Data Science Dojo

Regression

datasciencedojo

data science for everyone

Agenda

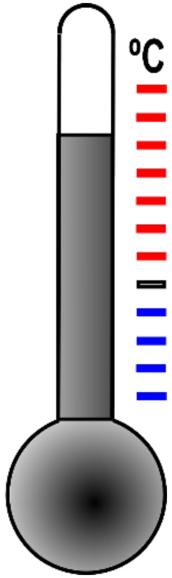
- Introduction
- Cost Function & Gradient Descent
  - Minimization
  - Implementation
- Hands-on Example
- Evaluating Regression Models
- Regularization

INTRODUCTION

Regression

Sales Forecasts

Housing Price Predictions



Daily Temperature Highs & Lows

Regression vs Classification

- Classification
  - Target is discrete with finite value set
  - **Examples:** survived/dead, face/non-face, fraud/non-fraud
- Regression
  - Target is continuous
  - **Examples:** price, weight, height, temperature

Notation: Titanic Dataset

Passenger Id	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
1	0	3	Braund, Mr. Owen Harris	male	22	1	0	A/5 21171	7.25		S
2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38	1	0	PC 17599	71.2833	C85	C
3	1	3	Heikkinen, Miss. Laina	female	26	0	0	STON/O2. 3101282	7.925		S
4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35	1	0	113803	53.1	C123	S
5	0	3	$\boxed{\text{Allen, Mr. William Henry}}$	male	35	0	0	373450	8.05		S

$$x_4^5$$

5: The passenger is in the 5^{th} row

4: The passenger's name is the 4^{th} column

Notation: Ozone Dataset

So how do we describe all the rows?

	ozone	radiation	temperature	wind
Row 1	41	190	67	7.4
Row 2	36	118	72	8.0
Row 3	12	149	74	12.6
	18	313	62	11.5
	23	299	65	8.6
	19	99	59	13.8

$x^1 = [190, 67, 7.4]$

$x^2 = [118, 72, 8.0]$

$x^3 = [149, 74, 12.6]$

Notation: Ozone Dataset

The ozone dataset uses radiation, temperature and wind to predict ozone levels.

	Y	x_1	x_2	x_3	
	ozone	radiation	temperature	wind	
	41	190	67	7.4	
	36	118	72	8.0	
Y	12	149	74	12.6	X
	18	313	62	11.5	
	23	299	65	8.6	
	19	99	59	13.8	

Using this notation, we can describe all the columns of the dataset.

Notation Summary

x^i – Each row of features
x_j – Each column of features
X – Set of all the feature columns

$\Big\}$ Features

y^i – Each row of the target
Y – The target column

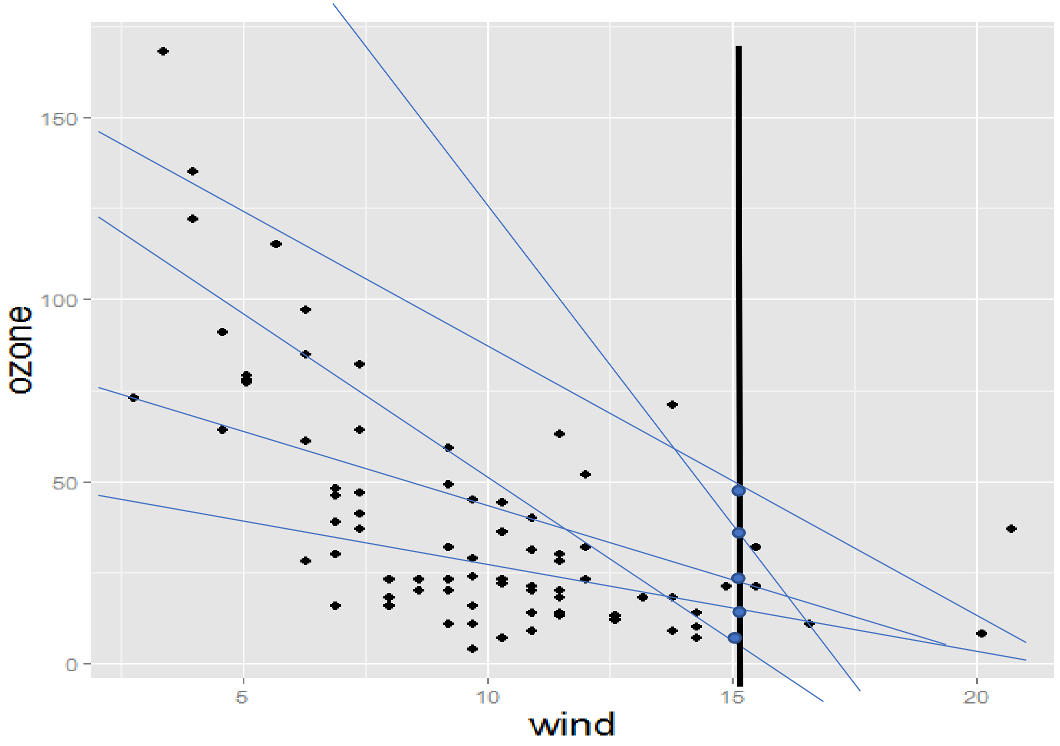
$\Big\}$ Target

n – Number of rows in the dataset
m – Number of columns in the dataset

COST FUNCTION AND GRADIENT DESCENT

What is a good regression line?

- Wind Speed=15 mph
- Ozone = ?
- Use the line that is **somewhere in the middle**
- How do we define "middle"?



$$h_\theta(x) = \theta_0 + \theta_1 x$$

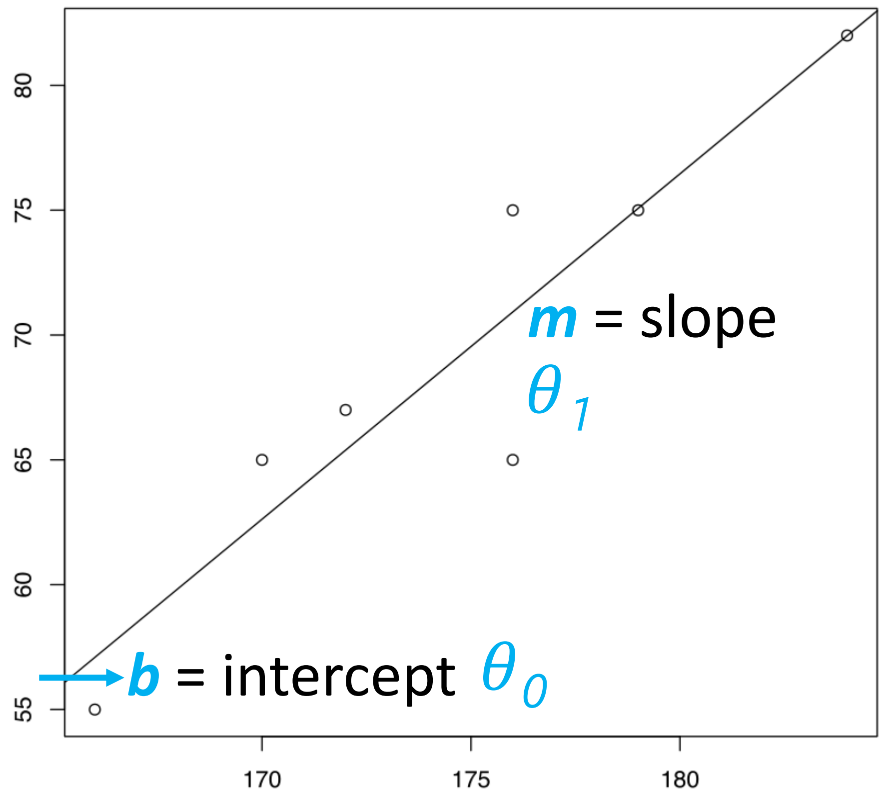
Defining a line

How do we define a line in slope-intercept notation?

- $y = \boldsymbol{m}x + \boldsymbol{b}$

In θ notation

- $h_\theta(\mathrm{x}) = \boldsymbol{\theta}_1\mathrm{x} + \boldsymbol{\theta}_0$



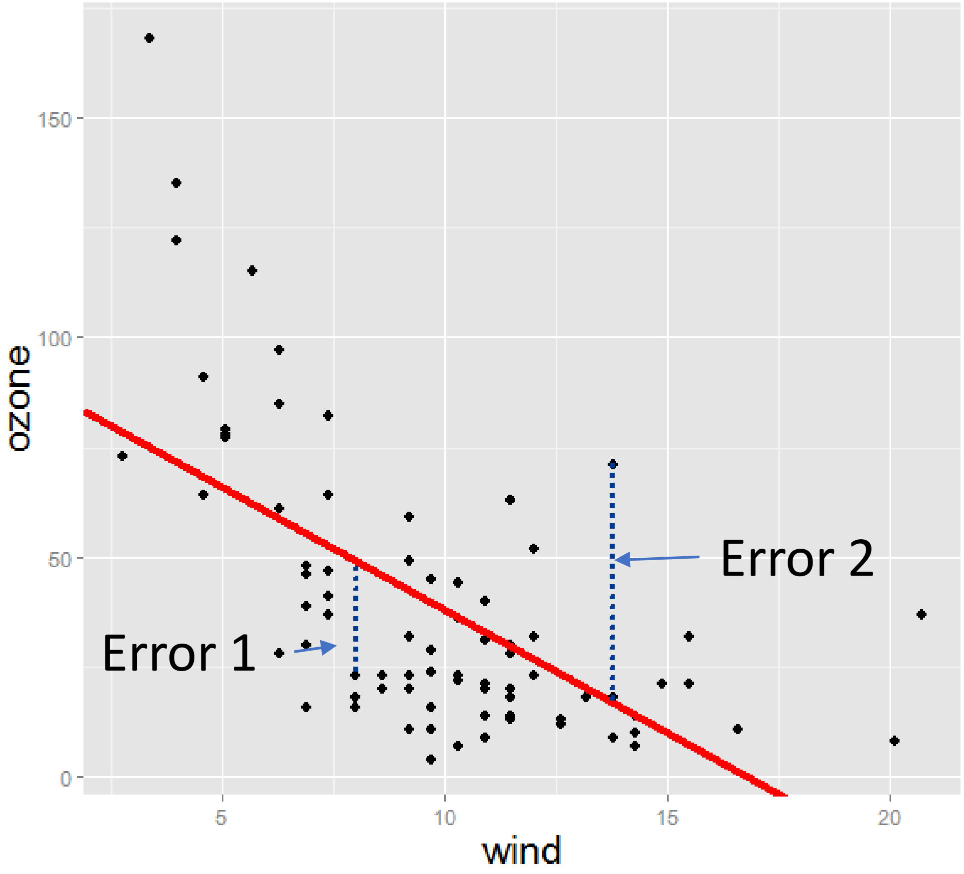
More Features

y	x_1	x_2	x_3
ozone	radiation	temperature	wind
41	190	67	7.4
36	118	72	8.0
12	149	74	12.6
18	313	62	11.5
23	299	65	8.6
19	99	59	13.8

$$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3$$

Residuals (or "Errors")

Difference between hypothesis $\boldsymbol{h_\theta(x)}$ (predicted value) and true value (known target)

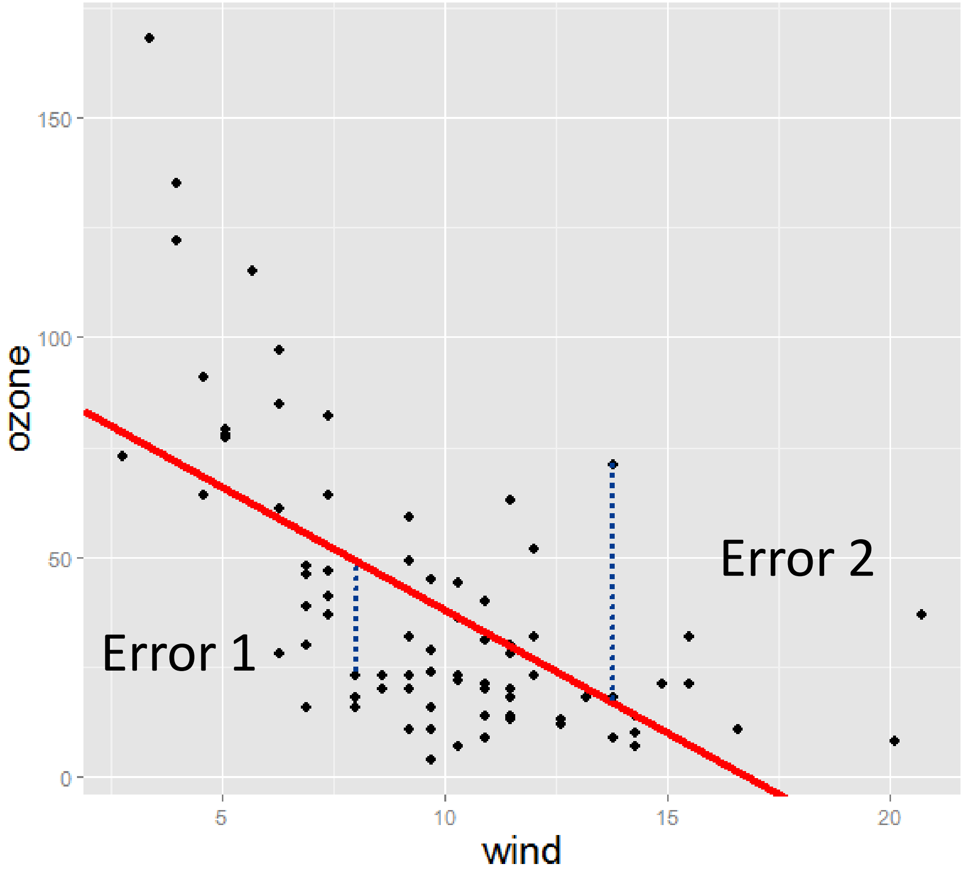


Cost Function

Minimize the 'cost' or 'loss' function – $J(\theta)$

- Smaller for lower error
- Larger for higher error

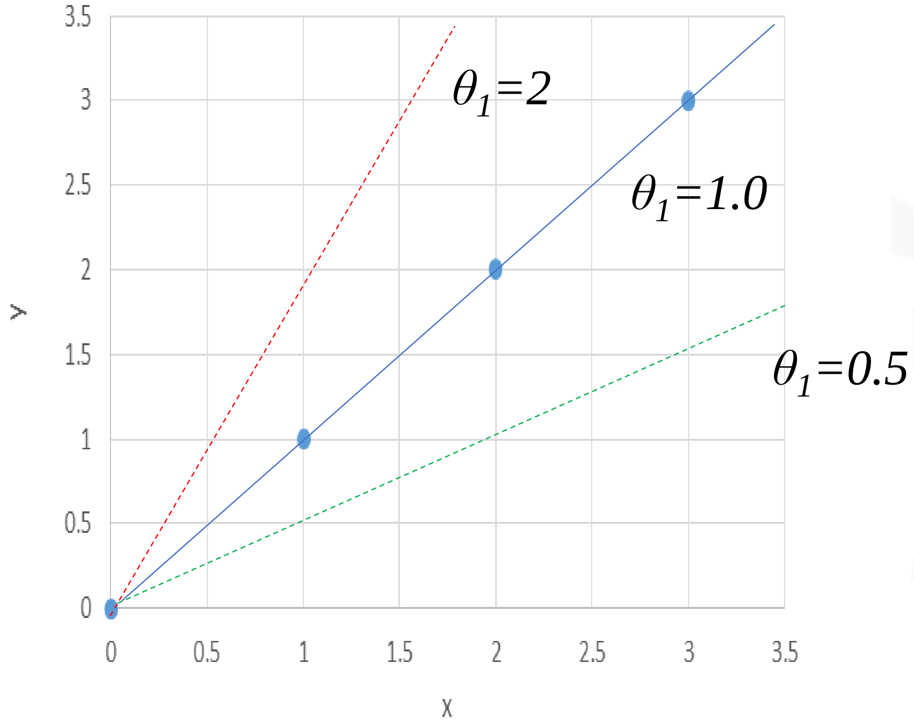
$$J(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta\left(x^i\right) - y^i\right)^2$$



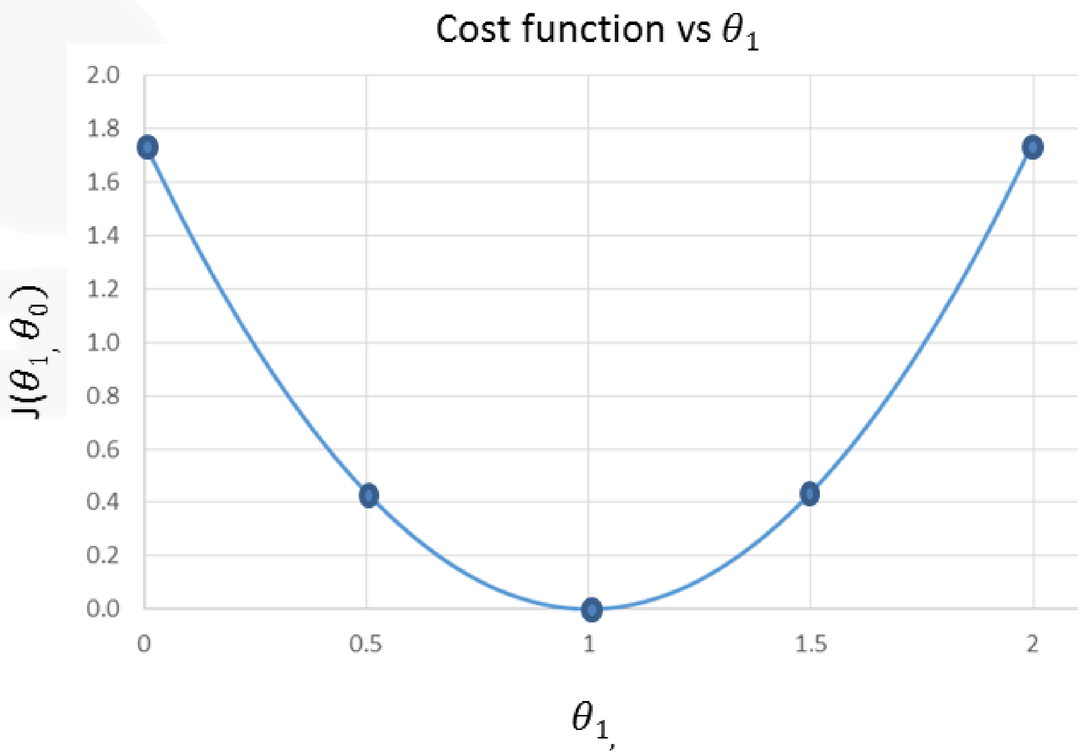
Cost Function

$$h_\theta(x) = \theta_0 + \theta_1 x$$

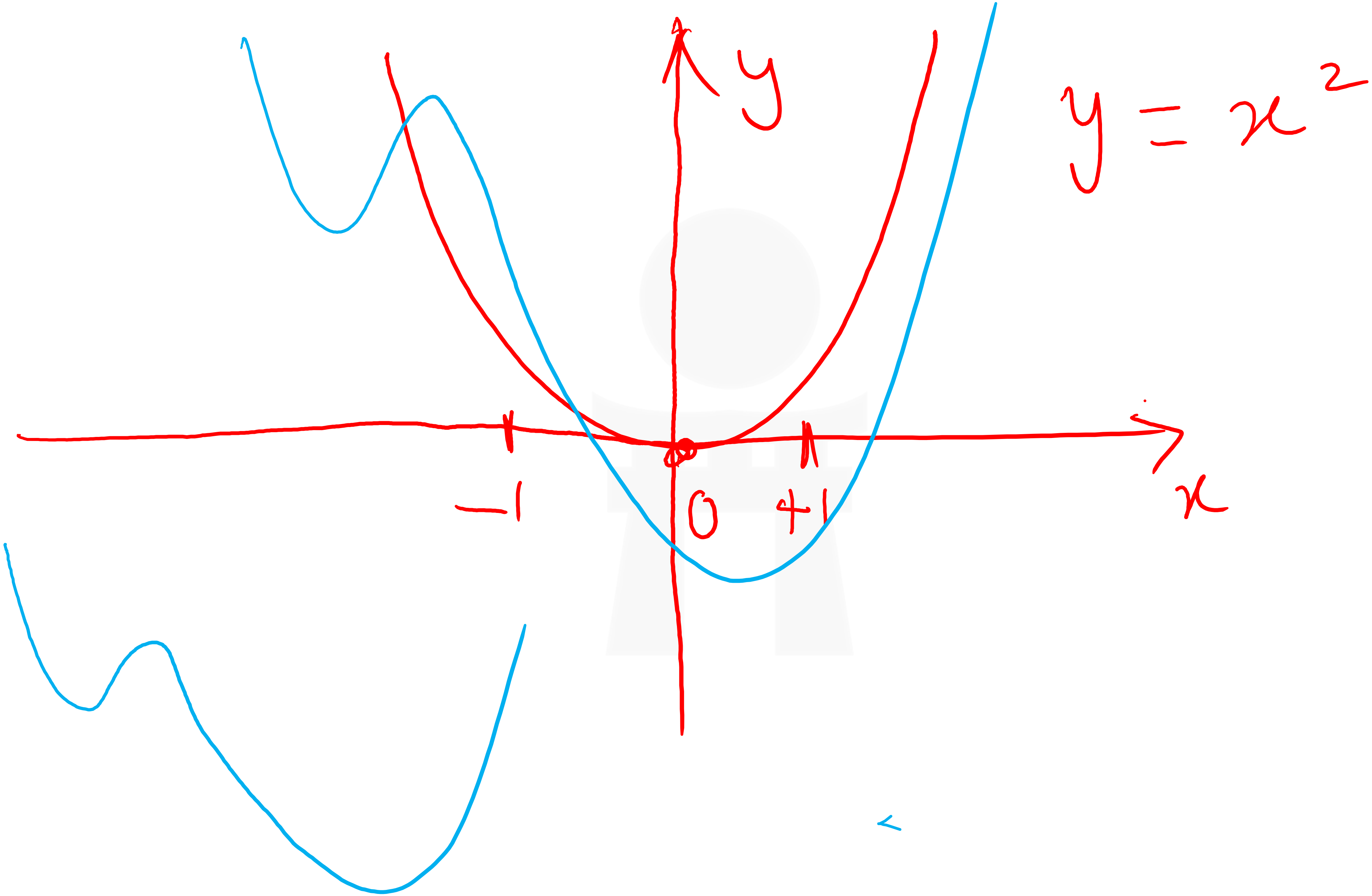
$$J(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta(x^i) - y^i\right)^2$$



θ_0=0

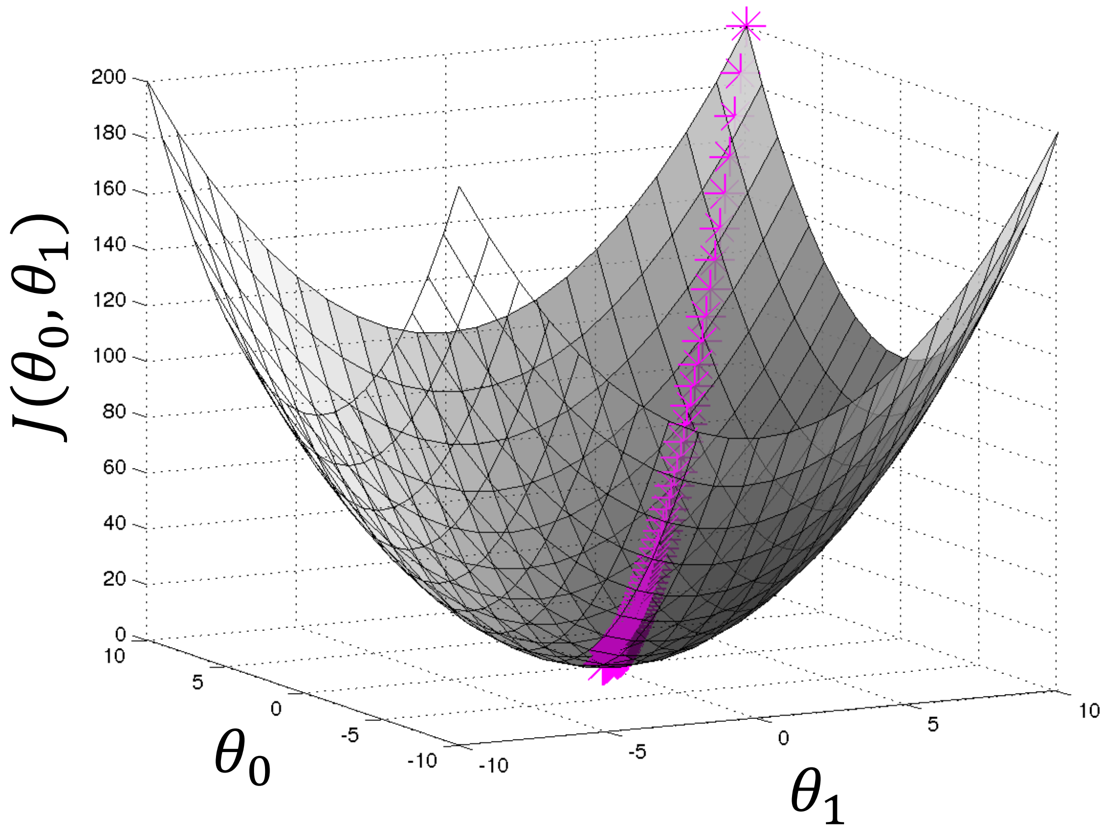


Each point on the parabola corresponds to a line on the graph on the left


y
x
-1
0
+1
y = x^2

Cost function in three dimensions

$$J(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta\left(x^i\right) - y^i\right)^2$$



HOW DO WE FIND THE MINIMUM OF THE COST FUNCTION

Maximum/Minimum Problem

*Find **two non-negative** numbers whose **sum is 9** and so that the product of one number and the square of the other number is a **maximum**.*

$\boxed{x + y = 9}$ contraint

$P = x y^2 \rightarrow$

Solution (1/2)

Sum of number is 9

$$9 = x + y$$

Product of two numbers is

$$P = x\,y^2$$
$$= x\,(9-x)^2$$

Solution (2/2)

Using the product rule and chain rule from Calculus 101:

P' = x (2) (9-x)(-1) + (1) (9-x)2
= (9-x) [-2x + (9-x)]
= (9-x) [9-3x]
= (9-x) (3)[3-x]
= 0

x=9 or x=3

Maximum Problem

There are **50 apple trees** in an orchard.

Each tree produces **800 apples**. For each additional tree planted in the orchard, the apple output per tree drops by **10 apples**.

Question: *How many additional trees should be planted in the existing orchard in order to maximize the apple output of the orchard?*

Solution

$$A = (50 + t) \times (800 - 10t)$$
$$A = 40{,}000 + 300t - 10t^2$$

Solve for A′ and set to 0 to find maximum.

$$A' = -20t + 300 = 0$$
$$t = 15$$

Adding 15 trees will maximize apple production

Gradient Descent

- Goal : minimize $J(\theta)$
- Start with some initial θ and then perform an update on each θ_j in turn:

$$\theta_j^{k+1} := \theta_j^k - \alpha \frac{\partial}{\partial \theta_j} J(\theta^k)$$

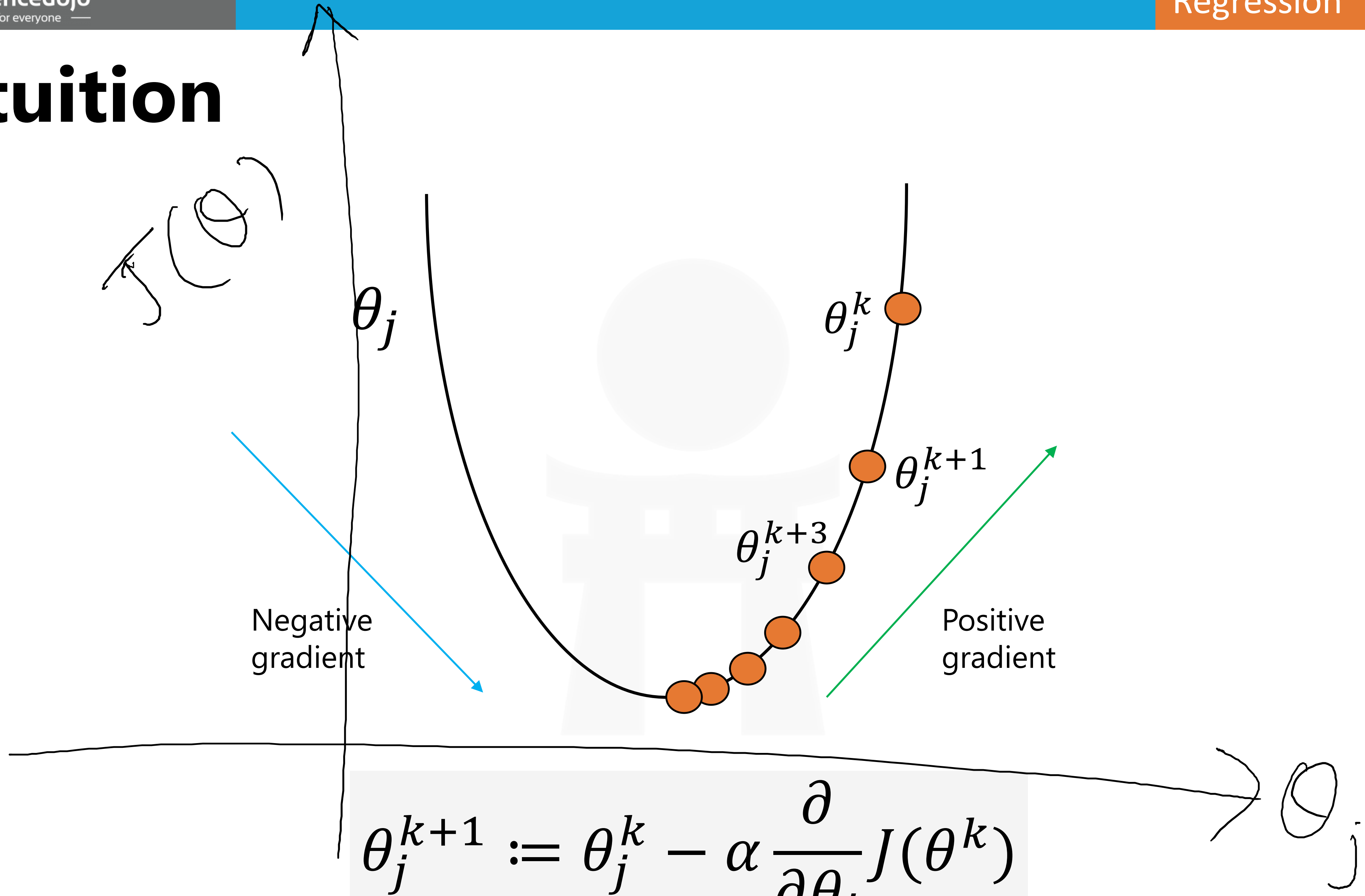
- Repeat until θ converges

Gradient Descent

$$\theta_j^{k+1} := \theta_j^k - \alpha \frac{\partial}{\partial \theta_j} J(\theta^k)$$

- α is known as the learning rate; set by user
- Each time the algorithm takes a step in the direction of the steepest descent and $J(\theta)$ decreases.
- α determines how quickly or slowly the algorithm will converge to a solution

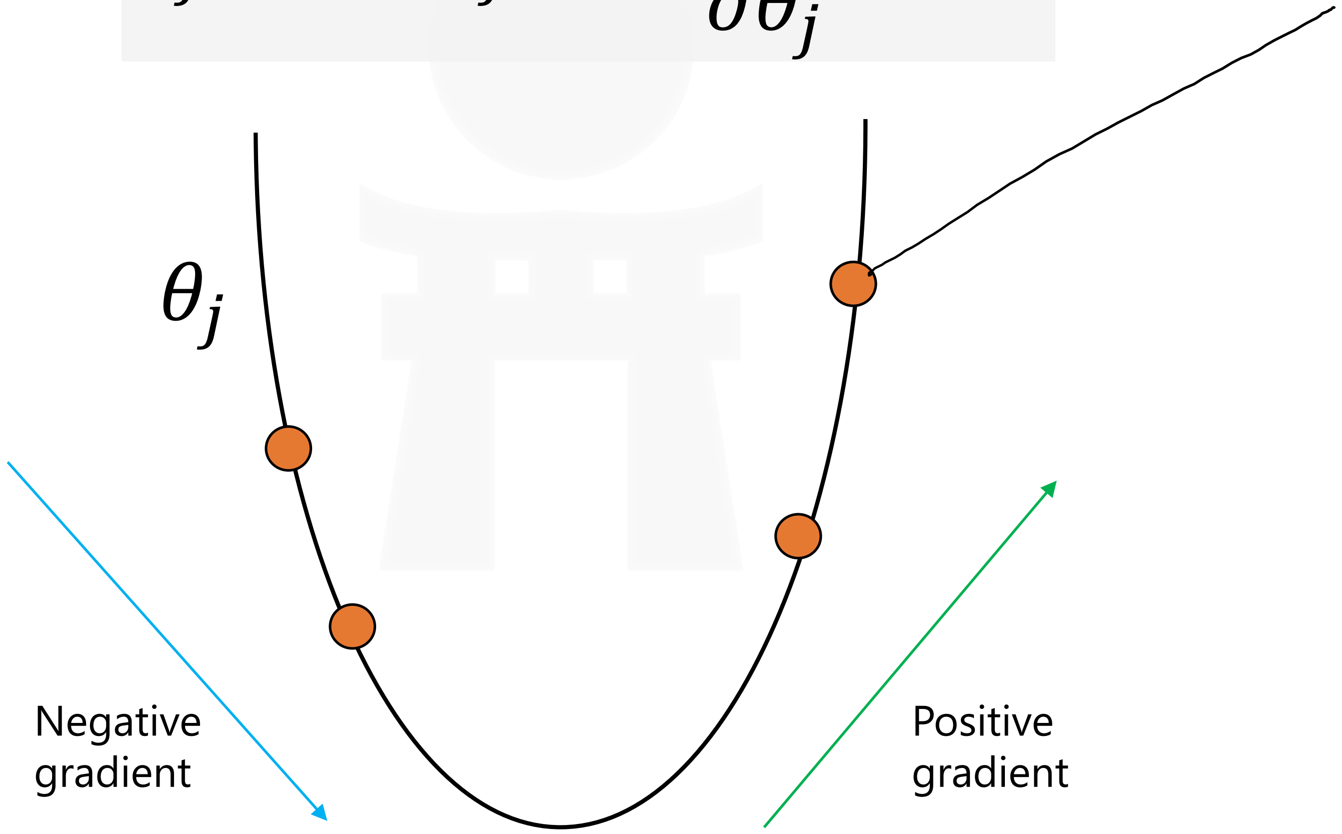
Intuition



$$\theta_j^{k+1} := \theta_j^k - \alpha \frac{\partial}{\partial \theta_j} J(\theta^k)$$

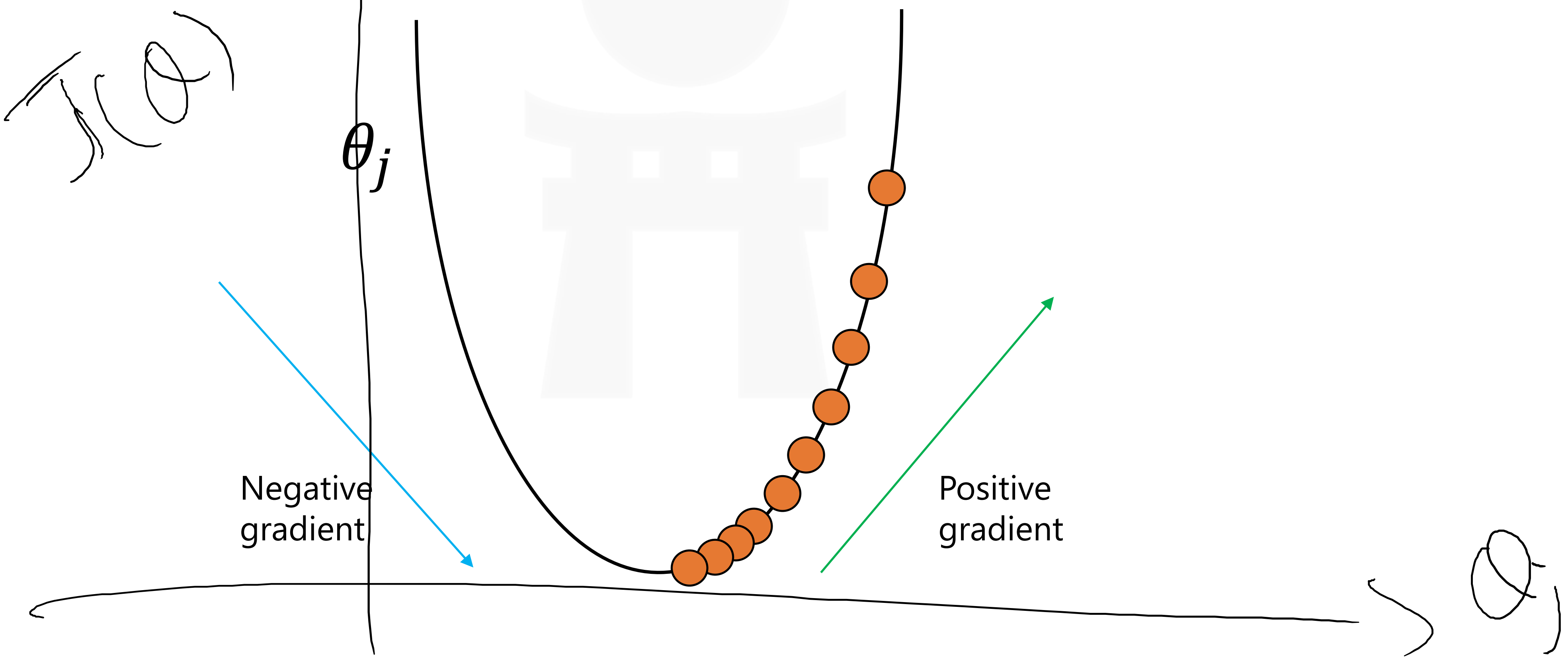
Effect of High Learning Rate: Large α

$$\theta_j^{k+1} := \theta_j^k - \alpha \frac{\partial}{\partial \theta_j} J(\theta^k)$$



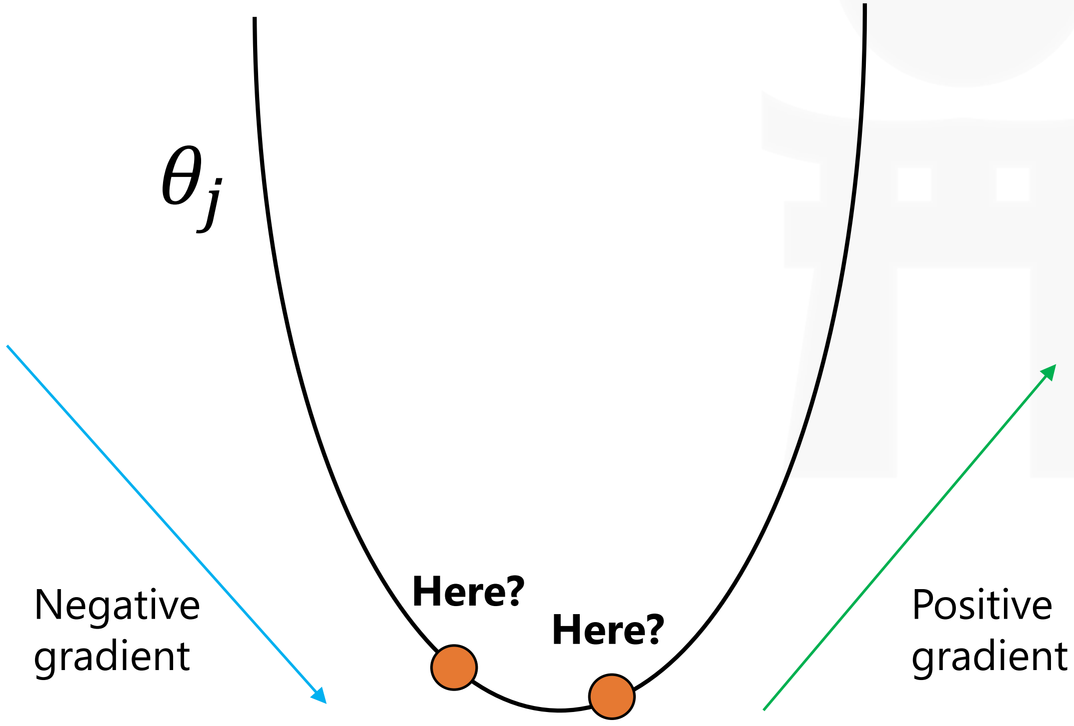
Learning Rate Effects Small α

$$\theta_j^{k+1} := \theta_j^k - \alpha \frac{\partial}{\partial \theta_j} J(\theta^k)$$



Gradient Descent Implementation

When do we stop updating?



- When θ_j^{k+1} is close to θ_j^k
- When $J(\theta^{k+1})$ is close to $J(\theta^k)$ [Error does not change]

Batch Gradient Descent

$$\theta_j^{k+1} := \theta_j^k - \alpha \frac{\partial}{\partial \theta_j} J(\theta^k)$$

Each θ_j represents one feature

- How do we incorporate all our data?
- Loop!

For j from 0 to m:

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

- h_θ is updated only once the loop has completed
- Weaknesses?

Batch Gradient Descent

ozone	radiation	temperature	wind
41	190	67	7.4
36	118	72	8.0
12	149	74	12.6
18	313	62	11.5
23	299	65	8.6
19	99	59	13.8

- Loop!

  For j from 0 to m:

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

Stochastic Gradient Descent

- Consider an alternative approach:

for i from 1 to n:

for j from 0 to m:

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

- h_θ is updated when inner loop is complete
- If the training set is big, converges quicker than batch
- May oscillate around a minimum of $J(\theta)$ and never converge

* We're now only taking one random observation at a time as a sample, instead of averaging across observations

Batch vs. Stochastic

Which is the better to use? It depends.

	Batch Gradient Descent	Stochastic Gradient Descent
Function	Updates hypothesis by scanning whole dataset	Updates hypothesis by scanning one training sample at a time
Rate of convergence	Slowly	Quickly (but may oscillate at minimum)
Appropriate Dataset Size	Small	Large

EVALUATING REGRESSION MODELS

Evaluation metrics for regression

- Mean Absolute Error (MAE)
- Root-Mean-Square Error (RMSE)
  - Root-Mean-Square Deviation
- Coefficient of Determination (R^2)

Mean Absolute Error

$$MAE(\theta) = \frac{\sum_{i=1}^{n} \left| h_\theta\left(x^i\right) - y^i \right|}{n}$$

- Mean of residual values
- "Pure" measure of error

Mean Absolute Error - Example

$$y = \{36, 19, 34, 6, 1, 45\}$$

$$h_\theta(x) = \{27, -2.6, 13, -7.3, -2.6, 48\}$$

$$|h_\theta(x) - y| = \{9, 21.6, 21, 13.3, 3.6, 3\}$$

$$MAE(\theta) = \frac{71.5}{6} = 11.9$$

Root-Mean-Square Error

$$RMSE(\theta) = \sqrt{\frac{\sum_{i=1}^{n} (h_\theta(x^i) - y^i)^2}{n}}$$

- Square root of mean of squared residuals
- Penalizes large errors more than small
- Good measure to use to accentuate outliers

RMSE - Example

Create a hand out using slides 50 — 52 to show difference b/w RMSE & MAE for two examples.

$$y = \{36, 19, 34, 6, 1, 45\}$$

$$h_\theta(x) = \{27, -2.6, 13, -7.3, -2.6, 48\}$$

$$(h_\theta(x) - y)^2 = \{81, 467, 441, 177, 13, 9\}$$

$$RSME(\theta) = \sqrt{\frac{1187}{6}} = 14.1$$

Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

where $$SS_{res} = \sum_{i=1}^{n} \left(h_\theta\left(x^i\right) - y^i\right)^2 \qquad SS_{tot} = \sum_{i=1}^{n} \left(y^i - \bar{y}\right)^2$$

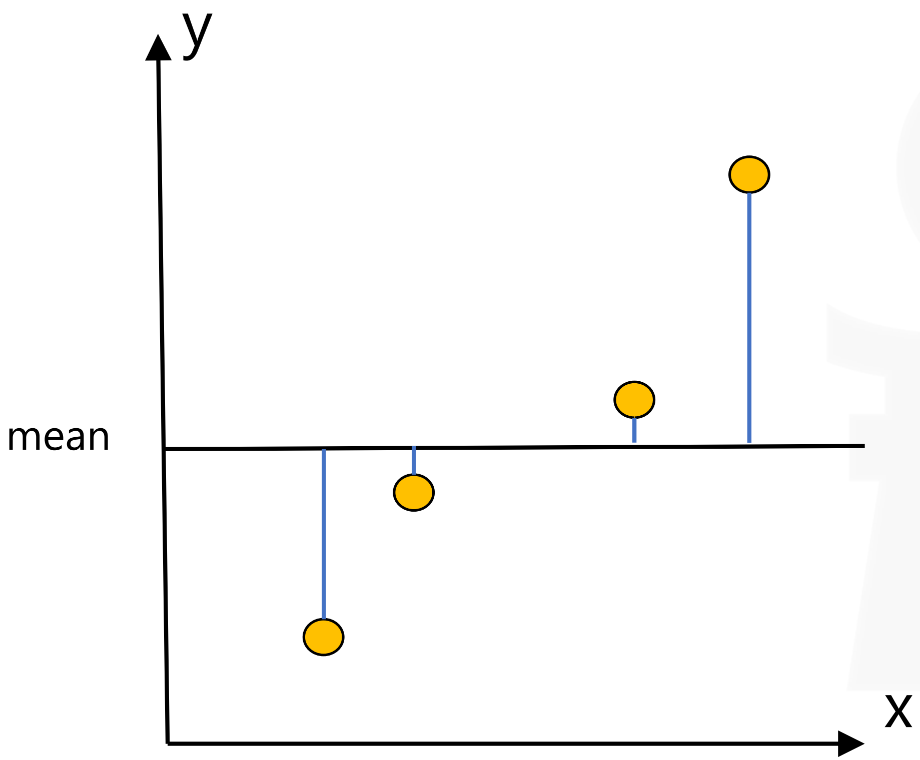
SS_{res} – Sum of squared residuals (i.e. total squared error)

SS_{tot} –Sum of squared differences from mean (i.e. total variation in dataset)

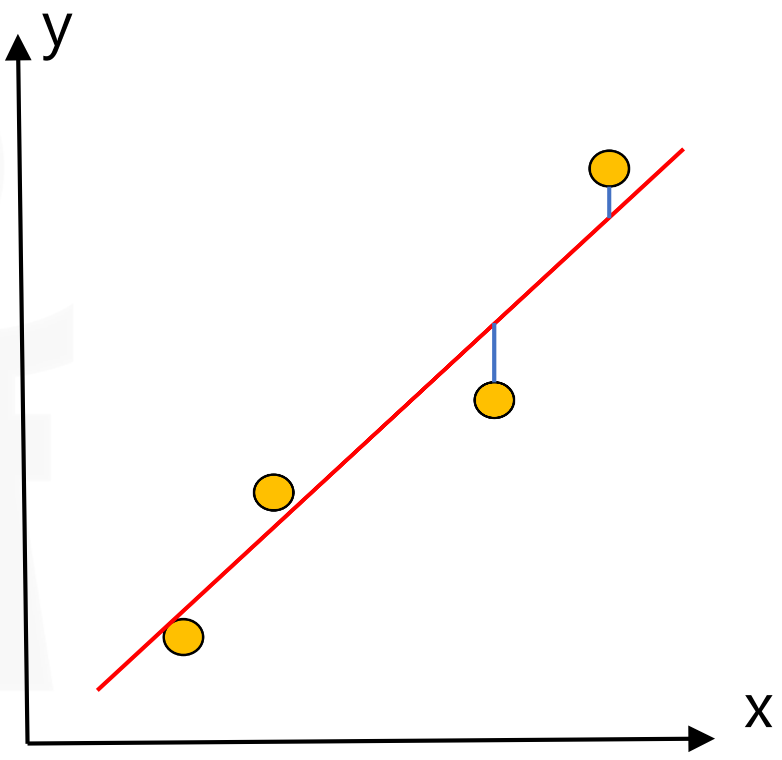
Result: Measure of how well the model explains the data

- "Fraction of variation in data explained by model"

Coefficient of Determination



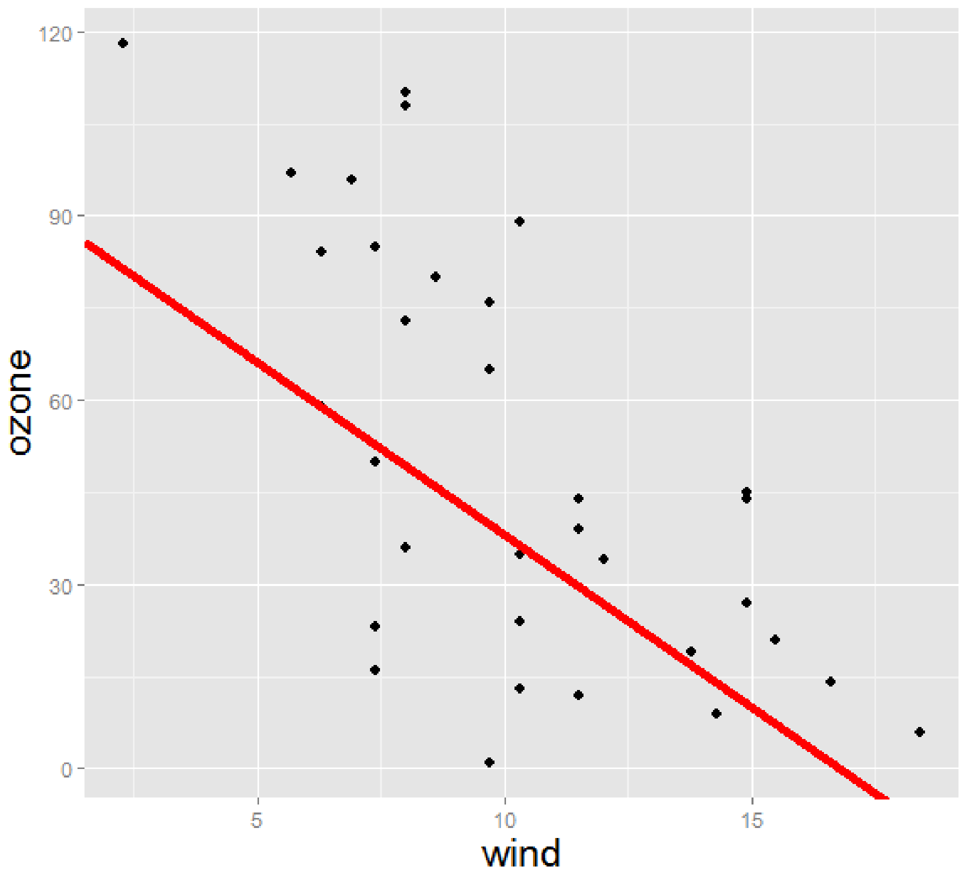
SS_{tot}



SS_{res}

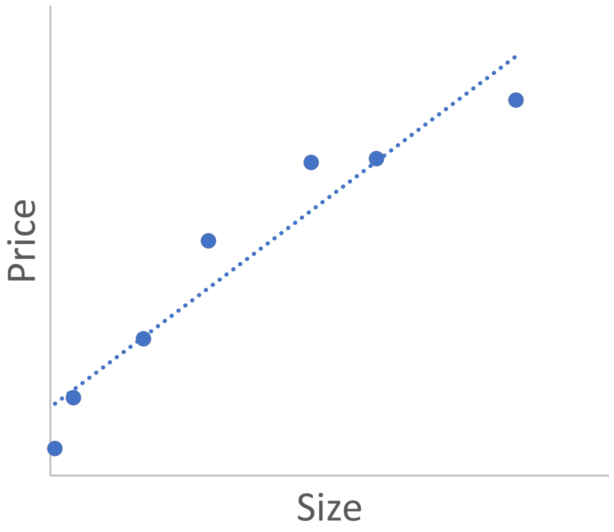
R^2 Example

- $R^2 = 0.277$
- Want a much better model for real application
- $R^2 = 0.6$ can be a good model

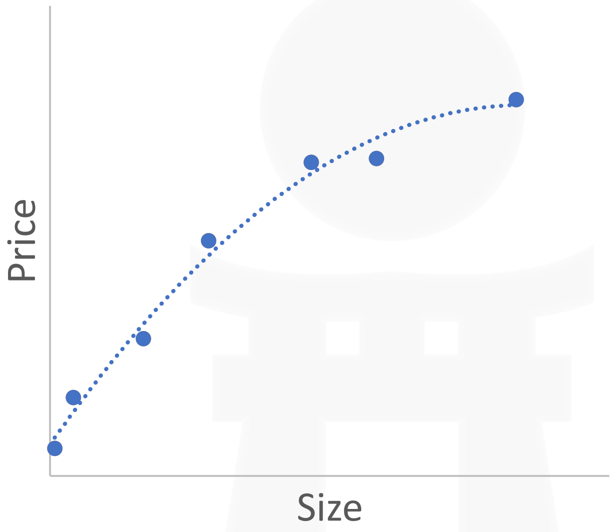


REGULARIZATION

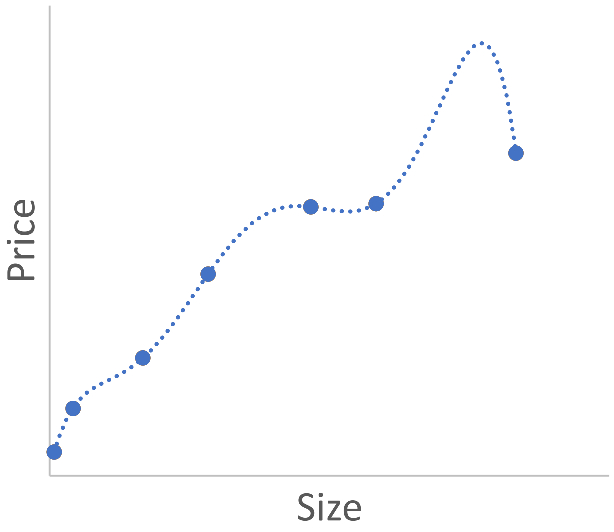
Overfitting



$$\theta_0 + \theta_1 x$$

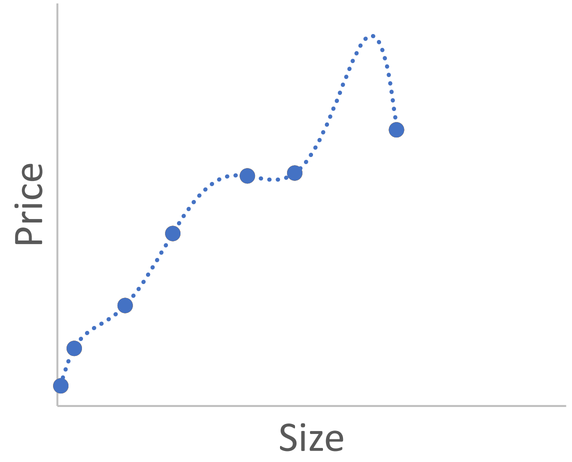


$$\theta_0 + \theta_1 x + \theta_2 x^2$$

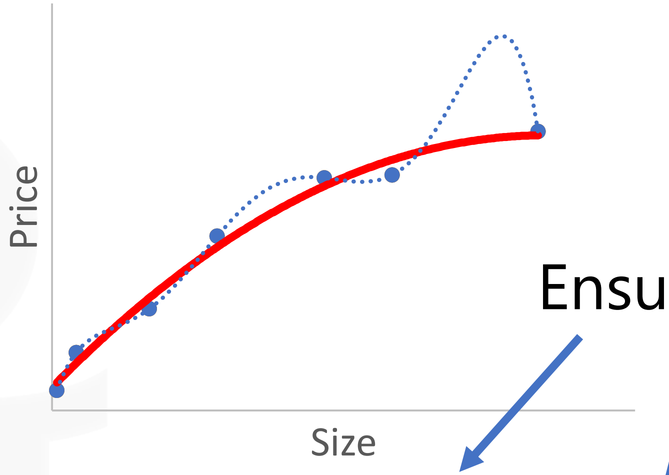


$$\theta_0 + \theta_1 x + \theta_2 x^2 + \theta_3 x^3 + \theta_4 x^4$$

Intuition



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



Ensure Small

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

- Want to discourage complex models automatically – How?
- Adjust the cost function!
    - Penalize models with large high-order θ terms

$$J'(\theta) = J(\theta) + Penalty$$

Definitions

- Two most common methods
  - L1 regularization
    - lasso regression

$$J_{L1}(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta\left(x^i\right) - y^i\right)^2 + \lambda\sum_{j=1}^{m}\left|\theta_j\right|$$

  - L2 regularization
    - ridge regression
    - weight decay

$$J_{L2}(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta\left(x^i\right) - y^i\right)^2 + \lambda\sum_{j=1}^{m}\theta_j^2$$

Regularized Regression

$$J_{L1}(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta\left(x^i\right) - y^i\right)^2 + \lambda\sum_{j=1}^{m}|\theta_j|$$

$$J_{L2}(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta\left(x^i\right) - y^i\right)^2 + \lambda\sum_{j=1}^{m}\theta_j^2$$

- Find the best fit
- Keep the θ_j terms as small as possible.
- λ is a user-set parameter which controls the trade off

Regularized Regression

$$J_{L1}(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta\left(x^i\right) - y^i\right)^2 + \lambda\sum_{j=1}^{m}\left|\theta_j\right|$$

$$J_{L2}(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\left(h_\theta\left(x^i\right) - y^i\right)^2 + \lambda\sum_{j=1}^{m}\theta_j^2$$

- Size of λ important
  - λ too high => no fitting
  - λ too low => no regularization

QUESTIONS