Questions

1. In lecture 5, we showed that the solution of the least squares regression problem used the pseudoinverse:

$$\mathbf{A}^+ = \mathbf{A}^{\mathbf{T}} \mathbf{A}^{-1} \mathbf{A}^{\mathbf{T}}$$

Using the singular value decomposition of $\mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V^T}$, show that

$$A^+ = V \Sigma^{-1} U^T$$

To do this correctly, you will need to review how transposes and inverses work, and also keep dimensions in mind.

2. Show that

$$AA^+ = UU^{\mathbf{T}}$$

Note that $\mathbf{U}\mathbf{U}^{\mathbf{T}}$ is an $m \times m$ matrix, when \mathbf{U} is $m \times n$.

What can you say about the elements of matrix? (In the lecture video, I mistakenly claimed that it was diagonal, and then had to correct that slide afterwards.)

Answers

1.

$$\begin{split} \mathbf{A}^+ &= & (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T \\ &= & ((\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T)^T(\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T))^{-1}(\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T)^T \\ &= & ((\mathbf{V}\boldsymbol{\Sigma}\mathbf{U}^T\mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T)^{-1}\mathbf{V}\boldsymbol{\Sigma}\mathbf{U} \\ &= & ((\mathbf{V}\boldsymbol{\Sigma}^2\mathbf{V}^T)^{-1}\mathbf{V}\boldsymbol{\Sigma}\mathbf{U}, \text{ since } \mathbf{U}^T\mathbf{U} = \mathbf{I} \\ &= & \mathbf{V}\boldsymbol{\Sigma}^{-2}\mathbf{V}^T\mathbf{V}\boldsymbol{\Sigma}\mathbf{U}, \text{ since } \mathbf{V}^{-1} = \mathbf{V}^T \\ &= & \mathbf{V}\boldsymbol{\Sigma}^{-1}\mathbf{U} \end{split}$$

2. From the previous question, we have

$$\begin{aligned} \mathbf{A}\mathbf{A}^+ &= & (\mathbf{U}\boldsymbol{\Sigma}\mathbf{V^T})(\mathbf{V}\boldsymbol{\Sigma}^{-1}\mathbf{U^T}) \\ &= & & \mathbf{U}\boldsymbol{\Sigma}\boldsymbol{\Sigma}^{-1}\mathbf{U^T} \\ &= & & & \mathbf{U}\mathbf{U^T} \end{aligned}$$

Note that when m > n, the matrix $\mathbf{U}\mathbf{U}^{\mathbf{T}}$ is not the identity. The reason is that \mathbf{U} only has n independent columns.

To understand what the element of this matrix are, note that $\mathbf{U}\mathbf{U}^{\mathbf{T}}\mathbf{x} = \mathbf{x}$ when \mathbf{x} is a column of \mathbf{U} so it behaves like the identity matrix. However, $\mathbf{U}\mathbf{U}^{\mathbf{T}}\mathbf{x} = \mathbf{0}$ when \mathbf{x} is orthogonal to all the columns of \mathbf{U} (or rows of $\mathbf{U}^{\mathbf{T}}$), so clearly it is not the identity matrix!