

# Greedy Algorithms

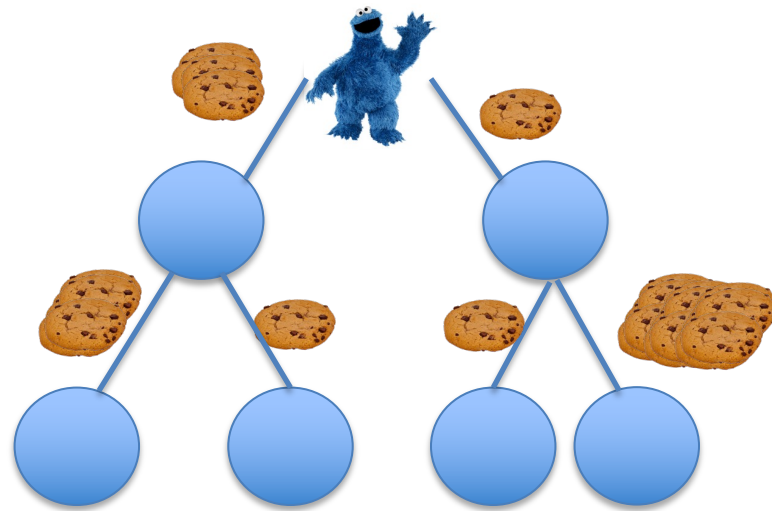


NYIT CSCI-651

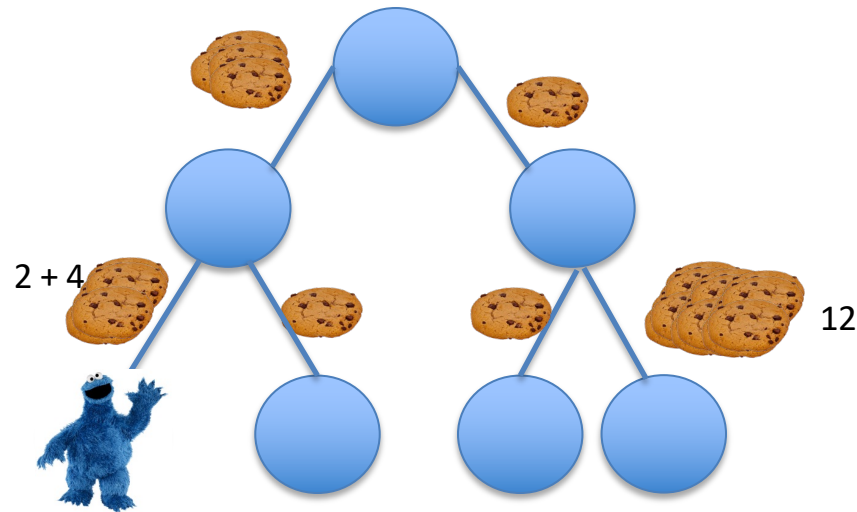
# Greedy Algorithms

- A ***greedy algorithm*** always makes the choice that looks best at the moment.
- **Local optimal** choices with the **hope** that the global solution would be optimal too.
- They **do not** always provide the **optimal** answer but for **some** problems, **they do**.

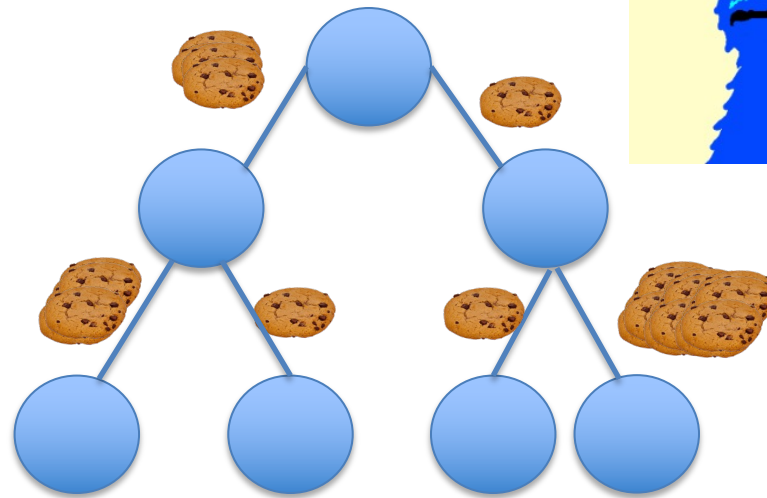
# Greedy Algorithms



# Greedy Algorithms



# Greedy Algorithms



# Optimal Substructure

- A problem has **optimal substructure** if an optimal solution can be constructed from optimal solutions of its subproblems. (i.e., optimal solution to the problem contains optimal solutions to subproblems)
- This property is a key ingredient of assessing the applicability of dynamic programming as well as greedy algorithms.
- Example: If the shortest route from Seattle to Los Angeles passes through Portland and then Sacramento, then the shortest route from Portland to Los Angeles must pass through Sacramento too.

# Some points about greedy strategy

- In a greedy algorithm, **we make whatever choice seems best at the moment and then solve the subproblem that remains.**
- The choice made by a greedy algorithm may depend on choices **so far**, but it **cannot** depend on any **future** choices
- a greedy strategy usually progresses in a **top-down** fashion, making one greedy choice after another, reducing each given problem instance to a **smaller** one.

# Elements of the greedy strategy

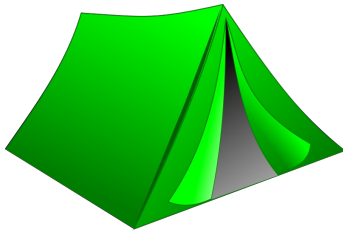
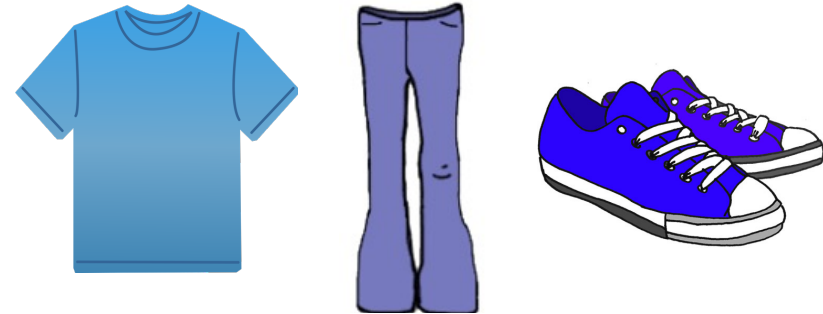
- Determine the optimal structure of the problem
- Develop a recursive structure
- Show that with the greedy choice, only one subproblem is remained.
- Prove that it is always safe to use the greedy choice.
- Develop a recursive algorithm that implements the greedy choice.
- Convert the recursive algorithm to an iterative algorithm.



# Example



# Example



M kg



...

# Example

200 gr



200 gr



400 gr



50 gr



2000 gr



300 gr



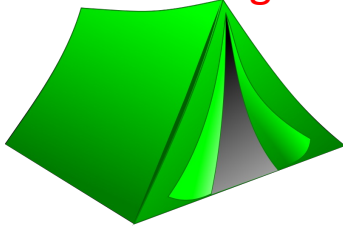
20 gr



250 gr



3000 gr



40 gr



800 gr



M kg

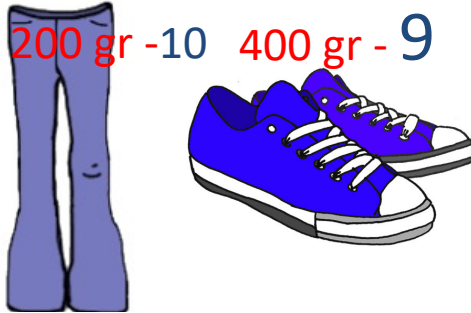
1000 gr



...

# Example

200 gr - 11



200 gr - 10    400 gr - 9



50 gr - 5



2000 gr - 6



300 gr - 8



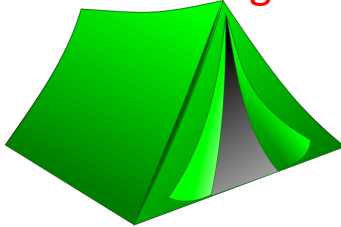
20 gr - 2



250 gr - 4



3000 gr - 1



40 gr -



800 gr -



M kg

1000 gr - 7



...

# Example

- Knapsack Problem
- You have a list of items
  - with value  $v_i$  and weight  $w_i$ .
- How do you select items so you can collect the highest value without going over the weight limit



# 0/1 Knapsack Problem

- a.k.a discrete knapsack problem
  - Take whole or nothing
  - Versus **fractional** ( or continuous) knapsack



100 kg

# Fractional Knapsack problem

- First Approach
  - Select the **highest value** items

Item	W	V
1	10	20
2	20	30
3	30	66
4	40	40
5	50	60



100 kg

Items 3, 5, and half of 4

$$66 + 60 + 20 = 146$$

# Fractional Knapsack problem

- Second Approach
  - Select the **lightest** items

Item	W	V
1	10	20
2	20	30
3	30	66
4	40	40
5	50	60



100 kg

Items 1, 2, 3, and 4

$$20 + 30 + 66 + 40 = 156$$



# Fractional Knapsack problem

- Third Approach
  - Select the item with highest  $V_i/W_i$

Item	W	V
1	10	20
2	20	30
3	30	66
4	40	40
5	50	60



100 kg

# Fractional Knapsack problem

- Third Approach
  - Select the item with highest  $V_i/W_i$

Item	W	V	$V/W$
1	10	20	2.0
2	20	30	1.5
3	30	66	2.2
4	40	40	1.0
5	50	60	1.2



100 kg

Items 3, 1, 2, and 5

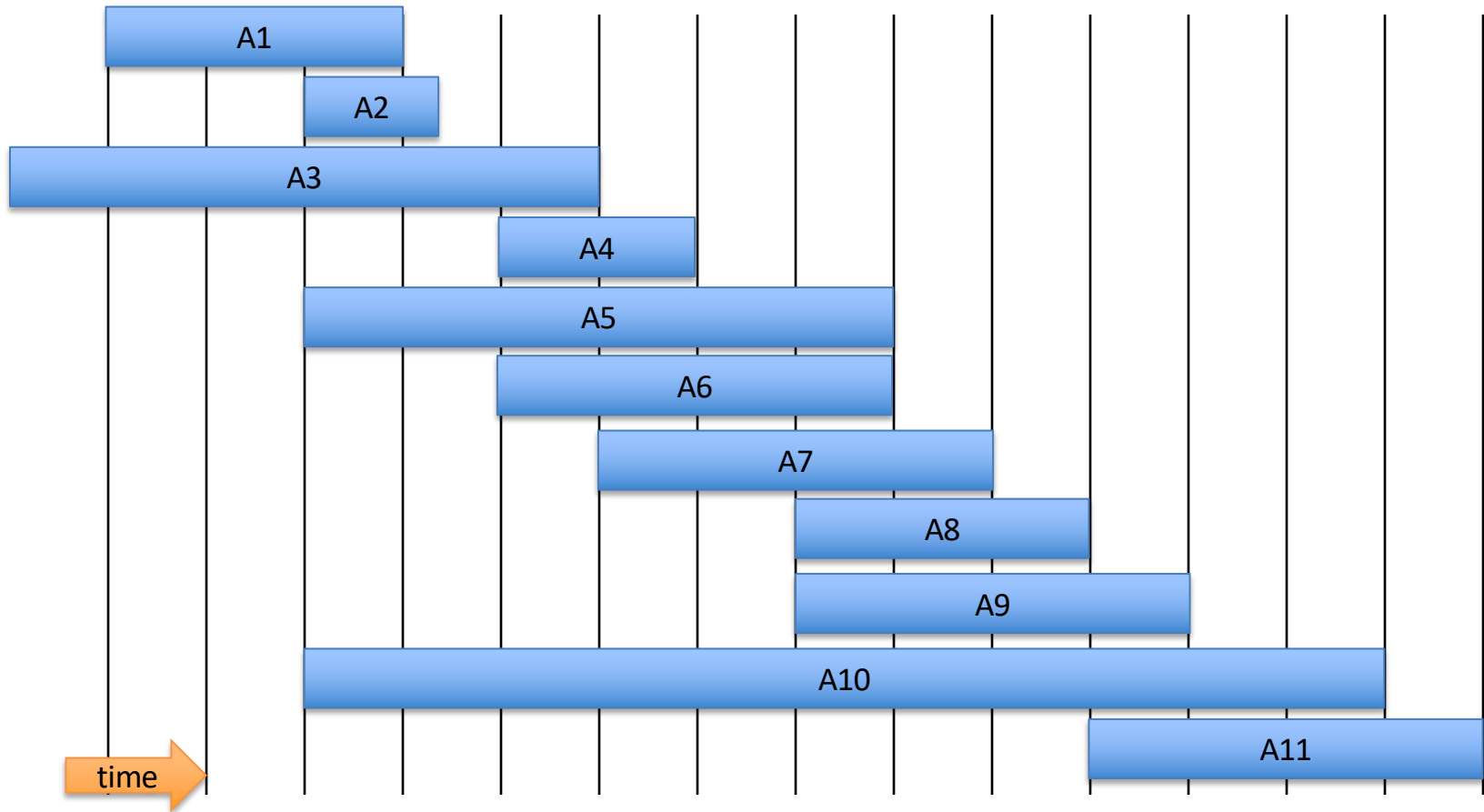
$$66 + 20 + 30 + 0.8(60) = 164$$

$$30 + 10 + 20 + 0.8(50)$$

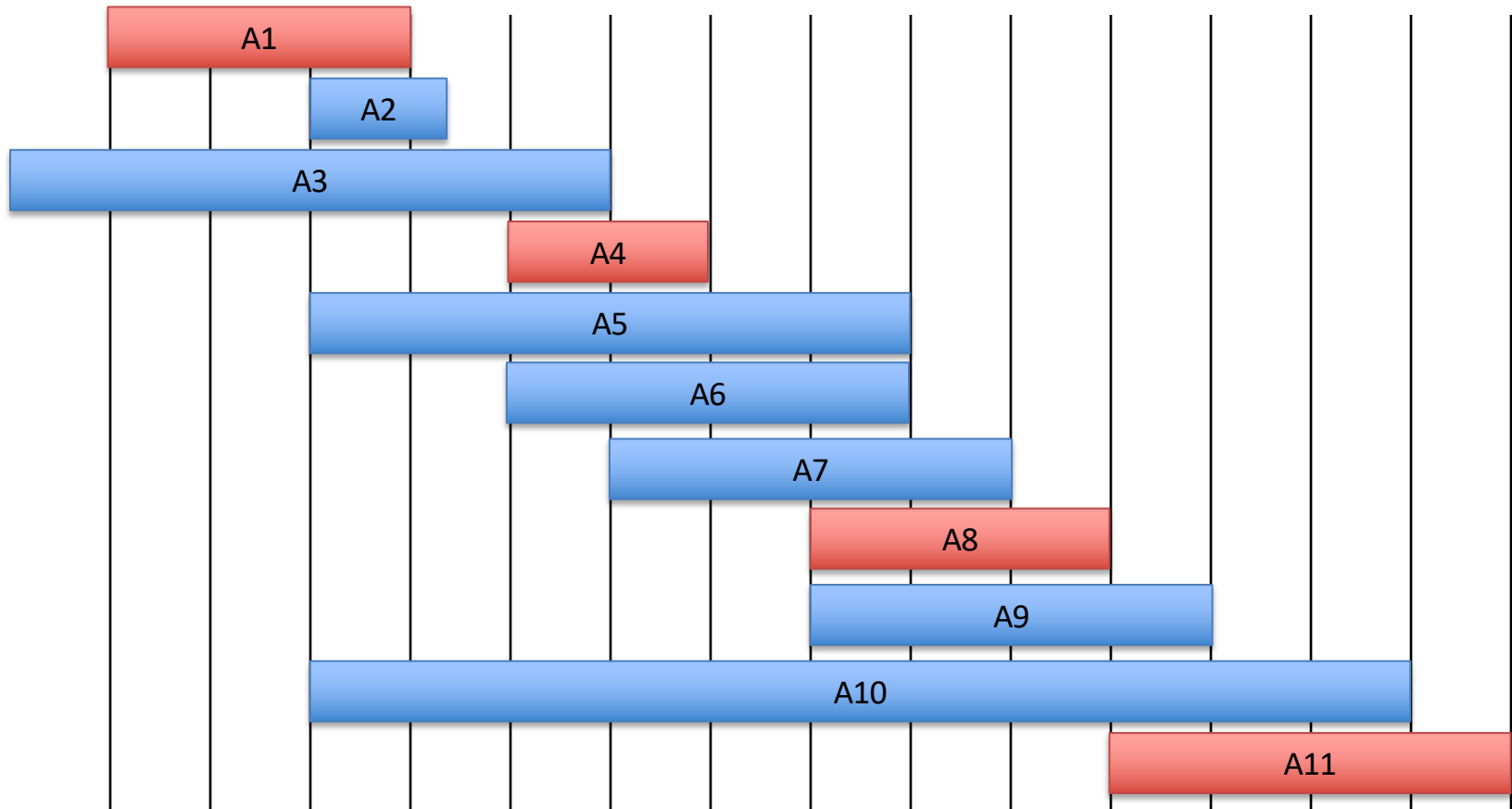
# An activity-selection problem

- We have a set of competing activities that require exclusive use of a common resource. Each activity has a start time  $s$  and finish time  $f$ .
- In the ***activity-selection problem***, we wish to select a maximum-size subset of mutually compatible activities.
- Two activities  $a_i$  and  $b_j$  are compatible if two activities have **no overlaps** (a comes after b or otherwise)
- Activities  $a_i$  and  $a_j$  are compatible if  $s_i \geq f_j$  or  $s_j \geq f_i$

# An activity-selection problem



# An activity-selection problem



# An activity-selection problem - Example

- Find a set of compatible activities for the following activities

$i$	1	2	3	4	5	6	7	8	9	10	11
$s_i$	1	3	0	5	3	5	6	8	8	2	12
$f_i$	4	5	6	7	9	9	10	11	12	14	16

(1, 4, 8, 11)

(1, 4, 9, 11)

(3, 8, 11)

(2, 4, 8, 11)

# An activity-selection problem - Example

- Select a **maximum-size subset** of mutually compatible activities.

$i$	1	2	3	4	5	6	7	8	9	10	11
$s_i$	1	3	0	5	3	5	6	8	8	2	12
$f_i$	4	5	6	7	9	9	10	11	12	14	16

# An activity-selection problem

- What is the greedy choice here?
- What is our intuition?
  - We should select an activity that leaves the resource available for as many activities as possible.



# An activity-selection problem

- What does that mean?
  - The activity that finishes first
  - Since that would leave the resource available for as many activities as possible.

# An activity-selection problem

- Let's say that the activities are sorted monotonically based on the finish time.

$i$	1	2	3	4	5	6	7	8	9	10	11
$s_i$	1	3	0	5	3	5	6	8	8	2	12
$f_i$	4	5	6	7	9	9	10	11	12	14	16

What if it is not sorted? Sort it with  $O(n \log n)$ .

# An activity-selection problem

- Let's say that the activities are sorted monotonically.

$i$	1	2	3	4	5	6	7	8	9	10	11
$s_i$	1	3	0	5	3	5	6	8	8	2	12
$f_i$	4	5	6	7	9	9	10	11	12	14	16

- What is the first chosen activity?
  - The greedy choice is activity  $a_1$
- We have only one remaining subproblem to solve:
  - finding activities that start after  $a_1$  finishes.

# An activity-selection problem

- Let  $S_k = \{a_i \in S: s_i \geq f_k\}$  be the set of activities that start after activity  $a_k$  finishes
- If we make a greedy choice of  $a_1$  as the first activity, then  $S_1$  remains the only sub problem to solve
- When do we have an optimal solution?
  - When the solution of  $S_1$  is also optimal

# An activity-selection problem

- Optimal substructure tells us that if  $a_1$  is in the optimal solution, then an **optimal solution to the original problem** consists of
  - activity  $a_1$  and
  - all the activities in an optimal solution to the sub problem  $S_1$

# Question

- Is our intuition correct?
- Is the greedy choice—in which we choose the first activity to finish—always part of some optimal solution?
- The following theorem shows that it is.

***Theorem 16.1***

Consider any nonempty subproblem  $S_k$ , and let  $a_m$  be an activity in  $S_k$  with the earliest finish time. Then  $a_m$  is included in some maximum-size subset of mutually compatible activities of  $S_k$ .

The activity with the earliest finish time is always included in the solution.

# Solution

1. We can repeatedly choose the activity that finishes first
2. Keep only the compatible activities
3. Repeat until no activity remains



# A recursive greedy algorithm

## An array of start times

```
RECURSIVE-ACTIVITY-SELECTOR( $s, f, k, n$ )
1   $m = k + 1$ 
2  while  $m \leq n$  and  $s[m] < f[k]$       // find the first activity in  $S_k$  to finish
3       $m = m + 1$ 
4  if  $m \leq n$ 
5      return  $\{a_m\} \cup \text{RECURSIVE-ACTIVITY-SELECTOR}(s, f, m, n)$ 
6  else return  $\emptyset$ 
```

We first start with  $(s, f, 0, n)$

In order to start, we add the fictitious activity  $a_0$  with  $f_0 = 0$ , so that sub problem  $S_0$  is the entire set of activities  $S$ .

The initial call, which solves the entire problem, is  $\text{RECURSIVE-ACTIVITY-SELECTOR}(s, f, 0, n)$

# A recursive greedy algorithm

## An array of finish times

RECURSIVE-ACTIVITY-SELECTOR ( $s, f, k, n$ )

```
1   $m = k + 1$ 
2  while  $m \leq n$  and  $s[m] < f[k]$       // find the first activity in  $S_k$  to finish
3       $m = m + 1$ 
4  if  $m \leq n$ 
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The initial call, which solves the entire problem, is RECURSIVE-ACTIVITY-SELECTOR  $(s, f, 0, n)$

# A recursive greedy algorithm

## Number of activities

RECURSIVE-ACTIVITY-SELECTOR( $s, f, k, n$ )

```
1   $m = k + 1$ 
2  while  $m \leq n$  and  $s[m] < f[k]$       // find the first activity in  $S_k$  to finish
3       $m = m + 1$ 
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The initial call, which solves the entire problem, is RECURSIVE-ACTIVITY-SELECTOR( $s, f, 0, n$ )

# A recursive greedy algorithm

## Index of the sub-problem

RECURSIVE-ACTIVITY-SELECTOR( $s, f, k, n$ )

```
1   $m = k + 1$ 
2  while  $m \leq n$  and  $s[m] < f[k]$       // find the first activity in  $S_k$  to finish
3       $m = m + 1$ 
4  if  $m \leq n$ 
5      return  $\{a_m\} \cup \text{RECURSIVE-ACTIVITY-SELECTOR}(s, f, m, n)$ 
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```

We first start with  $(s, f, 0, n)$

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The initial call, which solves the entire problem, is RECURSIVE-ACTIVITY-SELECTOR( $s, f, 0, n$ )

RECURSIVE-ACTIVITY-SELECTOR( $s, f, k, n$ )

```

1   $m = k + 1$ 
2  while  $m \leq n$  and  $s[m] < f[k]$       // find the first activity in  $S_k$  to finish
3       $m = m + 1$ 
4  if  $m \leq n$ 
5      return  $\{a_m\} \cup \text{RECURSIVE-ACTIVITY-SELECTOR}(s, f, m, n)$ 
6  else return  $\emptyset$ 

```

$i$	1	2	3	4	5	6	7	8	9	10	11
$s_i$	1	3	0	5	3	5	6	8	8	2	12
$f_i$	4	5	6	7	9	9	10	11	12	14	16

Assuming that the activities have already been sorted by finish times, the running time of the call RECURSIVE-ACTIVITY-SELECTOR.  $O(n)$

Over all recursive calls, each activity is examined exactly once in the **while** loop test of line 2.

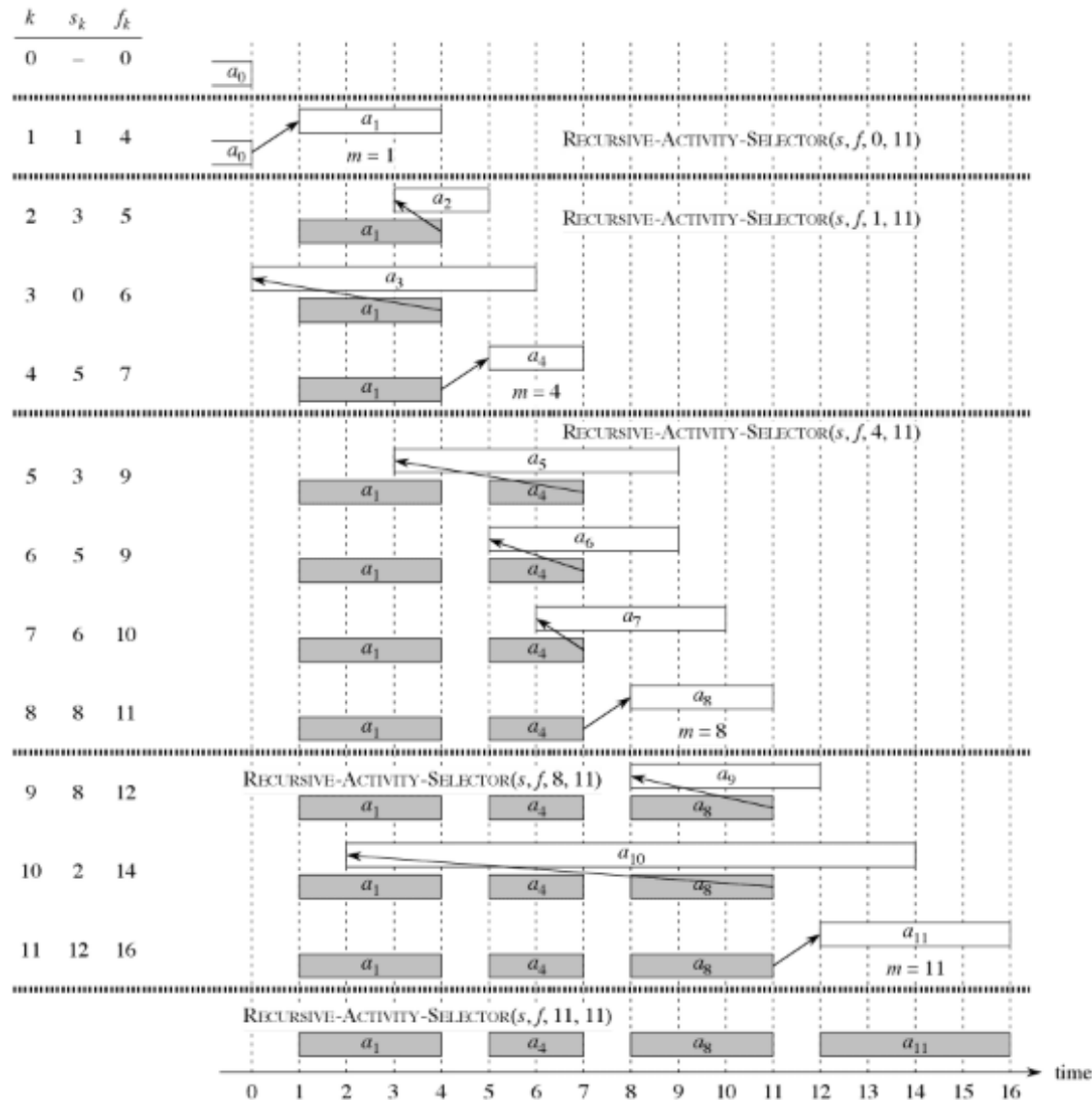
# Analysis of Running Time

- Assuming that the activities have already been sorted by finish times, the running time of the call

RECURSIVE-ACTIVITY-SELECTOR ( $s, f, 0, n$ ) is  $\Theta(n)$ ,  
which we can see as follows:

- Over all recursive calls, each activity is examined exactly once in the while loop test of line 2

# A recursive greedy algorithm



# Non recursive algorithm

- Find a non recursive algorithm

In **traditional recursion**, the typical model is that you perform your recursive calls first, and then you take the return value of the recursive call and calculate the result. In this manner, you don't get the result of your calculation until you have returned from every recursive call.

In **tail recursion**, you perform your calculations first, and then you execute the recursive call, passing the results of your current step to the next recursive step. This results in the last statement being in the form of (return (recursive-function params)). **Basically, the return value of any given recursive step is the same as the return value of the next recursive call.**



# Non recursive algorithm

GREEDY-ACTIVITY-SELECTOR( $s, f$ )

```
1   $n = s.length$ 
2   $A = \{a_1\}$ 
3   $k = 1$ 
4  for  $m = 2$  to  $n$ 
5      if  $s[m] \geq f[k]$ 
6           $A = A \cup \{a_m\}$ 
7           $k = m$ 
8  return  $A$ 
```

Like the recursive version, GREEDY-ACTIVITY-SELECTOR schedules a set of  $n$  activities in  $O(n)$  time, assuming that the activities were already sorted initially by their finish times.

# Data Compression Problem

- Given a text that uses 32 symbols (26 different letters, space, and some punctuation characters), how can we encode this text in bits?
- We need to assign a binary code to each letter.

A:00

B:01

C:10

Y:11

BABY

01000111

How many bits? Can we do better?

# Data Compression

- Given a text that uses 32 symbols (26 different letters, space, and some punctuation characters), how can we encode this text in bits?
- We need to assign a binary code to each letter.

A:0

B:01

C:10

Y:1

BABY: 010011

010011:AYAAYY

is this unique?

# Data Compression

- How to differentiate between letters?
  - One possibility is to use a separation symbol (not very efficient, you need extra bits for each letter)

**BABY: 01,0,01,1**

- Use codes in such a way that there is no ambiguity:  
by ensuring that **no code** is a **prefix** of another one.

Prefix codes are desirable because they simplify decoding. Since no codeword is a prefix of any other, the codeword that begins an encoded file is unambiguous.

# Data Compression

- A prefix code for a set  $S$  is a function  $c$  that maps each  $x \in S$  to  $1$ s and  $0$ s in such a way that for  $x, y \in S$ ,  $x \neq y$ ,  $c(x)$  is not a prefix of  $c(y)$ .

$c(A) = 11$

$c(O) = 01$

$c(E) = 001$

$c(C) = 10$

$c(D) = 000$

What is 1001000001?

There is no ambiguity!

# Data Compression

- It is desired that letters with **higher frequency** have **smaller** length.

# Data Compression

- The **average bits per letter** of a prefix code  $c$  is the sum over all symbols of its frequency times the number of bits of its encoding

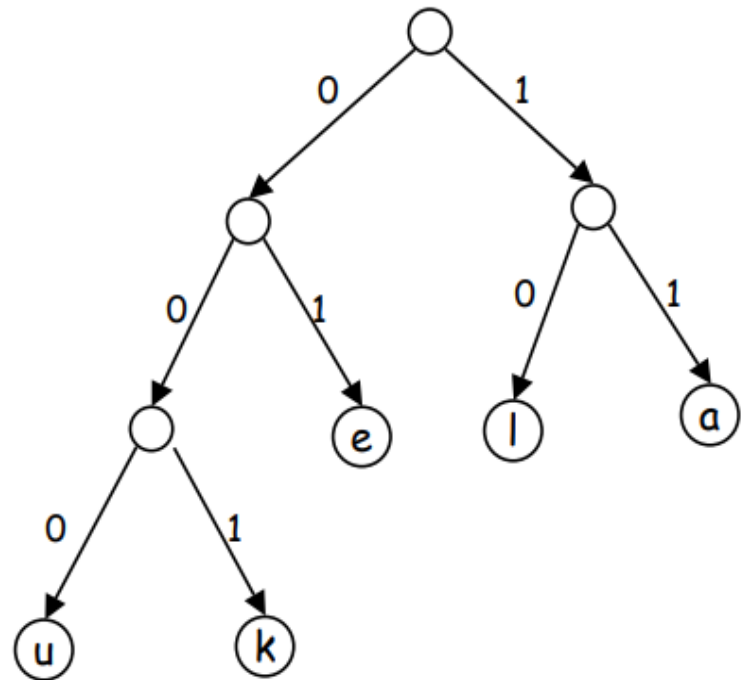
$$ABL(c) = \sum_{x \in S} f_x \cdot |c(x)|$$

- We would like to find a prefix code that has the lowest possible average bits per letter.

# Binary Tree

The decoding process needs a convenient representation for the prefix code so that we can easily pick off the initial codeword. A binary tree whose **leaves are the given characters** provides one such representation.

$c(a) = 11$   
 $c(e) = 01$   
 $c(k) = 001$   
 $c(l) = 10$   
 $c(u) = 000$



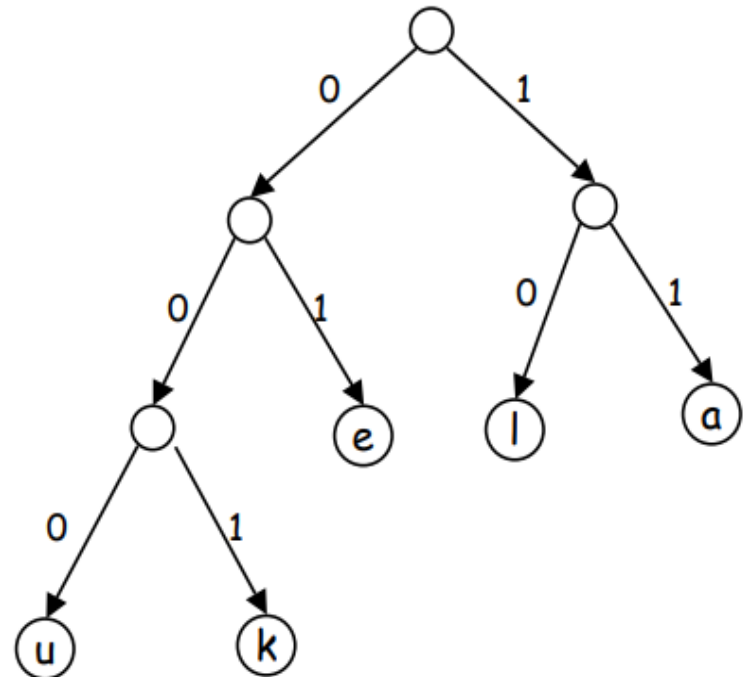


# Binary Tree

We interpret the binary codeword for a character as **the simple path from the root to that character**, where **0** means “go to the **left** child” and **1** means “go to the **right** child.”

$c(a) = 11$   
 $c(e) = 01$   
 $c(k) = 001$   
 $c(l) = 10$   
 $c(u) = 000$

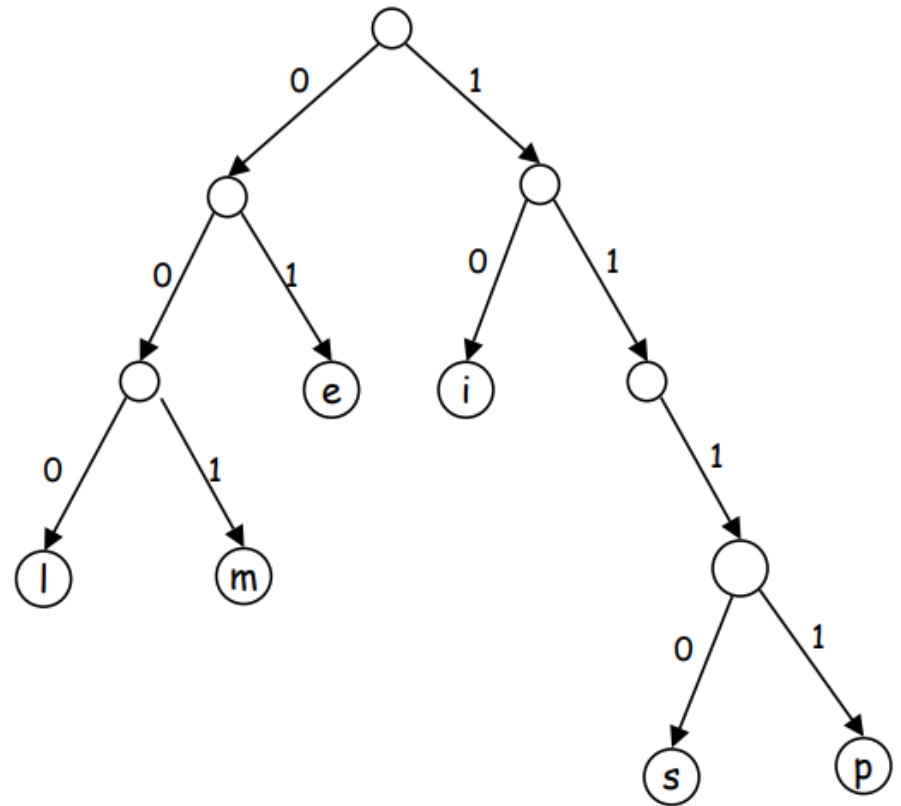
Only leaves have labels



What is 11101000111100001 ?

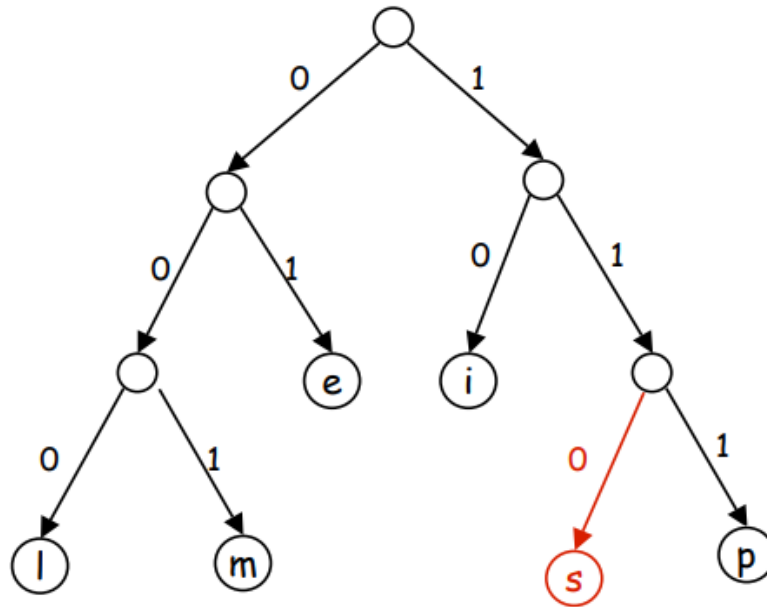
simple

How can this prefix code  
be made more efficient?



simple

An optimal code for a file is always represented by a **full binary tree**, in which every non-leaf node has two children



This tree is full: Each node that is not a leaf has two children

# Binary tree

- The binary tree corresponding to the optimal prefix code is full. Otherwise we are wasting bits
- Where in the tree of an optimal prefix code should letters be placed with a high frequency?
  - High frequency letters should be placed at leaves whose the depth is the lowest.

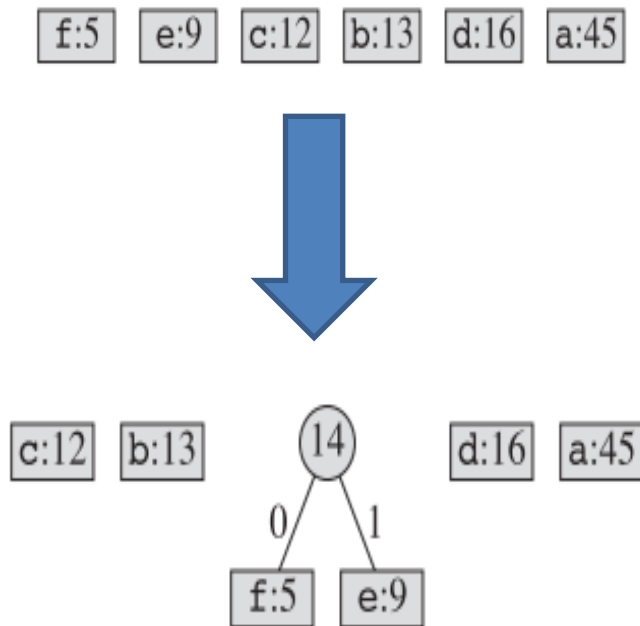
# Huffman Coding

- How to make an efficient full tree for encoding the letters?

f:5	e:9	c:12	b:13	d:16	a:45
-----	-----	------	------	------	------

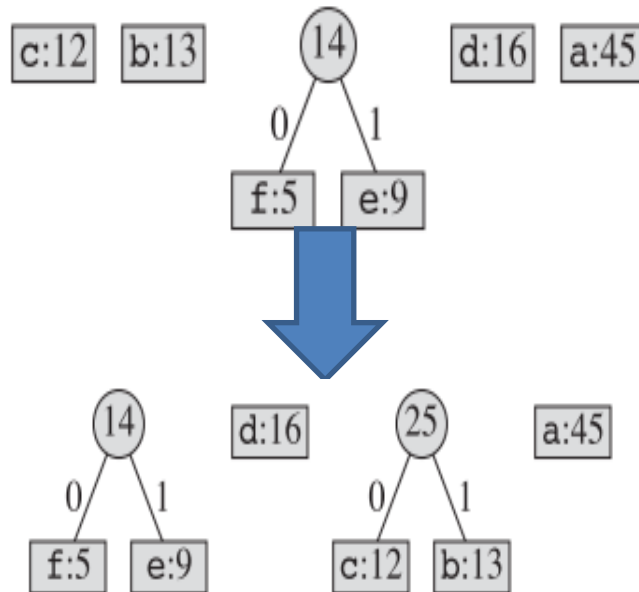
# Huffman Coding

- Recursively combine two elements with lowest frequency



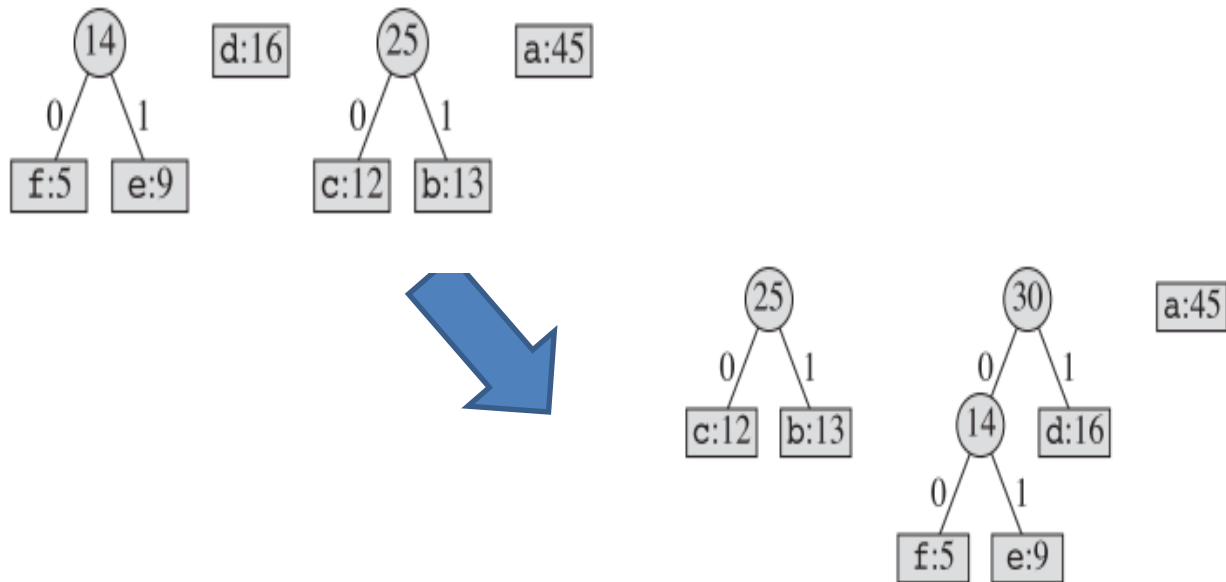
# Huffman Coding

- Recursively combine two elements with lowest frequency



# Huffman Coding

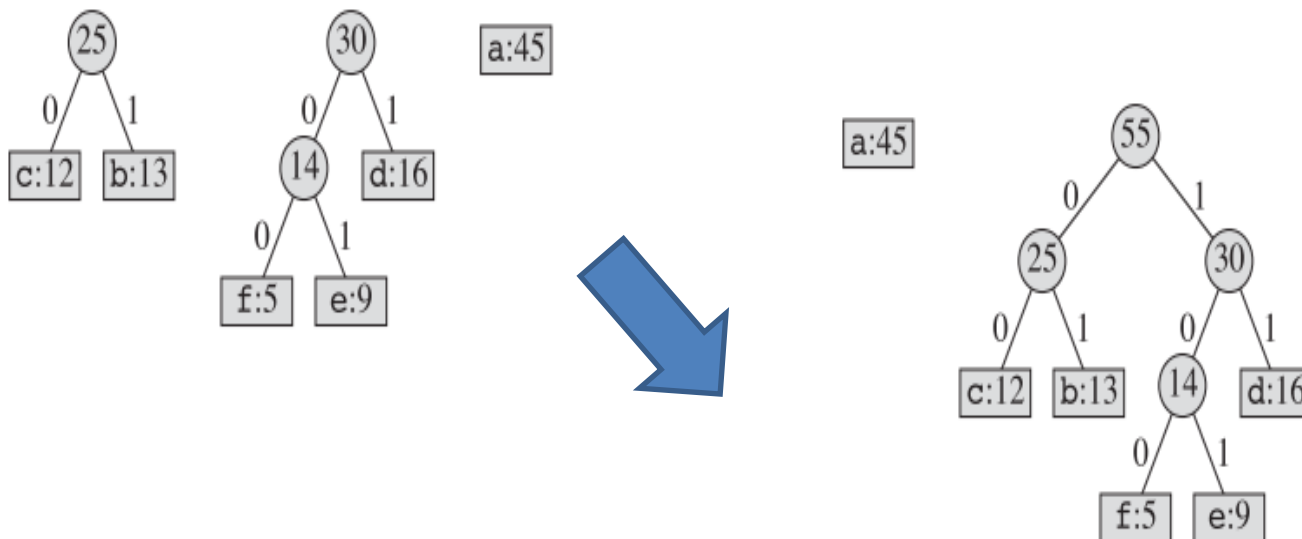
- Recursively combine two elements with lowest frequency





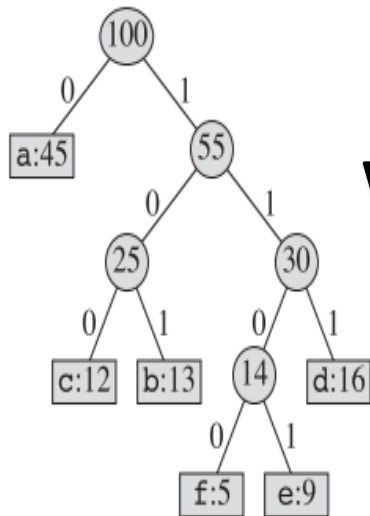
# Huffman Coding

- Recursively combine two elements with lowest frequency



# Huffman Coding

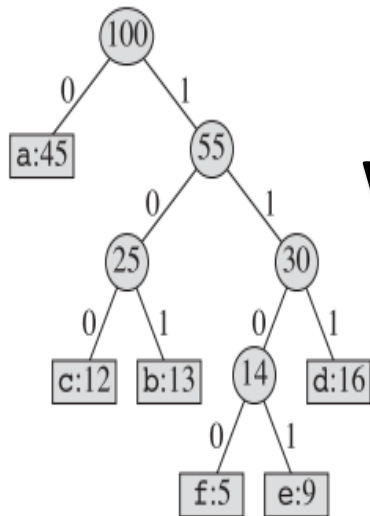
- Recursively combine two elements with lowest frequency



What is 0111100?

# Huffman Coding

- Recursively combine two elements with lowest frequency



What is 0111100?  
adc

# Huffman Coding - Algorithm

we assume that  $Q$  is implemented as a binary min-heap

For a set  $C$  of  $n$  characters, we can initialize  $Q$  in line 2 in  $O(n)$  time using the BUILD-MIN-HEAP procedure.

```
HUFFMAN( $C$ )
1   $n = |C|$ 
2   $Q = C$ 
3  for  $i = 1$  to  $n - 1$ 
4      allocate a new node  $z$ 
5       $z.left = x = \text{EXTRACT-MIN}(Q)$ 
6       $z.right = y = \text{EXTRACT-MIN}(Q)$ 
7       $z.freq = x.freq + y.freq$ 
8       $\text{INSERT}(Q, z)$ 
9  return  $\text{EXTRACT-MIN}(Q)$     // return the root of the tree
```

$O(n \log n)$

$O(\log n)$

The **for** loop in lines 3–8 exactly  $n - 1$  times, and each heap operation requires time  $O(\lg n)$ , thus the loop contributes  $O(n \lg n)$ .

# Exercise

Frequency	Value
5	a
7	b
10	c
13	d
20	e
45	f

How many bits are saved compared to fixed-length coding?