Google Stock Price Prediction using RNN - LSTM

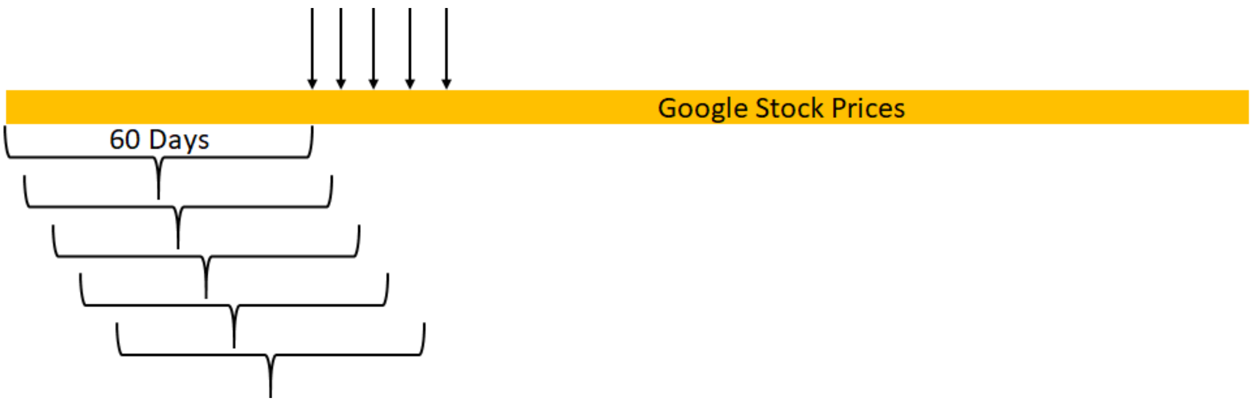
Watch Full Video Here: https://youtu.be/arydWPLDnEc

What is RNN

Ref- https://colah.github.io/posts/2015-08-Understanding-LSTMs/

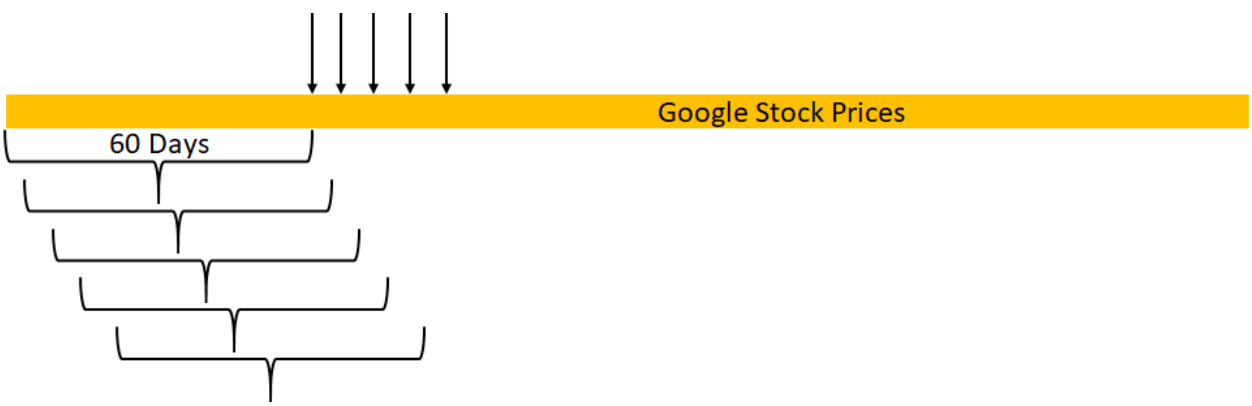
Download Dataset- https://finance.yahoo.com/quote/GOOG/history/

Recurrent Neural Networks are the first of its kind State of the Art algorithms that can Memorize/remember previous inputs in memory, When a huge set of Sequential data is given to it. Recurrent Neural Networks are the first of its kind State of the Art algorithms that can Memorize/remember previous inputs in memory, When a huge set of Sequential data is given to it.



These loops make recurrent neural networks seem kind of mysterious. However, if you think a bit more, it turns out that they aren't all that different than a normal neural network. A recurrent neural network can be thought of as multiple copies of the same network, each passing a message to a successor.

Different types of RNN's



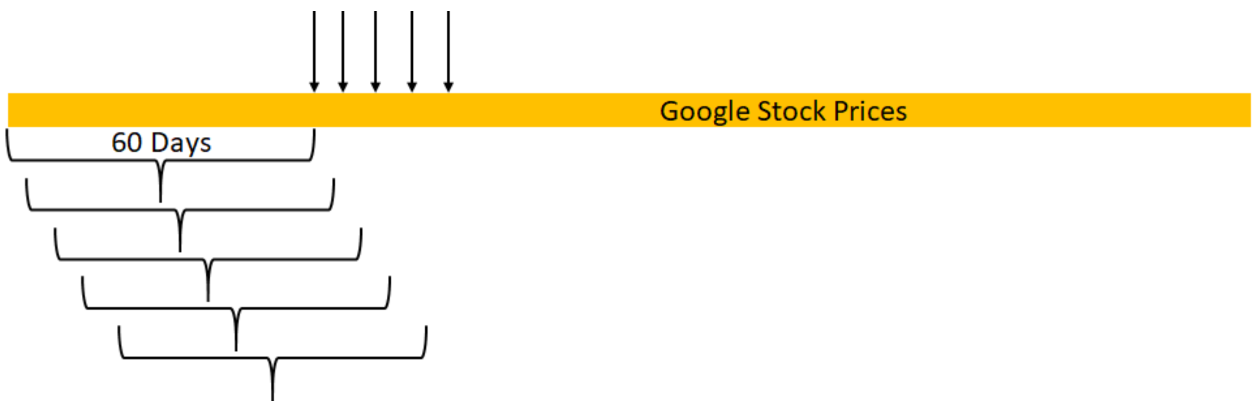
Different types of Recurrent Neural Networks.

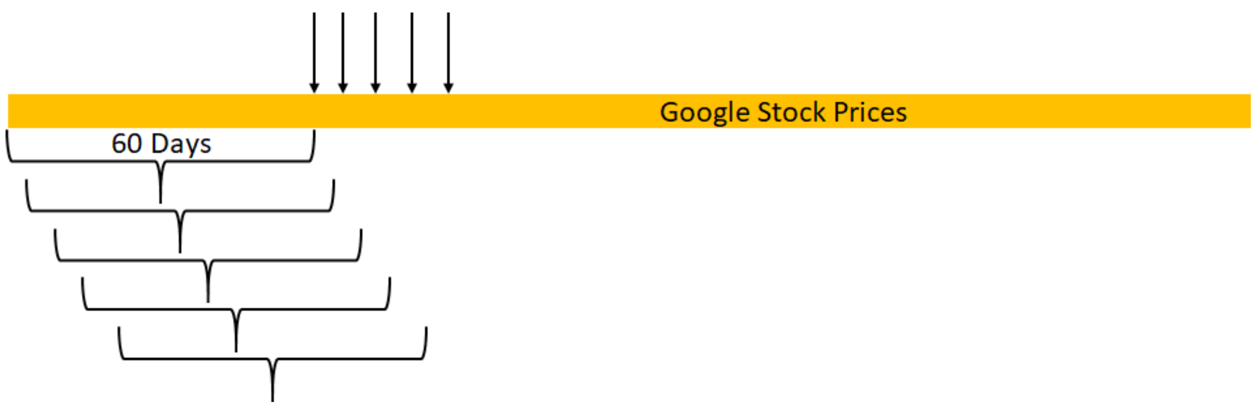
- Image Classification

- Sequence output (e.g. image captioning takes an image and outputs a sentence of words).
- Sequence input (e.g. sentiment analysis where a given sentence is classified as expressing positive or negative sentiment).
- Sequence input and sequence output (e.g. Machine Translation: an RNN reads a sentence in English and then outputs a sentence in French).
- Synced sequence input and output (e.g. video classification where we wish to label each frame of the video)

The Problem of Long-Term Dependencies

Vanishing Gradient

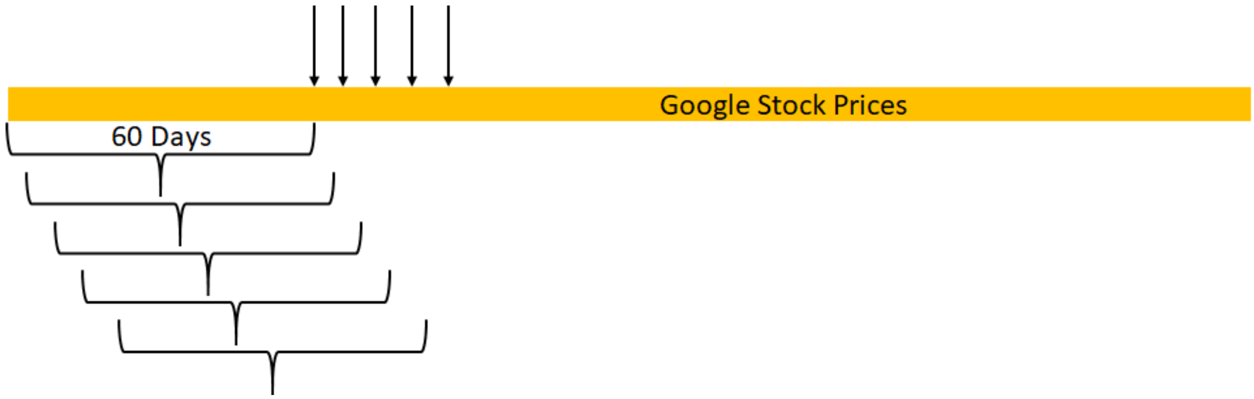




If the partial derivation of Error is less than 1, then when it get multiplied with the Learning rate which is also very less. then Multiplying learning rate with partial derivation of Error wont be a big change when compared with previous iteration.

Exploding Gradient

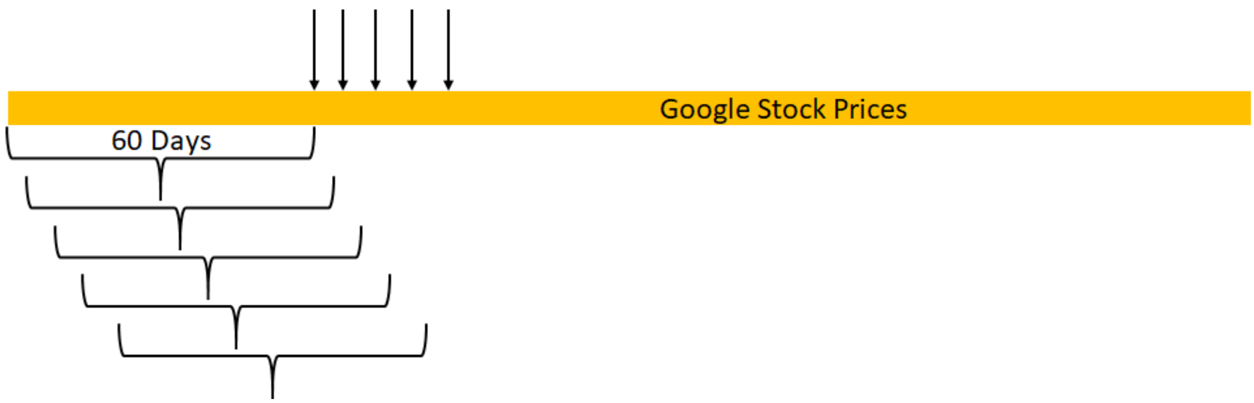
We speak of Exploding Gradients when the algorithm assigns a stupidly high importance to the weights, without much reason. But fortunately, this problem can be easily solved if you truncate or squash the gradients

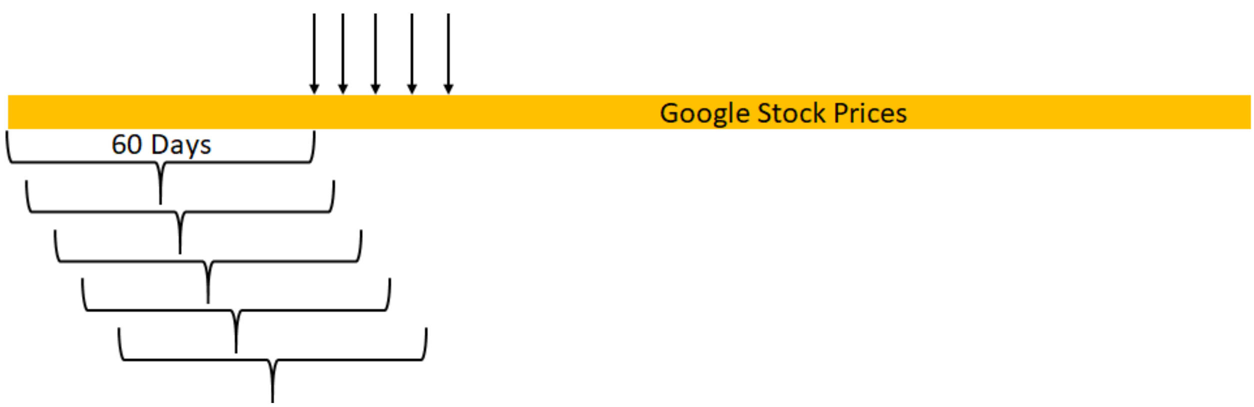


Long Short Term Memory (LSTM) Networks

Long Short Term Memory networks – usually just called "LSTMs" – are a special kind of RNN, capable of learning long-term dependencies.

LSTMs are explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is practically their default behavior, not something they struggle to learn!





Steps to build stock prediction model

- Data Preprocessing
- Building the RNN
- Making the prediction and visualization

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

data = pd.read_csv('GOOG.csv', date_parser = True)
data.tail()

            Date         Open         High          Low
Close  \
3804  2019-09-30  1220.969971  1226.000000  1212.300049  1219.000000

3805  2019-10-01  1219.000000  1231.229980  1203.579956  1205.099976

3806  2019-10-02  1196.979980  1196.979980  1171.290039  1176.630005

3807  2019-10-03  1180.000000  1189.060059  1162.430054  1187.829956

3808  2019-10-04  1191.890015  1211.439941  1189.170044  1209.000000
```

```
        Adj Close   Volume
3804  1219.000000  1404100
3805  1205.099976  1273500
3806  1176.630005  1615100
3807  1187.829956  1621200
3808  1209.000000  1021092
```

```
data_training = data[data['Date']<'2019-01-01'].copy()
data_test = data[data['Date']>='2019-01-01'].copy()

data_training = data_training.drop(['Date', 'Adj Close'], axis = 1)

scaler = MinMaxScaler()
data_training = scaler.fit_transform(data_training)
data_training
```

```
array([[3.30294890e-04, 9.44785459e-04, 0.00000000e+00, 1.34908021e-
04,
        5.43577404e-01],
       [7.42148227e-04, 2.98909923e-03, 1.88269054e-03, 3.39307537e-
03,
        2.77885613e-01],
       [4.71386886e-03, 4.78092896e-03, 5.42828241e-03, 3.83867225e-
03,
        2.22150736e-01],
       ...,
       [7.92197108e-01, 8.11970141e-01, 7.90196475e-01, 8.15799920e-
01,
        2.54672037e-02],
       [8.18777193e-01, 8.21510648e-01, 8.20249255e-01, 8.10219301e-
01,
        1.70463908e-02],
       [8.19874096e-01, 8.19172449e-01, 8.12332341e-01, 8.09012935e-
01,
        1.79975186e-02]])
```

```
# create RNN with 60 timesteps, i.e. look 60 previous time steps

data_training[0:10]
```

```
array([[3.30294890e-04, 9.44785459e-04, 0.00000000e+00, 1.34908021e-
04,
        5.43577404e-01],
       [7.42148227e-04, 2.98909923e-03, 1.88269054e-03, 3.39307537e-
03,
        2.77885613e-01],
       [4.71386886e-03, 4.78092896e-03, 5.42828241e-03, 3.83867225e-
03,
        2.22150736e-01],
       [4.91367646e-03, 4.01532941e-03, 3.15578542e-03, 1.98678849e-
03,
```

```
        1.85522018e-01],
       [2.35285614e-03, 2.54928676e-03, 3.28434064e-03, 2.44873974e-
03,
        1.11762967e-01],
       [2.34877785e-03, 2.52892558e-03, 3.60779701e-03, 3.22955376e-
03,
        8.62763771e-02],
       [3.63326671e-03, 2.80177162e-03, 4.03492722e-03, 2.51005881e-
03,
        7.55243925e-02],
       [2.48334262e-03, 1.52712947e-03, 2.50886935e-03, 8.17608079e-
04,
        6.31682127e-02],
       [1.26817570e-03, 8.02253103e-04, 2.57107531e-03, 9.64778600e-
04,
        5.97732318e-02],
       [1.43128522e-03, 5.00900100e-04, 1.53849690e-03, 9.81131336e-
05,
        1.11151095e-01]])
```

```
X_train = []
y_train = []

for i in range(60, data_training.shape[0]):
    X_train.append(data_training[i-60:i])
    y_train.append(data_training[i, 0])

X_train, y_train = np.array(X_train), np.array(y_train)

X_train.shape
```

```
(3557, 60, 5)
```

Building LSTM

```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout

regressior = Sequential()

regressior.add(LSTM(units = 60, activation = 'relu', return_sequences
= True, input_shape = (X_train.shape[1], 5)))
regressior.add(Dropout(0.2))

regressior.add(LSTM(units = 60, activation = 'relu', return_sequences
= True))
regressior.add(Dropout(0.2))

regressior.add(LSTM(units = 80, activation = 'relu', return_sequences
= True))
regressior.add(Dropout(0.2))
```

```
regressor.add(LSTM(units = 120, activation = 'relu'))
regressor.add(Dropout(0.2))

regressor.add(Dense(units = 1))

regressor.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_5 (LSTM)                (None, 60, 60)            15840     
_________________________________________________________________
dropout_4 (Dropout)          (None, 60, 60)            0         
_________________________________________________________________
lstm_6 (LSTM)                (None, 60, 60)            29040     
_________________________________________________________________
dropout_5 (Dropout)          (None, 60, 60)            0         
_________________________________________________________________
lstm_7 (LSTM)                (None, 60, 80)            45120     
_________________________________________________________________
dropout_6 (Dropout)          (None, 60, 80)            0         
_________________________________________________________________
lstm_8 (LSTM)                (None, 120)               96480     
_________________________________________________________________
dropout_7 (Dropout)          (None, 120)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 121       
=================================================================
Total params: 186,601
Trainable params: 186,601
Non-trainable params: 0
_________________________________________________________________
```

```
regressor.compile(optimizer='adam', loss = 'mean_squared_error')

regressor.fit(X_train, y_train, epochs=50, batch_size=32)
```

```
Train on 3557 samples
Epoch 1/50
3557/3557 [==============================] - 16s 5ms/sample - loss:
0.0137
Epoch 2/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0022
Epoch 3/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0018
Epoch 4/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
```

```
0.0016
Epoch 5/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0016
Epoch 6/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0016
Epoch 7/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0014
Epoch 8/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0016
Epoch 9/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0013
Epoch 10/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0013
Epoch 11/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0013
Epoch 12/50
3557/3557 [==============================] - 12s 3ms/sample - loss:
0.0013
Epoch 13/50
3557/3557 [==============================] - 17s 5ms/sample - loss:
0.0013
Epoch 14/50
3557/3557 [==============================] - 18s 5ms/sample - loss:
0.0011
Epoch 15/50
3557/3557 [==============================] - 14s 4ms/sample - loss:
0.0012
Epoch 16/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
9.7986e-04
Epoch 17/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
0.0011
Epoch 18/50
3557/3557 [==============================] - 14s 4ms/sample - loss:
0.0010
Epoch 19/50
3557/3557 [==============================] - 15s 4ms/sample - loss:
8.0842e-04
Epoch 20/50
3557/3557 [==============================] - 14s 4ms/sample - loss:
9.6403e-04
```

```
Epoch 21/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
9.2826e-04
Epoch 22/50
3557/3557 [==============================] - 14s 4ms/sample - loss:
9.3406e-04
Epoch 23/50
3557/3557 [==============================] - 14s 4ms/sample - loss:
9.3298e-04
Epoch 24/50
3557/3557 [==============================] - 14s 4ms/sample - loss:
8.5449e-04
Epoch 25/50
3557/3557 [==============================] - 14s 4ms/sample - loss:
9.3350e-04
Epoch 26/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
8.9023e-04
Epoch 27/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
9.0078e-04
Epoch 28/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
8.7865e-04
Epoch 29/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
7.7264e-04
Epoch 30/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
6.7656e-04
Epoch 31/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
8.1103e-04
Epoch 32/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
8.3787e-04
Epoch 33/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
7.0893e-04
Epoch 34/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
7.5235e-04
Epoch 35/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
7.4276e-04
Epoch 36/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
7.5183e-04
Epoch 37/50
```

```
3557/3557 [==============================] - 13s 4ms/sample - loss:
7.6802e-04
Epoch 38/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
6.9164e-04
Epoch 39/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
6.8079e-04
Epoch 40/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
6.7066e-04
Epoch 41/50
3557/3557 [==============================] - 14s 4ms/sample - loss:
7.2075e-04
Epoch 42/50
3557/3557 [==============================] - 14s 4ms/sample - loss:
7.1259e-04
Epoch 43/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
7.1577e-04
Epoch 44/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
6.5169e-04
Epoch 45/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
6.5112e-04
Epoch 46/50
3557/3557 [==============================] - 13s 4ms/sample - loss:
6.0908e-04
Epoch 47/50
3557/3557 [==============================] - 15s 4ms/sample - loss:
6.6632e-04
Epoch 48/50
3557/3557 [==============================] - 15s 4ms/sample - loss:
6.9701e-04
Epoch 49/50
3557/3557 [==============================] - 16s 4ms/sample - loss:
6.2277e-04
Epoch 50/50
3557/3557 [==============================] - 16s 4ms/sample - loss:
6.4571e-04

<tensorflow.python.keras.callbacks.History at 0x230c796f940>
```

Prepare test dataset

```
data_test.head()

            Date         Open         High          Low
Close  \
```

```
3617  2019-01-02  1016.570007  1052.319946  1015.710022  1045.849976

3618  2019-01-03  1041.000000  1056.979980  1014.070007  1016.059998

3619  2019-01-04  1032.589966  1070.839966  1027.417969  1070.709961

3620  2019-01-07  1071.500000  1074.000000  1054.760010  1068.390015

3621  2019-01-08  1076.109985  1084.560059  1060.530029  1076.280029


        Adj Close   Volume
3617  1045.849976  1532600
3618  1016.059998  1841100
3619  1070.709961  2093900
3620  1068.390015  1981900
3621  1076.280029  1764900
```

```
data_training.tail(60)
```

```
            Date         Open         High          Low
Close  \
3557  2018-10-04  1195.329956  1197.510010  1155.576050  1168.189941

3558  2018-10-05  1167.500000  1173.500000  1145.119995  1157.349976

3559  2018-10-08  1150.109985  1168.000000  1127.364014  1148.969971

3560  2018-10-09  1146.150024  1154.349976  1137.572021  1138.819946

3561  2018-10-10  1131.079956  1132.170044  1081.130005  1081.219971

3562  2018-10-11  1072.939941  1106.400024  1068.270020  1079.319946

3563  2018-10-12  1108.000000  1115.000000  1086.401978  1110.079956

3564  2018-10-15  1108.910034  1113.446045  1089.000000  1092.250000

3565  2018-10-16  1104.589966  1124.219971  1102.500000  1121.280029

3566  2018-10-17  1126.459961  1128.989990  1102.189941  1115.689941

3567  2018-10-18  1121.839966  1121.839966  1077.089966  1087.969971

3568  2018-10-19  1093.369995  1110.359985  1087.750000  1096.459961

3569  2018-10-22  1103.060059  1112.229980  1091.000000  1101.160034

3570  2018-10-23  1080.890015  1107.890015  1070.000000  1103.689941

3571  2018-10-24  1104.250000  1106.119995  1048.739990  1050.709961
```

3572	2018-10-25	1071.790039	1110.979980	1069.550049	1095.569946
3573	2018-10-26	1037.030029	1106.530029	1034.089966	1071.469971
3574	2018-10-29	1082.469971	1097.040039	995.830017	1020.080017
3575	2018-10-30	1008.460022	1037.489990	1000.750000	1036.209961
3576	2018-10-31	1059.810059	1091.939941	1057.000000	1076.770020
3577	2018-11-01	1075.800049	1083.974976	1062.459961	1070.000000
3578	2018-11-02	1073.729980	1082.974976	1054.609985	1057.790039
3579	2018-11-05	1055.000000	1058.469971	1021.239990	1040.089966
3580	2018-11-06	1039.479980	1064.344971	1038.069946	1055.810059
3581	2018-11-07	1069.000000	1095.459961	1065.900024	1093.390015
3582	2018-11-08	1091.380005	1093.270020	1072.204956	1082.400024
3583	2018-11-09	1073.989990	1075.560059	1053.109985	1066.150024
3584	2018-11-12	1061.390015	1062.119995	1031.000000	1038.630005
3585	2018-11-13	1043.290039	1056.604980	1031.150024	1036.050049
3586	2018-11-14	1050.000000	1054.563965	1031.000000	1043.660034
3587	2018-11-15	1044.709961	1071.849976	1031.780029	1064.709961
3588	2018-11-16	1059.410034	1067.000000	1048.979980	1061.489990
3589	2018-11-19	1057.199951	1060.790039	1016.260010	1020.000000
3590	2018-11-20	1000.000000	1031.739990	996.020020	1025.760010
3591	2018-11-21	1036.760010	1048.560059	1033.469971	1037.609985
3592	2018-11-23	1030.000000	1037.589966	1022.398987	1023.880005
3593	2018-11-26	1038.349976	1049.310059	1033.910034	1048.619995
3594	2018-11-27	1041.000000	1057.579956	1038.489990	1044.410034
3595	2018-11-28	1048.760010	1086.839966	1035.760010	1086.229980
3596	2018-11-29	1076.079956	1094.244995	1076.000000	1088.300049
3597	2018-11-30	1089.069946	1095.569946	1077.880005	1094.430054

3598	2018-12-03	1123.140015	1124.650024	1103.665039	1106.430054
3599	2018-12-04	1103.119995	1104.420044	1049.979980	1050.819946
3600	2018-12-06	1034.260010	1071.199951	1030.770020	1068.729980
3601	2018-12-07	1060.010010	1075.260010	1028.500000	1036.579956
3602	2018-12-10	1035.050049	1048.449951	1023.289978	1039.550049
3603	2018-12-11	1056.489990	1060.599976	1039.839966	1051.750000
3604	2018-12-12	1068.000000	1081.650024	1062.790039	1063.680054
3605	2018-12-13	1068.069946	1079.760010	1053.930054	1061.900024
3606	2018-12-14	1049.979980	1062.599976	1040.790039	1042.099976
3607	2018-12-17	1037.510010	1053.150024	1007.900024	1016.530029
3608	2018-12-18	1026.089966	1049.479980	1021.440002	1028.709961
3609	2018-12-19	1033.989990	1062.000000	1008.049988	1023.010010
3610	2018-12-20	1018.130005	1034.219971	996.359985	1009.409973
3611	2018-12-21	1015.299988	1024.020020	973.690002	979.539978
3612	2018-12-24	973.900024	1003.539978	970.109985	976.219971
3613	2018-12-26	989.010010	1040.000000	983.000000	1039.459961
3614	2018-12-27	1017.150024	1043.890015	997.000000	1043.880005
3615	2018-12-28	1049.619995	1055.560059	1033.099976	1037.079956
3616	2018-12-31	1050.959961	1052.699951	1023.590027	1035.609985

	Adj Close	Volume
3557	1168.189941	2209500
3558	1157.349976	1184300
3559	1148.969971	1932400
3560	1138.819946	1308700
3561	1081.219971	2675700
3562	1079.319946	2949000
3563	1110.079956	2101300
3564	1092.250000	1372400
3565	1121.280029	1928500
3566	1115.689941	1467200
3567	1087.969971	2094500

3568	1096.459961	1267600
3569	1101.160034	1514200
3570	1103.689941	1848700
3571	1050.709961	1982400
3572	1095.569946	2545800
3573	1071.469971	4187600
3574	1020.080017	3880700
3575	1036.209961	3212700
3576	1076.770020	2529800
3577	1070.000000	1482000
3578	1057.790039	1839000
3579	1040.089966	2441400
3580	1055.810059	1233300
3581	1093.390015	2058400
3582	1082.400024	1488200
3583	1066.150024	1343200
3584	1038.630005	1471800
3585	1036.050049	1513700
3586	1043.660034	1565900
3587	1064.709961	1836100
3588	1061.489990	1658100
3589	1020.000000	1858600
3590	1025.760010	2449100
3591	1037.609985	1534300
3592	1023.880005	691500
3593	1048.619995	1942800
3594	1044.410034	1803200
3595	1086.229980	2475400
3596	1088.300049	1468900
3597	1094.430054	2580200
3598	1106.430054	1991200
3599	1050.819946	2345200
3600	1068.729980	2769200
3601	1036.579956	2101200
3602	1039.550049	1807700
3603	1051.750000	1394700
3604	1063.680054	1523800
3605	1061.900024	1329800
3606	1042.099976	1686600
3607	1016.530029	2385400
3608	1028.709961	2192500
3609	1023.010010	2479300
3610	1009.409973	2673500
3611	979.539978	4596000
3612	976.219971	1590300
3613	1039.459961	2373300
3614	1043.880005	2109800
3615	1037.079956	1414800
3616	1035.609985	1493300

```
past_60_days = data_training.tail(60)

df = past_60_days.append(data_test, ignore_index = True)
df = df.drop(['Date', 'Adj Close'], axis = 1)
df.head()
```

```
          Open         High          Low        Close   Volume
0  1195.329956  1197.510010  1155.576050  1168.189941  2209500
1  1167.500000  1173.500000  1145.119995  1157.349976  1184300
2  1150.109985  1168.000000  1127.364014  1148.969971  1932400
3  1146.150024  1154.349976  1137.572021  1138.819946  1308700
4  1131.079956  1132.170044  1081.130005  1081.219971  2675700
```

```
inputs = scaler.transform(df)
inputs
```

```
array([[0.93805611, 0.93755773, 0.92220906, 0.91781776, 0.0266752 ],
       [0.91527437, 0.91792904, 0.91350452, 0.90892169, 0.01425359],
       [0.90103881, 0.91343268, 0.89872289, 0.90204445, 0.02331778],
       ...,
       [0.93940683, 0.93712442, 0.93529076, 0.9247443 , 0.01947328],
       [0.92550693, 0.93064972, 0.92791493, 0.9339358 , 0.01954719],
       [0.93524016, 0.94894575, 0.95017564, 0.95130949, 0.01227612]])
```

```
X_test = []
y_test = []

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

X_test, y_test = np.array(X_test), np.array(y_test)
X_test.shape, y_test.shape
```

```
((192, 60, 5), (192,))
```

```
y_pred = regressior.predict(X_test)

scaler.scale_
```

```
array([8.18605127e-04, 8.17521128e-04, 8.32487534e-04, 8.20673293e-04,
       1.21162775e-08])
```

```
scale = 1/8.18605127e-04
scale
```

```
1221.5901990069017
```

```
y_pred = y_pred*scale
y_test = y_test*scale
```

Visualization

```
# Visualising the results
plt.figure(figsize=(14,5))
plt.plot(y_test, color = 'red', label = 'Real Google Stock Price')
plt.plot(y_pred, color = 'blue', label = 'Predicted Google Stock
Price')
plt.title('Google Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('Google Stock Price')
plt.legend()
plt.show()
```