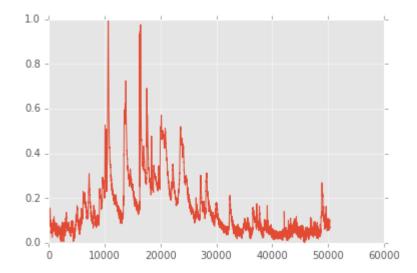
```
In [1]: # Based on Recurrent Neural Networks
        %matplotlib inline
        from __future__ import print_function
        import os
        os.environ["THEANO_FLAGS"] = "mode=FAST_RUN,device=gpu,floatX=float32"
        import numpy as np
        import matplotlib.pyplot as plt
        import pandas
        import math
        from keras.models import Sequential
        from keras.layers import Dense
        from keras.layers import LSTM
        from sklearn.preprocessing import MinMaxScaler
        plt.style.use('ggplot')
        Using Theano backend.
        Using gpu device 0: GeForce GTX 960 (CNMeM is disabled, cuDNN not available)
In [2]: # fix random seed for reproducibility
        np.random.seed(10)
In [3]: #Use the flood_data.csv dataset
        dataframe = pandas.read_csv('dataset/flood_train.csv', usecols=[1], engine='pythorizon')
        dataset = dataframe.values
        dataset
                 = dataset.astype('float32')
        dataframe.head()
Out[3]:
            waterlevel
         0
                0.27
         1
                0.26
         2
                0.27
         3
                0.28
                0.28
```

```
In [18]: plt.plot(dataset)
```

Out[18]: [<matplotlib.lines.Line2D at 0x7fbfbccf5210>]

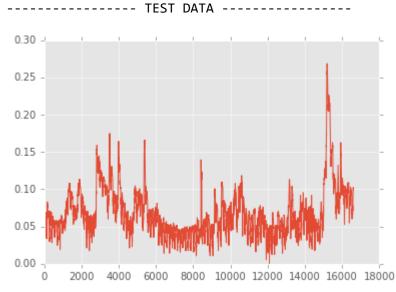


```
In [5]: # normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)
```

```
In [6]: # split into train and test sets
    train_size = int(len(dataset) * 0.67)
    test_size = len(dataset) - train_size
    train, test = dataset[0:train_size,:], dataset[train_size:len(dataset),:]
    print(len(train), len(test))
```

33710 16604



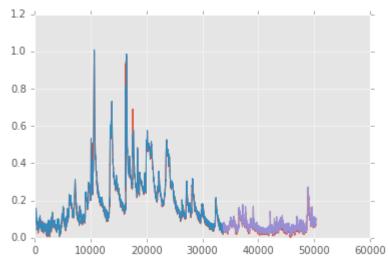


```
In [8]: # This function creates a sliding window of the dataset.

def create_dataset(dataset, sliding_window=1):
    dataX, dataY = [], []
    for i in range(len(dataset)-sliding_window-1):
        a = dataset[i:(i+sliding_window), 0]
        dataX.append(a)
        dataY.append(dataset[i + sliding_window, 0])
    return np.array(dataX), np.array(dataY)
```

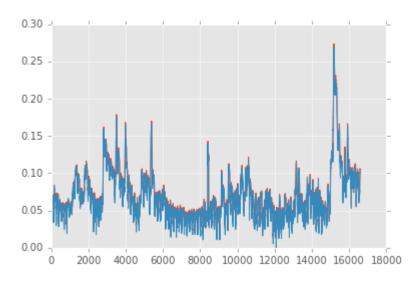
```
In [9]: # use a n-10 sliding window equivalent to 2.5 hours of historical data
         slide window = 10
         trainX, trainY = create dataset(train, slide window)
         testX, testY = create dataset(test, slide window)
In [10]: trainX = np.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
         testX = np.reshape(testX, (testX.shape[0], 1, testX.shape[1]))
In [11]: | #Setup the LSTM
         model = Sequential()
         model.add(LSTM(4, input dim=slide window))
         model.add(Dense(1))
         model.compile(loss='mean squared error', optimizer='adam')
         model.fit(trainX, trainY, nb_epoch=50, batch_size=1, verbose=2)
         Epoch 1/70
         104s - loss: 2.7772e-04
         Epoch 2/70
         98s - loss: 1.1746e-04
         Epoch 3/70
         98s - loss: 1.0950e-04
         Epoch 4/70
         99s - loss: 1.0798e-04
         Epoch 5/70
         99s - loss: 1.0540e-04
         Epoch 6/70
         98s - loss: 1.0358e-04
         Epoch 7/70
         98s - loss: 1.0405e-04
         Epoch 8/70
         98s - loss: 1.0088e-04
         Epoch 9/70
         98s - loss: 9.6544e-05
         Epoch 10/70
               1 --- 1 0214 - 04
         # Print out the evaluation for both the
In [12]:
         trainScore = model.evaluate(trainX, trainY, verbose=0)
         trainScore = math.sqrt(trainScore)
         trainScore = scaler.inverse transform(np.array([[trainScore]]))
         print('Train Score: %.2f RMSE' % (trainScore))
         testScore = model.evaluate(testX, testY, verbose=0)
         testScore = math.sqrt(testScore)
         testScore = scaler.inverse_transform(np.array([[testScore]]))
         print('Test Score: %.2f RMSE' % (testScore))
         Train Score: 0.06 RMSE
         Test Score: 0.03 RMSE
```

```
In [13]: trainPredict = model.predict(trainX)
                                          testPredict = model.predict(testX)
                                          # shift train predictions for plotting
                                                                                                                                = np.empty like(dataset)
                                         trainPredictPlot
                                          trainPredictPlot[:, :] = np.nan
                                          trainPredictPlot[slide window:len(trainPredict)+slide window, :] = trainPredict
                                          # shift test predictions for plotting
                                         testPredictPlot
                                                                                                                                          = np.empty_like(dataset)
                                          testPredictPlot[:, :] = np.nan
                                          testPredictPlot[len(trainPredict)+(slide_window*2)+1:len(dataset)-1, :] = testPredictPlot[len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_window*2)+1:len(trainPredict)+(slide_wi
                                          # plot baseline and predictions
                                          plt.plot(dataset)
                                         plt.plot(trainPredictPlot)
                                          plt.plot(testPredictPlot)
                                          plt.show()
```



```
In [16]: plt.plot(testPredict)
    plt.plot(testY)
```

Out[16]: [<matplotlib.lines.Line2D at 0x7fbfbd0a6910>]



```
In [20]: # Test the network on an unseen data
unseen = pandas.read_csv('dataset/flood_test.csv',sep=',')
```

In [21]: unseen.head()

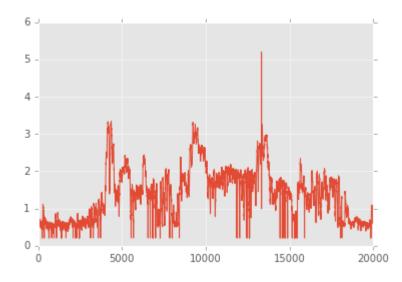
Out[21]:

	datetime	rainfall	waterlevel
0	1/1/2013 0:10	0.0	0.21
1	1/1/2013 0:21	0.0	0.21
2	1/1/2013 0:30	0.0	0.40
3	1/1/2013 1:30	0.0	0.49
4	1/1/2013 1:40	0.0	0.59

```
In [22]: unseen_test = unseen['waterlevel'].values
```

```
In [24]: plt.plot(unseen_test[0:20000])
```

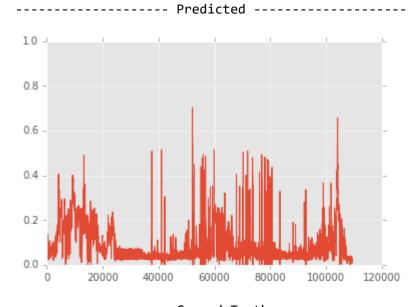
Out[24]: [<matplotlib.lines.Line2D at 0x7fbfbc57b350>]

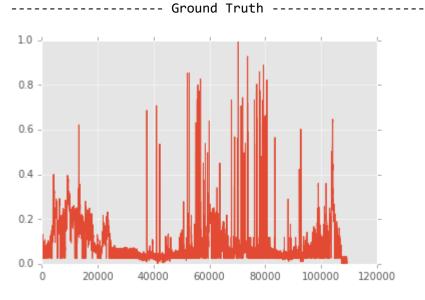


```
In [84]: unseen_clean = []
    for i in unseen_test:
        unseen_clean.append([i])
    unseen_clean = np.asarray(unseen_clean).astype('float32')
    unseen_clean = scaler.fit_transform(unseen_clean)
```

```
In [85]: features,labels = create_dataset(unseen_clean, slide_window)
    features = np.reshape(features, (109186,1, 10))
```

```
In [86]: unseen_results = model.predict(features)
```





```
In [112]: # Check the root mean squared error for the new test set

testScore = model.evaluate(features, labels, verbose=0)
testScore = math.sqrt(testScore)
testScore = scaler.inverse_transform(np.array([[testScore]]))
print('Test Score: %.2f RMSE' % (testScore))
```

Test Score: 0.16 RMSE

It seems that the network is having a hard time predicting higher flood level values

Checking the first 20000 data shows that the network is relatively comfortable on predicting ahead of time flood level values when the flood level aren't extreme

```
In [119]:
         plt.gca().set_ylim(bottom=0)
         plt.gca().set ylim(top=1)
         print('----')
         plt.plot(unseen results[0:20000])
         plt.show()
         print('-----')
         plt.plot(labels[0:20000])
         plt.show()
                  ----- Predicted -----
         1.0 -
          0.8
          0.6
          0.4
          0.2
          0.0
                             10000
                    5000
                        Ground Truth ----
          0.7 -
          0.6
          0.5
          0.4
          0.3
          0.2
          0.0
                    5000
                             10000
                                       15000
                                                 20000
 In [ ]:
```