

Chapter 11

More Dynamic Programming

OLD CS 473: Fundamental Algorithms, Spring 2015

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11.1 All Pairs Shortest Paths

11.1.0.1 Shortest Path Problems

Shortest Path Problems

Input A (undirected or directed) graph $G = (V, E)$ with edge lengths (or costs). For edge $e = (u, v)$, $\ell(e) = \ell(u, v)$ is its length.

- (A) Given nodes s, t find shortest path from s to t .
- (B) Given node s find shortest path from s to all other nodes.
- (C) Find shortest paths for all pairs of nodes.

11.1.0.2 Single-Source Shortest Paths

Single-Source Shortest Path Problems

Input A (undirected or directed) graph $G = (V, E)$ with edge lengths. For edge $e = (u, v)$, $\ell(e) = \ell(u, v)$ is its length.

- (A) Given nodes s, t find shortest path from s to t .
- (B) Given node s find shortest path from s to all other nodes.

Dijkstra's algorithm for non-negative edge lengths. Running time: $O((m+n) \log n)$ with heaps and $O(m + n \log n)$ with advanced priority queues.

Bellman-Ford algorithm for arbitrary edge lengths. Running time: $O(nm)$.

11.1.0.3 All-Pairs Shortest Paths

All-Pairs Shortest Path Problem

Input A (undirected or directed) graph $G = (V, E)$ with edge lengths. For edge $e = (u, v)$, $\ell(e) = \ell(u, v)$ is its length.

- (A) Find shortest paths for all pairs of nodes.
- (A) Apply single-source algorithms n times, once for each vertex.
- (B) Non-negative lengths. $O(nm \log n)$ with heaps and $O(nm + n^2 \log n)$ using advanced priority queues.
- (C) Arbitrary edge lengths: $O(n^2 m)$.
 $\Theta(n^4)$ if $m = \Omega(n^2)$.
- (D) **Q:** Can we do better?

11.1.0.4 Shortest Paths and Recursion

- (A) Compute the shortest path distance from s to t recursively?
- (B) What are the smaller sub-problems?
- (C) **Prefix property:**

Lemma 11.1.1. Let G be a directed graph with arbitrary edge lengths. If $s = v_0 \rightarrow v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_k$ is shortest path from s to v_k then for $1 \leq i < k$:

(A) $s = v_0 \rightarrow v_1 \rightarrow v_2 \rightarrow \dots \rightarrow v_i$ is shortest path from s to v_i

- (D) Sub-problem idea: paths of fewer hops/edges

11.1.0.5 Hop-based Recur': Single-Source Shortest Paths

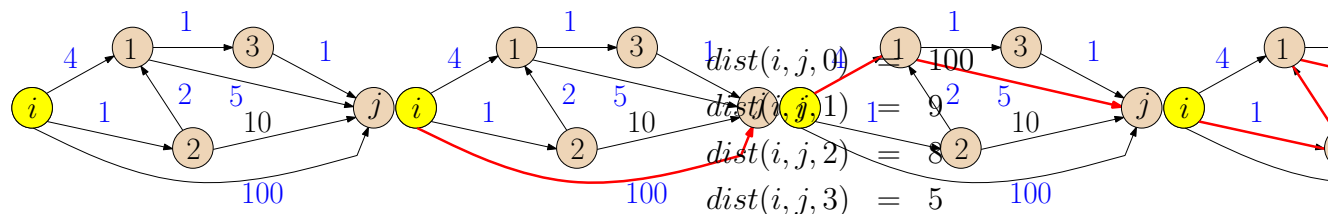
- (A) Single-source problem: fix source s .
- (B) $OPT(v, k)$: shortest path dist. from s to v using at most k edges.
- (C) Note: $dist(s, v) = OPT(v, n - 1)$. Recursion for $OPT(v, k)$:
- (D) $OPT(v, k) = \min \begin{cases} \min_{u \in V} (OPT(u, k - 1) + c(u, v)). \\ OPT(v, k - 1) \end{cases}$

Base case: $OPT(v, 1) = c(s, v)$ if $(s, v) \in E$ otherwise ∞

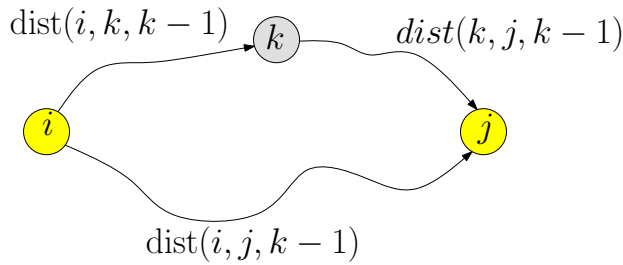
- (E) Leads to Bellman-Ford algorithm — see text book.
- (F) $OPT(v, k)$ values are also of independent interest: shortest paths with at most k hops.

11.1.0.6 All-Pairs: Recursion on index of intermediate nodes

- (A) Number vertices arbitrarily as v_1, v_2, \dots, v_n
- (B) $dist(i, j, k)$: shortest path distance between v_i and v_j among all paths in which the largest index of an *intermediate node* is at most k



11.1.0.7 All-Pairs: Recursion on index of intermediate nodes



$$dist(i, j, k) = \min \begin{cases} dist(i, j, k-1) \\ dist(i, k, k-1) + dist(k, j, k-1) \end{cases}$$

Base case: $dist(i, j, 0) = c(i, j)$ if $(i, j) \in E$, otherwise ∞

Correctness: If $i \rightarrow j$ shortest path goes through k then k occurs only once on the path — otherwise there is a negative length cycle.

11.1.1 Floyd-Warshall Algorithm

11.1.1.1 for All-Pairs Shortest Paths

```

Check if  $G$  has a negative cycle // Bellman-Ford:  $O(mn)$  time
if there is a negative cycle then return ‘‘Negative cycle’’

for  $i = 1$  to  $n$  do
  for  $j = 1$  to  $n$  do
     $dist(i, j, 0) = c(i, j)$  (*  $c(i, j) = \infty$  if  $(i, j) \notin E$ , 0 if  $i = j$  *)

for  $k = 1$  to  $n$  do
  for  $i = 1$  to  $n$  do
    for  $j = 1$  to  $n$  do
       $dist(i, j, k) = \min \begin{cases} dist(i, j, k-1), \\ dist(i, k, k-1) + dist(k, j, k-1) \end{cases}$ 

```

Correctness: Recursion works under the assumption that all shortest paths are defined (no negative length cycle).

Running Time: $\Theta(n^3)$, **Space:** $\Theta(n^3)$.

11.1.2 Floyd-Warshall Algorithm

11.1.2.1 for All-Pairs Shortest Paths

Do we need a separate algorithm to check if there is negative cycle?

```

for  $i = 1$  to  $n$  do
  for  $j = 1$  to  $n$  do
     $dist(i, j, 0) = c(i, j)$  (*  $c(i, j) = \infty$  if  $(i, j) \notin E$ , 0 if  $i = j$  *)
  not edge, 0 if  $i = j$  *)

  for  $k = 1$  to  $n$  do
    for  $i = 1$  to  $n$  do
      for  $j = 1$  to  $n$  do
         $dist(i, j, k) = \min(dist(i, j, k - 1), dist(i, k, k - 1) + dist(k, j, k - 1))$ 

  for  $i = 1$  to  $n$  do
    if ( $dist(i, i, n) < 0$ ) then
      Output that there is a negative length cycle in  $G$ 

```

Correctness: exercise

11.1.2.2 Floyd-Warshall Algorithm: Finding the Paths

Question: Can we find the paths in addition to the distances?

- (A) Create a $n \times n$ array Next that stores the next vertex on shortest path for each pair of vertices
- (B) With array Next, for any pair of given vertices i, j can compute a shortest path in $O(n)$ time.

11.1.3 Floyd-Warshall Algorithm

11.1.3.1 Finding the Paths

```

for  $i = 1$  to  $n$  do
  for  $j = 1$  to  $n$  do
     $dist(i, j, 0) = c(i, j)$  (*  $c(i, j) = \infty$  if  $(i, j)$  not edge, 0 if  $i = j$  *)
     $Next(i, j) = -1$ 
  for  $k = 1$  to  $n$  do
    for  $i = 1$  to  $n$  do
      for  $j = 1$  to  $n$  do
        if ( $dist(i, j, k - 1) > dist(i, k, k - 1) + dist(k, j, k - 1)$ ) then
           $dist(i, j, k) = dist(i, k, k - 1) + dist(k, j, k - 1)$ 
           $Next(i, j) = k$ 

  for  $i = 1$  to  $n$  do
    if ( $dist(i, i, n) < 0$ ) then
      Output that there is a negative length cycle in  $G$ 

```

Exercise: Given Next array and any two vertices i, j describe an $O(n)$ algorithm to find a i - j shortest path.

11.1.3.2 Summary of results on shortest paths

Single vertex		
No negative edges	Dijkstra	$O(n \log n + m)$
Edges cost might be negative But no negative cycles	Bellman Ford	$O(nm)$

All Pairs Shortest Paths	No negative edges	$n * \text{Dijkstra}$	$O(n^2 \log n + nm)$
	No negative cycles	$n * \text{Bellman Ford}$	$O(n^2 m) = O(n^4)$
	No negative cycles	Floyd-Warshall	$O(n^3)$

11.2 Knapsack

11.2.0.3 Knapsack Problem

Input Given a Knapsack of capacity W lbs. and n objects with i th object having weight w_i and value v_i ; assume W, w_i, v_i are all positive integers

Goal Fill the Knapsack without exceeding weight limit while maximizing value.

Basic problem that arises in many applications as a sub-problem.

11.2.0.4 Knapsack Example

Item	I_1	I_2	I_3	I_4	I_5
Example 11.2.1. Value	1	6	18	22	28
Weight	1	2	5	6	7

If $W = 11$, the best is $\{I_3, I_4\}$ giving value 40.

Special Case When $v_i = w_i$, the Knapsack problem is called the **Subset Sum Problem**.

11.2.0.5 Greedy Approach

- (A) Pick objects with greatest value
 - (A) Let $W = 2$, $w_1 = w_2 = 1$, $w_3 = 2$, $v_1 = v_2 = 2$ and $v_3 = 3$; greedy strategy will pick $\{3\}$, but the optimal is $\{1, 2\}$
- (B) Pick objects with smallest weight
 - (A) Let $W = 2$, $w_1 = 1$, $w_2 = 2$, $v_1 = 1$ and $v_2 = 3$; greedy strategy will pick $\{1\}$, but the optimal is $\{2\}$
- (C) Pick objects with largest v_i/w_i ratio
 - (A) Let $W = 4$, $w_1 = w_2 = 2$, $w_3 = 3$, $v_1 = v_2 = 3$ and $v_3 = 5$; greedy strategy will pick $\{3\}$, but the optimal is $\{1, 2\}$
 - (B) Can show that a slight modification always gives half the optimum profit: pick the better of the output of this algorithm and the largest value item. Also, the algorithm gives better approximations when all item weights are small when compared to W .

11.2.0.6 Towards a Recursive Solution

First guess: $\text{Opt}(i)$ is the optimum solution value for items $1, \dots, i$.

Observation 11.2.2. Consider an optimal solution \mathcal{O} for $1, \dots, i$

Case item $i \notin \mathcal{O}$ \mathcal{O} is an optimal solution to items 1 to $i - 1$

Case item $i \in \mathcal{O}$ Then $\mathcal{O} - \{i\}$ is an optimum solution for items 1 to $n - 1$ in knapsack of capacity $W - w_i$.

Subproblems depend also on remaining capacity. Cannot write subproblem only in terms of $\text{Opt}(1), \dots, \text{Opt}(i - 1)$.

$\text{Opt}(i, w)$: optimum profit for items 1 to i in knapsack of size w

Goal: compute $\text{Opt}(n, W)$

11.2.0.7 Dynamic Programming Solution

Definition 11.2.3. Let $\text{Opt}(i, w)$ be the optimal way of picking items from 1 to i , with total weight not exceeding w .

$$\text{Opt}(i, w) = \begin{cases} 0 & \text{if } i = 0 \\ \text{Opt}(i - 1, w) & \text{if } w_i > w \\ \max \begin{cases} \text{Opt}(i - 1, w) \\ \text{Opt}(i - 1, w - w_i) + v_i \end{cases} & \text{otherwise} \end{cases}$$

11.2.0.8 An Iterative Algorithm

```
for  $w = 0$  to  $W$  do
   $M[0, w] = 0$ 
for  $i = 1$  to  $n$  do
  for  $w = 1$  to  $W$  do
    if  $(w_i > w)$  then
       $M[i, w] = M[i - 1, w]$ 
    else
       $M[i, w] = \max(M[i - 1, w], M[i - 1, w - w_i] + v_i)$ 
```

Running Time

(A) Time taken is $O(nW)$

(B) Input has size $O(n + \log W + \sum_{i=1}^n (\log v_i + \log w_i))$; so running time not polynomial but “pseudo-polynomial”!

11.2.0.9 Knapsack Algorithm and Polynomial time

- (A) Input size for Knapsack: $O(n) + \log W + \sum_{i=1}^n (\log w_i + \log v_i)$.
- (B) Running time of dynamic programming algorithm: $O(nW)$.
- (C) Not a polynomial time algorithm.
- (D) Example: $W = 2^n$ and $w_i, v_i \in [1..2^n]$. Input size is $O(n^2)$, running time is $O(n2^n)$ arithmetic/comparisons.
- (E) Algorithm is called a **pseudo-polynomial** time algorithm because running time is polynomial if *numbers* in input are of size polynomial in the **combinatorial size** of problem.
- (F) Knapsack is **NP-Hard** if numbers are not polynomial in n .

11.3 Traveling Salesman Problem

11.3.0.10 Traveling Salesman Problem

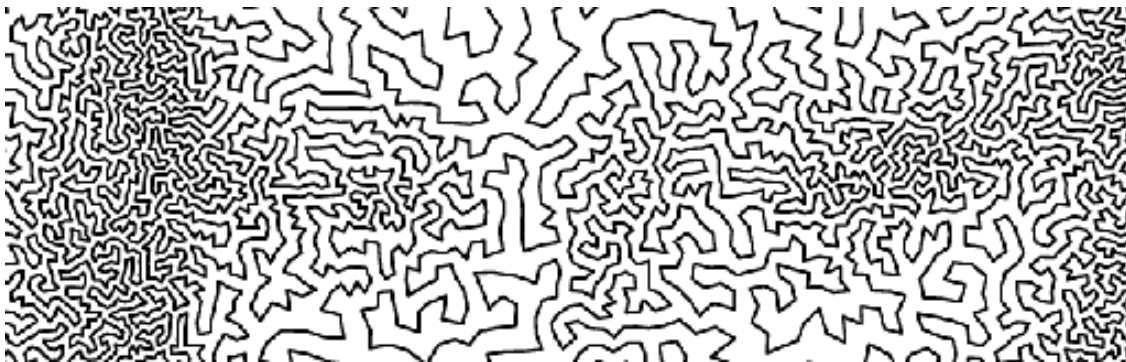
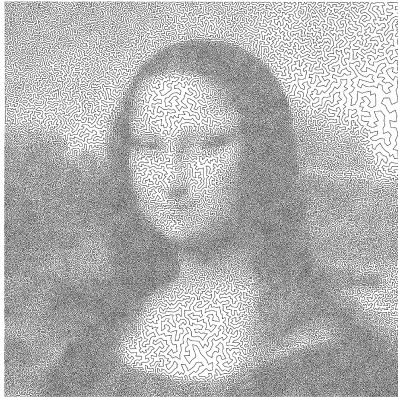
Input A graph $G = (V, E)$ with non-negative edge costs/lengths. $c(e)$ for edge e

Goal Find a tour of minimum cost that visits each node.

No polynomial time algorithm known. Problem is **NP-Hard**.

11.3.0.11 Drawings using TSP





11.3.0.12 Example: optimal tour for cities of a country (which one?)



11.3.0.13 An Exponential Time Algorithm

How many different tours are there? $n!$

Stirling's formula: $n! \simeq \sqrt{n}(n/e)^n$ which is $\Theta(2^{cn \log n})$ for some constant $c > 1$

Can we do better? Can we get a $2^{O(n)}$ time algorithm?

11.3.0.14 Towards a Recursive Solution

- (A) Order vertices as v_1, v_2, \dots, v_n
- (B) $OPT(S)$: optimum **TSP** tour for the vertices $S \subseteq V$ in the graph restricted to S . Want $OPT(V)$.

Can we compute $OPT(S)$ recursively?

- (A) Say $v \in S$. What are the two neighbors of v in optimum tour in S ?
- (B) If u, w are neighbors of v in an optimum tour of S then removing v gives an optimum *path* from u to w visiting all nodes in $S - \{v\}$.

Path from u to w is not a recursive subproblem! Need to find a more general problem to allow recursion.

11.3.0.15 A More General Problem: TSP Path

Input A graph $G = (V, E)$ with non-negative edge costs/lengths($c(e)$ for edge e) and two nodes s, t

Goal Find a path from s to t of minimum cost that visits each node exactly once.

Can solve **TSP** using above. Do you see how?

Recursion for optimum **TSP** Path problem:

- (A) $OPT(u, v, S)$: optimum **TSP** Path from u to v in the graph restricted to S (here $u, v \in S$).

11.3.1 A More General Problem: TSP Path

11.3.1.1 Continued...

What is the next node in the optimum path from u to v ? Suppose it is w . Then what is $OPT(u, v, S)$?

$$OPT(u, v, S) = c(u, w) + OPT(w, v, S - \{u\})$$

We do not know w ! So try all possibilities for w .

11.3.1.2 A Recursive Solution

$$OPT(u, v, S) = \min_{w \in S, w \neq u, v} \left(c(u, w) + OPT(w, v, S - \{u\}) \right)$$

What are the subproblems for the original problem $OPT(s, t, V)$?

$OPT(u, v, S)$ for $u, v \in S, S \subseteq V$.

How many subproblems?

- (A) number of distinct subsets S of V is at most 2^n
- (B) number of pairs of nodes in a set S is at most n^2
- (C) hence number of subproblems is $O(n^2 2^n)$

Exercise: Show that one can compute **TSP** using above dynamic program in $O(n^3 2^n)$ time and $O(n^2 2^n)$ space.

Disadvantage of dynamic programming solution: memory!

11.3.1.3 Dynamic Programming: Postscript

Dynamic Programming = Smart Recursion + Memoization

- (A) How to come up with the recursion?
- (B) How to recognize that dynamic programming may apply?

11.3.1.4 Some Tips

- (A) Problems where there is a *natural* linear ordering: sequences, paths, intervals, **DAGs** etc. Recursion based on ordering (left to right or right to left or topological sort) usually works.
- (B) Problems involving trees: recursion based on subtrees.
- (C) More generally:
 - (A) Problem admits a natural recursive divide and conquer
 - (B) If optimal solution for whole problem can be simply composed from optimal solution for each separate pieces then plain divide and conquer works directly
 - (C) If optimal solution depends on all pieces then can apply dynamic programming if *interface/interaction* between pieces is *limited*. Augment recursion to not simply find an optimum solution but also an optimum solution for each possible way to interact with the other pieces.

11.3.1.5 Examples

- (A) Longest Increasing Subsequence: break sequence in the middle say. What is the interaction between the two pieces in a solution?
- (B) Sequence Alignment: break both sequences in two pieces each. What is the interaction between the two sets of pieces?
- (C) Independent Set in a Tree: break tree at root into subtrees. What is the interaction between the subtrees?
- (D) Independent Set in an graph: break graph into two graphs. What is the interaction? Very high!
- (E) Knapsack: Split items into two sets of half each. What is the interaction?

Bibliography