Greedy Algorithms

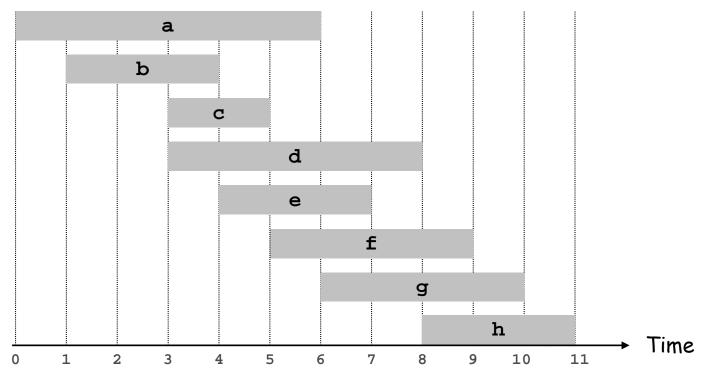
Greedy Algorithms

- Build up a solution to an optimization problem at each step shortsightedly choosing the option that currently seems the best.
 - Sometimes good
 - Often does not work
- Key to designing greedy algorithms: find **structure** that ensures you don't leave behind other options



Interval Scheduling Problem

- •Job j starts at s_j and finishes at f_j .
- •Two jobs are **compatible** if they do not overlap.
- •Find: maximum subset of mutually compatible jobs.



Possible Greedy Strategies

Consider jobs in some natural order. Take next job if it is compatible with the ones already taken.

- Earliest start time: ascending order of s_i.
- Earliest finish time: ascending order of f_i.
- Shortest interval: ascending order of $(f_i s_i)$.
- Fewest conflicts: For each job j, count the number of conflicting jobs c_i . Schedule in ascending order of c_i .

Greedy: Counterexamples



Formulating an Algorithm

Input: arrays of start and finishing times

$$- s_1, s_2, ..., s_n$$

$$-f_1, f_2, ..., f_n$$

Input length?

$$-2n = \Theta(n)$$

Greedy Algorithm

•Earliest finish time: ascending order of f_i.

• Implementation:

- How do we quickly test if j is compatible with A?
- Store job j^* that was added last to A.
- Job j is compatible with A if $s_j \ge f_{j*}$.

Time and space analysis

```
Sort jobs by finish times so that
O(n \log n)
                            f_1 \leq f_2 \leq \ldots \leq f_n.
                   A ← (empty) // Queue of selected jobs
                   j^* \leftarrow 0
                   for j = 1 to n
                  if (f<sub>j*</sub> ≤ s<sub>j</sub>)
  enqueue(j onto A)
  j* ← j
                   return A
```

O(n log n) time; O(n) space.

Theorem. Greedy algorithm's solution is optimal.

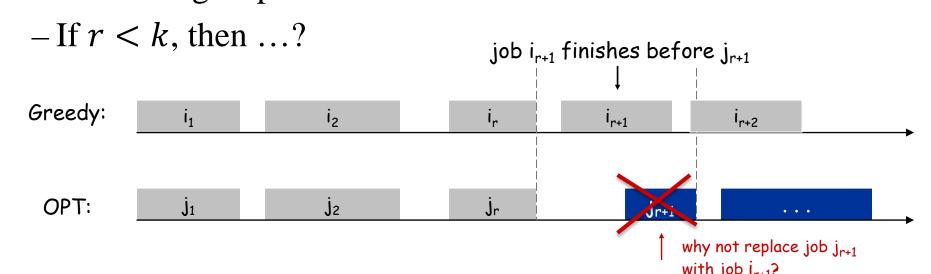
Proof strategy (by contradiction):

- Suppose greedy is not optimal.
- Consider an optimal solution...
 - which one?
 - optimal solution that agrees with the greedy solution for as many initial jobs as possible
- Look at the first place in the list where optimal solution differs from the greedy solution
 - Show a new optimal solution that agrees more w/ greedy
 - Contradiction!

Theorem: Greedy algorithm's solution is optimal.

Proof (by contradiction): Suppose greedy not optimal.

- Let $i_1, i_2, \dots i_k$ denote set of jobs selected by greedy.
- Let $j_1, j_2, ..., j_m$ be the optimal solution with $i_1 = j_1, i_2 = j_2, ..., i_r = j_r$ for the largest possible value of r.



Theorem: Greedy algorithm's solution is optimal.

Proof (by contradiction): Suppose greedy not optimal.

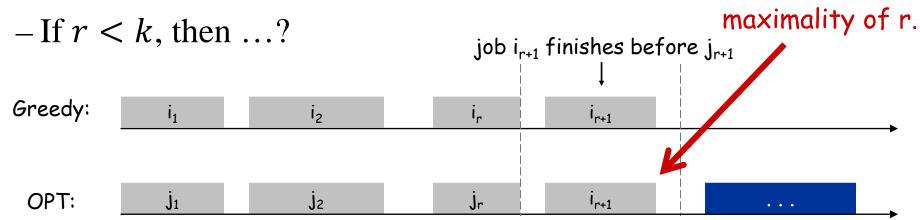
solution still

feasible and

optimal, but

contradicts

- Let $i_1, i_2, \dots i_k$ denote set of jobs selected by greedy.
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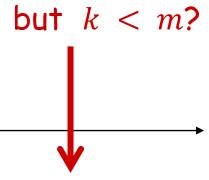
Proof (by contradiction): Suppose greedy not optimal.

- Let $i_1, i_2, \dots i_k$ denote set of jobs selected by greedy.
- Let $j_1, j_2, \dots j_m$ be the optimal solution with

$$i_1 = j_1, i_2 = j_2, ..., i_r = j_r$$
 for the largest possible value of r .

 $-\operatorname{If} r < k$, then we get contradiction.

Greedy:



Could it be

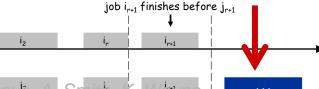
that r = k

OPT: j_1 j_2 j_r i_{r+1} ...

Theorem: Greedy algorithm's solution is optimal.

Proof (by contradiction): Suppose greedy not optimal.

- Let $i_1, i_2, \dots i_k$ denote set of jobs selected by greedy.
- Let $j_1, j_2, ..., j_m$ be the optimal solution with $i_1 = j_1, i_2 = j_2, ..., i_r = j_r$ for the largest possible value of r.
- If r < k, we get a contradiction by replacing j_{r+1} with i_{r+1} because we get an optimal solution with larger r.
- If r = k but m > k, we get a contradiction because greedy algorithm stopped before all jobs were considered.



Alternate Way to See the Proof

Induction statement

P(k): There is an optimal solution that agrees with the greedy solution in the first k jobs.

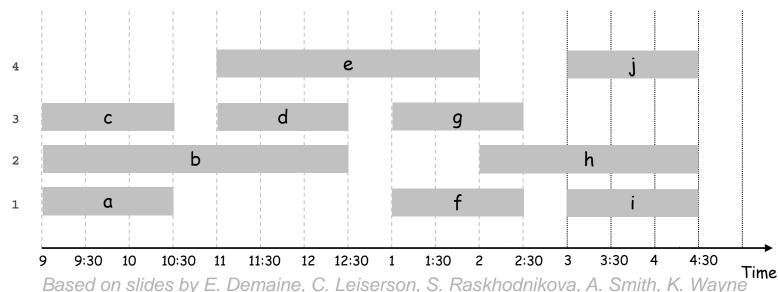
- P(n) is what we want to prove.
- Base case: P(0)
- We essentially proved the induction step...

Interval Partitioning



Interval Partitioning

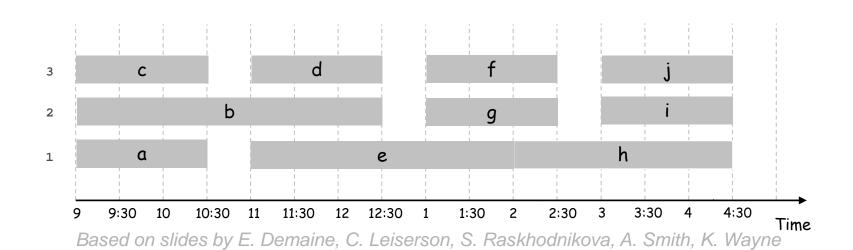
- Lecture j starts at s_j and finishes at f_j .
- **Input**: $s_1, ..., s_n$ and $f_1, ..., f_n$.
- Goal: find minimum number of classrooms to schedule all lectures so that no two occur at the same time in the same room.
- E.g.: 10 lectures are scheduled in 4 classrooms.





Interval Partitioning

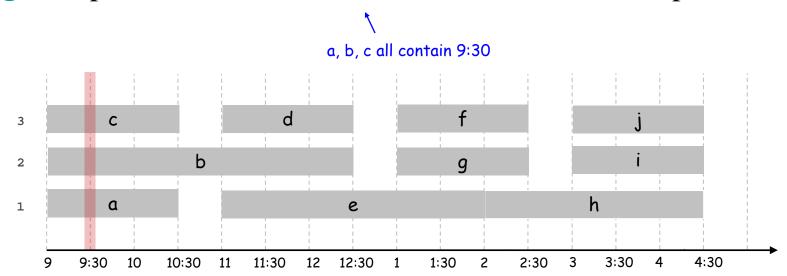
- Lecture j starts at s_j and finishes at f_j .
- **Input**: $s_1, ..., s_n$ and $f_1, ..., f_n$.
- Goal: find minimum number of classrooms to schedule all lectures so that no two occur at the same time in the same room.
- E.g.: Same lectures scheduled in 3 classrooms.





Lower Bound

- **Definition**. The **depth** of a set of open intervals is the maximum number that contain any given time.
- **Key lemma**. Number of classrooms needed ≥ depth.
- E.g.: Depth of this schedule = $3 \Rightarrow$ this schedule is optimal.



• Q: Is it always sufficient to have number of classrooms = depth?



Greedy Algorithm

Consider lectures in increasing order of start time: assign lecture to any compatible classroom.

```
Sort intervals by starting time so that s_1 \leq s_2 \leq \ldots \leq s_n. d \leftarrow 0 // Number of allocated classrooms for j = 1 to n
   if (lecture j is compatible with some classroom k)        schedule lecture j in classroom k
   else
        allocate a new classroom d + 1        schedule lecture j in classroom d + 1        d \leftarrow d + 1
```

- Implementation. $O(n \log n)$ time; O(n) space.
- For each classroom, maintain the finish time of the last job added.
- Keep the classrooms in a priority queue
 - Using a heap, main loop takes $O(n \log d)$ time



Analysis: Structural Argument

Observation. Greedy algorithm never schedules two incompatible lectures in the same classroom.

- Theorem. Greedy algorithm is optimal.
- **Proof:** Let d = number of classrooms allocated by greedy.
 - Classroom d is opened because we needed to schedule a lecture, say j, that is incompatible with all d-1 last lectures in other classrooms.
 - These d lectures each end after s_i .
 - Since we sorted by start time, they start no later than s_i .
 - Thus, we have d lectures overlapping at time $s_i + \varepsilon$.
 - Key lemma \Rightarrow all schedules use ≥ d classrooms. •

Duality

- Our first example of "duality"!
- High-level overview of proof of correctness:
 - Identify obstacles to scheduling in few classrooms
 - Sets of overlapping lectures
 - Show that our algorithm's solution matches some obstacle
 - If our solution uses *d* classrooms, then there is a set of *d* overlapping lectures
 - Conclude that our solution cannot be improved

Scheduling to minimize lateness

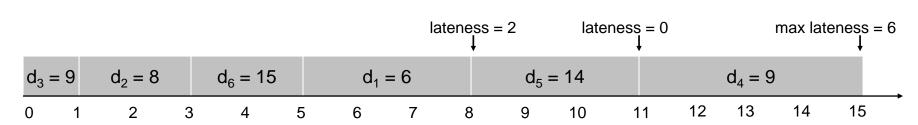


Scheduling to Minimizing Lateness

Minimizing lateness problem.

- 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: $\ell_j = \max \{ 0, f_j d_j \}$.
- Goal: schedule all jobs to minimize maximum lateness $L = \max \ell_j$.

	1	2	3	4	5	6
t _j	3	2	1	4	3	2
d _j	6	8	9	9	14	15



Greedy strategies?

Minimizing Lateness: Greedy Strategies

Greedy template: consider jobs in some order.

- [Shortest processing time first] Consider jobs in ascending order of processing time t_i.
- [Earliest deadline first] Consider jobs in ascending order of deadline d_i.
- [Smallest slack] Consider jobs in ascending order of slack d_i t_i.

Minimizing Lateness: Greedy Strategies

Greedy template: consider jobs in some order.

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

	1	2
t _j	1	10
d _j	100	10

counterexample

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

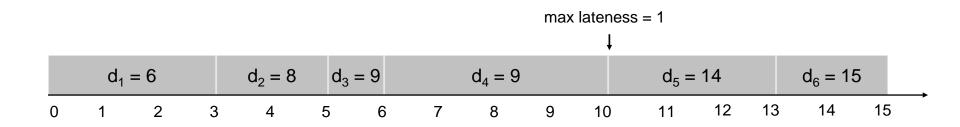
	1	2
t _j	1	10
d _j	2	10

counterexample

Minimizing Lateness: Greedy Algorithm

• [Earliest deadline first]

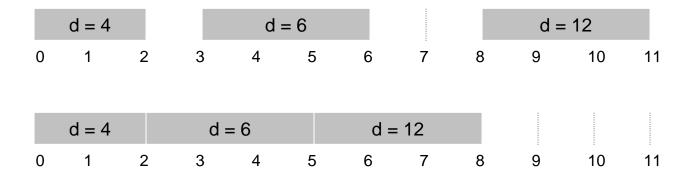
```
Sort n jobs by deadline so that d_1 \leq d_2 \leq ... \leq d_n t \leftarrow 0 for j = 1 to n  \text{Assign job j to interval } [t, t + t_j]  s_j \leftarrow t, f_j \leftarrow t + t_j t \leftarrow t + t_j output intervals [s_j, f_j]
```





Minimizing Lateness: No Idle Time

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



Observation. The greedy schedule has no idle time.



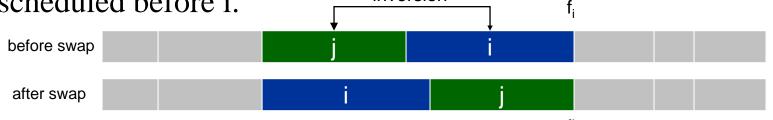
Minimizing Lateness: Inversions

• An inversion in schedule S is a pair of jobs i and j such that $d_i < d_j$ but j scheduled before i.

- Observation. Greedy schedule has no inversions.
- Observation. If a schedule (with no idle time) has an inversion, it has one with a pair of inverted jobs scheduled consecutively.

Minimizing Lateness: Inversions

• An inversion in schedule S is a pair of jobs i and j such that $d_i < d_j$ but j scheduled before i.



- Claim. Swapping two adjacent, inverted jobs reduces the number of inversions by one and does not increase the max lateness.
- **Proof:** Let ℓ be the lateness before the swap, and let ℓ be the lateness afterwards.
 - $\ell'_k = \ell_k$ for all $k \neq i, j$
 - $-\ell'_{i} \leq \ell_{i}$
 - If job j is late:

$$\ell'_{j} = f'_{j} - d_{j}$$
 (definition)
 $= f_{i} - d_{j}$ (j finishes at time f_{i})
 $\leq f_{i} - d_{i}$ ($d_{i} < d_{j}$)
 $\leq \ell_{i}$ (definition)

Minimizing Lateness: Analysis

Theorem. Greedy schedule S is optimal.

Proof: Define S* to be an optimal schedule that has the fewest number of inversions.

- Can assume S* has no idle time.
- If S^* has no inversions, then $S = S^*$.
- If S* has an inversion, let i-j be an adjacent inversion.
 - Swapping i and j does not increase the maximum lateness and strictly decreases the number of inversions.
 - This contradicts the definition of S*.

Alternative Proof

- Fix an input *t*, *d*.
- Define S* to be an optimal schedule that has the fewest number of inversions.
 - If S^* has no inversions, then $S = S^*$.
 - − If S* has an inversion, let i-j be an adjacent inversion.
 - swapping i and j does not increase the maximum lateness and strictly decreases the number of inversions
 - this contradicts definition of S* •



Summary: 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.