LSTM with Google Trend

May 17, 2021

[1]:
```python
import pandas as pd
from pandas import DataFrame
from pandas import concat
from math import sqrt
from numpy import concatenate
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as pyplot
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from keras import Sequential
from keras.layers import LSTM, Dense, Dropout, Activation
from pandas import read_csv

# Load dataset by using Pandas library
dataset = pd.read_csv(r"E:\PhD study\ELEG5491 Introduction to Deep␣
 ↪Learning\bitcoin\datasets\bitcoinwithgoogleonly.csv", header=0, index_col=0)
print(dataset.head())
values = dataset.values
```

```
               Open     High      Low    Close      Volume  bitcoin  \
Date
2014-10-20  389.231  390.084  378.252  382.845  16419000.0     1.74
2014-10-21  382.421  392.646  380.834  386.475  14188900.0     2.04
2014-10-22  386.118  388.576  382.249  383.158  11641300.0     1.71
2014-10-23  382.962  385.048  356.447  358.417  26456900.0     1.80
2014-10-24  358.591  364.345  353.305  358.345  15585700.0     1.98

            blockchain  bitcoinrise  buy bitcoin  sell bitcoin
Date
2014-10-20        1.50        11.18         0.42          0.00
2014-10-21        2.37        11.18         1.47          1.34
2014-10-22        2.04         7.31         1.29          0.00
2014-10-23        1.11         3.87         0.42          0.00
2014-10-24        2.37         7.74         1.59          0.00
```

[2]:
```python
# convert series to supervised learning
def series_to_supervised(data, n_in=1, n_out=1, dropnan=True):
        n_vars = 1 if type(data) is list else data.shape[1]
```

```
        df = DataFrame(data)
        cols, names = list(), list()
        # Here is created input columns which are (t-n, ... t-1)
        for i in range(n_in, 0, -1):
                cols.append(df.shift(i))
                names += [('var%d(t-%d)' % (j+1, i)) for j in range(n_vars)]
        # Here is created output/forecast column which are (t, t+1, ... t+n)
        for i in range(0, n_out):
                cols.append(df.shift(-i))
                if i == 0:
                        names += [('var%d(t)' % (j+1)) for j in range(n_vars)]
                else:
                        names += [('var%d(t+%d)' % (j+1, i)) for j in␣
↪range(n_vars)]
        # put it all together
        agg = concat(cols, axis=1)
        agg.columns = names
        # drop rows with NaN values
        if dropnan:
                agg.dropna(inplace=True)
        return agg
```

[3]:
```
# here checked values numeric format
values = values.astype('float32')

# Dataset values are normalized by using MinMax method
scaler = MinMaxScaler(feature_range=(0,1))
scaled = scaler.fit_transform(values)
#print(scaled)

# Normalized values are converted for supervised learning
reframed = series_to_supervised(scaled,1,1)
```

[4]:
```
# Dataset is splitted into two groups which are train and test sets
values = reframed.values
train_size = int(len(values)*0.60)
validation_size = int(len(values)*0.80)
train = values[:train_size,:]
validation =values[train_size:validation_size,:]
test = values[validation_size:,:]

# Splitted datasets are splitted to trainX, trainY, testX and testY
trainX, trainY = train[:,:-1], train[:,13]
validationX, validationY = validation[:,:-1], validation[:,13]
testX, testY = test[:,:-1], test[:,13]
print(trainY, trainY.shape)
```

```python
# Train and Test datasets are reshaped in 3D size to be used in LSTM
trainX = trainX.reshape((trainX.shape[0],1,trainX.shape[1]))
validationX = validationX.reshape((validationX.shape[0],1,validationX.shape[1]))
testX = testX.reshape((testX.shape[0],1,testX.shape[1]))
print(trainX.shape, trainY.shape,testX.shape,testY.shape)
```

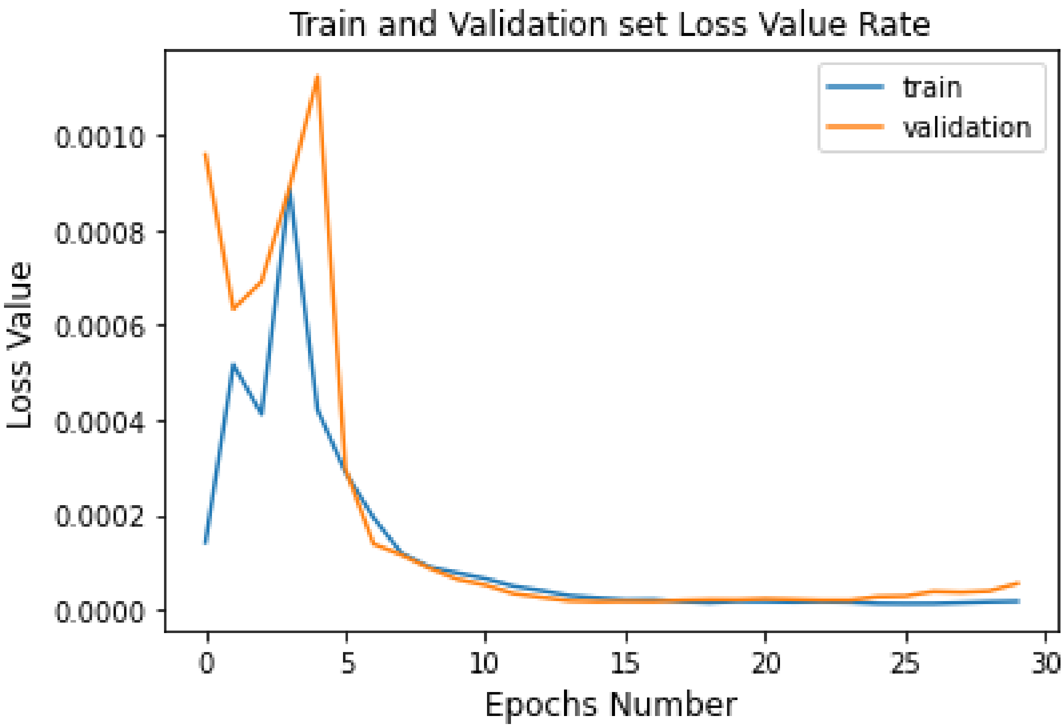
```
[0.0034123  0.00335798 0.00295282 … 0.11233079 0.11488003 0.11618144] (1413,)
(1413, 1, 19) (1413,) (471, 1, 19) (471,)
```

[5]:
```python
# LSTM model is created and adjusted neuron structure
model = Sequential()
model.add(LSTM(128, input_shape=(trainX.shape[1], trainX.shape[2])))
model.add(Dropout(0.01))
model.add(Dense(1))
#model.add(Activation('linear'))
model.compile(loss='mean_squared_error', optimizer='adam')
# Dataset is trained by using trainX and trainY
history = model.fit(trainX, trainY, epochs=30, batch_size=25,␣
 ↪validation_data=(validationX, validationY), verbose=2, shuffle=False)
```

```
Epoch 1/30
57/57 - 0s - loss: 1.4175e-04 - val_loss: 9.5979e-04
Epoch 2/30
57/57 - 0s - loss: 5.1683e-04 - val_loss: 6.3418e-04
Epoch 3/30
57/57 - 0s - loss: 4.1262e-04 - val_loss: 6.9180e-04
Epoch 4/30
57/57 - 0s - loss: 8.8880e-04 - val_loss: 8.9123e-04
Epoch 5/30
57/57 - 0s - loss: 4.2145e-04 - val_loss: 0.0011
Epoch 6/30
57/57 - 0s - loss: 2.8953e-04 - val_loss: 2.9638e-04
Epoch 7/30
57/57 - 0s - loss: 1.9421e-04 - val_loss: 1.3869e-04
Epoch 8/30
57/57 - 0s - loss: 1.1911e-04 - val_loss: 1.1559e-04
Epoch 9/30
57/57 - 0s - loss: 9.0237e-05 - val_loss: 8.7551e-05
Epoch 10/30
57/57 - 0s - loss: 7.7649e-05 - val_loss: 6.4103e-05
Epoch 11/30
57/57 - 0s - loss: 6.5608e-05 - val_loss: 5.1993e-05
Epoch 12/30
57/57 - 0s - loss: 4.9678e-05 - val_loss: 3.3824e-05
Epoch 13/30
57/57 - 0s - loss: 4.0273e-05 - val_loss: 2.6082e-05
Epoch 14/30
57/57 - 0s - loss: 2.9600e-05 - val_loss: 1.8638e-05
```

```
Epoch 15/30
57/57 - 0s - loss: 2.4752e-05 - val_loss: 1.7113e-05
Epoch 16/30
57/57 - 0s - loss: 2.0933e-05 - val_loss: 1.7754e-05
Epoch 17/30
57/57 - 0s - loss: 2.1481e-05 - val_loss: 1.7240e-05
Epoch 18/30
57/57 - 0s - loss: 1.7215e-05 - val_loss: 1.9856e-05
Epoch 19/30
57/57 - 0s - loss: 1.4937e-05 - val_loss: 2.1369e-05
Epoch 20/30
57/57 - 0s - loss: 1.7720e-05 - val_loss: 2.1118e-05
Epoch 21/30
57/57 - 0s - loss: 1.7358e-05 - val_loss: 2.3043e-05
Epoch 22/30
57/57 - 0s - loss: 1.6188e-05 - val_loss: 2.1702e-05
Epoch 23/30
57/57 - 0s - loss: 1.6760e-05 - val_loss: 2.0116e-05
Epoch 24/30
57/57 - 0s - loss: 1.5823e-05 - val_loss: 2.0071e-05
Epoch 25/30
57/57 - 0s - loss: 1.3106e-05 - val_loss: 2.7359e-05
Epoch 26/30
57/57 - 0s - loss: 1.2656e-05 - val_loss: 2.8583e-05
Epoch 27/30
57/57 - 0s - loss: 1.2780e-05 - val_loss: 3.8487e-05
Epoch 28/30
57/57 - 0s - loss: 1.4623e-05 - val_loss: 3.6778e-05
Epoch 29/30
57/57 - 0s - loss: 1.6659e-05 - val_loss: 3.9495e-05
Epoch 30/30
57/57 - 0s - loss: 1.7821e-05 - val_loss: 5.5435e-05
```

[6]:
```python
# Loss values are calculated for every training epoch and are visualized
pyplot.plot(history.history['loss'], label='train')
pyplot.plot(history.history['val_loss'], label='validation')
pyplot.title("Train and Validation set Loss Value Rate")
pyplot.xlabel('Epochs Number', fontsize=12)
pyplot.ylabel('Loss Value', fontsize=12)
pyplot.legend()
pyplot.show()
```



[7]:
```
# Prediction process is performed for train dataset
trainPredict = model.predict(trainX)
trainX = trainX.reshape((trainX.shape[0], trainX.shape[2]))
print(trainX.shape)

validationPredict = model.predict(validationX)
validationX = validationX.reshape((validationX.shape[0], validationX.shape[2]))
print(validationX.shape)

# Prediction process is performed for test dataset
testPredict = model.predict(testX)
testX = testX.reshape((testX.shape[0], testX.shape[2]))
print(testX.shape)
```

```
(1413, 19)
(471, 19)
(471, 19)
```

[8]:
```
# Trains dataset inverts scaling for training
trainPredict = concatenate((trainPredict, trainX[:, -9:]), axis=1)
trainPredict = scaler.inverse_transform(trainPredict)
trainPredict = trainPredict[:,0]
```

```python
validationPredict = concatenate((validationPredict, validationX[:, -9:]),␣
↪axis=1)
validationPredict = scaler.inverse_transform(validationPredict)
validationPredict = validationPredict[:,0]

# Test dataset inverts scaling for forecasting
testPredict = concatenate((testPredict, testX[:, -9:]), axis=1)
testPredict = scaler.inverse_transform(testPredict)
testPredict = testPredict[:,0]
```

[9]:
```python
# invert scaling for actual
trainY = trainY.reshape((len(trainY), 1))
inv_trainy = concatenate((trainY, trainX[:, -9:]), axis=1)
inv_trainy = scaler.inverse_transform(inv_trainy)
inv_trainy = inv_trainy[:,0]

validationY = validationY.reshape((len(validationY), 1))
inv_validationy = concatenate((validationY, validationX[:, -9:]), axis=1)
inv_validationy = scaler.inverse_transform(inv_validationy)
inv_validationy = inv_validationy[:,0]

testY = testY.reshape((len(testY), 1))
inv_testy = concatenate((testY, testX[:, -9:]), axis=1)
inv_testy = scaler.inverse_transform(inv_testy)
inv_testy = inv_testy[:,0]
```

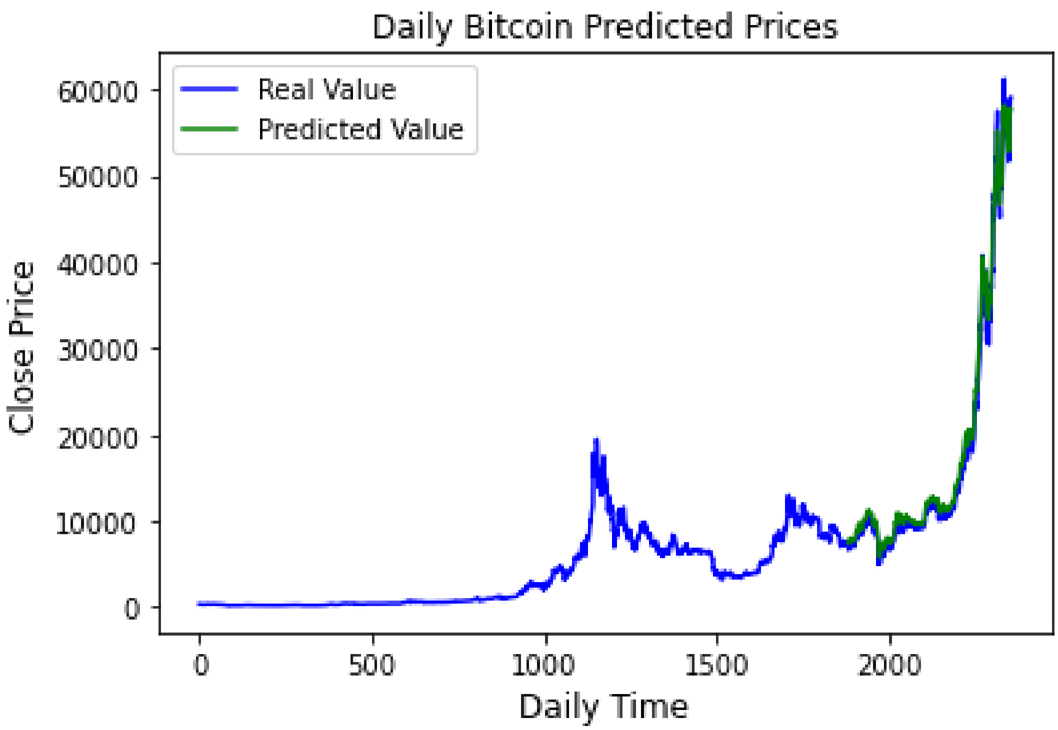
[10]:
```python
#It should be noted that RMSE would be different each time run the code
#becasue of dropout layer.
# Performance measure calculated by using mean_squared_error for train and test␣
↪prediction
rmset = sqrt(mean_squared_error(inv_trainy, trainPredict))
print('Train RMSE: %.3f' % rmset)
rmsev = sqrt(mean_squared_error(inv_validationy, validationPredict))
print('Validation RMSE: %.3f' % rmsev)
rmse = sqrt(mean_squared_error(inv_testy, testPredict))
print('Test RMSE: %.3f' % rmse)
```

```
Train RMSE: 386.528
Validation RMSE: 454.503
Test RMSE: 1140.703
```

[12]:
```python
# Three parts of datasets are concatenated
final = np.append(trainPredict, validationPredict)
final = np.append(final, testPredict)
final = pd.DataFrame(data=final, columns=['Close'])
actual = dataset.Close
actual = actual.values
```

```
actual = pd.DataFrame(data=actual, columns=['Close'])

# Finally result are visualized
pyplot.plot(actual.Close, 'b', label='Real Value')
pyplot.plot(final.Close[1884:len(final)], 'g' , label='Predicted Value')
pyplot.title("Daily Bitcoin Predicted Prices")
pyplot.xlabel('Daily Time', fontsize=12)
pyplot.ylabel('Close Price', fontsize=12)
pyplot.legend(loc='best')
pyplot.show()
```




```
[ ]:
```