

Greedy Algorithm (informal def): an alg that sequentially constructs a solution through a series of myopic (short-sighted = local = not global = not thinking about future) decisions

Typical properties

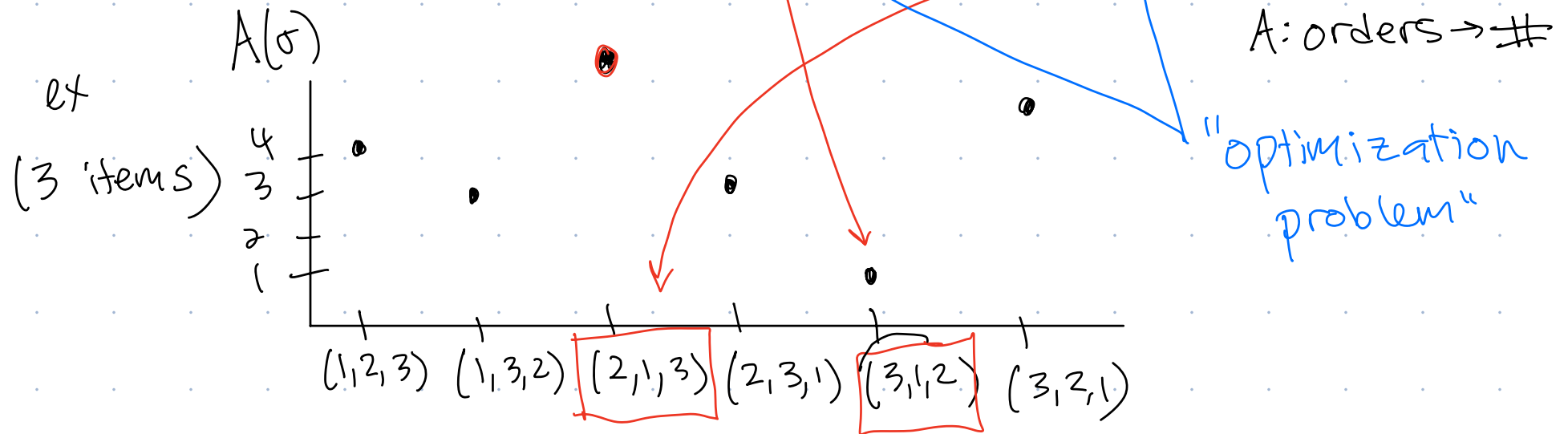
- Easy to create
- Easy to analyze runtime
- Not optimal
- Hard to prove correct

Ordering Problem (Abstract)

"objective function"

Input: n items

Output: Order σ that minimizes (or maximizes) $A(\sigma)$



Brute Force: Evaluate $A(\sigma)$ for every ordering $\Omega(n!)$
+ find the min-value ordering

Greedy: • Design a simple scoring function $f: \text{item} \rightarrow \text{score}$
• Evaluate score for each item $\Omega(n)$

$O(n \log n)$ • Return σ that puts items in increasing/decreasing score order

Scheduling Tasks

Input: n tasks: time, weight

↑
larger means more important

task	1	2	3
time	3	4	2
weight	5	1	2

Output: Ordering σ that minimizes

$$A(\sigma) = \sum_{i=1}^n w_i \cdot C_i(\sigma)$$

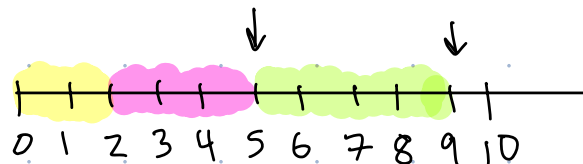
Applications: CPU, hw scheduling

$C_i(\sigma) = \text{completion}_{\text{time}}^{\text{time}}$ of task i given ordering σ

ex:

task	1	2	3
time	3	4	2

$$\sigma = (3, 1, 2)$$



$$C_1(3, 1, 2) = 5$$

$$C_2(3, 1, 2) = 9$$

$$C_3(3, 1, 2) = 2$$

What is $C_3(2, 1, 3)$?

A) 2

B) 3

C) 7

D) 9

Calculate $A(\sigma)$ + determine best order: (Brute force)

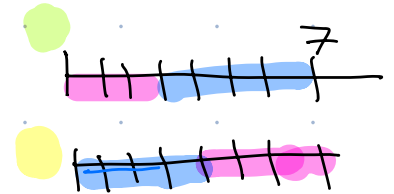
task	1	2
time	3	4
weight	5	1

Order	(1,2)	(2,1)
$A(\sigma)$	22	39

Order	(1,2)	(2,1)
$C_1(\sigma)$	3	7
$C_2(\sigma)$	7	4

$$5 \cdot 3 + 1 \cdot 7 = 22$$

$$A(\sigma) = \sum_{i=1}^n w_i \cdot C_i(\sigma)$$



What is this objective function optimizing? What time/weight jobs is it prioritizing?

Output: Ordering σ that minimizes

$$A(\sigma) = \sum_{i=1}^n w_i C_i(\sigma)$$

Creating Scoring Functions + Counterexamples

Creating a greedy algorithm Easy

Creating a ^{good} greedy algorithm Hard

To create:

$f(i) = t_i$ (increasing of f)

task	1	2
time	3	4
weight	5	1
f	3	4

"Greedy Ordering" $\rightarrow (1, 2)$

Yay! Correct!

But will this greedy ordering always be correct?

Try to find a counterexample:

- think extreme

- create tasks that are similar in score but diff otherwise

$f(i) = t_i$ (increasing)

task	1	2
time	1	2
weight	1	100
f	1	2

Greedy Ordering
 $\rightarrow (1, 2)$

Order	(1,2)	(2,1)
$A(\sigma)$	300	203

Optimal Ordering: (2,1)

Group Exercise

Create counterexamples for scoring functions

A) $f(i) = w_i$ (decreasing) B) $f(i) = w_i - t_i$ (decreasing)

A)

task	1	2
time	1000	1
weight	2	1
f	2	1

Greedy
 $\rightarrow (1, 2)$

Brute Force

Order	(1,2)	(2,1)
$A(\sigma)$	3001	2002

Optimal:
(2,1)

B)

task	1	2
time	2	100
weight	1	98
f	-1	-2

$\rightarrow (1, 2)$

Brute Force:

Order	(1,2)	(2,1)
$A(\sigma)$	9998	9902

Optimal
(2,1)

One approach to designing greedy alg:

- create several reasonable scoring functions $w_i - t_i$ (decr)
 w/t (decr)
- test, try to create counterex. $w^2 - 2t$ (dec)
- No counterex. try prove correct, or just use (heuristic)

Thm: Ordering jobs by $f = \frac{w_i}{t_i}$ (decreasing) is optimal for minimizing $A(\sigma) = \sum_i w_i C_i(\sigma)$ if w_i/t_i are all distinct.

Pf: [Exchange Argument $\rightarrow$ Type of Pf by Contradiction]

WLOG relabel tasks so $w_1/t_1 > w_2/t_2 > w_3/t_3 \dots > w_n/t_n$

so greedy ordering $\sigma = (1, 2, 3, \dots, n)$. Assume for contradiction the greedy ordering σ is not the optimal ordering. Then $\exists \sigma^*$ that is optimal and $\sigma^* \neq \sigma$.

Since $\sigma^* \neq \sigma$, there must be tasks in σ^* that are next to each other but out of numerical order

$$\sigma^* = (\dots, y, b, \dots) \text{ but } b < y$$

ex: $\sigma^* = (3, 1, 2)$

What is b, y in this example?

A) $b = 1$
 $y = 3$

B) $b = 3$
 $y = 1$

C) $b = 2$
 $y = 3$

D) No unique
 b, y

Let $\sigma^{*'}$ be the same sequence as σ^* but with b, y exchanged to be in correct order

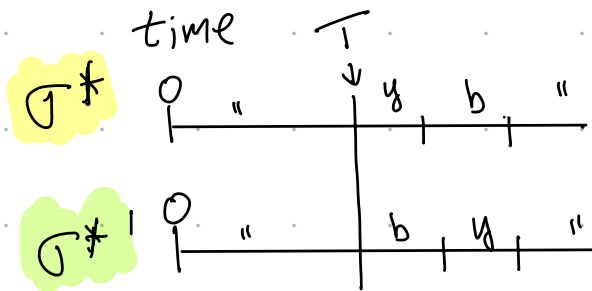
$$\sigma^* = (\dots, y, b, \dots)$$

$$\sigma^{*'} = (\dots, b, y, \dots)$$

$$\sigma^* = (3, 1, 2)$$

$$\sigma^{*'} = (1, 3, 2)$$

What is $A(\sigma^*) - A(\sigma^{*'}) < 0$ ($A(\sigma) = \sum_{i=1}^n w_i C_i(\sigma)$)



$$w_y, w_b$$

$$t_y, t_b$$

$\sigma^*(i) = i^{\text{th}}$ job in ordering σ^*

$$(T + t_y)$$

$$(T + t_y + t_b)$$

$$A(\sigma^*) = w_{\sigma^*(1)} C_{\sigma^*(1)} + w_{\sigma^*(2)} C_{\sigma^*(2)} + \dots + w_y C_y(\sigma^*) + w_b C_b(\sigma^*) + \dots$$

$$(T + t_b)$$

$$(T + t_b + t_y)$$

$$A(\sigma^{*'}) = w_{\sigma^{*'}(1)} C_{\sigma^{*'}(1)} + w_{\sigma^{*'}(2)} C_{\sigma^{*'}(2)} + \dots + w_b C_b(\sigma^{*'}) + w_y C_y(\sigma^{*'}) + \dots$$

$$= w_b t_y - w_y t_b$$

$$0 > \frac{A(\sigma^*) - A(\sigma^{*'})}{t_y t_b} = \frac{w_b t_y - w_y t_b}{t_y t_b} \quad \text{Divide both sides by } t_y t_b$$

$$0 > \quad " \quad = \frac{w_b}{t_b} - \frac{w_y}{t_y} > 0 \quad \text{But } b < y \text{ so by greedy ordering}$$

$$\frac{w_b}{t_b} > \frac{w_y}{t_y}$$

$$0 > \frac{w_b}{t_b} - \frac{w_y}{t_y} \quad \searrow$$

$$0 < \frac{w_b}{t_b} - \frac{w_y}{t_y} \rightarrow \text{Contradiction!}$$

We had said that $A(\sigma^*)$ was optimal so it must have the smallest A value, but now we've shown that $\sigma^{*'}$ has a smaller A value, a contradiction.

Thus, our assumption that σ (our greedy ordering) was not optimal was incorrect, and so σ is optimal.

□

Structure of Exchange Proof

1. Assume greedy ordering σ (ordering from f) is not optimal
 2. There must be some other ordering that is optimal σ^*
 3. Modify σ^* by exchanging 2 elements to make it more like σ (called σ^{*1})
 4. Show σ^{*1} is better (in A value) than σ^*
- Contradiction

What is the runtime of our greedy scheduling algorithm?

A) $O(1)$ B) $O(n)$ C) $O(n \log n)$ D) $O(n^2)$

Where did we use w_i/t_i
are all distinct?

$O(n)$ {
+
 $O(n \log n)$ {

Schedule(n):

• For $i \leftarrow 1$ to n :
 | Calculate w_i/t_i (score)
• Sort by score

Recall

$$A(\sigma^*) - A(\sigma^{*'}) = w_b t_y - w_y t_b. \quad \text{Divide both sides by } t_y t_b:$$

$$\frac{A(\sigma^*) - A(\sigma^{*'})}{t_y t_b} = \frac{w_b}{t_b} - \frac{w_y}{t_y}. \quad \text{But } b < y, \text{ so } \frac{w_b}{t_b} > \frac{w_y}{t_y}, \text{ so}$$

$$\frac{A(\sigma^*) - A(\sigma^{*'})}{t_y t_b} > 0, \quad \text{and } t_y, t_b > 0, \text{ so}$$

$$A(\sigma^*) - A(\sigma^{*'}) > 0. \quad \text{We said}$$

$A(\sigma^*)$ was optimal so it must have the smallest A -value, but now we've shown $\sigma^{*'}$ has a smaller A -value, a contradiction.

Thus our assumption that σ was not optimal was incorrect, and σ must be optimal.

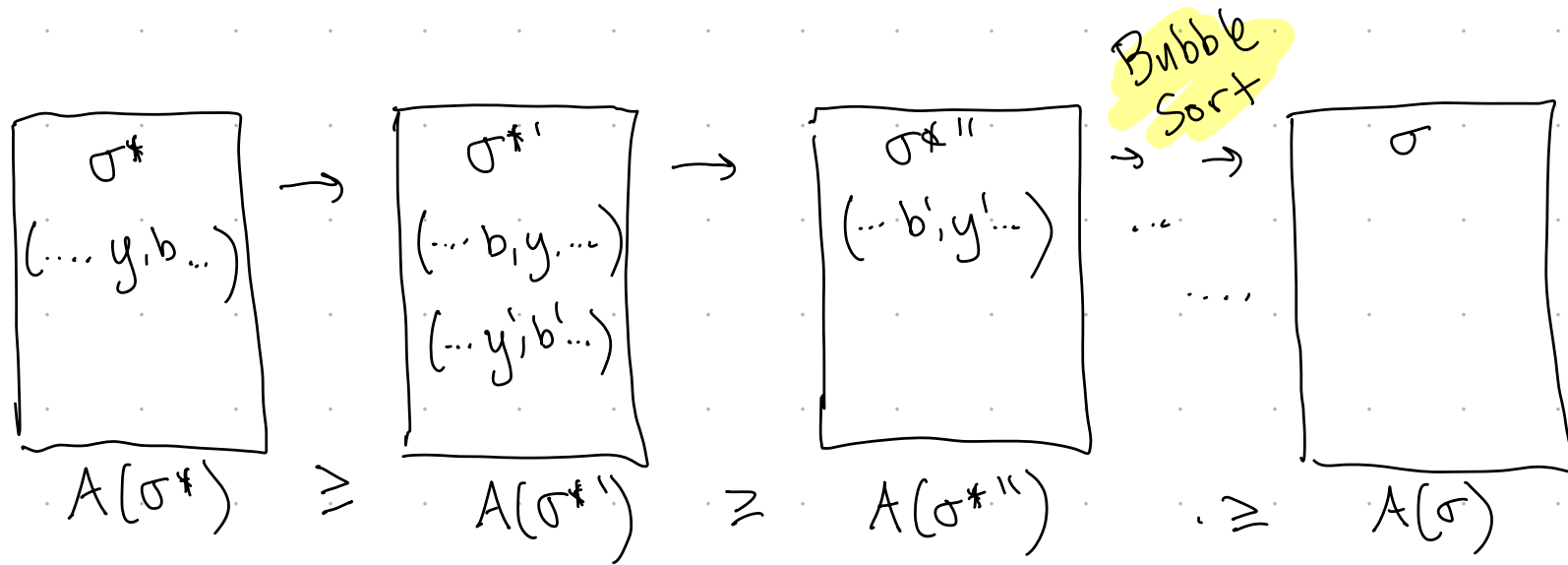
Lose contradiction!

Thm: Ordering jobs by decreasing value of w_i/t_i is optimal for minimizing $A(\sigma) = \sum w_i C_i(\sigma)$ ~~if w_i/t_i are all distinct.~~

Pf sketch: Choose some relabelling of tasks so that

$$w_1/t_1 \geq w_2/t_2 \geq w_3/t_3 \dots \geq w_n/t_n$$

We call $\sigma = (1, 2, 3, \dots, n)$ this greedy ordering. Let σ^* be any other ordering.



We have shown for every other ordering $A(\sigma^*) \geq A(\sigma)$, so σ must be optimal.

What is the runtime of our greedy scheduling algorithm?

A) $O(1)$

B) $O(n)$

C) $O(n \log n)$

D) $O(n^2)$

Work backwards to find optimal scoring function

Thm: Ordering jobs by decreasing value of w_i/t_i is optimal for minimizing $A(\sigma) = \sum_i w_i C_i(\sigma)$ if w_i/t_i are all distinct.

Pf: [Exchange Argument = Type of Pf by Contradiction]

WLOG, relabel so $f_1 > f_2 > f_3$
 $w_1/t_1 > w_2/t_2 > w_3/t_3$ so greedy ordering is $\sigma = (1, 2, 3, \dots, n)$. Assume for contradiction that σ is not optimal. Then $\exists \sigma^*$ that is optimal.

Since $\sigma^* \neq \sigma$, there must be tasks b, y in σ^* that are next to each other but out of order

$$\sigma^* = (\dots y, b \dots) \quad b < y$$

ex: $n=3$

$$\sigma = (1, 2, 3)$$

$$\sigma^* = (\boxed{3, 1}, 2)$$

$\uparrow \quad \uparrow$
 $y \quad b$

Let σ^{*1} be the same sequence as σ^* , but with b, y exchanged to be in the correct order

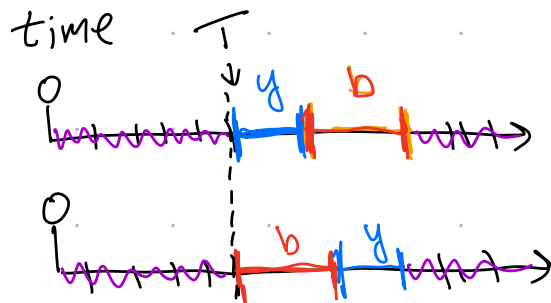
$$\sigma^* = (\dots y, b \dots)$$

$$\sigma^* = (3, 1, 2)$$

$$\sigma^{*1} = (\dots b, y \dots)$$

$$\sigma^{*1} = (1, 3, 2)$$

What is $A(\sigma^*) - A(\sigma^{*1})$? ($A(\sigma) = \sum_{i=1}^n w_i C_i(\sigma)$)



σ^*

σ^{*1}

$\sigma^*(i) = i^{\text{th}}$ job in ordering σ^*

$$A(\sigma^*) = w_{\sigma^*(1)} C_{\sigma^*(1)} + w_{\sigma^*(2)} C_{\sigma^*(2)} + \dots w_y (\cancel{T + t_y}) + w_b (\cancel{T + t_y + t_b}) + \dots$$

$$- A(\sigma^{*1}) = w_{\sigma^{*1}(1)} C_{\sigma^{*1}(1)} + w_{\sigma^{*1}(2)} C_{\sigma^{*1}(2)} + \dots w_b (\cancel{T + t_b}) + w_y (\cancel{T + t_b + t_y}) + \dots$$

$$= w_b t_y - w_y t_b$$

$$A(\sigma^*) - A(\sigma^{*'}) = w_b t_y - w_y t_b. \quad \text{Divide both sides by } t_y t_b:$$

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