Numerical Optimization Homework 1

James Allen

October 2, 2015

1 Problem 1

Let $P \in \mathbb{R}^{n \times n}$ be a non zeros projector.

Show that $||P||_2 \ge 1$, and that this hold with equality if and only if P is an orthogonal projector.

From Trefethen & Bau "A Projector is a square matrix P that satisfies $P^2 = P$ "

Using the Cauchy-Schwarz inequality: $|(x \cdot y)| \le ||x|| \cdot ||y||$ where $(j \cdot i)$ is the dot product of j and i Now applying this to P:

$$||(P \cdot P)|| \le ||P|| \cdot ||P||$$

$$||P^2|| \le ||P|| \cdot ||P||$$

$$\frac{\left\|P^2\right\|}{\|P\|} \le \|P\|$$

Since $P = P^2$

$$\frac{\|P\|^{2}}{\|P\|^{2}} \leq \|P\|$$

$$1 \le ||P||$$

*"Orthogonal projector is any projector that is Hermitian, satisfying $P^T = P$ "

If the projector is symmetric and diagonalizable then you can do Eigenvalue Decomposition

$$\begin{split} P &= Q\Lambda Q^{-1} \\ \left\| \left(Q\Lambda Q^{-1} \overline{Q} \Lambda Q^{-1} \right) \right\| \leq \left\| Q\Lambda Q^{-1} \right\| \cdot \left\| Q\Lambda Q^{-1} \right\| \\ \left\| \left(Q\Lambda \Lambda \overline{Q}^{\Lambda_2^2} \right) \right\| \leq \left\| Q\Lambda Q^{-1} \right\| \cdot \left\| Q\Lambda Q^{-1} \right\| \\ \left\| \left(Q\Lambda^2 Q^{-1} \right) \right\| \leq \left\| Q\Lambda Q^{-1} \right\| \cdot \left\| Q\Lambda Q^{-1} \right\| \end{split}$$

This can only be true if the eigenvalues of P are 1? so ||P|| = 1?

Suppose that *A* is m - by - n, with $m \ge n$ and *A* full rank.

2.a Show that a minimizer x and corresponding residual r of the problem

$$\min_{x} \left\{ \frac{1}{2} \left\| Ax - b \right\|^2 \right\}$$

(where $\|\cdot\|$ is the 2-norm)

can be obtained by solving the augmented linear system

$$\left(\begin{array}{cc} I & A \\ A^T & 0 \end{array}\right) \left(\begin{array}{c} r \\ x \end{array}\right) = \left(\begin{array}{c} b \\ 0 \end{array}\right)$$

$$\left(\begin{array}{c} r + Ax \\ A^T r \end{array}\right) = \left(\begin{array}{c} b \\ 0 \end{array}\right)$$

2.b Now write down the augmented linear system that gives the solution and residual of

$$\min_{x} \left\{ \frac{1}{2} \|Ax - b\|^2 + \frac{1}{2} \delta^2 \|x\|^2 + c^T x \right\}$$

Expanding this

$$\frac{1}{2}x^{T}A^{T}Ax - x^{T}A^{T}b + \frac{1}{2}b^{T}b + \frac{1}{2}\delta^{2}x^{T}x + c^{T}x$$

Grouping like terms

$$\frac{1}{2}\boldsymbol{x}^{T}\left(\boldsymbol{A}^{T}\boldsymbol{A}+\boldsymbol{\delta}^{2}\boldsymbol{I}\right)\boldsymbol{x}+\left(\left(-\boldsymbol{b}^{T}\boldsymbol{A}+\boldsymbol{c}\right)^{T}\boldsymbol{x}\right)^{T}+\frac{1}{2}\boldsymbol{b}^{T}\boldsymbol{b}$$

3

Completing the square

$$\frac{1}{2} \left\| \left(A^{T} A + \delta^{2} I \right)^{1/2} x + \left(A^{T} A + \delta^{2} I \right)^{-1} \left(A^{T} b + c \right) \right\|^{2}$$

Showing that this actually is completing the square:

$$\frac{1}{2} \left\| \left(A^T A + \delta^2 I \right)^{1/2} x + \left(A^T A + \delta^2 I \right)^{-1} \left(A^T b + c \right) \right\|^2$$

$$\frac{1}{2} x^T \left(A^T A + \delta^2 I \right) x + \left(A^T A + \delta^2 I \right)^{-1/2} \left(A^T b + c \right) x + \left(A^T A + \delta^2 I \right)^{-2} \left(A^T b + c \right)^2$$

Set A by m - by - n, with the SVD $A = U\Sigma V^T$. Compute the SVD of the following matrices in terms of the factors of *A*:

Some useful notes:

$$(AB)^{-1} = B^{-1}A^{-1}$$

$$(AB)^T = B^T A^T$$

3.a
$$(A^T A)^{-1}$$

$$\left(\left(U\Sigma V^T\right)^T U\Sigma V^T\right)^{-1}$$

Since the Left (U) and Right (V) singular vectors are orthogonal to their respective transposes:

$$\left(V\Sigma^{T}U^{T}U\Sigma^{T}\right)^{-1}$$

$$\left(V\Sigma^{T}\Sigma^{T}V^{T}\right)^{-1}$$

$$\left(V\Sigma^{T}\Sigma V^{T}\right)^{-1}$$

As well it is known that Σ is a square diagonal matrix

$$(V\Sigma^2V^T)^{-1}$$

$$\left(V^{T}\right)^{-1}\Sigma^{-2}V^{-1}$$

3.b
$$(A^T A)^{-1} A^T$$

Carrying the simplified form of $(A^TA)^{-1}$ from the previous problem:

$$(V\Sigma^2V^T)^{-1}(U\Sigma V^T)^T$$

simplifying the transpose:

$$(V\Sigma^2V^T)^{-1}V\Sigma^TU^T$$

factoring out the inverse

$$(V^T)^{-1} (\Sigma^2)^{-1} V^{-1} V \Sigma^T U^T$$

$$(V^T)^{-1} (\Sigma^2)^{-1} \Sigma^T U^T$$

 $(V^T)^{-1}\Sigma^{-1}U^T$

3.c
$$A(A^{T}A)^{-1}$$

Carrying the simplified form of $(A^TA)^{-1}$ from the first problem

$$U\Sigma V^T (V\Sigma^2 V^T)^{-1}$$

factoring out the inverse

$$U\Sigma V^{T} (V^{T})^{-1} (\Sigma^{2})^{-1} V^{-1}$$

$$U\Sigma (\Sigma^{2})^{-1} V^{-1}$$

$$U\Sigma^{-1} V^{-1}$$

3.d
$$A(A^{T}A)^{-1}A^{T}$$

Carrying the simplified form of $(A^TA)^{-1}$ from the first problem

$$U\Sigma V^T (V\Sigma^2 V^T)^{-1} (U\Sigma V^T)^T$$

simplifying the transpose:

$$U\Sigma V^T (V\Sigma^2 V^T)^{-1} V\Sigma^T U^T$$

factoring out the inverse

$$U\Sigma V^{T}(V^{T})^{-1}(\Sigma^{2})^{-1}V^{-1}V\Sigma^{T}U^{T}$$

$$U\Sigma (\Sigma^{2})^{-1}\Sigma^{T}U^{T}$$

$$UU^{T}$$

$$\begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

Suppose that the m - by - n matrix, with m < n, is full rank. Then the problem $\min ||Ax - b||$ is under determined.

4.a Show that the solution is an (n-m)-dimensional set.

$$A = \underbrace{U}_{mxm} \underbrace{\sum}_{mxm} \underbrace{V}^{T}$$

$$A^{\dagger} = V \Sigma U^T$$

and the solution to this is

$$A^{\dagger} \left(A A^{\dagger} \right)^{-1}$$

So we must show that

$$A^{\dagger} \left(A A^{\dagger} \right)^{-1} = A^{\dagger}$$

$$V\Sigma U^T \left(U\Sigma V^T V\Sigma U^T\right)^{-1}$$

$$V\Sigma U^T \left(U\Sigma^2 U^T\right)^{-1}$$

$$V\Sigma U^{T}(U^{T})^{-1}\Sigma^{-2}U^{-1}$$

$$\underbrace{V}_{n \times m} \underbrace{\Sigma^{-1}}_{m \times m} \underbrace{U^{-1}}_{m \times m} = n \times m$$

4.b Show how to compute the unique minimum 2-norm solution using an appropriately modified:

4.b.1 normal equations

In Dremmel:

they state that $x = (A^T A)^{-1} A^T b$ is the minimizer of $||Ax - b||_2^2$, this is shown by completing the square in the text:

$$(Ax' - b)^{T} (Ax' - b) = (Ay + Ax - b)^{T} (Ay + Ax - b)$$
$$(Ay)^{T} (Ay) + (Ax - b)^{T} (Ax - b) + 2 (Ay)^{T} (Ax - b)$$
$$||Ay||_{2}^{2} + ||Ax - b||_{2}^{2}$$

and they go on to say that this is minimized when y=0... and something about orthogonal space.

4.b.2 QR decomposition

$$(A^TA)^{-1}A^T$$

and A = QR

$$\left(\left(R^{T}Q^{T}\right)QR\right)^{-1}\left(R^{T}Q^{T}\right)$$

$$R^{-1}Q^{-1}Q^{-T}R^{-T}R^{T}Q^{T}$$

$$R^{-1}O^{-1} = (OR)^{-1}$$

4.b.3 SVD

$$(A^TA)^{-1}A^T$$

and $A = U\Sigma V^T$

$$(V\Sigma^2V^T)^{-1}(U\Sigma V^T)^T$$

$$\left(V\Sigma^2V^T\right)^{-1}V\Sigma^TU^T$$

$$\left(V^{T}\right)^{-1}\left(\Sigma^{2}\right)^{-1}V^{-1}V^{T}U^{T}$$

$$\left(V^{T}\right)^{-1} \left(\Sigma^{2}\right)^{-1} \Sigma^{T} U^{T}$$

$$(V^T)^{-1}\Sigma^{-1}U^T$$

 $https://github.com/jamestallen/MAT258A/blob/master/HW_1_Plots.ipynb$