# CMPSCI 611: Advanced Algorithms 

Lecture 8: Dynamic Programming

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## Outline

## Dynamic Programming

## Shortest Paths

## Knapsack Warmup

## Problem

- Input: $n$ items each with value $w_{i} \in \mathbb{N}$ and a capacity $W \in \mathbb{N}$
- Output: Subset $S$ that maximizes $\sum_{i \in S} w_{i}$ subject to $\sum_{i \in S} w_{i} \leq W$


## Example

Consider input $\{7,5,4\}$ and $W=10$. Optimal is 9 .

## Try something like divide and conquer...

## Definition

Let $\operatorname{knap}(i, j)$ be the optimal solution obtained by using only first $i$ items and capacity $j$ where $\operatorname{knap}(i, j)=-\infty$ for $j<0$

To compute knap $(i, j)$ :

- If $i=0: \operatorname{knap}(i, j)=0$
- Otherwise:
- Compute $\operatorname{knap}(i-1, j)$ and $\operatorname{knap}\left(i-1, j-w_{i}\right)$
- $\operatorname{knap}(i, j)=\max \left(\operatorname{knap}(i-1, j), \operatorname{knap}\left(i-1, j-w_{i}\right)+w_{i}\right)$

Claim
The above recursive algorithm will return knap( $n, W$ ) correctly.
But it's very inefficient because evaluating both $\operatorname{knap}(i-1, j)$ and $\operatorname{knap}\left(i-1, j-w_{i}\right)$ requires a lot of duplication of work.

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## Dynamic Programming Table

Construct a $(n+1) \times(W+1)$ table $K$ where $K_{i, j}=\operatorname{knap}(i, j)$ :

- Fill in "0" for each entry of first row
- To fill in $i$-th row use entries of $(i-1)$-th row:

$$
K_{i, j}= \begin{cases}\max \left(K_{i-1, j}, K_{i-1, j-w_{i}}+w_{i}\right) & \text { if } j \geq w_{i} \\ K_{i-1, j} & \text { if } j<w_{i}\end{cases}
$$

Claim
Running time is $O(n W)$ and space required is $O(W)$.
Easy to tweak algorithm to find $S$ and not just $\sum_{i \in S} w_{i}$
Actually Knapsack is NP-complete, have we proved that $P=N P$ ?

## When to use dynamic programming. . .

- Optimal Substructure: The solution to the problem can be found using solutions to smaller sub-problems.
- Overlap of Sub-Problems: By taking advantage of the fact that many identical sub-problems are created, a dynamic programming algorithm may be more efficient than a divide and conquer algorithm.


## Outline

## Dynamic Programming

Shortest Paths

## Shortest Paths

Let $G=(V, E)$ be a directed graph with weights $w: E \rightarrow \mathbb{R}^{+}$.
Definition
For path $p=\left(v_{1}, \ldots, v_{k}\right)$ be a path, define

$$
w(p)=\sum_{i=1}^{k-1} w\left(v_{i}, v_{i+1}\right) .
$$

The shortest path between $u$ and $v$ is

$$
\delta(u, v)=\min \{w(p): p \text { is a path from } u \text { to } v\}
$$

if there is a path from $u$ to $v$ and $\infty$ otherwise.

## Floyd-Warshall Warm-Up

Problem: Find $\delta(u, v)$ for all $u, v \in V$.

- Define sub-problems by limiting the set of intermediate nodes
- Let $d_{i j}^{(k)}=$ length of shortest path from $i$ to $j$ for which all intermediate vertices are in $\left\{v_{1}, \ldots, v_{k}\right\}$
- Easy: $d_{i j}^{(0)}=w(i, j)$ if $(i, j) \in E$ and $d_{i j}^{(0)}=\infty$ otherwise
- For $k \geq 1$ :

$$
d_{i j}^{(k)}=\min \left(d_{i j}^{(k-1)}, d_{i k}^{(k-1)}+d_{k j}^{(k-1)}\right)
$$

## Floyd-Warshall Algorithm

## Algorithm

1. Let $d_{i j}^{(0)}=w(i, j)$ if $(i, j) \in E$ and $d_{i j}^{(0)}=\infty$ otherwise.
2. For $k=1$ to $n$ :
2.1 For $i, j \in[n]$ : let

$$
d_{i j}^{(k)}=\min \left(d_{i j}^{(k-1)}, d_{i k}^{(k-1)}+d_{k j}^{(k-1)}\right)
$$

3. Return $d_{i j}^{(n)}$

Running Time: $\Theta\left(n^{3}\right)$ where $n=|V|$

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