



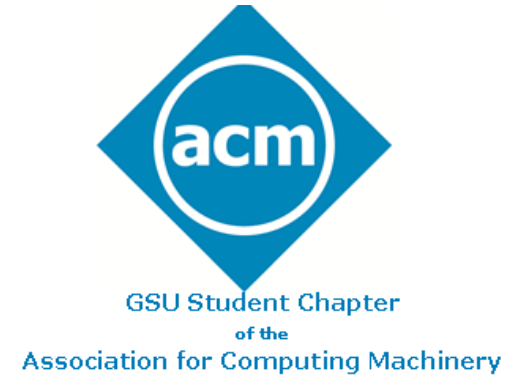
# YOU READY?

An Introduction to Data Science in RStudio

Andira Putri  
GSU 2018 -- Xylem Inc.

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# WORKSHOP STRUCTURE

1. Introduction
  - About Me
  - What is Data Science?
2. Linear Regression
3. Logistic Regression
4. Resampling Methods
5. Case Study
6. Questions?





# INTRODUCTION

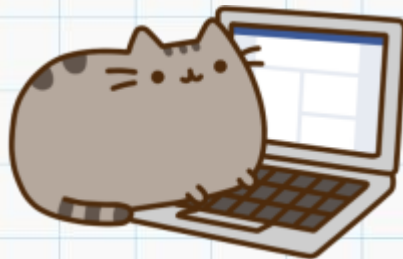
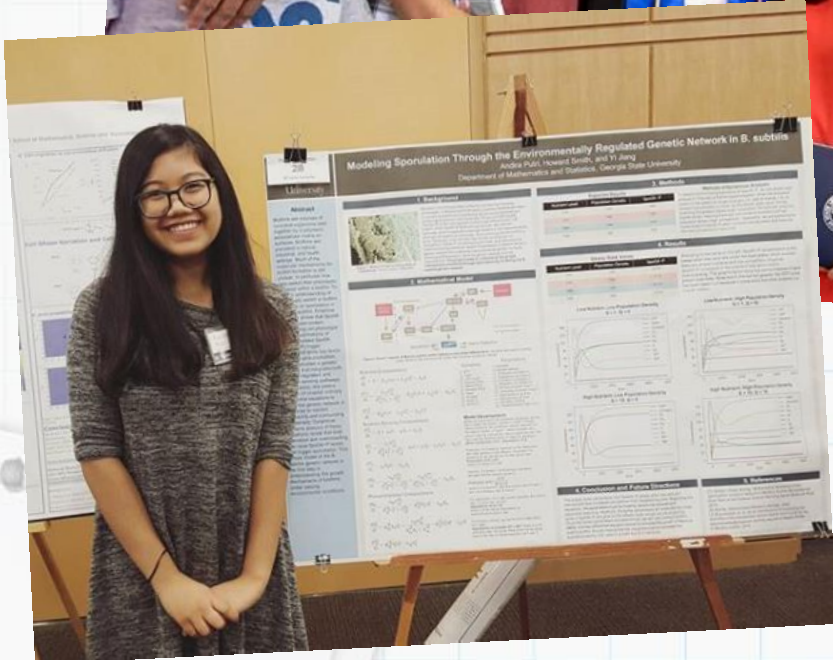
## About Me



- Graduated from Georgia State in Spring 2018 – B.S. in Mathematics

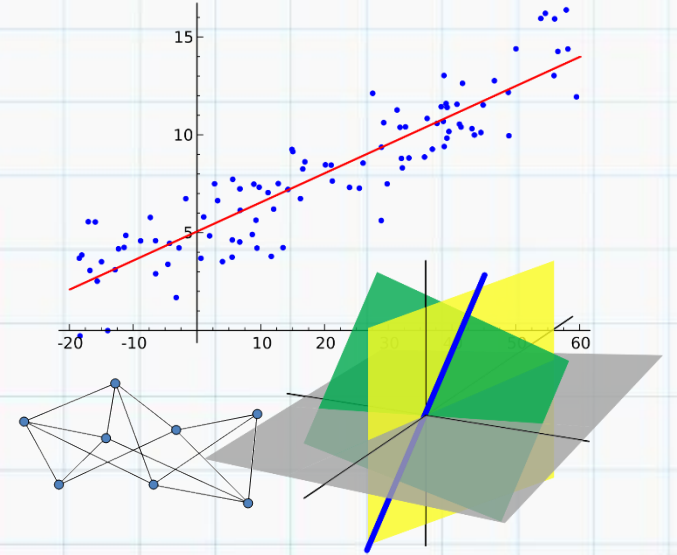
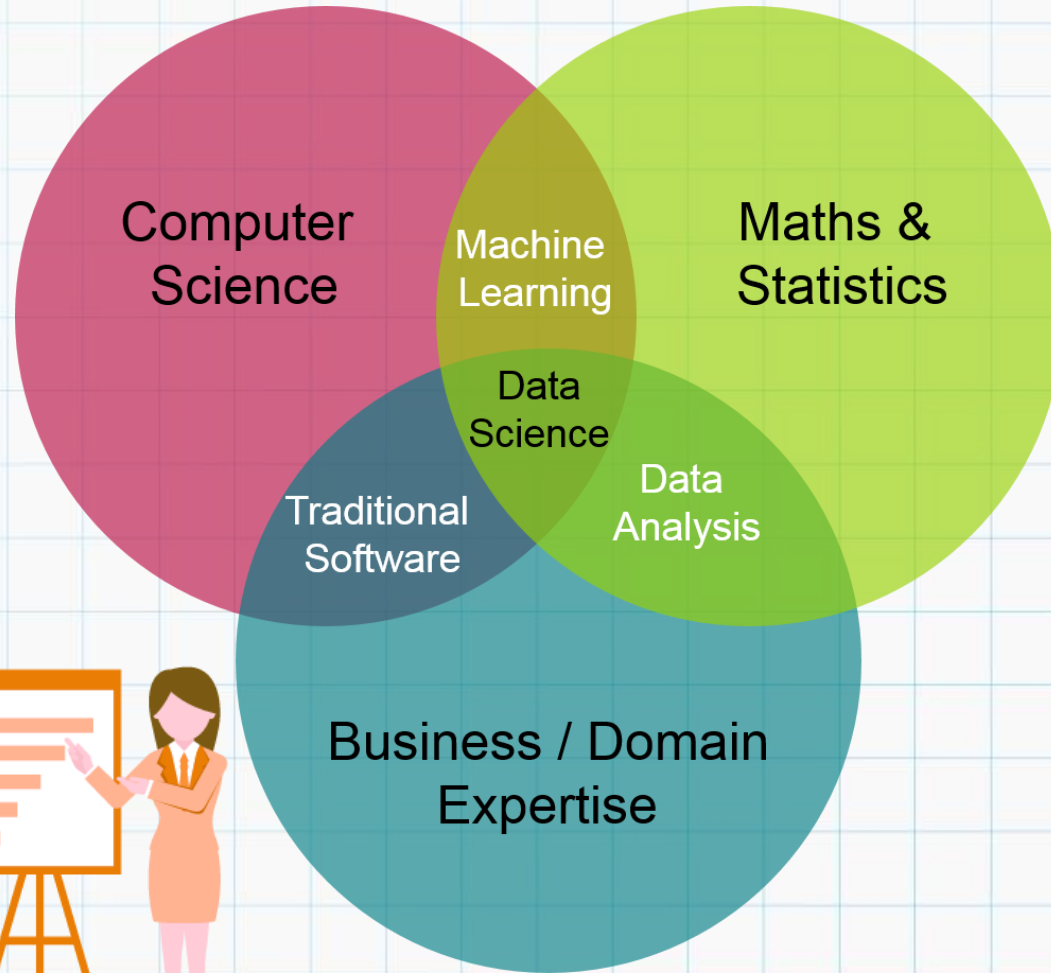
- Data Scientist at Xylem Inc. in Research Triangle Park, NC

- Will be pursuing an M.S. in Statistics soon at North Carolina State University



# INTRODUCTION

What is Data Science?



# INTRODUCTION

## The Perfect Data Scientist





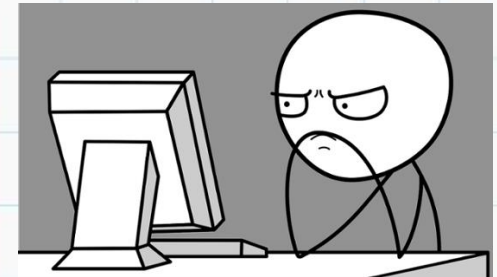
# INTRODUCTION

## A Typical Project Breakdown



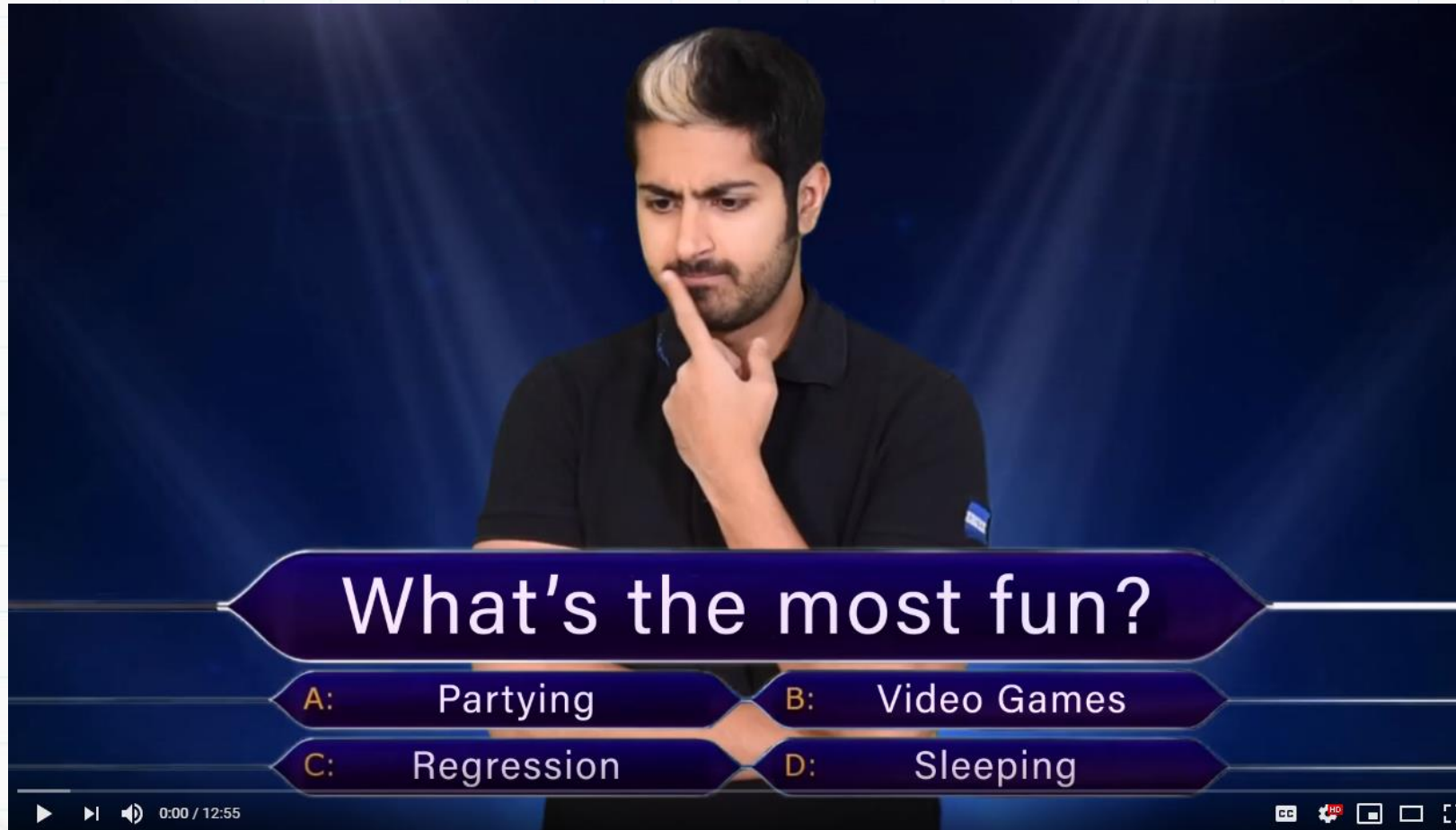
85% Data Mining

15% Applications,  
Productizing, Writing



# REGRESSION

You Must Know It!



Siraj Raval



# LINEAR REGRESSION

## A Foundation of Data Science

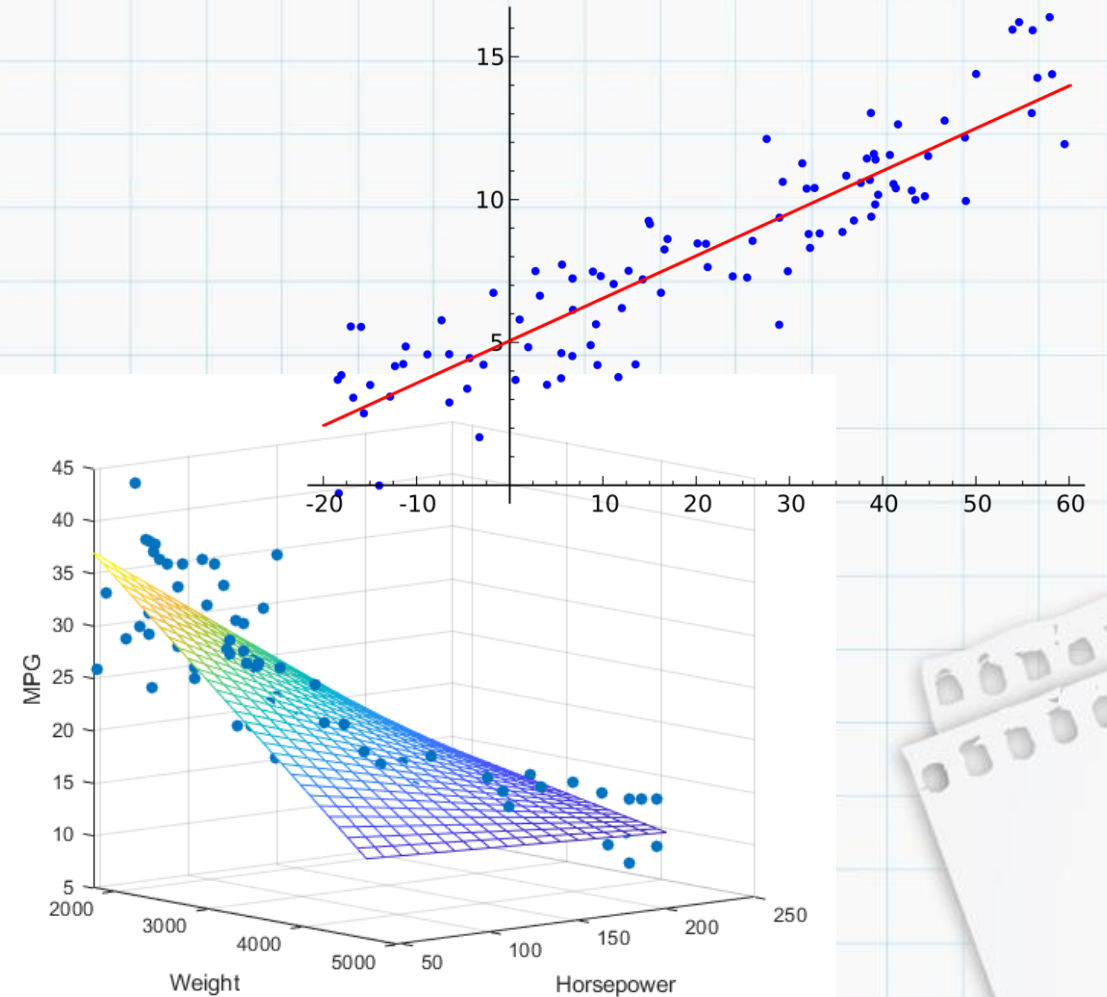
- Assumes a linear relationship between predictors  $X_{1...n}$  and a response  $Y$

$$Y = \beta_0 + \beta_1 X_1 + \varepsilon + \beta_2 X_2 + \dots + \beta_n X_n$$

Simple

Multiple

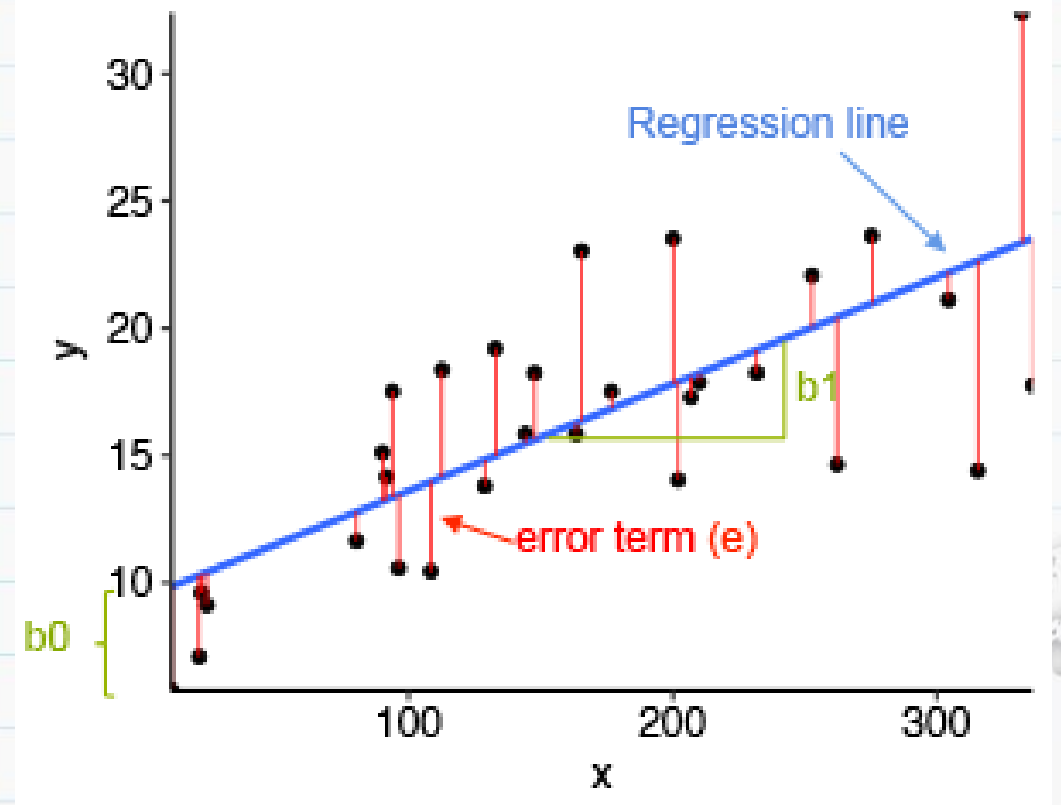
- $\beta_0, \beta_1 \dots \beta_n$  are known as regression coefficients
  - $\beta_0 \rightarrow$  expected mean when predictors = 0
  - $\beta_1 \dots \beta_n \rightarrow$  association between predictor and response
  - $\varepsilon \rightarrow$  error (the residual)



# LINEAR REGRESSION

## A Foundation of Data Science

- Coefficients are estimated by least squares method
- How accurate is our model? We can assess our model using:
  - R-Squared and Adjusted R-Squared
  - Residual Standard Error (RSE)
  - F-statistics
- All values can be called using the `summary()` function in R



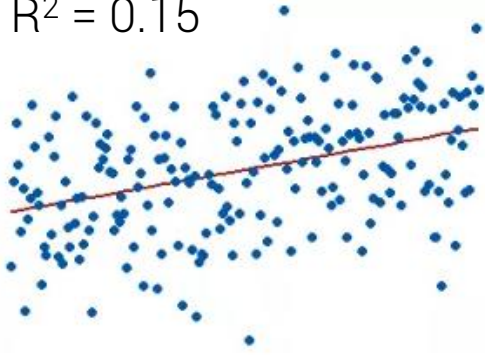
# LINEAR REGRESSION

## A Foundation of Data Science

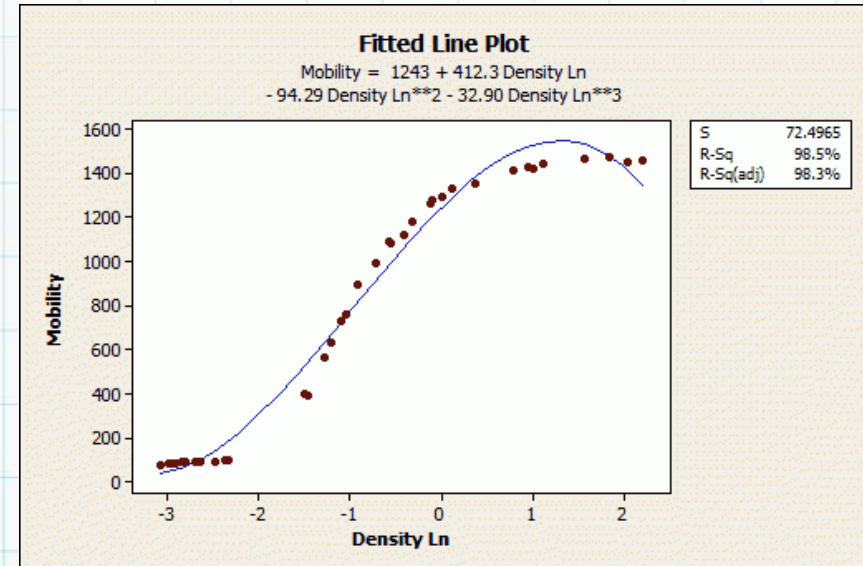
### $R^2$ and Adjusted- $R^2$ Values

- Represents the proportion of variation in the response that can be explained by the predictors
- $R^2 \in [0,1]$  ; the closer to 1, the better
- **$R^2$  IS NOT ALWAYS RELIABLE**  
It increases when you add more predictors – predictors could be weakly related to the response
- Adjusted-  $R^2$  corrects for the additional predictors

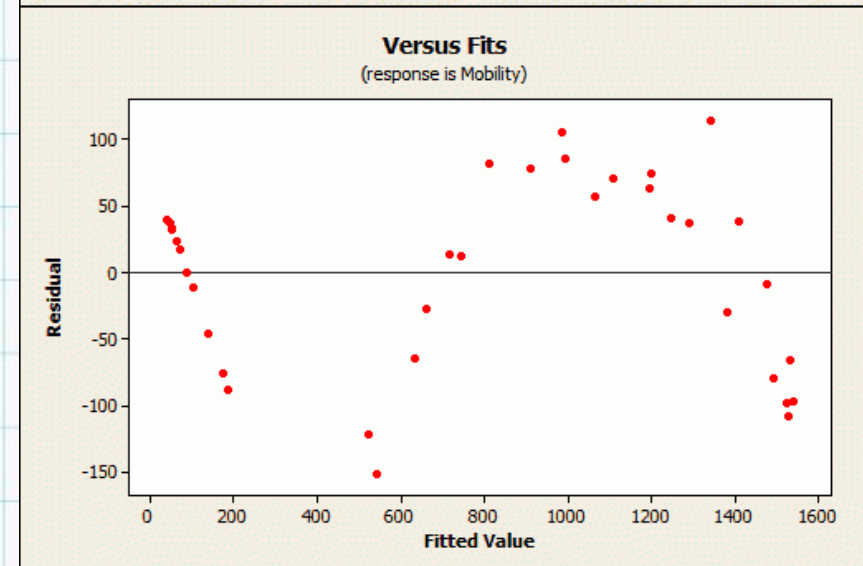
$R^2 = 0.15$



$R^2 = 0.85$



$R^2 = 0.99$



Bias!

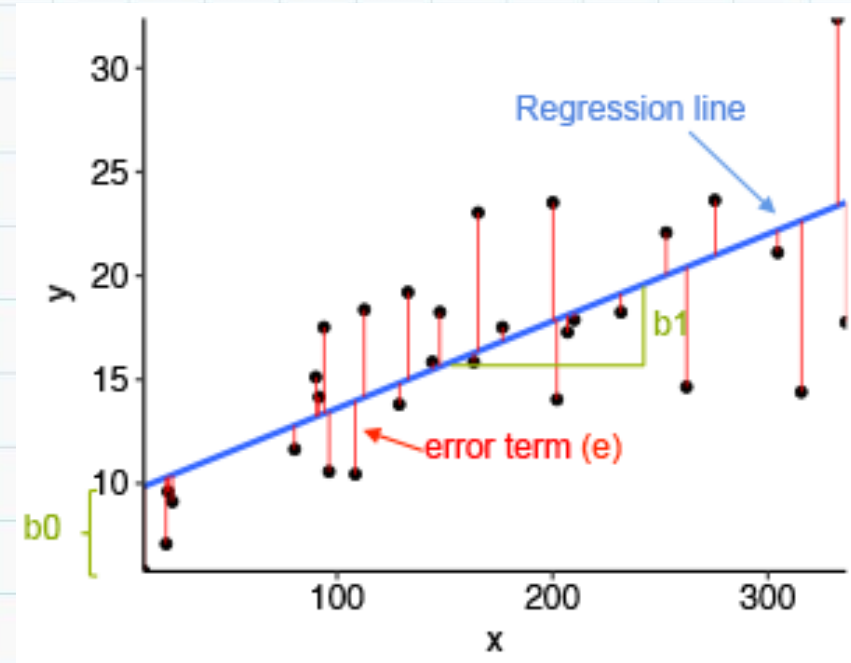


# LINEAR REGRESSION

## A Foundation of Data Science

### Residual Standard Error (RSE)

- Represents roughly the average difference between the true response values and the predicted values by the model
- The smaller, the better!
- Dividing the RSE by the average value of the response will give you the prediction error rate

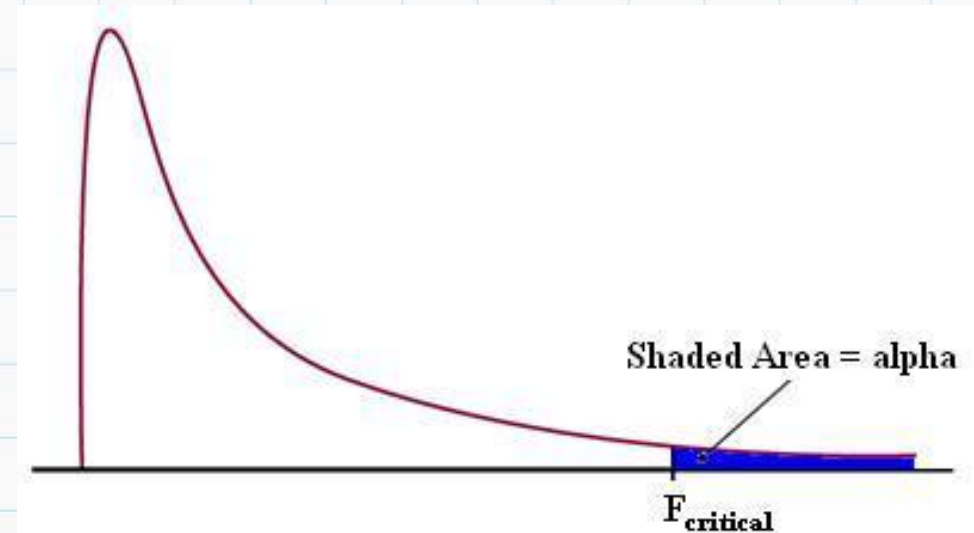


# LINEAR REGRESSION

## A Foundation of Data Science

### F-statistic

- Gives the overall significance of the model - assesses whether at least one predictor variable has a non-zero coefficient
- Useful for multiple regression
- We want a large F-statistic, which gives a statistically significant p-value for a confidence level  $\alpha$  (e.g. at  $\alpha = 95\%$ , we want  $p < 0.05$ )



# CASE STUDY

## In the Market

Let's predict the prices of homes in Boston.





# RESAMPLING METHODS

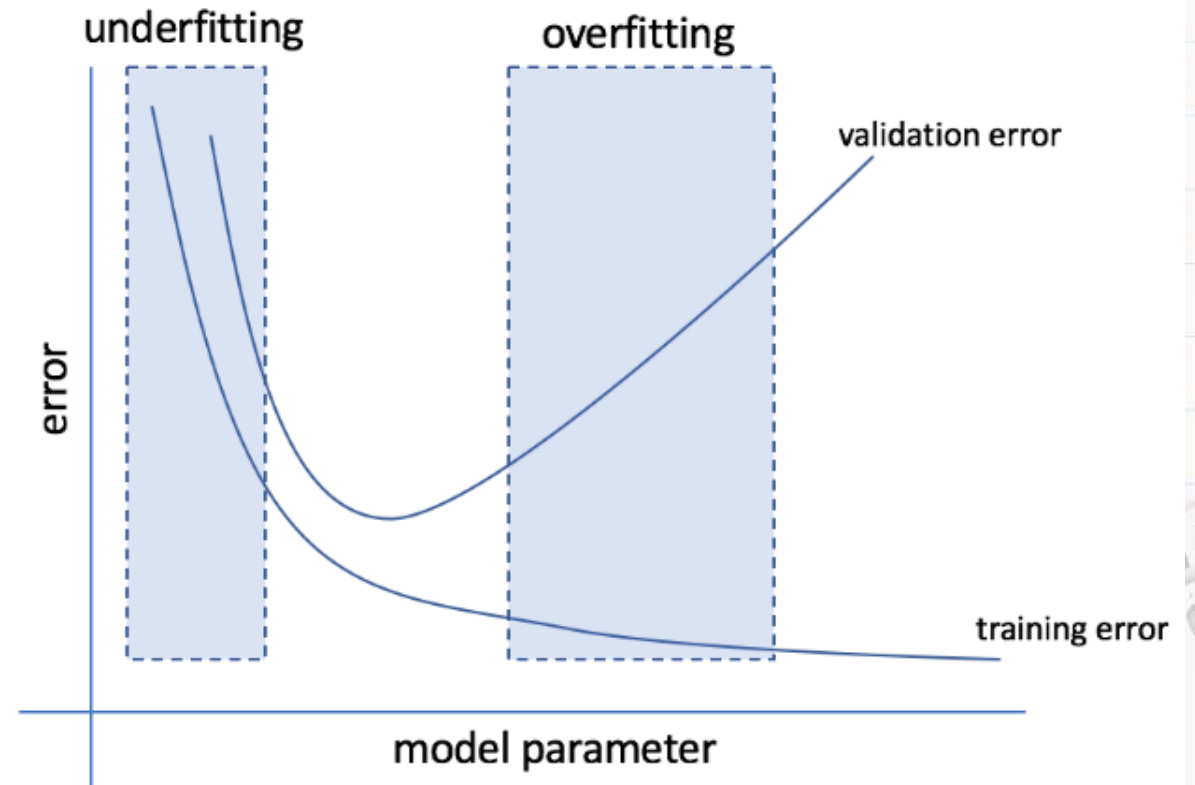
- Involves repeatedly drawing samples from a training set and refitting a model of interest on each sample in order to obtain additional information about the fitted model

- Can our model generalize to new data?

- Two ways: cross-validation and bootstrap

Cross-validation is used to assess model performance

Bootstrap can estimate confidence intervals, accuracy of parameter estimate, etc.



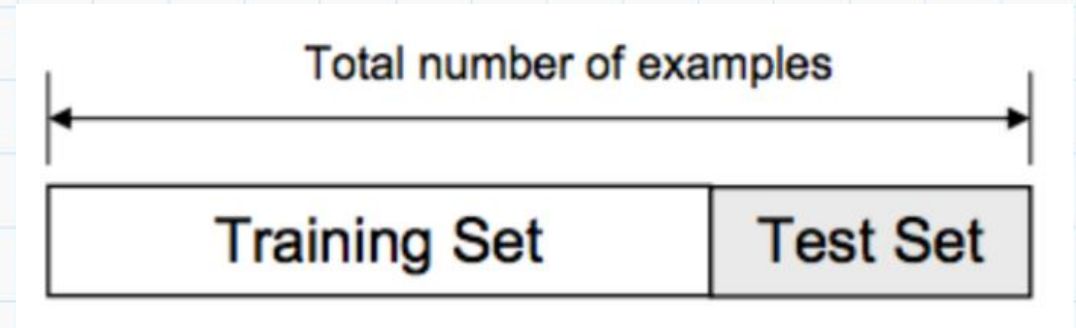
# TRAIN / TEST SPLIT

- The simplest resampling method
- You just need to make sure the sets are not overlapping
- **NOT THE BEST**  
Subsets may not be completely randomized  
Training set could have people with same age, people who live in the same state, etc.

**OVERFITTING!**

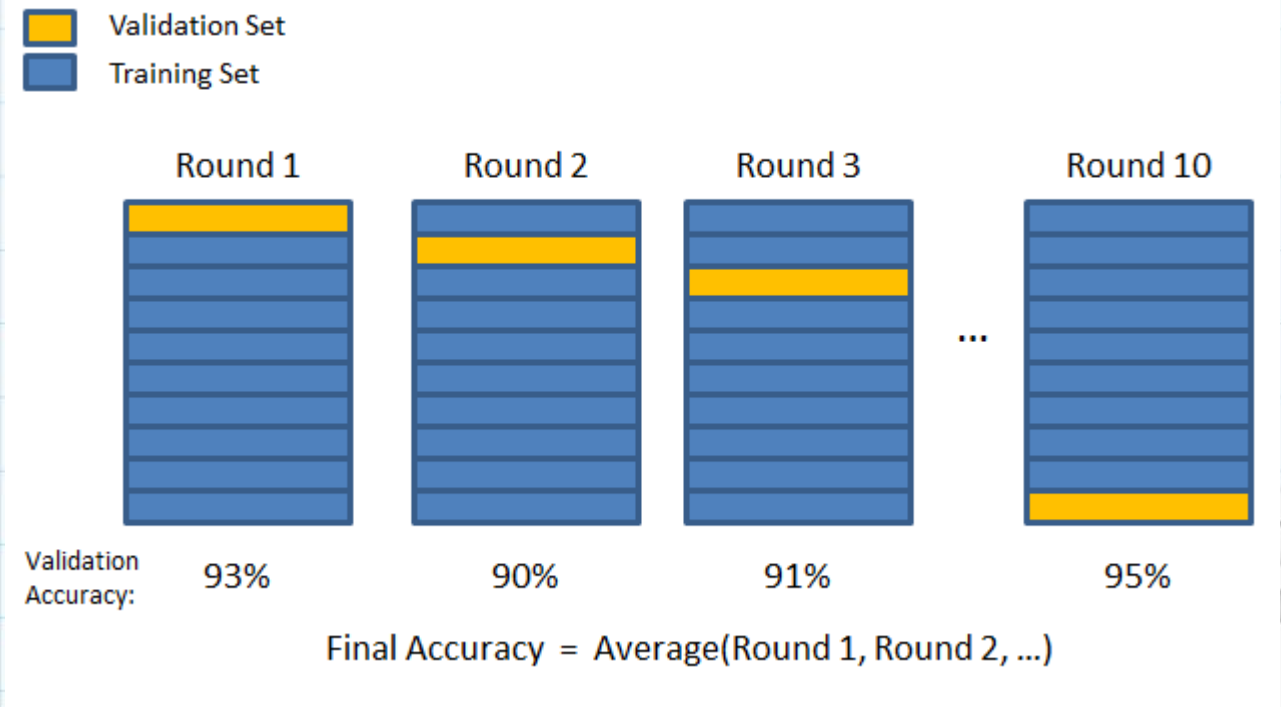
Also, it causes a reduction in training data size

**UNDERFITTING!**



# K-FOLD CROSS VALIDATION

- Train/test split → 2 groups  
k-fold cross validation → k # of groups
- Essentially an iterative / repeated train/test split
- Average the resulting accuracies after repeating k times
- Reduces OVERFITTING  
Most data is being used in the test set
- Reduces UNDERFITTING  
Most data is being used in the training set

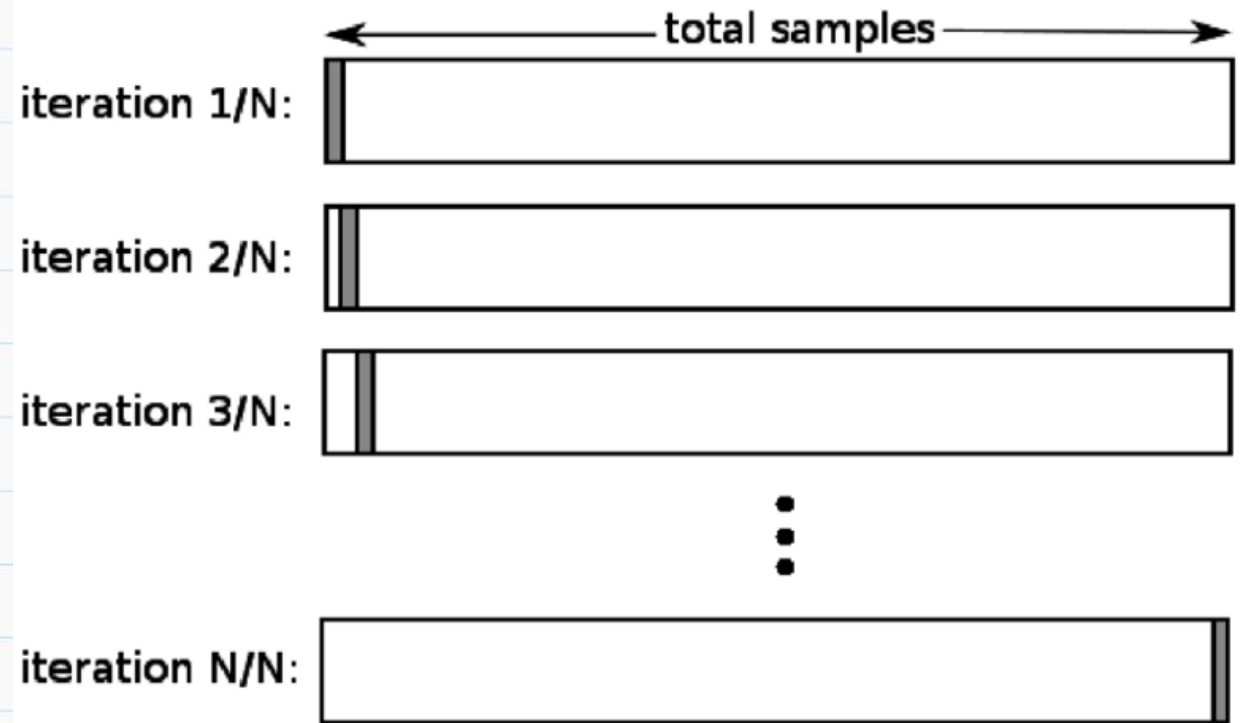


General guideline is k=5 or k=10



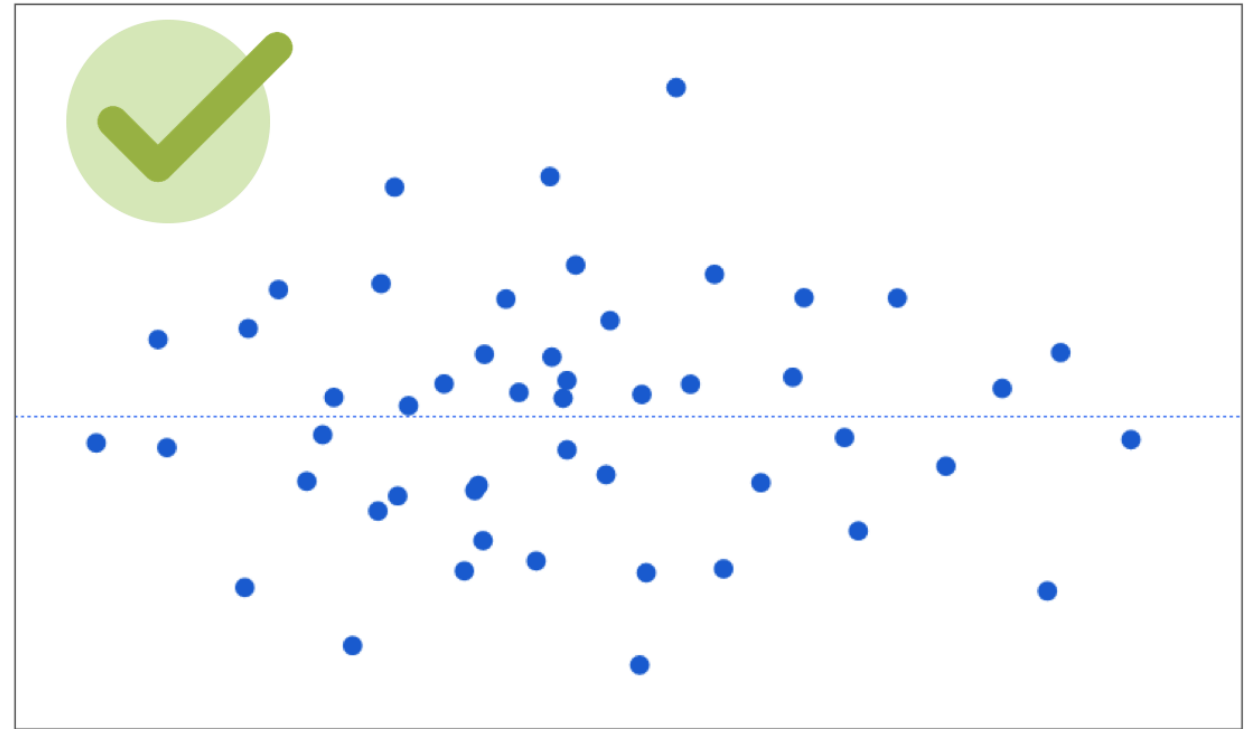
# LEAVE ONE OUT

- A special case of k-fold cross validation
- We have  $n$  # of observations  
Repeat train/test split  $n$  times  
Only one element in the test set
- Great if you have small data sets
- Computationally eXpEnSiVe



# ASSUMPTIONS

1. The true relationship is linear
2. Errors are normally distributed
3. Homoscedasticity of errors
4. Observations are independent
5. Variables are not correlated with one another



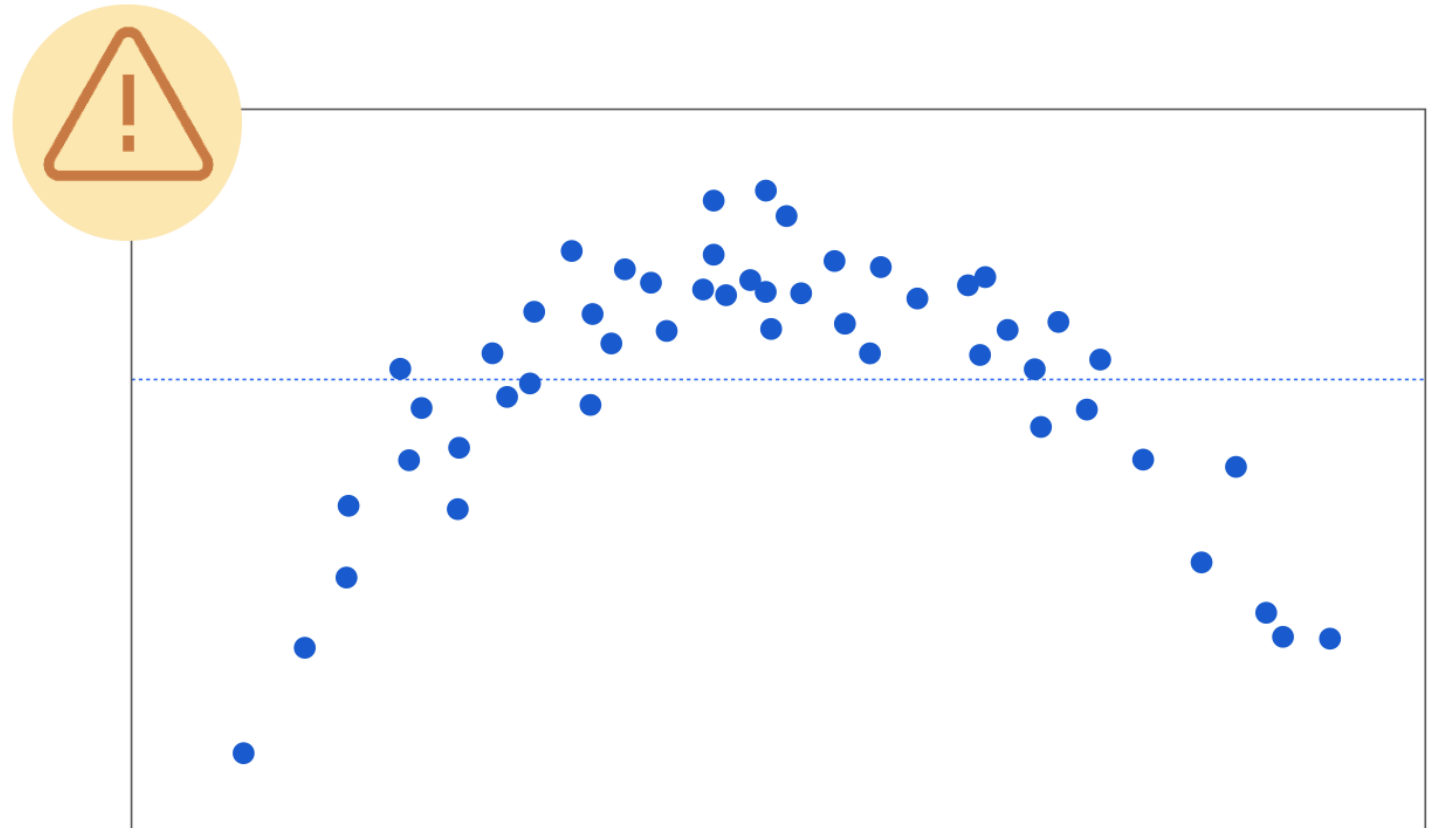
# ASSUMPTIONS

VIOLATION in this residual plot!

There is an obvious curvature in the plot → non-linear relationship

A nonlinear regression would be more informative than a linear one

Under-predicts and over-predicts values → model bias





# ASSUMPTIONS

VIOLATION in this residual plot!

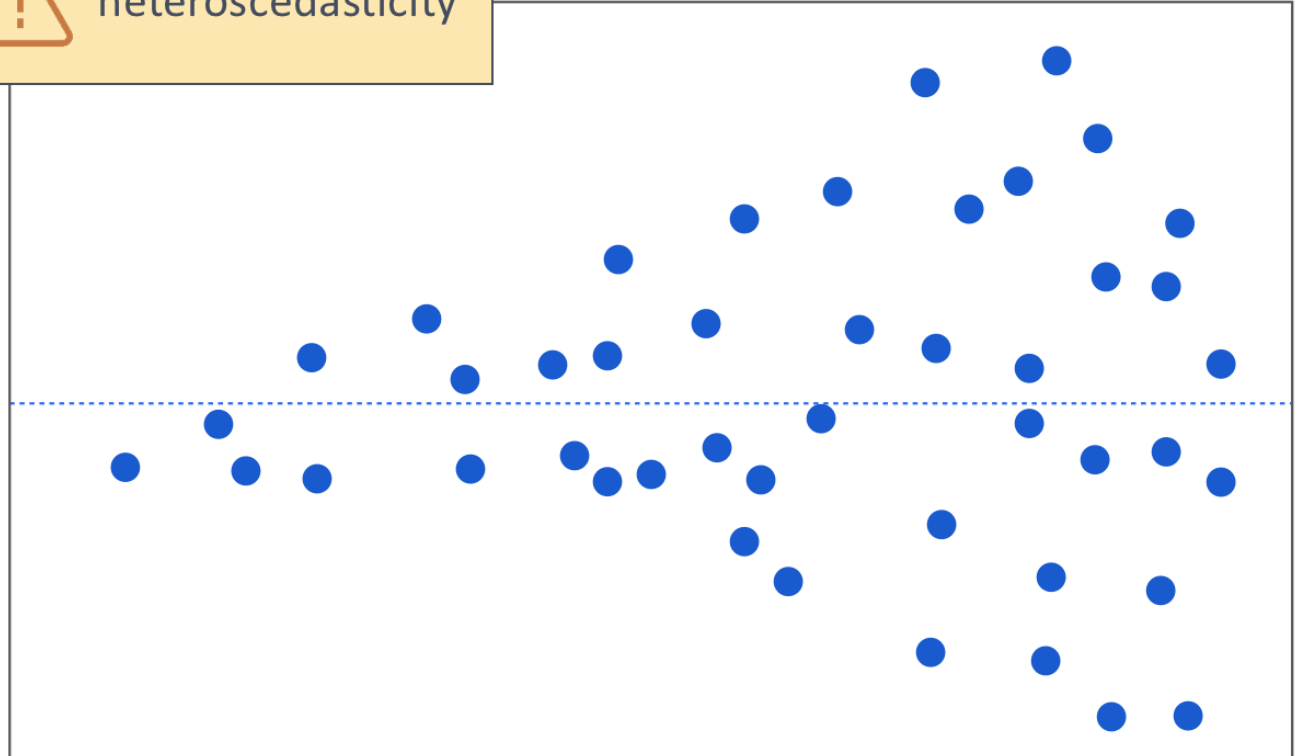
We have heteroscedasticity

Variance is unequal across the range of values

Predicting low values = high accuracy  
High values = low accuracy  
Model should not be trusted!



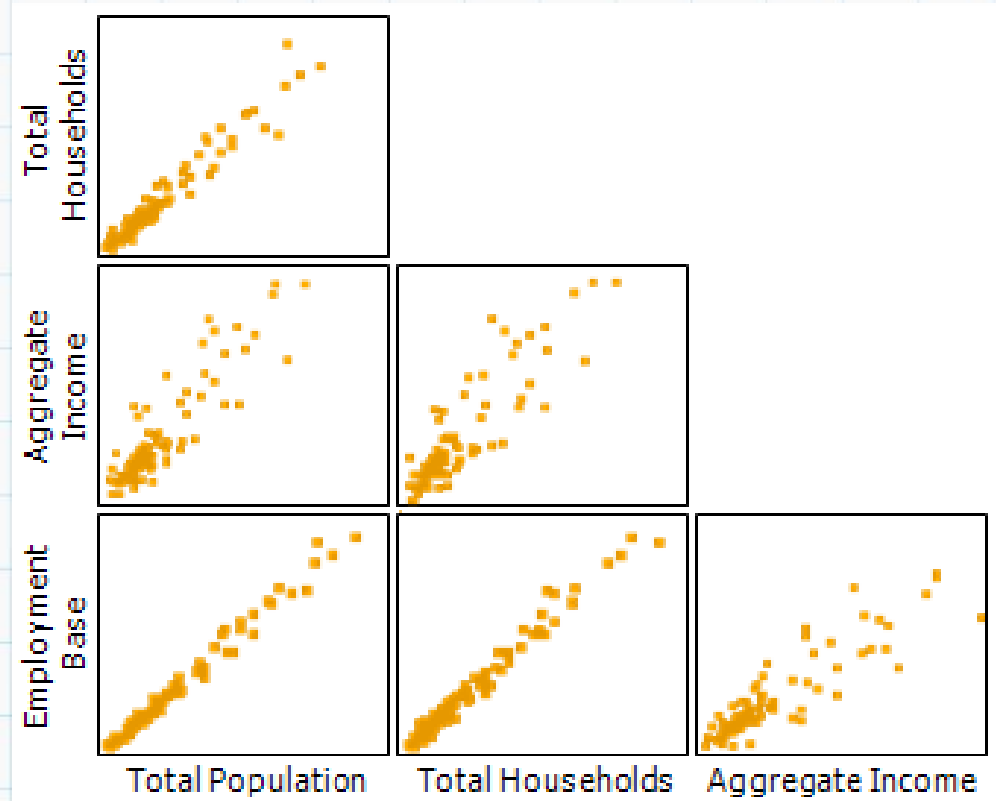
heteroscedasticity



# ASSUMPTIONS

## Collinearity (violation)

- Occurs when predictors are highly correlated with each other
- Classic symptom:  
Small change in data can cause big change in coefficients  
**OVERFITTING**
- Tell-tale signs:  
High  $R^2$  but low t-scores  
Variation Inflation Factor (VIF)  $> 5$
- You may be able to ignore it if you are just worried about prediction accuracy



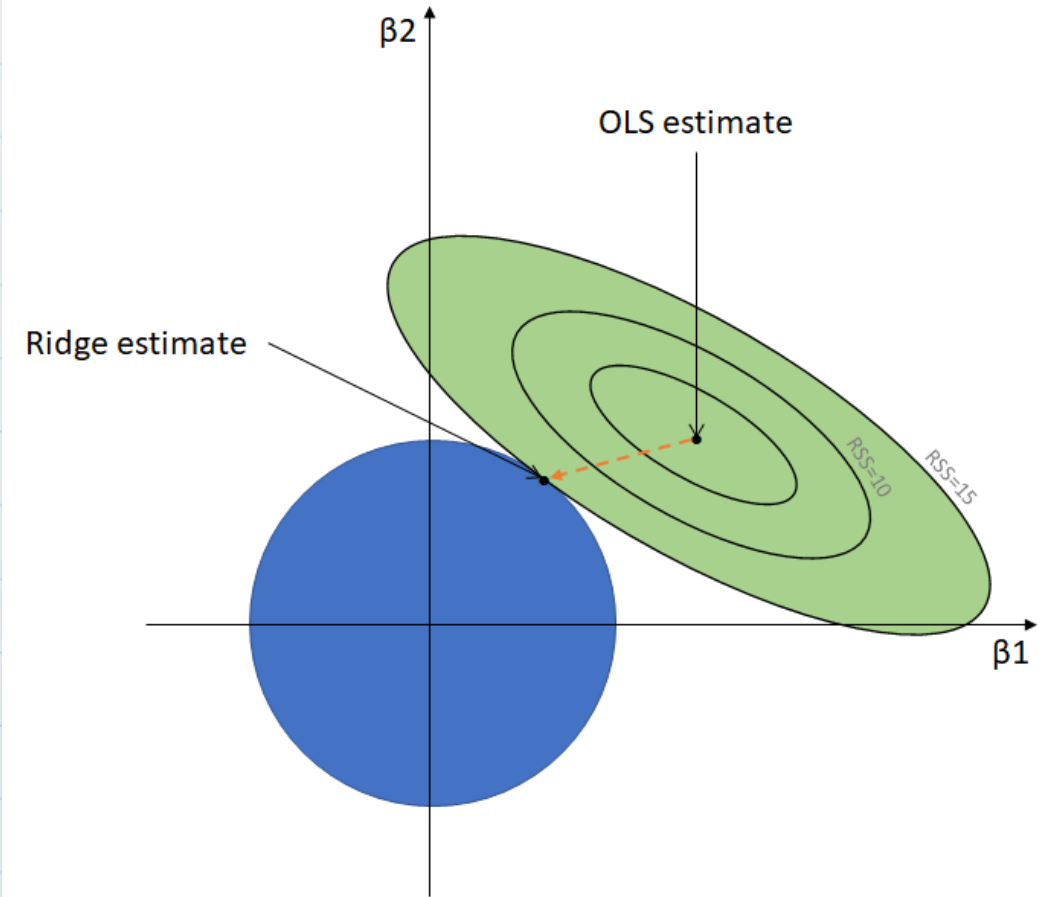
# RIDGE REGRESSION

- To address collinearity, ridge regression adds a bias term to our standard equation  
Reduces variance
  - Least squares will want to minimize residual sum of squares (RSS)

$$RSS + \lambda \sum_{j=1}^p \beta_j^2$$

The summation is called the shrinkage penalty

- $\lambda$  is the tuning parameter  
Higher  $\lambda \rightarrow$  more shrinkage, and coefficients shrink towards 0
- $\lambda$  is determined through cross-validation



# THE LASSO

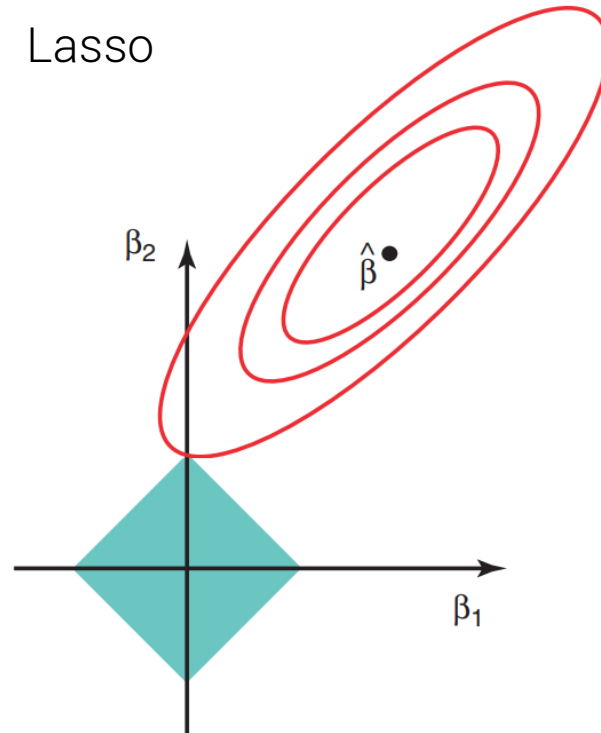
- Very similar to ridge regression except we have the ability to set coefficients to zero if irrelevant – HUGE effect on variance

- Bias term:

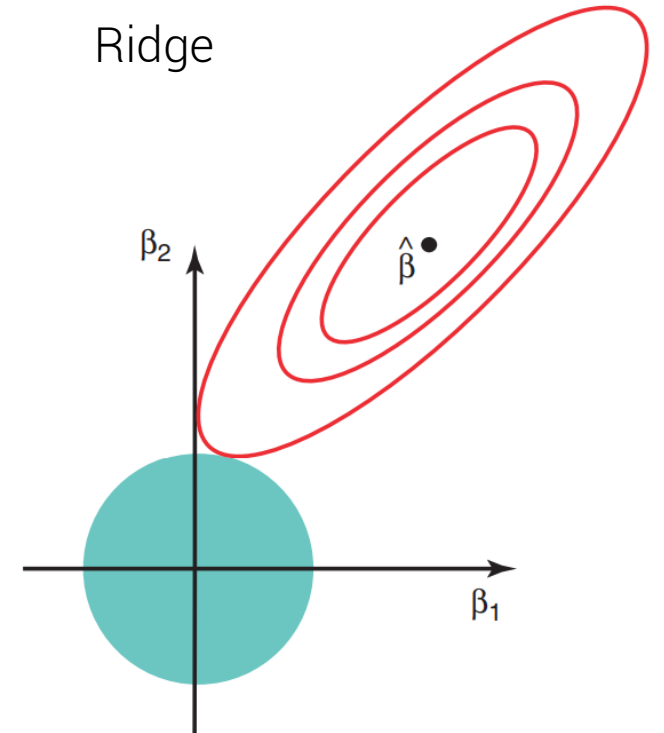
$$\text{RSS} + \lambda \sum_{j=1}^p |\beta_j|$$

- This is my preferred shrinkage method

Lasso



Ridge





# CASE STUDY

## In the Market

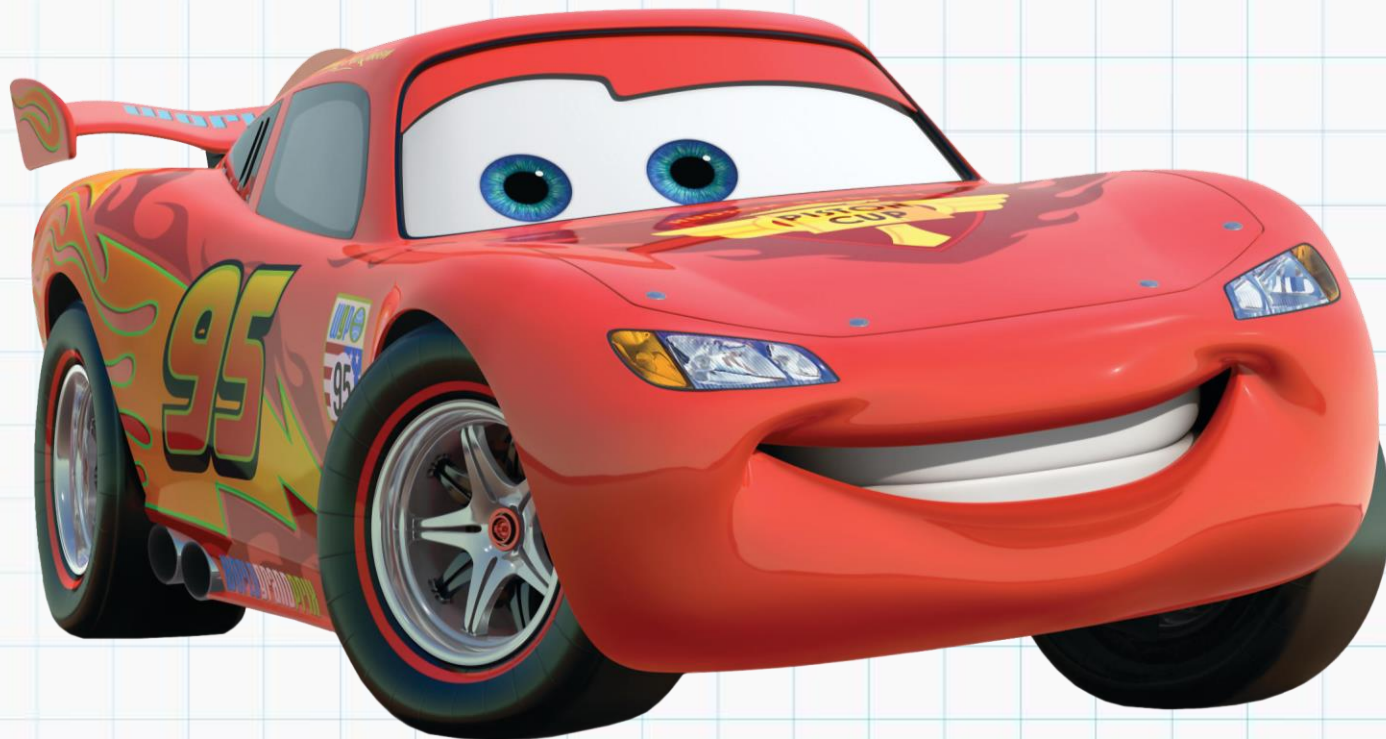
Revisiting our Boston home price prediction....



# CASE STUDY

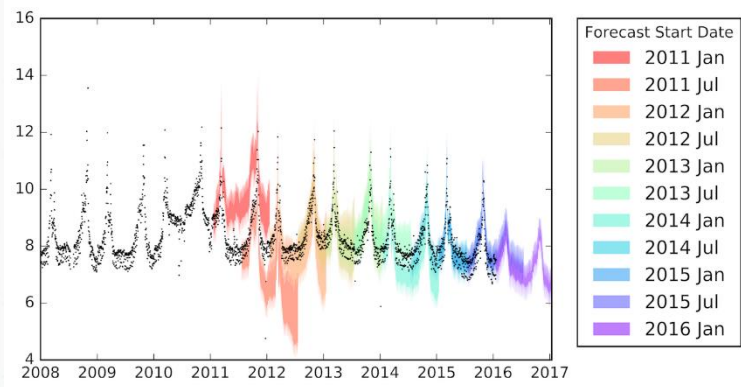
Ka-Chow!

Let's fit some regression models to predict MPG for different cars



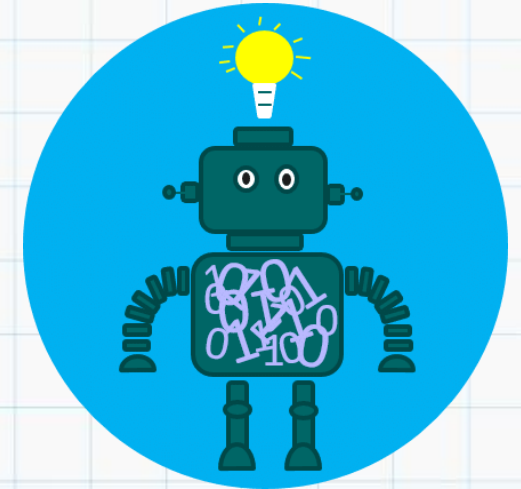
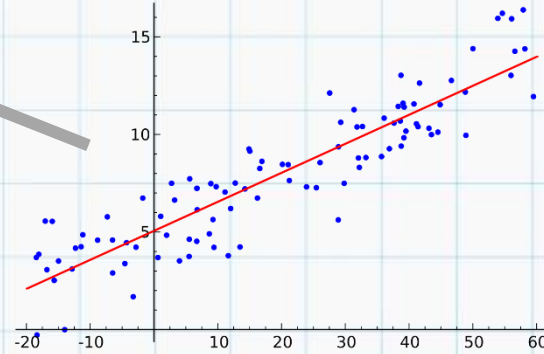
# LINEAR REGRESSION

A Foundation of Data Science



Time Series Analytics

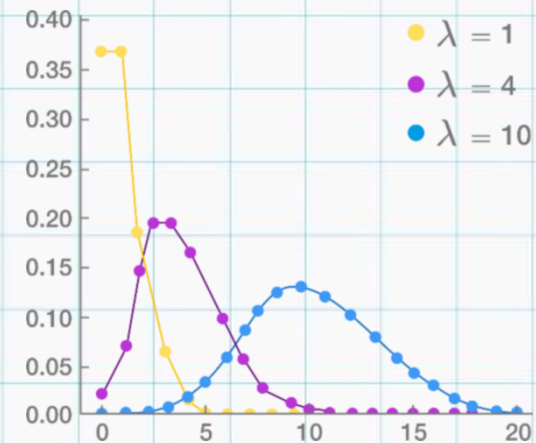
Linear Regression



Machine Learning



Neural Networks



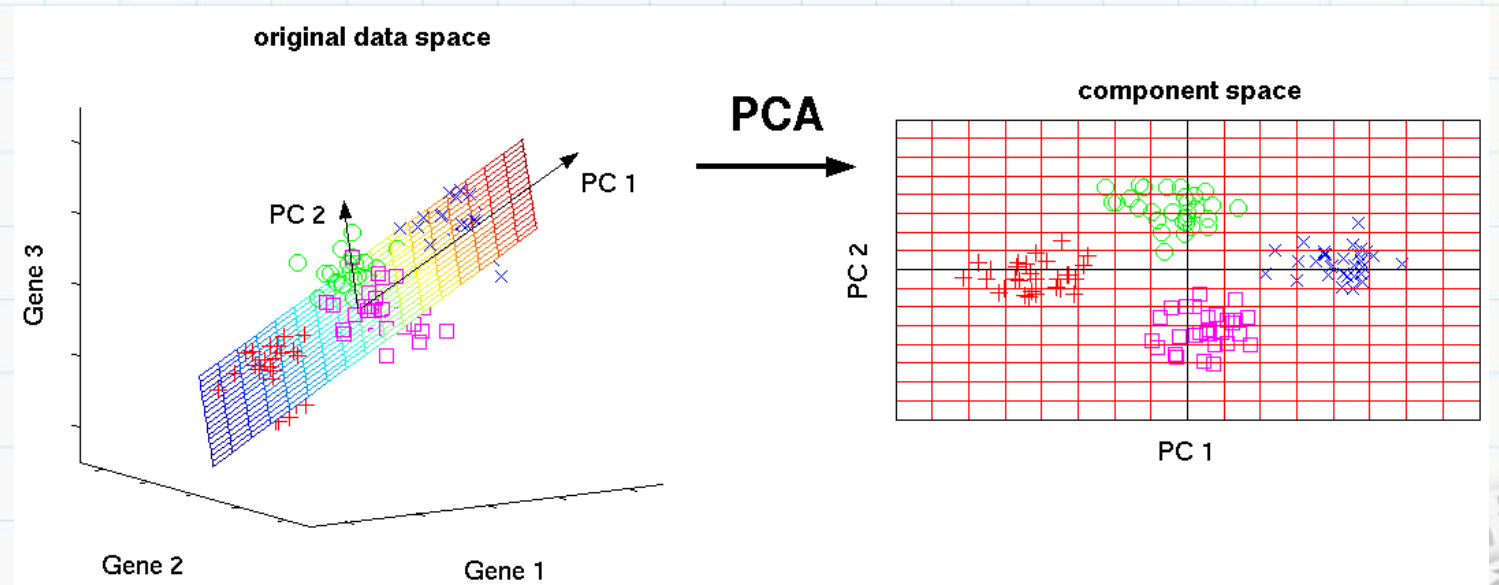
Count  
Data  
Analysis

# LINEAR REGRESSION

## A Foundation of Data Science

Additional \*Important\* Topics:

- Residual Analysis
  - Normal Q-Q
  - Leverage
  - Cook's Distance
- Nonlinear Regression
  - Regression Splines
- Model/Variable Selection
  - AIC, BIC,  $C_p$
  - Subsetting
- Dimensionality Reduction
  - Principal Components Analysis

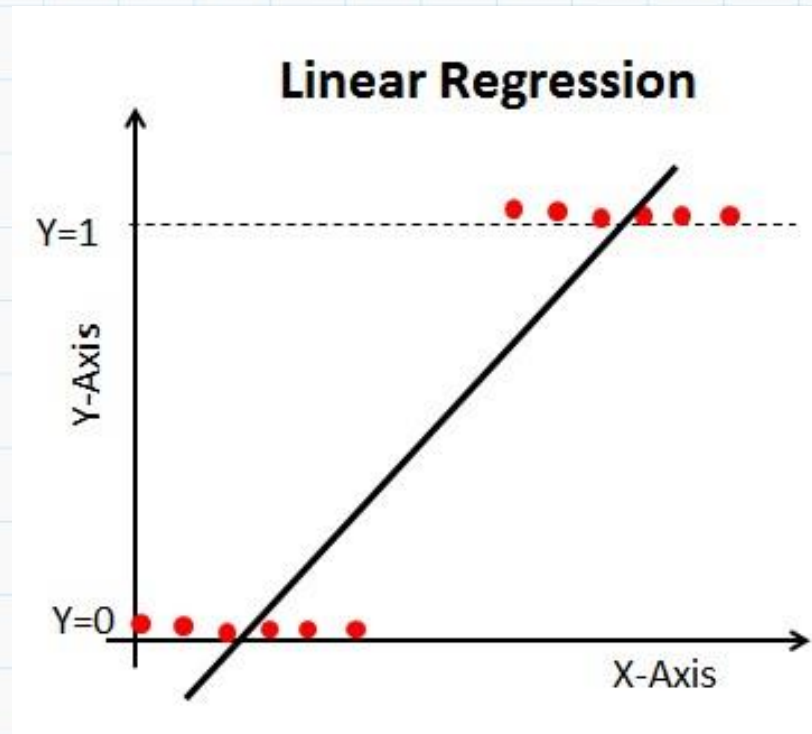




# What about qualitative responses?

I want to perform a linear regression to predict if I'll get accepted into a college or not.  $Y=1$  if YES and  $Y=0$  if NO.

Dummy Variables

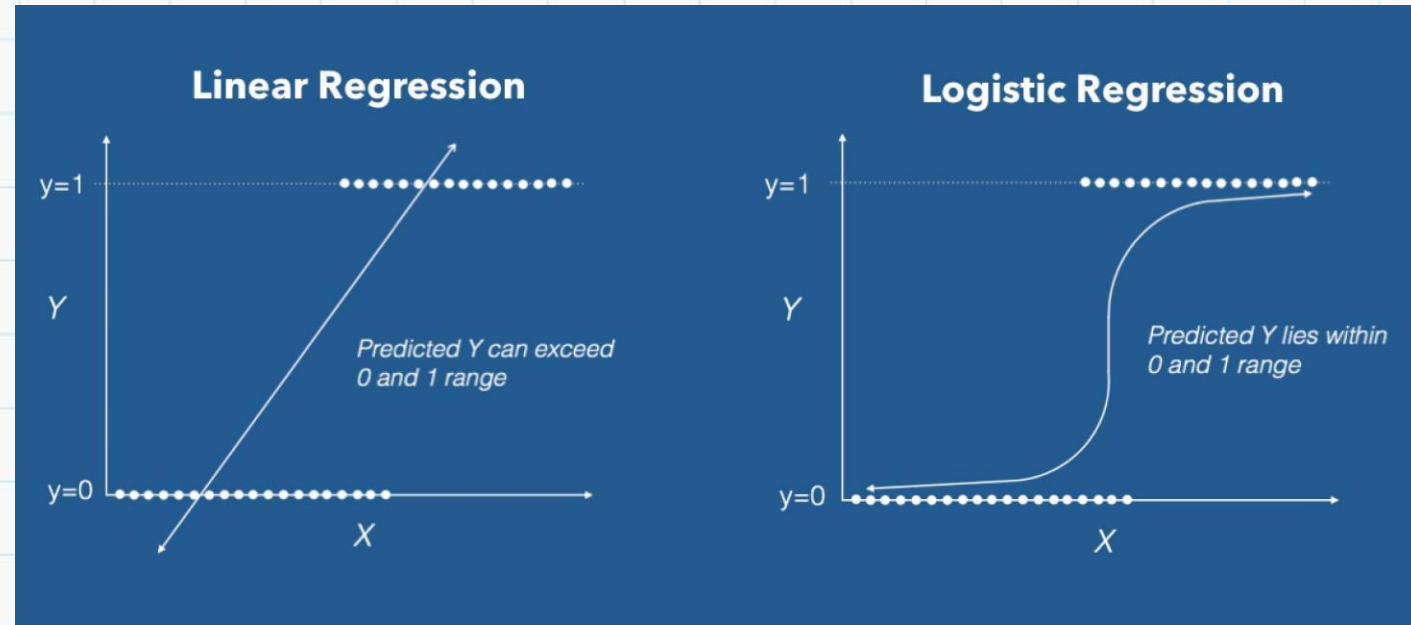


What could be wrong with this approach?

# LOGISTIC REGRESSION

## Classification

- A simple classification method for binary categorical responses
- Predicts the probability of an outcome that can only have two values
- Linear regression is unbounded; logistic regression only falls within  $[0,1]$
- Typically for predicting a TRUE/FALSE or YES/NO problem
  - An email is spam (1) or not spam (0)
  - Will I get accepted into a college (1) or not (0)?



# LOGISTIC REGRESSION

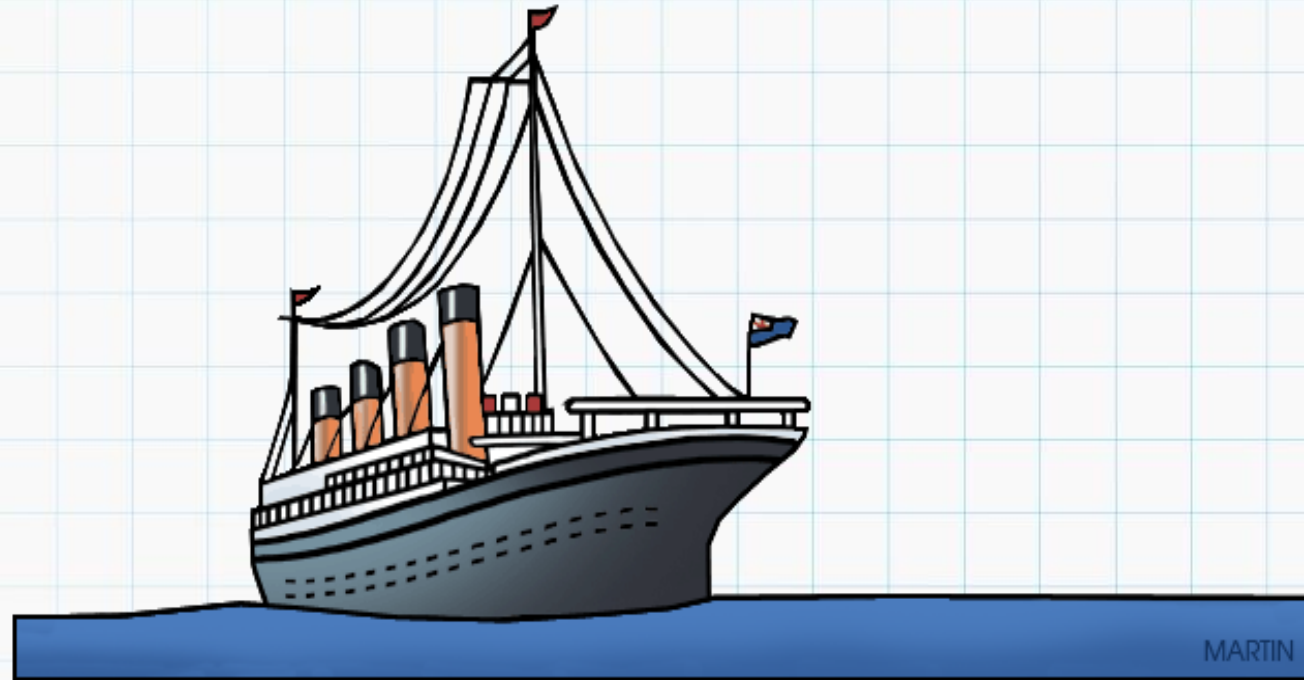
## Odds and Log-Odds

- I will derive the logistic regression equations on the board
- The Odds
  - Value of odds close to 0 = very low probabilities  
 $\infty$  = very high probabilities
- The Log-Odds / Logit
  - Coefficients are estimated by the maximum likelihood estimation
  - Essentially,  $\beta_0, \beta_1$  are determined such that  $p(x) = 1$  when an observation belongs to a class  
 $p(x) = 0$  when it does NOT belong to a class
- Not all values of  $p(x) = 0$  or 1; we need to define a threshold. Usually, it's 0.5
  - If  $p(x) < 0.5$ , we round down to  $p(x) = 0$  and state that the observation does NOT belong to a class

# CASE STUDY

## Sinking Ship

Would you survive the Titanic?

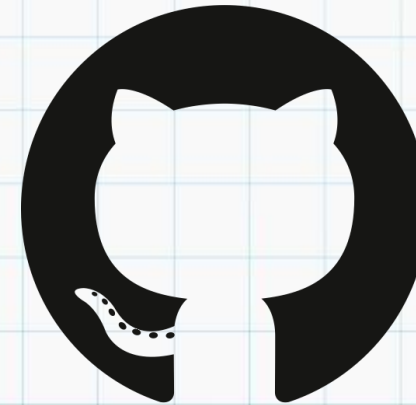




# CONNECT WITH ME



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@diramputri



[diramputri@gmail.com](mailto:diramputri@gmail.com)

# THAT'S ALL FOLKS!

Thank You



Association for  
Computing Machinery



**QUESTIONS?**