

# HW4\_P1\_3

October 14, 2018

```
In [1]: import numpy as np
import matplotlib.pyplot as plt
import csv
# load feature variables and their names
X = np.loadtxt("nuclear_x.csv", delimiter=",", skiprows=1)
with open("nuclear_x.csv", "r") as f:
    X_colnames = next(csv.reader(f))
# load salaries
y = np.loadtxt("nuclear_y.csv", delimiter=",", skiprows=1)

In [2]: def GD(X, y, Lambda, theta):
    n = len(X)
    soft_margin = np.zeros(n)
    gradient = np.zeros(len(X[0])+1)
    b = theta[0]
    w = theta[1:]
    for i in range(len(X)):
        soft_margin[i] = 1 - y[i] * (np.dot(w, X[i,:]) + b)

    soft_margin[soft_margin < 0] = 0
    soft_margin[soft_margin > 0] = 1

    gradient[0] = (-1/n) * sum(soft_margin*y)
    gradient[1:] = np.array([sum(soft_margin*(1/n)*(-y*X[:,0] + Lambda*w[0])), sum(soft

    return gradient

In [3]: def checkObjective(X, y, Lambda, theta):
    n = len(X)
    Loss_i = np.zeros(n)
    b = theta[0]
    w = theta[1:]
    for i in range(len(X)):
        Loss_i[i] = (1/n) * max(0, 1 - y[i] * (np.dot(w, X[i,:]) + b))
    Loss = sum(Loss_i) + (Lambda/2)*np.linalg.norm(theta[1:])
    return Loss

In [4]: # Problem1-3 gradient decent
#np.random.seed(0)
```

```

theta_0_GD = np.random.rand(len(X[0])+1) # theta = [b w].T

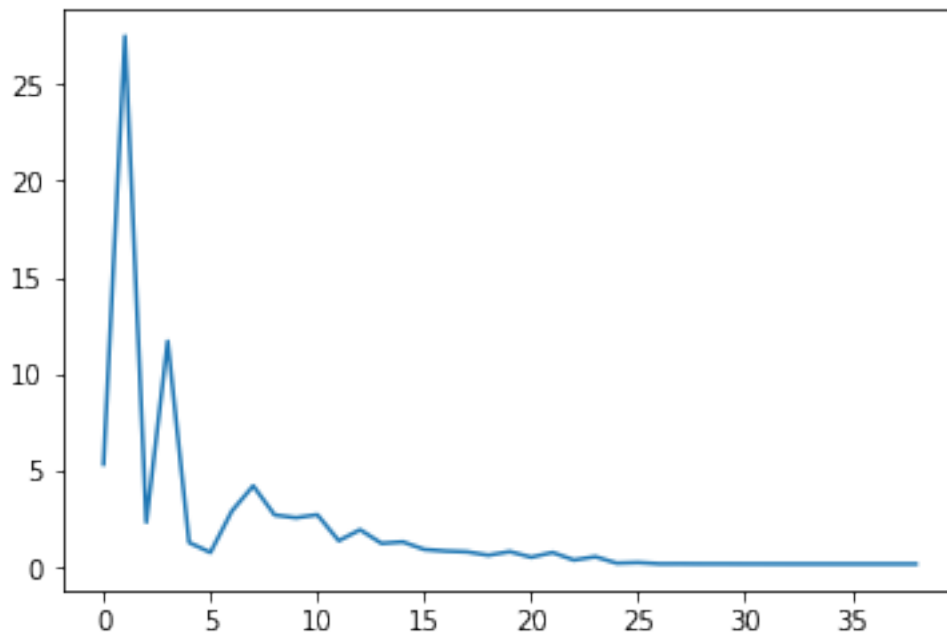
steps = 40
Loss_GD = np.zeros(steps-1)
Lambda = 0.001
theta_GD = theta_0_GD
for k in range(1,steps):
    theta_GD = theta_GD - (100/k) * GD(X, y, Lambda, theta_GD) # thetak+1 = thetak -
    #print(theta)
    Loss_GD[k-1] = checkObjective(X, y, Lambda, theta_GD)
    #print(Loss)

```

```

In [5]: plt.plot(Loss_GD)
plt.show()

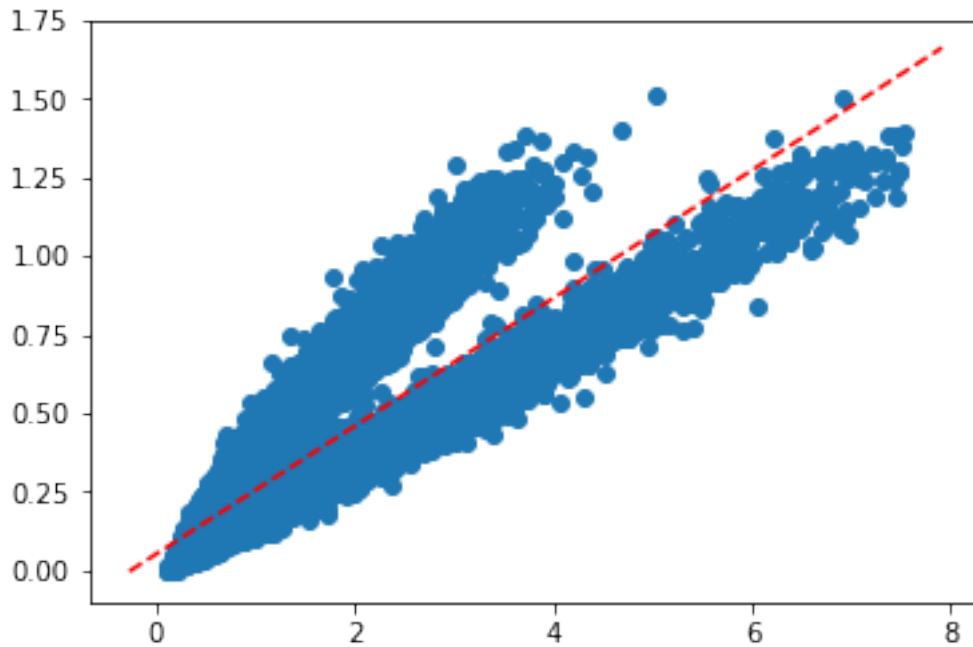
```



```

In [18]: plt.scatter(X[:,0],X[:,1])
    slope = -theta_GD[1] / theta_GD[2]
    axes = plt.gca()
    x_vals = np.array(axes.get_xlim())
    y_vals = slope * x_vals + (-theta_GD[0]/theta_GD[2])
    plt.plot(x_vals, y_vals, '--', color='red')
    plt.show()

```



```
In [20]: theta_GD
```

```
Out[20]: array([-1.08775537, -4.20154906, 20.65468971])
```

```
In [21]: Loss_GD[-1]
```

```
Out[21]: 0.17706469002736333
```

```
In [9]: def SGM(X, y, Lambda, theta):
        n = len(X)
        soft_margin = np.zeros(n)
        gradient = np.zeros((len(X), len(X[0])+1))
        b = theta[0]
        w = theta[1:]
        order = np.random.permutation(n)
        for i in range(len(X)):
            soft_margin[order[i]] = 1 - y[order[i]] * (np.dot(w, X[order[i],:]) + b)
        soft_margin[soft_margin < 0] = 0
        soft_margin[soft_margin > 0] = 1

        gradient[:,0] = (-1/n) * soft_margin * y
        gradient[:,1:] = np.array([soft_margin*(1/n)*(-y*X[:,0] + Lambda*w[0]), soft_margin*(1/n)*(-y*X[:,1] + Lambda*w[1]),
                                   soft_margin*(1/n)*(-y*X[:,2] + Lambda*w[2])])

        return gradient
```

```
In [10]: # Problem1-3 stochastic gradient method
         #np.random.seed(0)
```

```

theta_0 = np.random.rand(len(X[0])+1) # theta = [b w].T

n = len(X)
it = 40
steps = it*n
Loss = [] #np.zeros(steps-1)
Lambda = 0.001
theta = theta_0
for k in range(1,it):
    #if (k-1) % n == 0:
    J_temp = SGM(X, y, Lambda, theta)
    for i in range(n):
        theta = theta - (100/k) * J_temp[i,:] # theta_{k+1} = theta_k - alpha_k * g_i(theta_k)
        #theta = theta - (100/((k-1)/n + 1)) * J_temp[i,:] # theta_{k+1} = theta_k - alpha_k * g_i(theta_k)
        #print(theta)
        #Loss[k-1+i] = checkObjective(X, y, Lambda, theta)
        #print(k-1+i)
    Loss.append(checkObjective(X, y, Lambda, theta))
    #print(Loss)
    if (i+1) % 5000 == 0:
        print('[k, i]: ', [k, i])
        print(Loss[-1])

[k, i]: [1, 4999]
13.279524368150613
[k, i]: [1, 9999]
26.807850824331823
[k, i]: [1, 14999]
40.4911721614336
[k, i]: [2, 4999]
43.97356389907819
[k, i]: [2, 9999]
34.36788320413823
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24.936821510208464
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2.659479570299297
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1.165575692847243
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2.8716606433199634
[k, i]: [5, 4999]

```

3.2635207965341224  
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[k, i]: [36, 14999]  
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[k, i]: [37, 4999]



```

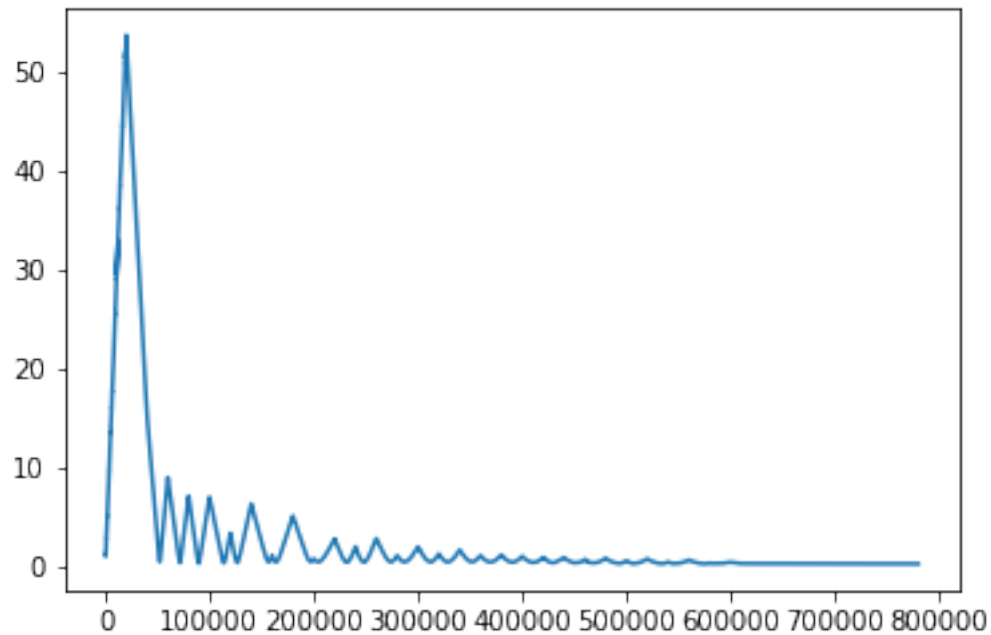
0.18616001630019124
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[k, i]: [38, 14999]
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[k, i]: [39, 4999]
0.18393771603572798
[k, i]: [39, 9999]
0.18267584797953823
[k, i]: [39, 14999]
0.18275942888767868

```

```

In [11]: plt.plot(Loss)
         plt.show()

```

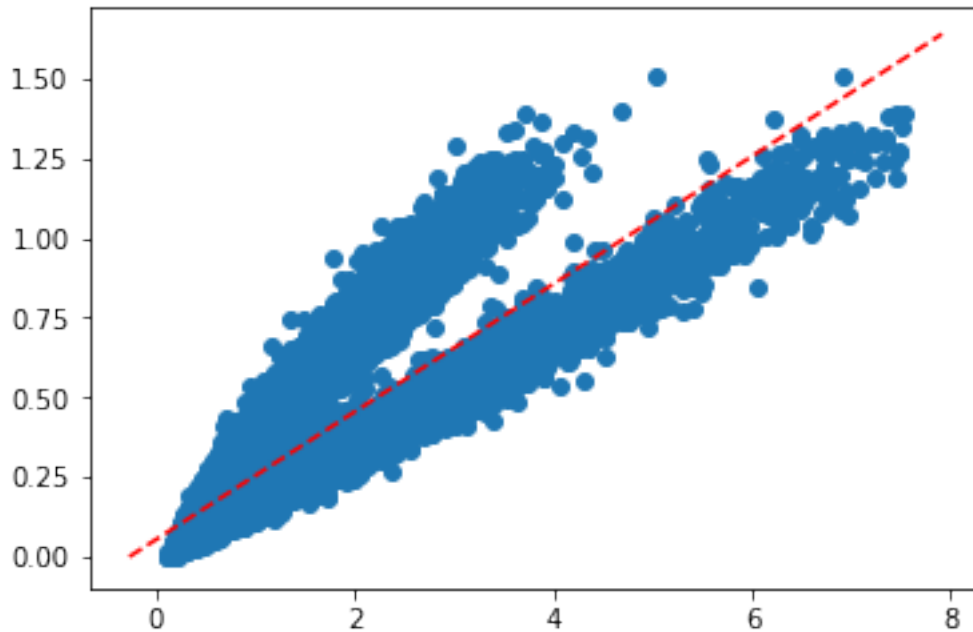


```

In [19]: plt.scatter(X[:,0],X[:,1])
         slope = -theta[1] / theta[2]
         axes = plt.gca()
         x_vals = np.array(axes.get_xlim())

```

```
y_vals = slope * x_vals + (-theta[0]/theta[2])  
plt.plot(x_vals, y_vals, '--', color='red')  
plt.show()
```



```
In [13]: print([X[index_min,0], X[index_max,0]], [y1, y2])
```

```
[0.38204828657061907, 3.2769927100934244] [-0.003303984298747231, 7.531590858610133]
```

```
In [14]: theta
```

```
Out[14]: array([-0.97315986, -3.62502033, 18.0781542 ])
```

```
In [22]: Loss[-1]
```

```
Out[22]: 0.1846215997454534
```

```
In [ ]:
```