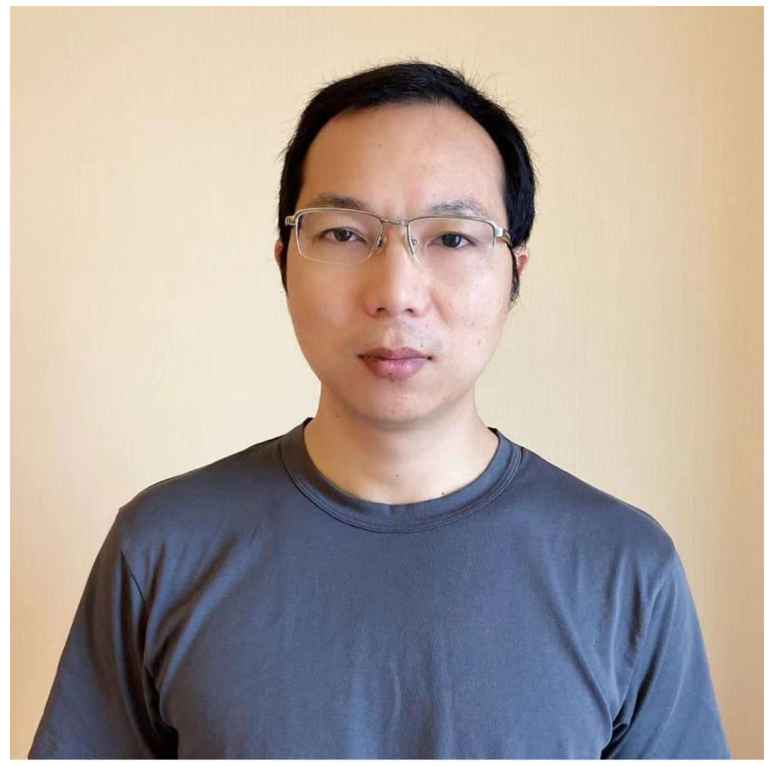
Learning-Augmented Streaming Algorithms for Approximating Max-Cut

Yinhao Dong (董寅灏)

University of Science and Technology of China (USTC)

Based on joint work with



Pan Peng

USTC

Ali Vakilian

TTIC -> Virginia Tech

第六届 CCF 理论计算机科学博士生论坛

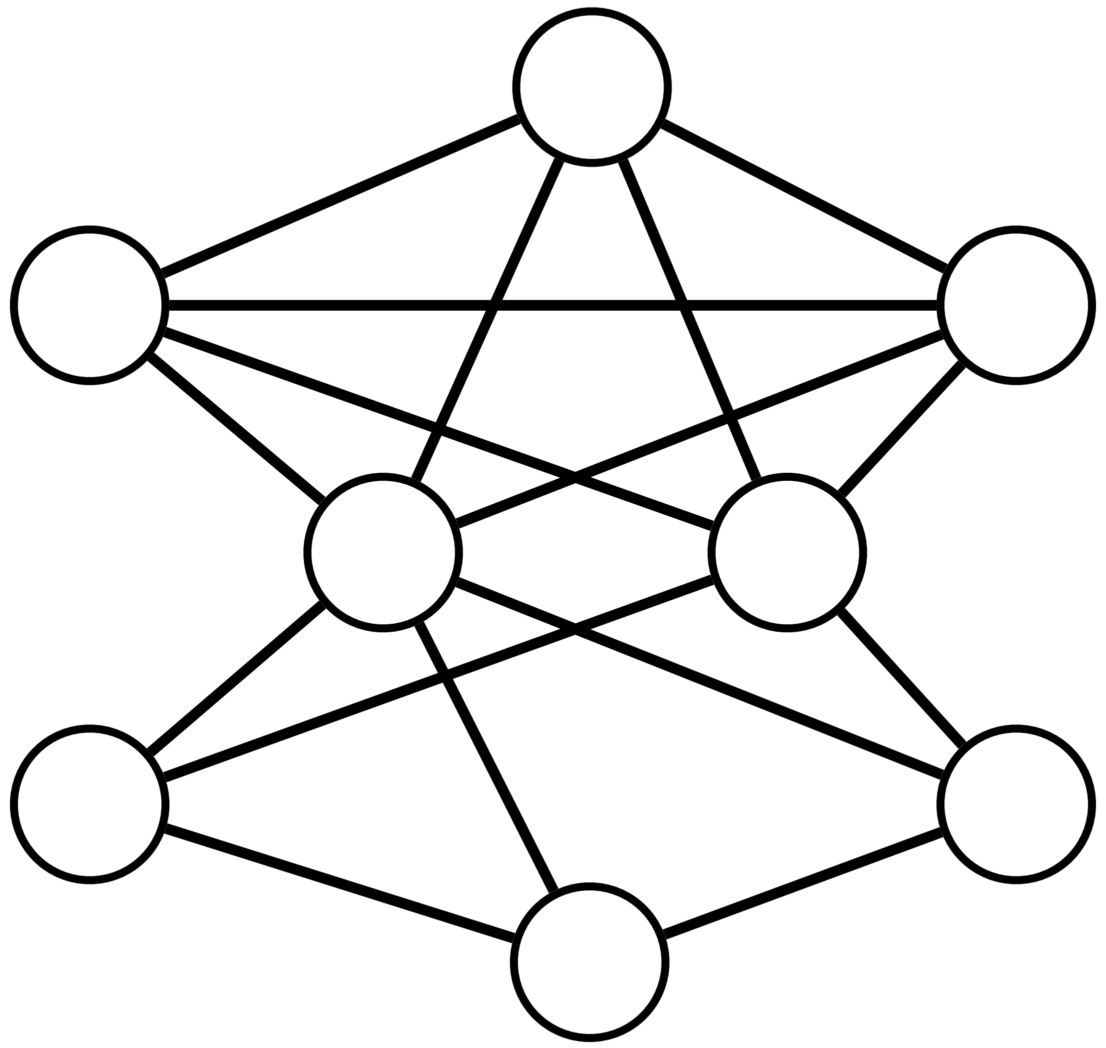
中南大学 · 2025 年 11 月

Max-Cut

Input: An undirected, unweighted graph $G = (V, E)$

Goal: Find a *bipartition* of V into S and T that maximizes the cut value

$$|E(S,T)| = |\{(u,v) \in E : u \in S \wedge v \in T\}|$$



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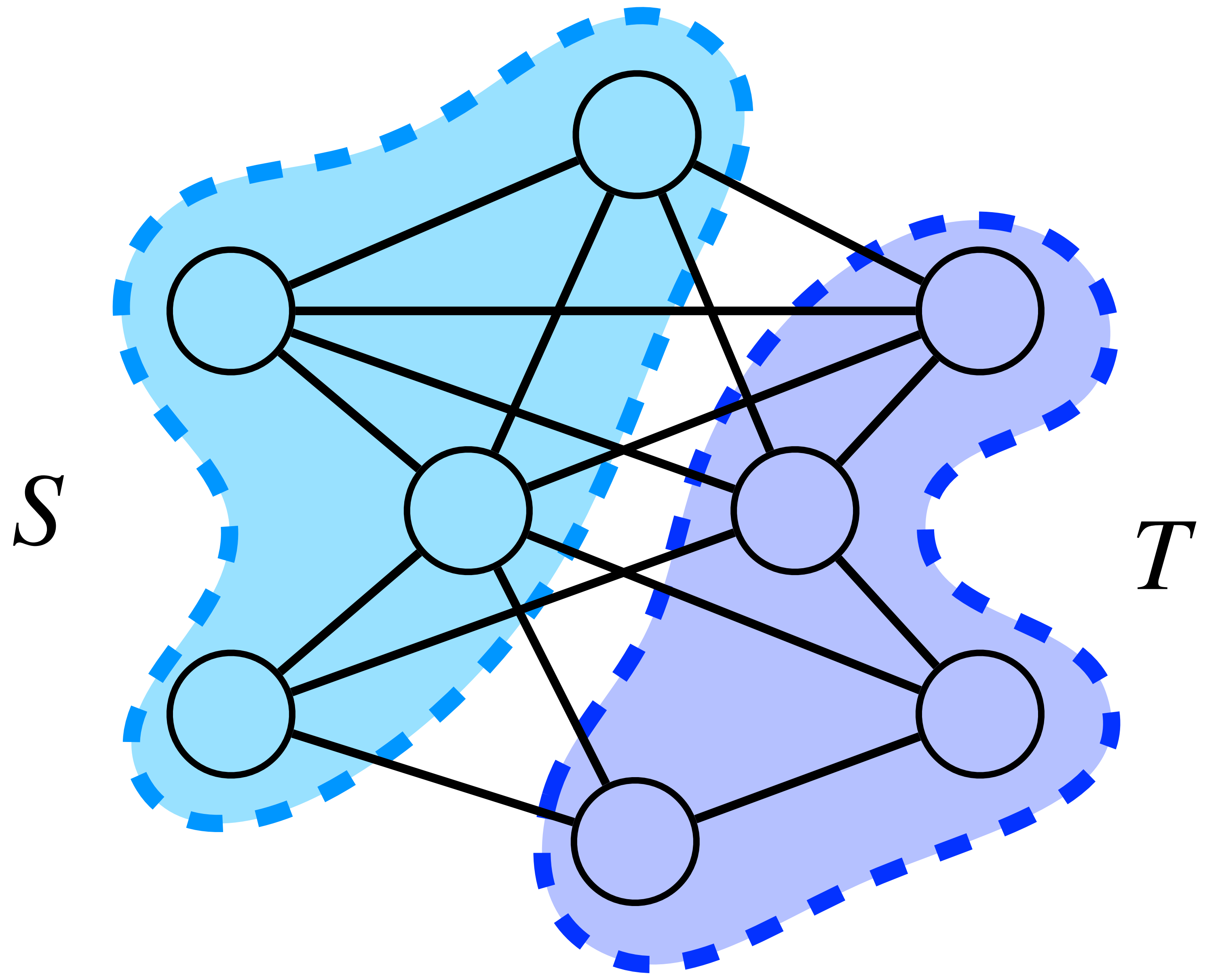

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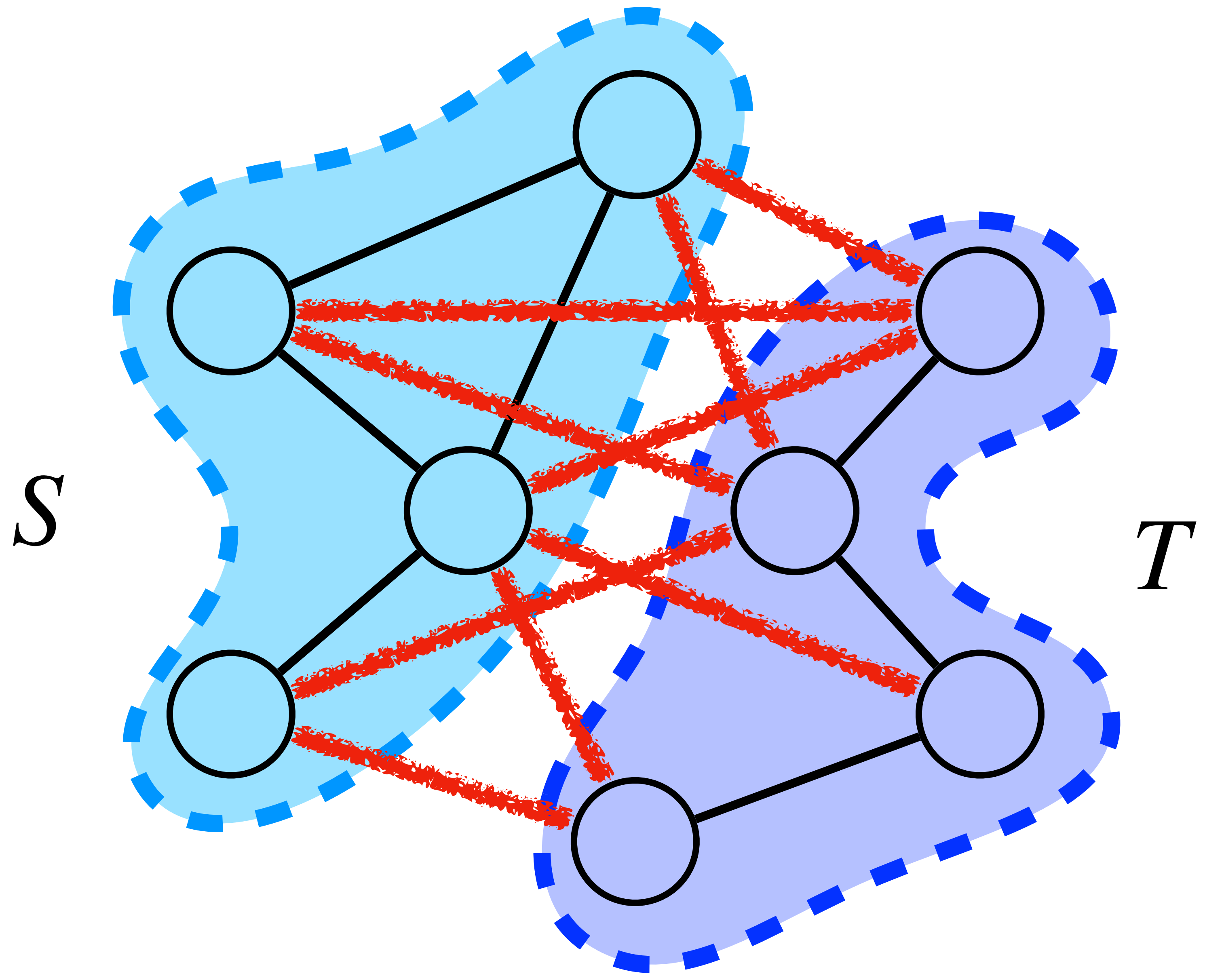

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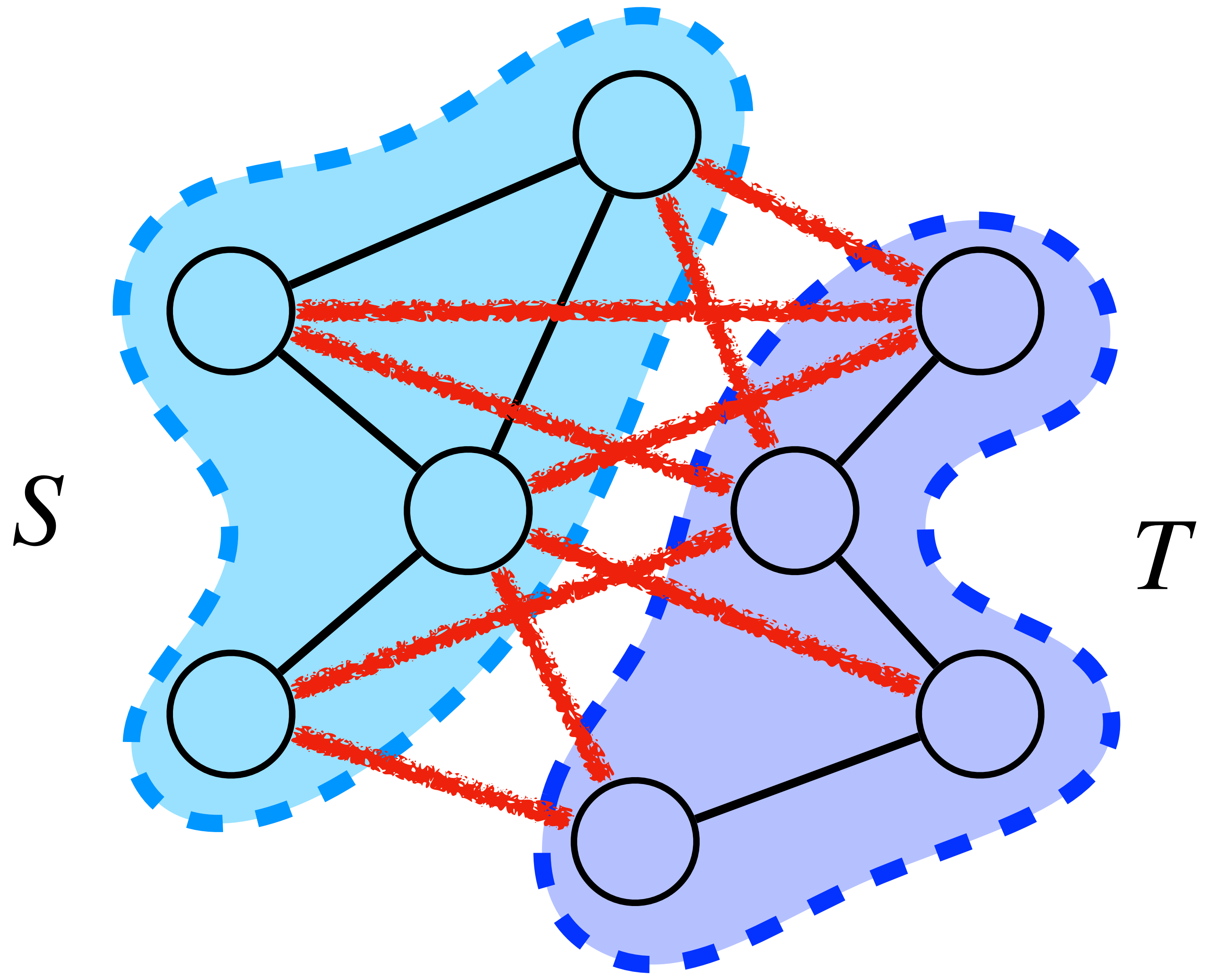

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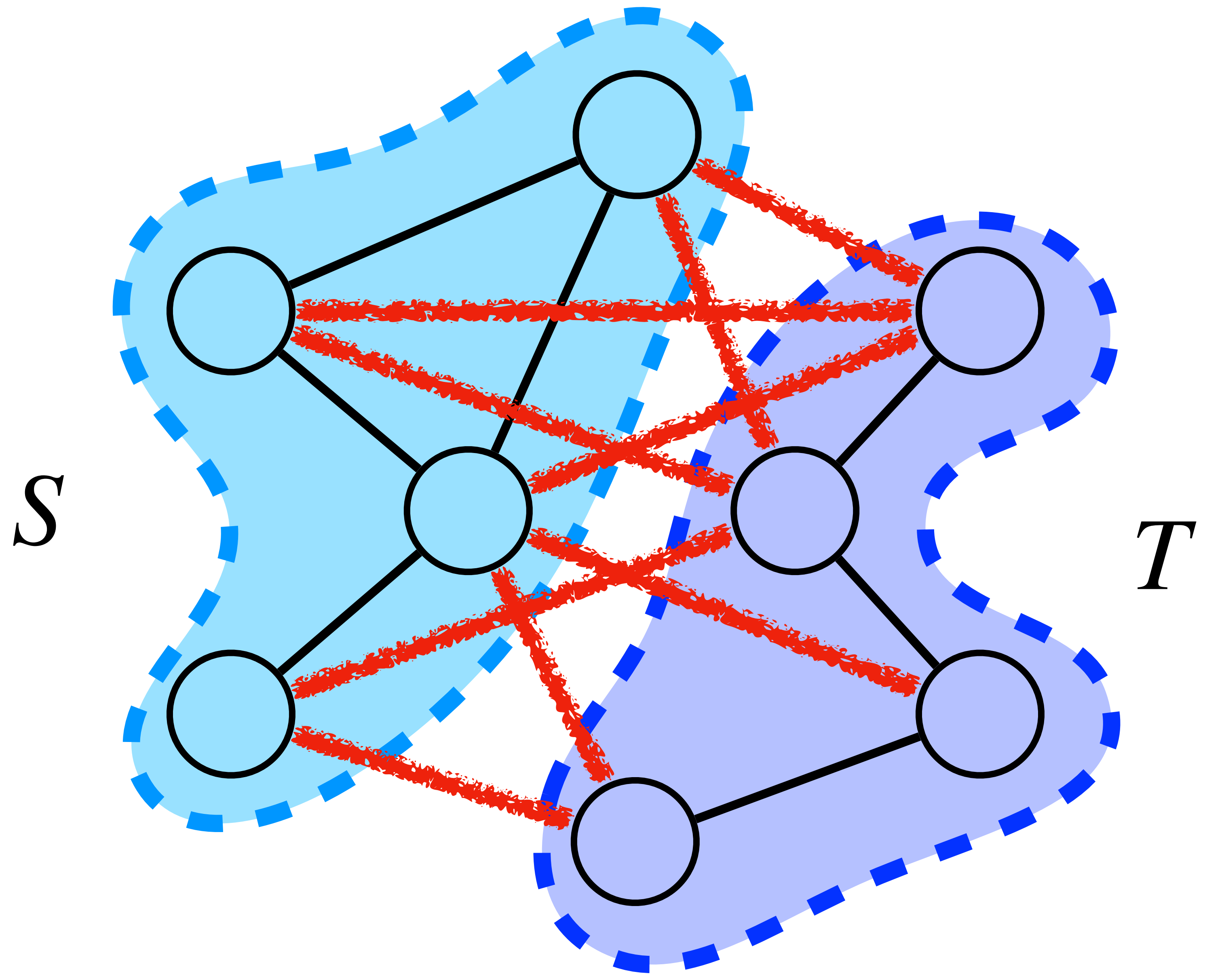

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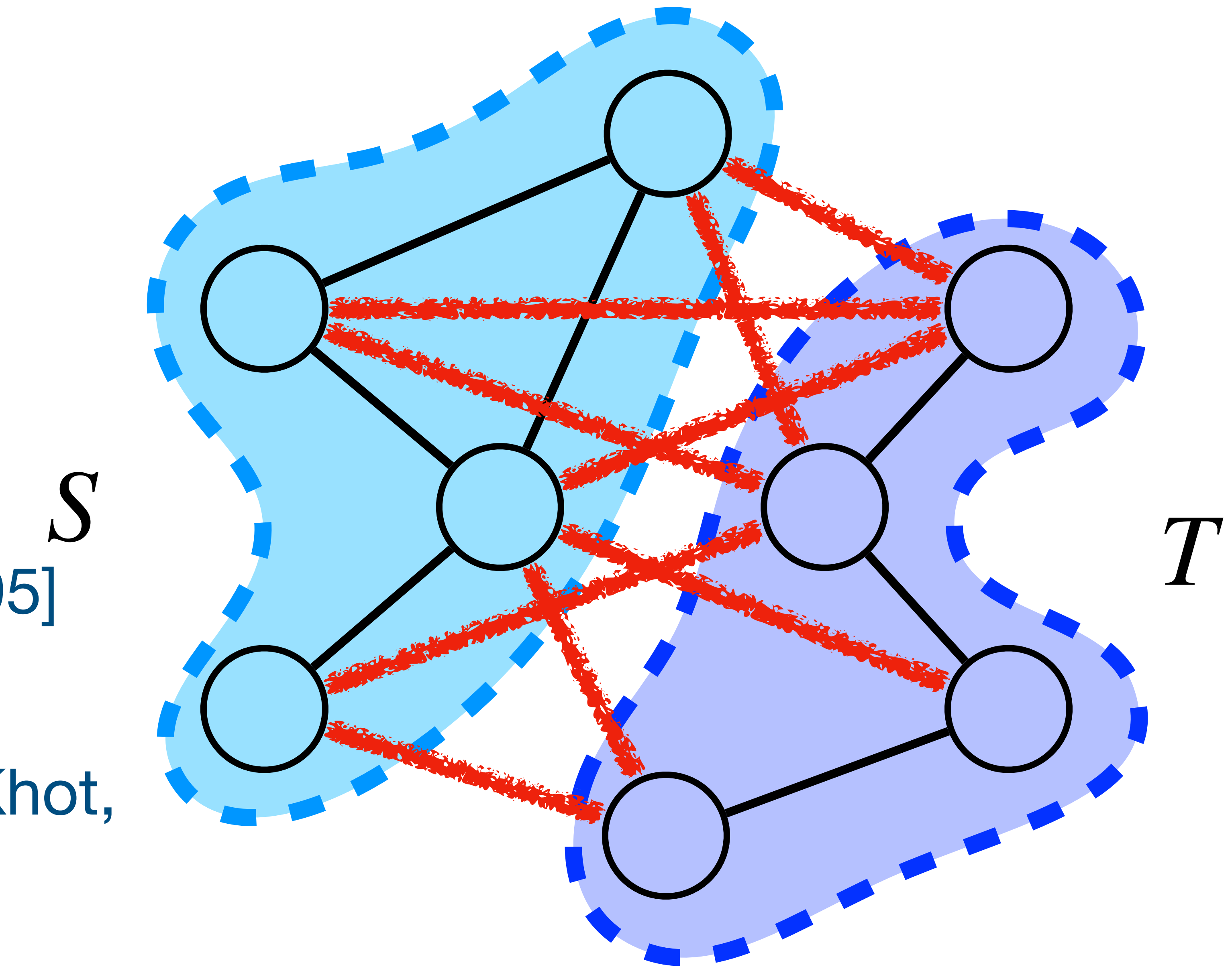
- SDP rounding: 0.878-approx [Goemans, Williamson, JACM'95]
  - Unique Games Conjecture $\Longrightarrow$ best possible [Khot, Kindler, Mossel, O'Donnell, SICOMP'07]



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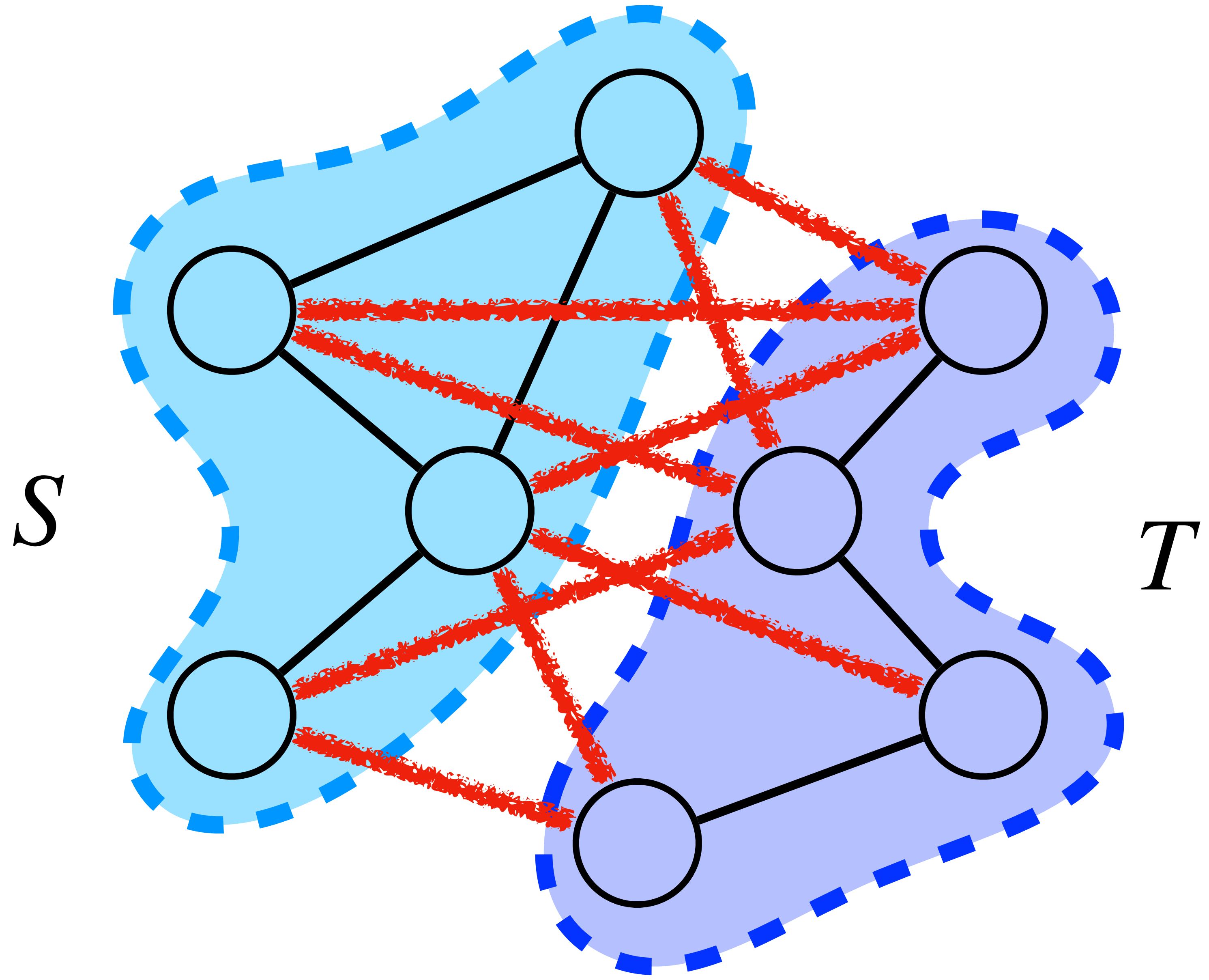
Compute an *estimate* v of the Max-Cut value



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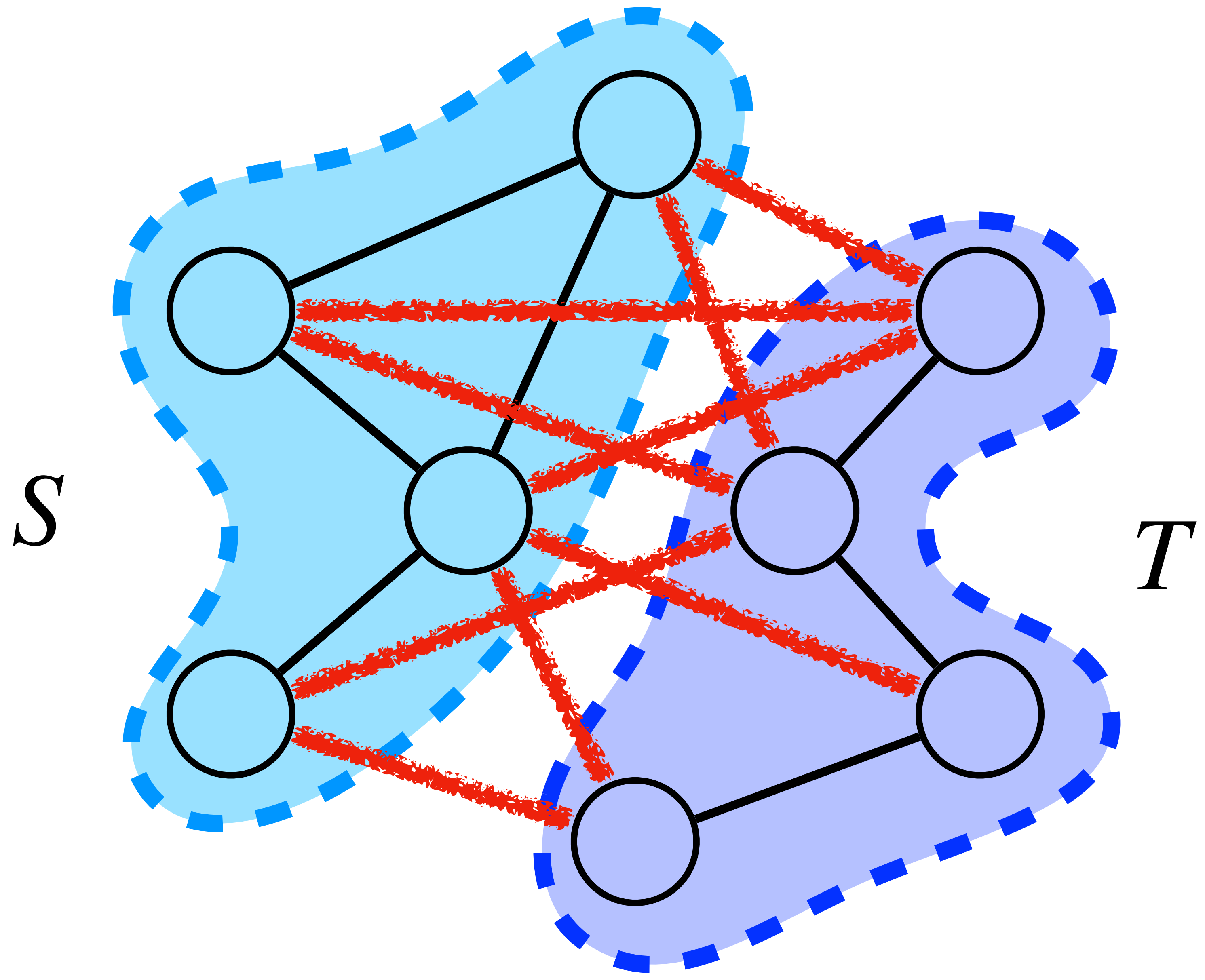

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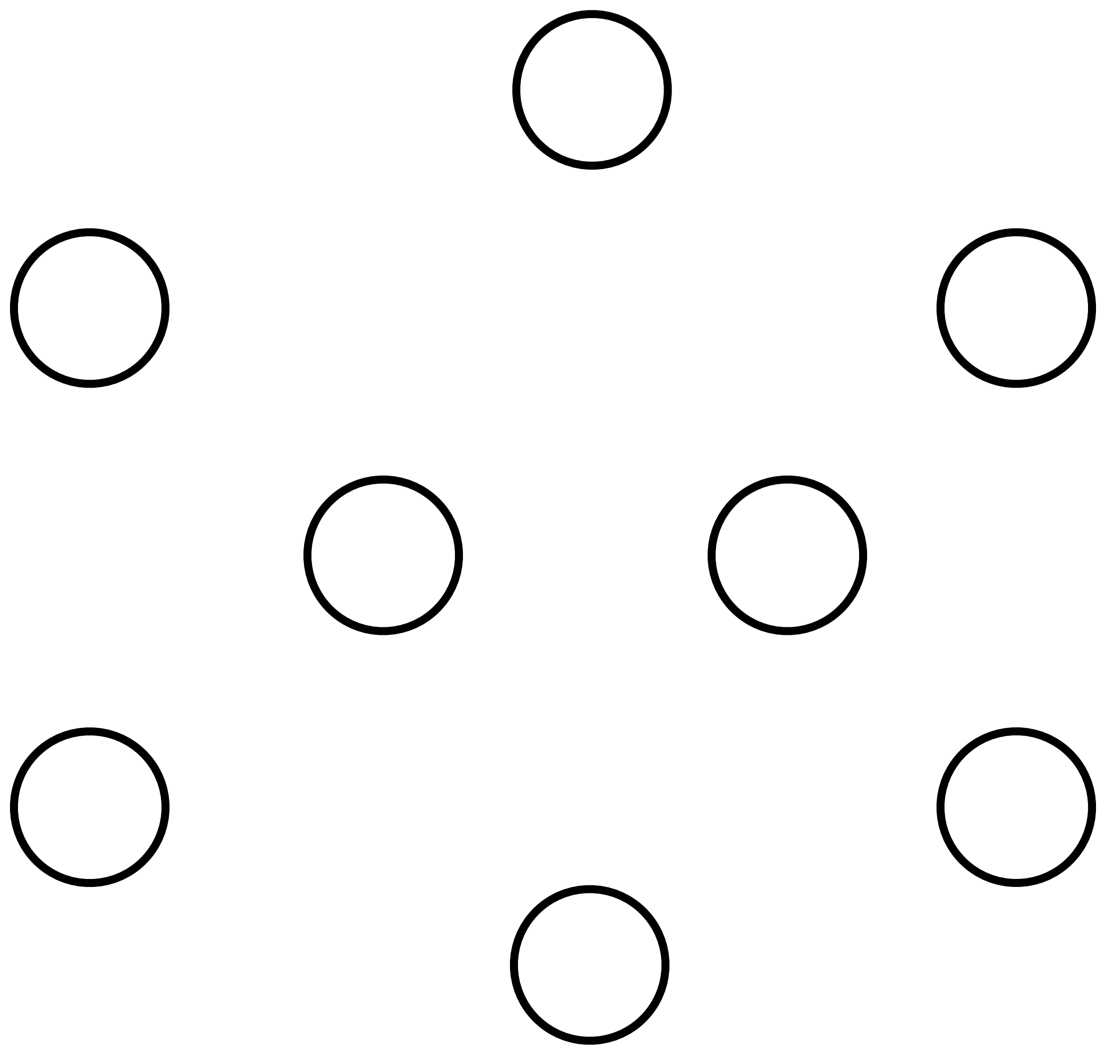

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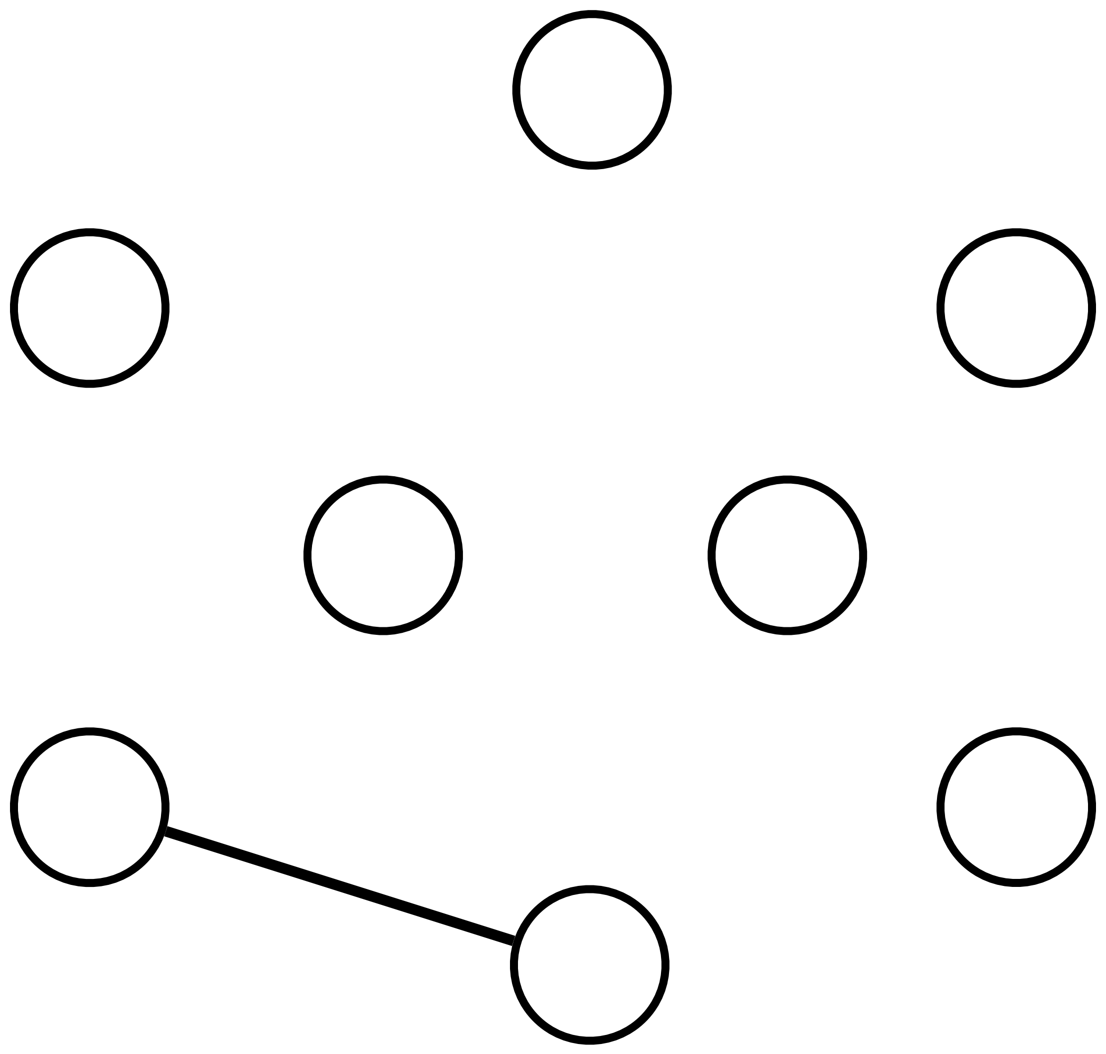

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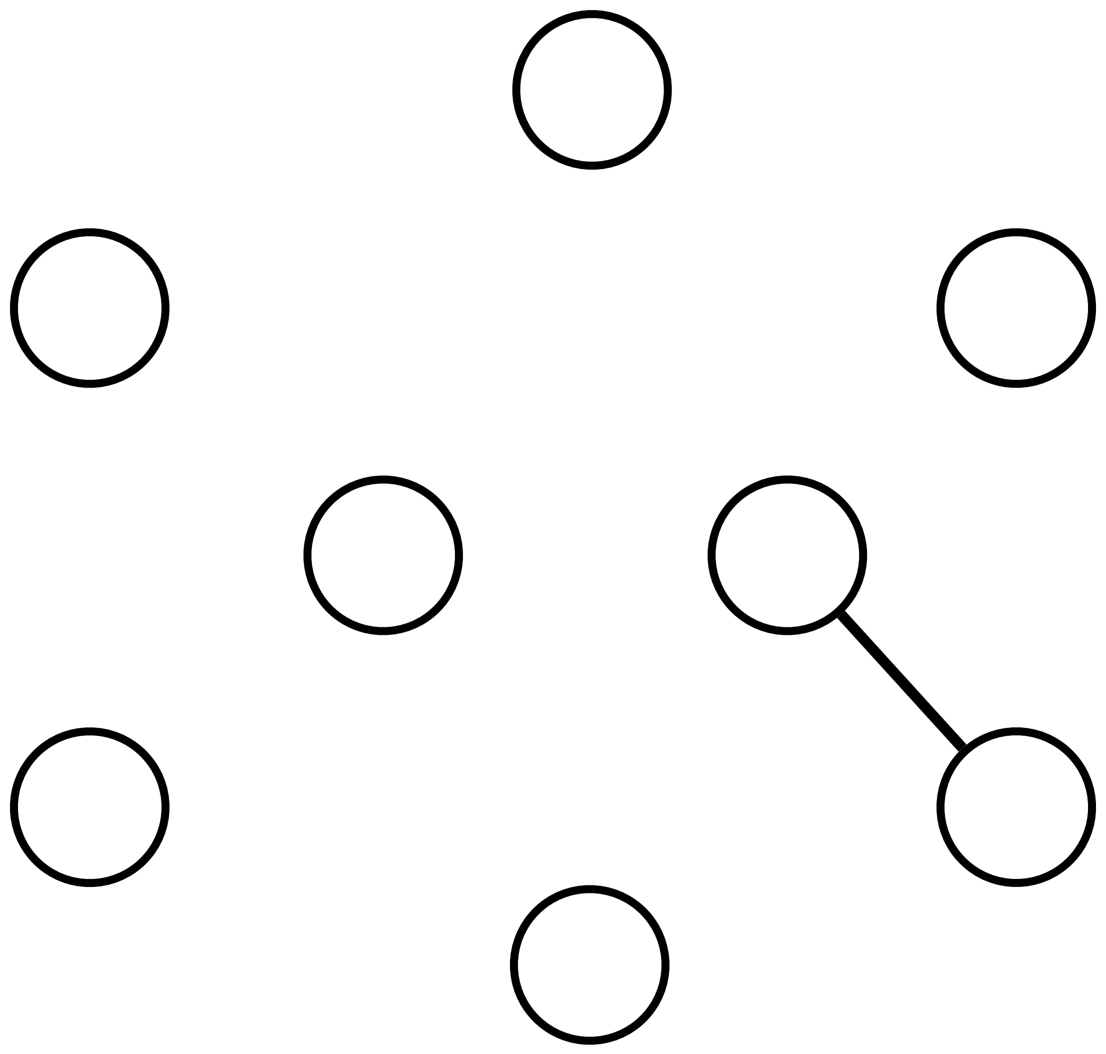

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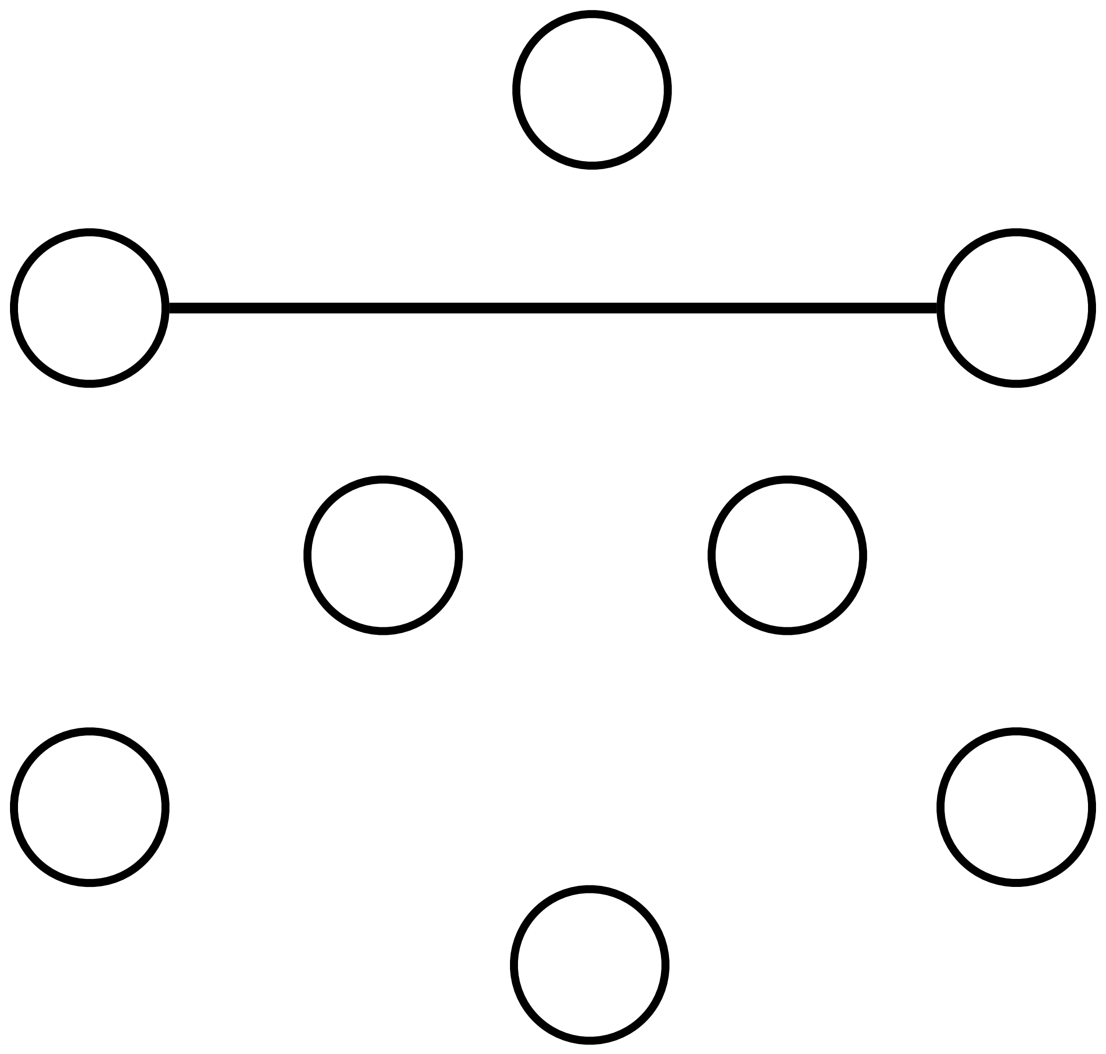

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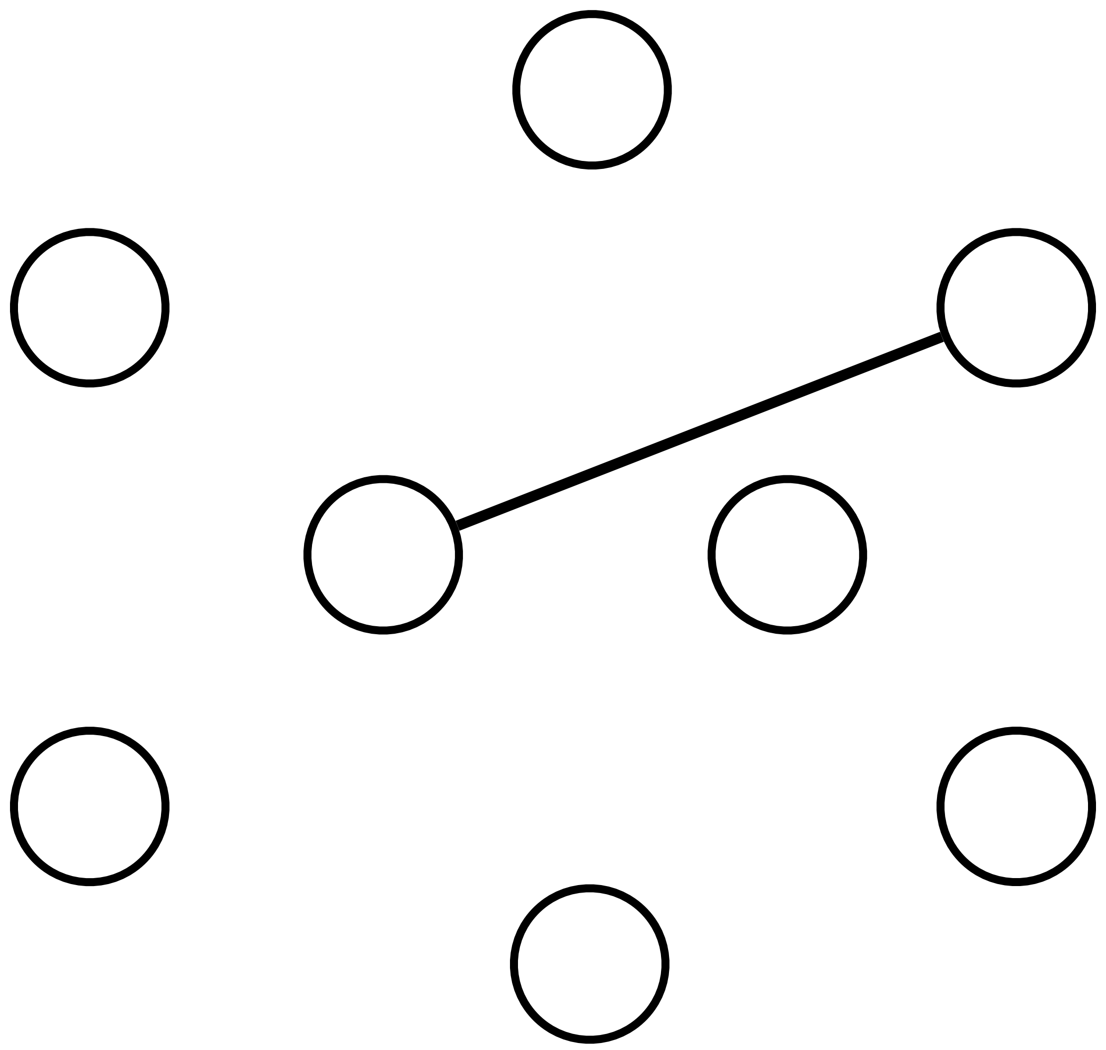

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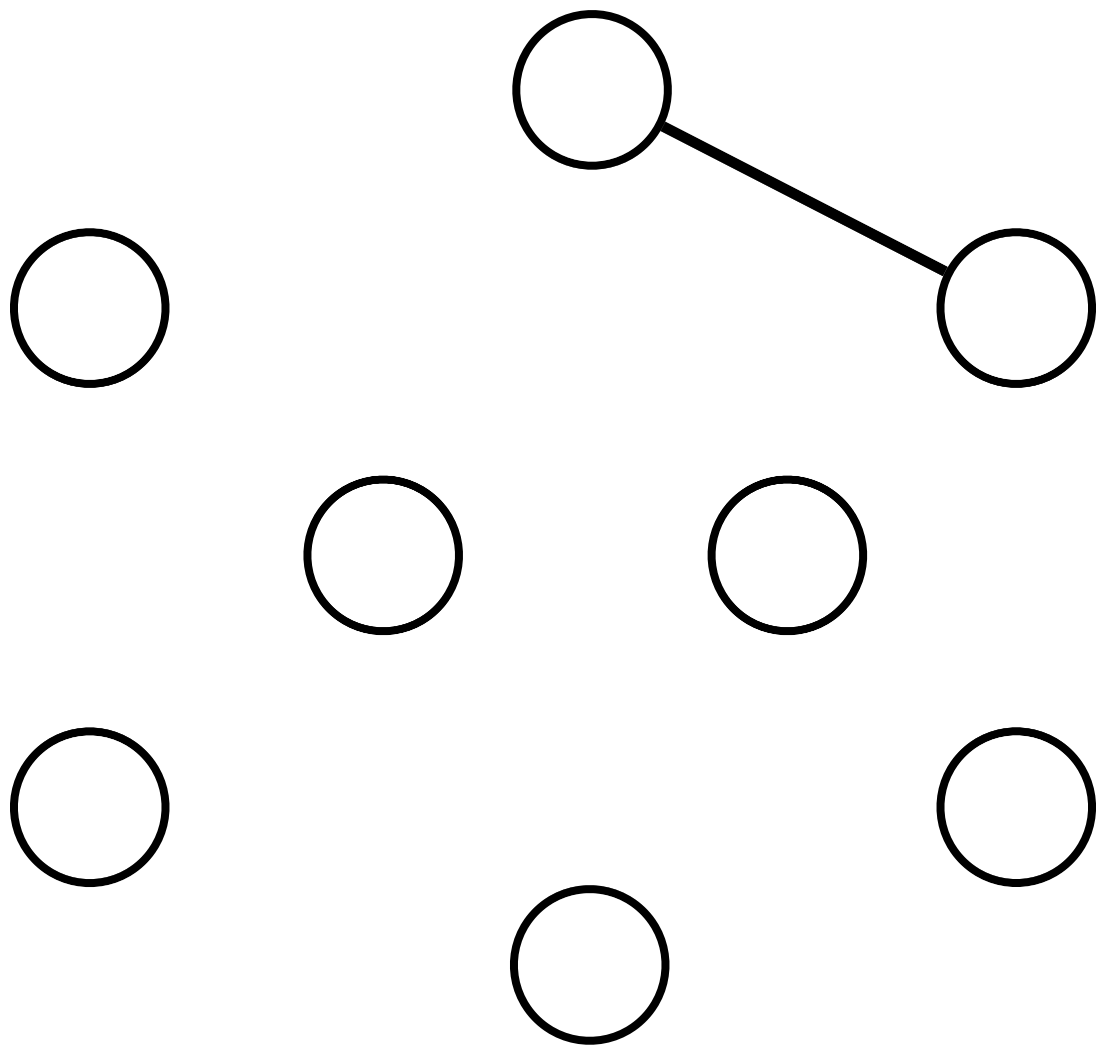

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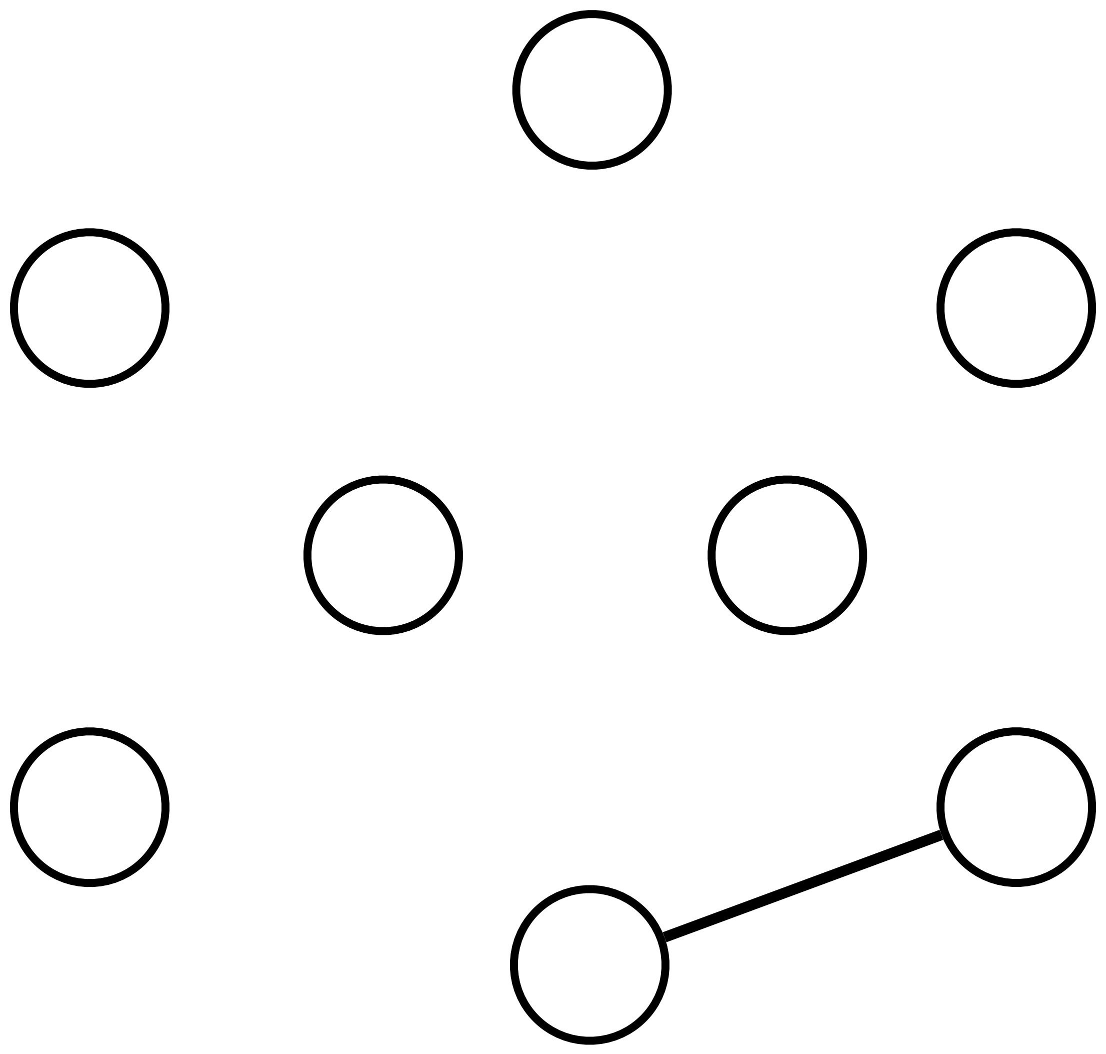

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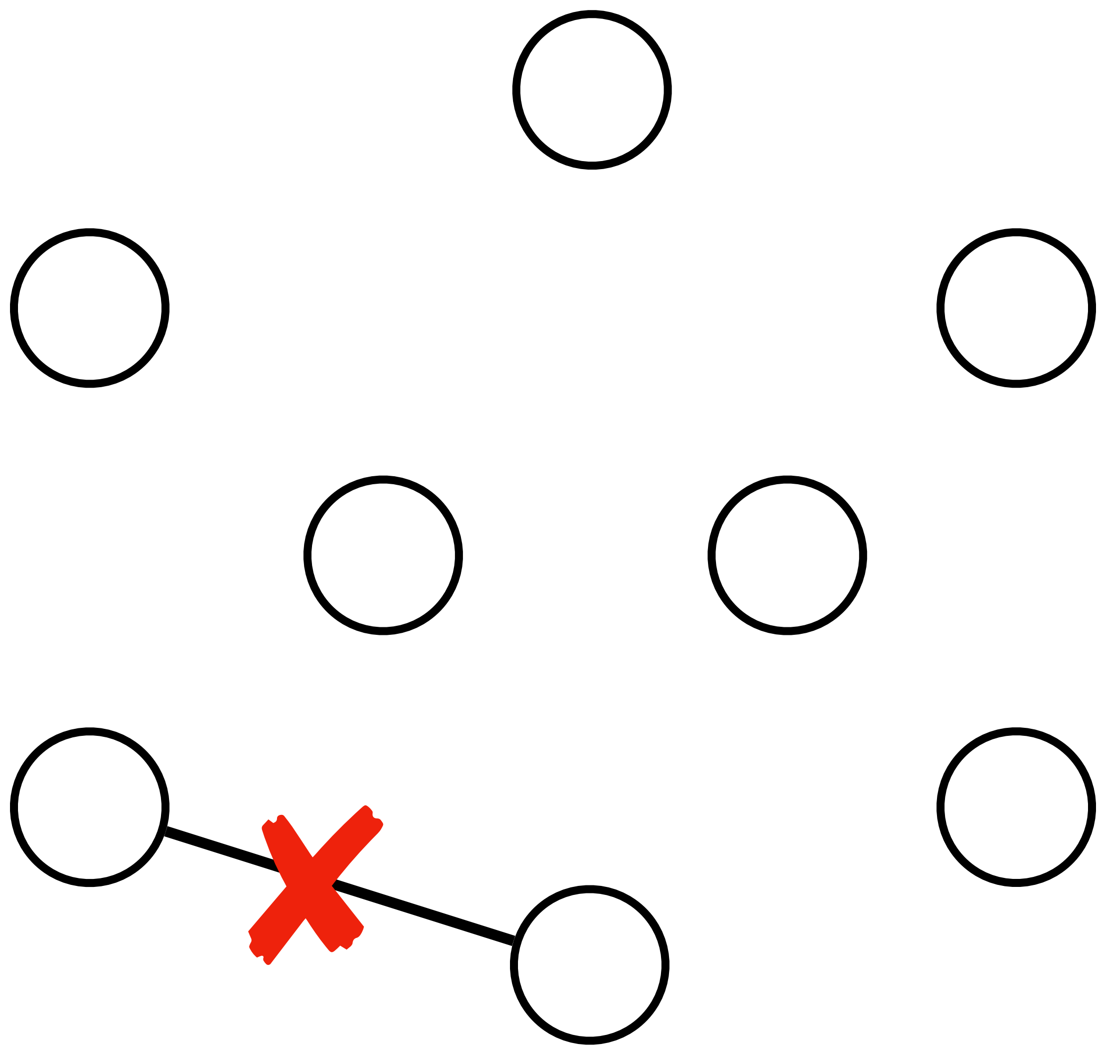

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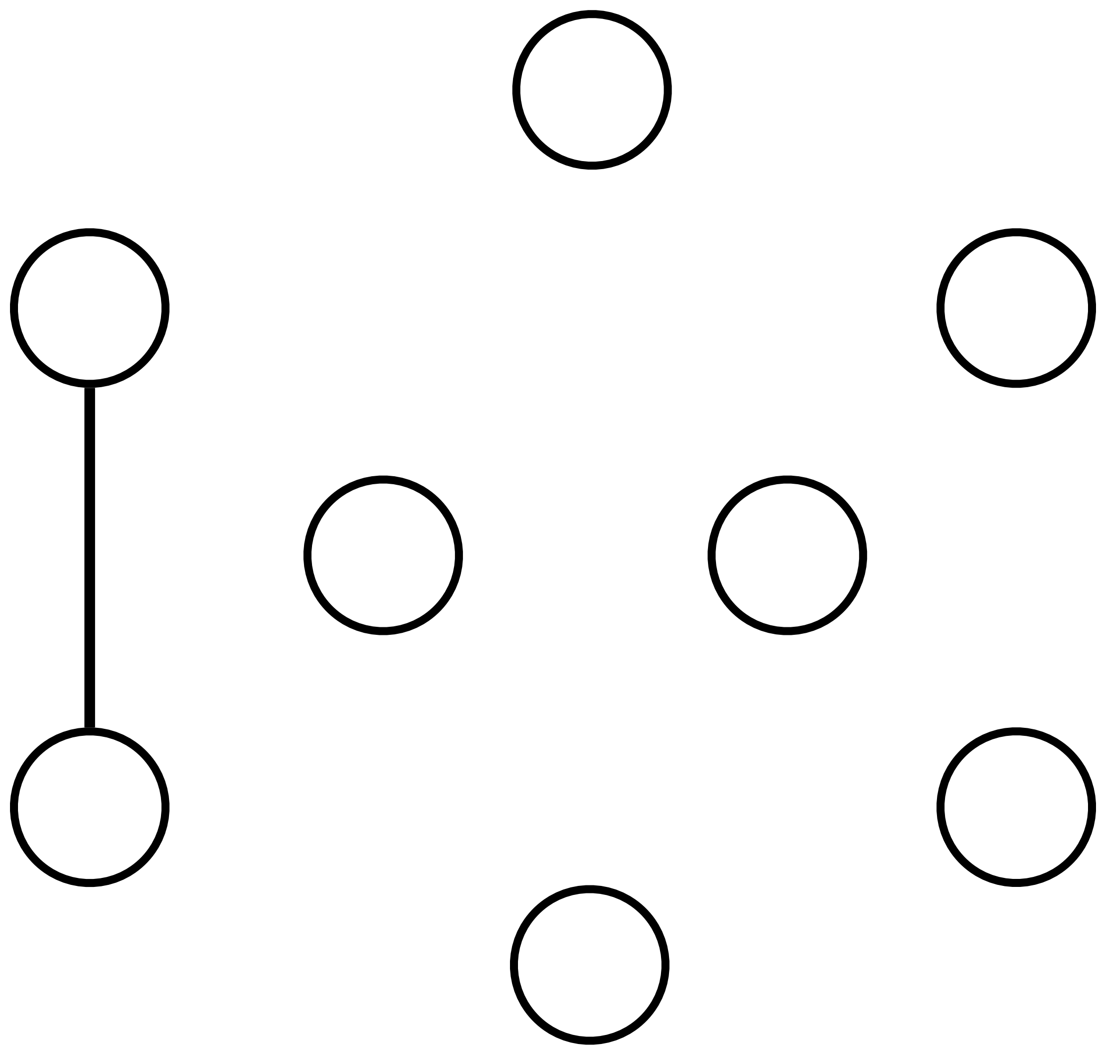

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- **Goal:** in **one pass**, using **small space**, compute the solution

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What if we can obtain extra information about the input?

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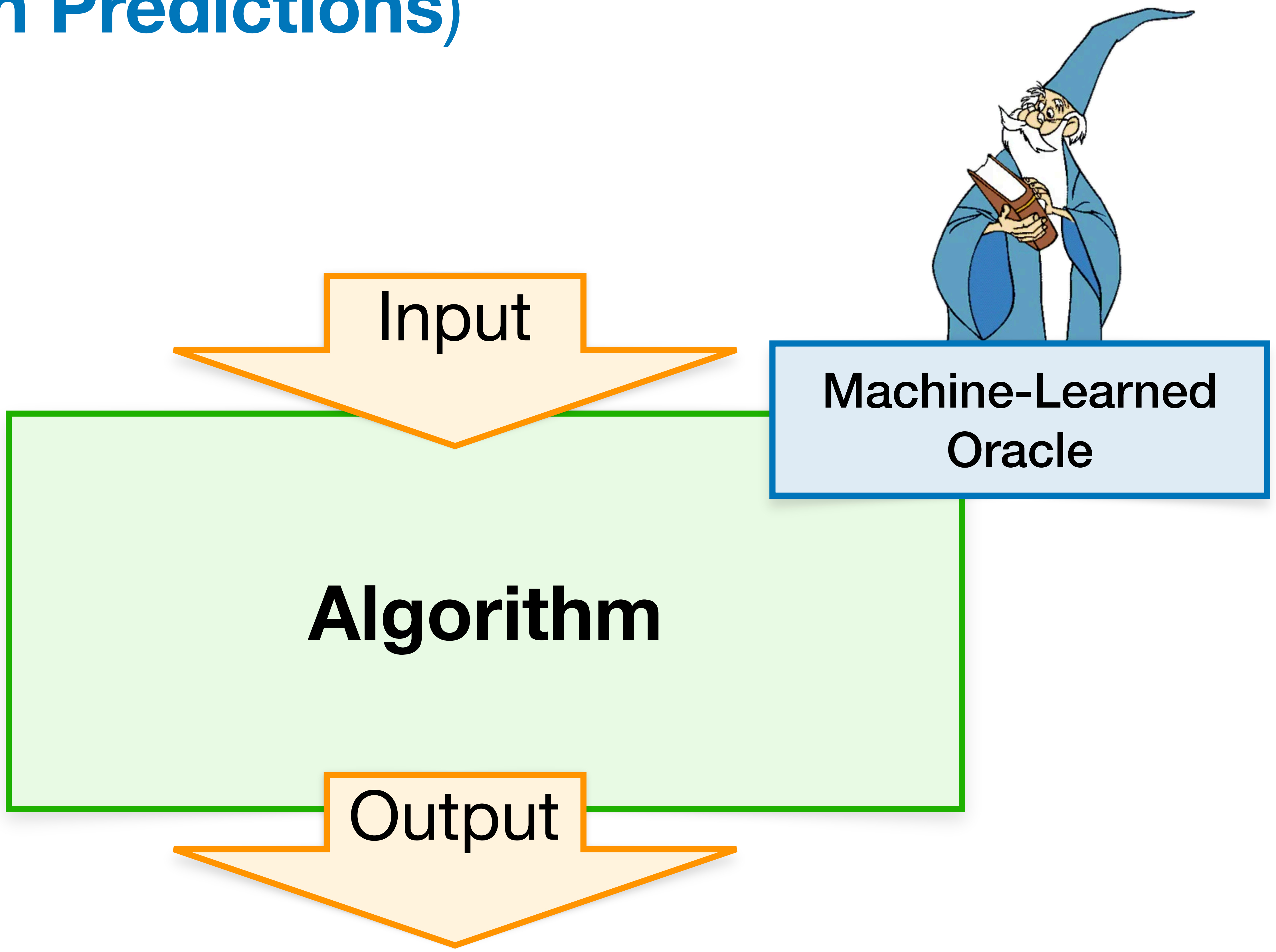

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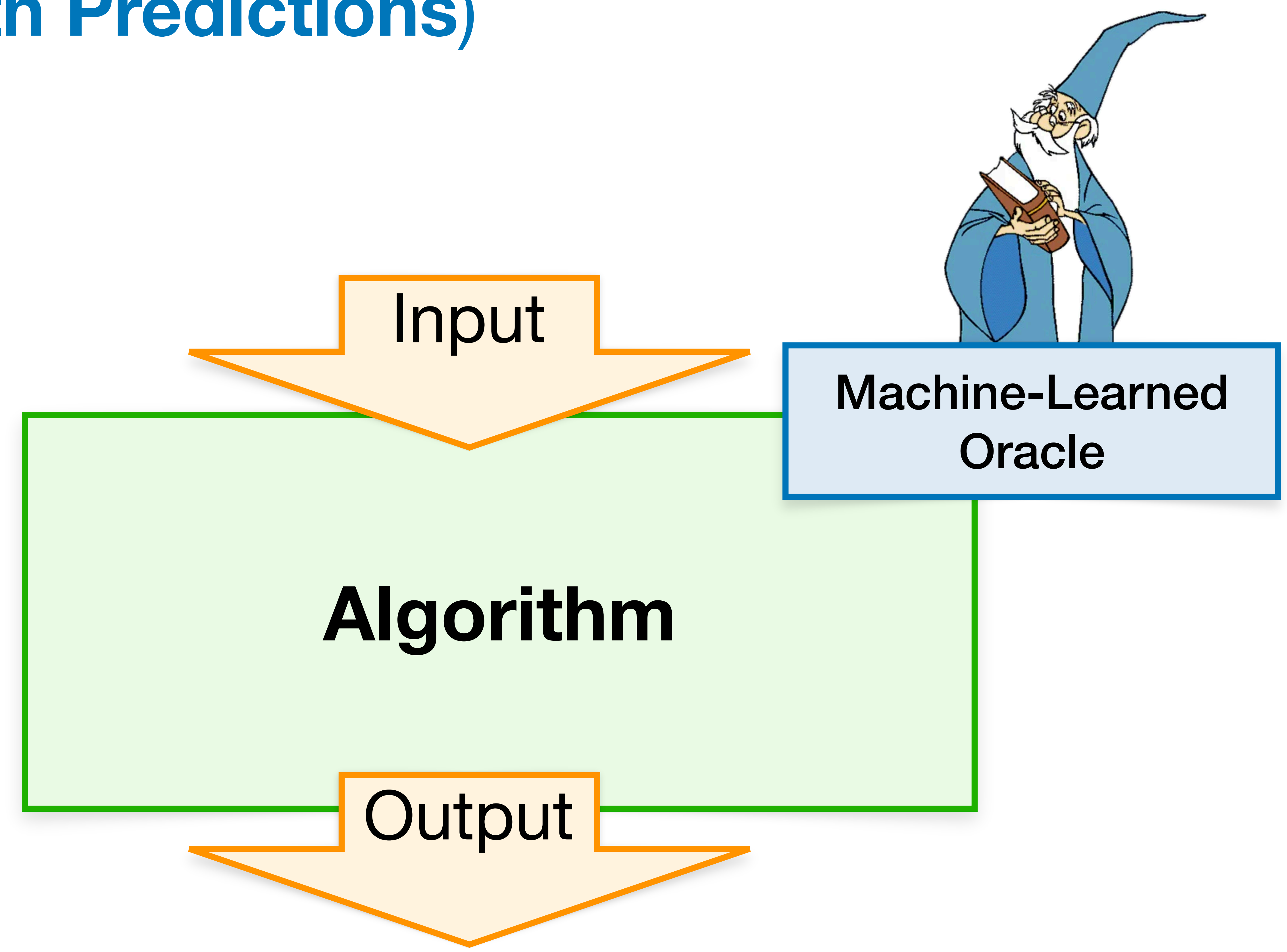

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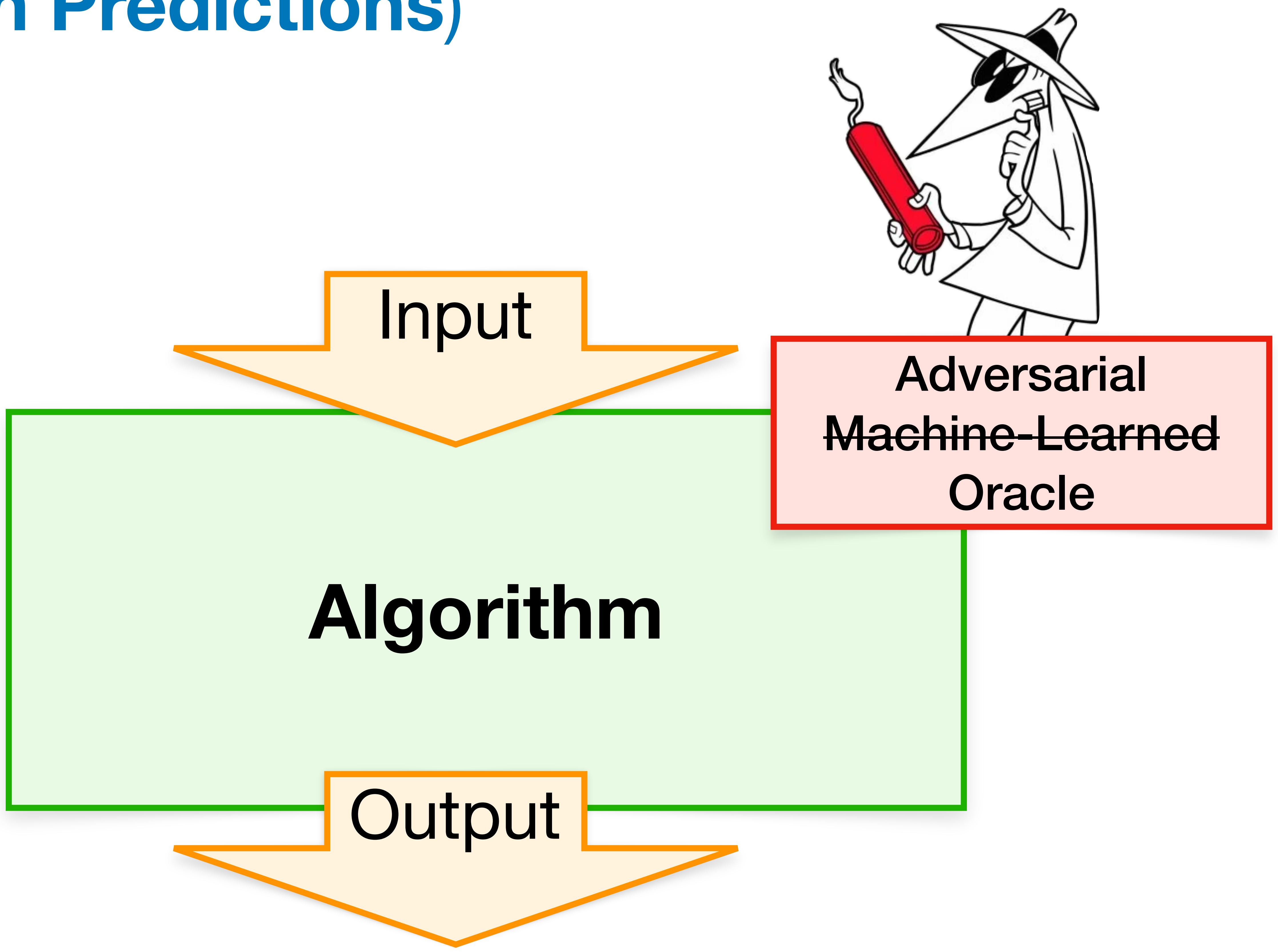

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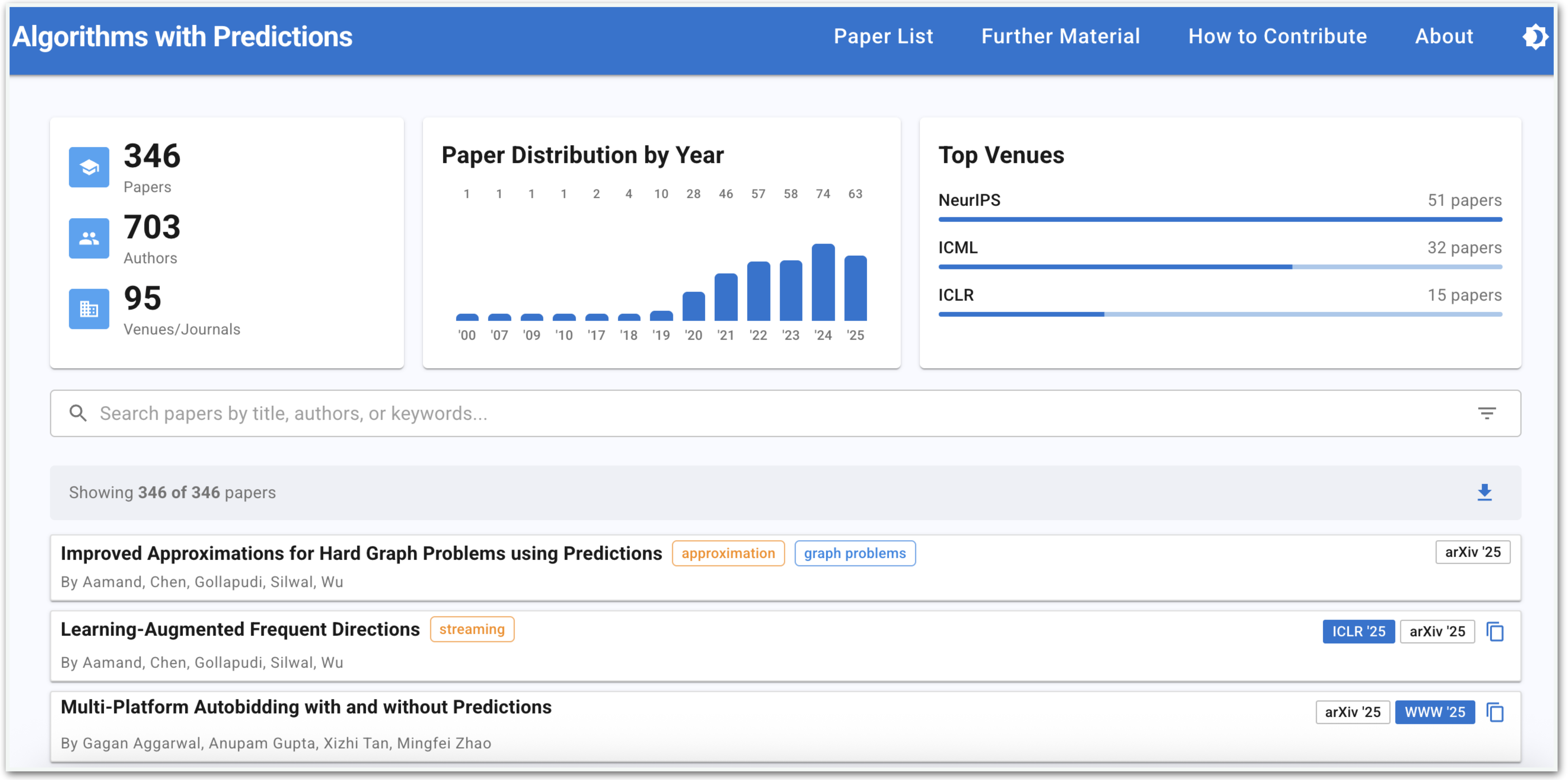

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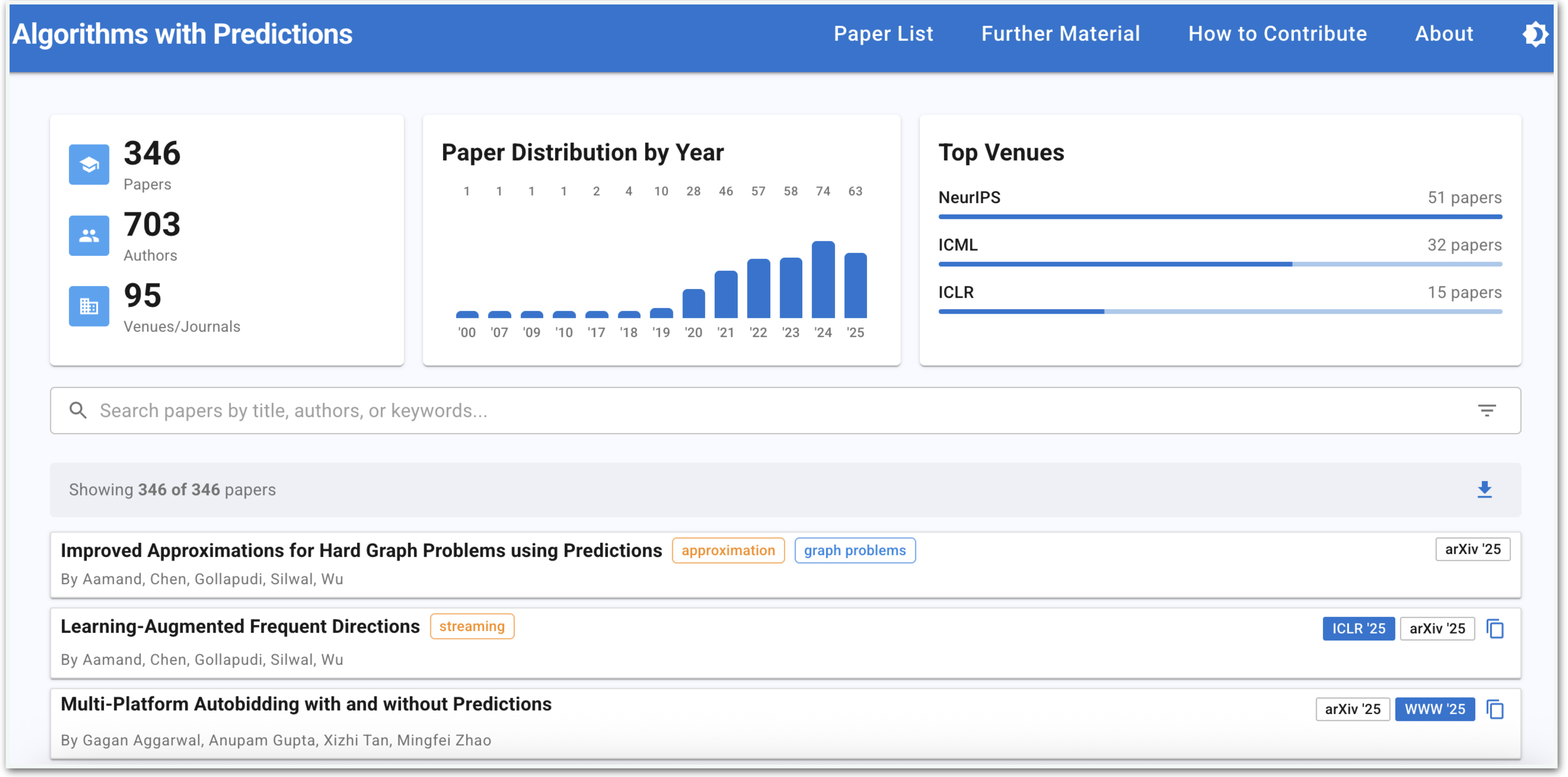

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How to define predictions?

Our Prediction Model

- **ϵ-accurate predictions** [Cohen-Addad, d'Orsi, Gupta, Lee, Panigrahi, NeurIPS'24] [Braverman, Dharangutte, Shah, Wang, APPROX'24] [Ghoshal, Makarychev, Makarychev, SODA'25]

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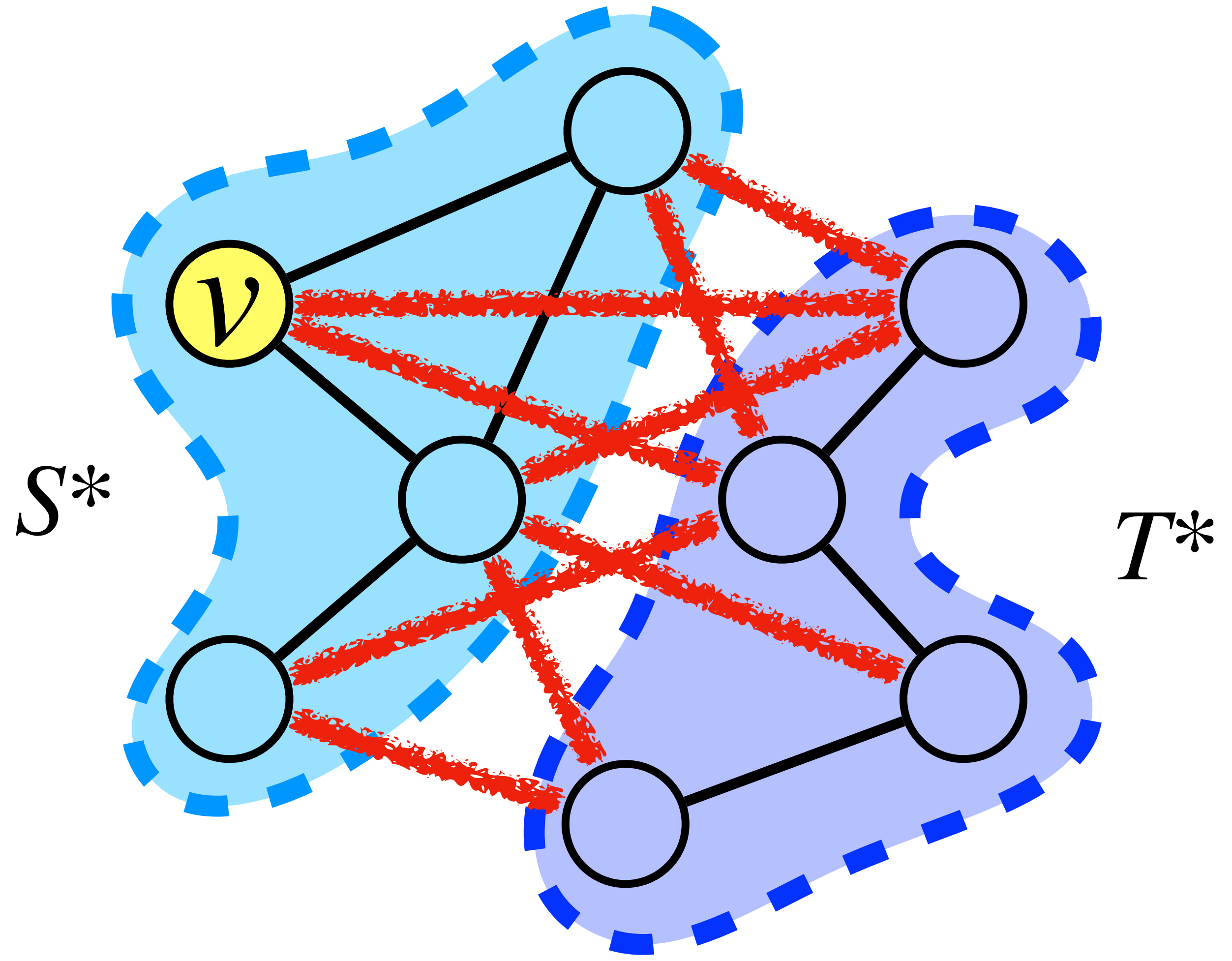

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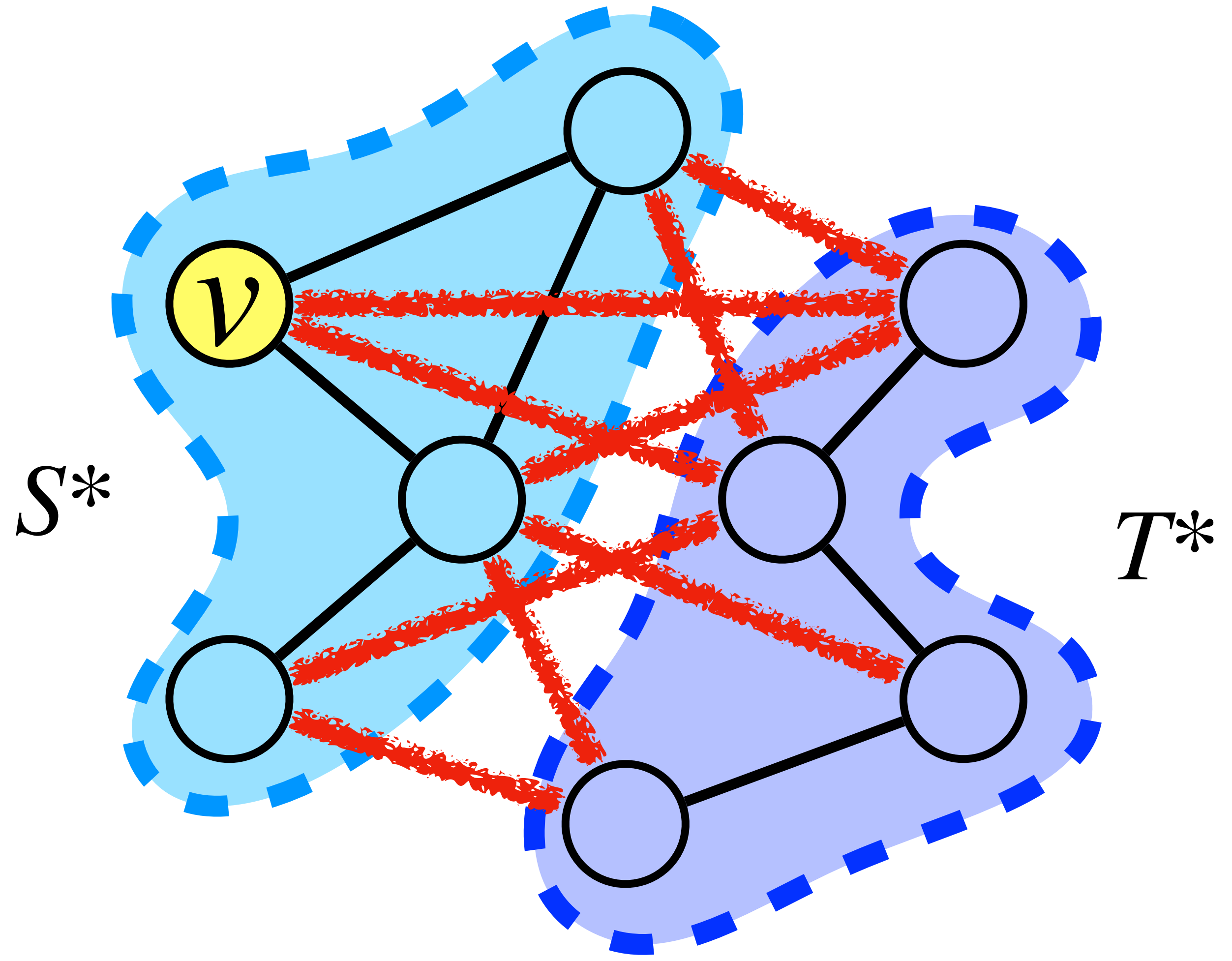

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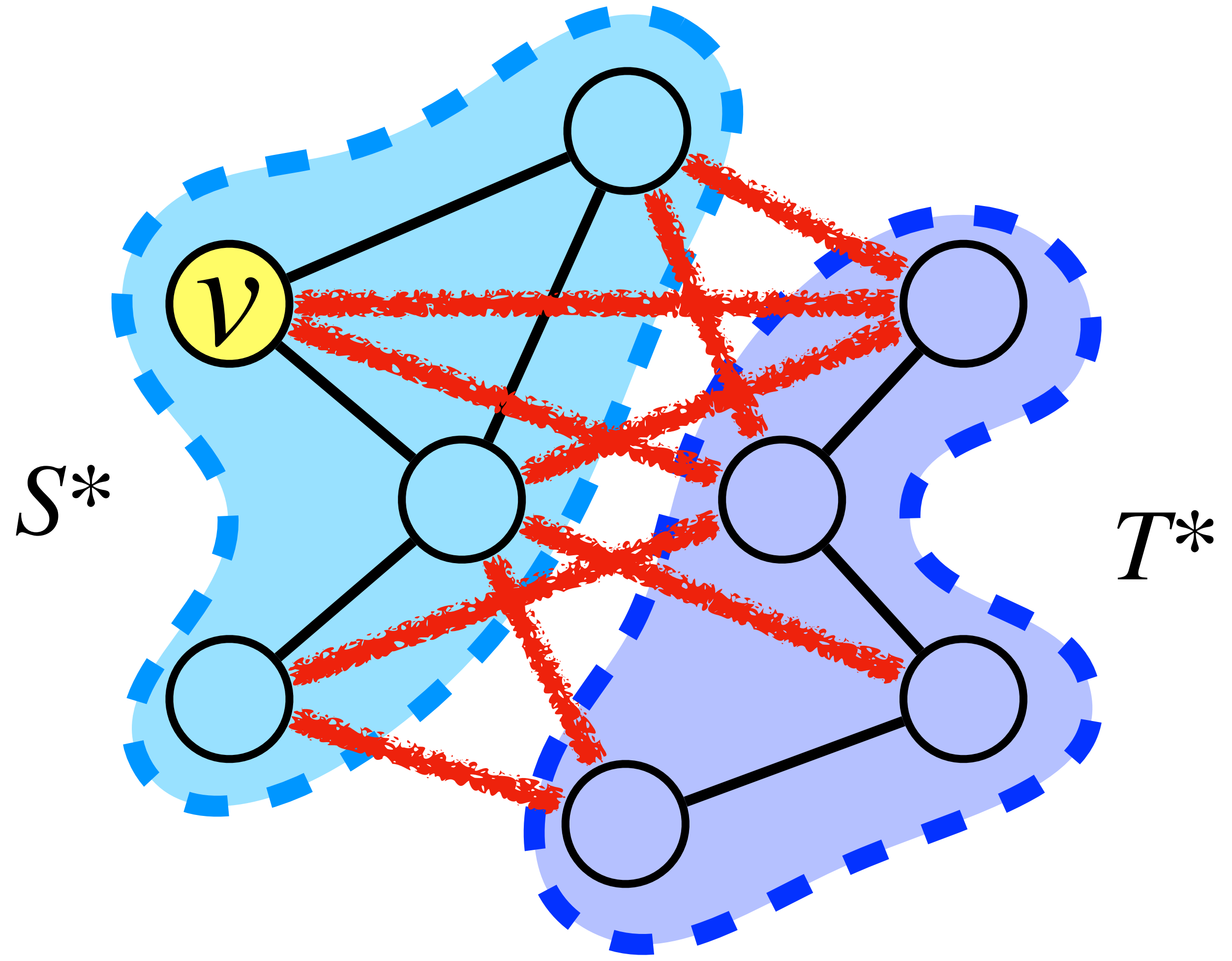

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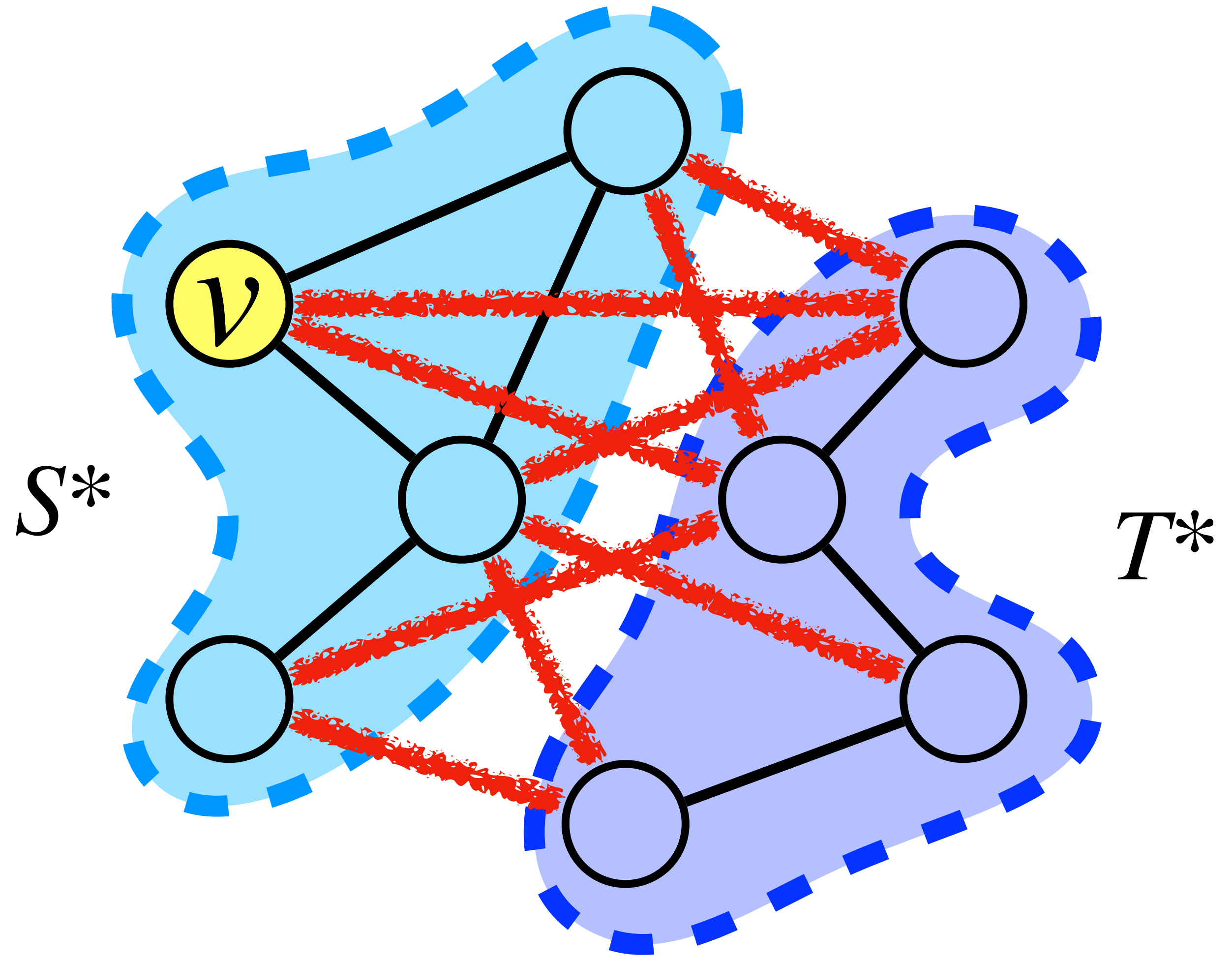

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Only slightly better than a random guess!

Our Results

Theorem [**D.**, Peng, Vakilian, ITCS'25]**:**
Given ϵ-accurate predictions, there exists a single-pass streaming algorithm achieving a $(1/2 + \Omega(\epsilon^2))$-approx with high probability, that uses

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- Bypass the classical $(1/2 + \epsilon)$-approx vs $\Omega_\epsilon(n)$ space trade-off [Kapralov, Krachun, STOC'19]
- No need to store predictions (only oracle access suffices)

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Algorithm for Low-Degree Graphs

- initially $X = 0$
- **for each** edge (u, v) in the stream **do**:
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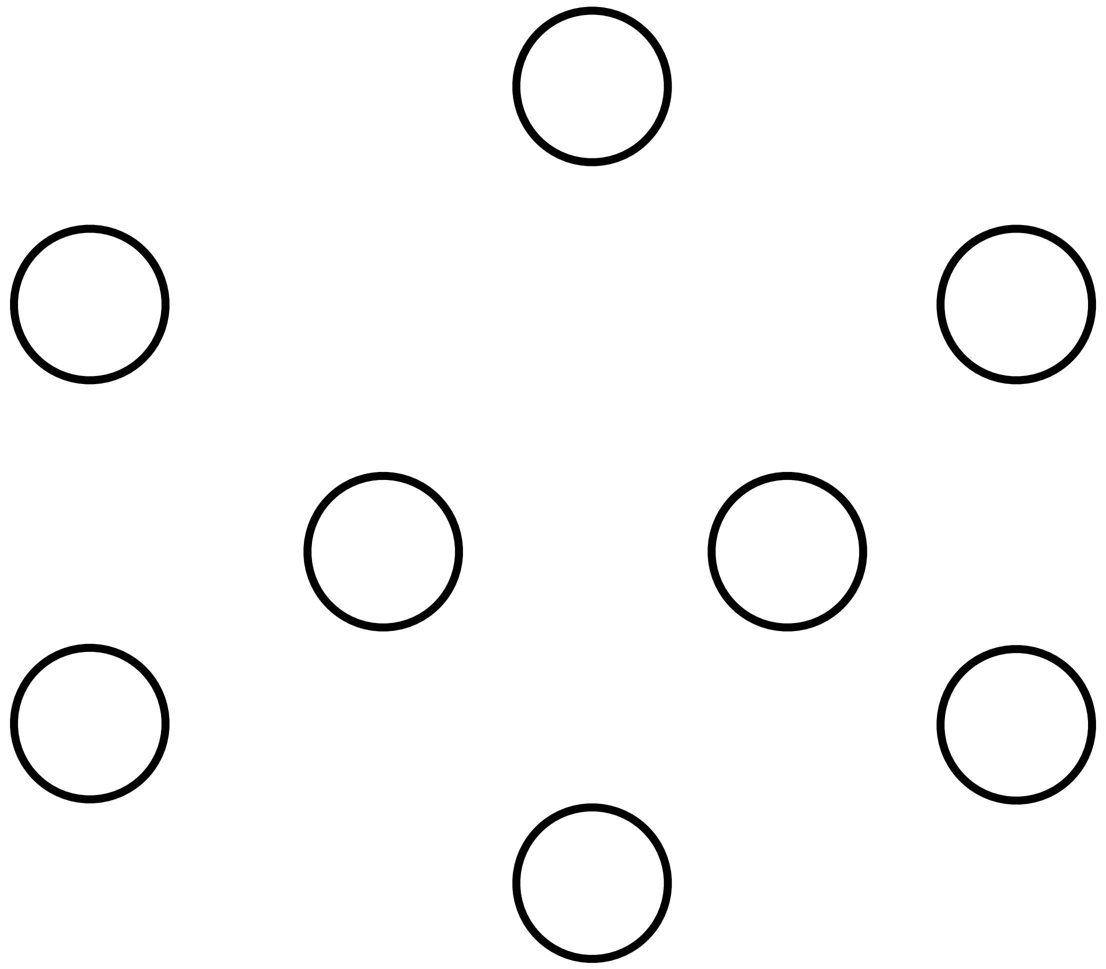

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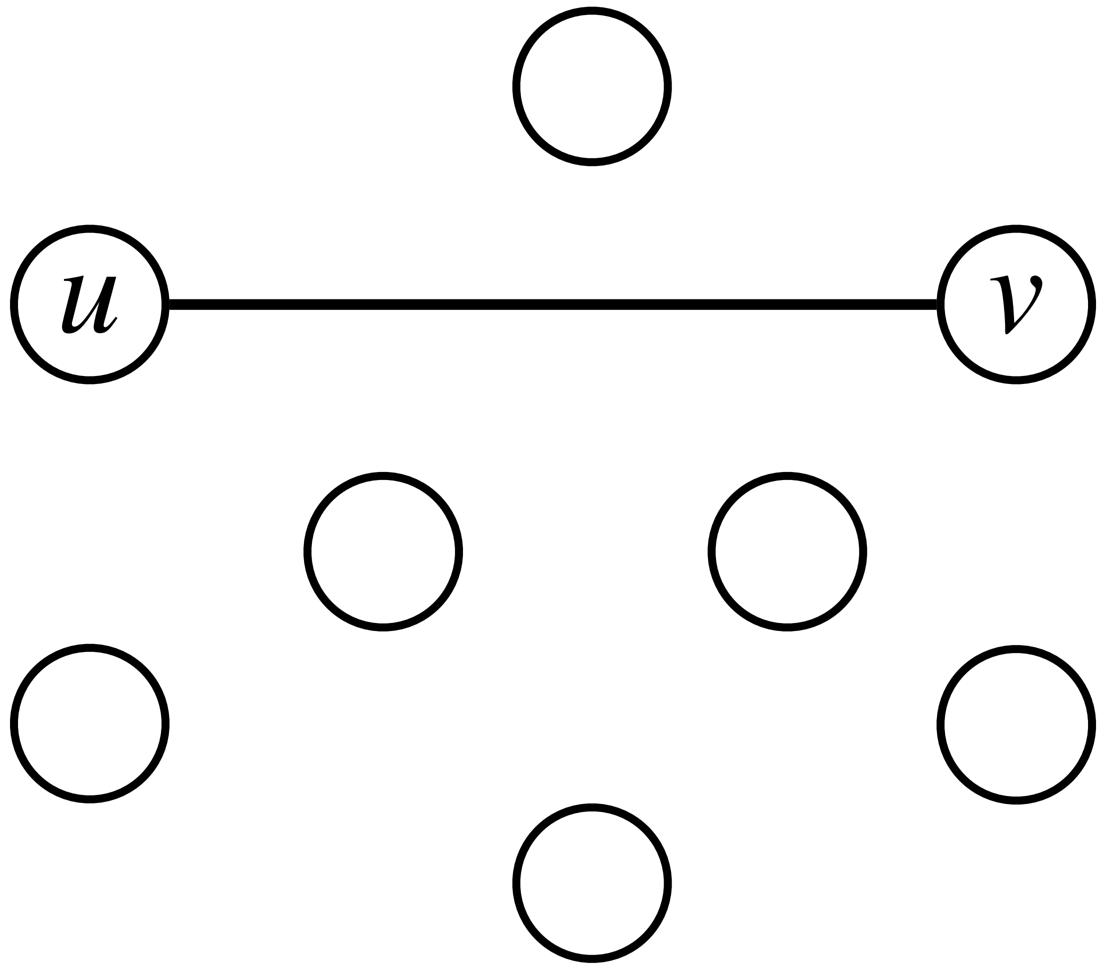

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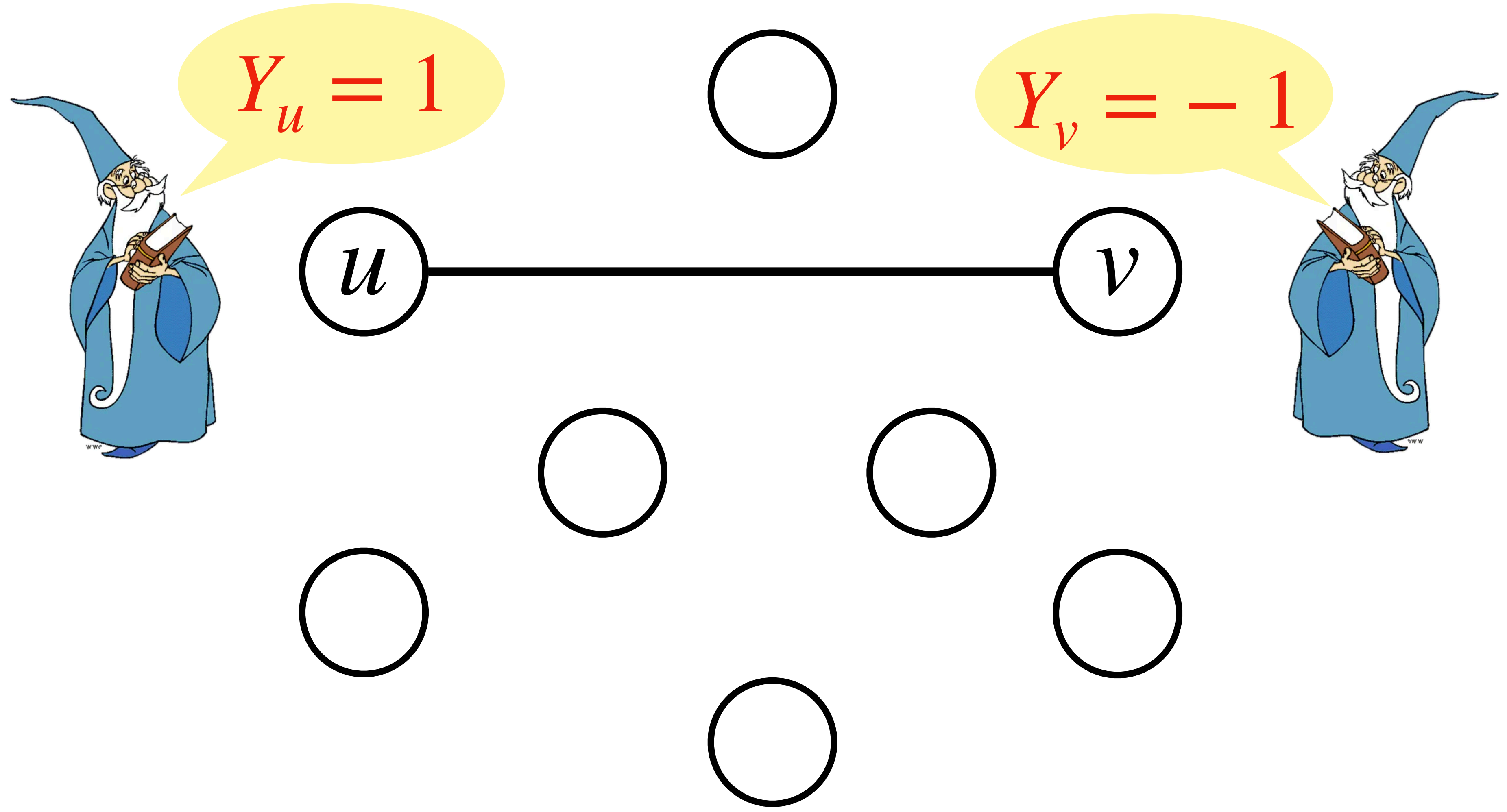

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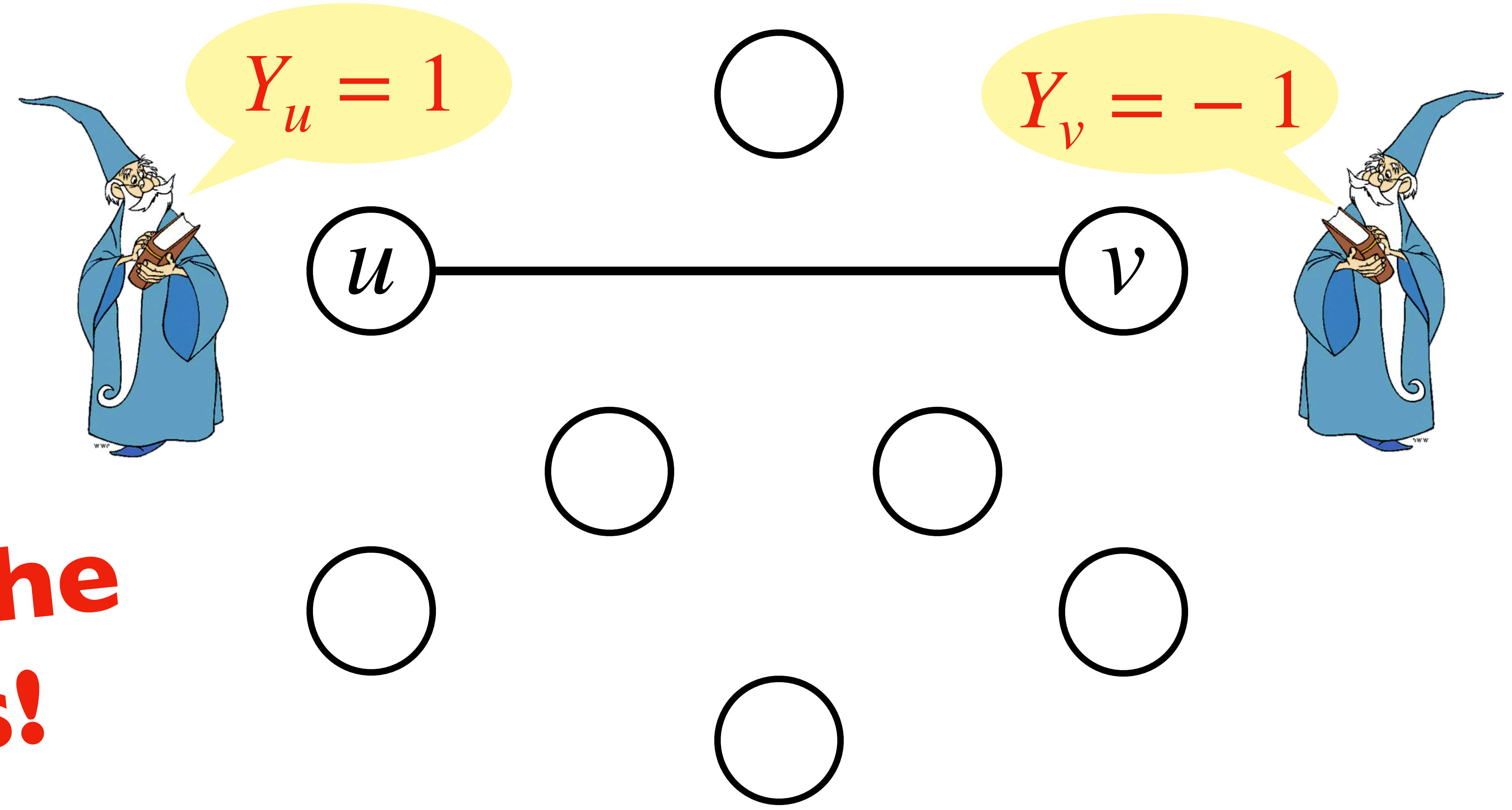

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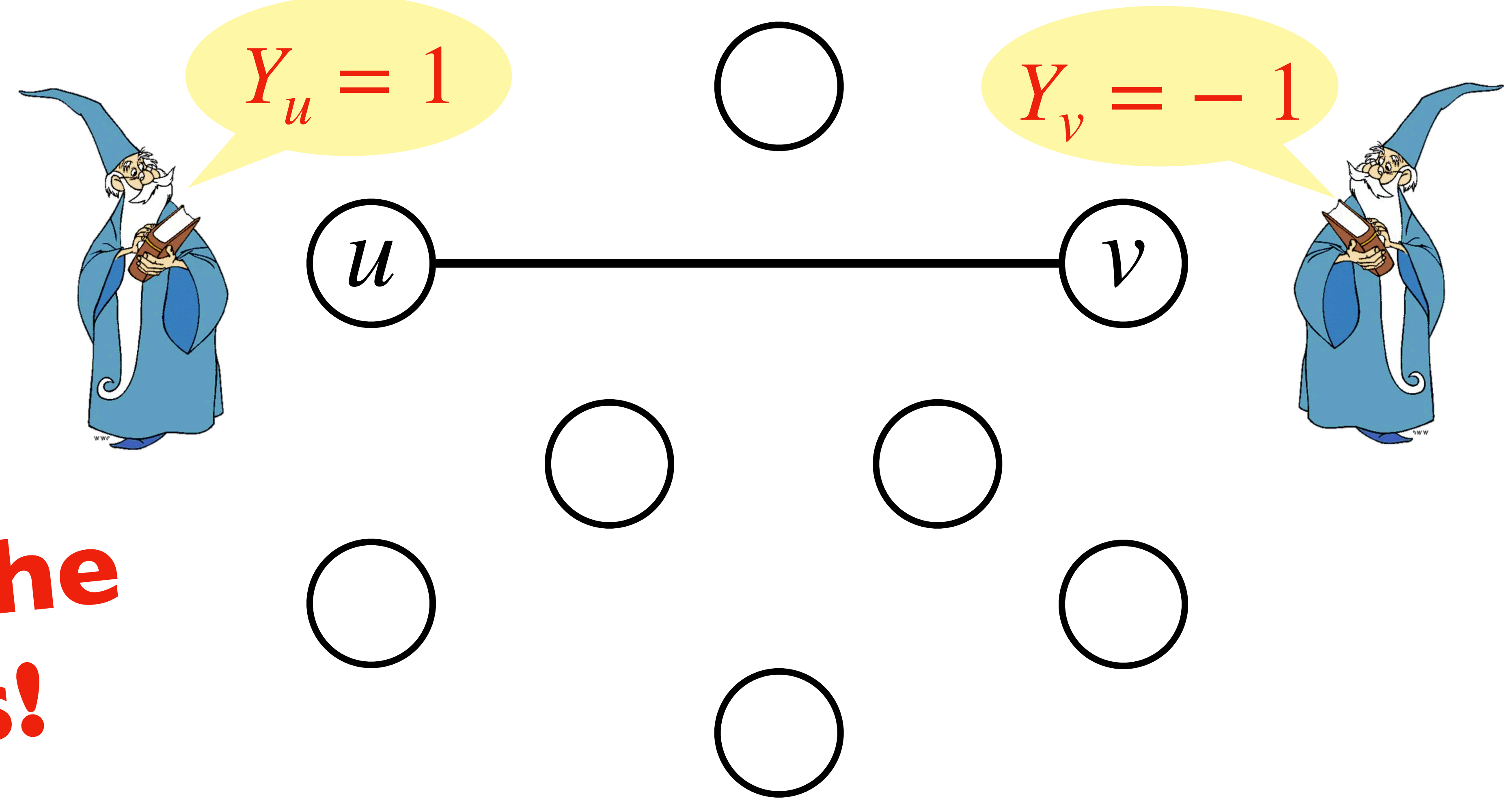


Just Follow the Predictions!

Observation:

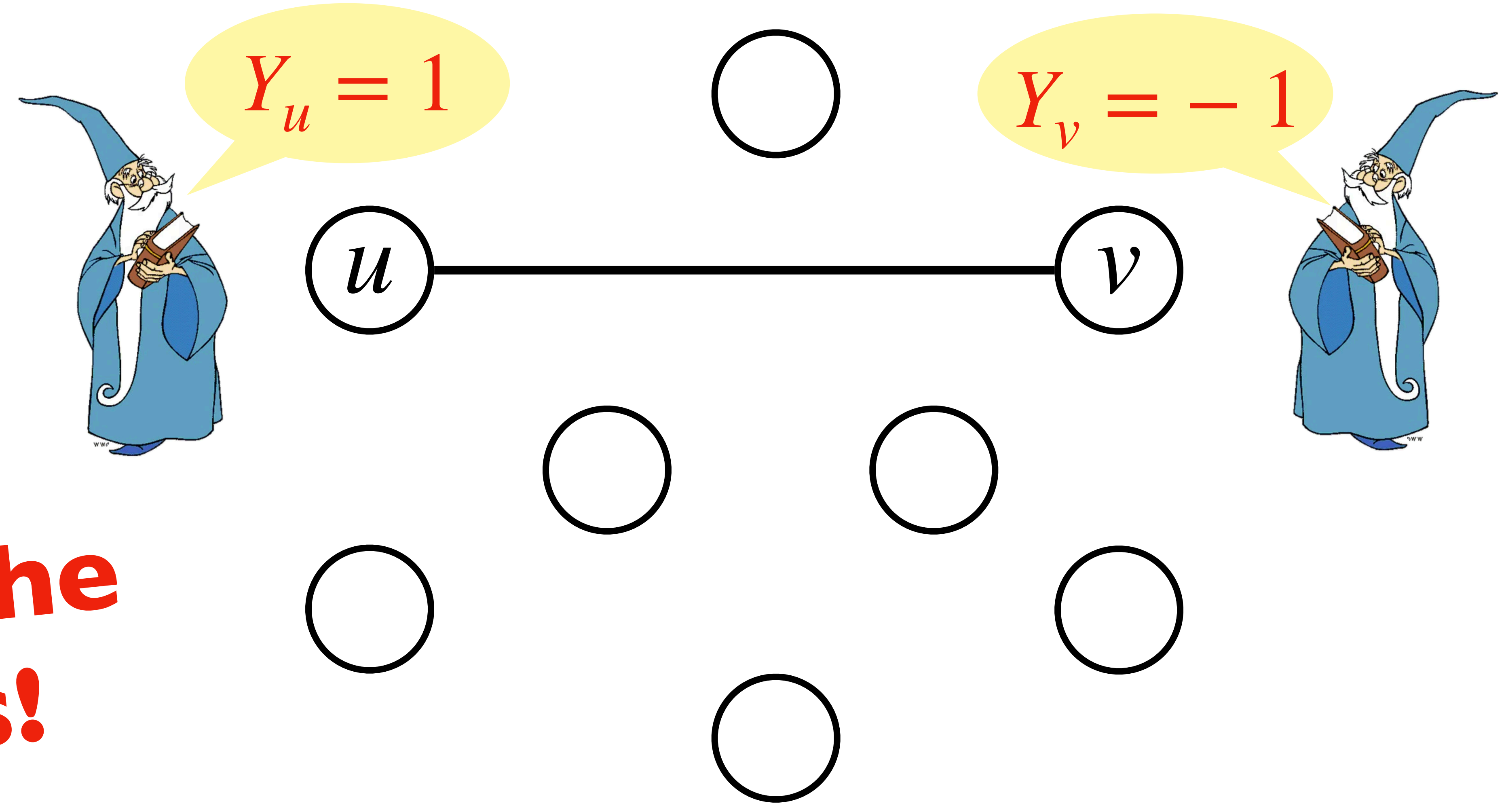
ϵ-accurate predictions $\xrightarrow{\text{w.p.} \geq 2/3}$ $(1/2 + \epsilon^2)$-approx., $O(1)$ words of space

Simple Case: Low-Degree Graphs

Low-Degree Graphs: Graphs with maximum degree $\Delta = \Theta(\epsilon^2 m)$

Algorithm for Low-Degree Graphs

- initially $X = 0$
- **for each** edge (u, v) in the stream **do**:
  - $Y_u = \mathcal{O}(u), Y_v = \mathcal{O}(v)$
  - if $Y_u \neq Y_v$ then $X = X + 1$
- **return** X



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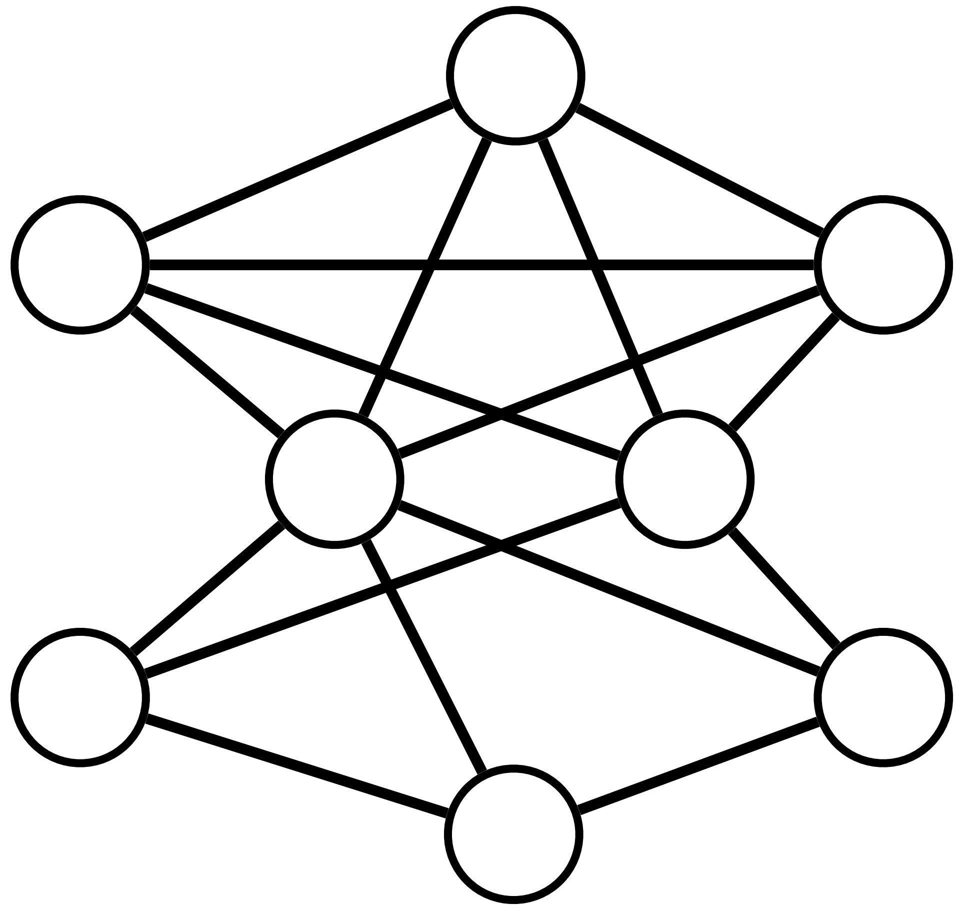
What to do in general graphs?

High-Level Overview of Our Algorithm

High-Level Overview of Our Algorithm

Offline Algorithm for General Graphs



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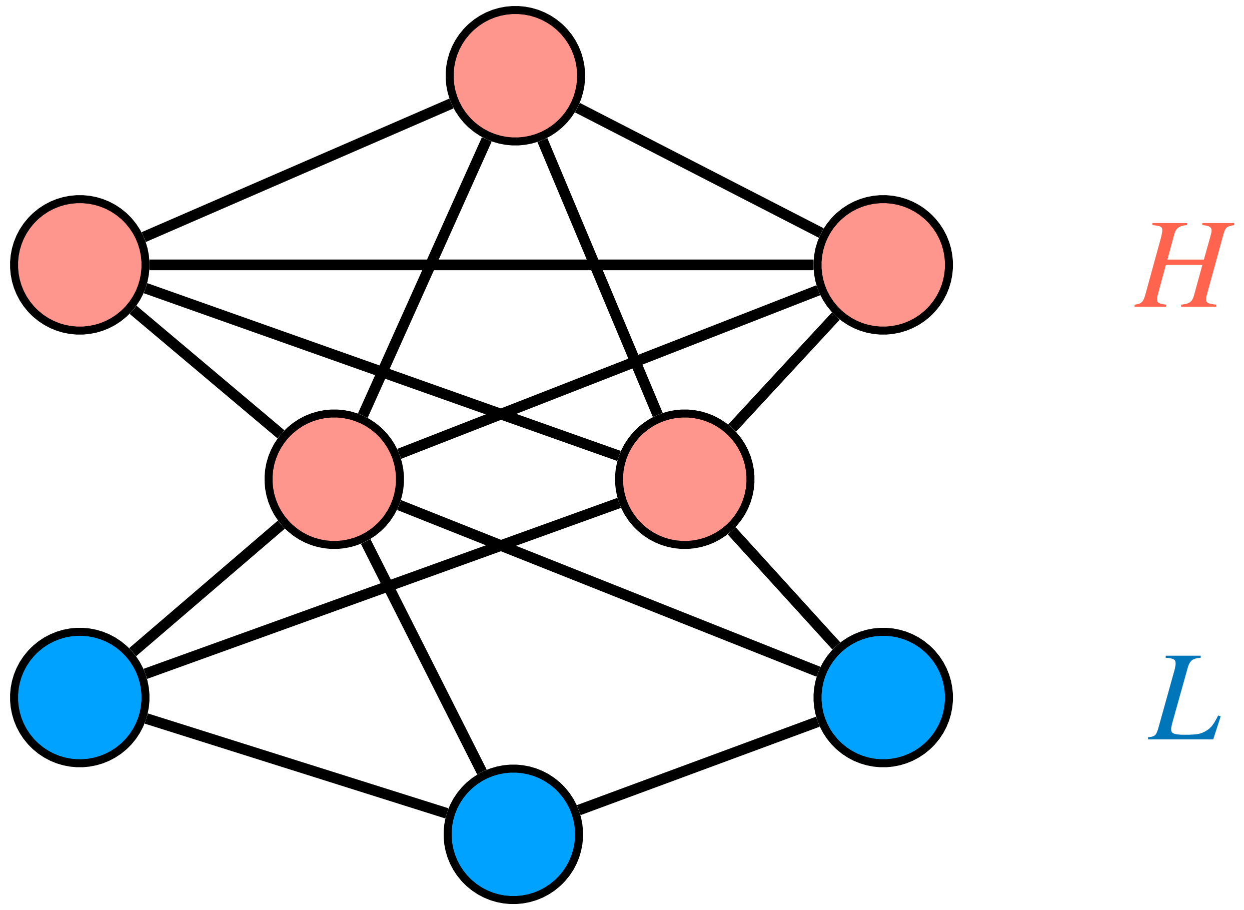

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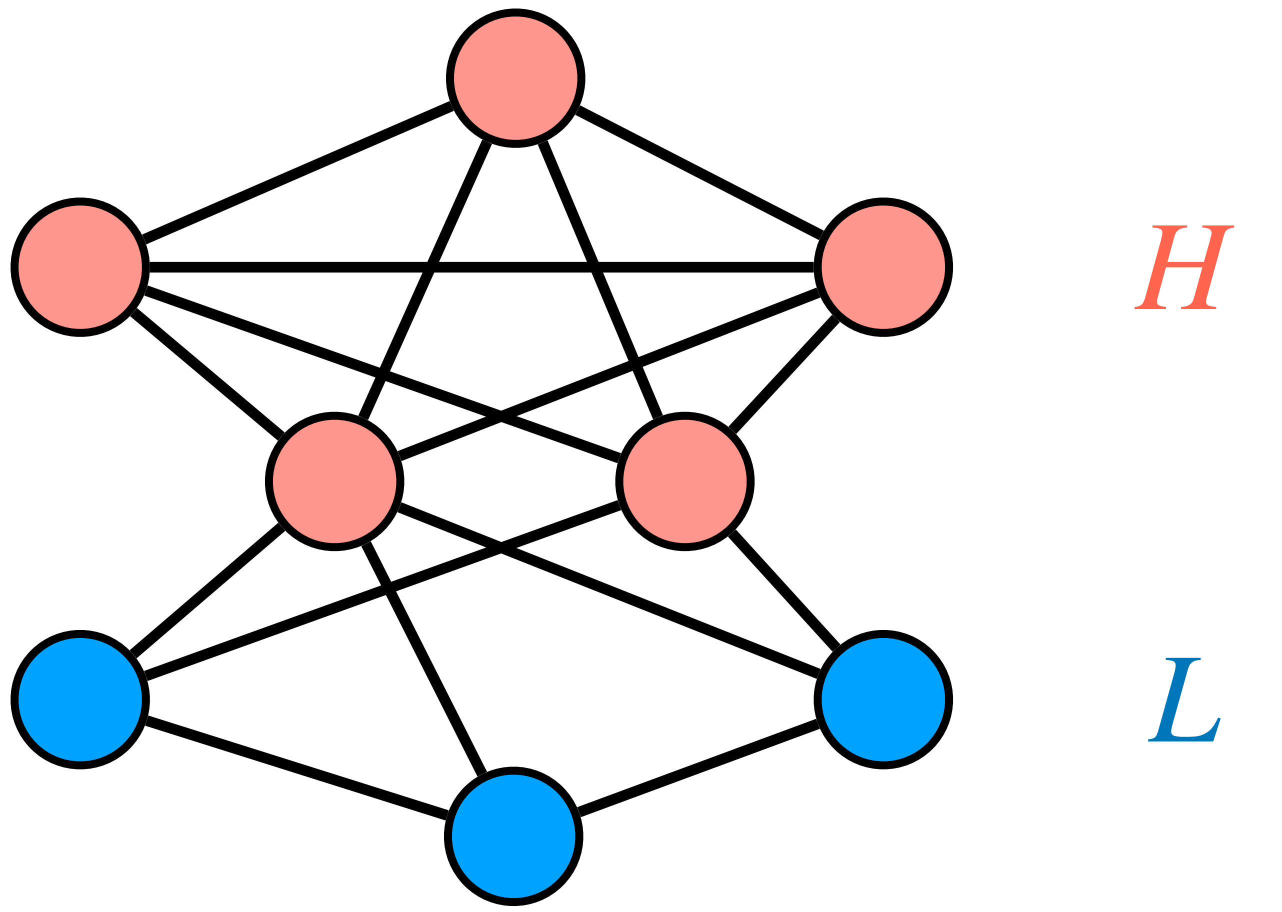

- Degree threshold is $\Theta(\epsilon^2 m)$, so
  - $|H| \leq 1/\epsilon^2$, and $|E(H)| < |H|^2 \leq 1/\epsilon^4$

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- Divide V into H (high-degree) and L (low-degree)
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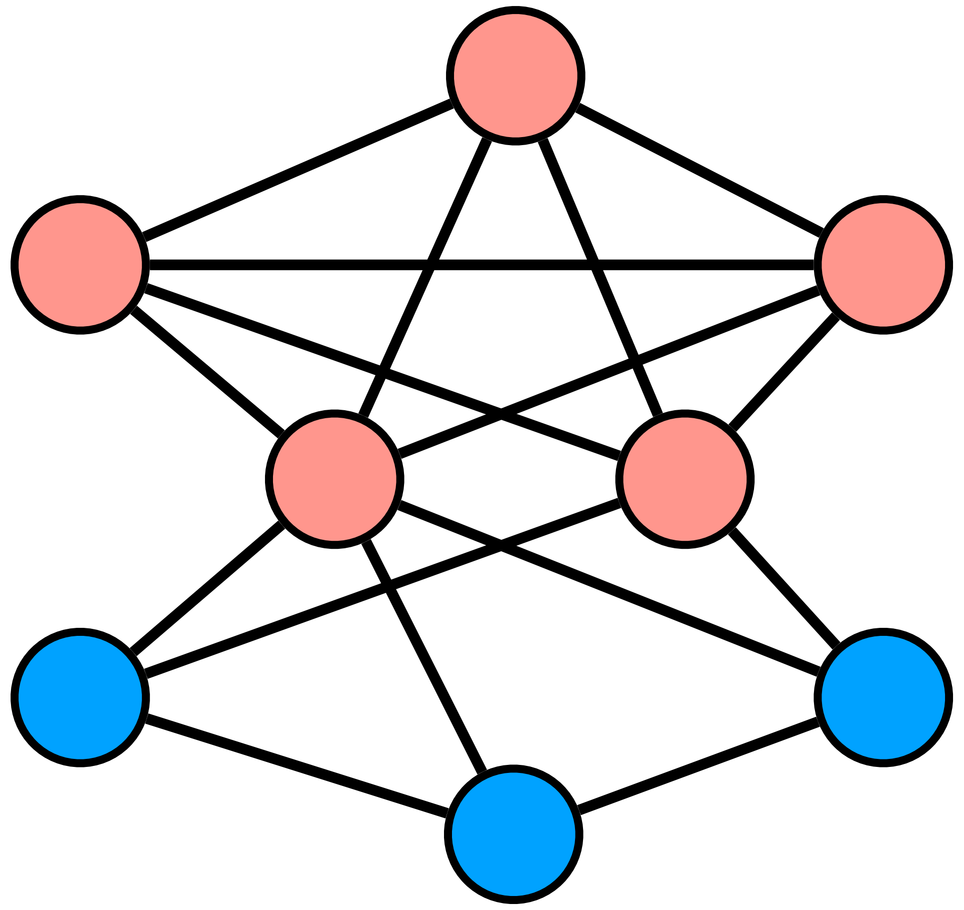

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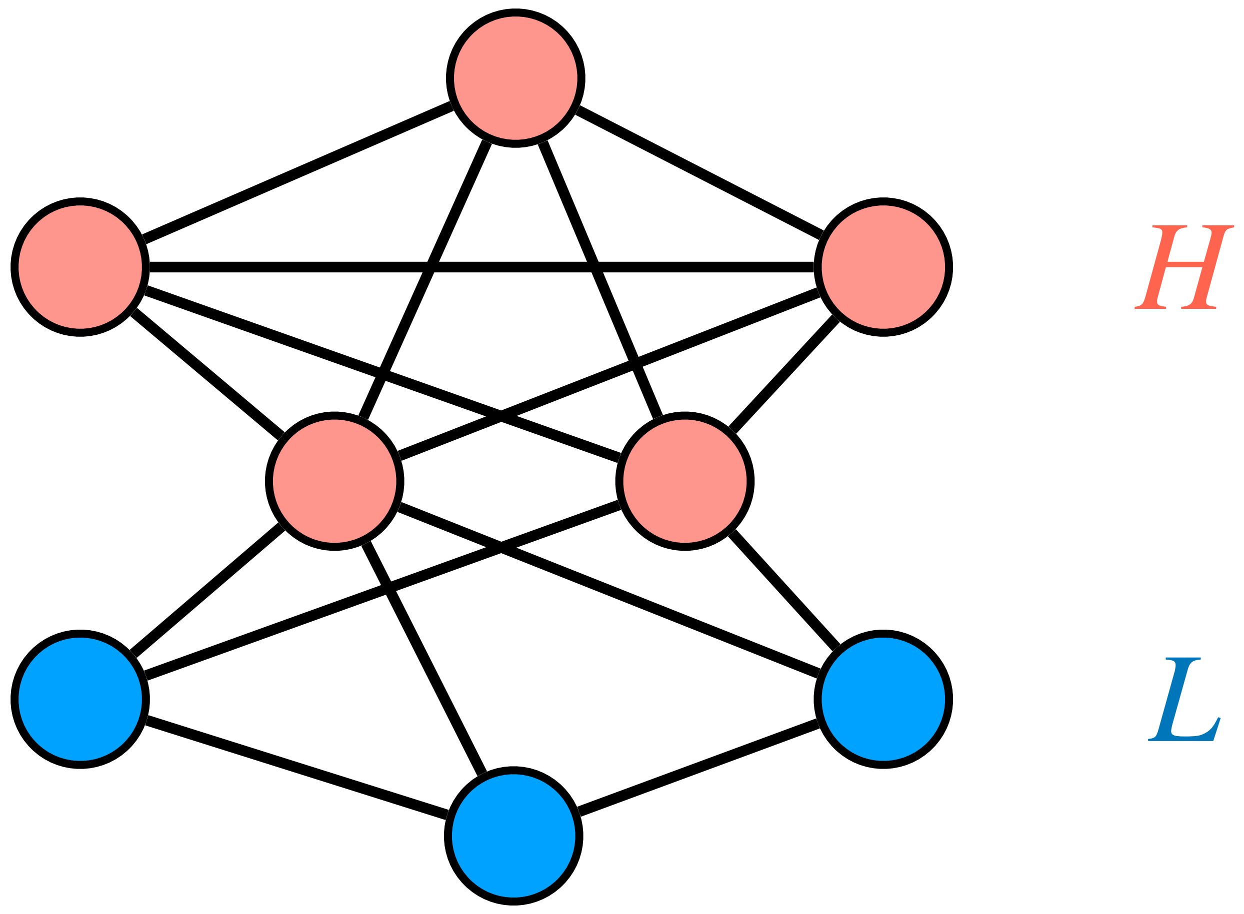

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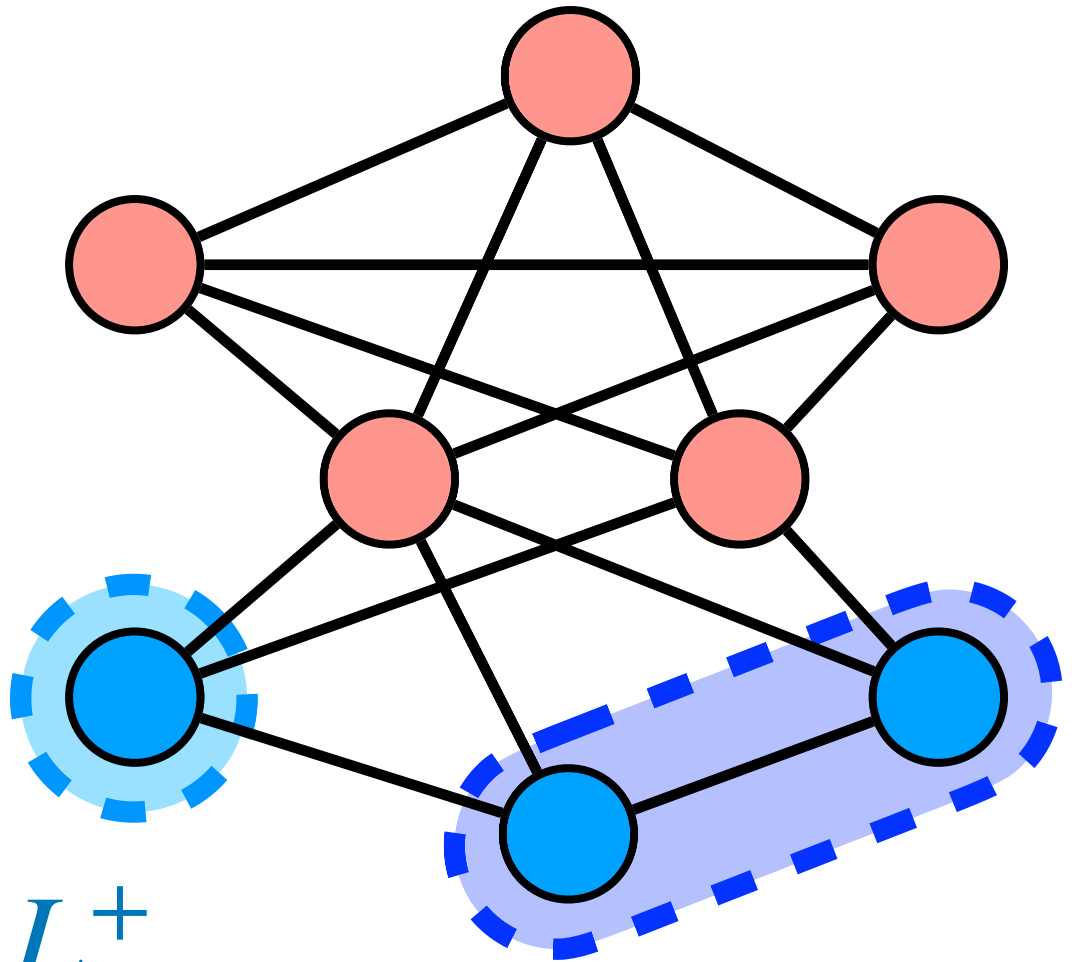

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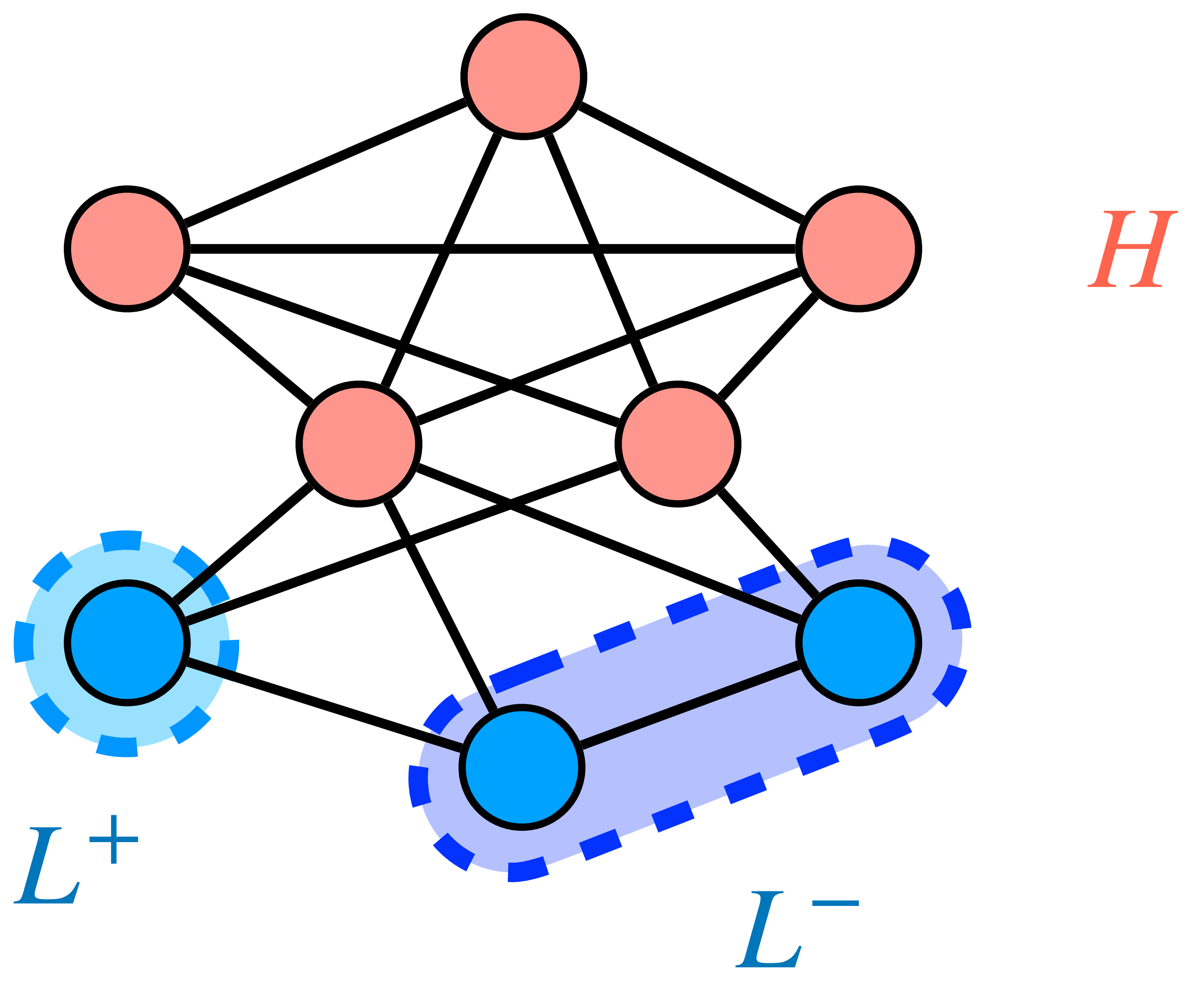

Observation on Low-Degree Graphs:

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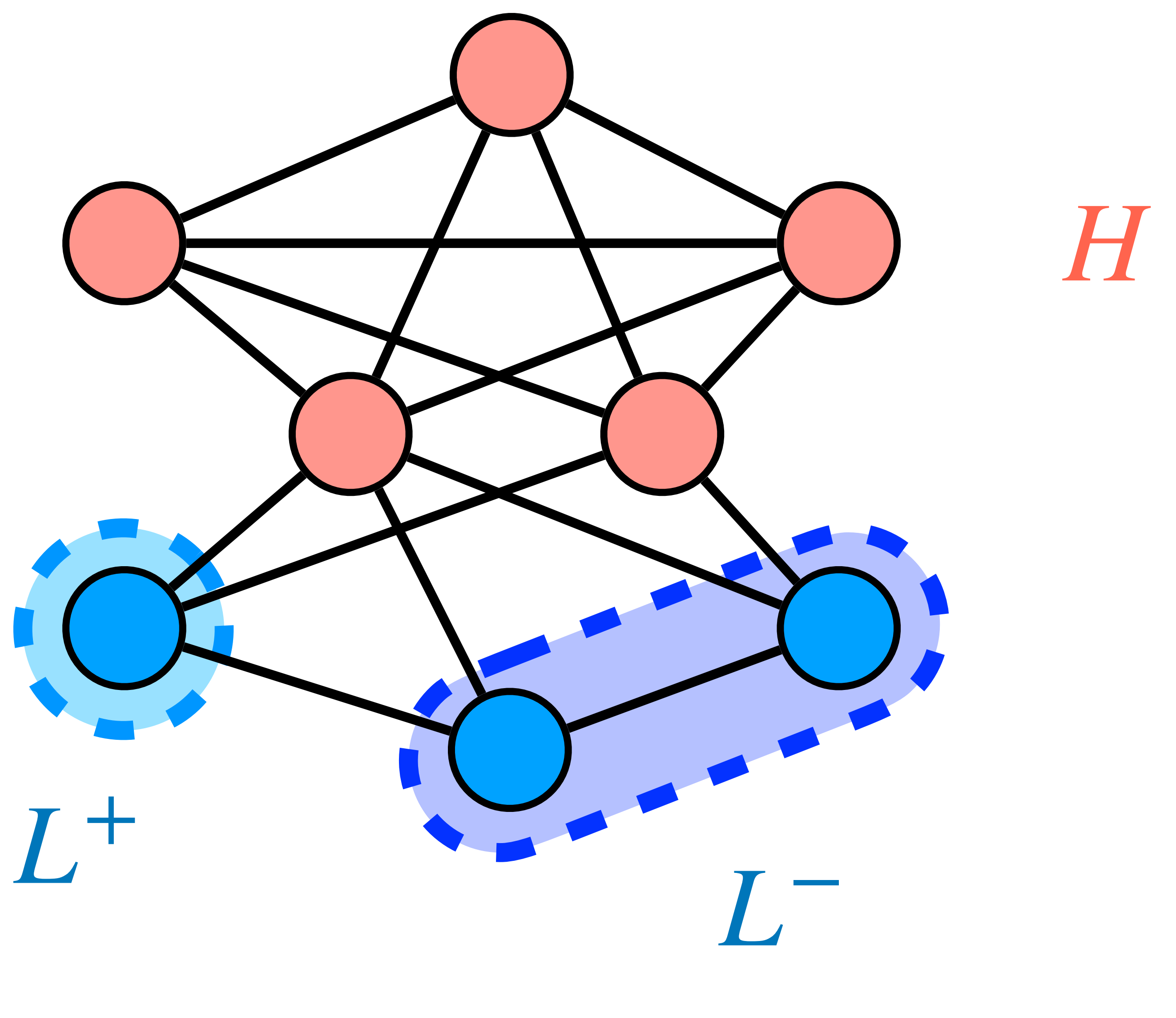

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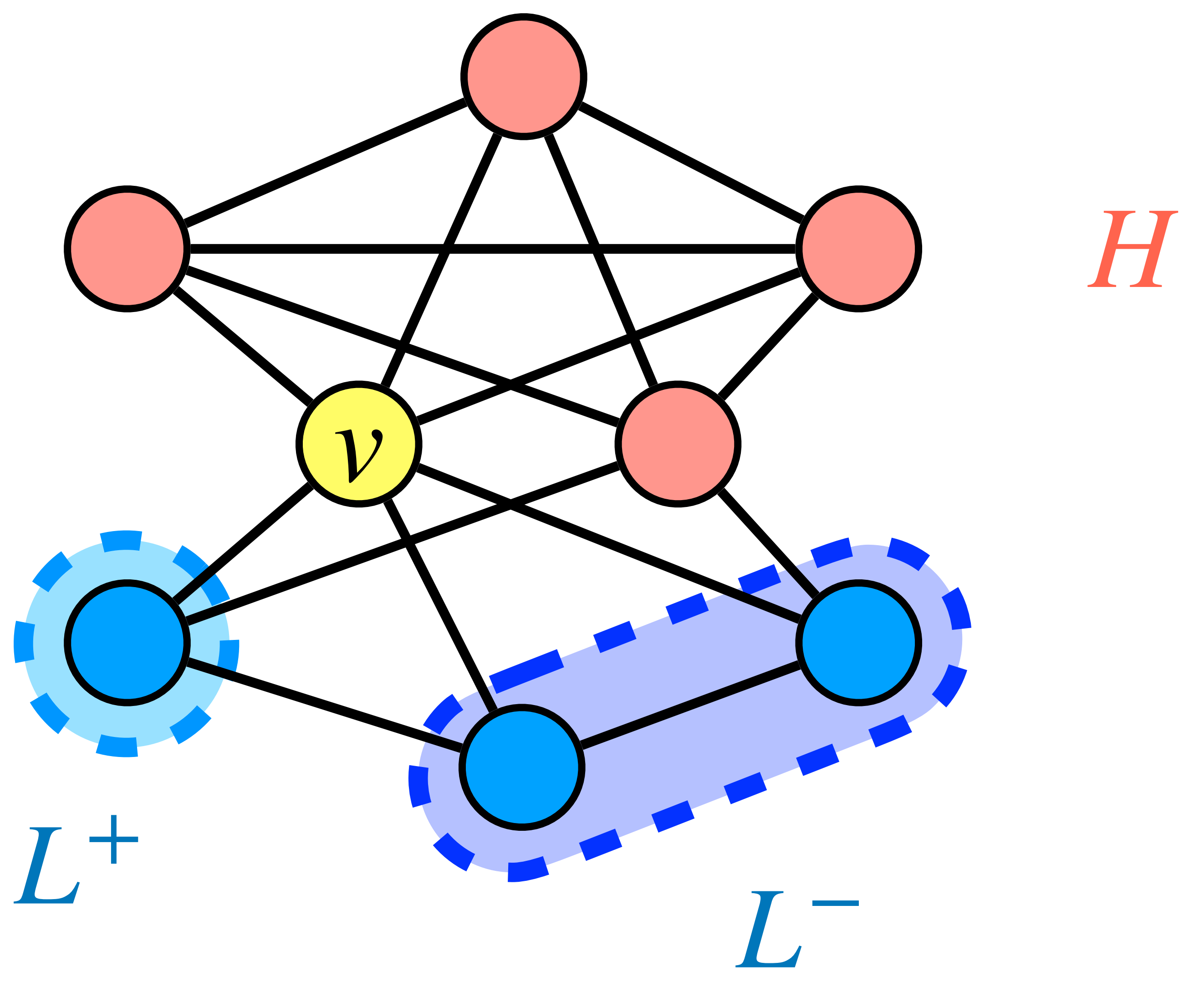

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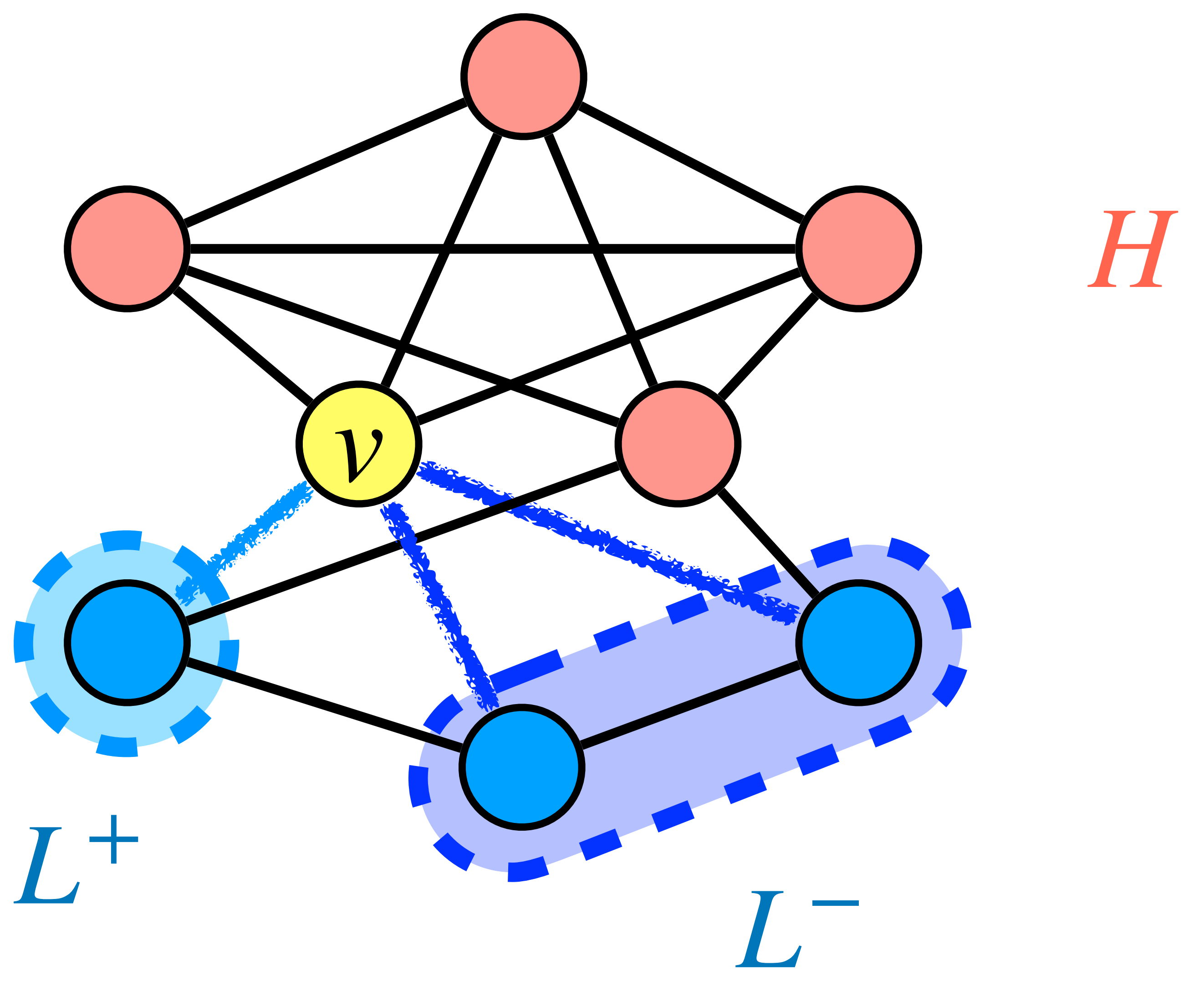

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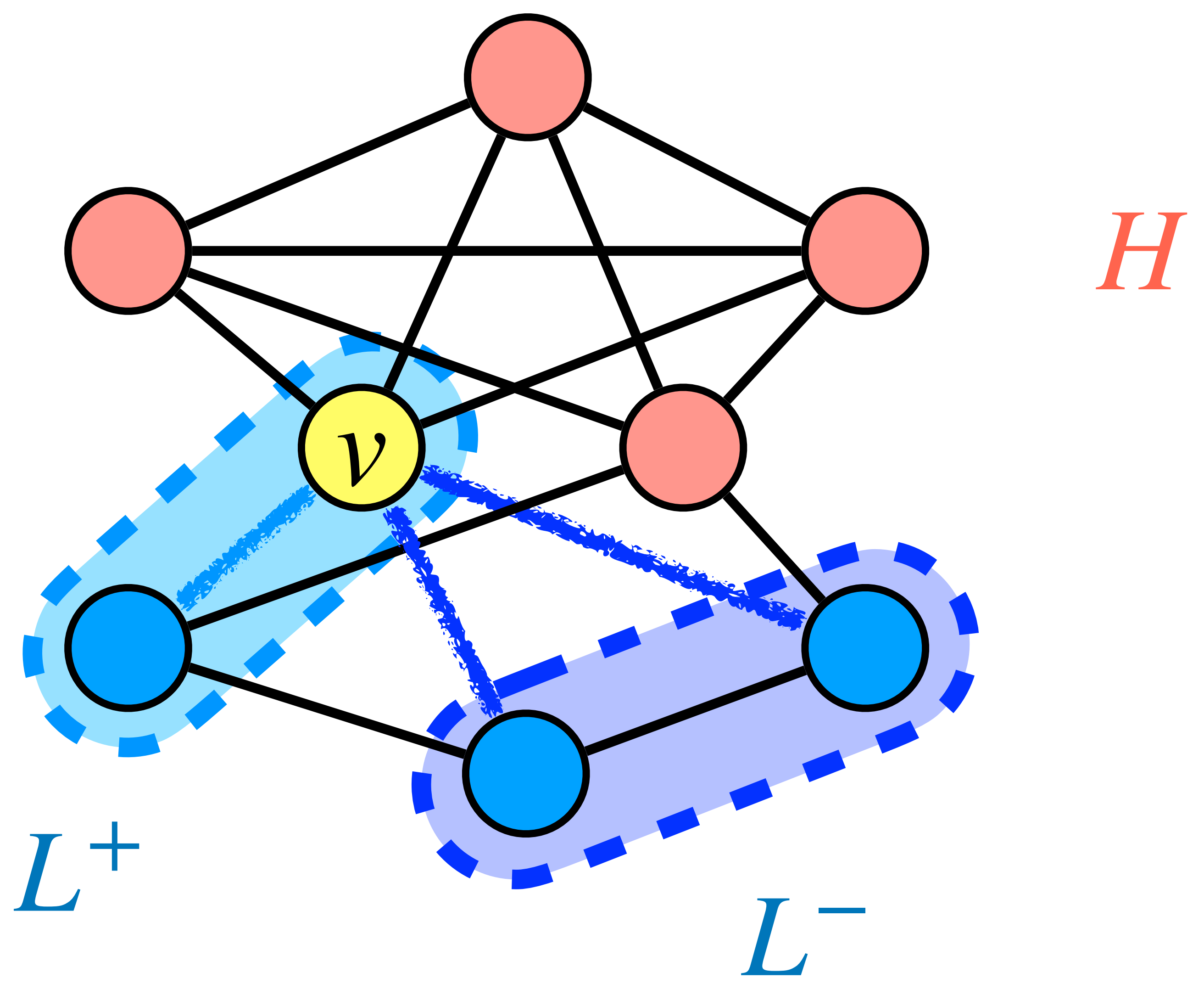

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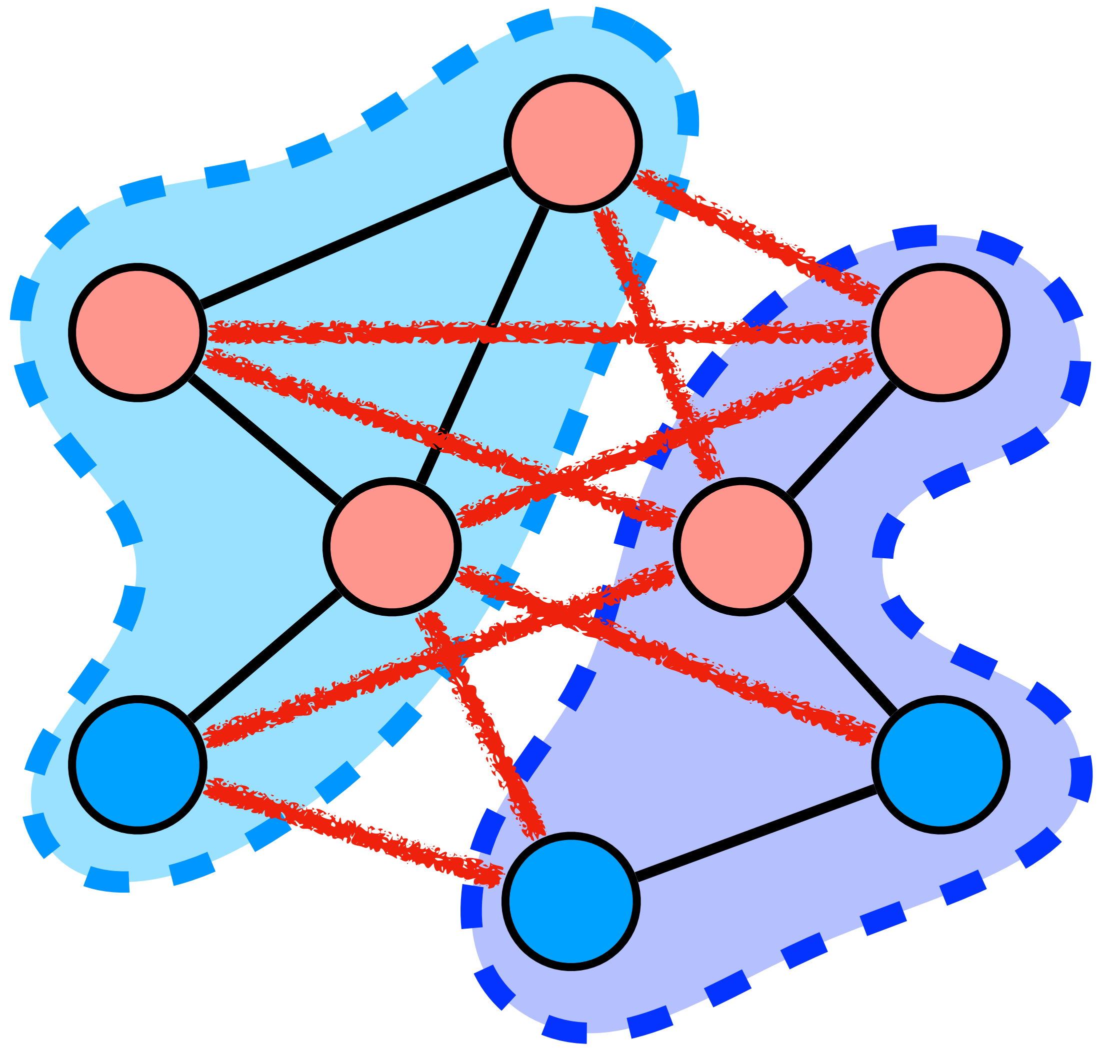

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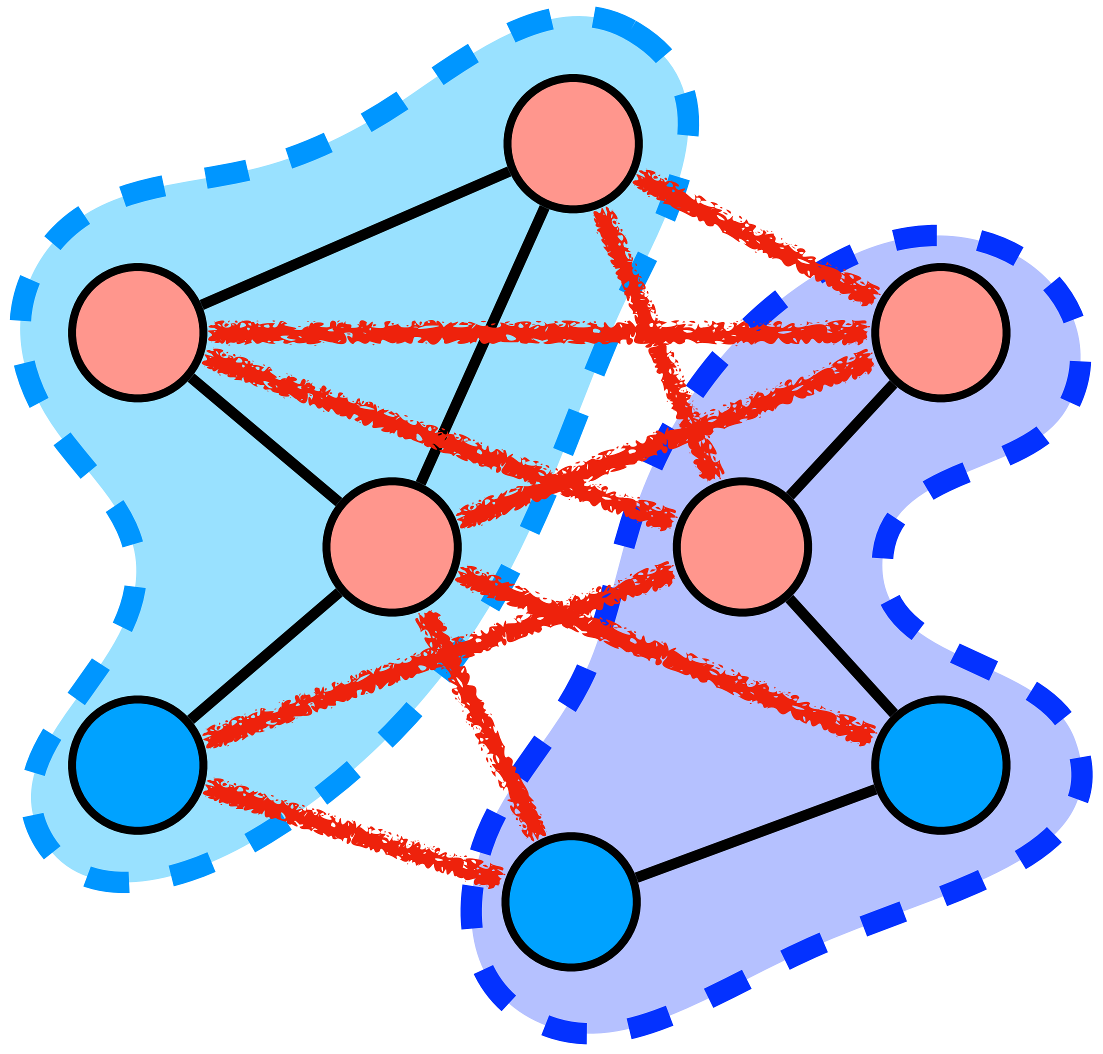

- $$Z_1 = |E(L^+, L^-)| + \sum_{v \in H} \max\{\, |E(v, L^+)|, |E(v, L^-)| \,\}$$

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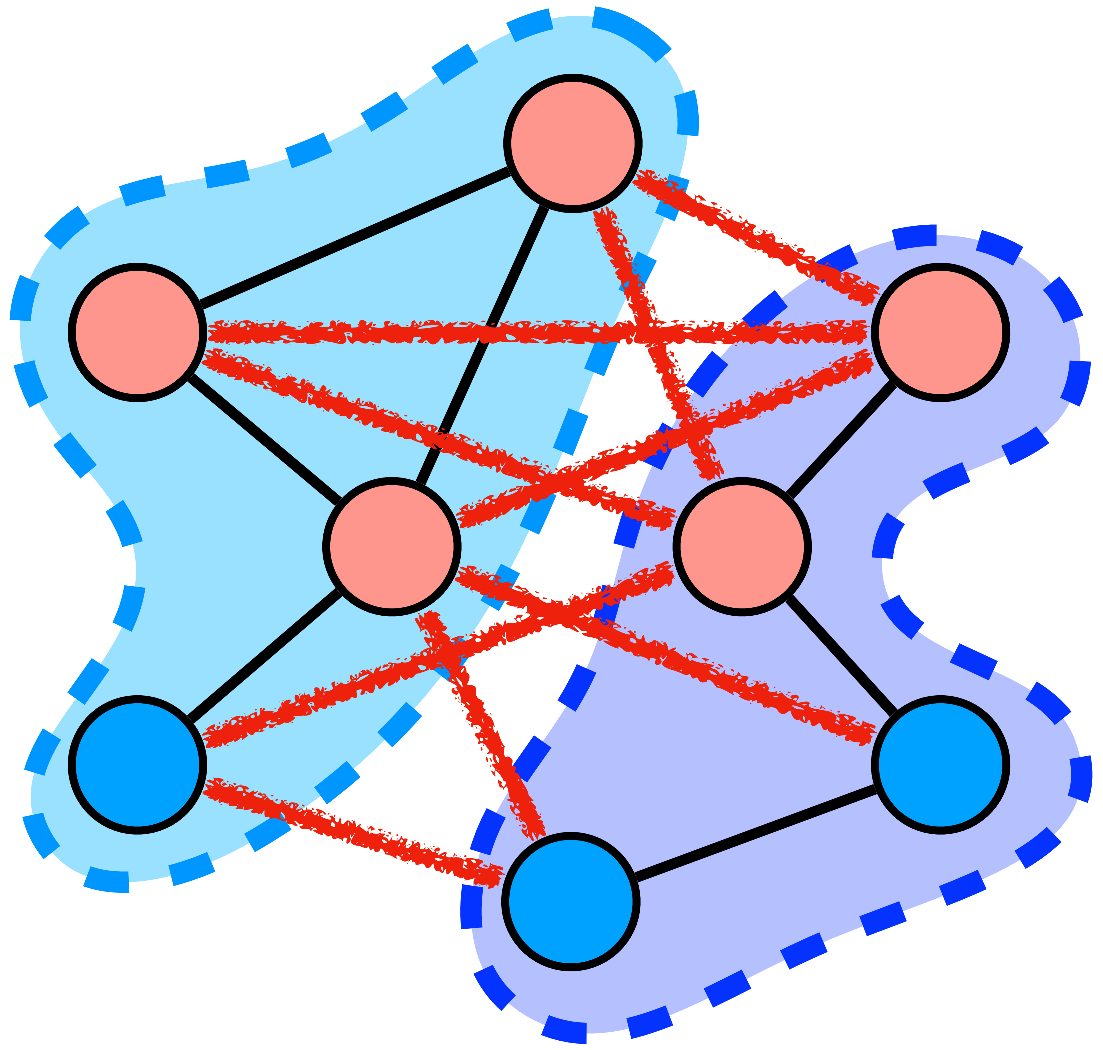

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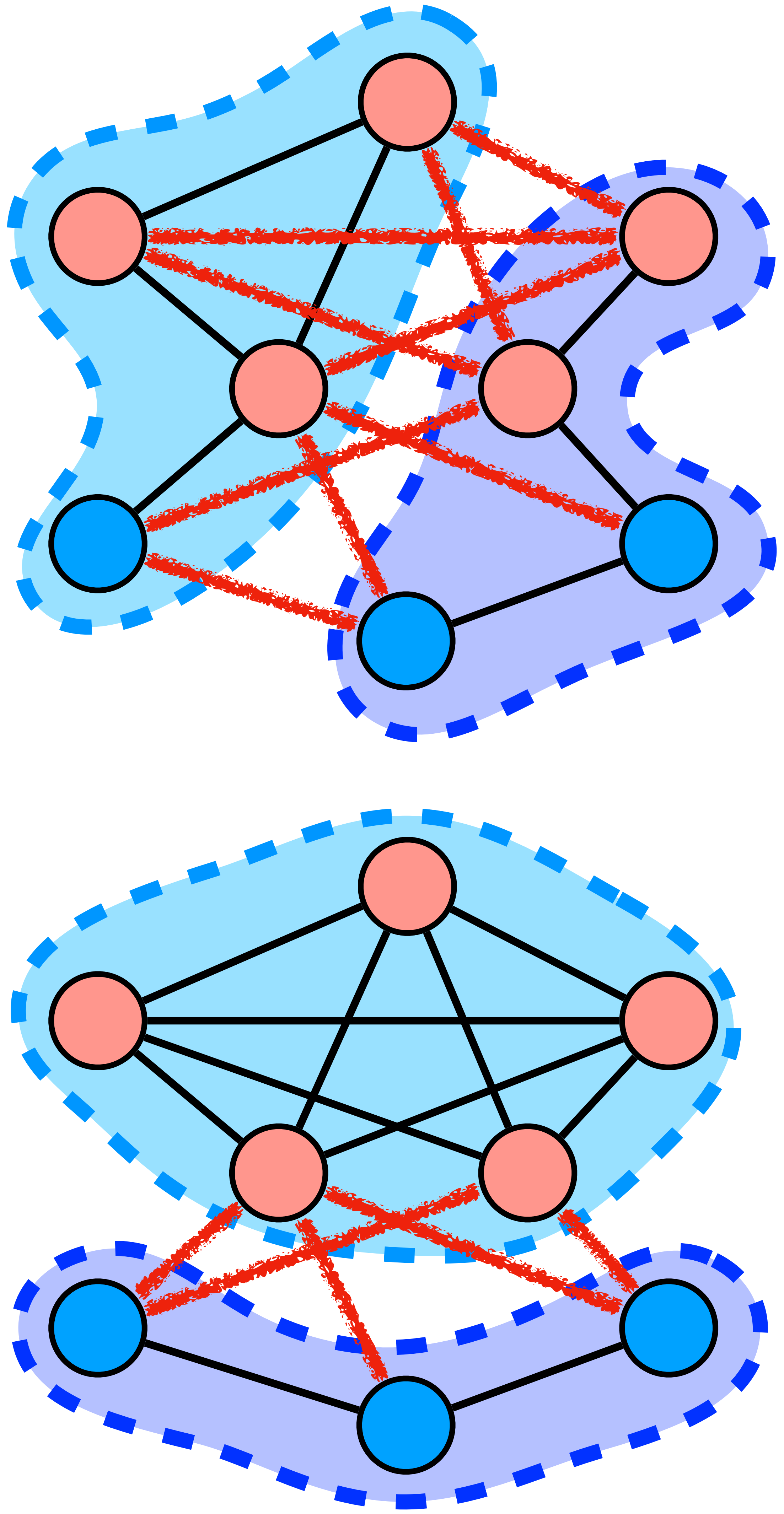

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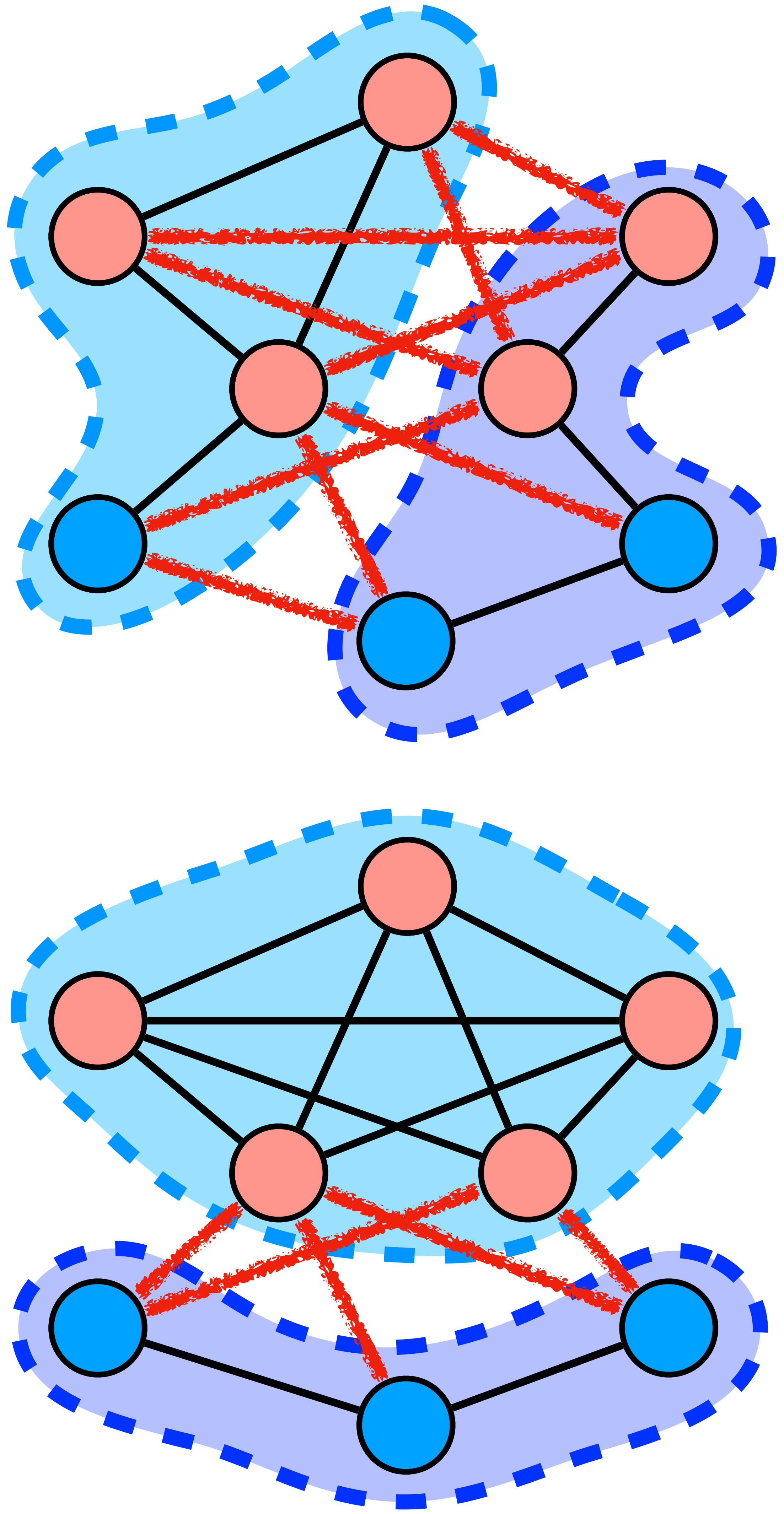

- $Z_1 = |E(L^+, L^-)| + \sum_{v \in H} \max\{|E(v, L^+)|, |E(v, L^-)|\}$
- $Z_2 = |E(H, L)|$

Approximation Analysis of Our Algorithm

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$$\geq \left(\frac{1}{2} + \epsilon^2\right) \cdot \text{OPT}_L + \frac{|E(H, L)|}{2}$$

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Observation: $|E(L^+, L^-)| \geq (1/2 + \epsilon^2) \cdot \mathrm{OPT}_L$

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Lemma: Suppose $|E(H,L)| = \alpha \cdot \mathrm{OPT}$ where $\alpha < 1/2 + \epsilon^2$, then $\mathrm{OPT}_L > (1 - \alpha - \epsilon^4) \cdot \mathrm{OPT}$

- $\mathrm{OPT} \le \mathrm{OPT}_L + \mathrm{OPT}_H + |E(H,L)|$
- $\mathrm{OPT}_H \le |E(H)| \le 1/\epsilon^4$

- **Goal:** To prove $\max\{Z_1, Z_2\} \ge (1/2 + \Omega(\epsilon^2)) \cdot \mathrm{OPT}$
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Implementation of Our Algorithm in Streaming

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- Random Order Streams (insertion-only)
- Arbitrary Order Streams (insertion-only)
- Dynamic Streams

Our Algorithm in Random Order Streams

Our Algorithm in Random Order Streams

Random Order Stream: Edges of the input graph arrive in a uniformly random order

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Random Order Stream: Edges of the input graph arrive in a uniformly random order

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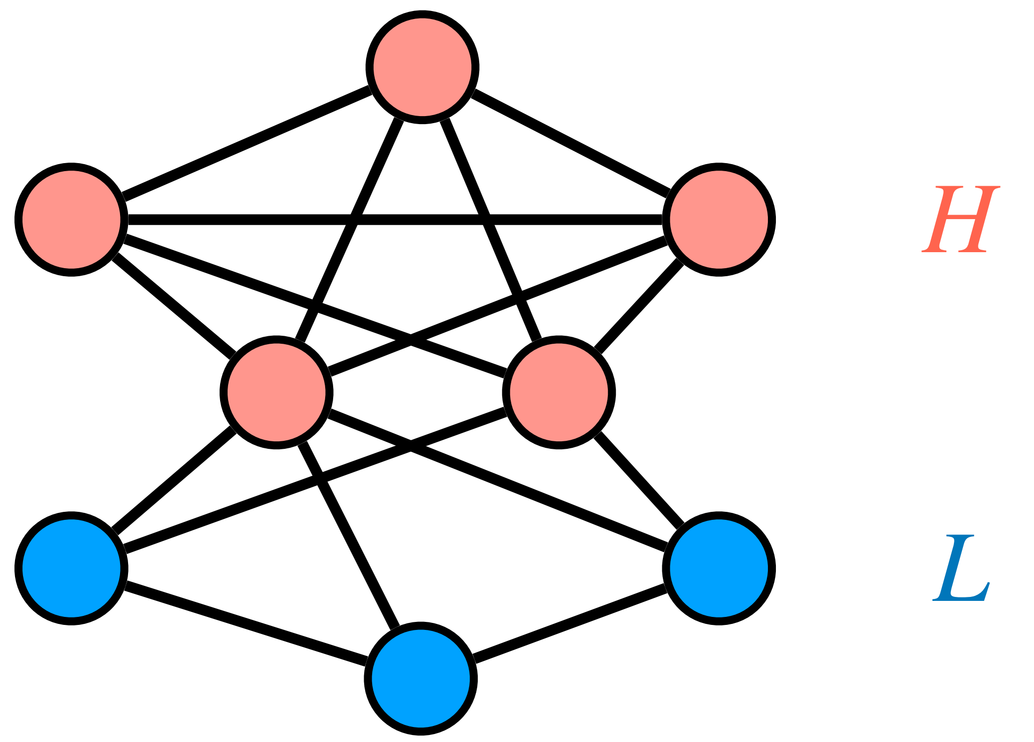

Our Algorithm in Random Order Streams

Random Order Stream: Edges of the input graph arrive in a uniformly random order

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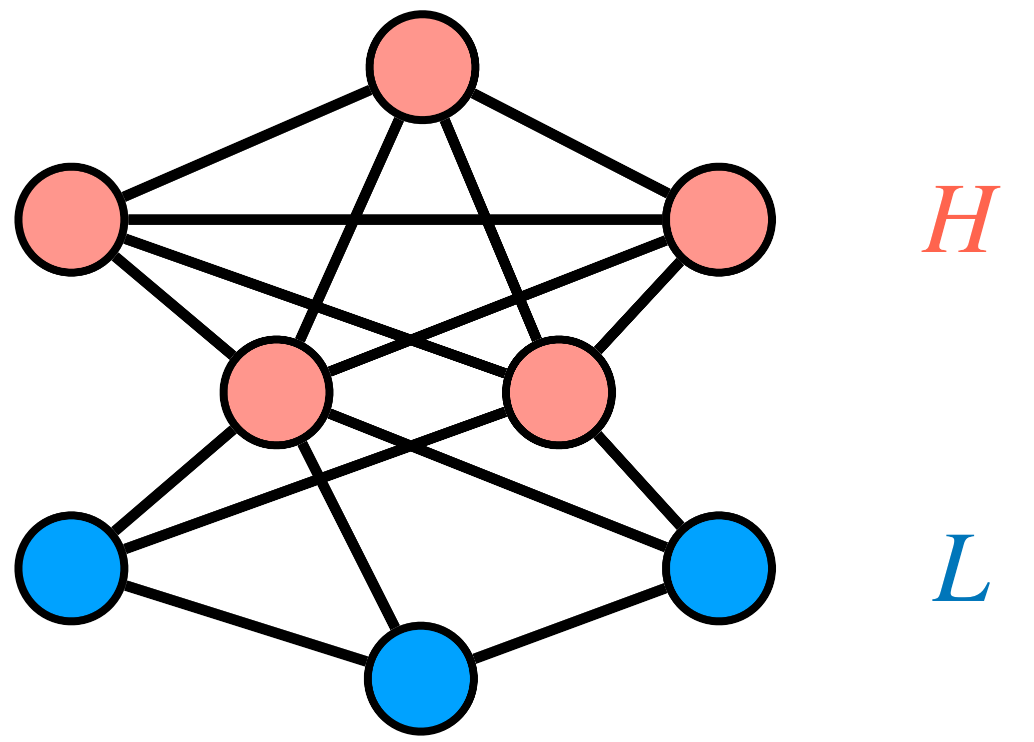

Algorithm in Random Order Streams

- **Streaming Phase:**
  - **Store the first $\mathrm{poly}(1/\epsilon)$ edges**, detect $\tilde{H} \supseteq H$ and $\tilde{L} \subseteq L$
  - Compute Estimate (1) and Estimate (2) w.r.t. $\tilde{H}$ and $\tilde{L}$
  - Store the degree info of $\tilde{H}$ and $E(\tilde{H})$
- **Post-Processing Phase:**
  - Correct H, L and the estimates using degree info of $\tilde{H}$

Our Algorithm in Random Order Streams

Random Order Stream: Edges of the input graph arrive in a uniformly random order

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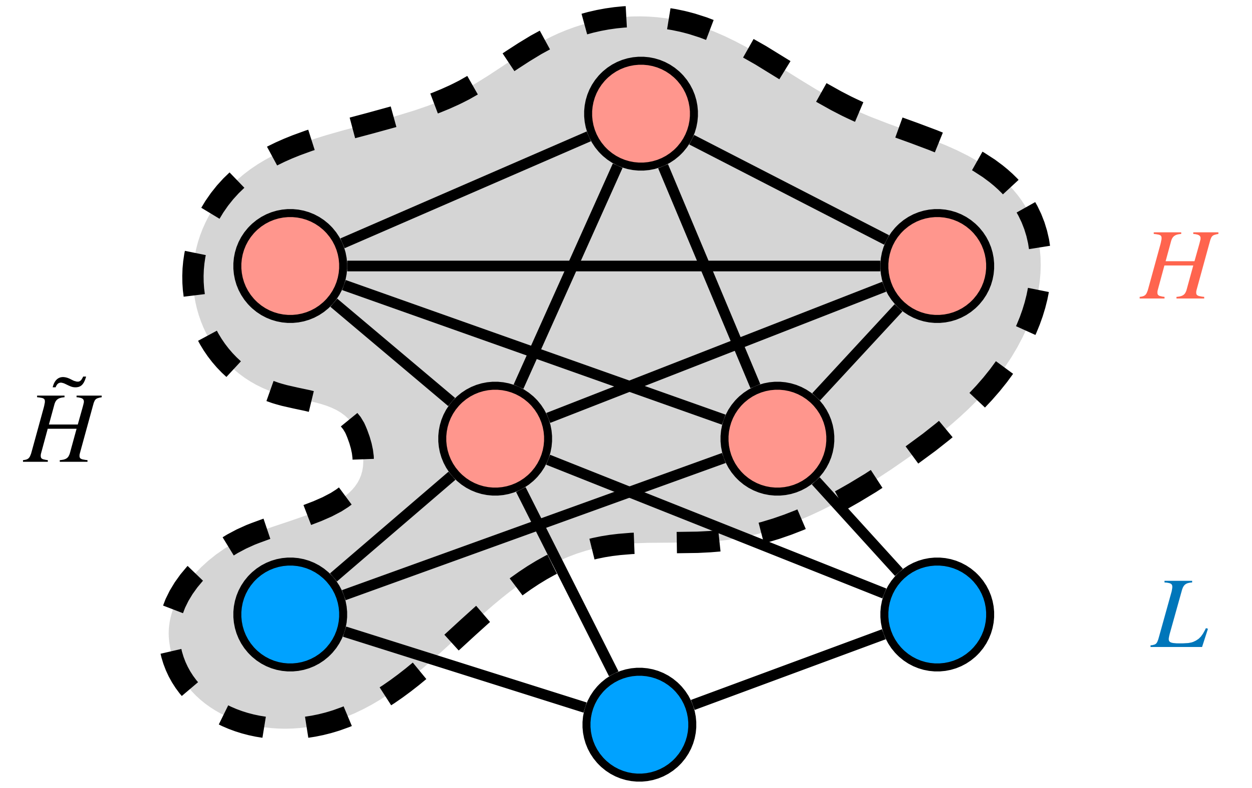

Algorithm in Random Order Streams

- **Streaming Phase:**
  - **Store the first** $\text{poly}(1/\epsilon)$ **edges**, detect $\tilde{H} \supseteq H$ and $\tilde{L} \subseteq L$
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  - Correct H, L and the estimates using degree info of $\tilde{H}$

Our Algorithm in Random Order Streams

Random Order Stream: Edges of the input graph arrive in a uniformly random order

Offline Algorithm

- Divide V into H (high-degree) and L (low-degree)
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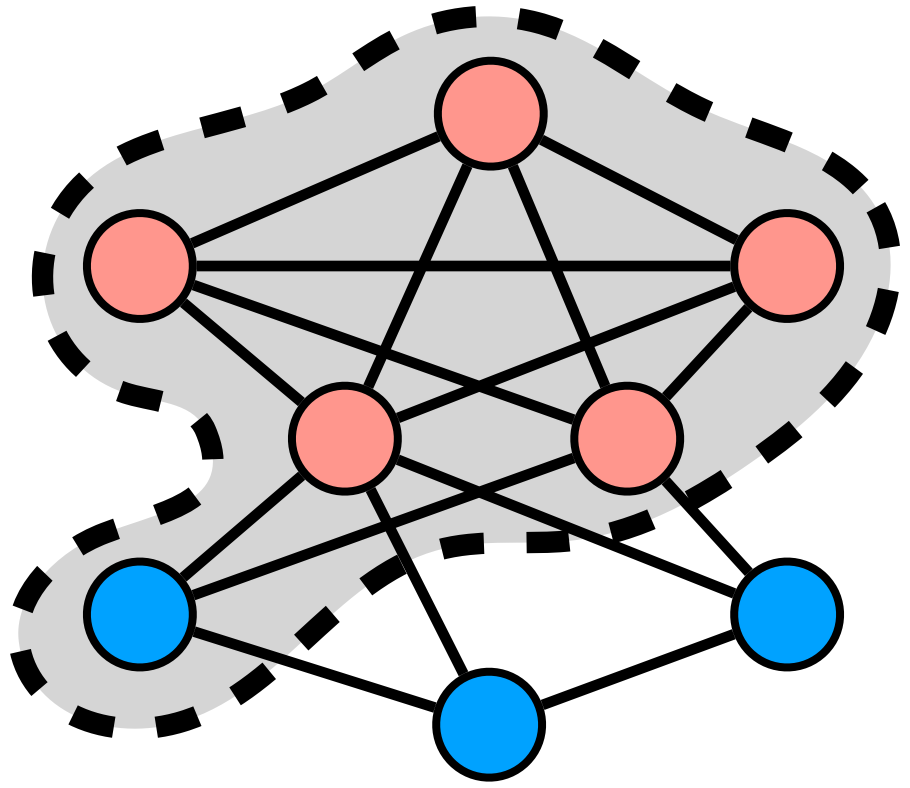

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Our Algorithm in Arbitrary Order Streams

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Arbitrary Order Stream: Edges of the input graph arrive in an arbitrary/adversarial order

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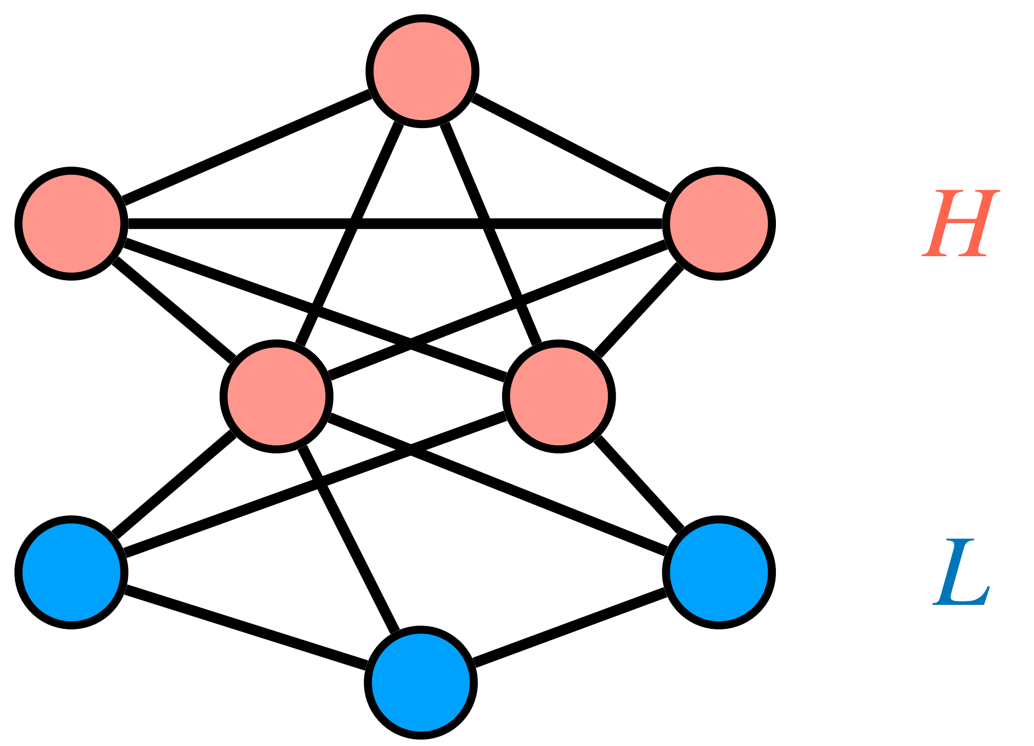

Algorithm in Arbitrary Order Streams

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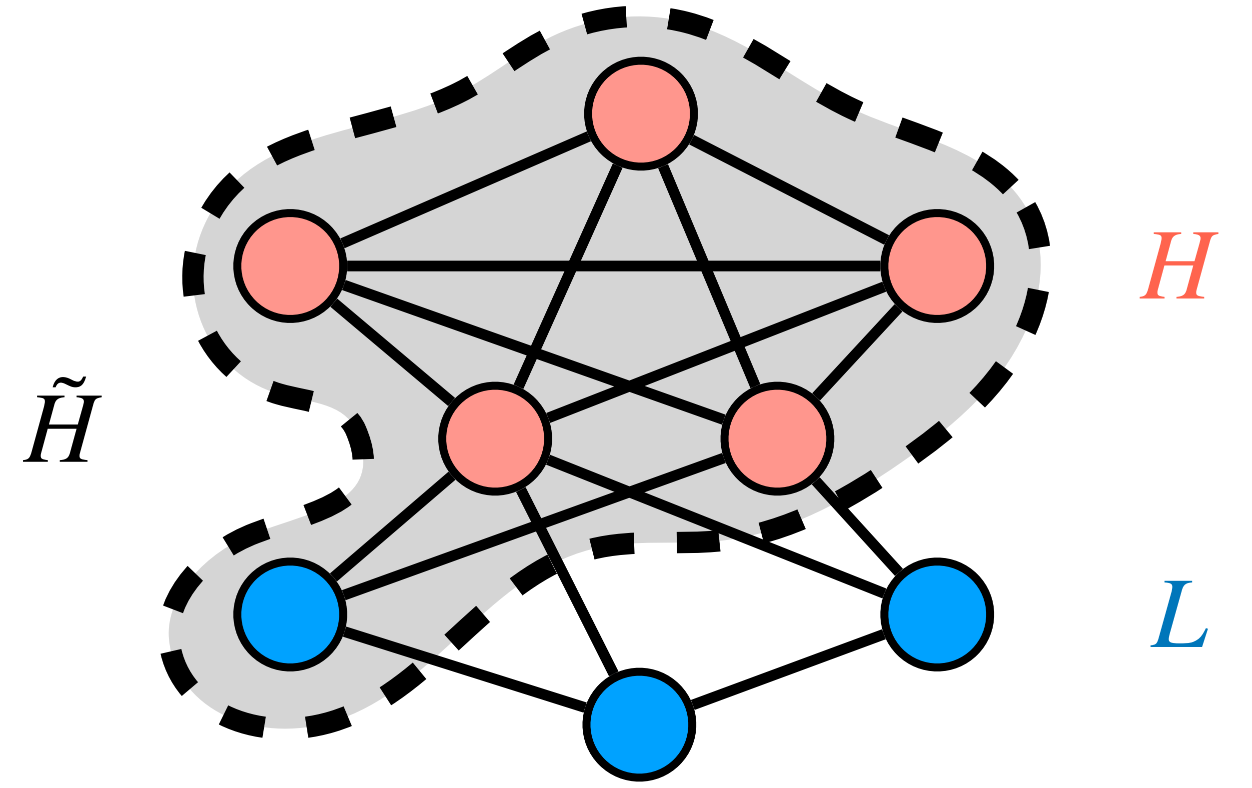

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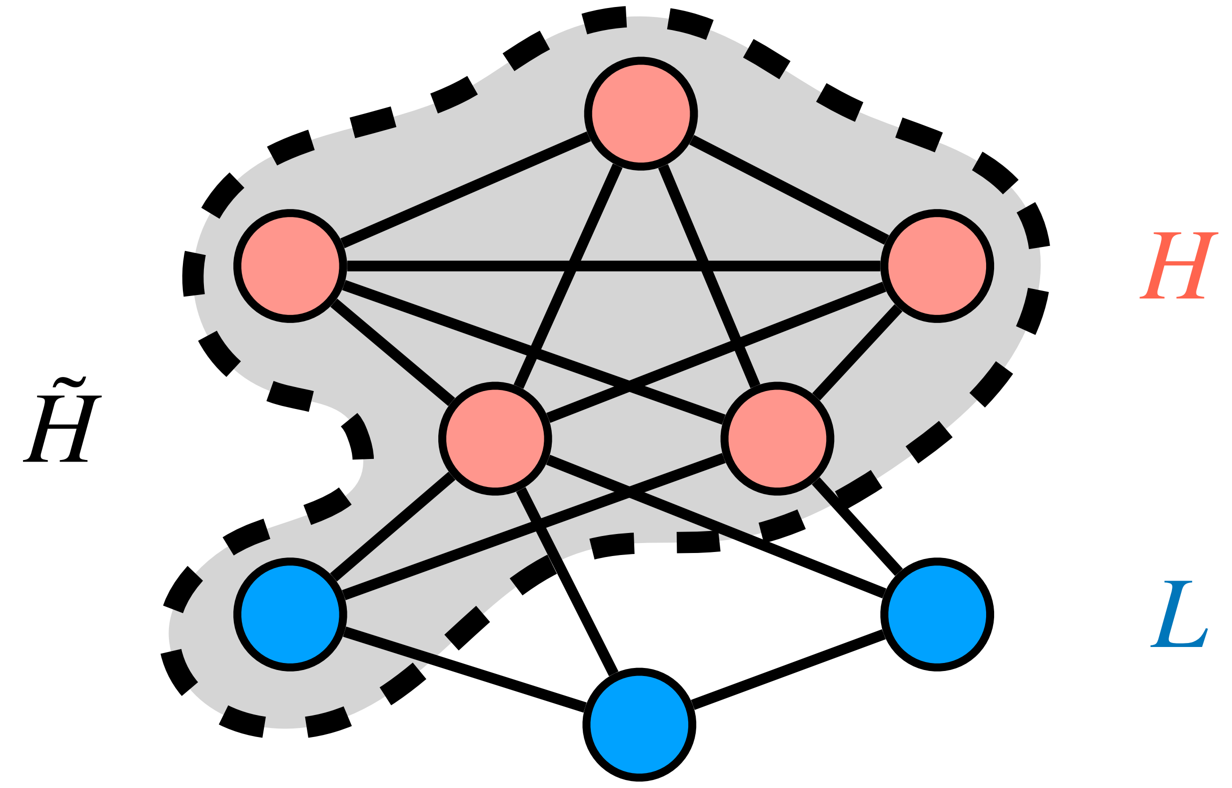

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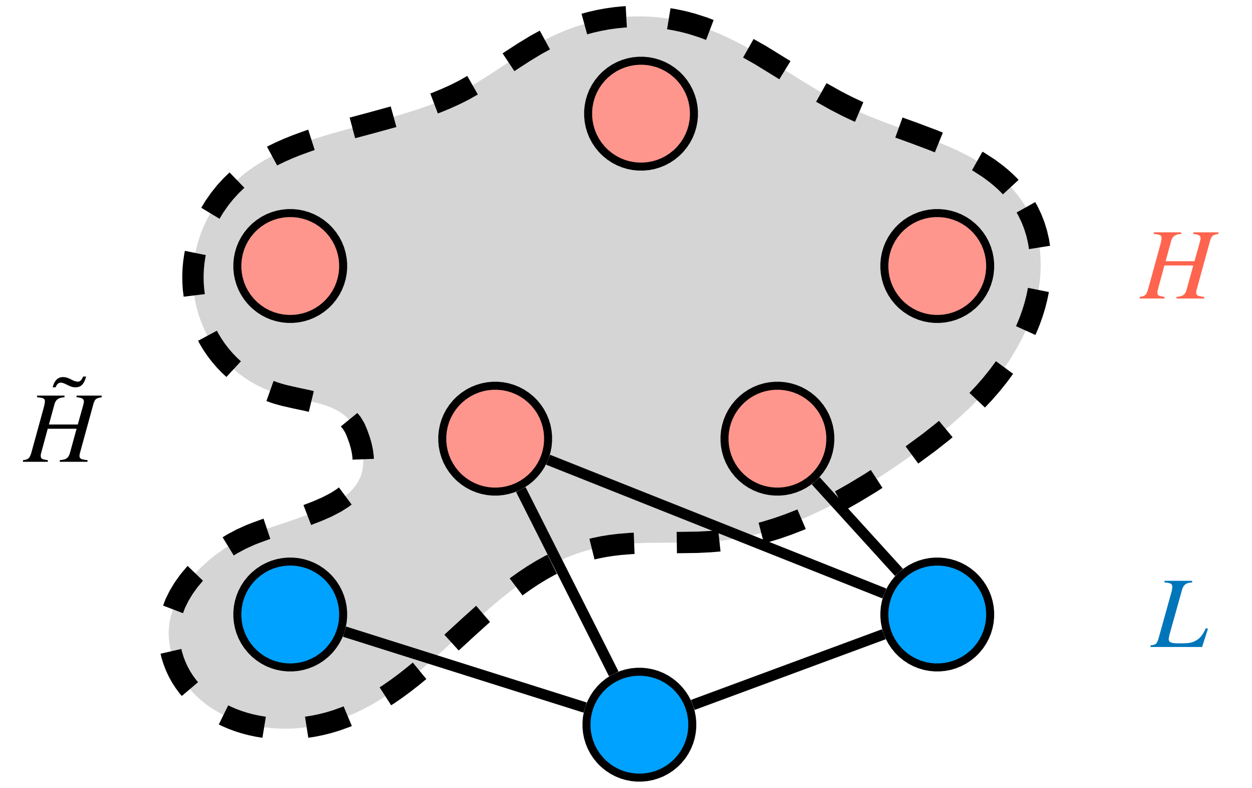

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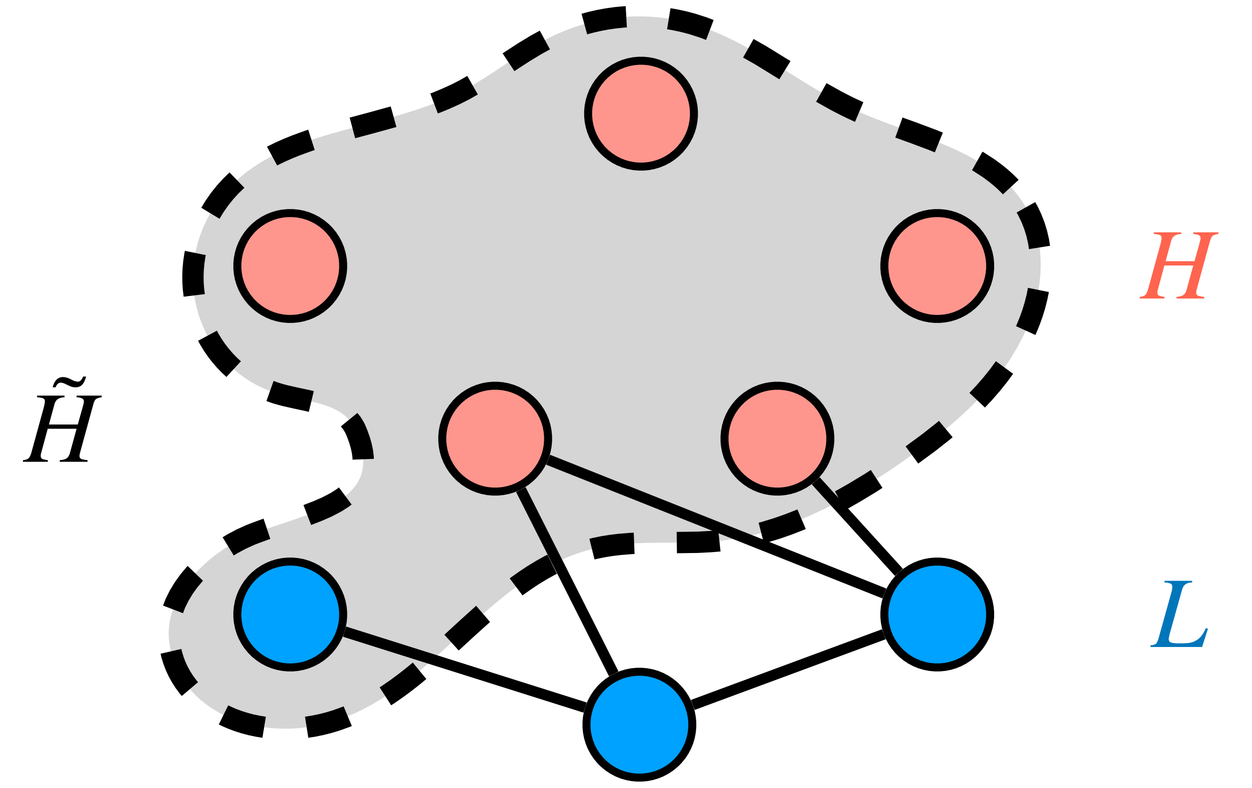

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Algorithm in Dynamic Streams

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Our Algorithm in Dynamic Streams

Dynamic Stream: The stream contains both edge insertions and deletions

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Thank you!