

Greedy Algorithms*

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Algorithm Course: Shanghai Jiao Tong University

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Outline

- 1 Basic Methodology
 - Interval Scheduling
 - Interval Partitioning
 - Scheduling to Minimize Lateness

- 2 More Examples
 - Optimal Caching
 - Coin Changing

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Interval Scheduling: An Introductory Example

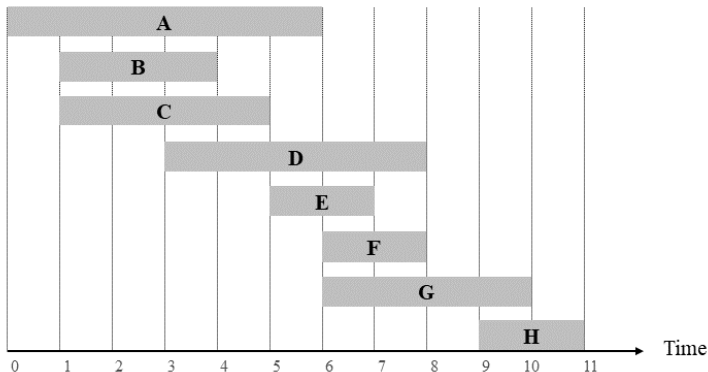
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Goal: find maximum subset of mutually compatible jobs.

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Optimization Problem: Given a problem Π with domain \mathbf{X} , choose a subset or determine a sequence according to some **maximization** or **minimization** objective. (Each $X \in \mathbf{X}$ is an instance of Π)

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General Template: Consider each item $x_i \in X$ of problem Π (in some order), make choice that looks **best** at the moment.

Note: it makes a *locally optimal* choice in hope that this choice will lead to a *globally optimal* solution.

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Interval Scheduling Problem: Consider jobs in some natural order. Take each job provided to judge its compatibility with the ones already taken.

Attempts

[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 $f_j - s_j$.

[Fewest conflicts] For each job j , count the number of conflicting jobs c_j . Schedule in ascending order of c_j .

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Greedy Interval Scheduling Algorithm

Algorithm 1: Greedy Interval Scheduling

```
1 Sort jobs by finish times so that  $f_1 \leq f_2 \leq \dots \leq f_n$ ;  
2  $A \leftarrow \emptyset$ ; // set of jobs selected  
3 for  $j = 1$  to  $n$  do  
4   if job  $j$  is compatible with  $A$  then  
5      $A \leftarrow A \cup \{j\}$ ;  
6 return  $A$ ;
```

Greedy Interval Scheduling Algorithm

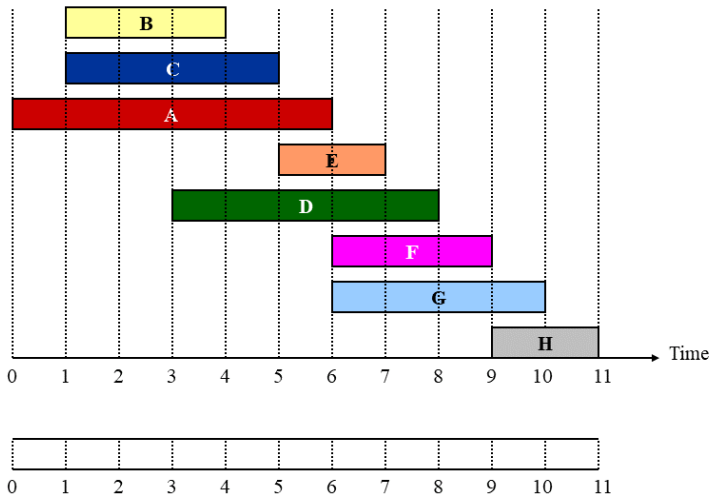
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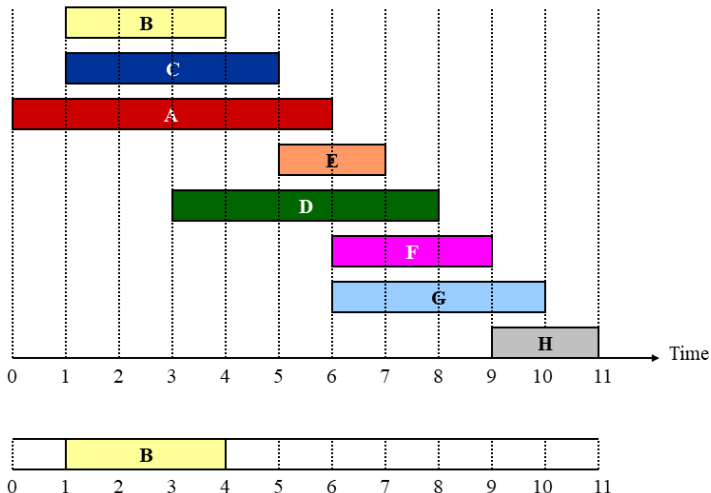
Implementation: $O(n \log n)$.

- After each iteration, set job j^* that was added last to A .
- Job j is compatible with A if $s_j \geq f_{j^*}$.

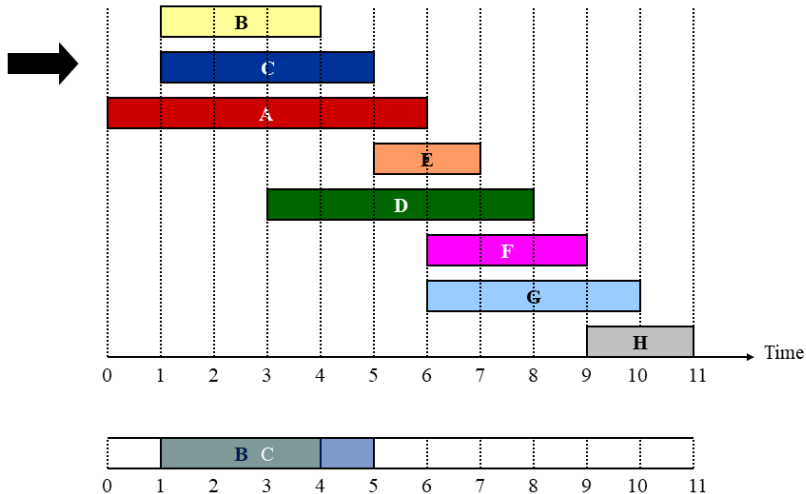
Demo



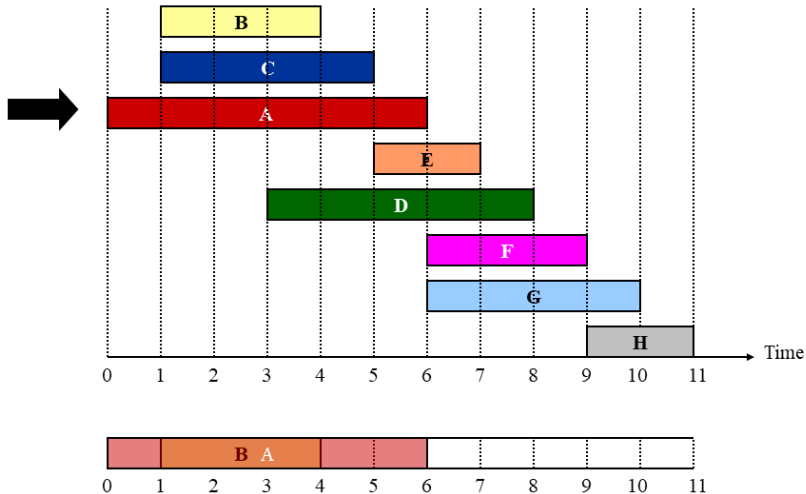
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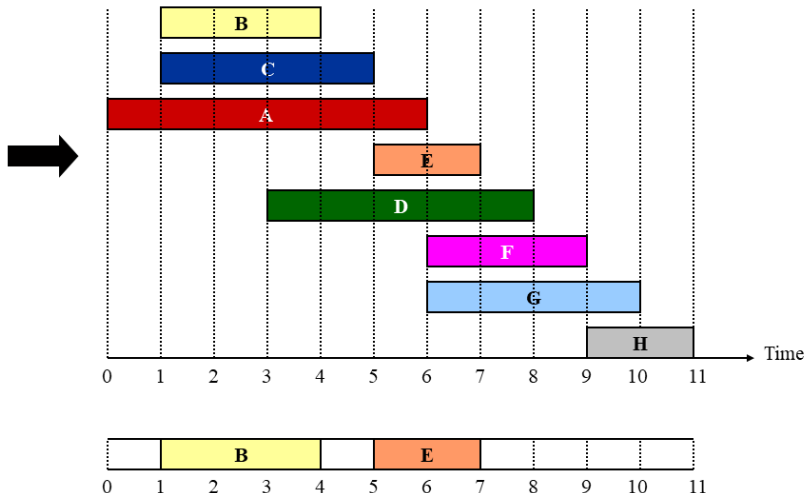
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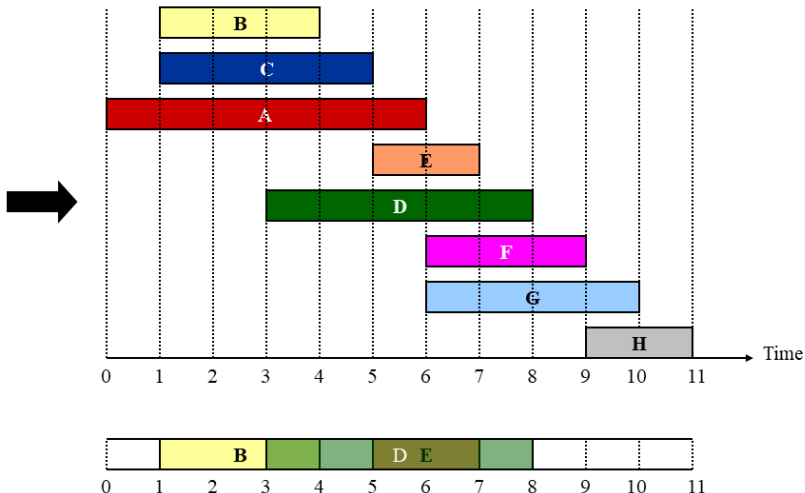
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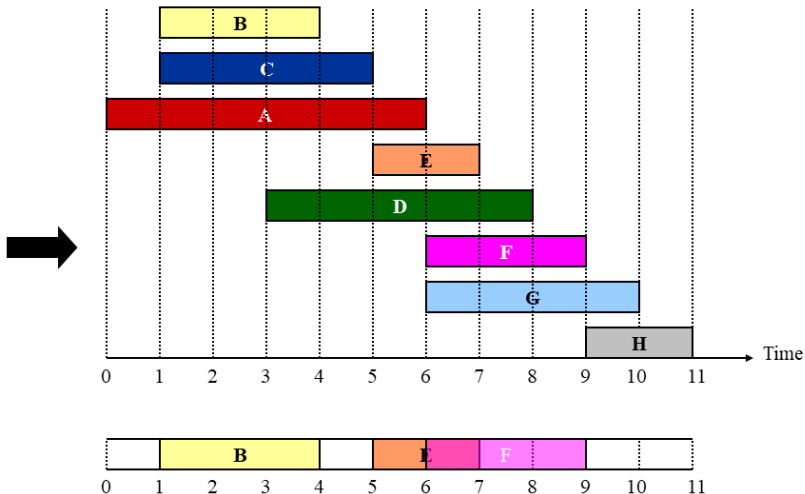
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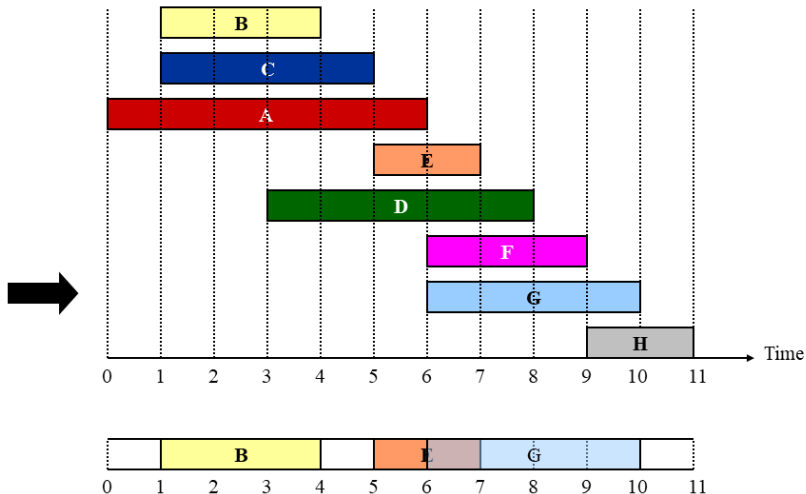
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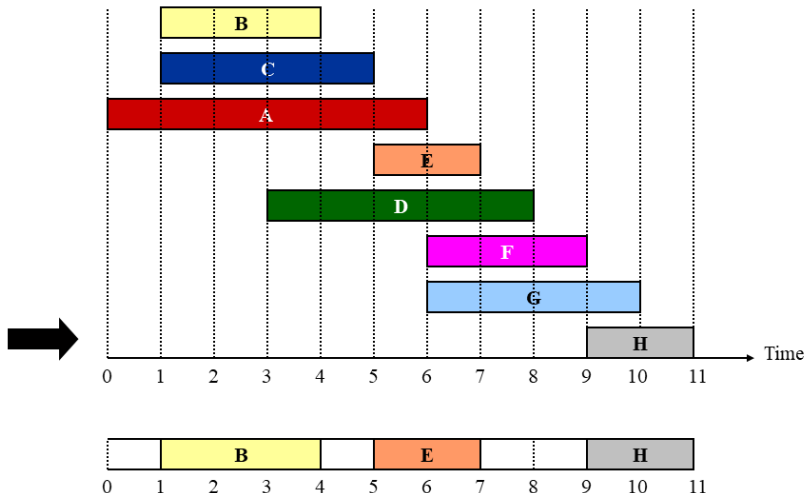
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Demo



Demo



Notation

Greedy Solution: $\{B, E, H\}$

Optimal Solutions: (not necessarily unique)

$\{A, F, H\}, \{B, E, H\}, \{B, F, H\}, \{C, E, H\}, \{C, F, H\}$

Feasible Solutions: (can work, but may not be the best)

$\emptyset, \{A\}, \{B\}, \{C\}, \{D\}, \{E\}, \{F\}, \{G\}, \{H\};$
 $\{A, F\}, \{A, G\}, \{A, H\}, \{B, E\}, \{B, F\}, \{B, G\}, \{B, H\},$
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Let j_1, j_2, \dots, j_m denote set of jobs in an optimal solution with $i_1 = j_1$, $i_2 = j_2, \dots, i_r = j_r$ for the largest possible value of r .

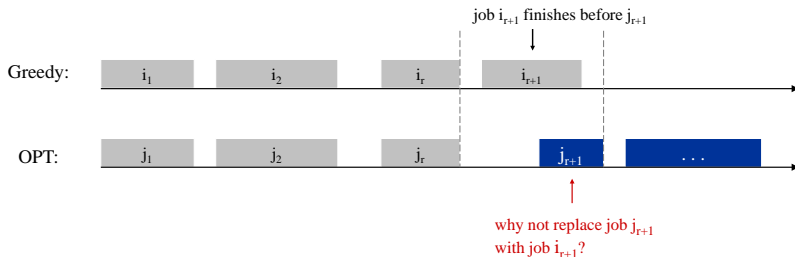
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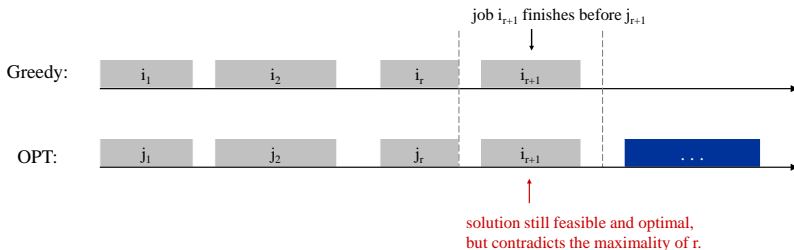
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Interval Partitioning

Lecture j starts at s_j and finishes at f_j .

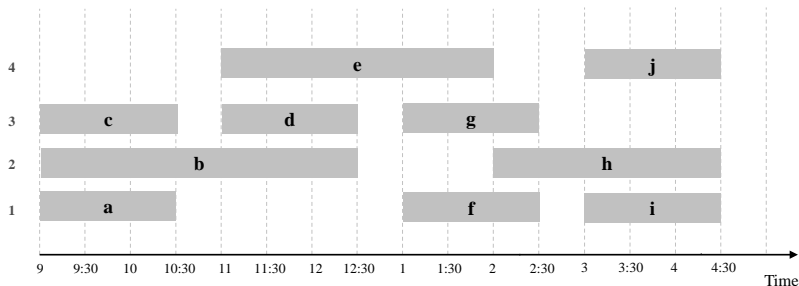
Goal: find minimum number of classrooms to schedule all lectures so that no two occur at the same time in the same room.

Interval Partitioning

Lecture j starts at s_j and finishes at f_j .

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Example: This schedule uses 4 classrooms to schedule 10 lectures.

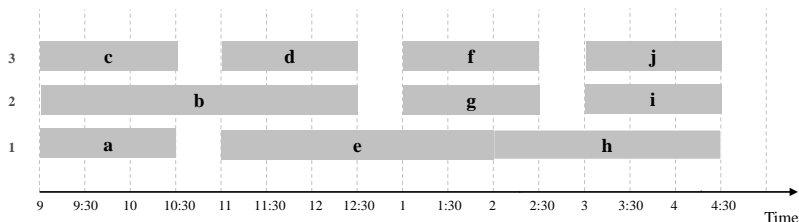


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Example: This schedule uses only 3.



Lower Bound on Optimal Solution

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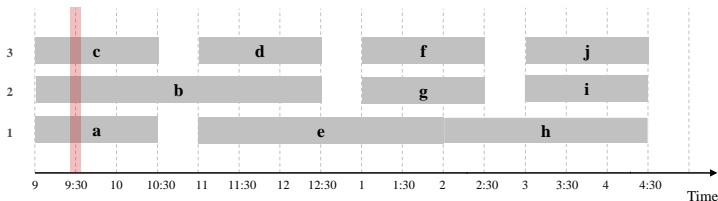
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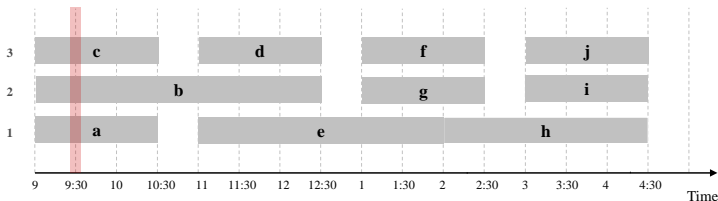


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Question. Does there always exist a schedule equal to depth of intervals?

Greedy Interval Partitioning Algorithm

Algorithm 2: Interval Partitioning Greedy Algorithm

```
1 Sort intervals by starting time so that  $s_1 \leq s_2 \leq \dots \leq s_n$ ;  
2  $d \leftarrow 0$ ; // number of allocated classrooms  
3 for  $j = 1$  to  $n$  do  
4   if lecture  $j$  is compatible with some classroom  $k$  then  
5     schedule lecture  $j$  in classroom  $k$ ;  
6   else  
7     allocate a new classroom  $d + 1$ ;  
8     schedule lecture  $j$  in classroom  $d + 1$ ;  
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Implementation: $O(n \log n)$.

- For classroom k , maintain the finish time of the last job added.
- Keep the classrooms in a priority queue.

Correctness Proof

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

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Key observation \Rightarrow all schedules use $\geq d$ classrooms.

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Scheduling to Minimize 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: $l_j = \max\{0, f_j - d_j\}$.

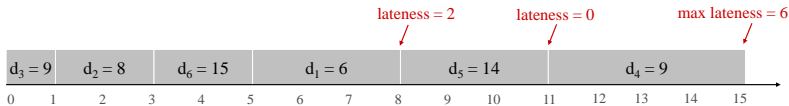
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	1	2	3	4	5	6
t_j	3	2	1	4	3	2
d_j	6	8	9	9	14	15



Attempt: Consider jobs in ascending order by some strategy

[Shortest processing time first] Sort by processing time t_j .

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counterexample

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A Greedy Algorithm: Earliest Deadline First

Algorithm 3: Greedy Minimizing Lateness

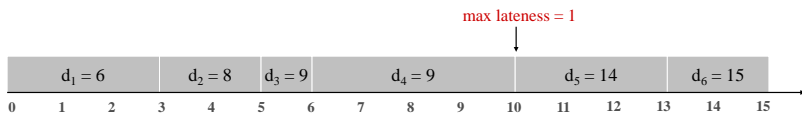
- 1 Sort n jobs by deadline so that $d_1 \leq d_2 \leq \dots \leq d_n$;
 - 2 $t \leftarrow 0$;
 - 3 **for** $j = 1$ **to** n **do**
 - 4 Assign job j to interval $[t, t + t_j]$;
 - 5 $s_j \leftarrow t, f_j \leftarrow t + t_j$;
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A Greedy Algorithm: Earliest Deadline First

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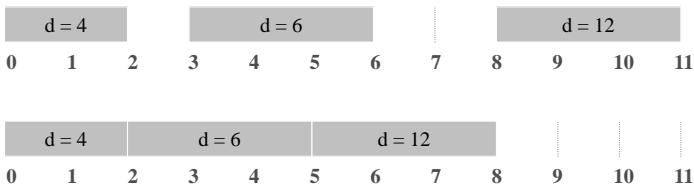
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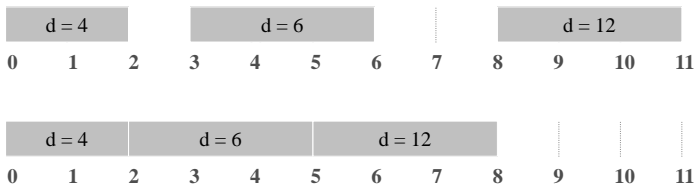
Correctness Proof: Reduce Optimal Solution

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



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Observation. The greedy schedule has no idle time.

Correctness Proof: Optimal Solution vs Algorithm Solution

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



[as before, we assume jobs are numbered so that $d_1 \leq d_2 \leq \dots \leq d_n$]

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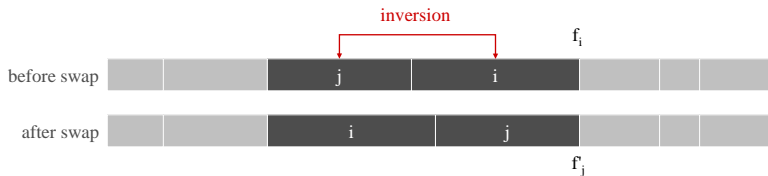
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Observation. Greedy schedule has no inversions.

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

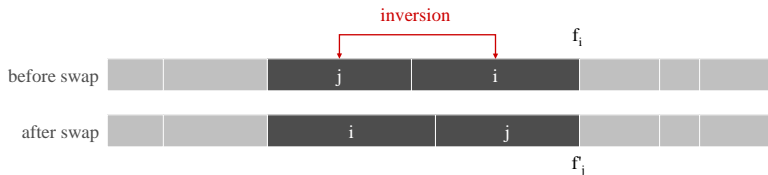
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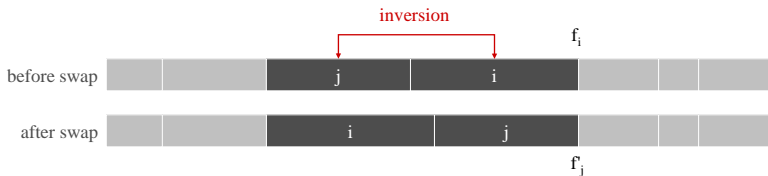


Proof. Let l be the lateness before the swap, and let l' be it afterwards.

- $l'_k = l_k$ for all $k \neq i, j$
- $l'_i \leq l_i$
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$$\begin{aligned}
 l'_j &= f'_j - d_j && \text{(definition)} \\
 &= f_i - d_j && (j \text{ finishes at time } f_i) \\
 &\leq f_i - d_i && (i < j) \\
 &\leq l_i && \text{(definition)}
 \end{aligned}$$

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- 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^* . □

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. Kruskal, Prim, Dijkstra, Huffman, ...

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Optimal Offline Caching

- Cache with capacity to store k items.
- Sequence of m item requests d_1, d_2, \dots, d_m .
- **Cache hit**: item already in cache when requested.
- **Cache miss**: item not in cache when requested: must bring requested item into cache, and evict some existing item, if full.

Goal. Eviction schedule that minimizes number of cache misses.

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Example. $k = 2$, initial cache = ab ,

requests: a, b, c, b, c, a, a, b .

requests	cache	
a	a	b
b	a	b
c	c	b
b	c	b
c	c	b
a	a	b
a	a	b
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red = cache miss

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Optimal eviction schedule: 2 cache misses.

requests	cache	
a	a	b
b	a	b
c	c	b
b	c	b
c	c	b
a	a	b
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red = cache miss

Optimal Strategy: Farthest-In-Future

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

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current cache:

a	b	c	d	e	f
---	---	---	---	---	---

future queries:

g	a	b	c	e	d	a	b	b	a	c	d	e	a	f	a	d	e	f	g	h	...
---	---	---	---	---	---	---	---	---	---	---	---	---	---	----------	---	---	---	---	---	---	-----

↑
cache miss

↑
eject this one

Optimal Strategy: Farthest-In-Future

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

current cache: **a** **b** **c** **d** **e** **f**

future queries: g a b c e d a b b a c d e a f a d e f g h ...
 ↑ ↑
 cache miss eject this one

Theorem. [Bellady, 1960s] FF is an optimal eviction schedule.

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

Reduced Eviction Schedules

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Intuition. Can transform an unreduced schedule into a reduced one with no more cache misses (means no more cache insertion/replacement here).

a	a	b	c
a	a	x	c
c	a	d	c
d	a	d	b
a	a	c	b
b	a	x	b
c	a	c	b
a	a	b	c
a	a	b	c

an unreduced schedule

a	a	b	c
a	a	b	c
c	a	b	c
d	a	d	c
a	a	d	c
b	a	d	b
c	a	c	b
a	a	c	b
a	a	c	b

a reduced schedule

Reduced Eviction Schedules

Claim. Given any unreduced schedule S , we can transform it into a reduced schedule S' with no more cache replacement (insertion).

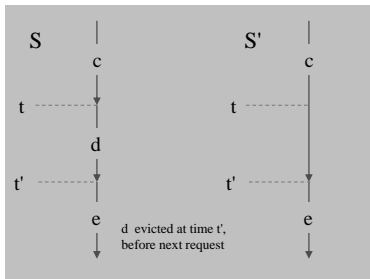
[†]doesn't enter cache at requested time

Reduced Eviction Schedules

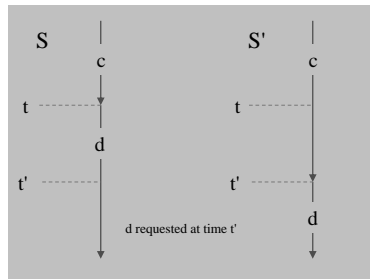
Claim. Given any unreduced schedule S , we can transform it into a reduced schedule S' with no more cache replacement (insertion).

Proof. (by induction on number of unreduced[†] items)

Suppose S brings d into the cache at time t , without a request. Let c be the item S evicts when it brings d into the cache.



Case 1



Case 2

[†]doesn't enter cache at requested time

Theorem. FF is an optimal eviction algorithm

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Invariant: There exists an optimal reduced schedule S that makes the same eviction schedule as S_{FF} through the first $j + 1$ requests.

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

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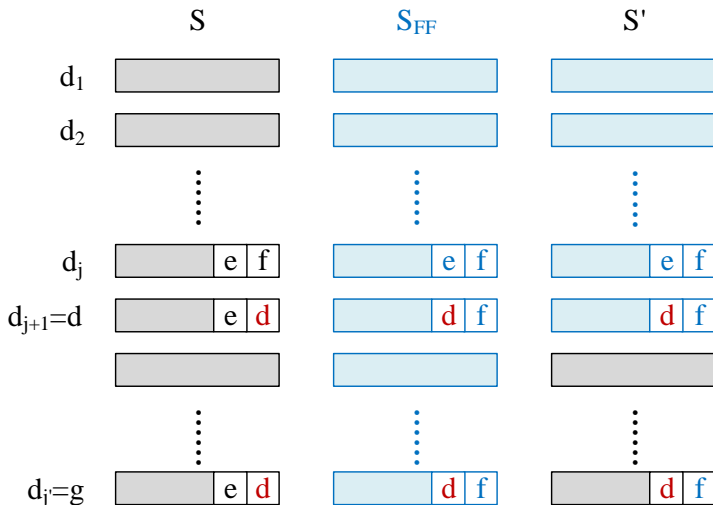
Let S be reduced schedule that satisfies invariant through j requests. We produce S' that satisfies invariant after $j + 1$ requests.

Consider $(j + 1)^{th}$ request $d = d_{j+1}$. Since S and S_{FF} have agreed up until now, they have the same cache contents before request $j + 1$.

- Case 1: (d is already in the cache) $S' = S$ satisfies invariant.
- Case 2: (d is not in the cache; S, S_{FF} evict same element) $S' = S$ satisfies invariant.
- Case 3: (d is not in the cache; S_{FF} evicts e ; S evicts $f \neq e$)

Let S' agree with S_{FF} at the $j + 1$ requests; we show that having element f in cache is no worse than having element e .

An Illustration of Case 3



Correctness Proof (Continued)

Let j' be the **first** time after $j + 1$ that S and S' take a different action (must involve e or f or both), and let g be item requested at time j' .

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第一次S和S'有不同的选择

分几种情况

S' 都不差于S $g=e$

cannot happen due to FF strategy



Correctness Proof (Continued)

Case 3a: $g = e$. Can't happen with Farthest-In-Future since there must be a request for f before e .

Case 3b: $g = f$. Element f can't be in cache of S , so let e' be the element that S evicts.

- if $e' = e$, S' accesses f from cache; now S and S' have same cache
- if $e' \neq e$, S' evicts e' and brings e into the cache; now S and S' have the same cache.

Case 3c: $g \neq e, f$. S must evict e (otherwise S' would take the same action). Make S' evict f ; now S and S' have the same cache. \square

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.

[‡]FF with direction of time reversed!

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Theorem. FF is optimal offline eviction algorithm.

- Provides basis for understanding and analyzing online algorithms.
- LRU is k -competitive. [Section 13.8 in Cornell Book]
- LIFO is arbitrarily bad.

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Outline

- 1 Basic Methodology
 - Interval Scheduling
 - Interval Partitioning
 - Scheduling to Minimize Lateness

- 2 More Examples
 - Optimal Caching
 - Coin Changing

Coin Changing

Goal. Given US currency denominations:

1 (cent), 5 (nickel), 10 (dime), 25 (quarter), 100 (dollar),

devise a changing method using fewest number of coins.

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Example. \$2.89.



Cashier's Algorithm

Algorithm 4: Cashier's Algorithm

```
1 Sort coins denominations by value:  $c_1 < c_2 < \dots < c_n$ ;  
2  $S \leftarrow \emptyset$ ; // coins selected  
3 while  $x \neq 0$  do  
4   let  $k$  be largest integer such that  $c_k < x$ ;  
5   if  $k = 0$  then  
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7    $x \leftarrow x - c_k$ ;  
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Question. Is cashier's algorithm optimal?

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Property. Number of pennies ≤ 4 .

Proof. Replace 5 pennies with 1 nickel.

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

Proof.

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



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If not, it needs enough coins of type c_1, \dots, c_{k-1} to add up to x .

k	c_k	All optimal solutions must satisfy	Max value of coins 1, 2, ..., k-1 in any OPT
1	1	$P \leq 4$	-
2	5	$N \leq 1$	4
3	10	$N + D \leq 2$	$4 + 5 = 9$
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Problem reduces to coin-changing $x - c_k$ cents, which, by induction, is optimally solved by greedy algorithm.

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Observation 1. Greedy is sub-optimal for US postal denominations:

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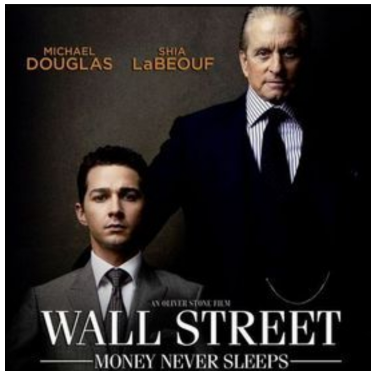
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Observation 2. Even no feasible solution with system $\mathcal{C}=\{7, 8, 9\}$.

- Cashier's algorithm: $15\text{¢} = 9 + ???$
- Optimal: $15\text{¢} = 7 + 8$.

Movie: Wall Street (1987)



§

Greed is good.

Greed is right.

Greed works.

Greed clarifies, cuts through, and captures the essence of the evolutionary spirit.

— Gordon Gecko
(Michael Douglas)

§ Watch the movie segment at the class webpage.