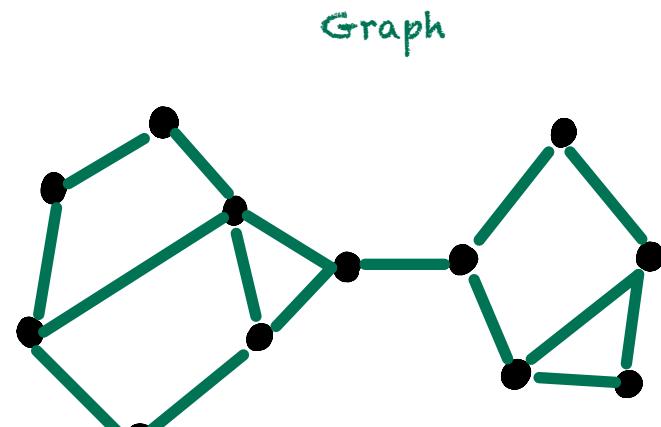
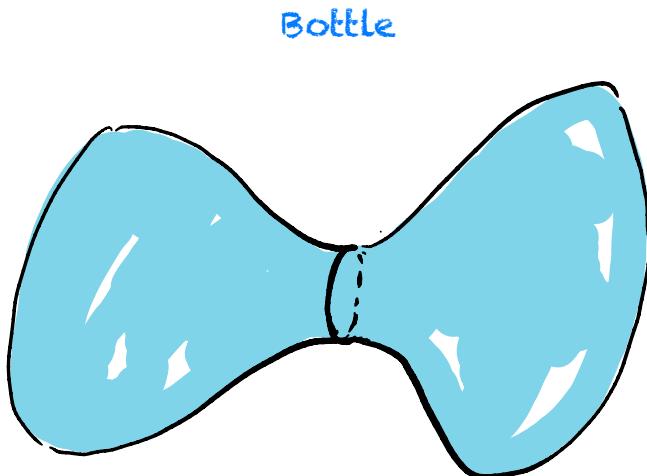


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# BOTTLENECKS

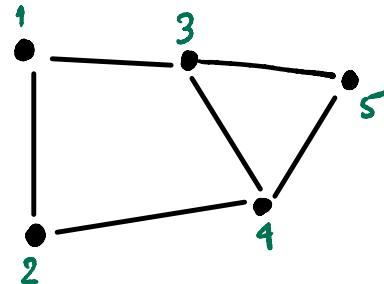


# GRAPH IS OFTEN JUST A MATRIX

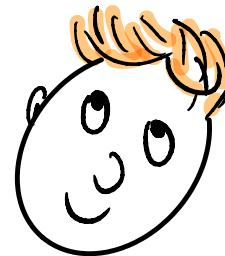
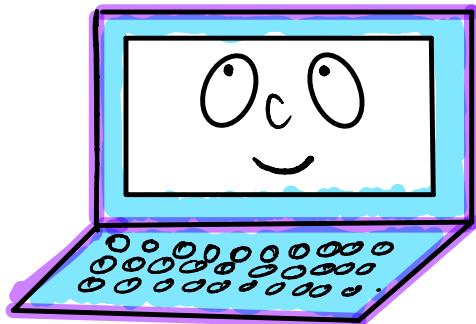
$$A = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \end{pmatrix}$$

Adjacency matrix

vs.

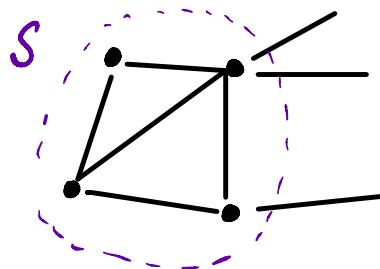


Drawing



# HOW TO DEFINE BOTTLENECKS?

- Let  $G = (V, E)$  be a  $d$ -regular graph. Let  $S \subseteq V$ .

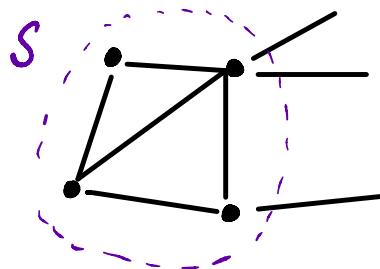


Expansion of  $S$

$$\phi(S) = \frac{E(S, \bar{S})}{d|S|}$$

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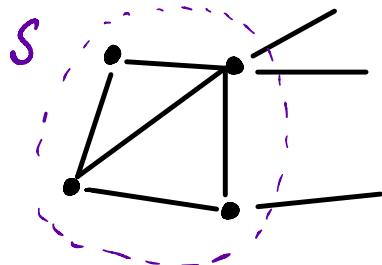
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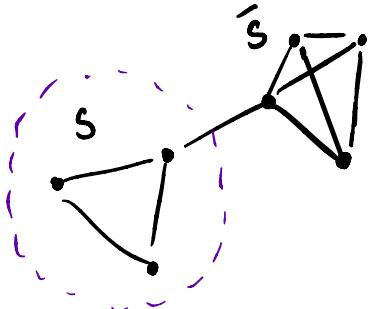
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- Note  $d|S|$  is the maximum number of edges that could go out of  $S$ .



Expansion of a cut  $(S, V-S)$

$$\phi(S, \bar{S}) := \max \{ \phi(S), \phi(\bar{S}) \} = \frac{E(S, \bar{S})}{d \cdot \min\{|S|, |\bar{S}|\}}$$

# CHEEGER'S INEQUALITY

- Let  $\mathcal{L}$  denote the normalized Laplacian.  $\mathcal{L} := I - \frac{1}{d} A$ .

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$$\frac{\lambda_2}{2} \leq \phi(G) \leq \sqrt{2\lambda_2}$$

$$\phi(G) = \min_{S: |S| \leq \frac{|V|}{2}} \phi(S)$$

# WHY LAPLACIAN ?

- $\mathcal{L} = I - \frac{1}{d} A.$

Some calculation  $\Rightarrow \forall f \in \mathbb{R}^V: \langle \mathcal{L}f, f \rangle = \frac{1}{d} \sum_{(u,v) \in E} (f(u) - f(v))^2$ .

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- 

$1\!\!1_{G_1}$



$G_1$



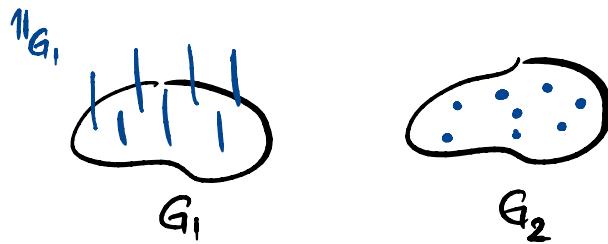
$G_2$

$$\langle \mathcal{L}1\!\!1_{G_1}, 1\!\!1_{G_1} \rangle = 0 \quad \text{and} \quad \langle \mathcal{L}1\!\!1_{G_2}, 1\!\!1_{G_2} \rangle = 0$$

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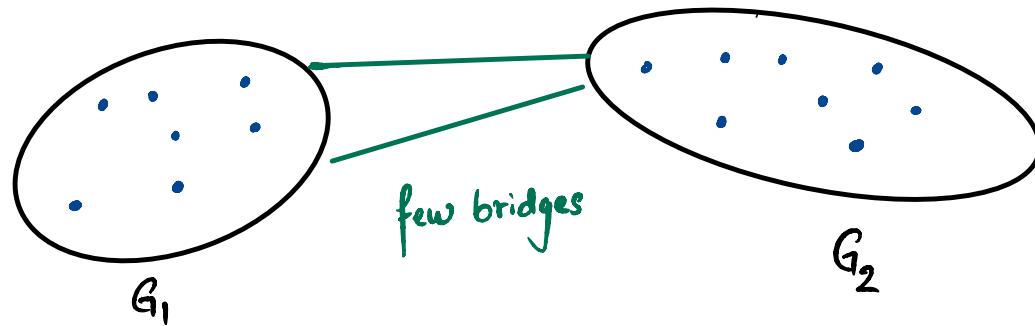
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-  $\|G_1\|$   
 $G_1$   
 $G_2$
- $$\langle \mathcal{L}\|G_1\|, \|G_1\| \rangle = 0 \quad \text{and} \quad \langle \mathcal{L}\|G_2\|, \|G_2\| \rangle = 0$$

- Multiplicity of 0 is the number of connected components.  
 $\lambda_1 = \lambda_2 = \dots = \lambda_k = 0 \Rightarrow k$  components

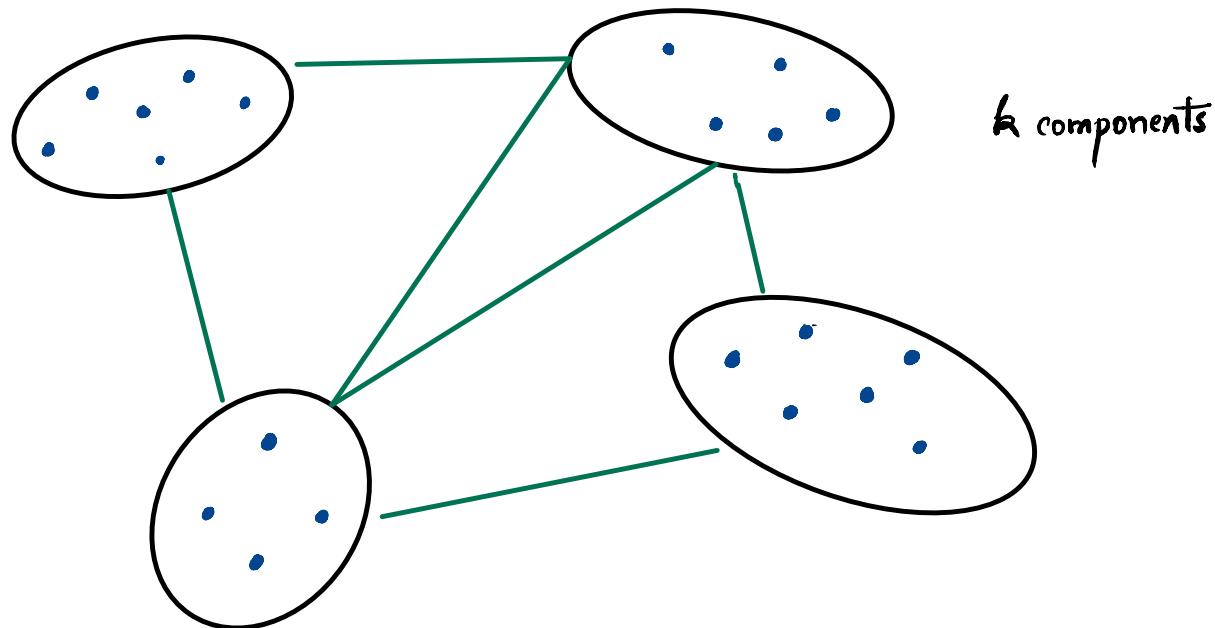
# WHAT IF $\lambda_2$ IS CLOSE TO ZERO?

Wishful thinking



# WHAT IF $\lambda_k$ IS CLOSE TO ZERO?

Wishful thinking



# HIGHER ORDER CHEEGER

Thm. For every graph  $G$ , and every  $k \in \mathbb{N}$ , we have

$$\frac{\lambda_k}{2} \leq p_G(k) \leq O(k^2) \sqrt{\lambda_k}$$

$$p_G(k) = \min_{\substack{S_1, \dots, S_k \\ \text{disjoint}}} \max \{ \phi_G(S_i) : i=1, 2, \dots, k \}$$

$$\phi_G(S_i) = \frac{w(E(S, \bar{S}))}{w(S)}$$

## WEAKER VERSION

Thm. For any weighted graph  $G = (V, E, \omega)$ , there exists a partition  $V = S_1 \cup S_2 \cup \dots \cup S_k$ , such that

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# WEAKER VERSION PROOF

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Step 1: It suffices to find disjointly supported functions  $\psi_1, \dots, \psi_K : V \rightarrow \mathbb{R}$  such that

$$R_G(\psi_i) \lesssim K^8 \lambda_K$$

# DISJOINT SETS TO DISJOINT FUNCTIONS

Thm For any  $\psi: V \rightarrow \mathcal{H}$ , there exists a subset  $S \subseteq \text{supp}(\psi)$  with

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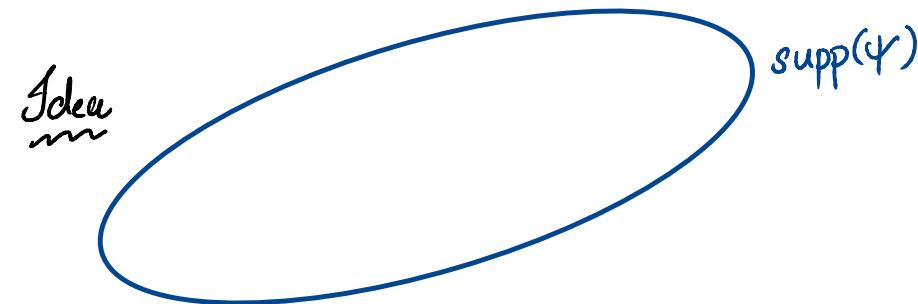
Idea



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$$= \frac{\text{Variation of } \psi \text{ across edges}}{\text{Total variation}}$$

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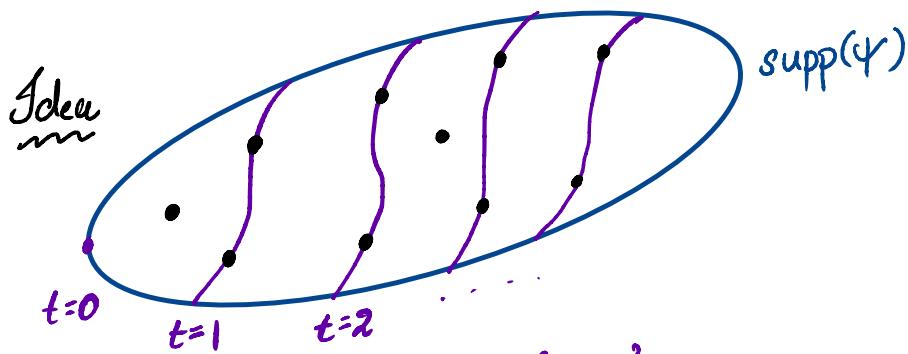
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$$S_t = \{u \in V : \|\psi(u)\|^2 > t\}$$

$$R_G(\psi) = \frac{\sum_{uv} w(u,v) \|\psi(u) - \psi(v)\|^2}{\sum_u w(u) \|\psi(u)\|^2}$$

$$= \frac{\text{Variation of } \psi \text{ across edges}}{\text{Total variation}}$$

If  $R_G(\psi)$  is small, maybe we can find a set  $S \subseteq \text{supp}(\psi)$  such that  $\phi_G(S)$  is small.

$$\int_0^\infty \omega(s_t) = \sum_{u \in V} \omega(u) \|\psi(u)\|^2$$

$$\int_0^\infty \omega(E(s_t, \bar{s}_t)) dt = \sum_{u \neq v} \omega(u, v) |\|\psi(u)\|^2 - \|\psi(v)\|^2|$$

$$\leq \sum_{u \neq v} \omega(u, v) \|\psi(u) - \psi(v)\| \|\psi(u) + \psi(v)\|$$

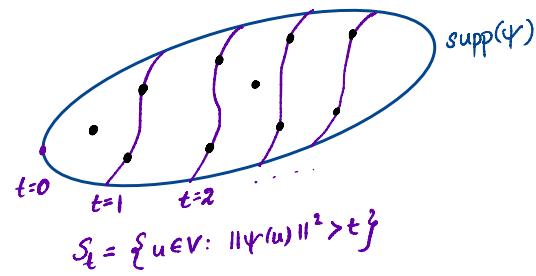
$$\leq \sqrt{\sum_{u \neq v} \omega(u, v) \|\psi(u) - \psi(v)\|^2} \sqrt{\sum_{u \neq v} \omega(u, v) \|\psi(u) + \psi(v)\|^2}$$

$$\leq \sqrt{\sum_{u \neq v} \omega(u, v) \|\psi(u) - \psi(v)\|^2} \sqrt{2 \sum_{u \in V} \omega(u) \|\psi(u)\|^2}$$

So,

$$\frac{\int_0^\infty \omega(E(s_t, \bar{s}_t)) dt}{\int_0^\infty \omega(s_t) dt} \leq \sqrt{2 R_G(\psi)}$$

$$\Rightarrow \exists t \in [0, \infty] \text{ for which } \phi(s_t) \leq \sqrt{2 R_G(\psi)}$$



# GRAPH THEORY TO LINEAR ALGEBRA

Take orthonormal eigenfunctions of  $\mathcal{L}$  —  $f_1, f_2, \dots, f_k: V \rightarrow \mathbb{R}$  ( $f_i$  has eigenvalue  $\lambda_i$ ).

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Spectral embedding -  $F: V \rightarrow \mathbb{R}^k$

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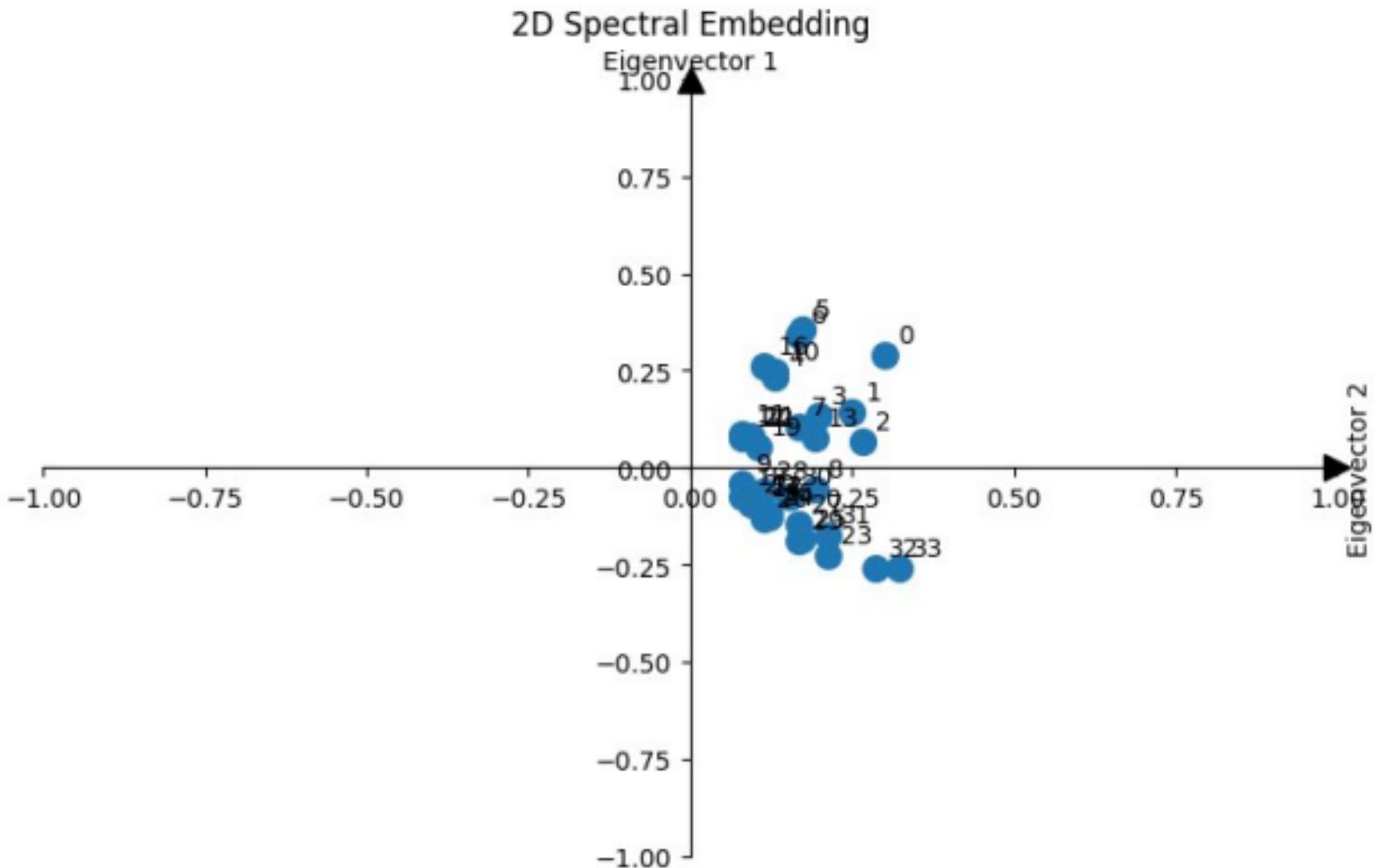
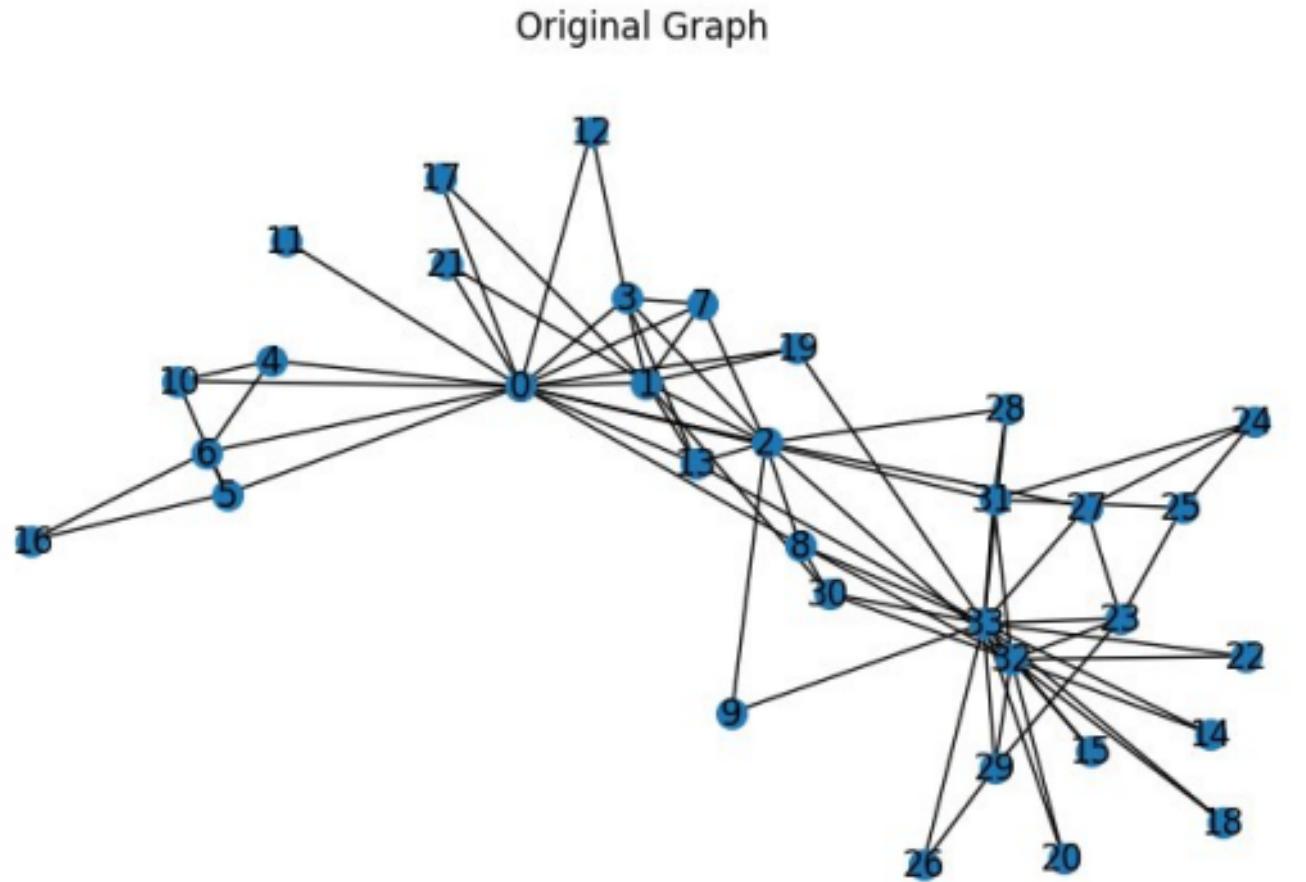
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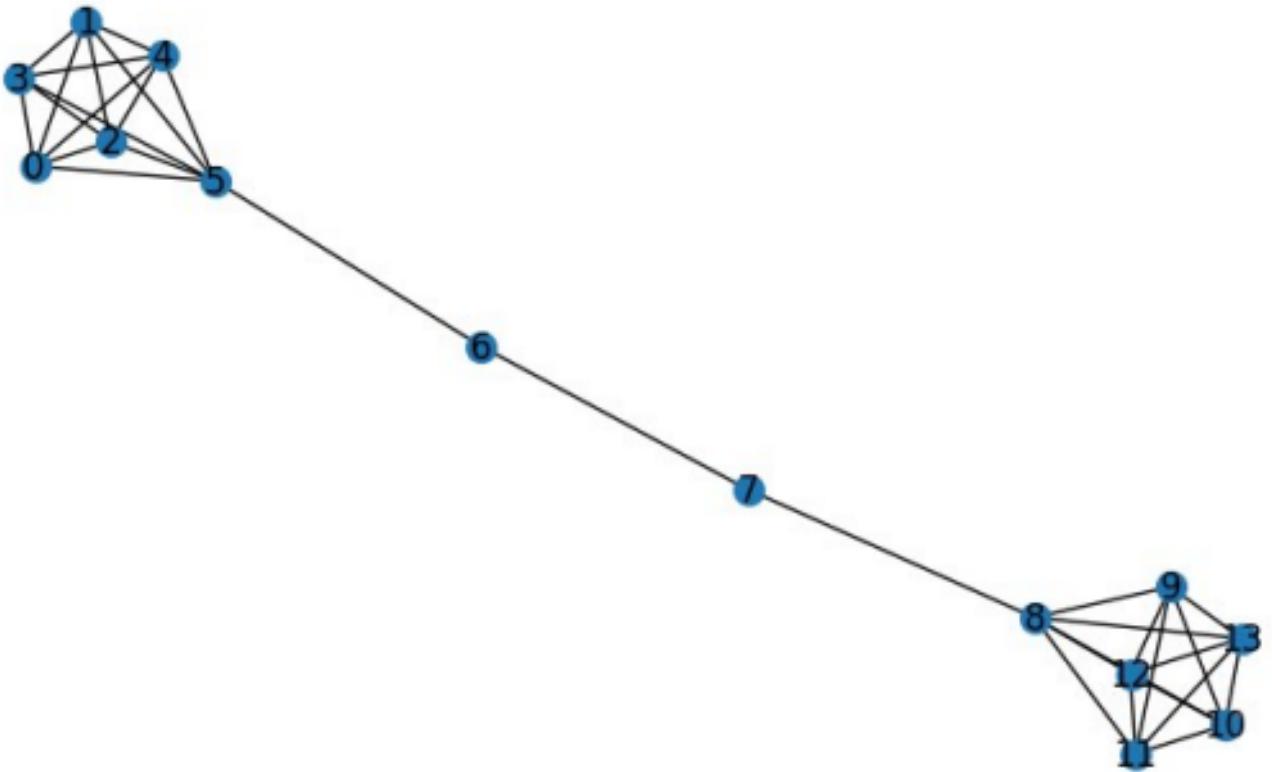
$$F(v) = (f_1(v), f_2(v), \dots, f_k(v))$$

Observe  $R_G(F) = \frac{\sum_{u \neq v} w(u,v) \|F(u) - F(v)\|^2}{\sum_{u \in V} w(u) \|F(u)\|^2}$

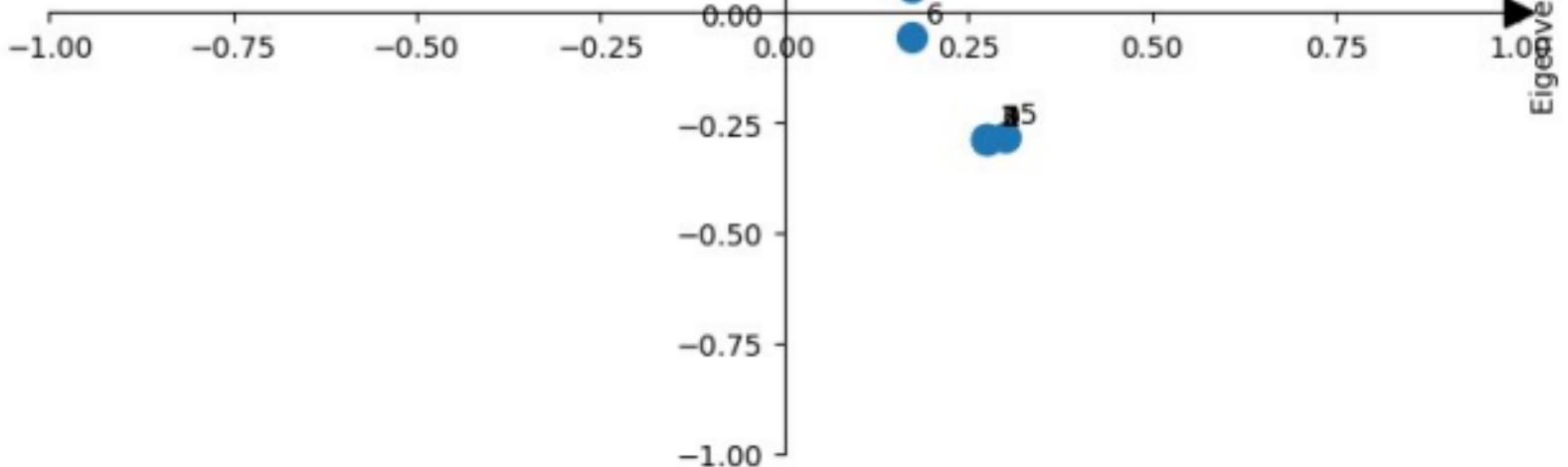
$$= \frac{\sum_{i=1}^k \sum_{u \neq v} w(u,v) |f_i(u) - f_i(v)|^2}{\sum_{i=1}^k \sum_{u \in V} w(u) |f_i(u)|^2}$$
$$= \frac{\lambda_1 + \dots + \lambda_k}{K} \leq \lambda_K$$



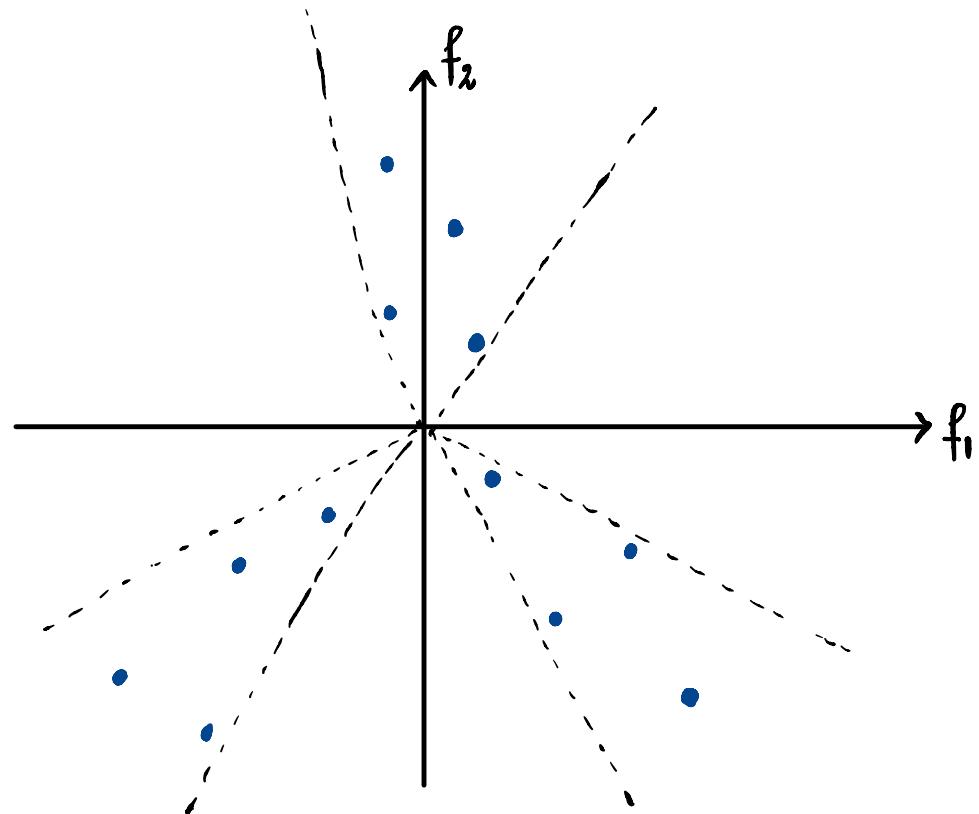
Original Graph



2D Spectral Embedding



# FIND $K$ REGIONS WITH LARGE CONCENTRATION



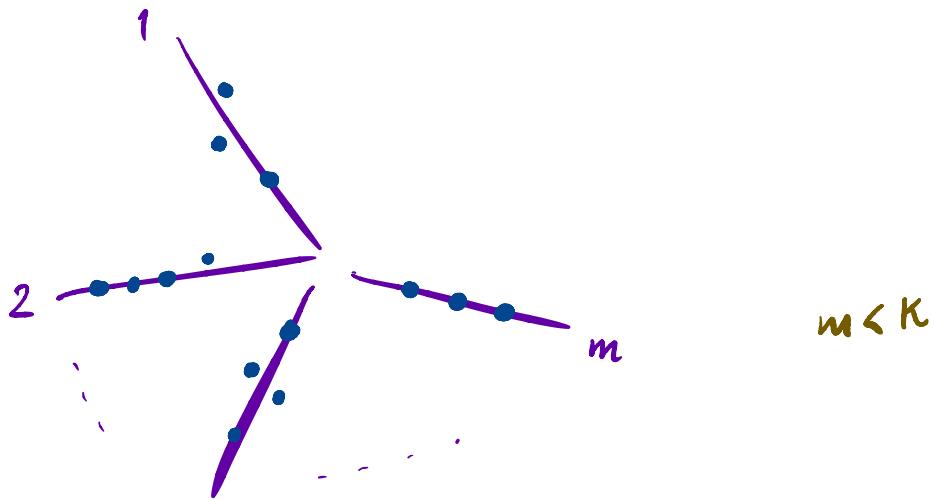
## ISOTROPY PROPERTY

We can show that  $\sum_{v \in V} \langle x, F(v) \rangle^2 = 1$ , for any  $x \in S^{k-1}$ . Also,  $\sum_{v \in V} \|F(v)\|^2 = k$

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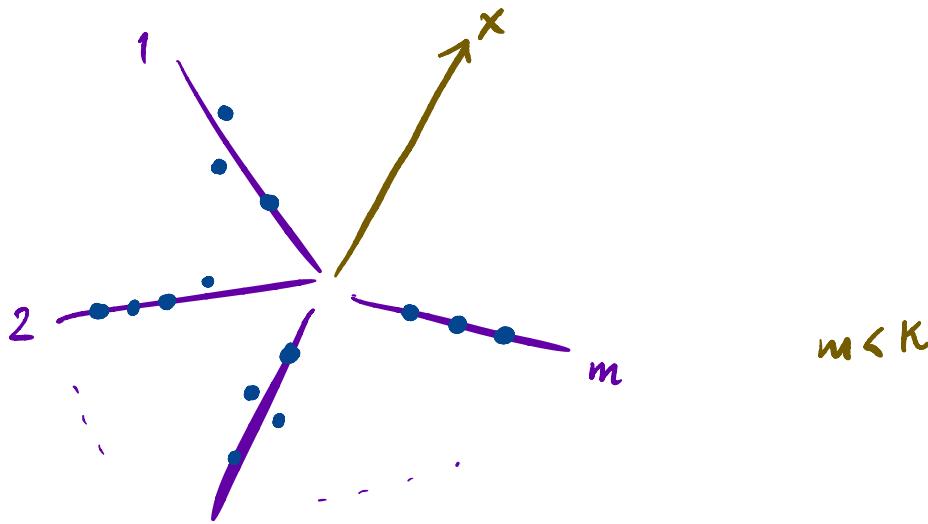
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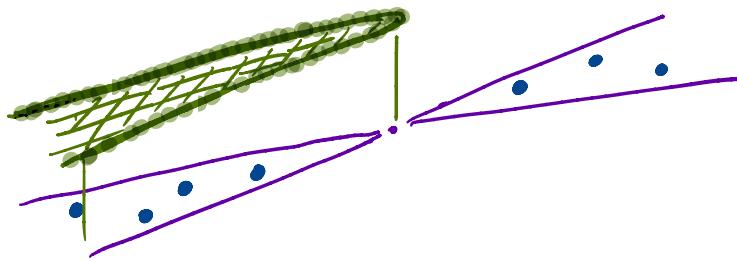
This implies



$\sum_{x \in V} \langle x, F(v) \rangle^2 \approx 0$ .  $F$  cannot concentrate along fewer than  $k$  lines.

# FIRST APPROACH TO GET $\psi_i$

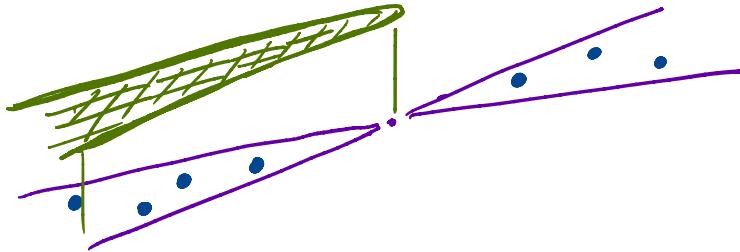
Find  $k$ -directions:  $x_1, \dots, x_k$



$$\psi_i(v) = \begin{cases} F(v) & \text{if } F(v) \text{ has large projection on } x_i \\ 0 & \text{otherwise} \end{cases}$$

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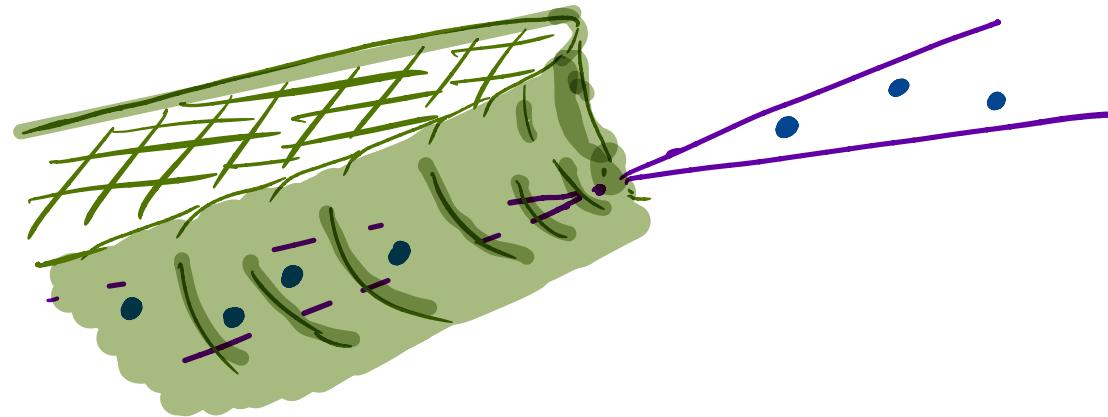
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$$\psi_i(v) = \begin{cases} F(v) & \text{if } F(v) \text{ has large projection on } x_i \\ 0 & \text{otherwise} \end{cases}$$

Cutoff is too sharp!  $\sum_{\{u,v\} \in E} \|\psi_i(u) - \psi_i(v)\|^2 \gg \sum_{\{u,v\} \in E} \|F(u) - F(v)\|^2$

# SMOOTH IT OUT



New distance:

$$d_F(u, v) = \left\| \frac{F(u)}{\|F(u)\|} - \frac{F(v)}{\|F(v)\|} \right\|$$

Radial distance

# GOAL

Find  $k$ -regions  $S_1, S_2, \dots, S_k$  such that

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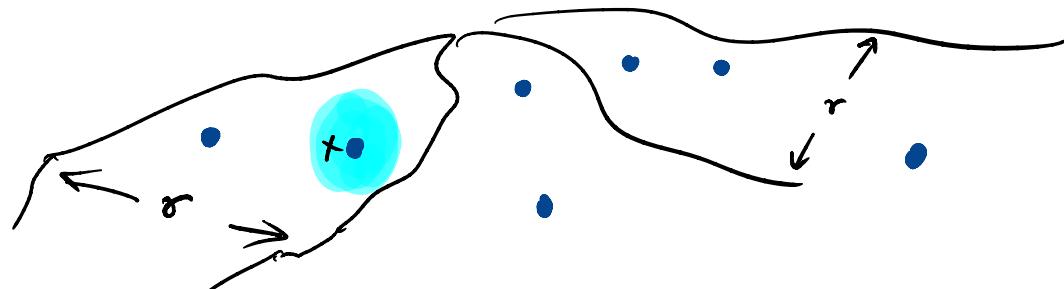
- each region contains a large fraction of the  $\ell^2$  mass of  $F$ .
- far enough apart to allow  $\Psi_i$  to smooth out.

# RANDOM PARTITIONS

Let  $(X, d)$  be a finite metric space. Let  $B(x, R) = \{y \in X : d(x, y) \leq R\}$  denote the closed ball of radius  $R$  around  $x$ .

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- An  $(r, \varepsilon)$ -padded decomposition of a metric space  $(X, d)$  is a distribution  $\mu$  over  $P$  (collection of partitions of  $X$ ) satisfying
  - 1) Bounded diameter:  $\text{diam}(c) \leq r$  & Cluster  $C$  in every partition  $P$  is support of  $\mu$ .
  - 2) Padding:  $\Pr_{\mu} [\pi_P(x) \geq \varepsilon r] \geq \frac{1}{2} \quad \forall x \in X$   
where  $\pi_P(x) = \sup \{t : \exists C \in P \text{ with } B(x, t) \subset C\}$

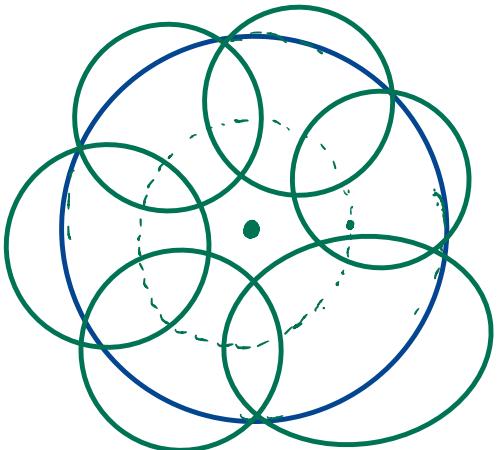


Thm. [Gupta, Krauthgamer, Lee] Let  $(X, d)$  be a finite metric space. Then for every  $r > 0$ , there exists an  $(r, \epsilon)$ -padded probabilistic decomposition of  $X$  with  $\frac{1}{\epsilon} \leq 64 \dim(X)$ . (Assume  $X \subseteq \mathbb{R}^k$ )

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### Doubling dimension

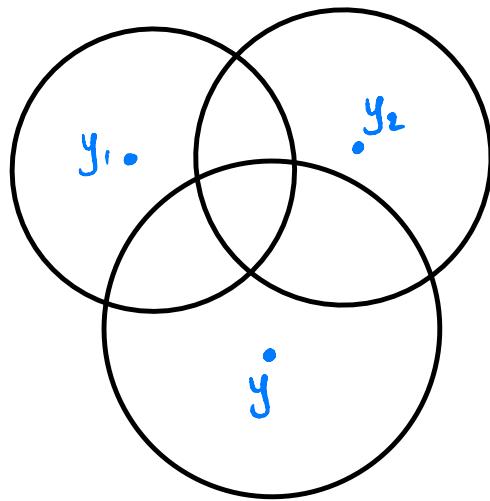
- doubling constant is the smallest value  $\lambda$  such that every ball in  $X$  can be covered by  $\lambda$  balls of half the radius
- doubling dimension  $\dim(X) = \log_2 \lambda$ .



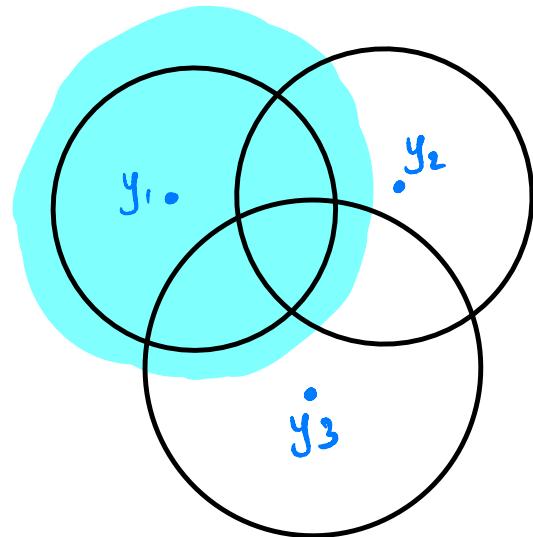
$\mathbb{R}^2$  has doubling constant 7  
 $\Rightarrow$  doubling dimension  $\log_2 7$

$\mathbb{R}^k$  has doubling dimension  $\Theta(k)$

Proof. Take a  $r$ -net  $N$ .  $\text{diam}(\text{Ball}) \leq r$ . Also ensure  $d(y_i, y_j) \geq r$

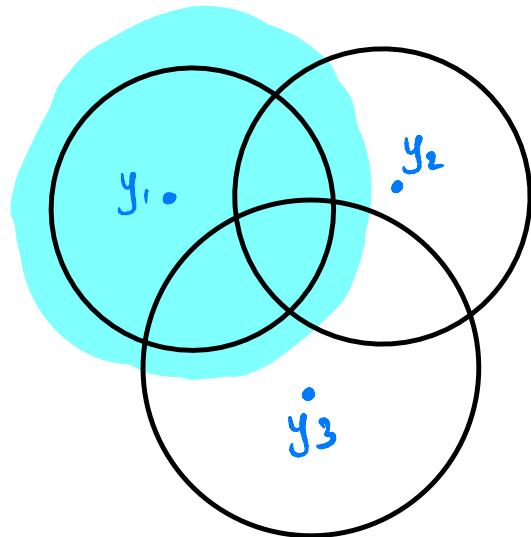


Proof. Take a  $r$ -net  $N$ .  $\text{diam}(B_{\text{all}}) \leq r$ . Also ensure  $d(y_i, y_j) \geq r$



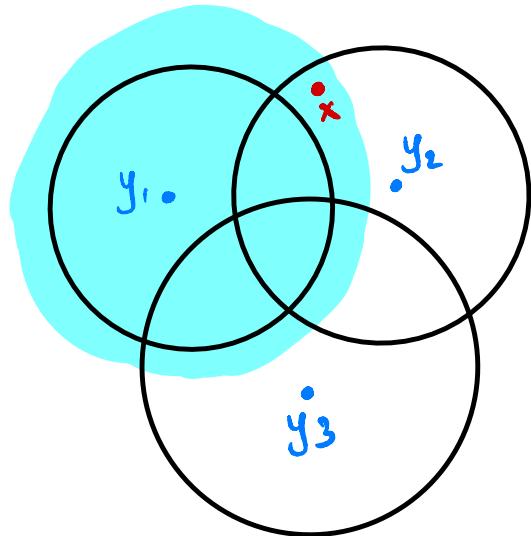
- Choose  $R \sim U[r, 2r]$   
create a ball  $B(y, R)$  around all  $y \in N$ .

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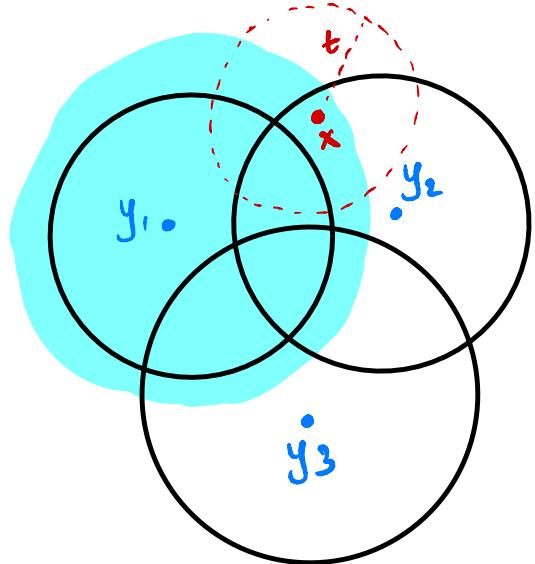
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- Choose  $R \sim U[r, 2r]$   
create a ball  $B(y, R)$  around all  $y \in N$ .
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of the net points
- Define clusters:  
 $\forall y \in N, C_y = \{x \in X : x \in B(y, R) \text{ and } \sigma(y) < \sigma(z) \text{ for all other } z \text{ where } x \in B(z, R)\}$

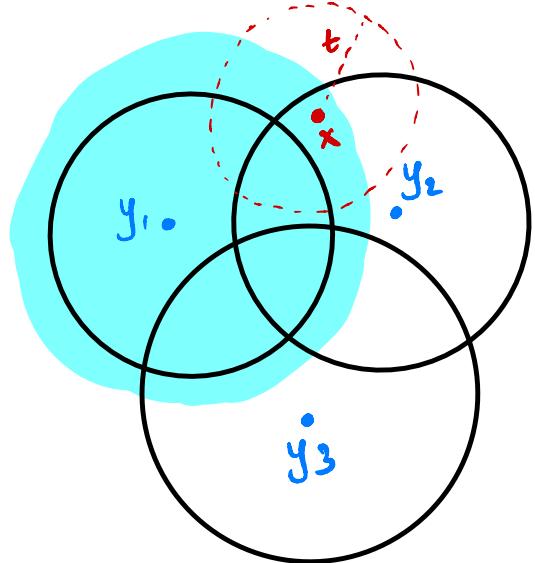
Example.  $x \in C_{y_1}$  if  $\sigma(y_1) < \sigma(y_2)$

Proof. Take a  $r$ -net  $N$ .  $\text{diam}(B_{\text{all}}) \leq r$ . Also ensure  $d(y_i, y_j) \geq r$

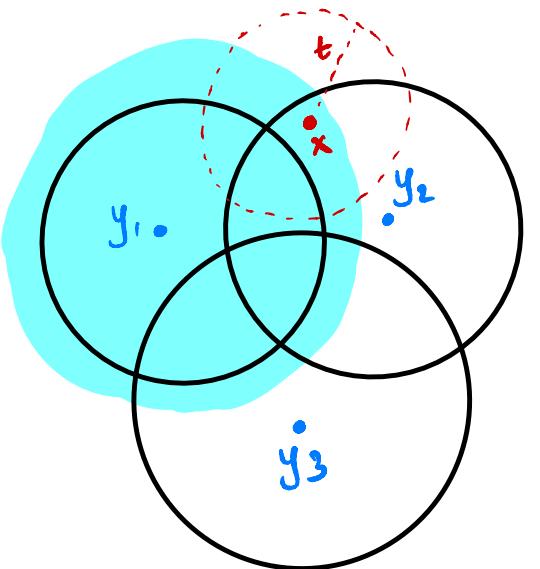


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- Define clusters:  
 $\forall y \in N, C_y = \{x \in X : x \in B(y, R) \text{ and } \sigma(y) < \sigma(z) \text{ for all other } z \text{ where } x \in B(z, R)\}$
- For  $x \in X$ , take  $B(x, t)$  with  $t \leq \epsilon r$   
 $W = B(x, 2r+t) \cap N$   
These are the only net points whose ball might  
cut  $B(x, t)$

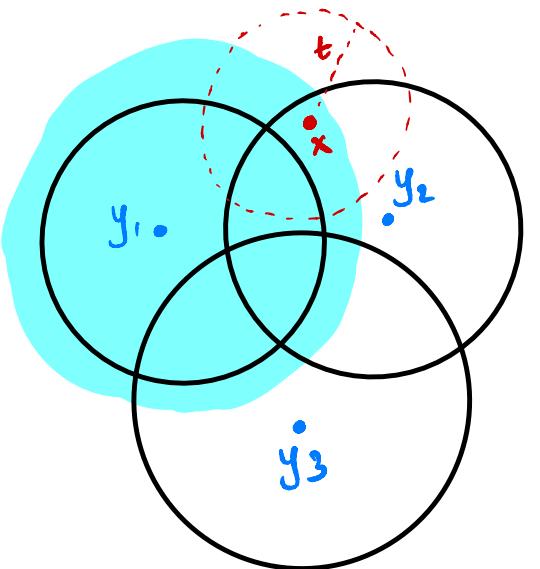
Proof. Take a  $r$ -net  $N$ .  $\text{diam}(B_{\text{all}}) \leq r$ . Also ensure  $d(y_i, y_j) \geq r$



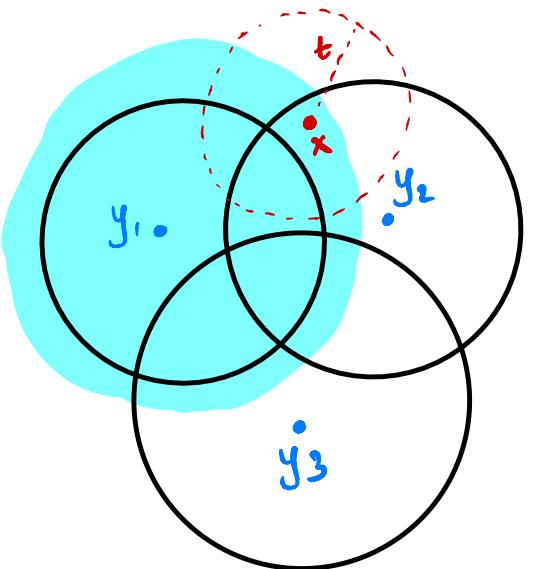
- Choose  $R \sim U[r, 2r]$   
create a ball  $B(y, R)$  around all  $y \in N$ .
- generate a random permutation  $\sigma$   
of the net points
- Define clusters:  
 $\forall y \in N, C_y = \{x \in X : x \in B(y, R) \text{ and } \sigma(y) < \sigma(z) \text{ for all other } z \text{ where } x \in B(z, R)\}$
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- $|W| \leq 2^k$ ? skip.



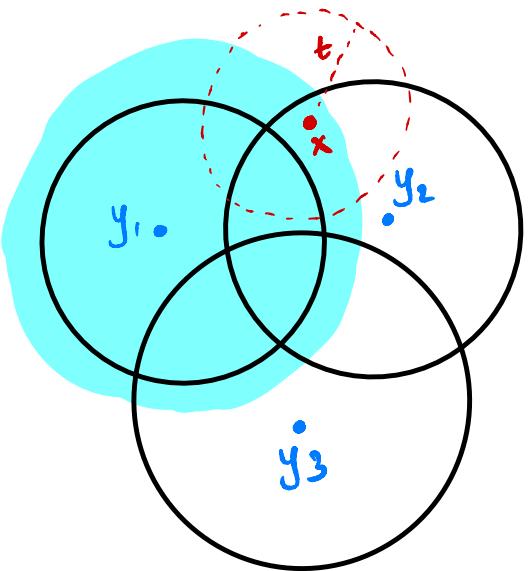
- Order points in  $W = \{w_1, \dots, w_m\}$  by distance from  $x$ .  
Let  $I_k = [d(x, w_k) - t, d(x, w_k) + t]$
- Let  $E_k$  event that  $w_k$ 's cluster cuts  $B(x, t)$ .



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  - $\Pr[E_k] = \Pr[R \in [d(x, w_k) - t, d(x, w_k) + t]  
and  $w_k$  has highest priority  
i.e.  $\sigma(w_k)$  is smallest]$
- $$\leq \Pr[R \in I_k] \cdot \Pr[\sigma(w_k) \text{ is smallest}]$$
- $$= \frac{|I_k|}{[r, 2r]|} \cdot \frac{1}{K}$$
- $$= \frac{2t}{r} \cdot \frac{1}{K}$$



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- $= \frac{2t}{r} \cdot \frac{1}{K}$
- Union Bound  $\sum_{k=1}^m \Pr[E_k] \leq \sum_{k=1}^m \frac{2t}{r} \frac{1}{K} \leq \frac{2t}{r} (1 + \ln m)$



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$$= \frac{|I_k|}{|[-r, 2r]|} \cdot \frac{1}{K}$$

$$= \frac{2t}{r} \cdot \frac{1}{K}$$

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$$\text{So, } \Pr[B(x, t) \text{ is cut}] \leq \frac{2t}{r} (1 + \ln 2)$$

$$\text{Set } t = \frac{r}{8K}$$

$$\Pr[B(x, t) \text{ is cut}] \leq \frac{2}{8K} (1 + \ln 2)$$

$$= \frac{1}{4K} + \frac{\ln 2}{4} \leq \frac{1}{2}$$