Member-only story

Time-Series Forecasting: Predicting Stock Prices Using An LSTM Model

In this post I show you how to predict stock prices using a forecasting LSTM model

Serafeim Loukas, PhD · Follow
Published in Towards Data Science
9 min read · Jul 10, 2020

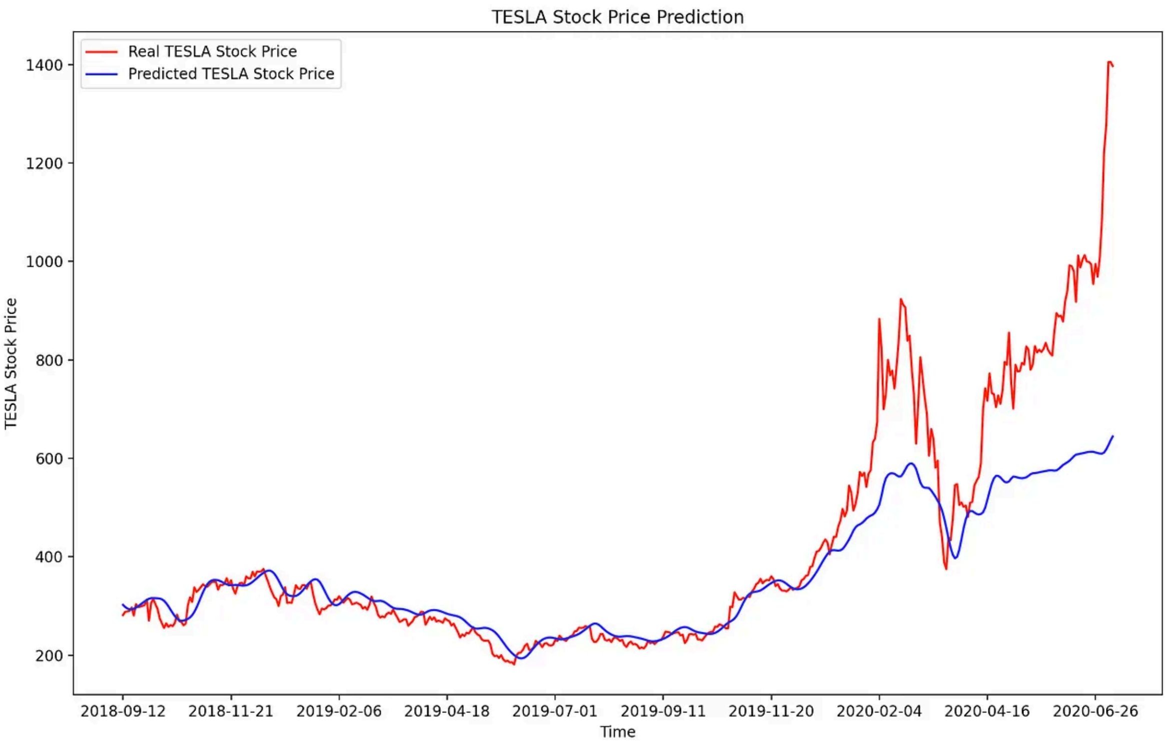


Figure created by the author.

1. Introduction

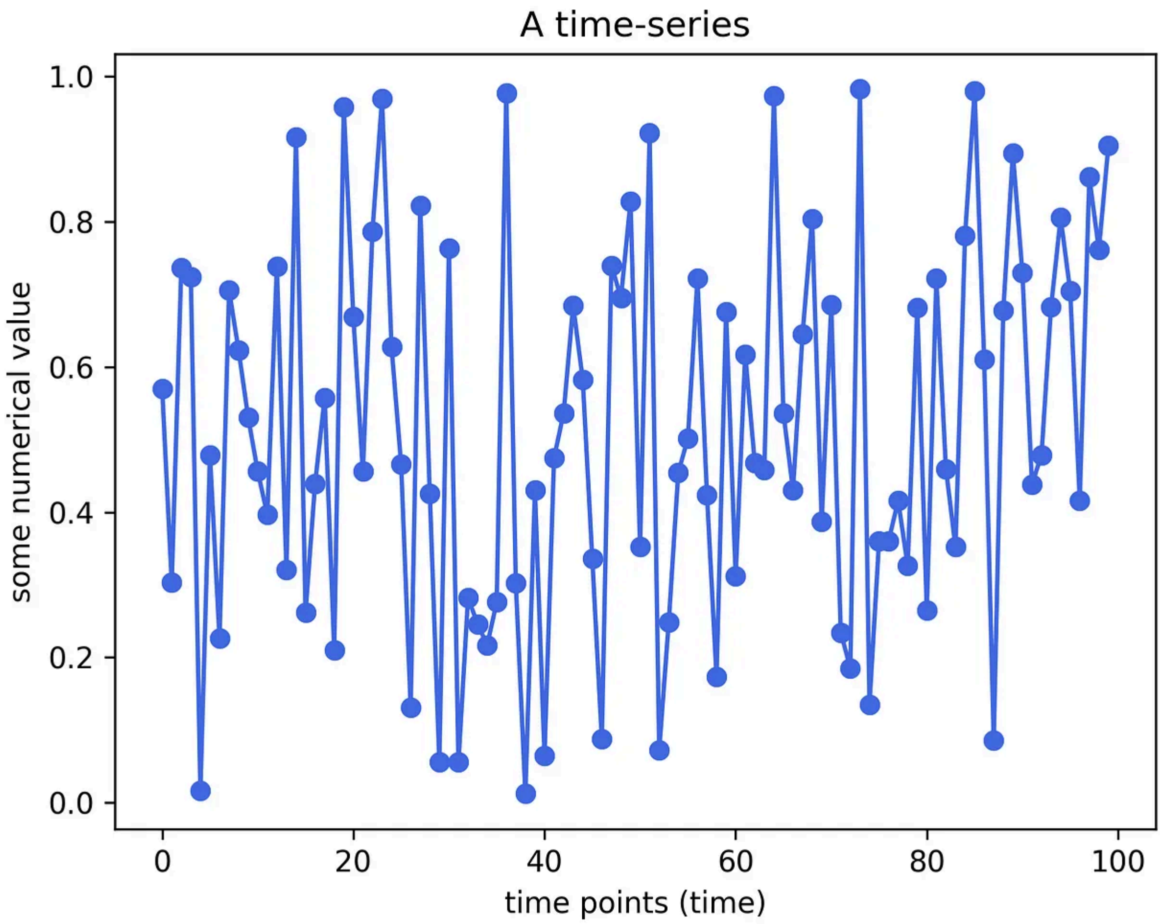
1.1. Time-series & forecasting models

Traditionally most machine learning (ML) models use as input features some observations (samples / examples) but there is no **time dimension** in the data.

Time-series forecasting models are the models that are capable to **predict future values** based on **previously observed values.** Time-series forecasting is widely used for **non-stationary data. Non-stationary data** are called the data whose statistical properties e.g. the mean and standard deviation are not constant over time but instead, these metrics vary over time.

These non-stationary input data (used as input to these models) are usually called **time-series.** Some examples of time-series include the temperature values over time, stock price over time, price of a house over time etc. So, the input is a **signal** (time-series) that is **defined by observations taken sequentially in time**.

> A time series is a sequence of observations taken sequentially in time.



An example of a time-series. Plot created by the author in Python.

Observation: Time-series data is recorded on a **discrete time scale.**

Disclaimer (before we move on): There have been attempts to predict stock prices using time series analysis algorithms, though they still cannot be used to place bets in the real market. This is just a tutorial article that does not intent in any way to "direct" people into buying stocks.

- My mailing list in just 5 seconds: https://seralouk.medium.com/subscribe
- Become a member and support me:https://seralouk.medium.com/membership
- **NEW:** After a great deal of hard work and staying behind the scenes for quite a while, we're excited to now offer our expertise through a platform, the "**Data Science Hub**" on Patreon (https://www.patreon.com/TheDataScienceHub). This hub is our way of providing you with **bespoke consulting services** and comprehensive **responses to all your inquiries**, ranging from Machine Learning to strategic data analytics

2. The LSTM model

Long short-term memory (**LSTM**) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. Unlike standard feedforward neural networks, LSTM has feedback connections. It can not only process single data points (e.g. images), but also entire sequences of data (such as speech or video inputs).

LSTM models are able to store information over a period of time.

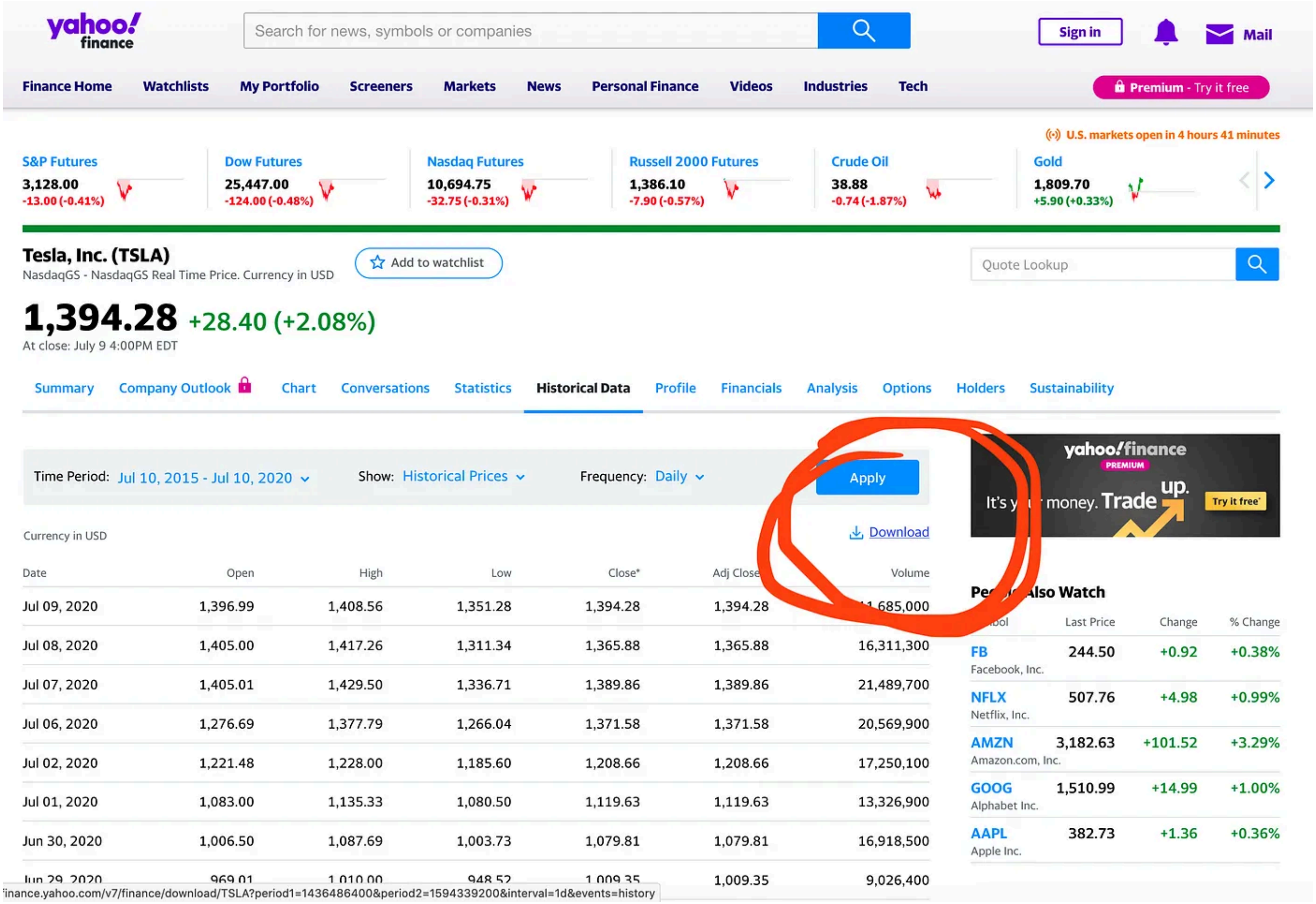
> In order words, they have a memory capacity. Remember that LSTM stands for Long Short-Term Memory Model.

This characteristic is extremely useful when we deal with Time-Series or Sequential Data. When using an LSTM model we are free and able to decide what information will be stored and what discarded. We do that using the "gates". The deep understanding of the LSTM is outside the scope of this post but if you are interested in learning more, have a look at the references at the end of this post.

3. Getting the stock price history data

Thanks to **Yahoo finance** we can get the data for **free**. Use the following link to get the stock price history of **TESLA**: https://finance.yahoo.com/quote/TSLA/history?period1=1436486400&period2=1594339200&interval=1d&filter=history&frequency=1d

You should see the following:



Date	Open	High	Low	Close*	Adj Close	Volume
Jul 09, 2020	1,396.99	1,408.56	1,351.28	1,394.28	1,394.28	11,685,000
Jul 08, 2020	1,405.00	1,417.26	1,311.34	1,365.88	1,365.88	16,311,300
Jul 07, 2020	1,405.01	1,429.50	1,336.71	1,389.86	1,389.86	21,489,700
Jul 06, 2020	1,276.69	1,377.79	1,266.04	1,371.58	1,371.58	20,569,900
Jul 02, 2020	1,221.48	1,228.00	1,185.60	1,208.66	1,208.66	17,250,100
Jul 01, 2020	1,083.00	1,135.33	1,080.50	1,119.63	1,119.63	13,326,900
Jun 30, 2020	1,006.50	1,087.69	1,003.73	1,079.81	1,079.81	16,918,500
Jun 29, 2020	969.01	1,010.00	948.52	1,009.35	1,009.35	9,026,400

Symbol	Last Price	Change	% Change
FB Facebook, Inc.	244.50	+0.92	+0.38%
NFLX Netflix, Inc.	507.76	+4.98	+0.99%
AMZN Amazon.com, Inc.	3,182.63	+101.52	+3.29%
GOOG Alphabet Inc.	1,510.99	+14.99	+1.00%
AAPL Apple Inc.	382.73	+1.36	+0.36%

Click on the **Download** and save the **.csv** file locally on your computer.

The data are from **2015** till now (**2020**) !

4.Python working example

Modules needed: Keras, Tensorflow, Pandas, Scikit-Learn & Numpy

We are going to build a **multi-layer LSTM recurrent neural network** to **predict** the **last value of a sequence of values** i.e. the TESLA stock price in this example.

Let's **load** the **data** and **inspect** them:

```
import math
import matplotlib.pyplot as plt
import keras
import pandas as pd
import numpy as np
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
```

```
from keras.layers import Dropout
from keras.layers import *
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import train_test_split
from keras.callbacks import EarlyStopping

df=pd.read_csv("TSLA.csv")
print('Number of rows and columns:', df.shape)
df.head(5)
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2015-07-10	262.220001	263.000000	257.820007	259.149994	259.149994	2610900
1	2015-07-13	262.250000	262.549988	256.049988	262.160004	262.160004	2960300
2	2015-07-14	262.100006	265.989990	260.510010	265.649994	265.649994	1907600
3	2015-07-15	266.739990	267.489990	262.079987	263.140015	263.140015	2021600
4	2015-07-16	264.220001	267.200012	263.160004	266.679993	266.679993	1616000

Output of the above code

The next step is to **split** the data into **training** and **test** sets to avoid **overfitting** and to be able to investigate the generalization ability of our model. To learn more about overfitting read this article:

Is your model overfitting? Or maybe underfitting? An example using a neural network in python

Overfitting, underfitting, generalization ability, cross-validation. Everything simply explained. I also provide a...

towardsdatascience.com

The target value to be predicted is going to be the "**Close**" stock price value.

```
training_set = df.iloc[:800, 1:2].values
test_set = df.iloc[800:, 1:2].values
```

It's a good idea to **normalize** the data before **model fitting.** This will boost the performance. You can read more here for the **Min-Max Scaler:**

Everything you need to know about Min-Max normalization in Python

In this post I explain what Min-Max scaling is, when to use it and how to implement it in Python using scikit-learn but…

towardsdatascience.com

Let's build the input features with time **lag of 1 day (lag 1):**

```
# Feature Scaling
sc = MinMaxScaler(feature_range = (0, 1))
training_set_scaled = sc.fit_transform(training_set)

# Creating a data structure with 60 time-steps and 1 output
X_train = []
y_train = []
for i in range(60, 800):
    X_train.append(training_set_scaled[i-60:i, 0])
    y_train.append(training_set_scaled[i, 0])
X_train, y_train = np.array(X_train), np.array(y_train)

X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1],
1))
#(740, 60, 1)
```

We have now **reshaped** the data into the following format (#values, #time-steps, #1 dimensional output).

Now, it's time to build the model. We will build the **LSTM** with 50 neurons and **4 hidden layers**. Finally, we will assign 1 neuron in the output layer for predicting the normalized stock price. We will use the MSE loss function and the Adam stochastic gradient descent optimizer.

Note: the following will take some time (~5min).

```
model = Sequential()

#Adding the first LSTM layer and some Dropout regularisation
model.add(LSTM(units = 50, return_sequences = True, input_shape =
(X_train.shape[1], 1)))
model.add(Dropout(0.2))

# Adding a second LSTM layer and some Dropout regularisation
model.add(LSTM(units = 50, return_sequences = True))
model.add(Dropout(0.2))

# Adding a third LSTM layer and some Dropout regularisation
model.add(LSTM(units = 50, return_sequences = True))
model.add(Dropout(0.2))
```

```
# Adding a fourth LSTM layer and some Dropout regularisation
model.add(LSTM(units = 50))
model.add(Dropout(0.2))

# Adding the output layer
model.add(Dense(units = 1))

# Compiling the RNN
model.compile(optimizer = 'adam', loss = 'mean_squared_error')

# Fitting the RNN to the Training set
model.fit(X_train, y_train, epochs = 100, batch_size = 32)
```

When the fitting is finished you should see something like this:

```
Epoch 95/100
24/24 [==============================] - 2s 70ms/step - loss: 0.0032
Epoch 96/100
24/24 [==============================] - 2s 69ms/step - loss: 0.0028
Epoch 97/100
24/24 [==============================] - 2s 69ms/step - loss: 0.0028
Epoch 98/100
24/24 [==============================] - 2s 72ms/step - loss: 0.0029
Epoch 99/100
24/24 [==============================] - 2s 69ms/step - loss: 0.0029
Epoch 100/100
24/24 [==============================] - 2s 69ms/step - loss: 0.0031
```

Prepare the test data (reshape them):

```
# Getting the predicted stock price of 2017
dataset_train = df.iloc[:800, 1:2]
dataset_test = df.iloc[800:, 1:2]

dataset_total = pd.concat((dataset_train, dataset_test), axis = 0)

inputs = dataset_total[len(dataset_total) - len(dataset_test) -
60:].values

inputs = inputs.reshape(-1,1)
inputs = sc.transform(inputs)
X_test = []
for i in range(60, 519):
    X_test.append(inputs[i-60:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))

print(X_test.shape)
# (459, 60, 1)
```

Make Predictions using the test set

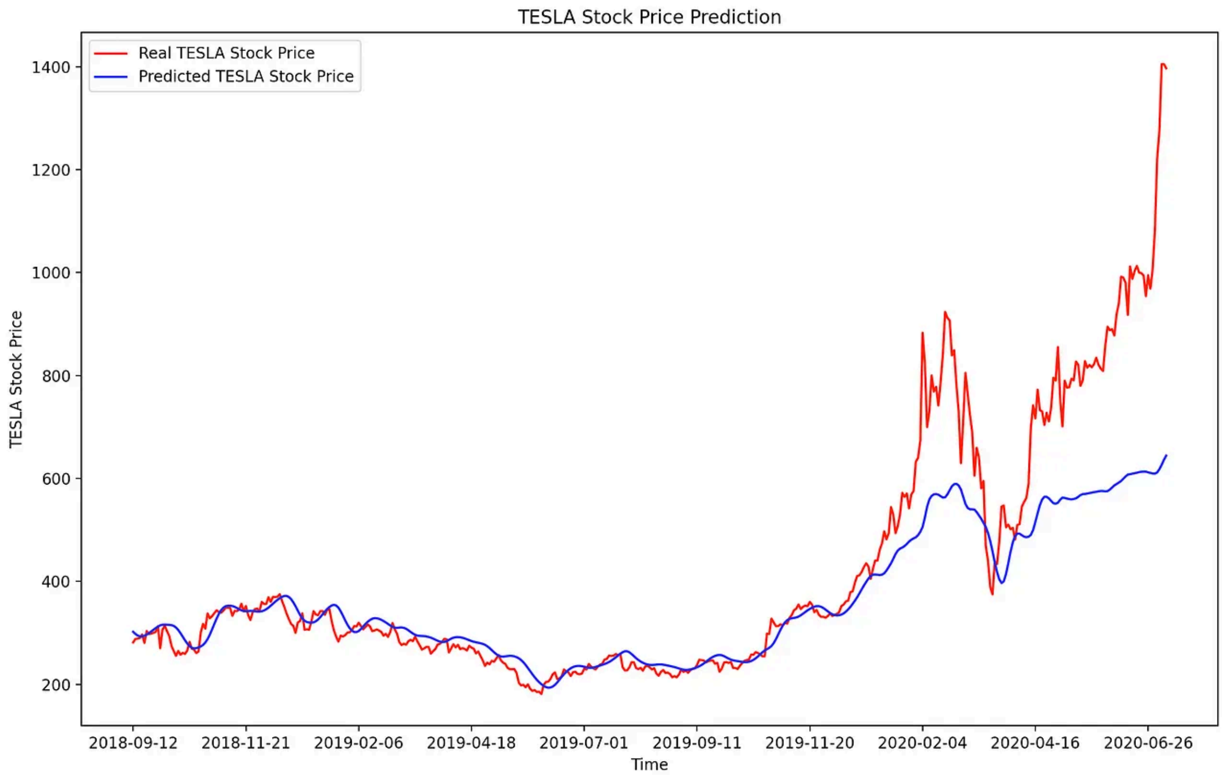
```
predicted_stock_price = model.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
```

Let’s visualize the results now:

```
# Visualising the results
plt.plot(df.loc[800:, ‘Date’],dataset_test.values, color = ‘red’,
label = ‘Real TESLA Stock Price’)
plt.plot(df.loc[800:, ‘Date’],predicted_stock_price, color = ‘blue’,
label = ‘Predicted TESLA Stock Price’)
plt.xticks(np.arange(0,459,50))
plt.title('TESLA Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('TESLA Stock Price')
plt.legend()
plt.show()
```

5. Results

Using a lag of 1 (i.e. step of one day):



Observation: Huge drop in March 2020 due to the COVID-19 lockdown !

We can clearly see that our model performed very good. It is able to accuretly follow most of the unexcepted jumps/drops however, for the most recent date stamps, we can see that the model expected (predicted) lower values compared to the real values of the stock price.

If you're passionate about diving deeper into machine learning with Python and sklearn, I highly recommend checking out **this book**; it's a game-changer in breaking down complex topics into digestible insights.

A note about the lag

The initial selected lag in this article was 1 i.e. using a step of 1 day. This can be easily changed by altering the code that builds the 3D inputs.

Example: One can change the following 2 blocks of code:

```
X_train = []
y_train = []
for i in range(60, 800):
    X_train.append(training_set_scaled[i-60:i, 0])
    y_train.append(training_set_scaled[i, 0])
```

and

```
X_test = []
y_test = []
for i in range(60, 519):
    X_test.append(inputs[i-60:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

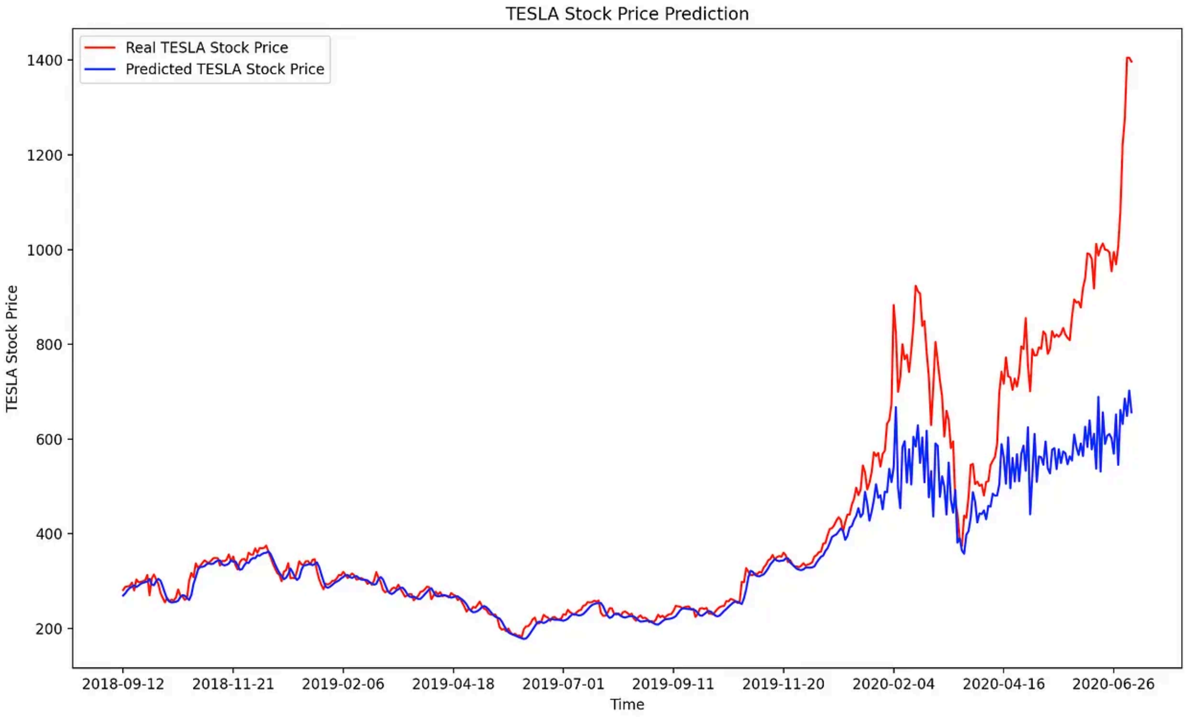
with the following new code:

```
X_train = []
y_train = []
for i in range(60, 800):
    X_train.append(training_set_scaled[i-50:i, 0])
    y_train.append(training_set_scaled[i, 0])
```

and

```
X_test = []
y_test = []
for i in range(60, 519):
    X_test.append(inputs[i-50:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
```

In that case the results look like this:



That's all folks ! Hope you liked this article!

- **NEW:** After a great deal of hard work and staying behind the scenes for quite a while, we're excited to now offer our expertise through a platform, the "**Data Science Hub**" on Patreon (https://www.patreon.com/TheDataScienceHub). This hub is our way of providing you with **bespoke consulting services** and comprehensive **responses to all your inquiries**, ranging from Machine Learning to strategic data analytics planning.

More readings:

Have a look at my Facebook Prophet model that I used to predict the GOOGLE stock price in another article.