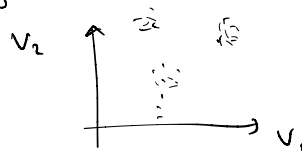


LECTURE 23

- Last class: How to visualize a high-dim. distribution? (e.g. human genome)
 $X \in \mathbb{R}^d$ r. vector, $\mathbb{E}X = 0$, $\text{Cov}(X) = \mathbb{E}XX^T =: \Sigma$.
e.g. X = genome of a random person in the world

Eigenvectors v_i of Σ = "principal components" of X

- PCA: reduce dimension $\mathbb{R}^d \rightarrow \mathbb{R}^2$ by projecting X onto $\text{span}\{v_1, v_2\}$



- PCA assumes that we can compute the population cov. matrix

$$\Sigma = \text{Cov}(X) = \mathbb{E}XX^T$$

average over $\uparrow$ population

But we don't have data of all population. We have:

- Finite sample $X_1, \dots, X_n \in \mathbb{R}^d$ iid copies of X . $\Rightarrow$ We approximate Σ by

$$\Sigma_n = \frac{1}{n} \sum_{i=1}^n X_i X_i^T$$

"Sample covariance matrix"

and hope that $\text{PCA}(\text{sample}) = \text{PCA}(\text{population})$, i.e.

$$\lambda_i(\Sigma_n) \approx \lambda_i(\Sigma) \text{ and } v_i(\Sigma_n) \approx v_i(\Sigma). \quad (*)$$

- How large is n ? $n = O(\log d)$? $n = O(d)$? $n = O(e^d)$?

COVARIANCE ESTIMATION PROBLEM

$\uparrow$
Curse of h.D?

- OUR GOAL $\boxed{n = O(d) \text{ suffices for } (*)}$

- PLAN
 1. Approximate $\Sigma_n \approx \Sigma$ in operator norm
 2. Use perturbation theory to conclude (*)

- By **HW** (operator norm for symmetric matrices),

$$\|\Sigma_n - \Sigma\| = \max_{v \in S^{d-1}} \underbrace{|v^T(\Sigma_n - \Sigma)v|}_{= v^T \Sigma_n v - v^T \Sigma v}$$

where S^{d-1} = unit sphere in $\mathbb{R}^d$

$$v^T \Sigma v = v^T \mathbb{E} X X^T v = \mathbb{E} \underbrace{v^T X}_{\langle X, v \rangle} \underbrace{X^T v}_{\langle X, v \rangle} = \mathbb{E} \langle X, v \rangle^2$$

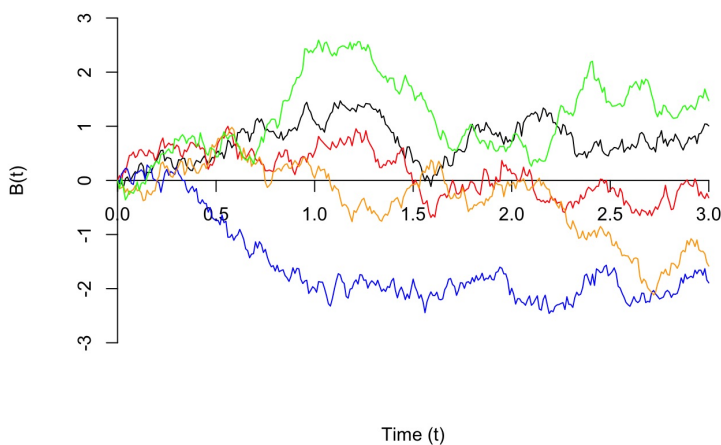
$$v^T \Sigma_n v = \frac{1}{n} \sum_{i=1}^n \langle X_i, v \rangle^2$$

$$\Rightarrow \|\Sigma_n - \Sigma\| = \max_{v \in S^{d-1}} \left| \frac{1}{n} \sum_{i=1}^n \langle X_i, v \rangle^2 - \mathbb{E} \langle X, v \rangle^2 \right|$$

$\hat{Z}(v)$ random variable.

- $(\hat{Z}(v))_{v \in S^{d-1}}$ Random process indexed by $v \in S^{d-1}$.

- Compare to the Brownian motion (a.k.a. Wiener process) $(B(t))_{t \in [0, \infty)}$ indexed by time.



$$\mathbb{E} \max_{t \leq T} |B(t)| \asymp \sqrt{T} \quad \mathbb{E} \max_{v \in S^{d-1}} |\hat{Z}(v)| \leq ?$$

- Difficulty: a continuum of points in S^{d-1} , $\Rightarrow$ Discretize:

THE ϵ -NET METHOD

Prop (Finding a net)

$\forall \epsilon > 0$, the unit sphere S^{d-1} has an ϵ -net $x_1, \dots, x_N$ with

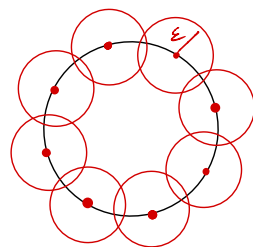
$$N \leq \left(\frac{2}{\epsilon} + 1\right)^d$$

i.e. $\forall p \in S^{d-1}$ is within dist. ϵ from some x_i :

$$\forall x \in S^{d-1} \exists i : \|x - x_i\|_2 \leq \epsilon$$



ϵ -balls centered at x_i cover S^{d-1}

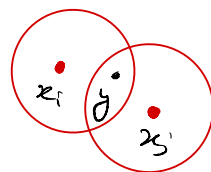


Algorithm

- Choose $\forall x_1$
- Choose $\forall x_2$ at dist $> \epsilon$ from x_1
- Choose $\forall x_3$ at dist $> \epsilon$ from $\{x_1, x_2\}$
- Choose $\forall x_4$ at dist $> \epsilon$ from $\{x_1, x_2, x_3\}$
- $\vdots$
- STOP whenever impossible

• Claim: The $(\epsilon/2)$ -balls centered at x_i are disjoint

If not, $\exists i \neq j, \exists y : \begin{cases} \|x_i - y\|_2 \leq \epsilon/2 \\ \|x_j - y\|_2 \leq \epsilon/2 \end{cases}$



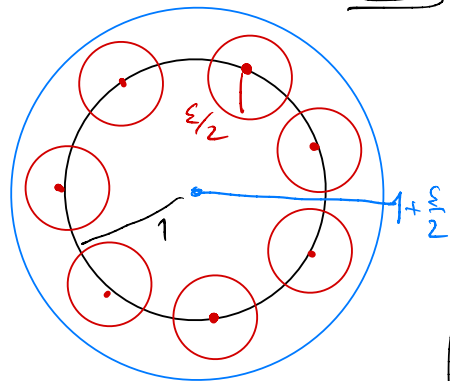
$$\Delta \Rightarrow \|x_i - x_j\|_2 \leq \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon$$

But all x_i are ϵ -separated by construction $\Leftarrow$

• All these balls lie in the $(1 + \epsilon/2)$ -ball centered at 0 $\Rightarrow$

$$\text{Vol}(B(1 + \epsilon/2)) \geq N \cdot \text{Vol}(B(\epsilon/2))$$

$$\Rightarrow N \leq \frac{\text{Vol}(B(1 + \epsilon/2))}{\text{Vol}(B(\epsilon/2))} = \left(\frac{1 + \epsilon/2}{\epsilon/2}\right)^d = \left(\frac{2}{\epsilon} + 1\right)^d$$



Remark Covering $\approx$ packing.

Prop (Computing the operator norm on a net)

Let A be an $m \times n$ matrix, $N \subset S^{n-1}$ an ε -net. Then

$$\|A\| \leq \frac{1}{1-\varepsilon} \max_{x \in N} \|Ax\|$$

By def of operator norm, $\exists u \in S^{n-1}$:

$$\|Au\|_2 = \|A\|. \quad (*)$$

By def of ε -net, $\exists x \in N$:

$$\|x-u\|_2 \leq \varepsilon.$$

$$\begin{aligned} \Rightarrow \|Ax - Au\|_2 &= \|A(x-u)\|_2 \leq \|A\| \cdot \|x-u\|_2 \quad (\text{def of operator norm}) \\ &\leq \|A\| \cdot \varepsilon. \quad (**) \end{aligned}$$

$$\begin{aligned} \Rightarrow \|Ax\|_2 &= \|Au - (Ax - Au)\|_2 \geq \|Au\|_2 - \|Ax - Au\|_2 \quad (\Delta \text{ineq.}) \\ &\geq \|A\| - \|A\| \cdot \varepsilon \quad (\text{by } (*) \text{ and } (**)) \\ &= (1-\varepsilon) \|A\|. \end{aligned}$$