Stock Price Forecasting

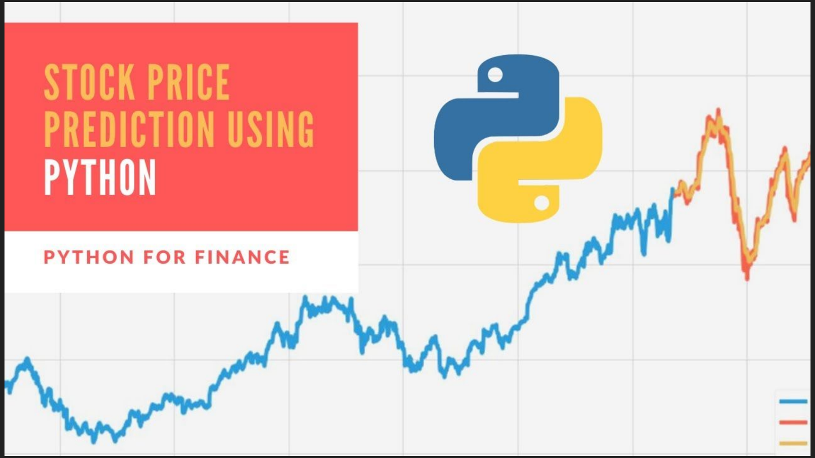
Michael Dyer

The Problem

Source: The Motley Fool

- The stock market plays a vital role in our economy.
- For years, industries, companies, and individuals have looked to capitalize on the stock market.

The Solution



Source: YouTube - Computer Science

- Use Machine Learning to create a model that can accurately forecast future prices or trends.

Why does this matter?

- Currently there are no legitimate ways to forecast prices or trends, only speculations
- Being able to accurately predict future prices and trends based upon the previous entries would be beneficial to anyone looking to profit from the market

The Data

AAPL_2006-01-01_to_2018-01-01.csv (153.62 KiB)

Detail Compact Column

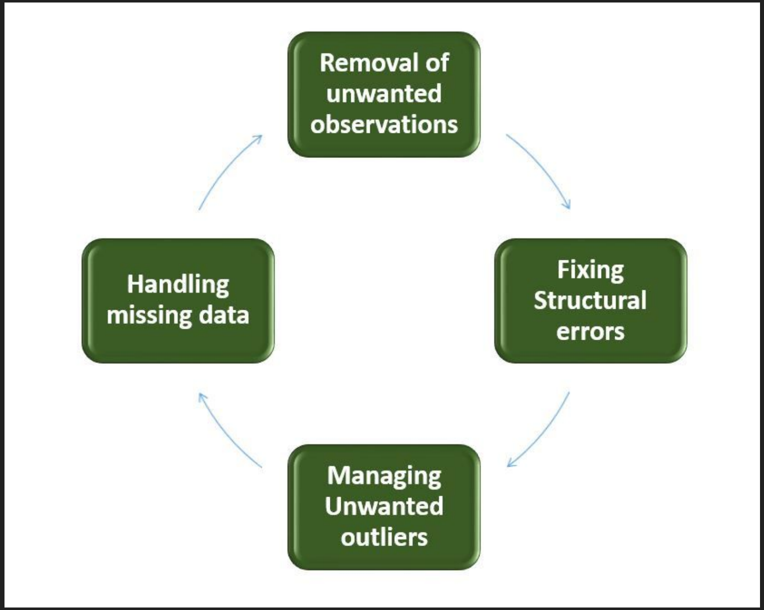
Date	Open	High	Low	Close	Volume	Name
2006-01-03	10.34	10.68	10.32	10.68	201853036	AAPL
2006-01-04	10.73	10.85	10.64	10.71	155225609	AAPL
2006-01-05	10.69	10.7	10.54	10.63	112396081	AAPL
2006-01-06	10.75	10.96	10.65	10.9	176139334	AAPL
2006-01-09	10.96	11.03	10.82	10.86	168861224	AAPL
2006-01-10	10.89	11.7	10.83	11.55	570088246	AAPL
2006-01-11	11.98	12.11	11.8	11.99	373548882	AAPL
2006-01-12	12.14	12.34	11.95	12.04	320201966	AAPL
2006-01-13	12.14	12.29	12.09	12.23	194153393	AAPL
2006-01-17	12.24	12.34	11.98	12.1	209215265	AAPL

Taken from https://www.kaggle.com/datasets/szrlee/stock-time-series-20050101-to-20171231?select=AAPL_2006-01-01_to_2018-01-01.csv

Data Wrangling

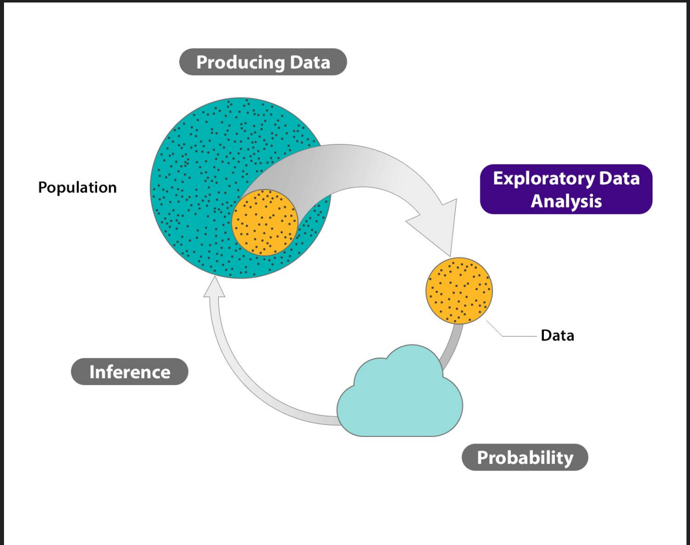
- Chose 5 stocks csv files
  - aapl, amzn, googl, nke, vz
- Each file contained:
  - Date, Open, Close, High, Low, Volume, Name
- Each file has a little over 3000 rows of information
- Converted to DataFrame
- All work done on Jupyter Notebook

Data Cleaning

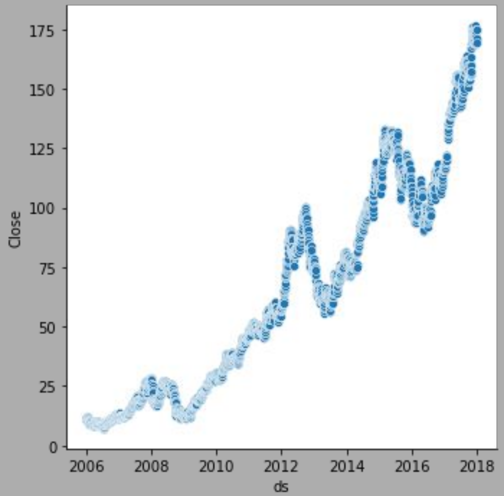


- There was only 1 missing value in all 5 csv files
  - Row was just dropped as there was ample data
- No “Incorrect” data values
- Created DateTime object for the date and deleted included date column

Exploratory Data Analysis



- Still checking integrity of Data
- Looked for correlations amongst features
- Need to go down to 2 features, with Date being one of them
- After checking many plots and graphs, Close value was chosen for the 2nd feature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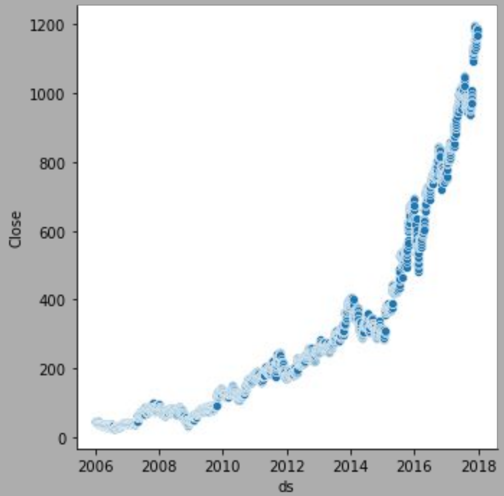
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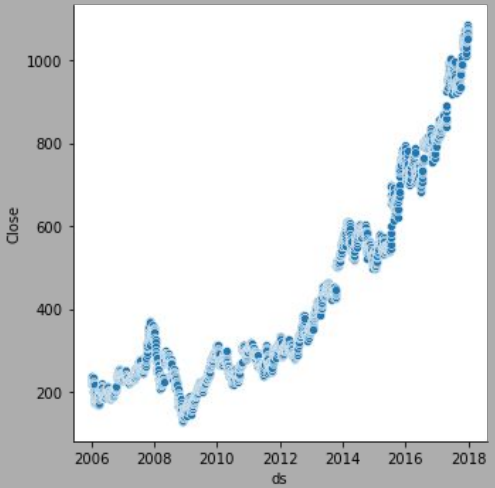
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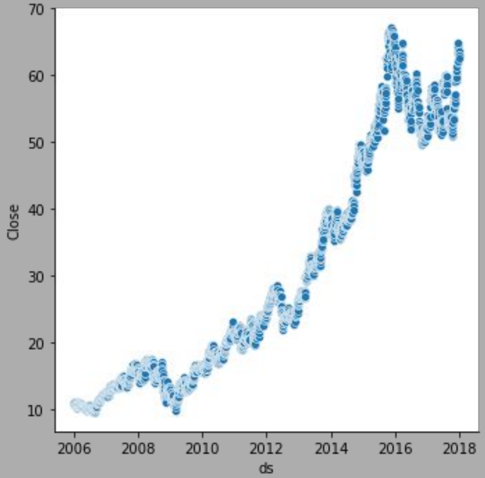
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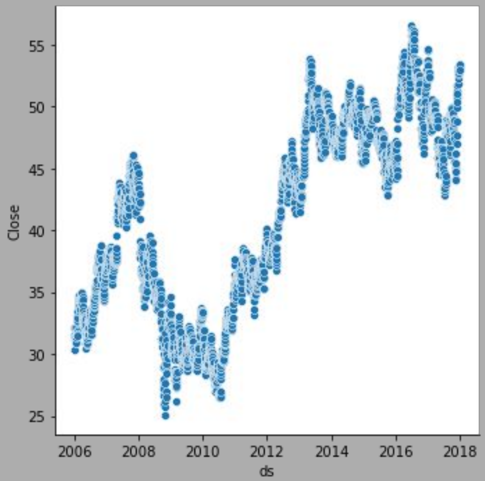
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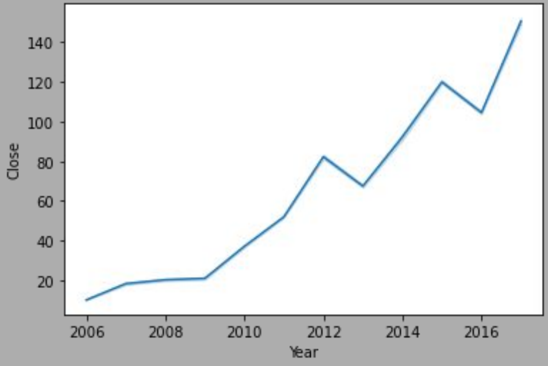
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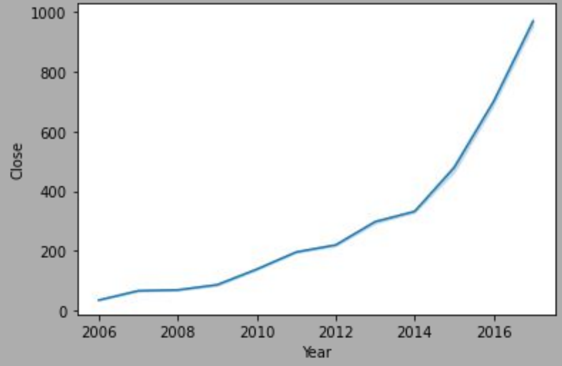
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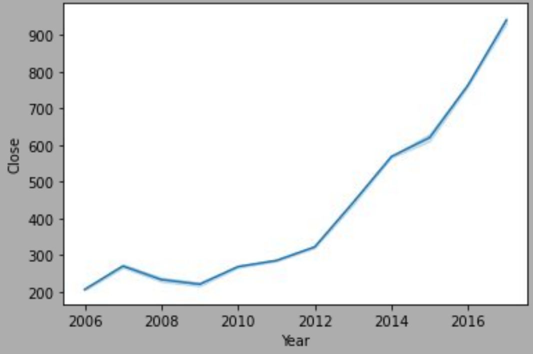
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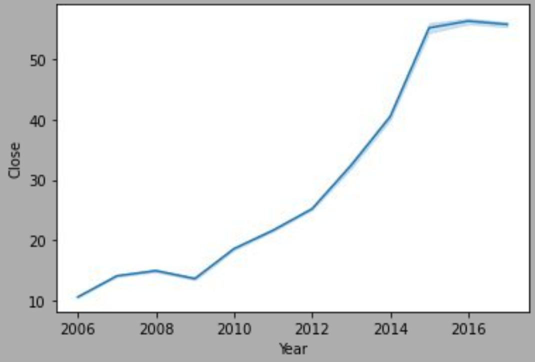
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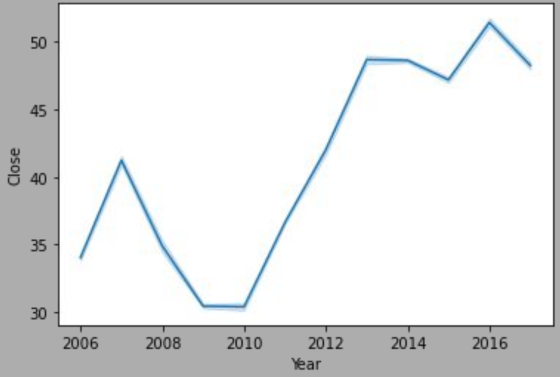
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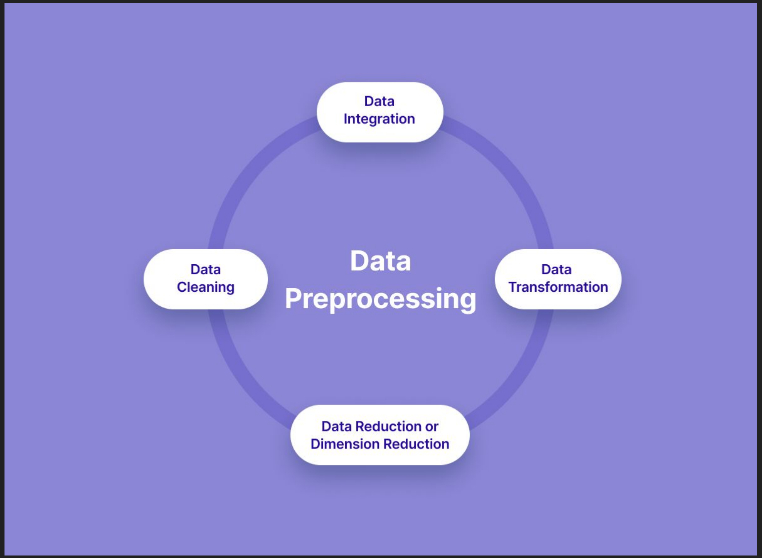
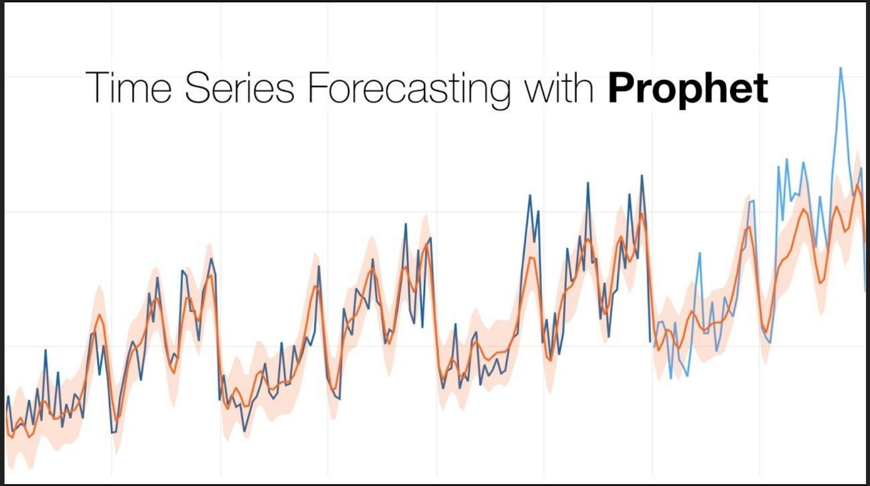
Pre-Processing



- There were no categorical values, so I did not need to create dummy variables
- There was no need to standardize any metrics
- For the FBProphet Model I needed two columns:
  - 1 marked ‘ds’, this was the DateTime column
  - 1 marked ‘y’, this was the price point for each stock

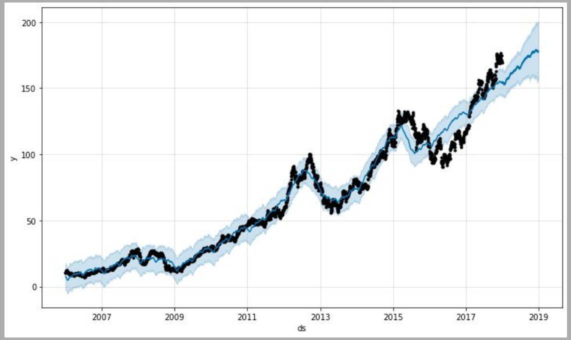
Modeling



Source: blog.exploratory.io

- I used 3 modeling methods
  - FBProphet
  - ARIMA
  - Exponential Smoothing
- I was most familiar with ARIMA and least familiar with Exp. Smoothing.
- Since I am using 5 stocks, and creating 3 models each, I will create a total of 15 models.
- I will compare the RMSE values of each model per stock, and the overall AVG RMSE of each Model

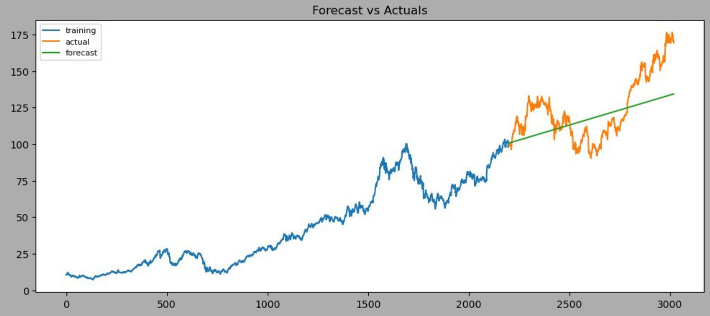
FBProphet



RMSE Values
aapl - 24.87553

AVG of all models = 25.00905

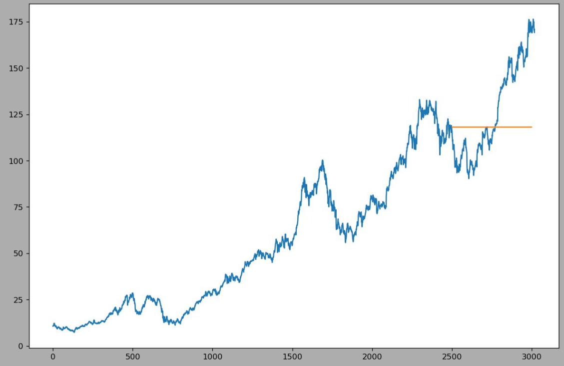
ARIMA



RMSE Values
aapl - 18.17807

AVG of all models = 49.90812

Exponential Smoothing



RMSE Values
aapl - 25.43805

AVG of all models = 73.75101

Arima did best for aapl stock, but FBProphet did best overall

Takeaways

RMSE SCORES BY MODEL

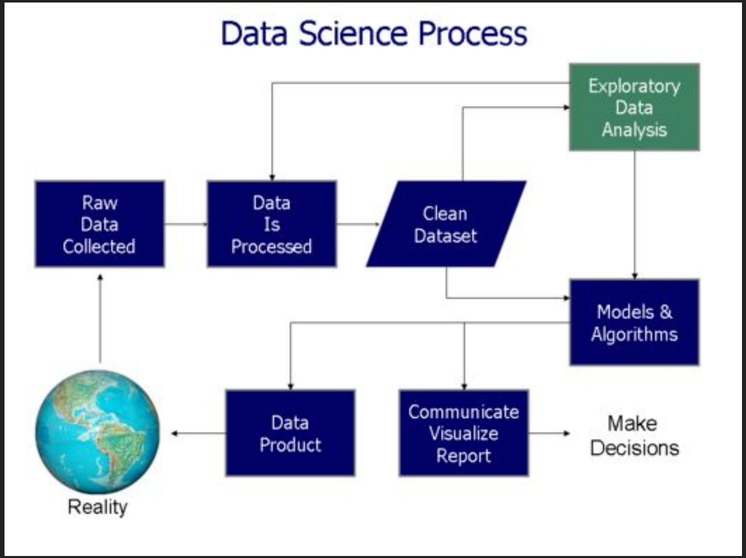
FBProphet - AVG ACROSS MODELS = 25.00905
aapl - 24.87553
amzn - 47.25800
googl - 41.67631
nke - 7.04094
vz - 4.19446

ARIMA - AVG ACROSS MODELS = 49.90812
aapl - 18.17807
amzn - 146.55111
googl - 66.06066
nke - 15.23596
vz - 3.51478

EXPONENTIAL SMOOTHING - AVG ACROSS MODELS = 73.75101
aapl - 25.43805
amzn - 208.51732
googl - 119.27863
nke - 10.85077
vz - 4.67031

- Each model had pro's and con's. The ARIMA Model was the most difficult to set up, while the FBProphet was probably the easiest
- FBProphet secured the best average RMSE score
- Overall, the RMSE scores **do not show** that any of the models predict in a way that can be considered accurate

Future Research



- I would love to be able to spend more time on the Models individually seeing if there are any other parameters that can be tuned.
- I would focus more on trend analysis and forecasting than price
- Collect more data