notebook-taller1

August 7, 2024

1 Maestria en Ciencia de Datos - Universidad Icesi

1.1 Fundamentos de Analítica de Datos II - Taller 1

1.1.1 Daniel Martinez Villegas & Luis Felipe Montenegro

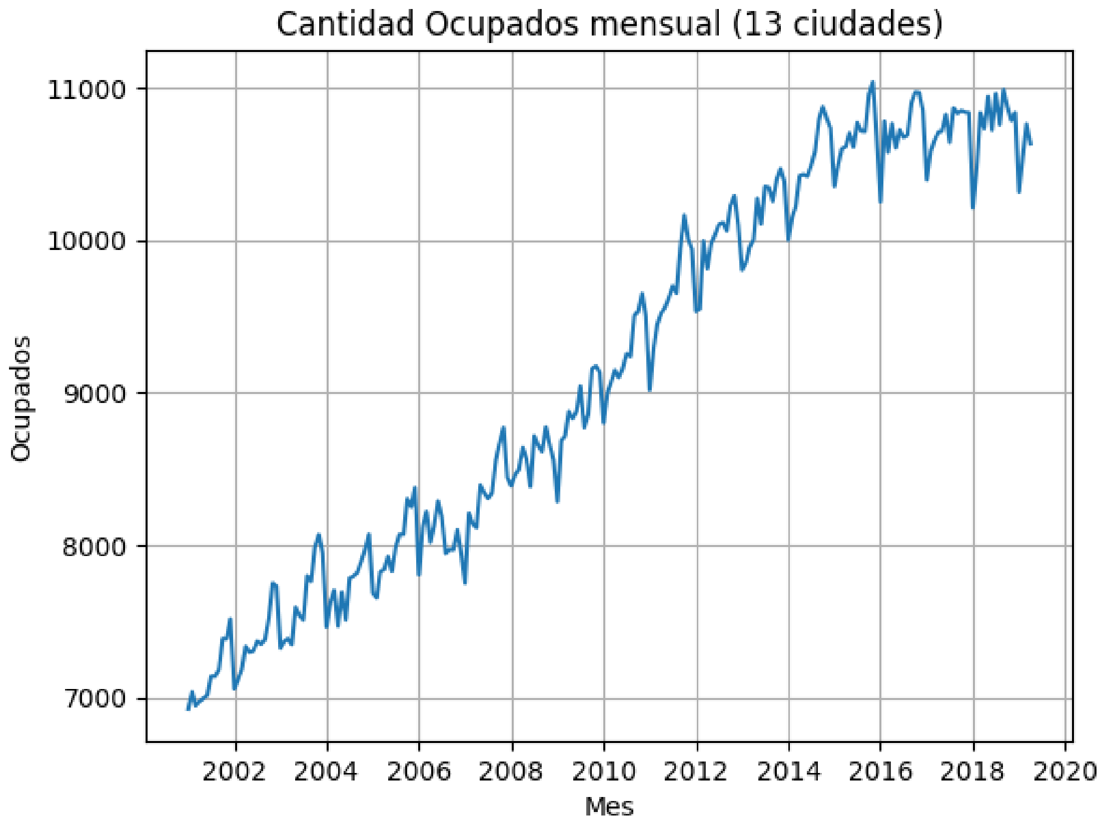
2 Series temporales simples

[1]:
```
import numpy as np
import pandas as pd # Operaciones con dataframes
from matplotlib import pyplot as plt # gráficos
from statsmodels.tsa.seasonal import seasonal_decompose # descomposición de␣
 ↪series
from statsmodels.tsa.holtwinters import SimpleExpSmoothing  # Holwinters simple
from statsmodels.tsa.holtwinters import ExponentialSmoothing # Holwinters doble␣
 ↪y tripe
from statsmodels.tsa.exponential_smoothing.ets import ETSModel
from sklearn.metrics import mean_squared_error
```

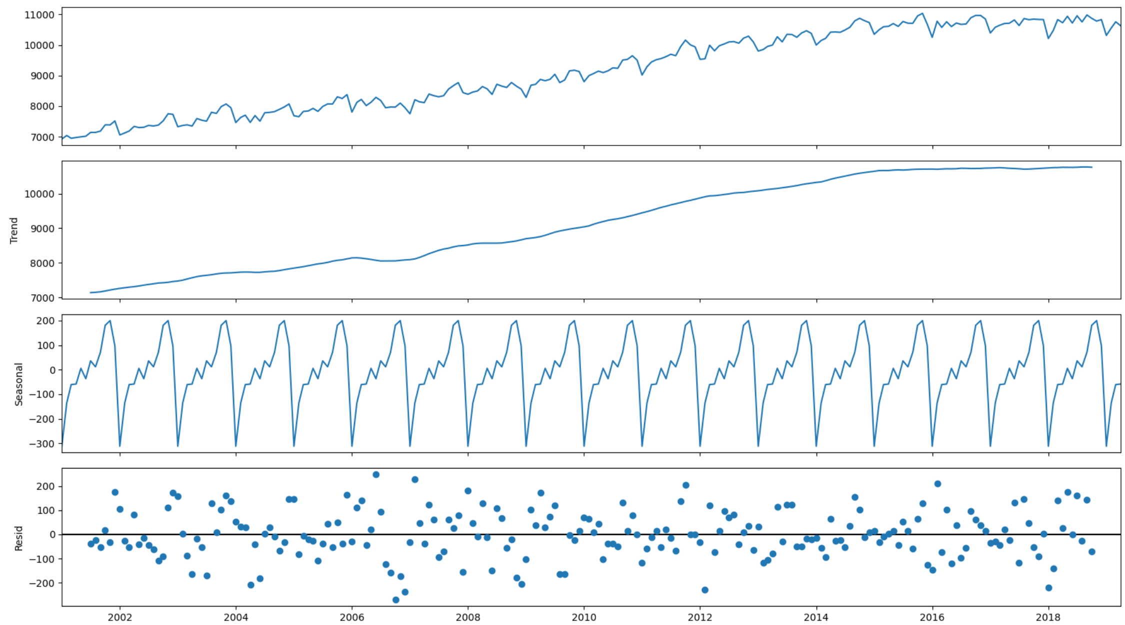
[2]:
```
data = pd.read_excel("datosEmpleo.xlsx",index_col='mes',parse_dates=True)
data.head()
```

[2]:
```
            TD_13ciudades  Ocupados  Desocupados  Inactivos
mes
2001-01-01      20.946380  6923.604     1834.507   4600.718
2001-02-01      19.894213  7037.746     1747.820   4596.805
2001-03-01      19.221565  6945.973     1652.823   4807.120
2001-04-01      17.888575  6973.079     1519.137   4937.280
2001-05-01      17.945654  6994.462     1529.720   4928.911
```

[3]:
```
# Graficando los datos
plt.title("Cantidad Ocupados mensual (13 ciudades)")
plt.xlabel("Mes")
plt.ylabel("Ocupados")
plt.plot(data[["Ocupados"]])
plt.grid()
plt.show()
```



[4]:
```python
#Componentes de la serie

td_componentes = seasonal_decompose(data[["Ocupados"]],model="additive")
fig = td_componentes.plot()
fig.set_size_inches((16, 9))
fig.tight_layout()
plt.show()
```



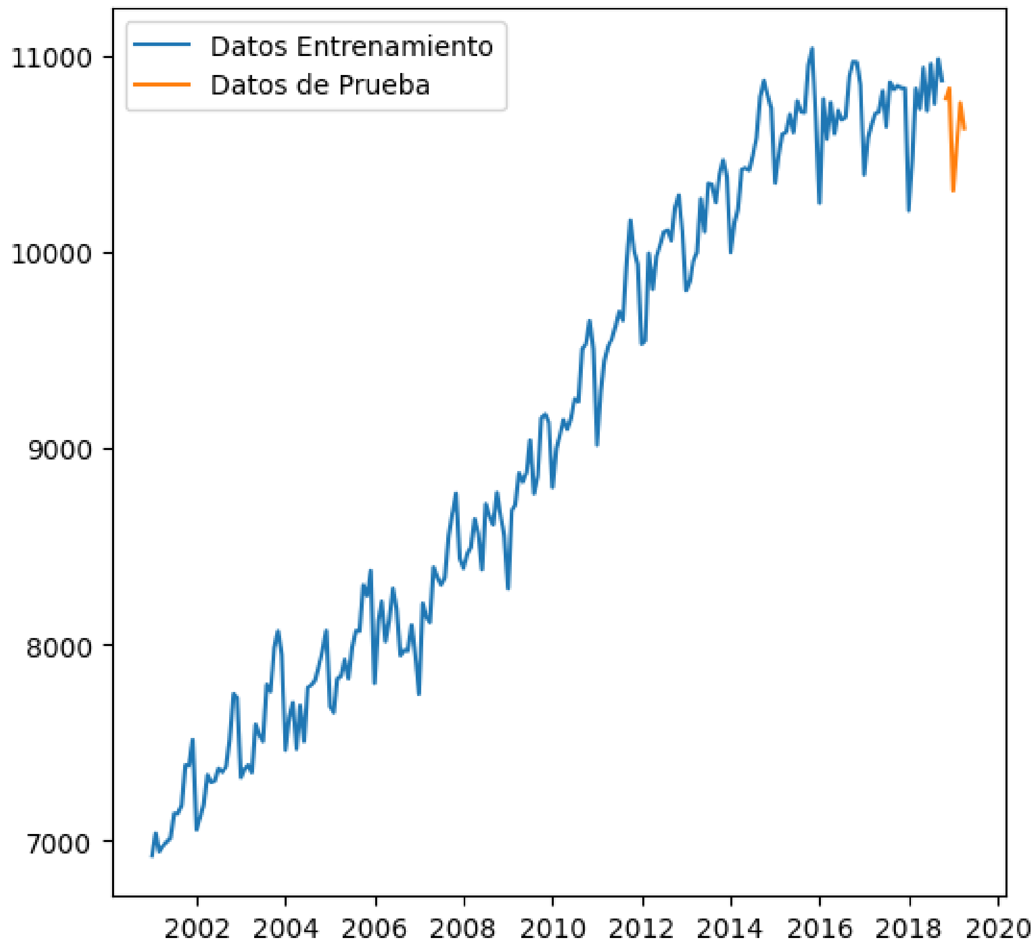
2.1 Evaluation Protocol

2.1.1 Train-test split

[4]:
```
data['year'] = data.index.year
print(data['year'].unique())
print(len(data['year'])) # 220
```

```
[2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014
 2015 2016 2017 2018 2019]
220
```

[5]:
```
total_data = len(data['year'])
horizon = 6

train_len = total_data - horizon
train_td = data[["Ocupados"]][:train_len]
test_td = data[["Ocupados"]][train_len:]

fig = plt.figure(figsize=(horizon, 6))
plt.plot(train_td,label="Datos Entrenamiento")
plt.plot(test_td,label="Datos de Prueba")
plt.legend()
plt.show()
```



2.2 Promedio Movil

- **w** represents the window size, which is the number of data points to consider when calculating the moving average.
- **h** represents the horizon, which is the number of future data points to forecast.

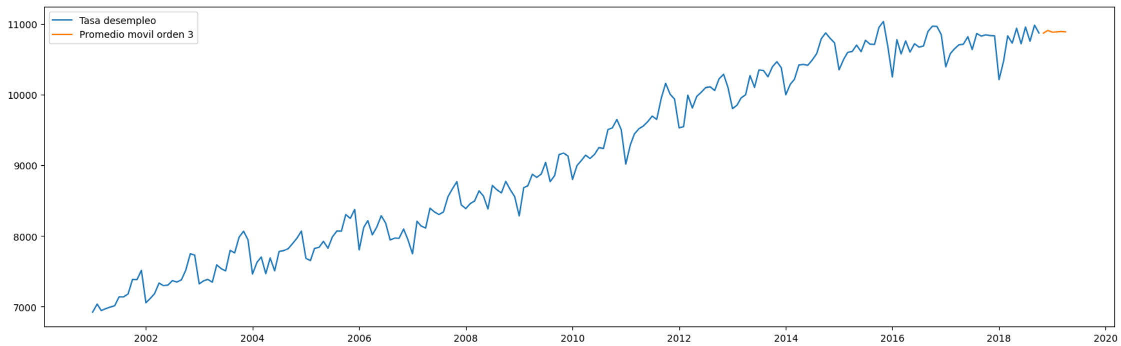
[6]:
```
def fore_ma(datos,w,h):
  data=datos.copy()
  for x in range(1,h+1):
    ind = data.index[-1]
    value = ind + pd.DateOffset(months=1)
    data.loc[value]= data[-w:].mean()
  return data[-h:]
```

[7]:
```
movil_avg = [fore_ma(train_td,x,horizon) for x in range(1,25)]
```

[8]:
```
for x in range(len(movil_avg)):
        print(x+1, "------>", np.sqrt(mean_squared_error(test_td,movil_avg[x])))
```

```
1 ------> 287.2354279175854
2 ------> 319.1849777906289
3 ------> 298.3770292088787
4 ------> 305.34686253059
5 ------> 291.01606293356485
6 ------> 291.5713004314995
7 ------> 283.4567470273245
8 ------> 279.3491656472429
9 ------> 270.13693523482465
10 ------> 258.0826859664414
11 ------> 245.42326872607504
12 ------> 221.08914545893433
13 ------> 214.50880659854403
14 ------> 213.5825179006286
15 ------> 212.44821683703358
16 ------> 214.88471083985425
17 ------> 218.159032263104
18 ------> 216.56731320777968
19 ------> 216.63618429400097
20 ------> 216.3239820128406
21 ------> 214.08726281143203
22 ------> 212.14619517863974
23 ------> 208.83714957580352
24 ------> 201.65678555054527
```

[9]:
```
fig = plt.figure(figsize=(20, 6))
plt.plot(train_td,label="Tasa desempleo")
plt.plot(movil_avg[2],label="Promedio movil orden 3")
plt.legend()
plt.show()
```



- [X] Suavización exponencial simple

- [X] Suavización exponencial lineal Holt
- [X] Suavización exponencial lineal Holt-Winters

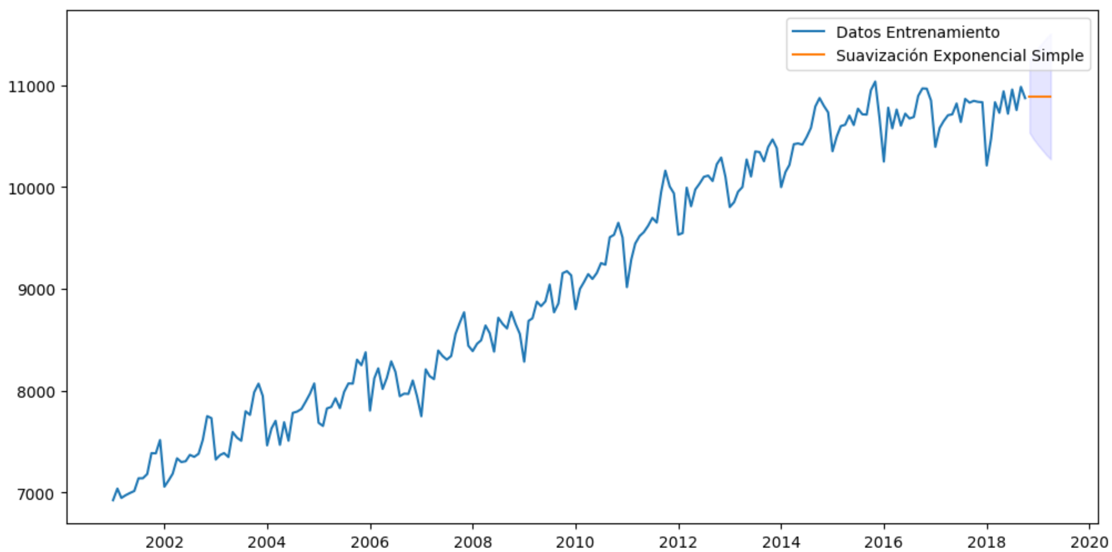
[10]:
```python
# Model
def build_ets_model(train_td, test_td, horizon, error='add', trend=None,␣
↪seasonal=None):
    # Build model
    ets_model = ETSModel(endog=train_td["Ocupados"], error=error, trend=trend,␣
↪seasonal=seasonal)
    ets_result = ets_model.fit()

    # Forecast
    point_forecast = ets_result.forecast(horizon)

    # Confidence intervals
    ci = ets_result.get_prediction(start=point_forecast.index[0],␣
↪end=point_forecast.index[-1])
    conf_forecast = ci.pred_int(alpha=0.05)
    limits = ci.predicted_mean

    # Prepare predictions DataFrame
    preds = pd.concat([limits, conf_forecast], axis=1)
    preds.columns = ['Point_forecast', 'lower_95', 'upper_95']
    print(preds)

    # Plot results
    fig = plt.figure(figsize=(12, 6))
    plt.plot(train_td, label="Datos Entrenamiento")
    plt.plot(preds['Point_forecast'], label="Suavización Exponencial Simple")
    plt.fill_between(preds.index, preds['lower_95'], preds['upper_95'],␣
↪color='blue', alpha=0.1)
    plt.legend()
    plt.show()

    # Calculate RMSE
    rmse = np.sqrt(mean_squared_error(test_td, point_forecast))
    print(f"RMSE: {rmse}")

    return {
        "rmse": rmse,
        "alpha": ets_result.alpha,
        "beta": getattr(ets_result, 'beta', None),
        "gamma": getattr(ets_result, 'gamma', None),
        "preds": preds,
        }
```

2.3 Suavizacion Exponencial Simple

[11]:
```
suavizacion_exp_simple_add_mse = build_ets_model(train_td, test_td, horizon,␣
↪error='add')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	10890.815856	10535.182689	11246.449022
2018-12-01	10890.815856	10469.673459	11311.958252
2019-01-01	10890.815856	10413.063946	11368.567765
2019-02-01	10890.815856	10362.485602	11419.146109
2019-03-01	10890.815856	10316.343206	11465.288506
2019-04-01	10890.815856	10273.641006	11507.990705



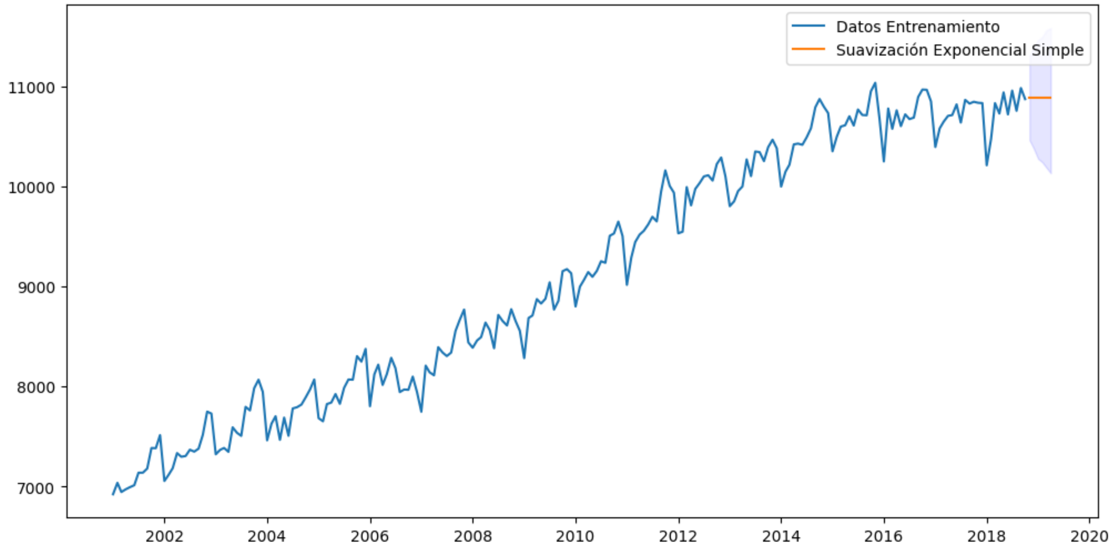

```
RMSE: 300.4290298412983
```

[12]:
```
suavizacion_exp_simple_mul_mse = build_ets_model(train_td, test_td, horizon,␣
↪error='mul')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	10890.814949	10464.244718	11304.797092
2018-12-01	10890.814949	10380.809451	11392.512090

```
2019-01-01    10890.814949  10278.748573  11463.078385
2019-02-01    10890.814949  10241.722351  11497.916098
2019-03-01    10890.814949  10189.526239  11563.594545
2019-04-01    10890.814949  10134.235013  11584.135945
```



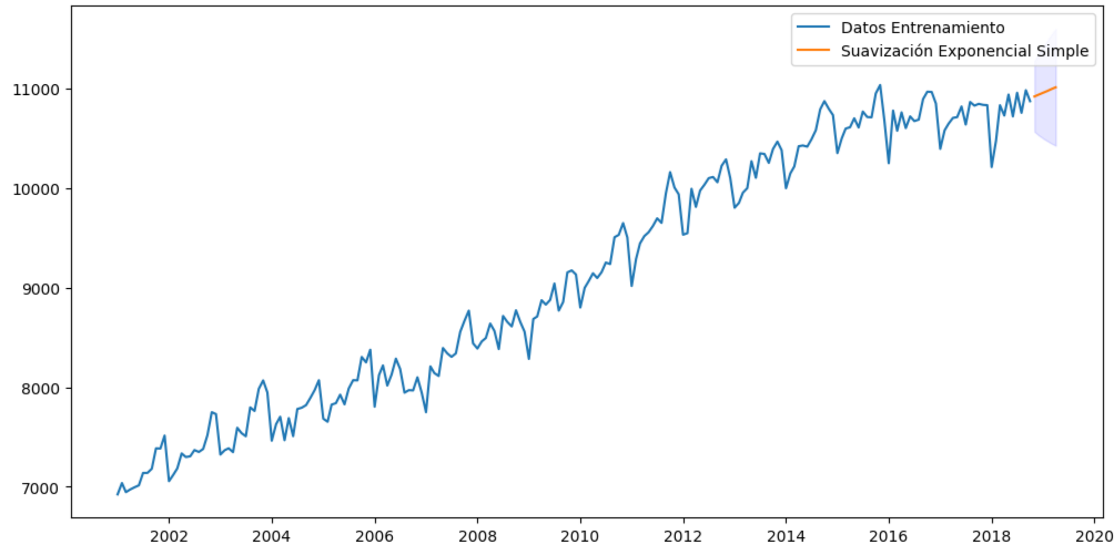

```
RMSE: 300.4282950082703
```

3 Suavización Exponencial Lineal (Holt)

[13]:
```python
suavizacion_exp_lin_holt_add_add_mse = build_ets_model(train_td, test_td,␣
↪horizon, error='add', trend='add')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	10921.837423	10568.380806	11275.294041
2018-12-01	10940.275438	10532.003993	11348.546883
2019-01-01	10958.713453	10501.184691	11416.242215
2019-02-01	10977.151468	10474.277712	11480.025224
2019-03-01	10995.589483	10450.297487	11540.881479
2019-04-01	11014.027498	10428.599401	11599.455595

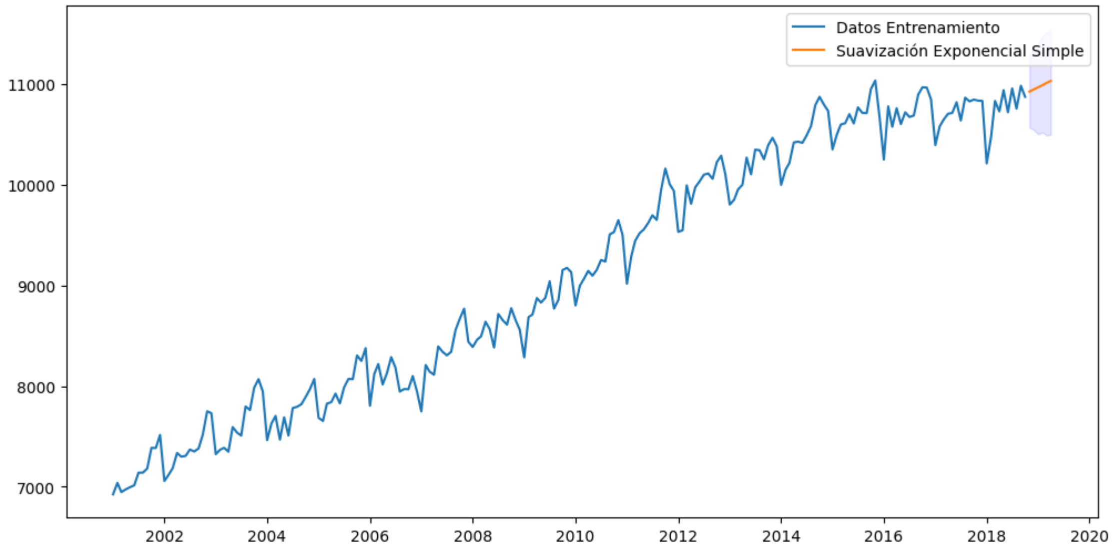


RMSE: 370.1579750635174

[14]:
```
suavizacion_exp_lin_holt_add_mul_mse = build_ets_model(train_td, test_td,␣
    ↪horizon, error='add', trend='mul')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	10927.114148	10568.117358	11287.435829
2018-12-01	10948.230528	10547.919996	11363.148374
2019-01-01	10969.387716	10503.325162	11401.242699
2019-02-01	10990.585789	10522.504264	11479.264207
2019-03-01	11011.824827	10493.492753	11510.523675
2019-04-01	11033.104908	10498.460692	11548.747724

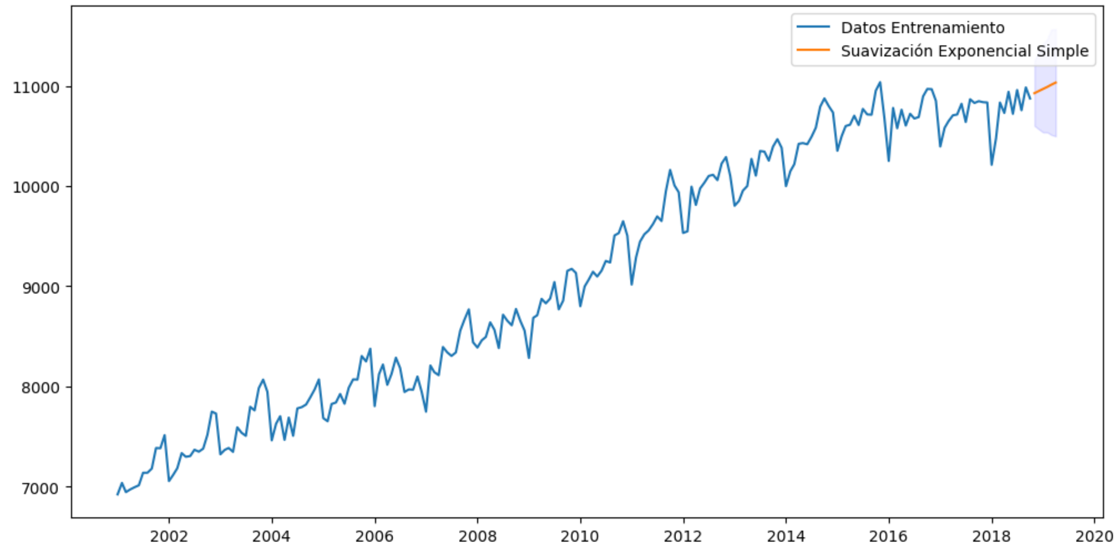


RMSE: 381.54588770018285

[15]:
```
suavizacion_exp_lin_holt_mul_mul_mse = build_ets_model(train_td, test_td,␣
    ↪horizon, error='add', trend='mul')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	10927.114148	10601.808696	11250.619328
2018-12-01	10948.230528	10568.695540	11339.042413
2019-01-01	10969.387716	10536.952426	11417.881998
2019-02-01	10990.585789	10536.010010	11468.750979
2019-03-01	11011.824827	10511.440099	11564.257832
2019-04-01	11033.104908	10497.476082	11567.432655

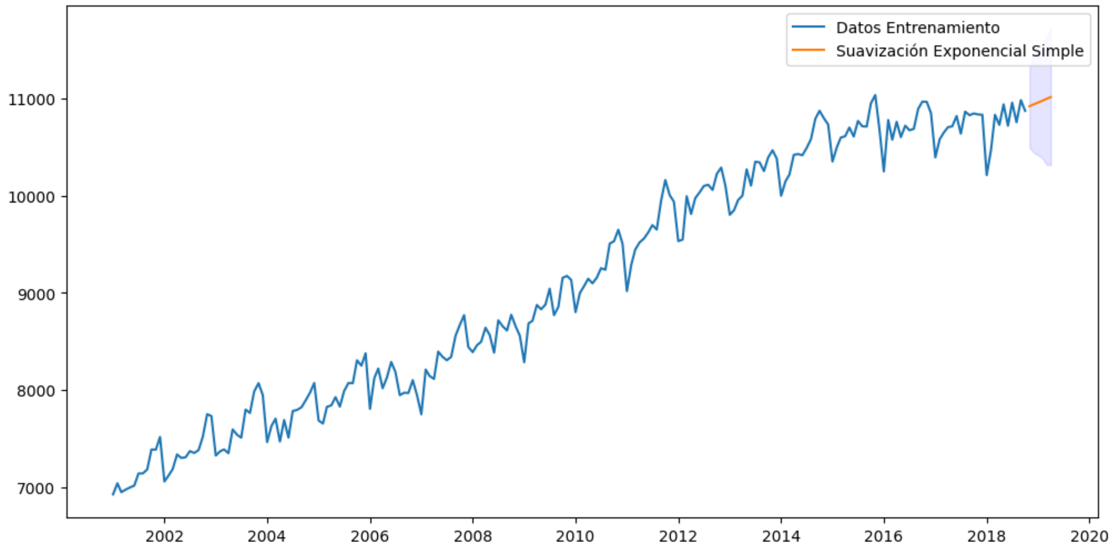


RMSE: 381.54588770018285

[16]:
```
suavizacion_exp_lin_holt_mul_add_mse = build_ets_model(train_td, test_td,␣
↪horizon, error='mul', trend='add')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	10922.345053	10495.554743	11322.527934
2018-12-01	10941.164971	10444.883868	11412.966759
2019-01-01	10959.984890	10419.964059	11473.942701
2019-02-01	10978.804809	10388.027086	11556.554252
2019-03-01	10997.624728	10322.711351	11620.302733
2019-04-01	11016.444647	10316.590987	11717.302760



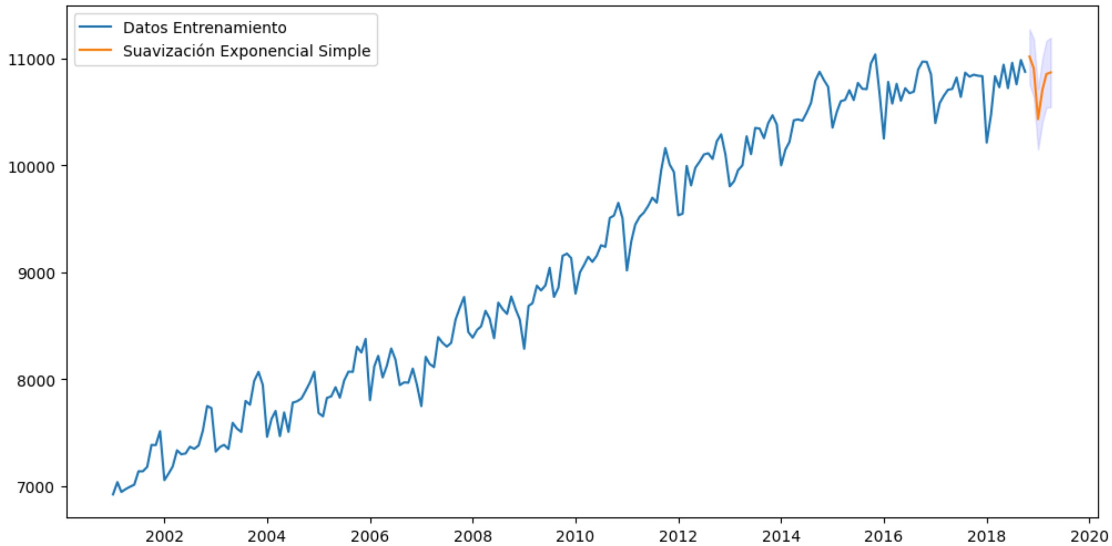

```
RMSE: 371.54436053379465
```

4 Suavización Exponencial Lineal de Winters (Holt-Winters)

[17]:
```
suavizacion_exp_lin_holt_winters_add_add_add_mse = build_ets_model(train_td,␣
↪test_td, horizon, error='add', trend='add', seasonal='add')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	11016.615370	10758.765337	11274.465403
2018-12-01	10910.345328	10638.016873	11182.673784
2019-01-01	10431.804223	10145.726486	10717.881959
2019-02-01	10707.064097	10407.865684	11006.262509
2019-03-01	10853.107263	10541.337405	11164.877121
2019-04-01	10868.686776	10544.830737	11192.542816

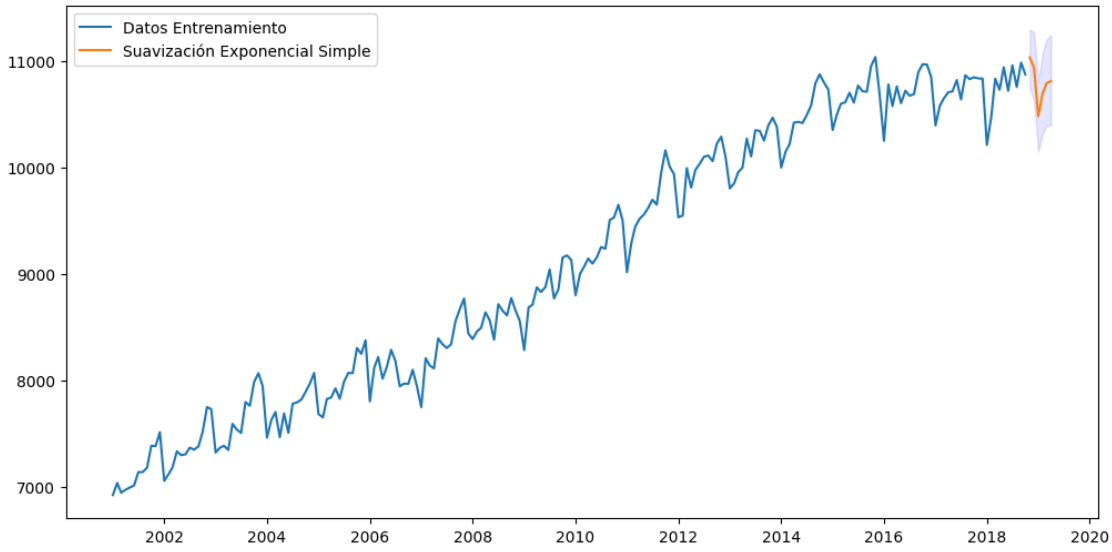


RMSE: 163.6081475588887

[18]:
```
suavizacion_exp_lin_holt_winters_mul_mul_mul_mse = build_ets_model(train_td,␣
↪test_td, horizon, error='mul', trend='mul', seasonal='mul')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	11033.314201	10745.375090	11298.025012
2018-12-01	10941.667798	10628.164994	11268.005370
2019-01-01	10481.956092	10148.392835	10805.996446
2019-02-01	10698.260889	10318.868849	11078.990850
2019-03-01	10791.000570	10392.957022	11204.690499
2019-04-01	10811.523619	10393.992564	11244.661472

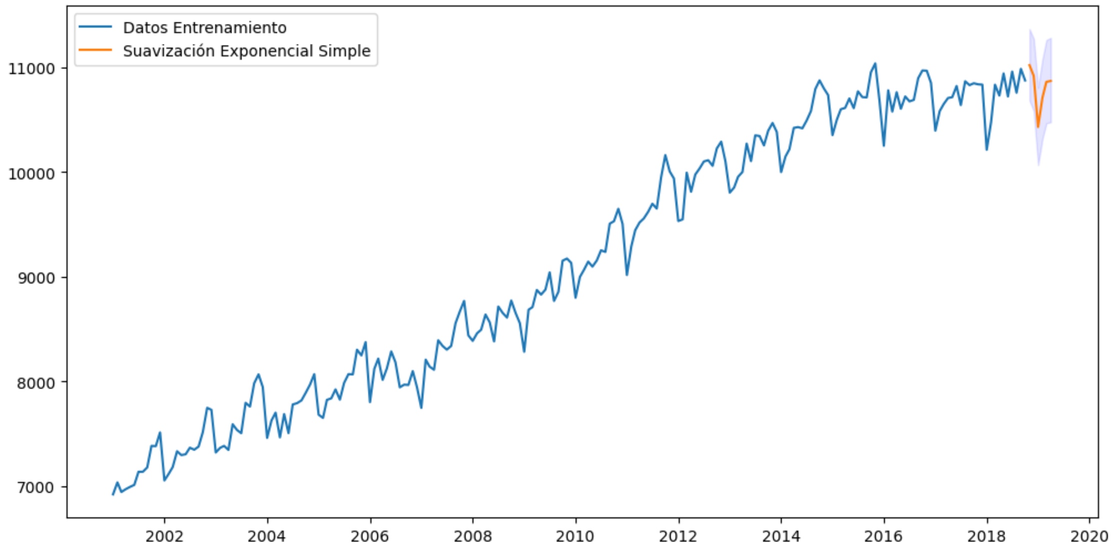



```
RMSE: 160.56763429342286
```

[19]:
```
suavizacion_exp_lin_holt_winters_mul_add_add_mse = build_ets_model(train_td,
    test_td, horizon, error='mul', trend='add', seasonal='add')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	11020.412574	10682.089945	11365.090619
2018-12-01	10918.631490	10583.678982	11271.840261
2019-01-01	10430.597045	10066.757909	10806.838204
2019-02-01	10709.637041	10319.300147	11077.954524
2019-03-01	10860.927613	10466.943594	11261.091712
2019-04-01	10869.560918	10475.711904	11281.063121

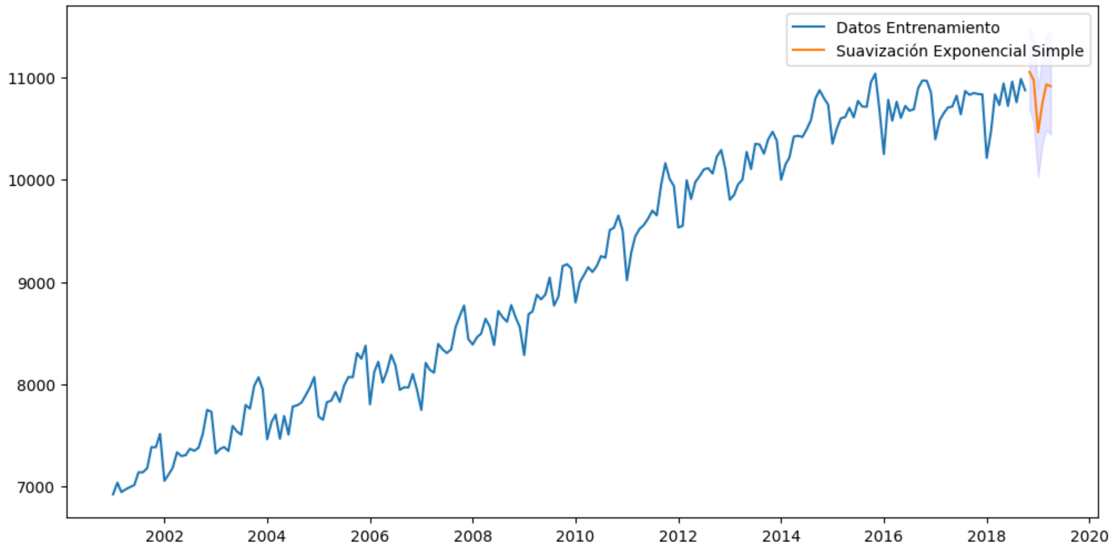


RMSE: 166.39049859272805

[20]:
```
suavizacion_exp_lin_holt_winters_mul_mul_add_mse = build_ets_model(train_td,␣
↪test_td, horizon, error='mul', trend='mul', seasonal='add')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	11052.042881	10691.720340	11472.922287
2018-12-01	10976.359576	10557.310188	11405.754579
2019-01-01	10464.205848	10024.924884	10887.874364
2019-02-01	10753.075830	10351.276726	11194.546482
2019-03-01	10932.161752	10488.035770	11422.547614
2019-04-01	10913.766433	10441.769343	11435.991247

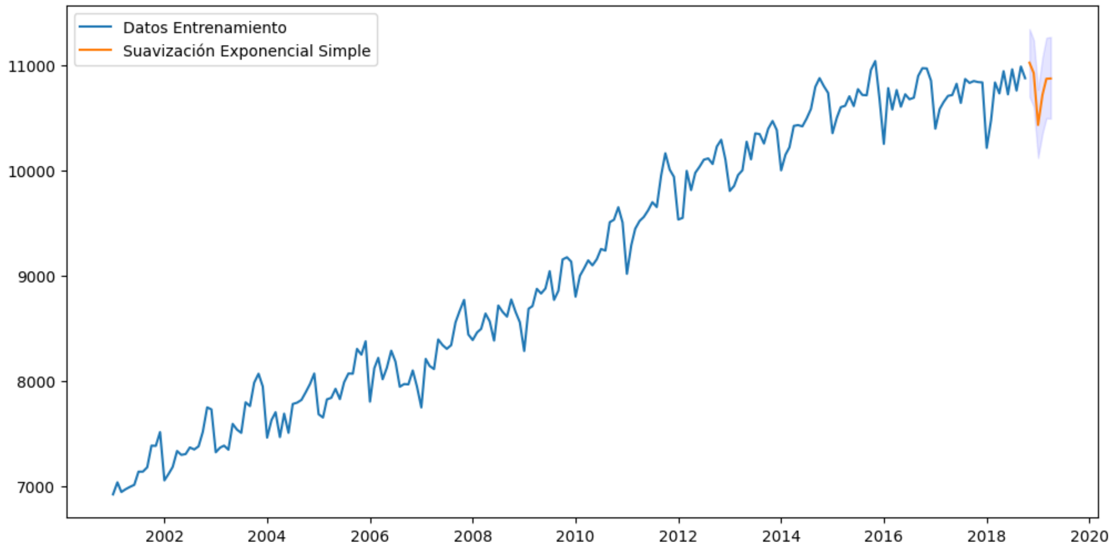



```
RMSE: 208.7105001239104
```

[21]:
```
suavizacion_exp_lin_holt_winters_add_mul_add_mse = build_ets_model(train_td,␣
↪test_td, horizon, error='add', trend='mul', seasonal='add')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	11021.454009	10698.663118	11341.163994
2018-12-01	10923.952572	10605.105126	11236.364424
2019-01-01	10430.847684	10118.152157	10766.084183
2019-02-01	10714.866687	10350.308152	11072.505606
2019-03-01	10869.083615	10495.514318	11258.534893
2019-04-01	10871.565260	10491.425589	11266.350183

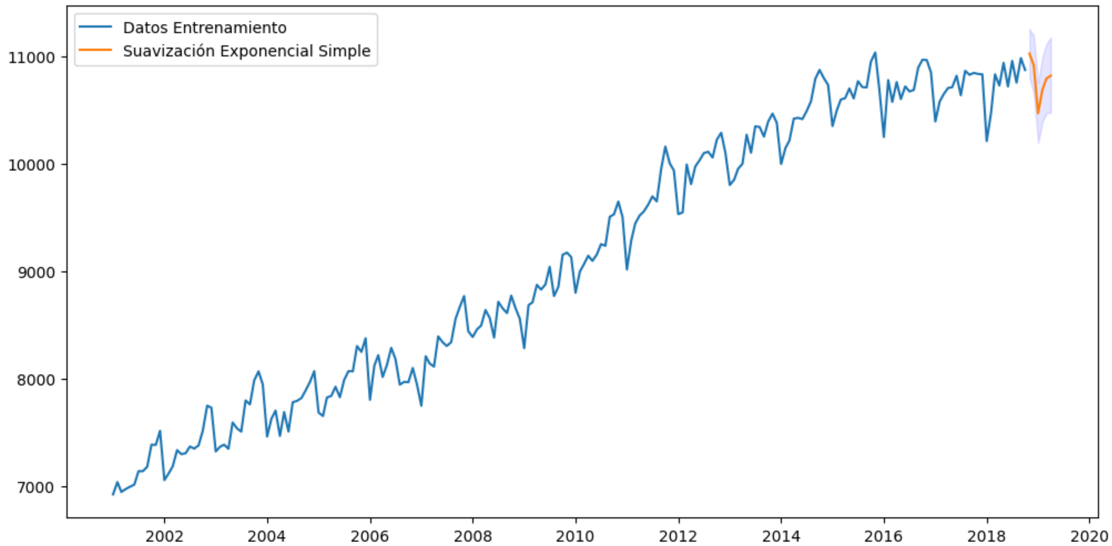



```
RMSE: 169.2398581225239
```

[22]:
```python
suavizacion_exp_lin_holt_winters_add_add_mul_mse = build_ets_model(train_td,
    test_td, horizon, error='add', trend='add', seasonal='mul')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

	Point_forecast	lower_95	upper_95
2018-11-01	11027.470105	10798.874263	11255.771614
2018-12-01	10921.685157	10660.819998	11195.552852
2019-01-01	10472.005916	10194.495079	10753.531830
2019-02-01	10691.000571	10391.511945	11000.272826
2019-03-01	10793.959412	10470.574174	11117.200920
2019-04-01	10821.997308	10478.932642	11177.612142



RMSE: 156.41470708036718

5 Revisión y Elección del Mejor Modelo

[23]:
```
mse_list = {
        "suavizacion_exp_lin_holt_winters_add_add_mul_mse":␣
↪suavizacion_exp_lin_holt_winters_add_add_mul_mse,
        "suavizacion_exp_lin_holt_winters_add_mul_add_mse":␣
↪suavizacion_exp_lin_holt_winters_add_mul_add_mse,
        "suavizacion_exp_lin_holt_winters_mul_mul_add_mse":␣
↪suavizacion_exp_lin_holt_winters_mul_mul_add_mse,
        "suavizacion_exp_lin_holt_winters_mul_add_add_mse":␣
↪suavizacion_exp_lin_holt_winters_mul_add_add_mse,
        "suavizacion_exp_lin_holt_winters_mul_mul_mul_mse":␣
↪suavizacion_exp_lin_holt_winters_mul_mul_mul_mse,
        "suavizacion_exp_lin_holt_winters_add_add_add_mse":␣
↪suavizacion_exp_lin_holt_winters_add_add_add_mse,
        "suavizacion_exp_lin_holt_mul_add_mse":␣
↪suavizacion_exp_lin_holt_mul_add_mse,
        "suavizacion_exp_lin_holt_mul_mul_mse":␣
↪suavizacion_exp_lin_holt_mul_mul_mse,
        "suavizacion_exp_lin_holt_add_mul_mse":␣
↪suavizacion_exp_lin_holt_add_mul_mse,
        "suavizacion_exp_lin_holt_add_add_mse":␣
↪suavizacion_exp_lin_holt_add_add_mse,
        "suavizacion_exp_simple_mul_mse": suavizacion_exp_simple_mul_mse,
        "suavizacion_exp_simple_add_mse": suavizacion_exp_simple_add_mse,
```

```
}


sorted_mse_list = dict(sorted(mse_list.items(), key=lambda item:
 ↪item[1]['rmse']))
for key, value in sorted_mse_list.items():
        print(key)
        print("RMSE:", value['rmse'])
        print("Alpha:", value['alpha'])
        print("Beta:", value['beta'])
        print("Gamma:", value['gamma'])
        print("-----------------------")
```

```
suavizacion_exp_lin_holt_winters_add_add_mul_mse
RMSE: 156.41470708036718
Alpha: 0.5133662616515942
Beta: 0.0013157804729060712
Gamma: 4.8663373834840584e-05
-----------------------
suavizacion_exp_lin_holt_winters_mul_mul_mul_mse
RMSE: 160.56763429342286
Alpha: 0.5465853506695763
Beta: 5.465853506695763e-05
Gamma: 4.5341464933042375e-05
-----------------------
suavizacion_exp_lin_holt_winters_add_add_add_mse
RMSE: 163.6081475588887
Alpha: 0.3397512482944894
Beta: 3.397512482944894e-05
Gamma: 0.3013646393190514
-----------------------
suavizacion_exp_lin_holt_winters_mul_add_add_mse
RMSE: 166.39049859272805
Alpha: 0.34897040496600673
Beta: 3.4897040496600676e-05
Gamma: 0.3261391871755503
-----------------------
suavizacion_exp_lin_holt_winters_add_mul_add_mse
RMSE: 169.2398581225239
Alpha: 0.3887356892308206
Beta: 3.887356892308206e-05
Gamma: 0.3372490744906431
-----------------------
suavizacion_exp_lin_holt_winters_mul_mul_add_mse
RMSE: 208.7105001239104
Alpha: 0.3063305159163973
Beta: 0.002575810200642496
```

```
Gamma: 0.4251748539290532
-----------------------
suavizacion_exp_simple_mul_mse
RMSE: 300.4282950082703
Alpha: 0.6342210778435239
Beta: None
Gamma: None
-----------------------
suavizacion_exp_simple_add_mse
RMSE: 300.4290298412983
Alpha: 0.6343030045478203
Beta: None
Gamma: None
-----------------------
suavizacion_exp_lin_holt_add_add_mse
RMSE: 370.1579750635174
Alpha: 0.571963780298305
Beta: 0.006149418787101443
Gamma: None
-----------------------
suavizacion_exp_lin_holt_mul_add_mse
RMSE: 371.54436053379465
Alpha: 0.5782798563009995
Beta: 0.005944765096908403
Gamma: None
-----------------------
suavizacion_exp_lin_holt_mul_mul_mse
RMSE: 381.54588770018285
Alpha: 0.5450401812292424
Beta: 5.450401812292424e-05
Gamma: None
-----------------------
suavizacion_exp_lin_holt_add_mul_mse
RMSE: 381.54588770018285
Alpha: 0.5450401812292424
Beta: 5.450401812292424e-05
Gamma: None
-----------------------
```

[30]:
```
# Definimos el diccionario con los valores de MSE
mse_list = {
    "suavizacion_exp_lin_holt_winters_add_add_mul_mse":␣
 ↪suavizacion_exp_lin_holt_winters_add_add_mul_mse,
    "suavizacion_exp_lin_holt_winters_add_mul_add_mse":␣
 ↪suavizacion_exp_lin_holt_winters_add_mul_add_mse,
    "suavizacion_exp_lin_holt_winters_mul_mul_add_mse":␣
 ↪suavizacion_exp_lin_holt_winters_mul_mul_add_mse,
```

```
    "suavizacion_exp_lin_holt_winters_mul_add_add_mse": suavizacion_exp_lin_holt_winters_mul_add_add_mse,
    "suavizacion_exp_lin_holt_winters_mul_mul_mul_mse": suavizacion_exp_lin_holt_winters_mul_mul_mul_mse,
    "suavizacion_exp_lin_holt_winters_add_add_add_mse": suavizacion_exp_lin_holt_winters_add_add_add_mse,
    "suavizacion_exp_lin_holt_mul_add_mse": suavizacion_exp_lin_holt_mul_add_mse,
    "suavizacion_exp_lin_holt_mul_mul_mse": suavizacion_exp_lin_holt_mul_mul_mse,
    "suavizacion_exp_lin_holt_add_mul_mse": suavizacion_exp_lin_holt_add_mul_mse,
    "suavizacion_exp_lin_holt_add_add_mse": suavizacion_exp_lin_holt_add_add_mse,
    "suavizacion_exp_simple_mul_mse": suavizacion_exp_simple_mul_mse,
    "suavizacion_exp_simple_add_mse": suavizacion_exp_simple_add_mse,
}

# Ordenamos los modelos según el RMSE

sorted_mse_list = dict(sorted(mse_list.items(), key=lambda item: item[1]['rmse']))

# Creamos una lista de diccionarios para crear el DataFrame

data = [{"Modelo": key, "RMSE": value['rmse']} for key, value in sorted_mse_list.items()]

# Convertimos la lista de diccionarios en un DataFrame de pandas

df = pd.DataFrame(data)

# Establecer el índice como el nombre del modelo (opcional, solo para esconder el índice numérico original)

df = df.set_index("Modelo")

# Resaltar el RMSE más bajo

def highlight_min(s):
    is_min = s == s.min()
    return ['background-color: lightgreen' if v else '' for v in is_min]

#Estilo

styled_df = df.style.apply(highlight_min, subset=['RMSE']).set_table_styles(
```

```
    [{'selector': 'th', 'props': [('border', '1px solid black')]},
     {'selector': 'td', 'props': [('border', '1px solid black')]}]
).set_properties(**{'text-align': 'center'})

styled_df
```

[30]: <pandas.io.formats.style.Styler at 0x77fd6b277dc0>

[24]:
```
suavizacion_exp_lin_holt_winters_add_add_mul_mse['preds']
```

[24]:

	Point_forecast	lower_95	upper_95
2018-11-01	11027.470105	10798.874263	11255.771614
2018-12-01	10921.685157	10660.819998	11195.552852
2019-01-01	10472.005916	10194.495079	10753.531830
2019-02-01	10691.000571	10391.511945	11000.272826
2019-03-01	10793.959412	10470.574174	11117.200920
2019-04-01	10821.997308	10478.932642	11177.612142

6 Usar Alpha, Beta y Gamma

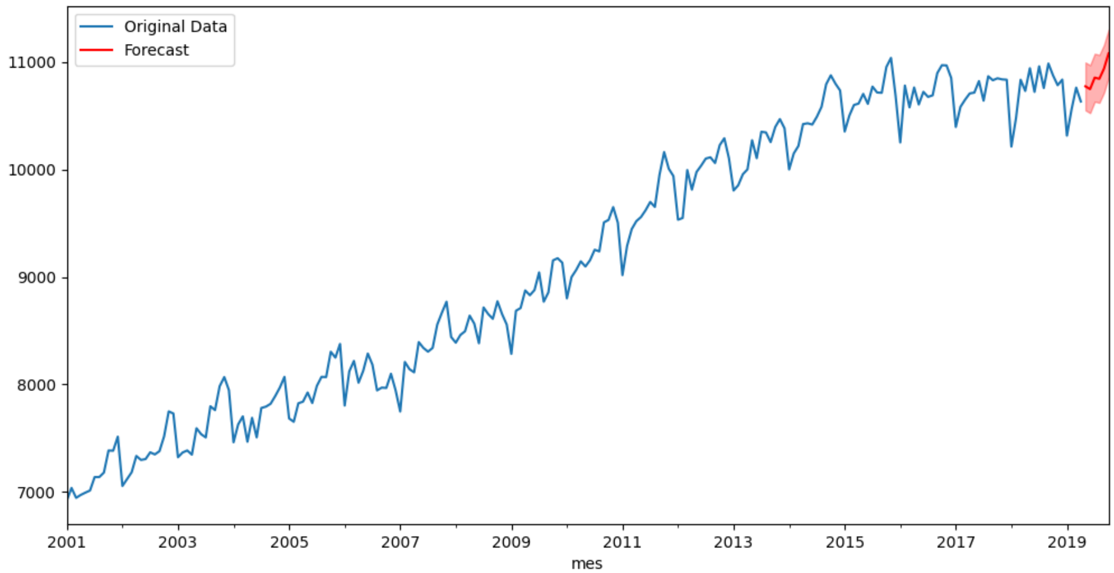
[25]:
```
## Ahora se ajusta el modelo final con todos los datos

final_model =␣
 ↪ETSModel(endog=data["Ocupados"],error="add",trend="add",seasonal="mul")
final_model_fit = final_model.fit_constrained({'smoothing_level': 0.
 ↪5133659457086996,'smoothing_trend': 0.
 ↪0013157803999827881,'smoothing_seasonal':4.866340542913004e-05})

print("alpha: ", final_model_fit.alpha)
print("beta: ", final_model_fit.beta)
print("gamma: ", final_model_fit.gamma)
```

```
alpha:  0.5133659457086996
beta:  0.0013157803999827881
gamma:  4.866340542913004e-05
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: No frequency information was provided, so inferred frequency MS
will be used.
  self._init_dates(dates, freq)
```

[26]:
```
forecast = final_model_fit.forecast(horizon)
fig, ax = plt.subplots(figsize=(12, 6))
data["Ocupados"].plot(ax=ax, label="Original Data")
forecast.plot(ax=ax, label="Forecast", color='red')
```

```
plt.fill_between(forecast.index, forecast - 1.96 * final_model_fit.resid.std(),
    forecast + 1.96 * final_model_fit.resid.std(), color='red', alpha=0.3)
plt.legend()
plt.show()
```



[27]:
```
# Confidence intervals
ci = final_model_fit.get_prediction(start=forecast.index[0], end=forecast.
    index[-1])
conf_forecast = ci.pred_int(alpha=0.05)
limits = ci.predicted_mean

preds_holt = pd.concat([limits, conf_forecast], axis=1)
preds_holt.columns = ['Point_forecast', 'lower_95', 'upper_95']
preds_holt
```

[27]:

	Point_forecast	lower_95	upper_95
2019-05-01	10772.637904	10547.849944	10972.776011
2019-06-01	10747.213943	10513.256674	10995.217142
2019-07-01	10853.759047	10576.236125	11131.321802
2019-08-01	10842.999845	10547.944334	11133.476429
2019-09-01	10936.731112	10603.521965	11251.860335
2019-10-01	11079.324058	10737.574795	11416.984862