Report on Fast Forward Neural Network

by Ruijie Rao

Library Import

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image
from numpy.random import RandomState
```

Data import

Data Prep

```
In [45]:
          X_{\text{train}} = \text{np. c}_{\text{[np. ones}}((X_{\text{train. shape}}[0], 1)), X_{\text{train}}[:, :]]
          X_{\text{test}} = \text{np.} c_{\text{np.}} \text{ones}((X_{\text{test.}} \text{shape}[0], 1)), X_{\text{test}}[:, :]]
          rs = RandomState(0)
In [46]:
          y train
         Out[46]:
                1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1,
                1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0,
                0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0,
                0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
                1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0
```

Neural Network - Perceptron Learning

Goal: Use Multiple Perceptrons to accomplish more complex classifications.

- 1. Dynamic Programming for efficiently computing the gradient.
 - Storing the outputs of subproblems and avoid re-calculating.
- 2. Stochastic Gradient Descent

Iterations:

1. Compute $x_j^{(l)}$ for all $1 \leq l \leq L$, $1 \leq j \leq d^{(l)}$ in the forward direction:

$$x_j^{(l)} = heta(\sum_{i=0}^{d^{l-1}} w_{ij}^{(l)} x_i^{(l-1)})$$

2. Compute $\delta_i^{(l)}$ for all $1 \leq l \leq L$, $1 \leq i \leq d^{(l)}$ in the reverse direction:

$$\delta_i^{(l-1)} = heta(x_i^{(l-1)})(1 - heta(x_i^{(l-1)}))(\sum_{j=0}^{d^{l-1}} w_{ij}^{(l)}\delta_j^{(l)})$$

Base case:

$$\delta_i^{(L)} = 2(heta(x_i^{(L)}) - y) heta(x_i^{(l-1)})(1 - heta(x_i^{(l-1)}))$$

3. For each $\boldsymbol{w}_{ij}^{(l)}$:

$$w_{ij}^{(l)} = w_{ij}^{(l)} - \eta \delta_j^{(l)} x_i^{(l-1)}$$

Model Script

Initialization

Will be using 1 hidden layer with a number of neurons equals to the mean of input and output neuron numbers.

```
In [8]:

def gen_d_list(Ni, No, Nn, Nh):
    d_list = [Nn for 1 in range(Nh)]
    d_list.insert(0, Ni)
    d_list.append(No)
    return d_list

def init_w(d_list):
    w_list = [rs.rand(d_list[i+1], d_list[i]) for i in range(len(d_list)-1)]
    w_list.insert(0, None)
    return w_list
```

Loss Function

Going to use Mean Square Error as the Loss Function

```
In [9]:
    def MSE(X, y, w):# X is NxD, w is 1xD, y is Nx1
    rss = np. sum(np. square(y-h(X, w)))
    mse = rss/len(X)
    return mse
```

Gradient of Loss Function

```
Loss Function:g = rac{1}{N} \sum_{i=1}^N (h(x^{(i)}) - y^{(i)})^2
```

Where its partial derivative with respect to $j^{th}w$: $\frac{dg}{dw_j} = \frac{2}{N}\sum_{i=1}^N (h(x^{(i)}) - y^{(i)})x_j^{(i)}$

```
In [10]:
    def dMSE(X, y, w):
        m = len(X)
        d = len(X[0])
        dw = np. array([(2/m)*np. sum((h(X, w)-y)@X[:, j]) for j in range(d)])
        return dw
```

Iteration Updates

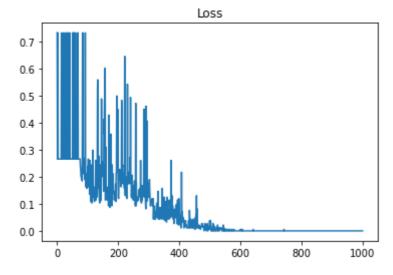
```
In [18]:
           class Neural Network:
               def init (self, X, y, Nh=1, Nn=5):
                    def gen_d_list(Ni, No, Nn, Nh):
                        d_{list} = [Nn for 1 in range(Nh)]
                        d list. insert (0, Ni)
                        d_list.append(No)
                        return d_list
                    def init_w(d_list):
                        w_list = [(self. rs. rand(d_list[i+1], d_list[i])*0.02)-0.01 for i in range
                        w list. insert (0, None)
                        return w_list
                    self. theta = 1 \text{ ambda } x: 1/(1+\text{np. } \exp(-x))
                    self.m = X. shape[0]
                    self.rs = RandomState (2022)
                    self.L = Nh+1
                    self.d = X. shape[1]
                    Ni = self.d # Number of Neurons in input layer
                    No = 1 # Number of Neurons in output layer
                    self. d list = gen d list (Ni, No, Nn, Nh)
                    self. X = X
                    self.y = y
               def dsigmoid(self, x):
                    return self. theta(x)*(1-self. theta(x))
               def update x(self, x in): # Compute all x in forward direction
                    x \text{ list} = [x \text{ in. reshape}(1, \text{self. d})]
                    for 1 in range (1, self. L+1):
                        z = x_1ist[1-1]@self.w_1ist[1].T # each x array should be 1xdi, w should
                        hx = self. theta(z)
                        x_list.append(hx)
                    return x_list # output list of lxdj
               def update delta(self, y in, x list): # Compute all delta in backward direction
                    delta\ list = [0\ for\ i\ in\ x\_list]
                    delta_list[-1] = 2*(x_list[-1]-y_in)*self.dsigmoid(x_list[-1])
                    for 1 in reversed (range (1, self. L+1)):
                        delta = self. \ dsigmoid(x\_list[1-1])*(delta\_list[1]@self. \ w\_list[1]) \ \# \ delta
                        delta_list[1-1] = delta
                    return delta_list # output list of 1xdi
               def update w(self, x list, delta list, alpha): # Update w
                    for 1 in range (1, self. L+1):
                        w = self. w_list[1] # djxdj
                        x = x_1ist[1-1] # 1xdi
                        delta = delta list[1] # 1xdj
```

```
w = w-alpha*(delta. T*x)
        self. w_list[1] = w
def predict(self, X):
    hx = X
    for 1 in range (1, self. L+1):
        z = hx@self.w_list[1].T # X should be mxdi, w should be djxdi, result mxd
        hx = self. theta(z)
    pred = np. array([0+int(p)=0.5) for p in hx])
    return pred
def loss(self, X, y):
    loss = np. sum(np. square(y-self. predict(X)))/self. m
    return loss
def plot_loss(self, loss_list):
    ax = p1t. gca()
    ax. set_title('Loss')
    ax. plot (np. arange (len (loss_list)), loss_list)
    plt. show()
def fit (self, alpha, epoch=1000):
    self. w list = init w(self. d list)
    self.loss_list = []
    for e in range (epoch):
        for i in range (self. m):
            random_p = self.rs.randint(0, self.m-1)
            x_in = self. X[random_p] # random x point
            y_in = self.y[random_p]
            x_list = self.update_x(x_in)
            delta list = self. update delta(y in, x list)
            self. update w(x list, delta list, alpha)
        current_loss = self. loss(self. X, self. y)
        if e\%50 == 0:
            #print(self.predict())
            print(f"Epoch: {e+1}, Loss: {current_loss}")
        self. loss_list. append(current_loss)
    self. plot_loss(self. loss_list)
    return self.w list
```

Test

```
In [19]:
           my NN = Neural Network(X train, y train, Nh=1, Nn=100)
In [40]:
           w = my NN. fit (alpha=1e-1, epoch=1000)
          Epoch: 1, Loss: 0.7336956521739131
          Epoch: 51, Loss: 0. 266304347826087
          Epoch: 101, Loss: 0.2391304347826087
          Epoch:151, Loss:0.25
          Epoch: 201, Loss: 0.125
          Epoch: 251, Loss: 0.11413043478260869
          Epoch: 301, Loss: 0.125
          Epoch: 351, Loss: 0.125
          Epoch: 401, Loss: 0.07065217391304347
          Epoch: 451, Loss: 0.016304347826086956
          Epoch: 501, Loss: 0.021739130434782608
          Epoch: 551, Loss: 0.0
          Epoch: 601, Loss: 0.005434782608695652
          Epoch: 651, Loss: 0.0
          Epoch: 701, Loss: 0.0
```

```
Epoch: 751, Loss: 0.0
Epoch: 801, Loss: 0.0
Epoch: 851, Loss: 0.0
Epoch: 901, Loss: 0.0
Epoch: 951, Loss: 0.0
```



Data Structure, Challenges, Optimizations

Data Structure

X data is an array shaped of (m,d), where m is the number of PGM images, d is the number of pixels in each image. PGM images are read by PIL library and converted into numpy array. Then, the values are computed and changed into a range of (0,1) which is greyscale. Finally, a column of 1 is added to the data.

Y data is an array of 0 or 1 describing the image is down gesture or not.

W list is a list of weights arrays, which are of different shapes. The first layer of the list is None type, because layer 0 is not computed.

Challenges

At first, I was copying the NN algorithm from last homework directly. However, the results were all wrong and I tried to look for what is going wrong. Soon, I figured out that the formula of update delta need to change since theta has changed from tanh to sigmoid in this problem.

Optimizations

Pocket Algorithm

0.04 0.03 0.02

200

400

600

800

1000

By butting the best solution in the pocket during stochastic GD.In this assignment, the best weight of the last epoch will be used at the start of the next epoch, so that accuracy during the fit will not fluctuate that much.

Moreover, I have changed the loss calculation to calculating test set instead of training set, which should influence the pocket algorithm.

```
In [215...
           def pocket(w, w_best, acc, acc_best):
               if acc>acc best:
                   w best = w
                   acc best = acc
               return w_best, acc_best
In [29]:
           my NN pocket = Neural Network Pocket (X train, y train, Nh=1, Nn=100)
In [30]:
           my_NN_pocket.fit(alpha=1e-1,epoch=1000)
          Epoch: 1, Loss: 0.10326086956521739
          Epoch: 51, Loss: 0.10326086956521739
          Epoch: 101, Loss: 0.07608695652173914
          C:\Users\ruiji\AppData\Local\Temp/ipykernel 17252/2999349955.py:13: RuntimeWarning: ov
          erflow encountered in exp
            self.theta = lambda x: 1/(1+np.exp(-x))
          Epoch: 151, Loss: 0.05434782608695652
          Epoch: 201, Loss: 0.043478260869565216
          Epoch: 251, Loss: 0.043478260869565216
          Epoch: 301, Loss: 0. 043478260869565216
          Epoch: 351, Loss: 0.03804347826086957
          Epoch: 401, Loss: 0.021739130434782608
          Epoch: 451, Loss: 0.021739130434782608
          Epoch: 501, Loss: 0.021739130434782608
          Epoch: 551, Loss: 0.021739130434782608
          Epoch: 601, Loss: 0. 021739130434782608
          Epoch: 651, Loss: 0.021739130434782608
          Epoch: 701, Loss: 0.021739130434782608
          Epoch: 751, Loss: 0.021739130434782608
          Epoch: 801, Loss: 0.021739130434782608
          Epoch: 851, Loss: 0.021739130434782608
          Epoch: 901, Loss: 0.021739130434782608
          Epoch: 951, Loss: 0.021739130434782608
                                      Loss
          0.10
          0.09
          0.08
          0.07
          0.06
          0.05
```

```
Out[30]: [None,
          array([[-3.93429413, 0.22188065, -0.25597181, ..., -0.16694019,
                  -0.19681044, 0.39793082,
                  [5.01085751, 0.17530102, -0.22583496, ..., -0.53740654,
                   -0.82081462, -0.35975643
                  [2.10201816, -0.2873033, 0.39469028, ..., -0.13227369,
                    0.37409951, 0.28554382],
                  [-5.12528733, -0.4836181, -0.12285077, ..., -0.56322968,
                  -0.25528401, 0.43731052,
                  [-3.20086322, 0.04773226, -0.04309797, ..., -0.26798285,
                   -0.32439349, -0.46770454],
                  [4.22818687, -0.19570363, -0.08724987, ..., -0.31207436,
                   -0.29198809, -0.29799917]),
          array([[ 2.2609612 , 1.8584726 , 1.52759858, -1.15612649, 1.63114621,
                    1.78153097, 1.6819914, 2.3790865, 1.74397238, 1.78813971,
                    2. 20273842, 0. 13972361, -1. 55220971, -2. 61854517, 0. 36970859,
                    2.\ 14784874,\ -3.\ 55663536,\ -3.\ 95391637,\ \ 1.\ 52128951,\ -0.\ 89413009,
                    2. 12809623, 1. 88349883, 1. 97634323, 1. 31338364, 1. 68355532,
                    3.36928578, -0.47540685, 2.02649673, 3.35514577, 2.45559907,
                    2.65488266, -7.06980863, -3.97083699, 2.8480033, -6.43112856,
                    1.8278666, -0.2882298, 1.8380488, 0.35009807, -5.01457966,
                    3. 56964021, -3. 02412067, 0. 25823574, 0. 62983676, 2. 88839583,
                    1. 38002384, 2. 00145728, 1. 42275561, 1. 57741092, 2. 27733777,
                    1. 56955291, 1. 77893799, 1. 78762041, 5. 39155509, 4. 77513748,
                    2.51728867, -1.98192734, 1.87973615, 2.31862207, 3.25615614,
                    1. 3302287 , 0. 38661685, 1. 86952565, -0. 47132689, 1. 94501216,
                    1.72699007,
                                 1. 93996482, 3. 40293881, -0. 72694248, -2. 41154206,
                    2.\ 2008919 \ , \quad 4.\ 49725921, \quad -3.\ 31355845, \quad 2.\ 34529595, \quad -1.\ 7604633 \ ,
                    2.48860381, 7.96878242, 1.94478109, -0.9667606, 1.51358944,
                    2. 30626737, -2. 48128781, 2. 20470441, 4. 44174359, 1. 86373887,
                    2.03196113, 1.58584339, 2.93622402, 1.38395592, 1.9014176,
                    1.67359967, 0.41653579, -1.55247383, 1.92884979, -3.44747575,
                    2.72082979, 2.00996614, -6.17503834, -5.26045323, 1.58406051]])]
In [31]:
          pred = my_NN_pocket.predict(X_test)
          sum(y test==pred)/len(y test)
         C:\Users\ruiji\AppData\Local\Temp/ipykernel 17252/2999349955.py:13: RuntimeWarning: ov
         erflow encountered in exp
            self. theta = lambda x: 1/(1+np. \exp(-x))
```

Out[31]: 0.9036144578313253

Accuracy has raised and loss fluctuation has stabilized.

Heavyball/Momentum

Heavyball algorithm works by increasing the momentum when GD is moving twds the right direction, and decreasing the momentum on the other hand.

$$p_k = \delta_j^{(l)} x_i^{(l-1)} \ w_{ij}^{(l)} = w_{ij}^{(l)} - \eta p_k + eta p_{k-1}$$

```
In [34]: my_NN_hb = Neural_Network_HeavyBall(X_train, y_train, Nh=1, Nn=100)
In [36]: my_NN_hb_fit(slabs=1a, l_bata=0, 4, spack=1000)
```

Epoch:1, Loss:0.10326086956521739

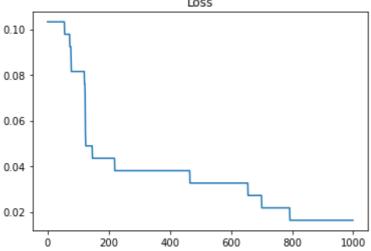
my NN hb. fit (alpha=1e-1, beta=0.4, epoch=1000)

```
Epoch: 51, Loss: 0. 10326086956521739
Epoch: 101, Loss: 0. 08152173913043478
```

 $\hbox{C:} \verb|Vsers| ruiji| AppData| Local| Temp/ipykernel_17252/949553836.py: 13: RuntimeWarning: overflow encountered in exp$

```
self. theta = lambda x: 1/(1+np. \exp(-x))
Epoch: 151, Loss: 0.043478260869565216
Epoch: 201, Loss: 0.043478260869565216
Epoch: 251, Loss: 0.03804347826086957
Epoch: 301, Loss: 0.03804347826086957
Epoch: 351, Loss: 0.03804347826086957
Epoch: 401, Loss: 0.03804347826086957
Epoch: 451, Loss: 0.03804347826086957
Epoch: 501, Loss: 0.03260869565217391
Epoch: 551, Loss: 0.03260869565217391
Epoch: 601, Loss: 0.03260869565217391
Epoch: 651, Loss: 0.03260869565217391
Epoch: 701, Loss: 0.02717391304347826
Epoch: 751, Loss: 0.021739130434782608
Epoch: 801, Loss: 0.016304347826086956
Epoch: 851, Loss: 0.016304347826086956
Epoch: 901, Loss: 0.016304347826086956
```

Epoch: 951, Loss: 0.016304347826086956



```
[None,
Out[36]:
          array([[ 0.86718058,
                                 0.29529779,
                                              0.86228808, ...,
                                                                0.1567525 ,
                    0.25631394, -0.04701554,
                                 0.02912094, -0.21592381, ...,
                  [-0.49487336,
                                                                0.39948672,
                    1.02029142,
                                 0.48245466],
                  2.30648691,
                                 0.04753675, -0.08333212, \ldots,
                                                                0.95806218,
                    0.37942808,
                                 0.46786333],
                  [-3.95507897, -0.18705484, 0.21006979, ..., -0.66926504,
                  -0.29793114, 0.05657624,
                  [-3.77231724, -0.48678279, -0.48567117, \ldots, -0.43607202,
                  -0.2993626, 0.05876564,
                  1.08920794,
                                 0.66957683, -0.20146079, \ldots, 0.96833632,
                    0.90545593,
                                 1.68873277]]),
          array([[ 6.41589882e-01, -5.42687092e-01,
                                                      2.09751630e+00,
                   -9.66293842e-01, 2.62468899e+00,
                                                      6.36161030e-01,
                    3.83344546e+00, -2.80636730e+00,
                                                      1.23241455e-01,
                    2. 48025569e-01, 6. 02157138e-02,
                                                      3.25409235e+00,
                   -4.63949350e+00, 8.67081282e-01,
                                                      1.76931888e+00,
                    2.88242172e-01, 6.90842421e-01, -1.16981863e-01,
                    3.31896181e-01, -2.54502818e-01,
                                                     1.14426358e+00,
                  -3.06680292e+00, -1.15001910e-01, -4.54431588e-01,
                  -5. 78318060e+00, 2. 03045184e+00, 5. 05221987e-01,
                    2.17787855e+00, -1.19672685e+00, 2.07153762e+00,
                    3.16005712e+00, 2.06609737e+00, 1.32772335e+00,
```

```
2.60803051e+00,
                                    3.86957013e-01, -1.66978419e+00,
                  -4.97545376e-02,
                                   1.16816870e+00, 1.93358714e+00,
                   8. 08081376e-02, 2. 62514623e+00, 4. 21428154e+00,
                  -6.98320259e-01,
                                    2.55313127e-01, -8.57871580e-01,
                  -1.92065176e+00, 2.42768835e+00, -1.62621994e+00,
                   4. 27721554e-02, -4. 90977426e-01, -4. 29911441e+00,
                   8.71214679e-01, 2.98806437e+00, 1.31958285e+00,
                  -3.10945520e+00, 2.06932936e+00,
                                                     1.25759677e+00,
                   1.77208628e+00, -4.89000217e+00, 8.86823541e-01,
                   3.02388718e+00, -9.27242213e-02, -1.05073752e+01,
                  -1.04154499e-02, -4.72998650e-01, -6.34947231e+00,
                   4.63587336e+00, -3.80163634e+00, 5.40698069e-01,
                   6.56090464e-02, 5.63157877e-01, 1.54554817e+00,
                   6.73977849e-01, 2.42974688e+00, 2.20118640e+00,
                   3.63215374e+00, 5.05645968e+00, 1.45828714e+00,
                   1.81311268e+00, 2.20552395e+00, -2.39645180e+00,
                   6.61941753e-01, -4.39505119e+00,
                                                     1.23270999e-01,
                   2.04217471e+00, -9.91139272e-01, -5.30974858e-01,
                  -7.57394916e-01, 3.56995105e+00, 1.84545525e+00,
                  -2.39491311e+00, 9.69998013e-01,
                                                     1.83883613e-01,
                   2.38687618e+00, 1.99463795e+00,
                                                      2.54830437e-02,
                   1.64546870e+00, -2.48032408e+00, -5.16413160e+00,
                   3.14975931e+00]])]
In [37]:
          pred = my_NN_hb.predict(X_test)
          sum(y test==pred)/len(y test)
         C:\Users\ruiji\AppData\Local\Temp/ipykernel_17252/949553836.py:13: RuntimeWarning: ove
         rflow encountered in exp
           self. theta = lambda x: 1/(1+np. \exp(-x))
         0.9397590361445783
Out[37]:
```

Accuracy has been raised again.