Analysis to Predict Closing Stock Prices from Company AT&T

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Abstract

The goal of our project is to develop a suitable model using regression analysis that would allow us to predict the closing stock prices of AT&T. We gathered the data from the years 2013-2016 in the price-split-adjusted dataset and added in the yearly fundamental data. Furthermore, we used visual graphs to analyze the residuals to help identify any underlying problems we came across when developing our model. Through data-splitting, our model could predict the closing prices roughly 69% of the time. The overall analysis of the model helped us subset and distinguish the effectiveness of each regressor we found to the response variable, however we were expecting our model to have a higher percentage predicting closing stock price of AT&T.

Contents

1 Introduction

The telecommunication industry is growing inevitably, and it is highly dependent on the rapid advancement of technology. The telecommunication industry is a key element for businesses and individuals to collaborate from anywhere across the world. As a result, there will be investment opportunities present, however it is not risk free. In our analysis, we designate our efforts toward one of the most well-known telecommunication companies around the world, AT&T. We start by combining the data from `fundamentals.csv` and `prices-split-adjusted.csv` of company AT&T. Our first model was used to predict the `close` price with `open`, `low`, `high` and `volume`. Due to high multicollinearity, we chose to use information from the `fundamentals.csv` dataset. Since the data from `fundamentals.csv` is annual, we merged the previous year's dataset with the following year's `prices-split-adjusted.csv` dataset to form the full dataset. Due to high multicollinearity with the columns from `fundamentals.csv`, the linear model can only take up to three variables from the `fundamentals.csv` dataset. We chose `capital surplus`, `gross margin` and `liabilities`. We also added `volume` from `prices-split-adjusted.csv` to the model to see if the daily number of stocks traded had any significance to affecting the daily `close` price. From the model adequacy plots, we see that the residuals meet the linear regression assumptions. There were signs of leverage points so we checked for those and removed them from the model which increased the R^2 by roughly 2%. We ran stepwise selection on the model to see if it provides any different models to compare to but the results left us with the full model. Next we did cross validation to investigate the prediction performance of the model.

2 Data Description

We are using three datasets: `securities.csv`, `fundamentals.csv`, and `prices-split-adjusted.csv`.

`Securities.csv` contains information on the stock companies such as the company's name and ticker symbol, the type of sector they are in, location of headquarters and others.

`Fundamentals.csv` contains information of yearly reports of fundamental information of each company such as `total revenue`, `accounts payable`, `liabilities` and many more.

`Prices-split-adjusted.csv` contains information of the stocks adjusted prices after splitting. The columns included are the `date`, `ticker symbol`, `close`, `open`, `low`, `high`,and `volume`.

For our linear regression model, we have selected to predict close prices of AT&T's stock. Our regressor variables are volume from the `prices-split-adjusted.csv` and `capital surplus`, `gross margin`, and `liabilities` from the `fundamentals.csv`. See Equation (1)

$$close = \beta_0 + \beta_1(volume) + \beta_2(CapitalSurplus) + \beta_3(GrossMargin) + \beta_4(Liabilities) + \epsilon \tag{1}$$

Since the data from the `fundamentals.csv` is annual, we merged the previous year's dataset with the following year's `prices-split-adjusted.csv` data of AT&T to form the full dataset. For example, if the `total revenue` for 2013 is \$1,000,000 so we made a column for total revenue and made every row that is in 2014 to be \$1,000,000. We ran a nested for loop to apply this for all years and columns. `Tprices` is the DataFrame with the columns of interest for our linear model. See Table 1.

Table 1: Column Names of DataFrame Tprices

Columns
close
volume
date
year
Capital.Surplus
Gross.Margin

Columns
Liabilities

`Close` corresponds to the price of the stock when the market closes on that day.

`Volume` is the number of trades that occurred that day.

`Date` is the date of the trading day.

`Year` is the year of the trading day.

`Capital.surplus` or share premium, most commonly refers to the surplus resulting after common stock is sold for more than its par value.

`Gross.margin` is a company's net sales revenue minus its cost of goods sold. The higher the gross margin, the more capital a company retains on each dollar of sales, which it can then use to pay other costs or satisfy debt obligations.

`Liabilities` are the debts and obligations of a company.

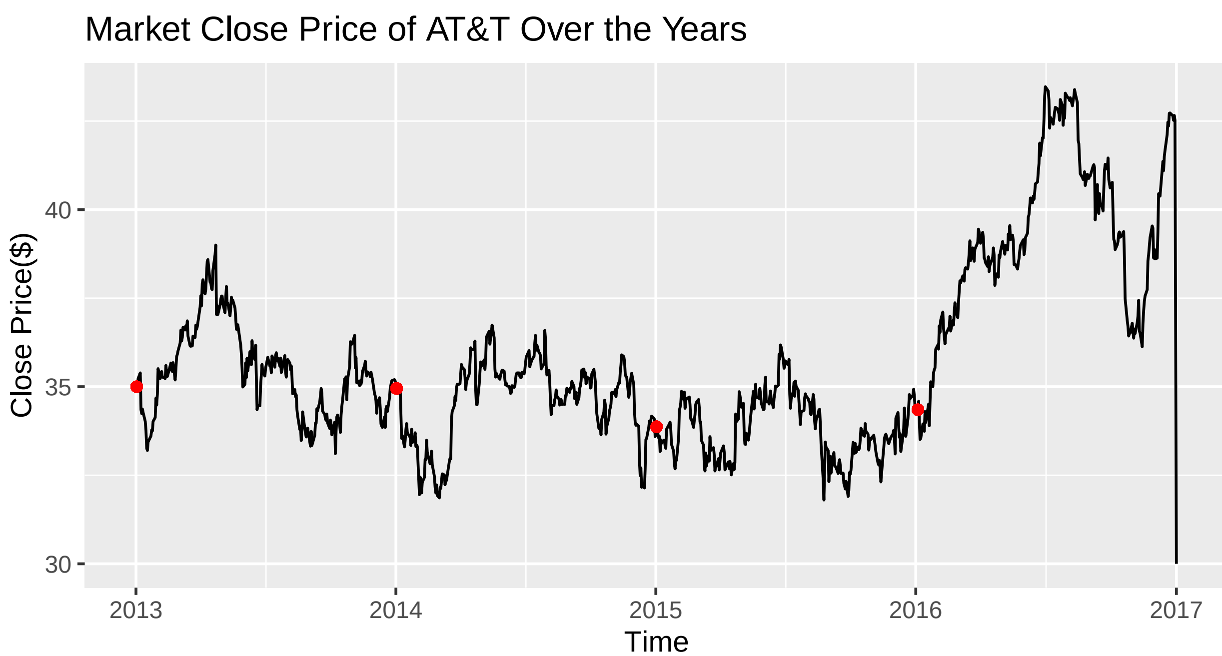


Figure 1: Daily Market Close Price of AT&T

Figure 1 represents the market closing price of the stock for AT&T over the span of 2013 to 2017. The red points on the line mark as an indication when the year begins. We notice that 2013 and 2014 closing prices both started around $35. Around spring of 2013, the stock shot up to about $39 which is the highest closing price until 2016. The stock drops to about $32 in the beginning of the year and before 2015. In 2016, the stock was starting to rise and in mid 2016, the stock got a new record of about $43.

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   30.00   33.96   35.10   35.77   36.74   43.47
```

In the five number summary of the close prices, the minimum is our added observation of $30 . Without the added observation, the lowest is $31.80. The max close price is $43.47. The mean close price is $35.77.

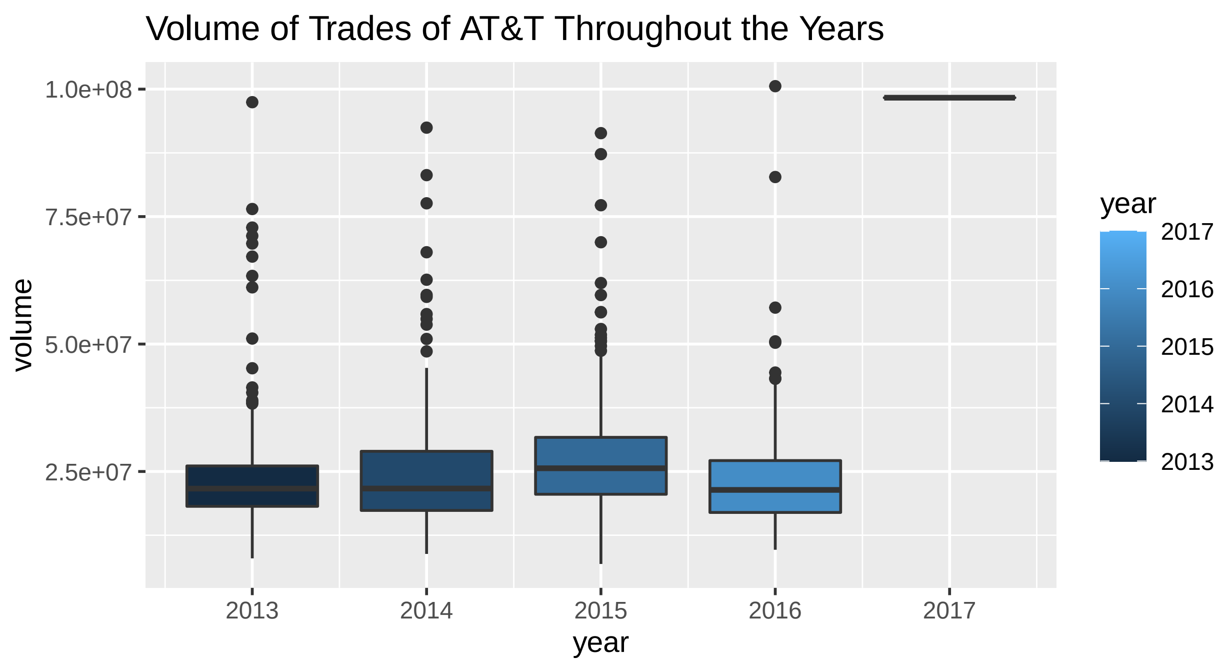


Figure 2: Daily Volume Traded of ATNT

Figure 2 shows the volume traded each year. The mean volume traded yearly is roughly the same except for 2015. The dots on the boxplot represent the outliers from that given year. There are days where the stock is traded more often than usual which could be caused by good news, low stock prices, etc. On the other hand, there are also days where volume is lower than usual since the stock price is higher causing people who own the stock to hold or the price being too high that does not incentivize buyers, etc.

```
## [1] "Summary of Volume in 2013"

##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##  7960000 18167000 21646500 23940484 26088200 97444100

## [1] "Summary of Volume in 2014"

##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##  8831900 17360725 21657950 24690541 28960075 92453000

## [1] "Summary of Volume in 2015"

##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##  6862400 20536525 25633950 28282645 31696250 91372900

## [1] "Summary of Volume in 2016"

##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
##   9645400  16962575  21388750  23596375  27142400 100586200
```

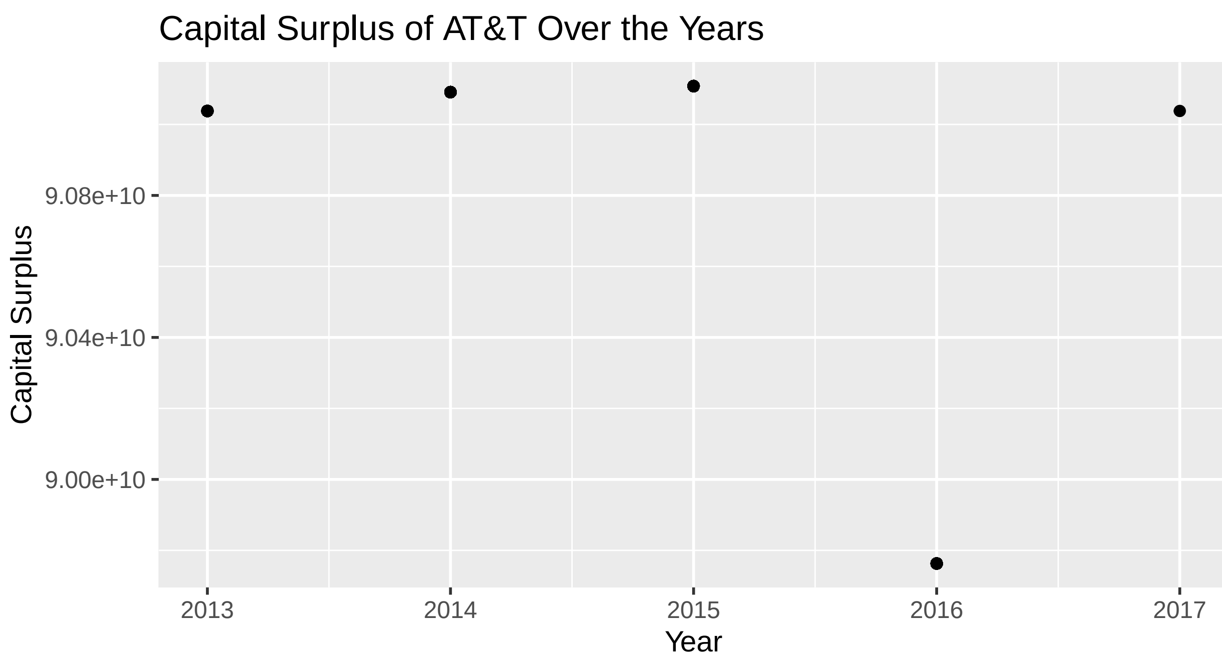


Figure 3: Capital Surplus of ATNT 2013-2016

Figure 3 shows the capital surplus of each year. It was rising up until 2016 where it dropped by significantly.

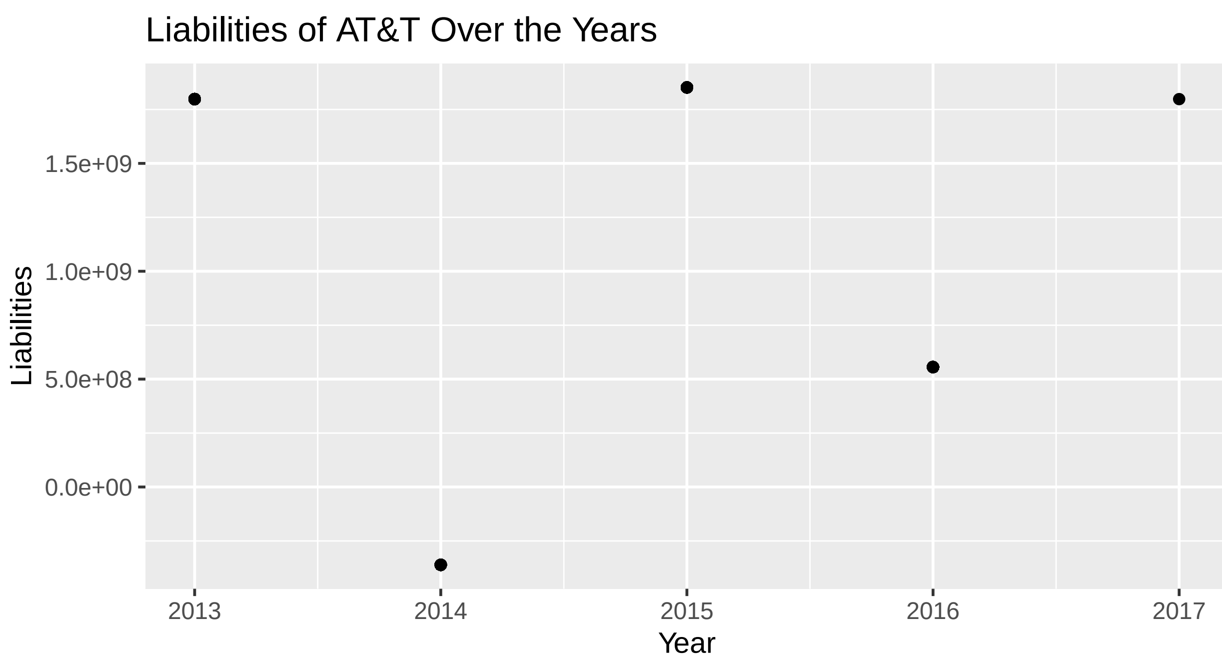


Figure 4: Liabilities of ATNT 2013-2016

Figure 4 shows the liabilities of each year. In 2013 and 2015, AT&T had the highest liabilities. In 2014, they had the lowest. In 2016, it was between the highest and lowest liabilities.

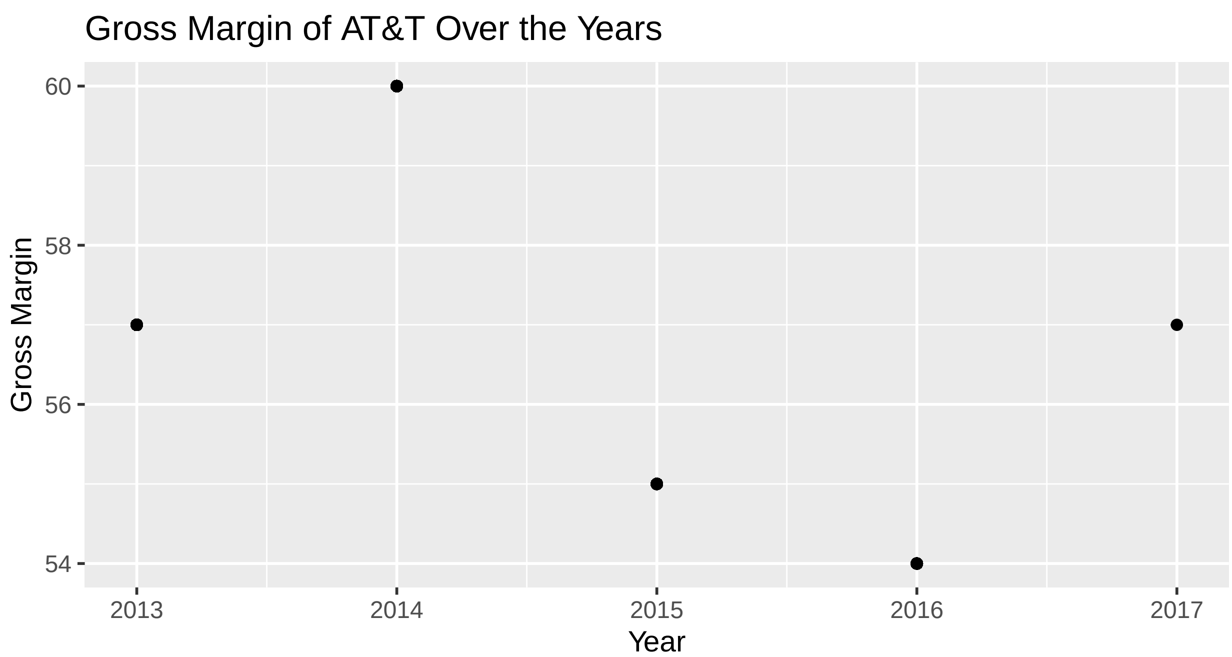


Figure 5: Gross Margin of ATNT 2013-2016

Figure 5 shows the gross margin of each year. From 2013 to 2014, it rose up to the highest of 60. In 2015 it fell down to 55 and 2016 dropped to 54.

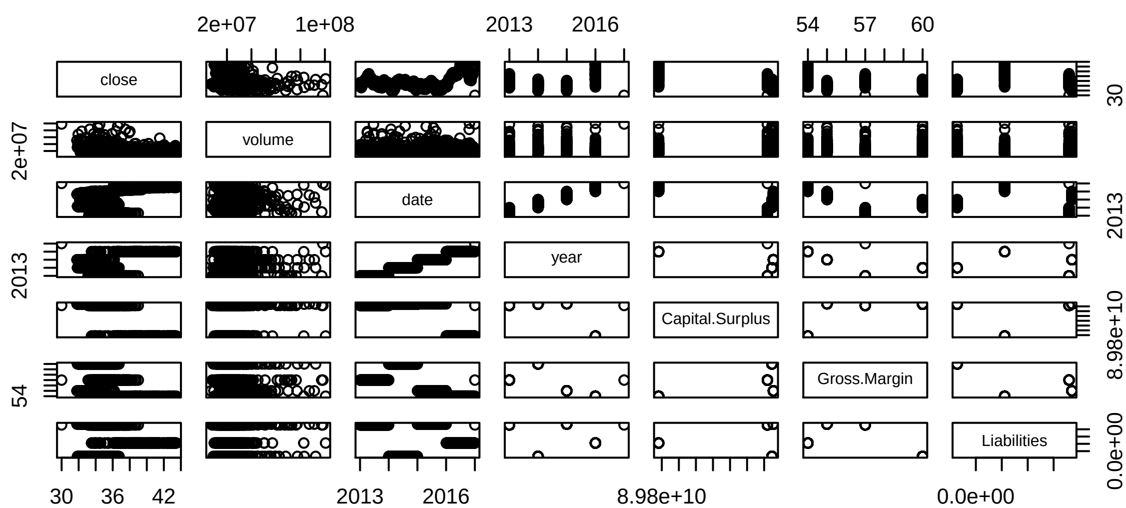


Figure 6: Pairs Plot of Columns of Tprices

Figure 6 shows the columns plotted against each other. Since the columns from the fundamentals.csv is yearly data, when plotted against other columns, they are shown as separate lines due to the values being the same daily for the year.

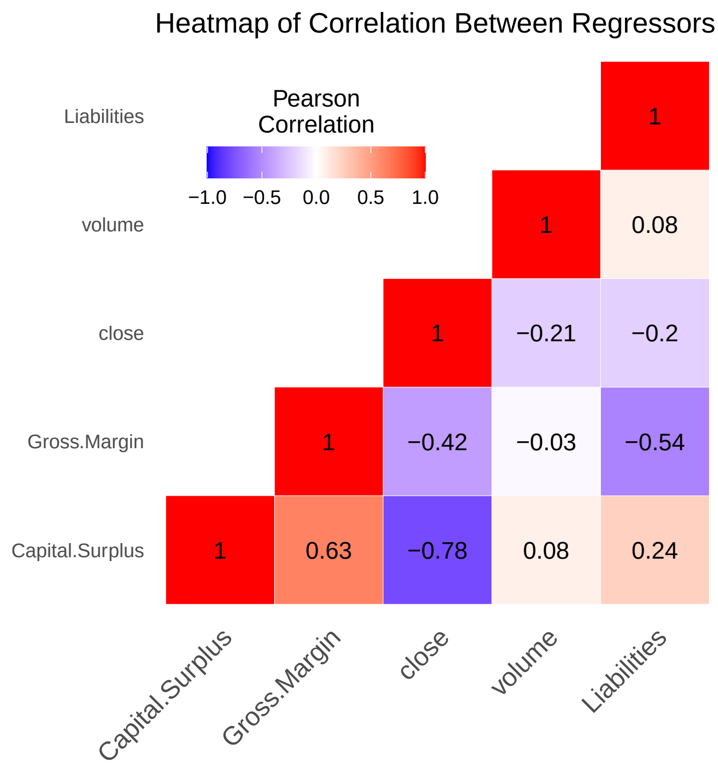


Figure 7: Correlation Between Variables

Figure 7 shows the correlation between each column.

3 Methods

3.1 Datasets

To begin, we chose to combine two of the four datasets offered, "Price-split-adjusted" (PSA) and "Fundamentals" (Fund). The PSA dataset accounts for all stocks traded in the NYSE daily from 2010-2016 and the Fund dataset accounts for the 10-K filing from 2012-2016, an annual comprehensive report required by the U.S. Securities and Exchanges Commission (SEC). Since the dates in the datasets varies from daily in PSA and annually in Fund, we attach the previous year's filing of the 10-K report to help predict the next year over.

Observation 1009 dated for Jan 01, 2017 is the added observation. We added this observation to see the effects it would have on our regression model. The observation should be recognized as an outlier which will be later classified as a high leverage point and removed. Observation 1009 has a significant decrease in stock price and increase in volume. A realistic example would be bad news being released on the company such as missing expectations in the earnings report which triggers a sell off and for the stock price to drop.

3.2 Choosing Regressors

When first developing the model, we included open as one of the predictors for close. As a result, the correlation of our model increased to 99%, this is because if a stock were to open higher than the average, it is most likely going to close higher than the average. Also, if other predictors were to be added with open, the variance inflation factor will be increased to a level where there are clear violations of multicollinearity. In the end, we decided not to include open as part of our model because it is unrealistic to be able to predict the model with 99% accuracy.

```
##
## Call:
## lm(formula = close ~ open + low + high + volume, data = ogdf)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.54358 -0.08214  0.00559  0.08498  0.83460
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.348e-02  2.835e-02   1.181   0.2377
## open        -4.845e-01  1.966e-02 -24.647   <2e-16 ***
## low          6.656e-01  2.036e-02  32.690   <2e-16 ***
## high         8.180e-01  2.164e-02  37.797   <2e-16 ***
## volume      -8.001e-10  3.212e-10  -2.491   0.0128 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.132 on 1757 degrees of freedom
## Multiple R-squared:  0.999,  Adjusted R-squared:  0.999
## F-statistic: 4.401e+05 on 4 and 1757 DF,  p-value: < 2.2e-16
```

This is the summary of our first model.

```
##      open       low      high    volume
## 676.47197 723.77829 828.08043   1.48055
```

These are the variance inflation factors. `Open`, `low`, and `high` have values vastly greater than 10, thus this model suffers from severe multicollinearity.

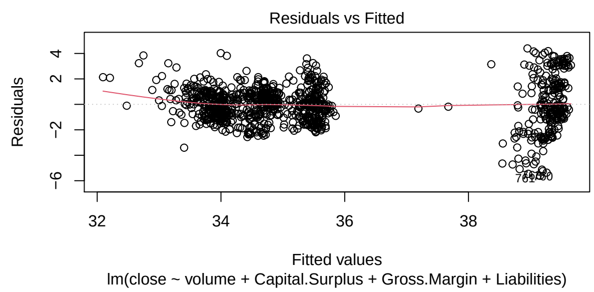
3.3 Subsetting Dataset

Since our datasets covers different years, we kept only the years that overlap in both datasets, 2013-2016. Lastly, we removed all companies other than our company of focus, AT&T. With 76 columns in `fundamentals.csv` that were added into `tprices` DataFrame, we ran into issues with fitting the model with all the columns. The error that came up was due to singularities with the columns. The singularities are due to the fact that many of the variables are dependent of each other. The model would fit up to four variables and the other coefficients would be NA. Due to this, we handpicked the variables `Capital.Surplus`, `Liabilities`, and `Gross.Margins`. We subsetted the DataFrame to just include `close`, `volume`, `date`, `year`, `year`, `Capital.Surplus`, `Gross.Margin`, and `Liabilities`. Table 2 presents the subsetted data.

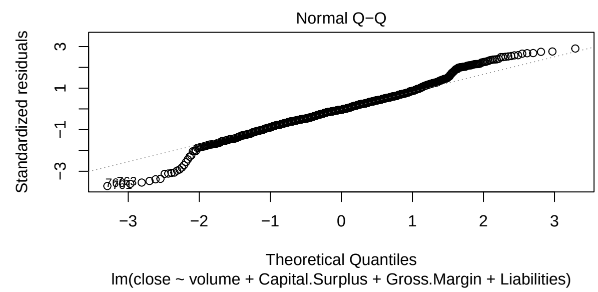
Table 2: First five rows of tprices DataFrame

close	volume	date	year	Capital.Surplus	Gross.Margin	Liabilities
35.00	38323500	2013-01-02	2013	9.1038e+10	57	1.798e+09
35.02	28932700	2013-01-03	2013	9.1038e+10	57	1.798e+09
35.23	21136600	2013-01-04	2013	9.1038e+10	57	1.798e+09
35.39	27500500	2013-01-07	2013	9.1038e+10	57	1.798e+09
34.35	29210300	2013-01-08	2013	9.1038e+10	57	1.798e+09

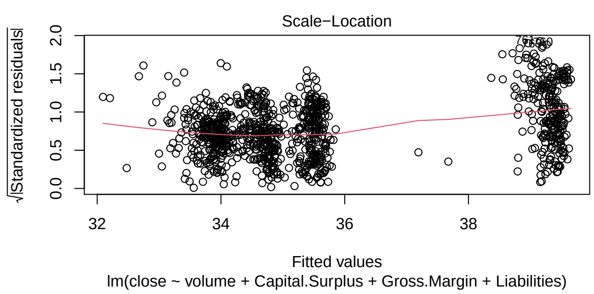
3.4 Model Adequacy



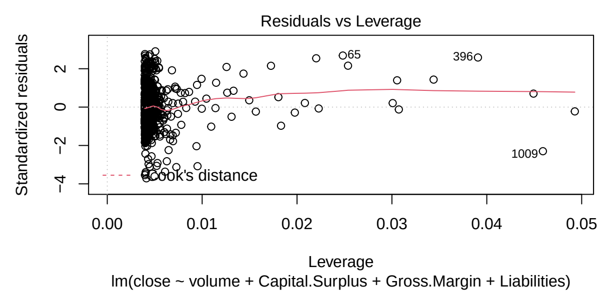
(a) Residuals vs Fitted Plot



(b) Normal QQ Plot



(c) Scale-Location Plot



(d) Residuals vs Leverage

Figure 8: Model Adequacy Plots

Checking model adequacy is an important step to measure the accuracy of the model. **The Residuals vs. Fitted values** in Figure 8(a) shows whether the residuals have a relationship with each other. Ideally, the points would be randomly scattered about zero with no patterns. In our plot, the spaces in between the four groups represent the four different years ranging from 2013-2016. When observing the residuals vs fitted, it seems as though the points are scattered randomly about zero, starting with a negative relationship into a more stable relationship as the plot moves from left to right. We also see that the scatter on the far right is more spread out which could point out to potential problems down the line.

The **normal Q-Q plot** in Figure 8(b) shows whether the errors are normally distributed. If the errors were normally distributed, points are expected to rest on the line with minimum gaps. Our plot has noticeable gaps on both ends labeling point 761 and 763 as potential outliers. The plot seems to be light tailed but nonetheless the plot is about normal due to the amount of observations.

The **scale-location plot** in Figure 8(c) shows whether the residuals are spread equally among the predictors and whether the assumption of constant variance is met. Ideally, the plot show has points scattered equally horizontally. In our plot, we see that there are four groups of points, the first three groups (from left to right) seem to follow constant variance but the points in the rightmost group have a wider spread compared to the previous three. The residuals in the plot do not meet constant variance assumption. Our plot points out point 761 and 763 as potential outliers.

The **residuals vs leverage plot** in Figure 8(d) points out the influential observations within our dataset. The dotted line represents the cook's distance and any points that fall outside of the dotted red line signifies a highly influential point to the regression results. If we were to exclude these observations, our regression will change and improve. In our case, no points fall outside of the cook's distance, this may be due to the large number of observations included in the data. The plot did highlight point 65, 396, and 1009 (our added point) as potential outliers.

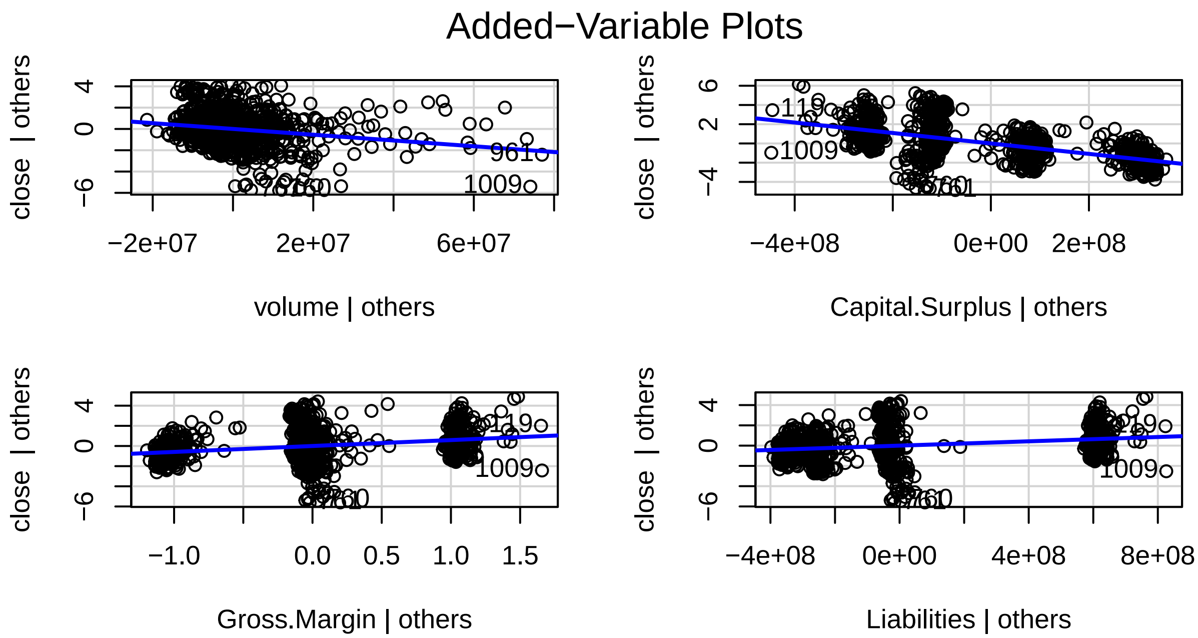


Figure 9: Added Variable Plot of Model

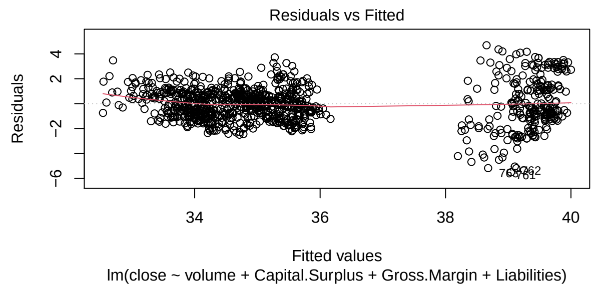
The Added Variable Plots in Figure 9 aim to compare each regressor against the response variable while controlling the presence of the other regressors. Since the variables in the fundamental dataset are presented annually and are merged with daily data, the variable-plot consists of grouping points.

We also investigated the leverage and influential points. A leverage point is when $h_{ii} > 2p/n$, where `p` is the number of predictors and `n` is the number of rows of the dataset. h_{ii} comes from the diagonal elements of the hat matrix((2)):

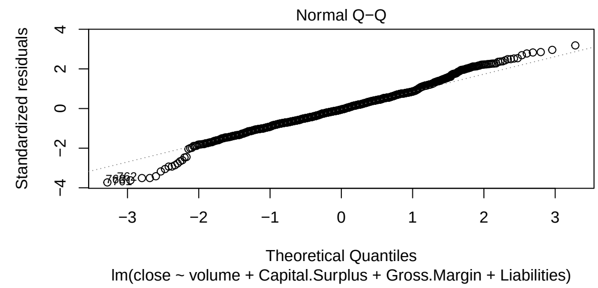
$$\boldsymbol{H} = \boldsymbol{X}(\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X} \tag{2}$$

The high leverage points are sorted here. Data point 1009 is the one data point that we added in. Measuring for leverage points caught this point.

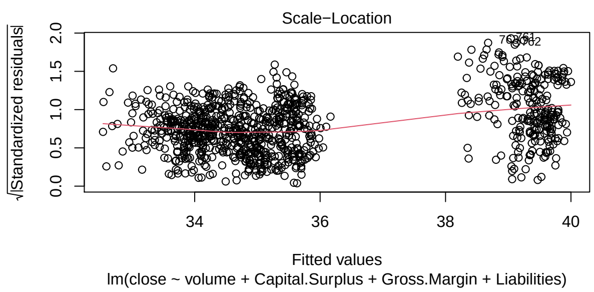
```
##         961        1009         119         396         581         960
## 0.049278243 0.045912513 0.044922337 0.039068133 0.034394745 0.030729741
##         645         271         347          65         666          64
## 0.030548797 0.030082971 0.025373101 0.024825409 0.022283334 0.022020309
##         120         192         274         121         623         193
## 0.020827655 0.019769046 0.018313347 0.018034662 0.017253045 0.015659610
##         306          78         329         489         658         877
## 0.014963038 0.014356594 0.013304578 0.013100958 0.012645405 0.012572914
##         598         457         291         308         524         610
## 0.011471124 0.011403934 0.010954989 0.010447714 0.009960494 0.009934028
##         768          51         773         307         647         451
## 0.009513285 0.009460517 0.009404053 0.009260503 0.008619798 0.008323023
##         643         748
## 0.008194445 0.007988696
```



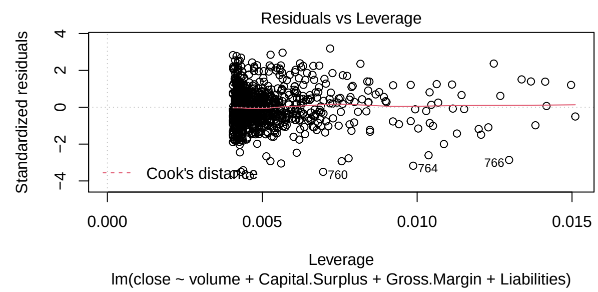
(a) Residuals vs Fitted Plot



(b) Normal QQ Plot



(c) Scale-Location Plot



(d) Residuals vs Leverage

Figure 10: Model Adequacy Plots

By removing the leverage points, the model adequacy plots in Figure 10 improve as the grouping of the points are less evident in all plots. There seems to be less clustering of points without the leverage points and for the residuals vs leverage plot in Figure 10(d), the data points looks more spread out.

```
##
## Call:
## lm(formula = close ~ volume + Capital.Surplus + Gross.Margin +
##     Liabilities, data = newdata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5033 -0.9369 -0.0740  0.8264  4.6954
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      4.889e+02  1.700e+01  28.756  < 2e-16 ***
## volume          -5.186e-08  6.433e-09  -8.063 2.20e-15 ***
## Capital.Surplus -5.330e-09  2.253e-10 -23.654  < 2e-16 ***
## Gross.Margin     5.465e-01  6.445e-02   8.480  < 2e-16 ***
## Liabilities      9.943e-10  1.274e-10   7.805 1.54e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.479 on 966 degrees of freedom
## Multiple R-squared:  0.6832, Adjusted R-squared:  0.6819
## F-statistic: 520.9 on 4 and 966 DF,  p-value: < 2.2e-16
```

By removing the leverage points, the R^2 improves from 0.6638 to 0.6832.

Here we checked the Variance Inflation Factor(`VIF`),

```
##          volume Capital.Surplus    Gross.Margin     Liabilities
##        1.025562        7.137102        9.378354        6.024813
```

The `VIF` for `Capital.Surplus`, `Gross.Margin`, and `Liabilities` are pretty high but they are less than 10 so they are acceptable.

3.5 Model Selection

By performing stepwise selection with our model, we discovered that our current model is the best for predicting closing stock price for AT&T therefore no variables need to be removed. See Equation (1) above.

```
## Start:  AIC=765.33
## close ~ volume + Capital.Surplus + Gross.Margin + Liabilities
##
##                   Df Sum of Sq    RSS     AIC
## <none>                         2113.7  765.33
## - Liabilities      1    133.31 2247.1  822.72
## - volume           1    142.24 2256.0  826.57
## - Gross.Margin     1    157.34 2271.1  833.05
## - Capital.Surplus  1   1224.33 3338.1 1207.01
```

```
##
## Call:
## lm(formula = close ~ volume + Capital.Surplus + Gross.Margin +
##     Liabilities, data = newdata)
##
## Coefficients:
##     (Intercept)           volume  Capital.Surplus     Gross.Margin
##       4.889e+02       -5.186e-08       -5.330e-09        5.465e-01
##     Liabilities
##       9.943e-10
```

3.6 Model Validation

After assessing the model adequacy, we go on to validate our model to see if it can function properly and successfully for the intended user. To do this, we sampled 80% of the AT&T data to form the training dataset, leaving 20% to be the testing set. The model and results will be shown in the following section.

4 Result

This is the summary of fitting a model on the training data.

```
##
## Call:
## lm(formula = close ~ volume + Capital.Surplus + Gross.Margin +
##     Liabilities, data = train_data)
```

```
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.3926 -0.9254 -0.0857  0.8235  4.4956
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      4.745e+02  1.882e+01  25.217  < 2e-16 ***
## volume          -5.709e-08  7.008e-09  -8.146 1.51e-15 ***
## Capital.Surplus -5.149e-09  2.497e-10 -20.622  < 2e-16 ***
## Gross.Margin     5.121e-01  7.164e-02   7.148 2.05e-12 ***
## Liabilities      9.177e-10  1.418e-10   6.472 1.72e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.459 on 772 degrees of freedom
## Multiple R-squared:  0.6828, Adjusted R-squared:  0.6811
## F-statistic: 415.4 on 4 and 772 DF,  p-value: < 2.2e-16
```

This is the summary of the full model without the leverage points.

```
##
## Call:
## lm(formula = close ~ volume + Capital.Surplus + Gross.Margin +
##     Liabilities, data = newdata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5033 -0.9369 -0.0740  0.8264  4.6954
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      4.889e+02  1.700e+01  28.756  < 2e-16 ***
## volume          -5.186e-08  6.433e-09  -8.063 2.20e-15 ***
## Capital.Surplus -5.330e-09  2.253e-10 -23.654  < 2e-16 ***
## Gross.Margin     5.465e-01  6.445e-02   8.480  < 2e-16 ***
## Liabilities      9.943e-10  1.274e-10   7.805 1.54e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.479 on 966 degrees of freedom
## Multiple R-squared:  0.6832, Adjusted R-squared:  0.6819
## F-statistic: 520.9 on 4 and 966 DF,  p-value: < 2.2e-16
```

When comparing the coefficients and p values from the two models, the coefficients remain similar and the regressors that were previously found to be significant are still significant.

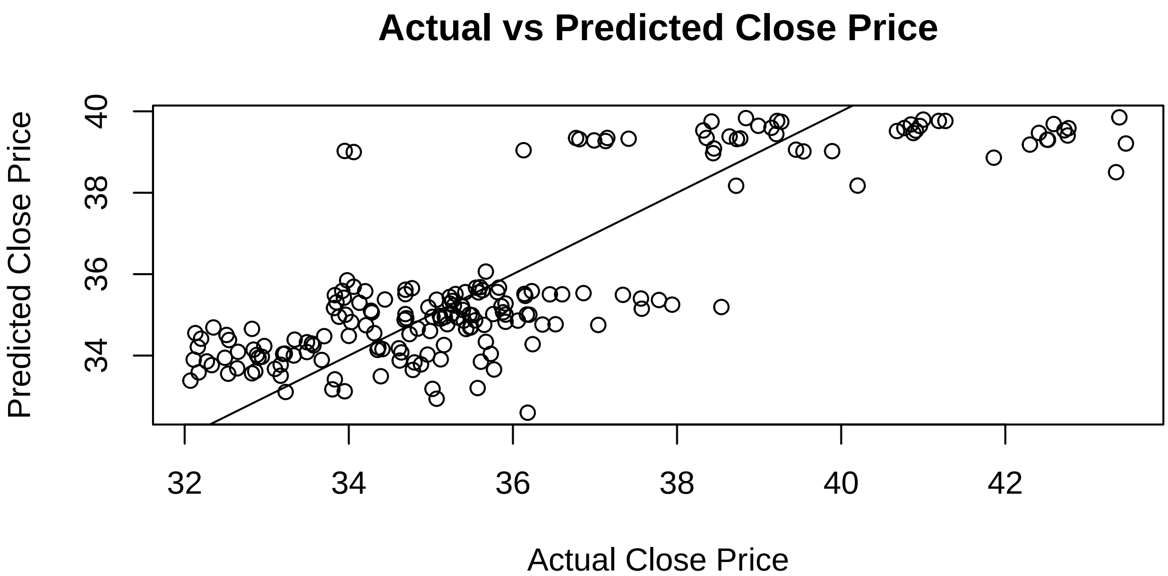


Figure 11: Predicted Values Plotted with Actual Values With y=x Line

Figure 11 shows the relationship between predicted close price (y-axis) versus actual close price (x-axis). We notice that the fitted line provides a positive slope across the plot indicating that there is a positive linear relationship between the predicted and actual close price. In addition, the points are evenly scattered around the fitted line which is a sign of constant variance. However, the points do not rest directly on the line which means that our model is not capable of perfectly predicting closing price. Although the two points on the top left of the plot could be potential outliers, removing them will not make a significant difference in the overall pattern so we can leave it as is.

Table 3: Table containing $R^2_{Prediction}$, Root Mean Square Prediction Error, Mean Absolute Prediction Error, Normalized Standard Error

R2	RMSPE	MAPE	NSE
0.6860785	1.563026	1.214033	0.5630319

In Table 3, we generated the $R^2_{Prediction}$, Root Mean Square Prediction Error, Mean Absolute Prediction Error and Normalized Standard Error. After sampling 80% of the data, $R^2_{Prediction}$ uses the same regressors as the original model but uses the sampled data (train dataset) instead of the full data. By calling the summary using the predicted linear model, we can observe the correlation between regressors and response of the train dataset. The sampled data is capable of predicting the remaining 20% of the data 69% of the time.

The Root Mean Square Prediction Error (Equation (3)) is the standard deviation of the residuals. It is a measure of how far the data points deviate from the regression line.

$$\boldsymbol{RMSPE} = \sqrt{\frac{1}{\boldsymbol{n}}\sum_{i=1}^{n}(\boldsymbol{y_i} - \boldsymbol{\hat{y}_i})^2} \tag{3}$$

The Mean Absolute Prediction Value measures the average magnitude of the data points that deviate from the fitted line. See Equation (4).

$$\boldsymbol{MAPE} = \frac{1}{\boldsymbol{n}} \sum_{i=1}^{n} |\boldsymbol{y_i} - \boldsymbol{\hat{y}_i}| \tag{4}$$

The Normalized Standard Error(Equation (5)) is the normalized Root Mean Square Prediction Error. Normalizing it tells us if the Root Mean Square Prediction Error value is a low value or not. It tells us how much variability we have explained. For example, a value of 1 says the model explains none of the variability.

$$\boldsymbol{NSE} = \frac{\boldsymbol{RMSPE}}{\boldsymbol{\sigma_{test}}} \tag{5}$$

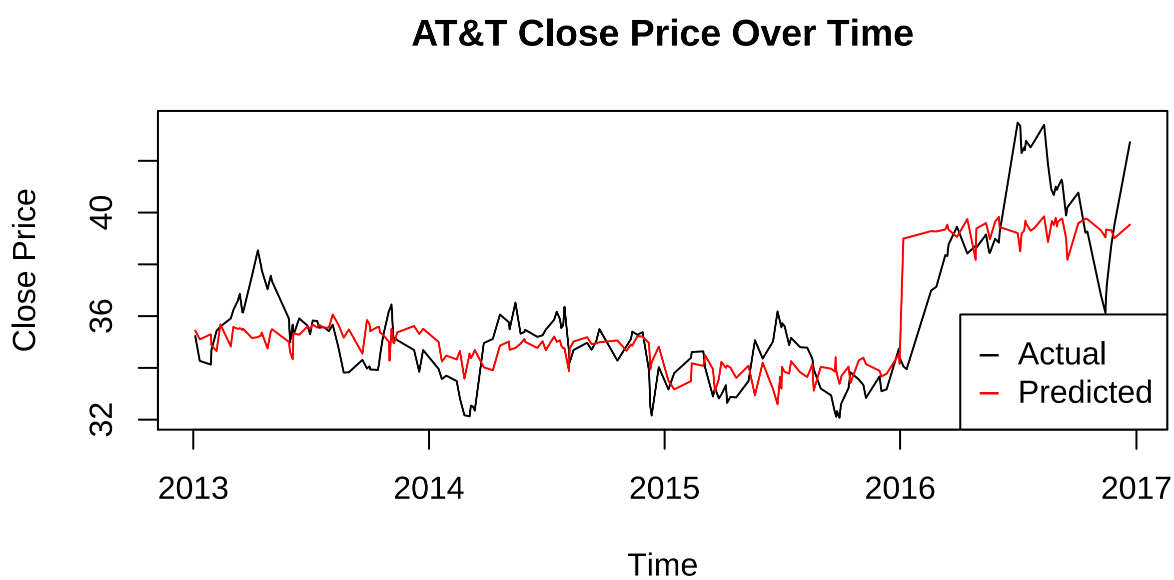


Figure 12: Time Series Plot of Actual Close Price and Predicted Close Price

Figure 12 shows the overall pattern of close prices of AT&T stocks over years 2013 to 2016 with the one data point that we added for 2017. This plot gives a visual representation of the difference between the predicted closing price (labelled in red) versus the actual closing price (labelled in black).We see that our predicted prices are generally more stable than the actual prices meaning that there are some variations between what we predicted versus what the actual price of the closing stock is at a certain point in time. From the results we see our prediction is not 100% accurate but it does show that it is not completely off as it provides similar patterns to the actual closing price which the 0.69 from the R^2 prediction explains.Furthermore, we also notice a large shift in the pattern from the beginning to the end of 2016 where the closing price has been the highest since recent years. This is an indication that the value of the company has grown.

5 Conclusion

In our analysis of closing stock prices for AT&T we discovered a few underlying issues limiting the progression of our model. Due to the lack of data presented in the fundamental dataset from 2010 - 2012, we are given fragments of information that would be incapable of integrating into our prediction analysis. Categories such as company's quarterly earnings report, and day to day stock activities would have been a great addition to help explain the volatility of the stocks and given us more flexibility with predictors to work with however such options were unavailable.

Listed below are some of the examples of better predictors of stock price excluding the ones already included in the dataset.

1. `Price to Earnings Ratio` – determines market value of stock compared to the company's reported earnings.
2. `Market Capitalization` – refers to the total value of all the company's shares in stock. Market capitalization is the total from (number of common shares * stock price).
3. `Earnings per Share` – how much a company earns per share, higher EPS means stock has higher value than those in the same industry.

By having quarterly information on the earnings reports of AT&T, the user of the dataset would have been able to better predict how the stock would react in the following days after the earnings report is released. For context, if AT&T's earning report were to beat the expectations, the stock would perform better on the following days. In conjunction with adding extra predictors listed above, the predictive power of the model would most likely increase.

In conclusion, the model we developed was successful at predicting the closing prices of AT&T 69% of the time. Although our model is not able to predict the missing data with more accuracy, our equation provides an adequate fit to the data, there is no assurance that it will be a successful predictor as influential factors first unknown when model building may affect the new predicted observations Montgomery, Peck, Vining, 2012. The results of and the limitations presented by the datasets points towards the complexity of the stock market that must be accounted for in order to build a successful prediction model.

6 Appendix

6.1 URL:

Repository containing all files

6.2 Data Files:

fundamentals.csv
prices-split-adjusted.csv
securities.csv

6.3 Raw Code:

rawcode.Rmd

6.4 Report:

atntReport.Rmd
atntReport.pdf

6.5 Text Files:

README.md
my_header.tex

6.6 Required Libraries:

```
lubridate
tidyverse
faraway
caret
reshape2
car
knitr
bookdown
```

6.7 Textbook Reference:

Montgomery, Douglas C., et al. Introduction to Linear Regression Analysis. Pearson, 2012