The background of the slide features a complex, light blue network graph pattern. It consists of numerous circular nodes of varying sizes, some solid and some hollow, interconnected by a dense web of thin, light blue lines. The pattern is more concentrated in the center and fades out towards the edges.

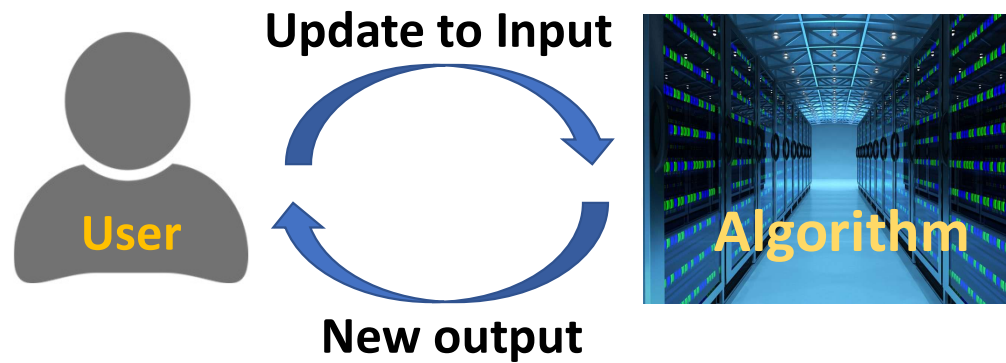
Design Templates of Dynamic Graph Algorithms

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December 8, 2025

Dynamic Algorithms: Algorithms that Interact



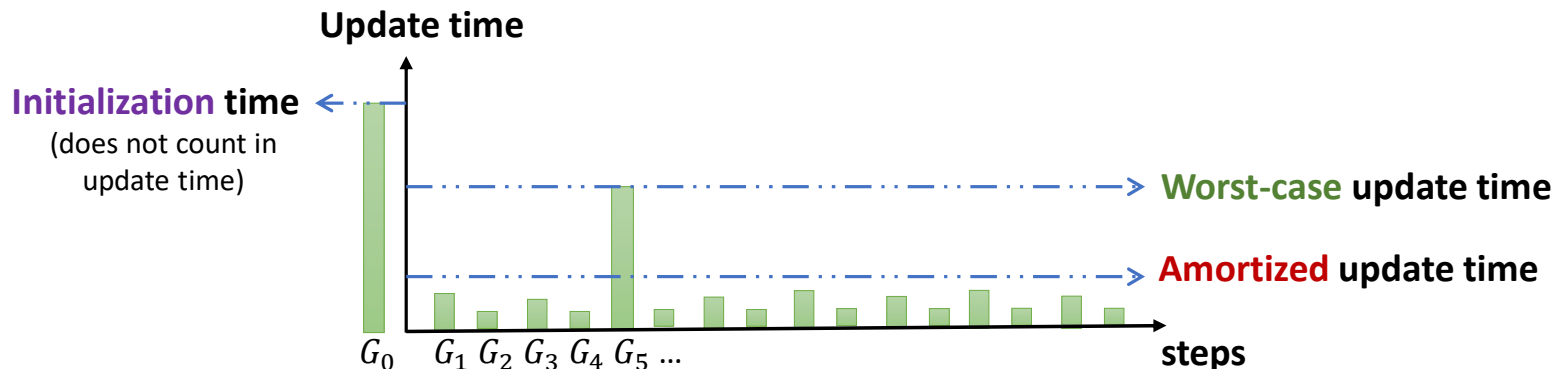
Dynamic graph algorithms

Setting:

1. Given an input graph G_0 , preprocess it.
2. Then, for each time **step**,
 - Given an update or a query (generated *online/on the fly*),
 - update the data structure and/or answer the query.
- Update are often **insertions** and **deletions** of an edge (a vertex sometimes)
- Example of tasks
 - **Answer queries:** Is G connected? what is (s, t) -distance?
 - **Maintain objects:** minimum spanning tree, maximal matching, etc.

Terminology

- G_i = the graph after i steps
- **Update sequence**: the sequence of updates/queries
- **Update time**: time needed at each step.
 - T **worst-case** update time: **every** step requires $\leq T$ time.
 - T **amortized** update time: after k steps (for large enough k), the **total time** is $\leq kT$
- **Preprocessing/initialization time**: time to process G_0



Fully dynamic vs. Partially Dynamic

- **Fully dynamic** algorithms handle **both insertions** and **deletions**
- **Partially Dynamic**
 - **incremental** algorithms handle only **insertions**
 - **decremental** algorithms handle only **deletions**

In this talk, you will learn...

3 templates for designing dynamic graph algorithms

1. Rebuild in the background
2. Batching
3. Vertex sparsifiers

All templates are general.

They work for every problem.

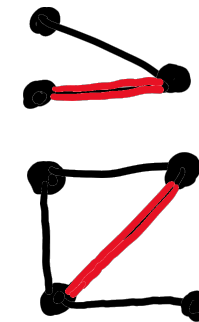
Only Template 3 is specific to graphs.

For each template, I will give a complete proof
of a concrete algorithm.

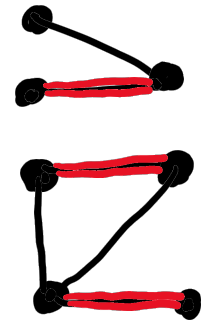
Template 0 (warm-up):
Rebuild

Fully dynamic $(1 + \epsilon)$ -approx. matching

- Def:
 - **Matching** is a set of vertex-disjoint edges
 - Given graph G , $\mu(G)$ = **size of maximum matching**
- Problem:
 - Init: graph G with n vertices
 - Then: **online** sequence of edge **insertions/deletions**
 - **Goal: maintain $(1 + \epsilon)$ -approx. of $\mu(G)$**
- Algo:
 - **Trivial:** $O(|E(G)|/\epsilon) = O(n^2/\epsilon)$ update time. (**recompute from scratch** after edge update)
 - **Today:** $O(n/\epsilon^2)$ update time.

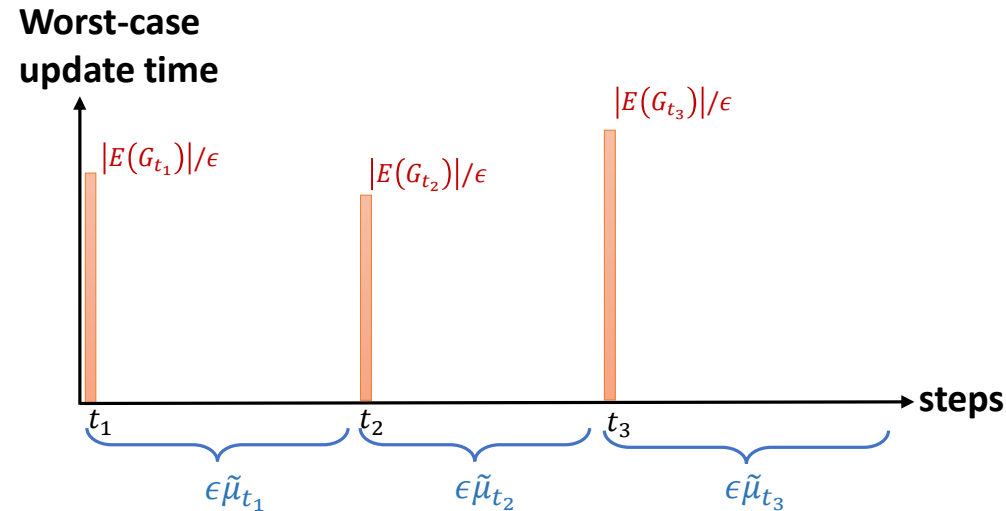


not - max
matching



max
matching
 $\mu(G) = 3$

Algorithm



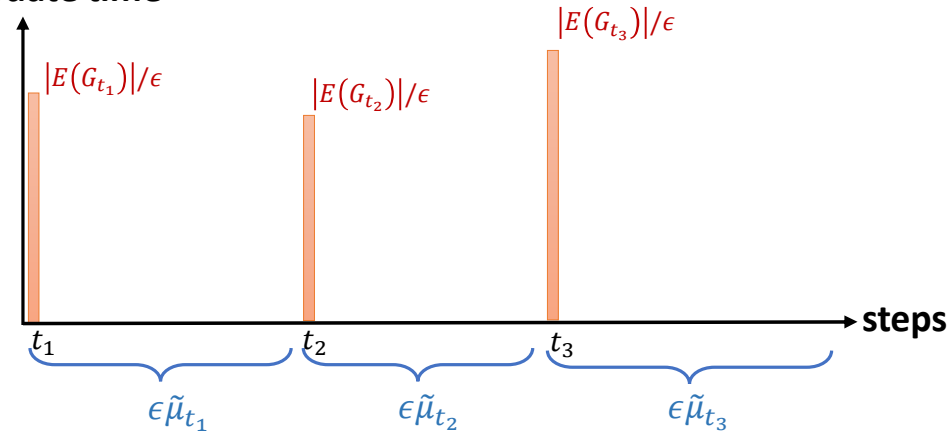
- Repeat:
 - **(Rebuild step):** $\tilde{\mu} \leftarrow (1 + \epsilon)$ -approx. of $\mu(G)$ computing from scratch
 - For the next $\epsilon \tilde{\mu}$ steps, just return $\tilde{\mu}$.
- **Correct:**
 - Each edge update may change the size of $\mu(G)$ by at most 1.
 - So, $\mu(G) = (1 \pm \epsilon) \tilde{\mu} \pm \epsilon \tilde{\mu}$ at all time.
 - That is, $\tilde{\mu}$ is always $(1 + O(\epsilon))$ -approx. of $\mu(G)$

Analysis

- **Update time:**

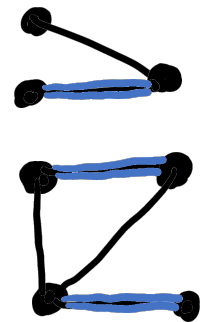
- $O\left(\frac{|E(G_t)|/\epsilon}{\epsilon\mu(G_t)}\right)$ **amortized** update time.
- $= O(n/\epsilon^2)$. Why?

Worst-case
update time



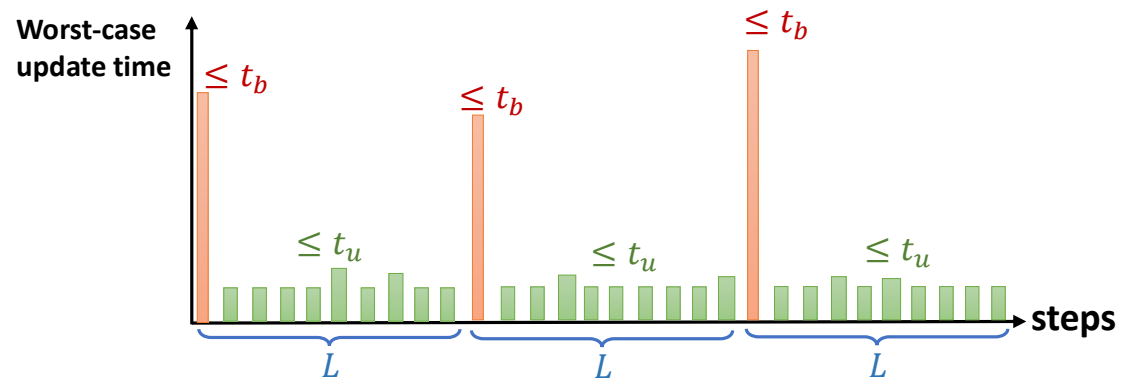
- **Claim:** $|E(G)| \leq \mu(G) \cdot 2n$

- Let M^* be a maximum matching $|M^*| = \mu(G)$
- **Observe:** every edge is incident to M^* (otherwise M^* is not max).
- Deleting an edge $e = (u, v)$ in M^* removes at most $\deg(u) + \deg(v) \leq 2n$ edges in G
- Repeat $\mu(G)$ times, no edge left.



Template 0: Rebuild

- Given algo \mathcal{A}
 - can handle L updates
 - t_b = rebuild time
 - t_u = worst-case update time
- Obtain algo \mathcal{A}'
 - can handle infinite updates
 - $O(\frac{t_b}{L} + t_u)$ **amortized** update time

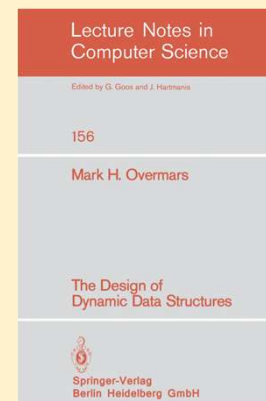


- In our case, fully dynamic $(1 + \epsilon)$ -matching with $O(n/\epsilon^2)$ **amortized** update time
 - $L = \Theta(\epsilon \mu(G))$, $t_b = O(\frac{E(G)}{\epsilon})$, $t_u = O(1)$
- **Next:** worst-case update time instead

Template 1: Rebuild in the Background

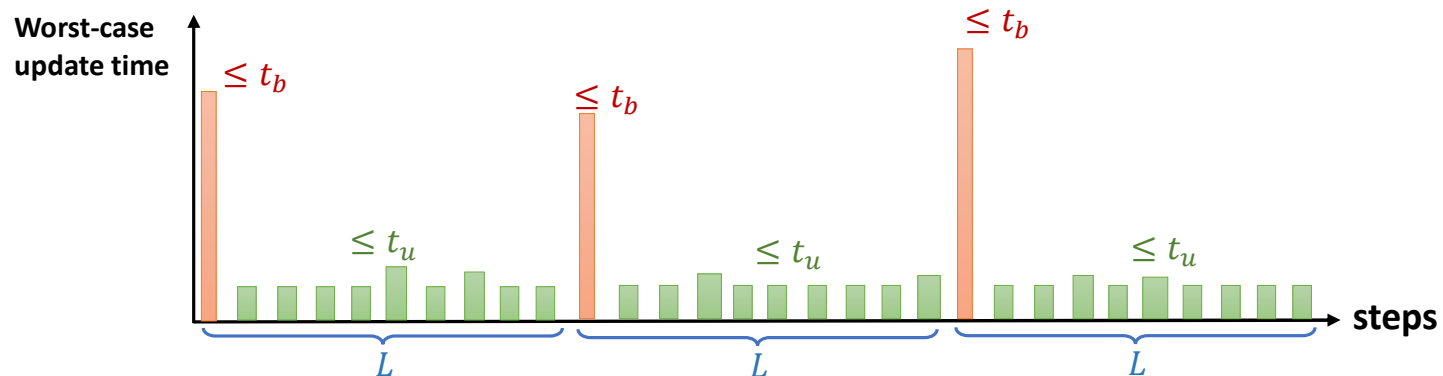
Overmars'83 “Global Rebuilding”

Used in many many papers.



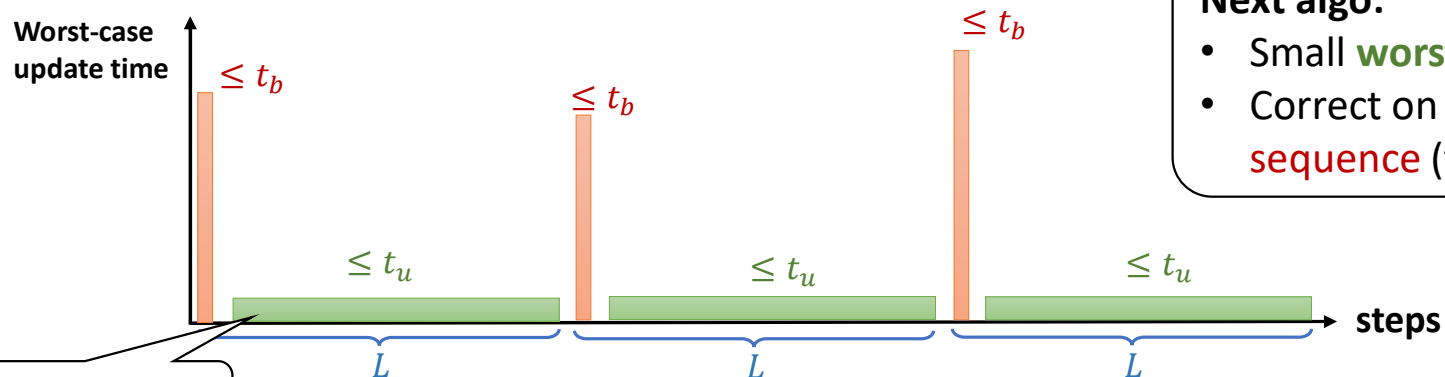
Recall

- Given algo \mathcal{A}
 - can handle L updates
 - t_b = rebuild time
 - t_u = worst-case update time
- algo \mathcal{A}' with $O(\frac{t_b}{L} + t_u)$ amortized update time



Recall

- Given algo \mathcal{A}
 - can handle L updates
 - t_b = rebuild time
 - t_u = worst-case update time
- algo \mathcal{A}' with $O(\frac{t_b}{L} + t_u)$ amortized update time



Simplified picture

Next algo:

- Small **worst-case** update time.
- Correct on **half of update sequence** (this is easy to fix)

Algorithm \mathcal{A}'' : $O(\frac{t_b}{L} + t_u)$ worst-case update time

Divide each phase of L steps from $[t_0, t_0 + L]$ into 3 periods

1. **(Rebuild)** first $L/4$ steps:

- Rebuild data structure for G_{t_0} but distribute the work evenly on the period.
- Ignore updates.

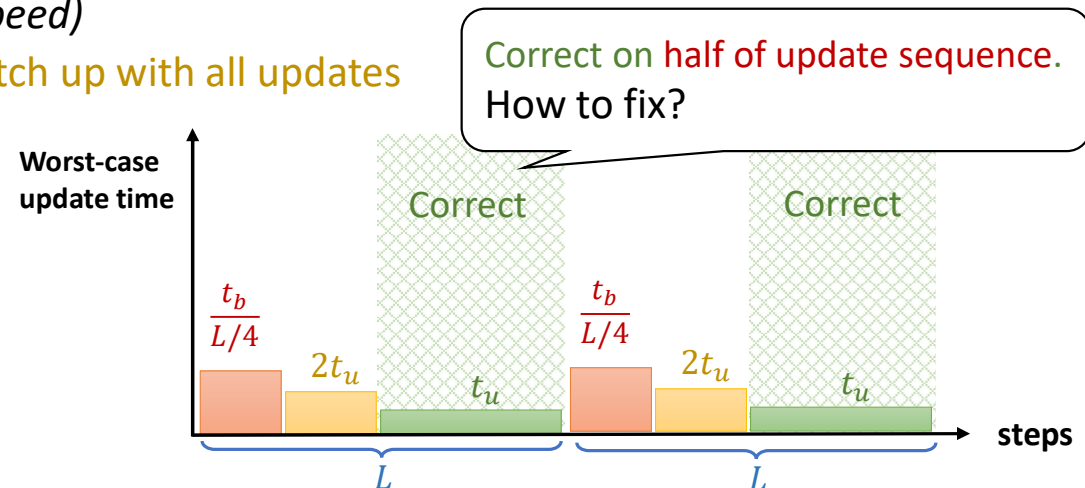
2. **(Catch-up)** next $L/4$ steps:

- Each step, feed two updates. (*Double speed*)
- **Observe:** At the end, data structures catch up with all updates

3. **(Active)** last $L/2$ steps:

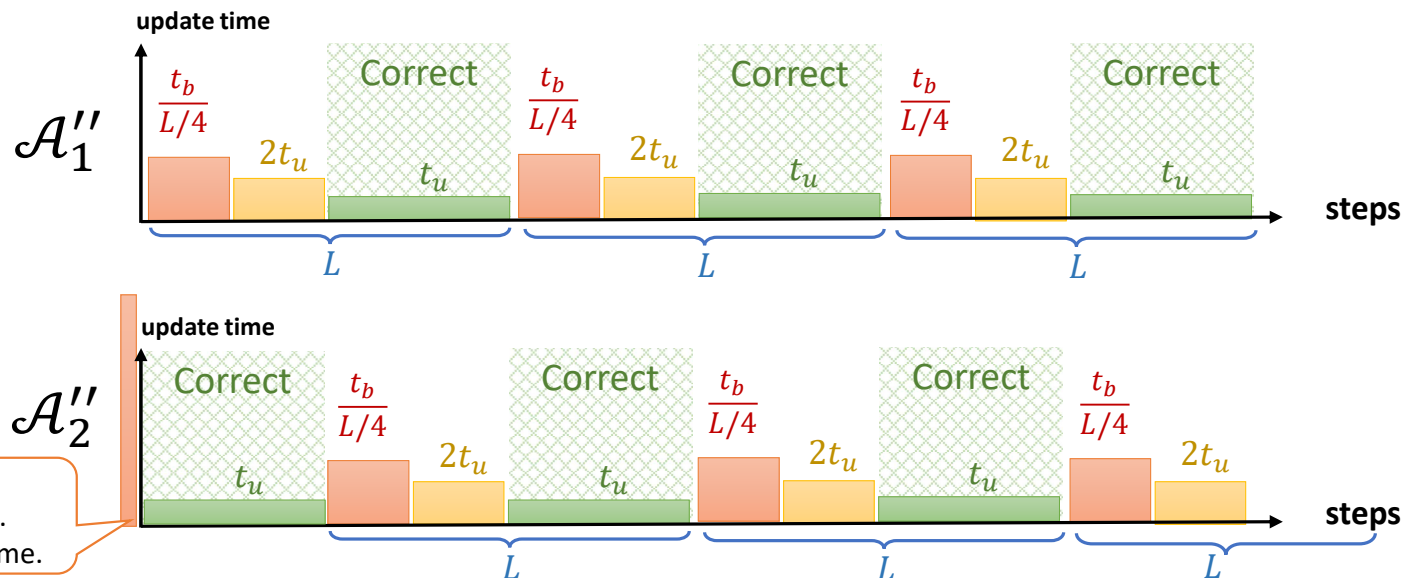
- Feed update normally.
- Get correct answers in this period

Worst-case update time: $O(\frac{t_b}{L} + t_u)$



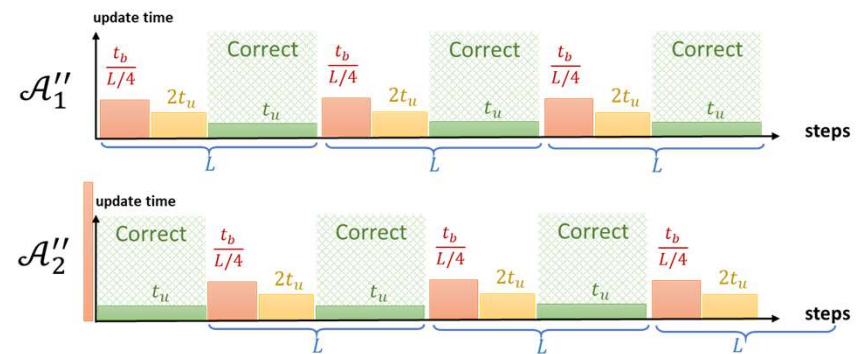
Correct answers at all steps

- Make two instances \mathcal{A}_1'' and \mathcal{A}_2'' . (Increase update time by factor 2.)
 - Schedule their periods so that...
 - At every step, one of them is correct.



Conclude: Rebuild in the background

- Given algo \mathcal{A}
 - can handle L updates
 - t_b = rebuild time
 - t_u = worst-case update time
- Obtain algo \mathcal{A}''
 - $O(\frac{t_b}{L} + t_u)$ worst-case update time
- **Conclude:**
 - fully dynamic $(1 + \epsilon)$ -matching with $O(n/\epsilon^2)$ worst-case update time.
 - Exercise: $O(\deg_{\max}(G)/\epsilon^2)$ worst-case update time Hint: $|E(G)| \leq \mu(G) \cdot 2\deg_{\max}(G)$



Template 2: Batching

Used in

- Dynamic MST [[HK'01](#)]
- Dynamic APSP with worst-case update time [[Thorup'05](#)] [[ACK'17](#)] [[PW'20](#)]
- Expander pruning with worst-case update time [[NSW'17](#)] [[BBGNSSS'22](#)] [[JS'22](#)]
- Dynamic DFS [[BCKK'16](#)]
- Let me know more

Decremental connectivity

- Problem:
 - Init: graph G with n vertices and m edges
 - Then: online sequence of edge deletions only
 - **Maintain: is G connected?**
- Algo:
 - Trivial: $O(m)$ worst-case update time. (BFS, for example)
 - Today: $\tilde{O}(m^{2/3})$ worst-case update time.

One-batch decremental connectivity

Often easier
to design

- Setting for one-batch algorithms
 - Init: graph G
 - Update: a **single batch** D of d edge deletions.
 - Answer: is $G' = G \setminus D$ connected?
- **Will show later:** one-batch algo $\mathcal{A}_{\text{batch}}$ with
 - Init time: $\tilde{O}(m)$
 - Update time: $\tilde{O}(d^2)$
- **Next:** how to get $O(m^{2/3})$ worst-case update time using $\mathcal{A}_{\text{batch}}$

Reduction to one-batch algorithms

- **Simple idea:** to handle update *sequence* with *one-batch* algo $\mathcal{A}_{\text{batch}}$,
 - Given the i^{th} update u_i ,
feed the **batch of first i updates** (u_1, \dots, u_i) into $\mathcal{A}_{\text{batch}}$ (using $\tilde{O}(i^2)$ time, for us)
- Obtain algo \mathcal{A} that
 - can handle L updates
 - rebuild time: $t_b = \tilde{O}(m)$
 - update time: $t_u = \tilde{O}(L^2)$
- Get algo \mathcal{A}' with $\tilde{O}(m/L + L^2) = \tilde{O}(m^{2/3})$ worst-case update time
 - by choosing $L = m^{1/3}$

Recall:

Given algo \mathcal{A}

can handle L updates

t_b = rebuild time

t_u = worst-case update time

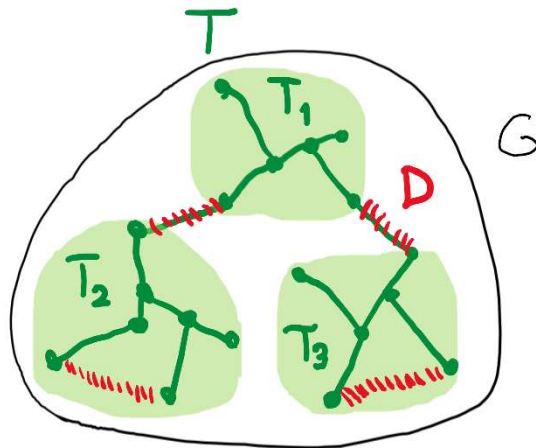
Obtain algo \mathcal{A}''

$O(\frac{t_b}{L} + t_u)$ worst-case update time

Remain to show $\mathcal{A}_{\text{batch}} \dots$

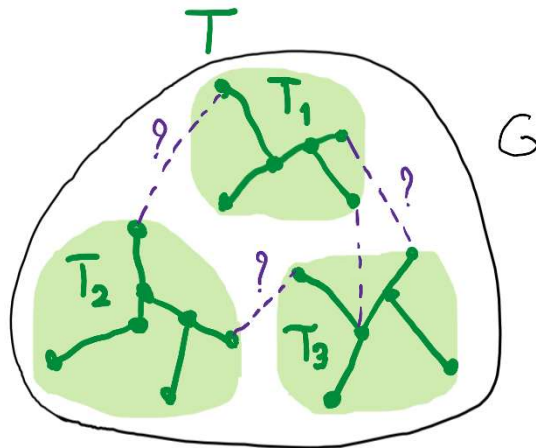
Ideas of one-batch algo $\mathcal{A}_{\text{batch}}$

- **Init:** $T \leftarrow$ spanning tree of G
- **Update:** given a set D of d edge deletions,
 1. $T_1, \dots, T_{d'} \leftarrow$ connected components of $T \setminus D$. ($d' \leq d + 1$)
 2. Sufficient: find a non-tree-edge between T_i and T_j , if exists, for $i, j \in [d']$



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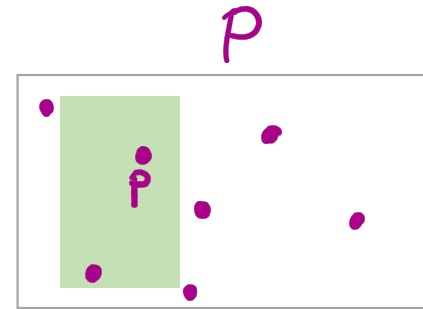


Next:

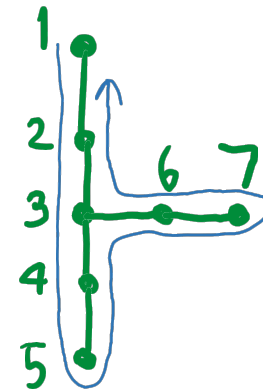
- show how to find these edges
- Need two tools:
 - Euler-tour
 - 2d-range query

Basic tools for one-batch algo $\mathcal{A}_{\text{batch}}$

- 2d-range query: P is a set of points in 2d.
 1. **Update**: Insert/delete a point in P in $\tilde{O}(1)$ time
 2. **Query**: Given rectangle $I_x \times I_y$, return a point $p \in P \cap (I_x \times I_y)$ in $\tilde{O}(1)$ time

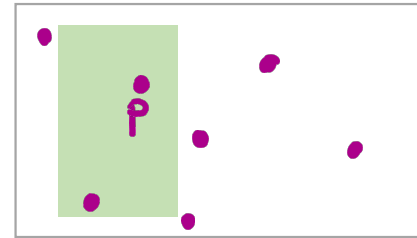


- Euler-tour:
 - Represent any tree T as a path.
 - See example:
 - Euler tour of T is $\text{Eu}(T) = (1, 2, 3, 4, 5, 4, 3, 6, 7, 6, 3, 2)$
 - Each edge in T corresponds to 2 edges in $\text{Eu}(T)$

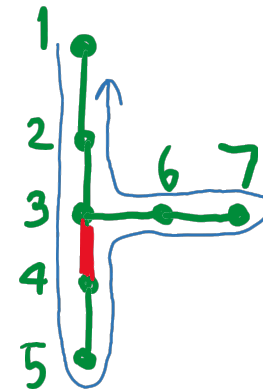


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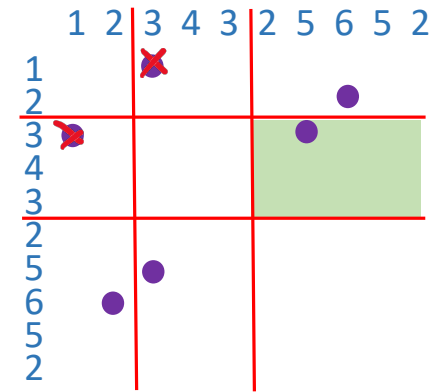
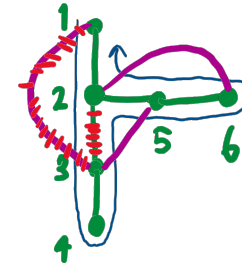
One-batch algo $\mathcal{A}_{\text{batch}}$

- **Init:**

- $$\tilde{O}(m)_{\text{time}} \left\{ \begin{array}{l} 1. \quad T \leftarrow \text{spanning tree of } G \\ 2. \quad \text{Eu}(T) \leftarrow \text{Euler-tour of } T \\ 3. \quad \text{For each non-tree edge } (u, v), \\ \quad \quad \text{add } (\text{minrank}_{\text{Eu}(T)}(u), \text{minrank}_{\text{Eu}(T)}(v)) \text{ to set } P \end{array} \right.$$

- **Update:** given a set D of d edge deletions,

- $$\begin{array}{l} \tilde{O}(d) \text{ time} \left\{ \begin{array}{l} 1. \text{ Delete points in } P \text{ corresponding to deleted non-tree edges} \\ 2. I_1, \dots, I_{d''} \leftarrow \text{intervals of Eu}(T) \text{ after deleting tree edges. } d'' = O(d) \end{array} \right. \\ \tilde{O}(d^2) \text{ time} \left\{ \begin{array}{l} 3. \text{ Query } I_i \times I_j \text{ to for all } i, j \in [d''] \\ \rightarrow \text{ Find a non-tree-edge between } T_i \text{ and } T_j \text{ for all } i, j \in [d'] \end{array} \right. \end{array}$$



Conclude: dynamic algo from one-batch algo

- **Get:** one-batch algo $\mathcal{A}_{\text{batch}}$ with
 - Init time: $\tilde{O}(m)$
 - Update time: $\tilde{O}(d^2)$
- **By previous reduction:** from $\mathcal{A}_{\text{batch}}$, we get
 - Decremental connectivity algorithm with $O(m^{2/3})$ worst-case update time

Conclude: dynamic algo from one-batch algo

- **If we have:** one-batch algo $\mathcal{A}_{\text{batch}}$ with
 - Init time: $\tilde{O}(m)$
 - Update time: $\tilde{O}(d)$
- **By previous reduction:** from $\mathcal{A}_{\text{batch}}$, we **would get**
 - Decremental connectivity algorithm with $O(m^{1/2})$ update time

Exercise

- Setting for 2-batch algorithms:

- Init: graph G
- First update: a batch D_1 of d_1 edge deletions.
- Second update: a batch D_2 of d_2 edge deletions.
- Answer: is $G' = G \setminus (D_1 \cup D_2)$ connected?

Remark:

- Most **2-batch** algos generalize to the **k-batch** setting. (not for 1-batch algos)
- For example, Today's 1-batch algorithm does not work in the 2-batch setting. Why?

Exercise:

Given 2-batch algo $\mathcal{A}_{\text{batch}}$ with

- Init time: $\tilde{O}(m)$
- First update time: $\tilde{O}(d_1)$
- Second update time: $\tilde{O}(d_2)$

1. Show a dynamic algorithm with $\tilde{O}(m^{1/3})$ worst-case update time.
2. Generalize to the k -batch setting, get $\tilde{O}(m^{1/(k+1)})$ worst-case update time

Before Template 3: Introduction to Vertex Sparsifiers

Extensively studied in both approximation and FPT (kernelization) communities.

Vertex Sparsifiers (aka Mimicking Networks)

Setting:

- Input: graph $G = (V, E)$, terminal set $S \subseteq V$
- Output: graph H s.t. $S \subseteq V(H)$ and
 - $|E(H)| \approx |S|$
 - H preserves information in G related to S . Write " $H \approx G$ w.r.t. S "
- H is called a **sparsifier of G w.r.t. S** .
- Example: **Vertex sparsifier for shortest paths** [CGHPS'20] based on [TZ'05]
 - For any k , there exists H s.t.
 - $|E(H)| = O(|S|n^{1/k})$
 - For each $u, v \in S$, $\text{dist}_H(u, v) \approx \text{dist}_G(u, v)$ up to $O(k)$ factor.
- Today: **Vertex sparsifier for minmax paths**

Minmax paths and Minimum Spanning Trees (MST)

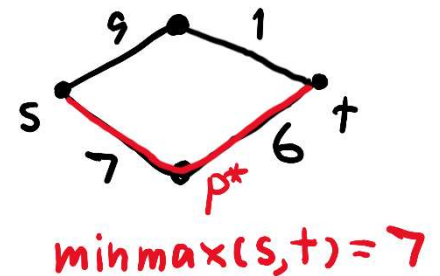
- (s, t) -minmax path P^* has minimum $\max_{e \in P^*} w(e)$ ($w(e)$ is weight of edge e)

- $\text{minmax}(s, t) := \max_{e \in P^*} w(e)$

- Key point: **MST preserves all minmax paths**

Remember this.

- T : MST of G .
- $P_T(s, t)$: unique (s, t) -path in T



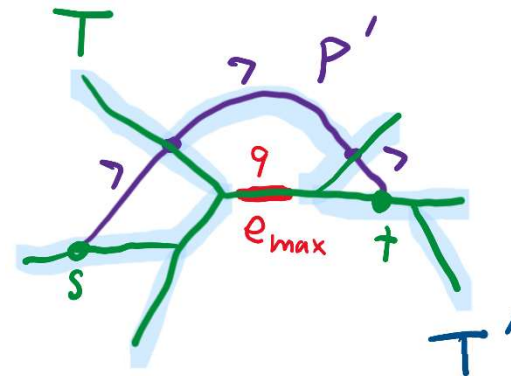
- Claim: $P_T(s, t)$ is (s, t) -minmax path in G for all s, t

- **Proof**: Otherwise, there is another (s, t) -path P' s.t.

- $e_{\max} \leftarrow$ heaviest edge in $P_T(s, t)$
- $\max_{e \in P^*} w(e) < w(e_{\max})$

- So, there is $e' \in P'$ s.t.

- $T' = T \cup e' \setminus e_{\max}$ is a spanning tree
- but $w(T') < w(T)$. **Contradiction.**



Vertex sparsifier for minmax paths

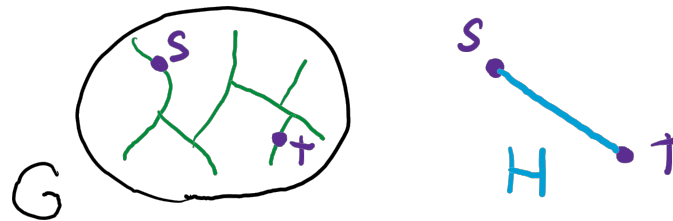
Input: graph $G = (V, E)$, terminal set $S \subseteq V$

Output: graph H

- $|E(H)| = O(|S|)$
- For all $u, v \in S$, $\text{minmax}_H(u, v) = \text{minmax}_G(u, v)$. (Write $H \equiv_{\text{minmax}} G$ w.r.t S)

Warming-up Algo:

- What if $S = \{u, v\}$?
- Easy: $H \leftarrow \{(u, v)\}$ where $w_H(u, v) \leftarrow \text{minmax}_G(u, v)$



Vertex sparsifier for minmax paths

Input: graph $G = (V, E)$, terminal set $S \subseteq V$

Output: H where $S \subseteq V(H)$

- $|E(H)| = O(|S|)$
- For all $u, v \in S$, $\text{minmax}_H(u, v) = \text{minmax}_G(u, v)$

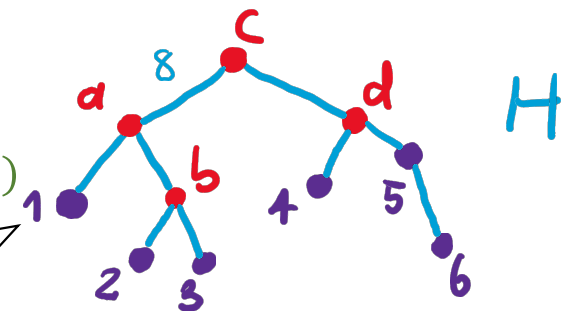
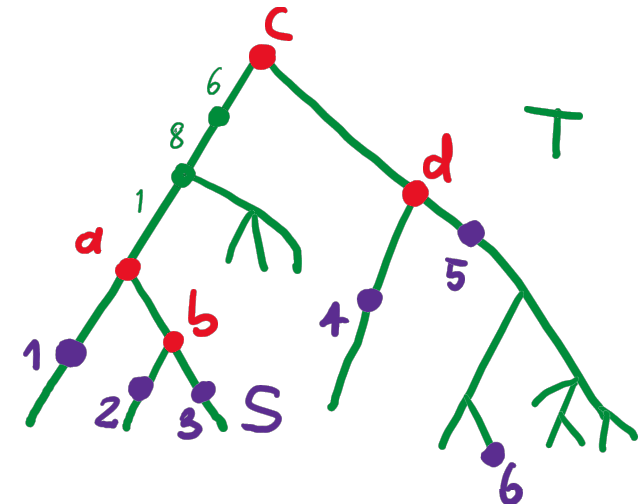
Algo:

1. $T \leftarrow \text{MST of } G$.
2. $S' \leftarrow \text{LCA_Closure}_T(S)$.
 - For all $u, v \in S'$, $\text{LCA}(u, v) \in S'$.
 - Note that $|S'| \leq 2|S|$.
3. For each "adjacent" $u, v \in S'$,
Add (u, v) into H where $w_H(u, v) \leftarrow \text{max weight in } P_T(u, v)$

Correctness: Exercise

Hint: (MST preserves all minmax paths + the warm-up case)

Time: $\tilde{O}(m)$ **Size:** $O(|S|)$



Composability

Def: The similarity relation “ \approx ” is **composable** if

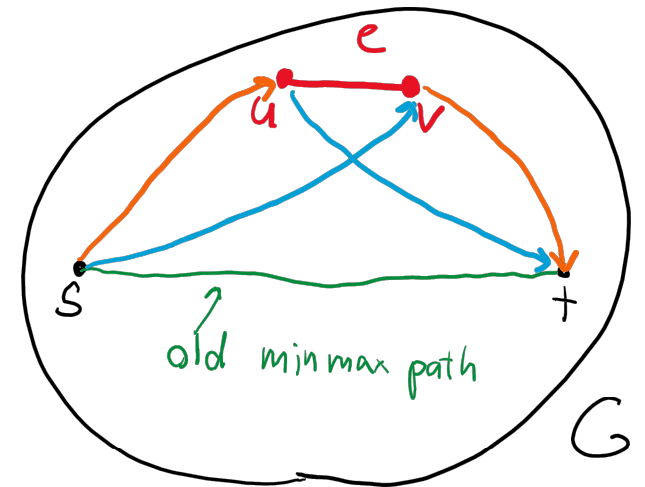
1. $H \approx G$ w.r.t. S
2. $e = (u, v)$ where $u, v \in S$,

Then, $H + e \approx G + e$ w.r.t. S

Lemma: The relation \equiv_{minmax} is composable.

Proof: Suppose $H \equiv_{\text{minmax}} G$ w.r.t. S . For any (s, t) where $s, t \in S$,

$$\text{minmax}_{G+e}(s, t) = \min \begin{cases} \text{minmax}_G(s, t) \\ \max\{\text{minmax}_G(s, u), w(u, v), \text{minmax}_G(v, t)\} \\ \max\{\text{minmax}_G(s, v), w(v, u), \text{minmax}_G(u, t)\} \end{cases}$$



Composability

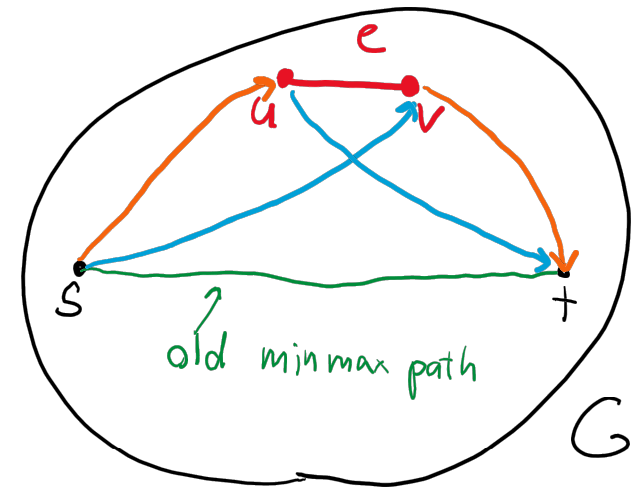
Def: The similarity relation “ \approx ” is **composable** if

1. $H \approx G$ w.r.t. S
2. $e = (u, v)$ where $u, v \in S$,

Then, $H + e \approx G + e$ w.r.t. S

Lemma: The relation \equiv_{minmax} is composable.

Proof: Suppose $H \equiv_{\text{minmax}} G$ w.r.t. S . For any (s, t) where $s, t \in S$,



$$\text{minmax}_{G+e}(s, t) = \min \begin{cases} \text{minmax}_G(s, t) \\ \max\{\text{minmax}_G(s, u), w(u, v), \text{minmax}_G(v, t)\} \\ \max\{\text{minmax}_G(s, v), w(v, u), \text{minmax}_G(u, t)\} \end{cases} = \min \begin{cases} \text{minmax}_H(s, t) \\ \max\{\text{minmax}_H(s, u), w(u, v), \text{minmax}_H(v, t)\} \\ \max\{\text{minmax}_H(s, v), w(v, u), \text{minmax}_H(u, t)\} \end{cases} = \text{minmax}_{H+e}(s, t)$$

Template 3: Vertex Sparsifiers

Used in

- The template is explicit in [[GHP'17](#), [CGHPS'20](#)]
- Offline dynamic algo for MST [[Epp'94](#)] and $O(1)$ -connectivity [[PSS'19](#), [CDLKPPSV'20](#)]. Non-offline version [[NSW'17](#), [JS'20](#)]
- Dynamic effective resistance [[GHP'18](#), [DGGP'19](#)]
- [Modern max flows algorithms](#)

Plan

1. Show reduction

- Given a fast algorithm for vertex sparsifier for minmax paths,
- Obtain **offline** dynamic algorithm for minmax paths

The template work for any problem.

2. Discuss how to get **non-offline** dynamic algorithms

3. Open problems (a lot of growth, promising)

Anyway, what are **offline** algorithms?

Offline fully dynamic minmax paths

- Assume for notational convenience:
 - At step i , we are given **both** edge insert/delete (u_i, v_i) **AND** query (s_i, t_i)
- Input: **whole** sequence of m updates/queries (Think $|E(G_i)| \leq m$ for all steps i)
 - **“Offline”**: get **whole** sequence, not revealed to us one by one like before
- Output: for all i , compute $\text{minmax}_{G_i}(s_i, t_i)$
- Trivial: $O(m^2)$ time.
- Today: $\tilde{O}(m^{1.5})$ time... then $\tilde{O}(m)$ time (Think $\tilde{O}(1)$ per update/query)

Offline algo: high-level idea

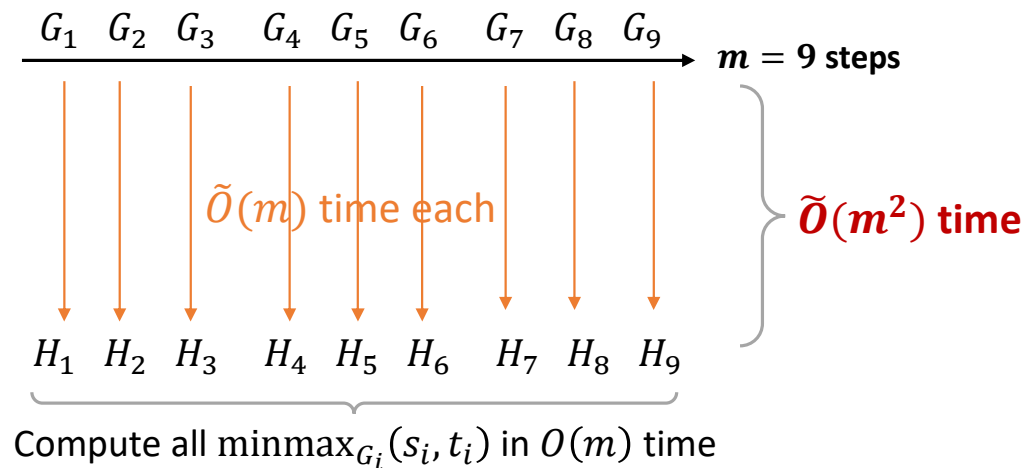
- **Our goal:**

- For all i , compute $H_i \equiv G_i$ w.r.t. $\{s_i, t_i\}$. Note $|E(H_i)| = O(1)$.

- **Then:**

- For all i , compute $\text{minmax}_{G_i}(s_i, t_i) = \text{minmax}_{H_i}(s_i, t_i)$ in $O(m)$ total time.

Trivial way
to compute H_i



Offline algo: high-level idea

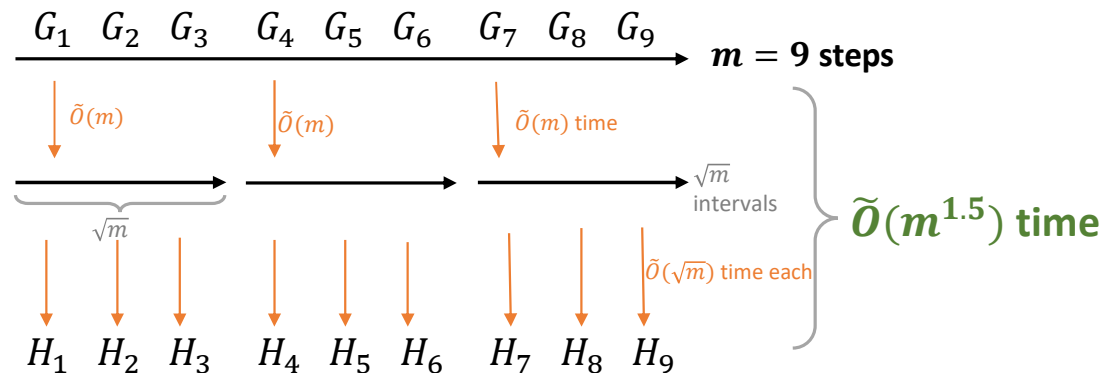
- **Our goal:**

- For all i , compute $H_i \equiv G_i$ w.r.t. $\{s_i, t_i\}$. Note $|E(H_i)| = O(1)$.

- **Then:**

- For all i , compute $\text{minmax}_{G_i}(s_i, t_i) = \text{minmax}_{H_i}(s_i, t_i)$ in $O(m)$ total time.

**Less trivial way
to compute H_i**

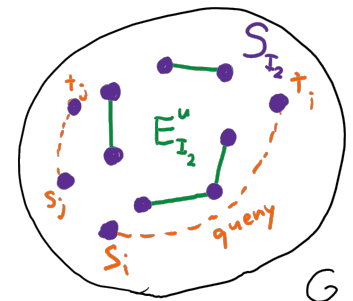
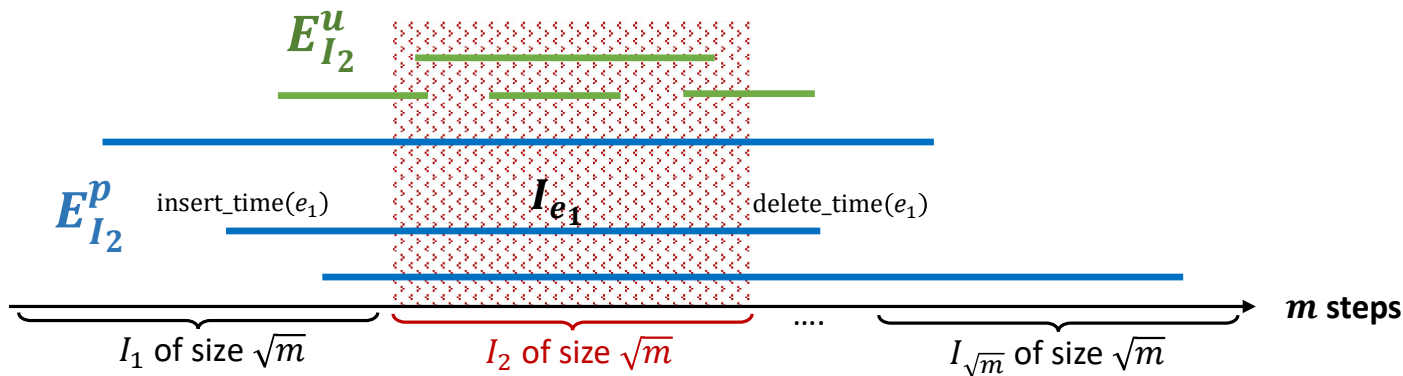


Let's see the details...

Set up notations

Divide update sequence into intervals $\mathcal{I} = \{I_1, \dots, I_{\sqrt{m}}\}$ of length \sqrt{m} . Fix $I \in \mathcal{I}$.

- Interval of edge e : $I_e = [\text{insert_time}(e), \text{delete_time}(e)]$
- Permanent edges in I : $E_I^p = \{e \mid I \subseteq I_e\}$ $|E_I^p| \approx m$
- Updated edges in I : $E_I^u = \{e \mid I \cap I_e \neq \emptyset, I\}$ $|E_I^u| \approx \sqrt{m}$
- Terminals for I : $S_I = V(E_I^u) \cup V(Q_I)$ where $Q_I = \cup_{i \in I} \{s_i, t_i\}$. $|S_I| \approx \sqrt{m}$
 - Think: S_I are endpoints of updates/queries during interval I .



$m^{1.5}$ -time offline algo

Permanent edges in I :

$$E_I^p = \{e \mid I \subseteq I_e\}$$

Updated edges in I :

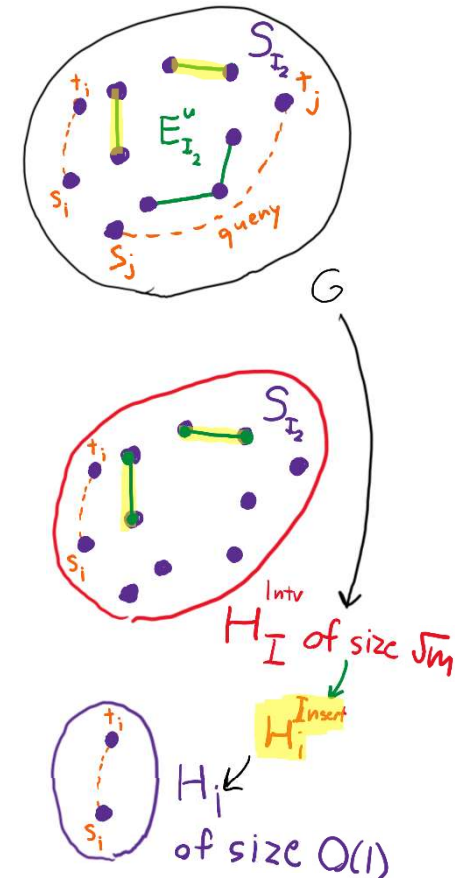
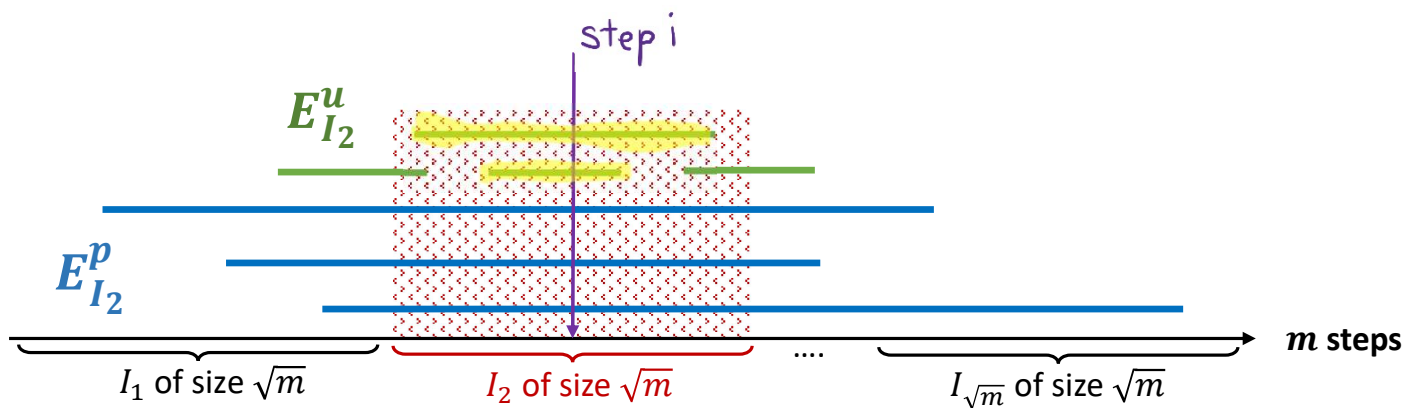
$$E_I^u = \{e \mid I \cap I_e \neq \emptyset, I\}$$

Terminals for I :

$$S_I = V(E_I^u) \cup V(Q_I)$$

Algo: For all $I \in \mathcal{I}$,

1. Build $H_I^{\text{Interval}} \equiv E_I^p$ w.r.t. S_I
2. For each $i \in I$
 - $H_i^{\text{Insert}} \leftarrow H_I^{\text{Interval}} \cup (G_i \setminus E_I^p)$
 - Build $H_i \equiv H_i^{\text{Insert}}$ w.r.t. $\{s_i, t_i\}$



$m^{1.5}$ -time offline algo

Permanent edges in I :

$$E_I^p = \{e \mid I \subseteq I_e\}$$

Updated edges in I :

$$E_I^u = \{e \mid I \cap I_e \neq \emptyset, I\}$$

Terminals for I :

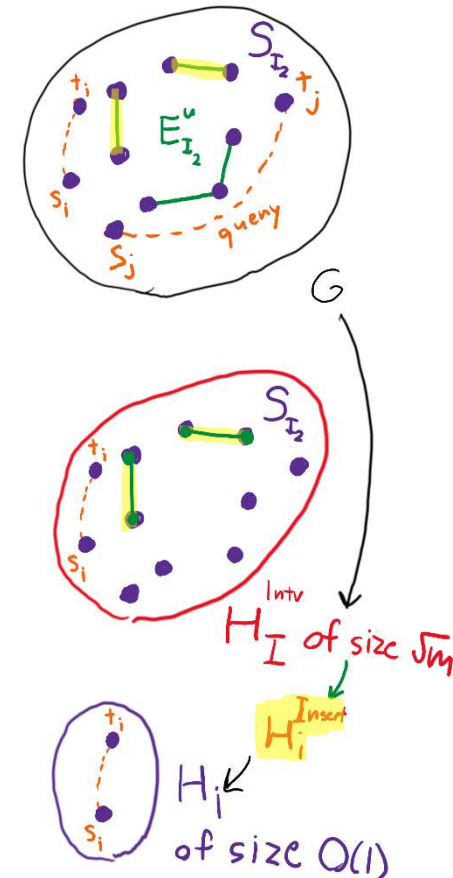
$$S_I = V(E_I^u) \cup V(Q_I)$$

Algo: For all $I \in \mathcal{I}$,

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2. For each $i \in I$
 - $H_i^{\text{Insert}} \leftarrow H_I^{\text{Interval}} \cup (G_i \setminus E_I^p)$
 - Build $H_i \equiv H_i^{\text{Insert}}$ w.r.t. $\{s_i, t_i\}$

Correctness: Want to show $H_i \equiv G_i$ w.r.t. $\{s_i, t_i\}$ for each i

- $H_i^{\text{Insert}} \equiv G_i$ w.r.t. S_I
 - $H_I^{\text{Interval}} \equiv E_I^p$ w.r.t. S_I from Step 1
 - $H_I^{\text{Interval}} \cup (G_i \setminus E_I^p) \equiv E_I^p \cup (G_i \setminus E_I^p)$ w.r.t. S_I by **composability**



$m^{1.5}$ -time offline algo

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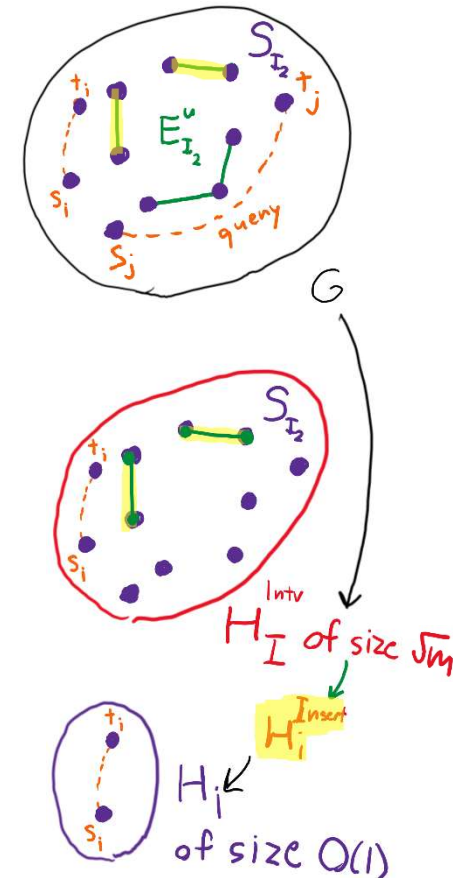
2. For each $i \in I$

• $H_i^{\text{Insert}} \leftarrow H_I^{\text{Interval}} \cup (G_i \setminus E_I^p)$

• Build $H_i \equiv H_i^{\text{Insert}}$ w.r.t. $\{s_i, t_i\}$

Correctness:

- $H_i^{\text{Insert}} \equiv G_i$ w.r.t. S_I
- $H_i^{\text{Insert}} \equiv G_i$ w.r.t. $\{s_i, t_i\}$ as $S_I \supseteq \{s_i, t_i\}$.
- $H_i \equiv H_i^{\text{Insert}}$ w.r.t. $\{s_i, t_i\}$ by Step 2.2
- $H_i \equiv G_i$ w.r.t. $\{s_i, t_i\}$ (**DONE**)



$m^{1.5}$ -time offline algo

Permanent edges in I :

$$E_I^p = \{e \mid I \subseteq I_e\}$$

Updated edges in I :

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Terminals for I :

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2. For each $i \in I$
 - $H_i^{\text{Insert}} \leftarrow H_I^{\text{Interval}} \cup (G_i \setminus E_I^p)$
 - Build $H_i \equiv H_i^{\text{Insert}}$ w.r.t. $\{s_i, t_i\}$

\sqrt{m} loops

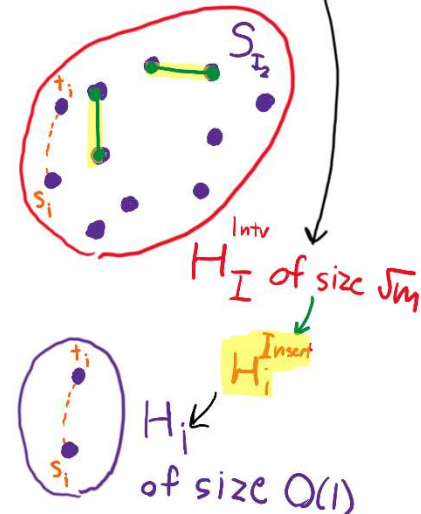
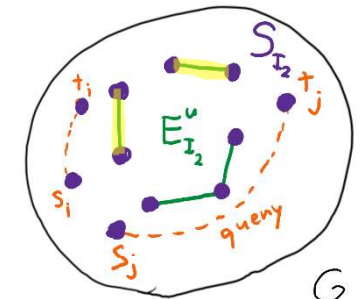
$\tilde{O}(m)$ time

m total loops

$\tilde{O}(\sqrt{m})$ time

$\tilde{O}(\sqrt{m})$ time

$\tilde{O}(m^{1.5})$

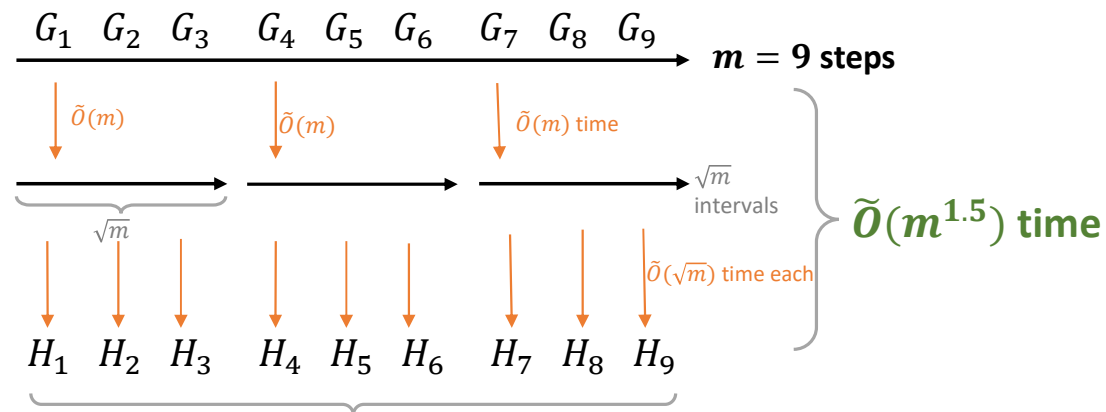


Correctness:

- $H_i^{\text{Insert}} \equiv G_i$ w.r.t. S_I
- $H_i^{\text{Insert}} \equiv G_i$ w.r.t. $\{s_i, t_i\}$ as $S_I \supseteq \{s_i, t_i\}$.
- $H_i \equiv H_i^{\text{Insert}}$ w.r.t. $\{s_i, t_i\}$ by Step 2.2
- $H_i \equiv G_i$ w.r.t. $\{s_i, t_i\}$ (**DONE**)

Summary: $\tilde{O}(m^{1.5})$ -time offline algo

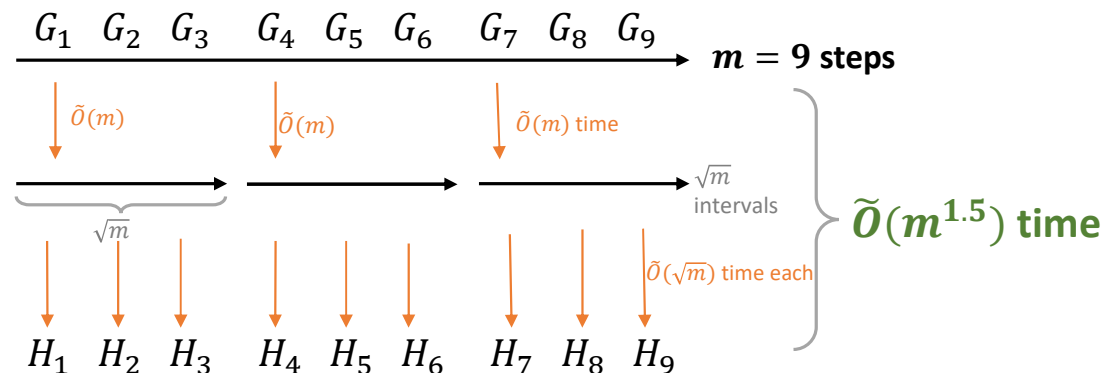
- For all i , obtain $H_i \equiv G_i$ w.r.t. $\{s_i, t_i\}$ in $\tilde{O}(m^{1.5})$ time



Then, compute all $\min \max_{G_i}(s_i, t_i)$ in $O(m)$ time

$\tilde{O}(m)$ -time offline algo

- 2 levels of sparsifiers $\rightarrow \tilde{O}(m^{1.5})$ -time algorithm



- k levels of sparsifiers $\rightarrow \tilde{O}(m^{1+1/k})$ -time algorithm
 - Note:** If sparsifiers have α -approx., get α^k -approx. offline dynamic algorithms.
- For us, $\alpha = 1$ (exact). Setting $k \leftarrow \log n$, get $\tilde{O}(m)$ time

Conclude: dynamic algo from vertex sparsifier

- We saw a black-box transformation:

Fast vertex-sparsifier algorithms → Fast **offline** **fully dynamic** algorithms

- Can get **non-offline dynamic** algorithm too (very similar, omitted).
 - If, additionally, vertex-sparsifier algorithm can...

Many sparsifier algorithms
naturally support **add-terminals**

If handle **add-terminal** operation → Fast **incremental** algorithms

If handle **add-terminal & delete** operations → Fast **fully dynamic** algorithms

*omit polylog(n) in size

Open problems in Dynamic vertex sparsifiers

Promising and rich area. **Every red highlight below** shows that some aspect might be improved.

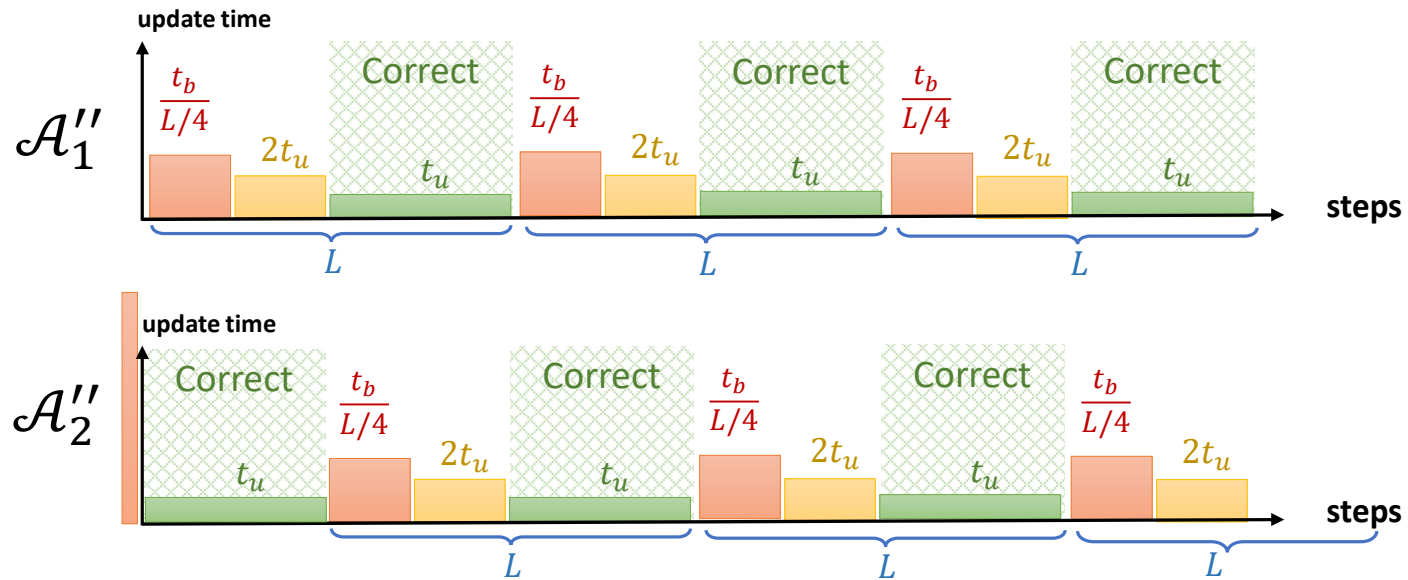
Problems	Setting	Approx	Size	Time
Minmax paths	Fully dyn [Epp'94] [NSW'17]	1	$ S $	$n^{o(1)}$
Shortest paths	Incremental [TZ'05] [CGHPS'20]	k	$ S n^{1/k}$	$\tilde{O}(n^{1/k})$
	Fully dyn [CGHPS'20]	$\log n$	$\beta n + S$	$\tilde{O}(1/\beta)$
c-connectivity	Static [Liu'23]	1	$ S c^3$	Poly
	Fully dyn [CDLKPPSV'20] [JS'20]	1	$ S c^{O(c)}$	$n^{o(1)}c^{O(c)}$
Max flow (multicommodity)	Static	$\log S$	$ S $	Poly
	Incremental [RST'14] [CGHPS'20]	$\log^4 n$	$ S $	$\tilde{O}(1)$
	Fully dyn unweighted [GRST'21]	$n^{o(1)}$	$ S $	$n^{o(1)}$
	Fully dyn [CGHPS'20]	polylog n	$\beta n + S$	$\tilde{O}(1/\beta)$
Effective resistance	Static [KS'16] [DKPRS'16]	$1 + \epsilon$	$ S $	$\tilde{O}(m)$
	Fully dyn [DGGP'19] [BGJLLPS'21]	$1 + \epsilon$	$\beta m + S$	$\tilde{O}(1/\beta^2)$
Low stretch trees	Fully dyn [CKLPPS'22]	$\log n$	m/k	$kn^{o(1)}$

Conclusion

You have learned

- 3 templates for designing dynamic graph algorithms
 1. Rebuild in the background
 2. Batching
 3. Vertex sparsifiers
- Along the way, many terminology in the area
 - **worst-case** vs. **amortized** update time
 - **fully dynamic** vs. **partially dynamic (incremental/decremental)**
 - **one-batch** algorithms (a.k.a. sensitivity oracles, emergency algorithms)
 - **offline** dynamic algorithms

Template 1: Rebuild in the background



Template 2: Batching

Often easy to
design

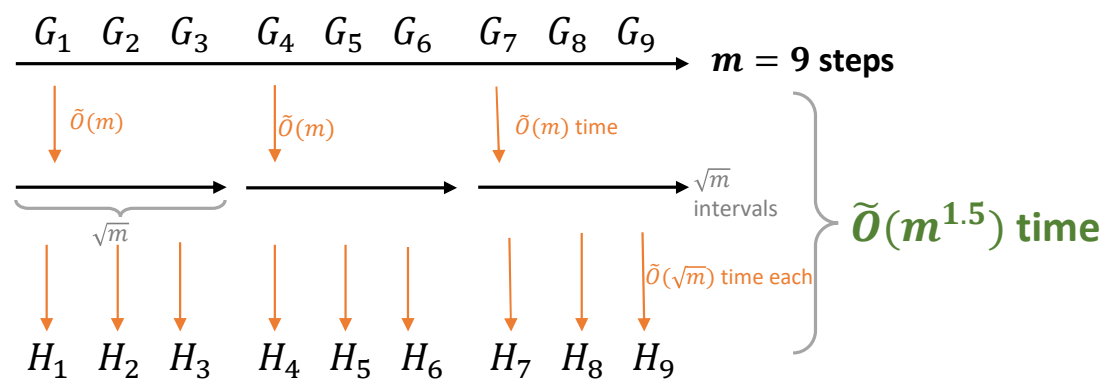
One-batch algorithms + rebuild in the background



It works for k -batch algorithms too [\[NSW'17\]](#) [\[BBGNSSS'22\]](#) [\[JS'22\]](#)

Dynamic algorithms

Template 3: Vertex sparsifiers



Learn more templates

1. **(Recent and promising):** Optimization methods for dynamic algos.
 - Static solutions robust against update
(congestion balancing [[BGS'20](#), ['21](#)], entropy-regularized solutions [[JJST'22](#)])
 - Dynamic Multiplicative Weight Update [[Gupta'14](#)] [[BKS'22](#)] [[BBLS'23](#)]
 - Dynamic Interior Point Methods [[BLS'22](#)]
2. Given incremental algo → get offline fully dynamic algo [[PR'22](#)]
3. Given decremental algo → get fully dynamic algo
 - Problem-specific: Connectivity, MST, APSP
4. Any “decomposable” problems → get fully dynamic algo [[Overmars' book](#)]
 - E.g. dynamic range searching, quad-tree, other geometric objects

Other Generic Techniques in Dynamic Graphs

- Expander decomposition
 - Used for dynamic connectivity, shortest paths in both undirected and directed graphs
 - My tutorial: [Part 1 and 2](#)
 - [My course](#) on using expanders for fast algorithm (updated version in 1-2 months!)
- Edge-degree constrained subgraph (EDCS):
 - key objects for dynamic matching
 - [Aaron's tutorial](#)
- Randomized Greedy:
 - General approach for both dynamic maximal matching and maximal independent set
 - [Soheil's tutorial](#)

Thank you!