

CpE 520: HW #2

West Virginia University

Ali Zafari

Question 1

Part (a): Inverse of $\mathbf{y}_{n \times 1} = \mathbf{A}_{n \times m} \mathbf{x}_{m \times 1}$ where $n > m$ and $\text{rank} = m$

In this case there are more unknowns than equations so the system is underdetermined. Because the matrix A is full rank with $\text{rank} = n$, AA^T will be an $n \times n$ non-singular square matrix. Therefore, there will be an inverse for it like below:

$$(AA^T)(AA^T)^{-1} = I \quad (*)$$

As it is clear from the above equation, we may use $A^T(AA^T)^{-1}$ as a right inverse for matrix A . We first assume that the inverse we are seeking for has an equation like $\mathbf{x}_{m \times 1} = \mathbf{R}_{m \times n} \mathbf{y}_{n \times 1}$. Finding $\mathbf{R}_{m \times n}$ will be the goal. We propose $\mathbf{R}_{m \times n} = A^T(AA^T)^{-1}$ and through the equations below we will check if it will result in our main equation:

$$\boxed{\mathbf{x} = \mathbf{A}^T(\mathbf{A}\mathbf{A}^T)^{-1}\mathbf{y}}$$

$$\mathbf{x} = \mathbf{A}^T(\mathbf{A}\mathbf{A}^T)^{-1}\mathbf{y}$$

$$\xrightarrow{\times A} \mathbf{A}\mathbf{x} = \mathbf{A}\mathbf{A}^T(\mathbf{A}\mathbf{A}^T)^{-1}\mathbf{y}$$

$$\xrightarrow{\text{using } *} \mathbf{A}\mathbf{x} = \mathbf{y}$$

Part (b): Inverse of $\mathbf{y}_{n \times 1} = \mathbf{A}_{n \times m} \mathbf{x}_{m \times 1}$ where $n < m$ and $\text{rank} = m$

In this case there are more equations than unknowns, so the system is overdetermined. Because the matrix A is full rank with $\text{rank} = m$, $A^T A$ will be an $m \times m$ non-singular square matrix. Therefore, there will be an inverse for it like below:

$$(A^T A)^{-1}(A^T A) = I \quad (**)$$

As it is clear from the above equation, we may use $(A^T A)^{-1} A^T$ as a left inverse for matrix A .

$$\mathbf{A}\mathbf{x} = \mathbf{y}$$

$$\xrightarrow{\times A^T} \mathbf{A}^T \mathbf{A}\mathbf{x} = \mathbf{A}^T \mathbf{y}$$

$$\xrightarrow[\text{using } *]{\times (A^T A)^{-1}} \mathbf{x} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{y}$$

$$\boxed{\mathbf{x} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{y}}$$

Question 2

**Part (a): Minimizing $\tilde{x} = \min_x \{\|x\|_2^2 + \frac{1}{2}\lambda^T(y - Ax)\}$
to find the solution of $y_{n \times 1} = A_{n \times m}x_{m \times 1}$ where $n > m$ and $\text{rank} = m$**

(Underdetermined System)

We define the function $J(x, \lambda)$ as:

$$J(x, \lambda) = \|x\|_2^2 + \frac{1}{2}\lambda^T(y - Ax)$$

now we find its partial derivatives and let them be zero:

$$\frac{\partial J}{\partial x} = 2x - \frac{1}{2}A^T\lambda = 0 \rightarrow x = \frac{1}{4}A^T\lambda \quad (1)$$

$$\frac{\partial J}{\partial \lambda} = \frac{1}{2}(y - Ax) = 0 \rightarrow y = Ax \quad (2)$$

by putting equation (1) into (2):

$$y = \frac{1}{4}AA^T\lambda$$

we know that AA^T is invertible so we can multiply both sides by $(AA^T)^{-1}$:

$$\lambda = 4(AA^T)^{-1}y$$

we use this λ to replace it in equation (1):

$$x = \frac{1}{4}A^T(4(AA^T)^{-1}y)$$

$$\boxed{x = A^T(AA^T)^{-1}y}$$

**Part (b-1): Minimizing $\tilde{x} = \min_x \{(y - Ax)^2\}$
to find the solution of $y_{n \times 1} = A_{n \times m}x_{m \times 1}$ where $n < m$ and $\text{rank} = m$**

(Overdetermined System)

We define the function $J(x)$ as:

$$\begin{aligned} J(x) &= (y - Ax)^2 = \|y - Ax\|_2^2 \\ &= (y - Ax)^T(y - Ax) \\ &= y^T y - 2y^T Ax + x^T A^T Ax \end{aligned}$$

now we find its partial derivatives and let them be zero:

$$\frac{\partial J}{\partial x} = -2A^T y + 2A^T Ax = 0$$

$$A^T Ax = A^T y$$

we know that $A^T A$ is invertible so we can multiply both sides by $(A^T A)^{-1}$:

$$\boxed{x = (A^T A)^{-1}A^T y}$$

**Part(b-2) : Minimizing $\tilde{\mathbf{x}} = \min_{\mathbf{x}} \{(\mathbf{y} - \mathbf{A}\mathbf{x})^2 + \frac{1}{2}\lambda\|\mathbf{x}\|_2^2\}$
to find the solution of $\mathbf{y}_{n \times 1} = \mathbf{A}_{n \times m} \mathbf{x}_{m \times 1}$ where $n \neq m$ and $\text{rank}=m$**

(Overdetermined System)

We define the function $J(x)$ as:

$$\begin{aligned} J(x) &= (y - Ax)^2 + \frac{1}{2}\lambda\|x\|_2^2 = \|y - Ax\|_2^2 + \frac{1}{2}\lambda\|x\|_2^2 \\ &= (y - Ax)^T(y - Ax) + \frac{1}{2}\lambda x^T x \\ &= y^T y - 2y^T Ax + x^T A^T Ax + \frac{1}{2}\lambda x^T x \end{aligned}$$

now we find its partial derivatives and let them be zero:

$$\begin{aligned} \frac{\partial J}{\partial x} &= -2A^T y + 2A^T Ax + \lambda x = 0 \\ (A^T A + \frac{1}{2}\lambda I)x &= A^T y \end{aligned}$$

$$x = (A^T A + \frac{1}{2}\lambda I)^{-1} A^T y$$