CO3093 COURSEWORK 1 - Report

Big Data & Predictive Analytics - Simulation-based & Regression Models

Ihtasham Chaudhry

Department of Informatics
University of Leicester
23rd February 2018

Question 1

Analysing historic data for BPL

It is important to consider missing values in our data set and to filter out the columns based on this information so that we have all the information we need to make predictions and have *clean* data. In the case of our problem (predicting a winner), the most important factors that we must consider are win/loss statistics and goals scored/conceded statistics.
We can then draw some conclusions from the data such as:

1. The average number of goals scored per match throughout the tournament by each team playing at home is 1.49 and away is 1.18. We also notice that the median of these values falls close to the minimum values which indicates that the data on this column is positively skewed and has a longer tail towards higher values.

2. From this data we can also observe that on average teams win more games playing home than they do playing away, The mean (μ) of wins at home for each team is larger than the median of the dataset, this indicates that the distribution is skewed towards large values. The standard deviation (σ) is very small relative to the min and max values, this indicates that the distribution has "long tails".

3. Following from the previous point, the same observation can be made regarding the number of "FTHG" or "Full Time Home Goals" by each team per match. The data again is skewed towards larger values.

Comparing Man.Utd. And Man.City.

As we are only considering two teams; Manchester United and Manchester City, we can further filter the data and extract only the games played by both of those teams where they are playing either home or away. When we accumulate the data by teams and their home and away games to see how they perform for each category. After doing this we can draw some analysis from the data.

Table 1: Mean goals scored per game over the season (higher is better)

	Home	Away
Man Utd	2.25	1.83
Man City	3.50	2.33

Table 2: Mean goals conceded per game over the season (lower is better)

	Home	Away
Man Utd	0.41	0.91
Man City	0.75	0.75

We can see that over 24 games played by both teams over the course of the season, Man City has a higher average of goals both in the home and away side compared to Manchester United, and have conceded a higher average of goals home but a lesser average of goals home compared to Manchester United.

Visualising Data

We can visualise this information and compare the offensive and defensive performance of the two teams. To do this we will consider goal scores. To measure the defensive performance of a team we can see how many goals were conceded by the team playing home, lower is better in this case, i.e we want to see that the distribution is skewed towards less goals. And in contrast to this to measure offensive performance we can see how many goals they scored away, higher is better in this case and alternatively we want to see that the data is skewed more towards the right to see which is the better team.

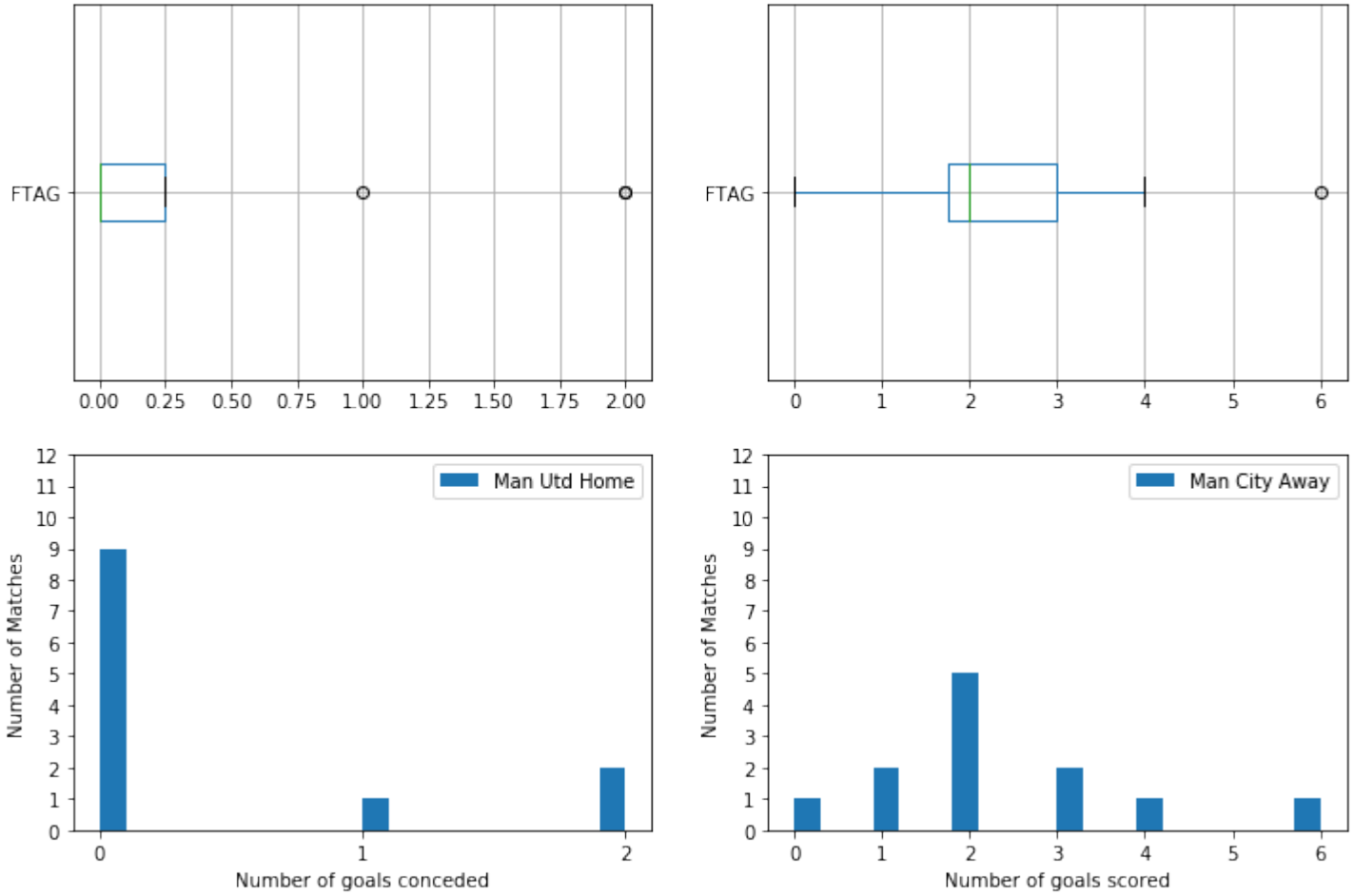


Figure 1: A comparison of M.U's Home defence against M.C's away offence.

From this graph we can see that Manchester United's defence is quite strong, this is because out of 12 games playing at home they only conceded goals in 3 out of those 12 games. Furthermore, we can also see that Manchester City's offence is fairly strong and we can tell that the number of goals they score on the away side is almost distributed in a Poisson distribution manner. From the boxplots we can see that Manchester City's goals away were between 2 and 3.

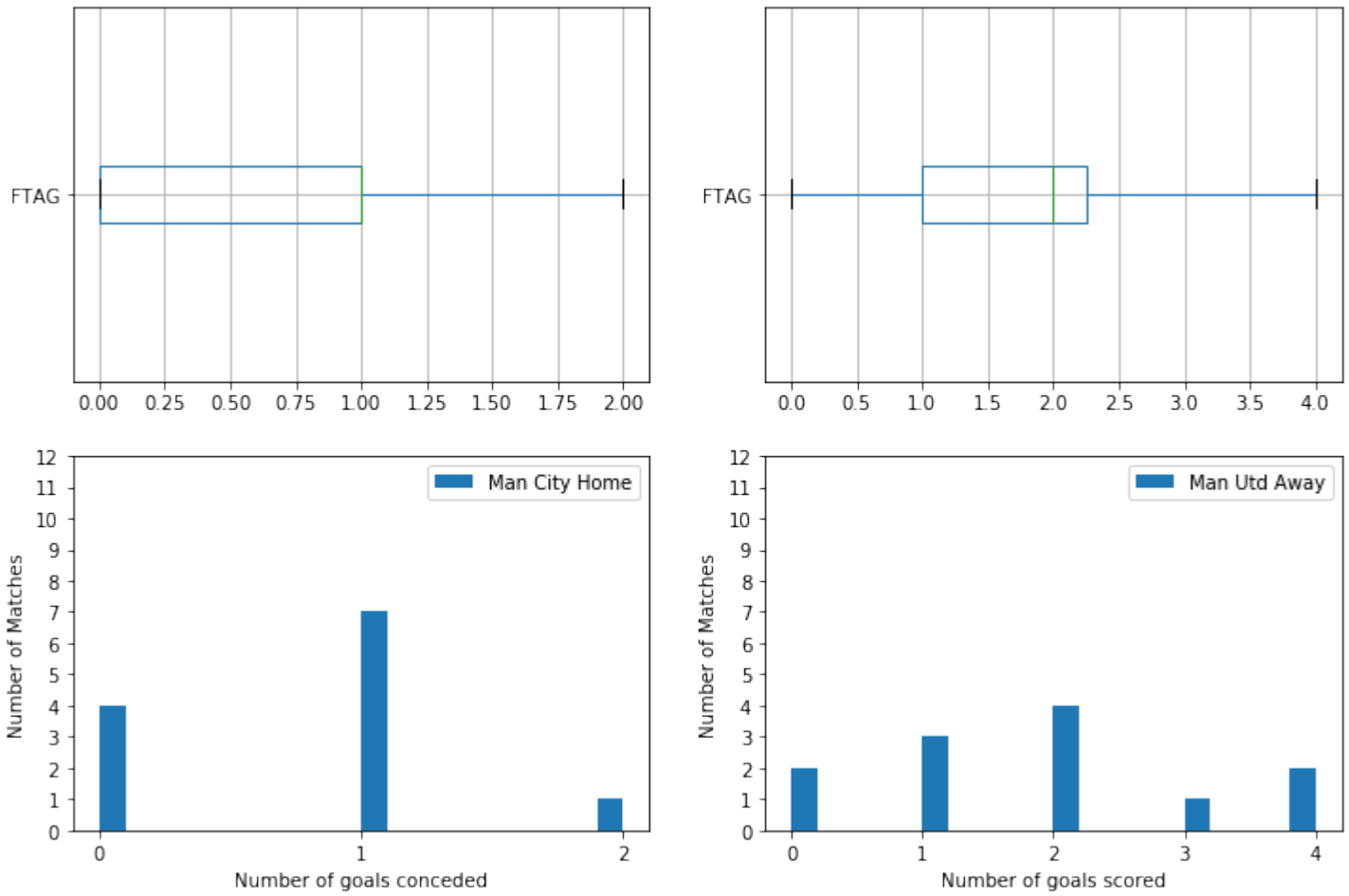


Figure 2: A comparison of M.C's Home defence against M.U's away offence.

In contrast to the above graph, we can see that Manchester City's home defence is worse than Manchester United's home defence. We can assert this by seeing that Manchester City conceded at least 1 goal in 8 matches compared to the 3 that Manchester United conceded at home. Furthermore, we can also see that Manchester United's goals scored away are more spread out and have a higher mean than Man City's. However we can also see that at most Man Utd only scored 4 goals in any one game over the whole season compared to the 6 scored by Man City which could indicate a higher level of offence.

Simulation

To simulate the matches between Manchester United and Manchester City we can use a Poisson distribution model because it concerns a discrete probability distribution which is relevant to the case of football matches. Furthermore, in our model we also consider that each event or match is independent from each other.

By using this we can generate scores between the two teams based on the historical data of the two teams and create paired random drawings. It is obvious that the higher number of fantasy games we create, the more accurate our model will be able to predict as a higher sample size means that we have more confidence in our prediction. In this case we will generate 10000 matches per side for each team, i.e. 1000 games where MU plays home, 1000 games where MU plays away and the same for MC. After pairing these results we will get 1000 games played by each team on the home side and away side resulting in a total of 2000 simulated fantasy games. After running this simulation, we may get the following result.

Table 3: Wins for each team and the side they played on

	MC Win	MU Win
Home	691	386
Away	427	174

And we can also consider the number of times the teams drawed against each other which in this case was: **322**.

We can then find the probability of who will win the match based on the simulation from the fantasy games we've generated. In the most basic finding we can simply find out the probability of a team winning a match. For this we can observe the following probabilities:

$P(ManUtdWin)$
$P(ManCityWin)$
$P(Draw)$

After calculating these probabilities we get the following results:

$P(ManUtdWin) = \mathbf{0.2845}$
$P(ManCityWin) = \mathbf{0.5585}$
$P(Draw) = \mathbf{0.157}$

Here we can see that Manchester City has a much larger chance of winning the game based on the simulations we've done and even looking at the data from the premier league it is obvious that Manchester City was the better team. However, to break down these results we can also observe the following probabilities to give us a better outlook into the chances of winning for each team:

$P(ManUnitedWin \mid Home) = \mathbf{0.492}$
$P(ManUnitedWin \mid Away) = \mathbf{0.194}$
$P(ManCityWin \mid Home) = \mathbf{0.806}$
$P(ManCityWin \mid Away) = \mathbf{0.508}$

From this we can observe that Manchester City has a higher chance of winning both playing home or away compared to Manchester United. From this we can confidently predict that in a match up of Manchester United vs Manchester City in the Premier League, based on the historical data; Manchester City will win the game.

Our sample of 1000 may be very good because it is not so trivial that it would produce biased results but also we are not generating too many results that will take long and not offer much of an improvement.

Verifying our model

To test our simulation further, we can observe the scores for another team and try to predict what results we can obtain. For an example let us take Chelsea vs Arsenal as a candidate match-up. We can see that in the premier league, the following scores were observed between the two teams:

Table 4: Matchups between Chelsea and Arsenal in the BPL

Home Team	Away Team	FTHG	FTAG	Winner
Chelsea	Arsenal	0	0	Draw
Arsenal	Chelsea	2	2	Draw

Here we can see that these teams drew in both their games together, but we can look a little bit further into their mean goals scored per game over the premier league per match:

Table 5: Mean goals scored per match

	Mean goals home	Mean goals away
Chelsea	1.75	2.00
Arsenal	2.58	1.67

Here we can see that Chelsea has a better chance of scoring more goals if they're playing away and Arsenal has a higher chance of scoring more goals if they're playing home. We can now generate a small number of matches with these teams and stack them up against each other to see how our simulation performs.

After creating fantasy games between Chelsea and Arsenal based on our simulation model we get the following results:

Table 6: Number of wins by each team

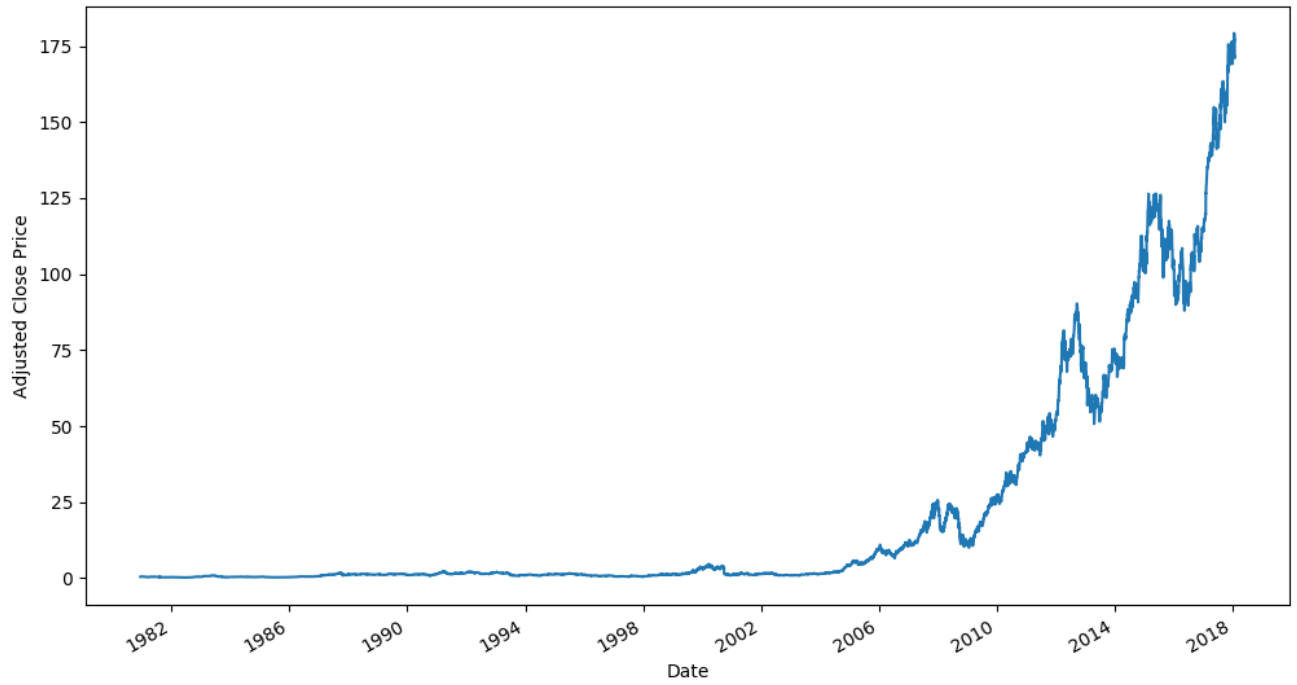
	Wins at Home	Wins Away
Chelsea	4	3
Arsenal	7	1

In addition to this data, there was a total of 5 draws between the teams. Looking over the data in Table 5 we can verify that these are feasible predictions by our model because Chelsea is winning more goals home than away and this is evident from Arsenal's home performance. Thus we can conclude that our model is very likely perform accurately when predicting a winner.

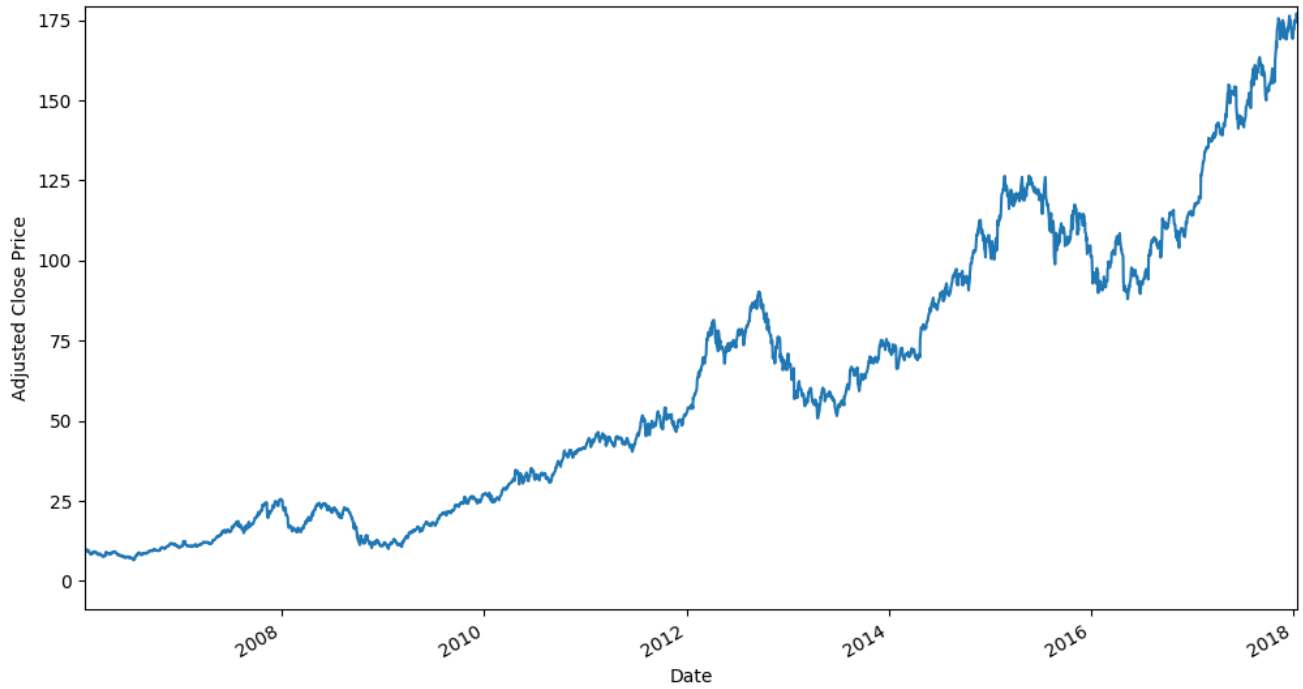
Question 2

Analysing historic data for Apple

From the provided csv file we can generate a time-series using the "adjusted close" column and plot the data. After doing this we obtain the following figures:



(a) Time series of Apple Stock closing prices from 1980 to 2018



(b) Time series of Apple Stock closing prices from 2007 to 2018

Figure 3: Time series of the Apple stock prices with different time ranges

By observing Figure 3 we can make the following analyses:

1. Up until 2004 the stock price was very low and remained low, there were no peaks or changes in the price.
2. From 2005/2006 the stock prices started rising at an exponential rate, peaking in 2012 at $90.30. And then started to heavily decline thereafter. This is a reaction to the release of the first smartphone by Apple which gave them the boost into the world of technology. However many other companies started joining the trend and this started to cause a decline in the Apple market share.
3. The stock prices then started to rise between 2013 and 2015 where they peaked and started to fall once again and the same trend occurred between the years of 2016 and 2018.
4. Overall we can also see that from 2006 to 2018, in the matter of 12 years the stock prices have multiplied by roughly 16 times, which shows that Apple has been a very successful company.
5. Though the prices have increased in this time period, we can also observe that the prices have been very unstable and there seems to be a trend of prices increasing all year round and then falling the beginning of the next annual year. Upon close inspection of the prices this becomes more clear. This can be seen in Figure 3(b). However it is still evident that the prices are generally inclining each year.

Modelling

The model that we will mainly be concerned with is the Multiple Linear Regression model where we have more than one predictor. The reason for this is because we have more than one attribute that may help us predict an output. Multiple linear regression aims to model a relationship between multiple variables which we call predictors and fit a linear equation over our observations and predictions using those predictors [1]. In essence we will be able to create a linear function based on predictors which will model like the following (for n observations):

$$f(x_i) = b_0 + b_1 x_{i,1} + b_2 x_{i,2} + b_n x_{i,n}$$

In the case of predicting stock prices we will use 5 predictors as that would be enough to take into account the features we need. Furthermore if we have too many predictors, we may run into the issue of the curse of dimensionality, this is bad as it would take us a long time to find a solution. We will also make use of the `linear` kernel for selecting features and the `feature_selection` feature from sklearn to pick the top n features to use and build our model with.

Firstly we can attempt to build a model selecting the best features from our data-set and predicting the prices, this will be the first iteration where we can test the linear model.

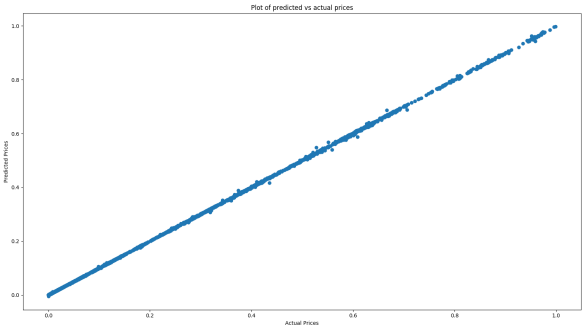


Figure 4: Plot for the linear model.

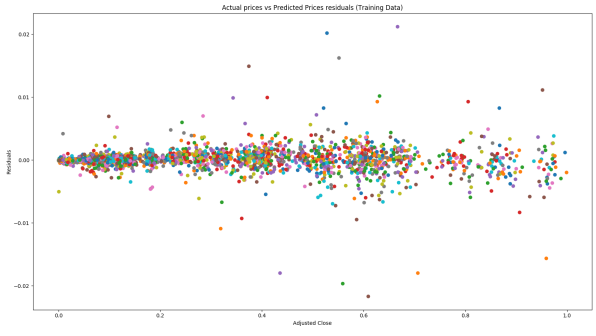


Figure 5: Residuals for the plot.

In the above run we consider the following features: `['Open', 'High', 'Low', 'Close', 'Volume']`. From these plots we can see that the linear plot in Figure 4 is very good and is almost a perfect straight line, however from the residual plots in Figure 5 we can see that there are a lot of outliers and furthermore the data is almost following a straight line pattern which is not what we hope for. At this point, as we are trying to calculate prices in a five day span, we can create another column which shifts our prices by five days and this five day shift may help us predict the price in say, five days time.

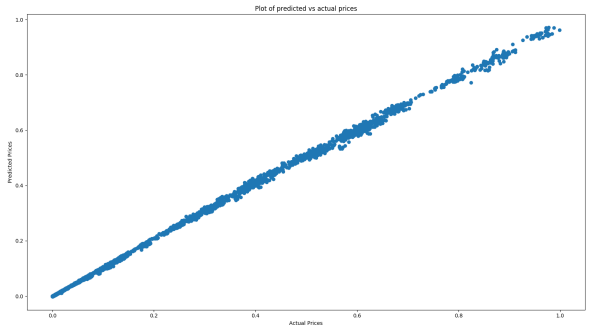


Figure 6: Plot for the linear model.

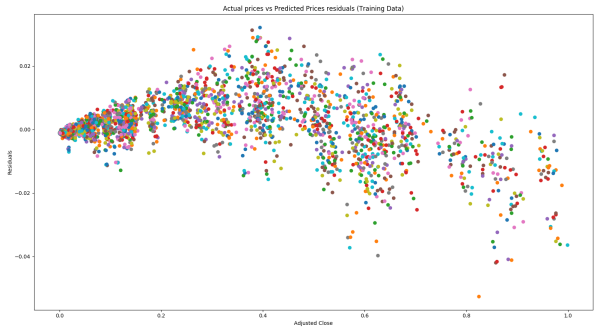


Figure 7: Residuals for the plot.

In this case, we can again select the best 5 features that will fit our model well and in this case the features we observe are: `['Open', 'High', 'Low', 'Close', 'Volume', 'FDS']`, where `FDS = Five Day Shift`. Here we can see that in Figure 6, the plot is a little bit more spread out compared to before, so it's not a perfect straight line. This might be good because it means that we are not overfitting out linear model and that we have some variation. However inspecting Figure 7 shows that there is a lot of randomness in residuals and this is something we want to encourage. The data is more spread out and it is a good indicator that our model might be good. Here we obtain the following:

r^2 for training data	0.9993025502681001
Score against test data	0.9993652749498734
MSE	3.134759360515633e-05

Here we notice that our r^2 value is really close to 1 and this indicates that there is not much variance between our observed data and predicted data; i.e. there is strong positive linear relationship between our variables.

Finally, we can aim to improve our predictions by considering a technique called Moving Average. This method is used especially when the time series has regular fluctuations [2], this is evident from Figure 3. To smooth out these fluctuations when predicting, we can add another column `['FDSMA']` which corresponds to the Moving Average of our previously created five day shift column. And we can apply this to see if our model can product better results.

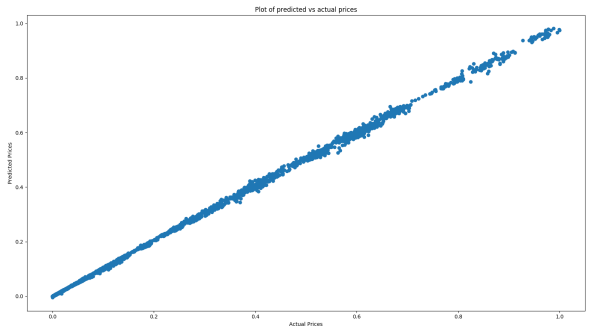


Figure 8: Plot for the linear model.

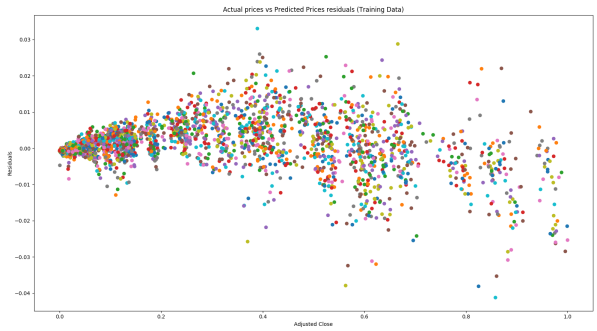


Figure 9: Residuals for the plot.

In this final step we have now converted our five day shift into a five day shift moving average, this will allow us to smooth out the data when making predictions. In this run we select the following features: `['Open', 'High', 'Low', 'Close', 'FDSMA']`. From this we observe the following values:

r^2 for training data	0.9995984286965355
Score against test data	0.9995592761414388
MSE	1.7798954234818795e-05

Compared to the previous run, we observe that we are able to obtain a more closer fit to our observed data and furthermore, comparing Figure 9 to Figure 7 we can see that the residuals for this run is more closer to 0 but is still very random which shows that our linear model is good. However, it is to be noted that the r^2 value does not tell us the whole story, so we must look at the residuals to get a better understanding of the accuracy of the model.

From this model our linear regression model produces the following equation that we can use to make predictions:

$$\text{Adj Close} = -0.00067 + 0.131 \times \text{Open} - 0.463 \times \text{High} + 0.136 \times \text{Low} + 0.482 \times \text{Close} + 0.699 \times \text{FDSMA}$$

Profitability

As with any predictive model, it can be rather difficult to measure the accuracy of it with the given data. Though our model looks like it's performing well, there may be circumstances in the real world which might heavily influence actual stock prices and may not work in the favour of our model. The R-Squared value does not always tell us whether our model is good enough, so through we have obtained very good values in the model above, it may turn out that it is not able to predict our future stock market prices correctly. The best way to overcome this is to look at other regression models that are feasible and test against live data which will hopefully increase the reliability of the model.

It is also important to consider that we are taking in very few features here for prediction. In essence the stock market is far too complex and a lot of things happen for instance in Figure 3 we an see that for a long time the Apple stock stayed at a very low price but suddenly started to rise very quickly, if we were trying to create a linear regression model to predict prices in say, 2002 when the prices were relatively staying the same; our predictions will not be accurate. The same can be said throughout time, multiple factors may influence a price and our model is not aware of these things. Apple could lose all it's customers next week bringing the stock prices to the ground, but we won't be able to predict real-life anomalies like this.

References

[1] Multiple Linear Regression - http://www.stat.yale.edu/Courses/1997-98/101/linmult.htm

[2] SIMPLE MOVING AVERAGE VS LINEAR REGRESSION FORECAST - http://www.universitateaeuropeanadragan.ro/images/imguploads/cercetare_ued/journal_annals_economy_series/journal_annals_no_16_2013/the_authors/nicolae_adrian_mateia.pdf