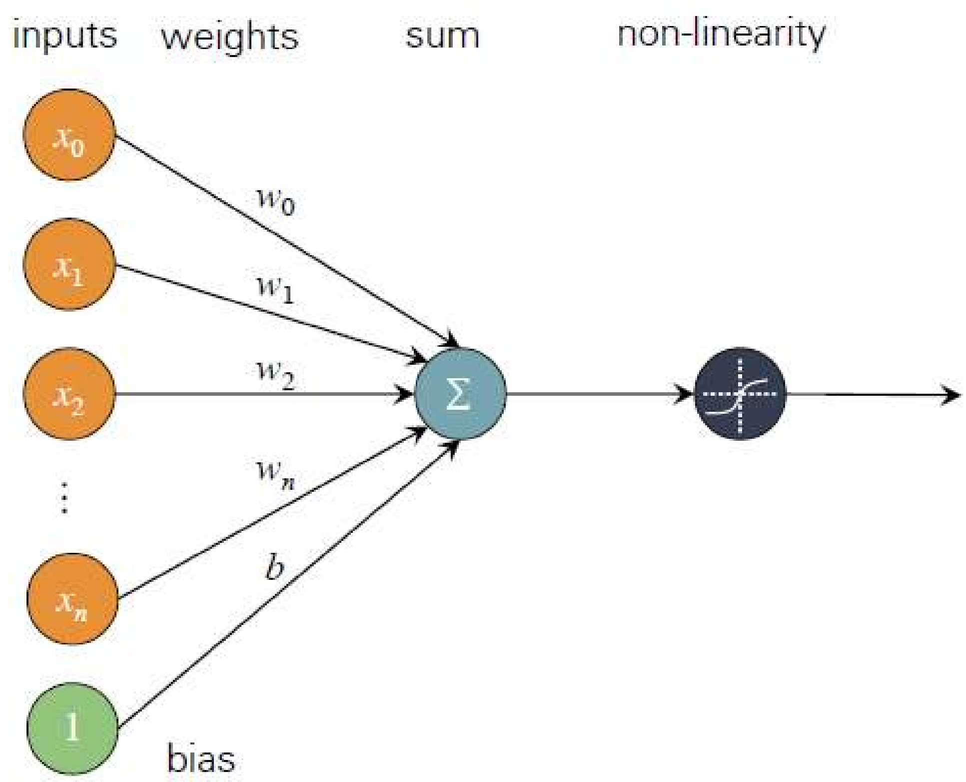






http://cs231n.github.io/neural-networks-1/

Perceptron



inputs
weights
sum
non-linearity
x_0
x_1
x_2
x_n
1
w_0
w_1
w_2
w_n
b
Σ
bias

Perceptron Forward Pass

- Neuron pre-activation (or input activation)

$$a(\mathbf{x}) = b + \sum_i w_i x_i = b + \mathbf{w}^\top \mathbf{x}$$

- Neuron output activation:

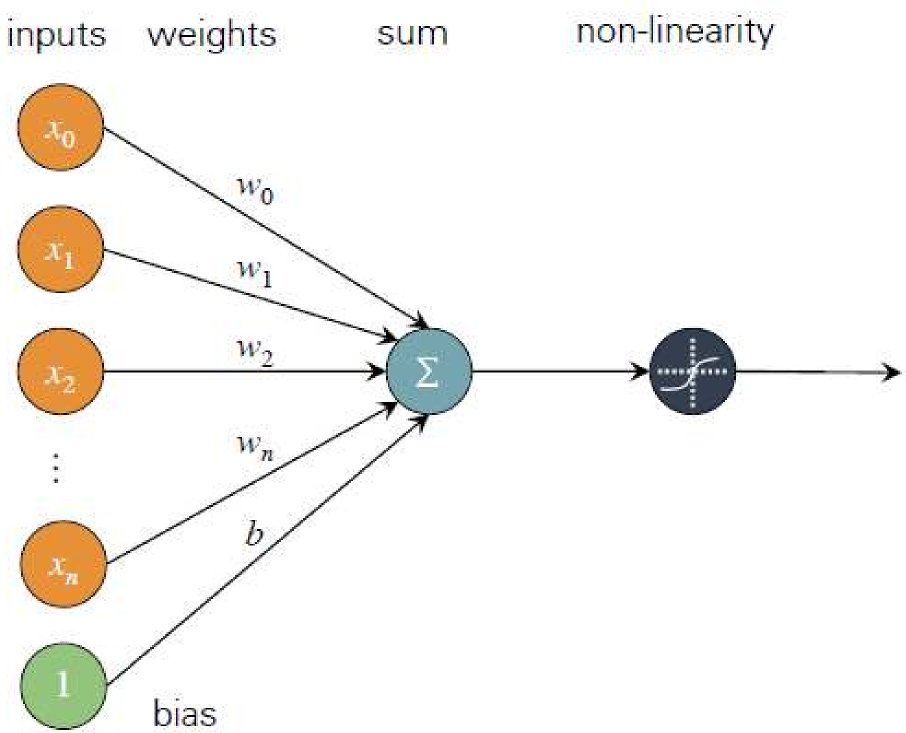
$$h(\mathbf{x}) = g(a(\mathbf{x})) = g(b + \sum_i w_i x_i)$$

where

$\mathbf{w}$ are the weights (parameters)

b is the bias term

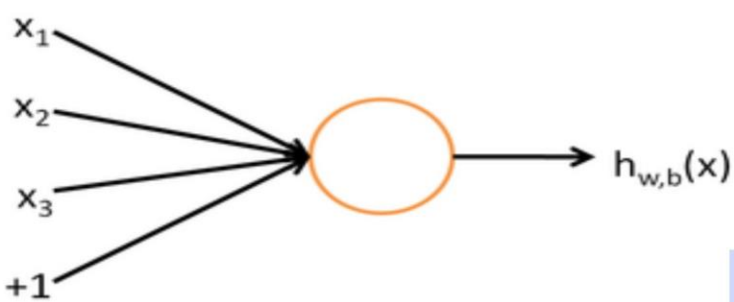
$g(\cdot)$ is called the activation function

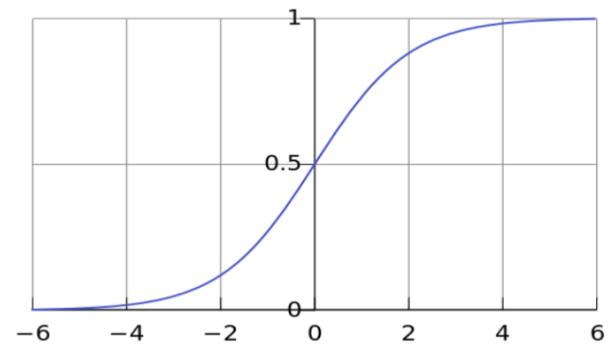


Tek bir nöron logistic regression oluşturur

$$h_{w,b}(x) = f(w^{\top}x + b)$$

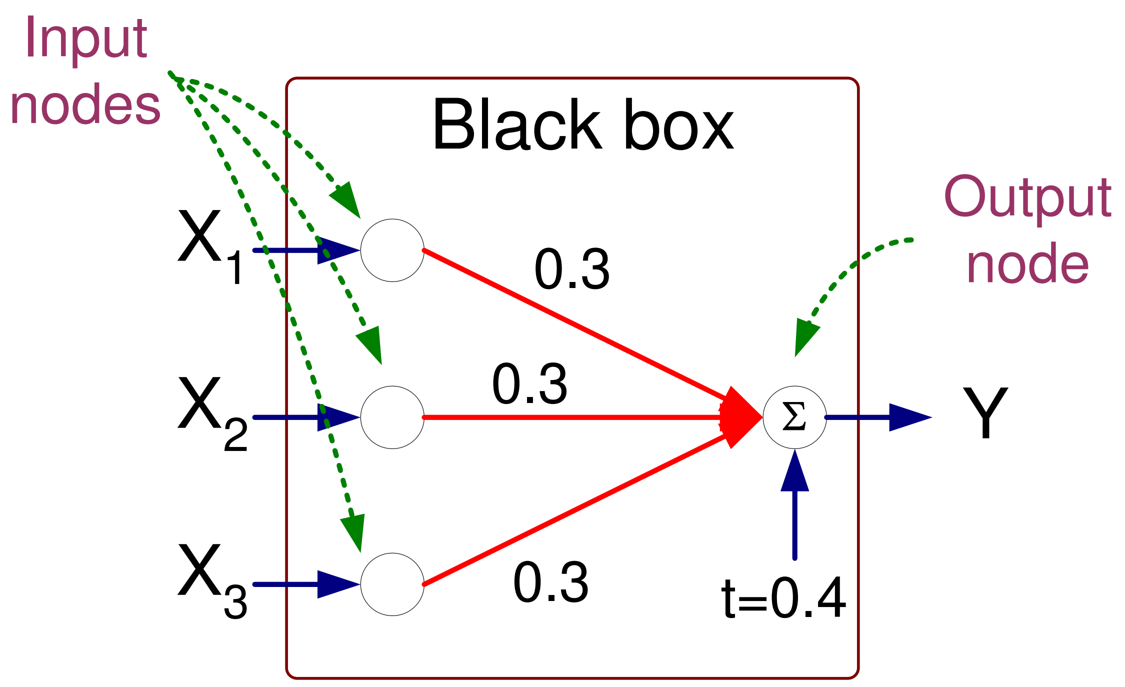
$$f(z) = \frac{1}{1+e^{-z}}$$





Artificial Neural Networks (ANN)

X_1	X_2	X_3	Y
1	0	0	0
1	0	1	1
1	1	0	1
1	1	1	1
0	0	1	0
0	1	0	0
0	1	1	1
0	0	0	0



$$Y = I(0.3X_1 + 0.3X_2 + 0.3X_3 - 0.4 > 0)$$

$$\text{where } I(z) = \begin{cases} 1 & \text{if } z \text{ is true} \\ 0 & \text{otherwise} \end{cases}$$

Neural Network

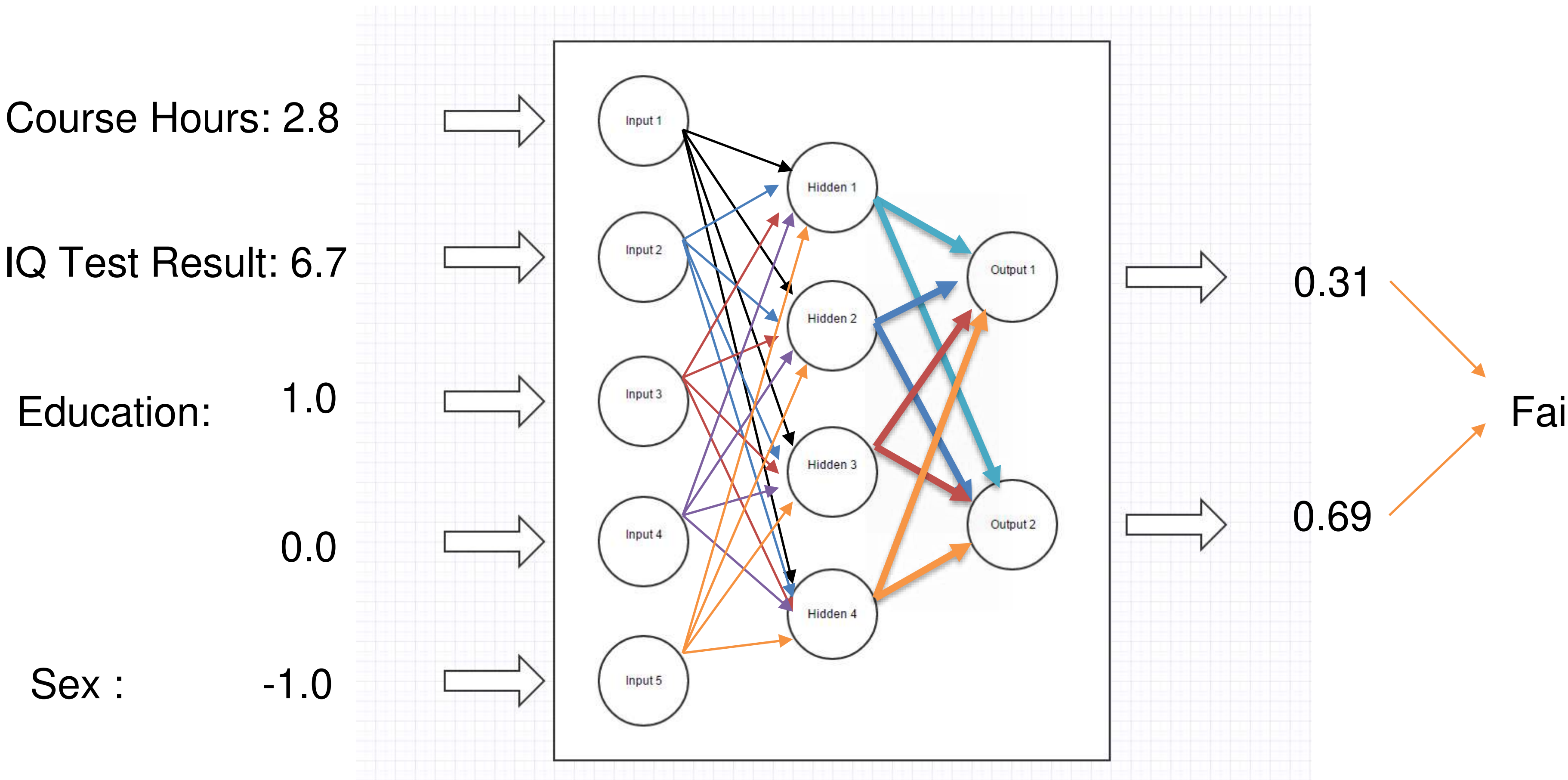
Course Hours	IQ Test Result	Education	Sex	Result
28	109	High School	M	1
20	72	High School	M	0
12	121	Undergraduate	F	1
8	86	Graduate	M	0
32	94	Undergraduate	F	1
28	67	Graduate	M	?

Training Data

Predictors

Predict the outcome

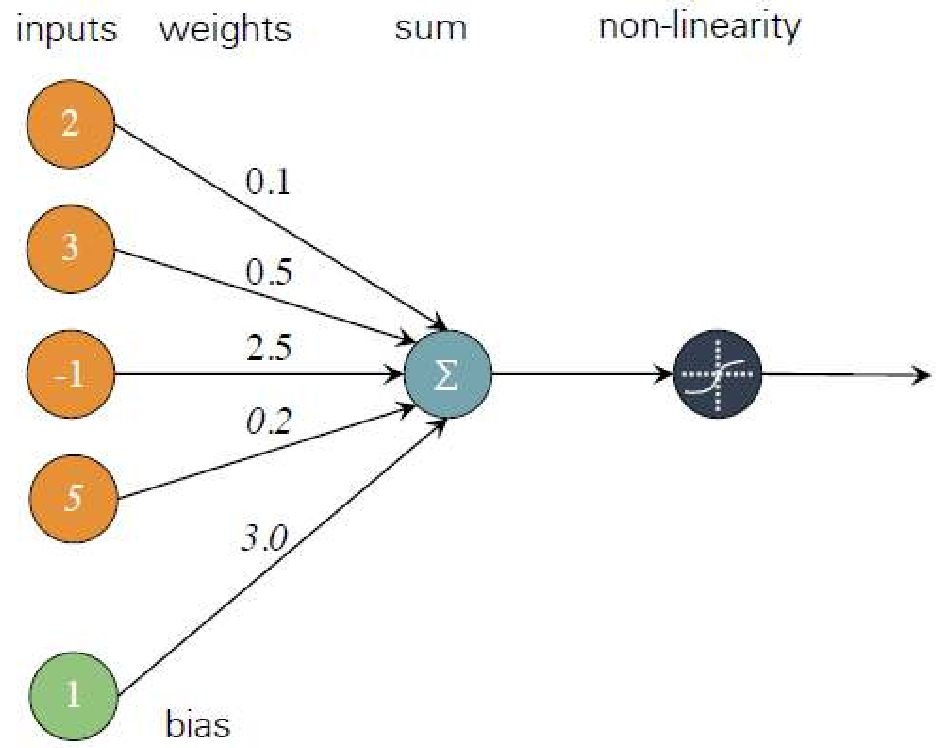
Network


Course Hours: 2.8
IQ Test Result: 6.7
Education: 1.0
0.0
Sex : -1.0
Input 1
Input 2
Input 3
Input 4
Input 5
Hidden 1
Hidden 2
Hidden 3
Hidden 4
Output 1
Output 2
0.31
0.69
Fail

Perceptron Forward Pass

$$h(\mathbf{x}) = g(a(\mathbf{x})) = g(b + \sum_i w_i x_i)$$

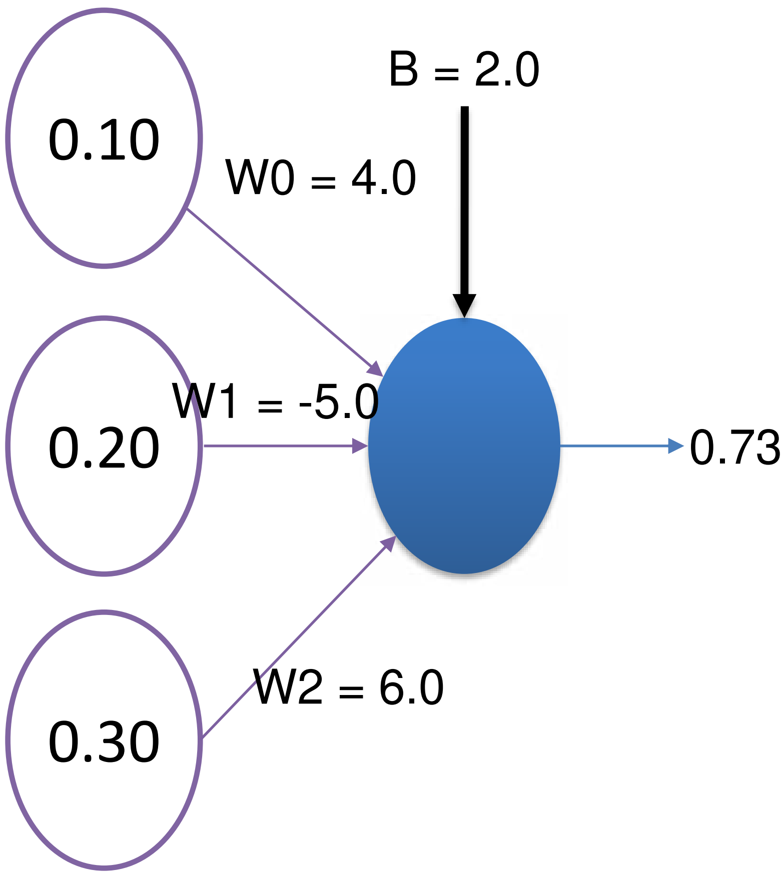
$$h(\mathbf{x}) = g((2*0.1) + (3*0.5) + (-1*2.5) + (5*0.2) + (1*3.0))$$



$$h(\mathbf{x}) = g(3.2) = \sigma(3.2)$$

$$\frac{1}{1+e^{-3.2}} = 0.96$$

Feed-Forward ve Aktivasyon

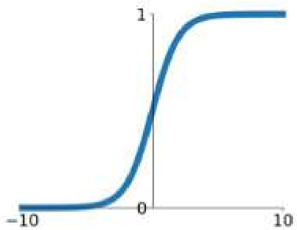


- 0.10*4.0 + 0.20*-5.0 + 0.30*6.0 + 2.0*1 = 3.2
- Activation(3.2) = 0.73
- Output = 0.73

Activation Functions

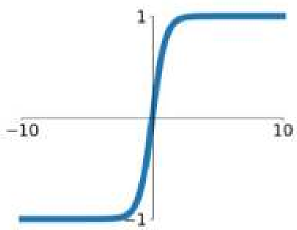
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



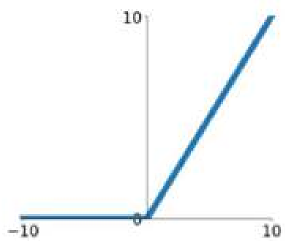
tanh

$\tanh(x)$



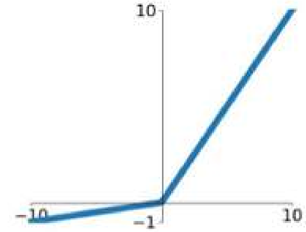
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

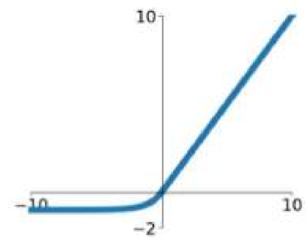


Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Multi-Layer Perceptron(MLP)

- Hidden layer pre-activation:

$$\mathbf{a}(\mathbf{x}) = \mathbf{b}^{(1)} + \mathbf{W}^{(1)}\mathbf{x}$$

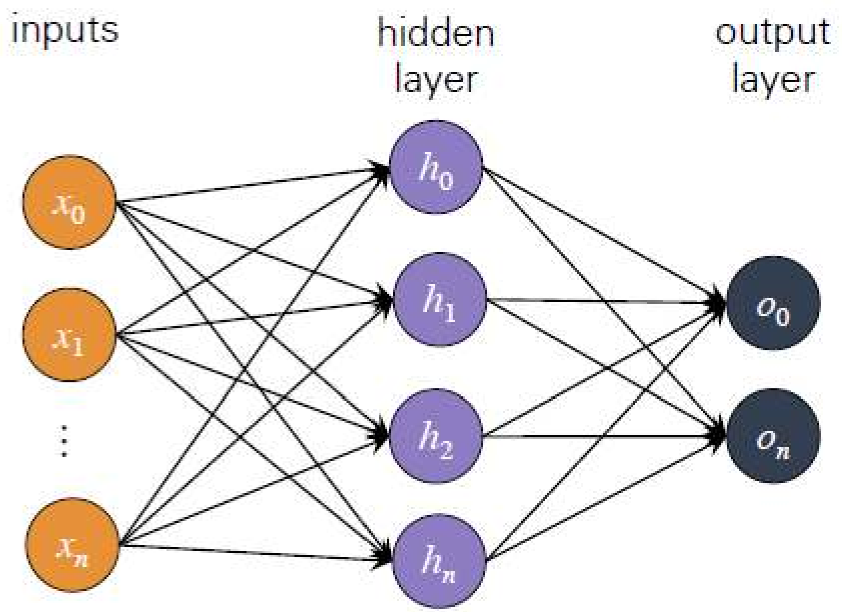
$$\left(a(\mathbf{x})_i = b_i^{(1)} + \sum_j W_{i,j}^{(1)} x_j\right)$$

- Hidden layer activation:

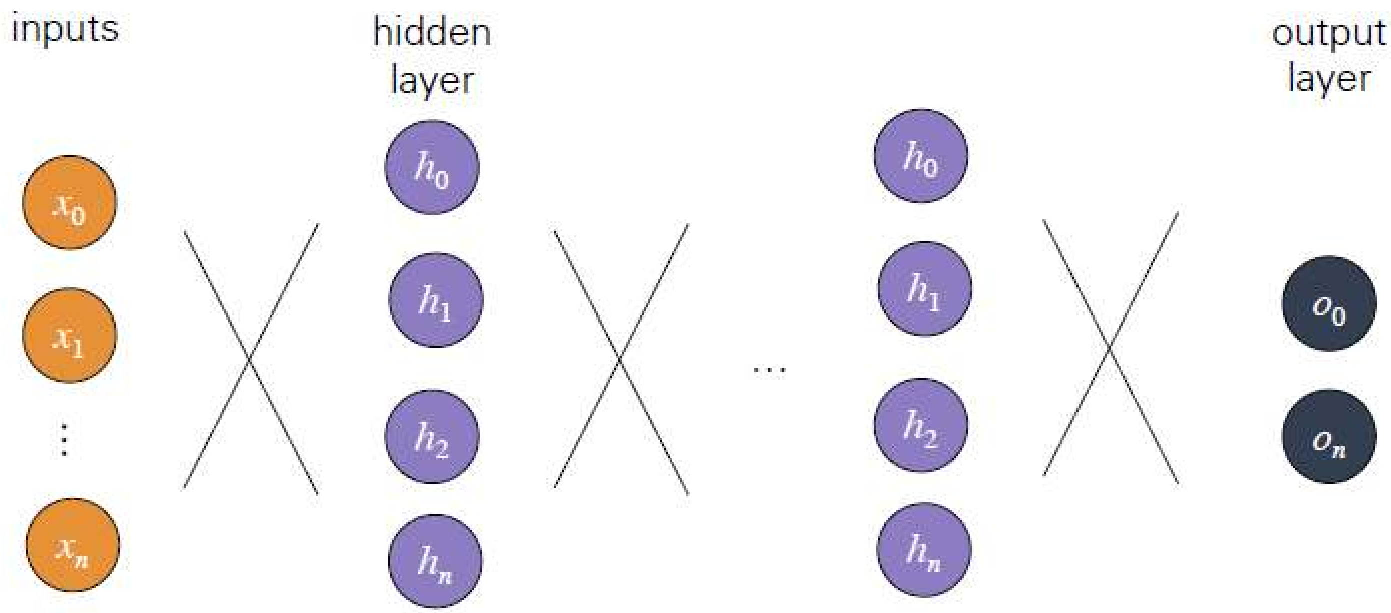
$$\mathbf{h}(\mathbf{x}) = \mathbf{g}(\mathbf{a}(\mathbf{x}))$$

- Output layer activation:

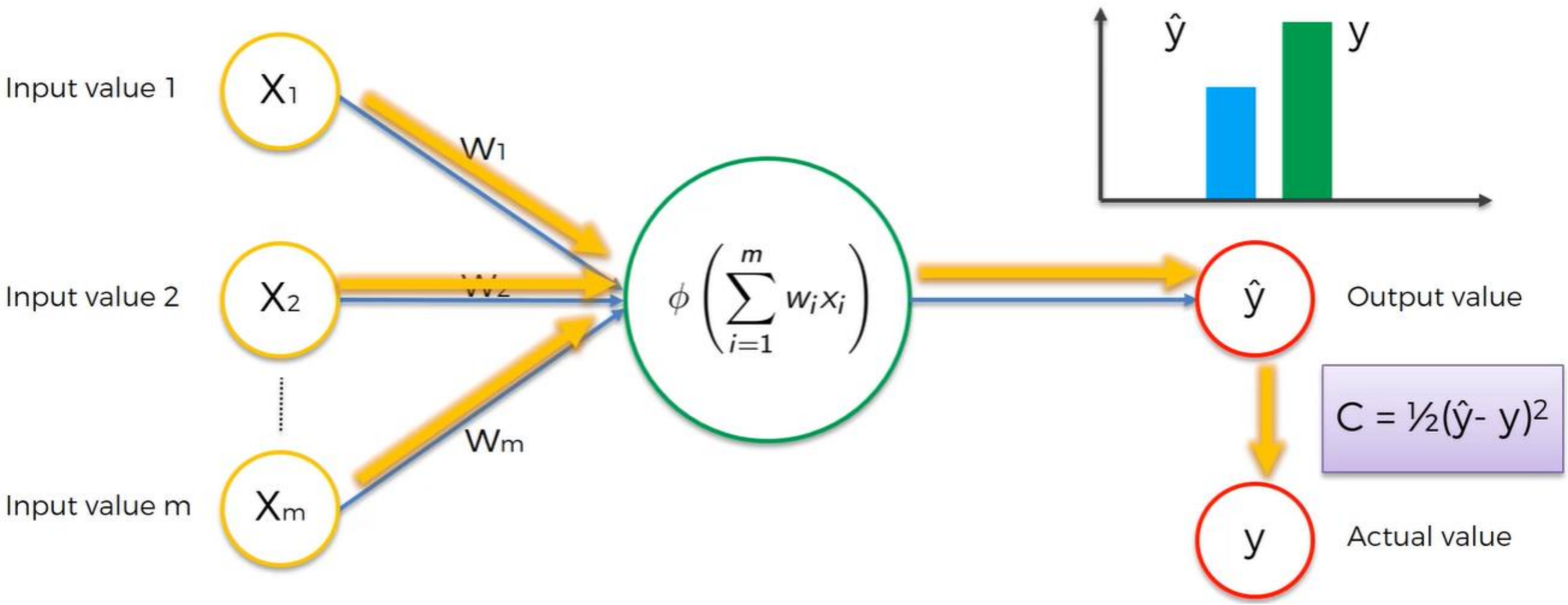
$$\mathbf{o}(\mathbf{x}) = \mathbf{o}\left(b^{(2)} + \mathbf{w}^{(2)^\top}\mathbf{h}^{(1)}\mathbf{x}\right)$$



Deep Neural Networks (DNN)



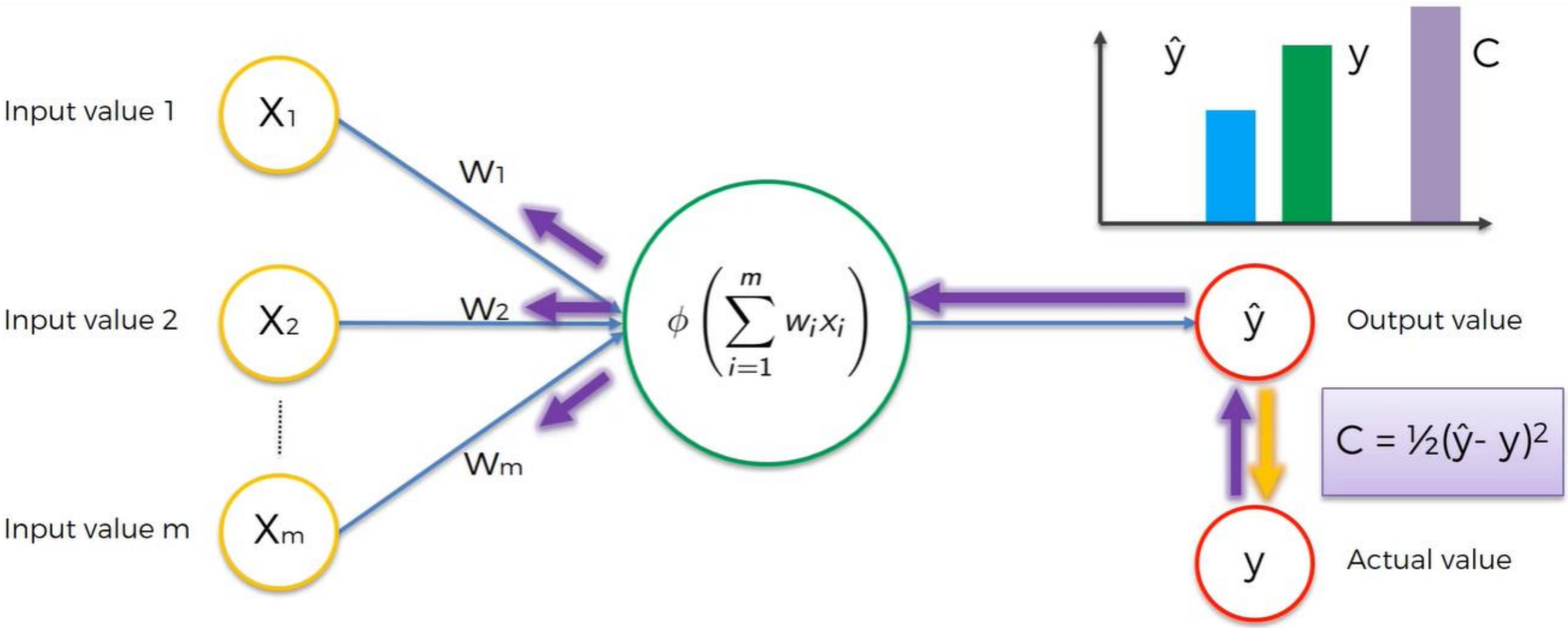
Training(Feed Forward)



Error ve Accuracy

- Mean Squared Error
- $E_{total} = \sum \frac{1}{2}(target - output)^2$

Training(Back Propagation)



Training

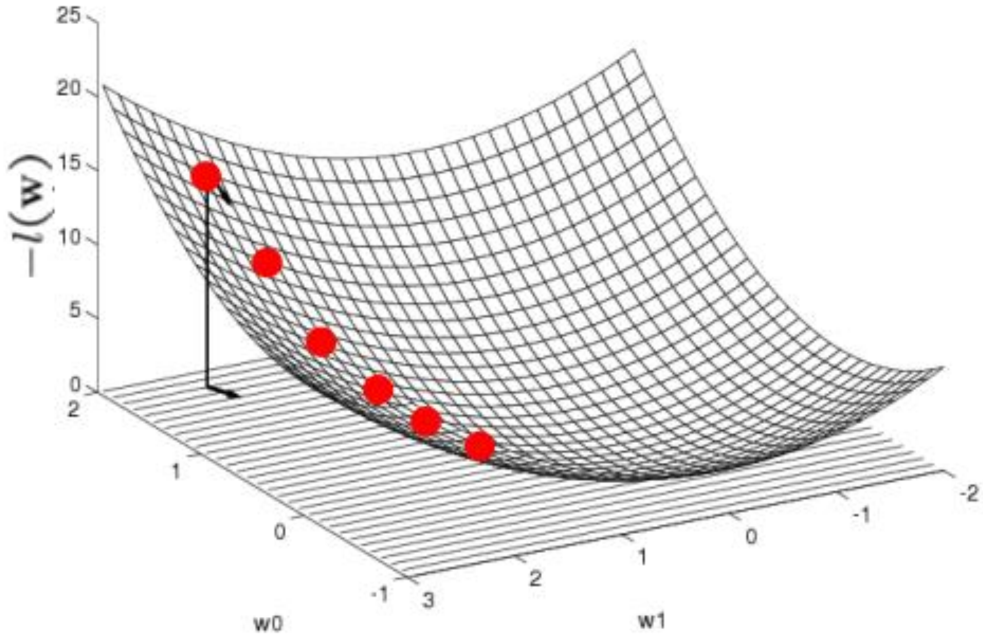
$$\boxed{J(\theta)} = \arg\min_{\boldsymbol{\theta}} \frac{1}{T} \sum_t \underbrace{l(f(\mathbf{x}^{(t)}; \boldsymbol{\theta}), y^{(t)})}_{\text{Loss function}} + \underbrace{\lambda \Omega(\boldsymbol{\theta})}_{\text{Regularizer}}$$

$$\theta = W_1, W_2 \ldots W_n$$

- Learning is cast as optimization.
  - For classification problems, we would like to minimize classification error
  - Loss function can sometimes be viewed as a surrogate for what we want to optimize (e.g. upper bound)

Gradient descent

- Optimizing convex function: **Gradient descent (convex)**



Gradient:

$$\nabla_{\mathbf{w}} l(\mathbf{w}) = [\frac{\partial l(\mathbf{w})}{\partial w_0}, \ldots, \frac{\partial l(\mathbf{w})}{\partial w_d}]'$$

Update rule: **Learning rate, η>0**

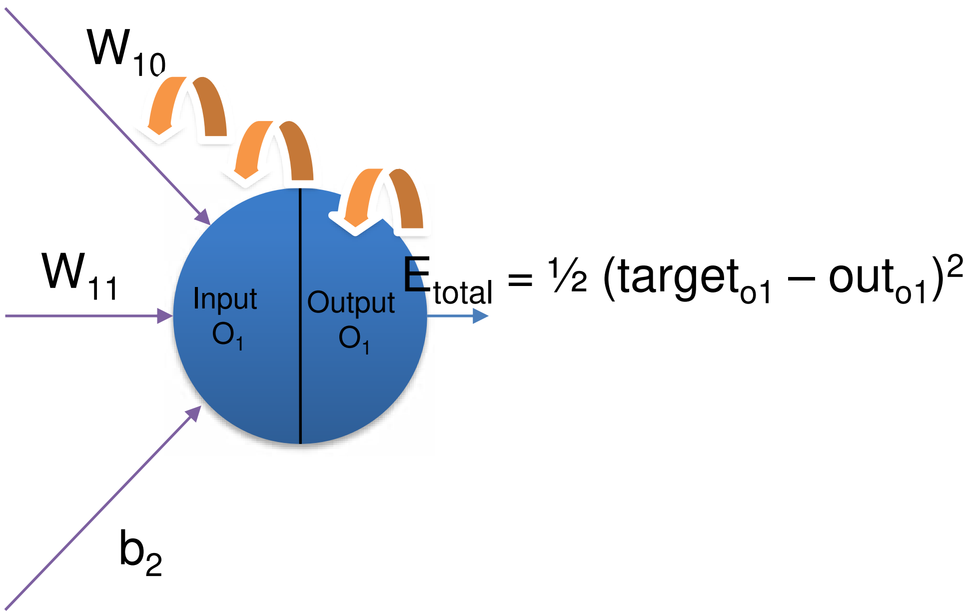
$$\Delta \mathbf{w} = \eta \nabla_{\mathbf{w}} l(\mathbf{w})$$

$$w_i^{(t+1)} \leftarrow w_i^{(t)} + \eta \left.\frac{\partial l(\mathbf{w})}{\partial w_i}\right|_t$$

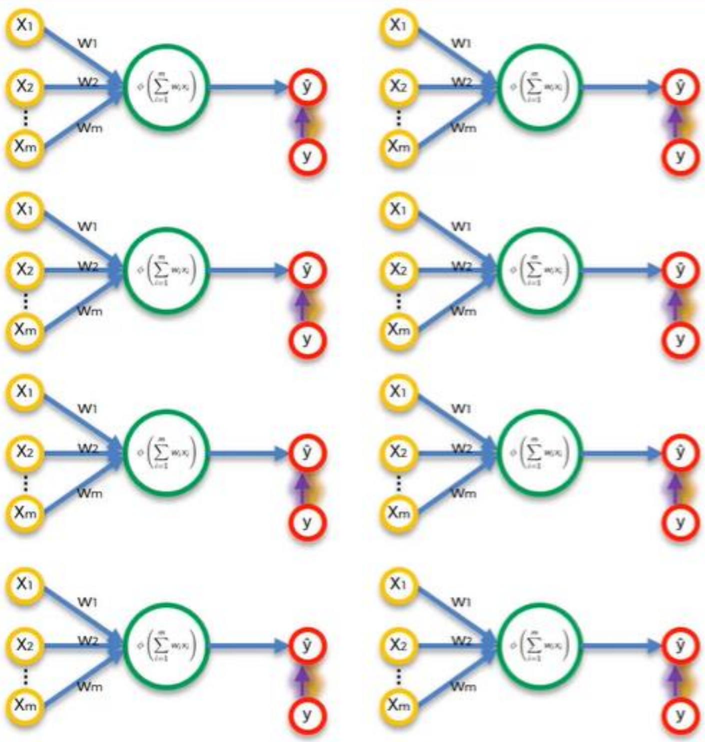
Training (Back Propagation)

- W_{10} ağırlık değerini değiştirmenin etkisini bulma

$$\frac{d\,E_{total}}{d\,W_{10}} = \frac{d\,E_{total}}{d\,out_{O_1}} * \frac{d\,out_{O_1}}{d\,in_{O_1}} * \frac{d\,in_{O_1}}{d\,W_{10}}$$



Training(Back Propagation)

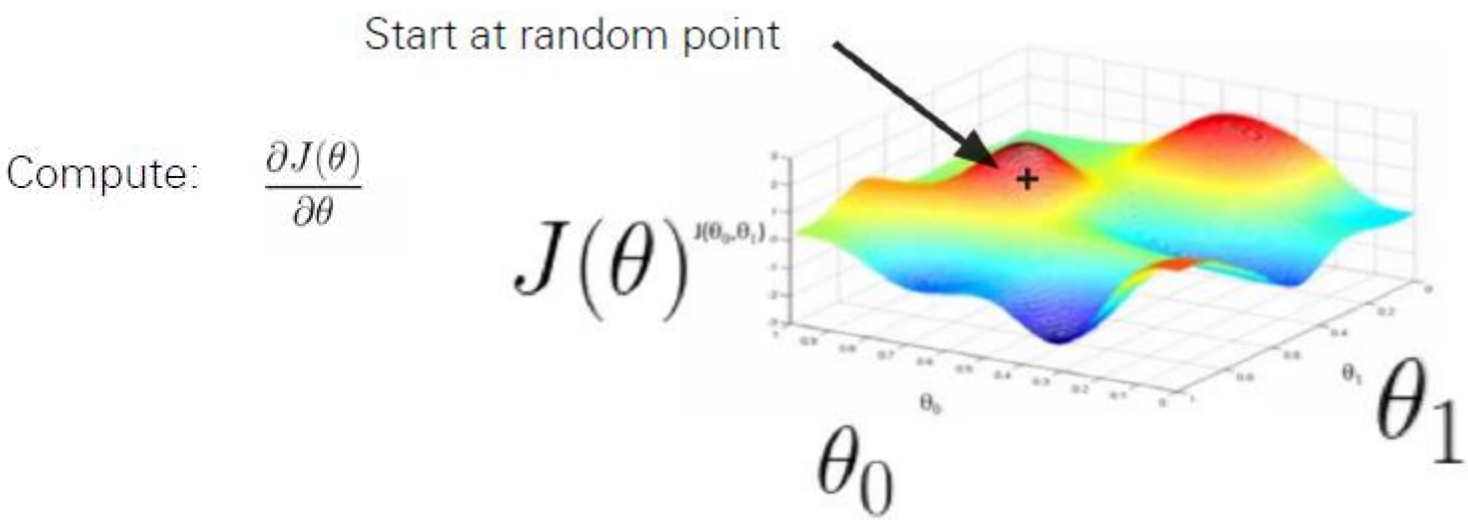


Row ID	Study Hrs	Sleep Hrs	Quiz	Exam
1	12	6	78%	93%
2	22	6.5	24%	68%
3	115	4	100%	95%
4	31	9	67%	75%
5	0	10	58%	51%
6	5	8	78%	60%
7	92	6	82%	89%
8	57	8	91%	97%

$$C = \sum \tfrac{1}{2}(\hat{y} - y)^2$$

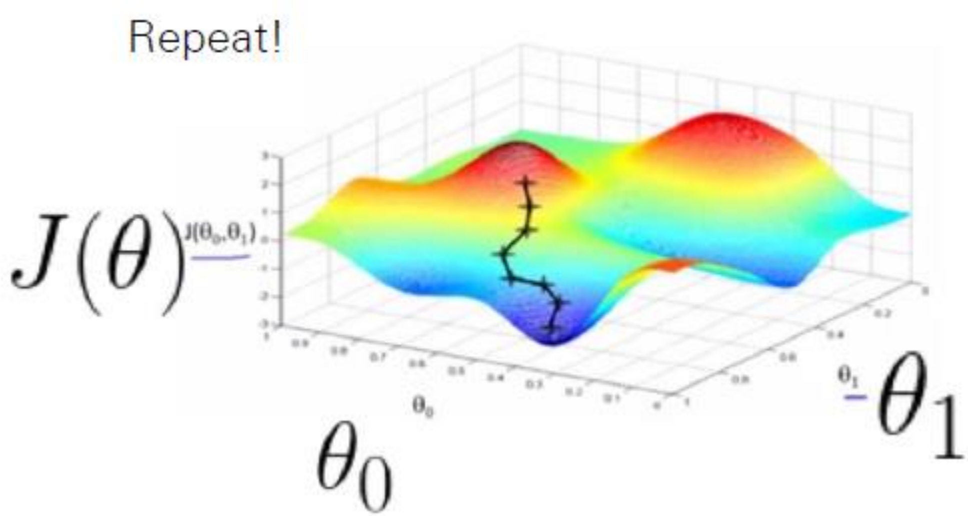
Training

Loss, modelin ağırlık parametreleri fonksiyonudur.
Nasıl minimize edilir?



Stochastic Gradient Descent (SGD)

Loss, azalan yönde iterative şekilde ilerler



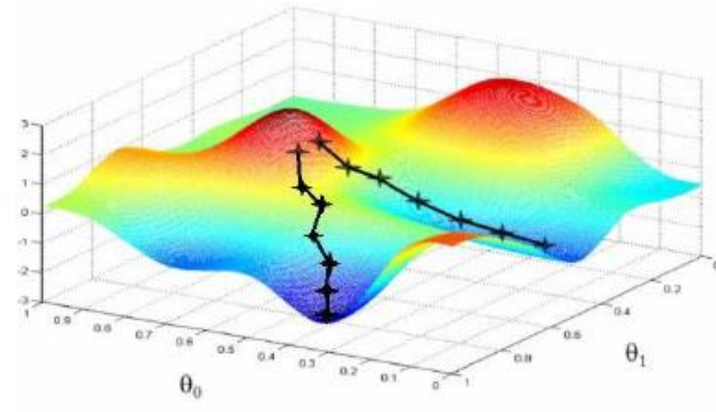
Stochastic Gradient Descent (SGD)

- Initialize θ randomly
- For N Epochs
  - For each training batch $\{(x_0, y_0), \ldots, (x_B, y_B)\}$:

    More accurate estimate!

    - Compute Loss Gradient: $\dfrac{\partial J(\theta)}{\partial \theta} = \dfrac{1}{B}\sum_i^B \dfrac{\partial J_i(\theta)}{\partial \theta}$
    - Update θ with update rule:

$$\theta := \theta - \eta \frac{\partial J(\theta)}{\partial \theta}$$



Advantages:

- More accurate estimation of gradient
  - Smoother convergence
  - Allows for larger learning rates
- Minibatches lead to fast training!
  - Can parallelize computation + achieve significant speed increases on GPU's

Neural Network Sınıflandırıcı

- Zayıflıkları
  - **Uzun eğitim süresi**
  - Ağ topolojisi veya "yapı" gibi tipik olarak en iyi **deneysel** olarak belirlenen bir dizi **parametre** gerektirir.
  - **Kötü yorumlanabilirlik**: Öğrenilen ağırlıkların ve ağdaki "gizli birimlerin" arkasındaki sembolik anlamı yorumlamak zordur

- Güçlü tarafları
  - **Noise verilere** toleransı yüksek
  - Eğitim setinde **görülmemiş kalıpları** sınıflandırma yeteneği
  - **Sürekli değerli** girdi ve çıktılar için çok uygun
  - **Çok çeşitli** gerçek dünya verileri üzerinde başarılı
  - **Algoritmalar** doğası gereği **paraleldir**
  - **Sinir ağlarından kuralların çıkarılması** için son zamanlarda teknikler geliştirilmiştir.

Deep learning kullanılmalı?

- Çok noise varsa ve sorunun yapısı basitse -> hayır kullanma
- Az noise varsa ve sorunun yapısı karmaşıksa-> evet, deep learning kullan
- İyi ve basit bir temel algoritma ile başlamak faydalı:
    - Hangi algoritmayı iyi biliyorsanız onunla başlayın
    - Logistic regression, SVM, boosted decision tree gayet iyi çalışan yöntemler

(Goodfellow 2016)