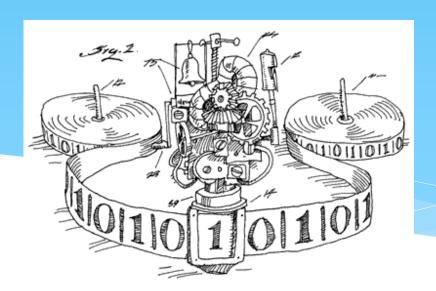
EECS 376: Foundations of Computer Science

Seth Pettie Lecture 5





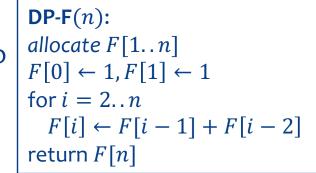
Agenda

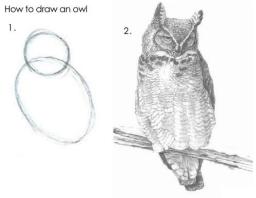
- * Dynamic programming, continued: how to design a dynamic programming algorithm
- * All-Pairs Shortest Path
 - * The Floyd-Warshall algorithm



- * Dynamic Programming
 - * Step 1: Find a recurrence relation
- $F(n) = \begin{cases} 1 & \text{if } n = 0,1\\ F(n-1) + F(n-2) & \text{if } n \ge 2 \end{cases}$

- * Step 2: Fill out a table
 - * One cell for each possible set of inputs to the recurrence
 - * Starting with the base cases, use the recurrence to fill the table







- * Step 1, how to recurse:
 - * principle of optimality part of the optimal solution must be the optimal solution to a smaller part of the problem
 - * Example: If 146 is an LCS of X = 1546, Y = 7146, then 14 must be the optimal solution to a smaller problem (the LCS of X[1...3], Y[1...3])
 - Want that optimal solution to the smaller problems, plus minimal info from the original problem, to be enough to find the optimal solution

LCS(i, j) = length of longest common subsequence of X[1..i]and Y[1..j]

$$LCS(i,j) = \begin{cases} 0 & i = 0 \text{ or } j = 0\\ 1 + LCS(i-1,j-1) & X[i] = Y[j]\\ \max \left\{ \frac{LCS(i-1,j)}{LCS(i,j-1)} \right\} & X[i] \neq Y[j] \end{cases}$$



- * Step 1, how to recurse:
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LIS(i) = length of longest increasing subsequence of X[1..i]

- * Example: Given LIS(i-1) = 5, and A[i] = 10, what is LIS(i)?
 - * Not clear how to do this. Have to keep track of many candidate increasing subsequences.
 - * This is why we moved to $LIS_{at}(i)$



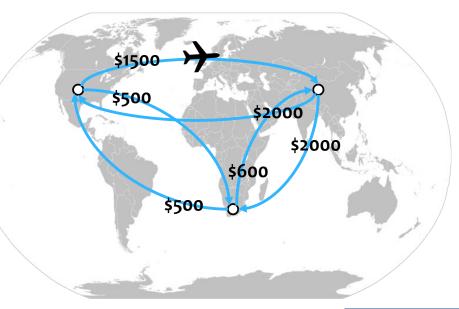
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 - Want that optimal solution to the smaller problems, plus minimal info from the original problem, to be enough to find the optimal solution
 - * Runtime: $O(\# \text{ of cells} \cdot \text{ time per cell})$
 - * Goal is to minimize number of distinct inputs to the recurrence



All-Pairs Shortest Paths

c(i,j) might be different from c(j,i)

- * Given n eities and (possibly asymmetric) costs c(i, j) to directly fly from city i to j
- * **Goal:** for <u>every</u> pair of cities *i*, *j*, find the <u>minimum</u> cost, d(i,j), to fly from city *i* to city *j*, <u>when layovers are allowed</u>



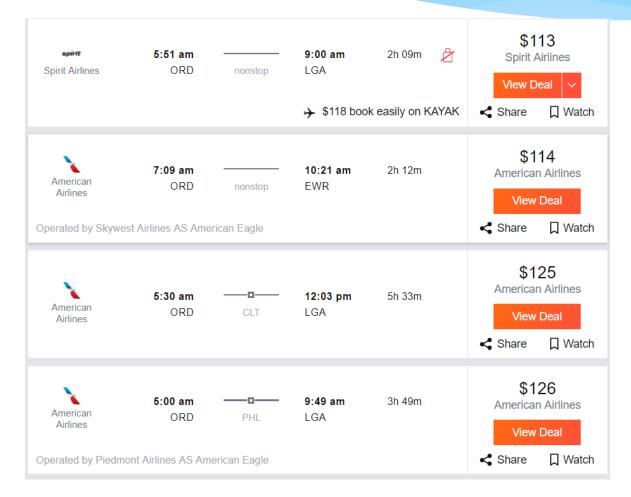


Example

Layover Airports

- ✓ Atlanta (ATL)
- ✓ Boston (BOS)
- ✓ Buffalo (BUF)
- ✓ Charlotte (CLT)
- Cincinnati (CVG)
- ✓ Cleveland (CLE)
- Columbus (CMH)
- ✓ Denver (DEN)
- ✓ Detroit (DTW)
- ✓ Fort Lauderdale (FLL)
- ✓ Houston (IAH)
- ✓ Las Vegas (LAS)
- ✓ Los Angeles (LAX)
- ✓ Minneapolis (MSP)
- Myrtle Beach (MYR)
- ✓ Nashville (BNA)
- ✓ Norfolk (ORF)
- ✓ Philadelphia (PHL)

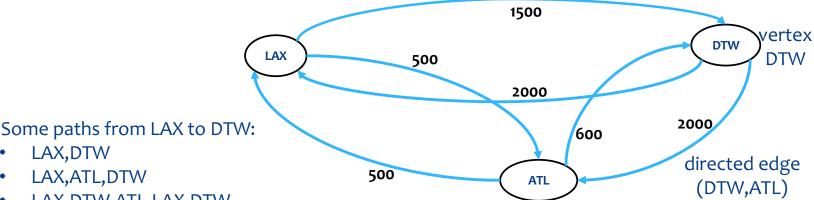






Review: Graph theory

- A directed graph G consists of some number n of (uniquely labeled) vertices and directed edges between them
- A weighted graph has its edges labeled with numbers
 - * Assume weights can be positive or negative.
- A path from vertex i to vertex j is a sequence of vertices i = 1 $v_0, v_1, \dots, v_\ell = j$ such that each (v_{i-1}, v_i) is an edge
- The **cost** of a path is the sum of the weights along its edges.
 - Assume no negative cycles!





LAX, DTW

LAX,ATL,DTW

LAX, DTW, ATL, LAX, DTW

A recurrence

principle of optimality – part of the optimal solution must be the optimal solution to a smaller part of the problem

 Idea: Any subpath of a cheapest path is the cheapest path between its endpoints





A recurrence

principle of optimality – part of the optimal solution must be the optimal solution to a smaller part of the problem

- Idea: Any subpath of a cheapest path is the cheapest path between its endpoints
- * Let d(i,j) be the minimum cost to fly from i to j, i.e., the cost of a cheapest path from i to j
- * Recurrence: every cheapest path from *i* to *j* is either:
 - * An edge from *i* to *j* (a direct flight)
 - * An edge from i to some other k, and then a cheapest path from k to j
- * $d(i,j) = \min\{c(i,j), \min\{c(i,k) + d(k,j) \mid k \notin \{i,j\}\}\}$
- * What goes wrong with this recurrence?
 - * Computing d(i,j) requires d(k,j) which requires d(i,j)...



A recurrence

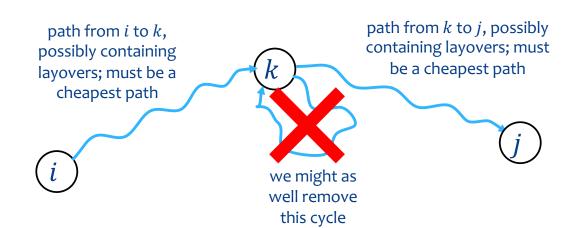
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Finding a better recurrence

- * Idea 2: No vertex (city) need ever be visited twice in a cheapest path
 - * If there are no <u>negative cycles</u>, then there needn't be any duplicate vertices in the cheapest path





Finding a better recurrence

Goal is to minimize number of distinct inputs to the recurrence, runtime: $O(\# \text{ of cells} \cdot \text{ time per cell})$

- * Idea 2: No vertex (city) need ever be visited twice in a cheapest path
- * Recurrence: every cheapest path from *i* to *j* is either:
 - * An edge from *i* to *j* (a direct flight)
 - * An edge from *i* to some other *k*, and then a cheapest path from *k* to *j* that does not visit *i*
- * $R(G,i,j) = \min\{c(i,k) + R(G\setminus\{i\},k,j) \mid k \in G\setminus\{i,j\}\} \cup \{c(i,j)\}$
- * Q: How many distinct inputs are there? How long will dynamic programming take to run?
 - * $O(2^n \cdot n \cdot n)$ distinct inputs
- * Why were there too many inputs?

Finding a better recurrence

optimal solution to the smaller problems + minimal info from the original problem = enough to find the optimal solution

- * $R(G,i,j) = \min\{c(i,k) + R(G\setminus\{i\},k,j) \mid k \in G\setminus\{i,j\}\} \cup \{c(i,j)\}$
- * "Given remaining vertices not yet chosen, which vertex k should follow i in the cheapest path from i to j?"
 - * To answer this, need to know exactly which vertices have already been chosen, for which there are $O(2^n)$ possibilities
- * Given remaining vertices not yet chosen, is vertex k in the cheapest path from i to j?

* min
$$\begin{cases} R(G\setminus\{k\},i,j) \\ R(G\setminus\{k\},i,k) + R(G\setminus\{k\},k,j) \end{cases}$$

* Q: Do we still need to recurse over all possible sets of remaining vertices?



Floyd-Warshall

- * Idea 3: Check whether vertex k is in cheapest path, and then recurse on k-1
- * Recurrence: every cheapest path from *i* to *j* is either:
 - * A cheapest path from i to j that visits only intermediate vertices $\{1, ..., k-1\}$, or
 - * A cheapest path from i to k that visits only intermediate vertices $\{1, ..., k-1\}$, followed by a cheapest path from k to j that visits only intermediate vertices $\{1, ..., k-1\}$

Implementation

$$FW(i,j,k) = \begin{cases} c(i,j) & k = 0\\ \min\{FW(i,k,k-1) + FW(k,j,k-1), FW(i,j,k-1)\} & k > 0 \end{cases}$$

```
Floyd-Warshall(C[1..n][1..n]): ||C[i][j] = c(i,j) allocate D[1..n][1..n][0..n] ||D[i][j][k] = FW(i,j,k) for all i, j : D[i][j][0] \leftarrow C[i][j] Runtime: O(n^3) D[i][j][k] \leftarrow \min \begin{cases} D[i][k][k-1] + D[k][j][k-1], \\ D[i][j][k-1] \end{cases}
```

This is Floyd and Warshall's algorithm for finding *all-pairs shortest* paths in a directed graph with weighted edges. (Missing edges have weight ∞ .)

