Forecasting using RNN

Out[4]: '1.3.0'

Alok Jadhav

```
In [1]:
        #What are we working with?
        import sys
        sys.version
Out[1]: '3.6.3 | Anaconda custom (64-bit) | (default, Oct 13 2017, 12:02:49) \n[GCC
        7.2.01'
In [3]: #Import Libraries
        import tensorflow as tf
        import pandas as pd
        import numpy as np
        import os
        import matplotlib
        import matplotlib.pyplot as plt
        import random
        %matplotlib inline
        import tensorflow as tf
        import shutil
        import tensorflow.contrib.learn as tflearn
        import tensorflow.contrib.layers as tflayers
        from tensorflow.contrib.learn.python.learn import learn_runner
        import tensorflow.contrib.metrics as metrics
        import tensorflow.contrib.rnn as rnn
In [4]: #TF Version
        tf.__version__
```

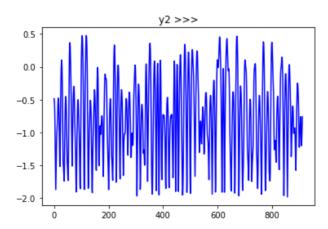
```
In [ ]: # for each experiment value of l1,l2,m1,m2 and th1,th2,w1,w2 are same so
        explicitely add these features after training.
        G = 9.8 # acceleration due to gravity, in m/s^2
        L1 = 1.0 # length of pendulum 1 in m
        L2 = 1.0 # length of pendulum 2 in m
        M1 = 1.0 # mass of pendulum 1 in kg
        M2 = 1.0 # mass of pendulum 2 in kg
        def derivs(state, t):
            dydx = np.zeros_like(state)
            dydx[0] = state[1]
            del = state[2] - state[0]
            den1 = (M1 + M2)*L1 - M2*L1*cos(del_)*cos(del_)
            dydx[1] = (M2*L1*state[1]*state[1]*sin(del )*cos(del ) +
                       M2*G*sin(state[2])*cos(del_) +
                       M2*L2*state[3]*state[3]*sin(del_) -
                       (M1 + M2)*G*sin(state[0]))/den1
            dydx[2] = state[3]
            den2 = (L2/L1)*den1
            dydx[3] = (-M2*L2*state[3]*state[3]*sin(del_)*cos(del_) +
                        (M1 + M2)*G*sin(state[0])*cos(del)
                        (M1 + M2)*L1*state[1]*state[1]*sin(del ) -
                       (M1 + M2)*G*sin(state[2]))/den2
            return dydx
        # create a time array from 0..100 sampled at 0.05 second steps
        dt = 0.1
        t = np.arange(0.0, 100, dt)
        # th1 and th2 are the initial angles (degrees)
        # w10 and w20 are the initial angular velocities (degrees per second)
        th1 = 120.0
        w1 = 0.0
        th2 = 0.0
        w2 = 0.0
        # initial state
        state = np.radians([th1, w1, th2, w2])
        # integrate your ODE using scipy.integrate.
        y = integrate.odeint(derivs, state, t)
        x1 = L1*sin(y[:, 0])
        y1 = -L1*cos(y[:, 0])
        #print("x1 : ",x1)
        #print("y1 : ",y1)
        x2 = L2*sin(y[:, 2]) + x1
        y2 = -L2*cos(y[:, 2]) + y1
        #print("x2 : ",x2)
        #print("y2 : ",y2)
        fig = plt.figure()
        ax = fig.add subplot(111, autoscale on=False, xlim=(-2, 2), ylim=(-2, 2)
        ax.grid()
        line. = ax.plot([]. []. 'o-'. lw=2)
```

Generate some data

```
In [5]:
        random.seed(111)
        rng = pd.date_range(start='2000', periods=9, freq='M')
        ts = pd.Series(np.random.uniform(-10, 10, size=len(rng)), rng).cumsum()
        #ts.head(10)
        f = open("data/y2.txt", "r")
        t = open("data/time slots.txt" , "r")
        array1 = []
        array2 = []
        for line in f.read().split('\n') :
          array1.append(line )
        for line in t.read().split('\n') :
          array2.append(line )
        f.close()
        t.close()
        array1.pop()
        array2.pop()
        data = []
        for i in range(len(array1)):
            data.append([array1[i]])
        test = np.array(data)
        mylist = test.astype(np.float)
        print("length of test data : ",len(mylist))
        print(mylist.shape)
        mylist.reshape(1,-1)
        #print(mylist)
        ts = np.delete(mylist,[i for i in range(912,1001)],0)
        print("length of test data : ",len(ts))
        print(ts.shape)
        ts.reshape(1,-1)
        #print(ts)
        plt.plot(ts,c='b')
        plt.title('y2 >>>')
        plt.show()
```

length of test data : 1000
(1000, 1)
length of test data : 912
(912, 1)

/home/omkarthawakar/anaconda3/lib/python3.6/site-packages/ipykernel_launc her.py:32: DeprecationWarning: in the future out of bounds indices will r aise an error instead of being ignored by `numpy.delete`.



Convert data into array that can be broken up into training "batches" that we will feed into our RNN model. Note the shape of the arrays.

```
In [6]: TS = np.array(ts)
    num_periods = 100
    f_horizon = 1 #forecast horizon, one period into the future

    x_data = TS[:(len(TS)-(len(TS) % num_periods))]
    print(x_data.shape)
    x_batches = x_data.reshape(-1, 100, 1)
    print (len(x_batches))
    print (x_batches.shape)
    #print ("x_batches : ",x_batches)
    y_data = TS[1:(len(TS)-(len(TS) % num_periods))+f_horizon]
    print(y_data.shape)
    y_batches = y_data.reshape(-1, 100, 1)

    print ("y_batches : ",y_batches)
    print (y_batches.shape)
```

```
(900, 1)
(9, 100, 1)
(900, 1)
y batches : [[[ -5.24476449e-01]
  [ -6.48676966e-011
  [ -8.71019532e-01]
  [ -1.20275951e+00]
  [ -1.62066548e+00]
  [ -1.86911222e+00]
  [ -1.59735687e+00]
  [ -1.31756139e+00]
  [ -1.13473550e+00]
  [ -1.02169831e+00]
   -9.32942575e-011
   -8.55187067e-01]
  [ -7.49839803e-01]
  [ -5.67737096e-01]
  [ -4.75580003e-01]
  [ -4.92185552e-01]
  [ -5.85496494e-01]
    -7.55875900e-01]
  [ -1.01412612e+00]
  [ -1.29605878e+001
  [ -1.51912616e+00]
  [ -1.38845605e+00]
  [ -8.96292936e-01]
  [ -4.91861962e-01]
    -2.08158459e-01]
   -2.10590930e-02]
    8.99717824e-021
    1.03748882e-011
   -1.26967951e-02]
  [ -2.78601145e-01]
  [ -6.96712328e-01]
    -1.18360217e+00]
  [ -1.42744340e+00]
  [ -1.51295215e+00]
  [ -1.57100333e+00]
  [ -1.66760359e+00]
  [ -1.74005964e+00]
   -1.47478390e+00]
   -1.10170996e+00]
  [ -7.99786295e-01]
  [ -5.89758230e-01]
  [ -4.72670174e-01]
  [ -4.50507424e-01]
  [ -5.26004251e-01]
   -6.99907560e-01]
  [ -9.65328322e-01]
  [ -1.27579873e+00]
  [ -1.45013129e+00]
  [ -1.51995661e+00]
  [ -1.62507518e+00]
   -1.73144610e+001
   -1.67600030e+00]
  [ -1.18787200e+00]
  [ -6.04400981e-01]
  [ -1.48154495e-01]
    1.57790117e-01]
     3.24794483e-01]
     3.68930359e-01]
     3.05609755e-01]
    1.57121559e-01]
  [ -3.99164153e-02]
  [ -2.58930410e-01]
  [ -5.27611174e-01]
  [ -8.93537907e-01]
```

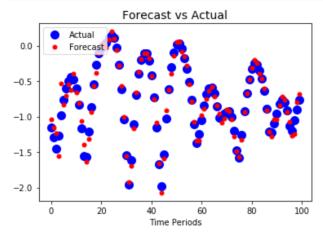
Pull out our test data

```
In [7]: def test_data(series,forecast,num_periods):
            test_x_setup = TS[-(num_periods + forecast):]
            testX = test_x_setup[:num_periods].reshape(-1, 100, 1)
            testY = TS[-(num\_periods):].reshape(-1, 100, 1)
            return testX,testY
        X test, Y test = test data(TS,f horizon,num periods )
        print (X test.shape)
        \#print(X_{test})
        print (Y test.shape)
        (1, 100, 1)
        (1, 100, 1)
In [8]: tf.reset default graph() #We didn't have any previous graph objects ru
        nning, but this would reset the graphs
        num_periods = 100
                               #number of periods per vector we are using to pre
        dict one period ahead
        inputs = 1
                              #number of vectors submitted
        hidden = 100
                              #number of neurons we will recursively work throug
        h, can be changed to improve accuracy
        output = 1
                              #number of output vectors
        X = tf.placeholder(tf.float32, [None, num periods, inputs])
                                                                      #create va
        riable objects
        y = tf.placeholder(tf.float32, [None, num periods, output])
        basic_cell = tf.contrib.rnn.BasicRNNCell(num_units=hidden, activation=tf
                   #create our RNN object
        .nn.relu)
        rnn output, states = tf.nn.dynamic rnn(basic cell, X, dtype=tf.float32)
        #choose dynamic over static
        learning_rate = 0.001 #small learning rate so we don't overshoot the m
        inimum
        stacked rnn output = tf.reshape(rnn output, [-1, hidden])
                                                                             #cha
        nge the form into a tensor
        stacked outputs = tf.layers.dense(stacked rnn output, output)
                                                                              #sp
        ecify the type of layer (dense)
        outputs = tf.reshape(stacked outputs, [-1, num periods, output])
        #shape of results
        loss = tf.reduce sum(tf.square(outputs - y))
                                                        #define the cost functio
        n which evaluates the quality of our model
        optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate)
        #gradient descent method
        training op = optimizer.minimize(loss)
                                                        #train the result of the
        application of the cost_function
        init = tf.global_variables_initializer()
                                                           #initialize all the v
        ariables
```

```
In [13]: epochs = 2000  #number of iterations or training cycles, includes bot
    h the FeedFoward and Backpropogation
    errors = []
    iterations = []
    with tf.Session() as sess:
        init.run()
        for ep in range(epochs):
            sess.run(training_op, feed_dict={X: x_batches, y: y_batches})
        errors.append(loss.eval(feed_dict={X: x_batches, y: y_batches}))
        iterations.append(ep)
        if ep % 100 == 0:
            mse = loss.eval(feed_dict={X: x_batches, y: y_batches})
            print(ep, "\tMSE:", mse)
        y_pred = sess.run(outputs, feed_dict={X: X_test})
        print(y_pred)
```

```
MSE: 976.734
100
        MSE: 23.7015
        MSE: 9.74641
200
300
        MSE: 5.50508
400
        MSE: 3.8686
500
        MSE: 3.03159
600
        MSE: 3.02459
700
        MSE: 2.70022
800
        MSE: 2.36303
        MSE: 1.82926
900
1000
        MSE: 1.91116
1100
        MSE: 1.75556
1200
        MSE: 1.48153
1300
        MSE: 1.36247
        MSE: 1.304
MSE: 1.14388
1400
1500
        MSE: 1.50855
1600
        MSE: 1.17008
1700
1800
        MSE: 1.82753
1900
        MSE: 1.58235
[[[-1.03502464]
  [-1.15167904]
  [-1.23701942]
  [-1.55589604]
  [-0.53603297]
  [-0.83044797]
  [-0.70525253]
  [-0.540323791]
  [-0.62140155]
  [-0.39356789]
  [-0.66593486]
  [-0.80497718]
  [-1.06383657]
  [-1.40197682]
  [-1.63456631]
  [-1.31720948]
  [-0.93527901]
  [-0.56344503]
  [-0.38245267]
  [-0.10980153]
  [ 0.016493
  [ 0.01546127]
  [-0.03424772]
  [ 0.08681718]
  [ 0.19851047]
  [ 0.10346407]
  [-0.06481653]
  [-0.2791754]
  [-0.56324613]
  [-1.0036602]
  [-1.55512249]
  [-1.9276197]
  [-1.7000798]
  [-1.16608512]
  [-0.66216338]
  [-0.37122253]
  [-0.19513896]
  [-0.11288485]
  [-0.10370913]
  [-0.17433986]
  [-0.43649754]
  [-0.74766672]
  [-1.08541369]
  [-1.66275942]
  [-2.07369518]
  [-1.59218204]
  [-0.9147315]
  [-0.6282292 ]
```

```
In [14]: plt.title("Forecast vs Actual", fontsize=14)
plt.plot(pd.Series(np.ravel(Y_test)), "bo", markersize=10, label="Actual
")
#plt.plot(pd.Series(np.ravel(Y_test)), "w*", markersize=10)
plt.plot(pd.Series(np.ravel(y_pred)), "r.", markersize=10, label="Forecast")
plt.legend(loc="upper left")
plt.xlabel("Time Periods")
plt.show()
```



```
In [15]: #!/usr/bin/env python
import numpy as np
import matplotlib.mlab as mlab
import matplotlib.pyplot as plt

errors=np.array(errors)
iterations=np.array(iterations)
print(errors.shape)
#print(errors)

plt.hist(errors,iterations,label='errors', facecolor='orange')

plt.xlabel('iterations')
plt.ylabel('mean square error ')
plt.title('histogram of errors>>>>')
plt.legend()
plt.show()
```

(2000,)

```
In [16]: #!/usr/bin/env python
    import numpy as np
    import matplotlib.mlab as mlab
    import matplotlib.pyplot as plt

errors=np.array(errors)
    iterations=np.array(iterations)
    print(errors.shape)
    #print(errors)

plt.plot(errors,iterations,label='errors',color='green')

plt.xlabel('iterations')
    plt.ylabel('mean square error ')
    plt.title('plot of errors>>>>')
    plt.legend()
    plt.show()
```

(2000,)

