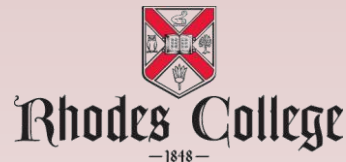


COMP 355

Advanced Algorithms

**Dynamic Programming:
Knapsack & LCS
Section 6.4 (KT)**



Knapsack Problem

There are two versions of the problem:

- (1) “0-1 knapsack problem” and
- (2) “Fractional knapsack problem”

(1) Items are indivisible; you either take an item or not. Solved with *dynamic programming*

(2) Items are divisible: you can take any fraction of an item. Solved with a *greedy algorithm*.

Knapsack Problem

Knapsack problem.

- Given n objects and a "knapsack."
- Item i weighs $w_i > 0$ kilograms and has value $v_i > 0$.
- Knapsack has capacity of W kilograms.
- Goal: fill knapsack so as to maximize total value.

$$W = 11$$

Ex: { 3, 4 } has value 40.

Item	Value	Weight
1	1	1
2	6	2
3	18	5
4	22	6
5	28	7

Greedy: repeatedly add item with maximum ratio v_i / w_i .

Ex: { 5, 2, 1 } achieves only value = 35 \Rightarrow greedy not optimal.

Knapsack Problem: Bottom-Up

Knapsack. Fill up an n -by- W array.

```
Input:  $n, w_1, \dots, w_N, v_1, \dots, v_N$ 
```

```
for  $w = 0$  to  $W$ 
```

```
     $M[0, w] = 0$ 
```

```
for  $i = 1$  to  $n$ 
```

```
    for  $w = 1$  to  $W$ 
```

```
        if ( $w_i > w$ )
```

```
             $M[i, w] = M[i-1, w]$ 
```

```
        else
```

```
             $M[i, w] = \max \{M[i-1, w], v_i + M[i-1, w-w_i]\}$ 
```

```
return  $M[n, W]$ 
```

Knapsack Algorithm

	W + 1 →											
	0	1	2	3	4	5	6	7	8	9	10	11
ϕ	0	0	0	0	0	0	0	0	0	0	0	0
{ 1 }	0	1	1	1	1	1	1	1	1	1	1	1
{ 1, 2 }	0	1	6	7	7	7	7	7	7	7	7	7
{ 1, 2, 3 }	0	1	6	7	7	18	19	24	25	25	25	25
{ 1, 2, 3, 4 }	0	1	6	7	7	18	22	24	28	29	29	40
{ 1, 2, 3, 4, 5 }	0	1	6	7	7	18	22	28	29	34	34	40

$n + 1$ ↓

OPT: { 4, 3 }
 value = 22 + 18 = 40

W = 11

Item	Value	Weight
1	1	1
2	6	2
3	18	5
4	22	6
5	28	7

Knapsack Problem: Running Time

Running time. $\Theta(nW)$.

- Not polynomial in input size!
- "Pseudo-polynomial."
- Decision version of Knapsack is NP-complete.

Knapsack approximation algorithm. There exists a polynomial algorithm that produces a feasible solution that has value within 0.01% of optimum.

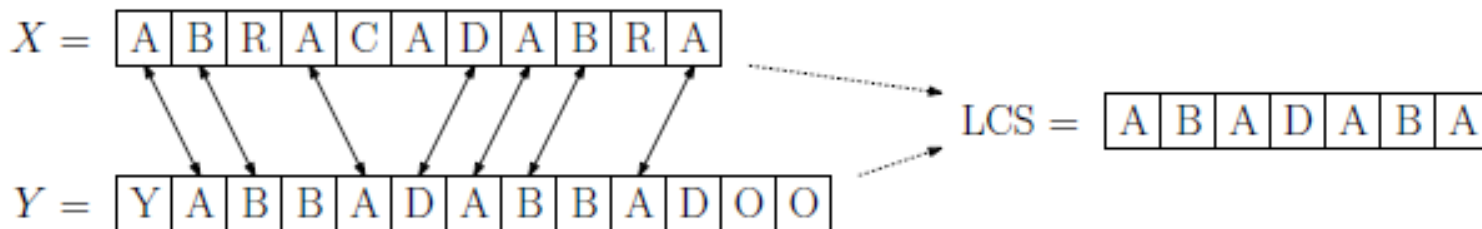
Using DP to compare strings

- Determining the degree of similarity between two strings
 - Applications in computational biology (sequence alignment)
 - Applications in document processing and retrieval
- One common measure of similarity between two strings is the lengths of their longest common subsequence.

Longest Common Subsequence (LCS)

Given two sequences $X = \langle x_1, x_2, \dots, x_m \rangle$ and $Z = \langle z_1, z_2, \dots, z_k \rangle$, we say that Z is a subsequence of X if there is a strictly increasing sequence of k indices $\langle i_1, i_2, \dots, i_k \rangle$ ($1 \leq i_1 < i_2 < \dots < i_k \leq m$) such that $Z = \langle x_{i_1}, x_{i_2}, \dots, x_{i_k} \rangle$.

For example, let $X = \langle \text{ABRACADABRA} \rangle$ and let $Z = \langle \text{AADAA} \rangle$, then Z is a subsequence of X .



LCS Problem: Given two sequences $X = \langle x_1, \dots, x_m \rangle$ and $Y = \langle y_1, \dots, y_n \rangle$ determine the length of their longest common subsequence, and more generally the sequence itself.