

Approximate Gomory-Hu Tree in \sim Max-Flow Time

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joint work with Debmalya Panigrahi (Duke)

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Introduction

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Gomory-Hu tree: a tree on same vertex set s.t. $\text{mincut}_T(u,v) = \text{mincut}_G(u,v)$

- Can be computed using $n-1$ max-flows [Gomory-Hu'61]
- **No faster algorithm for general graphs!**
- Unweighted graphs: $\tilde{O}(mn)$ time [BHKP'07], $m^{3/2}n^{1/6}$ [AKT SODA'20]

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This talk: approximations

- Approximate all-pairs mincut in $\tilde{O}(n^2)$ time [AKT FOCS'20]
- Nothing better known for GH tree

This work: $(1+\epsilon)$ -approximate GH tree and SSMC in exact max-flow time

Outline

New primitive: **Cut Threshold** algorithm

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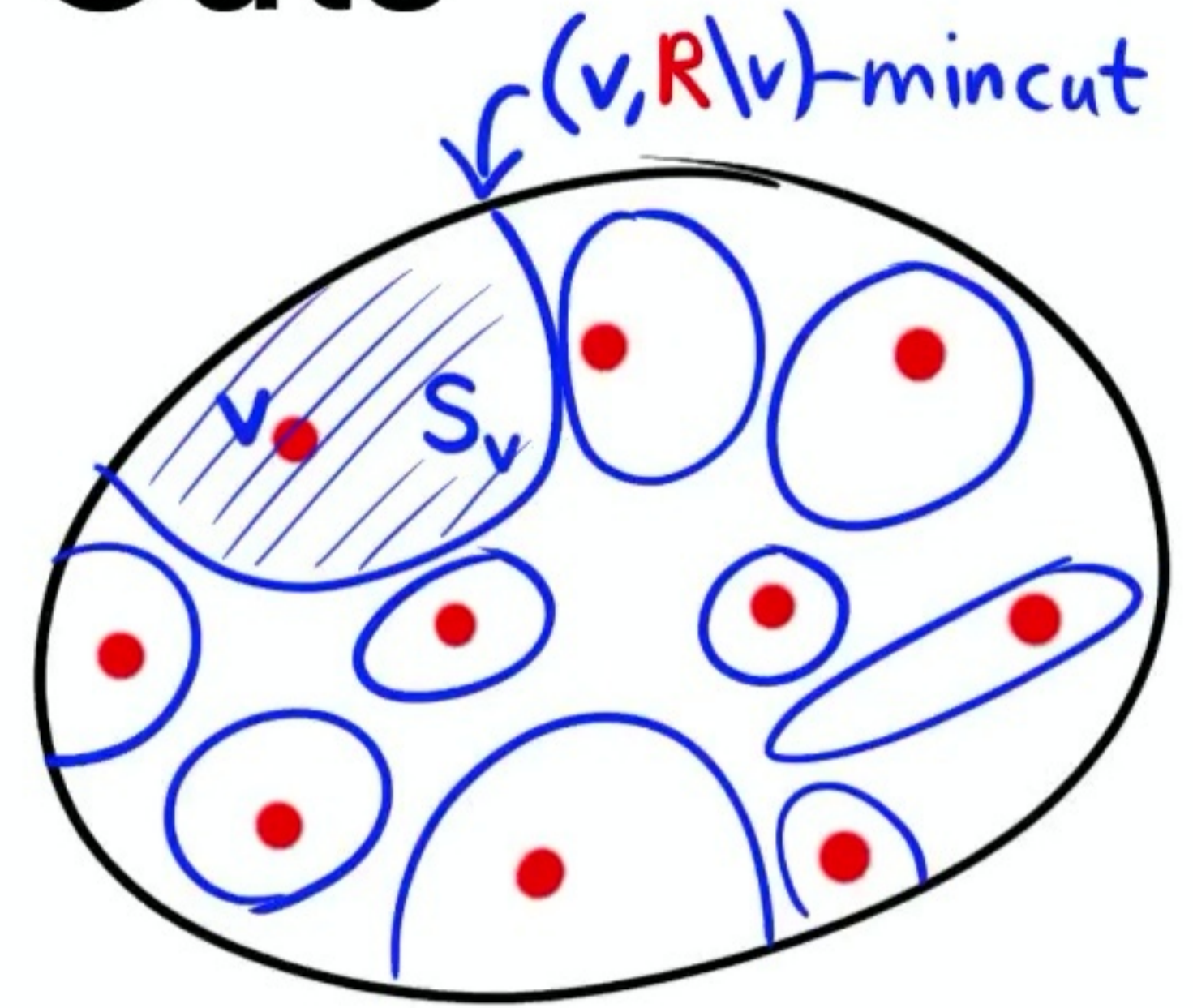
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Cut Threshold \Rightarrow approximate single-source mincut
(\Rightarrow approximate all-pairs mincut [AKT20])

Cut Threshold \Rightarrow approximate Gomory-Hu tree

Minimum Isolating Cuts

Given a graph and a set R of terminals, find, for each terminal v , the mincut S_v that **isolates** that terminal

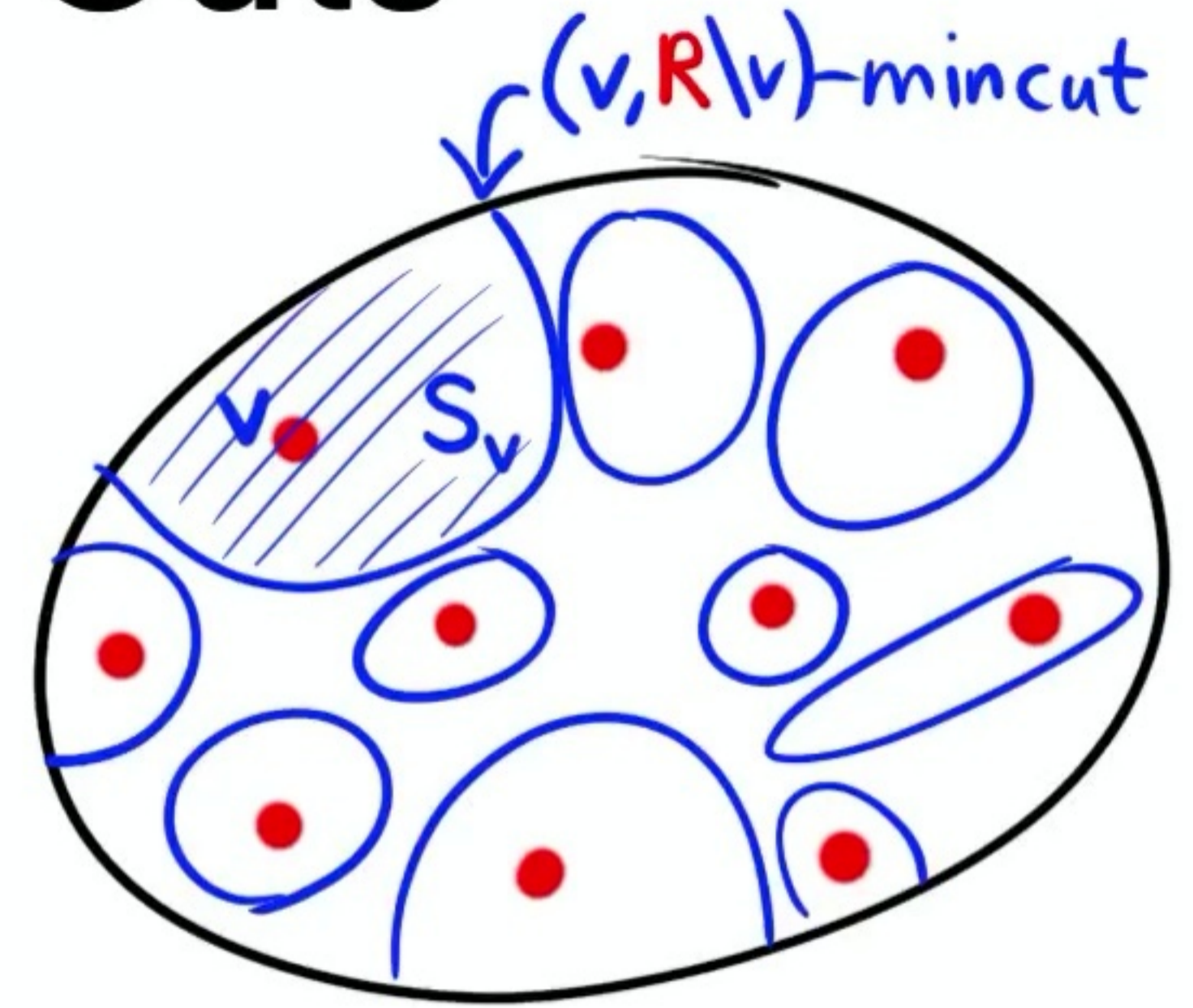


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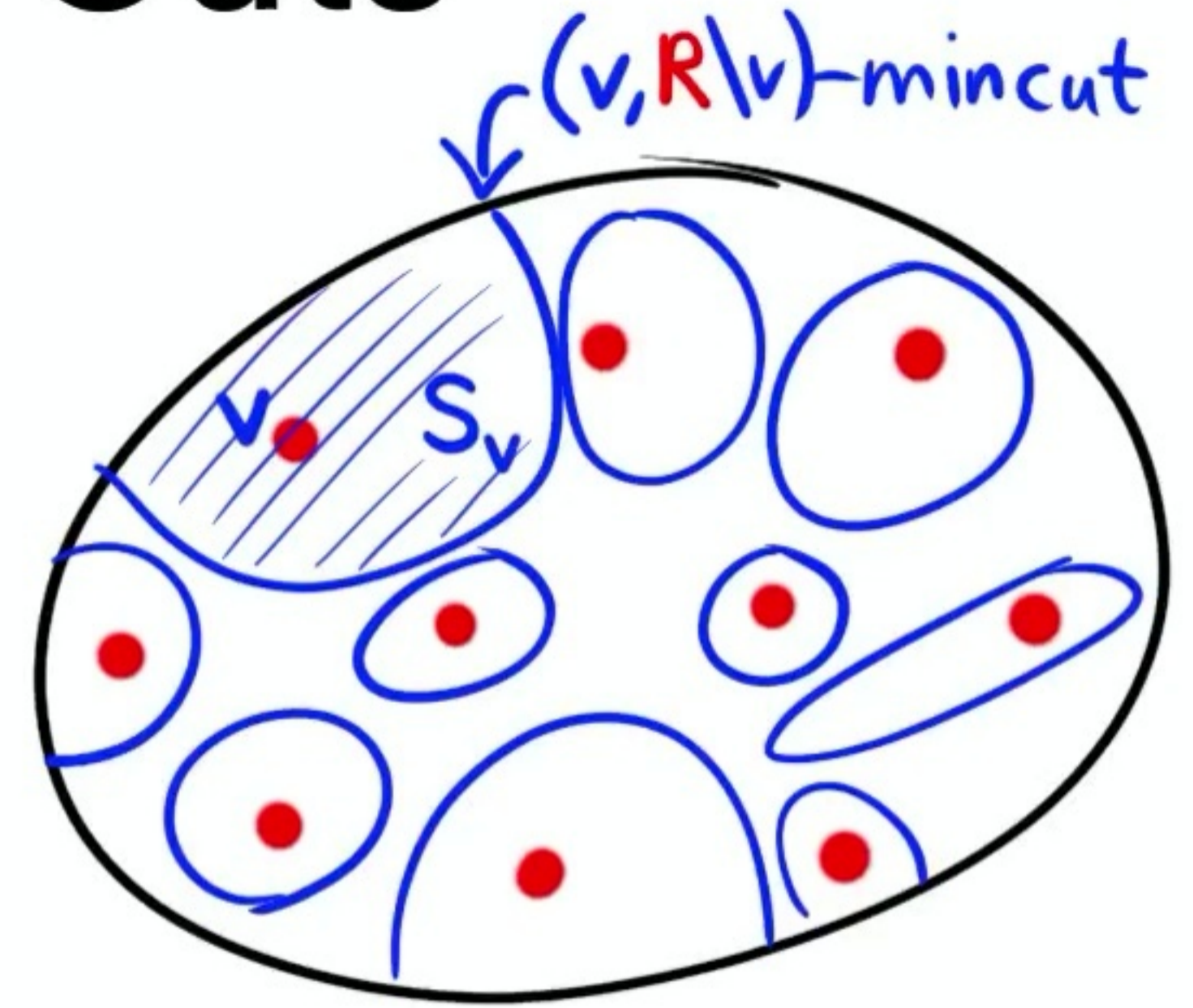
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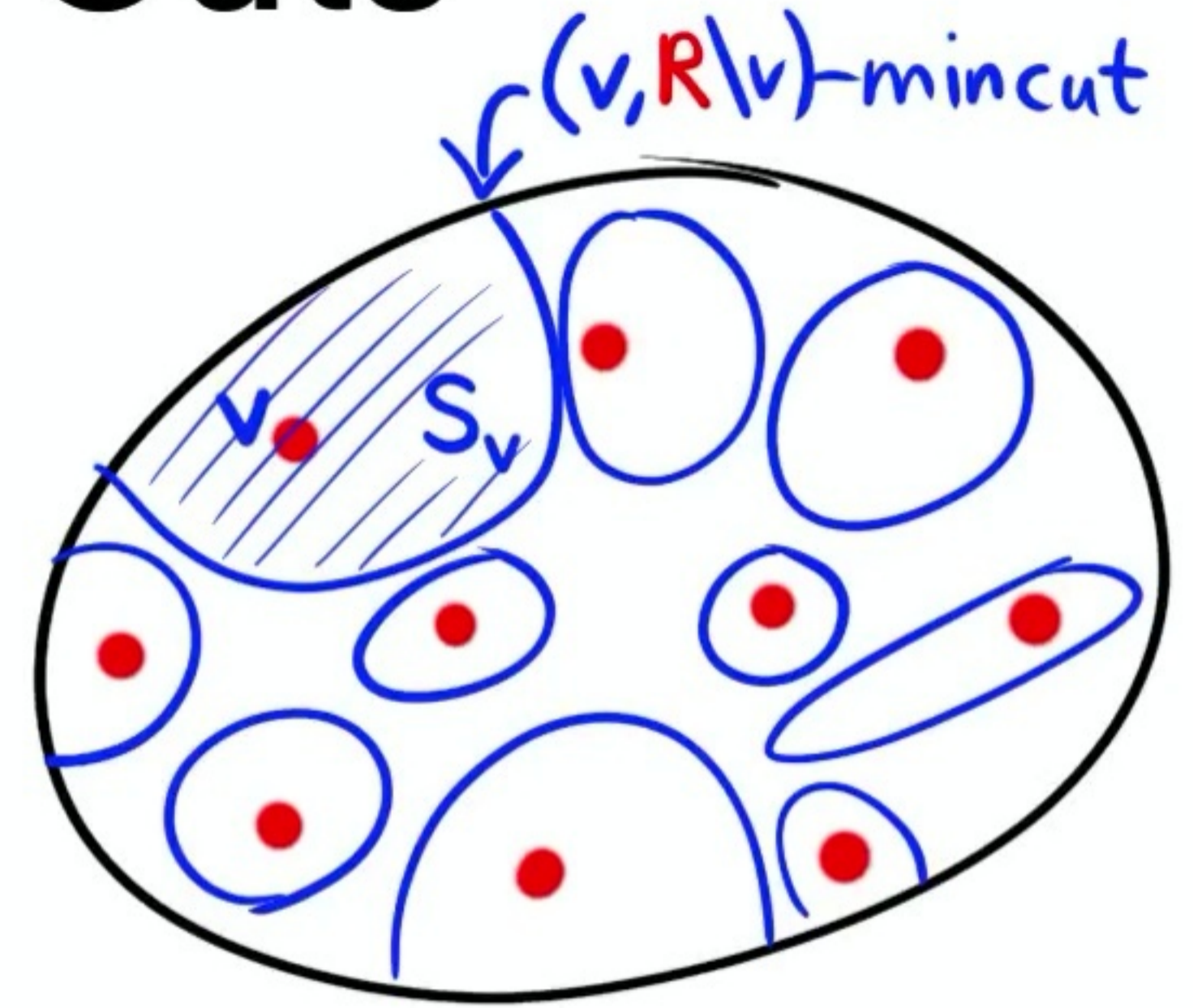
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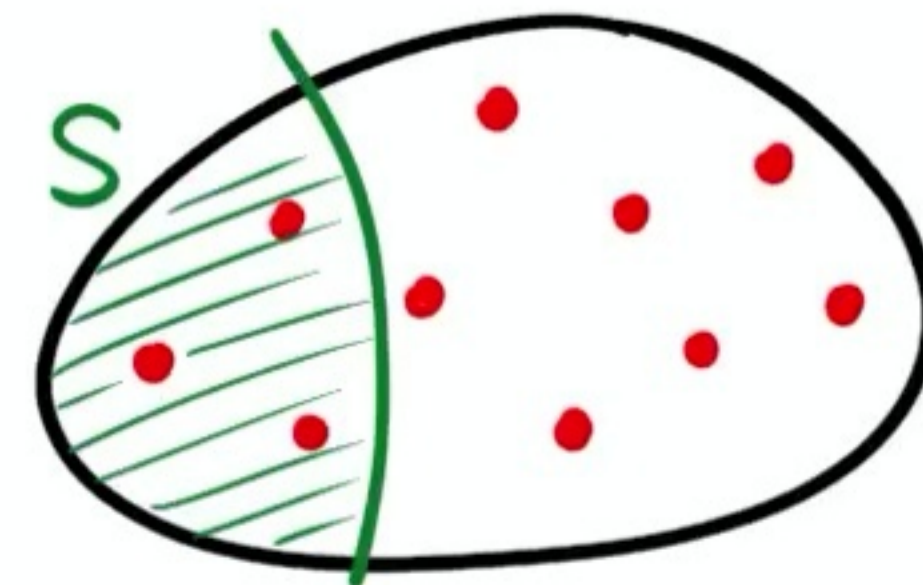
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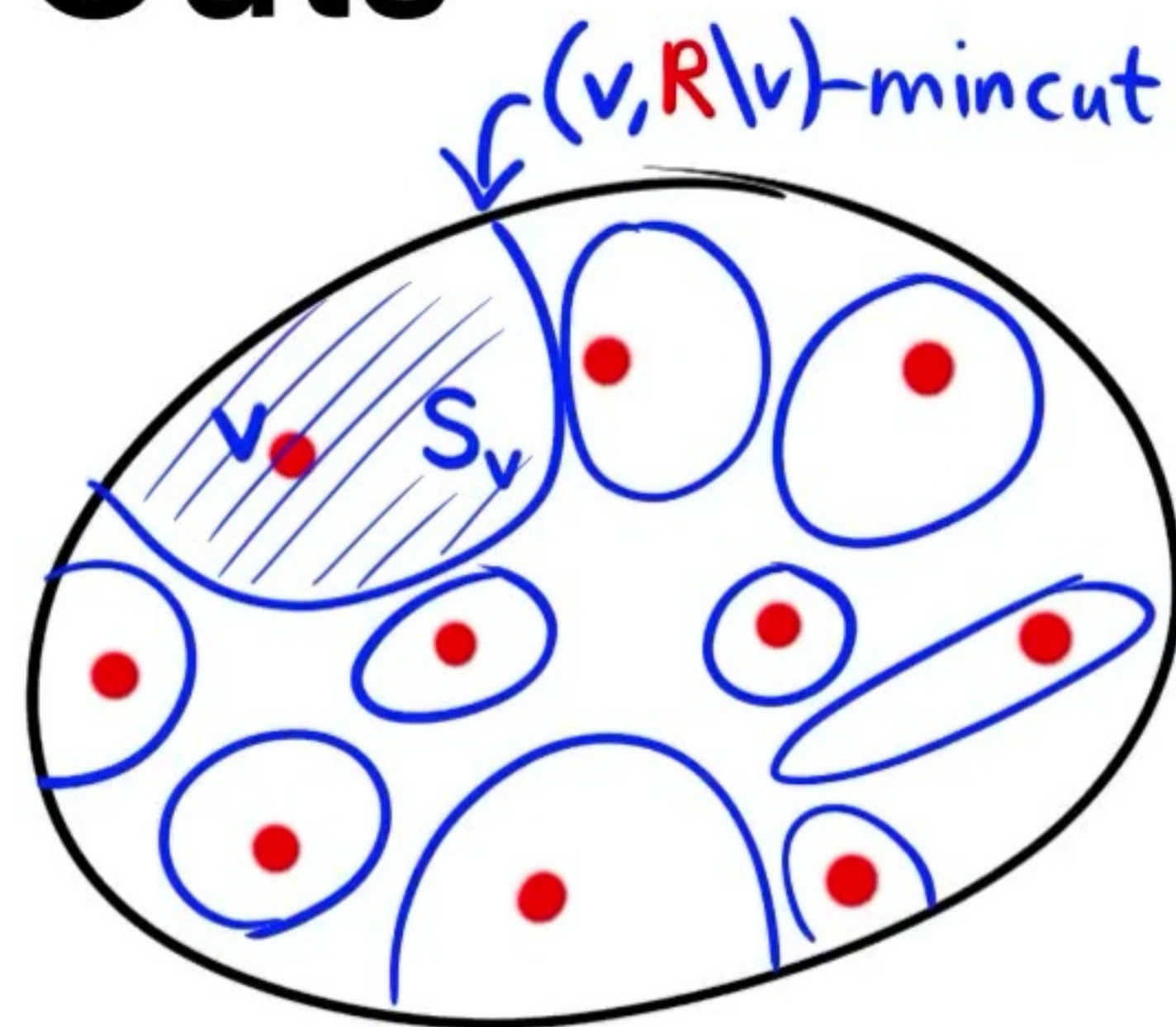
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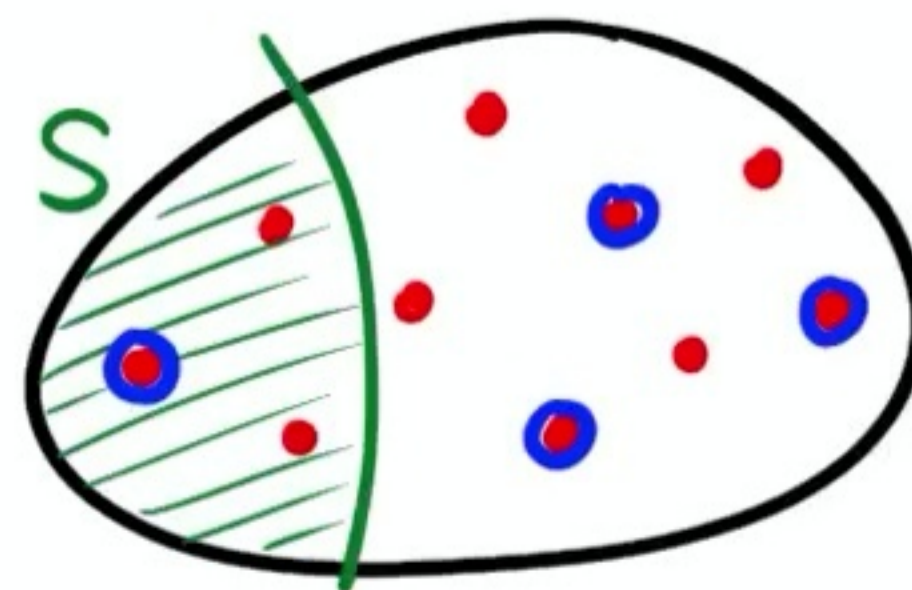
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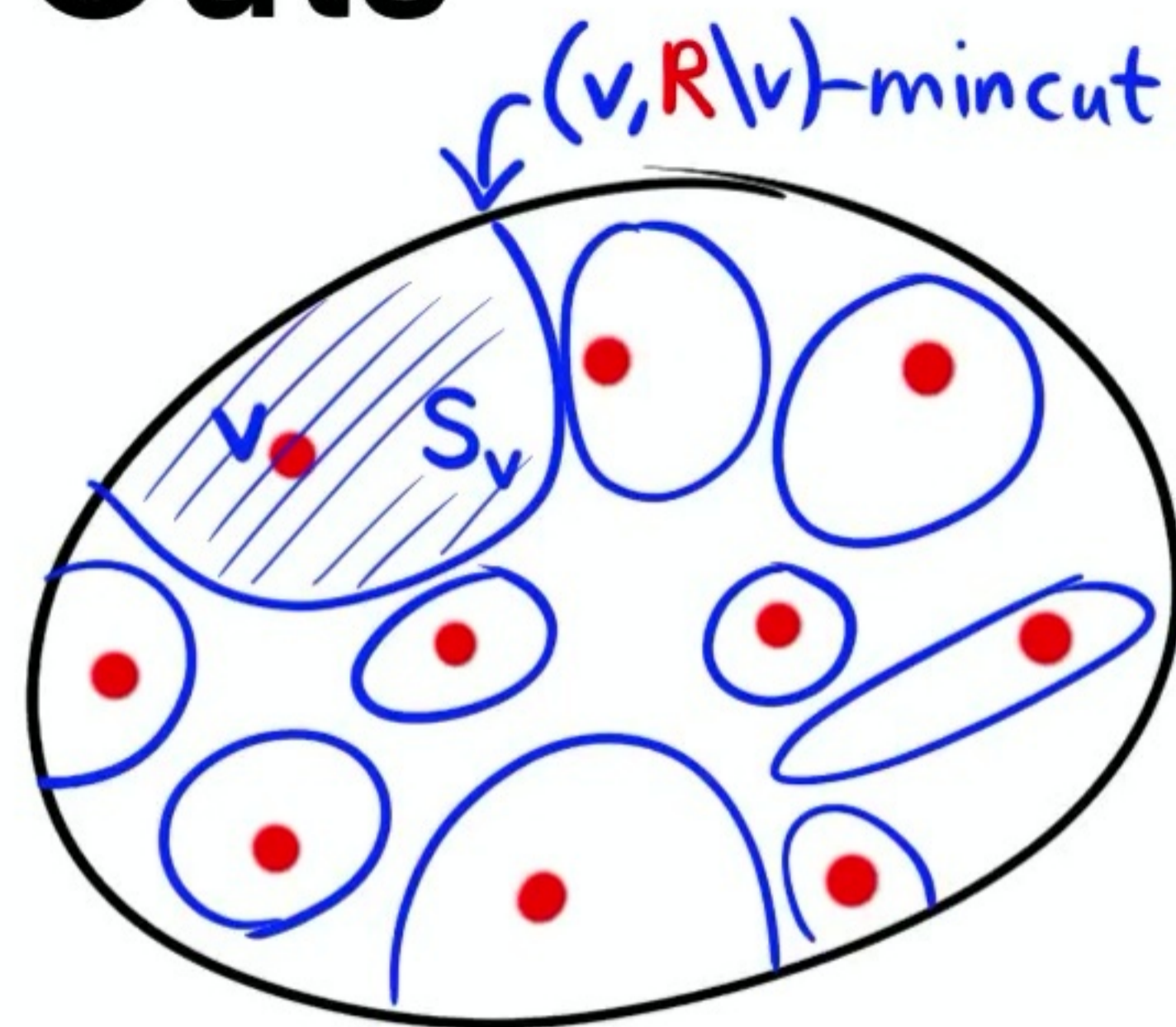
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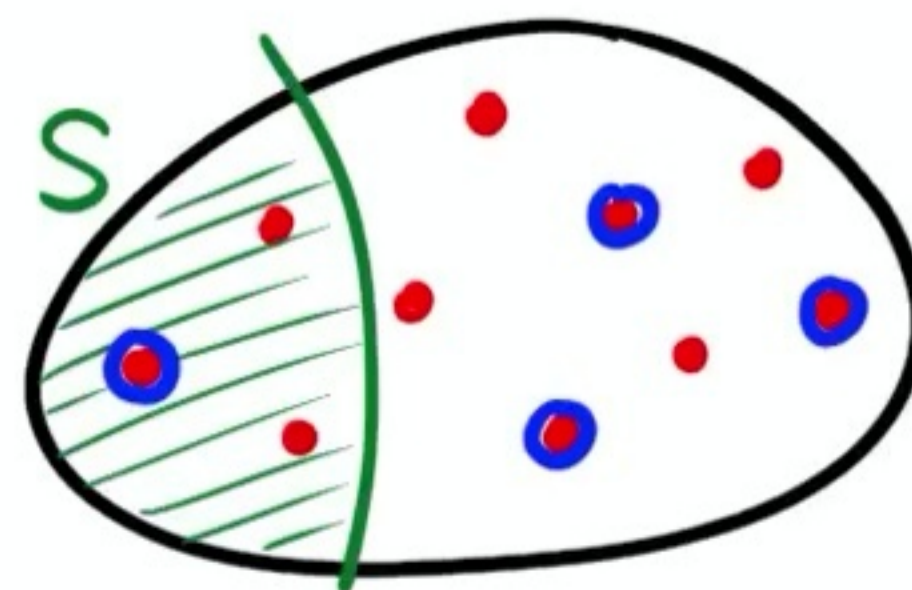


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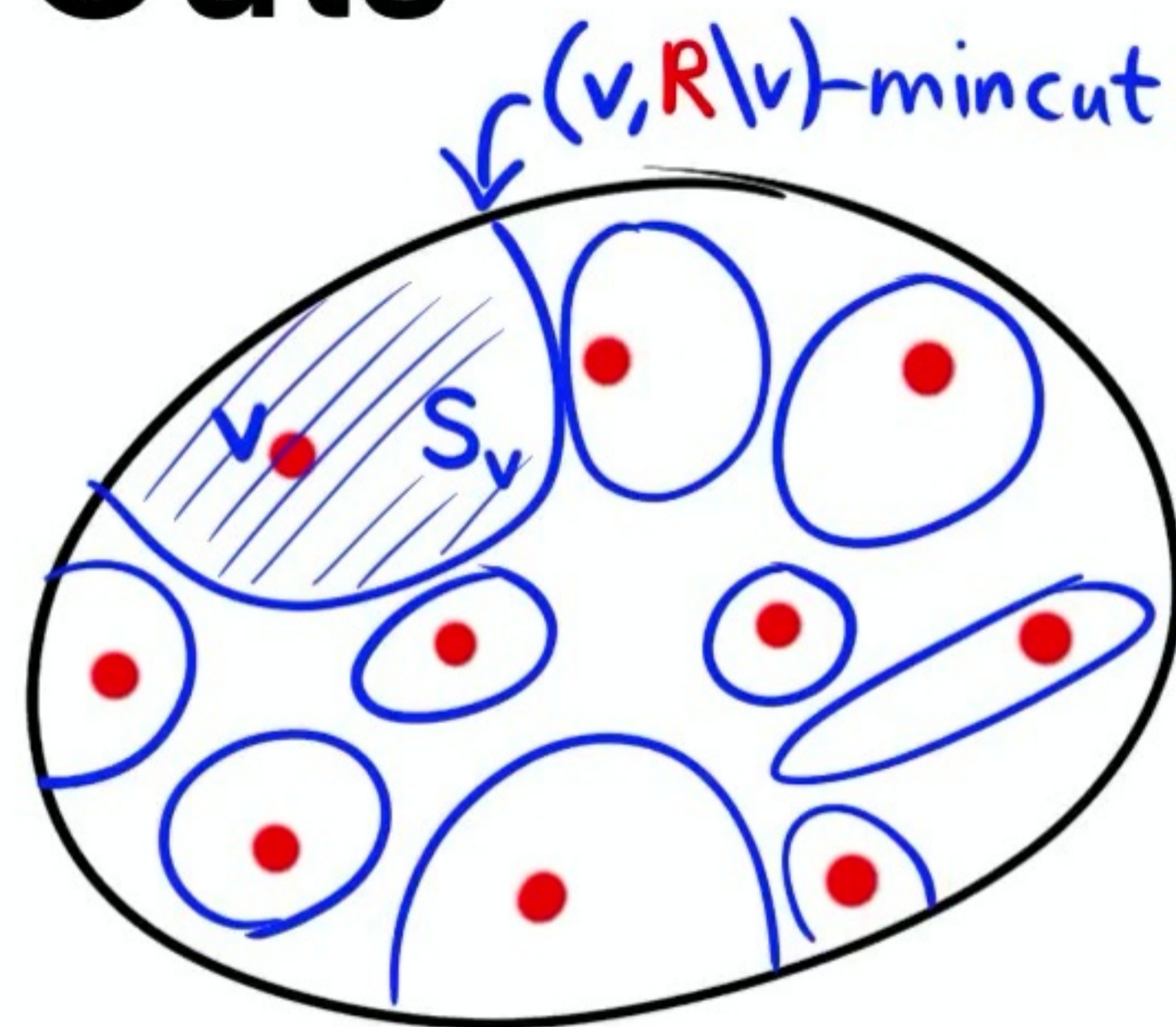
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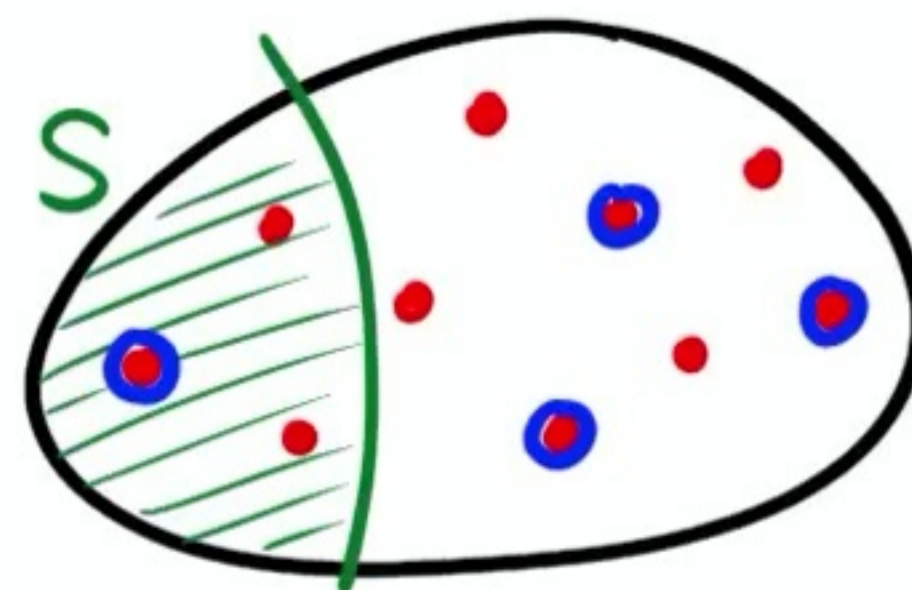
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Sample at rate $1/2, 1/4, 1/8, \dots$

If sample at rate $\sim \frac{1}{|S \cap R|}$, then
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Cut Threshold Algorithm

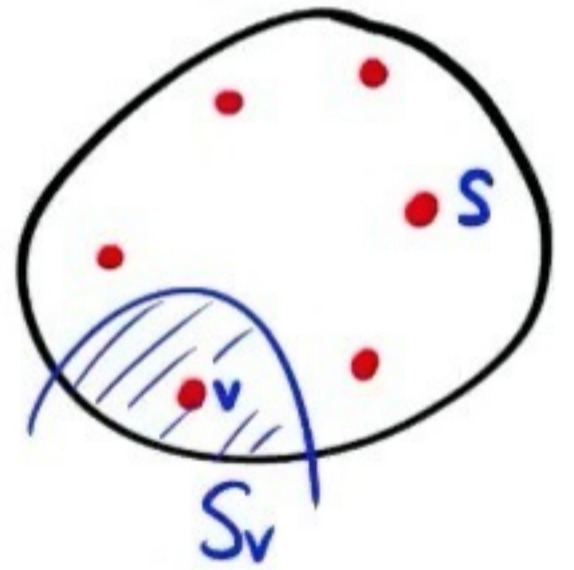
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Algorithm $\text{CutThresholdStep}(G, s, R)$:

- For each $i=1,2,\dots,\log n$
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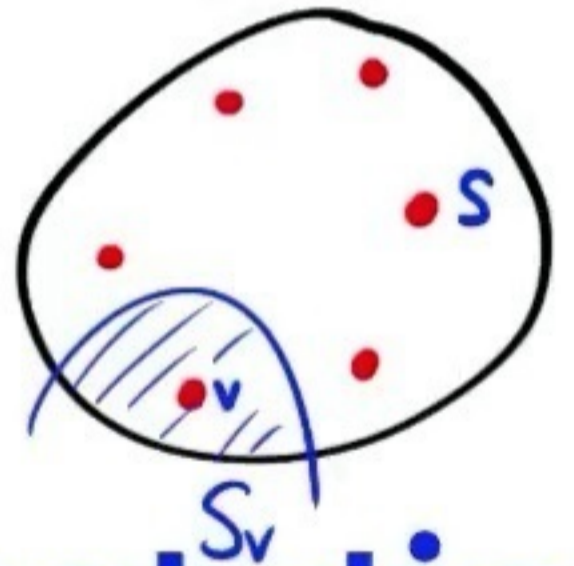


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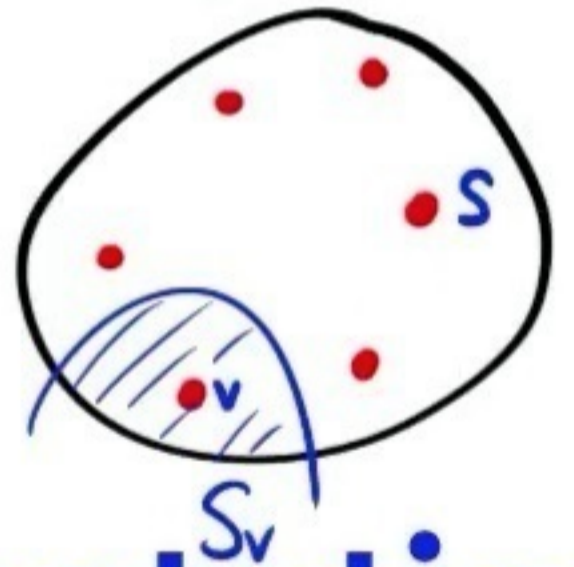
Claim: Certify $\Omega(1/\log n)$ fraction in expectation

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Algorithm CutThreshold :

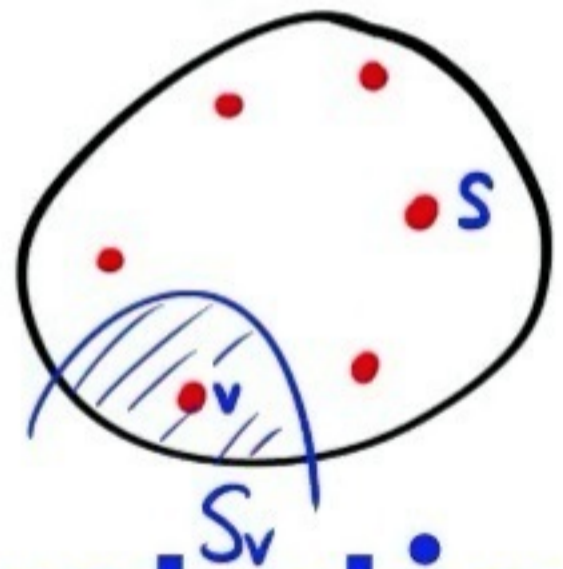
repeat $O(\log^2 n)$ times: call $\text{CutThresholdStep}(G,s,R)$
where $R = \{\text{still uncertified}\}$

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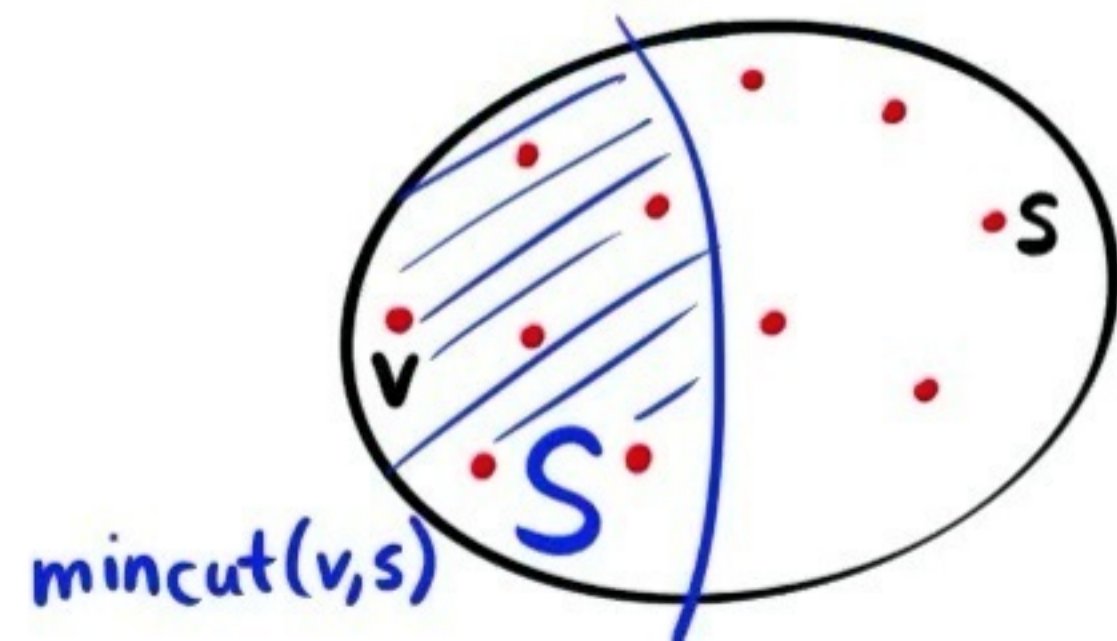
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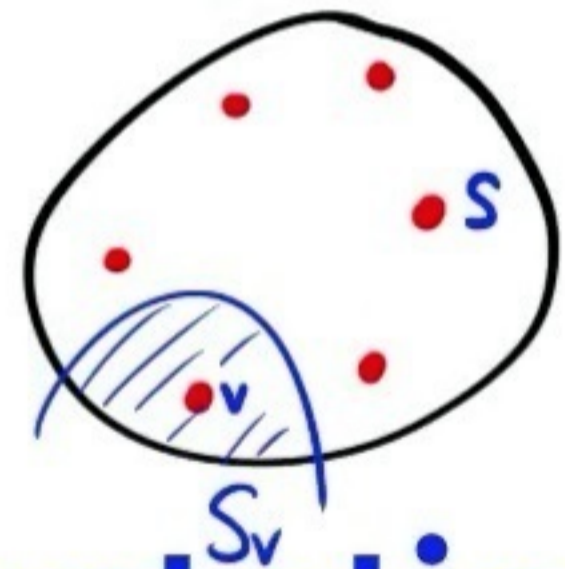


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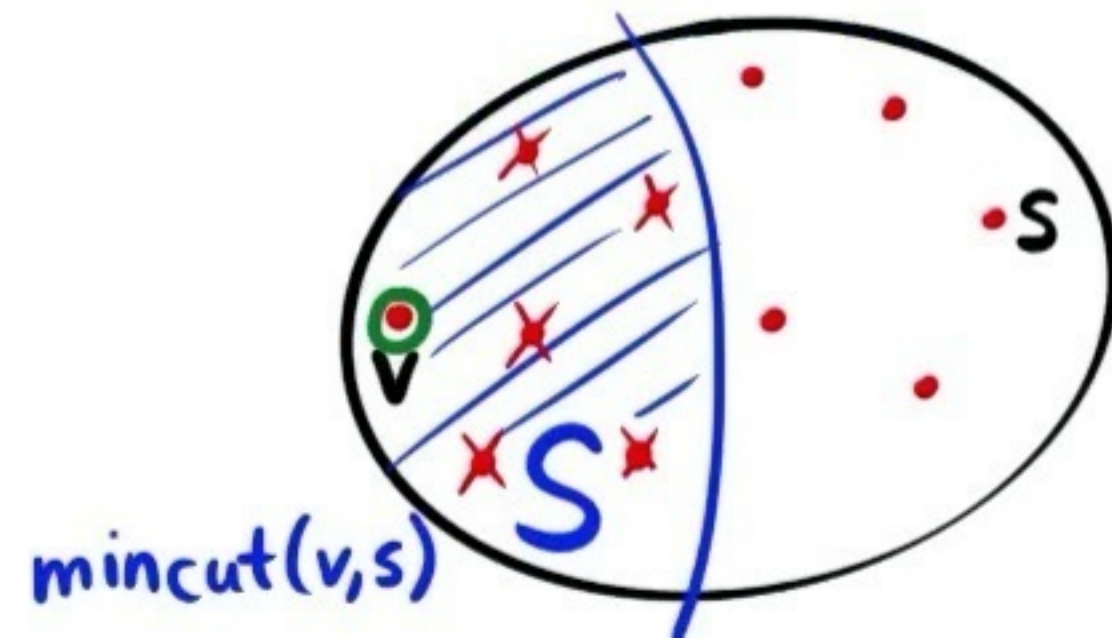
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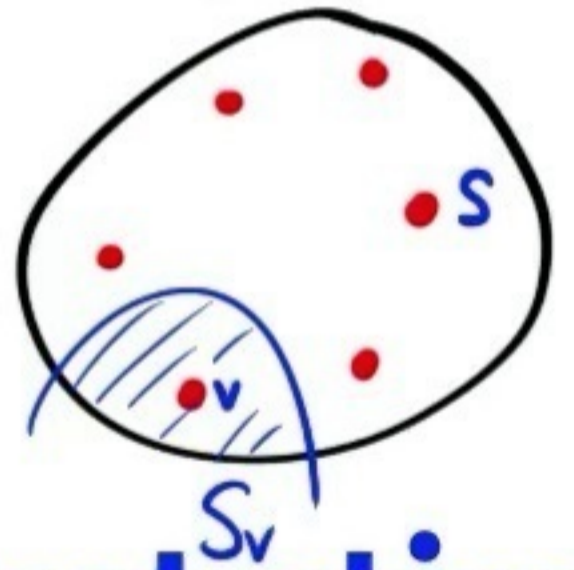


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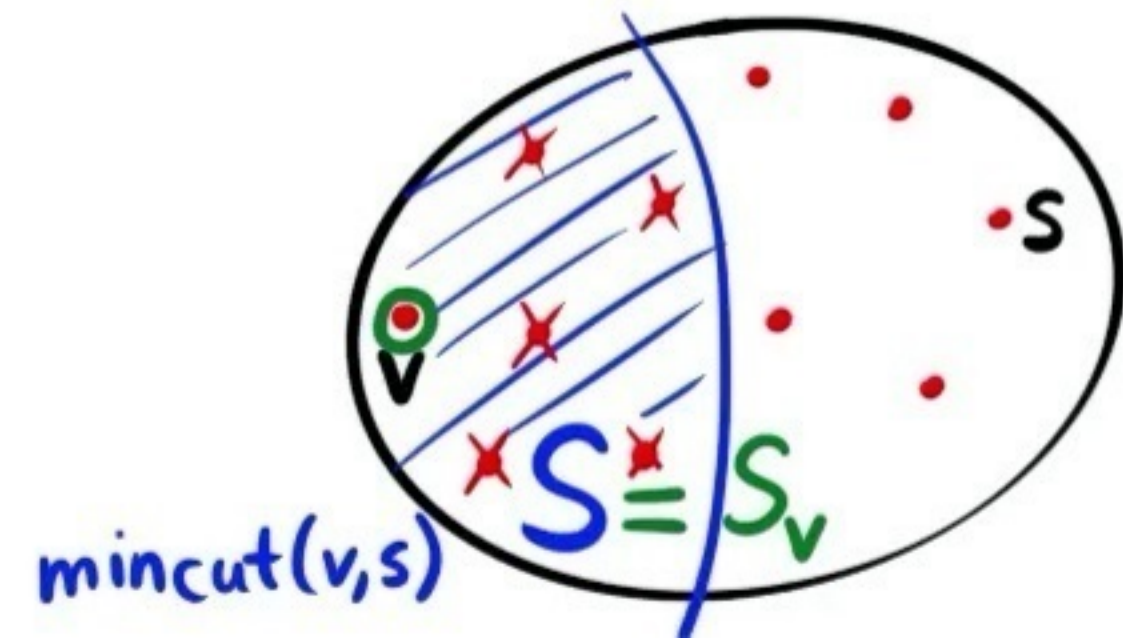
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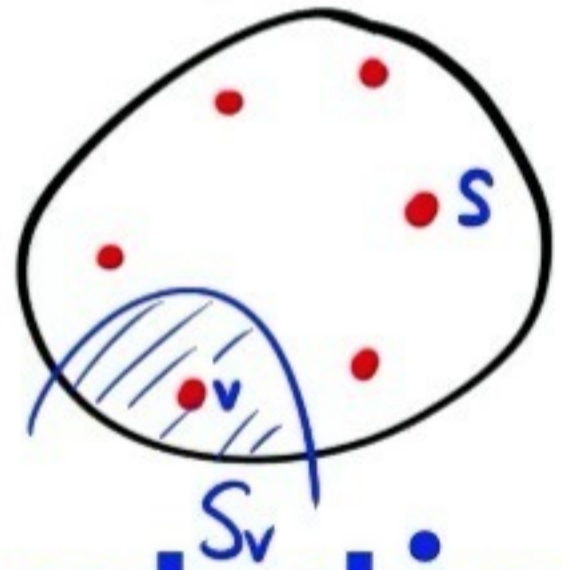


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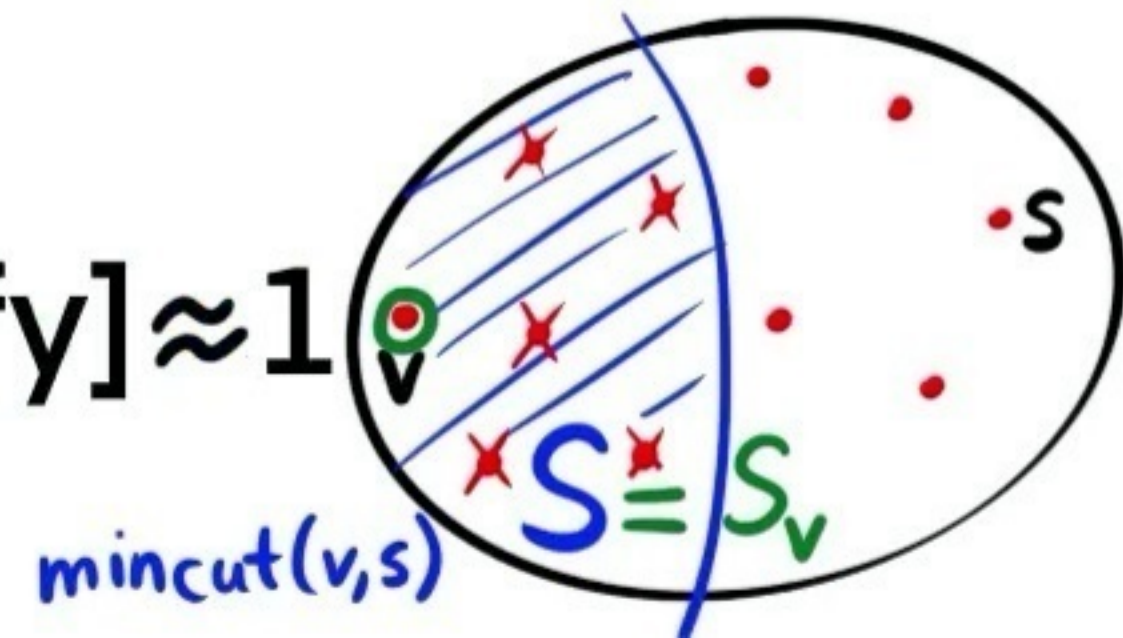


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with prob. $\sim 1/|S \cap R|$, certify $|S \cap R|$ vertices $\Rightarrow E[\#\text{certify}] \approx 1$

over all v certifiable, $E[\#\text{certify}] \approx \#\text{certifiable}$

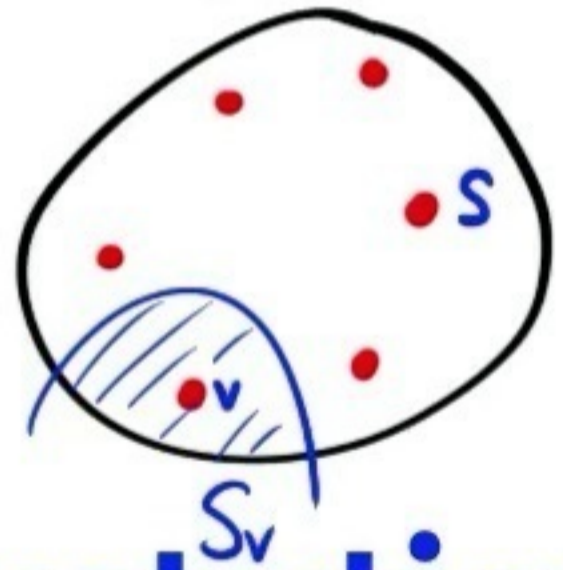


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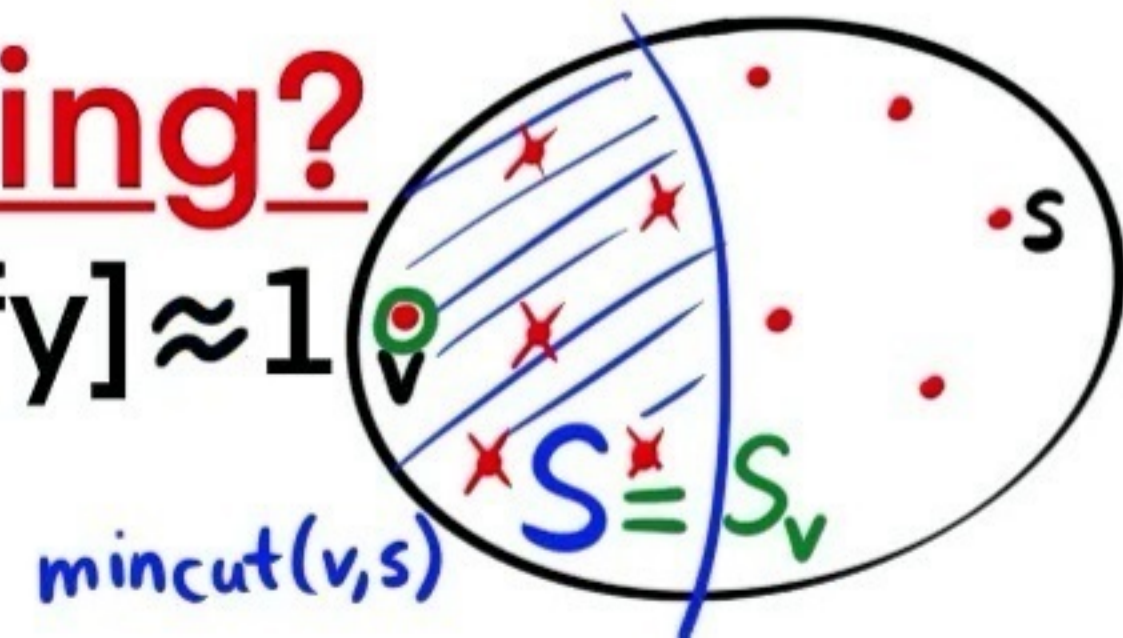


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Intuition: fix $v \in R$ certifiable ($\text{mincut}(s,v) \leq \lambda$) overcounting?

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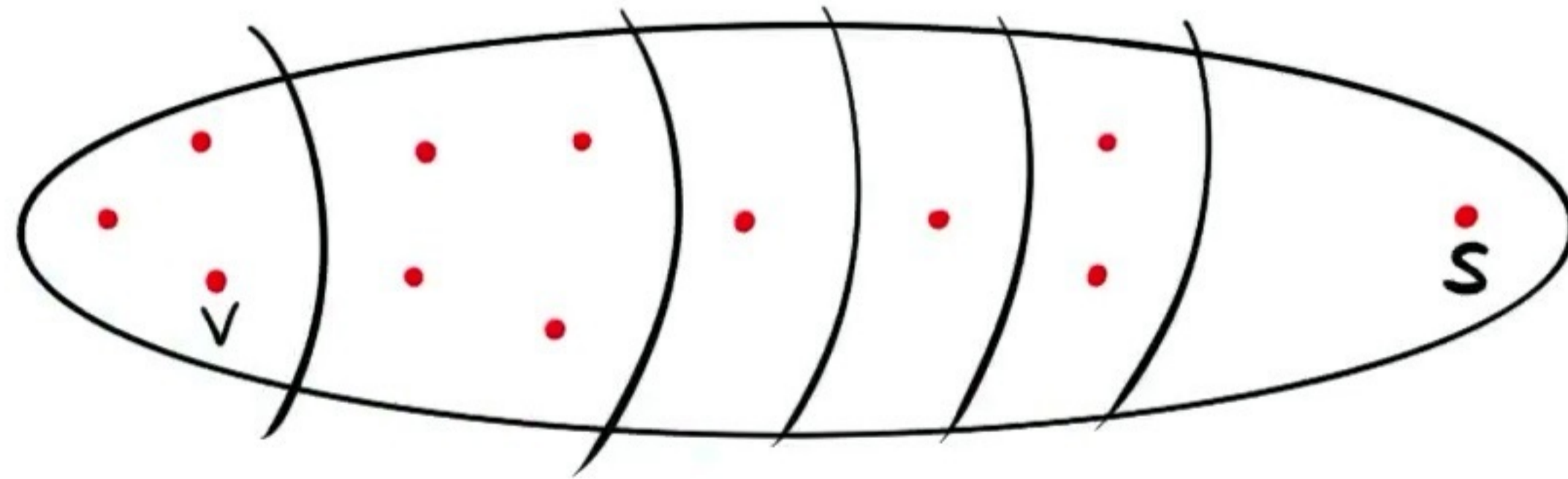
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Claim: each vertex overcounted $O(\log n)$ times w.h.p.

Proof: use fact that s - t mincuts are laminar:

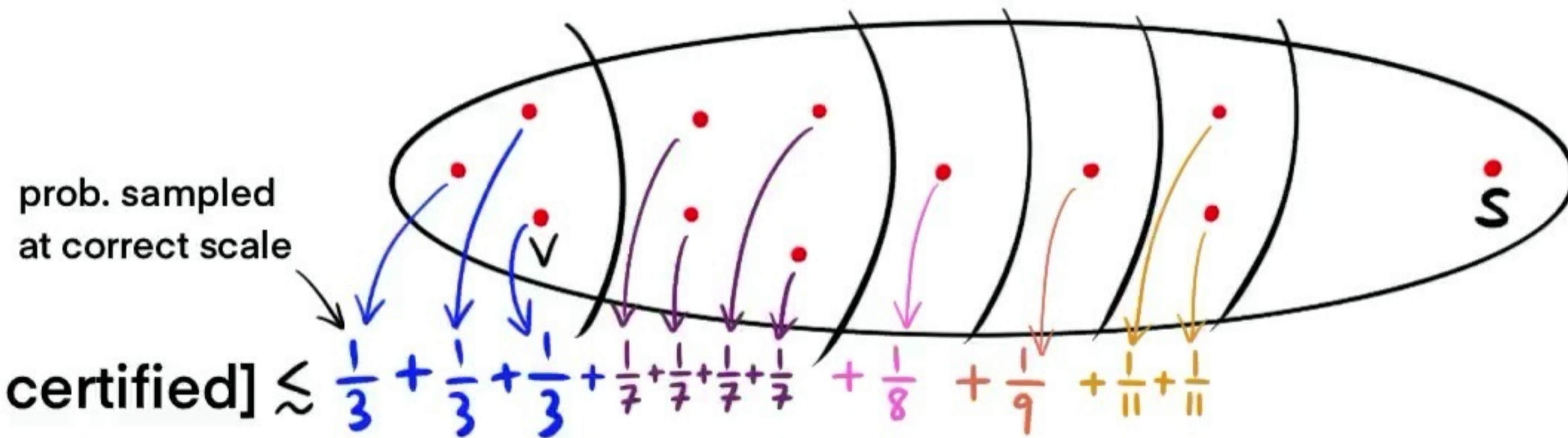


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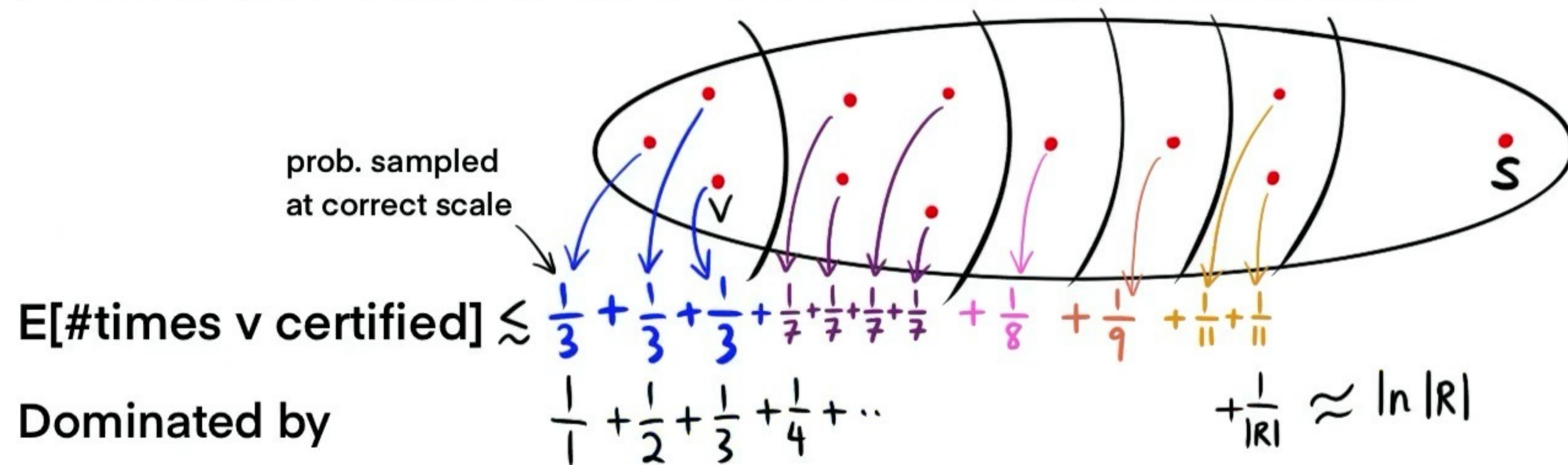


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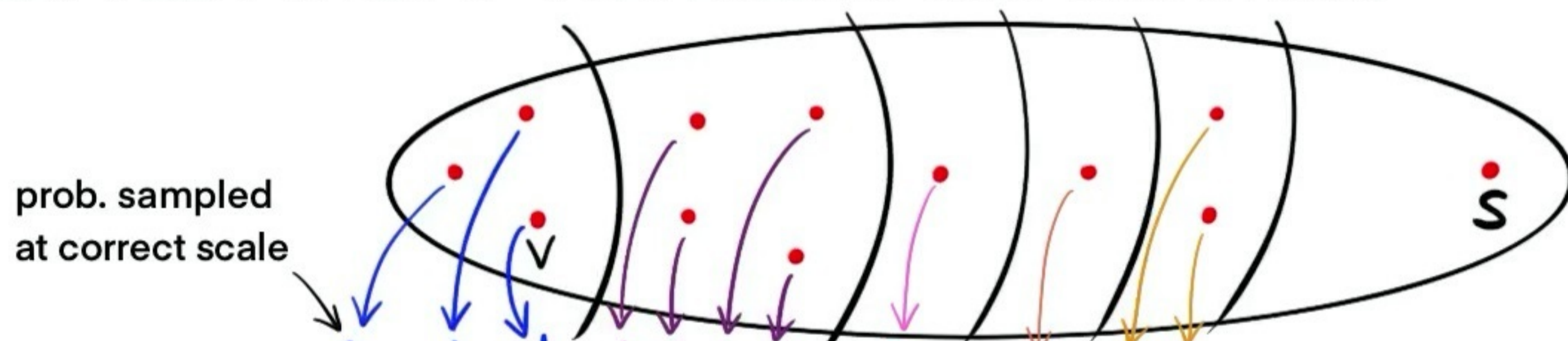


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$E[\# \text{times } v \text{ certified}] \lesssim \frac{1}{3} + \frac{1}{3} + \frac{1}{3} + \frac{1}{7} + \frac{1}{7} + \frac{1}{7} + \frac{1}{7} + \frac{1}{8} + \frac{1}{9} + \frac{1}{11} + \frac{1}{11} + \frac{1}{|R|} \approx \ln |R|$

Dominated by $\frac{1}{1} + \frac{1}{2} + \frac{1}{3} + \frac{1}{4} + \dots$

$E[\# \text{times } v \text{ certified}] \lesssim O(\log |R|)$. Chernoff bound: $O(\log n)$ w.h.p.

Approximate SSMC and GH Tree

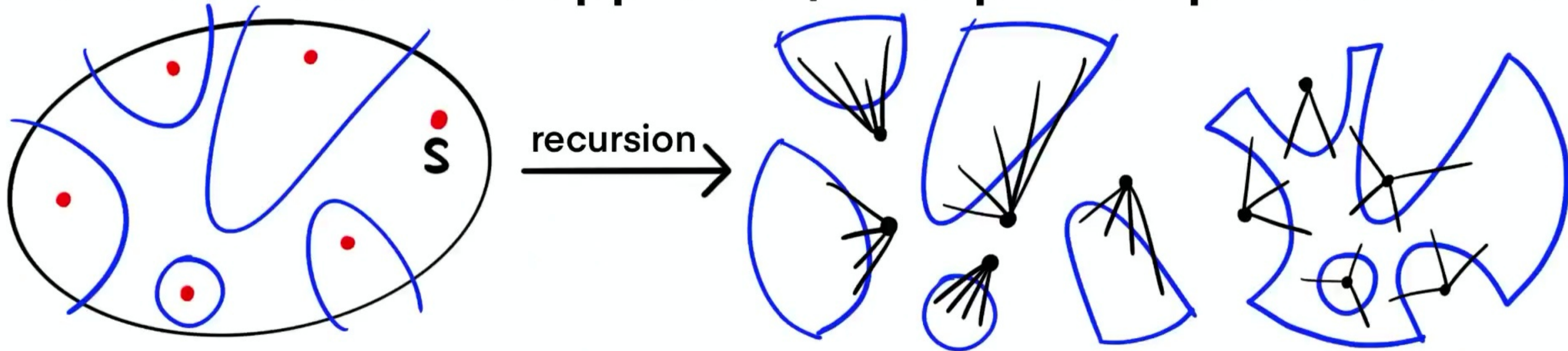
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standard recursive approach, except multiple branches

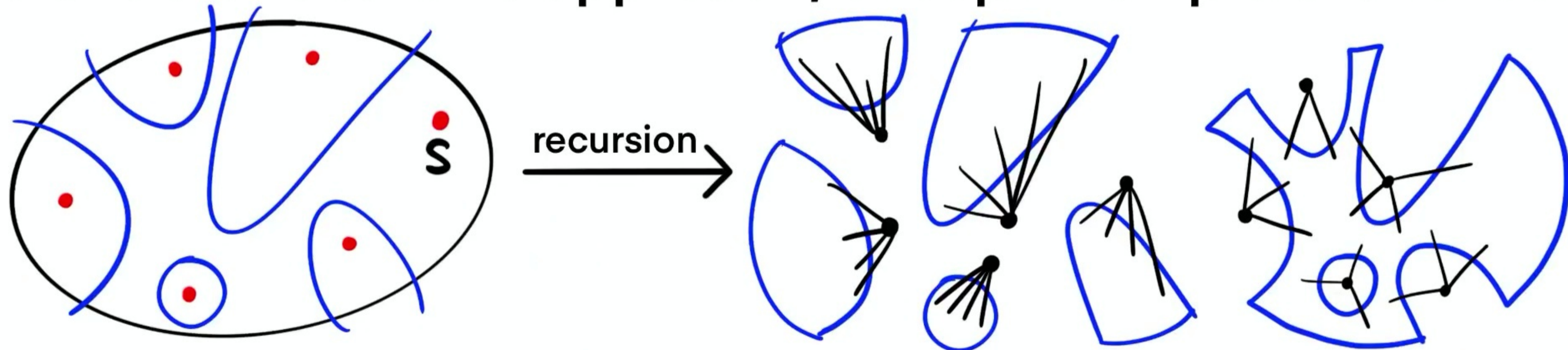


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select s **uniformly at random** [AKT'20]

Control the approximation factor (nontrivial)

Conclusion and Open Questions

Algorithms for Cut Threshold, $(1+\varepsilon)$ -SSMC, $(1+\varepsilon)$ -GHTree
in \sim max-flow time

Main tools: minimum isolating cuts + random sampling

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Open questions:

- Faster exact GH tree? Reduces to exact SSMC values
- SSMC values faster than $n-1$ max-flows?
- Approximate GH tree in near-linear time?
- More applications of Minimum Isolating Cuts?