

Algorithms (VIII)

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Review of the Previous Lecture

Chapter 4. Paths in graphs

Distances

DFS does not necessarily find the shortest paths.

Definition

The **distance** between two nodes is the length of the shortest path between them.

Breadth-first search

The algorithm

BFS(G, s)

Input: Graph $G = (V, E)$, directed or undirected; vertex $s \in V$

Output: For all vertices u reachable from s , $\text{dist}(u)$ is set to the distance from s to u .

1. **for all** $u \in V$ **do**
2. $\text{dist}(u) = \infty$
3. $\text{dist}(s) = 0$
4. $Q = [s]$ (**queue** containing just s)
5. **while** Q is not empty **do**
6. $u = \text{eject}(Q)$
7. **for all** edge $(u, v) \in E$ **do**
8. **if** $\text{dist}(v) = \infty$ **then**
9. $\text{inject}(Q, v)$
10. $\text{dist}(v) = \text{dist}(u) + 1$

Correctness and efficiency

Lemma

For each $d = 0, 1, 2, \dots$, there is a moment at which (1) all nodes at distance $\leq d$ from s have their distances correctly set; (2) all other nodes have their distances set to ∞ ; and (3) the queue contains exactly the nodes at distance d .

Lemma

BFS has a running time of $O(|V| + |E|)$.

Lengths on edges

BFS treats all edges as having *the same length*, which is rarely true in applications where shortest paths are to be found.

Every edge $e \in E$ with a length ℓ_e .

If $e = (u, v)$, we will sometimes also write

$$\ell(u, v) \quad \text{or} \quad \ell_{uv}.$$

Dijkstra's algorithm

An adaption of breadth-first search

BFS finds shortest paths in any graph whose edges have **unit** length. Can we adapt it to a more general graph $G = (V, E)$ whose *edge lengths ℓ_e are positive integers*?

A simple trick:

For any edge $e = (u, v)$ of E , replace it by ℓ_e edges of length 1, by adding $\ell_e - 1$ dummy nodes between u and v .

It might take time

$$O\left(|V| + \sum_{e \in E} \ell_e\right),$$

which is bad in case we have edges with long length.

Alarm clocks

- ▶ Set an alarm clock for node s at time 0.
- ▶ Repeat until there are no more alarms:
Say the next alarm goes off at time T , for node y . Then:
 - ▶ The distance from s to u is T .
 - ▶ For each neighbor v of u in G :
 - ▶ If there is no alarm yet for v , set one for time $T + \ell(u, v)$.
 - ▶ If v 's alarm is set for later than $T + \ell(u, v)$, then reset it to this earlier time.

Priority queue

Priority queue is a data structure usually implemented by *heap*.

- ▶ *Insert*. Add a new element to the set.
- ▶ *Decrease-key*. Accommodate the decrease in key value of a particular element.
- ▶ *Delete-min*. Return the element with the smallest key, and remove it from the set.
- ▶ *Make-queue*. Build a priority queue out of the given elements, with the given key values. (In many implementations, this is significantly faster than inserting the elements one by one.)

Dijkstra's shortest-path algorithm

DIJKSTRA(G, ℓ, s)

Input: Graph $G = (V, E)$, directed or undirected;
positive edge length $\{\ell_e \mid e \in E\}$; vertex $s \in V$

Output: For all vertices u reachable from s , $\text{dist}(u)$ is set
to the distance from s to u .

1. **for all** $u \in V$ **do**
2. $\text{dist}(u) = \infty$
3. $\text{prev}(u) = \text{nil}$
4. $\text{dist}(s) = 0$
5. $H = \text{makequeue}(V)$ (using dist -values as keys)
6. **while** H is not empty **do**
7. $u = \text{deletemin}(H)$
8. **for all** edge $(u, v) \in E$ **do**
9. **if** $\text{dist}(v) > \text{dist}(u) + \ell(u, v)$ **then**
10. $\text{dist}(v) = \text{dist}(u) + \ell(u, v)$
11. $\text{prev}(v) = u$
12. $\text{decreasekey}(H, v)$

An alternative derivation

1. Initialize $\text{dist}(s) = 0$, other $\text{dist}(\cdot)$ to ∞
2. $R = \{ \}$ (the “known region”)
3. **while** $R \neq V$ **do**
4. Pick the node $v \notin R$ with smallest $\text{dist}(\cdot)$
5. Add v to R
6. **for all** edge $(v, z) \in E$ **do**
7. **if** $\text{dist}(z) > \text{dist}(v) + \ell(v, z)$ **then**
8. $\text{dist}(z) = \text{dist}(v) + \ell(v, z)$

Key property

At the end of each iteration of the while loop, the following conditions hold:

- (1) there is a value d such that all nodes in R are at distance $\leq d$ from s and all nodes outside R are at distance $\geq d$ from s ;
- (2) for every node u , the value $\text{dist}(u)$ is the length of the shortest path from s to u whose intermediate nodes are constrained to be in R (if no such path exists, the value is ∞).

Running time

Since `makequeue` takes at most as long as $|V|$ insert operations, we get a total of $|V|$ `deletemin` and $|V| + |E|$ `insert/decreasekey` operations.

The time needed for these varies by implementation; for instance, a *binary heap* gives an overall running time of

$$O((|V| + |E|) \log |V|).$$

Which heap is best?

Implementation	deletemin	insert/ decreasekey	$ V \times \text{deletemin} +$ $(V + E) \times \text{insert}$
Array	$O(V)$	$O(1)$	$O(V ^2)$
Binary heap	$O(\log V)$	$O(\log V)$	$O((V + E) \log V)$
d -ary heap	$O\left(\frac{d \log V }{\log d}\right)$	$O\left(\frac{\log V }{\log d}\right)$	$O\left(\frac{(d V + E) \log V }{\log d}\right)$
Fibonacci heap	$O(\log V)$	$O(1)$ (amortized)	$O(V \log V + E)$

Priority queue implementations

Array

The simplest implementation of a priority queue is as an *unordered array* of key values for all potential elements (the vertices of the graph, in the case of Dijkstra's algorithm).

Initially, these values are set to ∞ .

An insert or decreasekey is fast, because it just involves adjusting a key value, an $O(1)$ operation.

To deletemin, on the other hand, requires a linear-time scan of the list.

Binary heap

Here elements are stored in *a complete binary tree*.

In addition, a special ordering constraint is enforced:

the key value of any node of the tree is less than or equal to that of its children.

In particular, therefore, the root always contains the smallest element.

To insert, place the new element at the bottom of the tree (in the first available position), and let it “*bubble up*.”

The number of *swaps* is at most the height of the tree $\lfloor \log_2 n \rfloor$, when there are n elements.

A decreasekey is similar, except the element is already in the tree, so we let it bubble up from its current position.

To deletemin, return the root value.

To then remove this element from the heap, take the last node in the tree (in the rightmost position in the bottom row) and place it at the root.

Then let it “*sift down*.” Again this takes $O(\log n)$ time.

d -ary heap

A d -ary heap is identical to a binary heap, except that nodes have d children.

This reduces the height of a tree with n elements to

$$\Theta(\log_d n) = \Theta((\log n)/(\log d))$$

Inserts are therefore speeded up by a factor of $\Theta(\log d)$.

Delete-min operations, however, take a little longer, namely $O(d \log_d n)$.

Shortest paths in the presence of negative edges

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They start off at ∞ , and the only way they ever change is by updating along an edge:

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$$\text{dist}(v) = \min\{\text{dist}(v), \text{dist}(u) + \ell(u, v)\}$$

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It doesn't matter what other updates occur on these edges, or what happens in the rest of the graph, because updates are *safe*.

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Input: Graph $G = (V, E)$;

edge lengths $\{\ell_e \mid e \in E\}$ with **no negative cycles**, vertex $s \in V$

Output: For all vertices u reachable from s , $\text{dist}(u)$ is set to the distance from s to u .

1. **for all** $u \in V$ **do**
2. $\text{dist}(u) = \infty$
3. $\text{prev}(u) = \text{nil}$
4. $\text{dist}(s) = 0$
5. repeat $|V| - 1$ times:
6. **for all** $e \in E$ **do**
7. $\text{update}(e)$

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Running time: $O(|V| \cdot |E|)$.

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How to detect the existence of negative cycles:

Instead of stopping after $|V| - 1$ iterations, perform one extra round.
There is a negative cycle if and only if some dist value is reduced during this final round.

Shortest paths in dags

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In any path of a dag, the vertices appear in increasing linearized order.

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4. $\text{dist}(s) = 0$
5. Linearize G
6. **for each** $u \in V$ in linearized order **do**
7. **for all** edges $(u, v) \in E$ **do**
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In particular, we can find longest paths in a dag by the same algorithm: *just negate all edge lengths.*

Chapter 5. Greedy algorithms

Minimum spanning trees

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This translates into a graph problem in which

- ▶ nodes are computers,
- ▶ undirected edges are potential links, each with a *maintenance cost*.

The goal is to

- ▶ pick enough of these edges that the nodes are *connected*,
- ▶ the total maintenance cost is *minimum*.

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Removing a cycle edge cannot disconnect a graph.

So the solution must be connected and acyclic: undirected graphs of this kind are called **trees**. A tree with *minimum total weight*, is a **minimum spanning tree**.

Input: An undirected graph $G = (V, E)$; edge weights w_e

Output: A tree $T = (V, E')$ with $E' \subseteq E$ that *minimizes*

$$\text{weight}(T) = \sum_{e \in E'} w_e.$$

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Any connected, undirected graph $G = (V, E)$ with $|E| = |V| - 1$ is a tree.

Lemma (4)

*An undirected graph is a tree if and only if there is a **unique** path between any pair of nodes.*

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Repeatedly add the next lightest edge that doesn't produce a cycle.

The correctness of Kruskal's method follows from a certain *cut property*.

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Lemma (Cut property)

Suppose edges X are part of a minimum spanning tree (MST) of $G = (V, E)$. Pick any subset of nodes S for which X does not cross between S and $V \setminus S$, and let e be the *lightest* edge across this partition. Then

$$X \cup \{e\}$$

is part of some MST.

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The cut property says that it is always safe to add the lightest edge across any cut (that is, between a vertex in S and one in $V \setminus S$), provided X has no edges across the cut.

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T' is connected by Lemma (1), since e' is a cycle edge.

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T' is connected by Lemma (1), since e' is a cycle edge. And it has the same number of edges as T ; so by Lemmas (2) and (3), it is also a tree.

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Since T is an MST, it must be the case that $\text{weight}(T') = \text{weight}(T)$ and that T' is also an MST.

Kruskal's algorithm

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KRUSKAL(G, w)

Input: A connected undirected graph $G = (V, E)$ with edge weight w_e

Output: A minimum spanning tree defined by the edges X .

1. **for all** $u \in V$ **do**
2. **makeset**(u)
3. $X = \{\}$
4. Sort the edges E by weight
5. **for all** edge $\{u, v\} \in E$ in increasing order of weight **do**
6. **if** $\text{find}(u) \neq \text{find}(v)$ **then**
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$ V $	makeset (x)	create a singleton set containing x
$2 \cdot E $	find (x)	find the set that x belongs to
$ V - 1$	union (x, y)	merge the sets containing x and y

A data structure for disjoint sets

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In addition to a parent pointer π , each node also has a **rank** that, for the time being, should be interpreted as the height of the subtree hanging from that node.

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The tree actually gets built via the third operation, **union**, and so we must make sure that this procedure keeps trees *shallow*.

Union

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UNION(x, y)

$r_x = \text{find}(x)$

$r_y = \text{find}(y)$

if $r_x = r_y$ **then** return

if $\text{rank}(r_x) > \text{rank}(r_y)$

then $\pi(r_u) = r_x$

else

$\pi(r_x) = r_y$

if $\text{rank}(r_x) = \text{rank}(r_y)$ **then** $\text{rank}(r_y) = \text{rank}(r_y) + 1$

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Lemma (3)

If there are n elements overall, there can be at most $n/2^k$ nodes of rank k .