Efficient Algorithms for Geometric Partial Matching

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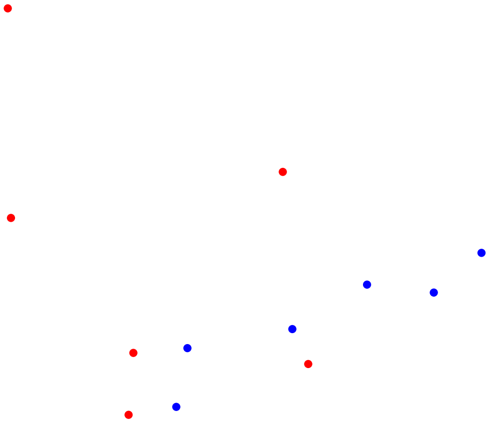
Geometric (bipartite) matching

A, B



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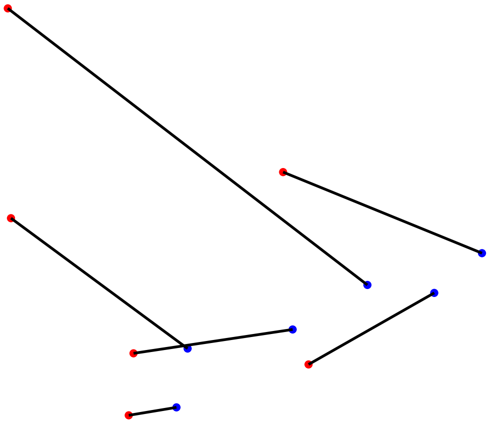

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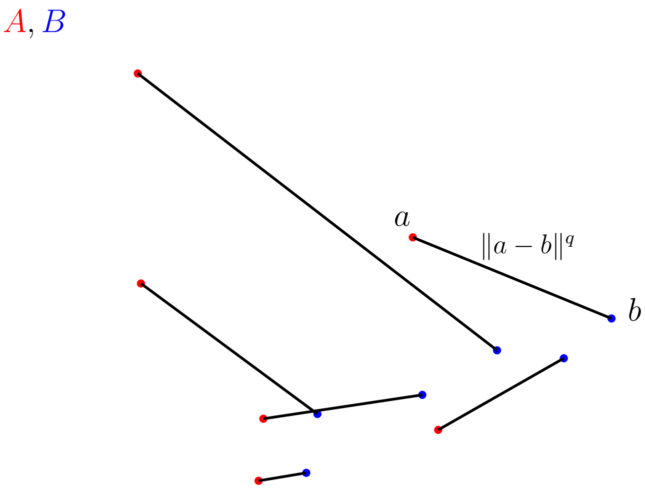

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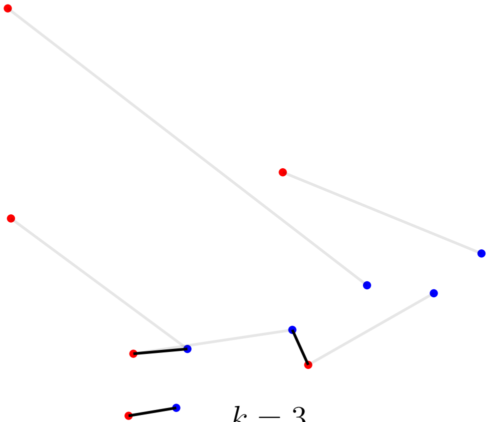


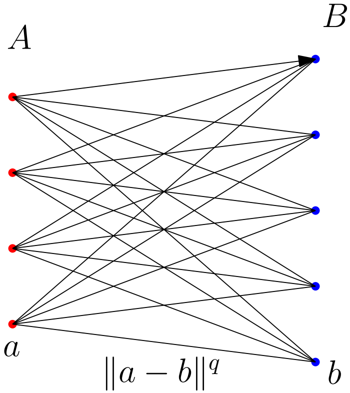
$k = 3$

Prior work

	approx.	time	valid q
Hungarian algorithm (Kuhn)	exact	$O(km + k^2 \log n)$	$q \geq 1$
		$O(kn \operatorname{polylog} n)$	
Ramshaw, Tarjan 2012	exact[1]	$O(m\sqrt{k} \log(kC))$	$q \geq 1$
	$(1+\varepsilon)$	$O(n\sqrt{k} \operatorname{polylog} n \log(1/\varepsilon))$	
Sharathkumar, Agarwal 2012	$(1+\varepsilon)$	$O(n \operatorname{poly}(\log n, 1/\varepsilon))$	$q = 1$
new (Hungarian)	1	$O((n + k^2) \operatorname{polylog} n)$	$q \geq 1$
new (cost-scaling)	$(1+\varepsilon)$	$O((n + k\sqrt{k}) \operatorname{polylog} n \log(1/\varepsilon))$	$q \geq 1$

[1] Assuming integer costs $\leq C$.

Unit-capacity min-cost flow formulation



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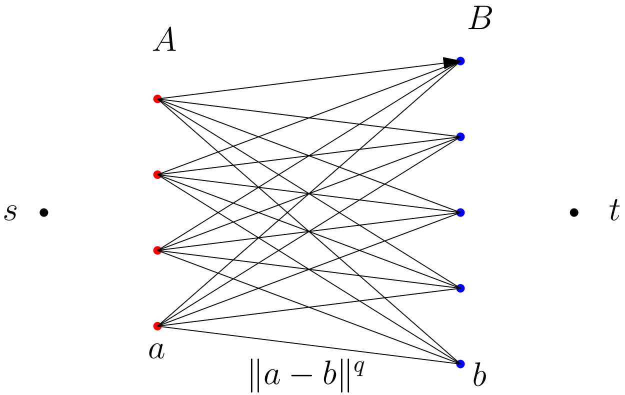

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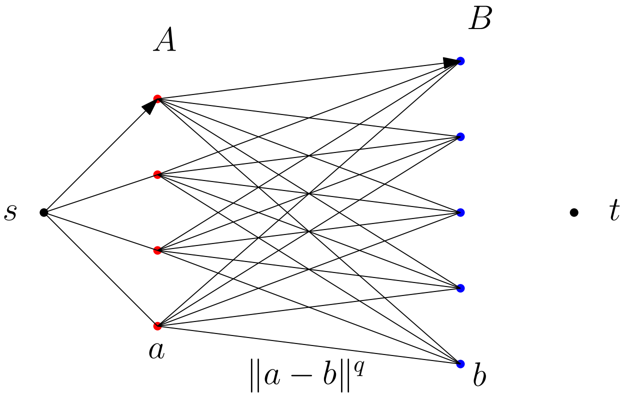

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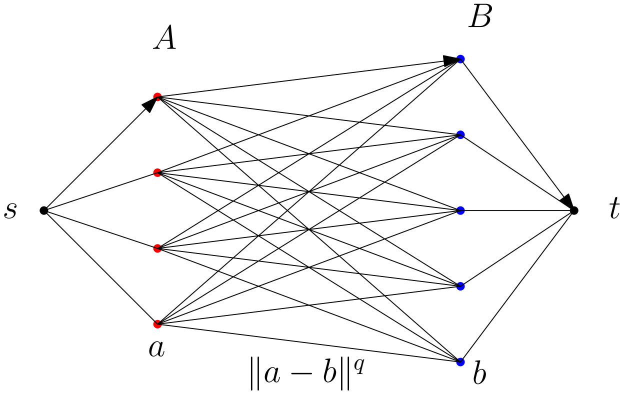

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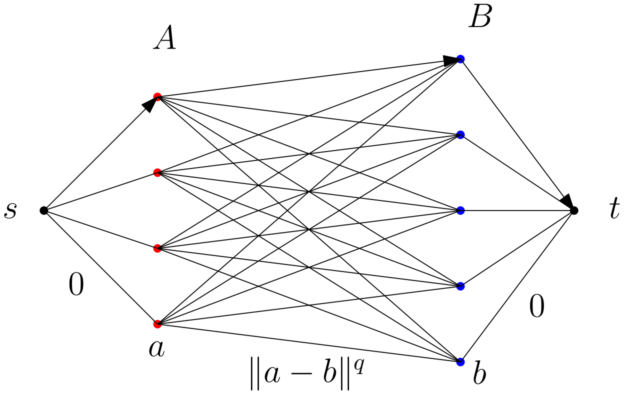

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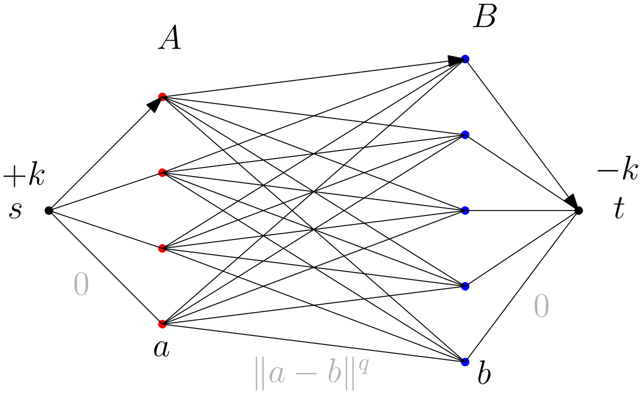

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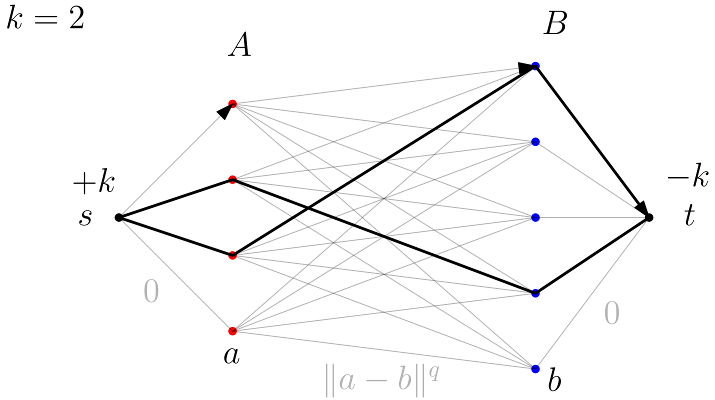

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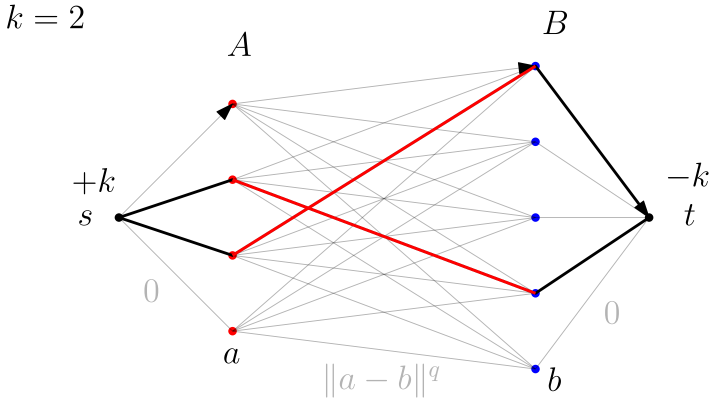
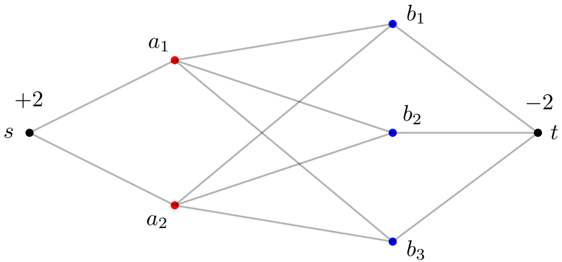


Flow terminology



- Reduced cost: $c_\pi(v \to w) := c(v \to w) - \pi(v) + \pi(w)$
- θ-optimality: $c_\pi(v \to w) \geq -\theta$ on all residual arcs
- admissible residual arcs: $c_\pi(v \to w) \leq 0$

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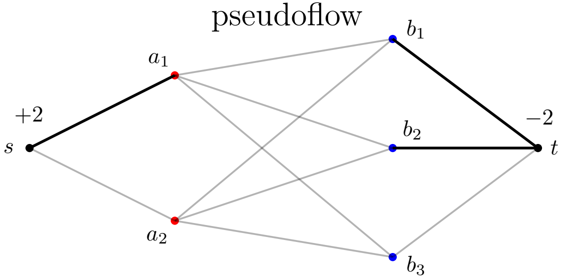

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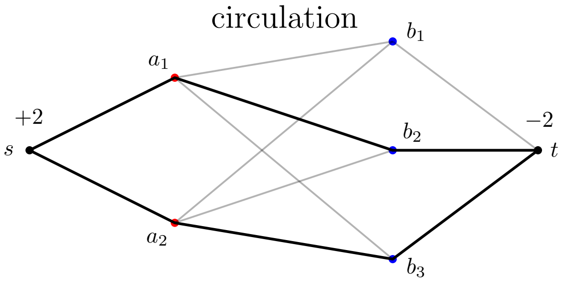

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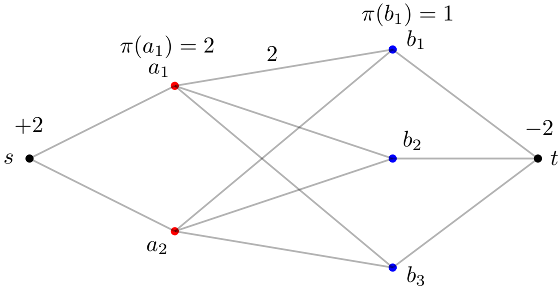

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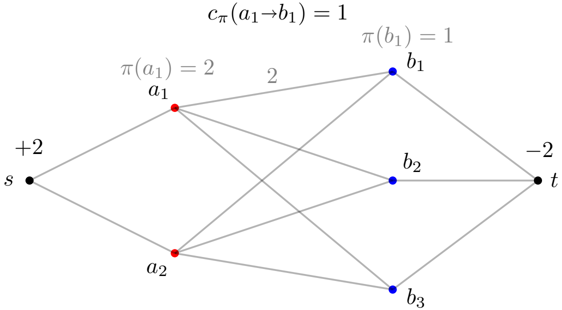

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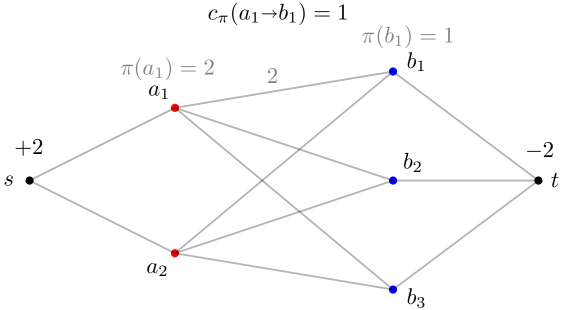

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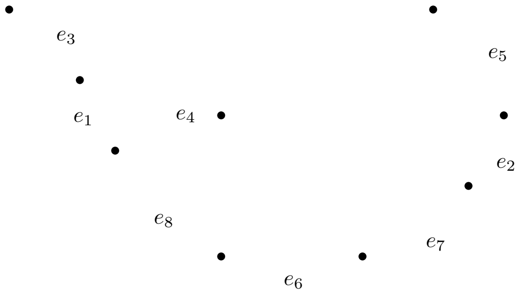
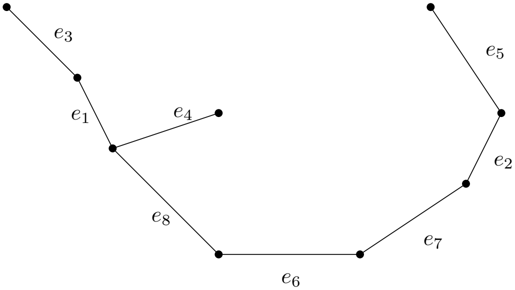
Cost-scaling (Ramshaw-Tarjan)

- θ-optimality: $c_\pi(v \to w) \geq -\theta$ on all residual arcs
- θ-optimal circulation is $+n\theta$ approx. in general ($+6k\theta$ in our graph).
- Find θ-optimal circulations for geometrically decreasing values of θ:
  1. Reduce $\theta \leftarrow \theta/2$, while creating $O(k)$ excess.
  2. Refine this pseudoflow into a circulation, while preserving θ-optimality



- Compute $\alpha \geq 0$ satisfying:
  1. there exists a k-matching whose longest edge has cost $\leq n^q \cdot \alpha$
  2. a $(\varepsilon\alpha/6k)$-optimal circulation is $(1+\varepsilon)$-approx.
- $(1+\varepsilon)$-approx. geometric partial matching by executing $O(\log(n^q/\varepsilon))$ cost scales.

Cost-scaling for geometric partial matching



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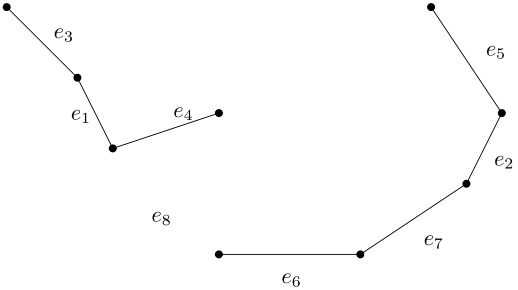

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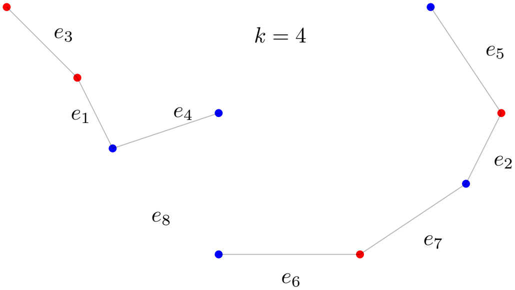

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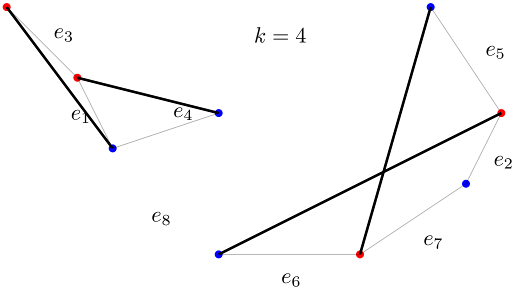

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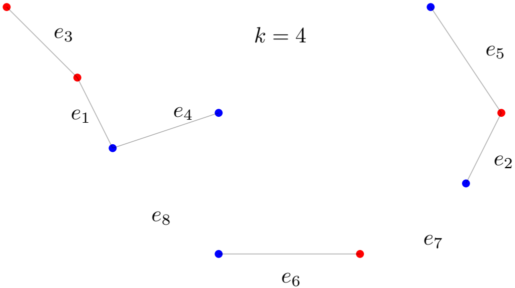

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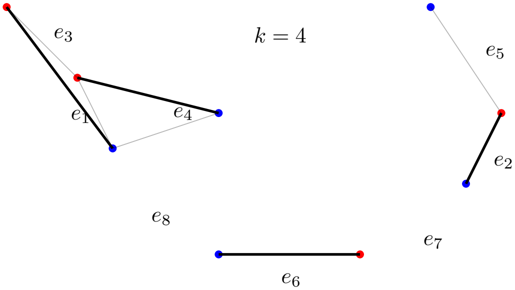

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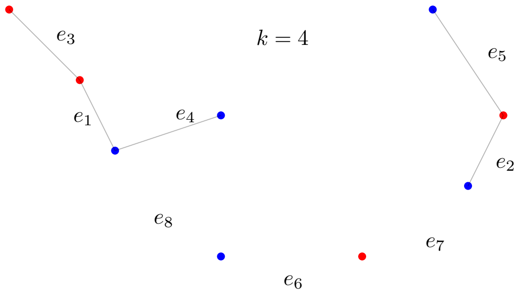

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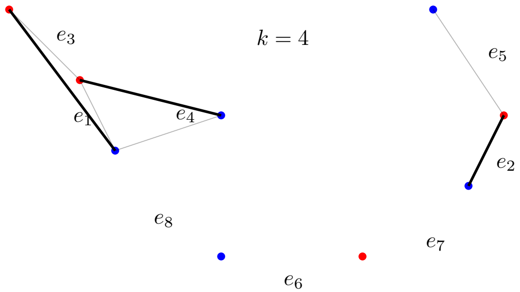

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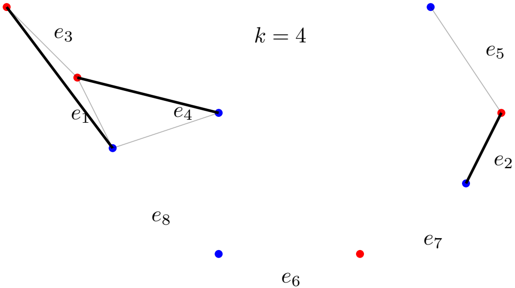

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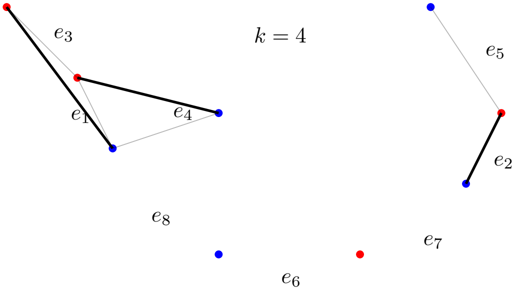

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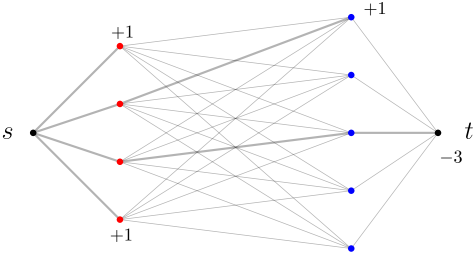
  1. Hungarian search: raise potentials until an excess-deficit admissible path exists.
  2. Augment by an admissible blocking flow.



- $O(\sqrt{k})$ blocking flows before f becomes a circulation.

Refinement by blocking flows (Ramshaw-Tarjan)

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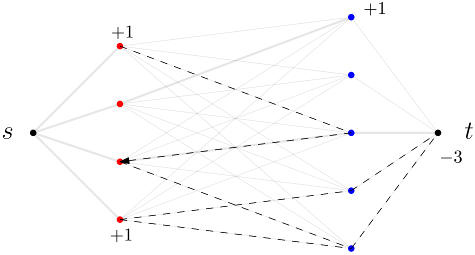

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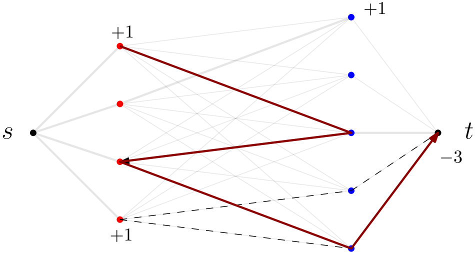

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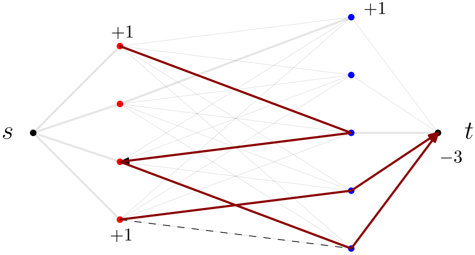

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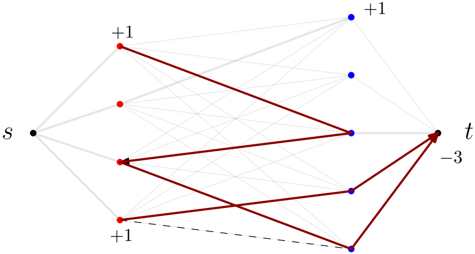

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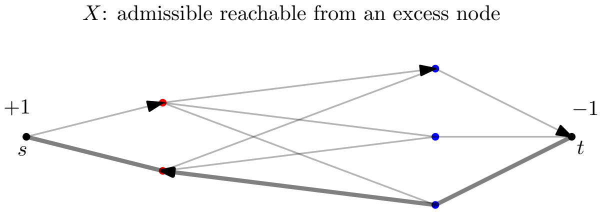
High-level goal per scale

- Inside Refine:
  1. Hungarian search: raise potentials until an excess-deficit admissible path exists.
  2. Augment by an admissible blocking flow.
- After $O(n \operatorname{polylog} n)$-time preprocessing, perform Hungarian search and find each blocking flow in $O(k \operatorname{polylog} n)$ time.

Hungarian search with BCP (Agarwal-Efrat-Sharir)



- Dynamic 2D BCP with $O(\mathrm{polylog}\, n)$ update time, $O(\log^2 n)$ query time (Kaplan *et al.* SODA'17)
- Possible to batch potential updates (Vaidya) — only need to bound number of relaxations.

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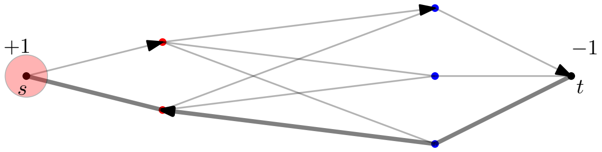
X: admissible reachable from an excess node



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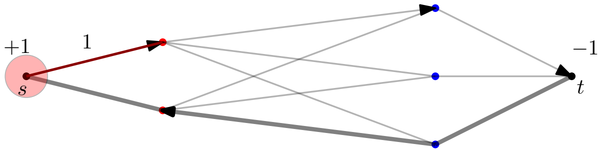

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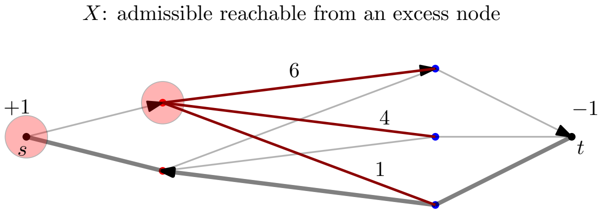

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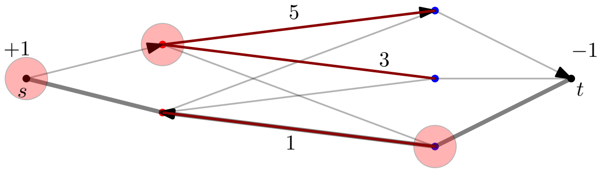

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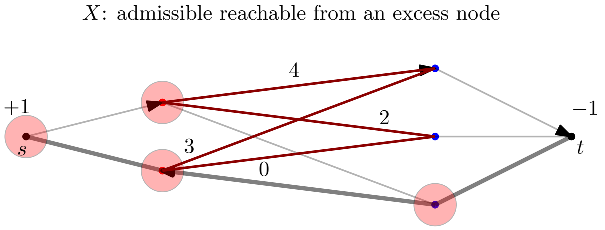

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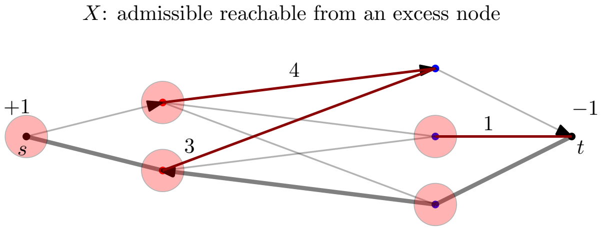

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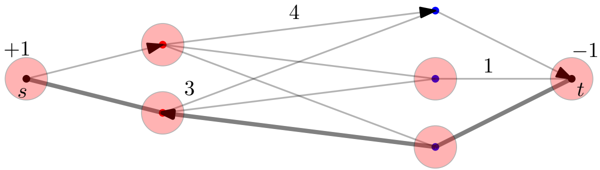

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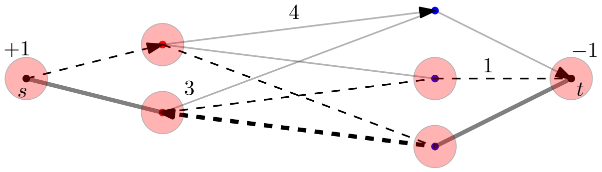

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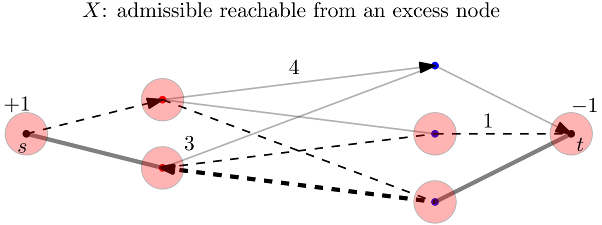

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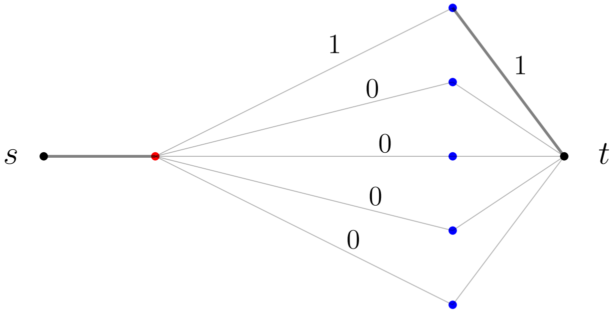
Problem: Hungarian search looks at too many nodes



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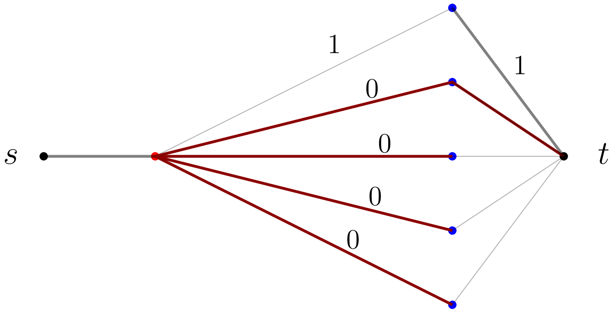

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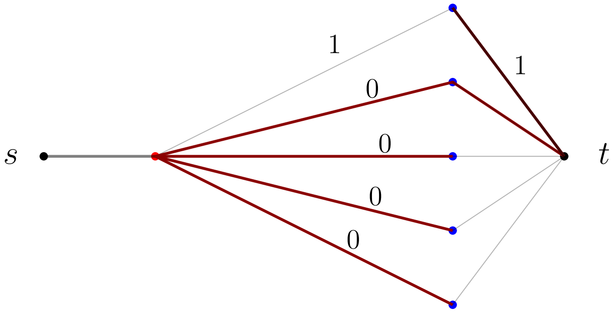

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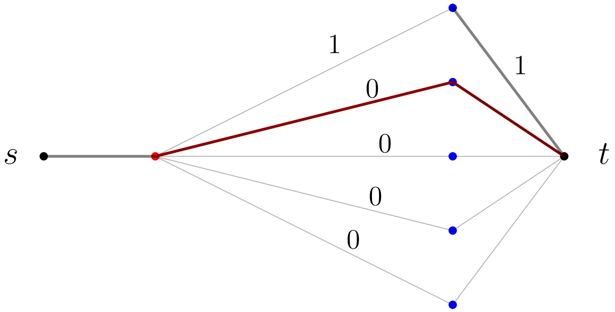
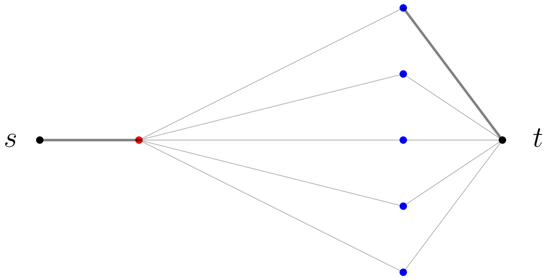


Dead/alive nodes

- Alive nodes: nonzero excess/deficit, or adjoining flow support arcs.
- Dead nodes: ones which aren't alive.



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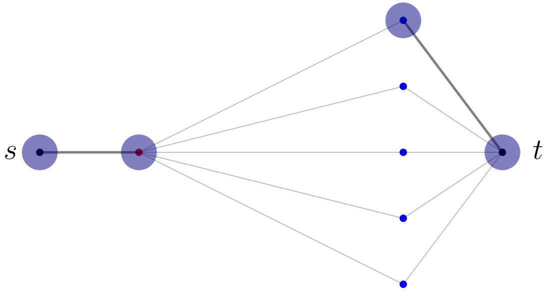

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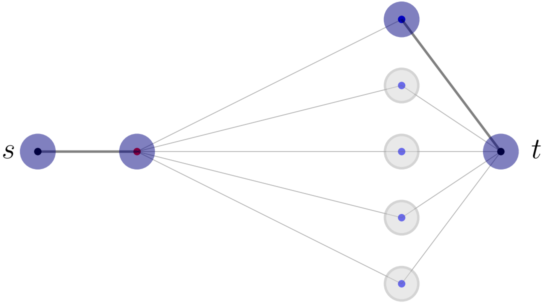

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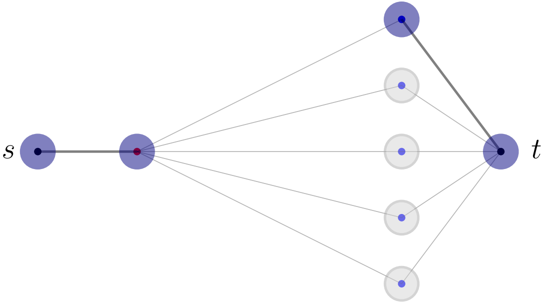

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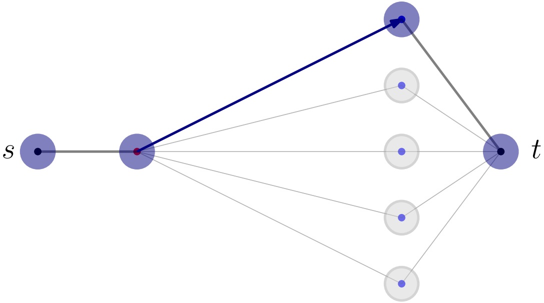

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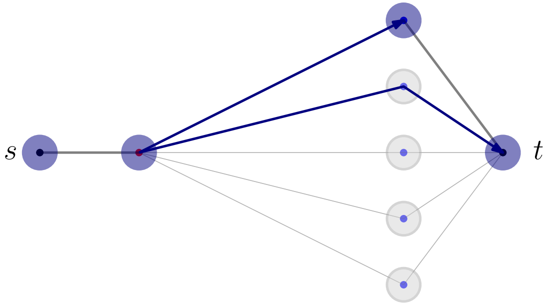

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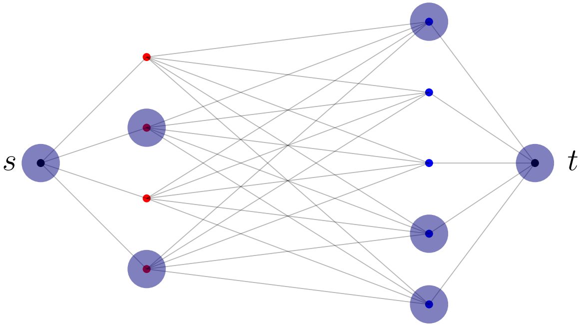
Relaxing alive paths

- Alive paths have length 1, 2, or 3.



- Telescoping: $c_\pi(s \to a \to b) = c(a \to b) - \pi(s) + \pi(b)$ (use BCP)
- Only $O(k)$ relaxations per Hungarian search.
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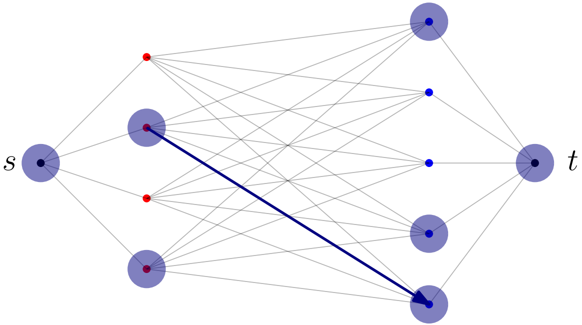

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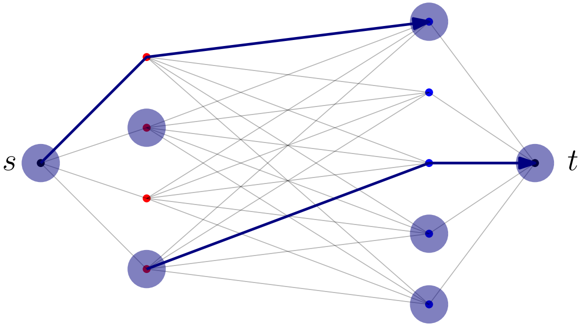

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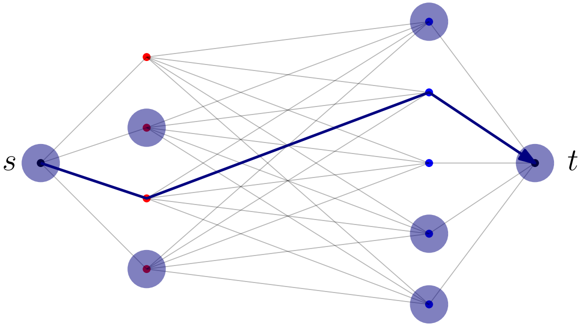

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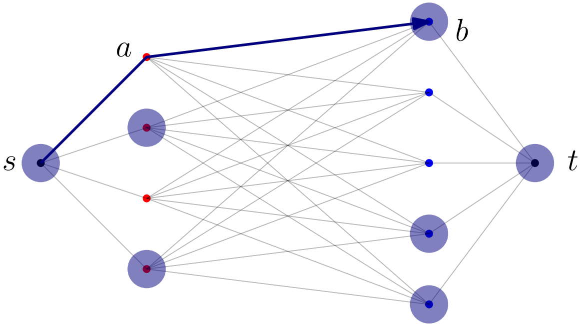

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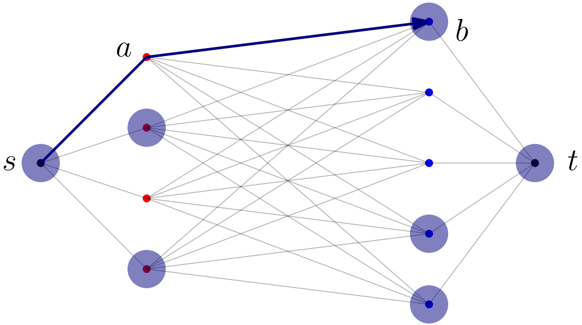

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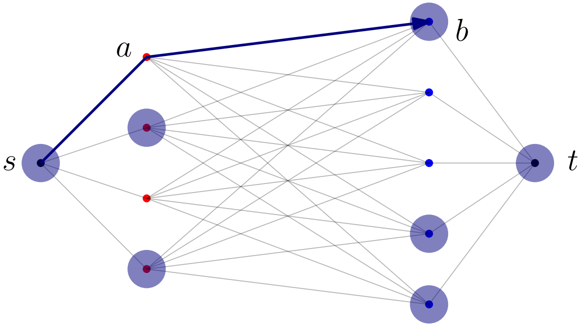

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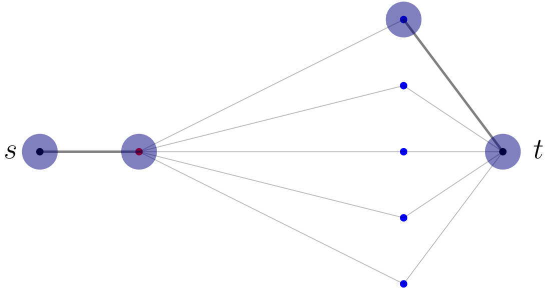
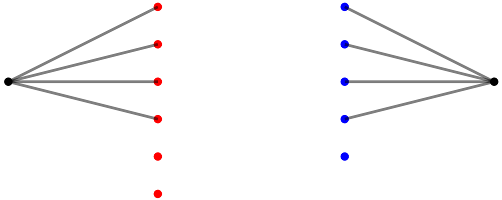
Problem: BCP initialization

- Dynamic 2D BCP with $O(\operatorname{polylog} n)$ update time, $O(\log^2 n)$ query time (Kaplan *et al.* SODA'17)



- Some BCP may begin a Hungarian search with $\Theta(n)$ vertices.
- Can't afford to construct from scratch for every Hungarian search.

Initial BCP by rewinding



- X_t and X_{t+1} differ by the newly-matched A nodes.
- Generate X_{t+1} by rewinding the BCP updates done on X_t, then deleting the newly-matched nodes.
  Same number of BCP updates as the Hungarian search.
- Persistence?
- Construct once in $O(n \operatorname{polylog} n)$, then spend $O(k \operatorname{polylog} n)$ to rewind and generate the next BCP.

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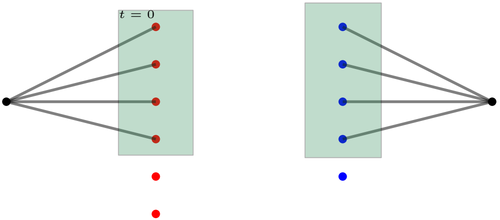

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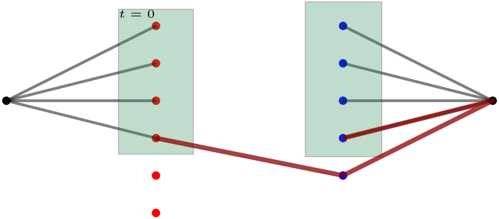

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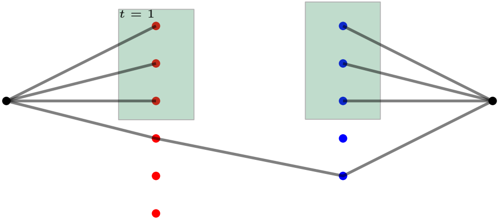

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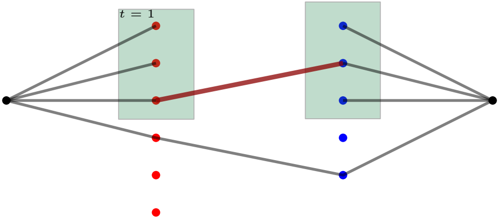

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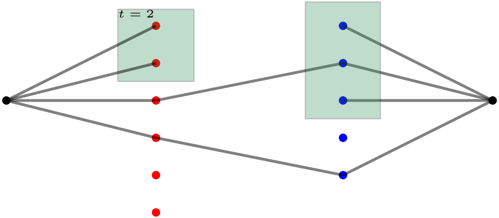

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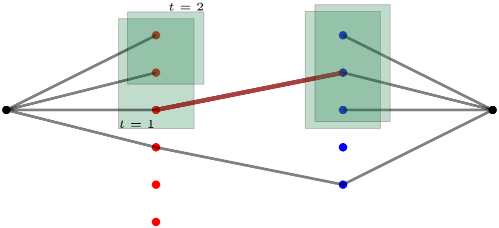

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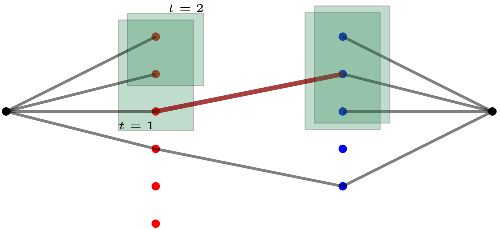

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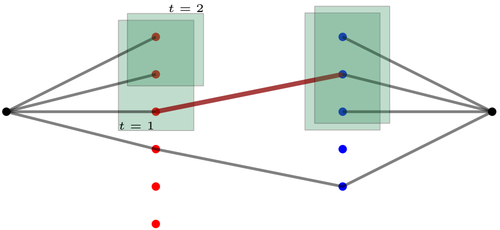

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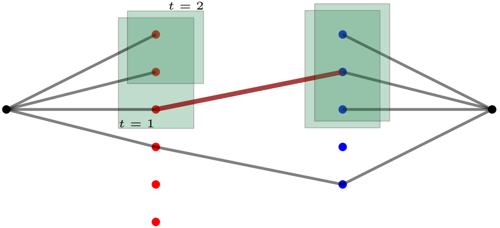

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The End

Thank you.