arios-modelos-14nov-version9-final

November 23, 2023

[85]:
```
#!pip install pmdarima
#!pip install skforecast
#!pip install --upgrade statsmodels pmdarima
#!pip install train_feature
!pip install ForecasterAutoreg
```

```
ERROR: Could not find a version that satisfies the requirement
ForecasterAutoreg (from versions: none)
ERROR: No matching distribution found for ForecasterAutoreg
```

[3]:
```
# Manipulación y tratamiento de Datos
import numpy as np
import pandas as pd
import os

# Visualización de datos
import plotly.express as px
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')

# Modelación Arima
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller

# Modelo Auto-Arima
from pmdarima import auto_arima
import pmdarima as pm

# Métrica de Evaluación
from sklearn.metrics import mean_squared_error
from statsmodels.tools.eval_measures import rmse
from sklearn import metrics
```

```
# No presentar advertencias
import warnings
warnings.filterwarnings("ignore")
```

[40]:
```
# ruta de archivos

#files = os.listdir("c:\\archivos\proyecto")
#os.chdir(r'C:\archivos\proyecto')

csv_path = 'urgencias final_nov.txt'

# Intentar leer el archivo con diferentes codificaciones y manejo de errores
encodings_to_try = ['utf-8', 'latin-1', 'ISO-8859-1']

for encoding in encodings_to_try:
    try:
        df_real = pd.read_csv(csv_path, sep=";", header=None, encoding=encoding)
        # Si se llega a este punto, la lectura fue exitosa, así que puedes␣
 ↪salir del bucle
        break
    except UnicodeDecodeError:
        print(f"Error al leer con la codificación {encoding}. Intentando con␣
 ↪otra.")
```

```
Error al leer con la codificación utf-8. Intentando con otra.
```

[41]:
```
headers =␣
 ↪["FECHA_LLEGADA","TIEMPO_TOTAL_FINAL","CENTRO_ATENCION","CLASIFICACION_TRIAGE","PACIENTE_ED
print("headers\n", headers)
df_real.columns = headers
df_real = df_real.drop(0)
```

```
headers
 ['FECHA_LLEGADA', 'TIEMPO_TOTAL_FINAL', 'CENTRO_ATENCION',
'CLASIFICACION_TRIAGE', 'PACIENTE_EDAD', 'PACIENTE_#_DOCUMENTO', 'EDAD_RANGO',
'NOMBRE_ENTIDAD', 'SEXO', 'Month']
```

[42]:
```
# convertir y arreglar datos
df_real['Month'] = pd.to_datetime(df_real['Month'])

# crear indice de frecuencia
df_real['Month'] = df_real['Month'].dt.to_period('M')
# nuevo_df.index.freq = 'MS'

# indexar
df_real = df_real.set_index("Month")
```

```python
# numerico
df_real["TIEMPO_TOTAL_FINAL"] = pd.
 ↪to_numeric(df_real["TIEMPO_TOTAL_FINAL"],errors='coerce')

# Calcular la mediana y arreglar datos

#df["TIEMPO_TOTAL_FINAL"] = pd.
 ↪to_numeric(df["TIEMPO_TOTAL_FINAL"],errors='coerce')
median = df_real['TIEMPO_TOTAL_FINAL'].median()

# Corregir valores atípicos
df_real.loc[df_real['TIEMPO_TOTAL_FINAL'] > 420, 'TIEMPO_TOTAL_FINAL'] = median
df_real.loc[df_real['TIEMPO_TOTAL_FINAL'] < 0, 'TIEMPO_TOTAL_FINAL'] = median
```

[43]:
```python
df_real['FECHA_LLEGADA'] = pd.to_datetime(df_real['FECHA_LLEGADA'])
df_real['DIA_SEMANA'] = df_real['FECHA_LLEGADA'].dt.dayofweek
df_real['ANUAL'] = df_real['FECHA_LLEGADA'].dt.year
```

[44]:
```python
# Filtrar a partir del año 2021

anho_inicio = 2022
data1 = df_real[df_real['ANUAL'] >= anho_inicio]
#df_hearth.to_csv('ind_urgencias_final_2023.txt', sep=';', index=False)
```

[45]:
```python
data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
PeriodIndex: 224412 entries, 2023-07 to 2023-04
Freq: M
Data columns (total 11 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   FECHA_LLEGADA         224412 non-null  datetime64[ns]
 1   TIEMPO_TOTAL_FINAL    224410 non-null  float64
 2   CENTRO_ATENCION       224412 non-null  object
 3   CLASIFICACION_TRIAGE  224412 non-null  object
 4   PACIENTE_EDAD         224412 non-null  object
 5   PACIENTE_#_DOCUMENTO  224412 non-null  object
 6   EDAD_RANGO            224412 non-null  object
 7   NOMBRE_ENTIDAD        224412 non-null  object
 8   SEXO                  224412 non-null  object
 9   DIA_SEMANA            224412 non-null  int64
 10  ANUAL                 224412 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(2), object(7)
memory usage: 20.5+ MB
```

[46]:
```
df = data1
```

[47]:
```
data = data1
```

[48]:
```
data
```

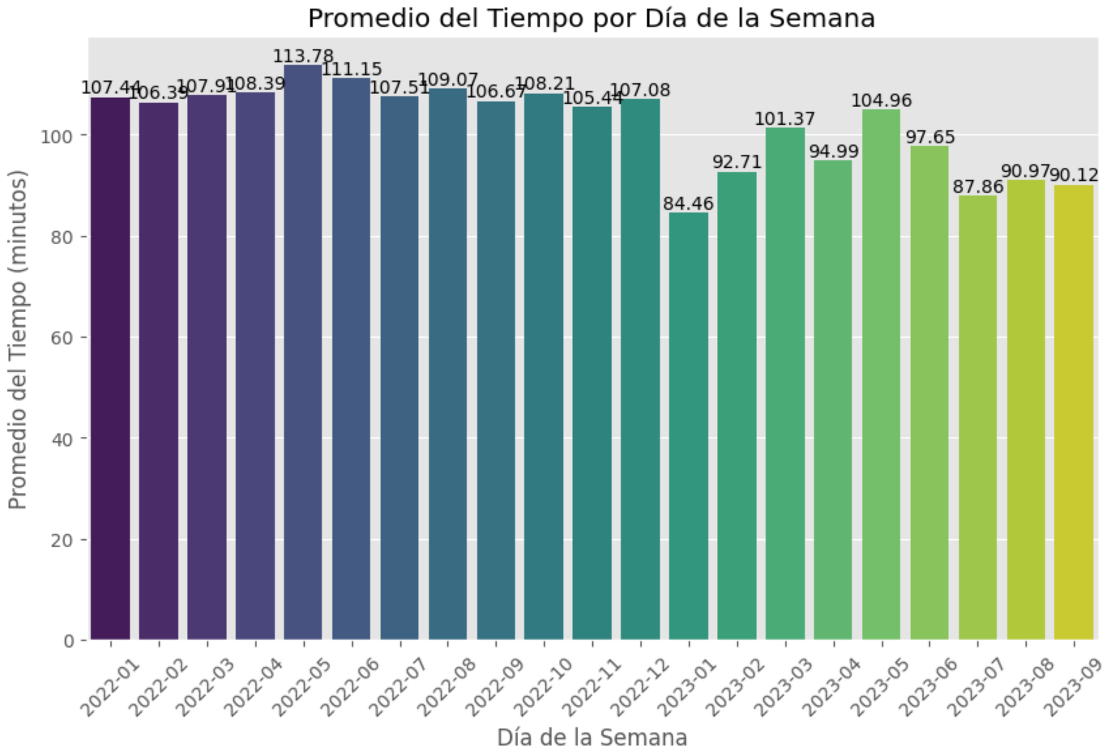
[48]:
```
                FECHA_LLEGADA  TIEMPO_TOTAL_FINAL  \
Month
2023-07 2023-07-11 21:19:10               15.00
2023-02 2023-02-24 05:31:45               16.00
2023-08 2023-08-07 23:16:10               16.00
2023-09 2023-09-13 01:56:53               17.00
2023-06 2023-06-29 02:42:38               18.00
…                       …                   …
2022-07 2022-07-21 10:27:00               84.33
2022-12 2022-12-15 14:50:00               84.33
2023-04 2023-04-10 18:02:25               84.33
2023-07 2023-07-01 16:37:54               84.33
2023-04 2023-04-13 17:48:28               84.33

                              CENTRO_ATENCION  \
Month
2023-07                                    VC
2023-02                                    VB
2023-08                                    VC
2023-09                                    UC
2023-06                                    UC
…                                         …
2022-07                 ME - HOSPITAL MEISSEN
2022-12  UC - CENTRO DE SALUD SANTA LIBRADA I
2023-04                                    ME
2023-07                                    TN
2023-04                                    ME

                                 CLASIFICACION_TRIAGE PACIENTE_EDAD  \
Month
2023-07                                             3            24
2023-02                                             3            69
2023-08                                             3            50
2023-09                                             3            79
2023-06                                             3            72
…                                                 …           …
2022-07  3 - TRIAGE III - NO DEBE SUPERAR LAS 3 HORAS     58 ANO(S)
2022-12  3 - TRIAGE III - NO DEBE SUPERAR LAS 3 HORAS     54 ANO(S)
2023-04                                             3             4
2023-07                                             3             3
2023-04                                             3            17
```

```
        PACIENTE_#_DOCUMENTO        EDAD_RANGO             NOMBRE_ENTIDAD  \
Month
2023-07           1024595942          JUVENTUD                     EPSC34
2023-02              4450531      ADULTO MAYOR                     EPSC34
2023-08              5267156            ADULTO                     EPSC34
2023-09              5667630      ADULTO MAYOR                     EPSC34
2023-06              3014617      ADULTO MAYOR                     EPSS05
…                        …               …                          …
2022-07             39532594           ADULTEZ  CAPITAL SALUD EPS-S S.A.S
2022-12             39723106           ADULTEZ  CAPITAL SALUD EPS-S S.A.S
2023-04           1033822858   PRIMERA INFANCIA                    EPSC34
2023-07           1243858533   PRIMERA INFANCIA                    EPSC34
2023-04           1010176536        ADOLECENCIA                    EPSS41

              SEXO  DIA_SEMANA  ANUAL
Month
2023-07  MASCULINO           1   2023
2023-02  MASCULINO           4   2023
2023-08   FEMENINO           0   2023
2023-09  MASCULINO           2   2023
2023-06  MASCULINO           3   2023
…             …          …    …
2022-07   FEMENINO           3   2022
2022-12   FEMENINO           3   2022
2023-04  MASCULINO           0   2023
2023-07   FEMENINO           5   2023
2023-04   FEMENINO           3   2023

[224412 rows x 11 columns]
```

[51]:

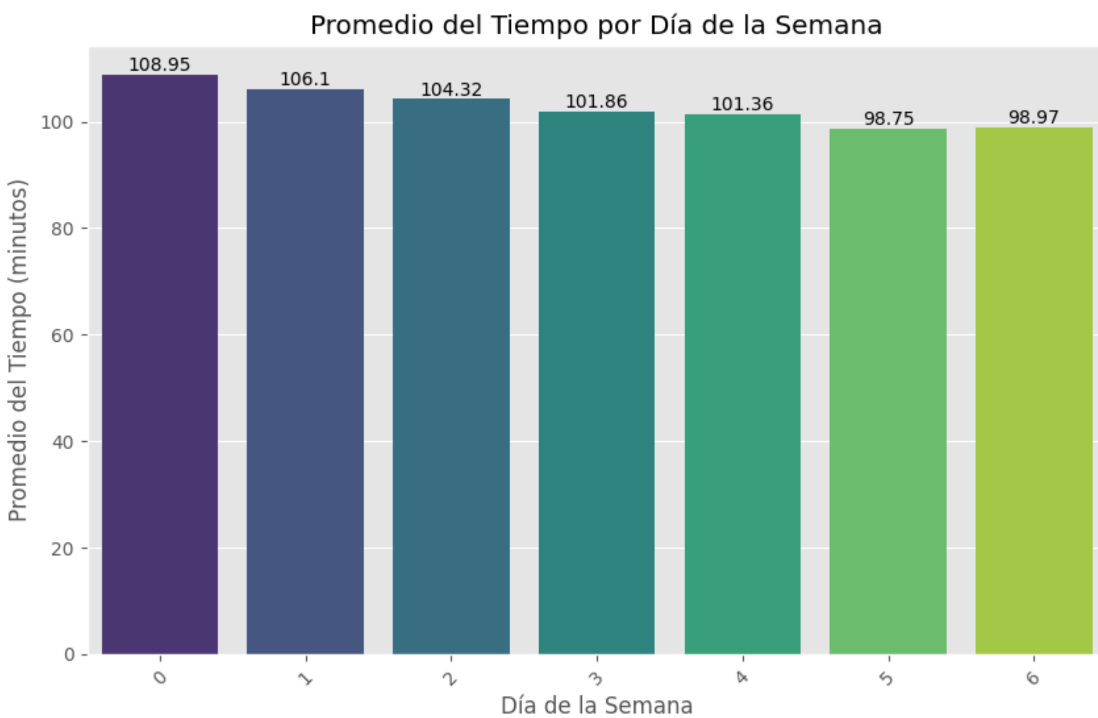
```python
import seaborn as sns

# Agrupar por día de la semana y calcular el promedio del Tiempo_total_minutos
 ↪en cada grupo

promedio_tiempo_por_grupo =data1.groupby(['Month'])['TIEMPO_TOTAL_FINAL'].
 ↪mean().reset_index()

# Renombrar la columna del promedio
promedio_tiempo_por_grupo = promedio_tiempo_por_grupo.
 ↪rename(columns={'TIEMPO_TOTAL_FINAL': 'Promedio_Tiempo'})

plt.figure(figsize=(10, 6))
ax = sns.barplot(data=promedio_tiempo_por_grupo, x='Month',
 ↪y='Promedio_Tiempo', palette='viridis')
plt.xlabel('Día de la Semana')
```

```
plt.ylabel('Promedio del Tiempo (minutos)')
plt.title('Promedio del Tiempo por Día de la Semana')
plt.xticks(rotation=45)

# Agregar etiquetas en las barras
for index, row in promedio_tiempo_por_grupo.iterrows():
    ax.annotate(str(round(row['Promedio_Tiempo'], 2)), (index,␣
↪row['Promedio_Tiempo']), ha='center', va='bottom')
plt.show()
```



[52]:
```
import seaborn as sns

# Agrupar por día de la semana y calcular el promedio del Tiempo_total_minutos␣
↪en cada grupo

promedio_tiempo_por_grupo =data1.groupby(['DIA_SEMANA'])['TIEMPO_TOTAL_FINAL'].
↪mean().reset_index()

# Renombrar la columna del promedio
promedio_tiempo_por_grupo = promedio_tiempo_por_grupo.
↪rename(columns={'TIEMPO_TOTAL_FINAL': 'Promedio_Tiempo'})
```

```python
plt.figure(figsize=(10, 6))
ax = sns.barplot(data=promedio_tiempo_por_grupo, x='DIA_SEMANA',␣
 ↪y='Promedio_Tiempo', palette='viridis')
plt.xlabel('Día de la Semana')
plt.ylabel('Promedio del Tiempo (minutos)')
plt.title('Promedio del Tiempo por Día de la Semana')
plt.xticks(rotation=45)

# Agregar etiquetas en las barras
for index, row in promedio_tiempo_por_grupo.iterrows():
    ax.annotate(str(round(row['Promedio_Tiempo'], 2)), (index,␣
 ↪row['Promedio_Tiempo']), ha='center', va='bottom')
plt.show()
```



[53]:
```python
# Funcion para evaluar

def evaluacion_metrica(y_true, y_pred):

    def mean_absolute_percentage_error(y_true, y_pred):
        y_true, y_pred = np.array(y_true), np.array(y_pred)
        return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
    print('Evaluation metric results:-')
    print(f'MSE is : {metrics.mean_squared_error(y_true, y_pred)}')
```

```
    print(f'MAE is : {metrics.mean_absolute_error(y_true, y_pred)}')
    print(f'RMSE is : {np.sqrt(metrics.mean_squared_error(y_true, y_pred))}')
    print(f'MAPE is : {mean_absolute_percentage_error(y_true, y_pred)}')
    print(f'R2 is : {metrics.r2_score(y_true, y_pred)}',end='\n\n')
```

[60]:
```
# Agrupar de acuerdo a la grafica

# agrupamiento de mes
nuevo_df = df.groupby('Month')['TIEMPO_TOTAL_FINAL'].mean().reset_index()

df6 = nuevo_df.copy()

# Convierte el índice Period a cadena
#df6.index = df6.index.astype(str)
df6['Month1'] = df6['Month'].astype(str)

# Crea el gráfico de líneas
fig = px.line(df6, x='Month1', y='TIEMPO_TOTAL_FINAL', template='plotly_dark',␣
 ↪title='Total minutos')

# Muestra el gráfico
fig.show()
```

[62]:
```
# División de para entrenamiento y prueba
train_data = df6[:len(df6)-5]
test_data = df6[len(df6)-5:]
test=test_data.copy()

df6=df6.reset_index()

df_fb=df6.rename(columns={"Month":"ds", "TIEMPO_TOTAL_FINAL":"y"} )

train_data_pr = df_fb.iloc[:len(df6)-5]
test_data_pr = df_fb.iloc[len(df6)-5:]
```

[63]:
```
# 1. Modelo : Prophet Forecast

from prophet import Prophet

train_data_pr['ds'] = train_data_pr['ds'].dt.to_timestamp()
m = Prophet()
m.fit(train_data_pr)

future = m.make_future_dataframe(periods=5,freq='MS')
prophet_pred = m.predict(future)
# prophet_pred.tail()    ---  ver detalle
```

```python
# asignar a prophet_pred
prophet_pred = pd.DataFrame({"Date" : prophet_pred[-5:]['ds'], "Pred" :␣
↪prophet_pred[-5:]["yhat"]})
prophet_pred = prophet_pred.set_index("Date")
prophet_pred.index.freq = "MS"
prophet_pred
test_data["Prophet_Predictions"] = prophet_pred['Pred'].values
test_data.head()

# Grafica test_data
a=test_data[["TIEMPO_TOTAL_FINAL","Prophet_Predictions"]]
fig = px.line(a, x=test_data.index, y=a.columns,template = "plotly_dark",
              title="Predicción con Modelo Prophet")
fig.show()

# evaluacion de Prophet_Predictions
evaluacion_metrica(test_data["TIEMPO_TOTAL_FINAL"],test_data["Prophet_Predictions"])
```

```
INFO:prophet:Disabling yearly seasonality. Run prophet with
yearly_seasonality=True to override this.
INFO:prophet:Disabling weekly seasonality. Run prophet with
weekly_seasonality=True to override this.
INFO:prophet:Disabling daily seasonality. Run prophet with
daily_seasonality=True to override this.
INFO:prophet:n_changepoints greater than number of observations. Using 11.
DEBUG:cmdstanpy:input tempfile: /tmp/tmp6jfyo2yv/so_ou8rj.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmp6jfyo2yv/h3sk1zyi.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.10/dist-
packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=62709', 'data',
'file=/tmp/tmp6jfyo2yv/so_ou8rj.json', 'init=/tmp/tmp6jfyo2yv/h3sk1zyi.json',
'output',
'file=/tmp/tmp6jfyo2yv/prophet_modelkyr1dxed/prophet_model-20231114195133.csv',
'method=optimize', 'algorithm=newton', 'iter=10000']
19:51:33 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
19:51:33 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```

```
Evaluation metric results:-
MSE is : 26.468700671305225
MAE is : 4.183549665873139
RMSE is : 5.144774112758035
MAPE is : 4.32849893927382
R2 is : 0.3213828643966856
```

[19]:
```python
# 2.  Modelo : ARIMA

#train_data['Month'] = train_data['Month'].dt.to_timestamp()
train_data['Month_numeric'] = train_data['Month'].dt.year * 12 +␣
↪train_data['Month'].dt.month

# Luego, utiliza 'Month_numeric' como la serie temporal en auto_arima
modelo_auto = auto_arima(train_data['Month_numeric'], start_p=0, d=1, start_q=0,
                         max_p=4, max_d=2, max_q=4, start_P=0,
                         D=1, start_Q=0, max_P=2, max_D=1,
                         max_Q=2, m=9, seasonal=True,
                         suppress_warnings=True, stepwise=True,
                         random_state=20, n_fits=50)
print(modelo_auto)

arima_model = SARIMAX(train_data["TIEMPO_TOTAL_FINAL"], order = (0,1,0),␣
↪seasonal_order = (0,1,0,9))
arima_result = arima_model.fit()
arima_result.summary()
```

```
ARIMA(0,1,0)(0,1,0)[9] intercept
```

[19]:

Dep. Variable:	TIEMPO_TOTAL_FINAL	**No. Observations:**	12
Model:	SARIMAX(0, 1, 0)x(0, 1, 0, 12)	**Log Likelihood**	0.000
Date:	Tue, 14 Nov 2023	**AIC**	2.000
Time:	19:24:55	**BIC**	nan
Sample:	0 - 12	**HQIC**	nan
Covariance Type:	opg		

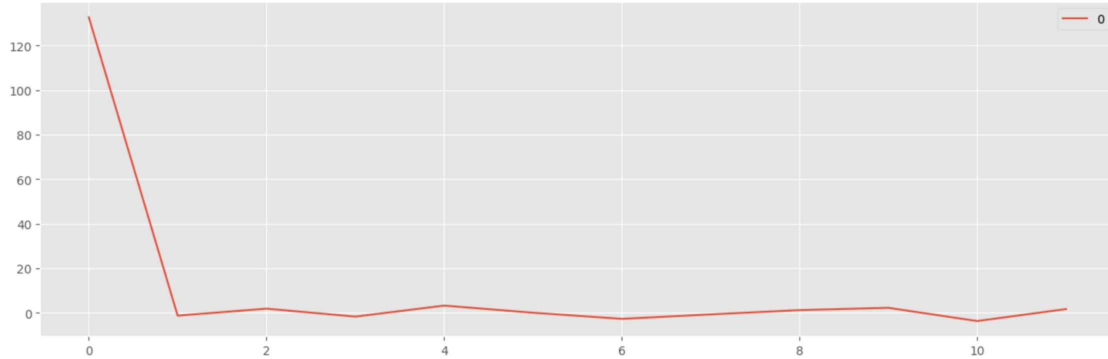
	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
sigma2	1e-10	0	inf	0.000	1e-10	1e-10

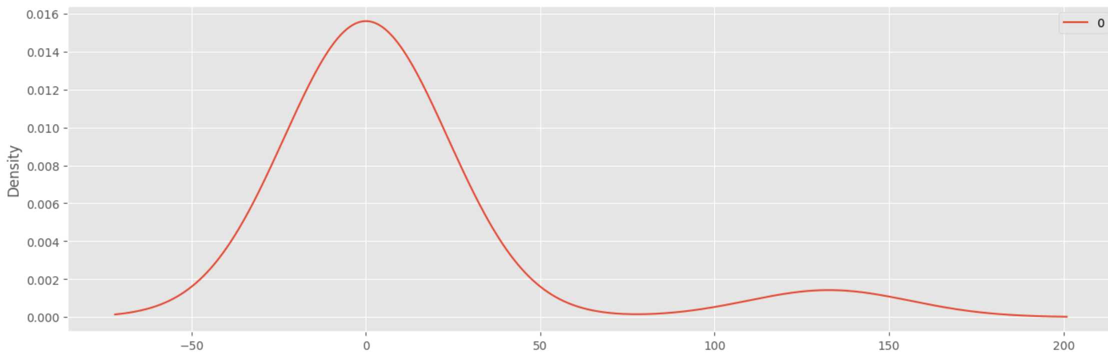
Ljung-Box (L1) (Q):	nan	**Jarque-Bera (JB):**	nan
Prob(Q):	nan	**Prob(JB):**	nan
Heteroskedasticity (H):	nan	**Skew:**	nan
Prob(H) (two-sided):	nan	**Kurtosis:**	nan

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number inf. Standard errors may be unstable.

[20]:
```python
# line plot of residual errors
residuals = pd.DataFrame(arima_result.resid)
residuals.plot(figsize = (16,5));
plt.show();

# kernel density plot of residual errors
```

```
residuals.plot(kind='kde', figsize = (16,5))
plt.show()
print(residuals.describe())
```





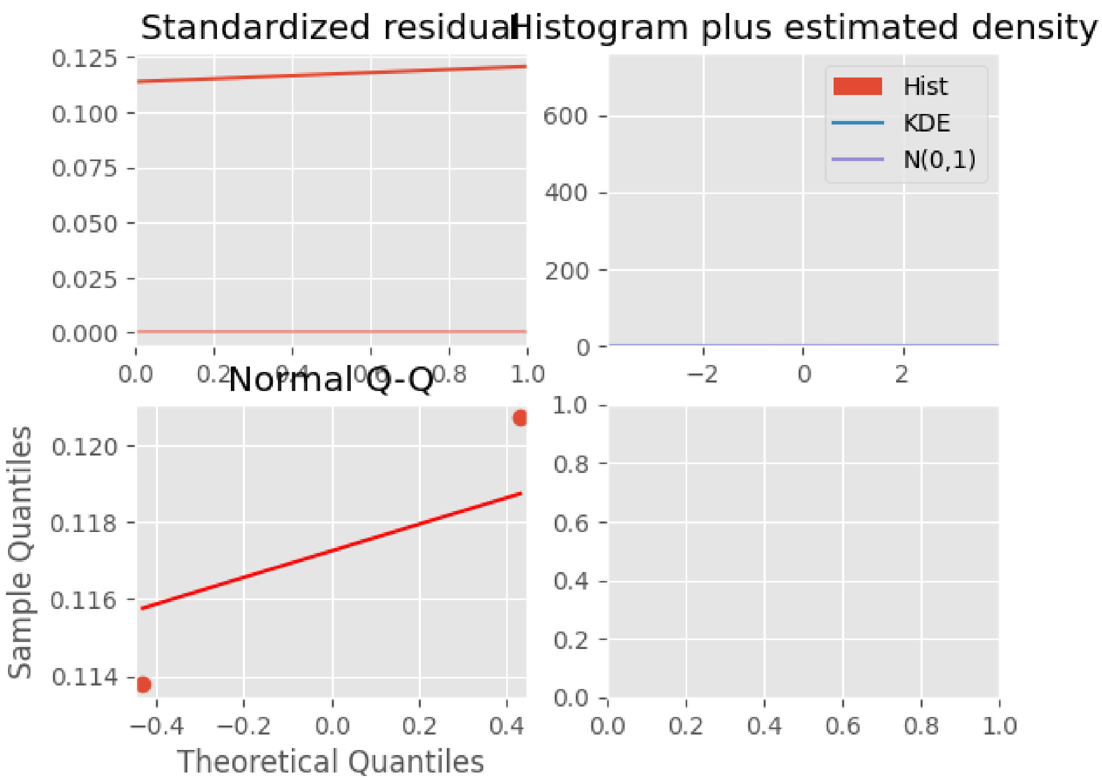

```
                0
count   12.000000
mean    11.101323
std     38.363697
min     -3.668906
25%     -1.356471
50%      0.651822
75%      1.987594
max    132.736505
```

[33]:
```
# Obtener los diagnósticos del modelo ARIMA ajustado por auto_arima
arima_diagnostics = modelo_auto.plot_diagnostics(lags=9)  # Ajusta el número de␣
 ↪lags según tus necesidades
plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
```

```
<ipython-input-33-b8a04f291845> in <cell line: 2>()
      1 # Obtener los diagnósticos del modelo ARIMA ajustado por auto_arima
----> 2 arima_diagnostics = modelo_auto.plot_diagnostics(lags=9)  # Ajusta el␣
 ↪número de lags según tus necesidades
      3 plt.show()

/usr/local/lib/python3.10/dist-packages/pmdarima/utils/metaestimators.py in␣
 ↪<lambda>(*args, **kwargs)
     51
     52         # lambda, but not partial, allows help() to work with␣
 ↪update_wrapper
---> 53         out = (lambda *args, **kwargs: self.fn(obj, *args, **kwargs))
     54         # update the docstring of the returned function
     55         update_wrapper(out, self.fn)

/usr/local/lib/python3.10/dist-packages/pmdarima/arima/arima.py in␣
 ↪plot_diagnostics(self, variable, lags, fig, figsize)
   1395         ax = fig.add_subplot(224)
   1396         from statsmodels.graphics import tsaplots
-> 1397         tsaplots.plot_acf(resid, ax=ax, lags=lags)
   1398         ax.set_title('Correlogram')
   1399

/usr/local/lib/python3.10/dist-packages/pandas/util/_decorators.py in␣
 ↪wrapper(*args, **kwargs)
    209                 else:
    210                     kwargs[new_arg_name] = new_arg_value
--> 211             return func(*args, **kwargs)
    212
    213         return cast(F, wrapper)

/usr/local/lib/python3.10/dist-packages/statsmodels/graphics/tsaplots.py in␣
 ↪plot_acf(x, ax, lags, alpha, use_vlines, adjusted, fft, missing, title, zero,␣
 ↪auto_ylims, bartlett_confint, vlines_kwargs, **kwargs)
    225         acf_x, confint = acf_x[:2]
    226
--> 227     _plot_corr(

    228         ax,
    229         title,

/usr/local/lib/python3.10/dist-packages/statsmodels/graphics/tsaplots.py in␣
 ↪_plot_corr(ax, title, acf_x, confint, lags, irregular, use_vlines,␣
 ↪vlines_kwargs, auto_ylims, **kwargs)
     47
     48     if use_vlines:
---> 49         ax.vlines(lags, [0], acf_x, **vlines_kwargs)
     50         ax.axhline(**kwargs)
     51
```

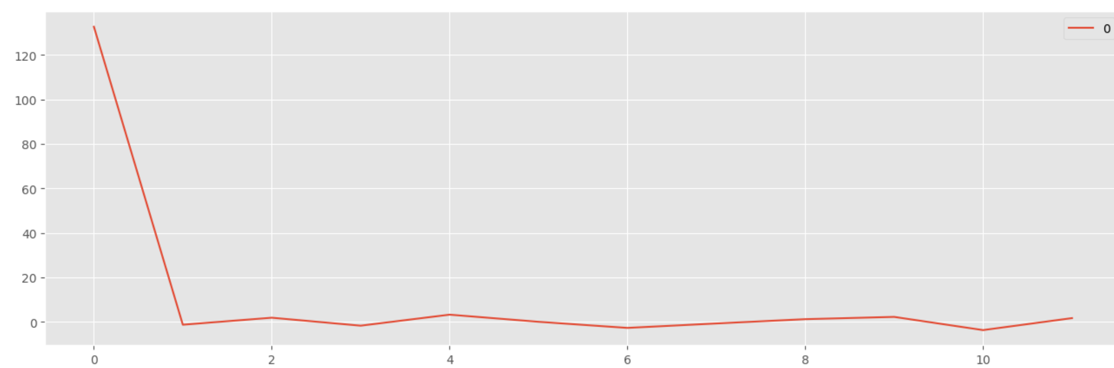
```
/usr/local/lib/python3.10/dist-packages/matplotlib/__init__.py in inner(ax, data, *args, **kwargs)
   1440     def inner(ax, *args, data=None, **kwargs):
   1441         if data is None:
-> 1442             return func(ax, *map(sanitize_sequence, args), **kwargs)
   1443
   1444         bound = new_sig.bind(ax, *args, **kwargs)

/usr/local/lib/python3.10/dist-packages/matplotlib/axes/_axes.py in vlines(self, x, ymin, ymax, colors, linestyles, label, **kwargs)
   1170         masked_verts[:, 0, 1] = ymin
   1171         masked_verts[:, 1, 0] = x
-> 1172         masked_verts[:, 1, 1] = ymax
   1173
   1174         lines = mcoll.LineCollection(masked_verts, colors=colors,

/usr/local/lib/python3.10/dist-packages/numpy/ma/core.py in __setitem__(self, indx, value)
   3375         if _mask is nomask:
   3376             # Set the data, then the mask
-> 3377             _data[indx] = dval
   3378             if mval is not nomask:
   3379                 _mask = self._mask = make_mask_none(self.shape, _dtype)

ValueError: could not broadcast input array from shape (2,) into shape (10,)
```

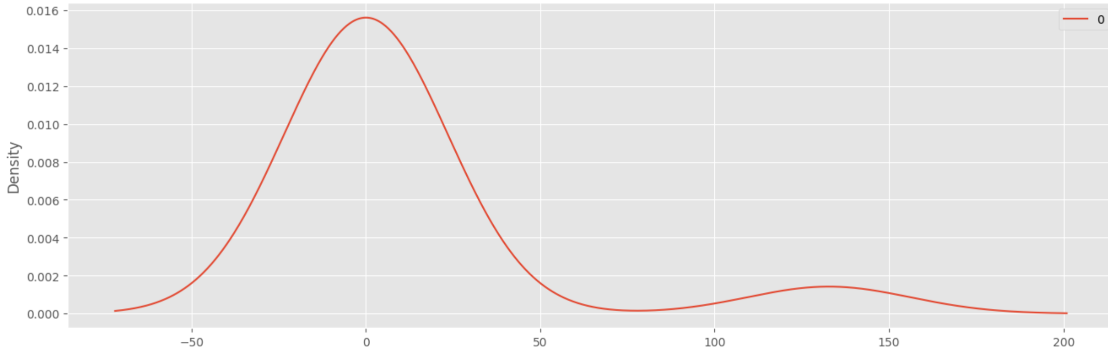



```
[34]: # 2.  Modelo : ARIMA

#train_data['Month'] = train_data['Month'].dt.to_timestamp()
train_data['Month_numeric'] = train_data['Month'].dt.year * 12 +␣
 ↪train_data['Month'].dt.month

# Luego, utiliza 'Month_numeric' como la serie temporal en auto_arima
modelo_auto = auto_arima(train_data['Month_numeric'], start_p=0, d=1, start_q=0,
                         max_p=4, max_d=2, max_q=4, start_P=0,
                         D=1, start_Q=0, max_P=2, max_D=1,
                         max_Q=2, m=9, seasonal=True,
                         suppress_warnings=True, stepwise=True,
                         random_state=20, n_fits=50)
print(modelo_auto)

arima_model = SARIMAX(train_data["TIEMPO_TOTAL_FINAL"], order = (0,1,0),␣
 ↪seasonal_order = (0,1,0,12))
arima_result = arima_model.fit()
arima_result.summary()

# line plot of residual errors
residuals = pd.DataFrame(arima_result.resid)
```

```python
residuals.plot(figsize = (16,5));
plt.show();

# kernel density plot of residual errors
residuals.plot(kind='kde', figsize = (16,5))
plt.show()
print(residuals.describe())

modelo_auto.plot_diagnostics(figsize=(20,8))
plt.show()

print(modelo_auto.summary())

arima_pred = arima_result.predict(start = len(train_data), end = len(df6)-1,␣
 ↪typ="levels").rename("ARIMA Predictions")
test_data['ARIMA_Predictions'] = arima_pred

# Grafica test_data
a=test_data[["TIEMPO_TOTAL_FINAL","ARIMA_Predictions"]]
fig = px.line(a, x=test_data.index, y=a.columns,template = "plotly_dark",
              title="Predicción con Modelo ARIMA")
fig.show()

# evalaucion metricas de Modelo : Arima
evaluacion_metrica(test_data["TIEMPO_TOTAL_FINAL"],test_data["ARIMA_Predictions"])
```

```
ARIMA(0,1,0)(0,1,0)[9] intercept
```



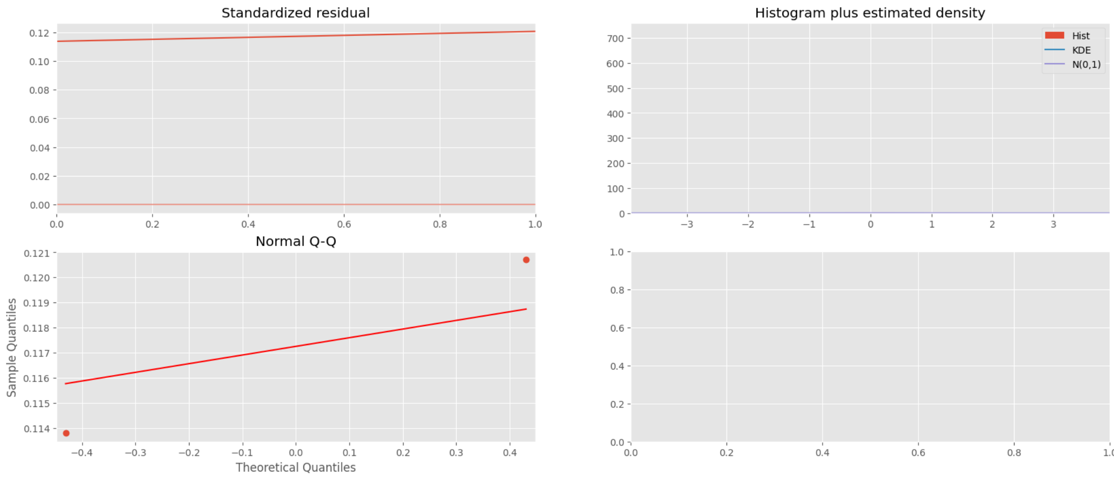



```
                0
count   12.000000
mean    11.101323
std     38.363697
min     -3.668906
25%     -1.356471
50%      0.651822
75%      1.987594
max    132.736505
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-34-571ec03d9461> in <cell line: 29>()
     27 print(residuals.describe())
     28
---> 29 modelo_auto.plot_diagnostics(figsize=(20,8))
     30 plt.show()
     31

/usr/local/lib/python3.10/dist-packages/pmdarima/utils/metaestimators.py in␣
 ↪<lambda>(*args, **kwargs)
     51
     52         # lambda, but not partial, allows help() to work with␣
 ↪update_wrapper
---> 53         out = (lambda *args, **kwargs: self.fn(obj, *args, **kwargs))
     54         # update the docstring of the returned function
     55         update_wrapper(out, self.fn)

/usr/local/lib/python3.10/dist-packages/pmdarima/arima/arima.py in␣
 ↪plot_diagnostics(self, variable, lags, fig, figsize)
   1395         ax = fig.add_subplot(224)
   1396         from statsmodels.graphics import tsaplots
-> 1397         tsaplots.plot_acf(resid, ax=ax, lags=lags)
   1398         ax.set_title('Correlogram')
```

```
   1399

/usr/local/lib/python3.10/dist-packages/pandas/util/_decorators.py in wrapper(*args, **kwargs)
    209                 else:
    210                     kwargs[new_arg_name] = new_arg_value
--> 211             return func(*args, **kwargs)
    212
    213         return cast(F, wrapper)

/usr/local/lib/python3.10/dist-packages/statsmodels/graphics/tsaplots.py in plot_acf(x, ax, lags, alpha, use_vlines, adjusted, fft, missing, title, zero, auto_ylims, bartlett_confint, vlines_kwargs, **kwargs)
    225         acf_x, confint = acf_x[:2]
    226
--> 227     _plot_corr(
    228         ax,
    229         title,

/usr/local/lib/python3.10/dist-packages/statsmodels/graphics/tsaplots.py in _plot_corr(ax, title, acf_x, confint, lags, irregular, use_vlines, vlines_kwargs, auto_ylims, **kwargs)
     47
     48     if use_vlines:
---> 49         ax.vlines(lags, [0], acf_x, **vlines_kwargs)
     50         ax.axhline(**kwargs)
     51

/usr/local/lib/python3.10/dist-packages/matplotlib/__init__.py in inner(ax, data, *args, **kwargs)
   1440     def inner(ax, *args, data=None, **kwargs):
   1441         if data is None:
-> 1442             return func(ax, *map(sanitize_sequence, args), **kwargs)
   1443
   1444         bound = new_sig.bind(ax, *args, **kwargs)

/usr/local/lib/python3.10/dist-packages/matplotlib/axes/_axes.py in vlines(self, x, ymin, ymax, colors, linestyles, label, **kwargs)
   1170         masked_verts[:, 0, 1] = ymin
   1171         masked_verts[:, 1, 0] = x
-> 1172         masked_verts[:, 1, 1] = ymax
   1173
   1174         lines = mcoll.LineCollection(masked_verts, colors=colors,

/usr/local/lib/python3.10/dist-packages/numpy/ma/core.py in __setitem__(self, indx, value)
   3375         if _mask is nomask:
   3376             # Set the data, then the mask
```

```
-> 3377                _data[indx] = dval
   3378                if mval is not nomask:
   3379                    _mask = self._mask = make_mask_none(self.shape, _dtype)

ValueError: could not broadcast input array from shape (2,) into shape (11,)
```



[ ]:
```
# 2.  Modelo : ARIMA

import pandas as pd
import matplotlib.pyplot as plt
from pmdarima import auto_arima
from statsmodels.tsa.statespace.sarimax import SARIMAX
import plotly.express as px

#train_data['Month'] = train_data['Month'].dt.to_timestamp()
train_data['Month_numeric'] = train_data['Month'].dt.year * 12 +␣
 ↪train_data['Month'].dt.month

# Luego, utiliza 'Month_numeric' como la serie temporal en auto_arima
modelo_auto = auto_arima(train_data['Month_numeric'], start_p=0, d=1, start_q=0,
                         max_p=4, max_d=2, max_q=4, start_P=0,
                         D=1, start_Q=0, max_P=2, max_D=1,
                         max_Q=2, m=9, seasonal=True,
                         suppress_warnings=True, stepwise=True,
                         random_state=20, n_fits=50)
print(modelo_auto)

arima_model = SARIMAX(train_data["TIEMPO_TOTAL_FINAL"], order = (0,1,0),␣
 ↪seasonal_order = (0,1,0,12))
arima_result = arima_model.fit()
```

```
arima_result.summary()

# line plot of residual errors
residuals = pd.DataFrame(arima_result.resid)
residuals.plot(figsize = (16,5));
plt.show();

# kernel density plot of residual errors
residuals.plot(kind='kde', figsize = (16,5))
plt.show()
print(residuals.describe())

#modelo_auto.plot_diagnostics(figsize=(20,8))
#plt.show()

# Ajustar auto_arima y obtener el mejor modelo
modelo_auto.fit(train_data['Month_numeric'])
best_order = modelo_auto.order
best_seasonal_order = modelo_auto.seasonal_order

# Crear y ajustar manualmente el mejor modelo
best_model = SARIMAX(train_data["TIEMPO_TOTAL_FINAL"], order=best_order,␣
↪seasonal_order=best_seasonal_order)
best_result = best_model.fit()

# Mostrar los diagnósticos
best_result.plot_diagnostics(figsize=(20, 8))
plt.show()

print(modelo_auto.summary())

arima_pred = arima_result.predict(start = len(train_data), end = len(df6)-1,␣
↪typ="levels").rename("ARIMA Predictions")
test_data['ARIMA_Predictions'] = arima_pred

# Grafica test_data
a=test_data[["TIEMPO_TOTAL_FINAL","ARIMA_Predictions"]]
fig = px.line(a, x=test_data.index, y=a.columns,template = "plotly_dark",
              title="Predicción con Modelo ARIMA")
fig.show()

# evalaucion metricas de Modelo : Arima
evaluacion_metrica(test_data["TIEMPO_TOTAL_FINAL"],test_data["ARIMA_Predictions"])
```

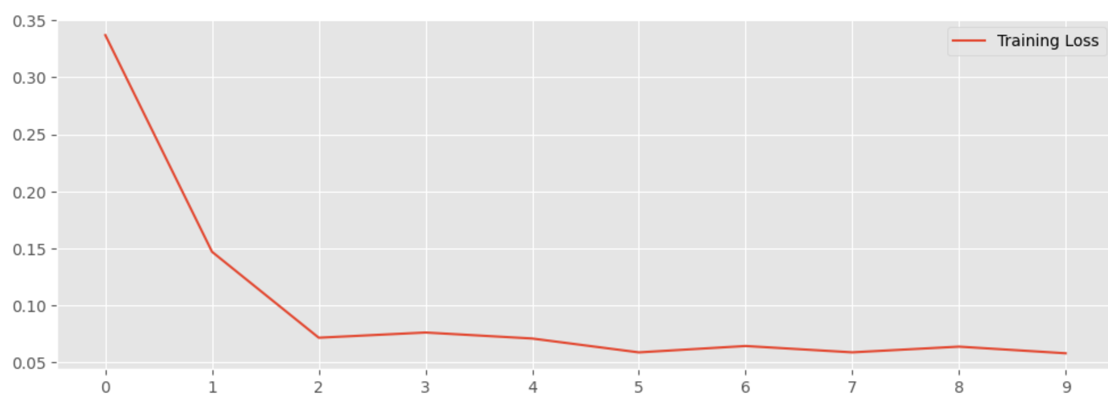
[64]:
```
# 3. Modelo : LSTM_Predictions

from sklearn.preprocessing import MinMaxScaler
```

```python
from keras.preprocessing.sequence import TimeseriesGenerator
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM

# train_data = train_data_ori

# Seleccionar solo columnas numéricas
numeric_columns = train_data.select_dtypes(include=['float64']).columns

# Aplicar MinMaxScaler solo a las columnas numéricas
scaler = MinMaxScaler()
scaler.fit(train_data[numeric_columns])

# Transformar el conjunto de entrenamiento y prueba solo en las columnas numéricas
scaled_train_data = scaler.transform(train_data[numeric_columns])
scaled_test_data = scaler.transform(test_data[numeric_columns])

# Definir parámetros
n_input = 5
n_features = 1

# Antes de crear el modelo LSTM, debemos crear un objeto Generador de series temporales.

# Crear el generador
generator = TimeseriesGenerator(scaled_train_data, scaled_train_data, length=n_input, batch_size=1)

# Crear el modelo LSTM
lstm_model = Sequential()
lstm_model.add(LSTM(200, activation='relu', input_shape=(n_input, n_features)))
lstm_model.add(Dense(1))
lstm_model.compile(optimizer='adam', loss='mse')

# Resumen del modelo
lstm_model.summary()

# Entrenar el modelo utilizando el generador
lstm_model.fit(generator, epochs=10)  # Ajusta el número de épocas según sea necesario

# Obtener el historial de entrenamiento
history = lstm_model.history

# Verificar si hay algún error durante el entrenamiento
```

```
if history is None:
    print("Error: El objeto History no se ha devuelto. Revisa tu código.")
else:
    # Acceder a las métricas de entrenamiento
    losses_lstm = history.history['loss']
    plt.figure(figsize=(12, 4))
    plt.xticks(np.arange(0, 21, 1))
    plt.plot(range(len(losses_lstm)), losses_lstm, label='Training Loss')
    plt.legend()
    plt.show()


lstm_predictions_scaled = list()

batch = scaled_train_data[-n_input:]
current_batch = batch.reshape((1, n_input, n_features))

for i in range(len(test_data)):
    lstm_pred = lstm_model.predict(current_batch)[0]
    lstm_predictions_scaled.append(lstm_pred)
    current_batch = np.append(current_batch[:,1:,:],[[lstm_pred]],axis=1)

lstm_predictions_scaled
lstm_predictions = scaler.inverse_transform(lstm_predictions_scaled)
lstm_predictions
test_data['LSTM_Predictions'] = lstm_predictions

test_data = test_data.drop(columns=['Month1'])

ai=test_data[["TIEMPO_TOTAL_FINAL","LSTM_Predictions"]]
fig = px.line(ai, x=test_data.index, y=ai.columns,title="Predicción con Modelo␣
 ↪LSTM")
fig.show()

# evalaucion metricas de Modelo : LSTM
evaluacion_metrica(test_data["TIEMPO_TOTAL_FINAL"],test_data["LSTM_Predictions"])
```

```
Model: "sequential_2"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 200)               161600

 dense_2 (Dense)             (None, 1)                 201

=================================================================
Total params: 161801 (632.04 KB)
```

```
Trainable params: 161801 (632.04 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
Epoch 1/10
11/11 [==============================] - 3s 16ms/step - loss: 0.3369
Epoch 2/10
11/11 [==============================] - 0s 18ms/step - loss: 0.1469
Epoch 3/10
11/11 [==============================] - 0s 25ms/step - loss: 0.0716
Epoch 4/10
11/11 [==============================] - 0s 22ms/step - loss: 0.0761
Epoch 5/10
11/11 [==============================] - 0s 29ms/step - loss: 0.0709
Epoch 6/10
11/11 [==============================] - 0s 20ms/step - loss: 0.0587
Epoch 7/10
11/11 [==============================] - 0s 19ms/step - loss: 0.0643
Epoch 8/10
11/11 [==============================] - 0s 18ms/step - loss: 0.0587
Epoch 9/10
11/11 [==============================] - 0s 19ms/step - loss: 0.0637
Epoch 10/10
11/11 [==============================] - 0s 18ms/step - loss: 0.0579
```

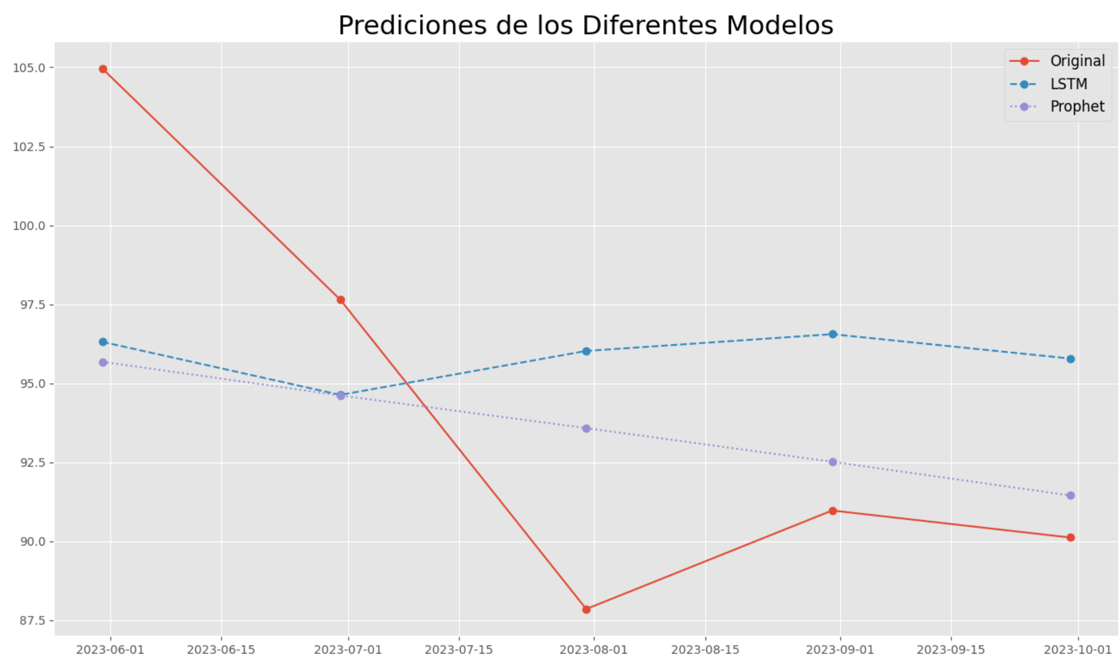



```
1/1 [==============================] - 0s 494ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 33ms/step
```

```
Evaluation metric results:-
MSE is : 42.779276156479
MAE is : 6.215969210720715
RMSE is : 6.540586835787673
```

```
MAPE is : 6.609435367074856
R2 is : -0.09679542675720532
```

[65]:
```
# mostrar todas los modelos

plt.figure(figsize=(16,9))
plt.plot_date(test_data["Month"],␣
 ↪test_data["TIEMPO_TOTAL_FINAL"],label="Original", linestyle="-")
#plt.plot_date(test_data["Month"], test_data["ARIMA_Predictions"],␣
 ↪label="Arima",linestyle="-.")
plt.plot_date(test_data["Month"], test_data["LSTM_Predictions"],label="LSTM",␣
 ↪linestyle="--")
plt.plot_date(test_data["Month"], test_data["Prophet_Predictions"],␣
 ↪label="Prophet",linestyle=":")
plt.legend(fontsize=12)
plt.title("Prediciones de los Diferentes Modelos", fontsize=22)
plt.show();
```



[66]:
```
test_data
```

[66]:

	index	Month	TIEMPO_TOTAL_FINAL	Prophet_Predictions	LSTM_Predictions
16	16	2023-05	104.964626	95.680576	96.312116
17	17	2023-06	97.646652	94.614332	94.632453
18	18	2023-07	87.855113	93.582482	96.022866
19	19	2023-08	90.973791	92.516238	96.554446

```
20     20  2023-09           90.118430           91.449993          95.783160
```

[39]:
```
df
```

[39]:
```
              FECHA_LLEGADA  TIEMPO_TOTAL_FINAL  \
Month
2023-02 2023-02-24 05:31:45               16.00
2023-08 2023-08-07 23:16:10               16.00
2023-09 2023-09-13 01:56:53               17.00
2023-06 2023-06-29 02:42:38               18.00
2023-01 2023-01-20 13:25:45               20.00
…                        …                  …
2022-07 2022-07-21 10:27:00              994.45
2022-12 2022-12-15 14:50:00              994.80
2023-04 2023-04-10 18:02:25              994.92
2023-07 2023-07-01 16:37:54              995.08
2023-04 2023-04-13 17:48:28              998.92

                               CENTRO_ATENCION  \
Month
2023-02                                     VB
2023-08                                     VC
2023-09                                     UC
2023-06                                     UC
2023-01                                     UC
…                                          …
2022-07                   ME - HOSPITAL MEISSEN
2022-12  UC - CENTRO DE SALUD SANTA LIBRADA I
2023-04                                     ME
2023-07                                     TN
2023-04                                     ME

                             CLASIFICACION_TRIAGE PACIENTE_EDAD  \
Month
2023-02                                         3            69
2023-08                                         3            50
2023-09                                         3            79
2023-06                                         3            72
2023-01                                         3            48
…                                             …           …
2022-07  3 - TRIAGE III - NO DEBE SUPERAR LAS 3 HORAS     58 AÑO(S)
2022-12  3 - TRIAGE III - NO DEBE SUPERAR LAS 3 HORAS     54 AÑO(S)
2023-04                                         3             4
2023-07                                         3             3
2023-04                                         3            17

        PACIENTE_#_DOCUMENTO        EDAD_RANGO            NOMBRE_ENTIDAD  \
```

```
Month
2023-02            4450531      ADULTO MAYOR                     EPSC34
2023-08            5267156            ADULTO                     EPSC34
2023-09            5667630      ADULTO MAYOR                     EPSC34
2023-06            3014617      ADULTO MAYOR                     EPSS05
2023-01           52277907            ADULTO                     EPSC34
…                        …                 …                          …
2022-07           39532594           ADULTEZ  CAPITAL SALUD EPS-S S.A.S
2022-12           39723106           ADULTEZ  CAPITAL SALUD EPS-S S.A.S
2023-04         1033822858  PRIMERA INFANCIA                     EPSC34
2023-07         1243858533  PRIMERA INFANCIA                     EPSC34
2023-04         1010176536       ADOLECENCIA                     EPSS41

              SEXO  DIA_SEMANA  ANUAL  TIEMPO_TOTAL_FINAL_change
Month
2023-02  MASCULINO           4   2023                   0.066667
2023-08   FEMENINO           0   2023                   0.000000
2023-09  MASCULINO           2   2023                   0.062500
2023-06  MASCULINO           3   2023                   0.058824
2023-01   FEMENINO           4   2023                   0.111111
…              …          …     …                         …
2022-07   FEMENINO           3   2022                   0.000251
2022-12   FEMENINO           3   2022                   0.000352
2023-04  MASCULINO           0   2023                   0.000121
2023-07   FEMENINO           5   2023                   0.000161
2023-04   FEMENINO           3   2023                   0.003859

[224409 rows x 12 columns]
```

[68]:
```python
test_data
```

[68]:
```
    index    Month  TIEMPO_TOTAL_FINAL  Prophet_Predictions  LSTM_Predictions  \
17     17  2023-06           97.646652            94.614332         94.632453
18     18  2023-07           87.855113            93.582482         96.022866
19     19  2023-08           90.973791            92.516238         96.554446
20     20  2023-09           90.118430            91.449993         95.783160

    TIEMPO_TOTAL_FINAL_change
17                  -0.069718
18                  -0.100275
19                   0.035498
20                  -0.009402
```

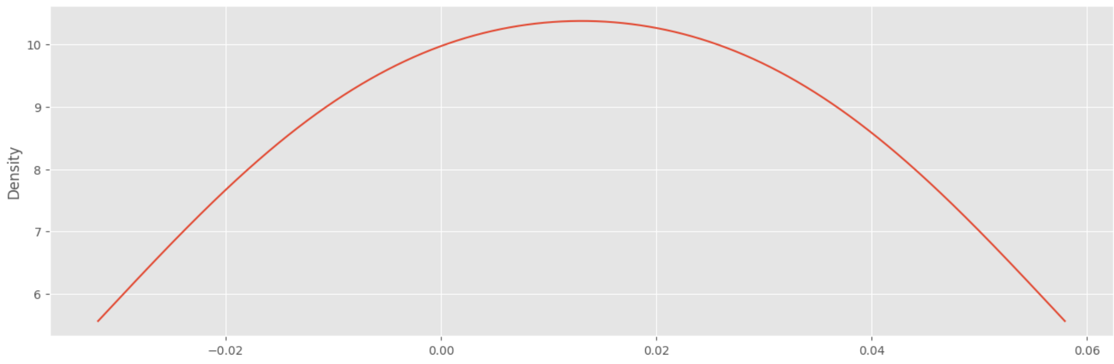
[70]:
```python
# 4. Modelo :  Random Forest
df5 = test_data
#df5 = test_data
```

```
df5['TIEMPO_TOTAL_FINAL_change']= df5['TIEMPO_TOTAL_FINAL'].pct_change()
df5.dropna(inplace=True)
df5.head()
df5['TIEMPO_TOTAL_FINAL_change'].describe()
```

[70]:
```
count    2.000000
mean     0.013048
std      0.031749
min     -0.009402
25%      0.001823
50%      0.013048
75%      0.024273
max      0.035498
Name: TIEMPO_TOTAL_FINAL_change, dtype: float64
```

[71]:
```
# Convertir la columna 'Month' a un formato serializable (cadena)
df5['Month'] = df5['Month'].dt.strftime('%Y-%m')  # Ajusta el formato según tus␣
↪necesidades

# Crear el gráfico
fig = px.line(df5, x="Month", y="TIEMPO_TOTAL_FINAL_change",␣
↪template="plotly_dark",
              title="Porcentaje de Cambio")

# Mostrar el gráfico
fig.show()
```

[74]:
```
df5['TIEMPO_TOTAL_FINAL_change'].plot(kind='kde',figsize = (16,5));

# Seasonality variables

df5['Month'] = pd.to_datetime(df5['Month'], format='%Y-%m')

# Ahora puedes continuar con las otras conversiones
df5['Year'] = df5['Month'].apply(lambda x: x.year)
df5['Mes'] = df5['Month'].apply(lambda x: x.month)
```



[ ]:
```
# Adding a year of lagged data
df5['L1'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(1)
df5['L2'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(2)
df5['L3'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(3)
df5['L4'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(4)
df5['L5'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(5)
df5['L6'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(6)

df5.head(13)

# df5 = df5.dropna()
df5= df5.set_index("Month")
df5.head()
```

[78]:
```
df5
```

[78]:
```
            index  TIEMPO_TOTAL_FINAL  Prophet_Predictions  LSTM_Predictions  \
Month
2023-08-01     19           90.973791            92.516238         96.554446
2023-09-01     20           90.118430            91.449993         95.783160

            TIEMPO_TOTAL_FINAL_change  Year  Mes        L1   L2   L3   L4   L5  \
Month
2023-08-01                   0.035498  2023    8       NaN  NaN  NaN  NaN  NaN
2023-09-01                  -0.009402  2023    9  0.035498  NaN  NaN  NaN  NaN

            L6  L7
Month
2023-08-01 NaN NaN
2023-09-01 NaN NaN
```

[79]:
```
# Modelación
furn = df5
# split into lagged variables (features) and original time series data (target)
X2= df5.iloc[:,2:-1]  # slice all rows and start with column 0 and go up to but␣
 ↪not including the last column
y2 = furn.iloc[:,1]  # slice all rows and last column, essentially separating␣
 ↪out 't' column
X2

# Target Train-Test split
from pandas import read_csv

Y2 = y2
```

```
traintarget_size = int(len(Y2) * 0.80)    # Set split
train_target, test_target = Y2[0:traintarget_size], Y2[traintarget_size:len(Y2)]

print('Observations for Target: %d' % (len(Y2)))
print('Training Observations for Target: %d' % (len(train_target)))
print('Testing Observations for Target: %d' % (len(test_target)))
```

```
Observations for Target: 2
Training Observations for Target: 1
Testing Observations for Target: 1
```

[80]:

```
# Random Forest
from sklearn.ensemble import RandomForestRegressor

# Creamos el modelo con 500 árboles
rfr = RandomForestRegressor(n_estimators=500)

# Entrenamos el modelo
rfr.fit(train_feature, train_target)

# Hacemos las predicciones
fcst = rfr.predict(test_feature)

b=pd.DataFrame({"Actual":test_target, "Random Forest":fcst})
b

fig = px.line(b, x=b.index, y=b.columns,template = "plotly_dark",
              title="Predicción con Modelo Random Forest")
fig.show()

# Evaluacion metricas del modelo : Random Forest
evaluacion_metrica(test_target,fcst)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-80-ad6d3717ffaf> in <cell line: 8>()
      6
      7 # Entrenamos el modelo
----> 8 rfr.fit(train_feature, train_target)
      9
     10 # Hacemos las predicciones

NameError: name 'train_feature' is not defined
```

[67]:

```
# 4. Modelo :  Random Forest
df5 = test_data
```

```
#df5 = test_data

df5['TIEMPO_TOTAL_FINAL_change']= df5['TIEMPO_TOTAL_FINAL'].pct_change()
df5.dropna(inplace=True)
df5.head()
df5['TIEMPO_TOTAL_FINAL_change'].describe()

fig = px.line(df5, x="Month", y="TIEMPO_TOTAL_FINAL_change",template =␣
↪"plotly_dark",
              title="Porcentaje de Cambio")
fig.show()

df5['TIEMPO_TOTAL_FINAL_change'].plot(kind='kde',figsize = (16,5));

# Seasonality variables
df5['Month'] = df5['Month'].dt.to_timestamp()

# Ahora puedes continuar con las otras conversiones
df5['Year'] = df5['Month'].apply(lambda x: x.year)
df5['Mes'] = df5['Month'].apply(lambda x: x.month)

# Adding a year of lagged data
df5['L1'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(1)
df5['L2'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(2)
df5['L3'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(3)
df5['L4'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(4)
df5['L5'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(5)
df5['L6'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(6)
df5['L7'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(7)
df5['L8'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(8)
df5['L9'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(9)
df5['L10'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(10)
df5['L11'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(11)
df5['L12'] = df5["TIEMPO_TOTAL_FINAL_change"].shift(12)

df5.head(13)

# df5 = df5.dropna()
df5= df5.set_index("Month")
df5.head()


# Modelación
furn = df5
# split into lagged variables (features) and original time series data (target)
X2= df5.iloc[:,2:-1]  # slice all rows and start with column 0 and go up to but␣
↪not including the last column
```

```
y2 = furn.iloc[:,1]  # slice all rows and last column, essentially separating␣
 ↪out 't' column
X2

# Target Train-Test split
from pandas import read_csv

Y2 = y2
traintarget_size = int(len(Y2) * 0.80)   # Set split
train_target, test_target = Y2[0:traintarget_size], Y2[traintarget_size:len(Y2)]

print('Observations for Target: %d' % (len(Y2)))
print('Training Observations for Target: %d' % (len(train_target)))
print('Testing Observations for Target: %d' % (len(test_target)))


# Features Train-Test split

trainfeature_size = int(len(X2) * 0.80)
train_feature, test_feature = X2[0:trainfeature_size], X2[trainfeature_size:
 ↪len(X2)]
print('Observations for feature: %d' % (len(X2)))
print('Training Observations for feature: %d' % (len(train_feature)))
print('Testing Observations for feature: %d' % (len(test_feature)))

# Random Forest
from sklearn.ensemble import RandomForestRegressor

# Creamos el modelo con 500 árboles
rfr = RandomForestRegressor(n_estimators=500)

# Entrenamos el modelo
rfr.fit(train_feature, train_target)

# Hacemos las predicciones
fcst = rfr.predict(test_feature)

b=pd.DataFrame({"Actual":test_target, "Random Forest":fcst})
b

fig = px.line(b, x=b.index, y=b.columns,template = "plotly_dark",
              title="Predicción con Modelo Random Forest")
fig.show()

# Evaluacion metricas del modelo : Random Forest
evaluacion_metrica(test_target,fcst)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-67-935392045a18> in <cell line: 12>()
     10 fig = px.line(df5, x="Month", y="TIEMPO_TOTAL_FINAL_change",template =␣
 ↪"plotly_dark",
     11                  title="Porcentaje de Cambio")
---> 12 fig.show()
     13
     14 df5['TIEMPO_TOTAL_FINAL_change'].plot(kind='kde',figsize = (16,5));

/usr/local/lib/python3.10/dist-packages/plotly/basedatatypes.py in show(self,␣
 ↪*args, **kwargs)
   3407         import plotly.io as pio
   3408
-> 3409         return pio.show(self, *args, **kwargs)
   3410
   3411     def to_json(self, *args, **kwargs):

/usr/local/lib/python3.10/dist-packages/plotly/io/_renderers.py in show(fig,␣
 ↪renderer, validate, **kwargs)
    386
    387     # Mimetype renderers
--> 388     bundle = renderers._build_mime_bundle(fig_dict,␣
 ↪renderers_string=renderer, **kwargs)
    389     if bundle:
    390         if not ipython_display:

/usr/local/lib/python3.10/dist-packages/plotly/io/_renderers.py in␣
 ↪_build_mime_bundle(self, fig_dict, renderers_string, **kwargs)
    294                     setattr(renderer, k, v)
    295
--> 296                 bundle.update(renderer.to_mimebundle(fig_dict))
    297
    298         return bundle

/usr/local/lib/python3.10/dist-packages/plotly/io/_base_renderers.py in␣
 ↪to_mimebundle(self, fig_dict)
    377                 post_script.extend(self.post_script)
    378
--> 379         html = to_html(

    380             fig_dict,
    381             config=self.config,

/usr/local/lib/python3.10/dist-packages/plotly/io/_html.py in to_html(fig,␣
 ↪config, auto_play, include_plotlyjs, include_mathjax, post_script, full_html,␣
 ↪animation_opts, default_width, default_height, validate, div_id)
```

```
    142
    143     # ## Serialize figure ##
--> 144     jdata = to_json_plotly(fig_dict.get("data", []))
    145     jlayout = to_json_plotly(fig_dict.get("layout", {}))
    146

/usr/local/lib/python3.10/dist-packages/plotly/io/_json.py in to_json_plotly(plotly_object, pretty, engine)
    141
    142         return _safe(
--> 143             json.dumps(plotly_object, cls=PlotlyJSONEncoder, **opts), _swap_json
    144         )
    145     elif engine == "orjson":

/usr/lib/python3.10/json/__init__.py in dumps(obj, skipkeys, ensure_ascii, check_circular, allow_nan, cls, indent, separators, default, sort_keys, **kw)
    236         check_circular=check_circular, allow_nan=allow_nan, indent=indent,
    237         separators=separators, default=default, sort_keys=sort_keys,
--> 238         **kw).encode(obj)

    239
    240

/usr/local/lib/python3.10/dist-packages/_plotly_utils/utils.py in encode(self, o)
     57         """
     58         # this will raise errors in a normal-expected way
---> 59         encoded_o = super(PlotlyJSONEncoder, self).encode(o)
     60         # Brute force guessing whether NaN or Infinity values are in the string
     61         # We catch false positive cases (e.g. strings such as titles, labels etc.)

/usr/lib/python3.10/json/encoder.py in encode(self, o)
    197         # exceptions aren't as detailed.  The list call should be roughly
    198         # equivalent to the PySequence_Fast that ''.join() would do.
--> 199         chunks = self.iterencode(o, _one_shot=True)
    200         if not isinstance(chunks, (list, tuple)):
    201             chunks = list(chunks)

/usr/lib/python3.10/json/encoder.py in iterencode(self, o, _one_shot)
    255                 self.key_separator, self.item_separator, self.sort_keys
    256                 self.skipkeys, _one_shot)
--> 257         return _iterencode(o, 0)
    258
    259 def _make_iterencode(markers, _default, _encoder, _indent, _floatstr,
```

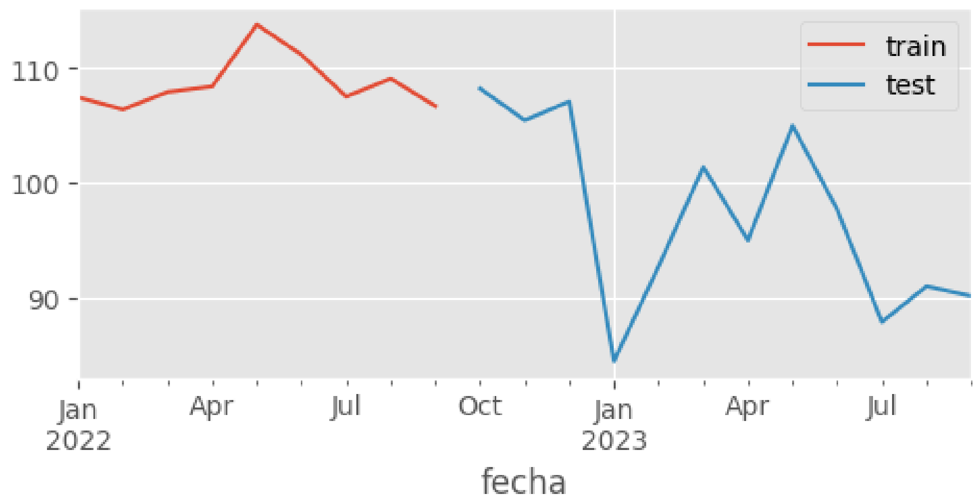
```
/usr/local/lib/python3.10/dist-packages/_plotly_utils/utils.py in default(self,␣
↪obj)
    134             except NotEncodable:
    135                 pass
--> 136         return _json.JSONEncoder.default(self, obj)
    137
    138     @staticmethod

/usr/lib/python3.10/json/encoder.py in default(self, o)
    177
    178         """
--> 179         raise TypeError(f'Object of type {o.__class__.__name__} '
    180                         f'is not JSON serializable')
    181

TypeError: Object of type Period is not JSON serializable
```

[ ]:
```
#  5. Modelo :  forecasting series temporales con Python y Scikit-learn

# Gráficos
# ==============================================================================
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
plt.rcParams['lines.linewidth'] = 1.5
plt.rcParams['font.size'] = 10

# Modelado y Forecasting
# ==============================================================================
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.preprocessing import StandardScaler

from skforecast.ForecasterAutoreg import ForecasterAutoreg
from skforecast.ForecasterAutoregCustom import ForecasterAutoregCustom
from skforecast.ForecasterAutoregDirect import ForecasterAutoregDirect
from skforecast.model_selection import grid_search_forecaster
from skforecast.model_selection import backtesting_forecaster
from skforecast.utils import save_forecaster
from skforecast.utils import load_forecaster
```

[83]:
```
# 5. Modelo : Multiple output forecasting

# Resetear el índice antes de la conversión
```

```python
df6 = df6.reset_index(drop=True)

# Convierte 'Month' a cadena y luego a formato Timestamp
df6['Month'] = pd.to_datetime(df6['Month'].astype(str), format='%Y-%m')

# Ahora puedes continuar con las otras conversiones
datos = df6
datos['fecha'] = pd.to_datetime(datos['Month'], format='%Y-%m-%d')
datos = datos.set_index('fecha')
datos = datos.rename(columns={'x': 'y'})
datos = datos.asfreq('MS')
datos = datos.sort_index()
datos = datos.rename(columns={'TIEMPO_TOTAL_FINAL': 'y'})

# Verificar que un índice temporal está completo
# ==============================================================================
(datos.index == pd.date_range(
                    start = datos.index.min(),
                    end   = datos.index.max(),
                    freq  = datos.index.freq)
).all()

# Separación datos train-test
# ==============================================================================
steps = 12
datos_train = datos[:-steps]
datos_test  = datos[-steps:]

print(f"Fechas train : {datos_train.index.min()} --- {datos_train.index.max()} ␣
  ↪(n={len(datos_train)})")
print(f"Fechas test  : {datos_test.index.min()} --- {datos_test.index.max()} ␣
  ↪(n={len(datos_test)})")

fig, ax = plt.subplots(figsize=(6, 2.5))
datos_train['y'].plot(ax=ax, label='train')
datos_test['y'].plot(ax=ax, label='test')
ax.legend();
```

```
Fechas train : 2022-01-01 00:00:00 --- 2022-09-01 00:00:00  (n=9)
Fechas test  : 2022-10-01 00:00:00 --- 2023-09-01 00:00:00  (n=12)
```



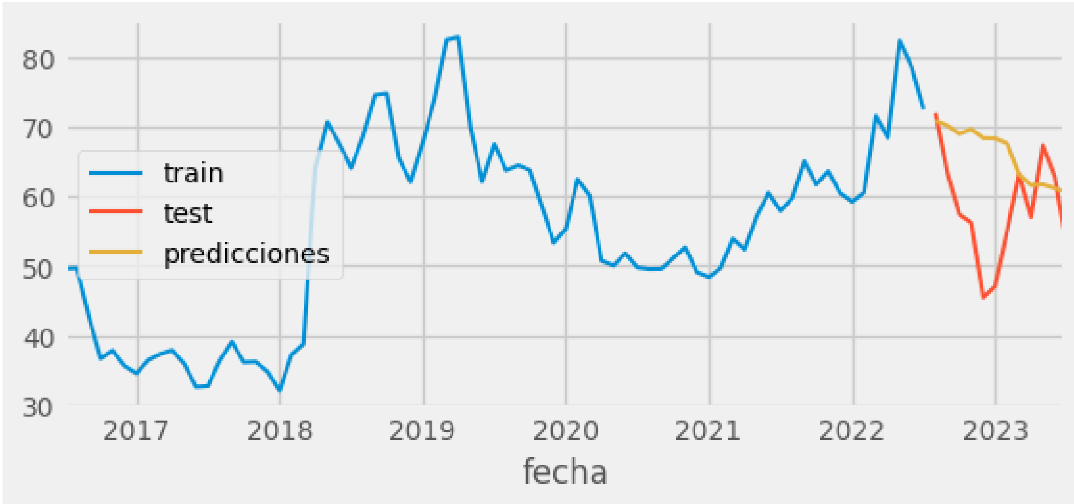
[84]:
```
# 6. Modelo : Forecasting autorregresivo recursivo

# Crear y entrenar forecaster
# ==============================================================================
forecaster = ForecasterAutoreg(
                regressor = RandomForestRegressor(random_state=123),
                lags = 6
             )

forecaster.fit(y=datos_train['y'])
forecaster

# Predicciones
# ==============================================================================
steps = 12
predicciones = forecaster.predict(steps=steps)
predicciones.head(5)

# Gráfico
# ==============================================================================
fig, ax = plt.subplots(figsize=(6, 2.5))
datos_train['y'].plot(ax=ax, label='train')
datos_test['y'].plot(ax=ax, label='test')
predicciones.plot(ax=ax, label='predicciones')
ax.legend();

# Error test
# ==============================================================================
error_mse = mean_squared_error(
```

```
                y_true = datos_test['y'],
                y_pred = predicciones
            )

print(f"Error de test (mse): {error_mse}")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-84-1e5d17cddc5b> in <cell line: 5>()
      3 # Crear y entrenar forecaster
      4 #␣
 ↪===========================================================================
----> 5 forecaster = ForecasterAutoreg(
      6                 regressor = RandomForestRegressor(random_state=123),
      7                 lags = 6

NameError: name 'ForecasterAutoreg' is not defined
```

[ ]:

```
# Crear y entrenar forecaster con mejores hiperparámetros
# ==============================================================================
regressor = RandomForestRegressor(max_depth=3, n_estimators=100,␣
 ↪random_state=123)
forecaster = ForecasterAutoreg(
                regressor = regressor,
                lags      = 20
             )

forecaster.fit(y=datos_train['y'])

# Predicciones
# ==============================================================================
predicciones = forecaster.predict(steps=steps)

# Gráfico
# ==============================================================================
fig, ax = plt.subplots(figsize=(6, 2.5))
datos_train['y'].plot(ax=ax, label='train')
datos_test['y'].plot(ax=ax, label='test')
predicciones.plot(ax=ax, label='predicciones')
ax.legend();
```



[ ]:
```python
# Grid search de hiperparámetros
# ==============================================================================
steps = 12
forecaster = ForecasterAutoreg(
                regressor = RandomForestRegressor(random_state=123),
                lags      = 12 # Este valor será remplazado en el grid search
             )

# Lags utilizados como predictores
lags_grid = [10, 20]

# Hiperparámetros del regresor
param_grid = {'n_estimators': [100, 500],
              'max_depth': [3, 5, 10]}

resultados_grid = grid_search_forecaster(
                        forecaster         = forecaster,
                        y                  = datos_train['y'],
                        param_grid         = param_grid,
                        lags_grid          = lags_grid,
                        steps              = steps,
                        refit              = False,
                        metric             = 'mean_squared_error',
                        initial_train_size = int(len(datos_train)*0.5),
                        fixed_train_size   = False,
                        return_best        = True,
                        n_jobs             = 'auto',
                        verbose            = False
                  )
```

```
# Resultados Grid Search
# ==============================================================================
resultados_grid
```

```
Number of models compared: 12.

lags grid:   0%|          | 0/2 [00:00<?, ?it/s]

params grid:   0%|          | 0/6 [00:00<?, ?it/s]

`Forecaster` refitted using the best-found lags and parameters, and the whole
data set:
  Lags: [ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20]
  Parameters: {'max_depth': 3, 'n_estimators': 100}
  Backtesting metric: 71.00953593067813
```

[ ]:

```
                                                 lags  \
6   [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14…
8   [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14…
10  [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14…
11  [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14…
9   [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14…
7   [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14…
2                     [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
3                     [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
5                     [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
4                     [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
1                     [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
0                     [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

                                     params  mean_squared_error  max_depth  \
6    {'max_depth': 3, 'n_estimators': 100}           71.009536          3
8    {'max_depth': 5, 'n_estimators': 100}           71.434458          5
10  {'max_depth': 10, 'n_estimators': 100}           71.552524         10
11  {'max_depth': 10, 'n_estimators': 500}           71.584441         10
9    {'max_depth': 5, 'n_estimators': 500}           71.617320          5
7    {'max_depth': 3, 'n_estimators': 500}           71.752363          3
2    {'max_depth': 5, 'n_estimators': 100}          198.464857          5
3    {'max_depth': 5, 'n_estimators': 500}          201.324686          5
5   {'max_depth': 10, 'n_estimators': 500}          203.142210         10
4   {'max_depth': 10, 'n_estimators': 100}          204.810631         10
1    {'max_depth': 3, 'n_estimators': 500}          206.166672          3
0    {'max_depth': 3, 'n_estimators': 100}          211.709367          3

    n_estimators
6            100
8            100
10           100
```

11	500
9	500
7	500
2	100
3	500
5	500
4	100
1	500
0	100