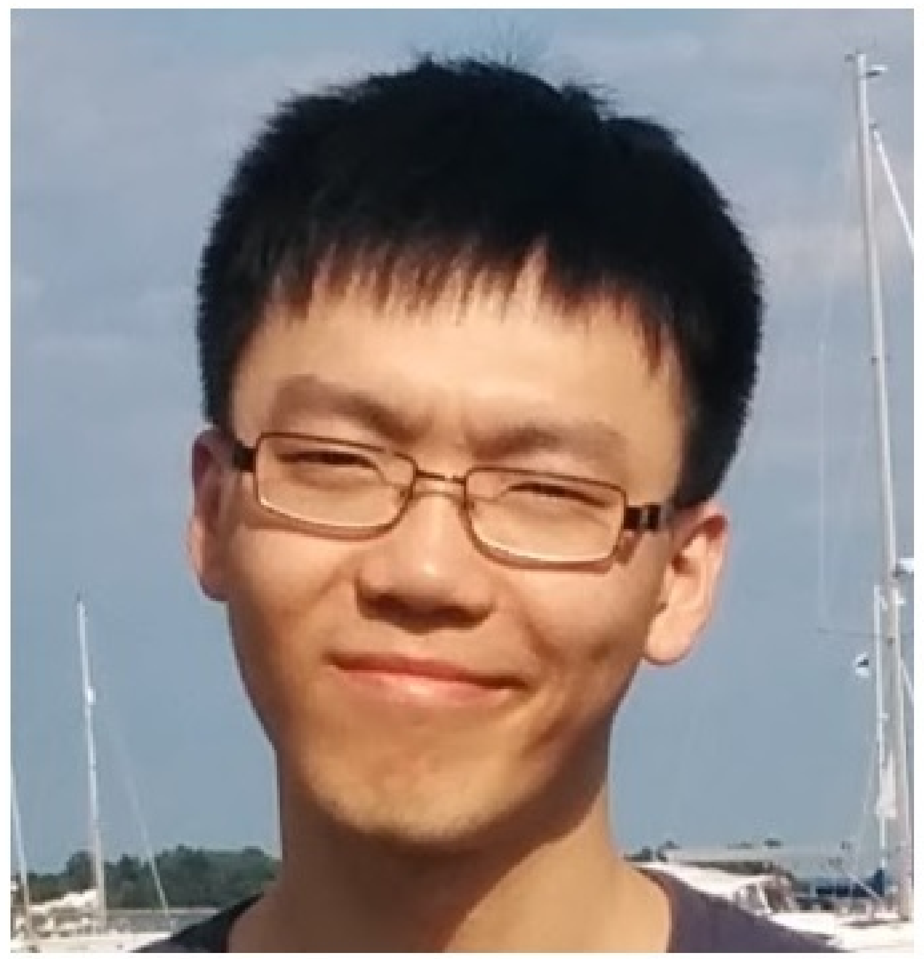
Deterministic Near-Linear Time Minimum Cut for Weighted Graphs

Jason Li (Berkeley→CMU)



with Monika Henzinger Satish Rao Di Wang

Introduction

- Global mincut problem:
  given a weighted undirected graph,
  delete edges of minimum weight
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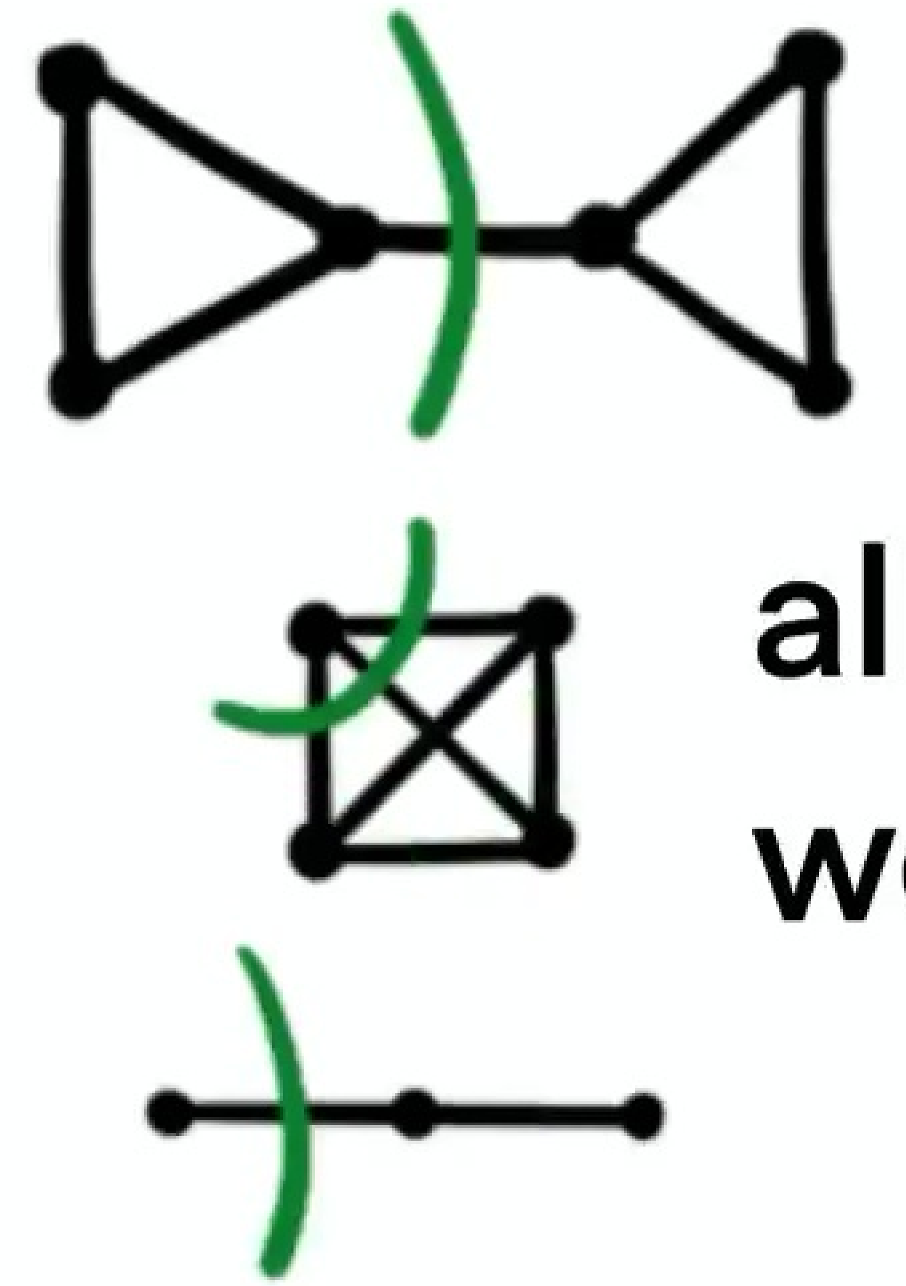

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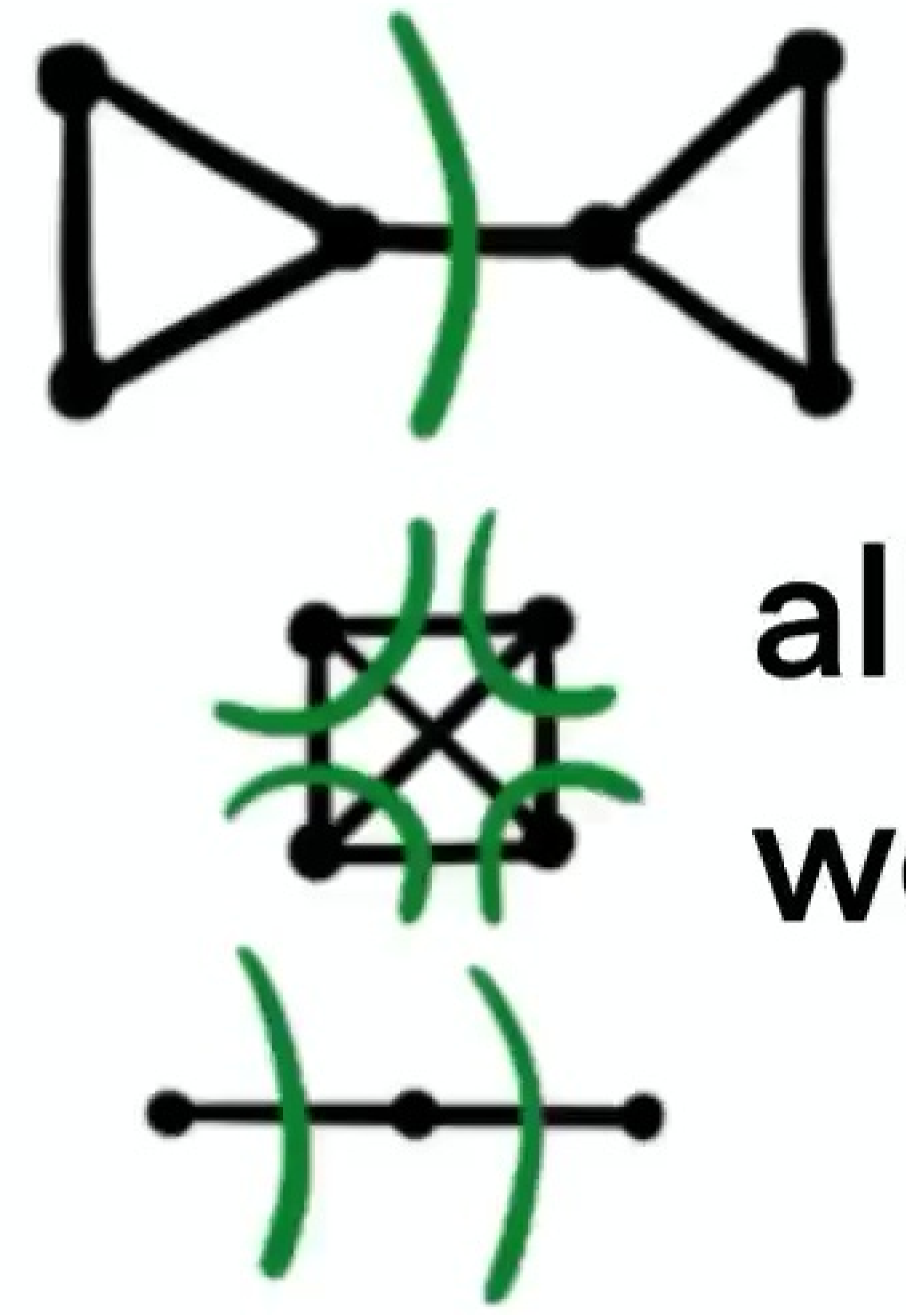

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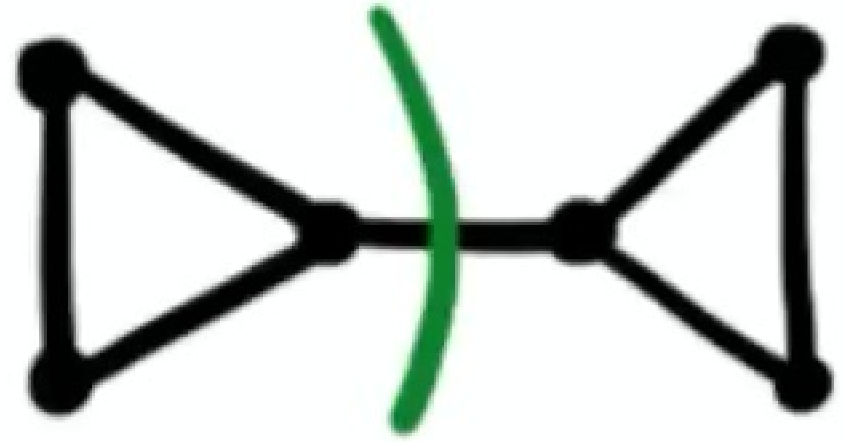

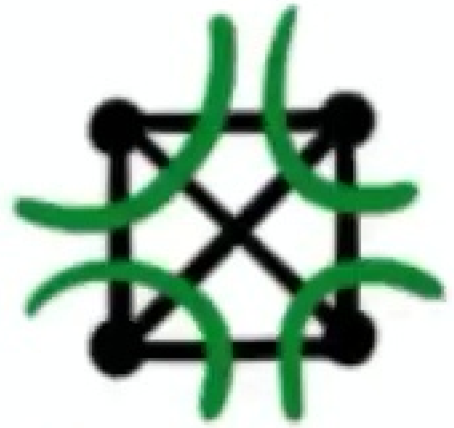

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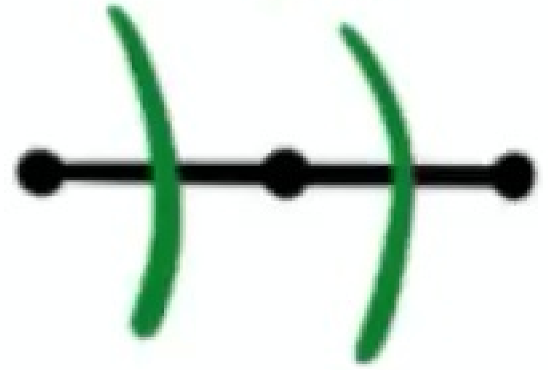

- [Karger'96] randomized algorithm in $O(m\log^3 n)$ time
  "Is there a deterministic near-linear time algorithm?"

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"almost-linear time"

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- [This work] $\tilde{O}(m)$ time, answering Karger's question

Outline

- Local win/win approach to global mincut

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- Our main structural theorem
- New randomized $(1+\varepsilon)$-approximate global mincut
  (main conceptual contribution)
- Derandomize and obtain exact mincut
  (technical: 40+ pages)

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win/win approach:

- if solution is local, then run local algorithm

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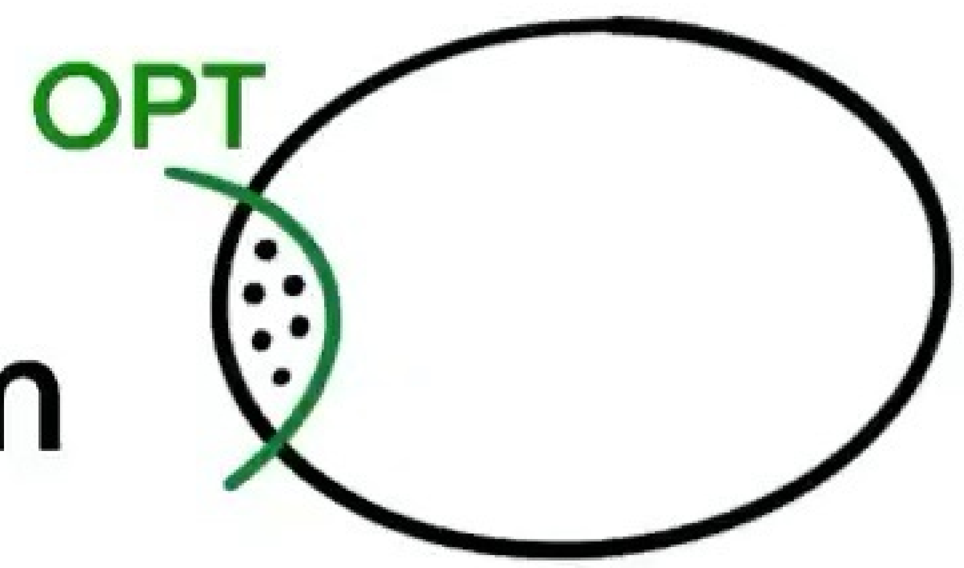

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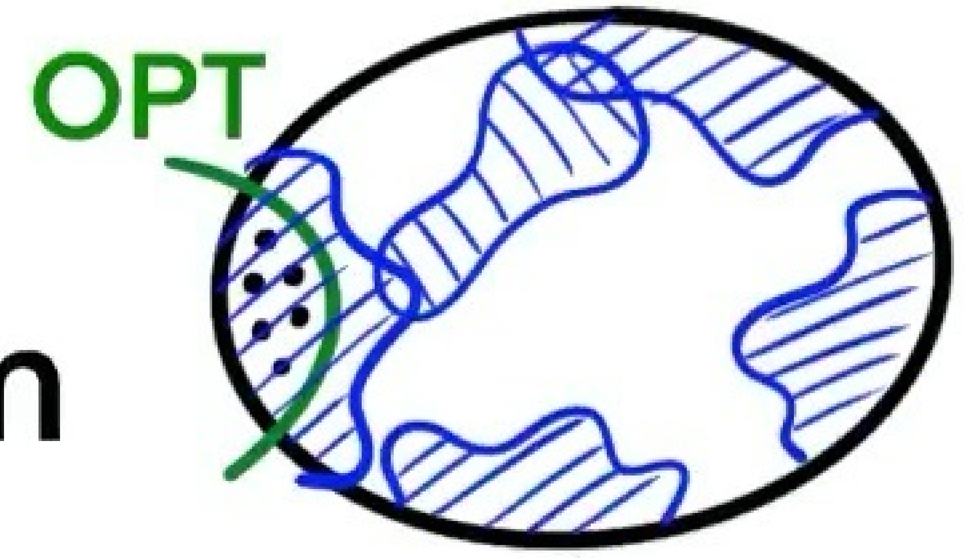

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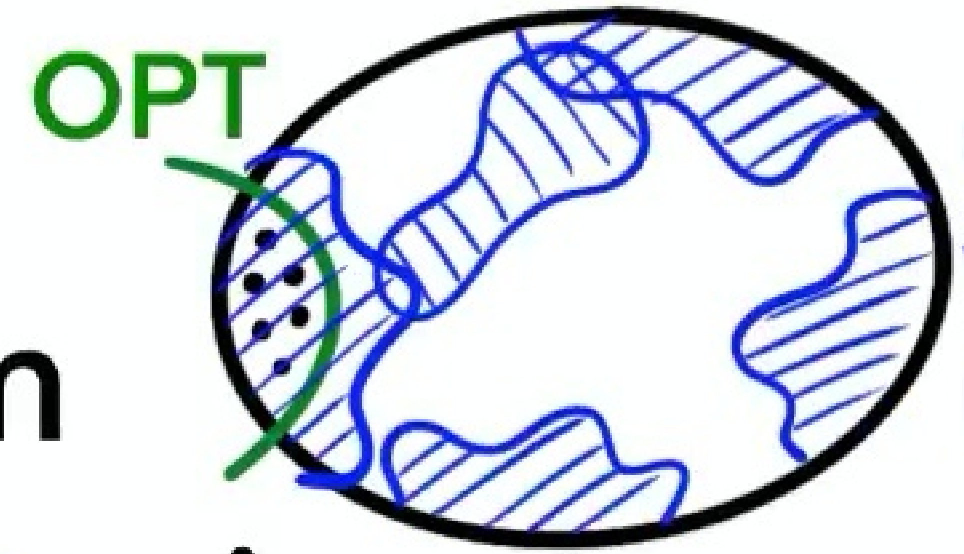

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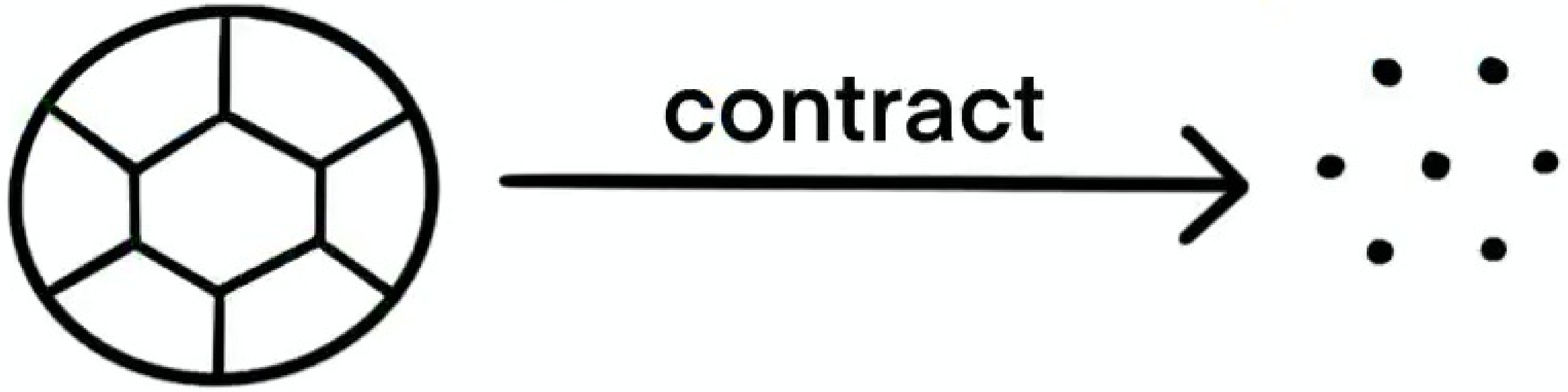

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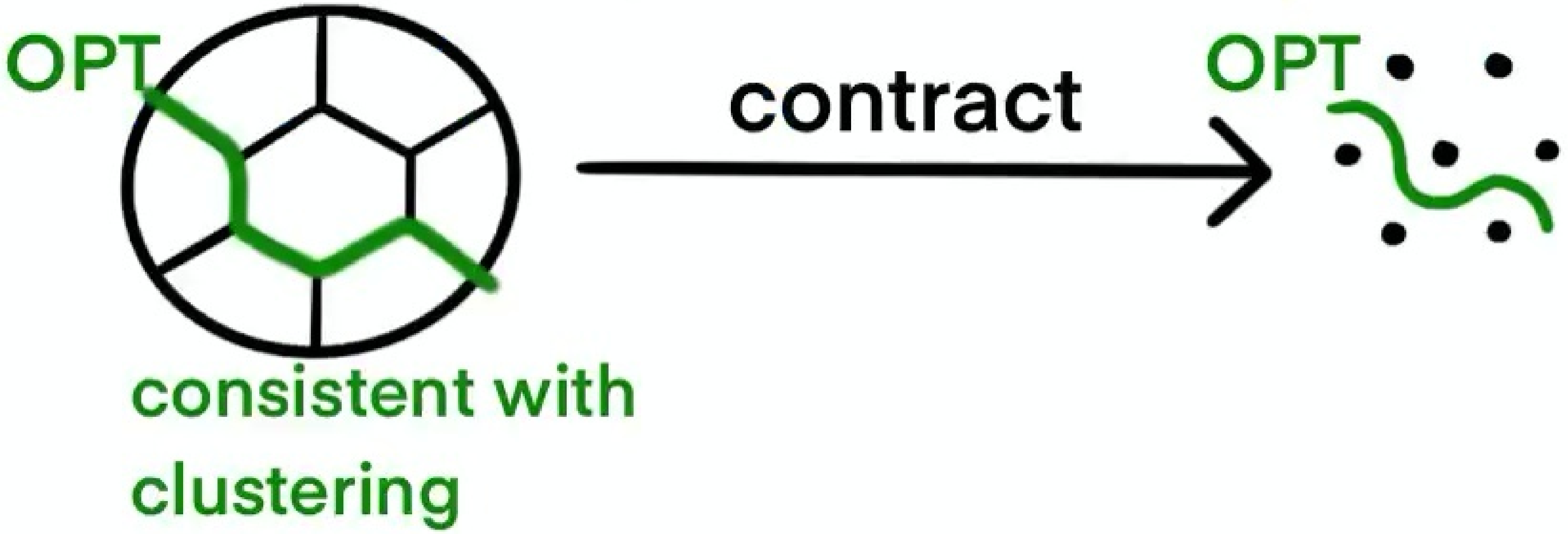

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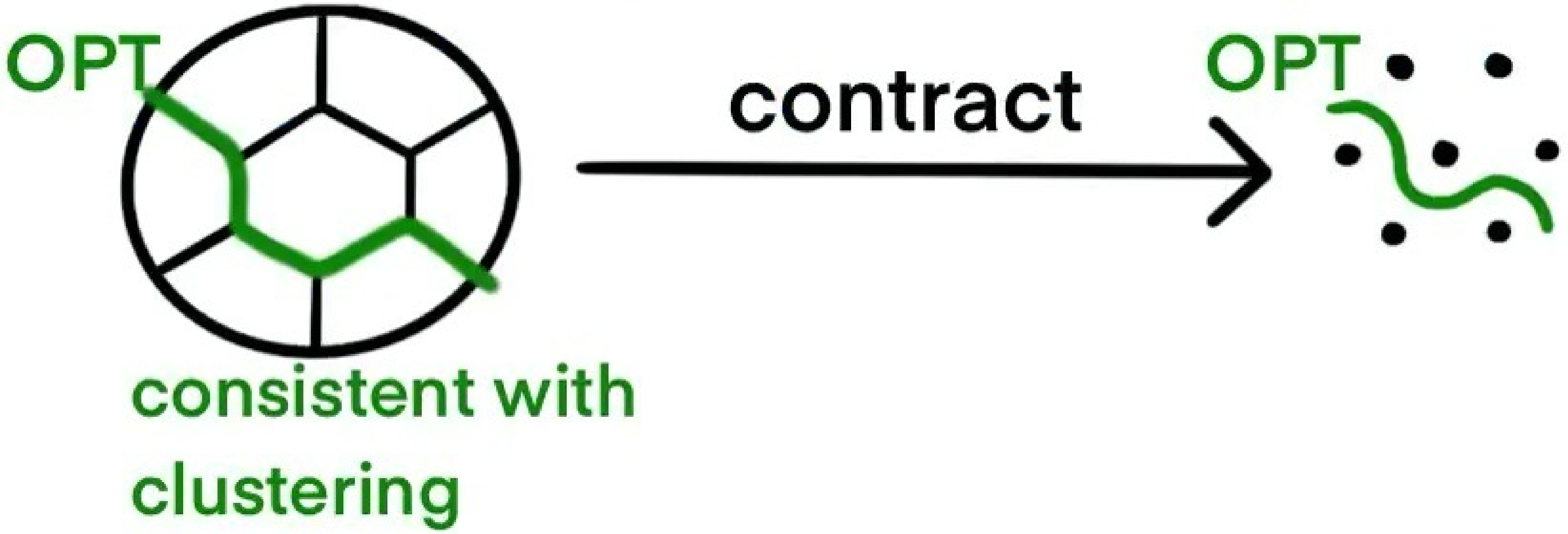

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Kawarabayashi-Thorup sparsification for global mincut on simple graphs [KT'15]:

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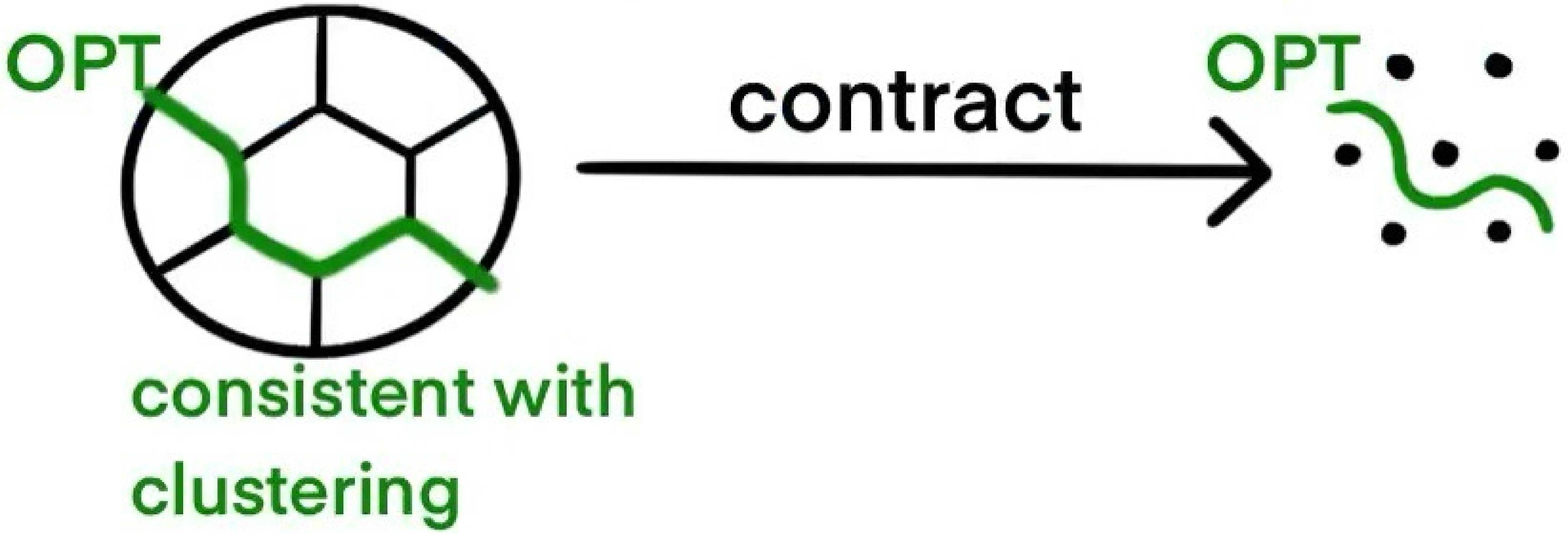

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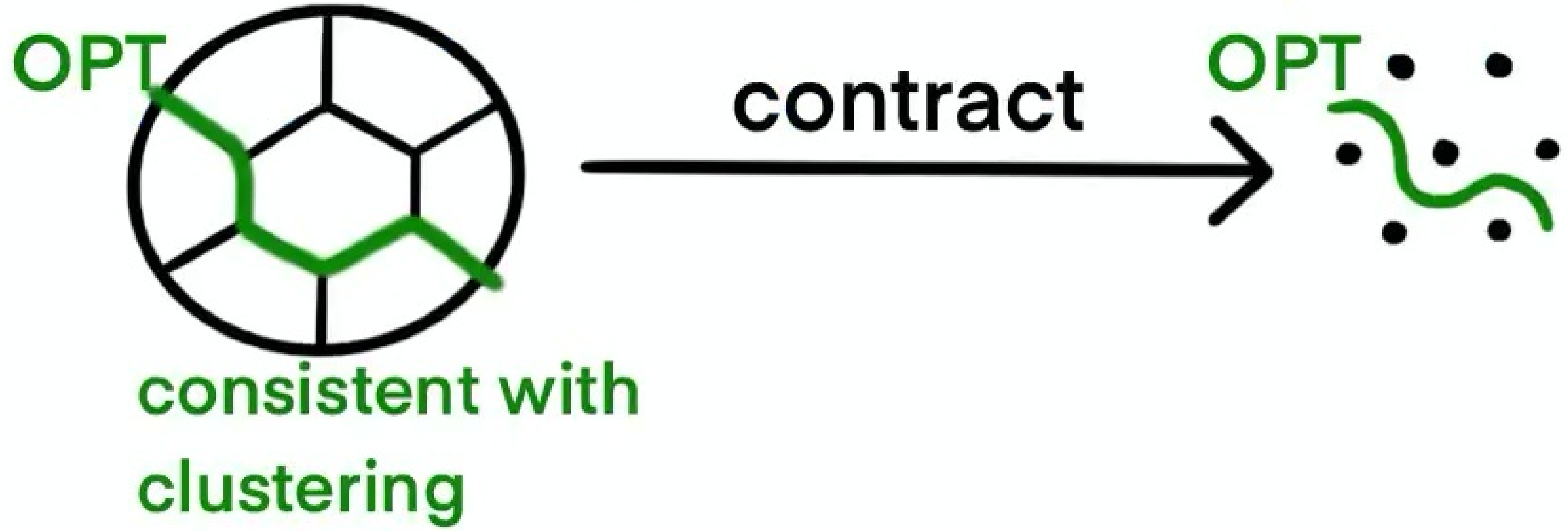

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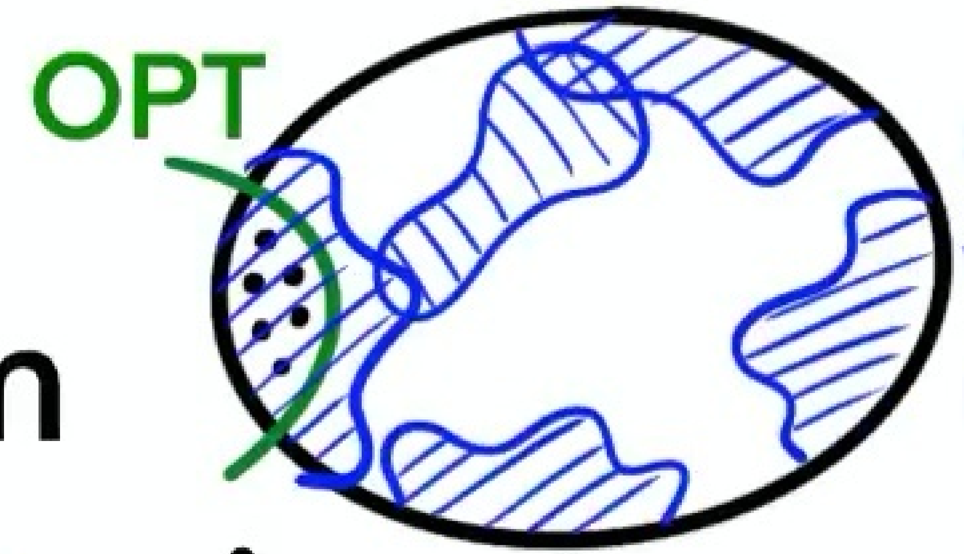

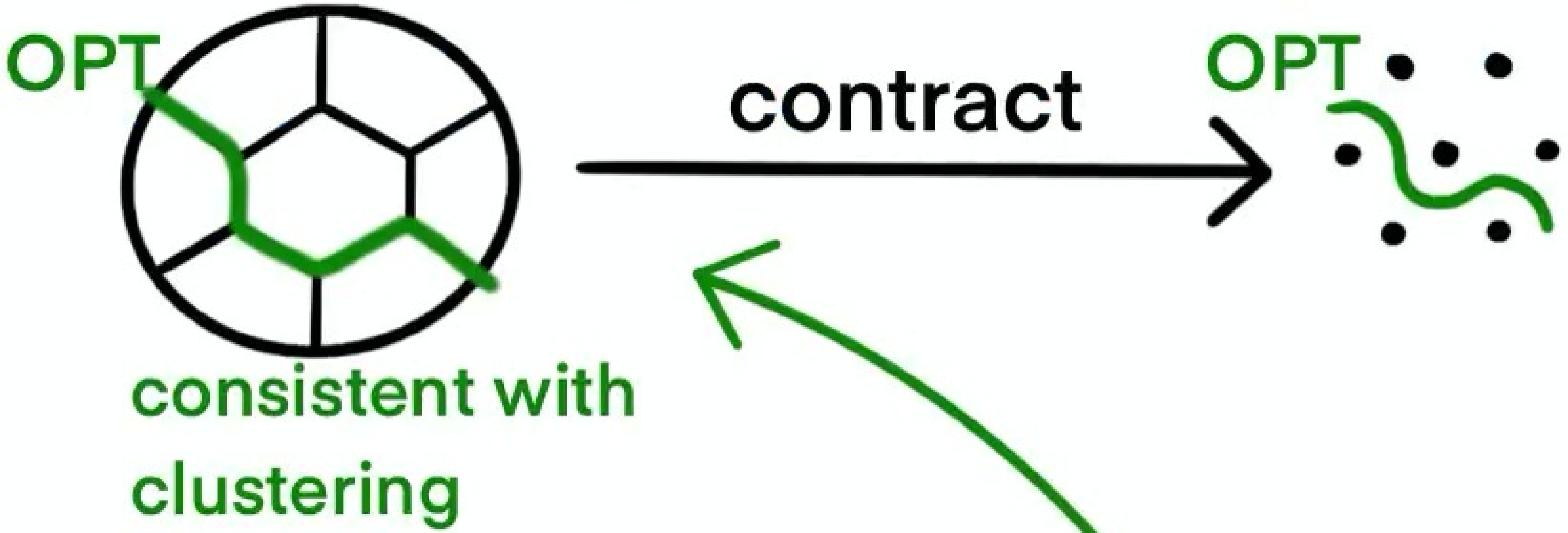

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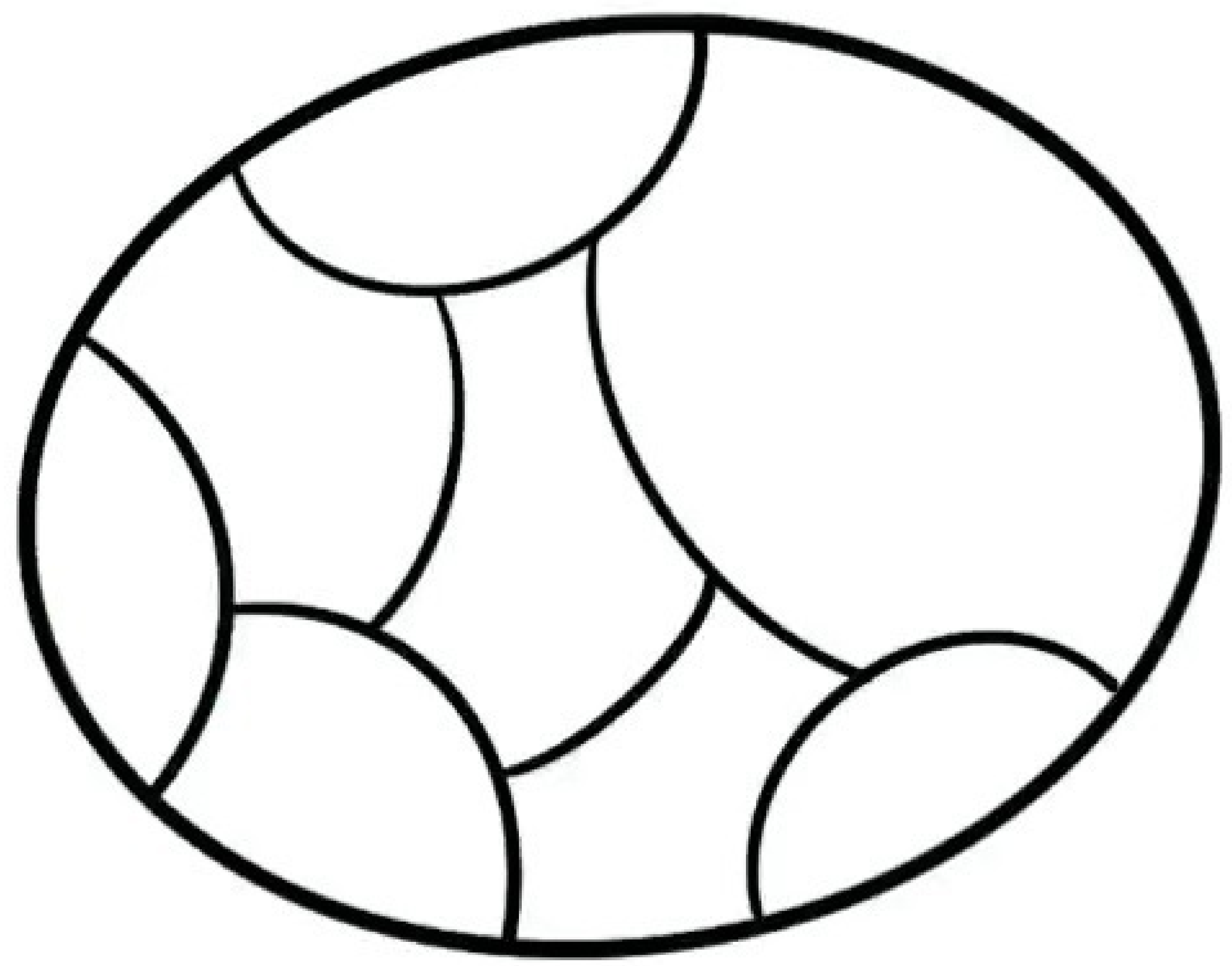
Theorem: for any weighted undirected graph, can group the vertices into <= n/2 clusters s.t.



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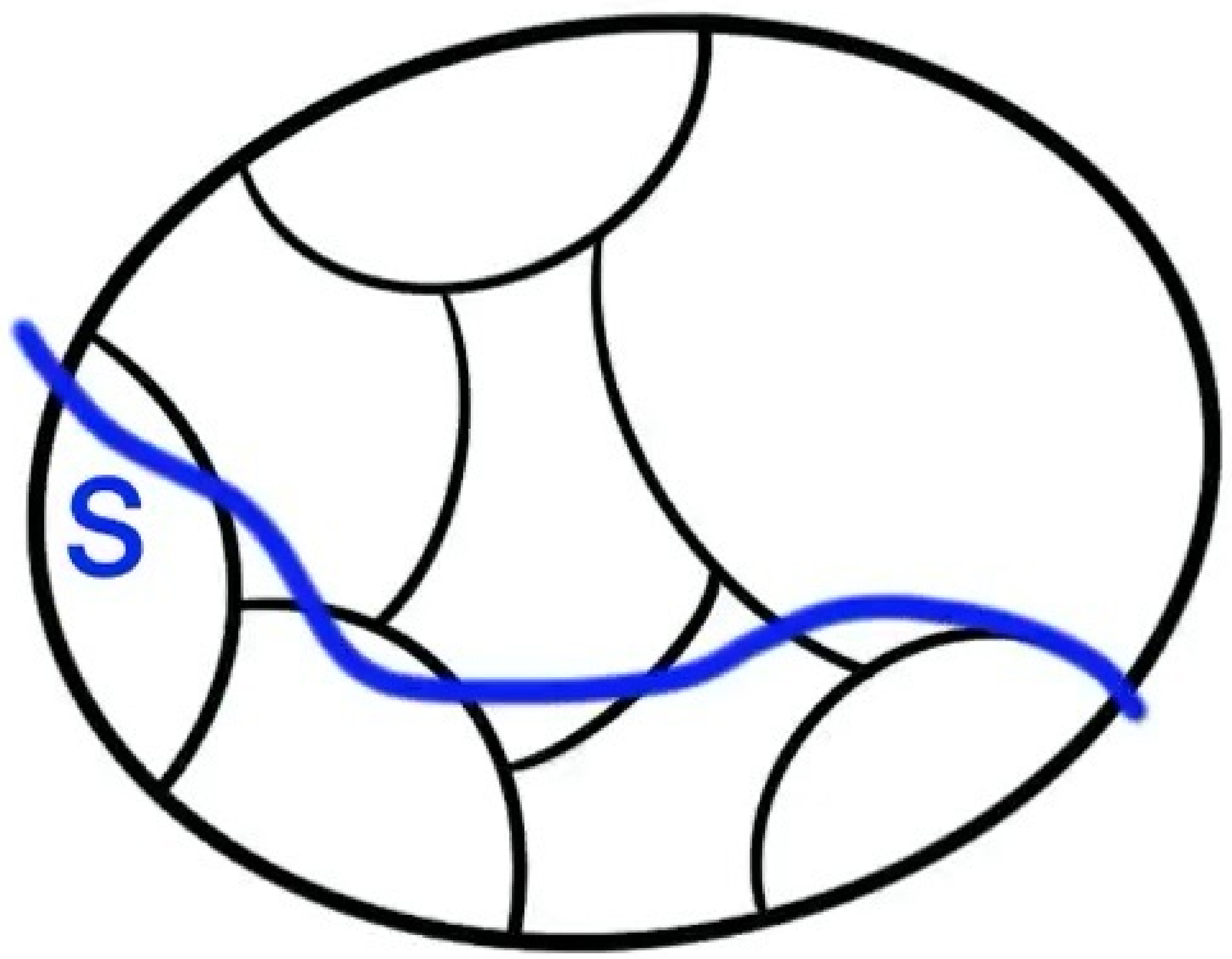

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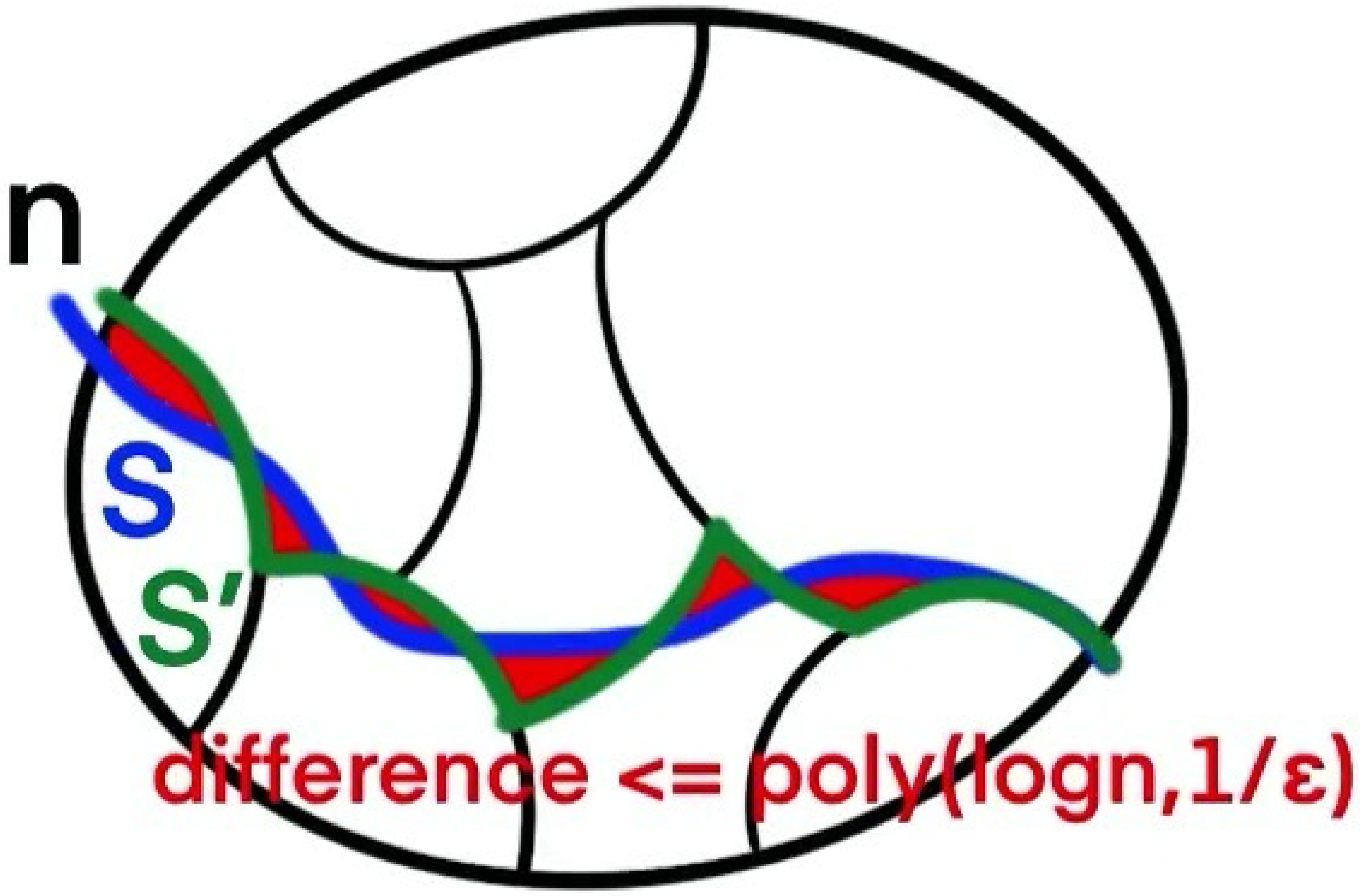

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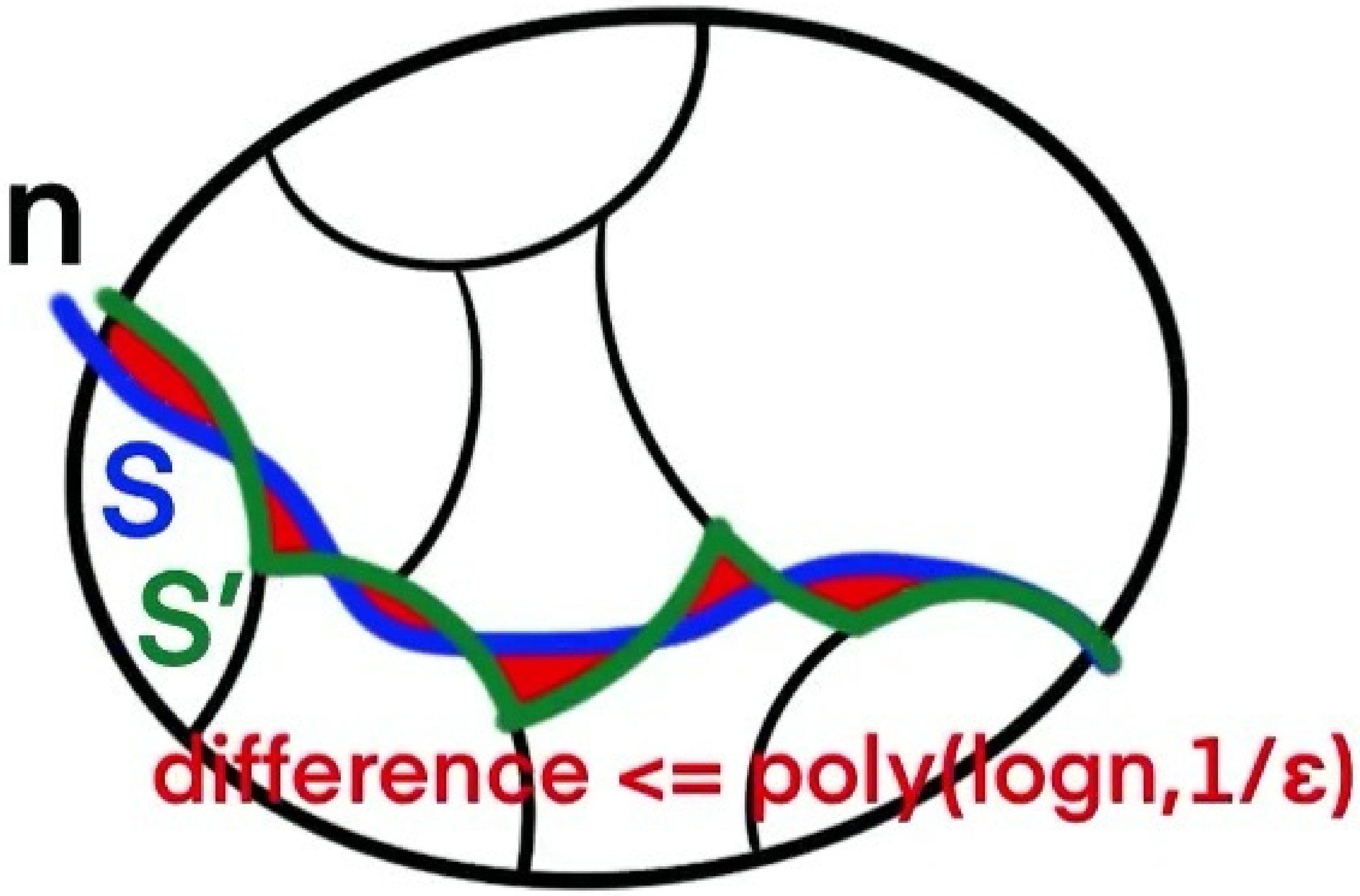

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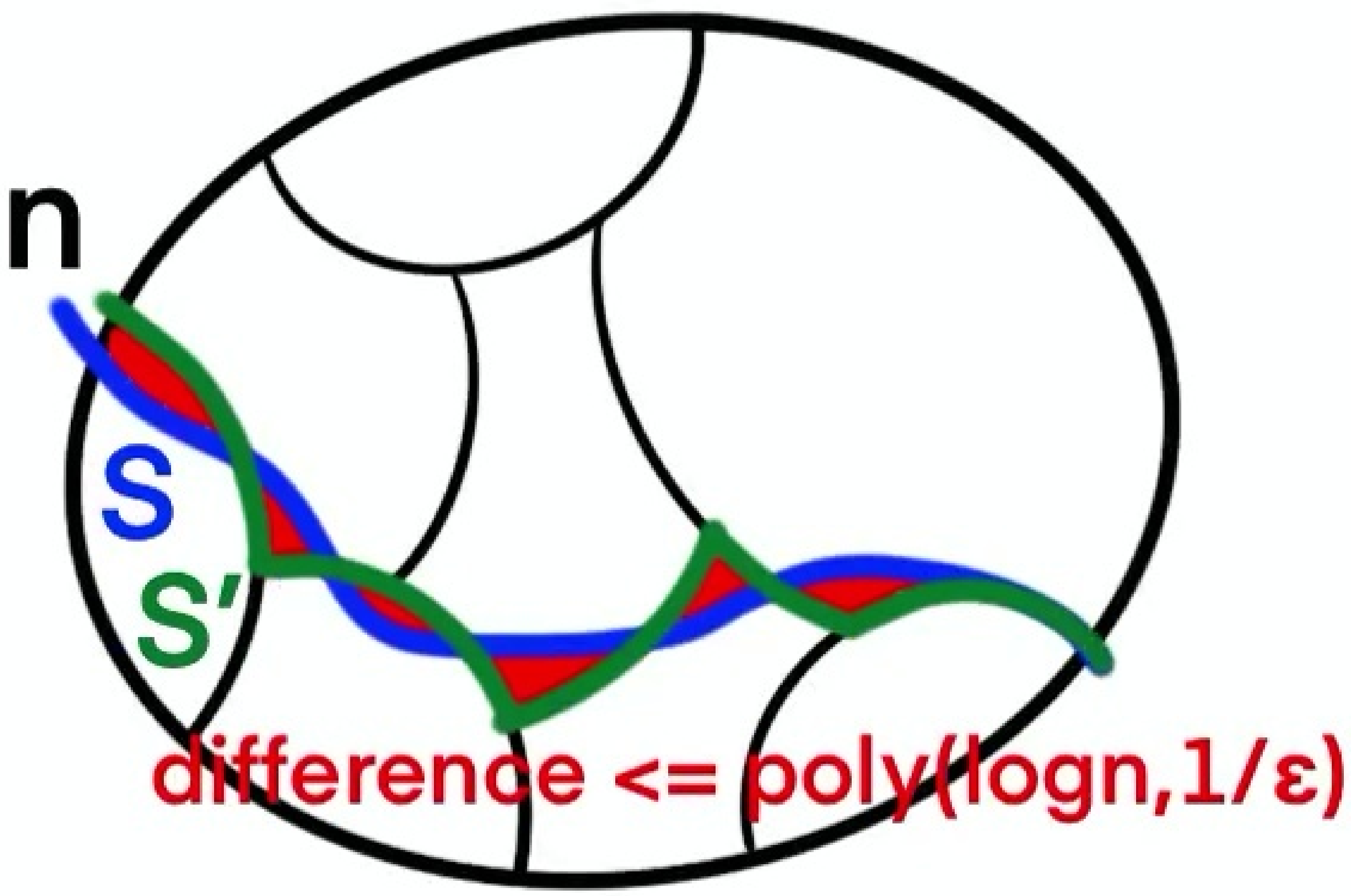

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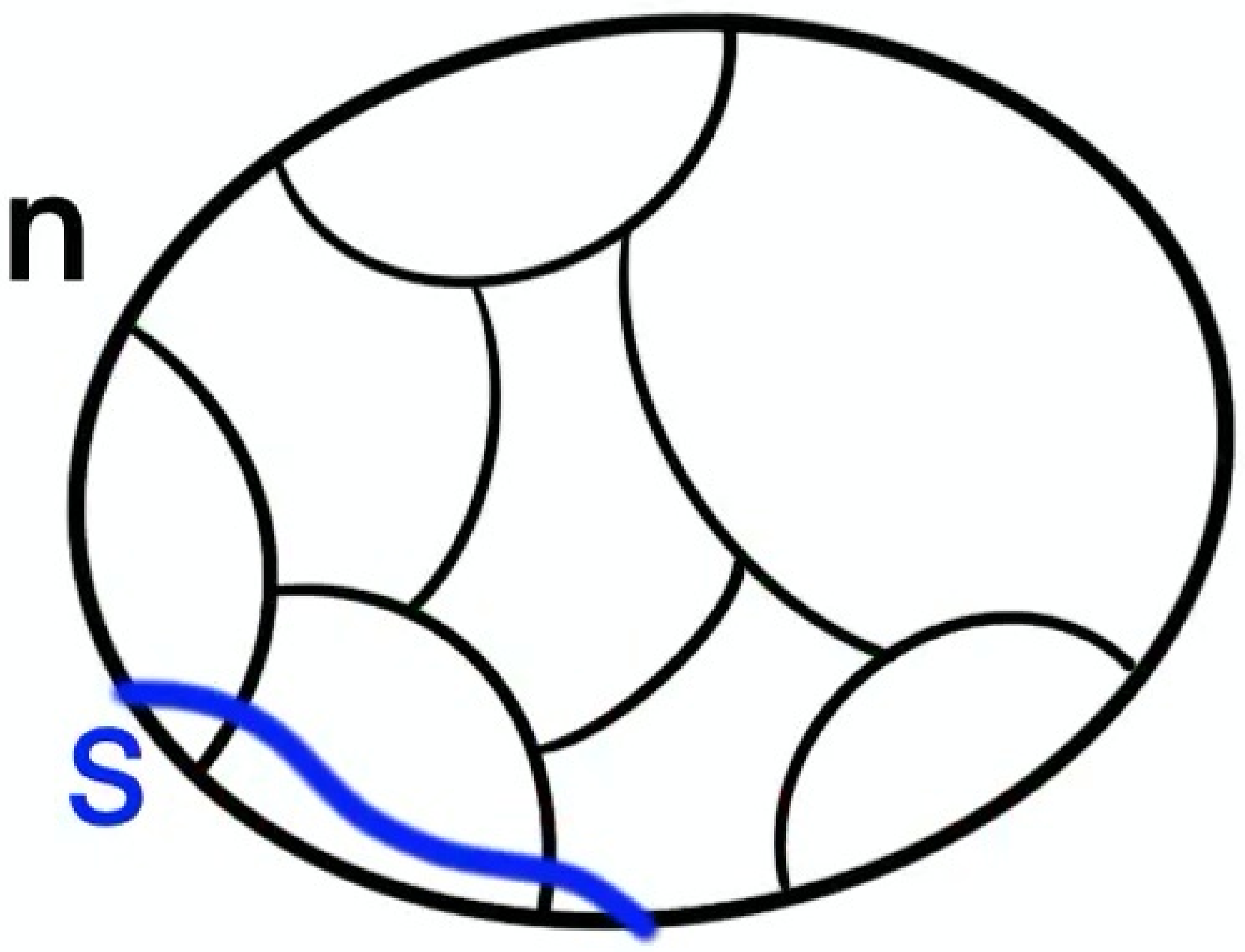

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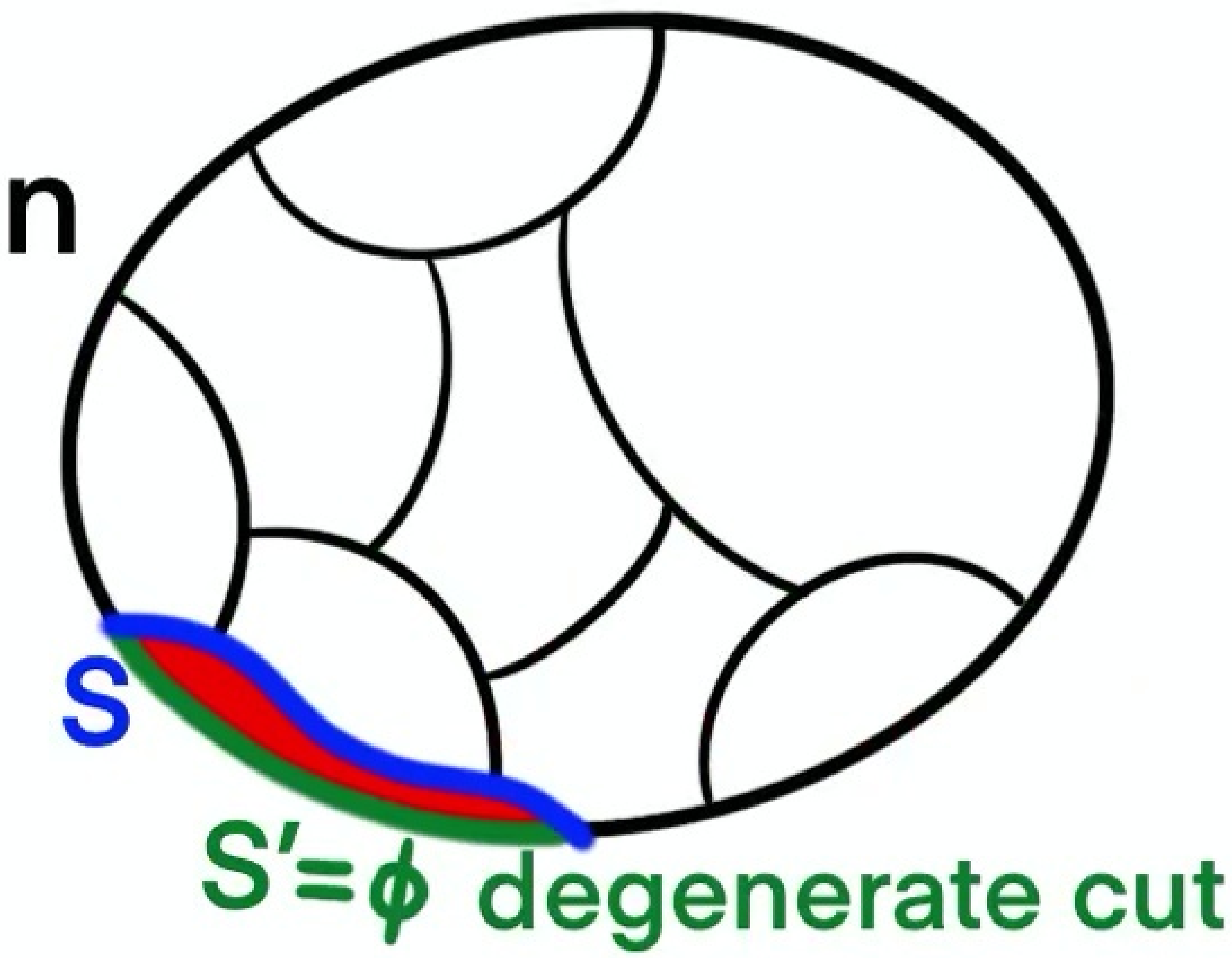

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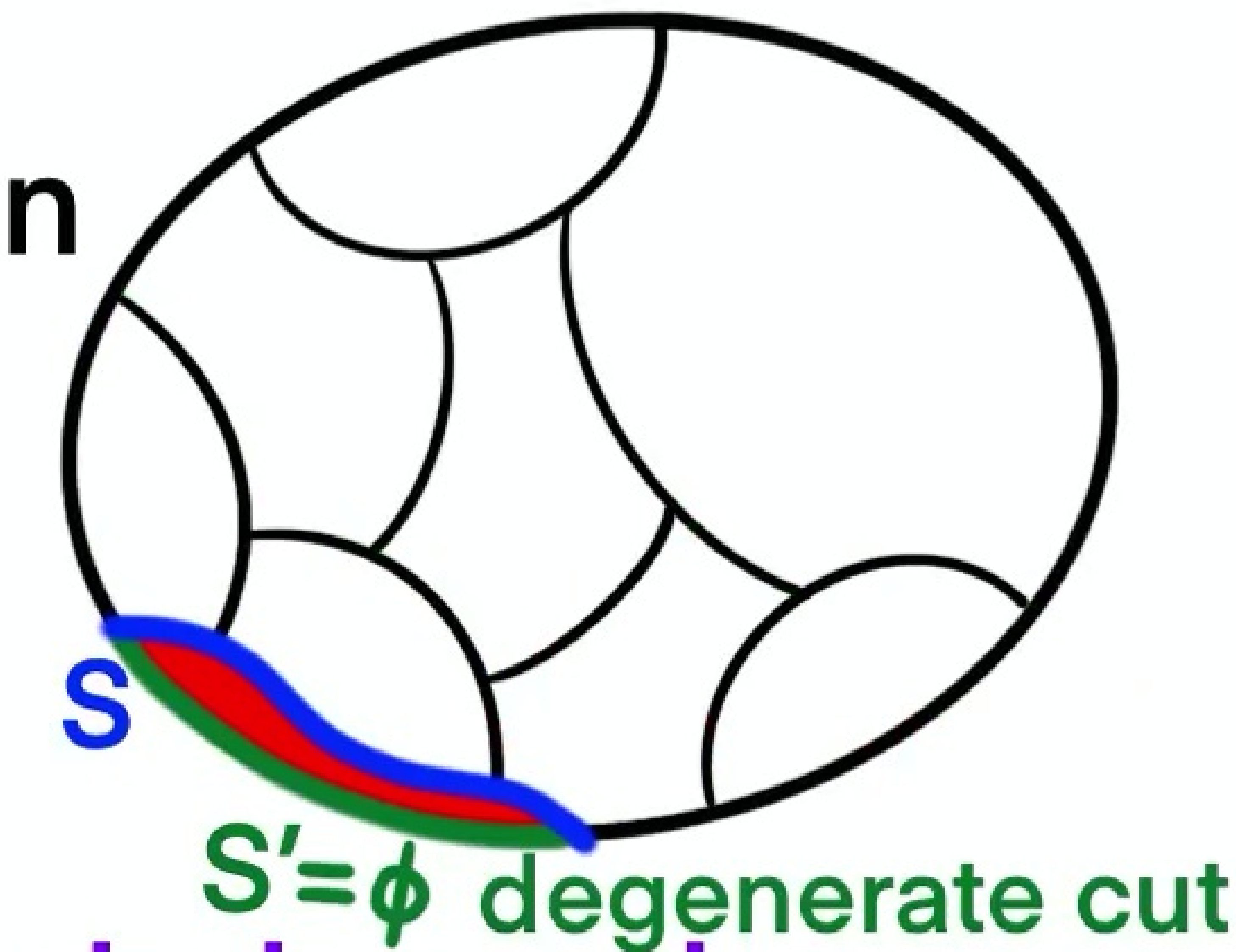

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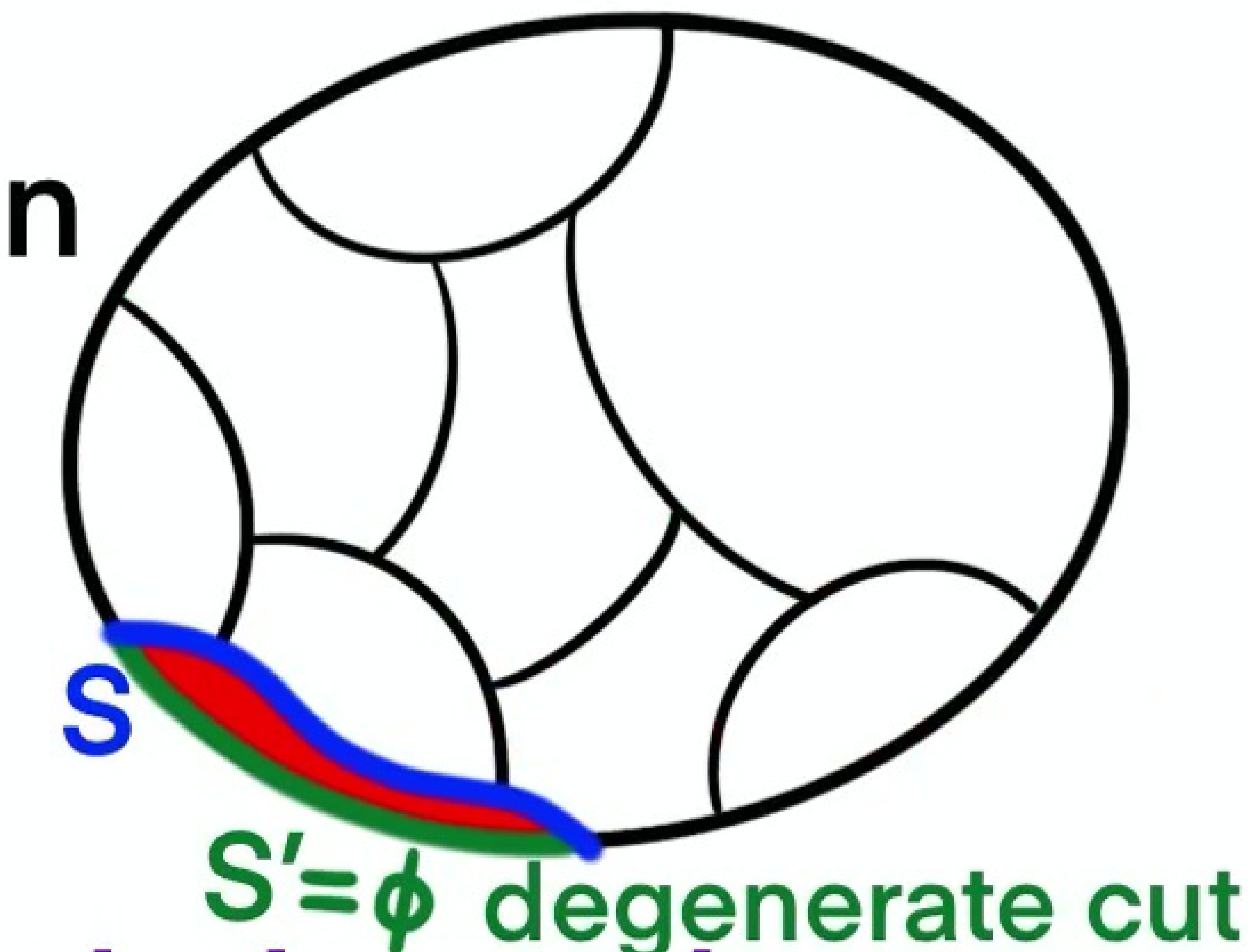

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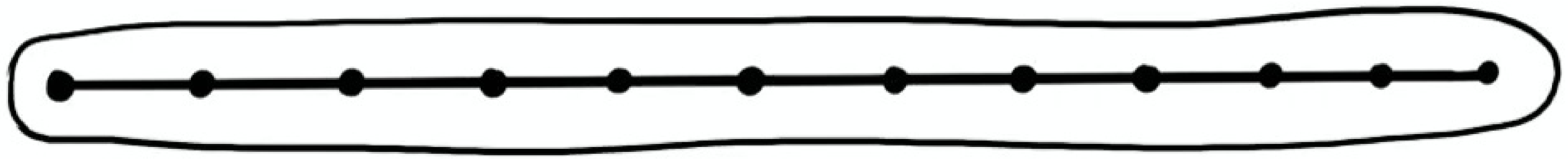

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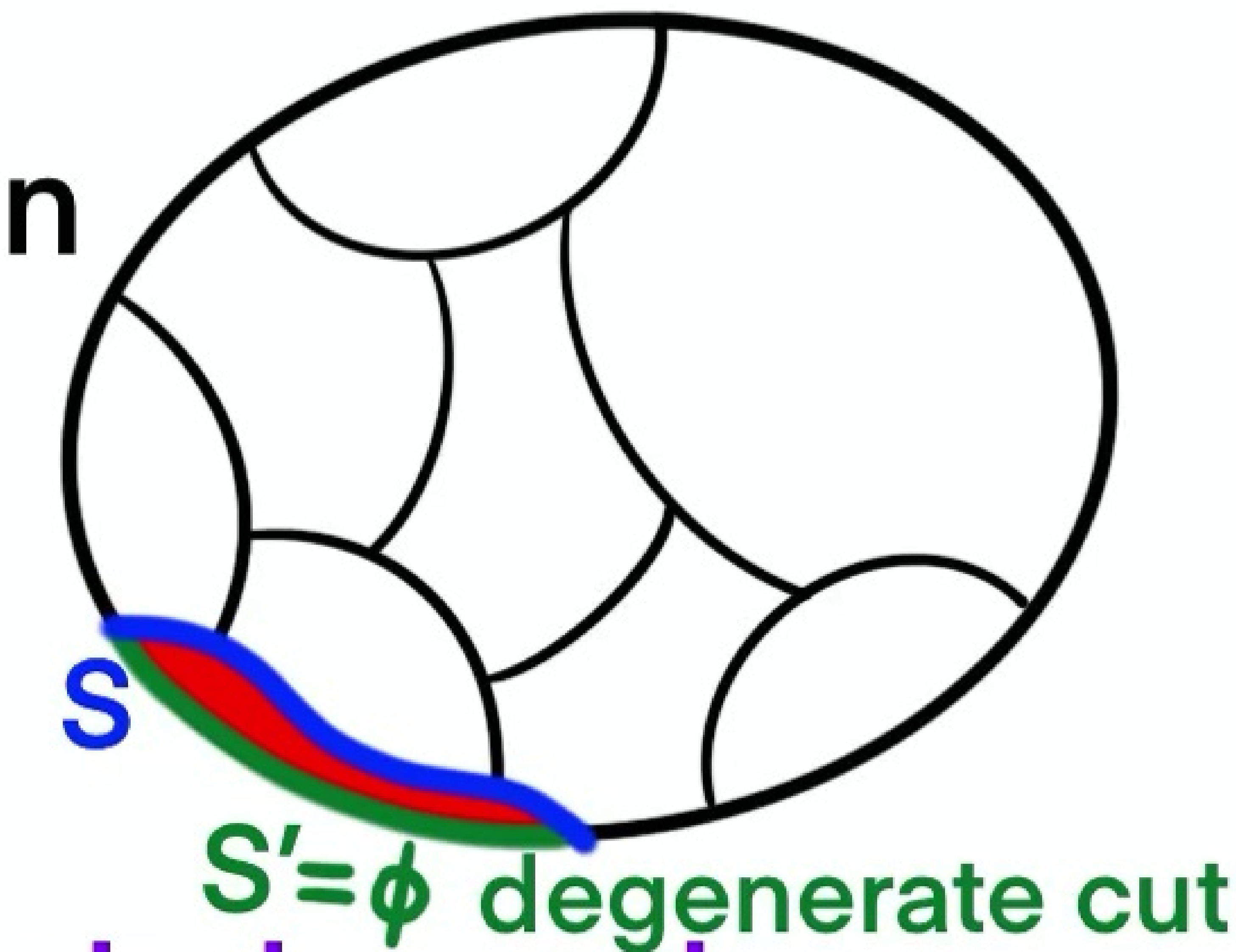

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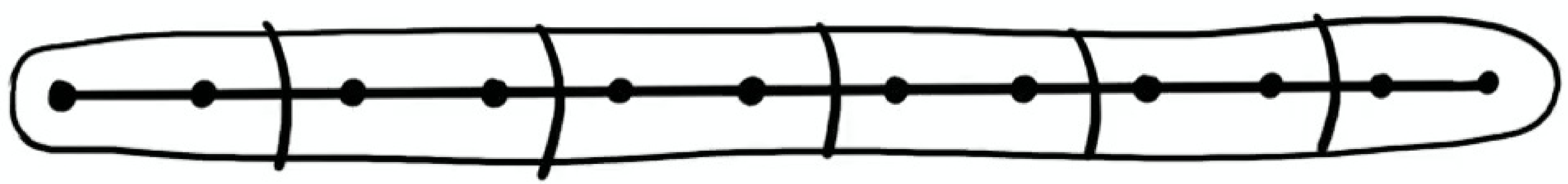

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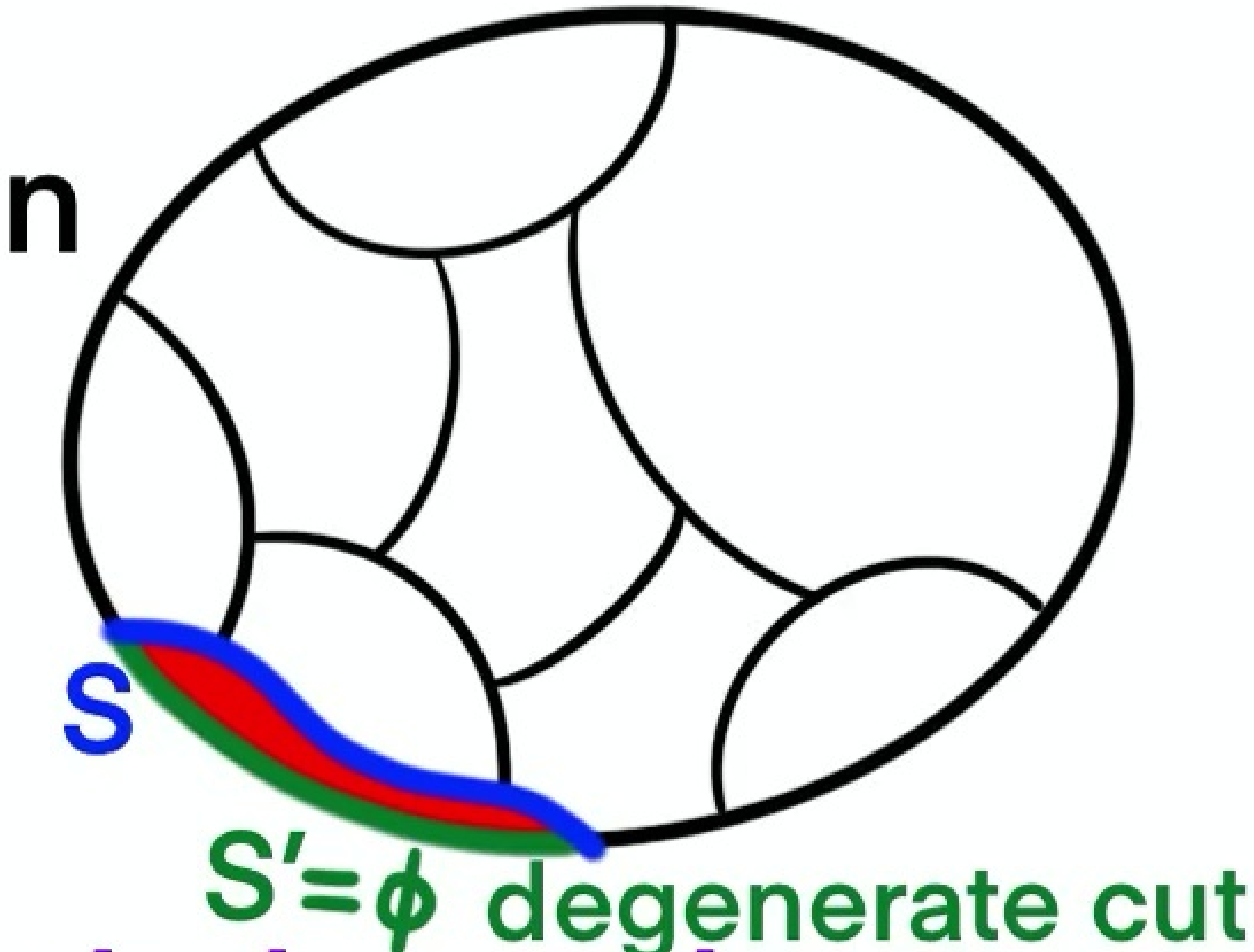

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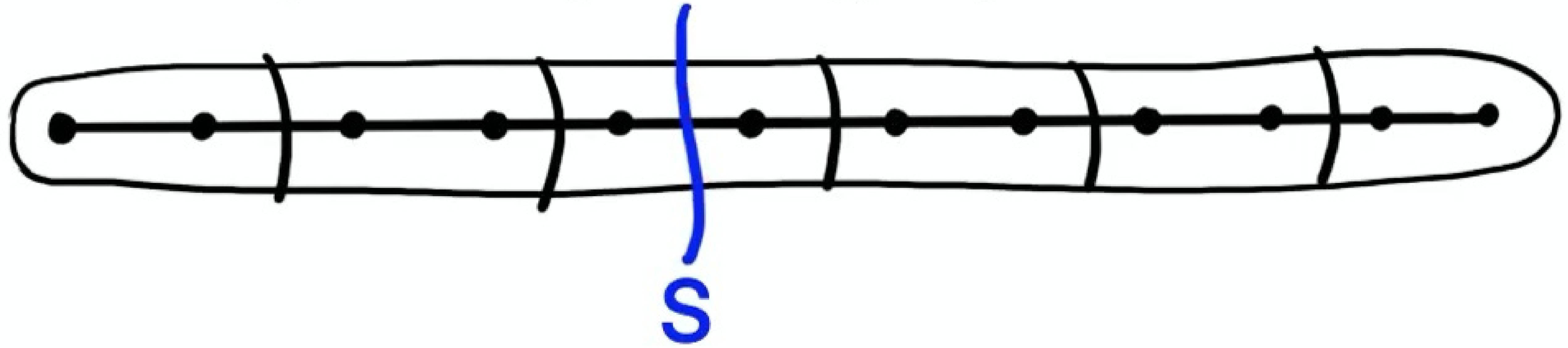

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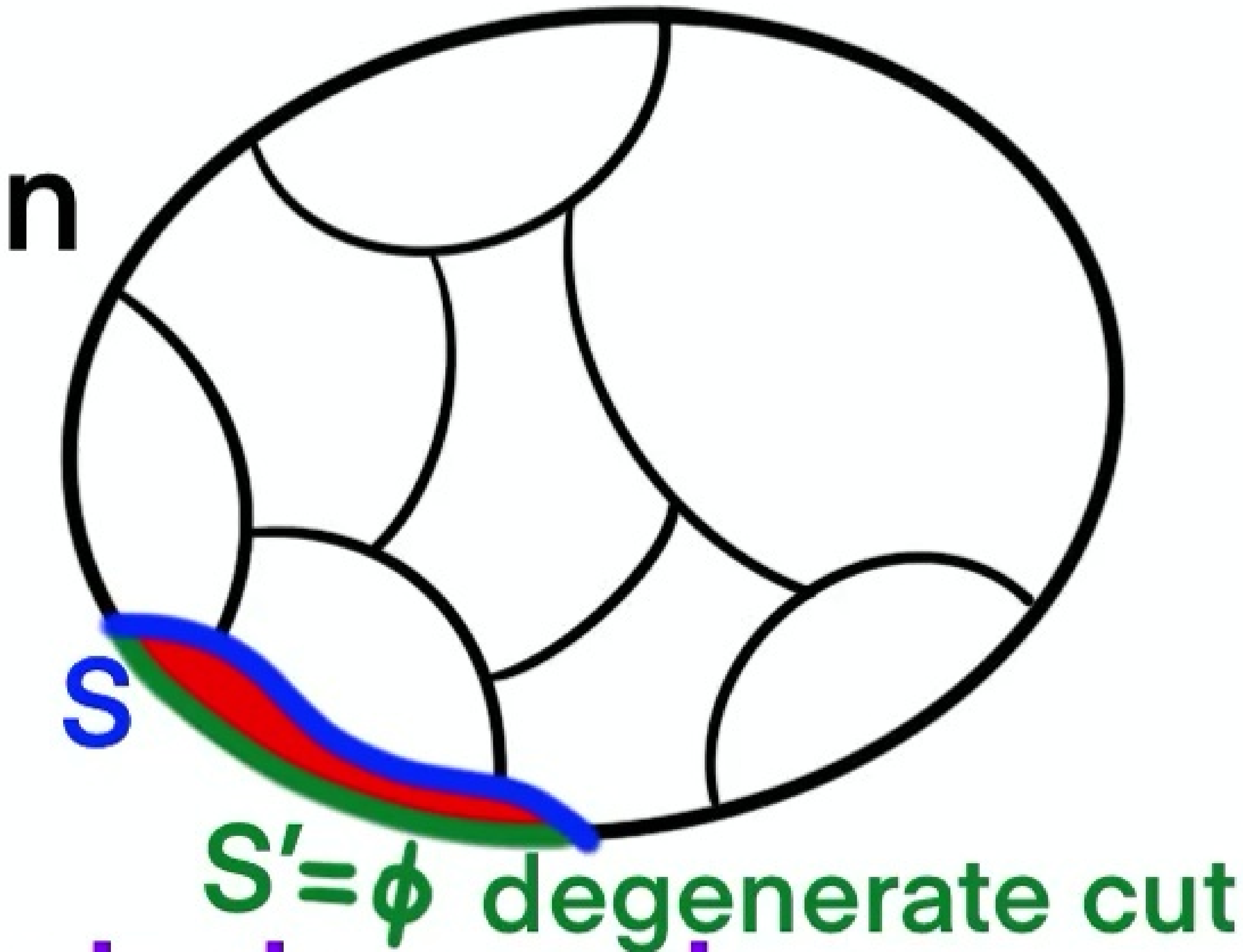

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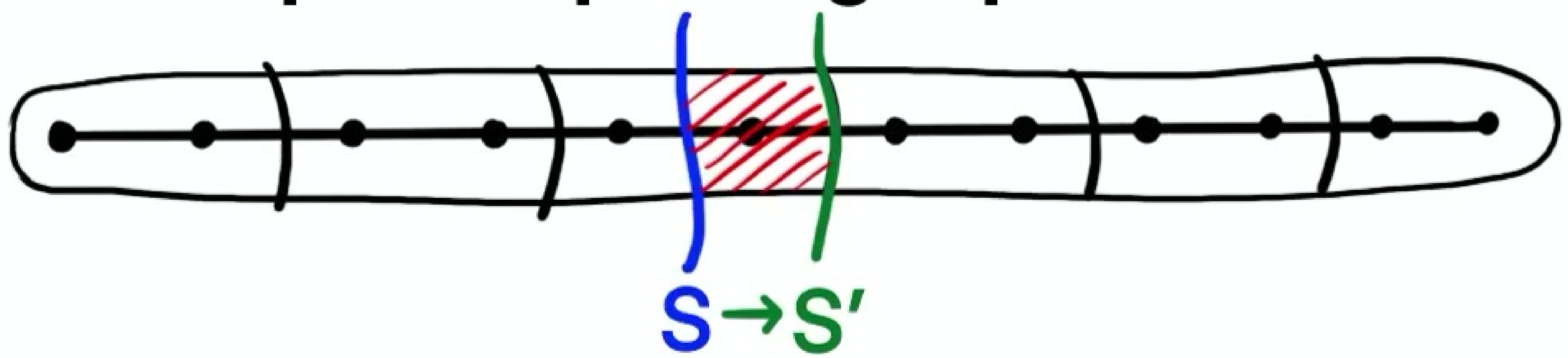

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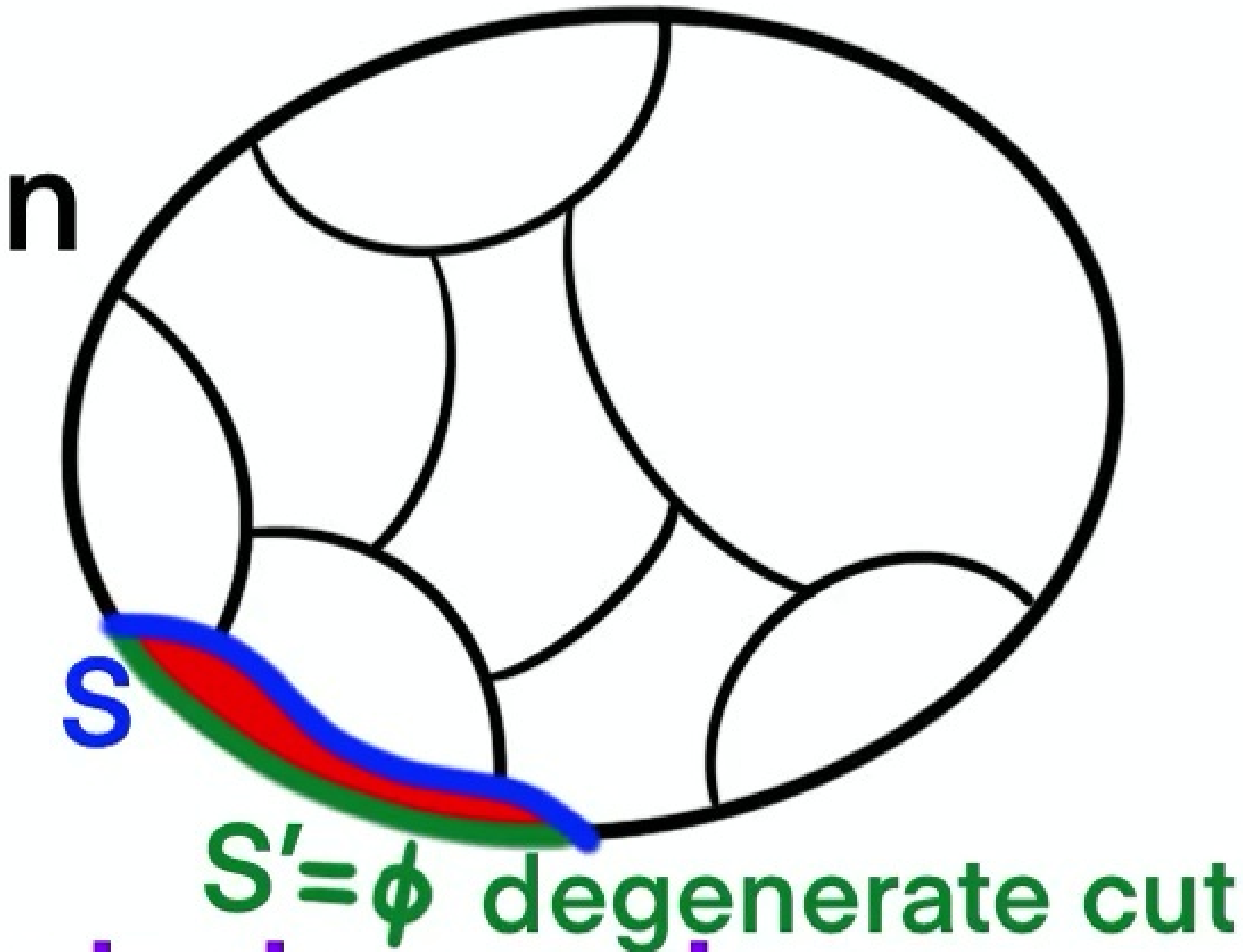

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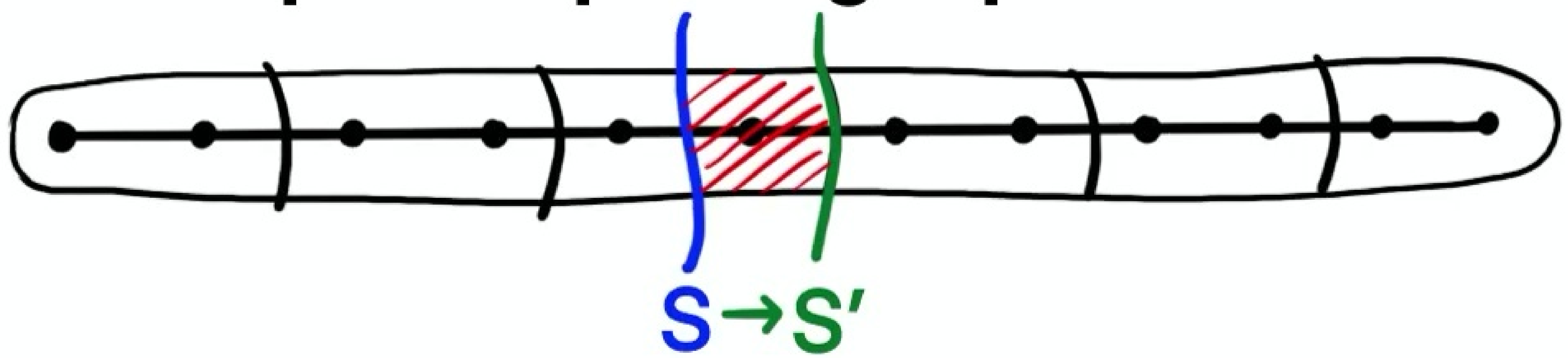

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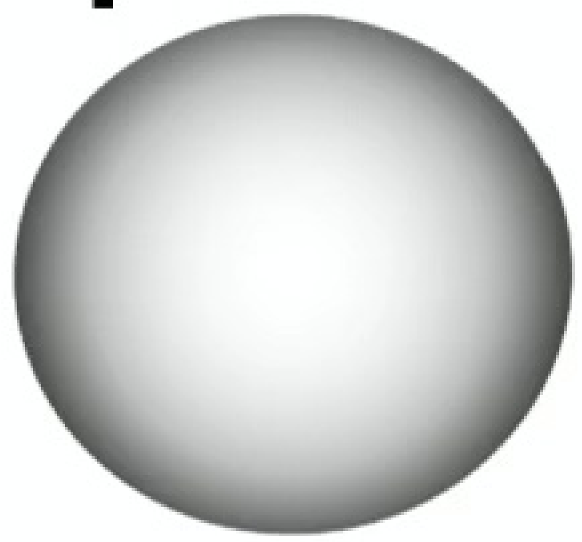

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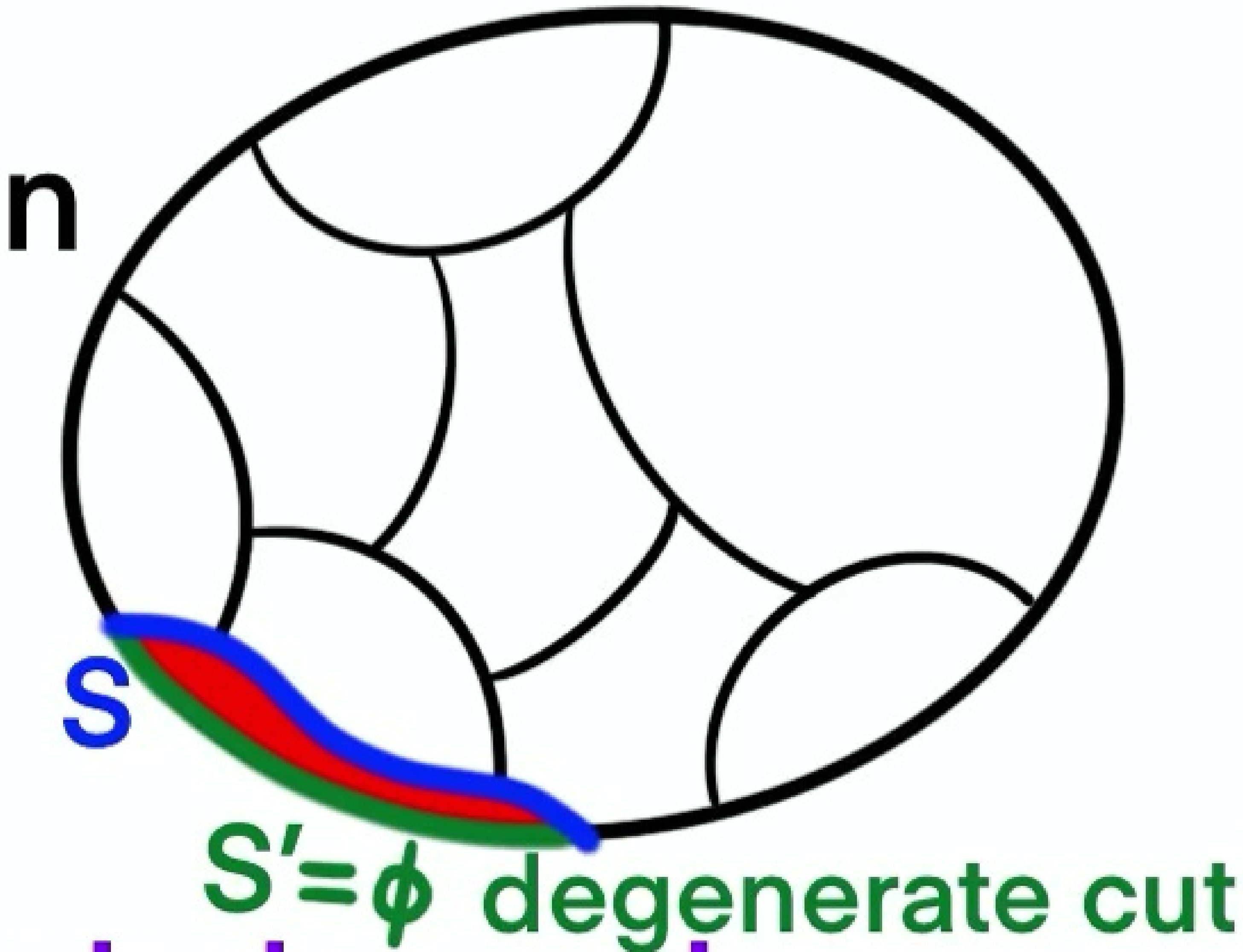

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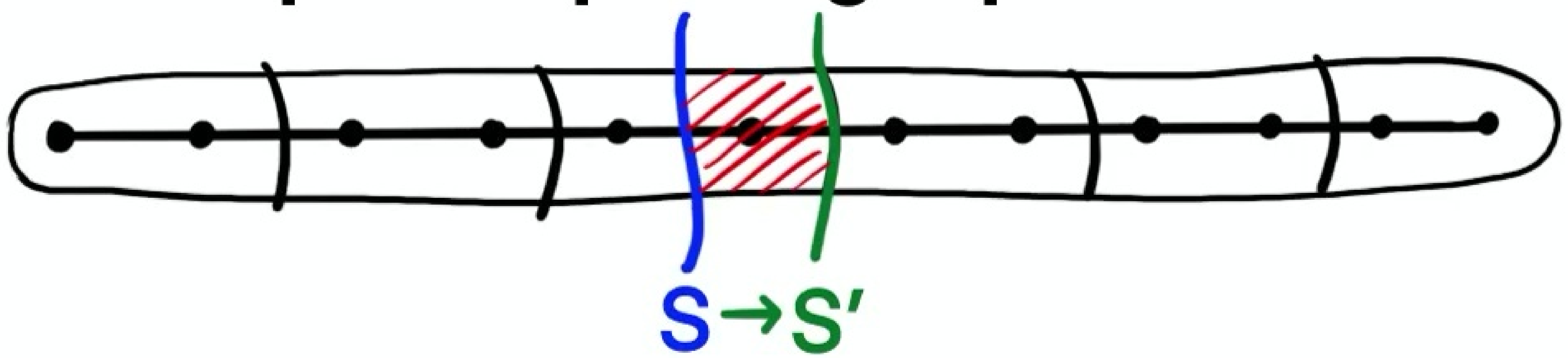

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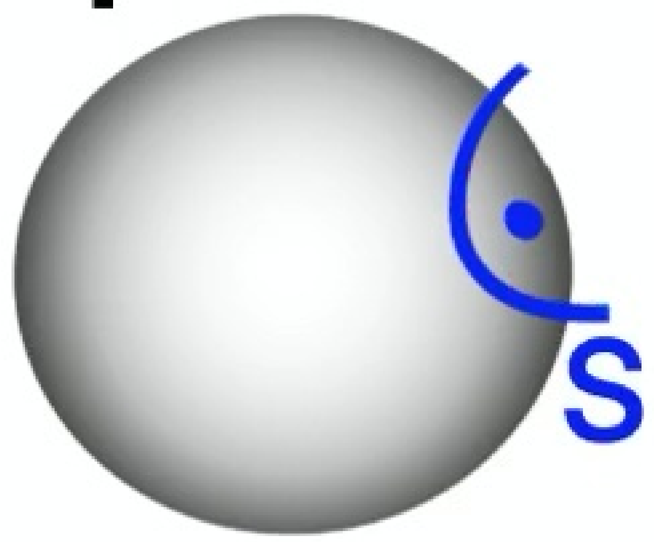

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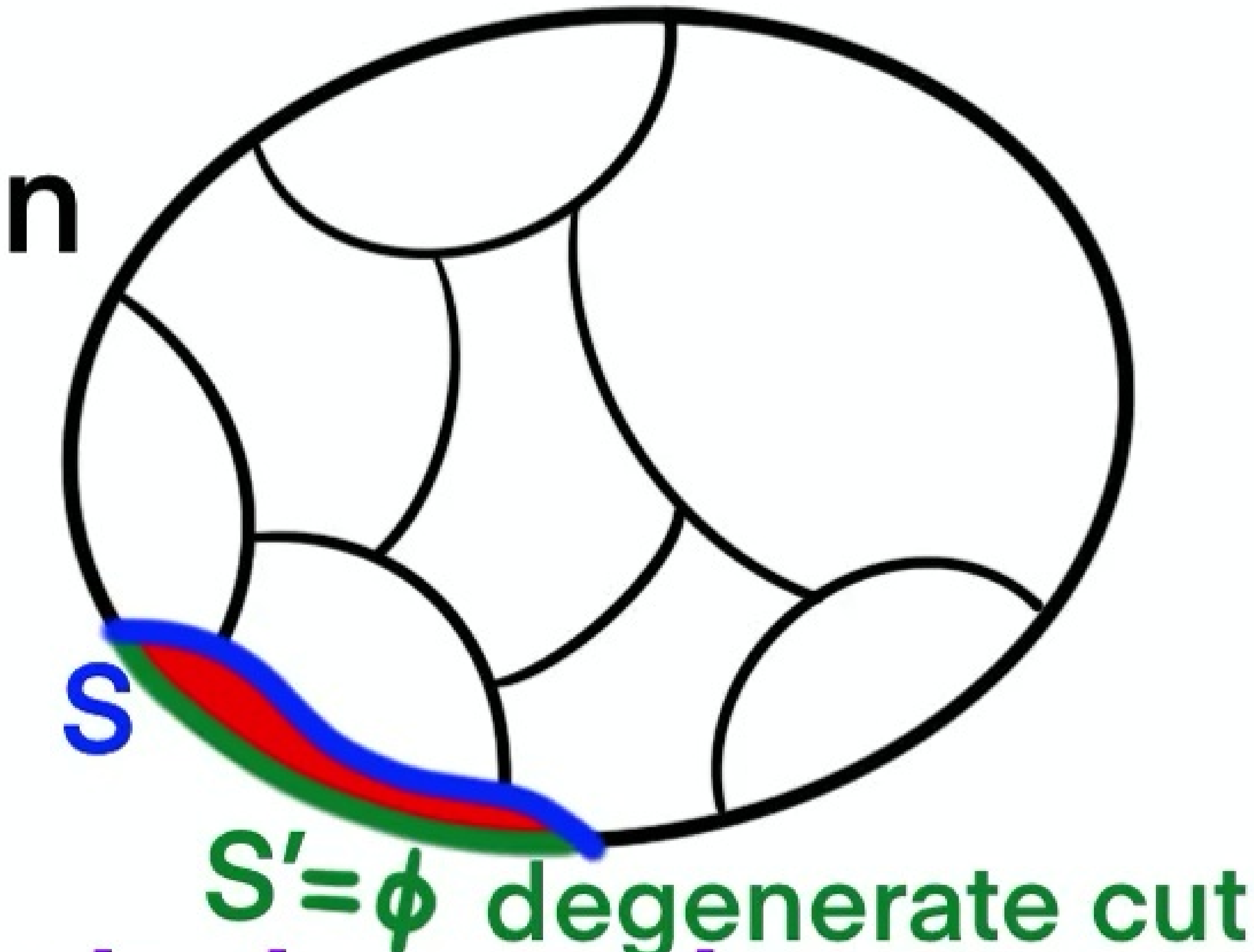

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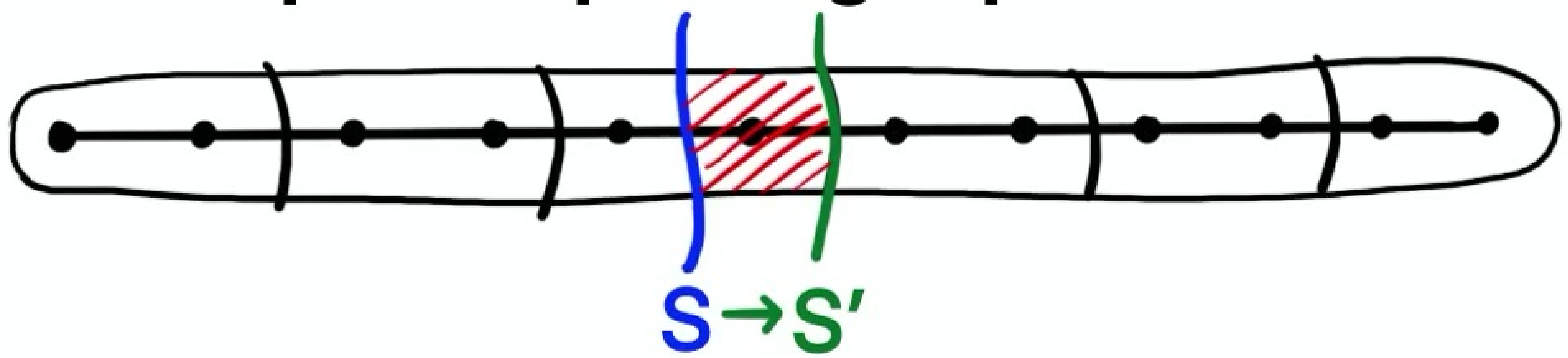

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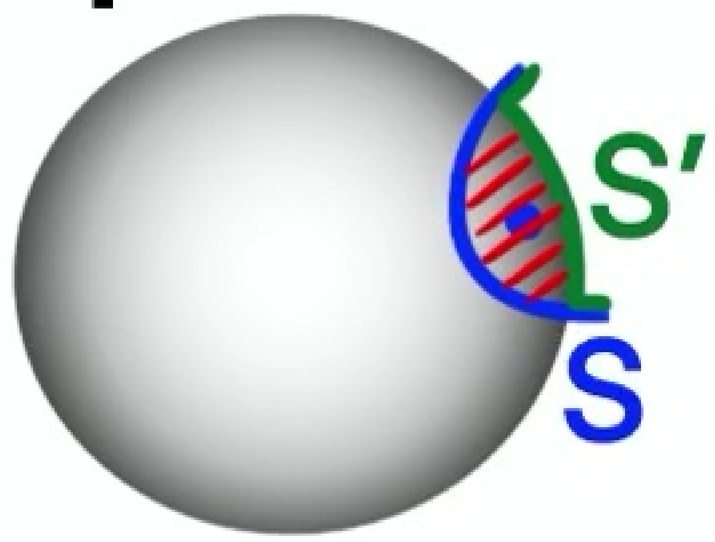

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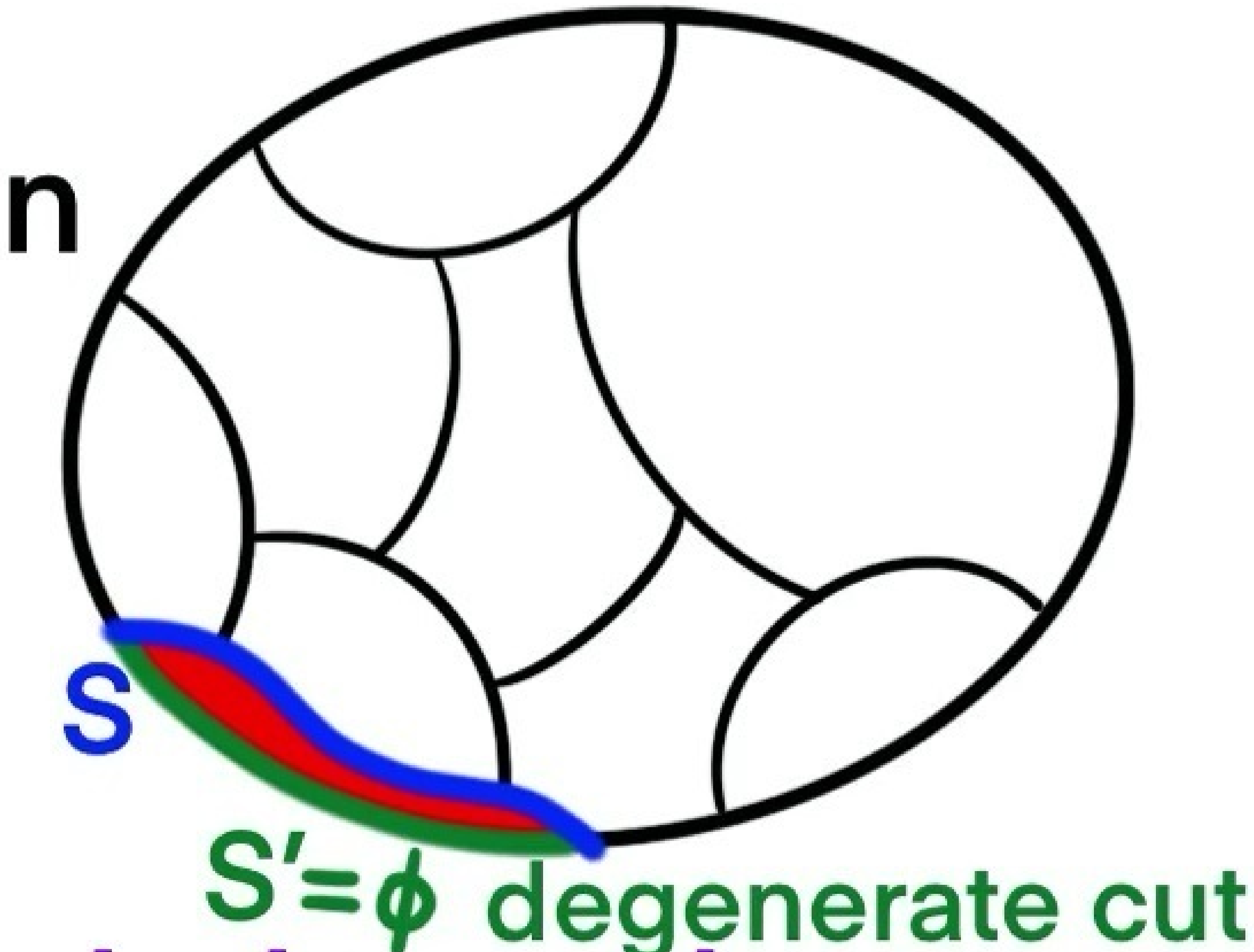

local algorithm [Kawarabayashi-Thorup]:

- if mincut is trivial (single vertex on one side): find min degree
- otherwise, cluster and contract to preserve global mincut

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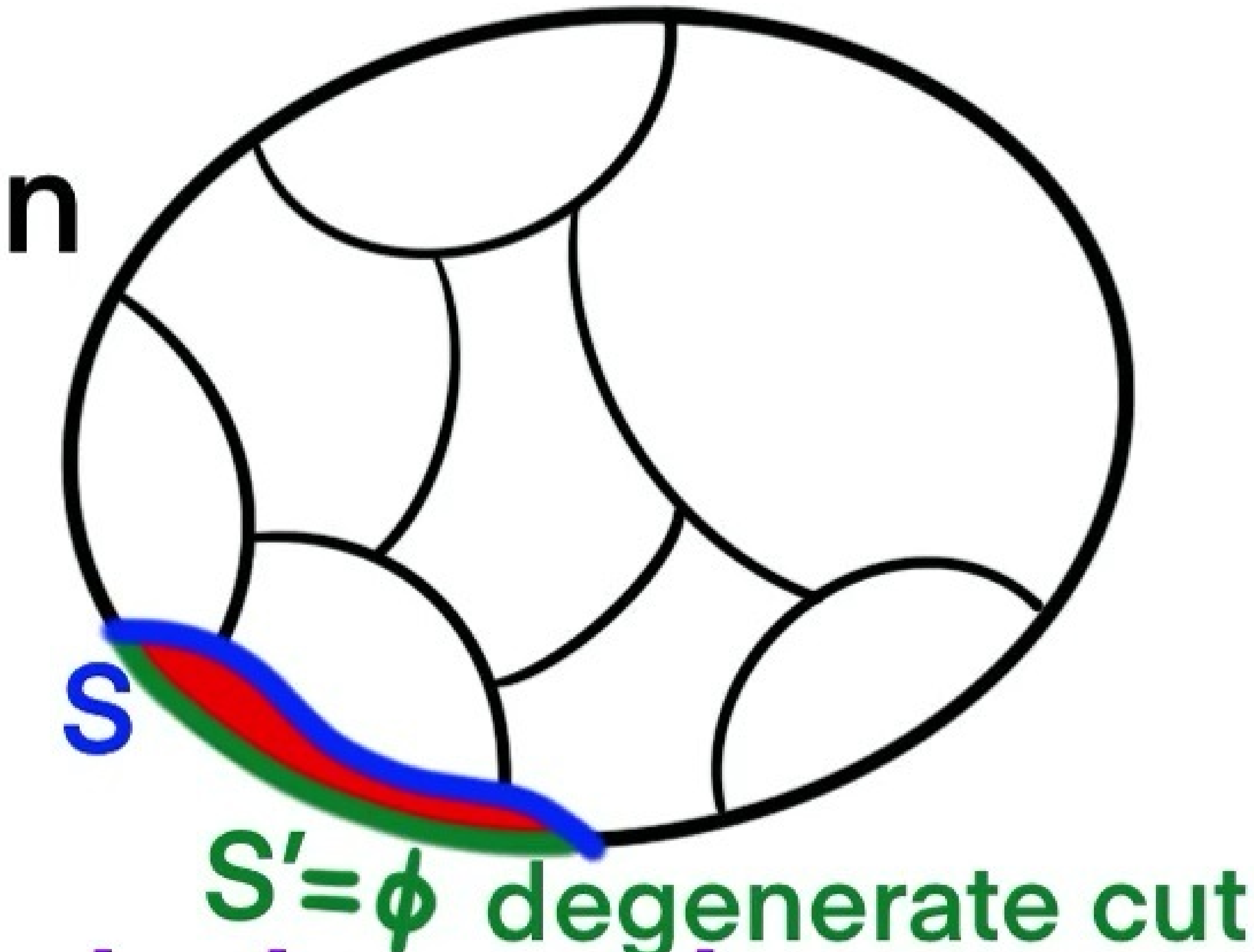

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Algorithm

unbalanced <= poly(logn,1/ε) vertices

run local algorithm

- if mincut is ~~trivial~~ unbalanced (~~single vertex~~ on one side): ~~find min degree~~ run local algorithm
- otherwise, cluster and contract to preserve global mincut up to (1+ε) factor

#vertices <= n/2

(1+ε)-approximate mincut

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Repeat $\log_2 n$ times: run local algorithm, then cluster+contract

$\rightarrow (1+\varepsilon)^{\log n}$ approximation. Set $\varepsilon \ll 1/\log n \rightarrow (1+o(1))$-approx

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"Local Karger contraction" [Nalam-Saranurak'23]:

$mk^2\mathrm{polylog}(n)$ randomized time if k vertices on one side

$k=\mathrm{poly}(\log n,1/\varepsilon)=\mathrm{polylog}(n)$

$(1+\varepsilon)$-approximate mincut

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Repeat $\log_2 n$ times: run local algorithm, then cluster+contract

→ $(1+\varepsilon)^{\log n}$ approximation. Set $\varepsilon \ll 1/\log n$ → $(1+o(1))$-approx

"Local Karger contraction" [Nalam-Saranurak'23]:

$mk^2\mathrm{polylog}(n)$ randomized time if k vertices on one side

$k=\mathrm{poly}(\log n,1/\varepsilon)=\mathrm{polylog}(n)$

Overall: $m\,\mathrm{polylog}(n)$ randomized for $(1+o(1))$-approx mincut

Structure Theorem Proof Outline

Theorem: for any weighted undirected graph, can group the vertices into <= n/2 clusters s.t.

- for any 1.01-approx mincut S, can modify few vertices → S′ s.t.

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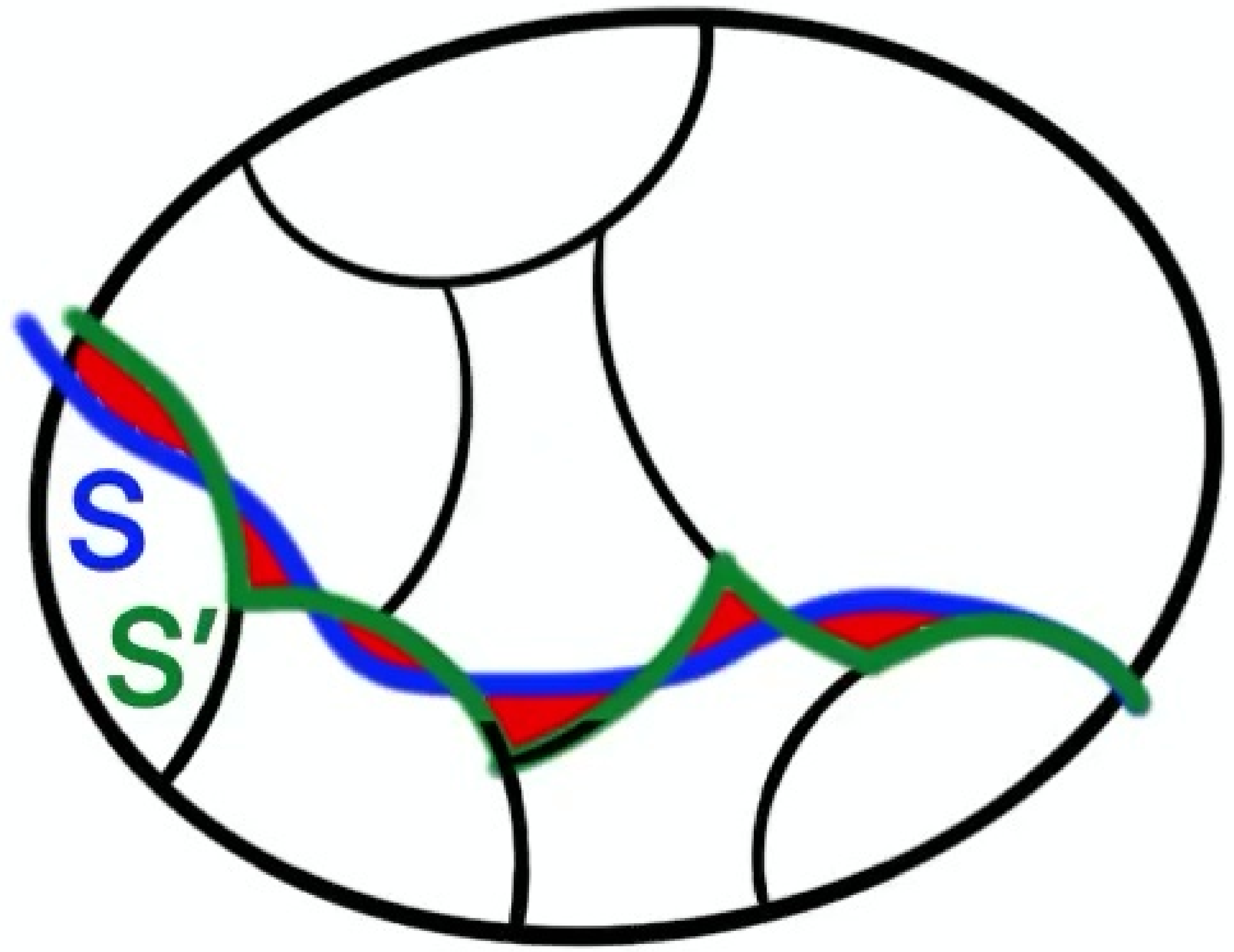

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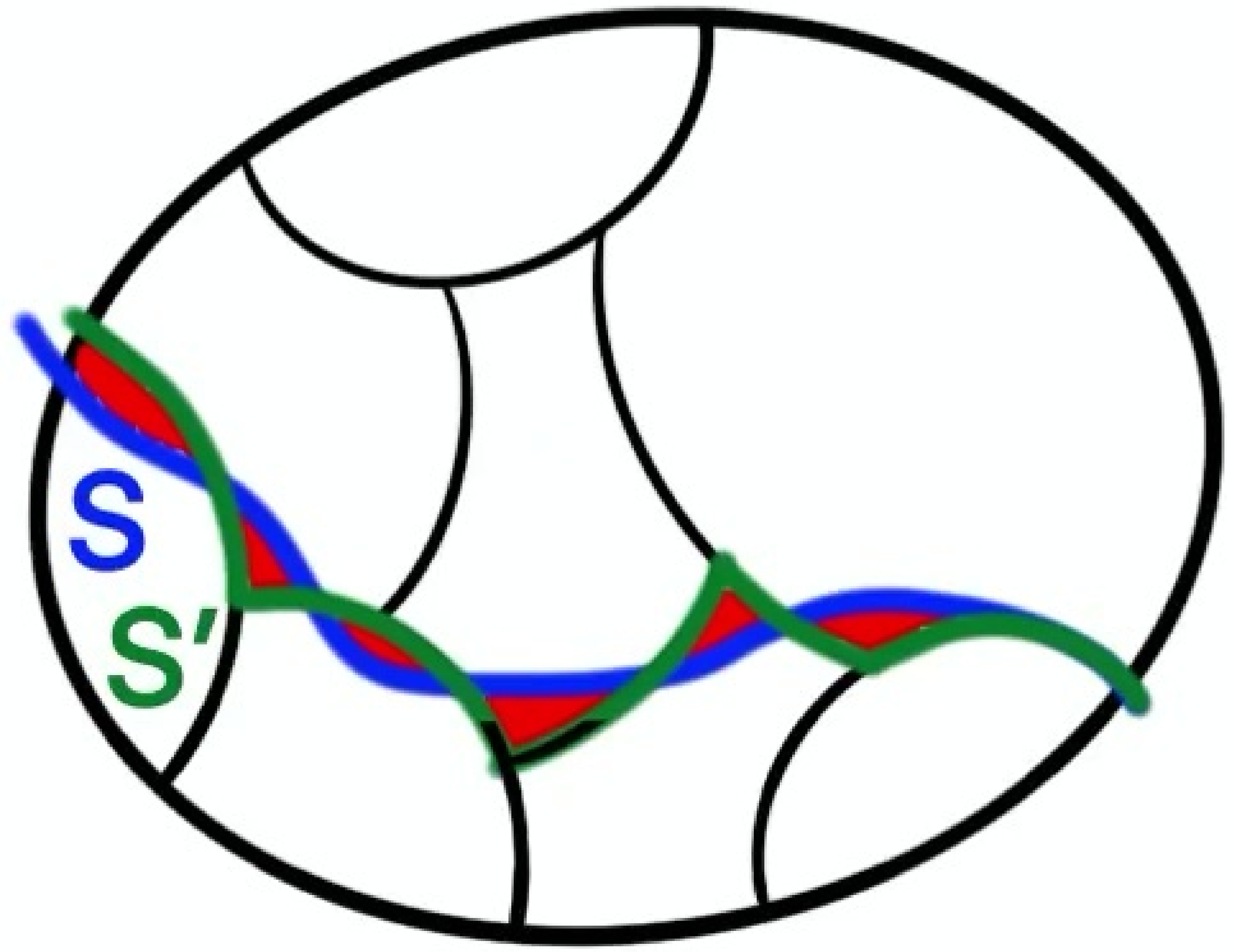

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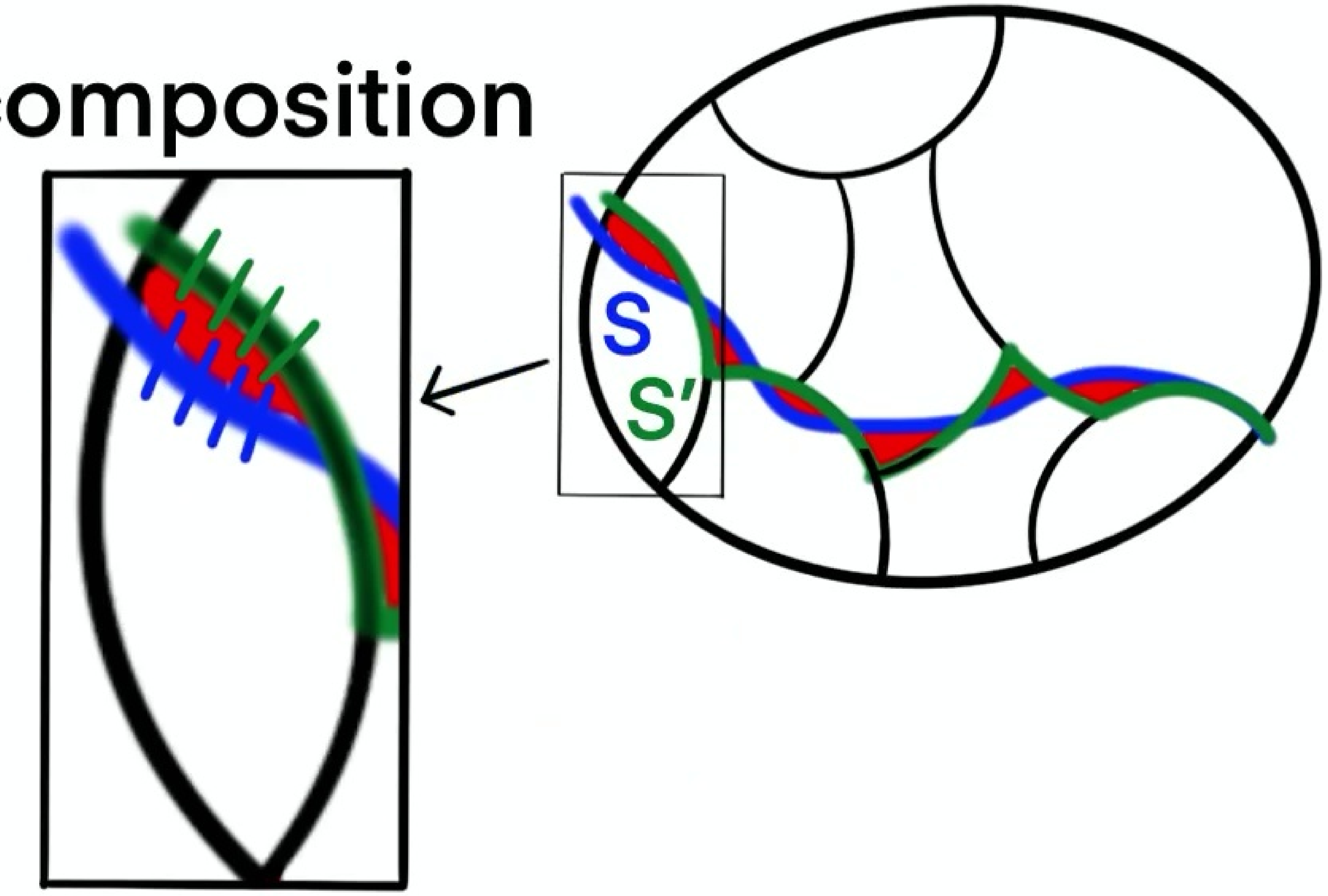

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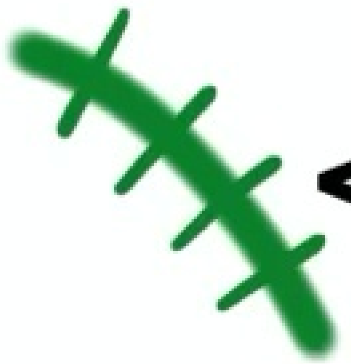
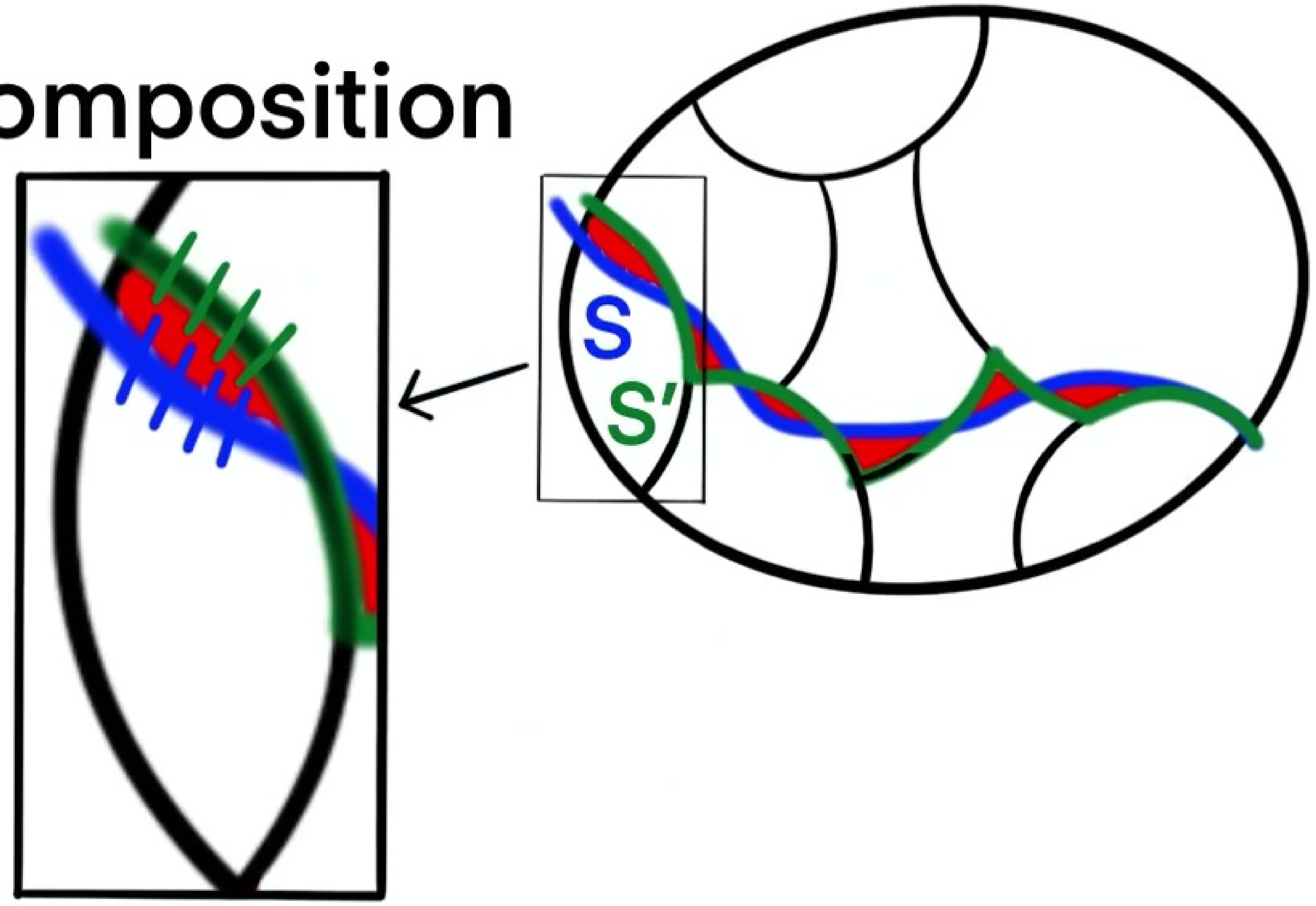
If  <= (1+ε)x  then



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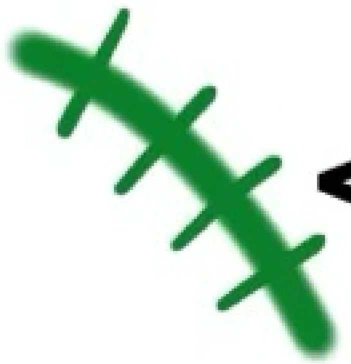
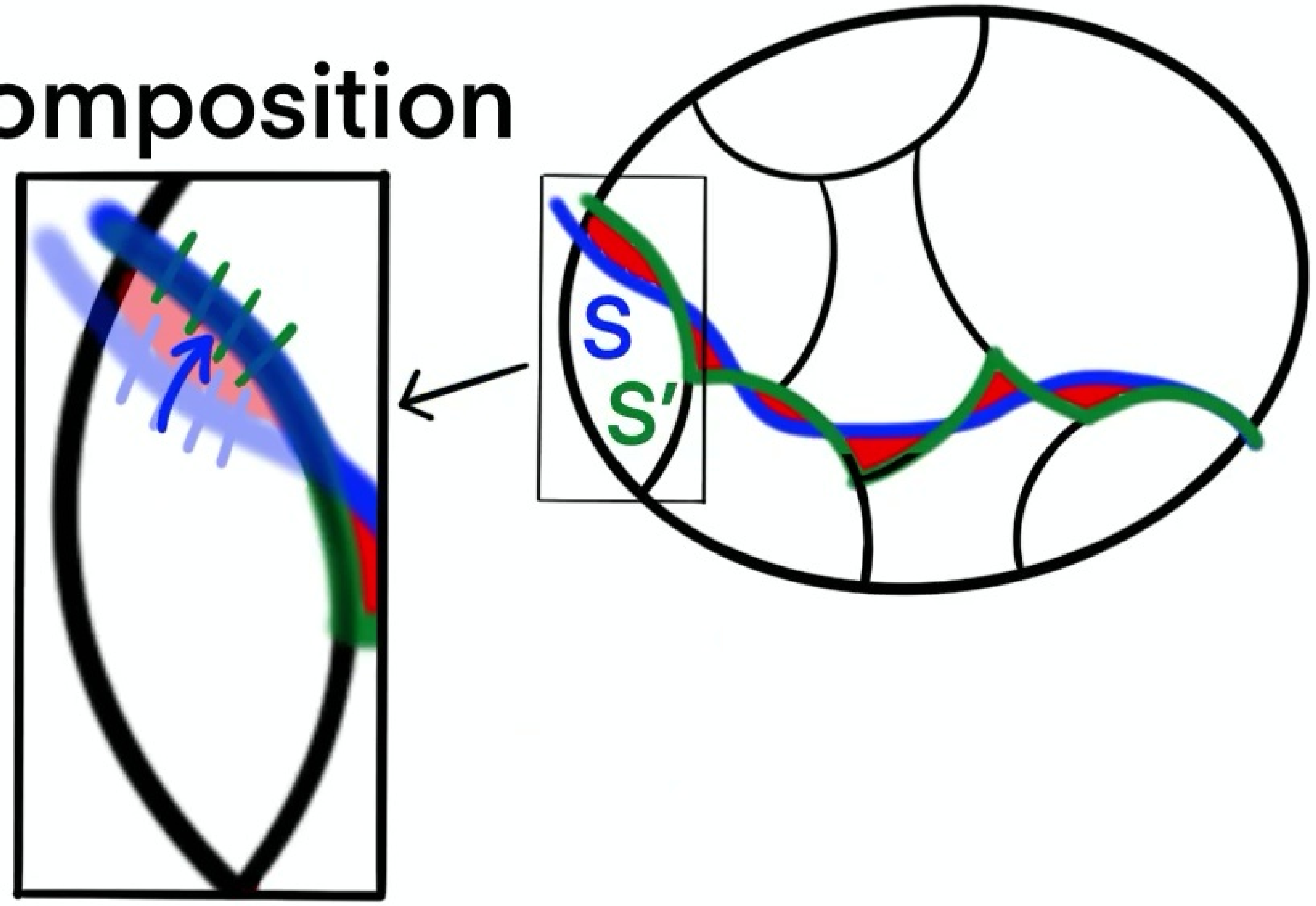
If  <= (1+ε)x  then 

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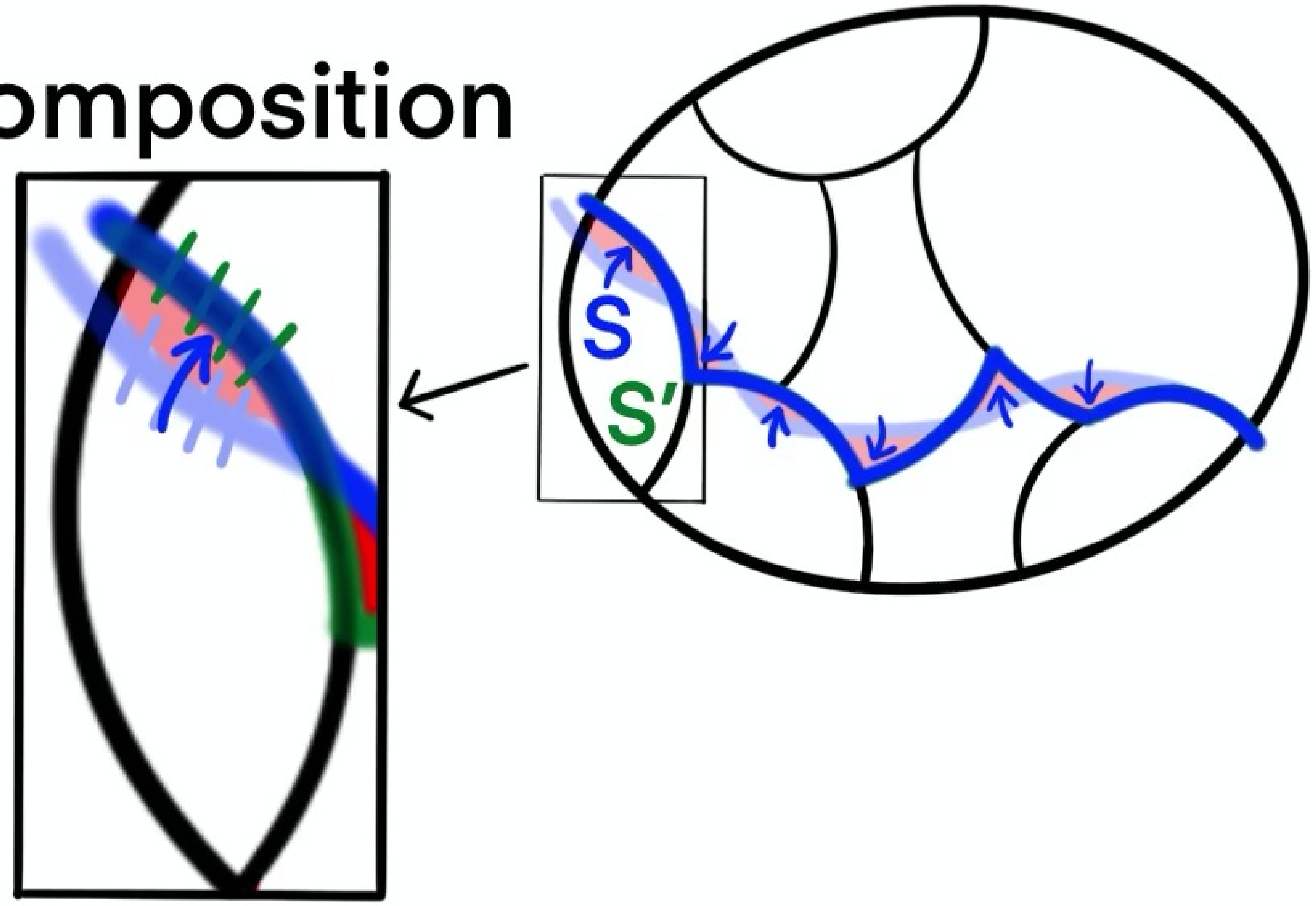

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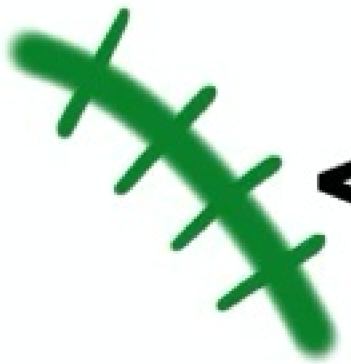
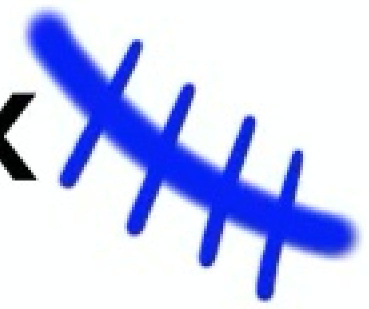
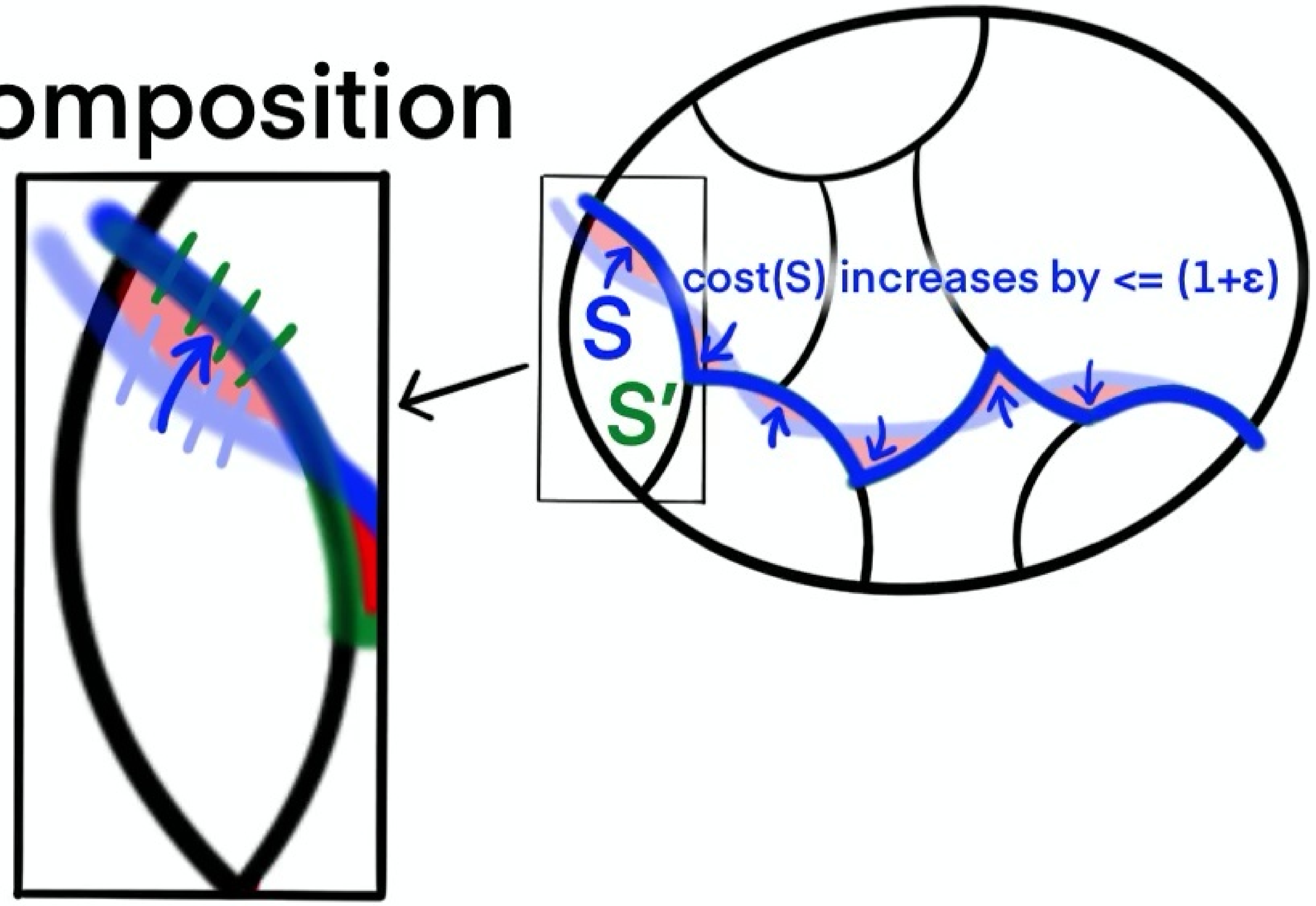
If  <= (1+ε)x  then 

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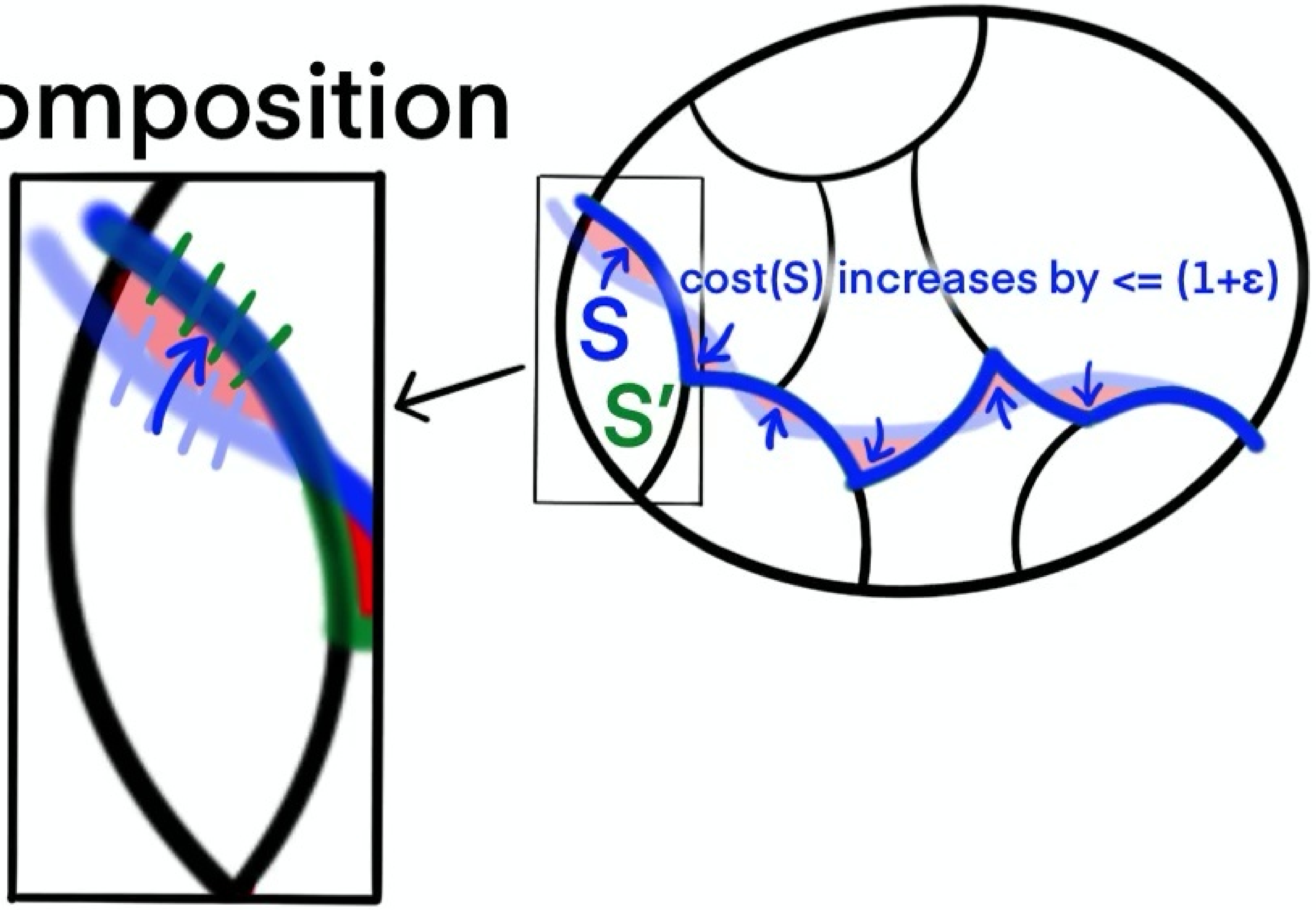

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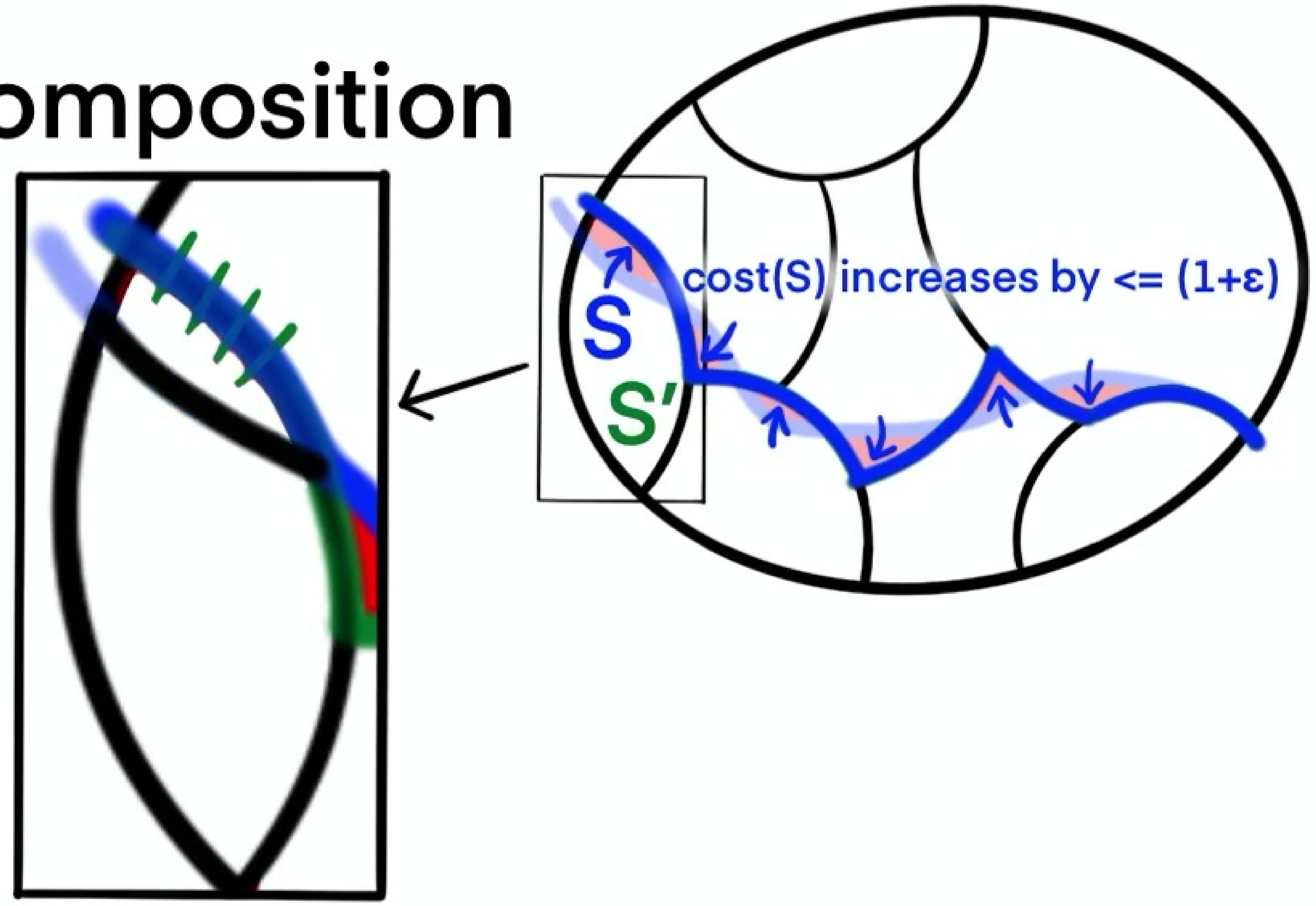

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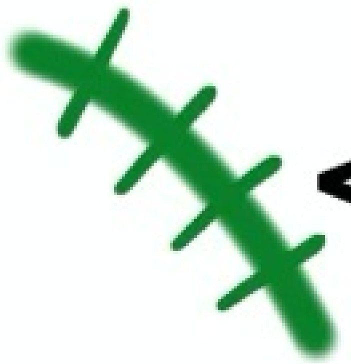
If  <= (1+ε)x  then

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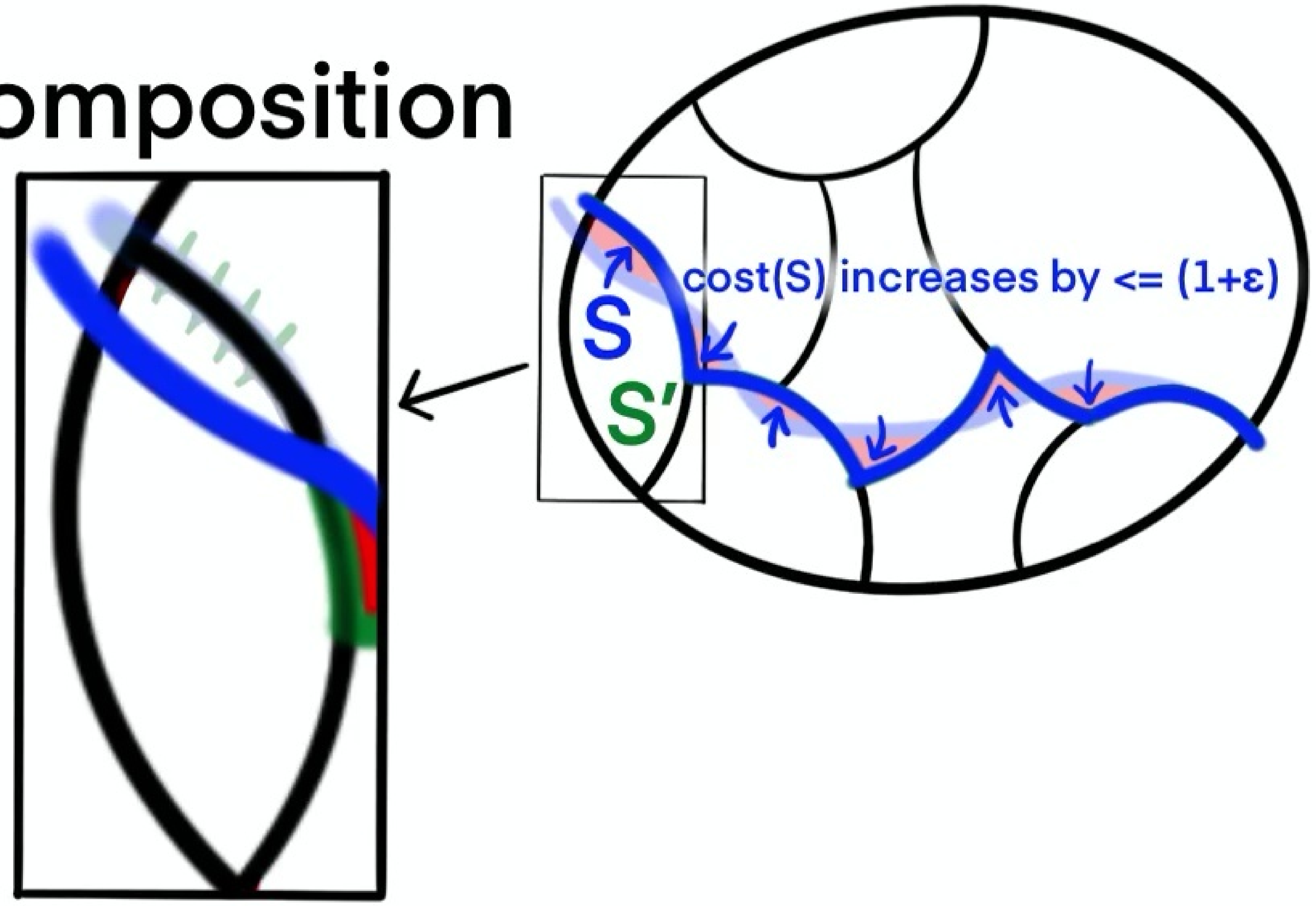

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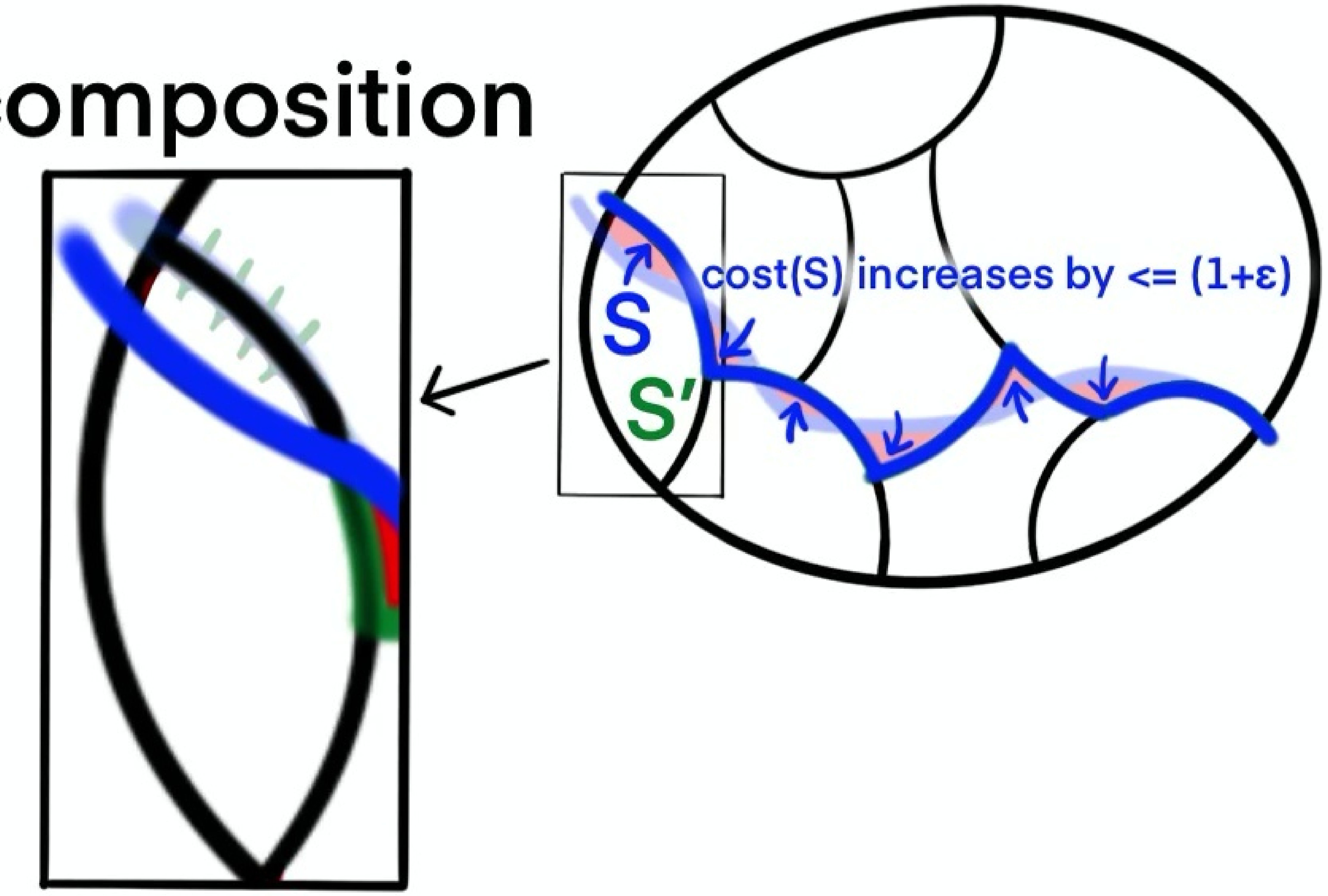

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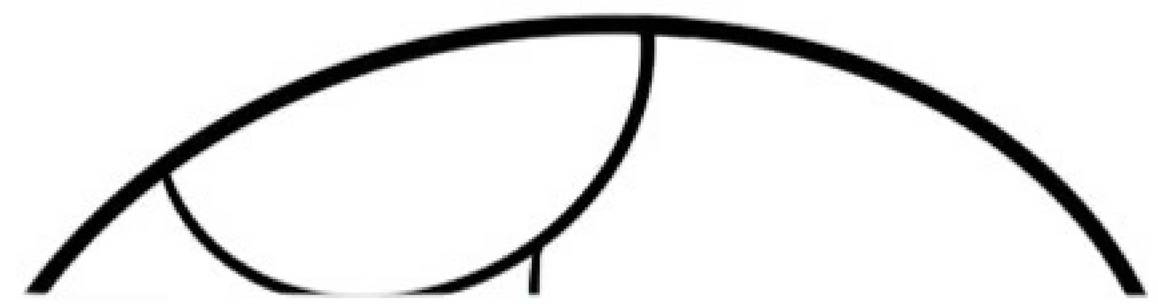

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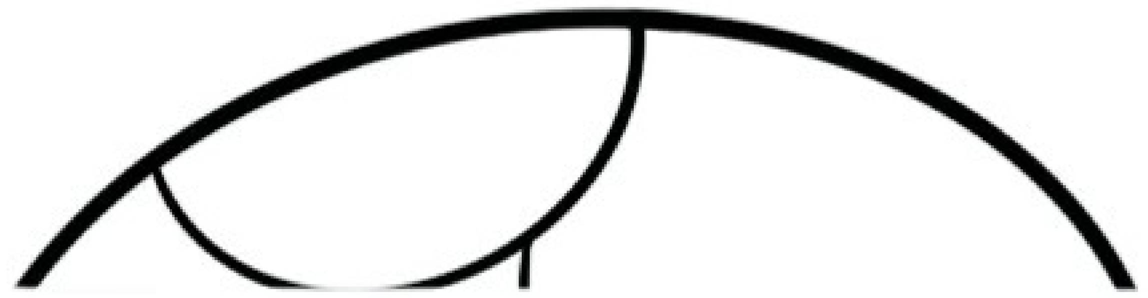

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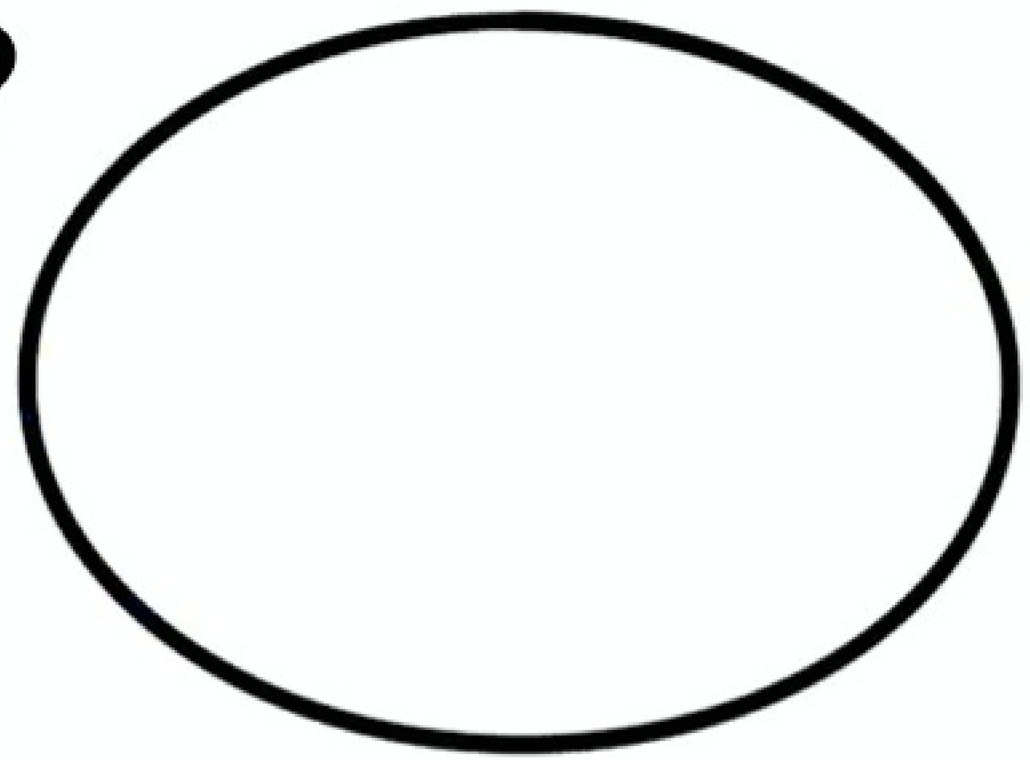

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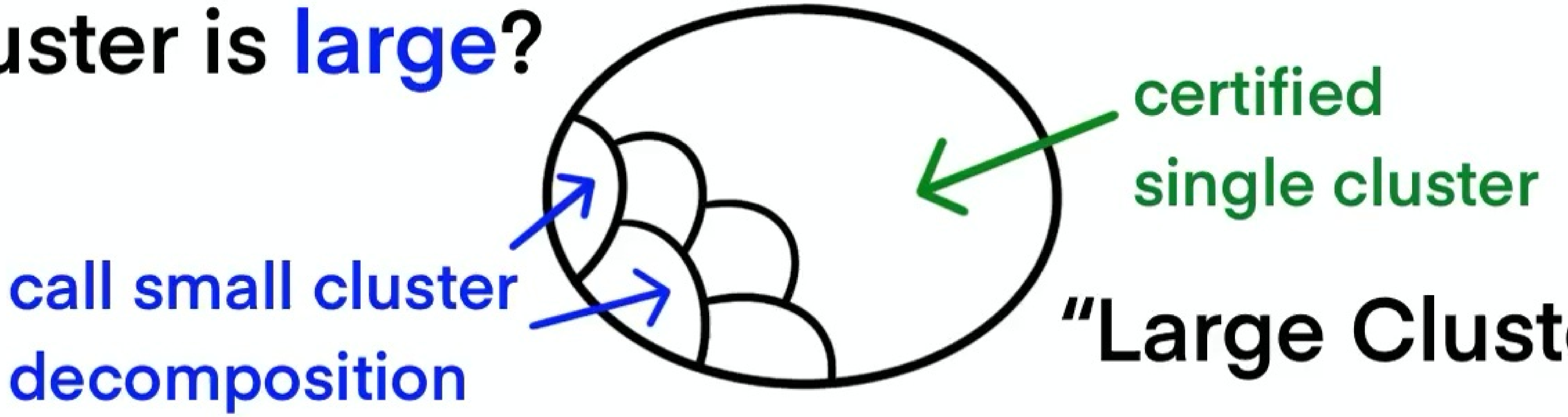

"Large Cluster Decomposition"

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  - Generalization of Kawarabayashi-Thorup sparsification to weighted graphs
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- Should be useful for global mincut in other settings (dynamic/streaming/distributed)