

Simple
Average-case Lower Bounds
for
Approximate Near-Neighbor
from
Isoperimetric Inequalities

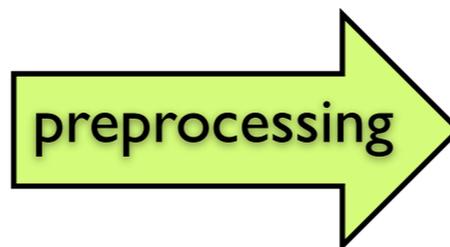
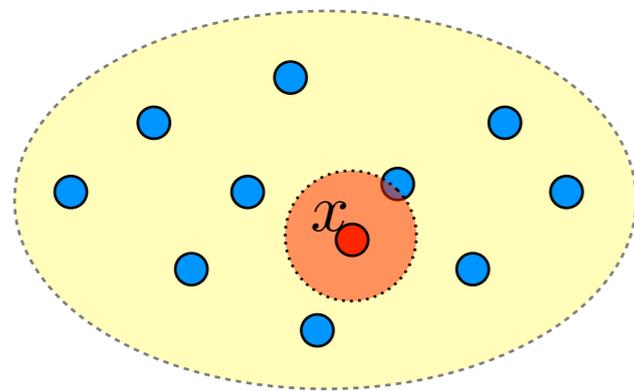
Yitong Yin
Nanjing University

Nearest Neighbor Search (NNS)

metric space (X, dist)

database

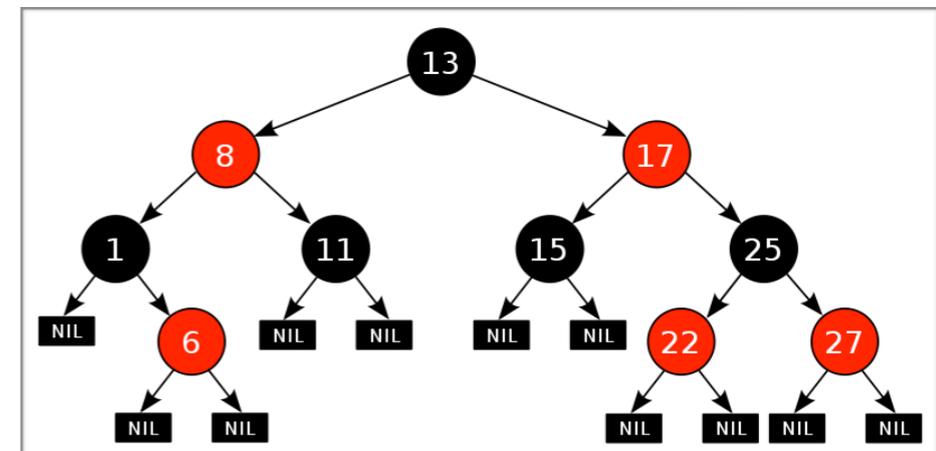
$$y = (y_1, y_2, \dots, y_n) \in X^n$$



query $x \in X$



data structure



output: database point y_i closest to the query point x

applications: *database, pattern matching, machine learning, ...*

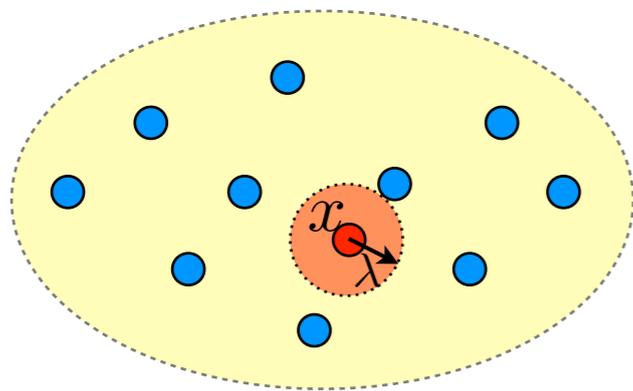
Near Neighbor Problem

(λ -NN)

metric space (X, dist)

database

$$y = (y_1, y_2, \dots, y_n) \in X^n$$



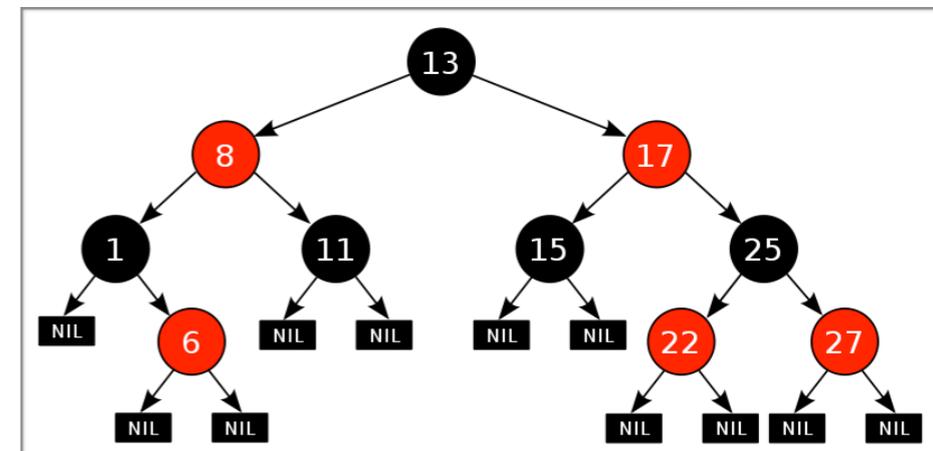
radius λ

preprocessing

query $x \in X$

access

data structure



λ -NN: answer “yes” if $\exists y_i$ that is $\leq \lambda$ -close to x

“no” if all y_i are $> \lambda$ -faraway from x

Approximate Near Neighbor (ANN)

metric space (X, dist)

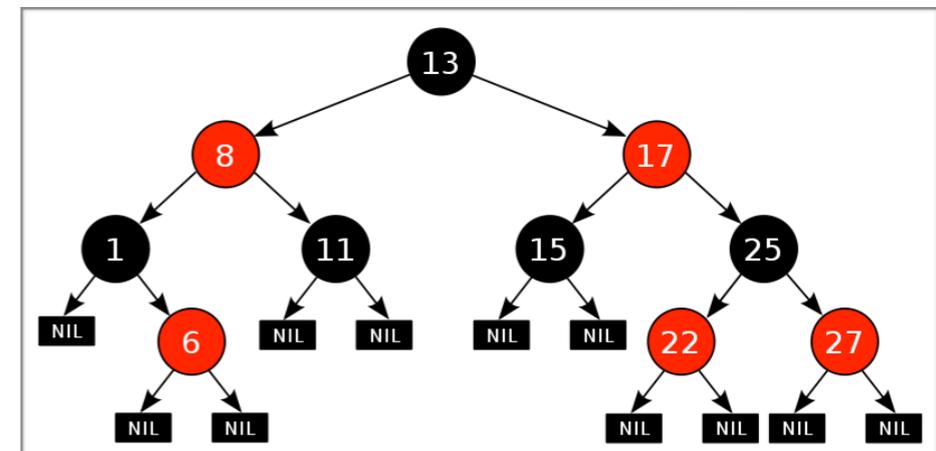
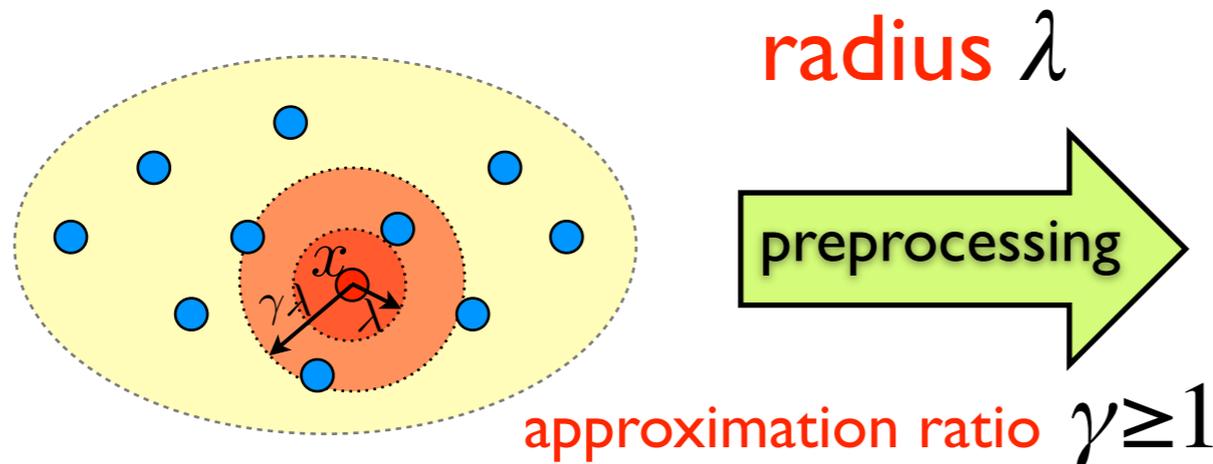
database

$$y = (y_1, y_2, \dots, y_n) \in X^n$$

query $x \in X$

access

data structure



(γ, λ) -ANN: answer “yes” if $\exists y_i$ that is $\leq \lambda$ -close to x
“no” if all y_i are $> \gamma\lambda$ -faraway from x
arbitrary if otherwise

Approximate Near Neighbor (ANN)

metric space (X, dist)

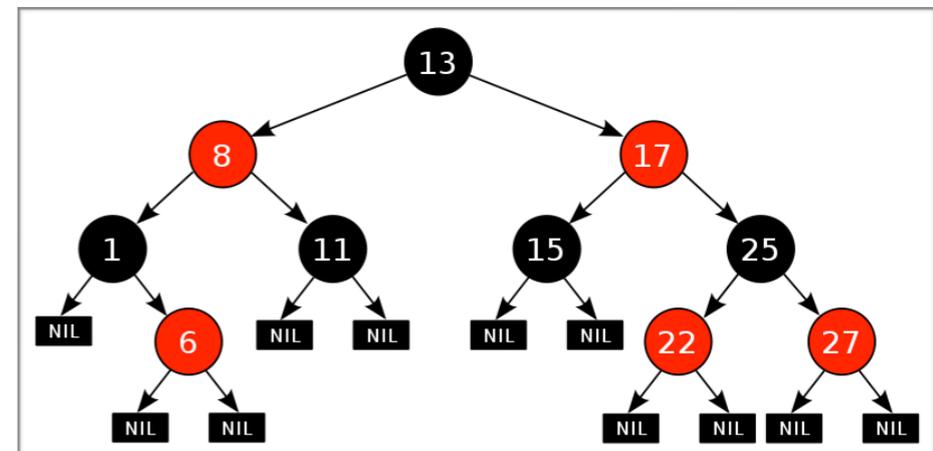
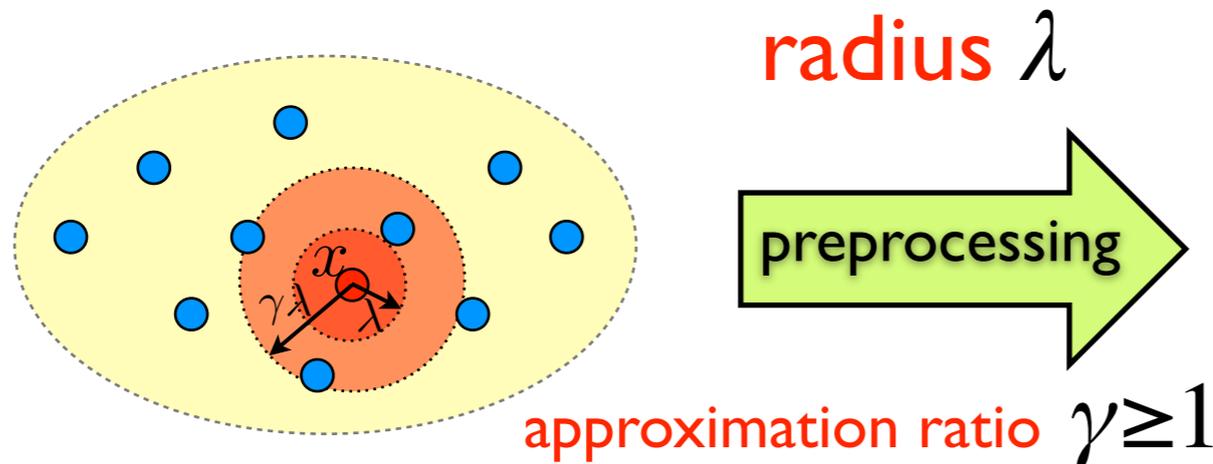
database

$$y = (y_1, y_2, \dots, y_n) \in X^n$$

query $x \in X$

access

data structure



Hamming space $X = \{0, 1\}^d$

$$\text{dist}(x, z) = \|x - z\|_1$$

Hamming distance

$$100 \log n < d < n^{o(1)}$$

Curse of dimensionality!

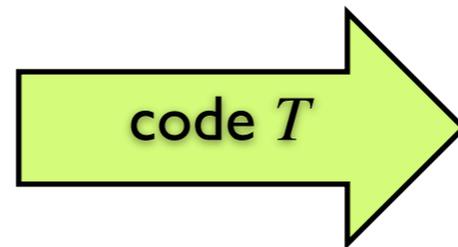
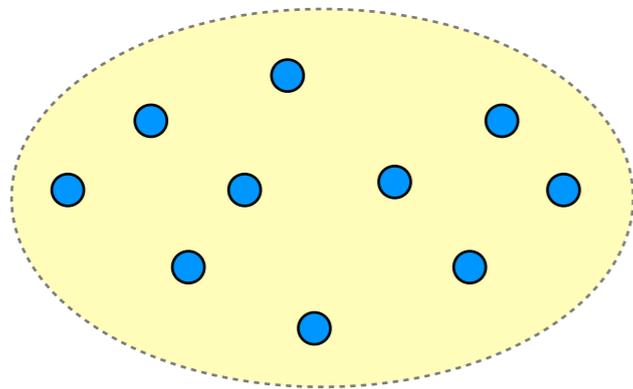
Cell-Probe Model

data structure problem:

$$f : X \times Y \rightarrow Z$$

database

$$y \in Y$$



$$T : Y \rightarrow \Sigma^s$$

where $\Sigma = \{0, 1\}^w$

query $x \in X$

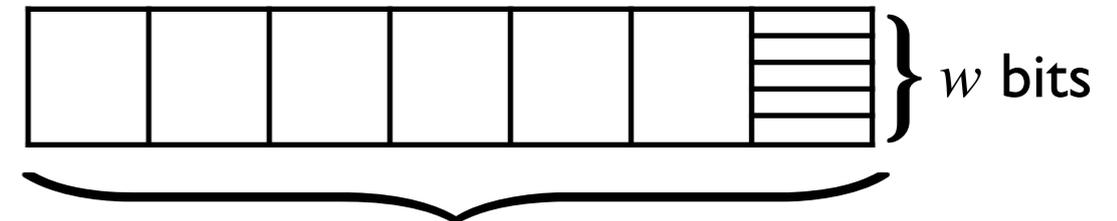
algorithm A :
(decision tree)



$$f(x, y)$$

table

t adaptive
cell-probes



protocol: the pair (A, T)

(s, w, t) -cell-probing scheme

Near-Neighbor Lower Bounds

Hamming space $X = \{0, 1\}^d$ database size: n

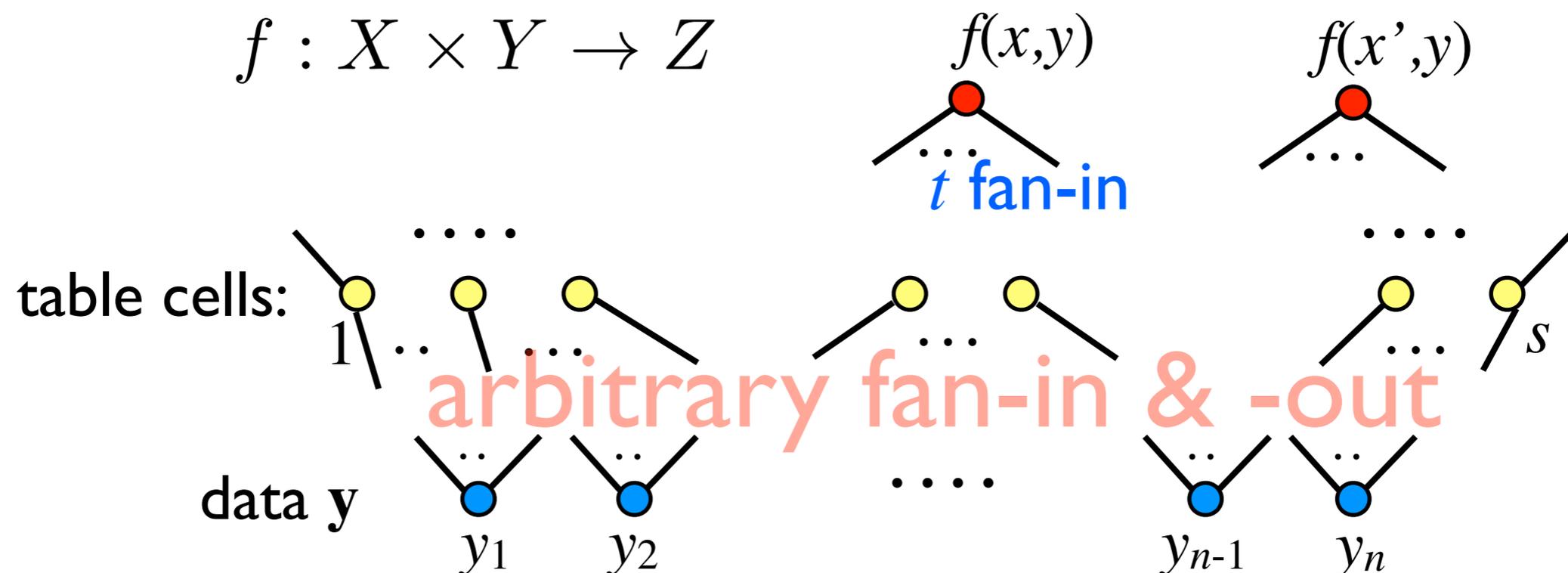
time: t cell-probes; line space cells, $\Theta(n)$ or $\Theta(d)$ each of w bits

Approximate Near-Neighbor (ANN)		Randomized Exact Near-Neighbor (RENN)
Deterministic	Randomized	
$t = \Omega\left(\frac{d}{\log s}\right)$ [Miltersen <i>et al.</i> 1995] [Liu 2004]	$t = O(1)$ for $s = \text{poly}(n)$ [Chakrabarti Regev 2004]	$t = \Omega\left(\frac{d}{\log s}\right)$ [Borodin Ostrovsky Rabani 1999] [Barkol Rabani 2000]
$t = \Omega\left(\frac{\log n}{\log \frac{w}{n}}\right)$ [Pătraşcu Thorup 2006]	$t = \Omega\left(\frac{\log m}{\log \frac{w}{n}}\right)$ [Panigrahy Talwar Wieder 2008, 2010]	$t = \Omega\left(\frac{\log n}{\log \frac{w}{n}}\right)$ [Pătraşcu Thorup 2006]
$t = \Omega\left(\frac{d}{\log \frac{w}{n}}\right)$ [Wang Y. 2014]		

- matches the highest known lower bounds for any data structure problems:
 Polynomial Evaluation [Larsen'12], ball-inheritance (range reporting) [Grønlund, Larsen'16]

Why are data structure lower bounds so difficult?

- (Observed by [Miltersen *et al.* 1995]) An $\omega(\log n)$ cell-probe lower bound on polynomial space for *any* function in \mathbf{P} would prove $\mathbf{P} \not\subseteq$ linear-time poly-size Boolean **branching programs**. (Solved in [Ajtai 1999])
- (Observed by [Brody, Larsen 2012]) Even *non-adaptive* data structures are **circuits with arbitrary gates of depth 2**:



Near-Neighbor Lower Bounds

Hamming space $X = \{0, 1\}^d$ **database size:** n

time: t cell-probes; **space:** s cells, each of w bits

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Deterministic	Randomized	
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Average-Case Lower Bounds

- **Hard distribution:** [Barkol Rabani 2000] [Liu 2004] [PTW'08 '10]
 - **database:** $y_1, \dots, y_n \in \{0,1\}^d$ *i.i.d. uniform*
 - **query:** uniform and independent $x \in \{0,1\}^d$
- *Expected* cell-probe complexity:
 - $\mathbf{E}_{(x,y)}$ [# of cell-probes to resolve query x on database y]
- “Curse of dimensionality” should hold on average.
- In *data-dependent LSH* [Andoni Razenshteyn 2015]: a key step is to solve the problem on random input.

Average-Case Lower Bounds

Hamming space $X = \{0, 1\}^d$ database size: n

time: t cell-probes; space: s cells, each of w bits

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<p>our result:</p> $t = \Omega\left(\frac{d}{\log \frac{sw}{nd}}\right)$		

Metric Expansion

[Panigrahy Talwar Wieder 2010]

metric space (X, dist)

λ -neighborhood: $\forall x \in X, N_\lambda(x) = \{z \in X \mid \text{dist}(x, z) \leq \lambda\}$
 $\forall A \subseteq X, N_\lambda(A) = \{z \in X \mid \exists x \in A \text{ s.t. } \text{dist}(x, z) \leq \lambda\}$

probability distribution μ over X

- λ -neighborhoods are **weakly independent** under μ :

$$\forall x \in X, \mu(N_\lambda(x)) < 0.99/n$$

- λ -neighborhoods are **(Φ, Ψ) -expanding** under μ :

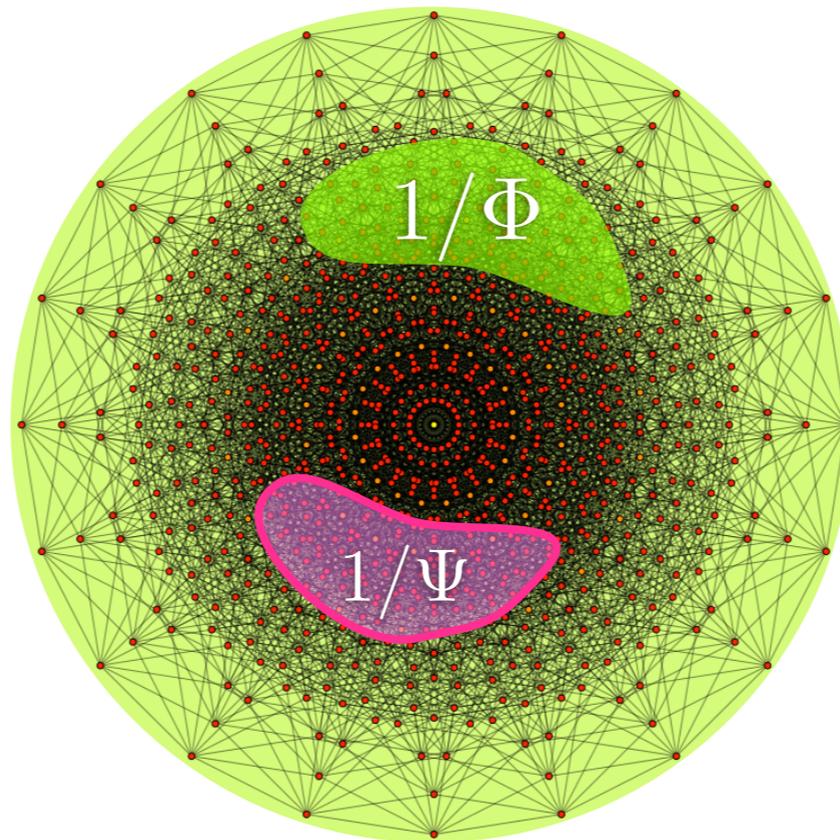
$$\forall A \subseteq X, \mu(A) \geq 1/\Phi \Rightarrow \mu(N_\lambda(A)) \geq 1 - 1/\Psi$$

Metric Expansion

[Panigrahy Talwar Wieder 2010]

metric space (X, dist) probability distribution μ over X

- λ -neighborhoods are **(Φ, Ψ) -expanding** under μ :
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vertex expansion, "blow-up" effect

Main Theorem:

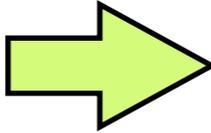
For (γ, λ) -ANN in metric space (X, dist) where

- $\gamma\lambda$ -neighborhoods are **weakly independent** under μ :
 $\mu(N_{\gamma\lambda}(x)) < 0.99/n$ for $\forall x \in X$
- λ -neighborhoods are **(Φ, Ψ) -expanding** under μ :
 $\forall A \subseteq X$ that $\mu(A) \geq 1/\Phi \Rightarrow \mu(N_\lambda(A)) \geq 1 - 1/\Psi$

\forall **deterministic** algorithm that makes t cell-probes **in expectation** on a table of size s cells, each of w bits (assuming $w + \log s < n / \log \Phi$), under the **input distribution**:

database $y = (y_1, y_2, \dots, y_n)$ where $y_1, y_2, \dots, y_n \sim \mu$, i.i.d.

query $x \sim \mu$, independently


$$t = \Omega \left(\frac{\log \Phi}{\log \frac{sw}{n \log \Psi}} \right)$$

Main Theorem:

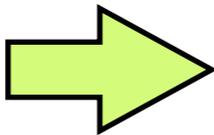
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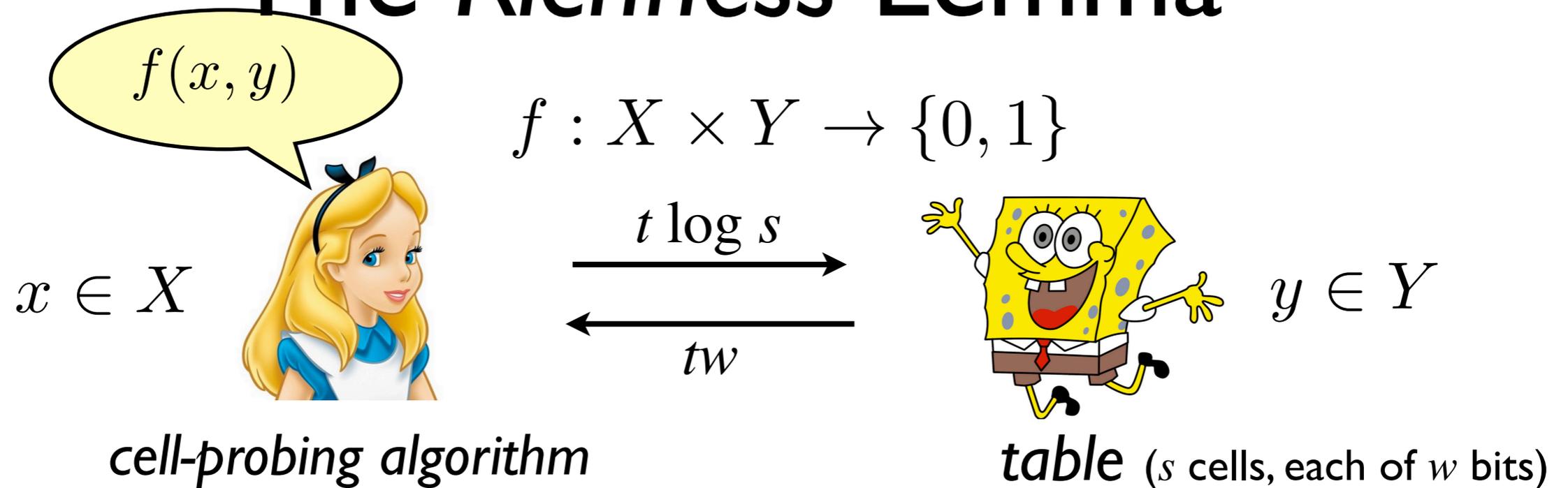
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query $x \sim \mu$, independently


$$t = \Omega \left(\frac{\log \Phi}{\log \frac{sw}{n \log \Psi}} \right)$$

The Richness Lemma



distributions μ over X , ν over Y

α -dense: density of 1s $\geq \alpha$ under $\mu \times \nu$

monochromatic 1-rectangle: $A \times B$ with $A \subseteq X$, $B \subseteq Y$

s.t. $\forall (x, y) \in A \times B, f(x, y) = 1$

Richness lemma (Miltersen, Nisan, Safra, Wigderson, 1995)

f is 0.01-dense under $\mu \times \nu$ } \longrightarrow f has 1-rectangle $A \times B$ with
 f has (s, w, t) -cell-probing scheme } $\left\{ \begin{array}{l} \mu(A) \geq 2^{-O(t \log s)} \\ \nu(B) \geq 2^{-O(t \log s + tw)} \end{array} \right.$

A **New** Richness Lemma

$f : X \times Y \rightarrow \{0, 1\}$ distributions μ over X , ν over Y

Richness lemma (Miltersen, Nisan, Safra, Wigderson, 1995)

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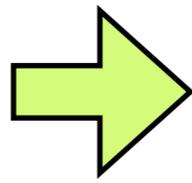
New Richness lemma

f is 0.01-dense under $\mu \times \nu$ } $\implies \forall \Delta \in [320000t, s],$
 f has **average-case** } f has 1-rectangle $A \times B$ with
 (s, w, t) -cell-probing scheme } $\left\{ \begin{array}{l} \mu(A) \geq 2^{-O(t \log (s/\Delta))} \\ \nu(B) \geq 2^{-O(\Delta \log (s/\Delta) + \Delta w)} \end{array} \right.$
 under $\mu \times \nu$

when $\Delta = O(t)$, it becomes the richness lemma (with slightly better bounds)

$f : X \times Y \rightarrow \{0, 1\}$ distributions μ over X , ν over Y

New Richness lemma

f is 0.01-dense under $\mu \times \nu$ }  $\forall \Delta \in [320000t, s]$,
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metric space (X, dist) , **query** $x \in X$, **database** $y = (y_1, \dots, y_n) \in X_n$

$\neg(\gamma, \lambda)$ -ANN: $f(x, y) = \bigwedge_{i=1}^n g(x, y_i)$

where

$$g(x, y_i) = \begin{cases} 1 & \text{dist}(x, y_i) > \gamma \lambda \\ 0 & \text{dist}(x, y_i) \leq \lambda \\ * & \text{otherwise} \end{cases}$$

Other examples: partial match, membership, range query, ...

New Richness lemma

f is 0.01-dense under $\mu \times \nu$ } $\implies \forall \Delta \in [320000t, s]$,
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 under $\mu \times \nu$

- $\gamma\lambda$ -neighborhoods are **weakly independent** under μ :

$$\mu(N_{\gamma\lambda}(x)) < 0.99/n \text{ for } \forall x \in X$$

\implies density of 0s in g is $\leq 0.99/n$ under $\mu \times \mu \implies f$ is 0.01-dense under $\mu \times \mu^n$

- λ -neighborhoods are **(Φ, Ψ) -expanding** under μ :

$$\forall A \subseteq X, \mu(A) \geq 1/\Phi \implies \mu(N_\lambda(A)) \geq 1 - 1/\Psi$$

$\implies g$ does not have 1-rectangle $A \times C$ with $\mu(A) > 1/\Phi$ and $\mu(C) > 1/\Psi$

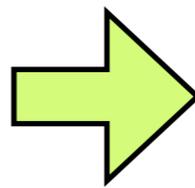
$\implies f$ does not have 1-rectangle $A \times B$ with $\mu(A) > 1/\Phi$ and $\mu^n(B) > 1/\Psi^n$

choose $\Delta = O\left(\frac{n \log \Psi}{w}\right)$ so that $\mu^n(B) \geq 2^{-O(\Delta \log(s/\Delta) + \Delta w)} > 1/\Psi^n$

$\implies 1/\Phi \geq \mu(A) \geq 2^{-O(t \log(s/\Delta))} \implies t = \Omega\left(\frac{\log \Phi}{\log \frac{sw}{n \log \Psi}}\right)$

New Richness lemma

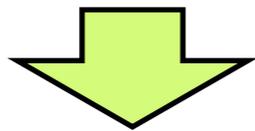
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 (s, w, t) -cell-probing scheme
 under $\mu \times \nu$



$\forall \Delta \in [320000t, s],$

f has 1-rectangle $A \times B$ with

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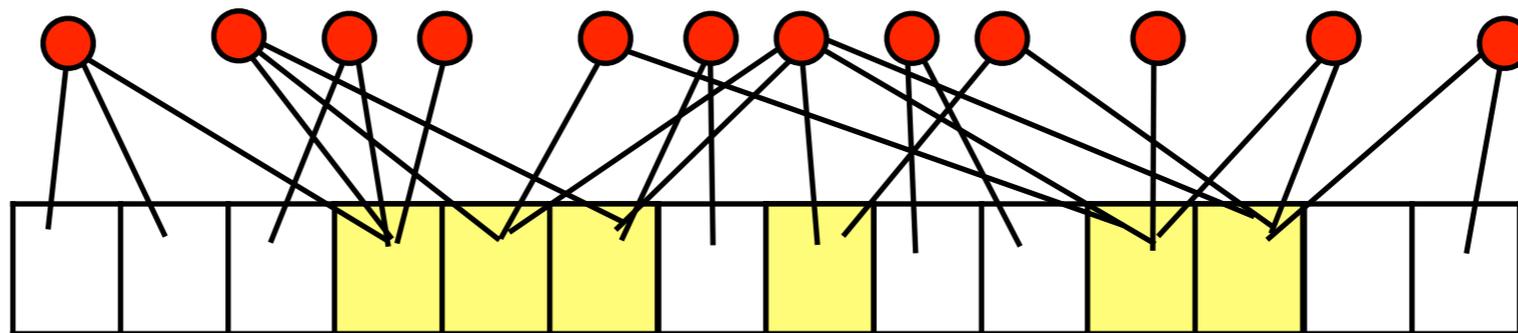
≥ 0.0025 -fraction (under ν) of databases $y \in Y$ are “**good**”:

s.t. \forall **good** database y ,

$$\begin{cases} \geq 0.005\text{-fraction of queries } x \in X \text{ are } \mathbf{positive} \\ \text{avg. cell-probes for positive queries} \leq 80000t \end{cases}$$

positive
queries:

T_y :



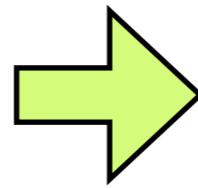
$\Rightarrow \exists \Delta$ cells resolving $2^{-O(t \log(s/\Delta))}$ fraction (under μ) **positive** queries

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New Richness lemma

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$\forall \Delta \in [320000t, s]$,

f has 1-rectangle $A \times B$ with

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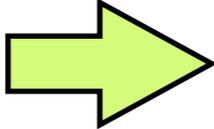
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$$t = \Omega \left(\frac{\log \Phi}{\log \frac{sw}{n \log \Psi}} \right)$$

Average-Case Lower Bounds

Hamming space $X = \{0, 1\}^d$ database size: n

time: t cell-probes; space: s cells, each of w bits

- database: $y_1, \dots, y_n \in \{0, 1\}^d$ *i.i.d. uniform*
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<p>our result:</p> $t = \Omega\left(\frac{d}{\log \frac{sw}{nd}}\right)$		

Thank you!