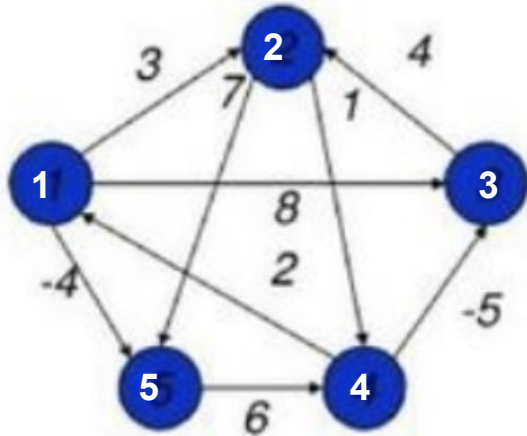


DP: All-Pairs Shortest Paths

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All-Pairs Shortest Path (APSP) Problems

The all pair shortest path algorithm is also known as Floyd-Warshall algorithm is used to find all pair shortest path problem from a given weighted graph. As a result of this algorithm, it will generate a matrix, which will represent the minimum distance from any node to all other nodes in the graph.



	To node:				
From node	1	2	3	4	5
1	0	1	-3	2	-4
2	3	0	-4	1	-1
3	7	4	0	5	3
4	2	-1	-5	0	-2
5	8	5	1	6	0

Many ways to solve All-Pairs Shortest Path (APSP) Prob.

Introduction

Different types of algorithms can be used to solve the all-pairs shortest paths problem:

- Dynamic programming
- Matrix multiplication
- Floyd-Warshall algorithm
- Johnson's algorithm
- Difference constraints

Single Source Shortest Path

$\lg V$ for extract key,
Constant amortized for
each decreased key
operation in Fibonacci
heap (Dijkstra)

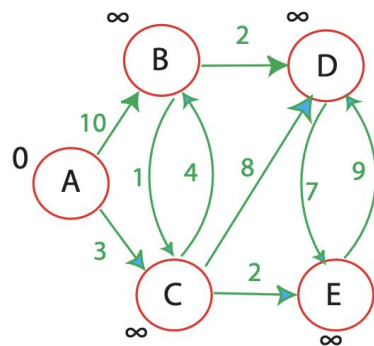
Single-source shortest paths

- given directed graph $G = (V, E)$, vertex $s \in V$ and edge weights $w : E \rightarrow \mathbb{R}$
- find $\delta(s, v)$, equal to the shortest-path weight $s \rightarrow v, \forall v \in V$ (or $-\infty$ if negative weight cycle along the way, or ∞ if no path)

Situation	Algorithm	Time	Linear Time
unweighted ($w = 1$)	BFS	$O(V + E)$	
non-negative edge weights	Dijkstra	$O(E + V \lg V)$	
general	Bellman-Ford	$O(VE)$	
acyclic graph (DAG)	Topological sort + one pass of B-F	$O(V + E)$	

All of the above results are the best known. We achieve a $O(E + V \lg V)$ bound on Dijkstra's algorithm using Fibonacci heaps.

Dijkstra's Algorithm



Dijkstra's Algorithm

For each edge $(u, v) \in E$, assume $w(u, v) \geq 0$, maintain a set S of vertices whose final shortest path weights have been determined. Repeatedly select $u \in V - S$ with minimum shortest path estimate, add u to S , relax all edges out of u .

Pseudo-code

```

Dijkstra ( $G, W, s$ )    //uses priority queue  $Q$ 
  Initialize ( $G, s$ )
   $S \leftarrow \phi$ 
   $Q \leftarrow V[G]$     //Insert into  $Q$ 
  while  $Q \neq \phi$ 
    do  $u \leftarrow \text{EXTRACT-MIN}(Q)$     //deletes  $u$  from  $Q$ 
     $S = S \cup \{u\}$ 
    for each vertex  $v \in \text{Adj}[u]$ 
      do RELAX ( $u, v, w$ )    ← this is an implicit DECREASE-KEY operation
  
```

$S = \{ \}$	{ A B C D E }	=	Q	
$S = \{ A \}$	0 ∞ ∞ ∞ ∞			
$S = \{ A, C \}$	0 10 3 ∞ ∞	←	after relaxing edges from A	
$S = \{ A, C \}$	0 7 3 11 5	←	after relaxing edges from C	
$S = \{ A, C, E \}$	0 7 3 11 5			
$S = \{ A, C, E, B \}$	0 7 3 9 5	←	after relaxing edges from B	

Figure 4: Dijkstra Execution

All-Pairs Shortest Path

All-pairs shortest paths

Parent pointer to get shortest path.

- given edge-weighted graph, $G = (V, E, w)$

- find $\delta(u, v)$ for all $u, v \in V$

A simple way of solving All-Pairs Shortest Paths (APSP) problems is by running a single-source shortest path algorithm from each of the V vertices in the graph.

Situation	Algorithm	Time	$E = \Theta(V^2)$	Dense graph
unweighted ($w = 1$)	$ V \times$ BFS	$O(VE)$	$O(V^3)$	
non-negative edge weights	$ V \times$ Dijkstra	$O(VE + V^2 \lg V)$	$O(V^3)$	
general	$ V \times$ Bellman-Ford	$O(V^2E)$	$O(V^4)$	
general	Johnson's	$O(VE + V^2 \lg V)$	$O(V^3)$	

These results (apart from the third) are also best known — don't know how to beat $|V| \times$ Dijkstra

Algorithms to solve APSP

Note that for all the algorithms described below, we assume that $w(u, v) = \infty$ if $(u, v) \notin E$.

Introduction

Different types of algorithms can be used to solve the all-pairs shortest paths problem:

- Dynamic programming
- Matrix multiplication
- Floyd-Warshall algorithm
- Johnson's algorithm
- Difference constraints

Dynamic Programming, attempt 1

If no negative weight cycles (how to know?)
No negative shortest distance, $d_{vv}(n-1)$

DP 1

1. **Sub-problems:** $d_{uv}^{(m)}$ = weight of shortest path $u \rightarrow v$ using $\leq m$ edges

2. **Guessing:** What's the last edge (x, v) ?

3. **Recurrence:**

$$d_{uv}^{(m)} = \min(d_{ux}^{(m-1)} + w(x, v) \text{ for } x \in V)$$

X: last vertex in incoming edges
(indegree)

$$d_{uv}^{(0)} = \begin{cases} 0 & \text{if } u = v \\ \infty & \text{otherwise} \end{cases}$$

No path (not connected)

4. **Topological ordering:** for $m = 0, 1, 2, \dots, n-1$: for u and v in V :

5. **Original problem:**

If graph contains no negative-weight cycles (by Bellman-Ford analysis), then
shortest path is simple $\Rightarrow \delta(u, v) = d_{uv}^{(n-1)} = d_{uv}^{(n)} = \dots$

Time complexity

In this Dynamic Program, we have $O(V^3)$ total sub-problems. u, x, v (for 3 vertices)

Each sub-problem takes $O(V)$ time to solve, since we need to consider V possible choices. This gives a total runtime complexity of $O(V^4)$.

Note that this is no better than $|V| \times$ Bellman-Ford

Bottom-up via relaxation steps

```

1  for  $m = 1$  to  $n$  by 1
2      for  $u$  in  $V$ 
3          for  $v$  in  $V$ 
4              for  $x$  in  $V$       Incoming edges (indegree)
5                  if  $d_{uv} > d_{ux} + d_{xv}$      $d_{uv}(m) > d_{ux}(m-1) + d_{xv}(w(x,v))$ 
6                       $d_{uv} = d_{ux} + d_{xv}$   $d_{uv}(m) = d_{ux}(m-1) + d_{xv}(w(x,v))$ 

```

In the above pseudocode, we omit superscripts because more relaxation can never hurt.

Note that we can change our relaxation step to $d_{uv}^{(m)} = \min(d_{ux}^{\lceil m/2 \rceil} + d_{xv}^{\lceil m/2 \rceil})$ for $x \in V$. This change would produce an overall running time of $O(n^3 \lg n)$ time. (student suggestion)

Matrix multiplication

MM1

Recall the task of standard matrix multiplication,

Given $n \times n$ matrices A and B , compute $C = A \cdot B$, such that $c_{ij} = \sum_{k=1}^n a_{ik} \cdot b_{kj}$.

- $O(n^3)$ using standard algorithm
- $O(n^{2.807})$ using Strassen's algorithm
- $O(n^{2.376})$ using Coppersmith-Winograd algorithm
- $O(n^{2.3728})$ using Vassilevska Williams algorithm

Connection to shortest paths

- Define $\oplus = \min$ and $\odot = +$
- Then, $C = A \odot B$ produces $c_{ij} = \min_k (a_{ik} + b_{kj})$
- Define $D^{(m)} = (d_{ij}^{(m)})$, $W = (w(i, j))$, $V = \{1, 2, \dots, n\}$

With the above definitions, we see that $D^{(m)}$ can be expressed as $D^{(m-1)} \odot W$. In other words, $D^{(m)}$ can be expressed as the circle-multiplication of W with itself m times.

Matrix multiplication algorithm

- $n - 2$ multiplications $\Rightarrow O(n^4)$ time (stil no better)
- Repeated squaring: $((W^2)^2)^{2^{\dots}} = W^{2^{\lg n}} = W^{n-1} = (\delta(i, j))$ if no negative-weight cycles. Time complexity of this algorithm is now $O(n^3 \lg n)$.

We can't use Strassen, etc. since our new multiplication and addition operations don't support negation.

Floyd-Warshall: Dynamic Programming, attempt 2

FW1

1. **Sub-problems:** $c_{uv}^{(k)}$ = weight of shortest path $u \rightarrow v$ whose intermediate vertices $\in \{1, 2, \dots, k\}$

2. **Guessing:** Does shortest path use vertex k ?

3. **Recurrence:**

Use k Not use k

$$c_{uv}^{(k)} = \min(c_{uv}^{(k-1)}, c_{uk}^{(k-1)} + c_{kv}^{(k-1)})$$

$$c_{uv}^{(0)} = w(u, v) \quad \text{Not using any intermediate vertex } k$$

4. **Topological ordering:** for k : for u and v in V : $O(V+E)$

5. **Original problem:** $\delta(u, v) = c_{uv}^{(n)}$. Negative weight cycle \Leftrightarrow negative $c_{uu}^{(n)}$

Time complexity

This Dynamic Program contains $O(V^3)$ problems as well. However, in this case, it takes only $O(1)$ time to solve each sub-problem, which means that the total runtime of this algorithm is $O(V^3)$.

Best for APSP in
dense graph

Bottom up via relaxation

```
1   $C = (w(u, v))$ 
2  for  $k = 1$  to  $n$  by 1
3      for  $u$  in  $V$ 
4          for  $v$  in  $V$ 
5              if  $c_{uv} > c_{uk} + c_{kv}$ 
6                   $c_{uv} = c_{uk} + c_{kv}$ 
```

As before, we choose to ignore subscripts.

Johnson's algorithm

Better for sparse graph. Never be worse than Floyd Warshall

JS1

1. Find function $h : V \rightarrow \mathbb{R}$ such that $w_h(u, v) = w(u, v) + h(u) - h(v) \geq 0$ for all $u, v \in V$ or determine that a negative-weight cycle exists.

To make all edges non-negative

2. Run Dijkstra's algorithm on (V, E, w_h) from every source vertex $s \in V \Rightarrow$ get $\delta_h(u, v)$ for all $u, v \in V$

|V| * Dijkstra

3. Given $\delta_h(u, v)$, it is easy to compute $\delta(u, v)$

Claim. $\delta(u, v) = \delta_h(u, v) - h(u) + h(v)$ Re-weighting preserves shortest path with parent pointers

Proof. Look at any $u \rightarrow v$ path p in the graph G

- Say p is $v_0 \rightarrow v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_k$, where $v_0 = u$ and $v_k = v$.

$$\begin{aligned} w_h(p) &= \sum_{i=1}^k w_h(v_{i-1}, v_i) \\ &= \sum_{i=1}^k [w(v_{i-1}, v_i) + h(v_{i-1}) - h(v_i)] \\ &= \sum_{i=1}^k w(v_{i-1}, v_i) + h(v_0) - h(v_k) \\ &= w(p) + h(u) - h(v) \end{aligned}$$

- Hence all $u \rightarrow v$ paths change in weight by the same offset $h(u) - h(v)$, which implies that the shortest path is preserved (but offset).

How to find h ? Function that makes all edges non-negative

We know that

$$w_h(u, v) = w(u, v) + h(u) - h(v) \geq 0$$

This is equivalent to,

$$h(v) - h(u) \leq w(u, v)$$

for all $(u, v) \in V$. This is called a **system of difference constraints**.

Theorem. *If (V, E, w) has a negative-weight cycle, then there exists no solution to the above system of difference constraints.*

Proof. Say $v_0 \rightarrow v_1 \rightarrow \cdots \rightarrow v_k \rightarrow v_0$ is a negative weight cycle.

Let us assume to the contrary that the system of difference constraints has a solution; let's call it h .

This gives us the following system of equations,

$$\begin{aligned}h(v_1) - h(v_0) &\leq w(v_0, v_1) \\h(v_2) - h(v_1) &\leq w(v_1, v_2) \\&\vdots \\h(v_k) - h(v_{k-1}) &\leq w(v_{k-1}, v_k) \\h(v_0) - h(v_k) &\leq w(v_k, v_0)\end{aligned}$$

Summing all these equations gives us

$$0 \leq w(\text{cycle}) < 0$$

which is obviously not possible.

From this, we can conclude that no solution to the above system of difference constraints exists if the graph (V, E, w) has a negative weight cycle.

Theorem. *If (V, E, w) has no negative-weight cycle, then we can find a solution to the difference constraints.*

Proof. Add a new vertex s to G , and add edges (s, v) of weight 0 for all $v \in V$.

- Clearly, these new edges do not introduce any new negative weight cycles to the graph
- Adding these new edges ensures that there now exists at least one path from s to v . This implies that $\delta(s, v)$ is finite for all $v \in V$
- We now claim that $h(v) = \delta(s, v)$. This is obvious from the triangle inequality:
$$\delta(s, u) + w(u, v) \geq \delta(s, v) \Leftrightarrow \delta(s, v) - \delta(s, u) \leq w(u, v) \Leftrightarrow h(v) - h(u) \leq w(u, v)$$

Time complexity

Check if G has negative weight cycle

1. The first step involves running Bellman-Ford from s , which takes $O(VE)$ time. We also pay a pre-processing cost to reweight all the edges ($O(E)$)
2. We then run Dijkstra's algorithm from each of the V vertices in the graph; the total time complexity of this step is $O(VE + V^2 \lg V)$
3. We then need to reweight the shortest paths for each pair; this takes $O(V^2)$ time.
h function

The total running time of this algorithm is $O(VE + V^2 \lg V)$.

Applications

Bellman-Ford consult any system of difference constraints (or report that it is unsolvable) in $O(VE)$ time where V = variables and E = constraints.

An exercise is to prove the Bellman-Ford minimizes $\max_i x_i - \min_i x_i$.

This has applications to

- Real-time programming
- Multimedia scheduling
- Temporal reasoning

For example, you can bound the duration of an event via difference constraint $LB \leq t_{end} - t_{start} \leq UB$, or bound a gap between events via $0 \leq t_{start2} - t_{end1} \leq \varepsilon$, or synchronize events via $|t_{start1} - t_{start2}| \leq \varepsilon$ or 0.

END