

Problem 1.

a. Let $X = U\Sigma V^T$ where $U \in \mathbb{R}^{m \times \ell}$ and $V \in \mathbb{R}^{\ell \times n}$ each have orthogonal columns, $\Sigma = \text{diag}[\sigma_1, \dots, \sigma_\ell]$ with $\sigma_1 \geq \dots \geq \sigma_\ell \geq 0$, and $\ell \leq \min(m, n)$. Show that $\|X\|_2 = \sigma_1$. Use this result to show that $\|A\|_2 = \|A^T\|_2$ when A is a rectangular matrix.

b. For symmetric matrices M and N , the notation $M \preceq N$ means that $N - M$ is positive semi-definite. Show that if M and N are both positive semidefinite, then $M \preceq N$ implies that $\|M\|_2 \leq \|N\|_2$.

Problem 2. An orthogonal projector on \mathbb{R}^n is a symmetric matrix P that satisfies $P^2 = P$.

a. Show that if P is an orthogonal projector, then $0 \preceq P \preceq I$.

b. Show that all the singular values of P are either 1 or 0.

c. Show that P is uniquely determined by its range.

Hint: If Q is another orthogonal projector with the same range, then use the singular value decompositions of P and Q to show that $P = Q$.

Problem 3. Implement the following randomized SVD algorithm and explore how it works for the matrix in the file `hw5.mat`. Test it for $q = 0, 1$ and 2 . In particular, compare the singular values obtained by this method to those obtained from the true SVD, and examine the (norm of the) difference between the true left singular matrix U and the one obtained by this method.

The algorithm comes from p. 227 of Halko, et al., SIAM Review 53, pp. 217-288, 2011.

Stage A:

1. Generate an $n \times 2k$ Gaussian test matrix Ω .

2. Form $Y = (AA^T)^q A\Omega$ by multiplying alternatively with A and A^T .

3. Construct a matrix Q whose columns form an orthonormal basis for the range of Y .

Stage B:

4. Form $B = Q^T A$.

5. Compute an SVD of the small matrix, $B = \tilde{U}\Sigma V^T$

6. Set $U = Q\tilde{U}$.