## **Question 1**

It is a well known theorem that all possible solutions to the LS problem comply with the normal equation:

$$X^T X w = X^T y$$

Using the X's SVD form, and some simplification:

$$egin{aligned} V \Sigma^T U^T U \Sigma V^T w &= V \Sigma^T U^T y \ V \Sigma^T \Sigma V^T w &= V \Sigma^T U^T y \ \Sigma^T \Sigma V^T w &= \Sigma^T U^T y \end{aligned}$$

Denoting  $z = V^T w$  and  $\hat{y} = U^T y$ :

$$\Sigma^T \Sigma z = \Sigma^T U^T \hat{y}$$

Let's look at this matrix quation:

$$egin{pmatrix} \sigma_1^2 & & & & & \ & \sigma_2^2 & & & 0 \ & & & \ddots & & \ & 0 & & \sigma_r^2 & & \ & & & & 0 \end{pmatrix} egin{pmatrix} z_1 \ dots \ z_r \ z_r+1 \ dots \ z_n \end{pmatrix} = egin{pmatrix} \sigma_1 & & & & & \ & \sigma_2 & & & 0 \ & & & \ddots & & \ & 0 & & & \sigma_r \ & & & & & 0 \end{pmatrix} egin{pmatrix} \hat{y}_1 \ dots \ \hat{y}_m \end{pmatrix}$$

Thus a solution can be written as:

$$z = \left(egin{array}{c} rac{\hat{y}_1}{\sigma_1} \ dots \ rac{\hat{y}_r}{\sigma_r} \ z_r + 1 \ dots \ z_n \end{array}
ight)$$

Where we have freedom of choice for the  $z_{r+1}$  to  $z_n$  values.

We should regard that this solution is not gurenteed to be optimal.

It's interesting to see that if we choose  $z_{r+1}$  to  $z_n$  to be 0, we get the most optimal solution in terms of L\_2 norm.

This optimal solution means that w=Vz is also an optimal solution (because V is orthonormal, and thus doesn't affect the norm).

Reconstructing this solution:

$$\hat{w}=Vegin{pmatrix} \sigma_1^{-1} & & & & & & \ & \sigma_2^{-1} & & & 0 & & \ & & \ddots & & & \ & 0 & & \sigma_r^{-1} & & \ & & & 0 \end{pmatrix}U^Ty$$

This  $\hat{w}$  solution is also our solution using the defintion of  $\Sigma^+$ :