Intro. Algorithms & Models of Computation

CS/ECE 374A, Fall 2024

Greedy Algorithms

Lecture 19 Tuesday, November 19, 2024

LATEXed: November 5, 2024 10:40

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19.1

Greedy algorithms by example

Why don't you do right?

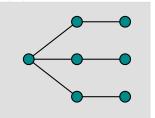
- 1. **greedy algorithms**: do locally the right thing...
- 2. ...and they suck

Problem: VertexCoverMin

Instance: Vertex Cover!Minimization

Question: A graph G.

Return the smallest subset $S \subseteq V(G)$, s.t. S touches all the edges of G.



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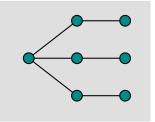
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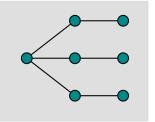
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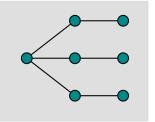
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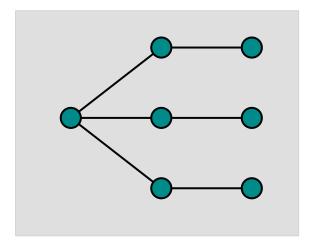
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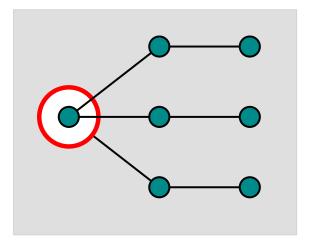
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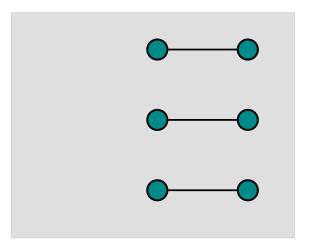
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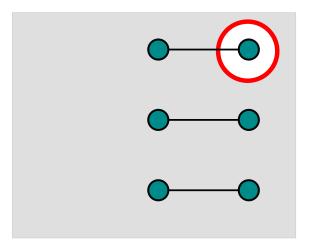
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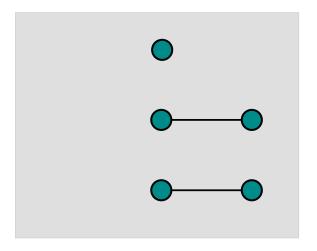


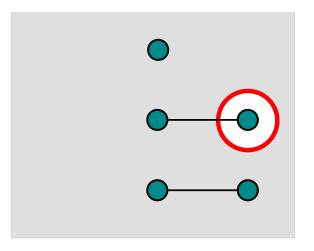


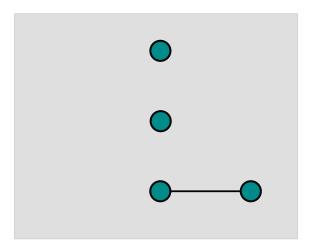


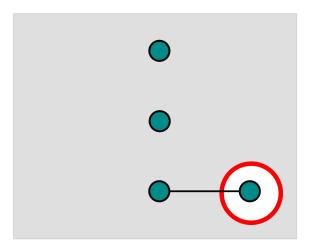


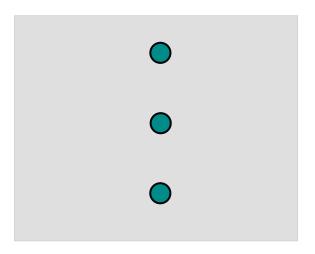


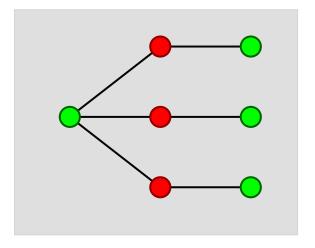




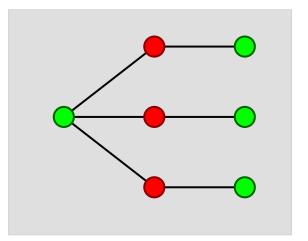








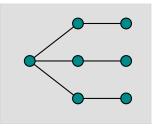
GreedyVertexCover in action...



Observation 19.1.

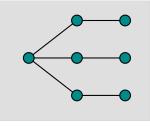
GreedyVertexCover returns 4 vertices, but opt is 3 vertices.

- GreedyVertexCover: pick vertex with highest degree, remove, repeat.
- 2. Returns 4, but opt is 3



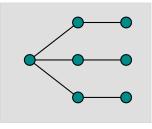
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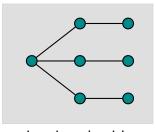
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Greedy Vertex Cover

Theorem 19.2.

There is a graph over n vertices, such that the smallest Vertex Cover has k vertices, but the greedy algorithm outputs a vertex cover of size $\Theta(k \log n)$ approximation.

Proof: Outside the scope of this class...

...left as a **hard** exercise to the interested reader.

Vertex Cover is **NP-Hard**: Believe it requires exponential time to solve exactly.

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19.2 Greedy algorithms

A list of greedy algorithms

- 1. Dijkstra/Prim/Kruskal/Boruvka.
- 2. Huffman's encoding.
- 3. Various interval scheduling.
- 4. Interval independent set.
- 5. Connect *n* ropes problem.

A list of where greedy algorithms FAIL

- 1. TSP (nearest neighbor heuristic).
- 2. Set cover.
- 3. Vertex cover.
- 4. Shortest path.
- 5. Change problem.

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19.3 Connecting ropes

Connecting ropes

Given n ropes of different lengths, the task is to connect all the ropes into one. We need to connect these ropes in minimum cost. The cost of connecting two ropes is the sum of their lengths.

Example: $\{3, 7, 9, 4, 24, 11\}$.

Connecting ropes: Greedy algorithm

Repeatedly connect two shortest ropes, put them back in the pile and repeat. Correctness: Simplified Huffman's encoding proof.

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19.4

Greedy Algorithms: Tools and Techniques

What is a Greedy Algorithm?

No real consensus on a universal definition.

Greedy algorithms

- 1. make decision incrementally in small steps without backtracking
- 2. decision at each step is based on improving <u>local or current</u> state in a myopic fashion without paying attention to the global situation
- 3. decisions often based on some fixed and simple priority rules

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Pros and Cons of Greedy Algorithms

Pros:

- 1. Usually (too) easy to design greedy algorithms
- 2. Easy to implement and often run fast since they are simple
- 3. Several important cases where they are effective/optimal
- 4. Lead to a first-cut heuristic when problem not well understood

Cons

- 1. **Very often** greedy algorithms don't work. Easy to lull oneself into believing they work
- Many greedy algorithms possible for a problem and no structured way to find effective ones

CS 374: Every greedy algorithm needs a proof of correctness

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Greedy Algorithm Types

Crude classification:

- 1. Non-adaptive: fix some ordering of decisions a priori and stick with the order
- 2. Adaptive: make decisions adaptively but greedily/locally at each step

Plan

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19.5

Scheduling Jobs to Minimize Average Waiting Time

- ightharpoonup n jobs J_1, J_2, \ldots, J_n .
- \triangleright Each J_i has non-negative processing time p_i
- One server/machine/person available to process jobs.
- ► Schedule/order jobs to min. total or average <u>waiting time</u>
- ▶ Waiting time of J_i in schedule σ : sum of processing times of all jobs scheduled before J_i

	J_1	J ₂	J ₃	J ₄	J ₅	J ₆
time	3	4	1	8	2	6

Example: schedule is $J_1, J_2, J_3, J_4, J_5, J_6$. Total waiting time is

$$0+3+(3+4)+(3+4+1)+(3+4+1+8)+\ldots =$$

Optimal schedule: Shortest Job First. $J_3, J_5, J_1, J_2, J_6, J_4$

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Optimality of Shortest Job First (SJF)

Theorem 19.1.

Shortest Job First gives an optimum schedule for the problem of minimizing total waiting time.

Proof strategy: exchange argument

Assume without loss of generality that job sorted in increasing order of processing time and hence $p_1 \leq p_2 \leq \ldots \leq p_n$ and SJF order is J_1, J_2, \ldots, J_n .

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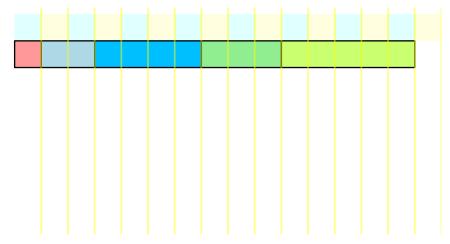
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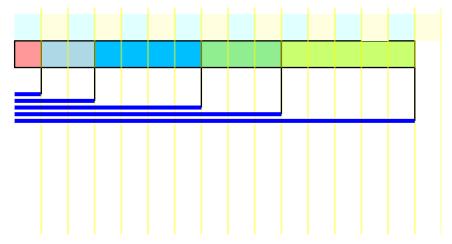
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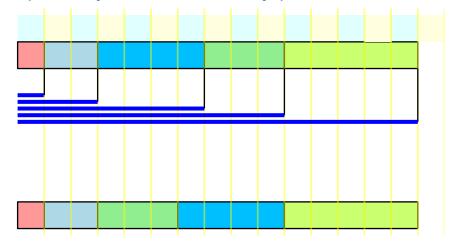
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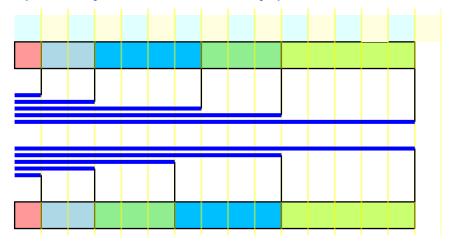
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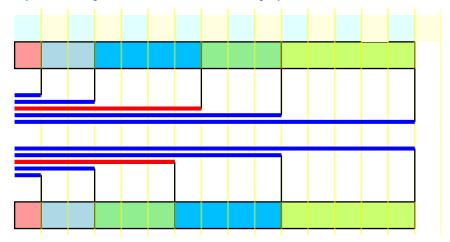
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Inversions

Definition 19.2.

A schedule $J_{i_1}, J_{i_2}, \ldots, J_{i_n}$ has an inversion if there are jobs J_a and J_b such that S schedules J_a before J_b , but $p_a > p_b$.

Claim 19.3.

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Proof: exercise.

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Proof of optimality of SJF

SJF = Shortest Job First

Recall SJF order is J_1, J_2, \ldots, J_n .

- Let $J_{i_1}, J_{i_2}, \ldots, J_{i_n}$ be an optimum schedule with fewest inversions.
- ▶ If schedule has no inversions then it is identical to SJF schedule and we are done.
- lackbox Otherwise there is an $1 \leq \ell < n$ such that $i_\ell > i_{\ell+1}$ since schedule has inversion among two adjacent scheduled jobs

Claim 19.4

The schedule obtained from $J_{i_1}, J_{i_2}, \ldots, J_{i_n}$ by exchanging/swapping positions of jobs J_{i_ℓ} and $J_{i_{\ell+1}}$ is also optimal and has one fewer inversion.

Assuming claim we obtain a contradiction and hence optimum schedule with fewest inversions must be the SJF schedule.

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- ► Schedule/order the jobs to minimize total or average waiting time
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- ► Goal: minimize total weighted waiting time.
- ▶ Formally, compute a permutation π that minimizes $\sum_{i=1}^{n} \left(\sum_{j=1}^{i-1} p_{\pi(j)} \right) w_{\pi(i)}$.

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weight	10	5	2	100	1	1

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19.5.1

Exercise: Scheduling Jobs to Minimize Weighted Average Waiting Time

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Job 1 first	Job 2 first				

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$p_1 w_2$	p_2w_1
	p_1w_2

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Correctness proof: Same as the unweighted case – if there is an inversion, then by the argument above, flip these jobs, and get a better schedule.

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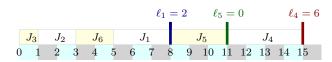
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19.6 Scheduling to Minimize Lateness

Scheduling to Minimize Lateness

- 1. Given jobs J_1, J_2, \ldots, J_n with deadlines and processing times to be scheduled on a single resource.
- 2. If a job i starts at time s_i then it will finish at time $f_i = s_i + t_i$, where t_i is its processing time. d_i : deadline.
- 3. The lateness of a job is $\ell_i = \max(0, f_i d_i)$.
- 4. Schedule all jobs such that $L = \max \ell_i$ is minimized.

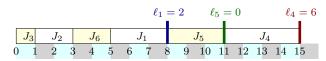
	J_1	J_2	<i>J</i> ₃	J_4	<i>J</i> ₅	J_6
ti	3	2	1	4	3	2
di	6	8	9	9	14	15



Scheduling to Minimize Lateness

- 1. Given jobs J_1, J_2, \ldots, J_n with deadlines and processing times to be scheduled on a single resource.
- 2. If a job i starts at time s_i then it will finish at time $f_i = s_i + t_i$, where t_i is its processing time. d_i : deadline.
- 3. The lateness of a job is $\ell_i = \max(0, f_i d_i)$.
- 4. Schedule all jobs such that $L = \max \ell_i$ is minimized.

	J_1	J ₂	J ₃	J ₄	J ₅	J ₆
ti	3	2	1	4	3	2
di	6	8	9	9	14	15



```
Initially R is the set of all requests curr\_time = 0 max\_lateness = 0 while R is not empty do choose \ i \in R curr\_time = curr\_time + t_i if (curr\_time > d_i) then max\_lateness = max(curr\_time - d_i, max\_lateness) return max\_lateness
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Main task: Decide the order in which to process jobs in R

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Three Algorithms

- 1. Shortest job first sort according to t_i .
- 2. Shortest slack first sort according to $d_i t_i$.
- 3. EDF = Earliest deadline first sort according to d_i .

Counter examples for first two: exercise

Three Algorithms

- 1. Shortest job first sort according to t_i .
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Counter examples for first two: exercise

Theorem 19.1.

Greedy with EDF rule minimizes maximum lateness.

Proof via an exchange argument

Idle time: time during which machine is not working.

Lemma 19.2.

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Inversions

EDF = Earliest Deadline First

Assume jobs are sorted such that $d_1 \leq d_2 \leq \ldots \leq d_n$. Hence EDF schedules them in this order.

Definition 19.3.

A schedule S is said to have an inversion if there are jobs i and j such that S schedules i before j, but $d_i > d_j$.

Claim 19.4

If a schedule S has an inversion then there is an inversion between two <u>adjacent</u> scheduled jobs.

Proof: exercise

Inversions

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Claim 19.4.

If a schedule **S** has an inversion then there is an inversion between two <u>adjacent</u> scheduled jobs.

Proof: exercise.

Proof sketch of Optimality of EDF

- Let **S** be an optimum schedule with smallest number of inversions.
- ▶ If S has no inversions then this is same as EDF and we are done.
- ▶ Else S has two adjacent jobs i and j with $d_i > d_j$.
- ightharpoonup Swap positions of i and j to obtain a new schedule S'

Claim 19.5.

Maximum lateness of S' is no more than that of S. And S' has strictly fewer inversions than S.

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19.7

Maximum Weight Subset of Elements: Cardinality and Beyond

Picking k elements to maximize total weight

- 1. Given n items each with non-negative weights/profits and integer $1 \le k \le n$.
- 2. Goal: pick k elements to maximize total weight of items picked.

	e_1	e_2	<i>e</i> ₃	e ₄	<i>e</i> ₅	e_6
weight	3	2	1	4	3	2

k=2:

k = 3:

k = 4:

```
m{N} is the set of all elements m{X} \leftarrow \emptyset (* m{X} will store all the elements that will be picked *) while |m{X}| < k and m{N} is not empty m{do} choose m{e}_j \in m{N} of maximum weight add m{e}_j to m{X} remove m{e}_j from m{N} return the set m{X}
```

Remark: One can rephrase algorithm simply as sorting elements in decreasing weight order and picking the top k elements but the above template generalizes to other settings a bit more easily.

Theorem 19.1.

Greedy is optimal for picking k elements of maximum weight.

```
N is the set of all elements X \leftarrow \emptyset (* X will store all the elements that will be picked *) while |X| < k and N is not empty do choose e_j \in N of maximum weight add e_j to X remove e_j from N return the set X
```

Remark: One can rephrase algorithm simply as sorting elements in decreasing weight order and picking the top k elements but the above template generalizes to other settings a bit more easily.

Theorem 19.1.

Greedy is optimal for picking k elements of maximum weight.

A more interesting problem

- 1. Given n items $N = \{e_1, e_2, \dots, e_n\}$. Each item e_i has a non-negative weight w_i .
- 2. Items partitioned into h sets N_1, N_2, \ldots, N_h . Think of each item having one of h colors.
- 3. Given integers k_1, k_2, \ldots, k_h and another integer k
- 4. Goal: pick k elements such that no more than k_i from N_i to maximize total weight of items picked.

	e_1	e_2	<i>e</i> ₃	e_4	<i>e</i> ₅	e_6	<i>e</i> ₇
weight	9	5	4	7	5	2	1

$$N_1 = \{e_1, e_2, e_3\}, N_2 = \{e_4, e_5\}, N_3 = \{e_6, e_7\}$$

 $k = 4, k_1 = 2, k_2 = 1, k_3 = 2$

```
N is the set of all elements X \leftarrow \emptyset (* X will store all the elements that will be picked *) while N is not empty do N' = \{e_i \in N \mid X \cup \{e_i\} \text{ is feasible}\} if N' = \emptyset then break choose e_j \in N' of maximum weight add e_j to X remove e_j from N return the set X
```

Theorem 19.2

Greedy is optimal for the problem on previous slide

Proof: exercise after class.

Special case of general phenomenon of Greedy working for maximum weight independent set in a matroid. Beyond scope of course.

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19.8 Interval Scheduling

Intro. Algorithms & Models of Computation

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19.8.1

Problem statement, and a few greedy algorithms that do not work

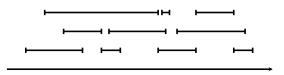
Interval Scheduling

Problem 19.1 (Interval Scheduling).

Input: A set of jobs with start and finish times to be scheduled on a resource (example: classes and class rooms).

Goal: Schedule as many jobs as possible

0.1 Two jobs with overlapping intervals cannot both be scheduled!



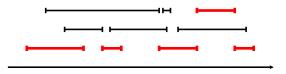
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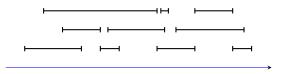


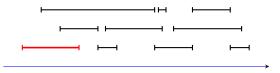
```
R is the set of all requests X \leftarrow \emptyset (* X will store all the jobs that will be scheduled *) while R is not empty do choose i \in R add i to X remove from R all requests that overlap with i return the set X
```

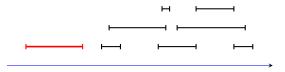
Main task: Decide the order in which to process requests in R

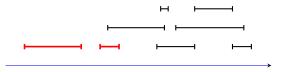
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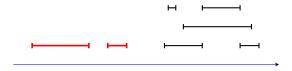
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Process jobs in the order of their starting times, beginning with those that start earliest.

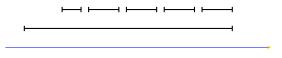


Figure: Counter example for earliest start time

Process jobs in the order of their starting times, beginning with those that start earliest.



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Figure: Counter example for earliest start time

Smallest Processing Time

Process jobs in the order of processing time, starting with jobs that require the shortest processing.

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Figure: Counter example for smallest processing time

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Process jobs in that ha	e the fewest "conflicts"	first.

Process jobs in that hav	ve the fev	west "conflict	s" first.	
	-			

Process jobs in that have the fewest "conflicts" first.

Figure: Counter example for fewest conflicts

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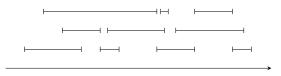
Figure: Counter example for fewest conflicts

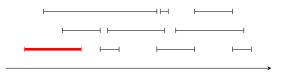
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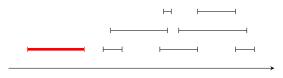
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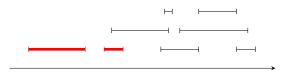
19.8.2

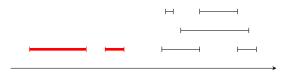
Interval Scheduling: Earliest finish time

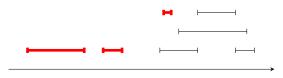














Optimal Greedy Algorithm

```
R is the set of all requests X \leftarrow \emptyset (* X stores the jobs that will be scheduled *) while R is not empty choose i \in R such that finishing time of i is smallest add i to X remove from R all requests that overlap with i return X
```

Theorem 19.2.

The greedy algorithm that picks jobs in the order of their finishing times is optimal.

Implementation and Running Time

```
Initially R is the set of all requests X \leftarrow \emptyset (* X stores the jobs that will be scheduled *) while R is not empty choose i \in R such that finishing time of i is least if i does not overlap with requests in X add i to X remove i from R return the set X
```

- ▶ Presort all requests based on finishing time. $O(n \log n)$ time
- Now choosing least finishing time is O(1)
- ► Keep track of the finishing time of the last request added to **A**. Then check if starting time of **i** later than that
- ▶ Thus, checking non-overlapping is O(1)
- ► Total time $O(n \log n + n) = O(n \log n)$

Comments

- 1. Interesting Exercise: smallest interval first picks at least half the optimum number of intervals.
- 2. All requests need not be known at the beginning. Such <u>online</u> algorithms are a subject of research

Weighted Interval Scheduling

Suppose we are given n jobs. Each job i has a start time s_i , a finish time f_i , and a weight w_i . We would like to find a set s of compatible jobs whose total weight is maximized. Which of the following greedy algorithms finds the optimum schedule?

- (A) Earliest start time first.
- (B) Earliest finish time fist.
- (C) Highest weight first.
- (D) None of the above.
- **(E)** IDK.

Weighted problem can be solved via dynamic programming. See notes.

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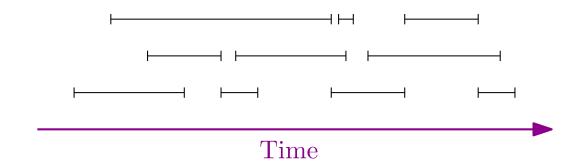
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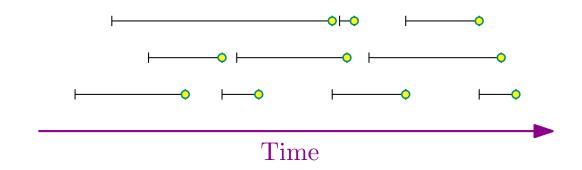
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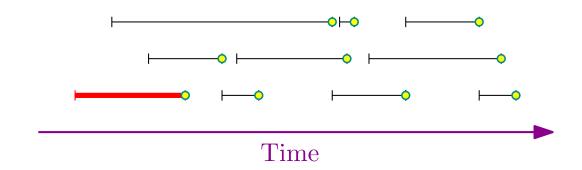
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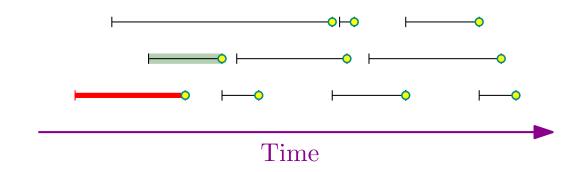
19.8.3

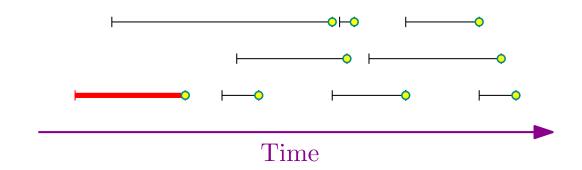
Proving optimality of earliest finish time

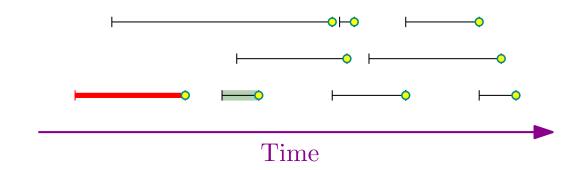


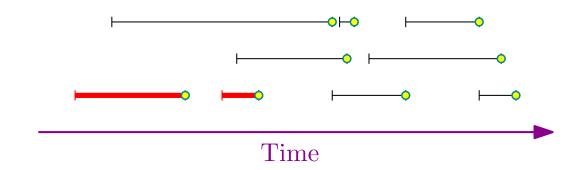


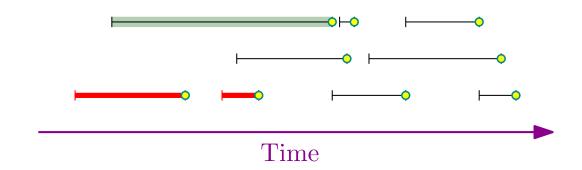


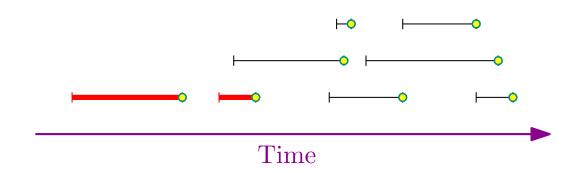


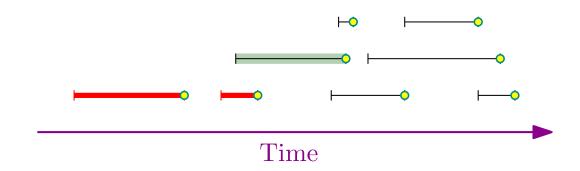


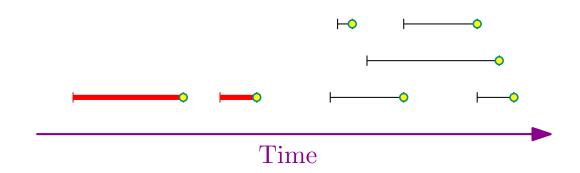


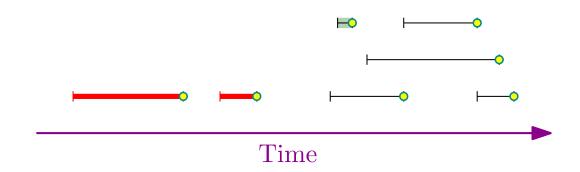


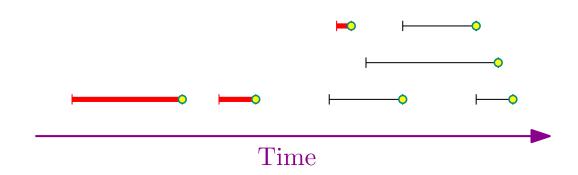


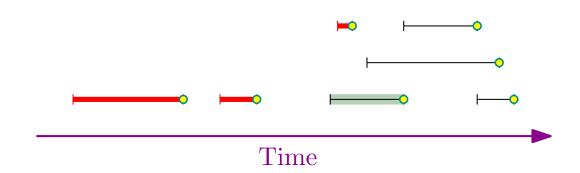


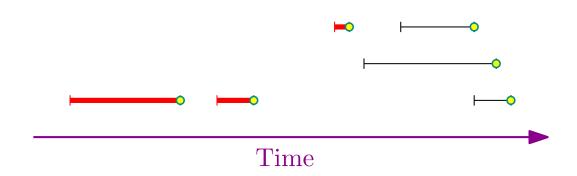


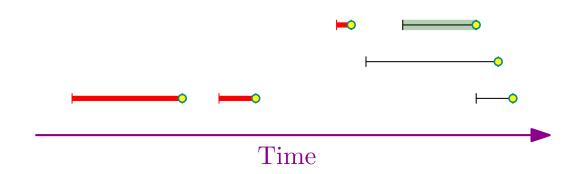


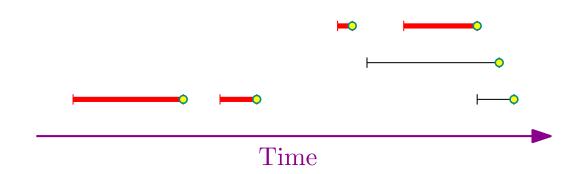


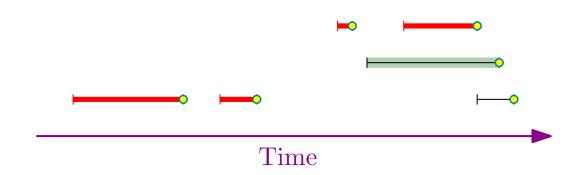


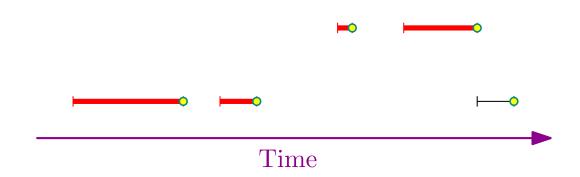


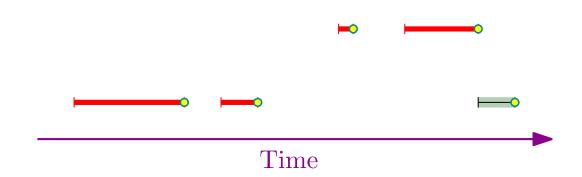


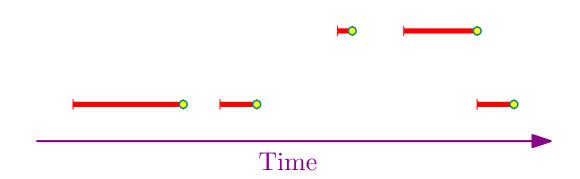








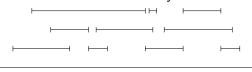




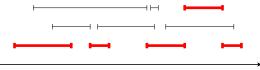
- 1. Correctness: Clearly the algorithm returns a set of jobs that does not have any conflicts
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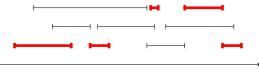
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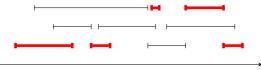
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Helper Claim

Claim 19.3.

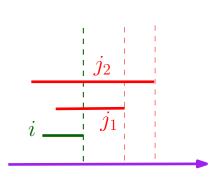
i be first interval picked by Greedy into solution.

O: Optimal solution.

If $i \notin O$, there is exactly one interval $j_1 \in O$ that conflicts with i.

Proof.

- 1. No $j \in O$ conflicts $i \implies O$ is not opt!
- 2. Suppose $j_1, j_2 \in O$ such that $j_1 \neq j_2$ and both j_1 and j_2 conflict with i.
- 3. Since i has earliest finish time, j_1 and i overlap at f(i).
- 4. For same reason j_2 also overlaps with i at f(i).
- 5. Implies that j_1, j_2 overlap at f(i) but intervals in O cannot overlap.



Proof of Optimality: Key Lemma

Lemma 19.4.

 $\emph{\textbf{i}}_1$ be first interval picked by Greedy. There exists an optimum solution that contains $\emph{\textbf{i}}_1$.

Proof.

Let O be an <u>arbitrary</u> optimum solution. If $i_1 \in O$ we are done.

By Claim 19.3 ...

- 1. Exists exactly one $j_1 \in O$ conflicting with i_1 .
- 2. Form a new set O' by removing j_1 from O and adding i_1 , that is $O' = (O \{j_1\}) \cup \{i_1\}$.
- 3. From claim, O' is a <u>feasible</u> solution (no conflicts).
- 4. Since |O'| = |O|, O' is also an optimum solution and it contains i_1 .

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Proof by Induction on number of intervals.

Base Case: n = 1. Trivial since Greedy picks one interval.

Induction Step: Assume theorem holds for i < n.

Let **K** be an input (i.e., instance) with **n** intervals

 $i_1 \leftarrow$ First interval picked by greedy algorithm.

 $K' \Leftarrow$ The result of removing i_1 and all conflicting intervals from K.

$$|K'| = |K| - 1$$
.

G(K), G(K'): Solution produced by Greedy on K and K', respectively.

Lemma 19.4 \Longrightarrow optimum solution O to K with $i_1 \in O$

Let $O' = O - \{i_1\}$. O' is a solution to K'.

$$|G(K)| = 1 + |G(K')|$$
 from Greedy description $\geq 1 + |O'|$ By induction, $G(I')$ is optimum for I') $= |O|$

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Let
$$O' = O - \{i_1\}$$
. O' is a solution to K'

$$|G(K)| = 1 + |G(K')|$$
 from Greedy description $\geq 1 + |O'|$ By induction, $G(I')$ is optimum for I') $= |O|$

Proof by Induction on number of intervals.

Base Case: n = 1. Trivial since Greedy picks one interval.

Induction Step: Assume theorem holds for i < n.

Let K be an input (i.e., instance) with n intervals

 $i_1 \leftarrow$ First interval picked by greedy algorithm.

 $K' \leftarrow$ The result of removing i_1 and all conflicting intervals from K

$$|K'| = |K| - 1.$$

G(K), G(K'): Solution produced by Greedy on K and K', respectively.

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Intro. Algorithms & Models of Computation

CS/ECE 374A, Fall 2024

19.9

Greedy algorithms – an epilogue

Greedy proof techniques: Overview

- 1. Greedy's first step leads to an optimum solution. Show that optimal solution can be modified to agree with greedy after first step. Then use induction. Example, Interval Scheduling.
- 2. Greedy algorithm stays ahead. Show that after each step the solution of the greedy algorithm is at least as good as the solution of any other algorithm. Example, Interval scheduling.
- 3. Structural property of solution. Observe some structural bound of every solution to the problem, and show that greedy algorithm achieves this bound. Example, Interval Partitioning (see Kleinberg-Tardos book).
- 4. Exchange argument. Gradually transform any optimal solution to the one produced by the greedy algorithm, without hurting its optimality.

Example: Minimizing lateness, and Interval scheduling

Takeaway Points

- 1. Greedy algorithms come naturally but often are incorrect. A proof of correctness is an absolute necessity.
- 2. Exchange arguments are often the key proof ingredient. Focus on why the first step of the algorithm is correct: need to show that there is an optimum/correct solution with the first step of the algorithm.
- 3. Thinking about correctness is also a good way to figure out which of the many greedy strategies is likely to work.