More Dynamic Programming

Lecture 10
February 22, 2011
Part I

All Pairs Shortest Paths
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.

- Given nodes \( s, t \) find shortest path from \( s \) to \( t \).
- Given node \( s \) find shortest path from \( s \) to all other nodes.
- Find shortest paths for all pairs of nodes.
Single-Source Shortest Paths

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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: \( O(nm) \).
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- Non-negative lengths. $O(nm \log n)$ with heaps and $O(nm + n^2 \log n)$ using advanced priority queues.
- Arbitrary edge lengths: $O(n^2m)$. Can we do better?
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Shortest Paths and Recursion

- Can we compute the shortest path distance from $s$ to $t$ recursively?
- What are the smaller sub-problems?

**Lemma**

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

- $s = v_0 \rightarrow v_1 \rightarrow v_2 \rightarrow \ldots \rightarrow v_i$ is a shortest path from $s$ to $v_i$

Sub-problem idea: paths of fewer hops/edges
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Sub-problem idea: paths of fewer hops/edges
Hop-based Recur’: Single-Source Shortest Paths

Single-source problem: fix source $s$.

$\text{OPT}(v, k)$: shortest path distance from $s$ to $v$ using at most $k$ edges.

Note: $\text{dist}(s, v) = \text{OPT}(v, n - 1)$

Recursion for $\text{OPT}(v, k)$:

$$\text{OPT}(v, k) = \min_{u \in V} (\text{OPT}(u, k - 1) + c(u, v)).$$

Base case: $\text{OPT}(v, 1) = c(s, v)$ if $(s, v) \in E$ otherwise $\infty$

Leads to Bellman-Ford algorithm — see text book.

$\text{OPT}(v, k)$ values are also of independent interest: shortest paths with at most $k$ hops
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All-Pairs: recursion on index of intermediate nodes

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

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\begin{array}{l}
\text{dist}(i, j, 0) = 100 \\
\text{dist}(i, j, 1) = 9 \\
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\end{array}
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\[
\begin{align*}
\text{dist}(i, k, k - 1) &\quad \rightarrow \quad k \\
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\[
\text{dist}(i, j, k - 1)
\]

\[
\frac{\text{dist}(i, j, k)}{k} = \min(\text{dist}(i, j, k-1), \text{dist}(i, k, k-1)+\text{dist}(k, j, k-1))
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Base case: \( \text{dist}(i, j, 0) = c(i, j) \) if \((i, j) \in E\), otherwise \( \infty \)

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.
Floyd-Warshall Algorithm
for All-Pairs Shortest Paths

Check if $G$ has a negative cycle using Bellman-Ford in $O(mn)$ time
If there is a negative cycle return

```
for i = 1 to n do
    for j = 1 to n do
        dist(i, j, 0) = c(i, j) (* c(i, j) = ∞ 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))
```

Correctness: Recursion works under the assumption that all shortest paths are defined (no negative length cycle).
Running Time: $\Theta(n^3)$, Space: $\Theta(n^3)$. 
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Do we need a separate algorithm to check if there is negative cycle?

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\end{align*}
\]

\[
\begin{align*}
\text{for } i &= 1 \text{ to } n \text{ do} \\
&\quad \text{if } (\text{dist}(i, i, n - 1) < 0) \text{ then} \\
&\quad \quad \text{Output that there is a negative length cycle in } G
\end{align*}
\]

Correctness: exercise
Floyd-Warshall Algorithm
for All-Pairs Shortest Paths

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

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

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

- Create a $n \times n$ array $Next$ that stores the next vertex on shortest path for each pair of vertices.
- With array $Next$, for any pair of given vertices $i, j$ can compute a shortest path in $O(n)$ time.
**Question:** Can we find the paths in addition to the distances?

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- With array `Next`, for any pair of given vertices $i, j$ can compute a shortest path in $O(n)$ time.
Floyd-Warshall Algorithm
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($i$, $i$, $n - 1$) < 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.
### Summary of results on shortest paths

<table>
<thead>
<tr>
<th>Single vertex</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No negative edges</td>
<td>Dijkstra</td>
<td>$O(n \log n + m)$</td>
</tr>
<tr>
<td>Edges cost might be negative</td>
<td>Bellman Ford</td>
<td>$O(nm)$</td>
</tr>
<tr>
<td>But no negative cycles</td>
<td></td>
<td></td>
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</table>

### All Pairs Shortest Paths

<table>
<thead>
<tr>
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<td>No negative cycles</td>
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</tr>
<tr>
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</tr>
</tbody>
</table>
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.
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Knapsack Example

Example

<table>
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<tr>
<th>Item</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>1</td>
<td>6</td>
<td>18</td>
<td>22</td>
<td>28</td>
</tr>
<tr>
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<td>1</td>
<td>2</td>
<td>5</td>
<td>6</td>
<td>7</td>
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</tbody>
</table>

If $W = 11$, the best is \{3, 4\} giving value 40.

Special Case

When $v_i = w_i$, the Knapsack problem is called the Subset Sum Problem.
Greedy Approach

- Pick objects with greatest value
  - 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 $\{1, 2\}$

- Pick objects with smallest weight
  - 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 $\{2\}$

- Pick objects with largest $v_i/w_i$ ratio
  - 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 $\{1, 2\}$
  - 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 algorithms gives better approximations when all item weights are small when compared to $W$. 
Towards a Recursive Solution

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

Observation

Consider an optimal solution \( \mathcal{O} \) for \( 1, \ldots, i \)

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 \( \text{Opt}(1), \ldots, \text{Opt}(i - 1) \).

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

Goal: compute \( \text{Opt}(n, W) \)
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Dynamic Programming Solution

Definition

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

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

Sariel (UIUC)
An Iterative Algorithm

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

Running Time

- Time taken is $O(nW)$
- 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”!
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
            \( M[i, w] = \max(M[i - 1, w], M[i - 1, w - w_i] + v_i) \)

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Knapsack Algorithm and Polynomial time

Input size for Knapsack: \( O(n) + \log W + \sum_{i=1}^{n} (\log w_i + \log v_i) \)

Running time of dynamic programming algorithm: \( O(nW) \)

Not a polynomial time algorithm.
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.

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.
Knapsack is NP-hard if numbers are not polynomial in \( n \).
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Part III

Traveling Salesman Problem
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.
Traveling Salesman Problem

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No polynomial time algorithm known. Problem is NP-Hard.
Example: optimal tour for cities of a country (which one?)
An Exponential Time Algorithm

How many different tours are there? \( n! \)

Stirling’s formula: \( n! \approx \sqrt{n} (n/e)^n \) 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?
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Towards a Recursive Solution

- Order vertices as $v_1, v_2, \ldots, v_n$
- $\text{OPT}(S)$: optimum TSP tour for the vertices $S \subseteq V$ in the graph restricted to $S$. Want $\text{OPT}(V)$.

Can we compute $\text{OPT}(S)$ recursively?

- Say $v \in S$. What are the two neighbors of $v$ in optimum tour in $S$?
- 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.
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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:

1. $\text{OPT}(u, v, S)$: optimum TSP Path from $u$ to $v$ in the graph restricted to $S$ (here $u, v \in S$).
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What is the next node in the optimum path from $u$ to $v$? Suppose it is $w$. Then what is $OPT(u, v, S)$?

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

We do not know $w$! So try all possibilities for $w$. 
A More General Problem: TSP Path

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\text{OPT}(u, v, S) = c(u, w) + \text{OPT}(w, v, S - \{u\})
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We do not know \( w \)! So try all possibilities for \( w \).
A Recursive Solution

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

What are the subproblems for the original problem \(\text{OPT}(s, t, V)\)? \(\text{OPT}(u, v, S)\) for \(u, v \in S, S \subseteq V\).

How many subproblems?
- number of distinct subsets \(S\) of \(V\) is at most \(2^n\)
- number of pairs of nodes in a set \(S\) is at most \(n^2\)
- hence number of subproblems is \(O(n^22^n)\)

Exercise: Show that one can compute TSP using above dynamic program in \(O(n^32^n)\) time and \(O(n^22^n)\) space.

Disadvantage of dynamic programming solution: memory!
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Dynamic Programming = Smart Recursion + Memoization

- How to come up with the recursion?
- How to recognize that dynamic programming may apply?
Dynamic Programming: Postscript

Dynamic Programming = Smart Recursion + Memoization

- How to come up with the recursion?
- How to recognize that dynamic programming may apply?
Some Tips

- 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.
- Problems involving trees: recursion based on subtrees.
- More generally:
  - Problem admits a natural recursive divide and conquer
  - If optimal solution for whole problem can be simply composed from optimal solution for each separate pieces then plain divide and conquer works directly
  - 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.
Examples

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