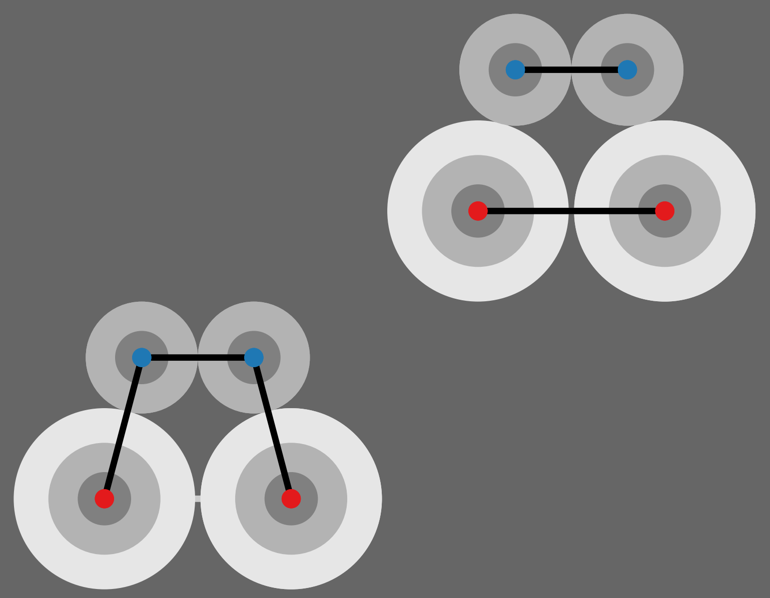

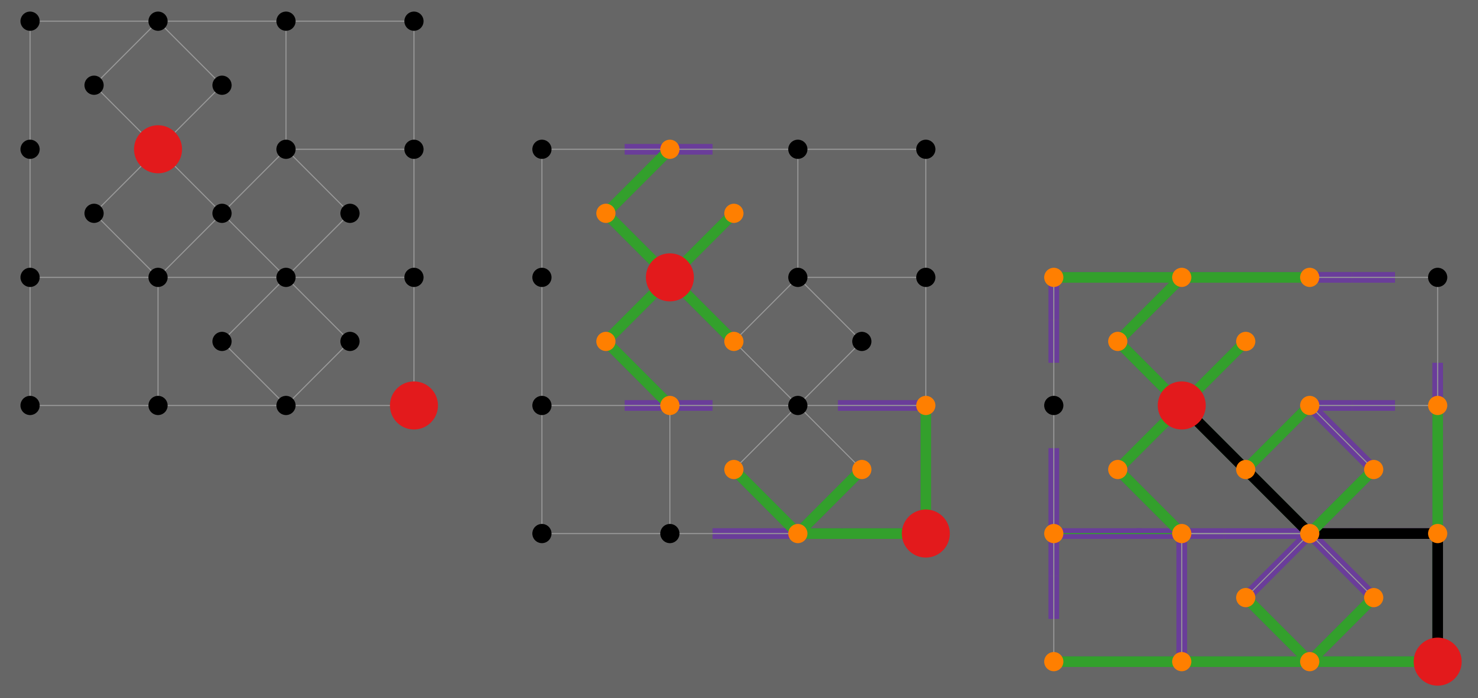

Model-Agnostic Approximation of Constrained Forest Problems

Corinna Coupette, Alipasha Montaseri and Christoph Lenzen

Motivation

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Steiner Forest: Generalization of Steiner Tree

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Classic Input: Components $\{V_i \mid i \in [k]\}$ to be connected

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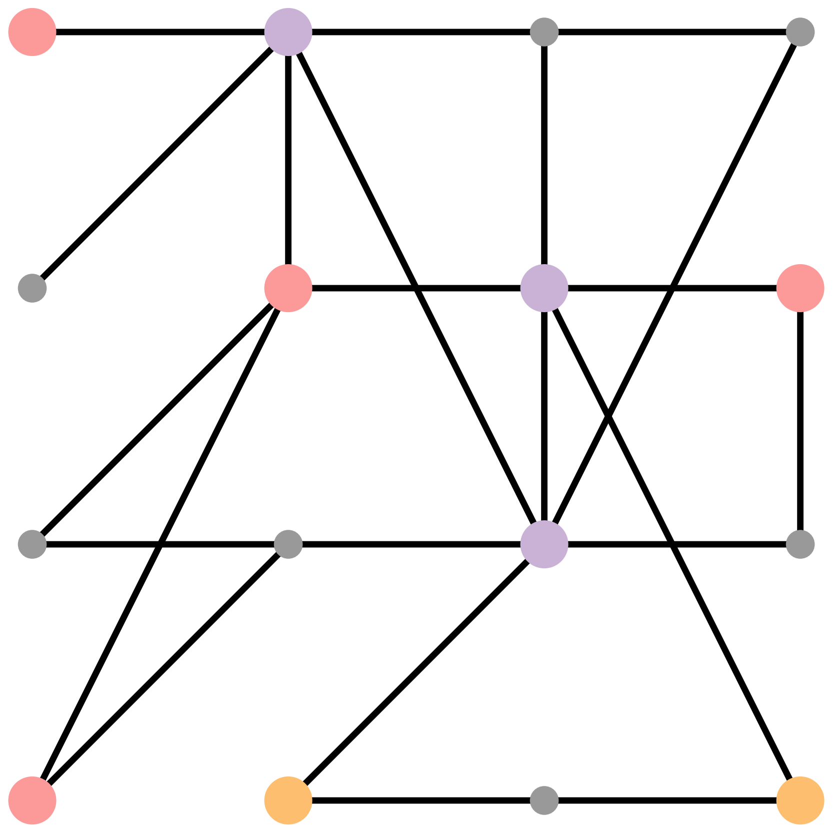

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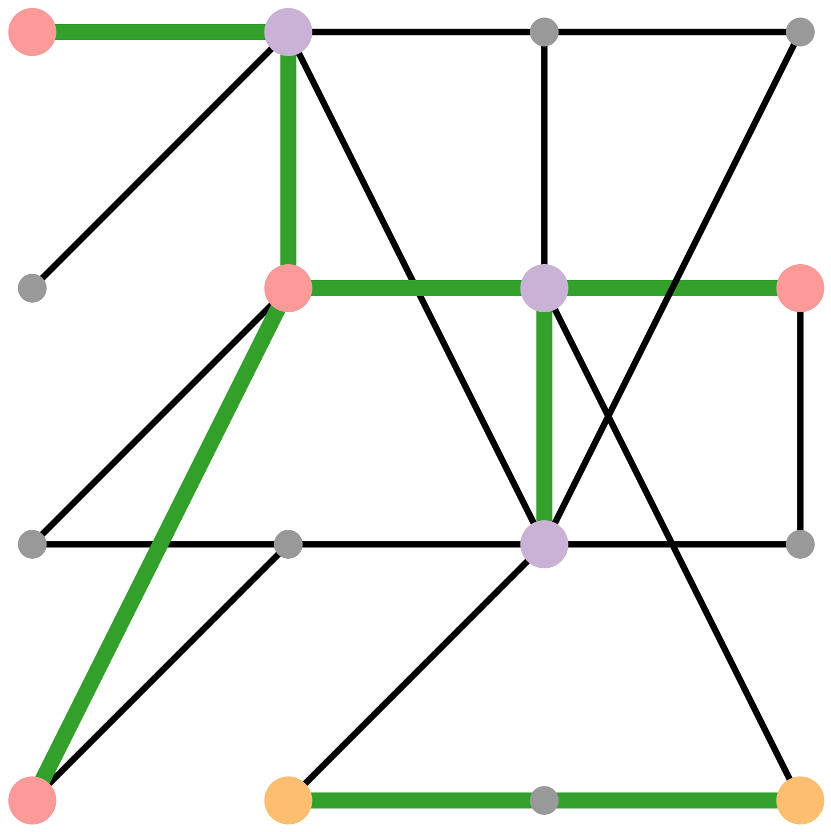

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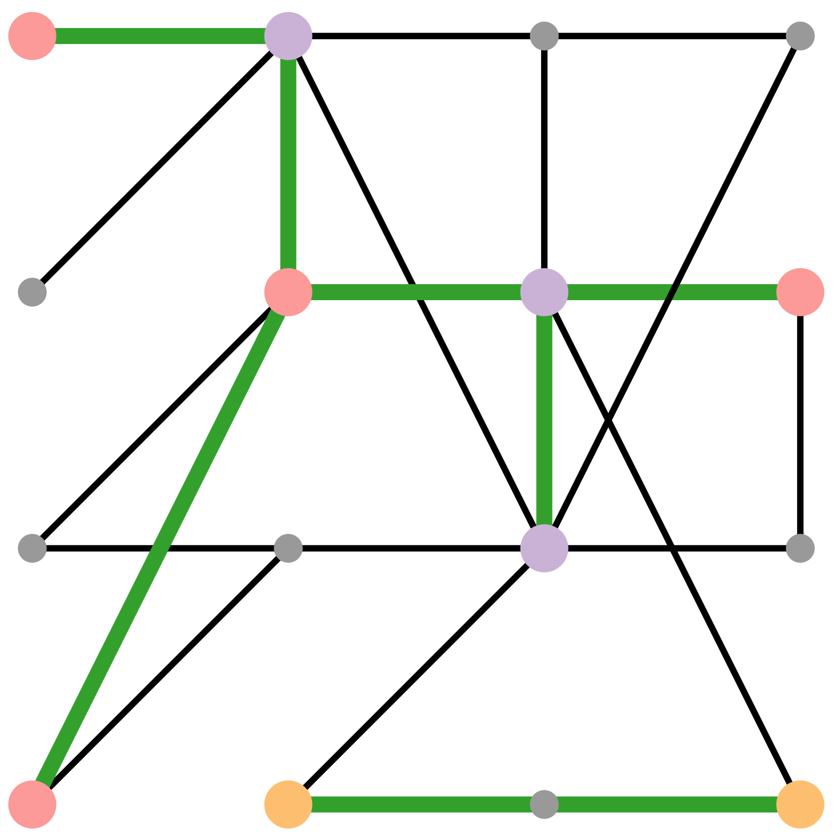

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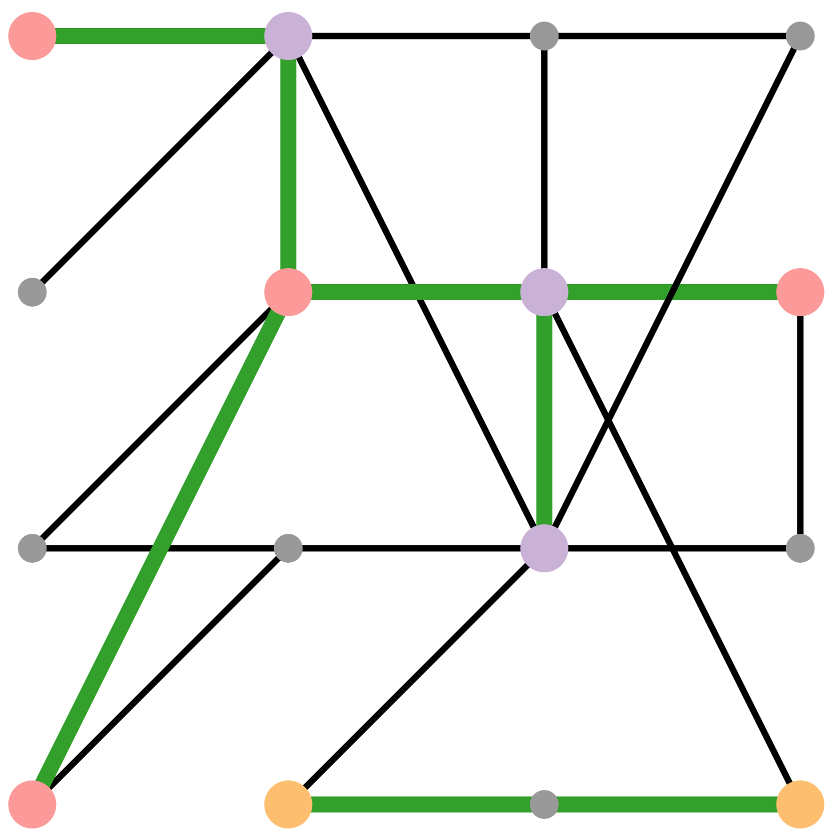

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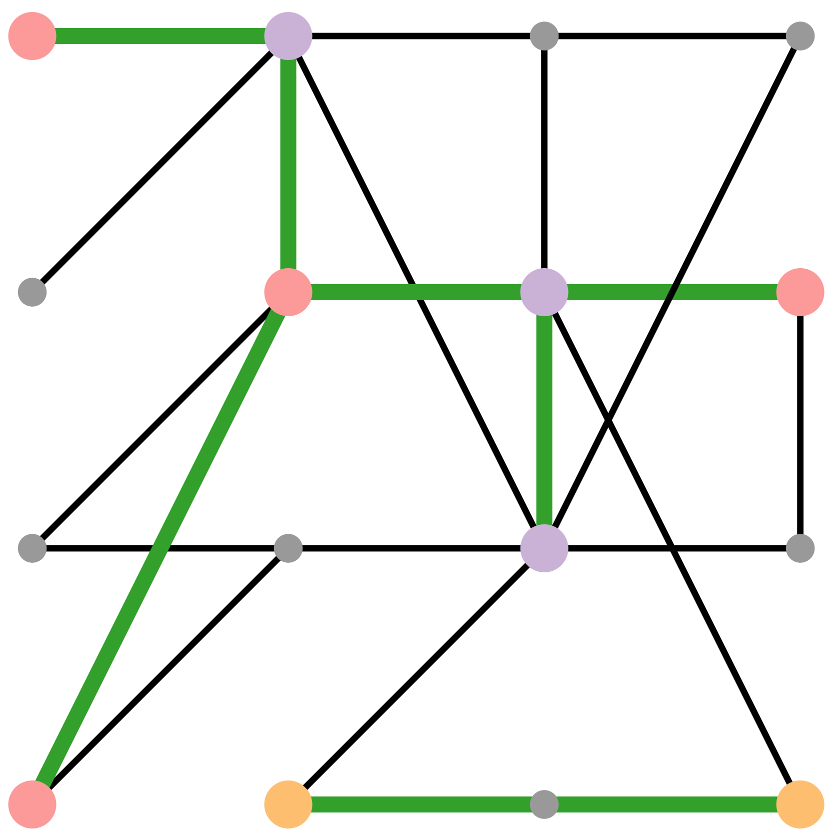
Existential Lower Bound (Das Sarma et al. 2012): $\widetilde{\Omega}(\sqrt{n})$



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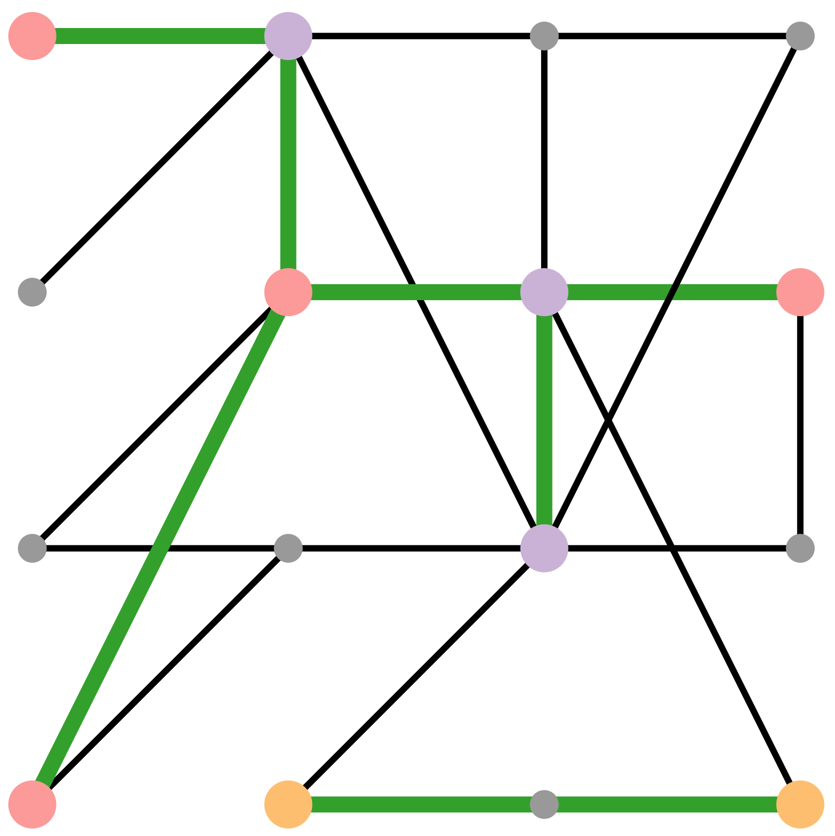

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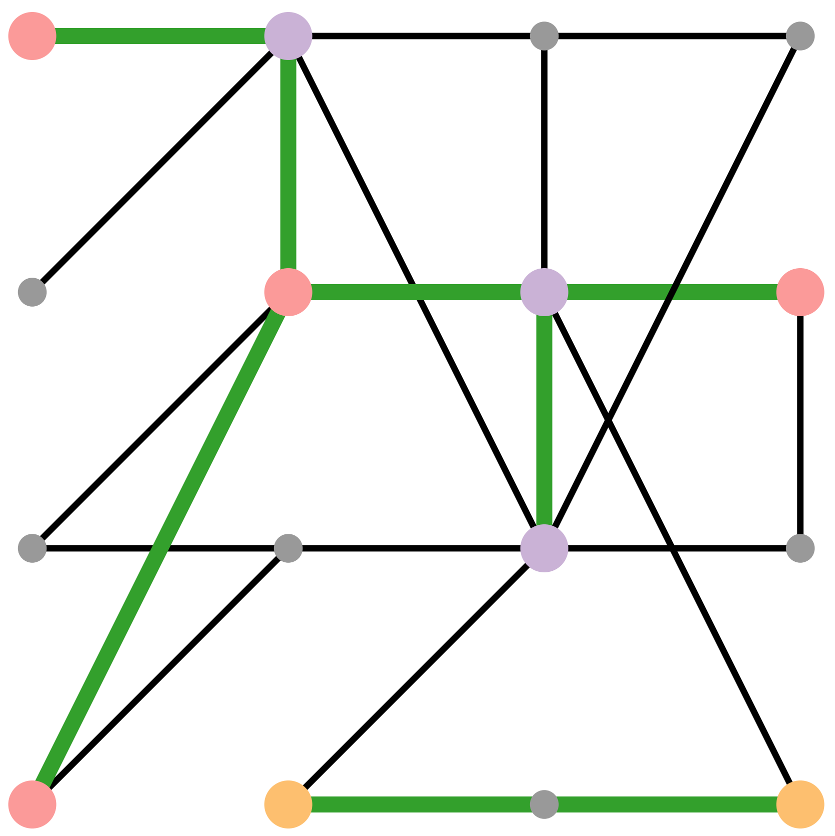

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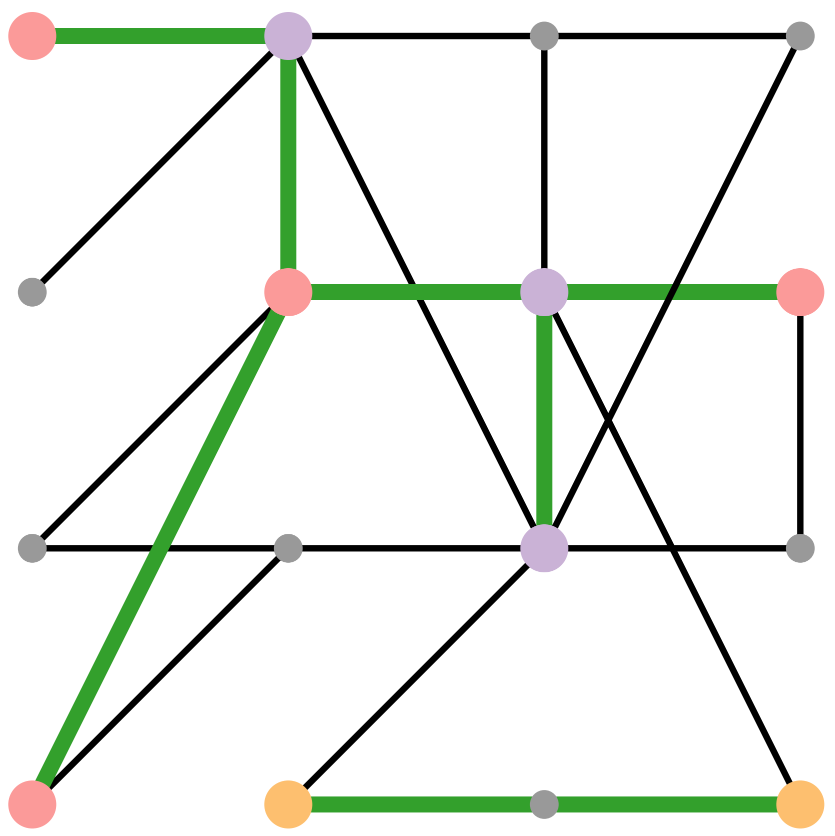
Challenges:

Model Specificity $\longrightarrow$ Model Agnosticism (works across computational models)



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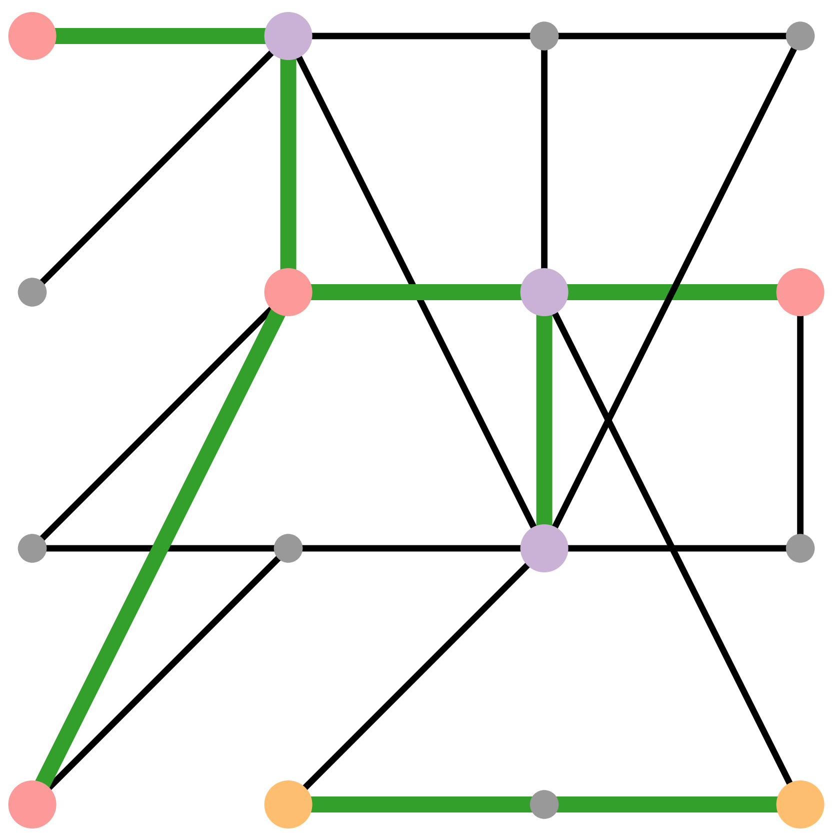

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Existential Optimality

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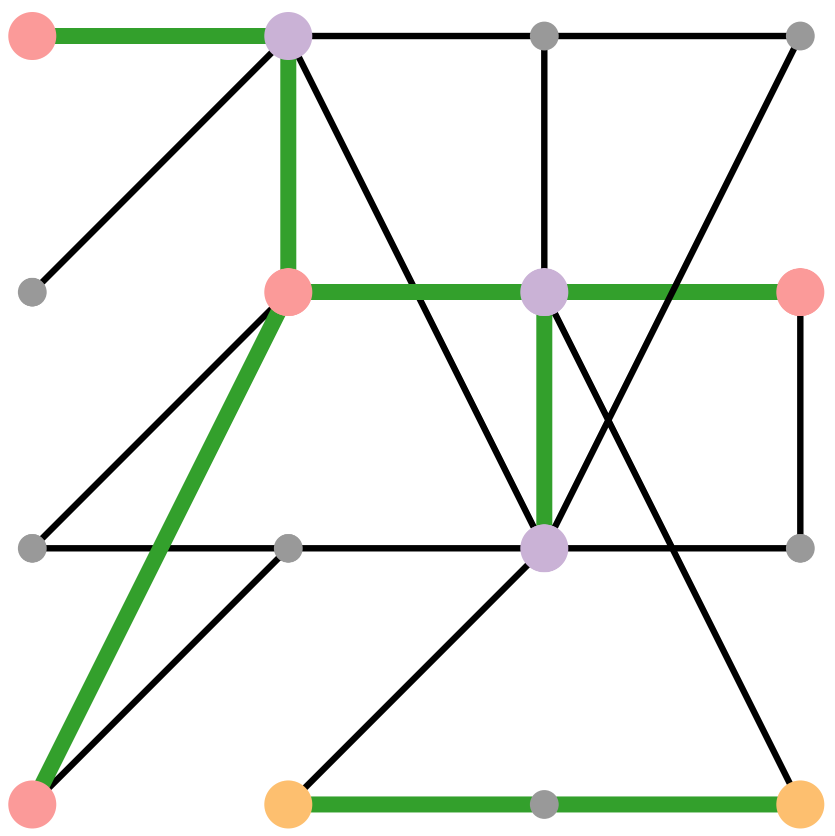

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Challenges:

Model Specificity	$\longrightarrow$ Model Agnosticism (works across computational models)
Existential Optimality	$\longrightarrow$ Universal Optimality (best on given topology)

Constrained Forest Problems (CFPs)

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≈ Problems on weighted graphs with forests as solutions

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Primal IP

$$
\begin{aligned}
&\min \sum_{e \in E} c(e) x_e \\
\text{s.t.}\quad & x(\partial(S)) \geq f(S) \quad \forall\, \emptyset \neq S \subset V \\
& x_e \in \{0,1\} \quad \forall\, e \in E
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Dual LP

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We focus on CFPs with *proper* functions f (zero, symmetry, disjointness)

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We focus on CFPs with *proper* functions f (zero, symmetry, disjointness)

Steiner Forest: $f(S) = 1 \Leftrightarrow \emptyset \neq S \cap V_i \neq V_i$ for some $i \in [k]$

The Goemans-Williamson Algorithm

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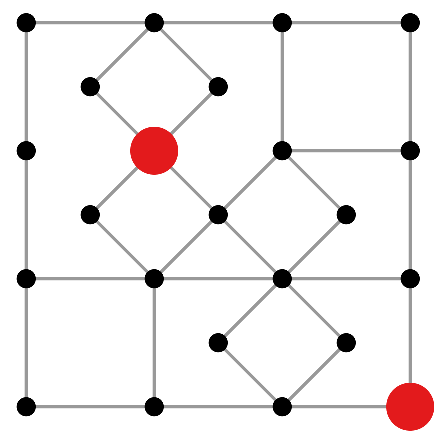
Input: Graph with edge costs c, proper forest function f



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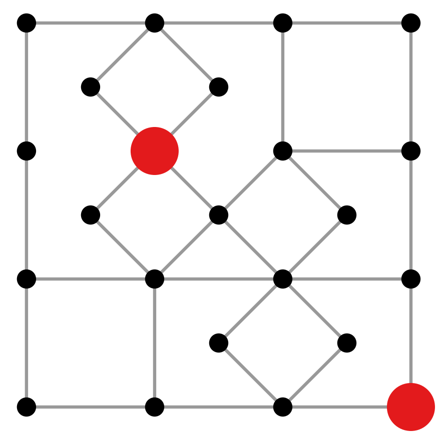
Output: Forest F and lower-bound value LB



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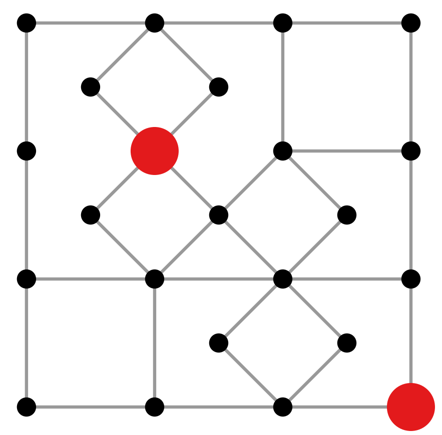

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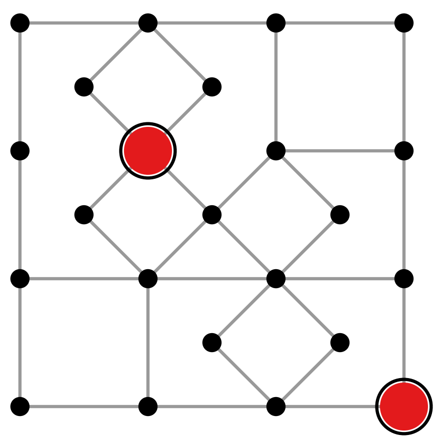

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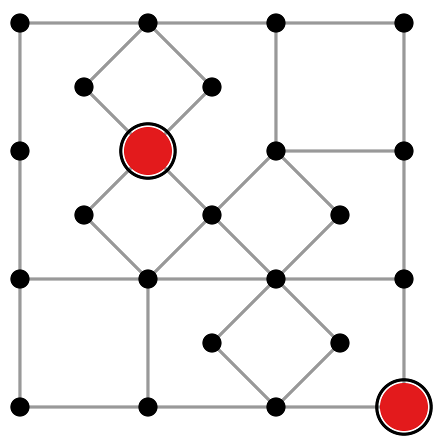

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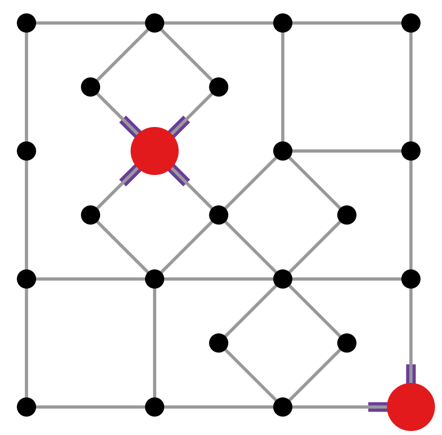

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Increase dual variables of all edges incident with active components, adding to LB

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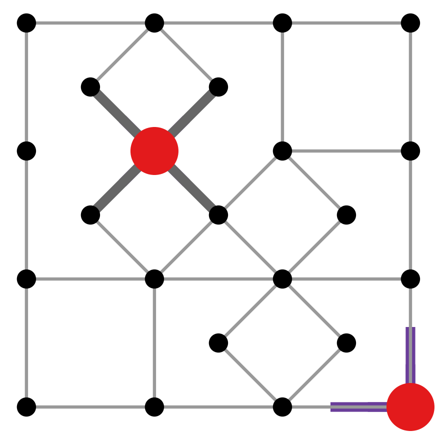

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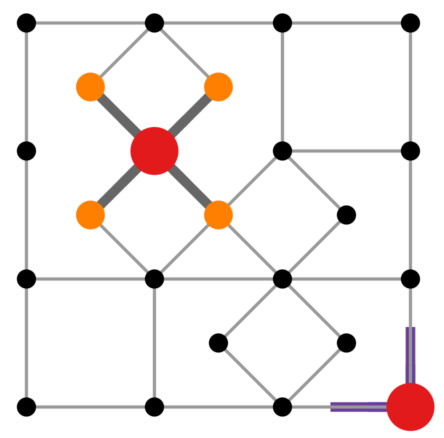

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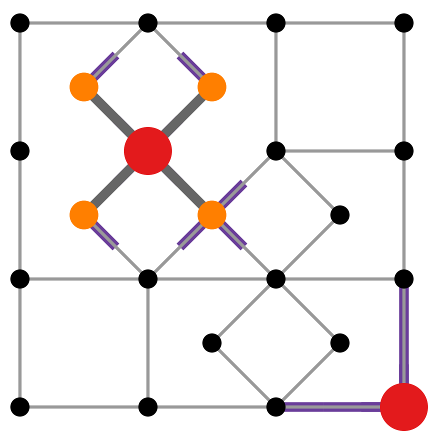

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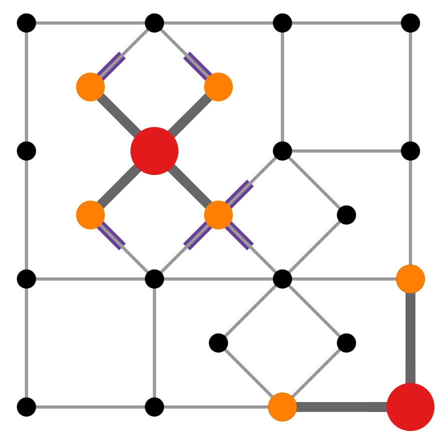

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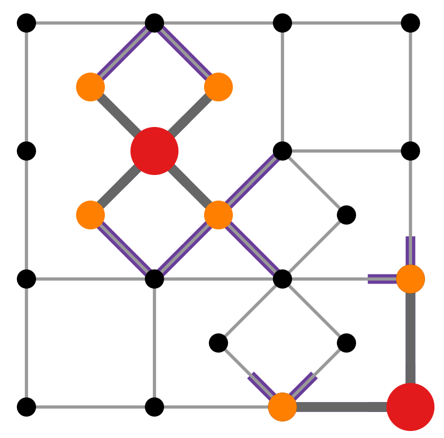

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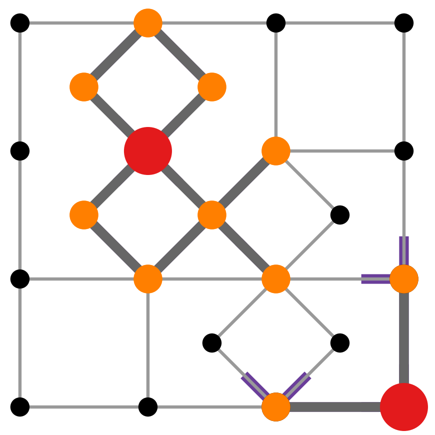

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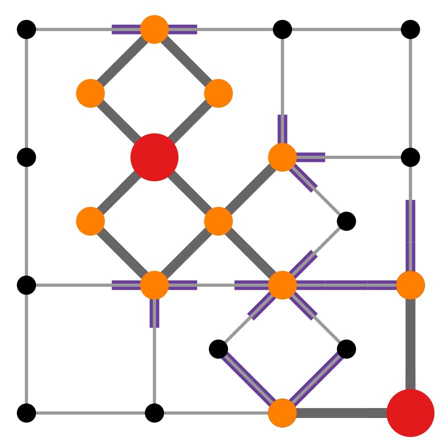

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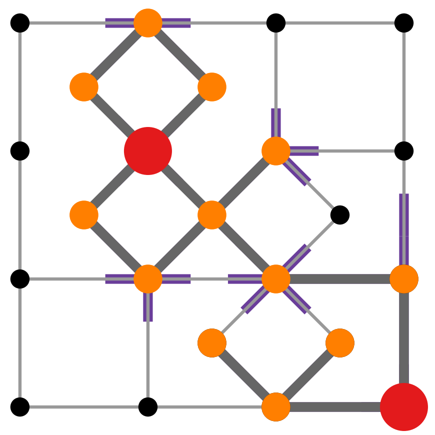

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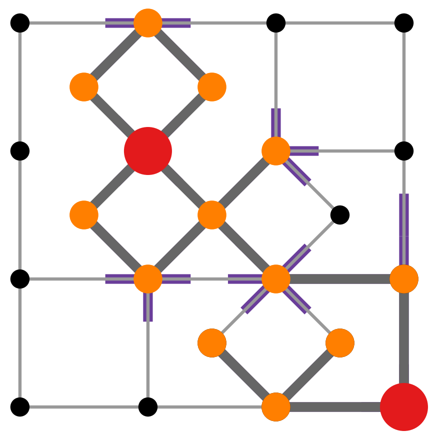

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  - Merge components represented by endpoints of e
- Remove unnecessary edges from F

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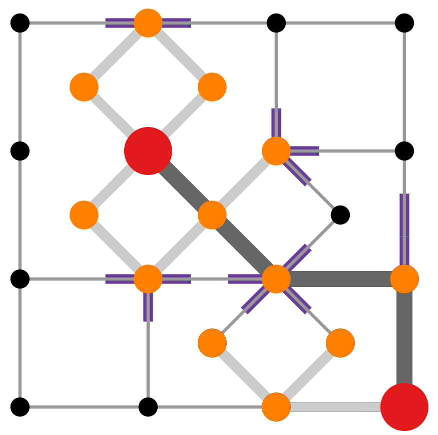

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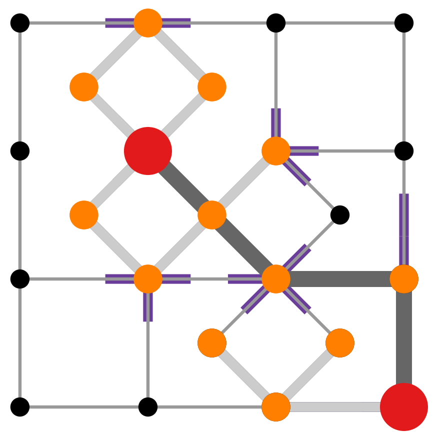

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Remove unnecessary edges from F

Approximation Guarantee: $2 - {}^{2}/_{t}$

Toward Model Agnosticism

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Challenge

Goemans-Williamson

Our Approach

Toward Model Agnosticism

Challenge	Goemans-Williamson	Our Approach
Solution-Set Construction	Filtering	Incremental

Toward Model Agnosticism

Challenge	Goemans-Williamson	Our Approach
Solution-Set Construction	Filtering	Incremental
Pairwise Distance Computations	Exact	Approximate

Toward Model Agnosticism

Challenge	Goemans-Williamson	Our Approach
Solution-Set Construction	Filtering	Incremental
Pairwise Distance Computations	Exact	Approximate
Forest-Function Evaluation	Many (Each Edge)	Deferred (Each Phase)

The Shell-Decomposition Algorithm: Approximation Intuition

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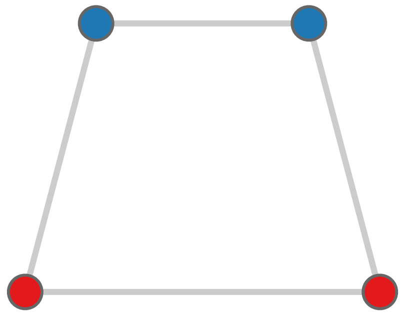
Start



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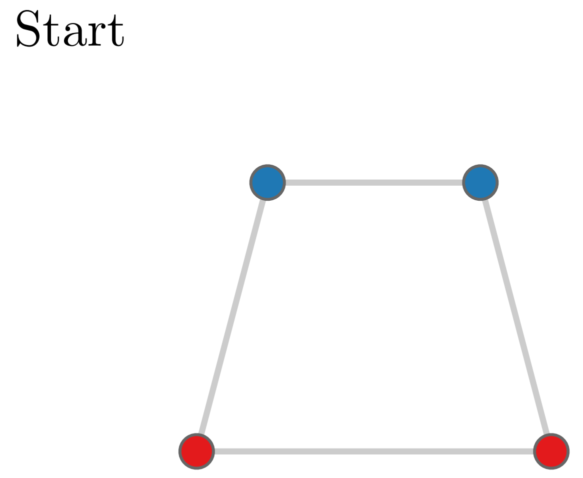

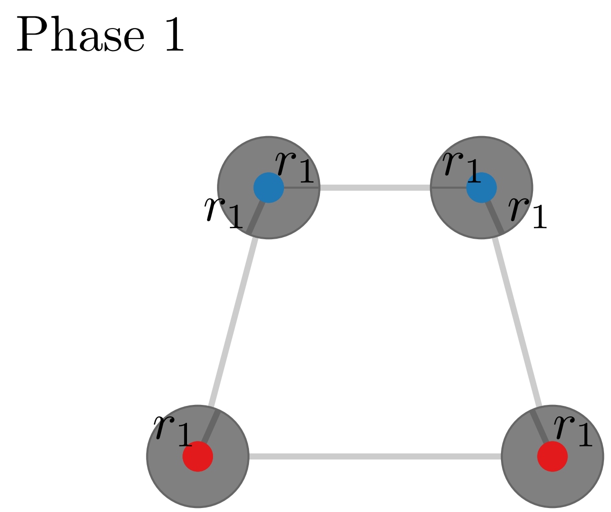

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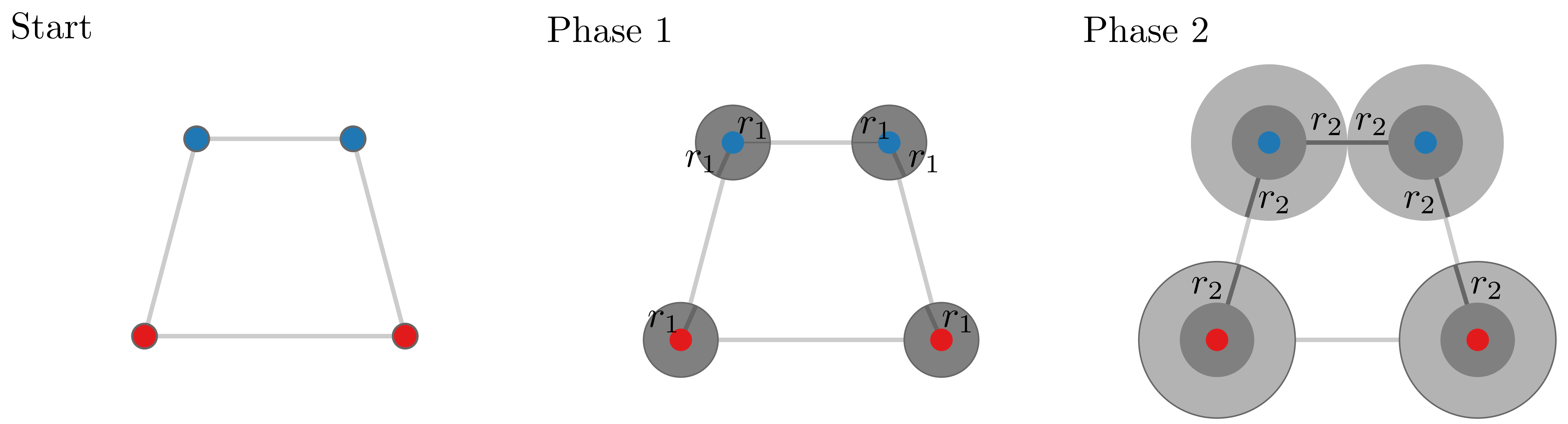
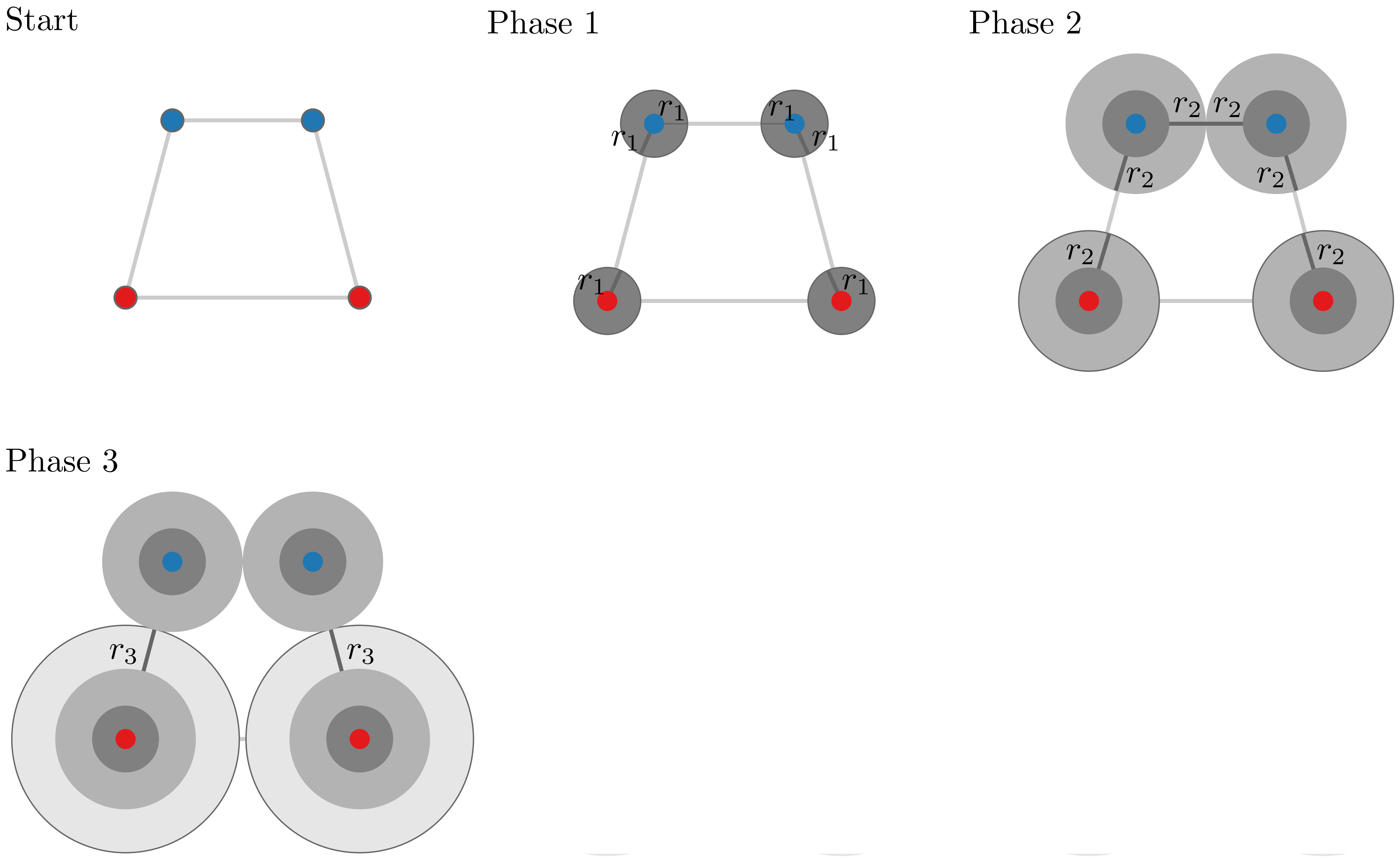


The Shell-Decomposition Algorithm: Approximation Intuition



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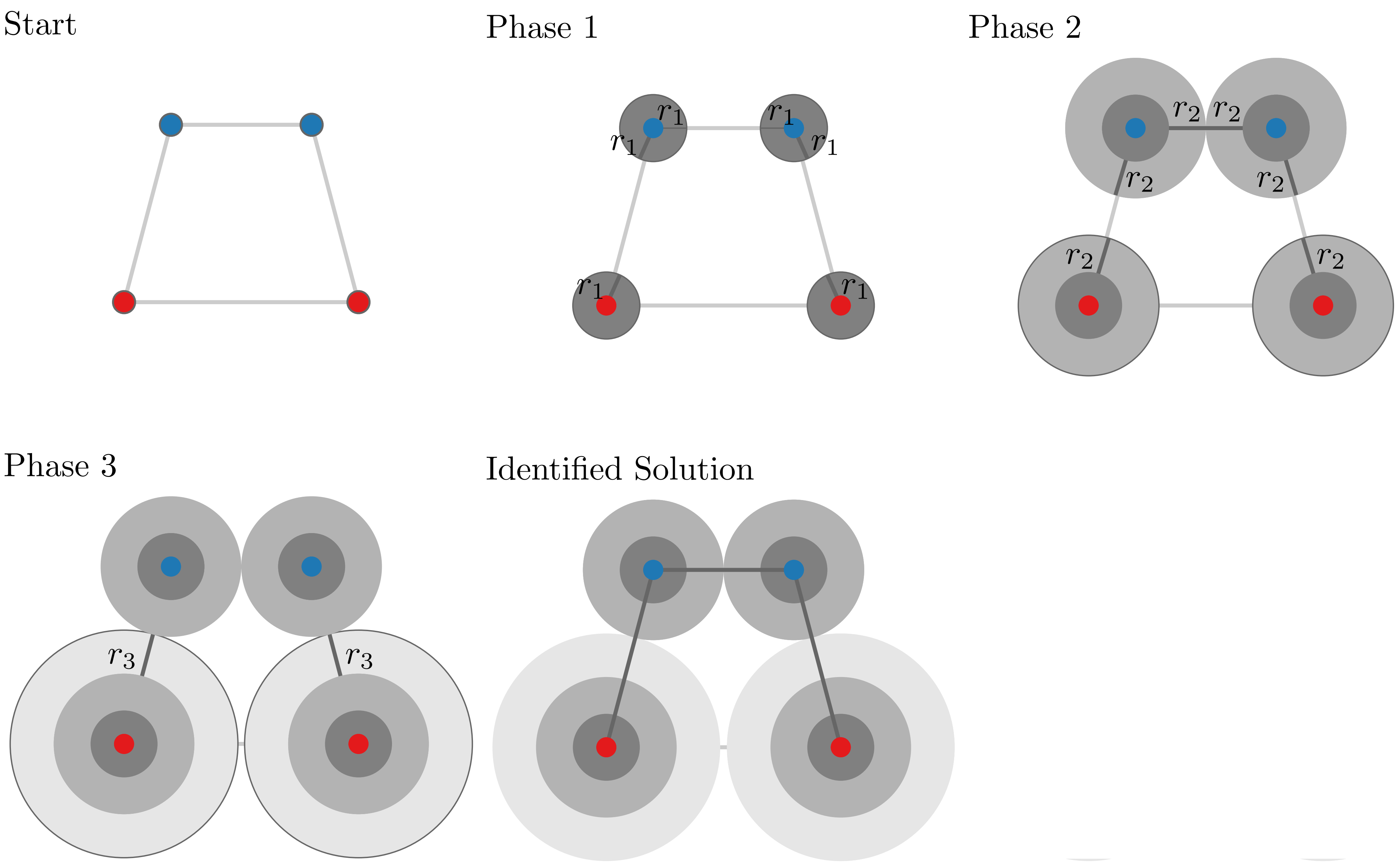

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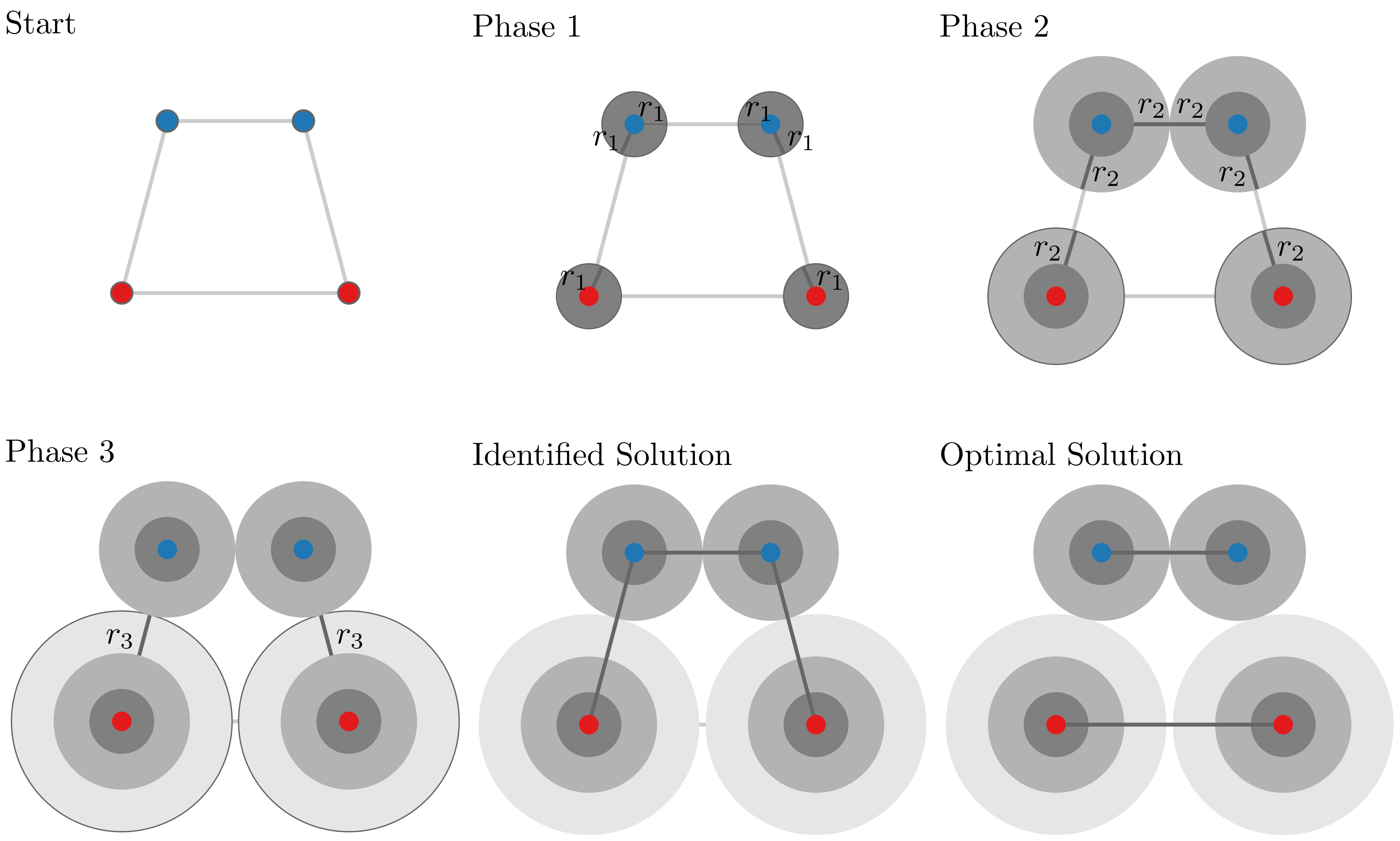

The Shell-Decomposition Algorithm: Building Blocks

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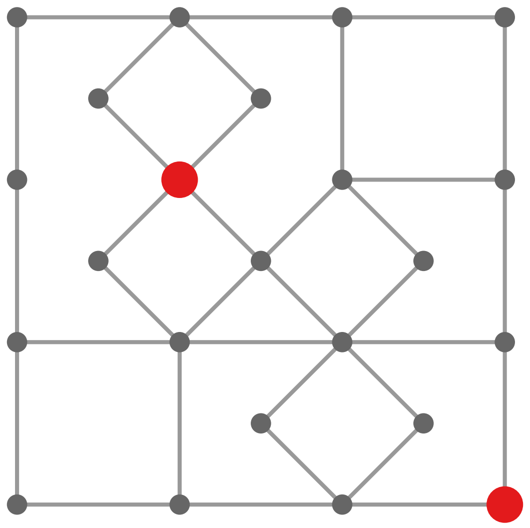
Initialization



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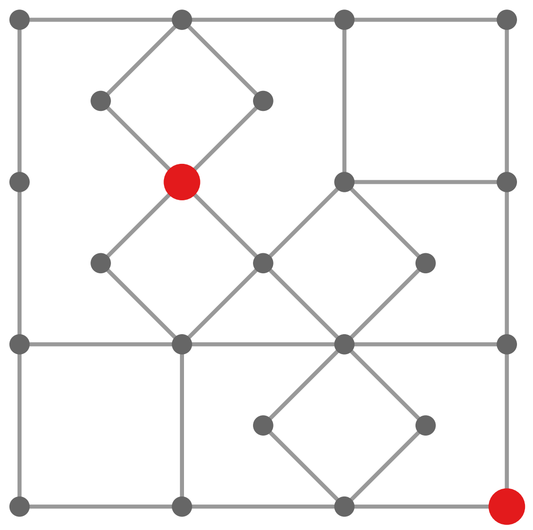
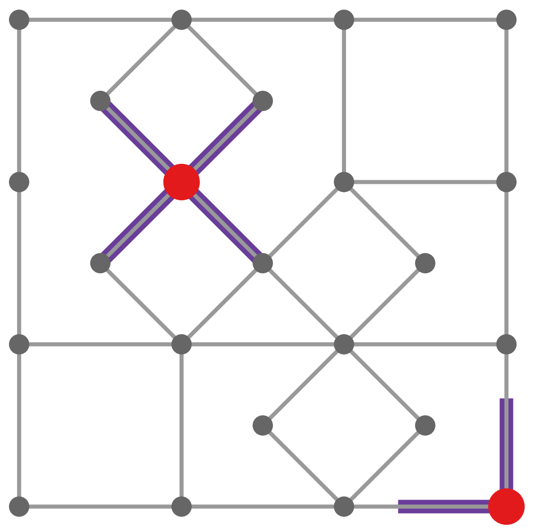


(0) Ball Growth

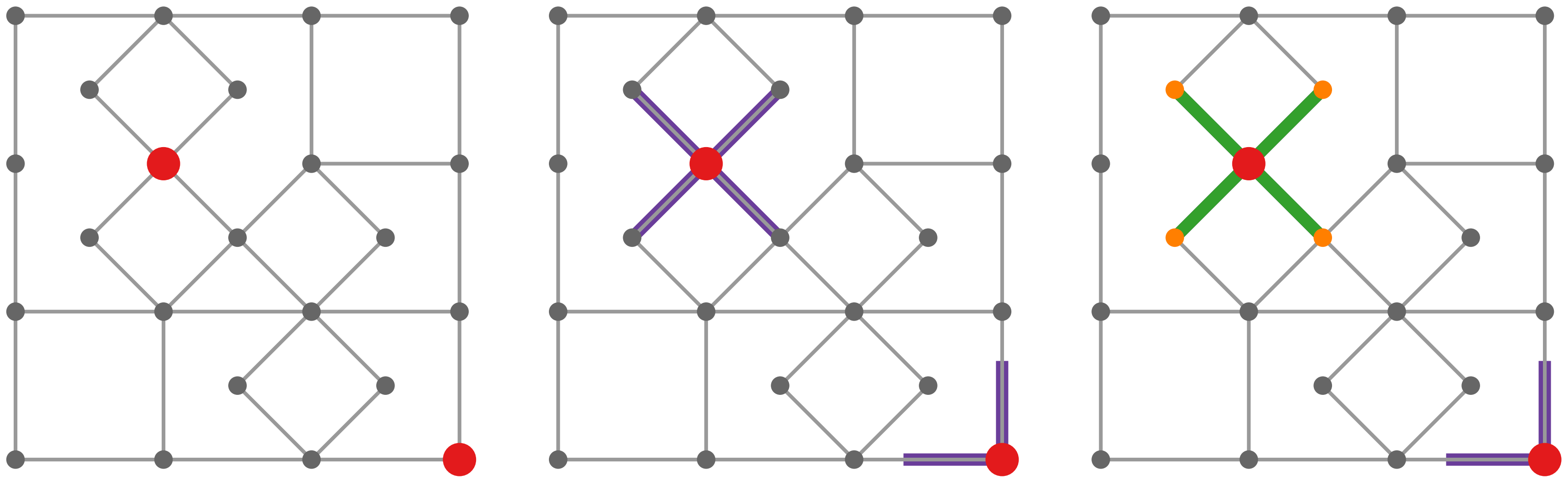


The Shell-Decomposition Algorithm: Building Blocks

Initialization

(0) Ball Growth

(0) SSSP Cover



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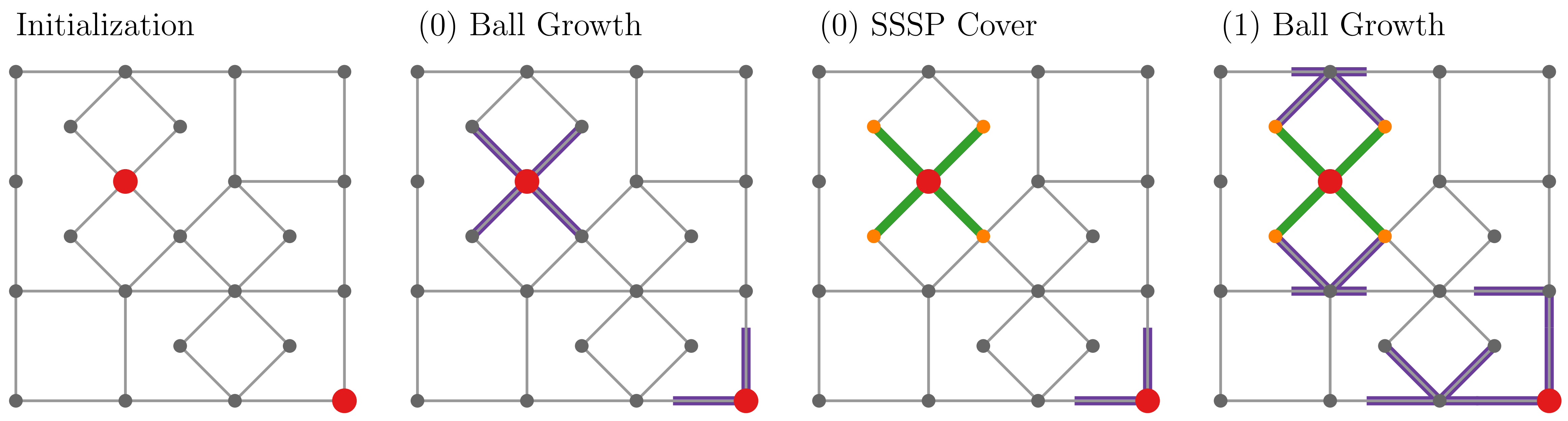

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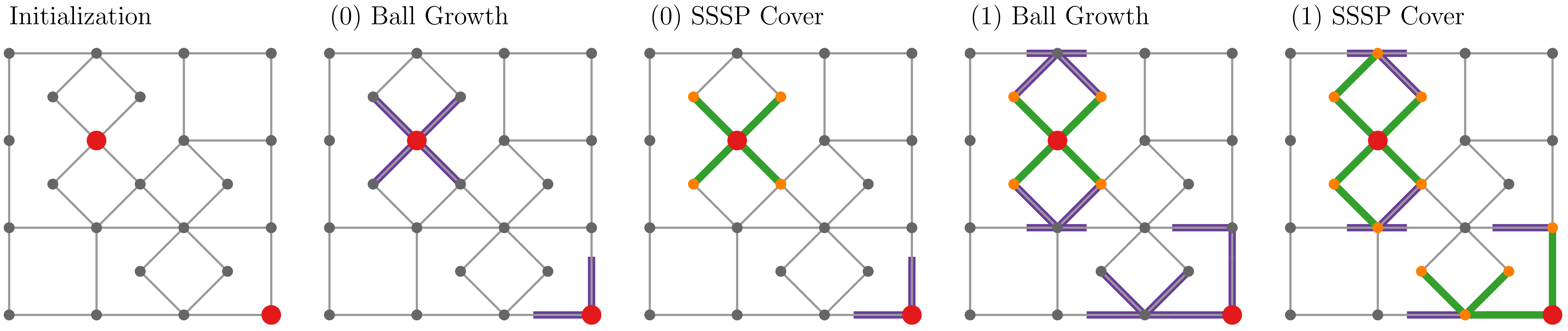

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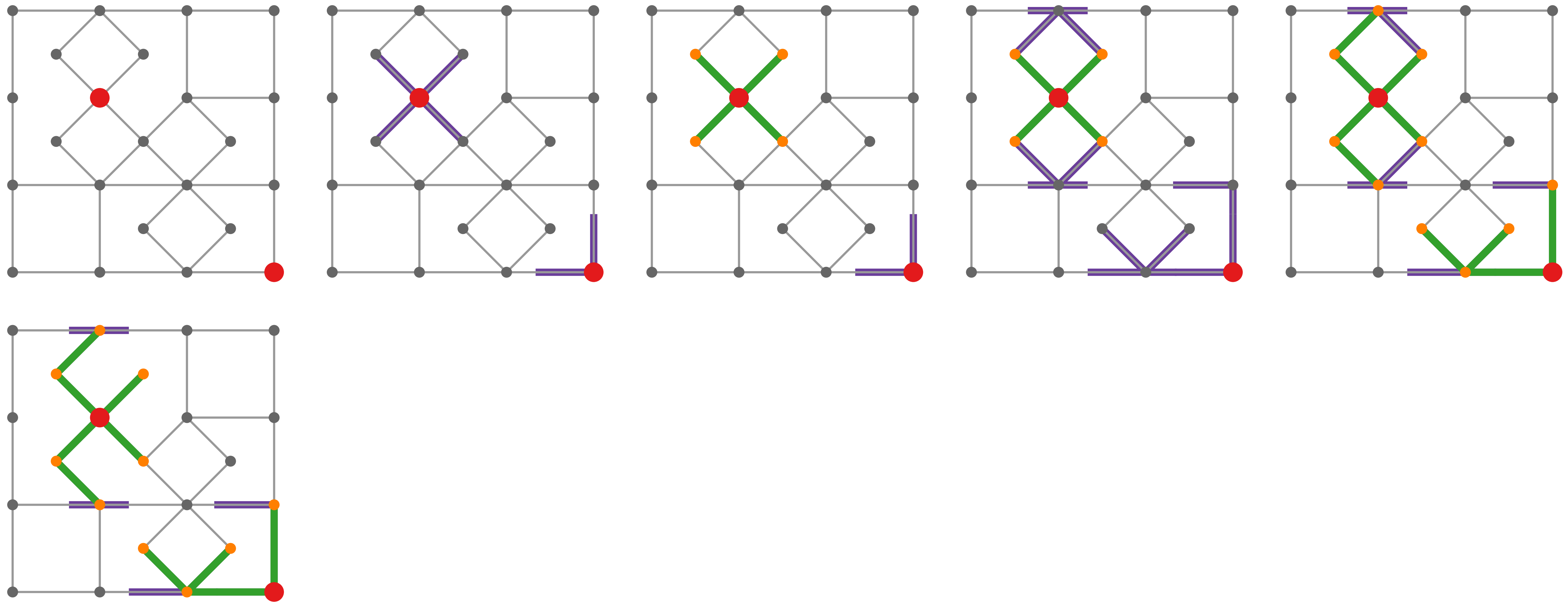

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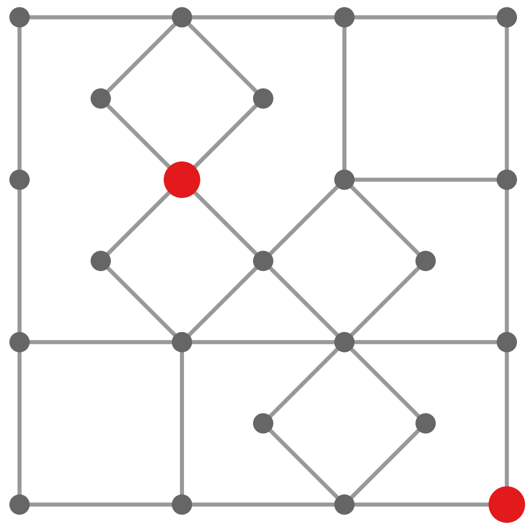

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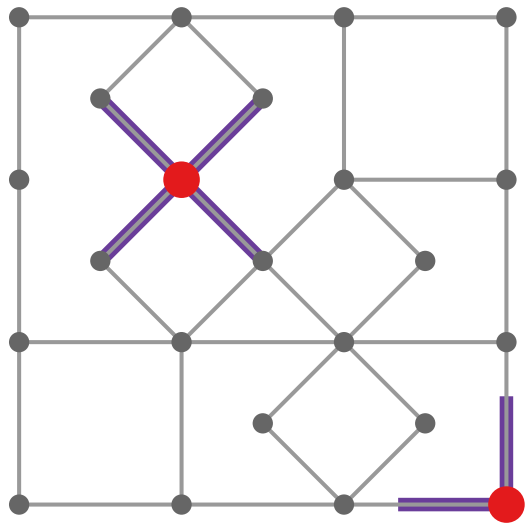
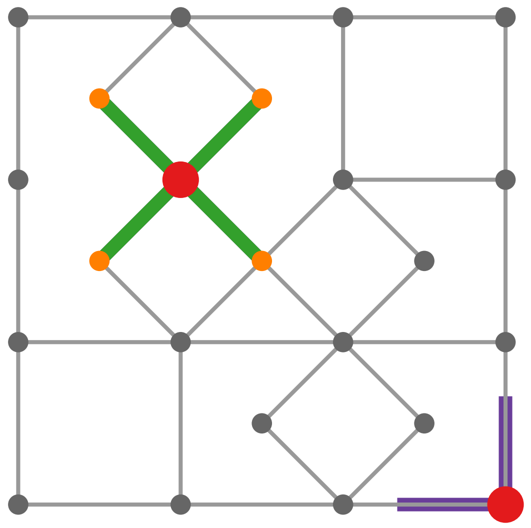
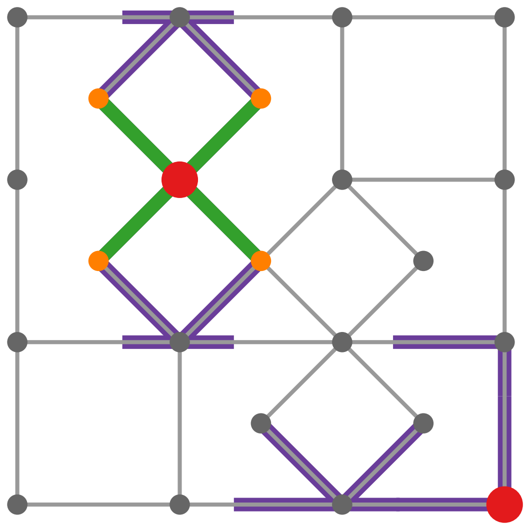


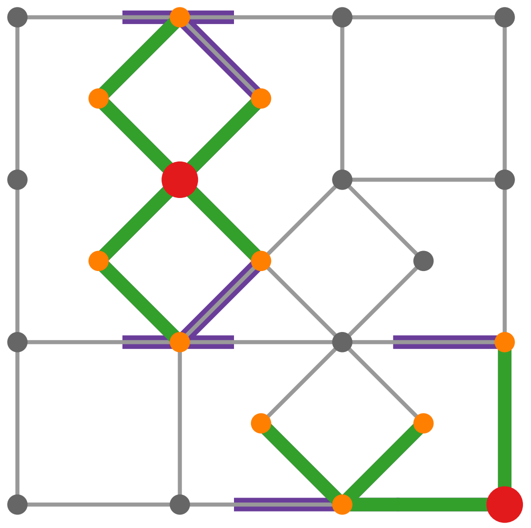
(0) SSSP Cover

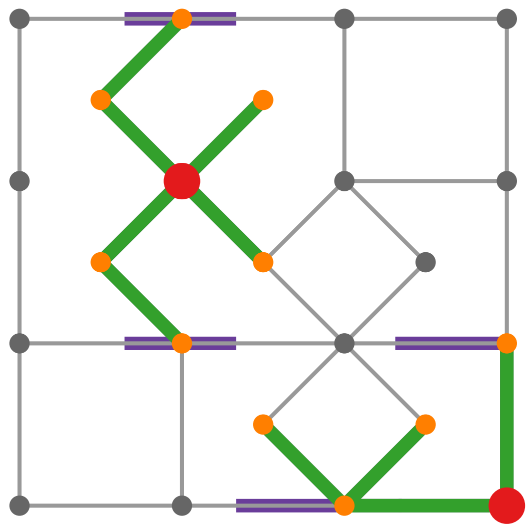


(1) Ball Growth

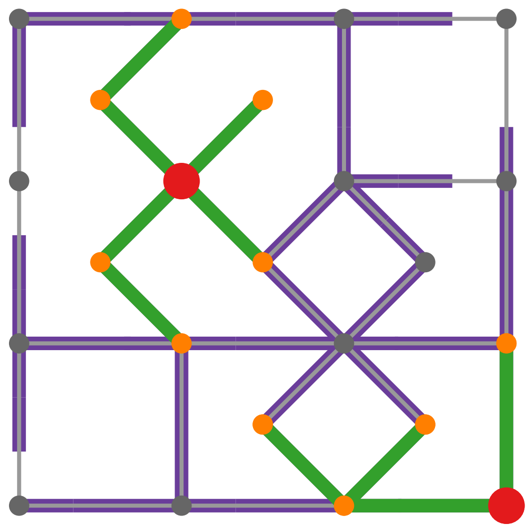


(1) SSSP Cover





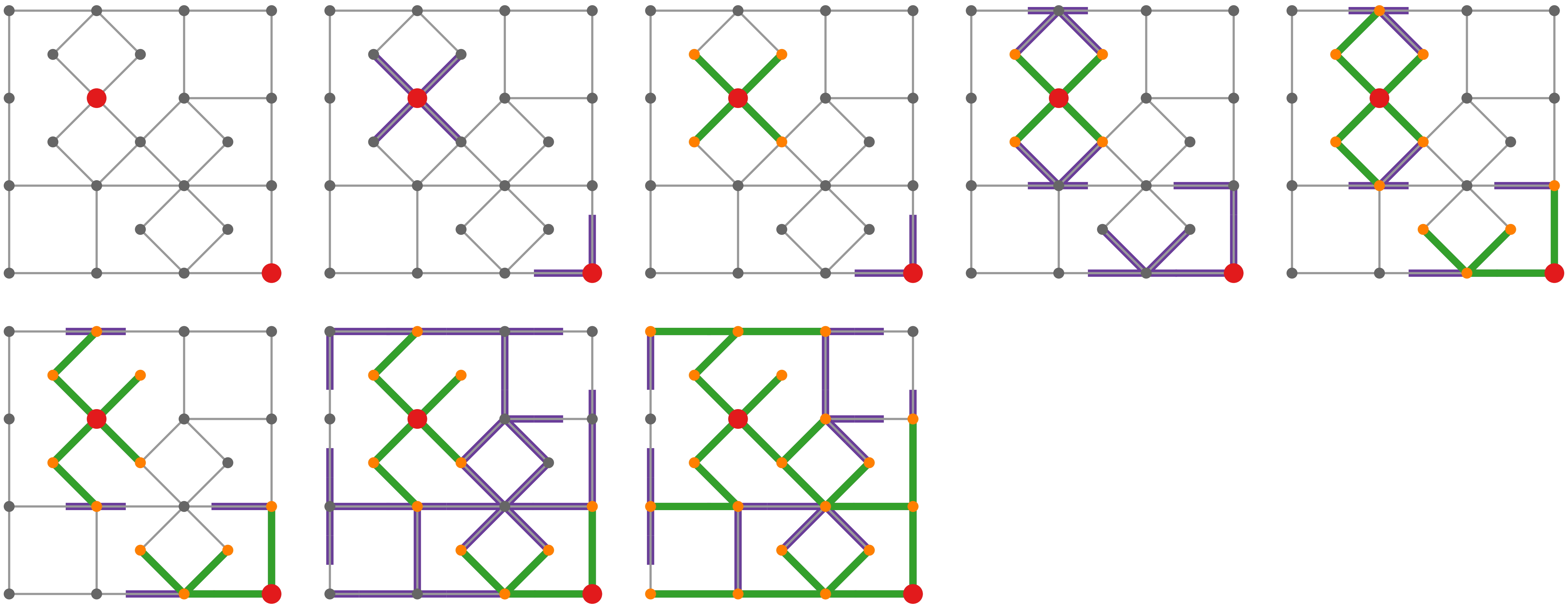
(1) Edge Deletion



(2) Ball Growth

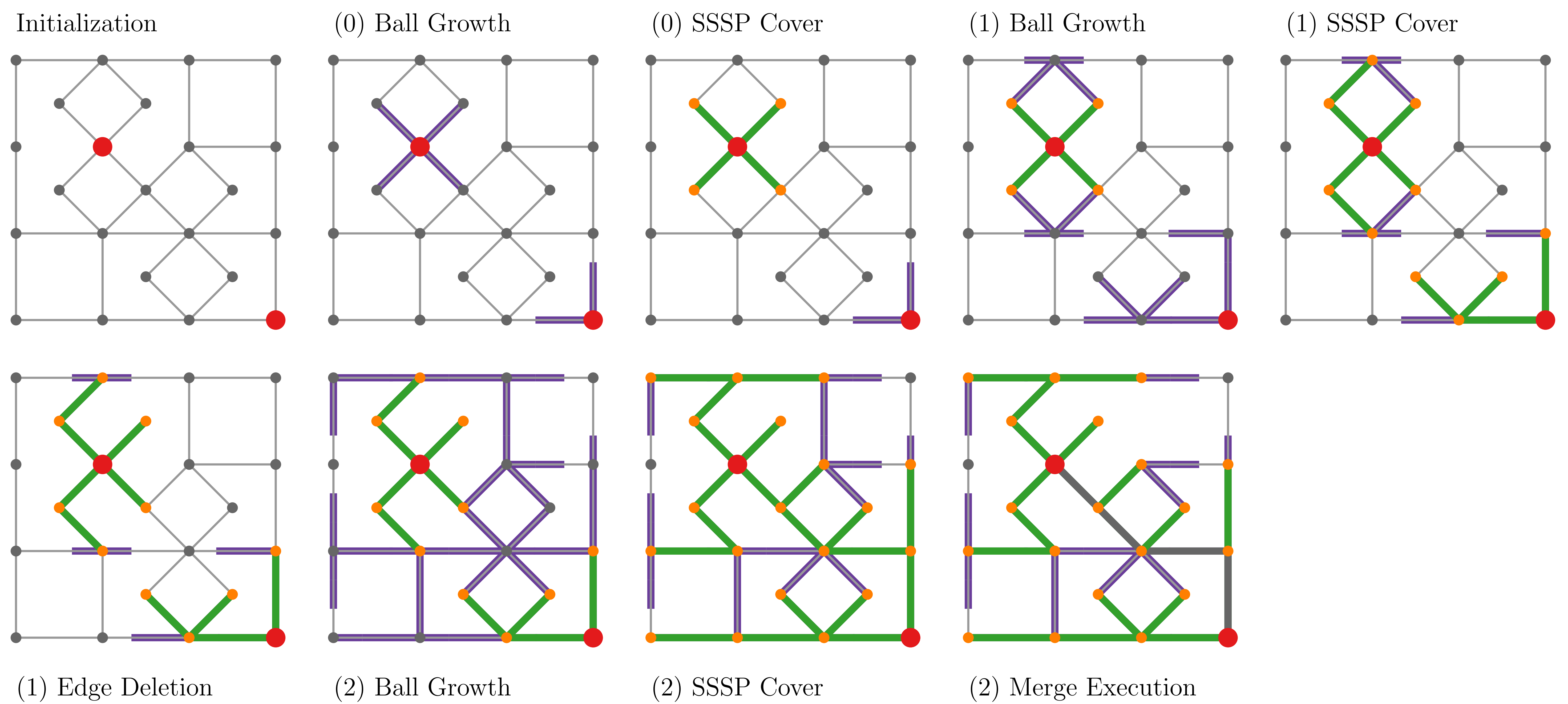
The Shell-Decomposition Algorithm: Building Blocks

Initialization (0) Ball Growth (0) SSSP Cover (1) Ball Growth (1) SSSP Cover



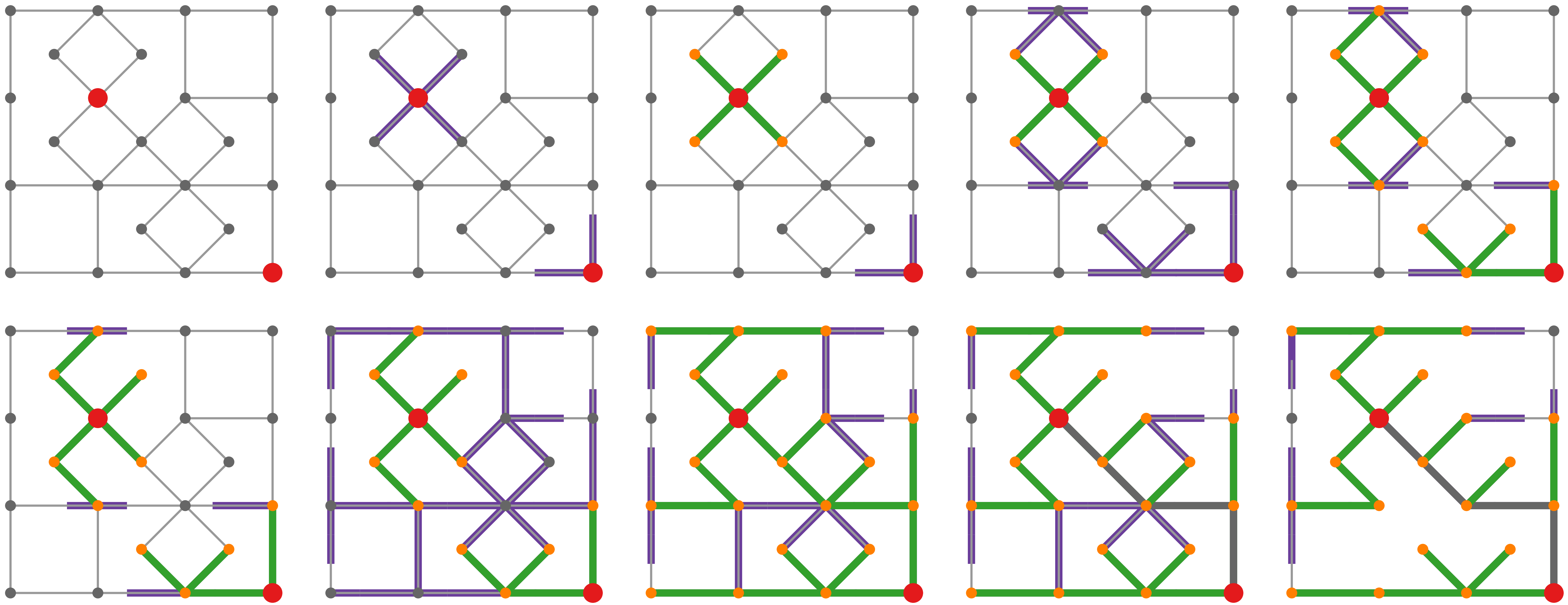
(1) Edge Deletion (2) Ball Growth (2) SSSP Cover

The Shell-Decomposition Algorithm: Building Blocks



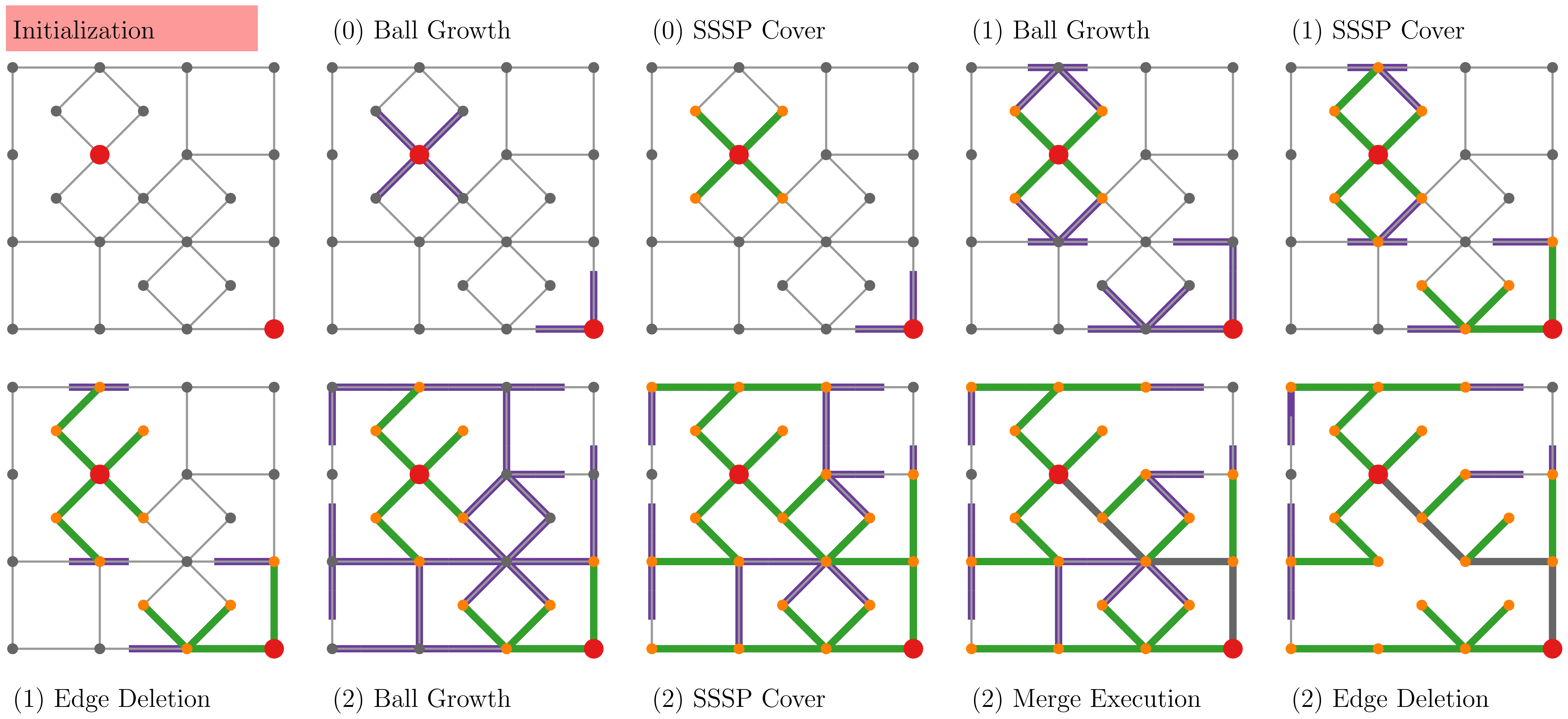
The Shell-Decomposition Algorithm: Building Blocks

Initialization · (0) Ball Growth · (0) SSSP Cover · (1) Ball Growth · (1) SSSP Cover



(1) Edge Deletion · (2) Ball Growth · (2) SSSP Cover · (2) Merge Execution · (2) Edge Deletion

The Shell-Decomposition Algorithm: Building Blocks



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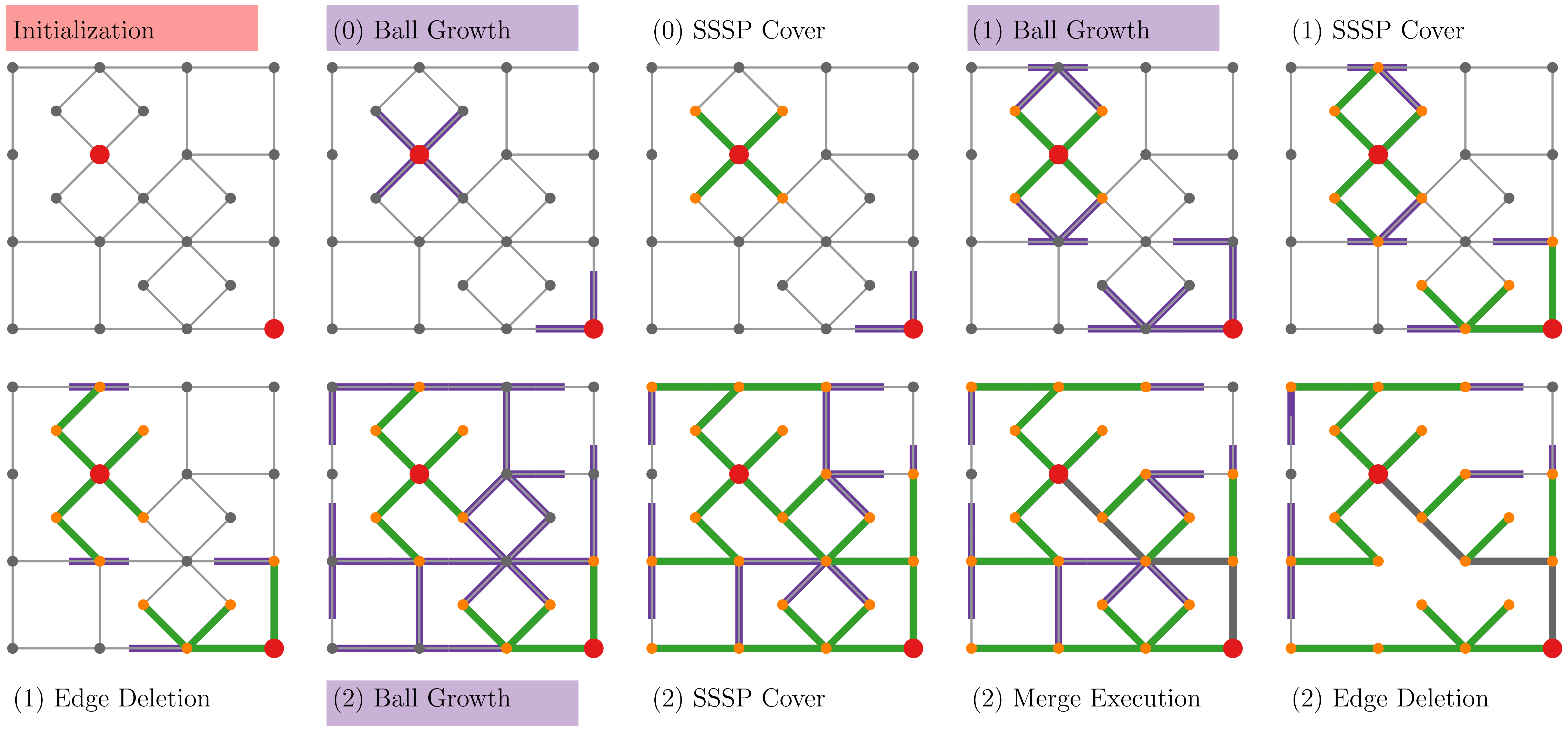

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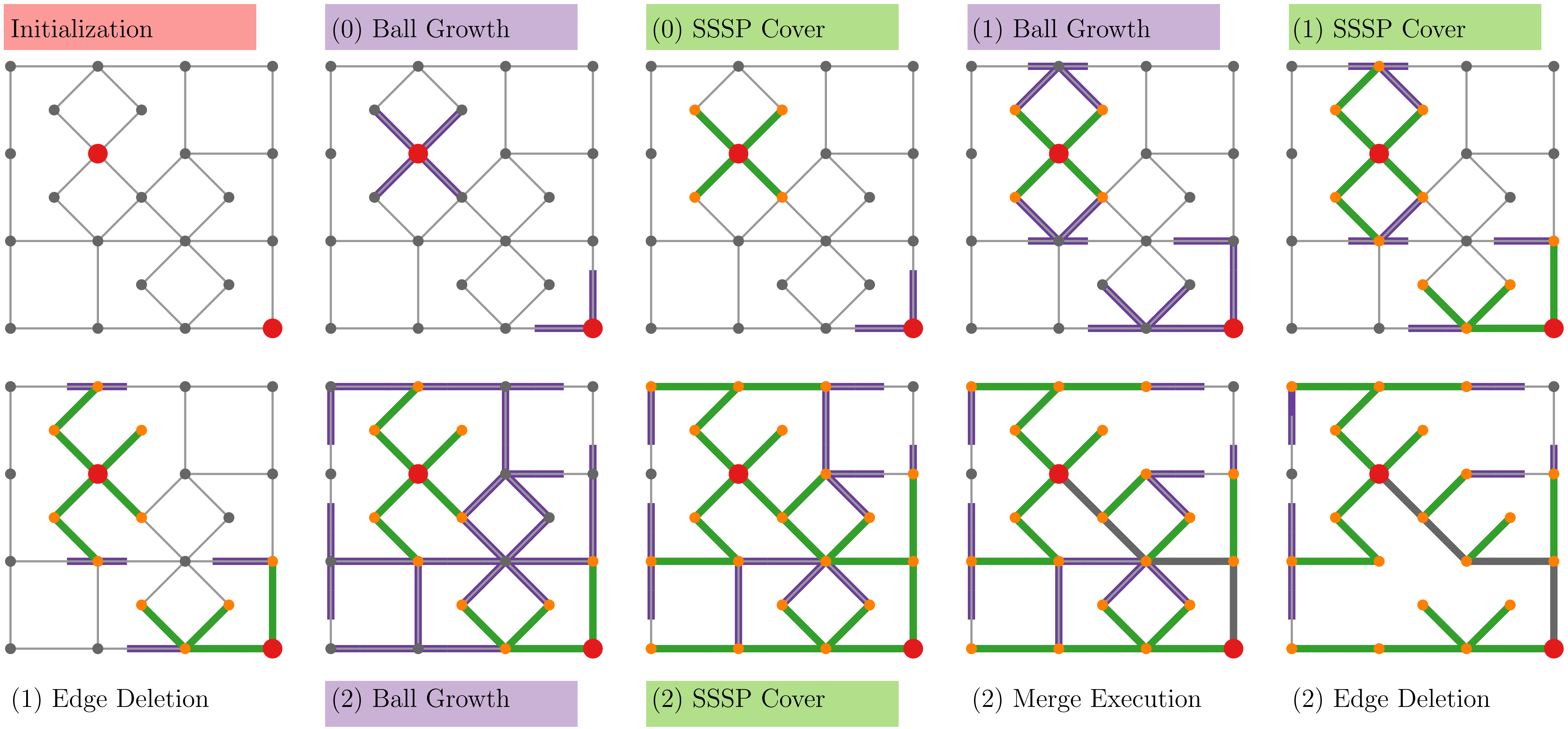

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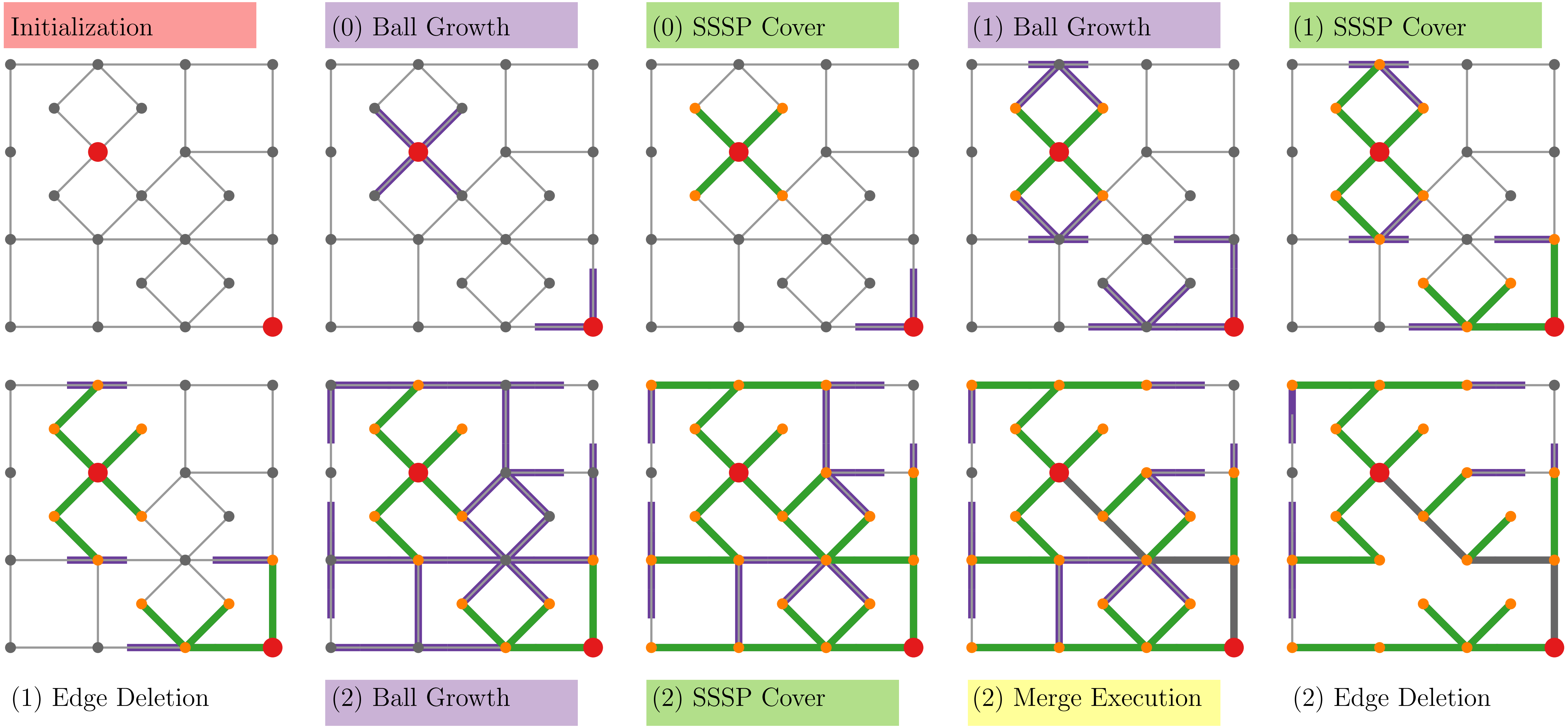

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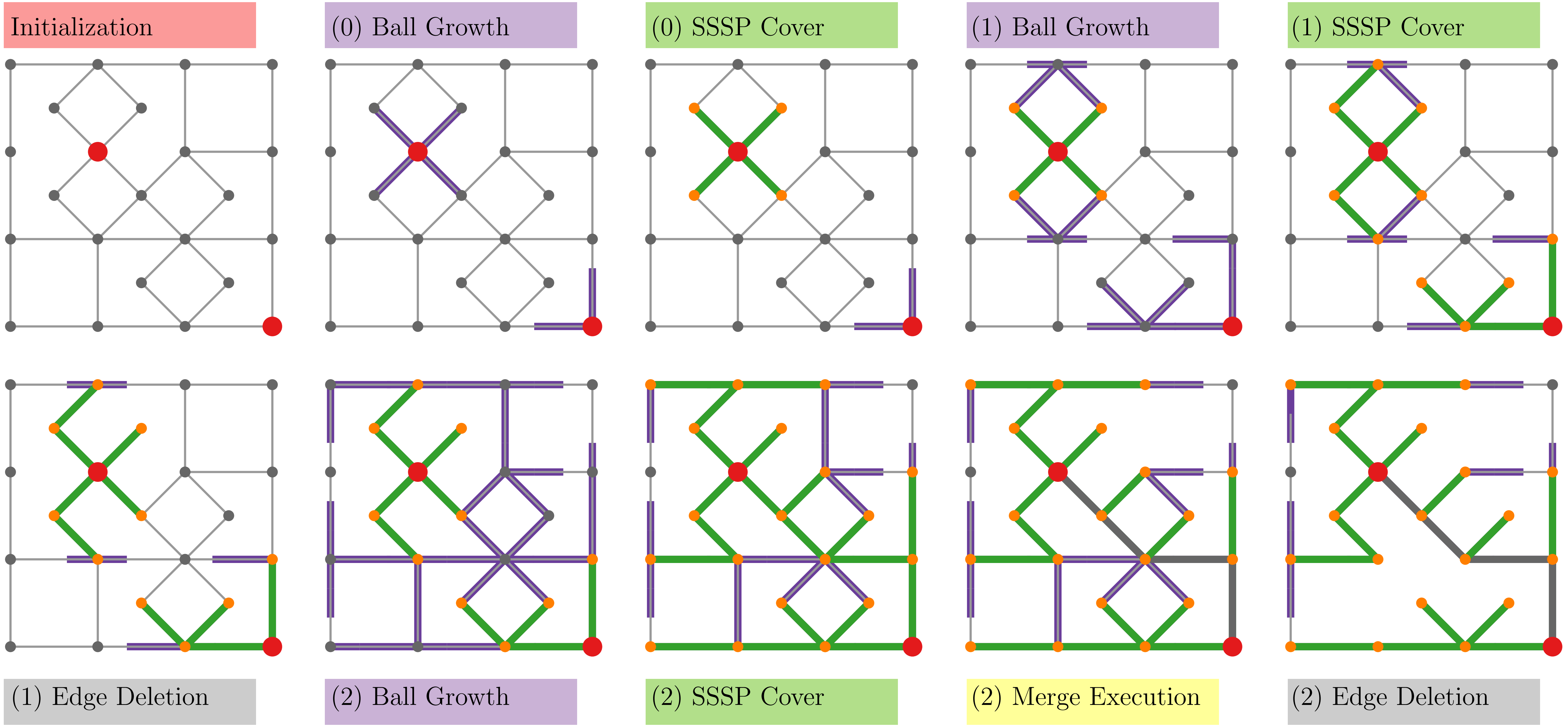
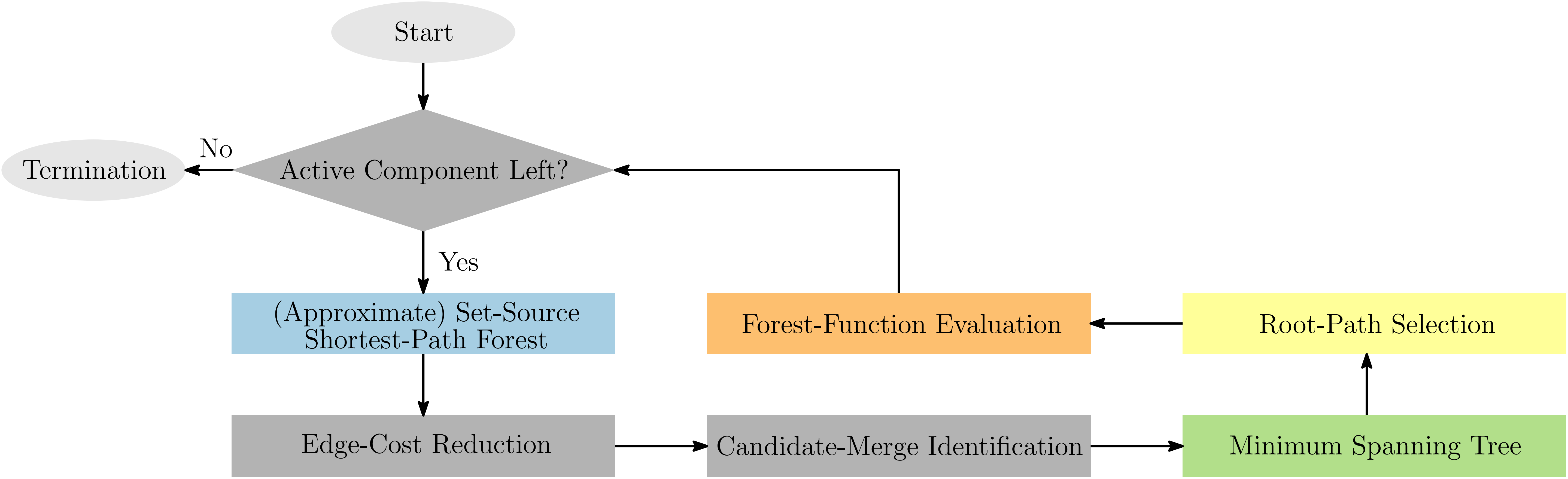


Model-Agnostic Specification

Approximation Guarantee: $2 + \varepsilon$



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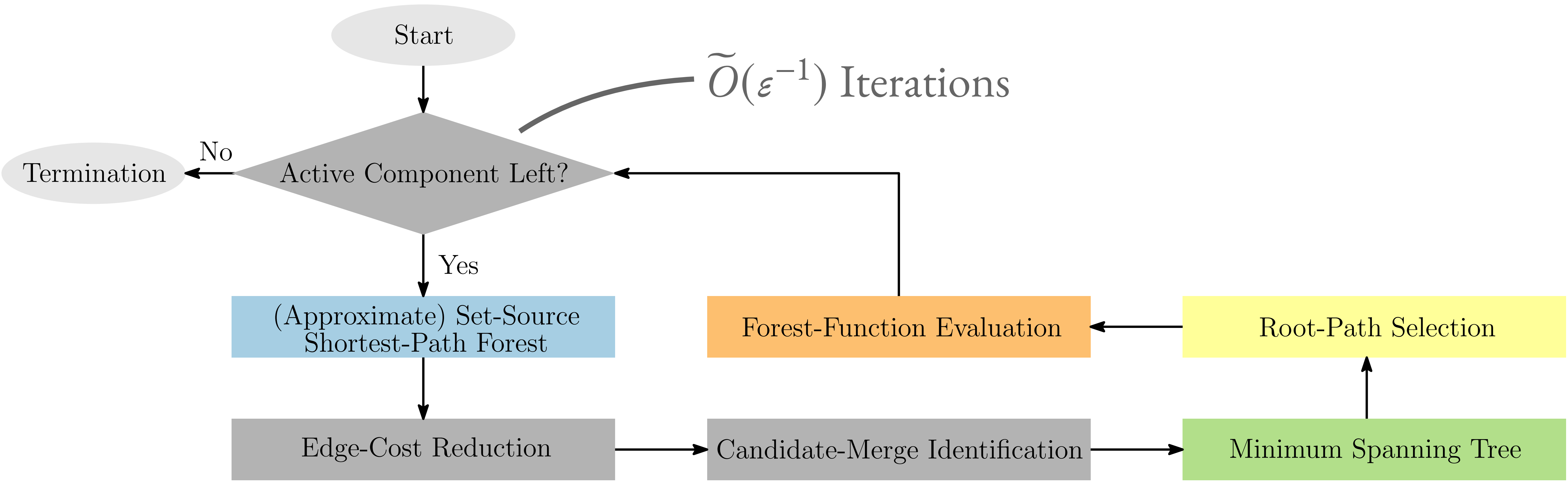

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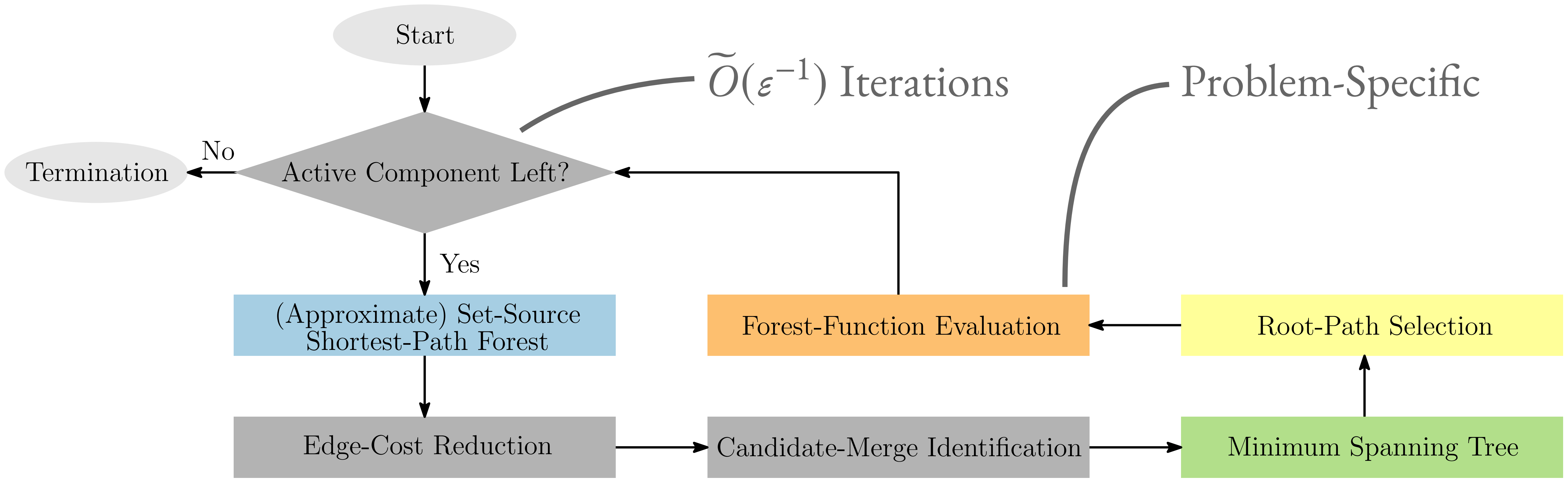

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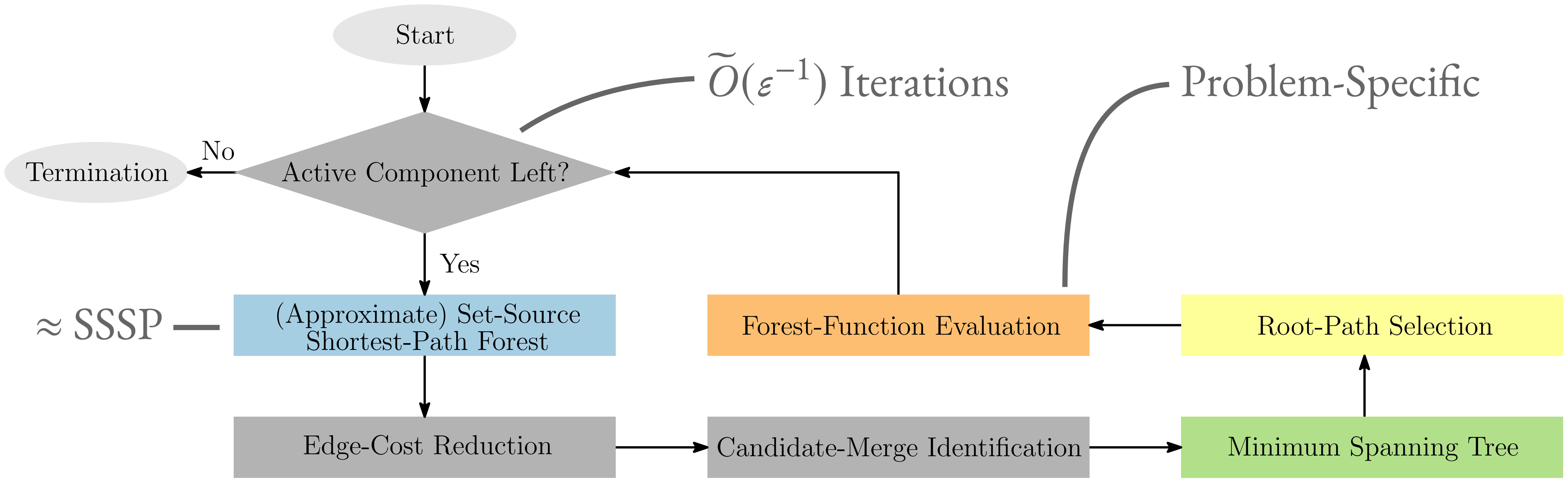

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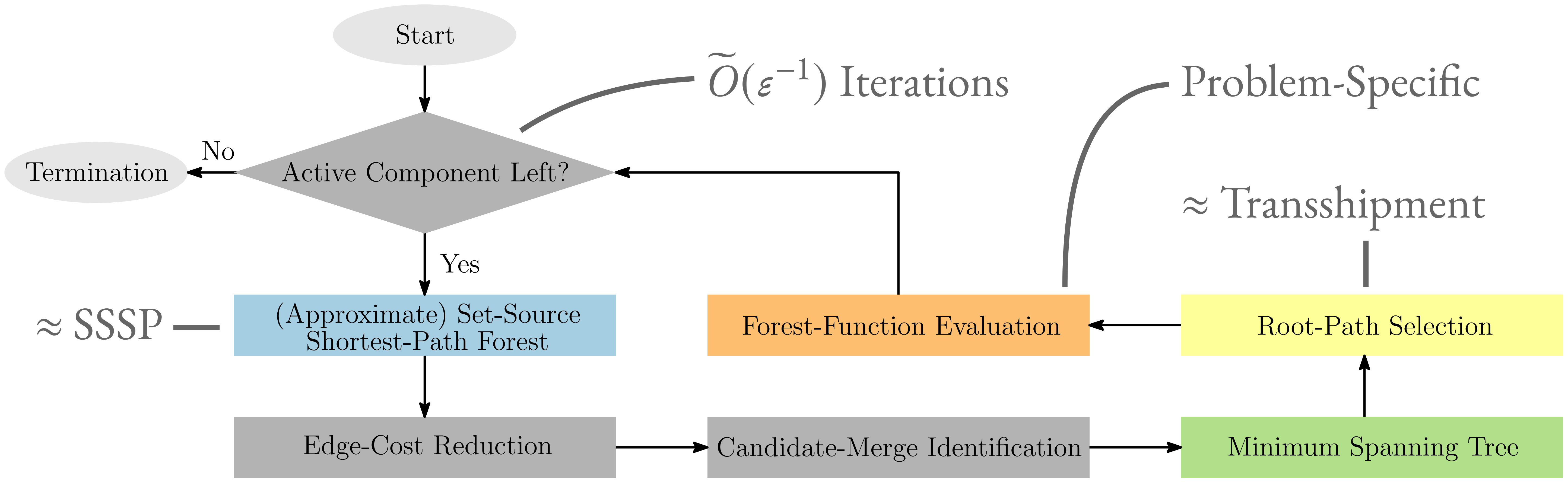

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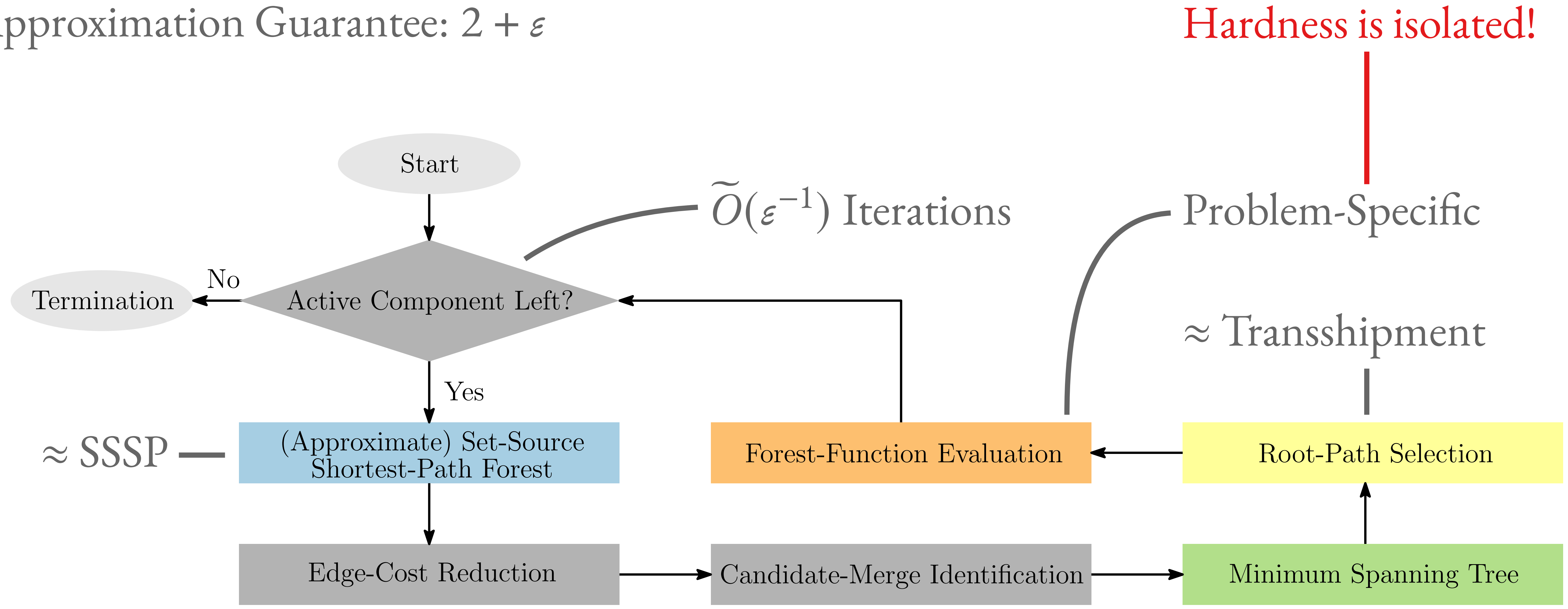

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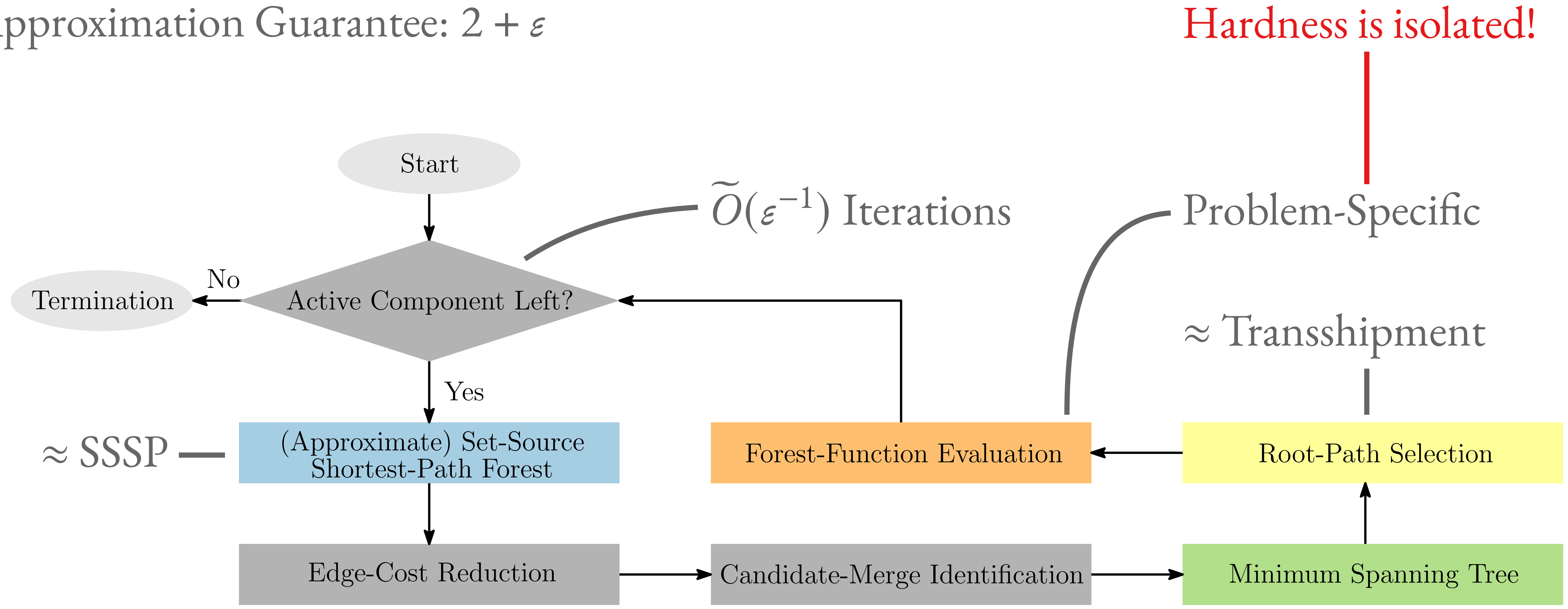
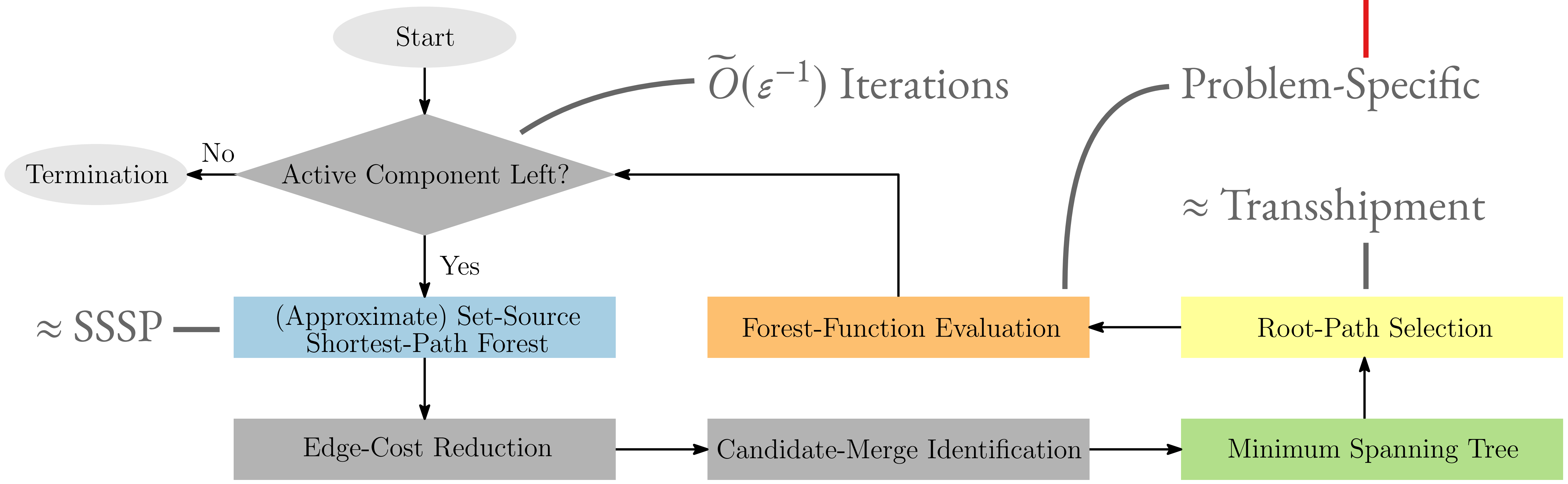


Complexity: $\widetilde{O}\left((\text{aSSSP} + \text{MST} + \text{RPS} + \text{FFE})\varepsilon^{-1}\right)$

Model-Agnostic Specification

Approximation Guarantee: $2 + \varepsilon$

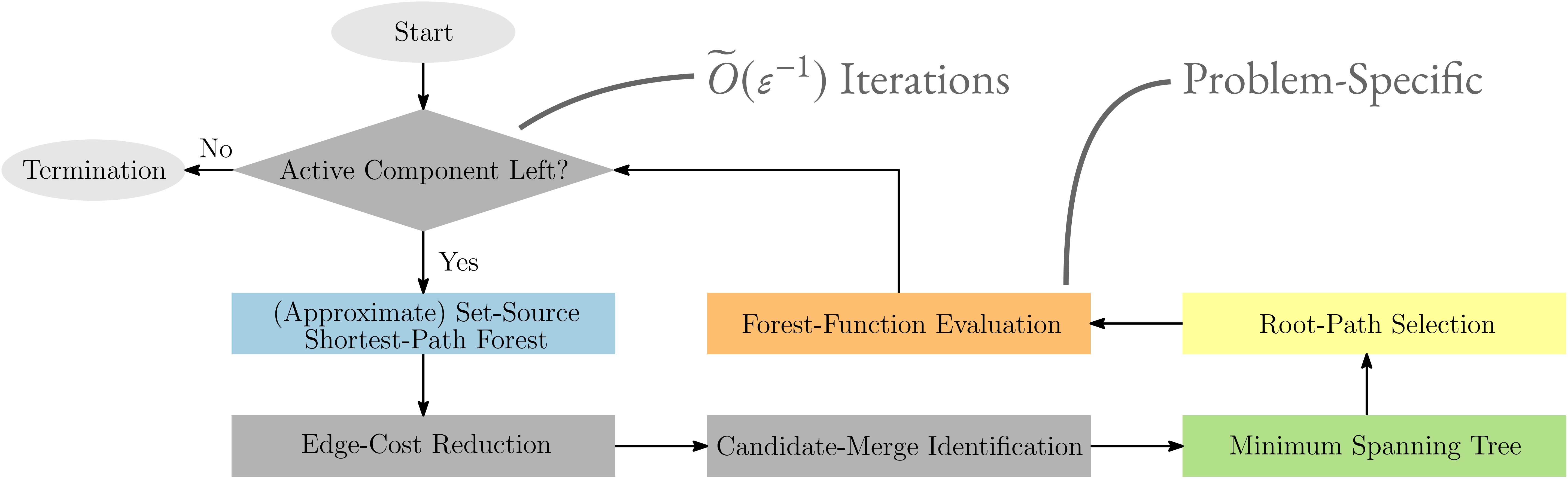
Hardness is isolated!



Complexity: $\widetilde{O}\left((\text{aSSSP} + \text{MST} + \text{RPS} + \text{FFE})\varepsilon^{-1}\right)$ — Model-agnostic!

Model-Specific Implementation: CONGEST

$(2+\varepsilon)$-approximation with…



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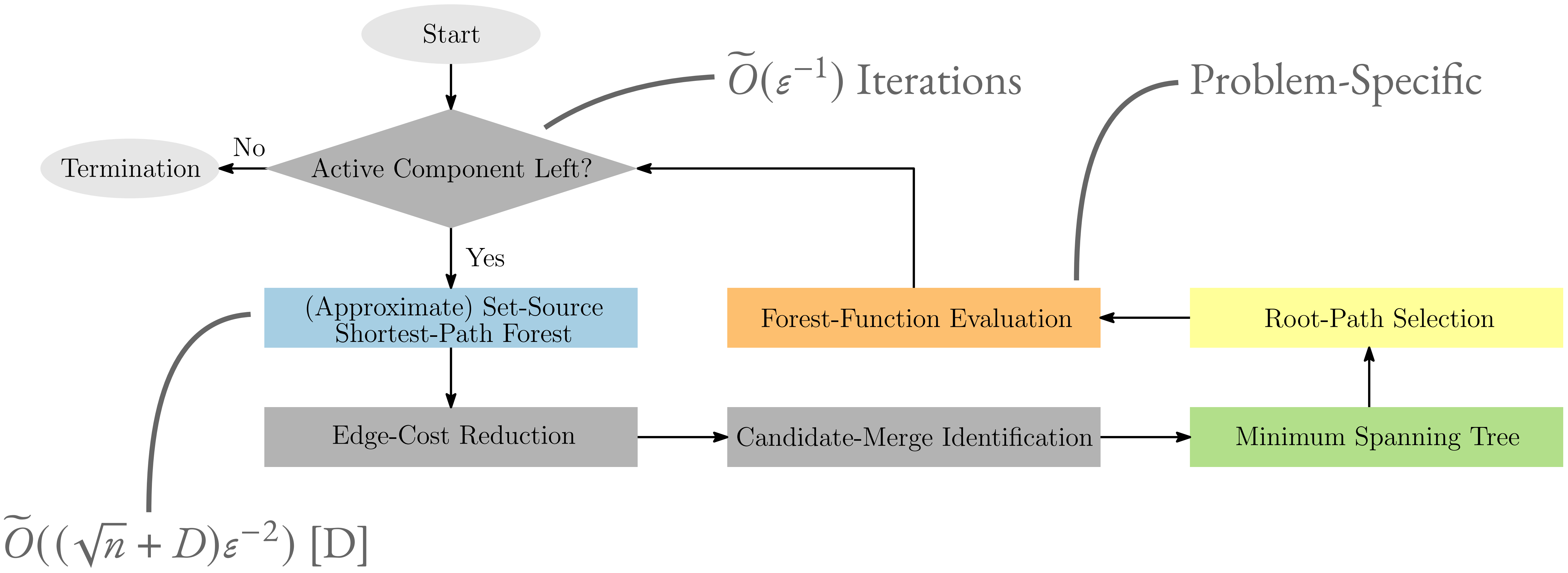

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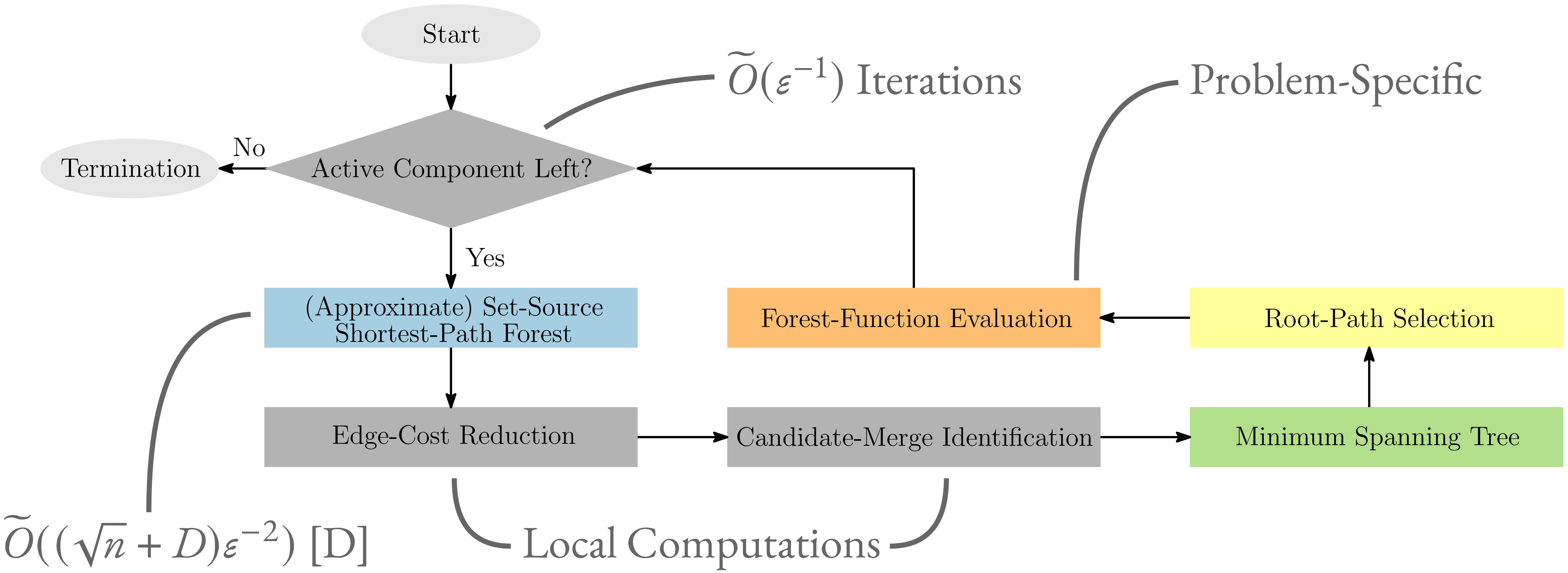

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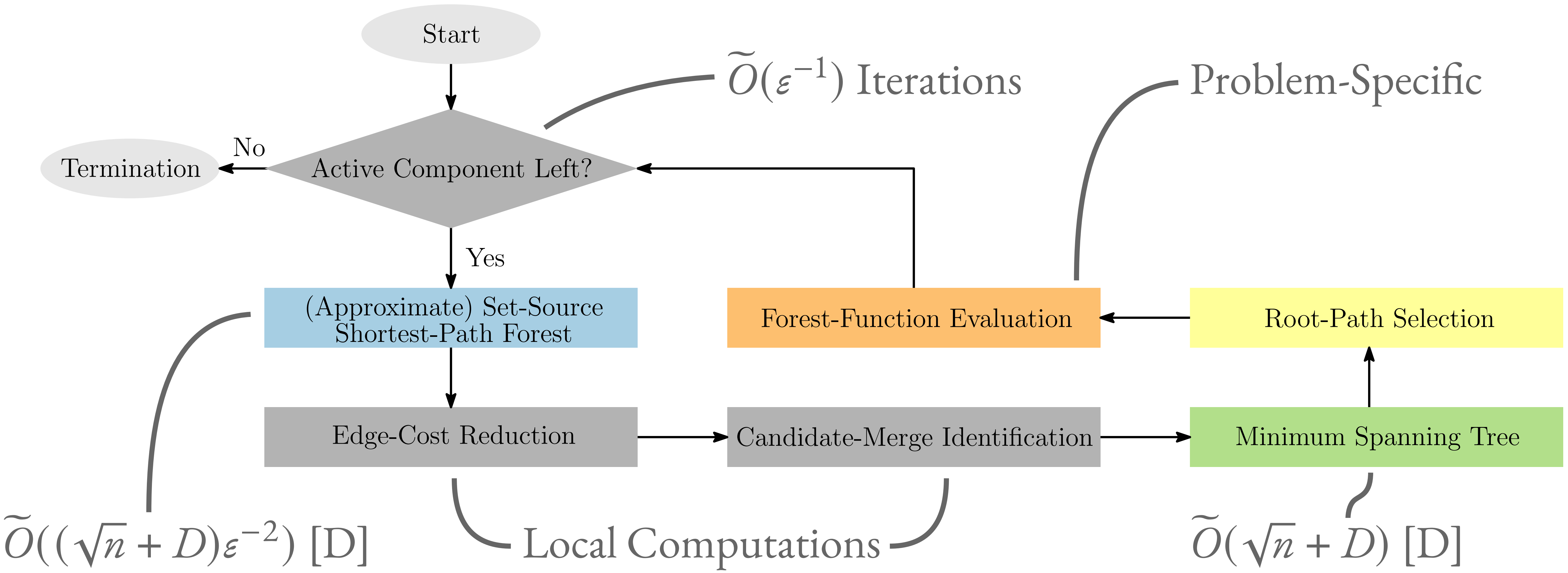

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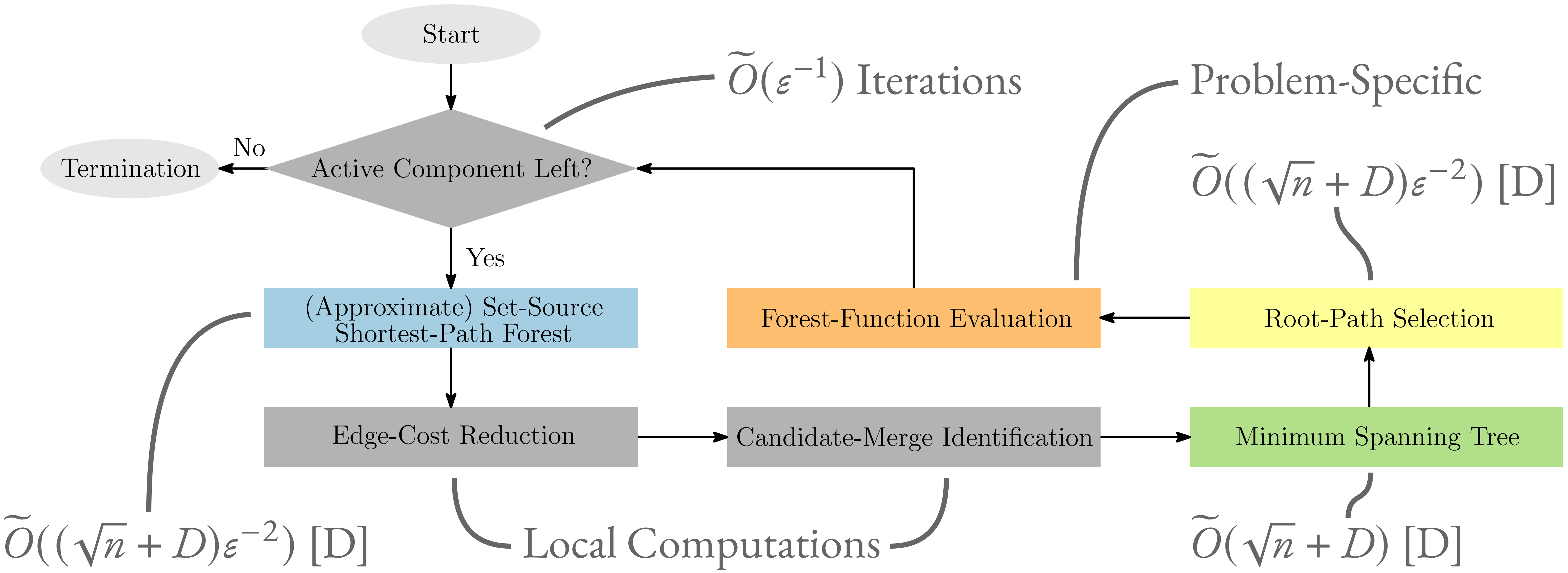
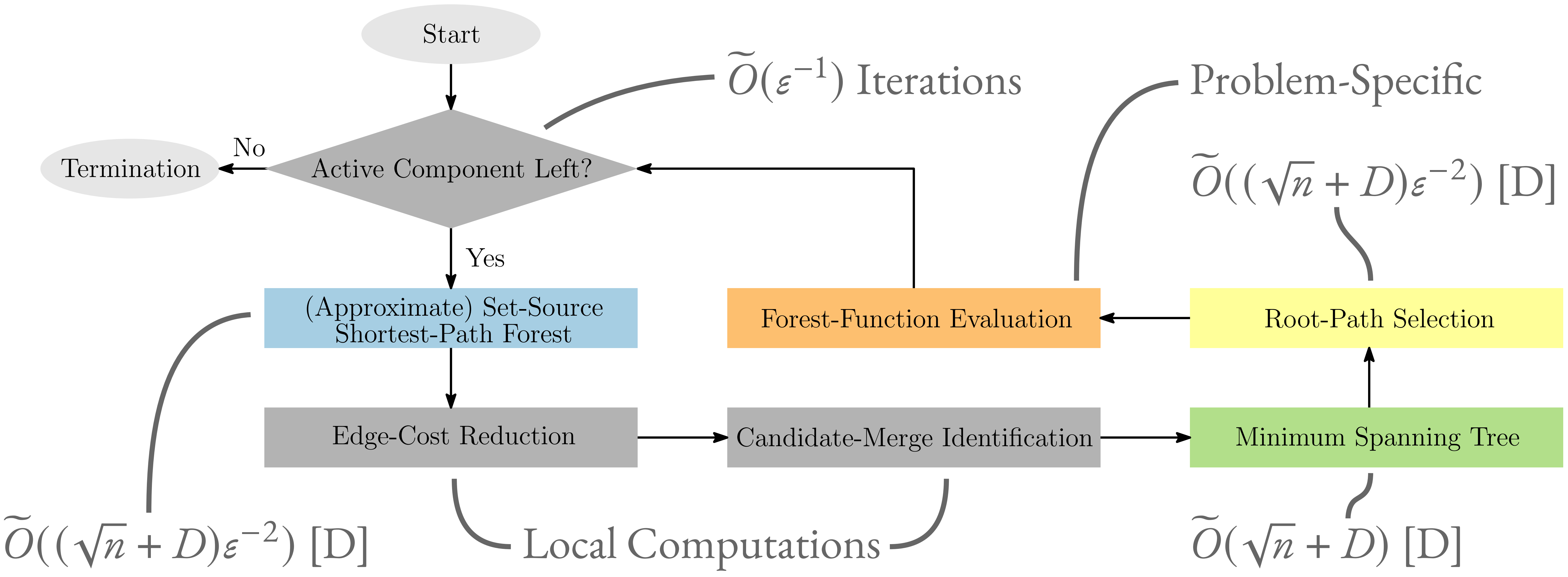


Model-Specific Implementation: Congest

$(2+\varepsilon)$-approximation with…

Toward universal optimality,
we can replace $\sqrt{n}+D$ by $T^{PA}n^{o(1)}$



Problem-Specific Implementation: Steiner Forest in Congest

Interestingly, Congest complexity differs depending on the SF input representation!

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Problem	Input	LB	APX	Complexity
SF–IC	Component identifiers $\lambda\colon V \to [k] \cup \{\perp\}$; node v knows λ_v	$\widetilde{\Omega}(Q + k)$ R	$(2 + \varepsilon)$ D	$\widetilde{O}(\min\{T^{PA} n^{o(1)}, \sqrt{n} + D\} + k)$

Problem-Specific Implementation: Steiner Forest in Congest

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SF–CIC	As in SF–IC, but node v knows λ_v *and* $\lvert\{u \in V \mid \lambda_u = \lambda_v\}\rvert$	$\widetilde{\Omega}(Q+k)$ D	$(2+\varepsilon)$ R	$\widetilde{O}(n^{2/3}+D)$

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SF–CR	Each node v is given $\mathcal{R}_v \subseteq V \setminus \{v\}$	$\widetilde{\Omega}(Q+t)$ R	$(2+\varepsilon)$ D	$\widetilde{O}(\min\{T^{PA} n^{o(1)}, \sqrt{n}+D\}+t)$

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SF–SCR	$\mathcal{R} \subseteq \binom{V}{2}$; node v knows $\mathcal{R}_v = \{u \in V \mid \{u,v\} \in \mathcal{R}\}$	$\widetilde{\Omega}(Q+t)$ D	$(2+\varepsilon)$ R	$\widetilde{O}(\min\{T^{PA} n^{o(1)}, \sqrt{n}+D\})$

Outlook

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Our Main Contribution: Shell-Decomposition Algorithm

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General Framework for Model-Agnostic Approximation of CFPs

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- Instantiated in 3 Models for 3 Problems, improving SOTA esp. for SF in Congest

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Open Questions

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- Problem Classes

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  - Analog to Universal Optimality in Multi-Pass Streaming?

Thank You!

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