

```
In [ ]: import datetime
import pandas as pd
import pandas_datareader.data as web
```

```
In [ ]: start = datetime.datetime(2004, 8, 19) # or start = '1/1/2016'
end = datetime.date.today()
df = web.DataReader('GOOG', 'yahoo', start, end)
print (df.head()) # print first rows of the prices data
```

```
In [1]: import time
import math
from keras.models import Sequential
from keras.layers.core import Dense, Dropout, Activation
from keras.layers.recurrent import LSTM
import numpy as np
import pandas as pd
import tensorflow as tf
import sklearn.preprocessing as prep
from keras import backend
```

Using TensorFlow backend.

```
In [2]: import os
s=os.getcwd()
s
```

```
Out[2]: '/Users/Yuffie/USA/SCU/COEN281DataMining/TermProject'
```

```
In [3]: df = pd.read_csv('/Users/Yuffie/USA/SCU/COEN281DataMining/TermProject/data/GOOG.csv')
df.head()
```

Out[3]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2004-08-19	49.676899	51.693783	47.669952	49.845802	49.845802	44994500
1	2004-08-20	50.178635	54.187561	49.925285	53.805050	53.805050	23005800
2	2004-08-23	55.017166	56.373344	54.172661	54.346527	54.346527	18393200
3	2004-08-24	55.260582	55.439419	51.450363	52.096165	52.096165	15361800
4	2004-08-25	52.140873	53.651051	51.604362	52.657513	52.657513	9257400

```
In [4]: # Data preparation
col_list = df.columns.tolist()
col_list
```

Out[4]: ['Date', 'Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume']

```
In [5]: col_list.remove('Close')
col_list.append('Close')
col_list.remove('Date')
col_list.remove('Volume')
col_list
```

Out[5]: ['Open', 'High', 'Low', 'Adj Close', 'Close']

```
In [6]: df = df[col_list]
df.head()
```

Out[6]:

	Open	High	Low	Adj Close	Close
0	49.676899	51.693783	47.669952	49.845802	49.845802
1	50.178635	54.187561	49.925285	53.805050	53.805050
2	55.017166	56.373344	54.172661	54.346527	54.346527
3	55.260582	55.439419	51.450363	52.096165	52.096165
4	52.140873	53.651051	51.604362	52.657513	52.657513

```
In [7]: # Save data
df.to_csv('GOOG-adjust.csv', index=False)
validate_df = pd.read_csv('GOOG-adjust.csv')
validate_df.head()
```

Out[7]:

	Open	High	Low	Adj Close	Close
0	49.676899	51.693783	47.669952	49.845802	49.845802
1	50.178635	54.187561	49.925285	53.805050	53.805050
2	55.017166	56.373344	54.172661	54.346527	54.346527
3	55.260582	55.439419	51.450363	52.096165	52.096165
4	52.140873	53.651051	51.604362	52.657513	52.657513

```
In [8]: # Standardization the dataset
def standard_scaler(X_train, X_test):
    train_samples, train_nx, train_ny = X_train.shape
    test_samples, test_nx, test_ny = X_test.shape

    X_train = X_train.reshape((train_samples, train_nx * train_ny))
    X_test = X_test.reshape((test_samples, test_nx * test_ny))

    preprocessor = prep.StandardScaler().fit(X_train)
    X_train = preprocessor.transform(X_train)
    X_test = preprocessor.transform(X_test)

    X_train = X_train.reshape((train_samples, train_nx, train_ny))
    X_test = X_test.reshape((test_samples, test_nx, test_ny))

    return X_train, X_test
```

```
In [9]: # Split the data to X_train, y_train, X_test, y_test
def preprocess_data(stock, seq_len):
    amount_of_features = len(stock.columns)
    data = stock.as_matrix()

    sequence_length = seq_len + 1
    result = []
    for index in range(len(data) - sequence_length):
        result.append(data[index : index + sequence_length])

    result = np.array(result)
    row = round(0.9 * result.shape[0])
    train = result[: int(row), :]
    y_test_org = result[int(row) :, -1][ : ,-1]

    train, result = standard_scaler(train, result)

    X_train = train[:, : -1]
    y_train = train[:, -1][: ,-1]
    X_test = result[int(row) :, : -1]
    y_test = result[int(row) :, -1][ : ,-1]

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

    return [X_train, y_train, X_test, y_test, y_test_org]
```

```

In [10]: # Build LSTM Neural Network
# LSTM --> Dropout --> LSTM --> Dropout --> Fully-Conneted(Dense)
def build_model(layers):
    model = Sequential()

    # By setting return_sequences to True we are able to stack another LSTM layer
    model.add(LSTM(
        return_sequences=True,
        input_shape=(None, 5), units=20))
    model.add(Dropout(0.4))

    model.add(LSTM(
        layers[2],
        return_sequences=False))
    model.add(Dropout(0.3))

    model.add(Dense(
        units=1))
    model.add(Activation("linear"))

    start = time.time()
    model.compile(loss="mse", optimizer="rmsprop", metrics=['accuracy'])
    print("Compilation Time : ", time.time() - start)
    return model

```

```

In [11]: window = 20
X_train, y_train, X_test, y_test, y_test_org = preprocess_data(df[:, -1], window)
print("X_train", X_train.shape)
print("y_train", y_train.shape)
print("X_test", X_test.shape)
print("y_test", y_test.shape)

X_train (2993, 20, 5)
y_train (2993,)
X_test (333, 20, 5)
y_test (333,)

```

```

In [12]: model = build_model([X_train.shape[2], window, 100, 1])

Compilation Time : 0.027528762817382812

```

```
In [13]: # Training the model
model.fit(
    X_train,
    y_train,
    batch_size=768,
    epochs=300,
    validation_split=0.1,
    verbose=0)
```

Out[13]: <keras.callbacks.History at 0x11a338f60>

```
In [14]: trainScore = model.evaluate(X_train, y_train, verbose=0)
print('Train Score: %.2f MSE (%.2f RMSE)' % (trainScore[0], math.sqrt(trainScore[0])))
print(model.metrics_names)
testScore = model.evaluate(X_test, y_test, verbose=0)
print('Test Score: %.2f MSE (%.2f RMSE)' % (testScore[0], math.sqrt(testScore[0])))
```

```
Train Score: 0.01 MSE (0.10 RMSE)
['loss', 'acc']
Test Score: 0.03 MSE (0.18 RMSE)
Test Accuracy: 0.0
```

```
In [15]: #Visualize the Prediction
diff = []
ratio = []
pred = model.predict(X_test)
for u in range(len(y_test)):
    pr = pred[u][0]
    ratio.append((y_test[u] / pr) - 1)
    diff.append(abs(y_test[u] - pr))
print('error_ratio', ratio)
#print('error_abs', diff)
#print(pred)
```



error\_ratio [0.1133188270722516, 0.12113117333001178, 0.12434312271378367, 0.11442692494278739, 0.1257696360  
1427349, 0.11864027114397868, 0.11005930226036575, 0.075574684509538859, 0.084678743835904458, 0.10894661668  
503991, 0.11055392153412047, 0.056963478914290544, 0.046109114754503411, 0.066633294650770392, 0.08816201648  
1074135, 0.10856129348853449, 0.13054266722684593, 0.1165475983346318, 0.12465535042704268, 0.13225768293636  
753, 0.11455260024952674, 0.12563889971341391, 0.11823949618952434, 0.14284994499788484, 0.1083994796314171  
6, 0.090535262817867723, 0.10001035004008019, 0.10948303129434866, 0.12223594338050647, 0.11856326514441684,  
0.13144598700601251, 0.15916624908582722, 0.16153487170182634, 0.14432027095464384, 0.15431753890243072, 0.1  
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9823435731, 0.10164919702920261, 0.10143304131299202, 0.1055631708226239, 0.10462790667290789, 0.08828725015  
6050101, 0.093981031494910106, 0.10969986917575847, 0.11725084849272149, 0.099319146574329054, 0.09850793309  
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0.15831727588603961, 0.15802949814080347, 0.15313531258879554, 0.15407437499206034, 0.15491660350933611, 0.1  
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0.13880652627899659, 0.12519887675323282, 0.11542357612988541, 0.12717126134501089, 0.15560366732458242, 0.14950994063135004, 0.15825699766686152, 0.16092780466168932, 0.15678487186743872, 0.17672980410378036, 0.16748271585781493, 0.15128635951276159, 0.13992194601888985, 0.13402770535358854, 0.12359198496382739, 0.13286655763769328, 0.14314819279481417, 0.14385677537929409, 0.1472155624118261, 0.14412771746223063, 0.14600565836431945, 0.15515498161762675, 0.14552306353655498, 0.14323712477653516, 0.1287130238205938, 0.14775701471718716, 0.13993042992392168, 0.14884767789061204, 0.14896264473076792, 0.14997815331664865, 0.15654611497504956, 0.15826037608391497, 0.16129701959532228, 0.15731200483823082, 0.16468057962750615, 0.16932265570901994, 0.16121146093794803, 0.16118715056978838, 0.17426556488530776, 0.16988807834810271, 0.16437299734156263, 0.168545655345477, 0.16420629049699786, 0.15415255493304492, 0.14625562883581655, 0.14824412991573288, 0.14783147407647657, 0.14487152841661688, 0.14720189798935057, 0.15077684008444869, 0.15922301510983949, 0.17163535703985344, 0.17448969680822612, 0.16481663483320075, 0.16620699535604455, 0.15631215185561831, 0.15579418302141956, 0.13425194250306927, 0.14070871267349783, 0.14097375400492251, 0.1694651206793869, 0.16774144292360349, 0.15962631227039359, 0.16405879742671026, 0.13633217644446538, 0.12478173982516316, 0.12187389479433608, 0.12337844400843889, 0.13647372502196609, 0.13451072261689601, 0.14951437865673878, 0.15769677022123463, 0.14749711406343735, 0.17411876538044169, 0.21378779971440998, 0.2245964789007675, 0.20409076825660999, 0.19522722592484176, 0.19897990728575565, 0.19832901769227562, 0.19633026924419261, 0.19885816535971834, 0.19911727333859308, 0.19143277624491772, 0.18650214048406299, 0.18718944083107969, 0.18296792730318256, 0.18697594490492264, 0.18956682048592599, 0.1929037796635511, 0.18842957203659116, 0.19392617715564708, 0.20673912009707363, 0.2016336967655632, 0.19749690021781729, 0.19965503247535432, 0.19879625021665781, 0.19465105537454064, 0.19661673568056282, 0.20144793500142799, 0.20349226538433562, 0.20285479695905617, 0.20798332458387869, 0.20984301497551594, 0.21301765046941279, 0.21094281539512894, 0.21018546408171712, 0.21108186815549135, 0.20709266282994254, 0.20797705657082366, 0.20349848680961746, 0.20338556181727641, 0.19615581794240855, 0.19322983427300011, 0.19674655598703406, 0.19898090268026247, 0.19174611833834221, 0.19391141030298531]

```
In [16]: # Scale the representation back  
y_test = y_test_org  
pred_org = []  
for u in range(len(y_test)):  
    pred_org.append(y_test[u]/(ratio[u] + 1))  
    print(ratio[u])  
#print(pred_org)  
#print(y_test)
```

0.113318827072  
0.12113117333  
0.124343122714  
0.114426924943  
0.125769636014  
0.118640271144  
0.11005930226  
0.0755746845095  
0.0846787438359  
0.108946616685  
0.110553921534  
0.0569634789143  
0.0461091147545  
0.0666332946508  
0.0881620164811  
0.108561293489  
0.130542667227  
0.116547598335  
0.124655350427  
0.132257682936  
0.11455260025  
0.125638899713  
0.11823949619  
0.142849944998  
0.108399479631  
0.0905352628179  
0.10001035004  
0.109483031294  
0.122235943381  
0.118563265144  
0.131445987006  
0.159166249086  
0.161534871702  
0.144320270955  
0.154317538902  
0.139629866568  
0.15097689496  
0.227470575812  
0.198261873755  
0.192510290155  
0.171902726517  
0.177284461773

0.161456400269  
0.142861618751  
0.123726851514  
0.109036998234  
0.101649197029  
0.101433041313  
0.105563170823  
0.104627906673  
0.0882872501561  
0.0939810314949  
0.109699869176  
0.117250848493  
0.0993191465743  
0.0985079330926  
0.0971845361938  
0.106942490898  
0.106605462744  
0.115194293414  
0.123129471771  
0.128729146443  
0.120646258735  
0.117214952274  
0.0971582441139  
0.101308044633  
0.124384714345  
0.130719887808  
0.128825914297  
0.141465567535  
0.133880212861  
0.133879653114  
0.130146092548  
0.123852126713  
0.118581056871  
0.126531175853  
0.126215543653  
0.123713775778  
0.127440167528  
0.136122564414  
0.120812609971  
0.118409880877  
0.106361713466  
0.104821174023

0.10867015964  
0.0979274417862  
0.110706718454  
0.108021627706  
0.0966219681919  
0.0985564468257  
0.0980975060024  
0.0891524455148  
0.0925704893723  
0.0913485102234  
0.109491575572  
0.118457988983  
0.106298508495  
0.0992573868195  
0.101914685848  
0.103587410774  
0.0913884122734  
0.0697532071036  
0.0780626205068  
0.0870044262865  
0.112208021643  
0.10970732199  
0.110112498059  
0.1140910882  
0.128041061283  
0.122573958265  
0.114265621794  
0.114143106867  
0.121350055788  
0.111331217971  
0.119620646194  
0.112473685693  
0.114631963107  
0.0950713128786  
0.0918521120045  
0.107952285955  
0.12432894897  
0.123986502684  
0.124820223285  
0.124735780248  
0.135346510916  
0.137611033423

0.138913922899  
0.127430728527  
0.115183254389  
0.113994470467  
0.10560213337  
0.11955340205  
0.0921511738787  
0.098113292713  
0.121766312959  
0.106365982981  
0.10608306096  
0.128386460918  
0.149985341414  
0.159552746599  
0.150223960795  
0.153802397968  
0.14935887052  
0.171737658929  
0.169699454672  
0.162336347991  
0.167281571599  
0.164516426341  
0.161463390679  
0.156512978009  
0.146467666772  
0.14908917617  
0.148821240622  
0.141604917211  
0.140775140026  
0.135613755271  
0.13824921265  
0.14406473073  
0.146409076918  
0.14518105076  
0.142319591751  
0.142273881074  
0.131693031174  
0.145273169621  
0.165999391619  
0.174526557684  
0.18236316815  
0.184864291703

0.182341120768  
0.164851257405  
0.157960798516  
0.153369149003  
0.152877013953  
0.153593181921  
0.14922872972  
0.156321336672  
0.156003278516  
0.160241326514  
0.16772365789  
0.164368606872  
0.161915756028  
0.161245372004  
0.156202854347  
0.158863829461  
0.158317275886  
0.158029498141  
0.153135312589  
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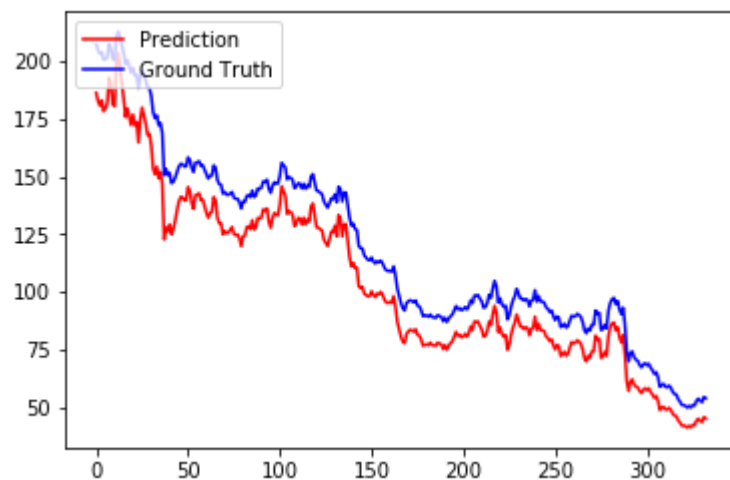
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```
In [17]: import matplotlib.pyplot as plt2

plt2.plot(pred_org, color='red', label='Prediction')
plt2.plot(y_test, color='blue', label='Ground Truth')
plt2.legend(loc='upper left')
plt2.show()
```



```
In [ ]:
```