

Algorithm Design, Analysis & Complexity

Lecture 5 - Graph Algorithms

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Shortest Path on Weighted Graph

Definition

Let $G = (V, E)$ be a weighted, directed graph with weight function $w : E \rightarrow \mathbb{R}$.

Let $P = \langle v_0, v_1, \dots, v_k \rangle$ be a path. The **weight** of P is defined as

$$w(P) := \sum_{i=0}^{k-1} w(v_i, v_{i+1}).$$

The **shortest path weight** $\delta(u, v)$ from u to v is defined as

$$\delta(u, v) := \begin{cases} \min\{w(P) \mid P \text{ is a path from } u \text{ to } v\} & \text{if such a path exists} \\ \infty & \text{otherwise.} \end{cases}$$

Shortest Path Problem

Problem

Given a weighted, directed graph $G = (V, E)$ with weight function $w : E \rightarrow \mathbb{R}$, compute a shortest path from a source node s to a destination node t .

Optimal substructure of a shortest path

Let $P = \langle v_0, \dots, v_k \rangle$ be a shortest path from v_0 to v_k . Then $\langle v_i, \dots, v_j \rangle$ is a shortest path from v_i to v_j for any $0 \leq i < j \leq k$.

Variations

The shortest path problem has a few variants.

1. Single source shortest path
2. Single destination shortest path
3. All pairs shortest path
4. Negative weights

Single source shortest path on nonnegative weights

```
1: procedure DIJKSTRA( $G = (V, E, w), s$ )
2:   Define array  $d$  of size  $|V|$ 
3:   Set  $d[v] = \infty$  for all  $v \in V$ 
4:   Set  $d[s] = 0$ 
5:   Define array  $\Pi$  of size  $|V|$ 
6:   Set  $\Pi[v] = NIL$  for all  $v \in V$ 
7:   Let  $Q$  be a priority queue initialized with  $(v, d[v])$  for  $v \in V$ 
8:    $S := \emptyset$ 
9:   while  $Q \neq \emptyset$  do
10:     $u = \text{Extract-Min}(Q)$ 
11:     $S = S \cup \{u\}$ 
12:    for each vertex  $v \in \text{Adj}[u]$  do
13:      if  $d[v] > d[u] + w[u, v]$  then
14:         $d[v] = d[u] + w[u, v]$ 
15:         $\Pi[v] = u$ 
16:         $\text{Decrease-Key}(Q, v)$ 
```

Proof of correctness

Theorem

After the DIJKSTRA algorithm terminates, we get

$$d[v] = \delta(s, v) \text{ for all } v \in V.$$

Proof.

By mathematical induction on the size of S .

Base Case. When $|S| = 1$, then $s \in S$ and $\delta(s, s) = 0 = d[s]$.

Ind. Hyp. Assume $\delta(s, x) = d[x]$ for all $x \in S$ when $|S| = i$.

Ind. Step. Show $\delta(s, u) = d[u]$, where u is the $(i + 1)^{th}$ element added to S .

Note that for u to be added to S , it has to be removed from Q , which means at this stage it has the minimum d value, i.e.,

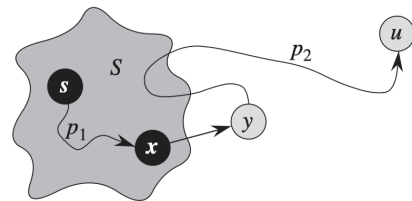
$$d[u] \leq d[z] \text{ for all } z \notin S.$$

Proof of correctness

Assume, for a contradiction, that there is a shortest path P from s to u of length $\delta(s, u) < d[u]$. Let $e = (x, y)$ be the edge where P crosses the boundary of S for the first time.

Observe the following:

1. $\delta(s, x) = d[x]$, since $x \in S$ (by Ind. Hyp.)
2. $d[u] \leq d[y]$ (by the algorithm)
3. $d[y] \leq d[x] + w[x, y]$ (by the algorithm)



By combining all these inequalities, we get

$$\delta(s, u) < d[u] \leq d[y] \leq d[x] + w[x, y] = \delta(s, x) + w[x, y] \leq \delta(s, u)$$

(the last inequality is because of nonnegative weights), which yields the necessary contradiction.

Hence, $d[u] = \delta(s, u)$.



Complexity

- ▶ The Extract-Min operation runs n times, and takes $\Theta(n \lg n)$ computations.
- ▶ The Decrease-Key operation runs m times, and takes $\Theta(m \lg n)$ computations, if implemented with a binary heap.

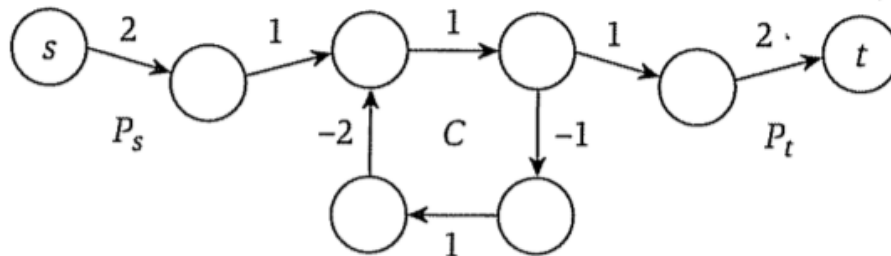
Thus, total time complexity if Q is implemented via a **binary heap** is $\Theta(m \lg n)$.

But if Q is implemented using **Fibonacci heap**, then the amortized cost of running all the Decrease-Key operations drops to $\Theta(n \lg n)$. The inside loop still runs m times across all runs of the outer loop, giving a total complexity of $\Theta(m + n \lg n)$.

Single-destination shortest path on negative weights

Unfortunately, DIJKSTRA doesn't work when the weights are allowed to be negative. Having the weights to be nonnegative is a crucial part in the proof of DIJKSTRA.

When weights are allowed to be negative, there can be more complications. For example, if there is a negative weight cycle (all edges on the cycle have negative weights), then the shortest path weight between two vertices on the cycle is $-\infty$, i.e., there is no “shortest” path between those two vertices.



Fortunately, that's the only hindrance to having a shortest path!

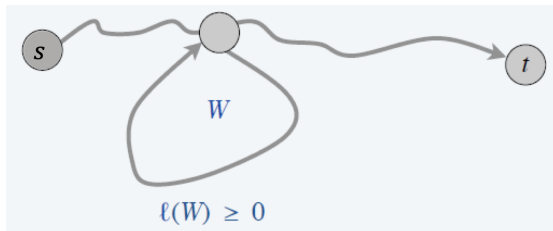
Why?

Lemma

If $G = (V, E)$ has no negative cycle and t is reachable from s , then there is a shortest path from s to t that is simple (i.e., does not repeat nodes), and hence has at most $|V|-1$ edges.

Proof.

Since every cycle has nonnegative weight, the shortest path P from s to t with the fewest number of edges does not repeat any vertex v .



For if P did repeat a vertex v , the portion of P between consecutive visits to v can be removed, resulting in a path of no greater cost. □

DP Solution

We will use DP to solve the shortest path problem on weighted graphs with negative weights.

Define $OPT(i, v)$ to be the shortest path weight from v to t using at most i edges. By Lemma 2, our goal is to compute the value of $OPT(n-1, s)$.

Let P be an optimal path representing $OPT(i, v)$. Now, two things can happen:

1. P uses at most $i-1$ edges. In this case,
 $OPT(i, v) = OPT(i-1, v)$.
2. P uses i edges with the first edge being (v, u) . In this case,
 $OPT(i, v) = w(v, u) + OPT(i-1, u)$.

This gives the following recursive formula: if $i > 0$, then

$$OPT(i, v) = \min\{OPT(i-1, v), \min_{u \in V}\{OPT(i-1, u) + w(v, u)\}\}.$$

DP Solution

Define an array M such that $M[i, v]$ denotes $OPT(i, v)$.

Now, we write a bottom-up iterative algorithm to compute M .

```
1: procedure SHORTESTPATH( $G = (V, E, w), t$ )
2:   Let  $n := |V|, m := |E|$ 
3:   Define 2-D array  $M[0, \dots, n-1, v_0, \dots, v_{n-1}]$ 
4:    $M[0, t] = 0$  and  $M[0, v] = \infty$  for all  $v \in V \setminus \{t\}$ 
5:   for  $i = 1, \dots, n-1$  do
6:     for  $v \in V$  do
7:        $M[i, v] = M[i-1, v]$ 
8:       for  $u \in Adj[v]$  do
9:         if  $M[i, v] > M[i-1, u] + w[v, u]$  then
10:            $M[i, v] = M[i-1, u] + w[v, u]$ 
11:   return  $M$ 
```

Complexity: $\Theta(n \sum_{v \in V} n_v) = \Theta(nm)$.

Here n_v is the **degree** of node v (number of edges going out of v).

Space Complexity

Space complexity: $\Theta(n^2)$.

But a close look at the algorithm shows that we don't need to store $M[i, v]$ for all values of i . We just need the values at stage $i-1$ to compute the values for stage i .

Hence, we can use a 1-D array, and rewrite the above algorithm as follows.

Bellman-Ford Algorithm

```
1: procedure BELLMAN-FORD( $G = (V, E, w), t$ )
2:   Let  $n := |V|, m = |E|$ 
3:   Define 1-D array  $M[v_0, \dots, v_{n-1}]$ 
4:    $M[t] = 0$  and  $M[v] = \infty$  for all  $v \in V \setminus \{t\}$ 
5:   for  $i = 1, \dots, n-1$  do
6:     for  $v \in V$  do
7:       for  $u \in Adj[v]$  do
8:         if  $M[v] > M[u] + w[v, u]$  then
9:            $M[v] = M[u] + w[v, u]$ 
10:  for each edge  $(v, u) \in E$  do
11:    if  $M[v] > M[u] + w[v, u]$  then
12:      return NIL
13:  return  $M$ 
```

Time Complexity: $\Theta(nm)$.

Space Complexity: $\Theta(n)$.

BELLMAN-FORD Analysis

BELLMAN-FORD not only computes M for a graph with negative weights, but it also returns whether the graph has a negative cycle or not. If there is a negative cycle, it returns NIL; otherwise, it returns the computed array M .

Claim

If there is a negative weight cycle in G that can reach t , BELLMAN-FORD returns NIL.

Proof.

Assume G contains a negative weight cycle that can reach t . Let this cycle be $c = \langle v_0, v_1, \dots, v_k \rangle$ where $v_0 = v_k$. Then

$$\sum_{i=1}^k w(v_{i-1}, v_i) < 0.$$

Assume for a contradiction that BELLMAN-FORD does not return NIL. Thus, $M[v_{i-1}] \leq M[v_i] + w(v_{i-1}, v_i)$ for $i = 1, \dots, k$.

BELLMAN-FORD Analysis

Proof (cont.)

Summing the inequalities around the cycle c gives

$$\begin{aligned}\sum_{i=1}^k M[v_{i-1}] &\leq \sum_{i=1}^k \left(M[v_i] + w(v_{i-1}, v_i) \right) \\ &= \sum_{i=1}^k M[v_i] + \sum_{i=1}^k w(v_{i-1}, v_i) \\ &= \sum_{i=1}^k M[v_{i-1}] + \sum_{i=1}^k w(v_{i-1}, v_i) \quad (\text{since } v_0 = v_k).\end{aligned}$$

This implies $\sum_{i=1}^k w(v_{i-1}, v_i) \geq 0$, a contradiction. Hence, BELLMAN-FORD returns NIL. □

Exercise: Modify BELLMAN-FORD to find an actual shortest path from any vertex v to t .

All-pairs shortest path

Let $G = (V, E)$ be a weighted directed graph with $|V| = n$ and $|E| = m$. The goal now is to find a shortest path from *any* vertex to *any* other vertex in G .

An obvious thing to do is to run a single source shortest path algorithm from every vertex in the graph.

On non-negative weighted graph, we can apply DIJKSTRA from each vertex. This has a complexity of $\Theta(n^2 \lg n + nm)$.

On a graph with negative weights but no negative cycle, we can apply BELLMAN-FORD from each vertex. This has a complexity of $\Theta(n^2 m)$.

Question: Can we do any better?

Generalization of BELLMAN-FORD

Define $\ell_{ij}^{(m)} :=$ shortest path weight from vertex v_i to vertex v_j that contains at most m edges. Then

$$\ell_{ij}^{(0)} = \begin{cases} 0 & \text{if } i = j \\ \infty & \text{if } i \neq j, \end{cases}$$

and for $m \geq 1$,

$$\begin{aligned} \ell_{ij}^{(m)} &= \min \left\{ \ell_{ij}^{(m-1)}, \min_{1 \leq k \leq n, k \neq j} \{ \ell_{ik}^{(m-1)} + w(k, j) \} \right\} \\ &= \min_{1 \leq k \leq n} \{ \ell_{ik}^{(m-1)} + w(k, j) \} \quad (\text{since } w(j, j) = 0) \end{aligned}$$

We now use this recurrence to compute a series of matrices $L^{(1)}, L^{(2)}, \dots, L^{(n-1)}$, where $L^{(k)} = (\ell_{ij}^{(k)})$, starting with $L^{(1)} = W = (w(i, j))$ and ending with $L^{(n-1)}$ which contains the actual shortest path weights.

Generalization of BELLMAN-FORD

```
1: procedure SLOW-ALL-PAIRS-SHORTEST-PATHS( $W$ )
2:    $n :=$  number of rows of  $W$ 
3:    $L^{(1)} := W$ 
4:   for  $k = 2, \dots, n-1$  do
5:      $L^{(k)} = \text{EXTEND-SHORTEST-PATHS}(L^{(k-1)}, W)$ 
6:   return  $L^{(n-1)}$ 
```

Generalization of BELLMAN-FORD

```
1: procedure EXTEND-SHORTEST-PATHS( $L, W$ )
2:    $n :=$  number of rows of  $L$ 
3:   Let  $L'$  be a new  $n \times n$  matrix
4:   for  $i = 1, \dots, n$  do
5:     for  $j = 1, \dots, n$  do
6:        $L'[i, j] = \infty$ 
7:       for  $k = 1, \dots, n$  do
8:         if  $L'[i, j] > L[i, k] + W[k, j]$  then
9:            $L'[i, j] = L[i, k] + W[k, j]$ 
10:  return  $L'$ 
```

Complexity

The complexity of the EXTEND-SHORTEST-PATHS is $\Theta(n^3)$.

Thus, the complexity of SLOW-ALL-PAIRS-SHORTEST-PATHS is $\Theta(n^4)$.

Unfortunately, this is no better than running BELLMAN-FORD from every vertex.

However, the complexity can be improved to $\Theta(n^3 \lg n)$ by computing $L^{(n-1)}$ as follows:

$$\begin{aligned} L^{(1)} &= W \\ L^{(2)} &= W \cdot W = W^2 \\ L^{(4)} &= W^2 \cdot W^2 = W^4 \\ L^{(8)} &= W^4 \cdot W^4 = W^8 \\ &\vdots \\ L^{(2^{\lceil \lg(n-1) \rceil})} &= W^{2^{\lceil \lg(n-1) \rceil}}. \end{aligned}$$

A different DP solution

Redefining the DP subproblems in a different way gives us a better algorithm.

Let $G = (V, E)$ with $V = \{1, 2, \dots, n\}$.

Define $d_{ij}^{(k)} :=$ shortest path weight from vertex i to vertex j for which all intermediate vertices are in the set $\{1, \dots, k\}$.

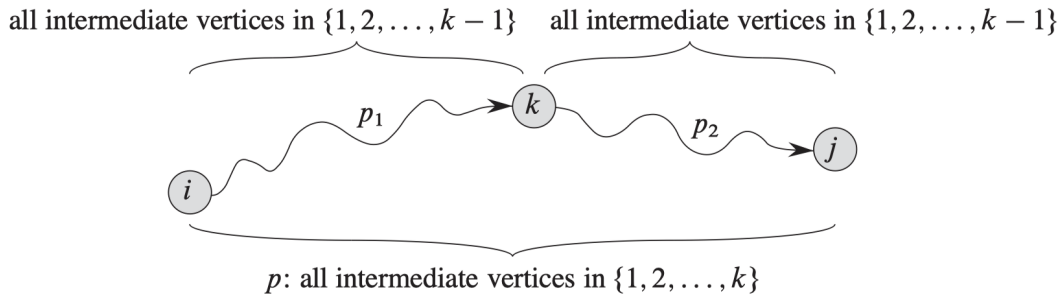
(An **intermediate** vertex on a path from i to j is any vertex on the path other than i or j .)

For $k = 0$, we have $d_{ij}^{(0)} = w(i, j)$ (direct edges).

Now, consider a shortest path P from i to j where all the intermediate vertices are in the set $\{1, \dots, k\}$. Then two things can happen:

1. k is not an intermediate vertex on P : in this case,
$$d_{ij}^{(k)} = d_{ij}^{(k-1)}.$$
2. k is an intermediate vertex on P : in this case,
$$d_{ij}^{(k)} = d_{ik}^{(k-1)} + d_{kj}^{(k-1)}.$$

A different DP solution



Consequently, we obtain the following recurrence:

$$d_{ij}^{(k)} = \min\{d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)}\}.$$

We now use this recurrence to compute a series of matrices $D^{(0)}, D^{(1)}, \dots, D^{(n)}$, where $D^{(k)} = (d_{ij}^{(k)})$, starting with $D^{(0)} = W = (w(i, j))$ and ending with $D^{(n)}$ which contains the actual shortest path weights.

Floyd-Warshall Algorithm

```
1: procedure FLOYD-WARSHALL( $W$ )
2:    $n :=$  number of rows of  $W$ 
3:    $D^{(0)} := W$ 
4:   for  $k = 1, \dots, n$  do
5:     Let  $D^{(k)}$  be a new  $n \times n$  matrix
6:     for  $i = 1, \dots, n$  do
7:       for  $j = 1, \dots, n$  do
8:         if  $D^{(k-1)}[i, j] > D^{(k-1)}[i, k] + D^{(k-1)}[k, j]$  then
9:            $D^{(k)}[i, j] = D^{(k-1)}[i, k] + D^{(k-1)}[k, j]$ 
10:        else
11:           $D^{(k)}[i, j] = D^{(k-1)}[i, j]$ 
12:   return  $D^{(n)}$ 
```

Complexity: $\Theta(n^3)$.

Exercise: Modify FLOYD-WARSHALL to find an actual shortest path from any vertex i to any vertex j .

Johnson's algorithm for sparse graphs

If we have a graph with negative weights, then one might hope to somehow re-weight the edges to nonnegative weights such that the shortest paths do not change. The following lemma gives one such way.

Lemma

Given a weighted directed graph $G = (V, E)$ with weight function $w : E \rightarrow \mathbb{R}$, let $h : V \rightarrow \mathbb{R}$ be any function mapping vertices to real numbers. For each edge $(u, v) \in E$, define

$$\hat{w}(u, v) = w(u, v) + h(u) - h(v).$$

Let $P = \langle v_0, v_1, \dots, v_k \rangle$ be any path from v_0 to v_k . Then P is a shortest path from v_0 to v_k with weight function w if and only if it is a shortest path with weight function \hat{w} .

Furthermore, G has a negative weight cycle using w if and only if G has a negative weight cycle using \hat{w} .

Proof of lemma

Proof.

$$\begin{aligned}\hat{w}(P) &= \sum_{i=1}^k \hat{w}(v_{i-1}, v_i) \\ &= \sum_{i=1}^k \left(w(v_{i-1}, v_i) + h(v_{i-1}) - h(v_i) \right) \\ &= \sum_{i=1}^k w(v_{i-1}, v_i) + h(v_0) - h(v_k) \\ &= w(P) + h(v_0) - h(v_k).\end{aligned}$$

Thus, the new weight of any path P depends on the old weight of P and the values of the function h at the starting and the ending vertices. Since all path weights between two given vertices change by a constant amount, the shortest paths do not change under the new weight function \hat{w} .

If P is a cycle, then $v_0 = v_k$, and hence $w(P) = \hat{w}(P)$. This proves the second statement of the claim. □

How to define h ?

The big question now is: how to come up with a function h so that all negative weights under w become nonnegative under \hat{w} ?

The following idea works!

Given a graph $G = (V, E, w)$, introduce a new vertex s and make a new graph $G' = (V', E', w')$, where

$$\begin{aligned}V' &= V \cup \{s\} \\E' &= E \cup \{(s, v) \mid v \in V\} \\w'(s, v) &= 0 \text{ for all } v \in V.\end{aligned}$$

Assume G and G' have no negative-weight cycles.

Define $h(v) = \delta(s, v)$ for all $v \in V'$ (where $\delta(s, v)$ stands for the shortest path weight from s to v).

By triangle inequality of shortest path weights, it follows that $h(v) \leq h(u) + w(u, v)$ for all $(u, v) \in E'$.

Thus, $w'(u, v) := w(u, v) + h(u) - h(v) \geq 0$ for all $(u, v) \in E'$.

Johnson's Algorithm

```
1: procedure JOHNSON( $G, w$ )
2:   Define  $G'$  where  $V' = V \cup \{s\}$ ,  $E' = E \cup \{(s, v) \mid v \in V\}$ 
3:   Set  $w(s, v) = 0$  for all  $v \in V$ 
4:   if BELLMAN-FORD( $G', w, s$ ) == NIL then
5:     return NIL
6:   else
7:     for  $v \in V$  do
8:       Set  $h(v) := \delta(s, v)$  as computed by BELLMAN-FORD
9:     for  $(u, v) \in E$  do
10:      Set  $\hat{w}(u, v) := w(u, v) + h(u) - h(v)$ 
11:     Let  $D = (d_{uv})$  be a new  $n \times n$  matrix
12:     for  $u \in V$  do
13:       Run DIJKSTRA( $G, \hat{w}, u$ ) to compute  $\hat{\delta}(u, v) \ \forall v \in V$ 
14:       for  $v \in V$  do
15:          $D[u, v] = \hat{\delta}(u, v) - (h(u) - h(v))$ 
16:     return  $D$ 
```

Complexity

Note that we run BELLMAN-FORD only once from the vertex s . We use that to compute h , and consequently, \hat{w} .

After that we run DIJKSTRA n times, since all the weights $\hat{w}(u, v)$ are now nonnegative.

Hence, the total complexity of JOHNSON is $\Theta(n^2 \lg n + nm)$.

For sparse graphs (where $m \ll n^2$), this is better than $\Theta(n^3)$.