

```
In [1]: import datetime
import pandas as pd
import pandas_datareader.data as web
```

```
In [2]: start = datetime.datetime(1999, 1, 22) # or start = '1/1/2016'
end = datetime.date.today()
df = web.DataReader('NVDA', 'yahoo', start, end)
print (df.head()) # print first rows of the prices data
```

	Open	High	Low	Close	Adj Close	Volume
Date						
1999-01-22	1.750000	1.953125	1.552083	1.640625	1.521034	67867200
1999-01-25	1.770833	1.833333	1.640625	1.812500	1.680380	12762000
1999-01-26	1.833333	1.869792	1.645833	1.671875	1.550005	8580000
1999-01-27	1.677083	1.718750	1.583333	1.666667	1.545177	6109200
1999-01-28	1.666667	1.677083	1.651042	1.661458	1.540348	5688000

```
In [3]: 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 [4]: #import os
#s=os.getcwd()
#s
```

```
In [5]: #df = pd.read_csv('/Users/Yuffie/USA/SCU/COEN281DataMining/TermProject/data/GOOG.csv')
#df.head()
```

```
In [6]: # Data preparation
col_list = df.columns.tolist()
col_list
```

```
Out[6]: ['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume']
```

```
In [7]: col_list.remove('Close')
col_list.append('Close')
#col_list.remove('Date')
col_list.remove('Volume')
col_list
```

```
Out[7]: ['Open', 'High', 'Low', 'Adj Close', 'Close']
```

```
In [8]: df = df[col_list]
df.head()
```

```
Out[8]:
```

	Open	High	Low	Adj Close	Close
Date					
1999-01-22	1.750000	1.953125	1.552083	1.521034	1.640625
1999-01-25	1.770833	1.833333	1.640625	1.680380	1.812500
1999-01-26	1.833333	1.869792	1.645833	1.550005	1.671875
1999-01-27	1.677083	1.718750	1.583333	1.545177	1.666667
1999-01-28	1.666667	1.677083	1.651042	1.540348	1.661458

```
In [9]: # Save data
df.to_csv('NVDA-adjust.csv', index=False)
validate_df = pd.read_csv('NVDA-adjust.csv')
validate_df.head()
```

Out[9]:

	Open	High	Low	Adj Close	Close
0	1.750000	1.953125	1.552083	1.521034	1.640625
1	1.770833	1.833333	1.640625	1.680380	1.812500
2	1.833333	1.869792	1.645833	1.550005	1.671875
3	1.677083	1.718750	1.583333	1.545177	1.666667
4	1.666667	1.677083	1.651042	1.540348	1.661458

```
In [10]: # 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 [11]: # 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(0.95 * 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 [12]: # 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 [13]: 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 (4492, 20, 5)
y_train (4492,)
X_test (236, 20, 5)
y_test (236,)
```

```
In [14]: model = build_model([X_train.shape[2], window, 100, 1])

Compilation Time : 0.056817054748535156
```

```
In [15]: # Training the model
model.fit(
    X_train,
    y_train,
    batch_size=768,
    epochs=300,
    validation_split=0.1,
    verbose=0)
```

Out[15]: <keras.callbacks.History at 0x11cc537b8>

```
In [16]: 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 (0.11 RMSE)
['loss', 'acc']
Test Score: 0.01 MSE (0.08 RMSE)
```

```
In [17]: #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 [0.1342657551982076, 0.14280182793684548, 0.14155707060567391, 0.13226028506682619, 0.14638416915918362, 0.14826904824697129, 0.15198380230167596, 0.16055808023283591, 0.16175237413459076, 0.15260626430529212, 0.1409174508463511, 0.1355999442226572, 0.13488999796526135, 0.133861098323665, 0.12975807316055477, 0.13986157869723614, 0.13374830113607517, 0.13963565595481953, 0.13529156931333541, 0.14806061670808401, 0.15346215104857186, 0.13872752048749626, 0.1306557710728673, 0.1300561065286765, 0.12517925851240341, 0.11249662928796167, 0.11742069758461171, 0.1575607899215119, 0.15620886739895612, 0.15791945919117389, 0.16561517631150613, 0.15436377836641224, 0.15499472931013791, 0.15764907403292705, 0.14979355251242743, 0.14276613609201738, 0.14316539176240894, 0.13670961235978019, 0.1443809610045923, 0.15411871305470082, 0.15693943212006034, 0.15747270421858017, 0.15837702672402054, 0.14761439397256826, 0.13931122385385986, 0.14689072725486008, 0.14033113724236479, 0.14183536997623314, 0.14475855984631014, 0.1460445136233508, 0.14054154087000525, 0.134817448165647, 0.13456044784485299, 0.13359739982093966, 0.13212717521390549, 0.13269458276629598, 0.13185028785918296, 0.13850654567411591, 0.13251589985778933, 0.14513292515875831, 0.15178810224763684, 0.14985340318122664, 0.145255933272469, 0.14230710477816078, 0.13366832274967688, 0.14184791521005424, 0.14621451932774843, 0.13648575466868418, 0.12878987718951374, 0.13285342675898226, 0.12491969617509069, 0.1248105977277858, 0.12852867255030609, 0.12915623427485068, 0.13291303120577203, 0.13165962855361868, 0.12987499610866204, 0.13415294353508367, 0.13415919611081151, 0.13537887210621968, 0.13598975640959421, 0.13782120874864745, 0.13633252433101961, 0.13065272661438465, 0.1416137297476574, 0.1404322704668961, 0.14582780159014597, 0.14215903985889455, 0.13981139991903491, 0.13779289551589358, 0.12986409975467161, 0.13012937308395922, 0.15316344800127868, 0.15234384843698812, 0.1483932478950214, 0.14078930050578631, 0.13797680922250644, 0.14215477739189275, 0.14713191103418888, 0.14671533128953973, 0.14437838486231414, 0.14240855126858154, 0.14220498742243071, 0.14098703972168103, 0.13799047056433955, 0.13871272467707785, 0.13908130749190417, 0.1396676950005975, 0.1406458218655231, 0.14024578810340738, 0.14006491612634053, 0.13973820905583456, 0.13538154009765435, 0.13309668636519834, 0.13258857043120664, 0.13185537715040452, 0.13582063785107645, 0.13787481377521527, 0.1348913577087798, 0.13605846644410735, 0.14134947591807046, 0.14800254076224006, 0.14730724586758037, 0.14283716826526849, 0.14115689711097756, 0.14532817734006698, 0.13871560298298258, 0.14454656957719103, 0.14380067821001075, 0.14337116549683215, 0.14299775607157539, 0.14009829866956491, 0.14064910144145704, 0.13858721450718914, 0.14211045942028133, 0.13875657817740294, 0.13656038744884014, 0.13928325426057198, 0.13936585369257992, 0.13638023206211325, 0.13517252010561864, 0.13633723837651734, 0.13853646312046131, 0.14071504734412232, 0.14120212638699781, 0.14108558703380325, 0.14227918828381325, 0.13865711658827262, 0.13854854926079896, 0.13926453176153131, 0.13866171348179979, 0.1386074546575784, 0.13931470823983805, 0.13905539493811347, 0.13721891480640536, 0.13094320355178679, 0.12936434913525163, 0.13583054593189781, 0.14082057048600882, 0.13634216635863661, 0.1368613872219453, 0.13970025697770905, 0.14371663862161266, 0.14262185303917296, 0.14156247891052987, 0.13877158811305867, 0.13953692617091318, 0.13465773095274014, 0.13580750063257008, 0.13788799206397662, 0.13838961692983798, 0.13800709699663605, 0.14552144486130847, 0.14018818349960549, 0.13563010204042425, 0.13259308430757, 0.13539359224038905, 0.13513032041620954, 0.13272350473975014, 0.13715251275462248, 0.14014112664867939, 0.13776178656512528, 0.13454267849962287, 0.13164243870130465, 0.1318438956210759, 0.13557861877026989, 0.14368604679307539, 0.14058291940322487, 0.13710270951791914, 0.13434890665013333, 0.1409226712657845, 0.13281276065464231, 0.13694887870945704, 0.14493830683158127, 0.14485357376700914, 0.14228689452146659, 0.13534474982705014, 0.13308625391936779, 0.13491455858353185, 0.13729602910556937, 0.13856275934418627, 0.13593651287982711, 0.14055626733979776, 0.13870140407704046, 0.1345630434474645, 0.13381297321109975, 0.13806506561051313, 0.13957788716201058, 0.14403892108548777, 0.14094921487998957, 0.13368951580068744, 0.13368375176349123, 0.135497374269546, 0.13227723471317465, 0.13138844744430078, 0.14254790807200202, 0.147235902630451


```
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774978864722, 0.13481528016836641, 0.13562883131292347, 0.12954394049658768]
```

```
In [18]: # 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)
```

[3.3795721879394511, 3.2449484323059146, 3.2576119895844973, 3.413157779151383, 3.162116241241153, 3.0843529270487253, 2.9478131491216191, 2.7016459179457524, 2.5643734984567881, 2.6027968898886589, 2.7161982645643143, 2.7747817495332447, 2.7856955349577159, 2.8203780910447485, 2.9182132691265723, 2.7689765660908781, 2.8803791782776411, 2.7878058951552798, 2.8672880940786563, 2.6403222581502002, 2.5015272476664872, 2.6985533806054542, 2.8191604213680481, 2.839091777359096, 2.9439753487630473, 3.2069382558789981, 3.1974680688509949, 2.5781583360320584, 2.5721632862843458, 2.4739052248080875, 2.2430927918025518, 2.3100750820280505, 2.1915684424914041, 2.0425732227836986, 2.0746480920749617, 2.1193093875552038, 2.059340684177466, 2.1397654894028948, 1.9979867525870389, 1.8051288627717261, 1.6926841160659618, 1.5929101336732874, 1.4747642266622789, 1.5612099407345239, 1.6457311757691482, 1.4895342332124177, 1.575748430710521, 1.5371813189116168, 1.4650102290784857, 1.413376165362759, 1.4795603137021864, 1.569635717955576, 1.5791728007118082, 1.6126757174008746, 1.6607745500365287, 1.6829338013999386, 1.7302049758754334, 1.6377446463392711, 1.7613810104127343, 1.5554962754678039, 1.4108497881067898, 1.3860462521489023, 1.4007061246268617, 1.4088811960182503, 1.5436613733331015, 1.4048867442253878, 1.3177437334207345, 1.4619259354327405, 1.6057018552583082, 1.5631616219463047, 1.7408647094176142, 1.8058595856967385, 1.8045248202670026, 1.849648380448673, 1.8297229733457749, 1.8869781567884416, 1.9544932028813751, 1.9195673849896899, 1.9471102536334219, 1.9496064744394093, 1.9577271603478494, 1.9408435903815502, 1.9663038346239528, 2.0729176561737943, 1.8910511881082517, 1.8998646882492727, 1.7909174460177872, 1.824030566056178, 1.8369267057240584, 1.8493409550126754, 1.9821702455067673, 2.0001400316068678, 1.6169286350792595, 1.5819210580874461, 1.5828271398598148, 1.6572955226366188, 1.6796985531769799, 1.596033248805933, 1.4892210595552731, 1.4625103146689729, 1.465496921459049, 1.4680238502571537, 1.4454865966973598, 1.4470295827398141, 1.48745358048611, 1.4727884949872638, 1.4677398259490644, 1.4532745003350576, 1.4291973623624898, 1.4251313330460913, 1.4207892700563522, 1.4211965406879221, 1.49545940288404, 1.5444401356549136, 1.5727246826460828, 1.6151577638854764, 1.5774207126485713, 1.5654182502644638, 1.6337836986822758, 1.627520109759216, 1.5492406465405242, 1.4200386690064202, 1.3891222301091848, 1.4218998516355699, 1.419429706906004, 1.3187635036691601, 1.3996031983973944, 1.2787090004914781, 1.2658822709092248, 1.2481362509958749, 1.2303173759791175, 1.260856192555929, 1.2374164834884955, 1.2625295468667179, 1.1947907391485082, 1.2440472592196981, 1.2831108809567269, 1.2434721520764018, 1.243382005357377, 1.2970640973974943, 1.3259729013348145, 1.3200306646141835, 1.2946076368605948, 1.2601744873506047, 1.245944926953126, 1.2369431496098526, 1.2037337404928403, 1.2533035443329332, 1.2488488092344858, 1.2343489688261036, 1.2441509038431753, 1.2487842005457541, 1.2388657758843511, 1.2437208991727478, 1.2732086858109339, 1.3908010544297638, 1.4573091502845879, 1.3848166045838222, 1.3148430514020051, 1.39335936558064, 1.3927229984202918, 1.3481246411880481, 1.2750824380395109, 1.2763041386974099, 1.2706417973585873, 1.298914563236492, 1.2706187634176187, 1.3495259039166396, 1.3389883401483051, 1.3182316805006447, 1.3176508092593127, 1.3272474345601244, 1.1912330459821414, 1.2607567950650467, 1.3300255050356482, 1.3933733322809521, 1.3669999642479824, 1.3948468924867159, 1.46218383662881, 1.4106876448033236, 1.3704443805064717, 1.4145096267107575, 1.4782017739675164, 1.5464248601425152, 1.5737594264468564, 1.5410645912786678, 1.4117362055149065, 1.4521083665417172, 1.5023559311755199, 1.5519184526731902, 1.4425456180777336, 1.586206531573322, 1.5346266069416432, 1.4010947056520928, 1.3830004432708585, 1.3952274228512995, 1.4955078624872733, 1.5444543554797487, 1.5373774059059089, 1.5158392853581077, 1.5050044329457979, 1.5589189888003361, 1.4886744728168257, 1.5185429593823621, 1.5929410097021954, 1.6215566794874641, 1.5651565572346704, 1.5402264468040412, 1.4522740174115532, 1.4881617672865437, 1.6079508318576394, 1.6217415104874469, 1.609977302832615, 1.6927541605881748, 1.7493257991724684, 1.6046005485176256, 1.5254055386407406, 1.5182198335570514, 1.4676008033531931, 1.4465244071321266, 1.5383525378782315, 1.5299353020127544, 1.4415091386750971, 1.3206895624386648, 1.3379396121528708, 1.3988108223180988, 1.4535648665300509, 1.4086606067904155,

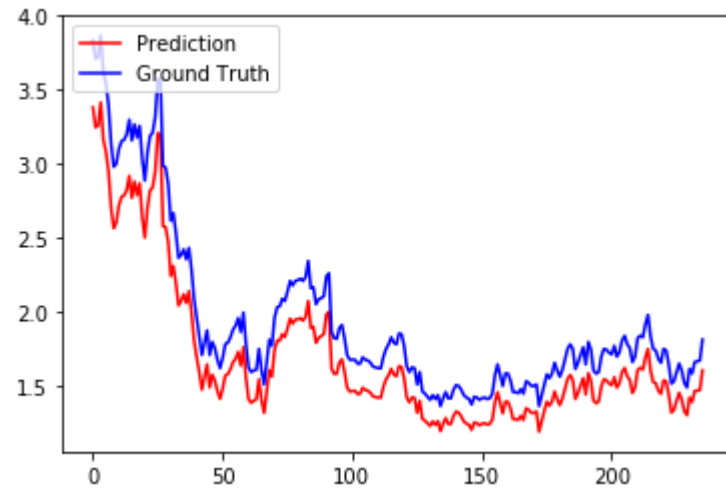
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[ 3.833333 3.708333 3.71875 3.864583 3.625 3.541667 3.395833
 3.135417 2.979167 3. 3.098958 3.151042 3.161458 3.197917
 3.296875 3.15625 3.265625 3.177083 3.255208 3.03125 2.885417
 3.072917 3.1875 3.208333 3.3125 3.567708 3.572917 2.984375
 2.973958 2.864583 2.614583 2.666667 2.53125 2.364583 2.385417
 2.421875 2.354167 2.432292 2.286458 2.083333 1.958333 1.84375
 1.708333 1.791667 1.875 1.708333 1.796875 1.755208 1.677083
 1.619792 1.6875 1.78125 1.791667 1.828125 1.880208 1.90625
 1.958333 1.864583 1.994792 1.78125 1.625 1.59375 1.604167
 1.609375 1.75 1.604167 1.510417 1.661458 1.8125 1.770833
 1.958333 2.03125 2.036458 2.088542 2.072917 2.135417 2.208333
 2.177083 2.208333 2.213542 2.223958 2.208333 2.234375 2.34375
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 1.708333 1.677083 1.677083 1.677083 1.651042 1.651042 1.692708
 1.677083 1.671875 1.65625 1.630208 1.625 1.619792 1.619792
 1.697917 1.75 1.78125 1.828125 1.791667 1.78125 1.854167
 1.848958 1.768225 1.630208 1.59375 1.625 1.619792 1.510417
 1.59375 1.463542 1.447917 1.427083 1.40625 1.4375 1.411458
 1.4375 1.364583 1.416667 1.458333 1.416667 1.416667 1.473958
 1.505208 1.5 1.473958 1.4375 1.421875 1.411458 1.375
 1.427083 1.421875 1.40625 1.416667 1.421875 1.411458 1.416667
 1.447917 1.572917 1.645833 1.572917 1.5 1.583333 1.583333
 1.536458 1.458333 1.458333 1.450517 1.479167 1.447917 1.53125
 1.520833 1.5 1.5 1.510417 1.364583 1.4375 1.510417
 1.578125 1.552083 1.583333 1.65625 1.604167 1.5625 1.609375
 1.677083 1.75 1.78125 1.75 1.614583 1.65625 1.708333
 1.760417 1.645833 1.796875 1.744792 1.604167 1.583333 1.59375
 1.697917 1.75 1.744792 1.723958 1.713542 1.770833 1.697917
 1.729167 1.807292 1.838542 1.78125 1.755208 1.661458 1.697917
 1.822917 1.838542 1.828125 1.916667 1.979167 1.833333 1.75
 1.739583 1.682292 1.65625 1.75 1.739583 1.645833 1.515625
 1.53125 1.59375 1.651042 1.604167 1.520833 1.489583 1.614583
 1.583333 1.661458 1.666667 1.671875 1.8125 ]

```

```
In [19]: 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 [ ]:
```