Many coffee consumers find themselves choosing between two major competitors on a daily basis; Starbucks and Dunkin. While some swear loyalty to Starbuck's superior quality, others flock to Dunkin Donuts cheap yet still passable options, and even others see no difference between the two and split their purchases evenly. For our part in this debate, we want to respond to the following questions: Which coffee super power is truly more successful? How are these two companies correlated? Which company will continue their success as time goes on? The initial hypotheses based on the questions are: Starbucks is rising in value while Dunkin is gradually decreasing, and Starbucks and Dunkin are negatively correlated. In order to find the answers, we have focused on a multitude of interesting factors.

It is beneficial to describe here that according to the financial statements, both companies tend to depend on similar factors mostly involving the economy and the general coffee market. There only exist two glaring differences. First, Starbucks owns the majority of their locations, while Dunkin franchises most of its business. Because of this difference, Dunkin tends to depend more on their franchisees, and the suppliers their franchisees use for income, and stability. The second difference is that Starbucks buys coffee and equipment from generally set suppliers, while Dunkin's franchisees are able to choose coffee and equipment suppliers from an approved company list and often even use local shops. In order to explore the results of these differences, we will look at a variety of financial data.

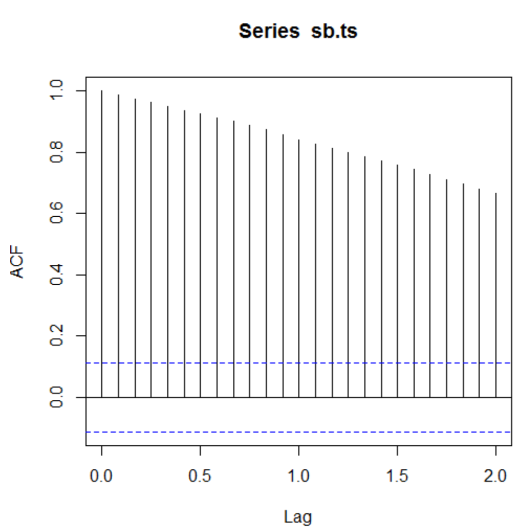
Stock price

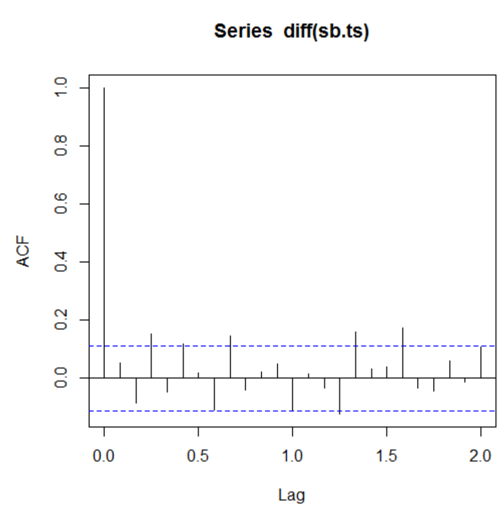
To begin our research, we looked at the year to date monthly stock price data for both companies. The graph showing the relationship is shown below.

We note here that from the time Dunkin Donuts began publicly trading stock in 2011, it has risen in a similar fashion to Starbucks stock, yet remained somewhat behind in price. A closer look at this relationship can be shown below. In fact, the correlation between the two companies' stock prices is about 0.82. The dashed line represents Dunkin stock price from July, 2011 until now, and the solid line represents Starbucks stock price from July, 2011 onward.

This close look allows us to see that for a while, until around 2015, Dunkin actually did better than starbucks in terms of stock price. Around this same time is when Starbucks split their shares. Although the value of the stock does not change, the stock price is lower, and more people are willing to purchase at the time. It also doubles the amount of shares held by current owners They also introduced their handcrafted cold brew coffee around this time. These two factors seem to be the most likely causes of the company's sudden success.

In order to forecast future stock prices for both companies we first must find models to fit our data. Stock Price is influenced by a variety of factors, some of which include: an earnings base (earnings per share), inflation, economic strength of market, substitutes, incidental transactions (e.g.portfolio creation), demographics of investors, trends, and liquidity. Each of these factors can follow different trends at any given time. Furthermore, some factors, like incidental transaction, have little to do with increasing or decreasing value of a company. Because stock price changes are due in a large part to error, stock price can be viewed as a stochastic process rather than a deterministic one. First, we will look at the monthly stock price data for Starbucks. We can show that the data can be fitted to a Random Walk model through the graphs below. Notice that the Correlogram of the autocorrelation for each lag slowly decreases in an almost linear fashion from unity, and that the correlogram of the differences of the data shows

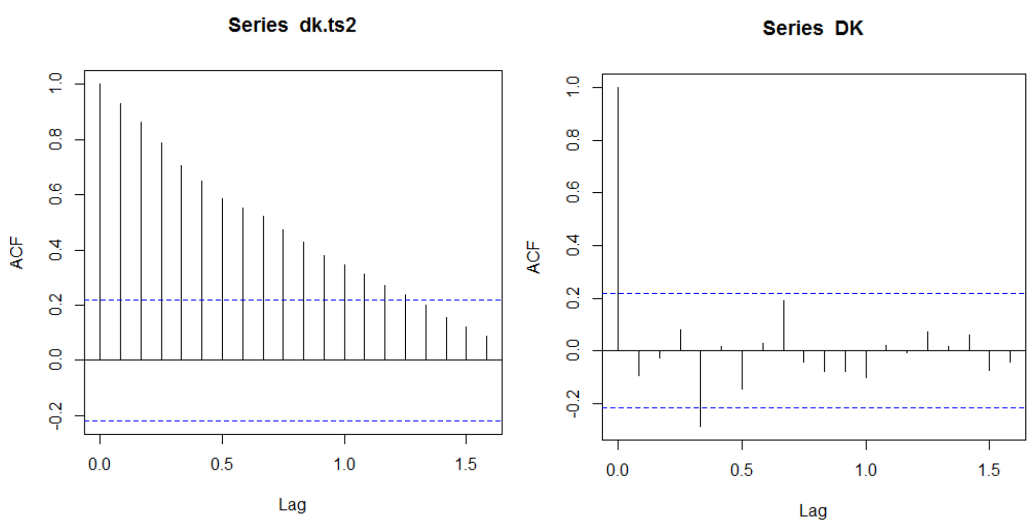




that autocorrelation for each lag appears to be mostly within the 95% Confidence interval (illustrated by the blue lines).

Furthermore, there is evidence that we should include a drift component in the model because there is significant evidence that the mean of the differences in the time series model is greater than 0 (we are 95% confident that the true mean is between 0.04736893 and 0.33115759).

Next, we look at Dunkin Donuts monthly stock price data. Similarly to Starbucks, Dunkin's stock price data also appears to follow a random walk model as shown in the graphs below.

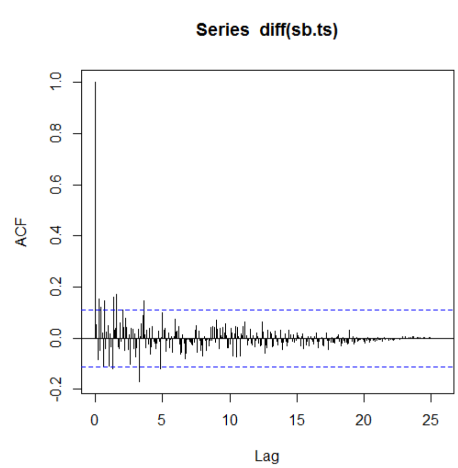


Notice that the Correlogram of the autocorrelation for each lag once again slowly decreases from unity (although at a faster rate than for Starbucks), and that the residuals autocorrelation for each lag appears to be mostly within the 95% Confidence interval (illustrated by the blue lines). Unlike Starbucks, Dunkin Donuts stock price data, does not include a drift component in its model. The 95% confidence interval of the mean differences between the data does include zero. (confidence interval = (-0.2303675 0.9993675)).

Normally, the best future prediction at time t+k for data modeled by random walk is the value at time t+k-1. (the last known historical value). Starbucks stock price data, however, includes a drift component (denoted δ) which adds a deterministic component to the otherwise stochastic model. The prediction for time t+1, therefore, is $x_{t+k} = x_t + 2\delta$, where x_t is the last known value of the time series data set, k is the amount of steps ahead in the future we want to predict, and δ is the drift component. Shown below is the two year ahead prediction or starbucks stock price data.

```
> (ts.sb.monthly[310] + c(1:8)*(mean(DS)))
[1] 59.01927 59.20853 59.39779 59.58706 59.77632 59.96558 60.15484 60.34411
```

We should note here however, that a company's stock price can be volatile upon its initial entrance to the market before stabilizing as it becomes more well known with the public. Therefore, the differences between historical stock price data are very large initially, but then stabilize and become smaller and smaller as time goes on. A closer look at the correlogram of the differences between Starbucks' stock price data shows this effect.

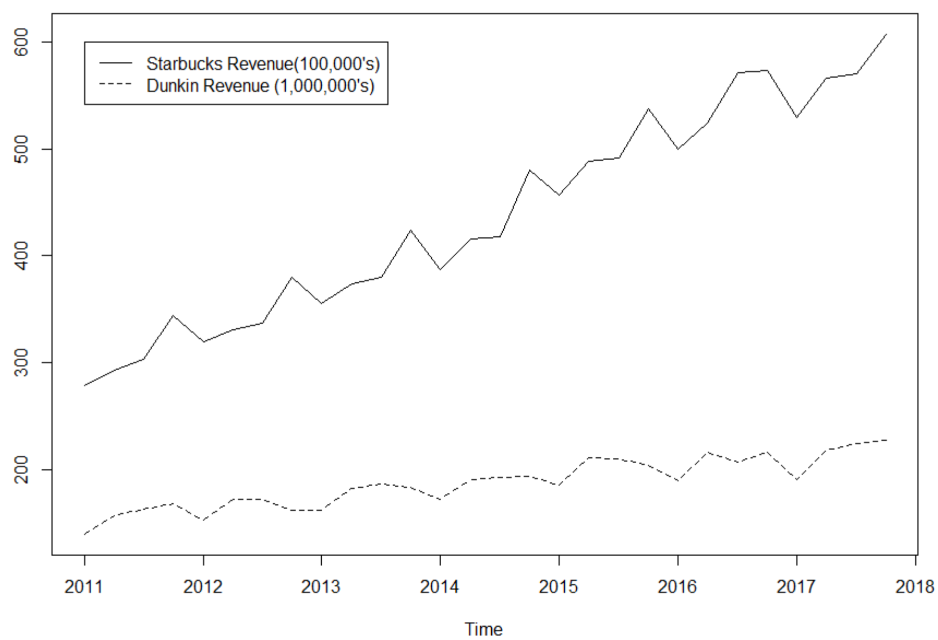


Our forecasts, therefore, underestimates the true stock price values initially, but now probably overestimate future stock price values.

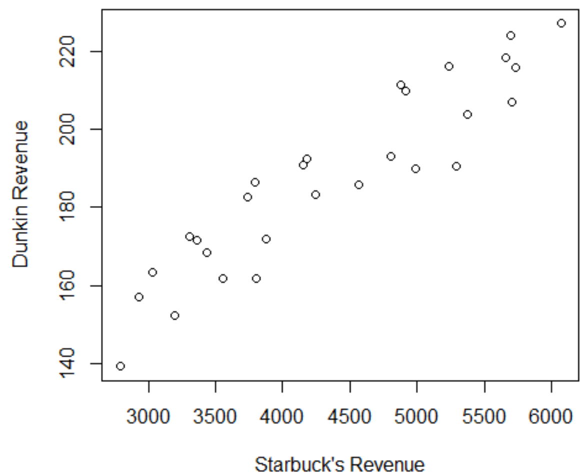
As previously mentioned, Dunkin donuts stock price data is not modeled with drift, and therefore, the best prediction at time t+k is simply the last known historical value because it is equally likely to be above or below the last value collected. In this case that value is 59.69.

Income

The next set of data we looked at was quarterly income for Dunkin and Starbucks. A graph of the two companies' income together can be shown below.

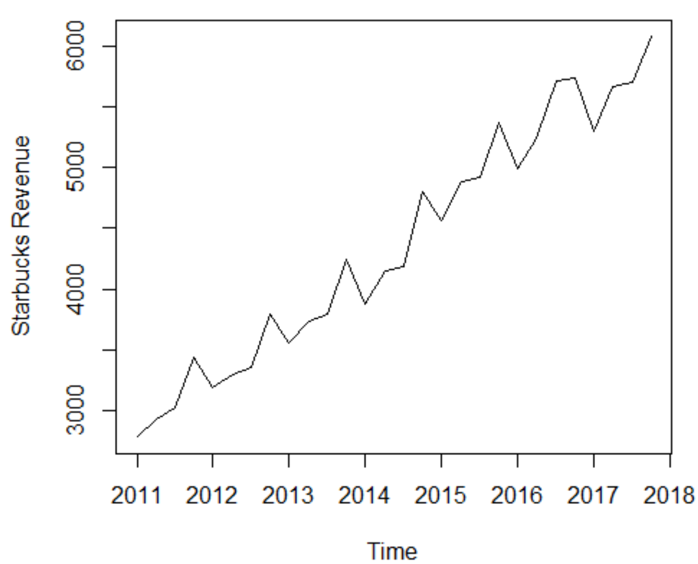


Notice that starbucks's revenue is scaled by 1/10 of Dunkin's revenue, so that Starbucks' revenue is in 100,000s of dollars and Dunkin's is graphed in millions of dollars. Starbucks tends to bring in significantly more revenue than Dunkin Donuts. The two companies, however, are very strongly correlated (with a correlation coefficient of .93), so that as one company's revenue increases, the other does as well. In fact, about 86% of the variation in Starbucks revenue can be explain by the variation in Dunkin's revenue. Notice that this is contrary our initial belief that one company's success would negatively impact the other's success.

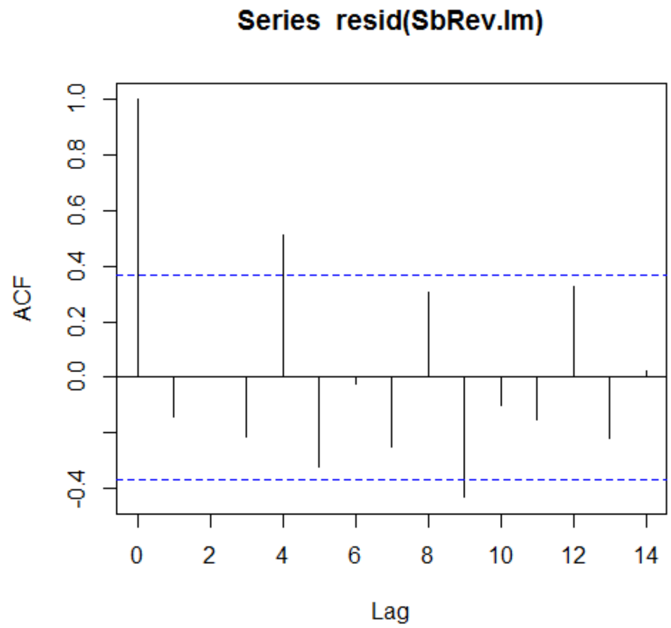


In order to fit model to this data, we must first decide whether or not the data is deterministic. Unlike our data for stock price, our revenue appears to have a clear trend and distinct additive seasonal effect. Therefore, we decided to model our data deterministically.

First, we will look at quarterly revenue for starbucks. Looking at the graph, we see that there is roughly a linear upward trend with some constant seasonal effect.



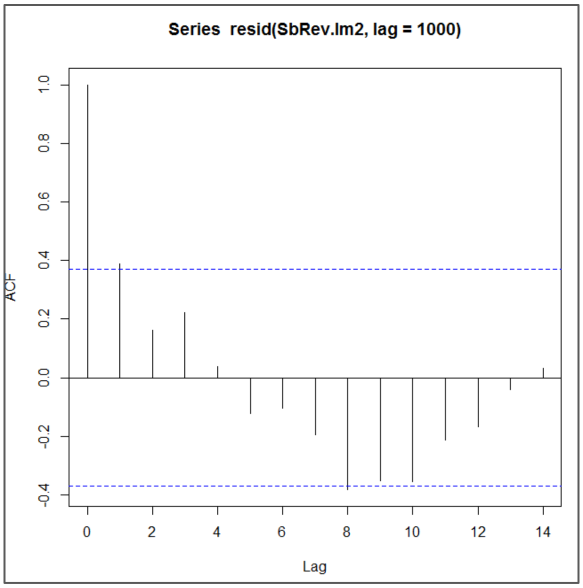
Because of this we first model the data as a linear model in R using the lm( ) function. We then plotted a correlogram of the residuals in order to see if our line was a good fit.



Here, we can clearly see the seasonal effect in the slight curve in the correlogram, and so we decided to use ols but adding a seasonal component. This is done by inputting the following code.

```
> seas<-cycle(SbRev)
> time <- time(SbRev)
> SbRev.lm2<- lm(SbRev ~ 0 + time + factor(seas))
```

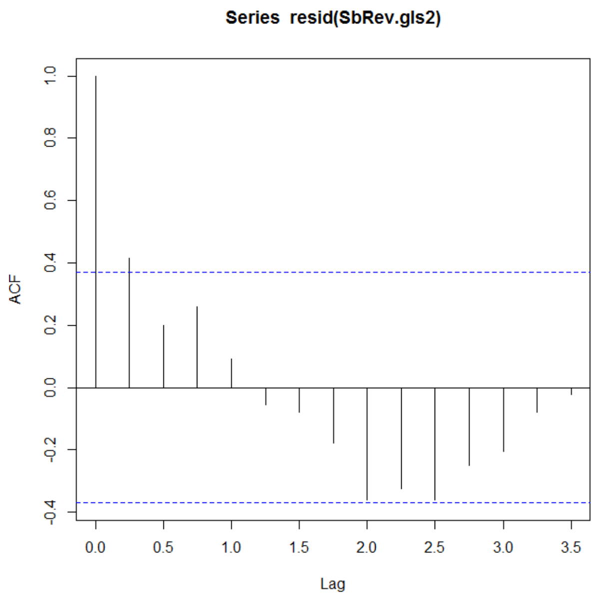
Looking at our new correlogram of the differences in revenue, we see that this model is an improved fit for our data.



Although, most of the points are within the required 95% confidence interval, there is significant positive autocorrelation. In fact, the correlegram suggests an AR(1) model. To account for this we use the gls function, still with a seasonal component, using the lag one significant autocorrelation from the above correlogram. This is done using the following code.

```
> library(nlme)
> SbRev.gls2 <- gls(SbRev~0+time+factor(seas), cor = corAR1(.388))
```

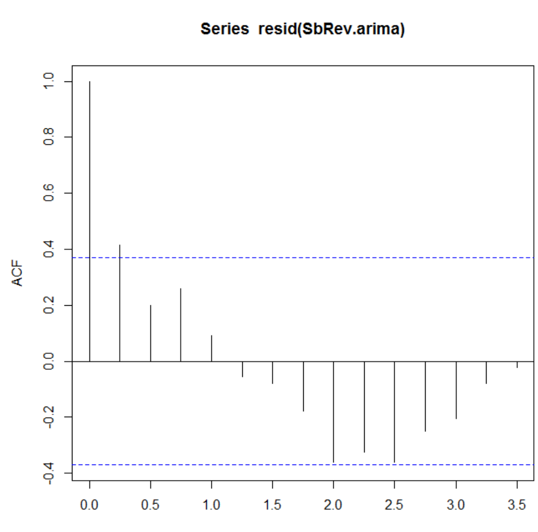
Although the standard error is larger here and the confidence interval for the slope is wider to account for the autocorrelation, the correlogram of the residuals still appear positively autocorrelated.



We then used a loop in R shown below to attempt to find the best fitting ARIMA to model the residuals of our gls function. The best order found was ARIMA(1, 0, 0), which is equivalent to an AR(1) model. This is to be expected considering the original correlogram was autocorrelated with a significant value at lag 1.

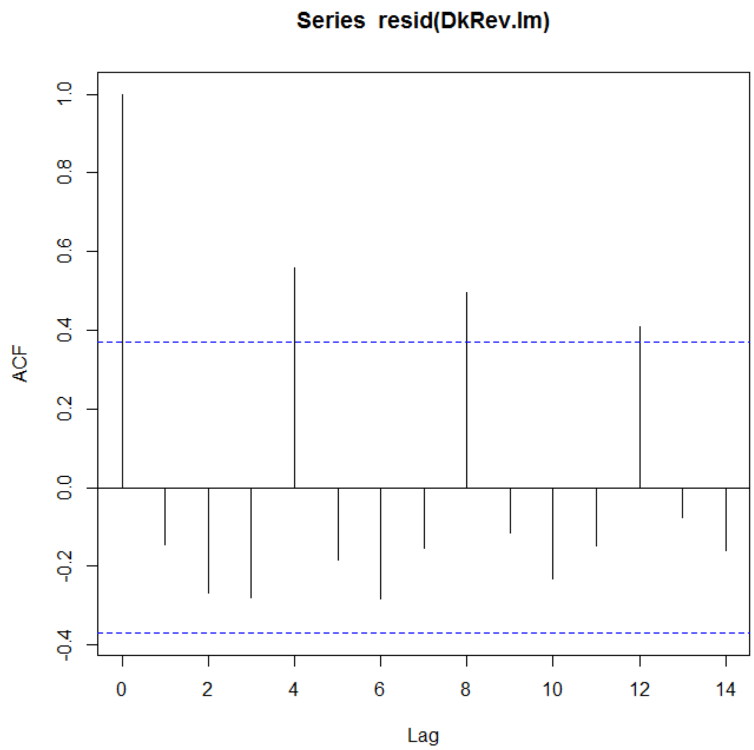
```
> best.order <- c(0,0,0)
> best.aic<-Inf
> for(i in 0:2) for (j in 0:2) {
+ fit.aic <- AIC(arima(resid(SbRev.gls2), order = c(i,0,j)))
+ if(fit.aic < best.aic) {
+ best.order <- c(i,0,j)
+ best.arma <- arima(resid(SbRev.gls2), order = best.order)
+ best.aic <- fit.aic
+ }
+ }
> best.order
[1] 1 0 0
```

The correlogram of the residuals of the arima model of the residuals of the gls model is shown below.



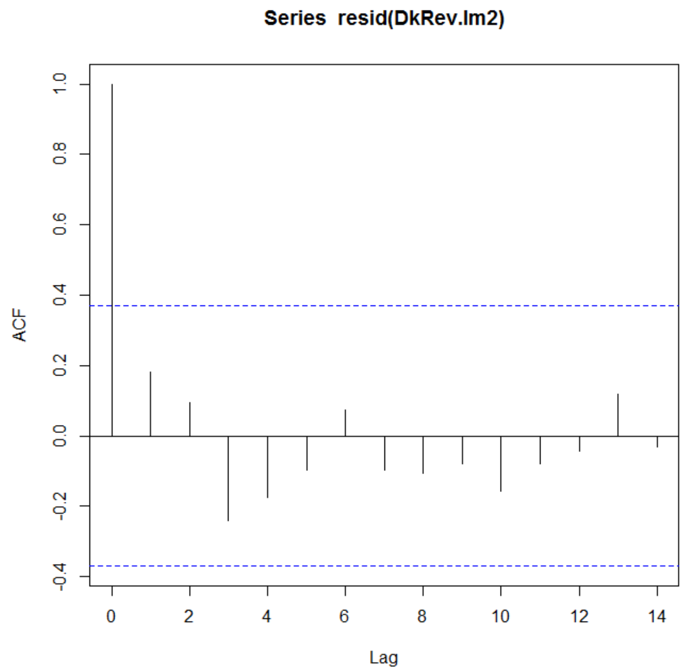
As the reader can see, the residuals do not resemble white noise any more than previously. Before discussing forecasts for this data, we will first look at the best model fit for Dunkin Donuts revenue data.

Similarly to Starbucks there appears to be a linear increase over time with some constant seasonal effect. Again, because of this linear trend, we first modeled the data using the OLS method. The correlogram of the resulting residuals in shown below.



Once again, however, we can model the data better when taking seasonal effect into account. In order to do this we input the following code and get a new slope and correlogram that is noticeable better than the original.

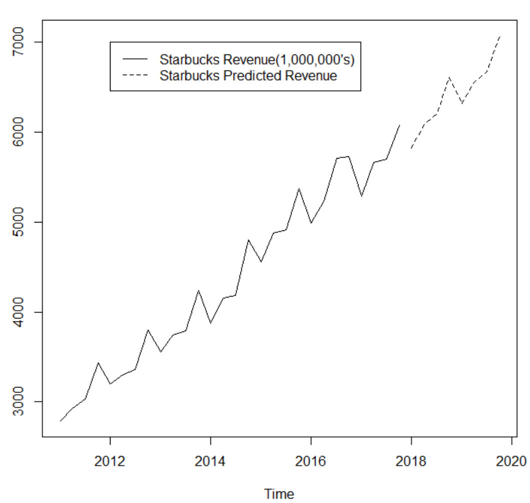
```
> seas<-cycle(DkRev)
> time <- time(DkRev)
> DkRev.lm2<- lm(DkRev ~ 0 + time + factor(seas))
```



Now that we know how to model our data, we can use those models to forecast and find predictions for future revenue of both companies.

For starbucks we used a mixture of the gls model of the revenue data, and the arima(1,0,0) model for the residuals of the gls model to make the following predictions.

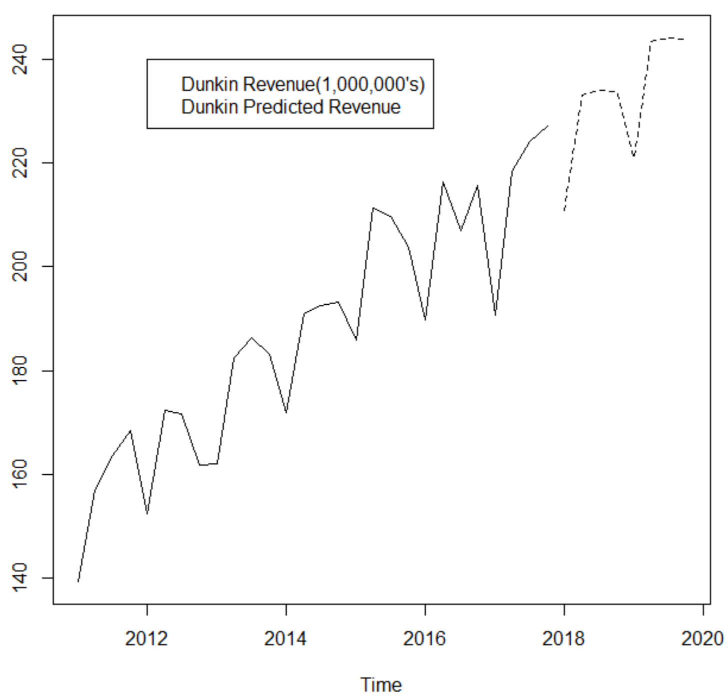
	Qtr1	Qtr2	Qtr3	Qtr4
2018	5859.716	6099.854	6215.819	6616.018
2019	6316.963	6557.101	6673.066	7073.265



The reader can notice here that this graph is visually pleasing and seems to follow the previous trend well. In fact, the actual revenue for Starbucks 2018 quarter one revenue was 6,073.7 million dollars, which is close to our estimate of 5859.72 million dollars. If our model continues to accurately predict results, we expect the revenue for a quarter increase by about 457.25 million dollars each year. Recall that using arima to model the residuals of our gls model did not yield very significant results. Therefore, adding the arima model of the residuals of the gls model to our forecast does not change our predictions significant from the predictions acquired when only modeling our data using the gls method.

Next we will make forecasts for Dunkin Donuts future revenue using our OLS model with an added seasonal component. The predictions and graph are shown below.

```
       1        2        3        4        5        6        7        8
210.8101 233.2566 234.1521 233.8632 220.9471 243.3937 244.2891 244.0003
```

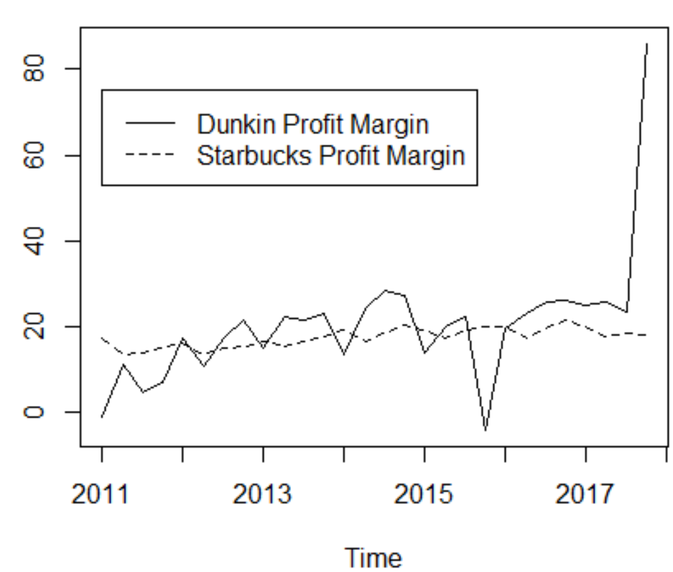


Like Starbucks, these predictions were very visually pleasing and seems to follow previous trends. The actual revenue for Dunkin in their first quarter of 2018 was about 301 million dollars. This seems off of our prediction. At the start of this quarter, however, new accounting guidelines were adopted which changed the way revenue was calculated for the company. If we look at the new retrospective value for quarter one of 2017 (294.6 million dollars) the increases to 301 million seems accurately predicted by the slope of our regression equation that tells us to expect a revenue increase for a specific quarter of 10.12 million dollars each year. Therefore, we can conclude that our model would still be effective after scaling all historical revenue data to their appropriate values given the new guidelines.

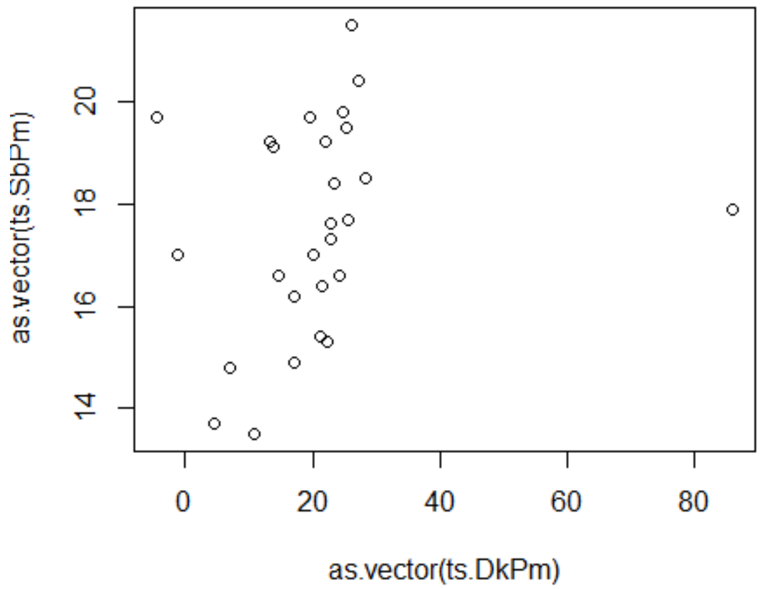
Based on the information gathered here, it appears that although both companies' revenue will steadily increase, Starbuck's revenue will increase at a faster rate. Revenue, however, is far from the only component used to measure a company's' financial health.

Profit Margin

The next financial component we will analyze for each company is profit margin. For the reader who is unfamiliar with the term, profit margin tells us the percent a company keeps of its revenue after deducting all of its costs and is calculated by taking revenue divided by net income. The graph showing profit margin for both Starbucks and Dunkin from 2011 through 2017 is shown to the right.



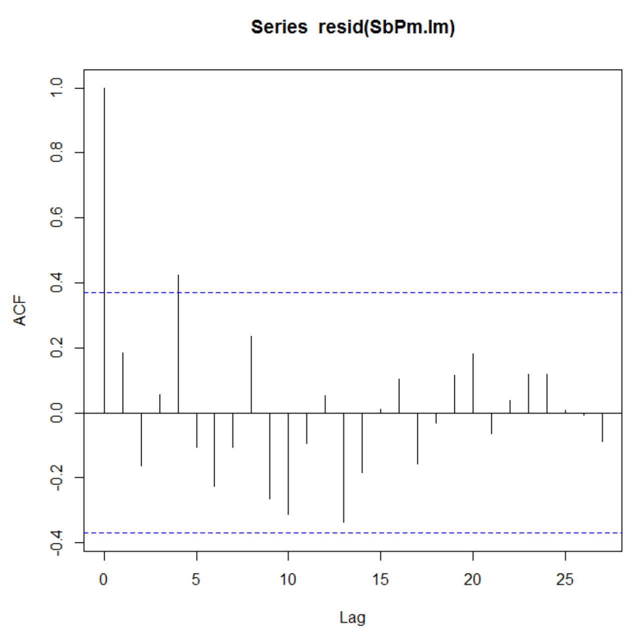
The two sets of data seem to follow a similar trend aside from the large spike in Dunkin's profit margin at the end of 2017 (this will be discussed later). Even so, the two sets of data are not very correlated. Even after removing the outlier, the two companies are only 36% correlated.



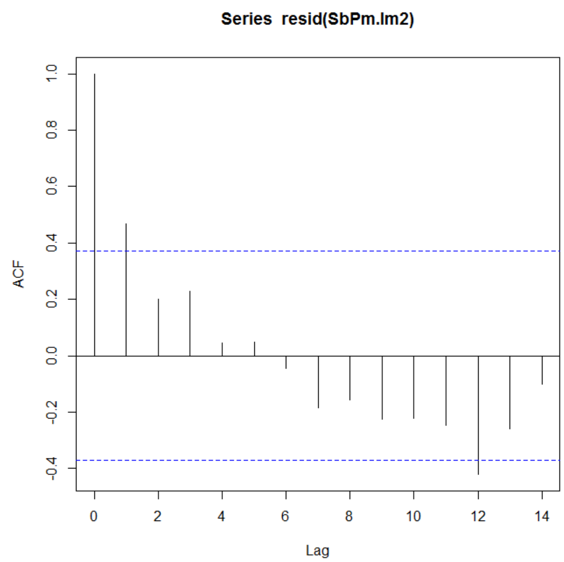

```
> cor(ts.DkPm, ts.SbPm)
[1] 0.2371534
```

Both, however do seem to be generally increasing. Like revenue, we will also model our profit margin data for both companies deterministically, as the margin is generally determined by the revenue and costs of the company.

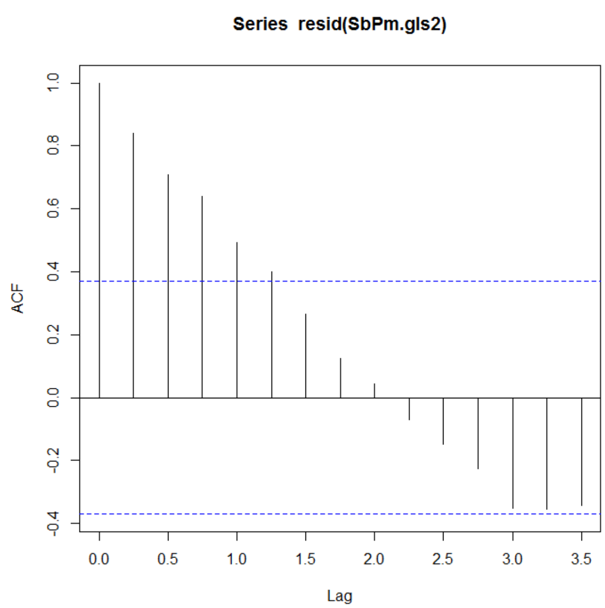
First, we will fit a model to our profit margin data for Starbucks. We start out using the basic OLS method. The correlogram of the residuals from this method is shown below.



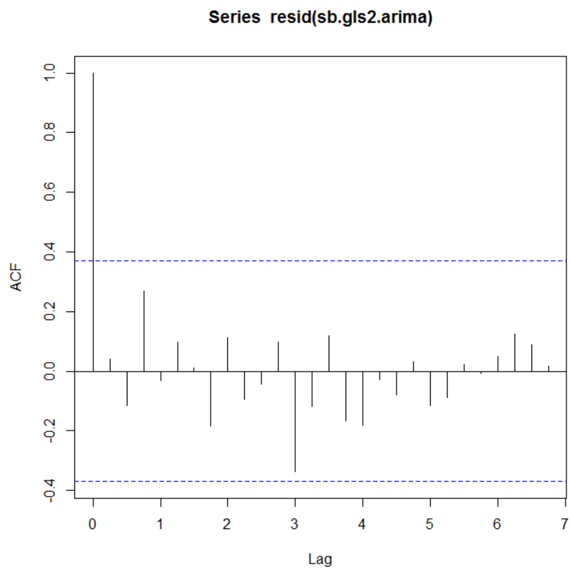
Again, it appears we should add a seasonal component to the OLS model, as the noticeable curve in the correlogram above indicates seasonal effect in our model. After updating our OLS model to include the seasonal component, the correlogram of those residuals is shown below.



Because the residuals are positively autocorrelated and seems to resemble an AR(1) model, we use gls to model the data using the significant autocorrelation at lag one. We end with the following correlogram of the residuals.

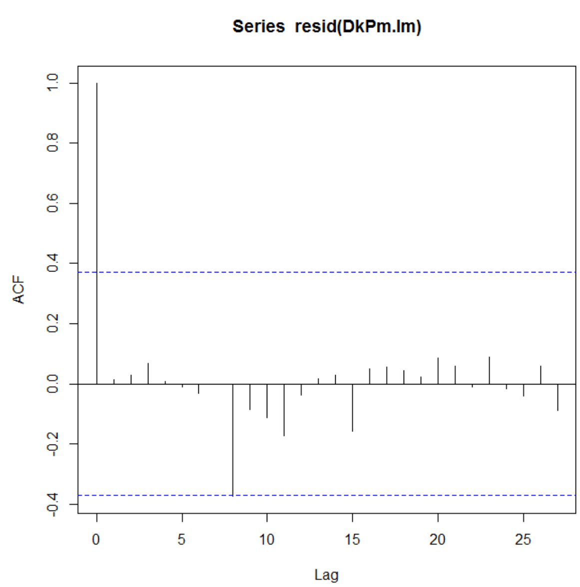


Because these residuals show this model is inadequate as is be able to forecast, we find the best arima model for the residuals of the gls model and use this model in conjunction with the gls model of the profit margin data. The best model turns out to be arima(1,0,0) and the correlogram if its residuals is shown below.

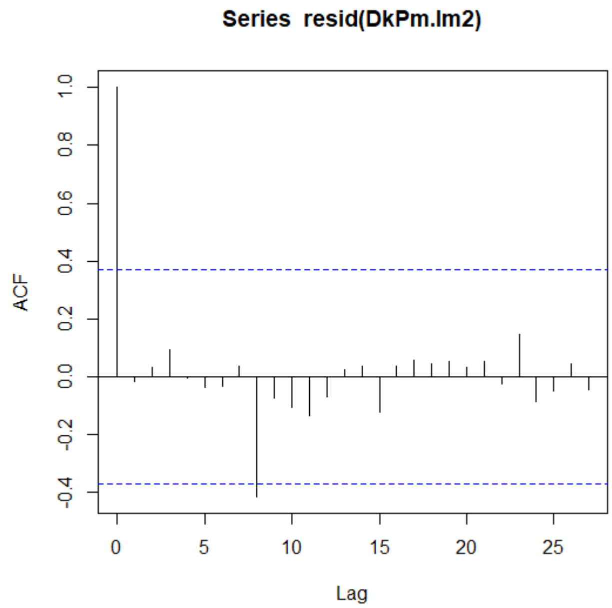


Although models were found that yielded more appropriate residuals, the AIC's of those models were larger than the AIC of the arima(1,0,0) model. Before reviewing our predictions for Starbucks future profit margin, we will fit the most appropriate model to Dunkin Donuts profit margin data.

Starting by using the ols method to model Dunkin's profit margin data, we have the following correlogram of the residuals. The curve indicates seasonal effect. We also saw this effect in the original plot of the data. Therefore, it is appropriate to add a seasonal component to our ols model of the data. The correlogram of those



residuals is shown below and show the model is a good fit for the data.



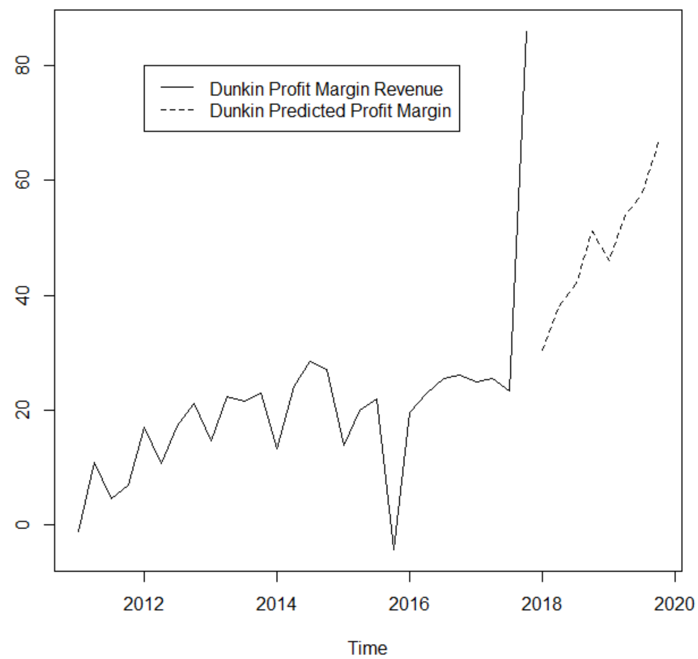
Now that we have our models, we can forecast future values for both companies' profit margin. First, recall that Starbucks is modeled using a combination of the gls model as well as an arima model of the residuals of the gls model. This combination is used to give the following predictions for our data.

	Qtr1	Qtr2	Qtr3	Qtr4
2018	18.23374	15.95918	17.43810	18.47344
2019	18.74333	16.41585	17.85089	18.84987

Starbucks actual profit margin for quarter one of 2018 was 18.4%. This is close to our predicted value of 18.23%. Our model appears to generate reliable forecasts based on this. The actual profit margin for quarter two, however, was about 12.8%, whereas our predicted value was 15.96%. In their earnings release the company said this value was indeed lower than expected, citing a food mix change in the Americas, more investment in their employees, as well as a management change in East Asia. They expect their profit margin to increase again as these aforementioned factors stabilize.

For Dunkin Donuts, we use code corresponding to our ols model with a seasonal component in order to forecast future values. These are shown below.

```
       1        2        3        4        5        6        7        8
30.34929 38.24067 42.03062 51.19629 46.11286 54.00424 57.79420 66.95987
```

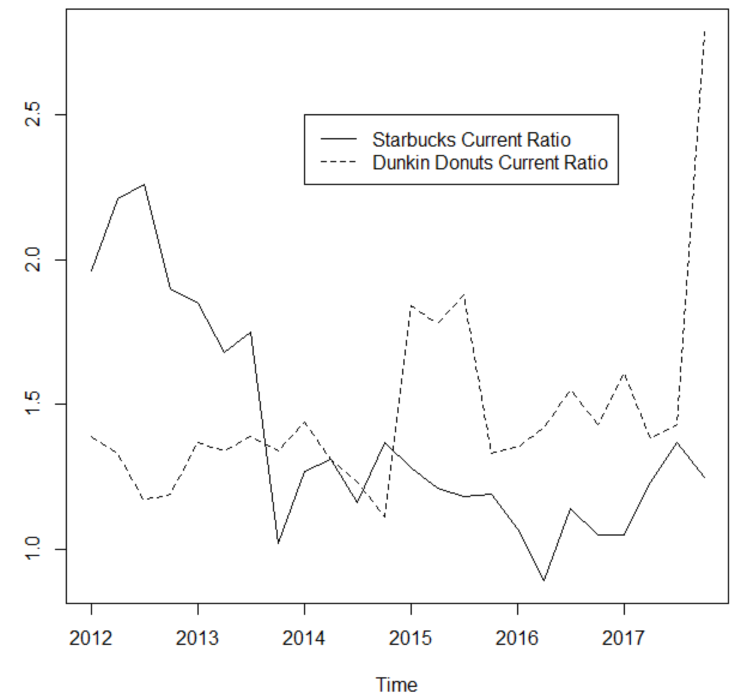


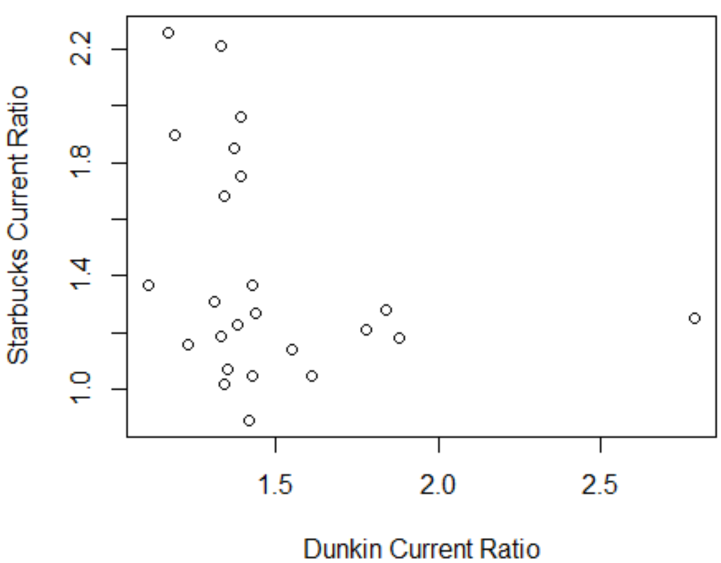
The reader will notice that Dunkin went from around a 25% profit margin to over an 80% profit margin in a single quarter. Net income for the quarter rose over 200% due to a large tax return as well as an increase in sales. In their financial statements, Dunkin attributed this success to a large volume of iced coffee and frozen hot chocolate sales and a marketing push to increase traffic at key times of the day. At the end of this quarter they fully implemented a more simplified version of their menu that they expect to yield beneficial results as well.

Based on the forecasting information for both companies, it appears that although profit margins are rising, Dunkin will take in a large percentage of profit than Starbucks in the near future.

Liquidity

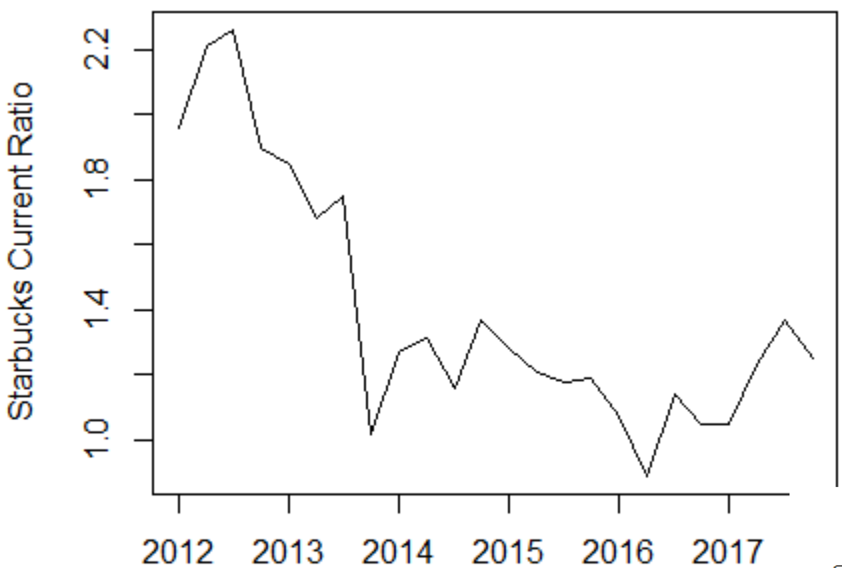
The final financial statistic we will analyze for the two companies is the current ratio. The current ratio is calculated as the current assets divided by the current liabilities and is a measure of how well a company can pay off its debts if they came due right now. For example, if a company's current ratio is 2.5, for every dollar of debt, the company has $2.50 to pay it off. Shown below is a graph of the current liabilities for Dunkin and Starbucks. The first thing we should notice is that there does not appear to be any significant seasonal effect in either data set. After decomposing the data, this assumption is confirmed. Although it appears that the two companies current ratios are

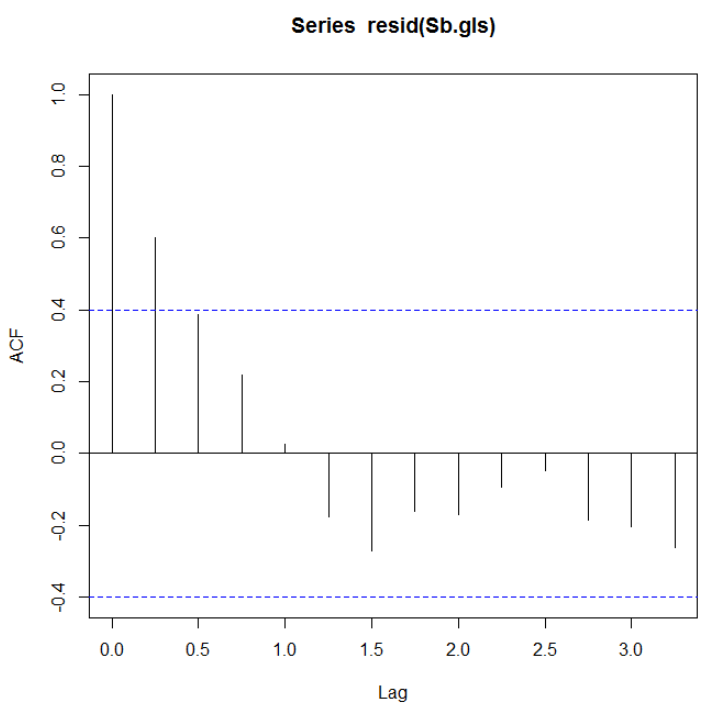


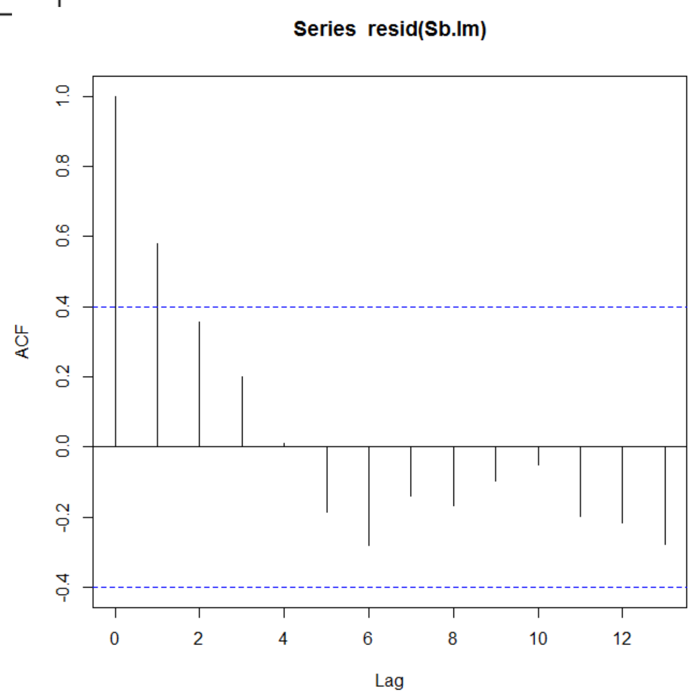


negatively associated, a closer look will show that there is no meaningful relationship between them. In fact, only about 8% of the variation in Starbucks current ratio can be explained by the variation in Dunkin current ratio. Although the argument could be made to model the data using a stochastic model, we decided to model this data deterministically. Current assets for both companies will increase as the company expands, as will current liabilities. Other factors affect the current ratio, such as accounts receivable, inventory, etc. The main point however, is that current ratio depends on how much the company takes in (in regards to capital, not profit) versus how much it puts out. Therefore, we can identify factors that affect the trend of the data aside from randomness.

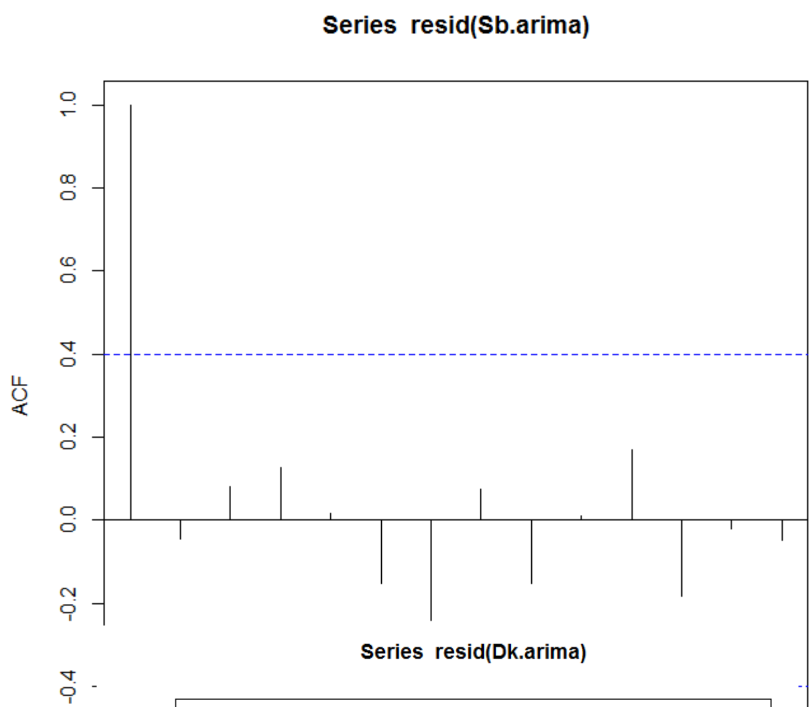
First, we will look at quarterly current ratio for Starbucks from 2012 to 2018. The graph is shown below. Recall that we determined that the time series data for current ratio did not contain any significant seasonal effect. We therefore first tried to model the data using ols. This resulted in the following





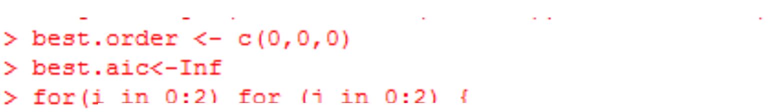


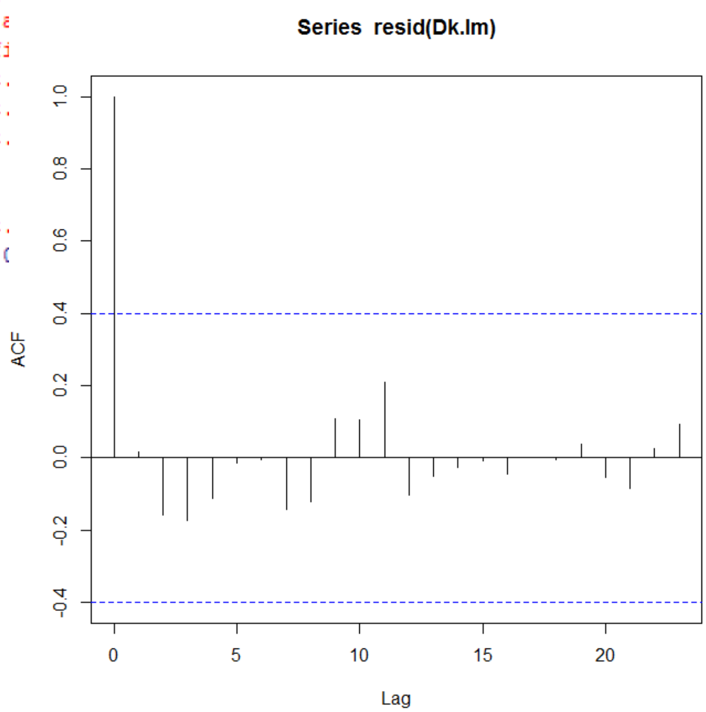
correlogram of the residuals. Based on the correlogram the series appears to be positively autocorrelated with a significant value at lag one. Therefore, we model the data using gls and the aforementioned lag one autocorrelation to model the data. This results in the following correlogram. Although the standard error is larger using this model (resulting in wider intervals of the slope, etc.) the residual correlogram still appears to be positively autocorrelated. Therefore, we use arima to find a model to fit the residuals of the gls model using the for loop. This process is shown below.



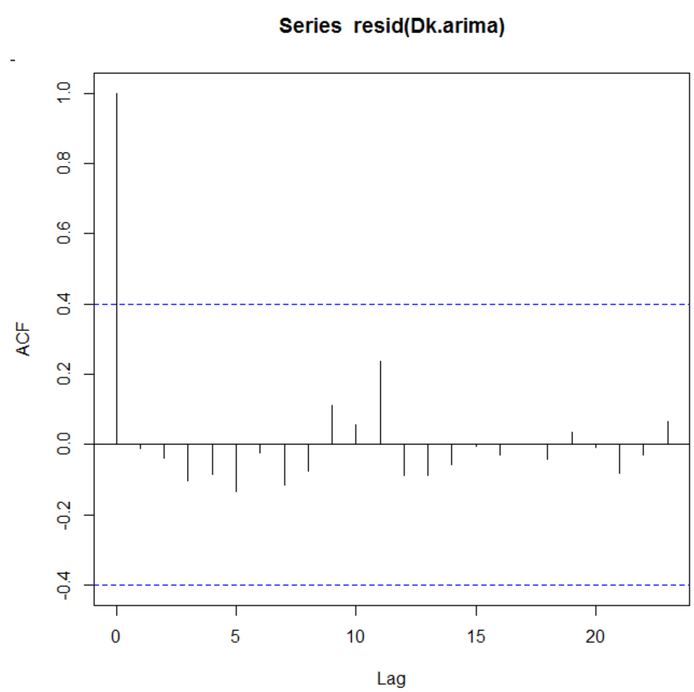
This correlogram shows that Arima(1,0,0) is a good fit to model the residuals of the gls model.

Next, we look at the current ratio data


```
> best.order <- c(0,0,0)
> best.aic<-Inf
> for(i in 0:2) for (j in 0:2) {
+ fit.a
+ if(fi
+ best.
+ best.
+ best.
+ }
+ }
> best.
[1] 1 (
```



for

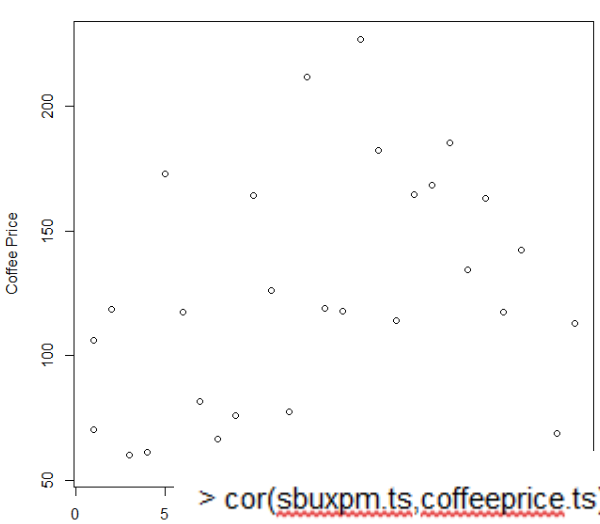


Dunkin Donuts. Like starbucks, we first try modeling our data using ols. This resulted in the following correlogram. There does not appear to be any autocorrelation or any significant lags, so it appears that linear modeling is a good fit for our data. Because other data sets wie have studied during out research were able to find an improved fit by using arima to model the residuals of the existing model, we decided to try it here to see if it yielded even better results. This process is shown below.

```
> best.order <- c(0,0,0)
> best.aic<-Inf
> for(i in 0:2) for (j in 0:2) {
+ fit.aic <- AIC(arima(resid(Dk.lm), order = c(i,0,j)))
+ if(fit.aic < best.aic) {
+ best.order <- c(i,0,j)
+ best.arma <- arima(resid(Dk.lm), order = best.order)
+ best.aic <- fit.aic
+ }
+ }
> best.order
[1] 2 0 1
```

Although we find that the best fitting arima model for the residuals of the ols model is arima(2,0,1), the correlogram shown above does not differ much from the correlogram of the residuals of the ols model. Therefore, we should note that although we will include the arima component in our predictions here, the predictions resulting from the ols model and those resulting from the combination of the ols and arima models will not differ significantly.

Finally, we can forecast future values for both data sets. To forecast future values for Starbucks current ratio, we use a combination of a gls model of the data and an arima(1,0,0)



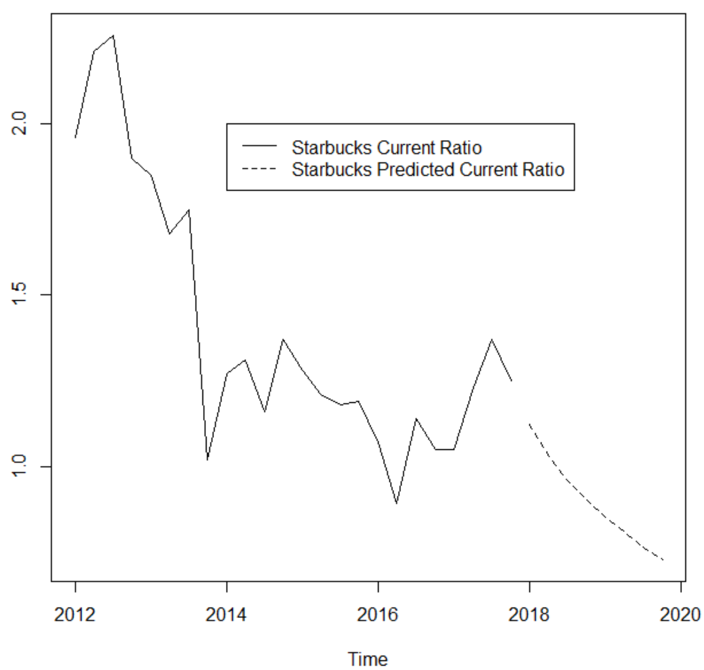

```
> cor(sbuxpm.ts,coffeeprice.ts)
[1] 0.5473975
```

model of the residuals of the gls model. This process is shown below.

And results in the following predictions.

```
> Sb.arima <- arima(resid(Sb.gls), order = c(1,0,0))
> new.time <- seq(2018, length = 2*4, by = 1/4)
> new.data <- data.frame(timeSb = new.time)
> predict.gls<-predict(Sb.gls, new.data)
> predict.arima <- predict(Sb.arima, n.ahead = 8)
> pm.predict <- (predict.gls + predict.arima$pred)
```

```
          Qtr1      Qtr2      Qtr3      Qtr4
2018 1.1219556 1.0291504 0.9580712 0.9003870
2019 0.8509610 0.8066267 0.7654315 0.7261716
```



The actual value for Starbucks current ratio in the first quarter of 2018 was 1.01 and the current ratio for the second quarter of 2018 was 1.09. As you can see, our model overestimates the current ratio in quarter 1 and underestimates the current ratio in quarter 2 of 2018. In 2013, 2015, and the end of 2017, the company's current liabilities spiked.[1] This could be due to a variety of factors, including the implementation of their college achievement plan, commitment to hiring more refugees and "opportunity youth", as well as overall expansion.[2] Although our model predicts that Starbucks current ratio will continually decrease for the next two years, this is unlikely. They're at a point

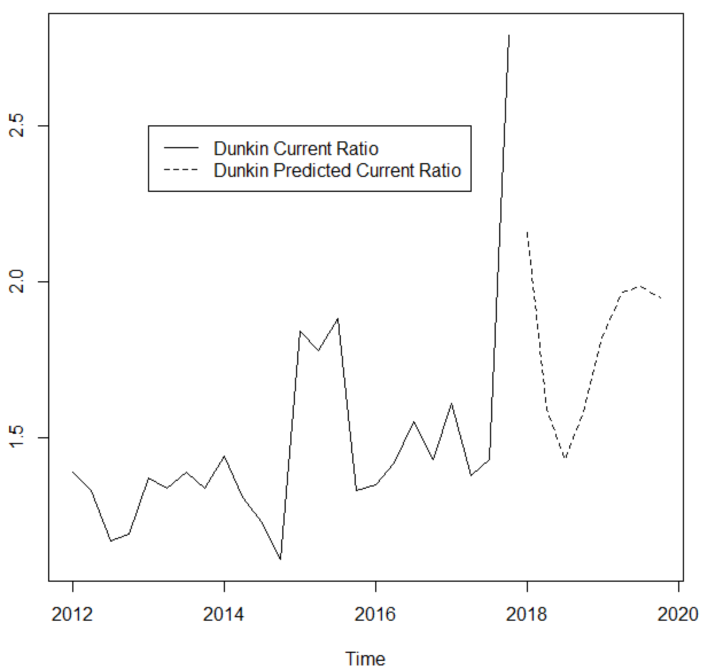
[1] https://www.stock-analysis-on.net/NASDAQ/Company/Starbucks-Corp/Ratios/Liquidity/Quarterly-Data#Current-Ratio

[2] https://news.starbucks.com/uploads/documents/AboutUs-Timeline-1.25.18.pdf

now where their current liabilities and current assets are meeting in the middle and Starbucks current ratio may increase as current assets continue to increase and current liabilities stabilize..

In order to predict future current ratio values for Dunkin Donuts, we forecast using a combination of the ols model and the arima model of the ols residuals.[3] This process and the resulting predictions are shown below

```
> Dk.lm <- lm(ts.DkCr~timeDk)
> Dk.arima <- arima(resid(Dk.lm), order = c(2,0,1))
> new.time <- seq(2018, length = 8, by = 1/4)
> new.data <- data.frame(timeDk = new.time)
> predict.lm<-predict(Dk.lm, new.data)
> predict.arima <- predict(Dk.arima, n.ahead = 8)
> pm.predict <- ts(predict.lm[1:8] + predict.arima$pred, start = 2018, frequency = 4)
         Qtr1     Qtr2     Qtr3     Qtr4
 2018 2.155954 1.591099 1.431232 1.591194
 2019 1.826808 1.967176 1.985904 1.946175
```



The actual value for Dunkin Donuts 2018 first quarter current ratio was 1.505. This is very different from our predicted value of 2.15. The predicted value for quarter 2 however, is close to this value. This leads us to believe that the spike in current ratio in 2018 was a one time thing and that although our model was affected by the spike, it may be a good predictor in the future.[4]

Based on our predictions for both companies, it appears that Dunkin will have a better current ratio in the near future. Even after the expected drop, it is expected to increase as time goes on. We should be careful in putting too

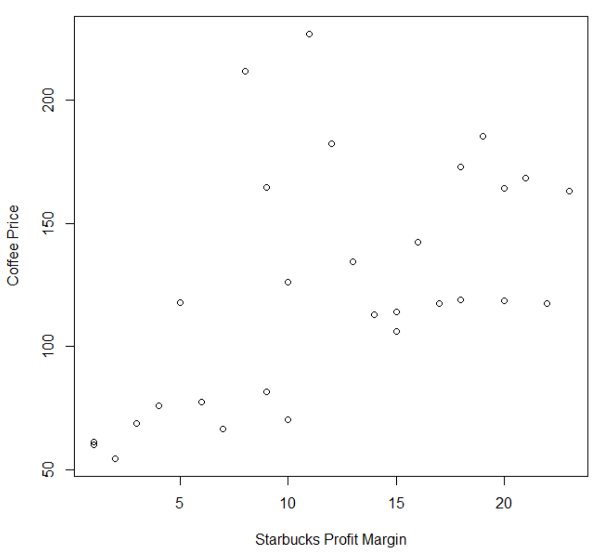
[3] The reasoning for this is described previously

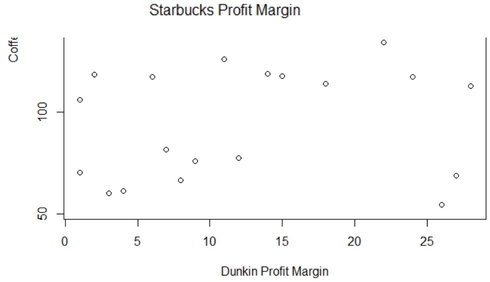
[4] Note that we should be careful in using the model to predict too far ahead

much faith in either prediction, however. We discussed that our prediction for Starbucks seemed unlikely. Even if the current ratio for Starbucks increases slowly, it should still increase or remain stable in the future.Therefore, it is difficult to interpret which company is "healthier" in regards to liquidity.

Future Research

After looking over all the data that was collected we considered other factors that might have a effect on either companies financial data. The first factor that was considered was the price of coffee. Since it was found that both companies use the same type of coffee bean, it was simple to find the pricing for the bean, and preliminary analysis was performed. What the objective of this research was to see if all the financial data for each company was similarly correlated to coffee data as the other companies data was. Most of the components had similar correlations, except for the price margin. Dunkin Donuts profit margin was only 24% correlated while Starbucks profit margin was about 54%.These results are shown below. Since correlation does not imply causation, we looked into why this might have occured. The best solution found was Dunkin is not heavily relying on the coffee aspect of their business. Some other topics based off our research are to compare other companies that may have a similar make up as both companies. For example Dunkin Donuts versus Krispy Kreme, or Starbucks versus Coffee house may be





easier to compare. Another topic would be looking at the local markets of each company especially since it was found that Dunkin does better internationally than in the United States, while starbucks does not have as much difference betweens markets. With looking at the smaller parts of the company and comparing it being a franchise vs company owned.

Research Concerns

An issue found with the research was due to Dunkin and Starbucks not being as reliant on the same aspects of their menu.This makes comparing the companies less useful since it adds too many variables to compare overall performance of the two companies. Another potential problem is that the firms are attempting to meet the need of the customers and social issues. This may lead to more randomness in the financials which may lead to the actual data to fall out of the prediction range. There have been a few events recently that could apply to this concern. First, Starbuck has just lost a lawsuit that is forcing them to put a label that says their coffee has a cancerous material in it. This law applies to every coffee company in California (though Starbucks headlines most articles on this topic). Another event that concerns Starbucks is the incident involving a manager having two African Americans arrested without proper cause. This incident was just settled by Starbucks and has caused them to increase awareness on the issue company wide. Lastly, both of the companies have recently acquired smaller companies. This would bolster their menu which is great for business, but possibly problematic for research purposes. This issue is a combination of the previous two concerns, since adding smaller companies helps them differ from competitors and improve on the customer base. The major addition for each company was, Baskin Robbins for Dunkin, and Teavana for Starbucks. Both of these add a different component to menu options and have helped in financials. Specifically Baskin Robbins as it has helped Dunkin in its international sales.

In Conclusion..

Taking into consideration the discussed problems and research concerns we had, it is appropriate now to answer our original question? Which company is doing “better”: Starbucks or Dunkin? Starbucks is expected to see an increased revenue at a faster rate than Dunkin Donuts. Dunkin Donuts is expected to take a larger percentage of their profits home each quarter (larger profit margin). According to only predictions, Dunkin is also expected to have a higher current ratio in the near future and will be better able to pay off debts. Remember, however, that our test for liquidity health was inconclusive due to predictions for starbucks that are not expected to be accurate considering information in Starbucks financial reports. With both companies tied, we can finally conclude, that although each company has its positive points, both Starbucks and Dunkin are healthy and doing equally well in their markets. It will be interesting to monitor these companies in the future to see how they are affected and deal with real life scenarios.

Bibliography

"Dunkin Brands Group Profit Margin (Quarterly):" *YCharts*, ycharts.com/companies/DNKN/profit_margin.

"Dunkin' Brands Group (DNKN) Current Ratio." *MacroTrends*, www.macrotrends.net/stocks/charts/DNKN/current-ratio/dunkin-brands-current-ratio-history.

"Financial Data." *Starbucks Corporation - Financial Data - Annual Reports*, investor.starbucks.com/financial-data/quarterly-results/default.aspx.

"Quarterly Results." *Dunkin Brands, Inc.*, investor.dunkinbrands.com/financial-information/quarterly-results.

Starbucks Company Timeline. Starbucks Coffee Company, 2018, news.starbucks.com/uploads/documents/AboutUs-Timeline-1.25.18.pdf.

"Starbucks Corp. (SBUX) | Liquidity (Q)." *Stock Analysis on Net*, www.stock-analysis-on.net/NASDAQ/Company/Starbucks-Corp/Ratios/Liquidity/Quarterly-Data#Current-Ratio.

Code Used

STOCK PRICE

##input data and change class to time series

```
stock_price <- read.table(file = "D:/mat 353 project/stock_price.txt", fill = TRUE, header =
TRUE)
attach(stock_price)
sb.ts <- ts(sb_close, start = c(1992, 6), frequency = 12)
dk.ts <- ts(dk_close, start = c(2011, 7), frequency = 12)
dk.ts2 <- window(dk.ts, start = c(2011, 7), end = c(2018, 3))
```

##plot both data sets on same graph

```
intersect <- ts.intersect(window(sb.ts, start = c(2011,7)), dk.ts2)
ts.plot(intersect, lty = c(1,2))
```

##creates correlograms of time series data and difference of time series data

```
acf(sb.ts)
```

```
acf(dk.ts2)
DS <-diff(sb.ts)
DK <-diff(dk.ts2)
acf(DS)
acf(DK)

##test for random drift
mean(DS)+c(-2,2)*sd(DS)/sqrt(length(DS))
mean(DS)
(sb.ts[310] + c(1:8)*(mean(DS))) ###forecasts using drift component

mean(DK)+c(-2,2)*sd(DK)/sqrt(length(DK))
mean(DK)
```

REVENUE

```
##input data and change class to time series
revenue <- read.table (file = "D:/mat 353 project/revenue.txt", header = TRUE)
attach(revenue)
ts.DkRev <- ts( DkRev, start = c(2011, 1), frequency = 4)
ts.SbRev <- ts( SbRev, start = c(2011, 1), frequency = 4)

##uses ols to model starbucks revenue data
SbRev <- window(ts.SbRev, start = c(2011,1))
SbRev.lm <- lm(SbRev ~ time(SbRev))
acf(resid(SbRev.lm))
coef(SbRev.lm)
confint(SbRev.lm)

##adds seasonal component to ols for sbux revenue
seas<-cycle(SbRev)
time <- time(SbRev)
SbRev.lm2<- lm(SbRev ~ 0 + time + factor(seas))
acf(resid(SbRev.lm2))

##models data using gls and seasonal component
acf(resid(SbRev.lm2))[1]
seas<-cycle(SbRev)
```

```
time <- time(SbRev)
library(nlme)
SbRev.gls2 <- gls(SbRev~0+time+factor(seas), cor = corAR1(.388))
acf(resid(SbRev.gls2))
```

##finds best fitting arima model

```
best.order <- c(0,0,0)
best.aic<-Inf
for(i in 0:2) for (j in 0:2) {
   fit.aic <- AIC(arima(resid(SbRev.gls2), order = c(i,0,j)))
   if(fit.aic < best.aic) {
         best.order <- c(i,0,j)
         best.arma <- arima(resid(SbRev.gls2), order = best.order)
         best.aic <- fit.aic
}
}
best.order
```

##forecasts starbucks revenue and plots historical and predicted values

```
SbRev.arima <- arima(resid(SbRev.gls2, order = c(1, 0, 0)))
new.t <-seq(2018, len = 2*4, by = 1/4)
new.dat <- data.frame (time = new.t, seas = rep(1:4, 2))
predict.gls2<-predict(SbRev.gls2, new.dat)[1:8]
predict.arima <- predict(SbRev.arima, n.ahead = 8)
pm.predict <- ts(predict.gls2 + predict.arima$pred, start = 2018, freq = 4)
pm.predict
ts.plot(cbind(ts.SbRev, pm.predict), lty = 1:2)
legend(2012,7000, legend = c("Starbucks Revenue(1,000,000's)", "Starbucks Predicted
Revenue"), lty = 1:2)
```

##uses ols to model Dunkin revenue data

```
DkRev <- window(ts.DkRev, start = c(2011,1))
DkRev.lm <- lm(DkRev ~ time(DkRev))
DkRev.lm$coefficients
acf(resid(DkRev.lm))
```

##adds seasonal component to ols for dnkn revenue

```
seas<-cycle(DkRev)
time <- time(DkRev)
DkRev.lm2<- lm(DkRev ~ 0 + time + factor(seas))
coef(DkRev.lm2)
```

##forecasts Dunkin revenue and plots historical and predicted values

```
new.t <-seq(2018, len = 2*4, by = 1/4)
new.dat <- data.frame (time = new.t, seas = rep(1:4, 2))
Dk.predict<-predict(DkRev.lm2, new.dat)[1:8]
ts.Dk.pred<-ts(Dk.predict, start = c(2018,1), end = c(2019,4), freq = 4)
ts.plot(DkRev, ts.Dk.pred, lty = 1:2)
legend(2011,220, legend = c("Dunkin Revenue(1,000,000's)", "Dunkin Predicted Revenue"), lty
= 1:2)
```

PROFIT MARGIN

##input data and change class to time series

```
profit_margin <- read.table(file = "D:/mat 353 project/profitmargin.txt", header = TRUE)
attach(profit_margin)
ts.SbPm <- ts(SbPm, start = c(2011,1), frequency = 4)
ts.DkPm <- ts(DkPm, start = c(2011,1), frequency = 4)
```

##uses ols to model starbucks profit margin data

```
SbPm.lm <- lm(ts.SbPm ~ time(ts.SbPm))
acf(resid(SbPm.lm))
```

##uses ols with seasonal component to model starbucks profit margin data

```
seas<-cycle(ts.SbPm)
time <- time(ts.SbPm)
SbPm.lm2<- lm(ts.SbPm ~ 0 + time + factor(seas))
acf(resid(SbPm.lm2))
```

##uses gls to model starbucks profit margin data

```
library(nlme)
SbPm.gls2<-gls(ts.SbPm ~ 0 + time + factor(seas), cor = corAR1(.468))
acf(resid(SbPm.gls2))
```

##finds best fitting arima for residuals of gls model for starbucks

```
best.order <- c(0,0,0)
best.aic<-Inf
for(i in 0:5) for (j in 0:5) {
   fit.aic <- AIC(arima(resid(SbPm.gls2), order = c(i,0,j)))
   if(fit.aic < best.aic) {
          best.order <- c(i,0,j)
          best.arma <- arima(resid(SbPm.gls2), order = best.order)
          best.aic <- fit.aic
}
}
best.order
```

##forecasts Starbucks profit margin

```
sb.gls2.arima <-arima(resid(SbPm.gls2), order = c(1,0,0))
new.time <- seq(2018, length = 2*4, by = 1/4)
new.data <- data.frame(time = new.time, seas = rep(1:4,2))
predict.gls2<-predict(SbPm.gls2, new.data)[1:8]
predict.arima <- predict(sb.gls2.arima, n.ahead = 8)
pm.predict <- ts(predict.gls2 + predict.arima$pred, start = 2018, freq = 4)
ts.plot(cbind(ts.SbPm, pm.predict), lty = 1:2)
legend(2012,20, legend = c("Starbucks Profit Margin", "Starbucks Predicted Profit Margin"), lty
= 1:2)
```

##uses ols to model Dunkin profit margin data

```
DkPm.lm <- lm(ts.DkPm ~ time(ts.DkPm))
acf(resid(DkPm.lm))
```

##uses ols with added seasonal component to model Dunkin profit margin data

```
seas<-cycle(ts.DkPm)
time <- time(ts.DkPm)
DkPm.lm2<- lm(ts.DkPm ~ 0 + time + factor(seas))
acf(resid(DkPm.lm2))
```

##forecasts Dunkin profit margin

```
new.t <-seq(2018, length = 8)
new.dat <- data.frame (time = new.t, seas = rep(1:4, 2))
```

dk.lm.predict<-predict(DkPm.lm2, new.dat)
predict.ts <- ts(dk.lm.predict, start = c(2018, 1), frequency = 4)
ts.plot(ts.DkPm, predict.ts, lty = 1:2)
legend(2012,80, legend = c("Dunkin Profit Margin Revenue", "Dunkin Predicted Profit Margin"), lty = 1:2)

CURRENT RATIO

##input data and change class to time series

```
current_ratio <- read.table(file = "D:/mat 353 project/currentratio.txt",fill = TRUE, header = TRUE)
attach(current_ratio)
ts.SbCr <- ts(SbCr, start = c(2012,1), frequency = 4)
ts.DkCr <- ts(DkCr, start = c(2012,1), frequency = 4)
```

##uses ols to model Starbucks and Dunkin data

```
timeSb <- time(ts.SbCr)
Sb.lm <- lm(ts.SbCr~timeSb)
timeDk <- time(ts.DkCr)
Dk.lm <- lm(ts.DkCr~timeDk)
acf(resid(Sb.lm))
acf(resid(Dk.lm))
```

##Uses gls to model Starbucks Data

```
library(nlme)
Sb.gls <- gls(ts.SbCr~timeSb, cor = corAR1(.579))
acf(resid(Sb.gls))
```

##finds best fitting arima models for residuals of ols model for Dunkin and for residuals of gls model for Starbucks

```
best.order <- c(0,0,0)
best.aic<-Inf
for(i in 0:2) for (j in 0:2) {
   fit.aic <- AIC(arima(resid(Dk.lm), order = c(i,0,j)))
   if(fit.aic < best.aic) {
         best.order <- c(i,0,j)
         best.arma <- arima(resid(Dk.lm), order = best.order)
         best.aic <- fit.aic
```

```
}
}
best.order
best.order <- c(0,0,0)
best.aic<-Inf
for(i in 0:2) for (j in 0:2) {
   fit.aic <- AIC(arima(resid(Sb.gls), order = c(i,0,j)))
   if(fit.aic < best.aic) {
          best.order <- c(i,0,j)
          best.arma <- arima(resid(Sb,gls), order = best.order)
          best.aic <- fit.aic
}
}
best.order
```

##forecasts future values for Starbucks and Dunkin

```
Sb.arima <- arima(resid(Sb.gls), order = c(1,0,0))
new.time <- seq(2018, length = 2*4, by = 1/4)
new.data <- data.frame(timeSb = new.time)
predict.gls<-predict(Sb.gls, new.data)
predict.arima <- predict(Sb.arima, n.ahead = 8)
pm.predict <- (predict.gls + predict.arima$pred)
ts.plot(ts.SbCr, pm.predict,lty = 1:2)
legend(2014,2.0, legend = c("Starbucks Current Ratio", "Starbucks Predicted Current Ratio"), lty
= 1:2)

Dk.arima <- arima(resid(Dk.lm), order = c(2,0,1))
new.time <- seq(2018, length = 8, by = 1/4)
new.data <- data.frame(timeDk = new.time)
predict.lm<-predict(Dk.lm, new.data)
predict.arima <- predict(Dk.arima, n.ahead = 8)
pm.predict <- ts(predict.lm[1:8] + predict.arima$pred, start = 2018, frequency = 4)
ts.plot(ts.DkCr, pm.predict, lty = 1:2)
pm.predict
legend(2013,2.5, legend = c("Dunkin Current Ratio", "Dunkin Predicted Current Ratio"), lty =
1:2)
```