

Some Recent Results in Database Theory

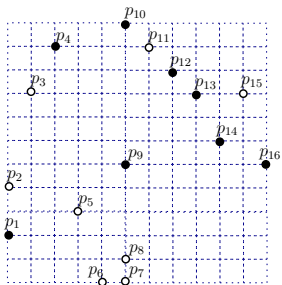
Yufei Tao

CSE Dept
Chinese University of Hong Kong

This talk aims to give you a flavor of fundamental database research.

I: Machine Learning

Classification

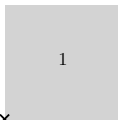


Monotone Classifier

$\begin{smallmatrix} 1 \\ \times \end{smallmatrix}$

\Rightarrow

$\begin{smallmatrix} 1 \\ \times \end{smallmatrix}$



1

$\begin{smallmatrix} -1 \\ \times \end{smallmatrix}$

\Rightarrow

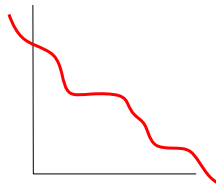
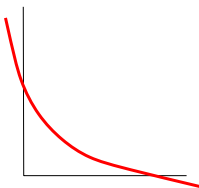
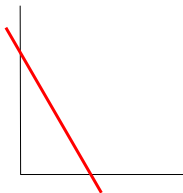
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-1

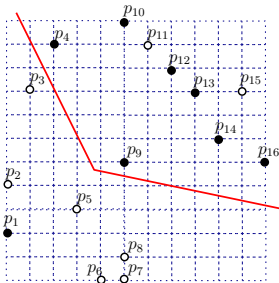
Monotone Classifier

Examples:



k^* = minimum error of all monotone classifiers

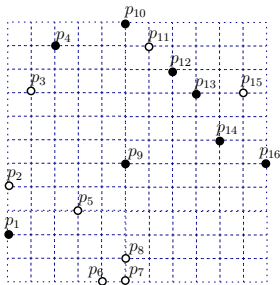
k^* = minimum error of all monotone classifiers



(black = 1, white = -1)

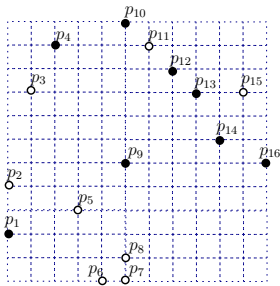
$$k^* = 3$$

Active Monotone Classification



Question: How many points must we probe to return a monotone classifier whose error is k^* ?

Dominance width w of P



$$w = 6$$

Thm 1 [Tao and Wang'21]:
 $\Omega(n)$ to ensure error k^* , even in 1D.

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Thm 3 [Tao and Wang'21]:
 $O(w \log \frac{n}{w} \cdot \log n)$ to ensure error $(1+\epsilon)k^*$, for any constant $\epsilon > 0$.

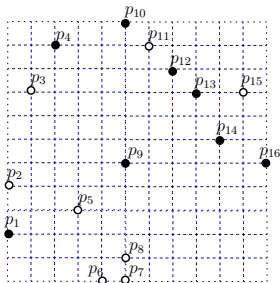
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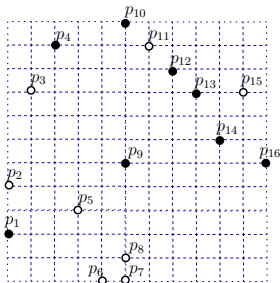
Thm 3 [Tao and Wang'21]:
 $O(w \log \frac{n}{w} \cdot \log n)$ to ensure error $(1 + \epsilon) k^*$, for any constant $\epsilon > 0$.

Thm 4 [Tao'18]:
 $O(w \log \frac{n}{w})$ (expected) probes to ensure (expected) $2k^*$.

2-Approximate Algorithm

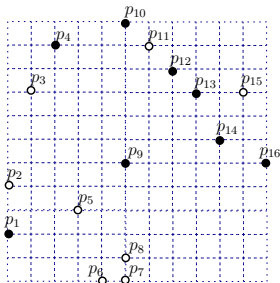


2-Approximate Algorithm



First probe = p_1

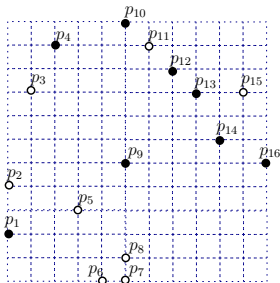
2-Approximate Algorithm



First probe = p_1

Second = p_8

2-Approximate Algorithm



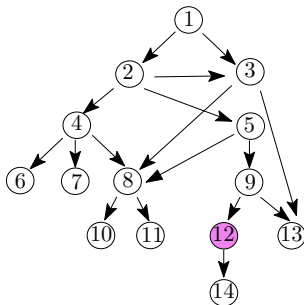
First probe = p_1

Second = p_8

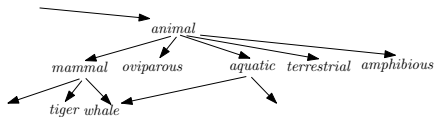
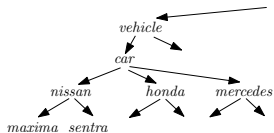
Returns a classifier with error 5

II: Crowdsourcing

Partial Order Search



Crowdsourcing



n = number of nodes

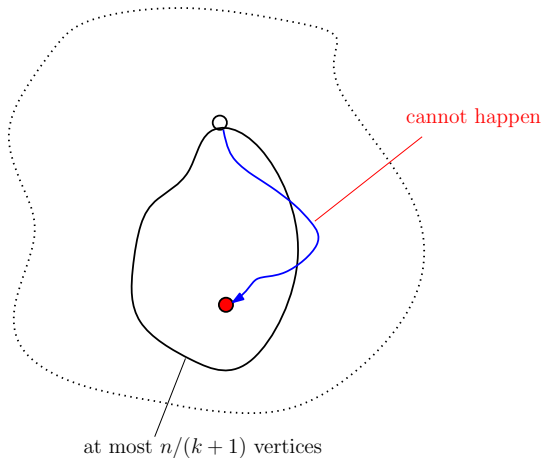
d = maximum out-degree

k = number of questions in each round

Thm 1 [Lu, Martens, Niewerth, Tao'21]
 $\Omega(\log_{1+k} n + \frac{d}{k} \log_{1+d} n)$ probes necessary.

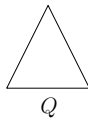
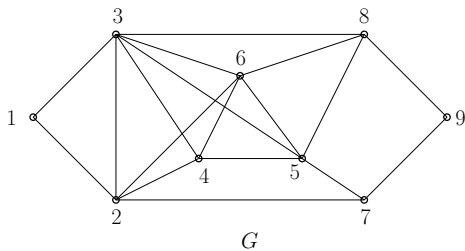
Thm 2 [Lu, Martens, Niewerth, Tao'21]
 $O(\log_{1+k} n + \frac{d}{k} \log_{1+d} n)$ probes suffice.

With roughly $1 + d/k$ probes, we can achieve:

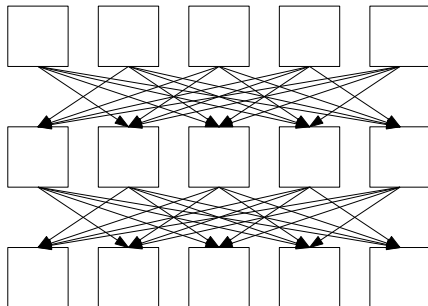


III: Massively Parallel Computation

Subgraph Enumeration

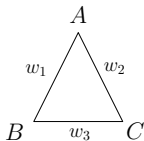


MPC



Goal: Minimize the amount of communication on every machine.

AGM Bound



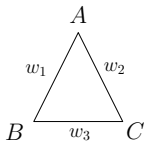
Minimize $w_1 + w_2 + w_3$ subject to

$$w_1 + w_2 \geq 1$$

$$w_1 + w_3 \geq 1$$

$$w_2 + w_3 \geq 1$$

AGM Bound



Minimize $w_1 + w_2 + w_3$ subject to

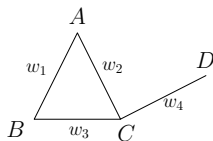
$$w_1 + w_2 \geq 1$$

$$w_1 + w_3 \geq 1$$

$$w_2 + w_3 \geq 1$$

Answer: 1.5 — the **fractional edge covering number** ρ

AGM Bound



Minimize $w_1 + w_2 + w_3 + w_4$ subject to

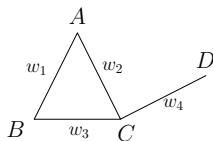
$$w_1 + w_2 \geq 1$$

$$w_1 + w_3 \geq 1$$

$$w_2 + w_3 + w_4 \geq 1$$

$$w_4 \geq 1$$

AGM Bound



Minimize $w_1 + w_2 + w_3 + w_4$ subject to

$$w_1 + w_2 \geq 1$$

$$w_1 + w_3 \geq 1$$

$$w_2 + w_3 + w_4 \geq 1$$

$$w_4 \geq 1$$

Answer: 2 — the **fractional edge covering number** ρ

AGM Bound

The maximum number of occurrences of Q in a graph of m edges is $\Theta(m^\rho)$.

p = number of machines

Thm 1 At least one machine must communicate $\Omega(m/p^{1/\rho})$.

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But in the worst case G has $\Omega(m^\rho)$ occurrences of Q

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$$\Rightarrow p \cdot L^\rho = \Omega(m^\rho)$$

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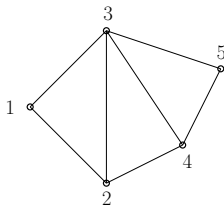
$$\Rightarrow p \cdot L^\rho = \Omega(m^\rho)$$

Thm 2 [Kestman, Suci, Tao'20]

$\tilde{O}(m/p^{1/\rho})$ communication per machine suffices.

IV: Dynamic Graphs

Triangle Counting



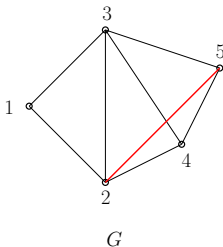
G

3 triangles

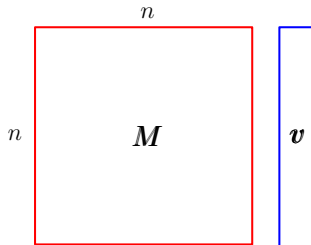
Dynamic Triangle Counting

Design a structure to support

- **update**(e): insert/delete e
- **query**: count the number of triangles



OMv Conjecture



Need to calculate Mv_i for $i = 1, 2, \dots, n$.

Can do $O(n^{3-\delta})$?

Dynamic Triangle Counting

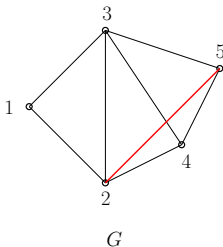
Thm 1 Subject to the OMv conjecture:

- either update needs $\Omega(\sqrt{m})$ time
- or a query needs $\Omega(m)$ time.

Approximate Dynamic Triangle Counting

Design a structure to support

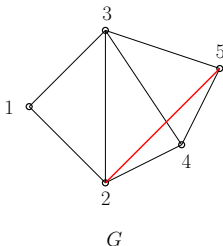
- **update**(e): insert/delete e
- **query**: count the number of triangles up to **relative error** ϵ



Approximate Dynamic Triangle Counting

Design a structure to support

- **update**(e): insert/delete e
- **query**: count the number of triangles up to **relative error** ϵ



Thm 2 Subject to the OMv conjecture, for $\epsilon = 0.49$,

- either update needs $\Omega(\sqrt{m})$ time
- or a query needs $\Omega(m)$ time.

Approximate Dynamic Triangle Counting

(ϵ, Γ) -guarantee:

- $\Gamma(m)$: a function of m
- If at least $\Gamma(m)$ triangles, **relative** error ϵ .
Otherwise, **absolute** error $\epsilon \cdot \Gamma(m)$.

Approximate Dynamic Triangle Counting

(ϵ, Γ) -guarantee:

- $\Gamma(m)$: a function of m
- If at least $\Gamma(m)$ triangles, **relative** error ϵ .
Otherwise, **absolute** error $\epsilon \cdot \Gamma(m)$.

Design a structure to support

- **update**(e)
- **query**: give an estimate with the (ϵ, Γ) -guarantee.

Approximate Dynamic Triangle Counting

Thm 3 [Lu and Tao'21]

Subject to the OMv conjecture, for $\epsilon = 0.49$,

- either update needs $\Omega(\frac{\sqrt{m}}{\Gamma(m)})$ time
- or a query needs $\Omega(m^{2/3})$ time.

Approximate Dynamic Triangle Counting

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Subject to the OMv conjecture, for $\epsilon = 0.49$,

- either update needs $\Omega(\frac{\sqrt{m}}{\Gamma(m)})$ time
- or a query needs $\Omega(m^{2/3})$ time.

Thm 4 [Lu and Tao'21]

Can do $\tilde{O}(\frac{\sqrt{m}}{\Gamma(m)})$ per update and $O(1)$ per query for any constant $\epsilon > 0$.

THANK YOU