# HW 3

May 2, 2020

```
[1]: #import numpy as np
import matplotlib.pyplot as plt
import autograd.numpy as np
from autograd import grad
from sklearn.linear_model import *
import sklearn.metrics as metrics
```

## 1 Problem 6.13

```
[2]: def model(x, w):
         return w[0] + np.dot(x.T, w[1:])
     def softmax(w):
         return np.sum(np.log(1 + np.exp(-y.flatten() * model(x, w)))) / np.size(y)
     def perceptron(w):
         cost = 0
         xpTw = -y.flatten() * model(x, w)
         for i in range(xpTw.size):
             cost += np.max([0, xpTw[i]])
         return cost / np.size(y)
     def classify(x, y, w):
         y_p = y.flatten()
         I = 0
         y_hat_p = np.sign(model(x, w))
         for i in range(y.size):
             if not np.isclose(y_hat_p[i], y_p[i]):
                 T += 1
         return I
```

```
[3]: data = np.loadtxt("breast_cancer_data.csv", delimiter=',')
x, y = data[:-1, :], data[-1:, :]
```

```
[4]: w_soft = 3*np.ones(x.shape[0] + 1)
cost_soft = []
```

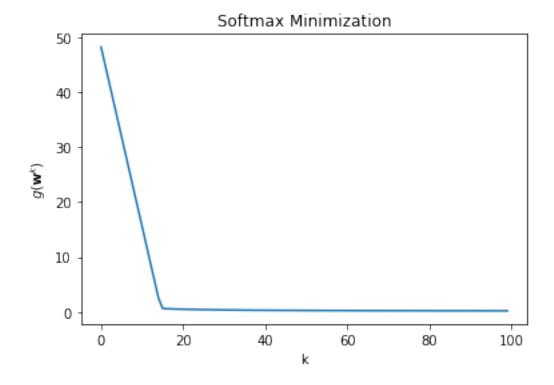
```
grad_softmax = grad(softmax)
for i in range(100):
    cost_soft.append(softmax(w_soft))
    w_soft -= 0.1 * grad_softmax(w_soft)

print("Number of mis-classifications: ", classify(x, y, w_soft))
print("Percent misclassified: %0.2f " % (100 * classify(x, y, w_soft) / y.size))
```

Number of mis-classifications: 45 Percent misclassified: 6.44

```
[5]: plt.plot(cost_soft)
  plt.xlabel("k")
  plt.ylabel("$g(\\mathbf{w}^k)$")
  plt.title("Softmax Minimization")
```

#### [5]: Text(0.5, 1.0, 'Softmax Minimization')



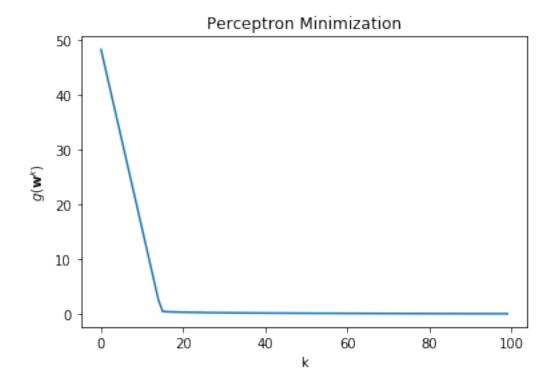
```
[6]: w_per = 3*np.ones(x.shape[0] + 1)
    cost_per = []
    grad_percep = grad(perceptron)
    for i in range(100):
        cost_per.append(perceptron(w_per))
        w_per -= 0.1 * grad_percep(w_per)
```

```
print("Number of mis-classifications: ", classify(x, y, w_per))
print("Percent misclassified: %0.2f " % (100 * classify(x, y, w_per) / y.size))
```

Number of mis-classifications: 33 Percent misclassified: 4.72

```
[7]: plt.plot(cost_per)
   plt.xlabel("k")
   plt.ylabel("$g(\\mathbf{w}^k)$")
   plt.title("Perceptron Minimization")
```

[7]: Text(0.5, 1.0, 'Perceptron Minimization')



# 2 Problem 6.15

```
[8]: #Load and split the data
data = np.loadtxt("credit_dataset.csv", delimiter=',')

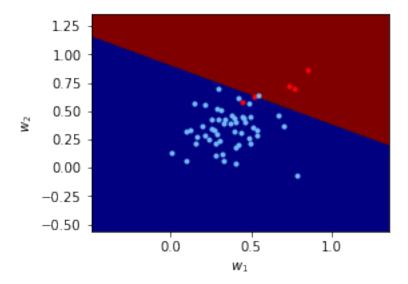
x, y = data[:-1, :], data[-1:, :]
print(x.shape, y.shape)

#Transform it via z-score
```

```
transformed = np.zeros(x.shape)
     mean = np.nanmean(x, axis=1)
     std = np.nanstd(x, axis=1)
     for i in range(len(mean)):
         transformed[i, :] = (x[i, :] - mean[i]) / std[i]
     (20, 1000) (1, 1000)
 [9]: #Initialize the Perceptron fitter and fit our data
     clf = Perceptron(max_iter=100000, early_stopping=True, fit_intercept=True,_u
      →warm_start=True)
     clf.fit(transformed.T, y.flatten())
 [9]: Perceptron(alpha=0.0001, class_weight=None, early_stopping=True, eta0=1.0,
                fit_intercept=True, max_iter=100000, n_iter_no_change=5, n_jobs=None,
                penalty=None, random_state=0, shuffle=True, tol=0.001,
                validation_fraction=0.1, verbose=0, warm_start=True)
[10]: #Determine the predicted values
     y_p_hat = clf.predict(transformed.T)
[11]: #Get elements of confusion matrix
     A, B, C, D = metrics.confusion_matrix(y.T, y_p_hat).flatten()
[12]: #Print all the statistical metrics out using the confusion matrix
     print("Accuracy of fit: %0.1f percent" % (100 * (A + D) / 1000))
     print("----")
     print("Good credit correctly predicted: ", D)
     print("Good credit incorrectly predicted: ", C)
     print("Good credit accuracy: %0.1f percent" % (100 * D / (C + D)))
     print("----")
     print("Bad credit correctly predicted: ", A)
     print("Bad credit incorrectly predicted: ", B)
     print("Bad credit accuracy: %0.1f percent" % (100 * A / (A + B)))
     Accuracy of fit: 74.3 percent
     Good credit correctly predicted: 576
     Good credit incorrectly predicted: 124
     Good credit accuracy: 82.3 percent
     Bad credit correctly predicted: 167
     Bad credit incorrectly predicted: 133
     Bad credit accuracy: 55.7 percent
```

## 3 Problem 6.16

```
[13]: data = np.loadtxt("3d_classification_data_v2_mbalanced.csv", delimiter=',')
      x, y = data[:-1, :], data[-1:, :].flatten()
      print(x.shape, y.shape)
     (2, 55) (55,)
[14]: #Softmax regression with no penalty
      clf = LogisticRegression(multi_class='multinomial', solver='newton-cg', __
       →penalty='none')
[15]: #Equal weights and fit the data
      beta = np.ones(y.shape)
      clf.fit(x.T, y, sample_weight=beta)
      #Determine the accuracy
      y_hat_p = clf.predict(x.T)
      A, B, C, D = metrics.confusion_matrix(y.T, y_hat_p).flatten()
      print("Accuracy: %0.1f percent" % (100 * (A + D) / (A + B + C + D)))
     Accuracy: 94.5 percent
[16]: x_{min}, x_{max} = x[0, :].min() - .5, <math>x[0, :].max() + .5
      y_{min}, y_{max} = x[1, :].min() - .5, <math>x[1, :].max() + .5
      h = .001 # step size in the mesh
      xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
      Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
      # Put the result into a color plot
      Z = Z.reshape(xx.shape)
      plt.figure(1, figsize=(4, 3))
      plt.pcolormesh(xx, yy, Z, cmap='jet', alpha=0.1)
      plt.plot(x[0, y==1], x[1, y==1], '.', color='xkcd:bright red')
      plt.plot(x[0, y==-1], x[1, y==-1], '.', color='xkcd:sky blue')
      plt.ylabel("$w_2$")
      plt.xlabel("$w_1$")
[16]: Text(0.5, 0, '$w_1$')
```



```
[17]: #Red weights 5x higher than others
beta = np.ones(y.shape)
beta[y == 1] = 5.0
clf.fit(x.T, y, sample_weight=beta)

#Determine the accuracy
y_hat_p = clf.predict(x.T)
A, B, C, D = metrics.confusion_matrix(y.T, y_hat_p).flatten()
print("Accuracy: %0.1f percent" % (100 * (A + D) / (A + B + C + D)))
```

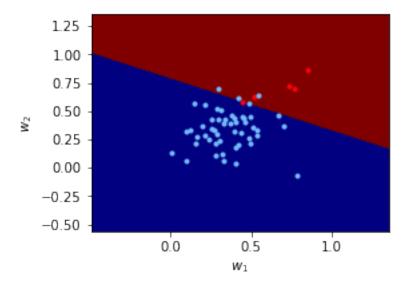
Accuracy: 92.7 percent

```
[18]: Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])

# Put the result into a color plot

Z = Z.reshape(xx.shape)
plt.figure(1, figsize=(4, 3))
plt.pcolormesh(xx, yy, Z, cmap='jet', alpha=0.1)
plt.plot(x[0, y==1], x[1, y==1], '.', color='xkcd:bright red')
plt.plot(x[0, y==-1], x[1, y==-1], '.', color='xkcd:sky blue')
plt.ylabel("$w_2$")
plt.xlabel("$w_1$")
```

[18]: Text(0.5, 0, '\$w\_1\$')



```
[19]: #Red weights 10x higher than others
beta = np.ones(y.shape)
beta[y == 1] = 10.0
clf.fit(x.T, y, sample_weight=beta)

#Get the accuracy
y_hat_p = clf.predict(x.T)
A, B, C, D = metrics.confusion_matrix(y.T, y_hat_p).flatten()
print("Accuracy: %0.1f percent" % (100 * (A + D) / (A + B + C + D)))
```

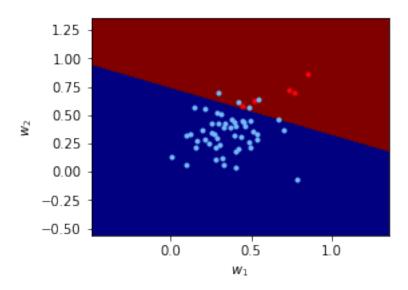
Accuracy: 90.9 percent

```
[20]: Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])

# Put the result into a color plot

Z = Z.reshape(xx.shape)
plt.figure(1, figsize=(4, 3))
plt.pcolormesh(xx, yy, Z, cmap='jet', alpha=0.1)
plt.plot(x[0, y==1], x[1, y==1], '.', color='xkcd:bright red')
plt.plot(x[0, y==-1], x[1, y==-1], '.', color='xkcd:sky blue')
plt.ylabel("$w_2$")
plt.xlabel("$w_1$")
```

[20]: Text(0.5, 0, '\$w\_1\$')



[]: