BBM 202 - ALGORITHMS

HACETTEPE UNIVERSITY

DEPT. OF COMPUTER ENGINEERING

GREEDY ALGORITHMS

Acknowledgement: The course slides are adapted from the slides prepared by K. Wayne of Princeton University.

Greedy Choice

- Optimal substructure property exploited by both Greedy and DP strategies
- Greedy Choice Property: A sequence of locally optimal choices ⇒ an optimal solution
 - We make the choice that seems best at the moment
 - Then solve the subproblem arising after the choice is made

DP: We also make a choice/decision at each step, but the choice may depend on the optimal solutions to subproblems

Greedy: The choice may depend on the choices made so far, but it cannot depend on any future choices or on the solutions to subproblems

Proof of Correctness

- Examine a globally optimal solution
- Apply induction to show that a greedy choice can be used at every step
- Show that this solution can be modified so that
 - 1.A greedy choice is made as the first step
 - 2. This choice reduces the problem to a similar but smaller problem

Showing (2) reduces the proof of correctness to proving that the problem exhibits optimal substructure property

Proof of Correctness

Greedy Choice Property: A globally optimal solution can be arrived at by making locally optimal (greedy) choices

- In DP, we make a choice at each step but the choice may depend on the solutions to subproblems
- In Greedy Algorithms, we make the choice that seems best at that moment then solve the subproblems arising after the choice is made
 - The choice may depend on choices so far, but it cannot depend on any future choice or on the solutions to subproblems
- DP solves the problem bottom-up
- Greedy usually progresses in a top-down fashion by making one greedy choice after another reducing each given problem instance to a smaller one

Proof of Correctness

- We must prove that a greedy choice at each step yields a globally optimal solution
- The proof examines a globally optimal solution
- Shows that the solution can be modified so that a greedy choice made as the first step reduces the problem to a similar but smaller subproblem
- Then induction is applied to show that a greedy choice can be used at each step
- Hence, this induction proof reduces the proof of correctness to demonstrating that an optimal solution must exhibit optimal substructure property

Optimal Substructure

- Optimal substructure property is exploited by both Greedy and dynamic programming strategies
- Hence one may
 - Try to generate a dynamic programming solution to a problem when a greedy strategy suffices
 - Or, may mistakenly think that a greedy solution works when in fact a DP solution is required

Example: Knapsack Problems(S, w)

Knapsack Problems

The 0-1Knapsack Problem (S,W)

- A thief robbing a store finds n items $S = \{i_1, i_2, \dots, i_n\}$, the *i*th item is worth v_i dollars and weighs w_i pounds, where v_i and w_i are integers
- He wants to take as valuable a load as possible, but he can carry at most W pounds in his knapsack, where W is an integer
- The thief cannot take a fractional amount of an item

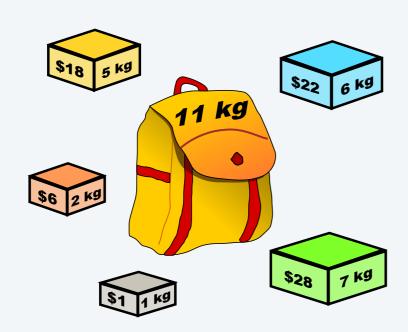
The Fractional Knapsack Problem (S, W)

- The scenario is the same
- But, the thief can take fractions of items rather than having to make binary (0-1)
 choice for each item

Knapsack Problems

Although the problems are similar

- the Fractional Knapsack Problem is solvable by Greedy strategy
- whereas, the 0-1 Knapsack Problem is not



i	v_i	W_i	_
1	\$1	1 kg	
2	\$6	2 kg	weights and values can be arbitrary
3	\$18	5 kg	positive integers
4	\$22	6 kg	
5	\$28	7 kg	

knapsack instance (weight limit W = 11)

Greedy Solution to Fractional Knapsack

- 1. Compute the value per pound v_i/w_i for each item
- 2. The thief begins by taking, as much as possible, of the item with the greatest value per pound
- 3.If the supply of that item is exhausted before filling the knapsack he takes, as much as possible, of the item with the next greatest value per pound
- 4.Repeat (2-3) until his knapsack becomes full

Thus, by sorting the items by value per pound the greedy algorithm runs in O(nlogn) time

GREEDY ALGORITHMS

- coin changing
- interval scheduling
- interval partitioning
- scheduling to minimize lateness
- optimal caching

Coin changing

Goal. Given U. S. currency denominations { 1, 5, 10, 25, 100 }, devise a method to pay amount to customer using fewest coins.

Ex. 34¢.



Cashier's algorithm. At each iteration, add coin of the largest value that does not take us past the amount to be paid.

Ex. \$2.89.



Cashier's algorithm

At each iteration, add coin of the largest value that does not take us past the amount to be paid.

```
CASHIERS-ALGORITHM (x, c_1, c_2, ..., c_n)
SORT n coin denominations so that 0 < c_1 < c_2 < ... < c_n.
S \leftarrow \emptyset. \leftarrow multiset of coins selected
WHILE (x > 0)
  k \leftarrow \text{largest coin denomination } c_k \text{ such that } c_k \leq x.
  IF (no such k)
      RETURN "no solution."
  ELSE
       x \leftarrow x - c_k.
      S \leftarrow S \cup \{k\}.
RETURN S.
```

Cashier's algorithm (for arbitrary coin denominations)

- Q. Is cashier's algorithm optimal for any set of denominations?
- A. No. Consider U.S. postage: 1, 10, 21, 34, 70, 100, 350, 1225, 1500.
 - Cashier's algorithm: 140¢ = 100 + 34 + 1 + 1 + 1 + 1 + 1 + 1.
 - Optimal: 140¢ = 70 + 70.



















- A. No. It may not even lead to a feasible solution if $c_1 > 1$: 7, 8, 9.
 - Cashier's algorithm: 15¢ = 9 + ?.
 - Optimal: 15¢ = 7 + 8.

Properties of any optimal solution (for U.S. coin denominations)

Property. Number of pennies ≤ 4 .

Pf. Replace 5 pennies with 1 nickel.

Property. Number of nickels ≤ 1 .

Property. Number of quarters ≤ 3 .

Property. Number of nickels + number of dimes ≤ 2 . Pf.

- Recall: ≤ 1nickel.
- Replace 3 dimes and 0 nickels with 1 quarter and 1 nickel;
- Replace 2 dimes and 1 nickel with 1 quarter.



Optimality of cashier's algorithm (for U.S. coin denominations)

Theorem. Cashier's algorithm is optimal for U.S. coins { 1, 5, 10, 25, 100 }.

Pf. [by induction on amount to be paid x]

- Consider optimal way to change $c_k \le x < c_{k+1}$: greedy takes coin k.
- We claim that any optimal solution must take coin k.
 - if not, it needs enough coins of type $c_1, ..., c_{k-1}$ to add up to x
 - table below indicates no optimal solution can do this
- Problem reduces to coin-changing $x c_k$ cents, which, by induction, is optimally solved by cashier's algorithm. \blacksquare

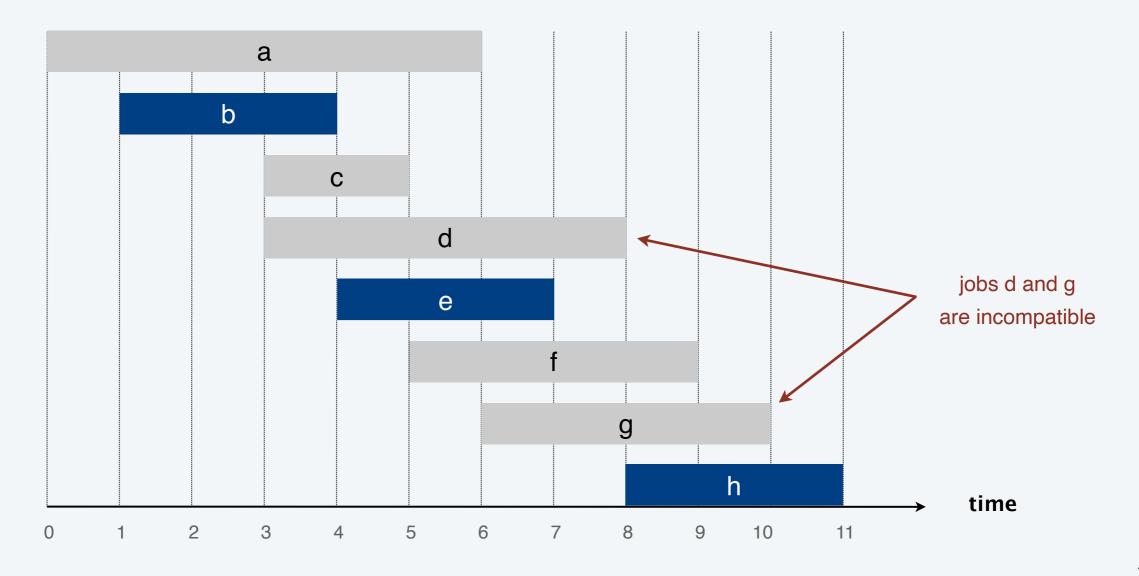
k	c_k	all optimal solutions must satisfy	max value of coin denominations $c_1, c_2,, c_{k-1}$ in any optimal solution
1	1	$P \leq 4$	-
2	5	$N \leq 1$	4
3	10	$N+D \leq 2$	4 + 5 = 9
4	25	$Q \leq 3$	20 + 4 = 24
5	100	no limit	75 + 24 = 99

GREEDY ALGORITHMS

- coin changing
- interval scheduling
- interval partitioning
- scheduling to minimize lateness
- optimal caching

Interval scheduling

- Job j starts at s_j and finishes at f_j .
- Two jobs are 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.

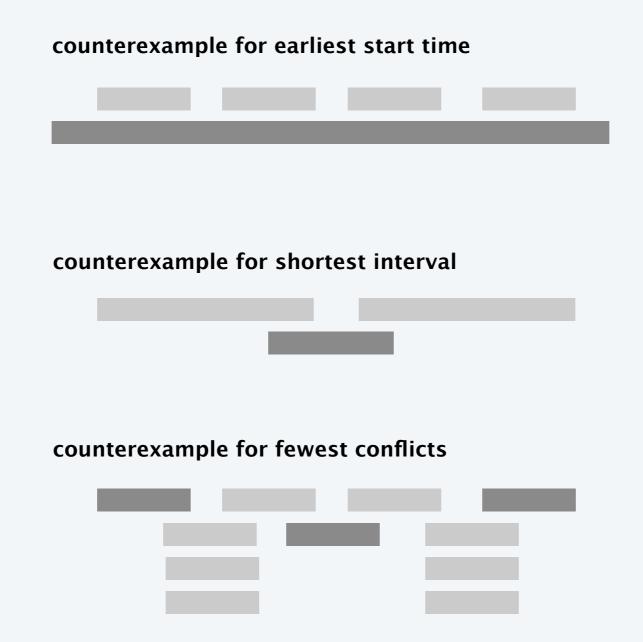
Take each job provided it's compatible with the ones already taken.

- [Earliest start time] Consider jobs in ascending order of s_j .
- [Earliest finish time] Consider jobs in ascending order of f_j .
- [Shortest interval] Consider jobs in ascending order of $f_i s_j$.
- [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.



Interval scheduling: earliest-finish-time-first algorithm

EARLIEST-FINISH-TIME-FIRST $(n, s_1, s_2, ..., s_n, f_1, f_2, ..., f_n)$

SORT jobs by finish times and renumber so that $f_1 \le f_2 \le ... \le f_n$.

$$S \leftarrow \emptyset$$
. \longleftarrow set of jobs selected

FOR
$$j = 1$$
 TO n

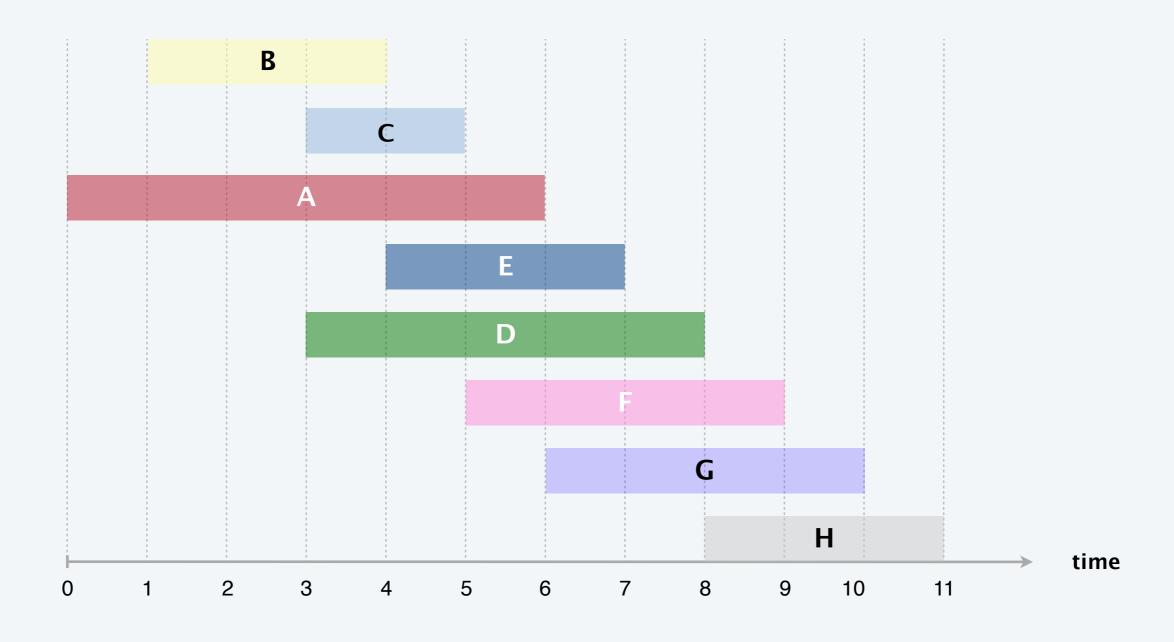
IF (job *j* is compatible with *S*)

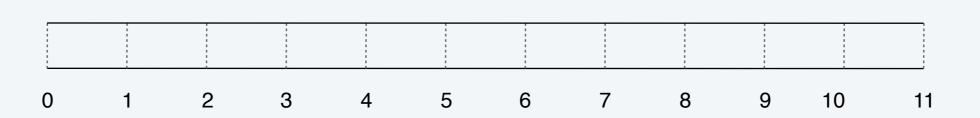
$$S \leftarrow S \cup \{ j \}.$$

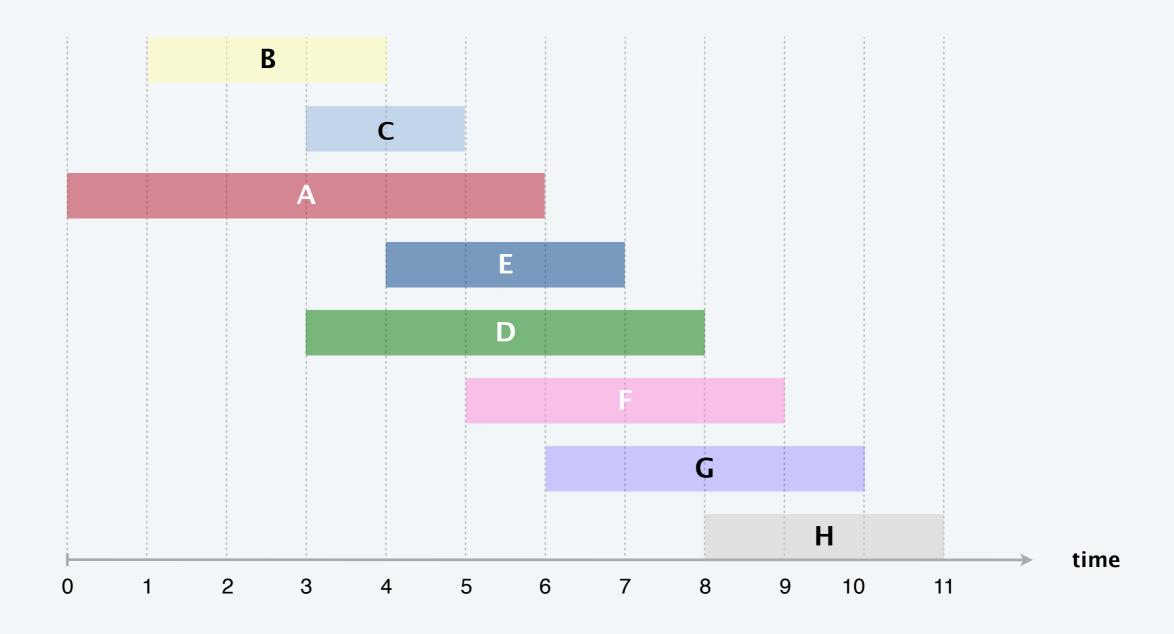
RETURN S.

Proposition. Can implement earliest-finish-time first in $O(n \log n)$ time.

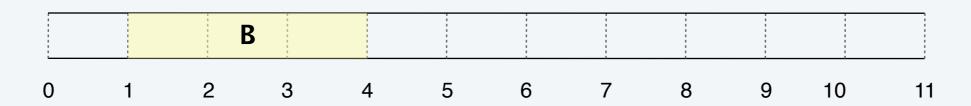
- Keep track of job j^* that was added last to S.
- Job *j* is compatible with *S* iff $s_j \ge f_{j^*}$.
- Sorting by finish times takes $O(n \log n)$ time.

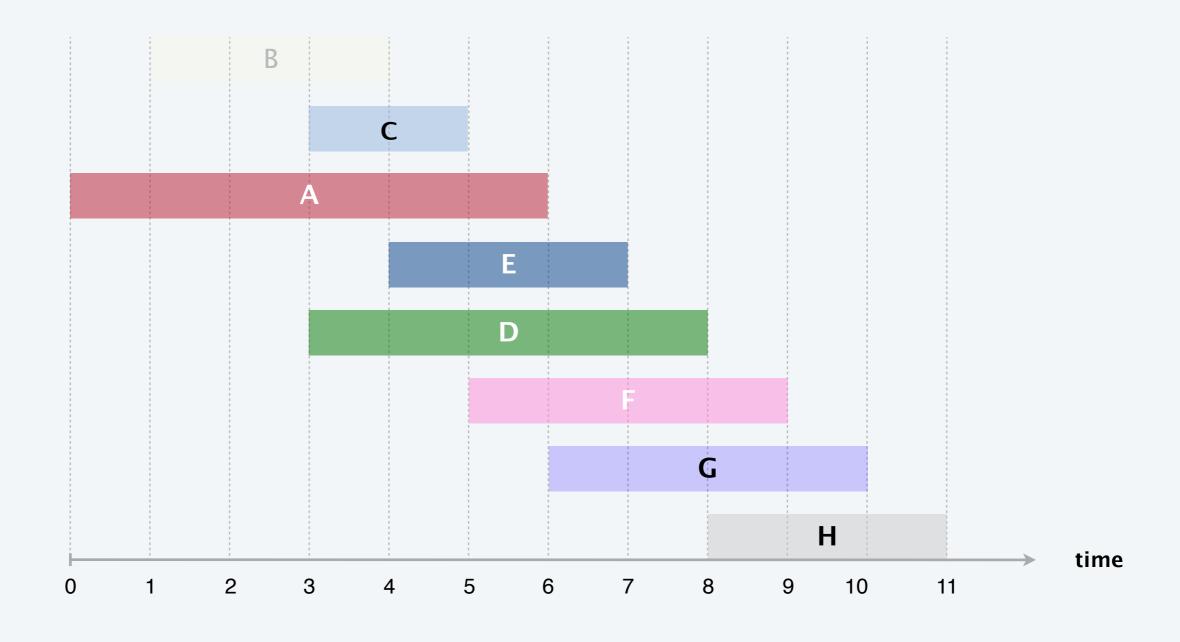


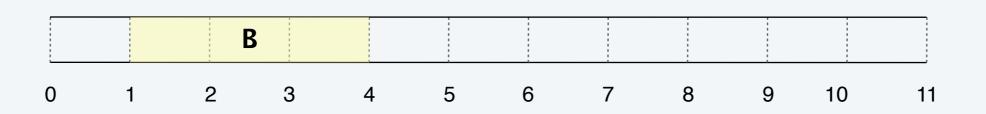


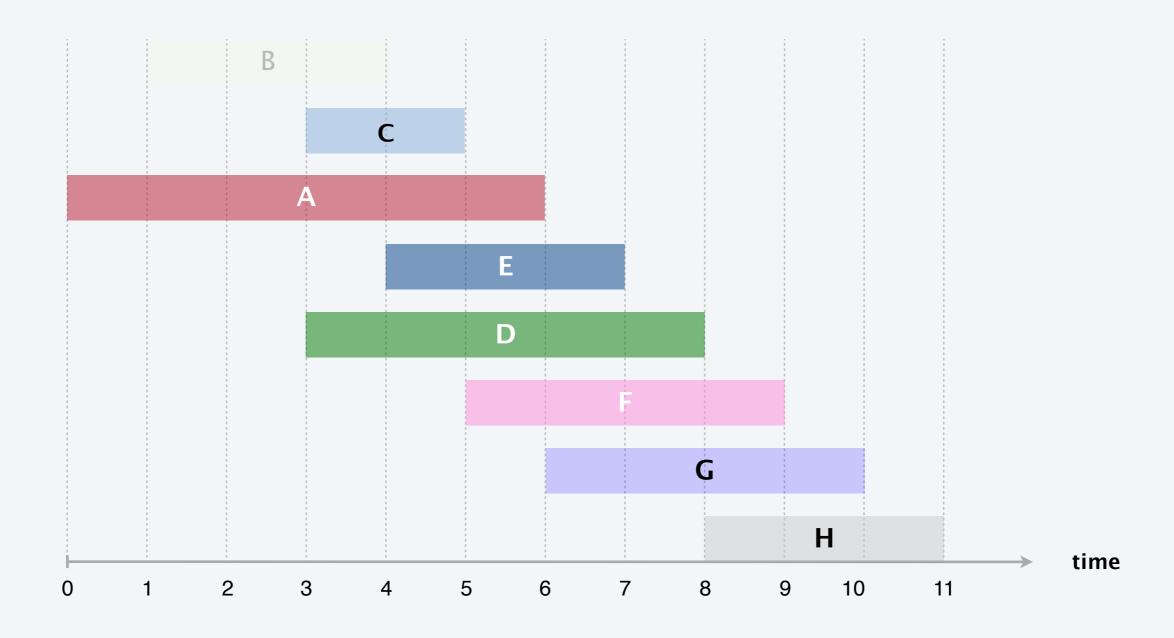


job B is compatible (add to schedule)

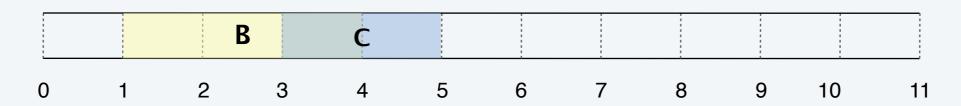


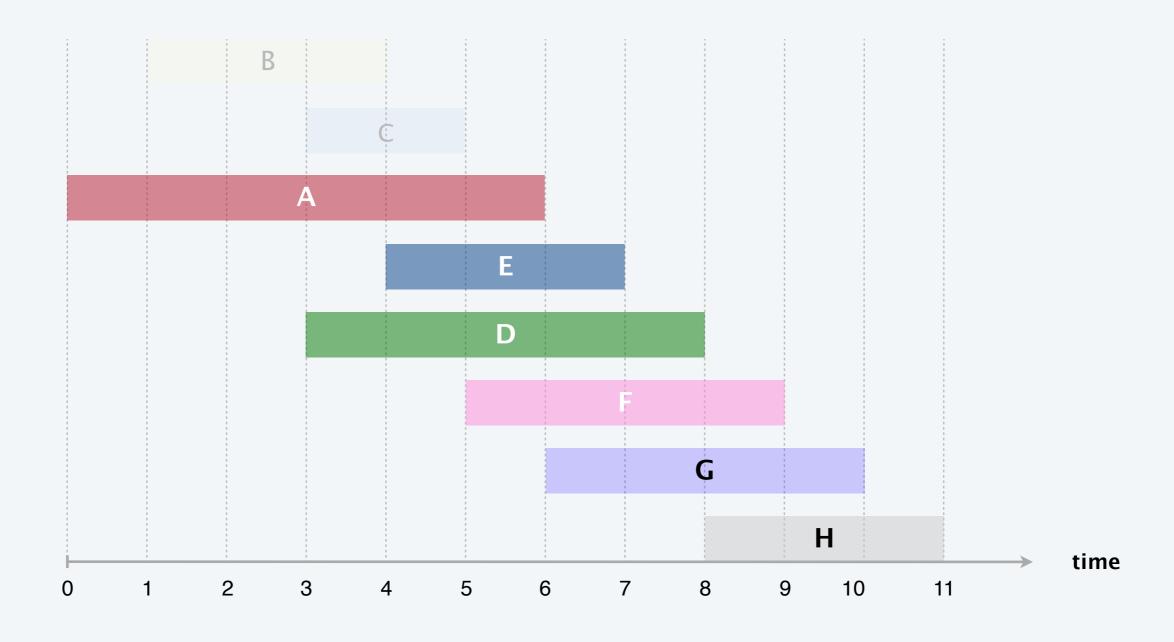


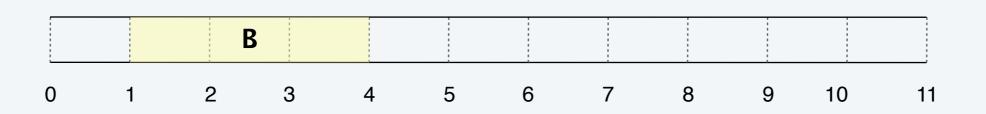


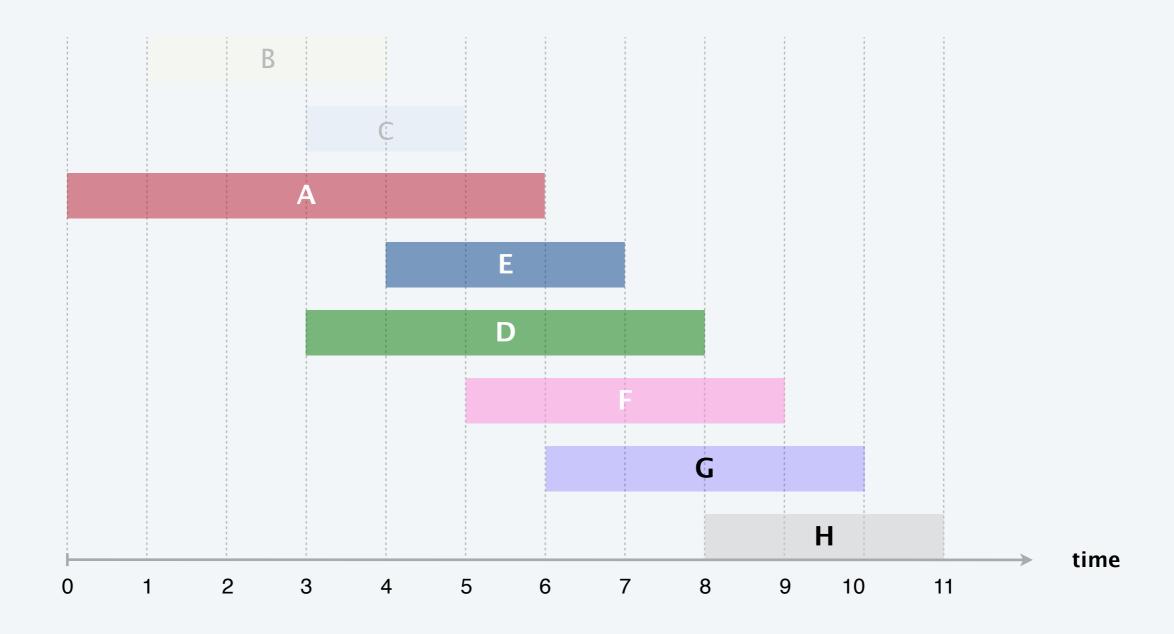


job C is incompatible (do not add to schedule)

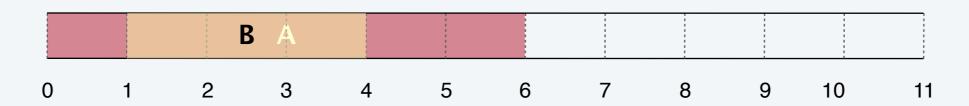


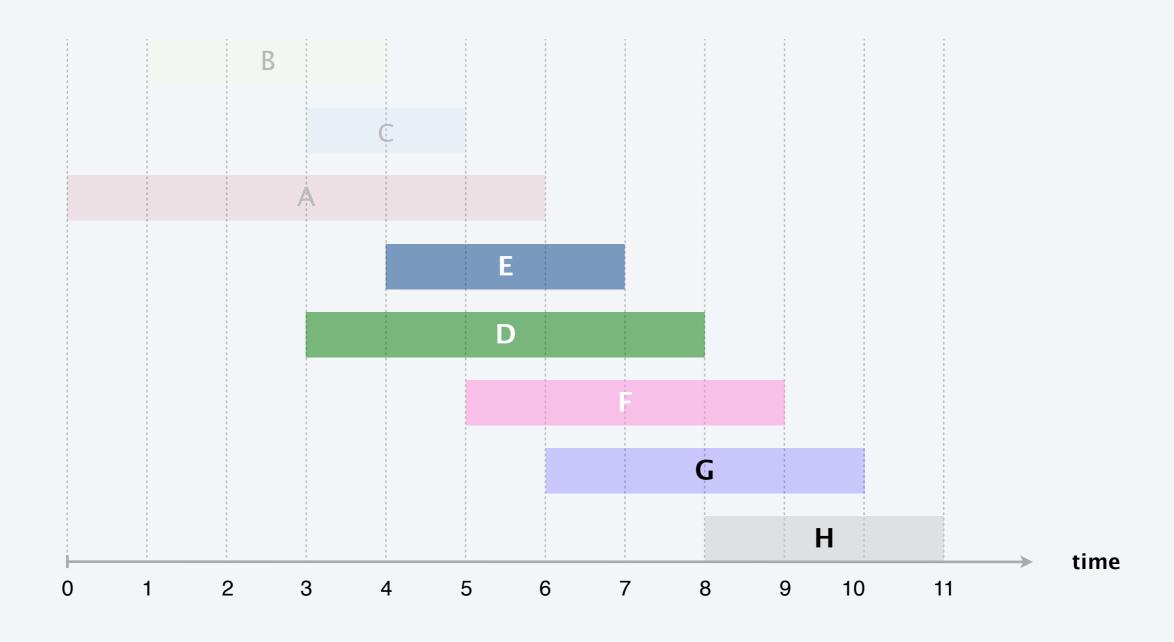


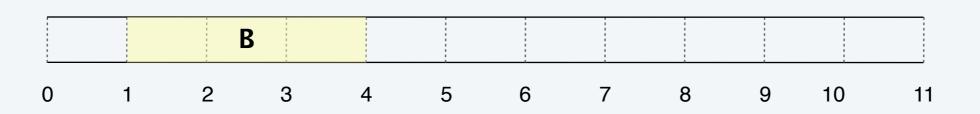


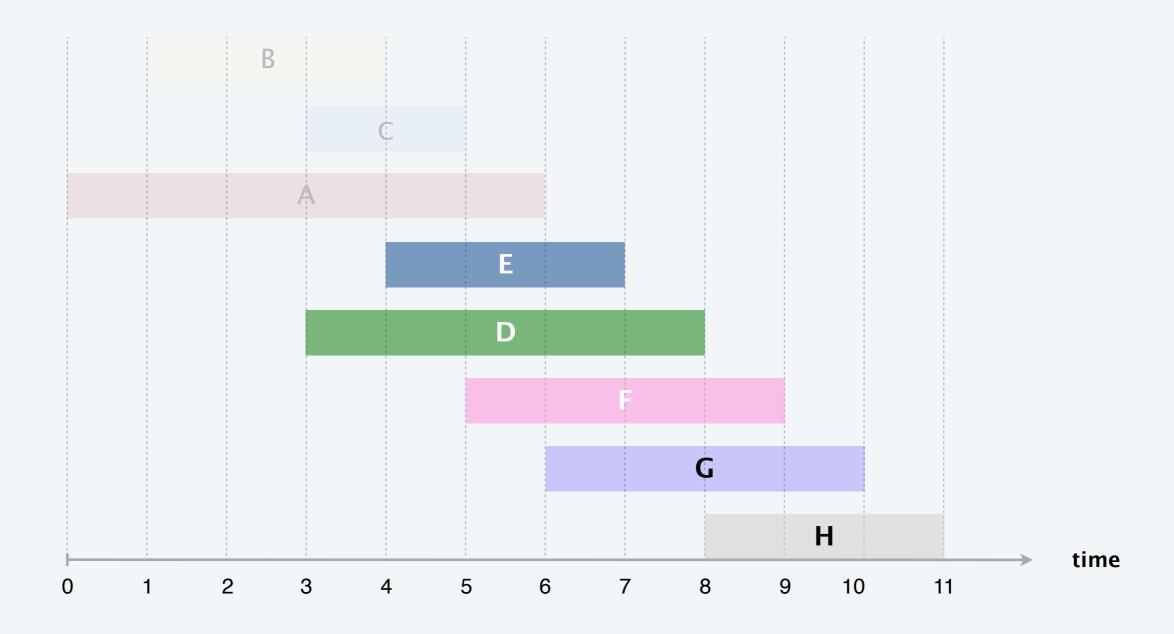


job A is incompatible (do not add to schedule)

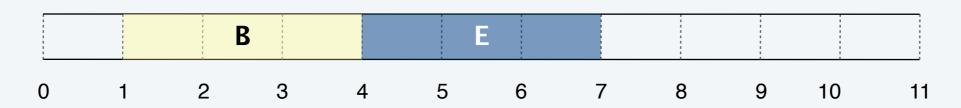


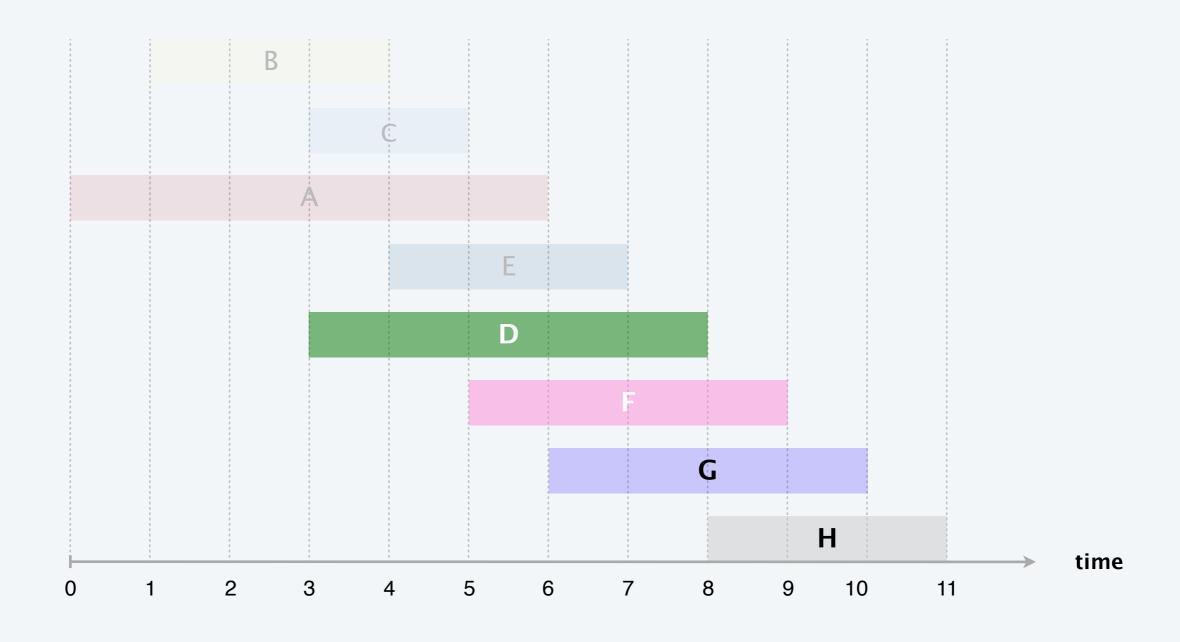


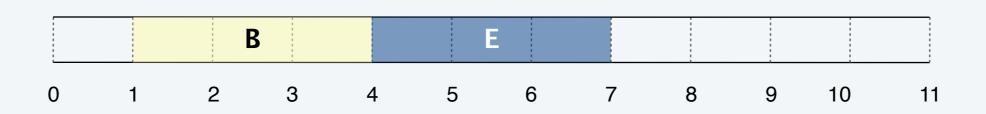


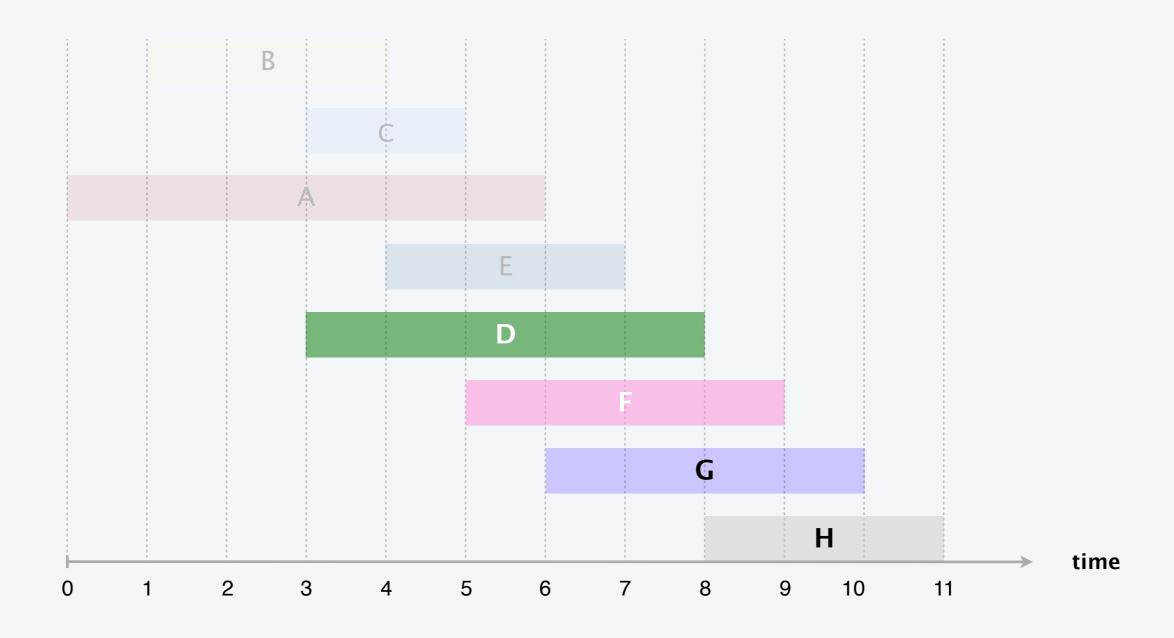


job E is compatible (add to schedule)

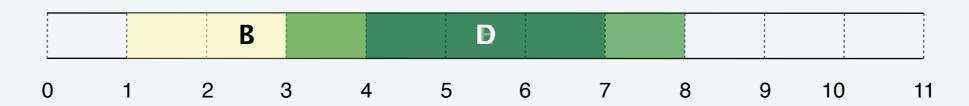


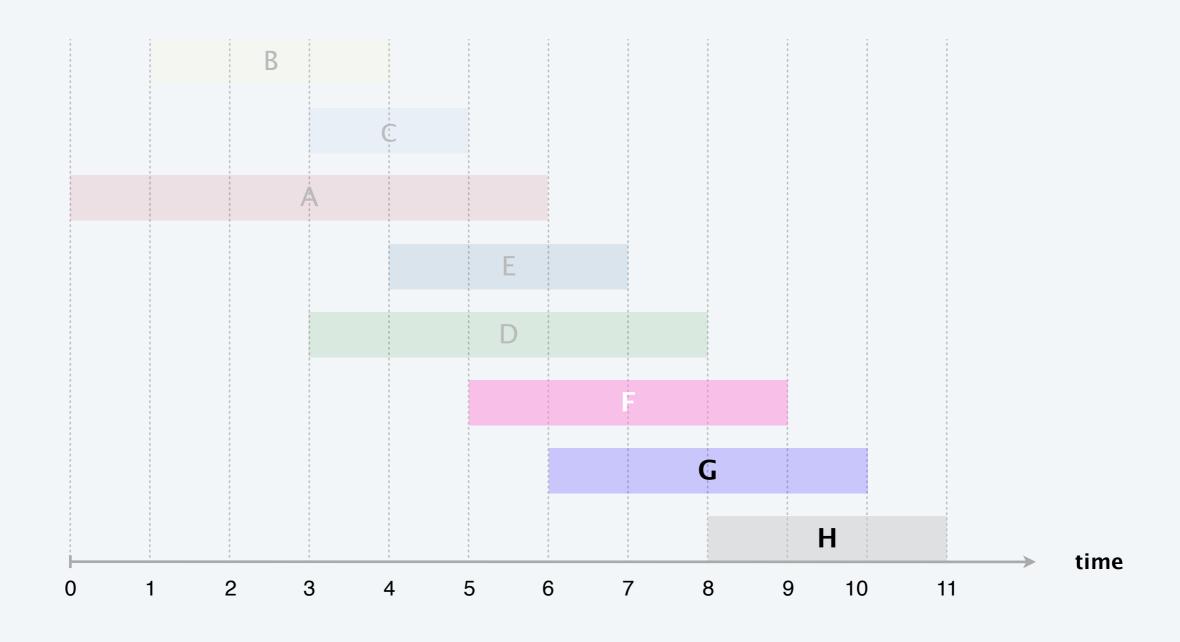


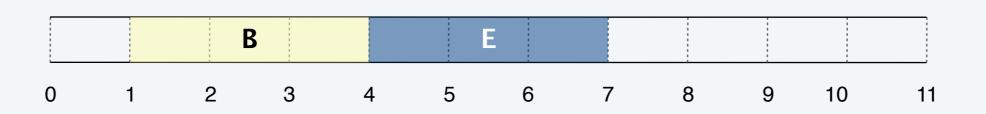


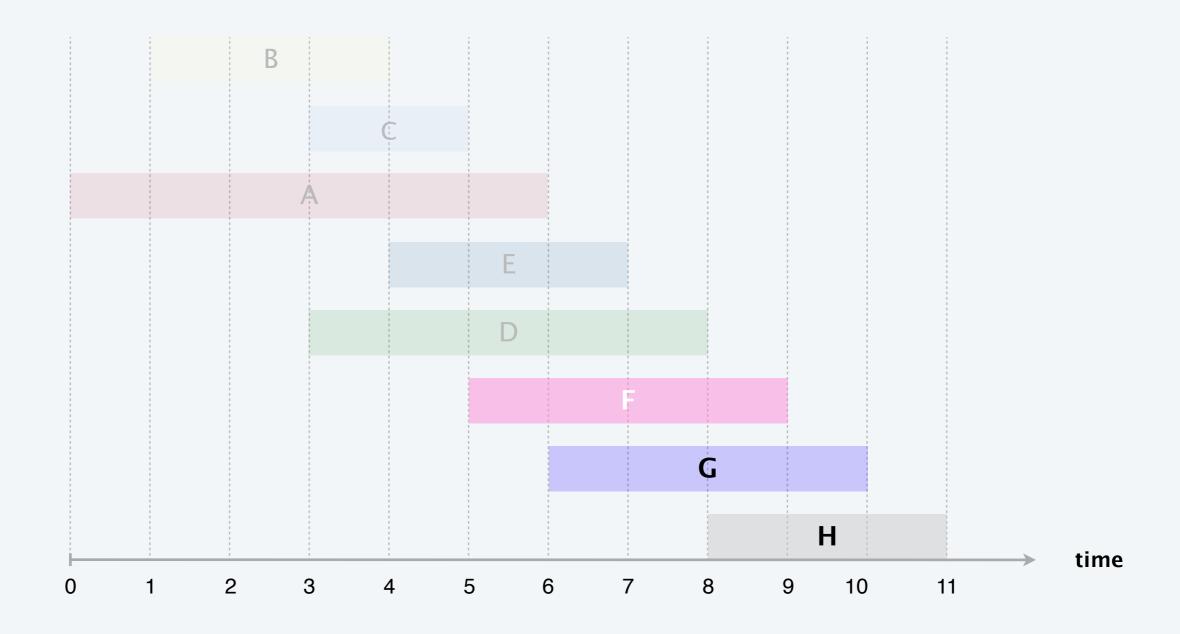


job D is incompatible (do not add to schedule)

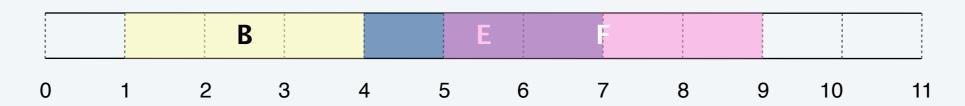


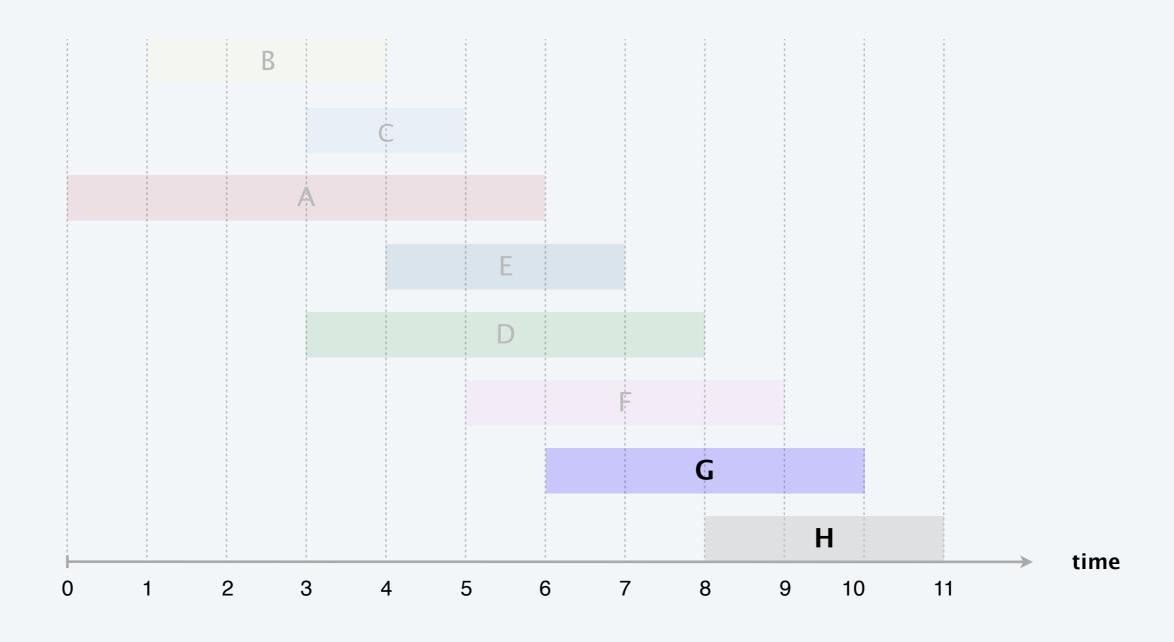


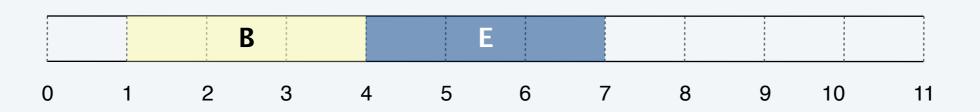


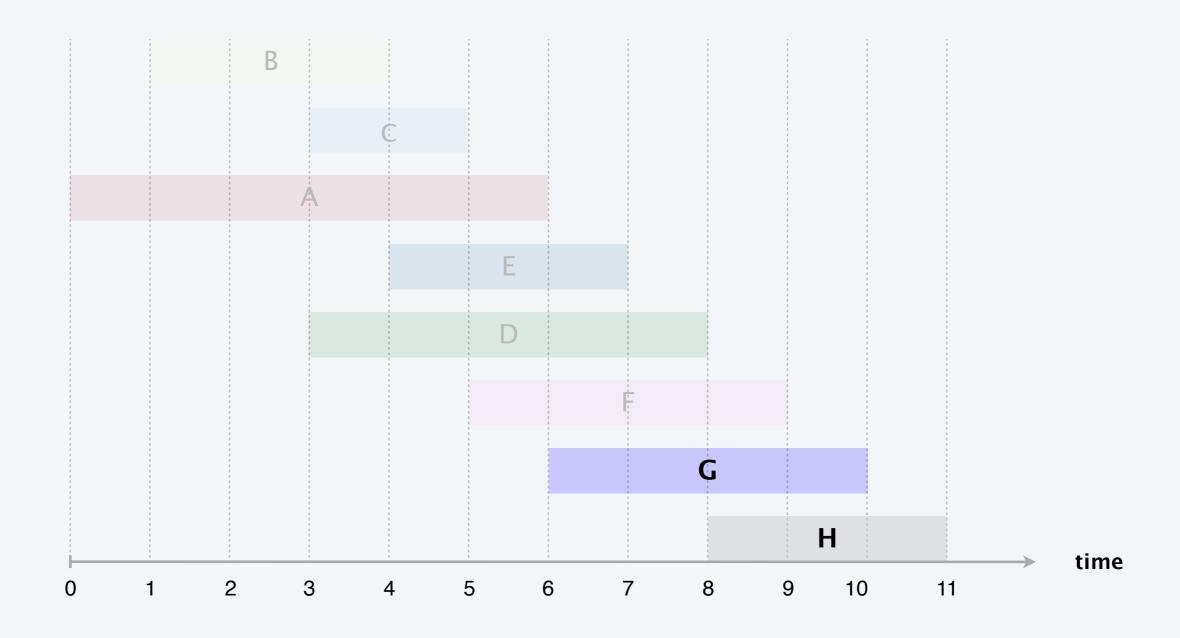


job F is incompatible (do not add to schedule)

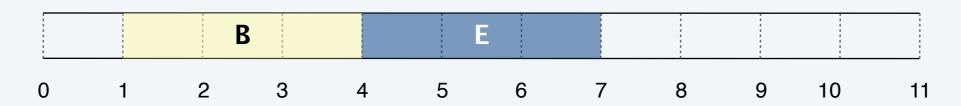


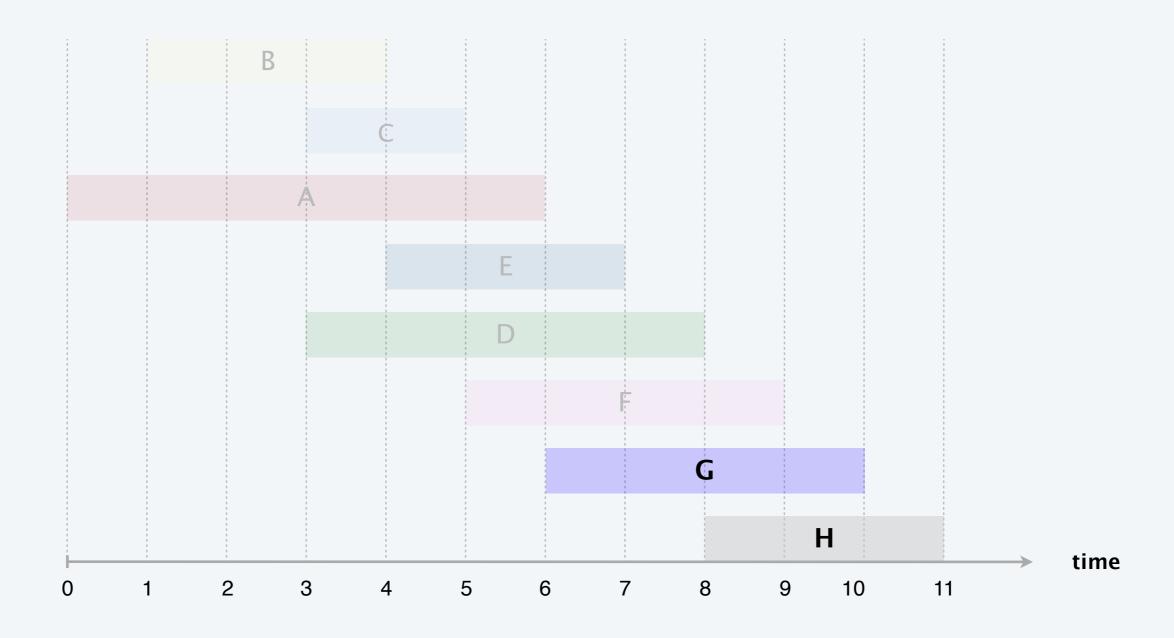




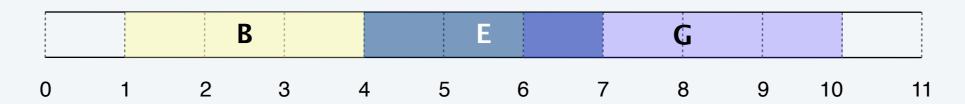


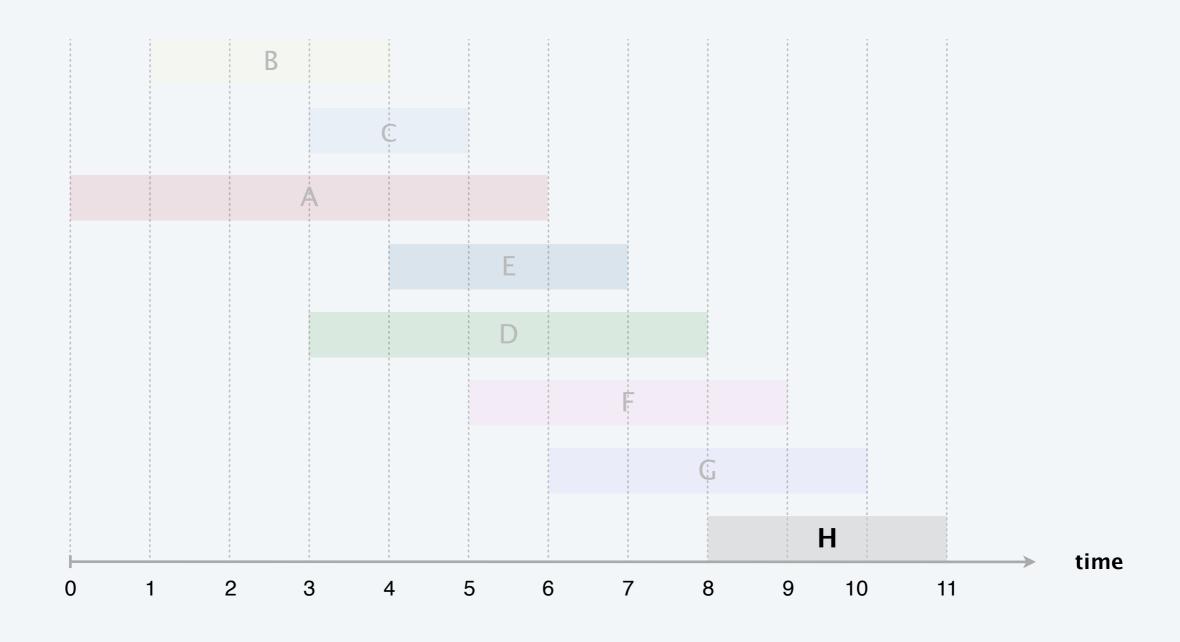
job G is incompatible (do not add to schedule)

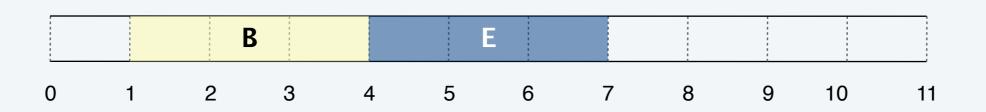




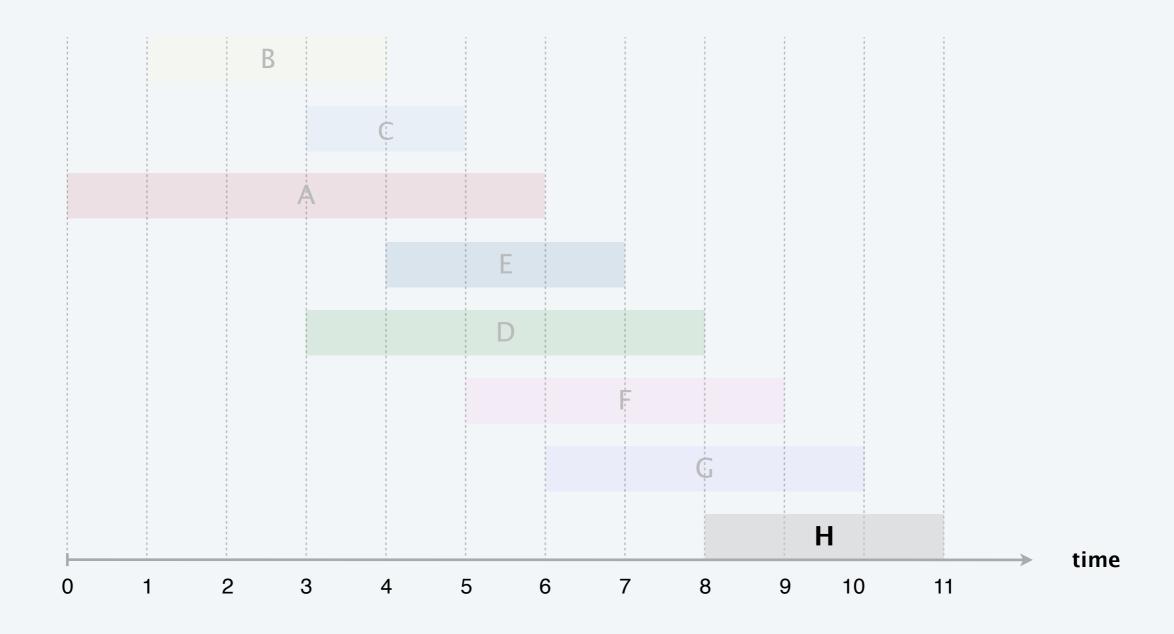
job G is incompatible (do not add to schedule)



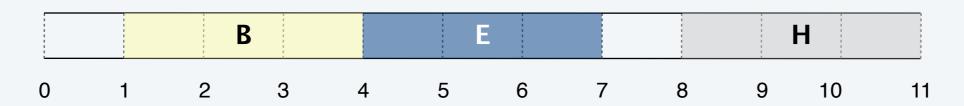




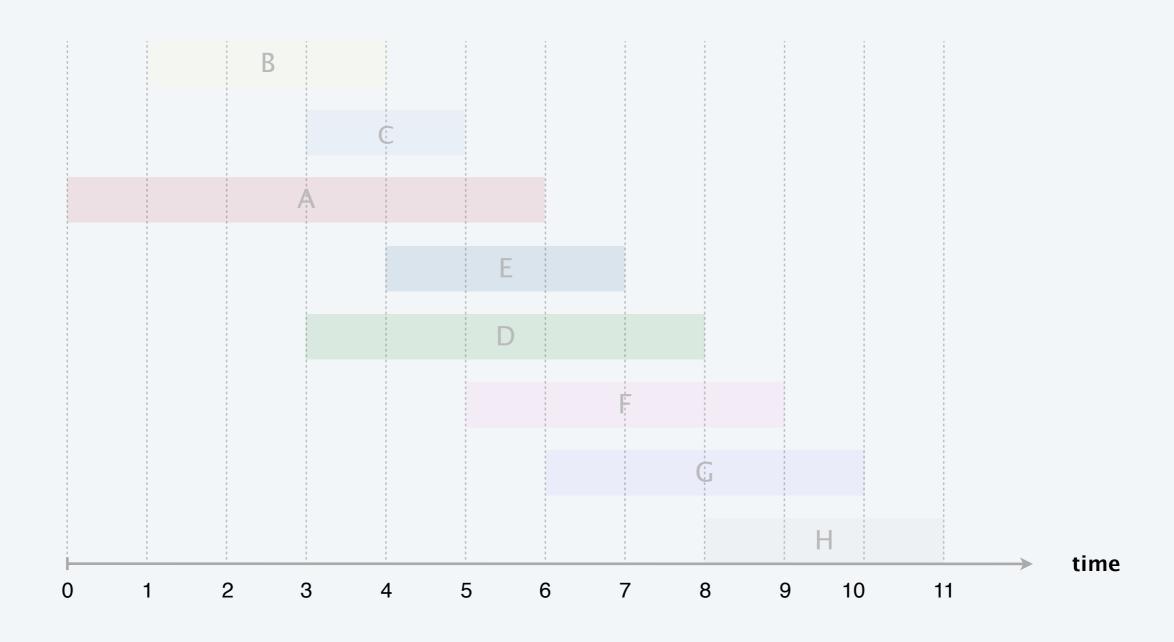
Earliest-finish-time-first algorithm demo

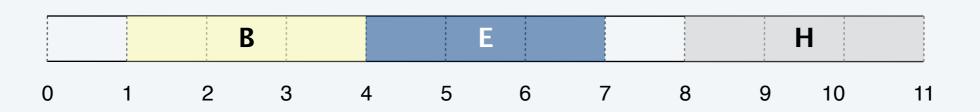


job H is compatible (add to schedule)

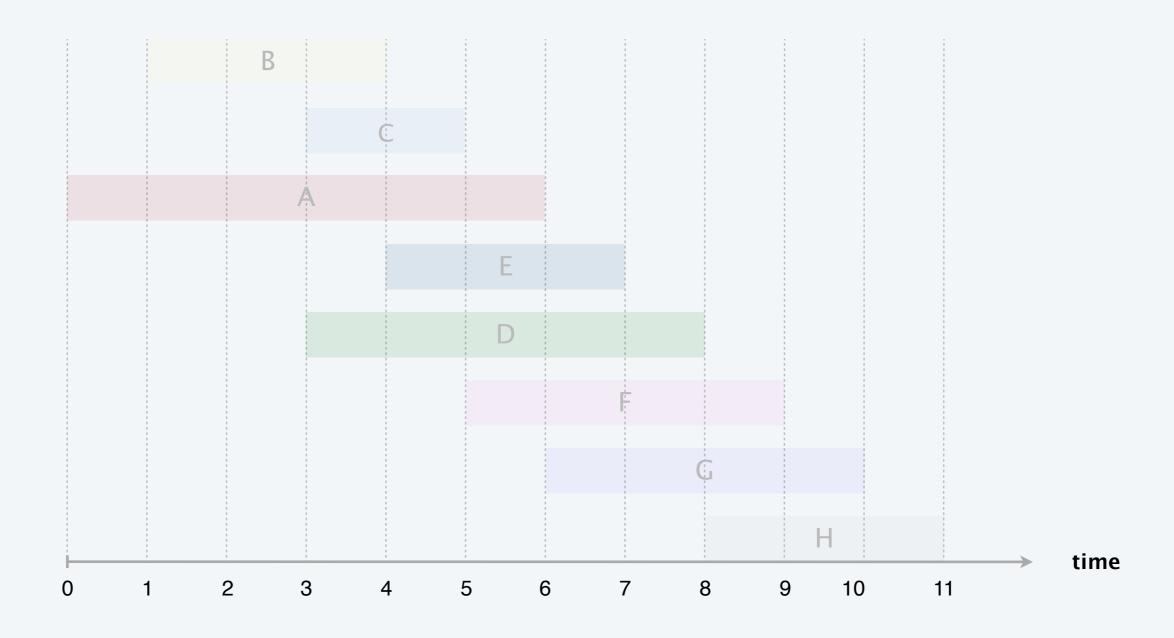


Earliest-finish-time-first algorithm demo

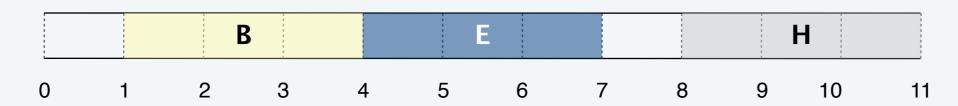




Earliest-finish-time-first algorithm demo



done (an optimal set of jobs)

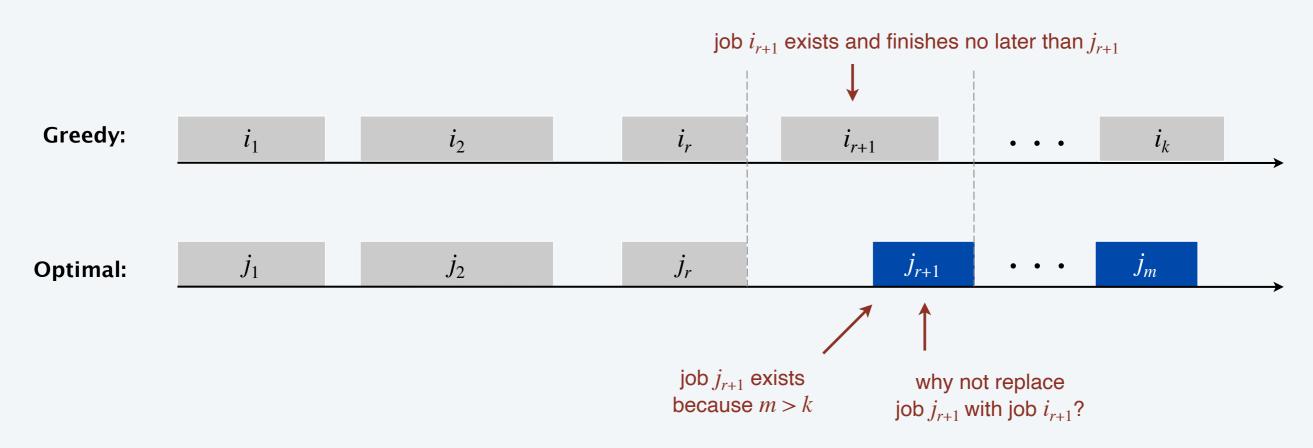


Interval scheduling: analysis of earliest-finish-time-first algorithm

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

Pf. [by contradiction]

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

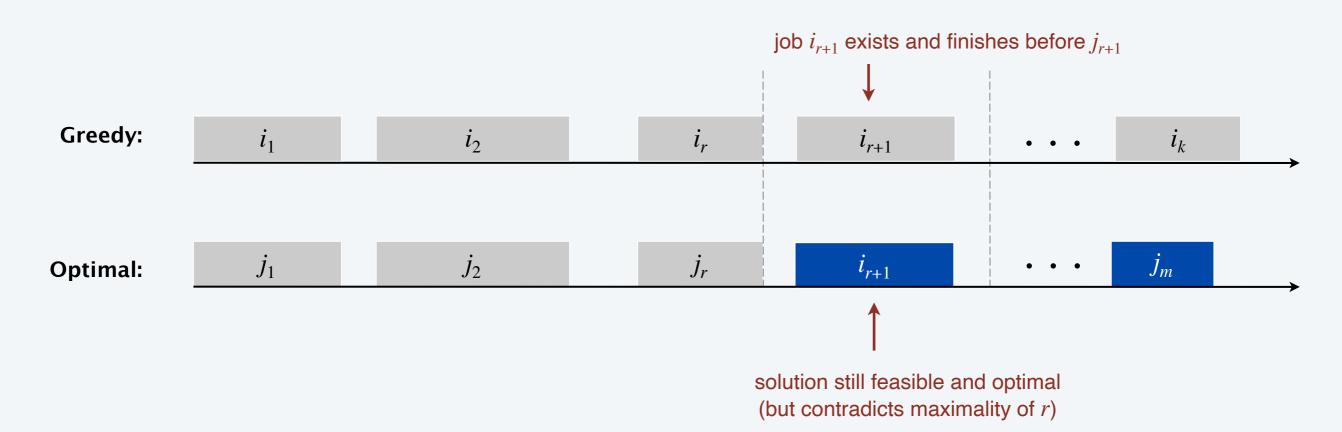


Interval scheduling: analysis of earliest-finish-time-first algorithm

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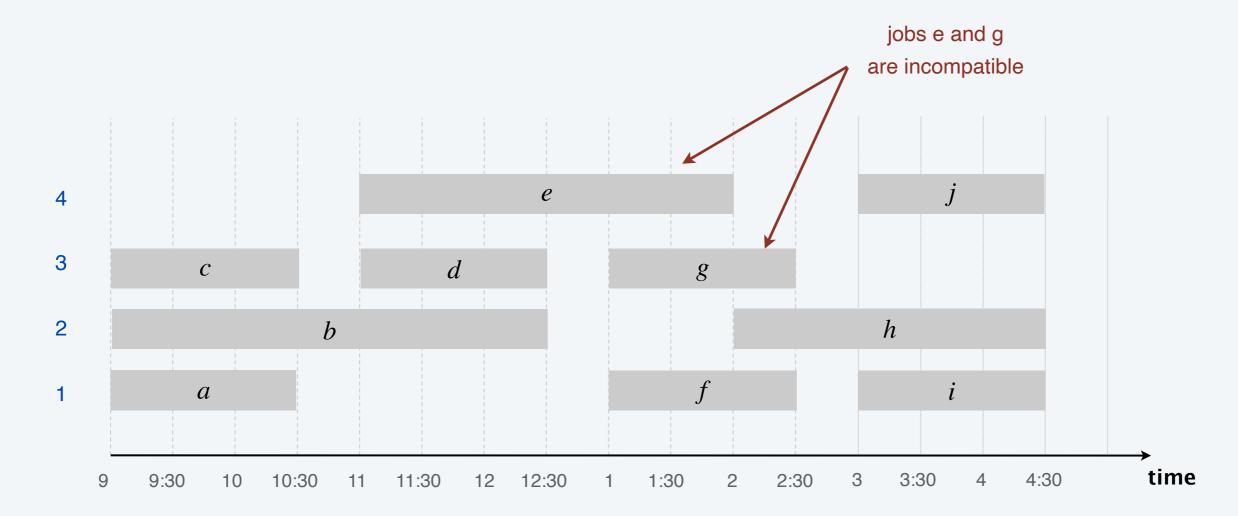
GREEDY ALGORITHMS

- coin changing
- interval scheduling
- interval partitioning
- scheduling to minimize lateness
- optimal caching

Interval partitioning

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

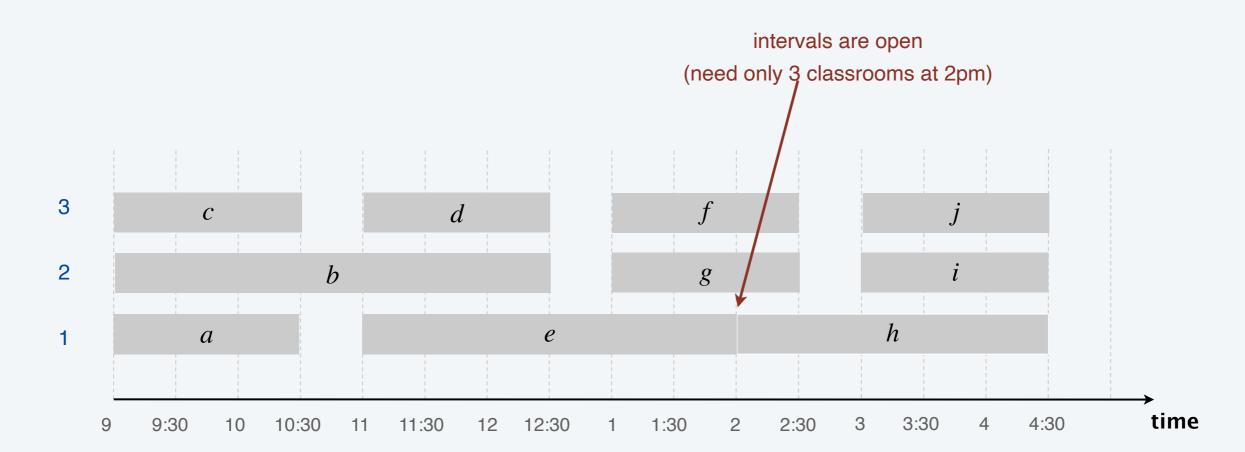
Ex. This schedule uses 4 classrooms to schedule 10 lectures.



Interval partitioning

- Lecture j starts at s_j and finishes at f_j .
- Goal: find minimum 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.



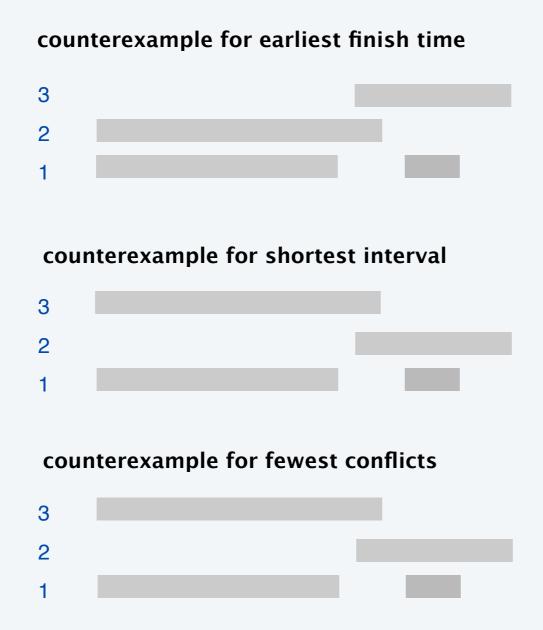
Interval partitioning: greedy algorithms

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.

- [Earliest start time] Consider lectures in ascending order of s_i .
- [Earliest finish time] Consider lectures in ascending order of f_i .
- [Shortest interval] Consider lectures in ascending order of $f_j s_j$.
- [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.

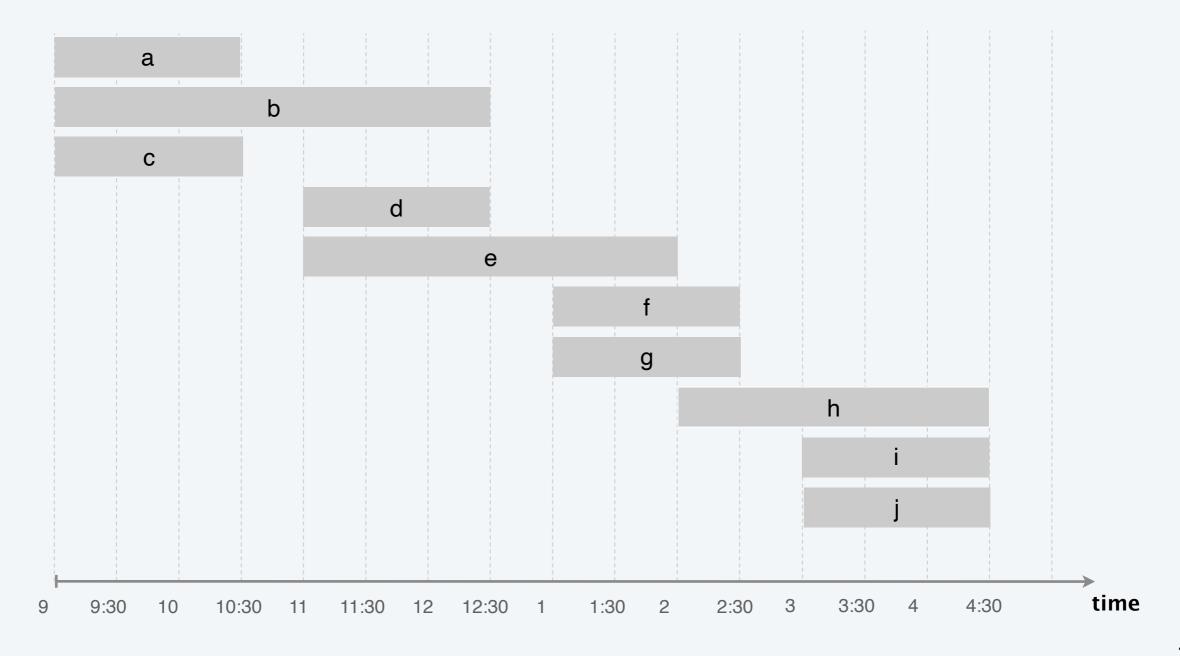


Interval partitioning: earliest-start-time-first algorithm

EARLIEST-START-TIME-FIRST $(n, s_1, s_2, ..., s_n, f_1, f_2, ..., f_n)$ SORT lectures by start times and renumber so that $s_1 \le s_2 \le ... \le s_n$. $d \leftarrow 0$. — number of allocated classrooms FOR j = 1 TO nIF (lecture *j* is compatible with some classroom) Schedule lecture *j* in any such classroom *k*. **ELSE** Allocate a new classroom d + 1. Schedule lecture j in classroom d + 1. $d \leftarrow d + 1$. RETURN schedule.

Consider lectures in order of start time:

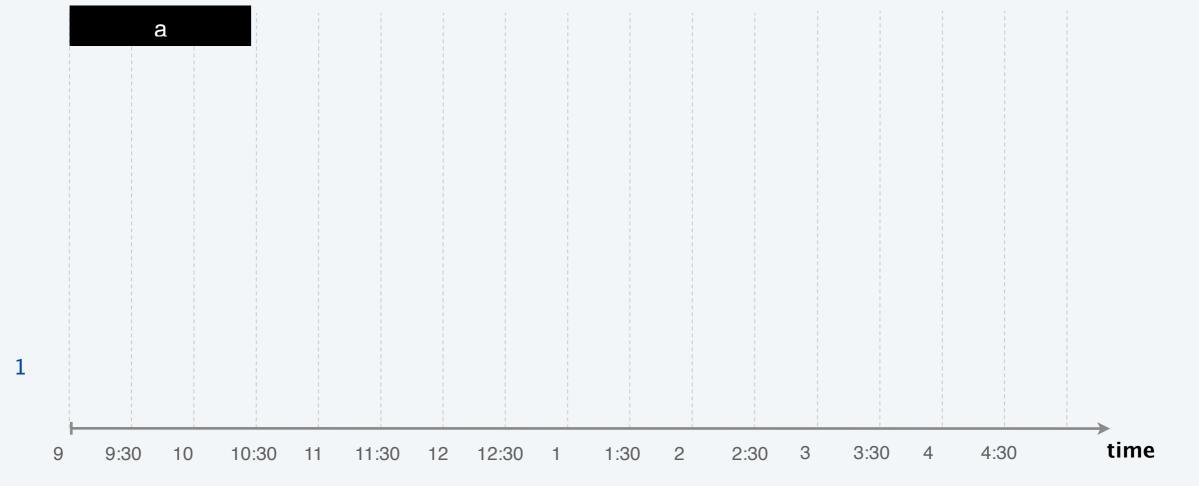
- Assign next lecture to any compatible classroom (if one exists).
- Otherwise, open up a new classroom.



Consider lectures in order of start time:

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

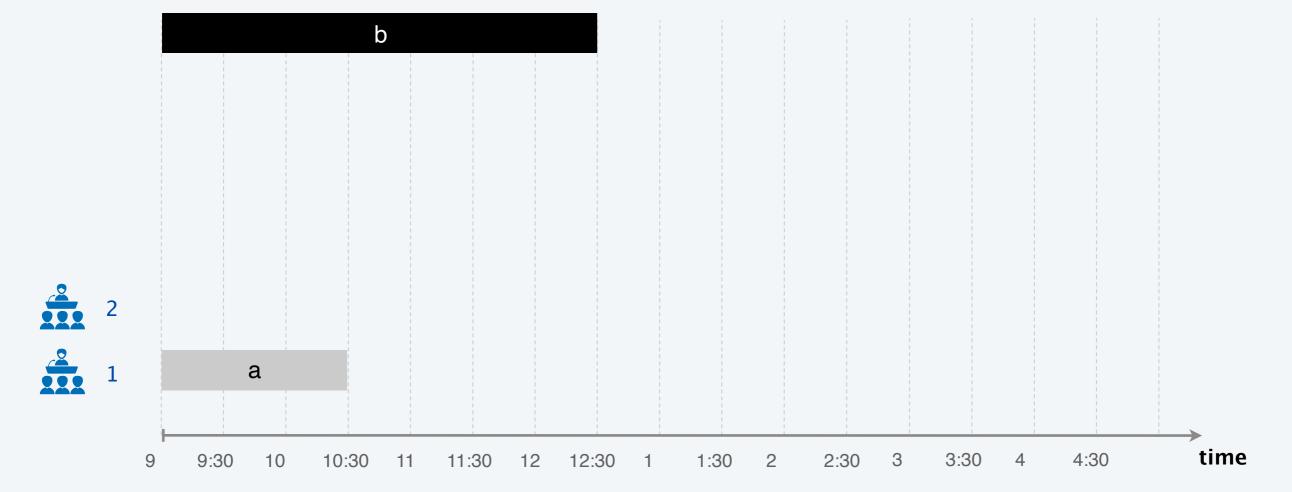
no compatible classroom: open up a new classroom and assign lecture to it



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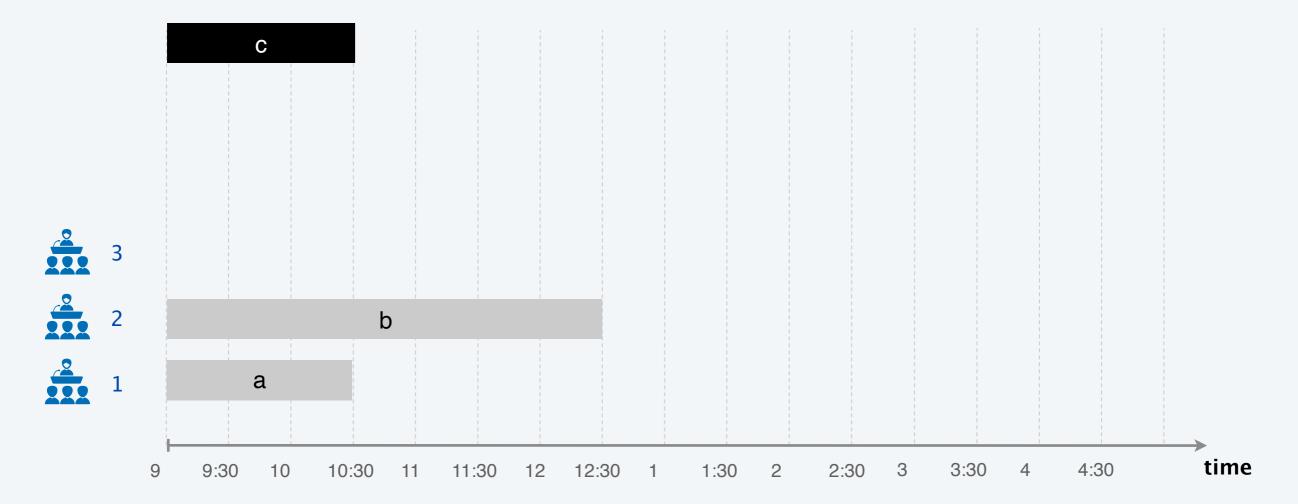
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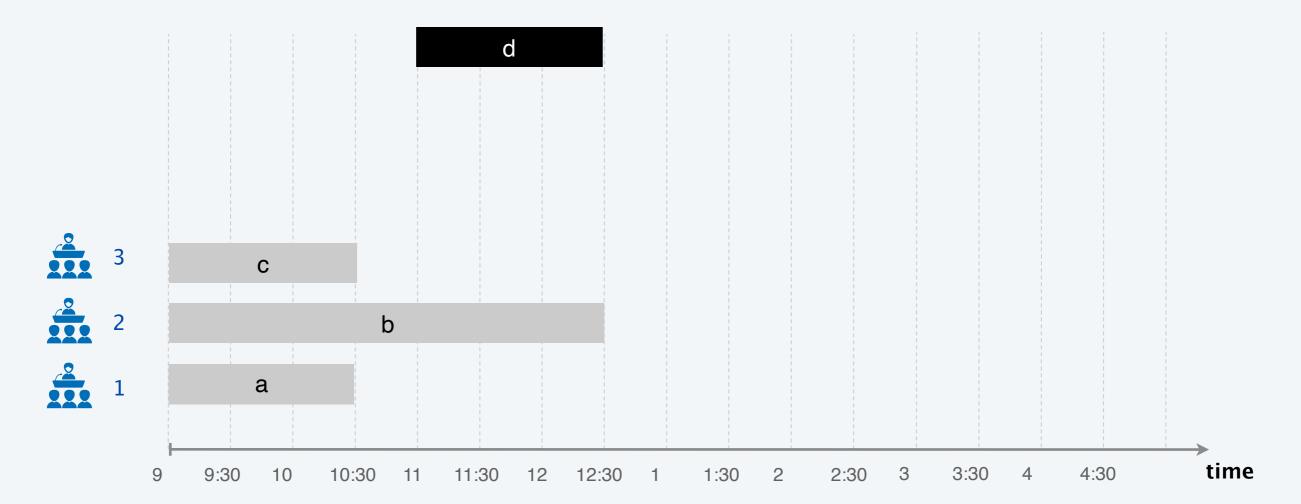
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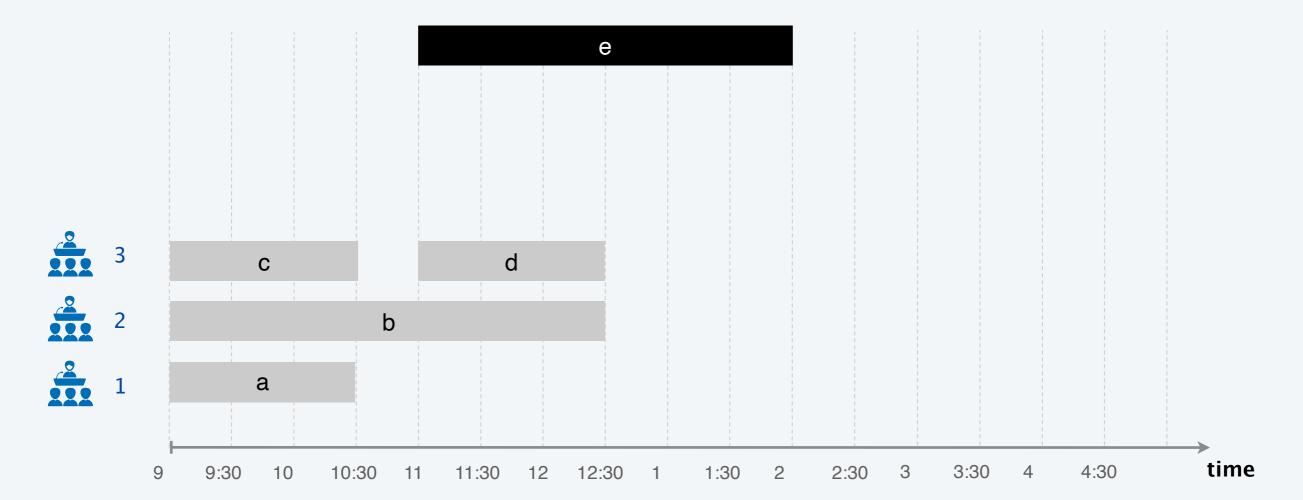
lecture d is compatible with classrooms 1 and 3



Consider lectures in order of start time:

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

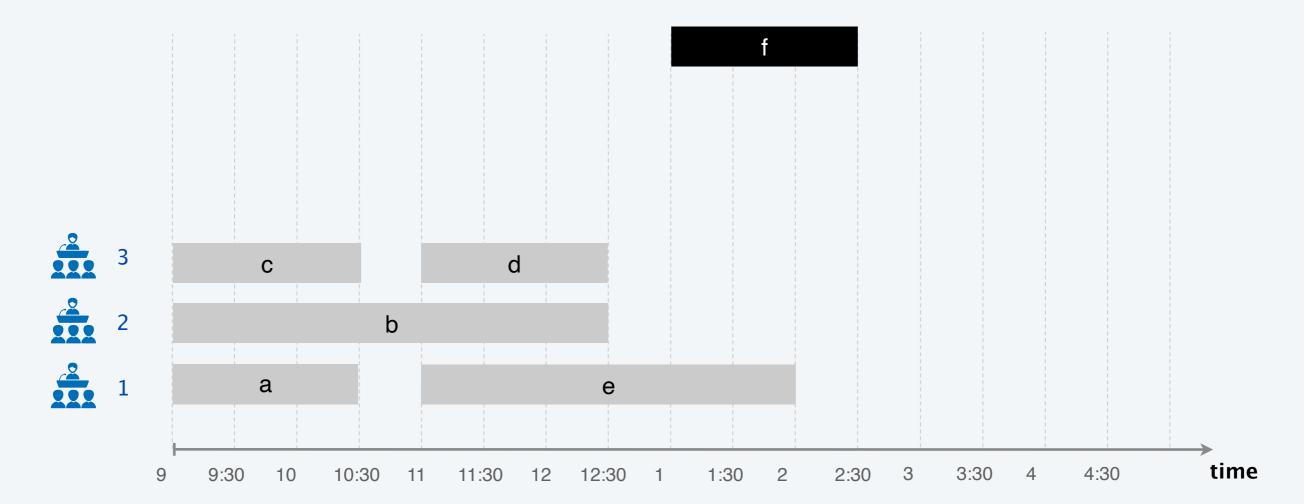
lecture e is compatible with classroom 1



Consider lectures in order of start time:

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

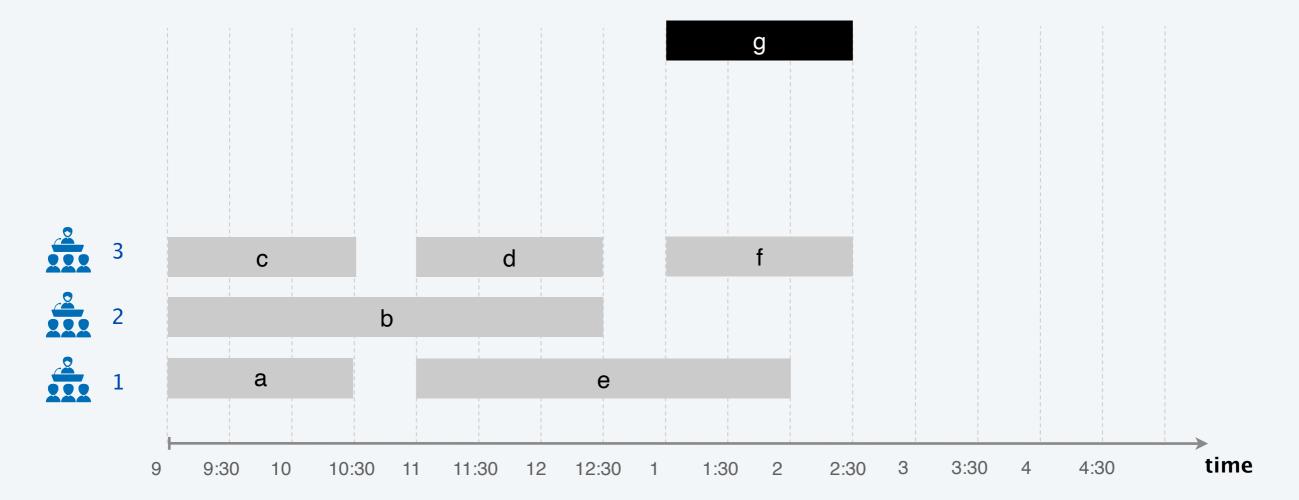
lecture f is compatible with classroom 2 and 3



Consider lectures in order of start time:

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

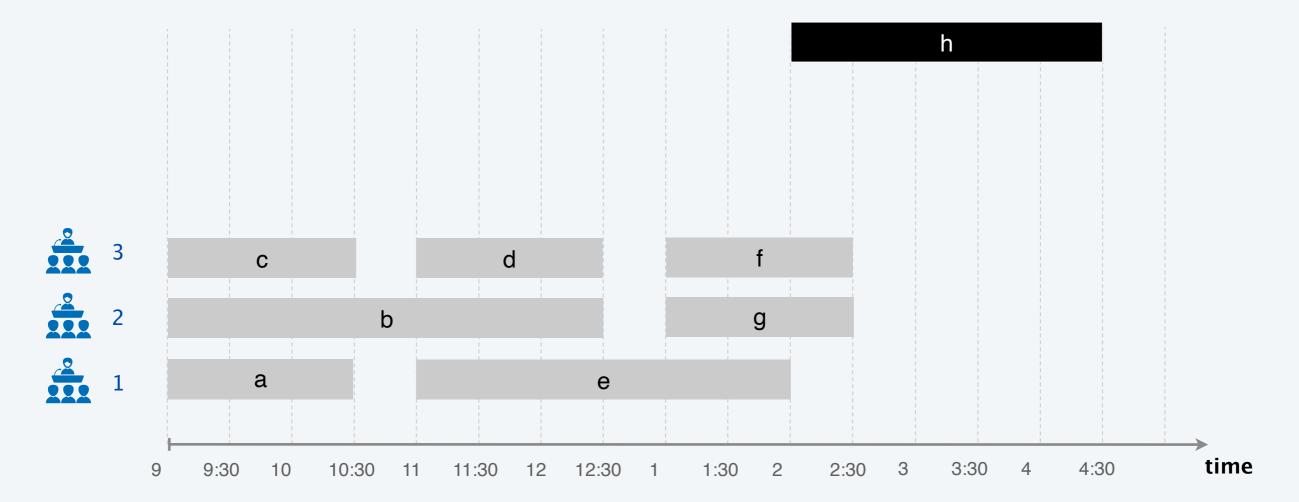
lecture g is compatible with classroom 2



Consider lectures in order of start time:

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

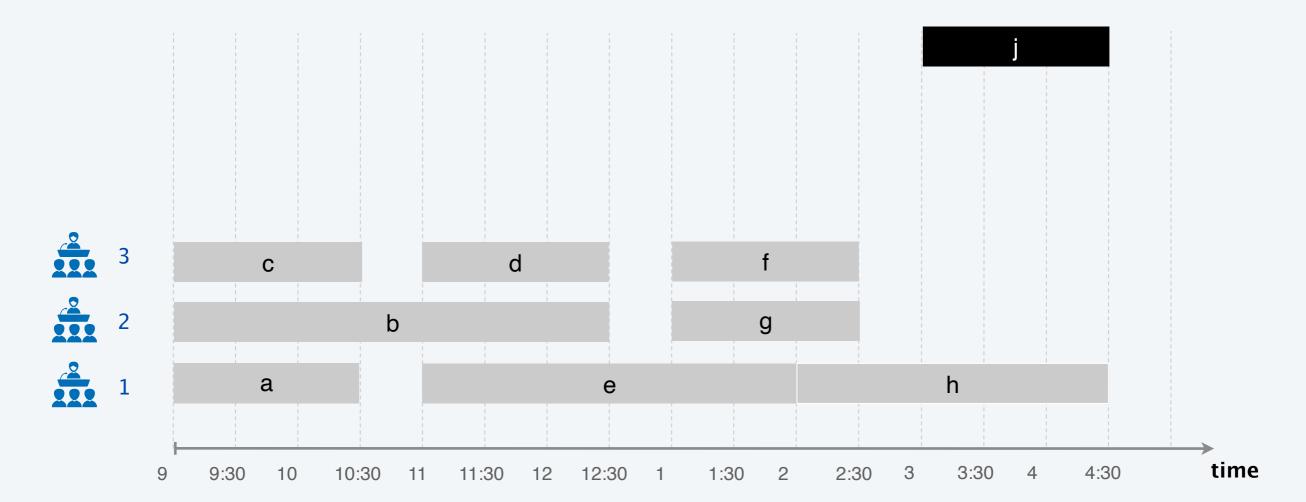
lecture h is compatible with classroom 1



Consider lectures in order of start time:

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

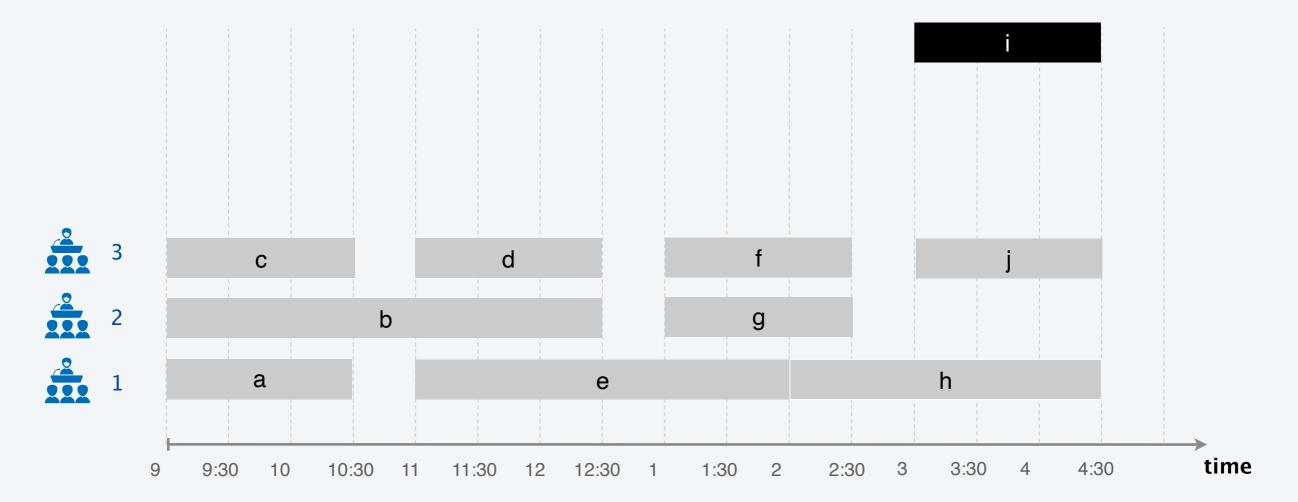
lecture j is compatible with classrooms 2 and 3



Consider lectures in order of start time:

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

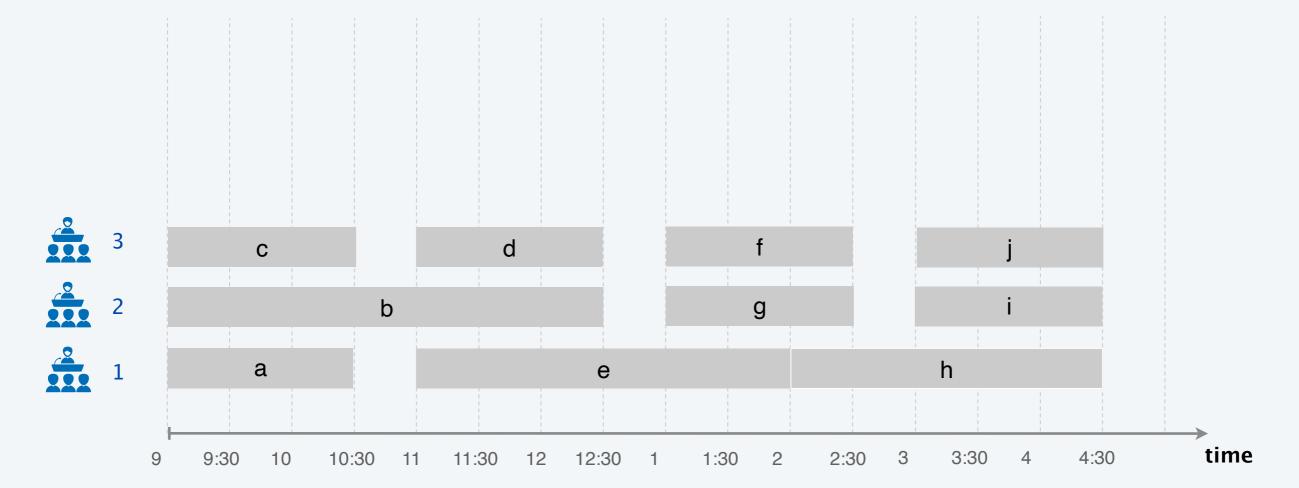
lecture i is compatible with classroom 2



Consider lectures in order of start time:

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

done



Interval partitioning: earliest-start-time-first algorithm

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

Pf.

- Sorting by start times takes $O(n \log n)$ time.
- Store classrooms in a priority queue (key = finish time of its last lecture).
 - to allocate a new classroom, INSERT classroom onto priority queue.
 - to schedule lecture j in classroom k, INCREASE-KEY of classroom k to f_j .
 - to determine whether lecture j is compatible with any classroom,
 compare s_j to FIND-MIN
- Total # of priority queue operations is O(n); each takes $O(\log n)$ time. •

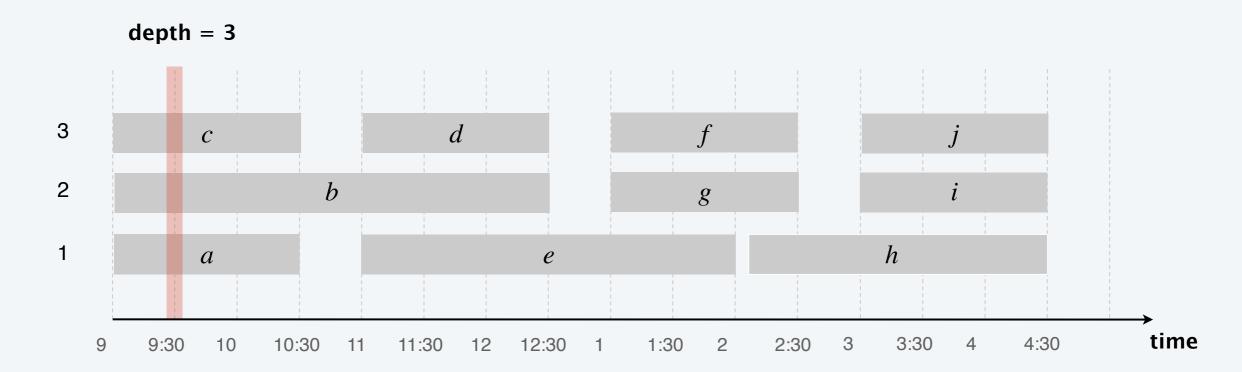
Remark. This implementation chooses a classroom k whose finish time of its last lecture is the earliest.

Interval partitioning: lower bound on optimal solution

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

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.

- 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 a lecture in each of d-1 other classrooms.
- Thus, these d lectures each end after s_i .
- Since we sorted by start time, each of these incompatible lectures start no later than s_i.
- Thus, we have d lectures overlapping at time $s_i + \varepsilon$.
- Key observation ⇒ all schedules use ≥ d classrooms.

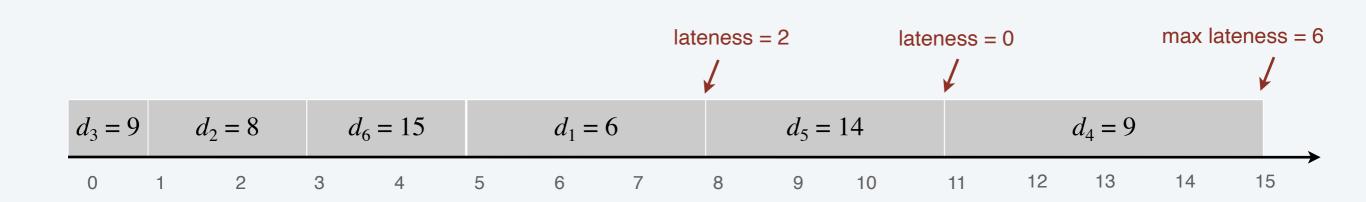
GREEDY ALGORITHMS

- coin changing
- interval scheduling
- interval partitioning
- scheduling to minimize lateness
- optimal caching

Scheduling to minimizing lateness

- Single resource processes one job at a time.
- Job j requires t_j units of processing time and is due at time d_j .
- If j starts at time s_j , it finishes at time $f_j = s_j + t_j$.
- Lateness: $\ell_i = \max \{ 0, f_i d_i \}$.
- Goal: schedule all jobs to minimize maximum lateness $L = \max_{i} \ell_{i}$.

	1	2	3	4	5	6
t_{j}	3	2	1	4	3	2
d_{j}	6	8	9	9	14	15



Minimizing lateness: greedy algorithms

Greedy template. Schedule jobs according to some natural order.

• [Shortest processing time first] Schedule jobs in ascending order of processing time t_i .

• [Earliest deadline first] Schedule jobs in ascending order of deadline d_i .

• [Smallest slack] Schedule jobs in ascending order of slack $d_j - t_j$.

Minimizing lateness: greedy algorithms

Greedy template. Schedule jobs according to some natural order.

• [Shortest processing time first] Schedule jobs in ascending order of processing time t_i .

counterexample	2	1		
	10	1	tj	
	10	100	dj	

• [Smallest slack] Schedule jobs in ascending order of slack $d_j - t_j$.

	2	1		
counterexample	10	1	tj	
	10	2	dj	

Minimizing lateness: earliest deadline first

EARLIEST-DEADLINE-FIRST $(n, t_1, t_2, ..., t_n, d_1, d_2, ..., d_n)$

SORT jobs by due times and renumber so that $d_1 \le d_2 \le ... \le d_n$. $t \leftarrow 0$.

FOR j = 1 TO n

Assign job j to interval $[t, t + t_j]$.

$$s_j \leftarrow t$$
; $f_j \leftarrow t + t_j$.

$$t \leftarrow t + t_i$$
.

RETURN intervals $[s_1, f_1], [s_2, f_2], ..., [s_n, f_n].$

max lateness L = 1

 $d_1 = 6$ $d_3 = 9$ $d_4 = 9$ $d_6 = 15$ $d_2 = 8$ $d_5 = 14$ 12 13 15 0 3 5 6 7 8 9 10 11

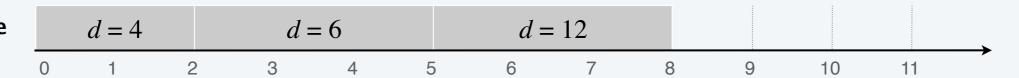
Minimizing lateness: no idle time

Observation 1. There exists an optimal schedule with no idle time.

an optimal schedule



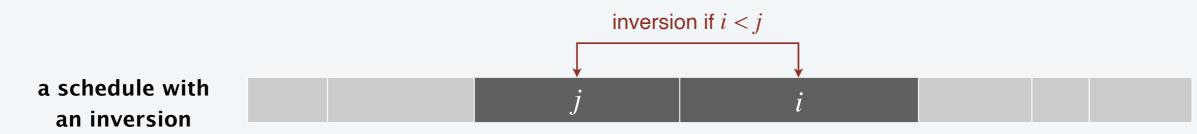
an optimal schedule with no idle time



Observation 2. The earliest-deadline-first schedule has no idle time.

Minimizing lateness: inversions

Def. Given a schedule S, an inversion is a pair of jobs i and j such that: i < j but j is scheduled before i.



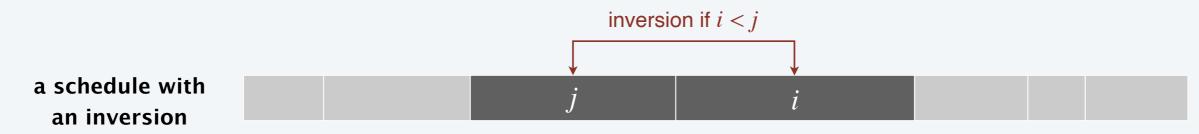
recall: we assume the jobs are numbered so that $d_1 \le d_2 \le ... \le d_n$

Observation 3. The earliest-deadline-first schedule is the unique idle-free schedule with no inversions.



Minimizing lateness: inversions

Def. Given a schedule S, an inversion is a pair of jobs i and j such that: i < j but j is scheduled before i.



recall: we assume the jobs are numbered so that $d_1 \le d_2 \le ... \le d_n$

Observation 4. If an idle-free schedule has an inversion, then it has an adjacent inversion.

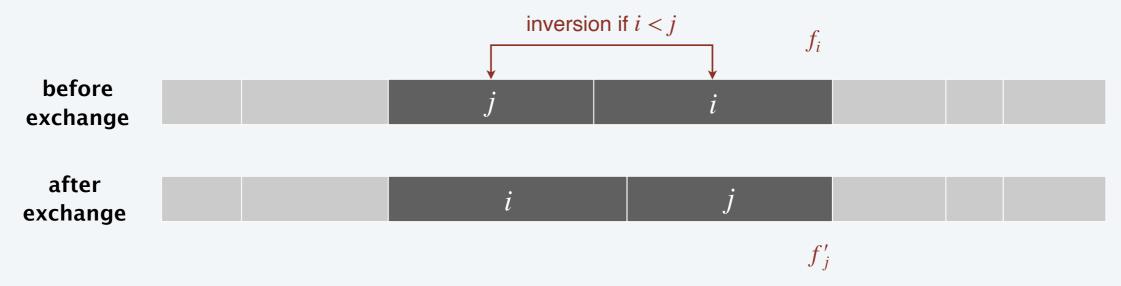
Pf. two inverted jobs scheduled consecutively

- Let i-j be a closest inversion.
- Let *k* be element immediately to the right of *j*.
- Case 1. [j > k] Then j-k is an adjacent inversion.
- Case 2. [j < k] Then i-k is a closer inversion since i < j < k. *



Minimizing lateness: inversions

Def. Given a schedule S, an inversion is a pair of jobs i and j such that: i < j but j is scheduled before i.



Key claim. Exchanging two adjacent, inverted jobs i and j reduces the number of inversions by 1 and does not increase the max lateness.

Pf. Let ℓ be the lateness before the swap, and let ℓ' be it afterwards.

- $\ell'_k = \ell_k$ for all $k \neq i, j$.
- $\ell'_i \leq \ell_i$.

• If job
$$j$$
 is late, ℓ'_j = $f'_j - d_j$ \longleftarrow definition
$$= f_i - d_j \qquad \longleftarrow j \text{ now finishes at time } f_i$$
 $\leq f_i - d_i \qquad \longleftarrow i < j \Rightarrow d_i \leq d_j$ $\leq \ell_i$. \longleftarrow definition

Minimizing lateness: analysis of earliest-deadline-first algorithm

Theorem. The earliest-deadline-first schedule S is optimal.

Pf. [by contradiction]

optimal schedule can
have inversions

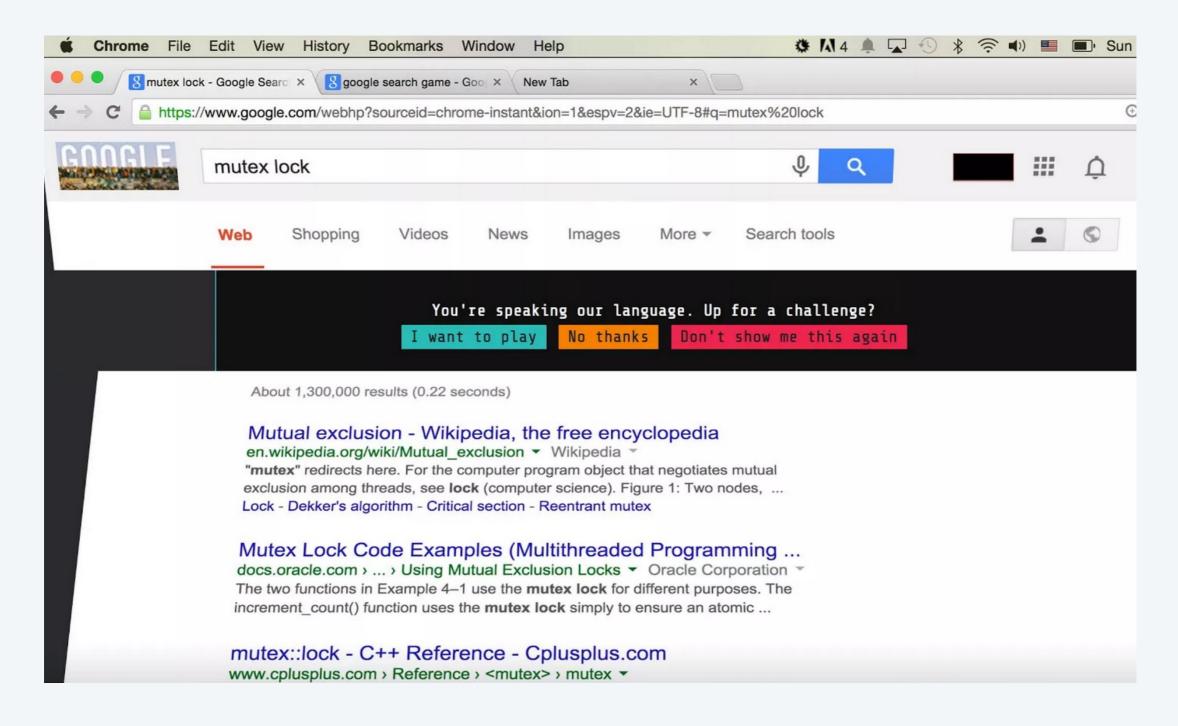
Define S^* to be an optimal schedule with the fewest inversions.

- Can assume S* has no idle time. ← Observation 1
- Case 1. [S^* has no inversions] Then $S = S^*$. \longleftrightarrow Observation 3
- Case 2. [S* has an inversion]
 - let *i*−*j* be an adjacent inversion ← Observation 4
 - exchanging jobs i and j decreases the number of inversions by 1 without increasing the max lateness \longleftarrow key claim
 - contradicts "fewest inversions" part of the definition of S^* *

Google's foo.bar challenge

A "secret" web tool that Google uses to recruit developers.

- Triggered by specific searches related to programming.
- Algorithmic coding challenges of increasing difficulty.



Google's foo.bar challenge

https://foobar.withgoogle.com/

Quantum antimatter fuel comes in small pellets, which is convenient since the many moving parts of the LAMBCHOP each need to be fed fuel one pellet at a time. However, minions dump pellets in bulk into the fuel intake. You need to figure out the most efficient way to sort and shift the pellets down to a single pellet at a time.

The fuel control mechanisms have three operations:

- Add 1 fuel pellet
- Remove 1 fuel pellet
- Divide the entire group of fuel pellets by 2 (due to the destructive energy released when a quantum antimatter pellet is cut in half, the safety controls will only allow this to happen if there is an even number of pellets)

Write a function called answer(n) which takes a positive integer n as a string and returns the minimum number of operations needed to transform the number of pellets to 1.

$$29 \rightarrow 28 \rightarrow 14 \rightarrow 7 \rightarrow 8 \rightarrow 4 \rightarrow 2 \rightarrow 1$$

Google's foo.bar challenge

```
Level 3 complete. You are now on level 4. Challenges to complete level: 2.
0% [......]
Level 4
Level 5 0% [......]
 Excellent! You've destroyed Commander Lambda's doomsday device and saved Bunny Planet! But
 there's one small problem: the LAMBCHOP was a wool-y important part of her space station,
 and when you blew it up, you triggered a chain reaction that's tearing the station apart.
 Can you rescue the imprisoned bunnies and escape before the entire thing explodes?
Type request to request a new challenge now, or come back later.
[#1] The code is strong with this one. Share solutions with a Google recruiter?
[Y]es [N]o [A]sk me later: A
Response: contact postponed.
To share your progress at any time, use the recruitme command.
```

GREEDY ALGORITHMS

- coin changing
- interval scheduling
- interval partitioning
- scheduling to minimize lateness
- optimal caching

Optimal offline caching

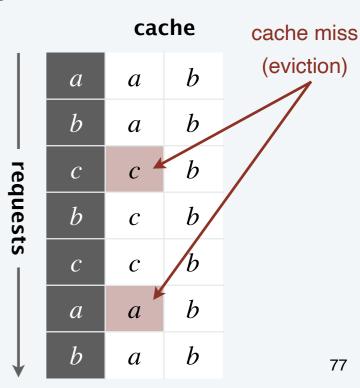
Caching.

- Cache with capacity to store k items.
- Sequence of m item requests $d_1, d_2, ..., d_m$.
- Cache hit: item in cache when requested.
- Cache miss: item not in cache when requested.
 (must evict some item from cache and bring requested item into cache)

Applications. CPU, RAM, hard drive, web, browser,

Goal. Eviction schedule that minimizes the number of evictions.

Ex. k = 2, initial cache = ab, requests: a, b, c, b, c, a, b. Optimal eviction schedule. 2 evictions.



Optimal offline caching: greedy algorithms

LIFO/FIFO. Evict item brought in least (most) recently.

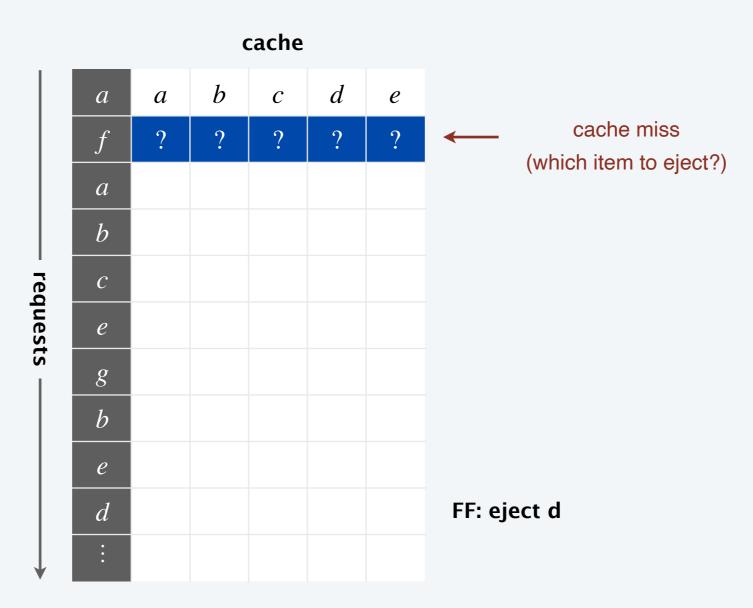
LRU. Evict item whose most recent access was earliest.

LFU. Evict item that was least frequently requested.

	(cache			
				•	
a	W	х	y	z	FIFO: eject a
a	W	х	d	Z	LRU: eject d
a	W	X	d	z	
a	b	x	d	\mathcal{Z}	
a	b	c	d	z	
a	b	c	d	e	LIFO: eject e
?	?	?	?	?	
					cache miss
					(which item to eject?)
	a a a a a a a	 . a a a a a b a b a b 	. . . a w x a w x a b x a b c a b c a b c	a w x y a w x d a w x d a b x d a b c d a b c d c d d d a w x y z a w x d z a w x d z a b x d z a b c d z a b c d e

Optimal offline caching: farthest-in-future (clairvoyant algorithm)

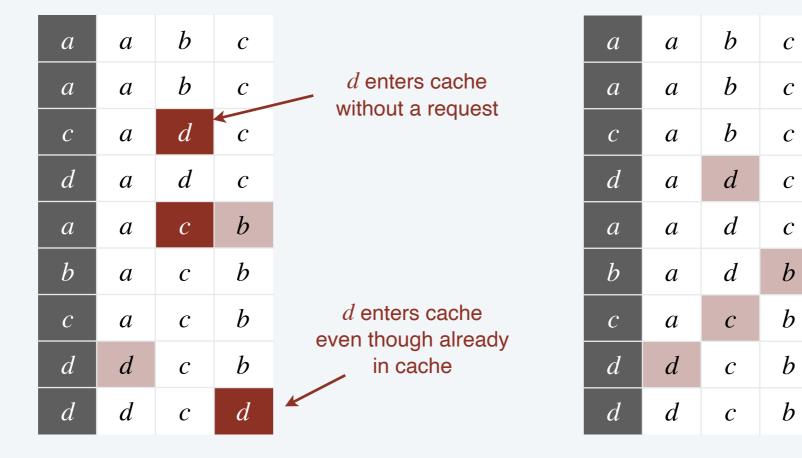
Farthest-in-future. Evict item in the cache that is not requested until farthest in the future.



Theorem. [Bélády 1966] FF is optimal eviction schedule.

Pf. Algorithm and theorem are intuitive; proof is subtle.

Def. A reduced schedule is a schedule that brings an item d into the cache in step j only if there is a request for d in step j and d is not already in the cache.



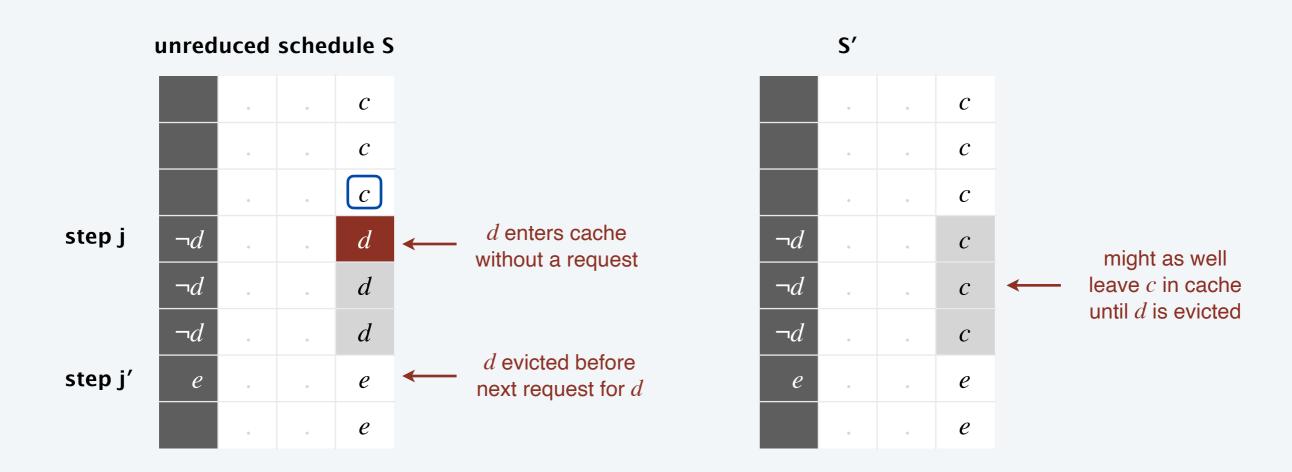
an unreduced schedule

a reduced schedule

Claim. Given any unreduced schedule S, can transform it into a reduced schedule S' with no more evictions.

Pf. [by induction on number of steps *j*]

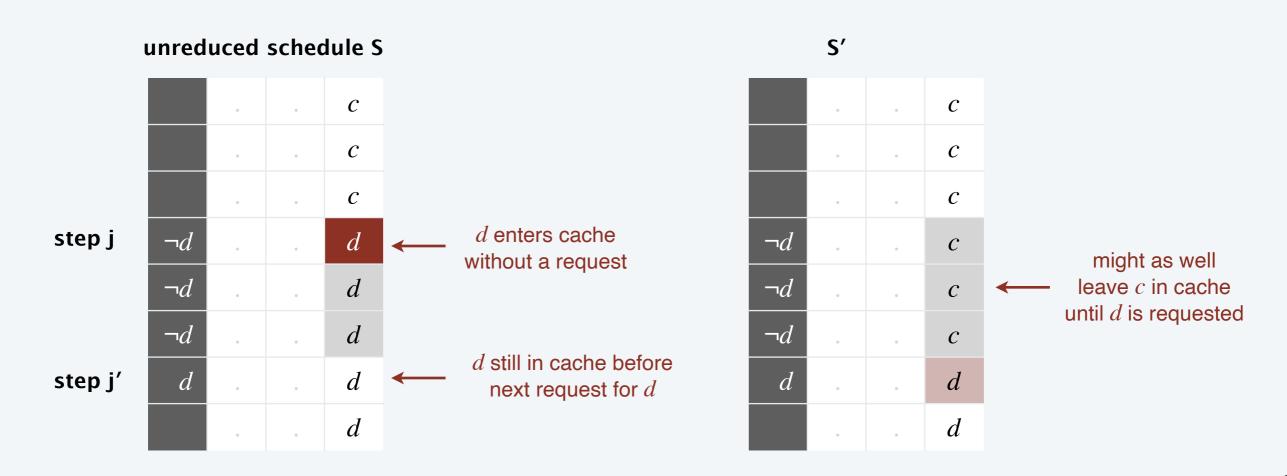
- Suppose S brings d into the cache in step j without a request.
- Let *c* be the item *S* evicts when it brings *d* into the cache.
- Case 1a: d evicted before next request for d.



Claim. Given any unreduced schedule S, can transform it into a reduced schedule S' with no more evictions.

Pf. [by induction on number of steps *j*]

- Suppose S brings d into the cache in step j without a request.
- Let *c* be the item *S* evicts when it brings *d* into the cache.
- Case 1a: d evicted before next request for d.
- Case 1b: next request for d occurs before d is evicted.



Claim. Given any unreduced schedule S, can transform it into a reduced schedule S' with no more evictions.

Pf. [by induction on number of steps j]

- Suppose S brings d into the cache in step j even though d is in cache.
- Let *c* be the item *S* evicts when it brings *d* into the cache.
- Case 2a: d evicted before it is needed.

	unred	uced	sche	dule S			S'				
		d_1	a	c			d_1	a	С		
		d_1	a	c			d_1	a c			
		d_1	a	c	d_3 enters cache even though d_1 is		d_1	a	C	—	might as well leave c in cache
step j	d	d_1	a	d_3	\leftarrow already in cache	d	d_1	a	C		
	d	d_1	a	d_3	\leftarrow d_3 not needed	d	d_1	a	c		until d_3 in evicted
	c	С	a	d_3		c	c	a	c		
step j'	b	c	a	b	\leftarrow d_3 evicted	b	C	a	b		
	d	c	a	d_3	\leftarrow d_3 needed	d	c	a	d_3		

Claim. Given any unreduced schedule S, can transform it into a reduced schedule S' with no more evictions.

Pf. [by induction on number of steps j]

- Suppose S brings d into the cache in step j even though d is in cache.
- Let *c* be the item *S* evicts when it brings *d* into the cache.
- Case 2a: d evicted before it is needed.
- Case 2b: d needed before it is evicted.

	unred	uced	sched	dule S		S'					
		d_1	a	c			d_1	a	c		
step j		d_1	a	С			d_1	a	С	—	might as well leave c in cache until d_3 in needed
		d_1	a	c	d_3 enters cache even though d_1 is		d_1	a	С		
	d	d_1	a	d_3	- already in cache	d	d_1	a	С		
	d	d_1	a	d_3	\leftarrow d_3 not needed	d	d_1	a	c		
	C	C	a	d_3		C	c	a	C		
	а	C	a	d_3		а	c	a	C		
step j'	d	C	a	d_3	\leftarrow d_3 needed	d	c	a	d_3		

Claim. Given any unreduced schedule S, can transform it into a reduced schedule S' with no more evictions.

Pf. [by induction on number of steps j]

- Case 1: S brings d into the cache in step j without a request.
- Case 2: S brings d into the cache in step j even though d is in cache.
- If multiple unreduced items in step j, apply each one in turn,
 dealing with Case 1 before Case 2.

resolving Case 1 might trigger Case 2

Theorem. FF is optimal eviction algorithm.

Pf. Follows directly from the following invariant.

Invariant. There exists an optimal reduced schedule S that has the same eviction schedule as S_{FF} through the first j steps.

Pf. [by induction on number of steps j]

Base case: j = 0.

Let S be reduced schedule that satisfies invariant through j steps.

We produce S' that satisfies invariant after j + 1 steps.

- Let d denote the item requested in step j + 1.
- Since S and S_{FF} have agreed up until now, they have the same cache contents before step j + 1.
- Case 1: d is already in the cache.

S' = S satisfies invariant.

• Case 2: d is not in the cache and S and S_{FF} evict the same item.

S' = S satisfies invariant.

Pf. [continued]

- Case 3: d is not in the cache; S_{FF} evicts e; S evicts $f \neq e$.
 - begin construction of S' from S by evicting e instead of f



- now S' agrees with S_{FF} for first j+1 steps; we show that having item f in cache is no worse than having item e in cache
- let S' behave the same as S until S' is forced to take a different action
 (because either S evicts e; or because either e or f is requested)

Let j' be the first step after j+1 that S' must take a different action from S; let g denote the item requested in step j'.

involves either e or f (or both)



- Case 3a: g = e. S' agrees with S_{FF} through first j + 1 steps

 Can't happen with FF since there must be a request for f before e.
- Case 3b: g = f.
 Element f can't be in cache of S; let e' be the item that S evicts.
 - if e' = e, S' accesses f from cache; now S and S' have same cache
 - if $e' \neq e$, we make S' evict e' and bring e into the cache; now S and S' have the same cache

We let S' behave exactly like S for remaining requests.

S' is no longer reduced, but can be transformed into a reduced schedule that agrees with FF through first j+1 steps

Let j' be the first step after j+1 that S' must take a different action from S; let g denote the item requested in step j'.

| involves wither e or f (or both)

same e step j' same f

otherwise S' could have taken the same action



- Case 3c: $g \neq e, f$. S evicts e.
 - make S' evict f.



- now *S* and *S'* have the same cache
- let S' behave exactly like S for the remaining requests ■

Caching perspective

Online vs. offline algorithms.

- Offline: full sequence of requests is known a priori.
- Online (reality): requests are not known in advance.
- Caching is among most fundamental online problems in CS.

LIFO. Evict item brought in most recently.

LRU. Evict item whose most recent access was earliest.

1

FF with direction of time reversed!

Theorem. FF is optimal offline eviction algorithm.

- Provides basis for understanding and analyzing online algorithms.
- LIFO can be arbitrarily bad.
- LRU is *k*-competitive: for any sequence of requests σ , $LRU(\sigma) \le kFF(\sigma) + k$.
- Randomized marking is $O(\log k)$ -competitive.

Greedy analysis strategies

Greedy algorithm stays ahead. Show that after each step of the greedy algorithm, its solution is at least as good as any other algorithm's.

Structural. Discover a simple "structural" bound asserting that every possible solution must have a certain value. Then show that your algorithm always achieves this bound.

Exchange argument. Gradually transform any solution to the one found by the greedy algorithm without hurting its quality.

Other greedy algorithms. Gale-Shapley, Kruskal, Prim, Dijkstra, Huffman, ...

