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## Previsão do comportamento de preço do Bitcoin

Neste projeto faremos a implementação de um LSTM para previsão do preço do Bitcoin de dezembro de 2014 a maio de 2018. Para isso, utilizaremos Tensorflow e Keras, além da biblioteca Numpy para operações matemáticas e Scikit-Learn para funções de métricas de avaliação.

```
Importação das Bibliotecas
%pip install tensorflow
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: tensorflow in
/usr/local/lib/python3.9/dist-packages (2.11.0)
Requirement already satisfied: tensorflow-estimator<2.12,>=2.11.0
in /usr/local/lib/python3.9/dist-packages (from tensorflow) (2.11.0)
Requirement already satisfied: gast<=0.4.0,>=0.2.1 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (0.4.0)
Requirement already satisfied: six>=1.12.0 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (1.15.0)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (1.51.3)
Requirement already satisfied: libclang>=13.0.0 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (15.0.6.1)
Requirement already satisfied: wrapt>=1.11.0 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (1.15.0)
Requirement already satisfied: tensorflow-io-qcs-filesystem>=0.23.1 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (0.31.0)
Requirement already satisfied: typing-extensions>=3.6.6 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (4.5.0)
Requirement already satisfied: flatbuffers>=2.0 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (23.3.3)
Requirement already satisfied: protobuf<3.20,>=3.9.2 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (3.19.6)
Requirement already satisfied: tensorboard<2.12,>=2.11 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (2.11.2)
Requirement already satisfied: keras<2.12,>=2.11.0 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (2.11.0)
Requirement already satisfied: termcolor>=1.1.0 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (2.2.0)
Requirement already satisfied: absl-py>=1.0.0 in
```

```
/usr/local/lib/python3.9/dist-packages (from tensorflow) (1.4.0)
Requirement already satisfied: packaging in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (23.0)
Requirement already satisfied: astunparse>=1.6.0 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: h5py>=2.9.0 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (3.1.0)
Requirement already satisfied: setuptools in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (57.4.0)
Requirement already satisfied: opt-einsum>=2.3.2 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (3.3.0)
Requirement already satisfied: google-pasta>=0.1.1 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (0.2.0)
Requirement already satisfied: numpy>=1.20 in
/usr/local/lib/python3.9/dist-packages (from tensorflow) (1.22.4)
Requirement already satisfied: wheel<1.0,>=0.23.0 in
/usr/local/lib/python3.9/dist-packages (from astunparse>=1.6.0-
>tensorflow) (0.38.4)
Requirement already satisfied: werkzeug>=1.0.1 in
/usr/local/lib/python3.9/dist-packages (from tensorboard<2.12,>=2.11-
>tensorflow) (2.2.3)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in
/usr/local/lib/python3.9/dist-packages (from tensorboard<2.12,>=2.11-
>tensorflow) (0.4.6)
Requirement already satisfied: requests<3,>=2.21.0 in
/usr/local/lib/python3.9/dist-packages (from tensorboard<2.12,>=2.11-
>tensorflow) (2.25.1)
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0
in /usr/local/lib/python3.9/dist-packages (from
tensorboard<2.12,>=2.11->tensorflow) (0.6.1)
Requirement already satisfied: google-auth<3,>=1.6.3 in
/usr/local/lib/python3.9/dist-packages (from tensorboard<2.12,>=2.11-
>tensorflow) (2.16.2)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in
/usr/local/lib/python3.9/dist-packages (from tensorboard<2.12,>=2.11-
>tensorflow) (1.8.1)
Requirement already satisfied: markdown>=2.6.8 in
/usr/local/lib/python3.9/dist-packages (from tensorboard<2.12,>=2.11-
>tensorflow) (3.4.1)
Requirement already satisfied: rsa<5,>=3.1.4 in
/usr/local/lib/python3.9/dist-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.12,>=2.11->tensorflow) (4.9)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in
/usr/local/lib/python3.9/dist-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.12,>=2.11->tensorflow) (5.3.0)
Requirement already satisfied: pyasn1-modules>=0.2.1 in
/usr/local/lib/python3.9/dist-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.12,>=2.11->tensorflow) (0.2.8)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/usr/local/lib/python3.9/dist-packages (from google-auth-
```

```
oauthlib<0.5,>=0.4.1- tensorboard<2.12,>=2.11- tensorflow) (1.3.1)
Requirement already satisfied: importlib-metadata>=4.4 in
/usr/local/lib/python3.9/dist-packages (from markdown>=2.6.8-
>tensorboard<2.12,>=2.11->tensorflow) (6.0.0)
Requirement already satisfied: chardet<5,>=3.0.2 in
/usr/local/lib/python3.9/dist-packages (from requests<3,>=2.21.0-
>tensorboard<2.12.>=2.11->tensorflow) (4.0.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.9/dist-packages (from requests<3,>=2.21.0-
>tensorboard<2.12,>=2.11->tensorflow) (2022.12.7)
Requirement already satisfied: idna<3,>=2.5 in
/usr/local/lib/python3.9/dist-packages (from requests<3,>=2.21.0-
>tensorboard<2.12,>=2.11->tensorflow) (2.10)
Reguirement already satisfied: urllib3<1.27,>=1.21.1 in
/usr/local/lib/python3.9/dist-packages (from requests<3,>=2.21.0-
>tensorboard<2.12,>=2.11->tensorflow) (1.26.14)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/usr/local/lib/python3.9/dist-packages (from werkzeug>=1.0.1-
>tensorboard<2.12,>=2.11->tensorflow) (2.1.2)
Requirement already satisfied: zipp>=0.5 in
/usr/local/lib/python3.9/dist-packages (from importlib-metadata>=4.4-
>markdown>=2.6.8->tensorboard<2.12,>=2.11->tensorflow) (3.15.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in
/usr/local/lib/python3.9/dist-packages (from pyasn1-modules>=0.2.1-
>qoogle-auth<3,>=1.6.3->tensorboard<2.12,>=2.11->tensorflow) (0.4.8)
Requirement already satisfied: oauthlib>=3.0.0 in
/usr/local/lib/python3.9/dist-packages (from requests-oauthlib>=0.7.0-
>google-auth-oauthlib<0.5,>=0.4.1->tensorboard<2.12,>=2.11-
>tensorflow) (3.2.2)
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
import tensorflow as tf
import io
import math
%matplotlib inline
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM
from sklearn.metrics import mean_squared_error
A fim de trabalharmos com valores determinísticos, instanciamos uma seed manual.
np.random.seed(10)
tf.random.set seed(10)
```

```
url = 'https://raw.githubusercontent.com/brianmwangy/predicting-
bitcoin-prices-using-LSTM/master/btc.csv'
df = pd.read_csv(url)
df = df.iloc[::-1].reset index(drop=True)
```

# Análise 1 (Configuração Base)

# Anállise de Dados

A partir do banco de preços fornecido no arquivo .csv , vamos fazer a análise dos dados informativos:

# df.head(5)

Date	Symbol	0pen	High	Low	Close	Volume	e From	Volume
To 0 12/1/2014 19.53	BTCUSD	300.0	370.0	300.00	370.0	0	. 05656	
1 12/2/2014 5675.07	BTCUSD	370.0	378.0	370.00	378.0	15	.01000	
2 12/3/2014 206.52	BTCUSD	378.0	378.0	377.01	378.0	0	.54660	
3 12/4/2014 3.77	BTCUSD	378.0	378.0	377.10	377.1	0	.01000	
4 12/5/2014 0.00	BTCUSD	377.1	377.1	377.10	377.1	0	. 00000	
df.describe()								
Volume From	Open		High		Low	(	Close	
	000000	1273.0	00000	1273.00	0000	1273.00	90000	
	589018	2594.9	08704	2382.98	2019	2504.25	56002	
	446583	3959.1	66670	3560.43	0575	3788.55	59184	
min 120. 0.000000	000000	184.0	00000	0.06	0000	120.00	90000	
	000000	340.0	00000	340.00	0000	340.00	90000	
	870000	639.9	90000	620.59	0000	634.97	70000	
	450000	2776.9	50000	2551.06	0000	2664.99	90000	
	000000	19891.9	90000	19010.00	0000	19650.00	90000	

Volume To count 1.273000e+03 mean 4.454886e+07

```
std 1.055807e+08
min 0.000000e+00
25% 2.042181e+06
50% 3.532958e+06
75% 3.532348e+07
max 1.237771e+09
```

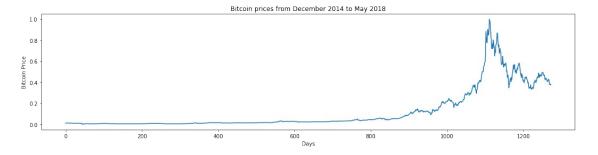
Acima, temos estatísticas descritivas dos dados trabalhados.

```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1273 entries, 0 to 1272
Data columns (total 8 columns):
                  Non-Null Count
#
     Column
                                   Dtype
 0
     Date
                  1273 non-null
                                   object
     Symbol
 1
                  1273 non-null
                                   obiect
 2
                  1273 non-null
                                   float64
     0pen
 3
                                   float64
     High
                  1273 non-null
 4
     Low
                  1273 non-null
                                   float64
5
                  1273 non-null
                                   float64
     Close
 6
     Volume From 1273 non-null
                                   float64
     Volume To
                  1273 non-null
                                   float64
dtypes: float64(6), object(2)
memory usage: 79.7+ KB
```

## Normalização e Plot

Como os dados possuem valor absoluto alto, faremos uma normalização dos dados, a fim de evitar que alguns parâmetros se sobressaiam a outros no processo de treinamento.

```
df_to_use = df['Close'].values
scaler = MinMaxScaler()
scaled_df = scaler.fit_transform(df_to_use.reshape(-1,1))
figure = plt.figure(figsize=(18,4))
sns.lineplot(data=scaled_df, legend=None)
plt.xlabel('Days')
plt.ylabel('Bitcoin Price')
plt.title('Bitcoin prices from December 2014 to May 2018')
plt.show()
```



## Funções Auxiliares

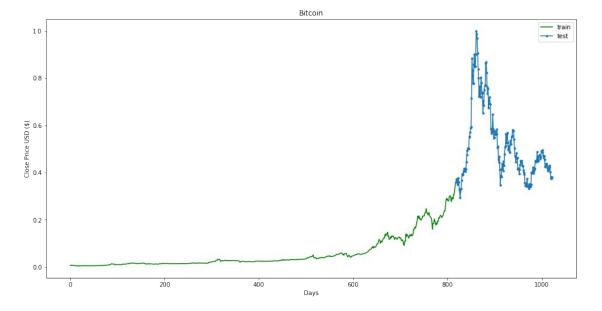
min\_delta=0,
patience=10,
verbose=1,

Trabalharemos com uma função para fazer a separação de treino e teste.

Usaremos a função create\_x\_y, que possui a finalidade de instanciar janelas de treinamento em sequências de dados.

```
def create x y(data, time steps=1):
    x, y = [], []
    for i in range(len(data) - time steps):
        v = data[i:(i + time_steps), 0] # pega todos os dias antes do
dia que queremos prever
        x.append(v)
        y.append(data[i + time steps, 0]) # pega o dia que queremos
prever
    return np.array(x), np.array(y)
A fim de separar o dataset base, a função split_data é chamada.
# 818 instâncias para treino e 205 para teste, com um test size de 20%
def split data(data, test size, time steps):
    X, y = create \times y(data, time steps)
    length = X.shape[0]
    split = int(length * (1 - test size))
    X train, y train = X[:split], y[:split]
    X test, y test = X[split:], y[split:]
    return X train, y train, X test, y test
time steps = 250 # primeiramente, vamos treinar olhando para os 250
dias anteriores
X train, y train, X test, y test = split data(scaled df, 0.2,
time steps)
print(X train.shape)
print(y_train.shape)
print(X test.shape)
print(y_test.shape)
(818, 250)
(818,)
(205, 250)
(205,)
Aqui, instanciaremos a função que implementará o algoritmo de Early Stopping em cada
um dos modelos manipulados.
callback = tf.keras.callbacks.EarlyStopping(
    monitor="loss",
```

```
mode="auto",
    baseline=None,
    restore_best_weights=False,
    start from epoch=0,
)
Treino e Teste
X train = X train.reshape(X train.shape[0], X train.shape[1], 1)
X test = X test.reshape(X test.shape[0], X test.shape[1], 1)
y train = y train.reshape(-1, 1)
y_{\text{test}} = y_{\text{test}} \cdot \text{reshape}(-1, 1)
print(X train.shape)
print(y_train.shape)
print(X test.shape)
print(y test.shape)
(818, 250, 1)
(818, 1)
(205, 250, 1)
(205, 1)
Abaixo, temos o plot do nosso dataset segmentado
plt.figure(figsize=(16,8))
plt.plot(np.arange(0, len(y_train)), y_train, 'g', label='train')
plt.plot(np.arange(len(y_train), len(y_train) + len(y_test)), y_test,
marker='.', label='test')
plt.title('Bitcoin')
plt.xlabel('Days')
plt.ylabel('Close Price USD ($)')
plt.legend()
plt.show()
```



# Arquitetura da Rede e Configuração dos Parâmetros

Nessa etapa, configuramos os parâmetros a serem utilizados e manipulados no treino.

```
EPOCHS = 30
BATCH_SIZE = 16
LEARNING_RATE = 0.001
DROPOUT = 0.1
VERBOSE = 1
OPT = tf.keras.optimizers.Adam
Instanciando o modelo de LSTM:
model_LSTM = tf.keras.Sequential()
model_LSTM.add(LSTM(time_steps, input_shape=(time_steps, X_train.shape[-1]), dropout=DROPOUT))
model_LSTM.add(Dense(1, activation='linear'))
model_LSTM.compile(
    optimizer=OPT(learning_rate = LEARNING_RATE),
    loss="mse")
model_LSTM.summary()
```

Model: "sequential 37"

Layer (type)	Output Shape	Param #
lstm_74 (LSTM)	(None, 250)	252000
dense_33 (Dense)	(None, 1)	251

\_\_\_\_\_\_

Total params: 252,251

Trainable params: 252,251 Non-trainable params: 0

05 - val loss: 6.1398e-04

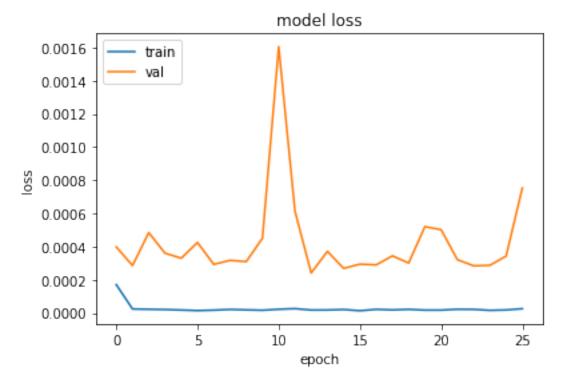
Agora, faremos o treinamento do modelo sem a manipulação de parâmetros. history LSTM = model LSTM.fit( np.array(X train).reshape(X train.shape[0], X train.shape[1], 1), y train, batch size=BATCH SIZE, epochs=EPOCHS, verbose=VERBOSE, validation split=0.2, callbacks=[callback]) Epoch 1/30 04 - val loss: 3.9778e-04 Epoch  $2/\overline{30}$ 05 - val loss: 2.8530e-04 Epoch 3/30 05 - val loss: 4.8413e-04 Epoch 4/30 05 - val loss: 3.6000e-04 Epoch 5/30 05 - val loss: 3.2969e-04 Epoch 6/30 05 - val loss: 4.2462e-04 Epoch 7/30 05 - val loss: 2.9256e-04 Epoch 8/30 05 - val loss: 3.1680e-04 Epoch 9/30 05 - val loss: 3.0901e-04 Epoch 10/30 05 - val\_loss: 4.5046e-04 Epoch 11/30 05 - val loss: 0.0016 Epoch 12/30

```
Epoch 13/30
05 - val loss: 2.4083e-04
Epoch 14/30
05 - val loss: 3.7126e-04
Epoch 15/30
05 - val loss: 2.6833e-04
Epoch 16/30
05 - val loss: 2.9398e-04
Epoch 17/30
05 - val loss: 2.8929e-04
Epoch 18/30
05 - val loss: 3.4406e-04
Epoch 19/30
05 - val loss: 3.0061e-04
Epoch 20/30
05 - val loss: 5.2023e-04
Epoch 21/30
05 - val loss: 5.0141e-04
Epoch 22/30
05 - val loss: 3.2105e-04
Epoch 23/30
05 - val loss: 2.8393e-04
Epoch 24/30
05 - val loss: 2.8673e-04
Epoch 25/30
05 - val loss: 3.4262e-04
Epoch 26/30
05 - val loss: 7.5304e-04
Epoch 26: early stopping
A fim de facilitar o processo de avaliação dos modelos referentes no documento, usaremos
```

a função model\_evaluation abaixo:

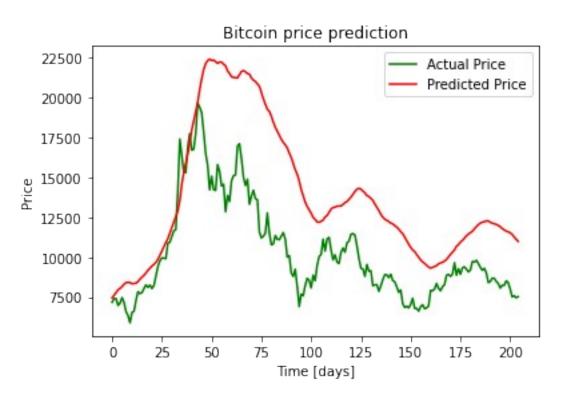
```
def model_evaluation(history, model, scaler, X_test, X_train, y_train,
  plt.plot(history.history['loss'])
```

```
plt.plot(history.history['val loss'])
  plt.title('model loss')
  plt.ylabel('loss')
  plt.xlabel('epoch')
  plt.legend(['train', 'val'], loc = 'upper left')
  plt.show()
 y hat = model.predict(X test)
 y t = model.predict(X train)
 y test inverse = scaler.inverse transform(y test)
  v hat inverse = scaler.inverse_transform(y_hat)
  plt.plot(y test inverse, label='Actual Price', color = 'green')
  plt.plot(y hat inverse, label='Predicted Price', color = 'red')
  plt.title('Bitcoin price prediction')
  plt.xlabel('Time [days]')
  plt.ylabel('Price')
  plt.legend(['Actual Price', 'Predicted Price'], loc = 'upper right')
  ## adicionar legenda com os parametros atuais
  trainScore = math.sqrt(mean squared error(y train[0], y t[0]))
  print('Train Score: %.4f RMSE' % (trainScore))
  testScore = math.sqrt(mean_squared_error(y_test[0], y_hat[0]))
  print('Test Score: %.4f RMSE' % (testScore))
  plt.show()
Com o plot dos dados, conseguimos ter uma avaliação mais palpável do treinamento.
Assim, faremos esse processo a seguir:
model evaluation(history LSTM, model LSTM, scaler, X test, X train,
y train, y test)
```



7/7 [======] - 0s 11ms/step 26/26 [==========] - 0s 10ms/step

Train Score: 0.0010 RMSE Test Score: 0.0144 RMSE



#### Análise de Resultados

A partir dos dados obtidos, observamos um comportamento similar (no quesito de aumento ou diminuição do valor do Bitcoin ao longo do tempo) do conjunto de treino e teste. Apesar de as magnitudes se encontrarem na ordem de grandeza, suas valorações ainda divergem. Por fim, obtivemos um test score de 0.0244 RMSE.

## **Análise 2 (Número de Camadas LSTM)**

Nessa etapa, faremos testes com diferentes números de camadas LSTM, a fim de analisar e encontrar a melhor estrutura a ser aplicada no projeto

## 2 camadas de LSTM

Usando 2 camadas de LSTM:

```
model_LSTM_2 = tf.keras.Sequential()
model_LSTM_2.add(LSTM(time_steps, input_shape=(time_steps,
X_train.shape[-1]), dropout=DROPOUT, return_sequences=True))
model_LSTM_2.add(LSTM(time_steps, dropout=DROPOUT))
model_LSTM_2.add(Dense(1, activation='linear'))
model_LSTM_2.compile(
    optimizer=OPT(learning_rate = LEARNING_RATE),
    loss="mse"
)
model_LSTM_2.summary()
```

Model: "sequential 38"

Layer (type)	Output Shape	Param #
lstm_75 (LSTM)	(None, 250, 250)	252000
lstm_76 (LSTM)	(None, 250)	501000
dense_34 (Dense)	(None, 1)	251

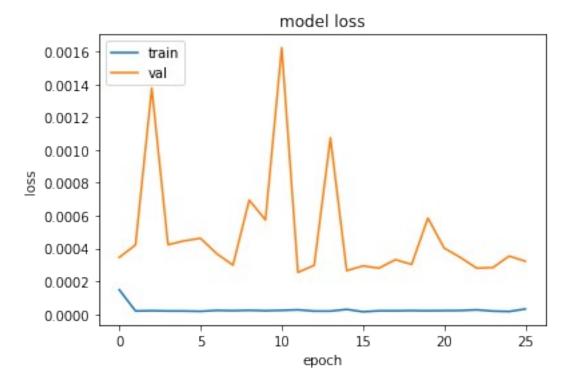
\_\_\_\_\_\_

Total params: 753,251 Trainable params: 753,251 Non-trainable params: 0

```
history_LSTM_2 = model_LSTM_2.fit(
    np.array(X_train).reshape(X_train.shape[0], X_train.shape[1], 1),
    y_train,
    batch_size=BATCH_SIZE,
    epochs=EPOCHS,
    verbose=VERBOSE,
    validation_split=0.2,
```

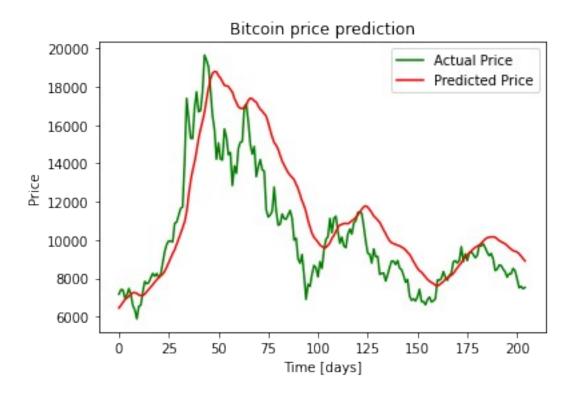
```
callbacks=[callback]
)
Epoch 1/30
04 - val loss: 3.4576e-04
Epoch 2/30
05 - val loss: 4.2218e-04
Epoch 3/30
05 - val loss: 0.0014
Epoch 4/30
05 - val loss: 4.2291e-04
Epoch 5/30
05 - val loss: 4.4707e-04
Epoch 6/30
05 - val loss: 4.6208e-04
Epoch 7/30
05 - val loss: 3.6850e-04
Epoch 8/30
05 - val loss: 2.9873e-04
Epoch 9/30
05 - val loss: 6.9500e-04
Epoch 10/30
05 - val loss: 5.7406e-04
Epoch 11/30
05 - val loss: 0.0016
Epoch 12/30
05 - val loss: 2.5451e-04
Epoch 13/30
05 - val loss: 2.9780e-04
Epoch 14/30
05 - val loss: 0.0011
Epoch 15/30
05 - val loss: 2.6506e-04
Epoch 16/30
```

```
05 - val loss: 2.9392e-04
Epoch 17/30
05 - val loss: 2.8058e-04
Epoch 18/30
05 - val loss: 3.3208e-04
Epoch 19/30
05 - val loss: 3.0290e-04
Epoch 20/30
05 - val loss: 5.8555e-04
Epoch 21/30
05 - val loss: 4.0280e-04
Epoch 22/30
05 - val loss: 3.4561e-04
Epoch 23\overline{/}30
05 - val loss: 2.8047e-04
Epoch 24/30
05 - val loss: 2.8364e-04
Epoch 25/30
05 - val loss: 3.5396e-04
Epoch 26/30
05 - val loss: 3.2242e-04
Epoch 26: early stopping
model evaluation(history LSTM 2, model LSTM 2, scaler, X test,
X train, y train, y test)
```



7/7 [======] - 1s 12ms/step 26/26 [==========] - 0s 11ms/step

Train Score: 0.0023 RMSE Test Score: 0.0368 RMSE



#### Análise de Resultados

A partir dos resultados obtidos, nota-se uma perfomance superior ao teste com uma camada.

### 3 camadas de LSTM

Usando 3 camadas de LSTM, temos:

```
model LSTM 3 = tf.keras.Sequential()
model LSTM 3.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 3.add(LSTM(time steps, dropout=DROPOUT,
return sequences=True))
model LSTM 3.add(LSTM(time steps, dropout=DROPOUT))
model_LSTM_3.add(Dense(1, activation='linear'))
model LSTM 3.compile(
  optimizer=OPT(learning rate = LEARNING RATE),
  loss="mse"
)
history LSTM 3 = model LSTM 3.fit(
  np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  y train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 4.8255e-04
Epoch 2/30
05 - val loss: 4.7518e-04
Epoch 3/30
05 - val loss: 5.8620e-04
Epoch 4/30
05 - val loss: 0.0012
Epoch 5/\overline{30}
05 - val loss: 5.1182e-04
Epoch 6/30
05 - val loss: 4.1045e-04
Epoch 7/30
```

```
05 - val loss: 5.3114e-04
Epoch 8/30
05 - val loss: 4.9065e-04
Epoch 9/30
05 - val loss: 9.1324e-04
Epoch 10/30
05 - val loss: 6.2901e-04
Epoch 11/30
05 - val loss: 0.0023
Epoch 12/30
05 - val loss: 9.1474e-04
Epoch 13/30
05 - val loss: 3.1582e-04
Epoch 14\overline{/}30
05 - val loss: 0.0012
Epoch 15/30
05 - val loss: 4.0100e-04
Epoch 16/30
05 - val loss: 3.9951e-04
Epoch 17\overline{/}30
05 - val loss: 5.8313e-04
Epoch 18/30
05 - val loss: 4.5544e-04
Epoch 19\overline{/}30
05 - val loss: 3.2992e-04
Epoch 20/30
05 - val loss: 0.0012
Epoch 21/30
05 - val loss: 3.1777e-04
Epoch 22/30
05 - val_loss: 5.6612e-04
Epoch 23/30
05 - val loss: 7.1961e-04
Epoch 24/30
```

05 - val loss: 3.3351e-04

Epoch 25/30

05 - val loss: 7.7180e-04

Epoch 26/30

05 - val\_loss: 4.6664e-04 Epoch 26: early stopping

model\_LSTM\_3.summary()

Model: "sequential 39"

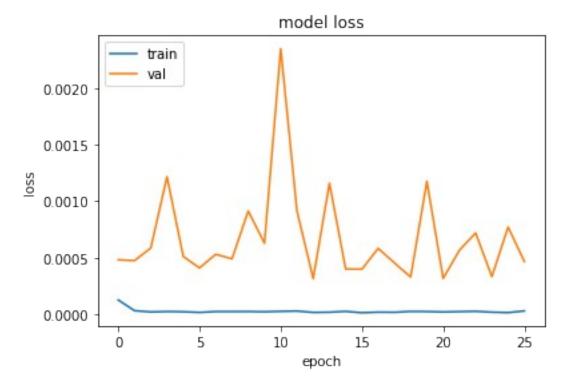
Layer (type)	Output Shape	Param #
lstm_77 (LSTM)	(None, 250, 250)	252000
lstm_78 (LSTM)	(None, 250, 250)	501000
lstm_79 (LSTM)	(None, 250)	501000
dense_35 (Dense)	(None, 1)	251

\_\_\_\_\_

Total params: 1,254,251 Trainable params: 1,254,251 Non-trainable params: 0

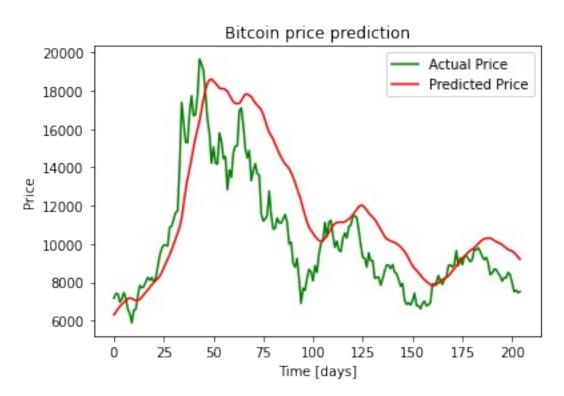
\_\_\_\_\_

model\_evaluation(history\_LSTM\_3, model\_LSTM\_3, scaler, X\_test,
X\_train, y\_train, y\_test)



7/7 [======] - 1s 31ms/step 26/26 [==========] - 0s 18ms/step

Train Score: 0.0029 RMSE Test Score: 0.0443 RMSE



#### Análise de Resultados

A partir dos resultados obtidos, nota-se uma performance inferior ao teste com duas camadas. Sendo assim, até o momento, duas camadas aparenta ser a estrutura mais coerente.

### 4 camadas de LSTM

Usando 4 camadas de LSTM:

```
model LSTM 4 = tf.keras.Sequential()
model LSTM 4.add(LSTM(time steps, input shape=(time steps,
X_train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 4.add(LSTM(time steps, dropout=DROPOUT,
return sequences=True))
model LSTM 4.add(LSTM(time steps, dropout=DROPOUT,
return sequences=True))
model LSTM_4.add(LSTM(time_steps, dropout=DROPOUT))
model LSTM 4.add(Dense(1, activation='linear'))
model LSTM 4.compile(
  optimizer=OPT(learning rate = LEARNING RATE),
  loss="mse"
)
history LSTM 4 = model LSTM 4.fit(
  np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  v train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
1.6856e-04 - val loss: 8.2629e-04
Epoch 2/30
05 - val loss: 8.0060e-04
Epoch 3/30
05 - val loss: 0.0012
Epoch 4/\overline{30}
05 - val loss: 0.0048
Epoch 5/\overline{30}
05 - val loss: 7.9948e-04
Epoch 6/30
```

```
05 - val loss: 5.1834e-04
Epoch 7/30
05 - val loss: 0.0010
Epoch 8/30
05 - val loss: 5.5652e-04
Epoch 9/30
05 - val loss: 6.8680e-04
Epoch 10/30
05 - val loss: 5.6907e-04
Epoch 11/30
05 - val loss: 0.0025
Epoch 12/30
05 - val loss: 4.9168e-04
Epoch 13\overline{/}30
05 - val loss: 0.0011
Epoch 14/30
05 - val loss: 5.4134e-04
Epoch 15/30
05 - val loss: 4.1717e-04
Epoch 16/30
05 - val loss: 4.9970e-04
Epoch 17/30
05 - val loss: 0.0015
Epoch 18\overline{/}30
05 - val loss: 4.3720e-04
Epoch 19/30
05 - val loss: 3.8467e-04
Epoch 20/30
05 - val loss: 0.0011
Epoch 21/30
05 - val loss: 3.8716e-04
Epoch 22/30
05 - val loss: 8.0057e-04
Epoch 23/30
```

```
05 - val loss: 3.5449e-04
Epoch 24\overline{/}30
05 - val loss: 0.0015
Epoch 25/30
05 - val loss: 6.8908e-04
Epoch 26/30
05 - val loss: 4.8835e-04
Epoch 27/30
05 - val loss: 0.0023
Epoch 28/30
05 - val loss: 3.8022e-04
Epoch 29/30
05 - val loss: 0.0036
Epoch 30/30
05 - val loss: 8.4763e-04
model LSTM 4.summary()
```

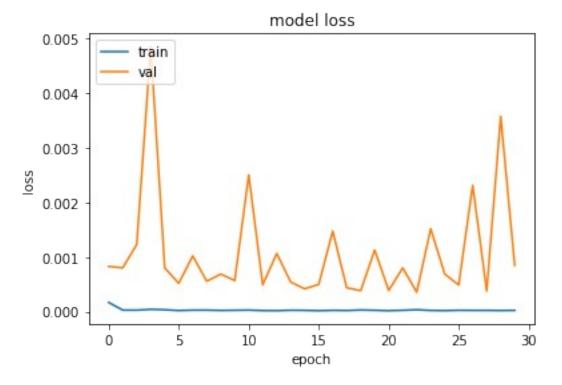
Model: "sequential 40"

Layer (type)	Output Shape	Param #
lstm_80 (LSTM)	(None, 250, 250)	252000
lstm_81 (LSTM)	(None, 250, 250)	501000
lstm_82 (LSTM)	(None, 250, 250)	501000
lstm_83 (LSTM)	(None, 250)	501000
dense_36 (Dense)	(None, 1)	251

\_\_\_\_\_\_

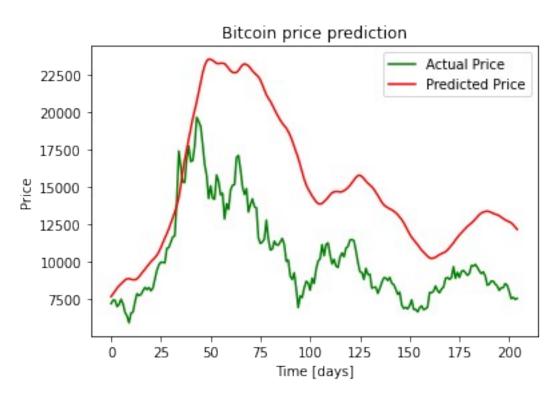
Total params: 1,755,251 Trainable params: 1,755,251 Non-trainable params: 0

model\_evaluation(history\_LSTM\_4, model\_LSTM\_4, scaler, X\_test,
X\_train, y\_train, y\_test)



7/7 [======] - 1s 39ms/step 26/26 [==========] - 1s 22ms/step

Train Score: 0.0032 RMSE Test Score: 0.0241 RMSE



#### Análise de Resultados

A partir dos resultados obtidos, nota-se uma performance inferior ao teste com duas camadas.

### Continuidade

Em virtude dos resultados encontrados, utilizaremos a partir de agora a rede com 2 camadas LSTM.

## Análise 3 (Algoritmo de Otimização)

Agora, vamos analisar a influência dos diferentes algoritmos de otimização aplicados na rede com 2 LSTMs.

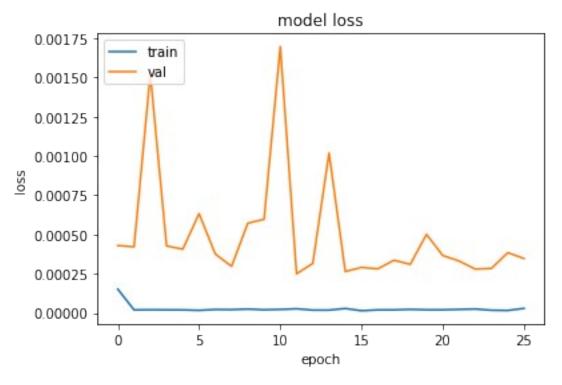
### **ADAM Optmizer**

## Aplicando o ADAM Optimizer:

```
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
  optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
  loss="mse"
history LSTM 2 adam = model LSTM 2 adam.fit(
   np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  y train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation_split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 4.2931e-04
Epoch 2/\overline{30}
05 - val loss: 4.2122e-04
Epoch 3/30
05 - val loss: 0.0015
Epoch 4/30
05 - val loss: 4.2688e-04
```

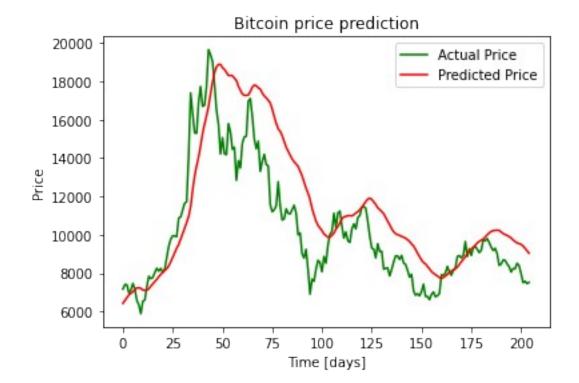
```
Epoch 5/30
05 - val loss: 4.0646e-04
Epoch 6/30
05 - val loss: 6.3256e-04
Epoch 7/30
05 - val loss: 3.7542e-04
Epoch 8/30
05 - val loss: 2.9706e-04
Epoch 9/30
05 - val loss: 5.7168e-04
Epoch 10/30
05 - val loss: 5.9683e-04
Epoch 11/30
05 - val loss: 0.0017
Epoch 12/30
05 - val loss: 2.4947e-04
Epoch 13\overline{/}30
05 - val loss: 3.1591e-04
Epoch 14/30
05 - val loss: 0.0010
Epoch 15/30
05 - val loss: 2.6422e-04
Epoch 16/30
05 - val loss: 2.9046e-04
Epoch 17/30
05 - val loss: 2.8112e-04
Epoch 18/30
05 - val loss: 3.3595e-04
Epoch 19/30
05 - val_loss: 3.0983e-04
Epoch 20/30
05 - val loss: 5.0080e-04
Epoch 21/30
```

```
05 - val loss: 3.6597e-04
Epoch 22/30
05 - val loss: 3.3112e-04
Epoch 23/30
05 - val loss: 2.7964e-04
Epoch 24/30
05 - val loss: 2.8455e-04
Epoch 25/30
05 - val loss: 3.8437e-04
Epoch 26/30
05 - val loss: 3.4706e-04
Epoch 26: early stopping
model_evaluation(history_LSTM_2_adam, model_LSTM_2_adam, scaler,
X test, X train, y train, y test)
```



7/7 [======] - 1s 21ms/step 26/26 [==========] - 0s 13ms/step

Train Score: 0.0020 RMSE Test Score: 0.0379 RMSE

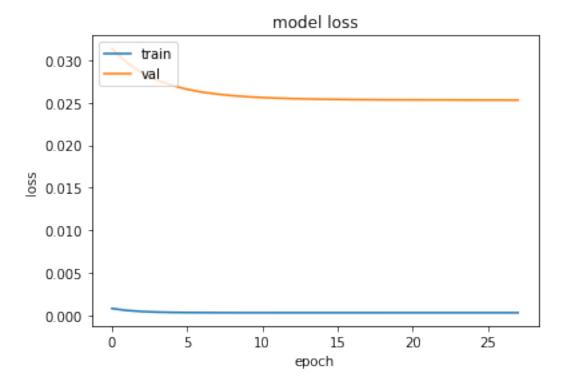


### **Stochastic Gradient Descent**

```
model_LSTM_2_sgd = tf.keras.Sequential()
model LSTM 2 sgd.add(LSTM(time steps, input shape=(time steps,
X_train.shape[-1]), dropout=DROPOUT, return_sequences=True))
model LSTM 2 sqd.add(LSTM(time steps, dropout=DROPOUT))
model_LSTM_2_sgd.add(Dense(1, activation='linear'))
model LSTM 2 sgd.compile(
   optimizer=tf.keras.optimizers.SGD(learning rate = LEARNING RATE),
   loss="mse"
)
history_LSTM_2_sgd = model_LSTM 2 sgd.fit(
   np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
   y train,
   batch size=BATCH SIZE,
   epochs=EPOCHS,
   verbose=VERBOSE,
   validation split=0.2,
   callbacks=[callback]
)
Epoch 1/30
41/41 [========
                       ========] - 6s 51ms/step - loss: 7.9524e-
04 - val loss: 0.0314
Epoch 2/30
04 - val loss: 0.0297
Epoch 3/30
```

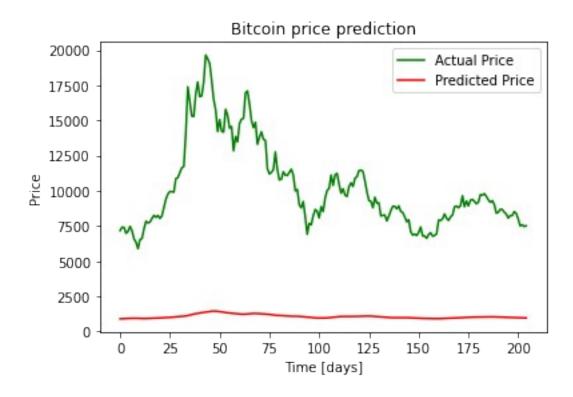
```
04 - val loss: 0.0285
Epoch 4/30
04 - val loss: 0.0277
Epoch 5/30
04 - val loss: 0.0270
Epoch 6/30
04 - val loss: 0.0266
Epoch 7/30
04 - val loss: 0.0263
Epoch 8/30
04 - val loss: 0.0260
Epoch 9/30
04 - val loss: 0.0258
Epoch 10/30
04 - val loss: 0.0257
Epoch 11/30
04 - val loss: 0.0256
Epoch 12/30
04 - val loss: 0.0255
Epoch 13/30
04 - val loss: 0.0255
Epoch 14/30
04 - val loss: 0.0255
Epoch 15/30
04 - val loss: 0.0254
Epoch 16/30
04 - val loss: 0.0254
Epoch 17/30
04 - val loss: 0.0254
Epoch 18/30
04 - val loss: 0.0254
Epoch 19/30
04 - val loss: 0.0254
```

```
Epoch 20/30
04 - val loss: 0.0254
Epoch 21/30
04 - val loss: 0.0253
Epoch 2\overline{2/30}
04 - val loss: 0.0253
Epoch 23/30
04 - val loss: 0.0253
Epoch 24/30
04 - val loss: 0.0253
Epoch 25/30
04 - val loss: 0.0253
Epoch 26/30
04 - val loss: 0.0253
Epoch 27/30
04 - val loss: 0.0253
Epoch 28/30
04 - val_loss: 0.0253
Epoch 28: early stopping
model evaluation(history LSTM 2 sqd, model LSTM 2 sqd, scaler, X test,
X train, y train, y test)
```



7/7 [======] - 1s 11ms/step 26/26 [==========] - 0s 11ms/step

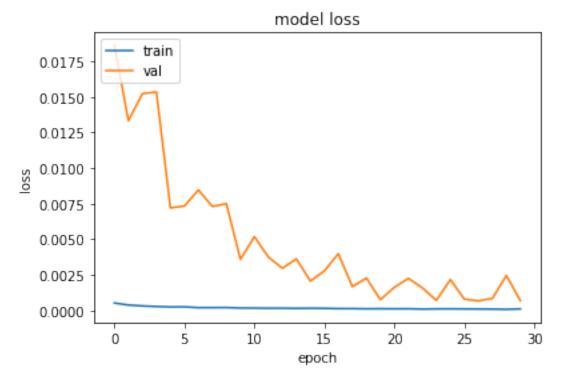
Train Score: 0.0188 RMSE Test Score: 0.3211 RMSE



```
RMSprop
model LSTM 2 rms = tf.keras.Sequential()
model LSTM 2 rms.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 2 rms.add(LSTM(time steps, dropout=DROPOUT))
model LSTM 2 rms.add(Dense(1, activation='linear'))
model LSTM 2 rms.compile(
  optimizer=tf.keras.optimizers.RMSprop(learning rate =
LEARNING RATE),
  loss="mse"
history LSTM 2 rms = model LSTM 2 rms.fit(
  np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  y train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 0.0186
Epoch 2/30
04 - val loss: 0.0133
Epoch 3/30
04 - val loss: 0.0152
Epoch 4/30
04 - val loss: 0.0153
Epoch 5/30
04 - val loss: 0.0072
Epoch 6/30
04 - val loss: 0.0073
Epoch 7/30
04 - val loss: 0.0085
Epoch 8/30
04 - val loss: 0.0073
Epoch 9/30
04 - val loss: 0.0075
Epoch 10/30
```

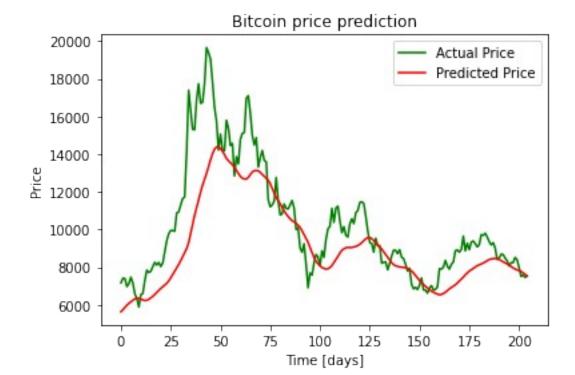
```
04 - val loss: 0.0036
Epoch 11/30
04 - val loss: 0.0052
Epoch 12/30
04 - val loss: 0.0037
Epoch 13/30
04 - val loss: 0.0030
Epoch 14/30
04 - val loss: 0.0036
Epoch 15/30
04 - val loss: 0.0021
Epoch 16/30
04 - val loss: 0.0028
Epoch 17/30
04 - val loss: 0.0040
Epoch 18/30
04 - val loss: 0.0017
Epoch 19/30
04 - val loss: 0.0023
Epoch 20/30
04 - val loss: 7.6359e-04
Epoch 21/30
04 - val loss: 0.0016
Epoch 22/30
04 - val loss: 0.0023
Epoch 23/30
04 - val loss: 0.0016
Epoch 24/30
04 - val loss: 7.0944e-04
Epoch 25/30
04 - val loss: 0.0022
Epoch 26/30
04 - val loss: 7.9747e-04
```

model\_evaluation(history\_LSTM\_2\_rms, model\_LSTM\_2\_rms, scaler, X\_test,
X\_train, y\_train, y\_test)



7/7 [=======] - 1s 11ms/step 26/26 [==========] - 0s 11ms/step

Train Score: 0.0120 RMSE Test Score: 0.0787 RMSE

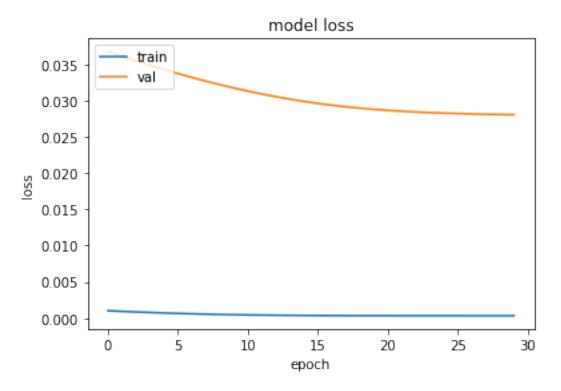


### Adadelta model I

```
model LSTM 2 ada = tf.keras.Sequential()
model LSTM 2 ada.add(LSTM(time steps, input shape=(time steps,
X_train.shape[-1]), dropout=DROPOUT, return_sequences=True))
model LSTM 2 ada.add(LSTM(time steps, dropout=DROPOUT))
model_LSTM_2_ada.add(Dense(1, activation='linear'))
model LSTM 2 ada.compile(
   optimizer=tf.keras.optimizers.Adadelta(learning rate =
LEARNING RATE),
   loss="mse"
history LSTM 2 ada = model LSTM 2 ada.fit(
   np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
   y train,
   batch size=BATCH SIZE,
   epochs=EPOCHS,
   verbose=VERBOSE,
   validation_split=0.2,
   callbacks=[callback]
)
Epoch 1/30
val loss: 0.0368
Epoch 2/30
04 - val loss: 0.0361
```

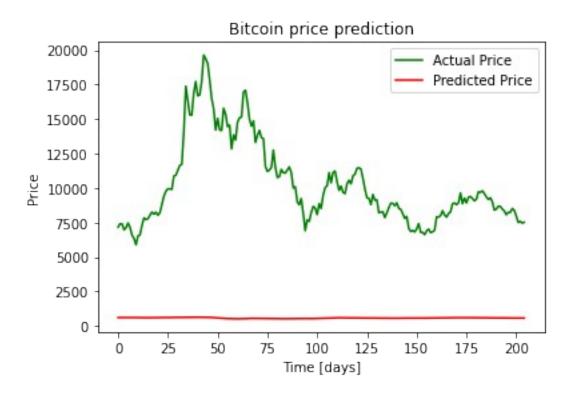
```
Epoch 3/30
04 - val loss: 0.0355
Epoch 4/30
04 - val loss: 0.0349
Epoch 5/\overline{30}
04 - val loss: 0.0343
Epoch 6/30
04 - val loss: 0.0337
Epoch 7/30
04 - val loss: 0.0332
Epoch 8/30
04 - val loss: 0.0327
Epoch 9/30
04 - val loss: 0.0322
Epoch 10/30
04 - val loss: 0.0317
Epoch 11/30
04 - val loss: 0.0313
Epoch 12/30
04 - val loss: 0.0309
Epoch 13/30
04 - val loss: 0.0305
Epoch 14/30
04 - val loss: 0.0302
Epoch 15/30
04 - val loss: 0.0299
Epoch 16/30
04 - val loss: 0.0296
Epoch 17/30
04 - val loss: 0.0294
Epoch 18/30
04 - val loss: 0.0291
Epoch 19/30
```

```
04 - val loss: 0.0290
Epoch 20/30
04 - val loss: 0.0288
Epoch 21/30
04 - val loss: 0.0287
Epoch 22/30
04 - val loss: 0.0285
Epoch 23/30
04 - val loss: 0.0284
Epoch 24/30
04 - val loss: 0.0283
Epoch 25/30
04 - val loss: 0.0283
Epoch 26/30
04 - val loss: 0.0282
Epoch 27/30
04 - val loss: 0.0282
Epoch 28/30
04 - val loss: 0.0281
Epoch 29/30
04 - val loss: 0.0281
Epoch 30/30
04 - val_loss: 0.0281
model evaluation(history LSTM 2 ada, model LSTM 2 ada, scaler, X test,
X train, y train, y test)
```



7/7 [======] - 1s 22ms/step 26/26 [==========] - 0s 15ms/step

Train Score: 0.0194 RMSE Test Score: 0.3360 RMSE



#### Continuidade

Observando o RMSE dos algoritmos testados, notamos que obtemos uma menor raiz quadrada média do erro com o otimizador ADAM na rede com 2 camadas. Dessa forma, seguiremos utilizando esse modelo para as próximas análises.

## Análise 4 (Taxa de Aprendizagem)

```
Taxa de Aprendizado: 0.001
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model_LSTM_2_adam.add(LSTM(time steps, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
  optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
  loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
  np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  y train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation_split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 3.0589e-04
Epoch 2/30
05 - val loss: 4.2482e-04
Epoch 3/30
05 - val loss: 0.0015
Epoch 4/30
05 - val loss: 4.4432e-04
Epoch 5/30
05 - val loss: 3.8975e-04
Epoch 6/30
05 - val loss: 4.2484e-04
Epoch 7/30
05 - val loss: 4.2534e-04
Epoch 8/30
```

```
05 - val loss: 2.9327e-04
Epoch 9/30
05 - val loss: 6.8013e-04
Epoch 10/30
05 - val loss: 6.1389e-04
Epoch 11/30
05 - val loss: 0.0017
Epoch 12/30
05 - val loss: 2.4704e-04
Epoch 13/30
05 - val loss: 2.9859e-04
Epoch 14/30
05 - val loss: 0.0010
Epoch 15/30
05 - val loss: 2.6419e-04
Epoch 16/30
05 - val loss: 2.8456e-04
Epoch 17/30
05 - val loss: 2.8540e-04
Epoch 18/30
05 - val_loss: 3.4035e-04
Epoch 19/30
05 - val loss: 3.1666e-04
Epoch 20/30
05 - val loss: 4.4616e-04
Epoch 21/30
05 - val loss: 3.1974e-04
Epoch 22/30
05 - val loss: 3.4482e-04
Epoch 23/30
05 - val loss: 2.9991e-04
Epoch 24/30
05 - val loss: 2.8306e-04
```

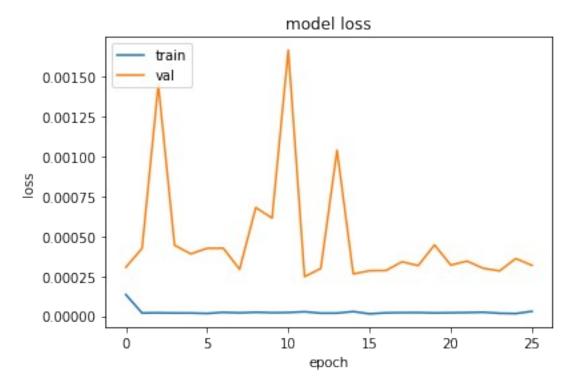
Epoch 25/30

05 - val\_loss: 3.6062e-04

Epoch 26/30

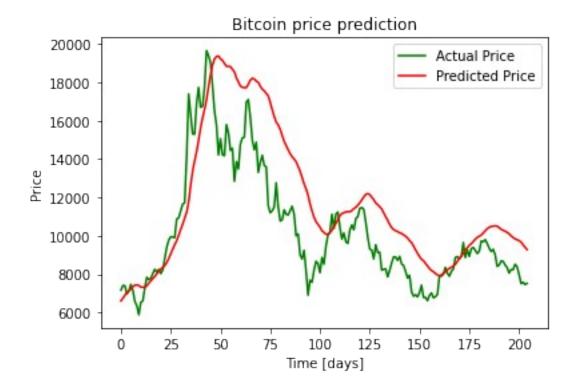
05 - val\_loss: 3.1808e-04 Epoch 26: early stopping

model\_evaluation(history\_LSTM\_2\_adam, model\_LSTM\_2\_adam, scaler,
X\_test, X\_train, y\_train, y\_test)



7/7 [======] - 1s 22ms/step 26/26 [==========] - 0s 13ms/step

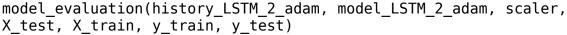
Train Score: 0.0020 RMSE Test Score: 0.0288 RMSE

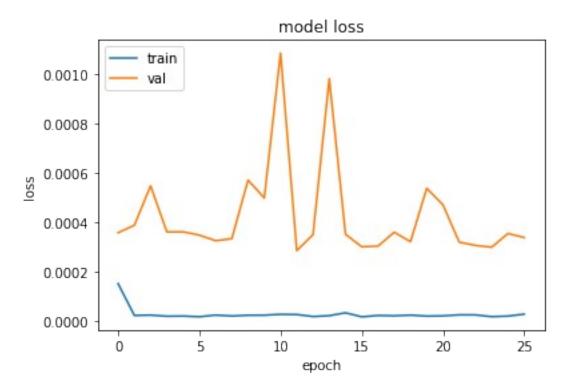


```
Taxa de Aprendizado: 0.00075
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model_LSTM_2_adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
   optimizer=tf.keras.optimizers.Adam(learning rate =
LEARNING RATE*0.75),
   loss="mse"
history LSTM 2 adam = model LSTM 2 adam.fit(
   np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
   y train,
   batch size=BATCH SIZE,
   epochs=EPOCHS,
   verbose=VERBOSE,
   validation_split=0.2,
   callbacks=[callback]
)
Epoch 1/30
04 - val loss: 3.5713e-04
Epoch 2/30
05 - val loss: 3.8746e-04
```

```
Epoch 3/30
05 - val loss: 5.4779e-04
Epoch 4/30
05 - val loss: 3.6059e-04
Epoch 5/\overline{30}
05 - val loss: 3.6084e-04
Epoch 6/30
05 - val loss: 3.4729e-04
Epoch 7/30
05 - val loss: 3.2476e-04
Epoch 8/\overline{30}
41/41 [============= ] - 1s 27ms/step - loss: 1.8500e-
05 - val loss: 3.3271e-04
Epoch 9/30
05 - val loss: 5.7123e-04
Epoch 10/30
05 - val loss: 4.9826e-04
Epoch 11/30
05 - val loss: 0.0011
Epoch 12/30
05 - val loss: 2.8431e-04
Epoch 13/30
05 - val loss: 3.4924e-04
Epoch 14/30
05 - val loss: 9.8400e-04
Epoch 15/30
05 - val loss: 3.5081e-04
Epoch 16/30
05 - val loss: 2.9984e-04
Epoch 17/30
05 - val loss: 3.0263e-04
Epoch 18/30
05 - val loss: 3.5909e-04
Epoch 19/30
```

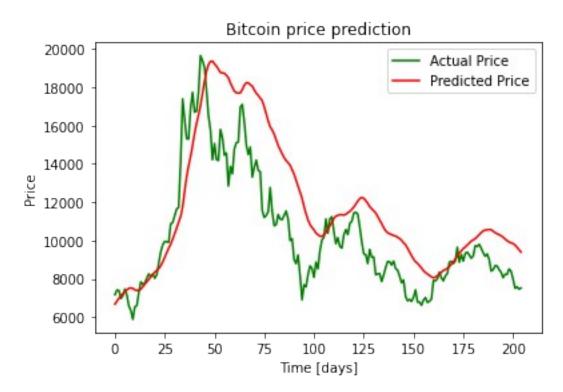
```
05 - val loss: 3.2058e-04
Epoch 20/30
05 - val loss: 5.3790e-04
Epoch 21/30
41/41 [============== ] - 1s 27ms/step - loss: 1.8930e-
05 - val loss: 4.7059e-04
Epoch 22/30
05 - val loss: 3.1894e-04
Epoch 23/30
05 - val loss: 3.0547e-04
Epoch 24/30
05 - val loss: 2.9807e-04
Epoch 25/30
05 - val loss: 3.5397e-04
Epoch 26/30
05 - val loss: 3.3739e-04
Epoch 26: early stopping
```





```
7/7 [======] - 1s 22ms/step 26/26 [==========] - 0s 17ms/step
```

Train Score: 0.0000 RMSE Test Score: 0.0250 RMSE

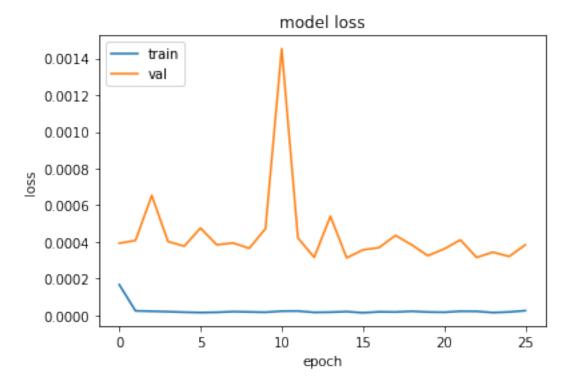


### Taxa de Aprendizado: 0.0005

```
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
    optimizer=tf.keras.optimizers.Adam(learning rate =
LEARNING RATE*0.5),
    loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
    np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
    y train,
    batch size=BATCH SIZE,
    epochs=EPOCHS,
    verbose=VERBOSE,
    validation split=0.2,
    callbacks=[callback]
)
```

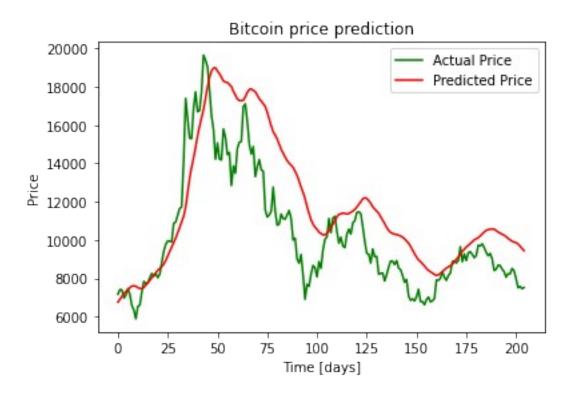
```
Epoch 1/30
04 - val loss: 3.9274e-04
Epoch 2/30
05 - val loss: 4.0824e-04
Epoch 3/30
05 - val loss: 6.5347e-04
Epoch 4/30
05 - val loss: 4.0204e-04
Epoch 5/30
05 - val loss: 3.7695e-04
Epoch 6/\overline{3}0
05 - val loss: 4.7567e-04
Epoch 7/30
05 - val loss: 3.8450e-04
Epoch 8/\overline{30}
05 - val loss: 3.9446e-04
Epoch 9/\overline{30}
05 - val loss: 3.6522e-04
Epoch 10/30
05 - val loss: 4.7226e-04
Epoch 11/30
05 - val loss: 0.0015
Epoch 12/30
05 - val loss: 4.2170e-04
Epoch 13/30
05 - val loss: 3.1590e-04
Epoch 14\overline{/}30
05 - val loss: 5.3998e-04
Epoch 15/30
05 - val loss: 3.1319e-04
Epoch 16/30
05 - val loss: 3.5675e-04
Epoch 17/30
```

```
05 - val loss: 3.6916e-04
Epoch 18/30
05 - val loss: 4.3563e-04
Epoch 19/30
05 - val loss: 3.8457e-04
Epoch 20/30
05 - val loss: 3.2488e-04
Epoch 21/30
05 - val loss: 3.6197e-04
Epoch 22/30
05 - val loss: 4.1112e-04
Epoch 23/30
05 - val loss: 3.1544e-04
Epoch 24/30
05 - val loss: 3.4416e-04
Epoch 25/30
05 - val loss: 3.2091e-04
Epoch 26/30
05 - val loss: 3.8403e-04
Epoch 26: early stopping
model evaluation(history LSTM 2 adam, model LSTM 2 adam, scaler,
X_test, X_train, y_train, y_test)
```



7/7 [======] - 1s 11ms/step 26/26 [==========] - 0s 12ms/step

Train Score: 0.0006 RMSE Test Score: 0.0213 RMSE

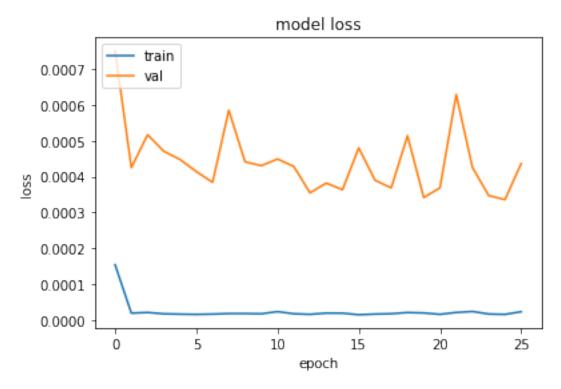


```
Taxa de Aprendizado: 0.00025
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
  optimizer=tf.keras.optimizers.Adam(learning rate =
LEARNING RATE*0.25),
  loss="mse"
history LSTM 2 adam = model LSTM 2 adam.fit(
  np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  y train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 7.5242e-04
Epoch 2/30
05 - val loss: 4.2541e-04
Epoch 3/30
05 - val loss: 5.1731e-04
Epoch 4/30
05 - val loss: 4.7111e-04
Epoch 5/30
05 - val loss: 4.4811e-04
Epoch 6/30
05 - val loss: 4.1440e-04
Epoch 7/30
05 - val loss: 3.8434e-04
Epoch 8/30
05 - val loss: 5.8582e-04
Epoch 9/30
05 - val loss: 4.4171e-04
Epoch 10/30
```

```
05 - val loss: 4.3090e-04
Epoch 11/30
05 - val loss: 4.4951e-04
Epoch 12/30
05 - val loss: 4.2875e-04
Epoch 13/30
05 - val loss: 3.5498e-04
Epoch 14/30
05 - val loss: 3.8231e-04
Epoch 15/30
05 - val_loss: 3.6365e-04
Epoch 16/30
05 - val loss: 4.8070e-04
Epoch 17/30
05 - val loss: 3.9011e-04
Epoch 18/30
05 - val loss: 3.6883e-04
Epoch 19/30
05 - val loss: 5.1471e-04
Epoch 20/30
05 - val loss: 3.4175e-04
Epoch 21/30
05 - val loss: 3.6903e-04
Epoch 22/30
05 - val loss: 6.2971e-04
Epoch 23/30
05 - val loss: 4.2591e-04
Epoch 24/30
05 - val loss: 3.4743e-04
Epoch 25/30
05 - val loss: 3.3586e-04
Epoch 26/30
```

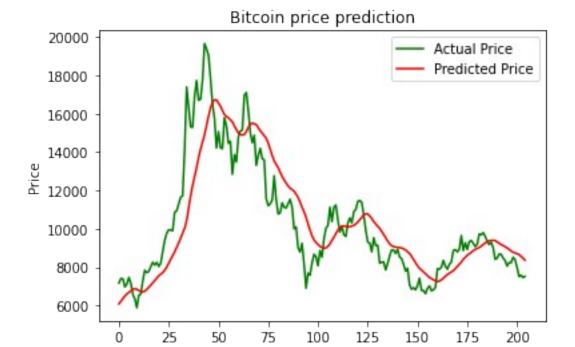
05 - val\_loss: 4.3654e-04 Epoch 26: early stopping

model\_evaluation(history\_LSTM\_2\_adam, model\_LSTM\_2\_adam, scaler, X\_test, X\_train, y\_train, y\_test)



7/7 [======] - 1s 11ms/step 26/26 [==========] - 0s 11ms/step

Train Score: 0.0009 RMSE Test Score: 0.0554 RMSE

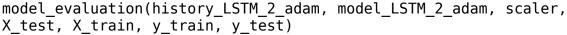


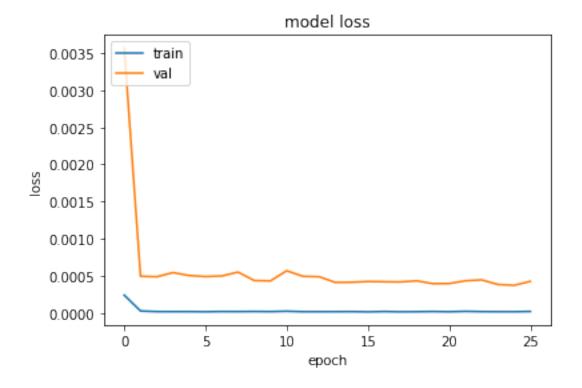
```
Taxa de Aprendizado: 0.0001
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model_LSTM_2_adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
   optimizer=tf.keras.optimizers.Adam(learning rate =
LEARNING RATE*0.1),
   loss="mse"
history LSTM 2 adam = model LSTM 2 adam.fit(
   np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
   y train,
   batch_size=BATCH SIZE,
   epochs=EPOCHS,
   verbose=VERBOSE,
   validation_split=0.2,
   callbacks=[callback]
)
Epoch 1/30
04 - val loss: 0.0036
Epoch 2/\overline{3}0
05 - val loss: 4.9329e-04
```

Time [days]

```
Epoch 3/30
05 - val loss: 4.8666e-04
Epoch 4/30
05 - val loss: 5.4236e-04
Epoch 5/\overline{30}
05 - val loss: 5.0289e-04
Epoch 6/30
05 - val loss: 4.8874e-04
Epoch 7/30
05 - val loss: 4.9652e-04
Epoch 8/30
05 - val loss: 5.4923e-04
Epoch 9/30
05 - val loss: 4.3539e-04
Epoch 10/30
05 - val loss: 4.3033e-04
Epoch 11/30
05 - val loss: 5.6763e-04
Epoch 12/30
05 - val loss: 4.9198e-04
Epoch 13/30
05 - val loss: 4.8680e-04
Epoch 14/30
05 - val loss: 4.0939e-04
Epoch 15/30
05 - val loss: 4.1223e-04
Epoch 16/30
05 - val loss: 4.2223e-04
Epoch 17/30
05 - val loss: 4.1895e-04
Epoch 18/30
05 - val loss: 4.1634e-04
Epoch 19/30
```

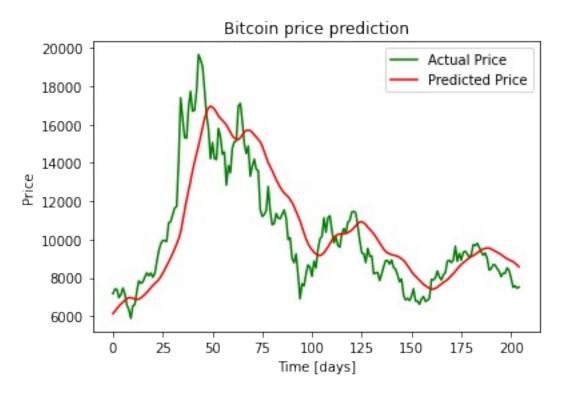
```
05 - val loss: 4.3131e-04
Epoch 20/30
05 - val loss: 3.9327e-04
Epoch 21/30
05 - val loss: 3.9440e-04
Epoch 22/30
05 - val loss: 4.3190e-04
Epoch 23/30
05 - val_loss: 4.4411e-04
Epoch 24/30
05 - val loss: 3.8204e-04
Epoch 25/30
05 - val loss: 3.7097e-04
Epoch 26/30
05 - val loss: 4.2459e-04
Epoch 26: early stopping
```





```
7/7 [======] - 1s 21ms/step 26/26 [==========] - 0s 13ms/step
```

Train Score: 0.0016 RMSE Test Score: 0.0528 RMSE



### Continuidade

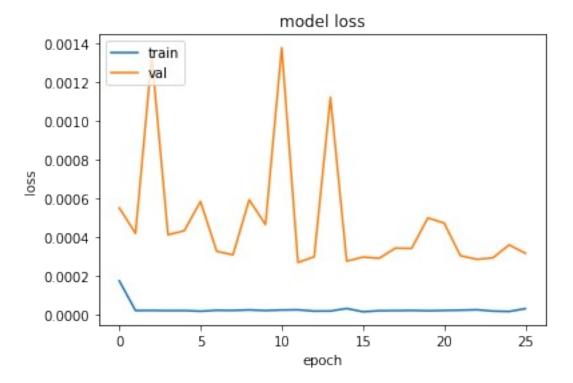
Observando o RMSE de teste e treinamento, para evitar overfitting, utilizaremos o learning rate 0,001 nas próximas análises.

## **Análise 5 (Dropout)**

```
Dropout: 0.1
model_LSTM_2_adam = tf.keras.Sequential()
model_LSTM_2_adam.add(LSTM(time_steps, input_shape=(time_steps,
X_train.shape[-1]), dropout=DROPOUT, return_sequences=True))
model_LSTM_2_adam.add(LSTM(time_steps, dropout=DROPOUT))
model_LSTM_2_adam.add(Dense(1, activation='linear'))
model_LSTM_2_adam.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate = LEARNING_RATE),
    loss="mse"
)
history_LSTM_2_adam = model_LSTM_2_adam.fit(
    np.array(X_train).reshape(X_train.shape[0], X_train.shape[1], 1),
    y_train,
    batch_size=BATCH_SIZE,
    epochs=EPOCHS,
```

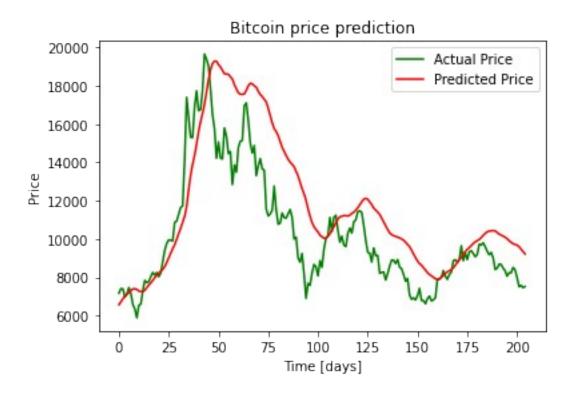
```
verbose=VERBOSE,
 validation split=0.2,
 callbacks=[callback]
)
Epoch 1/30
04 - val loss: 5.4991e-04
Epoch 2/30
05 - val loss: 4.1826e-04
Epoch 3/30
05 - val loss: 0.0013
Epoch 4/30
05 - val loss: 4.1109e-04
Epoch 5/30
05 - val loss: 4.3191e-04
Epoch 6/30
05 - val loss: 5.8285e-04
Epoch 7/30
05 - val loss: 3.2571e-04
Epoch 8/30
05 - val loss: 3.0797e-04
Epoch 9/30
05 - val loss: 5.9160e-04
Epoch 10/30
05 - val loss: 4.6348e-04
Epoch 11/30
05 - val loss: 0.0014
Epoch 12/30
05 - val_loss: 2.6856e-04
Epoch 13\overline{/}30
05 - val loss: 2.9772e-04
Epoch 14\overline{/}30
05 - val loss: 0.0011
Epoch 15/30
05 - val loss: 2.7517e-04
```

```
Epoch 16/30
05 - val loss: 2.9626e-04
Epoch 17/30
05 - val loss: 2.8978e-04
Epoch 18/30
05 - val loss: 3.4249e-04
Epoch 19/30
05 - val loss: 3.4110e-04
Epoch 20/30
05 - val loss: 4.9816e-04
Epoch 21/30
05 - val loss: 4.7152e-04
Epoch 22/30
05 - val loss: 3.0345e-04
Epoch 23/30
05 - val loss: 2.8516e-04
Epoch 24/30
05 - val loss: 2.9209e-04
Epoch 25/30
05 - val loss: 3.5908e-04
Epoch 26/30
05 - val loss: 3.1582e-04
Epoch 26: early stopping
model evaluation(history LSTM 2 adam, model LSTM 2 adam, scaler,
X test, X train, y train, y test)
```



7/7 [======] - 1s 11ms/step 26/26 [==========] - 0s 12ms/step

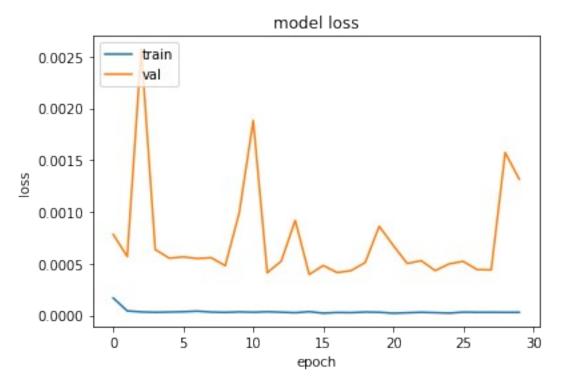
Train Score: 0.0017 RMSE Test Score: 0.0307 RMSE



```
Dropout: 0.2
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT*2, return sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
  optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
  loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
  np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  v train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 7.8196e-04
Epoch 2/30
05 - val loss: 5.6842e-04
Epoch 3/30
05 - val loss: 0.0026
Epoch 4/30
05 - val loss: 6.3638e-04
Epoch 5/30
05 - val loss: 5.5301e-04
Epoch 6/30
05 - val loss: 5.6519e-04
Epoch 7/30
05 - val loss: 5.4933e-04
Epoch 8/30
05 - val loss: 5.5771e-04
Epoch 9/30
05 - val loss: 4.8019e-04
Epoch 10/30
```

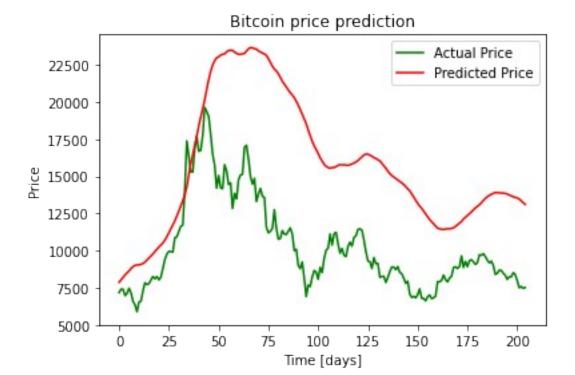
```
05 - val loss: 9.9092e-04
Epoch 11/30
05 - val loss: 0.0019
Epoch 12/30
05 - val loss: 4.1203e-04
Epoch 13/30
05 - val loss: 5.2391e-04
Epoch 14/30
05 - val loss: 9.1849e-04
Epoch 15/30
05 - val loss: 3.9490e-04
Epoch 16/30
05 - val loss: 4.8221e-04
Epoch 17\overline{/}30
05 - val_loss: 4.1341e-04
Epoch 18/30
05 - val loss: 4.3326e-04
Epoch 19/30
05 - val loss: 5.1104e-04
Epoch 20/30
05 - val loss: 8.6104e-04
Epoch 21/30
05 - val loss: 6.7644e-04
Epoch 2\overline{2/30}
05 - val loss: 5.0173e-04
Epoch 23/30
05 - val loss: 5.2880e-04
Epoch 24/30
05 - val loss: 4.3255e-04
Epoch 25/30
05 - val loss: 4.9777e-04
Epoch 26/30
05 - val loss: 5.2200e-04
Epoch 27/30
```

model\_evaluation(history\_LSTM\_2\_adam, model\_LSTM\_2\_adam, scaler,
X\_test, X\_train, y\_train, y\_test)



7/7 [======] - 1s 21ms/step 26/26 [===========] - 0s 16ms/step

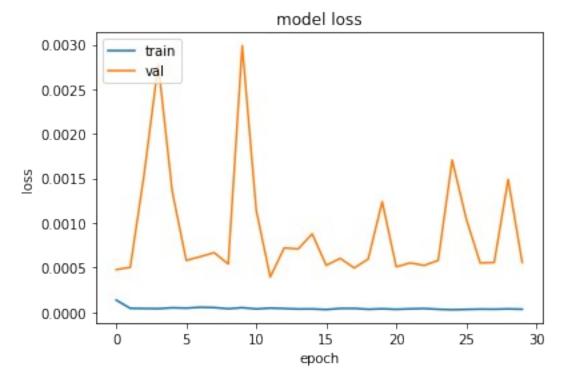
Train Score: 0.0006 RMSE Test Score: 0.0356 RMSE



```
Dropout: 0.3
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time_steps, input_shape=(time_steps,
X_train.shape[-1]), dropout=DROPOUT*3, return_sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model_LSTM_2_adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
   optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
   loss="mse"
)
history_LSTM_2_adam = model_LSTM 2 adam.fit(
   np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
   y train,
   batch size=BATCH SIZE,
   epochs=EPOCHS,
   verbose=VERBOSE,
   validation split=0.2,
   callbacks=[callback]
)
Epoch 1/30
41/41 [=========
                       ========] - 7s 52ms/step - loss: 1.3537e-
04 - val loss: 4.7734e-04
Epoch 2/30
41/41 [======
                      05 - val loss: 5.0296e-04
Epoch 3/30
```

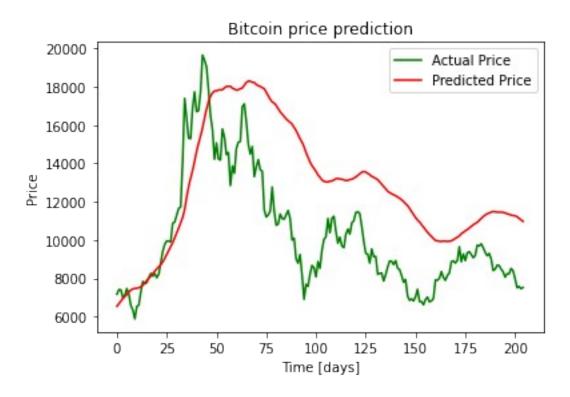
```
05 - val loss: 0.0016
Epoch 4/30
05 - val loss: 0.0028
Epoch 5/30
05 - val loss: 0.0014
Epoch 6/30
05 - val loss: 5.8002e-04
Epoch 7/30
05 - val loss: 6.2242e-04
Epoch 8/30
05 - val_loss: 6.6707e-04
Epoch 9/30
05 - val loss: 5.3938e-04
Epoch 10/30
05 - val loss: 0.0030
Epoch 11/30
05 - val loss: 0.0011
Epoch 12/30
05 - val loss: 3.9398e-04
Epoch 13/30
05 - val loss: 7.2009e-04
Epoch 14/30
05 - val loss: 7.0901e-04
Epoch 15/30
05 - val loss: 8.7826e-04
Epoch 16/30
05 - val loss: 5.2492e-04
Epoch 17/30
05 - val loss: 6.0375e-04
Epoch 18/30
05 - val loss: 4.9568e-04
Epoch 19/30
05 - val loss: 5.9582e-04
```

```
Epoch 20/30
05 - val loss: 0.0012
Epoch 21/30
05 - val loss: 5.0864e-04
Epoch 2\overline{2/30}
05 - val loss: 5.5217e-04
Epoch 23/30
05 - val loss: 5.2463e-04
Epoch 24/30
05 - val loss: 5.8044e-04
Epoch 25/30
05 - val loss: 0.0017
Epoch 26/30
05 - val loss: 0.0010
Epoch 27/30
05 - val loss: 5.5184e-04
Epoch 28/30
05 - val loss: 5.5670e-04
Epoch 29/30
05 - val loss: 0.0015
Epoch 30/30
05 - val loss: 5.5759e-04
model evaluation(history LSTM 2 adam, model LSTM 2 adam, scaler,
X_test, X_train, y_train, y_test)
```



7/7 [======] - 1s 12ms/step 26/26 [==========] - 0s 11ms/step

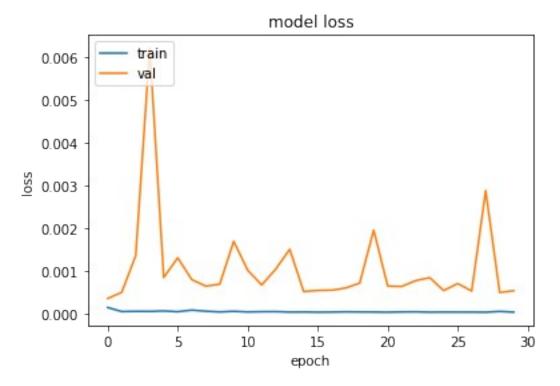
Train Score: 0.0026 RMSE Test Score: 0.0323 RMSE



```
Dropout: 0.4
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT*4, return_sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
  optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
  loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
  np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  v train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 3.5905e-04
Epoch 2/30
05 - val loss: 5.0390e-04
Epoch 3/30
05 - val loss: 0.0014
Epoch 4/30
05 - val loss: 0.0062
Epoch 5/30
05 - val loss: 8.5023e-04
Epoch 6/30
05 - val loss: 0.0013
Epoch 7/30
05 - val loss: 8.0257e-04
Epoch 8/30
05 - val loss: 6.4824e-04
Epoch 9/30
05 - val loss: 6.9258e-04
Epoch 10/30
```

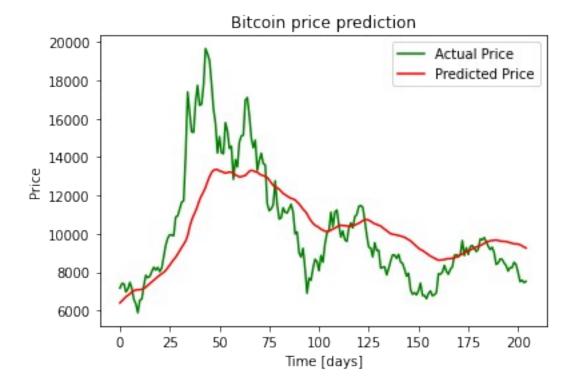
```
05 - val loss: 0.0017
Epoch 11/30
05 - val loss: 0.0010
Epoch 12/30
05 - val loss: 6.7642e-04
Epoch 13/30
05 - val loss: 0.0010
Epoch 14/30
05 - val loss: 0.0015
Epoch 15/30
05 - val loss: 5.2261e-04
Epoch 16/30
05 - val loss: 5.4781e-04
Epoch 17\overline{/}30
05 - val loss: 5.5306e-04
Epoch 18/30
05 - val loss: 6.0544e-04
Epoch 19/30
05 - val loss: 7.1920e-04
Epoch 20/30
05 - val loss: 0.0020
Epoch 21/30
05 - val loss: 6.5116e-04
Epoch 2\overline{2/30}
05 - val loss: 6.4176e-04
Epoch 23/30
05 - val loss: 7.7565e-04
Epoch 24/30
05 - val loss: 8.4709e-04
Epoch 25/30
05 - val loss: 5.4500e-04
Epoch 26/30
05 - val loss: 7.0908e-04
Epoch 27/30
```

model\_evaluation(history\_LSTM\_2\_adam, model\_LSTM\_2\_adam, scaler, X\_test, X\_train, y\_train, y\_test)



7/7 [======] - 1s 23ms/step 26/26 [==========] - 0s 17ms/step

Train Score: 0.0039 RMSE Test Score: 0.0393 RMSE



#### Continuidade

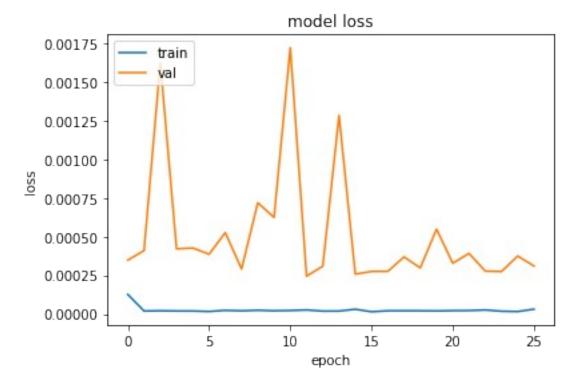
Considerando essas análises, utilizaremos o valor de dropout de 10%, já que observamos um baixo RMSE tanto para o treinamento (0,0017) quanto para os testes (0,0307).

# Análise 6 (Batch Size)

```
Batch Size: 16
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model_LSTM_2_adam.add(LSTM(time_steps, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
    optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
    loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
    np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
    y train,
    batch_size=BATCH_SIZE,
    epochs=EPOCHS,
    verbose=VERBOSE,
    validation_split=0.2,
    callbacks=[callback]
)
```

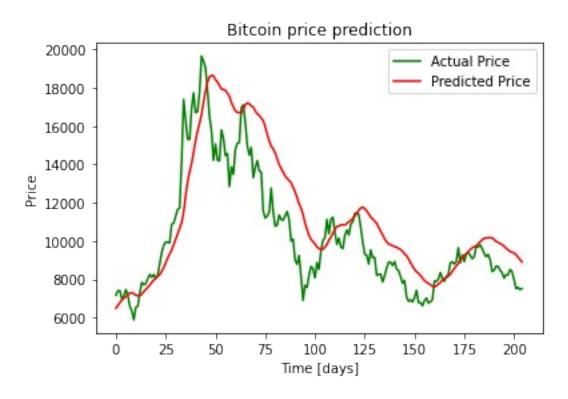
```
Epoch 1/30
04 - val loss: 3.4805e-04
Epoch 2/30
05 - val loss: 4.0972e-04
Epoch 3/30
05 - val loss: 0.0016
Epoch 4/30
05 - val loss: 4.2090e-04
Epoch 5/30
05 - val loss: 4.2650e-04
Epoch 6/30
05 - val loss: 3.8597e-04
Epoch 7/30
05 - val loss: 5.2547e-04
Epoch 8/\overline{30}
05 - val loss: 2.9087e-04
Epoch 9/\overline{30}
05 - val loss: 7.1788e-04
Epoch 10/30
05 - val loss: 6.2378e-04
Epoch 11/30
05 - val loss: 0.0017
Epoch 12/30
05 - val loss: 2.4449e-04
Epoch 13/30
05 - val loss: 3.0893e-04
Epoch 14\overline{/}30
05 - val loss: 0.0013
Epoch 15/30
05 - val loss: 2.5768e-04
Epoch 16/30
05 - val loss: 2.7517e-04
Epoch 17/30
```

```
05 - val loss: 2.7561e-04
Epoch 18/30
05 - val loss: 3.6872e-04
Epoch 19/30
05 - val loss: 2.9799e-04
Epoch 20/30
05 - val loss: 5.4800e-04
Epoch 21/30
05 - val loss: 3.2782e-04
Epoch 22/30
05 - val loss: 3.9117e-04
Epoch 23/30
05 - val loss: 2.7717e-04
Epoch 24\overline{/}30
05 - val loss: 2.7442e-04
Epoch 25/30
05 - val loss: 3.7463e-04
Epoch 26/30
05 - val loss: 3.0966e-04
Epoch 26: early stopping
model evaluation(history LSTM 2 adam, model LSTM 2 adam, scaler,
X_test, X_train, y_train, y_test)
```



7/7 [======] - 1s 12ms/step 26/26 [==========] - 0s 12ms/step

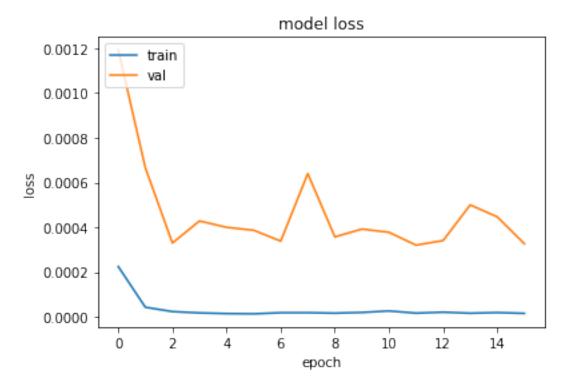
Train Score: 0.0024 RMSE Test Score: 0.0346 RMSE



```
Batch Size: 32
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
  optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
  loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
  np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  v train,
  batch size=BATCH SIZE*2,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 0.0012
Epoch 2/30
21/21 [============= ] - 1s 33ms/step - loss: 4.2957e-
05 - val loss: 6.6606e-04
Epoch 3/30
05 - val loss: 3.2983e-04
Epoch 4/30
21/21 [============= ] - 1s 33ms/step - loss: 1.7639e-
05 - val loss: 4.2857e-04
Epoch 5/30
21/21 [============= ] - 1s 33ms/step - loss: 1.4691e-
05 - val loss: 3.9993e-04
Epoch 6/30
05 - val loss: 3.8705e-04
Epoch 7/30
21/21 [============= ] - 1s 33ms/step - loss: 1.8555e-
05 - val loss: 3.3839e-04
Epoch 8/30
05 - val loss: 6.4013e-04
Epoch 9/30
05 - val loss: 3.5731e-04
Epoch 10/30
```

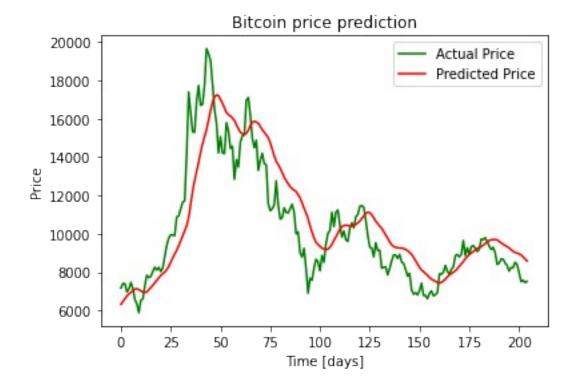
```
05 - val loss: 3.9232e-04
Epoch 11/30
21/21 [============= ] - 1s 34ms/step - loss: 2.6367e-
05 - val loss: 3.7770e-04
Epoch 12/30
21/21 [============= ] - 1s 33ms/step - loss: 1.6652e-
05 - val loss: 3.2035e-04
Epoch 13/30
05 - val loss: 3.4109e-04
Epoch 14/30
05 - val loss: 5.0020e-04
Epoch 15/30
05 - val loss: 4.4674e-04
Epoch 16/30
21/21 [============= ] - 1s 37ms/step - loss: 1.5684e-
05 - val loss: 3.2661e-04
Epoch 16: early stopping
```

model\_evaluation(history\_LSTM\_2\_adam, model\_LSTM\_2\_adam, scaler,
X\_test, X\_train, y\_train, y\_test)



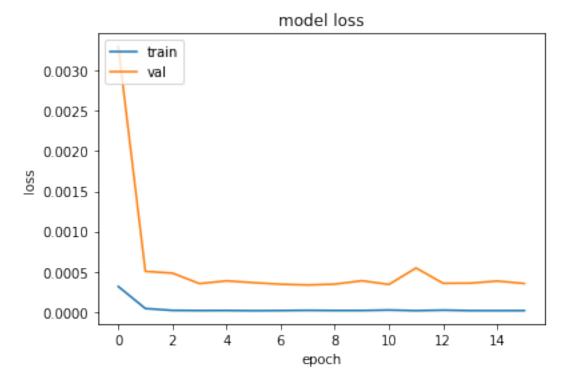
7/7 [=======] - 1s 21ms/step 26/26 [==========] - 0s 14ms/step

Train Score: 0.0010 RMSE Test Score: 0.0434 RMSE



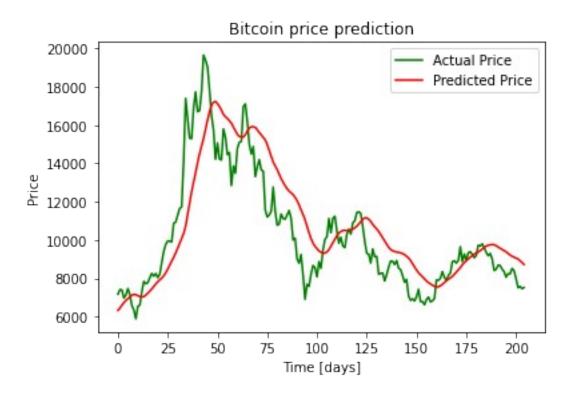
```
Batch Size: 64
model_LSTM_2_adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model_LSTM_2_adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
   optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
   loss="mse"
)
history_LSTM_2_adam = model_LSTM 2 adam.fit(
   np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
   y train,
   batch size=BATCH SIZE*4,
   epochs=EPOCHS,
   verbose=VERBOSE,
   validation split=0.2,
   callbacks=[callback]
)
Epoch 1/30
3.1587e-04 - val loss: 0.0033
Epoch 2/30
05 - val loss: 5.0383e-04
Epoch 3/30
```

```
05 - val loss: 4.8198e-04
Epoch 4/30
05 - val loss: 3.5166e-04
Epoch 5/30
05 - val loss: 3.8538e-04
Epoch 6/30
05 - val loss: 3.6315e-04
Epoch 7/30
05 - val loss: 3.4364e-04
Epoch 8/30
05 - val loss: 3.3428e-04
Epoch 9/30
05 - val loss: 3.4504e-04
Epoch 10/30
05 - val loss: 3.8694e-04
Epoch 11/30
05 - val loss: 3.4150e-04
Epoch 12/30
05 - val loss: 5.4607e-04
Epoch 13/30
05 - val loss: 3.5549e-04
Epoch 14/30
05 - val loss: 3.5685e-04
Epoch 15/30
05 - val loss: 3.8336e-04
Epoch 16/30
05 - val loss: 3.5278e-04
Epoch 16: early stopping
model_evaluation(history_LSTM_2_adam, model_LSTM_2_adam, scaler,
X test, X train, y train, y test)
```



7/7 [======] - 1s 11ms/step 26/26 [==========] - 0s 11ms/step

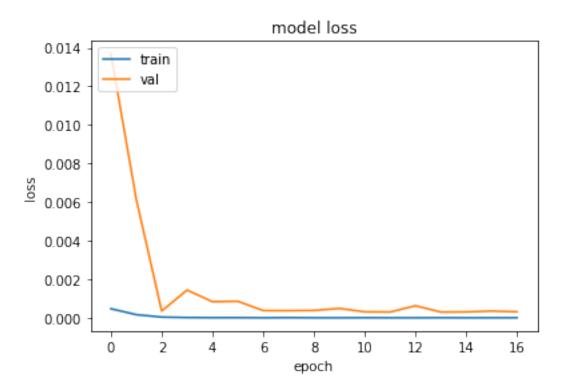
Train Score: 0.0022 RMSE Test Score: 0.0434 RMSE



```
Batch Size: 128
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(time steps, input shape=(time steps,
X train.shape[-1]), dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(time steps, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
   optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
   loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
   np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
   v train,
   batch size=BATCH SIZE*8,
   epochs=EPOCHS,
   verbose=VERBOSE,
   validation split=0.2,
   callbacks=[callback]
)
Epoch 1/30
04 - val loss: 0.0137
Epoch 2/30
6/6 [============ ] - Os 77ms/step - loss: 1.8026e-04
- val loss: 0.0061
Epoch 3/30
6/6 [============ ] - Os 75ms/step - loss: 5.5321e-05
- val loss: 3.6662e-04
Epoch 4/30
6/6 [============ ] - Os 72ms/step - loss: 3.1434e-05
- val loss: 0.0015
Epoch 5/30
- val loss: 8.5220e-04
Epoch 6/30
6/6 [============== ] - 0s 76ms/step - loss: 2.5095e-05
- val loss: 8.7103e-04
Epoch 7/30
6/6 [=============== ] - 0s 77ms/step - loss: 1.6094e-05
- val loss: 3.9221e-04
Epoch 8/30
6/6 [============== ] - 0s 73ms/step - loss: 2.5482e-05
- val loss: 3.8857e-04
Epoch 9/30
6/6 [============ ] - Os 73ms/step - loss: 1.7047e-05
- val loss: 3.9910e-04
Epoch 10/30
6/6 [============== ] - 0s 73ms/step - loss: 1.6220e-05
```

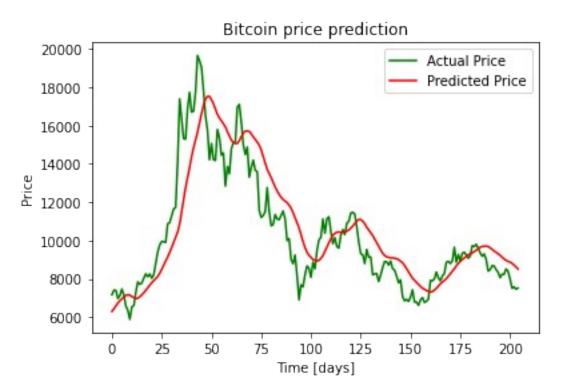
```
- val loss: 5.0256e-04
Epoch 11/30
6/6 [=============== ] - 0s 72ms/step - loss: 2.0959e-05
- val loss: 3.2712e-04
Epoch 12/30
6/6 [============ ] - 0s 72ms/step - loss: 1.6846e-05
- val loss: 3.1626e-04
Epoch 13/30
6/6 [============= ] - 0s 77ms/step - loss: 1.6276e-05
- val loss: 6.4190e-04
Epoch 14/30
6/6 [============ ] - Os 73ms/step - loss: 2.0155e-05
- val_loss: 3.1491e-04
Epoch 15/30
6/6 [============= ] - Os 77ms/step - loss: 1.6670e-05
- val loss: 3.2195e-04
Epoch 16/30
6/6 [=============== ] - 0s 77ms/step - loss: 1.7525e-05
- val loss: 3.6745e-04
Epoch 17/30
6/6 [============== ] - 0s 76ms/step - loss: 1.9048e-05
- val loss: 3.2933e-04
Epoch 17: early stopping
```

model\_evaluation(history\_LSTM\_2\_adam, model\_LSTM\_2\_adam, scaler,
X\_test, X\_train, y\_train, y\_test)



```
7/7 [======] - 1s 11ms/step 26/26 [===========] - 0s 11ms/step
```

Train Score: 0.0002 RMSE Test Score: 0.0445 RMSE



### Continuidade

Observando os resultados encontrados, o batch size de tamanho 16 já é suficiente.

### Análise 7 (Tamanho da Janela)

Nesta análise, testamos diferentes tamanhos de janela variando a quantidade de dias anteriores a serem utilizados na previsão. Para isso, utilizamos os parâmetros que consideramos melhores nas análises anteriores.

```
Tamanho da Janela: 50
X_train, y_train, X_test, y_test = split_data(scaled_df, 0.2, time_steps=50)

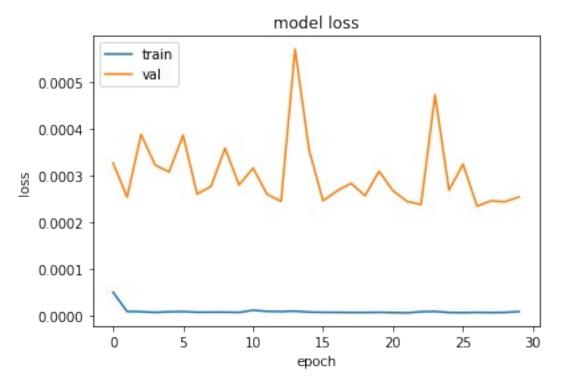
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)

y_train = y_train.reshape(-1, 1)
y_test = y_test.reshape(-1, 1)
model_LSTM_2_adam = tf.keras.Sequential()
model_LSTM_2_adam.add(LSTM(50, input_shape=(50, X_train.shape[-1]), dropout=DROPOUT, return sequences=True))
```

```
model LSTM 2 adam.add(LSTM(50, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model_LSTM_2_adam.compile(
  optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
  loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
  np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
  y train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
05 - val loss: 3.2727e-04
Epoch 2/30
06 - val loss: 2.5429e-04
Epoch 3/30
06 - val loss: 3.8843e-04
Epoch 4/30
06 - val loss: 3.2334e-04
Epoch 5/30
06 - val loss: 3.0813e-04
Epoch 6/30
06 - val loss: 3.8691e-04
Epoch 7/30
06 - val loss: 2.6102e-04
Epoch 8/30
06 - val loss: 2.7734e-04
Epoch 9/30
06 - val loss: 3.5902e-04
Epoch 10/30
06 - val loss: 2.8039e-04
Epoch 11/30
05 - val loss: 3.1660e-04
Epoch 12/30
```

```
06 - val loss: 2.6059e-04
Epoch 13/30
06 - val loss: 2.4530e-04
Epoch 14/30
05 - val loss: 5.7157e-04
Epoch 15/30
06 - val loss: 3.5534e-04
Epoch 16/30
06 - val loss: 2.4652e-04
Epoch 17/30
06 - val_loss: 2.6769e-04
Epoch 18/30
06 - val loss: 2.8396e-04
Epoch 19/30
06 - val loss: 2.5742e-04
Epoch 20/30
06 - val loss: 3.0973e-04
Epoch 21/30
06 - val loss: 2.6800e-04
Epoch 22/30
49/49 [============== ] - 1s 14ms/step - loss: 6.5679e-
06 - val_loss: 2.4513e-04
Epoch 23/30
49/49 [============= ] - 1s 14ms/step - loss: 8.9149e-
06 - val loss: 2.3838e-04
Epoch 24/30
49/49 [============= ] - 1s 12ms/step - loss: 9.5267e-
06 - val loss: 4.7318e-04
Epoch 25/30
06 - val loss: 2.6925e-04
Epoch 26/30
06 - val loss: 3.2495e-04
Epoch 27/30
06 - val loss: 2.3504e-04
Epoch 28/30
06 - val loss: 2.4650e-04
```

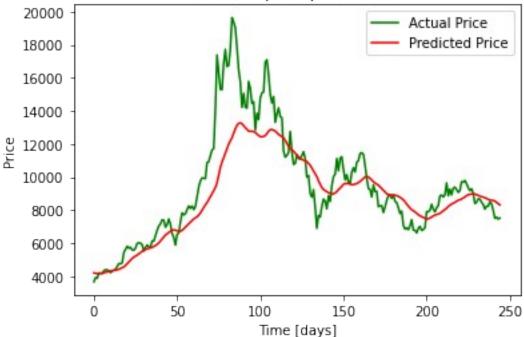
model\_evaluation(history\_LSTM\_2\_adam, model\_LSTM\_2\_adam, scaler,
X\_test, X\_train, y\_train, y\_test)



8/8 [=======] - 1s 4ms/step 31/31 [===========] - 0s 4ms/step

Train Score: 0.0015 RMSE Test Score: 0.0273 RMSE



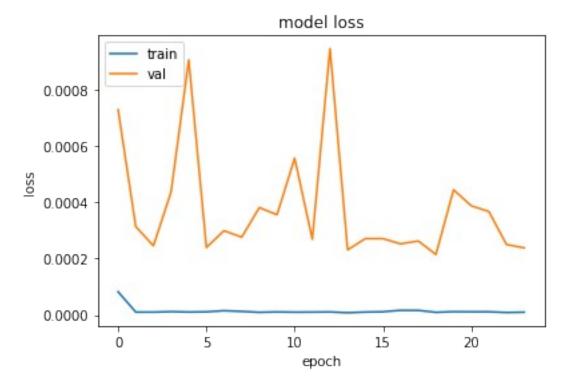


## Tamanho da Janela: 100

```
X train, y train, X test, y test = split data(scaled df, 0.2,
time steps=100)
X train = X train.reshape(X train.shape[0], X train.shape[1], 1)
X test = X test.reshape(X test.shape[0], X test.shape[1], 1)
y train = y train.reshape(-1, 1)
y test = y test.reshape(-1, 1)
model_LSTM_2_adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(100, input shape=(100, X train.shape[-1]),
dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(100, dropout=DR0POUT))
model_LSTM_2_adam.add(Dense(1, activation='linear'))
model_LSTM_2_adam.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate = LEARNING_RATE),
    loss="mse"
)
history_LSTM_2_adam = model_LSTM_2_adam.fit(
    np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
    y train,
    batch size=BATCH SIZE,
    epochs=EPOCHS,
    verbose=VERBOSE,
    validation split=0.2,
```

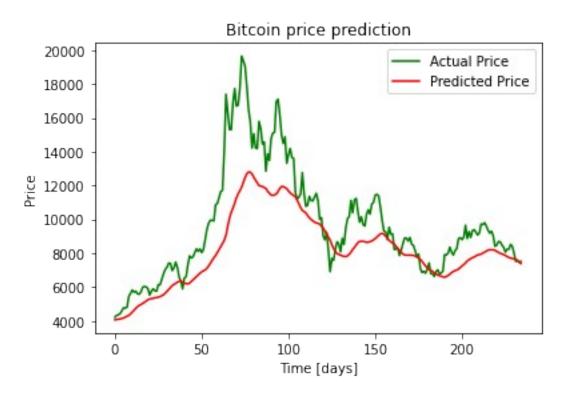
```
callbacks=[callback]
)
Epoch 1/30
05 - val loss: 7.2754e-04
Epoch 2/30
05 - val loss: 3.1344e-04
Epoch 3/30
05 - val loss: 2.4524e-04
Epoch 4/\overline{30}
05 - val loss: 4.3634e-04
Epoch 5/30
47/47 [============= ] - 1s 11ms/step - loss: 1.0670e-
05 - val loss: 9.0417e-04
Epoch 6/30
05 - val loss: 2.3943e-04
Epoch 7/30
05 - val loss: 2.9884e-04
Epoch 8/30
05 - val loss: 2.7590e-04
Epoch 9/30
06 - val loss: 3.8085e-04
Epoch 10/30
05 - val loss: 3.5520e-04
Epoch 11/30
05 - val loss: 5.5597e-04
Epoch 12/30
05 - val loss: 2.6855e-04
Epoch 13/30
05 - val loss: 9.4435e-04
Epoch 14/30
06 - val loss: 2.3073e-04
Epoch 15/30
05 - val loss: 2.7096e-04
Epoch 16/30
```

```
05 - val loss: 2.7085e-04
Epoch 17/30
05 - val loss: 2.5214e-04
Epoch 18/30
05 - val loss: 2.6241e-04
Epoch 19/30
06 - val loss: 2.1460e-04
Epoch 20/30
05 - val loss: 4.4380e-04
Epoch 21/30
05 - val loss: 3.8731e-04
Epoch 22/30
05 - val loss: 3.6676e-04
Epoch 23/30
06 - val loss: 2.4971e-04
Epoch 24/30
05 - val loss: 2.3808e-04
Epoch 24: early stopping
model_evaluation(history_LSTM_2_adam, model_LSTM_2_adam, scaler,
X_test, X_train, y_train, y_test)
```



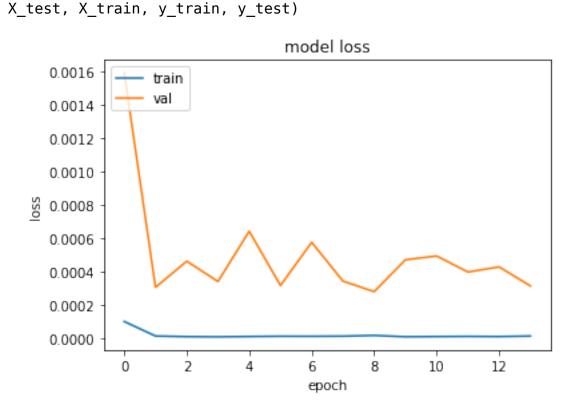
8/8 [=======] - 1s 7ms/step 30/30 [==========] - 0s 7ms/step

Train Score: 0.0004 RMSE Test Score: 0.0079 RMSE



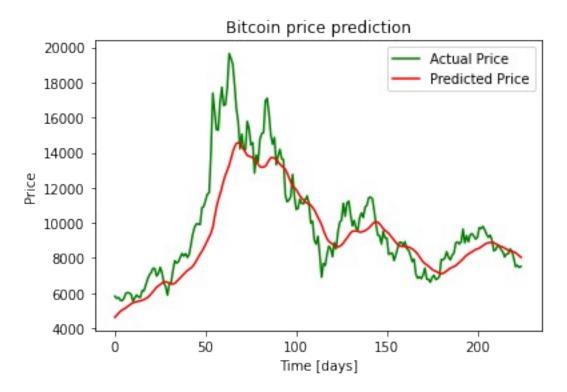
```
Tamanho da Janela: 150
X_train, y_train, X_test, y_test = split_data(scaled_df, 0.2,
time steps=150)
X train = X train.reshape(X train.shape[0], X train.shape[1], 1)
X test = X test.reshape(X test.shape[0], X test.shape[1], 1)
y_train = y_train.reshape(-1, 1)
y test = y test.reshape(-1, 1)
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(150, input shape=(150, X train.shape[-1]),
dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(150, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
   optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
   loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
   np.array(X_train).reshape(X_train.shape[0], X_train.shape[1], 1),
   y train,
   batch size=BATCH SIZE,
   epochs=EPOCHS,
   verbose=VERBOSE,
   validation split=0.2,
   callbacks=[callback]
)
Epoch 1/30
04 - val loss: 0.0016
Epoch 2/30
05 - val loss: 3.0612e-04
Epoch 3/30
45/45 [============= ] - 1s 18ms/step - loss: 1.0047e-
05 - val loss: 4.6295e-04
Epoch 4/30
06 - val loss: 3.4103e-04
Epoch 5/30
45/45 [============= ] - 1s 14ms/step - loss: 1.0873e-
05 - val loss: 6.4266e-04
Epoch 6/30
05 - val loss: 3.1723e-04
Epoch 7/30
```

```
05 - val loss: 5.7638e-04
Epoch 8/30
45/45 [============= ] - 1s 14ms/step - loss: 1.2966e-
05 - val loss: 3.4335e-04
Epoch 9/30
05 - val loss: 2.7999e-04
Epoch 10/30
06 - val loss: 4.7128e-04
Epoch 11/30
45/45 [============= ] - 1s 14ms/step - loss: 1.0549e-
05 - val_loss: 4.9423e-04
Epoch 12/30
05 - val loss: 3.9801e-04
Epoch 13/30
45/45 [============== ] - 1s 14ms/step - loss: 1.0513e-
05 - val loss: 4.2870e-04
Epoch 14\overline{/}30
05 - val loss: 3.1480e-04
Epoch 14: early stopping
model_evaluation(history_LSTM_2_adam, model_LSTM_2_adam, scaler,
```



```
8/8 [=======] - 1s 5ms/step 29/29 [==========] - 0s 5ms/step
```

Train Score: 0.0020 RMSE Test Score: 0.0614 RMSE

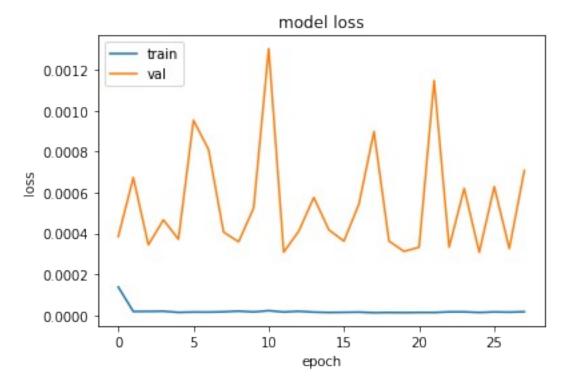


### Tamanho da Janela: 200

```
X train, y train, X test, y test = split data(scaled df, 0.2,
time steps=200)
X train = X train.reshape(X train.shape[0], X train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)
y_train = y_train.reshape(-1, 1)
y \text{ test} = y \text{ test.reshape}(-1, 1)
model LSTM 2 adam = tf.keras.Sequential()
model_LSTM_2_adam.add(LSTM(200, input_shape=(200, X_train.shape[-1]),
dropout=DROPOUT, return sequences=True))
model_LSTM_2_adam.add(LSTM(200, dropout=DR0P0UT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
    optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
    loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
    np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
    y_train,
```

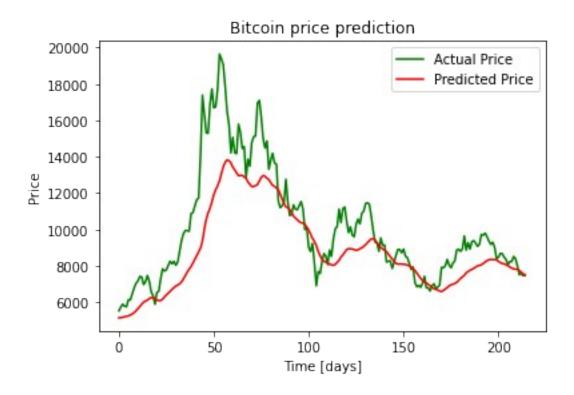
```
batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 3.8431e-04
Epoch 2/30
05 - val loss: 6.7280e-04
Epoch 3/30
43/43 [============= ] - 1s 20ms/step - loss: 1.8059e-
05 - val loss: 3.4374e-04
Epoch 4/30
05 - val loss: 4.6605e-04
Epoch 5/\overline{30}
43/43 [============= ] - 1s 22ms/step - loss: 1.3375e-
05 - val loss: 3.7136e-04
Epoch 6/30
05 - val loss: 9.5330e-04
Epoch 7/30
05 - val loss: 8.1061e-04
Epoch 8/30
43/43 [============= ] - 1s 20ms/step - loss: 1.6177e-
05 - val loss: 4.0604e-04
Epoch 9/30
43/43 [============== ] - 1s 20ms/step - loss: 1.9431e-
05 - val loss: 3.5886e-04
Epoch 10/30
43/43 [============= ] - 1s 22ms/step - loss: 1.5492e-
05 - val loss: 5.2353e-04
Epoch 11/30
43/43 [============= ] - 1s 22ms/step - loss: 2.1529e-
05 - val loss: 0.0013
Epoch 12/30
05 - val loss: 3.0808e-04
Epoch 13/30
43/43 [============== ] - 1s 20ms/step - loss: 1.8644e-
05 - val loss: 4.1036e-04
Epoch 14/30
43/43 [============== ] - 1s 20ms/step - loss: 1.4636e-
05 - val loss: 5.7571e-04
Epoch 15/30
```

```
05 - val loss: 4.1737e-04
Epoch 16/30
05 - val loss: 3.6177e-04
Epoch 17/30
43/43 [============= ] - 1s 20ms/step - loss: 1.4628e-
05 - val loss: 5.4309e-04
Epoch 18/30
05 - val loss: 8.9826e-04
Epoch 19/30
05 - val loss: 3.6204e-04
Epoch 20/30
05 - val_loss: 3.1158e-04
Epoch 21/30
43/43 [============= ] - 1s 20ms/step - loss: 1.2939e-
05 - val loss: 3.3196e-04
Epoch 22/30
43/43 [============== ] - 1s 20ms/step - loss: 1.2723e-
05 - val loss: 0.0011
Epoch 23/30
43/43 [============== ] - 1s 21ms/step - loss: 1.5813e-
05 - val loss: 3.3275e-04
Epoch 24/30
05 - val loss: 6.1969e-04
Epoch 25/30
05 - val loss: 3.0741e-04
Epoch 26/30
43/43 [============= ] - 1s 21ms/step - loss: 1.5555e-
05 - val loss: 6.2829e-04
Epoch 27/30
05 - val loss: 3.2582e-04
Epoch 28/30
05 - val loss: 7.0768e-04
Epoch 28: early stopping
model_evaluation(history_LSTM_2_adam, model_LSTM_2_adam, scaler,
X test, X train, y train, y test)
```



7/7 [======] - 1s 15ms/step 27/27 [=========] - 0s 12ms/step

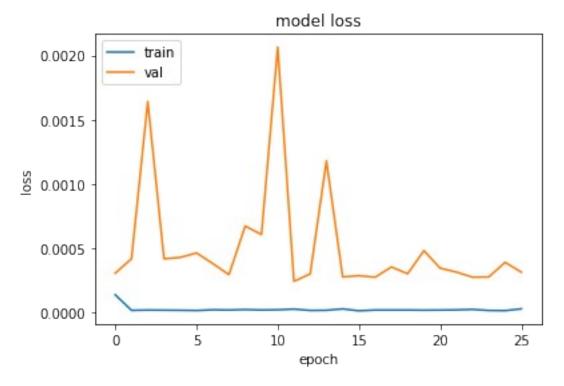
Train Score: 0.0016 RMSE Test Score: 0.0196 RMSE



```
Tamanho da Janela: 250
X_train, y_train, X_test, y_test = split_data(scaled_df, 0.2,
time steps=250)
X train = X train.reshape(X train.shape[0], X train.shape[1], 1)
X test = X test.reshape(X test.shape[0], X test.shape[1], 1)
y_train = y_train.reshape(-1, 1)
y test = y test.reshape(-1, 1)
model LSTM 2 adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(250, input shape=(250, X train.shape[-1]),
dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(250, dropout=DROPOUT))
model LSTM 2 adam.add(Dense(1, activation='linear'))
model LSTM 2 adam.compile(
  optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
  loss="mse"
)
history LSTM 2 adam = model LSTM 2 adam.fit(
   np.array(X_train).reshape(X_train.shape[0], X_train.shape[1], 1),
  y train,
  batch size=BATCH SIZE,
  epochs=EPOCHS,
  verbose=VERBOSE,
  validation split=0.2,
  callbacks=[callback]
)
Epoch 1/30
04 - val loss: 3.0756e-04
Epoch 2/30
05 - val loss: 4.1934e-04
Epoch 3/30
05 - val loss: 0.0016
Epoch 4/30
05 - val loss: 4.1954e-04
Epoch 5/30
05 - val loss: 4.2983e-04
Epoch 6/30
41/41 [============= ] - 1s 27ms/step - loss: 1.7320e-
05 - val loss: 4.6493e-04
Epoch 7/30
```

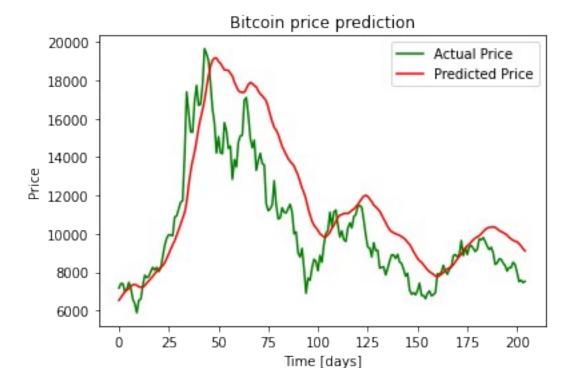
```
05 - val loss: 3.8226e-04
Epoch 8/30
05 - val loss: 2.9591e-04
Epoch 9/30
05 - val loss: 6.7387e-04
Epoch 10/30
05 - val loss: 6.0760e-04
Epoch 11/30
05 - val loss: 0.0021
Epoch 12/30
05 - val loss: 2.4381e-04
Epoch 13/30
05 - val loss: 3.0202e-04
Epoch 14\overline{/}30
05 - val loss: 0.0012
Epoch 15/30
05 - val loss: 2.7817e-04
Epoch 16/30
05 - val loss: 2.8805e-04
Epoch 17/30
05 - val loss: 2.7615e-04
Epoch 18/30
05 - val loss: 3.5594e-04
Epoch 19\overline{/}30
05 - val loss: 3.0261e-04
Epoch 20/30
05 - val loss: 4.8265e-04
Epoch 21/30
05 - val loss: 3.4654e-04
Epoch 22/30
05 - val_loss: 3.1591e-04
Epoch 23/30
05 - val loss: 2.7634e-04
Epoch 24/30
```

model\_evaluation(history\_LSTM\_2\_adam, model\_LSTM\_2\_adam, scaler,
X\_test, X\_train, y\_train, y\_test)



7/7 [======] - 1s 21ms/step 26/26 [=========] - 0s 13ms/step

Train Score: 0.0026 RMSE Test Score: 0.0323 RMSE



```
Tamanho da Janela: 300
X train, y train, X test, y test = split data(scaled df, 0.2,
time steps=300)
X train = X train.reshape(X train.shape[0], X train.shape[1], 1)
X test = X test.reshape(X test.shape[0], X test.shape[1], 1)
y train = y train.reshape(-1, 1)
y test = y test.reshape(-1, 1)
model_LSTM_2_adam = tf.keras.Sequential()
model LSTM 2 adam.add(LSTM(300, input shape=(300, X train.shape[-1]),
dropout=DROPOUT, return sequences=True))
model LSTM 2 adam.add(LSTM(300, dropout=DROPOUT))
model_LSTM_2_adam.add(Dense(1, activation='linear'))
model_LSTM_2_adam.compile(
    optimizer=tf.keras.optimizers.Adam(learning rate = LEARNING RATE),
    loss="mse"
)
history_LSTM_2_adam = model_LSTM_2_adam.fit(
    np.array(X train).reshape(X train.shape[0], X train.shape[1], 1),
    y train,
    batch size=BATCH SIZE,
    epochs=EPOCHS,
    verbose=VERBOSE,
    validation split=0.2,
```

```
callbacks=[callback]
)
Epoch 1/30
39/39 [============= ] - 8s 60ms/step - loss: 1.5022e-
04 - val loss: 0.0013
Epoch 2/30
05 - val loss: 5.8094e-04
Epoch 3/30
39/39 [============ ] - 1s 37ms/step - loss: 2.7317e-
05 - val loss: 4.1755e-04
Epoch 4/\overline{30}
05 - val loss: 0.0012
Epoch 5/30
39/39 [============ ] - 1s 37ms/step - loss: 3.7953e-
05 - val loss: 4.4349e-04
Epoch 6/30
05 - val loss: 0.0015
Epoch 7/30
39/39 [============ ] - 1s 38ms/step - loss: 3.5204e-
05 - val loss: 8.9232e-04
Epoch 8/30
39/39 [============ ] - 1s 38ms/step - loss: 1.8590e-
05 - val loss: 3.9149e-04
Epoch 9/30
39/39 [============ ] - 1s 38ms/step - loss: 3.5390e-
05 - val loss: 0.0021
Epoch 10/30
39/39 [============ ] - 1s 37ms/step - loss: 3.9818e-
05 - val loss: 7.5343e-04
Epoch 11/30
05 - val loss: 0.0010
Epoch 12/30
39/39 [============= ] - 1s 38ms/step - loss: 3.5221e-
05 - val loss: 4.1082e-04
Epoch 13/30
05 - val loss: 5.9703e-04
Epoch 14/30
05 - val loss: 6.3030e-04
Epoch 15/30
39/39 [============= ] - 1s 38ms/step - loss: 2.8491e-
05 - val loss: 0.0018
Epoch 16/30
39/39 [============ ] - 2s 39ms/step - loss: 3.5663e-
```

05 - val loss: 0.0011

Epoch 17/30

39/39 [============= ] - 1s 38ms/step - loss: 2.7126e-

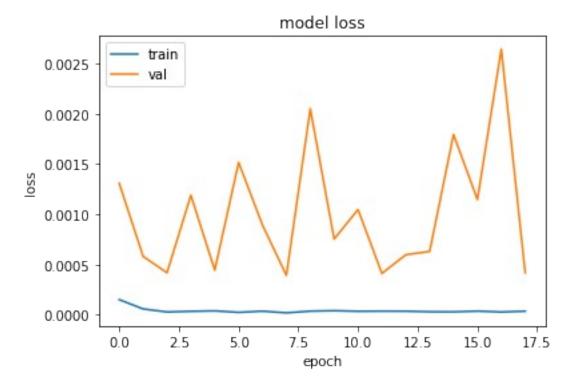
05 - val\_loss: 0.0026

Epoch 18/30

39/39 [============= ] - 1s 38ms/step - loss: 3.4817e-

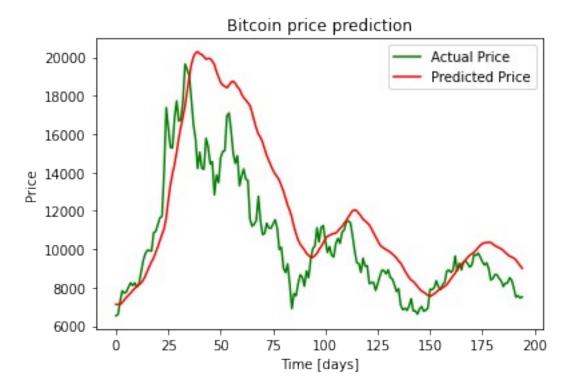
05 - val\_loss: 4.1656e-04
Epoch 18: early stopping

model\_evaluation(history\_LSTM\_2\_adam, model\_LSTM\_2\_adam, scaler,
X\_test, X\_train, y\_train, y\_test)



7/7 [======] - 1s 26ms/step 25/25 [==========] - 0s 18ms/step

Train Score: 0.0053 RMSE Test Score: 0.0305 RMSE



### Continuidade

Olhando para os scores com RMSE, vemos que o melhor modelo é com tamanho de janela igual a 100.

# Conclusão

Dessa forma, a partir dessa abordagem, os melhores parâmetros encontrados para a previsão de valores dee Bitcoin, com RMSE 0,0004 de treinamento e 0,0079 de teste, foram:

2 camadas LSTM

Algoritmo de Otimização: ADAMTaxa de aprendizagem: 0.001

Dropout: 10%Batch Size: 16

• Tamanho da janela: 100