UPS Air Finance Division

Forecasting the Funding Requirements for the non-UPS segment

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Executive Summary

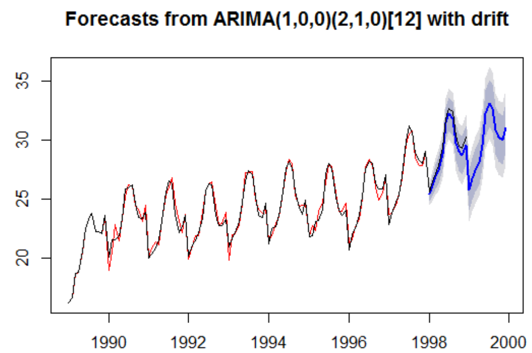
The purpose of this study is find the best model to predict the funding requirements for the Non-UPS Air Finance Division segment. Funding forecasts for this market segment have been highly subjective and unreliable. Thus, we are interested in finding out objective patterns of the funding histories for this segment and forecasting for UPS Air Finance Division.

We collected monthly time series data of this market segment from 1989 to 1998. The frequency of this data is in months.

We applied the following forecasting models to the data:

- Moving Average Smoothing
- Double Moving Average Smoothing
- Holt-Winters Additive Smoothing
- Holt-Winters Multiplicative Smoothing
- Multiple Linear Regression
- Classical Time Series Decomposition
- ARIMA Model
- Ensemble ARIMA Model

After examining the results of the forecasts, we determined that the **ARIMA Model (1, 0, 0) (2, 1, 0) [12] with drift** provided the best forecast for our dataset. We found that the data have strong monthly seasonality: summer months (June and July) have the highest funding and winter months (January and December) have the lowest funding. This is because funding activities are much more active in summer periods, whereas in winter seasons funding campaigns are dormant. The graph of the final forecast for new funding requirements for non-UPS market segment and the corresponding prediction intervals are as follows:



Point	Forecast	Lo 95	Hi 95
Jan-99	25.8	23.2	28.4
Feb-99	26.7	24.0	29.5
Mar-99	27.4	24.6	30.3
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Nov-99	30.0	26.8	33.2
Dec-99	31.1	27.8	34.3

Introduction and Motivation

The United Parcel Service Financial Corporation is a wholly owned subsidiary of United Parcel Service (UPS). It has several divisions, the Air Finance Division being of them. Specifically, the Air Finance Division provide independent financial advisory to the holding company regarding jet aircraft acquisitions. However, this division also operates a separate business: provide financing for independent outside entities with respect to aviation purchases.

The non-UPS financing segment of the Air Finance Division has outperformed than the UPS segment with a higher rate of return. The downside is that this distinct line of business is more costly to pursue. Hence, it is of the interest of the Air Finance Division to tap the undiscovered profitability potentials of the non-ups market segment. The division has collected historic data about the funding requirements for the non-ups market segment. Considering that the funding forecasts for this specific segment has been subjective and unreliable, we dedicate this project to offering an objective analysis of the funding time series data and generating reliable forecasts.

Data

Source

We obtained our data from secondary source - *Blackboard.usc.edu*.

Data Frequency:

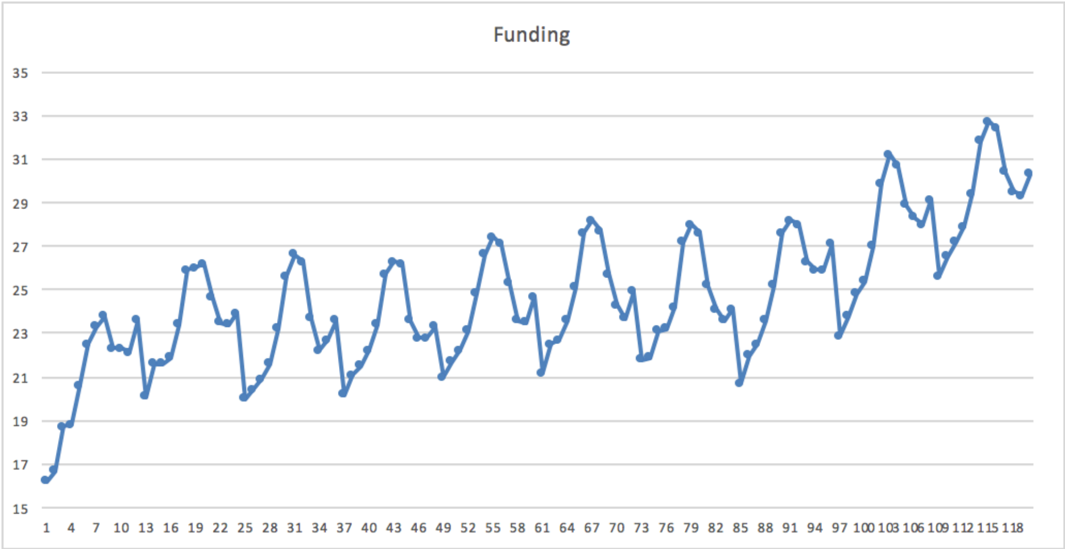
Monthly data would be appropriate for our analysis. Since past forecasts has been highly subjective, the Air Finance Division might have been missing out on important information about the funding requirements. Analyzing monthly data can potentially help us uncover more what has been unknown to the company than quarterly data. Hence, we use monthly frequency to conduct time series analyses.

Data Horizon:

The collected data range from 1989 to 1998. We believe a 10-year-dataset is enough for us perform even the more complicated time series models on. Since we have monthly data, we have a total number of 120 observations.

Data Exploration and Visualization:

We plotted the monthly funding requirements versus time to visualize the true signals of the data pattern. The graph is shown below:



Seasonal Component:
The data show strong seasonality, with a full seasonal cycle of 12 months. More specifically, summer months including June and July contain the highest funding. On the other end of the spectrum, winter seasons including December, January and February have the lowest funding of the year. Additionally, the seasonality is more addictive than multiplicative.

Trend Component:
The data show a slight upward trending pattern from 1989 to 1998. Although the rate of increase is not dramatic, upon a closer look, we found that the upward sloping pattern is consistent and steady. Thus, the trend component is also strong in this dataset.

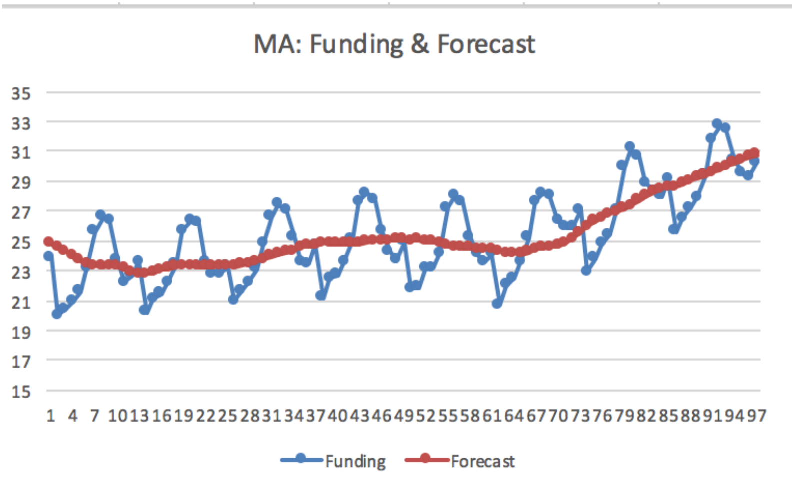
Cyclical Component:
The data also demonstrate some cyclical component. In year 1998 and 1999, there's a more drastic increase in funding requirements. We hypothesize that this is because of the **dot-com bubble** in the US. The dot-com bubble saw the burgeoning of e-commerce business. Online retail company such Amazon and Ebay were representative of the emerging business segment. More importantly, delivery & shipping is an indispensable part of the online shopping experience. The Air Finance Division might be experience huge demand of air transportation for non-UPS clients. We believe that e-commerce during the dot-com bubble has strong cyclical impact on the funding requirements.

Forecasting Methodologies

1. *Moving Average Smoothing:*

We started our analysis with moving average smoothing. The reason is that we already knew that this dataset contains visibly strong seasonal component. However, we were not 100% confident the trend pattern and cyclical component are as significant. So, we made a moving average model to test out our hypothesis about the persistent mildly upward trend and also the cyclical component in the last two years. This will serve as good starting point if we can make sure of the time component.

The graph of actual versus forecasted values is shown below (full table can be found under “MA” tab in excel file):



From the graph, we can see that the Moving Average model with a window of 12 captures an upward trend and also the drastic increase in funding in 1998 and 1999. This model, thus, confirms our previous observations about the time and cyclical components.

The RMSE of the training and testing datasets is shown in the table below:

MA						
Trainging	MSE	4.54		Validation	MSE	4.08
	RMSE	2.13			RMSE	2.02

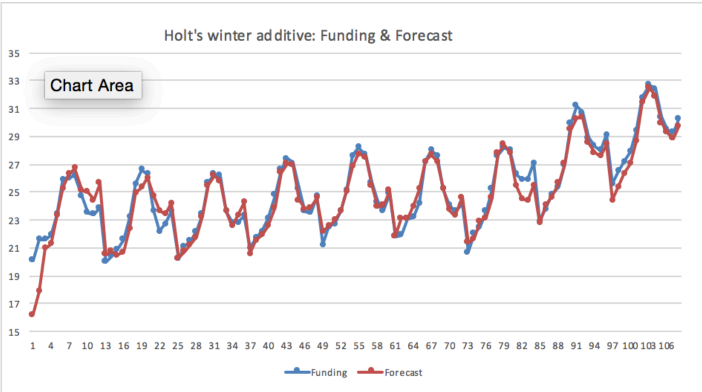
We were not surprised to see such a high RMSE for Moving average model, because we knew the seasonality would not be accounted for. This model should not be selected to generate forecast for the above reason. From then on, we went on to other forecasting techniques to model the seasonality and time component.

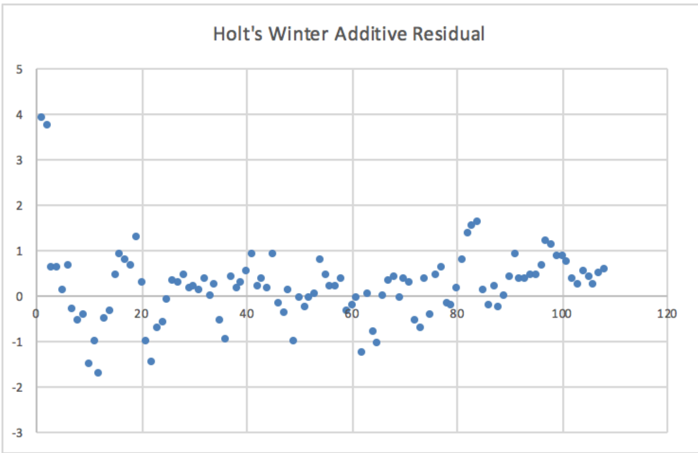
2. Double Moving Average Smoothing & Weighted Moving Average Smoothing:

We performed the double moving average smoothing and weighted moving average smoothing to look further into the trend. The two models confirmed our hypothesis about the trend in the data. Because we were confident about the time component, from then on, we went on to other forecasting techniques to model the seasonality and time component.

3. Holt-Winter Smoothing (Additive):

For the Hol-Winter's additive smoothing method, we used **alpha of 0.29, beta of 0.01, and gamma 1.00** of to produce a forecast on the training and validation set. The graph of actual versus forecasted values is shown below (full table can be found under "Holts winter additive model" tab in excel file):





We can see from the graph that the fitted values align very well with the actual values. This smoothing model captures the time, additive seasonality and cyclical component of the time series.

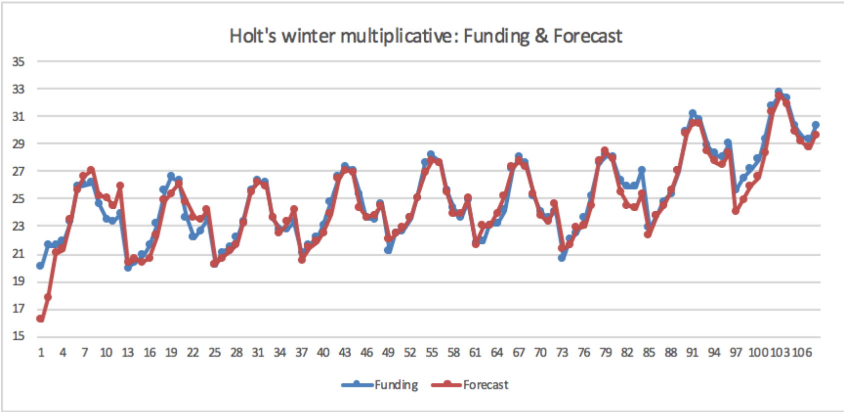
The RMSE of the training and testing datasets is shown in the table below:

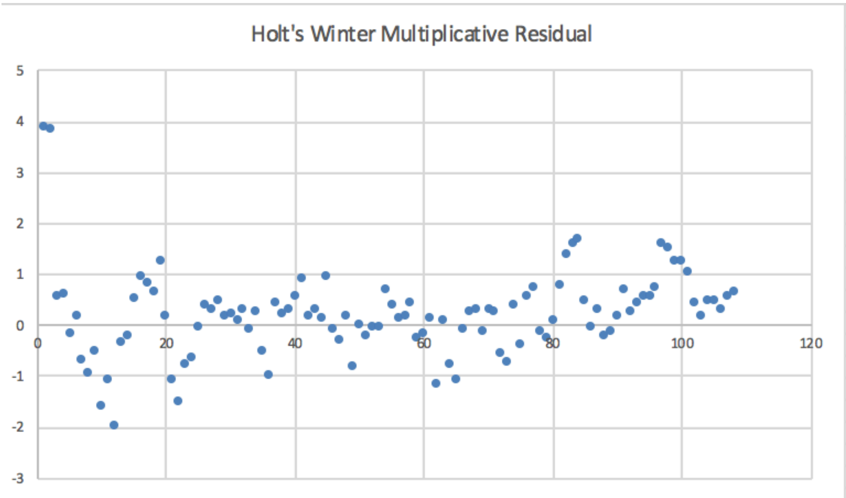
Holt's winter additive	Training	MSE	0.708	Validation	MSE	0.501
		RMSE	0.841		RMSE	0.708

The error measures obtained significantly improved from our previous moving average smoothing models.

4. Holt-Winter's Smoothing (Multiplicative):

To refine our previous additive model, we performed the multiplicative version to further explore the seasonal component. For the Hol-Winter's multiplicative smoothing method, we used **alpha of 0.26, beta of 0.01, and gamma 1.00** of to produce a forecast on the training and validation set.





We can see from the graph that the fitted values still align well with the actual values, but not as well as the additive seasonality model. This smoothing model captures the time and cyclical component of the time series. However, the seasonality of the data is rather additive than multiplicative.

The error measures confirmed our observations:

Holt's winter multiplicative	Training	MSE	0.736	Validation	MSE	0.901
		RMSE	0.858		RMSE	0.949

This concludes our analyses with smoothing models.

5. Regression Model

We started regression analysis with Time, Time^2, Seasonal with December as dummy.

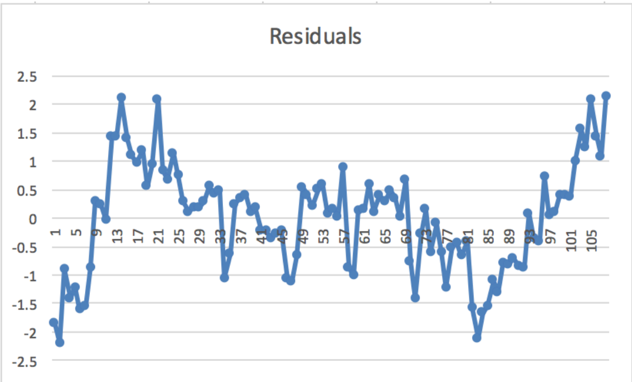
The P-value for each variable is shown below:

	P-value
Intercept	8.7E-72
Time	1.9E-03
Time^2	2.9E-01
Jan	9.4E-14
Feb	4.6E-10
Mar	3.1E-07
Apr	4.5E-05
May	3.0E-01
Jun	5.6E-05
Jul	1.1E-07
Aug	9.8E-07
Sep	4.9E-01
Oct	1.2E-01
Nov	4.6E-02

We removed Time^2, May, September and October to run the regression again because these variables are insignificant according to their p-values. The P-value for the remaining variables is shown below:

	P-value
Intercept	5.162E-99
Time	4.64195E-30
Jan	1.51633E-16
Feb	9.38748E-12
Mar	4.85516E-08
Apr	2.99881E-05
Jun	9.13492E-09
Jul	9.34477E-13
Aug	2.12621E-11

Now that all the variables are statistically significant, we went on to analyze the residuals:

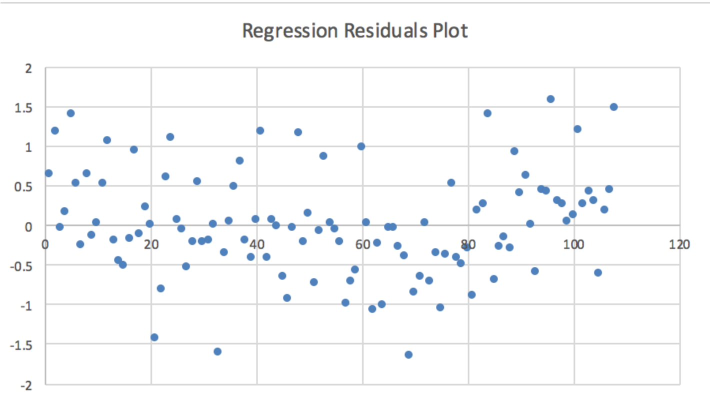


The residuals plot shows clear up-and-down pattern. Additionally, our 2nd regression model underestimated the funding requirements in the years of dot-com bubble.

From there, we decided to model lags in our 3rd regression. After looking at the correlation between each of the 12 lags with the actual values, we believed that Lag1 and Lag9 would be the most appropriate. Thus, we incorporated Lag1 and Lag9 into our 3rd regression. The P-value for all variables is shown below:

	P-value
Intercept	5.7135E-05
Time	2.5671E-05
Jan	2.303E-21
Jun	9.6733E-18
Jul	1.6487E-09
Aug	0.00036371
Lag 1	4.0982E-32
Lag 9	0.00096108

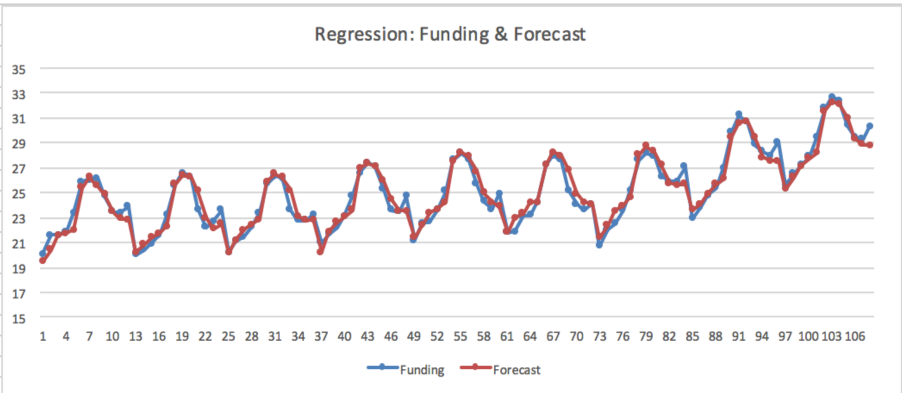
Since all variables are significant, we again went to analyze the residuals.



The residuals are much more random now than ever before. Error measures for the final regression model are as follows:

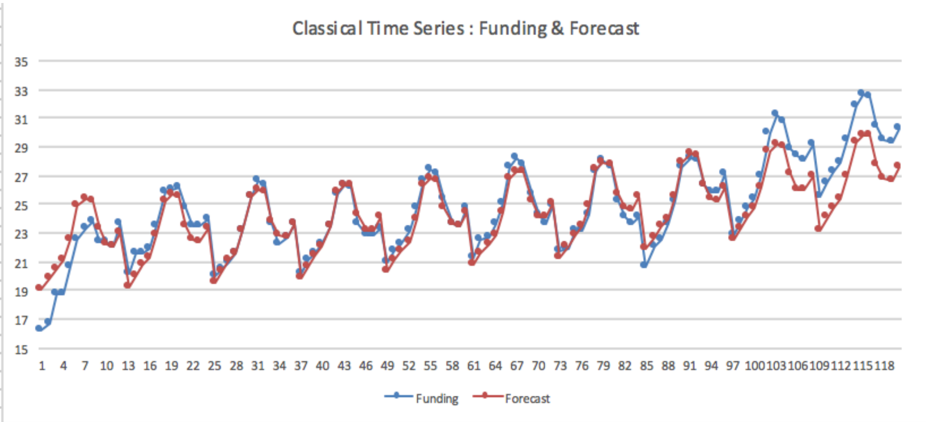
Regression	Training			Validation	
	MSE	0.436		MSE	0.393
	RMSE	0.660		RMSE	0.627

The regression model was able to capture the time, seasonal and cyclical component. However, it did a worse job than smoothing models. Therefore, we concluded that regression model is not the most useful to generate forecasts for the Air Finance Division.



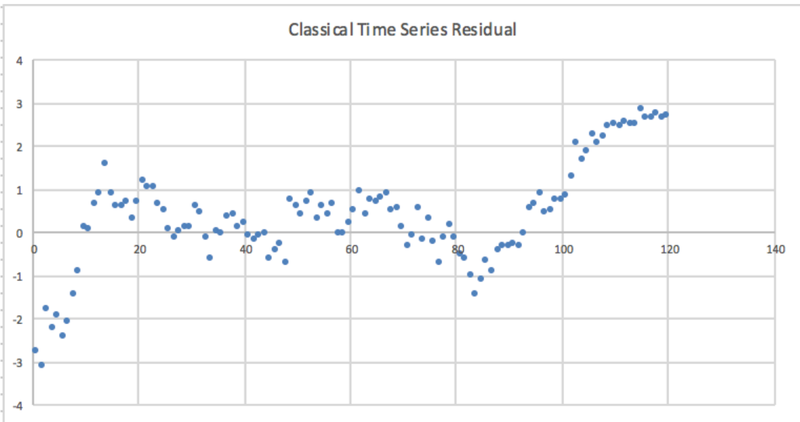
6. Classical Time Series Decomposition:

The graph of fitted values versus actual values is shown below:



It's clear from this graph that our classical time series decomposition model fails to capture the cyclical component of the funding data.

The plot of residuals shows visible patterns.

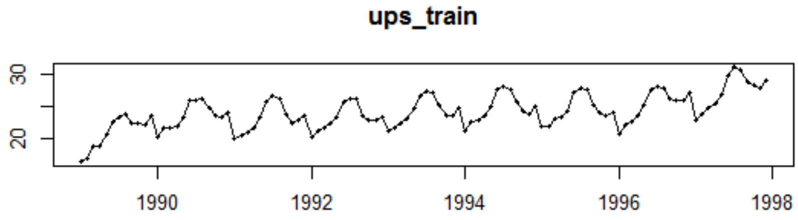


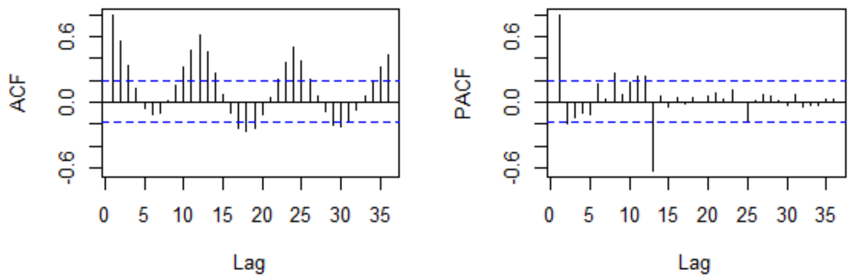
The error measures on the validation set are very large. Thus, we concluded that Classical Time Series Decomposition is not the best model to forecast funding requirements for Air Finance Division.

Classical Time Series	Training		Validation	
	MSE	0.940	MSE	6.693
	RMSE	0.970	RMSE	2.587

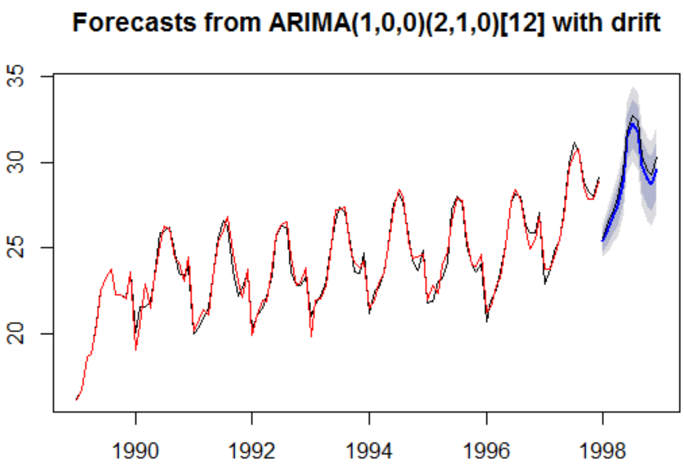
7. ARIMA

We started our ARIMA model by visualizing the training dataset. The ACF graph shows seasonal decay, meaning that the time series is not stationary.

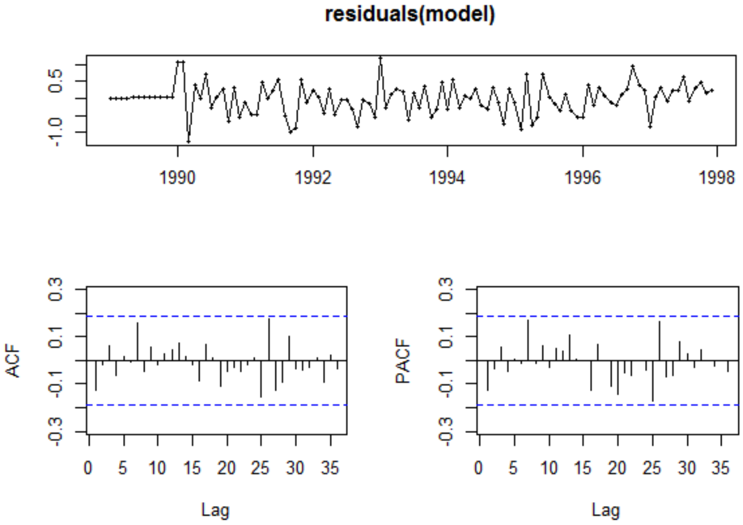




We performed the auto.arima() function in R, knowing that the algorithm will automatically differencing the data and choose the best ARIMA model. Consequently, **ARIMA(1,0,0)(2,1,0)[12] with drift** is the best model.



The residuals analysis is shown below:



The residuals show strong randomness and there's no significant autocorrelations indicated by the ACF analysis. Thus, we went on to use this model to test on our validation set.

The error measures shown below give us confidence that this ARIMA model is so far the best model. To further confirm the fit of this model, we plotted the residuals on the validation dataset. The residuals show that our forecast values are a little smaller than testing data. Other than the validation set, the fitted values align perfectly with actual values. Moreover, the RMSE for the validation set is the smallest by far.

ARIMA	Training	MSE	0.206		Validation	MSE	0.231
		RMSE	0.454			RMSE	0.481

Hence, we concluded that **ARIMA(1,0,0)(2,1,0)[12] with drift** was so far the best performing model that successfully captures the time, seasonal and some cyclical component.

8. Ensemble ARIMA

In this final model, we chose to ensemble some of our best-performing models so far: Regression, Holt-Winter's Additive Smoothing, and ARIMA model. Specifically, we performed the following Ensemble models:

- Equal Weight Ensemble model
- Regression Ensemble model
- Small Error Larger Weight Ensemble model with (alpha = , beta = , sigma =)
- Optimal Weight Ensemble model ()

The error measures for the validation set for the above ensemble models are shown below:

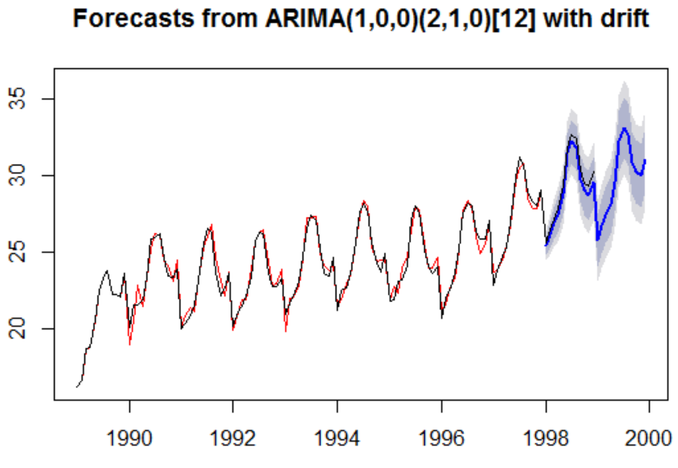
		Equal Weight Ensemble	Regression Ensemble	Small Error Larger Weight Ensemble	Optimal Weight Ensemble
Validation	MSE	0.356	0.249	0.271	0.226
	RMSE	0.597	0.499	0.521	0.475

Summary of Forecasting Methods Used:

The table below summarizes all the forecasting methods that we applied to the data.

Model	Method	Alpha	Beta	Gamma	MSE	RMSE
1	Holt's Winter Additive	0.292	0.012	1	0.501	0.708
2	Holt's Winter Multiplicative	0.259	0.010	1	0.901	0.949
3	Classical Time Series	-	-	-	6.693	2.587
4	Regression	-	-	-	0.393	0.627
5	Moving Average	-	-	-	4.083	2.021
6	Double Moving Average	-	-	-	6.935	2.633
7	Weighted Moving Average	-	-	-	1.587	1.260
8	ARIMA	-	-	-	0.231	0.481
9	Equal Weight Ensemble	0.33	0.33	0.33	0.356	0.597
10	Regression Ensemble	-	-	-	0.249	0.499
11	Small Error Larger Weight Ense	0.32	0.54	0.14	0.271	0.521
12	Optimal Weight Ensemble	0.15	0.85	0	0.226	0.475

Final Forecast for the non-UPS market segment of UPS Air Finance Division:
As discussed, we chose the **ARIMA(1,0,0)(2,1,0)[12] with drift** model to generate our final forecast. Using this method and the parameters noted above, we forecast the funding requirements up to December 1999 (next 12 months). Below is the time plot of actual versus fitted values by ARIMA model.



We can see from the graph that the fitted values align perfectly well with fitted values. Comparing all models we've run so far, ARIMA model has given us the most accurate forecast.

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Overall, the forecast of 1999 seems reasonable. We project that the cyclical e-commerce trend would culminate in year 1999 before the Dot.com bubble eventually burst.

Conclusion:

The purpose of this project was to find the best forecast for the funding requirements for the non-UPS segment of the UPS Air Finance Division. Through several moving average models, we found that the time component of the data was valid. Having this knowledge in mind, we performed more sophisticated smoothing techniques such as Holt-Winter's Additive and Multiplicative models. These analyses generated better forecast values because more true signals were modeled. We turned to regression analysis by modeling time component, seasonal component and cyclical component. The final regression model affirmed that all these three signals were present in the data. More specifically, we found that 1) the upward trend is linear, 2) winter and summer months are highly seasonal, and 3) starting 1998 there's a huge bump in funding. Respectively, 1) the funding for non-UPS segment increases as a result of growing business, 2) summer months tend to have more aviation financing activities, and 3) the rocketing e-commerce might have brought up the demand for air shipping.

Through our forecast, we predict that the funding requirements for 1999 would continue grow with the momentum in the business. July 1999 will see the highest funding requirement of the year: $33.1; January 1999 is forecasted to have the lower funding of the year: $25.8. Moreover, all funding values are forecasted to be a little higher than last year because of the upward time and cyclical components. Overall speaking, the Air Finance Division should expect to see annually growing funding requirements for the non-UPS market segment.