stock-prediction-model-1

April 3, 2024

1 Day 22 - Stock Price prediction using GRU

1.0.1 In this notebook we are going to learn , How can we attempt to predict future stock behavior? (Predicting the closing price stock price of GOOGLE inc using GRU)

```
[]:
```

Importing the dependencies

```
[]: import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, GRU, Dropout
```

Loading the Data

[]: scaled_data[:10]

```
[]: data.head()
```

```
[]:
             Date
                     Open
                             High
                                      Low
                                            Close
                                                     Volume
                                                              Name
                   211.47
                           218.05
                                           217.83
       2006-01-03
                                   209.32
                                                   13137450
                                                             GOOGL
    1 2006-01-04
                   222.17
                           224.70
                                   220.09
                                           222.84
                                                   15292353
                                                             GOOGL
    2 2006-01-05
                   223.22
                           226.00
                                           225.85
                                   220.97
                                                   10815661
                                                             GOOGL
                                                   17759521
    3 2006-01-06
                   228.66
                           235.49
                                           233.06
                                                             GOOGL
                                   226.85
    4 2006-01-09
                   233.44 236.94
                                   230.70
                                          233.68
                                                   12795837
                                                             GOOGL
```

Normalising the Closing price of the stocks on the time periods, We Just going the predict the Closing price of the stocks, so lets clean the data as well.

```
[]: data = data.sort_values('Date')
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data['Close'].values.reshape(-1, 1))
```

```
[]: array([[0.09305195],
            [0.09829122],
            [0.10143897],
            [0.10897892],
            [0.10962729],
            [0.11112273],
            [0.11210575],
            [0.1079227],
            [0.10929265],
            [0.10974232]])
[]: training_data_len = int(len(scaled_data) * 0.8)
     train_data = scaled_data[0:training_data_len, :]
[]: train_data[:10]
[]: array([[0.09305195],
            [0.09829122],
            [0.10143897],
            [0.10897892],
            [0.10962729],
            [0.11112273],
            [0.11210575],
            [0.1079227],
            [0.10929265],
            [0.10974232]])
```

The following loop iterates over the train data array:

- a. for i in range(60, len(train_data)) This loop starts from index 60 because it seems to be creating sequences of 60 data points (which is a common approach in sequence modeling tasks).
- b. **X_train.append(train_data[i-60:i, 0])** For each iteration, it appends a sequence of 60 data points to **X_train**. The sequence starts from index i-60 and ends at index i-1. The 0 index selects the first (and only) feature in the sequence.
- c. **y_train.append(train_data[i, 0])** It appends the target value (which is the next data point after the 60-point sequence) to y_train.

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

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))
```

```
[]: test_data = scaled_data[training_data_len-60:, :]
    X_test = []
    y_test = data['Close'][training_data_len:].values
    for i in range(60, len(test_data)):
        X_test.append(test_data[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))
```

1.1 Defining the model

Model: "sequential_1"

Layer (type)	Output Shape	Param #
gru (GRU)	(None, 60, 50)	7950
dropout (Dropout)	(None, 60, 50)	0
gru_1 (GRU)	(None, 60, 50)	15300
<pre>dropout_1 (Dropout)</pre>	(None, 60, 50)	0
gru_2 (GRU)	(None, 50)	15300
dropout_2 (Dropout)	(None, 50)	0
dense (Dense)	(None, 1)	51

Total params: 38601 (150.79 KB)
Trainable params: 38601 (150.79 KB)
Non-trainable params: 0 (0.00 Byte)

```
[]: model.compile(optimizer='adam', loss='mean_squared_error')
  model.fit(X_train, y_train, epochs=50, batch_size=32)
  scores = model.evaluate(X_test, y_test)
  print(f'Test loss: {scores}')
  Epoch 1/50
  74/74 [============= ] - 14s 94ms/step - loss: 0.0048
  Epoch 2/50
  Epoch 3/50
  74/74 [=============== ] - 7s 101ms/step - loss: 9.2688e-04
  Epoch 4/50
  Epoch 5/50
  74/74 [=============== ] - 8s 106ms/step - loss: 7.3345e-04
  Epoch 6/50
  Epoch 7/50
  74/74 [=============== ] - 8s 106ms/step - loss: 6.9005e-04
  Epoch 8/50
  Epoch 9/50
  74/74 [=============== ] - 8s 105ms/step - loss: 5.9840e-04
  Epoch 10/50
  Epoch 11/50
  74/74 [============= ] - 8s 107ms/step - loss: 5.9476e-04
  Epoch 12/50
  74/74 [=============== ] - 7s 101ms/step - loss: 5.2801e-04
  Epoch 13/50
  74/74 [=============== ] - 8s 107ms/step - loss: 5.6004e-04
  Epoch 14/50
  Epoch 15/50
  74/74 [============= ] - 8s 108ms/step - loss: 5.4221e-04
  Epoch 16/50
  74/74 [============= ] - 6s 87ms/step - loss: 4.9416e-04
  Epoch 17/50
  Epoch 18/50
  Epoch 19/50
  74/74 [============ ] - 8s 108ms/step - loss: 4.0347e-04
  Epoch 20/50
```

```
Epoch 21/50
Epoch 22/50
Epoch 23/50
74/74 [============== ] - 8s 109ms/step - loss: 3.6551e-04
Epoch 24/50
Epoch 25/50
74/74 [============== ] - 8s 110ms/step - loss: 3.9199e-04
Epoch 26/50
74/74 [============ ] - 7s 88ms/step - loss: 3.3643e-04
Epoch 27/50
74/74 [=============== ] - 8s 106ms/step - loss: 3.5228e-04
Epoch 28/50
Epoch 29/50
Epoch 30/50
Epoch 31/50
74/74 [================ ] - 8s 110ms/step - loss: 3.3078e-04
Epoch 32/50
Epoch 33/50
74/74 [=============== ] - 7s 100ms/step - loss: 2.8476e-04
Epoch 34/50
Epoch 35/50
74/74 [=============== ] - 7s 101ms/step - loss: 2.7241e-04
Epoch 36/50
74/74 [=============== ] - 7s 100ms/step - loss: 3.0730e-04
Epoch 37/50
Epoch 38/50
Epoch 39/50
Epoch 40/50
74/74 [=============== ] - 8s 102ms/step - loss: 2.8685e-04
Epoch 41/50
Epoch 42/50
74/74 [============== ] - 8s 104ms/step - loss: 2.5447e-04
Epoch 43/50
Epoch 44/50
```

```
74/74 [=============== ] - 8s 103ms/step - loss: 2.6718e-04
 Epoch 45/50
 Epoch 46/50
 Epoch 47/50
 74/74 [============= ] - 6s 87ms/step - loss: 2.6613e-04
 Epoch 48/50
 Epoch 49/50
 Epoch 50/50
 Test loss: 696394.625
[]: # Make predictions
  predictions = model.predict(X_test)
  predictions = scaler.inverse_transform(predictions)
 19/19 [=======] - 1s 67ms/step
[]:
```