

# Shortest paths: Floyd-Warshall

CS 2860: Algorithms and Complexity

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Shortest paths: All pairs, negative weights

# General all-pairs shortest paths problem

- ▶ Saw: **Dijkstra**, solving:
  - ▶ Compute shortest paths from **single source** to all destinations
  - ▶ Directed graphs, non-negative weights
- ▶ Complications today:
  1. Negative weights
  2. Computing **all** distances (from all, to all)
- ▶ Algorithm: **Floyd-Warshall**
  - ▶ Mystical procedure
  - ▶ Solution category: **Dynamic programming**

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# Negative weights in graph distances

# Negative weights

- ▶ Negative weights make shortest paths question more complex
- ▶ Beneficial detours
  - ▶ If an arc has negative weight, we may **gain** by taking a detour to include it
- ▶ “Improving” (negative-weight) cycles
  - ▶ If going around a cycle  $v_1 v_2 \dots v_n v_1$  has **negative total weight**, there is no sensible “shortest” solution
  - ▶ We may always take one more pass around the cycle for an **even cheaper** passage
  - ▶ Any path that can go through negative cycle treated as  $-\infty$  cost (can be made as low value as you want)
- ▶ Can still sensibly compute **shortest paths** when no such cycle exists



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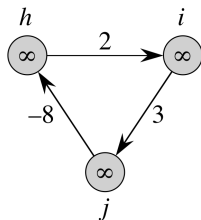
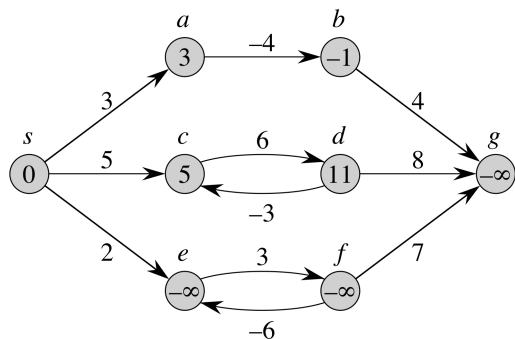
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# Illustration: Single-source, negative weights



Cycle **efe** is negative cycle, gets distance  $-\infty$

Cycle **cdc** has negative arc, but positive weight

Vertex **g** inherits distance  $-\infty$  from **f**

# Negative weights: Situations

1. Graph has no negative cycle at all (but negative weights)
  - ▶ Shortest paths computed by reasonable algorithms
2. Graph has negative cycle, but not reachable from  $u$  or to  $v$ 
  - ▶ We can still hope to compute a sensible path from  $u$  to  $v$
3. There is a negative cycle on  $u$  or  $v$ , or passable on the way from  $u$  to  $v$ 
  - ▶ Shortest path must be given as  $-\infty$
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# Observations

1. Negative weights are a **real** obstacle – can't handle by alternative bookkeeping
  - ▶ For example, **adding weight** to arcs until all weights are positive **warps and destroys** the shortest path situation
2. Dijkstra's algorithm is essentially unpatchable
  - ▶ A central notion is **marked vertices** – we are **done** with a vertex as soon as we have visited it (no more edge updates can occur)
  - ▶ With negative weights, an **improving update** to **v** (finding a shorter path) can occur by going through vertices that are **further away** than v
  - ▶ Would need to **keep updating** until it stabilises
3. The problems we investigate:
  - ▶ Compute **negative cycle** in graph
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# All-pairs shortest paths problem

# All-pairs shortest paths: Representation

- ▶ Want to know **all distances** between pairs of vertices
- ▶ Representation (e.g.) array **distance[u][v]**
- ▶ Note –  $\Omega(n^2)$  data
  - ▶ Unavoidable: Consider complete graph with edge weights
  - ▶ Takes  $\Theta(n^2)$  numbers to store
- ▶ To **recreate the paths**, would also need **parentOf** data
  - ▶ Example: array **previousNode[u][w]=v** records that on the shortest path from u to w, the last node before w is v
  - ▶ Like **parentOf** – basically, **previousNode[u][\*]** will encode a single-source tree rooted in u
- ▶ Will focus on **distances**, not to overload with complications

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# Computing all-pairs shortest paths

- ▶ Simple solution: Compute shortest paths from  $v$ , for every vertex  $v$ 
  - ▶ Non-negative weights: May use Dijkstra, time  $\mathcal{O}(|V| \cdot |E| \cdot \log |V|)$
  - ▶ Negative weights single-source paths: More expensive to compute, but algorithm exists (total time  $\mathcal{O}(|V|^2 \cdot |E|)$ )
- ▶ Will see **faster** algorithms, making gains by computing all distances **in parallel**
  1. Simple, slower mock-up algorithm
  2. **Floyd-Warshall**

## Preparation: A simple mock-up suggestion

- ▶ Let's fill out a large table  $\text{distance}(u,v,d)$ , storing the shortest path from  $u$  to  $v$  with at most  $d$  steps
- ▶ Fill out by induction: First steps easy
  1. When  $d=0$ :  $\text{distance}(u,u,0)=0$ , otherwise  $\text{distance}(u,v,0)=\infty$ ,  $u \neq v$
  2. When  $d=1$ :  $\text{distance}(u,v,1)=\text{weight}(uv)$  if  $u \neq v$  and the arc  $uv$  exists
- ▶ Future steps build on past steps
  - ▶  $\text{distance}(u,v,d+1) = \min(\text{distance}(u,v,d), \min_w \text{distance}(u,w,d) + \text{weight}(wv))$ , over all arcs  $wv$
- ▶ One iteration: There are  $n^2$  pairs to fill in, each pair requires looking at  $\mathcal{O}(n)$  further values
- ▶ Total time  $\Theta(n^3)$  to complete one iteration

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# Completing and using the distance info

- ▶ Observe: Every **sensible** path has length at most  $n$
- ▶ Therefore
  - ▶ After  $n$  iterations, time  $\mathcal{O}(n^4)$ , all sensible paths have been found
  - ▶ The only paths still improving after  $> n$  steps must contain a cycle
- ▶ Detects negative cycles:
  - ▶  $\text{distance}(u, u, d) < 0$  for some  $d \leq n$ , vertex  $u$  if and only if there is a negative cycle
- ▶ If there are no negative cycles,

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contains the shortest path data for all pairs of vertices  $u, v$ .



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# Dynamic programming strategy

- ▶ **Dynamic programming** is an advanced algorithm design principle (not fully covered in this course)
- ▶ Rough principle: Add **extra memory use** to speed up repetitive or complex computations
- ▶ In the mock-up:
  - ▶ Wanted the table  **$\text{distance}(u,v,n)$**  as final result
  - ▶ Used  $n - 1$  **temporary** tables  **$\text{distance}(u,v,d)$**  to produce it
  - ▶ Interpretation  **$\text{distance}(u,v,d)$**  stores path of **at most  $d$  steps**
- ▶ Floyd-Warshall:
  - ▶ Tables  $\delta^t(i,j)$  storing shortest paths using only certain vertices
  - ▶ Build towards  $\delta^n(i,j)$  which just stores shortest paths

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# Floyd-Warshall

- ▶ Graph  $G = (V, E)$ , rename vertices  $V = \{1, 2, \dots, n\}$
- ▶ Write  $\text{weight}(ij)$  for weight of arc  $ij \in E$ , if exists, otherwise  $\text{weight}(ij) := \infty$
- ▶ Temporary tables  $\delta_{ij}^t$ , meaning  
Shortest path from  $i$  to  $j$ , if all **intermediate** vertices (i.e., other than  $i$  or  $j$ ) have index **at most**  $t$ .
- ▶ As with the mock-up example:
  1. Can compute **base case** easily
  2. Can **use** tables  $\delta^t(i, j)$  to compute  $\delta^{t+1}(i, j)$
  3. Once we know  $\delta^n(i, j)$ , we are done
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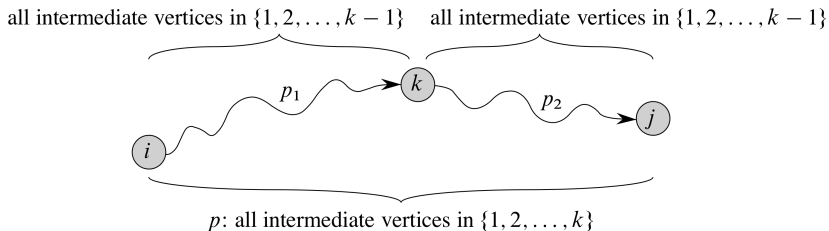
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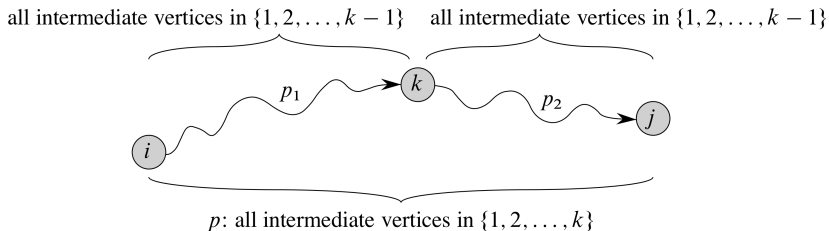
# Floyd-Warshall: Recursive case



- ▶ Values  $\delta^{k-1}(i, j)$  store information about paths whose **internal** vertices come from the set  $\{1, \dots, k-1\}$
- ▶ To compute  $\delta^k(i, j)$ , we need to add information about paths where also  $k$  may be internal
- ▶ Two varieties:
  1. New path does not use  $k$ :  $\delta^k(i, j) = \delta^{k-1}(i, j)$
  2. New path uses  $k$ : Break new path into **before**  $k$  and **after**  $k$  (see figure), getting

$$\delta^k(i, j) = \delta^{k-1}(i, k) + \delta^{k-1}(k, j)$$

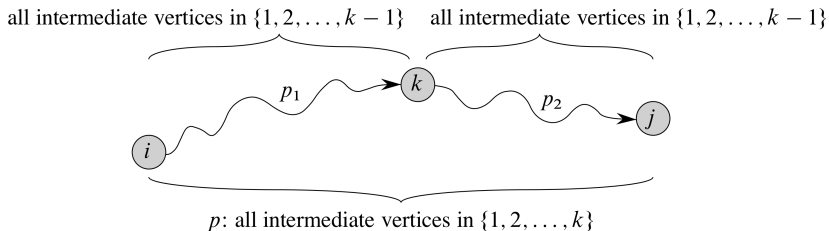
# Floyd-Warshall: Recursive case



- ▶ Values  $\delta^{k-1}(i, j)$  store information about paths whose **internal** vertices come from the set  $\{1, \dots, k-1\}$
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- ▶ Two varieties:
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# Algorithm: Floyd-Warshall

1. Initialise:
  - 1.1  $\delta^0(i, i) = 0$
  - 1.2  $\delta^0(i, j) = \text{weight}(ij)$ , otherwise
2. For  $k=1$  to  $n$ :
  - 2.1 Create the table  $\delta^k(i, j)$
  - 2.2 For every pair  $i, j \in V$ , compute

$$\delta^k(i, j) = \min(\delta^{k-1}(i, j), \quad \delta^{k-1}(i, k) + \delta^{k-1}(k, j))$$

3. Return the values  $\delta^n(i, j)$  as final distances

Graph contains negative cycle if and only if  $\delta^k(i, i) < 0$  at some point.

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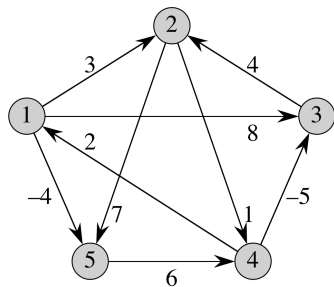
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# Example for Floyd-Warshall



$$D^{(0)} = \begin{pmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & \infty & -5 & 0 & \infty \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix}$$

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$$D^{(1)} = \begin{pmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & 5 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \quad \Pi^{(1)} = \begin{pmatrix} \text{NIL} & 1 & 1 & \text{NIL} & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 2 & 2 \\ \text{NIL} & 3 & \text{NIL} & \text{NIL} & \text{NIL} \\ 4 & 1 & 4 & \text{NIL} & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 5 & \text{NIL} \end{pmatrix}$$

$$D^{(2)} = \begin{pmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & 5 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \quad \Pi^{(2)} = \begin{pmatrix} \text{NIL} & 1 & 1 & 2 & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 2 & 2 \\ \text{NIL} & 3 & \text{NIL} & 2 & 2 \\ 4 & 1 & 4 & \text{NIL} & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 5 & \text{NIL} \end{pmatrix}$$

$\Pi^{(k)}$  entries  $\pi_{ij}^{(k)}$  are predecessors of  $j$  on the current best path from  $i$



$$D^{(3)} = \begin{pmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & -1 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \quad \Pi^{(3)} = \begin{pmatrix} \text{NIL} & 1 & 1 & 2 & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 2 & 2 \\ \text{NIL} & 3 & \text{NIL} & 2 & 2 \\ 4 & 3 & 4 & \text{NIL} & 1 \\ \text{NIL} & \text{NIL} & \text{NIL} & 5 & \text{NIL} \end{pmatrix}$$

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Using all  $\Pi^{(k)}$  one can get the shortest path from  $i$  to  $j$

# Shortest paths: Summary

- ▶ Single source, unit weights:
- ▶ Single source, non-negative weights:
- ▶ Single source, arbitrary weights: Omitted (see below)
- ▶ All pairs, arbitrary weights but no negative cycles:
- ▶ Omitted:
  - ▶ Directed Acyclic Graphs, special-purpose algorithms
  - ▶ Bellman-Ford: Single source, arbitrary weights

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# Negative edge weights: Application

# Illustration: Currency exchange

- ▶ Have: **Exchange rates** offered by different agencies
  - ▶ 1 GBP  $\rightarrow$  1.4 USD
  - ▶ 1 USD  $\rightarrow$  0.7 GBP
  - ▶ 1 Mexican Peso  $\rightarrow$  0.056 USD
  - ▶ 1 GBP  $\rightarrow$  9.4 Chinese Yuan
  - ▶ ...
- ▶ Seek **most profitable** exchange path
  - ▶ Example: 1 Peso  $\rightarrow$  0.056 USD  $\rightarrow$   $0.056 \cdot 0.7$  GBP  $\rightarrow$   $0.056 \cdot 0.7 \cdot 9.4$  Yuan
  - ▶ Makes path from 1 Peso to 0.368 Yuan
- ▶ **Arbitrage** options
  - ▶ What if a black market dealer offers 3 Peso per Yuan?
  - ▶  $0.368 \cdot 3 = 1.104 > 1$  Peso per Peso  $\Rightarrow$  profit!

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# Currency exchange/arbitrage, continued

- ▶ Casting the currency exchange situation as a graph problem
  1. Instead of GBP  $\rightarrow$  USD multiplier of 1.4...
  2. Create arc from GBP to USD, of weight  $-\log 1.4$
  3. Negative weight  $\Leftrightarrow$  less valuable target currency
  4. Rate 1.0 gets weight 0, rate 2.0 weight  $-1$
- ▶ Exchange rate multiplication becomes addition of logarithms
  - ▶ Two-step conversion from USD to Yuan  $0.7 \cdot 9.4$
  - ▶  $-\log(0.7 \cdot 9.4) = (-\log 0.7) + (-\log 9.4)$
  - ▶  $-\log 0.7 = 0.51$  and  $-\log 9.4 = -3.23$
- ▶ Now we have:
  1. Best exchange rate  $A \rightarrow B$  found via shortest path from A to B
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