

Quiz 2: ch4, 6-8, 11 ch16: Greedy Algorithms

Open book, paper notes
No electronic devices
Please show your work

29 Oct 2013

CMPT231

Dr. Sean Ho

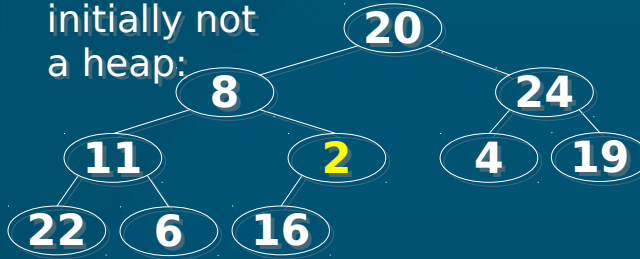
Trinity Western University

Quiz 2: 30pts

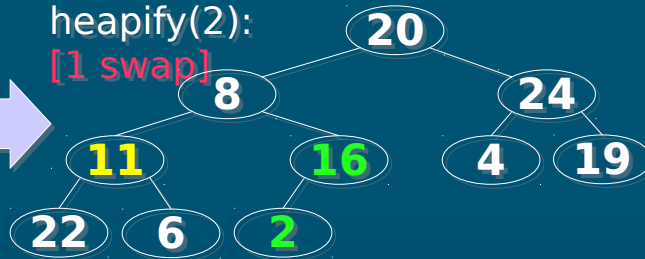
- **Input** for all: [20, 8, 24, 11, 2, 4, 19, 22, 6, 16]
- [10] Demonstrate each step of **Heapsort** on the input. How many non-trivial **swaps** are performed?
- [10] Demonstrate each step of (non-randomised) **Quicksort** on the input. How many non-trivial **swaps**?
- [10] Demonstrate **radix sort** on the input with base-4 digits.

Quiz 2: solutions #1

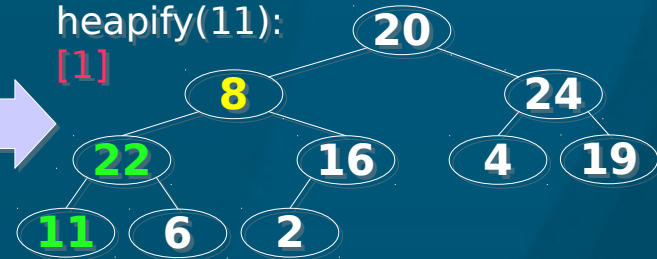
initially not a heap:



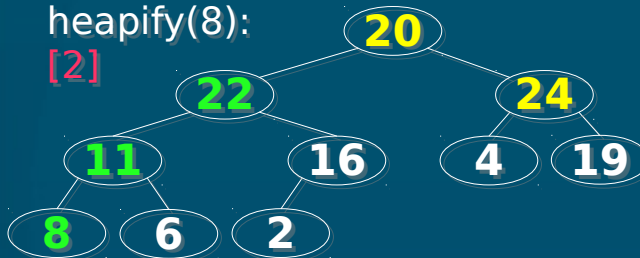
heapify(2):
[1 swap]



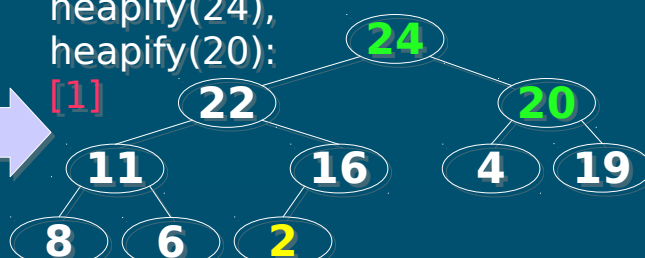
heapify(11):
[1]



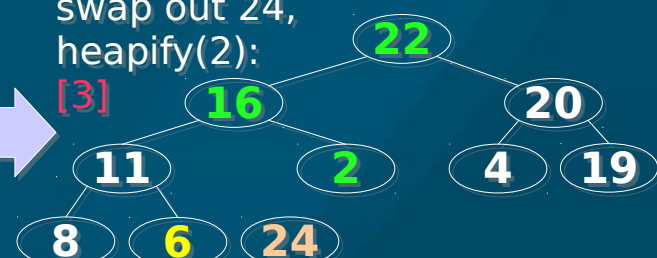
heapify(8):
[2]



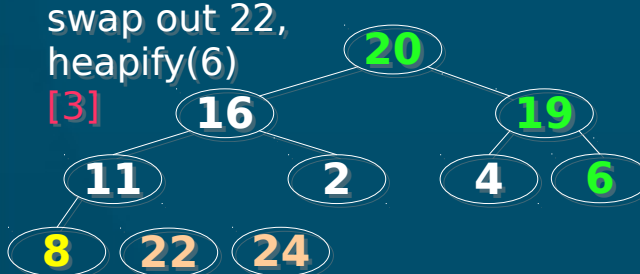
heapify(24),
heapify(20):
[1]



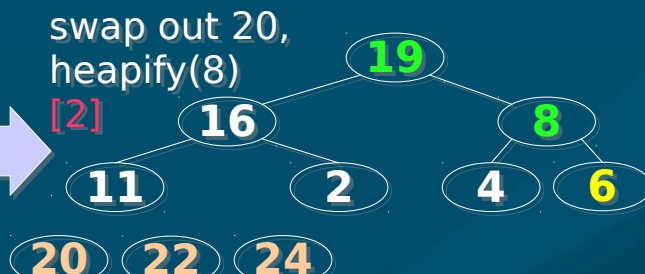
swap out 24,
heapify(2):
[3]



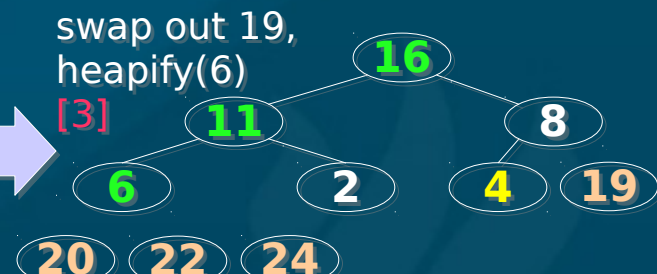
swap out 22,
heapify(6)
[3]



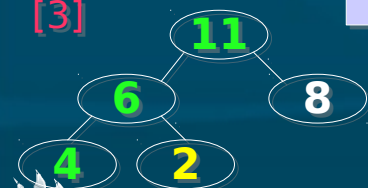
swap out 20,
heapify(8)
[2]



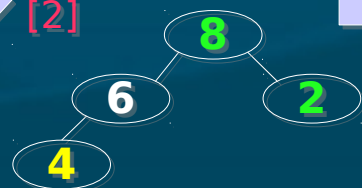
swap out 19,
heapify(6)
[3]



swap out 16,
heapify(4)
[3]



swap out 11,
heapify(2)
[2]



swap out 8,
heapify(4)
[2]



swap out 6,
heapify(2)
[2]



swap out 4
[1]

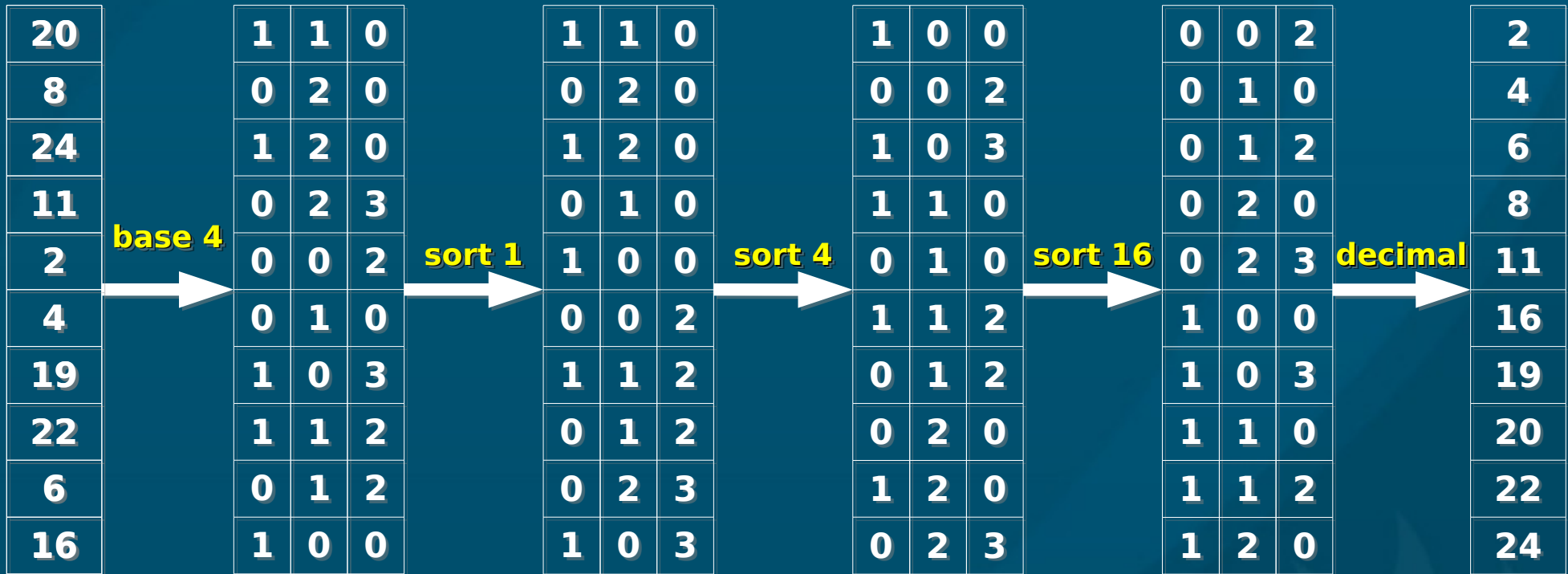


Quiz 2: solutions #1-2

- Heapsort: 26 swaps
- Quicksort: only 12 swaps!

Pivot=16:	20	8	24	11	2	4	19	22	6	16	Swaps
.	8	20	1
.	8	11	24	20	1
.	8	11	2	20	24	1
.	8	11	2	4	24	20	1
.	8	11	2	4	6	20	19	22	24	.	1
.	8	11	2	4	6	16	19	22	24	20	1
6:	8	11	2	4	6	16	19	22	24	20	.
2:	2	4	6	11	8	3
4:	2	4
8:	.	.	.	8	11	1
20:	19	20	24	22	1
22:	22	24	1

Quiz 2: solutions #3

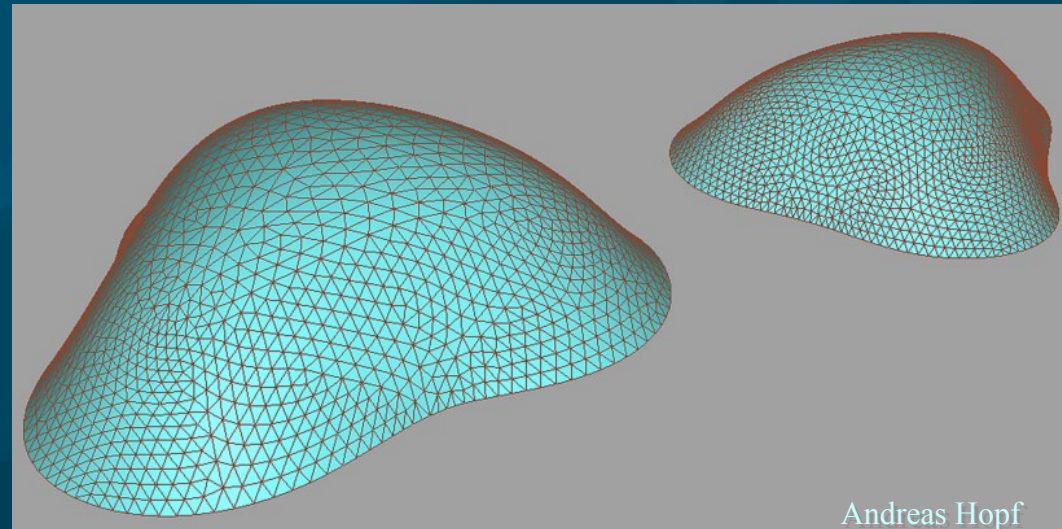


Outline for today

- Greedy algorithms
 - Example: Activity selection
 - Optimal substructure
 - ◆ Naive recursive solution
 - Greedy choice property
 - ◆ Recursive greedy solution
 - ◆ Iterative greedy solution
 - Example: Knapsack problems
 - Example: Huffman coding

Greedy algorithms

- Another approach to **optimisation**
 - **Faster** than dynamic programming, when applicable
- At each **decision** point, go for **immediate** gains
 - **Locally** optimal choices \Rightarrow **global** optimum
- Not all problems have optimal **substructure**
 - **Hybrid** optimisation strategies use large **jumps** to get to right “hill”, then greedy “**hill-climbing**” to get to the top



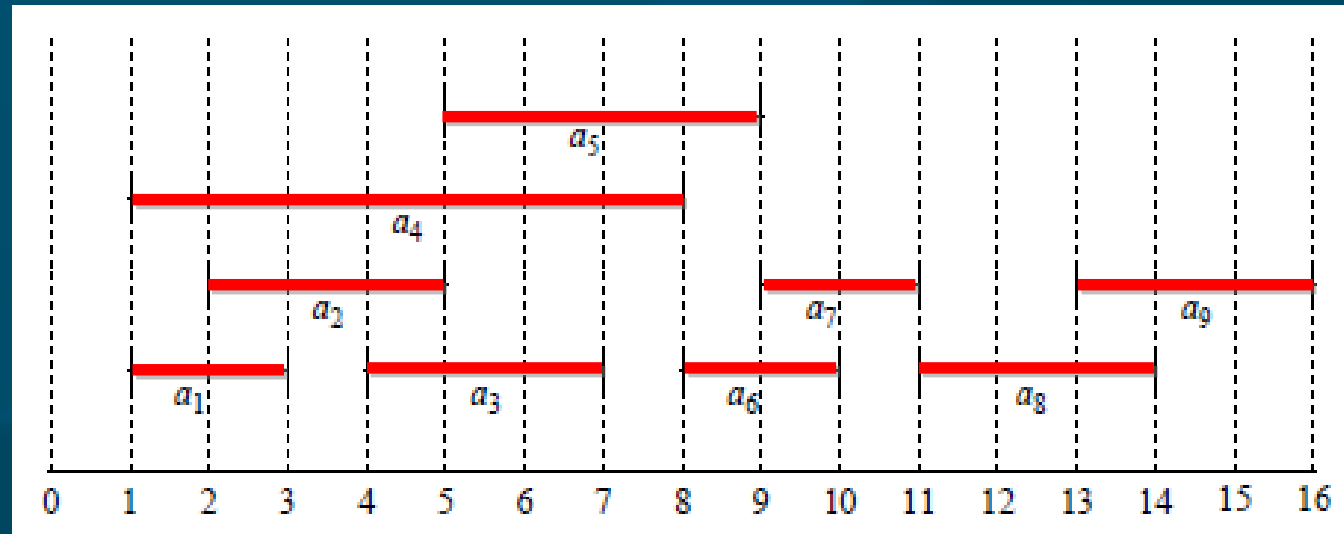
Problem-solving outline

- Find optimal **substructure** (e.g., **recurrence**)
- Convert to naïve **recursive** solution (**code**)
 - Could then be converted to **dynamic prog.**
- Use **greedy choice** to simplify the recurrence so only **one** subproblem remains
 - Don't have to **iterate** through all subproblems
 - Prove greedy choice yields **global** optimum!
- Convert to **recursive** greedy solution
- Convert to **iterative** greedy solution

Example: activity selection

- Activities $S = \{a_1, \dots, a_n\}$ which each require **exclusive** use of a shared resource
 - Each activity has **start/finish** times $[s_i, f_i)$
 - Activities are **sorted** by finish times
- \Rightarrow Find **largest** subset of S where all activities are **non-overlapping**
- e.g., a_2 and a_5 do not overlap:

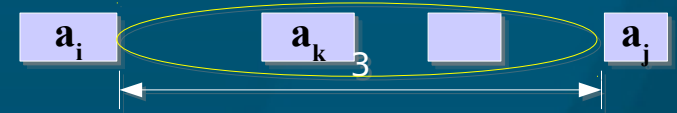
i	s	f
1	1	3
2	2	5
3	4	7
4	1	8
5	5	9
6	8	10
7	9	11
8	11	14
9	13	16



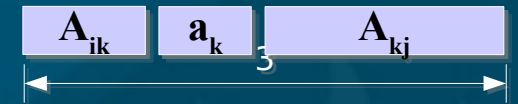
Solutions?

Solving: optimal substructure

- Let $S_{ij} = \{a_k \in S: f_i \leq s_k < f_k \leq s_j\}$: all activities that **start** after f_i and **finish** before s_j



- Any activity in S_{ij} will be **compatible** with:
 - Any activity that **finishes** by f_i
 - Any activity that **starts** no earlier than s_j
- Let A_{ij} be a **solution** for S_{ij} :
a largest mutually-compatible subset of activities
- Pick an activity $a_k \in A_{ij}$, and **partition** A_{ij} into
 - $A_{ik} = A_{ij} \cap S_{ik}$: those that finish **before** a_k starts
 - $A_{kj} = A_{ij} \cap S_{kj}$: those that start **after** a_k finishes



Proof of optimal substructure

■ Claim: A_{ik} and A_{kj} are **optimal** solutions for S_{ik} , S_{kj}

■ Proof (for A_{ik}): assume not:



- Let A'_{ik} be a **better** solution:
non-overlapping elements, and $|A'_{ik}| > |A_{ik}|$.
 - Then $A'_{ik} \cup \{a_k\} \cup A_{kj}$ would be a solution for S_{ij} ,
and its size is **larger** than $A_{ij} = A_{ik} \cup \{a_k\} \cup A_{kj}$.
 - **Contradicts** the premise that A_{ij} was **optimal**.
- \Rightarrow Optimal substructure: **split** on a_k ,
recurse twice on S_{ik} and S_{kj} ,
iterate over all choices of a_k and pick the **best**

Naive recursive solution

- Let $c[i,j]$ = size of optimal solution for S_{ij} :
 - Splitting on a_k yields $c[i,j] = c[i,k] + 1 + c[k,j]$
 - Which choice of a_k is best? Naive: try all
- Recurrence: $c[i,j] = \max_{a_k \in S_{ij}} (c[i,k] + 1 + c[k,j])$
 - Base case: if $S_{ij} = \emptyset$, then $c[i,j] = 0$
- Could implement this using dynamic programming
 - Fill in 2D table for $c[i,j]$, bottom-up
 - Auxiliary table storing the solutions A_{ij}
- With this problem, though, we can do better!

Outline for today

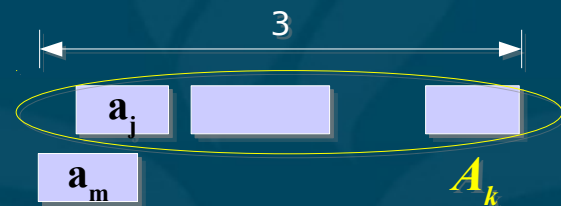
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Greedy choice

- Which **choice** of a_k leaves as **much** as possible of the resource available for other activities?
 - One which **finishes** the earliest
 - Since activities are **sorted** by finish time, just choose the **first** activity!
- Recurrence **simplifies**: to find optimal subset of S_{kj} , include a_k , then **recurse** on $S_k = \{a_i: s_i \geq f_k\}$: those that **start** after a_k finishes
 - Don't need to **iterate** over all choices of a_k
- We need to **prove** the greedy choice is **optimal**

Proof of greedy choice

- Let $S_k \neq \emptyset$ with $a_m \in S_k$ having **earliest** finish time.
 - Claim: \exists **optimal soln** for S_k which includes a_m .
- **Proof:** Let A_k be an **optimal solution** for S_k .
 - If it includes a_m , then we're done.
- If **not**, let a_j be the **first** in A_k to finish.
 - **Swap out** a_m for a_j : let $A'_k = A_k - \{a_j\} \cup \{a_m\}$.
- Then A'_k is an **optimal solution** for S_k :
 - **Size** is same as A_k , and
 - Elements are **non-overlapping**: $f_m \leq f_j$



Recursive greedy solution

- Input: arrays $s[]$, $f[]$, with $f[]$ sorted
 - Add a **dummy** entry $f[0] = 0$, so that $S_0 = S$.
- For each recursive **subproblem** S_k ,
 - **Skip** over activities that **overlap** with a_k
 - Include the **first** activity that **doesn't** overlap, and **recurse** on the rest:
 - **def ActivitySel(s, f, k, n):**
 - for m in $k+1 .. n$:
 - if ($s[m] \geq f[k]$):
 - return $\{a_m\} \cup \text{ActivitySel}(s, f, m, n)$
 - return NULL
 - Initial call: **ActivitySel**($s, f, 0, n$). ($\Theta(n)$!)

Iterative greedy solution

- Recursive solution is nearly **tail-recursive**, easy to convert to more efficient **iterative** solution:

```
→ def ActivitySel(s, f):  
    • A = {a1}  
    • k = 1  
    • for m in 2 .. length(f):  
        • if (s[m] ≥ f[k]):  
            • A = A ∪ {am}  
            • k = m  
    • return A
```

i	s	f
1	1	3
2	2	5
3	4	7
4	1	8
5	5	9
6	8	10
7	9	11
8	11	14
9	13	16

- **Complexity**: $\Theta(n)$

- If need to **pre-sort** on **f[]**, then $\Theta(n \lg n)$

Greedy vs dynamic prog.

- Dynamic prog. more **general**
 - Not all problems have greedy property
- Dynamic prog. **fills** in table **bottom-up**
 - Greedy choice done **top-down**
- **Choice** in dyn. prog. needs **all** smaller subprobs
 - Greedy choice is **simpler**, so can make choice **before** solving subproblem
- **Proving** the greedy property:
 - **Assume** an optimal solution
 - **Modify** it to include the greedy choice
 - **Show** that it's still optimal

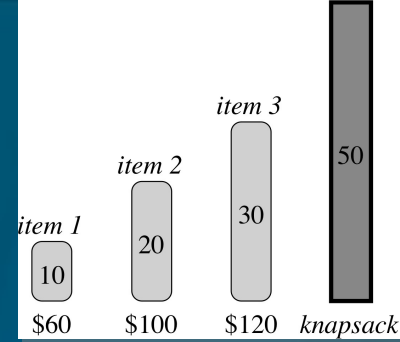
Optimising for greedy choice

- Often need to **pre-process** input to make the greedy choice easier
 - **Sorted** activities by **finish time**
 - Greedy **choice** can be done in **$O(1)$** each time
 - **Sorting** takes **$O(n \lg n)$**
- If input is **dynamically** generated (can't sort whole list in advance), then
 - **Priority queue**: pop the most optimal choice

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Knapsack problem



■ Fractional knapsack problem:

- n items, each with **weight** w_i and **value** v_i .
- Maximise total **value**, subject to total **weight** W
- Can take **fractions** of an item (think of liquids)

■ Greedy soln: sort items by **value-to-weight** ratio

- Greedy **choice**: take item with largest v_i / w_i .
- Last spot may be filled with **fractional** item

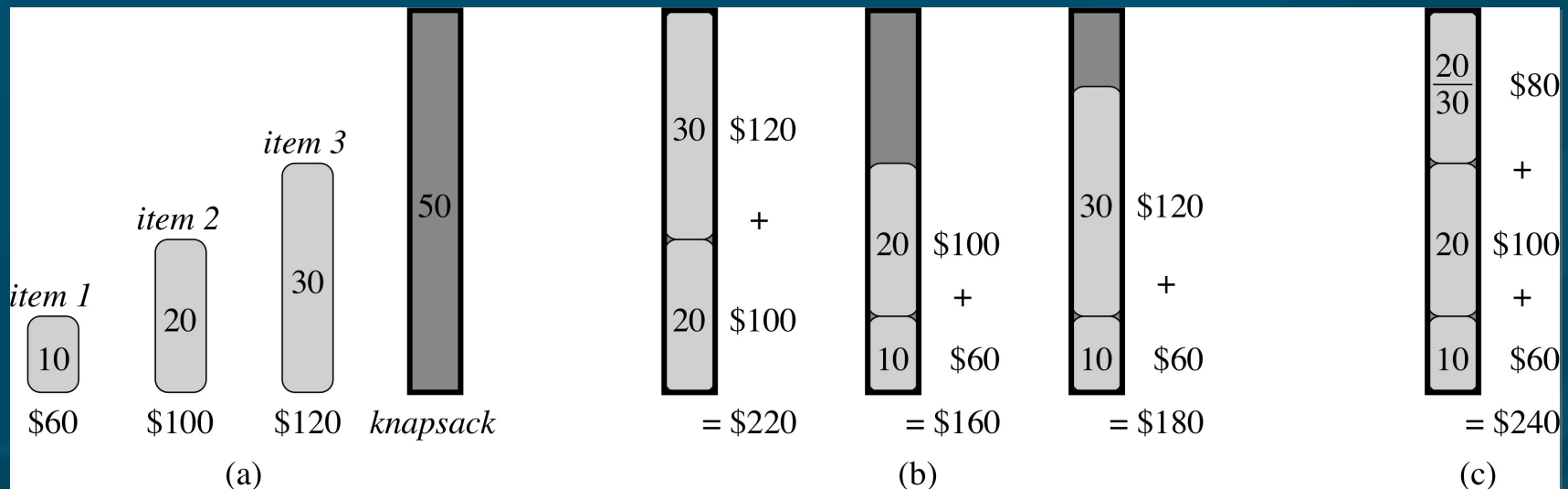
→ def FractionalKnapsack(v, w, W):

- while **totwt** $< W$:
 - add **next** item in decreasing order of **value-to-weight**
 - replace **last** item with $1 - (\text{totwt} - W)$ of itself

$\frac{20}{30}$	\$80
+	
20	\$100
+	
10	\$60
=	\$240

0-1 Knapsack

- Variant that does **not** allow fractions of an item
- Greedy strategy **no longer** works!
- Making initial **locally**-optimal choices locks us out of making later **globally**-optimal choices
- Still possible to solve using **dynamic programming** (Ex 16.2-2)



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 - **Example: Huffman coding**

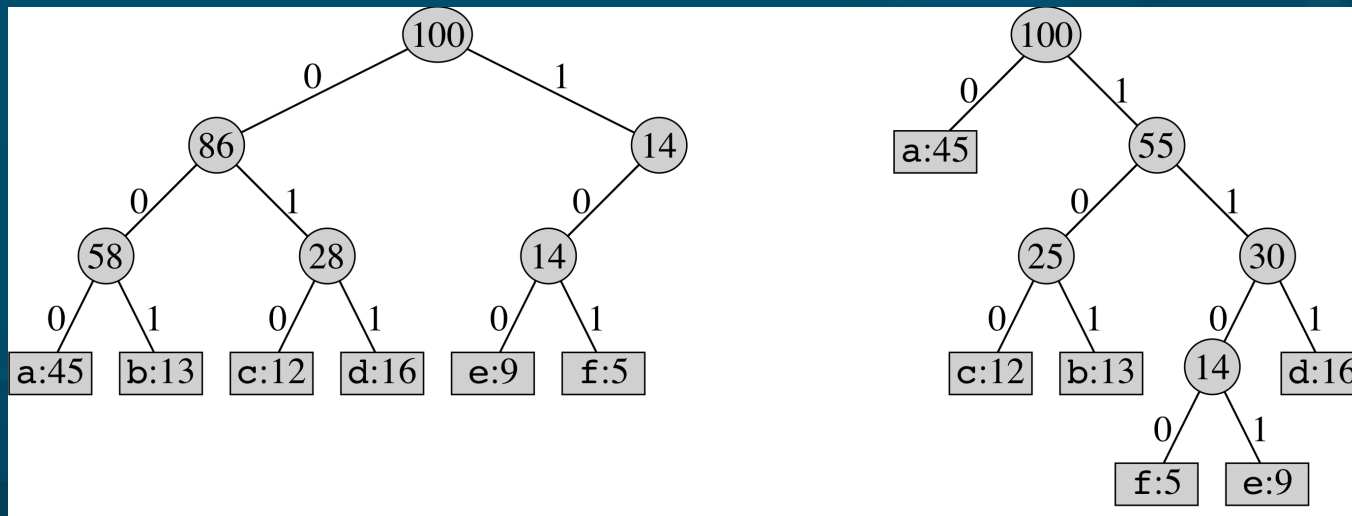
Encoding

	a	b	c	d	e	f
Frequency (in thousands)	45	13	12	16	9	5
Fixed-length codeword	000	001	010	011	100	101
Variable-length codeword	0	101	100	111	1101	1100

- Given a **text** with a known set of **characters**
 - Encode each character with a binary **codeword**
- **Fixed-length** code: all codewords same length
 - “cafe” \Rightarrow 010 000 101 100
- **Variable-length** code: some codes lower cost
 - “cafe” \Rightarrow 100 0 1100 1101
 - **Compression**: choose shorter codes for more frequent characters
- **Prefix code**: no code is a prefix of another
 - Unique **parsing**; don't need to **delimit** chars
 - “cafe” \Rightarrow 100011001101

Code trees

- Prefix code \Rightarrow **code tree**: binary tree where **nodes** represent **prefixes**; **characters** are at **leaves**
 - **Fixed-length** code \Rightarrow leaves all at **same level**
 - **Decoding** = **walk** down the tree
 - ◆ **Cost** of a char = **depth** in tree
- **Total cost** of encoding a file using a given tree:
 - $\sum_c [\text{freq}(c) * \text{depth}(c)]$



Huffman coding

- Build tree **bottom-up**
 - Start with two **least**-common chars
 - **Merge** to make new subtree with **combined** freq
- **Min-priority queue** manages the greedy choice
- **Input**: array of char nodes with **.freq** attribs

→ def **huffman**(chars):

- **Q** = new MinQueue(chars)
- for i in 1 .. length(chars)-1:
 - **z** = new Node
 - **z.left** = **Q.popmin()**
 - **z.right** = **Q.popmin()**
 - **z.freq** = **z.left.freq** + **z.right.freq**
 - **Q.push(z)**
- return **Q.popmin()**

char	freq
a	15
b	5
c	9
d	7
e	18
f	10