Project Report

Electronic Arts
Financial Forecasting Assessment

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PREDICTIVE ANALYTICS

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1. Introduction

The use of predictive analytics can lead to great insights on future outcomes. It provides different methods that help to objectively improve business models and by extension bring more success and efficiency to companies. Electronic Arts (EA) is a video game company that is responsible for developing games and online services for game consoles, mobile devices, and computers. With just over 300 million players registered to them worldwide, it is clear that EA is a leader in the industry for digital entertainment. *"In fiscal year 2018, EA posted GAAP net revenue of $5.15 billion. Headquartered in Redwood City, California, EA [was] recognized for a portfolio of critically acclaimed, high-quality brands such as The Sims™, Madden NFL, EA SPORTS™ FIFA, Battlefield™ Etc." (About EA, 2018).*

EA Sports currently make up the greatest part of their overall business, including the popular FIFA series. Although Electronic Arts does have an impressive resume, it is important to keep in mind that recently there has been a serious backlash in regards to the company's intrusive use of microtransactions. The negative public opinion and various legal implications of microtransactions will be explored in greater detail in order to shed light on what this could mean for Electronic Arts now and in the future.

The objective of this report aims to predict EA future net revenues and compare Electronic Arts' existing forecasts with each of the alternative forecasts that were performed. Using past financial data in conjunction with R codes, forecasts will be generated based on the actual net revenue data starting from Quarter 2 in 2004 and going all the way to Quarter 4 of 2015. Corporate quartiles for EA are not the same quartiles used on the calendar. The first quartile is from April 1st to June 30th. In addition, residuals will be presented and analyzed for Simple Exponential Smoothing, Damped Holt's Method, Holt Winter's Multiplicative Model, and ARIMA. Lastly, a comparative analysis of each forecasting method will be used in order to determine the optimal

choice for Electronic Arts in the future. Qualitative factors will be taken into account to ensure all factors that may affect EA's revenue are considered.

2. Potential Legal and Ethical Implications with Respect to Microtransactions

Microtransactions have become a major issue for EA and the gaming industry as whole due to the major public concern over the risk of these microtransactions creating gambling-like atmospheres in the games that use them. By definition, a microtransaction is characterized as monetary transaction conducted online. It is quite common for video games to have various microtransactions ranging anywhere from $0.10 to $1000 on average and even more in a great number of cases. Furthermore, a certain type of microtransaction commonly referred to as a *loot box* provides players with the ability pay a fee to receive a randomized item which ideally compliments their gameplay in a slot machine like manner. These items often range from very basic – cosmetics for game characters (e.g. clothing or shoes) – all the way to game changing upgrades that can significantly improve one's progress in a game and give them an advantage over other players (e.g. a powerful character or weapon).

The prevalence of *loot box* in games has drawn harsh public criticism due to the lack of differences they have when compared to conventional gambling. The threat of developing gambling-like addictions and other destructive behaviours seems to be the main topic of concern. In a relatively recent real-world example, Lance Perkins from Ontario found that, "his credit card was billed $7,625.88 in December 2015, [and had] accrued from a series of in-game purchases made by his 17-year-old son while he was playing a soccer game on his Xbox". (Li, 2016). This is just one instance of many that accurately depicts the potential to develop highly destructive habits from the availability of in-game microtransactions.

Numerous governing bodies across the globe are taking action or are at least planning, to combat the use of the gambling-like microtransactions found in video games. For example, “politicians and gambling-awareness organizations in the UK are calling for regulation” over the use of loot boxes in many popular games. (Busby, 2018). In addition to the UK example, “China [recently] passed a harsher law that outlawed virtual ‘lottery tickets’” (Hafer, 2018). A major example of gambling-like microtransactions is found in the popular football game known as Fifa which is the most profitable game right now offered by EA. If more countries take a tough stance on microtransactions, similar to that of China, than EA will be forced to make major adjustments to their current strategy surrounding the use of microtransactions.

The key takeaways to keep in mind from this analysis of the legal and ethical implications for microtransactions are the state of legislation and public opinion with respect to microtransactions has been extremely negative in recent years. The introduction of new legislation to restrict the way microtransactions are incorporated into games has already happened in various regions of the world, such as China and South Korea. In addition to this, the possibility of new legislation that could significantly limit or outright ban the use of microtransactions may be coming in the not so distant future. Finally, it is important to note that the vast majority of the profits that EA receives come from microtransactions. It will be imperative for EA to closely monitor and create action plans to help adapt to the legislations and public opinion around the world that pose threats to the future profitability of microtransactions in video games. Without a strong contingency plan to account for changes in microtransaction legislation and negative public opinion, EA runs the risk of losing a major profit in the future.

3. Simple Predictive Techniques

3.1 Naïve Method

Naïve Forecasting is the most cost-effective and efficient objective forecasting model. Despite its efficiencies, it is not the most accurate due to its simplicity. As shown in the Naïve Forecast Graph, Figure 1 below, the data is shifted one quarter to the right compared to the original data.

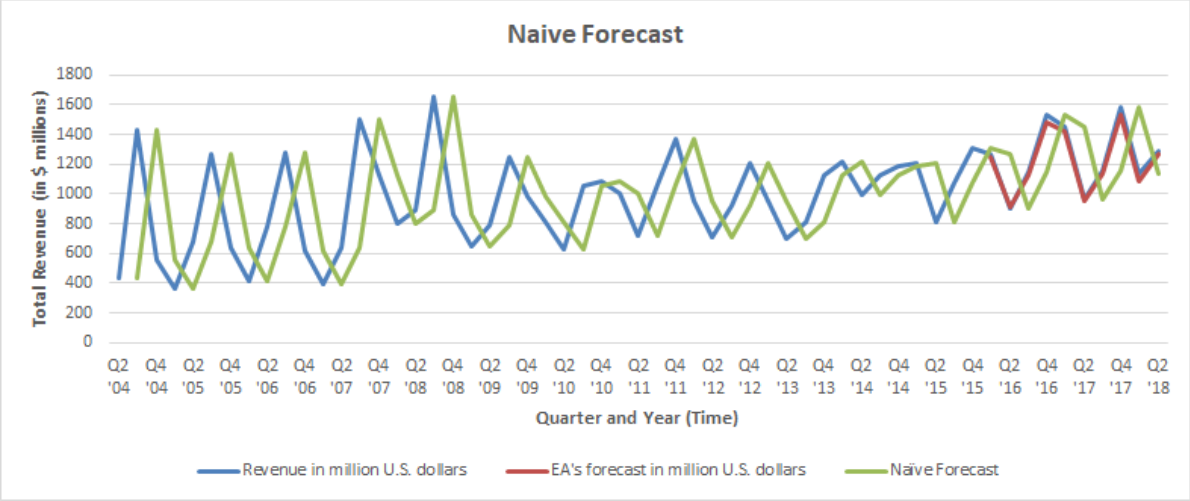


Figure 1. Naïve Forecast Quarterly Graph

3.2 Moving Average (Quarterly)

A quarterly moving average is best used when market demands stay steady over time. It is best used for short term irregularities. The moving average formula is:

$$MA = \frac{\sum Demand\ in\ previous\ n\ periods}{n}$$

Some disadvantages of the quarterly moving average are:

- It increases the size of the number of periods being averaged and smooths out fluctuations, but the method is less sensitive to picking up real changes in the data set such as seasonality.
- Moving averages do not pick up trends well. Since they are averages, they will always lag behind actual values.

- It requires an extensive record of past data.

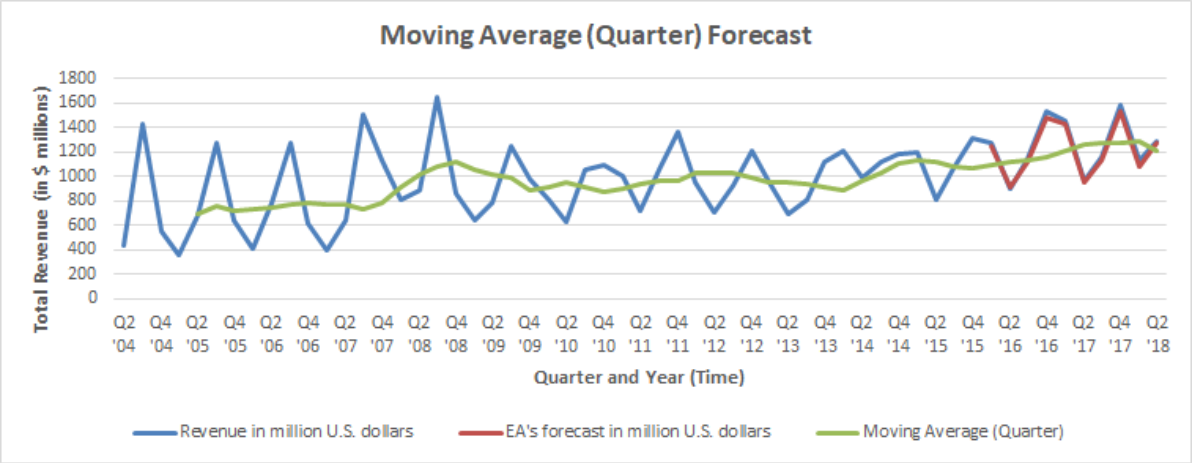


Figure 2. Moving Average Quarterly Graph

3.3 Weighted Moving Average

Weighted Moving Average is best used to smooth out sudden fluctuations in the demand pattern to provide stable estimates. The weighted moving average formula is:

$$\text{Weighted moving average} = \frac{\Sigma\,(\text{Weight for period } n)(\text{Demand in period } n)}{\Sigma \text{Weights}}$$

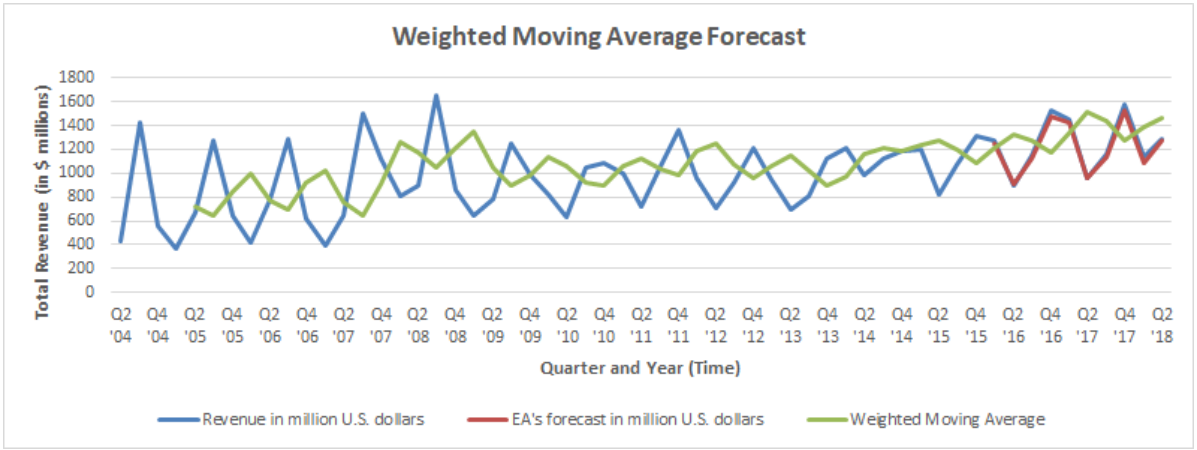


Figure 3. Weighted Moving Average Quarterly Graph

3.4 Exponential Smoothing Forecast

Exponential Smoothing is a sophisticated weighted moving average method. The new forecast this applies to is the quarterly moving average. The error was calculated by subtracting quarterly moving average from the actual data. The exponential formula is listed as:

$$\textbf{Exponential Smoothing Forecast} = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

where alpha is 0.8 since the underlying average is likely to change and it is not stable. The latest estimate of quarterly moving average is adjusted by a fraction of the difference between the last period's actual demand and the old estimate.

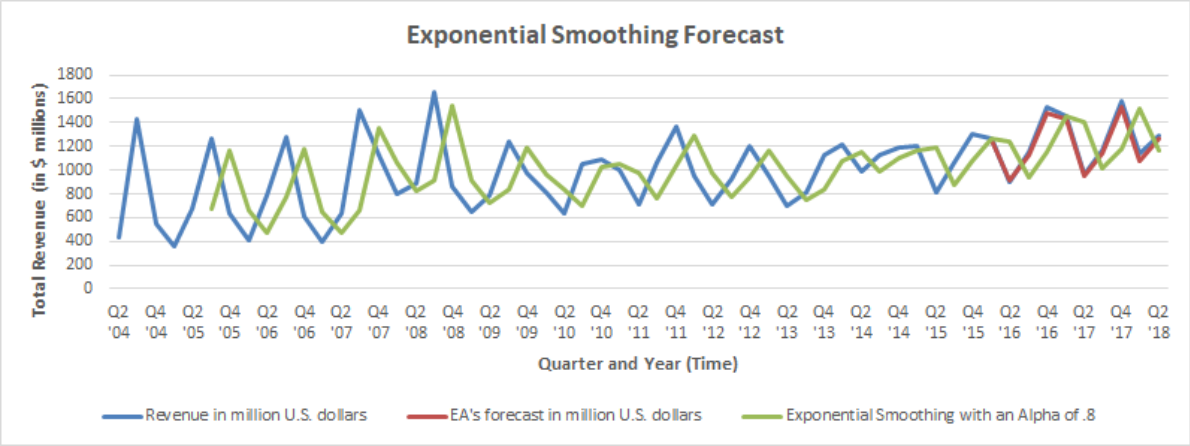


Figure 4. Exponential Smoothing Forecast Graph

Findings

Of the four simple predictive methods applied, the moving average and weighted moving average are the two better methods since the data fluctuations are smoothed out. The excel sheet of the data is plotted below in Chart 1. These four methods are simple types of forecasting and in the next section we will talk about better forecasting methods shown in R.

Quarter and Yea	evenue in million U.S. dollars	EA's forecast in million U.S. dollars	Naïve Forecas	Moving Average (Quarter	Weighted Moving Averag	Exponential Smoothing with an Alpha of .8
Q2 '04	432					
Q3 '04	1427		432			
Q4 '04	553		1427			
Q1 '05	365		553			
Q2 '05	675		365	694.25	714.6	
Q3 '05	1270		675	755	638.3	678.85
Q4 '05	641		1270	715.75	846.8	1167
Q1 '06	413		641	737.75	998.8	655.95
Q2 '06	784		413	749.75	765.9	477.95
Q3 '06	1281		784	777	696.9	777.15
Q4 '06	613		1281	779.75	923	1180.2
Q1 '07	395		613	772.75	1022.5	646.35
Q2 '07	640		395	768.25	759.6	470.55
Q3 '07	1503		640	732.25	640.2	665.65
Q4 '07	1127		1503	787.75	911.2	1348.85
Q1 '08	804		1127	916.25	1257.1	1059.15
Q2 '08	894		804	1018.5	1169.3	826.45
Q3 '08	1654		894	1082	1045.9	918.9
Q4 '08	860		1654	1119.75	1216.7	1539.6
Q1 '09	644		860	1053	1344.2	911.95
Q2 '09	788		644	1013	1043.4	725.8
Q3 '09	1,243		788	986.5	895.8	833
Q4 '09	979		1243	883.75	981.7	1191.7
Q1 '10	815		979	913.5	1137.2	959.95
Q2 '10	631		815	956.25	1061.4	834.7
Q3 '10	1,053		631	917	916.9	696.05
Q4 '10	1,090		1053	869.5	892.3	1025.8
Q1 '11	999		1090	897.25	1061.2	1045.9
Q2 '11	715		999	943.25	1118.4	978.65
Q3 '11	1,061		715	964.25	1037.3	760.65
Q4 '11	1,368		1061	966.25	984.6	1041.65

Chart 1: Data Applied for Simple Forecasting Methods

4. Predicting in R

4.1 Graph of raw data with predictions

The raw data extends from Quarter 2 in 2004 to Quarter 2 in 2018 and is shown in Figure 5. The blue line illustrates the actual quarterly total revenue in USD millions EA reported, and the orange line illustrates EA's own predictions from Q1 2016 onwards. Microsoft Excel is used to chart the raw data.

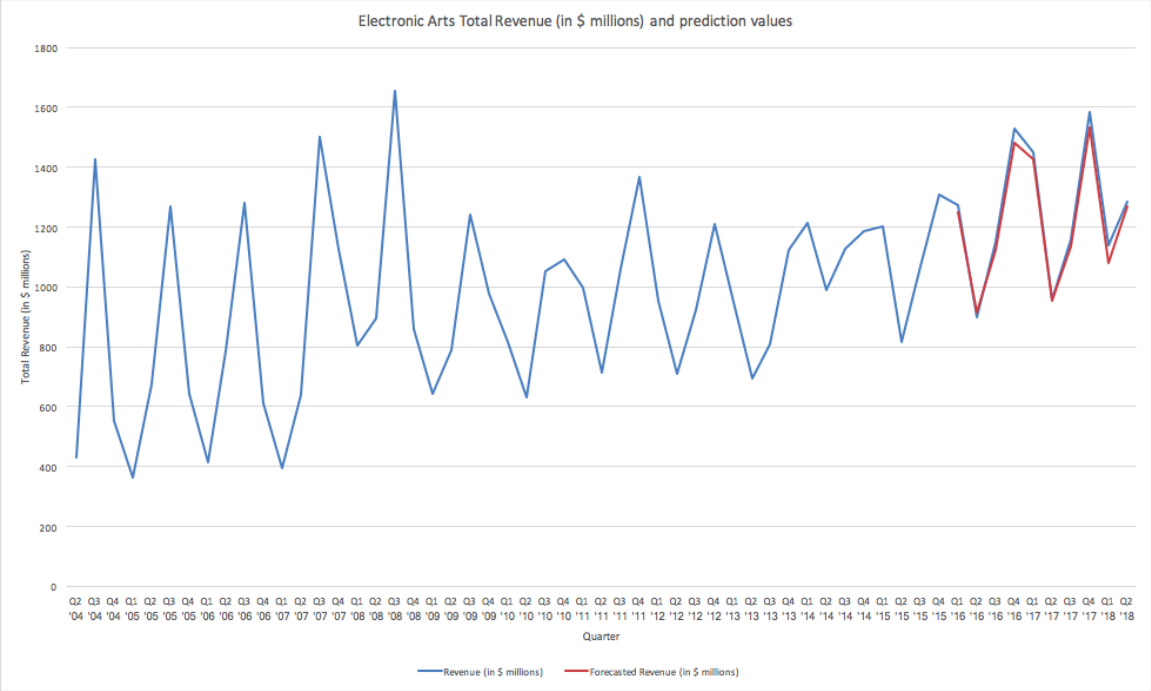
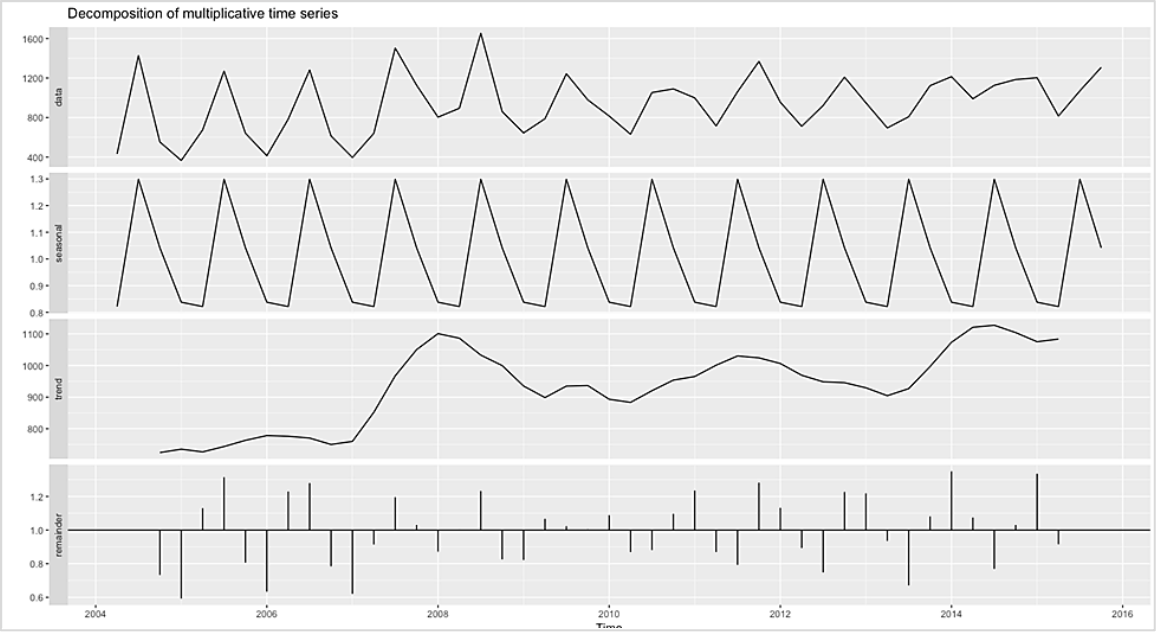


Figure 5. Exponential Smoothing Forecast Graph

4.2 Graph of Multiplicative Decomposition

Multiplicative was chosen over additive because the seasonal fluctuations are proportional to level of series, as can be seen in the graph of the raw data above. Figure 6 illustrates the multiplicative decomposition time series.



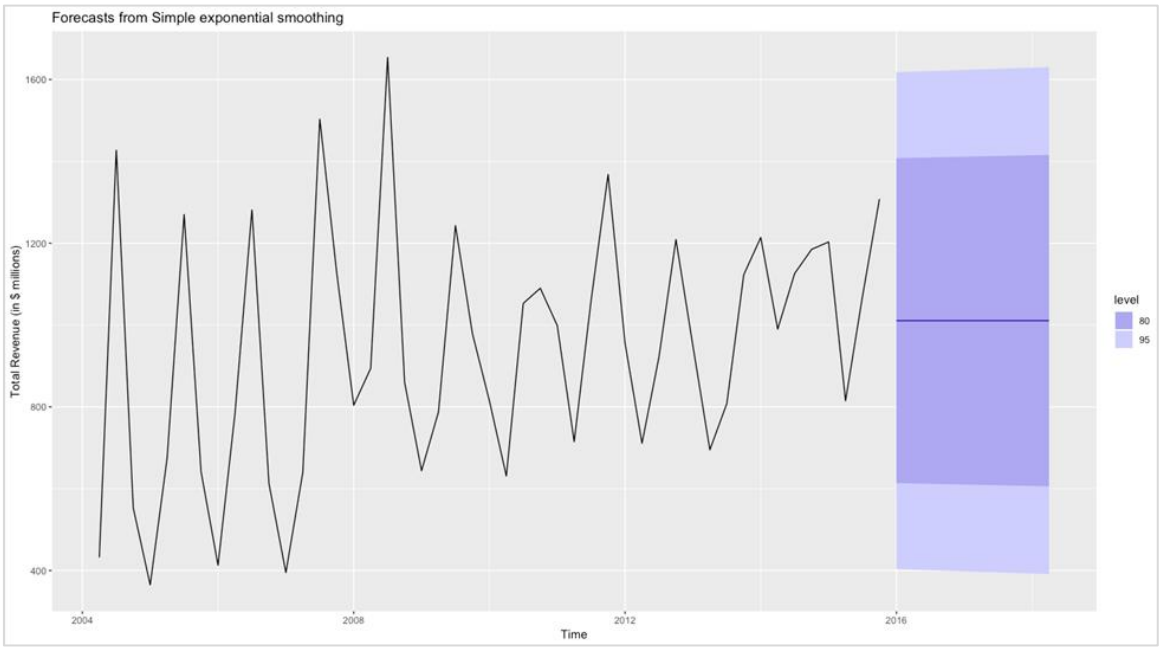

```
> project1%>%decompose(type = "multiplicative") %>%
+ autoplot()
>
```

Figure 6. Multiplicative Decomposition Graph

The first data point given occurs during quarter 2. As can be seen, there is very clear seasonality present in the data. The seasonality seems to show a climb in revenue for the second quarter until it peaks at the third quarter. This peak is likely due to the Christmas holidays where sales likely increase. In the case of EA, quarter 3 occurs during the holiday months. In the fourth and first quarters, there is a large drop, likely due to the post-winter season when the holidays have ended and demand for new games is lower. In terms of trend, the data increases and decreases every two to four years, but overall there is a visible increase in the trend.

4.3 First Forecasting Method: Simple Exponential Smoothing

The first forecasting method tested was the simple smoothing method. The graph and accuracy are shown in Figure 7.




```
> autoplot(simple)+ ylab("Total Revenue (in $ millions)") + xlab("Time")
> accuracy(simple)
                    ME     RMSE      MAE       MPE     MAPE     MASE        ACF1
Training set 50.12556 303.1679 240.9544 -6.58731 29.31819 1.590336 -0.01199392
>
```

Figure 7. Forecast from Simple Exponential Smoothing Graph

Looking at the forecast, it's clear that it will not prove useful. The forecast is a straight horizontal line and the prediction intervals are all very large. The RMSE was found to be 303.1679. Just by looking at the plot, it's clear that this forecast can be improved upon.

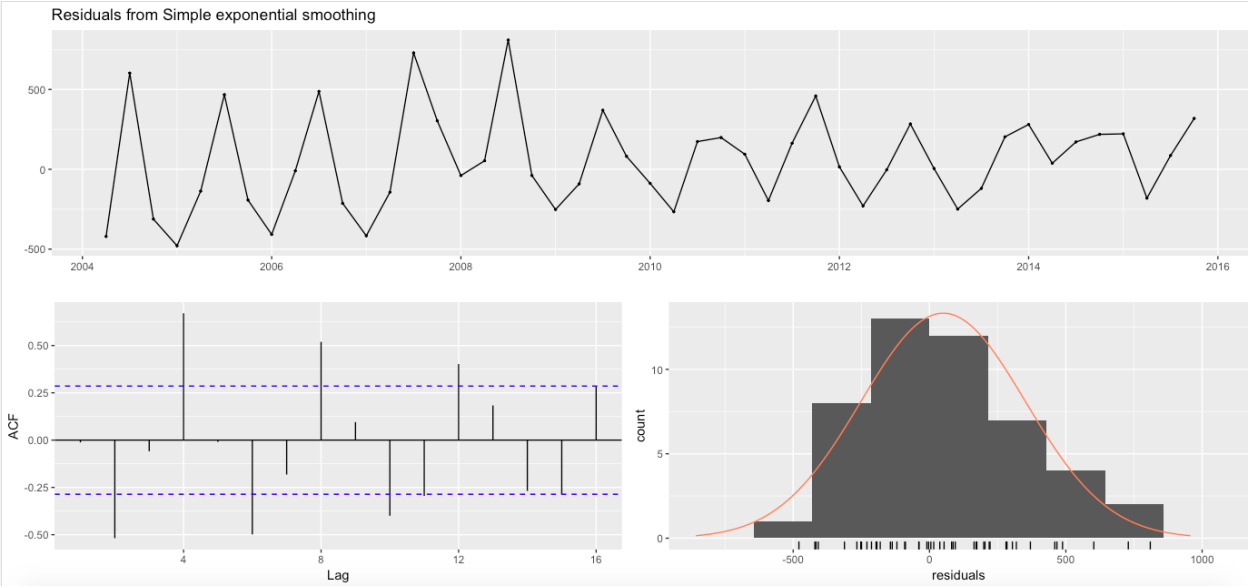
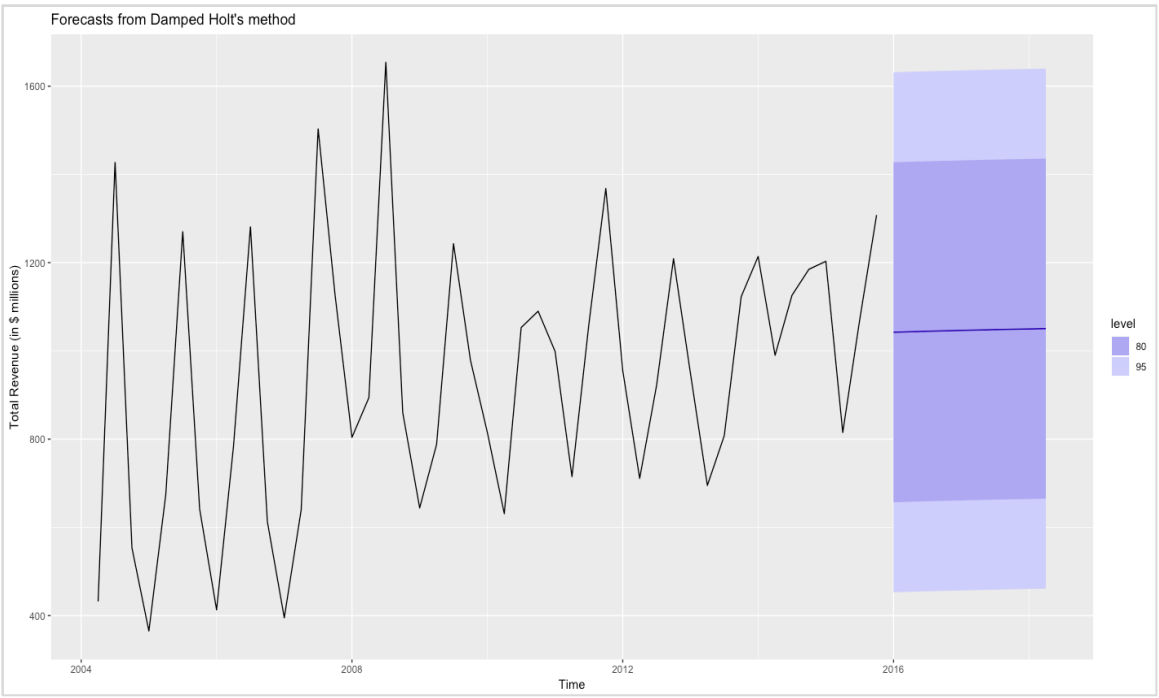


Figure 7.1: Residuals from Simple Exponential Smoothing

Furthermore, the residuals from the simple exponential smoothing the ACF graph demonstrates that there are many autocorrelation coefficients outside of the blue dotted line, which indicates that the series is not white noise. Also, the data in the histogram is skewed to the left.

4.4 Second Forecasting Method: Holt Damped Forecast

The second method tested was the Holt Damped Forecast. This method was chosen due to its dampening effect on the data which the simple smoothing method doesn't take into account. Since our data showed signs of trend, this forecast should be an improvement. The graph and accuracy are shown in Figure 8.



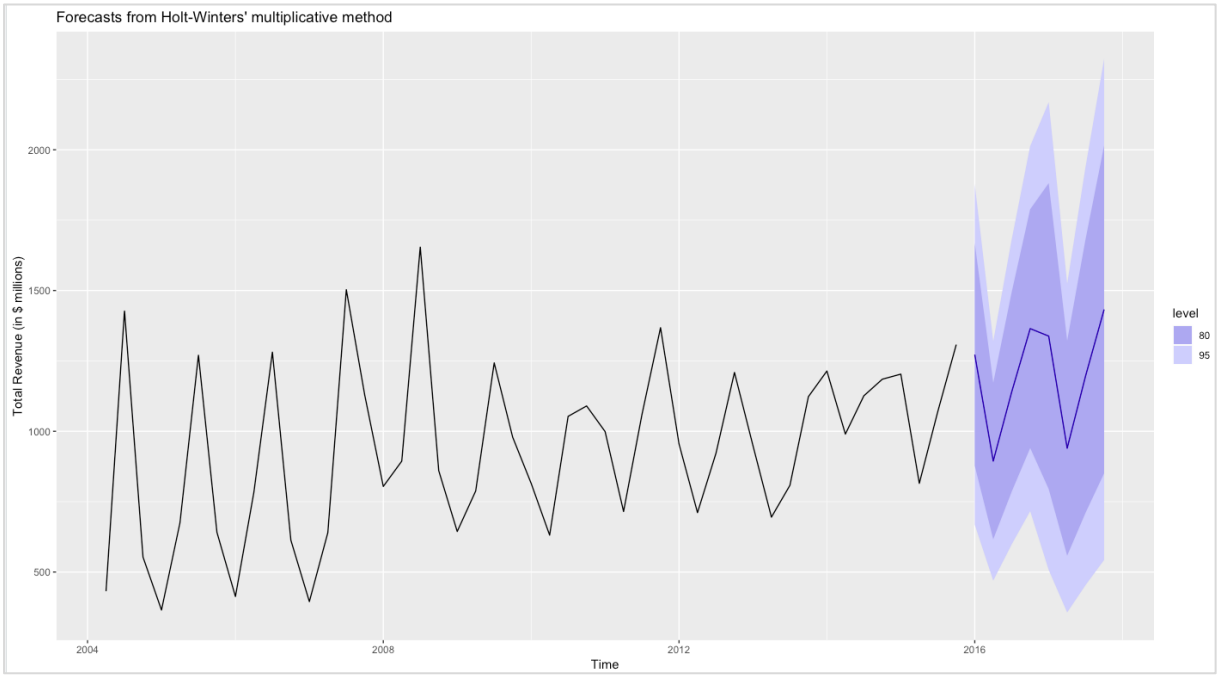

```
> damped<-holt(project1, damped = TRUE)
> autoplot(damped)+ ylab("Total Revenue (in $ millions)") + xlab("Time")
> accuracy(damped)
                     ME     RMSE      MAE       MPE     MAPE   MASE        ACF1
Training set -5.421087 284.2172 226.1917 -11.77379 28.39265 1.4929 -0.02770975
>
```

Figure 8. Forecast from Damped Holt's Method Graph

The RMSE was 284.2172, which was better than simple smoothing. This was to be expected, as trend was now taken into account. However, looking at the graph, it's still clear that the forecast can be improved upon. While still relatively horizontal, the forecast line now moves in a slight upward direction, but the prediction intervals are still very large.

4.5 Third Forecasting Method: Multiplicative Holt-Winter Method

The third method tested was Multiplicative Holt Winter method. This method was chosen because it takes into account both trend and seasonality, which we have already seen is present in the data. The graph and accuracy are shown in Figure 9.




```
> winter<-hw(project1,seasonal = "multiplicative")
> autoplot(winter)+ ylab("Total Revenue (in $ millions)") + xlab("Time")
> accuracy(winter)
                    ME      RMSE      MAE       MPE     MAPE      MASE
Training set -41.35397 190.5657 149.3344 -5.55298 16.43876 0.9856301
                   ACF1
Training set 0.2812593
>
```

Figure 9. Forecast from Holt-Winter's Multiplicative Method Graph

The RMSE was 190.5657, which is the best so far. From Figure 9, we can now see a minor upward trend and seasonality being taken into account, which is a large improvement over the past two forecasts. Moreover, the prediction intervals are much smaller than before, suggesting this forecast is more accurate.

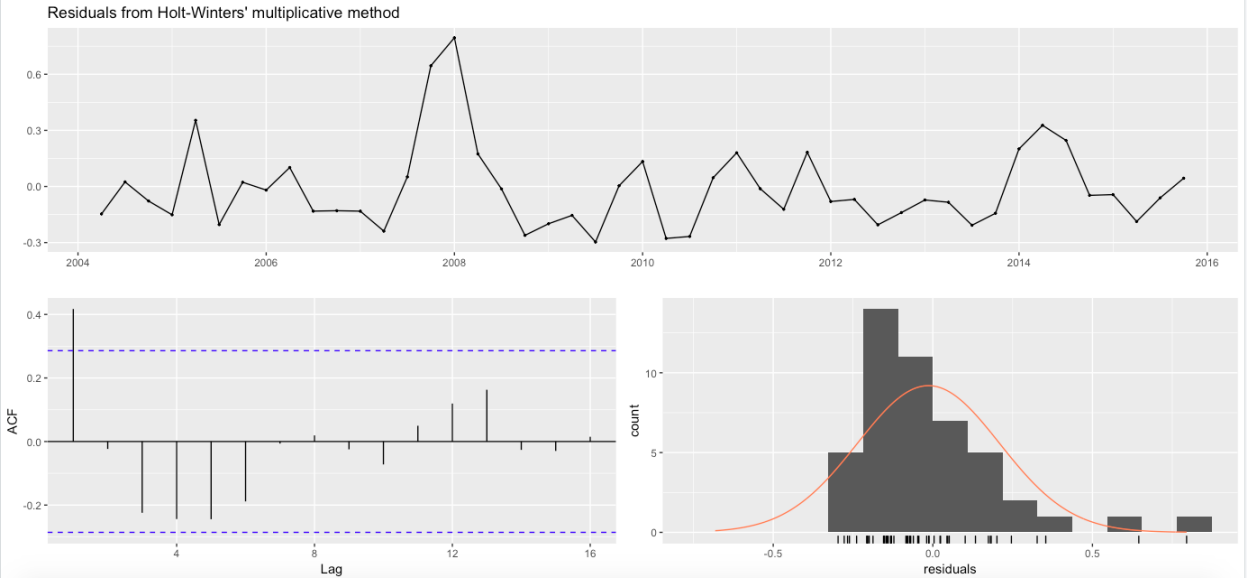


Figure 9. Residuals Holt-Winter's Multiplicative Method Graph

Based on the residuals from the Holt-Winter's Multiplicative Method Graph, the ACF graph demonstrates that there is only one autocorrelation coefficient that is outside of the blue dotted line which indicates that the series might be white noise. A Box Pierce Test or a Box-Ljung Test might need to be conducted to determine if this is actually the case. Also, the data in the histogram is skewed to the left.

4.6 Fourth Forecasting Method: ARIMA

The fourth method tested was ARIMA. First off, ARIMA only works if the data is stationary. The ACF graph was created and is shown in Figure 10.

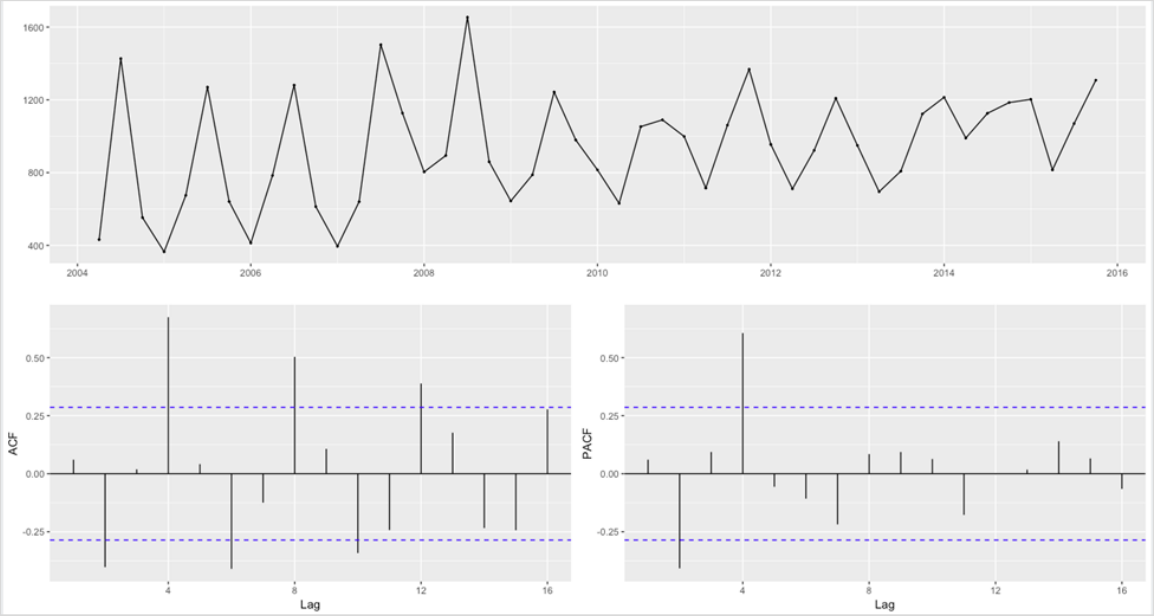
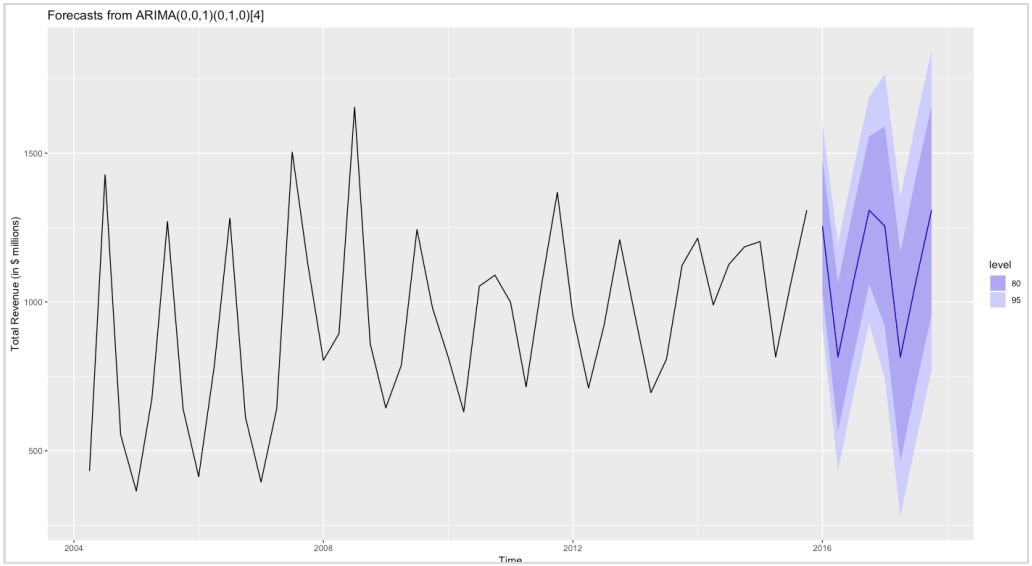


Figure 10. ARIMA Forecast Method Graph

Looking at the ACF graph, the lag points vary throughout and show no particular pattern. They are also a mixture of both positive and negative values. Finally, there are only five lag points significantly different from zero. Based on this, we can assume the data is stationary, so the ARIMA forecast can be performed on it. The Auto.ARIMA forecast was performed. The reason the ARIMA technique was chosen was because it combines the AR and MA techniques (ARMA) with differencing. The graph and accuracy are shown in Figure 11




```
> rima<-auto.arima(project1)
> rima%>%forecast()%>%autoplot()+ ylab("Total Revenue (in $ millions)") + xlab("Time")
> summary(rima)
Series: project1
ARIMA(0,0,1)(0,1,0)[4]

Coefficients:
         ma1
      0.4803
s.e.  0.1412

sigma^2 estimated as 30456:  log likelihood=-282.61
AIC=569.21   AICc=569.51   BIC=572.74

Training set error measures:
                    ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 23.91096 164.9735 126.3682 1.821916 13.31503 0.8340498 -0.02144983
>
```

Figure 11. Forecast from ARIMA (0,0,1) (0,1,0)[4] Graph

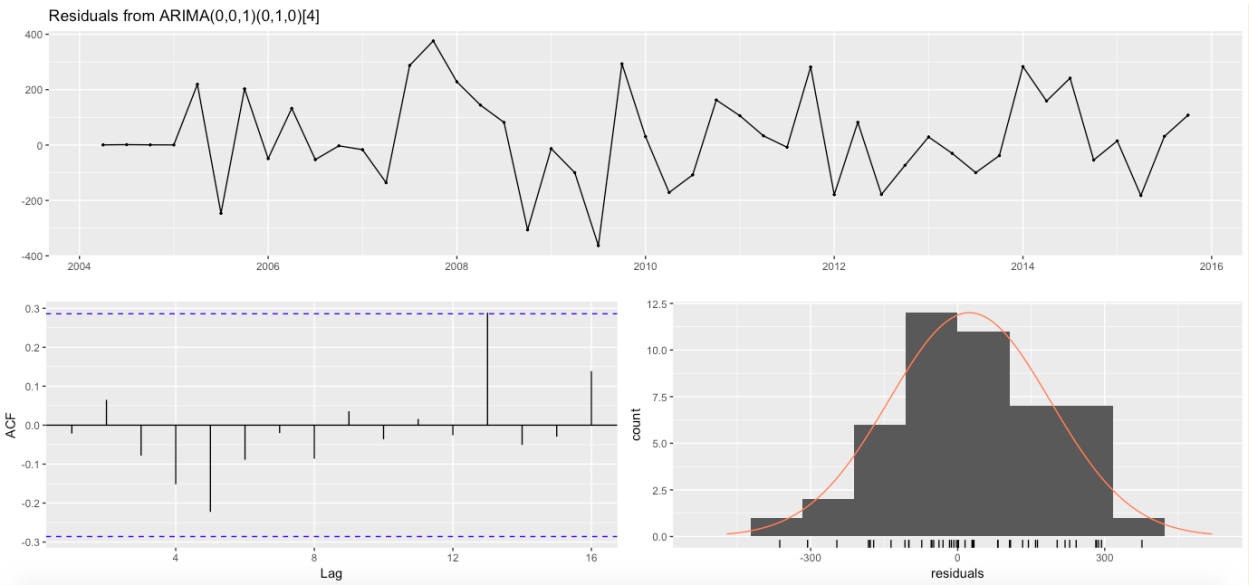
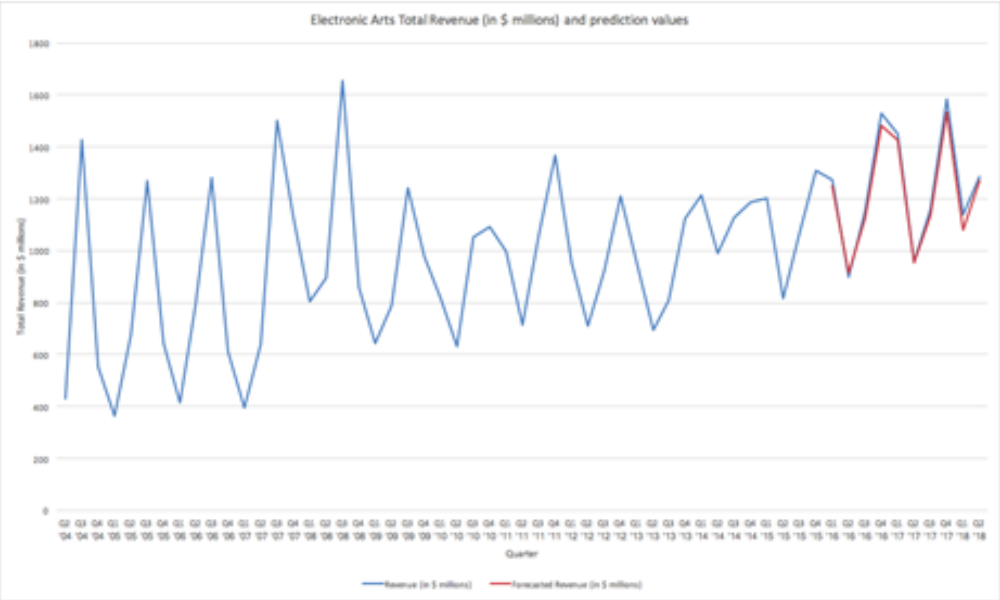


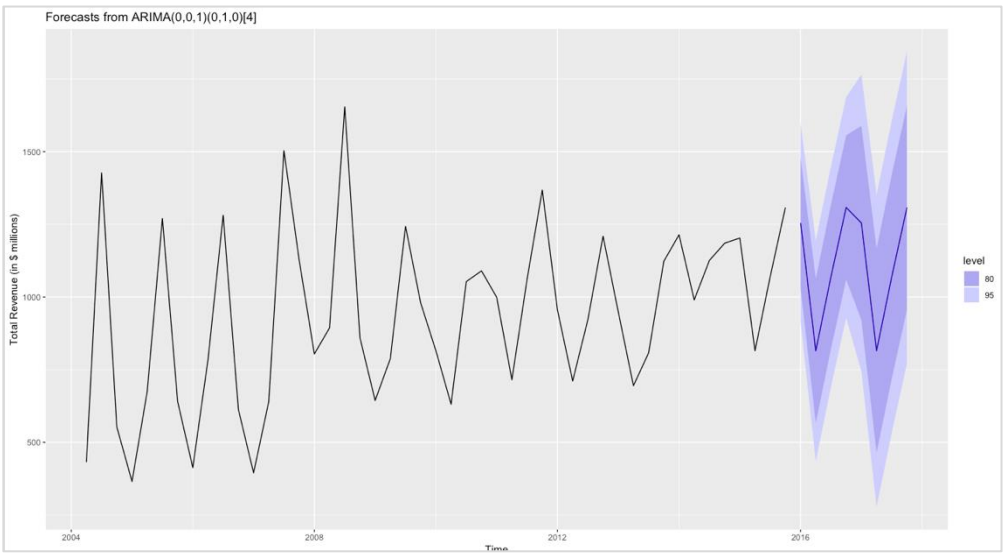
Figure 11.1. Residuals from the ARIMA (0,0,1) (0,1,0)[4] Graph

Looking at the output Auto.ARIMA produced, we can see that no differencing was needed, as we had assumed from the ACF graph, since the differencing output shows a zero in the middle (0,0,1). However, this Auto.ARIMA did take into account one seasonal differencing, as seen by the middle number in (0,1,0). With this forecast, ARIMA had the lowest RMSE so far, with 164.9735. Looking at Figure 11, we can see the forecasted data seems to take into seasonality, as did the Holt Winter method. However, in this forecast, the trend is less noticeable. Looking at the prediction intervals, they are significantly smaller, much smaller than with the Holt Winter method, which is an improvement. Furthermore, based on the residuals from the ARIMA Graph, the ACF graph demonstrates that there is no autocorrelation coefficients outside of the blue dotted line which indicates that the series is white noise. Since the RMSE is the lowest value so far at 164.9735, the graph indicates a reliable forecast, and from the white noise indicated from the ACF graph, we can conclude that the ARIMA forecast is the best forecasting method tested.

5. Comparative Forecast Analysis

The graph of EA's actual revenue data and their prediction for revenue from Q1 2016 to Q2 2018 Figure 5, as well as, the graph of the ARIMA forecast Figure 11 are presented below.





First, comparing EA's actual revenue with their own predictions, some things can be noted. EA's predictions are very similar to their actual data. The peaks of EA's actual data are slightly higher than their predictions, but overall, EA's own predictions are very accurate. In terms of the prediction's found using the ARIMA techniques, several things can also be noted. The seasonality from the ARIMA technique is very similar to EA's actual revenue data. They both follow almost the exact same pattern. However, in terms of trend, the ARIMA forecast shows much less upward trend than the actual data. The ARIMA forecast stays relatively the same in terms of trend, while the actual data, as well as EA's predictions, show an upward trend. Besides the trend however, the ARIMA forecast is still very similar to EA's actual data.

Conclusion

The objective of the report is to determine whether EA's forecasts were accurate or whether another forecasting technique should be used. After testing several different forecasting techniques, the ARIMA method was found to be the best, as it had the lowest RMSE value of 164.9735 and the ACF graph indicates the series is white noise. While EA's forecast was similar

to the ARIMA forecast in terms of seasonality, EA's forecast also took into account a trend the ARIMA forecast did not. This trend was also visible in the actual revenue data. Since the ARIMA forecast does not take this trend into account, and it's likely that this trend will continue to increase in the future, the current forecasting technique EA is using should continue being used instead of switching to an ARIMA technique.

However, one important variable that may affect the legitimacy of EA's current forecast is the loot box controversy. As previously mentioned, several countries are considering banning loot boxes on the grounds that they are a form of gambling. If these laws come into effect in more countries, a massive part of EA's revenue will decrease, and the forecasting method currently used will be broken. If this occurs, EA will need to use a new forecasting method, as the upward trend they currently find will likely not occur.

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Contributions

- All team members: discussed and planned assignment, viewed data together.
- Julien Montillet: oversaw the entire assignment process, helped with overseeing all of the R-coding, report writing, formatted and final editing of report.
- Ankica Basar: helped with writing the introduction
- James Windrem: helped with the code, researched legal issues of EA and worked on the qualitative aspects of predicting these methods
- Blake Bolkovic: worked on all the R-code for every model and writing the analysis
- Sarah Diep: help write the report, applied the simple prediction techniques on excel
- Robert Sharpe - worked on all the R-code for every model and writing the analysis (same as Blake)

Personal Ethics Statement

Group Assignment

By signing this Statement, I am attesting to the fact that I have reviewed not only my own work, but the work of my colleagues, in its entirety.

I attest to the fact that my own work in this project meets all of the rules of quotation and referencing in use at the Telfer School of Management at the University of Ottawa, as well as adheres to the fraud policies as outlined in the Academic Regulations in the University's Undergraduate Studies Calendar. http://www.uottawa.ca/academic-regulations/academic-fraud.html

To the best of my knowledge, I also believe that each of my group colleagues has also met the rules of quotation and referencing aforementioned in this Statement.

I understand that if my group assignment is submitted without a signed copy of this Personal Ethics Statement from each group member, it will be interpreted by the Telfer School that the missing student(s) signature is confirmation of non-participation of the aforementioned student(s) in the required work.

Signature — November 26, 2018 — Date

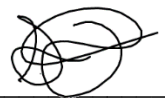
Basar, Ankica — 7342324

Last Name (print), First Name (print) — Student Number

Signature — November 26, 2018 — Date

Bolkovic, Blake — 7852594

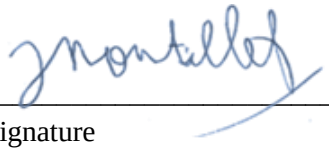
Last Name (print), First Name (print) — Student Number



Signature — November 26, 2018 — Date

Diep, Sarah — 7692071

Last Name (print), First Name (print) — Student Number

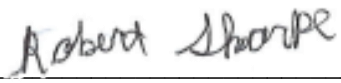


November 26, 2018

Signature Date

Montillet, Julien 7930769

Last Name (print), First Name (print) Student Number

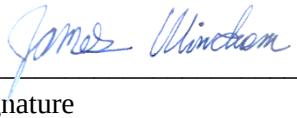


November 26, 2018

Signature Date

Sharpe, Robert 8134182

Last Name (print), First Name (print) Student Number



November 26, 2018

Signature Date

Windrem, James 7789672

Last Name (print), First Name (print) Student Number