## Tight Dynamic Problem Lower Bounds from Generalized BMM and OMv



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- Support small updates to $D$ (insertions, deletions, ...)
- Answer queries about $D$ (connectivity?...)
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- Unconditional Lower Bounds are stuck at polylog(n) :\%
- Higher LBs from Fine-Grained Conjectures!
- A long line of work
- [Pătraşcu STOC'10]
- [Abboud and Vassilevska Williams FOCS'14]
- [Henzinger, Krinninger, Nanongkai, and Saranurak STOC'15]


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- Current best: $\boldsymbol{n}^{3}(\log \log n)^{O(1)} /(\log \boldsymbol{n})^{4} \quad$ [Yu'15]


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- Current best: $n^{3} / 2^{\Omega(\sqrt{\log n})}$ time [Larsen-Williams'17]


## Dynamic Range-Mode Query

- Maintain an integer array $A[1], A[2], \ldots, A[n]$
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- Can these combinatorial algorithms be improved?


## Dynamic Range-Mode Query: Lower Bounds

- Static Range-Mode: Tight combinatorial LB
- Under BMM, no combinatorial algorithm can achieve $\boldsymbol{n}^{0.5-\varepsilon}$ query time and $n^{1.5-\varepsilon}$ preprocessing time [Chan-Durocher-Larsen-Morrison-Wilkinson'14]


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- Dynamic Range-Mode LB (NOT Tight $:$ ):
- Under OMv, no algorithm can achieve $\boldsymbol{n}^{\mathbf{0 . 5 - \varepsilon}}$ query \& update time and poly $(n)$ preprocessing time.


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## A proof template

## Static LB from

( $k-1$ )-clique hypothesis

Chan et al.'14: Static Range
Mode requires $n^{0.5-o(1)}$ time (from combinatorial 3-clique)

Use dynamic operations to efficiently enumerate the extra $k$-th node

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Tight combinatorial LBs for more dynamic problems:

- Dynamic 2D Orthogonal Range Color Counting $n^{2 / 3-o(1)}$ time $(k=4)$
- Dynamic $d$-Dimensional Orthogonal Range Mode $n^{1-\frac{1}{2 d+1}-o(1)}$ time $(k=2 d+2)$
- Dynamic 2-Pattern Document Retrieval $n^{2 / 3-o(1)}$ time $(k=4)$


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## Main takeaway:

(Combinatorial) $\boldsymbol{k}$-clique hypothesis is useful for dynamic lower bounds!
Previous dynamic LBs mostly used $k=3$ (BMM).
(exception: [Gutenberg, Vassilevska Williams, and Wein'20] reduction from 4-clique to dynamic shortest path)

## Dynamic Subgraph Connectivity

- Preprocess a static undirected graph $G$ with $m$ edges
- Maintain a dynamic vertex subset $S$ ("on" vertices)
- Turn on $u: S \leftarrow S \cup\{u\}$
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- Query $u, v$ : are $u$ and $v$ connected in the induced subgraph $G[S]$ ?


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- Combinatorial algorithm by Chan, Pătraşcu, and Roditty (FOCS'08) in
- $\widetilde{\boldsymbol{O}}\left(\boldsymbol{m}^{2 / 3}\right)$ update time (amortized)
- $\tilde{O}\left(m^{1 / 3}\right)$ query time
- ( $\widetilde{O}\left(m^{4 / 3}\right)$ preprocessing time)
- Can the $2 / 3$ exponent be improved?


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## A new fine-grained conjecture


[HKNS'15]

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## $\mathrm{OuMv}_{k}$ hypothesis

- Pre-process a subset $M \subseteq\{1,2, \ldots, n\}^{k}$
- Answer $n$ online queries:
- Given $k$ sets $U^{(1)}, U^{(2)}, \ldots, U^{(k)} \subseteq\{1,2, \ldots, n\}$,
- Is $\left(U^{(1)} \times U^{(2)} \times \cdots \times U^{(k)}\right) \cap M$ non-empty?
- Conjecture: No $O\left(n^{1+k-\varepsilon}\right)$-time algorithm exists
- Naturally generalizes OuMv [HKNS'15] (which is $\mathrm{OuMv}_{2}$ )


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- Conjecture: No $O\left(n^{1+k-\varepsilon}\right)$-time algorithm exists
- Naturally generalizes OuMv [HKNS'15] (which is $\mathrm{OuMv}_{2}$ )
- Useful for dynamic geometry problems in $\mathbf{R}^{k}$
- Obtain higher lower bounds as dimension $k$ increases


## Dynamic Skyline (Maximal) Points Counting

- Maintain a set $P$ of $n$ points in $\mathbf{R}^{d}$
- Insertion: $P \leftarrow P \cup\{x\}$
- Deletion: $P \leftarrow P \backslash\{x\}$
- Query: how many "skyline points" does $P$ have?
- $x \in P$ is a "skyline point"("maximal point") iff no other $y \in P$ dominates $x$ (i.e. $y_{i} \geq x_{i}$ for all $i=1,2, \ldots, d$ )


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Chan'03 (adapted): A semi-online algorithm in $\mathbf{R}^{2 k-1}$ with $\tilde{O}\left(n^{1-1 / k}\right)$ update time.

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Our result: this is tight under $\mathbf{O u M v}_{\boldsymbol{k}}$ hypothesis
(The $k=2$ case based on OMv was recently independently proved by Dallant \& lacono (2021) )

## Conclusion

- We used combinatorial $k$-clique hypothesis and $\mathrm{OuMv}_{k}$ hypothesis to prove tight fine-grained lower bounds for dynamic problems.

Open questions:

- Can Dynamic Subgraph Connectivity have update time better than $m^{2 / 3}$ using fast matrix multiplication?
- What is the optimal update time for Dynamic Skyline Points Counting in $\mathbf{R}^{2 k}$ ? (semi-online algorithms allowed)


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- Thanks!

