Comparación de Métodos de Predicción de Series Temporales aplicados a Acciones de MERVAL

Caso ALUA.BA (Aluar Aluminio Argentino S.A.I.C.) Período 2015-2021.

En este cuaderno se comparan distintos métodos de predicción de series temporales para un caso de Acciones de MERVAL obtenidas del servicio Yahoo Finance!.

El objetivo es comparar desde métodos clásicos como SARIMA hasta los más recientes como [Prophet](https://facebook.github.io/prophet/) de Facebook.

Se trata el problema de predicción de una manera general sin aplicar técnicas específicas de modelos matemáticos financieros o conocimientos del dominio financiero o del mercado bursátil, por lo tanto es trasladable a cualquier problema de series temporales univariable.

Cada serie temporal contiene los datos de un período:

- **Apertura (Open)**:
- **Alto (High)**:
- **Bajo (Low)**:
- **Cierre (Close)**:
- **Precio de Cierre Ajustado (Adj)**:
- **Volumen (Volume)**:

```
symbol = 'ALUA.BA' #ALUA.BA Aluar Aluminio Argentino S.A.I.C.
data_source='yahoo'
start_date = '2015-01-01'
end_date = None
```

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import timeit
```

```
STEPS_TO_PREDICT = 64
```

1. Descarga del dataset

```
from pandas_datareader import data
import fix_yahoo_finance as yf

yf.pdr_override()
```

```
df = data.get_data_yahoo(symbol, start_date, end_date)
df.head(5)
```

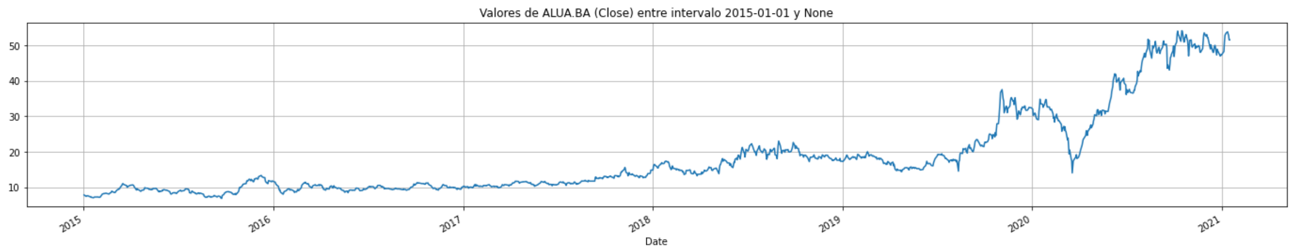
```
[*********************100%***********************]  1 of 1 downloaded
```

Date	Open	High	Low	Close	Adj Close	Volume
2015-01-02	7.54464	7.81250	7.41071	7.80357	6.517592	334621
2015-01-05	7.81250	7.81250	7.41071	7.51786	6.278966	157214
2015-01-06	7.50893	7.50893	7.23214	7.40178	6.182015	157115
2015-01-07	7.14286	7.53571	7.14286	7.53571	6.293874	181736
2015-01-08	7.71428	7.71428	7.36607	7.53571	6.293874	288559

```
#FIXME! Resampling
```

```
series_col = 'Close'
series = df[series_col]
```

```
fig,axes = plt.subplots(1,1,figsize=(24,4))
axes.set_title("Valores de %s (%s) entre intervalo %s y %s" % (symbol,series_co
series.plot(ax=axes,grid=True)
plt.show()
```



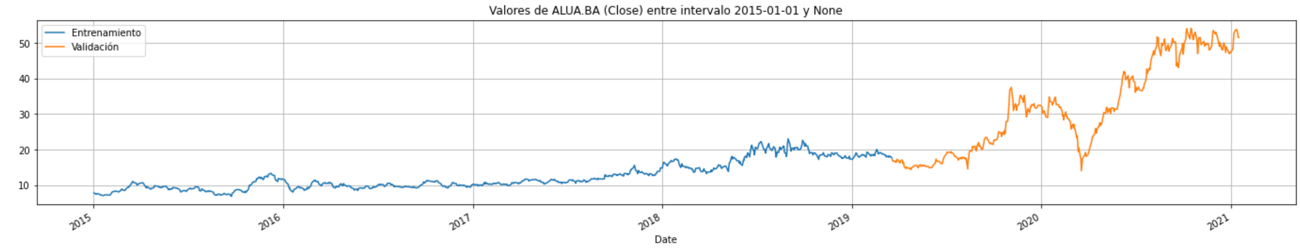
2. Separación del Dataset en Entrenamiento y Evaluación

```
def split_dataset(series, train_split):
  total_samples = len(series)
  split_point = int(train_split * total_samples)
  train, test = series[0:split_point], series[split_point:]
  return train, test
```

```
TRAIN_TEST_SPLIT = 0.7
train,test = split_dataset(series,TRAIN_TEST_SPLIT)
train_start = "%d-%d%d" % (train.index[0].year,train.index[0].month,train.index
train_end = "%d-%d-%d" % (train.index[-1].year,train.index[-1].month,train.inde
test_start = "%d-%d%d" % (test.index[0].year,test.index[0].month,test.index[0]
```

```
test_start = "%d-%d%d" % (test.index[0].year,test.index[0].month,test.index[0].
test_end = "%d-%d-%d" % (test.index[-1].year,test.index[-1].month,test.index[-1
print("Train (%s-%s): %d muestras." % (train_start, train_end, len(train) ) )
print("Test (%s-%s): %d muestras" % (test_start, test_end, len(test) ) )

fig,axes = plt.subplots(1,1,figsize=(24,4))
axes.set_title("Valores de %s (%s) entre intervalo %s y %s" % (symbol,series_co
train.plot(ax=axes,grid=True,label="Entrenamiento")
test.plot(ax=axes,grid=True,label="Validación")
axes.legend(["Entrenamiento","Validación"])
plt.show()
```

```
Train (2015-12-2019-3-19): 1030 muestras.
Test (2019-320-2021-1-15): 442 muestras
```



3. Evaluación del Dataset

Cada modelo será evaluado sobre el Test set con las siguientes métricas:

- Mean Square Error (MSE)
- Root Mean Square Error ($RMSE$)
- Mean Absolute Error (MAE)
- Mean Absolute Percentage Error ($MAPE$)
- R Squared (R^2)

```
model_metric_results = {}
```

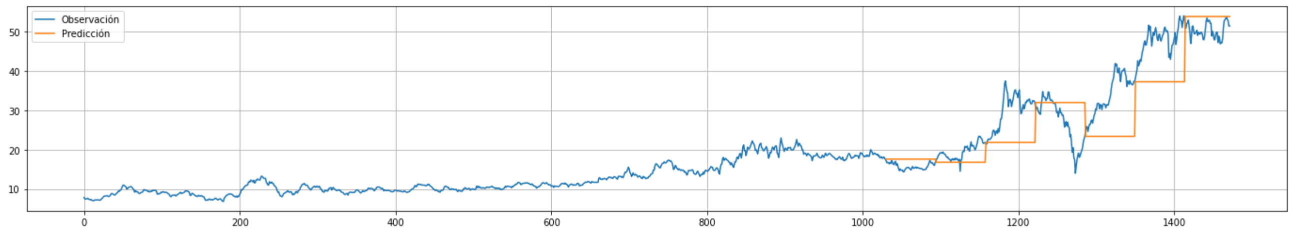
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn import metrics

def report_model(history,predictions,test):
  n_history = len(history)
  n_predicted = len(predictions)
  plt.figure(figsize=(24,4))
  plt.grid(which="Both")
  plt.plot(np.arange(n_history),history)
  plt.plot(np.arange(n_history-n_predicted,n_history),predictions)
  plt.legend(["Observación","Predicción"])
  plt.show()

  # report performance
```

```
  # report performance
  y_true, y_pred = np.array(test), np.array(predictions)
  mse = metrics.mean_squared_error(y_true, y_pred)
  rmse = np.sqrt(metrics.mean_squared_error(y_true, y_pred))
  mae = metrics.mean_absolute_error(y_true, y_pred)
  mape = np.mean(np.abs((y_true - y_pred) / y_true)) * 100
  r2 = metrics.r2_score(y_true, y_pred)
  print( 'MSE: %.3f ' % mse)
  print( 'RMSE: %.3f ' % rmse)
  print( 'MAE: %.3f ' % mae)
  print( 'MAPE: %.3f ' % mape)
  print( 'R2: %.3f ' % r2)

  return mse,rmse,mae,mape,r2
```

Modelo de Persistencia (Baseline).

```
def baseline_walk_forward(train,validation):
  x_train_values = train.values.astype( 'float32' )
  x_val_values = validation.values.astype( 'float32' )

  history = [x for x in x_train_values]
  predictions = list()

  for i in range(0,len(x_val_values),STEPS_TO_PREDICT):

    n_steps = min(STEPS_TO_PREDICT,len(x_val_values)-i)

    # predict
    yhat = history[-1]
    for j in range(n_steps):
      predictions.append(yhat)

      # observation
      obs = x_val_values[i+j]
      history.append(obs)
  return history, predictions

start_time=timeit.default_timer()
history, predictions = baseline_walk_forward(train,test)
prediction_time = timeit.default_timer()-start_time
training_time = 0
```

```
mse,rmse,mae,mape,r2 = report_model(history,predictions,test)
```




```
MSE: 62.663
```

```
print("Tiempo de Entrenamiento:", training_time)
print("Tiempo de Predicción:", prediction_time)
```

```
Tiempo de Entrenamiento: 0
Tiempo de Predicción: 0.00021047399966866556
```

```
model_metric_results["baseline"] = {
    "MSE": rmse,
    "RMSE": rmse,
    "MAE": mae,
    "MAPE": mape,
    "R2": r2,
    "Tiempo de Entrenamiento": training_time,
    "Tiempo de Predicción": prediction_time,
    "Descripción": "Modelo de base (Persistencia)"
}
```

4. Análisis Exploratorio de Datos

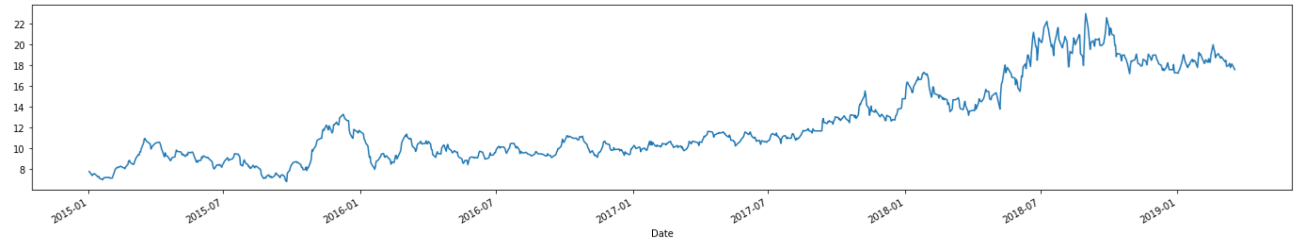
Resumen de 5 Números

```
train.describe()
```

```
count    1030.000000
mean       12.393756
std         3.921479
min         6.820000
25%         9.500000
50%        10.850000
75%        14.900000
max        23.000000
Name: Close, dtype: float64
```

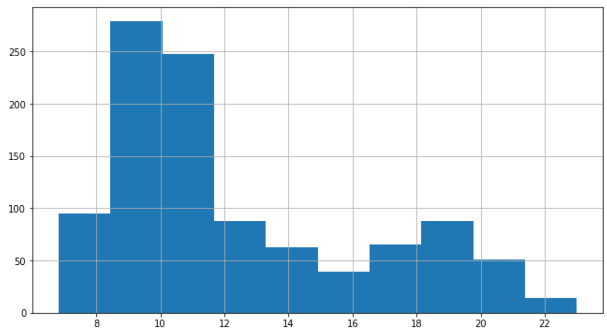
Gráfico de Tendencia.

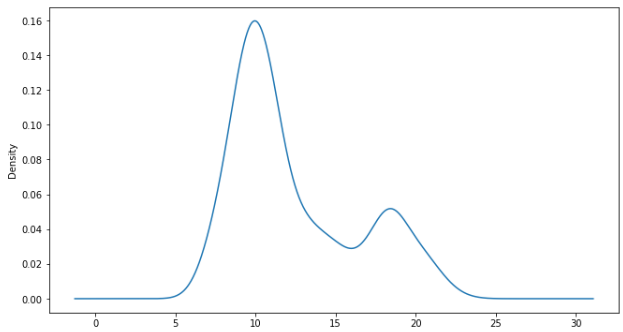
```
plt.figure(figsize=(24,4))
train.plot()
plt.show()
```



Histograma y Estimación de Densidad de Kernel

```
fig,axes = plt.subplots(1,2,figsize=(24,6))
train.hist(ax=axes[0])
train.plot(kind='kde',ax=axes[1])
plt.show()
```





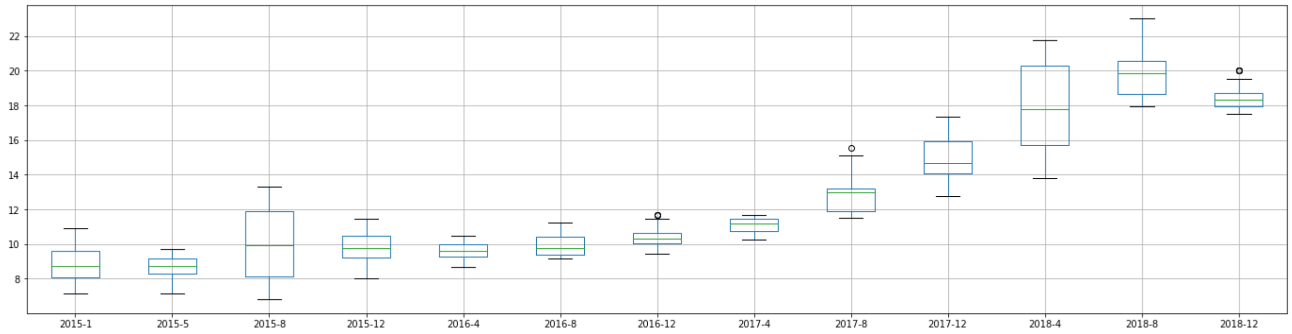
Observaciones:

- Se vé que no es una Gaussiana, por lo que se espera la transformación Box-Cox mejore el desempeño de los algoritmos de la familia SARIMA.

Diagrama de Box y Whisker

```
periods = pd.DataFrame()
for name,group in train.groupby(pd.Grouper(freq= '120D')):
  period_name = str(name.year)+"-"+str(name.month)
  periods[period_name] = group.sample(60,replace=True).values
fig,axes = plt.subplots(figsize=(24,6))
periods.boxplot(ax=axes)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb0923de128>
```



Observaciones:

- Se vé una tendencia ascendente, probablemente no lineal. Esto sugiere la necesidad de una diferenciación previa de los datos para usar en los modelos de la familia SARIMA.

Entrenamiento de Modelos

Modelo ARIMA

El modelo ARIMA requiere que una serie sea estacionaria. Para verificar si la serie es estacionaria se puede realizar el test de Dickey-Fuller Aumentado.

```
from statsmodels.tsa.stattools import adfuller

def test_stationarity(data):
  # check if stationary
  result = adfuller(data)
  print( 'ADF Statistic: %f' % result[0])
  print( 'p-value: %f' % result[1])
  print( 'Critical Values:'  )
  for key, value in result[4].items():
    print( '\t%s: %.3f' % (key, value))

  if result[0] < result[4]['1%']:
    print("Se rechaza H0. La serie es estacionaria.")
  else:
    print("No se rechaza H0. La serie no es estacionaria.")
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: Futu
  import pandas.util.testing as tm
```

```
test_stationarity(train)
```

```
ADF Statistic: -1.378470
p-value: 0.592553
Critical Values:
```

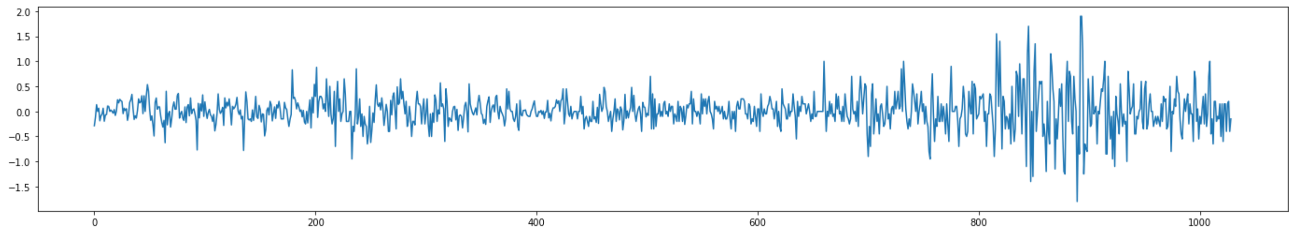
```
        1%: -3.437
        5%: -2.864
        10%: -2.568
No se rechaza H0. La serie no es estacionaria.
```

Una forma de hacer la serie estacionaria es aplicar una diferencia.

```
def difference(dataset):
  diff = list()
  for i in range(1, len(dataset)):
    value = dataset[i] - dataset[i - 1]
    diff.append(value)
  return pd.Series(diff)
```

```
train_diff = difference(train)
plt.figure(figsize=(24,4))
plt.plot(train_diff)
```

```
[<matplotlib.lines.Line2D at 0x7fb086577e48>]
```




```
test_stationarity(train_diff)
```

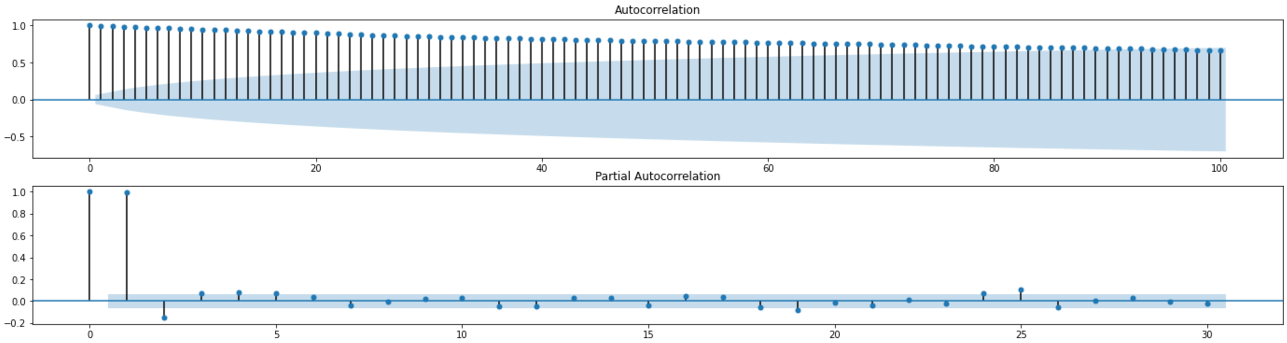
```
ADF Statistic: -6.662185
p-value: 0.000000
Critical Values:
        1%: -3.437
        5%: -2.864
        10%: -2.568
Se rechaza H0. La serie es estacionaria.
```

Rechazar la Hipótesis Nula significa con un nivel de significancia menor al 1% implica que el proceso no tiene raíz unitaria, y por lo tanto la serie es estacionaria y no tiene una estructura dependiente del tiempo.

```
# FIXME probar otros métodos.
```

El próximo paso es seleccionar los valores de lag para Autoregresión (AR) y Promedio Móvil (MA), parámetros p y q respectivamente. Un método es estudiando los gráficos de las funciones de Autocorrelación (ACF) y Autocorrelación Parcial (PACF).

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

fig,axes = plt.subplots(2,1,figsize=(24,6))
plot_acf(train, lags=100, ax=axes[0])
plot_pacf(train, lags=30, ax=axes[1])
plt.show()
```



- El gráfico de ACF muestra lags significativos hasta órdenes muy altos, cercanos a 80.
- El gráfico de PACF muestra lags significativos hasta el 1.

```
from statsmodels.tsa.arima_model import ARIMA
from tqdm.notebook import tqdm

def arima_walk_forward(train,validation,p,d,q):
  x_train_values = train.values.astype( 'float32' )
  x_val_values = validation.values.astype( 'float32' )

  history = [x for x in x_train_values]
  predictions = list()

  bar = tqdm(total=len(x_val_values))

  for i in range(0,len(x_val_values),STEPS_TO_PREDICT):

    n_steps = min(STEPS_TO_PREDICT,len(x_val_values)-i)

    # predict
    model = ARIMA(history, order=(p,d,q))
    model = model.fit(disp=0)
    yhat = model.forecast(n_steps)[0]
    for j in range(n_steps):
      predictions.append(yhat[j])
      # observation
      obs = x_val_values[i+j]
      history.append(obs)
    bar.update(n_steps)
```

```
  return history, predictions
```

Se entrenará un modelo sobre una partición del set de entrenamiento.

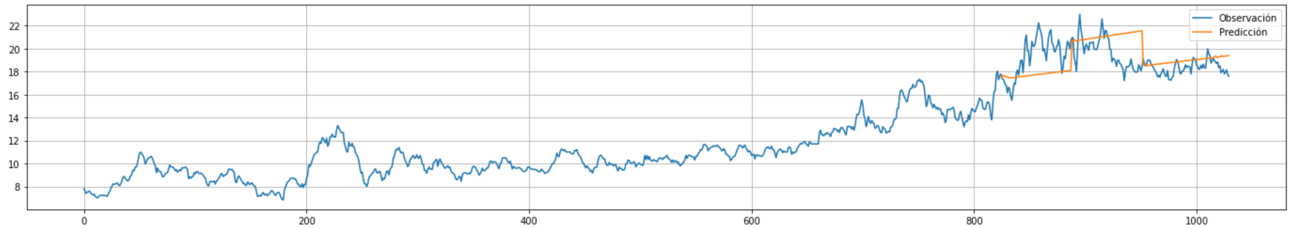
```
x_train,x_val = split_dataset(train,0.8)
```

Uno de los problemas de ARIMA es que el entrenamiento es lento para órdenes altos, por lo tanto, se intentará con valores inferiores a 10 para tener tiempos de entrenamiento aceptables.

```
p = 10
d = 1
q = 1
history, predictions = arima_walk_forward(x_train,x_val,p,d,q)
```

100% 206/206 [00:15<00:00, 8.72it/s]

```
mse,rmse,mae,mape,r2 = report_model(history,predictions,x_val)
```



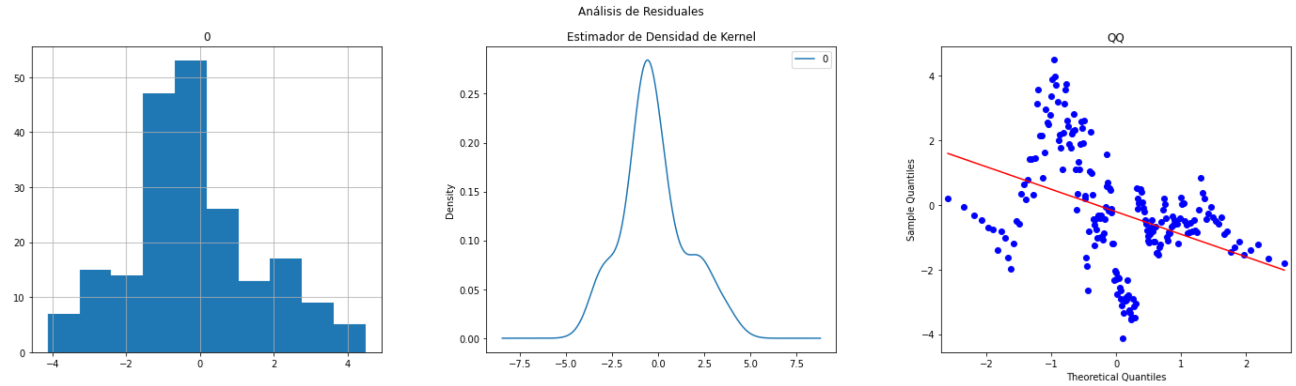

```
MSE: 3.073
RMSE: 1.753
MAE: 1.376
MAPE: 7.190
R2: -0.665
```

Análisis de Residuales

```
residuals = [x_val[i]-predictions[i] for i in range(len(x_val))]
residuals = pd.DataFrame(residuals)
residuals.describe()
```

	0
count	206.000000
mean	-0.210302
std	1.744656
min	-4.127633

```
from statsmodels.graphics.gofplots import qqplot

fig,axes = plt.subplots(1,3,figsize=(24,6))
plt.suptitle("Análisis de Residuales")
axes[0].set_title("Histograma")
residuals.hist(ax=axes[0])
axes[1].set_title("Estimador de Densidad de Kernel")
residuals.plot(kind='kde', ax=axes[1])
axes[2].set_title("QQ")
qqplot(residuals, line= 'r', ax=axes[2] )
plt.show()
```



Idealmente se espera que los residuales tengan una distribución gaussiana de media cero. No es exactamente una Gaussiana, pero la media es próxima a cero.

- FIXME: ver qué pasa con el QQPlot.

Entrenamiento con dataset completo

```
start_time=timeit.default_timer()
model = ARIMA(train.values, order=(p,d,q))
model = model.fit(disp=0)
model.save( 'arima.pkl' )
training_time = timeit.default_timer()-start_time
```

Validación contra Test Set

```
from statsmodels.tsa.arima_model import ARIMAResults
import numpy

def predict_with_arima(model,train,test,p,q,d):
  bar = tqdm(total=len(test))

  history = [x for x in train.values]
  predictions = []

  yhat = model.forecast(STEPS_TO_PREDICT)[0]
  for j in range(STEPS_TO_PREDICT):
    predictions.append(yhat[j])

  for i in range(STEPS_TO_PREDICT,len(test),STEPS_TO_PREDICT):
    # predict
    n_steps = min(STEPS_TO_PREDICT,len(test)-i)
    model = ARIMA(history, order=(p,d,q))
    model = model.fit(disp=0)
    yhat = model.forecast(steps=n_steps)[0]
    for j in range(n_steps):
      predictions.append(yhat[j])
      # observation
      obs = test[i+j]
      history.append(obs)
    bar.update(n_steps)
  return history,predictions
```

```
start_time=timeit.default_timer()
model = ARIMAResults.load( 'arima.pkl' )
history,predictions = predict_with_arima(model,train,test,p,q,d)
prediction_time = timeit.default_timer()-start_time
```

86% 378/442 [00:26<00:04, 13.73it/s]

```
mse,rmse,mae,mape,r2 = report_model(history,predictions,test)
```

```
print("Tiempo de Entrenamiento:", training_time)
print("Tiempo de Predicción:", prediction_time)
```

```
Tiempo de Entrenamiento: 3.3742280550000032
Tiempo de Predicción: 26.851007670999934
MSE: 60.374
```

```
model_metric_results["ARIMA"] = {
    "MSE": rmse,
    "RMSE": rmse,
    "MAE": mae,
    "MAPE": mape,
    "R2": r2,
    "Tiempo de Entrenamiento": training_time,
    "Tiempo de Predicción": prediction_time,
    "Descripción": "ARIMA (p=%d,d=%d,q=%d)" % (p,d,q)
}
```

Preparación de Dataset para modelos RNN

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

import tensorflow as tf
from sklearn.preprocessing import MinMaxScaler

tf.random.set_seed(42)
np.random.seed(42)
```

```
WINDOW_SIZE = STEPS_TO_PREDICT
```

```
train.shape,test.shape
```

```
((1030,), (442,))
```

Feature scaling.

```
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_train = scaler.fit_transform(train.values.reshape(-1, 1))
scaled_test = scaler.transform(test.values.reshape(-1, 1))
```

```
TRAIN_VAL_SPLIT = 0.8
split_point = int(TRAIN_VAL_SPLIT*len(scaled_train))
ts_train = scaled_train[0:split_point]
ts_val = scaled_train[split_point:]
```

```
def prepare_dataset(data,window_size,horizon):
```

```
def prepare_dataset(data,window_size,horizon):
  X,y = [], []
  n = len(data)
  for i in range(n-window_size-horizon):
    X.append(data[i:(i+window_size)])
    y.append(data[(i+window_size):(i+window_size+horizon)])
  return np.array(X), np.array(y)

x_train, y_train = prepare_dataset(ts_train,WINDOW_SIZE,STEPS_TO_PREDICT)
x_val, y_val = prepare_dataset(ts_val,WINDOW_SIZE,STEPS_TO_PREDICT)

x_train.shape,y_train.shape
```

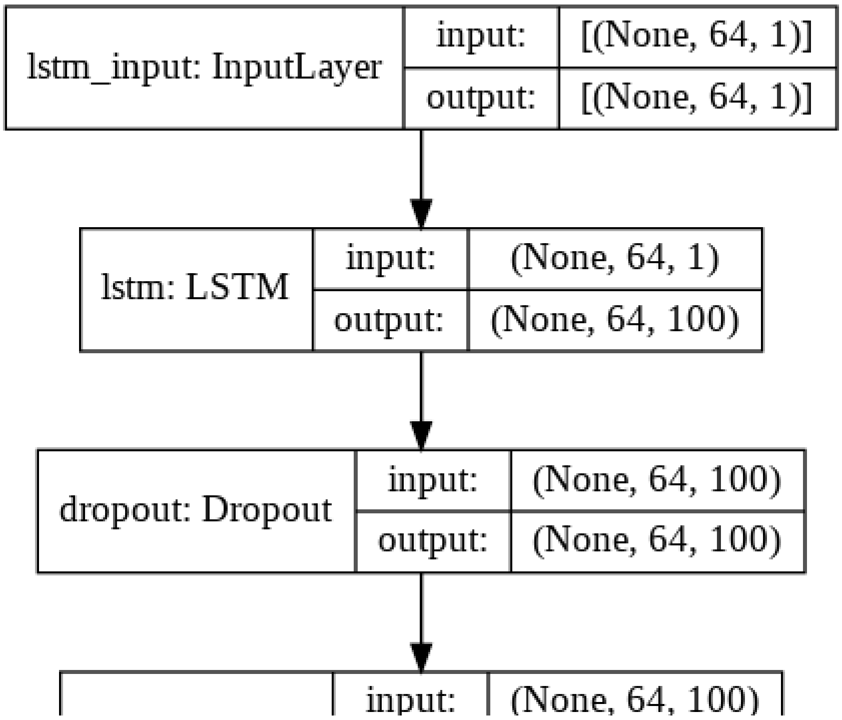
```
((696, 64, 1), (696, 64, 1))
```

Convertir los datos a tf.data mejora el rendimiento con GPU (ver: [Guide to Data Perfomance in Google Colab]()).

```
BATCH_SIZE = 256
BUFFER_SIZE = 150
train_uv = tf.data.Dataset.from_tensor_slices((x_train,y_train))
train_uv = train_uv.cache().shuffle(BUFFER_SIZE).batch(BATCH_SIZE).repeat()
val_uv = tf.data.Dataset.from_tensor_slices((x_val,y_val))
val_uv = val_uv.cache().shuffle(BUFFER_SIZE).batch(BATCH_SIZE).repeat()
```

Modelo LSTM

```
model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(100, input_shape=x_train.shape[-2:],return_sequences=T
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.LSTM(units=50,return_sequences=False),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(units=STEPS_TO_PREDICT),
])
model.compile(optimizer='adam', loss='mse')
tf.keras.utils.plot_model(model, show_shapes=True)
```

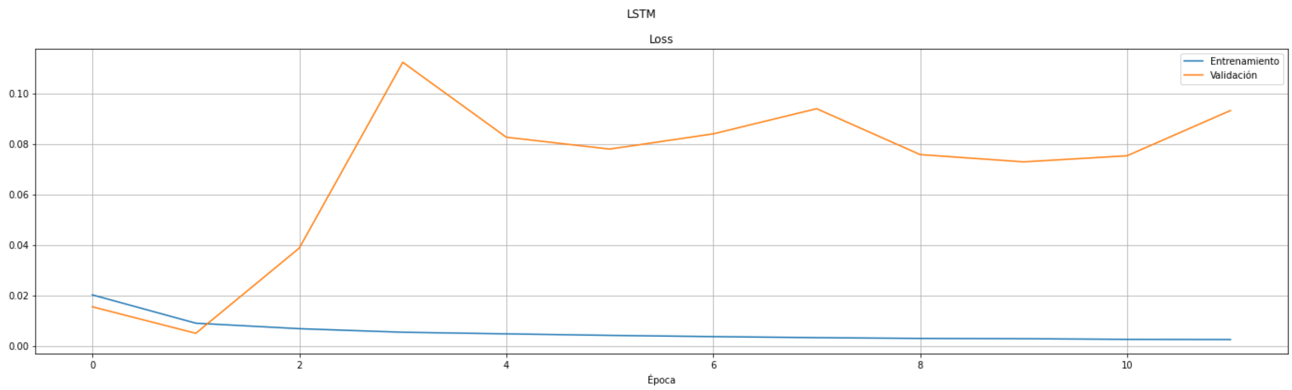



```
EVALUATION_INTERVAL = 100
NUM_EPOCHS = 150

start_time=timeit.default_timer()
history = model.fit(
    train_uv,
    epochs=NUM_EPOCHS,
    steps_per_epoch=EVALUATION_INTERVAL,
    validation_data=val_uv,
    validation_steps=50,
    verbose =1,
    callbacks =[
      tf.keras.callbacks.EarlyStopping(
          monitor='val_loss', min_delta=0, patience=10,verbose=1, mode='min'),
      tf.keras.callbacks.ModelCheckpoint('lstm_best.h5',
          monitor='val_loss', save_best_only=True, mode='min',verbose=0)
    ])
training_time = timeit.default_timer()-start_time
```

```
Epoch 1/150
100/100 [==============================] - 7s 23ms/step - loss: 0.0345 - val_
Epoch 2/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0093 - val_
Epoch 3/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0076 - val_
Epoch 4/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0056 - val_
Epoch 5/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0049 - val_
Epoch 6/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0043 - val_
Epoch 7/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0037 - val_
Epoch 8/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0032 - val_
Epoch 9/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0032 - val_
```

```
Epoch 10/150
100/100 [==============================] - 1s 14ms/step - loss: 0.0029 - val_
Epoch 11/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0026 - val_
Epoch 12/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0026 - val_
Epoch 00012: early stopping
```

```
n_trained_epochs = len(history.history['loss'])
fig,axes = plt.subplots(1,1,figsize=(24,6))
plt.suptitle("LSTM")
axes.set_title("Loss")
axes.plot(np.arange(n_trained_epochs),history.history['loss'])
axes.plot(np.arange(n_trained_epochs),history.history['val_loss'])
axes.legend(["Entrenamiento","Validación"])
axes.grid(which="Both")
axes.set_xlabel("Época")
plt.show()
```



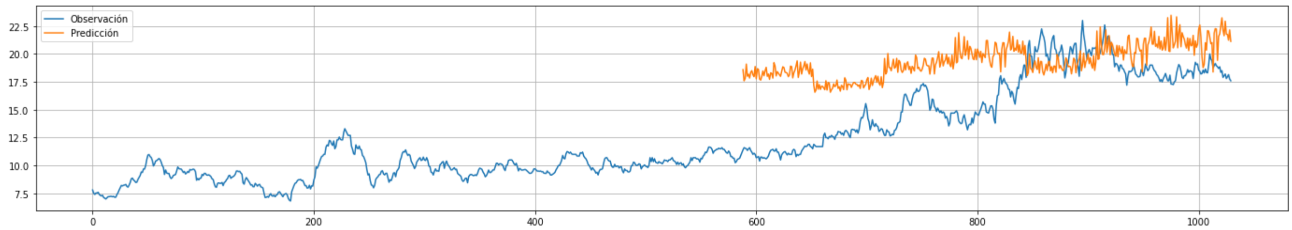

```
model = tf.keras.models.load_model('lstm_best.h5')
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm (LSTM)                  (None, 64, 100)           40800     
_________________________________________________________________
dropout (Dropout)            (None, 64, 100)           0         
_________________________________________________________________
lstm_1 (LSTM)                (None, 50)                30200     
_________________________________________________________________
dropout_1 (Dropout)          (None, 50)                0         
_________________________________________________________________
dense (Dense)                (None, 64)                3264      
=================================================================
Total params: 74,264
Trainable params: 74,264
```

```
Non-trainable params: 0
_________________________________________________________________
```

```
def predict_with_rnn(model,scaler,train,test):
  history = [x for x in train.values]
  predictions = []
  train_scaled = scaler.transform(train.values.reshape(-1, 1))
  test_scaled = scaler.transform(test.values.reshape(-1, 1))
  tmp_input = np.vstack([train_scaled[-WINDOW_SIZE:],test_scaled])
  for i in range(0,test_scaled.shape[0],STEPS_TO_PREDICT):
    yhat = model.predict(tmp_input[i:(i+WINDOW_SIZE)].reshape(1,WINDOW_SIZE, 1)
    yhat = scaler.inverse_transform(yhat).flatten()
    predictions.extend(yhat)
  predictions = np.array(predictions[:len(test)])
  return history,predictions
```

```
start_time = timeit.default_timer()
model = tf.keras.models.load_model('lstm_best.h5')
history,predictions = predict_with_rnn(model,scaler,train,test)
mse,rmse,mae,mape,r2 = report_model(history,predictions,test)
prediction_time = timeit.default_timer()-start_time
```




```
MSE: 291.479
RMSE: 17.073
MAE: 13.370
MAPE: 35.068
R2: -0.811
```

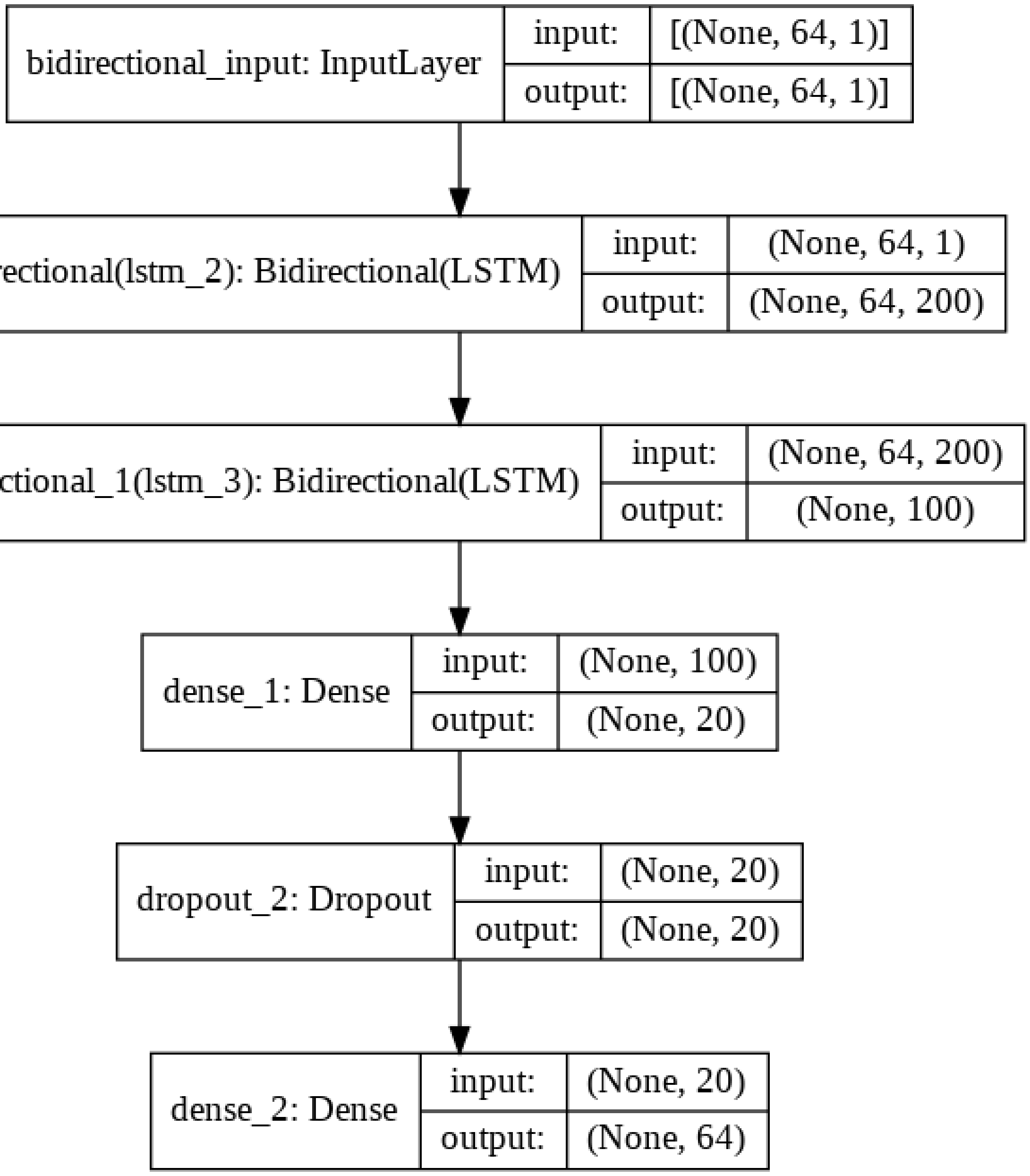
```
print("Tiempo de Entrenamiento:", training_time)
print("Tiempo de Predicción:", prediction_time)

model_metric_results["LSTM"] = {
    "MSE": rmse,
    "RMSE": rmse,
    "MAE": mae,
    "MAPE": mape,
    "R2": r2,
    "Tiempo de Entrenamiento": training_time,
    "Tiempo de Predicción": prediction_time,
    "Descripción": "LSTM (sin reentrenar)"
}
```

```
Tiempo de Entrenamiento: 20.74055405399986
```

```
Tiempo de Predicción: 1.4567058800002997
```

Modelo LSTM Bidireccional

```
model = tf.keras.models.Sequential([
  tf.keras.layers.Bidirectional(
      tf.keras.layers.LSTM(100,return_sequences=True),input_shape=x_train.shape
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(50)),
    tf.keras.layers.Dense(20, activation='softmax'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(units=STEPS_TO_PREDICT),
])

model.compile(optimizer='adam', loss='mse')
tf.keras.utils.plot_model(model, show_shapes=True)
```



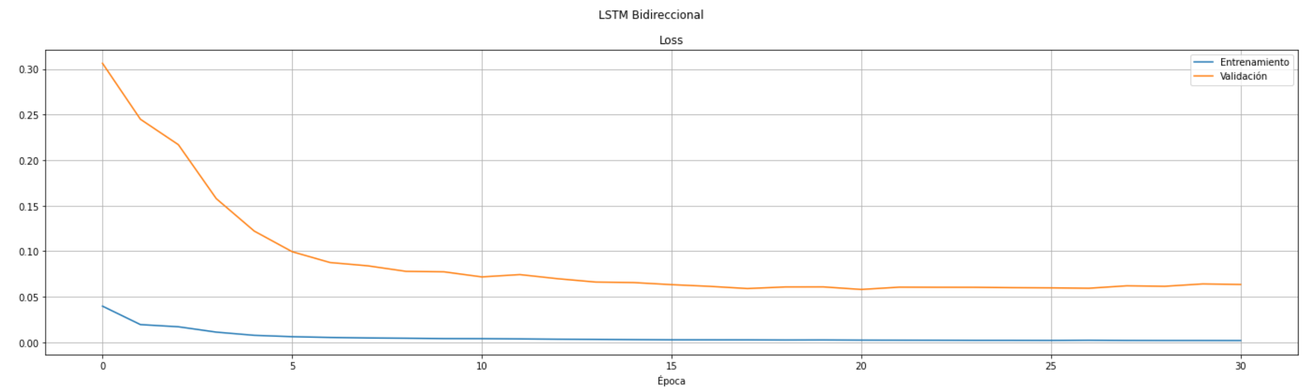

```
EVALUATION_INTERVAL = 100
NUM_EPOCHS = 150
```

```

start_time=timeit.default_timer()
history = model.fit(
    train_uv,
    epochs=NUM_EPOCHS,
    steps_per_epoch=EVALUATION_INTERVAL,
    validation_data=val_uv,
    validation_steps=50,
    verbose =1,
    callbacks =[
      tf.keras.callbacks.EarlyStopping(
          monitor='val_loss', min_delta=0, patience=10,verbose=1, mode='min'),
      tf.keras.callbacks.ModelCheckpoint('lstm_best.h5',
          monitor='val_loss', save_best_only=True, mode='min',verbose=0)
    ])
training_time = timeit.default_timer()-start_time
```

```
100/100 [==============================] - 2s 25ms/step - loss: 0.0180 - va
Epoch 4/150
100/100 [==============================] - 3s 25ms/step - loss: 0.0123 - va
Epoch 5/150
100/100 [==============================] - 3s 25ms/step - loss: 0.0082 - va
Epoch 6/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0066 - va
Epoch 7/150
100/100 [==============================] - 3s 25ms/step - loss: 0.0055 - va
Epoch 8/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0048 - va
Epoch 9/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0047 - va
Epoch 10/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0042 - va
Epoch 11/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0039 - va
Epoch 12/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0040 - va
Epoch 13/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0035 - va
Epoch 14/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0033 - va
Epoch 15/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0030 - va
Epoch 16/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0028 - va
Epoch 17/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0027 - va
Epoch 18/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0027 - va
Epoch 19/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0026 - va
Epoch 20/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0028 - va
Epoch 21/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0025 - va

Epoch 22/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0023 - va
Epoch 23/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0023 - va
Epoch 24/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0023 - va
```

```
Epoch 25/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0022 - va
Epoch 26/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0021 - va
Epoch 27/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0022 - va
Epoch 28/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0021 - va
Epoch 29/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0021 - va
Epoch 30/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0021 - va
Epoch 31/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0019 - va
Epoch 00031: early stopping
```

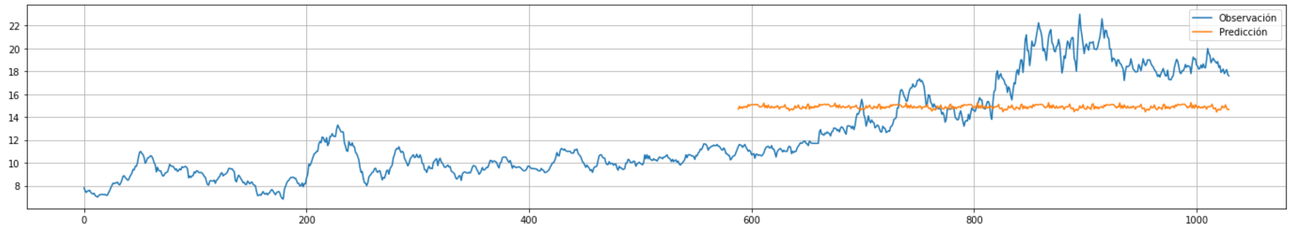
```
n_trained_epochs = len(history.history['loss'])
fig,axes = plt.subplots(1,1,figsize=(24,6))
plt.suptitle("LSTM Bidireccional")
axes.set_title("Loss")
axes.plot(np.arange(n_trained_epochs),history.history['loss'])
axes.plot(np.arange(n_trained_epochs),history.history['val_loss'])
axes.legend(["Entrenamiento","Validación"])
axes.grid(which="Both")
axes.set_xlabel("Época")
plt.show()
```




```
def predict_with_rnn2(model,scaler,train,test):
  history = [x for x in train.values]
  predictions = []
  train_scaled = scaler.transform(train.values.reshape(-1, 1))
  test_scaled = scaler.transform(test.values.reshape(-1, 1))
  tmp_input = np.vstack([train_scaled[-WINDOW_SIZE:],test_scaled])
  for i in range(0,test_scaled.shape[0],STEPS_TO_PREDICT):
    yhat = model.predict(tmp_input[i:(i+WINDOW_SIZE)].reshape(1,WINDOW_SIZE, 1)
    yhat = scaler.inverse_transform(yhat).flatten()
    predictions.extend(yhat)
```

```
  predictions = np.array(predictions[:len(test)])
  return history,predictions
```

```
start_time=timeit.default_timer()
model = tf.keras.models.load_model('lstm_best.h5')
history,predictions = predict_with_rnn2(model,scaler,train,test)
mse,rmse,mae,mape,r2 = report_model(history,predictions,test)
prediction_time = timeit.default_timer()-start_time
```




```
MSE: 447.765
RMSE: 21.160
MAE: 16.946
MAPE: 44.506
R2: -1.781
```

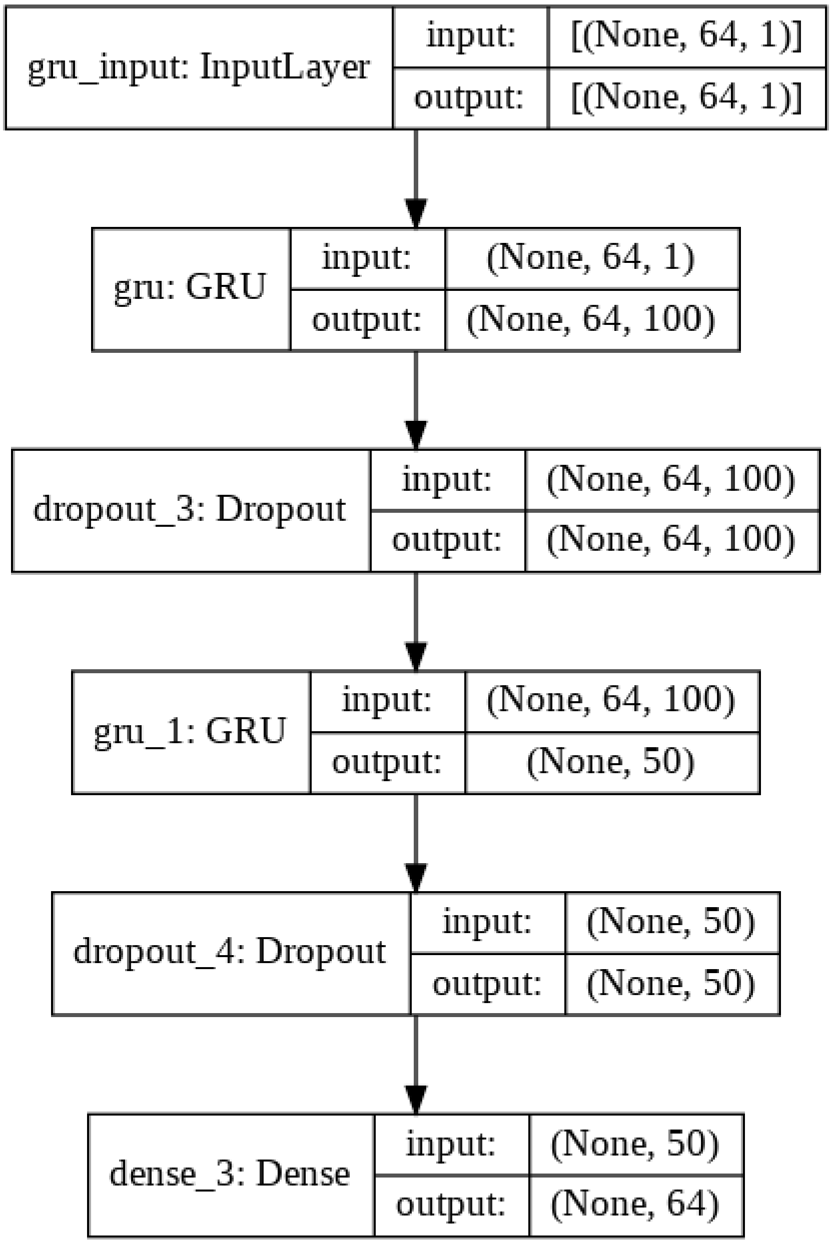
```
print("Tiempo de Entrenamiento:", training_time)
print("Tiempo de Predicción:", prediction_time)

model_metric_results["LSTM-Bi"] = {
    "MSE": rmse,
    "RMSE": rmse,
    "MAE": mae,
    "MAPE": mape,
    "R2": r2,
    "Tiempo de Entrenamiento": training_time,
    "Tiempo de Predicción": prediction_time,
    "Descripción": "LSTM Bidireccional (sin reentrenar)"
}
```

```
Tiempo de Entrenamiento: 87.26663182799984
Tiempo de Predicción: 2.5256501549997665
```

Modelo GRU

```
model = tf.keras.models.Sequential([
  tf.keras.layers.GRU(100, input_shape=x_train.shape[-2:],return_sequences=True
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.GRU(units=50,return_sequences=False),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(units=STEPS_TO_PREDICT),
])

```

```
model.compile(optimizer='adam', loss='mse')
tf.keras.utils.plot_model(model, show_shapes=True)
```




```
EVALUATION_INTERVAL = 100
NUM_EPOCHS = 150

start_time=timeit.default_timer()
history = model.fit(
    train_uv,
    epochs=NUM_EPOCHS,
    steps_per_epoch=EVALUATION_INTERVAL,
    validation_data=val_uv,
    validation_steps=50,
    verbose =1,
    callbacks =[
      tf.keras.callbacks.EarlyStopping(
          monitor='val_loss', min_delta=0, patience=10,verbose=1, mode='min'),
      tf.keras.callbacks.ModelCheckpoint('gru_best.h5',
          monitor='val_loss', save_best_only=True, mode='min',verbose=0)
    ])
training_time = timeit.default_timer()-start_time
```

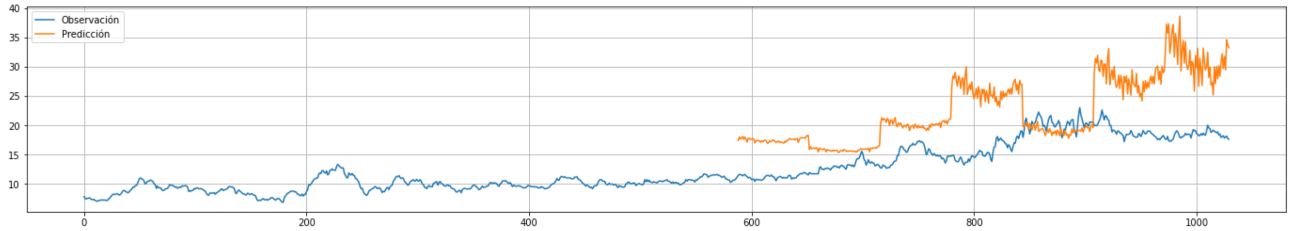
```
training_time = timeit.default_timer() - start_time
```

```
Epoch 1/150
100/100 [==============================] - 5s 19ms/step - loss: 0.0341 - val_
Epoch 2/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0097 - val_
Epoch 3/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0089 - val_
Epoch 4/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0083 - val_
Epoch 5/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0077 - val_
Epoch 6/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0075 - val_
Epoch 7/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0067 - val_
Epoch 8/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0053 - val_
Epoch 9/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0042 - val_
Epoch 10/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0040 - val_
Epoch 11/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0040 - val_
Epoch 12/150
100/100 [==============================] - 1s 12ms/step - loss: 0.0037 - val_
Epoch 13/150
100/100 [==============================] - 1s 13ms/step - loss: 0.0036 - val_
Epoch 00013: early stopping
```

```
n_trained_epochs = len(history.history['loss'])
fig,axes = plt.subplots(1,1,figsize=(24,6))
plt.suptitle("GRU")
axes.set_title("Loss")
axes.plot(np.arange(n_trained_epochs),history.history['loss'])
axes.plot(np.arange(n_trained_epochs),history.history['val_loss'])
axes.legend(["Entrenamiento","Validación"])
axes.grid(which="Both")
axes.set_xlabel("Época")
plt.show()
```

GRU

```
start_time=timeit.default_timer()
model = tf.keras.models.load_model('gru_best.h5')
history,predictions = predict_with_rnn(model,scaler,train,test)
mse,rmse,mae,mape,r2 = report_model(history,predictions,test)
prediction_time = timeit.default_timer()-start_time
```




```
MSE: 169.124
RMSE: 13.005
MAE: 10.432
MAPE: 28.679
R2: -0.051
```

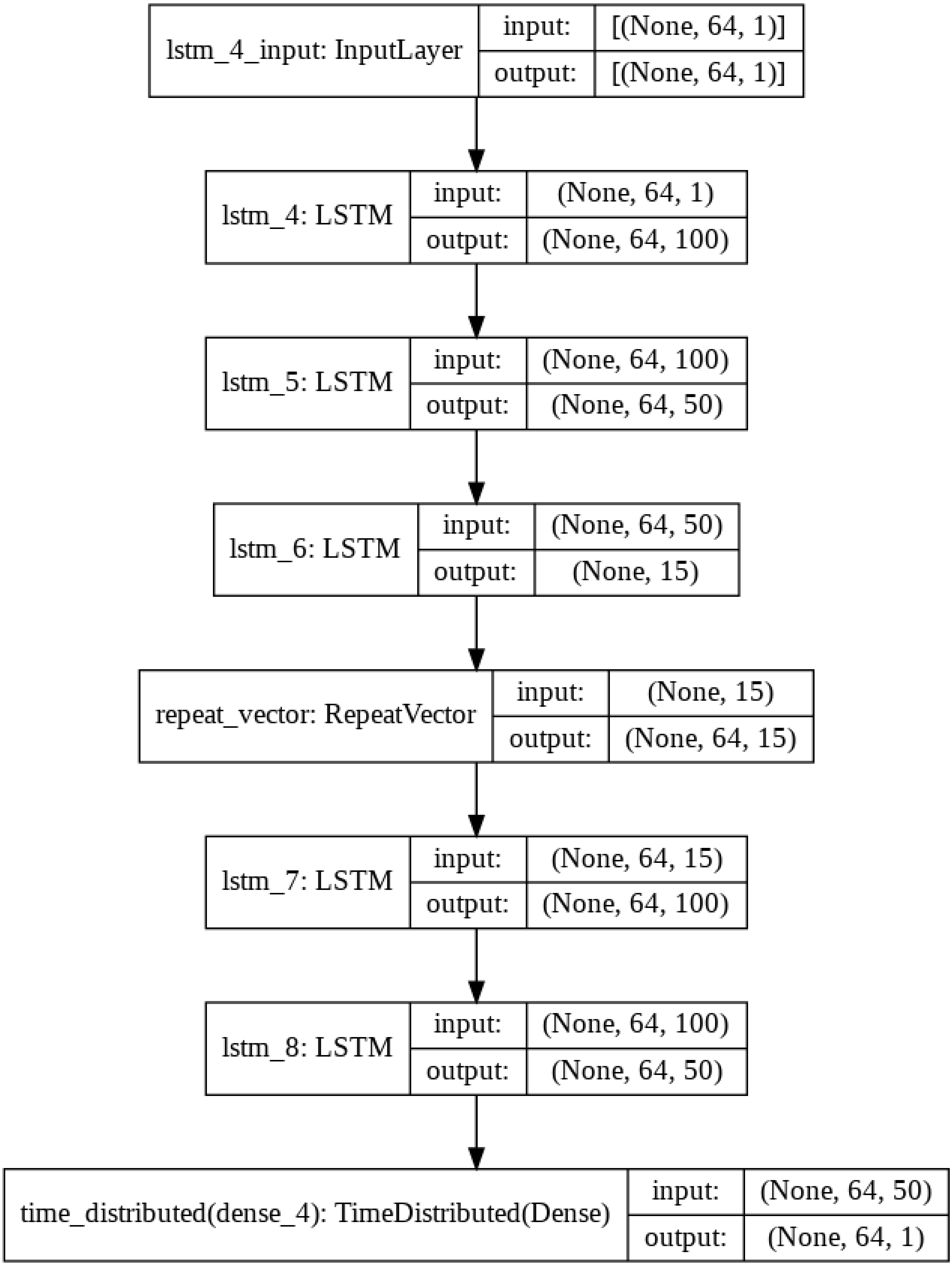
```
print("Tiempo de Entrenamiento:", training_time)
print("Tiempo de Predicción:", prediction_time)

model_metric_results["GRU"] = {
    "MSE": rmse,
    "RMSE": rmse,
    "MAE": mae,
    "MAPE": mape,
    "R2": r2,
    "Tiempo de Entrenamiento": training_time,
    "Tiempo de Predicción": prediction_time,
    "Descripción": "GRU (sin reentrenar)"
}
```

```
Tiempo de Entrenamiento: 19.531193582000014
Tiempo de Predicción: 1.3657522809999136
```

Autoencoder LSTM

```
model = tf.keras.models.Sequential([
  tf.keras.layers.LSTM(100, input_shape=x_train.shape[-2:], return_sequences=Tr
  tf.keras.layers.LSTM(units=50,return_sequences=True),
  tf.keras.layers.LSTM(units=15),
  tf.keras.layers.RepeatVector(y_train.shape[1]),
  tf.keras.layers.LSTM(units=100,return_sequences=True),
  tf.keras.layers.LSTM(units=50,return_sequences=True),
  tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(units=1))
])

```

```
model.compile(optimizer='adam', loss='mse')
tf.keras.utils.plot_model(model, show_shapes=True)
```

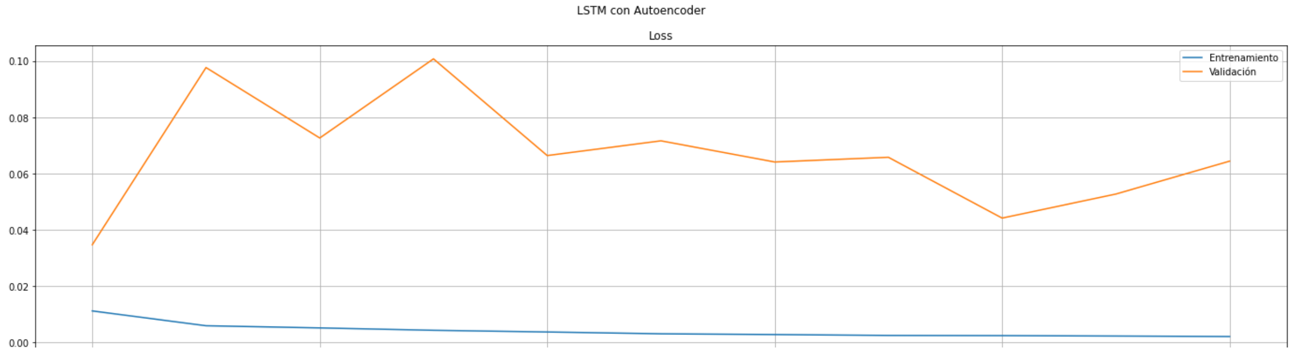



```
EVALUATION_INTERVAL = 100
NUM_EPOCHS = 150

start_time=timeit.default_timer()
history = model.fit(
    train_uv,
```

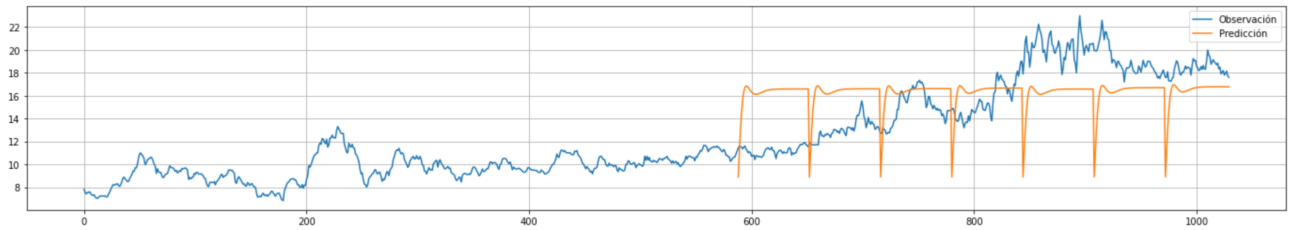
```
    epochs=NUM_EPOCHS,
    steps_per_epoch=EVALUATION_INTERVAL,
    validation_data=val_uv,
    validation_steps=50,
    verbose =1,
    callbacks =[
      tf.keras.callbacks.EarlyStopping(
          monitor='val_loss', min_delta=0, patience=10,verbose=1, mode='min'),
      tf.keras.callbacks.ModelCheckpoint('lstm_autoenc_best.h5',
          monitor='val_loss', save_best_only=True, mode='min',verbose=0)
    ])
training_time = timeit.default_timer()-start_time
```

```
Epoch 1/150
100/100 [==============================] - 10s 44ms/step - loss: 0.0163 - val
Epoch 2/150
100/100 [==============================] - 3s 26ms/step - loss: 0.0069 - val_
Epoch 3/150
100/100 [==============================] - 3s 28ms/step - loss: 0.0051 - val_
Epoch 4/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0043 - val_
Epoch 5/150
100/100 [==============================] - 3s 28ms/step - loss: 0.0039 - val_
Epoch 6/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0033 - val_
Epoch 7/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0028 - val_
Epoch 8/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0024 - val_
Epoch 9/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0026 - val_
Epoch 10/150
100/100 [==============================] - 3s 27ms/step - loss: 0.0024 - val_
Epoch 11/150
100/100 [==============================] - 3s 28ms/step - loss: 0.0022 - val_
Epoch 00011: early stopping
```

```
n_trained_epochs = len(history.history['loss'])
fig,axes = plt.subplots(1,1,figsize=(24,6))
plt.suptitle("LSTM con Autoencoder")
axes.set_title("Loss")
axes.plot(np.arange(n_trained_epochs),history.history['loss'])
axes.plot(np.arange(n_trained_epochs),history.history['val_loss'])
axes.legend(["Entrenamiento","Validación"])
axes.grid(which="Both")
axes.set_xlabel("Época")
plt.show()
```




```
start_time=timeit.default_timer()
model = tf.keras.models.load_model('lstm_autoenc_best.h5')
history,predictions = predict_with_rnn2(model,scaler,train,test)
mse,rmse,mae,mape,r2 = report_model(history,predictions,test)
prediction_time = timeit.default_timer()-start_time
```




```
MSE: 402.105
RMSE: 20.053
MAE: 15.838
MAPE: 41.245
R2: -1.498
```

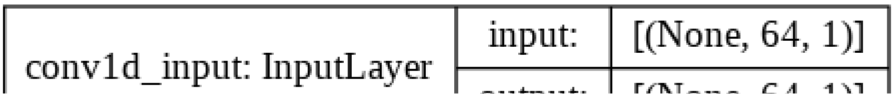
```
print("Tiempo de Entrenamiento:", training_time)
print("Tiempo de Predicción:", prediction_time)

model_metric_results["LSTM-Autoencoder"] = {
    "MSE": rmse,
    "RMSE": rmse,
    "MAE": mae,
    "MAPE": mape,
    "R2": r2,
    "Tiempo de Entrenamiento": training_time,
    "Tiempo de Predicción": prediction_time,
    "Descripción": "LSTM Autoencoder (sin reentrenar)"
}
```

```
Tiempo de Entrenamiento: 37.40004587800013
Tiempo de Predicción: 3.1523871290000898
```

Modelo CNN

```
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Conv1D(filters=64, kernel_size=3, activation='relu',
```

```
input_shape=(x_train.shape[1], x_train.shape[2])))
model.add(tf.keras.layers.MaxPool1D(pool_size=2))
model.add(tf.keras.layers.Dropout(0.2))
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(30, activation='relu'))
model.add(tf.keras.layers.Dropout(0.2))
model.add(tf.keras.layers.Dense(STEPS_TO_PREDICT))
model.compile(optimizer='adam', loss='mse')

model.compile(optimizer='adam', loss='mse')
tf.keras.utils.plot_model(model, show_shapes=True)
```

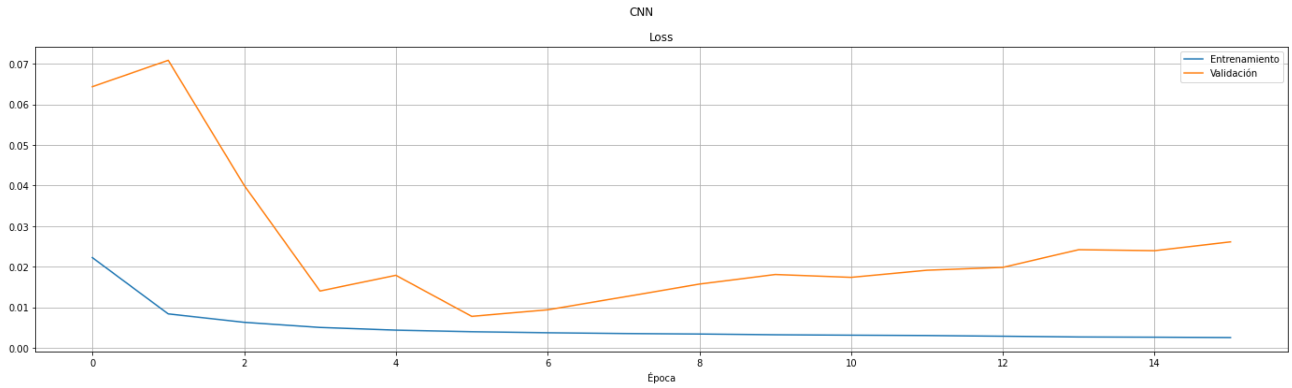



```
EVALUATION_INTERVAL = 100
NUM_EPOCHS = 150

start_time=timeit.default_timer()
history = model.fit(
    train_uv,
    epochs=NUM_EPOCHS,
    steps_per_epoch=EVALUATION_INTERVAL,
    validation_data=val_uv,
    validation_steps=50,
    verbose =1,
    callbacks =[
      tf.keras.callbacks.EarlyStopping(
          monitor='val_loss', min_delta=0, patience=10,verbose=1, mode='min'),
      tf.keras.callbacks.ModelCheckpoint('cnn_best.h5',
          monitor='val_loss', save_best_only=True, mode='min',verbose=0)
    ])
training_time = timeit.default_timer()-start_time
```

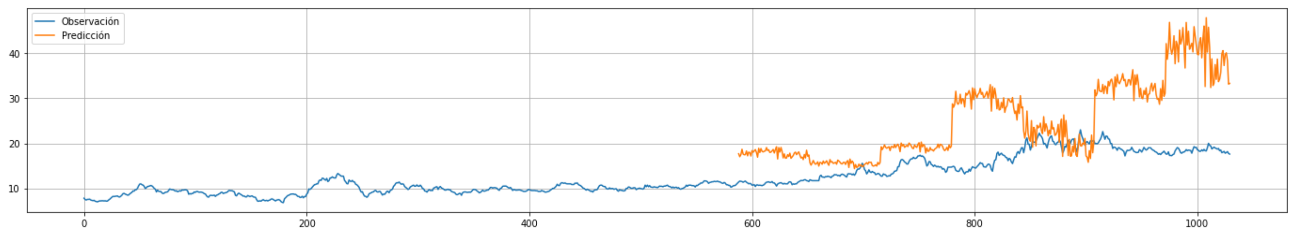
```
Epoch 1/150
100/100 [==============================] - 1s 5ms/step - loss: 0.0342 - val_l
Epoch 2/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0091 - val_l
Epoch 3/150
100/100 [==============================] - 1s 9ms/step - loss: 0.0068 - val_l
Epoch 4/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0052 - val_l
Epoch 5/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0045 - val_l
Epoch 6/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0041 - val_l
Epoch 7/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0038 - val_l
Epoch 8/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0036 - val_l
Epoch 9/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0035 - val_l
Epoch 10/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0032 - val_l
Epoch 11/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0031 - val_l
Epoch 12/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0031 - val_l
Epoch 13/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0029 - val_l
Epoch 14/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0028 - val_l
Epoch 15/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0027 - val_l
Epoch 16/150
100/100 [==============================] - 0s 4ms/step - loss: 0.0025 - val_l
Epoch 00016: early stopping
```

```
n_trained_epochs = len(history.history['loss'])
```

```
n_trained_epochs = len(history.history['loss'])
fig,axes = plt.subplots(1,1,figsize=(24,6))
plt.suptitle("CNN")
axes.set_title("Loss")
axes.plot(np.arange(n_trained_epochs),history.history['loss'])
axes.plot(np.arange(n_trained_epochs),history.history['val_loss'])
axes.legend(["Entrenamiento","Validación"])
axes.grid(which="Both")
axes.set_xlabel("Época")
plt.show()
```




```
start_time=timeit.default_timer()
model = tf.keras.models.load_model('cnn_best.h5')
history,predictions = predict_with_rnn(model,scaler,train,test)
mse,rmse,mae,mape,r2 = report_model(history,predictions,test)
prediction_time = timeit.default_timer()-start_time
```




```
MSE: 110.645
RMSE: 10.519
MAE: 8.465
MAPE: 25.037
R2: 0.313
```

```
print("Tiempo de Entrenamiento:", training_time)
print("Tiempo de Predicción:", prediction_time)

model_metric_results["CNN"] = {
    "MSE": rmse
```

```
    "MSE": mse,
    "RMSE": rmse,
    "MAE": mae,
    "MAPE": mape,
    "R2": r2,
    "Tiempo de Entrenamiento": training_time,
    "Tiempo de Predicción": prediction_time,
    "Descripción": "CNN (sin reentrenar)"
}
```

```
Tiempo de Entrenamiento: 7.540389727000274
Tiempo de Predicción: 0.5014217100001588
```

Modelo Prophet

```
import warnings
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn import metrics
from fbprophet import Prophet
```

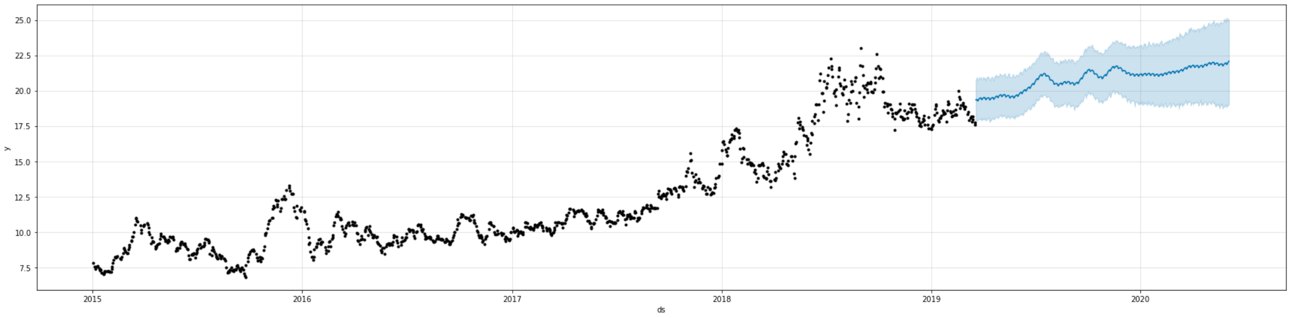
```
def prepare_for_prophet(series,series_col):
  df_prophet = series.to_frame()
  df_prophet['ds'] = df_prophet.index
  df_prophet = df_prophet.rename(columns={series_col: 'y'})
  df_prophet = df_prophet.reset_index()
  df_prophet.drop('Date', inplace=True, axis=1)
  df_prophet.head()
  return df_prophet

train_prophet = prepare_for_prophet(train,series_col)
```

Con Estacionalidad Diaria

```
start_time=timeit.default_timer()
model = Prophet(daily_seasonality=True)
model = model.fit(train_prophet)
training_time = timeit.default_timer() - start_time

start_time=timeit.default_timer()
future = model.make_future_dataframe(periods=len(test),freq='D',include_history
forecast = model.predict(future)
prediction_time = timeit.default_timer() - start_time
```

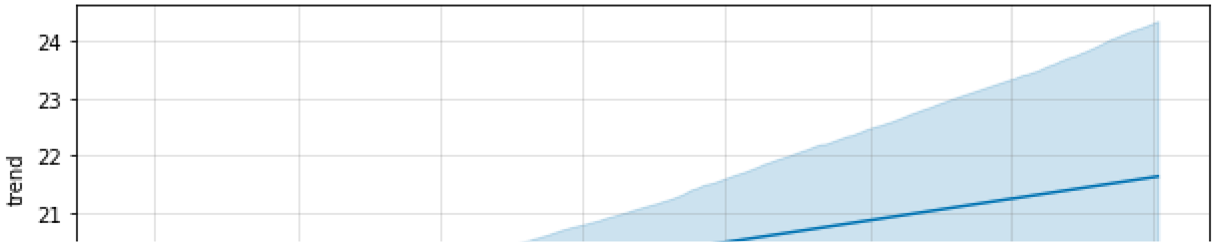
```
fig,axes=plt.subplots(1,1,figsize=(24,6))
model.plot(forecast,ax=axes),
```

```
(<Figure size 1728x432 with 1 Axes>,)
```

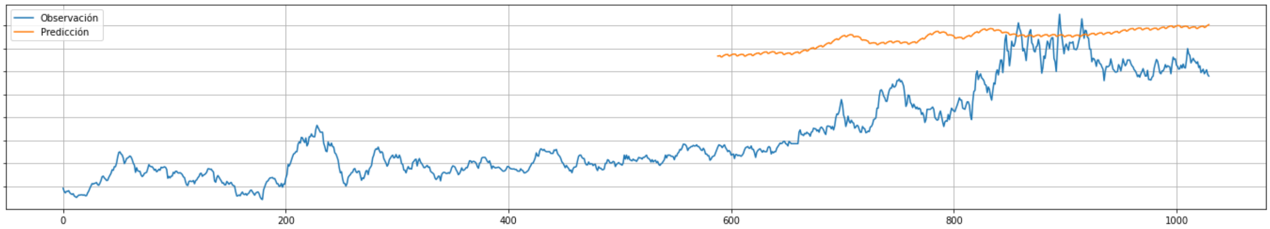



```
1 model.plot_components(forecast),
```

```
(<Figure size 648x864 with 4 Axes>,)
```




```
history = [x for x in train.values]
predictions = [x for x in forecast.yhat]
mse,rmse,mae,mape,r2 = report_model(history,predictions,test)
```




```
MSE: 265.914
RMSE: 16.307
MAE: 12.577
MAPE: 33.199
R2: -0.652
```

```
print("Tiempo de Entrenamiento:", training_time)
print("Tiempo de Predicción:", prediction_time)

model_metric_results["Prophet"] = {
    "MSE": rmse,
    "RMSE": rmse,
    "MAE": mae,
    "MAPE": mape,
    "R2": r2,
    "Tiempo de Entrenamiento": training_time,
    "Tiempo de Predicción": prediction_time,
    "Descripción": "Prophet (con estacionalidad diaria)"
}
```

```
Tiempo de Entrenamiento: 0.7991898319996835
Tiempo de Predicción: 2.8040095960000144
```


Sin Estacionalidad Diaria

```
start_time=timeit.default_timer()
model = Prophet(daily_seasonality=False)
model = model.fit(train_prophet)
training_time = timeit.default_timer() - start_time

start_time=timeit.default_timer()
```

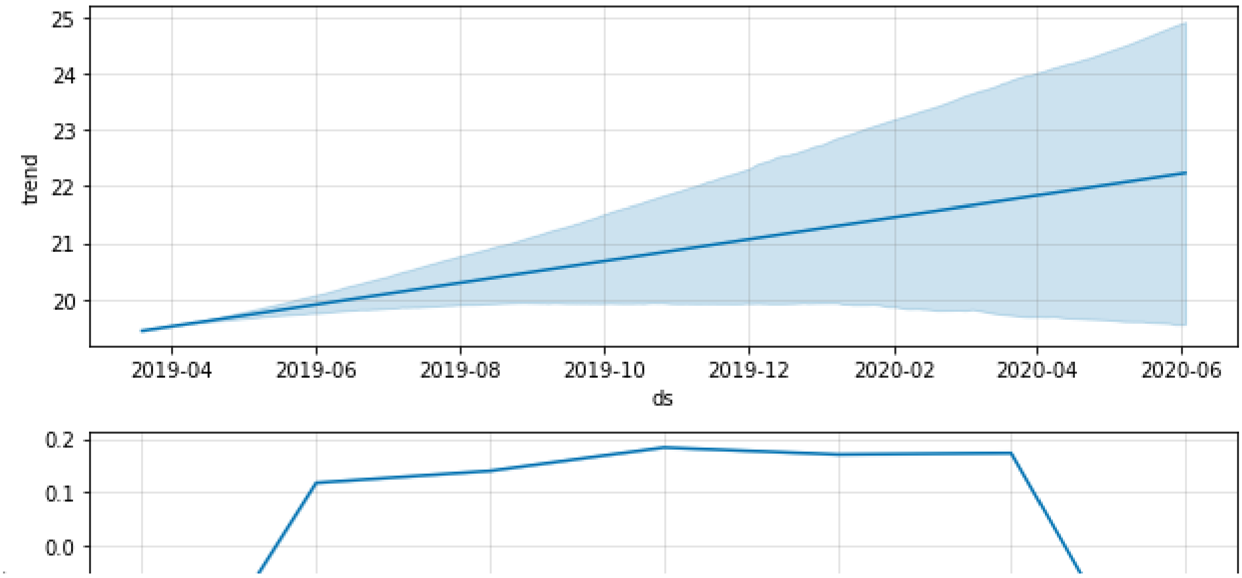
```
future = model.make_future_dataframe(periods=len(test),freq='D',include_history
forecast = model.predict(future)
prediction_time = timeit.default_timer() - start_time
```

```
fig,axes=plt.subplots(1,1,figsize=(24,6))
model.plot(forecast,ax=axes),
```

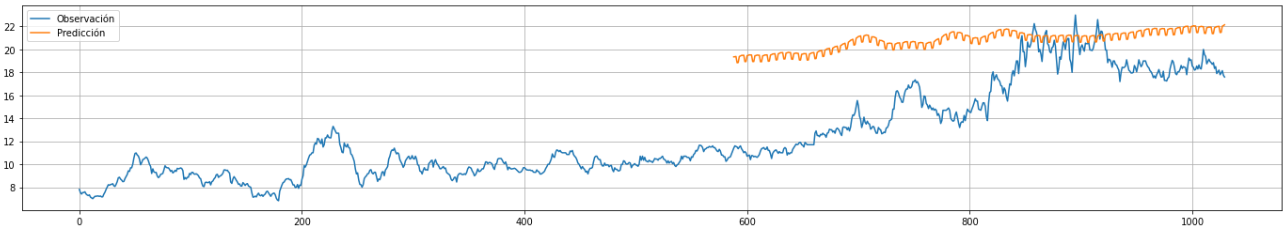
```
(<Figure size 1728x432 with 1 Axes>,)
```


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

```
(<Figure size 648x648 with 3 Axes>,)
```




```
history = [x for x in train.values]
predictions = [x for x in forecast.yhat]
mse,rmse,mae,mape,r2 = report_model(history,predictions,test)
```




```
MSE: 267.860
RMSE: 16.366
MAE: 12.618
MAPE: 33.238
R2: -0.664
```

```
print("Tiempo de Entrenamiento:", training_time)
print("Tiempo de Predicción:", prediction_time)

model_metric_results["Prophet-NDS"] = {
    "MSE": rmse,
    "RMSE": rmse,
    "MAE": mae,
    "MAPE": mape,
    "R2": r2,
    "Tiempo de Entrenamiento": training_time,
    "Tiempo de Predicción": prediction_time,
    "Descripción": "Prophet (sin estacionalidad diaria)"
}
```

```
Tiempo de Entrenamiento: 0.46586447199979375
Tiempo de Predicción: 2.8597310319996723
```

Resultados y conclusiones

```
1 model_metrics_df = pd.DataFrame.from_dict(model_metric_results, orient='index')
2 model_metrics_df.sort_values("RMSE",ascending=True)
```

	MSE	RMSE	MAE	MAPE	R2	Tiempo de Entrenamiento	P
ARIMA	7.770072	7.770072	6.083144	19.314586	0.624991	3.374228	
baseline	7.915971	7.915971	6.161426	19.487578	0.610776	0.000000	
CNN	10.518807	10.518807	8.464948	25.036543	0.312734	7.540390	
GRU	13.004758	13.004758	10.432283	28.678565	-0.050500	19.531194	
Prophet	16.306881	16.306881	12.577351	33.198582	-0.651709	0.799190	
Prophet-NDS	16.366439	16.366439	12.618079	33.237978	-0.663796	0.465864	
LSTM	17.072769	17.072769	13.369523	35.067643	-0.810505	20.740554	

Bibliografía y Referencias

- [1] "Hands-On Time Series Analysis with Python. From Basics to Bleeding Edge Techniques" - B V VIshwas, Ashish Patel. Apress (2020).
- [2] "Machine Learning for Time Series Forecasting with Python" - Francesca Lazzeri. Wiley (2021).
- [3] "Practical Time Series Analyisis". Avish Pal PKS Prackash. Packt (2017).