```python
# Importamos las librerias para el analisis exploratorio

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

# Cargamos los datasets

train =
pd.read_csv("/content/drive/MyDrive/CaixaBank-Hackaton/train.csv")
test =
pd.read_csv("/content/drive/MyDrive/CaixaBank-Hackaton/test_x.csv")

# Mostramos los 5 primeros registros del dataset de entrenamiento

train.head(5)
```

```
         Date         Open         High          Low        Close  \
0  1994-01-03  3615.199951  3654.699951  3581.000000  3654.500000
1  1994-01-04  3654.500000  3675.500000  3625.100098  3630.300049
2  1994-01-05  3625.199951  3625.199951  3583.399902  3621.199951
3  1994-01-06          NaN          NaN          NaN          NaN
4  1994-01-07  3621.199951  3644.399902  3598.699951  3636.399902

     Adj Close  Volume  Target
0  3654.496338     0.0       0
1  3630.296387     0.0       1
2  3621.196289     0.0       1
3          NaN     NaN       0
4  3636.396240     0.0       1
```

```python
# Vemos informacion estadistica al detalle de los datos de
entrenamiento

train.describe(include='all')
```

```
              Date         Open         High          Low
Close  \
count         6554  6421.000000  6421.000000  6421.000000
6421.000000
unique        6554          NaN          NaN          NaN
NaN
top     1994-01-03          NaN          NaN          NaN
NaN
freq             1          NaN          NaN          NaN
NaN
```

```
mean            NaN   8936.540448   9005.235576   8858.340567
8934.978558
std             NaN   2732.102441   2749.009324   2712.511028
2731.032625
min             NaN   2865.100098   2877.300049   2833.600098
2865.100098
25%             NaN   7732.399902   7817.200195   7641.500000
7727.799805
50%             NaN   9329.700195   9404.599609   9243.000000
9331.000000
75%             NaN  10525.500000  10590.299805  10441.200195
10523.400391
max             NaN  15999.200195  16040.400391  15868.599609
15945.700195

           Adj Close        Volume       Target
count    6421.000000  6.421000e+03  6554.000000
unique           NaN           NaN          NaN
top              NaN           NaN          NaN
freq             NaN           NaN          NaN
mean     8934.970624  8.218074e+07     0.516936
std      2731.030170  1.231845e+08     0.499751
min      2865.097168  0.000000e+00     0.000000
25%      7727.791992  0.000000e+00     0.000000
50%      9331.000000  1.966000e+05     1.000000
75%     10523.400391  1.773980e+08     1.000000
max     15945.683594  7.894902e+08     1.000000
```

```
# Tenemos datos nulos y hay que buscar un metodo de tratar esos datos

train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6554 entries, 0 to 6553
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       6554 non-null   object
 1   Open       6421 non-null   float64
 2   High       6421 non-null   float64
 3   Low        6421 non-null   float64
 4   Close      6421 non-null   float64
 5   Adj Close  6421 non-null   float64
 6   Volume     6421 non-null   float64
 7   Target     6554 non-null   int64
dtypes: float64(6), int64(1), object(1)
memory usage: 409.8+ KB
```

```
# Convierto la columna Date a formato fecha
train['Date'] = pd.to_datetime(train['Date'])
```

```python
# Relleno los datos faltantes mediante una interpolacion lineal

train_fixed = train.copy(deep=True)
columns_to_interpolated = ['Open','High','Low','Close','Adj
Close','Volume']
train_fixed[columns_to_interpolated] =
train_fixed[columns_to_interpolated].interpolate(method='linear',
axis=0)
train_fixed.head(5)
```

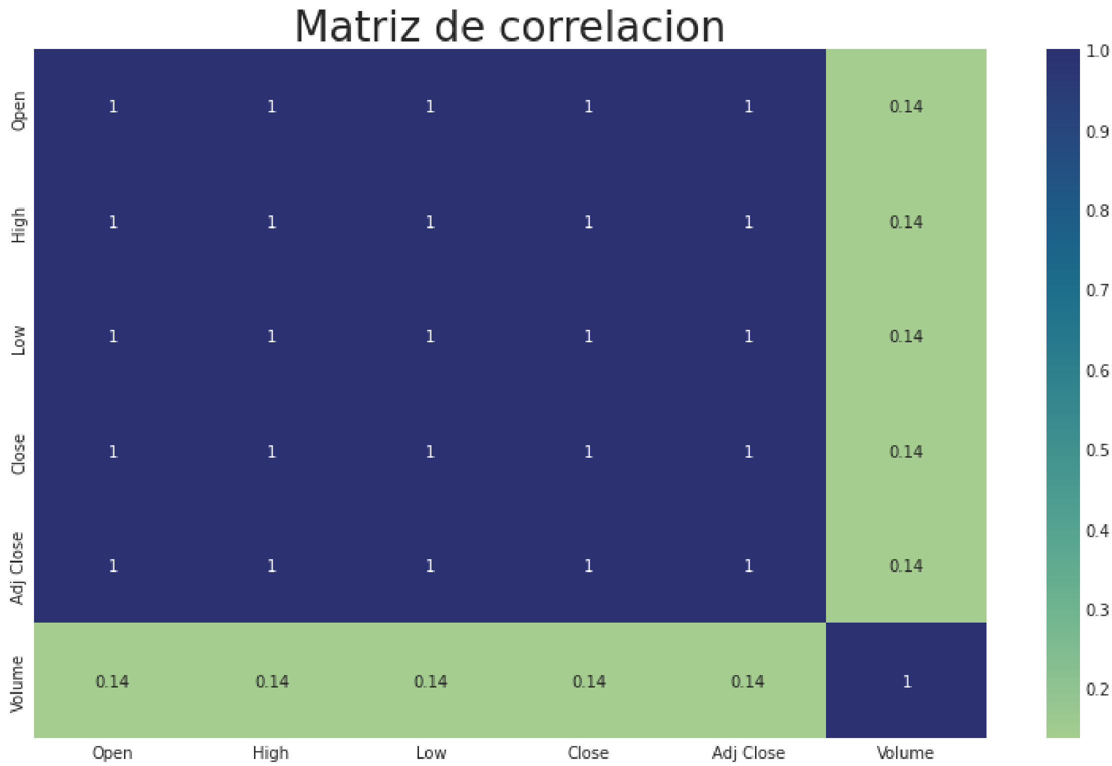
```
        Date         Open         High          Low        Close
Adj Close  \
0 1994-01-03  3615.199951  3654.699951  3581.000000  3654.500000
3654.496338
1 1994-01-04  3654.500000  3675.500000  3625.100098  3630.300049
3630.296387
2 1994-01-05  3625.199951  3625.199951  3583.399902  3621.199951
3621.196289
3 1994-01-06  3623.199951  3634.799926  3591.049926  3628.799926
3628.796264
4 1994-01-07  3621.199951  3644.399902  3598.699951  3636.399902
3636.396240

   Volume  Target
0     0.0       0
1     0.0       1
2     0.0       1
3     0.0       0
4     0.0       1
```

```python
# Ahora no tenemos datos NaN en el dataset

train_fixed.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6554 entries, 0 to 6553
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       6554 non-null   datetime64[ns]
 1   Open       6554 non-null   float64
 2   High       6554 non-null   float64
 3   Low        6554 non-null   float64
 4   Close      6554 non-null   float64
 5   Adj Close  6554 non-null   float64
 6   Volume     6554 non-null   float64
 7   Target     6554 non-null   int64
dtypes: datetime64[ns](1), float64(6), int64(1)
memory usage: 409.8 KB
```

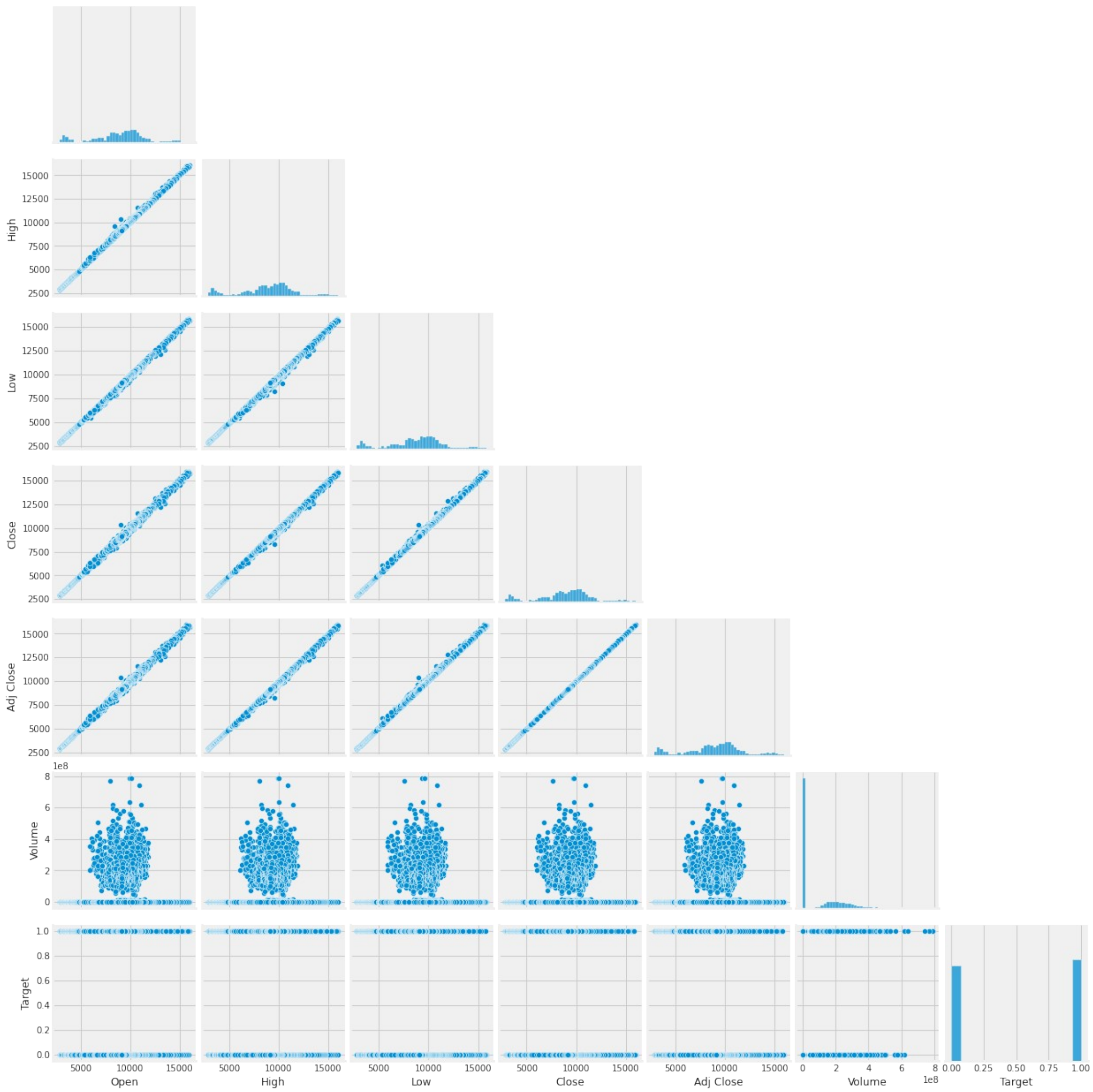
```
plt.figure(figsize=(12,8))
sns.heatmap(train_fixed.drop(columns=['Target']).corr(), annot=True,
cmap='crest')
plt.title('Matriz de correlacion', fontsize=26)
```

```
Text(0.5, 1.0, 'Matriz de correlacion')
```



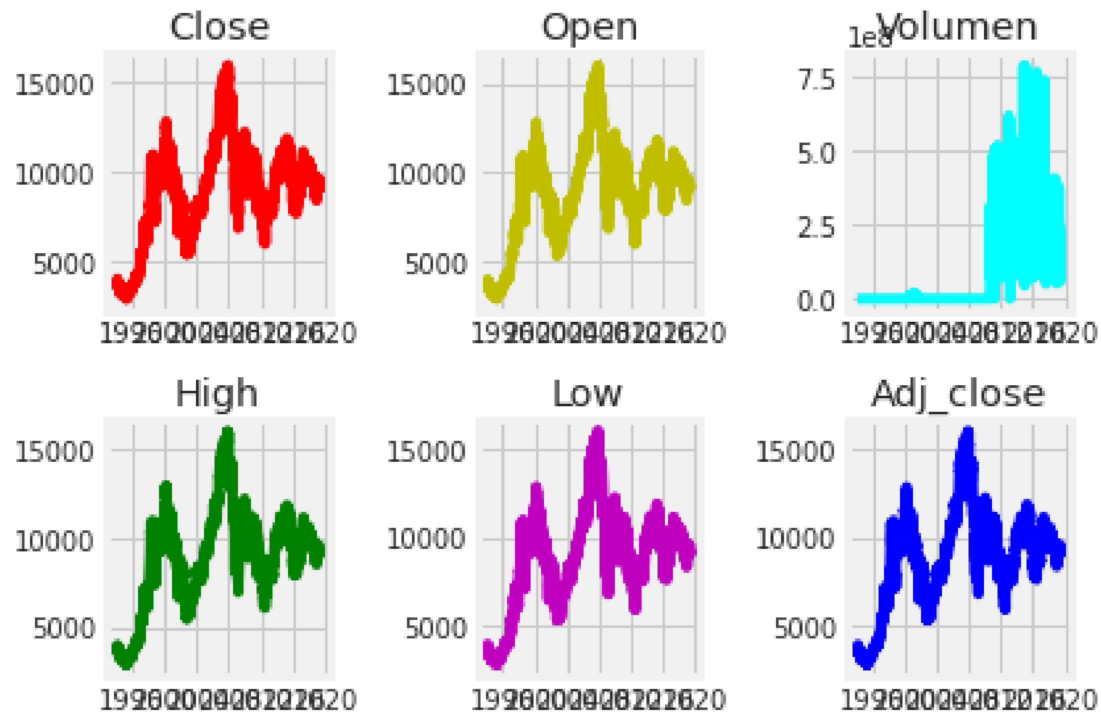

```
plt.figure(figsize=(2,2))
sns.pairplot(train_fixed, corner=True)
plt.show()
```

```
<Figure size 144x144 with 0 Axes>
```



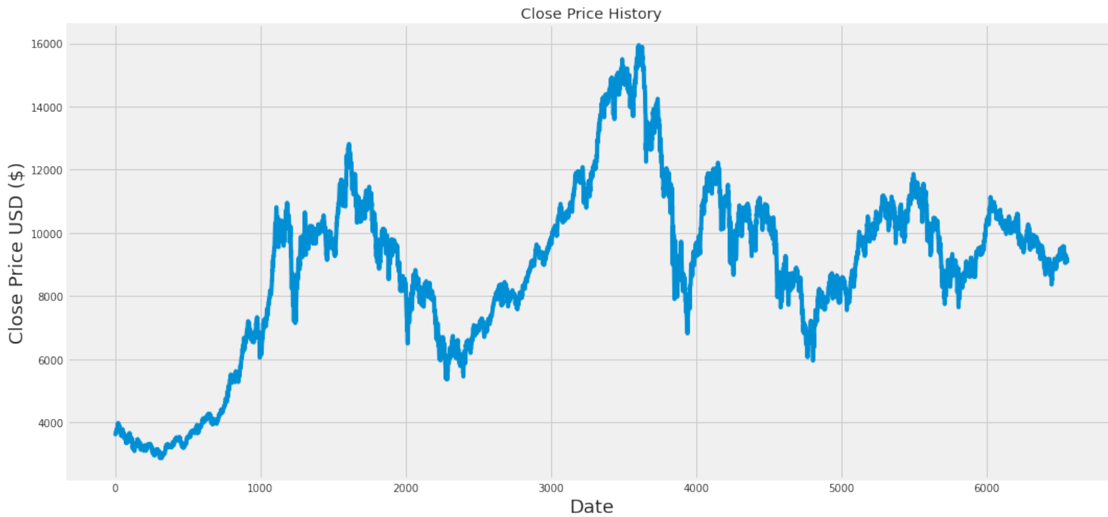

```
date = train_fixed['Date']
close = train_fixed['Close']
Open = train_fixed['Open']
High = train_fixed['High']
Low  = train_fixed['Close']
Adj_close  = train_fixed['Adj Close']
Volumen = train_fixed['Volume']
fig , ((axes1,axes2,axes3),(axes4,axes5,axes6))= plt.subplots(2,3)
axes1.plot(date,close,'r')
axes1.set_title('Close')
axes2.plot(date,Open,'y')
axes2.set_title('Open')
axes3.plot(date,Volumen,'cyan')
axes3.set_title('Volumen')
axes4.plot(date,High,'g')
axes4.set_title('High')
axes5.plot(date,Low,'m')
```

```
axes5.plot(date,Low,'m')
axes5.set_title('Low')
axes6.plot(date,Adj_close,'b')
axes6.set_title('Adj_close')
fig.tight_layout()
plt.show()
```



De esta matriz de correlacion notamos que la variable volumen está pobremente correlacionada o directamente no hay relación. **Ya que las otras variables están directamente relacionadas nos brindan la misma informacion y podemos usar solo una para hacer nuestras predicciones, en este caso tomaré la variable 'Close' para hacer las predicciones.**

```
# Vista historica del precio de cierre

plt.figure(figsize=(16,8))
plt.title('Close Price History')
plt.plot(train_fixed['Close'])
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.show()
```




```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
# TensorFlow y tf.keras
import tensorflow as tf
from tensorflow import keras

print(tf.__version__)
```

```
2.8.0
```

```
X, y = train_fixed.Close.values.reshape(-1, 1),
train_fixed.Target.values.reshape(-1, 1)


# Escalamos nuestros datos en el rango de 0 a 1

escaler = MinMaxScaler()

X = escaler.fit_transform(X)



X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.25, shuffle=False)

X_valid = X_test[:(X_test.size//2)]
X_test = X_test[(X_test.size//2):]
y_valid = y_test[:(y_test.size//2)]
y_test = y_test[(y_test.size//2):]

print(f'x_train.shape = {X_train.shape}')
print(f'y_train.shape = {y_train.shape}')
print(f'X_valid.shape = {X_valid.shape}')
print(f'y_valid.shape = {y_valid.shape}')
```

```
print(f'x_test.shape = {X_test.shape}')
print(f'y_test.shape = {y_test.shape}')
```

```
x_train.shape = (4915, 1)
y_train.shape = (4915, 1)
X_valid.shape = (819, 1)
y_valid.shape = (819, 1)
x_test.shape = (820, 1)
y_test.shape = (820, 1)
```

```
from tensorflow.keras import regularizers
```

```
model_basic = keras.Sequential([
              keras.layers.LSTM(
                  units=32,
                  activation='tanh',
                  return_sequences=True,
                  recurrent_activation='sigmoid',
                  use_bias=True, dropout=0.2,
                  kernel_regularizer = regularizers.l2(1e-5),
                  input_shape=(X_train.shape[1], 1)),
              keras.layers.Dense(64, activation='relu'),
              keras.layers.LSTM(units=128, activation='tanh',
return_sequences=False, recurrent_activation='sigmoid', use_bias=True,
dropout=0.2, kernel_regularizer = regularizers.l2(1e-5)),
              keras.layers.Dense(32, activation='relu'),
              keras.layers.Dense(1, activation='sigmoid')
])
```

```
model_basic.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 1, 32)             4352

 dense (Dense)               (None, 1, 64)             2112

 lstm_1 (LSTM)               (None, 128)               98816

 dense_1 (Dense)             (None, 32)                4128

 dense_2 (Dense)             (None, 1)                 33

=================================================================
Total params: 109,441
Trainable params: 109,441
Non-trainable params: 0
_________________________________________________________________
```

```python
model_basic.compile(
    metrics=['accuracy'],
    optimizer='adam',
    loss='binary_crossentropy'
)

history = model_basic.fit(X_train, y_train, epochs=20,
validation_data=(X_valid, y_valid))
```

```
Epoch 1/20
154/154 [==============================] - 12s 23ms/step - loss:
0.6935 - accuracy: 0.5009 - val_loss: 0.6917 - val_accuracy: 0.5409
Epoch 2/20
154/154 [==============================] - 2s 13ms/step - loss: 0.6930
- accuracy: 0.5123 - val_loss: 0.6917 - val_accuracy: 0.5409
Epoch 3/20
154/154 [==============================] - 2s 12ms/step - loss: 0.6930
- accuracy: 0.5123 - val_loss: 0.6911 - val_accuracy: 0.5409
Epoch 4/20
154/154 [==============================] - 2s 11ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6911 - val_accuracy: 0.5409
Epoch 5/20
154/154 [==============================] - 2s 12ms/step - loss: 0.6930
- accuracy: 0.5123 - val_loss: 0.6911 - val_accuracy: 0.5409
Epoch 6/20
154/154 [==============================] - 2s 10ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
Epoch 7/20
154/154 [==============================] - 2s 11ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6916 - val_accuracy: 0.5409
Epoch 8/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
Epoch 9/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6917 - val_accuracy: 0.5409
Epoch 10/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6930
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
Epoch 11/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
Epoch 12/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6912 - val_accuracy: 0.5409
Epoch 13/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6915 - val_accuracy: 0.5409
Epoch 14/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6916 - val_accuracy: 0.5409
```

```
Epoch 15/20
154/154 [==============================] - 1s 6ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6916 - val_accuracy: 0.5409
Epoch 16/20
154/154 [==============================] - 1s 6ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6918 - val_accuracy: 0.5409
Epoch 17/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
Epoch 18/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6913 - val_accuracy: 0.5409
Epoch 19/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
Epoch 20/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6913 - val_accuracy: 0.5409
```

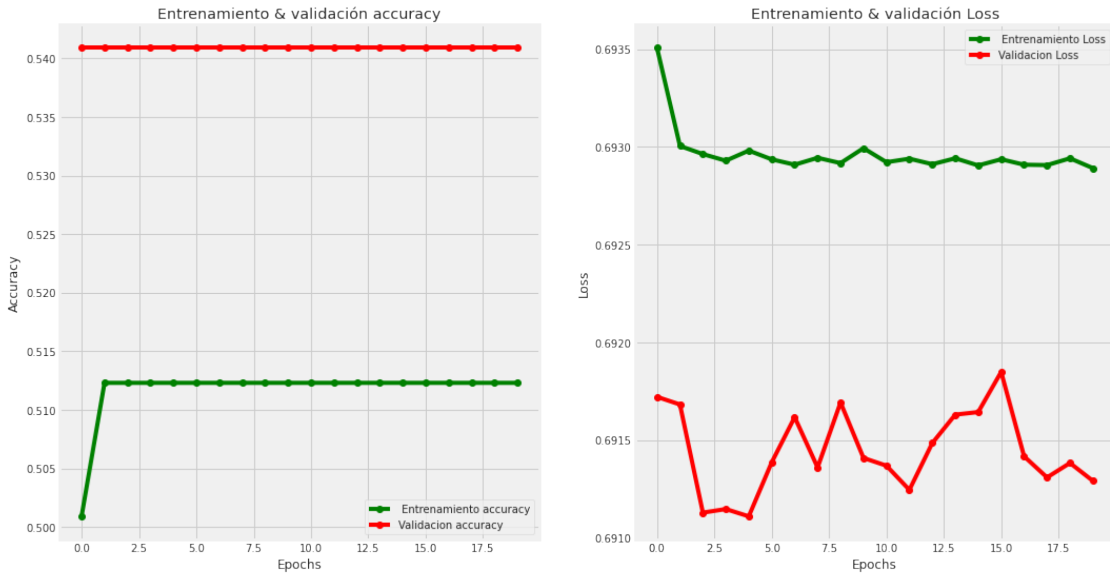
```
results = model_basic.evaluate(X_test, y_test)
```

```
26/26 [==============================] - 0s 4ms/step - loss: 0.6924 -
accuracy: 0.5207
```

```
def visualizacion_resultados(history):
  epochs = [i for i in range(20)]
  fig, ax = plt.subplots(1,2)
  train_acc = history.history["accuracy"]
  train_loss = history.history["loss"]
  val_acc = history.history["val_accuracy"]
  val_loss = history.history["val_loss"]
  fig.set_size_inches(16, 9)

  ax[0].plot(epochs, train_acc, "go-", label =" Entrenamiento 
accuracy")
  ax[0].plot(epochs, val_acc, "ro-", label= "Validacion accuracy")
  ax[0].set_title("Entrenamiento & validación accuracy")
  ax[0].legend()
  ax[0].set_xlabel("Epochs")
  ax[0].set_ylabel("Accuracy")

  ax[1].plot(epochs, train_loss, "go-", label =" Entrenamiento Loss")
  ax[1].plot(epochs, val_loss, "ro-", label= "Validacion Loss")
  ax[1].set_title("Entrenamiento & validación Loss")
  ax[1].legend()
  ax[1].set_xlabel("Epochs")
  ax[1].set_ylabel("Loss")

  plt.show()

print(history.history.keys())
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
visualizacion_resultados(history)
```




```
model_optimizer = keras.Sequential([
              keras.layers.LSTM(
                  units=64,
                  activation='tanh',
                  return_sequences=True,
                  recurrent_activation='sigmoid',
                  use_bias=True, dropout=0.2,
                  kernel_regularizer = regularizers.l2(1e-5),
                  input_shape=(X_train.shape[1], 1)),
              keras.layers.Dense(64, activation='relu'),
              tf.keras.layers.Dense(256, kernel_regularizer =
regularizers.l2(1e-5), activation = "relu"),
              keras.layers.LSTM(units=128, activation='tanh',
return_sequences=False, recurrent_activation='sigmoid', use_bias=True,
dropout=0.2, kernel_regularizer = regularizers.l2(1e-5)),
              keras.layers.Dense(64, activation='relu'),
              keras.layers.Dense(16, activation='relu'),
              keras.layers.Dense(1, activation='sigmoid')
])
```

```
model_optimizer.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 1, 64)             16896

 dense_3 (Dense)             (None, 1, 64)             4160
```

```
 dense_4 (Dense)             (None, 1, 256)            16640

 lstm_3 (LSTM)               (None, 128)               197120

 dense_5 (Dense)             (None, 64)                8256

 dense_6 (Dense)             (None, 16)                1040

 dense_7 (Dense)             (None, 1)                 17

=================================================================
Total params: 244,129
Trainable params: 244,129
Non-trainable params: 0
_________________________________________________________________
```

```
model_optimizer.compile(
    metrics=['accuracy'],
    optimizer='adam',
    loss='binary_crossentropy'
)

history_optimizer = model_optimizer.fit(X_train, y_train, epochs=20,
validation_data=(X_valid, y_valid))
```

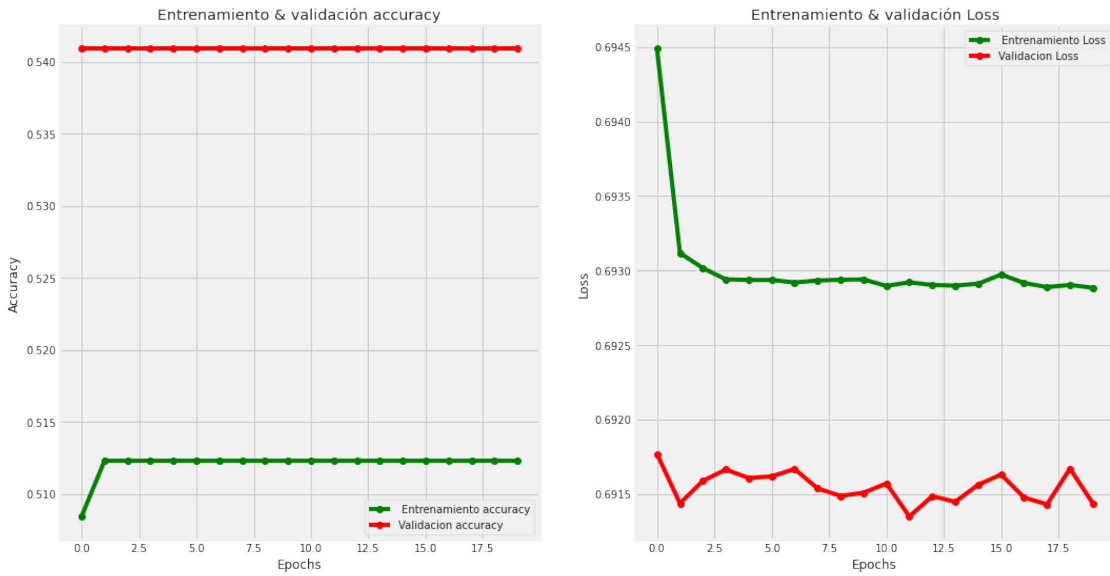
```
Epoch 1/20
154/154 [==============================] - 5s 13ms/step - loss: 0.6945
- accuracy: 0.5084 - val_loss: 0.6918 - val_accuracy: 0.5409
Epoch 2/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6931
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
Epoch 3/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6930
- accuracy: 0.5123 - val_loss: 0.6916 - val_accuracy: 0.5409
Epoch 4/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6917 - val_accuracy: 0.5409
Epoch 5/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6916 - val_accuracy: 0.5409
Epoch 6/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6916 - val_accuracy: 0.5409
Epoch 7/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6917 - val_accuracy: 0.5409
Epoch 8/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6915 - val_accuracy: 0.5409
Epoch 9/20
```

```
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6915 - val_accuracy: 0.5409
Epoch 10/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6915 - val_accuracy: 0.5409
Epoch 11/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6916 - val_accuracy: 0.5409
Epoch 12/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6913 - val_accuracy: 0.5409
Epoch 13/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6915 - val_accuracy: 0.5409
Epoch 14/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
Epoch 15/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6916 - val_accuracy: 0.5409
Epoch 16/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6930
- accuracy: 0.5123 - val_loss: 0.6916 - val_accuracy: 0.5409
Epoch 17/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6915 - val_accuracy: 0.5409
Epoch 18/20
154/154 [==============================] - 1s 7ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
Epoch 19/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6917 - val_accuracy: 0.5409
Epoch 20/20
154/154 [==============================] - 1s 8ms/step - loss: 0.6929
- accuracy: 0.5123 - val_loss: 0.6914 - val_accuracy: 0.5409
```

```
results = model_basic.evaluate(X_test, y_test)
```

```
26/26 [==============================] - 0s 4ms/step - loss: 0.6924 -
accuracy: 0.5207
```

```
visualizacion_resultados(history_optimizer)
```



Predicciones del dataser test.csv

```
test.head()

   test_index        Date         Open         High          Low
Close  \
0        6557  2019-06-05  9136.799805  9173.400391  9095.000000
9150.500000
1        6558  2019-06-06  9169.200195  9246.200195  9136.700195
9169.200195
2        6559  2019-06-07  9186.700195  9261.400391  9185.700195
9236.099609
3        6560  2019-06-10  9284.200195  9302.200195  9248.099609
9294.099609
4        6561  2019-06-11  9288.599609  9332.500000  9273.400391
9282.099609

     Adj Close       Volume
0  9150.500000  158753000.0
1  9169.200195  212720900.0
2  9236.099609  150664700.0
3  9294.099609  102323700.0
4  9282.099609  144701200.0

# Hacemos la prediccion

input_test = test.Close.values.reshape(-1,1)
input_test = escaler.fit_transform(input_test)
predictions_test = model_optimizer.predict(input_test, batch_size=64)
predictions_test

predictions_test.reshape(-1,1)
```

```python
predictions_test = pd.Series(predictions_test.reshape(-1,),
name='Target')

predictions_test = predictions_test.apply(lambda x: 1 if x >= 0.5 else
0)

predictions_test

prediction = pd.concat([test['test_index'],predictions_test],axis=1)

prediction
```

```
     test_index  Target
0          6557       1
1          6558       1
2          6559       1
3          6560       1
4          6561       1
..          ...     ...
721        7278       1
722        7279       1
723        7280       1
724        7281       1
725        7282       1

[726 rows x 2 columns]
```

```python
prediction.to_csv('predictions.csv')

prediction.to_json('predictions.json')
```