CPSC 768:
Scalable and Private Graph Algorithms

Lecture 25: Learning-Augmented Algorithms

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Announcements

- **Final project report and presentation: April 24th (last day of class)**
  - Final project presentation is a 30 min presentation
- **Last day of Open Problem Sessions: April 26th** (last week of classes)
  - Will be turned into a reading group/continue with OPS, stay tuned!

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  - Worst-case guarantees
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- **Learning-Augmented Algorithms**
  - Adaptive
  - Often has worst-case guarantees

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Often cannot satisfy all three!

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Learned Binary Search

- Suppose we have a **sorted** list of integers

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First decide go left or right

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Start doubling search

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$$\boldsymbol{O}(\log(\boldsymbol{L_1} - \boldsymbol{error}))$$

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Why is the prediction reasonable?

Many real-world instances give you a prediction—e.g. library books

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Satisfies all three desired properties!

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- **Many applications!**

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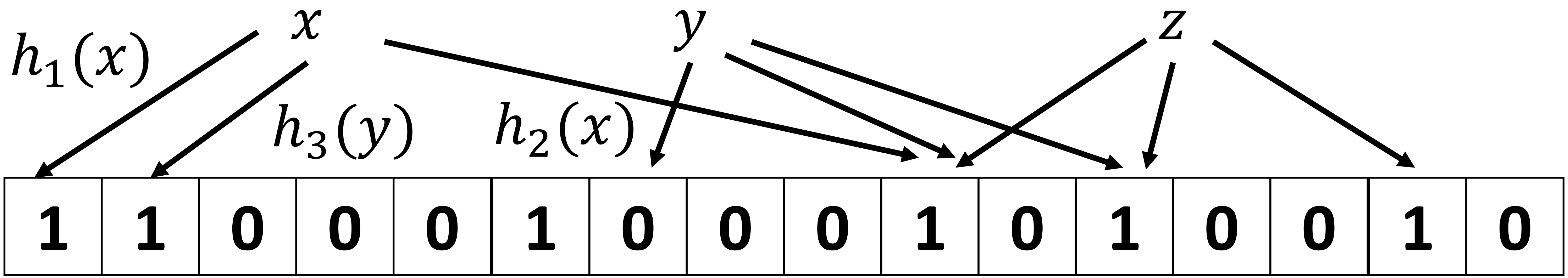

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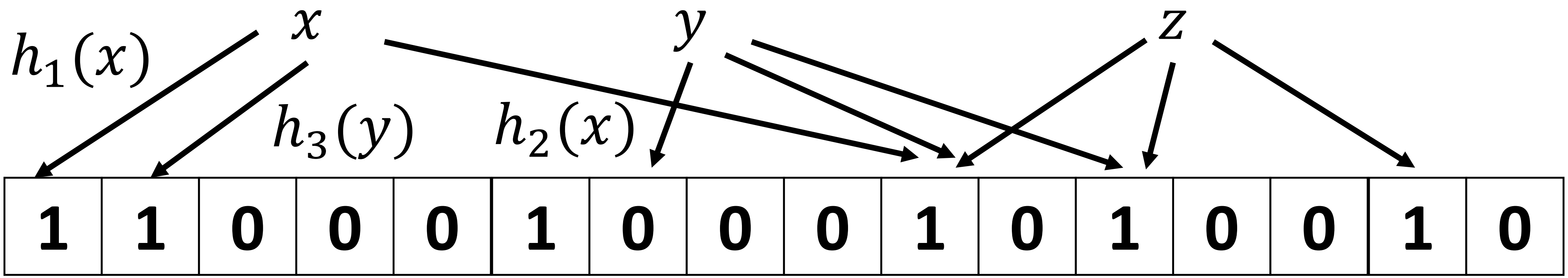

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    - Suppose pick $k = \log_2 n$ and $m = 3n \log_2 n$, then probability of failure is $\left(\frac{n \log_2 n}{3n \log_2 n}\right)^{\log_2 n} = \left(\frac{1}{3}\right)^{\log_2 n} < \frac{1}{n}$

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  - Will be non-zero **false positive and negative rate**

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On each element
$x \in S$ → **Oracle** $\boldsymbol{f(x)}$

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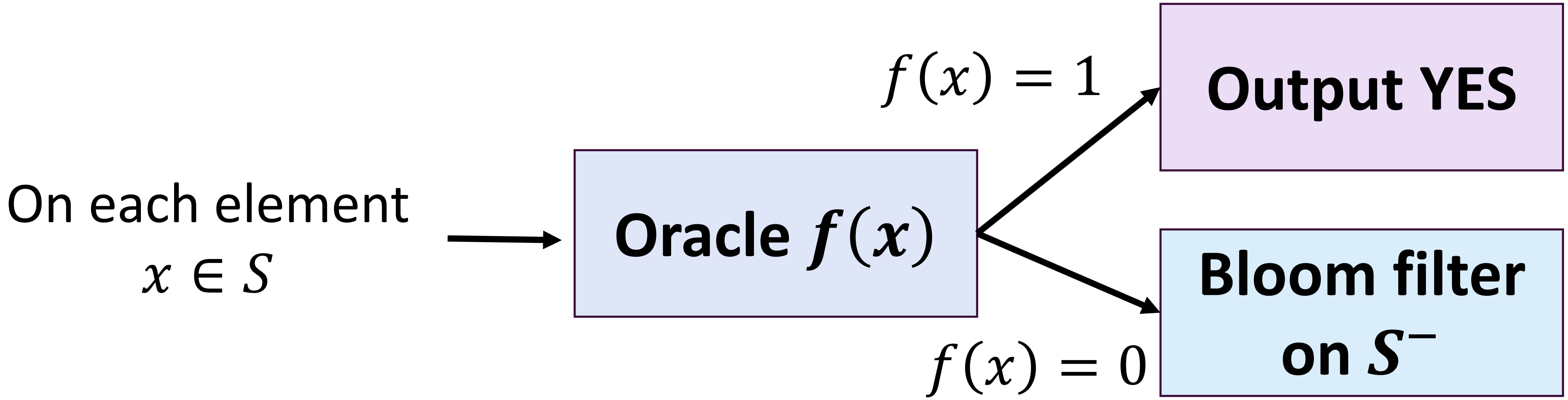

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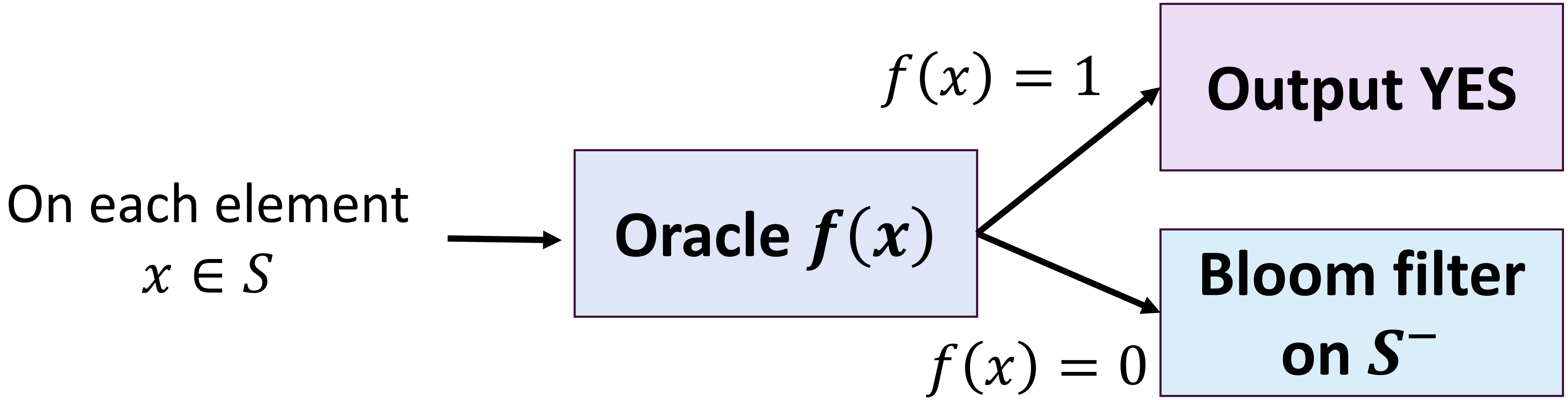

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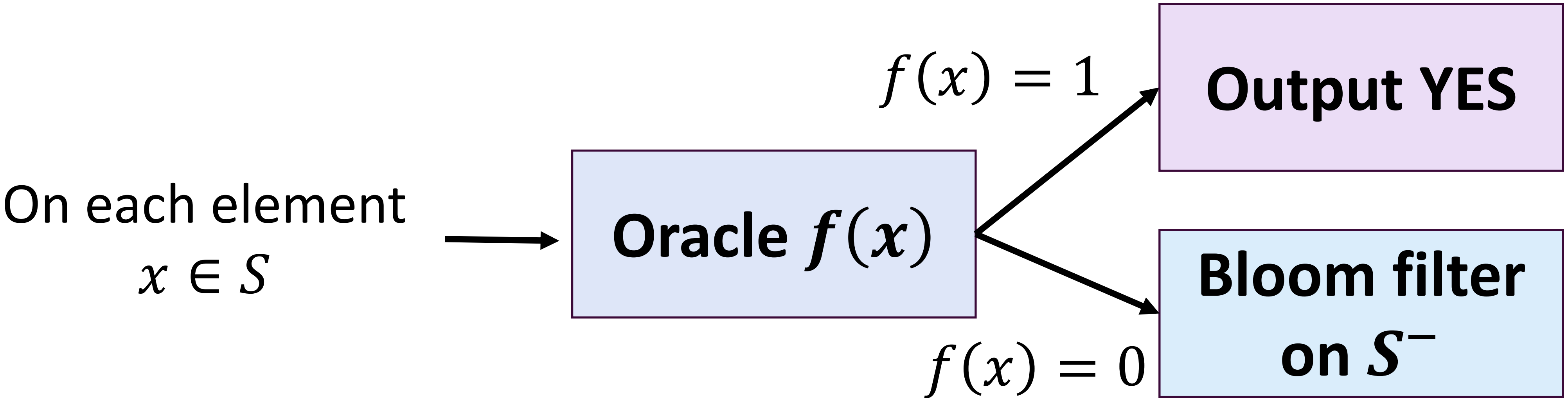

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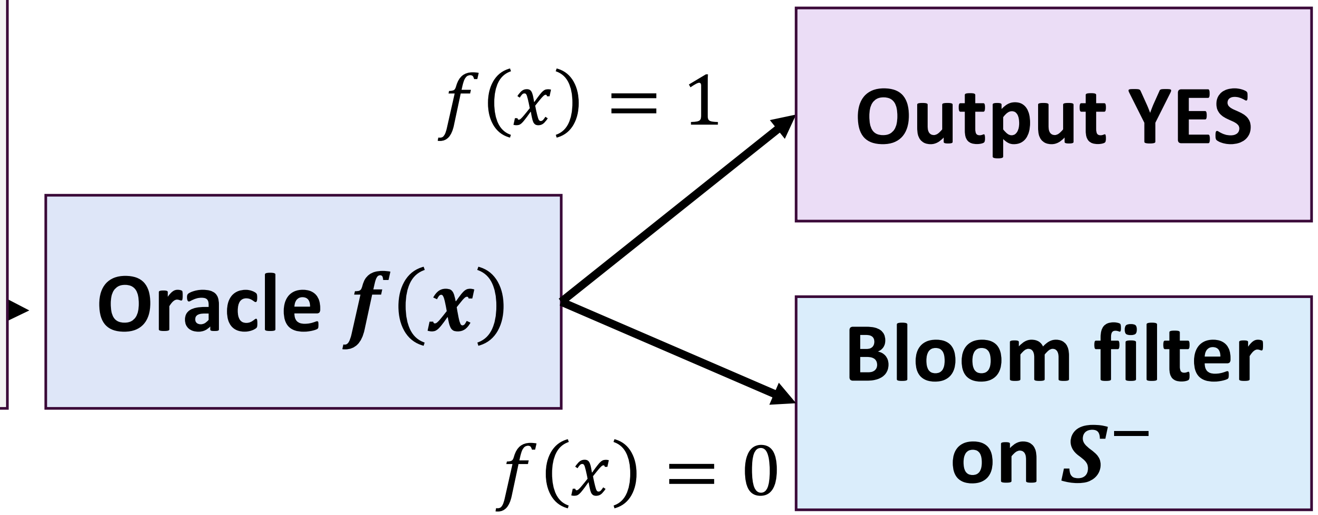
Caveat: false positive rate depends on the oracle



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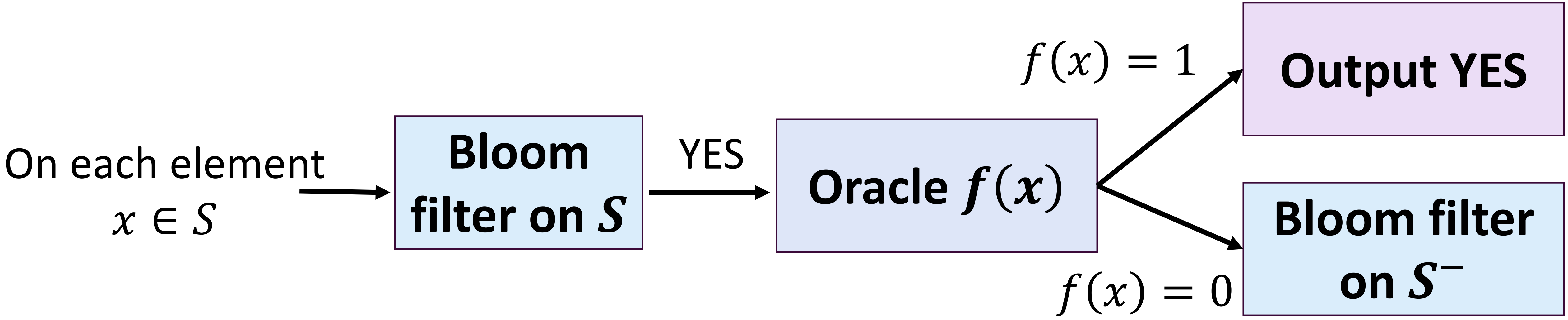

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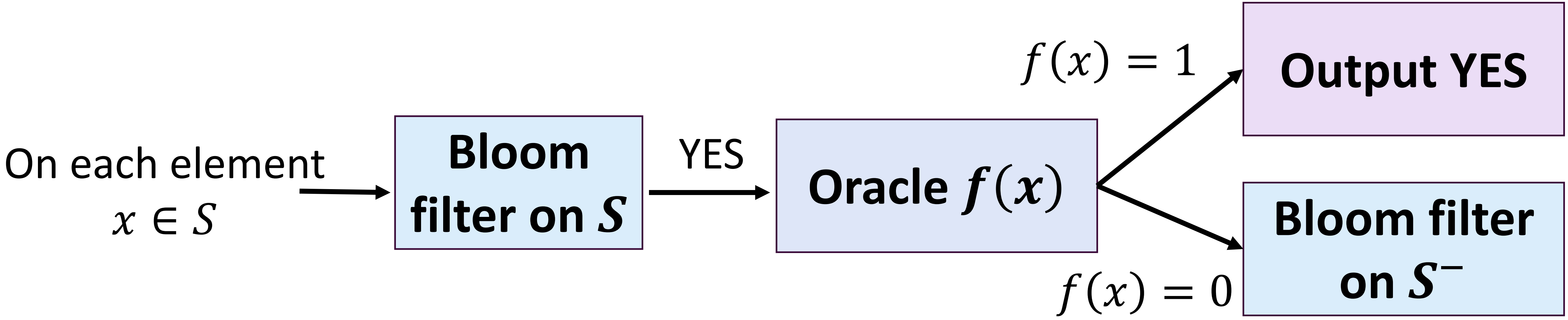

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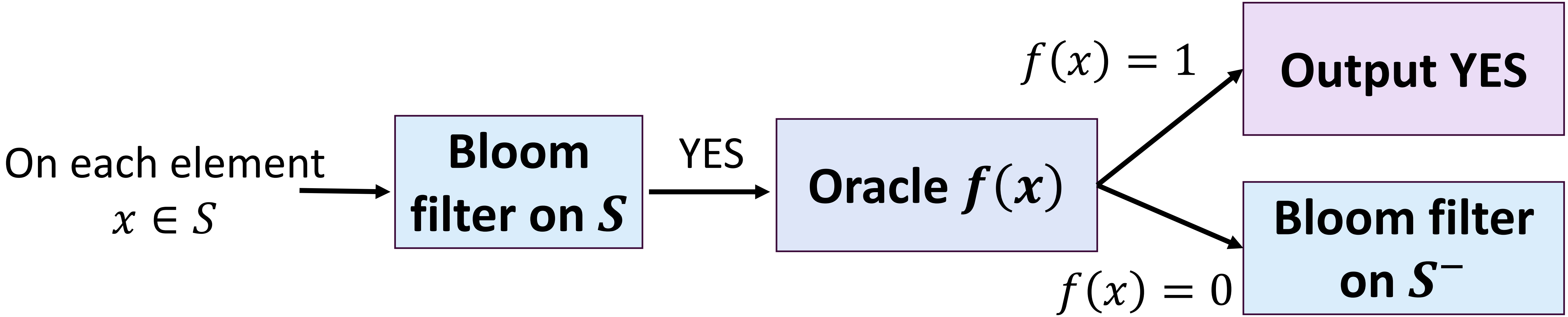
Better analysis and performance in practice!



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Learning-Augmented Dynamic Graph Algorithms

- Why do we need them?

Types of Dynamic Algorithms

- **Incremental/Decremental** vs. **Fully Dynamic**
  - Incremental/decremental algorithms:
    - Only edge insertions/deletions, respectively
- Sometimes **large gap in runtimes**
  - **Polynomial** or **exponential gaps** in runtimes

Types of Dynamic Algorithms

	Best Fully Dynamic		Best Partially Dynamic	
Planar Digraph APSP	$\widetilde{O}\left(n^{2/3}\right)$	[FR06, Kle05]	$\widetilde{O}(\sqrt{n})$	[DGWN22]
Triconnectivity	$O(n^{2/3})$	[GIS99]	$\widetilde{O}(1)$	[HR20, PSS17]
k-Edge Connectivity	$n^{o(1)}$	[JS22]	$\widetilde{O}(1)$	[CDK+21]
Dynamic DFS Tree	$\widetilde{O}\left(\sqrt{mn}\right)$	[BCCK19]	$\widetilde{O}(n)$	[BCCK19, CDW+18]
Minimum Spanning Forest	$\widetilde{O}(1)$	[HDLT01]	$\widetilde{O}(1)$	[Epp94]
APSP	$\left(\frac{256}{k^2}\right)^{4/k}$-Approx $\widetilde{O}\left(n^k\right)$ update $\widetilde{O}(n^{k/8})$ query	[FGNS23]	$(2r-1)^k$-Approx $\widetilde{O}\left(m^{1/(k+1)}n^{k/r}\right)$	[CGH+20]
AP Maxflow/Mincut	$O(\log(n)\log\log n)$-Approx $\widetilde{O}\left(n^{2/3+o(1)}\right)$	[CGH+20]	$O\left(\log^{8k}(n)\right)$-Approx. $\widetilde{O}\left(n^{2/(k+1)}\right)$	[Gor19, GHS19]
MCF	$(1+\varepsilon)$-Approx $\widetilde{O}(1)$ update $\widetilde{O}(n)$ query	[CGH+20]	$O(\log^{8k}(n))$-Approx. $\widetilde{O}\left(n^{2/(k+1)}\right)$ update $\widetilde{O}(P^2)$ query	[Gor19, GHS19]
Strongly Connected Components	$\Omega(m^{1-\varepsilon})$ query or update	[AW14]	$\widetilde{O}(m)$	[Rod13]
Uniform Sparsest Cut	$2^{O(\log^{5/6}(n))}$-Approx $2^{O(\log^{5/6}(n))}$ update $O(\log^{1/6}(n))$ query	[GRST21]	$O\left(\log^{8k}(n)\right)$-Approx $\widetilde{O}\left(n^{2/(k+1)}\right)$ $O(1)$ query	[Gor19, GHS19]
Submodular Max	$1/4$-Approx $\widetilde{O}(k^2)$	[DFL+23]	0.3178-Approx $\widetilde{O}(\text{poly}(k))$	[FLN+22]

[LS ’23]

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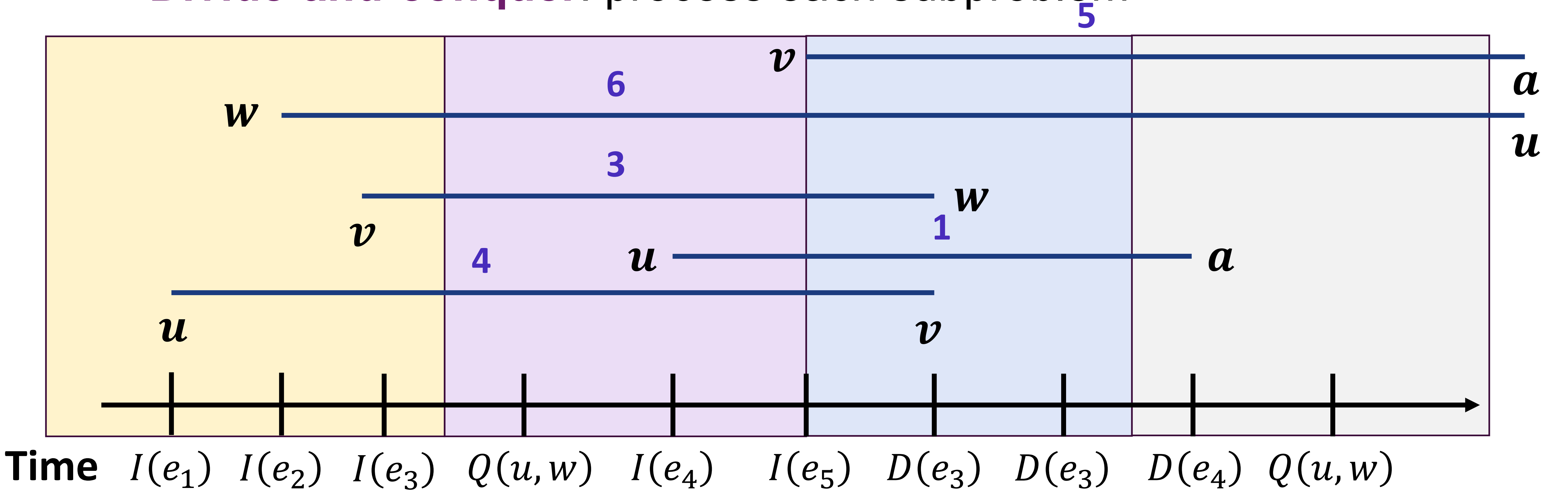
- **Predictions on the edge updates [L-Srinivas '23]**
  - For each edge update, give **prediction on when update occurs**
  - Assume one edge insertion/deletion occurs on a day, give prediction on the day of the edge insertion/deletion

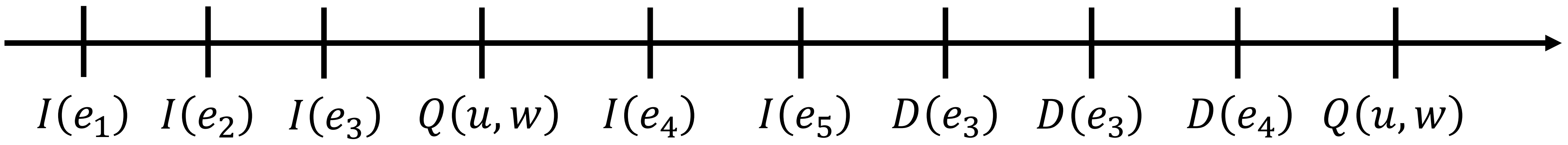
Offline-Dynamic Connectivity

- Geometric representation of the problem
- **Divide-and-conquer**: process each subproblem



Random Partition Tree Data Structure

Pick a uniformly at random divider for subproblems



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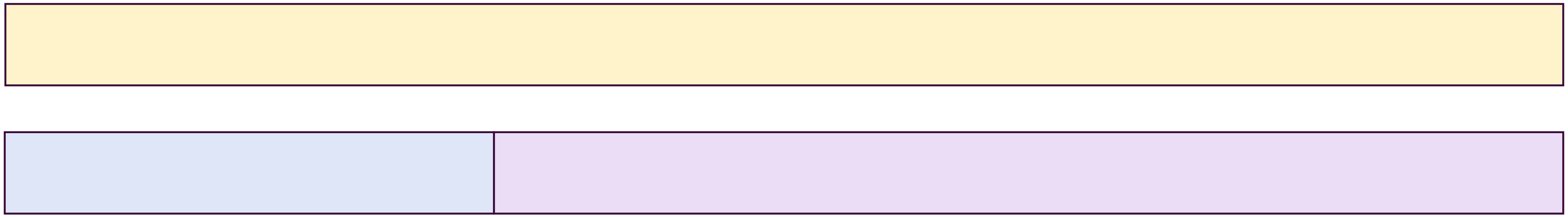

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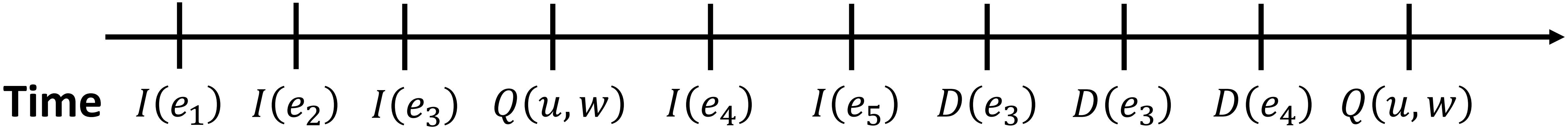

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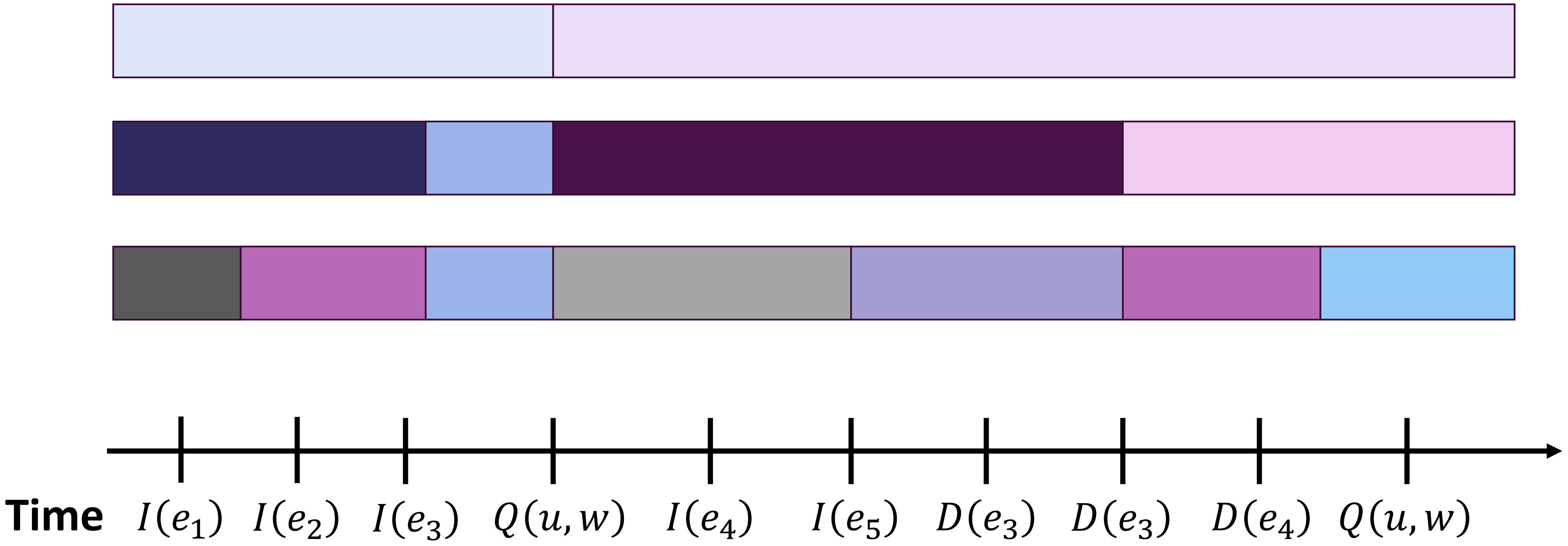

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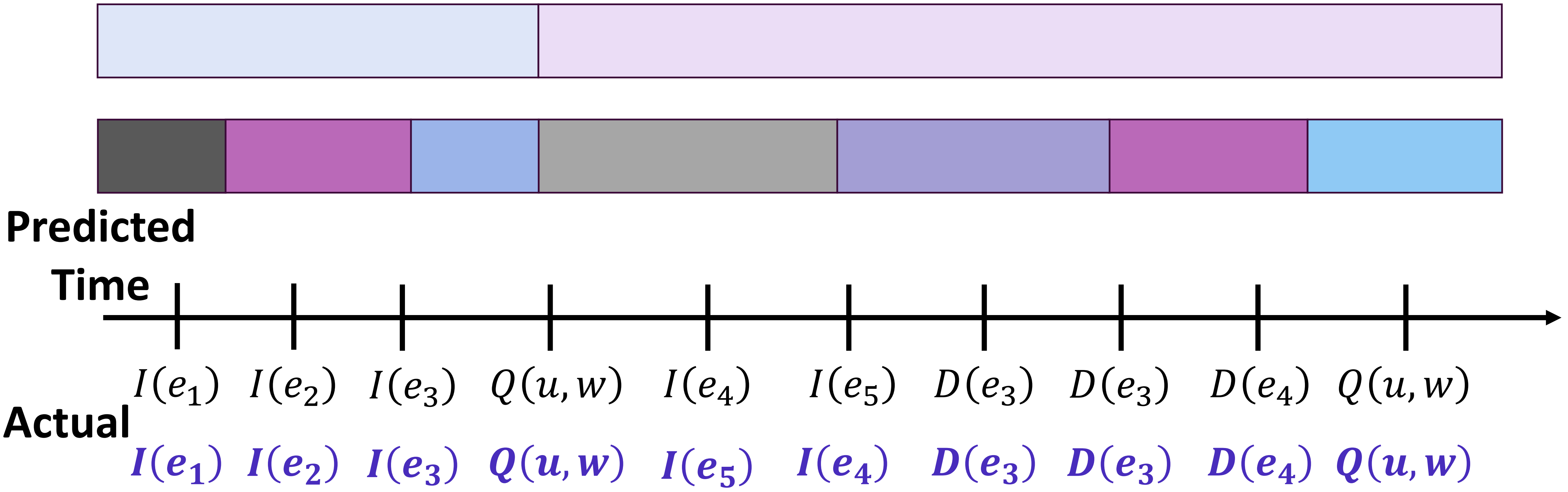

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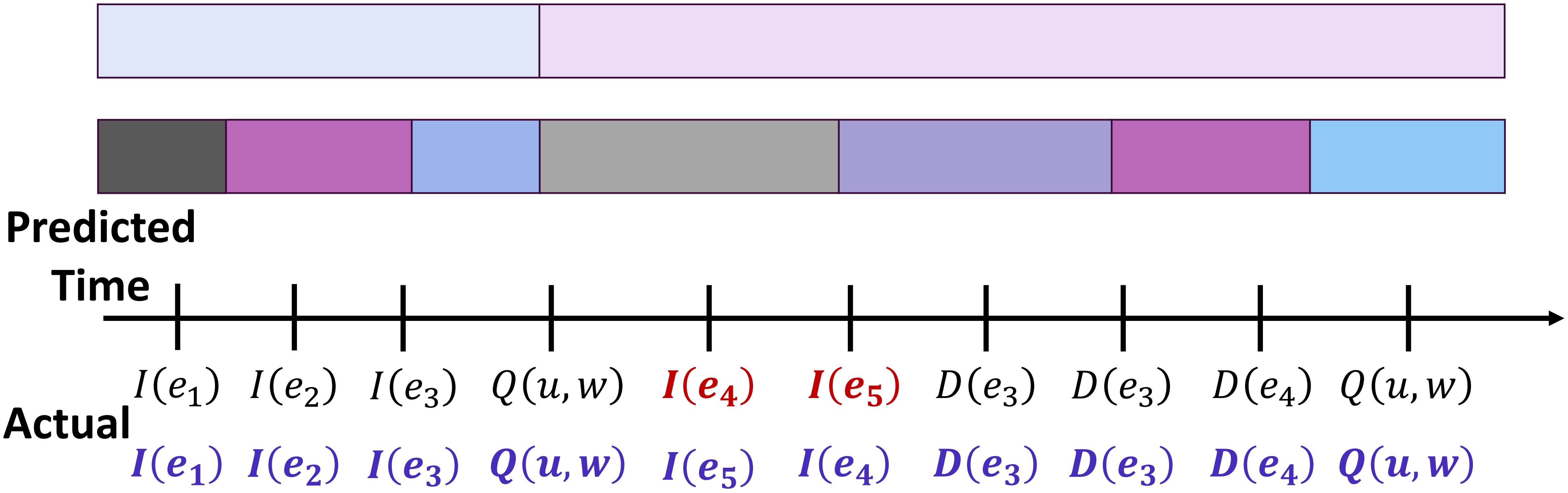
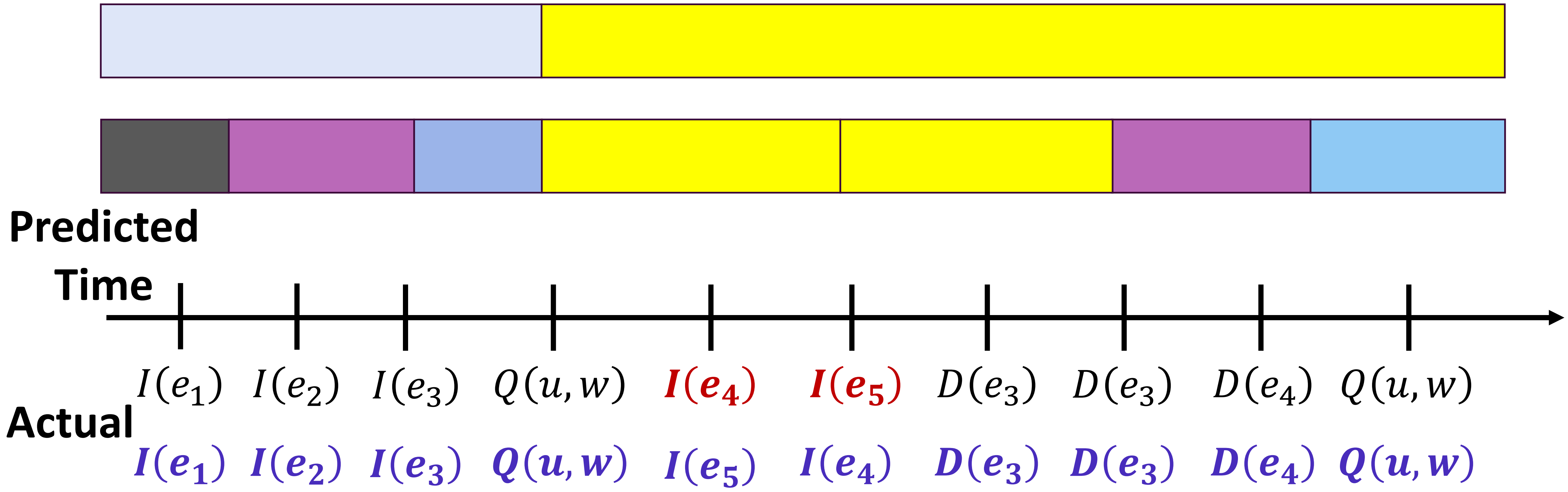


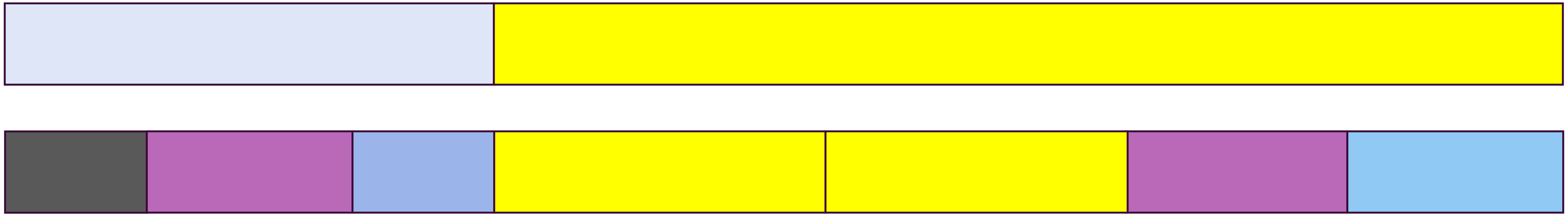
Random Partition Tree Data Structure

Recompute computation of largest subtree containing errors and children



Random Partition Tree Data Structure

Purpose of the random partition tree: in expectation size of subproblem (largest subtree) equal to error



Predicted

Time

$I(e_1)$ $I(e_2)$ $I(e_3)$ $Q(u,w)$ $\boldsymbol{I(e_4)}$ $\boldsymbol{I(e_5)}$ $D(e_3)$ $D(e_3)$ $D(e_4)$ $Q(u,w)$

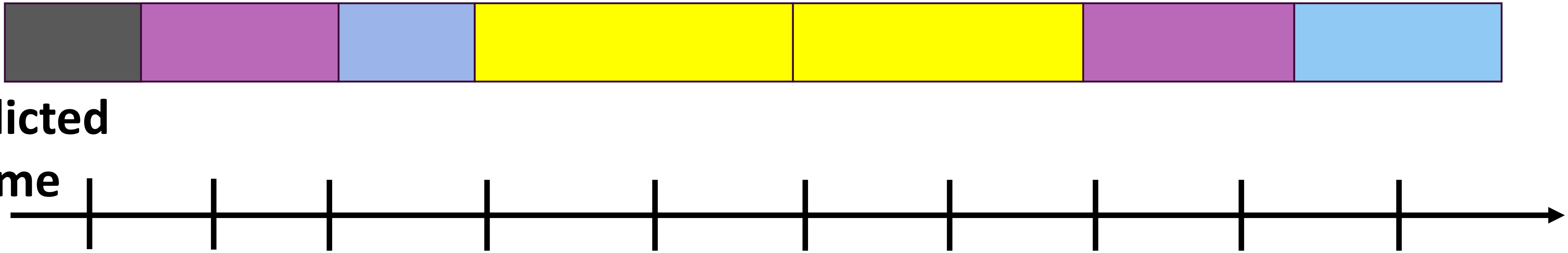
Actual

$\boldsymbol{I(e_1)}$ $\boldsymbol{I(e_2)}$ $\boldsymbol{I(e_3)}$ $\boldsymbol{Q(u,w)}$ $\boldsymbol{I(e_5)}$ $\boldsymbol{I(e_4)}$ $\boldsymbol{D(e_3)}$ $\boldsymbol{D(e_3)}$ $\boldsymbol{D(e_4)}$ $\boldsymbol{Q(u,w)}$

Random Partition Tree Data Structure

Purpose of the random partition tree: in expectation size of subproblem (largest subtree) equal to L_1 error

Bad event: very large subtree for small error



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Random Partition Tree Data Structure

Runtime same as partially dynamic with an additional $\widetilde{O}(\log(L_1 - error))$

[L-Srinivas '23]

Predicte

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Exciting new fields with lots of potential for development and broad impact

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