RNN, LSTM, And GRU For Trading

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In my previous article, we have developed a simple artificial neural network and predicted the stock price. However, in this article, we will use the power of RNN (Recurrent Neural Networks), LSTM (Short Term Memory Networks) & GRU (Gated Recurrent Unit Network) and predict the stock price. We are going to use TensorFlow 1.12 in python to coding this strategy.

You can access all python code and dataset from my GitHub a/c

If you have not gone through my previous article yet, I would recommend going through it before we start this project.

If you are new to Machine Learning and Neural Networks, I would recommend you to go through some basic understanding of Machine Learning, Deep learning, Artificial Neural network, RNN (Recurrent Neural Networks), LSTM (Short Term Memory Networks) & GRU (Gated Recurrent Unit Network) etc.

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Coding the Strategy

- Importing the dataset
- Scaling data
- Splitting the dataset and Building X & Y

Building the Model

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- Designing the network architecture
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- LSTM
- LSTM with peephole
- GRU

Coding the Strategy

We will start by importing all libraries. Please note if the below library not installed yet you need to install first in anaconda prompt before importing or else your python will throw an error message

```
import numpy as np
import pandas as pd
import math
import sklearn
import sklearn.preprocessing
import datetime
import os
import matplotlib.pyplot as plt
import tensorflow as tf
```

I am assuming you are aware of all the above python libraries that we are using here.

Importing the dataset

In this model, we are going to use daily OHLC data for the stock of “RELIANCE” trading on NSE for the time period from 1st January 1996 to 30 Sep 2018. We import our dataset.CSV file named ‘RELIANCE.NS.csv’ saved in the personal drive in your computer. This is done using the **pandas** library, and the data is stored in a dataframe

named dataset. We then drop the missing values in the dataset using the **dropna()** function. We choose only the OHLC data from this dataset, which would also contain the Date, Adjusted Close and Volume data.

```
# import dataset
dataset = pd.read_csv('Desktop/RELIANCE.NS.csv', index_col = 0)
df_stock = dataset.copy()
df_stock = df_stock.dropna()
df_stock = df_stock[['Open', 'High', 'Low', 'Close']]
```

Scaling data

Before we split the data set we have to standardize the dataset. This process makes the mean of all the input features equal to zero and also converts their variance to 1. This ensures that there is no bias while training the model due to the different scales of all input features. If this is not done the neural network might get confused and give a higher weight to those features which have a higher average value than others. Also, most common activation functions of the network's neurons such as tanh or sigmoid are defined on the [-1, 1] or [0, 1] interval respectively. Nowadays, **rectified linear unit** (ReLU) activations are commonly used activations which are unbounded on the axis of possible activation values. However, we will scale both the inputs and targets. We will do Scaling using sklearn's **MinMaxScaler**.

```
# data scaling (normalizing)
def normalize_data(df):
    min_max_scaler = sklearn.preprocessing.MinMaxScaler()
    df['Open'] = min_max_scaler.fit_transform(df.Open.values.reshape(-1,1))
    df['High'] = min_max_scaler.fit_transform(df.High.values.reshape(-1,1))
    df['Low'] = min_max_scaler.fit_transform(df.Low.values.reshape(-1,1))
    df['Close'] = min_max_scaler.fit_transform(df['Close'].values.reshape(-1,1))
    return df
df_stock_norm = df_stock.copy()
df_stock_norm = normalize_data(df_stock_norm)
```

Splitting the dataset and Building X & Y

Next, we split the whole dataset into train, valid and test data. Then we can build X & Y. So we will get x_train, y_train, x_valid, y_valid, x_test & y_test. This is a crucial part. Please remember **we are not simply slicing the data set like the previous project**. Here we are giving sequence length as 20.

```
# Splitting the dataset into Train, Valid & test data
valid_set_size_percentage = 10
test_set_size_percentage = 10
seq_len = 20 # taken sequence length as 20

def load_data(stock, seq_len):
    data_raw = stock.as_matrix()
    data = []
    for index in range(len(data_raw) - seq_len):
        data.append(data_raw[index: index + seq_len])
    data = np.array(data);
    valid_set_size = int(np.round(valid_set_size_percentage/100*data.shape[0]));
    test_set_size = int(np.round(test_set_size_percentage/100*data.shape[0]));
    train_set_size = data.shape[0] - (valid_set_size + test_set_size);
    x_train = data[:train_set_size,:-1,:]
    y_train = data[:train_set_size,-1,:]
    x_valid = data[train_set_size:train_set_size+valid_set_size,:-1,:]
    y_valid = data[train_set_size:train_set_size+valid_set_size,-1,:]
    x_test = data[train_set_size+valid_set_size:,:-1,:]
    y_test = data[train_set_size+valid_set_size:,-1,:]
    return [x_train, y_train, x_valid, y_valid, x_test, y_test]

x_train, y_train, x_valid, y_valid, x_test, y_test = load_data(df_stock_norm, seq_len)
print('x_train.shape = ',x_train.shape)
print('y_train.shape = ', y_train.shape)
print('x_valid.shape = ',x_valid.shape)
print('y_valid.shape = ', y_valid.shape)
print('x_test.shape = ', x_test.shape)
print('y_test.shape = ',y_test.shape)
```

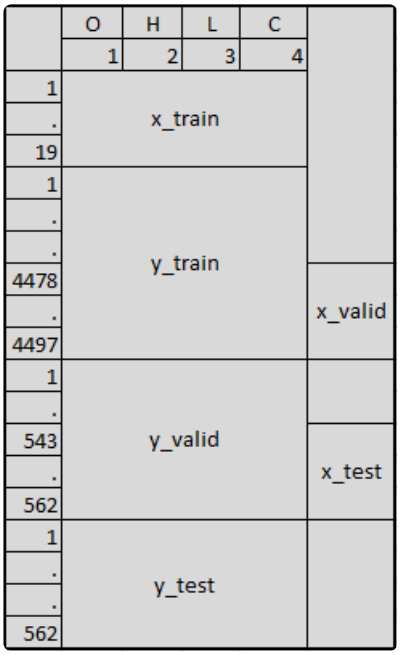
Our total data set is 5640.

So the first 19 data points are x_train.

The next 4497 data points are y_train out of which last 19 data points are x_valid.

The next 562 data points are y_valid out of which last 19 data are x_test.

Finally, the next and last 562 data points are y_test. I tried to draw this just to make you understand.



Building the Model

We will build four different models – Basic RNN Cell, Basic LSTM Cell, LSTM Cell with peephole connections and GRU cell. Please remember you can run one model at a time. I am putting everything into one coding. Whenever you run one model, make sure you put the other model as a comment or else your results will be wrong and python might throw an error.

Parameters, Placeholders & Variables

We will first fix the Parameters, Placeholders & Variables to building any model. The Artificial Neural Network starts with placeholders. We need two placeholders in order to fit our model: X contains the network's inputs (features of the stock (OHLC) at time T = t) and Y the network's output (Price of the stock at T+1). The shape of the placeholders corresponds to None, n_inputs with [None] meaning that the inputs are a 2-dimensional matrix and the outputs are a 1-dimensional vector. It is crucial to understand which input and output dimensions the neural net needs in order to design it properly. We define the variable batch size as 50 that controls the number of observations per training batch. We stop the training network when epoch reaches 100 as we have given epoch as 100 in our parameter.

```
# parameters & Placeholders
n_steps = seq_len-1
n_inputs = 4
n_neurons = 200
n_outputs = 4
n_layers = 2
learning_rate = 0.001
batch_size = 50
n_epochs = 100
train_set_size = x_train.shape[0]
test_set_size = x_test.shape[0]
tf.reset_default_graph()
X = tf.placeholder(tf.float32, [None, n_steps, n_inputs])
y = tf.placeholder(tf.float32, [None, n_outputs])
```

Designing the network architecture

Before we proceed, we have to write the function to run the next batch for any model. Then we will write the layers for each model separately.

```
# function to get the next batch
index_in_epoch = 0;
perm_array  = np.arange(x_train.shape[0])
np.random.shuffle(perm_array)

def get_next_batch(batch_size):
    global index_in_epoch, x_train, perm_array
    start = index_in_epoch
    index_in_epoch += batch_size
    if index_in_epoch > x_train.shape[0]:
        np.random.shuffle(perm_array) # shuffle permutation array
        start = 0 # start next epoch
        index_in_epoch = batch_size
    end = index_in_epoch
    return x_train[perm_array[start:end]], y_train[perm_array[start:end]]
```

Please remember you need to put the other models as a comment whenever you running one particular model. Here we are running only RNN basic so I kept all others as a comment. You can run one model after another.

```
# RNN
layers = [tf.contrib.rnn.BasicRNNCell(num_units=n_neurons, activation=tf.nn.elu)
          for layer in range(n_layers)]
# LSTM
#layers = [tf.contrib.rnn.BasicLSTMCell(num_units=n_neurons, activation=tf.nn.elu)
#          for layer in range(n_layers)]

#LSTM with peephole connections
#layers = [tf.contrib.rnn.LSTMCell(num_units=n_neurons,
#                                  activation=tf.nn.leaky_relu, use_peepholes = True)
#          for layer in range(n_layers)]

#GRU
#layers = [tf.contrib.rnn.GRUCell(num_units=n_neurons, activation=tf.nn.leaky_relu)
#          for layer in range(n_layers)]

multi_layer_cell = tf.contrib.rnn.MultiRNNCell(layers)
rnn_outputs, states = tf.nn.dynamic_rnn(multi_layer_cell, X, dtype=tf.float32)
stacked_rnn_outputs = tf.reshape(rnn_outputs, [-1, n_neurons])
stacked_outputs = tf.layers.dense(stacked_rnn_outputs, n_outputs)
outputs = tf.reshape(stacked_outputs, [-1, n_steps, n_outputs])
outputs = outputs[:,n_steps-1,:] # keep only last output of sequence
```

Cost function

We use cost function to optimize the model. The cost function is used to generate a measure of deviation between the network's predictions and the actual observed training targets. For regression problems, the **mean squared error (MSE)** function is commonly used. MSE computes the average squared deviation between predictions and targets.

```
# Cost function
loss = tf.reduce_mean(tf.square(outputs - y))
```

Optimizer

The optimizer takes care of the necessary computations that are used to adapt the network's weight and bias variables during training. Those computations invoke the calculation of gradients that indicate the direction in which the weights and biases have to be changed during training in order to minimize the network's cost function. The development of stable and speedy optimizers is a major field in neural network and deep learning research.

```
#optimizer
optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate)
training_op = optimizer.minimize(loss)
```

In this model we use **Adam** (Adaptive Moment Estimation) Optimizer, which is an extension of the stochastic gradient descent, is one of the default optimizers in deep learning development.

Fitting the neural network model & prediction

Now we need to fit the model that we have created to our train datasets. After having defined the placeholders, variables, initializers, cost functions and optimizers of the network, the model needs to be trained. Usually, this is done by mini batch training. During mini batch training random data samples of n = batch_size are drawn from the training data and fed into the network.