

**Please Add Your Name  
and Email to the google sheet:**

[https://docs.google.com/spreadsheets/d/  
1KeARd5uDzs5ZBTWhtMEhYm2I4ZzQXMcBpcjRQTbLReI/edit?usp=sharing](https://docs.google.com/spreadsheets/d/1KeARd5uDzs5ZBTWhtMEhYm2I4ZzQXMcBpcjRQTbLReI/edit?usp=sharing)

(So I can send you the class materials)



# **Python and Machine Learning**

By Craig Sakuma

# Introductions

Craig Sakuma

- Founder of QuantSprout
- Instructor at General Assembly
- MBA from Wharton
- B.Eng from Northwestern University

# Fun Fact

Developed a novelty BBQ product that was featured in USA Today



# Class Introductions

- Name
- What's your job?
- How do you plan to apply skills from the bootcamp?
- Fun Fact

# Course Structure

- Lectures on topics
  - Interaction is good
  - Feel free to ask questions
  - If there's not enough time to cover questions, we'll put it in a parking lot for after class
- Hands on exercises
  - Pair programming
  - Mix up partners

# Objectives for Class

- Get strong foundation of Python and Machine Learning
- Immediately use skills at work
- Remove barriers/frustration
- Develop skills to be self-sufficient after class
  - Learn and explore new topics
  - Troubleshoot problems

# Course Outline

## Day 1

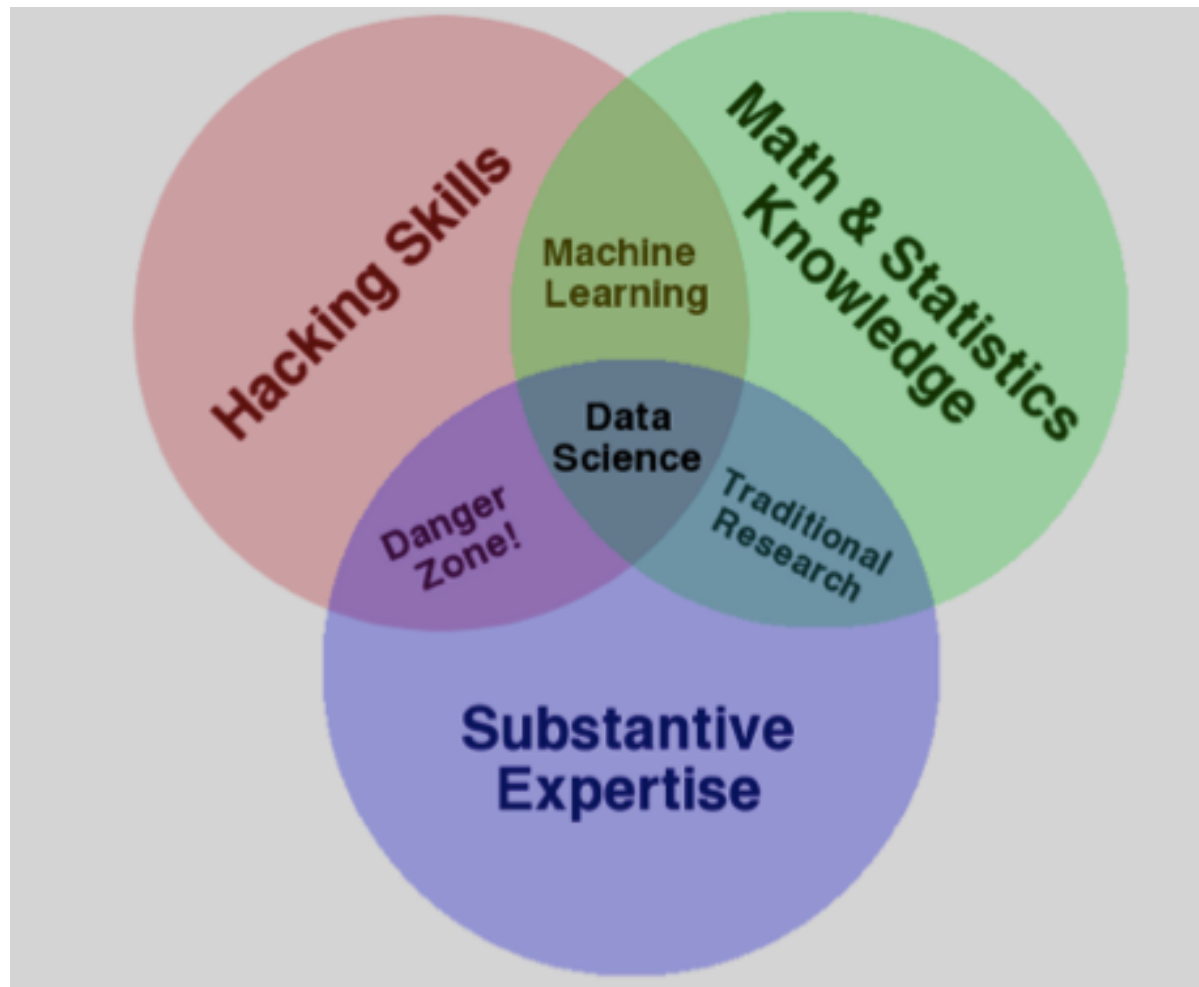
- Overview of Data Science
- Intro to Pandas / Exploring Data
- Cleaning Data
- Classification Algorithms

## Day 2

- Cross-validation
- Regression Algorithms
- Regularization



# What is Data Science?



# Data Science is OSEMN (Awesome)

Obtain Data

Scrub Data

Explore

Model Algorithms

interpret Results

**80%**

**20%**

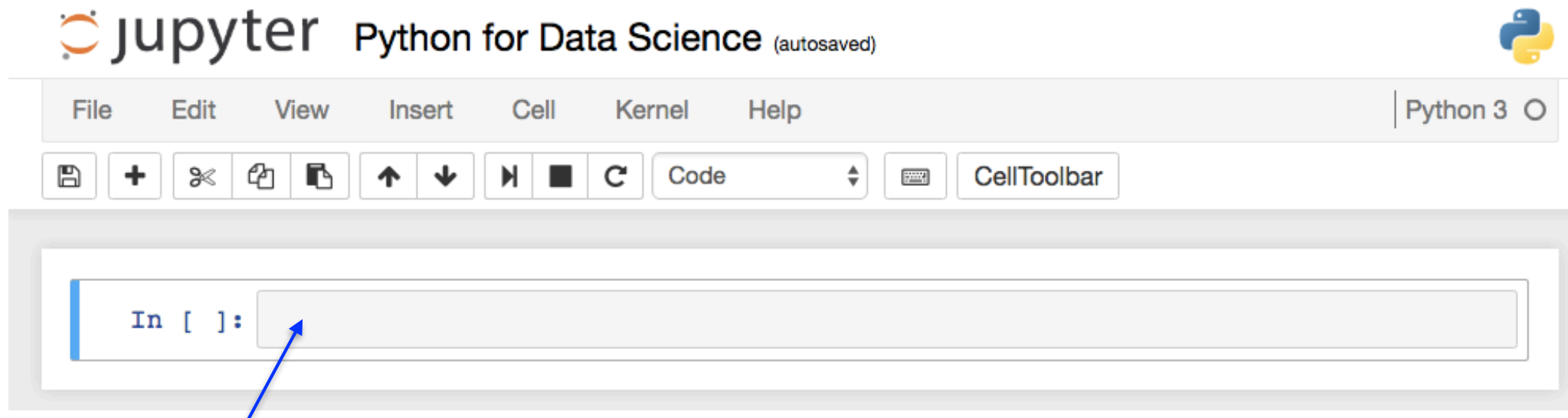
**Majority of time  
is spent  
data munging**

# Why Python?

- Readability
- Flexibility
- Supports multiple programming paradigms
  - Procedural
  - Functional
  - Object oriented

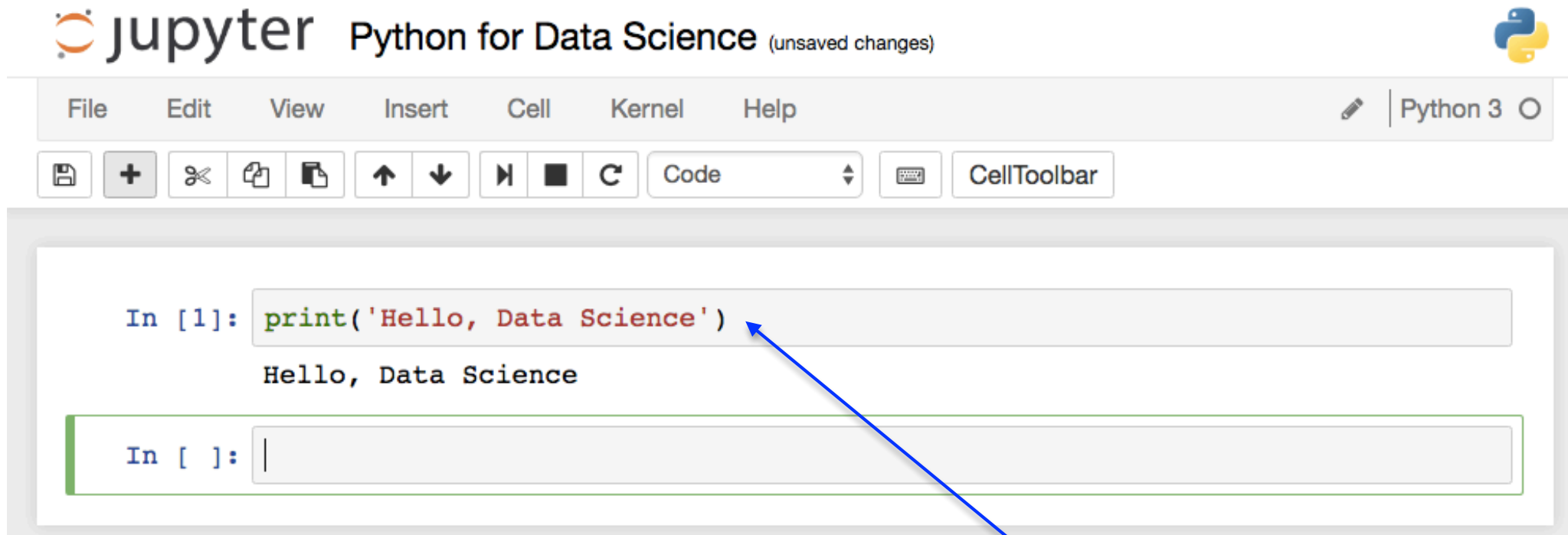
**Libraries of Tools for Data  
Analysis**

# Jupyter Notebook Basics



Enter code here

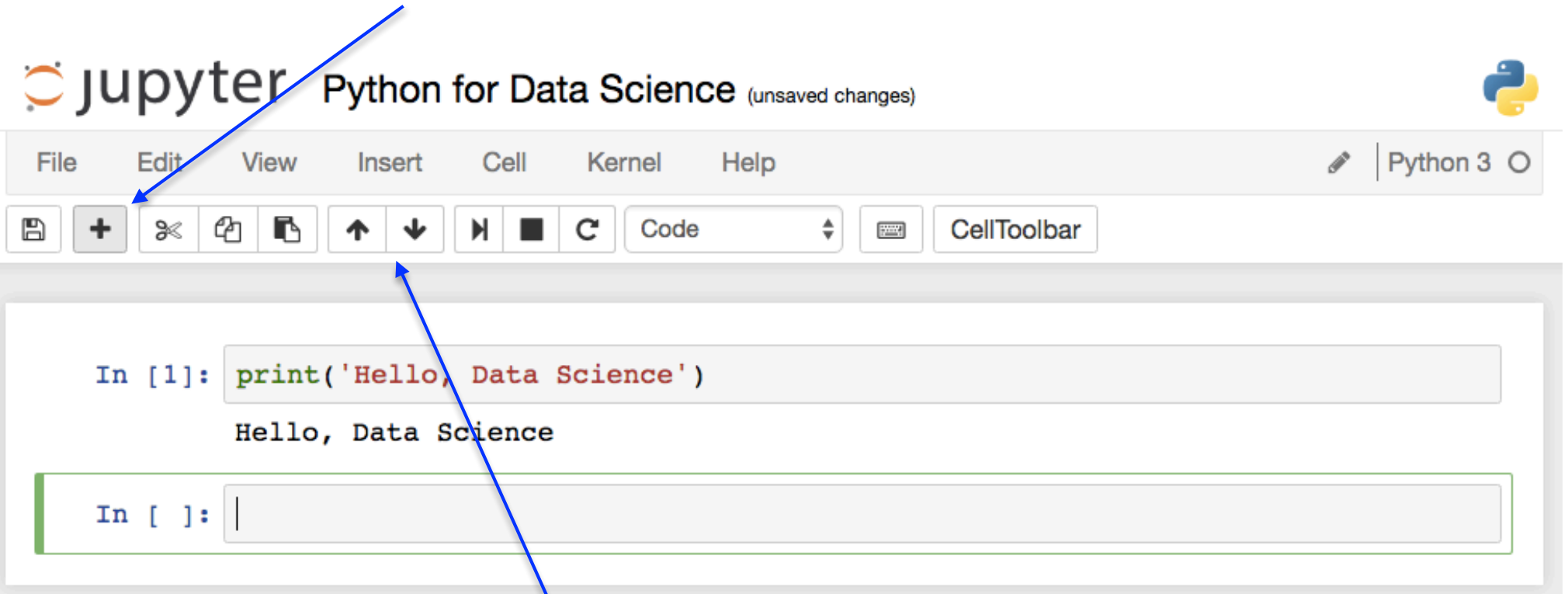
# Jupyter Notebook Basics



Shift + Enter runs code  
and returns results

# Jupyter Notebook Basics

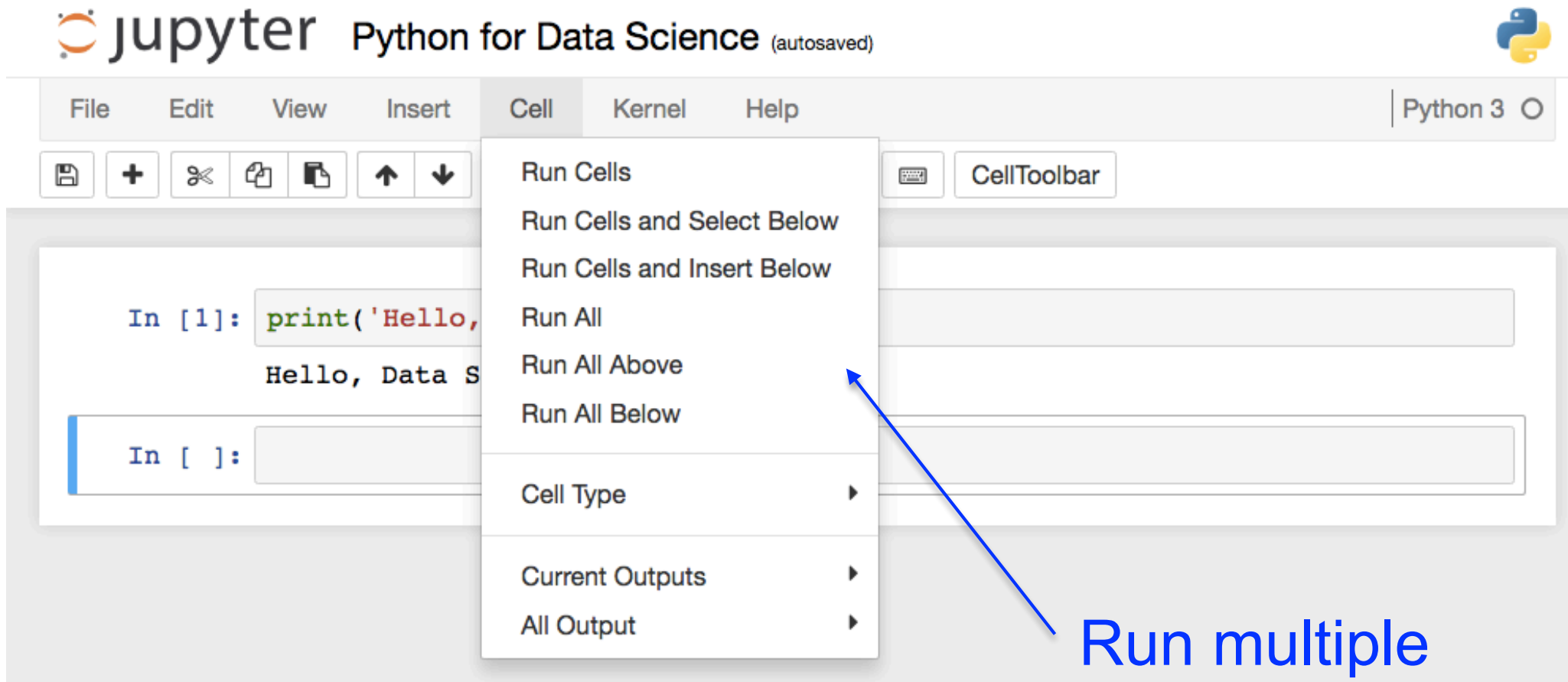
Add more code blocks



The screenshot displays the Jupyter Notebook interface. At the top, the title bar reads "jupyter Python for Data Science (unsaved changes)" with a Python logo on the right. Below this is a menu bar with options: File, Edit, View, Insert, Cell, Kernel, and Help. To the right of the menu bar is a status bar showing "Python 3" and a refresh icon. Below the menu bar is a toolbar containing icons for saving, adding a new cell, cutting, copying, pasting, moving up/down, running, and a dropdown menu currently set to "Code". A "CellToolbar" button is also present. The main workspace contains two code blocks. The first block, labeled "In [1]:", contains the code `print('Hello, Data Science')` and its output, "Hello, Data Science". The second block, labeled "In [ ]:", is empty and currently selected, indicated by a green border. Two blue arrows point to the interface: one from the text "Add more code blocks" to the "+" icon in the toolbar, and another from the text "Re-order code blocks" to the up/down arrow icons in the toolbar.

Re-order code blocks

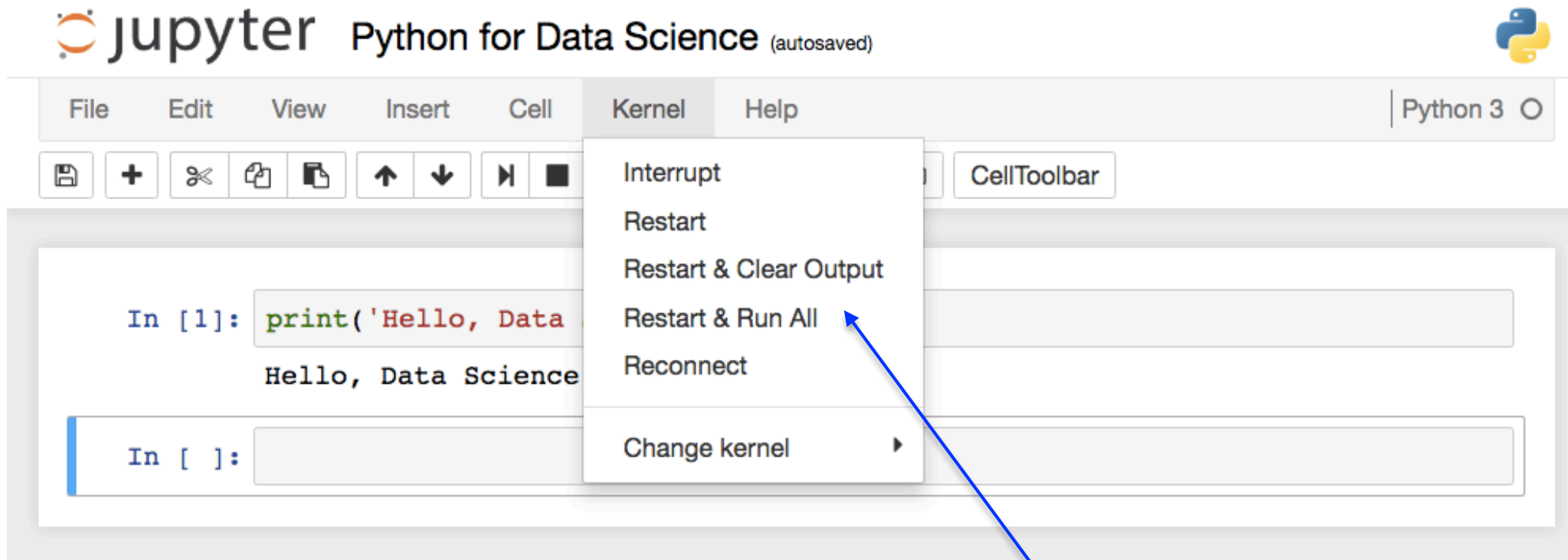
# Jupyter Notebook Basics



The screenshot displays the Jupyter Notebook interface. At the top, the header reads "Jupyter Python for Data Science (autosaved)" with the Python logo on the right. Below the header is a menu bar with "File", "Edit", "View", "Insert", "Cell", "Kernel", and "Help". The "Cell" menu is currently open, showing a list of options: "Run Cells", "Run Cells and Select Below", "Run Cells and Insert Below", "Run All", "Run All Above", "Run All Below", "Cell Type", "Current Outputs", and "All Output". A blue arrow points from the text "Run multiple code blocks" to the "Run Cells" option in the menu. The main workspace shows two code cells. The first cell contains the code `In [1]: print('Hello, Hello, Data S`. The second cell is empty and labeled `In [ ]:`. A "CellToolbar" is visible on the right side of the workspace.

Run multiple  
code  
blocks


# Jupyter Notebook Basics




Restart  
Notebook to  
Clear Memory



# Jupyter Notebook Basics

 **jupyter** Python for Data Science (autosaved)



File Edit View Insert Cell Kernel Help Python 3 

New Notebook  
Open...  
Make a Copy...  
Rename...  
Save and Checkpoint  
Revert to Checkpoint  
Print Preview  
Download as  
Trusted Notebook  
Close and Halt

↑ ↓ ⏮ ■ ⏭ Code CellToolbar

```
'Hello, Data Science')
```

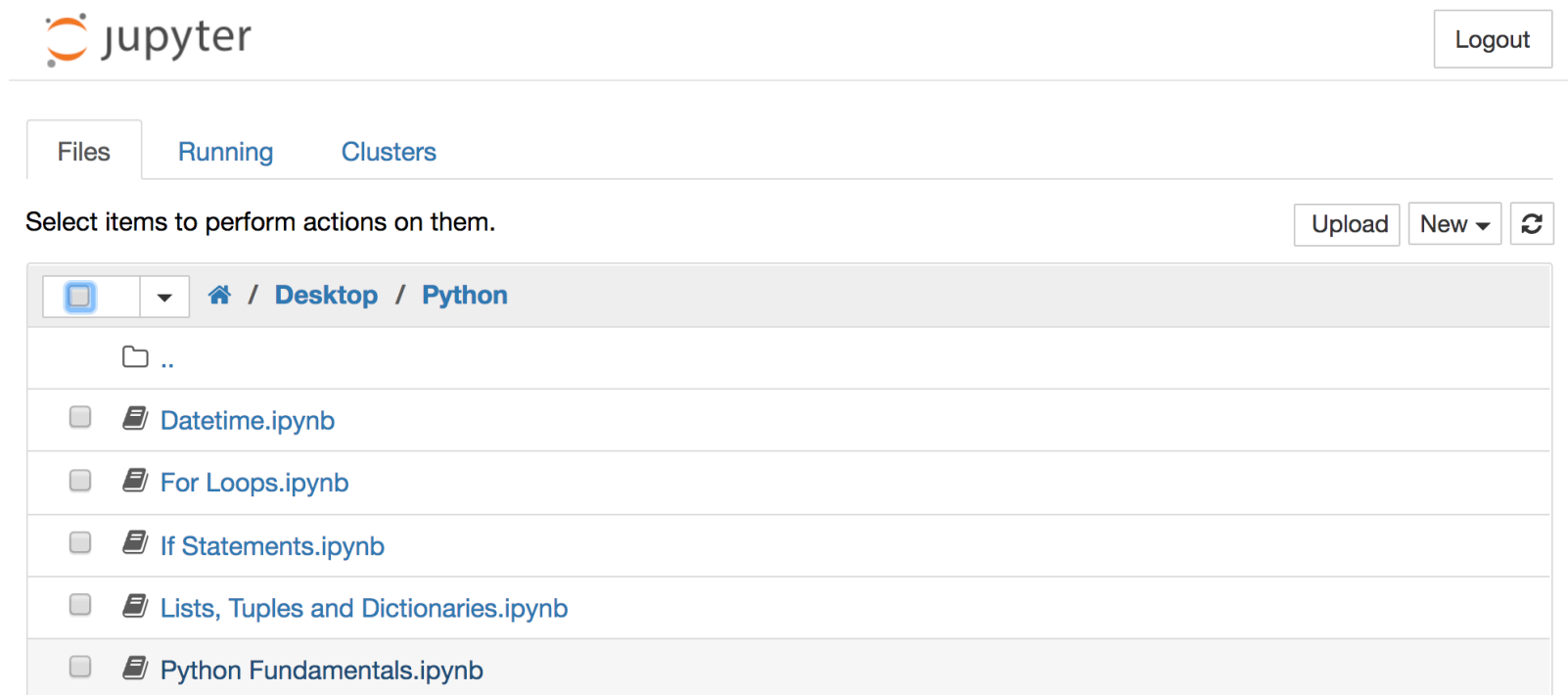
Data Science

IPython Notebook (.ipynb)  
Python (.py)  
HTML (.html)  
Markdown (.md)  
reST (.rst)  
PDF via LaTeX (.pdf)

Save or Download File

# Set Up for Jupyter Notebooks

- Create a folder on your Desktop Called “python\_ml”
- Copy the files from Slack into the folder
- Launch jupyter notebook



# Intro to Pandas

- Primary objects in Pandas are DataFrames
- DataFrames are like tables
  - Contain rows and columns of data
  - Columns have names
  - Rows have index values
- Pandas has easy functions for importing and exporting data
  - CSV files
  - Excel spreadsheets
  - SQL queries

# Data Cleaning

- Missing Values
  - Identify Missing Values
  - Drop Values
  - Impute Values
    - Zero
    - Mean
- Categorical Data
  - Convert Text to Numbers
  - Encode Labels as Boolean Variables

# What is Machine Learning?

“A field of study that gives computers the ability to learn without being explicitly programmed.” (1959)

- Arthur Samuel, AI Pioneer

# Supervised vs. Unsupervised

## Supervised

- Requires truth set of data for training algorithms
- Examples:
  - Forecasting sales
  - Classifying spam

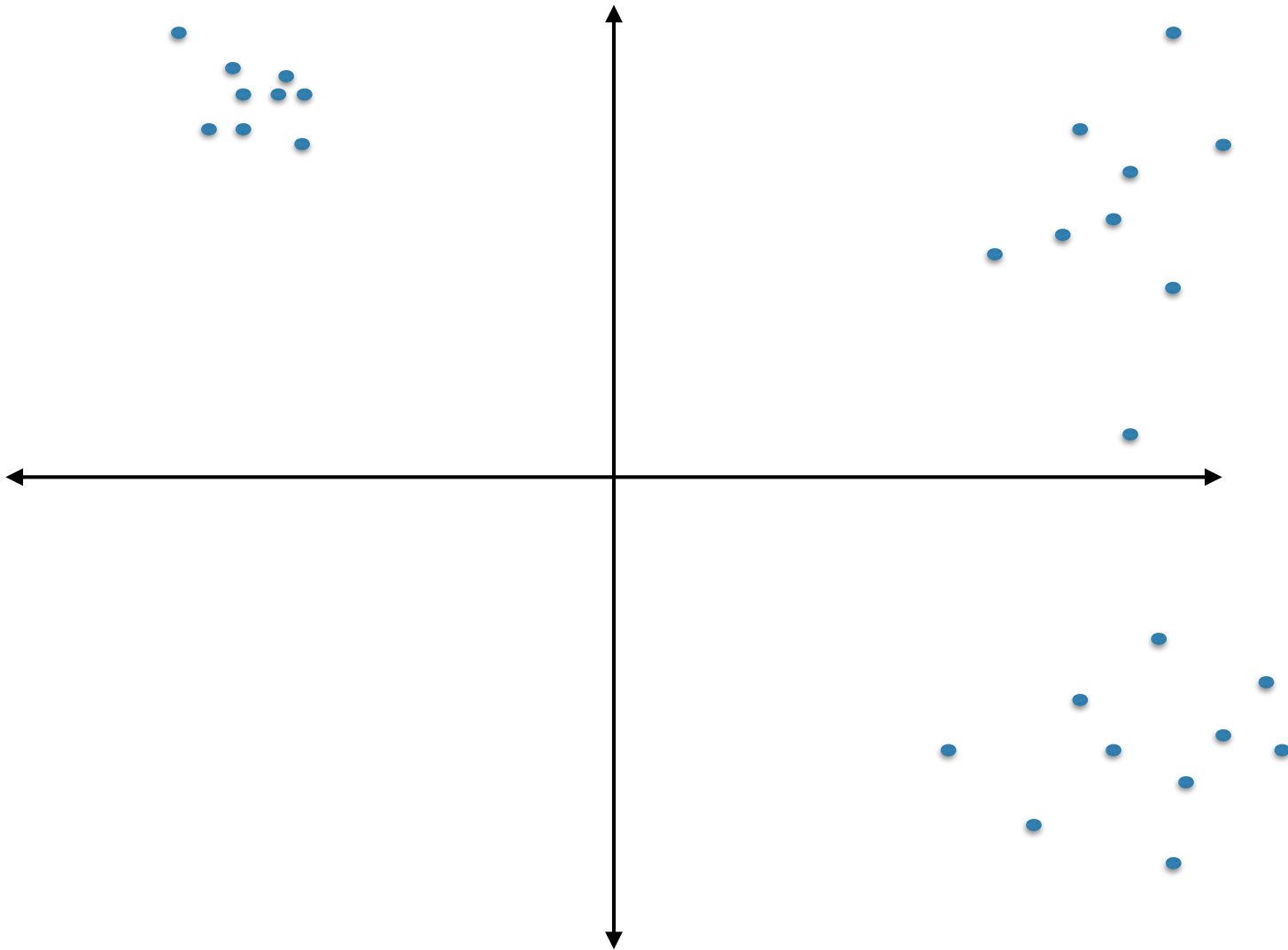
## Unsupervised

- Autonomous algorithm that requires no training
- Examples:
  - Cluster analysis
  - Anomaly detection

# Machine Learning Categories

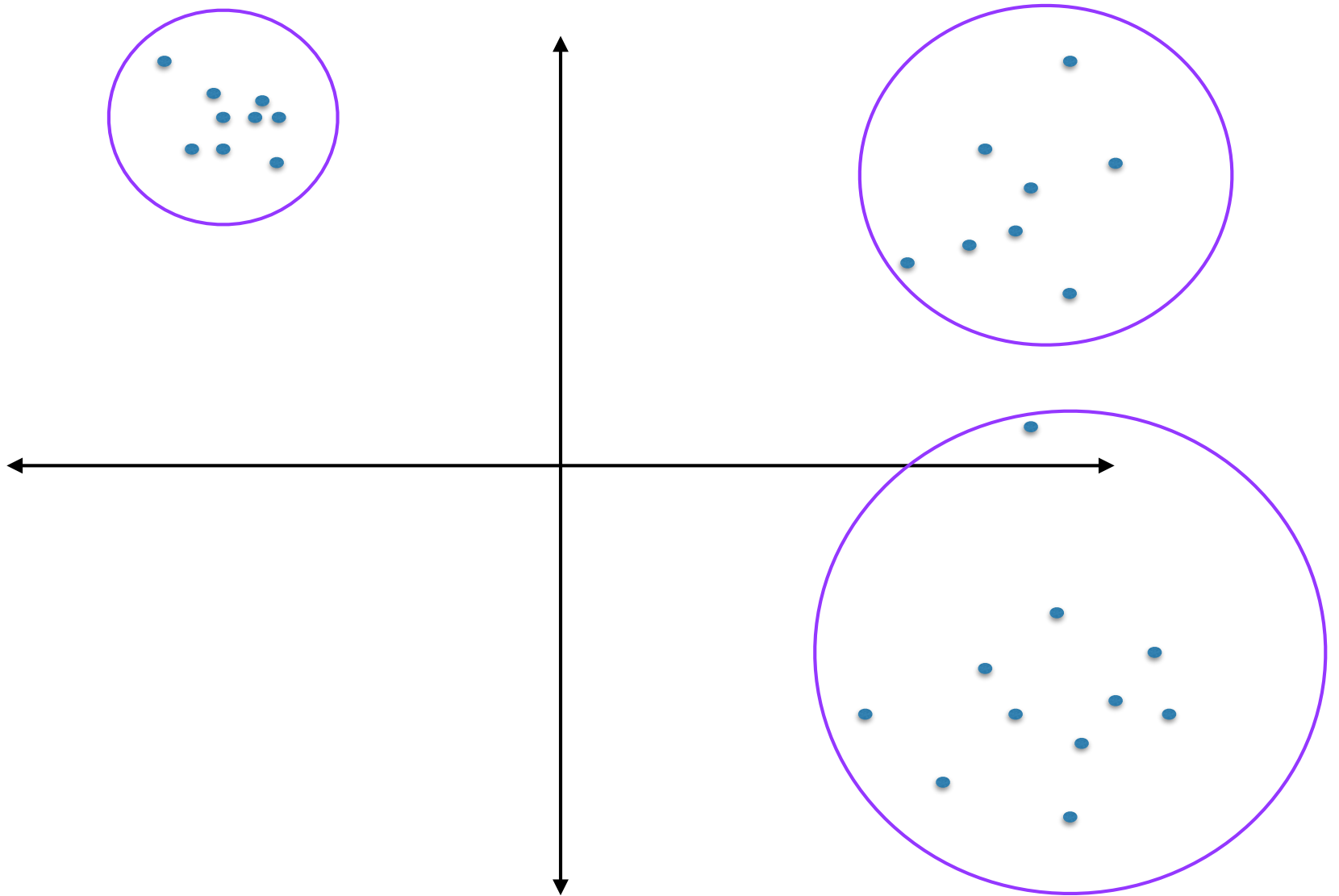
|              | Continuous          | Categorical    |
|--------------|---------------------|----------------|
| Supervised   | Regression          | Classification |
| Unsupervised | Dimension Reduction | Clustering     |

# Clustering



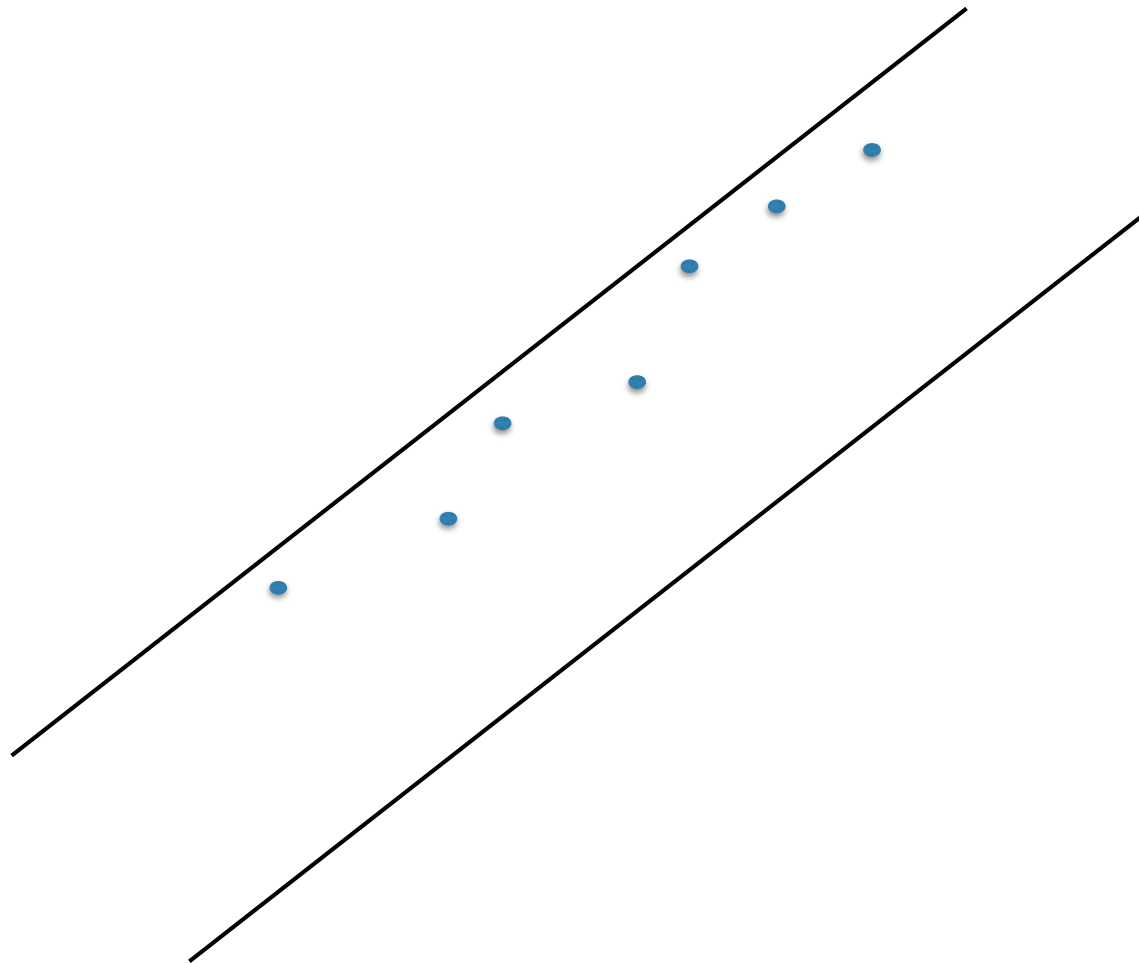


# Clustering



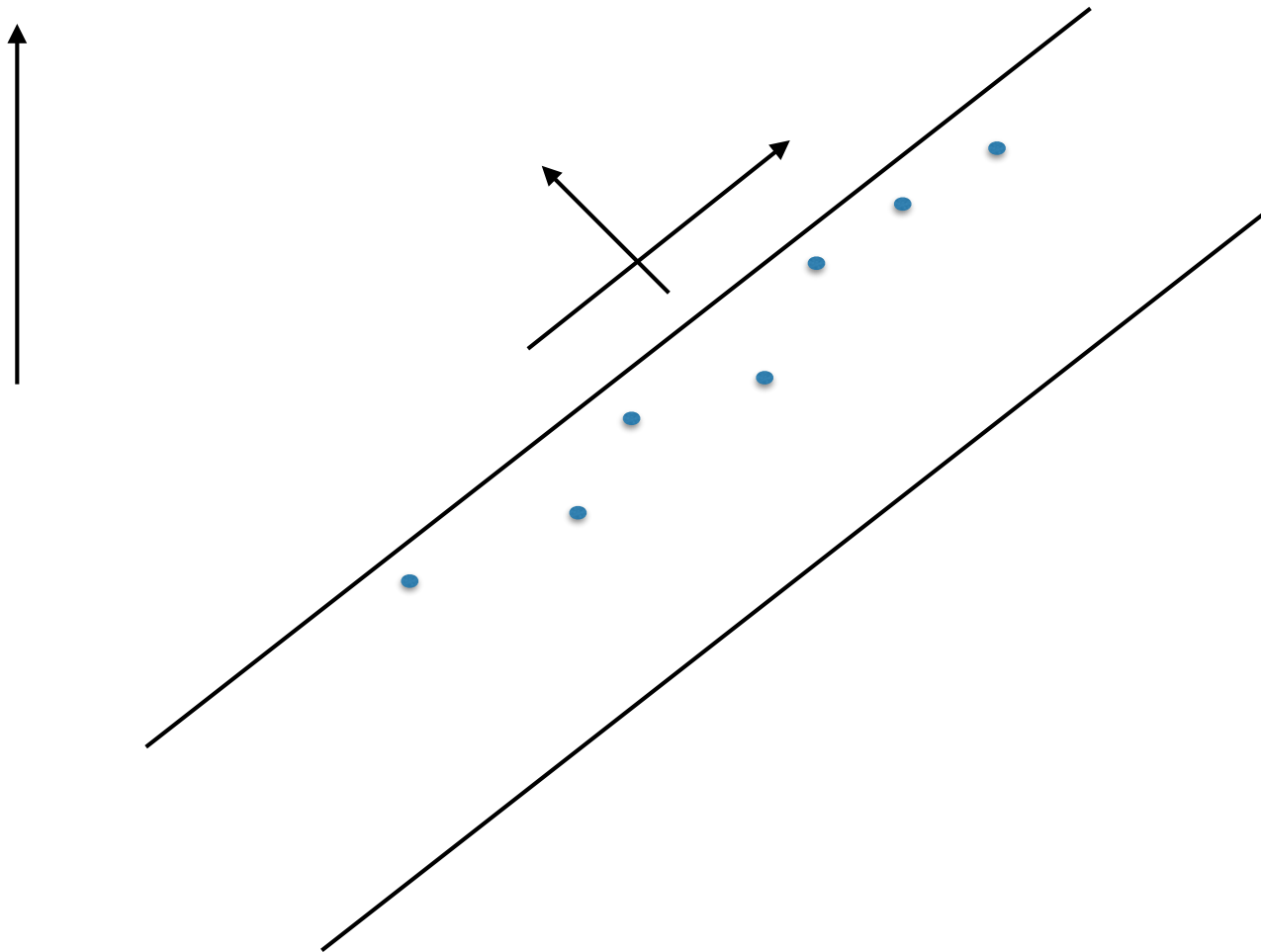
# Dimensionality Reduction

North



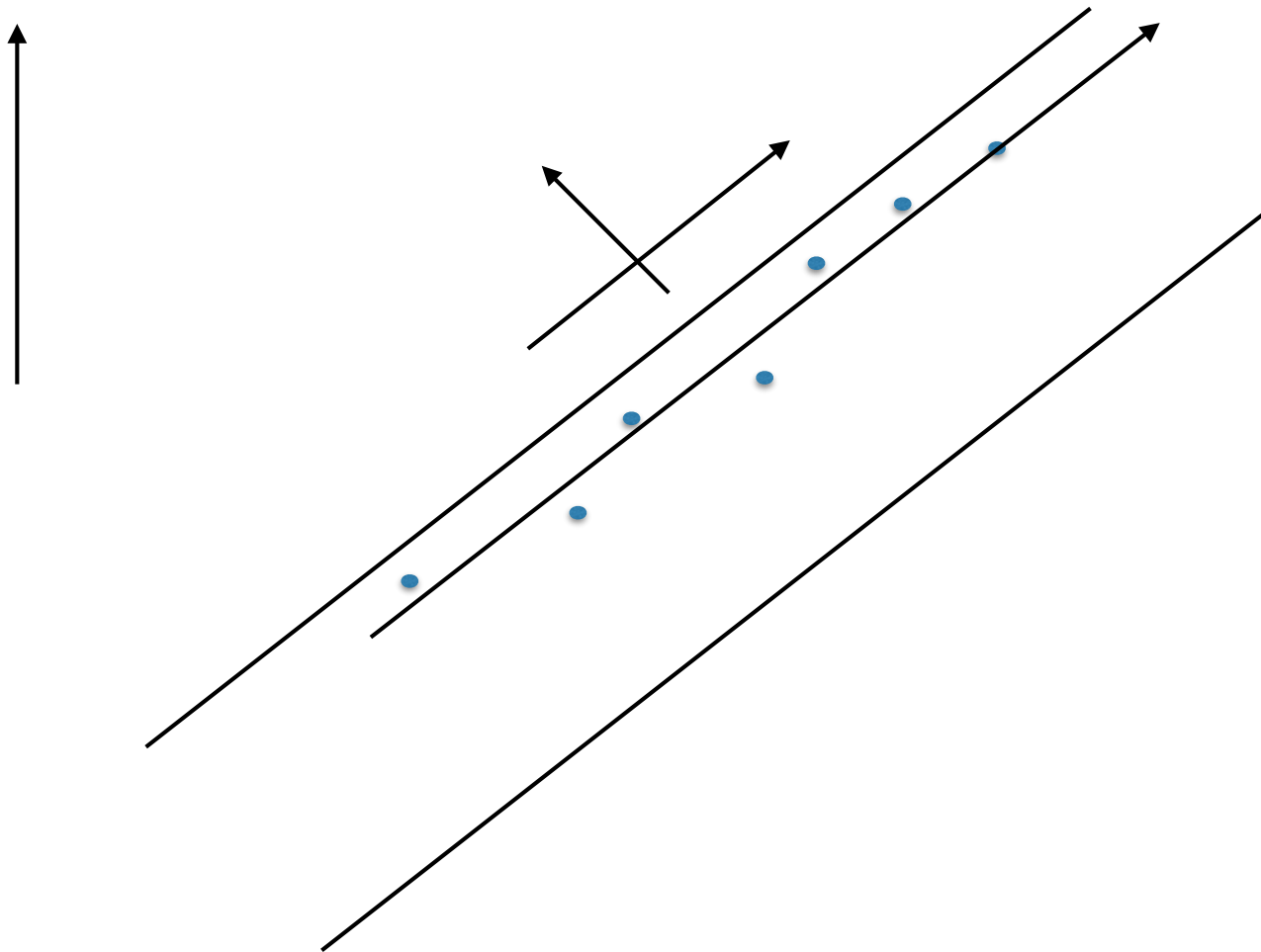
# Dimensionality Reduction

North



# Dimensionality Reduction

North



# Supervised Training

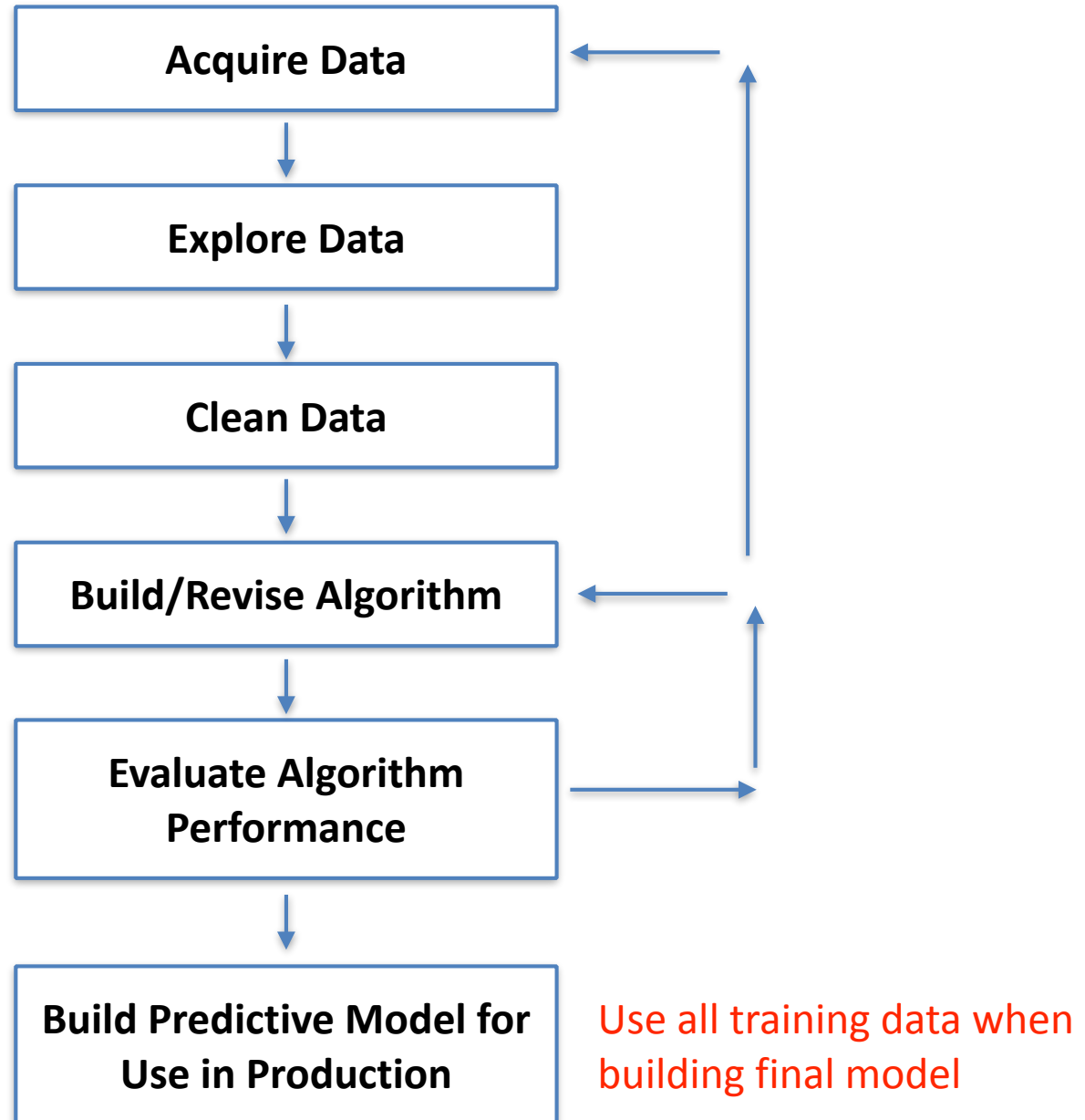
- Training Set
  - Data used to create coefficients for model
  - For example, data set used to create a linear regression
- Test Set
  - Data used to measure performance of trained model

# Training Set

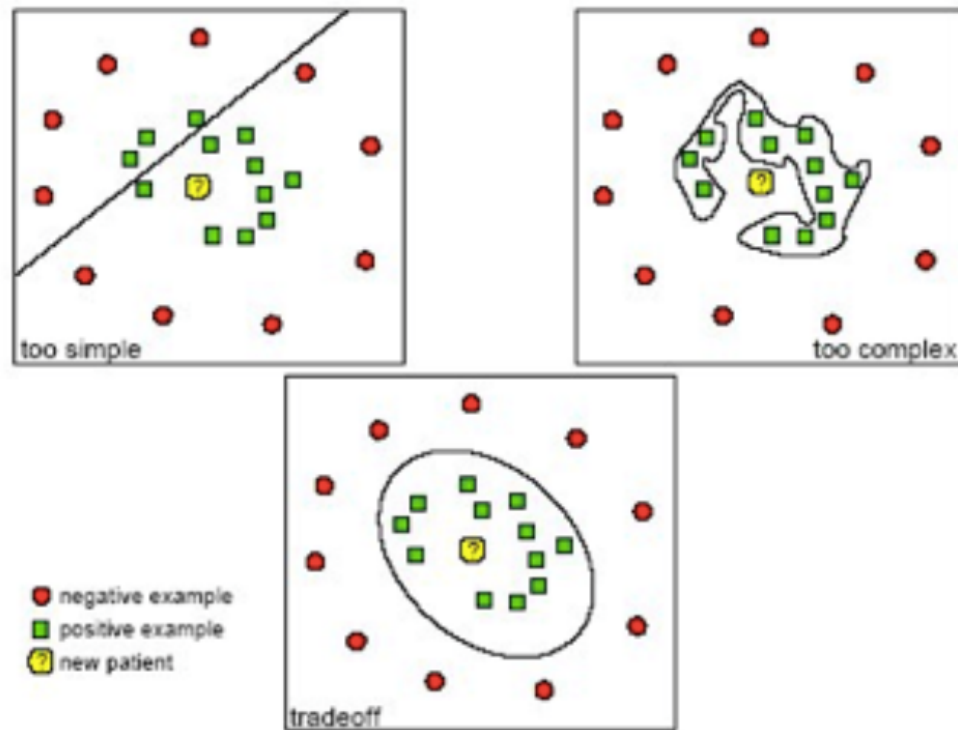
| <i>Age</i> | <i>Sex</i>    | <i>Pclass</i> | <i>Survived?</i> | Classes<br>(target) |
|------------|---------------|---------------|------------------|---------------------|
| <i>25</i>  | <i>Male</i>   | <i>3</i>      | <i>FALSE</i>     |                     |
| <i>17</i>  | <i>Female</i> | <i>1</i>      | <i>TRUE</i>      |                     |
| <i>40</i>  | <i>Male</i>   | <i>2</i>      | <i>FALSE</i>     |                     |
| <i>9</i>   | <i>Female</i> | <i>2</i>      | <i>TRUE</i>      |                     |

Independent Variables  
(features)

# Data Science Process



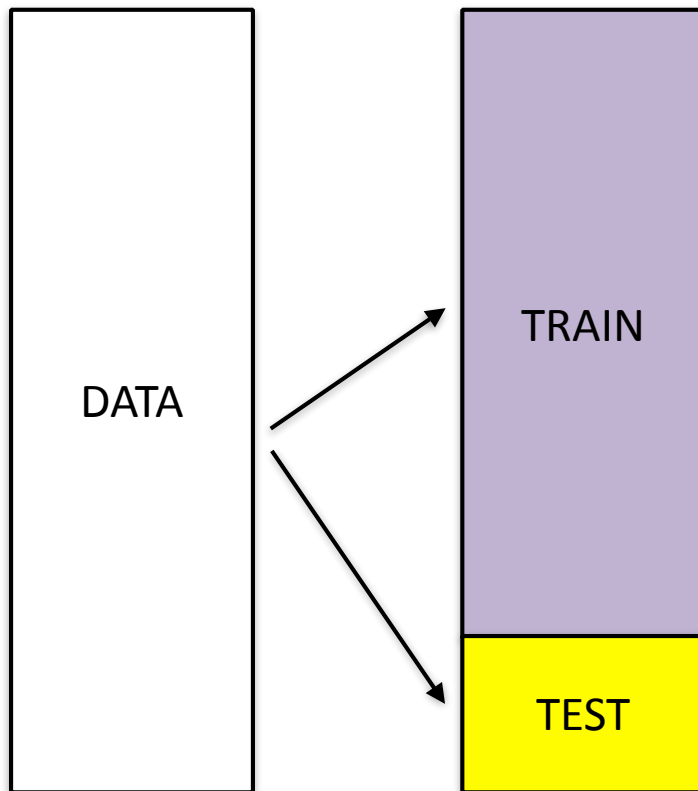
# Underfitting and Overfitting





# Cross-validation

## Split Data Set



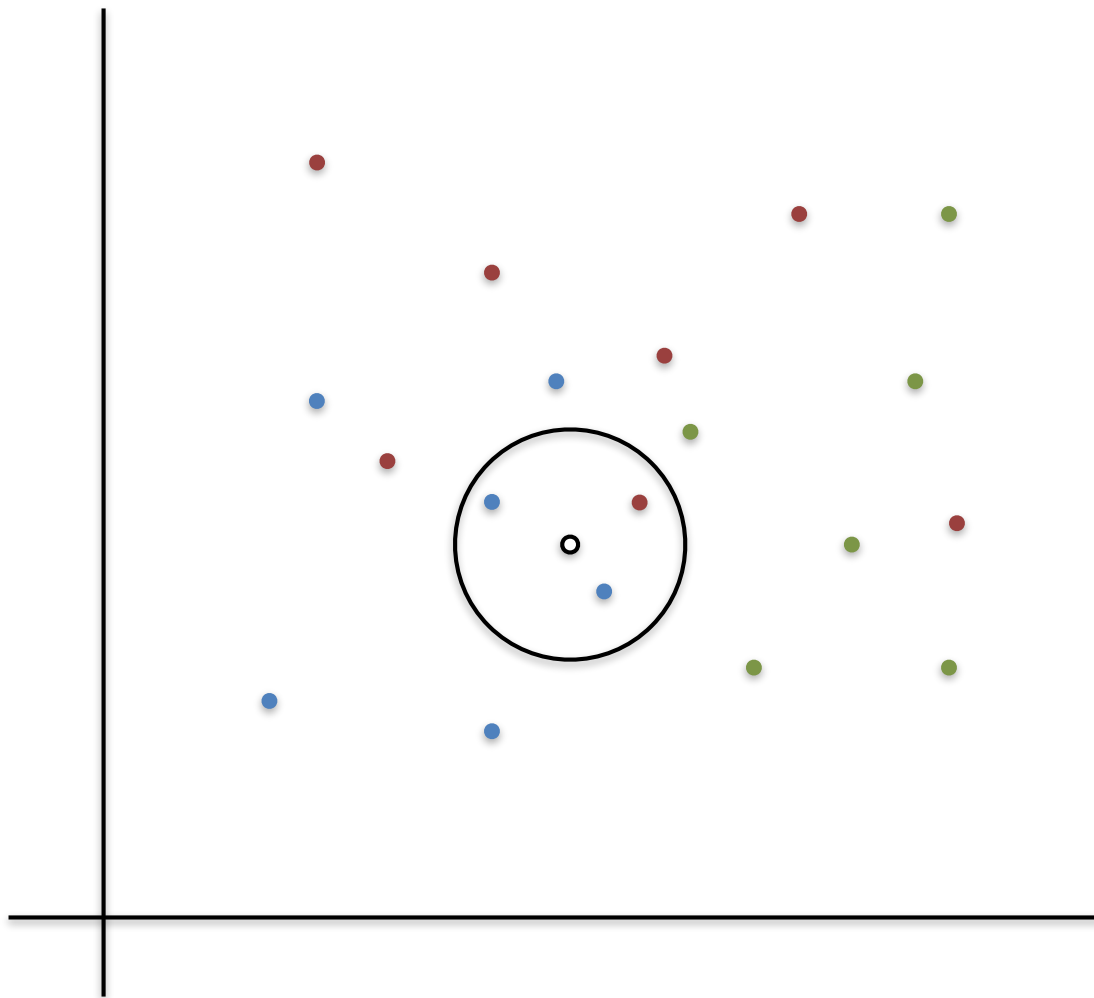
- Separate the data into two groups
- Use part of data to train the model
- Use trained model to predict out come for test data
- Compare predictions with actual results

**Measure model performance on accuracy of predictions**

# Classification Algorithms

- Logistic Regression
- Naive-Bayes
- Decision Trees
- Support Vector Machines
- Neural Networks
- K-Nearest Neighbors
- Random Forest

# K Nearest Neighbors



Suppose you want to predict the white dot

1. Pick a value for  $k$
2. Find colors of the  $k$  nearest neighbors
3. Assign the most common color

# KNN Considerations

- Scaling of Data has large impact on algorithm (normalization is frequently used)
- Adjust the parameters of the algorithm
  - Number of neighbors
  - Treat data points uniformly or weighted by distance
- Can become computationally expensive at large scale

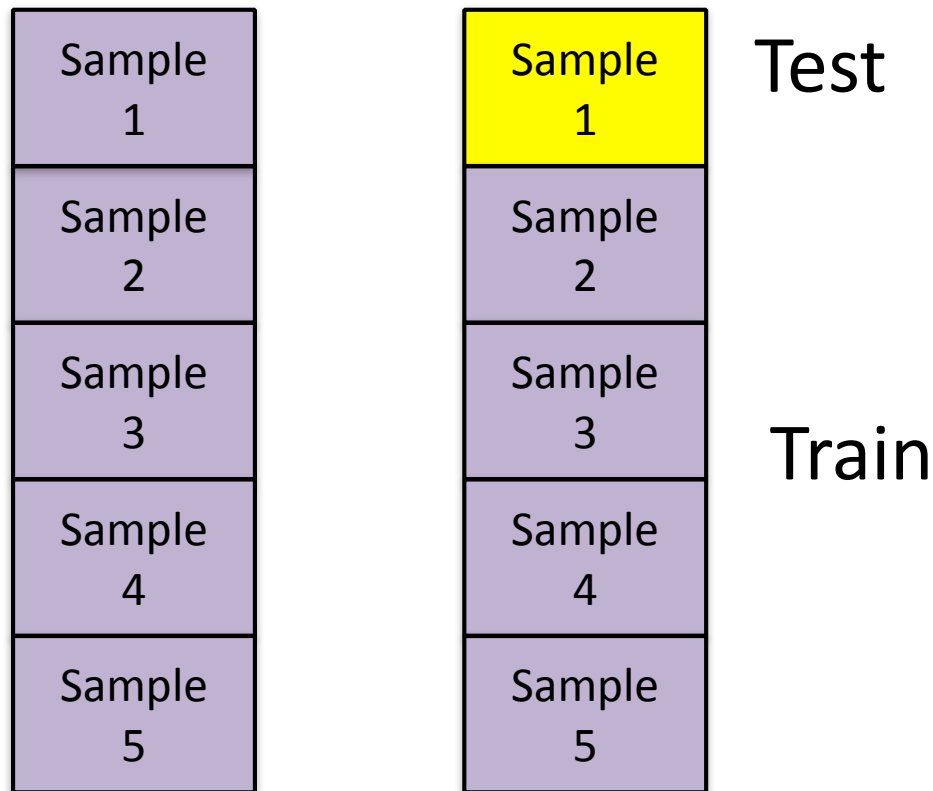
# Evaluating Algorithms

- Model performance will vary based on how you split the data into training and testing groups
- Taking an average of the model performance across different splits improves the measurement

## KFold Cross-validation

# K-Folds Cross-validation

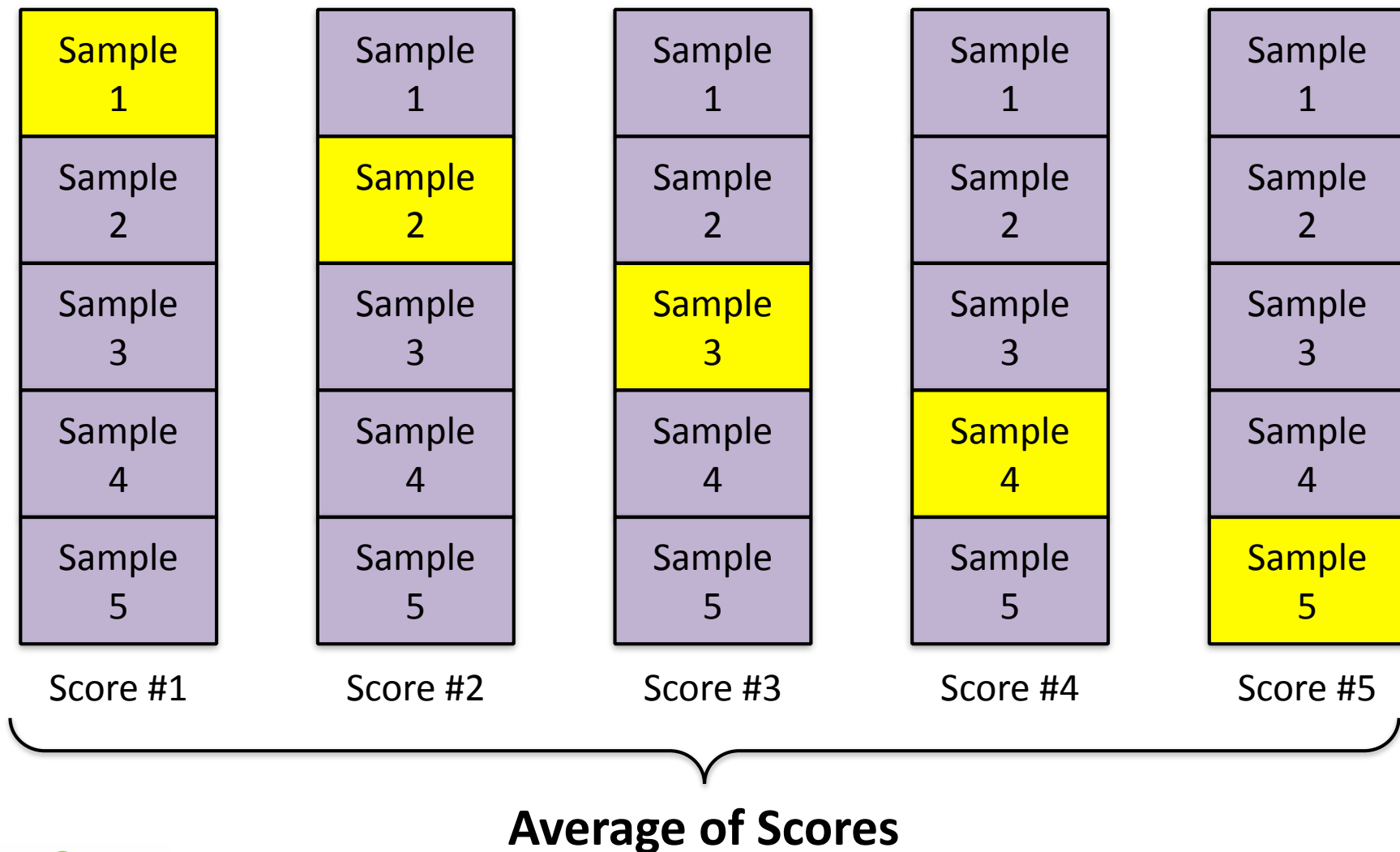
Data Set



- Separate the data into K groups (e.g., 5)
- Each group maintains the same samples for all tests
- Train and test K times
- Sample group for test changes for each test

**Every Data Point Is Tested Once**

# K-Folds Cross-validation

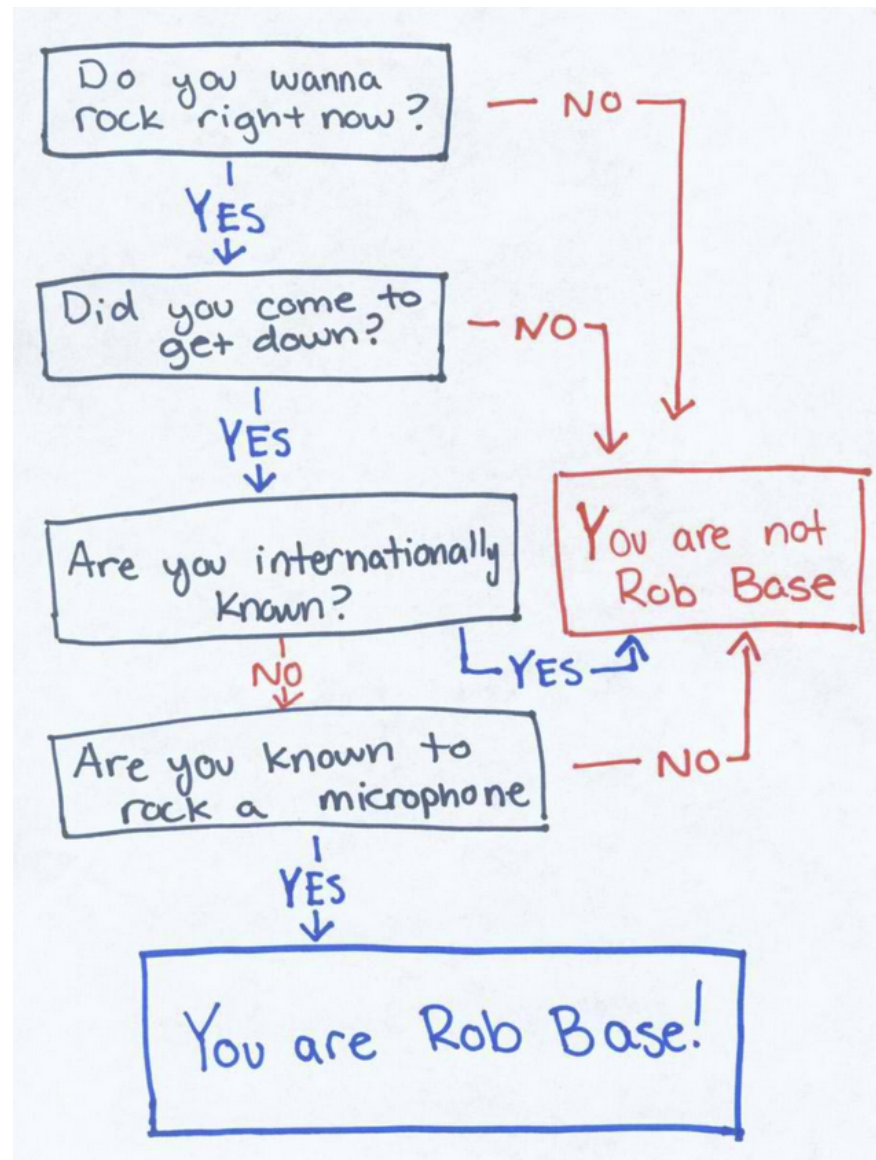


# Data Normalization

- Technique for adjusting the scale of data
- Calculate mean and standard deviation of all samples for each variable
- Subtract the mean and divide by the standard deviation

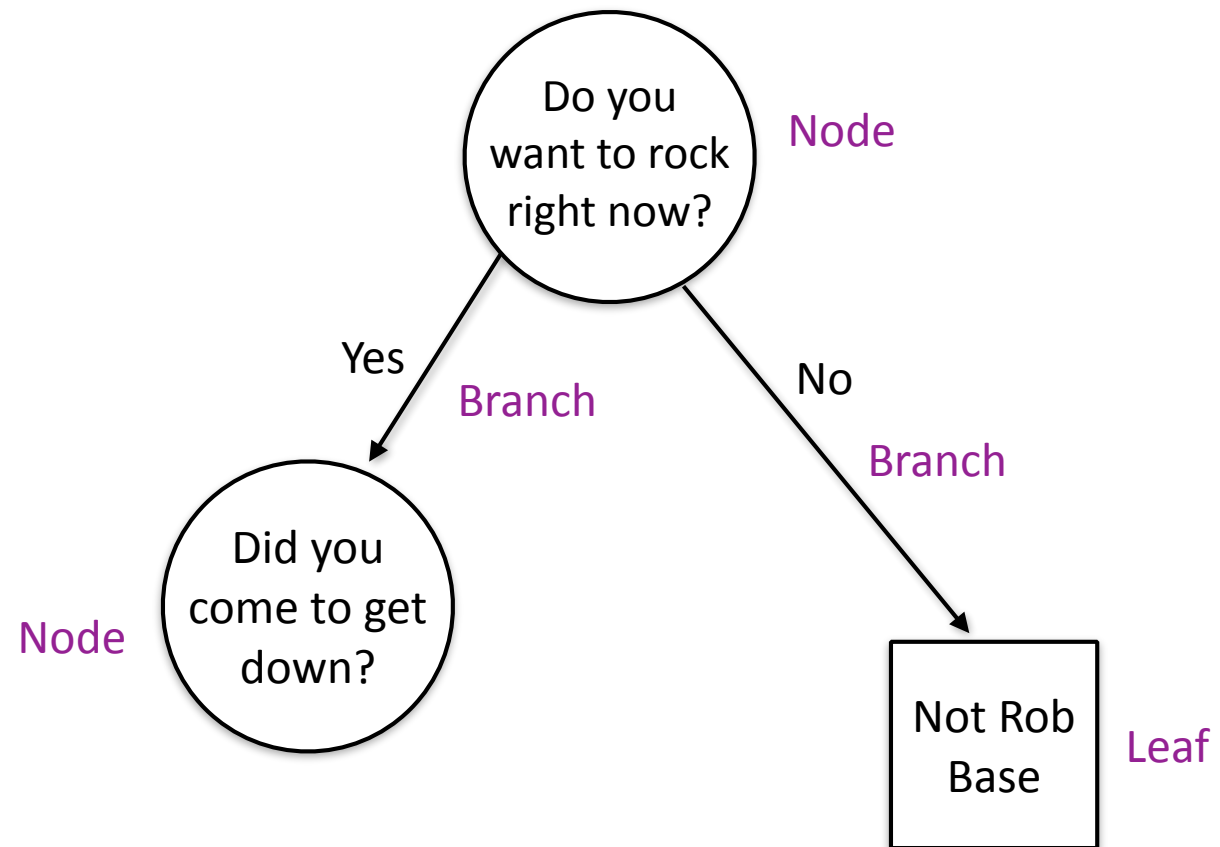


# Is This a Decision Tree?



# Decision Trees

- Trees consist of:
  - Nodes (questions)
  - Branches (answers)
  - Leaves (end points)
- Acyclic - flows in one direction
- No split is necessary when all records are from same class



# Decision Trees

- Algorithm selects optimal node that creates the largest increase in purity
- Decision trees are susceptible to overfitting
- Techniques for preventing overfitting
  - Minimum number of records for leaf
  - Maximum depth for branches
- One technique is to purposely overfit, but manually prune branches

# Random Forest

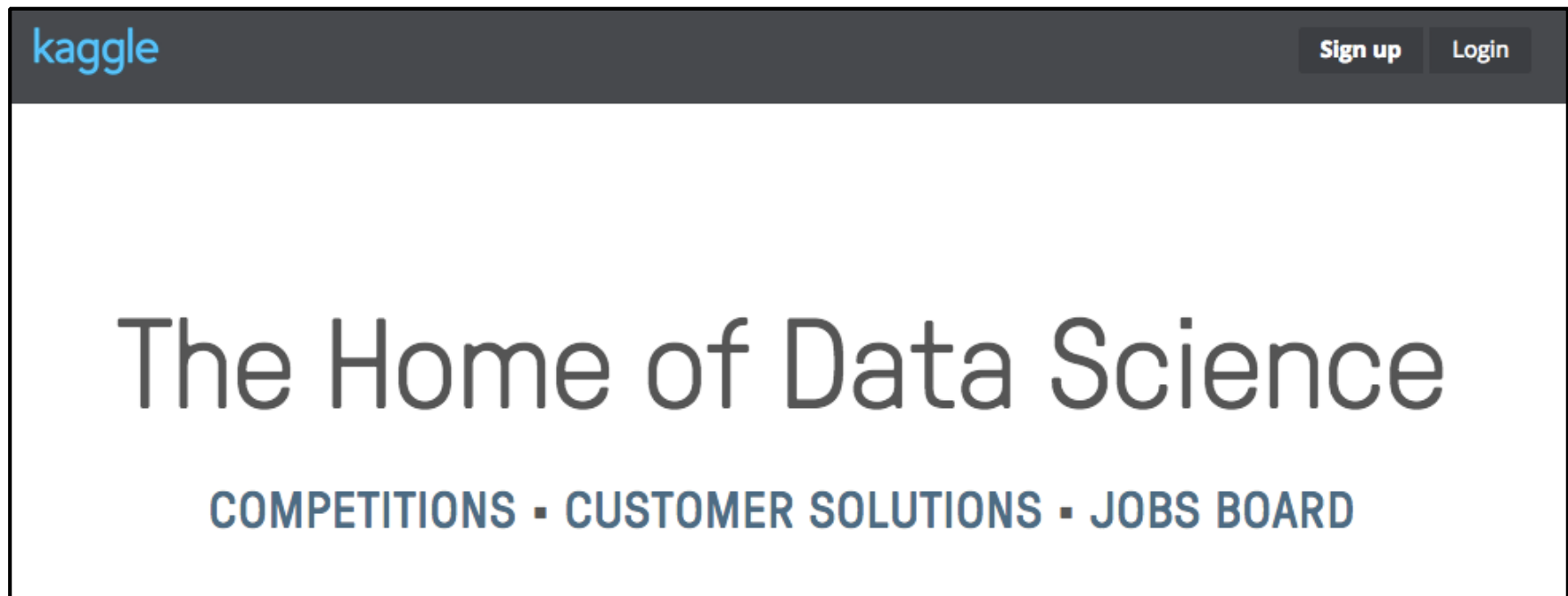
- Ensemble algorithm (mix of many models)
- Collection of decision trees
- Evaluates predictions from many models and selects the most common classification
- Features are randomly selected for each decision tree
- Bagging (Bootstrap Aggregating) is also applied to each tree
  - Sample of the data set is used for training
  - Samples are drawn with replacement

# Why Random Forest Is Popular?

- Add all your data and algorithm will prioritize
- Not susceptible to overfitting
- Doesn't require normalization
- Solid performance in wide range of applications

# Kaggle

- Data prediction competitions



# Kaggle

- Create an account
- Find “Titanic: Machine Learning from Disaster”
- Submission Instructions:

“You should submit a csv file with exactly 418 entries plus a header row. This must have exactly 2 columns: PassengerId (which can be sorted in any order), and Survived which contains your binary predictions: 1 for survived, 0 for did not.”

# Make Predictions

- Train your machine learning algorithm with training data
- Read the test.csv file
- Clean test data
- Predict outcomes for test data
- Convert predictions into a DataFrame
- Save DataFrame as a CSV file (remember to exclude the index)
- Submit predictions to Kaggle site



# Types of Regression Models

- Linear
  - Ordinary Least Squares
  - Generalized Linear Models
- Regularized Models
  - Ridge
  - Lasso
  - Elastic Net

# Types of Regression Models

- Non-linear
  - Logistic
  - Polynomial
- Trees
  - Random Forest
  - Gradient Boosted Trees
- Autoregression

# Regression Process

## Data Exploration

Model Selection

Feature Selection

Model Evaluation

- Visualization of data
- Data cleaning
- Correlation between features and target
- Correlation between different features
- Outlier detection

# Regression Process

Data Exploration

**Model Selection**

Feature Selection

Model Evaluation

- **Linear vs. Nonlinear**
- **Regularization**
- **Evaluate model pre-requisites**

# Regression Process

Data Exploration

Model Selection

**Feature Selection**

Model Evaluation

- **Under vs. Overfitting**
- **Feature Engineering**
- **Data Transformations**
- **Forward and Backward Stepwise Selection**
- **Multicollinearity**

# Regression Process

Data Exploration

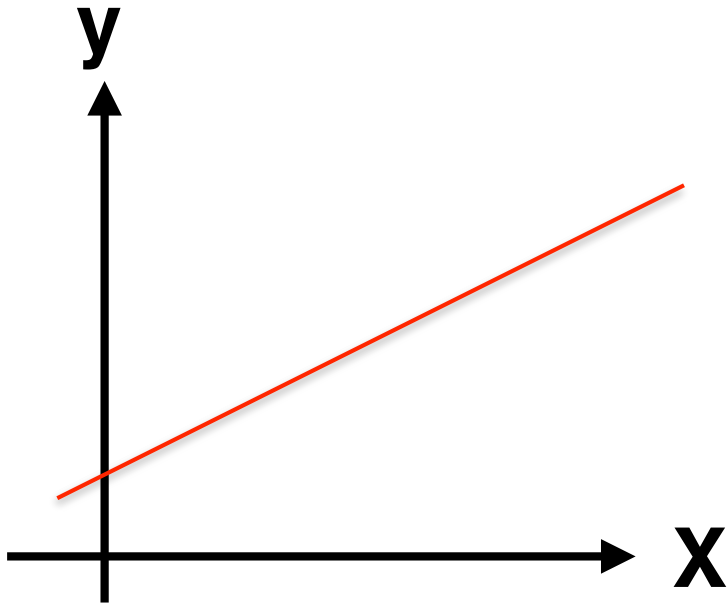
Model Selection

Feature Selection

**Model Evaluation**

- **Root Mean Square Error**
- **R-squared**
- **Residual Analysis**
- **Statistical Significance of Coefficients**
- **Crossvalidation**

# Simple Linear Regression

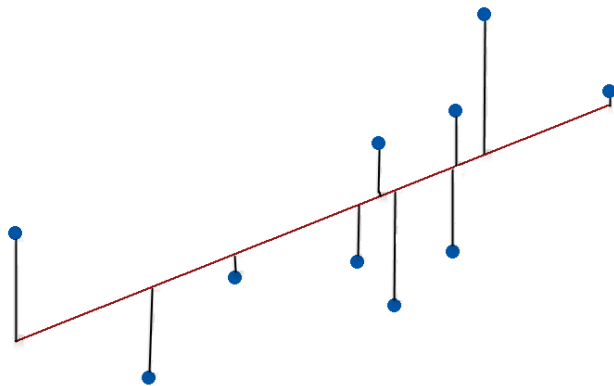


$$y = mx + b$$

- y - dependent variable (target)
- x - independent variable (feature)
- m - slope (change in y for each unit change in x)
- b - intercept with y axis

# Ordinary Least Squares (OLS)

- Algorithm to estimate coefficients of linear model (slope **m** and intercept **b**)
- Coefficients are adjusted to minimize an error term
- Error term is calculated by summing the square of the distance between the predictions and the actual data points

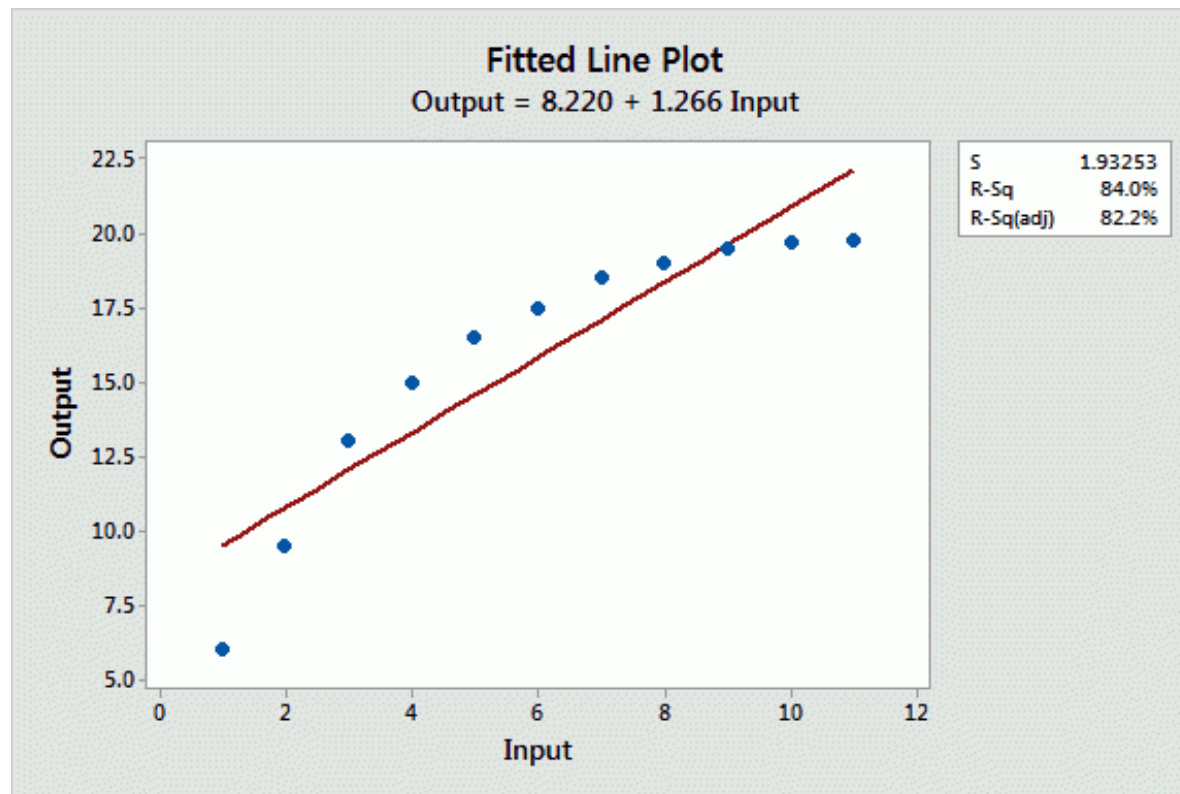


$$y = mx + b$$



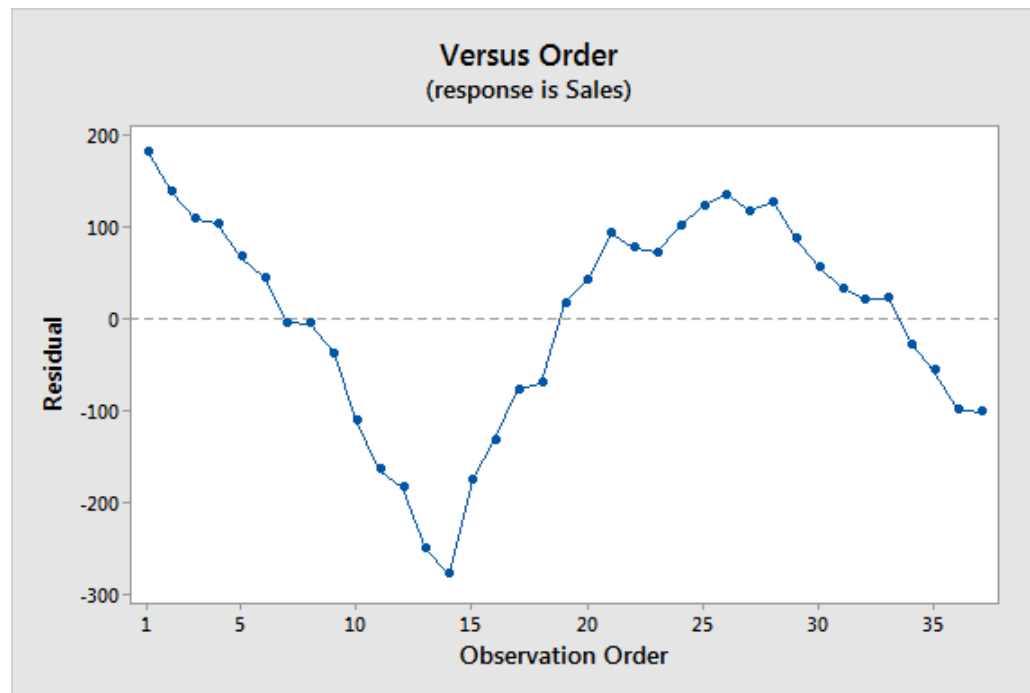
# OLS Requirements

- Linear relationship between independent and dependent variables



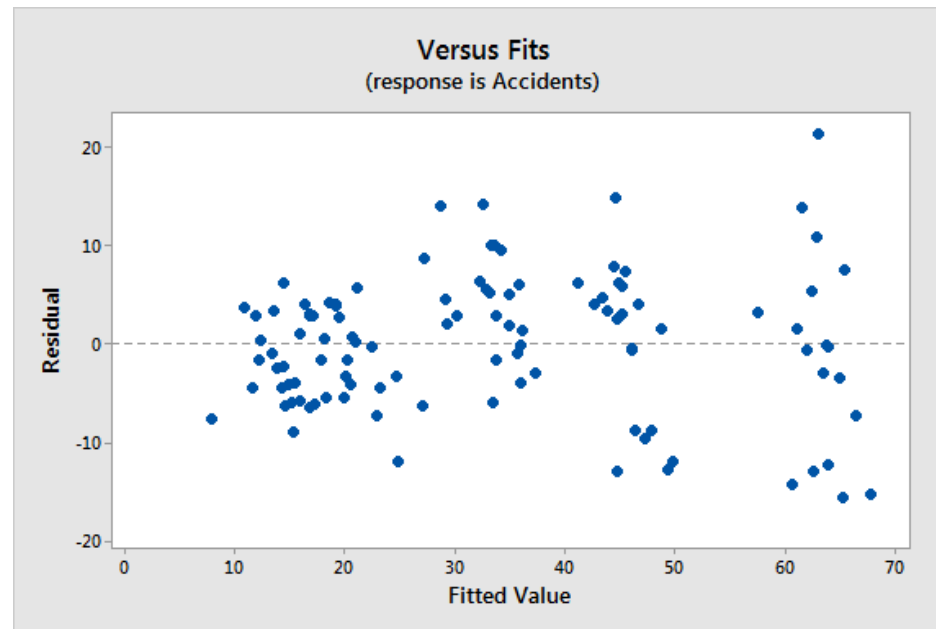
# OLS Requirements

- Error terms has population mean of zero
- Independent variables are uncorrelated with error terms
- Error terms are uncorrelated with each other



# OLS Requirements

- No independent variable is a perfect linear function of other explanatory variables
- Error term has constant variance (no heteroscedasticity)



# Root Mean Squared Error

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}}$$

- Standard deviation of residuals
- Metric for model accuracy
- Measurement in units of dependent variable

# R-squared

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

$$SS_{\text{res}} = \sum_i (y_i - f_i)^2$$

$$SS_{\text{tot}} = \sum_i (y_i - \bar{y})^2$$

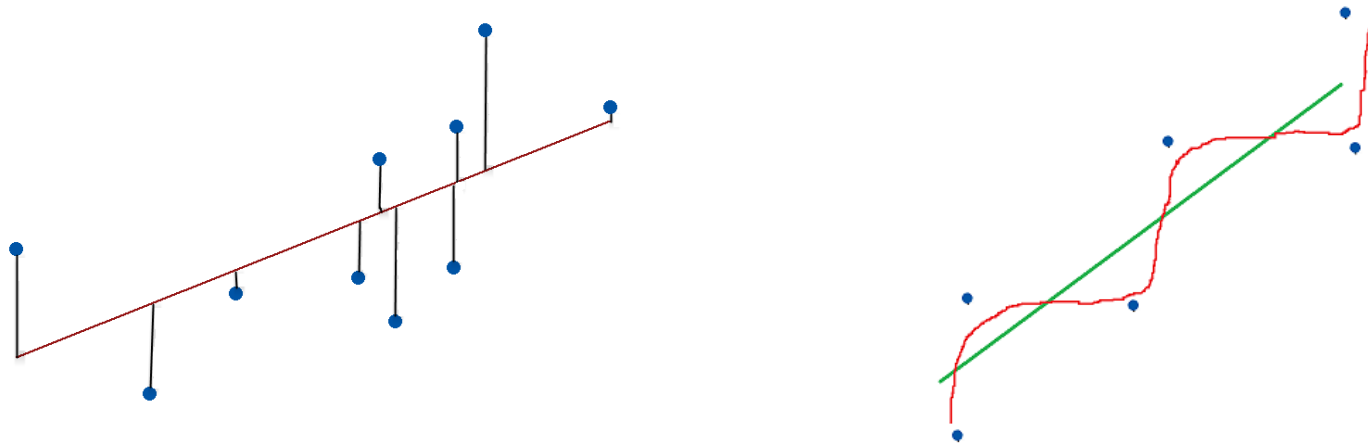
- Coefficient of determination
- Metric for model fit
- Proportion of variance in dependent variable that is predictable from independent variable
- Range: 0.0 ~ 1.0

# Outliers

- Not representative of population
- Skew calculation of coefficients
- Data visualization for detection

# Overfitting

- Error term from unobserved random variable / noise
- Simplify models (reduce features) to avoid overfitting
- Overfit models can misinterpret noise as a signal



$$y = mx + b + e$$

# Multicollinearity

- Independent variables are correlated
- Coefficients can swing wildly and become sensitive to small changes in model
- Difficult to interpret and trust coefficients
- p-values can become untrustworthy and hard to validate statistical significance of coefficients



# Regularized Models

- Models add penalties to complexity
- Naturally reduces overfitting
- Helpful for selecting features from large feature set
- Try Lasso model and Ridge Regression

# Next Steps

- Practice, Practice, Practice
  - Find a fun project
  - Kaggle Competitions
  - Pair programming buddy
- Join a Python Meetup
  - San Francisco Python - recommend Project Night event
  - Bay Area Python Interest Group (BayPIGgies)



[yelp.com/biz/quantSprout-san-francisco](https://www.yelp.com/biz/quantSprout-san-francisco)