

Problem 1: Low-rank approximation

Please solve the problem as follows

$$\min_{X \in \mathbb{R}^{m \times n}} \{\|A - X\|_F : \text{rank}(X) \leq K\}.$$

$\mathbf{X} = \mathbf{C}\mathbf{R} = (m \times k)(k \times n)$, By the SVD, we can require \mathbf{r} orthogonal columns in \mathbf{C} , and $\mathbf{C}^T\mathbf{C} = \mathbf{D}$, here \mathbf{D} is a diagonal matrix, and \mathbf{r} orthonormal rows in $\mathbf{R}\mathbf{R}^T = \mathbf{I}$. We are aiming for $\mathbf{C} = \mathbf{U}_K \Sigma_K$ and $\mathbf{R} = \mathbf{V}_K^T$.

Let $\mathbf{E} = \|\mathbf{A} - \mathbf{C}\mathbf{R}\|_F^2$ and minimize \mathbf{E}

$$(1) \frac{\partial \mathbf{E}}{\partial \mathbf{C}} = 2(\mathbf{C}\mathbf{R} - \mathbf{A})\mathbf{R}^T = 0$$

$$(2) \left(\frac{\partial \mathbf{E}}{\partial \mathbf{R}}\right)^T = 2(\mathbf{R}^T\mathbf{C}^T - \mathbf{A}^T)\mathbf{C} = 0$$

(1) gives $\mathbf{A}\mathbf{R}^T = \mathbf{C}\mathbf{R}\mathbf{R}^T = \mathbf{C}$ (2) gives $\mathbf{R}^T\mathbf{D} = \mathbf{A}^T\mathbf{C} = \mathbf{A}^T\mathbf{A}\mathbf{R}^T$. Since \mathbf{D} is diagonal, the columns of \mathbf{R}^T are eigenvectors of $\mathbf{A}^T\mathbf{A}$. They are right singular vectors \mathbf{v}_j of \mathbf{A} . Similarly, the columns of \mathbf{C} are eigenvectors of $\mathbf{A}\mathbf{A}^T$: $\mathbf{A}\mathbf{A}^T\mathbf{C} = \mathbf{A}\mathbf{R}^T\mathbf{D} = \mathbf{C}\mathbf{D}$. Then \mathbf{C} contains left singular vectors \mathbf{u}_j .

Since \mathbf{E} is a sum of σ^2 that are not involved in \mathbf{C} and \mathbf{R} . To minimize \mathbf{E} , those should be the largest singular values to produce the best $\mathbf{X} = \mathbf{C}\mathbf{R} = \mathbf{A}_K$, with $\|\mathbf{A} - \mathbf{C}\mathbf{R}\|_F^2 = \sum_{i=k+1}^r \sigma_i^2$

Therefore $\mathbf{X} = \mathbf{A}_K$