Singular Value Decomposition (SVD)
Principal Component Analysis (PCA)
and Linear Discriminant Analysis (LDA)
Machine Learning for Finance (FIN 570)

Instructor: Jaehyuk Choi

Peking University HSBC Business School, Shenzhen, China

2019-20 Module 3 (Spring 2020)

Eigen(spectral) decomposition

For a matrix $\boldsymbol{A}$, eigenvalue λ_k and eigenvector $\boldsymbol{v}_k$ satisfy

$$\boldsymbol{A}\boldsymbol{v}_k = \lambda_k \boldsymbol{v}_k.$$

$$AQ = Q\begin{bmatrix}\lambda_1 & & 0\\ & \ddots & \\ 0 & & \lambda_n\end{bmatrix}$$

The matrix $\boldsymbol{A}$ can be decomposed into

$$\boxed{\boldsymbol{A} = \boldsymbol{Q}\boldsymbol{\Lambda}\boldsymbol{Q}^{-1},}$$

where $\boldsymbol{\Lambda}$ is a diagonal matrix with values λ_k and $\boldsymbol{Q} = (\boldsymbol{v}_1 \cdots \boldsymbol{v}_n)$, i.e., $\boldsymbol{Q}_{*j} = \boldsymbol{v}_j$.
When $\boldsymbol{A}$ is real and symmetric, $\boldsymbol{Q}$ is an orthonormal matrix, $\boldsymbol{Q}\boldsymbol{Q}^T = \boldsymbol{I}$,

$$\boxed{\boldsymbol{A} = \boldsymbol{Q}\boldsymbol{\Lambda}\boldsymbol{Q}^T,}$$

$$A^2 = (Q\Lambda Q^T)(Q\Lambda Q^T) = Q\Lambda^2 Q^T \qquad \Lambda^2 = \begin{bmatrix}\lambda_1^2 & & 0\\ & \ddots & \\ 0 & & \lambda_n^2\end{bmatrix}$$

Singular Value Decomposition (SVD)

The single most useful practical concept in linear algebra:

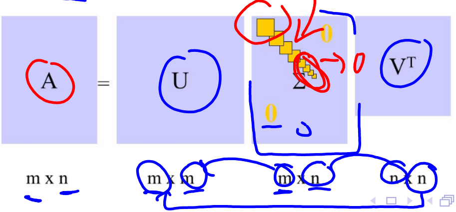
- Any matrix (even rectangular) has a SVD.
- SVD tells everything on a matrix.

For any $m \times n$ matrix A, there is a unique decomposition:

$$A = USV^T, \quad \text{where}$$

$Ax = USV^T x$

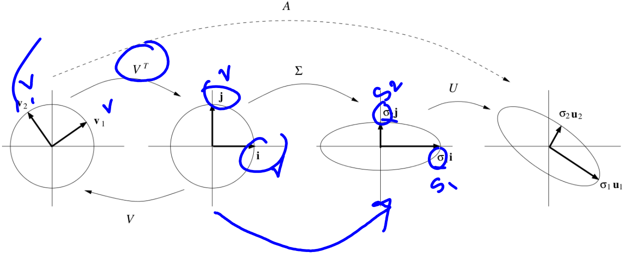
- U $(m \times m)$: orthonormal $(UU^T = U^T U = I)$
- S $(m \times n)$: diagonal. Singular values, $\boxed{s_k \geq 0}$, are in decreasing order for $1 \leq k \leq \min(m, n)$
- V $(n \times n)$: orthonormal $(VV^T = V^T V = I)$

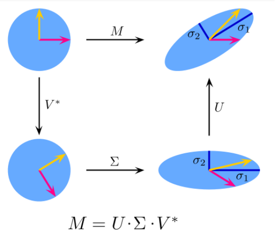


SVD: Intuition

Linear transformation A is decomposed into

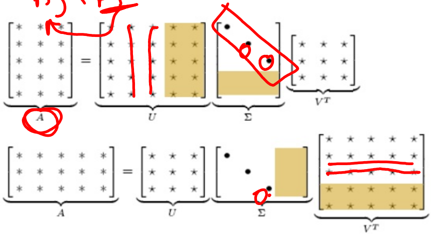
- a rotation by V^T
- a scaling by S
- a rotation by U

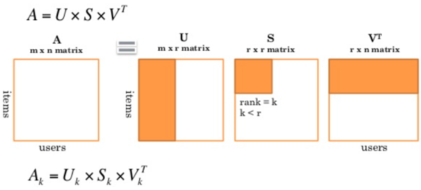




SVD: Compact Form, Low Rank Approximation

$A_j \neq A$





- For a non-square matrix, a compact form is enough: $U\ (m \times r)$, $S\ (r \times r)$, $V\ (n \times r)$ where $r = \min(m, n)$.
- If the rank is $k\ (\leq r)$, $s_{j>k} = 0$: $U\ (m \times k)$, $S\ (k \times k)$, $V\ (n \times k)$
- Using the first $j\ (\leq k)$ biggest singular values,

$$\boxed{A_j} = U_j S_j V_j^T = \sum_{i=1}^{j} \boldsymbol{u}_i s_i \boldsymbol{v}_i^T, \quad U_j\ (m \times j),\ S_j\ (j \times j),\ V_j\ (n \times j)$$

is the best approximation with rank j minimizing the norm $\|A - A_j\|_F$

jpg

An image file is nothing but a matrix, so the low-rank approximation of SVD works as an image compression method. The storage is reduced from $\boxed{mn}$ to $\boxed{(m+n+1)k}$.

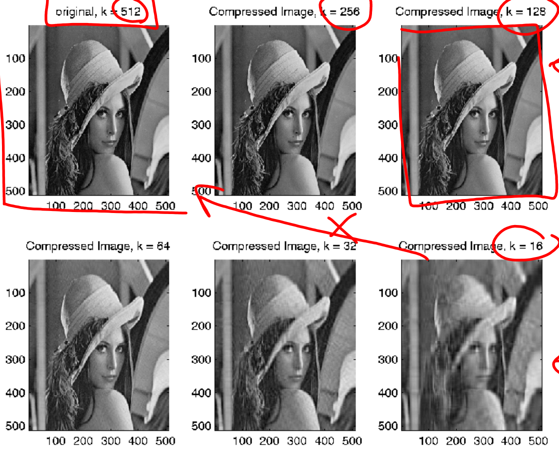
A: mn

U: mk

S k

V nk

k



A

loss

Principal Component Analysis (PCA)

If $\boldsymbol{X}$ is a matrix of n samples of p features $(n \times p)$, the covariance matrix is

$$\boldsymbol{\Sigma} = \frac{1}{n}\boldsymbol{X}^T\boldsymbol{X} : (p \times p) \text{ symmetric matrix}$$

The covariance matrix of the transformed space $\boldsymbol{Z} = \boldsymbol{X}\boldsymbol{W}$ is

$$\text{Cov}(\boldsymbol{Z}) = \frac{1}{n}(\boldsymbol{X}\boldsymbol{W})^T(\boldsymbol{X}\boldsymbol{W}) = \frac{1}{n}\boldsymbol{W}^T(\boldsymbol{X}^T\boldsymbol{X})\boldsymbol{W} = \boldsymbol{W}^T\Sigma\boldsymbol{W}$$

USV^T

If we pick $\boldsymbol{W}$ to be the orthogonal transformation of SVD, i.e., $\boldsymbol{\Sigma} = \boxed{\boldsymbol{W}\boldsymbol{S}\boldsymbol{W}^T}$,

$$\text{Cov}(\boldsymbol{Z}) = \boldsymbol{S} = \text{diag}(S_{11}, \cdots, S_{pp}).$$

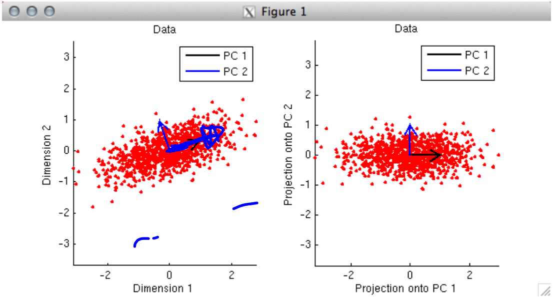
Notice that $\text{Cov}(Z_i, Z_j) = \boldsymbol{W}_{*i}^T\boldsymbol{\Sigma}\boldsymbol{W}_{*j} = S_{ij}$ is zero if $i \neq j$, so the extracted features are orthogonal.

$U = W$

Process of finding $\boldsymbol{W}$

Let $\boldsymbol{W} = (\boldsymbol{W}_{*1}\ \boldsymbol{W}_{*2}\ \cdots \boldsymbol{W}_{*p})$. $= U$ in SVD

- Find $\boldsymbol{W}_{*1}$ such that $|\boldsymbol{W}_{*1}| = 1$ and $|\boldsymbol{W}_{*1}^T \boldsymbol{\Sigma} \boldsymbol{W}_{*1}|$ is maximized.
- Find $\boldsymbol{W}_{*2}$ such that $|\boldsymbol{W}_{*2}| = 1$, $|\boldsymbol{W}_{*2}^T \boldsymbol{\Sigma} \boldsymbol{W}_{*2}|$ is maximized and $\boldsymbol{W}_{*1}^T \boldsymbol{W}_{*2} = 0$.
- $\cdots$
- Find $\boldsymbol{W}_{*k}$ such that $|\boldsymbol{W}_{*k}| = 1$, $|\boldsymbol{W}_{*k}^T \boldsymbol{\Sigma} \boldsymbol{W}_{*k}|$ is maximized and $\boldsymbol{W}_{*k}$ is orthogonal to $\{\boldsymbol{W}_{*j}\}$ for $j < k$.



Total and Explained Variance

SVD

The total variance is the variance of all original features. Under PCA,

$$\sum_{k=1}^{p} \mathrm{Var}(X_k) = \boxed{\sum_{k=1}^{p} S_{kk}}$$

Therefore the ratio

$$\frac{\sum_{j=1}^{k} S_{jj}}{\sum_{j=1}^{p} S_{jj}}$$

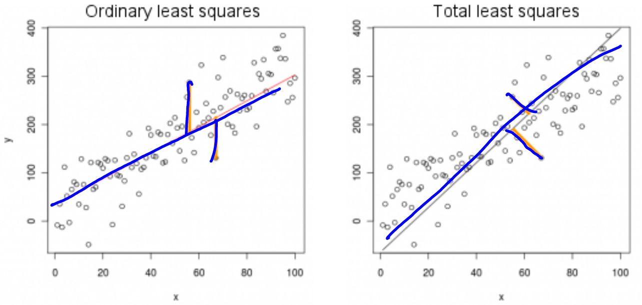
indicates how much of the total variance is *explained* by the first k PCA factors. Extracting features from PCA is an unsupervised learning, NOT supervised learning, because the response variable is not associated.

PCA vs Simple Linear Regression for (x, y)

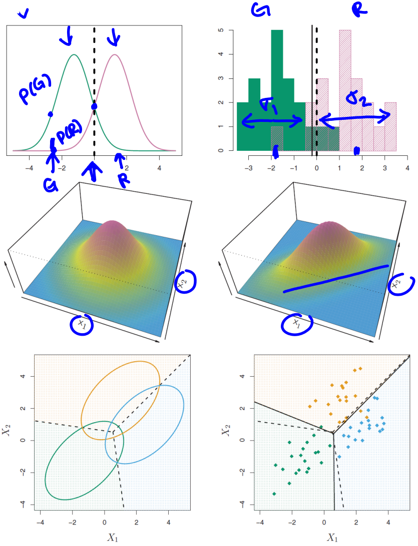
OLS

PCA is not same as Simple Linear regression (OLS)!

- **Linear Regression** minimize the the (squared) distance in y-axis.
- **PCA** (1st component) minimize the (squared) shortest distance.



- Assume the samples in each class follow normal (Gaussian) distribution.
- Estimate mean $\hat{\boldsymbol{\mu}}_k$ and variance $\hat{\boldsymbol{\Sigma}}_k$ of class k:
- Obtain multivariate normal PDF: $f_k(\boldsymbol{x}) = n(\boldsymbol{x}|\hat{\boldsymbol{\mu}}_k, \hat{\boldsymbol{\Sigma}}_k)$
- LDA if $\boldsymbol{\Sigma}_W = \sum_{k=1}^K \boldsymbol{\Sigma}_k$ (within covariance)is used for all $\boldsymbol{\Sigma}_k$.
- QDA if $\boldsymbol{\Sigma}_k$ is estimated for each class k
- A test sample $\boldsymbol{x}$ is classified to the class k for which $f_k(\boldsymbol{x})$ is largest.



LDA as a dimensionality reduction

- Given the LDA assumptions, which direction $\boldsymbol{w}$ best separates the feature?
- $\boldsymbol{w} \approx \boldsymbol{\mu}_2 - \boldsymbol{\mu}_1$? Probably not the best.
- If $(\mu_{1,2},\ \sigma^2_{1,2})$ is the mean and variance pair of the samples (1-D) projected on $\boldsymbol{w}$, $y = \boldsymbol{x}\boldsymbol{w}$, with $|\boldsymbol{w}| = 1$, we want to maximize the Fisher criterion:

$$J(\boldsymbol{w}) = \frac{(\mu_2 - \mu_1)^2}{N_1\sigma_1^2 + N_2\sigma_2^2} = \frac{\boldsymbol{w}^T(\boldsymbol{\mu}_2 - \boldsymbol{\mu}_1)^T(\boldsymbol{\mu}_2 - \boldsymbol{\mu}_1)\boldsymbol{w}}{\boldsymbol{w}^T\left(N_1\boldsymbol{\Sigma}_1 + N_2\boldsymbol{\Sigma}_2\right)\boldsymbol{w}} = \frac{\boldsymbol{w}^T\boldsymbol{S}_B\boldsymbol{w}}{\boldsymbol{w}^T\boldsymbol{S}_W\boldsymbol{w}},$$

where $\boldsymbol{S}_W$ and $\boldsymbol{S}_B$ are *within*- and *between*-class variance matrices

$$\boldsymbol{S}_W = \sum_{k=1,2} N_k\,\boldsymbol{\Sigma}_k, \quad \boldsymbol{S}_B = (\boldsymbol{\mu}_2 - \boldsymbol{\mu}_1)^T(\boldsymbol{\mu}_2 - \boldsymbol{\mu}_1)$$

LDA as a dimensionality reduction

- The direction $\boldsymbol{w}$ maximizing $J(\boldsymbol{w})$ is $\propto \boldsymbol{S}_W^{-1}(\boldsymbol{\mu}_2 - \boldsymbol{\mu}_1)$.
- In general, the eigenvectors, $\boldsymbol{W}$, of $\boldsymbol{S}_W^{-1}\boldsymbol{S}_B$ in the decreasing order of eigenvalue (similar to PCA) are the best directions to discriminate features.
- The transformation $\boldsymbol{z} = \boldsymbol{x}\boldsymbol{W}$ is the extracted factors with the best separability, which can be used for other ML methods.