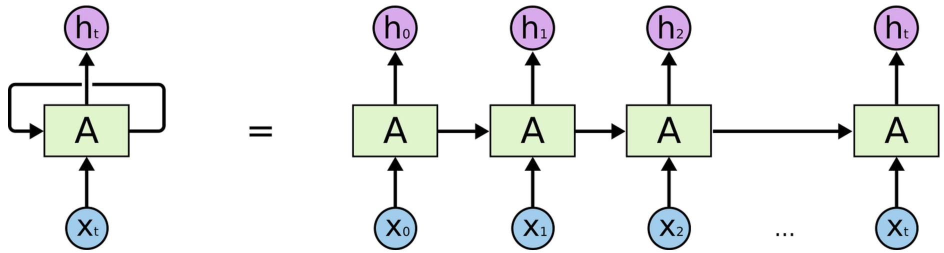
Things to remember

- If you are not familiar with keras or neural networks, refer to this kernel/tutorial of mine: https://www.kaggle.com/thebrownviking20/intro-to-keras-with-breast-cancer-data-ann
- Your doubts and curiousity about time series can be taken care of here: https://www.kaggle.com/thebrownviking20/everything-you-can-do-with-a-time-series
- Don't let the explanations intimidate you. It's simpler than you think.
- Eventually, I will add more applications of LSTMs. So stay tuned for more!
- The code is inspired from Kirill Eremenko's Deep Learning Course: https://www.udemy.com/deeplearning/

Recurrent Neural Networks

In a recurrent neural network we store the output activations from one or more of the layers of the network. Often these are hidden later activations. Then, the next time we feed an input example to the network, we include the previously-stored outputs as additional inputs. You can think of the additional inputs as being concatenated to the end of the "normal" inputs to the previous layer. For example, if a hidden layer had 10 regular input nodes and 128 hidden nodes in the layer, then it would actually have 138 total inputs (assuming you are feeding the layer's outputs into itself à la Elman) rather than into another layer). Of course, the very first time you try to compute the output of the network you'll need to fill in those extra 128 inputs with 0s or something.

Source: Quora



Source: Medium

Let me give you the best explanation of Recurrent Neural Networks that I found on internet: https://www.youtube.com/watch?v=UNmqTiOnRfg&t=3s

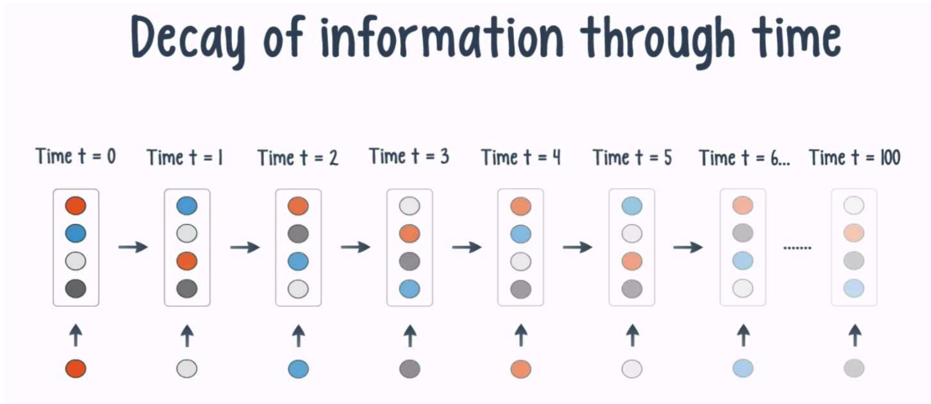
Now, even though RNNs are quite powerful, they suffer from **Vanishing gradient problem ** which hinders them from using long term information, like they are good for storing memory 3-4 instances of past iterations but larger number of instances don't provide good results so we don't just use regular RNNs. Instead, we use a better variation of RNNs: **Long Short Term Networks(LSTM).**

What is Vanishing Gradient problem?

Vanishing gradient problem is a difficulty found in training artificial neural networks with gradient-based learning methods and backpropagation. In such methods, each of the neural network's weights receives an update proportional to the partial derivative of the error function with respect to the current weight in each iteration of training. The problem is that in some cases, the gradient will be vanishingly small, effectively preventing the weight from changing its value. In the worst case, this may completely stop the neural network from further training. As one example of the problem cause, traditional activation functions such as the hyperbolic tangent function have gradients in the range (0, 1), and backpropagation computes gradients by the chain rule. This has the effect of multiplying n of these small numbers to compute gradients of the "front" layers in an n-layer

network, meaning that the gradient (error signal) decreases exponentially with n while the front layers train very slowly.

Source: Wikipedia



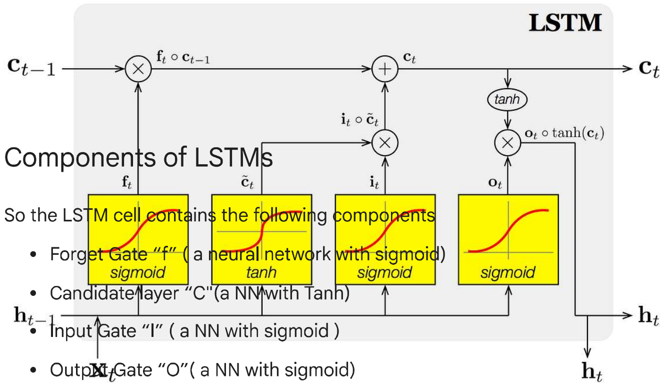
Source: Medium

Long Short Term Memory(LSTM)

Long short-term memory (LSTM) units (or blocks) are a building unit for layers of a recurrent neural network (RNN). A RNN composed of LSTM units is often called an LSTM network. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell is responsible for "remembering" values over arbitrary time intervals; hence the word "memory" in LSTM. Each of the three gates can be thought of as a "conventional" artificial neuron, as in a multi-layer (or feedforward) neural network: that is, they compute an activation (using an activation function) of a weighted sum. Intuitively, they can be thought as regulators of the flow of values that goes through the connections of the LSTM; hence the denotation "gate". There are connections between these gates and the cell.

The expression long short-term refers to the fact that LSTM is a model for the short-term memory which can last for a long period of time. An LSTM is well-suited to classify, process and predict time series given time lags of unknown size and duration between important events. LSTMs were developed to deal with the exploding and vanishing gradient problem when training traditional RNNs.

Source: Wikipedia



Gating variables

$$\mathbf{f}_t = \sigma(\mathbf{W}_f[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_t)$$
$$\mathbf{i}_t = \sigma(\mathbf{W}_i[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i)$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_o[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o)$$

Candidate (memory) cell state

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c)$$

Cell & Hidden state

$$\mathbf{c}_t = \mathbf{f}_t \circ \mathbf{c}_{t-1} + \mathbf{i}_t \circ \tilde{\mathbf{c}}_t$$
$$\mathbf{h}_t = \mathbf{o}_t \circ \tanh(\mathbf{c}_t)$$

Components of LSTMs

So the LSTM cell contains the following components

- Forget Gate "f" (a neural network with sigmoid)
- Candidate layer "C"(a NN with Tanh)
- Input Gate "I" (a NN with sigmoid)
- Output Gate "O"(a NN with sigmoid)
- Hidden state "H" (a vector)
- Memory state "C" (a vector)
- Inputs to the LSTM cell at any step are X_t (current input) , H_{t-1} (previous hidden state) and C_{t-1} (previous memory state).
- Outputs from the LSTM cell are H_t (current hidden state) and C_t (current memory state)

Source: Medium

The best LSTM explanation on internet: https://medium.com/deep-math-machine-learning-ai/chapter-10-1-deepnlp-lstm-long-short-term-memory-networks-with-math-21477f8e4235

Refer above link for deeper insights.

Working of gates in LSTMs

First, LSTM cell takes the previous memory state C_{t-1} and does element wise multiplication with forget gate (f) to decide if present memory state C_t. If forget gate value is 0 then previous memory state is completely forgotten else f forget gate value is 1 then previous memory state is completely passed to the cell (Remember f gate gives values between 0 and 1).

$C_t = C_{t-1} * f_t$

Calculating the new memory state:

$C_t = C_t + (I_t * C`_t)$

Now, we calculate the output:

$H_t = \tanh(C_t)$

And now we get to the code...

I will use LSTMs for predicting the price of stocks of IBM for the year 2017

```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout, GRU, Bidirectional
from keras.optimizers import SGD
import math
from sklearn.metrics import mean_squared_error
```

```
# Some functions to help out with
def plot_predictions(test,predicted):
```



```
    plt.plot(test, color='red',label='Real IBM Stock Price')
    plt.plot(predicted, color='blue',label='Predicted IBM Stock Price')
    plt.title('IBM Stock Price Prediction')
    plt.xlabel('Time')
    plt.ylabel('IBM Stock Price')
    plt.legend()
    plt.show()

def return_rmse(test,predicted):
    rmse = math.sqrt(mean_squared_error(test, predicted))
    print("The root mean squared error is {}.".format(rmse))
```

```
# First, we get the data
dataset = pd.read_csv('/content/IBM_2006-01-01_to_2018-01-01.csv', index_col='Date', parse_dates=['Date
dataset.head()
```

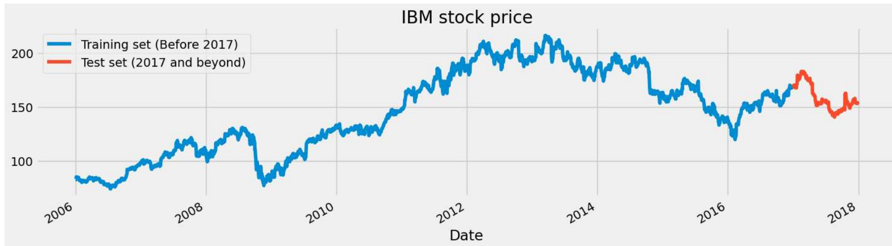
Date	Open	High	Low	Close	Volume	Name
2006-01-03	82.45	82.55	80.81	82.06	11715200	IBM
2006-01-04	82.20	82.50	81.33	81.95	9840600	IBM
2006-01-05	81.40	82.90	81.00	82.50	7213500	IBM
2006-01-06	83.95	85.03	83.41	84.95	8197400	IBM
2006-01-09	84.10	84.25	83.38	83.73	6858200	IBM

Next steps: Generate code with dataset | View recommended plots | New interactive sheet

```
# Checking for missing values
training_set = dataset[:'2016'].iloc[:,1:2].values
test_set = dataset['2017':].iloc[:,1:2].values
```

Start coding or generate with AI.

```
# We have chosen 'High' attribute for prices. Let's see what it looks like
dataset["High"][:'2016'].plot(figsize=(16,4),legend=True)
dataset["High"]['2017':].plot(figsize=(16,4),legend=True)
plt.legend(['Training set (Before 2017)','Test set (2017 and beyond)'])
plt.title('IBM stock price')
plt.show()
```




```
# Scaling the training set
sc = MinMaxScaler(feature_range=(0,1))
training_set_scaled = sc.fit_transform(training_set)
```

```
# Since LSTMs store long term memory state, we create a data structure with 60 timesteps and 1 output
# So for each element of training set, we have 60 previous training set elements
X_train = []
```

```
y_train = []
for i in range(60,2769):
    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)
```

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

```
# The LSTM architecture
regressor = Sequential()
# First LSTM layer with Dropout regularisation
regressor.add(LSTM(units=50, return_sequences=True, input_shape=(X_train.shape[1],1)))
regressor.add(Dropout(0.2))
# Second LSTM layer
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
# Third LSTM layer
regressor.add(LSTM(units=50, return_sequences=True))
regressor.add(Dropout(0.2))
# Fourth LSTM layer
regressor.add(LSTM(units=50))
regressor.add(Dropout(0.2))
# The output layer
regressor.add(Dense(units=1))

# Compiling the RNN
regressor.compile(optimizer='rmsprop',loss='mean_squared_error')
# Fitting to the training set
regressor.fit(X_train,y_train,epochs=50,batch_size=32)
```



```
85/85 ━━━━━━━━━━━━━━━━━━━━ 10s 118ms/step - loss: 0.0017
Epoch 43/50
85/85 ━━━━━━━━━━━━━━━━━━━━ 9s 104ms/step - loss: 0.0017
Epoch 44/50
85/85 ━━━━━━━━━━━━━━━━━━━━ 10s 118ms/step - loss: 0.0017
Epoch 45/50
85/85 ━━━━━━━━━━━━━━━━━━━━ 10s 117ms/step - loss: 0.0017
Epoch 46/50
85/85 ━━━━━━━━━━━━━━━━━━━━ 10s 118ms/step - loss: 0.0015
Epoch 47/50
85/85 ━━━━━━━━━━━━━━━━━━━━ 9s 108ms/step - loss: 0.0015
Epoch 48/50
85/85 ━━━━━━━━━━━━━━━━━━━━ 10s 104ms/step - loss: 0.0015
Epoch 49/50
85/85 ━━━━━━━━━━━━━━━━━━━━ 11s 118ms/step - loss: 0.0016
Epoch 50/50
85/85 ━━━━━━━━━━━━━━━━━━━━ 10s 119ms/step - loss: 0.0016
<keras.src.callbacks.history.History at 0x7b0a37c79b80>
```

```
# Now to get the test set ready in a similar way as the training set.
# The following has been done so forst 60 entires of test set have 60 previous values which is imposs
# 'High' attribute data for processing
dataset_total = pd.concat((dataset["High"][:'2016'],dataset["High"]['2017':]),axis=0)
inputs = dataset_total[len(dataset_total)-len(test_set) - 60:].values
inputs = inputs.reshape(-1,1)
inputs  = sc.transform(inputs)
```

```
# Preparing X_test and predicting the prices
X_test = []
for i in range(60,311):
    X_test.append(inputs[i-60:i,0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0],X_test.shape[1],1))
predicted_stock_price = regressor.predict(X_test)
predicted_stock_price = sc.inverse_transform(predicted_stock_price)
```

```
8/8 ━━━━━━━━━━━━━━━━━━━━ 1s 108ms/step
```

```
# Visualizing the results for LSTM
plot_predictions(test_set,predicted_stock_price)
```