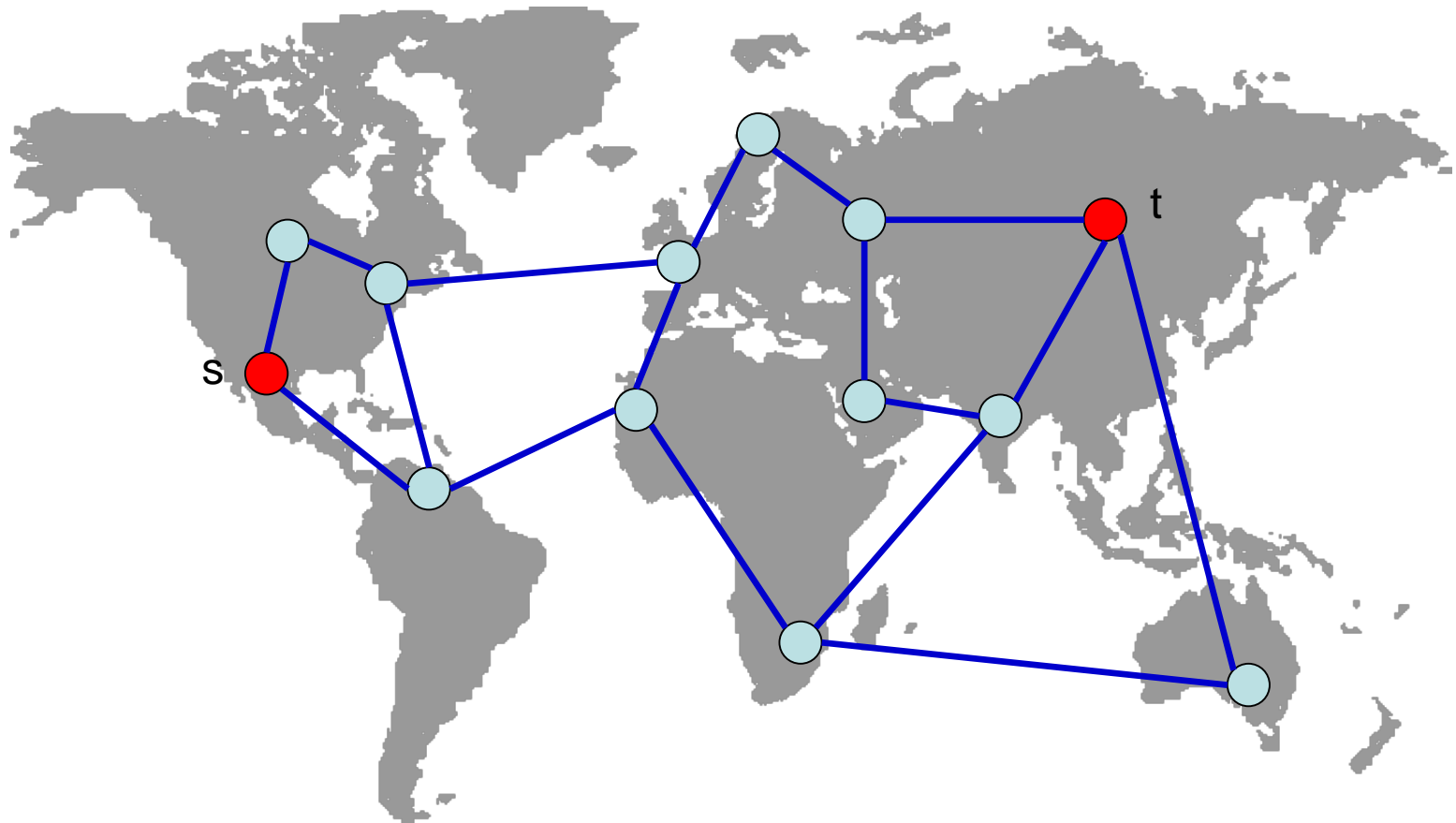


Fundamental Algorithms

Chapter 4: Shortest Paths

Christian Scheideler
WS 2017

Shortest Paths



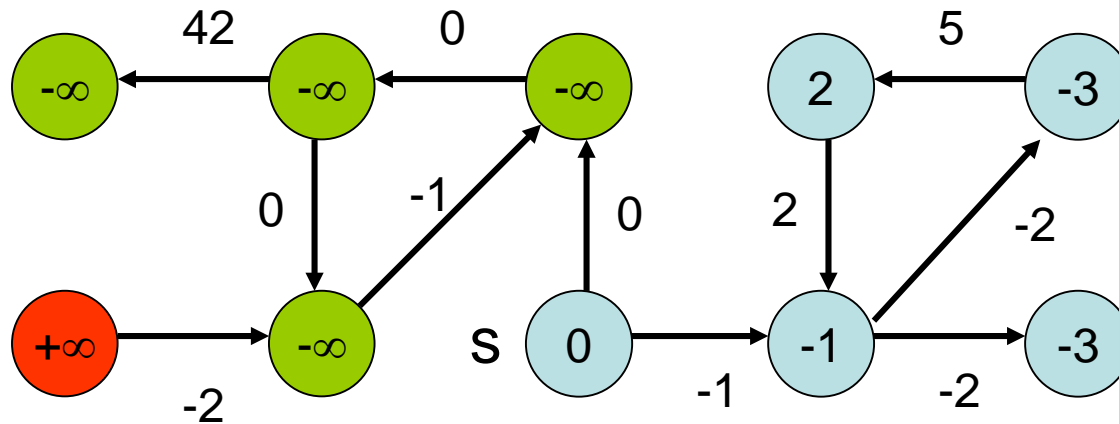
Central question: Determine fastest way to get from s to t.

Shortest Paths

Shortest Path Problem:

- directed/undirected graph $G=(V,E)$
- edge costs $c:E\rightarrow\mathbb{R}$
- **SSSP** (single source shortest path):
find shortest paths from a source node to all other nodes
- **APSP** (all pairs shortest path):
find shortest paths between all pairs of nodes

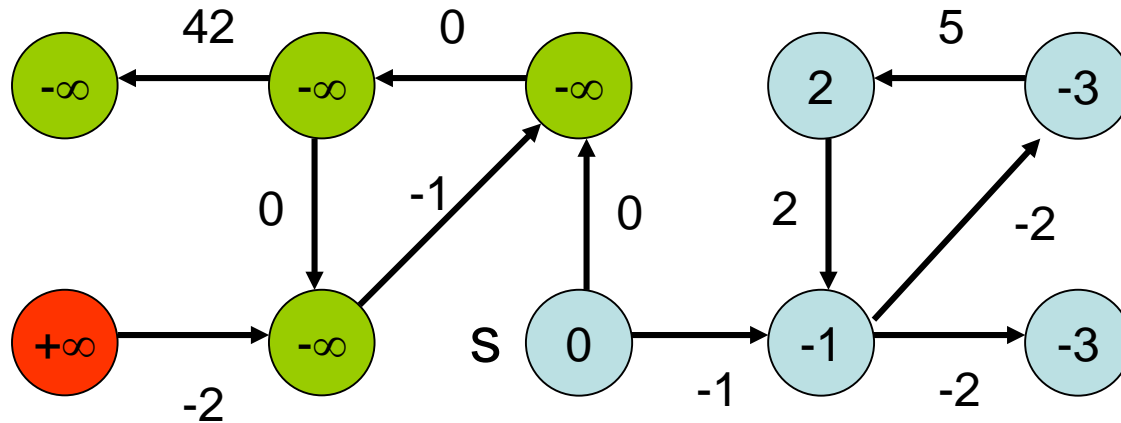
Shortest Paths



$\mu(s,v)$: distance between s and v

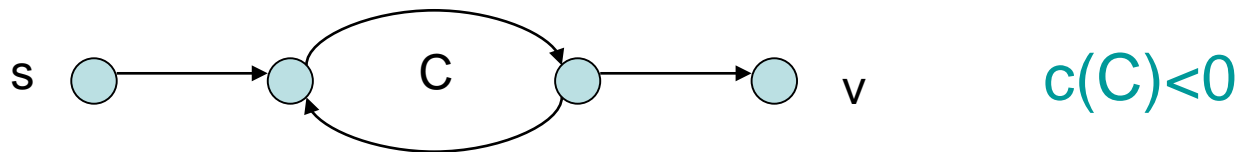
$$\mu(s,v) = \left\{ \begin{array}{l} \infty \quad \text{no path from } s \text{ to } v \\ -\infty \quad \text{path of arbitrarily low cost from } s \text{ to } v \\ \min\{ c(p) \mid p \text{ is a path from } s \text{ to } v \} \end{array} \right\}$$

Shortest Paths



When is the distance $-\infty$?

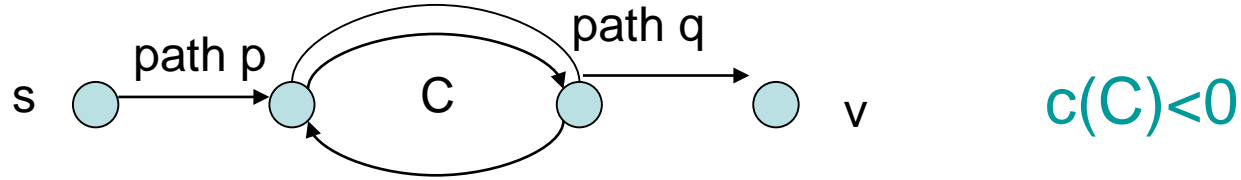
If there is a negative cycle:



Shortest Paths

Negative cycle necessary and sufficient for a distance of $-\infty$.

Negative cycle sufficient:



Cost for i -fold traversal of C :

$$c(p) + i \cdot c(C) + c(q)$$

For $i \rightarrow \infty$ this expression approaches $-\infty$.

Shortest Paths

Negative cycle necessary and sufficient for a distance of $-\infty$.

Negative cycle necessary:

- l : minimal cost of a **simple** path from s to v
- suppose there is a **non-simple** path p from s to v with cost $c(p) < l$
- p non-simple: continuously remove a cycle C till we are left with a simple path
- since $c(p) < l$, there must be a cycle C with $c(C) < 0$

Shortest Paths in Arbitrary Graphs

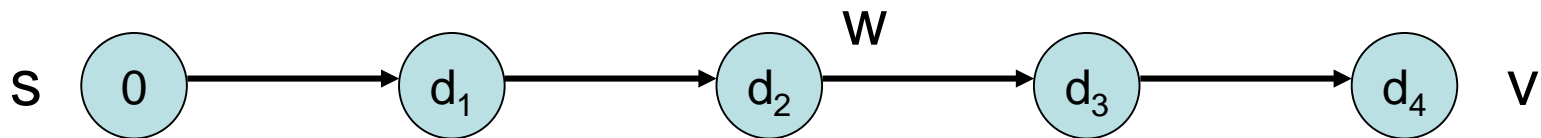
General Strategy:

- Initially, set $d(s) := 0$ and $d(v) := \infty$ for all other nodes
- Visit nodes in an order that **ensures** that **at least one** shortest path from s to every v is visited **in the order of its nodes**
- For every visited v , update distances to nodes w with $(v, w) \in E$, i.e., $d(w) := \min\{d(w), d(v) + c(v, w)\}$

Bellman-Ford Algorithm

Consider graphs with **arbitrary** edge costs.

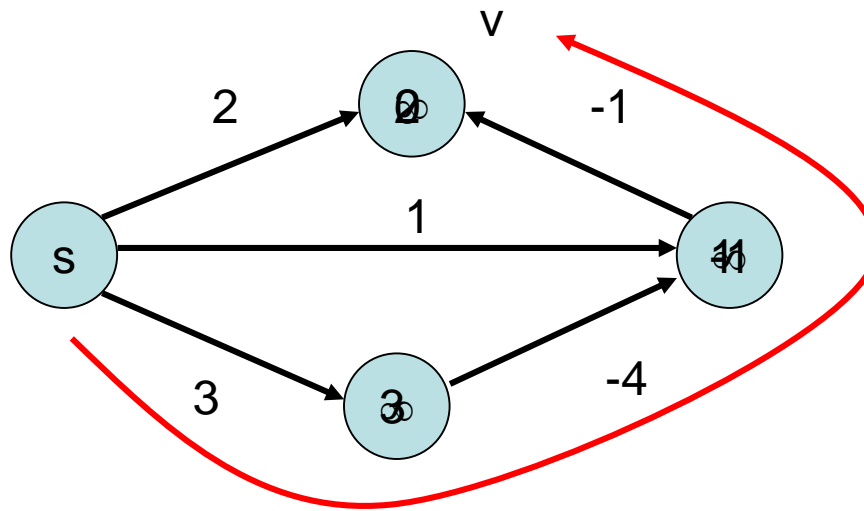
Problem: visit nodes along a shortest path from s to v in the right order



Dijkstra's algorithm cannot be used in this case any more.

Bellman-Ford Algorithm

Example:



Node v has wrong distance value!

Bellman-Ford Algorithm

Lemma 4.1: For every node v with $\mu(s,v) > -\infty$ there is a **simple** path (without cycle!) from s to v of length $\mu(s,v)$.

Proof:

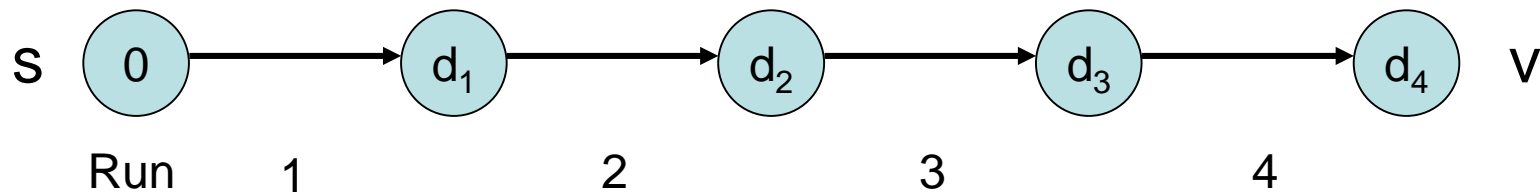
- Path with cycle of length ≥ 0 : removing the cycle does not increase the path length
- Path with cycle of length < 0 : distance from s is $-\infty$!

Bellman-Ford Algorithm

Conclusion: (graph with n nodes)

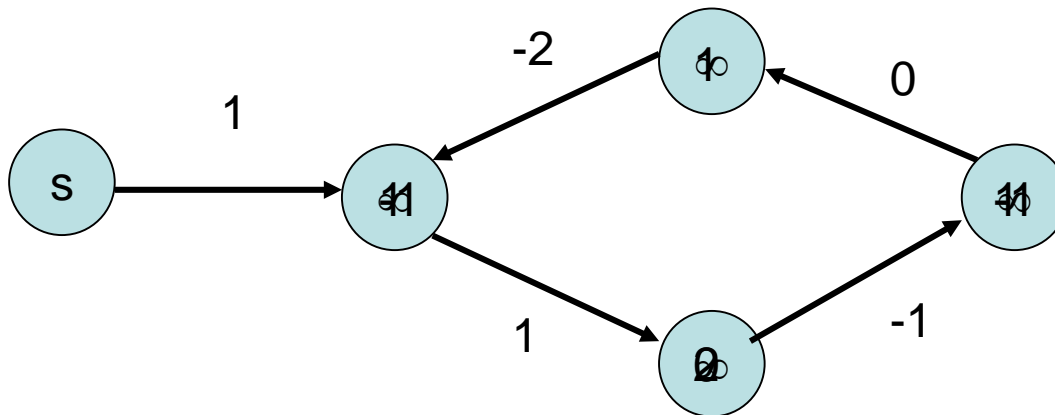
For every node v with $\mu(s,v) > -\infty$ there is a shortest path along $<n$ nodes to v .

Strategy: visit $(n-1)$ -times **all nodes** in the graph and update distances. Then all shortest paths have been considered.



Bellman-Ford Algorithm

Problem: detection of negative cycles



Conclusion: in a negative cycle, distance of at least one node keeps decreasing in each round, starting with a round $< n$

Bellman-Ford Algorithm

Lemma 4.2:

- **No decrease of a distance** in a round (i.e., $d[v]+c(v,w) \geq d[w]$ for all w):
Done because $d[w]=\mu(s,w)$ for all w
- **Decrease of a distance** even in n -th round (i.e., $d[v]+c(v,w) < d[w]$ for some w):
There are negative cycles for all of these nodes, so node w has distance $\mu(s,w)=-\infty$. If this is true for w , then also for all nodes reachable from w .

Proof: exercise

Bellman-Ford Algorithm

```
Procedure BellmanFord(s: NodeId)
  d=< $\infty$ ,..., $\infty$ >: NodeArray of  $\mathbb{R} \cup \{-\infty, \infty\}$ 
  parent=< $\perp$ ,...,  $\perp$ >: NodeArray of NodeId
  d[s]:=0; parent[s]:=s
  for i:=1 to n-1 do // update distances for n-1 rounds
    forall e=(v,w)  $\in$  E do
      if d[w] > d[v]+c(e) then // better distance?
        d[w]:=d[v]+c(e); parent[w]:=v
  forall e=(v,w)  $\in$  E do // still better in n-th round?
    if d[w] > d[v]+c(e) then infect(w)
```

```
Procedure infect(v) // set  $-\infty$ -distance starting with v
  if d[v]> $-\infty$  then
    d[v]:= $-\infty$ 
    forall (v,w)  $\in$  E do infect(w)
```

Bellman-Ford Algorithm

Runtime: $O(n \cdot m)$

Improvements:

- Check in each update round if we still have $d[v] + c[v, w] < d[w]$ for some $(v, w) \in E$.
No: done!
- Visit in each round only those nodes w with some edge $(v, w) \in E$ where $d[v]$ has decreased in the previous round.

All Pairs Shortest Paths

Assumption: graph with arbitrary edge costs, but no negative cycles

Naive Strategy for a graph with n nodes: run n times Bellman-Ford Algorithm (once for every node as the source)

Runtime: $O(n^2 m)$

All Pairs Shortest Paths

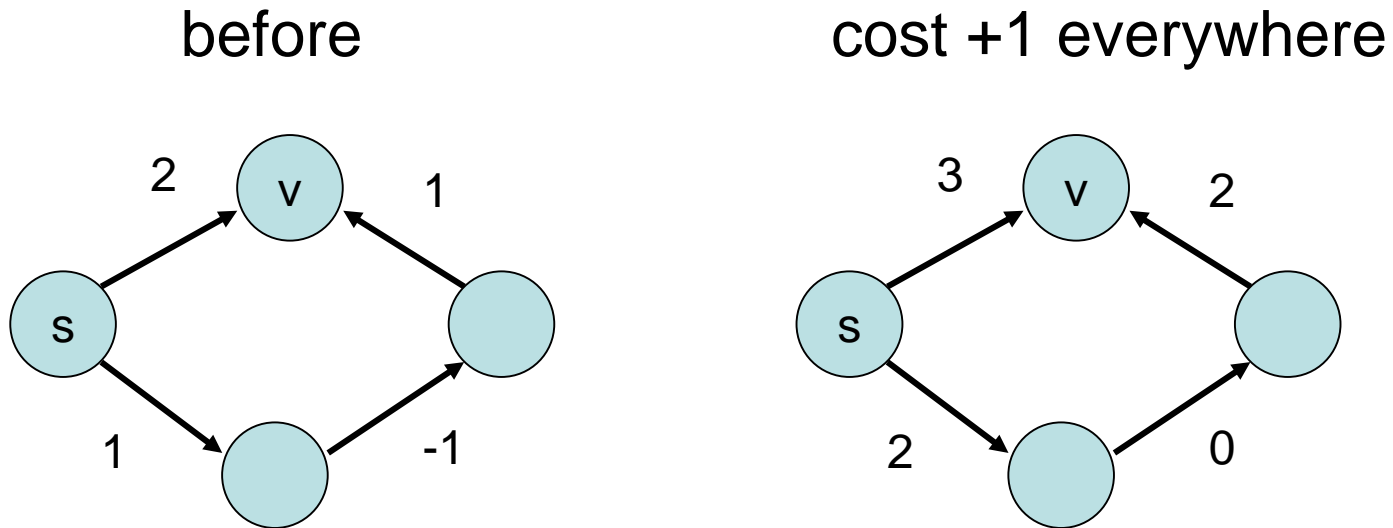
Better Strategy: Reduce n Bellman-Ford applications to n Dijkstra applications

Problem: we need **non-negative** edge costs

Solution: convert edge costs into non-negative edge costs without changing the shortest paths (not so easy!)

All Pairs Shortest Paths

Counterexample to additive increase by c :



— : shortest path

Johnson's Method

- Let $\phi: V \rightarrow \mathbb{R}$ be a function that assigns a **potential** to every node.
- The **reduced cost** of $e=(v,w)$ is:
$$r(e) := c(e) + \phi(v) - \phi(w)$$

Lemma 4.3: Let p and q be paths connecting the same endpoints in G . Then for every potential ϕ : $r(p) < r(q)$ if and only if $c(p) < c(q)$.

Johnson's Method

Lemma 4.3: Let p and q be paths connecting the same endpoints in G . Then for every potential ϕ : $r(p) < r(q)$ if and only if $c(p) < c(q)$.

Proof: Let $p = (v_1, \dots, v_k)$ be an arbitrary path and $e_i = (v_i, v_{i+1})$ for all i . It holds:

$$\begin{aligned} r(p) &= \sum_i r(e_i) \\ &= \sum_i (\phi(v_i) + c(e_i) - \phi(v_{i+1})) \\ &= \phi(v_1) + c(p) - \phi(v_k) \end{aligned}$$

Johnson's Method

Lemma 4.4: Suppose that G has no negative cycles and that all nodes can be reached from s . Let $\phi(v) = \mu(s, v)$ for all $v \in V$. With this ϕ , $r(e) \geq 0$ for all e .

Proof:

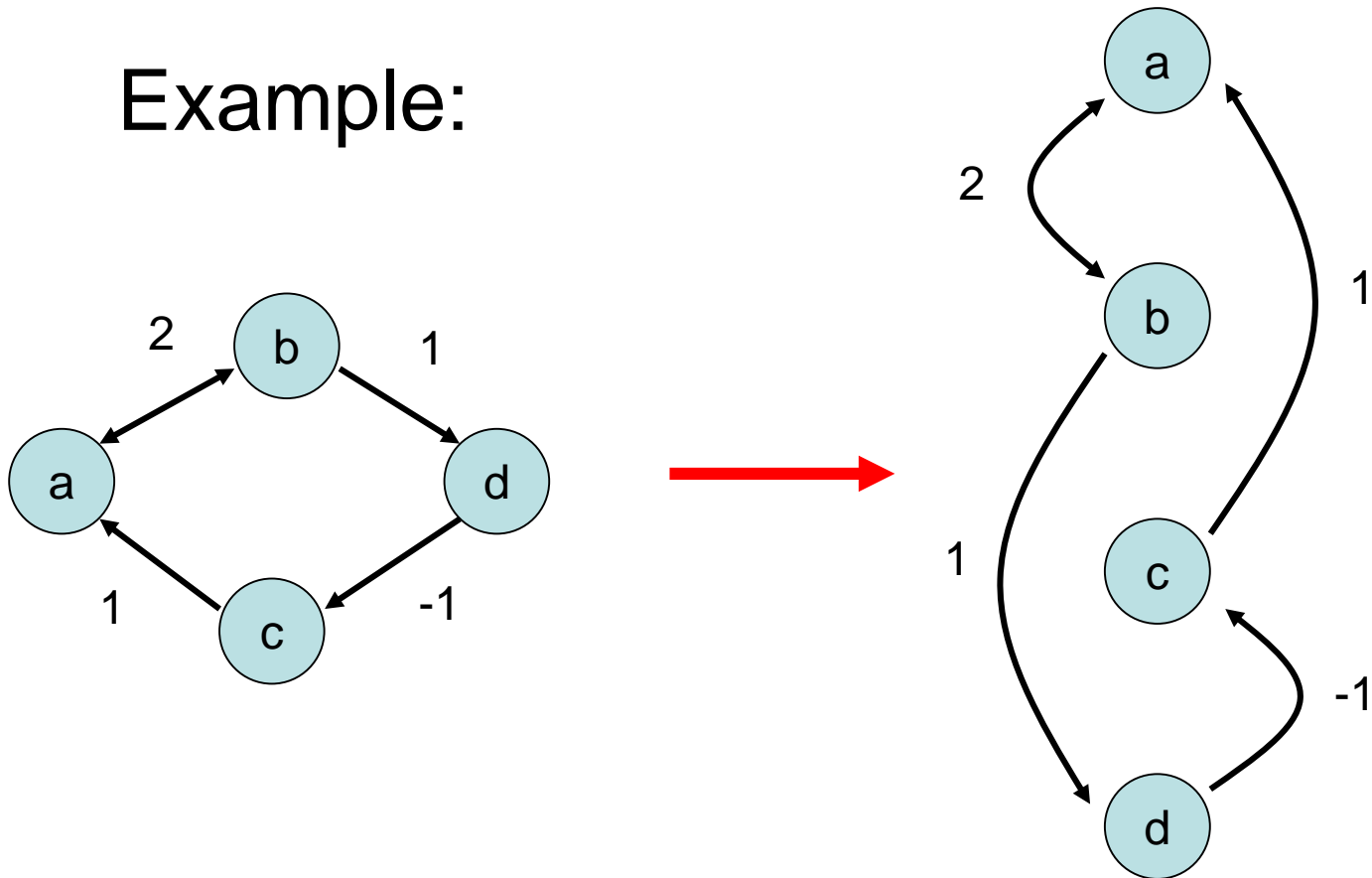
- According to our assumption, $\mu(s, v) \in \mathbb{R}$ for all v
- We know: for every edge $e = (v, w)$, $\mu(s, v) + c(e) \geq \mu(s, w)$ (otherwise, we have a contradiction to the definition of μ !)
- Therefore, $r(e) = \mu(s, v) + c(e) - \mu(s, w) \geq 0$

Johnson's Method

1. Create **new** node **s** and new edges (s,v) for all **v** in **G** with $c(s,v)=0$ (**all nodes reachable!**)
2. Compute $\mu(s,v)$ using **Bellman-Ford** and set $\phi(v):=\mu(s,v)$ for all **v**
3. Compute the reduced costs $r(e)$
4. Compute for all nodes **v** the distances $\bar{\mu}(v,w)$ using **Dijkstra** with the reduced costs on graph **G without node s**
5. Compute the correct distances $\mu(v,w)$ via $\mu(v,w):=\bar{\mu}(v,w)+\phi(w)-\phi(v)$

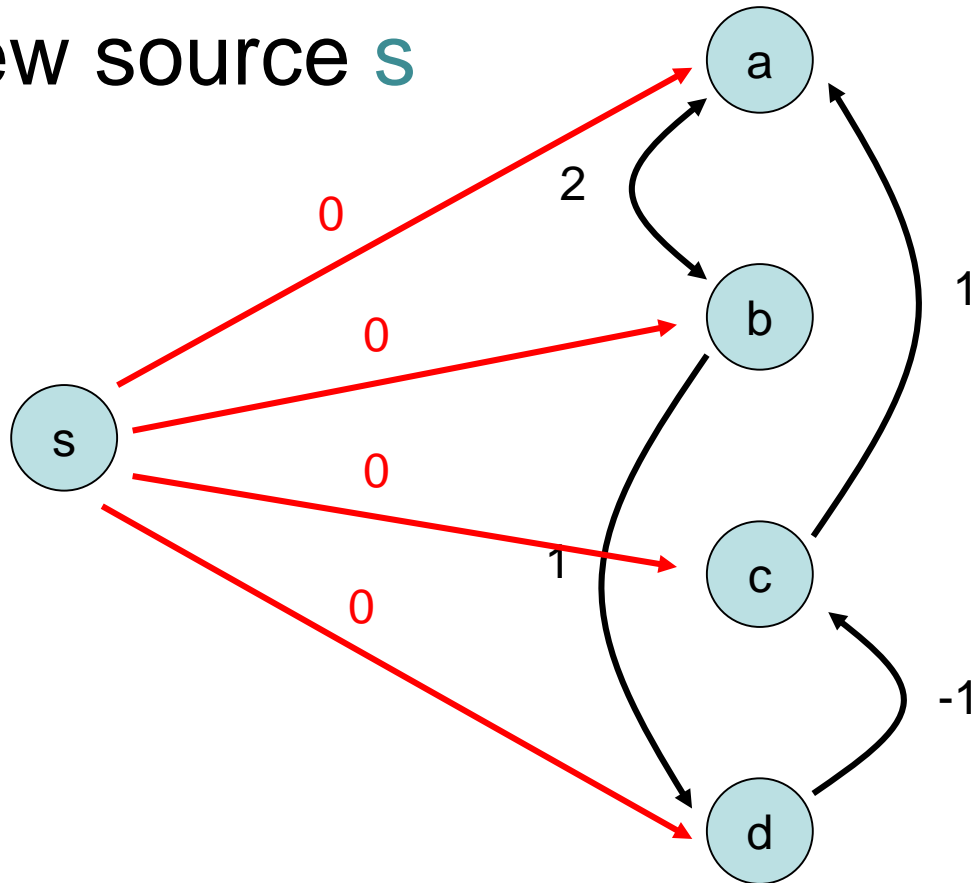
Johnson's Method

Example:



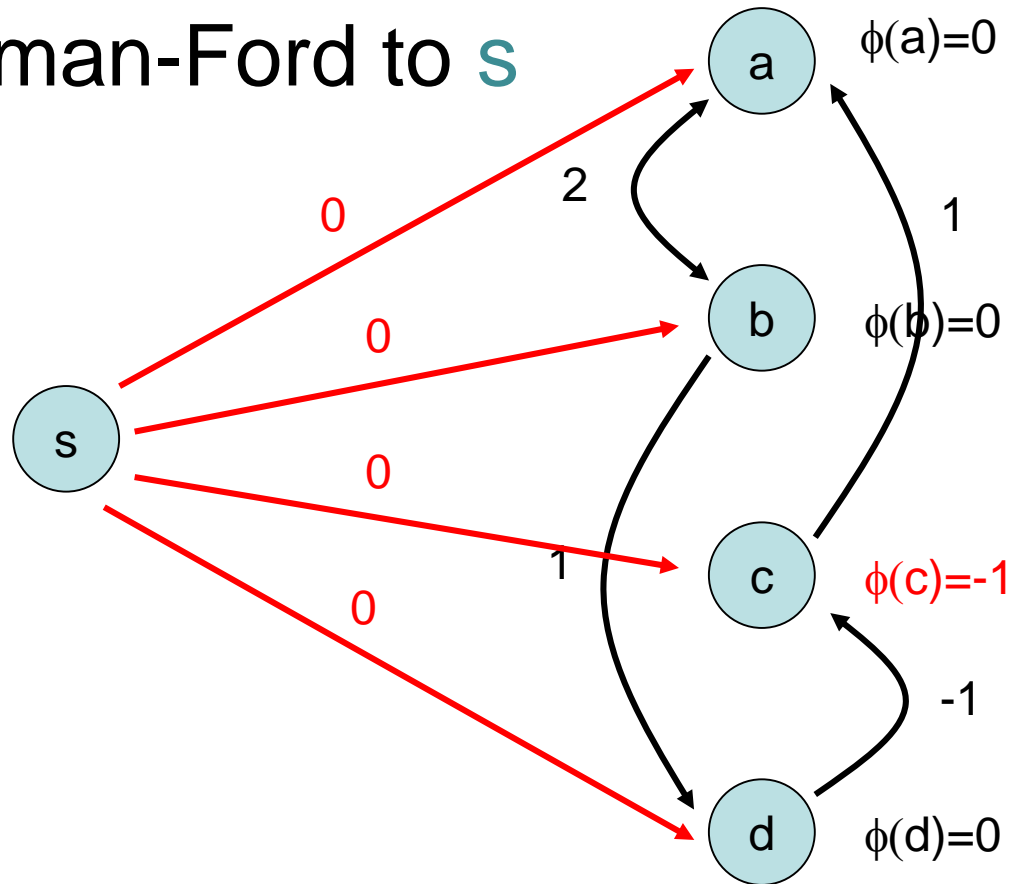
Johnson's Method

Step 1: create new source s



Johnson's Method

Step 2: apply Bellman-Ford to **s**

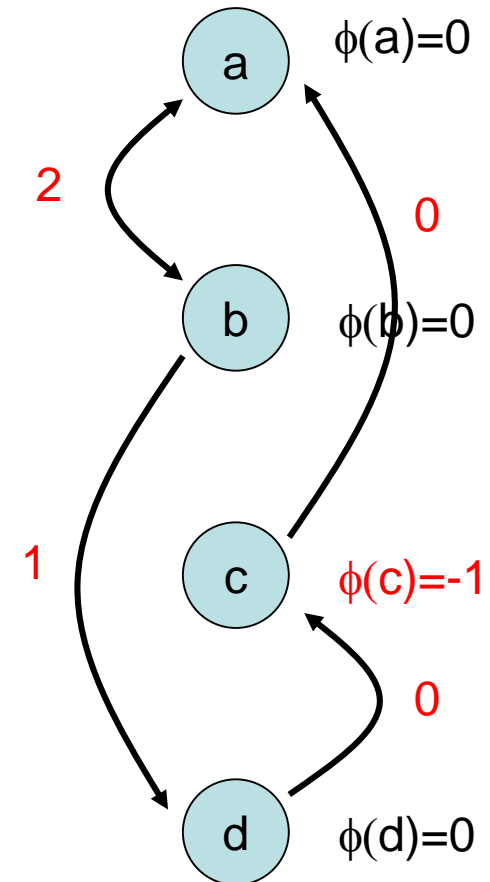


Johnson's Method

Step 3: compute $r(e)$ -values

The **reduced cost** of $e=(v,w)$ is:

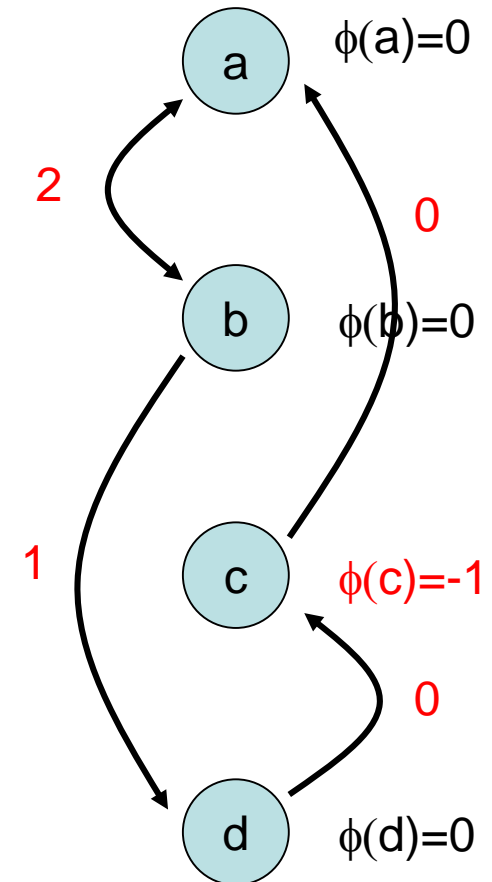
$$r(e) := \phi(v) + c(e) - \phi(w)$$



Johnson's Method

Step 4: compute all distances $\bar{\mu}(v,w)$ via Dijkstra

$\bar{\mu}$	a	b	c	d
a	0	2	3	3
b	1	0	1	1
c	0	2	0	3
d	0	2	0	0

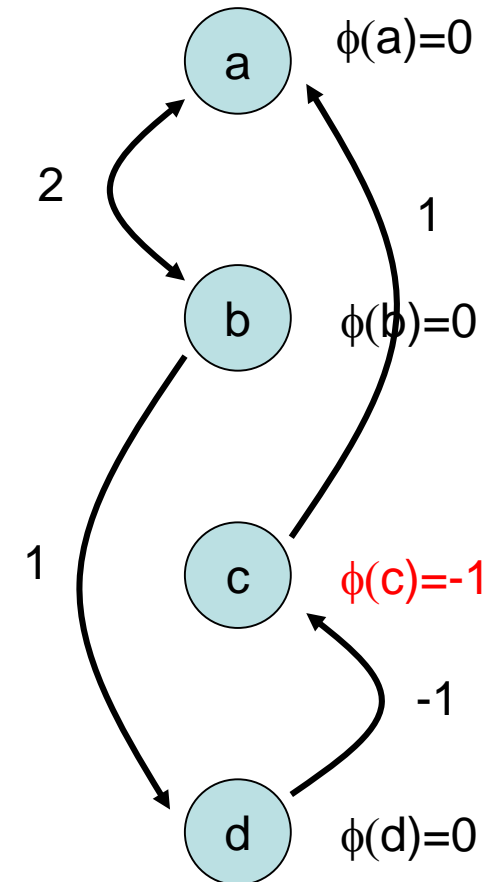


Johnson's Method

Step 5: compute correct distances via the formula

$$\mu(v,w) = \bar{\mu}(v,w) + \phi(w) - \phi(v)$$

μ	a	b	c	d
a	0	2	2	3
b	1	0	0	1
c	1	3	0	4
d	0	2	-1	0



All Pairs Shortest Paths

Runtime of Johnson's Method:

$$\begin{aligned} & O(T_{\text{Bellman-Ford}}(n, m) + n \cdot T_{\text{Dijkstra}}(n, m)) \\ &= O(n \cdot m + n(n \log n + m)) \\ &= O(n \cdot m + n^2 \log n) \end{aligned}$$

when using Fibonacci heaps.

- Problem with the runtime bound: m can be quite large in the worst case (up to $\sim n^2$)
- Can we significantly reduce m if we are fine with computing approximate shortest paths?

Graph Spanners

Definition 4.5: Given an undirected graph $G=(V,E)$ with edge costs $c:E\rightarrow\mathbb{R}$, a subgraph $H\subseteq G$ is an (α,β) -spanner of G iff for all $u,v\in V$,

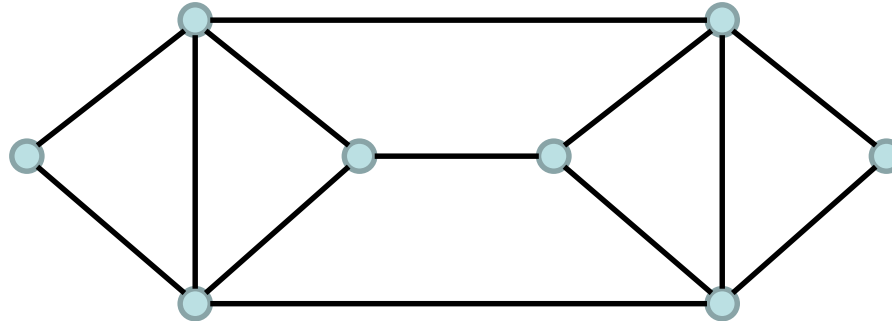
$$d_H(u,v) \leq \alpha \cdot d_G(u,v) + \beta$$

- $d_G(u,v)$: distance of u and v in G
- α : multiplicative stretch
- β : additive stretch

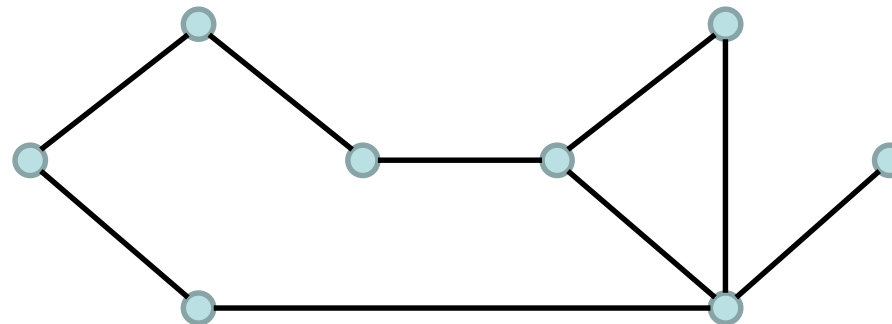
Graph Spanners

Example: all edge costs are 1

G



H



Graph Spanners

Consider the following Greedy algorithm by Althöfer et al. (Discrete Computational Geometry, 1993):

$E(H) := \emptyset$

for each $\{u, v\} \in E(G)$ in the order of **non-decreasing** edge costs do
if $(2k-1) \cdot c(u, v) < d_H(u, v)$ then
add $\{u, v\}$ to $E(H)$

Theorem 4.6: For any $k \geq 1$, $|E(H)| = O(n^{1+1/k})$ and the graph H constructed by the Greedy algorithm is a $(2k-1, 0)$ -spanner.

Thorup and Zwick have shown that for any graph G with **non-negative** edge costs a structure related to H can be built in expected time $O(k \cdot m \cdot n^{1/k})$, which implies that we can then solve the $(2k-1)$ -approximate APSP in time $O(k \cdot m \cdot n^{1/k} + n^{2+1/k})$.

We will get back to that when we talk about distance oracles.

Graph Spanners

Proof of Theorem 4.6:

Lemma 4.7: H is a $(2k-1, 0)$ -spanner of G .

Proof:

- Consider any edge $\{u, v\} \in E(G) \setminus E(H)$.
- Since $\{u, v\}$ was rejected by the algorithm, $d_H(u, v) \leq (2k-1) \cdot c(u, v)$.
- Consider now any shortest path p from node a to b in G .
- For every edge $\{u, v\}$ in p , there is a path of length at most $(2k-1) \cdot c(u, v)$ in H .
- Replacing each edge $\{u, v\}$ in p by this path results in a path from a to b in H of length at most $(2k-1) \cdot c(p)$.

Graph Spanners

Proof of Theorem 4.6:

Lemma 4.8: Let C be any cycle in H . Then $|C| > 2k$.

Proof:

- Assume that there is a cycle C of length at most $2k$ in H .
- Let $\{u,v\}$ be the last edge in C that was added by the algorithm.
- Clearly, $\{u,v\}$ has the largest cost of all edges in C .
- Also, when $\{u,v\}$ was considered, $(2k-1) \cdot c(u,v) < d_H(u,v)$ as otherwise $\{u,v\}$ would not have been added to H .
- However, since $C \setminus \{u,v\}$ results in a path of length at most $(2k-1) \cdot c(u,v)$ from u to v , $d_H(u,v) \leq (2k-1) \cdot c(u,v)$, leading to a contradiction.
- Hence, the lemma is true.

Graph Spanners

Proof of Theorem 4.6:

Lemma 4.8 implies that H has a **girth** (defined as the minimum cycle length in H) of more than $2k$.

Lemma 4.9: Let H be a graph of size n with girth $>2k$. Then $|E(H)|=O(n^{1+1/k})$.

Proof:

- Let H be any graph with girth $>2k$ and at least $n+2n^{1+1/k}$ edges.
- Repeatedly remove any node from H of degree at most $\lceil n^{1/k} \rceil$ and any edges incident to that node, until no such node exists.
- The total number of edges removed in this way is at most $n \cdot (n^{1/k} + 1)$.
- Hence, we obtain a subgraph H' of H of minimum degree more than $\lceil n^{1/k} \rceil$ with at least $n^{1+1/k}$ edges connecting at most n nodes.
- Exercise: show that there cannot be a graph G of size n with girth $>2k$ and minimum degree more than $\lceil n^{1/k} \rceil$.
- Thus, H' must have a girth of at most $2k$, and therefore also the original graph H . This, however, is a contradiction.

Graph Spanners

If we restrict ourselves to unweighted graphs (i.e., all edges have a cost of 1), we can also construct good **additive** spanners.

Theorem 4.10: Any n -node graph G has a $(1,2)$ -spanner with $O(n^{3/2} \log n)$ edges.

Proof:

We first need the notion of hitting sets.

Definition 4.11: Given a collection M of subsets of V , a subset $S \subseteq V$ is a **hitting set** of M if it intersects every set in M .

Lemma 4.12: Let $M=(S_1, \dots, S_n)$ be a collection of subsets of $V=\{1, \dots, n\}$ with $|S_i| \geq R$ for all i . There is an algorithm running in $O(nR \log n + (n/R) \log^2 n)$ time that finds a hitting set S of M with $|S| \leq (n/R) \ln n$.

Graph Spanners

Lemma 4.12: Let $M=(S_1, \dots, S_n)$ be a collection of subsets of $V=\{1, \dots, n\}$ with $|S_i| \geq R$ for all i . There is an algorithm running in $O(nR \log n + (n/R) \log^2 n)$ time that finds a hitting set S of M with $|S| \leq (n/R) \ln n$.

Proof:

- Assume w.l.o.g. that $|S_i|=R$ for all i . Run the following greedy algorithm:

$|S| := \emptyset$

for each $1 \leq j \leq n$, keep a counter $c(j) = |\{S_i \in M : j \in S_i\}|$

while $M \neq \emptyset$ do

$k := \operatorname{argmax}_j c(j)$

$S := S \cup \{k\}$

 remove any subsets from M containing k and

 update the counters $c(j)$ accordingly

- To obtain the runtime, we store the counts $c(j)$ in a data structure that can support the following operations in $O(\log n)$ time: insert an element, return element j with maximum $c(j)$, decrement a given $c(j)$.

Graph Spanners

$|S| := \emptyset$

for each $1 \leq j \leq n$, keep a counter $c(j) = |\{S_i \in M : j \in S_i\}|$

while $M \neq \emptyset$ do

$k := \operatorname{argmax}_j c(j)$

$S := S \cup \{k\}$

 remove any subsets from M containing k and
 update the counters $c(j)$ accordingly

- total number of inserts: n because of n counters
→ runtime $O(n \log n)$
- total number of decrements: nR because each of the n sets contains just R elements and each of them can only cause one decrement
→ runtime $O(nR \log n)$
- total number of argmax calls: depends on number of iterations of while loop

Graph Spanners

Proof of Lemma 4.12 (continued):

- We still need an upper bound on $|S|$ (which gives an upper bound on while loop)
- Let m_j be the number of sets remaining in M after j passes of the while loop. Then $m_0=n$.
- Let k_j be the j -th element added to S , so $m_j=m_{j-1}-c(k_j)$.
- Just before we add k_j , the sum of $c(j)$ over all $j \in V \setminus \{k_1, \dots, k_{j-1}\}$ must be $m_{j-1}R$, so $c(k_j)$ must be at least the average count, which is $m_{j-1}R/(n-j+1)$.
- Therefore,

$$m_j \leq (1-R/(n-j+1)) \cdot m_{j-1} \leq n \prod_{l=0}^{j-1} (1-R/(n-l))$$

$$< n \cdot (1-R/n)^j \leq n \cdot e^{-Rj/n} \quad (\text{using the fact that } 1-x \leq e^{-x} \text{ for all } x \in [0,1])$$
- Taking $j=(n/R) \ln n$ gives $m_j < 1$, and therefore $m_j=0$.
- Hence, $|S| \leq (n/R) \ln n$.
- Thus, the total runtime over all argmax calls is $O((n/R) \log^2 n)$.

Graph Spanners

Proof of Theorem 4.10 (continued):

- Let S be a hitting set of minimal size for $M = \{ N(v) \mid \deg(v) \geq \sqrt{n} \}$.
- From Lemma 4.12 ($R = \sqrt{n}$) we know that $|S| = O(\sqrt{n} \log n)$.
- Do a BFS search from each $s \in S$ and add the resulting n edges of the BFS tree to $E(H)$.
- For every $u \in V$ with $\deg(u) < \sqrt{n}$ (the **low-degree** nodes), add all edges incident to u to $E(H)$.
- By construction, $|E(H)| = |S| \cdot n + n\sqrt{n} = O(n^{3/2} \log n)$.
- Consider any pair $u, v \in V$ with shortest path p in G . We have two cases:
- (a): p contains only low-degree nodes. Then p is also contained in H , so $d_H(u, v) = d(u, v)$.
- (b): p contains a high-degree node x . Let $s \in S$ be a node adjacent to x . Then we append the shortest paths from u to s and s to v in H to obtain a path from u to v in H . It holds:
$$\begin{aligned} d_H(u, v) &\leq d_H(u, s) + d_H(s, v) = d(u, s) + d(v, s) \\ &\leq (d(u, x) + 1) + (d(v, x) + 1) = d(u, v) + 2 \end{aligned}$$
- Hence, H is indeed a $(1, 2)$ -spanner.

Graph Spanners

Runtime of the algorithm for (1,2)-spanner:

- $O(n^{3/2} \log n)$: construction of hitting set S
- $O(\sqrt{n} \log n (n+m))$: BFS for all nodes in S
- $O(n^{3/2})$: adding all edges of low-degree nodes to H

Total runtime: $O(\sqrt{n} (m+n) \log n)$.

Runtime of approximate APSP algorithm for an unweighted graph G based on (1,2)-spanner H :

$$\begin{aligned} & O(\sqrt{n} (m+n) \log n) + O(n \cdot n^{3/2} \log n + n^2 \log n) \\ & = O(n^{5/2} \log n) \end{aligned}$$

With a more complex approach the runtime can be reduced to $O(n^{7/3} \log n)$. For the details see:

D. Dor, S. Halperin, and U. Zwick. All-pairs almost shortest paths. SIAM Journal of Computing, 29(5): 1740-1759, 2000.

Graph Spanners

Interestingly, the following two results are known:

Theorem 4.13: Any n -node graph G has a $(1,6)$ -spanner with $O(n^{4/3})$ edges.

Theorem 4.14: In general, there is no additive spanner with $O(n^{4/3-\varepsilon})$ edges for n -node graphs for any $\varepsilon > 0$.

For more information on that see:

Amir Abboud and Greg Bodwin. The $4/3$ additive spanner exponent is tight. Proc. of the 48th ACM Symposium on Theory of Computing (STOC), 2016.

Distance Oracles

How to quickly answer distance requests?

Naive approach:

- Run an APSP algorithm and store all answers in a matrix

Problems:

- High runtime ($O(nm + n^2 \log n)$)
- High storage space ($\Theta(n^2)$)

Alternative approach, if approximate answers are sufficient:

- Compute additive or multiplicative spanner, and run an APSP algorithm on that spanner.
→ lower runtime
- But storage space is still high

Better solutions concerning the storage space have been investigated under the concept of **distance oracles**.

Distance Oracles

Definition 4.15: An α -approximate distance oracle is defined by two algorithms:

- a preprocessing algorithm that takes as its input a graph $G=(V,E)$ and returns a **summary** of G , and
- a query algorithm based on the summary of G that takes as its input two vertices $u,v \in V$ and returns an estimate $D(u,v)$ such that $d(u,v) \leq D(u,v) \leq \alpha \cdot d(u,v)$.

The quality of an α -approximate distance oracle is defined by its query time $q(n)$, preprocessing time $p(m,n)$, and storage space $s(n)$. The goal is to minimize all of these quantities.

Thorup and Zwick (STOC 2001) have shown the following result for graphs of **non-negative** edge costs:

Theorem 4.16: For all $k \geq 1$ there exists a $(2k-1)$ -approximate distance oracle using $O(k \cdot n^{1+1/k})$ space and $O(m \cdot n^{1/k})$ time for preprocessing that can answer queries in $O(k)$ time (where we hide logarithmic factors in the O -notation).

Distance Oracles

Theorem 4.16: For all $k \geq 1$ there exists a $(2k-1)$ -approximate distance oracle using $O(k \cdot n^{1+1/k})$ space and $O(m \cdot n^{1/k})$ time for preprocessing that can answer queries in $O(k)$ time (where we hide logarithmic factors in the O -notation).

Proof:

$k=1$: trivial. Just run our APSP algorithm.

$k=2$: Consider the following preprocessing algorithm:

```
A := random subset  $S \subseteq V$  of size  $O(\sqrt{n} \log n)$ 
for each  $a \in A$  run Dijkstra to compute  $d(a, v)$  for all  $v \in V$ 
for each  $v \in V \setminus A$  do
   $p_A(v) := \operatorname{argmin}_{y \in A} d(v, y)$ 
  run Dijkstra to compute  $A(v) := \{x \in V \mid d(v, x) < d(v, p_A(v))\}$ 
   $B(v) := A \cup A(v)$ 
  store  $p_A(v)$  under  $v$ 
  for all  $x \in B(v)$ , store  $d(v, x)$  under key  $(v, x)$  in a hash table
```

- It is easy to show that with high probability A is a hitting set of $M = \{N_{\sqrt{n}}(v) \mid v \in V\}$, where $N_{\sqrt{n}}(v)$ is the set containing the closest \sqrt{n} nodes to v .

Distance Oracles

Lemma 4.17: $|B(v)| \leq O(\sqrt{n} \log n)$.

Proof:

- It suffices to show that $|A(v)| \leq \sqrt{n}$ since by construction $|A| = O(\sqrt{n} \log n)$.
- Because A hits the closest \sqrt{n} nodes to v with high probability, some node $a \in A$ is also in $N_{\sqrt{n}}(v)$.
- Thus, all nodes closer to v than a are also in $N_{\sqrt{n}}(v)$.
- By the definition of $A(v)$, this implies that $A(v) \subseteq N_{\sqrt{n}}(v)$, and therefore, $|A(v)| \leq \sqrt{n}$.

Distance Oracles

Proof of Theorem 4.16 (continued):

Now we can bound the quality of the distance oracle.

- Lemma 4.17 implies that the storage space needed by our distance oracle is $O(n \cdot \sqrt{n} \log n)$.
- A query (u, v) is processed as follows:

```
if  $d(u, v)$  is stored in the hash table then
    return  $d(u, v)$ 
else
    return  $d(u, p_A(u)) + d(v, p_A(u))$ 
```

- This obviously takes constant time. We also need to show that $d(u, v) \leq D(u, v) \leq 3d(u, v)$.

Distance Oracles

Claim: $d(u,v) \leq D(u,v) \leq 3d(u,v)$.

- Suppose that $v \notin B(u)$, as otherwise $D(u,v) = d(u,v)$.

- By the triangle inequality we have

$$d(u,v) \leq d(u, p_A(u)) + d(v, p_A(u)) = D(u,v)$$

- In order to show that $D(u,v) \leq 3d(u,v)$, we use the triangle inequality again to obtain

$$\begin{aligned} D(u,v) &= d(u, p_A(u)) + d(p_A(u), v) \\ &\leq d(u, p_A(u)) + (d(p_A(u), u) + d(u, v)) \\ &= 2d(u, p_A(u)) + d(u, v) \\ &\leq 3d(u, v) \end{aligned}$$

Distance Oracles

Proof of Theorem 4.16 (continued):

It remains to determine the runtime for the preprocessing.

- For each $a \in A$ run Dijkstra to compute $d(a, v)$ for all $v \in V$:
runtime $O((m+n \log n) \cdot \sqrt{n} \log n)$.
- Determine $p_A(v)$ for each $v \in V \setminus A$: total runtime $O(n \cdot \sqrt{n} \log n)$
- Run Dijkstra to compute $A(v) := \{x \in V \mid d(v, x) < d(v, p_A(v))\}$:
We need to modify Dijkstra so that we start with a Fibonacci heap only containing v and we **only** include a node y into the heap (and therefore process it) if $d(x) + c(x, y) < d(v, p_A(v))$ for some processed x . Then the runtime for each $v \in V \setminus A$ is $O(|E(A(v))| + |A(v)| \log n)$, where $E(A(v))$ is the set of all edges containing vertices of $A(v)$.
- Let $C(v) = \{w \in V \mid v \in A(w)\}$. One can show (similarly to $A(v)$) that the expected size of $C(v)$ is at most $2\sqrt{n}$. Hence,

$$\begin{aligned} \sum_{w \in V} |E(A(w))| &\leq \sum_{w \in V, v \in A(w)} |E(v)| = \sum_{v \in V, w \in C(v)} |E(v)| \\ &= \sum_{v \in V} (|C(v)| \cdot |E(v)|) = O(m \cdot \sqrt{n}) \end{aligned}$$
- Thus, the overall runtime for the $A(v)$'s is $O(m \cdot \sqrt{n} + n\sqrt{n} \log n)$.
- Therefore, the preprocessing needs $O((m + n \log n) \cdot \sqrt{n} \log n)$ time.

Distance Oracles

Proof of Theorem 4.16 (continued):

The algorithm for general k proceeds by taking many related samples A_0, \dots, A_k instead of just a single sample A . Concretely, it does the following:

- Let $A_0 = V$ and $A_k = \emptyset$. For each $1 \leq i \leq k-1$, choose a random $A_i \subseteq A_{i-1}$ of size $(|A_{i-1}|/n^{1/k}) \log n = O(n^{1-i/k} \log n)$.
- Let $p_i(v)$ be the closest node to v in A_i . If $d(v, p_i(v)) = d(v, p_{i+1}(v))$ then let $p_i(v) = p_{i+1}(v)$.
- For all $v \in V$ and $i < k-1$, define
$$A_i(v) = \{ x \in A_i \mid d(v, x) < d(v, p_{i+1}(v)) \}$$
$$B(v) = A_{k-1} \cup \left(\bigcup_{i=0}^{k-2} A_i(v) \right)$$
- For all $v \in V$ and all $x \in B(v)$, store $d(v, x)$ in a hash table. Also store for each $v \in V$ and each $i \leq k-1$, $p_i(v)$.

A query for (u, v) then works as follows:

```
w := p_0 = v
for i = 1 to k do
  if w ∈ B(u) then return d(u, w) + d(w, v)
  else w := p_i(u) ; swap u and v
```

For more information see:

Mikkel Thorup and Uri Zwick. Approximate distance oracles. In Proc. of the 33rd ACM Symposium on Theory of Computing (STOC), 2001.

Next Chapter

Matching algorithms...