```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
plt.style.use("fivethirtyeight")
%matplotlib inline

# Para poder leer y trabajar con los precios de las acciones
from pandas_datareader.data import DataReader
import yfinance as yf
from pandas_datareader import data as pdr

yf.pdr_override()

# Para la fecha de los datos
from datetime import datetime


# Lista con el nombre de las acciones que vamos a utilizar
tech_list = ['AAPL', 'GOOG', 'MSFT', 'META']

# Defininimos qué fechas queremos de los datos
end = datetime.now()
start = datetime(end.year - 1, end.month, end.day)

for stock in tech_list:
    globals()[stock] = yf.download(stock, start ="2012-01-01", end =
"2024-01-05")


company_list = [AAPL, GOOG, MSFT, META]
company_name = ["APPLE", "GOOGLE", "MICROSOFT", "META"]

for company, com_name in zip(company_list, company_name):
    company["company_name"] = com_name

df = pd.concat(company_list, axis=0)
df.tail(10)
```

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

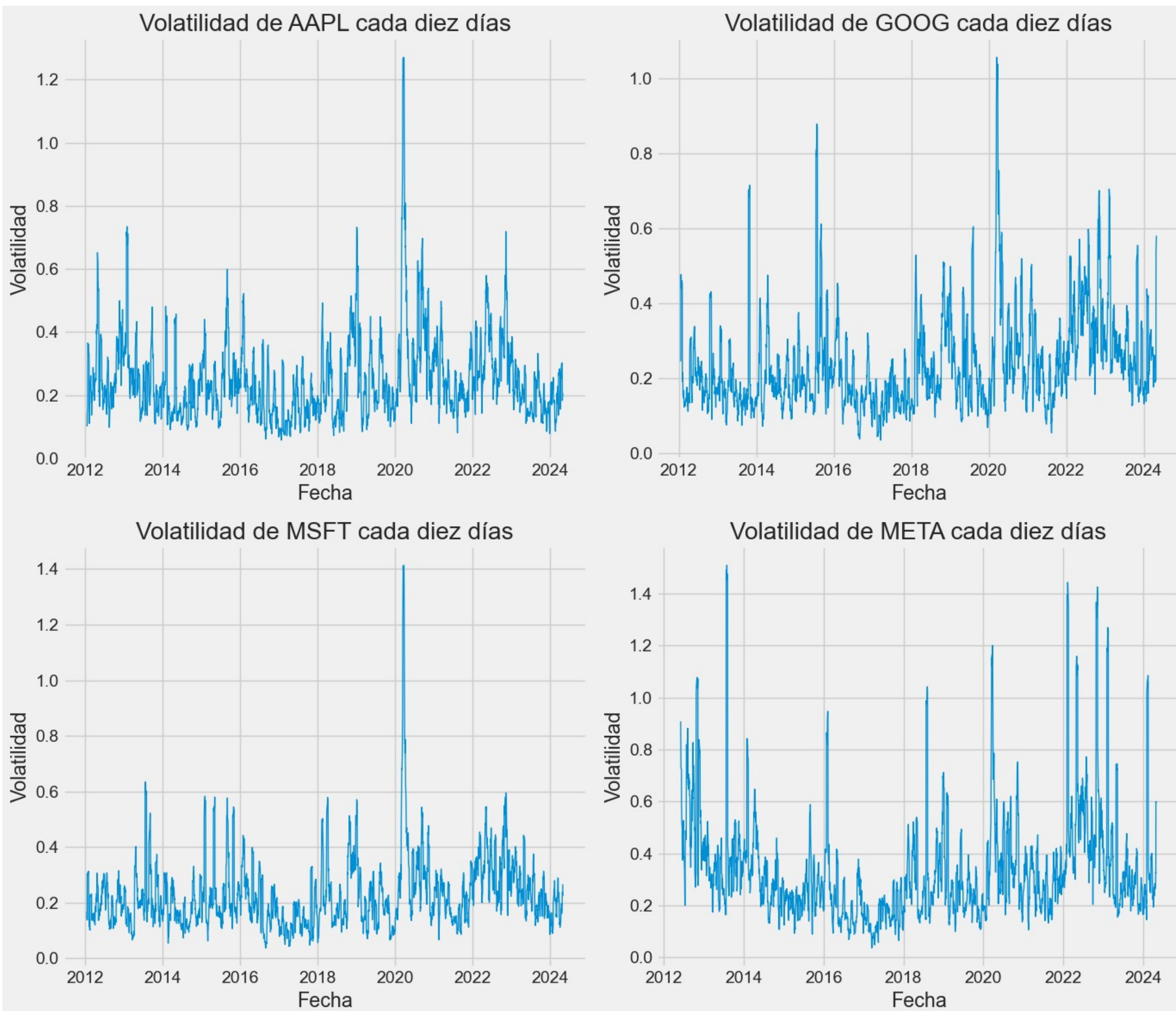
```
                  Open        High         Low       Close   Adj Close
\
Date

2023-12-20  348.649994  354.959991  347.790009  349.279999  348.909790
```

```
2023-12-21  352.980011  356.410004  349.209991  354.089996  353.714691
2023-12-22  355.579987  357.200012  351.220001  353.390015  353.015472
2023-12-26  354.989990  356.980011  353.450012  354.829987  354.453918
2023-12-27  356.070007  359.000000  355.309998  357.829987  357.450714
2023-12-28  359.700012  361.899994  357.809998  358.320007  357.940216
2023-12-29  358.989990  360.000000  351.820007  353.959991  353.584839
2024-01-02  351.320007  353.160004  340.010010  346.290009  345.922974
2024-01-03  344.980011  347.950012  343.179993  344.470001  344.104889
2024-01-04  344.500000  348.149994  343.399994  347.119995  346.752075

              Volume company_name
Date
2023-12-20  16369900         META
2023-12-21  15289600         META
2023-12-22  11764200         META
2023-12-26   9898600         META
2023-12-27  13207900         META
2023-12-28  11798800         META
2023-12-29  14980500         META
2024-01-02  19042200         META
2024-01-03  15451100         META
2024-01-04  12099900         META
```

```python
#Graficamos los precios de las acciones de este último año
plt.figure(figsize=(15, 10))
plt.subplots_adjust(top=1.25, bottom=1.2)

for i, company in enumerate(company_list, 1):
    plt.subplot(2, 2, i)
    company['Adj Close'].plot(linewidth = 1)

    plt.xlabel(None)
    plt.title(f"Cierre ajustado de {tech_list[i - 1]}")

plt.tight_layout()
```


```python
import yfinance as yf
import matplotlib.pyplot as plt

# Lista de tickers de las empresas
tickers = ["AAPL", "GOOG", "MSFT", "META"]

# Obtener los datos de precios de las acciones para el último año
start_date = "2012-01-01"
end_date = "2024-05-01"

data = yf.download(tickers, start=start_date, end=end_date)

# Calcular los retornos diarios
returns = data["Adj Close"].pct_change()

# Calcular la volatilidad para cada diez días
volatility_10_days = returns.rolling(window=10).std() * (252 ** 0.5)
# Ventana de 10 días, asumiendo 252 días hábiles en un año

# Crear subgráficos
fig, axes = plt.subplots(2, 2, figsize=(14, 12))

# Graficar la volatilidad para cada empresa en subgráficos separados
for i, ticker in enumerate(tickers):
    row = i // 2
```

```
    col = i % 2
    axes[row, col].plot(volatility_10_days[ticker], linewidth=1)
    axes[row, col].set_title(f'Volatilidad de {ticker} cada diez 
días')
    axes[row, col].set_xlabel('Fecha')
    axes[row, col].set_ylabel('Volatilidad')

plt.tight_layout()
plt.show()

[*******************100%%**********************]  4 of 4 completed
```

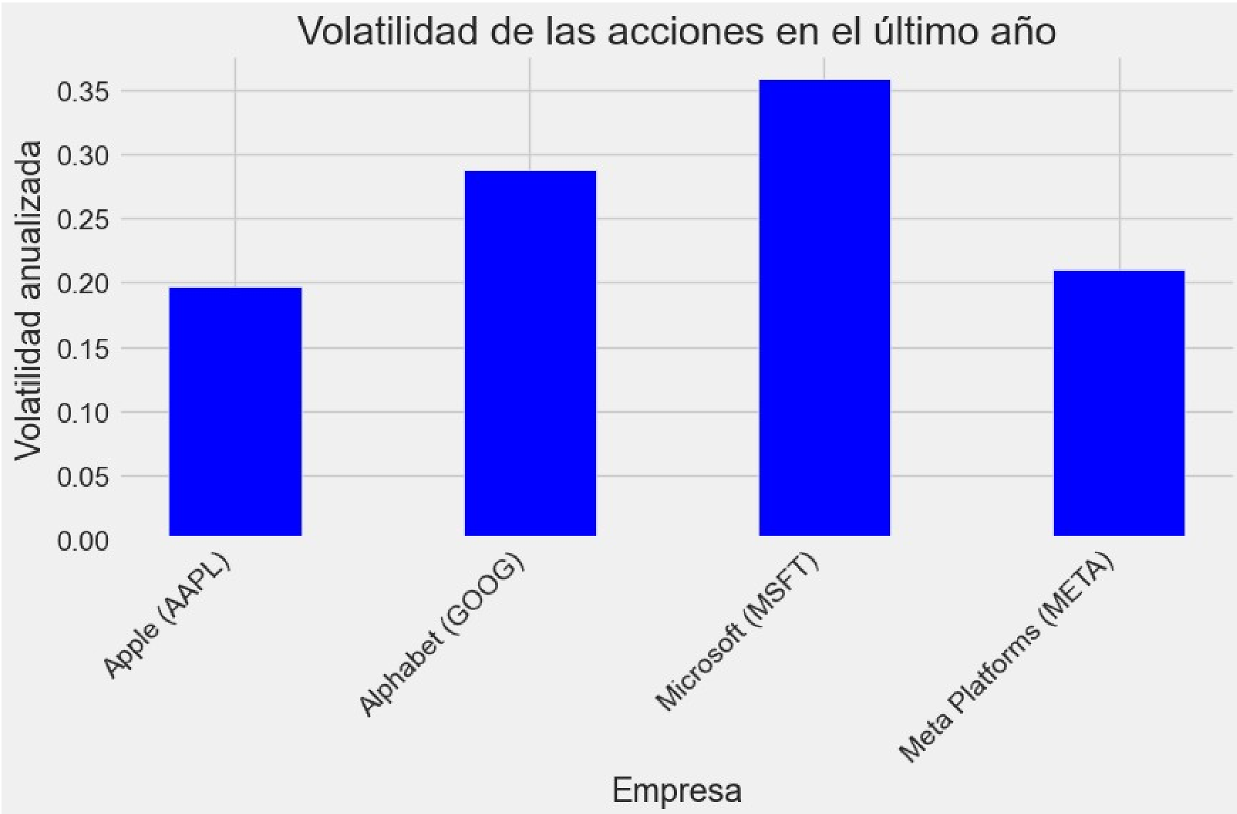



```
import yfinance as yf

# Lista de tickers de las empresas
tickers = ["AAPL", "GOOG", "MSFT", "META"]
```

```python
# Obtener los datos de precios de las acciones para el último año
start_date = "2023-05-01"
end_date = "2024-05-01"

data = yf.download(tickers, start=start_date, end=end_date)

# Calcular los retornos diarios
returns = data["Adj Close"].pct_change()

# Calcular la volatilidad anualizada asumiendo 252 días hábiles
volatility = returns.std() * (252 ** 0.5)

print("Volatilidad anualizada:")
for ticker, vol in zip(tickers, volatility):
    print(f"{ticker}: {vol:.2f}")

import matplotlib.pyplot as plt

# Lista de nombres de empresas
companies = ["Apple (AAPL)", "Alphabet (GOOG)", "Microsoft (MSFT)",
"Meta Platforms (META)"]

# Crear un gráfico de barras para visualizar la volatilidad
plt.figure(figsize=(9, 6))
plt.bar(companies, volatility, color='blue', width=0.45)
plt.title('Volatilidad de las acciones en el último año')
plt.xlabel('Empresa')
plt.ylabel('Volatilidad anualizada')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

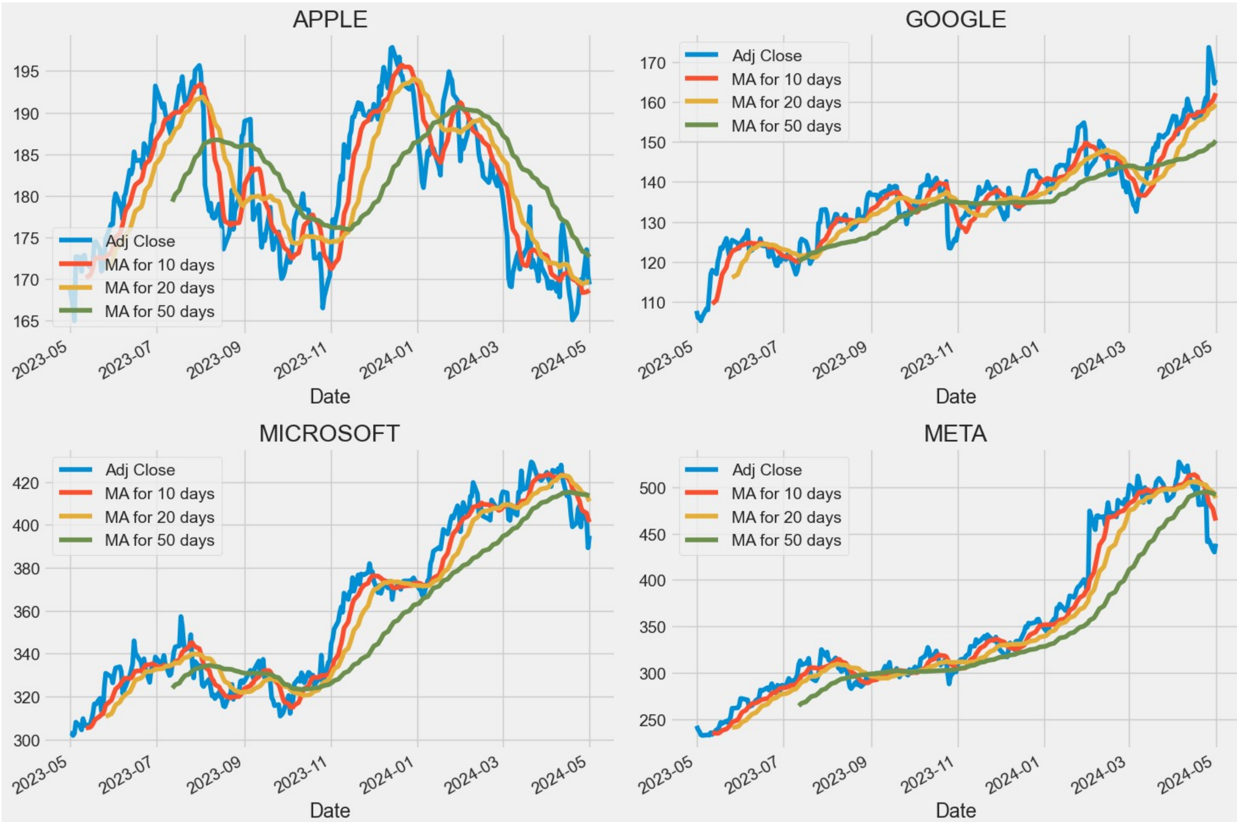
```
[*********************100%%**********************]  4 of 4 completed
```

```
Volatilidad anualizada:
AAPL: 0.20
GOOG: 0.29
MSFT: 0.36
META: 0.21
```



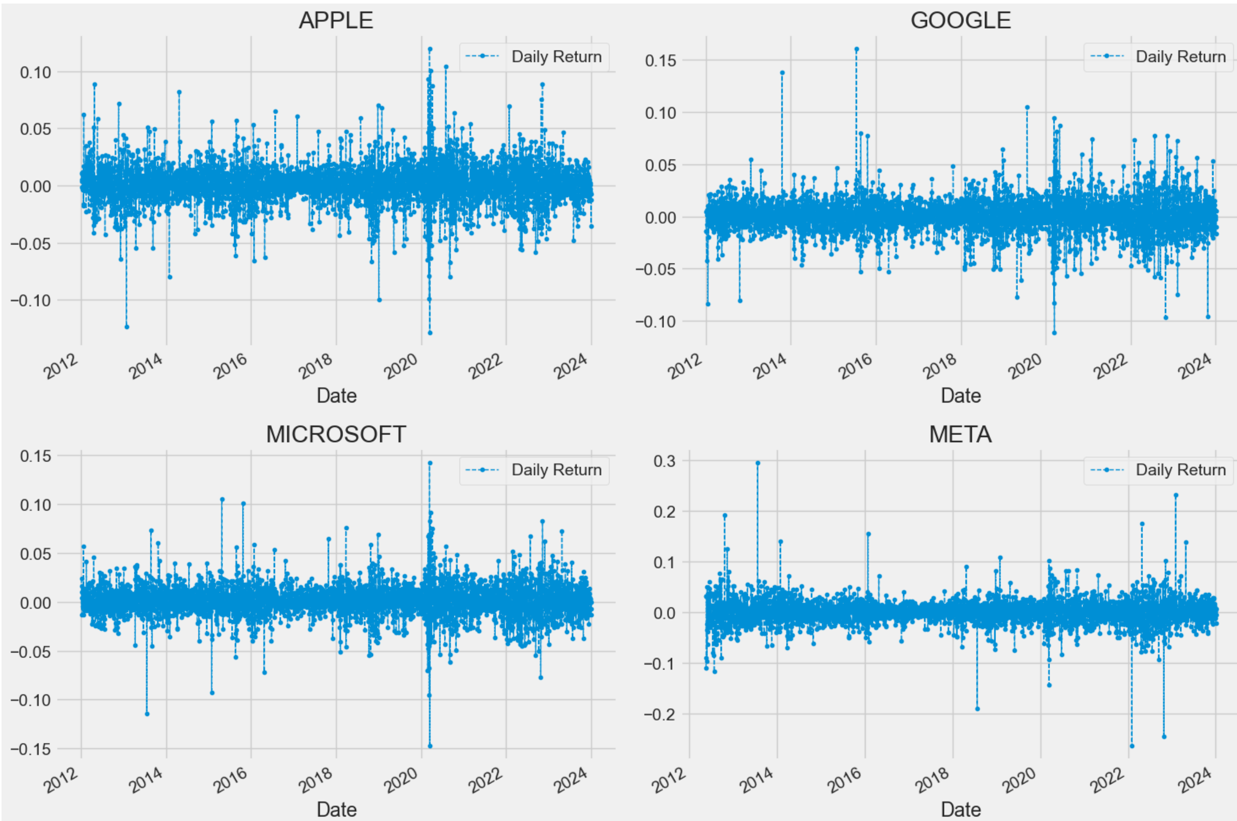

```
ma_day = [10, 20, 50]

for ma in ma_day:
    for company in company_list:
        column_name = f"MA for {ma} days"
        company[column_name] = company['Adj Close'].rolling(ma).mean()


fig, axes = plt.subplots(nrows=2, ncols=2)
fig.set_figheight(10)
fig.set_figwidth(15)

AAPL[['Adj Close', 'MA for 10 days', 'MA for 20 days', 'MA for 50
days']].plot(ax=axes[0,0])
axes[0,0].set_title('APPLE')

GOOG[['Adj Close', 'MA for 10 days', 'MA for 20 days', 'MA for 50
days']].plot(ax=axes[0,1])
axes[0,1].set_title('GOOGLE')

MSFT[['Adj Close', 'MA for 10 days', 'MA for 20 days', 'MA for 50
days']].plot(ax=axes[1,0])
axes[1,0].set_title('MICROSOFT')

META[['Adj Close', 'MA for 10 days', 'MA for 20 days', 'MA for 50
```

```
days']].plot(ax=axes[1,1])
axes[1,1].set_title('META')

fig.tight_layout()
```

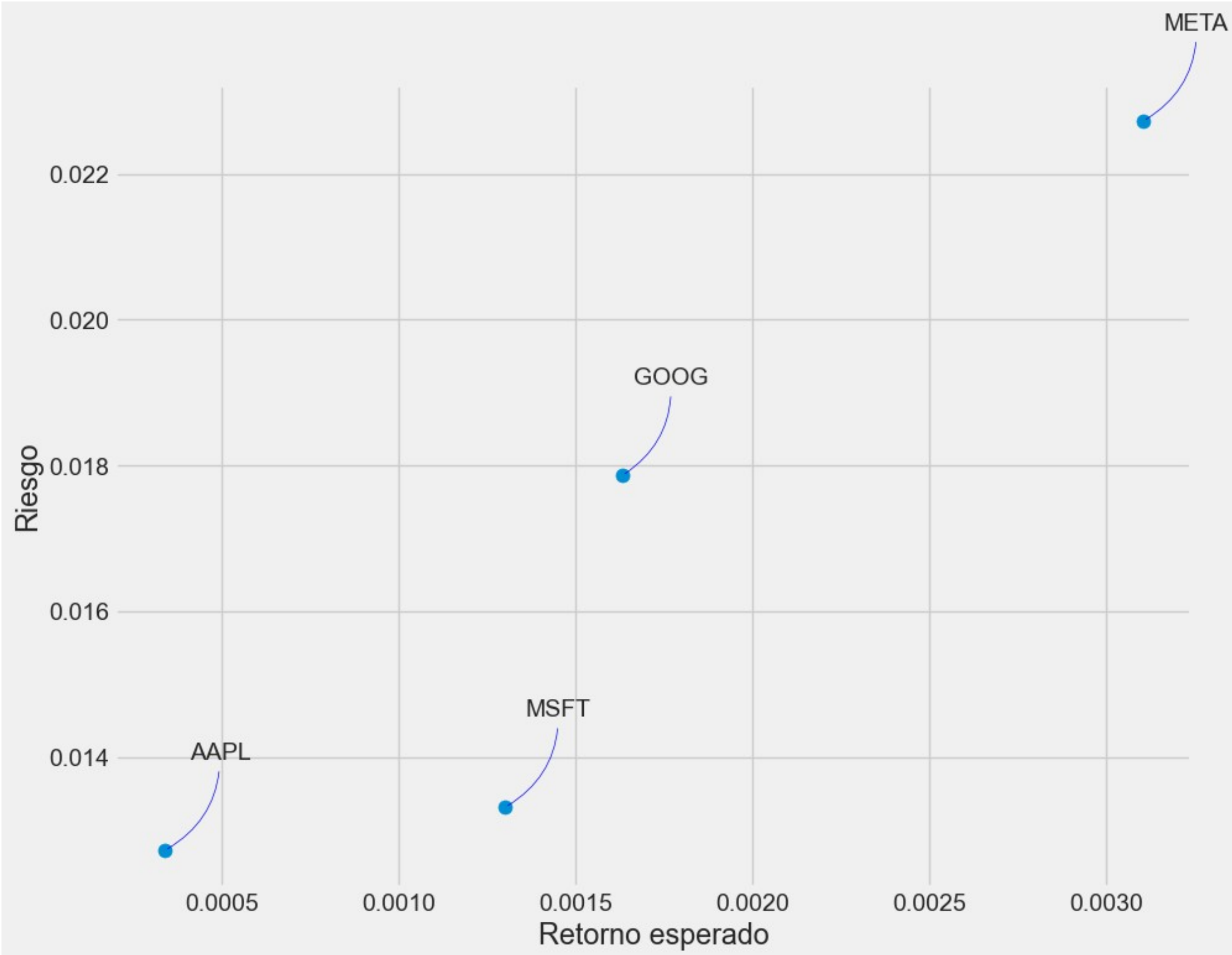



```
# Usamos pct_change para encontrar el porcentaje de cambio en el
precio cada día
for company in company_list:
    company['Daily Return'] = company['Adj Close'].pct_change()

# Graficamos
fig, axes = plt.subplots(nrows=2, ncols=2)
fig.set_figheight(10)
fig.set_figwidth(15)

AAPL['Daily Return'].plot(ax=axes[0,0], legend=True, linestyle='--',
marker='.', linewidth=1)
axes[0,0].set_title('APPLE')

GOOG['Daily Return'].plot(ax=axes[0,1], legend=True, linestyle='--',
marker='.', linewidth=1)
axes[0,1].set_title('GOOGLE')

MSFT['Daily Return'].plot(ax=axes[1,0], legend=True, linestyle='--',
```

```
marker='.', linewidth=1)
axes[1,0].set_title('MICROSOFT')

META['Daily Return'].plot(ax=axes[1,1], legend=True, linestyle='--',
marker='.', linewidth=1)
axes[1,1].set_title('META')

fig.tight_layout()
```




```
rets = tech_rets.dropna()

area = np.pi * 20

plt.figure(figsize=(10, 8))
plt.scatter(rets.mean(), rets.std(), s=area)
plt.xlabel('Retorno esperado')
plt.ylabel('Riesgo')

for label, x, y in zip(rets.columns, rets.mean(), rets.std()):
    plt.annotate(label, xy=(x, y), xytext=(50, 50), textcoords='offset
points', ha='right', va='bottom',
                 arrowprops=dict(arrowstyle='-', color='blue',
connectionstyle='arc3,rad=-0.3'))
```



Predicción con LSTM

```
# Cargamos los datos de las acciones que queremos analizar y predecir
df = pdr.get_data_yahoo('AAPL', start='2012-01-01',
end=datetime.now())

df

[*********************100%%**********************]  1 of 1 completed

                 Open       High        Low      Close  Adj Close  \
Date

2012-01-03  14.621429  14.732143  14.607143  14.686786  12.416983

2012-01-04  14.642857  14.810000  14.617143  14.765714  12.483713

2012-01-05  14.819643  14.948214  14.738214  14.929643  12.622309

2012-01-06  14.991786  15.098214  14.972143  15.085714  12.754258
```

```
2012-01-09   15.196429   15.276786   15.048214   15.061786   12.734027
...                ...         ...         ...         ...         ...
2024-05-13  185.440002  187.100006  184.619995  186.279999  186.279999
2024-05-14  187.509995  188.300003  186.289993  187.429993  187.429993
2024-05-15  187.910004  190.649994  187.369995  189.720001  189.720001
2024-05-16  190.470001  191.100006  189.660004  189.839996  189.839996
2024-05-17  189.380005  190.809998  189.220001  189.869995  189.869995

               Volume
Date
2012-01-03  302220800
2012-01-04  260022000
2012-01-05  271269600
2012-01-06  318292800
2012-01-09  394024400
...               ...
2024-05-13   72044800
2024-05-14   52393600
2024-05-15   70400000
2024-05-16   52845200
2024-05-17   37956559

[3114 rows x 6 columns]
```

```python
#Hacemos una gráfica con el histórico de precios
plt.figure(figsize=(16,6))
plt.title('Histórico de precios AAPL')
plt.plot(df['Adj Close'], linewidth = 1)
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre ajustado USD ($)', fontsize=18)
plt.show()
```


```
# Creamos un nuevo DataFrame con únicamente la columna Adj Close
data = df.filter(['Adj Close'])
# Convertimos el dataframe en un numpy array
dataset = data.values
# Número de filas para entrenar el modelo
training_data_len = int(np.ceil( len(dataset) * .95 ))

training_data_len

2959

# Escalamos y normalizamos los datos
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)

scaled_data

array([[0.00242952],
       [0.00278902],
       [0.00353566],
       ...,
       [0.95760493],
       [0.95825137],
       [0.95841298]])

# Creamos el data set para entrenamiento con los datos escalados
train_data = scaled_data[0:int(training_data_len), :]
# Separamos los datos entre x_train y y_train
x_train = []
y_train = []

for i in range(60, len(train_data)):
    x_train.append(train_data[i-60:i, 0])
```

```python
    y_train.append(train_data[i, 0])
    if i<= 61:
        print(x_train)
        print(y_train)
        print()

# Convertimos x_train y y_train en numpy arrays
x_train, y_train = np.array(x_train), np.array(y_train)

# Cambiamos la forma de los datos
x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
```

```
[array([0.00242952, 0.00278902, 0.00353566, 0.00424651, 0.00413752,
       0.00438316, 0.00427091, 0.0040822 , 0.0038252 , 0.00462065,
       0.00533801, 0.00511677, 0.00390492, 0.00506149, 0.00392281,
       0.00819283, 0.00786259, 0.00829366, 0.00922574, 0.0097902 ,
       0.00974301, 0.00956897, 0.0103107 , 0.01100855, 0.01179914,
       0.01307605, 0.01575844, 0.01579909, 0.01729238, 0.01840826,
       0.01649044, 0.01722893, 0.01721427, 0.01928502, 0.01899058,
       0.01953552, 0.02051477, 0.02105974, 0.02262947, 0.023773  ,
       0.02410324, 0.02421869, 0.02226349, 0.02179174, 0.02186169,
       0.02369983, 0.02421709, 0.02532813, 0.02794702, 0.03144112,
       0.03078715, 0.03078883, 0.033315  , 0.03410559, 0.03354275,
       0.03302875, 0.03249354, 0.0342715 , 0.03549148, 0.0360023 ])]
[0.034739983147894324]

[array([0.00242952, 0.00278902, 0.00353566, 0.00424651, 0.00413752,
       0.00438316, 0.00427091, 0.0040822 , 0.0038252 , 0.00462065,
       0.00533801, 0.00511677, 0.00390492, 0.00506149, 0.00392281,
       0.00819283, 0.00786259, 0.00829366, 0.00922574, 0.0097902 ,
       0.00974301, 0.00956897, 0.0103107 , 0.01100855, 0.01179914,
       0.01307605, 0.01575844, 0.01579909, 0.01729238, 0.01840826,
       0.01649044, 0.01722893, 0.01721427, 0.01928502, 0.01899058,
       0.01953552, 0.02051477, 0.02105974, 0.02262947, 0.023773  ,
       0.02410324, 0.02421869, 0.02226349, 0.02179174, 0.02186169,
       0.02369983, 0.02421709, 0.02532813, 0.02794702, 0.03144112,
       0.03078715, 0.03078883, 0.033315  , 0.03410559, 0.03354275,
       0.03302875, 0.03249354, 0.0342715 , 0.03549148, 0.0360023 ]),
array([0.00278902, 0.00353566, 0.00424651, 0.00413752, 0.00438316,
       0.00427091, 0.0040822 , 0.0038252 , 0.00462065, 0.00533801,
       0.00511677, 0.00390492, 0.00506149, 0.00392281, 0.00819283,
       0.00786259, 0.00829366, 0.00922574, 0.0097902 , 0.00974301,
       0.00956897, 0.0103107 , 0.01100855, 0.01179914, 0.01307605,
       0.01575844, 0.01579909, 0.01729238, 0.01840826, 0.01649044,
       0.01722893, 0.01721427, 0.01928502, 0.01899058, 0.01953552,
       0.02051477, 0.02105974, 0.02262947, 0.023773  , 0.02410324,
       0.02421869, 0.02226349, 0.02179174, 0.02186169, 0.02369983,
       0.02421709, 0.02532813, 0.02794702, 0.03144112, 0.03078715,
       0.03078883, 0.033315  , 0.03410559, 0.03354275, 0.03302875,
       0.03249354, 0.0342715 , 0.03549148, 0.0360023 , 0.03473998])]
```

```
[0.03473998314789432 4, 0.03306286956459417]
```

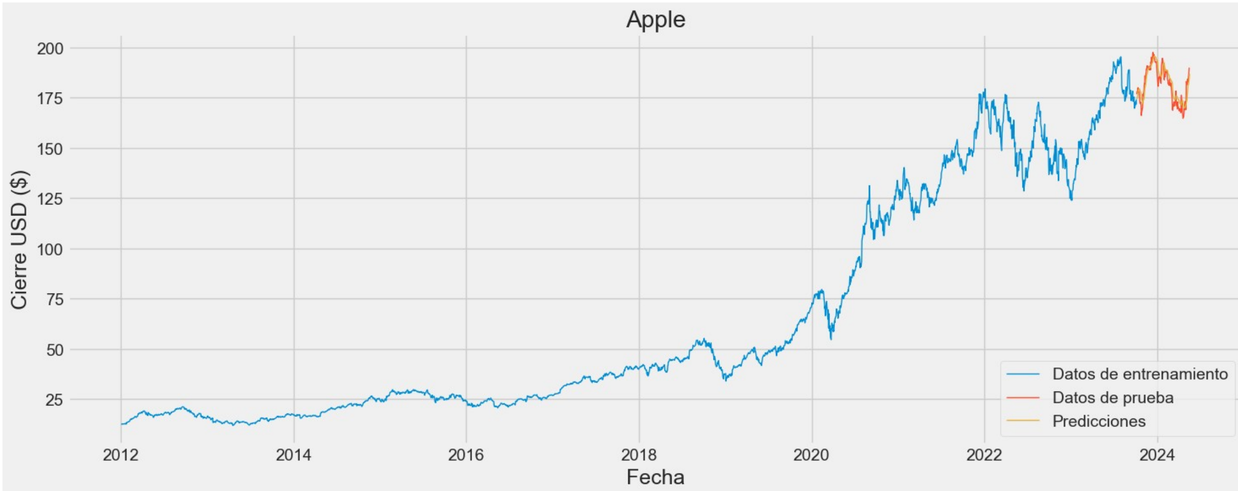
```python
from keras.models import Sequential
from keras.layers import LSTM, Dense

# Creamos el modelo LSTM
model = Sequential()

# Añadimos capas LSTM con 50 unidades
model.add(LSTM(50, return_sequences=True,
input_shape=(x_train.shape[1], 1)))
model.add(LSTM(50, return_sequences=False))
# Añadimos una capa densa con 25 unidades
model.add(Dense(25))
# Añadir una capa de salida densa con 1 unidad
model.add(Dense(1))

# Compilamos el modelo
model.compile(optimizer='adam', loss='mean_squared_error')

# Entrenamos el modelo
model.fit(x_train, y_train, batch_size=1, epochs=1)

# Creamos el conjunto de datos de prueba
test_data = scaled_data[training_data_len - 60: , :]
# Creamos los conjuntos de datos x_test y y_test
x_test = []
y_test = dataset[training_data_len:, :]
for i in range(60, len(test_data)):
    x_test.append(test_data[i-60:i, 0])

# Convertimos a un numpy array
x_test = np.array(x_test)

# Cambiamos la forma de los datos
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))

# Obtención de las predicciones
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)

# Calculamos el RMSE
rmse=np.sqrt(np.mean(((predictions- y_test)**2)))
print("Root Mean Square Error:",rmse)

# Calcular el NRMSE
range_y = np.max(y_test) - np.min(y_test)
nrmse = rmse / range_y
print("Normalized Root Mean Square Error (NRMSE):", nrmse)
```

```python
# Calculamos el MAE
mae = np.mean(np.abs(predictions - y_test))
print("Mean Absolute Error:", mae)

# Calculamos el coeficiente de determinación (R cuadrado)
from sklearn.metrics import r2_score

r2 = r2_score(y_test, predictions)
print("Coeficiente de determinación (R cuadrado):", r2)
```

```
c:\Users\Usuario\anaconda3\Lib\site-packages\keras\src\layers\rnn\rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)

2899/2899 ━━━━━━━━━━━━━━━━━━━━ 25s 8ms/step - loss: 0.0021
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
Root Mean Square Error: 4.225860178279189
Normalized Root Mean Square Error (NRMSE): 0.1287860834806857
Mean Absolute Error: 3.4758476995652723
Coeficiente de determinación (R cuadrado): 0.7764756512759355
```

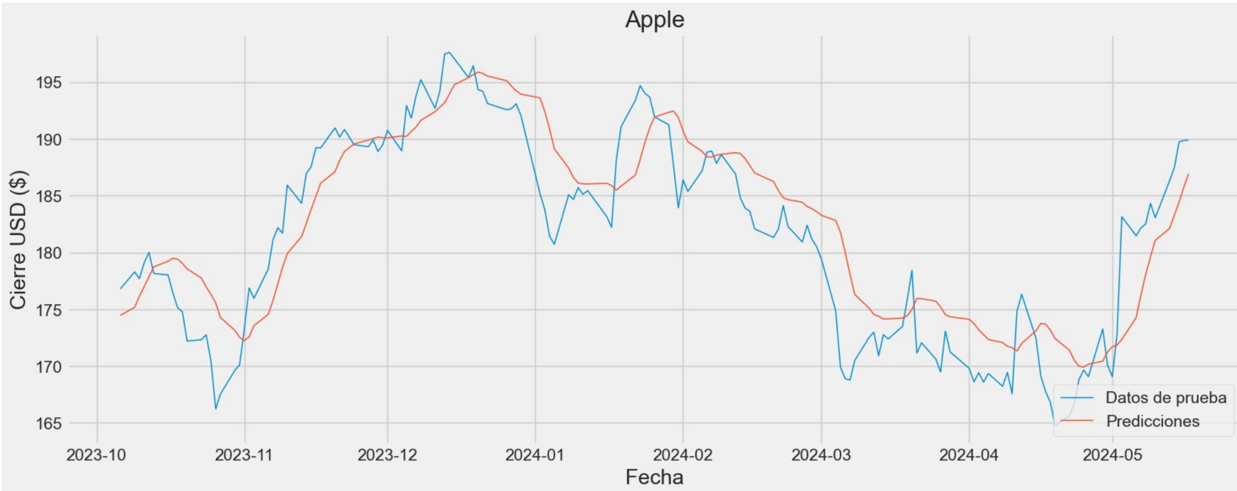
```python
# Graficamos los datos
train = data[:training_data_len]
valid = data[training_data_len:]
valid['Predictions'] = predictions

plt.figure(figsize=(16,6))
plt.title('Apple')
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre USD ($)', fontsize=18)
plt.plot(train['Adj Close'], linewidth = 1)
plt.plot(valid[['Adj Close', 'Predictions']], linewidth = 1)
plt.legend(['Datos de entrenamiento', 'Datos de prueba', 'Predicciones'], loc='lower right')
plt.show()
```

```
C:\Users\Usuario\AppData\Local\Temp\ipykernel_14880\3264202307.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```




```
# Separar los datos de prueba
valid = data[training_data_len:]
valid['Predictions'] = predictions

# Graficar los datos de prueba y las predicciones
plt.figure(figsize=(16, 6))
plt.title('Apple')
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre USD ($)', fontsize=18)
plt.plot(valid['Adj Close'], linewidth=1, label='Datos de prueba')
plt.plot(valid['Predictions'], linewidth=1, label='Predicciones')
plt.legend(loc='lower right')
plt.show()
```

```
C:\Users\Usuario\AppData\Local\Temp\ipykernel_14880\682196135.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```




```
# Cargamos los datos de las acciones que queremos analizar y predecir
df = pdr.get_data_yahoo('GOOG', start='2012-01-01',
end=datetime.now())

df

[*********************100%%**********************]  1 of 1 completed

                  Open        High         Low       Close   Adj Close  \
Date

2012-01-03   16.262545   16.641375   16.248346   16.573130   16.573130

2012-01-04   16.563665   16.693678   16.453827   16.644611   16.644611

2012-01-05   16.491436   16.537264   16.344486   16.413727   16.413727

2012-01-06   16.417213   16.438385   16.184088   16.189817   16.189817

2012-01-09   16.102144   16.114599   15.472754   15.503389   15.503389

...                ...         ...         ...         ...         ...

2024-05-13  165.847000  170.949997  165.759995  170.899994  170.899994

2024-05-14  171.589996  172.779999  170.419998  171.929993  171.929993

2024-05-15  172.300003  174.046005  172.029999  173.880005  173.880005

2024-05-16  174.600006  176.339996  174.050003  175.429993  175.429993

2024-05-17  175.647003  177.490005  174.979996  177.289993  177.289993


               Volume
```

```
Date
2012-01-03  147611217
2012-01-04  114989399
2012-01-05  131808205
2012-01-06  108119746
2012-01-09  233776981
...               ...
2024-05-13   19648600
2024-05-14   18729500
2024-05-15   20958200
2024-05-16   17247300
2024-05-17   16071736

[3114 rows x 6 columns]
```

```
#Hacemos una gráfica con el histórico de precios
plt.figure(figsize=(16,6))
plt.title('Histórico de precios GOOG')
plt.plot(df['Adj Close'], linewidth = 1)
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre ajustado USD ($)', fontsize=18)
plt.show()
```


```
# Creamos un nuevo DataFrame con únicamente la columna Adj Close
data = df.filter(['Adj Close'])
# Convertimos el dataframe en un numpy array
dataset = data.values
# Número de filas para entrenar el modelo
training_data_len = int(np.ceil( len(dataset) * .95 ))

training_data_len

2959
```

```python
# Escalamos y normalizamos los datos
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)

scaled_data
```

```
array([[0.01621556],
       [0.01665312],
       [0.01523982],
       ...,
       [0.97912669],
       [0.98861451],
       [1.        ]])
```

```python
# Creamos el data set para entrenamiento con los datos escalados
train_data = scaled_data[0:int(training_data_len), :]
# Separamos los datos entre x_train y y_train
x_train = []
y_train = []

for i in range(60, len(train_data)):
    x_train.append(train_data[i-60:i, 0])
    y_train.append(train_data[i, 0])
    if i<= 61:
        print(x_train)
        print(y_train)
        print()

# Convertimos x_train y y_train en numpy arrays
x_train, y_train = np.array(x_train), np.array(y_train)

# Cambiamos la forma de los datos
x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
```

```
[array([0.01621556, 0.01665312, 0.01523982, 0.01386922, 0.00966744,
       0.00977111, 0.01020105, 0.01076209, 0.01005316, 0.01060049,
       0.01126064, 0.01227602, 0.00410725, 0.0040356 , 0.00333581,
       0.00159168, 0.00137975, 0.00319097, 0.00284184, 0.00321079,
       0.00332056, 0.00397309, 0.00568368, 0.00762906, 0.00727536,
       0.00774493, 0.00799039, 0.00714424, 0.00810321, 0.00773121,
       0.00709088, 0.00723724, 0.00695062, 0.00837763, 0.00745373,
       0.00717473, 0.00775255, 0.0076626 , 0.00904693, 0.00902559,
       0.00965829, 0.00948296, 0.00841575, 0.0069994 , 0.00727993,
       0.00733177, 0.00628132, 0.00702837, 0.00895393, 0.00868103,
       0.00946468, 0.01006079, 0.01142377, 0.01134907, 0.01233852,
       0.01326395, 0.01273645, 0.01376402, 0.01341184, 0.01474433])]
[0.013623760824461206]
```

```
[array([0.01621556, 0.01665312, 0.01523982, 0.01386922, 0.00966744,
       0.00977111, 0.01020105, 0.01076209, 0.01005316, 0.01060049,
       0.01126064, 0.01227602, 0.00410725, 0.0040356 , 0.00333581,
       0.00159168, 0.00137975, 0.00319097, 0.00284184, 0.00321079,
       0.00332056, 0.00397309, 0.00568368, 0.00762906, 0.00727536,
       0.00774493, 0.00799039, 0.00714424, 0.00810321, 0.00773121,
       0.00709088, 0.00723724, 0.00695062, 0.00837763, 0.00745373,
       0.00717473, 0.00775255, 0.0076626 , 0.00904693, 0.00902559,
       0.00965829, 0.00948296, 0.00841575, 0.0069994 , 0.00727993,
       0.00733177, 0.00628132, 0.00702837, 0.00895393, 0.00868103,
       0.00946468, 0.01006079, 0.01142377, 0.01134907, 0.01233852,
       0.01326395, 0.01273645, 0.01376402, 0.01341184, 0.01474433]),
array([0.01665312, 0.01523982, 0.01386922, 0.00966744, 0.00977111,
       0.01020105, 0.01076209, 0.01005316, 0.01060049, 0.01126064,
       0.01227602, 0.00410725, 0.0040356 , 0.00333581, 0.00159168,
       0.00137975, 0.00319097, 0.00284184, 0.00321079, 0.00332056,
       0.00397309, 0.00568368, 0.00762906, 0.00727536, 0.00774493,
       0.00799039, 0.00714424, 0.00810321, 0.00773121, 0.00709088,
       0.00723724, 0.00695062, 0.00837763, 0.00745373, 0.00717473,
       0.00775255, 0.0076626 , 0.00904693, 0.00902559, 0.00965829,
       0.00948296, 0.00841575, 0.0069994 , 0.00727993, 0.00733177,
       0.00628132, 0.00702837, 0.00895393, 0.00868103, 0.00946468,
       0.01006079, 0.01142377, 0.01134907, 0.01233852, 0.01326395,
       0.01273645, 0.01376402, 0.01341184, 0.01474433, 0.01362376])]
[0.013623760824461206, 0.012530624495400211]
```

```python
from keras.models import Sequential
from keras.layers import LSTM, Dense

# Creamos el modelo LSTM
model = Sequential()

# Añadimos capas LSTM con 50 unidades
model.add(LSTM(50, return_sequences=True,
input_shape=(x_train.shape[1], 1)))
model.add(LSTM(50, return_sequences=False))
# Añadimos una capa densa con 25 unidades
model.add(Dense(25))
# Añadir una capa de salida densa con 1 unidad
model.add(Dense(1))

# Compilamos el modelo
model.compile(optimizer='adam', loss='mean_squared_error')

# Entrenamos el modelo
model.fit(x_train, y_train, batch_size=1, epochs=1)

# Creamos el conjunto de datos de prueba
```

```python
test_data = scaled_data[training_data_len - 60: , :]
# Creamos los conjuntos de datos x_test y y_test
x_test = []
y_test = dataset[training_data_len:, :]
for i in range(60, len(test_data)):
    x_test.append(test_data[i-60:i, 0])

# Convertimos a un numpy array
x_test = np.array(x_test)

# Cambiamos la forma de los datos
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))

# Obtención de las predicciones
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)

# Calculamos el RMSE
rmse=np.sqrt(np.mean(((predictions- y_test)**2)))
print("Root Mean Square Error:",rmse)

# Calcular el NRMSE
range_y = np.max(y_test) - np.min(y_test)
nrmse = rmse / range_y
print("Normalized Root Mean Square Error (NRMSE):", nrmse)

# Calculamos el MAE
mae = np.mean(np.abs(predictions - y_test))
print("Mean Absolute Error:", mae)

# Calculamos el coeficiente de determinación (R cuadrado)
from sklearn.metrics import r2_score

r2 = r2_score(y_test, predictions)
print("Coeficiente de determinación (R cuadrado):", r2)
```

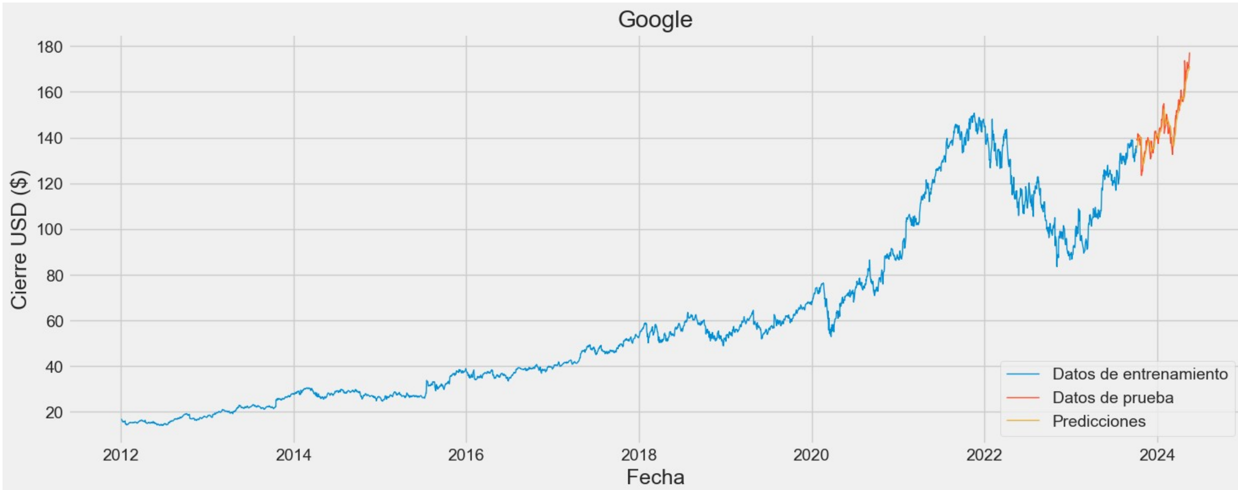
```
c:\Users\Usuario\anaconda3\Lib\site-packages\keras\src\layers\rnn\
rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

```
2899/2899 ━━━━━━━━━━━━━━━━━━━━ 25s 8ms/step - loss: 0.0018
WARNING:tensorflow:5 out of the last 11 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_dist
ributed at 0x000001F46CF6D4E0> triggered tf.function retracing.
Tracing is expensive and the excessive number of tracings could be due
to (1) creating @tf.function repeatedly in a loop, (2) passing tensors
with different shapes, (3) passing Python objects instead of tensors.
For (1), please define your @tf.function outside of the loop. For (2),
```

```
@tf.function has reduce_retracing=True option that can avoid
unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more
details.
1/5 ━━━━━━━━━━━━━━━━━━━━ 0s 212ms/stepWARNING:tensorflow:5 out of the
last 11 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_dist
ributed at 0x000001F46CF6D4E0> triggered tf.function retracing.
Tracing is expensive and the excessive number of tracings could be due
to (1) creating @tf.function repeatedly in a loop, (2) passing tensors
with different shapes, (3) passing Python objects instead of tensors.
For (1), please define your @tf.function outside of the loop. For (2),
@tf.function has reduce_retracing=True option that can avoid
unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more
details.
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
Root Mean Square Error: 3.914599464549233
Normalized Root Mean Square Error (NRMSE): 0.07264056528278061
Mean Absolute Error: 3.022977472120716
Coeficiente de determinación (R cuadrado): 0.892356244385851
```

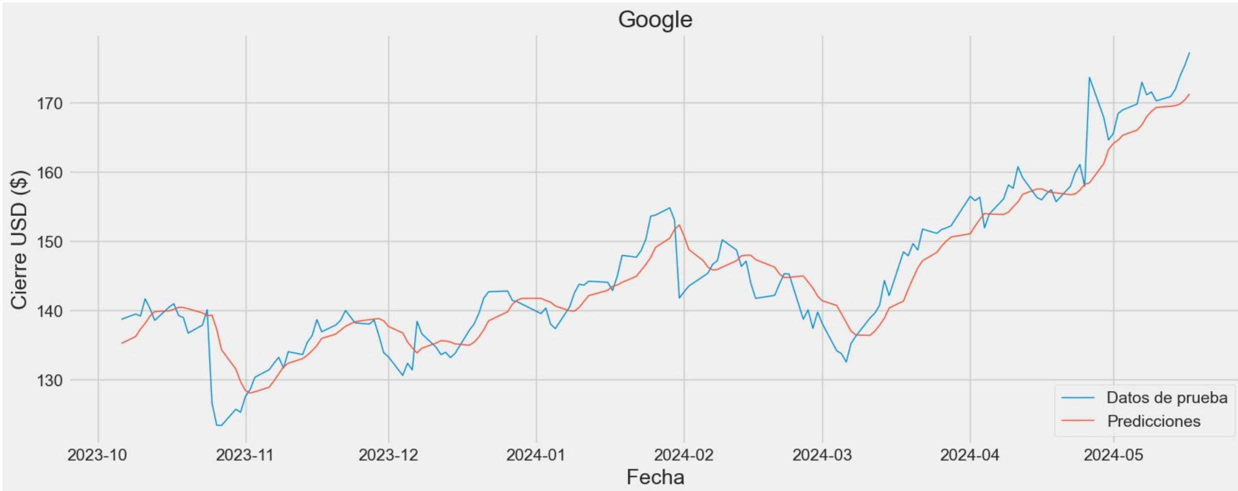
```python
# Graficamos los datos
train = data[:training_data_len]
valid = data[training_data_len:]
valid['Predictions'] = predictions

plt.figure(figsize=(16,6))
plt.title('Google')
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre USD ($)', fontsize=18)
plt.plot(train['Adj Close'], linewidth = 1)
plt.plot(valid[['Adj Close', 'Predictions']], linewidth = 1)
plt.legend(['Datos de entrenamiento', 'Datos de prueba',
'Predicciones'], loc='lower right')
plt.show()
```

```
C:\Users\Usuario\AppData\Local\Temp\ipykernel_14880\1792779524.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```




```
# Separar los datos de prueba
valid = data[training_data_len:]
valid['Predictions'] = predictions

# Graficar los datos de prueba y las predicciones
plt.figure(figsize=(16, 6))
plt.title('Google')
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre USD ($)', fontsize=18)
plt.plot(valid['Adj Close'], linewidth=1, label='Datos de prueba')
plt.plot(valid['Predictions'], linewidth=1, label='Predicciones')
plt.legend(loc='lower right')
plt.show()
```

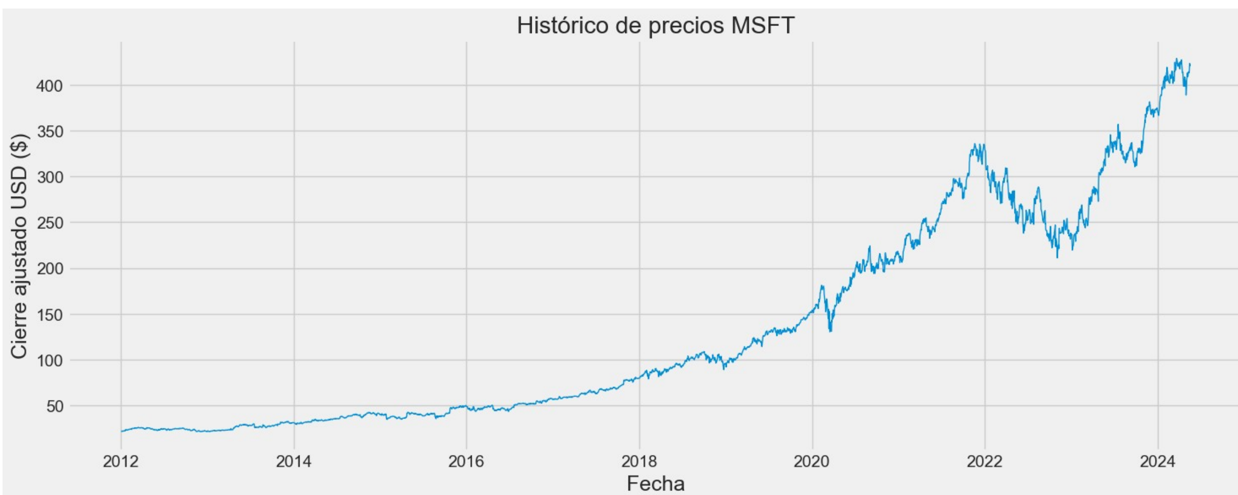
```
C:\Users\Usuario\AppData\Local\Temp\ipykernel_14880\549889742.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```




```
# Cargamos los datos de las acciones que queremos analizar y predecir
df = pdr.get_data_yahoo('MSFT', start='2012-01-01',
end=datetime.now())

df

[*********************100%%**********************]  1 of 1 completed

                  Open        High         Low       Close   Adj Close
\
Date

2012-01-03   26.549999   26.959999   26.389999   26.770000   21.200520

2012-01-04   26.820000   27.469999   26.780001   27.400000   21.699444

2012-01-05   27.379999   27.730000   27.290001   27.680000   21.921188

2012-01-06   27.530001   28.190001   27.530001   28.110001   22.261730

2012-01-09   28.049999   28.100000   27.719999   27.740000   21.968702

...                ...         ...         ...         ...         ...

2024-05-13  418.010010  418.350006  410.820007  413.720001  412.975098

2024-05-14  412.019989  417.489990  411.549988  416.559998  415.809998

2024-05-15  417.899994  423.809998  417.269989  423.079987  423.079987

2024-05-16  421.799988  425.420013  420.350006  420.989990  420.989990

2024-05-17  422.170013  422.920013  418.024994  420.209991  420.209991


              Volume
```

```
Date
2012-01-03  64731500
2012-01-04  80516100
2012-01-05  56081400
2012-01-06  99455500
2012-01-09  59706800
...              ...
2024-05-13  15440200
2024-05-14  15109300
2024-05-15  22239500
2024-05-16  17530100
2024-05-17  14250616

[3114 rows x 6 columns]
```

```
#Hacemos una gráfica con el histórico de precios
plt.figure(figsize=(16,6))
plt.title('Histórico de precios MSFT')
plt.plot(df['Adj Close'], linewidth = 1)
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre ajustado USD ($)', fontsize=18)
plt.show()
```




```
# Creamos un nuevo DataFrame con únicamente la columna Adj Close
data = df.filter(['Adj Close'])
# Convertimos el dataframe en un numpy array
dataset = data.values
# Número de filas para entrenar el modelo
training_data_len = int(np.ceil( len(dataset) * .95 ))

training_data_len
```

```
2959
```

```python
# Escalamos y normalizamos los datos
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)

scaled_data
```

```
array([[0.        ],
       [0.00122467],
       [0.00176896],
       ...,
       [0.98645806],
       [0.98132793],
       [0.97941334]])
```

```python
# Creamos el data set para entrenamiento con los datos escalados
train_data = scaled_data[0:int(training_data_len), :]
# Separamos los datos entre x_train y y_train
x_train = []
y_train = []

for i in range(60, len(train_data)):
    x_train.append(train_data[i-60:i, 0])
    y_train.append(train_data[i, 0])
    if i<= 61:
        print(x_train)
        print(y_train)
        print()

# Convertimos x_train y y_train en numpy arrays
x_train, y_train = np.array(x_train), np.array(y_train)

# Cambiamos la forma de los datos
x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
```

```
[array([0.        , 0.00122467, 0.00176896, 0.00260486, 0.00188559,
       0.00207998, 0.00184672, 0.002391  , 0.002877  , 0.00289645,
       0.00283814, 0.00262427, 0.00571513, 0.00575403, 0.00499588,
       0.00542357, 0.00530691, 0.00478206, 0.00552075, 0.00536523,
       0.00606504, 0.00618169, 0.00674543, 0.00666769, 0.00695926,
       0.00756189, 0.0077757 , 0.00725084, 0.00740636, 0.00715199,
       0.00676064, 0.00918698, 0.00910872, 0.00948049, 0.00914783,
       0.00934351, 0.00955876, 0.00930439, 0.01032189, 0.0100675 ,
       0.0111437 , 0.0107328 , 0.01018491, 0.00971529, 0.01026318,
       0.01059584, 0.0105567 , 0.01065454, 0.01188726, 0.01208295,
       0.01223948, 0.0117503 , 0.01096761, 0.0105567 , 0.01040015,
       0.01057625, 0.01059584, 0.01173073, 0.01159376, 0.01094803])]
```

```
[0.010811063577416284]

[array([0.        , 0.00122467, 0.00176896, 0.00260486, 0.00188559,
       0.00207998, 0.00184672, 0.002391  , 0.002877  , 0.00289645,
       0.00283814, 0.00262427, 0.00571513, 0.00575403, 0.00499588,
       0.00542357, 0.00530691, 0.00478206, 0.00552075, 0.00536523,
       0.00606504, 0.00618169, 0.00674543, 0.00666769, 0.00695926,
       0.00756189, 0.0077757 , 0.00725084, 0.00740636, 0.00715199,
       0.00676064, 0.00918698, 0.00910872, 0.00948049, 0.00914783,
       0.00934351, 0.00955876, 0.00930439, 0.01032189, 0.0100675 ,
       0.0111437 , 0.0107328 , 0.01018491, 0.00971529, 0.01026318,
       0.01059584, 0.0105567 , 0.01065454, 0.01188726, 0.01208295,
       0.01223948, 0.0117503 , 0.01096761, 0.0105567 , 0.01040015,
       0.01057625, 0.01059584, 0.01173073, 0.01159376, 0.01094803]),
array([0.00122467, 0.00176896, 0.00260486, 0.00188559, 0.00207998,
       0.00184672, 0.002391  , 0.002877  , 0.00289645, 0.00283814,
       0.00262427, 0.00571513, 0.00575403, 0.00499588, 0.00542357,
       0.00530691, 0.00478206, 0.00552075, 0.00536523, 0.00606504,
       0.00618169, 0.00674543, 0.00666769, 0.00695926, 0.00756189,
       0.0077757 , 0.00725084, 0.00740636, 0.00715199, 0.00676064,
       0.00918698, 0.00910872, 0.00948049, 0.00914783, 0.00934351,
       0.00955876, 0.00930439, 0.01032189, 0.0100675 , 0.0111437 ,
       0.0107328 , 0.01018491, 0.00971529, 0.01026318, 0.01059584,
       0.0105567 , 0.01065454, 0.01188726, 0.01208295, 0.01223948,
       0.0117503 , 0.01096761, 0.0105567 , 0.01040015, 0.01057625,
       0.01059584, 0.01173073, 0.01159376, 0.01094803, 0.01081106])]
[0.010811063577416284, 0.011085009761975122]
```

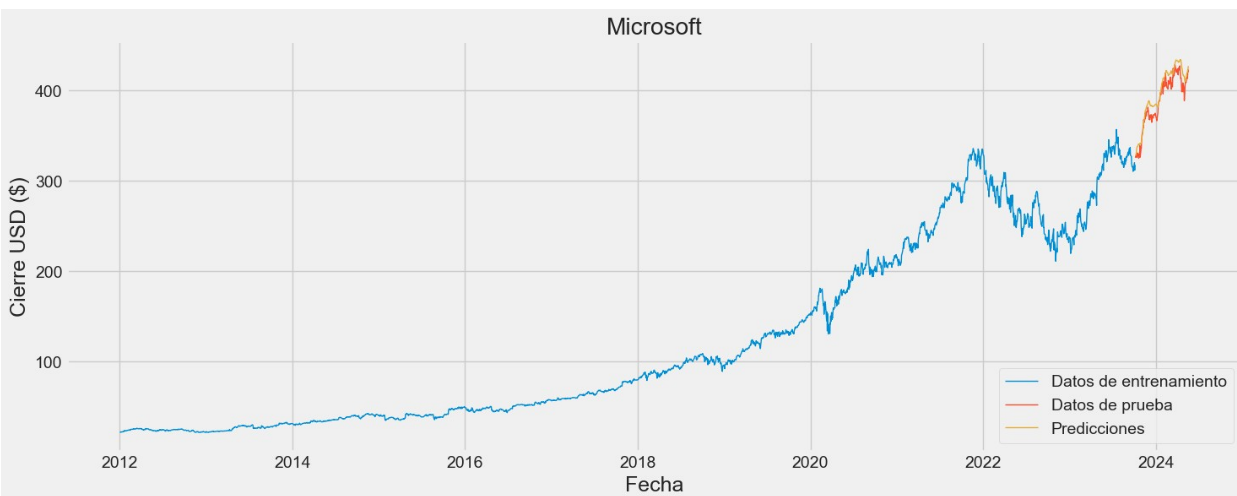
```
from keras.models import Sequential
from keras.layers import LSTM, Dense

# Creamos el modelo LSTM
model = Sequential()

# Añadimos capas LSTM con 50 unidades
model.add(LSTM(50, return_sequences=True,
input_shape=(x_train.shape[1], 1)))
model.add(LSTM(50, return_sequences=False))
# Añadimos una capa densa con 25 unidades
model.add(Dense(25))
# Añadir una capa de salida densa con 1 unidad
model.add(Dense(1))

# Compilamos el modelo
model.compile(optimizer='adam', loss='mean_squared_error')

# Entrenamos el modelo
model.fit(x_train, y_train, batch_size=1, epochs=1)
```

```python
# Creamos el conjunto de datos de prueba
test_data = scaled_data[training_data_len - 60: , :]
# Creamos los conjuntos de datos x_test y y_test
x_test = []
y_test = dataset[training_data_len:, :]
for i in range(60, len(test_data)):
    x_test.append(test_data[i-60:i, 0])

# Convertimos a un numpy array
x_test = np.array(x_test)

# Cambiamos la forma de los datos
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))

# Obtención de las predicciones
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)

# Calculamos el RMSE
rmse=np.sqrt(np.mean(((predictions- y_test)**2)))
print("Root Mean Square Error:",rmse)

# Calcular el NRMSE
range_y = np.max(y_test) - np.min(y_test)
nrmse = rmse / range_y
print("Normalized Root Mean Square Error (NRMSE):", nrmse)

# Calculamos el MAE
mae = np.mean(np.abs(predictions - y_test))
print("Mean Absolute Error:", mae)

# Calculamos el coeficiente de determinación (R cuadrado)
from sklearn.metrics import r2_score

r2 = r2_score(y_test, predictions)
print("Coeficiente de determinación (R cuadrado):", r2)
```

```
c:\Users\Usuario\anaconda3\Lib\site-packages\keras\src\layers\rnn\
rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)

2899/2899 ━━━━━━━━━━━━━━━━━━━━ 25s 8ms/step - loss: 0.0012
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
Root Mean Square Error: 10.859410012160629
Normalized Root Mean Square Error (NRMSE): 0.1046425412665281
Mean Absolute Error: 9.063875063004032
Coeficiente de determinación (R cuadrado): 0.8621789920178538
```

```
# Graficamos los datos
train = data[:training_data_len]
valid = data[training_data_len:]
valid['Predictions'] = predictions

plt.figure(figsize=(16,6))
plt.title('Microsoft')
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre USD ($)', fontsize=18)
plt.plot(train['Adj Close'], linewidth = 1)
plt.plot(valid[['Adj Close', 'Predictions']], linewidth = 1)
plt.legend(['Datos de entrenamiento', 'Datos de prueba',
'Predicciones'], loc='lower right')
plt.show()
```

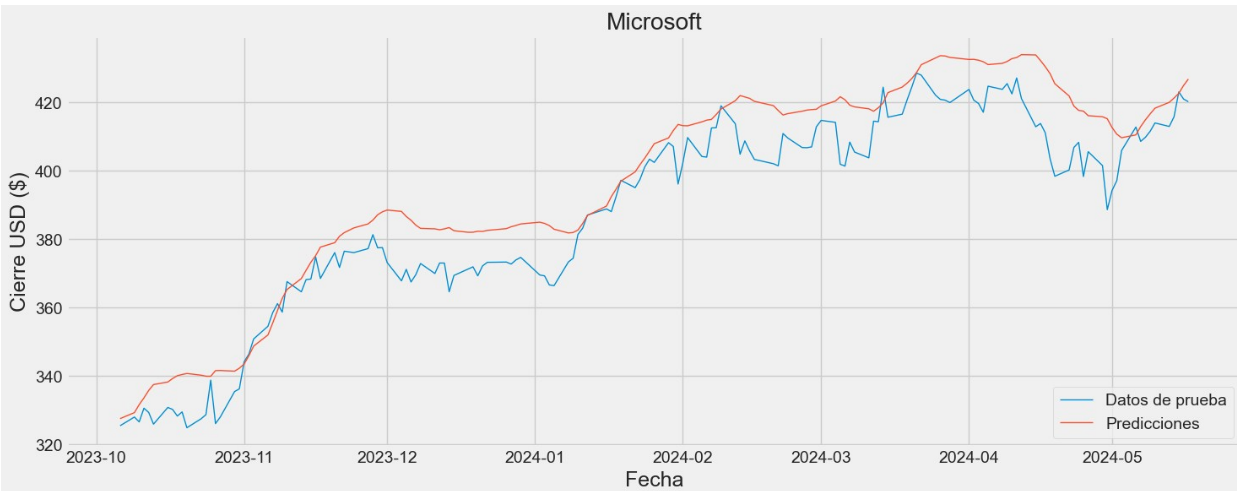
```
C:\Users\Usuario\AppData\Local\Temp\ipykernel_14880\3267775332.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```




```
# Separar los datos de prueba
valid = data[training_data_len:]
valid['Predictions'] = predictions

# Graficar los datos de prueba y las predicciones
plt.figure(figsize=(16, 6))
plt.title('Microsoft')
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre USD ($)', fontsize=18)
```

```
plt.plot(valid['Adj Close'], linewidth=1, label='Datos de prueba')
plt.plot(valid['Predictions'], linewidth=1, label='Predicciones')
plt.legend(loc='lower right')
plt.show()
```

```
C:\Users\Usuario\AppData\Local\Temp\ipykernel_14880\1228714177.py:3: 
SettingWithCopyWarning: 
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: 
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```

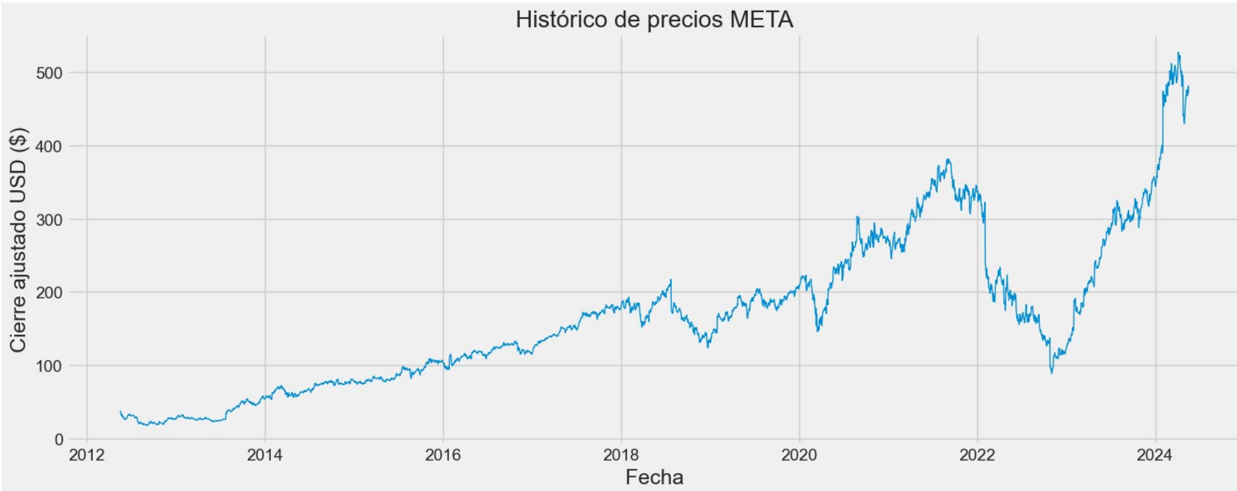



```
# Cargamos los datos de las acciones que queremos analizar y predecir
df = pdr.get_data_yahoo('META', start='2012-01-01', 
end=datetime.now())

df
```

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

                 Open       High        Low      Close  Adj Close  
\
Date                                                                

2012-05-18  42.049999  45.000000  38.000000  38.230000  38.189480   

2012-05-21  36.529999  36.660000  33.000000  34.029999  33.993931   

2012-05-22  32.610001  33.590000  30.940001  31.000000  30.967144   

2012-05-23  31.370001  32.500000  31.360001  32.000000  31.966084   
```

```
2012-05-24   32.950001   33.209999   31.770000   33.029999   32.994991
...                ...         ...         ...         ...         ...
2024-05-13  472.750000  473.350006  462.850006  468.010010  468.010010
2024-05-14  463.369995  472.540009  460.079987  471.850006  471.850006
2024-05-15  474.980011  482.500000  471.200012  481.540009  481.540009
2024-05-16  475.000000  477.690002  472.750000  473.230011  473.230011
2024-05-17  470.589996  472.250000  468.420013  471.910004  471.910004

               Volume
Date
2012-05-18  573576400
2012-05-21  168192700
2012-05-22  101786600
2012-05-23   73600000
2012-05-24   50237200
...               ...
2024-05-13   14668800
2024-05-14   10478600
2024-05-15   13100500
2024-05-16   16608200
2024-05-17    9964026

[3019 rows x 6 columns]
```

```python
#Hacemos una gráfica con el histórico de precios
plt.figure(figsize=(16,6))
plt.title('Histórico de precios META')
plt.plot(df['Adj Close'], linewidth = 1)
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre ajustado USD ($)', fontsize=18)
plt.show()
```




```python
# Creamos un nuevo DataFrame con únicamente la columna Adj Close
data = df.filter(['Adj Close'])
# Convertimos el dataframe en un numpy array
dataset = data.values
# Número de filas para entrenar el modelo
training_data_len = int(np.ceil( len(dataset) * .95 ))

training_data_len
```

```
2869
```

```python
# Escalamos y normalizamos los datos
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)

scaled_data
```

```
array([[0.04018272],
       [0.03195016],
       [0.02601096],
       ...,
       [0.91013063],
       [0.89382465],
       [0.89123452]])
```

```python
# Creamos el data set para entrenamiento con los datos escalados
train_data = scaled_data[0:int(training_data_len), :]
# Separamos los datos entre x_train y y_train
x_train = []
y_train = []
```

```python
for i in range(60, len(train_data)):
    x_train.append(train_data[i-60:i, 0])
    y_train.append(train_data[i, 0])
    if i<= 61:
        print(x_train)
        print(y_train)
        print()

# Convertimos x_train y y_train en numpy arrays
x_train, y_train = np.array(x_train), np.array(y_train)

# Cambiamos la forma de los datos
x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
```

```
[array([0.04018272, 0.03195016, 0.02601096, 0.02797109, 0.02999003,
       0.02779468, 0.02177707, 0.02050299, 0.02326678, 0.01958172,
       0.01797442, 0.01595548, 0.017798  , 0.01681794, 0.01836644,
       0.01819003, 0.01895448, 0.01869966, 0.020699  , 0.02407043,
       0.02681462, 0.02779468, 0.02718704, 0.02765747, 0.03002923,
       0.0280887 , 0.03012723, 0.02842192, 0.02671661, 0.02620697,
       0.02556013, 0.02640299, 0.02693222, 0.02744186, 0.02830431,
       0.02693222, 0.02595215, 0.02563853, 0.02546212, 0.0206206 ,
       0.02030698, 0.02230631, 0.02209069, 0.02162026, 0.02160066,
       0.02101262, 0.02275714, 0.01787641, 0.01172159, 0.01062392,
       0.00780133, 0.00617442, 0.00452791, 0.00658605, 0.00821295,
       0.00586079, 0.00586079, 0.00642924, 0.00799734, 0.00758571])]
[0.005194349294695536]

[array([0.04018272, 0.03195016, 0.02601096, 0.02797109, 0.02999003,
       0.02779468, 0.02177707, 0.02050299, 0.02326678, 0.01958172,
       0.01797442, 0.01595548, 0.017798  , 0.01681794, 0.01836644,
       0.01819003, 0.01895448, 0.01869966, 0.020699  , 0.02407043,
       0.02681462, 0.02779468, 0.02718704, 0.02765747, 0.03002923,
       0.0280887 , 0.03012723, 0.02842192, 0.02671661, 0.02620697,
       0.02556013, 0.02640299, 0.02693222, 0.02744186, 0.02830431,
       0.02693222, 0.02595215, 0.02563853, 0.02546212, 0.0206206 ,
       0.02030698, 0.02230631, 0.02209069, 0.02162026, 0.02160066,
       0.02101262, 0.02275714, 0.01787641, 0.01172159, 0.01062392,
       0.00780133, 0.00617442, 0.00452791, 0.00658605, 0.00821295,
       0.00586079, 0.00586079, 0.00642924, 0.00799734, 0.00758571]),
array([0.03195016, 0.02601096, 0.02797109, 0.02999003, 0.02779468,
       0.02177707, 0.02050299, 0.02326678, 0.01958172, 0.01797442,
       0.01595548, 0.017798  , 0.01681794, 0.01836644, 0.01819003,
       0.01895448, 0.01869966, 0.020699  , 0.02407043, 0.02681462,
       0.02779468, 0.02718704, 0.02765747, 0.03002923, 0.0280887 ,
       0.03012723, 0.02842192, 0.02671661, 0.02620697, 0.02556013,
       0.02640299, 0.02693222, 0.02744186, 0.02830431, 0.02693222,
       0.02595215, 0.02563853, 0.02546212, 0.0206206 , 0.02030698,
       0.02230631, 0.02209069, 0.02162026, 0.02160066, 0.02101262,
       0.02275714, 0.01787641, 0.01172159, 0.01062392, 0.00780133,
```

```
       0.00617442, 0.00452791, 0.00658605, 0.00821295, 0.00586079,
       0.00586079, 0.00642924, 0.00799734, 0.00758571, 0.00519435]])]
[0.005194349294695536, 0.006801659991111868]
```

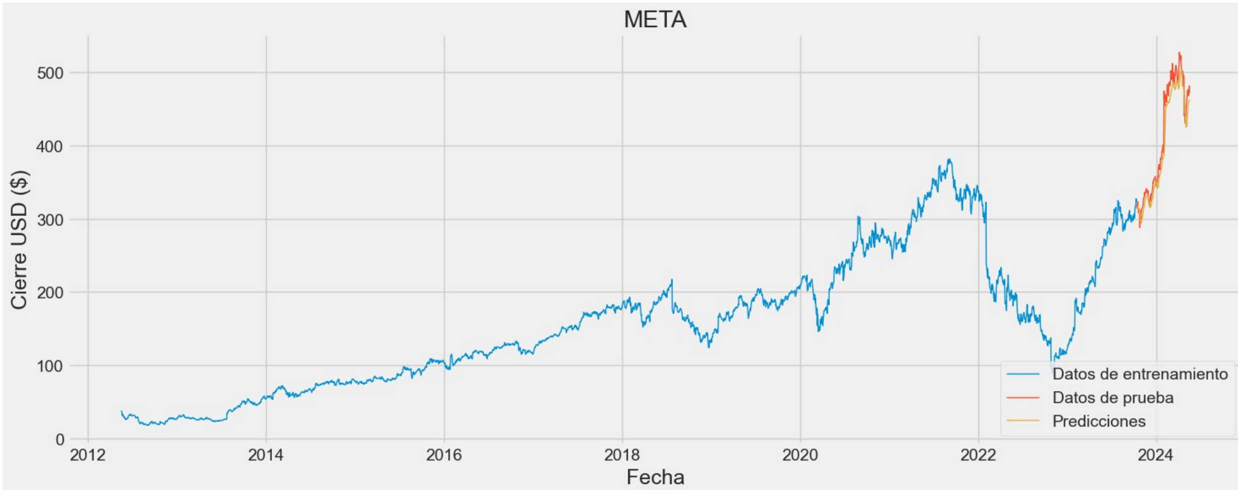
```python
from keras.models import Sequential
from keras.layers import LSTM, Dense

# Creamos el modelo LSTM
model = Sequential()

# Añadimos capas LSTM con 50 unidades
model.add(LSTM(50, return_sequences=True,
input_shape=(x_train.shape[1], 1)))
model.add(LSTM(50, return_sequences=False))
# Añadimos una capa densa con 25 unidades
model.add(Dense(25))
# Añadir una capa de salida densa con 1 unidad
model.add(Dense(1))

# Compilamos el modelo
model.compile(optimizer='adam', loss='mean_squared_error')

# Entrenamos el modelo
model.fit(x_train, y_train, batch_size=1, epochs=1)

# Creamos el conjunto de datos de prueba
test_data = scaled_data[training_data_len - 60: , :]
# Creamos los conjuntos de datos x_test y y_test
x_test = []
y_test = dataset[training_data_len:, :]
for i in range(60, len(test_data)):
    x_test.append(test_data[i-60:i, 0])

# Convertimos a un numpy array
x_test = np.array(x_test)

# Cambiamos la forma de los datos
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))

# Obtención de las predicciones
predictions = model.predict(x_test)
predictions = scaler.inverse_transform(predictions)

# Calculamos el RMSE
rmse=np.sqrt(np.mean(((predictions- y_test)**2)))
print("Root Mean Square Error:",rmse)

# Calcular el NRMSE
range_y = np.max(y_test) - np.min(y_test)
nrmse = rmse / range_y
```

```python
print("Normalized Root Mean Square Error (NRMSE):", nrmse)

# Calculamos el MAE
mae = np.mean(np.abs(predictions - y_test))
print("Mean Absolute Error:", mae)

# Calculamos el coeficiente de determinación (R cuadrado)
from sklearn.metrics import r2_score

r2 = r2_score(y_test, predictions)
print("Coeficiente de determinación (R cuadrado):", r2)
```

```
c:\Users\Usuario\anaconda3\Lib\site-packages\keras\src\layers\rnn\
rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)

2809/2809 ━━━━━━━━━━━━━━━━━━━━ 24s 8ms/step - loss: 0.0016
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
Root Mean Square Error: 18.694869492613222
Normalized Root Mean Square Error (NRMSE): 0.07812456748345288
Mean Absolute Error: 14.901309611002604
Coeficiente de determinación (R cuadrado): 0.9391195888533523
```

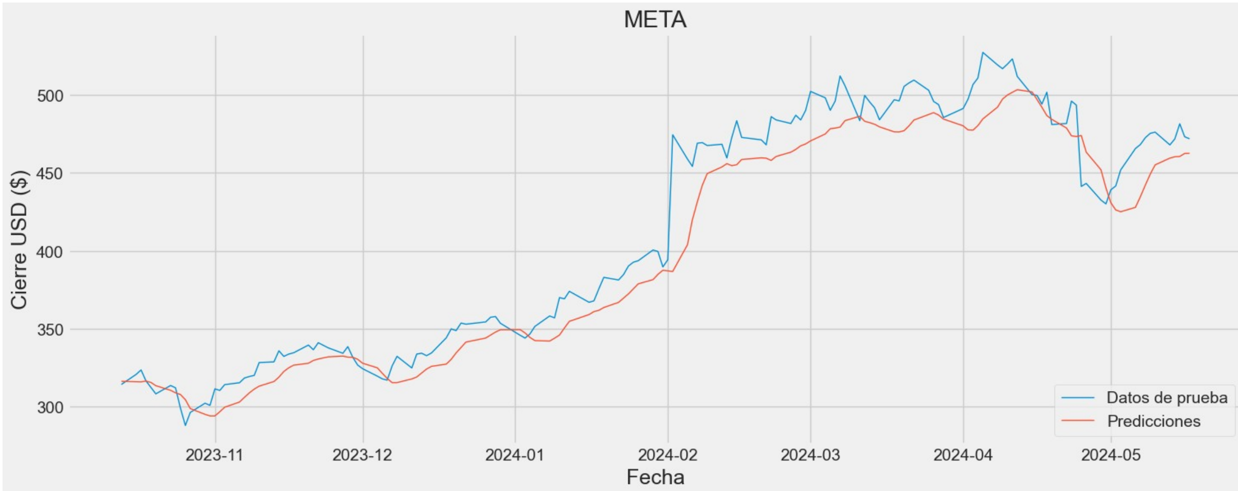
```python
# Graficamos los datos
train = data[:training_data_len]
valid = data[training_data_len:]
valid['Predictions'] = predictions

plt.figure(figsize=(16,6))
plt.title('META')
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre USD ($)', fontsize=18)
plt.plot(train['Adj Close'], linewidth = 1)
plt.plot(valid[['Adj Close', 'Predictions']], linewidth = 1)
plt.legend(['Datos de entrenamiento', 'Datos de prueba',
'Predicciones'], loc='lower right')
plt.show()
```

```
C:\Users\Usuario\AppData\Local\Temp\ipykernel_14880\474930955.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```




```
# Separar los datos de prueba
valid = data[training_data_len:]
valid['Predictions'] = predictions

# Graficar los datos de prueba y las predicciones
plt.figure(figsize=(16, 6))
plt.title('META')
plt.xlabel('Fecha', fontsize=18)
plt.ylabel('Cierre USD ($)', fontsize=18)
plt.plot(valid['Adj Close'], linewidth=1, label='Datos de prueba')
plt.plot(valid['Predictions'], linewidth=1, label='Predicciones')
plt.legend(loc='lower right')
plt.show()
```

```
C:\Users\Usuario\AppData\Local\Temp\ipykernel_14880\2918790472.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```



Predicción con XGBoost

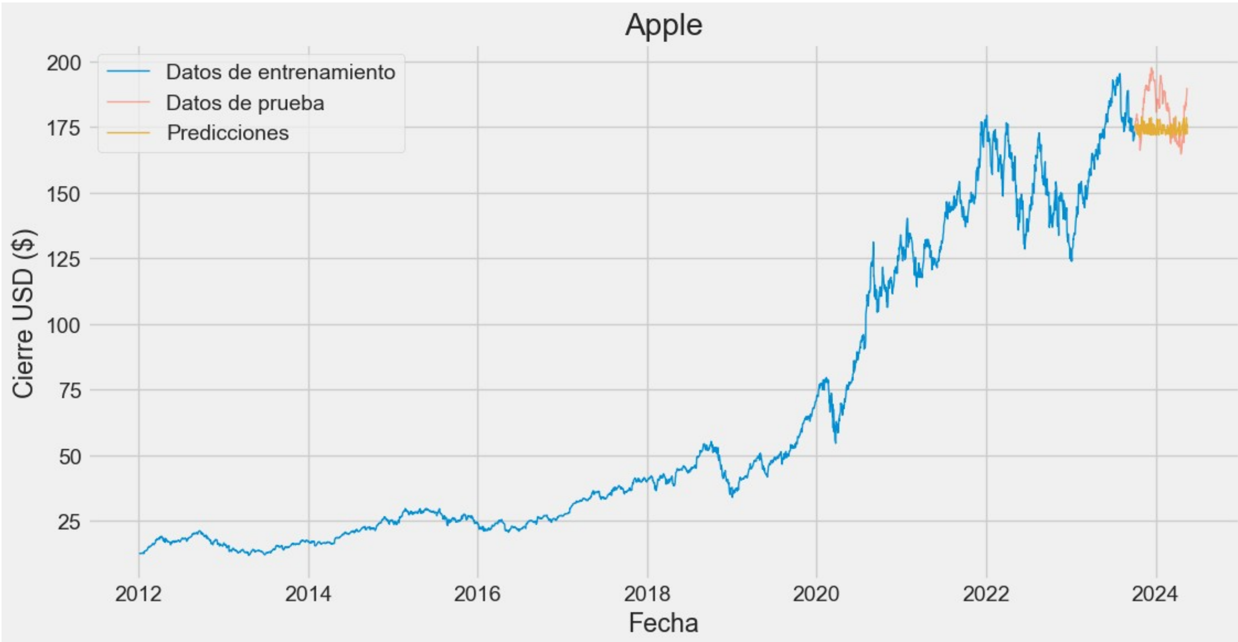
```
df2 = pdr.get_data_yahoo('AAPL', start='2012-01-01',
end=datetime.now())
Datos = df2.filter(["Date", "Adj Close"])
Datos.head()

[*********************100%%**********************]  1 of 1 completed

            Adj Close
Date
2012-01-03  12.416985
2012-01-04  12.483712
2012-01-05  12.622309
2012-01-06  12.754258
2012-01-09  12.734030

import numpy as np
import xgboost as xgb
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error
import pandas as pd

# Calculamos la diferencia de precios como una nueva característica
para conseguir una predicción más precisa
Datos['Price_Diff'] = Datos['Adj Close'].diff()

# Eliminamos la primera fila que contendría un valor NaN después del
cálculo de la diferencia
datos = Datos.dropna()

# Separamos los datos en conjuntos de entrenamiento y prueba
training_data_len = int(len(datos) * 0.95)
training_data = datos.iloc[:training_data_len]
test_data = datos.iloc[training_data_len:]
```

```
# Convertimos las fechas en características numéricas
X_train = np.array(range(len(training_data))).reshape(-1, 1)
X_train = np.hstack((X_train,
training_data['Price_Diff'].values.reshape(-1, 1)))
y_train = training_data['Adj Close'].values

# Iniciamos el modelo XGBoost
model_xgb = xgb.XGBRegressor(objective='reg:squarederror')

# Definimos los parámetros a ajustar
param_grid = {
    'max_depth': [3, 4, 5, 6, 7],
    'learning_rate': [0.01, 0.05, 0.1, 0,2],
    'n_estimators': [100, 200, 300, 400]
}

# Iniciamos el GridSearchCV
grid_search = GridSearchCV(estimator=model_xgb, param_grid=param_grid,
                           scoring='neg_root_mean_squared_error',
cv=3, n_jobs=-1, verbose=2)

# Realizamos la búsqueda de los mejores hiperparámetros
grid_search.fit(X_train, y_train)

# Obtenemos los mejores hiperparámetros
best_params = grid_search.best_params_
print("Mejores hiperparámetros:", best_params)

# Obtenemos el mejor modelo
best_model = grid_search.best_estimator_

# Convertimos las fechas de prueba en características numéricas
X_test = np.array(range(training_data_len, len(datos))).reshape(-1, 1)
X_test = np.hstack((X_test, test_data['Price_Diff'].values.reshape(-1,
1)))
y_test = test_data['Adj Close'].values

# Hacemos predicciones en el conjunto de prueba
predictions = best_model.predict(X_test)

# Calculamos el RMSE
rmse = np.sqrt(mean_squared_error(y_test, predictions))
print("Root Mean Square Error (XGBoost):", rmse)

# Calcular el NRMSE
range_y = np.max(y_test) - np.min(y_test)
nrmse = rmse / range_y
print("Normalized Root Mean Square Error (XGBoost):", nrmse)
```

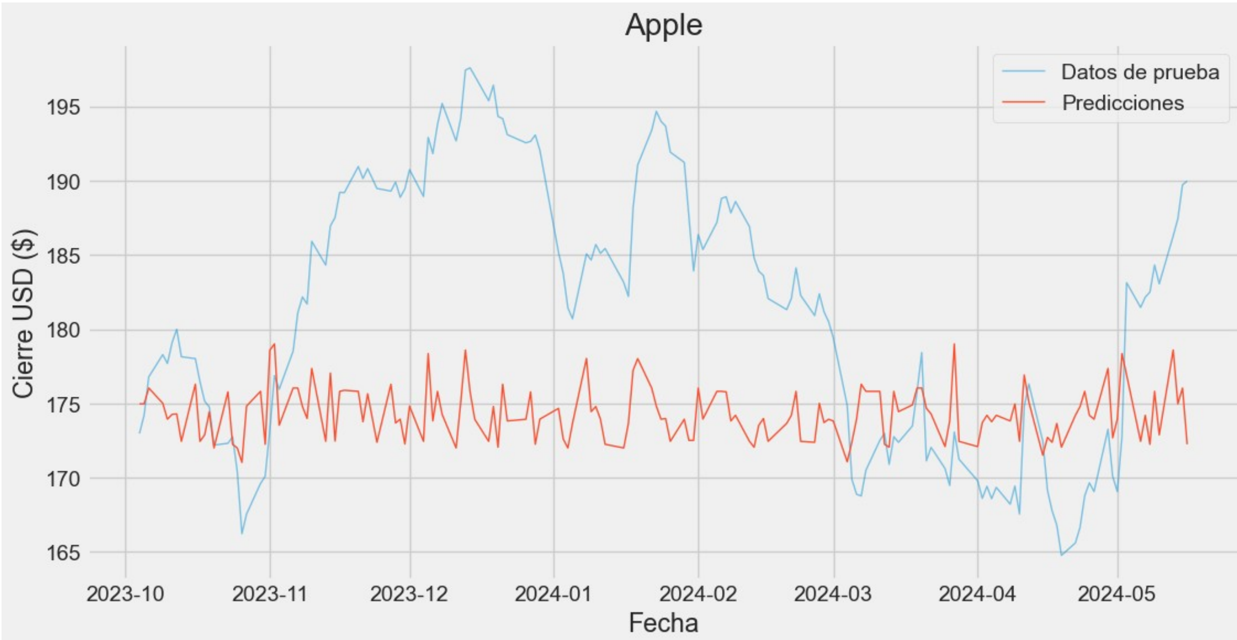
```python
# Calculamos el MAE
mae = np.mean(np.abs(predictions - y_test))
print("Mean Absolute Error:", mae)

# Calculamos el coeficiente de determinación (R cuadrado)
from sklearn.metrics import r2_score

r2 = r2_score(y_test, predictions)
print("Coeficiente de determinación (R cuadrado):", r2)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
Mejores hiperparámetros: {'learning_rate': 0.1, 'max_depth': 4,
'n_estimators': 200}
Root Mean Square Error (XGBoost): 11.093225389453506
Normalized Root Mean Square Error (XGBoost): 0.33807390467376586
Mean Absolute Error: 9.233179141313602
Coeficiente de determinación (R cuadrado): -0.5454802841811077
```

```python
import matplotlib.pyplot as plt

# Graficamos los datos
plt.figure(figsize=(12, 6))
plt.plot(training_data.index, training_data['Adj Close'], label='Datos
de entrenamiento', linewidth = 1)
plt.plot(test_data.index, test_data['Adj Close'], label='Datos de
prueba', alpha=0.5, linewidth = 1)
plt.plot(test_data.index, predictions, label='Predicciones',
linestyle='-', linewidth = 1)
plt.title('Apple')
plt.xlabel('Fecha')
plt.ylabel('Cierre USD ($)')
plt.legend()
plt.grid(True)
plt.show()
```




```
plt.figure(figsize=(12, 6))
plt.plot(test_data.index, test_data['Adj Close'], label='Datos de
prueba', alpha=0.5, linewidth=1)
plt.plot(test_data.index, predictions, label='Predicciones',
linestyle='-', linewidth=1)
plt.title('Apple')
plt.xlabel('Fecha')
plt.ylabel('Cierre USD ($)')
plt.legend()
plt.grid(True)
plt.show()
```



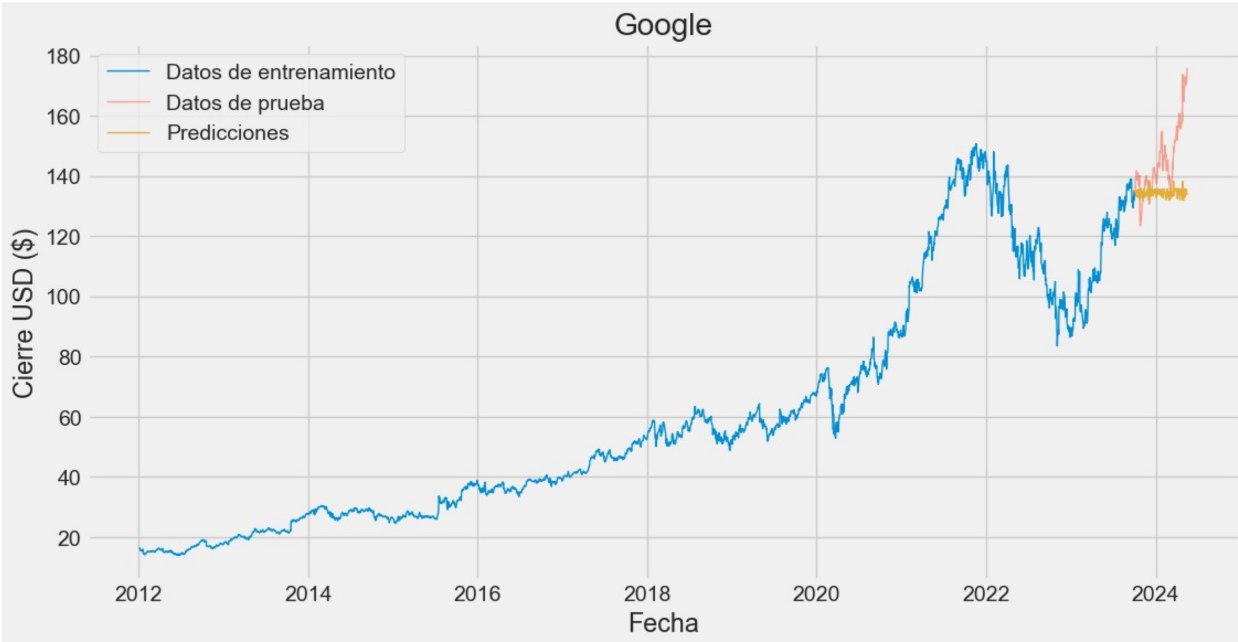

```
df2 = pdr.get_data_yahoo('GOOG', start='2012-01-01',
end=datetime.now())
Datos = df2.filter(["Date", "Adj Close"])
Datos.head()

[*********************100%%**********************]  1 of 1 completed

            Adj Close
Date
2012-01-03  16.573130
2012-01-04  16.644611
2012-01-05  16.413727
2012-01-06  16.189817
2012-01-09  15.503389


import numpy as np
import xgboost as xgb
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error
import pandas as pd

# Calculamos la diferencia de precios como una nueva característica
para conseguir una predicción más precisa
Datos['Price_Diff'] = Datos['Adj Close'].diff()

# Eliminamos la primera fila que contendría un valor NaN después del
cálculo de la diferencia
datos = Datos.dropna()

# Separamos los datos en conjuntos de entrenamiento y prueba
```

```python
training_data_len = int(len(datos) * 0.95)
training_data = datos.iloc[:training_data_len]
test_data = datos.iloc[training_data_len:]

# Convertimos las fechas en características numéricas
X_train = np.array(range(len(training_data))).reshape(-1, 1)
X_train = np.hstack((X_train,
training_data['Price_Diff'].values.reshape(-1, 1)))
y_train = training_data['Adj Close'].values

# Iniciamos el modelo XGBoost
model_xgb = xgb.XGBRegressor(objective='reg:squarederror')

# Definimos los parámetros a ajustar
param_grid = {
    'max_depth': [3, 4, 5, 6, 7],
    'learning_rate': [0.01, 0.05, 0.1, 0,2],
    'n_estimators': [100, 200, 300]
}

# Iniciamos el GridSearchCV
grid_search = GridSearchCV(estimator=model_xgb, param_grid=param_grid,
                           scoring='neg_root_mean_squared_error',
cv=3, n_jobs=-1, verbose=2)

# Realizamos la búsqueda de los mejores hiperparámetros
grid_search.fit(X_train, y_train)

# Obtenemos los mejores hiperparámetros
best_params = grid_search.best_params_
print("Mejores hiperparámetros:", best_params)

# Obtenemos el mejor modelo
best_model = grid_search.best_estimator_

# Convertimos las fechas de prueba en características numéricas
X_test = np.array(range(training_data_len, len(datos))).reshape(-1, 1)
X_test = np.hstack((X_test, test_data['Price_Diff'].values.reshape(-1,
1)))
y_test = test_data['Adj Close'].values

# Hacemos predicciones en el conjunto de prueba
predictions = best_model.predict(X_test)

# Calculamos el RMSE
rmse = np.sqrt(mean_squared_error(y_test, predictions))
print("Root Mean Square Error (XGBoost):", rmse)

# Calcular el NRMSE
range_y = np.max(y_test) - np.min(y_test)
```

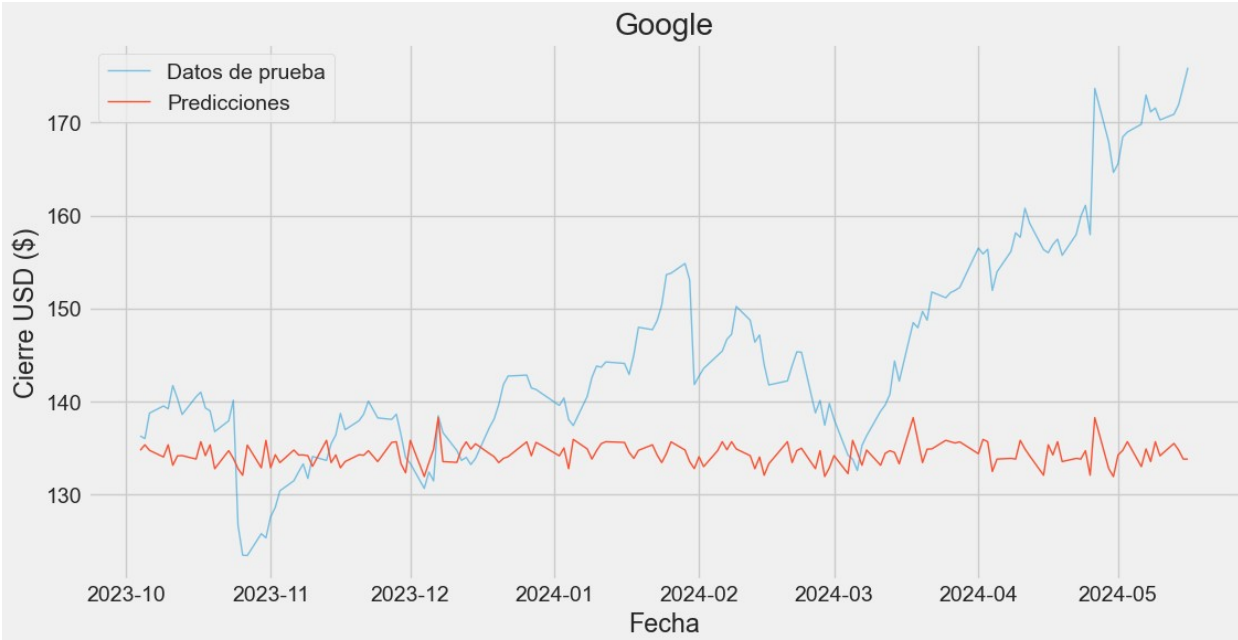
```
nrmse = rmse / range_y
print("Normalized Root Mean Square Error (XGBoost):", nrmse)

# Calculamos el MAE
mae = np.mean(np.abs(predictions - y_test))
print("Mean Absolute Error:", mae)

# Calculamos el coeficiente de determinación (R cuadrado)
from sklearn.metrics import r2_score

r2 = r2_score(y_test, predictions)
print("Coeficiente de determinación (R cuadrado):", r2)
```

```
Fitting 3 folds for each of 75 candidates, totalling 225 fits
Mejores hiperparámetros: {'learning_rate': 0.1, 'max_depth': 3,
'n_estimators': 300}
Root Mean Square Error (XGBoost): 15.776395795843193
Normalized Root Mean Square Error (XGBoost): 0.3003883626090438
Mean Absolute Error: 11.83697754297501
Coeficiente de determinación (R cuadrado): -0.8287643671716405
```

```
import matplotlib.pyplot as plt

# Graficamos los datos
plt.figure(figsize=(12, 6))
plt.plot(training_data.index, training_data['Adj Close'], label='Datos
de entrenamiento', linewidth = 1)
plt.plot(test_data.index, test_data['Adj Close'], label='Datos de
prueba', alpha=0.5, linewidth = 1)
plt.plot(test_data.index, predictions, label='Predicciones',
linestyle='-', linewidth = 1)
plt.title('Google')
plt.xlabel('Fecha')
plt.ylabel('Cierre USD ($)')
plt.legend()
plt.grid(True)
plt.show()
```




```
plt.figure(figsize=(12, 6))
plt.plot(test_data.index, test_data['Adj Close'], label='Datos de
prueba', alpha=0.5, linewidth=1)
plt.plot(test_data.index, predictions, label='Predicciones',
linestyle='-', linewidth=1)
plt.title('Google')
plt.xlabel('Fecha')
plt.ylabel('Cierre USD ($)')
plt.legend()
plt.grid(True)
plt.show()
```



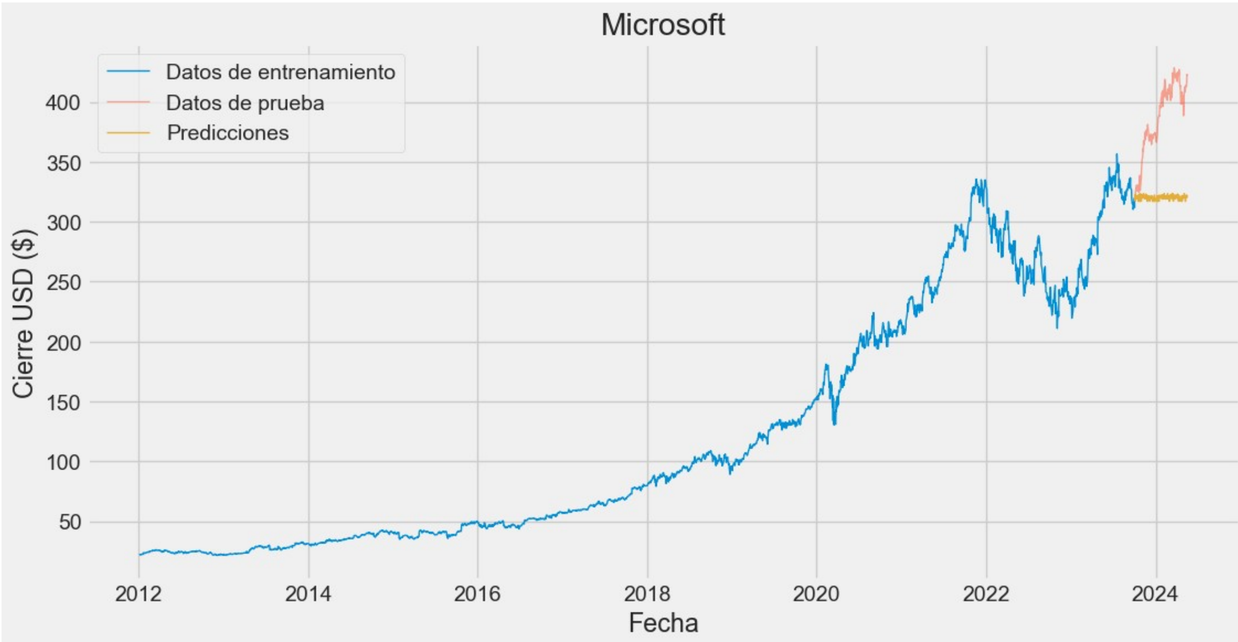

```
df2 = pdr.get_data_yahoo('MSFT', start='2012-01-01',
end=datetime.now())
Datos = df2.filter(["Date", "Adj Close"])
Datos.head()

[*********************100%%**********************]  1 of 1 completed

            Adj Close
Date
2012-01-03  21.200516
2012-01-04  21.699440
2012-01-05  21.921190
2012-01-06  22.261724
2012-01-09  21.968702

import numpy as np
import xgboost as xgb
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error
import pandas as pd

# Calculamos la diferencia de precios como una nueva característica
para conseguir una predicción más precisa
Datos['Price_Diff'] = Datos['Adj Close'].diff()

# Eliminamos la primera fila que contendría un valor NaN después del
cálculo de la diferencia
datos = Datos.dropna()

# Separamos los datos en conjuntos de entrenamiento y prueba
training_data_len = int(len(datos) * 0.95)
```

```python
training_data = datos.iloc[:training_data_len]
test_data = datos.iloc[training_data_len:]

# Convertimos las fechas en características numéricas
X_train = np.array(range(len(training_data))).reshape(-1, 1)
X_train = np.hstack((X_train,
training_data['Price_Diff'].values.reshape(-1, 1)))
y_train = training_data['Adj Close'].values

# Iniciamos el modelo XGBoost
model_xgb = xgb.XGBRegressor(objective='reg:squarederror')

# Definimos los parámetros a ajustar
param_grid = {
    'max_depth': [3, 4, 5, 6, 7],
    'learning_rate': [0.01, 0.05, 0.1, 0,2],
    'n_estimators': [100, 200, 300]
}

# Iniciamos el GridSearchCV
grid_search = GridSearchCV(estimator=model_xgb, param_grid=param_grid,
                           scoring='neg_root_mean_squared_error',
cv=3, n_jobs=-1, verbose=2)

# Realizamos la búsqueda de los mejores hiperparámetros
grid_search.fit(X_train, y_train)

# Obtenemos los mejores hiperparámetros
best_params = grid_search.best_params_
print("Mejores hiperparámetros:", best_params)

# Obtenemos el mejor modelo
best_model = grid_search.best_estimator_

# Convertimos las fechas de prueba en características numéricas
X_test = np.array(range(training_data_len, len(datos))).reshape(-1, 1)
X_test = np.hstack((X_test, test_data['Price_Diff'].values.reshape(-1,
1)))
y_test = test_data['Adj Close'].values

# Hacemos predicciones en el conjunto de prueba
predictions = best_model.predict(X_test)

# Calculamos el RMSE
rmse = np.sqrt(mean_squared_error(y_test, predictions))
print("Root Mean Square Error (XGBoost):", rmse)

# Calcular el NRMSE
range_y = np.max(y_test) - np.min(y_test)
nrmse = rmse / range_y
```

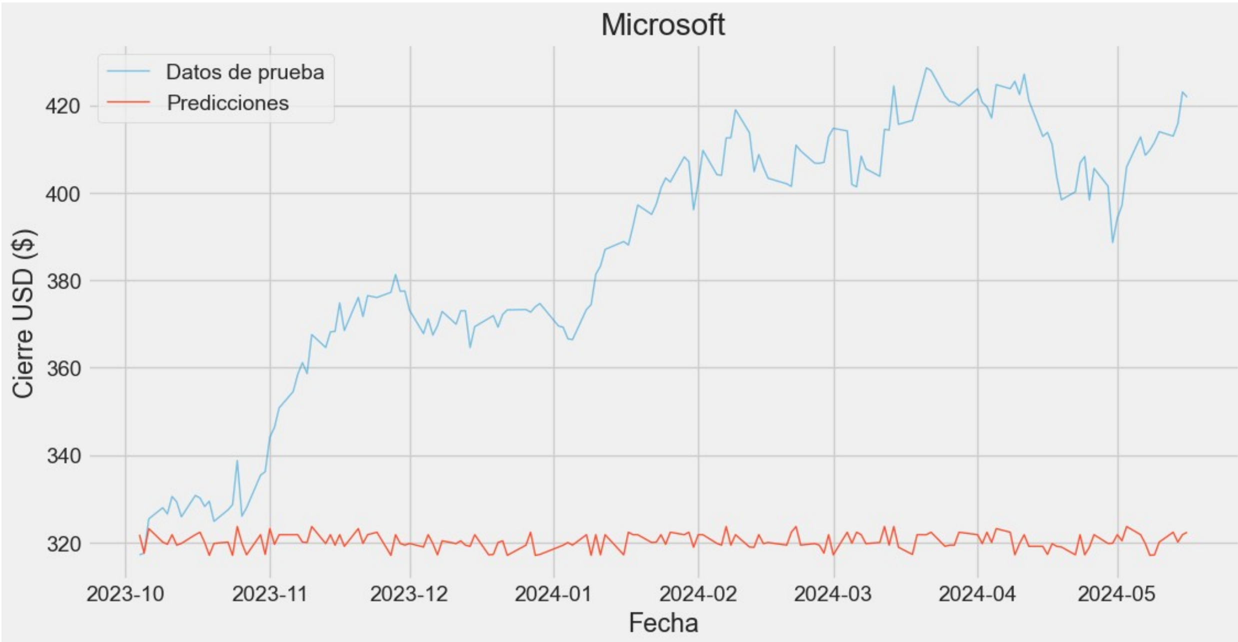
```python
print("Normalized Root Mean Square Error (XGBoost):", nrmse)

# Calculamos el MAE
mae = np.mean(np.abs(predictions - y_test))
print("Mean Absolute Error:", mae)

# Calculamos el coeficiente de determinación (R cuadrado)
from sklearn.metrics import r2_score

r2 = r2_score(y_test, predictions)
print("Coeficiente de determinación (R cuadrado):", r2)
```

```
Fitting 3 folds for each of 75 candidates, totalling 225 fits
Mejores hiperparámetros: {'learning_rate': 0.05, 'max_depth': 3,
'n_estimators': 200}
Root Mean Square Error (XGBoost): 72.83048199720946
Normalized Root Mean Square Error (XGBoost): 0.6535246335482785
Mean Absolute Error: 66.44710090832832
Coeficiente de determinación (R cuadrado): -4.853648411061348
```

```python
import matplotlib.pyplot as plt

# Graficamos los datos
plt.figure(figsize=(12, 6))
plt.plot(training_data.index, training_data['Adj Close'], label='Datos
de entrenamiento', linewidth = 1)
plt.plot(test_data.index, test_data['Adj Close'], label='Datos de
prueba', alpha=0.5, linewidth = 1)
plt.plot(test_data.index, predictions, label='Predicciones',
linestyle='-', linewidth = 1)
plt.title('Microsoft')
plt.xlabel('Fecha')
plt.ylabel('Cierre USD ($)')
plt.legend()
plt.grid(True)
plt.show()
```




```
plt.figure(figsize=(12, 6))
plt.plot(test_data.index, test_data['Adj Close'], label='Datos de
prueba', alpha=0.5, linewidth=1)
plt.plot(test_data.index, predictions, label='Predicciones',
linestyle='-', linewidth=1)
plt.title('Microsoft')
plt.xlabel('Fecha')
plt.ylabel('Cierre USD ($)')
plt.legend()
plt.grid(True)
plt.show()
```



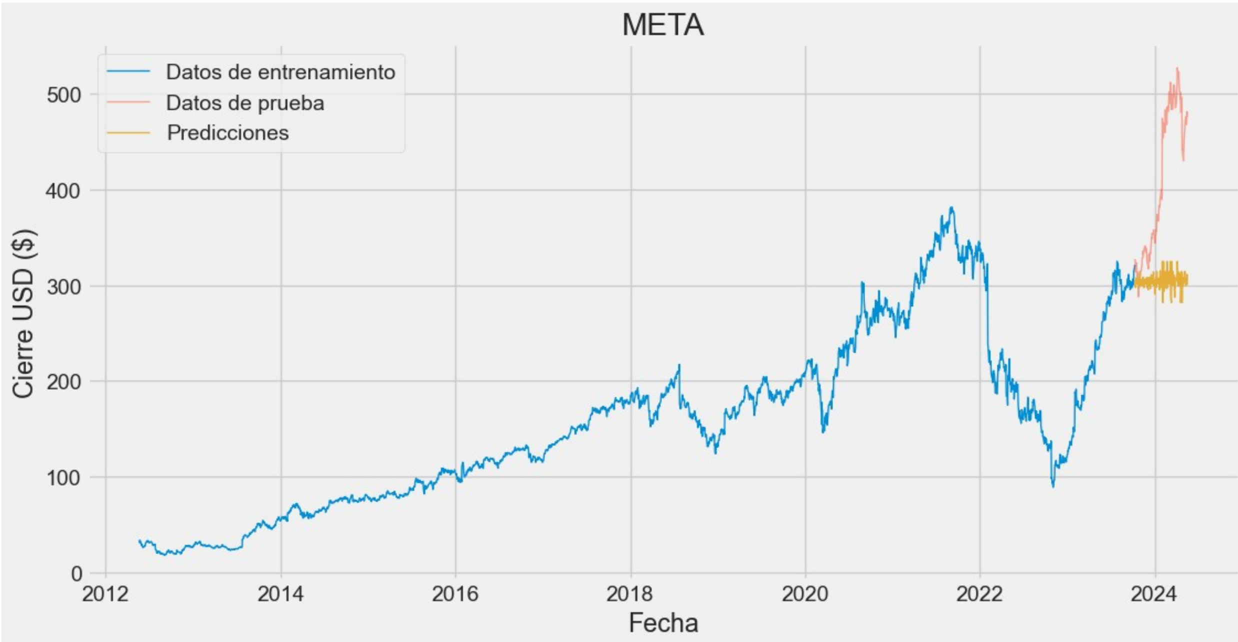

```
df2 = pdr.get_data_yahoo('META', start='2012-01-01',
end=datetime.now())
Datos = df2.filter(["Date", "Adj Close"])
Datos.head()

[*********************100%%**********************]  1 of 1 completed

            Adj Close
Date
2012-05-18  38.189480
2012-05-21  33.993931
2012-05-22  30.967144
2012-05-23  31.966084
2012-05-24  32.994991


import numpy as np
import xgboost as xgb
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error
import pandas as pd

# Calculamos la diferencia de precios como una nueva característica
para conseguir una predicción más precisa
Datos['Price_Diff'] = Datos['Adj Close'].diff()

# Eliminamos la primera fila que contendría un valor NaN después del
cálculo de la diferencia
datos = Datos.dropna()

# Separamos los datos en conjuntos de entrenamiento y prueba
```

```python
training_data_len = int(len(datos) * 0.95)
training_data = datos.iloc[:training_data_len]
test_data = datos.iloc[training_data_len:]

# Convertimos las fechas en características numéricas
X_train = np.array(range(len(training_data))).reshape(-1, 1)
X_train = np.hstack((X_train,
training_data['Price_Diff'].values.reshape(-1, 1)))
y_train = training_data['Adj Close'].values

# Iniciamos el modelo XGBoost
model_xgb = xgb.XGBRegressor(objective='reg:squarederror')

# Definimos los parámetros a ajustar
param_grid = {
    'max_depth': [3, 4, 5, 6, 7],
    'learning_rate': [0.01, 0.05, 0.1, 0,2, 1],
    'n_estimators': [100, 200, 300, 1100]
}

# Iniciamos el GridSearchCV
grid_search = GridSearchCV(estimator=model_xgb, param_grid=param_grid,
                           scoring='neg_root_mean_squared_error',
cv=3, n_jobs=-1, verbose=2)

# Realizamos la búsqueda de los mejores hiperparámetros
grid_search.fit(X_train, y_train)

# Obtenemos los mejores hiperparámetros
best_params = grid_search.best_params_
print("Mejores hiperparámetros:", best_params)

# Obtenemos el mejor modelo
best_model = grid_search.best_estimator_

# Convertimos las fechas de prueba en características numéricas
X_test = np.array(range(training_data_len, len(datos))).reshape(-1, 1)
X_test = np.hstack((X_test, test_data['Price_Diff'].values.reshape(-1,
1)))
y_test = test_data['Adj Close'].values

# Hacemos predicciones en el conjunto de prueba
predictions = best_model.predict(X_test)

# Calculamos el RMSE
rmse = np.sqrt(mean_squared_error(y_test, predictions))
print("Root Mean Square Error (XGBoost):", rmse)

# Calcular el NRMSE
range_y = np.max(y_test) - np.min(y_test)
```

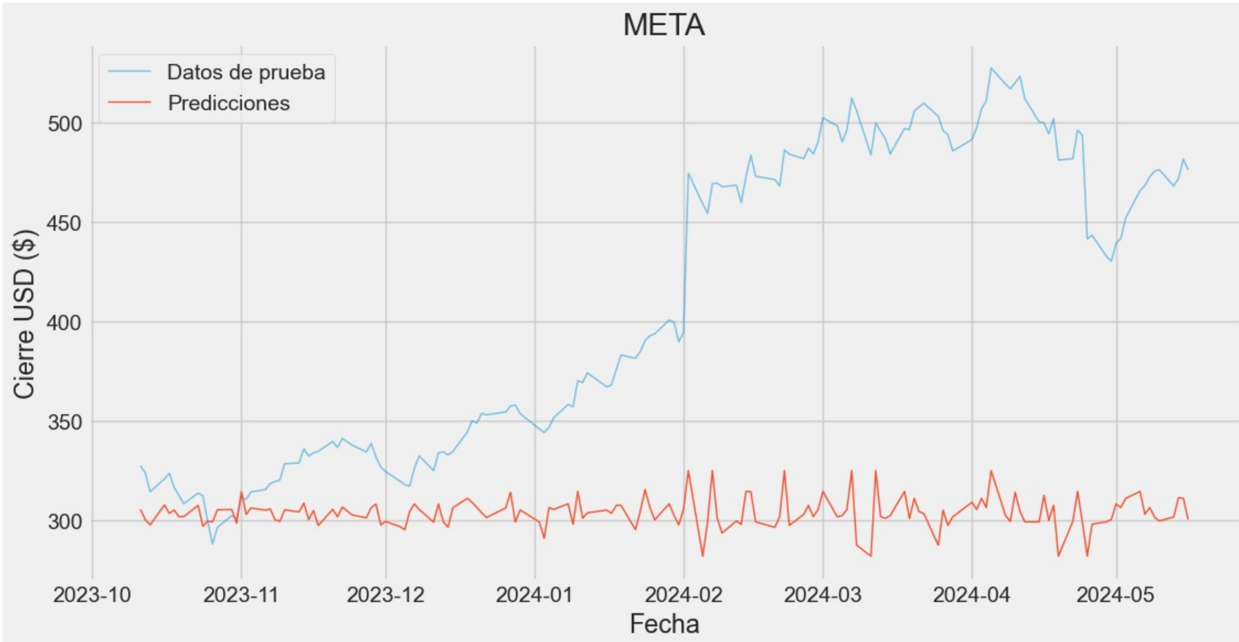
```python
nrmse = rmse / range_y
print("Normalized Root Mean Square Error (XGBoost):", nrmse)

# Calculamos el MAE
mae = np.mean(np.abs(predictions - y_test))
print("Mean Absolute Error:", mae)

# Calculamos el coeficiente de determinación (R cuadrado)
from sklearn.metrics import r2_score

r2 = r2_score(y_test, predictions)
print("Coeficiente de determinación (R cuadrado):", r2)
```

```
Fitting 3 folds for each of 120 candidates, totalling 360 fits
Mejores hiperparámetros: {'learning_rate': 0.1, 'max_depth': 3,
'n_estimators': 1100}
Root Mean Square Error (XGBoost): 130.3500841904394
Normalized Root Mean Square Error (XGBoost): 0.5447239924747002
Mean Absolute Error: 106.53563200085368
Coeficiente de determinación (R cuadrado): -1.9412845051687757
```

```python
import matplotlib.pyplot as plt

# Graficamos los datos
plt.figure(figsize=(12, 6))
plt.plot(training_data.index, training_data['Adj Close'], label='Datos
de entrenamiento', linewidth = 1)
plt.plot(test_data.index, test_data['Adj Close'], label='Datos de
prueba', alpha=0.5, linewidth = 1)
plt.plot(test_data.index, predictions, label='Predicciones',
linestyle='-', linewidth = 1)
plt.title('META')
plt.xlabel('Fecha')
plt.ylabel('Cierre USD ($)')
plt.legend()
plt.grid(True)
plt.show()
```




```
plt.figure(figsize=(12, 6))
plt.plot(test_data.index, test_data['Adj Close'], label='Datos de
prueba', alpha=0.5, linewidth=1)
plt.plot(test_data.index, predictions, label='Predicciones',
linestyle='-', linewidth=1)
plt.title('META')
plt.xlabel('Fecha')
plt.ylabel('Cierre USD ($)')
plt.legend()
plt.grid(True)
plt.show()
```



META
Datos de prueba
Predicciones
Cierre USD ($)
500
450
400
350
300
2023-10
2023-11
2023-12
2024-01
2024-02
2024-03
2024-04
2024-05
Fecha