

Given data:

$$\bar{X} = \left[\begin{array}{c|c|c|c|c} | & | & | & \dots & | \\ X_1 & X_2 & X_3 & \dots & X_m \\ | & | & | & & | \end{array} \right] \left\{ \begin{array}{l} \text{"snapshots in time" dim: } m \\ \text{Spatial dimension} \\ \text{dim: } n \end{array} \right.$$

SVD:

$$\bar{X} = U \Sigma V^*$$

complex conjugate transpose
for our cases that generally just
means transpose

U : unitary (orthonormal columns)

Σ : diagonal, padded w/ zeros

V : unitary (orthonormal columns)

Unitary Matrix: Square
rows & columns are orthonormal
inverse = conjugate transpose

When $n \geq m$ (more spatial than temporal dimensions):

$$X = U \Sigma V^* = \begin{bmatrix} \hat{U} & \hat{U}^\perp \end{bmatrix} \begin{bmatrix} \hat{\Sigma} \\ 0 \end{bmatrix} V^*$$

↳ full SVD

\hat{U}^\perp contains columns perpendicular to \hat{U}

Economy SVD: $\hat{U}, \hat{\Sigma}, V^*$

Full SVD

$$\begin{bmatrix} X \end{bmatrix} = \underbrace{\begin{bmatrix} \hat{U} & \hat{U}^\perp \end{bmatrix}}_U \underbrace{\begin{bmatrix} \hat{\Sigma} \\ 0 \end{bmatrix}}_\Sigma \begin{bmatrix} V^* \end{bmatrix}$$

Economy SVD

$$= \begin{bmatrix} \hat{U} \end{bmatrix} \begin{bmatrix} \hat{\Sigma} \end{bmatrix} \begin{bmatrix} V^* \end{bmatrix}$$

from Brunton & Kutz

Columns of U = "left singular vectors" of X

Columns of V = "right singular vectors" of X

diagonal elements of $\hat{\Sigma}$ = singular values, ordered from largest to smallest

SVD is a generalization of Eigenvale decomp.

Eigenvale decomp:

$$XV = V\Lambda \Rightarrow X = V\Lambda V^{-1}$$

\uparrow
 Σ is similar

If σ is a singular value of A ,

then σ^2 is an eigenvale of $\underbrace{A^*A}_{\text{square matrix}}$

Geometric Interpretation

Columns of U provide an orthonormal basis for columns of X .

Columns of V (= rows of V^*) provide an orthonormal basis for the rows of X .

$$\text{for } X = \begin{bmatrix} | & | & \dots & | \\ x_1 & x_2 & \dots & x_m \\ | & | & & | \end{bmatrix}$$

Columns of U encode spatial patterns

Rows of V^* encode temporal patterns

Compression

Eckart-Young thm:

A truncated SVD provides the best matrix

approximation of a given rank in the Frobenius norm.

F_r norm = sum of squares of all matrix entries.

It is the norm that appears in least squares problem statements.

$$\|A\|_{F_r} = \sqrt{\text{trace}(A^*A)}$$

So the F_r norm also describes the sum of the squares of the singular values of A .