

# CS 341: ALGORITHMS

## Lecture 6: greedy algorithms II

Readings: see website

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## OPTIMALITY PROOF

for greedy interval selection

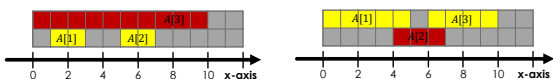
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**Goal:** choose **as many** disjoint intervals as possible, (i.e., without any overlap)

- Sort the intervals in increasing order of **finishing times**. At any stage, choose the **earliest finishing** interval that is disjoint from all previously chosen intervals (i.e., the local evaluation criterion is  $f_i$ ).

**Algorithm:**



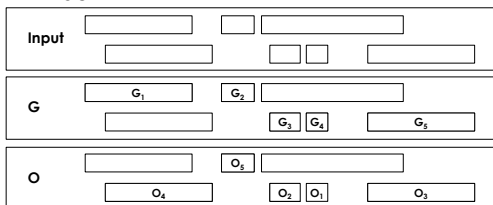
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## PROVING OPTIMALITY

- Consider an input  $A[1..n]$
- Let  $G$  be the greedy solution
- Let  $O$  be an optimal solution
- "Greedy stays ahead" argument
  - Intuition: out of a given set of intervals, greedy picks **as many as optimal**

## VISUAL EXAMPLE



How to compare G and O? **Imagine reordering O to match G!**

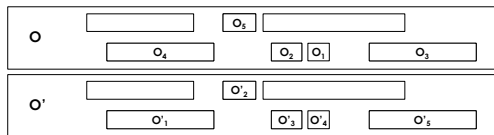
**CRUCIAL:** We are **NOT** assuming the optimal **algorithm** uses the same sort order!

We are merely **imagining reordering** the intervals chosen by the optimal algorithm so we can easily **compare their finish times** to intervals in **G**

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### REORDERING O BY INCREASING FINISH TIME

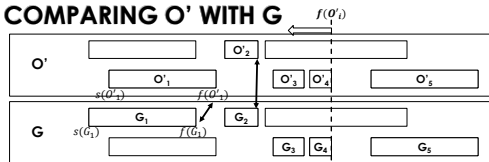


Now  $O'$  and  $G$  are both ordered by increasing finish time  
 This ordering helps us leverage what we know about  $G$   
 in our comparison with  $O'$ .

Argue for a prefix of the intervals sorted this way,  $G$  chooses **as many as**  $O'$

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### COMPARING O' WITH G



Looks like  $f(G_1) \leq f(O'_1)$  and  $f(G_2) \leq f(O'_2)$  ... Is  $f(G_i) \leq f(O'_i)$  for all  $i$ ?

<b>If</b> this trend holds in general, then	<b>out of the intervals with finish time <math>\leq f(O'_i)</math></b>
<b>G chooses as many intervals as O!</b>	

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### PROVING LEMMA: $f(G_i) \leq f(O'_i)$ FOR ALL $i$



Base case:  $f(G_1) \leq f(O'_1)$  since  $G$  chooses the interval with the earliest finish time first.

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### PROVING LEMMA: $f(G_i) \leq f(O'_i)$ FOR ALL $i$

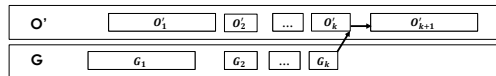


Inductive step: assume  $f(G_{i-1}) \leq f(O'_{i-1})$ . Show  $f(G_i) \leq f(O'_i)$ .

- Since  $O'$  is feasible,  $f(O'_{i-1}) \leq s(O'_i)$
- So  $f(G_{i-1}) \leq s(O'_i)$
- So  $G$  can choose  $O'_i$  if it has the smallest finish time
- So  $f(G_i) \leq f(O'_i)$

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### USING THIS LEMMA



- Suppose  $|O'| > |G|$  to obtain a contradiction
  - So if  $G$  chooses  $k$  intervals,  $O'$  chooses at least  $k + 1$
- By the lemma,  $f(G_k) \leq f(O'_k)$
- Since  $O'$  is feasible,  $f(O'_k) \leq s(O'_{k+1})$
- **But then  $G$  can, and would, pick  $O'_{k+1}$ .**
  - **Contradiction!**

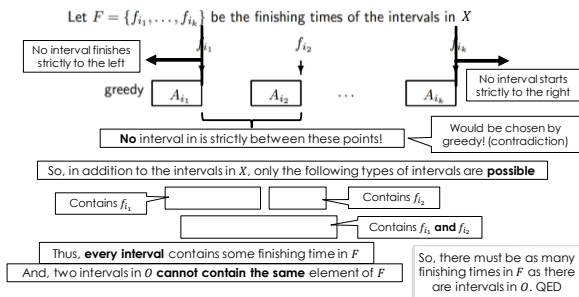
So assumption  $|O'| > |G|$  is wrong!  
 So  $G$  is optimal

### A DIFFERENT PROOF

"Slick" ad-hoc approaches are sometimes possible...

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## KNAPSACK PROBLEMS

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**Problem 4.4**  
**Knapsack**  
 Instance: Profits  $P = [p_1, \dots, p_n]$ ; weights  $W = [w_1, \dots, w_n]$ ; and a capacity  $M$ . These are all positive integers.  
 Feasible solution: An  $n$ -tuple  $X = [x_1, \dots, x_n]$  where  $\sum_{i=1}^n w_i x_i \leq M$ .

Gotta respect the weight limit M...



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**Problem 4.4**  
**Knapsack**  
 Instance: Profits  $P = [p_1, \dots, p_n]$ ; weights  $W = [w_1, \dots, w_n]$ ; and a capacity  $M$ . These are all positive integers.  
 Feasible solution: An  $n$ -tuple  $X = [x_1, \dots, x_n]$  where  $\sum_{i=1}^n w_i x_i \leq M$ .  
 In the 0-1 Knapsack problem (often denoted just as Knapsack), we require that  $x_i \in \{0, 1\}$ ,  $1 \leq i \leq n$ .  
 In the Rational Knapsack problem, we require that  $x_i \in \mathbb{Q}$  and  $0 \leq x_i \leq 1$ ,  $1 \leq i \leq n$ .  
 Find: A feasible solution  $X$  that maximizes  $\sum_{i=1}^n p_i x_i$ .

**0-1 Knapsack:**  
 NP Hard.  
 Probably requires exponential time to solve...

**Rational knapsack:**  
 Can be solved in polynomial time by a greedy alg!

Lets discuss this now... other one later

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### POSSIBLE GREEDY STRATEGIES FOR KNAPSACK PROBLEMS

**Strategy 1:** consider items in **decreasing** order of **profit** (i.e., we maximize the local evaluation criterion  $p_i$ )

- Let's try an example input
  - Profits  $P = [20, 50, 100]$
  - Weights  $W = [10, 20, 10]$
  - Weight limit  $M = 10$
- Algorithm selects last item for 100 profit
  - Looks optimal in this example

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### POSSIBLE GREEDY STRATEGIES FOR KNAPSACK PROBLEMS

**Strategy 1:** consider items in **decreasing** order of **profit** (i.e., we maximize the local evaluation criterion  $p_i$ )

- How about a **second example input**
  - Profits  $P = [20, 50, 100]$
  - Weights  $W = [10, 20, 100]$
  - Weight limit  $M = 10$
- Algorithm selects last item for 10 profit
  - Not optimal!**

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POSSIBLE GREEDY STRATEGIES FOR KNAPSACK PROBLEMS

**Strategy 2:** consider items in **increasing** order of **weight** (i.e., we minimize the local evaluation criterion  $w_i$ )

**Counterexample**

- Profits  $P = [20,50,100]$
- Weights  $W = [10,20,100]$
- Weight limit  $M = 10$

Algorithm selects first item for 20 profit

- It **could** select half of second item, for 25 profit!

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POSSIBLE GREEDY STRATEGIES FOR KNAPSACK PROBLEMS

**Strategy 3:** consider items in **decreasing** order of **profit divided by weight** (i.e., we maximize local evaluation criterion  $p_i/w_i$ )

- Let's try our first example input
  - Profits  $P = [20,50,100]$
  - Weights  $W = [10,20,10]$
  - Weight limit  $M = 10$

Profit divided by weight

- $P/W = [2, 2.5, 10]$

Algorithm selects last item for 100 profit (optimal)

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POSSIBLE GREEDY STRATEGIES FOR KNAPSACK PROBLEMS

**Strategy 3:** consider items in **decreasing** order of **profit divided by weight** (i.e., we maximize local evaluation criterion  $p_i/w_i$ )

Let's try our second example input

- Profits  $P = [20,50,100]$
- Weights  $W = [10,20,100]$
- Weight limit  $M = 10$

Profit divided by weight

- $P/W = [2, 2.5, 1]$

Algorithm selects second item for 25 profit (optimal)

If turns out strategy #3 is optimal...

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```

1 Preprocess(A[1..n], M) // A[i] = (p_i, w_i)
2 sort A by decreasing profit divided by weight
3 let p[1..n] be the profits in A
4 let w[1..n] be the weights in A
5 return GreedyRationalKnapsack(p, w, M)
6
7 GreedyRationalKnapsack(p[1..n], w[1..n], M)
8 X = [0, ..., 0]
9 weight = 0
10
11 for i = 1..n
12   if weight + w[i] > M then
13     X[i] = (M - weight) / w[i]
14     break
15   else
16     X[i] = 1
17     weight = weight + w[i]
18
19 return X
    
```

Annotations:

- No items are chosen yet
- Current weight of knapsack
- For all items
- If we cannot fit the entire item
- Put in as much of the item as you can, to **exactly fill** the knapsack
- Otherwise take the entire item

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Either  $X = [1, 1, \dots, 1, 0, \dots, 0]$  or  $X = [1, 1, \dots, 1, x_i, 0, \dots, 0]$  where  $x_i \in (0, 1)$

```

1 Preprocess(A[1..n], M) // A[i] = (p_i, w_i)
2 sort A by decreasing profit divided by weight
3 let p[1..n] be the profits in A
4 let w[1..n] be the weights in A
5 return GreedyRationalKnapsack(p, w, M)
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7 GreedyRationalKnapsack(p[1..n], w[1..n], M)
8 X = [0, ..., 0]
9 weight = 0
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11 for i = 1..n
12   if weight + w[i] > M then
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14     break
15   else
16     X[i] = 1
17     weight = weight + w[i]
18
19 return X
    
```

Annotations:

- Running time complexity?
- Can do preprocessing in  $\theta(\log n)$
- Create array in  $\theta(n)$  time
- $\theta(n)$  iterations each doing  $\theta(1)$  work
- Total  $\theta(n \log n)$  (or  $\theta(n)$  if input is already sorted)

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**INFORMAL FEASIBILITY ARGUMENT**

(SHOULD BE GOOD ENOUGH TO SHOW FEASIBILITY ON ASSESSMENTS)

**Feasibility:** all  $x_i$  are in  $[0, 1]$  and total weight is  $\leq M$

Either everything fits in the knapsack, or:

When we exit the loop, **weight is exactly M**

Every time we write to  $x_i$  it's either 0, 1 or  $(M - \text{weight})/w_i$  where  $\text{weight} + w[i] > M$

Rearranging the latter we get  $(M - \text{weight})/w_i < 1$

And  $\text{weight} \leq M$ , so  $(M - \text{weight})/w_i \geq 0$

So, we have  $x_i \in [0, 1]$

```

11 for i = 1..n
12   if weight + w[i] > M then
13     X[i] = (M - weight) / w[i]
14     break
15   else
16     X[i] = 1
17     weight = weight + w[i]
    
```

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MINOR MODIFICATION TO FACILITATE FORMAL PROOF

```

1 GreedyRationalKnapsack(p[1..n], w[1..n], M)
2 X = [0, ..., 0]
3 weight = 0
4
5 for i = 1..n
6   if weight + w[i] > M then
7     X[i] = (M - weight) / w[i]
8     weight = M
9     break
10  else
11    X[i] = 1
12    weight = weight + w[i]
13
14 return X
    
```

Optional slide, just for your notes

Does NOT change behaviour of the algorithm at all!

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FORMAL FEASIBILITY ARG

- Loop invariant:  $\forall_i : x_i \in [0,1]$  and  $weight = \sum_{i=1}^n w_i x_i \leq M$
- Base case. Initially  $weight = 0$  and  $\forall_i : x_i = 0$ .
  - So  $0 = weight = \sum_{i=1}^n w_i \cdot 0 = \sum_{i=1}^n w_i x_i \leq M$
- Inductive step.
  - Suppose invariant holds at start of iteration  $i$
  - Let  $weight', x_i'$  denote values of  $weight, x_i$  at end of iteration  $i$
  - Prove invariant holds at end of iteration  $i$
  - i.e.,  $\forall_i : x_i' \in [0,1]$  and  $weight' = \sum_{i=1}^n w_i x_i' \leq M$

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FORMAL FEASIBILITY ARG

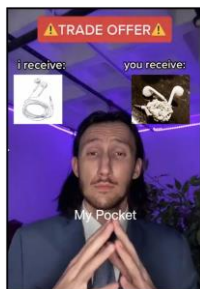
- WTP:  $\forall_i : x_i' \in [0,1]$  and  $weight' = \sum_{i=1}^n w_i x_i' \leq M$
- Case 1:  $weight + w_i \leq M$ 
  - $x_i' = 1$  which is in  $[0,1]$  (by line 11)
  - $weight' = weight + w_i$  (by line 12) and this is  $\leq M$  by the case
  - $weight' = \sum_{k=1}^n x_k w_k + w_i$  (by invariant)
  - $weight' = \sum_{k=1}^n x_k w_k + x_i' w_i$  (since  $x_i' = 1$ )
  - And  $x_k' = x_k$  for all  $k \neq i$  and  $x_i = 0$  so  $\sum_{k=1}^n x_k w_k = x_i' w_i + \sum_{k=1}^n x_k w_k$
  - Rearrange to get  $\sum_{k=1}^n x_k w_k = (\sum_{k=1}^n x_k' w_k - x_i' w_i)$
  - So  $weight' = (\sum_{k=1}^n x_k' w_k - x_i' w_i) + x_i' w_i = \sum_{k=1}^n x_k' w_k$

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FORMAL FEASIBILITY ARG

- WTP:  $\forall_i : x_i' \in [0,1]$  and  $weight' = \sum_{i=1}^n w_i x_i' \leq M$
- Case 2:  $weight + w_i > M$ 
  - We have  $w_i > M - weight$  and  $M - weight \geq 0$  (by case) (by invariant)
  - So  $0 \leq \frac{M-weight}{w_i} < 1$  which means  $x_i' \in [0,1]$
  - $weight' = M = weight + (M - weight)$  (by line 8)
  - $weight' = \sum_{k=1}^n x_k w_k + (M - weight)$  (by invariant)
  - But  $x_k' = x_k$  for all  $k \neq i$  and  $x_i = 0$  so  $\sum_{k=1}^n x_k w_k = x_i' w_i + \sum_{k=1}^n x_k w_k$
  - Rearrange to get  $\sum_{k=1}^n x_k w_k = (\sum_{k=1}^n x_k' w_k - x_i' w_i)$
  - So  $weight' = (\sum_{k=1}^n x_k' w_k - x_i' w_i) + (M - weight)$
  - And  $M - weight = x_i' w_i$  so  $weight' = \sum_{k=1}^n x_k' w_k$

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EXCHANGE ARGUMENT for proving optimality

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OPTIMALITY – AN EXCHANGE ARGUMENT

For simplicity, assume that the profit / weight ratios are all distinct, so

$$\frac{p_1}{w_1} > \frac{p_2}{w_2} > \dots > \frac{p_n}{w_n}$$

Suppose the greedy solution is  $X = (x_1, \dots, x_n)$  and the optimal solution is  $Y = (y_1, \dots, y_n)$ .

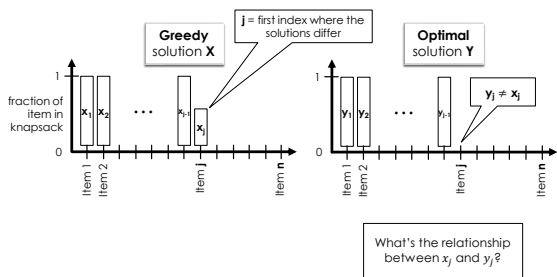
We will prove that  $X = Y$ , i.e.,  $x_j = y_j$  for  $j = 1, \dots, n$ . Therefore there is a unique optimal solution and it is equal to the greedy solution.

Suppose  $X \neq Y$ . To obtain a contradiction

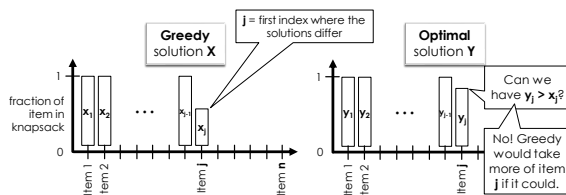
Pick the smallest integer  $j$  such that  $x_j \neq y_j$ .

$X$  and  $Y$  are identical up to  $x_j$  and  $y_j$ , respectively

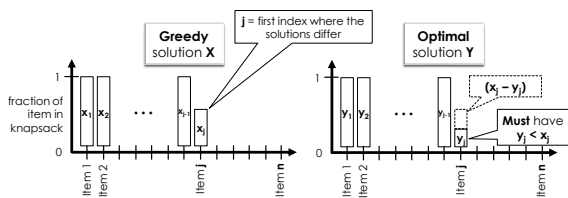
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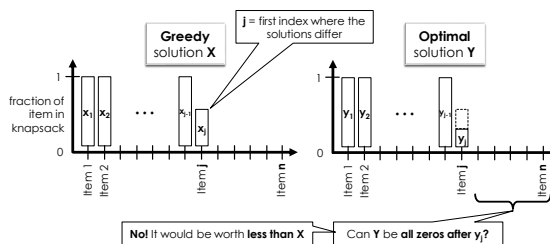
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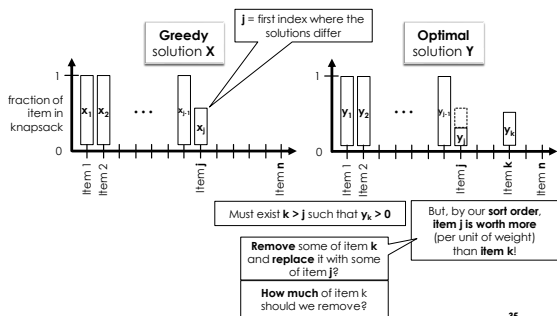
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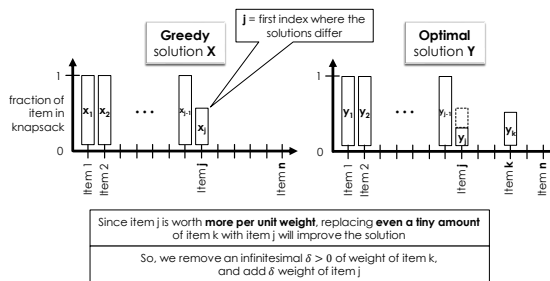
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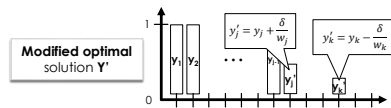
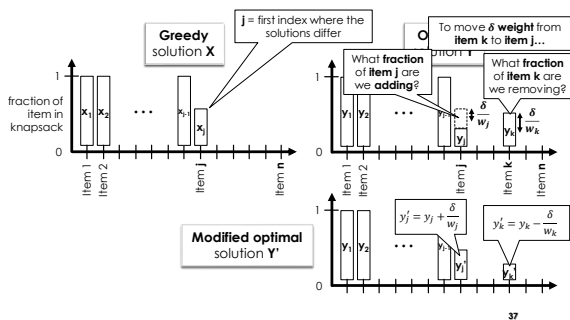
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The idea is to show that  $Y'$  is feasible, and  $\text{profit}(Y') > \text{profit}(Y)$ . This contradicts the optimality of  $Y$  and proves that  $X = Y$ . To show  $Y'$  is feasible, we show  $y_k' \geq 0, y_j' \leq 1$  and  $\text{weight}(Y') \leq M$

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### FEASIBILITY OF $Y'$

To show  $Y'$  is feasible, we show  $y_k' \geq 0, y_j' \leq 1$  and  $\text{weight}(Y') \leq M$   
Let's show  $y_k' \geq 0$

- By definition,  $y_k' = y_k - \frac{\delta}{w_k}$
- So,  $y_k' \geq 0$  iff  $y_k - \frac{\delta}{w_k} \geq 0$  iff  $\delta \leq y_k w_k$
- And we know  $y_k$  and  $w_k$  are both **positive**
- So, this constrains  $\delta$  to be smaller than this **positive number**
- Therefore, it is possible to choose positive  $\delta$  s.t.  $y_k' \geq 0$

Existence proof, but a non-constructive one

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### FEASIBILITY OF $Y'$

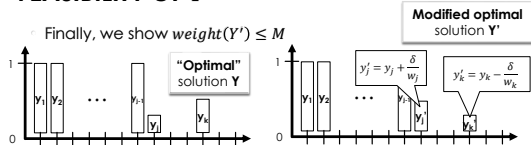
To show  $Y'$  is feasible, we show  $y_k' \geq 0, y_j' \leq 1$  and  $\text{weight}(Y') \leq M$   
Now let's show  $y_j' \leq 1$

- By definition,  $y_j' = y_j + \frac{\delta}{w_j}$
- So,  $y_j' \leq 1$  iff  $y_j + \frac{\delta}{w_j} \leq 1$  iff  $\delta \leq (1 - y_j)w_j$
- Recall  $y_j < x_j$ , so  $y_j < 1$ , which means  $(1 - y_j) > 0$
- So, this constrains  $\delta$  to be smaller than some **positive number**

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### FEASIBILITY OF $Y'$

Finally, we show  $\text{weight}(Y') \leq M$



- Recall changes to get  $Y'$  from  $Y$ 
  - We move  $\delta$  weight from item  $k$  to item  $j$
  - This does not change the total weight!
- So  $\text{weight}(Y') = \text{weight}(Y) \leq M$
- Therefore,  $Y'$  is **feasible!**

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### SUPERIORITY OF $Y'$

- Finally we compute  $\text{profit}(Y')$
- $\text{profit}(Y') = \text{profit}(Y) + \frac{\delta}{w_j} p_j - \frac{\delta}{w_k} p_k$
- $= \text{profit}(Y) + \delta \left( \frac{p_j}{w_j} - \frac{p_k}{w_k} \right)$
- Since  $j$  is before  $k$ , and we consider items with more profit per unit weight first, we have  $\frac{p_j}{w_j} > \frac{p_k}{w_k}$ .
- So, if  $\delta > 0$  then  $\delta \left( \frac{p_j}{w_j} - \frac{p_k}{w_k} \right) > 0$
- Since we can choose  $\delta > 0$ , we have  $\text{profit}(Y') > \text{profit}(Y)$ .

Contradicts optimality of  $Y!$  So assumption  $X \neq Y$  is bad. Therefore,  $X$  is optimal.

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Covering the next 9 slides is homework!

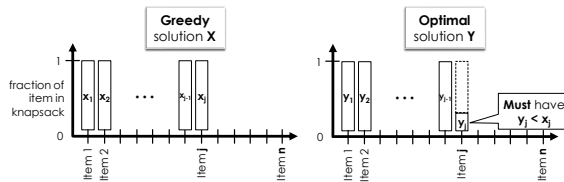
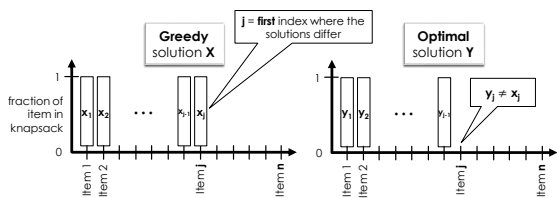
### WHAT IF ELEMENTS DON'T HAVE DISTINCT PROFIT/WEIGHT RATIOS?

### OPTIMALITY PROOF WITHOUT DISTINCTNESS

- There may be many optimal solutions
- **Key idea:** Let  $Y$  be an optimal solution that **matches  $X$  on a maximal number of indices**
- **Observe:** if  $X$  is really optimal, then  $Y = X$
- Suppose not for contra
  - We will modify  $Y$ , preserving its optimality, but making it match  $X$  on **one more index** (a contradiction!)

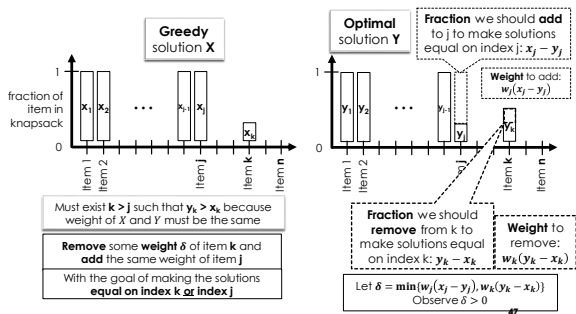
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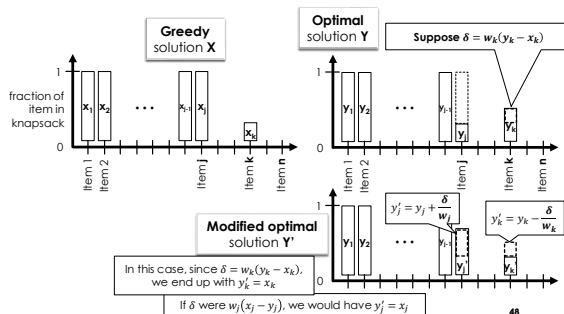


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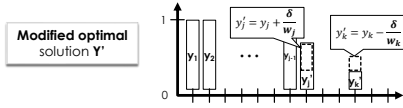


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To show  $Y'$  is feasible, we show  $weight(Y') \leq M$  and  $y'_k \geq 0, y'_j \leq 1$

**Weight** We move  $\delta$  weight from item  $k$  to item  $j$   
 This does not change the total weight!  
 So  $weight(Y') = weight(Y) = M$

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**FEASIBILITY OF  $Y'$**

- Showing  $y'_k \geq 0$ 
  - By definition,  $y'_k = y_k - \frac{\delta}{w_k} \geq 0$  **iff**  $\delta \leq y_k w_k$
  - But  $\delta$  is the **minimum** of  $w_j(x_j - y_j)$  and  $w_k(y_k - x_k) \leq w_k y_k$
  - And  $w_k(y_k - x_k) \leq w_k y_k$  **so**  $\delta \leq y_k w_k$
- Showing  $y'_j \leq 1$ 
  - $y'_j = y_j + \frac{\delta}{w_j} \leq 1$  **iff**  $\frac{\delta}{w_j} \leq 1 - y_j$  **iff**  $\delta \leq w_j(1 - y_j)$  (rearranging)
  - $\delta \leq w_j(x_j - y_j)$  (definition of  $\delta$ )
  - and  $w_j(x_j - y_j) \leq w_j(1 - y_j)$  (by feasibility of  $X$ , i.e.,  $x_j \leq 1$ )

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**PROFIT OF  $Y'$**  (fraction of item  $j$  added)  $\times$  (profit for entire item)

$$profit(Y') = profit(Y) + \frac{\delta}{w_j} p_j - \frac{\delta}{w_k} p_k = profit(Y) + \delta \left( \frac{p_j}{w_j} - \frac{p_k}{w_k} \right)$$

Since  $j$  is before  $k$ , and we consider items with more profit per unit weight first, we have  $\frac{p_j}{w_j} \geq \frac{p_k}{w_k}$ .

Since  $\delta > 0$  and  $\frac{p_j}{w_j} \geq \frac{p_k}{w_k}$ , we have  $\delta \left( \frac{p_j}{w_j} - \frac{p_k}{w_k} \right) \geq 0$

Since  $Y$  is optimal, this **cannot be positive**

So  $Y'$  is a new optimal solution that **matches  $X$  on one more index than  $Y$**

Contradiction:  $Y$  matched  $X$  on a **maximal** number of indices!

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**SUMMARIZING EXCHANGE ARGUMENTS**

- If inputs are distinct
  - So there is a unique optimal solution
  - Let  $O \neq G$  be an optimal solution that beats greedy
  - Show how to change  $O$  to obtain a better solution
- If not
  - There may be many optimal solutions
  - Let  $O \neq G$  be an optimal solution that matches greedy on as many choices as possible
  - Show how to change  $O$  to obtain an optimal solution  $O'$  that matches greedy for even more choices

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