Trabajo Final - Saul Esquivel Condori

Importamos los módulos necesarios

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib as mpl
from datetime import datetime
plt.rcParams.update({'figure.figsize': (10, 7), 'figure.dpi': 120})
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.api import ExponentialSmoothing, SimpleExpSmoothing, Holt


from google.colab import files


from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.m
```

Leemos nuestra serie de tiempo desde un archvo csv

```
# Importar datos en formato csv.
#custom_date_parser = lambda x: datetime.strptime(x, "%d/%m/%Y")
Salesd = pd.read_csv('/content/drive/MyDrive/Forecast/SalesDemand.csv',encoding='latin-1',


Salesd['date'] = pd.to_datetime(Salesd['date'], format='%d/%m/%Y')
#Salesd['periodo'] = Salesd['date'].dt.strftime('%Y%m')


#Validamos la correcta carga de la base de datos
#================================================
Salesd.head(10)
```

	date	store	item	sales
0	2013-01-01	1.0	1.0	13.0
1	2013-01-02	1.0	1.0	11.0
2	2013-01-03	1.0	1.0	14.0
3	2013-01-04	1.0	1.0	13.0

```
#list(Salesd.groupby('item'))
```

5	2013-01-06	1.0	1.0	12.0

```
Salesd.dtypes
```

```
date     datetime64[ns]
store           float64
item            float64
sales           float64
dtype: object
```

```
Salesd.shape
```

```
(958000, 4)
```

```
Salesd.info()
#debemos  filtrar los vacios, obtaremos por filtrar el campo 'date'
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 958000 entries, 0 to 957999
Data columns (total 4 columns):
 #   Column  Non-Null Count   Dtype         
---  ------  --------------   -----         
 0   date    913000 non-null  datetime64[ns]
 1   store   913000 non-null  float64       
 2   item    913000 non-null  float64       
 3   sales   913000 non-null  float64       
dtypes: datetime64[ns](1), float64(3)
memory usage: 29.2 MB
```

```
Sales = Salesd[Salesd["date"].notna()]
```

```
Sales.shape
#Hemos retirado 45'000 registros (4.7%) con date null.
```

```
(913000, 4)
```

```
Sales.info()
# observamos que desaparecieron los nulos en todos los campos.
# a continuación filtraremos algunas items y tiendas para empezar el analisis y posterior
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 913000 entries, 0 to 912999
Data columns (total 4 columns):
 #   Column  Non-Null Count   Dtype         
```

```
---  ------  --------------   -----
 0   date    913000 non-null  datetime64[ns]
 1   store   913000 non-null  float64
 2   item    913000 non-null  float64
 3   sales   913000 non-null  float64
dtypes: datetime64[ns](1), float64(3)
memory usage: 34.8 MB
```

```
Sales.head()
```

	date	store	item	sales
0	2013-01-01	1.0	1.0	13.0
1	2013-01-02	1.0	1.0	11.0
2	2013-01-03	1.0	1.0	14.0
3	2013-01-04	1.0	1.0	13.0
4	2013-01-05	1.0	1.0	10.0

```
Sales_store = Sales[['store','sales']]
Sales_store_2 = Sales_store.groupby(['store']).sum()
Sales_store_2.sort_values(by="sales", ascending=False)
#tomaremos las 5 tiendas con mayores ventas totales y que representan mas del 50% de venta
```

store	sales
2.0	6120128.0
8.0	5856169.0
3.0	5435144.0
10.0	5360158.0
9.0	5025976.0
4.0	5012639.0
1.0	4315603.0
5.0	3631016.0
6.0	3627670.0
7.0	3320009.0

```
Sales_item = Sales[['item','sales']]
Sales_item_2 = Sales_item.groupby(['item']).sum()
Sales_item_2.sort_values(by="sales", ascending=False)
#tomaremos los 18 items con mayores ventas totales y que representan mas del 50% de ventas
```

item	sales
15.0	1607442.0
28.0	1604713.0
13.0	1539621.0
18.0	1538876.0
25.0	1473334.0
45.0	1471467.0
38.0	1470330.0
22.0	1469971.0
36.0	1406548.0
8.0	1405108.0
10.0	1337133.0
11.0	1271925.0
12.0	1271534.0
29.0	1271240.0
33.0	1270183.0
24.0	1205975.0
50.0	1203009.0
35.0	1201541.0
14.0	1071531.0
31.0	1070845.0
46.0	1070764.0
2.0	1069564.0
7.0	1068777.0
6.0	1068281.0
9.0	938379.0
48.0	937703.0
43.0	936635.0
26.0	869981.0
20.0	867641.0
32.0	803107.0
39.0	801311.0

19.0 736892.0

```
Sales1 = Sales[Sales['store'].isin([2,8,3,10,9])]
Sales2 = Sales1[Sales1['item'].isin([15,28,13,18,25,45,38,22,36,8,10,11,12,29,33,24,50,35]
```

21.0 736190.0

```
Sales2.info()
# el analisis lo haremos sobre 73'040 registros
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 164340 entries, 129646 to 912999
Data columns (total 4 columns):
 #   Column  Non-Null Count   Dtype         
---  ------  --------------   -----         
 0   date    164340 non-null  datetime64[ns]
 1   store   164340 non-null  float64       
 2   item    164340 non-null  float64       
 3   sales   164340 non-null  float64       
dtypes: datetime64[ns](1), float64(3)
memory usage: 6.3 MB
```

34.0 469935.0

```
#Sales2[['date','sales']]
Sales3 = Sales2[Sales2['date']=='2013-01-01']
Sales3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 90 entries, 129646 to 911174
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   date    90 non-null     datetime64[ns]
 1   store   90 non-null     float64       
 2   item    90 non-null     float64       
 3   sales   90 non-null     float64       
dtypes: datetime64[ns](1), float64(3)
memory usage: 3.5 KB
```

```
Sales3 = Sales2[['date','sales']]


Sales4 = Sales3.groupby(['date']).sum()
Sales4.head()
# se observa que falta el index, que resetearemos a continuación.
```

date	sales
2013-01-01	4133.0
2013-01-02	4255.0
2013-01-03	4308.0
2013-01-04	4636.0
2013-01-05	5033.0

```
Sales4.reset_index(level=0, inplace=True)
#Sales4['Id'] = np.arange(len(Sales4)) sirve para agregar columna con numeros consecutivos
Sales4
```

	date	sales
0	2013-01-01	4133.0
1	2013-01-02	4255.0
2	2013-01-03	4308.0
3	2013-01-04	4636.0
4	2013-01-05	5033.0
...	...	...
1821	2017-12-27	6137.0
1822	2017-12-28	6595.0
1823	2017-12-29	7223.0
1824	2017-12-30	7714.0
1825	2017-12-31	8091.0

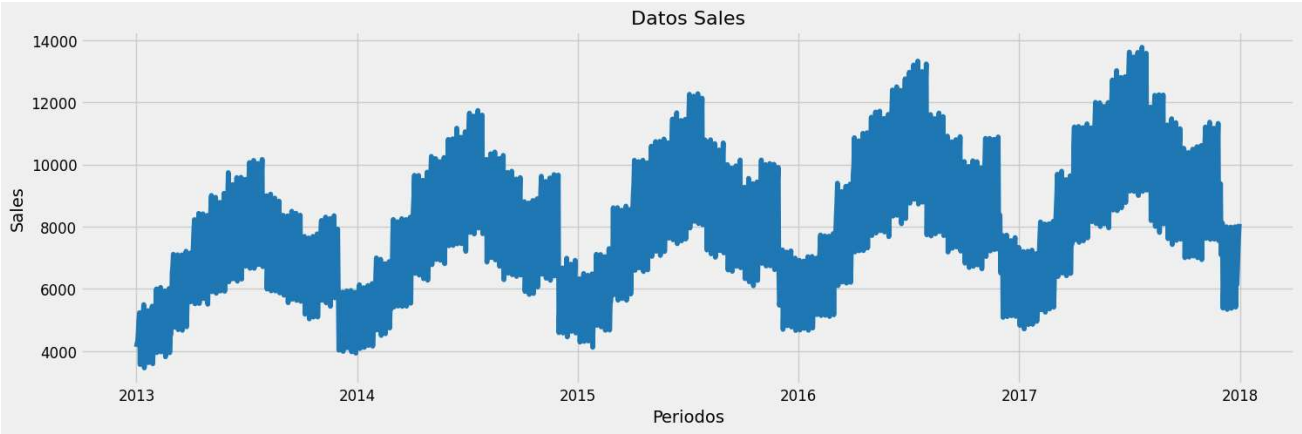
1826 rows × 2 columns

```
Sales4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1826 entries, 0 to 1825
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   date    1826 non-null   datetime64[ns]
 1   sales   1826 non-null   float64       
dtypes: datetime64[ns](1), float64(1)
memory usage: 28.7 KB
```

Graficamos la serie de tiempo

```
plt.figure(figsize=(16,5), dpi=100)
plt.plot(Sales4.date, Sales4.sales,color='tab:blue')
plt.xlabel('Periodos')
plt.ylabel('Sales')
plt.title('Datos Sales', fontsize=16)
#plt.gca().set(title='Serie CQI', xlabel=df_1.RESULT_TIME, ylabel=df_1.CQI)
plt.show()
```

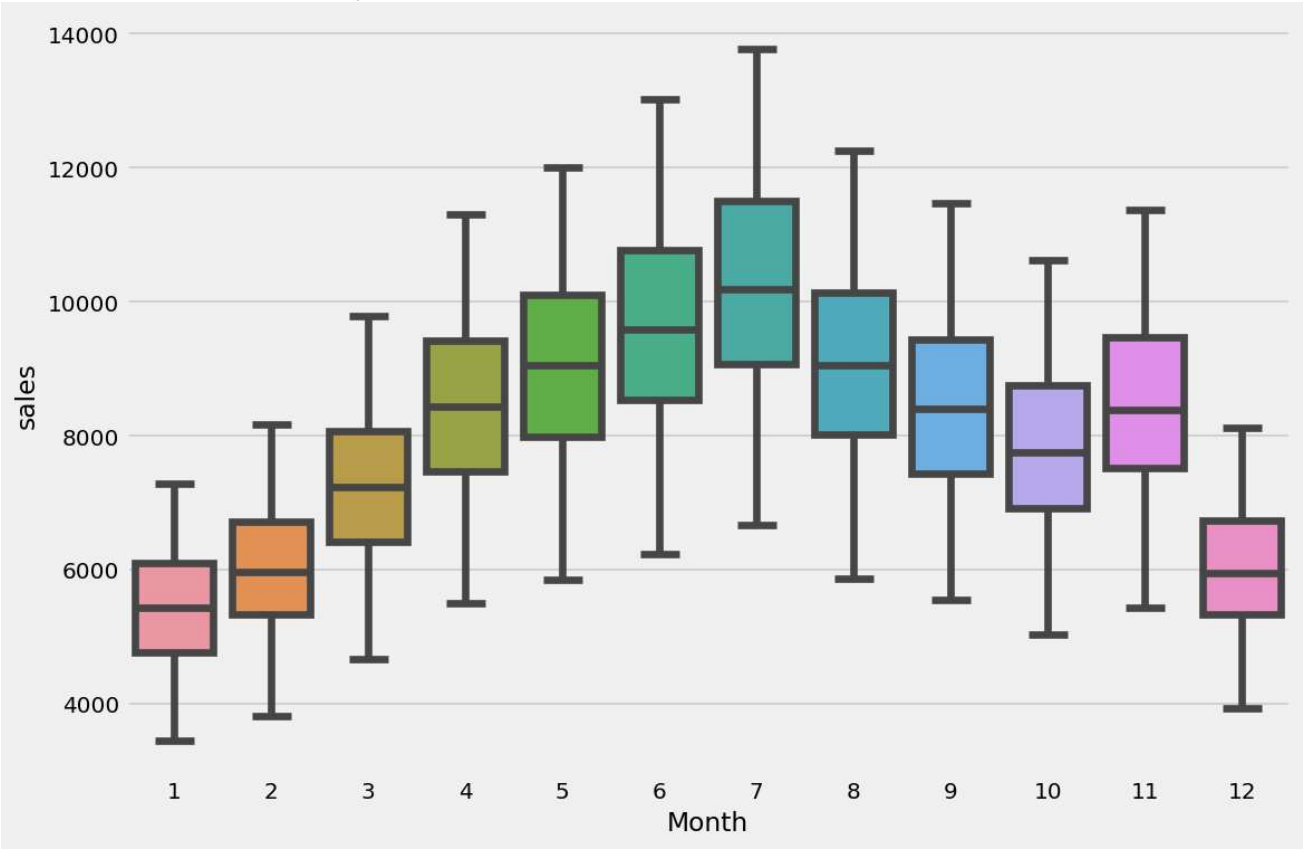



```
Sales4['Year'] = Sales4['date'].dt.strftime('%Y')
Sales4['Month'] = Sales4['date'].dt.strftime('%m')
Sales4['Month'] = Sales4.Month.astype(int)
Sales4.head()
Sales4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1826 entries, 0 to 1825
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   date    1826 non-null   datetime64[ns]
 1   sales   1826 non-null   float64       
 2   Year    1826 non-null   object        
 3   Month   1826 non-null   int64         
dtypes: datetime64[ns](1), float64(1), int64(1), object(1)
memory usage: 57.2+ KB
```

```
sns.boxplot(x = 'Month', y = 'sales', data = Sales4)
```

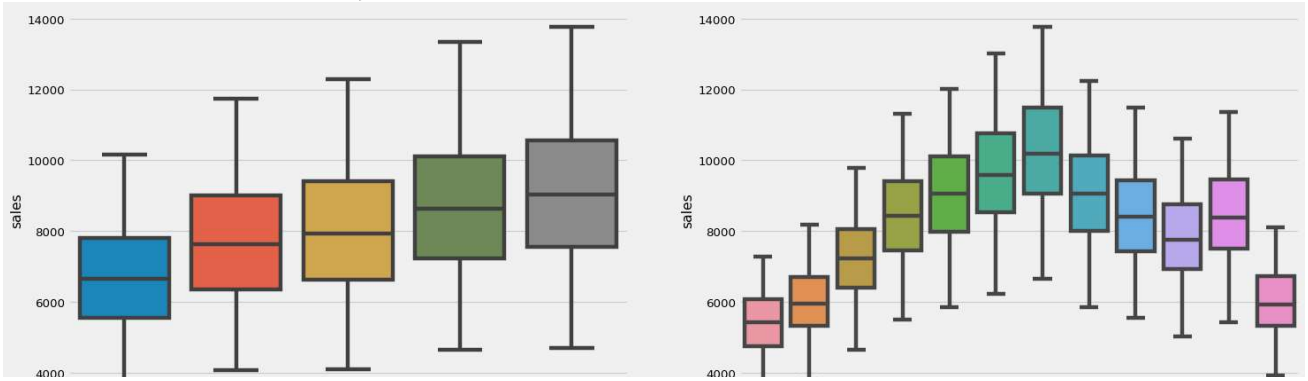
```
<Axes: xlabel='Month', ylabel='sales'>
```



Graficamos las cajas agregadas

```
# Draw Plot
fig, axes = plt.subplots(1, 2, figsize=(20,7), dpi= 80)
sns.boxplot(x='Year', y='sales', data=Sales4, ax=axes[0])
sns.boxplot(x='Month', y='sales', data=Sales4, ax=axes[1])
```

```
<Axes: xlabel='Month', ylabel='sales'>
```



Agrupando periodos

```
# agrupando por periodos específicos
Sales_mes= Sales4[['date','sales']]
```

```
Sales_mes.set_index('date',inplace = True)
```

```
Sales_mes.head(10)
```

date	sales
2013-01-01	4133.0
2013-01-02	4255.0
2013-01-03	4308.0
2013-01-04	4636.0
2013-01-05	5033.0
2013-01-06	5235.0
2013-01-07	3567.0
2013-01-08	4224.0
2013-01-09	4217.0
2013-01-10	4375.0

```
# agrupamos los datos
Sales_mes = Sales_mes.resample('M').sum()
Sales_year = Sales_mes.resample('Y').mean()
Sales_quarter = Sales_mes.resample('Q').mean()
```

```
Sales_mes.head()
```

date	sales
2013-01-31	138832.0
2013-02-28	140085.0
2013-03-31	189060.0
2013-04-30	208446.0

```
print(Sales_mes.shape)
print(Sales_year.shape)
print(Sales_quarter.shape)
```

```
(60, 1)
(5, 1)
(20, 1)
```

```
Sales_mes.head(10)
```

date	sales
2013-01-31	138832.0
2013-02-28	140085.0
2013-03-31	189060.0
2013-04-30	208446.0
2013-05-31	233266.0
2013-06-30	243439.0
2013-07-31	261151.0
2013-08-31	234651.0
2013-09-30	210757.0
2013-10-31	200192.0

```
Sales_quarter.head(10)
```

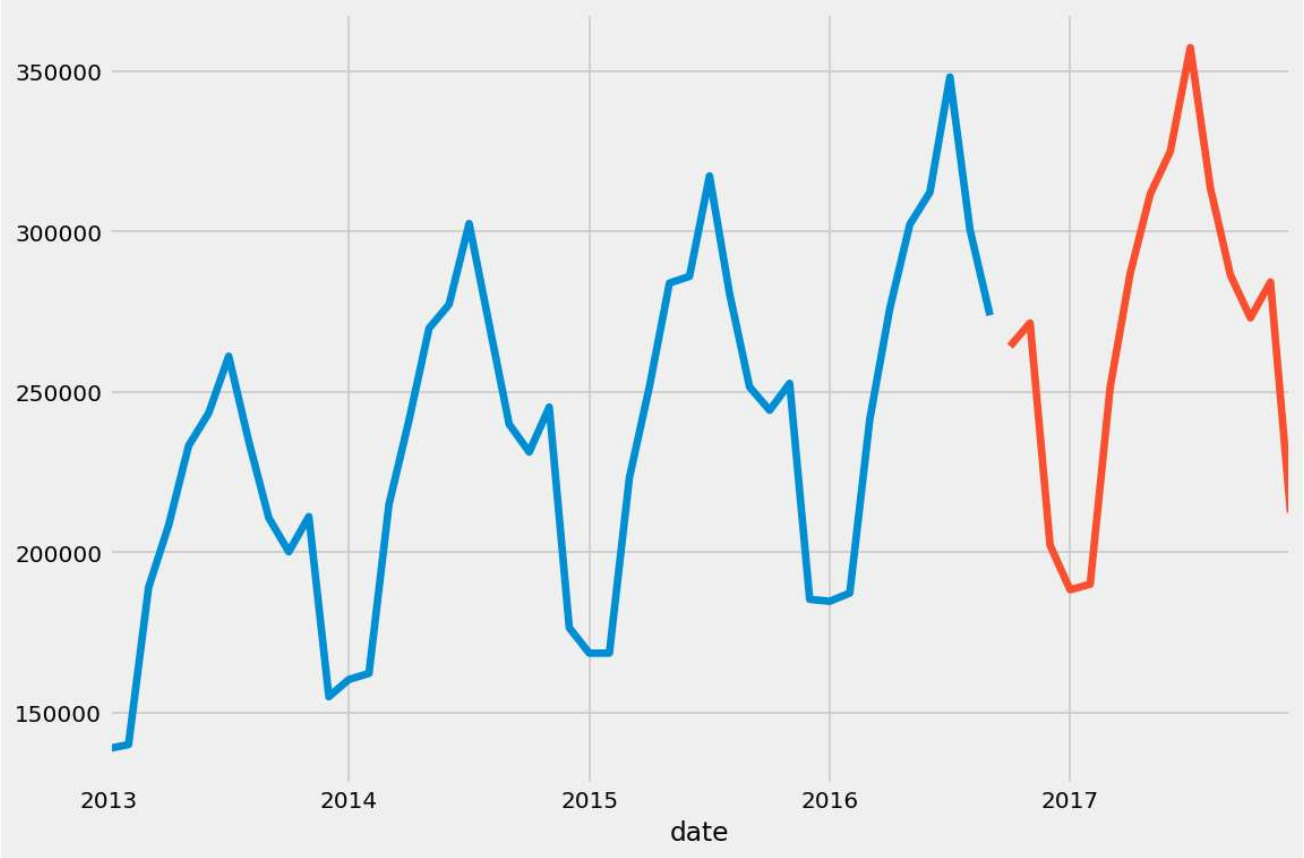
date	sales
2013-03-31	155992.333333
2013-06-30	228383.666667
2013-09-30	235519.666667
2013-12-31	188785.333333
2014-03-31	179207.333333
2014-06-30	262778.666667
2014-09-30	271198.666667
2014-12-31	217692.000000

```
plt.figure(figsize=(16,5), dpi=100)
plt.plot(Sales_mes.sales,color='tab:green',label='Mensual')
plt.plot(Sales_year.sales,color='tab:blue',label='Anual')
plt.plot(Sales_quarter.sales,color='tab:red',label='Trimestral')
plt.legend()
plt.show()
```

Prophet

```
#divide into train and validation set
train = Sales_mes[:int(0.75*(len(Sales_mes)))]
valid = Sales_mes[int(0.75*(len(Sales_mes))):]
```

```
#plotting the data
train['sales'].plot()
valid['sales'].plot()
plt.show()
```




```
train.head()
```

date	sales
2013-01-31	138832.0
2013-02-28	140085.0

```
print(train.shape)
print(valid.shape)
```

```
(45, 1)
(15, 1)
```

```
train_prophet = pd.DataFrame()
train_prophet['ds'] = train.index
train_prophet['y'] = train.sales.values
```

```
train_prophet.head()
```

	ds	y
0	2013-01-31	138832.0
1	2013-02-28	140085.0
2	2013-03-31	189060.0
3	2013-04-30	208446.0
4	2013-05-31	233266.0

```
import os
# Let cmdstanpy know where CmdStan is
os.environ["CMDSTAN"] = "./cmdstan-2.23.0"

from prophet import Prophet


#instantiate Prophet with only yearly seasonality as our data is monthly
model = Prophet()
model.fit(train_prophet) #fit the model with your dataframe
```

```
INFO:prophet:Disabling weekly seasonality. Run prophet with weekly_seasonality=True t
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to
DEBUG:cmdstanpy:input tempfile: /tmp/tmpivo66ed6/xhraar48.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpivo66ed6/_160n6tg.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.9/dist-packages/prophet/stan_m
04:06:19 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
04:06:20 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
<prophet.forecaster.Prophet at 0x7fabd1e91670>
```

```
# predict for five months in the furure and MS - month start is the frequency
future = model.make_future_dataframe(periods = 15, freq = 'MS')
future.head()
```

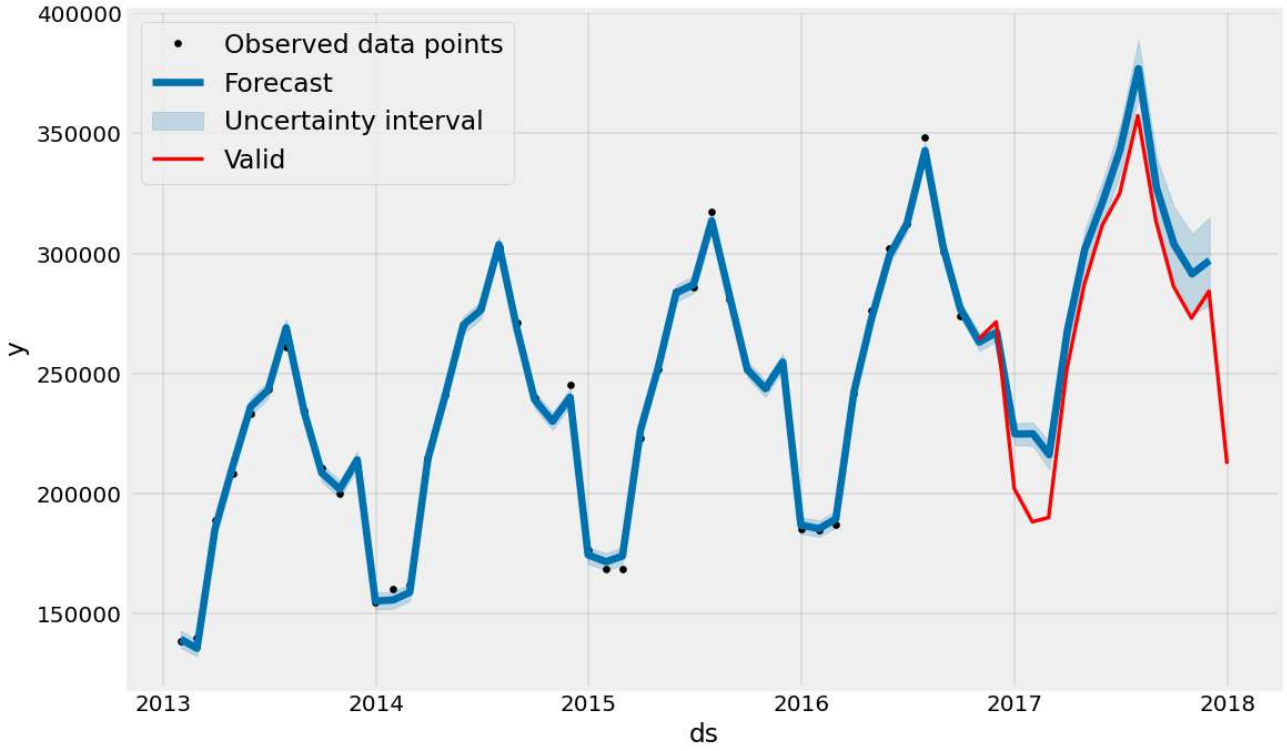
	ds
0	2013-01-31
1	2013-02-28
2	2013-03-31
3	2013-04-30
4	2013-05-31

```
# now lets make the forecasts
forecast = model.predict(future)
forecast[['ds', 'yhat']]
```

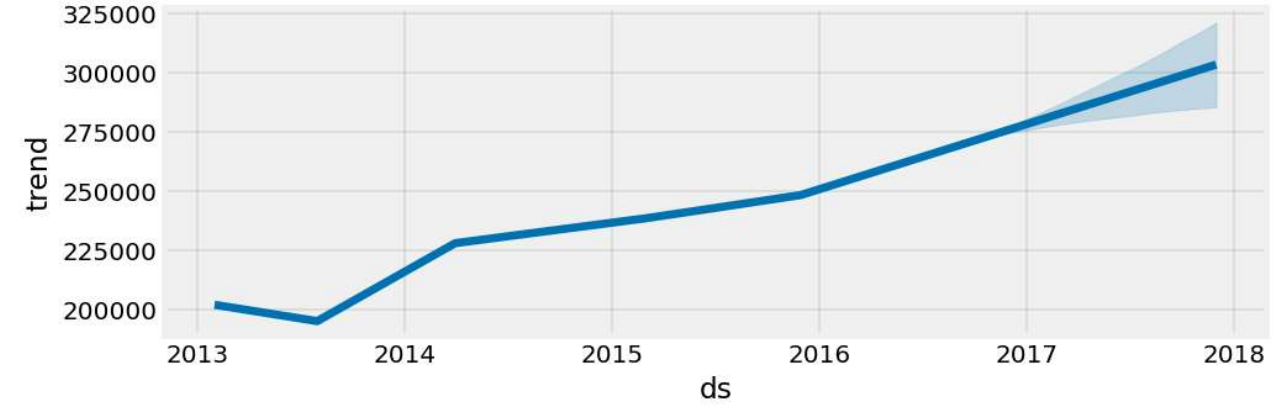
	ds	yhat
0	2013-01-31	139497.884045
1	2013-02-28	135657.692817
2	2013-03-31	185367.435162
3	2013-04-30	211182.155410
4	2013-05-31	236182.728521
5	2013-06-30	243149.344005
6	2013-07-31	269092.539389
7	2013-08-31	233979.690346
8	2013-09-30	208702.383870
9	2013-10-31	201909.467924
10	2013-11-30	214109.297663
11	2013-12-31	155329.494634
12	2014-01-31	155831.463600
13	2014-02-28	158974.757649
14	2014-03-31	214365.819564
15	2014-04-30	241084.893925
16	2014-05-31	270288.748775
17	2014-06-30	276433.475463
18	2014-07-31	303683.271513
19	2014-08-31	268563.029415
20	2014-09-30	239233.558177
21	2014-10-31	230118.372485
22	2014-11-30	240186.884288
23	2014-12-31	174553.507575
24	2015-01-31	171725.170424
25	2015-02-28	174106.312360
26	2015-03-31	226654.928860
27	2015-04-30	252307.292349
28	2015-05-31	283663.004499
29	2015-06-30	287024.215445
30	2015-07-31	313637.819870
31	2015-08-31	281915.705756

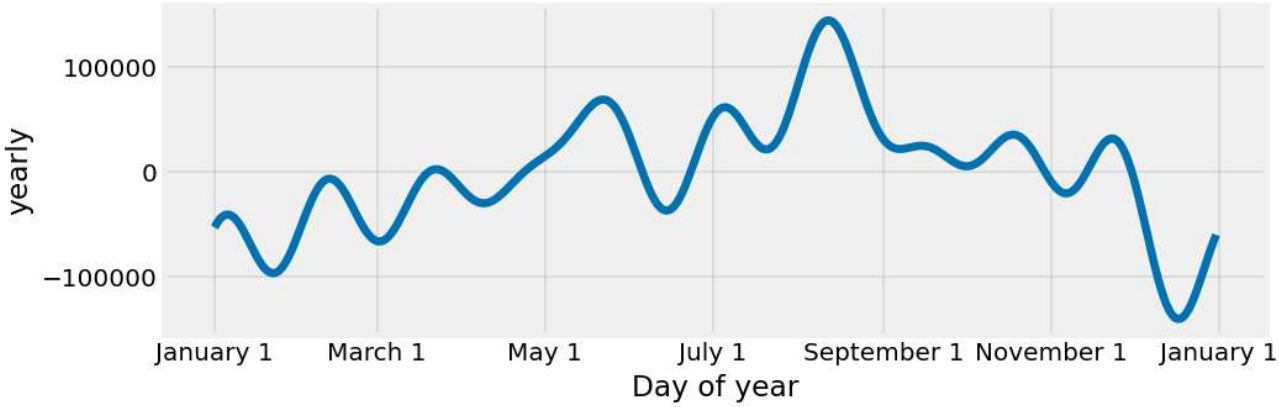
32 2015-09-30 251781.950573

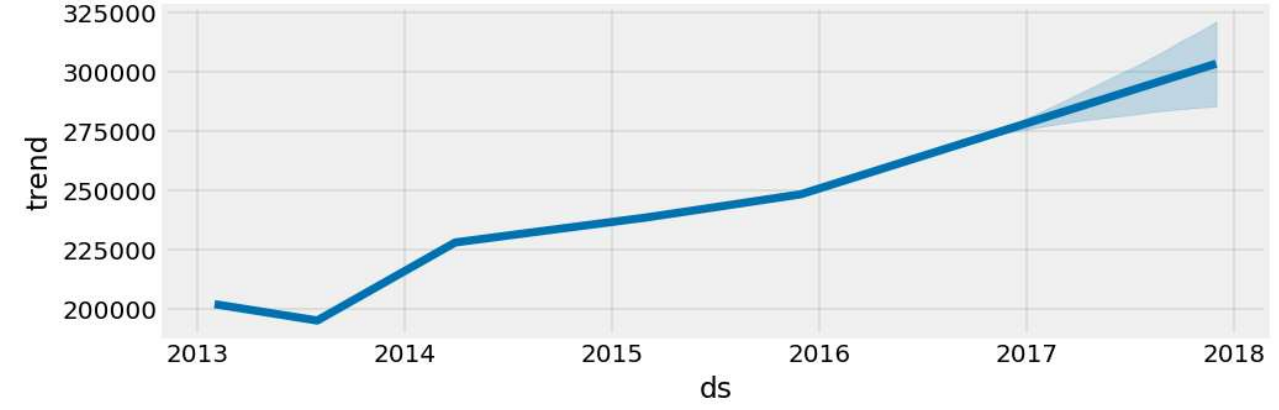
```
fig = model.plot(forecast)
#plot the predictions for validation set
plt.plot(valid, label='Valid', color = 'red', linewidth = 2)
plt.legend()
plt.show()
```

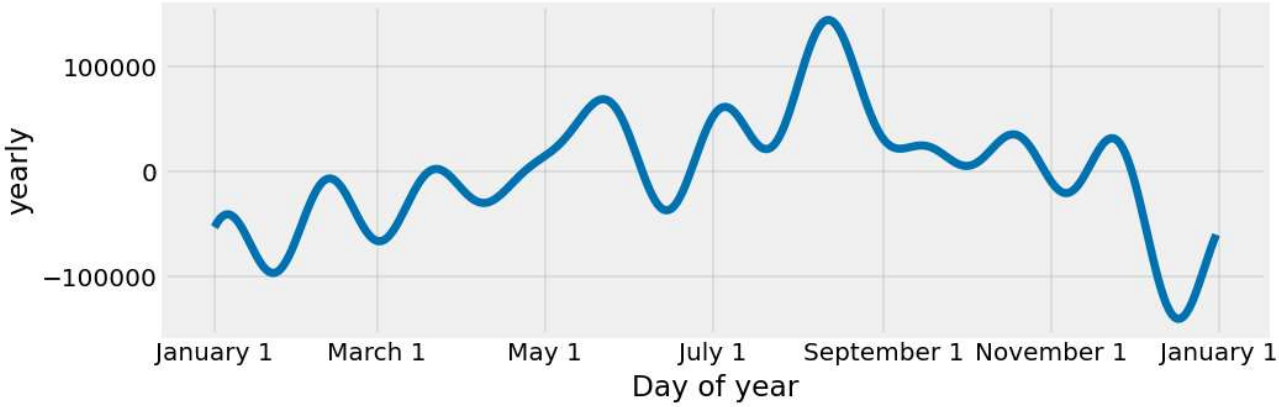



```
model.plot_components(forecast)
```


325000
300000
275000
250000
225000
200000
trend
2013
2014
2015
2016
2017
2018
ds


100000
0
−100000
yearly
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year


325000
300000
275000
250000
225000
200000
trend
2013
2014
2015
2016
2017
2018
ds


100000
0
−100000
yearly
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year

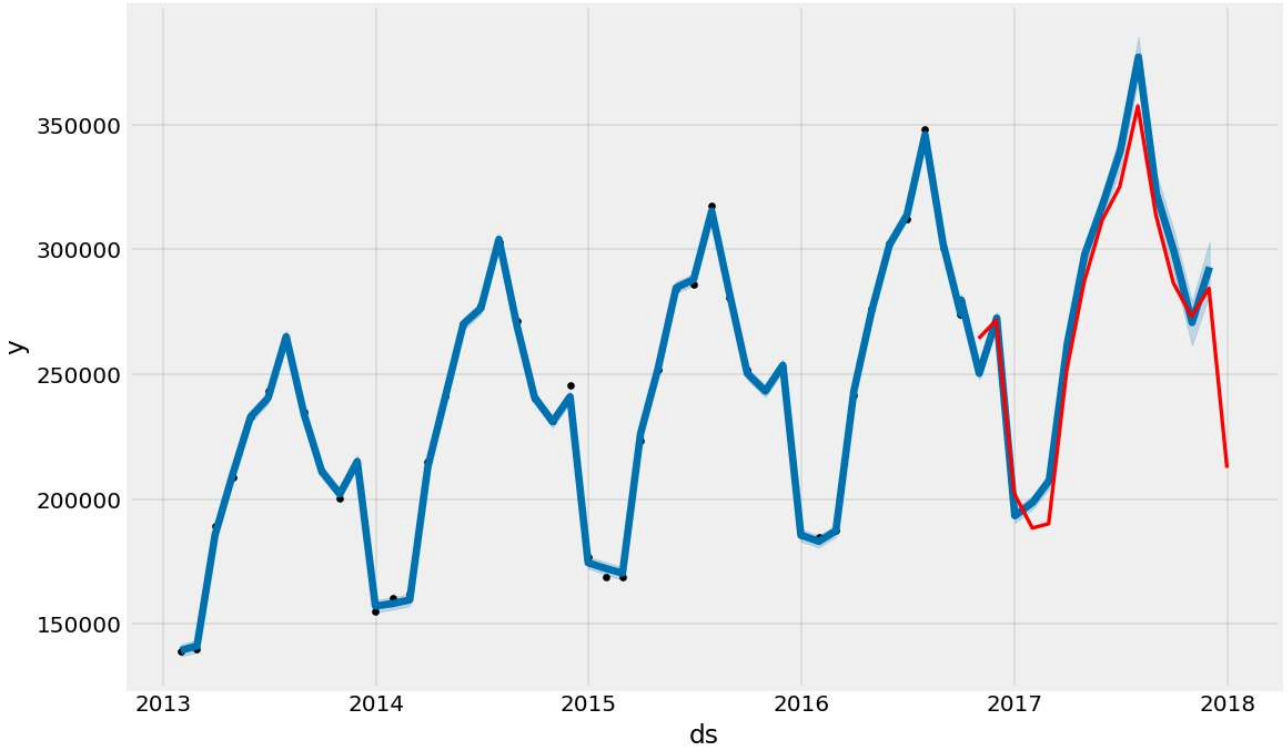
```
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, median_abso


def evaluate_forecast(y,pred):
    results = pd.DataFrame({'r2_score':r2_score(y, pred),
                            }, index=[0])
    results['mean_absolute_error'] = mean_absolute_error(y, pred)
    results['median_absolute_error'] = median_absolute_error(y, pred)
    results['mse'] = mean_squared_error(y, pred)
    results['msle'] = mean_squared_log_error(y, pred)
    results['rmse'] = np.sqrt(results['mse'])
    return results


evaluate_forecast(Sales_mes, forecast.yhat)
# se obtiene un r2 = 86%, continuemos buscando otro modelo que otorgue un mejor ajuste.
```

	r2_score	mean_absolute_error	median_absolute_error	mse	msle	
0	0.860022	9370.745482	2826.441965	3.850386e+08	0.005914	1962

```
#definiendo que la estacionalidad sea anual y el modelo multiplicativo
model = Prophet(yearly_seasonality=True,seasonality_mode= 'multiplicative')
model.fit(train_prophet) #fit the model with your dataframe
```

```
INFO:prophet:Disabling weekly seasonality. Run prophet with weekly_seasonality=True t
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to
DEBUG:cmdstanpy:input tempfile: /tmp/tmpivo66ed6/2tmnzzjq.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpivo66ed6/zczjhab9.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.9/dist-packages/prophet/stan_m
04:06:22 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
04:06:23 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
<prophet.forecaster.Prophet at 0x7fabce1d6160>
```

```
# predict for five months in the furure and MS - month start is the frequency
future = model.make_future_dataframe(periods = 15, freq = 'MS')
forecast = model.predict(future)
fig = model.plot(forecast)
#plot the predictions for validation set

plt.plot(valid, label='Valid', color = 'red', linewidth = 2)

plt.show()
```



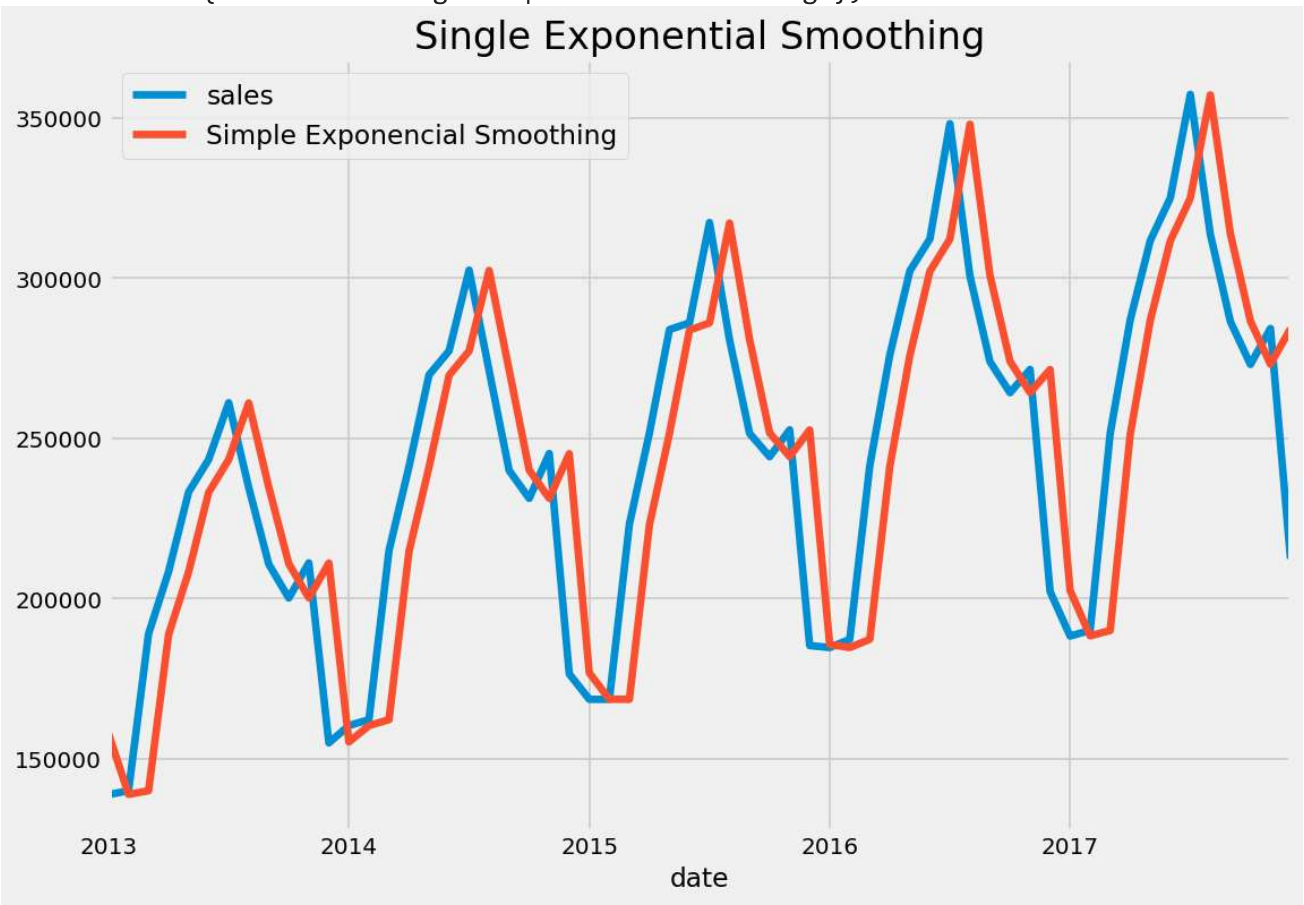

```
evaluate_forecast(Sales_mes, forecast.yhat)
#Se observa que los errores tanto del Prophet Aditivo como Multiplicativo son los mismos,
```

	r2_score	mean_absolute_error	median_absolute_error	mse	msle	
0	0.869003	8626.562976	1847.768639	3.603366e+08	0.005284	1898

Simple exponencial smoothing (SES)

```
HWES1 = SimpleExpSmoothing(Sales_mes, initialization_method="estimated").fit()
HWES1_fitted = HWES1.fittedvalues
HWES1_fitted.name = 'Simple Exponencial Smoothing'
pd.concat([Sales_mes, HWES1_fitted], axis=1).plot(title='Single Exponential Smoothing')
```

```
<Axes: title={'center': 'Single Exponential Smoothing'}, xlabel='date'>
```




```
results = pd.DataFrame(
    index=["SSE", "AIC", "BIC"])
results["Simple Exponencial"] = [HWES1.sse] + [HWES1.aic] + [HWES1.bic]
```

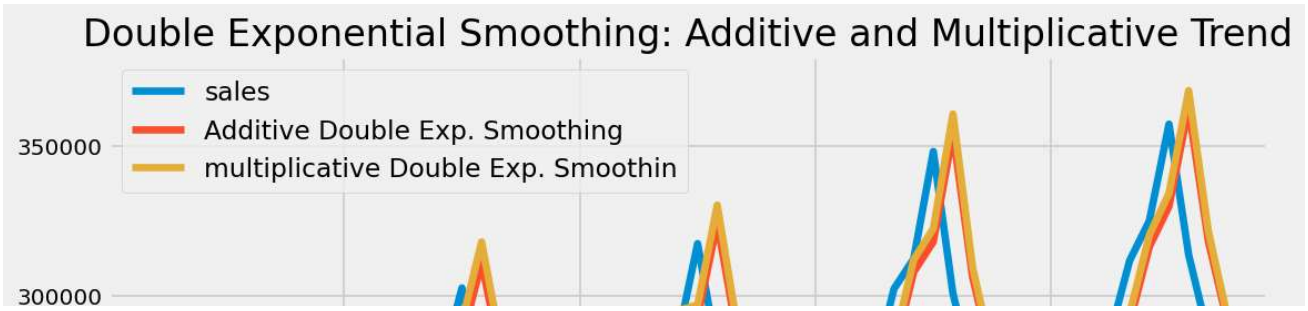
```
print(HWES1.summary())
```

```
                       SimpleExpSmoothing Model Results
==============================================================================
Dep. Variable:                   sales   No. Observations:                   60
Model:            SimpleExpSmoothing   SSE                  62997737631.460
Optimized:                       True   AIC                         1250.321
Trend:                           None   BIC                         1254.510
Seasonal:                        None   AICC                        1251.048
Seasonal Periods:                None   Date:                Sun, 16 Apr 2023
Box-Cox:                        False   Time:                        04:06:24
```

```
Box-Cox Coeff.:                  None
================================================================================
                        coeff                 code              optimized
--------------------------------------------------------------------------------
smoothing_level            0.9950000                alpha                 True
initial_level             1.5788e+05                  l.0                 True
--------------------------------------------------------------------------------
```

Double exponencial smoothing (DES)

```
HWES2_ADD = ExponentialSmoothing(Sales_mes,trend='add').fit()#.fittedvalues
HWES2_MUL = ExponentialSmoothing(Sales_mes,trend='mul').fit()#.fittedvalues
HWES2_ADD_fitted = HWES2_ADD.fittedvalues
HWES2_MUL_fitted = HWES2_MUL.fittedvalues
HWES2_ADD_fitted.name = 'Additive Double Exp. Smoothing'
HWES2_MUL_fitted.name = 'multiplicative Double Exp. Smoothin'
pd.concat([Sales_mes, HWES2_ADD_fitted, HWES2_MUL_fitted], axis=1).plot(title='Double Expo
```




```
results["Double Exp. - Additive"] = [HWES2_ADD.sse] + [HWES2_ADD.aic] + [HWES2_ADD.bic]
results["Double Exp. - Multiplicative"] = [HWES2_MUL.sse] + [HWES2_MUL.aic] + [HWES2_MUL.b
```

```
HWES2_ADD.summary()
```

ExponentialSmoothing Model Results

Dep. Variable:	sales	**No. Observations:**	60
Model:	ExponentialSmoothing	**SSE**	65329777624.011
Optimized:	True	**AIC**	1256.502
Trend:	Additive	**BIC**	1264.880
Seasonal:	None	**AICC**	1258.087
Seasonal Periods:	None	**Date:**	Sun, 16 Apr 2023
Box-Cox:	False	**Time:**	04:06:24
Box-Cox Coeff.:	None		

	coeff	code	optimized
smoothing_level	0.9950000	alpha	True
smoothing_trend	0.0236905	beta	True
initial_level	1.5788e+05	l.0	True
initial_trend	8746.5879	b.0	True

```
HWES2_MUL.summary()
```

ExponentialSmoothing Model Results

Dep. Variable:	sales	**No. Observations:**	60
Model:	ExponentialSmoothing	**SSE**	69923480990.441
Optimized:	True	**AIC**	1260.579
Trend:	Multiplicative	**BIC**	1268.957
Seasonal:	None	**AICC**	1262.164
Seasonal Periods:	None	**Date:**	Sun, 16 Apr 2023
Box-Cox:	False	**Time:**	04:06:24
Box-Cox Coeff.:	None		

	coeff	code	optimized
smoothing_level	0.9950000	alpha	True
smoothing_trend	0.0473810	beta	True
initial_level	1.5788e+05	l.0	True
initial_trend	1.0553996	b.0	True

*Continuamos buscando otro modelo, dado que las tecnicas de suavizamiento vistas no estan considerando estacionalidad

Triple exponencial smoothing (TES)

```
HWES3_ADD = ExponentialSmoothing(Sales_mes,trend='add',seasonal='add',seasonal_periods=12)
HWES3_MUL = ExponentialSmoothing(Sales_mes,trend='mul',seasonal='mul',seasonal_periods=12)

HWES3_ADD_fitted = HWES3_ADD.fittedvalues
HWES3_MUL_fitted = HWES3_MUL.fittedvalues
HWES3_ADD_fitted.name = 'Additive TES'
HWES3_MUL_fitted.name = 'multiplicative TES'
pd.concat([Sales_mes, HWES3_ADD_fitted, HWES3_MUL_fitted], axis=1).plot(title='Triple Expo
```

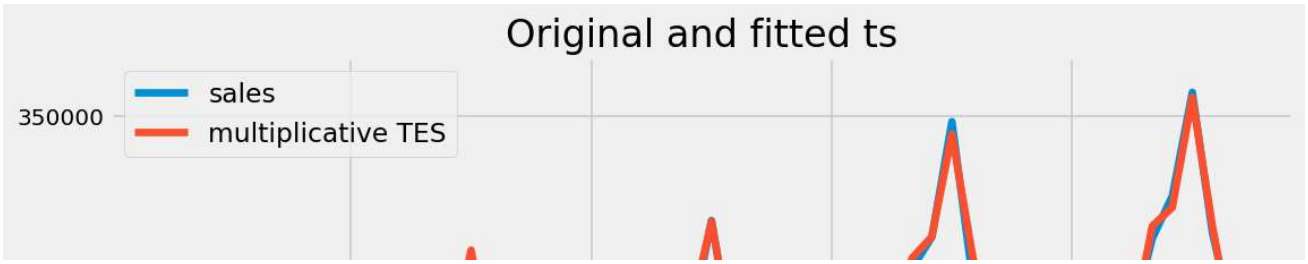
Triple Exponential Smoothing: Additive and Multiplicative Trend

```
results["Triple Exp. - Additive"] = [HWES3_ADD.sse] + [HWES3_ADD.aic] + [HWES3_ADD.bic]
results["Triple Exp. - Multiplicative"] = [HWES3_MUL.sse] + [HWES3_MUL.aic] + [HWES3_MUL.b
# El Triple Exponencial Multiplicativo resalta por tener menor error SSE en comparación a
```

```
results
```

	Simple Exponencial	Double Exp. - Additive	Double Exp. - Multiplicative	Triple Exp. - Additive	Triple Exp. - Multiplicative
SSE	6.299774e+10	6.532978e+10	6.992348e+10	1.556908e+09	7.267883e+08
AIC	1.250321e+03	1.256502e+03	1.260579e+03	1.056297e+03	1.010588e+03
BIC	1.254510e+03	1.264880e+03	1.268957e+03	1.089807e+03	1.044098e+03

```
pd.concat([Sales_mes, HWES3_MUL_fitted], axis=1).plot(title='Original and fitted ts');
```




```
HWES3_MUL.summary()
```

ExponentialSmoothing Model Results

Dep. Variable:	sales	**No. Observations:**	60
Model:	ExponentialSmoothing	**SSE**	726788287.742
Optimized:	True	**AIC**	1010.588
Trend:	Multiplicative	**BIC**	1044.098
Seasonal:	Multiplicative	**AICC**	1027.271
Seasonal Periods:	12	**Date:**	Sun, 16 Apr 2023
Box-Cox:	False	**Time:**	04:06:25
Box-Cox Coeff.:	None		

	coeff	code	optimized
smoothing_level	0.5707143	alpha	True
smoothing_trend	0.0815306	beta	True
smoothing_seasonal	0.0001	gamma	True
initial_level	1.9917e+05	l.0	True
initial_trend	1.0137598	b.0	True
initial_seasons.0	0.7183591	s.0	True
initial_seasons.1	0.7190422	s.1	True
initial_seasons.2	0.9394036	s.2	True
initial_seasons.3	1.0577767	s.3	True
initial_seasons.4	1.1636667	s.4	True
initial_seasons.5	1.1891510	s.5	True
initial_seasons.6	1.3025210	s.6	True
initial_seasons.7	1.1481031	s.7	True
initial_seasons.8	1.0252301	s.8	True
initial_seasons.9	0.9804144	s.9	True
initial_seasons.10	1.0165740	s.10	True
initial_seasons.11	0.7397581	s.11	True

Holt-Winters

```
fit1 = ExponentialSmoothing(
    Sales_mes,
    seasonal_periods=12,
    trend="add",
    seasonal="add",
    initialization_method="estimated",
).fit()

fit2 = ExponentialSmoothing(
```

```
    Sales_mes,
    seasonal_periods=12,
    trend="add",
    seasonal="mul",
    initialization_method="estimated",
).fit()

fit3 = ExponentialSmoothing(
    Sales_mes,
    seasonal_periods=12,
    trend="mul",
    seasonal="add",
    initialization_method="estimated",
).fit()

fit4 = ExponentialSmoothing(
    Sales_mes,
    seasonal_periods=12,
    trend="mul",
    seasonal="mul",
    initialization_method="estimated",
).fit()


results2 = pd.DataFrame(
    index=["SSE", "AIC", "BIC"])


results2["Holt Trend-Add Seas-Add"] = [fit1.sse] + [fit1.aic] + [fit1.bic]
results2["Holt Trend-Add Seas-Mul"] = [fit2.sse] + [fit2.aic] + [fit2.bic]
results2["Holt Trend-Mul Seas-Add"] = [fit3.sse] + [fit3.aic] + [fit3.bic]
results2["Holt Trend-Mul Seas-Mul"] = [fit4.sse] + [fit4.aic] + [fit4.bic]


results2
```

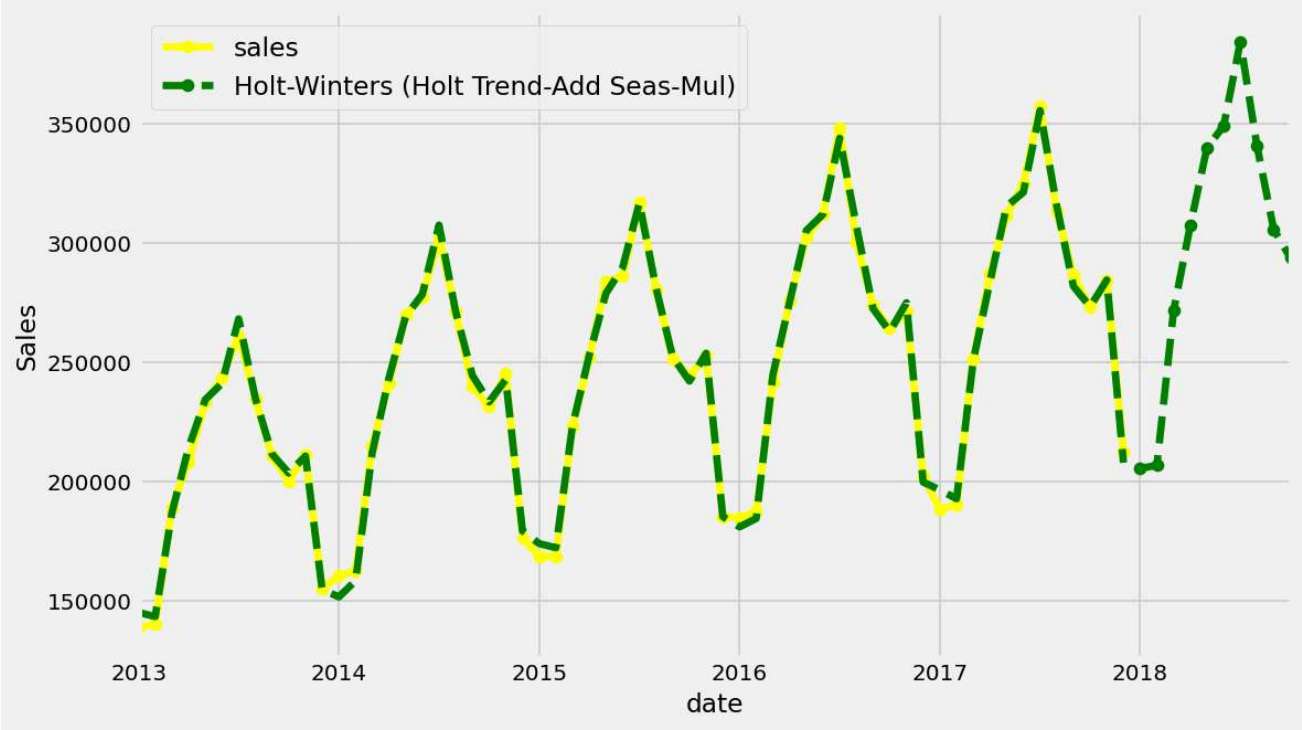
	Holt Trend-Add Seas-Add	Holt Trend-Add Seas-Mul	Holt Trend-Mul Seas-Add	Holt Trend-Mul Seas-Mul
SSE	1.556908e+09	7.054268e+08	1.600289e+09	7.267883e+08
AIC	1.056297e+03	1.008798e+03	1.057946e+03	1.010588e+03
BIC	1.089807e+03	1.042308e+03	1.091456e+03	1.044098e+03

Observamos que el mejor modelo lo otorga el '**Holt Trend-Add Seas-Mul**', dado que tiene un menor SSE que el Mul-Mul

Predicción

```
ax = Sales_mes.plot(
    figsize=(10, 6),
    marker="o",
    color="yellow",
```

```
)

ax.set_ylabel("Sales")
ax.set_xlabel("Year")
fit2.fittedvalues.plot(ax=ax, style="--", color="green")
fit2.forecast(10).rename("Holt-Winters (Holt Trend-Add Seas-Mul)").plot(
    ax=ax, style="--", marker="o", color="green", legend=True
)

plt.show()
# aqui obtamos solo por proyectar 10 periodos mensuales, dado que la base real tiene 60 pe
```




```
import numpy as np
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, median_abso


def evaluate_forecast(y,pred):
    results = pd.DataFrame({'r2_score':r2_score(y, pred),
```

```
                          }, index=[0])
    results['mean_absolute_error'] = mean_absolute_error(y, pred)
    results['median_absolute_error'] = median_absolute_error(y, pred)
    results['mse'] = mean_squared_error(y, pred)
    results['msle'] = mean_squared_log_error(y, pred)
    results['rmse'] = np.sqrt(results['mse'])
    return results


evaluate_forecast(Sales_mes.sales, fit2.fittedvalues)
```

	r2_score	mean_absolute_error	median_absolute_error	mse	msle	
0	0.995726	2717.015255	2512.463485	1.175711e+07	0.00028	3428.8

Auto - SARIMA

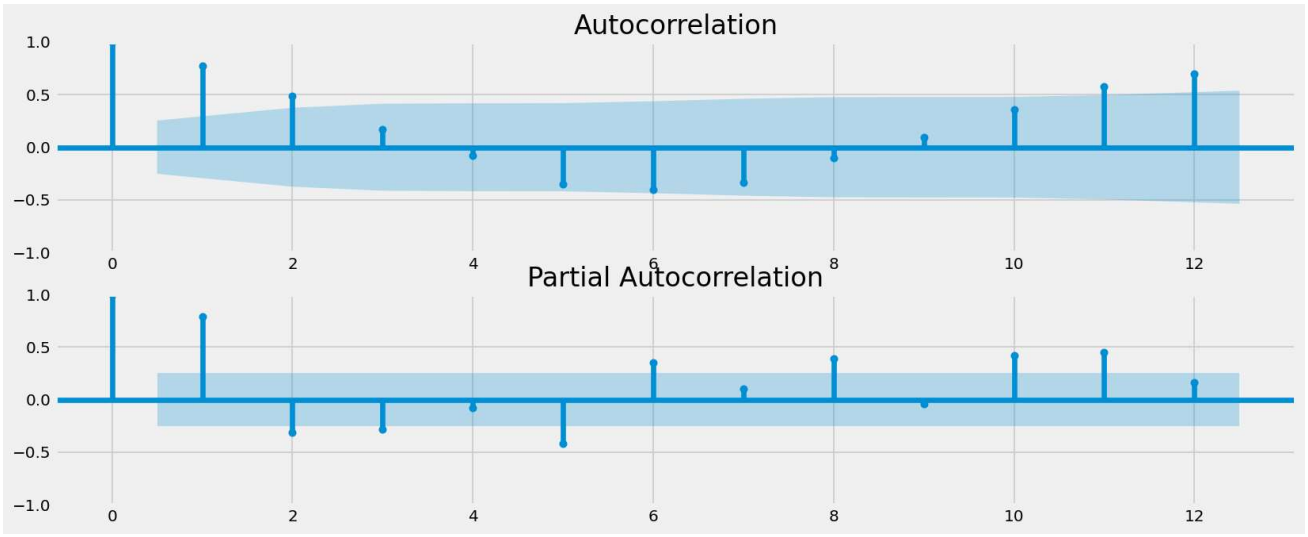
```
import warnings
warnings.filterwarnings("ignore")
def fxn():
    warnings.warn("deprecated", DeprecationWarning)
with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    fxn()


import itertools
import numpy as np
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')

import pandas as pd
pd.set_option('display.expand_frame_repr', False)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)

import statsmodels as sm
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose

from math import sqrt

import matplotlib
import matplotlib.pyplot as plt
matplotlib.rcParams['axes.labelsize'] = 14
matplotlib.rcParams['xtick.labelsize'] = 12
matplotlib.rcParams['ytick.labelsize'] = 12
matplotlib.rcParams['text.color'] = 'k'
import seaborn as sns
```

```
from random import random

from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error, median_abso


Sales_m = Sales_mes.rename(columns={'sales': 'y'})
Sales_m.head()
```

date	y
2013-01-31	138832.0
2013-02-28	140085.0
2013-03-31	189060.0
2013-04-30	208446.0
2013-05-31	233266.0

```
plt.figure(figsize=(15,6))
plt.plot(Sales_m)
plt.show()
```

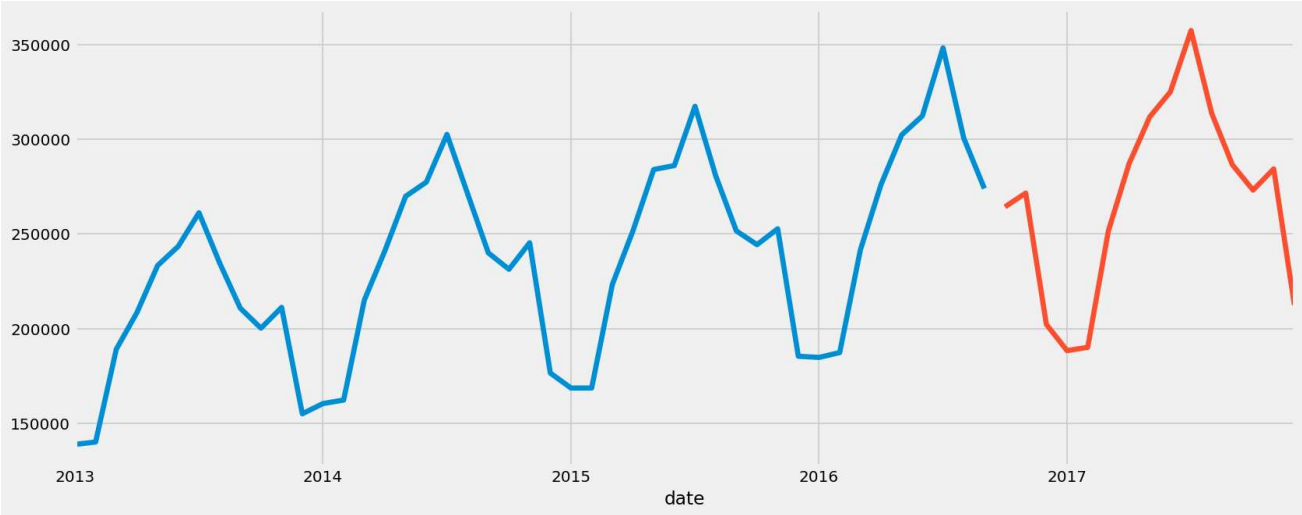

```
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf

plt.figure(figsize=(15,6))
plt.subplot(211)
plot_acf(Sales_m, ax=plt.gca(), lags = 12)
plt.subplot(212)
plot_pacf(Sales_m, ax=plt.gca(), lags = 12)
plt.show()
```




```
#divide into train and validation set
train_m = Sales_m[:int(0.75*(len(Sales_m)))]
valid_m = Sales_m[int(0.75*(len(Sales_m))):]

#plotting the data
plt.figure(figsize=(15,6))
```

```
train_m['y'].plot()
valid_m['y'].plot()
```

```
<Axes: xlabel='date'>
```



Aplicando AUTO SARIMA para encontrar los mejores parámetros

```
pip install pmdarima
```

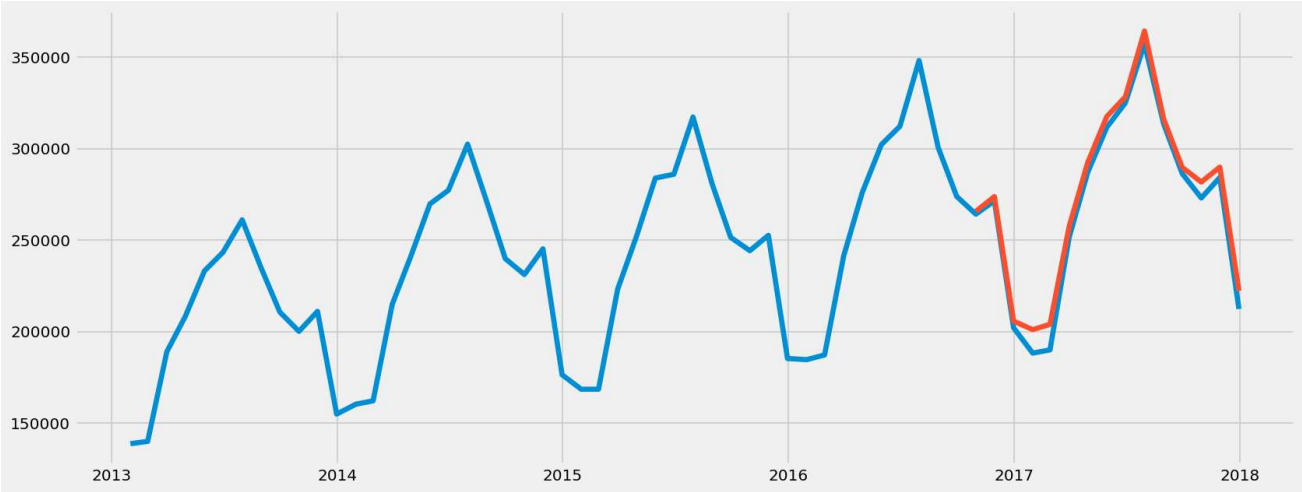
```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/p
Requirement already satisfied: pmdarima in /usr/local/lib/python3.9/dist-packages (2
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python3.9/dist-pa
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in /usr/local/lib/python3
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.9/dist-package
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in /usr/local/lib/pyt
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: statsmodels>=0.13.2 in /usr/local/lib/python3.9/dist-p
Requirement already satisfied: urllib3 in /usr/local/lib/python3.9/dist-packages (fro
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.9/dis
```

```
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.9/dist-
Requirement already satisfied: patsy>=0.5.2 in /usr/local/lib/python3.9/dist-packages
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.9/dist-packa
Requirement already satisfied: six in /usr/local/lib/python3.9/dist-packages (from pa
```

```
#building the model
from pmdarima import auto_arima
model = auto_arima(train_m, trace=True, error_action='ignore', suppress_warnings=True, sea
model.fit(train_m)
```

```
Performing stepwise search to minimize aic
```

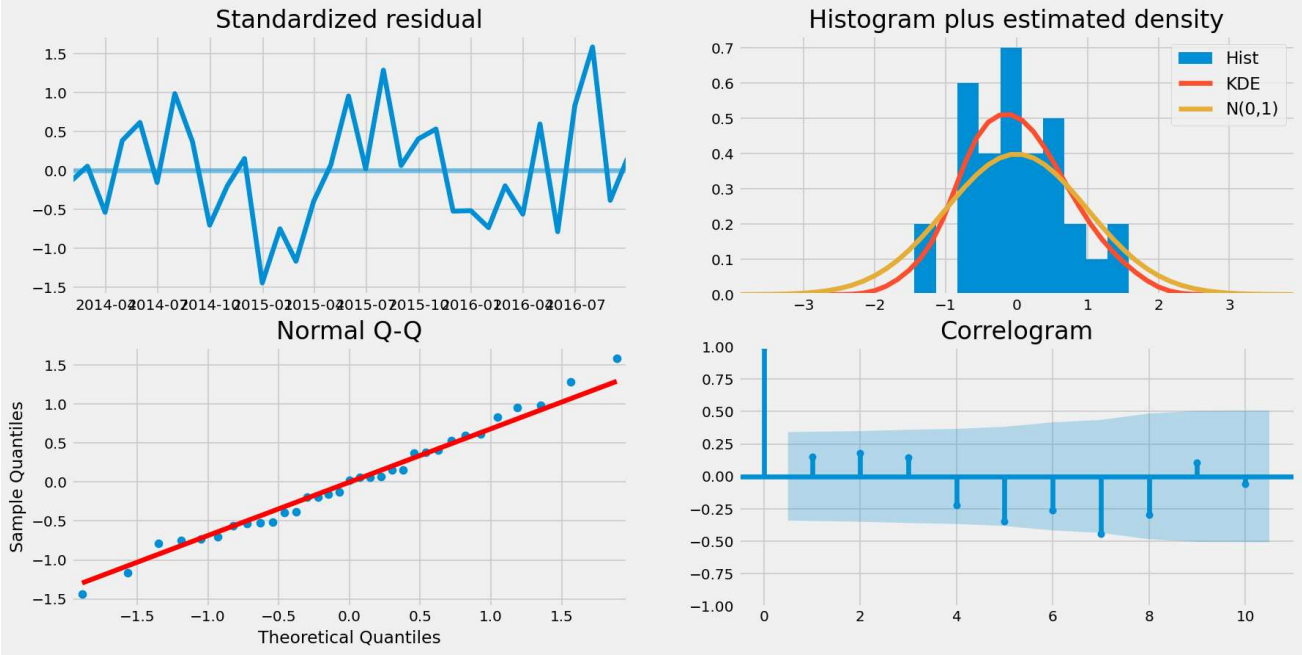
```
start_index = valid_m.index.min()
end_index = valid_m.index.max()

#Predictions
pred = model.predict()

pred = model.predict(n_periods=len(valid))
pred = pd.DataFrame(pred,index = valid.index,columns=['Prediction'])

forecast = model.predict(n_periods=len(valid))
forecast = pd.DataFrame(forecast,index = valid.index,columns=['Prediction'])

plt.figure(figsize=(15,6))
#plot the predictions for validation set
plt.plot(Sales_m.y, label='Train')
#plt.plot(valid, label='Valid')
plt.plot(forecast, label='Prediction')
plt.show()
```




```
evaluate_forecast(Sales_m[start_index:end_index], forecast)
```

	r2_score	mean_absolute_error	median_absolute_error	mse	msle	
0	0.979014	6138.773158	5682.704337	5.086282e+07	0.00101	7131.8

```
model.plot_diagnostics(figsize=(16, 8))
plt.show()
```



Diagnóstico del modelo:

*Nuestra principal preocupación es garantizar que los residuos de nuestro modelo no estén correlacionados y normalmente se distribuyan con media cero.

*Si el modelo estacional ARIMA no satisface estas propiedades, es una buena indicación de que puede mejorarse aún más.

El diagnóstico del modelo sugiere que el modelo residual se distribuye normalmente en función de lo siguiente:

*En la gráfica superior derecha, la línea roja de KDE sigue de cerca con la línea N (0,1). Donde, N (0,1) es la notación estándar para una distribución normal con media 0 y desviación estándar de 1. Esta es una buena indicación de que los residuos se distribuyen normalmente.

*La gráfica qq en la parte inferior izquierda muestra que la distribución ordenada de los residuos (puntos azules) sigue la tendencia lineal de las muestras tomadas de una distribución normal estándar. Nuevamente, esta es una fuerte indicación de que los residuos se distribuyen normalmente.

*Los residuos a lo largo del tiempo (gráfico superior izquierdo) no muestran ninguna estacionalidad obvia y parecen ser ruido blanco.

*Esto se confirma mediante el gráfico de autocorrelación (es decir, correlograma) en la parte inferior derecha, que muestra que los residuos de series temporales tienen una baja correlación con versiones rezagadas de sí mismo. Quitando el 0 que naturalmente es el mismo dato, y un dato que se escapa apenas del rango que debe ser por la variación que no es constante.

Comentarios finales

El mejor modelo obtenido en el analisis es el Holt-Winters (Holt Trend-Add Seas-Mul) con un R2 de 99.6% y un RMSE de 3'428.9 (casi la mitad de lo obtenido en el Auto Sarima)

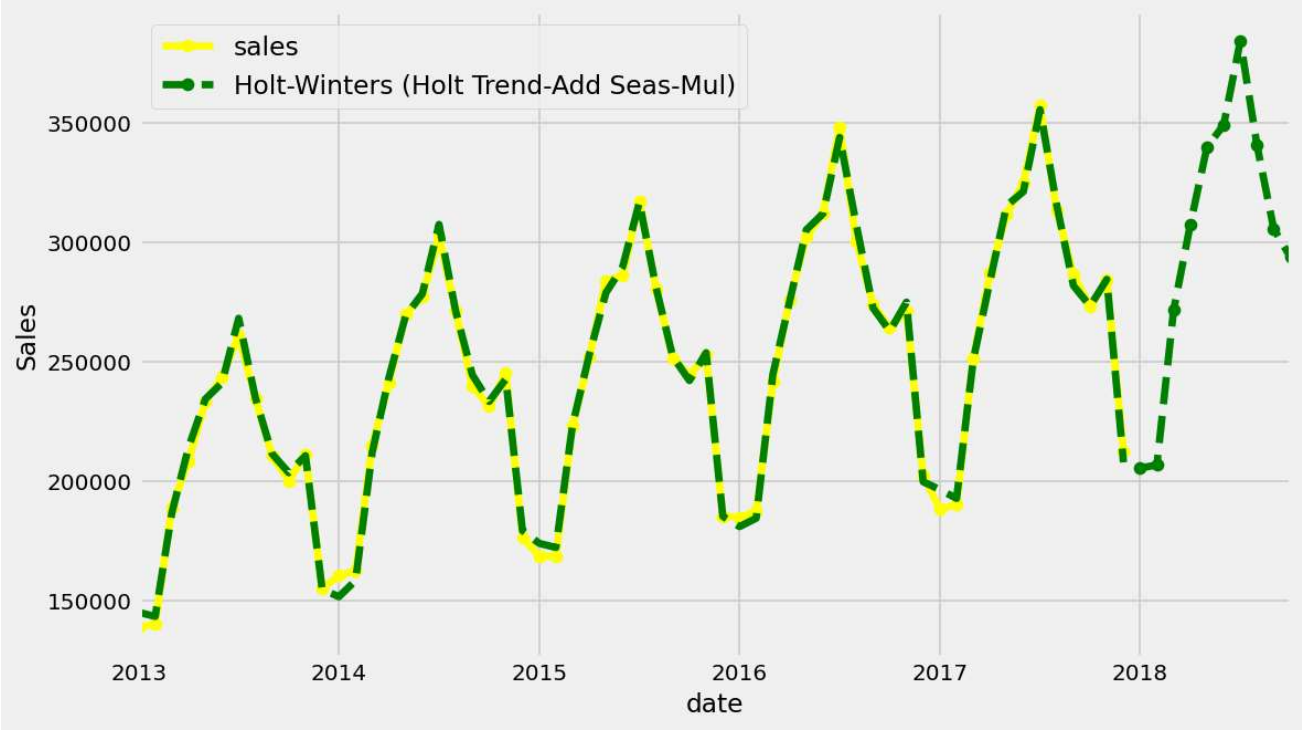
- A continuación los 10 periodos resultado del mejor modelo obtenido y su gráfico.

```
fit2.forecast(10)
```

```
2018-01-31    205481.374898
2018-02-28    206768.957393
2018-03-31    271563.688341
2018-04-30    307388.001497
2018-05-31    339927.085304
2018-06-30    349177.485214
2018-07-31    384443.701129
2018-08-31    340609.768508
2018-09-30    305714.398009
```

```
2018-10-31    293839.151553
Freq: M, dtype: float64
```

```
ax = Sales_mes.plot(
    figsize=(10, 6),
    marker="o",
    color="yellow",
)

ax.set_ylabel("Sales")
ax.set_xlabel("Year")
fit2.fittedvalues.plot(ax=ax, style="--", color="green")
fit2.forecast(10).rename("Holt-Winters (Holt Trend-Add Seas-Mul)").plot(
    ax=ax, style="--", marker="o", color="green", legend=True
)

plt.show()
```



✓ 0 s completado a las 23:08