

# CSC411 Project1 Report

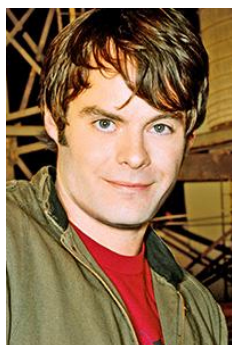
Yitian Ding

Febraury 2017

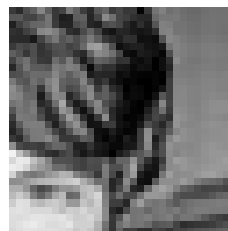
## 1 Part 1

Most of the bounding boxes are accurate, but some are not (like the example hader115 below) and the cropped-out faces are aligned with each other.

Examples are below:



Example of Hader115



Example of Chenoweth1



Example of vartan1



## 2 Part 2

First, I use a method `os.makedirs()` to create three folders including training, validation and test. Then, I the method `shutil.copy()` to copy images from my uncropped folder into three folders I created in the first step. This is my code:

```
def part2_separate(names):
    if not os.path.exists("validation-set"):
        os.makedirs("validation-set")
    else:
        shutil.rmtree("validation-set")
        os.makedirs("validation-set")
    if not os.path.exists("training-set"):
        os.makedirs("training-set")
    else:
        shutil.rmtree("training-set")
        os.makedirs("training-set")
    if not os.path.exists("test-set"):
        os.makedirs("test-set")
    else:
        shutil.rmtree("test-set")
        os.makedirs("test-set")

    image_files=os.listdir("cropped/")

    for n in names:
        name=n.split()[1].lower()
        count = 0
        for img in image_files:
            if img.startswith(name):
                if count<100:
                    shutil.copy("cropped/"+img,"training-set/")
                elif count<110:
                    shutil.copy("cropped/"+img,"validation-set/")
                elif count<120:
                    shutil.copy("cropped/"+img,"test-set/")
                count += 1
```

### 3 Part 3

Cost function I minimized:

$$J(\theta) = \frac{1}{2N} \sum_{i=1}^N (y - X\theta)_i^2$$

This is my code for f and df:

```
def f(x, y, theta):  
    return sum( (y - dot(x,theta)) ** 2)/(x.shape[0]*2)  
  
def df(x, y, theta):  
    return -dot(x.T,(y-dot(theta.T,x.T)))/(x.shape[0])
```

The value of the cost function on the training set: 100 and 100

The value of the cost function on the validation set: 10 and 7

The cost of the training set: 0.00139735275566

The cost of the validation set: 0.0550477179273

The system must work well with a proper  $\alpha$ , which cannot be too big or too small. In order to get a  $\alpha$  which can meet our requirement, we have to try mutiple values of  $\alpha$  until our requirement is met. That is,  $\theta$  will not move too much each time and also will not move too little each time.

Below is the gradient descent function I use:

```
def grad_descent(f, df, x, y, init_t, alpha):  
    EPS = 1e-8  
    prev_t = init_t - 10*EPS  
    t = init_t.copy()  
    max_iter = 30000  
    iter = 0  
    while norm(t - prev_t) > EPS and iter < max_iter:  
        prev_t = t.copy()  
        t -= alpha*df(x, y, t)  
        iter += 1  
    return t
```

And this is my function for part 3:

```
def part3(name1,name2,filename):  
    x,y=get_data(name1,name2,filename,100)  
    theta0=array([0.]*1025)  
    return x,grad_descent(f, df, x, y, theta0, 1e-7),y
```

And this is the helper function which I use to get data in the function part3:

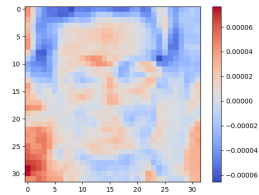
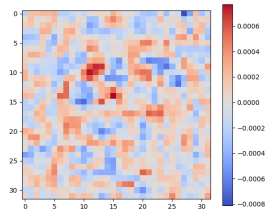
```

def get_data(names1,names2,filename , size ):
    alltraining=os.listdir(filename)
    data=[]
    y=[]
    for name1 in names1:
        counter=0
        for img in alltraining:
            if counter<size and img.startswith(name1):
                person1_data=imread(filename+"/"+img)
                data.append([1]+array(person1_data).flatten().tolist())
                y+= [1]
                counter+=1
    for name2 in names2:
        counter=0
        for img in alltraining:
            if counter<size and img.startswith(name2):
                person2_data=imread(filename+"/"+img)
                data.append([1]+array(person2_data).flatten().tolist())
                y+= [0]
                counter+=1
    all_data=array(data)
    return all_data ,array(y)

```

## 4 Part 4

A  $32 \times 32$  image of  $\theta$  is presented:



The left figure is from full training and the right figure is from two image per person.

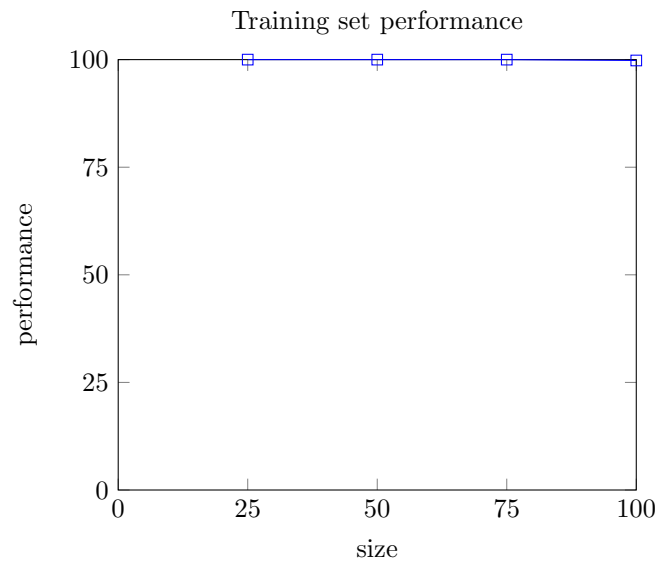
## 5 Part 5

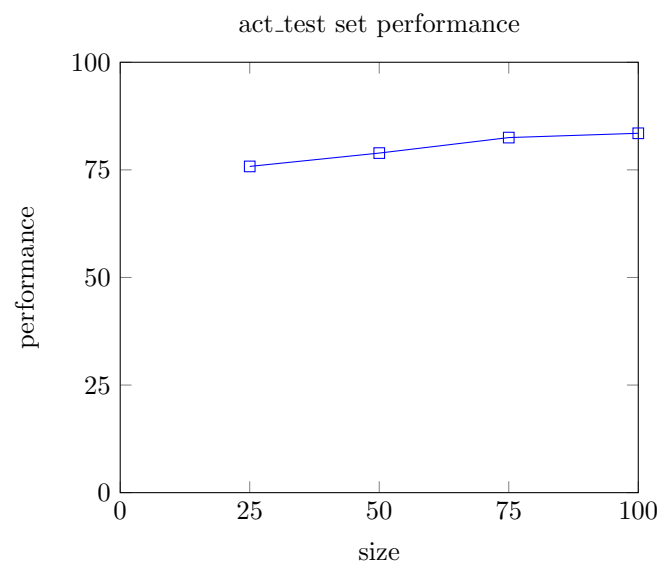
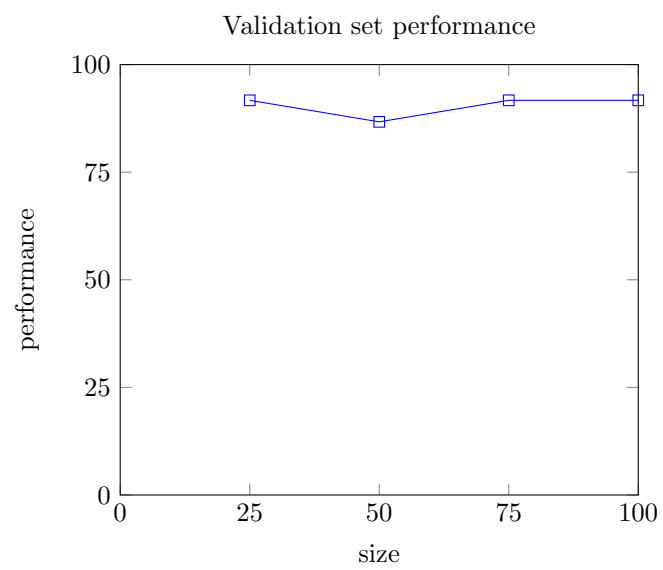
The performance is below:  
100 iamges for each person:  
Training set: 299 and 300, 99.8%  
Validation set: 28 and 27, 91.7%  
act\_test: 238 and 263, 83.5%

75 iamges for each person:  
Training set: 225 and 225, 100%  
Validation set: 28 and 27, 91.7%  
act\_test: 228 and 267, 82.5%

50 iamges for each person:  
Training set: 150 and 150, 100%  
Validation set: 28 and 24, 86.7%  
act\_test: 232 and 241, 78.9%

25 iamges for each person:  
Training set: 75 and 75, 100%  
Validation set: 29 and 26, 91.7%  
act\_test: 236 and 219, 75.8%





## 6 Part 6

6.1 a)

Let  $z(\theta) = \sum_j (\theta^T \vec{x} - \vec{y})_j^2$  be the cost of  $n \times 1$  vector  $x$  which the size of the training set is  $L$ .

$$\frac{\partial z}{\partial \theta_p} = \frac{\partial z}{\partial \theta_{qp}} = \frac{\partial z}{\partial \theta^T x_q} \cdot \frac{\partial \theta^T x_q}{\partial \theta_{qp}}$$

$$\frac{\partial z}{\partial \theta^T x_q} = \frac{\partial [(\theta^T x_1 - y_1)^2 + \dots + (\theta^T x_q - y_q)^2 + \dots + (\theta^T x_k - y_k)^2]}{\partial \theta^T x_q}$$

$$= \frac{\partial [(\theta^T x_q - y_q)^2]}{\partial \theta^T x_q}$$

$$= 2(\theta^T x_q - y_q)$$

$$\frac{\partial \theta^T x_q}{\partial \theta_{qp}} = \frac{\partial (\theta_{q1} x_1 + \dots + \theta_{qp} x_p + \dots + \theta_{qn} x_n)}{\partial \theta_{qp}}$$

$$= x_p$$

$$\frac{\partial z}{\partial \theta_{qp}} = \frac{\partial z}{\partial \theta^T x_q} \cdot \frac{\partial \theta^T x_q}{\partial \theta_{qp}} = 2(\theta^T x_q - y_q) \cdot x_p$$

$$\frac{\partial J}{\partial \theta_{qp}} = \frac{\partial J}{\partial \theta_{qp}} = \sum \frac{\partial z}{\partial \theta_{qp}} = \sum_i 2(\theta^T x^{(i)}_q - y^{(i)}_q) \cdot x_p^{(i)}$$



## 6.2 b)

$$\begin{aligned}
& \frac{\partial J(\theta)}{\partial \theta} \\
&= \frac{\partial(\theta^T X - Y)^T (\theta^T X - Y)}{\partial \theta} \\
&= \frac{\partial(X^T \theta \theta^T X - Y^T \theta^T X - X^T + Y^T Y)^T (\theta^T X - Y)}{\partial \theta} \\
&= \frac{\partial(X^T \theta \theta^T X - 2Y^T \theta^T X + Y^T Y)}{\partial \theta} \\
&= \frac{\partial(X^T (\theta)^2 X - 2Y^T \theta^T X + Y^T Y)}{\partial \theta} \\
&= 2X X^T \theta - 2X Y^T \\
&= 2X(X^T \theta - Y^T) \\
&= 2X(\theta^T X - Y)^T
\end{aligned}$$

Let  $n$  be the number of pixels+1,  $m$  be the number of training datas, and  $k$  be the number of lables, then the dimension of  $X$  is  $(n,m)$ , the dimension of  $\theta^T$  is  $(k,n)$ , and the dimension of  $Y$  is  $(k,m)$ .

## 6.3 c)

The code for my newf and newdf:

```

def newf(x,y,theta):
    return sum((dot(theta.T,x)-y)**2)

def newdf(x,y,theta):
    return (dot(x.T,(dot(x,theta)-y))*2)

```

## 6.4 d)

In this part, I check for three pairs of data.

First, I check 1st row and 2nd column:

Limit: -3.56727620776

Gradient descent: -3.56727618536

First, I check 1st row and 1st column:

Limit: -1.58994404309

Gradient descent: -1.5894405675

First, I check 0th row and 2nd column:

Limit: -3.32390110991

Gradient descent: -3.32390111448

From above we find that the results are almost the same using two different method.

The code to achieve this is below:

```
def limit(x,y,theta,a,b):
    h=1e-8
    list_h=[[0,0,0],[0,0,0],[0,0,0]]
    list_h[a][b]=h
    return (newf(x,y,theta+array(list_h))-newf(x,y,theta-array(list_h)))/(2*h)

def part6d(a,b):
    test_x=array([[3,2,1],[2,1,2],[0,1,1],[2,1,0]])
    test_y=array([[1,0,0],[0,1,0],[1,0,1],[0,0,1]])
    init_theta=array([[0.]*3]*3)
    theta=grad_descent(newf,newdf,test_x,test_y,init_theta,1e-7)
    print "using limit"
    print limit(test_x,test_y,theta,a,b)
    print "using gradient descent"
    print newdf(test_x,test_y,theta)[a][b]
```

## 7 Part 7

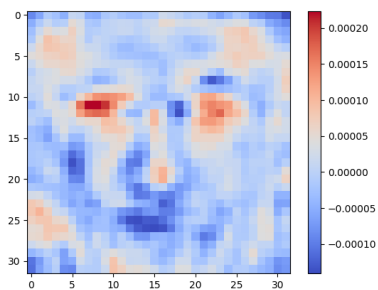
After I run gradient descent on the set of six actors act in order to perform face recognition, I got performance below:

Training set performance: [91, 93, 94, 96, 85, 88], 91.2%

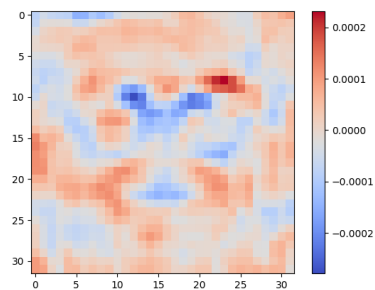
Validation set performance: [10, 6, 10, 9, 8, 10], 88.3%

For gradient descent, I choose parameter  $f$ ,  $df$ ,  $x$ ,  $y$ ,  $init\_t$ , and  $\alpha$ . These parameter make sense because we have to use them:  $f$  is the cost function,  $df$  is derivative  $df/d\theta$ ,  $x$  contains all the training data,  $y$  contains all the labels of images, and  $\alpha$  is used to move  $\theta$  properly.

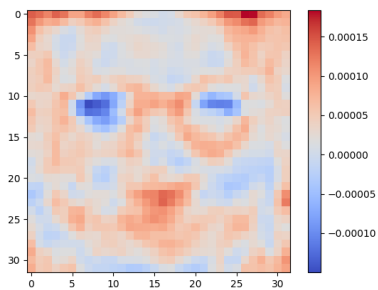
## 8 Part 8



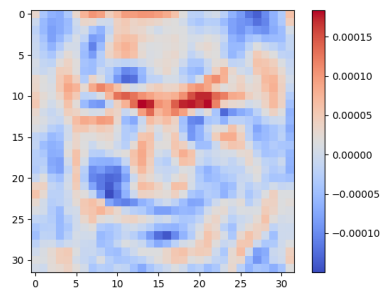
Baldwin



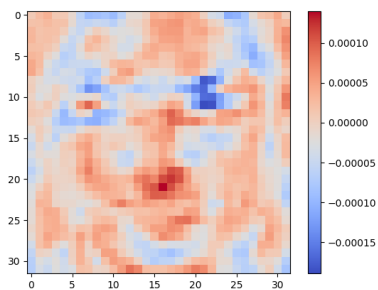
Carell



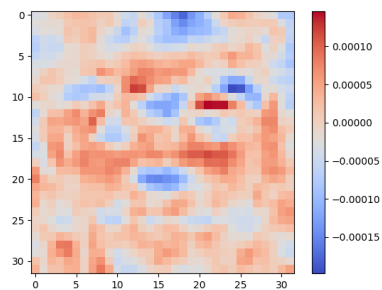
Chenoweth



Descher



Ferrera



Hader