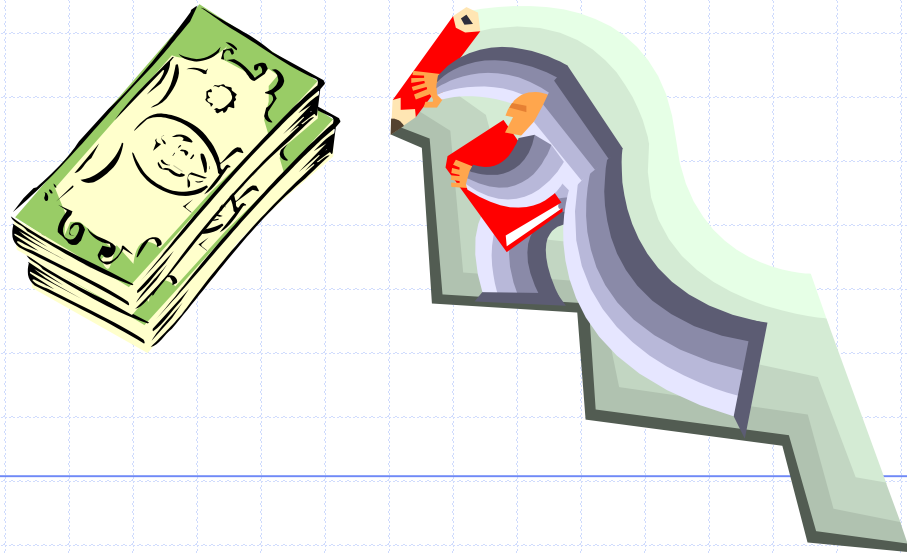


The Greedy Method

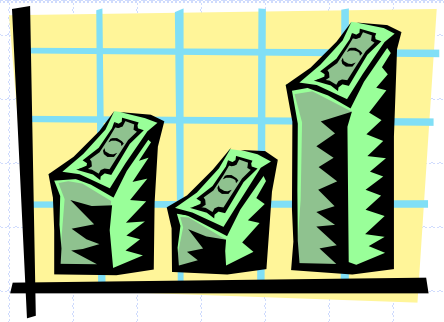


Outline and Reading



- ◆ The Greedy Method Technique (§5.1)
- ◆ Fractional Knapsack Problem (§5.1.1)
- ◆ Task Scheduling (§5.1.2)
- ◆ Minimum Spanning Trees (§7.3) [future lecture]

The Greedy Method Technique



- ◆ **The greedy method** is a general algorithm design paradigm, built on the following elements:
 - **configurations**: different choices, collections, or values to find
 - **objective function**: a score assigned to configurations, which we want to either maximize or minimize
- ◆ It works best when applied to problems with the **greedy-choice** property:
 - a globally-optimal solution can always be found by a series of local improvements from a starting configuration.

Making Change



- ◆ **Problem:** A dollar amount to reach and a collection of coin amounts to use to get there.
- ◆ **Configuration:** A dollar amount yet to return to a customer plus the coins already returned
- ◆ **Objective function:** Minimize number of coins returned.
- ◆ **Greedy solution:** Always return the largest coin you can
- ◆ **Example 1:** Coins are valued \$.32, \$.08, \$.01
 - Has the greedy-choice property, since no amount over \$.32 can be made with a minimum number of coins by omitting a \$.32 coin (similarly for amounts over \$.08, but under \$.32).
- ◆ **Example 2:** Coins are valued \$.30, \$.20, \$.05, \$.01
 - Does not have greedy-choice property, since \$.40 is best made with two \$.20's, but the greedy solution will pick three coins (which ones?)

The Fractional Knapsack Problem



- ◆ Given: A set S of n items, with each item i having
 - b_i - a positive benefit
 - w_i - a positive weight
- ◆ Goal: Choose items with maximum total benefit but with weight at most W .
- ◆ If we are allowed to take fractional amounts, then this is the **fractional knapsack problem**.
 - In this case, we let x_i denote the amount we take of item i






- Objective: maximize
$$\sum_{i \in S} b_i (x_i / w_i)$$

- Constraint:
$$\sum_{i \in S} x_i \leq W$$

Example



- ◆ Given: A set S of n items, with each item i having
 - b_i - a positive benefit
 - w_i - a positive weight
- ◆ Goal: Choose items with maximum total benefit but with weight at most W .

Items:					
	1	2	3	4	5
Weight:	4 ml	8 ml	2 ml	6 ml	1 ml
Benefit:	\$12	\$32	\$40	\$30	\$50
Value: (\$ per ml)	3	4	20	5	50



"knapsack"

10 ml

- Solution:
- 1 ml of 5
 - 2 ml of 3
 - 6 ml of 4
 - 1 ml of 2

The Fractional Knapsack Algorithm



- ◆ Greedy choice: Keep taking item with highest **value** (benefit to weight ratio)

- Since $\sum_{i \in S} b_i (x_i / w_i) = \sum_{i \in S} (b_i / w_i) x_i$
- Run time: $O(n \log n)$. Why?

- ◆ Correctness: Suppose there is a better solution

- there is an item i with higher value than a chosen item j (i.e., $v_i > v_j$) but $x_i < w_i$ and $x_j > 0$. If we substitute some i with j , we get a better solution
- How much of i : $\min\{w_i - x_i, x_j\}$
- Thus, there is no better solution than the greedy one

Algorithm *fractionalKnapsack*(S, W)

Input: set S of items w/ benefit b_i and weight w_i ; max. weight W

Output: amount x_i of each item i to maximize benefit with weight at most W

for *each item* i **in** S

$x_i \leftarrow 0$

$v_i \leftarrow b_i / w_i$ {value}

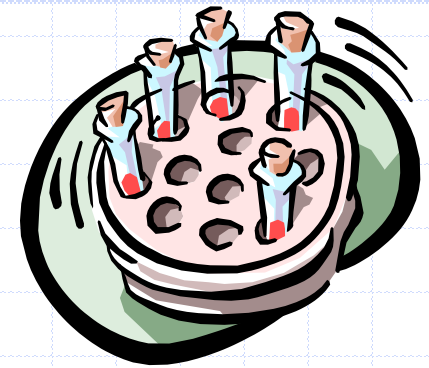
$w \leftarrow 0$ {total weight}

while $w < W$

remove item i with highest v_i

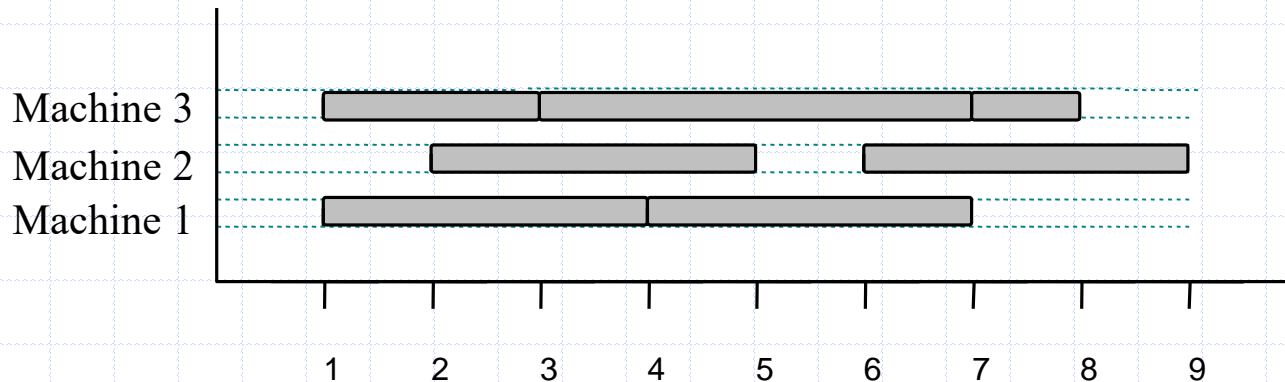
$x_i \leftarrow \min\{w_i, W - w\}$

$w \leftarrow w + \min\{w_i, W - w\}$

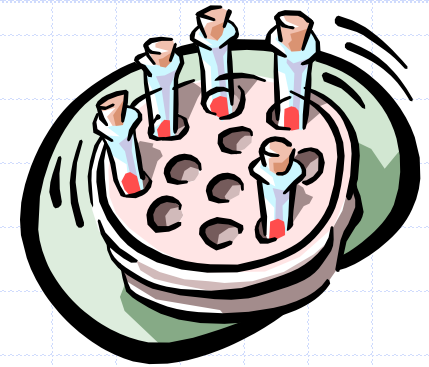


Task Scheduling

- ◆ Given: a set T of n tasks, each having:
 - A start time, s_i
 - A finish time, f_i (where $s_i < f_i$)
- ◆ Goal: Perform all the tasks using a minimum number of “machines.”



Task Scheduling Algorithm



- ◆ Greedy choice: consider tasks by their start time and use as few machines as possible with this order.
 - Run time: $O(n \log n)$. Why?
- ◆ Correctness: Suppose there is a better schedule.
 - We can use $k-1$ machines
 - The algorithm uses k
 - Let i be first task scheduled on machine k
 - Machine i must conflict with $k-1$ other tasks
 - But that means there is no non-conflicting schedule using $k-1$ machines

Algorithm *taskSchedule*(T)

Input: set T of tasks w/ start time s_i and finish time f_i

Output: non-conflicting schedule with minimum number of machines

$m \leftarrow 0$ {no. of machines}

while T is not empty

remove task i w/ smallest s_i

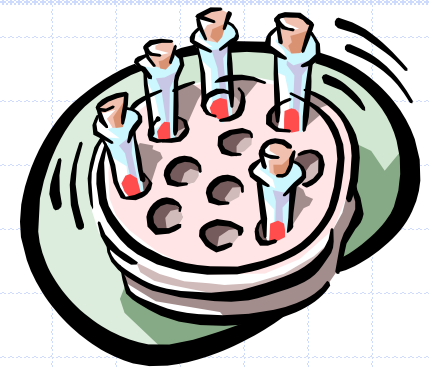
if *there's a machine j for i* **then**

schedule i on machine j

else

$m \leftarrow m + 1$

schedule i on machine m



Example

- ◆ Given: a set T of n tasks, each having:
 - A start time, s_i
 - A finish time, f_i (where $s_i < f_i$)
 - $[1,4], [1,3], [2,5], [3,7], [4,7], [6,9], [7,8]$ (ordered by start)
- ◆ Goal: Perform all tasks on min. number of machines

