Dimensionality reduction

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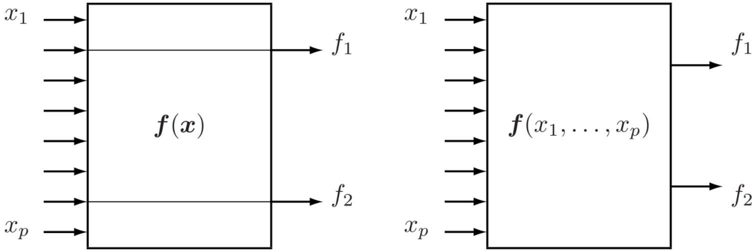
Dimensionality reduction

Feature selection / Feature extraction



(a) feature selector (b) feature extractor

Feature extraction: find transformation of original data which extracts most relevant information for machine learning task.

We will consider unsupervised dimensionality reduction methods, which try to preserve geometrical properties of the data.

Applications of dimensionality reduction

Applications:

- visualization in 2D or 3D
- reduce operational costs (less memory, disc, CPU usage on data transfer)
- remove multi-collinearity to improve performance of machine-learning models

Categorization

Supervision in dimensionality reduction:

- supervised (such as Fisher's direction)
- unsupervied

Mapping to reduced space:

- linear
- non-linear

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- Fisher's linear discriminant
- Supervised discriminant analysis

Problem statement

- Standard linear classification decision rule

$$\widehat{c} = \begin{cases} 1, & w^T x \geq -w_0 \\ 2, & w^T x < w_0 \end{cases}$$

  is equivalent to

  1. dimensionality reduction to 1-dimensinal space (defined by w)
  2. making classification in this space

- Idea of Fisher's LDA: find direction, giving most class discriminative projections.

Possible realization

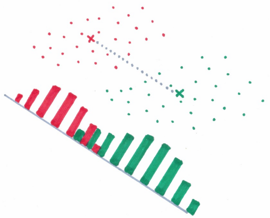
- Classification between ω_1 and ω_2.
- Define $C_1 = \{i : x_i \in \omega_1\}, \quad C_2 = \{i : x_i \in \omega_2\}$ and

$$m_1 = \frac{1}{N_1} \sum_{n \in C_1} x_n, \quad m_2 = \frac{1}{N_1} \sum_{n \in C_2} x_n$$

$$\mu_1 = w^T m_1, \quad \mu_2 = w^T m_2$$

Naive solution:

$$\begin{cases} (\mu_1 - \mu_2)^2 \to \max_w \\ \|w\| = 1 \end{cases}$$

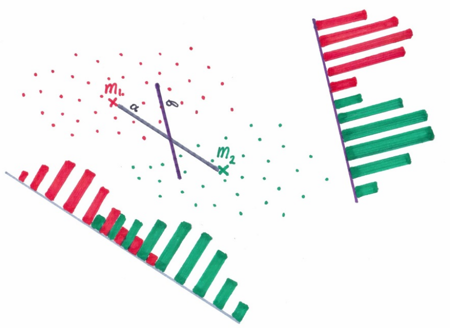


Fisher's LDA

- Define projected within class variances:

$$s_1 = \sum_{n \in C_1} (w^T x_n - w^T m_1)^2, \quad s_2 = \sum_{n \in C_2} (w^T x_n - w^T m_2)^2$$

- Fisher's LDA criterion: $\frac{(\mu_1 - \mu_2)^2}{s_1^2 + s_2^2} \to \max_w$



Equivalent representation

$$\frac{(\mu_1-\mu_2)^2}{s_1^2+s_2^2} = \frac{\left(w^T m_1 - w^T m_2\right)^2}{\sum_{n\in C_1}(w^T x_n - w^T m_1)^2 + \sum_{n\in C_2}(w^T x_n - w^T m_2)^2}$$

$$= \frac{\left[w^T(m_1-m_2)\right]^2}{\sum_{n\in C_1}\left[w^T(x_n-m_1)\right]^2 + \sum_{n\in C_2}\left[w^T(x_n-m_1)\right]^2}$$

$$= \frac{w^T(m_1-m_2)(m_1-m_2)^T w}{w^T\left[\sum_{n\in C_1}(x_n-m_1)(x_n-m_1)^T + \sum_{n\in C_2}(x_n-m_2)(x_n-m_2)^T\right]w}$$

$$= \frac{w^T S_B w}{w^T S_W w}$$

$$\begin{aligned} S_B &= (m_1-m_2)(m_1-m_2)^T, \\ S_W &= \sum_{n\in C_1}(x_n-m_1)(x_n-m_1)^T + \sum_{n\in C_2}(x_n-m_2)(x_n-m_2)^T \end{aligned}$$

Fisher's LDA solution

$Q(w) = \frac{w^T S_B w}{w^T S_W w} \to \max_w$

Using property that $\frac{d}{dw}\left(w^T A w\right) = 2Aw$ for any $A \in \mathbb{R}^{KxK}$, $A^T = A$

$$\frac{dQ(w)}{dw} \propto 2S_B w \left[w^T S_W w\right] - 2\left[w^T S_B w\right] S_W w = 0$$

which is equivalent to

$$\left[w^T S_W w\right] S_B w = \left[w^T S_B w\right] S_W w$$

So

$$w \propto S_W^{-1} S_B w \propto S_W^{-1}(m_1 - m_2)$$

2. Supervised dimensionality reduction
    - Fisher's linear discriminant
    - Supervised discriminant analysis

Idea of supervised discriminant analysis (SDA)

- We can find directions $w_1, w_2, ...w_D$, projections on which best separate classes.
- Ways to find w:
  - Fisher's LDA
  - Any linear classification $\langle w, x\rangle \gtrless$ *threshold* gives valuable supervised 1-D dimension w.
- We can find an orthonormal basis of such directions.

SDA algorithm

Listing 1: Finding orthonormal basis of supervised directions

INPUT:

* training set $(x_1, y_1), ...(x_N, y_N)$
* algorithm, fitting w in linear classification $\hat{y} = sign[\langle w, x\rangle - threshold]$

ALGORITHM:

for $d = 1, 2, ...D$:

w_d - classifier_direction[$(x_1, y_1), ...(x_N, y_N)$]

$w_d = \frac{w_d}{||w_d||}$

for $n = 1, 2, ...N$: # project to orthogonal supplement of w(d)

$x_n = x_n - \langle x_n, w_d\rangle w_d$

OUTPUT: $w_1, w_2, ...w_D$.

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Scalar product reminer

- Here we will assume $\langle a, b\rangle = a^T b$
- $\|a\| = \sqrt{\langle a, a\rangle}$
- Signed projection of $x$onto a is equal to $\langle x, a\rangle / \|a\|$
- Unsigned projection (length) of x onto a is equal to $|\langle x, a\rangle| / \|a\|$

Useful properties

- For any matrix $X\in\mathbb{R}^{NxD}$ $X^TX\in\mathbb{R}^{DxD}$ is symmetric and positive semi-definite:
    - $\{X^TX\}_{ij}=\sum_{n=1}^N x_{ni}x_{nj}=\sum_{n=1}^N x_{nj}x_{ni}=\{X^TX\}_{ji}$
    - $\forall a\in\mathbb{R}^D:\ \langle a,X^TXa\rangle=a^TX^TXa=\|Xa\|^2\ge 0$
- General properties:
    - if all eigenvalues are unique, eigenvectors are also unique (up to scalar multipliers).
    - if $A\succeq 0$ then all its eigenvalues are non-negative
- Since $X^TX\succeq 0$ it follows that all its eigenvalues are non-negative.
- We will assume that eigenvalues of X^TX are $\lambda_1\ge\lambda_2\ge...\ge\lambda_D\ge 0$.

Useful properties

For any $x, b \in \mathbb{R}^D$ it holds that:

$$\frac{\partial [b^T x]}{\partial x} = b$$

For any $x \in \mathbb{R}^D$ and symmetric $B \in \mathbb{R}^{DxD}$ it holds that:

$$\frac{\partial [x^T B x]}{\partial x} = 2Bx$$

3. Principal component analysis
    - Reminder
    - Definition
    - Applications of PCA
    - Application details
    - Construction of principal components
    - Proof of optimality of principal components

Best hyperplane fit

- For point x and subspace L denote:
  - p-the projection of x on L
  - h-orthogonal complement
- $x = p + h$, $\langle p, h \rangle = 0$.

Proposition 1

For x, its projection p and orthogonal complement h

$$\|x\|^2 = \|p\|^2 + \|h\|^2 .$$

- Prove proposition 1.
- For training set $x_1, x_2, ...x_N$ we and subspace L we can also find:
  - projections: $p_1, p_2, ...p_N$
  - orthogonal complements: $h_1, h_2, ...h_N$.

Best hyperplane fit

Definition 1

Best-fit k-dimensional subspace for a set of points $x_1, x_2, ...x_N$ is a subspace, spanned by k vectors $v_1, v_2, ...v_k$, solving

$$\sum_{n=1}^{N} \|h_n\|^2 \to \min_{v_1, v_2, ...v_k}$$

Proposition 2

Vectors $v_1, v_2, ...v_k$, solving

$$\sum_{n=1}^{N} \|p_n\|^2 \to \max_{v_1, v_2, ...v_k}$$

also define best-fit k-dimensional subspace.

- Prove 2 using proposition 1.

Definition of PCA

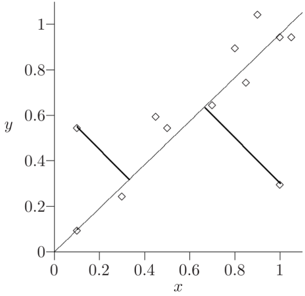
Definition 2

Principal components $a_1, a_2, ...a_k$ are vectors, forming orthonormal basis in the subspace of best fit.

- Properties:
  - Not invariant to translation:
    - Before applying PCA, we replace $x \leftarrow x - \mu$, where $\mu = \frac{1}{N}\sum_{n=1}^{N} x_n$.
    - Everywhere further we assume that $\mathbb{E}x = 0$.
  - Not invariant to scaling:
    - need to standardize each feature

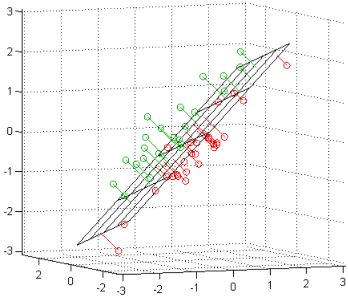
Example: line of best fit

- In PCA sum of squared of perpendicular distances to line is minimized.



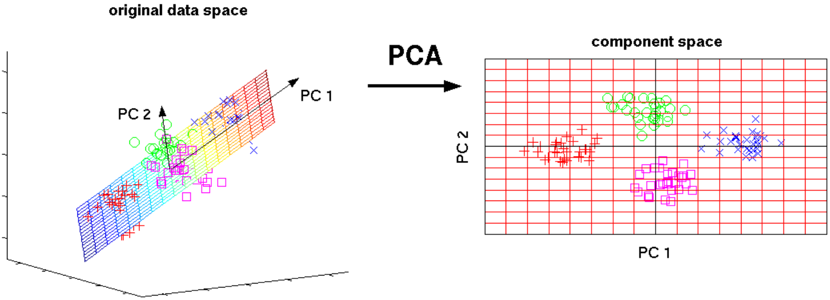
- *What is the difference with least squares minimization in regression?*

Best hyperplane fit



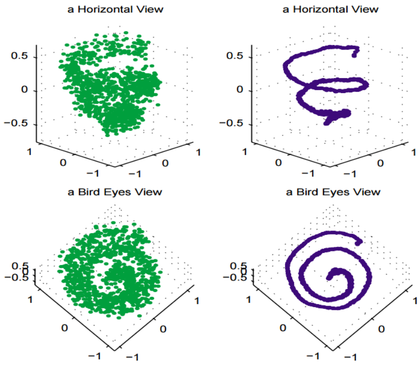
Subspace L_k or rank k best fits points $x_1, x_2, ...x_D$.

Visualization



Data filtering

Remove noise to get a cleaner picture of data distribution:



X. Huo and Jihong Chen (2002). Local linear projection (LLP). First IEEE Workshop on Genomic Signal Processing and Statistics (GENSIPS), Raleigh, NC, October. http://www.gensips.gatech.edu/proceedings/.

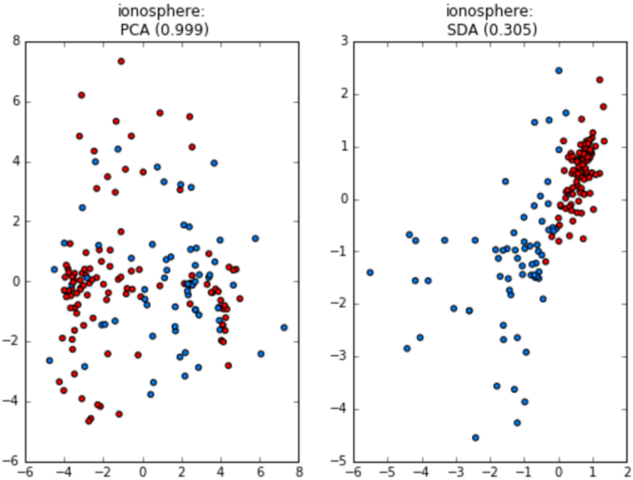
Economic description of data

Faces database:

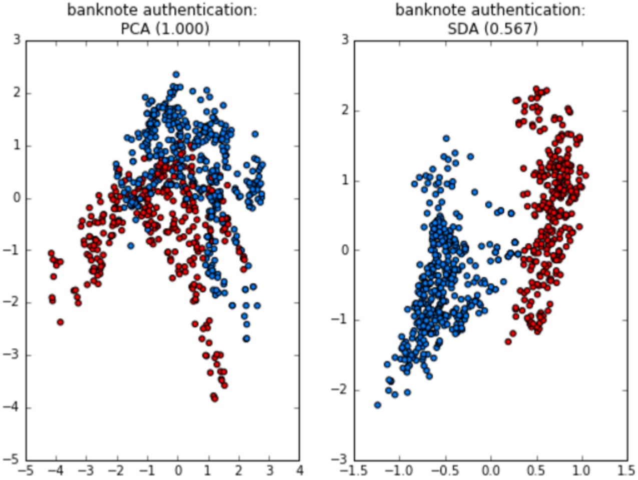
Eigenfaces

Eigenvectors are called eigenfaces. Projections on first several eigenfaces describe most of face variability.

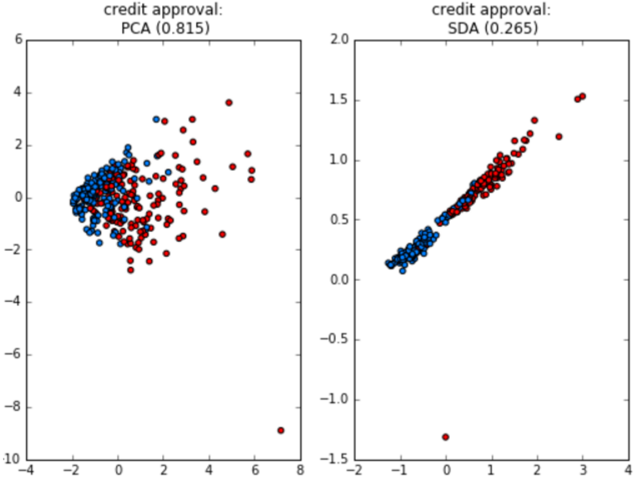
PCA vs. SDA


ionosphere:
PCA (0.999)
8
6
4
2
0
−2
−4
−6
−6
−4
−2
0
2
4
6
8
ionosphere:
SDA (0.305)
3
2
1
0
−1
−2
−3
−4
−5
−6
−5
−4
−3
−2
−1
0
1
2

PCA vs. SDA


banknote authentication:
PCA (1.000)
3
2
1
0
−1
−2
−3
−4
−5
−5
−4
−3
−2
−1
0
1
2
3
4
banknote authentication:
SDA (0.567)
3
2
1
0
−1
−2
−3
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

PCA vs. SDA


credit approval:
PCA (0.815)
6
4
2
0
−2
−4
−6
−8
-10
−4
−2
0
2
4
6
8
credit approval:
SDA (0.265)
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2
−1
0
1
2
3
4

Quality of approximation

Consider vector x. Since all D principal components form a full othonormal basis, x can be written as

$$x = \langle x, a_1 \rangle a_1 + \langle x, a_2 \rangle a_2 + ... + \langle x, a_D \rangle a_D$$

Let p^K be the projection of x onto subspace spanned by first K principal components:

$$p^K = \langle x, a_1 \rangle a_1 + \langle x, a_2 \rangle a_2 + ... + \langle x, a_K \rangle a_K$$

Error of this approximation is

$$h^K = x - p^K = \langle x, a_{K+1} \rangle a_{K+1} + ... + \langle x, a_D \rangle a_D$$

Quality of approximation

Using that $a_1, ...a_D$ is an orthonormal set of vectors, we get

$$\|x\|^2 = \langle x, x \rangle = \langle x, a_1 \rangle^2 + ... + \langle x, a_D \rangle^2$$
$$\left\| p^K \right\|^2 = \langle p^K, p^K \rangle = \langle x, a_1 \rangle^2 + ... + \langle x, a_K \rangle^2$$
$$\left\| h^K \right\|^2 = \langle h^K, h^K \rangle = \langle x, a_{K+1} \rangle^2 + ... + \langle x, a_D \rangle^2$$

We can measure how well first K components describe our dataset $x_1, x_2, ...x_N$ using relative loss

$$L(K) = \frac{\sum_{n=1}^{N} \left\| h_n^K \right\|^2}{\sum_{n=1}^{N} \|x_n\|^2}$$

or relative score

$$S(K) = \frac{\sum_{n=1}^{N} \left\| p_n^K \right\|^2}{\sum_{n=1}^{N} \|x_n\|^2}$$

Evidently $L(K) + S(K) = 1$.

Contribution of individual component

Contribution of a_k for explaining x is $\langle x, a_k\rangle^2$.
Contribution of a_k for explaining $x_1, x_2, ...x_N$ is:

$$\sum_{n=1}^{N}\langle x_n, a_k\rangle^2$$

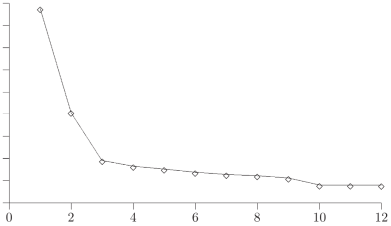
Explained variance ratio:

$$\frac{\sum_{n=1}^{N}\langle x_n, a_k\rangle^2}{\sum_{d=1}^{D}\sum_{n=1}^{N}\langle x_n, a_d\rangle^2}$$

Explained variance ratio measures relative contribution of component a_k to explaining our dataset $x_1, ...x_N$.

How many principal components to select?

- Data visualization: 2 or 3 components.
- Take most significant components until their variance falls sharply down:



- Or take minimum K such that $L(K) \leq t$ or$S(K) \geq 1 - t$, where typically $t = 0.95$.

Transformation $\xi \rightleftarrows x$

Dependence between original and transformed features:

$$\xi = A^T(x-\mu),\ x = A\xi + \mu,$$

where $\mu = \frac{1}{N}\sum_{n=1}^{N} x_n$.
Taking first r components - $A_r = [a_1|a_2|...|a_r]$, we get the image of the reduced transformation:

$$\xi_r = A_r^T(x-\mu)$$

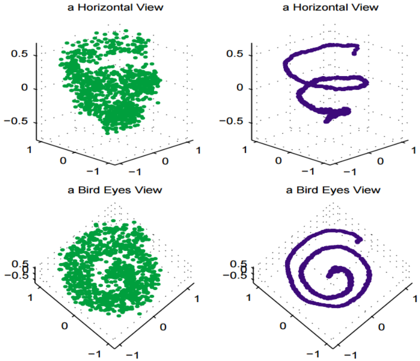
ξ_r will correspond to

$$x_r = A\begin{pmatrix}\xi_r \\ 0\end{pmatrix} + \mu = A_r\xi_r + \mu$$

$$x_r = A_rA_r^T(x-\mu) + \mu$$

$A_rA_r^T$ is projection matrix with rank r
(follows from the property $rank\left[AA^T\right] = rank\left[A^TA\right]$ for any A).

Local linear projection



X. Huo and Jihong Chen (2002). Local linear projection (LLP). First IEEE Workshop on Genomic Signal Processing and Statistics (GENSIPS), Raleigh, NC, October. http://www.gensips.gatech.edu/proceedings/.

Local linear projection

Local linear projection method makes denoised version of original data by locally projecting it onto hyperplane of small rank.

INPUT:
p-local dimensionality of data
K-number of nearest neighbours

for each x_i in X:
1) find K nearest neighbours of x_i: $x_{j(i,1)}, ... x_{j(i,K)}$
2) find linear hyperplane L_p of dimensionality p, describing $x_{j(i,1)}, ... x_{j(i,K)}$ # hyperplane-subspace with offset
3) let $\hat{x}_i$ be the projection of x_i onto this hyperplane

OUTPUT:
denoised version of objects $\hat{x}_1, \hat{x}_2, ... \hat{x}_K$.

Constructive definition of PCA

- Principal components $a_1, a_2, ...a_D \in \mathbb{R}^D$ are found such that $\langle a_i, a_j \rangle = \begin{cases} 1, & i = j \\ 0 & i \neq j \end{cases}$
- Xa_i is a vector of projections of all objects onto the i-th principal component.
- For any object x its projections onto principal components are equal to:
$$p = A^T x = [\langle a_1, x \rangle, ...\langle a_D, x \rangle]^T$$
where $A = [a_1; a_2; ...a_D] \in \mathbb{R}^{DxD}$.

Constructive definition of PCA

1. a_1 is selected to maximize $\|Xa_1\|$ subject to $\langle a_1, a_1 \rangle = 1$
2. a_2 is selected to maximize $\|Xa_2\|$ subject to $\langle a_2, a_2 \rangle = 1$, $\langle a_2, a_1 \rangle = 0$
3. a_3 is selected to maximize $\|Xa_3\|$ subject to $\langle a_3, a_3 \rangle = 1$, $\langle a_3, a_1 \rangle = \langle a_3, a_2 \rangle = 0$

etc.

Derivation: 1st component

$$\begin{cases} \|Xa_1\|^2 \to \max_{a_k} \\ \|a_1\| = 1 \end{cases} \quad (1)$$

Lagrangian of optimization problem (1):

$$L(a_1, \mu) = a_1^T X^T X a_1 - \mu(a_1^T a_1 - 1) \to \text{extr}_{a_1,\mu}$$

$$\frac{\partial L}{\partial a_1} = 2X^T X a_1 - 2\mu a_1 = 0$$

so a_1 is selected from a set of eigenvectors of $X^T X$.

Derivation: 1st component

Since

$$\|Xa_1\|^2 = (Xa_1)^T Xa_1 = a_1^T X^T Xa_1 = \lambda a_1^T a_1 = \lambda$$

a_1 should be the eigenvector, corresponding to the largest eigenvalue λ_1.

Comment: If many many eigenvector directions corrsponding to λ_1 exist, select arbitrary eigenvector, satisfying constraint of (1).

Derivation: 2nd component

$$\begin{cases} \|Xa_2\|^2 \to \max_{a_k} \\ \|a_2\| = 1 \\ a_2^T a_1 = 0 \end{cases} \tag{2}$$

Lagrangian of optimization problem (2):

$$L(a_2, \mu) = a_2^T X^T X a_2 - \mu(a_2^T a_2 - 1) - \alpha a_1^T a_2 \to \text{extr}_{a_2,\mu,\alpha}$$

$$\frac{\partial L}{\partial a_2} = 2X^T X a_2 - 2\mu a_2 - \alpha a_1 = 0 \tag{3}$$

Derivation: 2nd component

By multiplying by a_1^T we obtain:

$$a_1^T \frac{\partial L}{\partial a_1} = 2a_1^T X^T X a_2 - 2\mu a_1^T a_2 - \alpha a_1^T a_1 = 0 \tag{4}$$

Since a_2 is selected to be orthogonal to a_1:

$$2\mu a_1^T a_2 = 0$$

Since $a_1^T X^T X a_2$ is scalar and a_1 is eigenvector of $X^T X$:

$$a_1^T X^T X a_2 = \left(a_1^T X^T X a_2\right)^T = a_2^T X^T X a_1 = \lambda_1 a_2^T a_1 = 0$$

It follows that (4) simplifies to $\alpha a_1^T a_1 = \alpha = 0$ and (3) becomes

$$X^T X a_2 - \mu a_2 = 0$$

So a_2 is selected from a set of eigenvectors of $X^T X$.

Derivation: 2nd component

Since

$$\|Xa_2\|^2 = (Xa_2)^T Xa_2 = a_2^T X^T Xa_2 = \lambda a_2^T a_2 = \lambda$$

a_2 should be the eigenvector, corresponding to second largest eigenvalue λ_2.

Comment: If many many eigenvector directions corrsponding to λ_2 exist, select arbitrary eigenvector, satisfying constraints of (2).

Derivation: k-th component

$$\begin{cases} \|Xa_k\|^2 \to \max_{a_k} \\ \|a_k\| = 1 \\ a_k^T a_1 = ... = a_k^T a_{k-1} = 0 \end{cases} \tag{5}$$

Lagrangian of optimization problem (5):

$$L(a_k, \mu) = a_k^T X^T X a_k - \mu(a_k^T a_k - 1) - \sum_{j=1}^{k-1} \alpha_j a_k^T a_j \to \text{extr}_{a_k, \mu, \alpha_1, ... \alpha_{k-1}}$$

$$\frac{\partial L}{\partial a_k} = 2X^T X a_k - 2\mu a_k - \sum_{j=1}^{k-1} \alpha_j a_j = 0 \tag{6}$$

Derivation: k-th component

By multiplying by a_i^T for any $i = 1, 2, ...k - 1$ we obtain:

$$a_i^T \frac{\partial L}{\partial a_1} = 2a_i^T X^T X a_k - 2\mu a_i^T a_k - \alpha_1 a_i^T a_1 - ... - \alpha_{k-1} a_i^T a_{k-1} = 0 \tag{7}$$

Since a_i and a_j are selected to be orthogonal for $i \neq j$, we have:

$$2\mu a_i^T a_k = 0, \quad \alpha_j a_i^T a_j = 0 \; \forall i \neq j$$

Since $a_i^T X^T X a_2$ is scalar and a_i is eigenvector of $X^T X$:

$$a_i^T X^T X a_2 = \left(a_i^T X^T X a_k\right)^T = a_k^T X^T X a_i = \lambda_i a_k^T a_i = 0$$

It follows that (7) simplifies to $\alpha_i a_i^T a_i = \alpha_i = 0$. Since i was selected arbitrary from $i = 1, 2, ...k - 1$, $\alpha_1 = \alpha_2 = ... = \alpha_{k-1} = 0$ and (6) becomes

$$X^T X a_k - \mu a_k = 0$$

So a_k is selected from a set of eigenvectors of $X^T X$.

Derivation: k-th component

Since

$$\|Xa_k\|^2 = (Xa_k)^T Xa_k = a_k^T X^T Xa_k = \lambda a_k^T a_k = \lambda$$

a_k should be the eigenvector, corresponding to the k-th largest eigenvalue λ_k.

Comment: If many many eigenvector directions corrsponding to λ_k exist, select arbitrary eigenvector, satisfying constraints of (5).

3. Principal component analysis
    - Reminder
    - Definition
    - Applications of PCA
    - Application details
    - Construction of principal components
    - Proof of optimality of principal components

Componentwise optimization leads to best fit subspace

Theorem 1

Let L_k be the subspace spanned by $a_1, a_2, ...a_k$. Then for each k L_k is the best-fit k-dimensional subspace for X.

Proof: use induction. For $r = 1$ the statement is true by definition since projection maximization is equivalent to distance minimization.

Suppose theorem holds for $r - 1$. Let L_r be the plane of best-fit of dimension with $\dim L = r$. We can always choose a orthonormal basis of L_r $b_1, b_2, ...b_r$ so that

$$\begin{cases} \|b_r\| = 1 \\ b_r \perp a_1, b_r \perp a_2, ...b_r \perp a_{r-1} \end{cases} \tag{8}$$

by setting b_r perpendicular to projections of $a_1, a_2, ...a_{r-1}$ on L_r.

Componentwise optimization leads to best fit subspace

Consider the sum of squared projections:

$$\|Xb_1\|^2 + \|Xb_2\|^2 + ... + \|Xb_{r-1}\|^2 + \|Xb_r\|^2$$

By induction proposition $L[a_1, a_2, ...a_{r-1}]$ is space of best fit of rank $r-1$ and $L[b_1, ...b_{r-1}]$ is some space of same rank, so sum of squared projections on it is smaller:

$$\|Xb_1\|^2+\|Xb_2\|^2+...+\|Xb_{r-1}\|^2 \le \|Xa_1\|^2+\|Xa_2\|^2+...+\|Xa_{r-1}\|^2$$

and

$$\|Xb_r\|^2 \le \|Xa_r\|^2$$

since b_r by (8) satisfies constraints of optimization problem (**??**) and a_r is its optimal solution.

Conclusion

- For $x \in \mathbb{R}^D$ there exist D principal components.
- Principal component a_i is the i-th eigenvector of $X^T X$, corresponding to i-th largest eigenvalue λ_i.
- Sum of squared projections onto a_i is $\|Xa_i\|^2 = \lambda_i$.
- *Explained variance ratio* by component a_i is equal to

$$\frac{\lambda_i}{\sum_{d=1}^{D} \lambda_d}$$