

ADA Final Exam Preparation

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Contents

1	All-pairs distances problem	2
1.1	A DP algorithm	2
1.2	Floyd and Warshall's DP algorithm	3
1.3	Johnson's reweighting technique	3
2	Maximum flow	5
2.1	Ford-Fulkerson's algorithm	6

Chapter 1

All-pairs distances problem

Lecture 1

Problem 1.0.1.

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- Input: an edge-weighted directed graph G with $V(G) = \{1, 2, \dots, n\}$ that has no cycle of negative weight.
- Output: $d_G(i, j)$ for all vertices i and j of G .

Remark 1.0.1. Here we suppose G has no negative cycle to simplify the problem.

The Naive algorithm is to solve n single-source distances problems directly. Hence, the time complexity for using different algorithm is:

- General edge weights: Bellman-Ford's algorithm takes $O(mn^2)$ time, which can be $\Theta(n^4)$ when $m = \Theta(n^2)$.
- Acyclic: Lawler's algorithm takes $O(mn)$ time.
- Non-negative edge weights: Dijkstra's takes $O(mn + n^2 \log n)$ time.

However, naive method takes a lot of time to compute unnecessary things, so it takes a lot of times.

1.1 A DP algorithm

Definition 1.1.1. Let $w_k(i, j)$ be the length of a shortest (i, j) -path having at most k edges. Let it be ∞ if such a path does not exist.

We have

$$w_1(i, j) = w(ij) \text{ if } (i, j) \text{ is an edge, otherwise } w_1(i, j) = \infty.$$

$w_{n-1}(i, j) = d_G(i, j)$ since a shortest path has at most $n - 1$ edges (note that there is no negative cycle).

Hence, we have

$$w_{2k}(i, j) = \min_{1 \leq t \leq n} w_k(i, t) + w_k(t, j) \text{ for all } k \geq 1.$$

Also, note that even if $k \geq \frac{n}{2}$ this recurrence relation is still correct, so we can just compute $w_1(i, j)$ then $w_2(i, j)$ then $w_4(i, j)$ and so on, and after $O(\log n)$ rounds we can get the answer.

Now we analyze the time complexity. For each (i, j) -pair, we need $O(\log n)$ rounds, where each round takes $O(n)$ times, so each (i, j) -pair takes $O(n \log n)$ times. Note that we have $O(n^2)$ (i, j) -pairs, so it takes totally $O(n^3 \log n)$ times. This is pretty slow, but in general a little bit faster than doing Bellman-Ford's algorithm for n times.

1.2 Floyd and Warshall's DP algorithm

Definition 1.2.1. Let $d_k(i, j)$ be the length of any shortest (i, j) -path whose internal indices are at most k . If there is no such a path, then let $d_k(i, j) = \infty$.

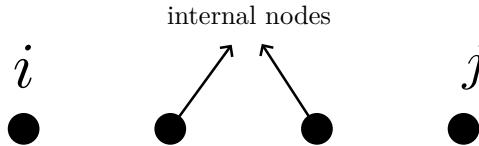


Figure 1.1: Internal Nodes

Thus, we have

$$d_0(i, j) = w(i, j), \quad d_n(i, j) = d_G(i, j).$$

Hence, we can define a recurrence relation:

$$\begin{cases} d_0(i, j) = w(i, j) \\ d_{k+1}(i, j) = \min \{d_k(i, j), d_k(i, k+1) + d_k(k+1, j)\}. \end{cases}$$

Note that it corresponds to two cases: walk through $k+1$ or not. If not, then it corresponds to $d_k(i, j)$. If so, then it corresponds to $d_k(i, k+1) + d_k(k+1, j)$ since excluding $k+1$ and separate this path into two parts, then internal nodes in each part can have indices of at most k .

Now we analyze the time complexity of Floyd and Warshall's DP algorithm: Fix (i, j) , then it takes $O(n)$ time to compute from $d_0(i, j)$ to $d_n(i, j)$, and since we have $O(n^2)$ (i, j) -pairs, so it takes totally $O(n^3)$ time.

1.3 Johnson's reweighting technique

As previously seen, if G is a non-negative weighted graph, then running Dijkstra's algorithm for n times needs $O(mn + n \log n)$ time. Now Johnson gives a method to reweight w into \hat{w} s.t.

- \hat{w} is non-negative
- any shortest (i, j) -path of G w.r.t. \hat{w} is a shortest (i, j) -path of G w.r.t. w .

The idea of reweighting is to

- Assign a weight $h(i)$ to each vertex i of G .
- Let $\hat{w}(i, j) = w(i, j) + h(i) - h(j)$.
- Then, for any (i, j) -path P , we have

$$\hat{w}(P) = w(P) + h(i) - h(j).$$

- Hence, P is a shortest (i, j) -path of G w.r.t. \hat{w} if and only if P is a shortest (i, j) -path of G w.r.t. w .

Remark 1.3.1. The challenge is to find a vertex weight h s.t. the resulting adjusted edge weight \hat{w} is non-negative. If \hat{w} is non-negative, then we can apply Dijkstra's algorithm to obtain all-pairs shortest path trees in $O(mn + n^2 \log n)$ time.

Algorithm 1.1: Johnson's Technique

- 1 Let H be obtained from G by adding a new vertex 0 and adding a weight-0 edge from vertex 0 to each vertex i of G .
 - 2 H has no negative cycle if and only if G has no negative cycle.
 - 3 Let $h(i)$ be the distance from vertex 0 to vertex i in H . That is, $h(i) = d_H(0, i)$.
 - 4 The vertex weight function h can be obtained by Bellman-Ford in $O(mn)$ time.
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Remark 1.3.2. H has no negative cycle if and only if G has no negative cycle since G is directed and vertex 0 has only out degree, so any cycle in H and G is induced by $\{1, 2, \dots, n\}$, which does not include 0.

Remark 1.3.3. $d_H(0, i) \leq 0$ and $d_H(0, i) < 0$ if there is a path of negative weight from j to i for some $j > 0$ since we can go from 0 to j first, then go from j to i .

Theorem 1.3.1. $\hat{w}(i, j) \geq 0$ for all $i, j \in [n]$.

Proof. Since

$$\hat{w}(i, j) = w(i, j) + h(i) - h(j) = w(i, j) + d_H(0, i) - d_H(0, j),$$

and note that $d_H(0, i) + w(i, j)$ is the shortest distance of a path from 0 and go through i to j , which is \geq the distance from 0 to j , which is $d_H(0, j)$. Hence, we have

$$d_H(0, i) + w(i, j) - d_H(0, j) \geq 0.$$

■

Now we analyze the time complexity of Johnson's algorithm for general edge weights: We first obtain h by doing one time Bellman-Ford's algorithm, which takes $O(mn)$ time. Then, we run Dijkstra's algorithm for all vertex i of G , which takes totally $O(mn + n^2 \log n)$ time. Note that to here we just store n shortest path tree, and we have to obtain the real distance by running through all n tree, which takes $O(n) \cdot n = O(n^2)$ time since a tree has $n - 1$ edges. Hence, it totally take $O(mn + n^2 \log n)$ time for Johnson's technique.

Chapter 2

Maximum flow

Problem 2.0.1 (The maximum flow problem).

- Input: A directed graph G with edge capacity $c : E(G) \rightarrow \mathbb{R}^+$ and two vertices, the source s and the sink t .
- Output: An (s, t) -flow with maximum (flow) value.

Remark 2.0.1. For convenience, we allow G has multiple/parallel edges, though merging multiple edges and increase the capacity to get an equivalent graph is not forbiden.

Remark 2.0.2. An (s, t) -flow is a function $f : E(G) \rightarrow \mathbb{R}^+ \cup \{0\}$ satisfying

- capacity constraint: $f(uv) \leq c(uv)$ for each edge uv of G .
- conservation law:

$$\sum_{uv \in E(G)} f(uv) = \sum_{vw \in E(G)} f(vw)$$

for each vertex v of G other than s and t .

The value of an (s, t) -flow f is

$$\sum_{sv \in E(G)} f(sv) - \sum_{us \in E(G)} f(us).$$

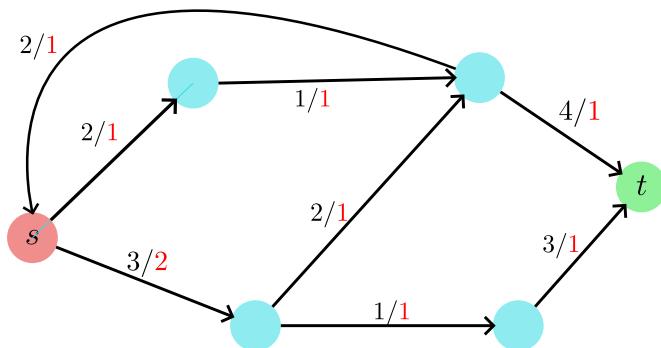


Figure 2.1: The maximum flow problem

2.1 Ford-Fulkerson's algorithm

Intuition. Reduce the maximum (s, t) -flow problem to the reachability problems for a sequence of graph R .

Definition 2.1.1 (Residual graph). The residual graph $R(f)$ with respect to a flow f of G with $V(R(f)) = V(G)$ is defined as follows for each edge uv of G :

- If $f(uv) < c(fg)$, then let $R(f)$ have an edge $\textcolor{red}{uv}$ with capacity $c(uv) - f(uv)$.
- If $f(uv) > 0$, then let $R(f)$ have an edge $\textcolor{blue}{vu}$ with capacity $f(uv)$.

Corollary 2.1.1. $R(f)$ is a graph with capacity of every edge positive, just like G .

Remark 2.1.1. Even if G has only one uv edge, $R(f)$ may have 2 uv edges if $f(uv) < c(uv)$ and $f(vu) > 0$.

Theorem 2.1.1. For any (s, t) -flow f of G , we have the following statements:

- (1) If $d_{R(f)}(s, t) = \infty$, then f is a maximum (s, t) -flow of G .
 - (2) If $d_{R(f)}(s, t) < \infty$ and g is an (s, t) -flow of the residual graph $R(f)$, then $f + g$ remains an (s, t) -flow of G , where
- $$(f + g)(uv) = f(uv) + g(uv) - g(vu)$$
- for each edge uv of G .

Appendix