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# **COMP2123**

## **Data structures and Algorithms**

### Lecture 9: Greedy Algorithms [GT 10]

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# Greedy algorithms

A class of algorithms where we build a solution one step at a time making locally optimal choices at each stage in the hope of finding a global optimum solution

Some of the most elegant algorithms and the simplest to implement, but often among the hardest to design and analyze

Even when they are not optimal in theory, greedy algorithms can be the basis of a very good heuristic.

## Generic form

```
def generic_greedy(input):  
  
    # initialization  
    initialize result  
  
    determine order in which to consider input  
  
    # iteratively make greedy choice  
    for each element i of the input (in above order) do  
        if element i improves result then  
            update result with element i  
  
    return result
```

# 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 of weight at most  $W$ .

Let  $x_i$  denote the amount we take of item  $i$

**Objective:** maximize

$$\sum_{i \in S} b_i(x_i / w_i)$$

[maximize benefit]

**Constraint:**

$$\sum_{i \in S} x_i \leq W$$

[total weight is bounded]

$$0 \leq x_i \leq w_i$$

[individual weight is bounded]

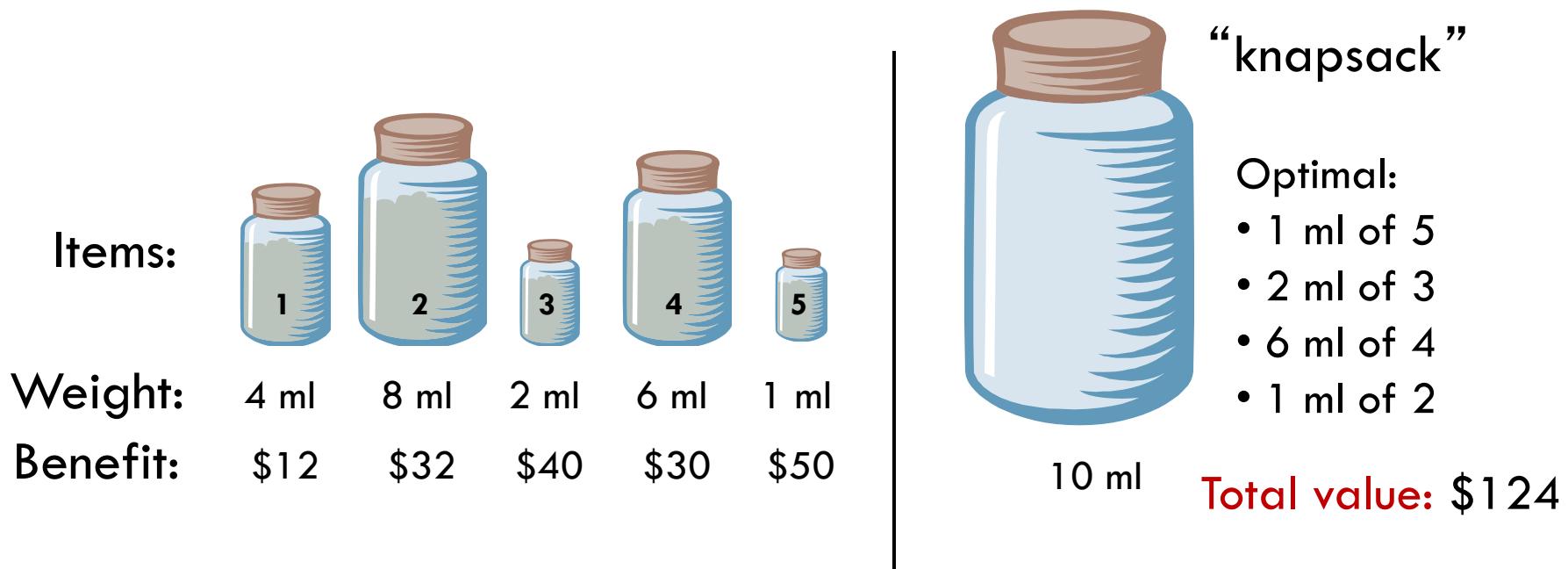
## Example



**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 of weight at most  $W$ .



# The Fractional Knapsack Algorithm



**Initial configuration:** no  
items chosen

**Each step:** identify the  
“best” item available and  
add as much as possible  
(all of it if you can) to the  
knapsack

What defines “**best**” choice  
of item to add next?

```
def fractional_knapsack(b, w, W):  
  
    # initialization  
    x ← array of size |b| of zeros  
    curr ← 0  
  
    # iteratively make greedy choice  
    while curr < W do  
        i ← “best” item not yet chosen  
        x[i] ← min(w[i], W - curr)  
        curr ← curr + x[i]  
    return x
```

# Different Strategies



**A greedy choice:** Keep taking as much as possible of the “**best**” item, where best means:

[highest benefit]: Select items with highest benefit.

[smallest weight]: Select items with smallest weight.

[benefit/weight]: Select items with highest benefit to weight ratio.

Each of these defines a different greedy strategy for this problem.

# What's “best”?



**Greedy choice:** Keep taking the “best” item.



[highest benefit]: Select items with highest benefit.

1 ml of 5 → \$50

2 ml of 3 → \$40

7 ml of 2 → \$28

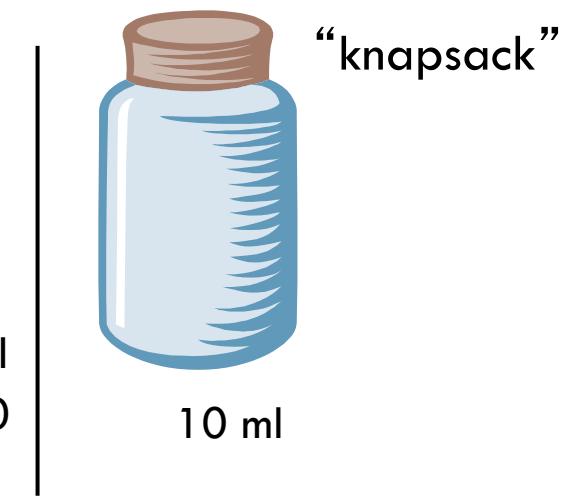
**Total value:** \$118

Items:



Weight: 4 ml 8 ml 2 ml 6 ml 1 ml

Benefit: \$12 \$32 \$40 \$30 \$50



# Counterexample

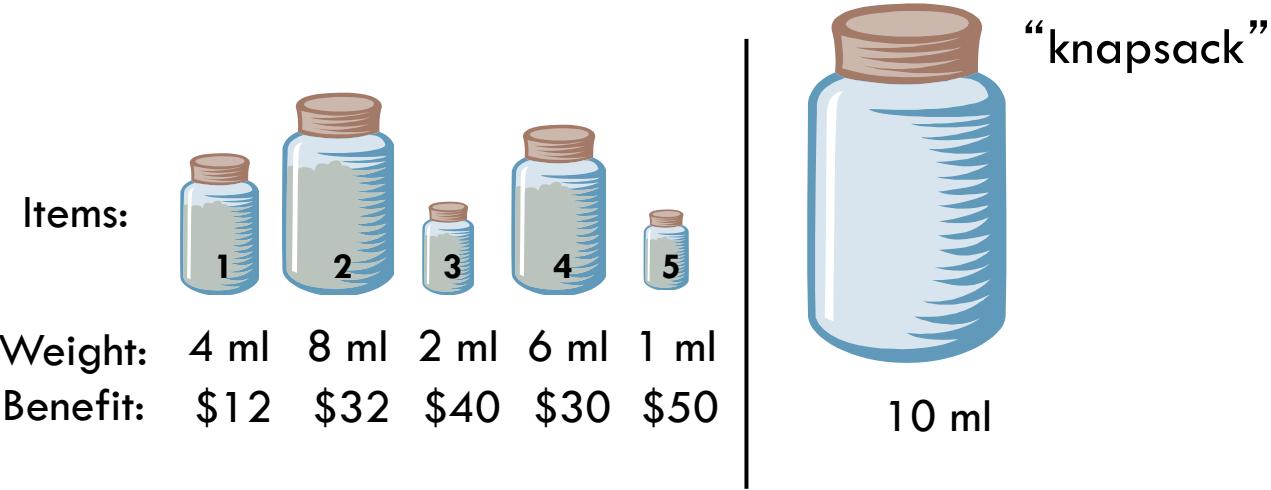
For a given algorithm: find an example where it does **not** return the correct solution.

Things you need to do:

- Describe your example (the instance)
- Describe what the solution of the given algorithm is and briefly explain why
- Show what the correct solution for your example is

# Counterexample (example)

Describe your example (the instance)



Solution of the given algorithm

1 ml of 5 → \$50

2 ml of 3 → \$40

7 ml of 2 → \$28

**Total value:** \$118

Optimal solution

1 ml of 5 → \$50

2 ml of 3 → \$40

6 ml of 4 → \$30

1 ml of 2 → \$4

**Total value:** \$124

# What's “best”?

**Greedy choice:** Keep taking the “best” item.



②

[smallest weight]: Select items with smallest weight.

1 ml of 5 → \$50

2 ml of 3 → \$40

4 ml of 1 → \$12

3 ml of 4 → \$15

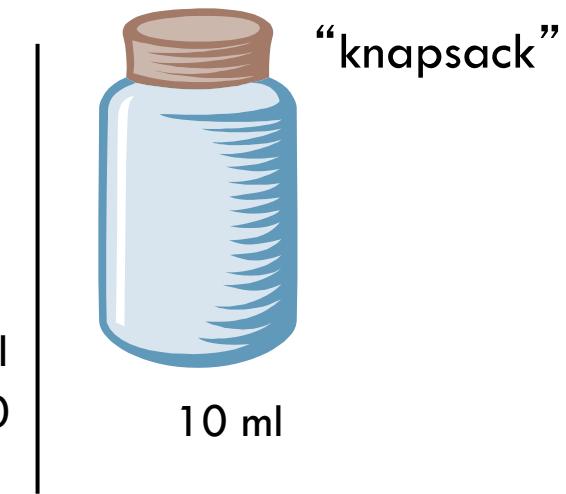
**Total value:** \$117

Items:



Weight: 4 ml 8 ml 2 ml 6 ml 1 ml

Benefit: \$12 \$32 \$40 \$30 \$50



# What's “best”?



**Greedy choice:** Keep taking the “best” item.

3

[benefit/weight]: Select items with highest benefit to weight ratio.

1 ml of 5 → \$50

2 ml of 3 → \$40

Total value: \$124

6 ml of 4 → \$30

1 ml of 2 → \$4

Items:



Weight: 4 ml 8 ml 2 ml 6 ml 1 ml

Benefit: \$12 \$32 \$40 \$30 \$50

Benefit/ml: 3 4 20 5 50



# The Fractional Knapsack Algorithm: Correctness

**Theorem:** The greedy strategy of picking item with highest benefit to weight ratio computes an optimal solution.

**Proof (sketch):**

- Use an exchange argument
- Assume for simplicity that all ratios are different  $b_i/w_i \neq b_k/w_k$
- Consider some feasible solution  $x$  different than the greedy one
- There must be items  $i$  and  $k$  s.t.  $x_i < w_i$ ,  $x_k > 0$  and  $b_i/w_i > b_k/w_k$
- If we replace some  $k$  with some of  $i$ , we get a better solution
- How much?  $\min\{w_i - x_i, x_k\}$
- Thus, there is no better solution than the greedy one

# The Fractional Knapsack Algorithm: Complexity

Sort items by their benefit-to-weight values, and then process them in this order.

Require  $O(n \log n)$  time to sort the items and then  $O(n)$  time to process them in the for-loop.

```
def fractional_knapsack(b, w, W):
    # initialization
    x ← array of size |b| of zeros
    curr ← 0

    # iteratively do greedy choice
    for i in descending b[i]/w[i] order do
        x[i] ← min(w[i], W - curr)
        curr ← curr + x[i]
    return x
```

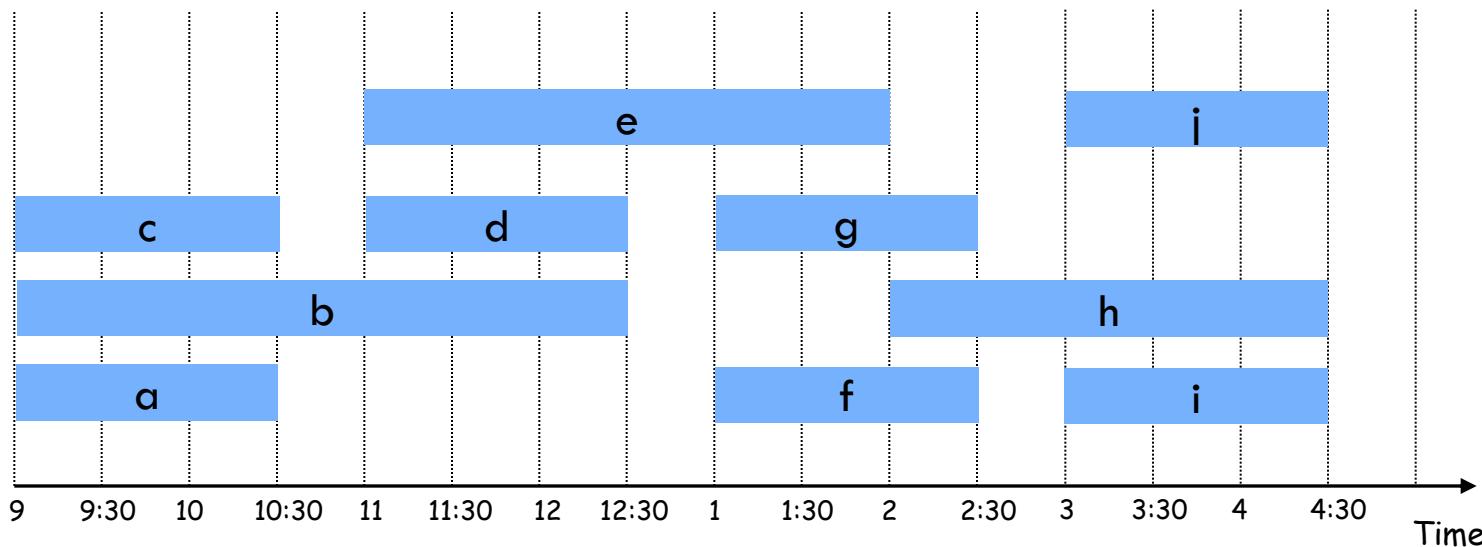
# Task scheduling

**Given:** A set  $S$  of  $n$  lectures

Lecture  $i$  starts at  $s_i$  and finishes at  $f_i$ .

**Goal:** Find the minimum number of classrooms to schedule all lectures so that no two occur at the same time in the same room.

Example: This schedule uses 4 classrooms to schedule 10 lectures.



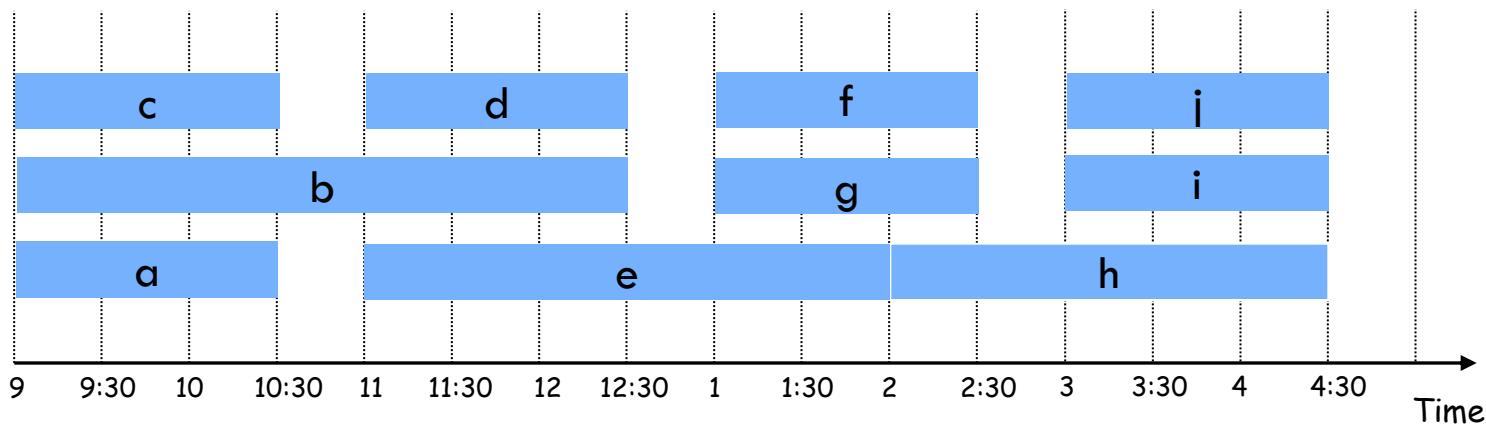
# Task scheduling

**Given:** A set  $S$  of  $n$  lectures

Lecture  $i$  starts at  $s_i$  and finishes at  $f_i$ .

**Goal:** Find the minimum number of classrooms to schedule all lectures so that no two occur at the same time in the same room.

**Example:** This schedule uses only 3!



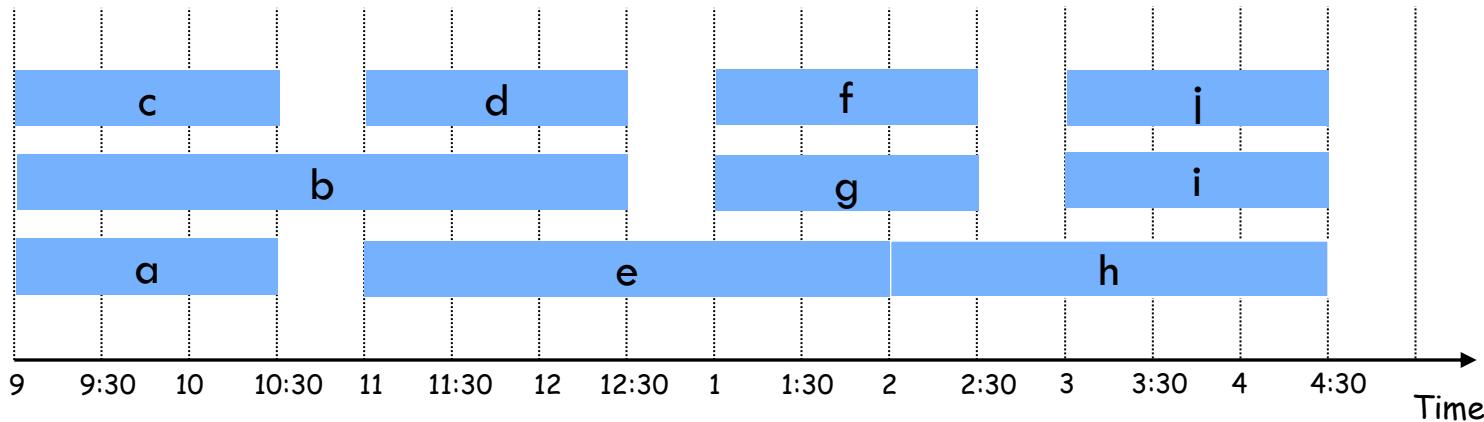
# Interval Partitioning: Lower bound

**Definition:** The **depth** of a set of open intervals is the maximum number that contain any given time.

**Observation:** Number of classrooms needed  $\geq$  depth. Why?

**Example:** Depth of schedule below is 3 [a, b, c all contain 9:30]  
 $\Rightarrow$  schedule below is optimal.

**Question:** Does there always exist a schedule equal to depth of intervals?



# Interval Partitioning: Greedy Algorithm

**Greedy algorithm:** Consider lectures in increasing order of start time: assign lecture to any compatible classroom.

```
def interval_partition(S):
    # initialization
    sort intervals in increasing starting time order
    d ← 0      # number of allocated classrooms

    # iteratively do greedy choice
    for i in increasing starting time order do
        if lecture i is compatible with some classroom k then
            schedule lecture i in classroom  $1 \leq k \leq d$ 
        else
            allocate a new classroom  $d+1$ 
            schedule lecture i in classroom  $d+1$ 
            d ← d+1
    return d
```

# Interval Partitioning: Greedy Algorithm

**Greedy algorithm:** Consider lectures in increasing order of start time: assign lecture to any compatible classroom.

```
def interval_partition(S):
    # initialization
    sort intervals in increasing starting time order
    d ← 0      # number of allocated classrooms

    # iteratively do greedy choice
    for i in increasing starting time order do
        if lecture i is compatible with some classroom k then
            schedule lecture i in classroom  $1 \leq k \leq d$ 
        else
            allocate a new classroom  $d+1$ 
            schedule lecture i in classroom  $d+1$ 
            d ← d+1
    return d
```

**Implementation:**  $O(n \log n)$ .

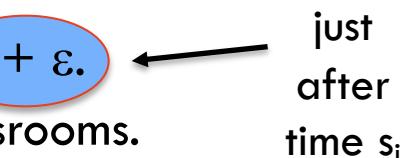
- For each classroom  $k$ , maintain the finish time of the last job added.
- Keep the classrooms in a priority queue.

# Interval Partitioning: Greedy Analysis

**Observation:** Greedy algorithm never schedules two incompatible lectures in the same classroom.

**Theorem:** Greedy algorithm is optimal.

**Proof:**

- $\underline{d}$  = number of classrooms that the greedy algorithm allocates.
- Classroom  $\underline{d}$  is opened because we needed to schedule a job, say  $i$ , that is incompatible with all  $\underline{d-1}$  other classrooms.
- Since we sorted by start time, all these incompatibilities are caused by lectures that start no later than  $s_i$ .
- Thus, we have  $d$  lectures overlapping at time  $s_i + \varepsilon$ .  just after time  $s_i$
- Key observation  $\Rightarrow$  all schedules use  $\geq d$  classrooms.

[Greedy algorithm stays “ahead”]

# Text Compression

**Given:** a string X

**Goal:** efficiently encode X into a smaller string Y  
(saves memory and/or bandwidth)

**Input:**

WWWWWWWWWWWWWWWWBWWWWWWWWWWWWWWWWBBBWWWWWW  
WW

**Run length encoding** (very simple approach):

12W1B12W3B24W1B14W

# Text Compression

**Given:** a string X

**Goal:** efficiently encode X into a smaller string Y  
(saves memory and/or bandwidth)

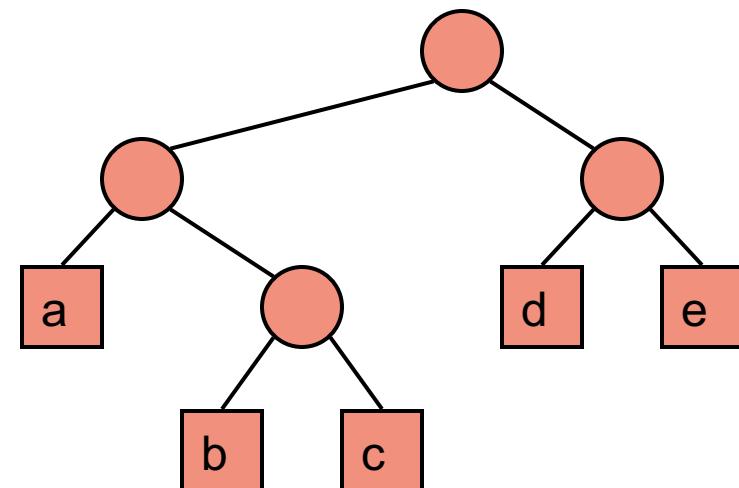
A better approach: **Huffman encoding**

- Let C be the set of characters in X
- Compute frequency  $f(c)$  for each character c in C
- Encode high-frequency characters with short code words
- No code word is a prefix of another code word
- Use an optimal encoding tree to determine the code words

# Encoding Tree Example

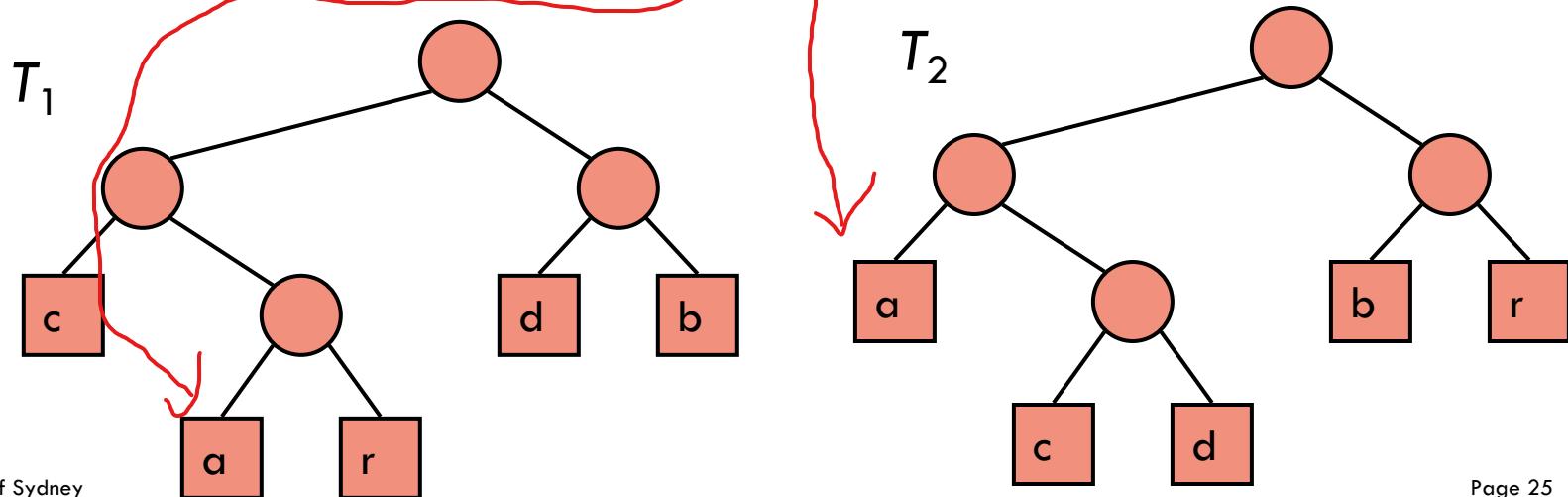
- A **binary code** is a mapping of each character of an alphabet to a binary code-word
- A **prefix code** is a code such that no code-word is the prefix of another code-word
- An **encoding tree** represents a prefix code
  - Each external node stores a character
  - The code-word of a character is given by the path from the root to the external node storing the character (0 for a left child and 1 for a right child)

00	010	011	10	11
a	b	c	d	e



# Encoding Tree Optimization

- Given a text string  $X$ , we want to find a prefix code for the characters of  $X$  that yields a small encoding for  $X$ 
  - Frequent characters should have short code-words
  - Rare characters should have long code-words
- Example
  - $X = \underline{a} \underline{b} \underline{r} \underline{a} \underline{c} \underline{a} \underline{d} \underline{a} \underline{b} \underline{r} \underline{a}$
  - $T_1$  encodes  $X$  into 29 bits
  - $T_2$  encodes  $X$  into 24 bits



# Huffman's Algorithm

Given a string  $X$ , Huffman's algorithm constructs a prefix code that minimizes the size of the encoding of  $X$

It runs in time  $O(n + d \log d)$ , where  $n$  is the size of  $X$  and  $d$  is the number of distinct characters of  $X$

The algorithm builds the encoding tree from the bottom up, merging trees as it goes along, using a priority queue to guide the process

End result minimizes bits needed to encode  $X$ :

$$\sum_{c \text{ in } C} f(c) * \text{depth}_T(c)$$

# Huffman's Algorithm

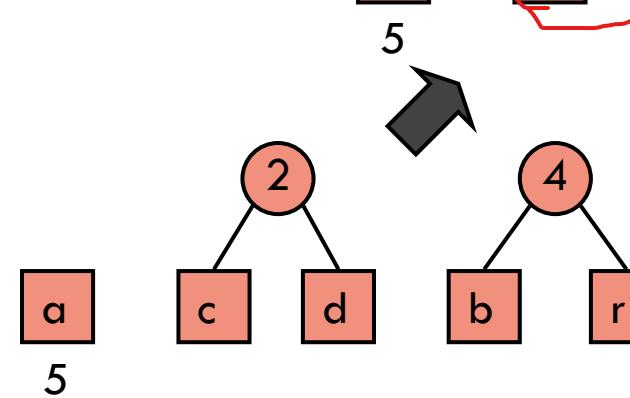
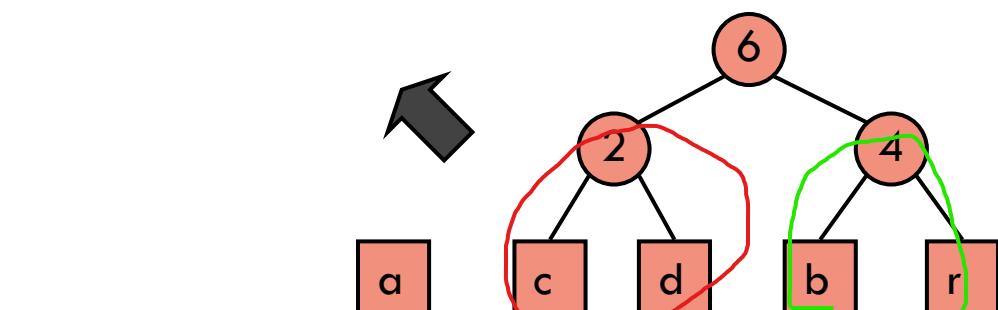
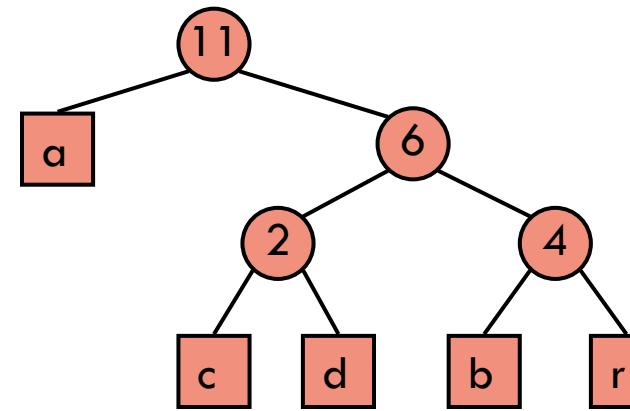
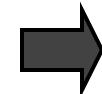
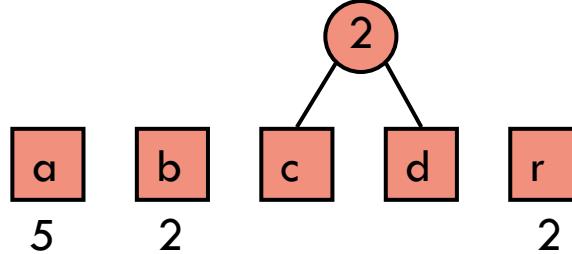
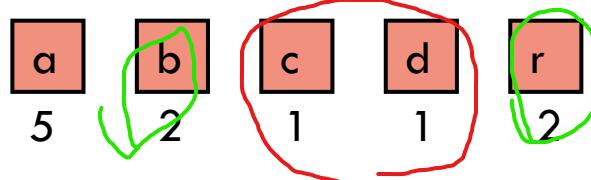
```
def huffman(C, f):  
  
    # initialize priority queue  
    Q ← empty priority queue  
    for c in C do  
        T ← single-node binary tree storing c  
        Q.insert(f[c], T)  
  
    # merge trees while at least two trees  
    while Q.size() > 1 do  
        f1, T1 ← Q.remove_min()  
        f2, T2 ← Q.remove_min()  
        T ← new binary tree with T1/T2 as left/right subtrees  
        f ← f1 + f2  
        Q.insert(f, T)  
  
    # return last tree  
    f, T ← Q.remove_min()  
    return T
```

# Example

$X = \text{abracadabra}$

Frequencies

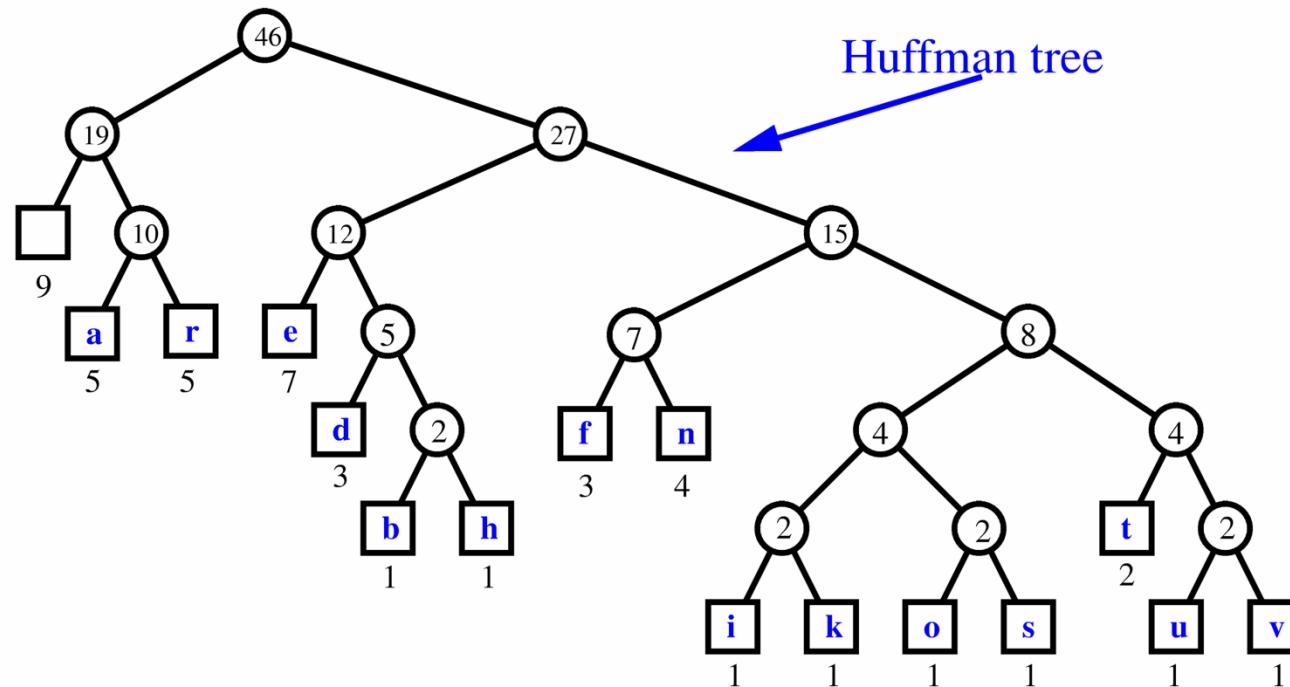
a	b	c	d	r
5	2	1	1	2



# Extended Huffman Tree Example

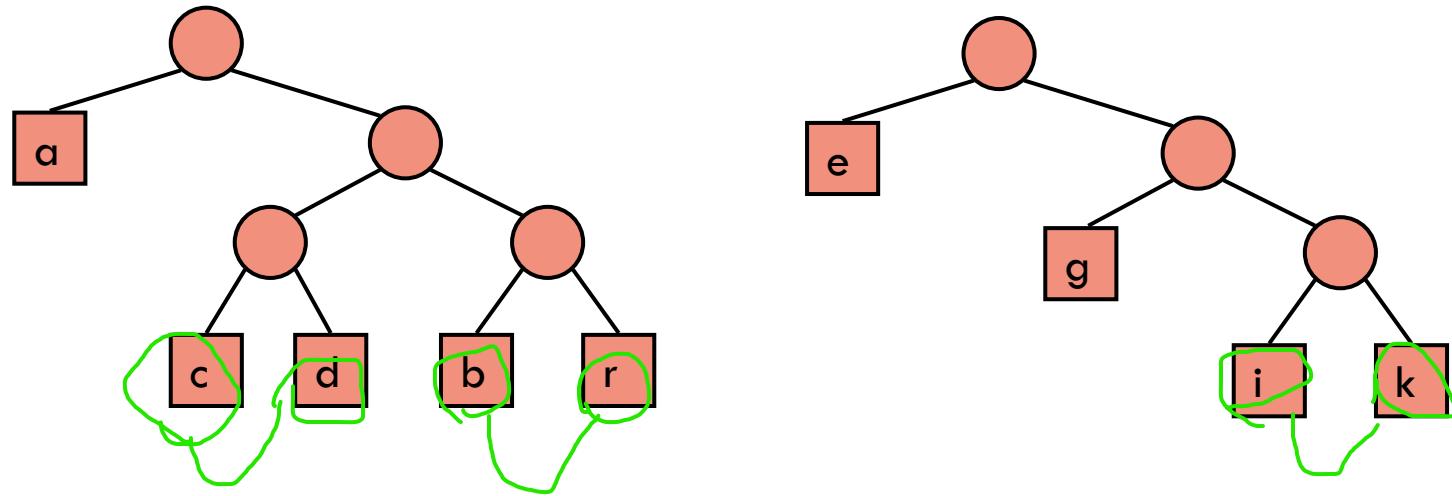
String: **a fast runner need never be afraid of the dark**

Character		a	b	d	e	f	h	i	k	n	o	r	s	t	u	v	
Frequency		9	5	1	3	7	3	1	1	1	4	1	5	1	2	1	1



# Huffman's Algorithm Correctness

Obs: Every encoding tree has a pair of leaves that are *siblings*.

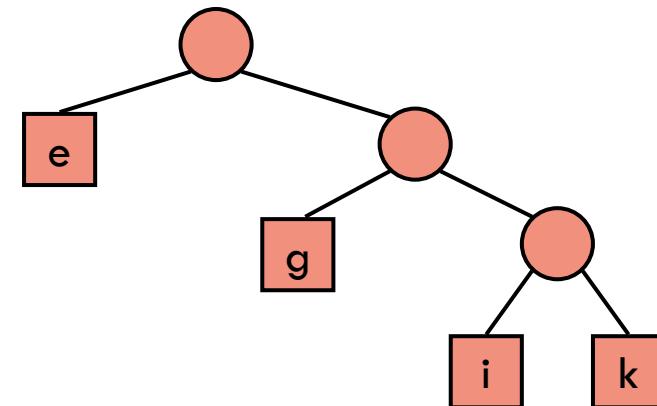


# Huffman's Algorithm Correctness



Obs: In an optimal encoding tree  $T$  for any  $a$  and  $b$  in  $C$ , if  $\text{depth}_T(a) < \text{depth}_T(b)$  then  $f(a) \geq f(b)$ .

$$\sum_{c \text{ in } C} f(c) * \text{depth}_T(c)$$

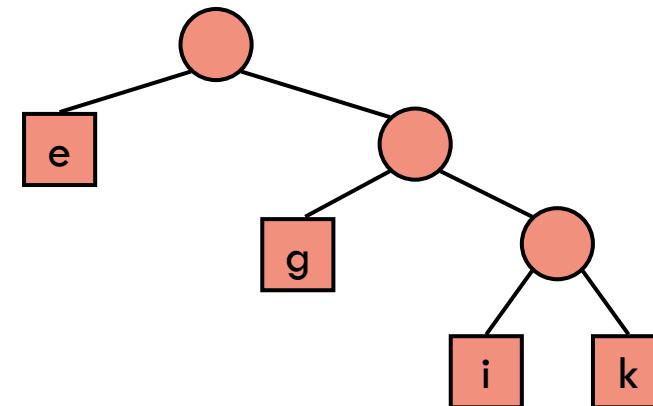


For example, if  $f(e) < f(g)$   
then swapping them leads  
to shorter encoding

# Huffman's Algorithm Correctness

**Obs:** There is an optimal encoding tree  $T$  where the two sibling leaves furthest from the root have lowest frequency.

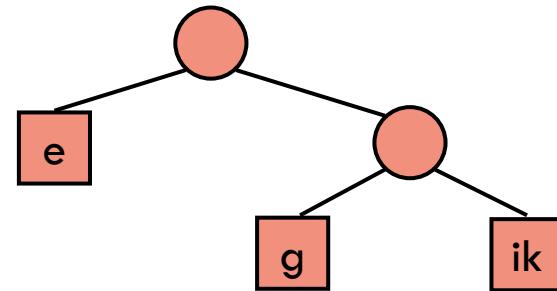
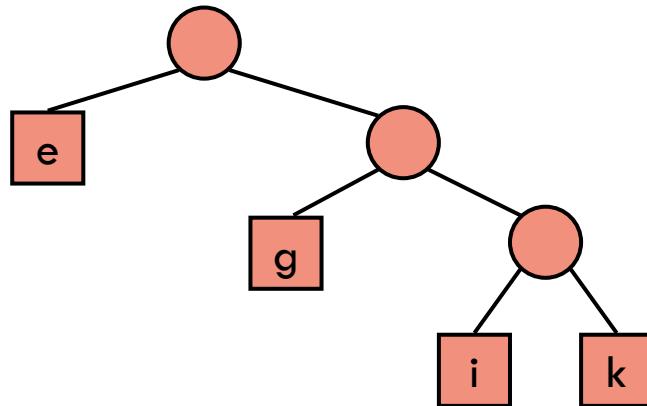
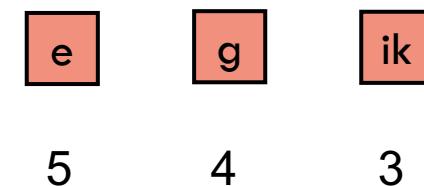
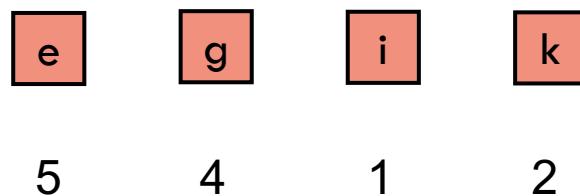
$$\sum_{c \text{ in } C} f(c) * \text{depth}_T(c)$$



For example, characters **i** and **k**  
have lowest frequency

# Huffman's Algorithm Correctness

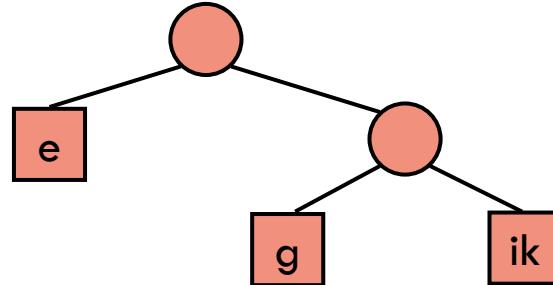
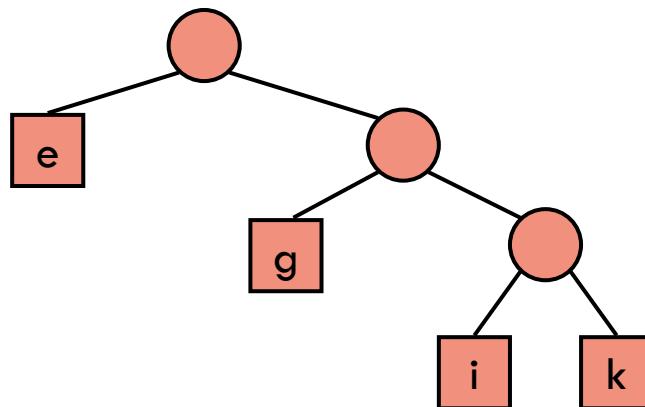
**Obs:** If we combine the two lowest frequency characters to get a new instance  $(C', f')$ , an optimal encoding tree  $T'$  for  $(C', f')$  can be expanded to get an optimal encoding tree  $T$  for  $(C, f)$



# Huffman's Algorithm Correctness

**Obs:** If we combine the two lowest frequency characters to get a new instance  $(C', f')$ , an optimal encoding tree  $T'$  for  $(C', f')$  can be expanded to get an optimal encoding tree  $T$  for  $(C, f)$

$$\begin{aligned} \sum_{c \text{ in } C} f(c) * \text{depth}_T(c) - \sum_{c \text{ in } C'} f'(c) * \text{depth}_{T'}(c) \\ = f(i) * \text{depth}_T(i) + f(k) * \text{depth}_T(k) - f'(ik) * \text{depth}_{T'}(ik) \\ = f(i) + f(k) \end{aligned}$$



# Huffman's Algorithm Correctness

**Thm:** Huffman's algorithm computes a minimum length encoding tree of  $(C, f)$

**Proof** (by induction):

- If  $|C| = 1$  then the encoding is trivially optimal
- If  $|C| > 1$  then let  $(C', f')$  be the contracted instance
- By inductive hypothesis, the encoding tree  $T'$  constructed for  $(C', f')$  is optimal
- Recall that

$$\sum_{c \text{ in } C} f(c) * \text{depth}_T(c) = \sum_{c \text{ in } C'} f'(c) * \text{depth}_{T'}(c) + f(i) + f(k)$$

thus, the tree  $T$  is optimal for  $(C, f)$

# Huffman's Algorithm

```
def huffman(C, f):  
  
    # initialize priority queue  
    Q ← empty priority queue  
    for c in C do  
        T ← single-node binary tree storing c  
        Q.insert(f[c], T)  
  
    # merge trees while at least two trees  
    while Q.size() > 1 do  
        f1, T1 ← Q.remove_min()  
        f2, T2 ← Q.remove_min()  
        T ← new binary tree with T1/T2 as left/right subtrees  
        f ← f1 + f2  
        Q.insert(f, T)  
  
    # return last tree  
    f, T ← Q.remove_min()  
    return T
```

Time complexity is dominated by PQ ops, which using heap take  $O(|C| \log |C|)$  time

# Greedy algorithms recap

Greedy heuristics are easy to design but they are not always optimal. And when they are, small modifications of the problem can render them suboptimal:

- 0-1 knapsack is hard
- if tasks/lectures have special needs the problem is hard
- if we use non-binary encodings, Huffman does not work