# Algorithms II, CS 502 <br> All-Pairs Shortest Paths 

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## All-pairs shortest paths

- Given a weighted, directed graph $\mathrm{G}=(\mathrm{V}, \mathrm{E})$ with a weight function $w: E \rightarrow R$ that maps edges to real-valued weights. We wish to find, for every pair of vertices $u, v \in V$, a shortest (least-weight) path from $u$ to $v$, where the weight of a path is the sum of the weights of its constituent edges.


## All-pairs shortest paths (SP)

- Running single-source SPs for each vertex as the source
$\square$ No negative weights: Use Dijkstra's algorithm with Fibonacci heap, resulting in $\mathrm{O}\left(\mathrm{V}^{2} \lg \mathrm{~V}+\mathrm{V} \mathrm{E}\right)$ run time.
$\square$ Negative weights: Use Bellman-Ford, resulting in $\mathrm{O}\left(\mathrm{V}^{2} \mathrm{E}\right)$ (=O $\left(\mathrm{V}^{4}\right)$ for dense graphs).


## All-pairs shortest paths (SP)

- Unlike single-source SP algorithms, we use adjacency matrix representation for all-pairs SPs. Why?
$\square$ Assume vertices are numbered $1,2, \ldots,|\mathrm{~V}|$, so that the input is an $n \times n$ matrix $W=\left(w_{i j}\right)$ representing the edge weights of an $n$-vertex directed graph $\mathrm{G}=(\mathrm{V}, \mathrm{E})$.

$$
w_{i j}=\left\{\begin{array}{cl}
0 & \text { if } i=j \\
\text { weight of directed edge }(i, j) & \text { if } i \neq j \text { and }(i, j) \in E \\
\infty & \text { if } i \neq j \text { and }(i, j) \notin E
\end{array}\right.
$$

## All-pairs shortest paths (SP)

$\square$ A predecessor matrix $\Pi=\left(\pi_{\mathrm{ij}}\right)$ maintains actual paths

```
Print-All-Pairs-Shortest-Path ( }\Pi,i,j
1 if }i==
2 print i
elseif }\mp@subsup{\pi}{ij}{}==\mathrm{ NIL
print "no path from" i "to" j "exists"
5 \text { else Print-All-Pairs-Shortest-Path( } \Pi , i , \pi _ { i j } )
6 print j
```


## Shortest paths \& matrix multiplication

- A dynamic programming (DP) solution to all-pairs SPs problem is similar to matrix multiplication
Each major loop of the dynamic program will invoke an operation that is very similar to matrix multiplication
$\square$ The algorithm will look like repeated matrix multiplication


## Shortest paths

- Steps for developing a DP solution:
$\square$ Characterize the structure of an optimal solution.
- Recursively define the value of an optimal solution.
- Compute the value of an optimal solution in a bottom-up fashion.
- Construct an optimal solution from computed information


## Shortest paths

- Characterize the structure of an optimal solution
- Already proved all subpaths of a shortest path are shortest paths
$\square$ Recursively define the value of an optimal solution
- $l_{i j}^{(m)}$ : the minimum weight of any path from vertex $i$ to vertex $j$ that contains at most m edges

$$
l_{i j}^{(0)}=\left\{\begin{array}{llll}
0 & \text { if } i=j, & l_{i j}^{(m)} & =\min \left(l_{i j}^{(m-1)}, \min _{1 \leq k \leq n}\left\{l_{i k}^{(m-1)}+w_{k j}\right\}\right) \\
\infty & \text { if } i \neq j . & & \min _{1 \leq k \leq n}\left\{l_{i k}^{(m-1)}+w_{k j}\right\}
\end{array}\right.
$$

## Shortest paths

- Compute the value of an optimal solution in a bottom-up fashion

```
Extend-Shortest-Paths (L,W)
n= L.rows
2 let }\mp@subsup{L}{}{\prime}=(\mp@subsup{l}{ij}{\prime})\mathrm{ be a new }n\timesn\mathrm{ matrix
3 for }i=1\mathrm{ to n
4 for }j=1\mathrm{ to }
5 l lij}=
6 for }k=1\mathrm{ to }
7 l l}\mp@subsup{l}{ij}{\prime}=\operatorname{min}(\mp@subsup{l}{ij}{\prime},\mp@subsup{l}{ik}{}+\mp@subsup{w}{kj}{}
return L'
```

- $\Theta\left(n^{3}\right)$ due to three nested loops


## Shortest paths \& matrix multiplication

- Very similar to computing the product $C=A x B$ for $n x n$ matrices $A$ and $B$.

$$
l_{i j}^{(m)}=\min _{1 \leq k \leq n}\left\{l_{i k}^{(m-1)}+w_{k j}\right\}
$$

$$
\begin{aligned}
l^{(m-1)} & \rightarrow a, \\
w & \rightarrow b, \\
l^{(m)} & \rightarrow c, \\
\min & \rightarrow+,
\end{aligned} \quad c_{i j}=\sum_{k=1}^{n} a_{i k} \cdot b_{k j}
$$

## Shortest paths

- Compute the shortest-path weights by extending shortest paths edge by edge in $\Theta\left(n^{4}\right)$ time

$$
\begin{aligned}
L^{(1)} & =L^{(0)} \cdot W \\
L^{(2)} & =L^{(1)} \cdot W=W \\
L^{(3)} & =L^{(2)} \cdot W=W^{2}, \\
\vdots & \\
L^{(n-1)} & =L^{(n-2)} \cdot W
\end{aligned}=W^{n-1}, ~ \$
$$

```
Slow-All-Pairs-Shortest-PathS ( W)
n=W.rows
L(1)}=
for }m=2\mathrm{ to }n-
    let }\mp@subsup{L}{}{(m)}\mathrm{ be a new }n\timesn\mathrm{ matrix
    L (m) = Extend-Shortest-PathS ( }\mp@subsup{L}{}{(m-1)},W
return }\mp@subsup{L}{}{(n-1)
```


## Shortest paths, improving running time

 - $\Theta\left(\mathrm{n}^{3} \lg \mathrm{n}\right)$ obtained by repeated squaring$$
\begin{array}{rlll}
L^{(1)} & =W & \\
L^{(2)} & =W^{2} & =W \cdot W, \\
L^{(4)} & = & W^{4} & =W^{2} \cdot W^{2} \\
L^{(8)} & = & W^{8} & =W^{4} \cdot W^{4}, \\
& & \vdots \\
L^{\left(2^{\lceil\lg (n-1)\rceil}\right)} & =W^{2 \lg (n-1)\rceil} & =W^{2^{\lceil\lg (n-1)\rceil-1}} \cdot W^{2^{\lceil\lg (n-1)\rceil-1}}
\end{array}
$$

```
FAStER-AlL-PAIRS-SHORTEST-PATHS ( \(W\) )
\(1 \quad n=W . r o w s\)
\(2 L^{(1)}=W\)
\(3 m=1\)
4 while \(m<n-1\)
\(5 \quad\) let \(L^{(2 m)}\) be a new \(n \times n\) matrix
\(6 \quad L^{(2 m)}=\) EXTEND-SHORTEST-PATHS \(\left(L^{(m)}, L^{(m)}\right)\)
\(7 \quad m=2 m\)
8 return \(L^{(m)}\)
```


## Shortest paths, improving running time



$$
\begin{array}{ll}
L^{(1)} & =\left(\begin{array}{rrrrr}
0 & 3 & 8 & \infty & -4 \\
\infty & 0 & \infty & 1 & 7 \\
\infty & 4 & 0 & \infty & \infty \\
2 & \infty & -5 & 0 & \infty \\
\infty & \infty & \infty & 6 & 0
\end{array}\right) \quad L^{(2)}=\left(\begin{array}{rrrrrr}
0 & 3 & 8 & 2 & -4 \\
3 & 0 & -4 & 1 & 7 \\
\infty & 4 & 0 & 5 & 11 \\
2 & -1 & -5 & 0 & -2 \\
8 & \infty & 1 & 6 & 0
\end{array}\right) \\
L^{(3)}=\left(\begin{array}{rrrrr}
0 & 3 & -3 & 2 & -4 \\
3 & 0 & -4 & 1 & -1 \\
7 & 4 & 0 & 5 & 11 \\
2 & -1 & -5 & 0 & -2 \\
8 & 5 & 1 & 6 & 0
\end{array}\right) \quad L^{(4)}=\left(\begin{array}{rrrrr}
0 & 1 & -3 & 2 & -4 \\
3 & 0 & -4 & 1 & -1 \\
7 & 4 & 0 & 5 & 3 \\
2 & -1 & -5 & 0 & -2 \\
8 & 5 & 1 & 6 & 0
\end{array}\right)
\end{array}
$$

## Floyd-Warshall algorithm

- Different DP formulation to solve all-pairs SPs on a directed graph $\mathrm{G}=(\mathrm{V}, \mathrm{E})$
$\square$ Negative edges OK but no negative cycles
- The structure of a shortest path
$\square$ For any pair of vertices $i, j \in V$, consider all paths from $i$ to $j$ whose intermediate vertices are all drawn from $\{1,2, \ldots, k\}$, and let $p$ be a minimum-weight (simple) path from among them.


## Floyd-Warshall algorithm

- Recursive solution
$\square d_{i j}^{(k)}$ : weight of a shortest path from vertex i to vertex $j$ for which all intermediate vertices are in the set $\{1,2, \ldots, k\}$

$$
d_{i j}^{(k)}= \begin{cases}w_{i j} & \text { if } k=0, \\ \min \left(d_{i j}^{(k-1)}, d_{i k}^{(k-1)}+d_{k j}^{(k-1)}\right) & \text { if } k \geq 1\end{cases}
$$

- Final answer $\quad D^{(n)}=\left(d_{i j}^{(i)}\right)$
$\square$ where $d_{i j}^{(i)}=\delta(i, j)$ for all $i, j \in V$


## Floyd-Warshall algorithm

- Computing SP weights bottom up

```
Floyd-Warshall ( \(W\) )
\(n=W\).rows
\(D^{(0)}=W\)
for \(k=1\) to \(n\)
    let \(D^{(k)}=\left(d_{i j}^{(k)}\right)\) be a new \(n \times n\) matrix
    for \(i=1\) to \(n\)
            for \(j=1\) to \(n\)
                \(d_{i j}^{(k)}=\min \left(d_{i j}^{(k-1)}, d_{i k}^{(k-1)}+d_{k j}^{(k-1)}\right)\)
return \(D^{(n)}\)
```

- $\Theta\left(n^{3}\right)$ due to three nested loops


## Floyd-Warshall algorithm

- Constructing a shortest path
$\square$ Compute predecessor matrix $\pi$ while the algorithm computes the matrices $D^{(k)}$.

$$
\pi_{i j}^{(0)}= \begin{cases}\text { NIL } & \text { if } i=j \text { or } w_{i j}=\infty, \\ i & \text { if } i \neq j \text { and } w_{i j}<\infty .\end{cases}
$$

$$
\pi_{i j}^{(k)}= \begin{cases}\pi_{i j}^{(k-1)} & \text { if } d_{i j}^{(k-1)} \leq d_{k}^{(k-1)}+d_{k}^{(k-1)}, \\ \pi_{k j}^{(k-1)} & \text { if } d_{i j}^{(k-1)}>d_{i k}^{(k-1)}+d_{k j}^{(k-1)} .\end{cases}
$$

## Floyd-Warshall algorithm



## Floyd-Warshall algorithm

$$
\begin{array}{ll}
D^{(0)} & =\left(\begin{array}{rrrrr}
0 & 3 & 8 & \infty & -4 \\
\infty & 0 & \infty & 1 & 7 \\
\infty & 4 & 0 & \infty & \infty \\
2 & \infty & -5 & 0 & \infty \\
\infty & \infty & \infty & 6 & 0
\end{array}\right) \quad \Pi^{(0)}=\left(\begin{array}{cccccc}
\mathrm{NIL} & 1 & 1 & \mathrm{NIL} & 1 \\
\mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} & 2 & 2 \\
\mathrm{NIL} & 3 & \mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} \\
4 & \mathrm{NIL} & 4 & \mathrm{NIL} & \mathrm{NIL} \\
\mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} & 5 & \mathrm{NIL}
\end{array}\right) \\
D^{(1)}=\left(\begin{array}{rrrrr}
0 & 3 & 8 & \infty & -4 \\
\infty & 0 & \infty & 1 & 7 \\
\infty & 4 & 0 & \infty & \infty \\
2 & 5 & -5 & 0 & -2 \\
\infty & \infty & \infty & 6 & 0
\end{array}\right) \quad \Pi^{(1)}=\left(\begin{array}{ccccc}
\mathrm{NIL} & 1 & 1 & \mathrm{NIL} & 1 \\
\mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} & 2 & 2 \\
\mathrm{NIL} & 3 & \mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} \\
4 & 1 & 4 & \mathrm{NIL} & 1 \\
\mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} & 5 & \mathrm{NIL}
\end{array}\right) \\
D^{(2)}=\left(\begin{array}{rrrrr}
0 & 3 & 8 & 4 & -4 \\
\infty & 0 & \infty & 1 & 7 \\
\infty & 4 & 0 & 5 & 11 \\
2 & 5 & -5 & 0 & -2 \\
\infty & \infty & \infty & 6 & 0
\end{array}\right) \quad \Pi^{(2)}=\left(\begin{array}{ccccc}
\mathrm{NIL} & 1 & 1 & 2 & 1 \\
\mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} & 2 & 2 \\
\mathrm{NIL} & 3 & \mathrm{NIL} & 2 & 2 \\
4 & 1 & 4 & \mathrm{NIL} & 1 \\
\mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} & 5 & \mathrm{NIL}
\end{array}\right)
\end{array}
$$

## Floyd-Warshall algorithm

$$
\begin{aligned}
& D^{(3)}=\left(\begin{array}{rrrrr}
0 & 3 & 8 & 4 & -4 \\
\infty & 0 & \infty & 1 & 7 \\
\infty & 4 & 0 & 5 & 11 \\
2 & -1 & -5 & 0 & -2 \\
\infty & \infty & \infty & 6 & 0
\end{array}\right) \\
& D^{(4)}=\left(\begin{array}{rrrrr}
0 & 3 & -1 & 4 & -4 \\
3 & 0 & -4 & 1 & -1 \\
7 & 4 & 0 & 5 & 3 \\
2 & -1 & -5 & 0 & -2 \\
8 & 5 & 1 & 6 & 0
\end{array}\right) \quad \Pi^{(3)}=\left(\begin{array}{ccccc}
\mathrm{NIL} & 1 & 1 & 2 & 1 \\
\mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} & 2 & 2 \\
\mathrm{NIL} & 3 & \mathrm{NIL} & 2 & 2 \\
4 & 3 & 4 & \mathrm{NIL} & 1 \\
\mathrm{NIL} & \mathrm{NIL} & \mathrm{NIL} & 5 & \mathrm{NIL}
\end{array}\right) \\
& D^{(5)}=\left(\begin{array}{rrrrr}
0 & 1 & -3 & 2 & -4 \\
3 & 0 & -4 & 1 & -1 \\
7 & 4 & 0 & 5 & 3 \\
2 & -1 & -5 & 0 & -2 \\
8 & 5 & 1 & 6 & 0
\end{array}\right) \quad \Pi^{(5)}=\left(\begin{array}{ccccc}
\mathrm{NIL} & 1 & 4 & 2 & 1 \\
4 & \mathrm{NIL} & 4 & 2 & 1 \\
4 & 3 & \mathrm{NIL} & 2 & 1 \\
4 & 3 & 4 & \mathrm{NIL} & 1 \\
4 & 3 & 4 & 5 & \mathrm{NIL}
\end{array}\right) \\
&
\end{aligned}
$$

## Transitive closure

- Given a directed graph $G=(V, E)$ with vertex set $V=\{1,2, \ldots, n\}$, we might wish to determine whether $G$ contains a path from $i$ to $j$ for all vertex pairs $(i, j) \in V$. We define the transitive closure of $G$ as the graph $\mathrm{G}^{*}=\left(\mathrm{V}, \mathrm{E}^{*}\right)$, where
$\square E^{*}=\{(i, j)$ : there is a path from vertex $i$ to $j$ in $G\}$


## Transitive closure

- Assign a weight of 1 to each edge and run Floyd-Warshall algorithm
$\square$ There is a path from vertex $i$ to $j$, then $d_{i j}<n$ (otherwise $d_{i j}=\infty$ )
- Runs in $\Theta\left(n^{3}\right)$ time


## Transitive closure

- Similar way (save time \& space in practice)
- Substitute OR for min and AND for + in Floyd-Warshall

$$
\begin{aligned}
& t_{i j}^{(0)}= \begin{cases}0 & \text { if } i \neq j \text { and }(i, j) \notin E, \\
1 & \text { if } i=j \text { or }(i, j) \in E,\end{cases} \\
& \text { and for } k \geq 1, \\
& t_{i j}^{(k)}=t_{i j}^{(k-1)} \vee\left(t_{i k}^{(k-1)} \wedge t_{k j}^{(k-1)}\right) .
\end{aligned}
$$

## Transitive closure

```
Transitive-Closure \((G)\)
\(n=|G \cdot V|\)
let \(T^{(0)}=\left(t_{i j}^{(0)}\right)\) be a new \(n \times n\) matrix
for \(i=1\) to \(n\)
    for \(j=1\) to \(n\)
        if \(i==j\) or \((i, j) \in G . E\)
            \(t_{i j}^{(0)}=1\)
        else \(t_{i j}^{(0)}=0\)
    for \(k=1\) to \(n\)
    let \(T^{(k)}=\left(t_{i j}^{(k)}\right)\) be a new \(n \times n\) matrix
    for \(i=1\) to \(n\)
        for \(j=1\) to \(n\)
        \(t_{i j}^{(k)}=t_{i j}^{(k-1)} \vee\left(t_{i k}^{(k-1)} \wedge t_{k j}^{(k-1)}\right)\)
    return \(T^{(n)}\)
```


## Transitive closure



$$
\begin{aligned}
& T^{(0)}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 1 & 1 \\
0 & 1 & 1 & 0 \\
1 & 0 & 1 & 1
\end{array}\right) \quad T^{(1)}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 1 & 1 \\
0 & 1 & 1 & 0 \\
1 & 0 & 1 & 1
\end{array}\right) \quad T^{(2)}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 1 & 1 \\
0 & 1 & 1 & 1 \\
1 & 0 & 1 & 1
\end{array}\right) \\
& T^{(3)}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 1 & 1 \\
0 & 1 & 1 & 1 \\
1 & 1 & 1 & 1
\end{array}\right) \quad T^{(4)}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1
\end{array}\right)
\end{aligned}
$$

## Johnson's algorithm for sparse graphs

- Uses both Dijkstra's algorithm and the Bellman-Ford algorithm as sub-routines
- Eliminates negative weights (assuming no negative cycles) by reweighting
- Runs Dijkstra's algorithm once from each vertex


## Johnson's algorithm for sparse graphs

- Assuming a Fibonacci heap min-priority queue implementation, running time is $\mathrm{O}\left(\mathrm{V}^{2} \lg \mathrm{~V}+\mathrm{V} \mathrm{E}\right)$
- Asymptotically faster than either repeated squaring of matrices or the Floyd-Warshall algorithm for sparse graphs


## Johnson's algorithm for sparse graphs

- New set of edge weights w' must satisfy:
- For all pairs of vertices $u, v \in V$, a path $p$ is a shortest path from $u$ to $v$ using weight function $w$ if and only if $p$ is also a shortest path from $u$ to using weight function w'.
- For all edges ( $u, v$ ), the new weight $w^{\prime}(u, v)$ is nonnegative.
- We can preprocess $G$ to determine the new weight function w' in $\mathrm{O}(\mathrm{V} E)$ time.


## Johnson's algorithm for sparse graphs

- Lemma 25.1 (Reweighting does not change shortest paths) Given a weighted, directed graph $\mathrm{G}=(\mathrm{V}, \mathrm{E})$ with weight function $\mathrm{w}: \mathrm{E} \rightarrow \mathrm{R}$, let $h: V \rightarrow R$ be any function mapping vertices to real numbers. For each edge $(u, v) \in E$, define $w^{\prime}(u, v)=w(u, v)+h(u)-h(v)$.
- Proof: Let $\mathrm{p}=<\mathrm{v}_{0}, \mathrm{v}_{1}, \ldots, \mathrm{v}_{\mathrm{k}}>$ be any path from vertex $\mathrm{v}_{0}$ to vertex $\mathrm{v}_{\mathrm{k}}$. Then $p$ is a shortest path from 0 to $k$ with weight function $w$ if and only if it is a shortest path with weight function w'. That is, $w(p)=\delta\left(v_{0}, v_{k}\right)$ if and only if $w^{\prime}(p)=\delta^{\prime}\left(v_{0}, v_{k}\right)$.
Furthermore, G has a negative-weight cycle using weight function wif and only if G has a negative-weight cycle using weight function $w^{\prime}$.


## Johnson's algorithm for sparse graphs



## Johnson's algorithm for sparse graphs



