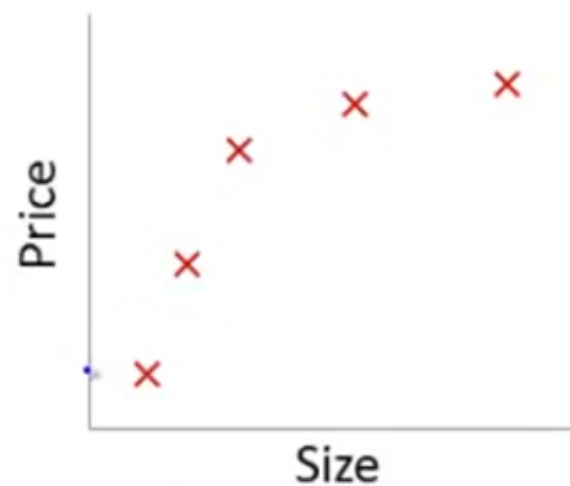


The Problem of Overfitting

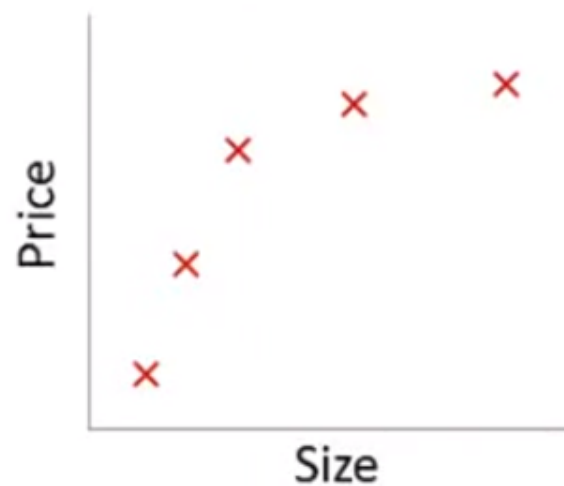
Solving the Problem of Overfitting

Regularization

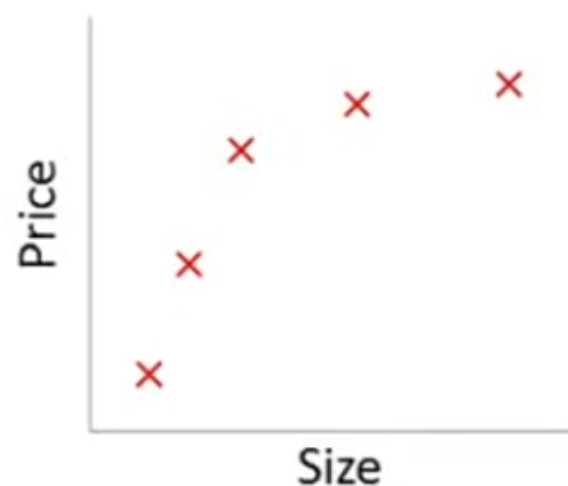
Example: Linear regression (housing prices)



$\rightarrow \theta_0 + \theta_1 x$

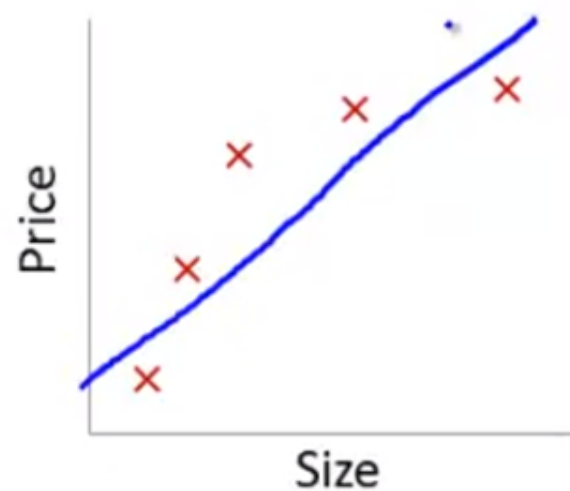


$\theta_0 + \theta_1 x + \theta_2 x^2$

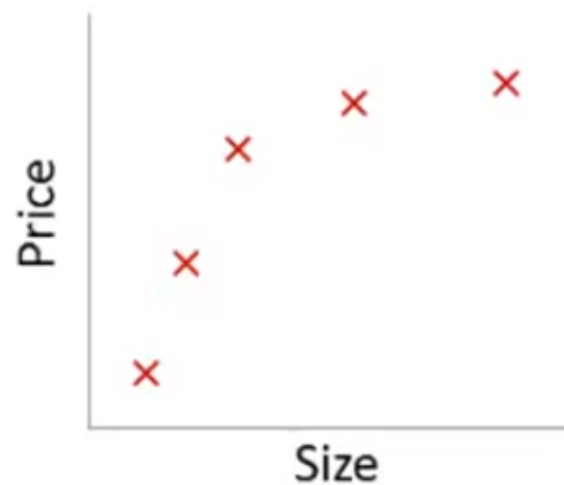


$\theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$

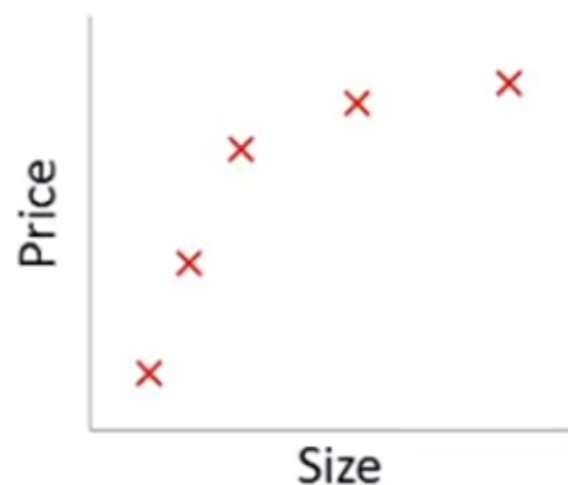
Example: Linear regression (housing prices)



→ $\theta_0 + \theta_1 x$

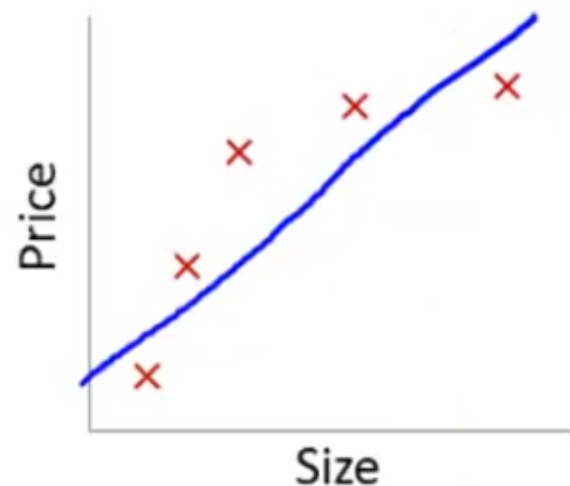


$\theta_0 + \theta_1 x + \theta_2 x^2$

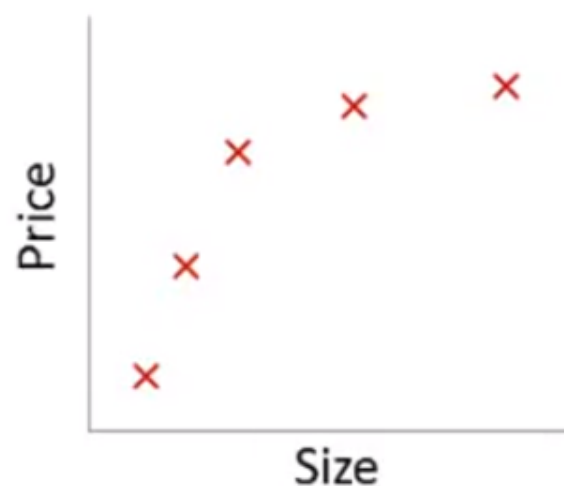


$\theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$

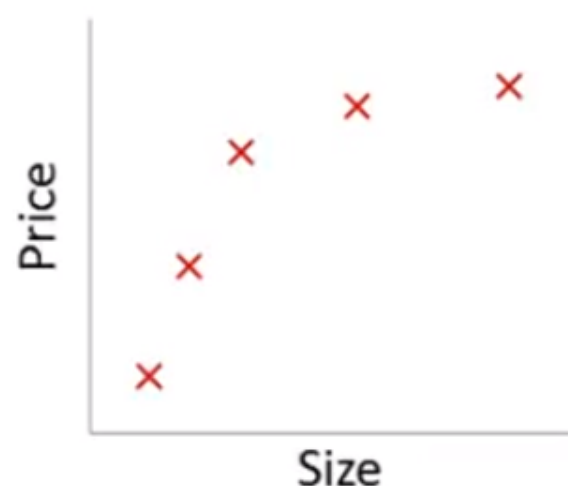
Example: Linear regression (housing prices)



→ $\theta_0 + \theta_1 x$
"Underfit" "High bias"

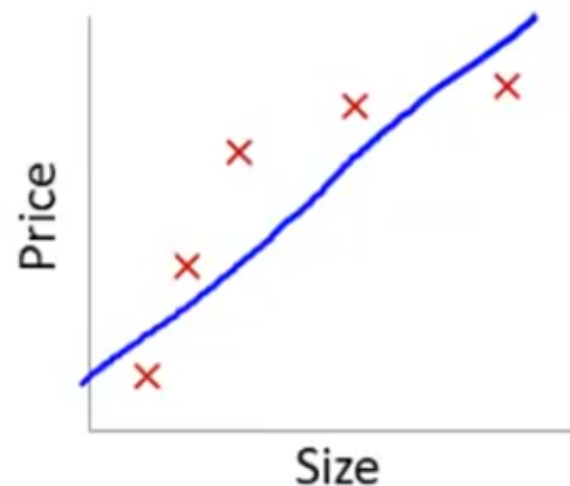


$$\theta_0 + \theta_1 x + \theta_2 x^2$$



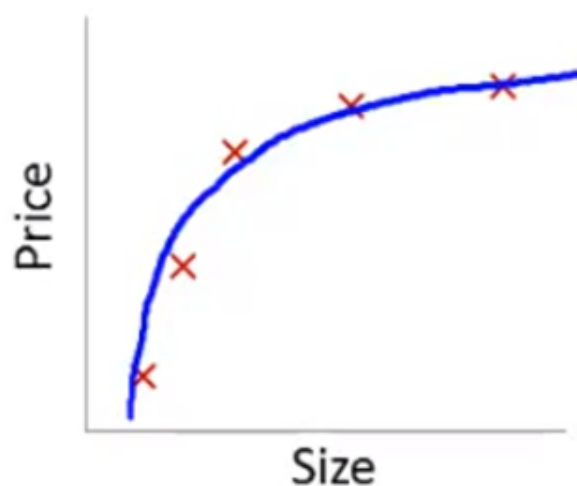
$$\theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$$

Example: Linear regression (housing prices)

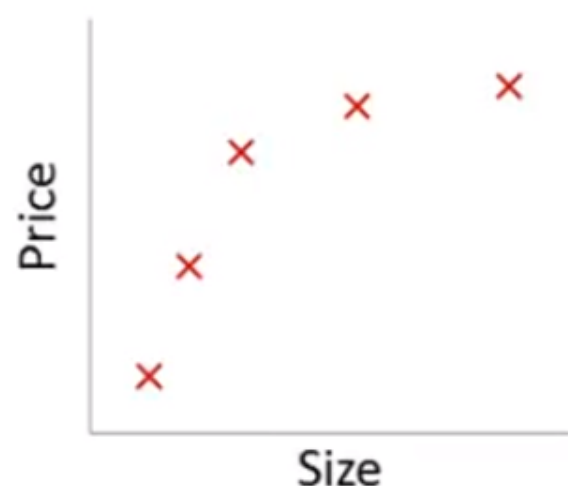


$$\rightarrow \theta_0 + \theta_1 x$$

"Underfit" "High bias"

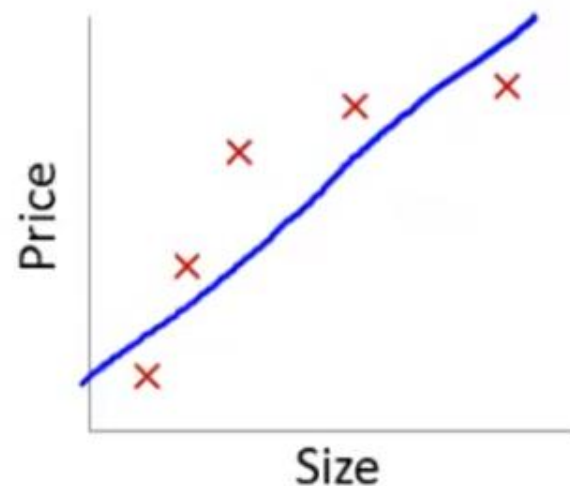


$$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2$$



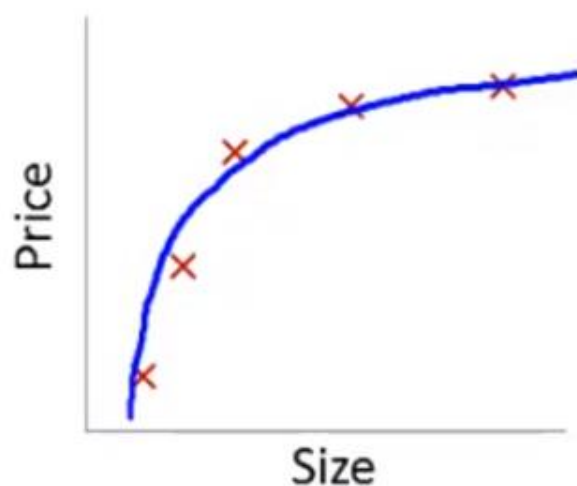
$$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 \underline{x^4}$$

Example: Linear regression (housing prices)

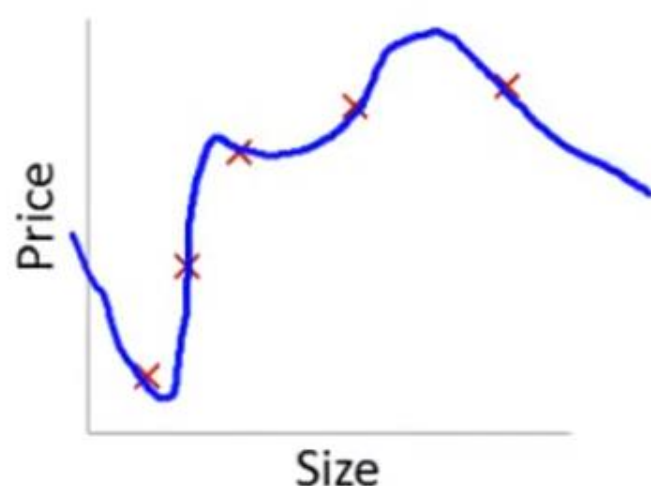


$$\rightarrow \theta_0 + \theta_1 x$$

"Underfit" "High bias"

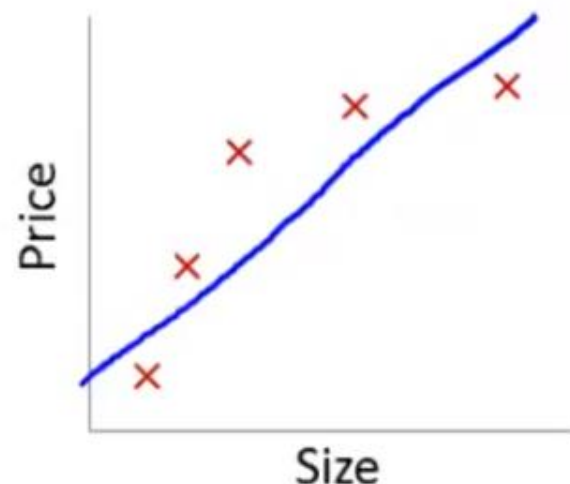


$$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2$$

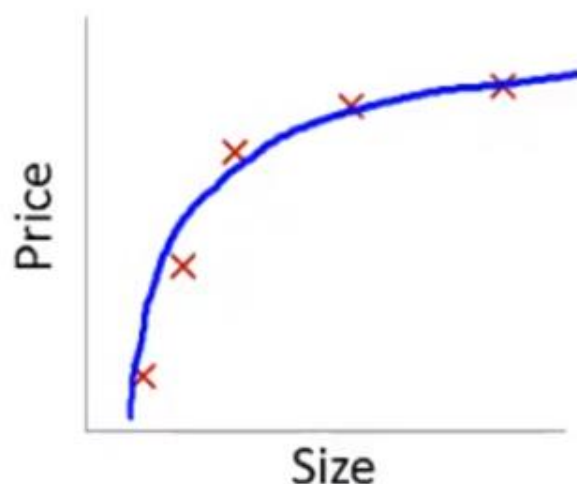


$$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 \underline{x^4}$$

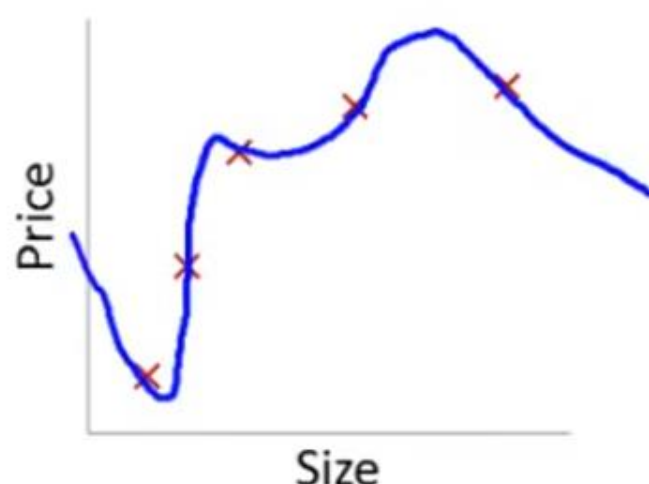
Example: Linear regression (housing prices)



$\rightarrow \theta_0 + \theta_1 x$
"Underfit" "High bias"

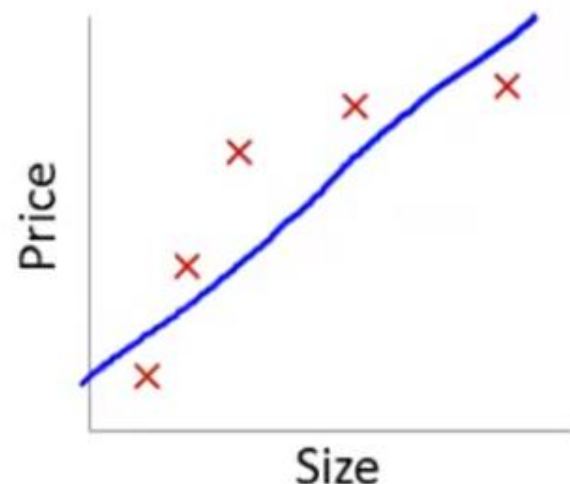


$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2$

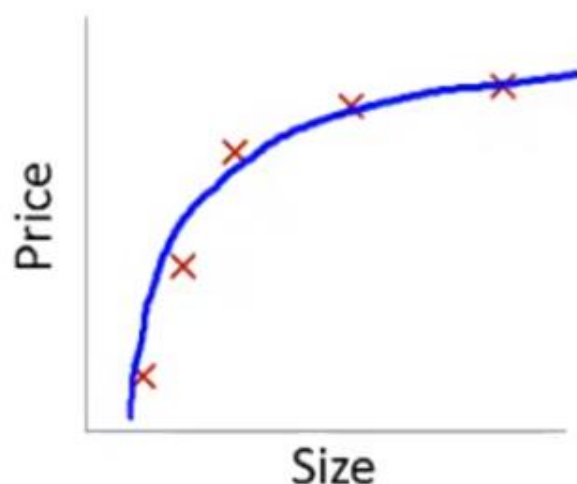


$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$
"Overfit" "High variance"

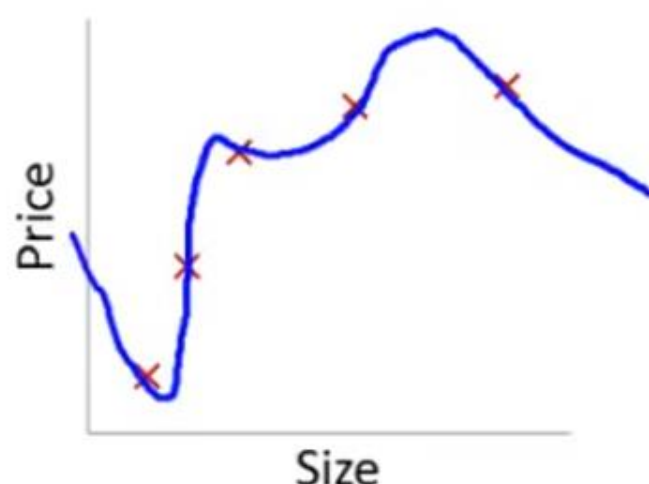
Example: Linear regression (housing prices)



$\rightarrow \theta_0 + \theta_1 x$
"Underfit" "High bias"

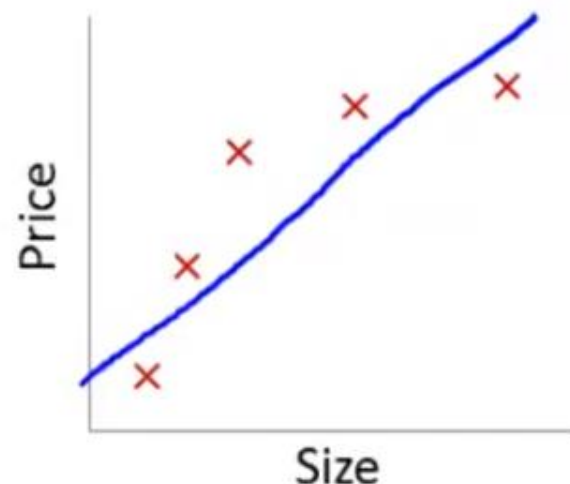


$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2$
"Just right"

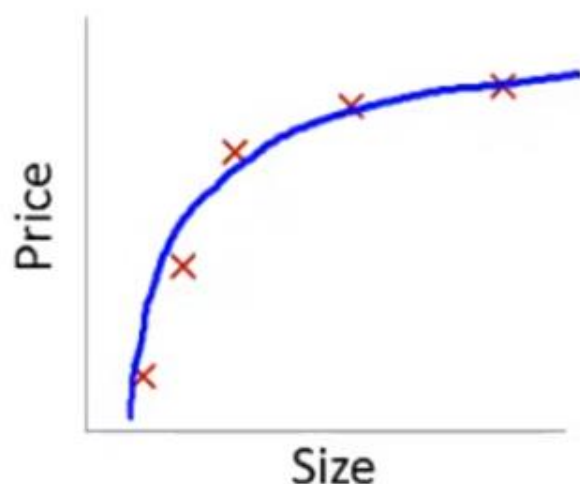


$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$
"Overfit" "High variance"

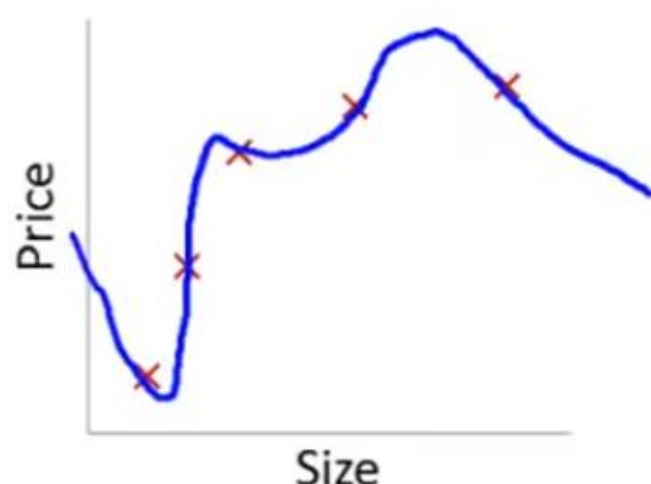
Example: Linear regression (housing prices)



$\rightarrow \theta_0 + \theta_1 x$
"Underfit" "High bias"



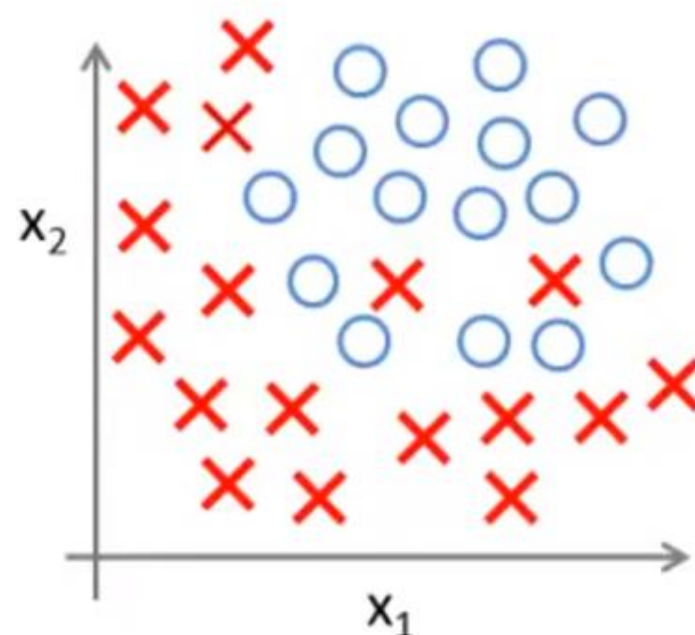
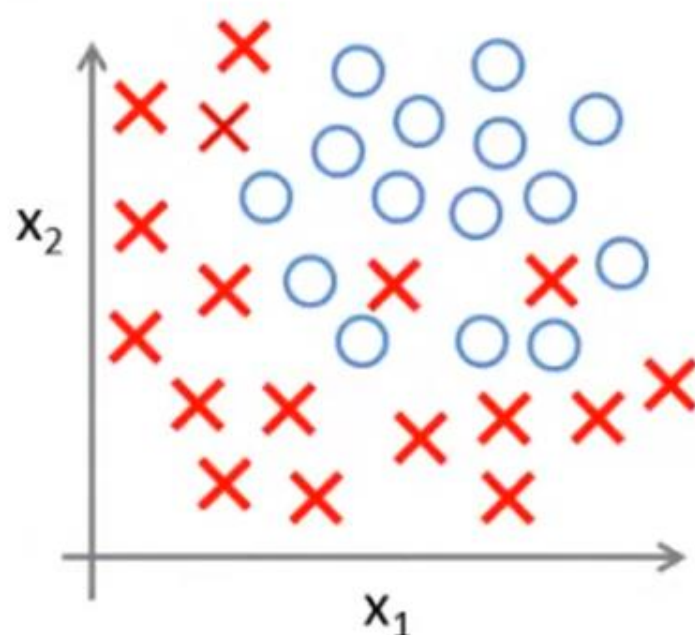
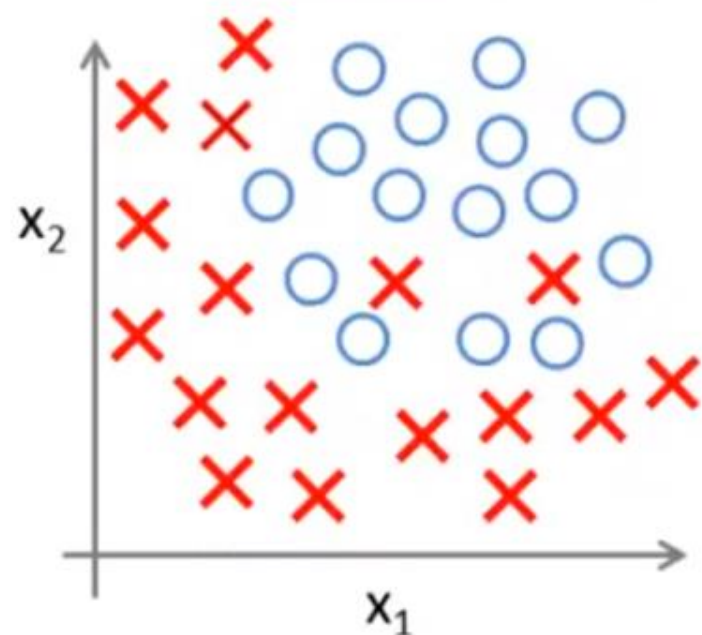
$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2$
"Just right"



$\rightarrow \theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$
"Overfit" "High variance"

Overfitting: If we have too many features, the learned hypothesis may fit the training set very well ($J(\theta) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 \approx 0$), but fail to generalize to new examples (predict prices on new examples).

Example: Logistic regression

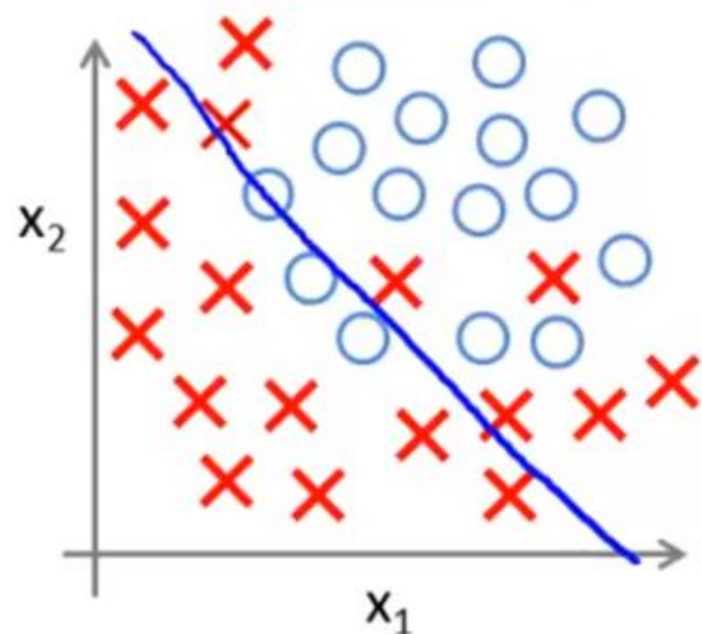


• $h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$
 (g = sigmoid function)

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

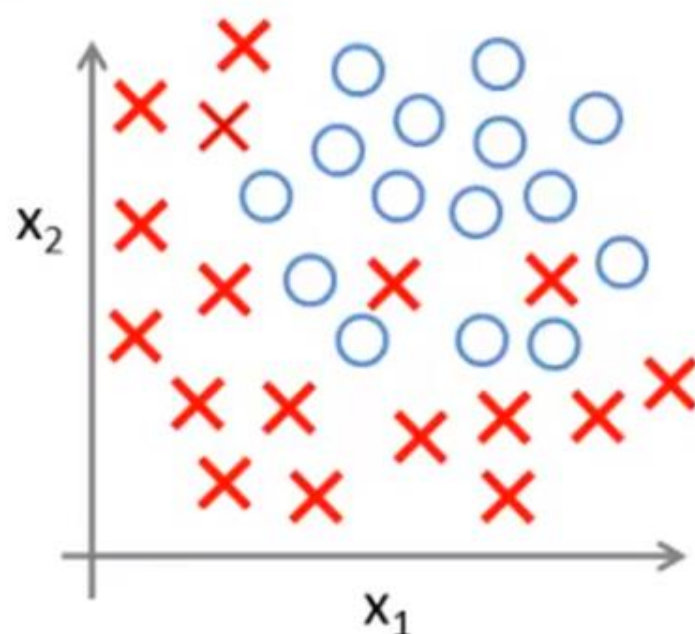
$g(\theta_0 + \theta_1 x_1 + \theta_2 x_1^2$
 $+ \theta_3 x_1^2 x_2 + \theta_4 x_1^2 x_2^2$
 $+ \theta_5 x_1^2 x_2^3 + \theta_6 x_1^3 x_2 + \dots)$

Example: Logistic regression

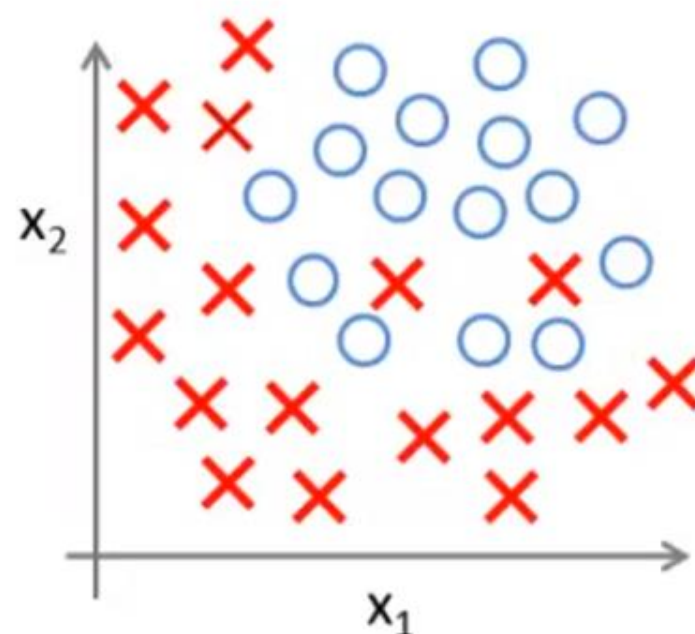


$\rightarrow h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$
(g = sigmoid function)

↖
"Underfit"

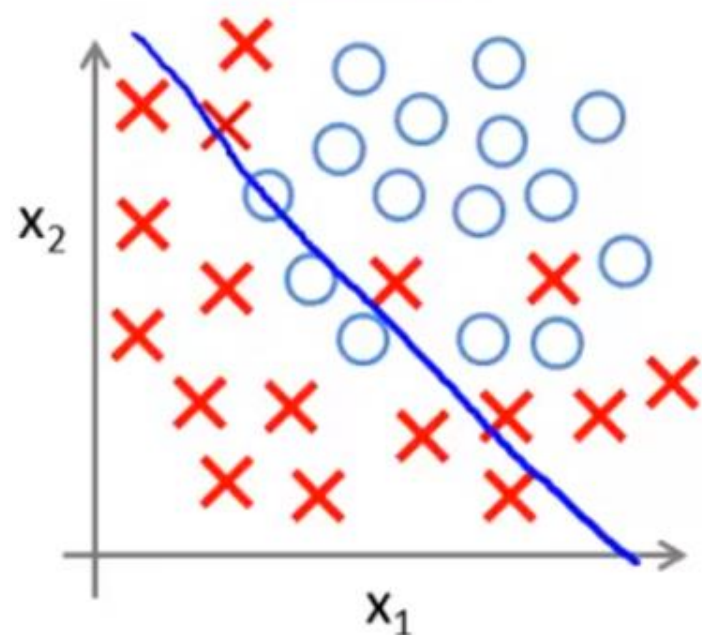


$$g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2 + \theta_5 x_1 x_2)$$



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

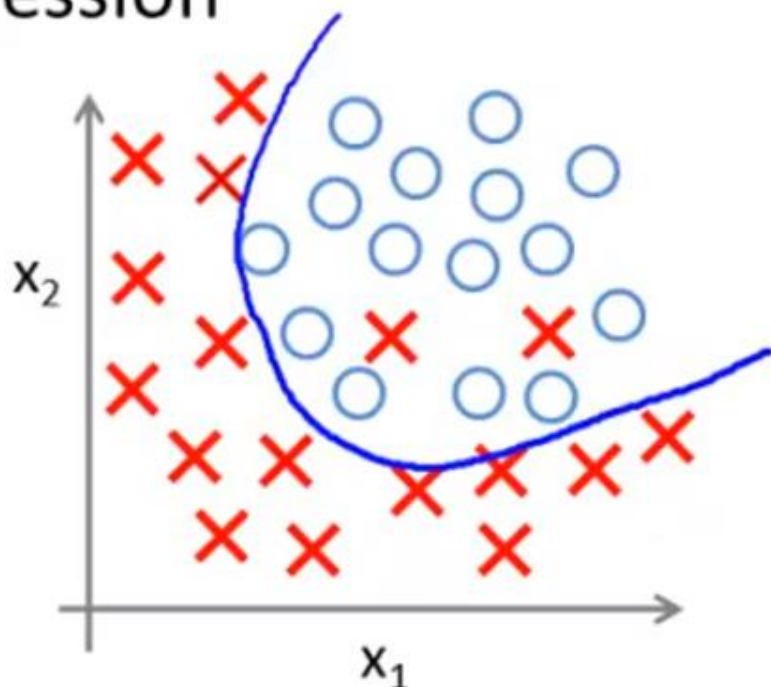
Example: Logistic regression



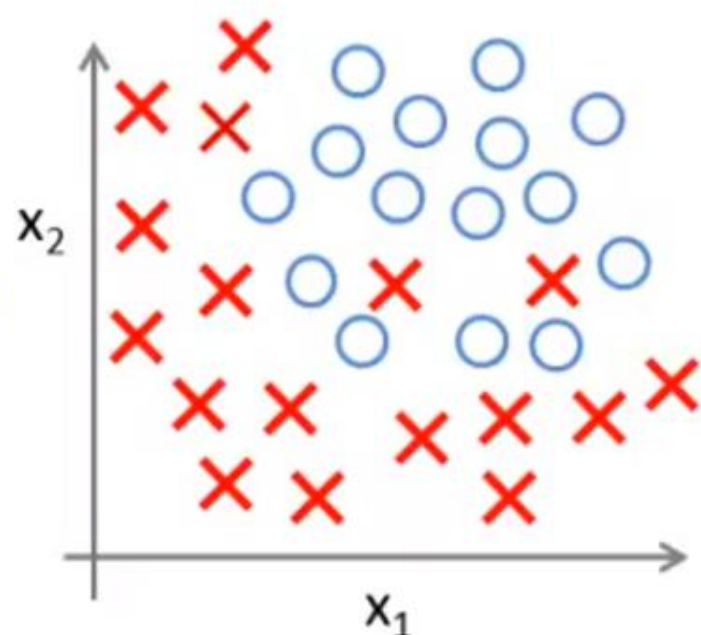
$$\rightarrow h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

(g = sigmoid function)

“Underfit”

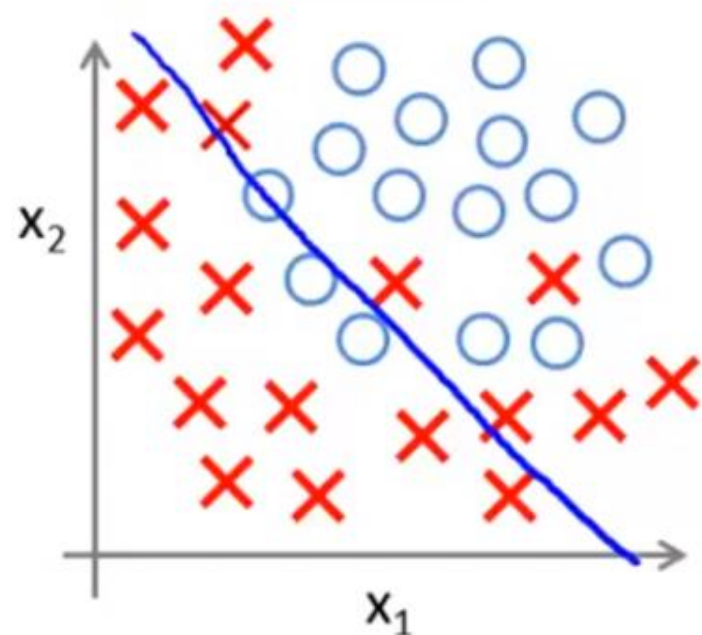


$$g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2 + \theta_5 \underline{x_1 x_2})$$



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

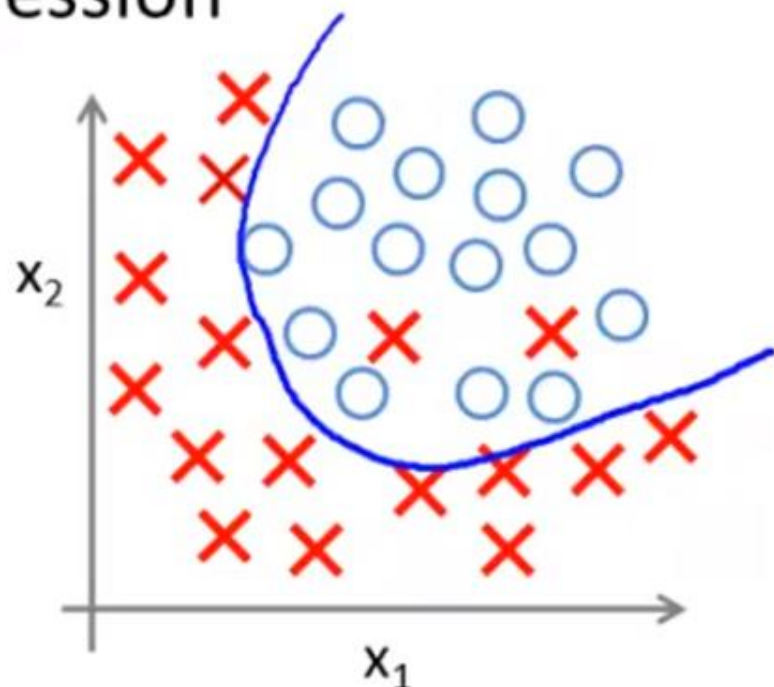
Example: Logistic regression



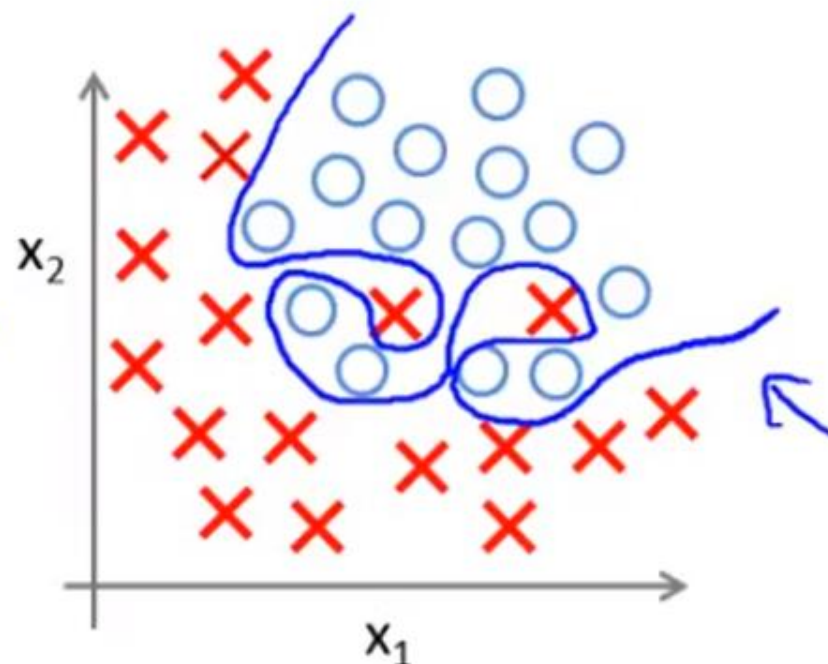
$$\rightarrow h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

(g = sigmoid function)

"Underfit"



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



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

"Overfit"

Exercise

- Consider the medical diagnosis problem of classifying tumors as malignant or benign. If a hypothesis $h(x)$ has overfit the training set, it means that:
 - It makes accurate predictions for examples in the training set and generalizes well to make accurate predictions on new, previously unseen examples.
 - It does not make accurate predictions for examples in the training set, but it does generalize well to make accurate predictions on new, previously unseen examples.
 - It makes accurate predictions for examples in the training set, but it does not generalize well to make accurate predictions on new, previously unseen examples.
 - It does not make accurate predictions for examples in the training set and does not generalize well to make accurate predictions on new, previously unseen examples.

Addressing overfitting:

x_1 = size of house

x_2 = no. of bedrooms

x_3 = no. of floors

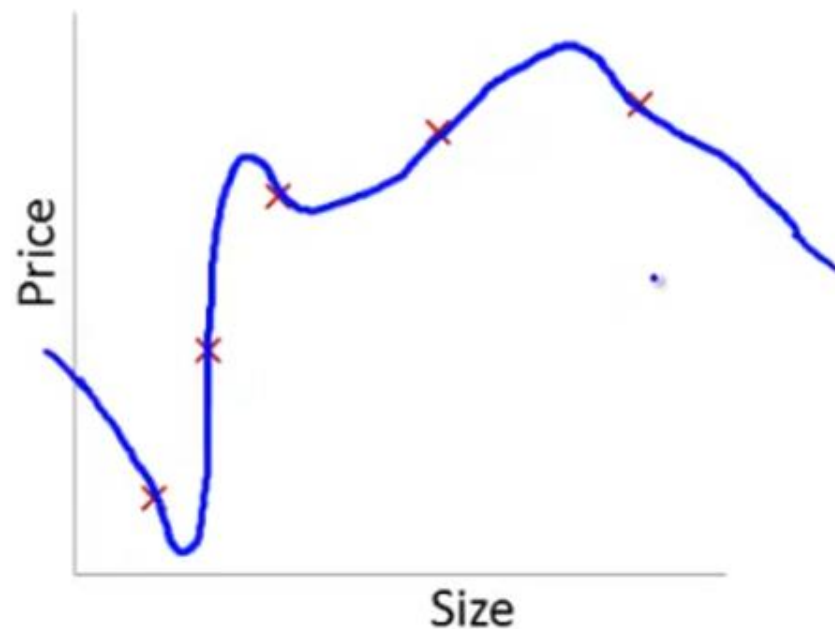
x_4 = age of house

x_5 = average income in neighborhood

x_6 = kitchen size

⋮

x_{100}



Addressing overfitting:

Options:

1. Reduce number of features.
 - Manually select which features to keep.
 - Model selection algorithm (later in course).

Addressing overfitting:

Options:

1. Reduce number of features.

→ — Manually select which features to keep.

→ — Model selection algorithm (later in course).

2. Regularization.

→ — Keep all the features, but reduce magnitude/values of parameters θ_j .

— Works well when we have a lot of features, each of which contributes a bit to predicting y .