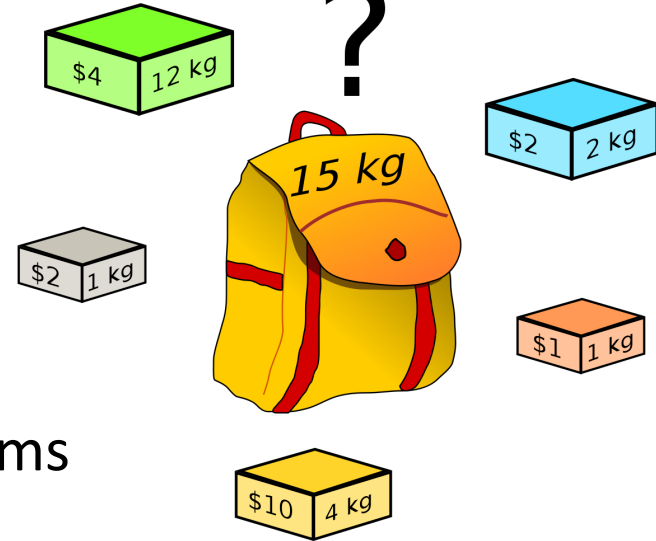


## Dynamic Programming

- a. Fibonacci Series
- b. Weighted Interval Scheduling
- c. Knapsack

(source: Wikipedia)

# The Knapsack Problem



- **Input:**  $n$  items for your knapsack
  - value  $v_i$  and a weight  $w_i \in \mathbb{N}$  for  $n$  items
  - capacity of your knapsack  $T \in \mathbb{N}$
- **Output:** the most valuable subset of items that fits in the knapsack

- Subset  $S \subseteq \{1, \dots, n\}$
- Value  $V_S = \sum_{i \in S} v_i$  as large as possible
- Weight  $W_S = \sum_{i \in S} w_i$  at most  $T$

- **Want:**  $\operatorname{argmax}_{S \subseteq \{1, \dots, n\}} V_S$  s.t.  $W_S \leq T$

- **(SubsetSum:**  $v_i = w_i$ ,
- **TugOfWar:**  $v_i = w_i, T = \frac{1}{2} \sum_i v_i$ )

$n =$   $T =$

$v_1 =$   $w_1 =$

$v_2 =$   $w_2 =$

$v_3 =$   $w_3 =$

$v_4 =$   $w_4 =$

$v_5 =$   $w_5 =$



# Do we really need DP?

Items with large  $\frac{v_i}{w_i}$  seem like good choices...

**Ex.**  $T = 8$ ,  $(v_1 = 6, w_1 = 5)$ ,  $(v_2 = 4, w_2 = 4)$ ,  $(v_3 = 4, w_3 = 4)$

- Strategy 1: Repeatedly pick items that fit with largest  $\frac{v_i}{w_i}$
- Is this optimal?



# Knapsack – what to do with n-th item?

**Want:**  $\operatorname{argmax}_{S \subseteq \{1, \dots, n\}} V_S$  s.t.  $W_S \leq T$



# Knapsack - subproblems

- Let  $O_n \subseteq \{1, \dots, n\}$  be the **optimal** subset of items given the first  $n$  items

- **Case 1:**  $n \notin O_n$

$$O_n =$$

- **Case 2:**  $n \in O_n$

$$O_n =$$



# Knapsack - recurrence

- Let  $\mathbf{OPT}(j, S)$  be the **value** of the optimal subset of items  $\{1, \dots, j\}$  in a knapsack of size  $S$
- **Case 1:**  $j \notin O_{j,S}$
- **Case 2:**  $j \in O_{j,S}$



# Knapsack - recurrence

- Let  $\mathbf{OPT}(j, S)$  be the **value** of the optimal subset of items  $\{1, \dots, j\}$  in a knapsack of size  $S$
- **Case 1:**  $j \notin O_{j,S}$ 
  - $OPT(j, S) = OPT(j - 1, S)$
- **Case 2:**  $j \in O_{j,S}$ 
  - $OPT(j, S) = v_j + OPT(j - 1, S - w_j)$

**Recurrence:**

$$OPT(j, S) =$$

**Base Cases:**

$$OPT(j, 0) =$$

$$OPT(0, S) =$$



# Knapsack - recurrence

- Let  $\mathbf{OPT}(j, S)$  be the **value** of the optimal subset of items  $\{1, \dots, j\}$  in a knapsack of size  $S$
- **Case 1:**  $j \notin O_{j,S}$ 
  - $OPT(j, S) = OPT(j - 1, S)$
- **Case 2:**  $j \in O_{j,S}$ 
  - $OPT(j, S) = v_j + OPT(j - 1, S - w_j)$

**Recurrence:**

$$OPT(j, S) = \begin{cases} \max\{OPT(j - 1, S), v_j + OPT(j - 1, S - w_j)\} & S \geq w_j \\ OPT(j - 1, S) & S < w_j \end{cases}$$

**Base Cases:**

$$OPT(j, 0) = OPT(0, S) = 0$$





# Knapsack (“Bottom-Up”)

```
// All inputs are global vars
FindOPT(n,T):
  M[0,S] ← 0, M[j,0] ← 0

  for (j = 1,...,n):
    for (S = 1,...,T):
      if (wj > S): M[j,S] ← M[j-1,S]
      else: M[j,S] ← max{M[j-1,S], vj + M[j-1,S-wj]}

  return M[n,T]
```



# Ask the Audience

Space:

- Input:  $T = 8, n = 3$ 
  - $w_1 = 2, v_1 = 4$
  - $w_2 = 3, v_2 = 5$
  - $w_3 = 5, v_3 = 8$

items	3									
	2									
	1									
	0									
	-	0	1	2	3	4	5	6	7	8
		capacities								

$OPT(j, S)$

$$= \begin{cases} \max\{OPT(j-1, S), v_j + OPT(j-1, S - w_j)\} & \text{if } S \geq w_j \\ OPT(j-1, S) & \text{if } S < w_j \end{cases}$$



# Filling the Knapsack

- Let  $O_{j,S}$  be the **optimal subset of items**  $\{1, \dots, j\}$  in a knapsack of size  $S$
- **Case 1:**  $j \notin O_{j,S}$ 
  - Use opt. solution for items 1 to  $j-1$  in a knapsack of size  $S$
- **Case 2:**  $j \in O_{j,S}$ 
  - Use  $j$  + opt. solution for items 1 to  $j-1$  in a knapsack of size  $S - w_j$



# Filling the Knapsack

```
// All inputs are global vars
// M[0:n,0:T] contains solutions to subproblems
FindSol(M,n,T):
  if (n = 0 or T = 0): return  $\emptyset$ 
  else:
    if ( $w_n > T$ ): return FindSol(M,n-1,T)
    else:
      if ( $M[n-1,T] > v_n + M[n-1,T-w_n]$ ):
        return FindSol(M,n-1,T)
      else:
        return {n} + FindSol(M,n-1,T- $w_n$ )
```



# Knapsack Wrapup

- Can solve knapsack problems in time/space  $O(nT)$ 
  - **Recipe:**
    - (1) identify a set of **subproblems**
    - (2) relate the subproblems via a **recurrence**
    - (3) find an **efficient implementation** of the recurrence (top down or bottom up)
    - (4) **reconstruct the solution** from the DP table



## Dynamic Programming

- a. Fibonacci Series
- b. Weighted Interval Scheduling
- c. Knapsack
- d. Longest Common Subsequence

# Common Subsequences

- Given a string  $x \in \Sigma^n$  a **subsequence** is any string obtained by deleting a subset of the symbols

r e c u r a n c e

- Given two strings  $x \in \Sigma^n, y \in \Sigma^m$ , a **common subsequence** is a **subsequence** of both  $x$  and  $y$

r e c u r a n c e

r e c u r r e n c e

# Longest Common Subsequence (LCS)

- **Input:** Two strings  $x \in \Sigma^n, y \in \Sigma^m$
- **Output:** The longest common subsequence of  $x$  and  $y$



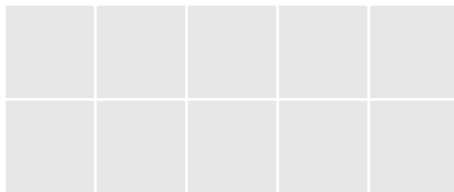
# Writing the Recurrence

- Consider the **LCS** of  $x, y$
- **Question:** Are the last symbols of  $x$  and  $y$  in the subsequence?
- **Observation:** Suppose  $x_n = y_m$ 
  - Then these symbols are always part of some LCS
  - **Ask the Audience:** Why?



# Writing the Recurrence

- Consider the **LCS** of  $x, y$
- **Question:** Are the last symbols of  $x$  and  $y$  in the subsequence?
- **Observation:** Suppose  $x_n \neq y_m$ 
  - **Case 1:**  $x_n$  is **not** in the LCS
  - **Case 2:**  $y_m$  is **not** in the LCS
  - **Case 3:** Neither is in the LCS



# Writing the Recurrence

- $LCS(i, j)$  = Length of LCS of  $x_{1:i}$  and  $y_{1:j}$
- **Equal:** If  $x_i = y_j$  then
- **Not Equal:**
  - **Case 1:**  $x_i$  is **not** in the LCS
  - **Case 2:**  $y_j$  is **not** in the LCS

**Recurrence:**

**Base Cases:**

# Writing the Recurrence

## Recurrence:

$$\text{LCS}(i, j) = \begin{cases} 1 + \text{LCS}(i - 1, j - 1) & \text{if } x_i = y_j \\ \max\{\text{LCS}(i - 1, j), \text{LCS}(i, j - 1)\} & \text{if } x_i \neq y_j \end{cases}$$

## Base Cases:

$$\text{LCS}(i, 0) = 0, \text{LCS}(0, j) = 0$$

# Solving the Recurrence: Bottom-Up

```
// All inputs are global vars
FindOPT(n,m):
    M[i,0] ← 0,    M[0,j] ← 0

    for (i= 1,...,n):
        for (j = 1,...,m):
            if (xi = yj):
                M[i,j] ← 1 + M[i-1,j-1]
            else:
                M[i,j] ← max{M[i-1,j],M[i,j-1]}

    return M[n,m]
```

# Ask the Audience

**x** = **peat**

**y** = **leapt**

Compute LCS(i,j) for  
each subproblem

	j=0	1	2	2	4	5
	-	l	e	a	p	t
i=0	-	0	0	0	0	0
1	p	0				
2	e	0				
3	a	0				
4	t	0				

# Ask the Audience

**x** = **peat**

**y** = **leapt**

Compute  $LCS(i,j)$  for each subproblem

	j=0	1	2	2	4	5	
	-	l	e	a	p	t	
i=0	-	0	0	0	0	0	
1	p	0	0	0	1	1	
2	e	0	0	1	1	1	
3	a	0	0	1	2	2	
4	t	0	0	1	2	2	3

# Finding the Solution

```
// All inputs are global vars
FindLCS(i,j):
  if (i = 0 or j = 0)
    return ""
  if (xi = yj):
    return FindLCS(i-1,j-1)+ xi
  else:
    if (M[i-1,j] > M[i,j-1])
      return FindLCS(i-1,j)
    else:
      return FindLCS(i,j-1)
return M[n,m]
```



# Summary

- Compute the **longest common subsequence** between two strings of length  $n$  and  $m$  in time  $O(nm)$
- Dynamic Programming:
  - Question: Which of the final letters are part of the LCS?
- **Ask the Audience:** How do we recover the LCS itself from the values  $LCS(i, j)$