

CPSC 536F

Oct 3, 2025

- Last time:

$N_1 \times N_2$ cyclic grid

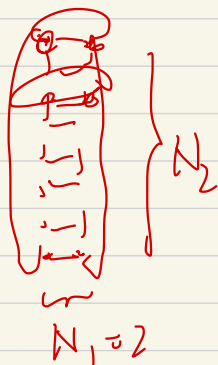
$n = N_1 N_2$
 N_2 {  }
 N_1

$$\lambda_1 = 4, \quad \lambda_2 \approx 4 - \frac{C_1}{(\max(N_1, N_2))^2}$$

e.g. $N_1 = N_2 = \sqrt{n}$

spectral gap

$$\lambda_1 - \lambda_2 \approx \frac{C_1}{n}$$



e.g. $N_1 = 3, N_2 = 3$

$$\lambda_1 - \lambda_2 \approx \frac{C_1}{(n/2)^2} \approx \frac{4C_1}{n^2}$$

Geometrically --- why

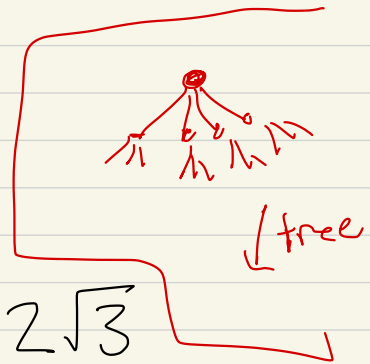
$$\frac{C_1}{n} \quad \text{vs.} \quad \frac{4C_1}{n^2}$$

Random 4-graph :

Claim :

$$(F_v) \quad \lambda_1 - \lambda_2 \approx 4 - 2\sqrt{3}$$

Geometry = "tree-like" ("Birthday Paradox")



G d -regular : ∂ = incidence matrix

$$\Delta_G = dI - A_G = \partial \partial^T$$

$\lambda_1(A_G) = d$

$$0 = \lambda_1(\Delta_G) \leq \dots \leq \lambda_n(\Delta_G) = 2d$$

Δ_G "graph Laplacian"

Today! Back to kernels,
ridge regression, ...

$K \in \mathbb{R}^{n \times n}$ is

- symmetric: $K^T = K \Rightarrow$ real eigenvectors
- pos semidef!

$$\forall \vec{v} \in \mathbb{R}^n, \quad \vec{v}^T K \vec{v} \geq 0$$

- pos def!

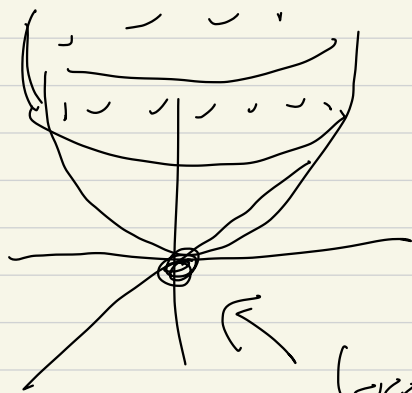
$$\vec{v}^T K \vec{v} = 0 \Leftrightarrow \vec{v} = \vec{0}$$

e.g. $f(\vec{x}) = x_1^2 + x_2^2 + x_3^2$, $K = (\text{Hess}(f))(0)$
(local min)

$$f(x_1, x_2) = x_1^2 + x_2^2$$

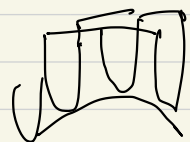
$$\text{Hess}(f) = \begin{bmatrix} f_{x_1 x_1} & f_{x_1 x_2} \\ f_{x_1 x_2} & f_{x_2 x_2} \end{bmatrix}$$

$$= \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \quad \leftarrow \begin{array}{l} \text{Sym} \\ \text{eig's} \\ = 2, 2 \end{array}$$



local minimum

saddle



$$x_1^2 - x_2^2$$

λ 's

$$2, -2$$



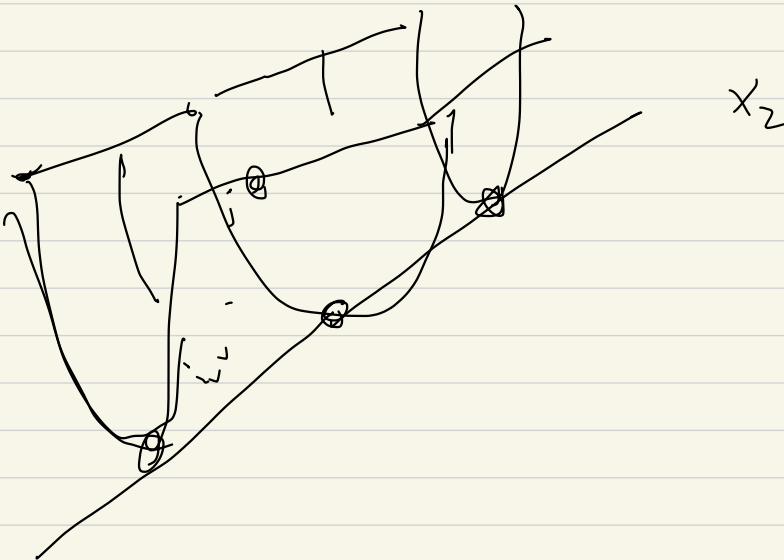
λ 's

$$-2, -2$$

"Degenerate"

$$f(x_1, x_2) = x_1^2 + 0 \cdot x_2^2$$

$$+ \underbrace{\left(x_1^3, x_1^2 x_2, \dots \right)}_{\text{higher order}}$$



Kernel: $k: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$

- symmetric

- pos semi-def

- pos def

restricted to
finite

$\mathcal{X}' \subset \mathcal{X}$

$\vdots$

Example:

$\Phi: \mathcal{X} \longrightarrow \mathbb{R}^m$ "features"

$$k(x, x') \stackrel{\text{def}}{=} \Phi(x) \cdot \Phi(x')$$

Thm: If $|\mathcal{X}| > m$, then

k is not positive definite.

$$\mathcal{X} = \mathbb{R}^2$$

$$\vec{x} = (x_1, x_2), \vec{x}' = (x'_1, x'_2)$$

$$k(\vec{x}, \vec{x}') \stackrel{\text{def}}{=}$$

$$\left(1, \sqrt{2} x_1, \sqrt{2} x_2, x_1^2, \sqrt{2} x_1 x_2, x_2^2 \right)$$

$$\bullet \left(1, \sqrt{2} x'_1, \sqrt{2} x'_2, (x'_1)^2, \sqrt{2} x'_1 x'_2, (x'_2)^2 \right)$$

$$k(\vec{x}, \vec{x}) =$$

$$\left(1 + \vec{x} \cdot \vec{x} \right)^2$$

kernel trick

$$k(\vec{x}, \vec{x}') = \left(1 + \underbrace{\vec{x} \cdot \vec{x}'}_{\mathbb{R}^2} \right)^2$$

Kernel function

$\mathcal{X}$ is a finite set

$$\mathcal{X} = \{1, \dots, n\}$$

kernel function on $[n]$

$\Leftrightarrow$ $n \times n$ matrix

Since

$$\begin{pmatrix} k(1,1) & k(1,2) & \dots & k(1,n) \\ k(2,1) & k(2,2) & \dots & \vdots \\ \vdots & & & \vdots \\ k(n,1) & \dots & \dots & k(n,n) \end{pmatrix} \stackrel{K}{\leftarrow}$$

$$k: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}, \quad |\mathcal{X}| < \infty$$

is symmetric if

$$K = \begin{bmatrix} k(x_1, x_1) & \dots & k(x_1, x_n) \\ \vdots & & \vdots \\ k(x_n, x_1) & \dots & k(x_n, x_n) \end{bmatrix}$$

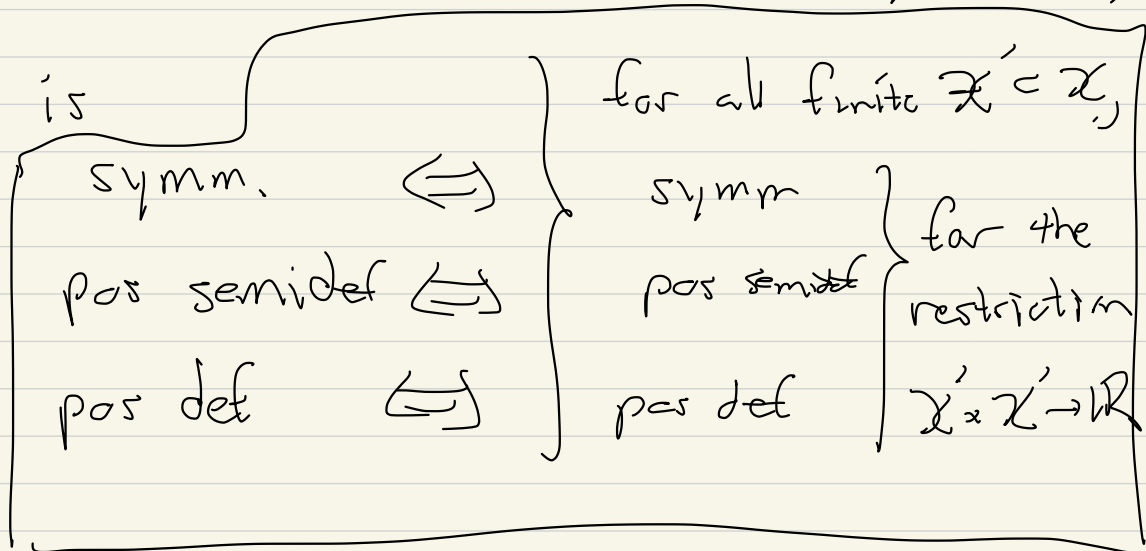
(where $\mathcal{X} = \{x_1, \dots, x_n\}$, $|\mathcal{X}| = n$)

k is symmetric

k is pos semidef if $K \dots$

k is pos def if $K \dots$

$k: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ if $|\mathcal{X}| = \infty$,



Other:

k symmetric if $k(x, x') = k(x', x)$
for all $x, x' \in \mathcal{X}$

k is pos ~~def~~ semidef if $\forall x_1, \dots, x_m \in \mathcal{X}$
for all $\alpha_1, \dots, \alpha_m \in \mathbb{R}$

$$\sum_{i,j=1}^m \alpha_i \alpha_j k(x_i, x_j) \geq 0$$

pos def iff $\uparrow$ equality

$$\text{iff } \alpha_1 = \alpha_2 = \dots = \alpha_m = 0$$

Example:

$$\Phi: \mathcal{X} \rightarrow \mathbb{R}^f \quad (f = \text{features})$$

Then

$$k(x, x') = \Phi(x) \cdot \Phi(x')$$

then: k is pos semidef

If k is pos def, then $|\mathcal{X}| \leq f$

① Applications

Which do you want more of?

- Graphs: Expanders
- Graphs: Symbolic Dynamics,
Shannon Entropy, RLL codes
- Markov chains: Mixing Time

② Applications

- SVD, PCA, Low Rank Approximation
- Regression, Ridge Regression

③ Kernel Viewpoint & Kernel Methods

kernel regression

HW Questions: - A, B, C
- Reg, *

- No designation

(Do you want :

Monday : Graph Thy

W, F : Kernel

or ---

(OR

6 classes kernel methods,
any

Other feedback ?

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Subject : --- 536F ---