

Greedy Algorithms

Greedy Algorithm

- ◆ Like dynamic programming, used to solve optimization problems.
- ◆ Problems exhibit optimal substructure (like DP).
- ◆ Problems also exhibit the **greedy-choice** property.
 - » When we have a choice to make, make the one that looks best *right now*. (i.e., **locally**)
 - » Make a **locally optimal choice** in hope of getting a **globally optimal solution**.

Greedy Technique

- ◆ Constructs a solution to an optimization problem piece by piece through a sequence of choices that are:
 - » feasible, i.e., it has to satisfy the problem's constraints
 - » locally optimal, i.e., it has to be the best local choice among all feasible choices available on that step
 - » Irrevocable, i.e., once made, it cannot be changed on subsequent steps of the Algorithm
- ◆ For some problems, yields an optimal solution.
- ◆ For most, does not but can be useful for fast approximations.

Applications of the Greedy Strategy

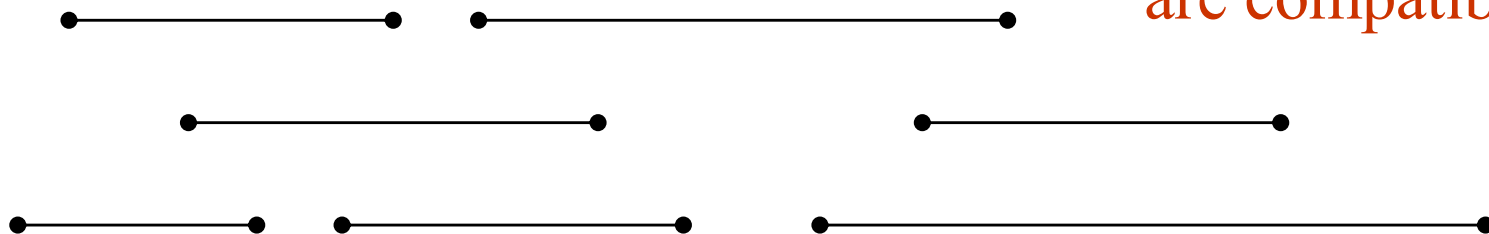
- ◆ Optimal solutions:
 - » minimum spanning tree (MST)
 - » single-source shortest paths
 - » simple scheduling or activity selection problems
 - » Huffman codes

- ◆ Approximations:
 - » traveling salesman problem (TSP)
 - » knapsack problem
 - » other combinatorial optimization problems

Activity-Selection Problem

- ◆ Input: Set S of n activities, a_1, a_2, \dots, a_n .
 - » s_i = start time of activity i .
 - » f_i = finish time of activity i .
- ◆ Output: Subset A of maximum number of compatible activities.
 - » Two activities are compatible if their intervals don't overlap.

Example:



Activities in each line
are compatible.

Optimal Substructure

- ◆ Assume activities are sorted by finishing times.
 - » $f_1 \leq f_2 \leq \dots \leq f_n$.
- ◆ Suppose an optimal solution includes activity a_k .
 - » This generates two subproblems.
 - » Selecting from a_1, \dots, a_{k-1} , activities compatible with one another, and that finish before a_k starts (compatible with a_k).
 - » Selecting from a_{k+1}, \dots, a_n , activities compatible with one another, and that start after a_k finishes.
 - » The solutions to the two subproblems must be optimal.
 - Prove using the cut-and-paste approach.

Recursive Solution

- ◆ Let S_{ij} = subset of activities in S that start after a_i finishes and finish before a_j starts.
- ◆ **Subproblems:** Selecting maximum number of mutually compatible activities from S_{ij} .
- ◆ Let $c[i, j]$ = size of maximum-size subset of mutually compatible activities in S_{ij} .

Recursive Solution:

$$c[i, j] = \begin{cases} 0 & \text{if } S_{ij} = \phi \\ \max_{i < k < j} \{c[i, k] + c[k, j] + 1\} & \text{if } S_{ij} \neq \phi \end{cases}$$

Greedy-Choice Property

- ◆ The problem also exhibits the **greedy-choice property**.
 - » There is an optimal solution to the subproblem S_{ij} that includes the activity with the smallest finish time in set S_{ij} . (**intuition: this leaves more time or resource for other tasks**)
 - » Can be proved easily.



- ◆ Hence, **there is an optimal solution to S that includes a_1** .
- ◆ Therefore, Greedy algorithm is: earliest finish time first.
 - » **Make** this **greedy choice** without solving subproblems first.
 - » Solve the subproblem resulted from this greedy choice.
 - » Combine the greedy choice and solution to the subproblem.

This is a top-down fashion instead of bottom-up!

Recursive Algorithm

Recursive-Activity-Selector (s, f, i, j)

1. $m \leftarrow i+1$
2. **while** $m < j$ and $s_m < f_i$
3. **do** $m \leftarrow m+1$
4. **if** $m < j$
5. **then return** $\{a_m\} \cup$
 Recursive-Activity-Selector(s, f, m, j)
6. **else return** ϕ

Initial Call: Recursive-Activity-Selector ($s, f, 0, n+1$)

Complexity: $\Theta(n)$, considering already sorted based on finish time.

Straightforward to convert the algorithm to an iterative one.

Typical Steps

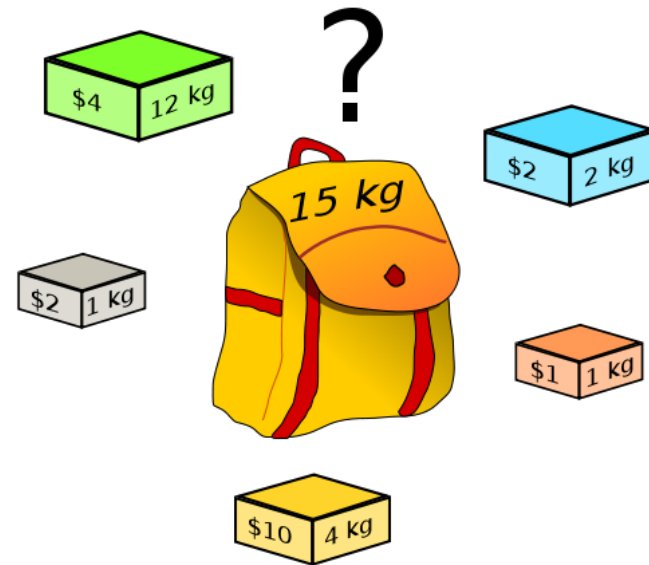
- ◆ Cast the optimization problem as one in which we make a choice and are left with one subproblem.
- ◆ Show that greedy choice and optimal solution to subproblem \Rightarrow optimal solution to the problem.
- ◆ Make the greedy choice and **solve top-down**.
 - » E.g., put an activity in optimal solution, then solve a smaller problem.
- ◆ May have to **preprocess input to put into greedy order**.
 - » Example: Sorting activities by finish time.

Elements of Optimal Greedy Alg

- ◆ Greedy-choice Property.
 - » A globally optimal solution can be arrived at by making a locally optimal (greedy) choice.
- ◆ Optimal Substructure.

0/1 Knapsack Problem

- Given n items of
integer weights: $w_1 \ w_2 \ \dots \ w_n$
values: $v_1 \ v_2 \ \dots \ v_n$
a knapsack of integer capacity W .
- Find most valuable subset of the items that fit into the knapsack.
- You take an item (1) or do not take (0) \rightarrow cannot take a fraction of an item.



Optimal Substructure

- ◆ *Let $F(i, j)$ be the value of an optimal solution i.e., the value of the most valuable subset of the first i items that fit into the knapsack of capacity j .*
- ◆ We can divide all the subsets of the first i items that fit the knapsack of capacity j into two categories:
 - » those that do not include the i -th item
 - » and those that do.

Our goal is to find $F(n, W)$

Optimal Substructure

1. Among the subsets that do not include the i -th item, the value of an optimal subset is, by definition, $F(i - 1, j)$
2. Among the subsets that do include the i -th item (hence, $j - w_i \geq 0$), an optimal subset is made up of this item and an optimal subset of the first $i - 1$ items that fits into the knapsack of capacity $j - w_i$.

The value of such an optimal subset is $v_i + F(i - 1, j - w_i)$

◆ These observations lead to the following recurrence:

$$F(i, j) = \begin{cases} \max\{F(i - 1, j), v_i + F(i - 1, j - w_i)\} & \text{if } j - w_i \geq 0, \\ F(i - 1, j) & \text{if } j - w_i < 0. \end{cases}$$

It is convenient to define the initial conditions as follows:

$$F(0, j) = 0 \text{ for } j \geq 0 \quad \text{and} \quad F(i, 0) = 0 \text{ for } i \geq 0.$$

Greedy Alg for 0/1 and Fractional

- ◆ Greedy choice does not work for 0/1 knapsack
 - » Does not exhibit greedy choice property
 - » Need to find optimal solution using DP (Use table of $n \times W$)
- ◆ Fractional knapsack: Can take any fraction of item
 - » Has greedy choice property.
 - » Optimal solution: take items in decreasing order of unit value: $O(n \log n)$ time.

Greedy Alg for 0/1 and Fractional

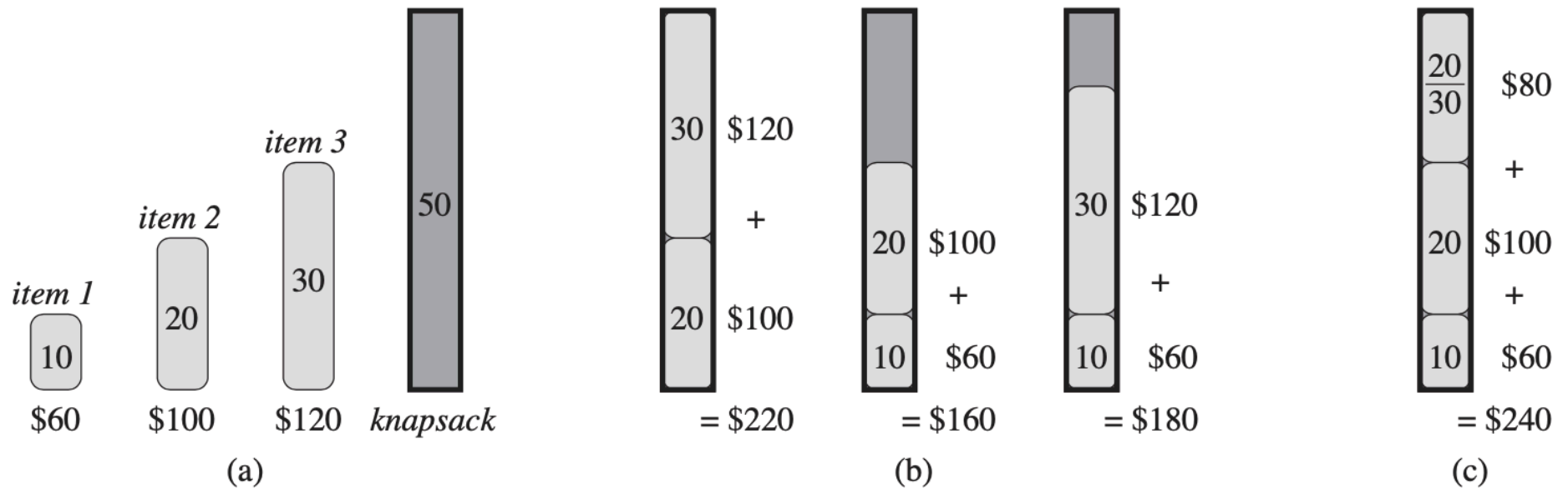


Figure 16.2 An example showing that the greedy strategy does not work for the 0-1 knapsack problem. (a) The thief must select a subset of the three items shown whose weight must not exceed 50 pounds. (b) The optimal subset includes items 2 and 3. Any solution with item 1 is suboptimal, even though item 1 has the greatest value per pound. (c) For the fractional knapsack problem, taking the items in order of greatest value per pound yields an optimal solution.

Data Compression Problem

- ♦ Input: A file of characters from set $C = \{c_1, c_2, \dots, c_n\}$.
 - » $f(c_i)$ denotes the frequency (number of times) that c_i appears in the input file.
- ♦ Output: Binary character encoding for C that minimizes the file size.
 - » Encoding may be variable-length:
 - Example : $a=0, b=101$;

Example: Optimal Data Compression

c_i	a	b	c	d	e	f
Frequency $f(c_i)$ (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

File-Size:

- Fixed-length:

$$3 \cdot (45 + 13 + 12 + 16 + 9 + 5) \cdot 1000 = 300,000 \text{ bits}$$

- Variable-length:

$$(45 \cdot 1 + 13 \cdot 3 + 12 \cdot 3 + 16 \cdot 3 + 9 \cdot 4 + 5 \cdot 4) \cdot 1000 = 224,000 \text{ bits}$$

Example: Optimal Data Compression

c_i	a	b	c	d	e	f
Frequency $f(c_i)$ (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

Prefix(free) Code:

No code is a prefix of another code.

File-Size:

•Fixed-length:

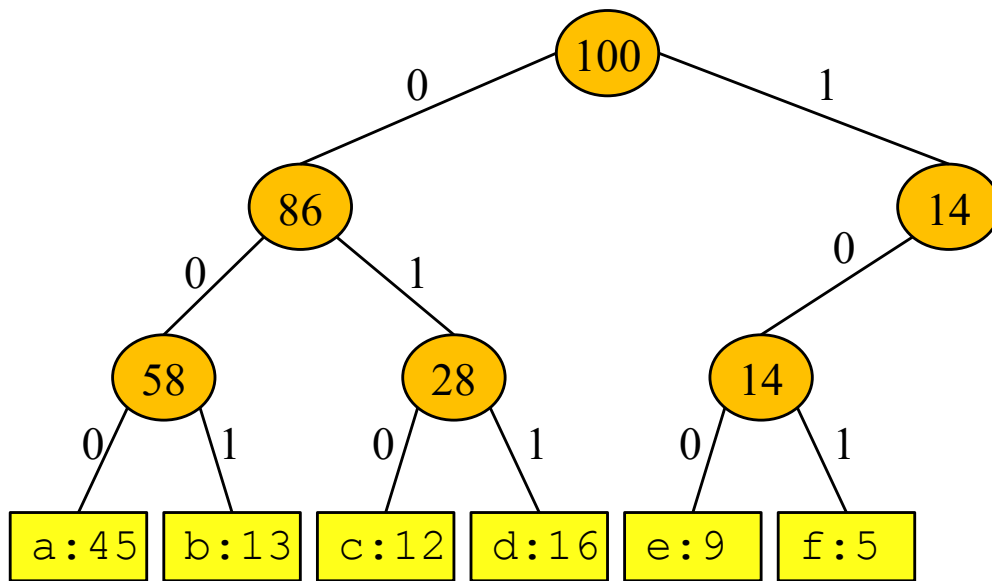
$$3 \cdot (45 + 13 + 12 + 16 + 9 + 5) \cdot 1000 = 300,000 \text{ bits}$$

•Variable-length:

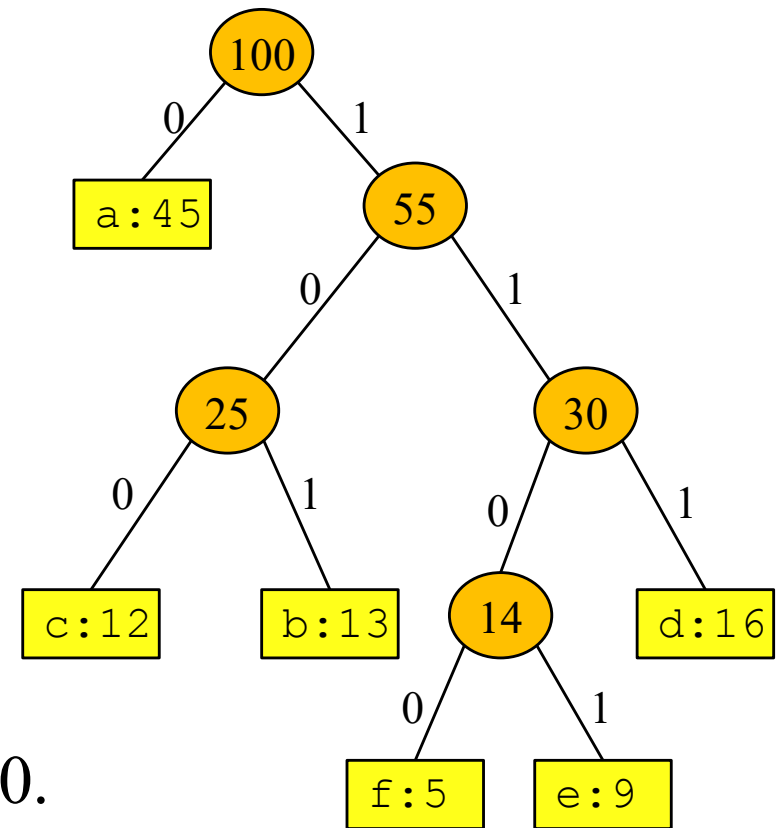
$$(45 \cdot 1 + 13 \cdot 3 + 12 \cdot 3 + 16 \cdot 3 + 9 \cdot 4 + 5 \cdot 4) \cdot 1000 = 224,000 \text{ bits}$$

Decoding

Fixed-length



Variable-length

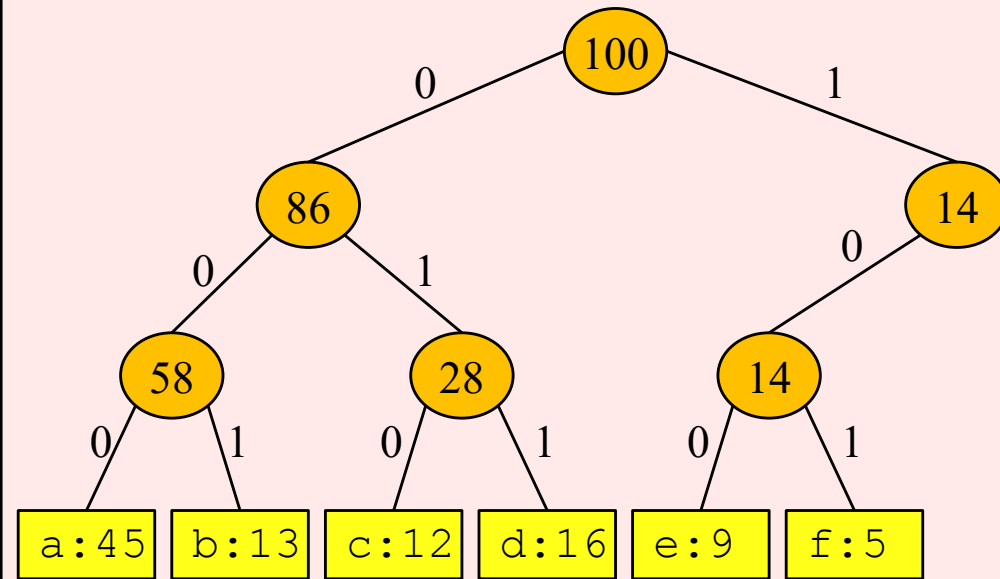


“Going left” in tree corresponds to 0.

“Going right” in tree corresponds to 1.

Decoding

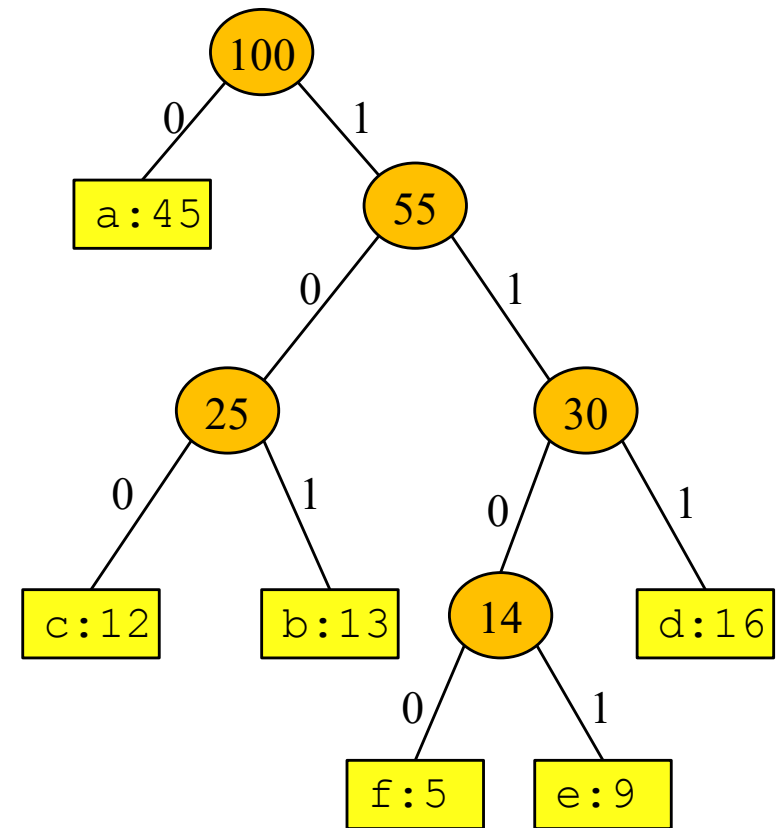
Fixed-length



Not full tree – can't be optimal encoding.
Why?

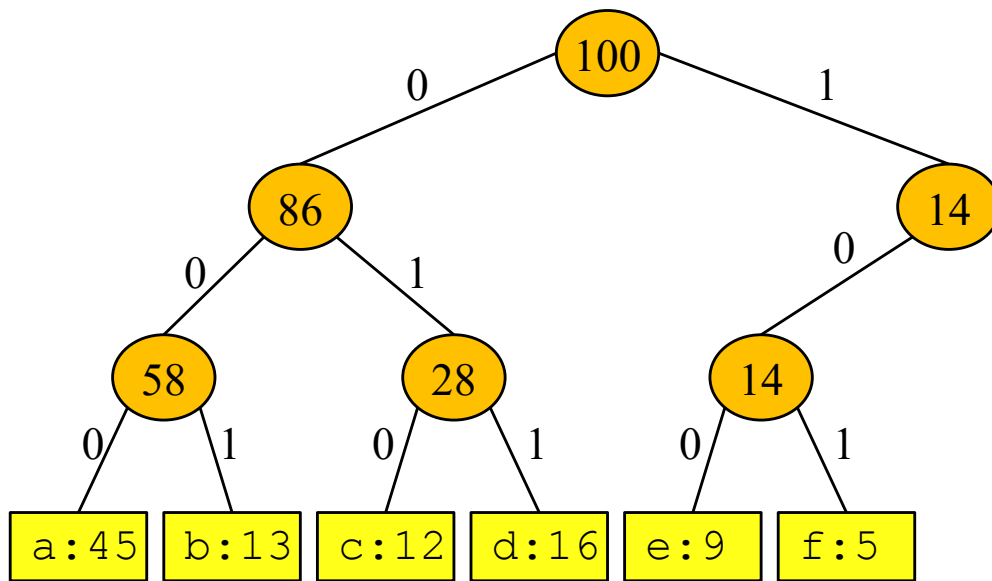
-- Missing right most child indicates we could have a shorter unique code, say 11.

Variable-length

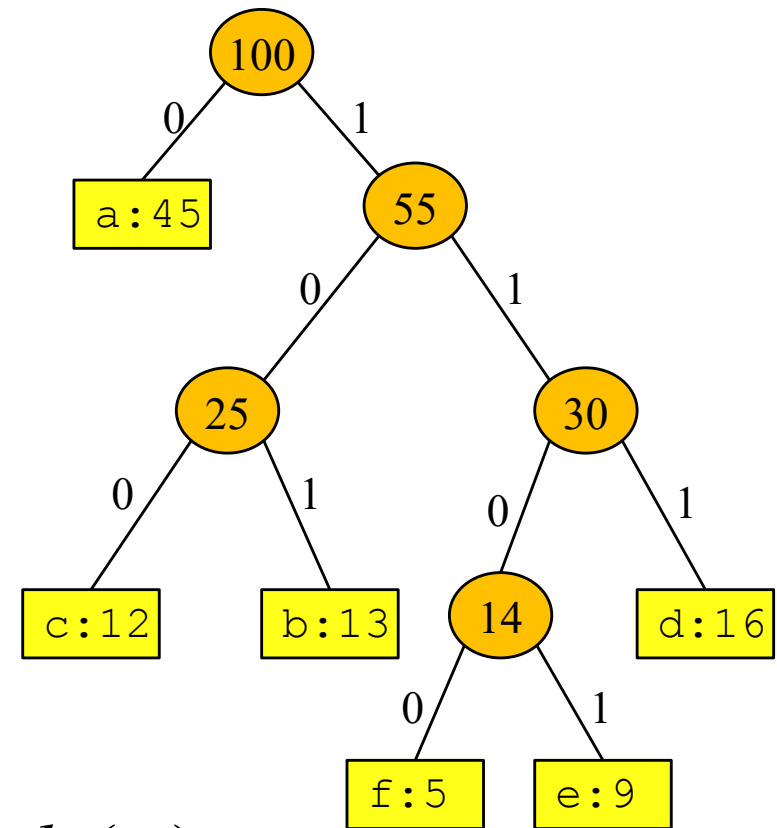


Decoding

Fixed-length



Variable-length



Cost of Encoding
for Tree T :

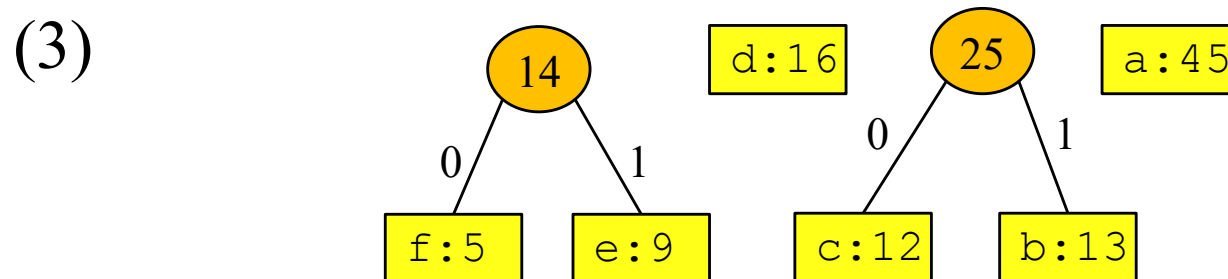
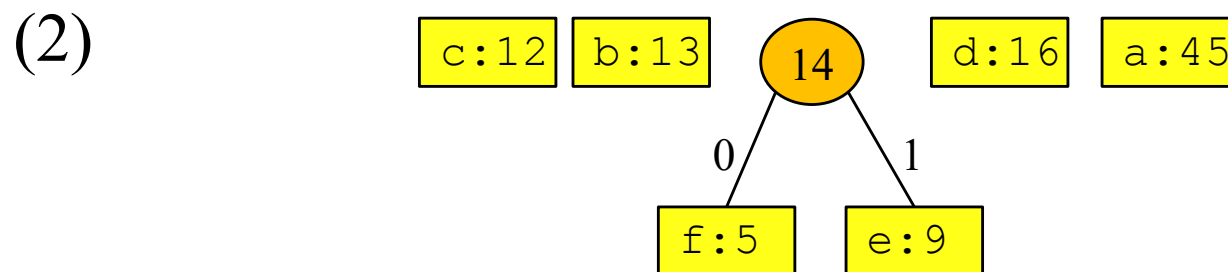
$$B(T) = \sum_{c_i \in C} f(c_i) d_T(c_i)$$

Depth of c_i in tree T .

Solution: Huffman Codes

- ♦ **Idea:** Sort characters in monotonically nondecreasing order and “merge” two least-frequently-used characters into a subtree; repeat until all characters are in tree.

Step:

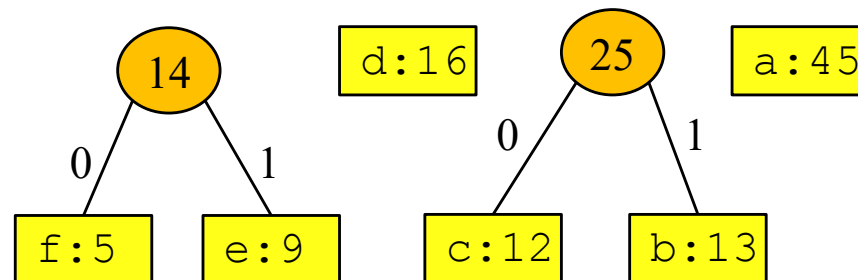


Solution: Huffman Codes

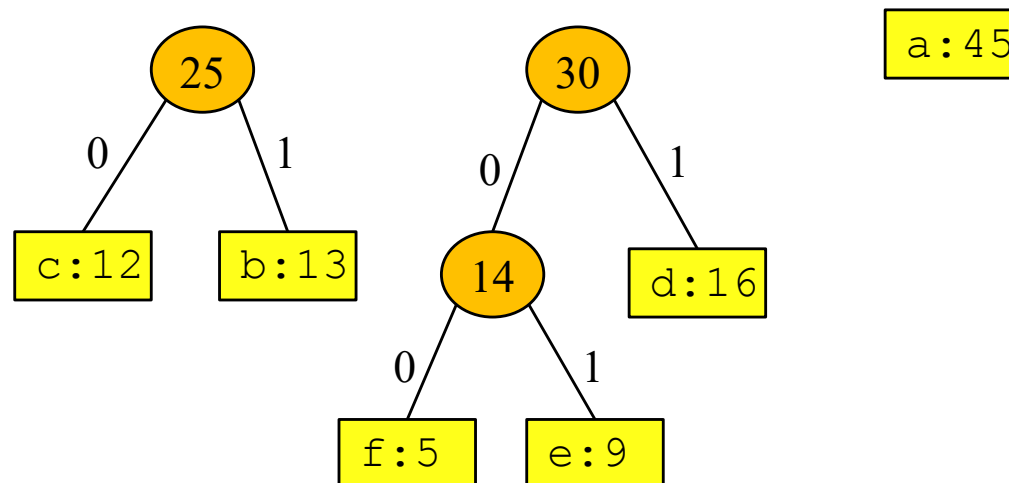
- ♦ Idea: Sort characters in monotonically nondecreasing order and “merge” two least-frequently-used characters into a subtree; repeat until all characters are in tree.

Step:

(3)



(4)

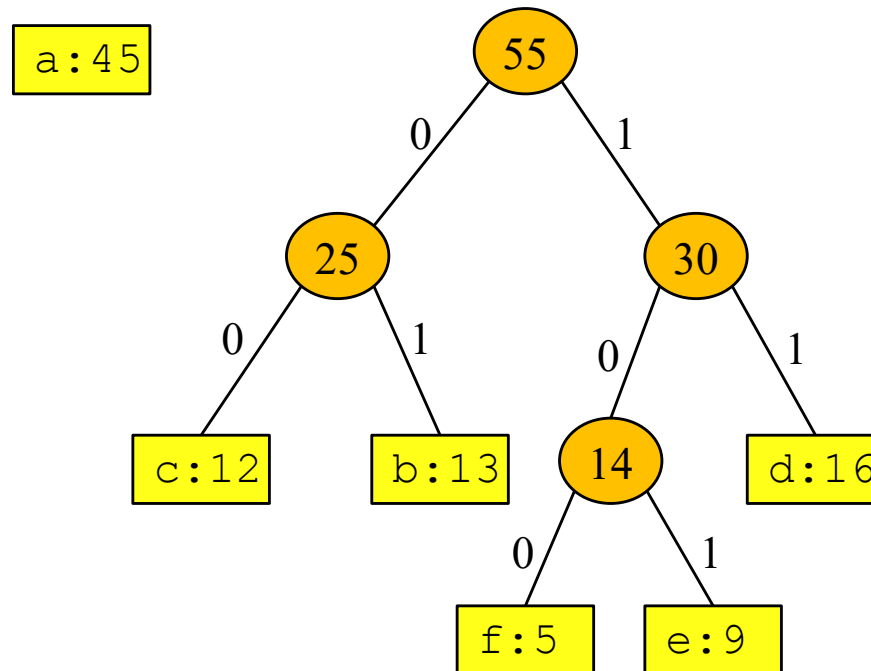


Solution: Huffman Codes

- ♦ Idea: Sort characters in monotonically nondecreasing order and “merge” two least-frequently-used characters into a subtree; repeat until all characters are in tree.

Step:

(5)

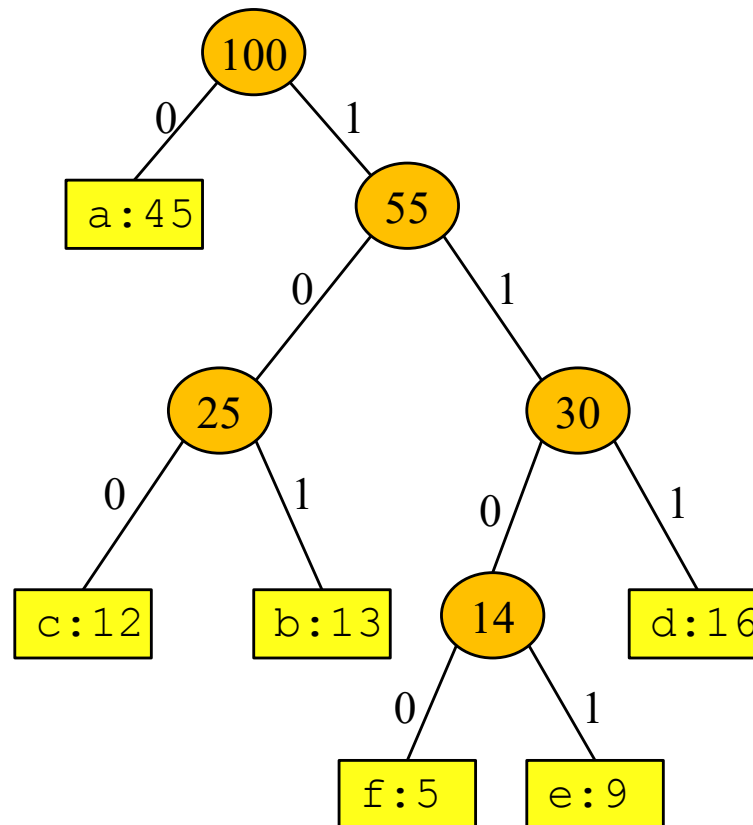


Solution: Huffman Codes

- ♦ Idea: Sort characters in monotonically nondecreasing order and “merge” two least-frequently-used characters into a subtree; repeat until all characters are in tree.

Step:

(6)



Solution: Huffman Codes

Huffman (C)

```
1.   $n \leftarrow |C|$ 
2.   $Q \leftarrow C$     //Make Min-Heap  $\leftarrow O(n)$ 
3.  for  $i \leftarrow 1$  to  $n - 1$ 
4.    do allocate a new node  $z$ 
5.       $left[z] \leftarrow x \leftarrow \text{Extract-Min}(Q) \leftarrow O(\lg n)$ 
6.       $right[z] \leftarrow y \leftarrow \text{Extract-Min}(Q)$ 
7.       $f[z] \leftarrow f[x] + f[y]$ 
8.       $\text{Insert}(Q, z)$ 
9.  return  $\text{Extract-Min}(Q)$  //return root of tree
```

What is
running
time?

Answer:
 $O(n \lg n)$.

Recall, we want to minimize:

$$B(T) = \sum_{c_i \in C} f(c_i) d_T(c_i)$$

Why does this approach
yield minimum $B(T)$?

Why is it
greedy?

Huffman Codes: Proof of Correctness

Lemma 1 ← “Greedy Choice” Property

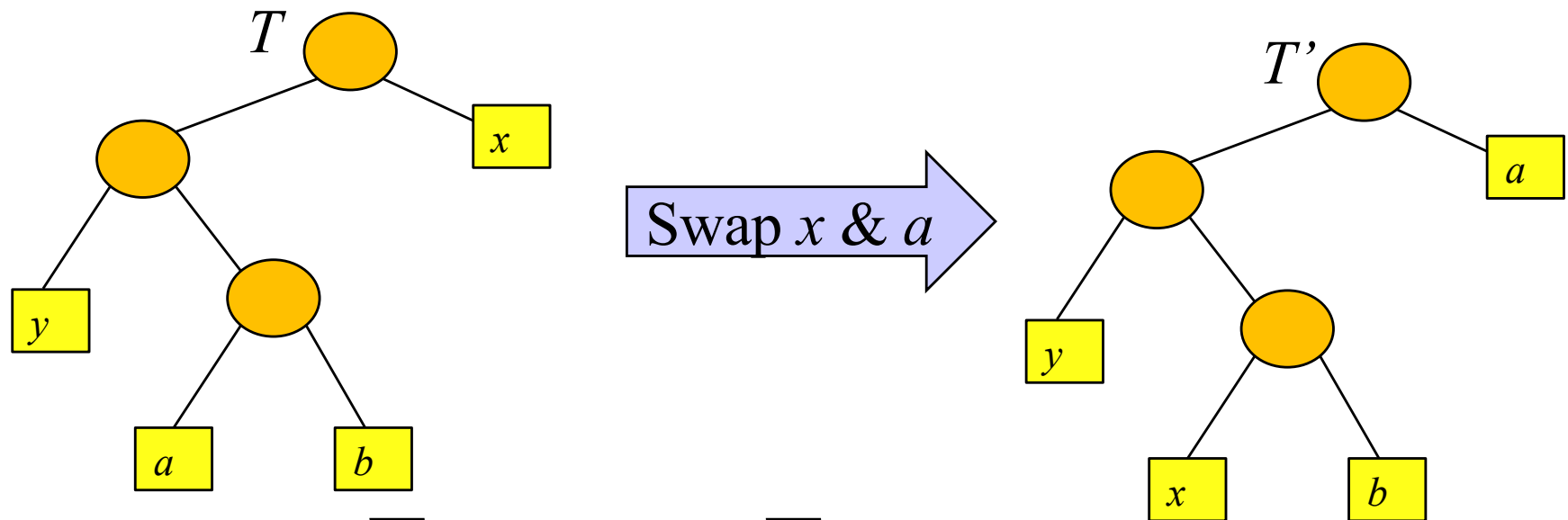
Let C be set of characters where each $c \in C$ has frequency $f(c)$. Let x and y be two characters having lowest frequencies. Then there exists an optimal prefix code for C in which the binary codewords for x and y have the same length and differ only in the last bit.

Proof: Let T represent the tree for any optimal encoding of C . We will show we can modify any such T to create new tree T'' , such that x and y are sibling leaves at maximum depth in T'' and $B(T) \geq B(T'')$.

Why does showing this prove the lemma?

Huffman Codes: Proof of Correctness

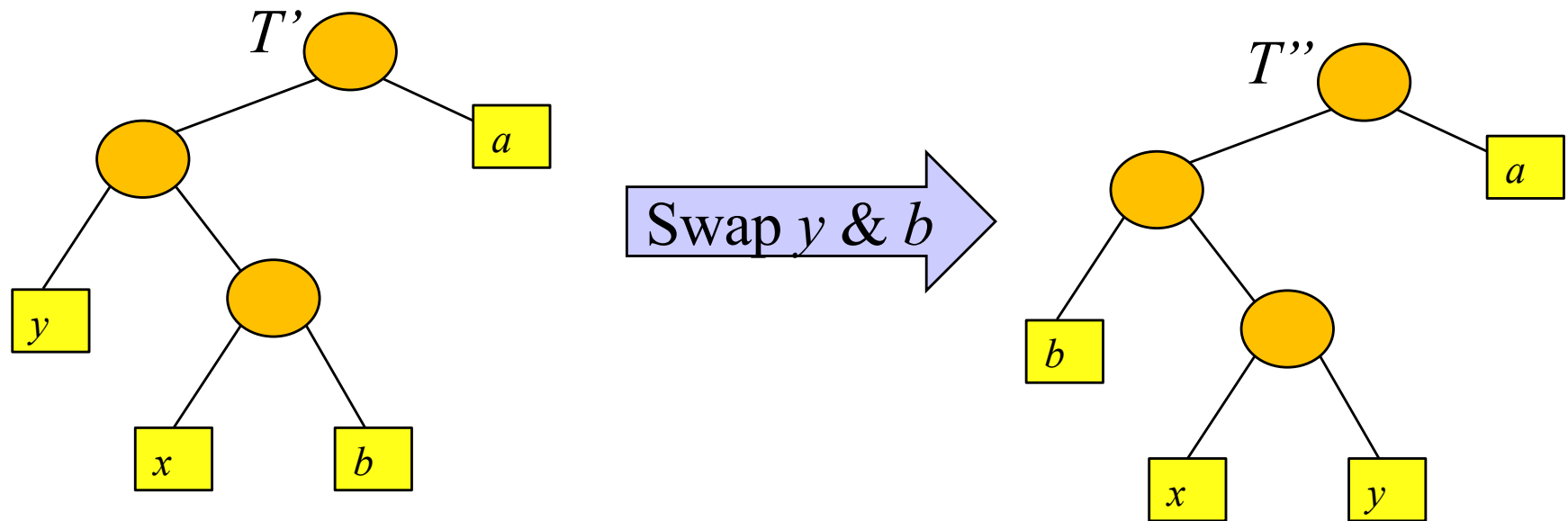
Proof (cont.): Let a and b be nodes at maximum depth in T and x has a lowest frequency. For example,



$$\begin{aligned}\text{So, } B(T) - B(T') &= \sum_{c_i \in C} f(c_i) d_T(c_i) - \sum_{c_i \in C} f(c_i) d_{T'}(c_i) \\ &= f(x) d_T(x) + f(a) d_T(a) - f(x) d_{T'}(x) - f(a) d_{T'}(a) \\ &= f(x) d_T(x) + f(a) d_T(a) - f(x) d_T(a) - f(a) d_T(x) \\ &= (f(a) - f(x))(d_T(a) - d_T(x)) \\ &\geq 0\end{aligned}$$

Huffman Codes: Proof of Correctness

Proof (con't): Similarly,



and show that $B(T') - B(T'') \geq 0$.

Thus, $B(T) - B(T'') \geq 0$. ■

Huffman Codes: Proof of Correctness

Lemma 2 ← “Optimal Substructure” Property

Let C be set of characters, where each $c \in C$ has frequency $f(c)$. Let x and y be two characters having the lowest frequencies. Let $C' = C - \{x, y\} \cup \{z\}$, where z is a “new” character with $f(z) = f(x) + f(y)$. Let T' be any tree representing an optimal prefix code for C' . Then the tree T obtained from T' by replacing z with the subtree containing x and y represents an optimal prefix code for C .

Proof Sketch: First, write $B(T)$ in terms of $B(T')$. Then, assume that T does not represent an optimal prefix code for C to derive a contradiction.

Huffman Codes: Proof of Correctness

Theorem

Procedure `Huffman` produces an optimal prefix code.

Proof: Follows immediately from Lemmas 1 & 2.

Matroid and Greedy Algs

- ◆ A matroid is a mathematical structure that generalizes the notion of linear independence from vector spaces to arbitrary sets.
- ◆ If an optimization problem has the structure of a matroid, then the appropriate greedy algorithm will solve it optimally

Matroid

A **matroid** is an ordered pair $M = (S, \mathcal{I})$ satisfying the following conditions.

1. S is a finite set.
2. \mathcal{I} is a nonempty family of subsets of S , called the **independent** subsets of S , such that if $B \in \mathcal{I}$ and $A \subseteq B$, then $A \in \mathcal{I}$. We say that \mathcal{I} is **hereditary** if it satisfies this property. Note that the empty set \emptyset is necessarily a member of \mathcal{I} .
3. If $A \in \mathcal{I}$, $B \in \mathcal{I}$, and $|A| < |B|$, then there exists some element $x \in B - A$ such that $A \cup \{x\} \in \mathcal{I}$. We say that M satisfies the **exchange property**.