softmax

January 31, 2023

0.1 Loading Data

```
[]: import os
     # Scientific and vector computation for python
     import numpy as np
     # Plotting library
     import matplotlib.pyplot as plt
     import pandas as pd
[]: SAVE_DIR = 'Plots'
[]: Data_Dir = 'DATA'
     df_train = pd.read_csv(os.path.join(Data_Dir, 'fashion-mnist_train.csv'))
     df_test = pd.read_csv(os.path.join(Data_Dir, 'fashion-mnist_test.csv'))
[]: label_map = {0: 'T-shirt/top', 1: 'Trouser', 2: 'Pullover', 3: 'Dress', 4:

¬'Coat', 5: 'Sandal', 6: 'Shirt', 7: 'Sneaker', 8: 'Bag', 9: 'Ankle boot'}

[]: def displayData_fashion(X,y,y_pred=None , save_img_dir=None):
         Displays the data from X
         11 11 11
         import random
         # Create figure
         fig, ax = plt.subplots(nrows=10, ncols=10, sharex=True, sharey=True, u

sigsize=(10, 12))
         for r in range(10):
             for c in range(10):
                 res = random.sample(range(1, 5000), 1)
                 ax[r, c].matshow(X[res][0].reshape((28,28)), cmap='binary')
                 if y_pred is not None:
                     if y[res][0] == y_pred[res][0]:
                         ax[r,c].title.set_color('green')
                         ax[r,c].title.set_text(label_map[y[res][0]])
                     else:
```



0.2 Preprocesing

The following preprocessing steps are performed:

- 1. Normalize the data
- 2. One-hot encode the labels
- 3. Train-test split

0.2.1 Normalize the data

```
[]: X = df_train.iloc[:,1:].values
y = df_train.iloc[:,0].values
X = np.insert(X, 0, 1, axis=1)

test_X = df_test.iloc[:,1:].values
test_X = np.insert(test_X, 0, 1, axis=1)
test_y = df_test.iloc[:,0].values

print(X.shape)
```

(10000, 785)

```
[]: X = X/255
test_X = test_X/255
```

0.2.2 One-hot encode the labels

```
[]: def one_hot(y,c):
    y_hot = np.zeros((y.shape[0],c))
    for i in range(y.shape[0]):
        y_hot[i,y[i]] = 1
    return y_hot
```

```
[ ]: y_one_hot = one_hot(y,10)
print(y_one_hot.shape)
```

(10000, 10)

0.2.3 Train-test split

```
[]: #train test split
ids = np.random.permutation(X.shape[0])
train_ids = ids[:int(X.shape[0]*0.8)]
test_ids = ids[int(X.shape[0]*0.8):]

X_train = X[train_ids]
y_train = y_one_hot[train_ids]

X_test = X[test_ids]
y_test = y_one_hot[test_ids]

assert X_train.shape[0] == y_train.shape[0]
assert X_train.shape[0] +X_test.shape[0] == X.shape[0]
```

0.3 Mathematical Formulation

The hypothesis function, for sigmoid regression has a form

$$h(\theta) = \sigma(\mathbf{w}^T X) = y$$

Here, y is just a scalar. Suppose there are k classes, then, in softmax, the hypothesis function itself returns a vector with $\hat{y} \in \mathbb{R}^k$. That is,

$$\mathbf{h}(\) = \operatorname{softmax}(W^T X) = \hat{y}$$

Note that I've written upper case W instead of bold lower case w because in case of softmax, the weight is a matrix with dimension of $k \times n$. The mathematical form of softmax is:

$$\phi(\mathbf{z}) = \frac{e^{\mathbf{z}}}{\sum_{j=1}^{k} e^{\mathbf{z}_j}}$$

where

$$\mathbf{z} = W^T X$$

The loss function, used for softmax is the cross-entropy, defined as:

$$J = -\sum_{c=1}^{k} y_c \log(\hat{y}_c)/(2m)$$

The update equation is the same:

$$W_j := W_j - \alpha \frac{\partial J}{\partial W_j}$$

The update equation is similar to that in binary classification:

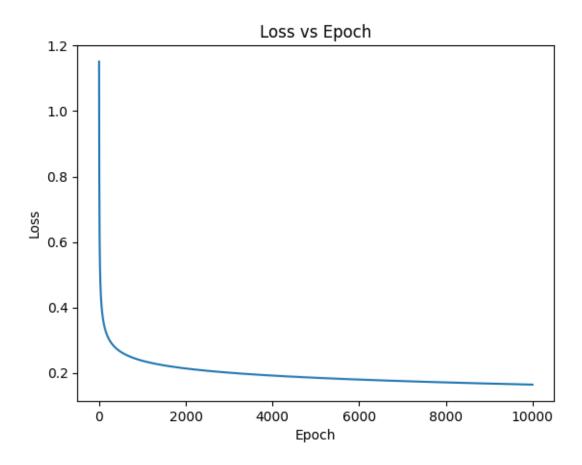
$$W := W - \alpha \frac{1}{m} \sum_{i=1}^{m} (\hat{y}^{(i)} - \mathbf{y^{(i)}}) \mathbf{x}^{(i)}$$

0.4 Implementation

```
[]: class SoftmaxBGD:
    def __init__(self,lr=0.1,n_iter=1000,see_loss=False, tol=None):
        self.lr = lr
        self.n_iter = n_iter
        self.w = None
        self.b = None
        self.loss = []
        self.tol = tol
```

```
self.see_loss = see_loss
    self.loss_old = 1
def softmax(self,z):
    return np.exp(z) / np.sum(np.exp(z),axis=1,keepdims=True)
def loss_fun(self,y,y_softmax):
    return -np.sum(y*np.log(y_softmax))*(1/(2*y.shape[0]))
def grad(self,X,y,y_softmax):
    return np.dot(X.T,y_softmax-y )
def fit(self,X,y):
    self.w = np.zeros((X.shape[1],y.shape[1]))
    for i in range(self.n_iter):
        z = np.dot(X,self.w)
        y_softmax = self.softmax(z)
        loss = self.loss_fun(y,y_softmax)
        self.loss.append(loss)
        self.w = self.w - (self.lr/X.shape[0])*self.grad(X,y,y_softmax)
        if self.see loss:
            if (i+1)\%1000 == 0:
                print("Epoch: {}, Loss: {}".format(i+1,loss))
        if self.tol is not None:
            if (abs(self.loss_old-loss)/self.loss_old) < self.tol:</pre>
                print("Converged at epoch: {}".format(i+1))
                break
            self.loss_old = loss
def predict(self,X):
    pred = self.softmax(np.dot(X,self.w))
    return np.argmax(pred,axis=1)
def accuracy(self,y,y_pred):
    return np.mean(y_pred == y)
def plot_loss(self, file_name):
    plt.plot(self.loss)
    plt.xlabel("Epoch")
    plt.ylabel("Loss")
    plt.title("Loss vs Epoch")
```

```
plt.savefig(os.path.join(SAVE_DIR,file_name))
[]: bgd = SoftmaxBGD(lr=0.1,n_iter=10000,see_loss=True)
     bgd.fit(X_train,y_train)
    Epoch: 1000, Loss: 0.23716906189038822
    Epoch: 2000, Loss: 0.21359095533081615
    Epoch: 3000, Loss: 0.20075306438501256
    Epoch: 4000, Loss: 0.19189882598172678
    Epoch: 5000, Loss: 0.18512175803620953
    Epoch: 6000, Loss: 0.17961993277953503
    Epoch: 7000, Loss: 0.17498213168979185
    Epoch: 8000, Loss: 0.17096974558439584
    Epoch: 9000, Loss: 0.1674318763241986
    Epoch: 10000, Loss: 0.16426683351094293
[]: y_pred_train= bgd.predict(X_train)
     y_pred_test = bgd.predict(X_test)
[]: train_acc = bgd.accuracy(np.argmax(y_train,axis=1),y_pred_train)
     test_acc = bgd.accuracy(np.argmax(y_test,axis=1),y_pred_test)
     print("Train Accuracy: {:.2f}%".format(train_acc*100))
     print("Test Accuracy: {:.2f}%".format(test_acc*100))
    Train Accuracy: 89.66%
    Test Accuracy: 83.45%
[]: fig = bgd.plot_loss("0602.png")
```



```
[]: y_train.shape

[]: (8000, 10)

[]: displayData_fashion(X_train[:, 1:],np.argmax(y_train, axis=1), y_pred_train, os.

→path.join(SAVE_DIR, '0603.png'))
```

