

2 (i) Part 1 discussed in class

$$\text{minimize } J(A_r) = \|A - A_r\|_F^2$$

given $A_{m \times n}$ $\rho(A) > r$

A_r is a rank r matrix

$$r < \min(m, n)$$

Find SVD of A

$$A = U \Sigma V^T$$

$A_{m \times n}$

$V_{n \times n}$, $U_{m \times m}$: Orthogonal Matrix

Σ : $m \times n$ diagonal entries whose entries are non-negative. (Singular Values)

Columns of U & V are called left singular and right singular ~~values~~ ^{vectors} of M .

Consider the r largest singular values & corresponding singular vectors

$$A_r = U_r \Sigma_r V_r^T \quad \text{sol}^n \quad \square$$

A rank- k approximation to the covariance matrix is used in PCA

$$(2) \min_{R^T = I} J(R) = \|RB - A\|_F^2$$

$$A_{n \times m} \quad B_{n \times m} \quad R_{n \times n}$$

Rigid Transform Estimation (Orthogonal Procrustes Problem)

Solⁿ $AB^T = USV^T$ (SVD)
 $R^T = UV^T$

Application:

Learning the Bases: Method 3- Union of Ortho-Normal Bases (Dictionary Learning)

Algo

for $m = 1:M$

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$$X_m = X - \sum_{j \neq m} A_j S_j;$$

$$S_m X_m^T = U \Lambda V^T;$$

$$A_m = V U^T$$

→ Orthogonal Procrustes

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Updating S_m : $S_m = \arg \min_{S^*} \|X_m - A_m S^*\|^2 + \lambda_t \|S^*\|_1$

Because we are solving

$$\min_A \|X_m - A S_m\|^2 \quad \text{st.} \quad A A^T = I$$

$$S = \begin{pmatrix} S_1 \\ S_2 \\ \vdots \\ S_m \end{pmatrix}$$

Coefficient Matrix

\vec{S}_m

A: dictionary

$$(X_m)_{p \times k}$$