

1 Regularized least squares and the SVD

Let $A \in \mathbb{R}^{n \times n}$ be a nonsingular matrix with singular-value decomposition

$$A = \sum_{i=1}^n \sigma_i u_i v_i^T.$$

(We consider the case where A is square and nonsingular for simplicity; it is not too hard to extend the following results to the general case.) Recall that the regularized approximate solution of $Ax = y$ is defined to be the vector $\hat{x}(\mu) \in \mathbb{R}^n$ that minimizes

$$\|Ax - y\|^2 + \mu\|x\|^2,$$

where $\mu > 0$ is the regularization parameter. The regularized solution is a linear function of y , so it can be expressed as $\hat{x}(\mu) = B(\mu)y$ for some matrix $B(\mu) \in \mathbb{R}^{n \times n}$.

(a) Let the singular-value decomposition of B be

$$B = U\Sigma V^T = \sum_{i=1}^n \tilde{\sigma}_i \tilde{u}_i \tilde{v}_i^T.$$

Express $\tilde{\sigma}_i$, \tilde{u}_i , and \tilde{v}_i in terms of σ_i , u_i , v_i , and μ . In particular, make sure that your answer follows the convention $\tilde{\sigma}_1 \geq \dots \geq \tilde{\sigma}_n$.

(b) Find the norm of B in terms of μ , and the SVD of A .

(c) Find the worst-case relative inversion error:

$$\max_{y \neq 0} \left\{ \frac{\|AB y - y\|}{\|y\|} \right\}.$$

Give your answer in terms of μ , and the SVD of A .