Homework #3

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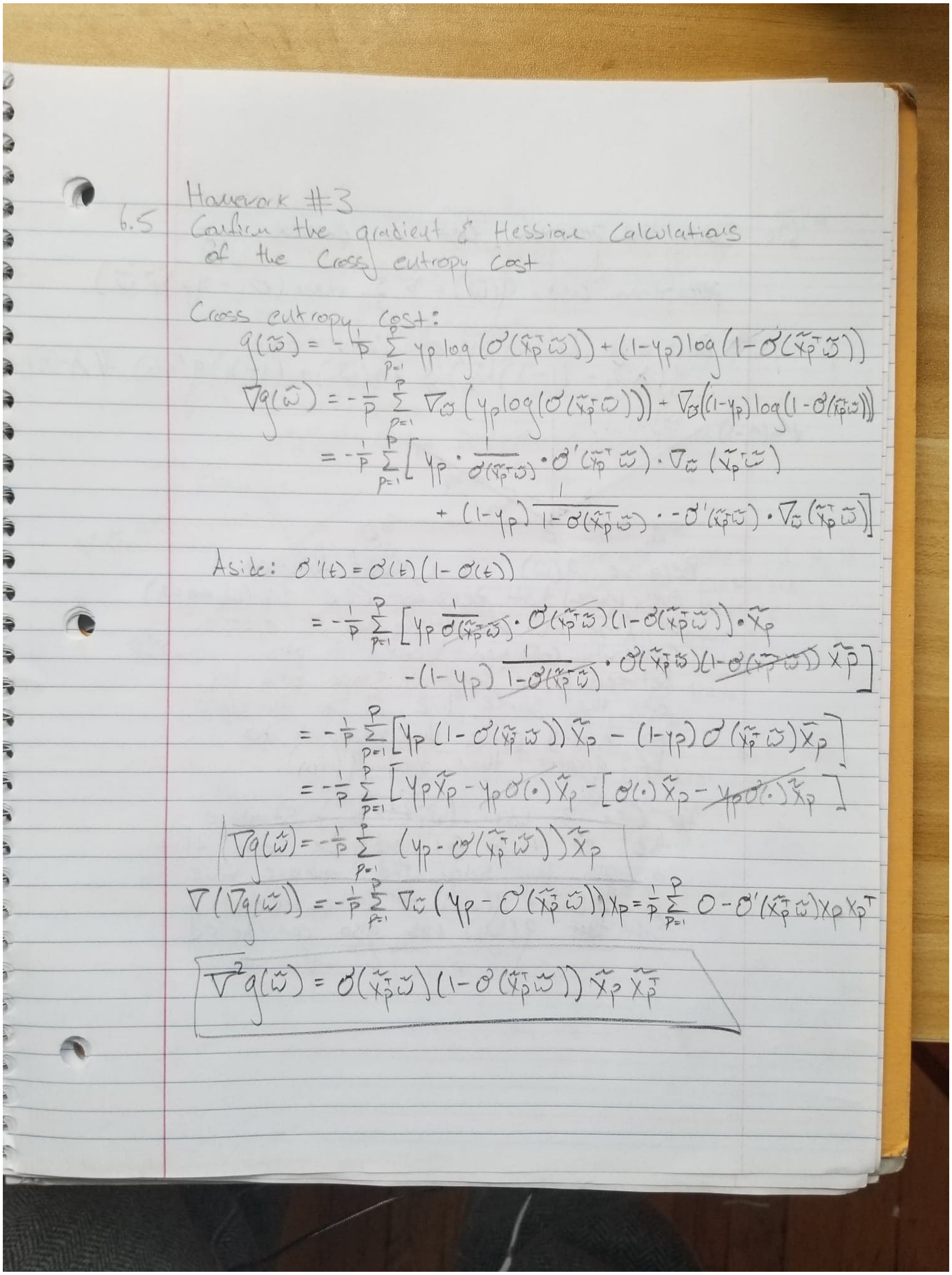
In [1]:
```
import sympy as sym
import numpy as np
%matplotlib notebook
from matplotlib import pyplot as plt
from IPython.display import Image
import pandas as pd
```

Problem 6.5

In [510]:
```
Image("65.jpg")
```

Out[510]:



Homework #3

6.5 Confirm the gradient & Hessian calculations of the cross entropy cost

Cross entropy cost:

$$g(\tilde{w}) = -\frac{1}{P}\sum_{p=1}^{P} y_p \log(\sigma(\tilde{x}_p^T\tilde{w})) + (1-y_p)\log(1-\sigma(\tilde{x}_p^T\tilde{w}))$$

$$\nabla g(\tilde{w}) = -\frac{1}{P}\sum_{p=1}^{P} \nabla_{\tilde{w}}\left(y_p\log(\sigma(\tilde{x}_p^T\tilde{w}))\right) + \nabla_{\tilde{w}}\left((1-y_p)\log(1-\sigma(\tilde{x}_p^T\tilde{w}))\right)$$

$$= -\frac{1}{P}\sum_{p=1}^{P}\Big[y_p \cdot \frac{1}{\sigma(\tilde{x}_p^T\tilde{w})}\cdot\sigma'(\tilde{x}_p^T\tilde{w})\cdot\nabla_{\tilde{w}}(\tilde{x}_p^T\tilde{w})$$
$$+ (1-y_p)\frac{1}{1-\sigma(\tilde{x}_p^T\tilde{w})}\cdot -\sigma'(\tilde{x}_p^T\tilde{w})\cdot\nabla_{\tilde{w}}(\tilde{x}_p^T\tilde{w})\Big]$$

Aside: $\sigma'(t) = \sigma(t)(1-\sigma(t))$

$$= -\frac{1}{P}\sum_{p=1}^{P}\Big[y_p\frac{1}{\cancel{\sigma(\tilde{x}_p^T\tilde{w})}}\cdot\cancel{\sigma(\tilde{x}_p^T\tilde{w})}(1-\sigma(\tilde{x}_p^T\tilde{w}))\cdot\tilde{x}_p$$
$$-(1-y_p)\frac{1}{\cancel{1-\sigma(\tilde{x}_p^T\tilde{w})}}\cdot\sigma(\tilde{x}_p^T\tilde{w})\cancel{(1-\sigma(\tilde{x}_p^T\tilde{w}))}\,\tilde{x}_p\Big]$$

$$= -\frac{1}{P}\sum_{p=1}^{P}\left[y_p(1-\sigma(\tilde{x}_p^T\tilde{w}))\tilde{x}_p - (1-y_p)\sigma(\tilde{x}_p^T\tilde{w})\tilde{x}_p\right]$$

$$= -\frac{1}{P}\sum_{p=1}^{P}\left[y_p\tilde{x}_p - \cancel{y_p\sigma(\cdot)\tilde{x}_p} - [\sigma(\cdot)\tilde{x}_p - \cancel{y_p\sigma(\cdot)\tilde{x}_p}\right]$$

$$\boxed{\nabla g(\tilde{w}) = -\frac{1}{P}\sum_{p=1}^{P}(y_p - \sigma(\tilde{x}_p^T\tilde{w}))\tilde{x}_p}$$

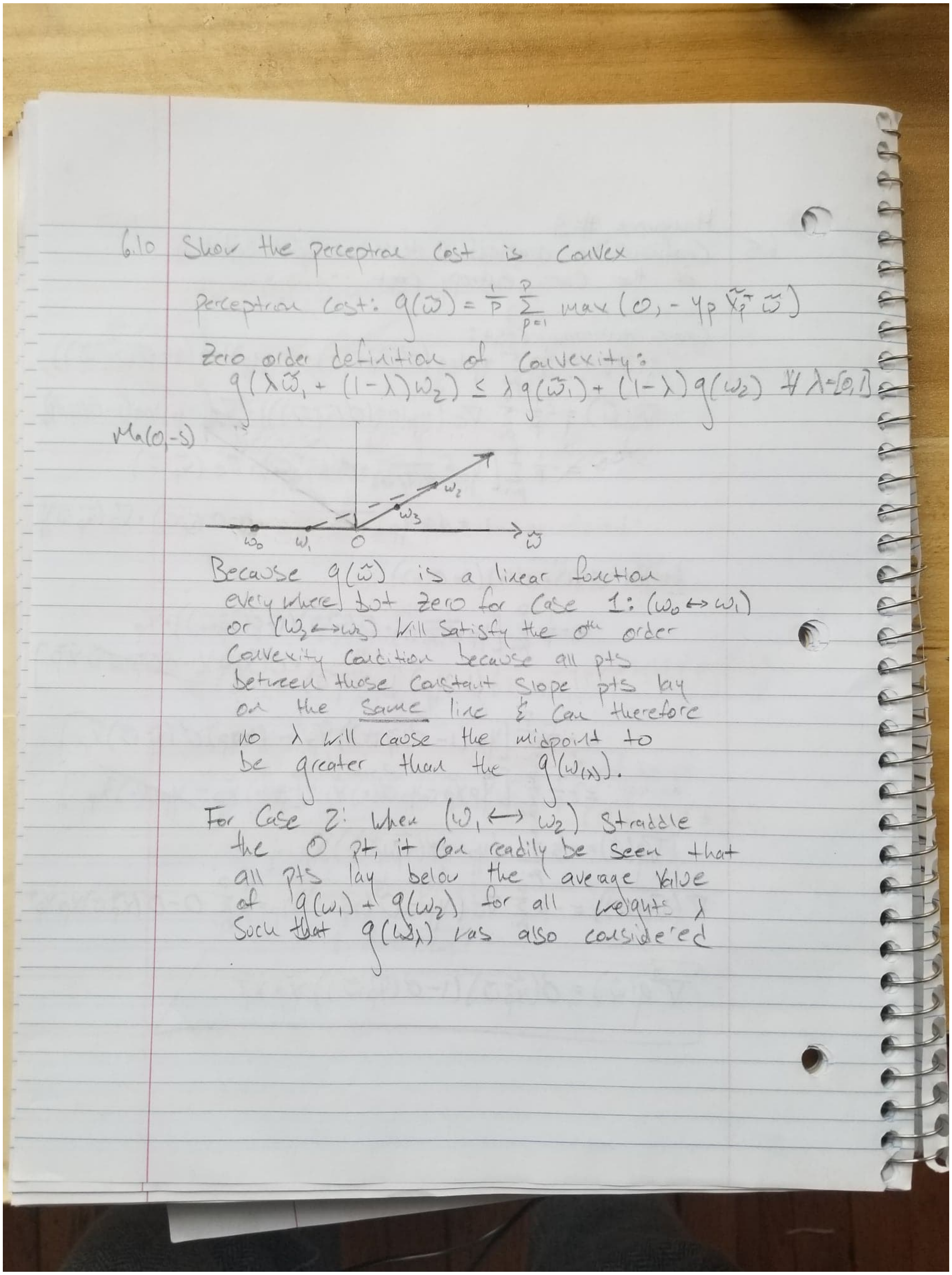
$$\nabla(\nabla g(\tilde{w})) = -\frac{1}{P}\sum_{p=1}^{P}\nabla_{\tilde{w}}(y_p - \sigma(\tilde{x}_p^T\tilde{w}))x_p = \frac{1}{P}\sum_{p=1}^{P} 0 - \sigma'(\tilde{x}_p^T\tilde{w})x_p x_p^T$$

$$\boxed{\nabla^2 g(\tilde{w}) = \sigma(\tilde{x}_p^T\tilde{w})(1-\sigma(\tilde{x}_p^T\tilde{w}))\tilde{x}_p\tilde{x}_p^T}$$

Problem 6.10

In [511]:
```
Image("610.jpg")
```

Out[511]:



6.10 Show the perceptron cost is convex

Perceptron cost: $g(\tilde{\omega}) = \frac{1}{P}\sum_{p=1}^{P} \max(0, -y_p \tilde{x}_p^T \tilde{\omega})$

Zero order definition of convexity:

$$g(\lambda\tilde{\omega}_1 + (1-\lambda)\omega_2) \le \lambda g(\tilde{\omega}_1) + (1-\lambda) g(\omega_2) \quad \forall \lambda = [0,1]$$

Ma(0,-s)

ω_0 ω_1 0 ω_3 ω_2 $\tilde{\omega}$

Because $g(\tilde{\omega})$ is a linear function everywhere but zero for case 1: $(\omega_0 \leftrightarrow \omega_1)$ or $(\omega_3 \leftrightarrow \omega_2)$ will satisfy the 0^{th} order convexity condition because all pts between those constant slope pts lay on the <u>same</u> line & can therefore no λ will cause the midpoint to be greater than the $g(\omega_{(\lambda)})$.

For Case 2: when $(\omega_1 \leftrightarrow \omega_2)$ straddle the 0 pt, it can readily be seen that all pts lay below the average value of $g(\omega_1) + g(\omega_2)$ for all weights λ such that $g(\omega_\lambda)$ was also considered

Probelm 6.13

Compare efficacy of Softmax vs Perceptron cost functions in terms of minimum number of misclassifications by pursuing gradient descent based minimization

In [61]:
```
bc_df = pd.read_csv("breast_cancer_dataset.csv", header=None, index_c
ol=None).dropna(axis=0)
```

In [118]:
```
yp = sym.symbols('y_p')
xp_tilde = sym.MatrixSymbol('\widetilde{x_p}', bc_df.shape[1], 1).as_
explicit()
w_tilde = sym.MatrixSymbol('\widetilde{w}', bc_df.shape[1], 1).as_exp
licit()
```

In [119]:
```
#percep
cost = sym.Matrix([sym.log(1 + sym.exp(-yp * xp_tilde.T * w_tilde)[0
])])
grad_cost = cost.jacobian(w_tilde)
cost_lam = sym.lambdify([yp, xp_tilde, w_tilde], cost)
grad_cost_lam = sym.lambdify([yp, xp_tilde, w_tilde],grad_cost)
# grad2_cost = grad_cost.jacobian(w_tilde)
# grad2_cost_lam = sym.lambdify([yp, xp_tilde, w_tilde], grad2_cost)
```

In [120]:
```
def p_cost(w_tilde):
    cost_sum = 0
    for i in range(bc_df.shape[0]):
        cost_sum += cost_lam(bc_df.iloc[i,-1], np.array([1,*bc_df.ilo
c[i, :-1].to_numpy()]), w_tilde)  * 1/bc_df.shape[0]

    ans = np.squeeze(cost_sum,axis=1)
    return ans
```

In [121]:
```
def grad_p_cost(w_tilde):
    grad_cost_sum = np.zeros(bc_df.shape[1])
    for i in range(bc_df.shape[0]):
#         thing = grad_cost_lam(bc_df.iloc[i,-1],np.array([1,*bc_df.i
loc[i, :-1].to_numpy()]), w_tilde)
#         print(thing.shape)
        grad_cost_sum += np.squeeze(grad_cost_lam(bc_df.iloc[i,-1],np
.array([1,*bc_df.iloc[i, :-1].to_numpy()]), w_tilde), axis=0) * 1/bc_
df.shape[0]
#         print(grad_cost_sum.shape)
    return grad_cost_sum
```

In [127]:
```
def grad_2_p_cost(w_tilde):
    grad_2_cost_sum = np.zeros((bc_df.shape[1],bc_df.shape[1]))
    for i in range(bc_df.shape[0]):
#         print(grad_2_cost_sum)
        grad_2_cost_sum += grad2_cost_lam(bc_df.iloc[i,-1] , np.array
([1,*bc_df.iloc[i, :-1].to_numpy()]) , w_tilde)

    return grad_2_cost_sum * 1/bc_df.shape[0]
```

```
In [130]: def grad_desc(w_last):
    eps = 10e-3
    cost_vals = np.zeros(3000)
    num_its = 0
    cost_vals[0] = p_cost(w_last)
    grad_last = grad_p_cost(w_last)
#     grad_2_last = grad_2_p_cost(w_last)
    num_its += 1

    while(np.linalg.norm(grad_last) > eps):
#         w_next = w_last - np.matmul(np.linalg.inv(grad_2_last), gra
d_last)
        w_next = w_last - .1 *grad_last
        num_its += 1
        if (num_its > 1000):
            break;

        w_last = w_next
        cost_vals[num_its] = p_cost(w_last)
        grad_last = grad_p_cost(w_last)
#         grad_2_last = grad_2_p_cost(w_last)
        print(np.linalg.norm(grad_last))


    return w_last, cost_vals, num_its
```

```
In [ ]: w_tilde = np.array([10, 1, 1, 1, 10, 1, 1, 1, 1, 1])
w, costs, its = grad_desc(w_tilde)
```

```
In [ ]: w_last = np.array([10, 1, 1, 1, 10, 1, 1, 1, 1, 1])
grad_last = grad_p_cost(w_last)
grad_2_last = grad_2_p_cost(w_last)
np.matmul(np.linalg.inv(grad_2_last), grad_last)
```

```
In [ ]: w_last = np.array([10, 1, 1, 1, 1, 1, 1, 1, 1, 1])

grad_last = np.expand_dims(grad_p_cost(w_last),1)
grad_2_last = grad_2_p_cost(w_last)
print(grad_2_last)
np.matmul(grad_2_last.T, grad_last)
```

```
In [148]: def misclass_calc_softmax(w_tilde):
    miscalc = 0
    for i in range(bc_df.shape[0]):
        xp_tilde = np.array([1,*bc_df.iloc[i, :-1].to_numpy()])
        yp = bc_df.iloc[i,-1]
        if np.sign(np.matmul(xp_tilde.T, w_tilde)) != np.sign(yp):
            miscalc +=1

    return miscalc
```

In [149]:
```
misclass_calc_softmax(w)
```
Out[149]: 20

In [152]:
```
def missclass_calc_perceptron(w_tilde):
    miscalc = 0
    for i in range(bc_df.shape[0]):
        xp_tilde = np.array([1,*bc_df.iloc[i, :-1].to_numpy()])
        yp = bc_df.iloc[i,-1]
        if np.maximum(0, -yp * np.matmul(xp_tilde, w_tilde)) != 0:
            miscalc += 1

    return miscalc
```

In [153]:
```
missclass_calc_perceptron(w)
```
Out[153]: 20

Both methods produced 20 misclassified elements

Problem 6.15

In [301]:
```
cd_df = pd.read_csv("credit_dataset.csv", header=None, index_col=None
).dropna(axis=0)
```

In [302]:
```
cd_mean = cd_df.iloc[:-1,:].mean(axis=1)
cd_std = cd_df.iloc[:-1,:].std(axis=1)
cd_std_norm = cd_df.iloc[:-1,:].sub(cd_mean, axis=0).div(cd_std, axis
=0)
```

In [341]:
```
def setup_symbols(df, axis):
    N = df.shape[axis]
    print(N)
    yp = sym.symbols('y_p')
    xp_tilde = sym.MatrixSymbol('\widetilde{x_p}', N, 1).as_explicit
()
    w_tilde = sym.MatrixSymbol('\widetilde{w}', N, 1).as_explicit()

    cost = sym.Matrix([sym.log(1 + sym.exp(-yp * xp_tilde.T * w_tilde
)[0])])
    grad_cost = cost.jacobian(w_tilde)
    cost_lam = sym.lambdify([yp, xp_tilde, w_tilde], cost)
    grad_cost_lam = sym.lambdify([yp, xp_tilde, w_tilde],grad_cost)
#     grad2_cost = grad_cost.jacobian(w_tilde)
#     grad2_cost_lam = sym.lambdify([yp, xp_tilde, w_tilde], grad2_co
st)

    return cost_lam, grad_cost_lam, grad2_cost_lam
```

In [308]:

```
#setup specific cost functions and link to df
cost_lam, grad_cost_lam, grad2_cost_lam = setup_symbols(cd_df, 0)
xp_tildes = cd_std_norm
yps = cd_df.iloc[-1,:].to_numpy()
df = cd_df
N = df.shape[0]
P = df.shape[1]
```

In [313]:

```
def cost(w_tilde):
    cost_sum = 0
#     print("AHHHHH")
    for i in range(P):
#         print(np.array([1,*xp_tildes.iloc[:,i].to_numpy()]).shape)
        cost_sum += cost_lam(yps[i], np.array([1,*xp_tildes.iloc[:,i]
.to_numpy()]), w_tilde)  * 1/P

    ans = np.squeeze(cost_sum,axis=1)
    return ans
```

In [314]:

```
def grad_cost(w_tilde):
    grad_cost_sum = np.zeros(N)
    for i in range(P):
        grad_cost_sum += np.squeeze(grad_cost_lam(yps[i], np.array([1
,*xp_tildes.iloc[:,i].to_numpy()]), w_tilde), axis=0) * 1/P
    return grad_cost_sum
```

In [315]:

```
# def grad_2_p_cost(w_tilde):
#     grad_2_cost_sum = np.zeros((cd_df.shape[0],cd_df.shape[0]))
#     for i in range(bc_df.shape[0]):
#         grad_2_cost_sum += grad2_cost_lam(bc_df.iloc[i,-1] , np.arr
ay([1,*bc_df.iloc[i, :-1].to_numpy()]) , w_tilde)

#     return grad_2_cost_sum * 1/df.shape[1]
```

In [318]:
```
def grad_desc(w_last):
    eps = 10e-3
    cost_vals = np.zeros(3000)
    num_its = 0
    cost_vals[0] = cost(w_last)
    grad_last = grad_cost(w_last)
    num_its += 1

    while(np.linalg.norm(grad_last) > eps):
        w_next = w_last - .1 *grad_last
        num_its += 1
        if (num_its > 1000):
            print("hit max its")
            break;

        w_last = w_next
        cost_vals[num_its] = cost(w_last)
        grad_last = grad_cost(w_last)
        print(np.linalg.norm(grad_last))


    return w_last, cost_vals, num_its
```

In [ ]:
```
w_tilde = np.ones(21)
w, costs, its = grad_desc(w_tilde)
```

In [320]:
```
def confusion_matrix_gen(w_tilde):
    confusion_matrix = pd.DataFrame(np.zeros((2,2)), index=["a_bad",
"a_good"], columns=["p_bad", "p_good"]).astype('int')
    for i in range(df.shape[1]):
        xp_tilde = np.array([1,*xp_tildes.iloc[:,i].to_numpy()])
        yp = yps[i]
        #correctly predicted
        if np.sign(np.matmul(xp_tilde.T, w_tilde)) == np.sign(yp):
            #pg, ag
            if (yp > 0):
                confusion_matrix.loc["a_good", "p_good"] += 1
            else:
                confusion_matrix.loc["a_bad", "p_bad"] += 1

        else:
            if (yp > 0):
                confusion_matrix.loc["a_good", "p_bad"] += 1
            else:
                confusion_matrix.loc["a_bad", "p_good"] += 1

    return confusion_matrix
```

In [321]:
```
confusion_matrix = confusion_matrix_gen(w)
```

In [322]:
```
confusion_matrix
```
Out[322]:

	p_bad	p_good
a_bad	146	154
a_good	76	624

In [323]:
```
acurracy = 1 - (confusion_matrix.loc["a_good", "p_bad"] + confusion_matrix.loc["a_bad", "p_good"])/1000
```
In [324]:
```
acurracy
```
Out[324]:
```
0.77
```

Therefore it can be seen that we achieved 77% accuracy

Probelm 6.16

In [458]:
```
mbal_df = pd.read_csv("3d_classification_data_v2_mbalanced.csv", header=None, index_col=None)
mbal_df.shape
```
Out[458]:
```
(3, 55)
```

In [463]:
```
#Non weighted calssification
#setup specific cost functions and link to df
# cost_lam, grad_cost_lam, grad2_cost_lam = setup_symbols(mbal_df, 0)
yp, betap = sym.symbols('y_p beta_p')
xp_tilde = sym.MatrixSymbol('\widetilde{x_p}', N, 1).as_explicit()
w_tilde = sym.MatrixSymbol('\widetilde{w}', N, 1).as_explicit()

cost = sym.Matrix([betap * sym.log(1 + sym.exp(-yp * xp_tilde.T * w_tilde)[0])])
grad_cost = cost.jacobian(w_tilde)
grad2_cost = grad_cost.jacobian(w_tilde)

cost_lam = sym.lambdify([yp, betap, xp_tilde, w_tilde], cost)
grad_cost_lam = sym.lambdify([yp, betap, xp_tilde, w_tilde],grad_cost)
grad2_cost_lam = sym.lambdify([yp, betap, xp_tilde, w_tilde], grad2_cost)

df = mbal_df
N = df.shape[0]
P = df.shape[1]
```

In [464]:
```
cost
```

Out[464]:

$$\left[\beta_p \log \left(e^{-y_p \widetilde{w}_{0,0} \widetilde{x}_{p0,0} - y_p \widetilde{w}_{1,0} \widetilde{x}_{p1,0} - y_p \widetilde{w}_{2,0} \widetilde{x}_{p2,0}} + 1 \right) \right]$$

In [465]:
```
yps = df.iloc[-1,:]
xp_tildes = df.iloc[:-1,:]
```

In [466]:
```
def cost(w_tilde, weight):
    cost_sum = 0
    for i in range(P):
        yp = yps[i]
        if (yp == 1):
            bp = 1
        elif (yp == -1):
            bp = weight
        cost_sum += cost_lam(yp, bp, np.array([1,*xp_tildes.iloc[:,i]
.to_numpy()]), w_tilde)  * 1/P

    ans = np.squeeze(cost_sum,axis=1)
    return ans
```

In [467]:
```
def grad_cost(w_tilde, weight):
    grad_cost_sum = np.zeros(N)
    for i in range(P):
        yp = yps[i]
        if (yp == 1):
            bp = 1
        elif (yp == -1):
            bp = weight
        grad_cost_sum += np.squeeze(grad_cost_lam(yp, bp, np.array([1
,*xp_tildes.iloc[:,i].to_numpy()]), w_tilde), axis=0) * 1/P

    return grad_cost_sum
```

In [468]:
```
def grad2_cost(w_tilde, weight):
    grad2_cost_sum = np.zeros((N,N))
    for i in range(P):
        yp = yps[i]
        if (yp == 1):
            bp = 1
        elif (yp == -1):
            bp = weight
        grad2_cost_sum += grad2_cost_lam(yp, bp, np.array([1,*xp_tild
es.iloc[:,i].to_numpy()]) , w_tilde) * 1/P

    return grad2_cost_sum
```

In [469]:

```
def grad_desc(w_last, weight):
    eps = 10e-3
    cost_vals = np.zeros(3000)
    num_its = 0
    cost_vals[0] = cost(w_last, weight)
    grad_last = grad_cost(w_last, weight)
    grad2_last = grad2_cost(w_last, weight)
    num_its += 1
    steps = 5
    eps = .001
    for i in range(steps):
        w_next = w_last - np.matmul(np.linalg.inv(grad2_last + eps * 
np.eye(N)),grad_last)
        num_its += 1
        if (num_its > 1000):
            print("hit max its")
            break;

        w_last = w_next
        cost_vals[num_its] = cost(w_last, weight)
        grad_last = grad_cost(w_last, weight)
        grad2_last = grad2_cost(w_last, weight)
        print(np.linalg.norm(grad_last))


    return w_last, cost_vals, num_its
```

In [494]:

```
w, costs, its = grad_desc(np.array([3, -1, -1]), 1)
```

```
0.09206934439191436
0.21174023643425482
0.027435087017300245
0.007084143461316065
0.002726270473563379
```

In [495]:

```
def missclass_calc(w_tilde):
    miscalc = 0
    for i in range(P):
        xp_tilde = np.array([1,*xp_tildes.iloc[:,i].to_numpy()])
        yp = yps[i]
        if np.maximum(0, -yp * np.matmul(xp_tilde, w_tilde)) != 0:
            miscalc += 1

    return miscalc
```

In [496]:

```
num_miss = missclass_calc(w)
```

In [497]:
```python
a_0 = "a_R"
a_1 = "a_B"
p_0 = "p_R"
p_1 = "p_B"
def confusion_matrix_gen(w_tilde):

    confusion_matrix = pd.DataFrame(np.zeros((2,2)), index=[a_0, a_1
], columns=[p_0,p_1]).astype('int')
    for i in range(P):
        xp_tilde = np.array([1,*xp_tildes.iloc[:,i].to_numpy()])
        yp = yps[i]
        #correctly predicted
        if np.sign(np.matmul(xp_tilde.T, w_tilde)) == np.sign(yp):
            #pg, ag
            if (yp > 0):
                confusion_matrix.loc[a_0, p_0] += 1
            else:
                confusion_matrix.loc[a_1, p_1] += 1

        else:
            if (yp > 0):
                confusion_matrix.loc[a_0, p_1] += 1
            else:
                confusion_matrix.loc[a_1, p_0] += 1

    return confusion_matrix
```

In [498]:
```python
confusion_matrix_unweight = confusion_matrix_gen(w)
```

In [499]:
```python
confusion_matrix_unweight
```

Out[499]:

	p_R	p_B
a_R	3	2
a_B	0	50

In [500]:
```
#unbalanced accuracy
unbal_acc = 1 - 1/ P *num_miss
#balanced accuracy
red_acc = 1 - 1/(confusion_matrix_unweight.loc["a_R"].sum()) * confus
ion_matrix_unweight.loc["a_R", "p_B"]
blue_acc = 1 - 1/(confusion_matrix_unweight.loc["a_B"].sum()) * confu
sion_matrix_unweight.loc["a_B", "p_R"]
balanced_acc = (red_acc + blue_acc) /2
print("WEIGHT B = 1")
print("unbalanced classification accuracy: {:0.4f}".format(unbal_acc
))
print("red class accuracy: {:.4f}".format(red_acc))
print("blue class accuracy: {:.4f}".format(blue_acc))
print("resulting balanced class accuracy: {:.4f}".format(balanced_acc
))
```

```
WEIGHT B = 1
unbalanced classification accuracy: 0.9636
red class accuracy: 0.6000
blue class accuracy: 1.0000
resulting balanced class accuracy: 0.8000
```

In [501]:
```
w, costs, its = grad_desc(np.array([3, -1, -1]), 1/5)
```

```
0.07390558410810351
0.024902714491193502
0.004050780550253439
0.001838294500389559
0.001423678064106507
```

In [502]:
```
num_miss = missclass_calc(w)
num_miss
```

Out[502]: 4

In [503]:
```
confusion_matrix_w5 = confusion_matrix_gen(w)
confusion_matrix_w5
```

Out[503]:

	p_R	p_B
a_R	4	1
a_B	3	47

In [504]:
```
#beta = 5
unbal_acc = 1 - 1/ P *num_miss
#balanced accuracy
red_acc = 1 - 1/(confusion_matrix_w5.loc["a_R"].sum()) * confusion_matrix_w5.loc["a_R", "p_B"]
blue_acc = 1 - 1/(confusion_matrix_w5.loc["a_B"].sum()) * confusion_matrix_w5.loc["a_B", "p_R"]
balanced_acc = (red_acc + blue_acc) /2
print("WEIGHT B = 5")
print("unbalanced classification accuracy: {:0.4f}".format(unbal_acc))
print("red class accuracy: {:.4f}".format(red_acc))
print("blue class accuracy: {:.4f}".format(blue_acc))
print("resulting balanced class accuracy: {:.4f}".format(balanced_acc))
```

```
WEIGHT B = 5
unbalanced classification accuracy: 0.9273
red class accuracy: 0.8000
blue class accuracy: 0.9400
resulting balanced class accuracy: 0.8700
```

In [505]:
```
w, costs, its = grad_desc(np.array([3, -1, -1]), 1/10)
```

```
0.053564114343693826
0.0038527327260003607
0.0021050375129540054
0.001608489211417099
0.001317451137449592
```

In [506]:
```
num_miss = missclass_calc(w)
num_miss
```

Out[506]: 5

In [507]:
```
confusion_matrix_w10 = confusion_matrix_gen(w)
confusion_matrix_w10
```

Out[507]:

	p_R	p_B
a_R	5	0
a_B	5	45

In [512]:

```python
#beta = 10
unbal_acc = 1 - 1/ P *num_miss
#balanced accuracy
red_acc = 1 - 1/(confusion_matrix_w10.loc["a_R"].sum()) * confusion_matrix_w10.loc["a_R", "p_B"]
blue_acc = 1 - 1/(confusion_matrix_w10.loc["a_B"].sum()) * confusion_matrix_w10.loc["a_B", "p_R"]
balanced_acc = (red_acc + blue_acc) /2
print("WEIGHT B = 10")
print("unbalanced classification accuracy: {:0.4f}".format(unbal_acc))
print("red class accuracy: {:.4f}".format(red_acc))
print("blue class accuracy: {:.4f}".format(blue_acc))
print("resulting balanced class accuracy: {:.4f}".format(balanced_acc))
```

```
WEIGHT B = 10
unbalanced classification accuracy: 0.9091
red class accuracy: 1.0000
blue class accuracy: 0.9000
resulting balanced class accuracy: 0.9500
```

In [ ]: