

Analysis and Synthesis of Algorithms

Design of Algorithms

Greedy Algorithms

Basic Features and Examples

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Outline

- Greedy Algorithms:
 - First Example: Selection of Activities
- Features of Greedy Algorithms
- Examples:
 - Knapsack Problem
 - Minimization of System Tasks
 - Huffman Codes
- Other Examples:
 - Minimum-Cost Spanning Trees: Kruskal, Prim,
 - Single-Source Shortest Paths: Dijkstra.

Algorithm Synthesis Techniques

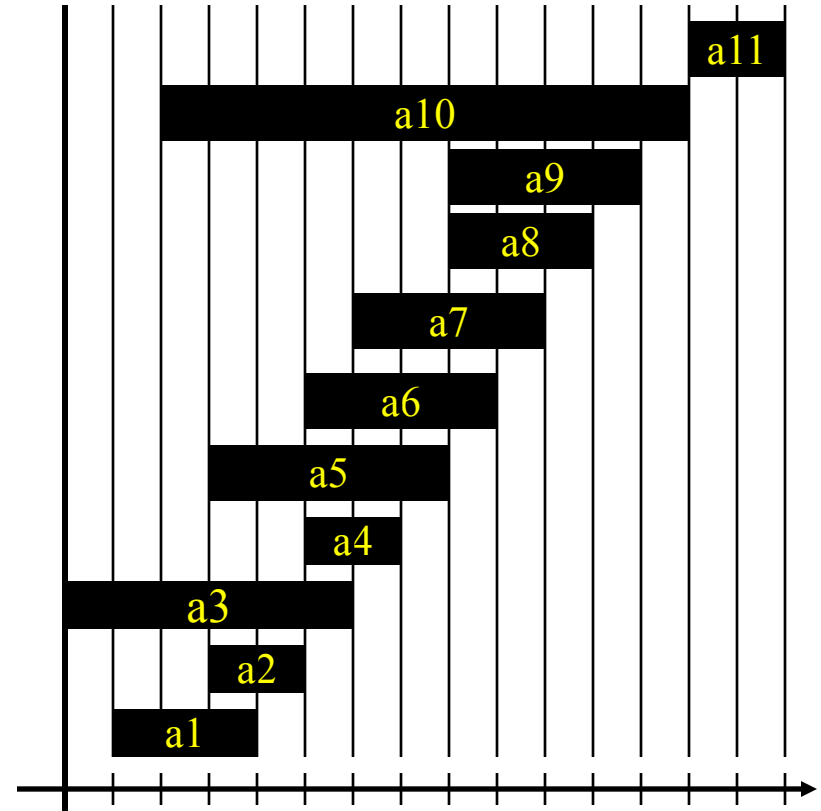
- Divide-and-Conquer
 - Split into independent sub-problems
- Dynamic Programming
 - Combination of dependent sub-problems
 - Use of table to avoid recomputation of sub-problems' solutions
- Greedy Algorithms
 - **Strategy:** At each Step of the Algorithm, Select the option that is locally the best to find the overall Optimal Solution
 - In many cases this strategy works
 - Examples:
 - Minimum-Cost Spanning Trees: Kruskal, Prim,
 - Single-Source Shortest Path: Dijkstra.

Example: Selection of Activities

- Let $S = \{1, 2, \dots, n\}$ be a set of activities that share a common resource
 - Resource can only be used by one activity at a time
 - Activity i is characterized by:
 - start time: s_i
 - finish time: f_i
 - activity execution interval: $[s_i, f_i[$
 - Activities i and j are **compatible** if $[s_i, f_i[$ and $[s_j, f_j[$ are disjoint
- **Objective:** Find a/the Maximal set of Activities that are Mutually Compatible

Example: Activity Selection

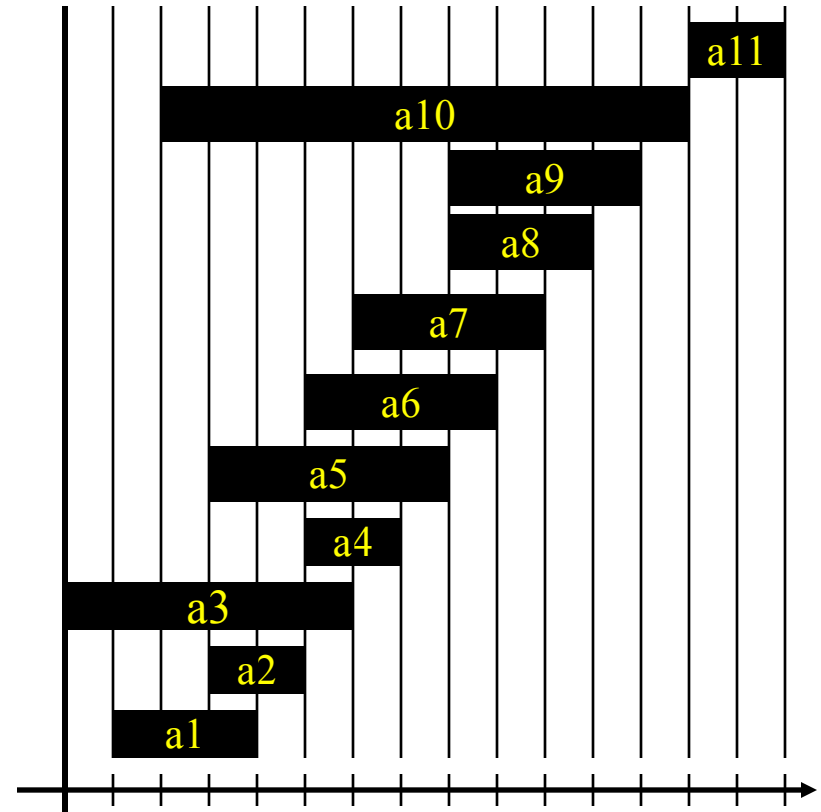
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s_i	1	3	0	5	3	5	6	8	8	2	12
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Example: Activity Selection

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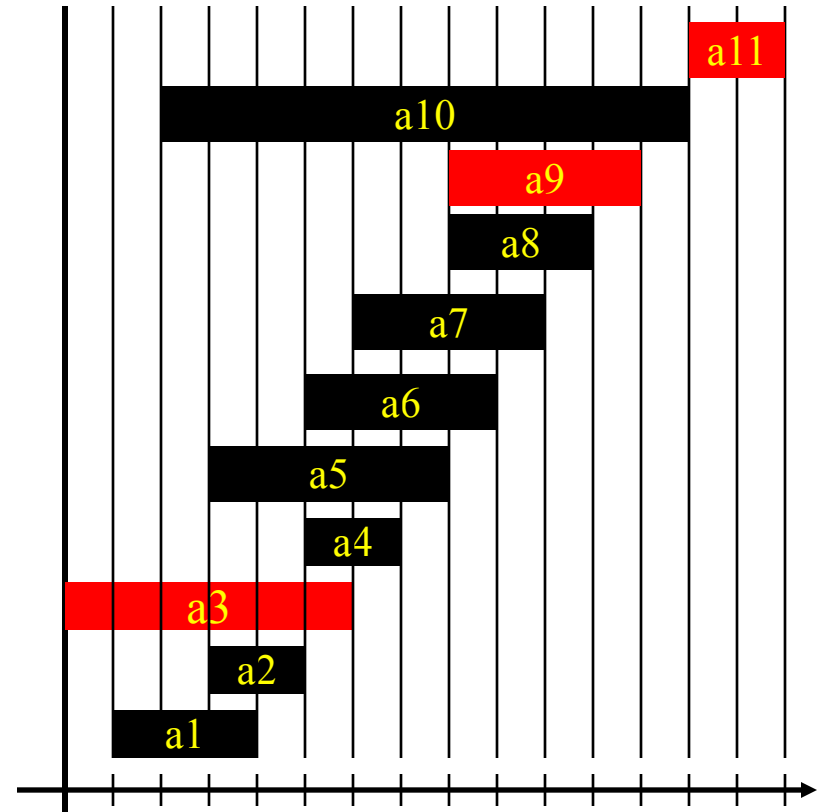
- It is possible to choose many mutually exclusive sets of tasks:



Example: Activity Selection

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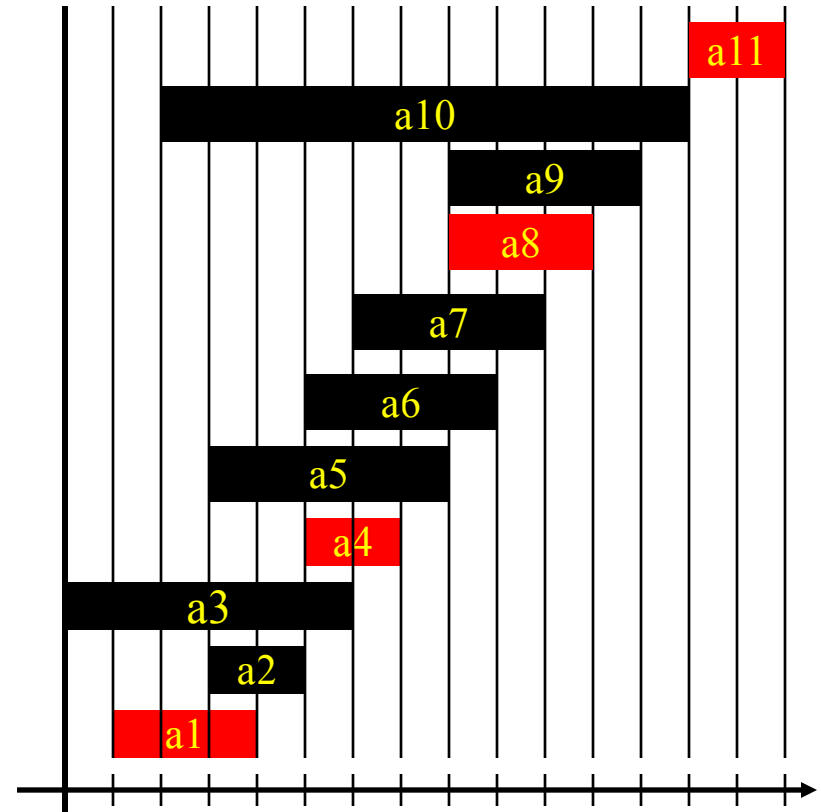
- It is possible to choose many mutually exclusive sets of tasks:
 - $\{a_3, a_9, a_{11}\}$



Example: Activity Selection

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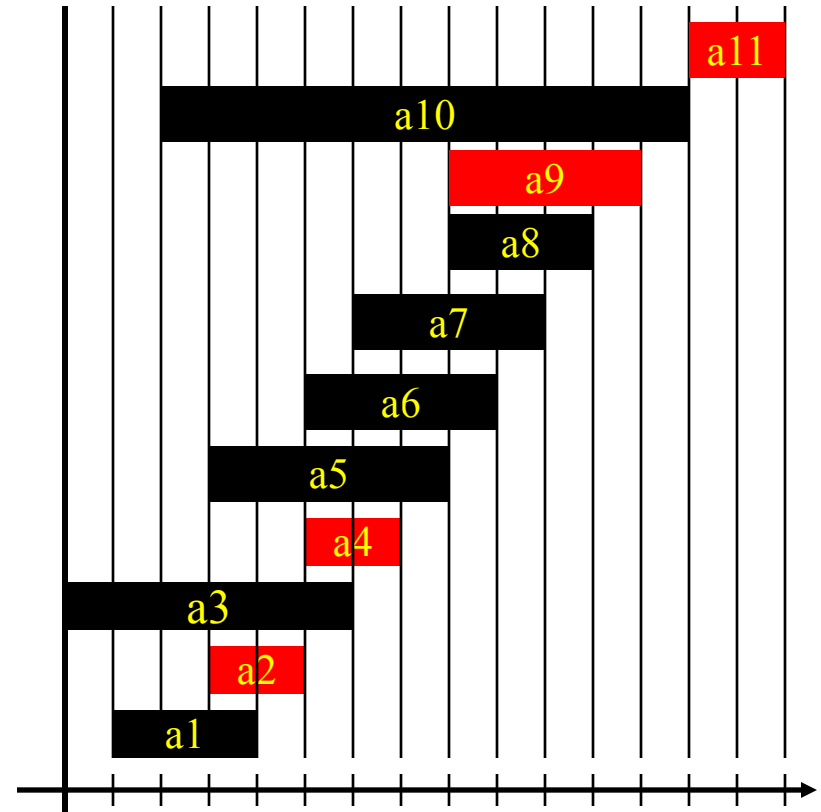
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- It is possible to choose many mutually exclusive sets of tasks:
 - $\{a_3, a_9, a_{11}\}$
 - $\{a_1, a_4, a_8, a_{11}\}$
 - $\{a_2, a_4, a_9, a_{11}\}$



Example: Activity Selection

- Assume Activities are sorted s.t. $f_1 \leq f_2 \leq \dots \leq f_n$
- Greedy Choice:
 - **Select Activity with lowest finish time f_k**
 - Rationale? Maximize time for remaining activities

function selectActivitiesGreedy(set S, set F)

$n = \text{size}[S];$

$A = \{ 1 \};$

$j = 1;$

for $i = 2$ **to** n **do**

if $(s_i \geq f_j)$ **then**

$A = A \cup \{ i \};$

$j = i;$

return A

Example: Activity Selection

- Assume Activities are sorted s.t. $f_1 \leq f_2 \leq \dots \leq f_n$
- Greedy Choice:
 - **Select Activity with lowest finish time f_k**
 - Rationale? Maximize time for remaining activities

```

function selectActivitiesGreedy(set S, set F)
    n = size[s];    // number of activities
    A = { 1 };      // first choice – the one that ends first
    j = 1;
    for i = 2 to n do
        if ( $s_i \geq f_j$ ) then // pick the first that begins right after
            A = A  $\cup$  { i }; // the last one ends, and add it to sol.
            j = i;           // “advance” time to end of j
    return A
    
```

Correctness of Greedy Algorithm

- Greedy Approach has the following Properties:
 - **Property 1.** There exists an optimal solution A starting with the greedy choice with activity 1.
 - Assume A is optimal solution starting with activity numbered k
 - Then we can define $B = A - \{k\} \cup \{1\}$
 - Since $f_1 \leq f_k$ and $f_1 \leq s_j$ for $j \neq k$
 - Activities are ordered ; Activity 1 is compatible with activities other than k
 - Activities in A and B are mutually disjoint and $|A| = |B|$ (we can trade k with 1)
 - Then B is also an optimal solution (**same number of tasks**)!
 - **Conclusion:** an optimal solution exists that begins with activity 1.
 - **Property 2.** After the first choice the problem resumes to finding a solution of activities compatible with activity 1.
 - Let A be an optimal solution starting with activity 1
 - Then $A' = A - \{1\}$ must be an optimal solution to $S' = \{i \in S : s_i \geq f_1\}$
 - Otherwise there would be a solution $|B'| > |A'|$ for S' that would allow is to obtain solution B for S with more activities than A; a contradiction !
 - **Apply Induction to the Number of Greedy Choices**
- **Conclusion:** Greedy Algorithm computes optimal solution !

Correctness of Greedy Algorithm

- Property 1 - The Greedy-Choice Property
 - A globally optimal solution that can be arrived at by making a locally optimal (greedy) choice.
- Property 2 – The Optimal substructure Property
 - An optimal solution to the problem contains within it optimal solutions to subproblems.

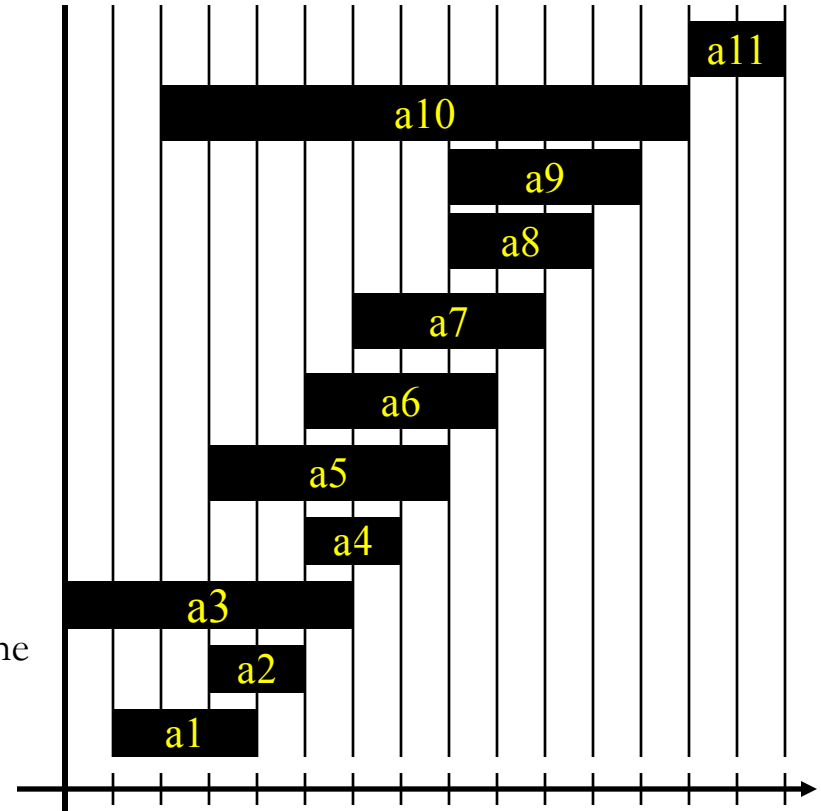
Features of Greedy Approaches

- Properties of Greedy Choices
 - Global Optimal choice can be made by making optimal local choices.
- Optimal Sub-structure
 - Optimal solution to problem includes optimal solutions to sub-problems
 - Matroid Structure...
- Similar to Dynamic Programming
 - Choices can be made entirely based on local criteria and without exploring multiple local solutions.

Example: Activity Selection

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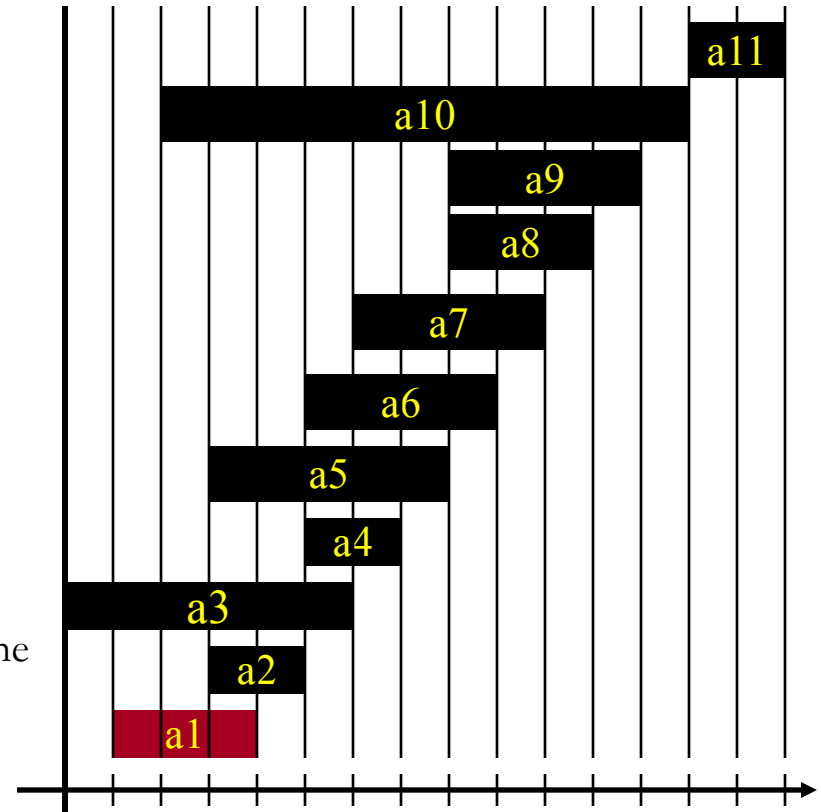
- Algorithm:
 - Select activity with lowest finishing time;
 - Check which other activities are compatible
 - Initialize activities by increasing finishing time



Example: Activity Selection

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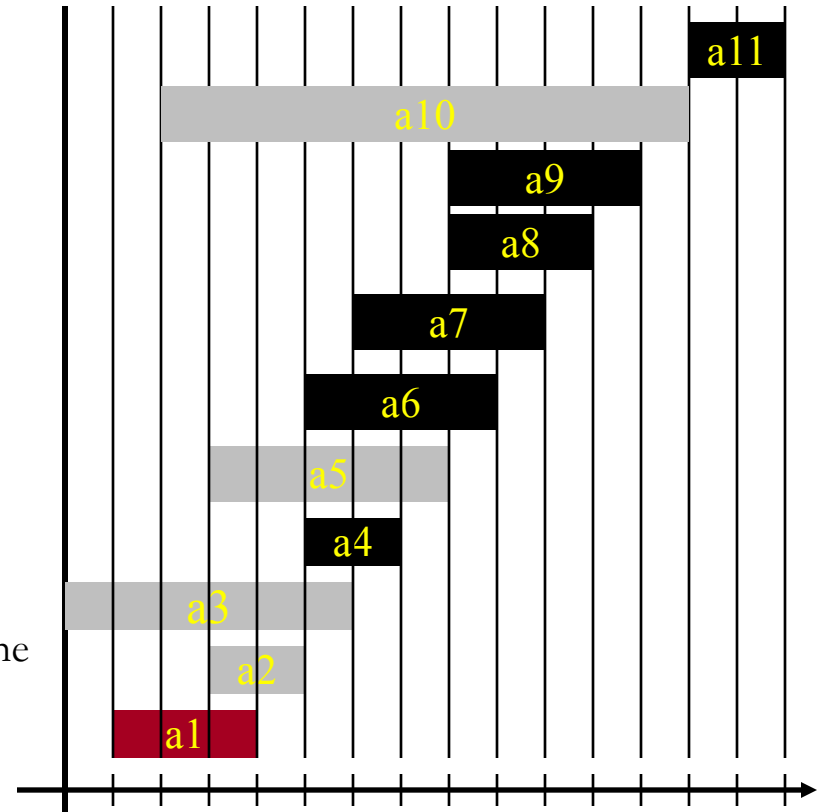
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- $\{ a_1 \}$



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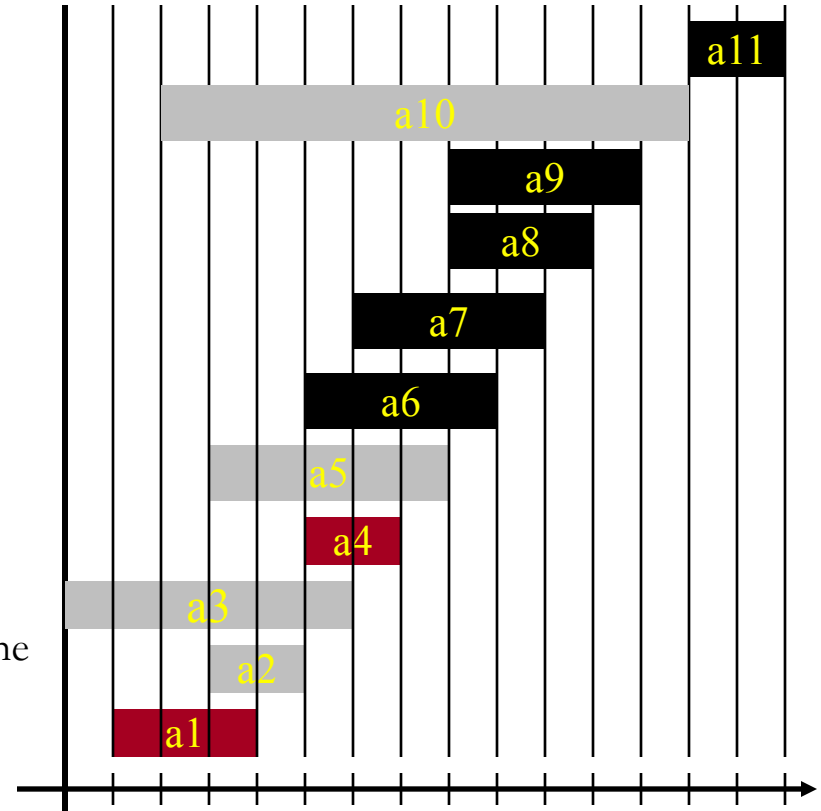
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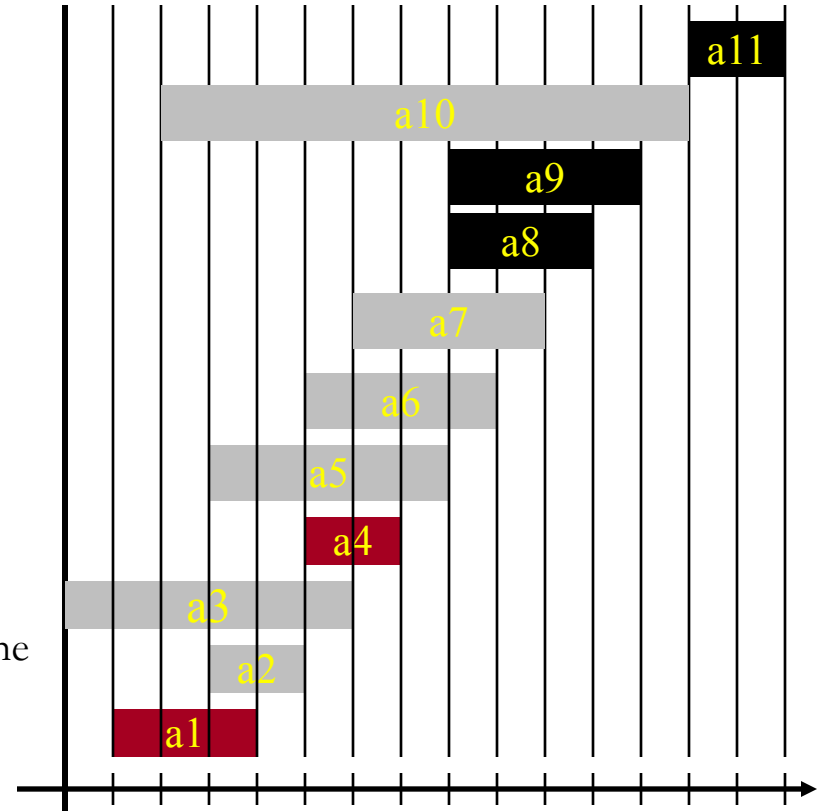
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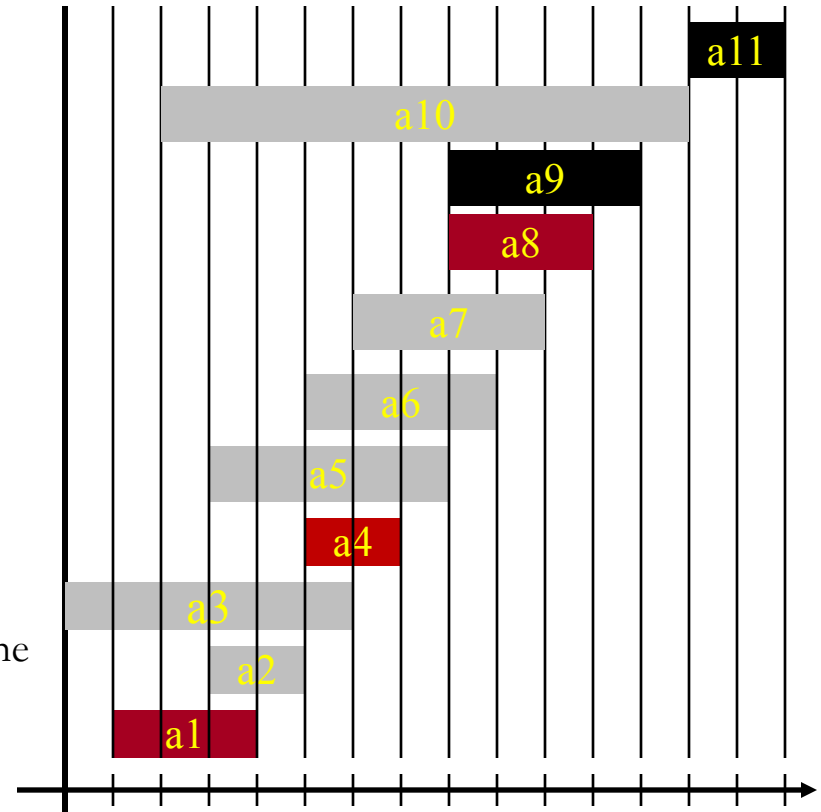
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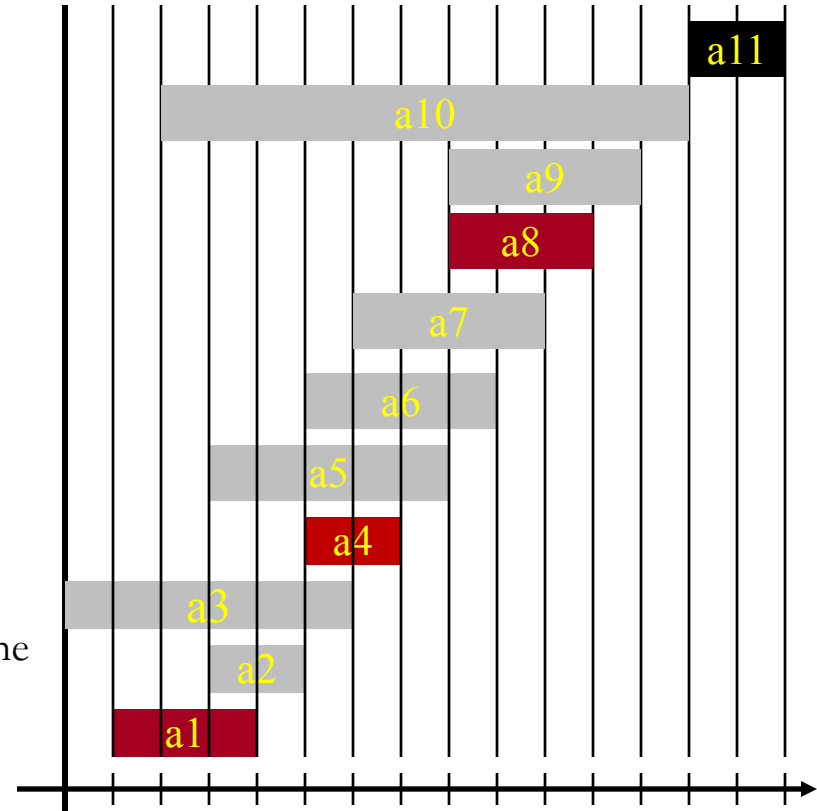
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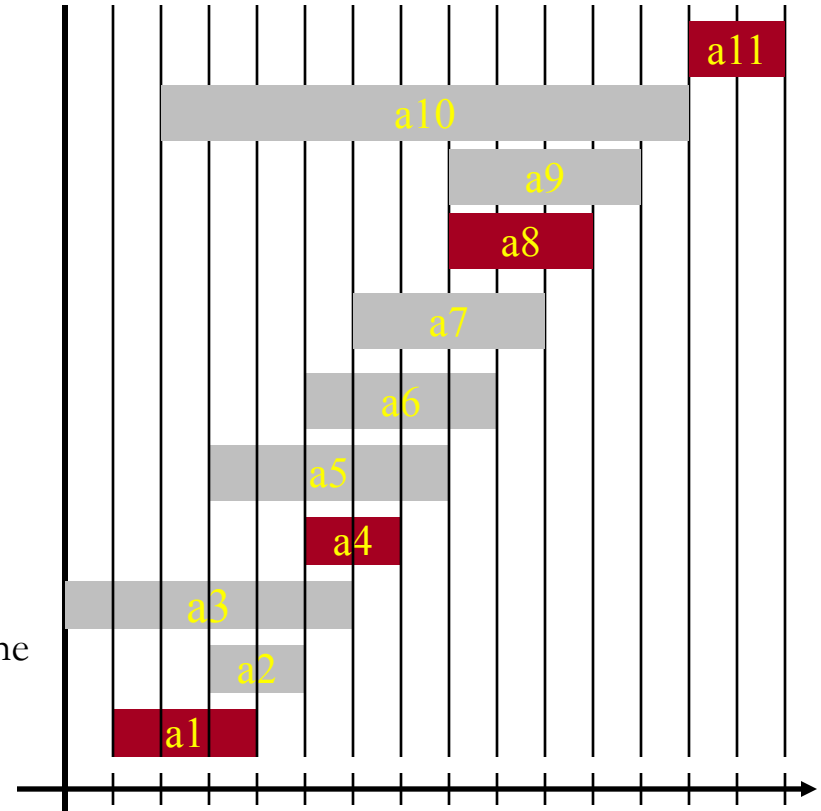
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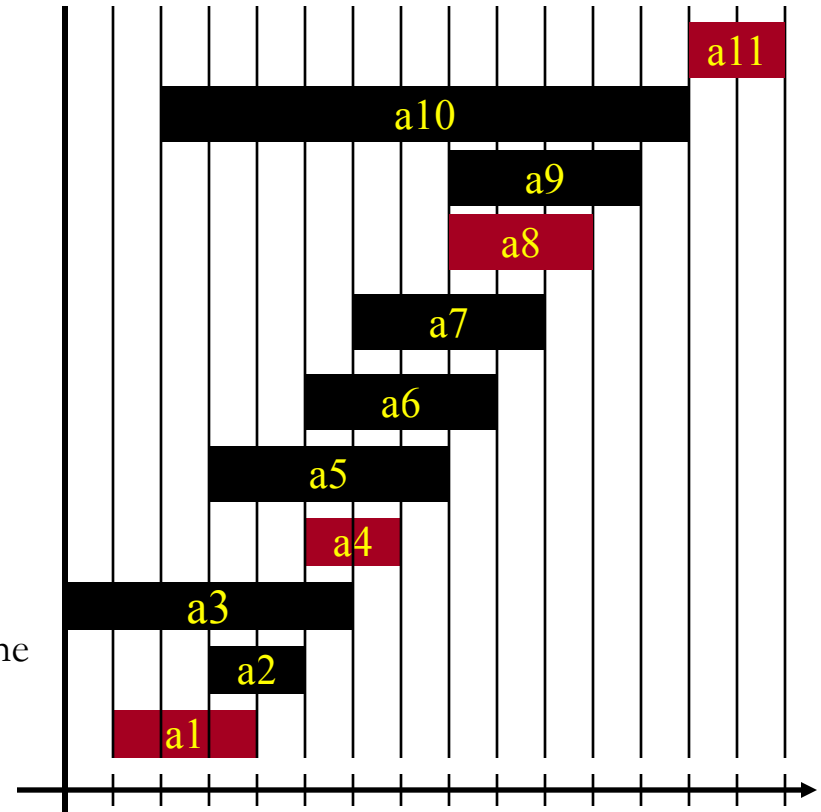
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- Algorithm:
 - Select activity with lowest finishing time;
 - Check which other activities are compatible
 - Initialize activities by increasing finishing time
- $\{ a_1, a_4, a_8, a_{11} \}$ optimal solution



- But not unique !**

Execution Time Complexity:
 $O(n \log n) + O(n) = O(n \log n)$

Example: Knapsack Problem

- Problem Definition:
 - Given n objects $(1, \dots, n)$ and a Knapsack of capacity W
 - Each object has value v_i and weight w_i
 - **It is possible to transport a fraction x_i of an object: $0 \leq x_i \leq 1$**
 - Transported weight cannot exceed W
 - Objective:
 - Maximize the transported value of objects while meeting the Knapsack's weight constraint

- Formalization:

$$\begin{array}{ll} \max & \sum_{i=1}^n x_i v_i \\ \text{such that} & \sum_{i=1}^n x_i w_i \leq W \\ & v_i \geq 0, w_i \geq 0, 0 \leq x_i \leq 1, 1 \leq i \leq n \end{array}$$

Example: Knapsack Problem

- Observations:
 - Sum of the selected objects cannot exceed weight limit W
 - Optimal solution must fill up knapsack entirely, $\sum x_i w_i = W$
 - Otherwise we could transport more *fractional* items, thus with larger aggregate value !

- Algorithm:

Execution Time:
 $O(n)$, or $O(n \log n)$

```

function fillUpKnapsackGreedy(v, w, W)
  weight = 0;
  while weight < W do
    select element i with maximal  $v_i/w_i$ 
    if ( $w_i + \text{weight} \leq W$ ) then
       $x_i = 1$ ; weight +=  $w_i$ 
    else
       $x_i = (W - \text{weight}) / w_i$ ; weight = W
  
```

Example: Knapsack Problem

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             $x_i = 1$ ; weight +=  $w_i$ 
        else
             $x_i = (W - \text{weight}) / w_i$ ; weight = W
  
```

fraction of last object
to fit into Knapsack

Knapsack Greedy Algorithm Optimality

- Proof by Contradiction:
 - Let item i be the item with the maximum value to weight ratio (v/w). We want to show that the optimal solution contains as much of item i as possible.
 - We prove that this statement is true by contradiction. We start by assuming that there is an optimal solution where we did not take as much of item i as possible and we also assume that our knapsack is full (If it is not full, just add more of item i !).
 - Since item i has the highest value to weight ratio, there must exist an item j in our knapsack such that $v_j/w_j < v_i/w_i$.
 - We can take item j of weight x from our knapsack and we can add item i of weight x to our knapsack (Since we take out x weight and put in x weight, we are still within capacity.).
 - The change $x (v_i/w_i) - x (v_j/w_j) = x ((v_i/w_i) - (v_j/w_j)) > 0$ since $v_j/w_j < v_i/w_i$
 - Therefore, we arrive at a contradiction because the "so-called" optimal solution in our starting assumption, can in fact be improved by taking out some of item j and adding more of item i .

Knapsack Greedy Algorithm Optimality

- **Greedy Choice Property:** The optimal solution contains the best item according to the algorithm's greedy criterion.
- **Optimal Substructure:** The optimal solution to problem S contains an optimal to subproblems of S .

Optimality: Greedy Choice Property

- Let item i be the item with the maximum value to weight ratio (v_i/w_i).
- **Goal:** Show that the optimal solution contains as much of item i as possible.
- **Proof:** (by contradiction — as sketched before)
 - Optimal solution X takes as much of item i as possible, say x_i
 - Solution Y has $y_i < x_i$ and is also “optimal”
 - Since v_i/w_i has the highest ratio, there must exist an item j in Y with $v_j/w_j < v_i/w_i$ then, we can take k weight of item j and assign it to item i , yielding a net value improvement of $k (v_i/w_i - v_j/w_j) > 0$.
 - Therefore, Y was not optimal after all (the contradiction).

Optimality Proof: Optimal Subproblem

- Assume that X is the Optimal solution to problem S with value V and knapsack capacity W .
- Then, $X' = X - x_j$ is an Optimal solution to subproblem $S' = S - \{j\}$ and knapsack capacity $W' = W - w_j$
- **Proof** (by contradiction):
 - Assume X' is not optimal to S' and that we have another solution X'' to S' that has a higher total value $V'' > V'$.
 - Then, $X'' \cup \{x_j\}$ is a solution to S with value $V'' + v_j > V' + v_j = V$.
 - This is a contradiction as V is assumed to be optimal.

Problem: Minimize System Processing Time

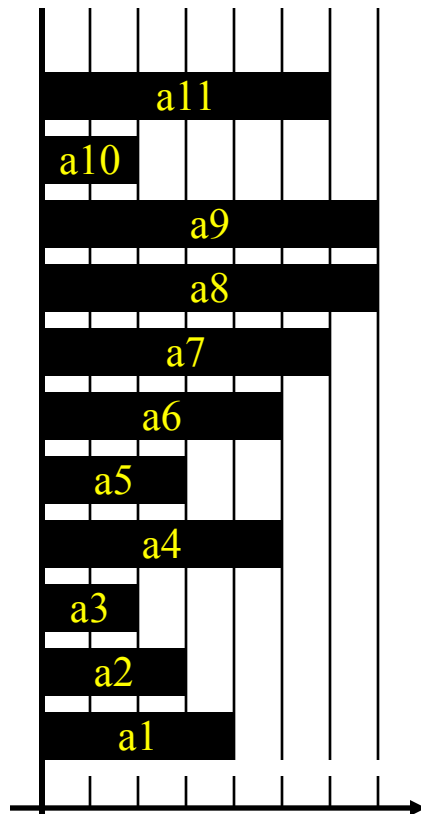
- Given a Server with n clients, each with known service time (*i.e.* client i takes time t_i), minimize the total time taken in the system serving all clients

$$\text{minimize } T = \sum_{i=1}^n (\text{total time in the system by client } i)$$

- Greedy Solution:
 - Process Clients by Increasing Order of Service Time
 - Rationale:** Take care of fast orders first, leads to lower aggregate wait time for others – fewer people waiting in line...

Example: Minimize System Processing Time

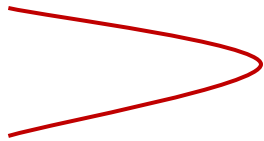
i	1	2	3	4	5	6	7	8	9	10	11
s _i	4	3	2	5	3	5	6	8	8	2	7



- Strategy 1: Process longest jobs first !
 - Order of service = { 9, 8, 7, 11, 4, 6, 1, 2, 3, 10 }
 - Total Service Time = $10 \times 8 + 9 \times 8 + 8 \times 7 + 7 \times 6 + 6 \times 5 + 5 \times 4 + 4 \times 3 + 3 \times 3 + 2 \times 2 + 1 \times 2 = 315$
- Strategy 2: Process shortest jobs first !
 - Order of service = { 10, 3, 2, 1, 6, 4, 11, 7, 8, 9 }
 - Total Service Time = $10 \times 2 + 9 \times 2 + 8 \times 3 + 7 \times 3 + 6 \times 4 + 5 \times 5 + 4 \times 6 + 3 \times 7 + 2 \times 8 + 1 \times 8 = 191$

Example (Cont.)

- Greedy Algorithm finds Optimal Solution
 - $P = p_1 p_2 \dots p_n$, is a permutation of the integer from 1 to n
 - Let $s_i = t_{p_i}$
 - e.g., $s_1 = t_{p_1} = t_5$
 - Given the client to be processed by order P , the service time for the client in position i is s_i
 - Total time spent by all clients in the system is:

$$T(P) = \sum_{k=1}^n (n - k + 1) s_k$$


s_1 shows up n times,
and s_n only once
 - Assume clients are sorted by increasing order of service time in P
 - If there are indices a and b , with $a < b$, and $s_a > s_b$

Example (Cont.)

- We can swap the order of the clients a and b , to get the order P'
 - Same as P with integers p_a and p_b swapped

$$T(P') = (n - a + 1) s_b + (n - b + 1) s_a + \sum_{\substack{k=1 \\ k \neq a, b}}^n (n - k + 1) s_k$$

- Yielding,

$$\begin{aligned} T(P) - T(P') &= (n - a + 1)(s_a - s_b) + (n - b + 1)(s_b - s_a) \\ &= (b - a)(s_a - s_b) > 0 \end{aligned}$$

- That is P' is a better order of service (with lower total service time)
- Algorithm finds the Optimal Solution !

Example: Huffman Codes

- Applications in data compression
- Example:
 - File with 100,000 characters
 - Fixed-length encoding: each symbol gets a code of the same length

	a	b	c	d	e	f
Frequency (x1000)	45	13	12	16	9	5
Code	000	001	010	011	100	101

- Compressed file size: $3 \times 100,000 = 300,000$ bits
- Variable-Length code may be better than Fixed-Length code
 - Associate shorter codes to more frequent characters

Example: Huffman Codes

- Variable-Length encoding:

	a	b	c	d	e	f
Frequency (x1000)	45	13	12	16	9	5
Variable Code	0	101	100	111	1101	1100

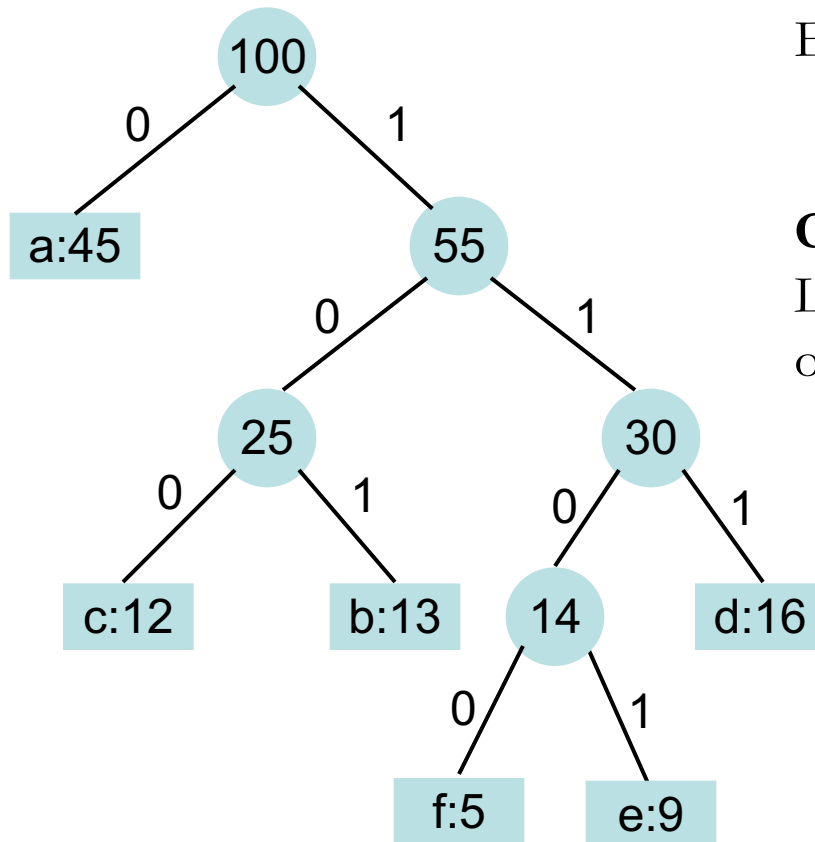
- Number of required bits:

- $(45 \times 1 + 13 \times 3 + 12 \times 3 + 16 \times 3 + 9 \times 4 + 5 \times 4) \times 1000 = 224,000$ bits

- Prefix-free codes:

- No code is prefix of another code
- 001011101 \rightarrow 0.0.101.1101
- Codes represented by a complete binary tree

Prefix-Free Codes



Complete Binary Tree:

Each internal node with two children

Observation:

Length of code for character = depth of character in the tree

Example: Huffman Codes

- Given a tree T associated with a prefix-free code
 - $f(c)$: frequency (occurrence) of character c in a file/stream
 - $d_T(c)$: depth of leaf c in the tree

$$B(T) = \sum_{c \in C} f(c) \cdot d_T(c) \quad \text{Number of required bits to represent file}$$

- Huffman Code:
 - Begin with each character $c \in C$ with frequency $f[c]$
 - Develop a prefix-free code for C represented by a binary tree T
 - Begin with $|C|$ leaves (for each character in the file) and perform $|C| - 1$ merge operation to obtain final tree
 - How?
 - Aggregating x, y characters in C with the least frequencies into a “symbol” with aggregate frequency
 - More frequent symbols will be closer to root of tree and thus with shorter code lengths.

Example: Huffman Codes

```
function Huffman(C)
    n = |C|;
    Q = C;                                // Constructs priority queue
    for i = 1 to n - 1 do
        z = AllocateNode();
        x = left[z] = ExtractMin(Q);
        y = right[z] = ExtractMin(Q);
        f[z] = f[x] + f[y];
        Insert(Q, z);
    return
```

Execution Time: $O(n \log n)$

Example

f:5

e:9

c:12

b:13

d:16

a:45

c:12

b:13

14

d:16

a:45

0

1

f:5

e:9

14

d:16

25

a:45

0

1

f:5

e:9

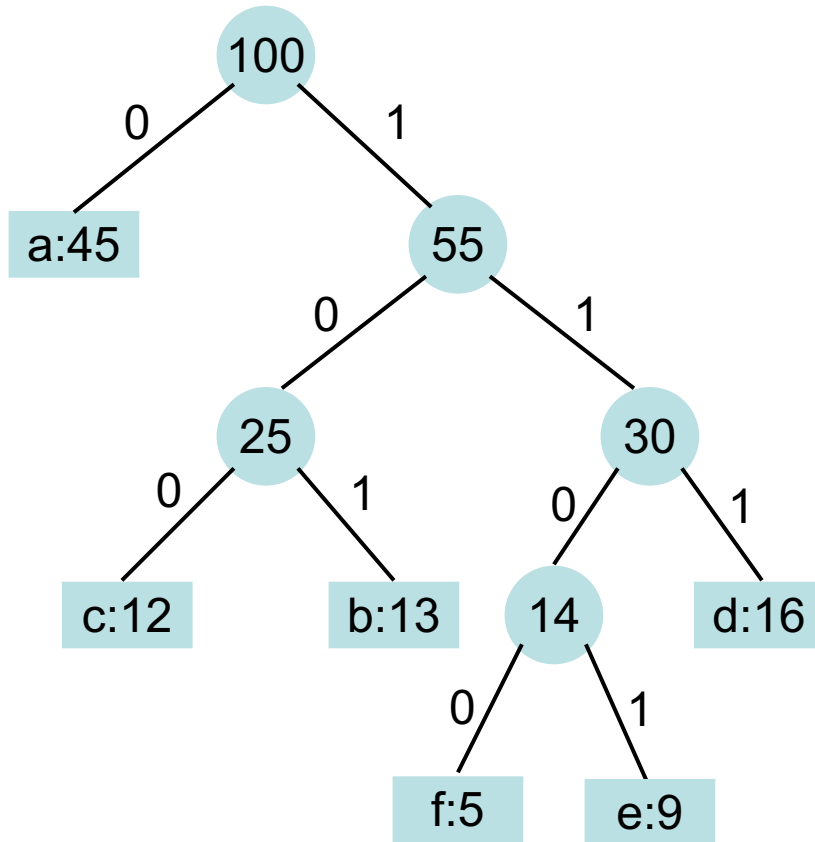
0

1

c:12

b:13

Example



- Codes:

a: 0
b: 101
c: 100
d: 111
e: 1101
f: 1100

	a	b	c	d	e	f
Frequency (x1000)	45	13	12	16	9	5
Variable Code	0	101	100	111	1101	1100

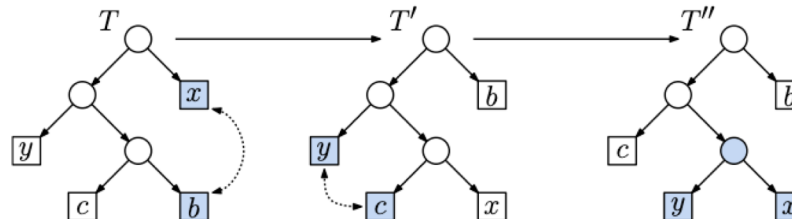
Huffman Greedy Algorithm Optimality

- **Greedy Choice Property:**

Theorem: There exists a prefix-free code for C such that the codes x and y (with the least frequencies) have the same length and differ only in the last bit

Proof: (by contradiction)

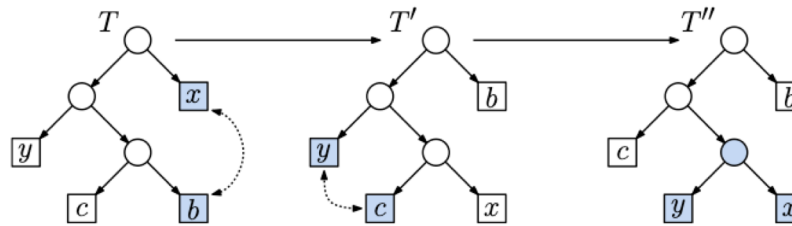
- Assume that T is optimal but x and y **do not have** the same code length, that is their depths in the tree are different.
- Then, in T there must be two symbols b and c (siblings) both at maximum depth (one of which may be either x or y but not both, by assumption).
- Assume, $f[b] \leq f[c]$, and $f[x] \leq f[y]$. Note that since x and y have the smallest frequencies, it follows that $f[x] \leq f[b]$, and $f[y] \leq f[c]$ (some may be identical pairwise).
- Because b and c are at the maximum depth, $d_T(b) \geq d_T(x)$ and $d_T(c) \geq d_T(y)$ and we have that $f[b] - f[x] \geq 0$ and $d_T(b) - d_T(x) \geq 0$ and hence their product is negative.
- Then, we can create another trees T' by swapping positions of x and b in T and then in T'' by swapping positions of c and y .



Huffman Greedy Algorithm Optimality

- **Greedy Choice Property: (cont)**

- In these new trees $B(T) \geq B(T') \wedge B(T') \geq B(T'')$ which is a contradiction since T is optimal $\Rightarrow B(T'), B(T'') \geq B(T)$



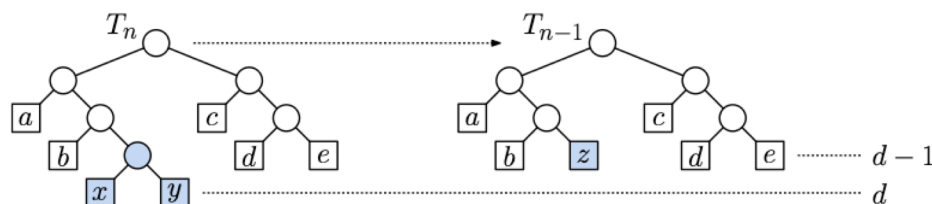
$$\begin{aligned}
 B(T) - B(T') &= \sum_{c \in C} f(c)d_T(c) - \sum_{c \in C} f(c)d_{T'}(c) \\
 &= f[x]d_T(x) + f[b]d_T(b) - f[x]d_{T'}(x) - f[b]d_{T'}(b) \\
 &= f[x]d_T(x) + f[b]d_T(b) - f[x]d_T(b) - f[b]d_T(x) \\
 &= (f[b] - f[x])(d_T(b) - d_T(x)) \\
 &\geq 0
 \end{aligned}$$

- This proof applies to just a pair of nodes, those with the lowest frequencies.
- Induction, requires we convert the problem of n to $n-1$ characters.

Huffman Greedy Algorithm Optimality

- Optimal Sub-structure Property:**

Theorem: Let z be an internal node of T , and x and y leaf nodes, then the tree $T' = T - \{x, y\}$ is an optimal prefix tree for $C' = C - \{x, y\} \cup \{z\}$ where z has $f[z] = f[x] + f[y]$.



Proof:

- $B(T) = B(T') + f[x] + f[y]$, as z is placed at a higher tree level and hence, its code length is smaller.
- If T' is not optimal, then there exists T'' such that $B[T''] < B[T']$
- But z is a leaf node in T'' (see Greedy choice property)
 - Adding x and y as children of z in T''
 - We get a prefix-free code for C with cost: $B[T''] + f[x] + f[y] < B[T]$
 - But T is optimal ($B[T''] + f[x] + f[y] \geq B[T]$); and so T' is also optimal

$$\begin{aligned} f[x]d_T(x) + f[y]d_T(y) &= (f[x] + f[y])(d_{T'}(z) + 1) \\ &= f[z]d_{T'}(z) + (f[x] + f[y]) \end{aligned}$$

The Huffman algorithm produces an optimal prefix-free code

Summary

- Greedy Algorithms:
 - Selection of Activities
 - Knapsack Problem
 - Minimization of System Tasks
 - Huffman Codes
- Features of Greedy Algorithms
 - Optimality of Greedy Choice
 - Optimality of Subproblems
 - Theory: Matroids