Introduction to Machine Learning

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TNT ML
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TRAIN AND TEST

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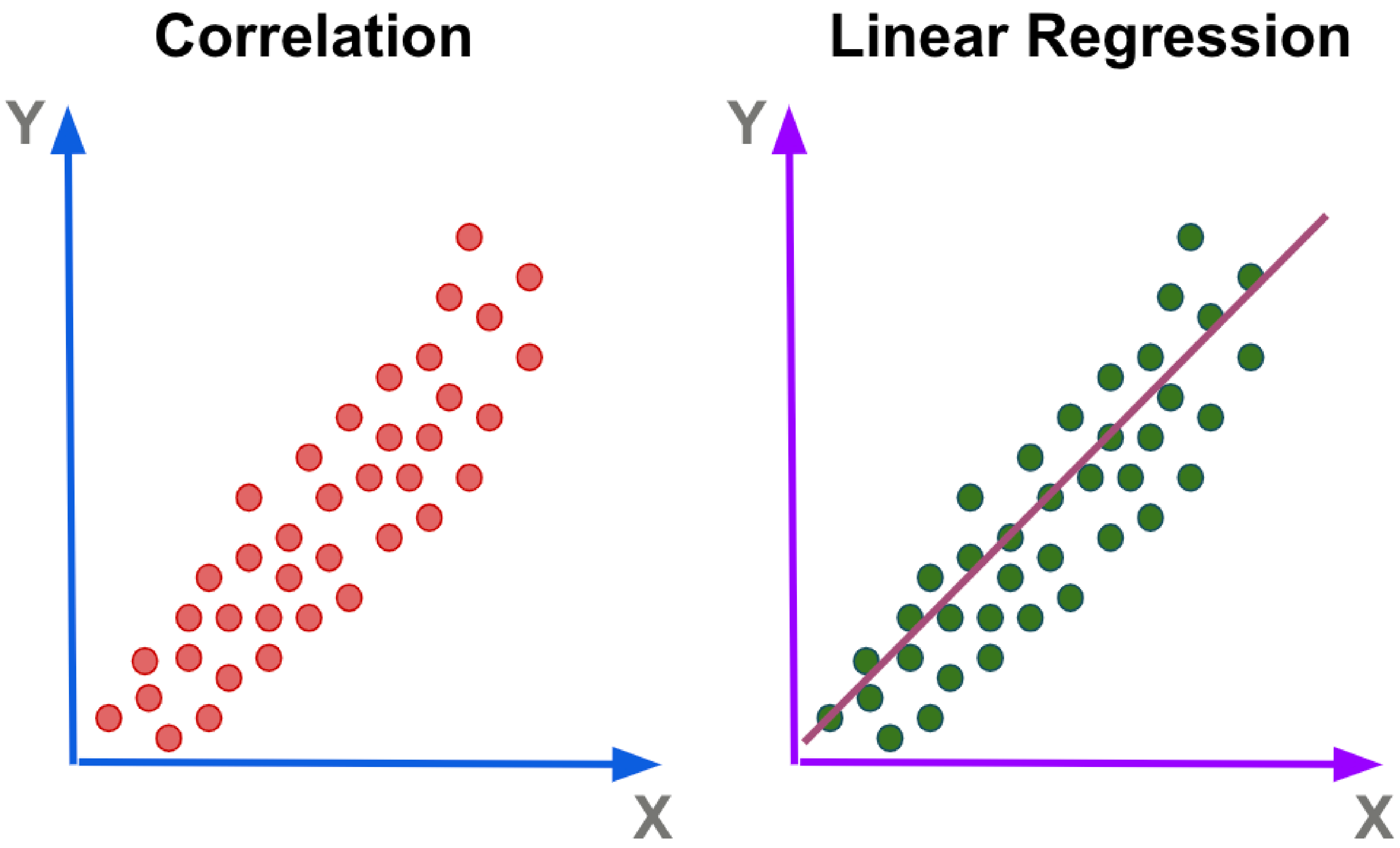
What We Learned

1. Overall Machine Learning

2. Regression

Regression



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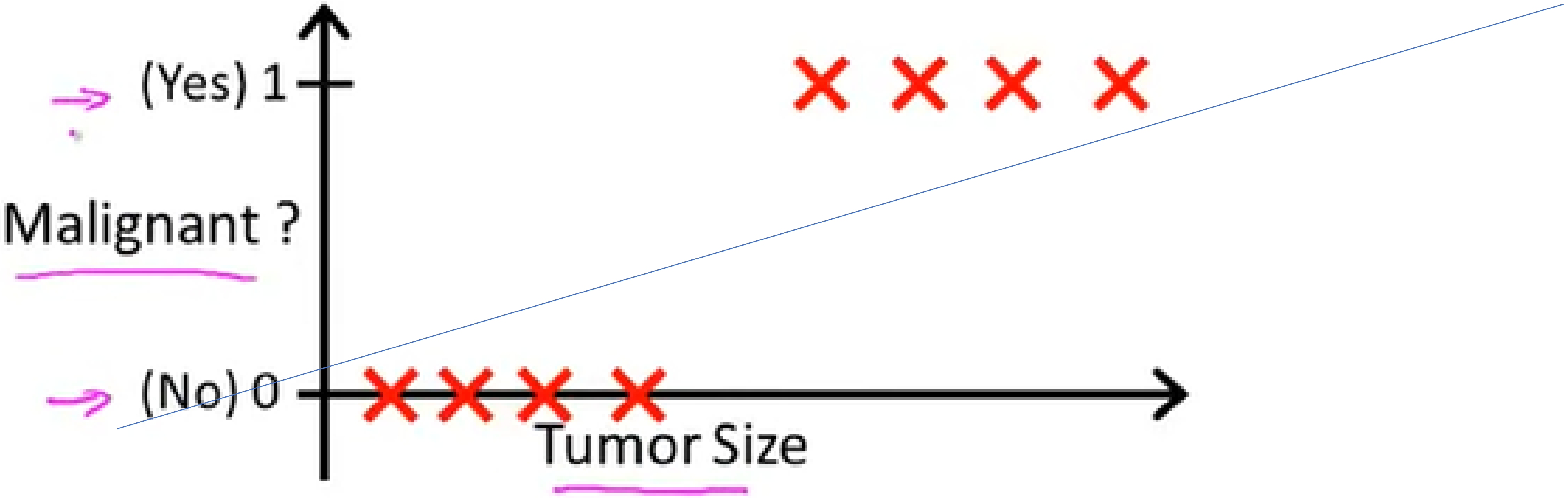
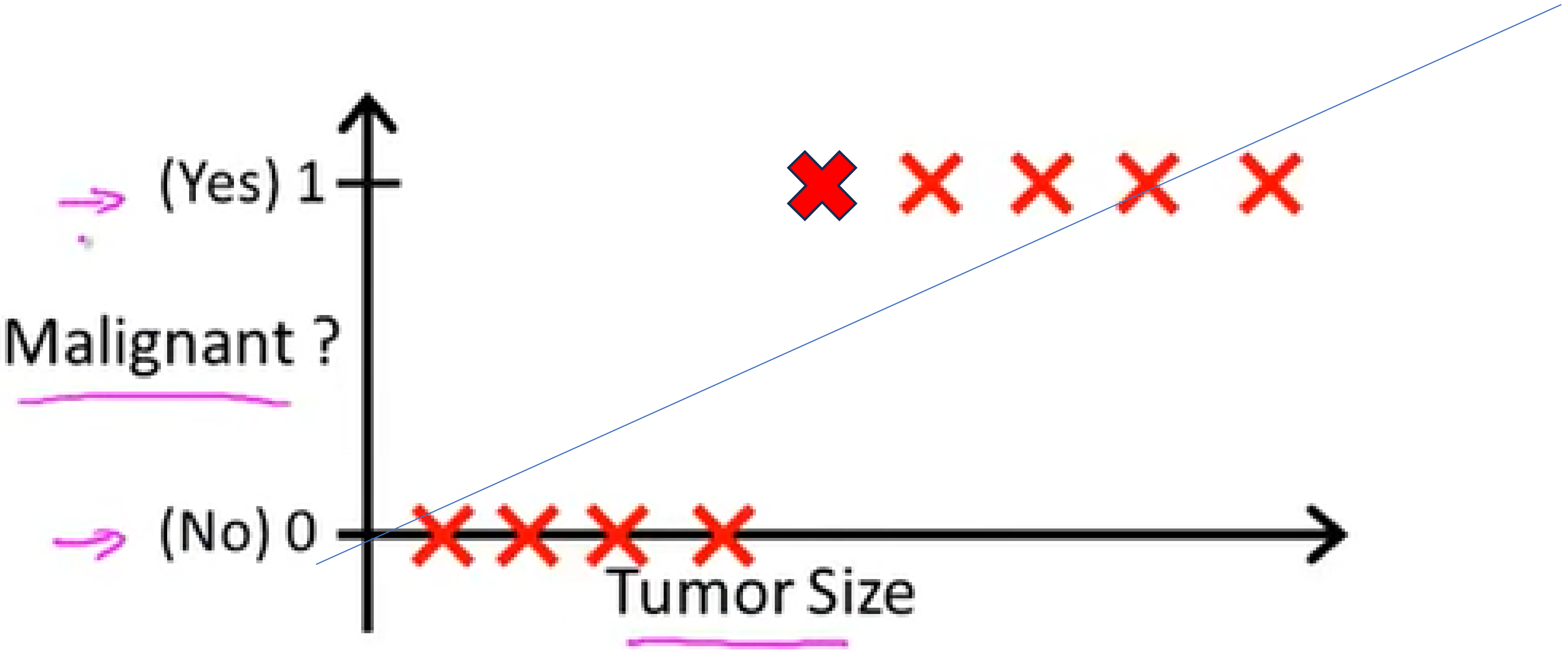
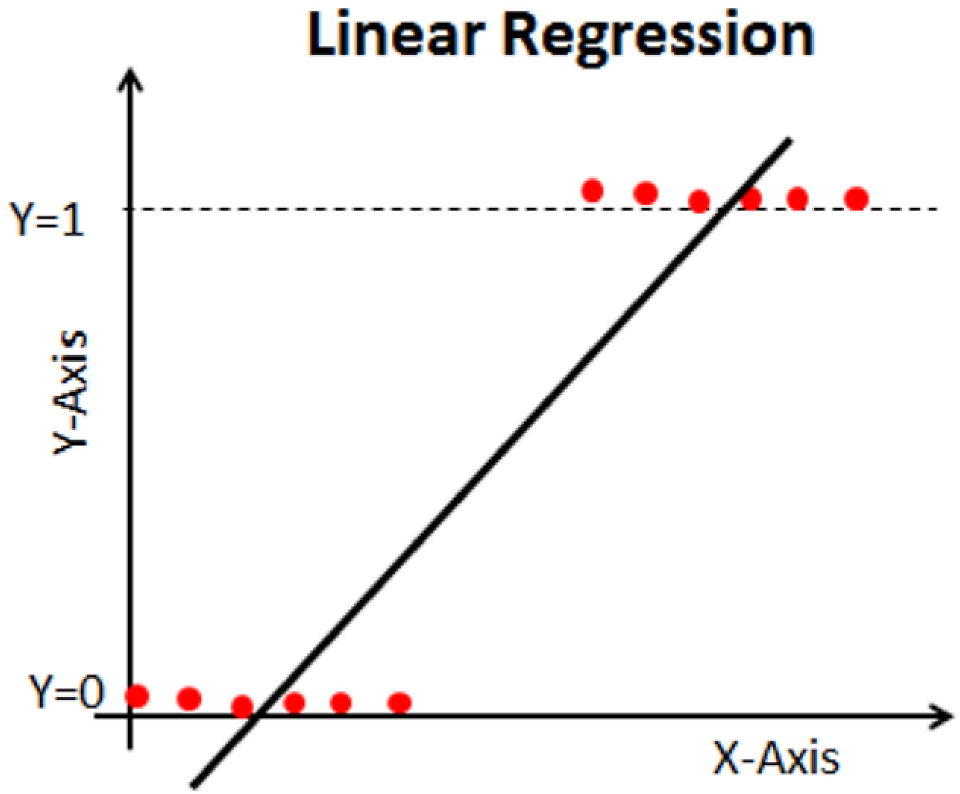
Logistic Regression



Logistic Regression



Logistic Regression



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Logistic Regression

$y \in \{0, 1\}$

0: “Negative Class” (e.g., benign tumor)

1: “Positive Class” (e.g., malignant tumor)

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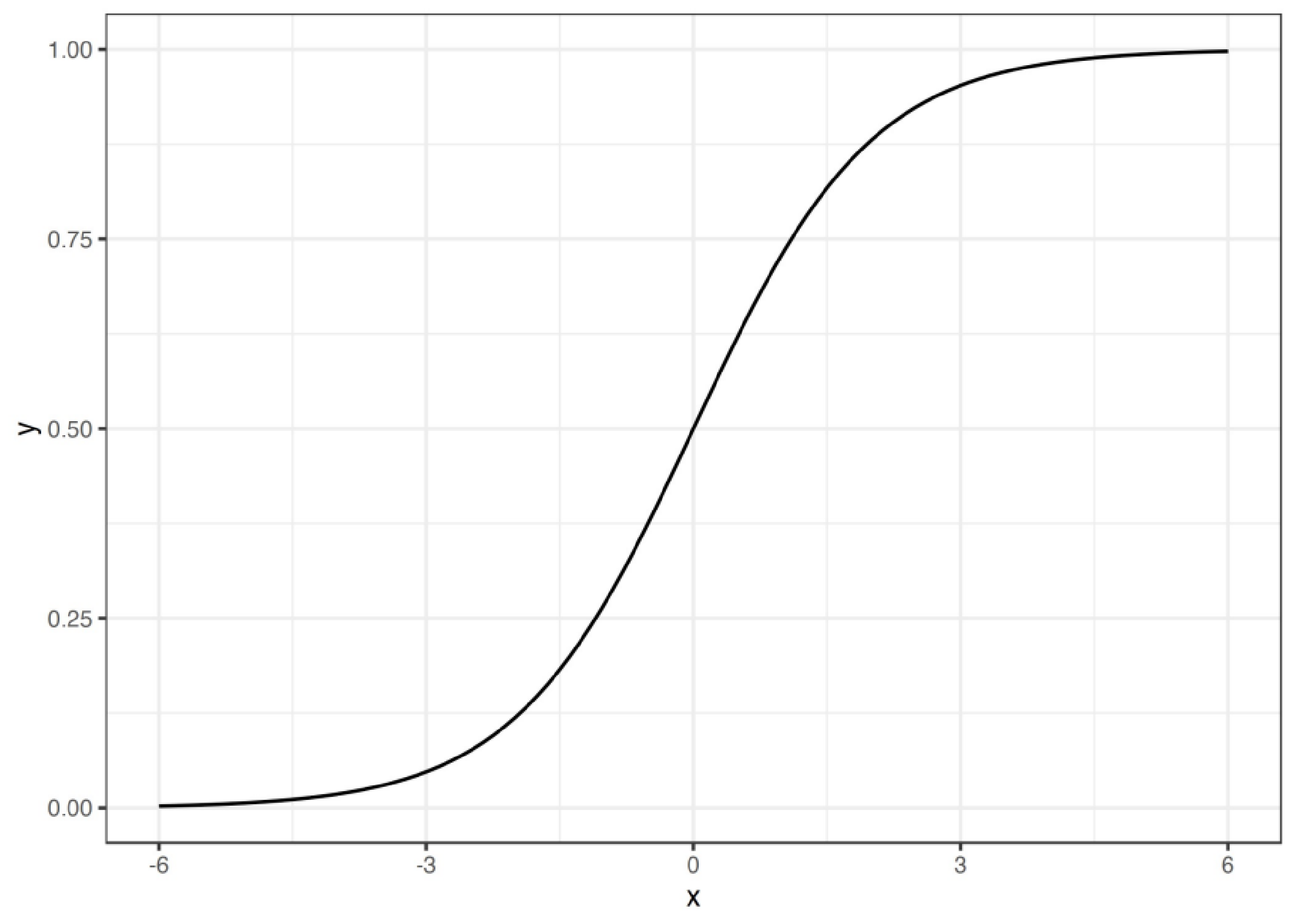
Logistic Regression

1. Classification

2. Then, why it’s a regression?

Logistic Regression

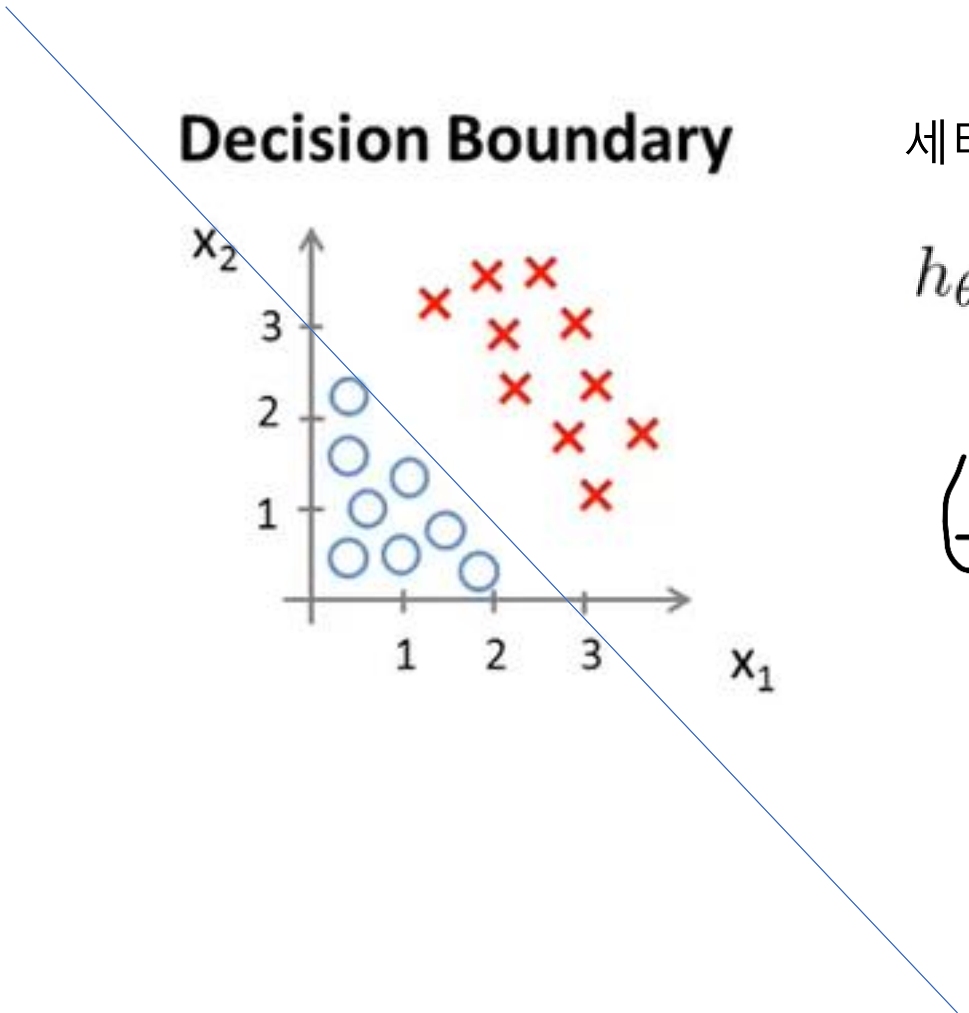


Logistic Function 수식

$$y = \frac{1}{1 + e^{-x}}$$

범위가 0과 1사이에 존재

Decision Boundary



세타는 파라미터

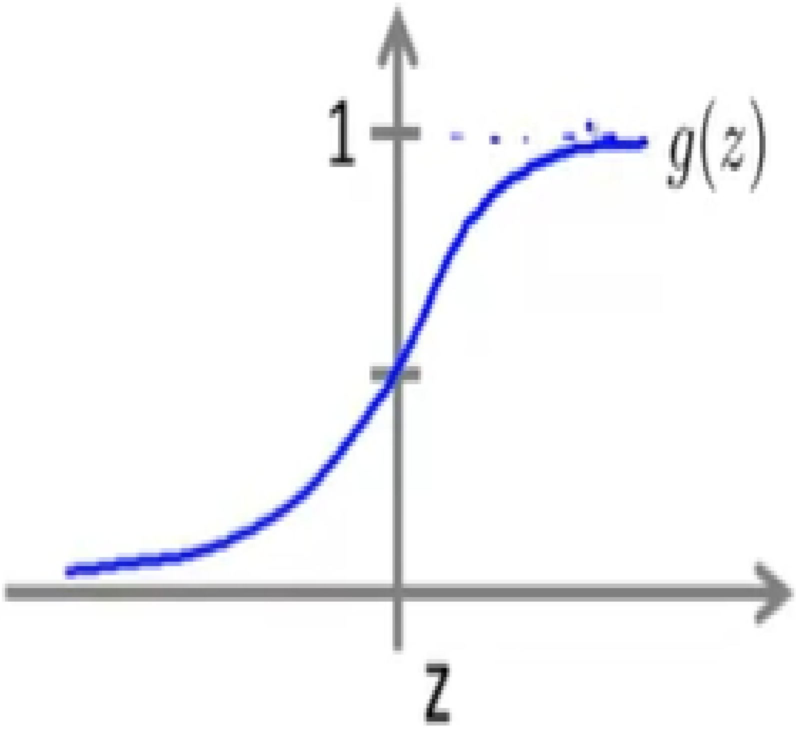
$$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

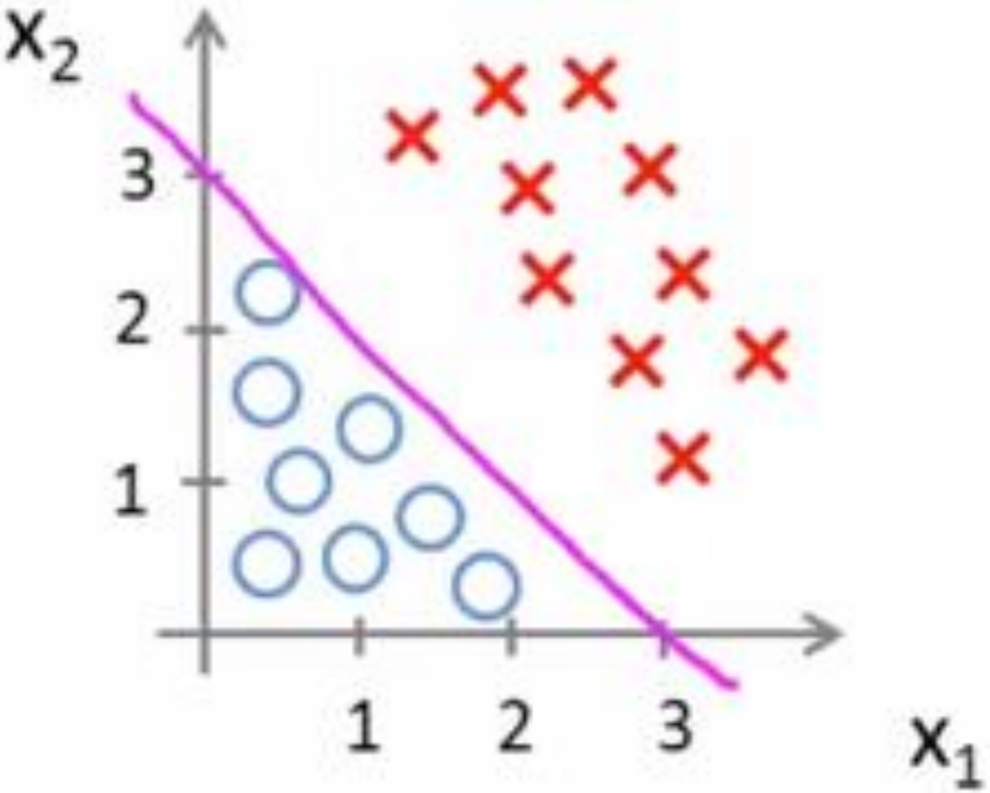
$$\theta = \begin{bmatrix} -3 \\ 1 \\ 1 \end{bmatrix} \rightarrow -3 + x_1 + x_2 \geq 0.$$

$$y = 1$$

$$x_1 + x_2 \geq 3$$

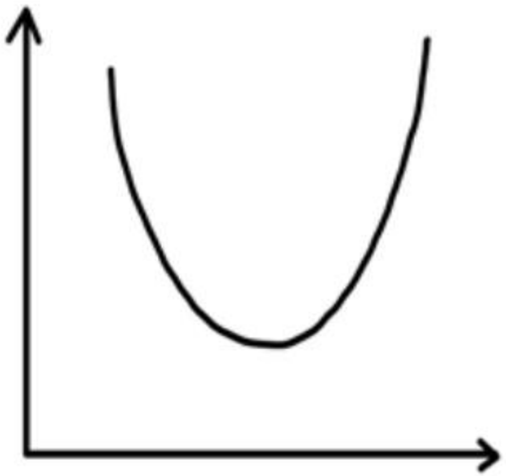
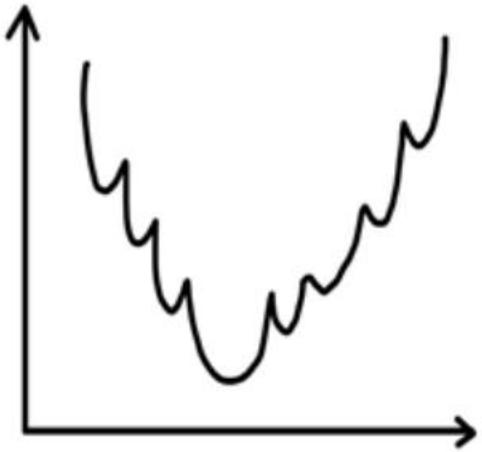
Decision Boundary





Loss Function for Logistic Regression

$$\frac{1}{N}\sum_{i=1}^{n}(h(x_i)-y_i)^2$$

<table>
<tr><td colspan="2">$$J(w) = \frac{1}{N}\sum_{i=1}^{n}\mathrm{cost}(h_w(x_i), y_i) = \frac{1}{N}\sum_{i=1}^{n}(h_w(x_i)-y_i)^2$$</td></tr>
<tr><td>선형회귀분석
$h_w(x) = w^T x$</td><td>로지스틱 회귀분석
$h(x) = \frac{1}{1+\exp(w^T x)}$</td></tr>
<tr><td></td><td></td></tr>
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Simplified Loss Function

$$\mathrm{cost}(h_w(x), y) = -y\log(h_w(x)) - (1-y)\log(1-h_w(x))$$

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Loss Function for Logistic Regression

$$\mathrm{cost}(h_w(x), y) = -y\log(h_w(x)) - (1-y)\log(1-h_w(x))$$

cost(hθ(x),y)=−ylog(hθ(x))−(1−y)log(1−hθ(x))

If y=1,cost(hθ(x),y)=−log(hθ(x))y=1,cost(hθ(x),y)=−log(hθ(x))
If y=0,cost(hθ(x),y)=−log(1−hθ(x))y=0,cost(hθ(x),y)=−log(1−hθ(x))

Logistic regression cost function

$$\mathrm{Cost}(h_\theta(x), y) = \begin{cases} -\log(h_\theta(x)) & \text{if } y = 1 \\ -\log(1 - h_\theta(x)) & \text{if } y = 0 \end{cases}$$

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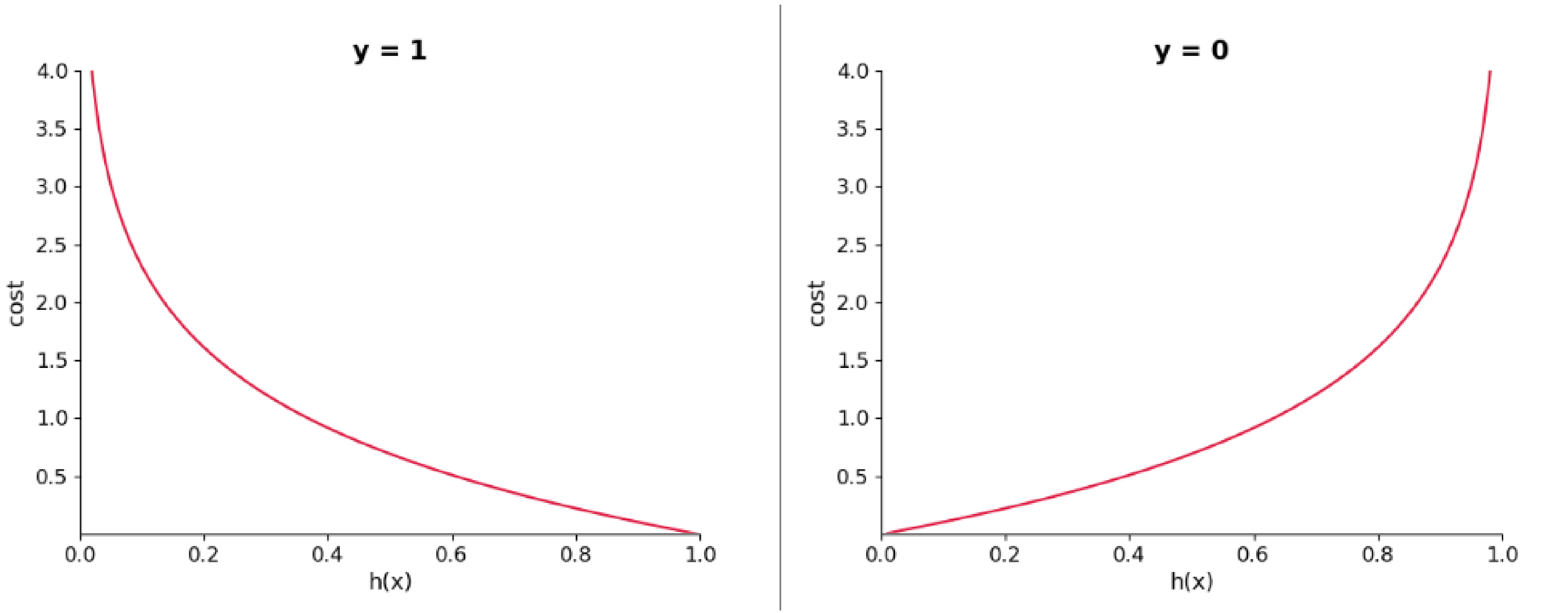
Loss Function for Logistic Regression



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Gradient Descent for Logistic Regression

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \quad (\text{동시업데이트 } j = 0, 1, \ldots, n)$$

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

$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right) x_j^{(i)}$$

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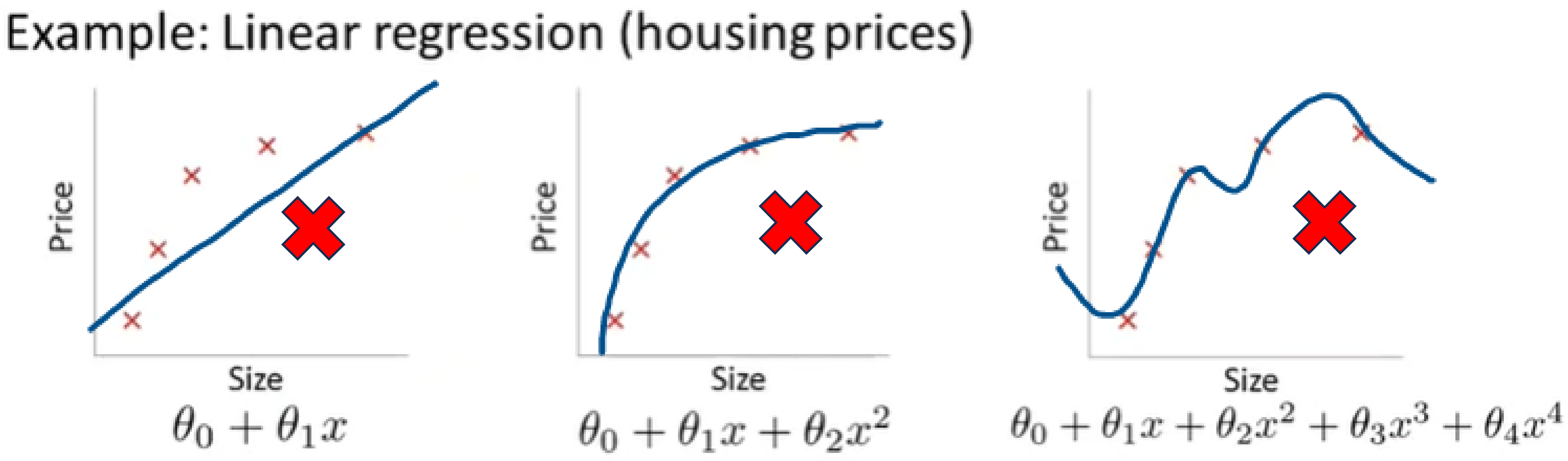
Overfitting



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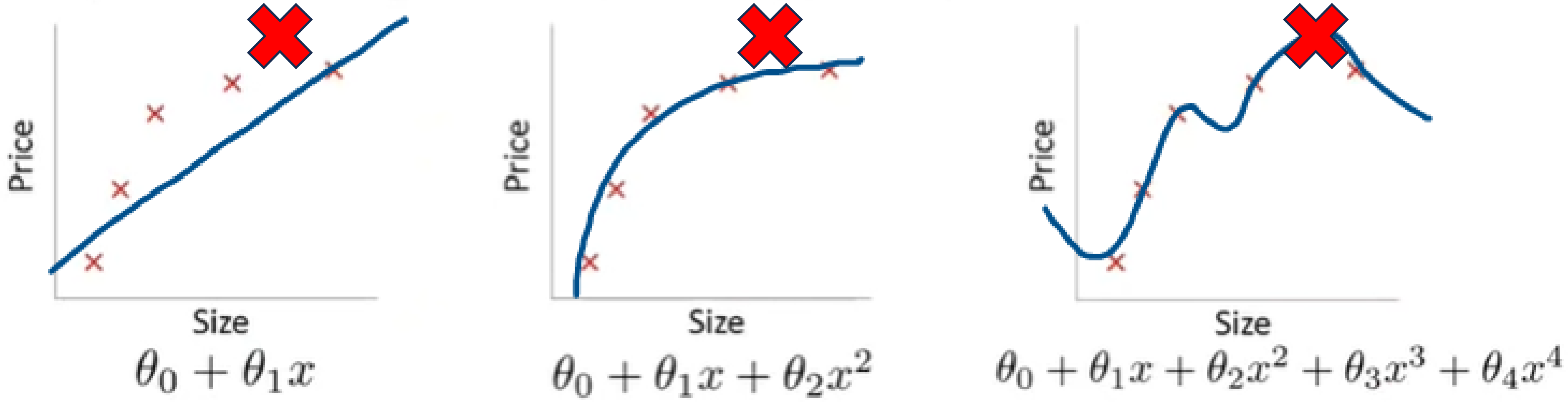
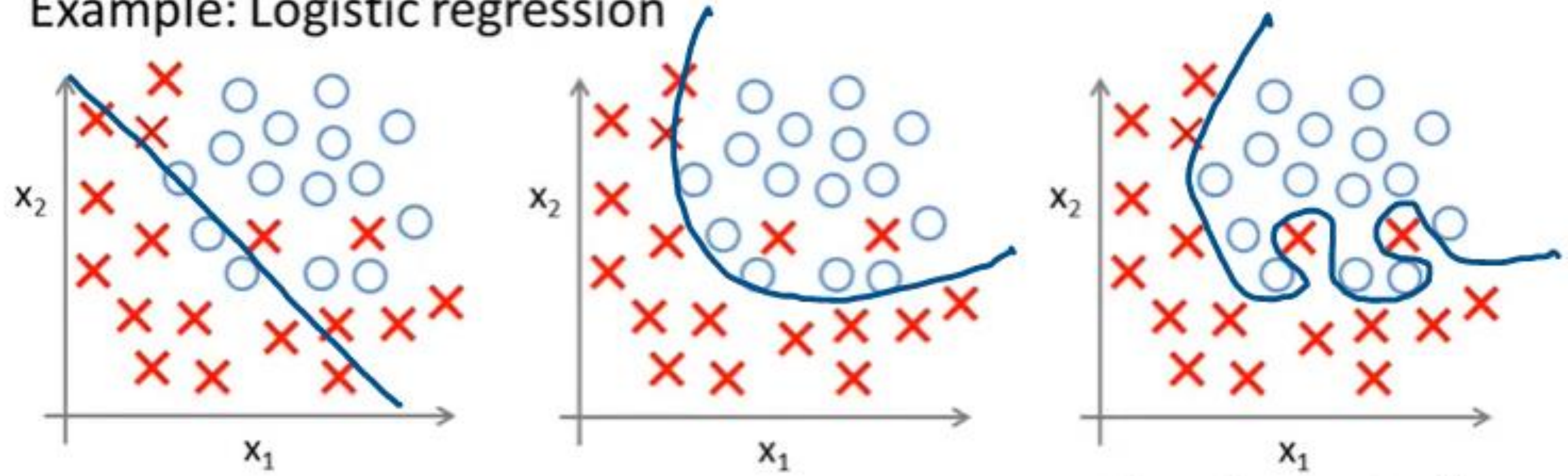
Overfitting

Example: Linear regression (housing prices)



Overfitting

Example: Logistic regression



$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$

(g = sigmoid function)

$g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2 + \theta_5 x_1 x_2)$

$g(\theta_0 + \theta_1 x_1 + \theta_2 x_1^2 + \theta_3 x_1^2 x_2 + \theta_4 x_1^2 x_2^2 + \theta_5 x_1^2 x_2^3 + \theta_6 x_1^3 x_2 + \dots)$

How to deal with overfitting?

1. Reduce the number of features

2. Regularization

4. K-fold Cross Validation

5. Dropout

6. Early Stopping

7. Data Augmentation

8. Ensemble – Bagging/Boosting

9. Collecting more data

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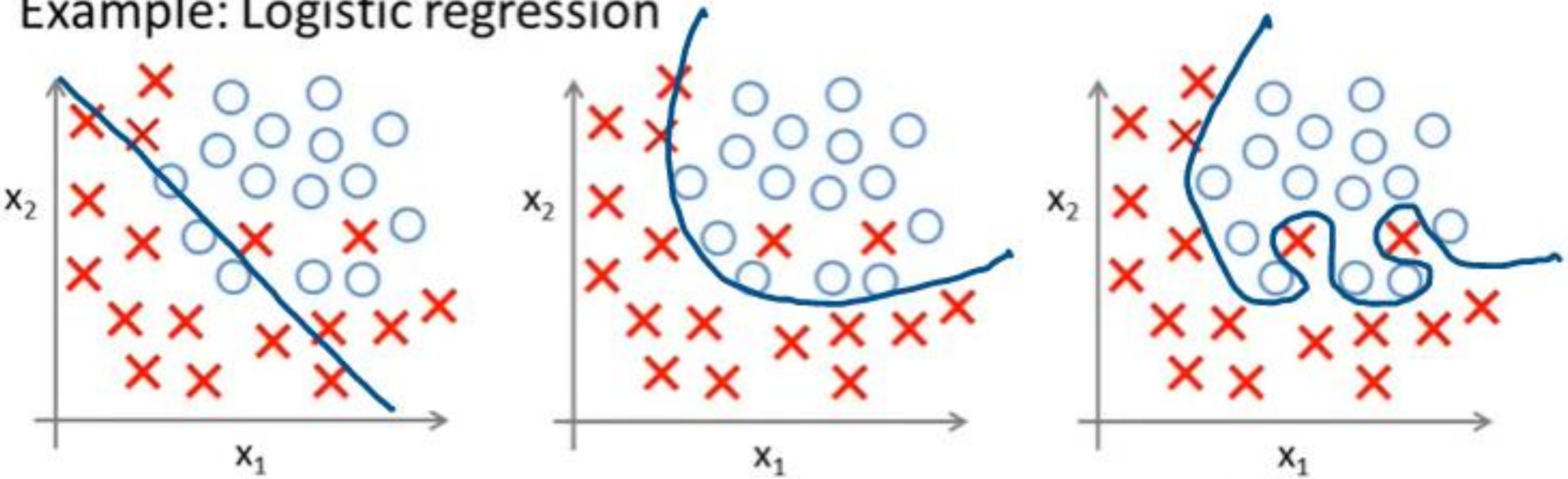
How to deal with overfitting?

1. Reduce the number of features

Example: Logistic regression



$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$

(g = sigmoid function)

$g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2 + \theta_5 x_1 x_2)$

$g(\theta_0 + \theta_1 x_1 + \theta_2 x_1^2 + \theta_3 x_1^2 x_2 + \theta_4 x_1^2 x_2^2 + \theta_5 x_1^2 x_2^3 + \theta_6 x_1^3 x_2 + \dots)$

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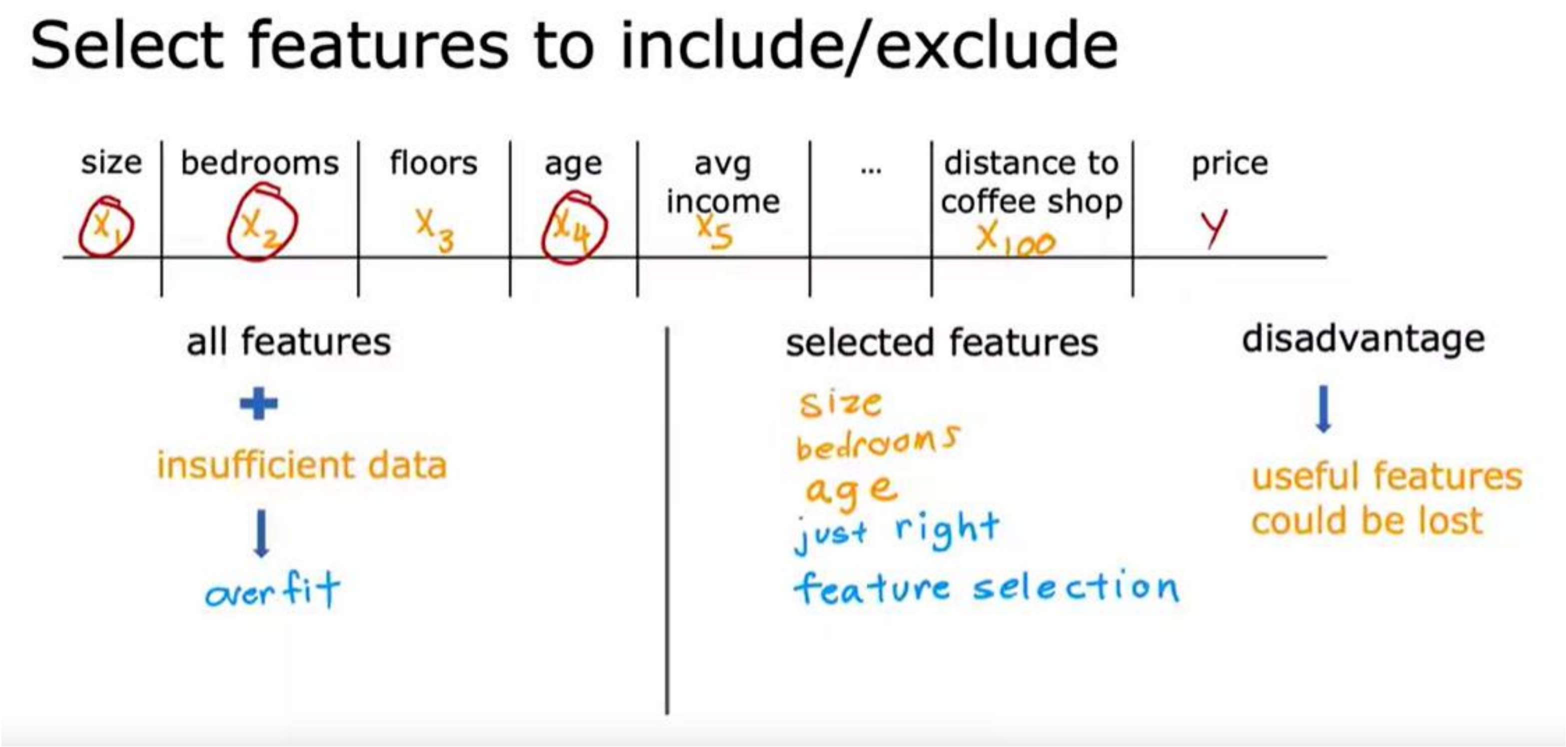
How to deal with overfitting?

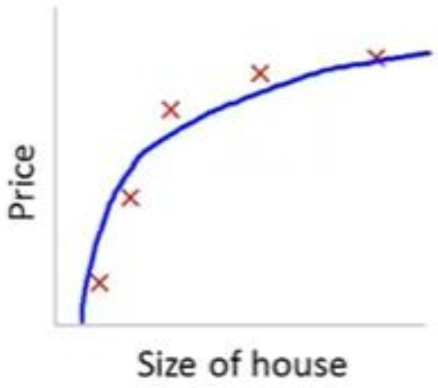
1. Reduce the number of features



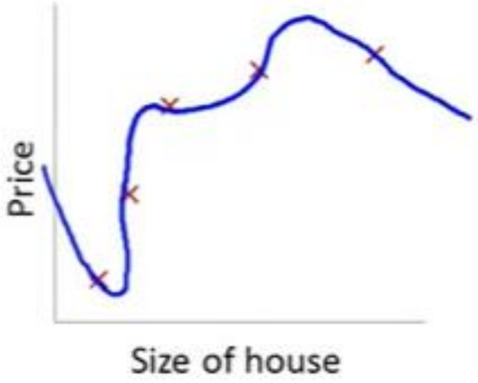
How to deal with overfitting?

2. Regularization

Intuition



$\theta_0 + \theta_1 x + \theta_2 x^2$



$\theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$

Suppose we penalize and make θ_3, θ_4 really small.

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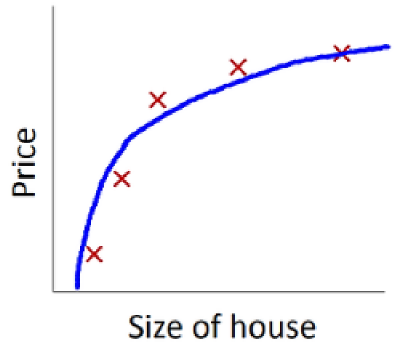
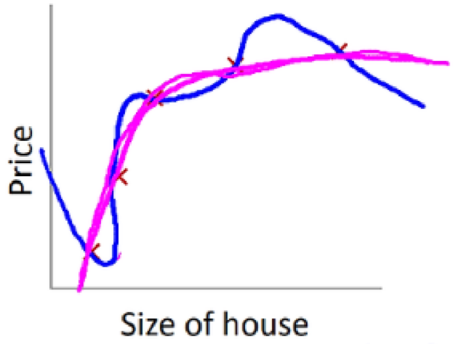
How to deal with overfitting?

2. Regularization

Intuition





$$\theta_0 + \theta_1 x + \theta_2 x^2 \qquad \theta_0 + \theta_1 x + \theta_2 x^2 + \cancel{\theta_3 x^3} + \cancel{\theta_4 x^4}$$

Suppose we penalize and make θ_3, θ_4 really small.

$$\min_\theta \frac{1}{2m} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2 + 1000\,\theta_3^2 + 1000\,\theta_4^2$$

$\theta_3 \approx 0 \quad \theta_4 \approx 0$

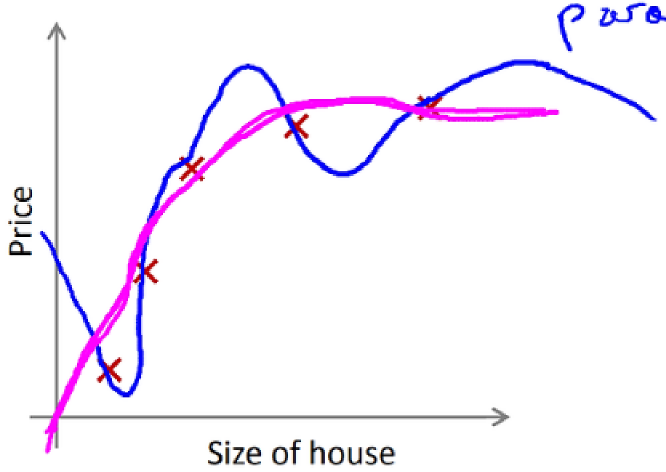
How to deal with overfitting?

2. Regularization

Regularization.

$$J(\theta) = \frac{1}{2m}\left[\underbrace{\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2}_{} + \underbrace{\lambda}_{\text{regularization parameter}} \sum_{j=1}^{n}\theta_j^2\right]$$

$$\min_\theta J(\theta)$$



Regularized Logistic Regression

$$J(\theta) = -\left[\frac{1}{m}\sum_{i=1}^{m} y^{(i)} \log h_\theta\left(x^{(i)}\right) + \left(1 - y^{(i)}\right)\log\left(1 - h_\theta\left(x^{(i)}\right)\right)\right] + \frac{\lambda}{2m}\sum_{j=1}^{n} {\theta_j}^2$$

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Overall Review

- Logistic Regression
- Decision Boundary
- Loss Function for Logistic Regression
- Simplified Loss Function
- Overfitting
- Regularized Logistic Regression

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