William Forman

Financial Forecasting Final Exam

Introduction

Netflix was founded in 1997 by Reed Hastings and Marc Randolph in Scotts Valley, California. Originally, it was founded as a competitor to Blockbuster, renting out DVD's by mail. Eventually, they pivoted to what they are currently – an American over-the-top content platform and production company, who's primary business is a subscription-based streaming service.

Back in 2013, Netflix began generating their own content and programming. Now, they are faced with a handful of concerns. Firstly, the production of their own content has proven a costly expenditure, so management would like to statistically demonstrate how this was a worthwhile investment. Secondly, Netflix would like to demonstrate how it is a recession-proof company. Given 9 years of revenue data, along with US GDP, Unemployment, CPI, and Personal Disposable Income, my goal is to determine the best forecasting model for Netflix.

Descriptives

After running a handful of descriptive statistics and time series plots on the Netflix revenue data from 2010 – 2019, it became immediately clear that the data has strong seasonality and an upward trend. This finding was corroborated after running an Autocorrelation (ACF) function on the data. Re-running the ACF function with 1 degree of differencing clearly helped normalize the data and running it a third time while differencing the data twice helped even more. This will be important to note as I begin doing ARIMA modeling later.

Multiple Regression

Due to the established seasonality I have found in this data, I added dummy variables for Quarters 1, 2, and 3, to see if the given month being any of those quarters made a statistically significant difference in the revenue. Initially, I ran a Multiple Regression model with all variables included – i.e. all three Quarters' dummy variables, GDP, CPI, and all others listed above. It seemed as though there might have been some multicollinearity with some of the variables present. For example, Unemployment and Personal Disposable Income are typically very negatively correlated, so it would not make sense to include both variables in the regression. Thus, I switched to a stepwise regression to remove any multicollinear or statistically insignificant variables. The resulting function:

$$Y = -74{,}769.744 + 3.803(GDP) + 2{,}205.637(Unemployment) -4{,}278.027(Q1) - 3032.623(Q2) - 1{,}596.889(Q3)$$

The Mean Absolute Deviation (MAD) for this model is $3,178.00, meaning in this case that the average distance from each value predicted by the forecast was $3,178.00 off of the actual observed value. Given that we are dealing with figures in the high millions or low billions, this did not feel like a bad start to me. The Mean Squared Error (MSE) is $13,057,027.23. The big benefit of using a Multiple Regression model is that it considers numerous statistically significant parameters to predict the dependent variable, instead of just analyzing the dependent variable itself. However, it does not take into account seasonality, which in the case of this data, is too large a component to be overlooked.

Seasonal Decomposition

Next, I ran two Seasonal Decomposition models – Additive and Multiplicative Seasonal Decomposition. One of the models resulted in lower MAD and MSE than with the final Multiple Regression model. A big advantage that Seasonal Decomposition has over Multiple Regression is that SD can account for seasonality in the data, which is a big weakness of MR. The Seasonal Indices created by the Additive model were – 1. -2,594.428, 2. -797.459, 3. 898.665, 4. 2493.222. The MAD for this model was $3,407.79, and the MSE was $17,763,256.90. The Multiplicative model was significantly more successful at predicting revenues than the Additive one. The indices generated by the Multiplicative model were – 1. 43.5%, 2. 83.2%, 3. 116.9%, 4. 156.3%. The MAD and MSE for the Multiplicative model were $2,352.68 and $7,748,455.87, respectfully. Given this information, the Multiplicative model is the better of the Seasonal Decomposition models that were run. The big strength of using a seasonal decomposition model is that, instead of running a flat trend line on the data, the data is broken down into multiple components so the seasonality can be reflected in the forecast.

Exponential Smoothing

I ran several Exponential Smoothing models to evaluate which one best fit our data. Given our data is clearly seasonal and non-linear, there was little chance that a Holt's Linear model would be helpful, but I ran one anyway just to be able to rule it out. The MAD and MSE of Holt's Linear on NFLX's revenue data was $4,059.00 and $21,453,402.00, so even compared to other models we've discussed thus far it does not make the cut. A Simple Seasonal model yielded better results, with a MAD and MSE of $2,030.75 and $6,306,727.25. Winter's Additive model was far better, with a MAD and MSE of $1,440.75 and $2,851,413.25, respectfully. However, the model was statistically significant, indicating not enough white noise, and one would therefore not use it. The Winter's Multiplicative model was by far the best of these. It had a MAD of $1,215.75, an MSE of $1,761,966.75, and a MAE of $57.91. In the context of this case, this means that the average prediction created by Winter's Multiplicative model is $1,215.75 off the actual observed value. In the scope of billions in revenues, this is a very strong model. The big weakness of exponential smoothing is that it lags. Thus, if the trend in the data changes over time, the forecast will be behind in reflecting that change. However, if the trend is assumed to stay steady over time, exponential smoothing normally works pretty well.

ARIMA

After looking at Autocorrelation & Partial Autocorrelation functions at the beginning of this project, it was very clear that Netflix's revenue data has an upward trend. I also determined that differencing the data twice helped to normalize it, so I made sure to include that in my ARIMA models as the second value. After running numerous combinations of ARIMA modeling and checking their significance, MAD, and MSE against one another, I've determined the best ARIMA model to fit this data is (0,2,0)(1,2,0). The MAD and MSE of this model are $1,464.00 and $2,169,077, respectfully. A big strength of ARIMA modeling is that they follow the data and their seasonality very well because they do more short-term forecasts. However, that short-term nature is also ARIMA's biggest weakness. It can result in the trend component of a series of data to become lost because it's only looking at a few previous datapoints, not the whole set.

Combination Models

For this dataset, two model combinations were tested – Multiple Regression & Exponential Smoothing, and Multiple Regression & ARIMA. After running and saving the best determined Exponential Smoothing and MR models, I created a new MR model using those two previous forecasts as the predictors of revenue. The constant was statistically insignificant, meaning the two models could be reasonably combined without it. The resulting equation is:

$$Y = 0.992(\text{Expo output at period } t) + 0.008(\text{MR output at period } t)$$

This combination model has a standard error of the estimate of 56.612. The MAD and MSE for this model are $1,209.18 and $1,712,722.53, respectfully – the lowest we've seen yet. Finally I ran the second combination model using Multiple Regression and ARIMA. Again, the constant produced by a joint MR model was statistically insignificant, meaning we can reasonably combine the two models into one. The resulting equation is :

Y = 0.852 (ARIMA output at period t) + 0.148 (MR output at period t)

This equation has a standard error of the estimate of 348.637, and a MAD and MSE of $1,305.80 and $2,036,430.57, respectively. It is important to note that, given neither of these models contain a constant, the R^2 information provided by SPSS is meaningless. These combination models are great at minimizing error since they are both pulling from different pieces of information. For example the Multiple Regression model we use makes its predictions off of different variables than the ARIMA or Exponential smoothing (stochastic) models do, so combination models can try and appropriately weight the value of each model in one equation.

Conclusion

Given all this analysis and the five different types of models run, the best one to forecast Netflix's revenue is the Multiple Regression & Exponential Smoothing combination model. Out of the 10+ individual models run, it has the lowest mean absolute deviation of $1,209.18, and the lowest mean squared error of $1,712,722.53. Winter's Multiplicative exponential smoothing model comes in at a very close second place, but the combination model still has the added benefit of incorporating a small weight of MR to help incorporate some other factors in the dataset. Netflix, as we've established, started producing its own content in 2013. Since then, the upward seasonal trend in its revenue has only continued to go up over the 6 following years reflected in this dataset. Given these findings, I would argue that it is a very lucrative part of the Netflix business, and one that will continue to yield results going forward. As for Netflix being recession-proof, we unfortunately do not have the data to back up that claim at this time.