Efficient Algorithms for Geometric Partial Matching

Pankaj K. Agarwal Hsien-Chih Chang Allen Xiao

Department of Computer Science, Duke University

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Geometric (bipartite) matching







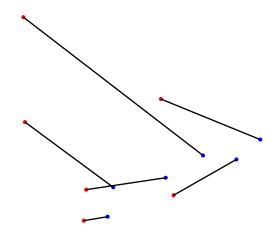






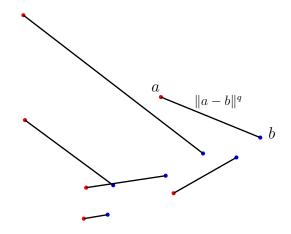
Geometric (bipartite) matching





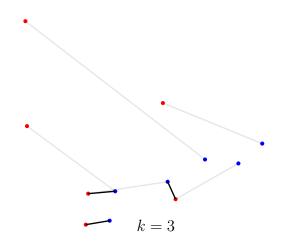
Geometric (bipartite) matching





Geometric (bipartite) partial matching





Prior work

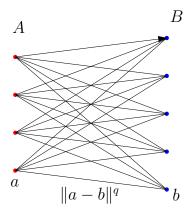


	approx.	time	
Hungarian algorithm (Kuhn)	exact	$O(km + k^2 \log n)$	$q \ge 1$
		$O(kn \operatorname{polylog} n)$	
Ramshaw, Tarjan 2012	exact ¹	$O(m\sqrt{k}\log(kC))$	$q \ge 1$
	$(1+\varepsilon)$	$O(n\sqrt{k}\operatorname{polylog} n\log(1/\varepsilon))$	
Sharathkumar, Agarwal 2012	$(1+\varepsilon)$	$O(n\operatorname{poly}(\log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

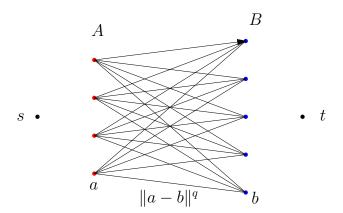


¹Assuming integer costs $\leq C$.

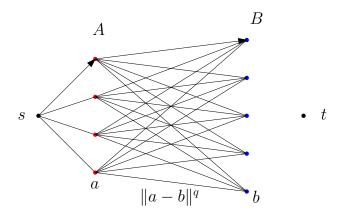




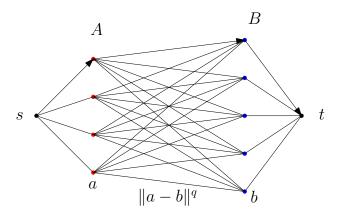




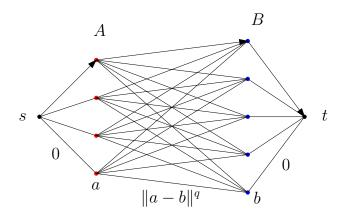




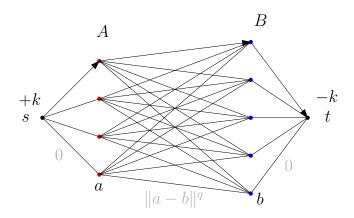




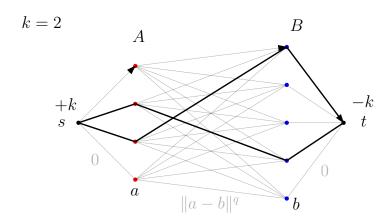




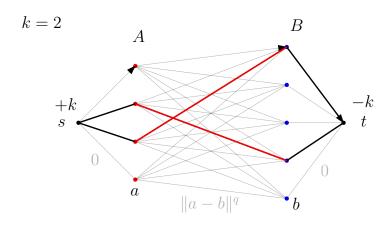




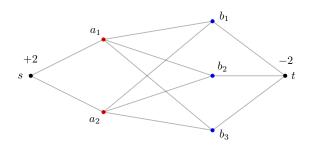








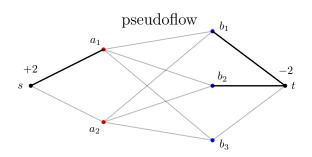




- ► Reduced cost: $c_{\pi}(v \rightarrow w) := c(v \rightarrow w) \pi(v) + \pi(w)$
- lacktriangledown heta-optimality: $c_{\pi}(v{
 ightarrow}w)\geq - heta$ on all residual arcs
- ▶ admissible residual arcs: $c_{\pi}(v \rightarrow w) \leq 0$



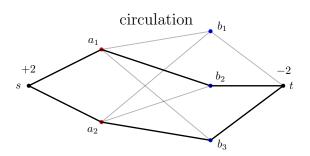




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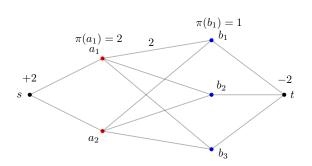




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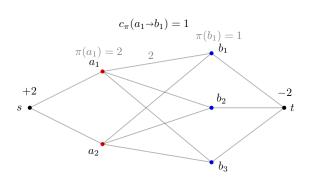






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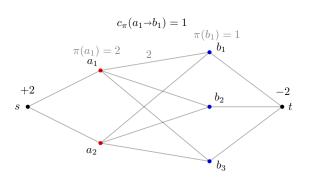




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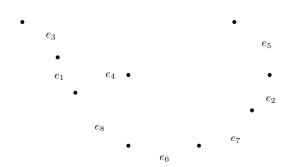


Cost-scaling (Ramshaw-Tarjan)



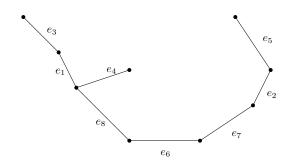
- ▶ θ -optimality: $c_{\pi}(v \rightarrow w) \geq -\theta$ on all residual arcs
- lacktriangledown heta-optimal circulation is +n heta approx. in general (+6k heta in our graph).
- ▶ Find θ -optimal circulations for geometrically decreasing values of θ :
 - 1. Reduce $\theta \leftarrow \theta/2$, while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





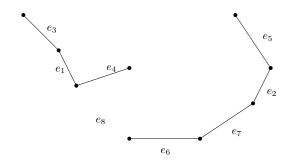
- ▶ Compute $\alpha \ge 0$ satisfying:
 - 1. there exists a k-matching whose longest edge has $\cos t \leq n^q \cdot \alpha$
 - 2. a $(\varepsilon \alpha/6k)$ -optimal circulation is $(1+\varepsilon)$ -approx.
- $(1+\varepsilon)$ -approx. geometric partial matching by executing $O(\log(n^q/\varepsilon))$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





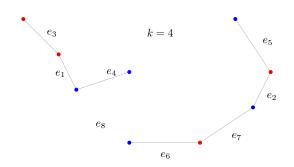
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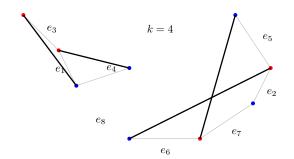
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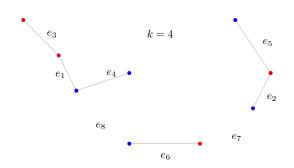
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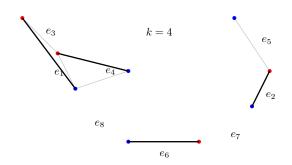
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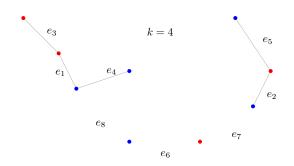
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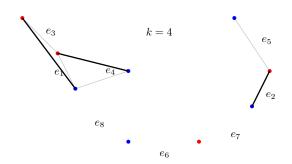
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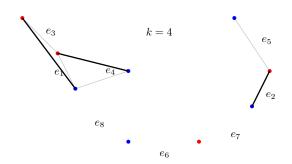
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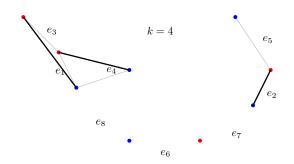
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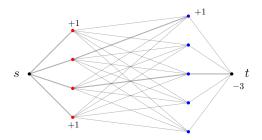




- ightharpoonup Compute $\alpha \geq 0$ satisfying:
 - 1. there exists a k-matching whose longest edge has cost $\leq n^q \cdot \alpha$
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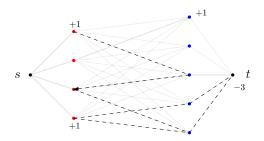


- ► Inside Refine:
 - Hungarian search: raise potentials until an excess-deficit admissible path exists.
 - 2. Augment by an admissible blocking flow.



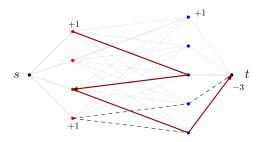


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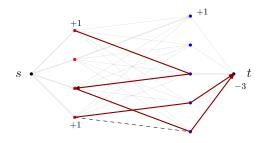


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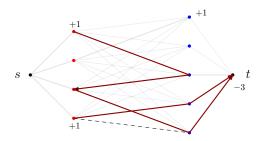
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Refinement by blocking flows (Ramshaw-Tarjan)



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

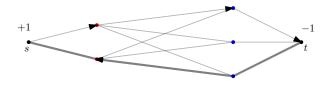
High-level goal per scale



- 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.

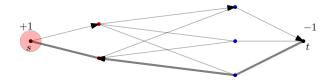
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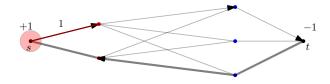
- ▶ Dynamic 2D BCP with $O(\operatorname{polylog} n)$ update time, $O(\log^2 n)$ query time (Kaplan *et al.* SODA'17)
- Possible to batch potential updates (Vaidya) only need to bound number of relaxations.





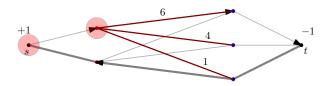
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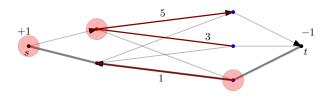
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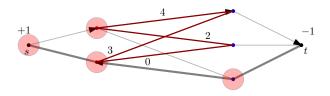
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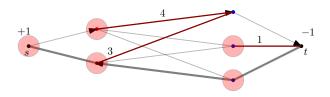
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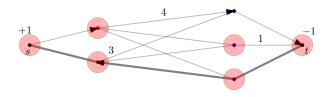
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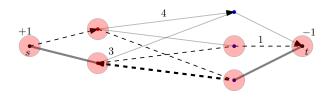
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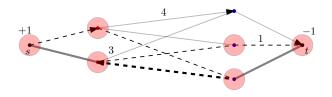
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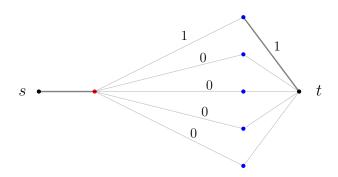
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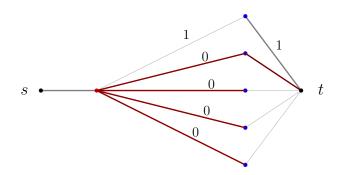


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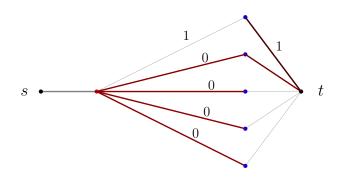




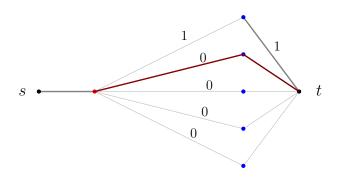






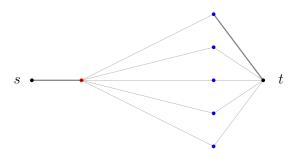






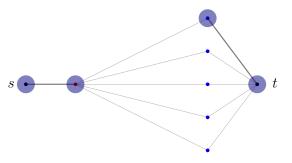


- Alive nodes: nonzero excess/deficit, or adjoining flow support arcs.
- ▶ Dead nodes: ones which aren't alive.



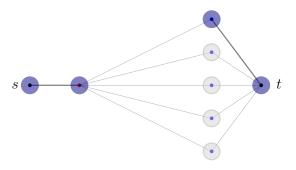


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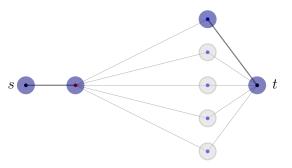


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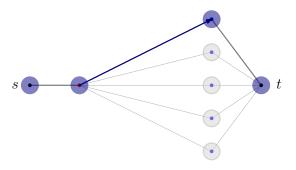


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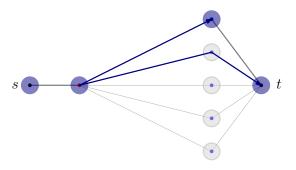


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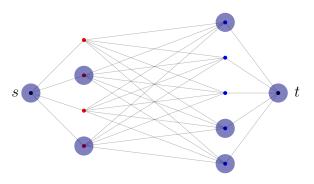




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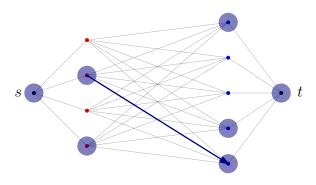






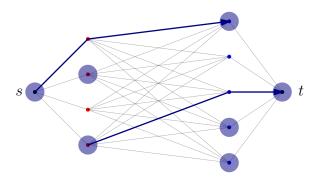
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- ▶ Only O(k) relaxations per Hungarian search.
- Also: find a blocking flow in O(k) relaxations (DFS).





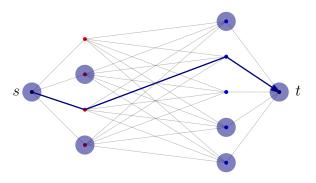
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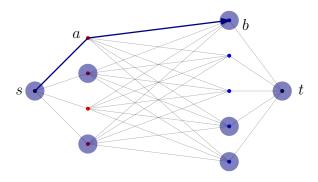
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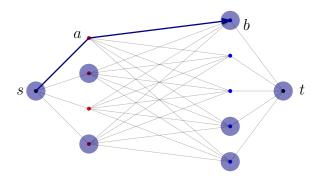
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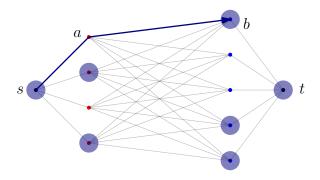




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- Also: find a blocking flow in O(k) relaxations (DFS).





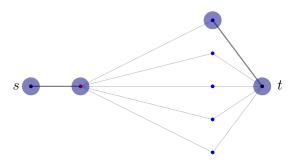


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Problem: BCP initialization

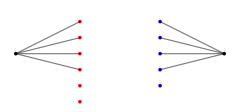


▶ Dynamic 2D BCP with $O(\operatorname{polylog} n)$ update time, $O(\log^2 n)$ query time (Kaplan *et al.* SODA'17)



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

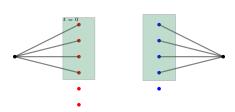




- Let X_t be the set X at the start of the t-th Hungarian search.
- $ightharpoonup X_t$ and X_{t+1} differ by only a few nodes (newly matched, dead/alive changes).
- ▶ To generate X_{t+1} :
 - 1. Rewind the BCP updates of the last Hungarian search to obtain X_t .
 - 2. Apply the few changes (newly matched, dead/alive).
- Persistence?



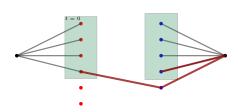




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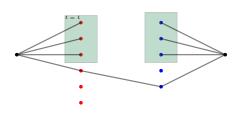




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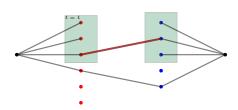




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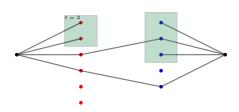




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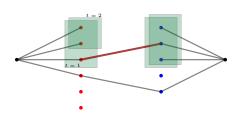




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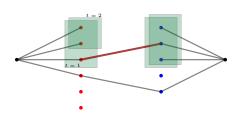




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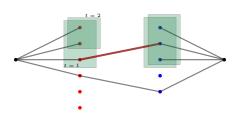




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- Each blocking flow's Hungarian search BCP can be initialized using the previous one in $O(k \operatorname{polylog} n)$ time (rewinding). Need to spend $O(n \operatorname{polylog} n)$ once per scale to build data structures for t=0.
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