



# Greedy Algorithms



# Overview

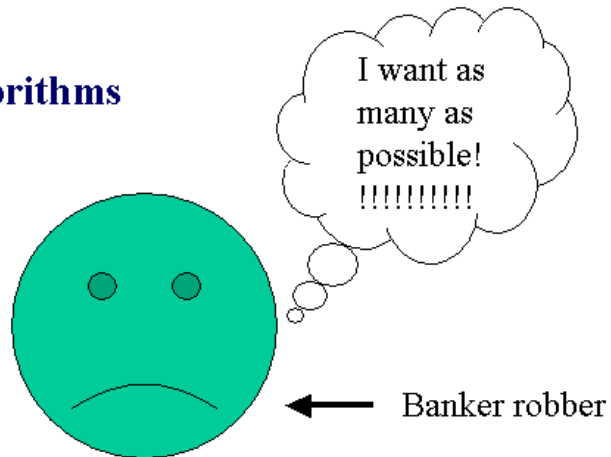
- Like dynamic programming, used to solve optimization problems.
- Dynamic programming can be overkill; greedy algorithms tend to be easier to code
- Problems exhibit optimal substructure (like DP).
- Problems also exhibit the **greedy-choice** property.
  - When we have a choice to make, make the one that looks best *right now*.
  - Make a **locally optimal choice** in hope of getting a **globally optimal solution**.



## Greedy Strategy

- The choice that seems best at the moment is the one we go with.
  - Prove that when there is a choice to make, one of the optimal choices is the greedy choice. Therefore, it's always safe to make the greedy choice.
  - Show that all but one of the subproblems resulting from the greedy choice are empty.

## Greedy algorithms

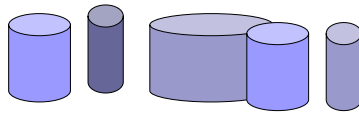


Makes a locally optimal choice

Does not always yield optimal solutions, but for many problems they do

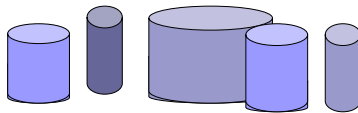
## The 0 - 1 knapsack problem

- A thief has a knapsack that holds at most  $W$  pounds.
- Item  $i$  :  $(v_i, w_i)$  ( $v$  = value,  $w$  = weight )
- Thief must choose items to maximize the value stolen and still fit into the knapsack.
- Each item must be taken or left ( 0 - 1 ).



# Fractional knapsack problem

The setup is same as (0-1) Knapsack, but the thief can take fractions of items, rather than having to make a binary choice(0-1) for each item.



## Contd...

- Both the 0 - 1 and fractional problems have the optimal substructure property
- Fractional:  $v_i / w_i$  is the value per pound.
- Clearly you take as much of the item with the greatest value per pound
- This continues until you fill the knapsack.  
Optimal (Greedy) algorithm takes  $O(n \log n)$  time, as we must sort on  $v_i / w_i = d_i$ .

## Example

- $W = 50$  lbs. (maximum knapsack capacity)

$$w_1 = 10$$

$$v_1 = 60$$

$$d_1 = 6$$

$$w_2 = 20$$

$$v_2 = 100$$

$$d_2 = 5$$

$$w_3 = 30$$

$$v_3 = 120$$

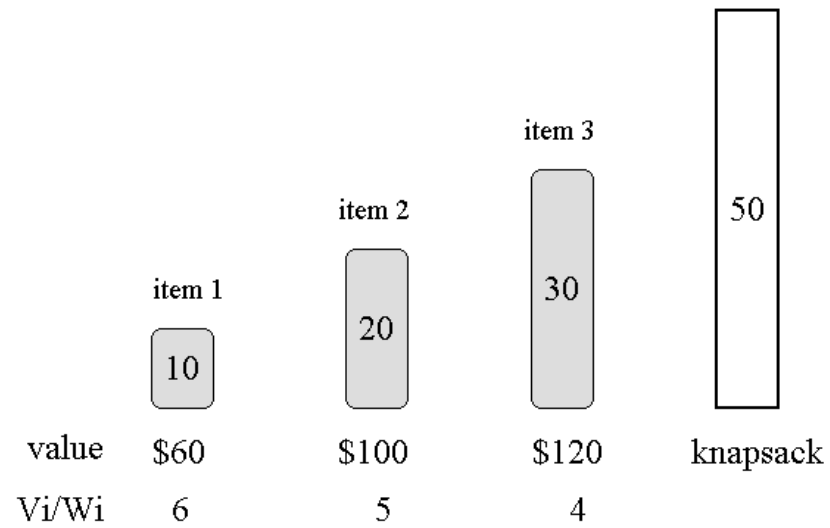
$$d_3 = 4$$

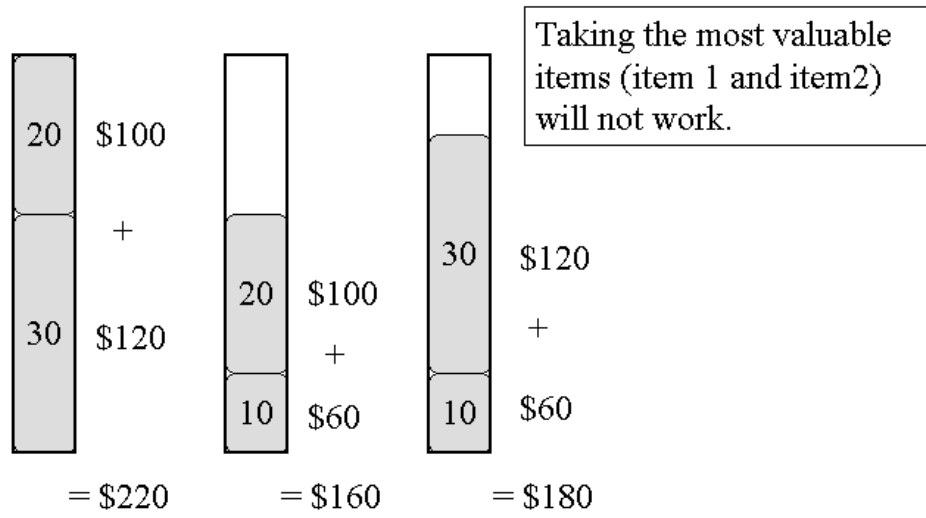
- where  $d$  is the value density



- **Greedy approach:** Take all of 1, and all of 2:  
 $v_1 + v_2 = 160$
- Optimal solution is to take all of 2 and 3:  $v_2 + v_3 = 220$ , other solution is to take all of 1 and 3  $v_1 + v_3 = 180$ . All below 50 lbs.
- When solving the 0 - 1 knapsack problem, empty space lowers the effective  $d$  of the load. Thus each time an item is chosen for inclusion we must consider both  $i$  included and excluded
- These are clearly overlapping sub-problems for different  $i$ 's and so best solved by DP!

**Greedy strategy doesn't work for the 0-1 knapsack problem.**



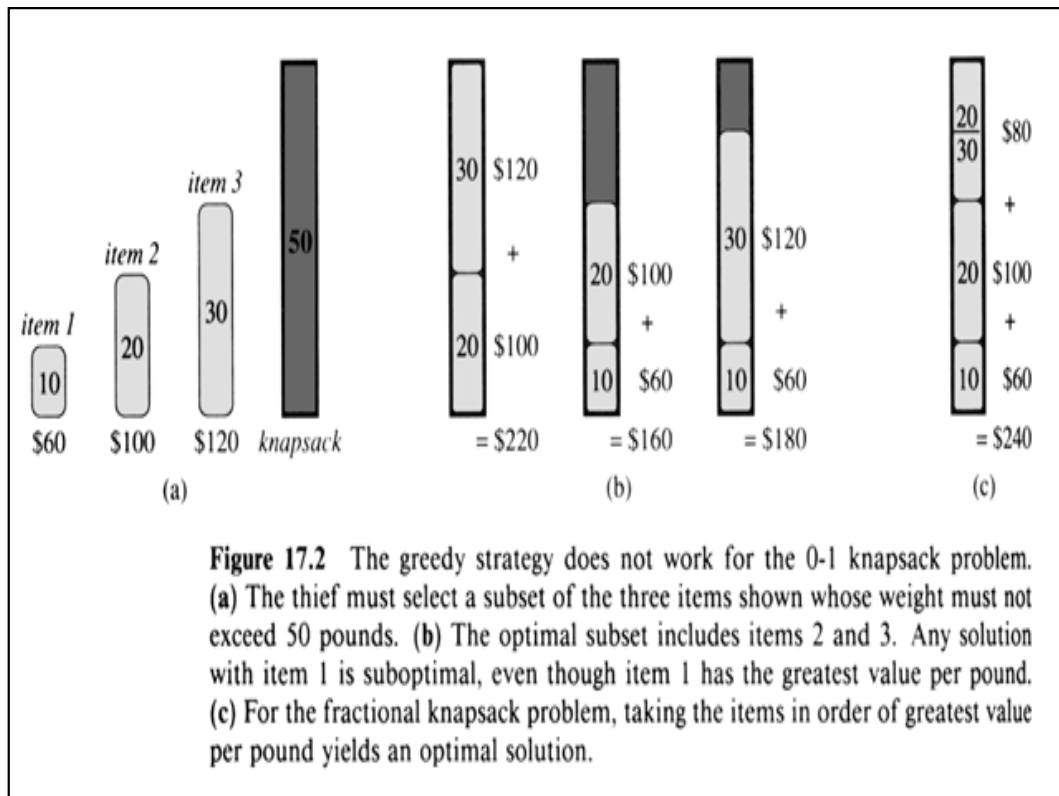


0-1 knapsack

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

Solvable by greedy algorithms

Fractional knapsack





## An activity selection problem

- **Problem:**

- ☐ Optimal scheduling of a resource among several competing activities (scheduling rehearsal times in a music studio)
- ☐ Want to select as many mutually compatible activities as possible.

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**For a set of activities to be scheduled**

1. Sort them by finish time  $S\{1,2,\dots,n\}$
2. Put 1 (the one with the earliest finish time) in the first place
3. Screen from 2, find the earliest one  $k$  compatible with 1, put  $k$  in the 2nd place
4. Screen from  $k+1$ , find the earliest one compatible with  $k$ , put in the 3rd place. So on.....

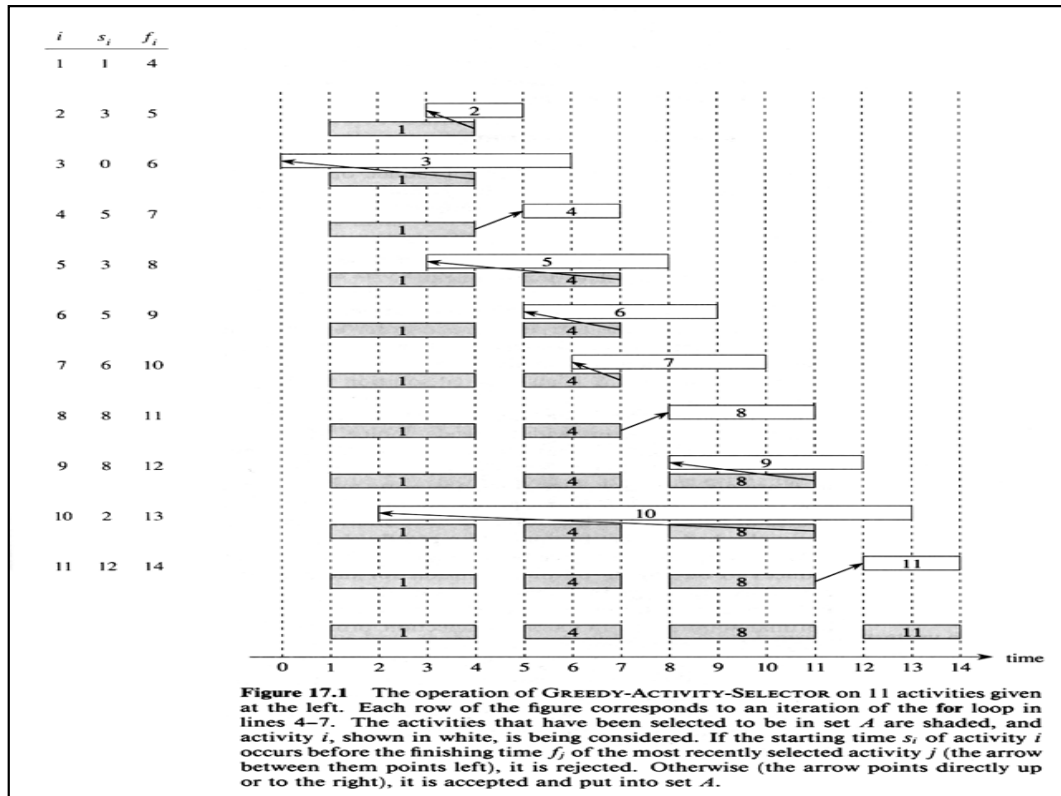
## Problem setup

- $S = \{1, 2, \dots, n\}$  a set of  $n$  proposed activities.
- Each activity  $i$  has  $s_i$  a start time, and  $f_i$  a finish time  $s_i \leq f_i$ .
- If activity  $i$  is selected, the resource is occupied in the interval  $[s_i, f_i)$ . We say  $i$  and  $j$  are compatible activities if  $[s_i, f_i) \cap [s_j, f_j) = \emptyset$



## Greedy-Activity-Selector ( $s, f$ )

- Assume that  $f_1 \leq f_2 \leq \dots \leq f_n$
- **Greedy-Activity-Selector (  $s, f$  )**  
     $n \leftarrow \text{length}[s]$   
     $A \leftarrow \{ 1 \}$   
     $j \leftarrow 1$   
    for  $i \leftarrow 2$  to  $n$   
        do if  $s_i \geq f_j$   
            then  $A \leftarrow A \cup \{ i \}$   
             $j \leftarrow i$   
    return  $A$



## Example (Contd...)

- The activity picked is always the first that is compatible. Greedy algorithms do not always produce optimal solutions.
- Running time for sorting  $n$  activities by  $f_j$   $O ( n \log n )$  and for Greedy-Activity-Selector is  $O ( n )$



## Theorem

Algorithm Greedy-Activity-Selector produces solutions of maximal size for the activities-selection problem.



## Elements of the Greedy Strategy

- In general there is no way to tell if a greedy algorithm will solve a particular optimization problem or not.
- But there are two ingredients that are exhibited by most problems that lend themselves to a greedy strategy.
  - **Greedy-Choice Property**
  - **Optimal Substructure**



## **Greedy Choice Property**

- A globally optimal solution can be arrived at by making a locally optimal (greedy) choice
- This property is where Greedy algorithms differ from dynamic programming.



## Greedy Vs Dynamic

- **Greedy Algorithm:**

- Make whatever choice seems best at the moment. The choice depends on so far, not depend on any future choice.

- **Dynamic Programming**

- The choice at each step depends on the solution to sub problems.

# Optimal Substructure

- A problem exhibits optimal substructure, if an optimal solution to the problem contains within it, optimal solution to sub problems.
- $A' = A - \{1\}$  (greedy choice)  $A'$  can be solved again with the greedy algorithm.
- This property is exploited by both greedy algorithm and dynamic programming.



## Optimal Sub-structure of ASP

- Once the greedy choice of activity 1 is made, the problem reduces to finding an optimal solution for the ASP over those activities in  $S$ , that are compatible with activity 1.
- If  $A$  is an optimal solution of the original problem, then  $A' = A - \{1\}$  is an optimal solution to the ASP  $S' = \{i \in S : s_i \geq f_1\}$



## Huffman Codes

- Effective technique for data compression
- Savings of 20-90% are typical
- Uses a table of frequencies of occurrences of characters to build up an optimal way of representing each character as a binary string

# Examples of Different Binary Encodings

- Fixed length code

- Each character in file represented by a different fixed length code
- Length of encoded file depends only on the number of characters in the file
- Example
  - 6 character alphabet (3 bit code), 25,000 character file takes 75,000 bits

## Binary encodings continued

- If shorter binary strings are used for more frequent characters, a shorter encoding could be used

	A	B	C	D	E	F
Frequency (in thousands)	5	2	3	4	10	1
Fixed-length codeword	000	001	010	011	100	101
Variable-length codeword	111	1001	101	110	0	1000

- Variable length encoding uses 58,000 bits



# Encoding and Decoding

- Encoding

- substitute code for the character

- Decoding

- Fixed length: take x number of characters at a time and look up character corresponding to code
  - Variable length: must be able to determine when one code ends and another begins

# Encoding

- Given a code (corresponding to some alphabet A') and a message it is easy to *encode* the message. Just replace the characters by the codewords.

Example:  $\Gamma = \{a, b, c, d\}$

If the code is

$$C_1\{a = 00, b = 01, c = 10, d = 11\}.$$

then *bad* is encoded into *010011*

If the code is

$$C_2 = \{a = 0, b = 110, c = 10, d = 111\}$$

then *bad* is encoded into *1100111*

## Decoding

$$C_1 = \{a = 00, b = 01, c = 10, d = 11\}.$$

$$C_2 = \{a = 0, b = 110, c = 10, d = 111\}.$$

$$C_3 = \{a = 1, b = 110, c = 10, d = 111\}$$

Given an encoded message, *decoding* is the process of turning it back into the original message. A message is *uniquely decodable* if it can only be decoded in one way.

For example relative to  $C_1$ , 010011 is uniquely decodable to bad.

Relative to  $C_2$  1100111 is uniquely decodable to bad.

But, relative to  $C_3$ , 1101111 is **not** uniquely decipherable since it could have encoded either bad or acad.

## Prefix Codes

- Each code has a unique prefix.

0   101   100

- Prefix constraint

- ☐ The prefixes of an encoding of one character cannot be equal to a complete encoding of another character

- Decoding is never ambiguous

- ☐ identify the first character
- ☐ remove it from the file and repeat
- ☐ Use binary tree to represent prefix codes for easy decoding



## Important Fact:

- Every message encoded by a prefix tree code is uniquely decipherable. Since no codeword is a prefix of any other we can always find the first codeword in a message, peel it off and continue decoding.

01101100 = 01101100 = *abba*

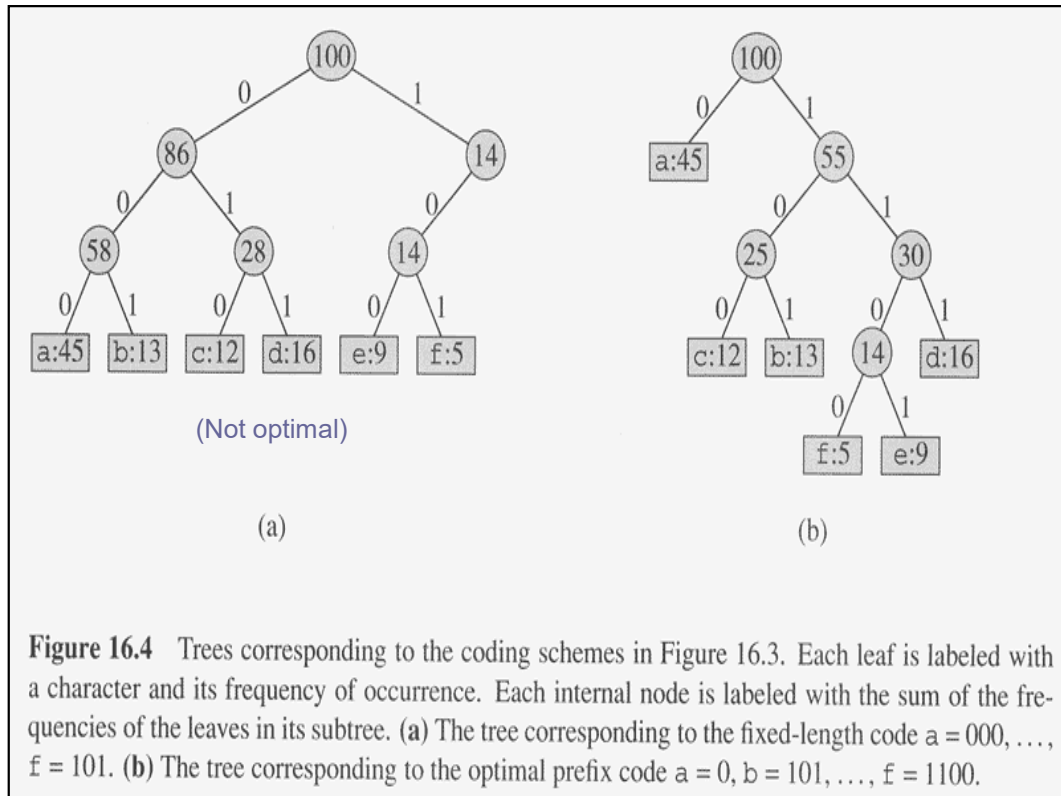


## Problem

- Given a text (a sequence of characters) find an encoding for the characters that satisfies the prefix constraint and that minimizes the number of bits need to encode the text.

## Binary Tree Representation of Prefix Code

- An optimal code is always represented by a **full binary tree**, in which every non-leaf node has two children
  - $|C|$  leaves and  $|C|-1$  internal nodes
- Each leaf represents a character
- A left child represents the character 0 and a right child represents the character 1.
- The path from the root to the leaf represents the encoding for the leaf





## Characteristics of Binary Tree

- Not a binary search tree
- The optimal code for a file is always represented by a full binary tree in which every non-leaf node has two children.
- If  $C$  is the alphabet, then a tree for the optimal prefix code has
  - $|C|$  leaves
  - $|C|-1$  internal nodes

## Cost of a Tree T

- For each character  $c$  in the alphabet  $C$ 
  - let  $f(c)$  be the frequency of  $c$  in the file
  - let  $d_T(c)$  be the depth of  $c$  in the tree
    - It is also the length of the codeword. Why?
- Let  $B(T)$  be the number of bits required to encode the file (called the cost of T)

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



## Constructing a Huffman Code

- Greedy algorithm for constructing an optimal prefix code was invented by Huffman
- Codes constructed using the algorithm are called Huffman codes
- Bottom up algorithms
  - Start with a set of  $|C|$  leaves
  - perform a sequence of  $|C|-1$  merging operations





# Huffman Codes

- A widely used compression algorithm
- Savings of 20% - 90%
- Uses the frequency of the characters
- Fixed codes versus variable-length codes:

Letter	freq	fixed code	variable
a	45	000	0
b	13	001	101
c	12	010	100
d	16	011	111
e	9	100	1101
f	5	101	1101





# Constructing a Huffman Tree

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

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# Constructing a Huffman Tree

c:12

b:13

0

f:5

14

e:9

1

d:16

a:45

42

# Constructing a Huffman Tree

0

14

1

f:5

e:9

d:16

0

25

1

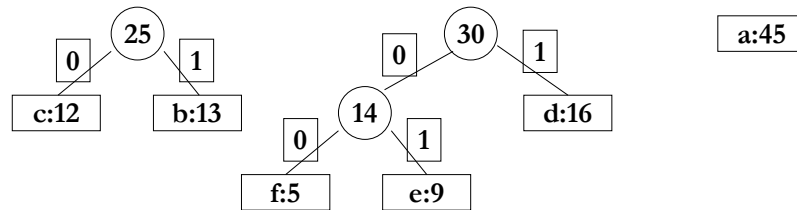
c:12

b:13

a:45

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# Constructing a Huffman Tree



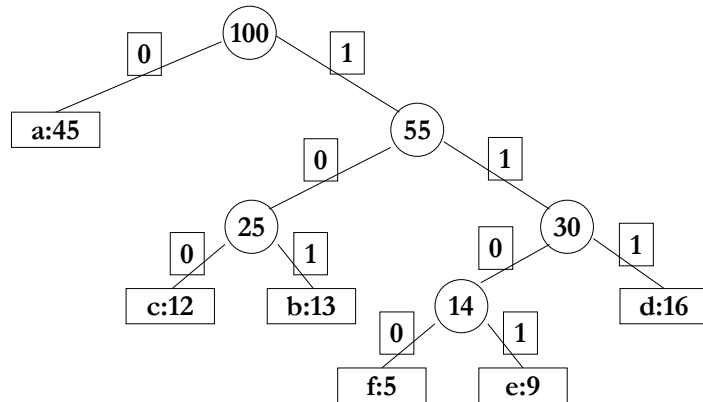
# Constructing a Huffman Tree

a:45

```
graph TD; 55((55)) -- 0 --> 25((25)); 55 -- 1 --> 30((30)); 25 -- 0 --> c["c:12"]; 25 -- 1 --> b["b:13"]; 30 -- 0 --> 14((14)); 30 -- 1 --> d["d:16"]; 14 -- 0 --> f["f:5"]; 14 -- 1 --> e["e:9"];
```

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# Constructing a Huffman Tree





HUFFMAN(C)

1  $n \leftarrow |C|$

2  $Q \leftarrow C$  ; Characters are in a priority queue

3 for  $i \leftarrow 1$  to  $n-1$

4     do  $z \leftarrow \text{ALLOCATE-NODE}()$


5          $x \leftarrow \text{left}[z] \leftarrow \text{EXTRACT-MIN}(Q)$

6          $y \leftarrow \text{right}[z] \leftarrow \text{EXTRACT-MIN}(Q)$

7          $f[z] \leftarrow f[x] + f[y]$

8          $\text{INSERT}(Q, z)$

9 return  $\text{EXTRACT-MIN}(Q)$



## Running Time of Huffman's Algorithm

- Assume Q implemented as a binary heap
- Assume n characters in alphabet