

# Double Pendulum Trajectory Forecasting using RNN

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```
In [11]: 1 #What are we working with?
          2 import sys
          3 sys.version
```

```
Out[11]: '3.6.3 |Anaconda custom (64-bit)| (default, Oct 6 2017, 12:04:38) \
n[GCC 4.2.1 Compatible Clang 4.0.1 (tags/RELEASE_401/final)]'
```

```
In [12]: 1 #Import Libraries
          2 import tensorflow as tf
          3 import pandas as pd
          4 import numpy as np
          5 import os
          6 import matplotlib
          7 import matplotlib.pyplot as plt
          8 import random
          9 %matplotlib inline
         10 import tensorflow as tf
         11 import shutil
         12 import tensorflow.contrib.learn as tflearn
         13 import tensorflow.contrib.layers as tflayers
         14 from tensorflow.contrib.learn.python.learn import learn_runner
         15 import tensorflow.contrib.metrics as metrics
         16 import tensorflow.contrib.rnn as rnn
         17
         18 from numpy import sin, cos
         19 import numpy as np
         20 import matplotlib.pyplot as plt
         21 import scipy.integrate as integrate
         22 import matplotlib.animation as animation
         23 import random
         24
```

```
In [13]: 1 #TF Version
          2 tf.__version__
          3
          4
```

```
Out[13]: '1.4.1'
```

```
In [14]: 1
          2 # for each experiment value of l1,l2,m1,m2 and th1,th2,w1,w2 are s
          3
          4 G = 9.8 # acceleration due to gravity, in m/s^2
          5 L1 = 1.0 # length of pendulum 1 in m
```

```

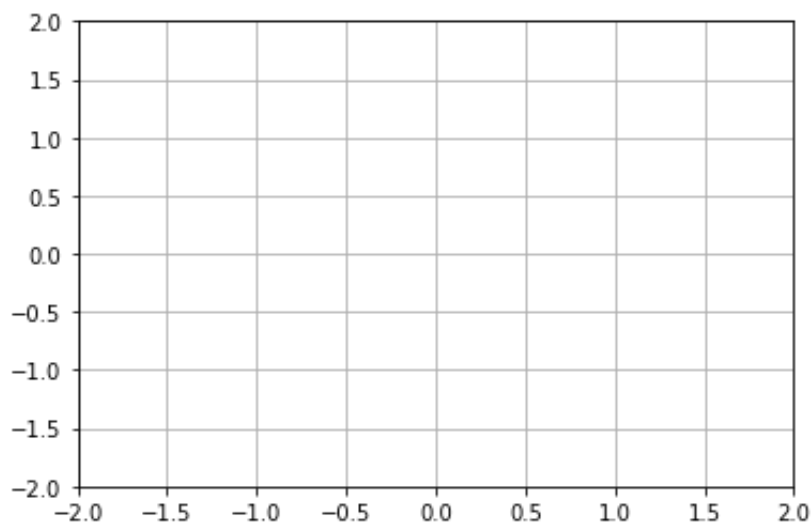
6 L2 = 1.0 # length of pendulum 2 in m
7 M1 = 1.0 # mass of pendulum 1 in kg
8 M2 = 1.0 # mass of pendulum 2 in kg
9
10
11 def derivs(state, t):
12
13     dydx = np.zeros_like(state)
14     dydx[0] = state[1]
15
16     del_ = state[2] - state[0]
17     den1 = (M1 + M2)*L1 - M2*L1*cos(del_)*cos(del_)
18     dydx[1] = (M2*L1*state[1]*state[1]*sin(del_)*cos(del_) +
19               M2*G*sin(state[2])*cos(del_) +
20               M2*L2*state[3]*state[3]*sin(del_) -
21               (M1 + M2)*G*sin(state[0]))/den1
22
23     dydx[2] = state[3]
24
25     den2 = (L2/L1)*den1
26     dydx[3] = (-M2*L2*state[3]*state[3]*sin(del_)*cos(del_) +
27               (M1 + M2)*G*sin(state[0])*cos(del_) -
28               (M1 + M2)*L1*state[1]*state[1]*sin(del_) -
29               (M1 + M2)*G*sin(state[2]))/den2
30
31     return dydx
32
33 # create a time array from 0..100 sampled at 0.05 second steps
34 dt = 0.1
35 t = np.arange(0.0, 100, dt)
36
37 # th1 and th2 are the initial angles (degrees)
38 # w10 and w20 are the initial angular velocities (degrees per seco.
39
40 th1 = 120.0
41 w1 = 0.0
42 th2 = 0.0
43 w2 = 0.0
44
45 # initial state
46 state = np.radians([th1, w1, th2, w2])
47
48 # integrate your ODE using scipy.integrate.
49 y = integrate.odeint(derivs, state, t)
50
51 x1 = L1*sin(y[:, 0])
52 y1 = -L1*cos(y[:, 0])
53
54 #print("x1 : ",x1)
55 #print("y1 : ",y1)
56
57 x2 = L2*sin(y[:, 2]) + x1
58 y2 = -L2*cos(y[:, 2]) + y1
59

```

```

60 #print("x2 : ",x2)
61 #print("y2 : ",y2)
62
63 fig = plt.figure()
64 ax = fig.add_subplot(111, autoscale_on=False, xlim=(-2, 2), ylim=(-2, 2))
65 ax.grid()
66
67 line, = ax.plot([], [], 'o-', lw=2)
68 time_template = 'time = %.1fs'
69 time_text = ax.text(0.05, 0.9, '', transform=ax.transAxes)
70
71
72 def init():
73     line.set_data([], [])
74     time_text.set_text('')
75     return line, time_text
76
77
78 def animate(i):
79     thisx = [0, x1[i], x2[i]]
80     thisy = [0, y1[i], y2[i]]
81
82     line.set_data(thisx, thisy)
83     time_text.set_text(time_template % (i*dt))
84     return line, time_text
85
86 ani = animation.FuncAnimation(fig, animate, np.arange(1, len(y)), interval=dt, repeat=False)
87
88

```



### Generate some data

```

In [15]: 1 random.seed(111)
          2 #ts.head(10)
          3
          4 f = open("data/x2.txt" , "r")
          5 t = open("data/time_steps.txt" , "r")

```

```

5 f = open( data/time_stops.txt , 'r' )
6 array1 = []
7 array2 = []
8
9 for line in f.read().split('\n') :
10     array1.append(line )
11 for line in t.read().split('\n') :
12     array2.append(line )
13 f.close()
14 t.close()
15 array1.pop()
16 array2.pop()
17 data = []
18
19 for i in range(len(array1)):
20     data.append([array1[i]])
21 test = np.array(data)
22 mylist = test.astype(np.float)
23
24 print("length of test data : ",len(mylist))
25 print(mylist.shape)
26 mylist.reshape(1,-1)
27 #print(mylist)
28
29 ts = np.delete(mylist,[i for i in range(912,1001)],0)
30
31 print("length of test data : ",len(ts))
32 print(ts.shape)
33 ts.reshape(1,-1)
34 #print(ts)
35
36 plt.plot(ts,c='b')
37 plt.title('x2 >>>')
38 plt.show()
39

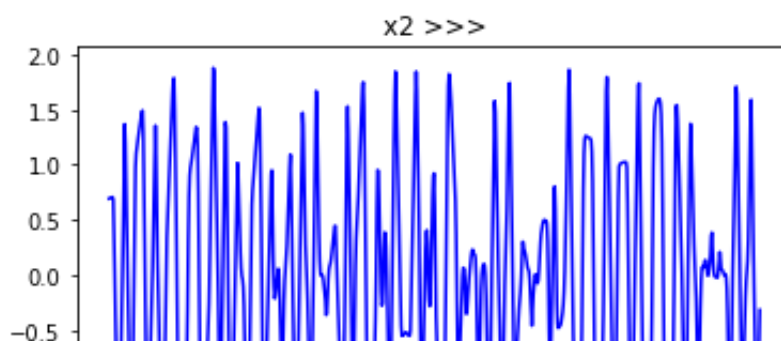
```

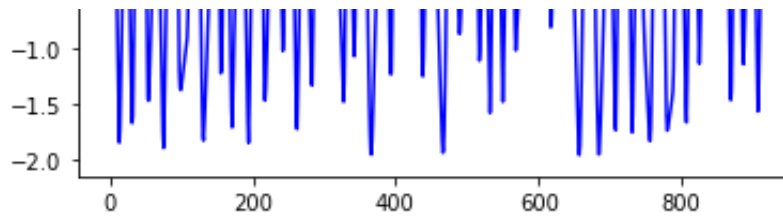
```

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

```

/Users/omkarchakradharthawakar/anaconda3/lib/python3.6/site-packages/ipykernel\_launcher.py:29: DeprecationWarning: in the future out of bounds indices will raise 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 [16]: 1 TS = np.array(ts)
2 num_periods = 100
3 f_horizon = 1 #forecast horizon, one period into the future
4
5 x_data = TS[: (len(TS)-(len(TS) % num_periods))]
6 #print(len(x_data))
7 #print("x_data : ",x_data)
8 x_batches = x_data.reshape(-1, 100, 1)
9
10 #print (len(x_batches))
11 print ("x_batches shape : ",x_batches.shape)
12 #print (x_batches[0:1])
13
14 y_data = TS[1:(len(TS)-(len(TS) % num_periods))+f_horizon]
15 #print(y_data.shape)
16 y_batches = y_data.reshape(-1, 100, 1)
17
18
19 #print ("y_batches : ",y_batches[0:1])
20 print ("y_batches shape : ",y_batches.shape)
```

```
x_batches shape : (9, 100, 1)
```

```
y_batches shape : (9, 100, 1)
```

**Pull out our test data**

In [17]:

```

1 def test_data(series,forecast,num_periods):
2     test_x_setup = TS[-(num_periods + forecast):]
3     testX = test_x_setup[:num_periods].reshape(-1, 100, 1)
4     testY = TS[-(num_periods):].reshape(-1, 100, 1)
5     return testX,testY
6
7 X_test, Y_test = test_data(TS,f_horizon,num_periods )
8 print (X_test.shape)
9 print(len(X_test))
10 #print (X_test)
11
12 print (Y_test.shape)
13 print(len(Y_test))
14 #print (Y_test)

```

(1, 100, 1)

1

(1, 100, 1)

1

In [18]:

```

1 tf.reset_default_graph()    #We didn't have any previous graph object
2
3 num_periods = 100           #number of periods per vector we are using
4 inputs = 1                  #number of vectors submitted
5 hidden = 100                #number of neurons we will recursively work
6 output = 1                  #number of output vectors
7
8 X = tf.placeholder(tf.float32, [None, num_periods, inputs])    #create
9 y = tf.placeholder(tf.float32, [None, num_periods, output])
10
11 print(X)
12
13
14 basic_cell = tf.contrib.rnn.BasicRNNCell(num_units=hidden, activation_fn=tf.nn.tanh)
15 rnn_output, states = tf.nn.dynamic_rnn(basic_cell, X, dtype=tf.float32)
16
17 learning_rate = 0.001      #small learning rate so we don't overshoot
18
19 stacked_rnn_output = tf.reshape(rnn_output, [-1, hidden])
20 stacked_outputs = tf.layers.dense(stacked_rnn_output, output)
21 outputs = tf.reshape(stacked_outputs, [-1, num_periods, output])
22
23 loss = tf.reduce_sum(tf.square(outputs - y))    #define the cost function
24 optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate)
25 training_op = optimizer.minimize(loss)          #train the result
26
27 init = tf.global_variables_initializer()        #initialize all

```

Tensor("Placeholder:0", shape=(?, 100, 1), dtype=float32)

```
In [19]: 1 with tf.Session() as sess:
          2     writer = tf.summary.FileWriter("outputs_x", sess.graph)
          3     print(sess.run(init))
          4     writer.close()
```

None

```
In [20]: 1 epochs = 5000      #number of iterations or training cycles, includ
          2 errors = []
          3 iterations = []
          4 with tf.Session() as sess:
          5     init.run()
          6     for ep in range(epochs):
          7         sess.run(training_op, feed_dict={X: x_batches, y: y_batches})
          8         errors.append(loss.eval(feed_dict={X: x_batches, y: y_batches}))
          9         iterations.append(ep)
         10         if ep % 100 == 0:
         11             mse = loss.eval(feed_dict={X: x_batches, y: y_batches})
         12             print(ep, "\tMSE:", mse)
         13     y_pred = sess.run(outputs, feed_dict={X: X_test})
         14     print(y_pred)
         15
```

```
0      MSE: 581.299
100    MSE: 21.9139
200    MSE: 12.3388
300    MSE: 8.77889
400    MSE: 6.77277
500    MSE: 5.22588
600    MSE: 4.9033
700    MSE: 6.821
800    MSE: 3.76563
900    MSE: 2.98707
1000   MSE: 2.75795
1100   MSE: 2.17701
1200   MSE: 2.0295
1300   MSE: 2.43033
1400   MSE: 1.79029
1500   MSE: 1.72781
1600   MSE: 5.30996
1700   MSE: 1.79617
1800   MSE: 1.8805
1900   MSE: 1.28517
```

```
In [21]: 1 for i in range(len(y_pred[0])):
          2     print(Y_test[0][i] , y_pred[0][i])
```

```
[ 0.65130467] [ 0.11410932]
[ 1.09132992] [ 0.89627552]
[ 1.37144135] [ 1.44897664]
[ 1.21651892] [ 1.71158433]
[ 0.97162507] [ 0.8172189]
[ 0.72589668] [ 0.46351272]
[ 0.48853033] [ 0.40691406]
```

```
[ 0.27832533] [ 0.38316971]
[ 0.11489424] [-0.00178191]
[-0.02420258] [-0.22794408]
[-0.21427559] [-0.26626092]
[-0.50669374] [-0.30810457]
[-0.85925168] [-0.73403341]
[-1.13167657] [-1.59167254]
[-0.95782469] [-1.36332059]
[-0.61549438] [-0.28320479]
[-0.30240578] [ 0.21157284]
[-0.05761067] [-0.14463066]
[ 0.06338403] [-0.32162577]
[ 0.07530041] [-0.12596682]
[ 0.06631454] [ 0.16767716]
[ 0.0894524] [ 0.29701078]
[ 0.12633476] [ 0.0917605]
[ 0.13430522] [ 0.20406596]
[ 0.09856873] [ 0.30929607]
[ 0.03986353] [-0.15431131]
[-0.00484348] [-0.25821829]
[-0.00530485] [-0.296938]
[ 0.03851473] [ 0.32963818]
[ 0.10526395] [ 0.20661542]
[ 0.19581869] [ 0.08956158]
[ 0.35444059] [ 0.19669402]
[ 0.38391367] [ 0.4662289]
[ 0.24240832] [ 0.24906678]
[ 0.09770974] [-0.07866869]
[ 0.01087227] [ 0.147808]
[-0.01532095] [-0.09739791]
[-0.01517639] [ 0.04980822]
[-0.01779135] [-0.09956768]
[-0.02711376] [-0.15162851]
[-0.02167907] [-0.05864833]
[ 0.02783662] [ 0.06854813]
[ 0.12130583] [ 0.17318968]
[ 0.20708524] [ 0.08733192]
[ 0.14766094] [ 0.30945748]
[ 0.05862946] [ 0.03614395]
[ 0.04653323] [-0.05074906]
[ 0.03991749] [-0.01027462]
[ 0.0202778] [-0.00997065]
[ 0.00221897] [ 0.14318383]
[ 0.00124234] [-0.01404033]
[ 0.0074545] [-0.01189621]
[-0.01629526] [-0.13261202]
[-0.12572245] [-0.06816506]
[-0.36588313] [-0.33585334]
[-0.72359457] [-0.72709185]
[-1.12660005] [-1.09314263]
[-1.4615919] [-1.50020337]
[-1.38285285] [-1.36206031]
[-0.91067614] [-0.95579511]
```



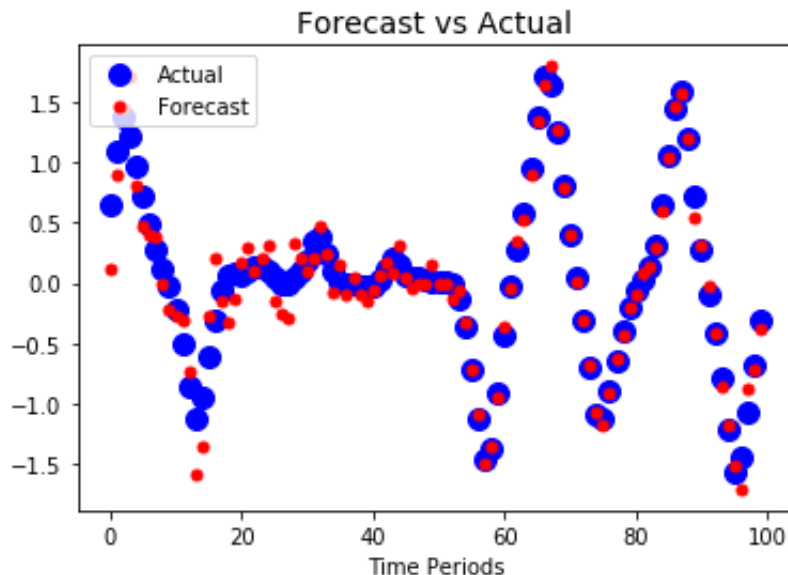
```
[-0.43405067] [-0.36643404]
[-0.03064884] [-0.03553419]
[ 0.27709761] [ 0.35466939]
[ 0.58015971] [ 0.53275359]
[ 0.95527806] [ 0.90614963]
[ 1.3693463] [ 1.34341359]
[ 1.70937176] [ 1.64881873]
[ 1.64389586] [ 1.80004609]
[ 1.25006619] [ 1.26295519]
[ 0.81802814] [ 0.79744136]
[ 0.40409593] [ 0.40137595]
[ 0.03812776] [ 0.01298887]
[-0.31645917] [-0.31637269]
[-0.71024779] [-0.68096083]
[-1.08525045] [-1.07467639]
[-1.13675535] [-1.18827653]
[-0.89340507] [-0.91509259]
[-0.64483472] [-0.62212855]
[-0.40788684] [-0.43438023]
[-0.20193168] [-0.20286737]
[-0.05761479] [-0.09417319]
[ 0.02882913] [ 0.07786477]
[ 0.12503108] [ 0.13308384]
[ 0.31956288] [ 0.29332834]
[ 0.64465777] [ 0.59997213]
[ 1.04973698] [ 1.03490579]
[ 1.44037188] [ 1.46780825]
[ 1.5906479] [ 1.56928825]
[ 1.20738599] [ 1.20467997]
[ 0.72600604] [ 0.53968328]
[ 0.27699223] [ 0.30956614]
[-0.09186728] [-0.01996212]
[-0.42028866] [-0.41483206]
[-0.79916594] [-0.86987001]
[-1.2227152] [-1.18975425]
[-1.56572053] [-1.5258019]
[-1.45399075] [-1.71298969]
[-1.07415974] [-0.88234341]
[-0.68102279] [-0.71233374]
[-0.31814455] [-0.3750999]
```

In [22]:

```

1 plt.title("Forecast vs Actual", fontsize=14)
2 plt.plot(pd.Series(np.ravel(Y_test)), "bo", markersize=10, label="Actual")
3 #plt.plot(pd.Series(np.ravel(Y_test)), "w*", markersize=10)
4 plt.plot(pd.Series(np.ravel(y_pred)), "r.", markersize=10, label="Forecast")
5 plt.legend(loc="upper left")
6 plt.xlabel("Time Periods")
7
8 plt.show()
9
10

```



In [23]:

```

1 error = []
2 print(y_pred[0][1][0])
3 print(abs(y_pred[0][0][0]-Y_test[0][0][0]))
4 print(len(y_pred[0]))
5 for i in range(len(y_pred[0])):
6     err = abs((y_pred[0][i][0]-Y_test[0][i][0])/Y_test[0][i][0])
7     error.append(err)
8 x = np.arange(len(error))
9 print(error)
10 plt.bar(x,error,align='center')
11 plt.xlabel('predicted points')
12 plt.ylabel('mean square error')
13 plt.title('mean square error histogram >>>')
14 plt.show()

```

0.896276

0.537195347766

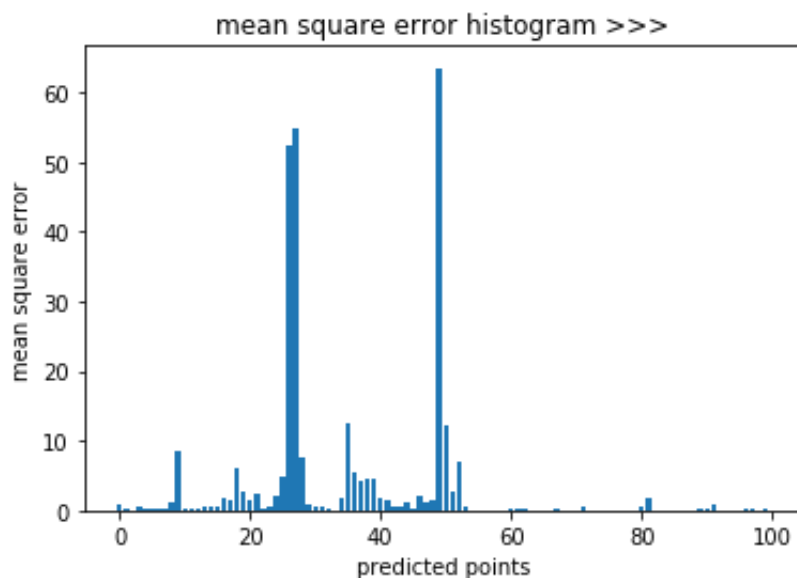
100

```

[0.82479885735421021, 0.17873091660864704, 0.056535617569429084, 0.4
0695249758644347, 0.15891538085358409, 0.36146185976063561, 0.167064
90159623735, 0.37669723502933816, 1.0155091389574211, 8.418172122594
4077, 0.24260970361966022, 0.39193135693594194, 0.1457294509909573,
0.40647299499562695, 0.42335084896025166, 0.53987427925879139, 1.699
6322698932671, 1.5104837776229436, 6.0742396569336385, 2.67285691210

```

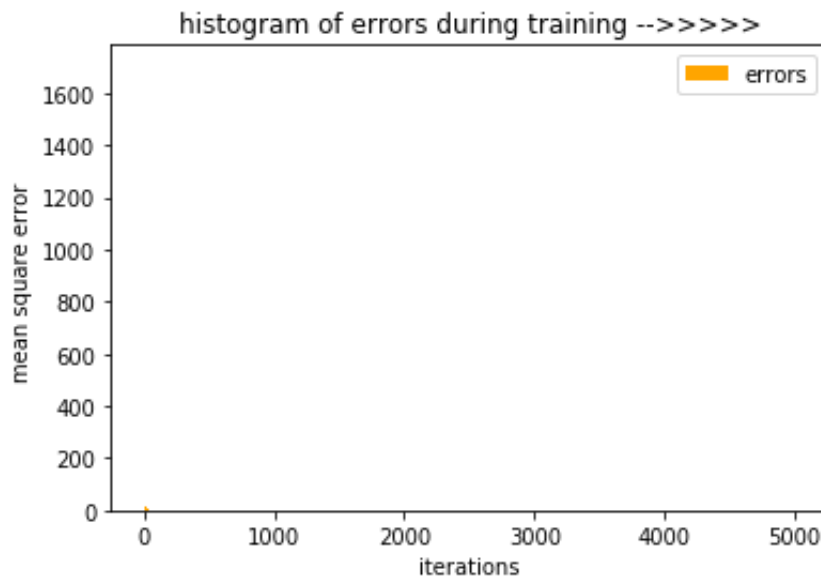
```
7068, 1.5285130009544887, 2.3203219634295973, 0.27367180022630683, 0
.51941940363727945, 2.1378719806526667, 4.870990104676693, 52.312515
634560341, 54.974767971748527, 7.5587561854505019, 0.962831735611528
57, 0.54263007557194132, 0.445057866894704, 0.21441077185500015, 0.0
27467981031326232, 1.8051264163052774, 12.594957531741299, 5.3571735
449221132, 4.2819539565130231, 4.5964089273276816, 4.592308004455262
, 1.7052968854886312, 1.4625166417764086, 0.42771118969625821, 0.578
28031735837893, 1.0957301414730016, 0.38351893693781069, 2.090598234
4459582, 1.2573964121394885, 1.4917026438121852, 63.527121249045472,
12.301524049537251, 2.5958423440047595, 7.1380747640804119, 0.457813
12562855658, 0.082074809021109002, 0.0048331963505130159, 0.02969769
3394686933, 0.026417409213273839, 0.015035978506083444, 0.0495444706
34499793, 0.15578050559248882, 0.15939762014323597, 0.27994388693558
858, 0.081712195277340499, 0.051428416898243491, 0.01893802141717678
5, 0.035424139704469705, 0.094987903422785569, 0.010310650719808804,
0.025166343796214376, 0.0067310288749893674, 0.65933311660153127, 0.
00027327175091571595, 0.041234843646573052, 0.0097434240177029473, 0
.045323013706180304, 0.024275118232454599, 0.03521239718329764, 0.06
4952794242754588, 0.0046337023317053515, 0.63453146201285737, 1.7009
061365881817, 0.064406023696921569, 0.08209506249118044, 0.069316847
122788933, 0.014128482133283772, 0.019048110675930204, 0.01342827050
5682459, 0.0022412213081291939, 0.25664078444630256, 0.1175986470904
7234, 0.7827070006285276, 0.012982994293059137, 0.088472320062014567
, 0.026957180517797014, 0.025495377064424764, 0.17812970002776218, 0
.1785733701256626, 0.045976355127444427, 0.17902349326050634]
```



In [24]:

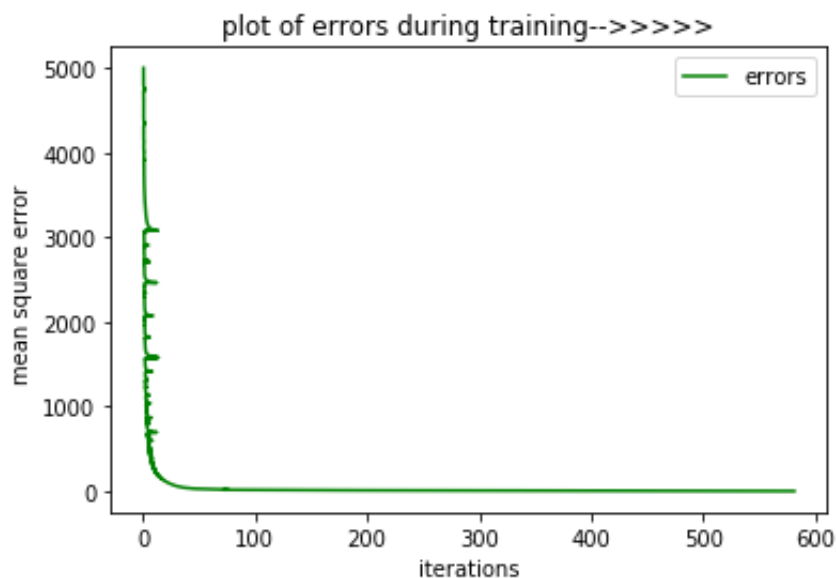
```
1 #!/usr/bin/env python
2 import numpy as np
3 import matplotlib.mlab as mlab
4 import matplotlib.pyplot as plt
5
6 errors=np.array(errors)
7 iterations=np.array(iterations)
8 print(errors.shape)
9 #print(errors)
10
11 plt.hist(errors,iterations,label='errors', facecolor='orange')
12
13 plt.xlabel('iterations')
14 plt.ylabel('mean square error ')
15 plt.title('histogram of errors during training -->>>>')
16 plt.legend()
17 plt.show()
```

(5000,)



```
In [25]: 1 #!/usr/bin/env python
2 import numpy as np
3 import matplotlib.mlab as mlab
4 import matplotlib.pyplot as plt
5
6 errors=np.array(errors)
7 iterations=np.array(iterations)
8 print(errors.shape)
9 #print(errors)
10
11 plt.plot(errors,iterations,label='errors',color='green')
12
13 plt.xlabel('iterations')
14 plt.ylabel('mean square error ')
15 plt.title('plot of errors during training-->>>>')
16 plt.legend()
17 plt.show()
```

(5000,)



```
In [ ]: 1
```