Econ 421: Economic Forecasting and Big Data

Assignment 4

Due: 5pm, Wednesday March 8, 2017

In the EXCEL spreadsheet titled Job Openings.xlsx you will find data on monthly job openings for the US economy from December 2000 until December 2016.

You assignment is to produce forecasts for January 2017 through to December 2017 using each of the following models:

- EWMA
- Holts
- Holts-Winters
- ETS – this is the most general approach which has a special case the other models mentioned above.

Report your forecasts in both a table and a graph.

Make sure you carefully define each model and explain how you obtained your forecasts. (Note: Just saying what command you used is not enough. you need to describe what the command is doing.)

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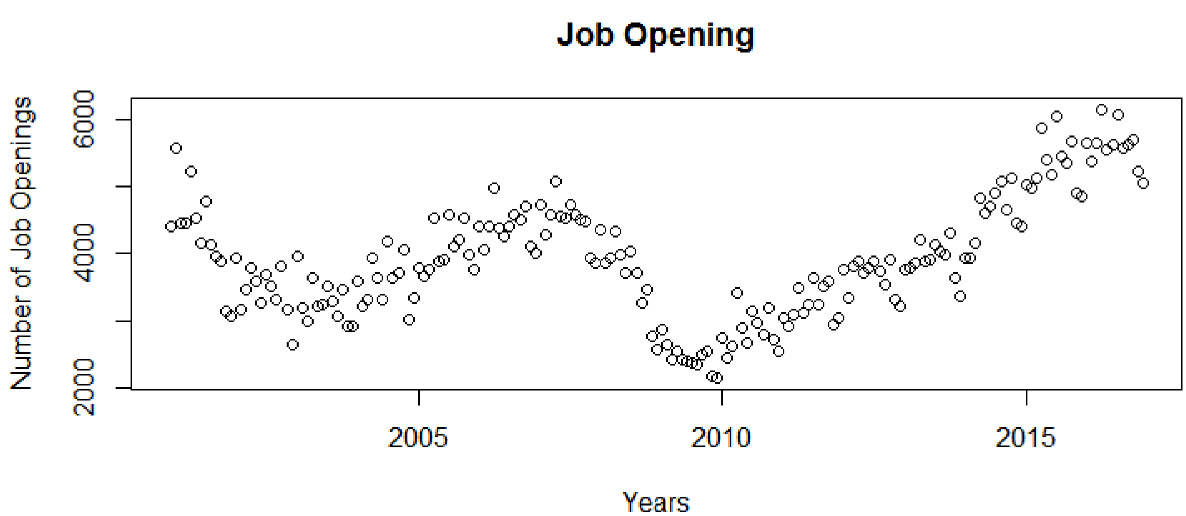
Forecasting and Big Data

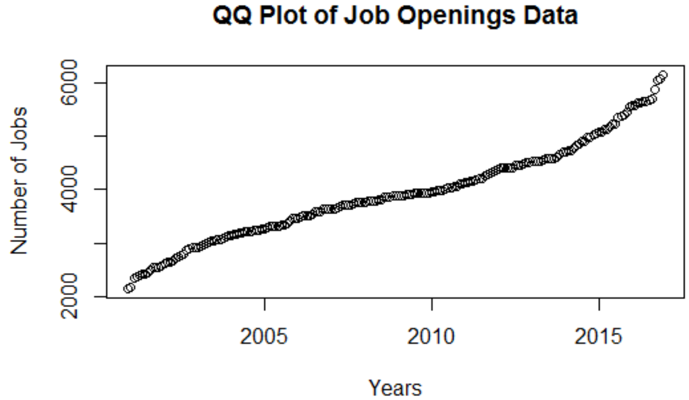
3/5/17

Assignment 4

My objective for this report was to model the Job Openings data from 2000 to 2016 to produce forecasts for January 2017 to December 2017. For this task, I used R Studio to program commands that would analyze the data and build models that are to be analyzed. In this, my commands can be slightly different then people who use R since my packages as me for slight differences in the code to produce the same results. For example, because Iused the forecasting package, by version tells me to specify package, then command, ex. forecast::ets(). I also build models using the EWMA, Holts, Holts-Winters, and the model R chose to be optimal in the case. I will explain each model in their respective sections and how they lead to the final model that I chose to be optimal. I have also provided point forecasts and confidence intervals for each model for each month that I am trying to forecast.

For the Job Openings data forecasts using the smoothing models, the first step I did was to graph the raw data so that that I see some of the patterns in the data. For the Job Openings figure below, you can see that the data has somewhat of a seasonal pattern and potentially a trend and that there could be some abnormality in the data. I used the plot() command in R to make this figure. After graphing the QQ-Plot using the qqplot() command in R, we can see that there are departures from normality, but it is not bad. We could assume normality for our sake. From this, we can see that the period we want to forecast, January 2017-December 2017, is within the next year, and that it can be forecasting using the simple forecasting methods we will outline.





For the project below, I used R programming to code each model, and will explain the method I used to code each model. To make the data into a time series model, I first had to use the ts() function to turn the dataset, Job, into a time series variable for R to read. I used the notation Job[,2] to tell R that I wanted to use the second column of the dataset as the Y variable but also maintain the dates in the dataset. I also specified the Start of the date as the year 2000, as the start of the observations that R would be using. The end of the data was 2016. These two commands in ts() is a vector of two numbers that tells R the end and beginning of the dataset for the time series. Frequency as also set to 12 for the number of observations per unit of time, ie 12 months to 1 year.

From there, I coded each model by first defining a function name for the ets() command. This command tells R that we will be using a smoothing average model and to construct a model using whichever method we specify. For the ets() command, I specified the time series variable, ts.Job, then the model, then the alpha level. The model differs depending on what the features of the model are for error, trend, and seasonal in that order. For example, EWMA would use a “ANN” code because it is an Additive Error, No Trend, No Seasonal model because it is a model that adds error but does not use any method to measure trend or seasonality. From there, you can specify an alpha level, or a level of smoothness for the forecasts for the model as it projects forward. I chose to let R pick the value of significance because I did not want to try to guess the optimal value. So, I set alpha equal to NULL. It is possible to tell R a numerical alpha level, like 0.95. Furthermore, I did not tell R to pick an optimal criterion, such as minimizing Mean Squared Errors, because I wanted to see what models R would produce without that command and gauge the models using other model specific statistics, which I will explain later on.

Another note on my code is that I produced a different function for the forecast, which I used a forecast() command for. Here I specified the number of times I wanted R to run simulations and bootstrap my code for purposes of accuracy and so R can find the optimal results using the model I told it to use. This is so R can run a simulation on the data using the smoothing model of my choice some number of times, which allows for more accuracy in the predictions of my forecasts. The number of times is specified by npaths, which I set to 5000 for this code. Also, I specified h-12 because I wanted R to understand time unit, which is 12 months to 1 year. For more notes on my code, please see the commands section for the models and look for a number symbol. The comment is attached there. Also, for full output and summary please see appendix.

The types of forecast that we will be producing uses EWMA, Holts, Holts-Winters, and what the program R thinks is the optimal model. For point forecasts, or individual points that are predicted, are calculated differently in each model. For confidence intervals, the formula is still the general formula, which is the point forecast added or subtracted with the significance level multiplied by the square root of twice the Mean Squared error divided by the number of observations. The difference is that we specifiied two different confidence intervals, 80% and 95% were we are that percent confident that the observation when it is recorded will fall in that interval. Also, plots in this report plot the original data, the forecast points and confidence intervals for each model. The forecasts are the blue line, the confidence intervals are the shadows around the line.

Even though I did report Mean Square Error and other error statistics that will tell you how much error your model produces, I did not use them to evaluate models because there are other ways to compare across models. Besides, the only error statistic you can use to compare across models is MAPE, or Mean Average Percentage Error, which takes the percent error produced by the model, and uses absolute errors from the observation and divides by the value of the observation. For the model to be optimal, you want to minimize AIC and BIC since they are the information criterion and use the maximum likelihood function to determine the quality of the model we have. In this case, lower values indicate a better quality of the model. These statistics are much easier to use to compare across models since they tell you using numbers what model is best.

The first model I worked with was EWMA. EWMA is Exponentially Weighted Moving Average method, which is the optimal model for data with on obvious trend or seasonal component. This method gives most weight to the most recent observations, so that when forecasting, you are taking the most recent data plus some of the error from the previous forecast and use that to produce point estimates and confidence intervals. You take the error as well because as you go further then one step ahead forecasting, you are also adding errors from the previous forecast. In this case, we are taking errors from 1-12 steps to produce the forecasts from January 2017 to December 2017. The commands for the EWMA Job Openings plot and forecasts are as follows:

EWMA Commands and Output

Commands:

```
> ts.Job=ts(Job[,2], start=c(2000,12), frequency=12, end=c(2016,12))
#creates Job data set into times series variable. This is used throughout the models and
assumed through every model.

> ewma=forecast::ets(ts.Job, model="ANN", alpha=NULL)
#creates variable ewma and specifies how we want R to model the data using ANN

> ewma.forecast=forecast::forecast(ewma, levels= c(90,95), simulate = TRUE, bootstrap = T
RUE, npaths= 5000, h=12)
#creates forecast variable for model and specifics confidence intervals (levels).
Also explains how many times you would like R to simulate and resample from the data
(simulate, bootstrap, and npaths) and the number of time period, h=12 for 12 months in 1
year

> summary(ewma.forecast)
#prints summary of forecast variable and specifications as for in the variable coded

>plot(ewma.forecast, xlab="Years", ylab="Number of Job Openings", main="EWMA Model")
#plots time series forecast graph and labels x,y, and title of graph
```

Summary Statistics:

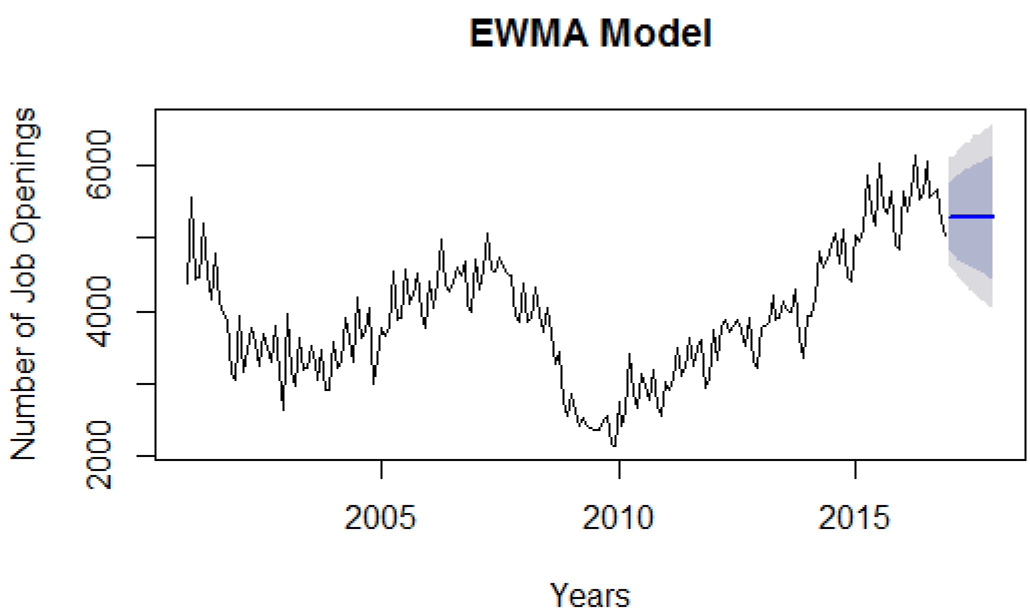
Smoothing parameters:
alpha = 0.4461

AIC	AICc	BIC
3307.430	3307.557	3317.218

Error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	6.433624	373.0011	302.0955	-0.6233537	7.918799	0.5853561	-0.04811806

Date	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2017	5281.91	4834.443	5764.112	4630.526	6122.609
Feb 2017	5281.91	4787.658	5807.340	4567.743	6124.287
Mar 2017	5281.91	4714.199	5859.653	4487.904	6205.423
Apr 2017	5281.91	4690.229	5899.895	4432.991	6259.813
May 2017	5281.91	4659.006	5937.796	4379.645	6290.579
Jun 2017	5281.91	4612.206	5955.685	4293.070	6307.722
Jul 2017	5281.91	4595.596	6006.617	4267.488	6400.995
Aug 2017	5281.91	4580.482	6017.213	4212.094	6408.011
Sep 2017	5281.91	4534.452	6021.845	4151.620	6448.349
Oct 2017	5281.91	4504.222	6081.491	4135.850	6498.740
Nov 2017	5281.91	4470.856	6098.365	4068.164	6529.309
Dec 2017	5281.91	4433.272	6128.903	4048.154	6588.188



As you can see, the EWMA method produces the same forecast at 5218.91 for each of the months in the period we want to forecast. This does not give a good forecast going forward after the 1-step ahead because the forecast is expected to move, not to remain the same value. Also, this model is not good in terms of how it does not take the seasonal component into account. You can see from the large AIC and BIC values of 3307.430 and 3317.218 that this is not the best model you can choose. Later, we will see other models that minimize these values better.

Also, you can see from the confidence levels that are reported from every month that the range changes for every month even though the point forecast is the same. Fore example, the 80% confidence interval is [4834.443 5764.112] while the February forecast's range is [4787.658 5807.340]. The length of the interval is larger, which means that there is more error in each interval since the interval is calculated using errors. Errors are increase after each forecast. These results, even though they can be used to try to come up with a confidence interval for the 12 months, is not as accurate as it can be based on the results we will see from confidence intervals in the next couple of models.

The next model I chose to try was the Holts Model. This model is good for data can that be model by a local mean, or a mean that moves with the data by taking averages from part of the data to project forward. In this case, the model will take the last couple of observations forecast the points. However, it will also run into the problem of using forecasts as a point to forecast the next point. So 12 steps forecast out it will lose accuracy quickly, but not as much as EWMA.

For the code, I used "AAN" as my model type. Holts is an Additive Error, Additive Trend, and No Seasonal model, which means that the model can account for trends in the data additively, but not seasonally. Errors are also additive, so they will be accounted for in the forecasts, which will be a problem with forecasts that are multiple steps ahead. This is because the model uses the model mean to forecast forward rather than the mean of the data set, but also adds any errors from the previous forecasts forward. Other then this modification, the code stayed the same from the previous code. The code and output for the model is as follows:

Holts Commands and Output:

Commands:

```
> holts=forecast::ets(ts.Job, model="AAN", alpha=NULL)
#creates variable holts and specifies how we want R to model the data using AAN

> holts.forecast=forecast::forecast(holts, levels= c(90,95), simulate = TRUE, bootstrap =
TRUE, npaths= 5000, h=12)
#creates forecast variable for model and specifics confidence intervals (levels).
Also explains how many times you would like R to simulate and resample from the data
(simulate, bootstrap, and npaths) and the number of time period, h=12 for 12 months in 1
year

> plot(holts.forecast, xlab="Years", ylab="Number of Job Openings", main="Holts Model")
#plots holts.forecast and labels x, y, and title of plot

> summary(holts.forecast)
#prints summary statistics of the model
```

Summary Statistics:

```
Forecast method: ETS(A,Ad,N)
```

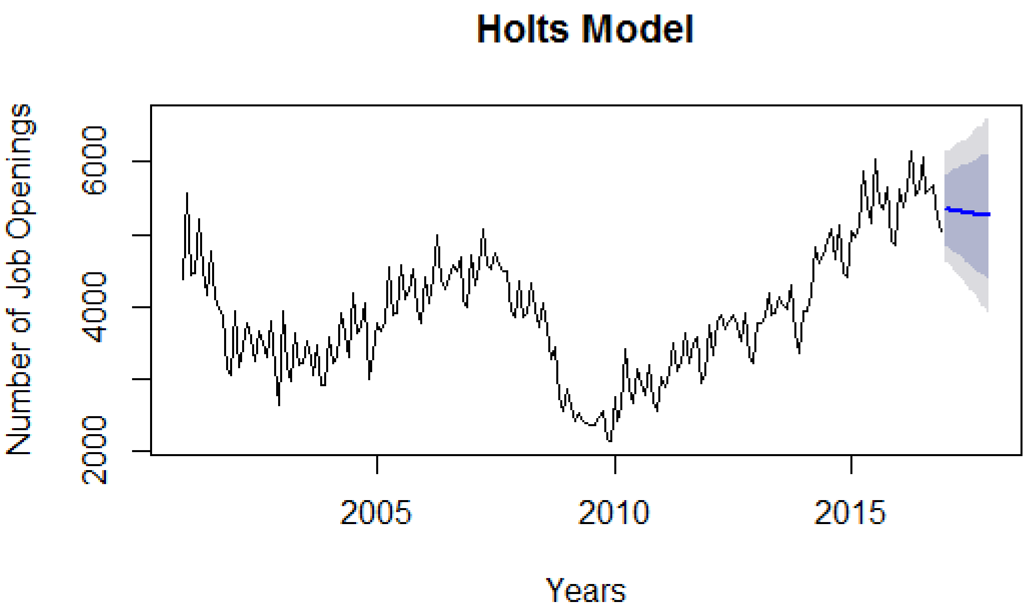
Smoothing parameters:
alpha = 0.3642
beta = 0.0241
phi = 0.9341

AIC	AICc	BIC
3308.502	3308.954	3328.078

Error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	9.884036	368.2697	295.5223	-0.3522497	7.710909	0.5726194	-0.02017484

	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2017	5347.390	4852.730	5809.772	4620.290	6187.425
Feb 2017	5336.105	4813.038	5856.984	4603.557	6135.524
Mar 2017	5325.565	4778.863	5901.651	4513.822	6200.951
Apr 2017	5315.719	4735.782	5909.055	4472.248	6264.928
May 2017	5306.523	4705.385	5954.166	4398.101	6287.760
Jun 2017	5297.933	4634.391	5958.100	4320.843	6284.212
Jul 2017	5289.909	4588.758	5988.645	4255.988	6345.556
Aug 2017	5282.414	4551.542	6003.628	4203.022	6411.176
Sep 2017	5275.413	4503.334	6040.048	4130.589	6466.062
Oct 2017	5268.874	4459.970	6090.985	4033.627	6490.140
Nov 2017	5262.765	4426.717	6101.253	3990.690	6596.824
Dec 2017	5257.060	4379.412	6127.461	3896.138	6589.351



You can see from the graph that the line is sensitive to the trend in the data, which is see in the angles of the forecast. This model produced a better forecast then EWMA because the model. AIC is lower than EWMA and so is the BIC (3308.5 and 3328.07 respectively). This means that the model is better then EWMA. The point forecasts for the model as also assumed to be more accurate because using the model linear mean would allow for the forecasts to be different from each other. You can see from Jan 2017 to Dec 2017, that the points are trending downwards from 5347.390 to 5257.060. This is also apparent in the confidence intervals as well, because they vary using the 80% and 95% confidence level around the point forecast. From January 2017, the 80% was [4852.730 5809.772] and the 90% was [4620.290 6187.425]. Both levels hovered around their respective point forecast.

However, this model is not accurate in the respect that it does not take account into the seasonal component of the data. This data has visible turning points, and trend models cannot predict a turning point. You can see that eventually, the trend will turn upwards. For this, we need to take the Holts model and modify it to take account seasonality.

For this, we can use the Additive model, or the Holts-Winter Additive Model. This model uses the code "AAA" to signal Additive Error, Additive Trend, and Additive Seasonal component. The advantages of this model is that the model will account for trend and the seasonal component using a modified version of the Holts model. There is also a added advantage in the fact that it is less work using this model over Holts. Holts model can be modified where seasonality is taken out, adjusted, then brought back into the model. Holts Winters, takes out that extra step of seasonally adjusting the data, and models it correctly the first time. It is efficient in that sense, plus this particular model uses the additive formulas for the Holts-Winters method where error, trend, and seasonality is added together rather then multipled. The commands and output are as follows:

Holts-Winters Additive Commands and Output

Commands:

```
> holts.add=forecast::ets(ts.Job, model="AAA", alpha=NULL)
#creates variable holts.add and specifies how we want R to model the data using AAA and s
ets alpha to whatever level R wishes

> holtsadd.forecast=forecast::forecast(holts.add, levels= c(90,95), simulate = TRUE, boot
strap = TRUE, npaths= 5000, h=12)
#creates forecast variable holtsadd.forecast for model and specifics confidence intervals
(levels).Also explains how many times you would like R to simulate and resample from the
data (simulate, bootstrap, and npaths) and the number of time period, h=12 for 12 months
in 1 year

> plot(holtsadd.forecast, xlab="Years", ylab="Number of Job Openings", main="Holts Model"
)
#creates plot of forecast and labels x, y, and title of plot

> summary(holtsadd.forecast)
#creates summary statistics of the model using the information from holtsadd.forecast
```

Summary Statistics:

```
Forecast method: ETS(A,Ad,A)

Model Information:
ETS(A,Ad,A)
```

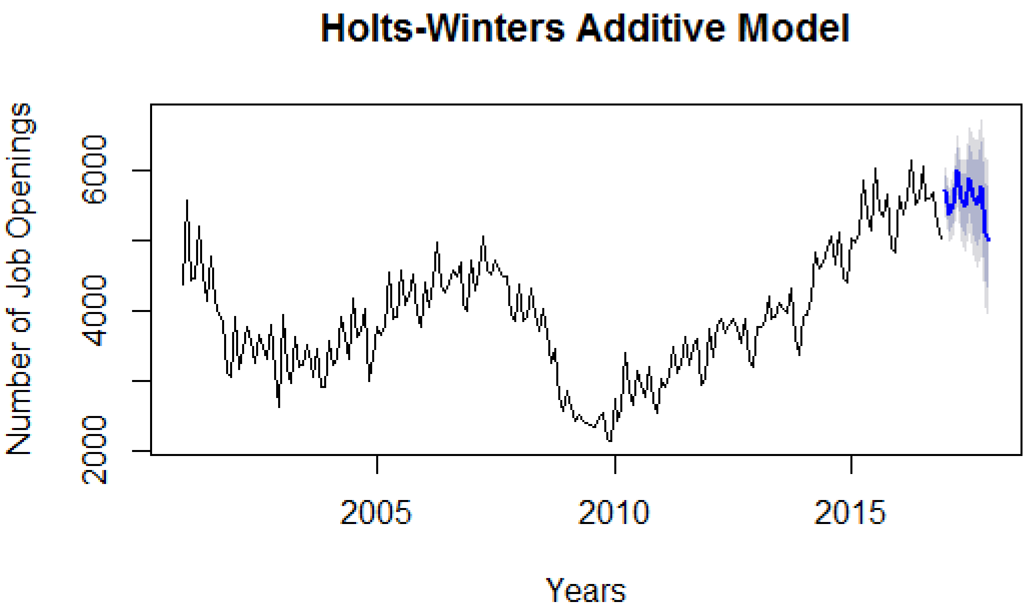
Smoothing parameters:
alpha = 0.3385
beta = 0.1712
gamma = 1e-04
phi = 0.8617

AIC	AICc	BIC
3058.500	3062.431	3117.228

Error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	4.201143	181.0849	145.6175	0.05968986	3.929973	0.2821562	-0.02843568

	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2017	5728.190	5502.693	5960.849	5341.606	6060.088
Feb 2017	5372.304	5116.078	5634.272	4980.232	5760.441
Mar 2017	5515.016	5220.009	5813.769	5053.131	5964.137
Apr 2017	5998.667	5667.587	6339.229	5482.171	6520.964
May 2017	5596.075	5210.250	5980.431	5004.392	6177.051
Jun 2017	5504.251	5060.087	5943.090	4828.317	6158.660
Jul 2017	5878.038	5393.411	6373.267	5132.918	6637.018
Aug 2017	5630.302	5100.968	6185.473	4802.393	6487.863
Sep 2017	5520.337	4926.462	6133.812	4599.775	6430.917
Oct 2017	5768.556	5125.760	6426.620	4780.906	6757.173
Nov 2017	5127.445	4438.095	5832.181	4065.710	6198.065
Dec 2017	4992.763	4227.287	5751.535	3849.565	6142.503



For this, we can see from the AIC and BIC statistics that this is a significant improvement over EWMA and Holts model. These values, 3058.5 and 3117.23, are smaller then EWMA and the Holts model. We can also see the alpha value, which is the smoothness of the model, is 0.338, which is the optimal alpha that R chose. This means that the model has a smoothness of that value. You can see how that smoothness is graphed, and you can see that it is not as smooth as the other two models. However, since we are also looking at two more models, we cannot say that this model is the optimal model yet.

We can also report the point forecasts. You can see from Jan 2017 to Dec 2017, that the points are trending downwards from 5728.190 to 4992.763. This difference is much more dramatic then estimated before, which can be because the model is now accounting for seasonality. We know that the model will have variation due to the seasonal component, but now it is reflecting in the forecast. This is also apparent in the confidence intervals as well, because they vary using the 80% and 95% confidence level around the point forecast. From January 2017, the 80% was [5502.693, 5960.849] and the 90% was [5341.606 6060.088]. Both levels hovered around January's point forecast where we are 80% confident and 95% confident that the observation when it comes in will be around these lengths.

The next model that we will be looking at is the Holts-Winter Multiplicative Model. This model uses the code "MAM" to signal Multiplicative Error, Additive Trend, and Multiplicative Seasonal component. The advantages of this model is that the model will account for trend and the seasonal component using a modified version of the Holts model, but using the multiplicative version instead. Holts-Winters method where error, trend, and seasonality is multiplied rather than added together. The reason we are testing for this model is to contrast the additive model and multiplicative model to see which will give a better result and how seasonality should be modeled in this data set. The commands and output are as follows:

Holts-Winters Multiplicative Commands and Output

Commands:

```
> holts.mul=forecast::ets(ts.Job, model="MAM", alpha=NULL)
#creates variable holts.mul and specifies how we want R to model the data using AAA and s
ets alpha to whatever level R wishes

> holtsmul.forecast=forecast::forecast(holts.mul, levels= c(90,95), simulate = TRUE, boot
strap = TRUE, npaths= 5000, h=12)
#creates forecast variable holtsadd.forecast for model and specifics confidence intervals
(levels).Also explains how many times you would like R to simulate and resample from the
data (simulate, bootstrap, and npaths) and the number of time period, h=12 for 12 months
in 1 year

> summary(holtsmul.forecast)
#creates summary of holtsmul.forecast and features specified in variable

> plot(holtsmul.forecast, xlab="Years", ylab="Number of Job Openings", main="Holts-Winter
s Multiplicative Model")
#creates plot of forecast and labels x and y axis and title
```

Summary Statistics:

```
Forecast method: ETS(M,Ad,M)

Model Information:
ETS(M,Ad,M)
```

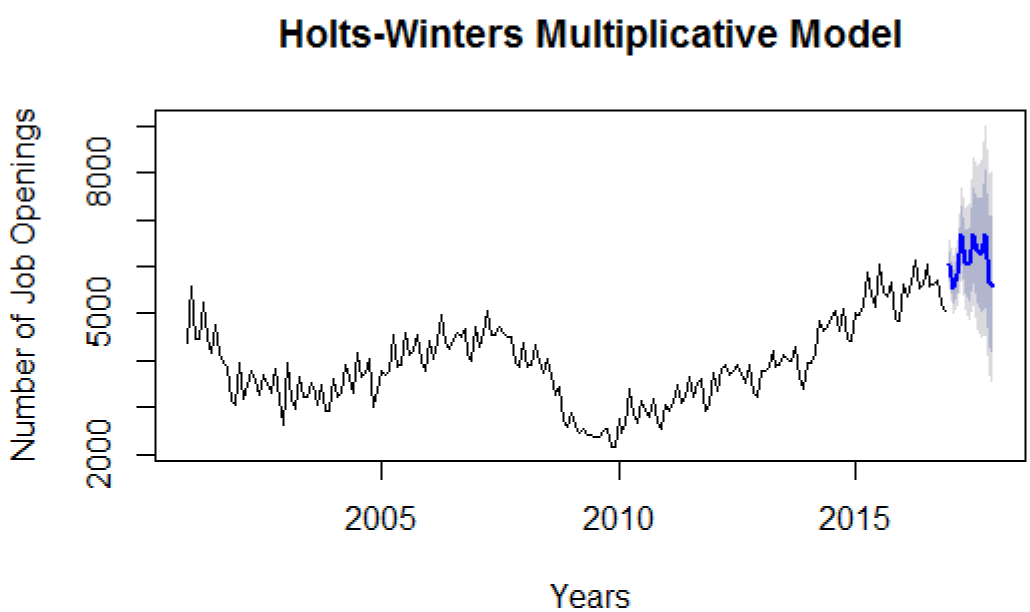
Smoothing parameters:
alpha = 0.3272
beta = 0.2085
gamma = 1e-04
phi = 0.9461

AIC	AICc	BIC
3062.389	3066.320	3121.118

Error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	3.949984	178.2909	144.3514	0.06384217	3.776261	0.2797029	-0.08112729

	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2017	6029.779	5699.048	6350.512	5527.055	6602.340
Feb 2017	5539.248	5181.344	5909.672	4968.378	6194.364
Mar 2017	5820.486	5378.840	6289.653	5144.278	6554.743
Apr 2017	6685.320	6054.325	7323.251	5720.286	7726.186
May 2017	6095.149	5424.110	6759.869	5086.484	7225.887
Jun 2017	6033.218	5249.771	6826.592	4834.517	7334.155
Jul 2017	6681.473	5643.144	7689.097	5183.104	8355.789
Aug 2017	6328.936	5213.768	7459.014	4681.058	8125.115
Sep 2017	6251.649	5025.540	7466.802	4456.783	8273.354
Oct 2017	6664.731	5162.876	8108.201	4536.663	9048.368
Nov 2017	5672.708	4280.206	7070.941	3671.816	7968.681
Dec 2017	5550.798	4061.737	7075.848	3415.975	8083.328



For this, we can see from the AIC and BIC statistics that this is a significant improvement over EWMA and Holts model, but not quite as good as the Additive model. These values, 3062.389 and 3121.118, are smaller than EWMA and the Holts model, but not as small as the Additive model. We can also see the alpha value, which is the smoothness of the model, is 0.32, which is the optimal alpha that R chose for this model. This value is smaller than than the additive model. You can see how that smoothness is graphed, and you can see that the smoothness of the line is like the additive model.

We can also report the point forecasts and confidence levels. You can see from Jan 2017 to Dec 2017, that the points are trending downwards from 6029.779 to 5550.798. This difference is similar to the Additive model, but is scaled up in comparison. We can see that seasonality in the Multiplicative model is different from the Additive model and caused the forecasts to be scaled up in value for this model. This is also apparent in the confidence intervals as well, because they vary using the 80% and 95% confidence level around the point forecast. From January 2017, the 80% was [5699.048 6350.512] and the 95% was [5527.055 6602.340]. Both levels hovered around January's point forecast where we are 80% confident and 95% confident that the observation when it comes in will be around these lengths.

Now, the last model is the model that R thinks is optimal in this case. We use the codel "ZZZ" to tell R to chose the model, and set alpha equal to NULL to let R decide that as well. Other factors, such as confidence intervals, are kept the same. The reason why I let R decide the model is because it will find the most efficient model in seconds and give fairly accurate results. The commands and code is as follows:

R's Optimal Model Commands and Output

Commands:

```
> optimal=forecast::ets(ts.Job, model="ZZZ", alpha=NULL)
#creates variable optimal and specifies how we want R to model the data using AAA and set
s alpha to whatever level R wishes

> optimal.forecast=forecast::forecast(optimal, levels= c(90,95), simulate = TRUE, bootstr
ap = TRUE, npaths= 5000, h=12)
#creates forecast variable optimal.forecast for model and specifics confidence intervals
(levels).Also explains how many times you would like R to simulate and resample from the
data (simulate, bootstrap, and npaths) and the number of time period, h=12 for 12 months
in 1 year

> summary(optimal.forecast)
#creates summary of optimal.forecast and features specified in variable

> plot(optimal.forecast, xlab="Years", ylab="Number of Job Openings", main="R's Optimal M
odel")
#creates plot of forecast and labels x and y axis and title
```

Summary Statistics:

```
Forecast method: ETS(A,Ad,A)

Model Information:
ETS(A,Ad,A)
```

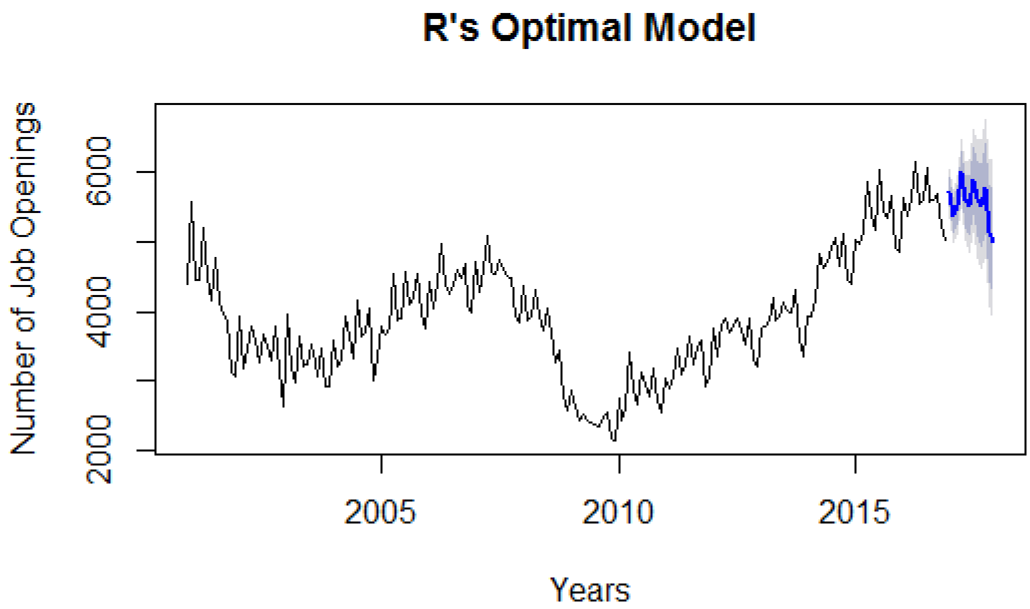
Smoothing parameters:
alpha = 0.3385
beta = 0.1712
gamma = 1e-04
phi = 0.8617

AIC	AICc	BIC
3058.500	3062.431	3117.228

Error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	4.201143	181.0849	145.6175	0.05968986	3.929973	0.2821562	-0.02843568

	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2017	5728.190	5504.482	5960.849	5341.606	6060.088
Feb 2017	5372.304	5117.837	5628.753	4977.273	5757.547
Mar 2017	5515.016	5225.586	5798.211	5071.843	5940.879
Apr 2017	5998.667	5666.076	6332.315	5492.116	6501.208
May 2017	5596.075	5213.081	5979.496	5015.406	6162.938
Jun 2017	5504.251	5078.023	5935.206	4839.146	6182.278
Jul 2017	5878.038	5393.175	6366.987	5143.307	6624.421
Aug 2017	5630.302	5087.452	6177.796	4778.904	6471.892
Sep 2017	5520.337	4913.001	6120.929	4600.676	6457.237
Oct 2017	5768.556	5099.482	6424.455	4754.490	6791.033
Nov 2017	5127.445	4410.245	5843.190	4068.045	6209.414
Dec 2017	4992.763	4211.753	5757.802	3830.492	6190.123



R chose the Additive model as the optimal model. You can see that the AIC and BIC, alpha, and point and confidence interval values are all the same as the Holts-Winters Additive Model coded before. We can tell that R chose this model because AIC and BIC are minimized and the lowest value between all models. Also, the alpha value reflects the data well since the data is not that smooth when plotted. We can tell that R chose this model because of these minimized values and optimized alpha. For specific values, please look at the tables in the R Optimal Model section and the Holts-Winters Additive Model section.

This means that the confidence intervals and point forecast from the Holts-Winters Additive model will be the most accurate forecasts going from January 2017-December 2017. I would recommend using the Holts-Winter-s Model based on the model's features and because R also chose this model as optimal out of all the smoothing models. To come to this conclusion, I use AIC and BIC to figure out which model was best by finding the model that minimizes the their values.

Appendix

All Outputs: EWMA, Holts, Holts-Winters Additive, Holts-Winters Multiplicative, R's Optimal in that order

```
Forecast method: ETS(A,N,N)

Model Information:
ETS(A,N,N)

Call:
 forecast::ets(y = ts.Job, model = "ANN", alpha = NULL)

  Smoothing parameters:
    alpha = 0.4461

  Initial states:
    l = 4728.0274

  sigma:  373.0011

     AIC     AICc      BIC
3307.430 3307.557 3317.218

Error measures:
                   ME     RMSE      MAE        MPE     MAPE      MASE        ACF1
Training set 6.433624 373.0011 302.0955 -0.6233537 7.918799 0.5853561 -0.04811806

Forecasts:
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
Jan 2017        5281.91 4834.443 5764.112 4630.526 6122.609
Feb 2017        5281.91 4787.658 5807.340 4567.743 6124.287
Mar 2017        5281.91 4714.199 5859.653 4487.904 6205.423
Apr 2017        5281.91 4690.229 5899.895 4432.991 6259.813
May 2017        5281.91 4659.006 5937.796 4379.645 6290.579
Jun 2017        5281.91 4612.206 5955.685 4293.070 6307.722
Jul 2017        5281.91 4595.596 6006.617 4267.488 6400.995
Aug 2017        5281.91 4580.482 6017.213 4212.094 6408.011
Sep 2017        5281.91 4534.452 6021.845 4151.620 6448.349
Oct 2017        5281.91 4504.222 6081.491 4135.850 6498.740
Nov 2017        5281.91 4470.856 6098.365 4068.164 6529.309
Dec 2017        5281.91 4433.272 6128.903 4048.154 6588.188


Forecast method: ETS(A,Ad,N)

Model Information:
ETS(A,Ad,N)

Call:
 forecast::ets(y = ts.Job, model = "AAN", alpha = NULL)

  Smoothing parameters:
    alpha = 0.3642
    beta  = 0.0241
    phi   = 0.9341

  Initial states:
    l = 5023.6935
    b = -83.455

  sigma:  368.2697
```

```
     AIC     AICc      BIC 
3308.502 3308.954 3328.078 

Error measures:
                   ME     RMSE      MAE        MPE     MAPE      MASE        ACF1
Training set 9.884036 368.2697 295.5223 -0.3522497 7.710909 0.5726194 -0.02017484

Forecasts:
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
Jan 2017       5347.390 4852.730 5809.772 4620.290 6187.425
Feb 2017       5336.105 4813.038 5856.984 4603.557 6135.524
Mar 2017       5325.565 4778.863 5901.651 4513.822 6200.951
Apr 2017       5315.719 4735.782 5909.055 4472.248 6264.928
May 2017       5306.523 4705.385 5954.166 4398.101 6287.760
Jun 2017       5297.933 4634.391 5958.100 4320.843 6284.212
Jul 2017       5289.909 4588.758 5988.645 4255.988 6345.556
Aug 2017       5282.414 4551.542 6003.628 4203.022 6411.176
Sep 2017       5275.413 4503.334 6040.048 4130.589 6466.062
Oct 2017       5268.874 4459.970 6090.985 4033.627 6490.140
Nov 2017       5262.765 4426.717 6101.253 3990.690 6596.824
Dec 2017       5257.060 4379.412 6127.461 3896.138 6589.351


Forecast method: ETS(A,Ad,A)

Model Information:
ETS(A,Ad,A) 

Call:
 forecast::ets(y = ts.Job, model = "AAA", alpha = NULL) 

  Smoothing parameters:
    alpha = 0.3385 
    beta  = 0.1712 
    gamma = 1e-04 
    phi   = 0.8617 

  Initial states:
    l = 4873.2012 
    b = -75.5908 
    s=-416.5924 223.4099 -26.1427 82.323 328.2579 -47.5737
           41.8605 441.6569 -45.1654 -191.6056 159.9241 -550.3525

  sigma:  181.0849

     AIC     AICc      BIC 
3058.500 3062.431 3117.228 

Error measures:
                   ME     RMSE      MAE        MPE     MAPE      MASE        ACF1
Training set 4.201143 181.0849 145.6175 0.05968986 3.929973 0.2821562 -0.02843568

Forecasts:
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
Jan 2017       5728.190 5502.693 5960.849 5341.606 6060.088
Feb 2017       5372.304 5116.078 5634.272 4980.232 5760.441
Mar 2017       5515.016 5220.009 5813.769 5053.131 5964.137
Apr 2017       5998.667 5667.587 6339.229 5482.171 6520.964
May 2017       5596.075 5210.250 5980.431 5004.392 6177.051
Jun 2017       5504.251 5060.087 5943.090 4828.317 6158.660
Jul 2017       5878.038 5393.411 6373.267 5132.918 6637.018
Aug 2017       5630.302 5100.968 6185.473 4802.393 6487.863
```

```
Sep 2017       5520.337 4926.462 6133.812 4599.775 6430.917
Oct 2017       5768.556 5125.760 6426.620 4780.906 6757.173
Nov 2017       5127.445 4438.095 5832.181 4065.710 6198.065
Dec 2017       4992.763 4227.287 5751.535 3849.565 6142.503


Forecast method: ETS(M,Ad,M)

Model Information:
ETS(M,Ad,M)

Call:
 forecast::ets(y = ts.Job, model = "MAM", alpha = NULL)

  Smoothing parameters:
    alpha = 0.3272
    beta  = 0.2085
    gamma = 1e-04
    phi   = 0.9461

  Initial states:
    l = 4881.098
    b = -75.8445
    s=0.8913 1.0547 0.997 1.0176 1.0837 0.9877
           1.0078 1.1172 0.9838 0.9477 1.0451 0.8662

  sigma:  0.0479

     AIC     AICc      BIC
3062.389 3066.320 3121.118

Error measures:
                   ME     RMSE      MAE        MPE     MAPE      MASE        ACF1
Training set 3.949984 178.2909 144.3514 0.06384217 3.776261 0.2797029 -0.08112729

Forecasts:
         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
Jan 2017       6029.779 5699.048 6350.512 5527.055 6602.340
Feb 2017       5539.248 5181.344 5909.672 4968.378 6194.364
Mar 2017       5820.486 5378.840 6289.653 5144.278 6554.743
Apr 2017       6685.320 6054.325 7323.251 5720.286 7726.186
May 2017       6095.149 5424.110 6759.869 5086.484 7225.887
Jun 2017       6033.218 5249.771 6826.592 4834.517 7334.155
Jul 2017       6681.473 5643.144 7689.097 5183.104 8355.789
Aug 2017       6328.936 5213.768 7459.014 4681.058 8125.115
Sep 2017       6251.649 5025.540 7466.802 4456.783 8273.354
Oct 2017       6664.731 5162.876 8108.201 4536.663 9048.368
Nov 2017       5672.708 4280.206 7070.941 3671.816 7968.681
Dec 2017       5550.798 4061.737 7075.848 3415.975 8083.328
```