Design and Analysis of Algorithms Part V: Greedy Algorithms

Lecture 10: The Fraction Knapsack Problem and The Huffman Coding Problem



Yongxin Tong (童咏昕)

School of CSE, Beihang University yxtong@buaa.edu.cn

Outline

Introduction to Part V

- The Fraction Knapsack Problem
 - Problem Definition
 - A Greedy Algorithm
 - Correctness

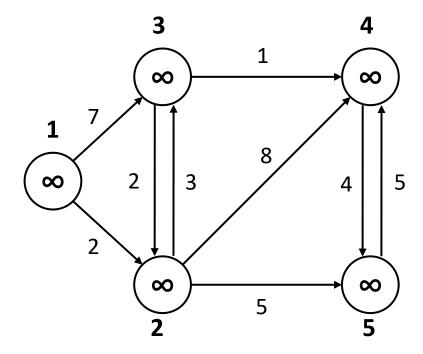
- Interval Scheduling and Interval Partitioning
 - Interval Scheduling
 - Interval Partitioning

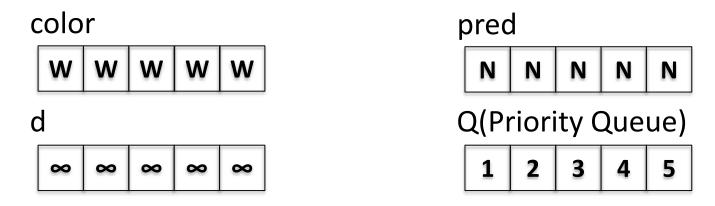
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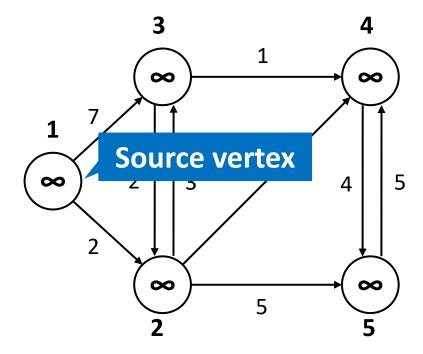
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- Examples already seen
 - Dijkstra's shortest path algorithm:

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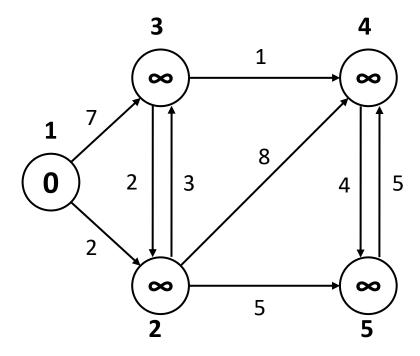


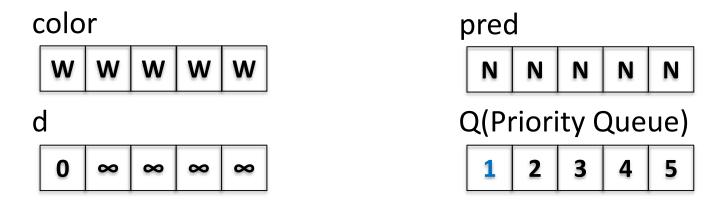


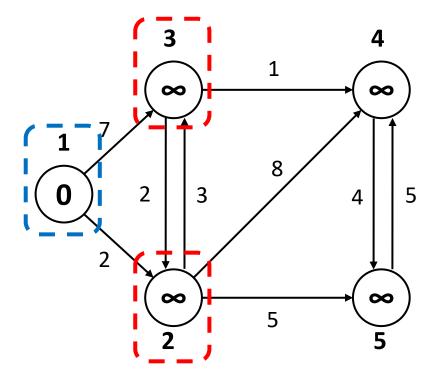


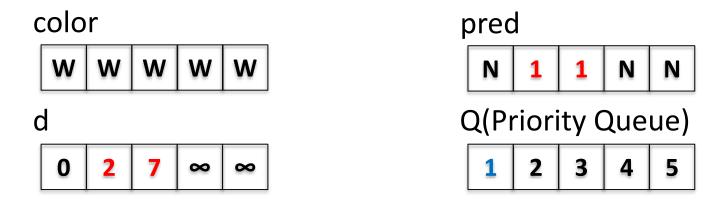


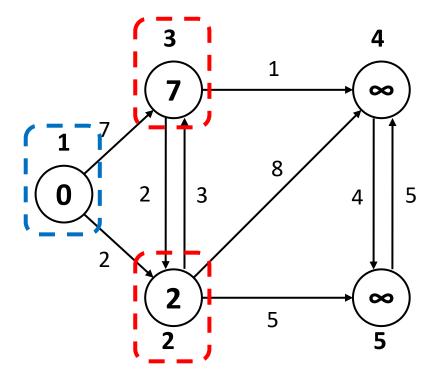


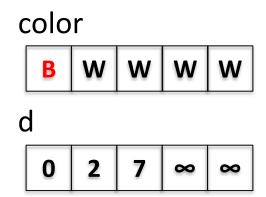


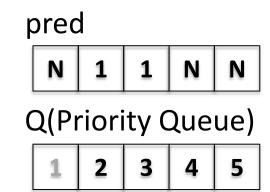


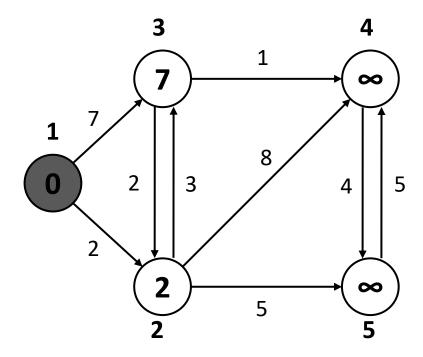


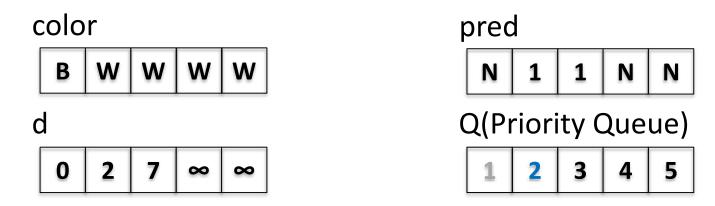


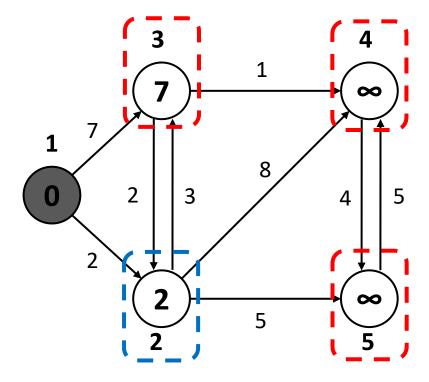


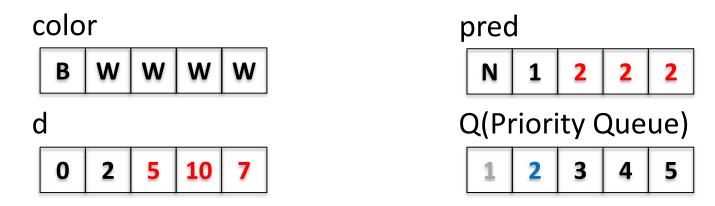


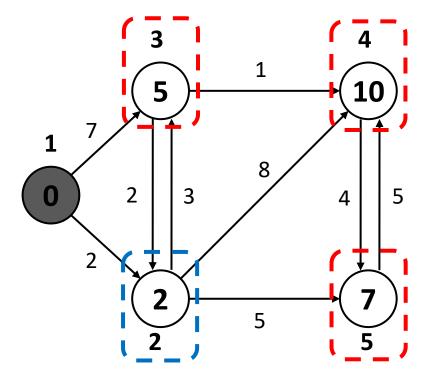


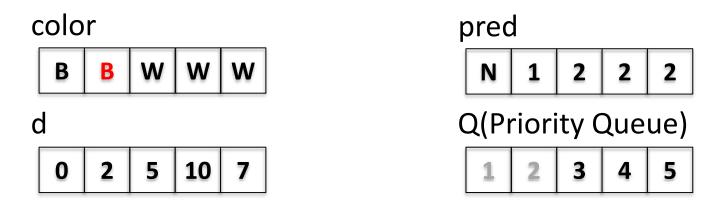


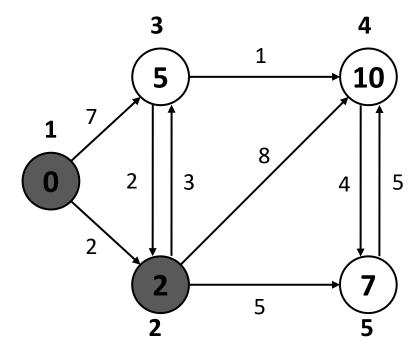


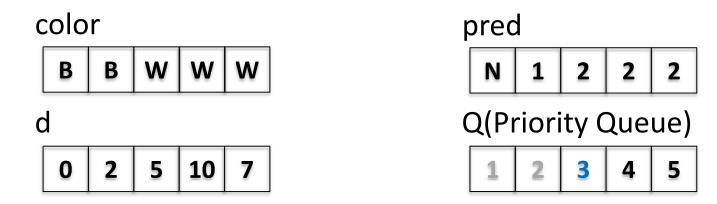


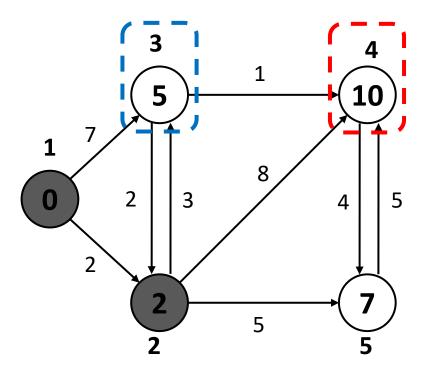


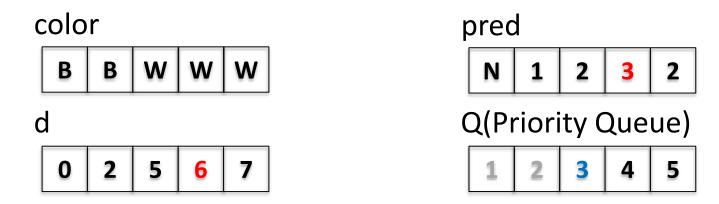


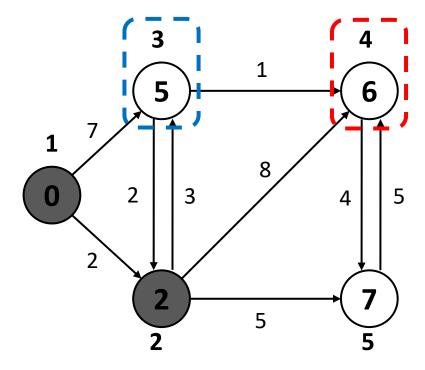


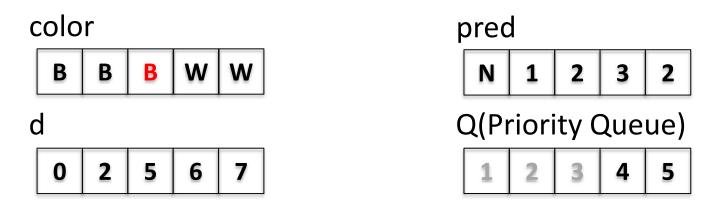


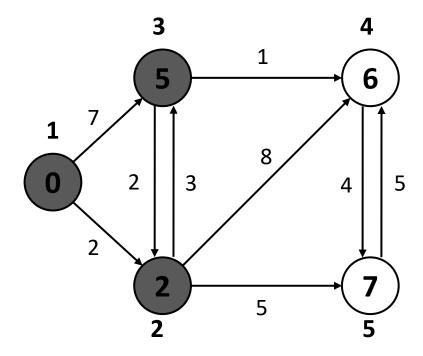


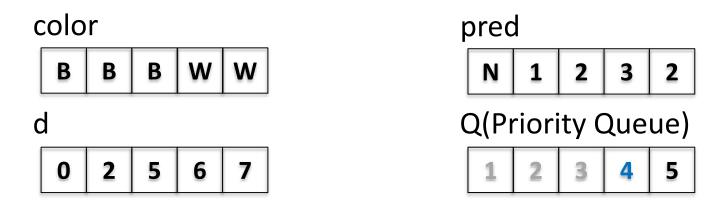


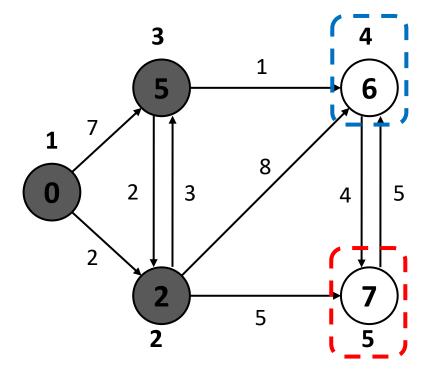


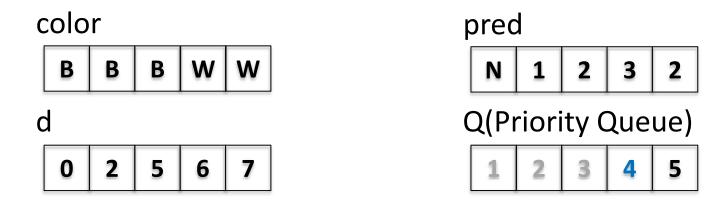


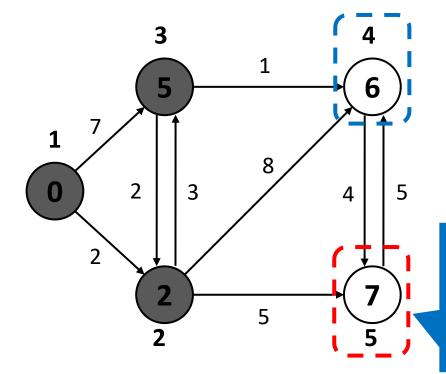




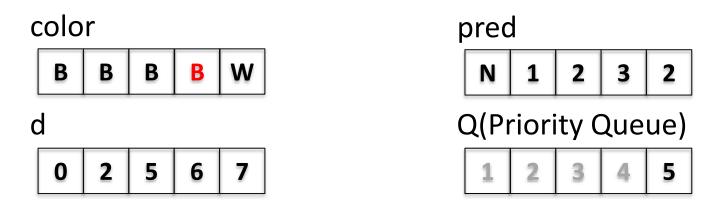


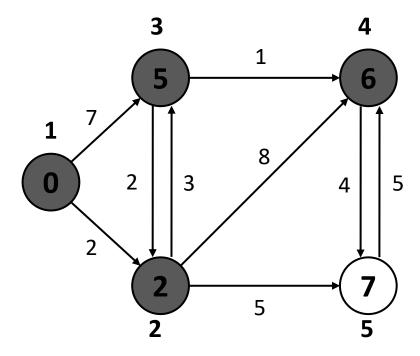


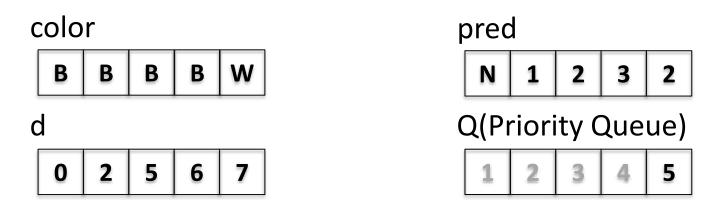


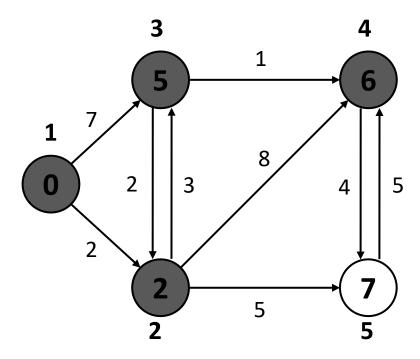


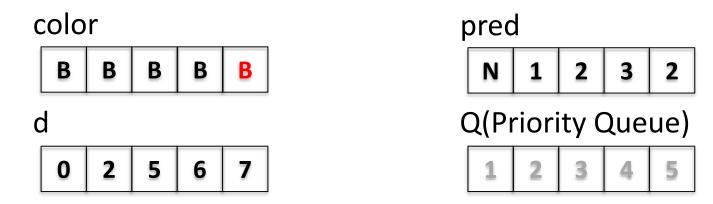
d[5] is not needed to be updated because d[4]+4 > d[5]

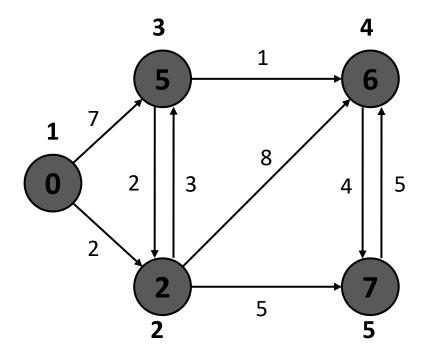


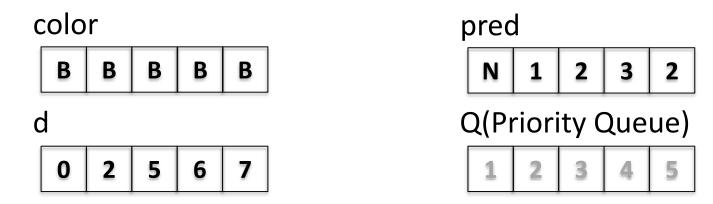


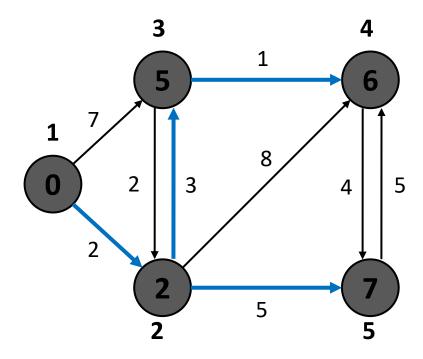










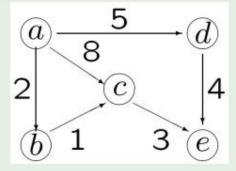


Optimal Substructure Property

Lemma

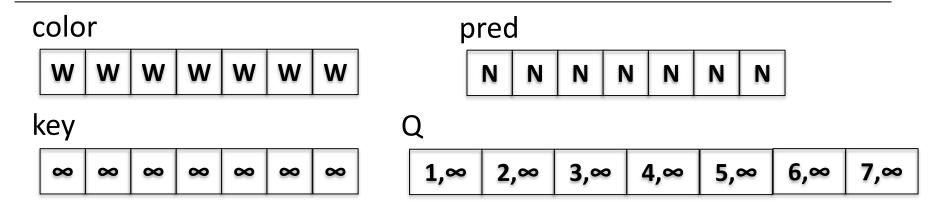
Any sub-path of a shortest path must also be a shortest path

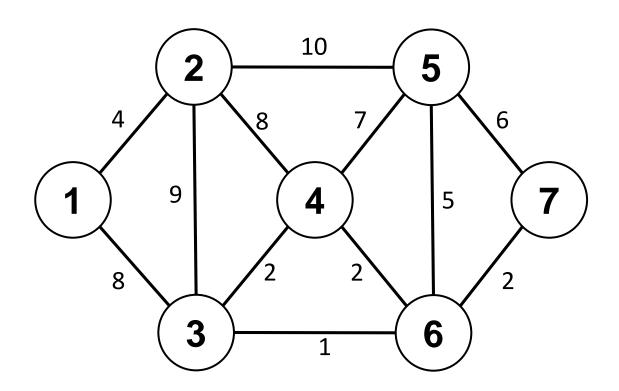
Example

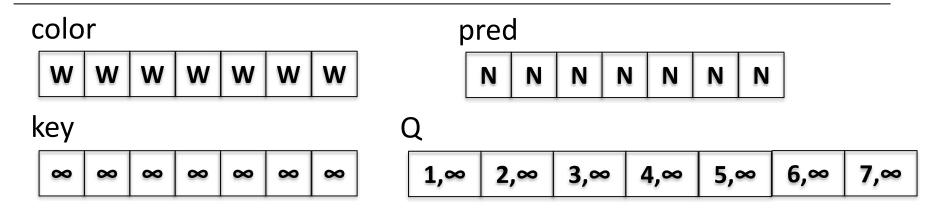


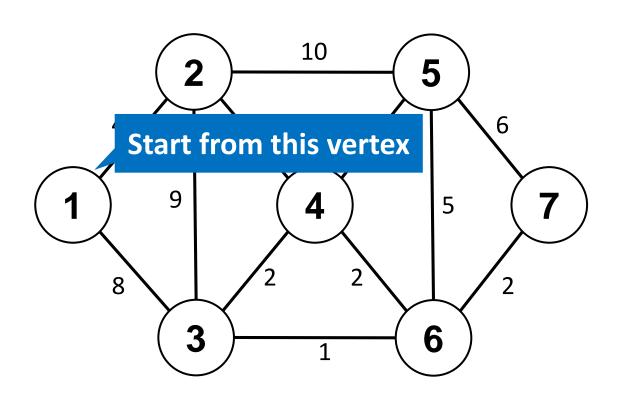
 $\langle a, b, c, e \rangle$ is a shortest path; sub-path $\langle a, b, c \rangle$ is also a shortest path.

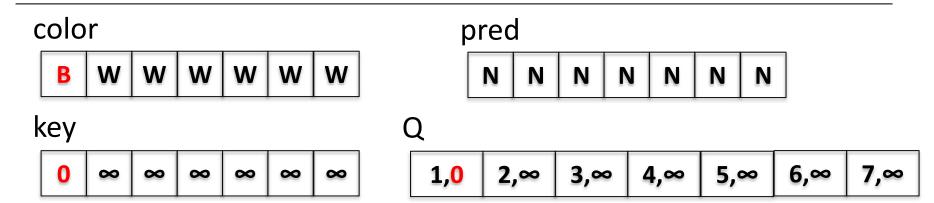
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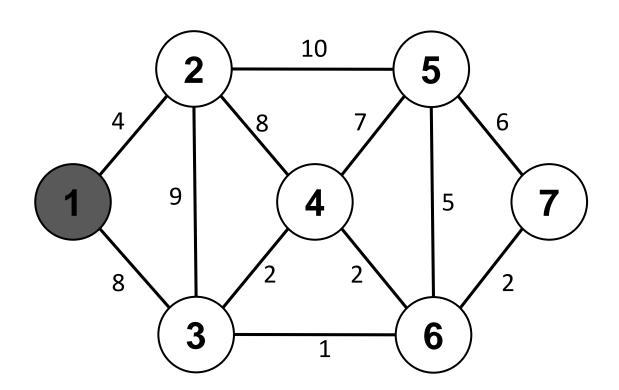


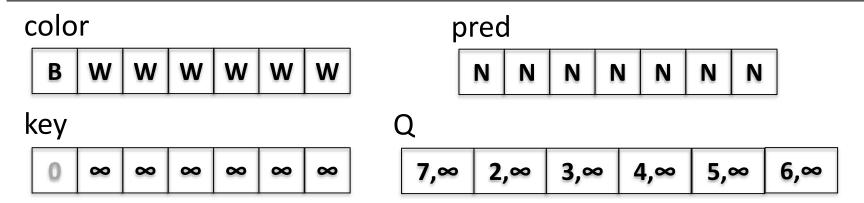


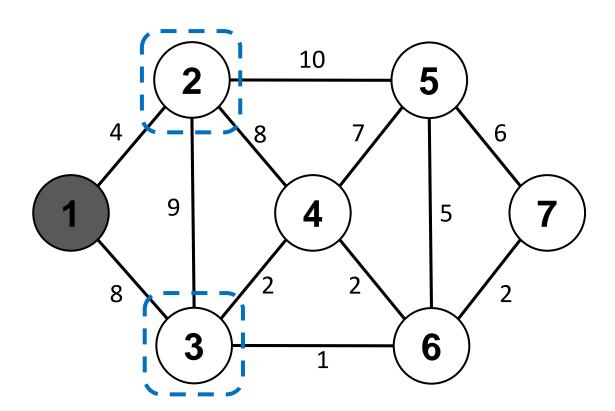


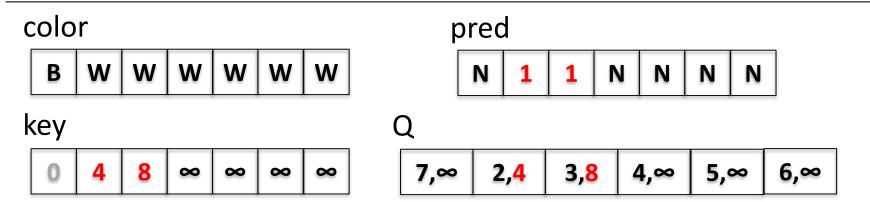


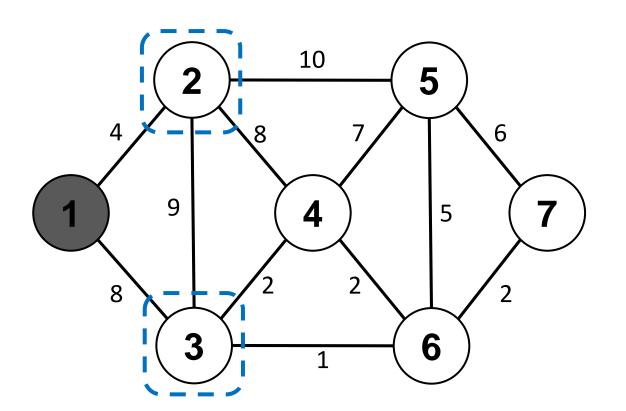


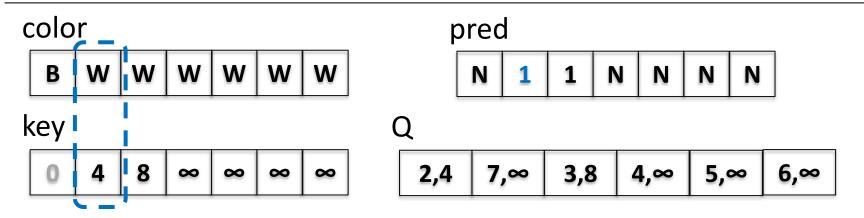


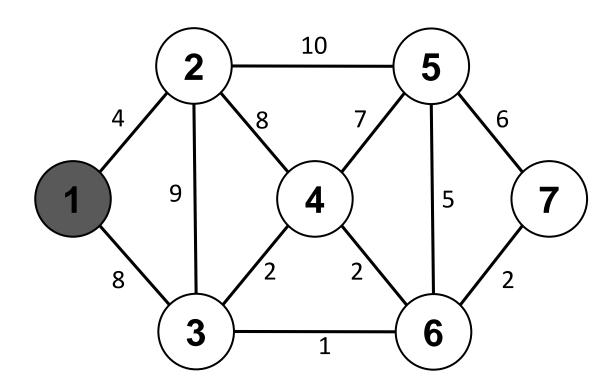


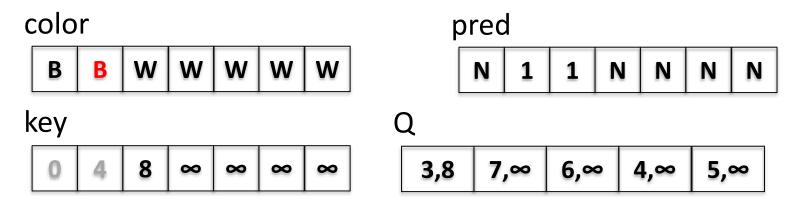


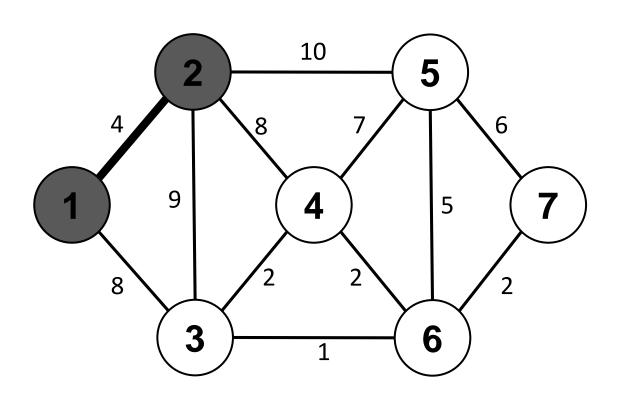


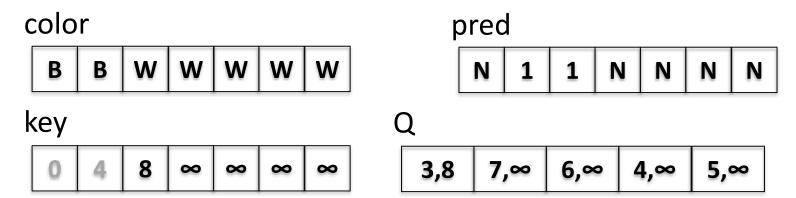


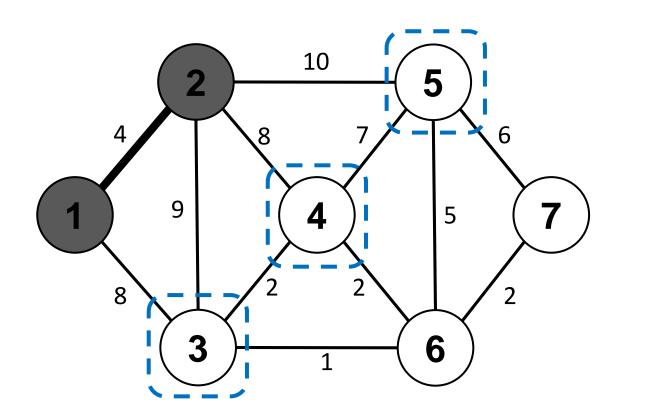


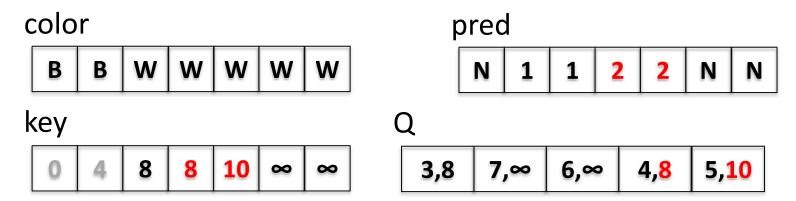


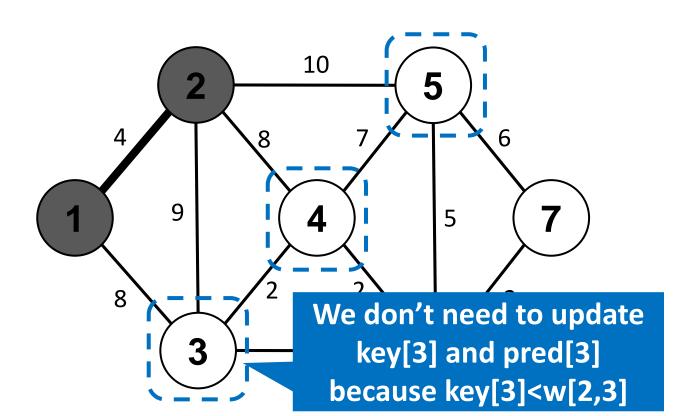


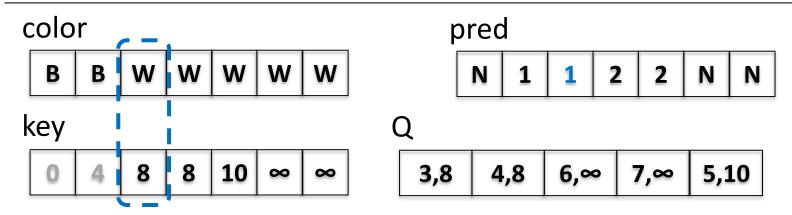


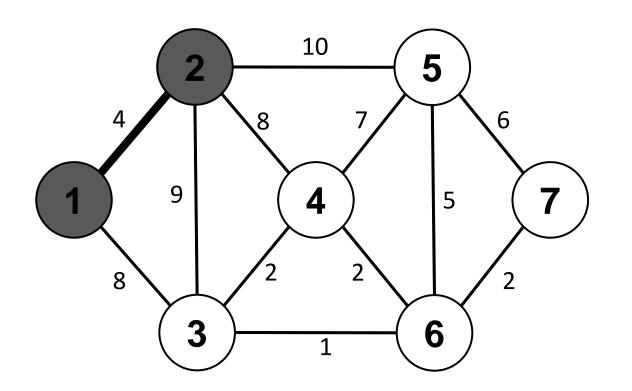


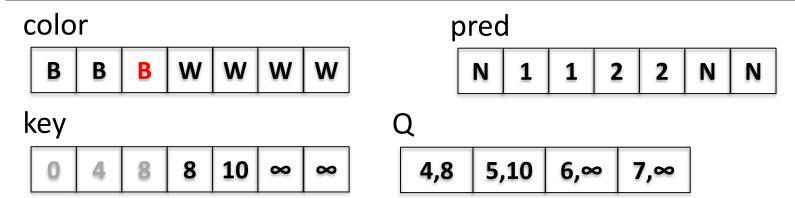


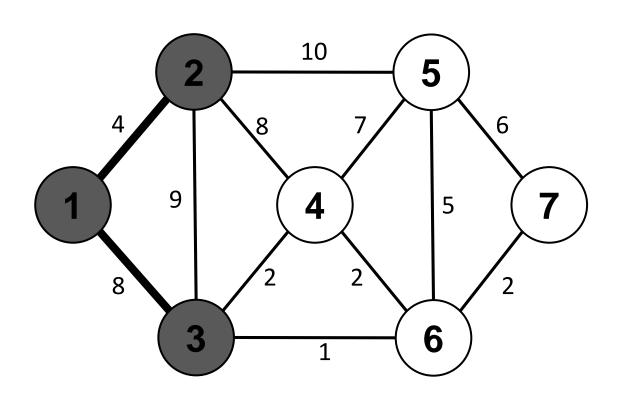


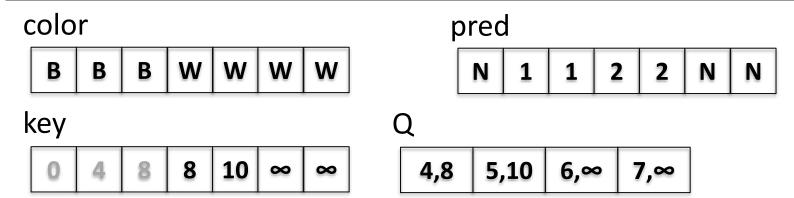


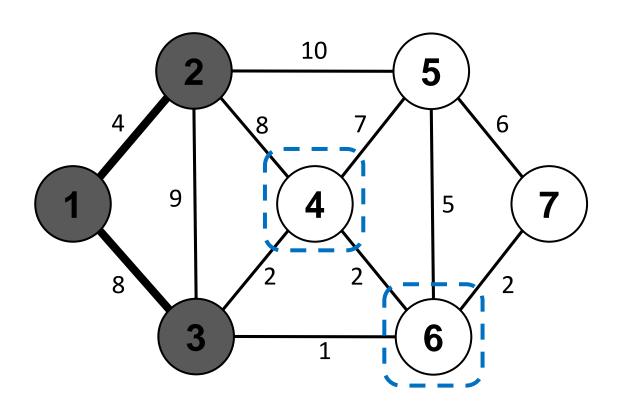


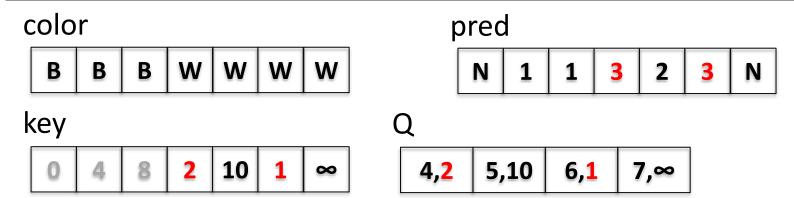


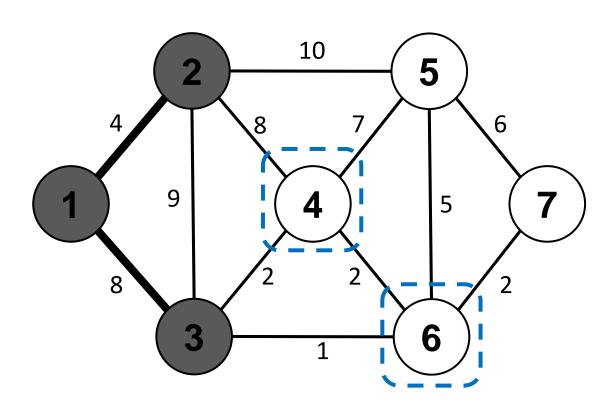


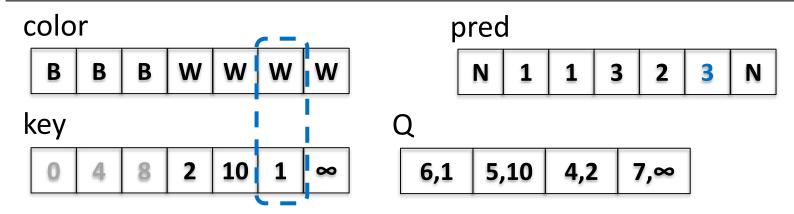


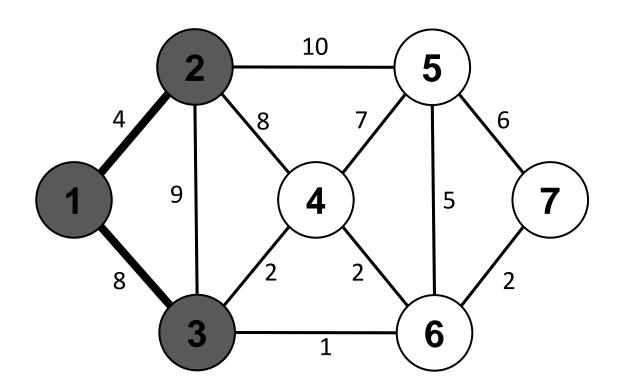


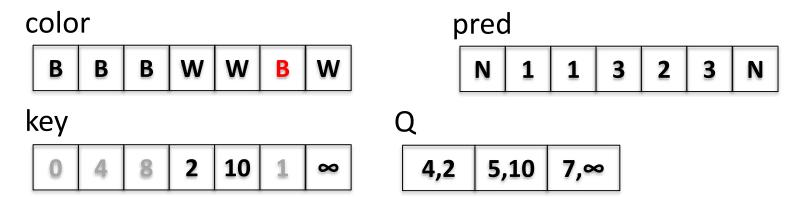


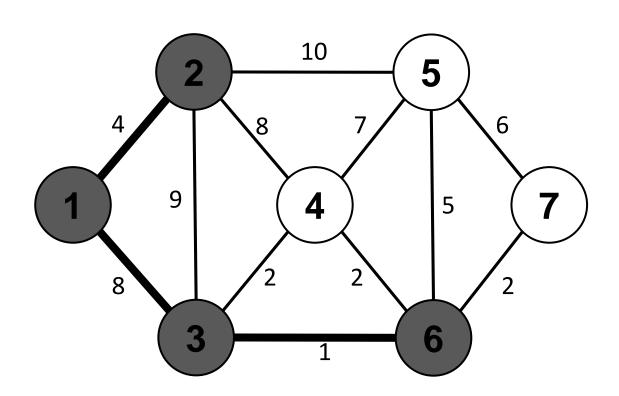


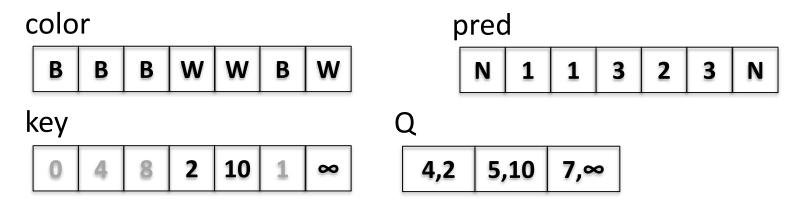


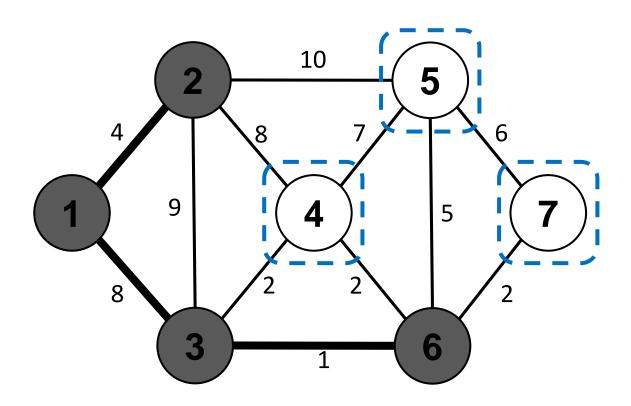


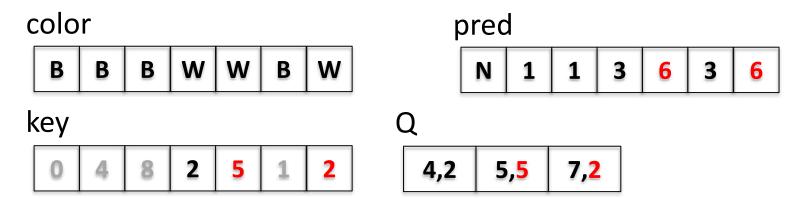


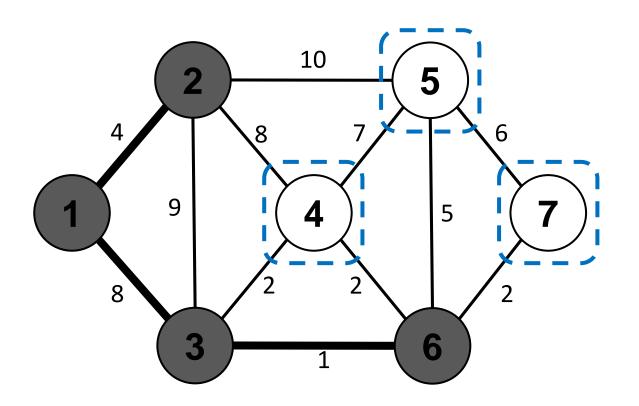


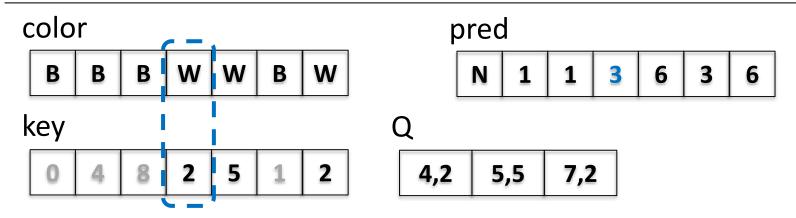


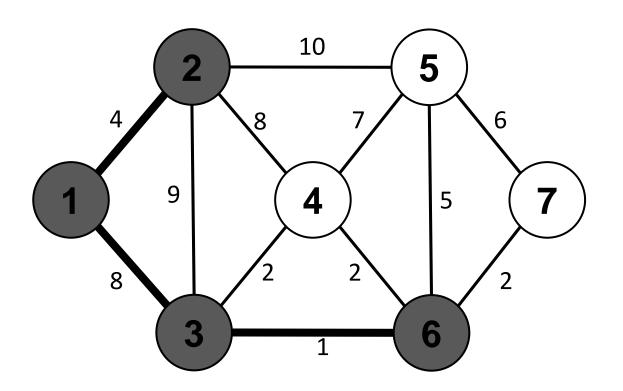


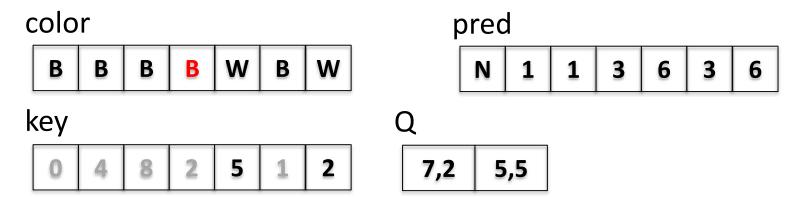


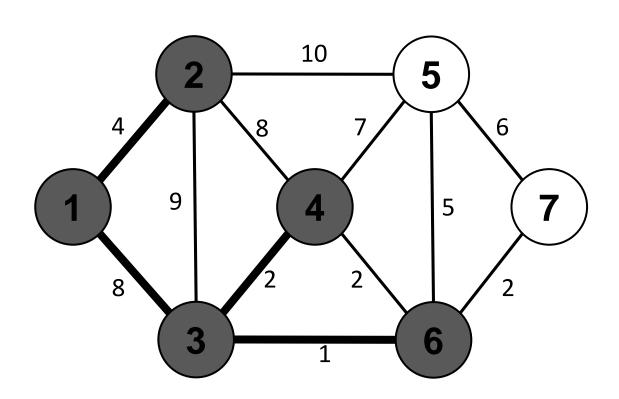


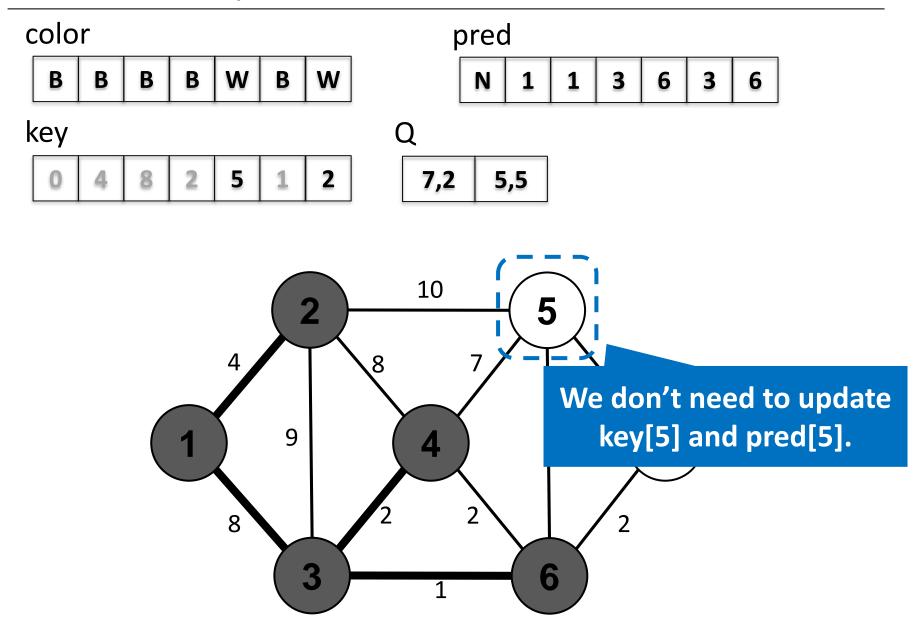


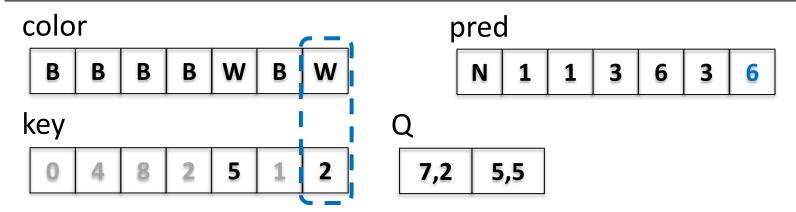


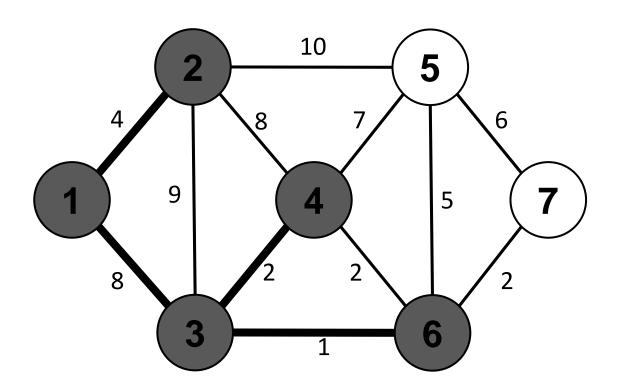


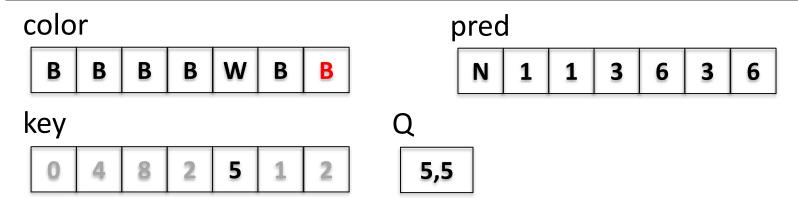


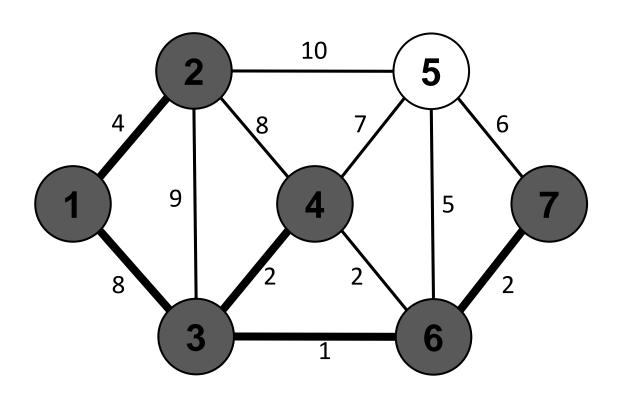


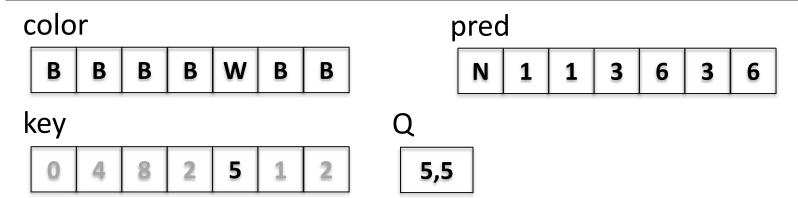


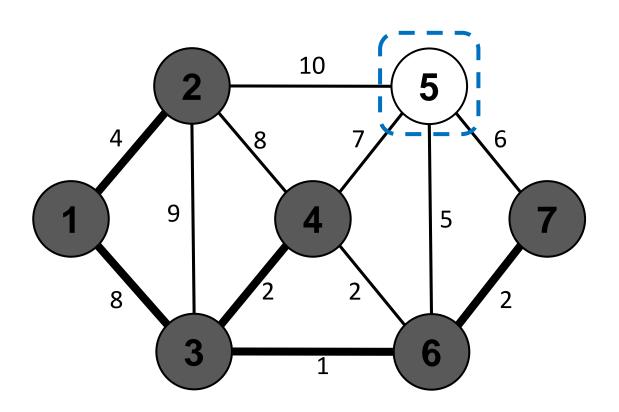


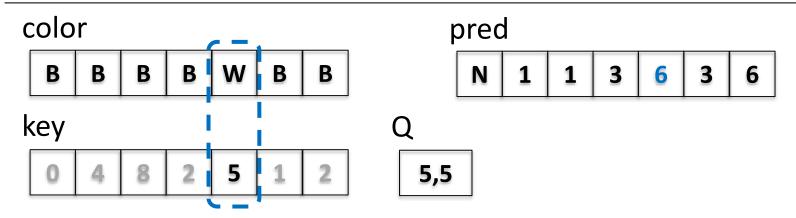


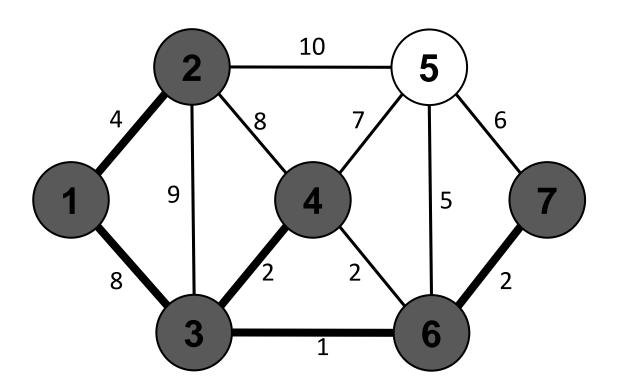


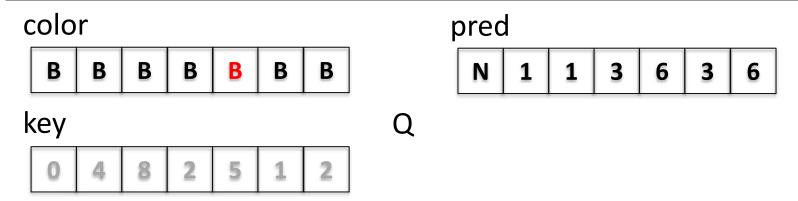


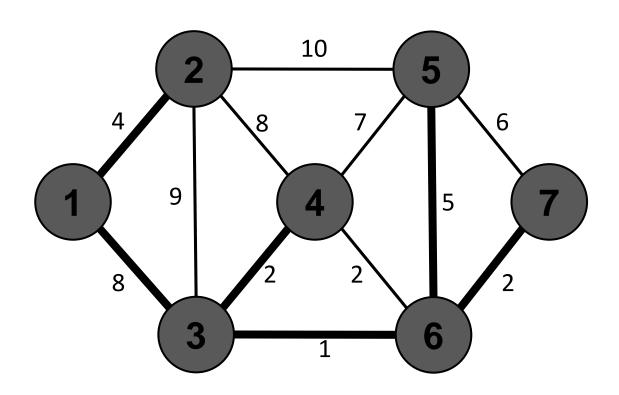
















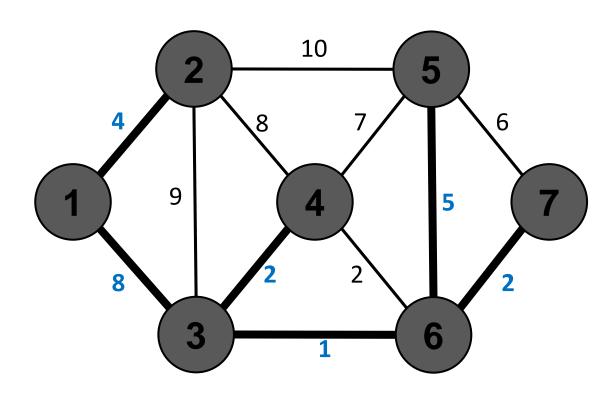
pred



key

0	4	8	2	5	1	2
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Weight of MST = **22**



Generic Algorithm for MST problem

Definition

Let A be a set of edges such that $A \subseteq T$, where T is a MST. An edge (u, v) is a safe edge for A, if $A \cup \{(u, v)\}$ is also a subset of some MST

• If at each step, we can find a safe edge (u, v), we can grow a MST

Generic-MST(G)

```
Input: A graph G
Output: A is the MST of G
A \leftarrow \text{EMPTY};
while A does not form a spanning tree do

| find an edge(u, v) that is safe for A;
| add (u, v) to A;
end
return A;
```

Optimal Substructure Property

- Start with an empty graph.
- Try to add edges one at a time, always making sure that what is built remains acyclic.
- If we are sure at each step that the resulting graph is a subset of some minimum spanning tree, we are done.

Lemma

- Let G = (V, E) be a connected, undirected graph with a real-valued weight function w defined on E
- Let A be a subset of E that is included in some minimum spanning tree for G.

Let

- (S, V S) be any cut of G that respects A
- (u, v) be a light edge crossing the cut (S, V S)

Then, edge (u, v) is safe for A.

Introduction to Greedy Algorithm

- A greedy algorithm for an optimization problem always makes the choice that looks best at the moment and adds it to the current subsolution.
- Examples already seen
 - Dijkstra's shortest path algorithm: Select the node, among all "candidate" nodes, that is closest to the source according to estimation d[u].
 - Prim/Kruskal's MST algorithms: Select the edge, among all "candidate" edges, that is the lightest.
- Greedy algorithms don't always yield optimal solutions but,

Introduction to Greedy Algorithm

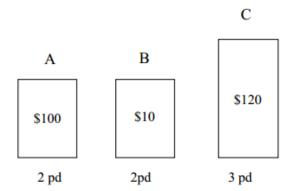
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- Greedy algorithms don't always yield optimal solutions but, when they do, they're usually the simplest and most efficient algorithms available.

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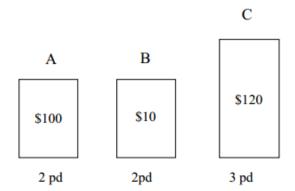
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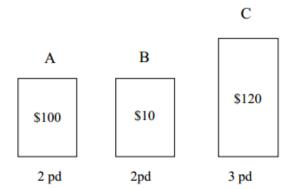


Capacity of knapsack: K = 4



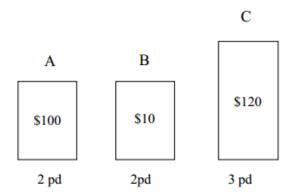
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Fractional Knapsack Problem:



Capacity of knapsack: K = 4

Fractional Knapsack Problem: Can take a fraction of an item.

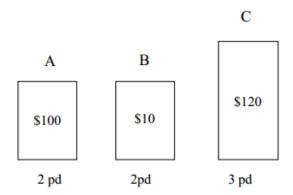


Capacity of knapsack: K = 4

Fractional Knapsack Problem: Can take a fraction of an item.

Solution:

2 pd	2 pd
A	C
\$100	\$80



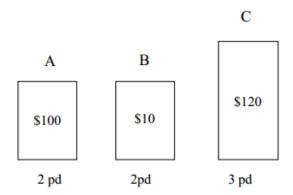
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0-1 Knapsack Problem:

Can only take or leave item. You can't take a fraction.

Solution:



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0-1 Knapsack Problem:Can only take or leave item. You can't take a fraction.

Solution:

2 pd	2 pd
A	C
\$100	\$80

Solution:

3 pd	
C	
\$120	

The Fractional Knapsack Problem: Formal Definition

Given K and a set of n items:

weight	w_1	<i>w</i> ₂	 Wn
value	<i>v</i> ₁	<i>v</i> ₂	 Vn

• Find: $0 \le x_i \le 1$, i = 1, 2, ..., n such that

$$\sum_{i=1}^{n} x_i w_i \le K$$

and the following is maximized:

$$\sum_{i=1}^{n} x_i v_i$$

Outline

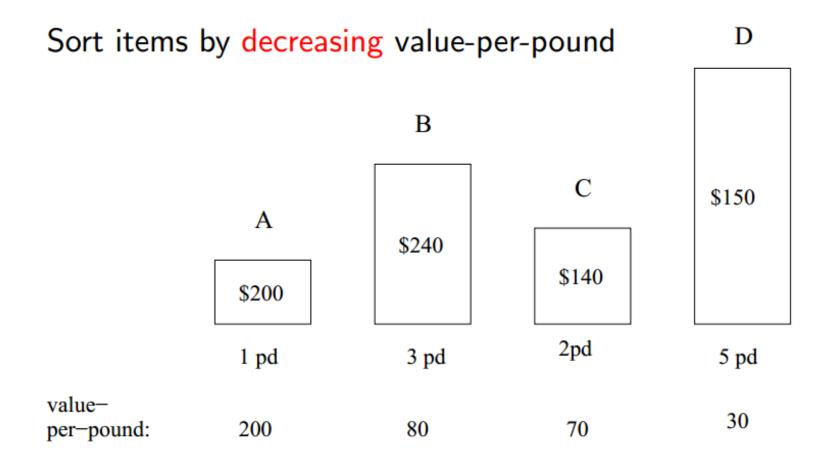
Introduction to Part V

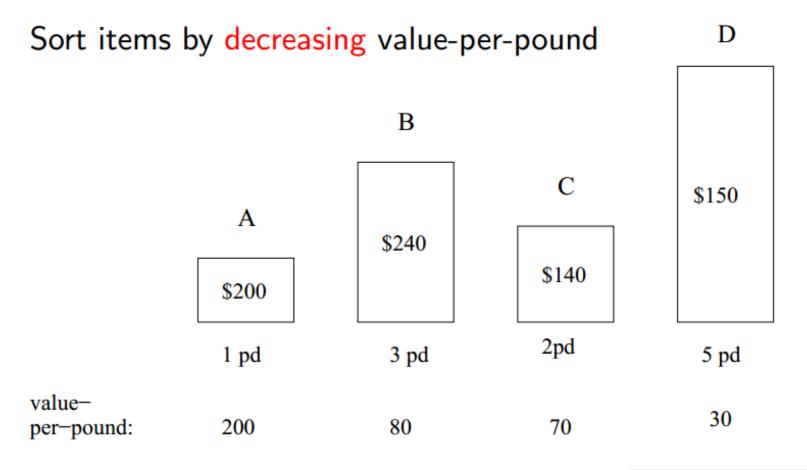
- The Fraction Knapsack Problem
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 - Interval Partitioning

Sort items by value-per-pound

Sort items by decreasing value-per-pound





If knapsack holds K = 5 pd, solution is:

1	pd	Α
3	pd	В
1	pd	C

• Calculate the value-per-pound $ho_i = rac{v_i}{w_i}$ for i = 1, 2, ..., n.

- Calculate the value-per-pound $\rho_i = \frac{v_i}{w_i}$ for i = 1, 2, ..., n.
- Sort the items by ρ_i .

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 - If $k \ge w_i$, set $x_i = 1$ (we take item i), and reduce k = 1

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 - If k < W_i,

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- Sort the items by decreasing ρ_i . Let the sorted item sequence be 1, 2, ..., i, ..., n, and the corresponding value-per-pound and weight be ρ_i and w_i respectively.
- Let k be the current weight limit (Initially, k = K). In each iteration, we choose item i from the head of the unselected list.
 - If $k \ge w_i$, set $x_i = 1$ (we take item i), and reduce $k = k w_i$, then consider the next unselected item.
 - If $k < w_i$, set $x_i = k/w_i$ (we take a fraction k/w_i of item i),

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Running time: O(n log n).

Pseudocode

Fraction-Knapsack(n,v,w,K)

```
Input: Value array \boldsymbol{v} and weight array \boldsymbol{w} of \boldsymbol{n} items, capacity of
          knapsack K.
Output: Solution of maximum value.
Let r[1..n], x[1..n] be two new arrays;
for i \leftarrow 1 to n do
   r[i] \leftarrow v[i]/w[i];
   x[i] \leftarrow 0;
end
Sort the items in decreasing order of their ratios r, rename the items if
 necessary so that the sorted order of items is \langle 1, 2, ..., n \rangle;
i \leftarrow 0;
while K > 0 and j \le n do
    j \leftarrow j + 1;
   if K > w[j] then
     x[j] \leftarrow 1;
     K \leftarrow K - w[j];
    end
    else
        x[j] \leftarrow k/w[j];
        break;
    end
end
return x;
```

K = 50

	1	2	3	4
v_{i}	60	75	100	120
$\overline{w_i}$	10	25	20	30

	1	2	3	4
v_i	60	75	100	120
w_i	10	25	20	30
r_i	6	3	5	4

$$K = 50$$

	1	3	4	2
v_i	60	100	120	75
w_i	10	20	30	25
r_i	6	5	4	3

$$K = 50$$

	, — — — , ,				ı
	1	3	4	2	
v_i	60	100	120	75	K = 50
w_i	10	20	30	25	
r_i	6	$w_i < F$	K	3	
x_i	0	0	0	0	

	(1)	3	4	2	
V _i	60	100	120	75	K = 40
w_i	10	20	30	25	
r_i	6	5	4	3	
x_i	1	0	0	0	

		1				I
		1	3	4	2	
	v_{i}	60	100	120	75	K = 20
	w_i	10	20	30	25	
	r_i	6	5	4	3	
•	x_i	1	1	0	0	

	1	3	4	2	
V _i	60	100	120	75	K = 20
w_i	10	20	30	25	
r_i	6	5	4	$v_i \geq K$	
x_i	1	1	0	U	

	1	3	4	2	
v_i	60	100	120	75	K = 20
w_i	10	20	30	25	
r_i	6	5	4	3	
$\overline{x_i}$	1	1	2/3	0	

	1	3	4	2
v_{i}	60	100	120	75
w_i	10	20	30	25
r_i	6	5	4	3
x_i	1	1	2/3	0

Result

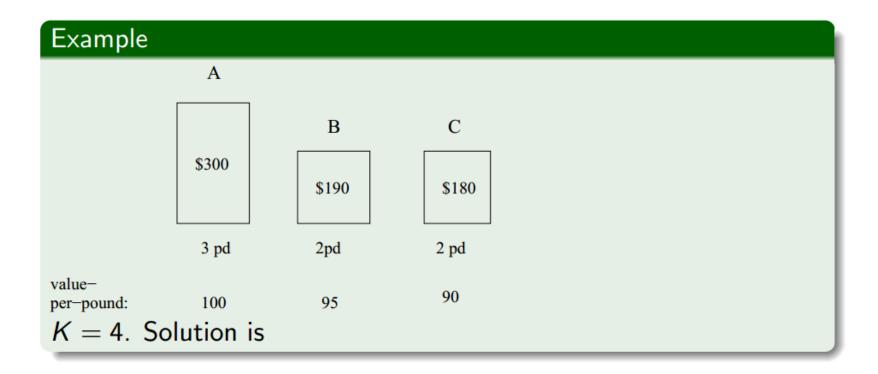
Outline

Introduction to Part V

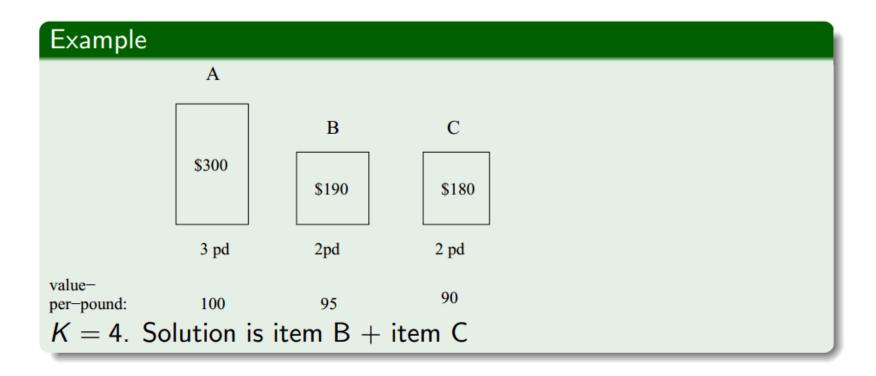
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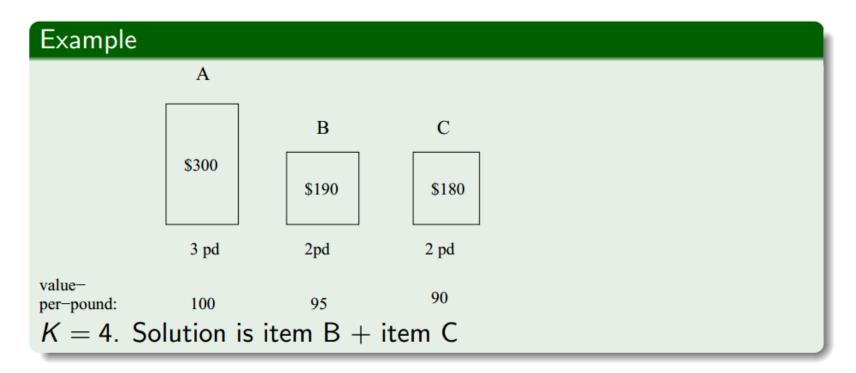
The 0-1 Knapsack Problem does not have a greedy solution!



The 0-1 Knapsack Problem does not have a greedy solution!



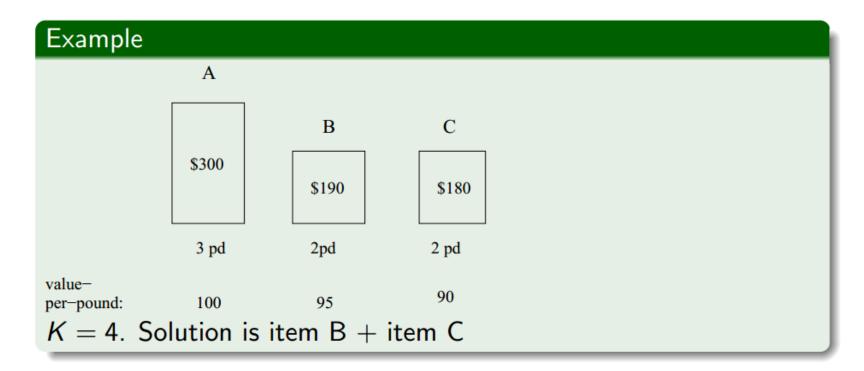
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Question

Suppose we try to prove the greedy algorithm for 0-1 knapsack problem is correct.

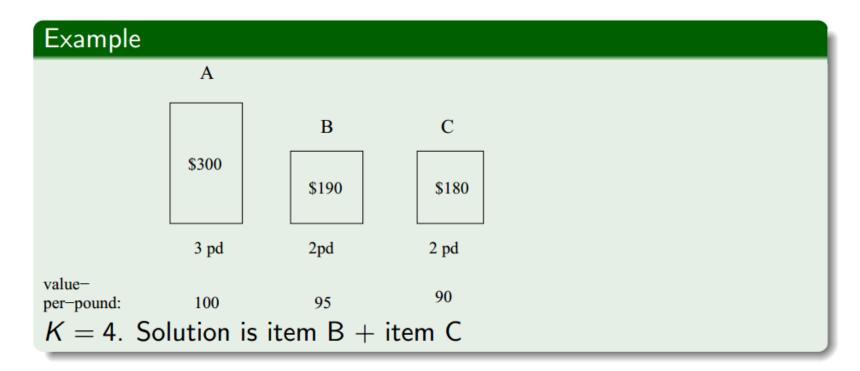
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Suppose we try to prove the greedy algorithm for 0-1 knapsack problem is correct. We follow exactly the same lines of arguments as fractional knapsack problem.

The 0-1 Knapsack Problem does not have a greedy solution!



Question

Suppose we try to prove the greedy algorithm for 0-1 knapsack problem is correct. We follow exactly the same lines of arguments as fractional knapsack problem. Of course, it must fail. Where is the problem in the proof?

Outline

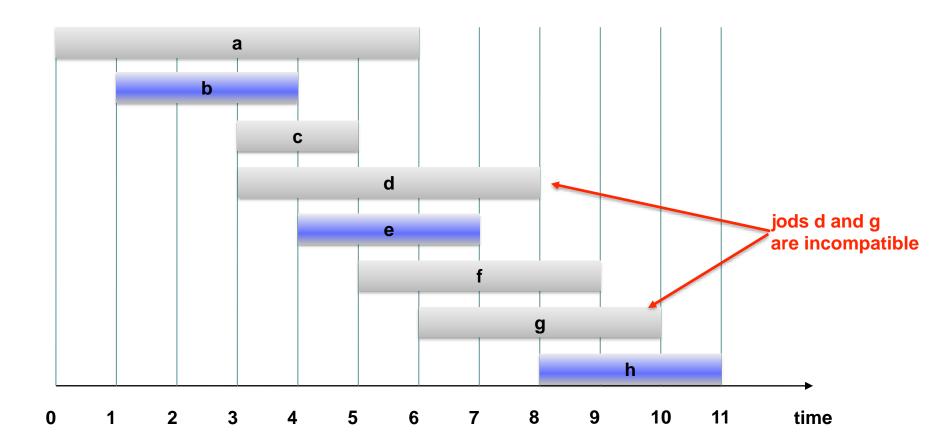
Introduction to Part V

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Interval Scheduling

- Job j starts at s_i and finishes at f_j .
- Two jobs compatible if they don't overlap.
- Goal: find maximum subset of mutually compatible jobs.



Interval Scheduling: greedy algorithms

Greedy template. Consider jobs in some natural order.

Take each job provided it's compatible with the ones already taken.

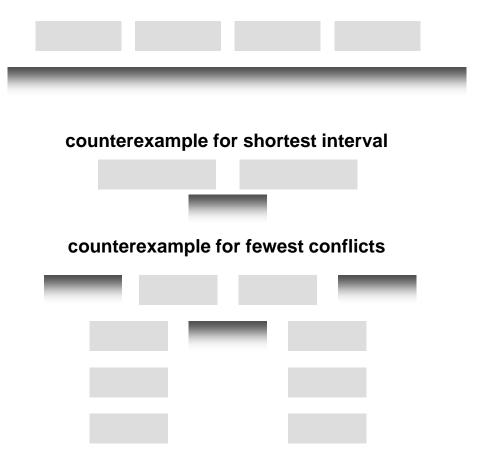
- \mathbb{O} [Earliest start time] Consider jobs in ascending order of $s_{j.}$
- \mathbb{O} [Earliest finish time] Consider jobs in ascending order of f_{j} .
- \mathbb{O} [Shortest interval] Consider jobs in ascending order of f_j $s_{j.}$
- $\mathbf{0}$ [Fewest conflicts] For each job j, count the number of conflicting jobs c_j . Schedule in ascending order of c_{j} .

Interval Scheduling: greedy algorithms

Greedy template. Consider jobs in some natural order.

Take each job provided it's compatible with the ones already taken.

counterexample for earliest start time



Interval Scheduling: earliest-finish-time-first algorithm

Earliest-Finish-Time-First $(n, s_1, s_2, ..., s_n, f_1, f_2, ..., f_n)$

```
Input: n jobs with start time s_i and finish time f_i.

Output: Schedule with maximum compatible jobs..

Sort jobs by finish time so that f_1 \leq f_2 \leq ... \leq f_n.

A \leftarrow \emptyset; for j \leftarrow 1 to n do

| if job j is compatible with A then
| A \leftarrow A \cup \{j\};
| end
| end
| return A;
```

Proposition. Can implement earliest-finish-time first in O(nlogn) time.

- $\mathbf{\Phi}$ Keep track of job j^* that was added last to A.
- **©**Job *j* is compatible with A iff $s_i \ge f_{i^*}$
- **©**Sorting by finish time takes O(*nlogn*) time.

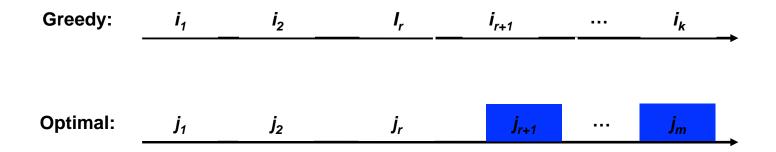
Interval Scheduling: earliest-finish-time-first algorithm

Theorem. The earliest-finish-time algorithm is optimal.

Pf.[by contradiction]

- Assume greedy is not optimal, and let's see what happens.
- **O**Let's i_1 , i_2 , ... i_k denote set of jobs selected by greedy.
- **©**Let $j_1, j_2, ... j_m$ denote set of in an optimal solution with $i_1 = j_1, i_2 = j_2, ... i_r = j_r$ for the largest possible value for r.

job i_{r+1} exists and finishes before j_{r+1}



job j_{r+1} exists because m > k

why not replace job j_{r+1} with job i_{r+1} ?

Interval Scheduling: earliest-finish-time-first algorithm

Theorem. The earliest-finish-time algorithm is optimal.

Pf.[by contradiction]

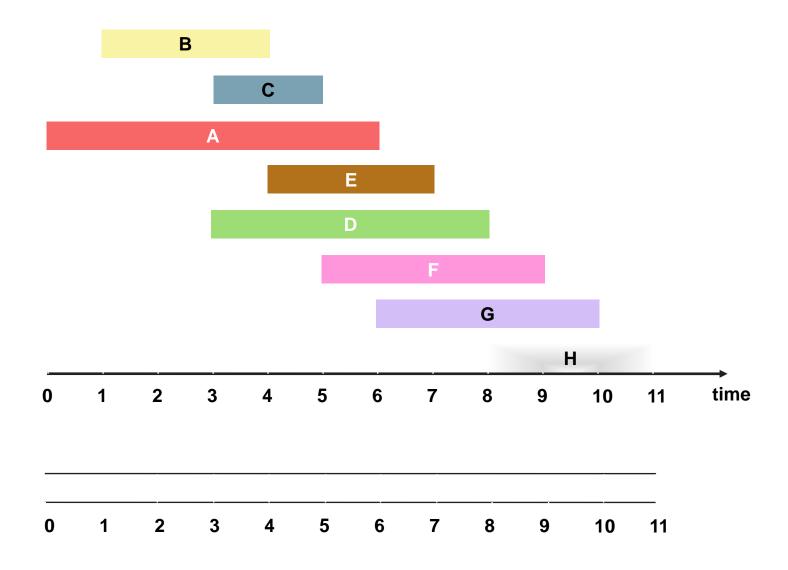
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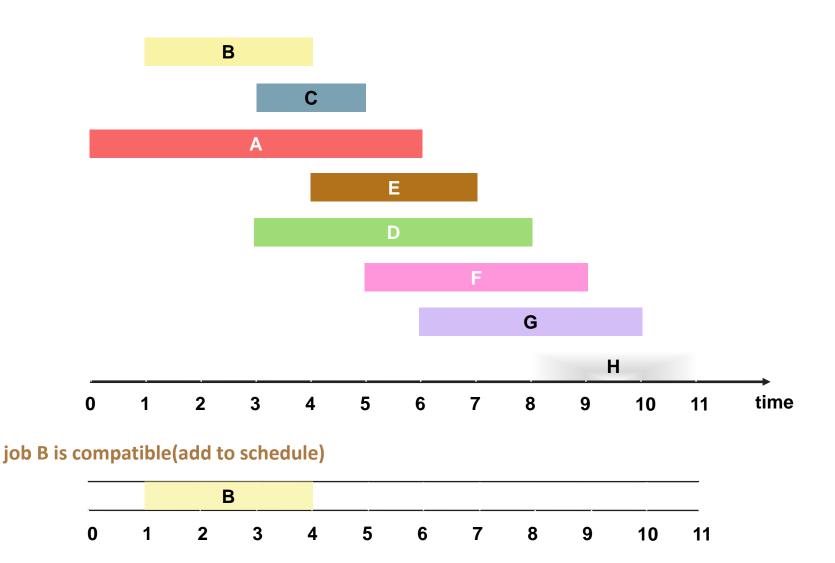
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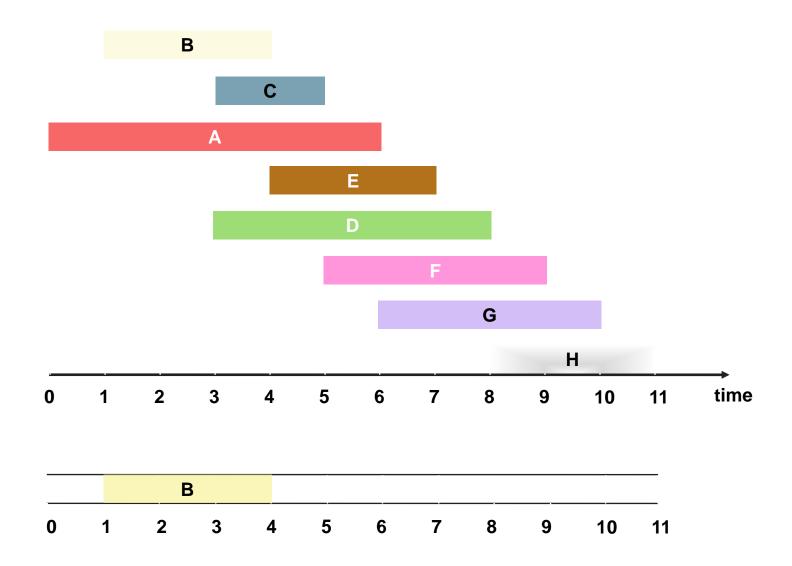
Greedy:	i ₁	i ₂	I _r	<i>i_{r+1}</i>		i _k	→
0.41							
Optimal:	\bar{J}_1	$ar{J}_2$	Ĵr	j_{r+1}	•••	Ĵ _m	

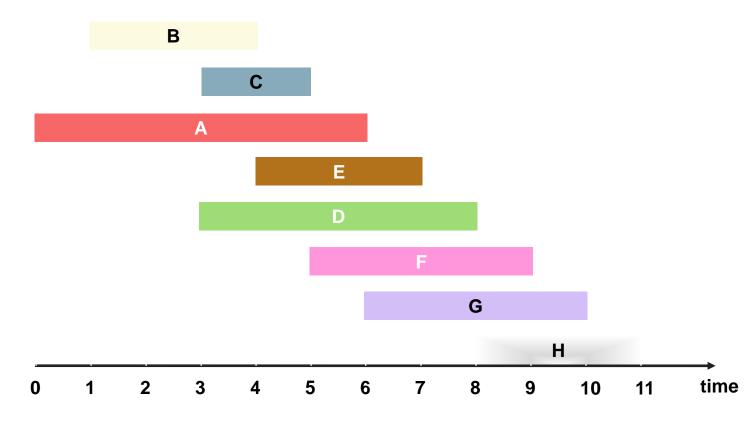
solution still feasible and optimal (but contradicts maximality of r)

Earliest-finish-time-first algorithm demo



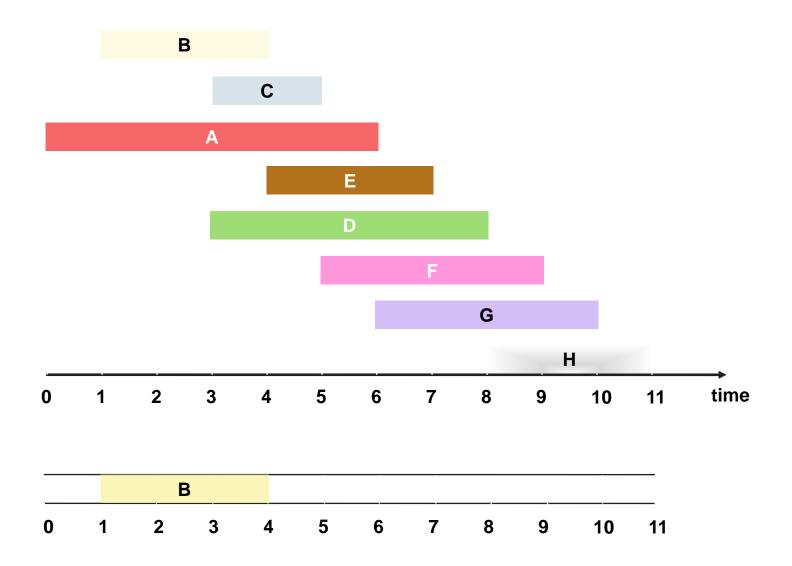


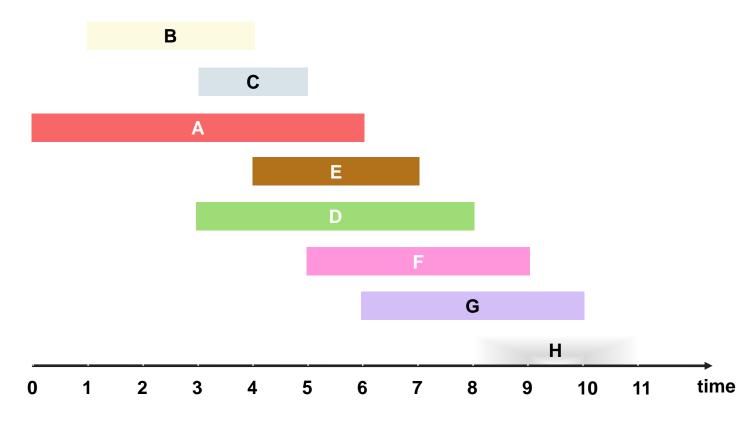




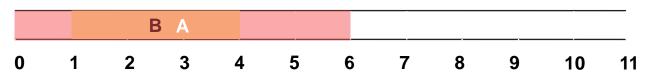
job C is incompatible(do not add to schedule)

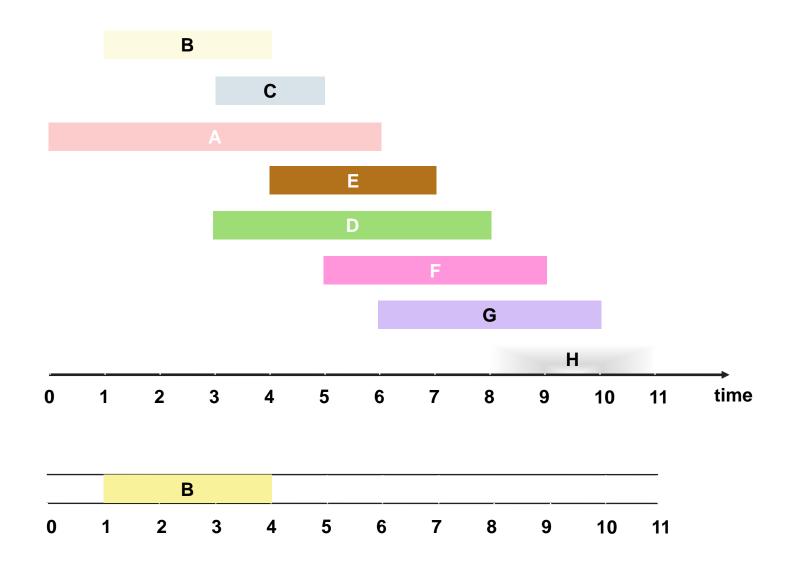


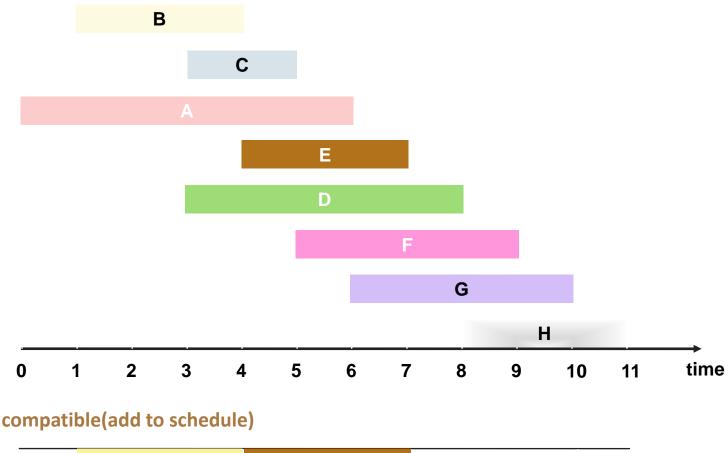




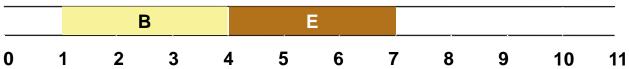
job A is incompatible(do not add to schedule)

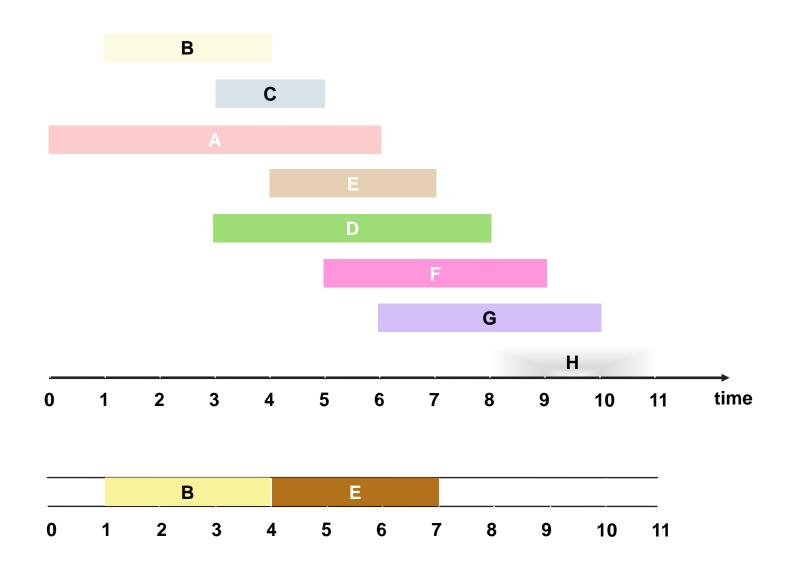


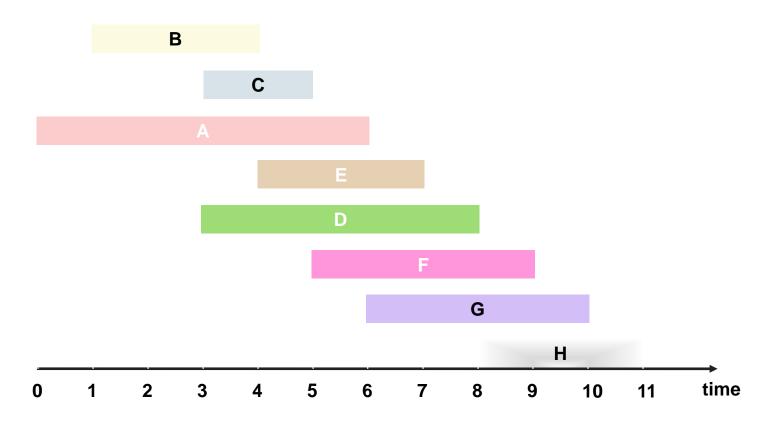




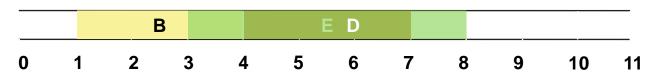


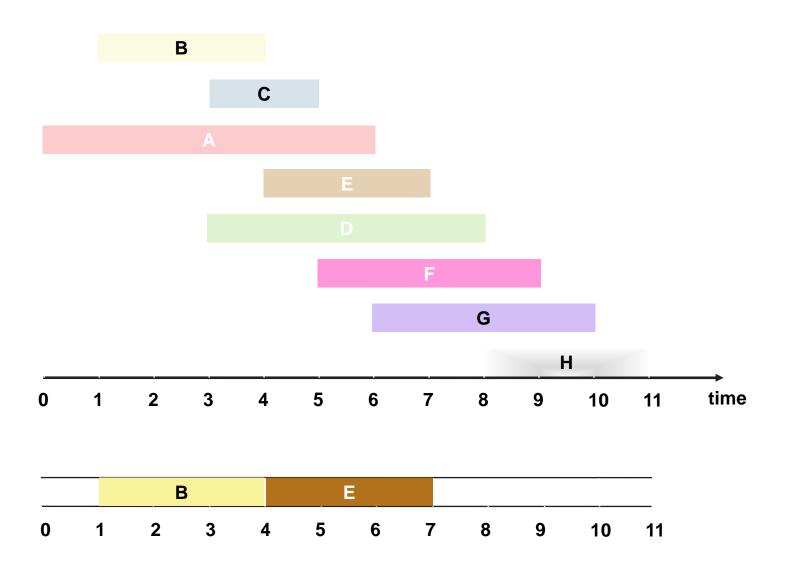


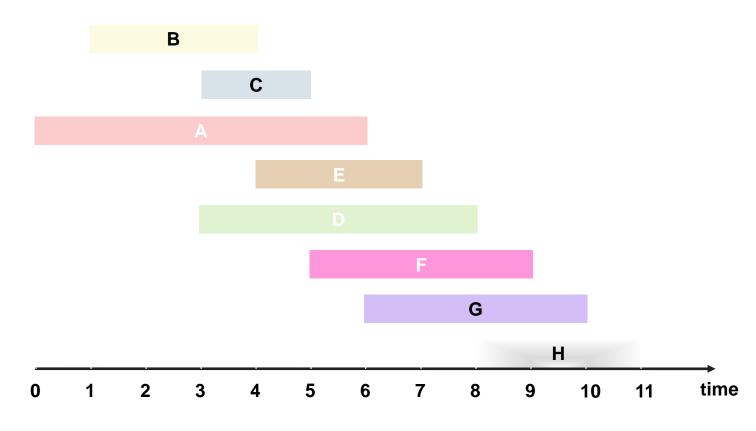




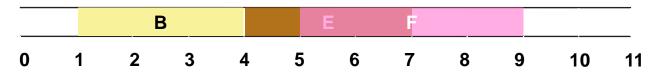
job D is incompatible(do not add to schedule)

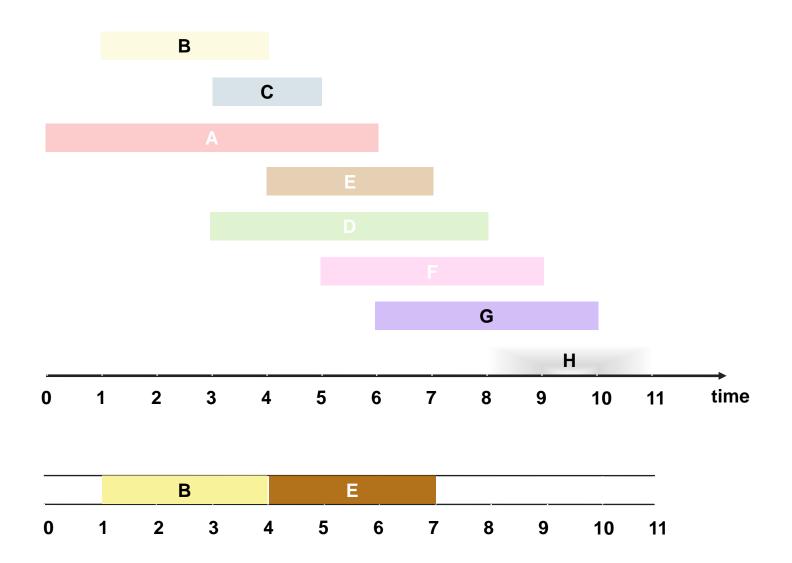


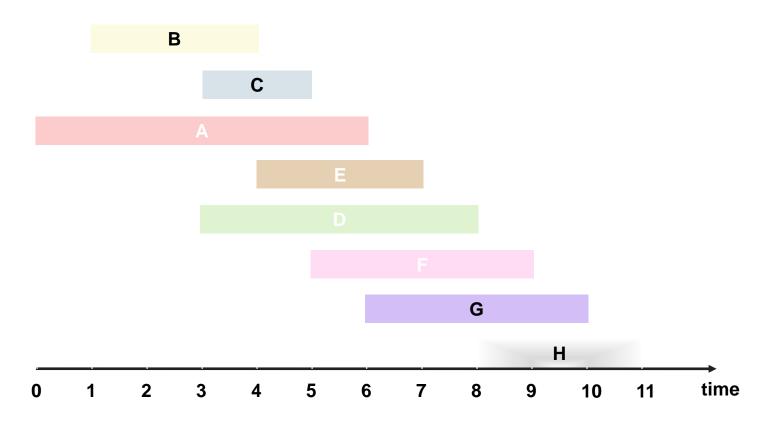




job F is incompatible(do not add to schedule)

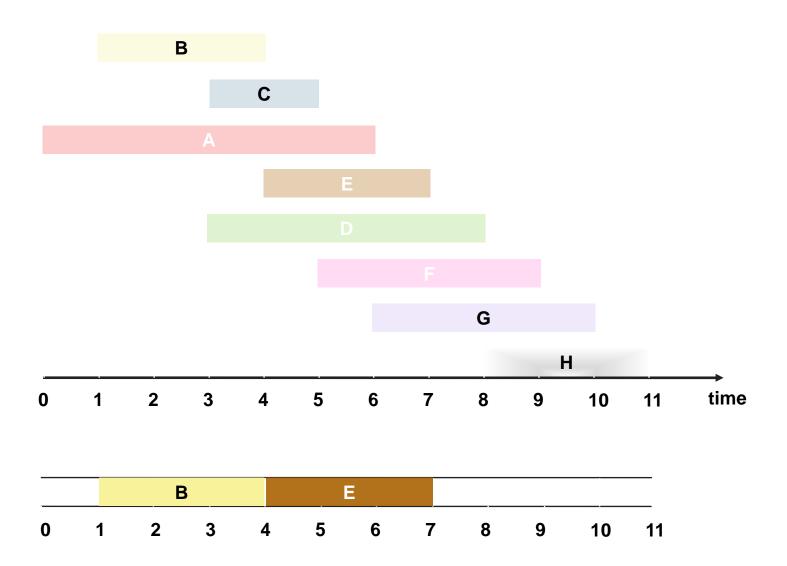


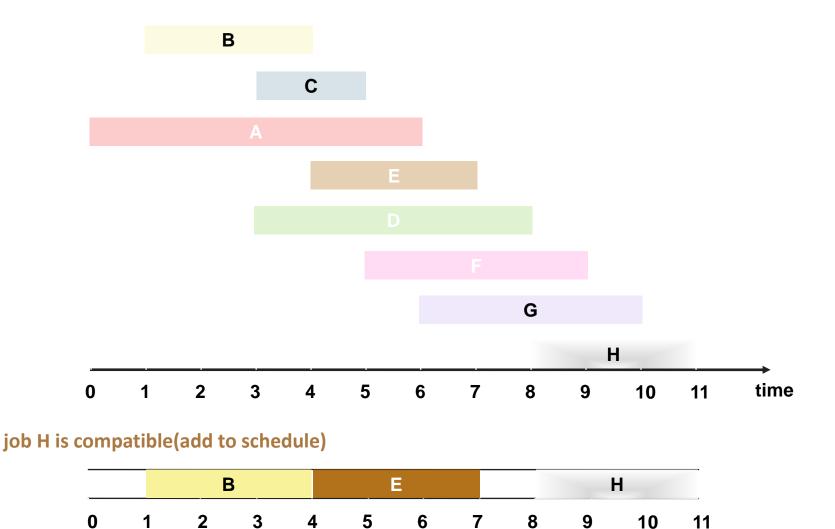


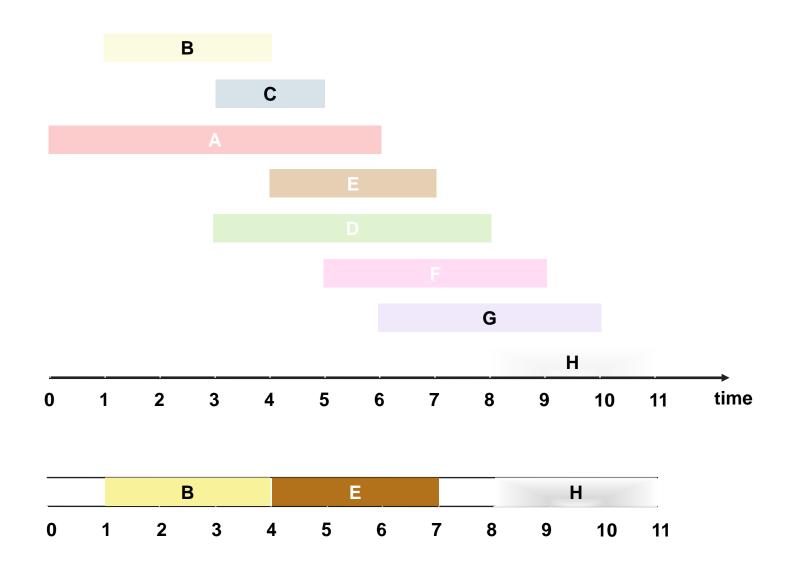


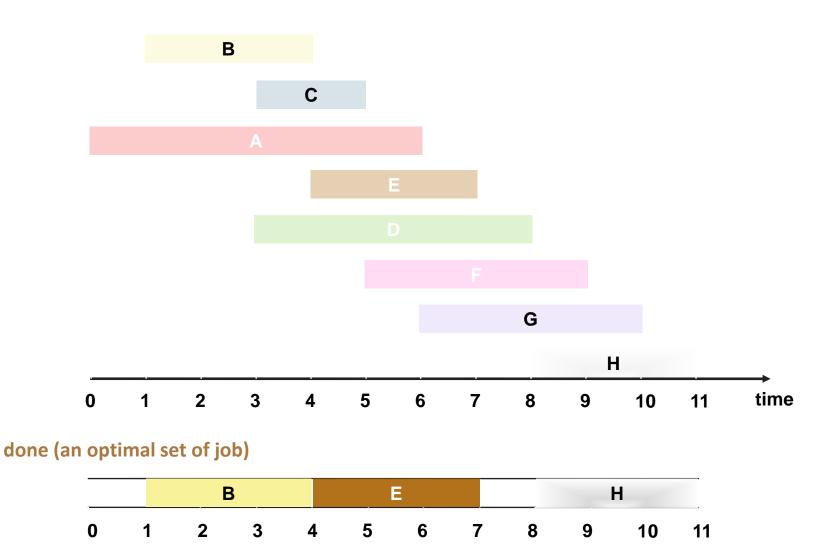
job G is incompatible(do not add to schedule)











Outline

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- The Fraction Knapsack Problem
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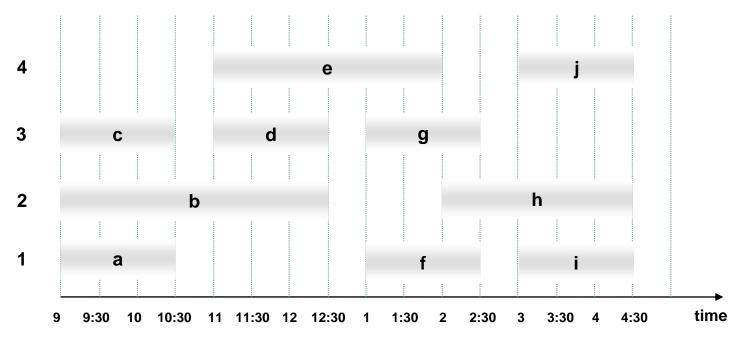
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 - Interval Partitioning

Interval Partitioning

Interval partitioning

- Lecture j starts at s_j and finishes at f_j .
- Goal: find manimum number of classrooms to schedule all lectures so that no two lectures occur at the same time in the same room.

Ex. This schedule uses 4 classrooms to schedule 10 lectures

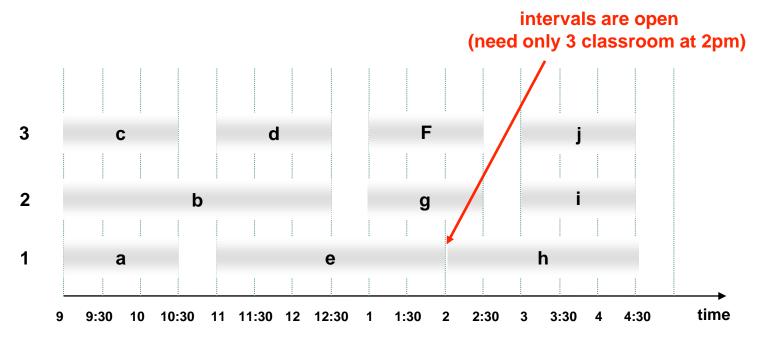


Interval Partitioning

Interval partitioning

- Lecture j starts at s_j and finishes at f_j .
- Goal: find manimum number of classrooms to schedule all lectures so that no two lectures occur at the same time in the same room.

Ex. This schedule uses 3 classrooms to schedule 10 lectures



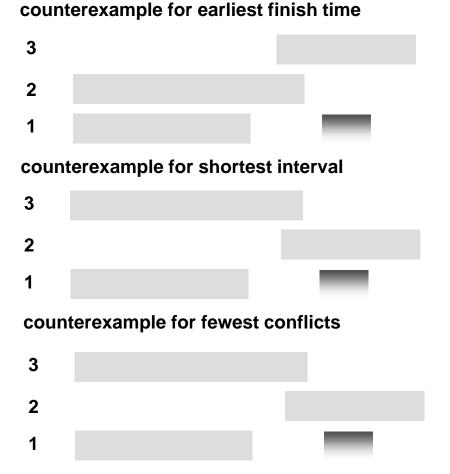
Interval Partitioning: greedy algorithms

Greedy template. Consider lectures in some natural order. Assign each lecture to an available classroom(which one?); Allocate a new classroom if none are available.

- \mathbb{O} [Earliest start time] Consider lectures in ascending order of s_{i} .
- $oldsymbol{\mathbb{O}}$ [Earliest finish time] Consider lectures in ascending order of $f_{j.}$
- \mathbf{O} [Shortest interval] Consider lectures in ascending order of f_j - $s_{i.}$
- \mathbb{O} [Fewest conflicts] For each lecture j, count the number of conflicting lectures c_i . Schedule in ascending order of c_i .

Interval Partitioning: greedy algorithms

Greedy template. Consider lectures in some natural order. Assign each lecture to an available classroom(which one?); Allocate a new classroom if none are available.



Interval Partitioning: earliest-start-time-first algorithm

Earliest-Start-Time-First $(n, s_1, s_2, ..., s_n, f_1, f_2, ..., f_n)$

```
Input: n jobs with start time s_i and finish time f_i.
Output: Schedule with minimum number of classrooms.
Sort lectures by finish time so that s_1 \leq s_2 \leq ... \leq s_n.
d \leftarrow 0;
for j = 1 to n do
   if Lecture j is compatible with some classroom then
       Schedule lecture j in any such class room k;
   end
   else
       Allocate a new classroom d + l;
       Schedule lecture j in classroom d + l;
   end
end
return schedule;
```

Interval Partitioning: earliest-start-time-first algorithm

Proposition. The earliest-time-first algorithm can be implemented in $O(n \log n)$ time.

- Pf. Store classroom in a priority queue (key = finish time of its last lecture).
 - **©**To determine whether lecture j is compatible with some classroom, compare s_j to key min classroom k in priority queue.
 - **©**To add lecture j to classroom k, increase key of classroom k to f_i .
 - **©**Total number of priority queue operation is O(n).
 - \odot Sorting by start time takes $O(n \log n)$ time.

Remark. This implement chooses a classroom *k* whose finish time of its last lecture is the earliest.

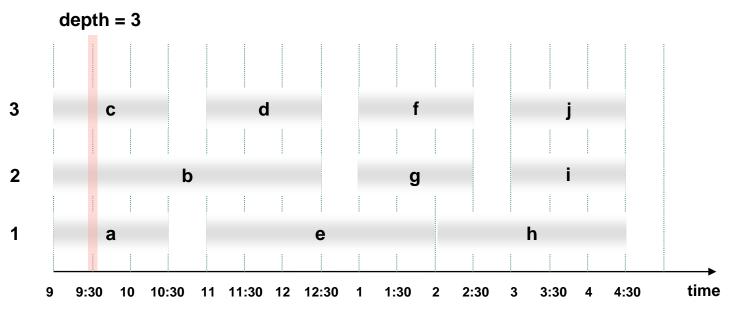
Interval Partitioning: lower bound on optimal solution

Def. The depth of a set of open interval is the maximum number of intervals that contain any given time.

Key observation. Number of classrooms needed ≥ depth.

Q. Does minimum number of classrooms needed always equal depth?

A. Yes! Moreover, earliest-start-time-first algorithm finds a schedule whose number of classrooms equals the depth.



Interval Partitioning:analysis of earliest-start-time-first algorithm

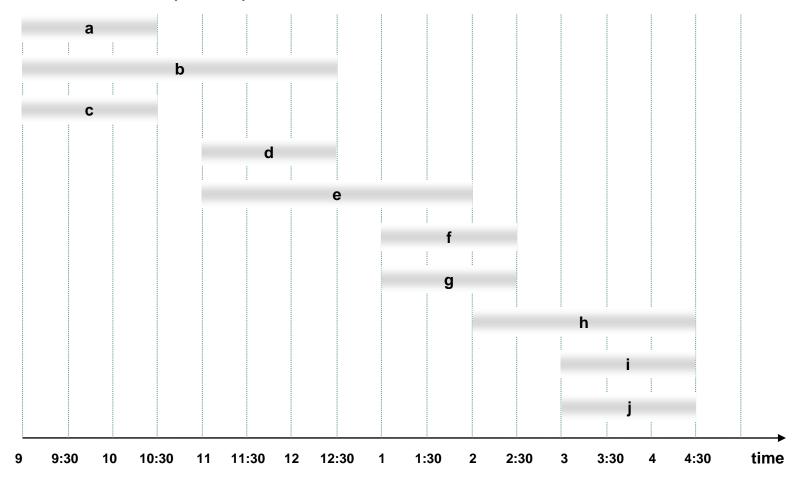
Observation. The earliest-start-time-first algorithm never schedules two incompatible lectures in the same classroom.

Theorem. Earliest-start-time-first algorithm is optimal. Pf.

- $\mathbf{\Phi}$ Let d = number of classrooms that the algorithm allocates.
- **©**Classroom d is opened because we needed to schedule a lecture, say j, that is incompatible with all d-1 other classrooms.
- **©**These d lectures each end after s_i .
- **©**Since we sorted by start time, all these incompatibilities are caused by lectures that start no later than s_i .
- **©**Thus, we have d lectures overlapping at time $s_i + \epsilon$.
- **©**Key observation => all schedules use $\ge d$ classrooms.

Consider lectures in order of start time:

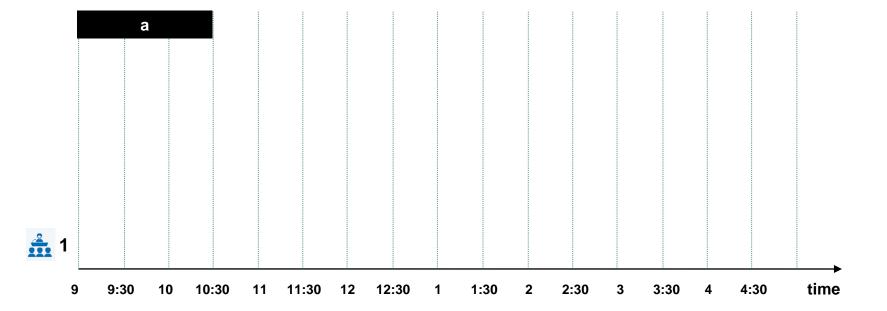
- Assign next lecture to any compatible classroom (if ones exists).
- Otherwise, open up a new classroom.



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- Otherwise, open up a new classroom.

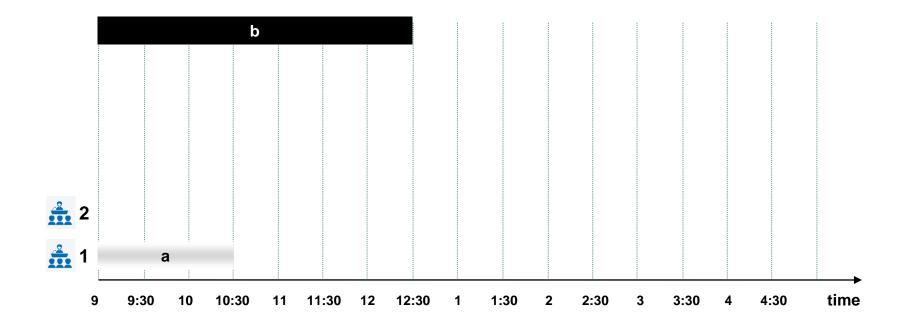
No compatible classroom: open up a new classroom and assign lecture to it.



Consider lectures in order of start time:

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- Otherwise, open up a new classroom.

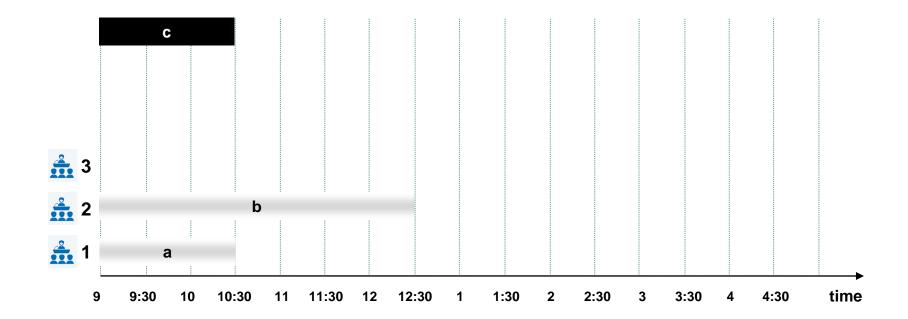
No compatible classroom: open up a new classroom and assign lecture to it.



Consider lectures in order of start time:

- **O**Assign next lecture to any compatible classroom (if ones exists).
- Otherwise, open up a new classroom.

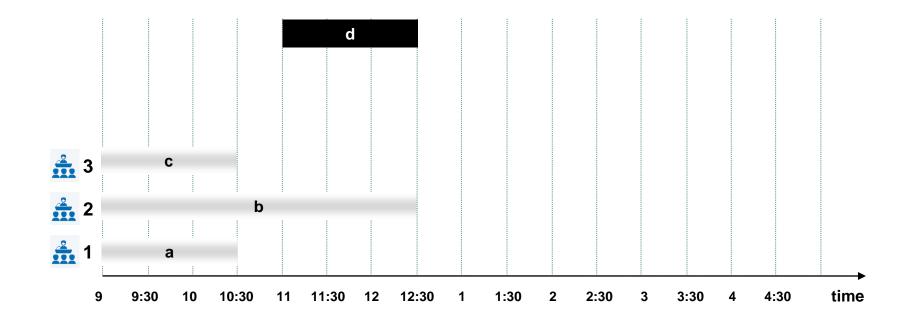
No compatible classroom: open up a new classroom and assign lecture to it.



Consider lectures in order of start time:

- Assign next lecture to any compatible classroom (if ones exists).
- Otherwise, open up a new classroom.

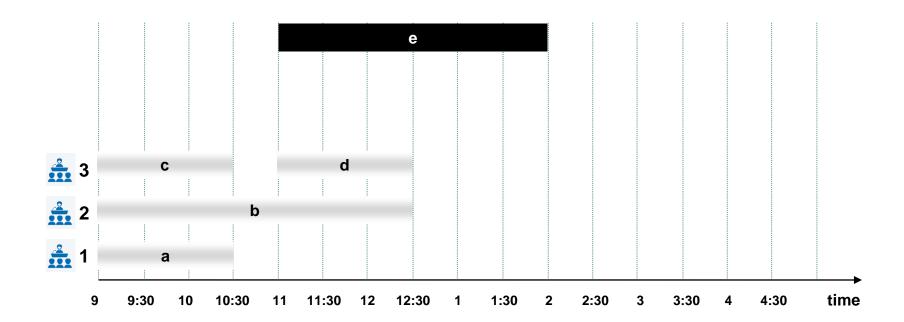
lecture d is compatible with classroom 1 and 3



Consider lectures in order of start time:

- Assign next lecture to any compatible classroom (if ones exists).
- Otherwise, open up a new classroom.

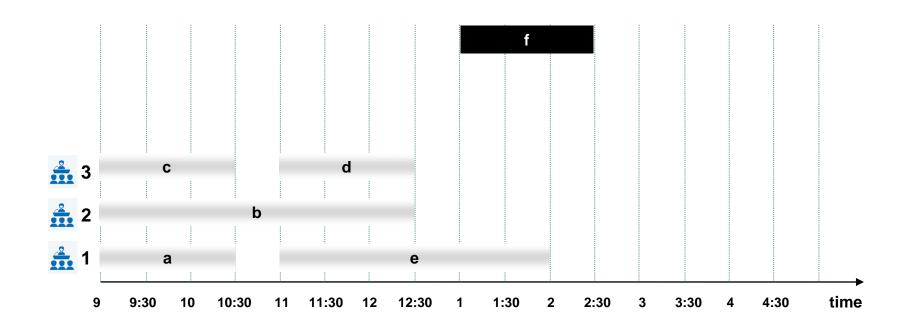
lecture e is compatible with classroom 1



Consider lectures in order of start time:

- Assign next lecture to any compatible classroom (if ones exists).
- Otherwise, open up a new classroom.

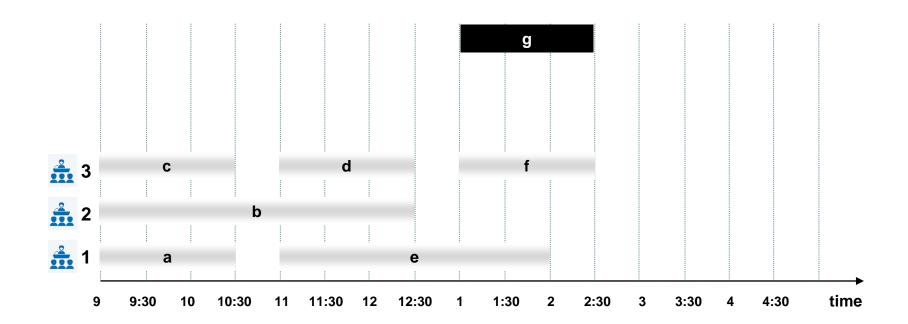
lecture f is compatible with classroom 2 and 3



Consider lectures in order of start time:

- Assign next lecture to any compatible classroom (if ones exists).
- Otherwise, open up a new classroom.

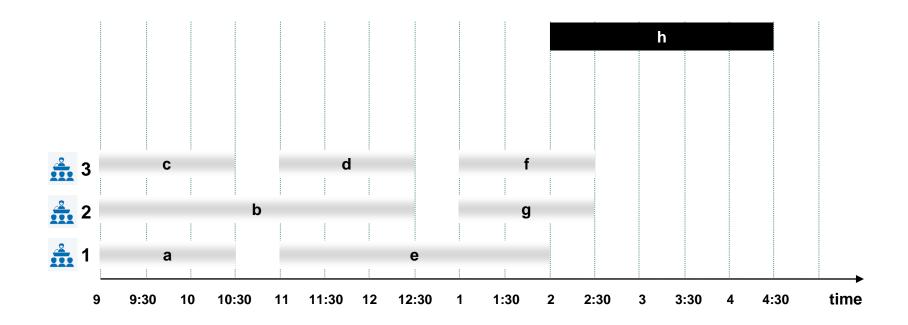
lecture g is compatible with classroom 2



Consider lectures in order of start time:

- Assign next lecture to any compatible classroom (if ones exists).
- Otherwise, open up a new classroom.

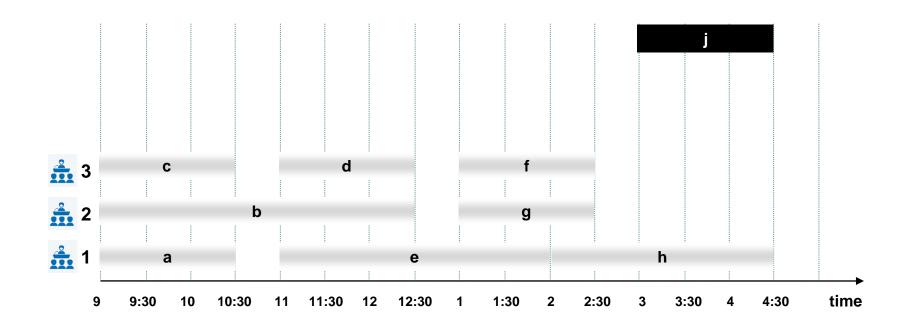
lecture h is compatible with classroom 1



Consider lectures in order of start time:

- Assign next lecture to any compatible classroom (if ones exists).
- Otherwise, open up a new classroom.

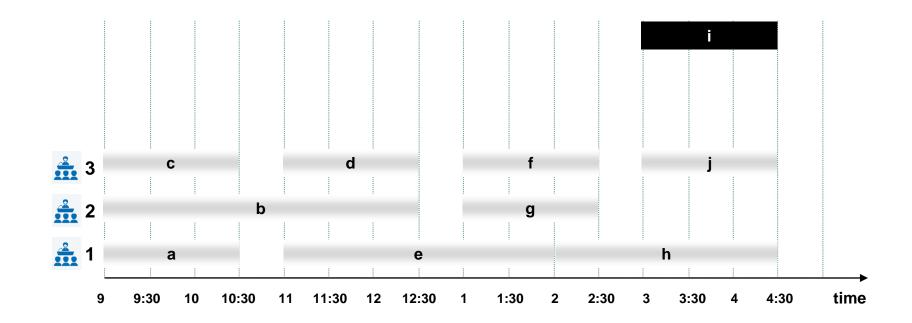
lecture j is compatible with classroom 2 and 3



Consider lectures in order of start time:

- Assign next lecture to any compatible classroom (if ones exists).
- Otherwise, open up a new classroom.

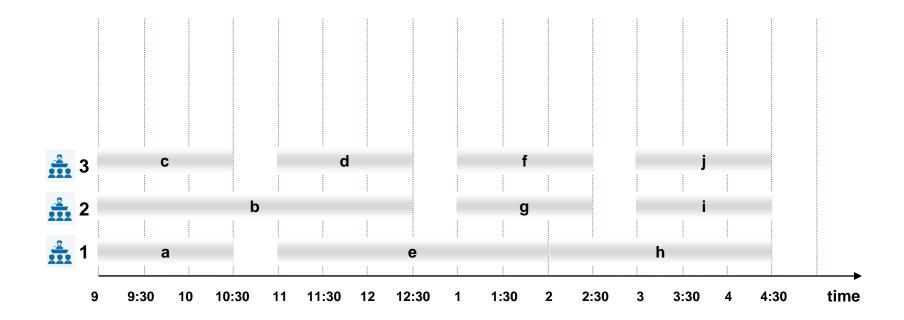
lecture i is compatible with classroom 2



Consider lectures in order of start time:

- Assign next lecture to any compatible classroom (if ones exists).
- **O**Otherwise, open up a new classroom.

done



dank u Tack ju faleminderit Asante ipi Tak mulţumesc

Salamat! Gracias
Terima kasih Aliquam

Merci Dankie Obrigado
köszönöm Grazie

Aliquam Go raibh maith agat
děkuji Thank you

gam