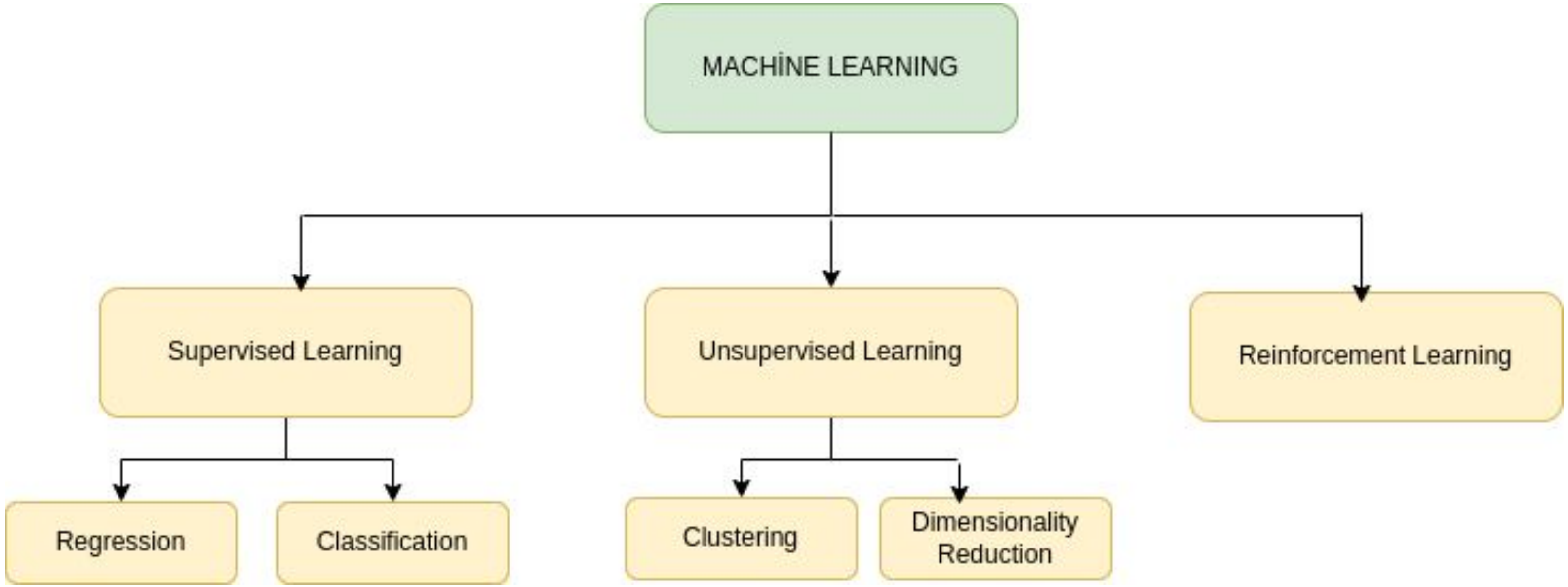
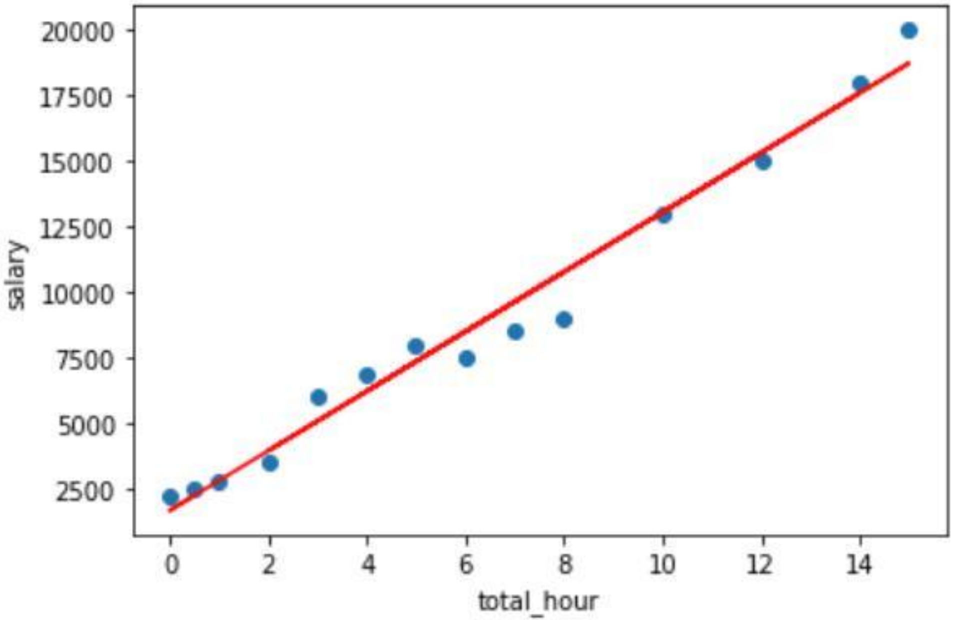
Machine Learning

Estü-Teknotam Akademi

Machine Learning



Linear Regression



$$h_\theta(x^{(i)}) = \theta_0 x_0 + \theta_1 x_1 + \ldots + \theta_i x_j$$

$$x_0 = 1, \quad j = the\ number\ of\ features$$

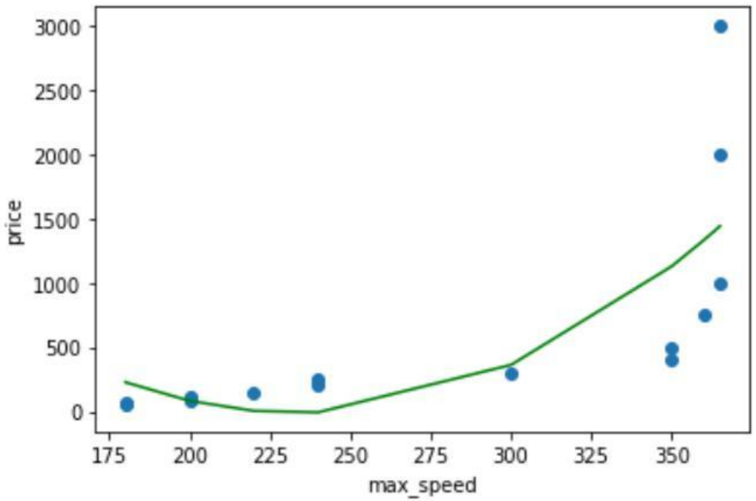
$$Least\ Squared\ Error = \frac{1}{2}(h_\theta(x^{(i)}) - y^{(i)})^2$$

$$Cost\ Function = J(\theta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2, \quad m = number\ of\ sample\ data$$

Derivative of cost function at θ_j:

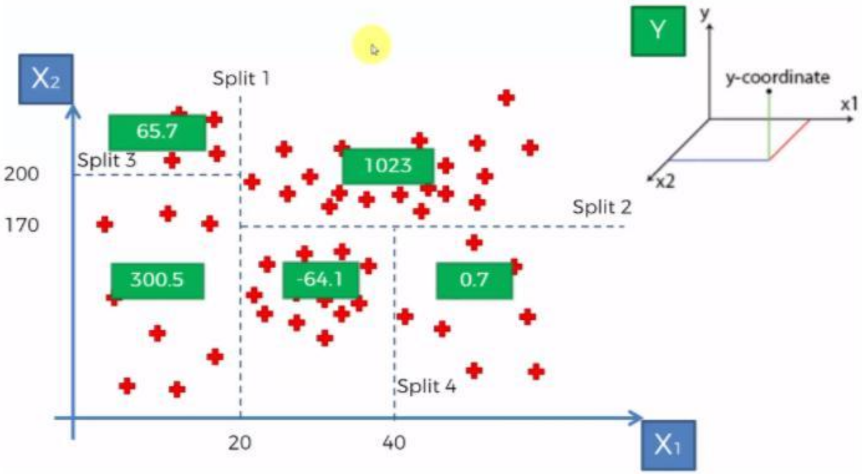
$$\frac{\partial J(\theta)}{\partial \theta_j} = \frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}$$

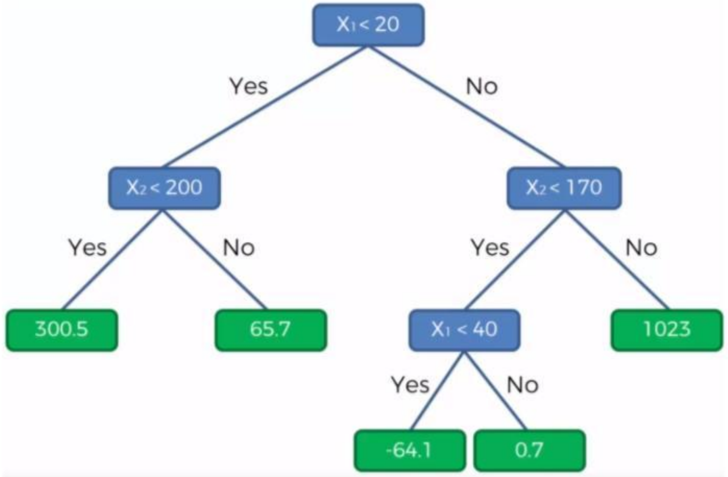
Polynomial Regression



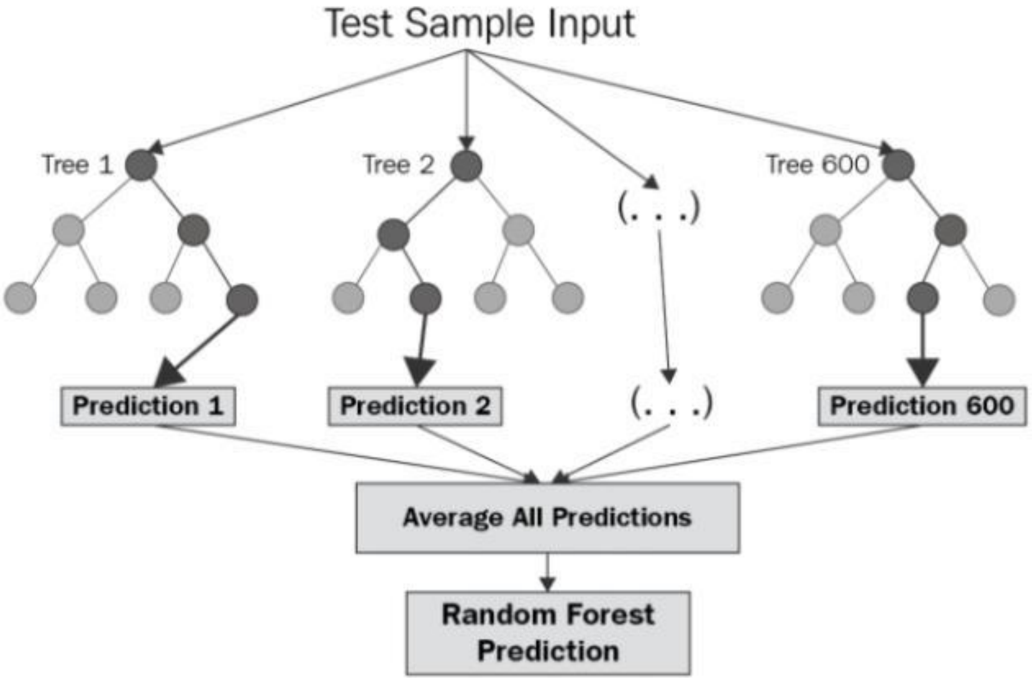
Simple Linear Regression	$y = b_0 + b_1 x_1$
Multiple Linear Regression	$y = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_n x_n$
Polynomial Linear Regression	$y = b_0 + b_1 x_1 + b_2 x_1^2 + \ldots + b_n x_1^n$

Decision Tree Regression

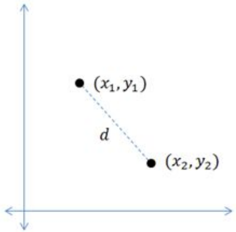




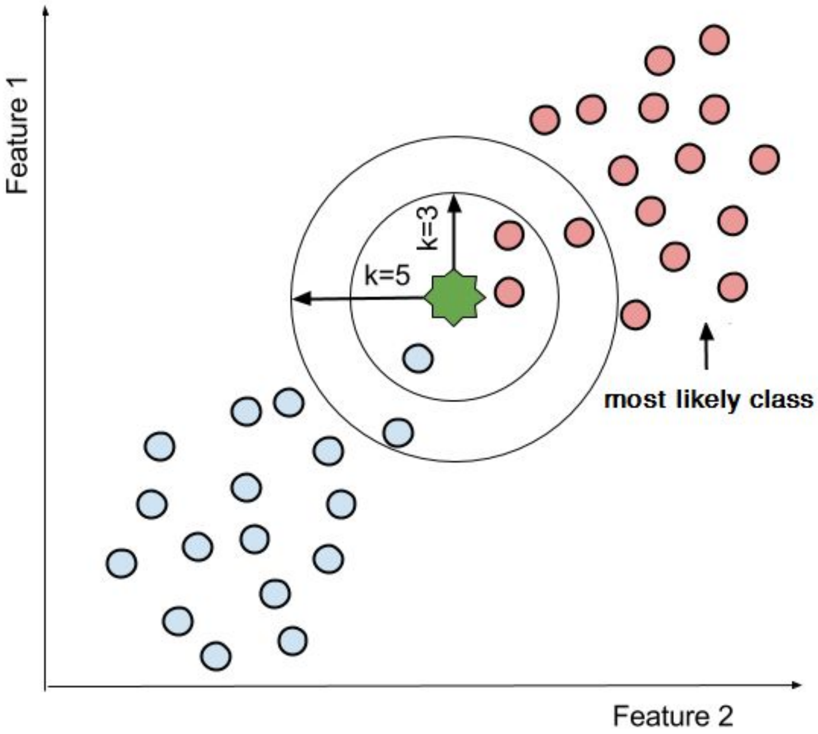
Random Forest Regression



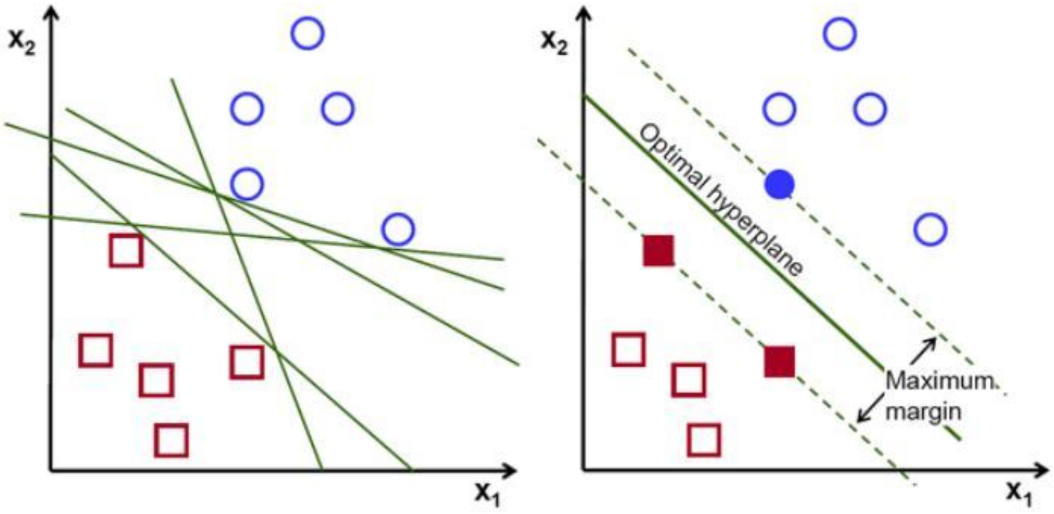
KNN Classification



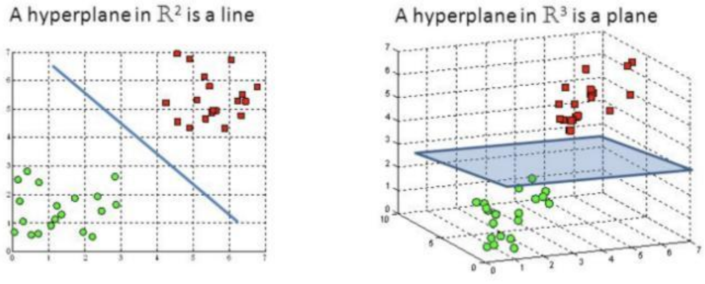
$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$



SVM

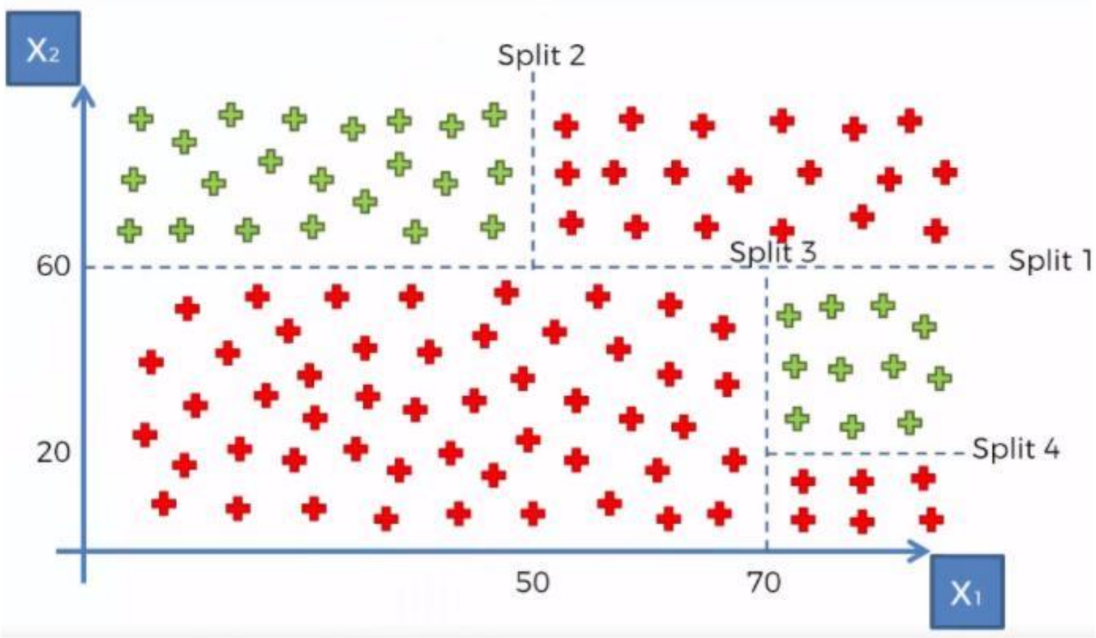


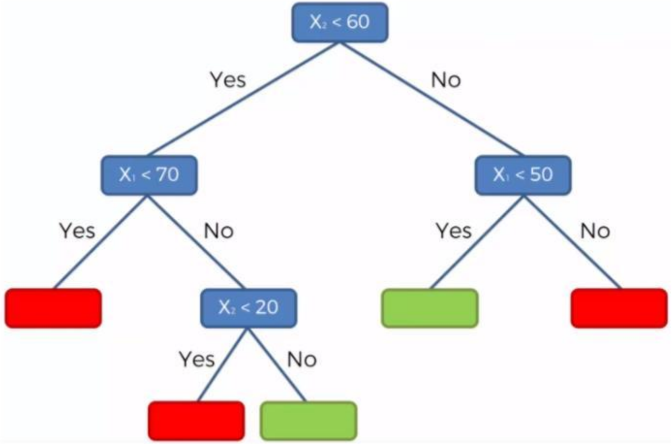
Possible hyperplanes



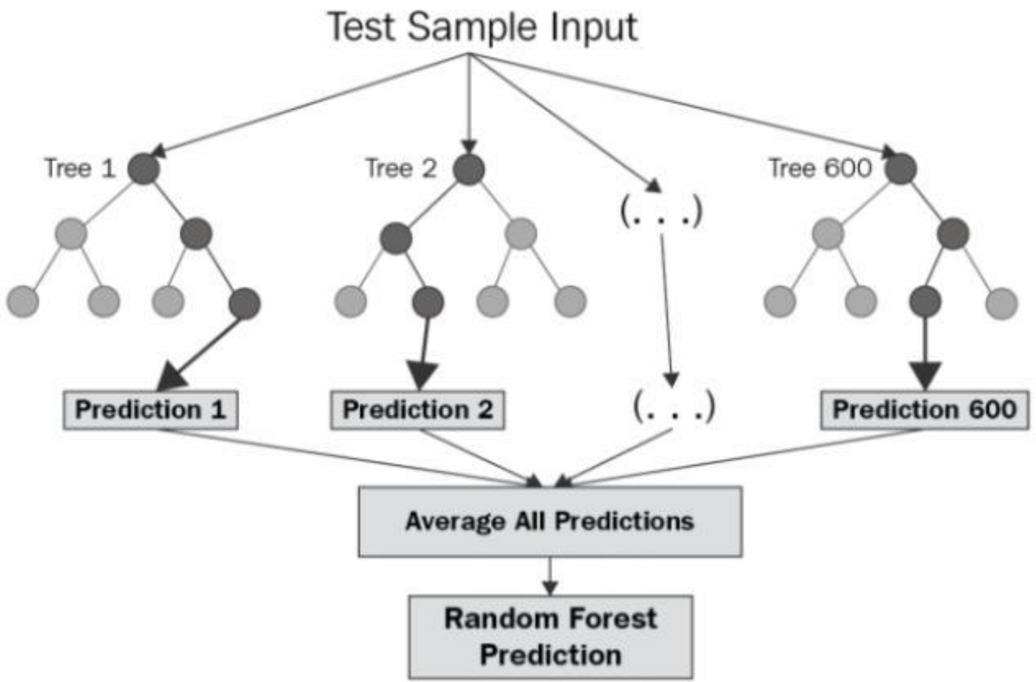
To separate the two classes of data points, there are many possible hyperplanes that could be chosen.
Our objective is to find a plane that has the maximum margin, i.e the maximum distance between data points of both classes

Decision Tree Classification





Random Forest Classification



Unsupervised Learning

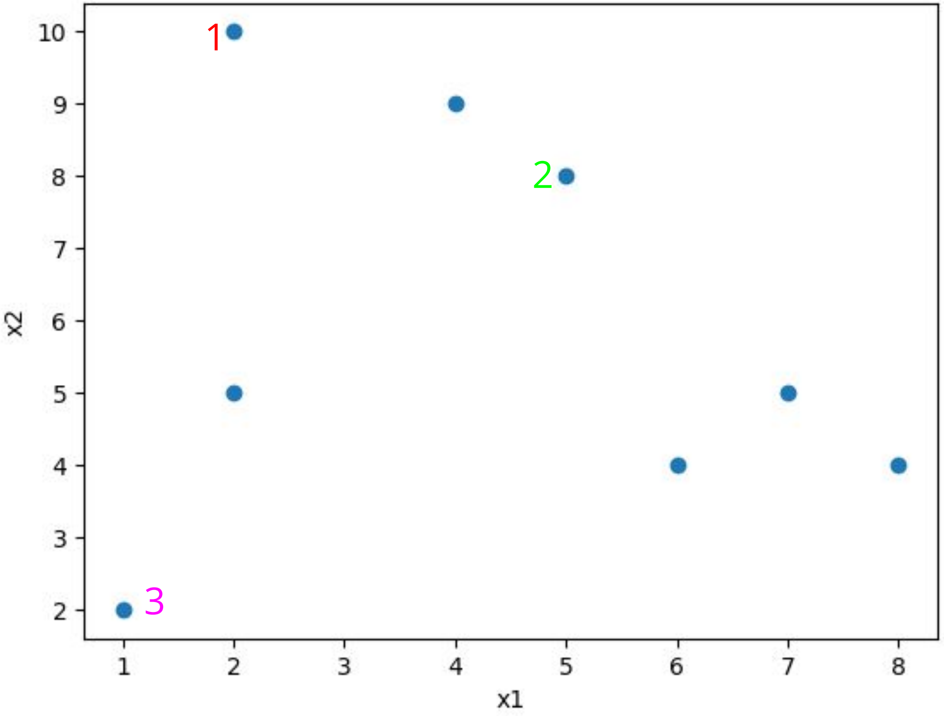
K-means Clustering

Knn clustering

Hierarchical Clustering

PCA

K-means Clustering



Iteration 1

		(2, 10)	(5, 8)	(1, 2)	
	Point	**Dist Mean 1**	**Dist Mean 2**	**Dist Mean 3**	**Cluster**
A1	(2, 10)	0	5	9	1
A2	(2, 5)	5	6	4	3
A3	(8, 4)	12	7	9	2
A4	(5, 8)	5	0	10	2
A5	(7, 5)	10	5	9	2
A6	(6, 4)	10	5	7	2
A7	(1, 2)	9	10	0	3
A8	(4, 9)	3	2	10	2

Cluster 1	Cluster 2	Cluster 3
(2, 10)	(8, 4)	(2, 5)
	(5, 8)	(1, 2)
	(7, 5)	
	(6, 4)	
	(4, 9)	

K-means Clustering

- For Cluster 1, we only have one point A1(2, 10), which was the old mean, so the cluster center remains the same.
- For Cluster 2, we have ((8+5+7+6+4)/5, (4+8+5+4+9)/5) = (6, 6)
- For Cluster 3, we have ((2+1)/2, (5+2)/2) = (1.5, 3.5)

K-means Clustering

		(2, 10)	(6, 6)	(1.5, 3.5)	
	Point	Dist Mean 1	Dist Mean 2	Dist Mean 3	**Cluster**
A1	(2, 10)	0	8	7	1
A2	(2, 5)	5	5	2	3
A3	(8, 4)	12	4	7	2
A4	(5, 8)	5	3	8	2
A5	(7, 5)	10	2	7	2
A6	(6, 4)	10	2	5	2
A7	(1, 2)	9	9	2	3
A8	(4, 9)	3	5	8	1

K-means Clustering

- In Cluster 1, we have points 1 and 8. Therefore the centroid is: $((2+4)/2,(10+9)/2)=(3,9.5)$
- In Cluster 2, we have points 3,4,5 and 6. Therefore, the centroid is: $((8+5+7+6)/4,(4+8+5+4)/4)=(6.5,5.25)$
- For Cluster 3, we have points 2 and 7. Therefore, the centroid is: $((2+1)/2,(5+2)/2)=(1.5,3.5)$

K-means Clustering

		(3, 9.5)	(6.5 ,5.25)	(1.5, 3.5)	
	Point	Dist Mean 1	Dist Mean 2	Dist Mean 3	**Cluster**
A1	(2, 10)	1.5	9.25	7	**1**
A2	(2, 5)	5.5	4.75	2	**3**
A3	(8, 4)	10.5	2.75	7	**2**
A4	(5, 8)	3.5	4.25	8	**1**
A5	(7, 5)	8.5	0.75	7	**2**
A6	(6, 4)	8.5	1.75	5	**2**
A7	(1, 2)	9.5	8.75	2	**3**
A8	(4, 9)	1.5	6.25	8	**1**

K-means Clustering

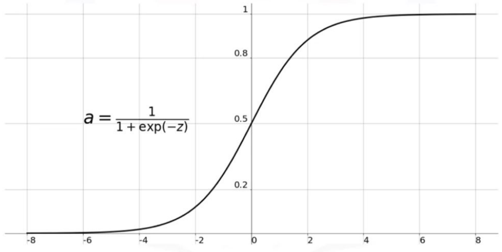
- In Cluster 1, we have points 1, 4, and 8. Therefore the centroid is: $((2+5+4)/2,(10+8+9)/2)=(3.67,9)$
- In Cluster 2, we have points 3,5 and 6. Therefore, the centroid is: $((8+7+6)/4,(4+5+4)/4)=(7,4.3)$
- For Cluster 3, we have points 2 and 7. Therefore, the centroid is: $((2+1)/2,(5+2)/2)=(1.5,3.5)$

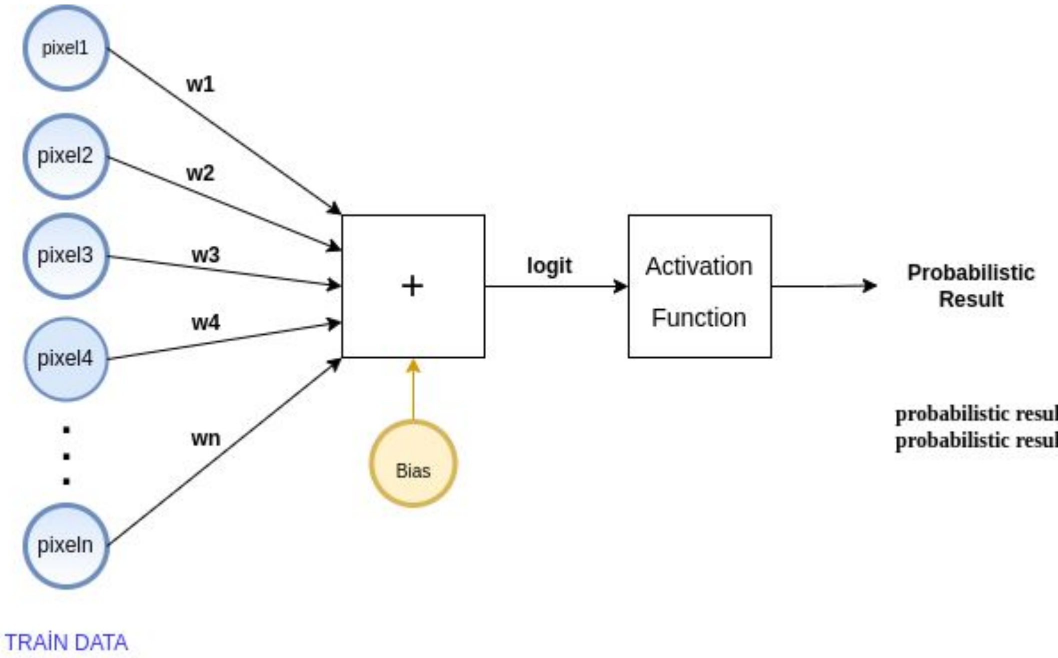
K-means Clustering

		(3.67, 9)	(7 ,4.3)	(1.5, 3.5)	
	Point	Dist Mean 1	Dist Mean 2	Dist Mean 3	**Cluster**
A1	(2, 10)	2.67	10.7	7	**1**
A2	(2, 5)	5.67	5.7	2	**3**
A3	(8, 4)	9.33	1.3	7	**2**
A4	(5, 8)	2.33	5.7	8	**1**
A5	(7, 5)	7.33	0.7	7	**2**
A6	(6, 4)	7.33	1.3	5	**2**
A7	(1, 2)	9.67	8.3	2	**3**
A8	(4, 9)	0.33	7.7	8	**1**

Logistic Regression

Sigmoid Function





probabilistic result < 0.5 --> first class
probabilistic result >= 0.5 --> second class

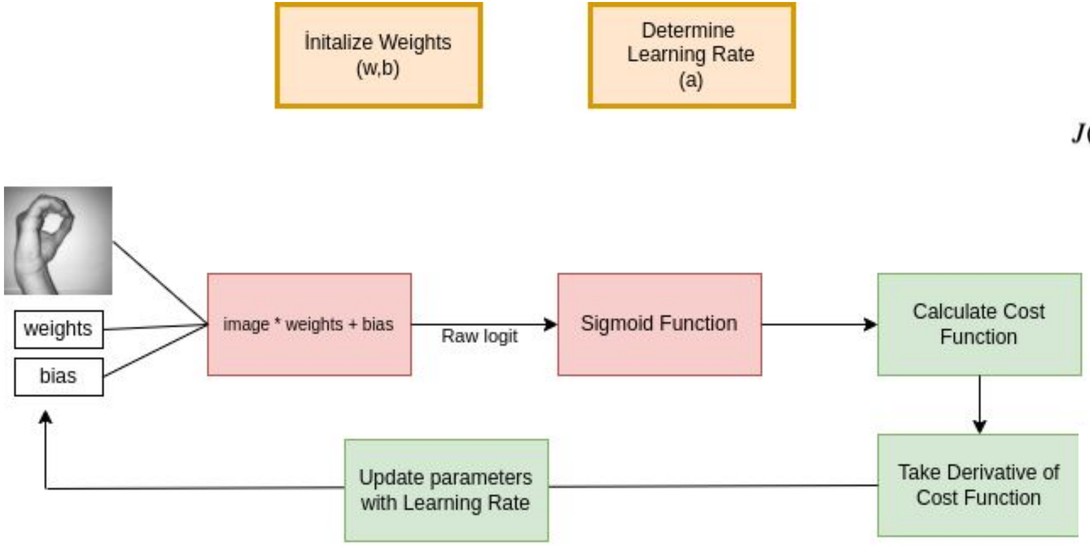
Step by step

$$Cost(h_\theta(x), y) = -ylog(h_\theta(x)) - (1-y)log(h_\theta(x))$$

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} Cost(h_\theta(x^{(i)}), y^{(i)})$$

$$J(\theta) = \frac{1}{m}[\sum_{i=1}^{m} -y^{(i)}log(h_\theta(x^{(i)})) + (1-y^{(i)})log(1-h_\theta(x^{(i)}))]$$

$$m = number\ of\ samples$$



$$\frac{\partial J}{\partial w} = \frac{1}{m} x(y_head - y)^T$$
$$\frac{\partial J}{\partial b} = \frac{1}{m}\sum_{i=1}^{m}(y_head - y)$$

Forward Propagation

Backward Propagation