

Practical No 04

Recurrent neural network (RNN) Use the Google stock prices dataset and design a time series analysis and prediction system using RNN.

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt

1 data_train=pd.read_csv('Google_Stock_Price_Train.csv')
2 data_train
3
```

	Date	Open	High	Low	Close	Volume
0	1/3/2012	325.25	332.83	324.97	663.59	7,380,500
1	1/4/2012	331.27	333.87	329.08	666.45	5,749,400
2	1/5/2012	329.83	330.75	326.89	657.21	6,590,300
3	1/6/2012	328.34	328.77	323.68	648.24	5,405,900
4	1/9/2012	322.04	322.29	309.46	620.76	11,688,800
...
1253	12/23/2016	790.90	792.74	787.28	789.91	623,400
1254	12/27/2016	790.68	797.86	787.66	791.55	789,100
1255	12/28/2016	793.70	794.23	783.20	785.05	1,153,800
1256	12/29/2016	783.33	785.93	778.92	782.79	744,300
1257	12/30/2016	782.75	782.78	770.41	771.82	1,770,000

1258 rows × 6 columns

```
1 data_train.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1258 entries, 0 to 1257
Data columns (total 6 columns):
#   Column  Non-Null Count  Dtype
---  ---
0    Date    1258 non-null     object
1    Open    1258 non-null     float64
2    High    1258 non-null     float64
3    Low     1258 non-null     float64
4    Close   1258 non-null     object
5    Volume  1258 non-null     object
dtypes: float64(3), object(3)
memory usage: 59.1+ KB
```

```
1 train = data_train.loc[:,["Open"]].values
2 print(train)
```

```
[[325.25]
 [331.27]
 [329.83]
 ...
 [793.7 ]
 [783.33]
 [782.75]]
```

```
1 from sklearn.preprocessing import MinMaxScaler
2 scaler = MinMaxScaler(feature_range=(0,1))
3
4 train_scaled = scaler.fit_transform(train)
5 print(train_scaled)
```

```

[[0.08581368]
 [0.09701243]
 [0.09433366]
 ...
 [0.95725128]
 [0.93796041]
 [0.93688146]]

1 # create a data structure with 50 timesteps and 1 output
2
3 x_train = []
4 y_train = []
5 timesteps = 5
6
7 for i in range(timesteps, 1258):
8     x_train.append(train_scaled[i - timesteps:i, 0])
9     y_train.append(train_scaled[i, 0])
10 x_train, y_train = np.array(x_train), np.array(y_train)

1 # Reshaping
2
3 x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
4 print(x_train)
5 print(y_train)

[[[0.08581368]
  [0.09701243]
  [0.09433366]
  [0.09156187]
  [0.07984225]]

  [[0.09701243]
  [0.09433366]
  [0.09156187]
  [0.07984225]
  [0.0643277 ]]

  [[0.09433366]
  [0.09156187]
  [0.07984225]
  [0.0643277 ]
  [0.0585423 ]]

  ...

  [[0.96294367]
  [0.96123223]
  [0.95475854]
  [0.95204256]
  [0.95163331]]

  [[0.96123223]
  [0.95475854]
  [0.95204256]
  [0.95163331]
  [0.95725128]]

  [[0.95475854]
  [0.95204256]
  [0.95163331]
  [0.95725128]
  [0.93796041]]]
[0.0643277  0.0585423  0.06568569 ... 0.95725128 0.93796041 0.93688146]

```

Create RNN Model

```

1 # Create RNN Model
2
3 # Importing the Keras Libraries and packages
4 from keras.models import Sequential
5 from keras.layers import Dense, SimpleRNN, Dropout
6
7 # initialisinig the RNN

```

```
8 regressor = Sequential()
9
10 # adding the first RNN layer and some Dropout regularisation
11 regressor.add(SimpleRNN(units = 100, activation="relu", return_sequences=True ,input_shape = (x_train.shape
12
13 # adding the second RNN layer and some Dropout regularisation
14 regressor.add(SimpleRNN(units = 100, activation="relu", return_sequences=True))
15
16 # adding the third RNN layer and some Dropout regularisation
17 regressor.add(SimpleRNN(units = 100 , activation="relu", return_sequences=True))
18
19 # adding the fourth RNN layer and some Dropout regularisation
20 regressor.add(SimpleRNN(units = 100))
21
22 # Adding the output Layer
23 regressor.add(Dense(units=1))
24
25 # Compiling the RNN
26 regressor.compile(optimizer= "adam", loss = "mean_squared_error")
27
28 # Fitting the RNN to the Training set
29 regressor.fit(x_train, y_train, epochs = 100, batch_size = 1)
```

```
1253/1253 [=====] - 9s 7ms/step - loss: 3.3444e-04
Epoch 100/100
1253/1253 [=====] - 9s 7ms/step - loss: 3.3444e-04
<keras.callbacks.History at 0x7fcf49543be0>
```

```
1 # Getting the real stock price of 2017
2
3 data_test = pd.read_csv('Google_Stock_Price_Train.csv')
4 data_test.head()
```

	Date	Open	High	Low	Close	Volume
0	1/3/2012	325.25	332.83	324.97	663.59	7,380,500
1	1/4/2012	331.27	333.87	329.08	666.45	5,749,400
2	1/5/2012	329.83	330.75	326.89	657.21	6,590,300
3	1/6/2012	328.34	328.77	323.68	648.24	5,405,900
4	1/9/2012	322.04	322.29	309.46	620.76	11,688,800

```
1 real_stock_price = data_test.loc[:, ["Open"]].values
2 print(real_stock_price)
```

```
[[325.25]
 [331.27]
 [329.83]
 ...
 [793.7 ]
 [783.33]
 [782.75]]
```

```
1 # Getting the predicted stock price of 2017
2
3 data_total = pd.concat((data_train["Open"], data_test["Open"]), axis = 0)
4 inputs = data_total[len(data_total) - len(data_test) - timesteps:].values.reshape(-1,1)
5 inputs = scaler.transform(inputs) # min max scaler
6 inputs
```

```
array([[0.95204256],
       [0.95163331],
       [0.95725128],
       ...,
       [0.95725128],
       [0.93796041],
       [0.93688146]])
```

```
1 x_test = []
2 for i in range(timesteps, 70):
3     if len(inputs[i-timesteps:i, 0]) == timesteps:
4         x_test.append(inputs[i-timesteps:i, 0])
5
6 x_test = np.array(x_test)
7 x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1))
8 predicte_stock_price = regressor.predict(x_test)
9 predicte_stock_price = scaler.inverse_transform(predicte_stock_price)
10
11 # visualising the results
12 plt.plot(real_stock_price, color = "red", label = "Real Google Stock Price")
13 plt.plot(predicte_stock_price, color = "blue", label = "Predicted Google Stock Price")
14 plt.title("Google Stock Price prediction")
15 plt.xlabel("Time")
16 plt.ylabel("Google Stock Price")
17 plt.legend()
18 plt.show()
```

3/3 [=====] - 2s 10ms/step



```
1 print(predicte_stock_price)
```

```
[[771.4349 ]  
[385.81143]  
[341.6283 ]  
[341.6052 ]  
[334.7052 ]  
[323.56116]  
[315.6009 ]  
[313.2511 ]  
[318.22314]  
[315.1569 ]  
[316.44202]  
[314.06595]  
[321.22067]  
[296.35992]  
[292.706 ]  
[297.14474]  
[292.77744]  
[287.4654 ]  
[287.55896]  
[291.37048]  
[293.35825]  
[293.2901 ]  
[292.97525]  
[296.0864 ]  
[298.53952]  
[304.1862 ]  
[304.73734]  
[305.7567 ]  
[304.08212]  
[305.67285]  
[306.73572]  
[307.2452 ]  
[301.95087]  
[303.02438]  
[303.50702]  
[307.11725]  
[304.34567]  
[303.85965]  
[304.08716]  
[305.99673]  
[310.22928]  
[311.8124 ]  
[310.97025]  
[310.2487 ]  
[304.4875 ]  
[305.24646]  
[306.86353]  
[305.23123]  
[300.63284]  
[305.23926]  
[309.19968]  
[308.8655 ]  
[310.3877 ]  
[311.9715 ]  
[315.93433]  
[317.8523 ]
```

```
[319.4329 ]  
[323.6765 ]
```

1

✓ 0s completed at 12:58 PM

● ✕