2021

Electric Production

Time Series Analysis

Group 5：Bruno BARRIENTOS/Dominique MUSY/Jiaxue LI/Shiyao ZHU/Zhanhao ZHANG

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1 Electric Production Data

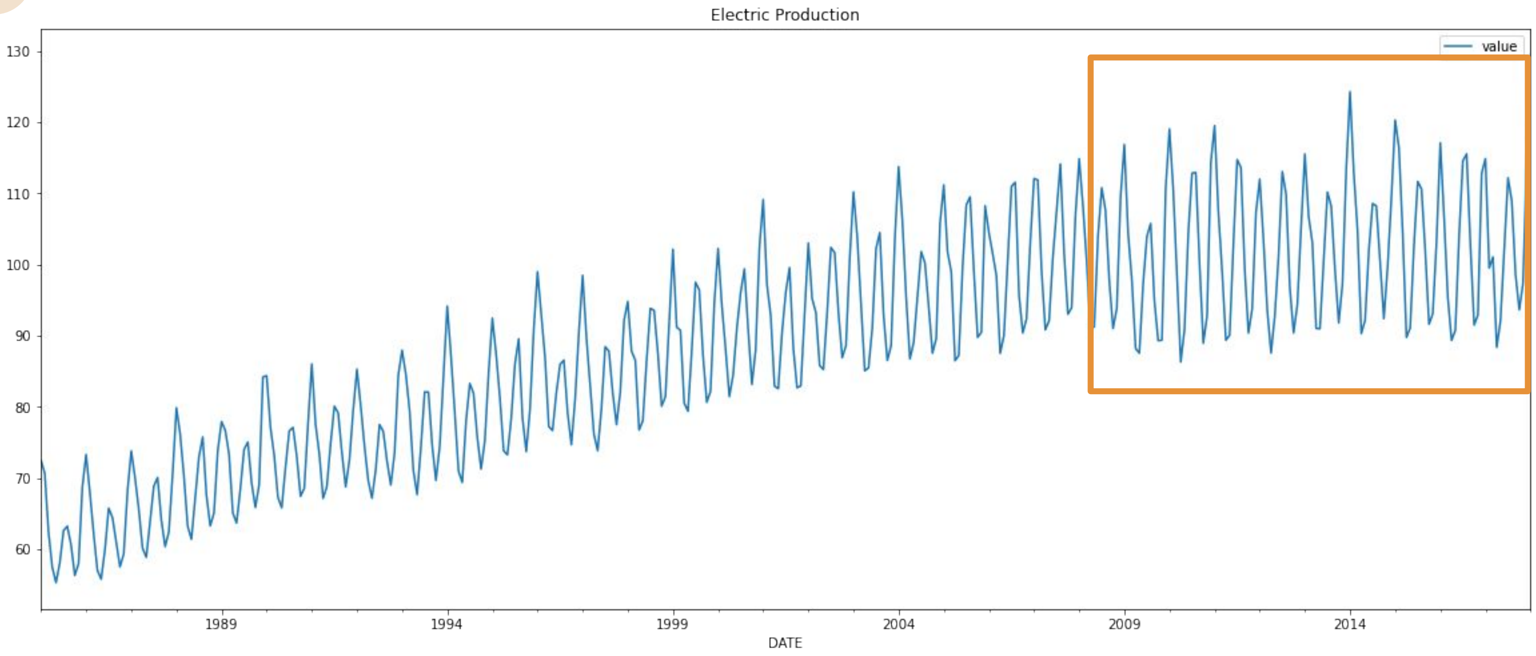
DATE	value
1985-01-01	72.5052
1985-02-01	70.6720
1985-03-01	62.4502
1985-04-01	57.4714
1985-05-01	55.3151

DATE	value
2017-09-01	98.6154
2017-10-01	93.6137
2017-11-01	97.3359
2017-12-01	114.7212
2018-01-01	129.4048

Electric Production

Industrial production of electric and gas utilities in the United States, from the years 1985–2018, with our frequency being Monthly production output. Data access: https://fred.stlouisfed.org/series/IPG2211A2N, Board of Governors of the Federal Reserve System (US)

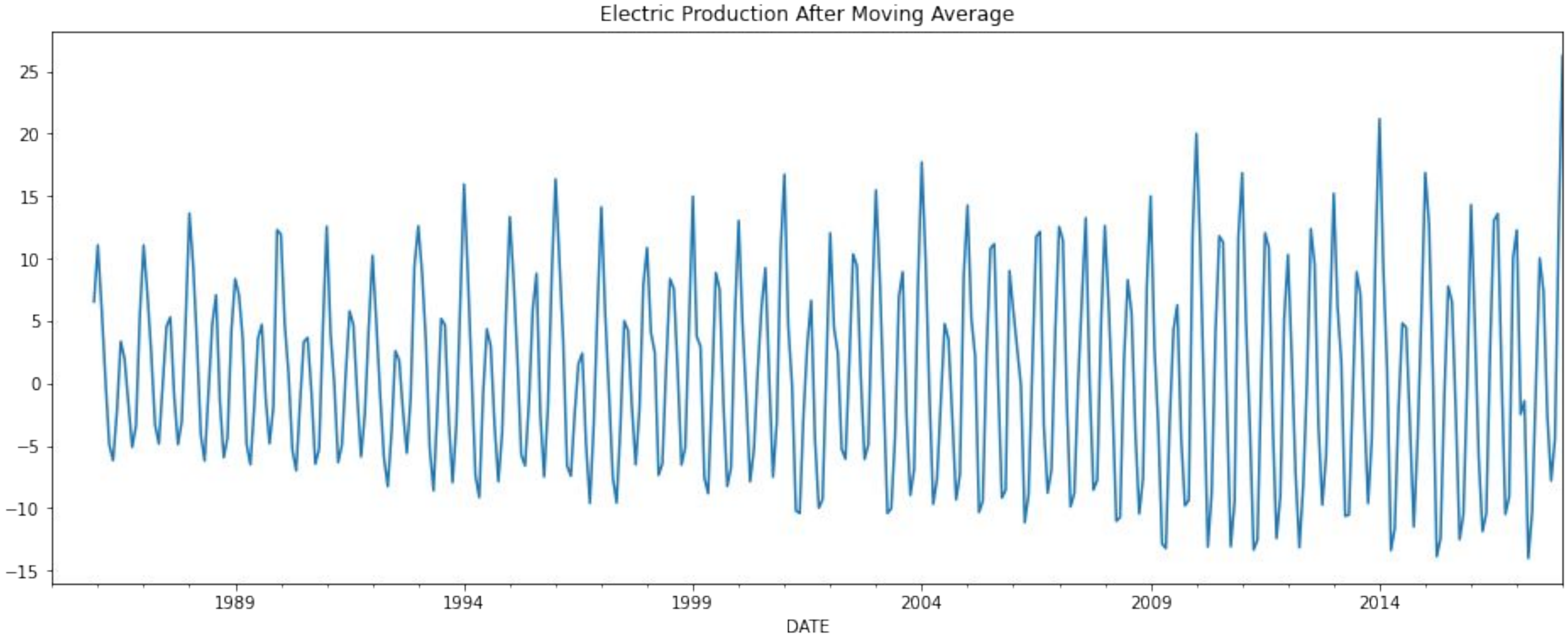
1 Data Characteristics



Non-stationary

Overall, there is an upward trend, but growth has slowed since 2008.

1 Data Characteristics



Removing Trend with Moving Average

There is seasonality here.

1 Modeling

Model Choosing

We decided to use two models to forecast and choose the better one after comparing the results.

Trend

Seasonality

To Forecast

We can use:

AR Model

MA Model

ES Model

ARIMA Model

……

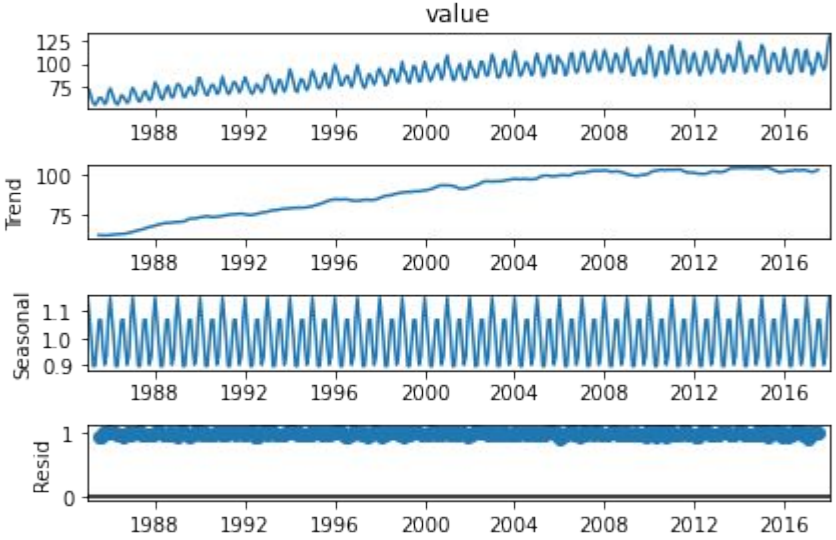
Model we used

Triple Exponential Smoothing

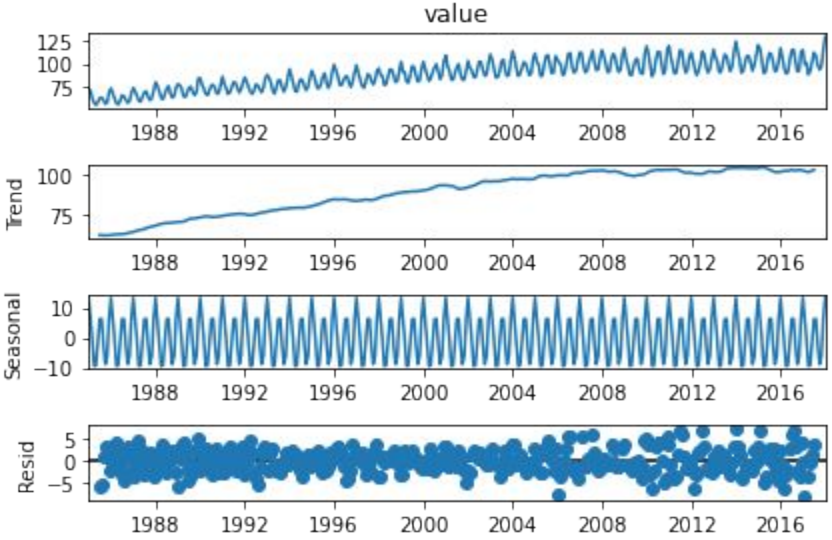
ARIMA-SARIMA Model

2 Decompose Result Multiplicative OR Additive?

Multiplicative



Additive

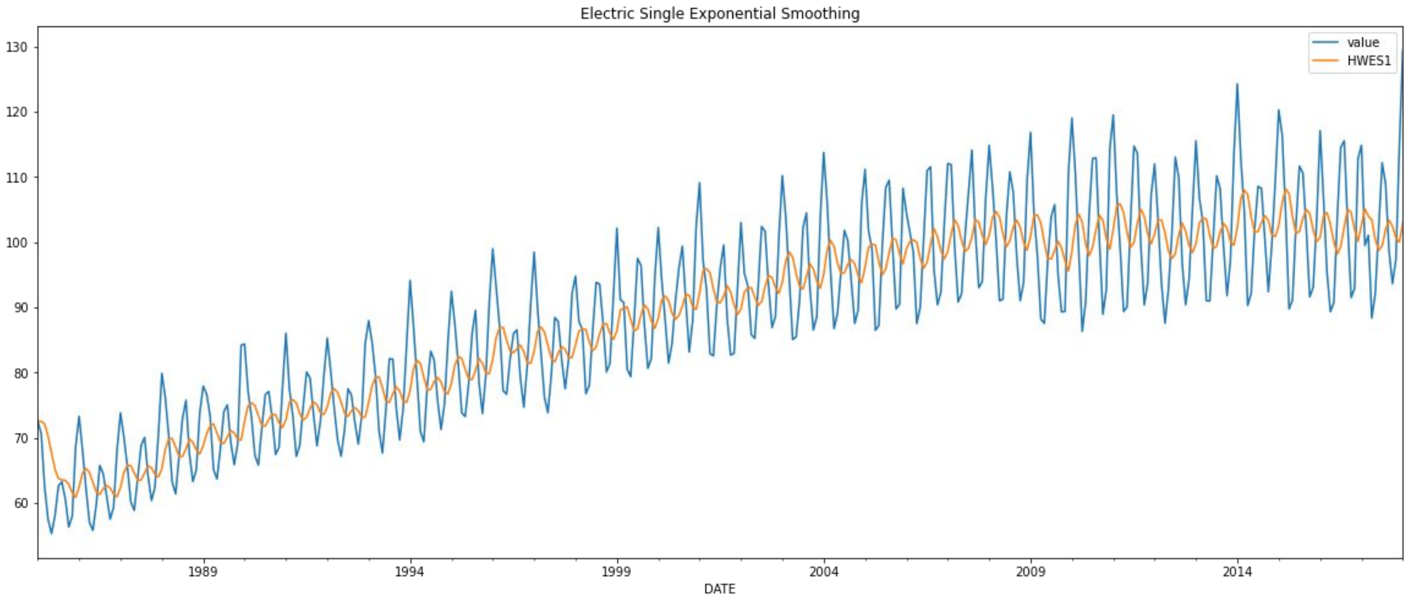


2 Single Exponential Smoothing
Which α is better?

When α = 0.2

MAE = 7.096

MSE = 71.680

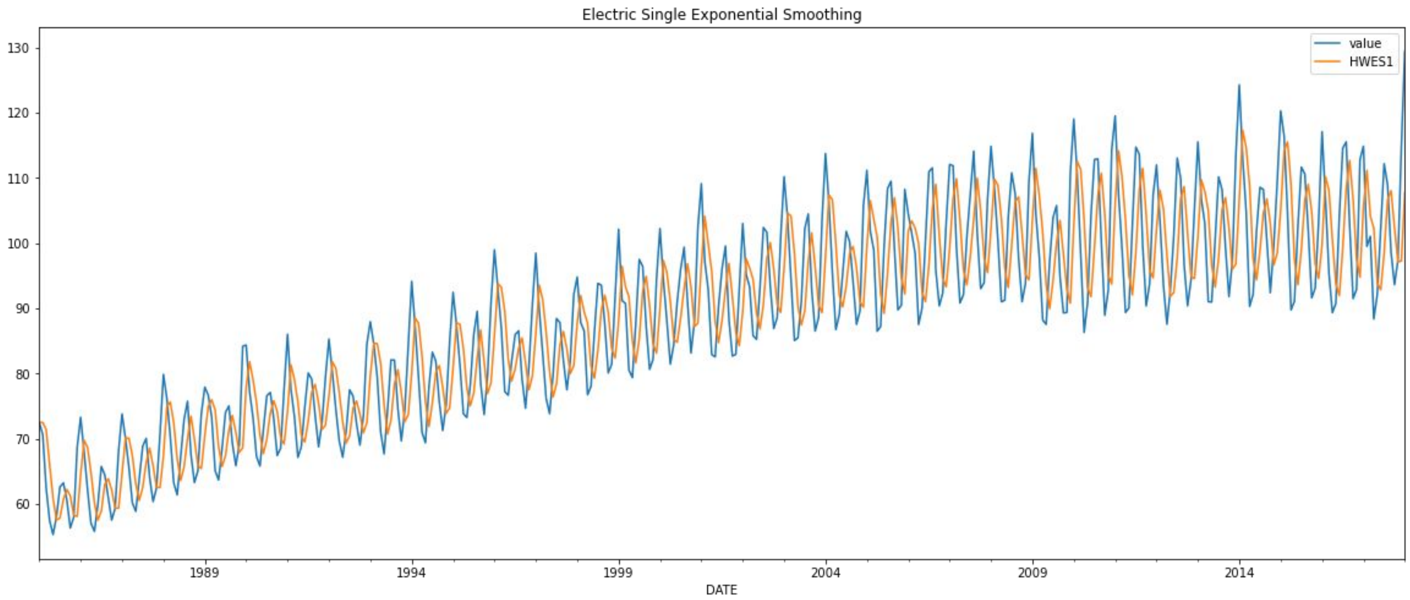


2 Single Exponential Smoothing
Which α is better?

When α = 0.6

MAE = 7.449

MSE = 75.196



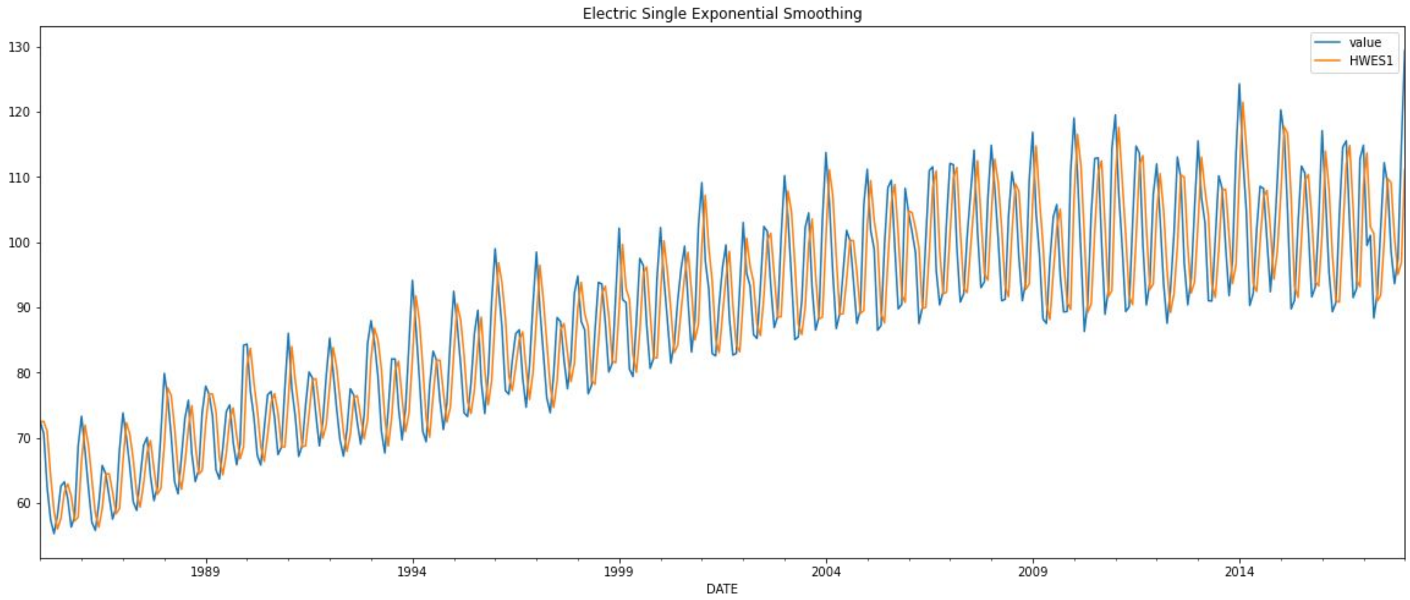
2 Single Exponential Smoothing Which α is better?

When α = 0.8

MAE = 7.055

MSE = 68.851

When the time series data is of the upward (or downward) trend type, α should take a larger value, between 0.6 and 1



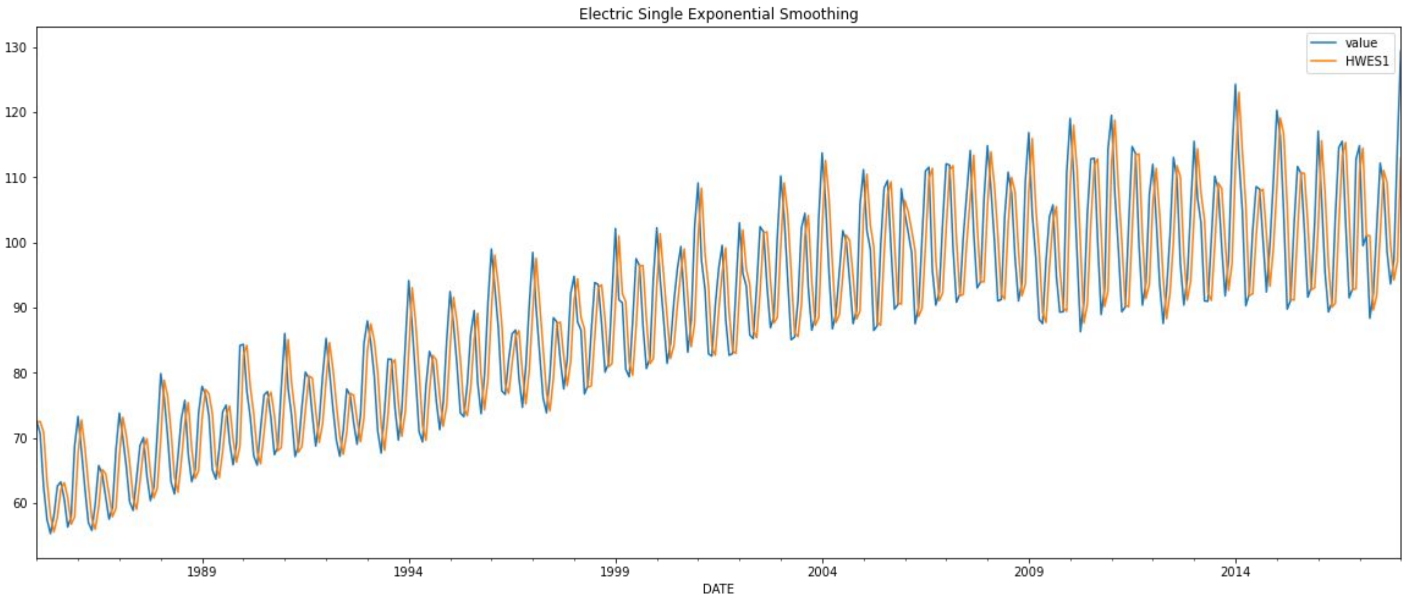
2 Single Exponential Smoothing Which α is better?

When α = 0.9

MAE = 6.807

MSE = 64.526

When the time series data is of the upward (or downward) trend type, α should take a larger value, between 0.6 and 1



2 Double Exponential Smoothing: Addictive Vs. Multiplicative Trend

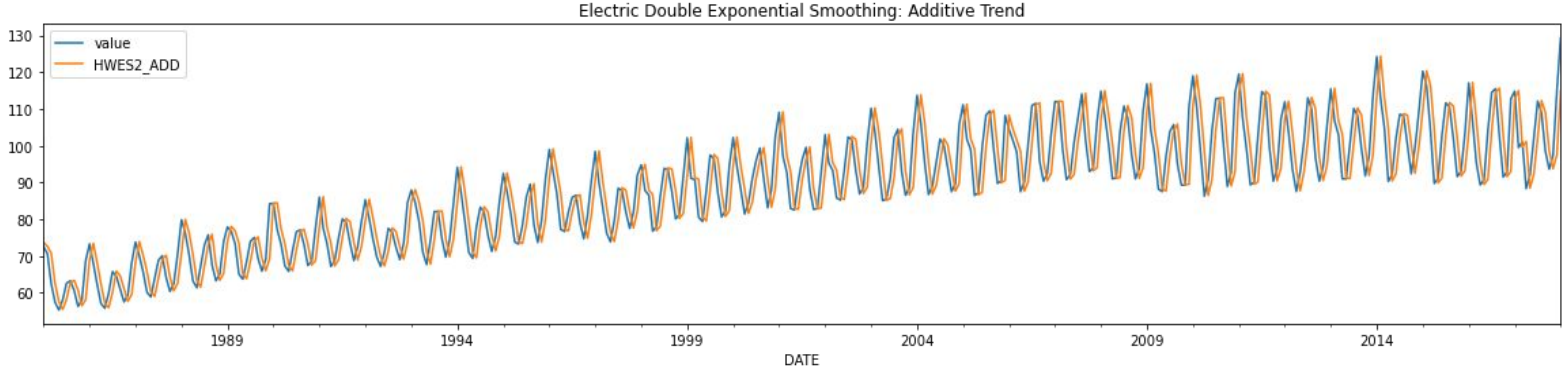
When α = 0.8

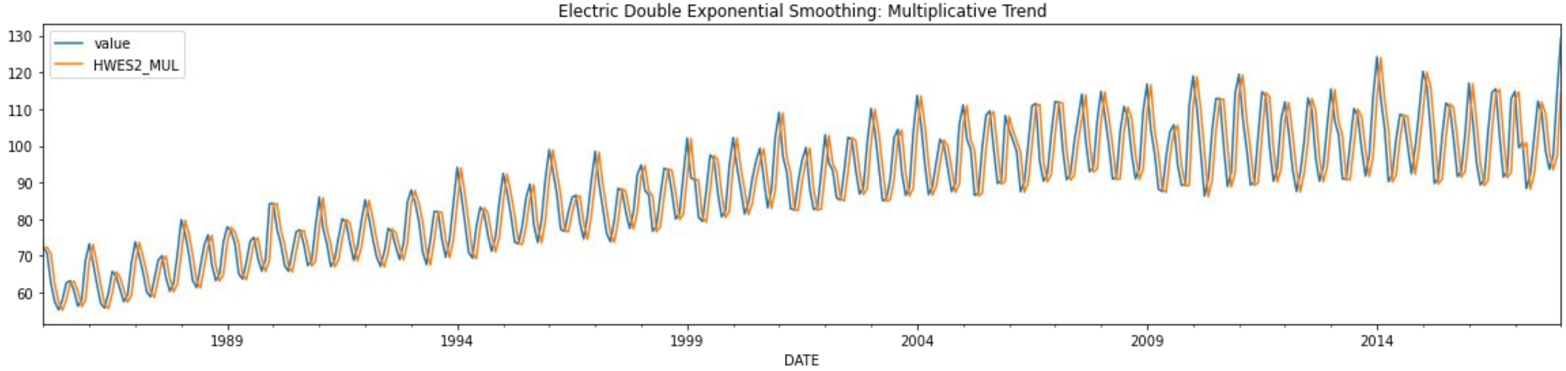
ADD and MUL

MAE = 6.574

MSE = 59.998

As we don't have β, the MAE and the MSE of both are the same.





2 Triple Exponential Smoothing: Addictive Vs. Multiplicative Seasonality

When α = 0.8

ADD

MAE = 1.949

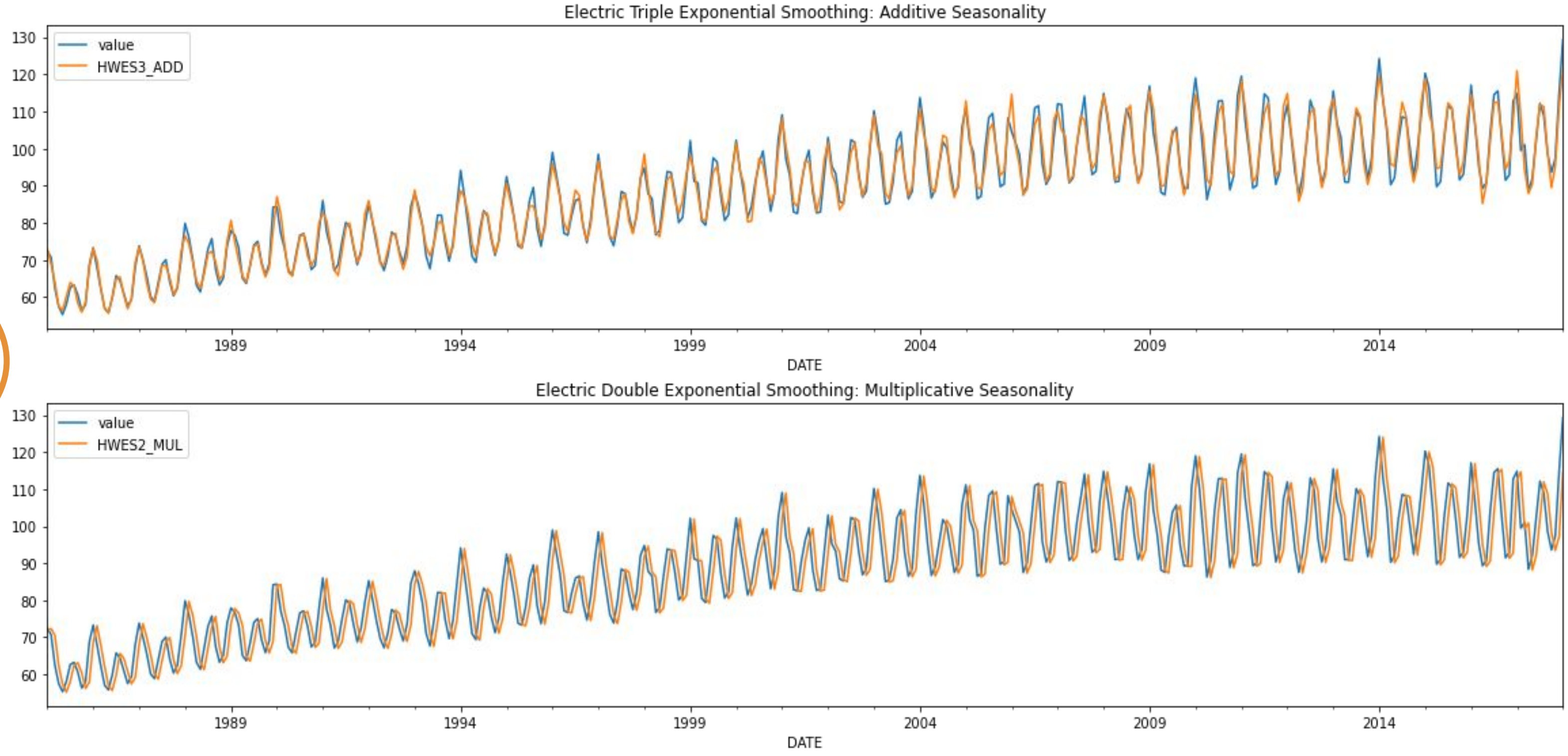
MSE = 6.358

MUL

MAE = 1.830

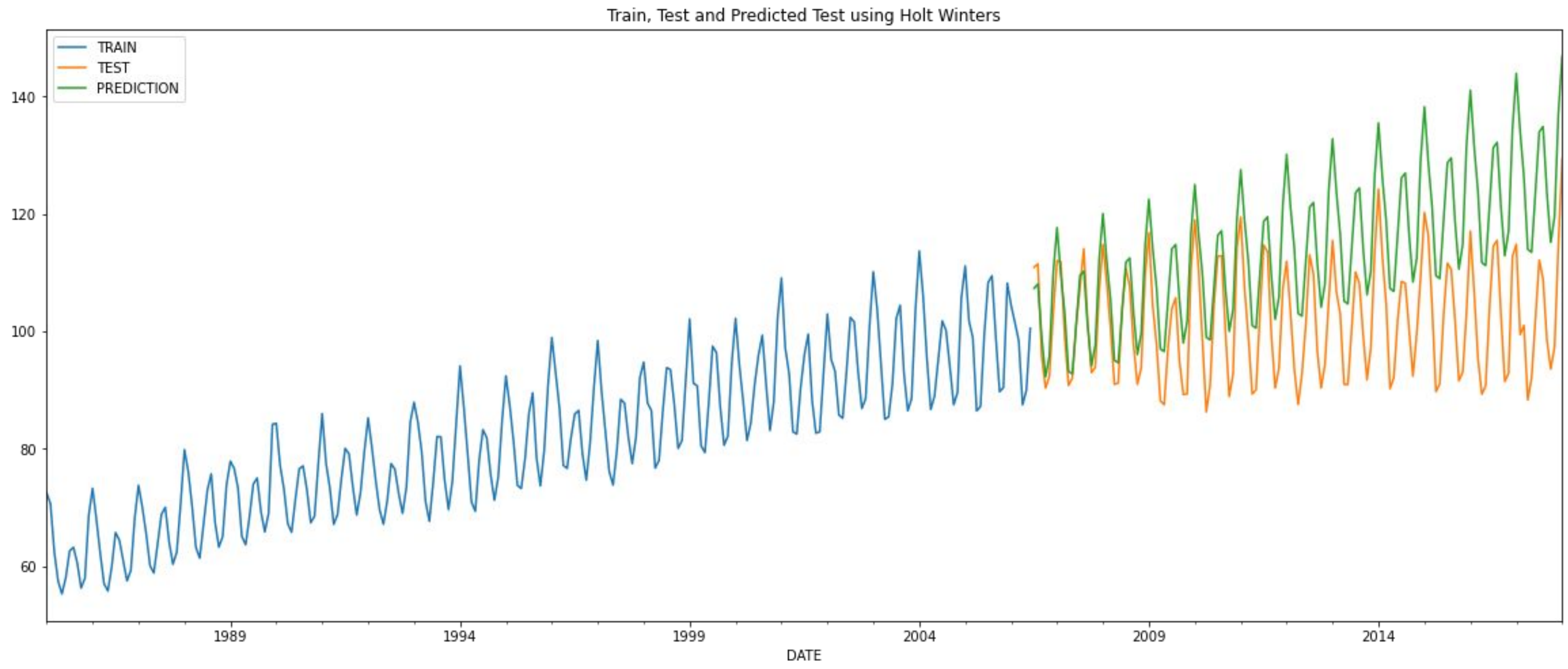
MSE = 5.626

Although we don’t have γ , the MAE and the MSE of both are different.



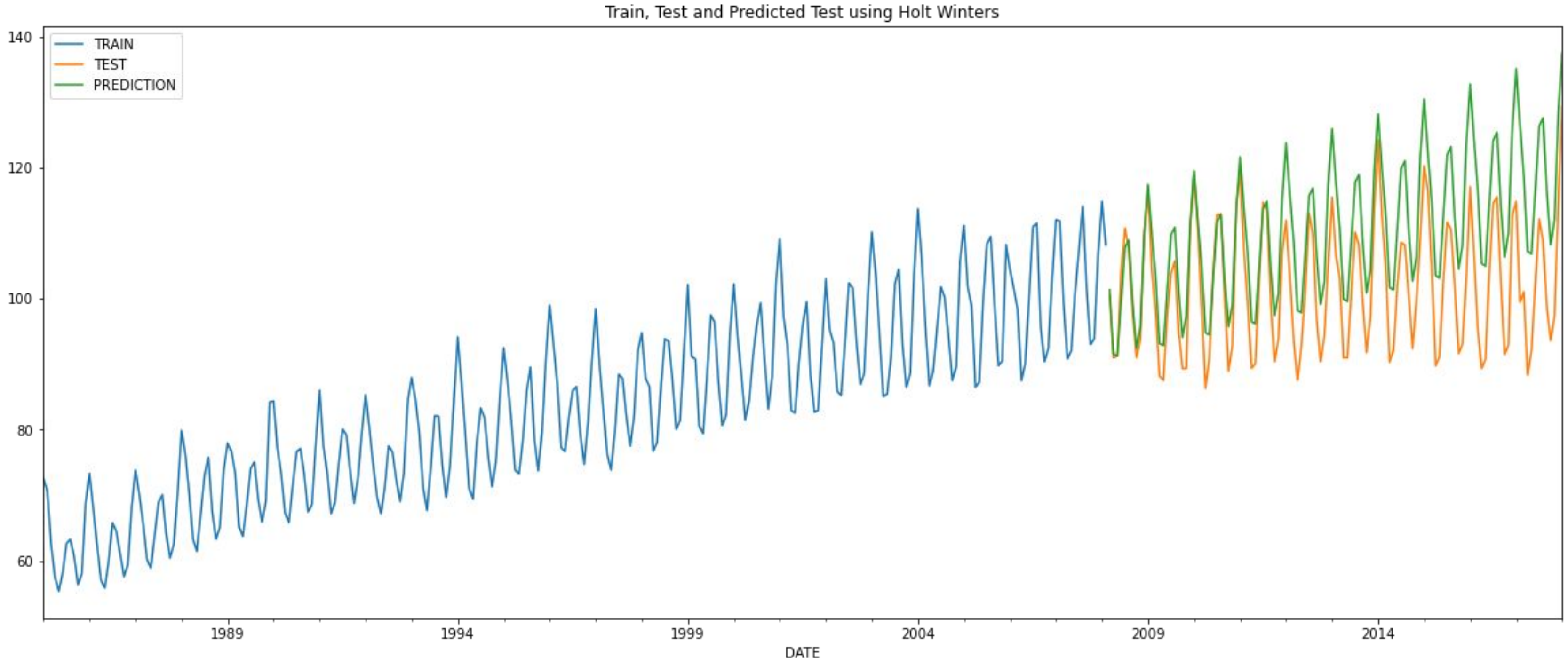
2 Train and Test Mul-HW model
What is the suitable train data size?

Train data: 258, which is 65% of the total data, then Test data: 397-258=139



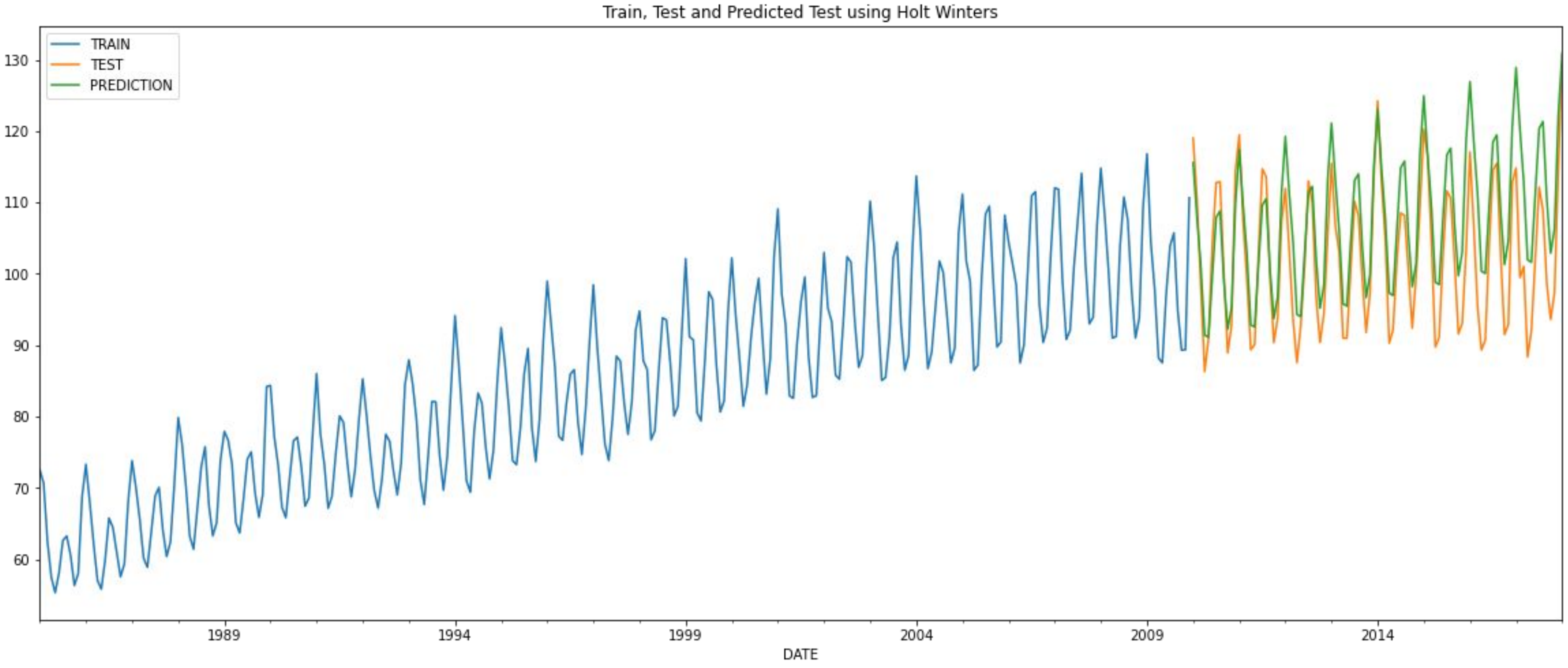
2 Train and Test Mul-HW model
What is the suitable train data size?

Train data: 278, which is 70% of the total data, then Test data: 397-278=119



2 Train and Test Mul-HW model
What is the suitable train data size?

Train data: 300, which is 75% of the total data, then Test data: 397-300=97



2 Train and Test Mul-HW model
To avoid Overfit, we choose 70%

When train data size = 65%

MAE = 12.577

MSE = 212.209

When train data size = 70%

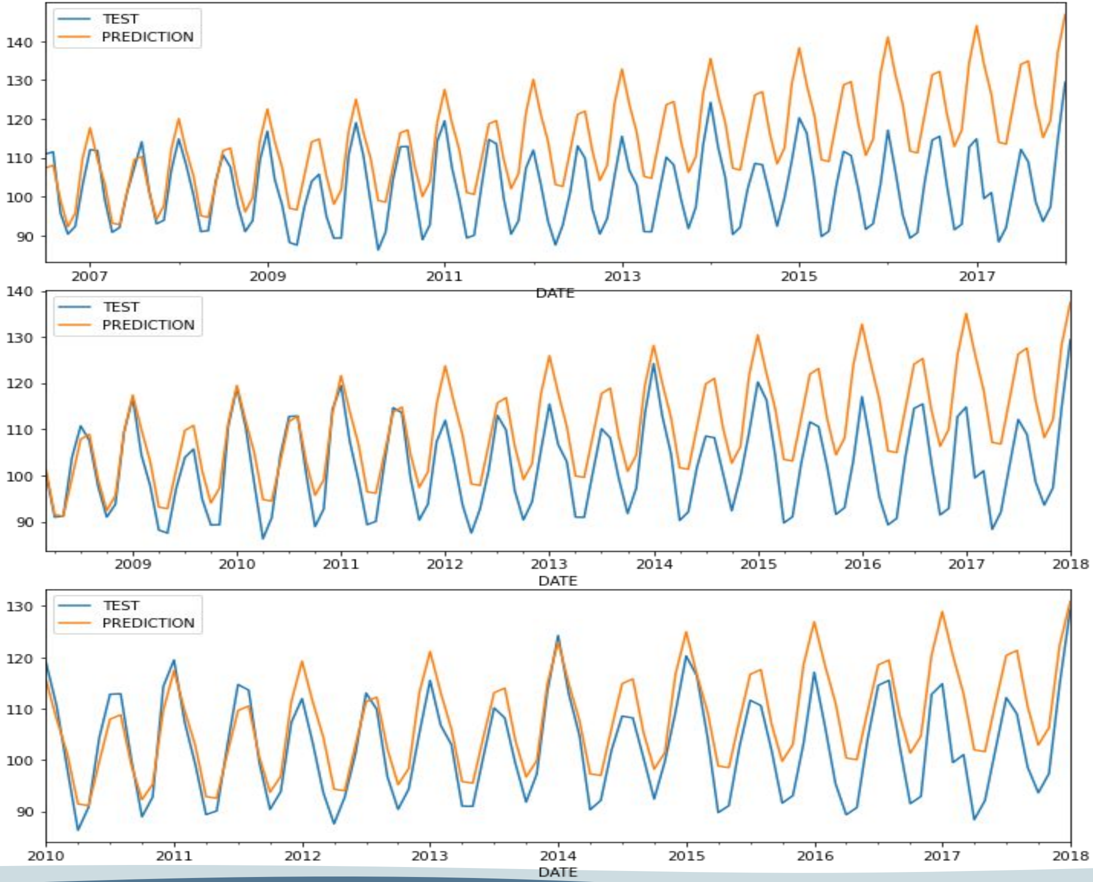
MAE = 8.628

MSE = 103.970

When train data size = 75%

MAE = 5.881

MSE = 49.111

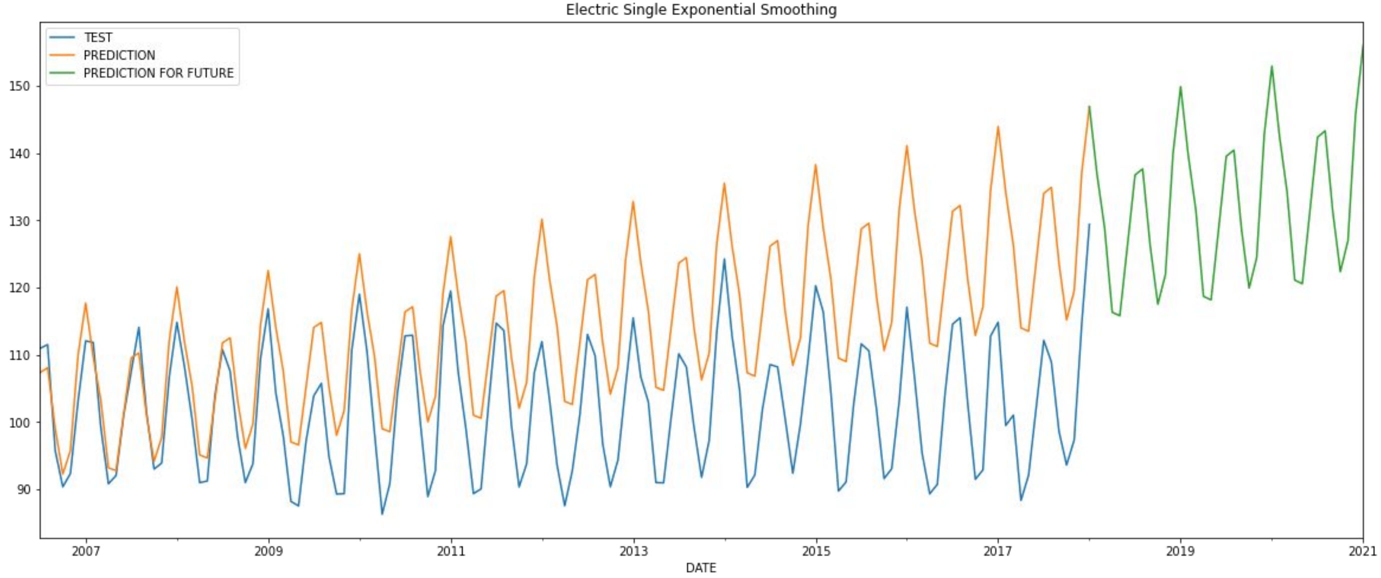


2 Prediction Data for the future 3 years

```
fitted_model.predict(start = 396,end = 432)
aaa=fitted_model.predict(start = 396,end = 432)
```

```
test_Electric['value'].plot(legend=True,label='TEST',figsize=(20,8))
test_predictions.plot(legend=True,label='PREDICTION')

aaa.plot(title='Electric Single Exponential Smoothing',figsize=(20,8),legend=True,label='PREDICTION FOR FUTURE')
```

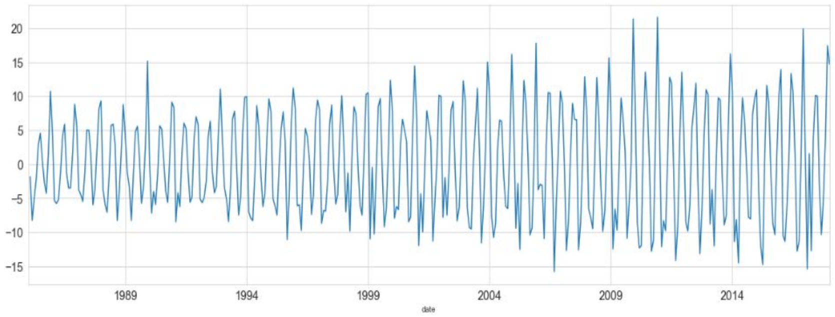


3 Transforming to Stationary

Checking for stationarity

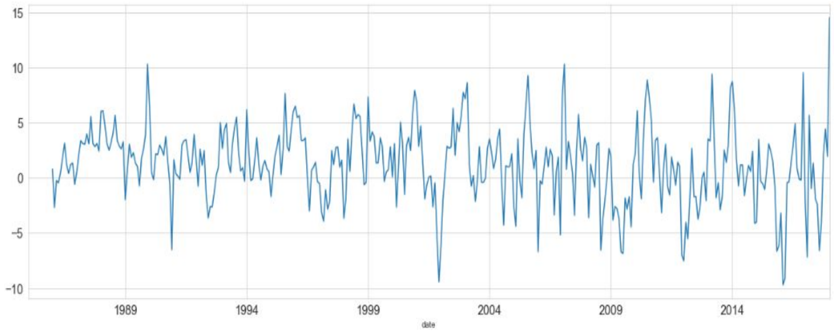
When applying Dickey-Fuller Test we got as result that our time series is not-stationary, so we proceed to apply differencing in two paths, one to remove trend and the other to remove seasonality

Differencing with lag = 1



without trend

Differencing with lag = 12

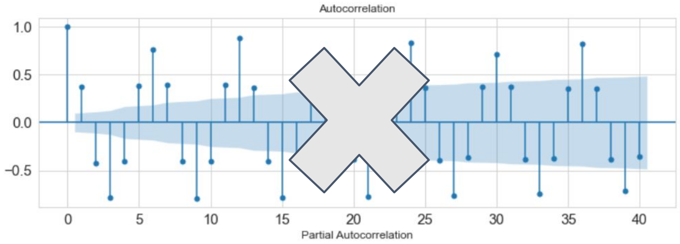


without seasonality

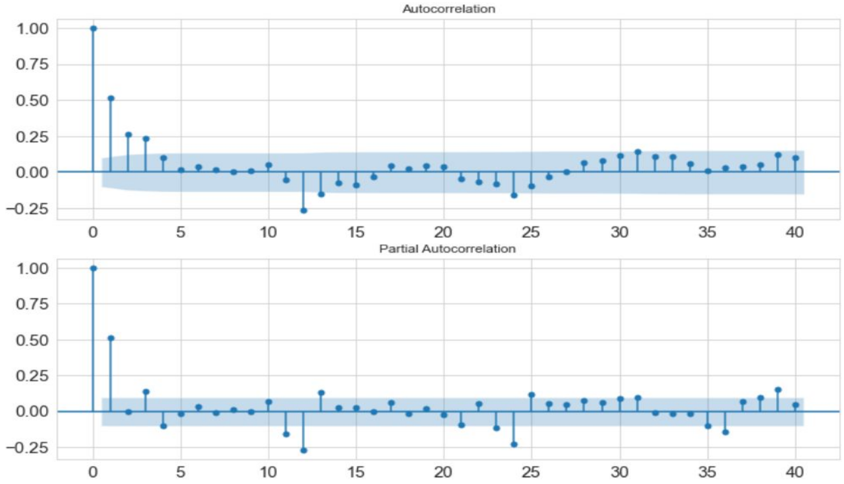
Applying Dickey-Fuller Test to the residuals we get that they both are now stationeries

3 Plotting ACF and PACF

When we plot the ACF/PACF graphs for the trend removal residuals, we identify that there is seasonality affecting our results, also we should only plot ACF/PACF with stationary data hence, we rather get our ARIMA values from the seasonal differencing residuals.



The ACF and PACF graphs for the seasonal differencing residuals are the following:



We can see a exponentially decay in ACF, we already did grade one differencing, then we proceed to apply ARIMA(3,1,3) and later SARIMA(3,1,3,12) to find out wich model is a better fit.

3 Forecasting Models

ARIMA Model

SARIMAX Results

Dep. Variable:	value	No. Observations:	397
Model:	ARIMA(3, 1, 3)	Log Likelihood	-1045.684
Date:	Mon, 06 Dec 2021	AIC	2105.369
Time:	00:11:43	BIC	2133.239
Sample:	01-01-1985	HQIC	2116.410
	- 01-01-2018		
Covariance Type:	opg		

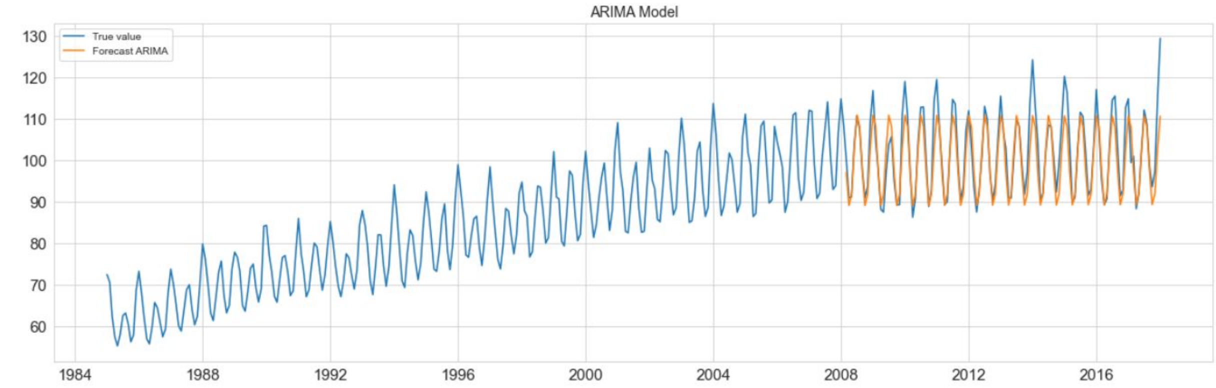
	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.0377	0.082	0.459	0.646	-0.123	0.199
ar.L2	-0.0372	0.082	-0.453	0.651	-0.198	0.124
ar.L3	-0.9620	0.082	-11.714	0.000	-1.123	-0.801
ma.L1	-0.0935	0.096	-0.973	0.331	-0.282	0.095
ma.L2	-0.0112	0.102	-0.110	0.913	-0.212	0.189
ma.L3	0.9309	0.098	9.533	0.000	0.739	1.122
sigma2	11.2175	0.654	17.165	0.000	9.937	12.498

Ljung-Box (L1) (Q):	6.24	Jarque-Bera (JB):	25.03
Prob(Q):	0.01	Prob(JB):	0.00
Heteroskedasticity (H):	2.19	Skew:	0.03
Prob(H) (two-sided):	0.00	Kurtosis:	4.23

To evaluate if we should use ARIMA or SARIMA model, we will use the concept of the Akaike Information Critera (AIC), which quantifies:

- The goodness of fit
- The simplicity/parsimony, of the model into a single statistic.

When comparing two models, the one with the lower AIC is generally "better".



3 Forecasting Models

SARIMA Model

SARIMAX Results

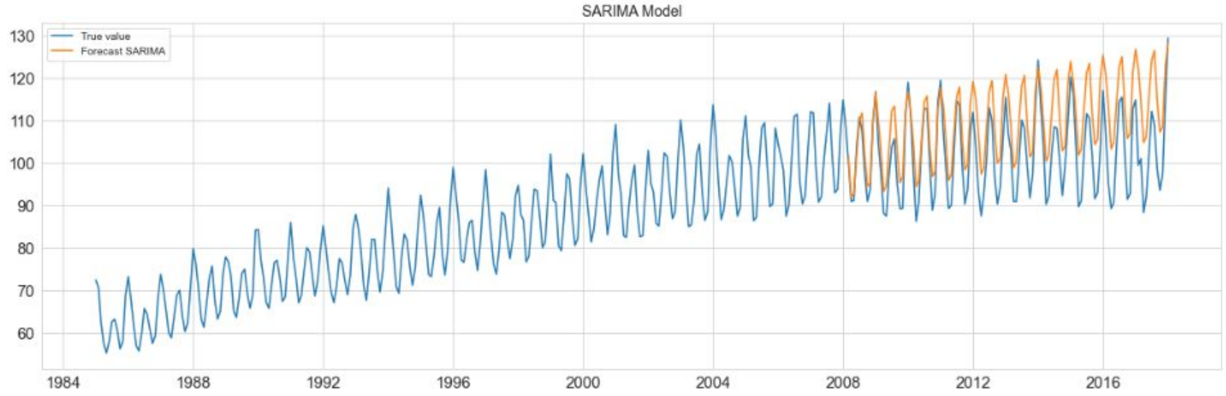
Dep. Variable:	value	No. Observations:	397
Model:	SARIMAX(3, 1, 3)x(3, 1, 3, 12)	Log Likelihood	-875.109
Date:	Mon, 06 Dec 2021	AIC	1776.219
Time:	00:11:55	BIC	1827.577
Sample:	01-01-1985	HQIC	1796.590
	- 01-01-2018		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.0106	0.134	-0.078	0.937	-0.274	0.253
ar.L2	-0.5926	0.122	-4.859	0.000	-0.832	-0.354
ar.L3	0.4764	0.069	6.934	0.000	0.342	0.611
ma.L1	-0.4287	0.129	-3.331	0.001	-0.681	-0.177
ma.L2	0.3150	0.155	2.030	0.042	0.011	0.619
ma.L3	-0.7804	0.125	-6.240	0.000	-1.026	-0.535
ar.S.L12	-0.2152	3.517	-0.061	0.951	-7.108	6.677
ar.S.L24	0.0960	1.884	0.051	0.959	-3.597	3.789
ar.S.L36	-0.2551	1.214	-0.210	0.834	-2.634	2.124
ma.S.L12	-0.4834	3.507	-0.138	0.890	-7.357	6.390
ma.S.L24	-0.4717	4.311	-0.109	0.913	-8.921	7.978
ma.S.L36	0.3928	1.707	0.230	0.818	-2.953	3.738
sigma2	5.3633	0.319	16.823	0.000	4.738	5.988

Ljung-Box (L1) (Q):	0.02	Jarque-Bera (JB):	23.12
Prob(Q):	0.89	Prob(JB):	0.00
Heteroskedasticity (H):	2.70	Skew:	-0.07
Prob(H) (two-sided):	0.00	Kurtosis:	4.19

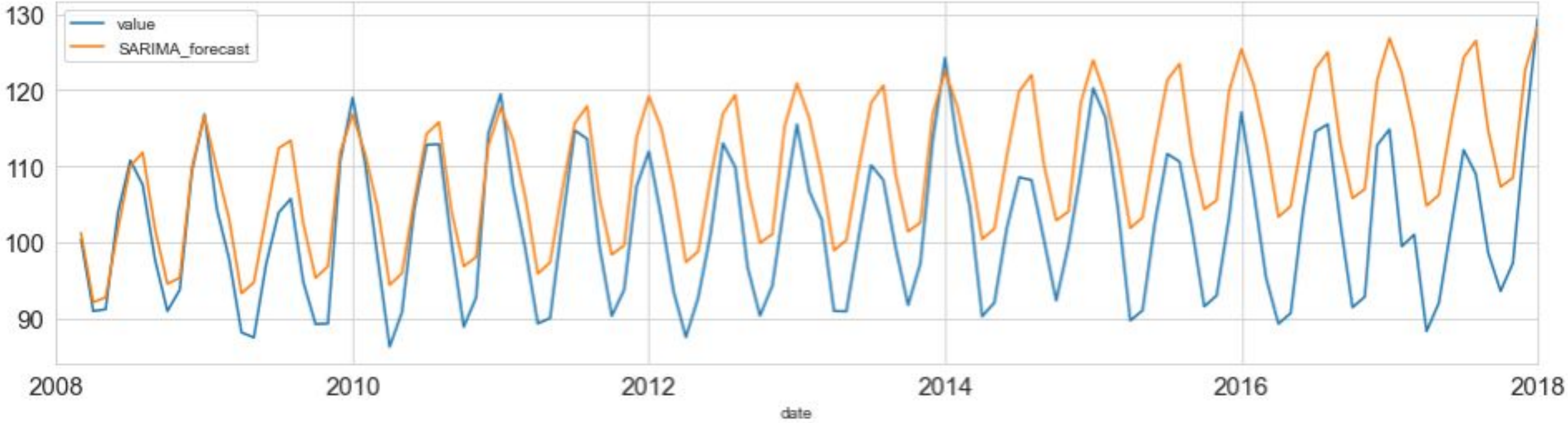
ARIMA model got a AIC value of 2105.35 while the SARIMA model gets a value of 1776.219.

- This means that SARIMA is a better fit for our time series data.



3 Obtaining the MSE and MAE

Comparing the SARIMA prediction with the real data, we obtain the next results:




```
Mean Absolute Error = 7.9058
Mean Squared Error = 82.6956
```

4 Conclusion

To compare the fit of our Triple Exponential Smoothing model versus SARIMA model we will use as parameters the values of MSE and MAE of their predictions.

Model	Mean Absolute Error (MAE)	Mean Squared Error (MSE)
SARIMA	7.905601	82.690408
Triple Exponential Smoothing	8.628000	103.970000

- **Multiplicative Holt-Winters' Model**

  When α = 0.8

  When train data size = 70%

  MAE = 8.628

  MSE = 103.970

- **ARIMA-SARIMA Model**

  When p,d,q is (3,1,3)

  MAE = 7.906

  MSE = 82.690

4 Forecasting three years from last value

With the results obtained, we conclude that our time series data is best represented by the model SARIMA(3,1,3,12).
The next graph represents a forecasting for the next 3 years from the last data point.