

4/4/2023

How to choose w to maximize $\frac{1}{n} \sum_{i=1}^n (w^T x^{(i)})^2$?

Recall: we restrict w to have $\|w\|=1$

$$\begin{aligned} & \frac{1}{n} \sum_{i=1}^n \underbrace{(w^T x^{(i)})}_{1 \times 1} \underbrace{(x^{(i)T} w)}_{1 \times 1} \\ &= \frac{1}{n} \sum_{i=1}^n \underbrace{w^T}_{1 \times d} \underbrace{\begin{pmatrix} x^{(i)} & x^{(i)T} \end{pmatrix}}_{d \times d} \underbrace{w}_{d \times 1} \\ &= \frac{1}{n} w^T \left(\sum_{i=1}^n x^{(i)} x^{(i)T} \right) w \end{aligned}$$

$$X X^T = \begin{bmatrix} x_{11}^2 & x_{11}x_{12} & \dots & x_{1d}^2 \\ x_{11}x_{12} & \dots & \dots & \dots \\ \vdots & \dots & \dots & \dots \\ x_{d1}^2 & \dots & \dots & x_{dd}^2 \end{bmatrix}$$

↑
is symmetric

Covariance matrix of data $\{x^{(1)}, \dots, x^{(n)}\} = \frac{1}{n} \sum_{i=1}^n x^{(i)} x^{(i)T}$
because mean of $x^{(i)}$ is 0

also symmetric

$$= w^T \Sigma w$$

↑ covariance matrix, is symmetric

Every symmetric matrix can be written as

$$\Sigma = U D U^T \quad \text{where: } D = \begin{bmatrix} \lambda_1 & & & 0 \\ & \dots & & \\ & & & 0 \\ 0 & & & \lambda_d \end{bmatrix} \quad \text{diagonal}$$

and U is orthonormal

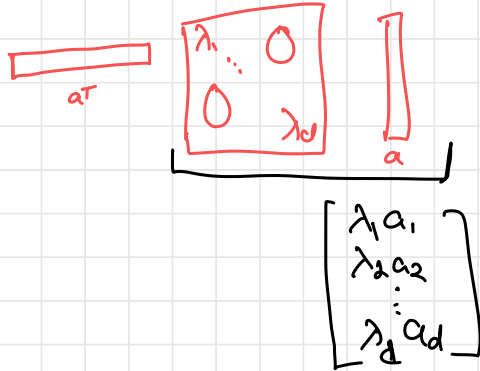
$$\begin{bmatrix} | \\ | \\ | \\ | \\ | \end{bmatrix} u_1$$

$$\begin{bmatrix} | \\ | \\ | \\ | \\ | \end{bmatrix} u_d$$

Each u_i is
unit vector and
 $u_i^T u_j = 0$
for $i \neq j$
(ie, they're orthogonal)

$$\underset{w}{\text{maximize}} \quad w^T \Sigma w = \underbrace{w^T U}_{a^T} D \underbrace{U^T w}_a$$

Define $a = U^T w$ Still a unit vector since w is unit vector & we just changed the basis
 → same as maximizing $a^T D a$



$$= \sum_{j=1}^d \lambda_j a_j^2$$

$$\text{Constraint: } \sum_{j=1}^d a_j^2 = 1$$

We can assume $\lambda_1 \geq \lambda_2 \dots \geq \lambda_d$

optimal solution: $a_1 = 1$, all other entries of $a = 0$

$$a = U^T w = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

u_1 $\begin{bmatrix} \text{---} \\ \vdots \\ \text{---} \end{bmatrix} w$ so: $w = u_1$

Recap: Given data $\{x^{(1)}, \dots, x^{(n)}\}$

- ① Mean-center data
- ② Compute $\Sigma = \frac{1}{n} \sum_{i=1}^n x^{(i)} x^{(i)T}$
- ③ Decompose Σ as $U D U^T$
- ④ Choose w to be eigenvector corresponding to largest eigenvalue

What if you want > 1 dimension?

e.g. $x^{(i)}$ is 1000-dimensional

want to visualize the data, so reduce it to 2 dimensions

Solution: Choose eigenvectors for 2 largest eigenvalues

- HW 3 due next tuesday

- Sections next 2 weeks

- Language models (this week)

- Vision models including image generation (next week)