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ML Practical 10

Stock price prediction using RNN

[22]
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout, Input
import yfinance as yf
```

[23]
```
def print_separator(title=""):
    print("\n" + "-" * 100)
    print(f"{title:^100}")
    print("-" * 100 + "\n")

print_separator("STEP 1: Fetching Stock Data")

ticker = "AAPL"
start_date = "2015-01-01"
end_date = "2020-01-01"

df = yf.download(ticker, start=start_date, end=end_date)

print(f"\nUnfetched {len(df)} rows of data for {ticker} from {start_date} to {end_date}.")
print(f"\nSample data \ \n\n{df.head()}")

# Using only the 'Open' prices for training
training_set = df['Open'].values.reshape(-1, 1)
```

```
[*********************100%***********************]  1 of 1 completed

----------------------------------------------------------------------------------------------------
                                        STEP 1: Fetching Stock Data
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Fetched 1258 rows of data for AAPL from 2015-01-01 to 2020-01-01.

Sample data :

Price                  Adj Close     Close      High       Low  \
Ticker                      AAPL      AAPL      AAPL      AAPL
Date
2015-01-02 00:00:00+00:00  24.347108  27.332500  27.860001  26.837500
2015-01-05 00:00:00+00:00  23.661274  26.562500  27.162500  26.352501
2015-01-06 00:00:00+00:00  23.663508  26.565001  26.857500  26.157499
2015-01-07 00:00:00+00:00  23.943779  26.879999  27.049999  26.674999
2015-01-08 00:00:00+00:00  24.917267  27.972500  28.037500  27.174999

Price                   Open    Volume
Ticker                  AAPL      AAPL
Date
2015-01-02 00:00:00+00:00  27.847500  212818400
2015-01-05 00:00:00+00:00  26.565001  257142000
2015-01-06 00:00:00+00:00  26.875000  263188400
2015-01-07 00:00:00+00:00  26.799999  160423600
2015-01-08 00:00:00+00:00  27.307501  237458000
```

[24]
```
print_separator("STEP 2: Feature Scaling")

sc = MinMaxScaler(feature_range=(0, 1))
training_set_scaled = sc.fit_transform(training_set)

print("Data has been scaled to the range [0, 1].")
print(f"\nSample scaled values : \n\n{training_set_scaled[:5]}")
```

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                                        STEP 2: Feature Scaling
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Data has been scaled to the range [0, 1].

Sample scaled values :

[[0.13633441]
 [0.12663376]
 [0.06223947]
 [0.08552107]
 [0.09561458]]
```

[25]
```
print_separator("STEP 3: Creating the Data Structure")

# Create training data with 60 timesteps
X_train = []
y_train = []

for i in range(60, len(training_set_scaled)):
    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)

print(f"Training data created with {X_train.shape[0]} samples and {X_train.shape[1]} timesteps.")
print(f"\nFirst sample {X_train[0]} :\n\n{X_train[0]}")
print(f"\nFirst target {y_train[0]} : {y_train[0]}")

# Reshaping for LSTM input
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
```

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----------------------------------------------------------------------------------------------------
                                        STEP 3: Creating the Data Structure
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Training data created with 1198 samples and 60 timesteps.

First sample [0.13633441 0.09904075 0.08223947 0.08552107 0.09561458 0.11271877
 0.11237072 0.10655331 0.09466986 0.09944312 0.08647581 0.08078325
 0.09422136 0.10073589 0.1168791  0.11863897 0.11147573 0.13738066
 0.13086753 0.14120992 0.13946899 0.14170645 0.14170645 0.14926411
 0.14926411 0.14195587 0.15008994 0.16293756 0.17929953 0.18536397
 0.18646012 0.18732222 0.19123854 0.19282466 0.19898373 0.21530439
 0.21530439 0.21530439 0.21530439 0.21530439 0.21530439 0.21530439
 0.19182979 0.19993876 0.18876266 0.18165622 0.17278242 0.16605855
 0.17104218 0.16865663 0.17850661 0.18394977 0.19267105 0.19018497
 0.18426665 0.18511339 0.18148259 0.16288786 0.17188754 0.16938191]

First target [y_train[0]] : 0.17964509354657606
```

[26]
```
print_separator("STEP 4: Building the RNN")

# Initialize the RNN
regressor = Sequential()

# Add LSTM layers with Dropout
regressor.add(Input(shape=(X_train.shape[1], 1)))
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units=50))
regressor.add(Dropout(0.2))

# Add the output layer
regressor.add(Dense(units=1))

# Compile the RNN
regressor.compile(optimizer='adam', loss='mean_squared_error')

print("RNN Model Summary : \n")
print(regressor.summary())
```

```
----------------------------------------------------------------------------------------------------
                                        STEP 4: Building the RNN
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RNN Model Summary :

Model: "sequential_4"
```

Layer (type)	Output Shape	Param #
lstm_16 (LSTM)	(None, 60, 50)	10,400
dropout_16 (Dropout)	(None, 60, 50)	0
lstm_17 (LSTM)	(None, 60, 50)	20,200
dropout_17 (Dropout)	(None, 60, 50)	0
lstm_18 (LSTM)	(None, 60, 50)	20,200
dropout_18 (Dropout)	(None, 60, 50)	0
lstm_19 (LSTM)	(None, 50)	20,200
dropout_19 (Dropout)	(None, 50)	0
dense_4 (Dense)	(None, 1)	51

```
Total params: 71,051 (277.54 KB)
Trainable params: 71,051 (277.54 KB)
Non-trainable params: 0 (0.00 B)
None
```

[28]
```
print_separator("STEP 5: Training the RNN")

epochs = 20
batch_size = 32
history = regressor.fit(X_train, y_train, epochs=epochs, batch_size=batch_size, verbose=1)

print(f"\nModel trained for {epochs} epochs with batch size {batch_size}.")
```

```
----------------------------------------------------------------------------------------------------
                                        STEP 5: Training the RNN
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Epoch 1/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 155ms/step - loss: 0.0025
Epoch 2/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 105ms/step - loss: 0.0024
Epoch 3/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 5s 119ms/step - loss: 0.0021
Epoch 4/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 147ms/step - loss: 0.0021
Epoch 5/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 5s 139ms/step - loss: 0.0020
Epoch 6/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 11s 145ms/step - loss: 0.0025
Epoch 7/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 106ms/step - loss: 0.0021
Epoch 8/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 5s 141ms/step - loss: 0.0021
Epoch 9/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 9s 108ms/step - loss: 0.0022
Epoch 10/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 7s 146ms/step - loss: 0.0022
Epoch 11/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 9s 124ms/step - loss: 0.0022
Epoch 12/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 5s 130ms/step - loss: 0.0016
Epoch 13/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 104ms/step - loss: 0.0016
Epoch 14/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 111ms/step - loss: 0.0019
Epoch 15/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 5s 119ms/step - loss: 0.0017
Epoch 16/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 5s 105ms/step - loss: 0.0017
Epoch 17/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 7s 154ms/step - loss: 0.0018
Epoch 18/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 104ms/step - loss: 0.0016
Epoch 19/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 4s 104ms/step - loss: 0.0015
Epoch 20/20
38/38 ━━━━━━━━━━━━━━━━━━━━ 5s 142ms/step - loss: 0.0018

Model trained for 20 epochs with batch size 32.
```

[29]
```
print_separator("STEP 6: Preparing the Test Data")

test_start_date = "2020-01-01"
test_end_date = "2023-01-01"

df_test = yf.download(ticker, start=test_start_date, end=test_end_date)
real_stock_price = df_test['Open'].values.reshape(-1, 1)

print(f"Fetched test data with {len(df_test)} rows from {test_start_date} to {test_end_date}.")
print(f"\nSample test data \n\n{df_test.head()}")

# Combine train and test sets for continuity
dataset_total = pd.concat((df['Open'], df_test['Open']), axis=0)
inputs = dataset_total[len(dataset_total) - len(df_test) - 60].values.reshape(-1, 1)
inputs = sc.transform(inputs)

X_test = []
for i in range(60, len(inputs)):
    X_test.append(inputs[i-60, 0])

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

print(f"Prepared test data with {X_test.shape[0]} samples.")
```

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----------------------------------------------------------------------------------------------------
                                        STEP 6: Preparing the Test Data
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[*********************100%***********************]  1 of 1 completedFetched test data with 756 rows from 2020-01-01 to 2023-01-01.

Sample test data :

Price                  Adj Close     Close      High       Low  \
Ticker                      AAPL      AAPL      AAPL      AAPL
Date
2020-01-02 00:00:00+00:00  72.796821  75.087502  75.150002  73.797501
2020-01-03 00:00:00+00:00  72.088295  74.357498  75.144997  74.125000
2020-01-06 00:00:00+00:00  72.662712  74.949997  74.989998  73.187500
2020-01-07 00:00:00+00:00  72.320976  74.597504  75.224998  74.370002
2020-01-08 00:00:00+00:00  73.484352  75.797501  76.110001  74.290001

Price                   Open    Volume
Ticker                  AAPL      AAPL
Date
2020-01-02 00:00:00+00:00  74.059998  135480400
2020-01-03 00:00:00+00:00  74.287498  146322800
2020-01-06 00:00:00+00:00  73.447502  118387200
2020-01-07 00:00:00+00:00  74.959999  108872000
2020-01-08 00:00:00+00:00  74.290001  132160200
Prepared test data with 756 samples.
```

[33]
```
print_separator("STEP 7: Predicting Stock Prices")

# Predict stock prices
predicted_stock_price = regressor.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)

print(f"\nPredicted stock prices for {len(predicted_stock_price)} test samples.")
```

```
----------------------------------------------------------------------------------------------------
                                        STEP 7: Predicting Stock Prices
----------------------------------------------------------------------------------------------------

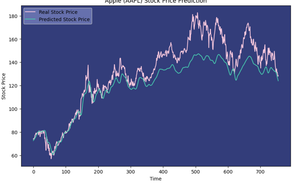

24/24 ━━━━━━━━━━━━━━━━━━━━ 1s 50ms/step

Predicted stock prices for 756 test samples.
```

[34]
```
print_separator("STEP 8: Visualizing the Results")

plt.figure(figsize=(10, 6))
plt.gca().set_facecolor('#333d79')
plt.plot(real_stock_price, color='#facad4', label='Real Stock Price')
plt.plot(predicted_stock_price, color='#4dc9b0', label='Predicted Stock Price')
plt.title(f'Apple {{ticker}} Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('Stock Price')
plt.legend(facecolor='#737d9f')
plt.show()
```

```
----------------------------------------------------------------------------------------------------
                                        STEP 8: Visualizing the Results
----------------------------------------------------------------------------------------------------
```



As seen here, the prediction got more accurate for time nearest to that of trained dataset, while less accurate for farther future time