

Simple label-correcting algorithms for partially dynamic approximate shortest paths in directed graphs

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Setting

- maintaining (approximate) shortest paths in weighted, directed graph G where weights are non-negative
- partially dynamic setting
- incremental setting:
 - edge can be inserted
 - weight of an edge can decrease
- decremental Setting:
 - edge deletions
 - weight of an edge can increase

Related Work and Motivation

- many existing solutions for different settings
- main focus: APSP in decremental setting

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using King's decremental transitive closure algorithm:
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h-SSSP algorithm (Bernstein) to maintain approximate distances
- $O(n^3 \log^3 n \log(nW)/\epsilon + \Delta)$ total update time
 $O(n^2 \log n \log(nW))$ space

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- this paper: $O(n^3 \log n \log(nW)/\epsilon + \Delta)$
additional space: $O(n^2)$

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- shortest path algorithms maintain distance estimates $d : V \rightarrow \mathbb{R}$ and relaxing edges/vertices

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A weighted edge uv is called relaxed, if $d(v) \leq d(u) + w(uv)$ where $w(uv)$ is the weight of edge uv , and tense otherwise.

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- relaxing a tense edge: set $d(v) = d(u) + w(uv)$
- also works in incremental setting
- decremental setting:

vertex relaxation

A vertex v is called relaxed, if $d(v) < \min_{uv \in E(G)}\{d(u) + w(uv)\}$ and we set $d(v) := \min_{uv \in E(G)}\{d(u) + w(uv)\}$

Approximate APSP - Idea

- each pair of vertices: maintain distance estimate $d(u, v)$
- distance estimates: $(1 + \epsilon)$ approximations of real distance
- relaxation operation:
 - compute $t(u, v)$: estimated length of shortest path from u to v
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 - compute $t(u, v)$: estimated length of shortest path from u to v
 - set distance estimate to $t(u, v)$
- when distance estimate increases
 - check all possibly affected distance estimates $d(w, z)$
 - increase them if $d(w, z) < t(w, z)$

Relaxation Operation

- $M_{u,v} = \{d(u,z) + d(z,v) : z \in V \setminus \{u,v\}\}$

$$t(u,v) := r_{1+\epsilon}(\min(M_{u,v}, w(uv)))$$

where:

$$r_{1+\epsilon}(x) = (1 + \epsilon)^{\lceil \log_{1+\epsilon} x \rceil}$$

we round the value $x > 0$ up to nearest $(1 + \epsilon)^i$ for $i \in \mathbb{N}_0$

Relaxation Operation

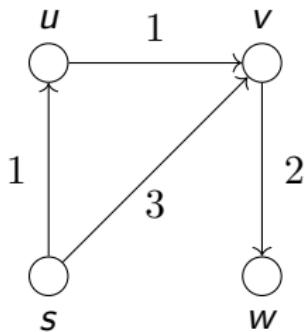
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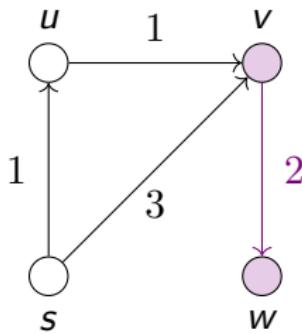
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$$t(u,v) = r_{1+\epsilon}(1) = 1$$

$$t(v,w) = r_{1+\epsilon}(2) = (1 + \epsilon)^j$$

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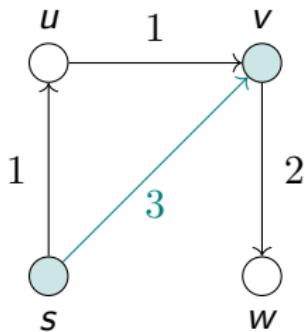
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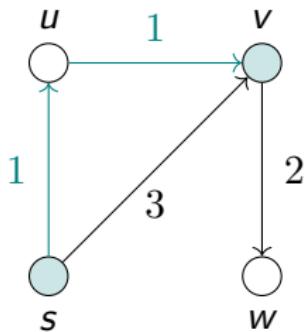
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$$M_{s,v} = \{(1 + 1), \infty\}$$

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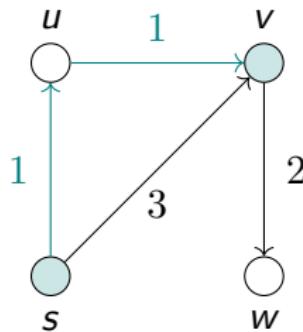
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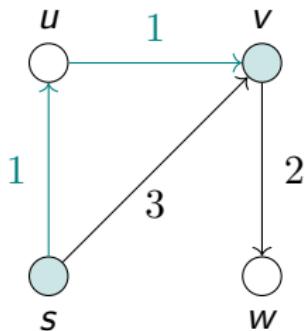
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Approximate APSP - Update

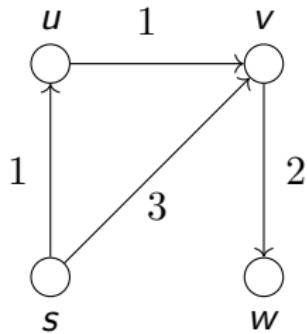
Update(u, v):

- Calculate $t(u, v)$
- If distance estimate $d(u, v) \neq t(u, v)$: update it
 - For every $y \in V \setminus \{u, v\}$:
Update(y, v) and Update(u, y)

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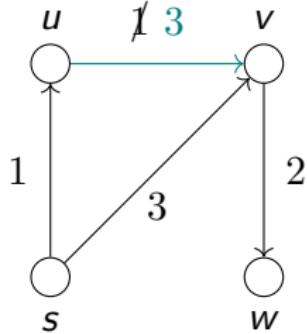


	s	u	v	w
s	0	1	$r(2)$	$r(2 r(2))$
u	∞	0	1	$r(r(2) + 1)$
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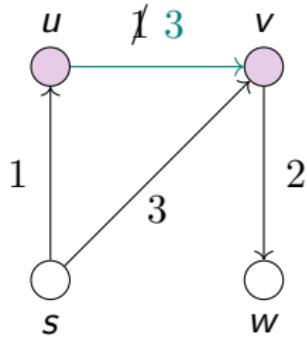


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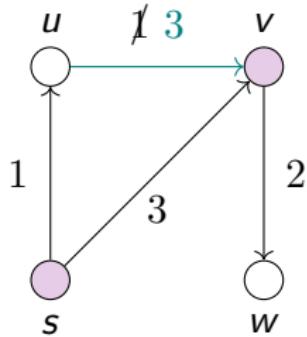


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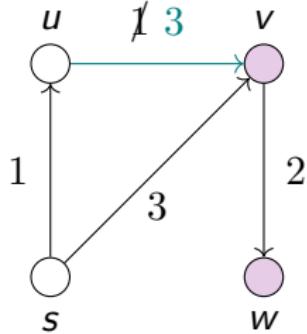


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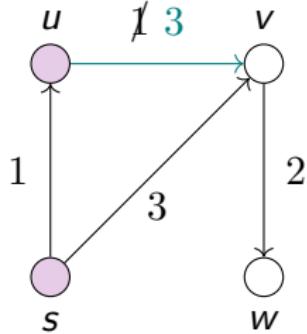


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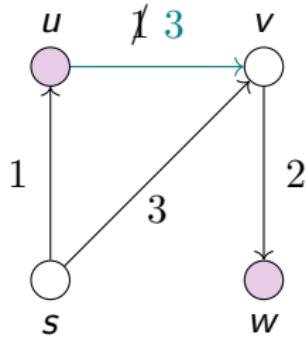


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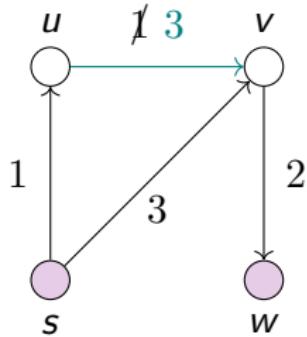


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Approximate APSP

- Eventually no distance estimate left to update
- invariant: $d(u, v) \leq t(u, v)$ at all times and $d(u, v) = t(u, v)$ after Update procedure stops
- weights only increase or edges deleted: $t(u, v)$ can only become larger or stay the same
- when $d(u, v)$ is not (yet) reset: $d(u, v) \leq t(u, v)$
Update(u, v) sets $d(u, v)$ to $t(u, v)$
- path from y to v contains path $u \rightarrow v$, $d(y, v)$ is also updated and set to $t(y, v)$
Similar for a path that begins with $u \rightarrow v$

Approximation

Repeated use of $r_{1+\epsilon}$: not a $(1 + \epsilon)$ -approximation

Specifically:

Lemma 1

Let G be a non-negatively weighted directed graph.

If $d : V \times V \rightarrow \mathbb{R} \cup \{\infty\}$ satisfies the following:

- ① $d(v, v) = 0$ for all $v \in V$
- ② $0 \leq d(u, v) = t(u, v)$ for all $u, v \in V$ such that $u \neq v$

Then for any $u, v \in V$ and any integer $h \geq 0$, we have

$$\delta_G(u, v) \leq d(u, v) \leq (1 + \epsilon)^{\lceil \log_2 h \rceil + 1} \delta_G^h(u, v)$$

where $\delta_G^h(u, v)$ is the length of the shortest path from u to v with at most h edges

Approximation - Proof

For: $\delta_G(u, v) \leq d(u, v)$

$d(u, v) = t(u, v)$ and $t(u, v)$ cannot underestimate the actual distance

For $d(u, v) < \infty$

- $d(u, v) = r_{1+\epsilon}(w(uv)) \rightarrow$ edge uv is in G
- $d(u, v) = r_{1+\epsilon}(d(u, w) + d(w, v))$ for some w

→ path P_1 from u to w , P_2 from w to v

→ eventually break down into edges

→ rounding only makes the values larger

Approximation - Proof

For: $\delta_G(u, v) \leq d(u, v)$

$d(u, v) = t(u, v)$ and $t(u, v)$ cannot underestimate the actual distance

Show that: $d(u, v) \leq (1 + \epsilon)^{\lceil \log_2 h \rceil + 1} \delta_G^h(u, v)$ by induction on h

Assume: $\delta_G^h(u, v) \leq \infty$

$h = 1$:

Edge uv is in G and therefore $\delta_G^h(u, v) \leq w(uv)$

By definition of $t(u, v)$ and (2) we have that:

$$\begin{aligned} d(u, v) &\leq r_{1+\epsilon}(w(uv)) \leq (1 + \epsilon)w(uv) \\ &= (1 + \epsilon)^{\lceil \log_2 h \rceil + 1} \delta_G^h(u, v) \end{aligned}$$

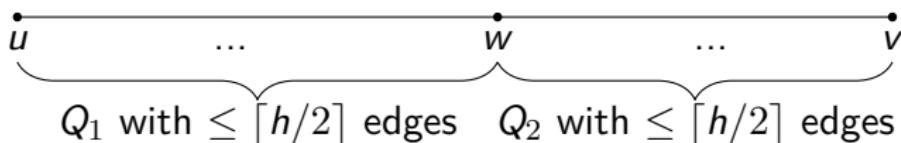
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$h \geq 2$:

Path Q with h edges:



By IH we get:

$$\begin{aligned} d(u, w) &\leq (1 + \epsilon)^{\lceil \log_2 \lceil h/2 \rceil \rceil + 1} \delta_G^{\lceil h/2 \rceil}(u, v) \\ &\leq (1 + \epsilon)^{\lceil \log_2 \lceil h/2 \rceil \rceil + 1} \text{length}(Q_1) \end{aligned}$$

Approximation - Proof

Since $h \geq 2$:

$$\begin{aligned} d(u, w) + d(w, v) &\leq (1 + \epsilon)^{\lceil \log_2 h/2 \rceil + 1} (\text{length}(Q_1) + \text{length}(Q_2)) \\ &\leq (1 + \epsilon)^{\lceil \log_2 h \rceil} \text{length}(Q) \end{aligned}$$

Also:

$$\begin{aligned} d(u, v) &\leq r_{1+\epsilon}(d(u, w) + d(w, v)) \\ &\leq (1 + \epsilon)(d(u, w) + d(w, v)) \\ &\leq (1 + \epsilon)^{\lceil \log_2 h \rceil + 1} \text{length}(Q) \end{aligned}$$

Also holds for shortest path with at most h edges between u and v .

$$d(u, v) \leq (1 + \epsilon)^{\lceil \log_2 h \rceil + 1} \delta_G^h(u, v)$$

$(1 + \epsilon)$ - Approximation

Approximation depends on the number of hops $h \leq n$ we allow.

To get $(1 + \epsilon)$ -approximation:

$$\text{Let } \epsilon' = \frac{\epsilon}{2^{\lceil (\log_2 n) \rceil}}$$

$$\left(1 + \frac{\epsilon}{2^{\lceil (\log_2 n) \rceil}}\right)^{\lceil \log_2 n \rceil + 1} \leq e^{\epsilon/2}$$

and since $\epsilon \in (0, 1)$

$$\leq 1 + \epsilon$$

Computing Minima

Recomputing $t(u, v)$ every time a distance between two vertices might have changed → Not very efficient!

Instead: store an approximation $t'(u, v)$ along with an index $\beta(u, v)$

- order vertices w_1, \dots, w_n in some way
- remember first index i for which:

$$r_{1+\epsilon}(d(u, w_i) + d(w_i, v)) = t'(u, v)$$

- reevaluating $t'(u, v)$:
 - if $r_{1+\epsilon}(w(uv)) = t'(u, v) \rightarrow t'(u, v)$ stays the same
 - look for alternative path that lets us keep distance $t'(u, v)$: Only need to look at indices $j \geq \beta(u, v)$
 - if estimated length of shortest path actually changed: recompute $t'(u, v)$

Total Update Time

How often can $d(u, v)$ change?

- for a $d(u, v) < \infty$: $d(u, v) \leq t(u, v) < (1 + \epsilon')^{\lceil \log_2 n \rceil + 2} n W$
- $d(u, v)$ can only increase
- $d(u, v)$ always non-negative integral power of $(1 + \epsilon')$

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$$O(n^3 \log(nW)/\epsilon' + \Delta)$$

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- total update time:

$$O(n^3 \log(nW)/\epsilon' + \Delta) = O(n^3 \log n \log(nW)/\epsilon + \Delta)$$

Computing Minima

In each call to $\text{Update}(u, v)$ compute $t(u, v)$

3 cases:

- relevant path not affected by changes (no change to $t'(u, v)$ and $\beta(u, v)$)
→ O(1)

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- alternative path can be found (only $\beta(u, v)$ increases)
→ at most n times before $t'(u, v)$ also changes
- $t'(u, v)$ is updated:

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- alternative path can be found (only $\beta(u, v)$ increases)
→ at most n times before $t'(u, v)$ also changes
- $t'(u, v)$ is updated:
→ $O(\log(nW)/\epsilon')$ times
- total cost to compute $t(u, v)$:

$$O(n \log(nW)/\epsilon')$$

Thank you for your attention!