

Compact, Provably-Good LP Relaxations for Orienteering and ~~RVRP~~

Zachary Friggstad

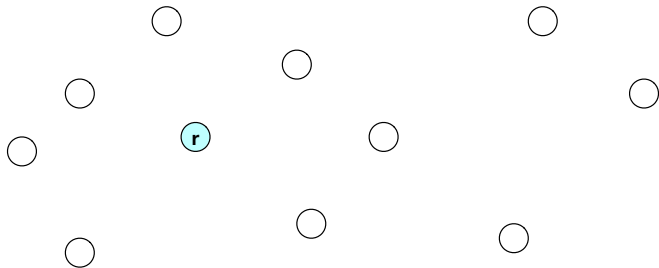
with

Chaitanya Swamy

BIRS TSP Workshop - 2018

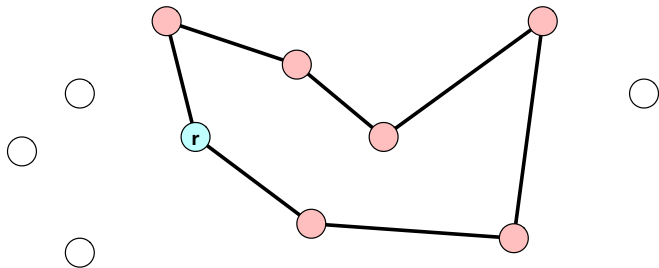
Orienteering

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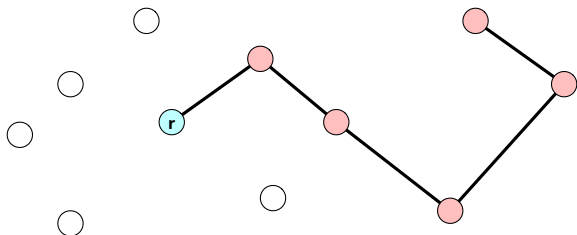


Rooted Orienteering

Given metric distances $d()$ over points $V \cup \{r\}$ where:

- ▶ V - clients
- ▶ r - depot

Each $v \in V$ has a **reward** $\rho(v) \geq 0$. Also have a **distance bound** $D \geq 0$.

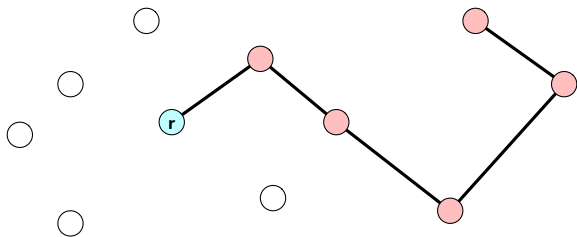


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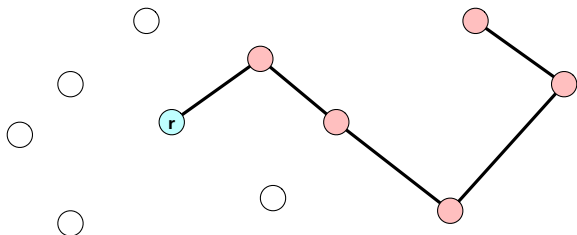
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Find an r -rooted path P with $d(P) \leq D$ of maximum reward $\rho(P)$.

If an end vertex t is also specified (could be $t = r$), we call this **Point-to-Point Orienteering**.

A Brief History

- ▶ First, a 4-approximation for rooted orienteering [Blum et al, 1994].
- ▶ Then, a 3-approximation for Point-to-Point Orienteering. [Bansal et al, 2004].
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- ▶ An $O(\log^2 OPT)$ -approximation. [Chekuri, Korula, and Pal, 2007].
- ▶ An $O(\rho \cdot \log n)$ -approximation: $\rho = \text{ATSP integrality gap}$. [Nagarajan and Ravi, 2007].
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Notice: The improved integrality gap bound for ATSP led to an improved approximation for a different problem!

Specific Results

Poly-size LP relaxations with the following integrality gap bounds.

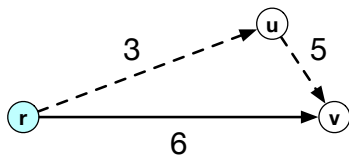
- ▶ **Rooted Orienteering:** 3
- ▶ **Point-to-Point Orienteering:** 6
- ▶ **RVRP:** A natural relaxation with a gap of 27, an unnatural relaxation with a gap of 15.
This beats a 28.86-approximation that used a large configuration LP [F. and Swamy, 2014].

The Regret Metric

We shift focus to a new metric called the **regret metric**.

$$d^{reg}(u, v) := d(r, u) + d(u, v) - d(r, v).$$

How much longer is $r \rightarrow u \rightarrow v$ than $r \rightarrow v$ directly?



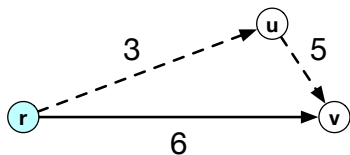
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Key Properties:

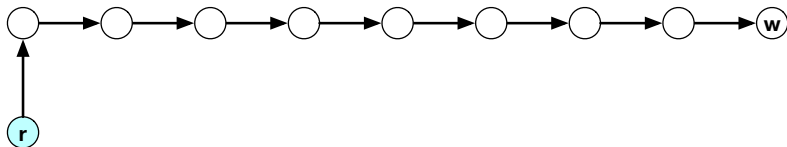
- ▶ For any $v \in V$, $d^{reg}(r, v) = 0$.
- ▶ For any $r \rightarrow v$ path P , $d^{reg}(P) = d(P) - d(r, v)$.

Pruning w.r.t. Regret

Before presenting the LP, we briefly discuss a slightly weaker goal.

Observe a rooted $r - w$ path P is a feasible orienteering solution iff $d^{reg}(P) \leq D - d(r, v)$.

Now suppose P is an $r - w$ path with $d^{reg}(P) \leq \alpha \cdot (D - d(r, w))$.

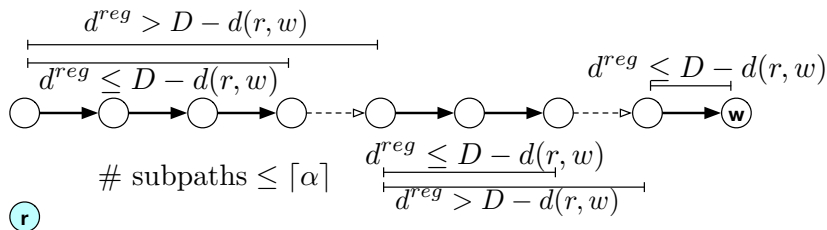


Claim

If w has maximum distance from r among all clients, we can *chop* P to a feasible solution with value $\geq \rho(P)/\lceil \alpha \rceil$.

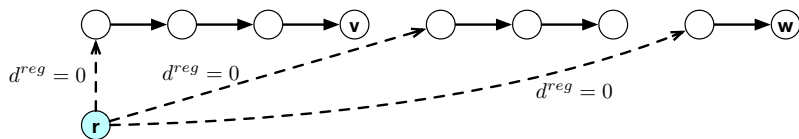
Pruning w.r.t. Regret

First, break $P - \{r\}$ into $\lceil \alpha \rceil$ subpaths, each having d^{reg} -distance $\leq D - d(r, w)$.



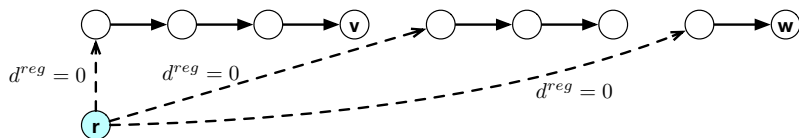
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Make each subpath a rooted path by prepending r . Recall $d^{reg}(r, x) = 0$ for all $x \in V$.



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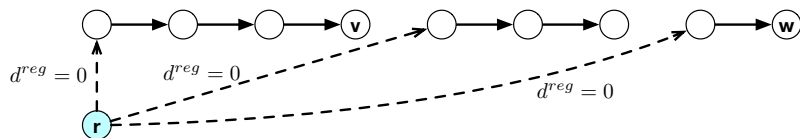


Any of these r -rooted subpaths P' ending at, say, v has length

$$d^{reg}(P') + d(r, v) \leq (D - d(r, w)) + d(r, v) \leq D.$$

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So the most profitable path has value $\geq \rho(P)/\lceil \alpha \rceil$.

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We deal with a **bidirected-cut** relaxation of the problem.

- ▶ z_v - indicating we visit v .
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$$\begin{array}{llll} \text{max :} & \sum_v \rho(v) \cdot z_v & & \\ \text{s.t. :} & x(\delta^{\text{in}}(v)) \geq x(\delta^{\text{out}}(v)) & v \in V & \text{(preflow)} \\ & x(\delta^{\text{in}}(S)) \geq z_v & v \in S \subseteq V & \text{(clients reachable)} \\ & x(\delta^{\text{out}}(r)) = 1 & & \text{(one path)} \\ & z_w = 1 & & \text{(visits } w) \\ & \sum_e d(e) \cdot x_e \leq D & & \text{(distance bound)} \\ & x, z \geq 0 & & \end{array}$$

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Notes: Can “fold” the guess into the LP to avoid guessing.
i.e. (x^w, z^w) variables. Can make poly-size using flow variables.

A Decomposition Theorem

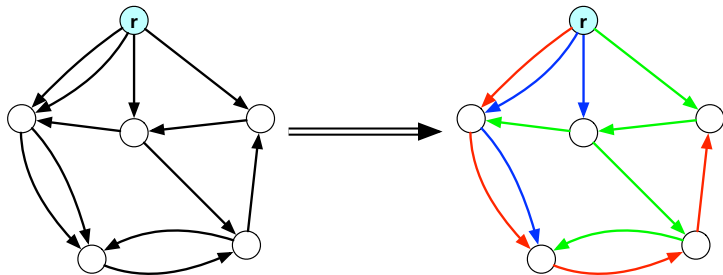
Let $D = (V + r, A)$ be a multi-digraph satisfying preflow conditions at each $v \in V$:

$$|\delta^{in}(v)| \geq |\delta^{out}(v)|.$$

Let λ_v be the $r - v$ edge connectivity.

Theorem (Bang-Jensen, Frank, and Jackson, 1995)

For any $K > 0$, there are K arc-disjoint r -branchings where each vertex v lies on $\min\{K, \lambda_v\}$ branchings.

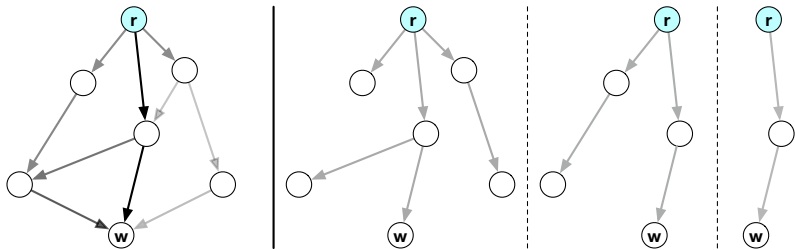


The fractional version:

Theorem

The preflow x dominates a convex combination of r -branchings where each $v \in V$ lies on a z_v -weight of these branchings.

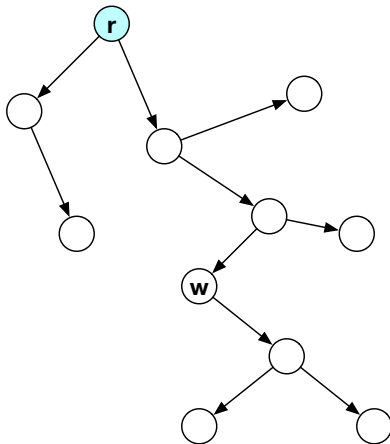
Note, w lies on each branching.



Can be found in poly-time [[Post and Swamy, 2015](#)].

The Rounding Algorithm

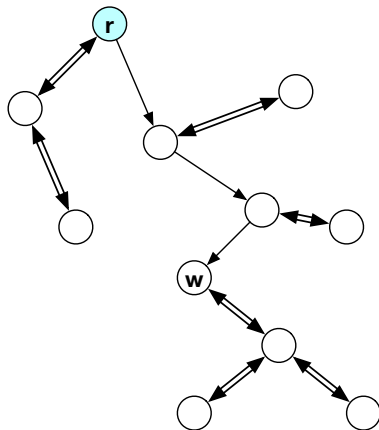
Sample a random branching B in the decomposition.



The **expected** $d()$ -cost of B is $\leq D$.

The Rounding Algorithm

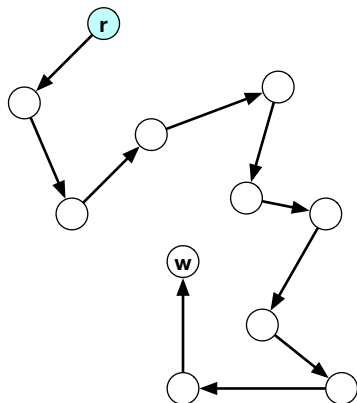
Double edges not on the $r - w$ path.



The **expected** $d()$ -cost is $\leq D + (D - d(r, w))$.

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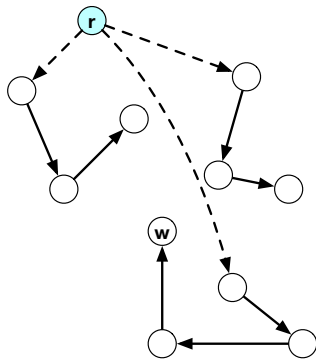
Of course, shortcut the resulting Eulerian walk to an $r - w$ path.



The **expected** $d()$ -cost of these paths is still $\leq D + (D - d(r, w))$.

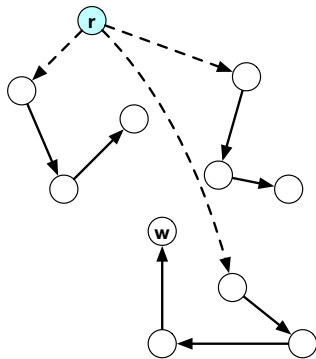
Equivalently: The **expected** $d^{reg}()$ -cost is $\leq 2 \cdot (D - d(r, w))$.

Chop into rooted paths with $d^{reg}()$ -distance $\leq D - d(r, w)$.
i.e. Feasible orienteering solutions!



If the original path P had regret $\alpha_P \cdot (D - d(r, w))$, this creates
 $\leq \lceil \alpha_P \rceil \leq \alpha_P + 1$ paths.

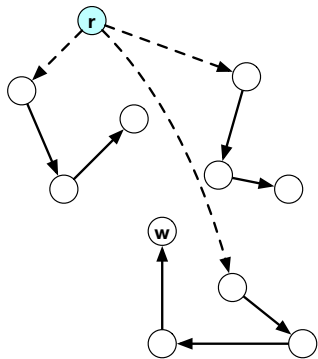
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Some subpath created this way has value $\geq OPT_{LP}/3$.

Algorithm Summary

1. Guess the furthest node w .
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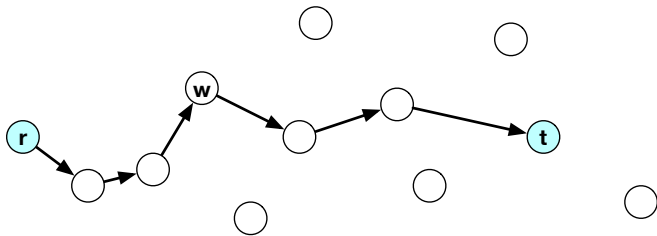
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Comment

Without the guess, the gap is very bad. Even if we just guess the furthest distance but not the node itself!

Point-to-Point Orienteering

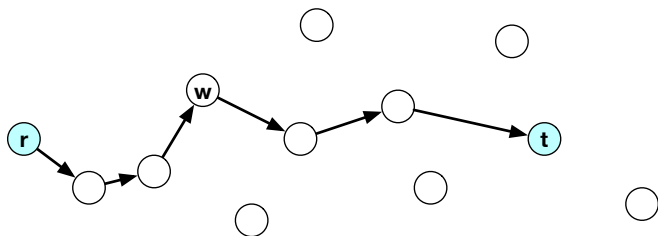
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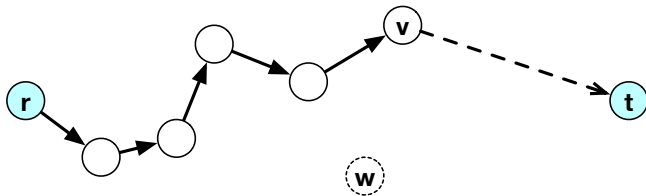
LP: one unit of $r - w$ flow x^L and one unit of $w - t$ flow x^R .

Also z_v^L and z_v^R variables indicating if v is visited before w or after w , respectively.

To round it, the x^L -flow is a preflow from r with cost at most $D - d(w, t)$, so do as before.

This produces a path ending at some v with length

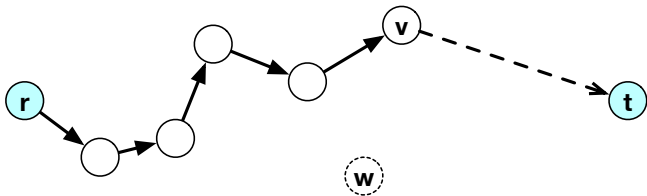
$$\leq D - d(w, t) + d(r, v) - d(r, w).$$



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Extending from v to an $r - t$ path yields a path with distance

$$D + [d(r, v) + d(v, t)] - [d(r, w) + d(w, t)] \leq D$$

with at least $1/3$ the value of z^L .

Similarly, the reverse of x^R is a preflow out of t so we can get a feasible solution with at least $1/3$ the value of z^R .

The best solution overall has value $\geq OPT_{LP}/6$.

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Post and Swamy describe a combinatorial, primal-dual algorithm for the Prize-Collecting Arborescence problem that finds a solution with cost \leq the optimum prize-collecting path solution..

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All done!
Thank You