

406\_a2

January 28, 2018

## 1 Exercise 1

### 1.0.1 a)

$$A = \begin{bmatrix} 1 & x_1^1 & x_2^1 \\ 1 & x_1^2 & x_2^2 \\ \vdots & & \\ 1 & x_1^n & x_2^n \end{bmatrix}, x = \begin{bmatrix} c_0 \\ c_1 \\ c_2 \end{bmatrix}, b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$

### 1.0.2 b)

```
In [4]: data = CSV.read("C:\\\\Users\\\\Kyle\\\\Desktop\\\\lsq_classification.csv"; datarow=1)
      mtx = convert(Array, data)
      n = size(mtx, 1)
      c = mtx[:,1:2]
      A = hcat(ones(n,1), mtx[:,1:2])
      betas = mtx[:,3:3]
```

Out [4]: 115×1 Array{Float64,2}:

1.0  
1.0  
1.0  
1.0  
1.0  
1.0  
1.0  
1.0  
1.0  
1.0  
1.0  
⋮  
-1.0  
-1.0  
-1.0  
-1.0  
-1.0

```
-1.0  
-1.0  
-1.0  
-1.0  
-1.0  
-1.0  
-1.0
```

i)

In [5]: # Solution via normal equation  $A^T A x = A^T b$   
xls = \(\*(\text{transpose}(A), A), \*(\text{transpose}(A), \text{betas}))

Out [5]: 3×1 Array{Float64,2}:  
-0.368611  
0.576988  
0.63353

ii)

In [6]: # Solution via QR  
QR = qrfact(A)  
Q = QR[:, Q]  
R = QR[:, R]  
m = size(R, 1)  
  
y = \*(\text{transpose}(Q), \text{betas})  
y = y[1:m]  
xqqr = \((R, y)

Out [6]: 3-element Array{Float64,1}:  
-0.368611  
0.576988  
0.63353

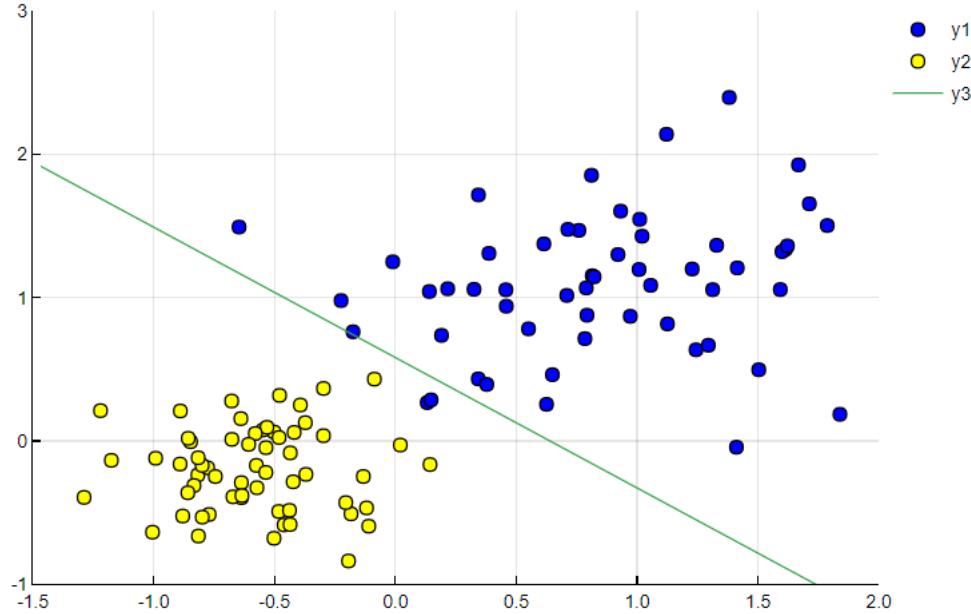
### 1.0.3 c)

In [7]: # define coefficients and function  
c0, c1, c2 = reshape(xls[1:1], 1)[1], reshape(xls[2:2], 1)[1], reshape(xls[3:3], 1)[1]  
f(x1) = (-c0 - c1\*x1) / c2  
  
# # # (x1, x2) where label = 1  
l11 = mtx[:, 1:1][mtx[:, 3:3] .== 1]  
l12 = mtx[:, 2:2][mtx[:, 3:3] .== 1]  
  
# # # (x1, x2) where label = -1  
l21 = mtx[:, 1:1][mtx[:, 3:3] .== -1]  
l22 = mtx[:, 2:2][mtx[:, 3:3] .== -1]

```

# # # plot data
scatter(111, 112, xlim=(-1.5,2), ylim=(-1, 3), colour="blue")
scatter!(121, 122, colour="yellow")
plot!(f)

```



## 2 Exercise 2

1-norm

$$f(\alpha) = \|\alpha e - b\| = \sum_{i=1}^n |\alpha - b_i|$$

This shows that by minimizing  $f(\alpha)$  we are really just minimizing the sum of the distances between  $a$  and the various values of  $b$ . To do this we should let  $a = \text{median}(b)$

2-norm

$$\begin{aligned} \min f(\alpha) &= \|\alpha e - b\| \Rightarrow \min f(\alpha)^2 = \min \sum_{i=1}^n (\alpha - b_i)^2 \\ &\Rightarrow 2\alpha n - 2 \sum_{i=1}^n b_i \\ &\Rightarrow \alpha n = \sum_{i=1}^n b_i \\ &\Rightarrow \alpha = \frac{1}{n} \sum_{i=1}^n b_i \\ &\Rightarrow \alpha = \text{mean}(b) \end{aligned}$$

inf-norm

$$\min_\alpha f(\alpha) = \min_\alpha \{\max_i \{|\alpha - b_i|\}\} = \min_\alpha \{\max_i \{\alpha - b_i, b_i - \alpha\}\}$$

To maximize  $\alpha - b_i$  we would pick the smallest  $b_i$ . To maximize  $b_i - \alpha$  we would pick the largest  $b_i$ . Therefore, to minimize both components we should let  $\alpha = \frac{\max b_i - \min b_i}{2}$

### 3 Exercise 3

$$f(x) = \frac{1}{2}(Ax - b)^T W(Ax - b) = \frac{1}{2}(Ax - b)^T QDQ(Ax - b)$$
$$= \frac{1}{2}(Ax - b)^T Q\sqrt{D}(\sqrt{D})^T Q(Ax - b)$$

Let  $Q\sqrt{D} = P$

$$\Rightarrow \frac{1}{2}(Ax - b)^T PP^T(Ax - b)$$
$$= \frac{1}{2}(P^T Ax - P^T b)^T (P^T Ax - P^T b)$$
$$= \frac{1}{2}(Bx - d)^T (Bx - d)$$

### 4 Exercise 4

a) Since A is underdetermined and consistent, should pick x such that

$$\begin{aligned} & \text{minimize } \|x\|^2 \\ & \text{subject to : } Ax = b \end{aligned}$$

$$\begin{aligned} & \text{let } L(x, \mu) = \|x\|^2 - \mu^T(b - Ax) \\ & \frac{\partial}{\partial x} = 2x - u^T A \end{aligned}$$

$$\Rightarrow x = \frac{1}{2}A^T\mu$$

$$\frac{\partial}{\partial \mu} = b - Ax$$

$$\Rightarrow b = Ax$$

$$\Rightarrow b = A(\frac{1}{2}A^T\mu)$$

$$\Rightarrow \mu = 2(AA^T)^{-1}b \Rightarrow x = A^T(AA^T)^{-1}b$$

Notice that  $A^T$  is overdetermined so let  $A^T = QR$

$$\Rightarrow x = QR(R^T Q^T QR)^{-1}b = QR^{-T}b$$

We know the norm is invariant to orthogonal transformations therefore :

$$\|x_{ls}\| = \|R^{-T}b\|$$

b)

In [11]: m = 5

n = 10

A = randn(5,10)

b = randn(5)

At = A'

QR = qrfact(At)

Q = QR[:,Q]

R = QR[:,R]

xls = (\*(\*(Q,inv(R')),b)

Out[11]: 10-element Array{Float64,1}:

1.01408

0.3956

0.187194

0.598118

-0.370701

```

-0.00259992
-0.391118
0.245214
0.801711
-0.0776825

```

## 5 Exercise 5

Proof: RLS has a unique solution, then  $\text{null}(A) \cap \text{null}(L) = \{0\}$ .

$$\begin{aligned} f(x) &= x^T A^T A x - 2x^T A^T b + b^T b + \lambda x^T L^T L x \\ \nabla f(x) &= 2A^T A x - 2A^T b + 2\lambda L^T L x \\ \Rightarrow A^T A x + \lambda L^T L x &= A^T b \\ \Rightarrow (A^T A + \lambda L^T L)x &= A^T b \end{aligned}$$

We know that  $(A^T A + \lambda L^T L)^{-1}$  must exist since RLS has a unique solution. So 0 is not an eigenvalue

$$\Rightarrow y^T (A^T A + \lambda L^T L)y \Rightarrow y^T A^T A y + \lambda y^T L^T L y \Rightarrow \|Ay\|^2 + \lambda \|Ly\|^2 > 0$$

Since there is not  $y$  s.t the above equation is 0, it must be the case that the  $\text{null}(A) \cap \text{null}(L) = \{0\}$

Proof:  $\text{null}(A) \cap \text{null}(L) = \{0\}$  then RLS has a unique solution. Proof by contradiction, suppose  $\text{null}(A) \cap \text{null}(L) = \{0\}$  and RLS does not have a unique solution

Let  $x, y \in \mathbb{R}^n, x \neq y$  and  $\phi(x) = \phi(y) = c_i = \text{the min to the RLS}$

Consider 3 cases :

1)  $x, y \in \text{null}(A) \cap \text{null}(L)$

$\Rightarrow$  since  $\text{null}(A) \cap \text{null}(L) = \{0\}$ , it must be that  $x = y = 0$

But we assumed  $x \neq y$  so this cannot be the case

2)  $x, y \in \text{null}(A) \cap x, y \notin \text{null}(L)$

$$f(x) = \|b\|^2 + \lambda \|Lx\|^2$$

$$\nabla f(x) = 2\lambda L^T L x \Rightarrow L^T L x = 0 \rightarrow x \in \text{null}(L^T L) \rightarrow x \in \text{null}(L)$$

But, it was assumed that  $x \notin \text{null}(L)$  so this case cannot be possible, a similar argument can be made for  $y$

3)  $x, y \in \text{null}(L) \cap x, y \notin \text{null}(A)$

$$f(x) = \|Ax - b\|^2$$

$$\nabla f(x) = 2A^T A x - 2A^T b \rightarrow A^T A x = A^T b$$

## 6 Exercise 6

```

In [14]: x1 = [0,0.5,1,1,0]
          x2 = [0,0,0,1,1]
          function circle_fit(A)
              A = A'
              new_A = 2*A[:,1:1]
              new_b = A[:,1:1].^2
              for i in 2:size(A,2)
                  new_A = hcat(new_A, 2*A[:,i:i])
                  new_b = new_b + A[:,i:i].^2
              end
              new_A = hcat(new_A, ones(size(A,1)))

```

```
    xls = *(inv(*(new_A',new_A)),*(new_A',new_b))
    return xls[1:size(xls,1)-1], xls[size(xls,1)]
end

x, r = circle_fit(vcat(x1',x2'))
```

Out[14]: ([0.5, 0.541667], -0.0833333333333304)