In [89]:
```
import numpy as np
import matplotlib.pyplot as pyp
x = np.load("assignment8_X.npy")
y = np.load("assignment8_Y.npy")
x = x.T
y = y.T

alpha = 0.01
n = x.shape[0] # n = 10
t = x.shape[1] # t = 25
#w1 = np.ones((m,n))*0.01
#w2 = np.ones((n,m))*0.01

print(n,t)

def NN1_forward_pass(x,y,w1,w2,w3):
    #print("before forward pass, x")
    #print(x)
    #print("w2")
    #print(w2)
    #print("w1")
    #print(w1)
    #print("y")
    #print(y)
    fwx = w3.dot(w2.dot(w1.dot(x)))
    #print("fwx")
    #print(fwx)
    loss = fwx - y
    #print("loss")
    #print(loss)
    return loss

def NN1_backprop(x,w1,w2,w3,n,m):
    dfdw3 = np.zeros((n,n,m))  # 10x10x25
    dfdw2 = np.zeros((n,m,m))  # 10x25x25
    dfdw1 = np.zeros((n,m,n))  # 10x25x10
    dfdh1 = w3.dot(w2)         # 10x25
    dfdh2 = w3                 # 10x25
    dh1dw1 = np.zeros((m,m,n)) # 25x25x10
    dh2dw2 = np.zeros((m,m,m)) # 25x25x25
    h1 = w1.dot(x)             # 25x1
    h2 = w2.dot(h1)            # 25x1
    #print("In BP, h1", x.shape)
    for i in range(n):
        dfdw3[i][i] = h2
    for i in range(m):
        dh1dw1[i][i] = x
        dh2dw2[i][i] = h1
    for i in range(n):
            for j in range(m):
                dfdw2[i] += dh2dw2[j]*dfdh2[i][j]
                dfdw1[i] += dh1dw1[j]*dfdh1[i][j]
    return dfdw1,dfdw2,dfdw3

def VecXTen(vec,tensor):
    result = np.zeros((tensor.shape[1],tensor.shape[2]))
```

```
    for i in range(len(vec)):
        result += vec[i]*tensor[i]
    return result
```

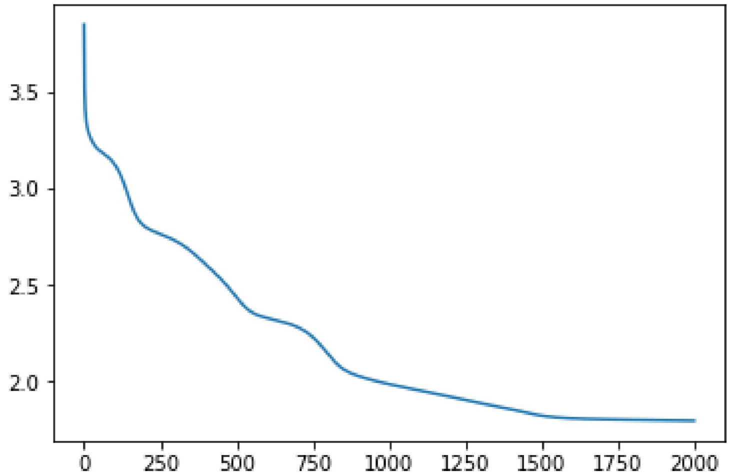
```
10 25
```

In [91]:

```
# NN1 with m = 10
m = 10
w1 = np.random.rand(m,n)*0.1
w2 = np.random.rand(m,m)*0.1
w3 = np.random.rand(n,m)*0.1
loss_list = []
for steps in range(2000):
    Gradient_w1 = np.zeros(w1.shape)
    Gradient_w2 = np.zeros(w2.shape)
    Gradient_w3 = np.zeros(w3.shape)
    total_loss = 0
    for col in range(t):
        loss = NN1_forward_pass(x[:,col],y[:,col],w1,w2,w3)
        total_loss += np.linalg.norm(loss)**2
        dfdw1,dfdw2,dfdw3 = NN1_backprop(x[:,col],w1,w2,w3,n,m)
        Gradient_w1 += VecXTen(loss,dfdw1)
        Gradient_w2 += VecXTen(loss,dfdw2)
        Gradient_w3 += VecXTen(loss,dfdw3)
    Gradient_w1 = Gradient_w1 * 2 / t
    Gradient_w2 = Gradient_w2 * 2 / t
    Gradient_w3 = Gradient_w3 * 2 / t
    w1 = w1 - alpha * Gradient_w1
    w2 = w2 - alpha * Gradient_w2
    w3 = w3 - alpha * Gradient_w3
    #print("at iteration ", steps, " loss is ", total_loss/t)
    loss_list.append(total_loss/t)
print("Final Loss: ", total_loss/t)
#print("final W2 * W1: ")
#print(w2.dot(w1))
pyp.plot(loss_list[1:])
pyp.show()

    #print("GradientW1: ")
    #print(Gradient_w1)
    #print("loss:")
    #print(loss)
    #print("dfdw1:")
    #print(dfdw1)
    #print("dfdw2:")
    #print(dfdw2)
```

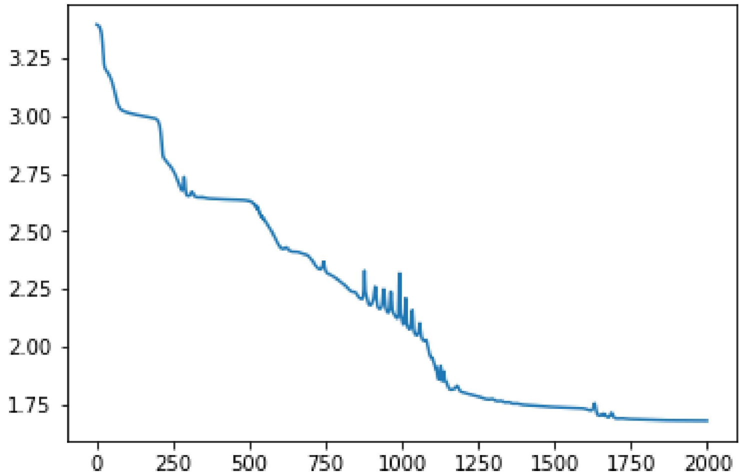
```
Final Loss:  1.7962366226647475
```



In [92]:
```
# NN1 with m = 25
m = 25
alpha = 0.05
w1 = np.random.rand(m,n)*0.01
w2 = np.random.rand(m,m)*0.01
w3 = np.random.rand(n,m)*0.01
loss_list = []
for steps in range(2000):
    Gradient_w1 = np.zeros(w1.shape)
    Gradient_w2 = np.zeros(w2.shape)
    Gradient_w3 = np.zeros(w3.shape)
    total_loss = 0
    for col in range(t):
        loss = NN1_forward_pass(x[:,col],y[:,col],w1,w2,w3)
        total_loss += np.linalg.norm(loss)**2
        dfdw1,dfdw2,dfdw3 = NN1_backprop(x[:,col],w1,w2,w3,n,m)
        Gradient_w1 += VecXTen(loss,dfdw1)
        Gradient_w2 += VecXTen(loss,dfdw2)
        Gradient_w3 += VecXTen(loss,dfdw3)
    Gradient_w1 = Gradient_w1 * 2 / t
    Gradient_w2 = Gradient_w2 * 2 / t
    Gradient_w3 = Gradient_w3 * 2 / t
    w1 = w1 - alpha * Gradient_w1
    w2 = w2 - alpha * Gradient_w2
    w3 = w3 - alpha * Gradient_w3
    #print("at iteration ", steps, " loss is ", total_loss/t)
    loss_list.append(total_loss/t)
print("Final Loss: ", total_loss/t)
#print("final W2 * W1: ")
#print(w2.dot(w1))
pyp.plot(loss_list[1:])
pyp.show()

    #print("GradientW1: ")
    #print(Gradient_w1)
    #print("loss:")
    #print(loss)
    #print("dfdw1:")
    #print(dfdw1)
    #print("dfdw2:")
    #print(dfdw2)
```

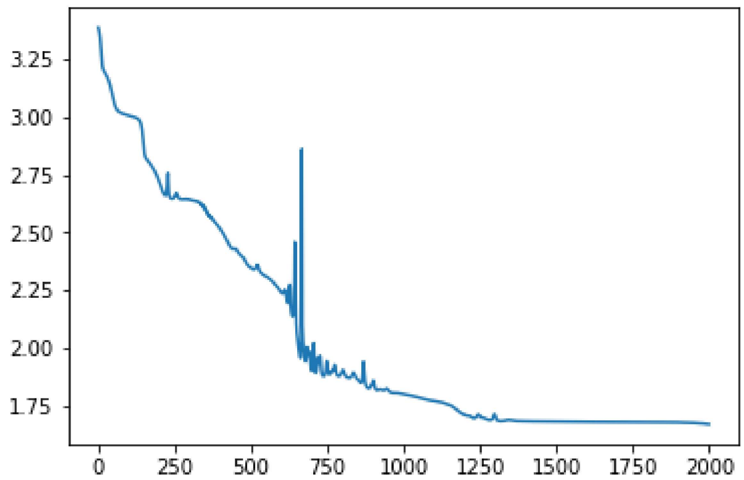
```
Final Loss:  1.6788260271653126
```



In [95]:
```
# NN1 with m = 50
m = 50
alpha = 0.05
w1 = np.random.rand(m,n)*0.01
w2 = np.random.rand(m,m)*0.01
w3 = np.random.rand(n,m)*0.01
loss_list = []
for steps in range(2000):
    Gradient_w1 = np.zeros(w1.shape)
    Gradient_w2 = np.zeros(w2.shape)
    Gradient_w3 = np.zeros(w3.shape)
    total_loss = 0
    for col in range(t):
        loss = NN1_forward_pass(x[:,col],y[:,col],w1,w2,w3)
        total_loss += np.linalg.norm(loss)**2
        dfdw1,dfdw2,dfdw3 = NN1_backprop(x[:,col],w1,w2,w3,n,m)
        Gradient_w1 += VecXTen(loss,dfdw1)
        Gradient_w2 += VecXTen(loss,dfdw2)
        Gradient_w3 += VecXTen(loss,dfdw3)
    Gradient_w1 = Gradient_w1 * 2 / t
    Gradient_w2 = Gradient_w2 * 2 / t
    Gradient_w3 = Gradient_w3 * 2 / t
    w1 = w1 - alpha * Gradient_w1
    w2 = w2 - alpha * Gradient_w2
    w3 = w3 - alpha * Gradient_w3
    #print("at iteration ", steps, " loss is ", total_loss/t)
    loss_list.append(total_loss/t)
print("Final Loss: ", total_loss/t)
#print("final W2 * W1: ")
#print(w2.dot(w1))
pyp.plot(loss_list[1:])
pyp.show()

    #print("GradientW1: ")
    #print(Gradient_w1)
    #print("loss:")
    #print(loss)
    #print("dfdw1:")
    #print(dfdw1)
    #print("dfdw2:")
    #print(dfdw2)
```

```
Final Loss:  1.668421258126552
```



In [119]:
```
x = np.load("assignment8_X.npy")
y = np.load("assignment8_Y.npy")
x = x.T
y = y.T

alpha = 0.01
n = x.shape[0] # n = 10
t = x.shape[1] # t = 25
def vec_sigmod(x):
    for i in range(len(x)):
        x[i] = 1/(1+np.exp(-x[i]))
    return x
def sigmod(x):
    return 1/(1+np.exp(-x))
def Sigmod_forward_pass(x,y,w1,w2,w3):
    #print("before forward pass, x")
    #print(x)
    #print("w2")
    #print(w2)
    #print("w1")
    #print(w1)
    #print("y")
    #print(y)
    fwx = w3.dot(vec_sigmod(w2.dot(vec_sigmod(w1.dot(x)))))
    #print("fwx")
    #print(fwx)
    loss = fwx - y
    #print("loss")
    #print(loss)
    return loss

def Sigmod_backprop(x,w1,w2,w3,n,m): # w1 25x10 w2 10x25
    dfdw3 = np.zeros((n,n,m))
    dfdw2 = np.zeros((n,m,m))
    dfdw1 = np.zeros((n,m,n))

    # Compute dv2dw2, dv1dw1
    dv2dw2 = np.zeros((m,m,m))
    dv1dw1 = np.zeros((m,m,n))
    h1 = vec_sigmod(w1.dot(x))
    h2 = vec_sigmod(w2.dot(h1))
    for i in range(m):
        dv2dw2[i][i] = h1.T
        dv1dw1[i][i] = x.T

    # Compute dfdv2,dfdv1
    dh2dv2 = np.zeros((m,m))    # 25x25
    dh1dv1 = np.zeros((m,m))    # 25x25
    v1 = w1.dot(x) # 25x1
    v2 = w2.dot(vec_sigmod(v1))
    for i in range(m):
        #dh2dv[i][i] = sigmod(v[i])(1-sigmod(v[i]))
        dh2dv2[i][i] = h2[i]*(1-h2[i])
        dh1dv1[i][i] = h1[i]*(1-h1[i])
    dfdv2 = w3.dot(dh2dv2)     # nxm
    dfdv1 = w3.dot(dh2dv2.dot(w2.dot(dh1dv1)))      # nxm
```

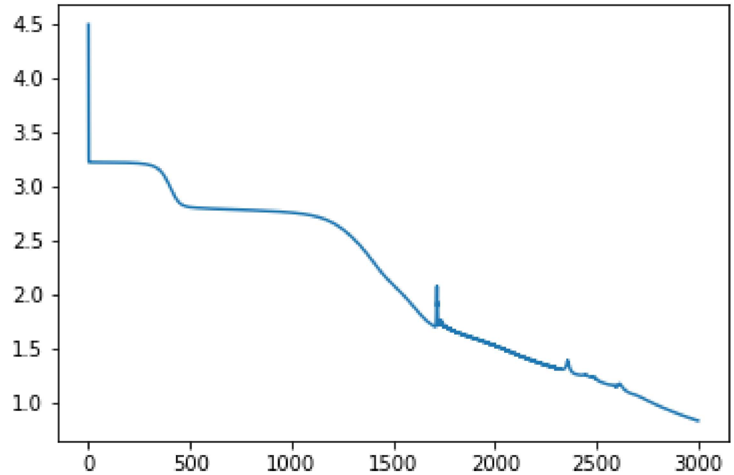
```
    # Compute dfdw1,dfdw2,dfdw3
    for i in range (n):
        for j in range(m):
            #print(dv2dw2.shape,dfdv2.shape)
            dfdw2[i] += dv2dw2[j]*dfdv2[i][j]
            dfdw1[i] += dv1dw1[j]*dfdv1[i][j]
    for i in range(n):
        dfdw3[i][i] = h2.T

    return dfdw1,dfdw2,dfdw3
```

In [80]:
```
# NN2 with m = 10
alpha = 0.1
m = 10
w1 = np.random.rand(m,n)*0.1 # 10x10
w2 = np.random.rand(m,m)*0.1 # 10x10
w3 = np.random.rand(n,m)*0.1 # 10x10

loss_list = []
for steps in range(3000):
    Gradient_w1 = np.zeros(w1.shape)
    Gradient_w2 = np.zeros(w2.shape)
    Gradient_w3 = np.zeros(w3.shape)
    total_loss = 0
    for col in range(t):
        loss = Sigmod_forward_pass(x[:,col],y[:,col],w1,w2,w3)
        total_loss += np.linalg.norm(loss)**2
        dfdw1,dfdw2,dfdw3 = Sigmod_backprop(x[:,col],w1,w2,w3,n,m)
        Gradient_w1 += VecXTen(loss,dfdw1)
        Gradient_w2 += VecXTen(loss,dfdw2)
        Gradient_w3 += VecXTen(loss,dfdw3)
    Gradient_w1 = Gradient_w1 * 2 / t
    Gradient_w2 = Gradient_w2 * 2 / t
    Gradient_w3 = Gradient_w3 * 2 / t
    w1 = w1 - alpha * Gradient_w1
    w2 = w2 - alpha * Gradient_w2
    w3 = w3 - alpha * Gradient_w3
    #print("at iteration ", steps, " loss is ", total_loss/t)
    loss_list.append(total_loss/t)
print("Final Loss: ", total_loss/t)
#print("final W2 * W1: ")
#print(w2.dot(w1))
pyp.plot(loss_list)
pyp.show()
    #print("GradientW1: ")
    #print(Gradient_w1)
    #print("loss:")
    #print(loss)
    #print("dfdw1:")
    #print(dfdw1)
    #print("dfdw2:")
    #print(dfdw2)
```

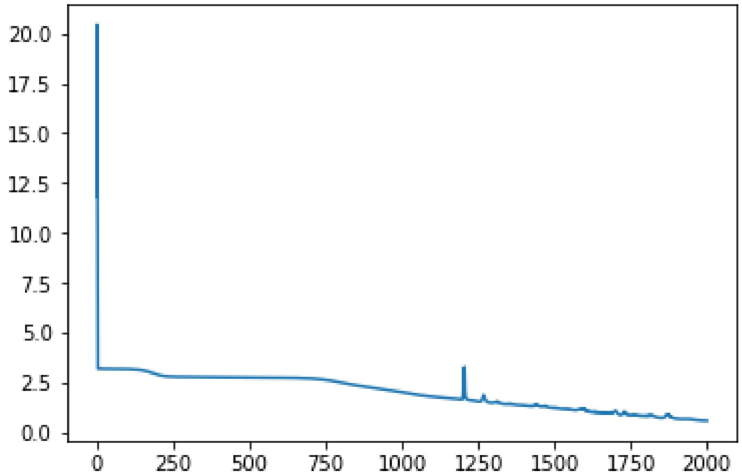
```
Final Loss:  0.8272811067483257
```



In [112]:
```
# NN2 with m = 25
alpha = 0.1
m = 25
w1 = np.random.rand(m,n)*0.1 # 10x10
w2 = np.random.rand(m,m)*0.1 # 10x10
w3 = np.random.rand(n,m)*0.1 # 10x10

loss_list = []
for steps in range(2000):
    Gradient_w1 = np.zeros(w1.shape)
    Gradient_w2 = np.zeros(w2.shape)
    Gradient_w3 = np.zeros(w3.shape)
    total_loss = 0
    for col in range(t):
        loss = Sigmod_forward_pass(x[:,col],y[:,col],w1,w2,w3)
        total_loss += np.linalg.norm(loss)**2
        dfdw1,dfdw2,dfdw3 = Sigmod_backprop(x[:,col],w1,w2,w3,n,m)
        Gradient_w1 += VecXTen(loss,dfdw1)
        Gradient_w2 += VecXTen(loss,dfdw2)
        Gradient_w3 += VecXTen(loss,dfdw3)
    Gradient_w1 = Gradient_w1 * 2 / t
    Gradient_w2 = Gradient_w2 * 2 / t
    Gradient_w3 = Gradient_w3 * 2 / t
    w1 = w1 - alpha * Gradient_w1
    w2 = w2 - alpha * Gradient_w2
    w3 = w3 - alpha * Gradient_w3
    #print("at iteration ", steps, " loss is ", total_loss/t)
    loss_list.append(total_loss/t)
print("Final Loss: ", total_loss/t)
#print("final W2 * W1: ")
#print(w2.dot(w1))
pyp.plot(loss_list)
pyp.show()
    #print("GradientW1: ")
    #print(Gradient_w1)
    #print("loss:")
    #print(loss)
    #print("dfdw1:")
    #print(dfdw1)
    #print("dfdw2:")
    #print(dfdw2)
```

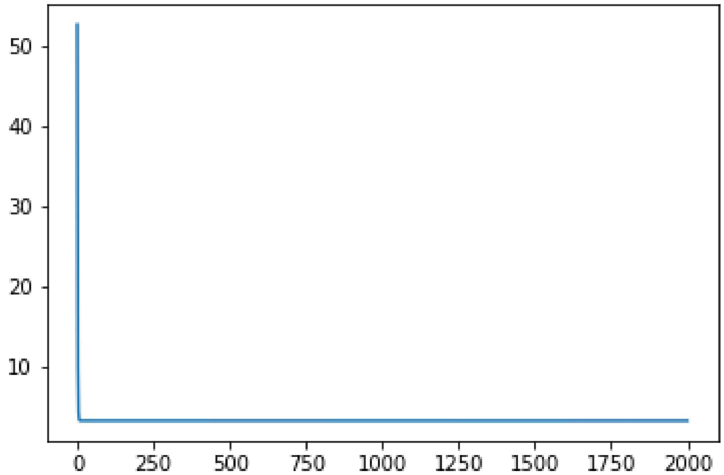
```
Final Loss:  0.6054593372685161
```



In [120]:
```
# NN2 with m = 50
alpha = 0.005
m = 50
w1 = np.random.rand(m,n)*0.1 # 10x10
w2 = np.random.rand(m,m)*0.1 # 10x10
w3 = np.random.rand(n,m)*0.1 # 10x10

loss_list = []
for steps in range(2000):
    Gradient_w1 = np.zeros(w1.shape)
    Gradient_w2 = np.zeros(w2.shape)
    Gradient_w3 = np.zeros(w3.shape)
    total_loss = 0
    for col in range(t):
        loss = Sigmod_forward_pass(x[:,col],y[:,col],w1,w2,w3)
        total_loss += np.linalg.norm(loss)**2
        dfdw1,dfdw2,dfdw3 = Sigmod_backprop(x[:,col],w1,w2,w3,n,m)
        Gradient_w1 += VecXTen(loss,dfdw1)
        Gradient_w2 += VecXTen(loss,dfdw2)
        Gradient_w3 += VecXTen(loss,dfdw3)
    Gradient_w1 = Gradient_w1 * 2 / t
    Gradient_w2 = Gradient_w2 * 2 / t
    Gradient_w3 = Gradient_w3 * 2 / t
    w1 = w1 - alpha * Gradient_w1
    w2 = w2 - alpha * Gradient_w2
    w3 = w3 - alpha * Gradient_w3
    print("at iteration ", steps, " loss is ", total_loss/t,end = '\r')
    loss_list.append(total_loss/t)
print("Final Loss: ", total_loss/t)
#print("final W2 * W1: ")
#print(w2.dot(w1))
pyp.plot(loss_list)
pyp.show()
    #print("GradientW1: ")
    #print(Gradient_w1)
    #print("loss:")
    #print(loss)
    #print("dfdw1:")
    #print(dfdw1)
    #print("dfdw2:")
    #print(dfdw2)
```

```
Final Loss:  3.2164977948406766
```



In [117]:
```
# Linear SVM NN
X = np.load("assignment9_X.npy")
Y = np.load("assignment9_Y.npy")
t = np.shape(X)[1]   # number of sameples 50 (=np.shape(Y))
n = np.shape(X)[0]   # dimension of samples 10
k = 10               # number of classes
L = 0                # loss
total_loss = 0       # total loss
L_list = []
alpha = 0.0012         # learning rate
W = np.random.rand(k,n)*0.01 # weight matrix
print(W)
fix_margin = 1
for steps in range(500):
    dLdW = np.zeros((k,n))    # partial devirative of L with respect to W
    for i in range(t):
        classOfx = Y[i]
        counter = 0
        for j in range(k):
            if j != classOfx:
                L += max(0,W[j].dot(X[:,i])-W[classOfx].dot(X[:,i])+fix_margin
)
                #print(X[:,i].shape)
                if(W[j].dot(X[:,i])-W[classOfx].dot(X[:,i])+fix_margin > 0):
                    counter += 1
                total_loss += L
                L = 0
        dLdW[classOfx] += -1 * counter * X[:,i].T
    W = W - alpha * dLdW
    print("at iteration ", steps, " loss is ", total_loss)
    L_list.append(total_loss)
    total_loss = 0
pyp.plot(L_list)
pyp.show()
```

```
[[8.82170745e-03 6.51767792e-03 4.83170777e-04 3.12632509e-03
  3.44929992e-03 6.32485414e-04 6.70754340e-03 9.67863364e-03
  9.74184241e-03 3.15140658e-03]
 [3.42461545e-03 1.16613653e-03 4.42279269e-03 3.18236657e-03
  2.66230012e-03 5.93047398e-03 8.32181071e-04 9.74430721e-04
  9.16559238e-03 5.19474588e-03]
 [3.41637217e-03 7.65376893e-03 4.89664086e-05 1.84454659e-03
  1.94596193e-03 6.51725776e-03 9.95429781e-03 3.39671833e-03
  9.74560035e-03 1.38977420e-03]
 [3.79535977e-03 4.55256780e-03 8.51263717e-03 2.91048980e-03
  2.67674836e-03 1.44121323e-03 7.43007463e-03 6.45583271e-03
  7.45040314e-03 7.36814178e-03]
 [2.03593260e-04 4.66136968e-03 5.07788448e-04 8.60040055e-03
  4.69964345e-03 3.98514680e-04 4.19040449e-03 4.57151144e-03
  6.03586983e-03 9.44339595e-03]
 [7.39933741e-03 6.16435030e-03 1.58942011e-03 9.83257620e-03
  8.60852475e-03 4.56539998e-03 7.17912102e-03 5.49473489e-03
  4.37423798e-03 9.48407957e-03]
 [1.27854065e-03 2.10066329e-03 6.95080975e-04 4.25437902e-03
  1.17729550e-03 6.38903193e-03 4.19433956e-03 7.52156802e-03
  8.43708843e-04 9.57001501e-03]
 [6.87275484e-03 7.04523792e-03 9.17211902e-03 8.62264233e-03
  8.14242901e-03 9.91243063e-03 5.20342050e-03 6.70041750e-03
  9.60506756e-03 9.93533579e-03]
 [5.40046408e-03 6.43865317e-03 3.06960023e-03 7.54368293e-03
  1.88765042e-03 4.25707131e-03 6.00494248e-03 3.12734824e-03
  2.19792357e-03 4.80650666e-03]
 [8.65927637e-03 1.43687575e-03 2.06771422e-03 4.73219682e-03
  6.62023161e-03 5.46751672e-03 3.51694815e-03 7.78769119e-03
  6.61765436e-03 5.87835841e-03]]
at iteration  0  loss is  445.6325758191826
at iteration  1  loss is  75.40443541049389
at iteration  2  loss is  28.694629213406166
at iteration  3  loss is  16.870884295660918
at iteration  4  loss is  13.45358840597196
at iteration  5  loss is  11.16285709660814
at iteration  6  loss is  9.989157528315022
at iteration  7  loss is  8.985071461519949
at iteration  8  loss is  8.013844581192785
at iteration  9  loss is  7.290567039195828
at iteration  10  loss is  7.110961238177746
at iteration  11  loss is  6.756232540383241
at iteration  12  loss is  6.412565593667965
at iteration  13  loss is  6.032772680275565
at iteration  14  loss is  5.912664967727434
at iteration  15  loss is  5.7362535461697135
at iteration  16  loss is  5.859867446697669
at iteration  17  loss is  5.491841490601571
at iteration  18  loss is  5.427853970831974
at iteration  19  loss is  5.4362167983950105
at iteration  20  loss is  5.362323016006433
at iteration  21  loss is  5.200597773853459
at iteration  22  loss is  5.143301615139715
at iteration  23  loss is  5.036757491387791
at iteration  24  loss is  4.974202679983251
at iteration  25  loss is  4.776677073022083
at iteration  26  loss is  4.729100689439595
```

```
at iteration  27  loss is  4.683093375767494
at iteration  28  loss is  4.5289347120920915
at iteration  29  loss is  4.524212569432346
at iteration  30  loss is  4.543268112339181
at iteration  31  loss is  4.359712767149455
at iteration  32  loss is  4.3345638625673155
at iteration  33  loss is  4.175104295418633
at iteration  34  loss is  4.096370006504833
at iteration  35  loss is  4.021126931053947
at iteration  36  loss is  3.927364173598807
at iteration  37  loss is  3.7884984064651963
at iteration  38  loss is  3.762209792259607
at iteration  39  loss is  3.612237171526668
at iteration  40  loss is  3.485623375292114
at iteration  41  loss is  3.514916208941019
at iteration  42  loss is  3.3273459532736185
at iteration  43  loss is  3.3217607556358764
at iteration  44  loss is  3.09652397711326
at iteration  45  loss is  3.0337147340207755
at iteration  46  loss is  3.0375763176502524
at iteration  47  loss is  2.8228962515757914
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at iteration  50  loss is  2.5024453385218663
at iteration  51  loss is  2.364886559817924
at iteration  52  loss is  2.219782827097463
at iteration  53  loss is  2.1875332224931627
at iteration  54  loss is  2.106644393273104
at iteration  55  loss is  2.046396383321575
at iteration  56  loss is  1.9544765588033766
at iteration  57  loss is  1.8308786082316661
at iteration  58  loss is  1.7351765282874219
at iteration  59  loss is  1.6374143425825052
at iteration  60  loss is  1.5589796821312198
at iteration  61  loss is  1.5474343541816555
at iteration  62  loss is  1.47564957449121
at iteration  63  loss is  1.3567598206395601
at iteration  64  loss is  1.2745806223657956
at iteration  65  loss is  1.2576952849131642
at iteration  66  loss is  1.1817159569805264
at iteration  67  loss is  1.0203604577781311
at iteration  68  loss is  0.9453778874024508
at iteration  69  loss is  0.9020608313286438
at iteration  70  loss is  0.84717493780194
at iteration  71  loss is  0.855315504857618
at iteration  72  loss is  0.7712685105203256
at iteration  73  loss is  0.6521694833856211
at iteration  74  loss is  0.607437105645702
at iteration  75  loss is  0.5541627798205955
at iteration  76  loss is  0.5824761152474074
at iteration  77  loss is  0.5295831241348958
at iteration  78  loss is  0.4212252772068741
at iteration  79  loss is  0.37286683879849036
at iteration  80  loss is  0.2982537100866791
at iteration  81  loss is  0.26438153778796636
at iteration  82  loss is  0.21146318353641114
at iteration  83  loss is  0.1319344111036802
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at iteration  84  loss is  0.09634831369308117
at iteration  85  loss is  0.11776651664328952
at iteration  86  loss is  0.07021323093616516
at iteration  87  loss is  0.08420905867520379
at iteration  88  loss is  0.0593744295858496
at iteration  89  loss is  0.059361736421451816
at iteration  90  loss is  0.0976269942789969
at iteration  91  loss is  0.046043333841330636
at iteration  92  loss is  0.06049941141682247
at iteration  93  loss is  0.03498961854172755
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at iteration  95  loss is  0.06475577364478902
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at iteration  97  loss is  0.04998606806184558
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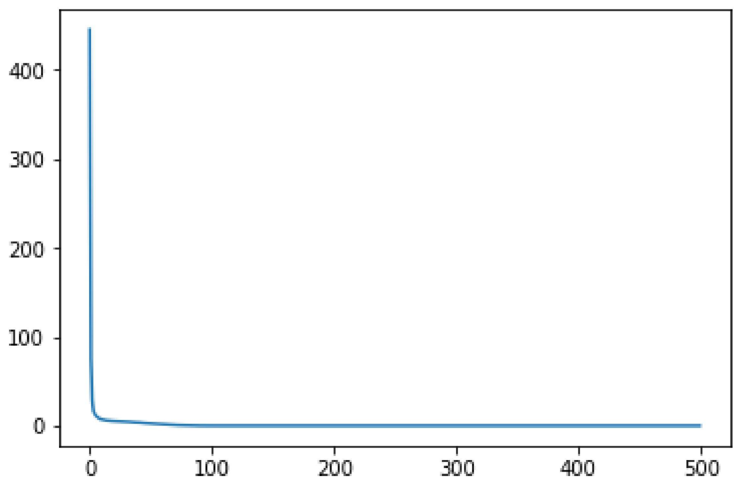

In [32]:
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Y
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Out[32]:
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