

CS 341: ALGORITHMS

Lecture 6: greedy algorithms II

Readings: see website

Trevor Brown

<https://student.cs.uwaterloo.ca/~cs341>

trevor.brown@uwaterloo.ca

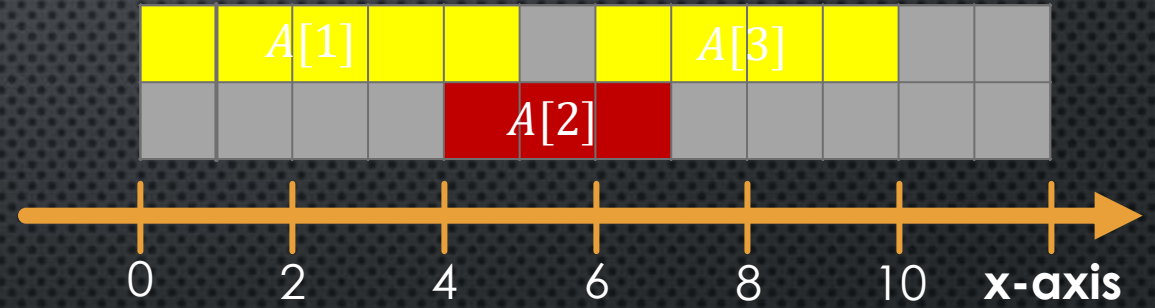
OPTIMALITY PROOF

for greedy interval selection

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

Algorithm:

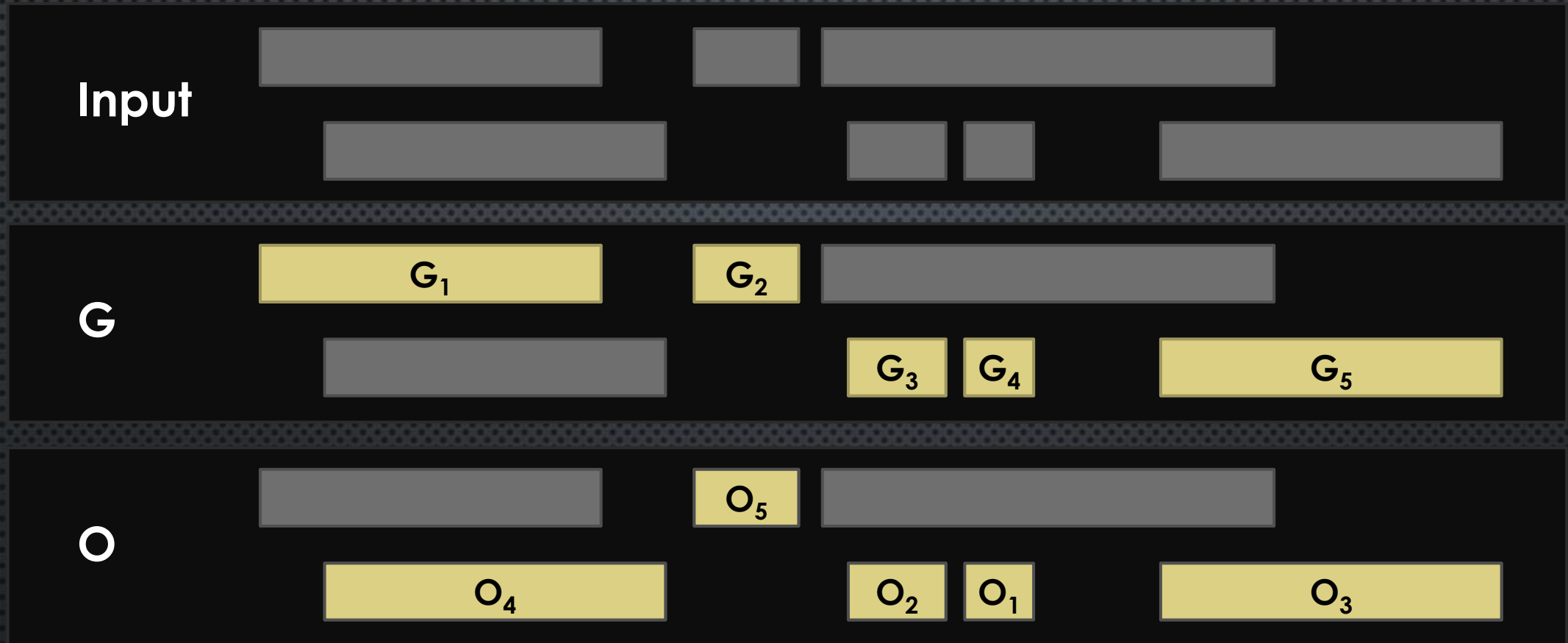
- Sort the intervals in increasing order of **finishing times**. At any stage, choose the **earliest finishing** interval that is disjoint from all previously chosen intervals (i.e., the local evaluation criterion is f_i).



PROVING OPTIMALITY

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

VISUAL EXAMPLE



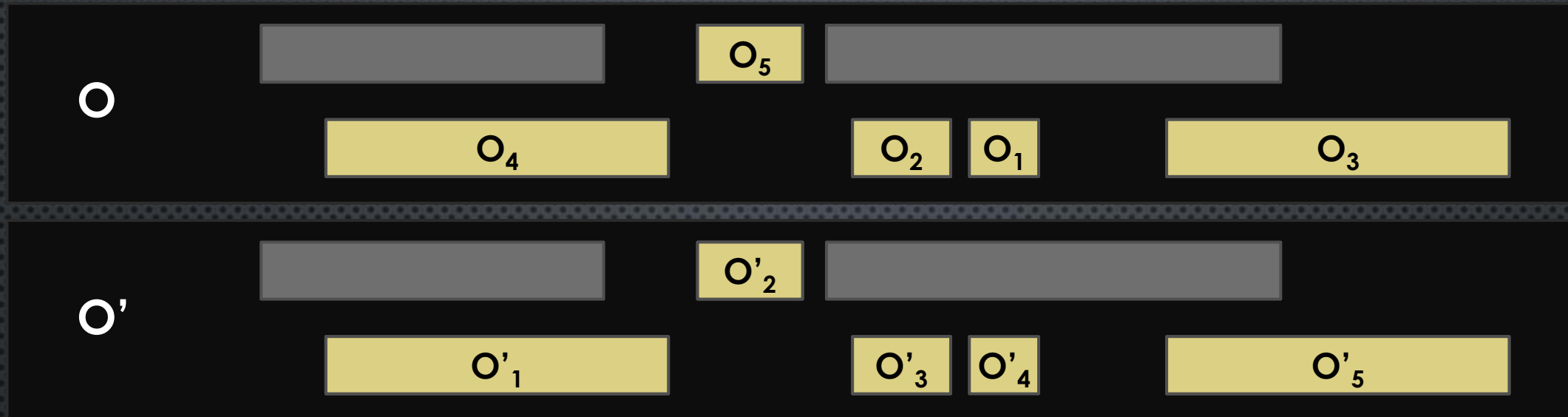
How to compare G and O ?

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**

REORDERING O BY INCREASING FINISH TIME

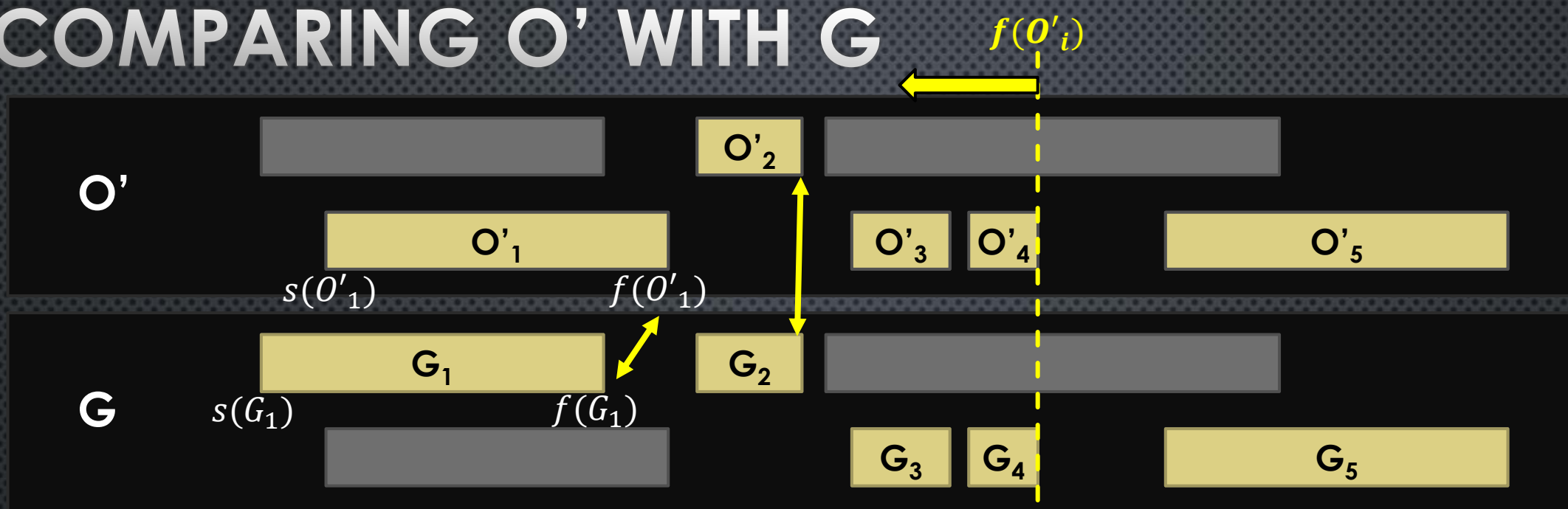


Now O' and G are both ordered by increasing finish time

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'**

COMPARING O' WITH G



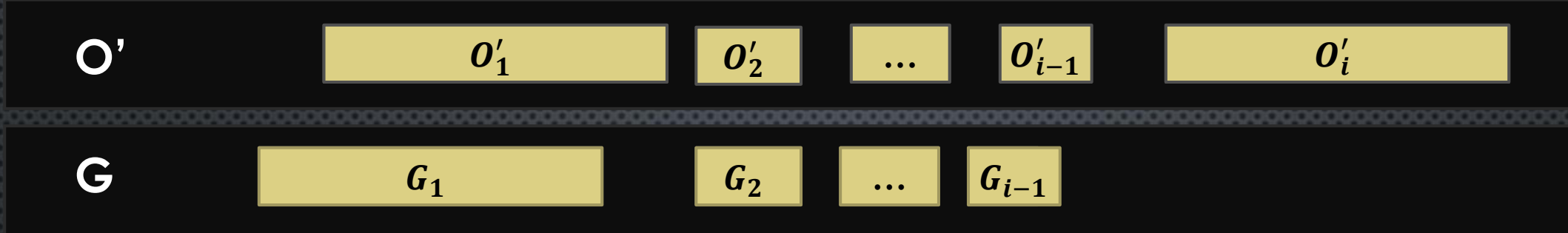
Looks like $f(G_1) \leq f(O'_1)$ and $f(G_2) \leq f(O'_2) \dots$ Is $f(G_i) \leq f(O'_i)$ for **all** i ?

If this trend holds in general, then

out of the intervals with finish time $\leq f(O'_i)$

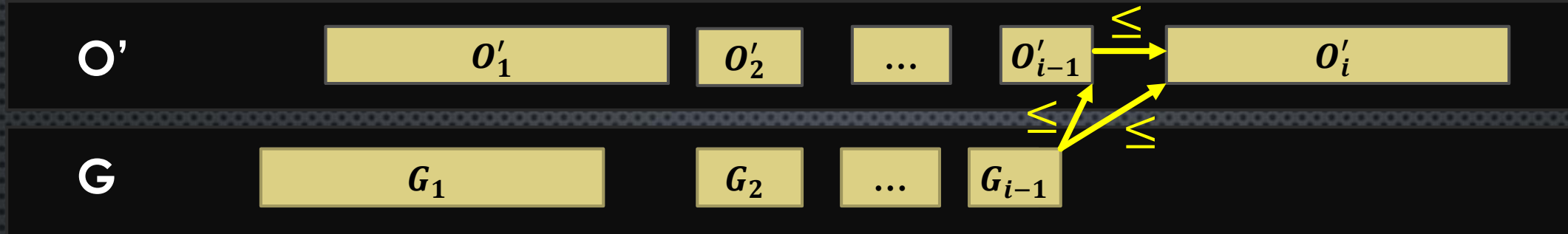
G chooses as many intervals as O!

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.

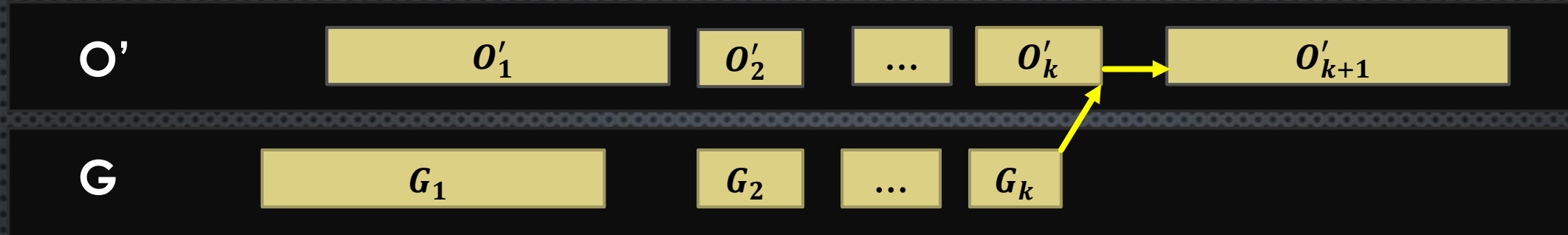
PROVING LEMMA: $f(G_i) \leq f(O'_i)$ FOR ALL i



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 $f(G_i) \leq f(O'_i)$**

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!**

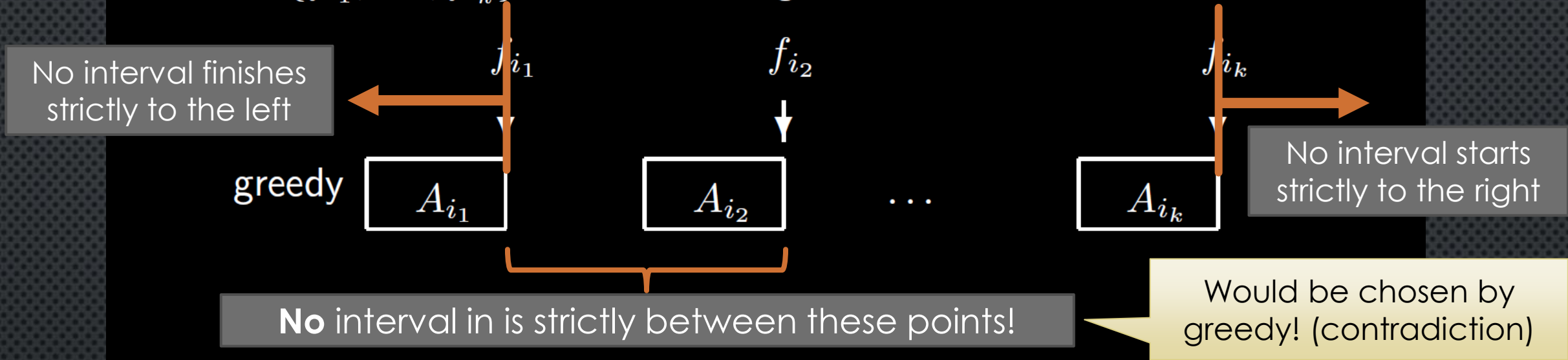
So assumption
 $|O'| > |G|$ is wrong!

So G is optimal

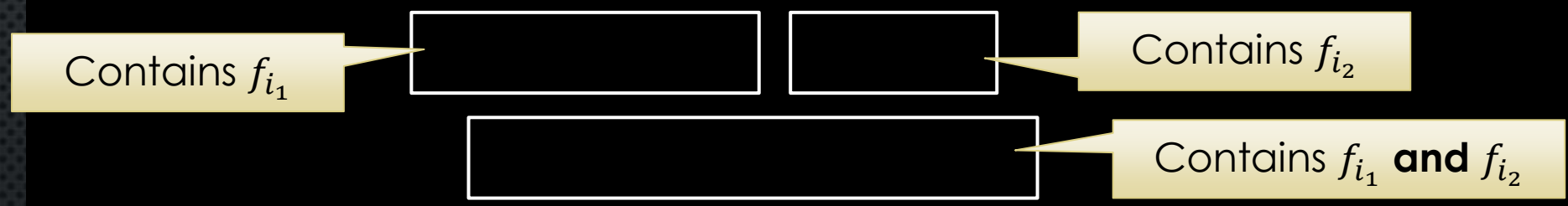
A DIFFERENT PROOF

“**Slick**” ad-hoc approaches are sometimes possible...

Let $F = \{f_{i_1}, \dots, f_{i_k}\}$ be the finishing times of the intervals in X



So, in addition to the intervals in X , only the following types of intervals are **possible**

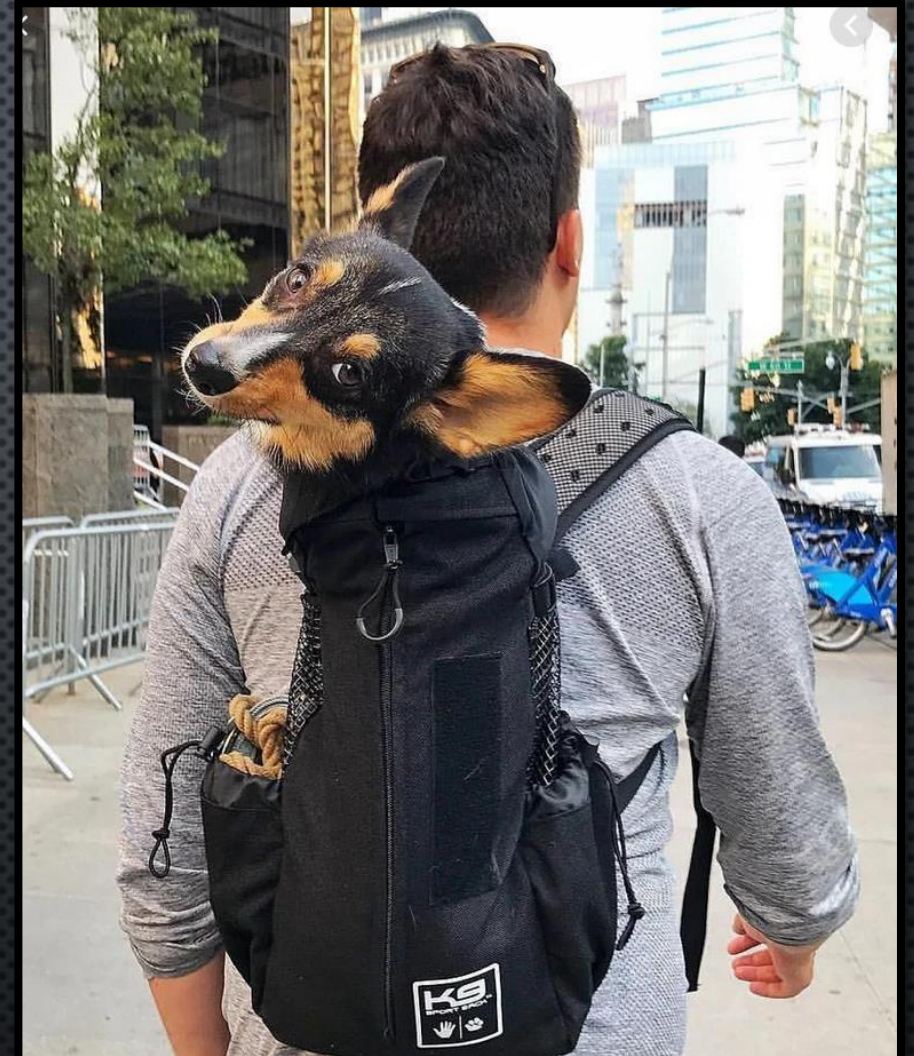


Thus, **every interval** contains some finishing time in F

And, two intervals in O **cannot contain the same** element of F

So, there must be as many finishing times in F as there are intervals in O . QED

KNAPSACK PROBLEMS



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...



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

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 $P = [20, 50, \mathbf{100}]$
 - Weights $W = [10, 20, 10]$
 - Weight limit $M = 10$
- Algorithm selects last item for 100 profit
 - Looks optimal in this example

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!**

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!

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)

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)

It turns out strategy #3 **is** optimal...

```

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

```

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 $x_i \in (0,1)$

Running time complexity?

Can do preprocessing in $\Theta(n \log n)$

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)

```
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
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
```

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]
```


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!

FORMAL FEASIBILITY ARG

- **Loop invariant:** $\forall_i : x_i \in [0,1]$
- **and** $weight = \sum_{i=1}^n w_i x_i \leq M$

```
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]
```

- 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** $weight' = \sum_{i=1}^n w_i x'_i \leq M$

Optional slide, just
for your notes

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 $weight' = (\sum_{k=1}^n x'_k w_k - x'_i w_i) + x'_i w_i = \sum_{k=1}^n x'_k w_k$

```
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]
```

Optional slide, just
for your notes

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 $weight' = \sum_{k=1}^n x'_k w_k$**

```
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]
```

Optional slide, just
for your notes

! TRADE OFFER !

i receive:



you receive:



My Pocket

EXCHANGE ARGUMENT
for proving optimality


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 $Y = (y_1, \dots, y_n)$.

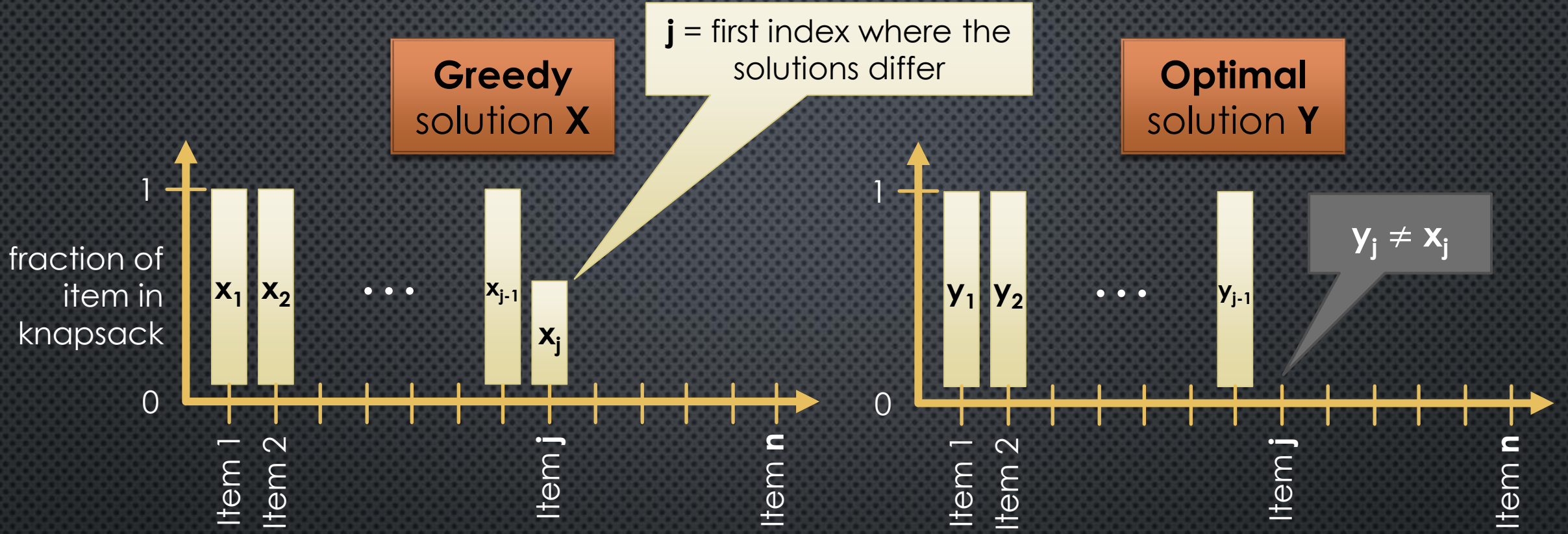
We will prove that $X = Y$, i.e., $x_j = y_j$ for $j = 1, \dots, n$. Therefore there is a unique optimal solution and it is equal to the greedy solution.

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

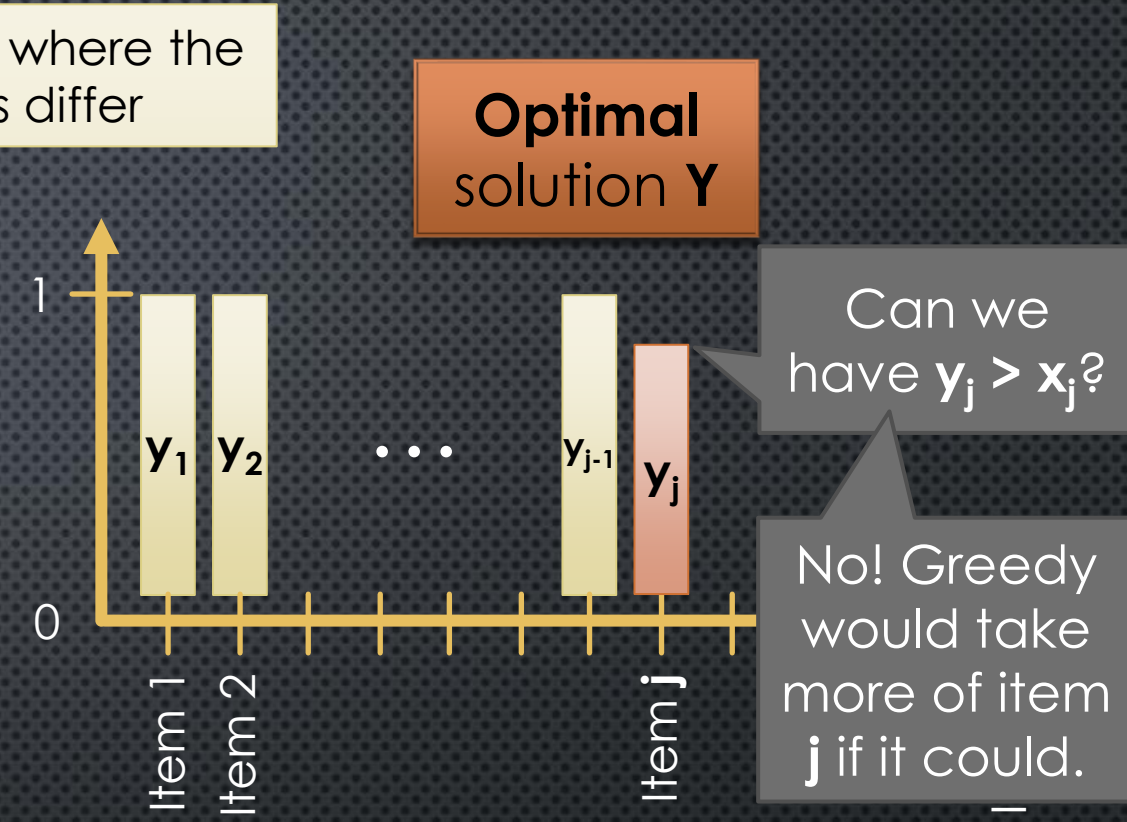
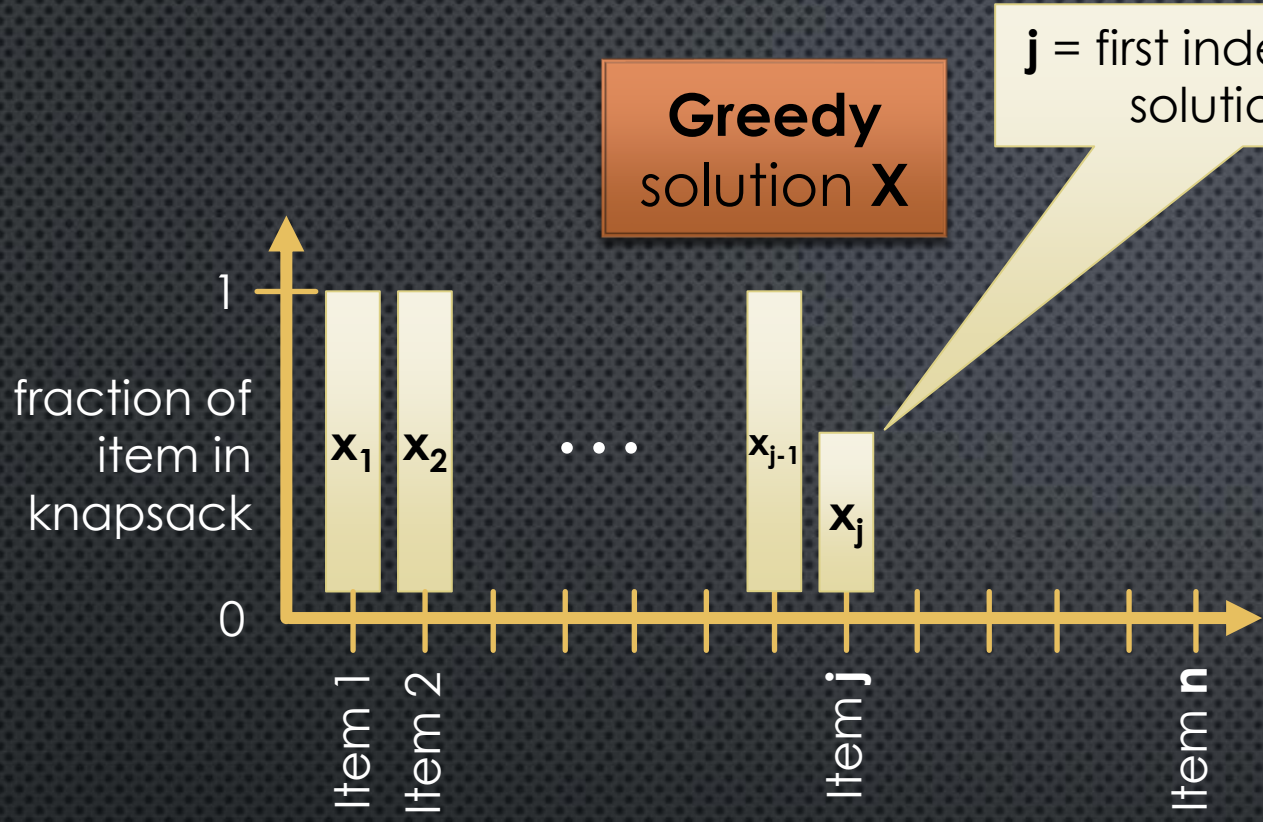
Pick the smallest integer j such that $x_j \neq y_j$.

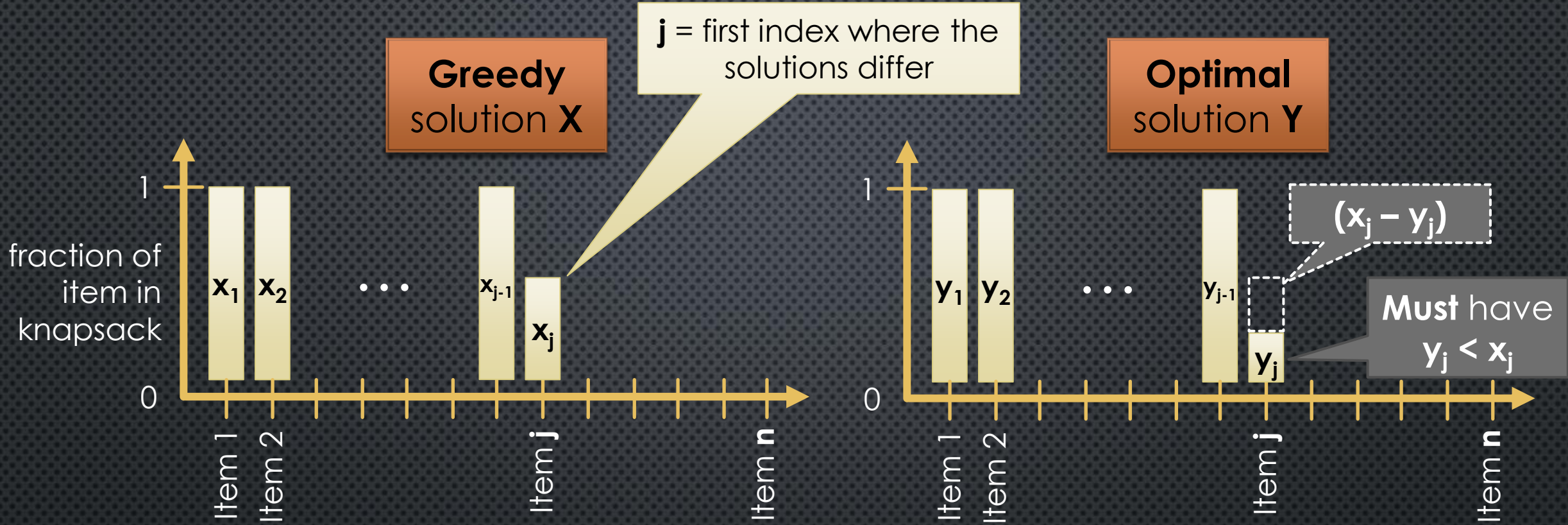


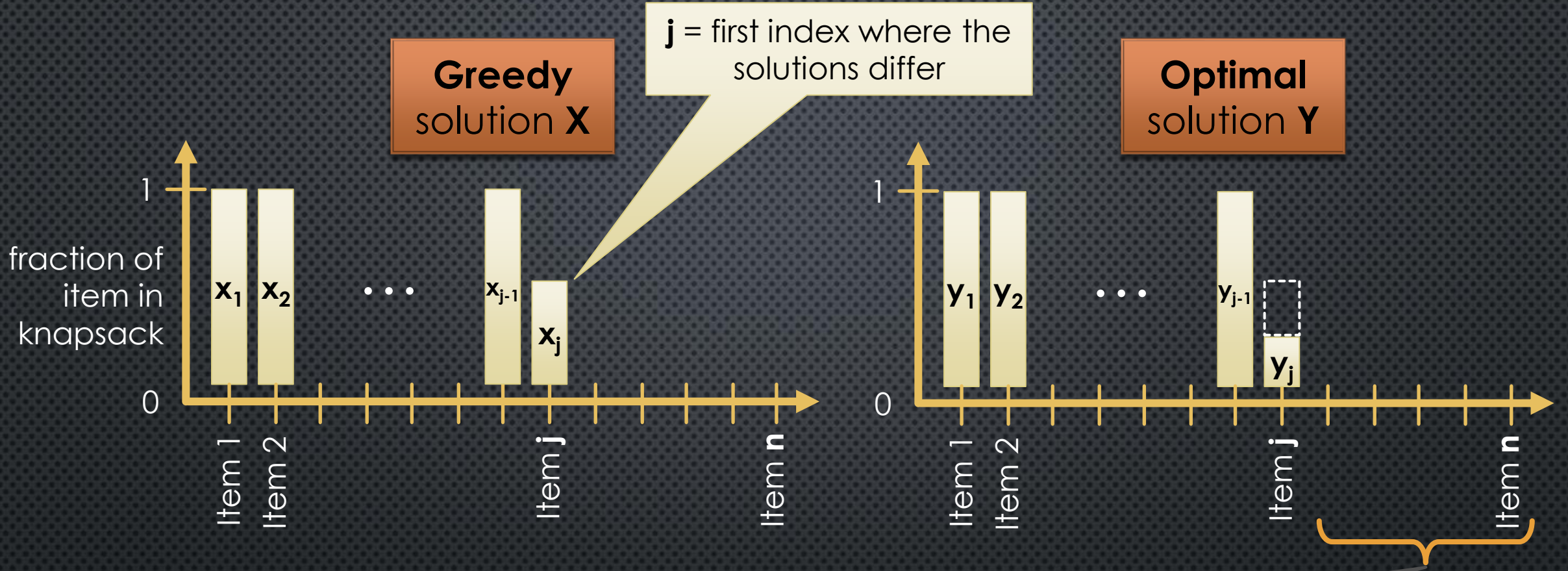
X and Y are **identical** up to x_j and y_j , respectively



What's the relationship between x_j and y_j ?

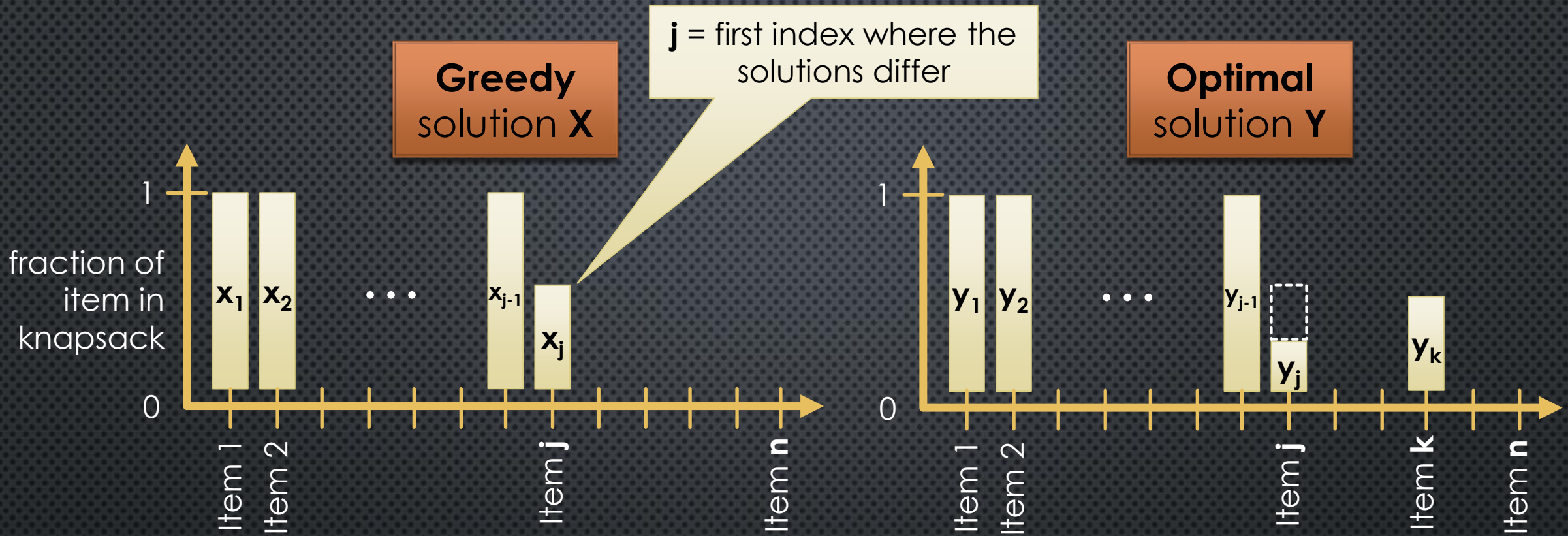






No! It would be worth less than X

Can Y be all zeros after y_j ?

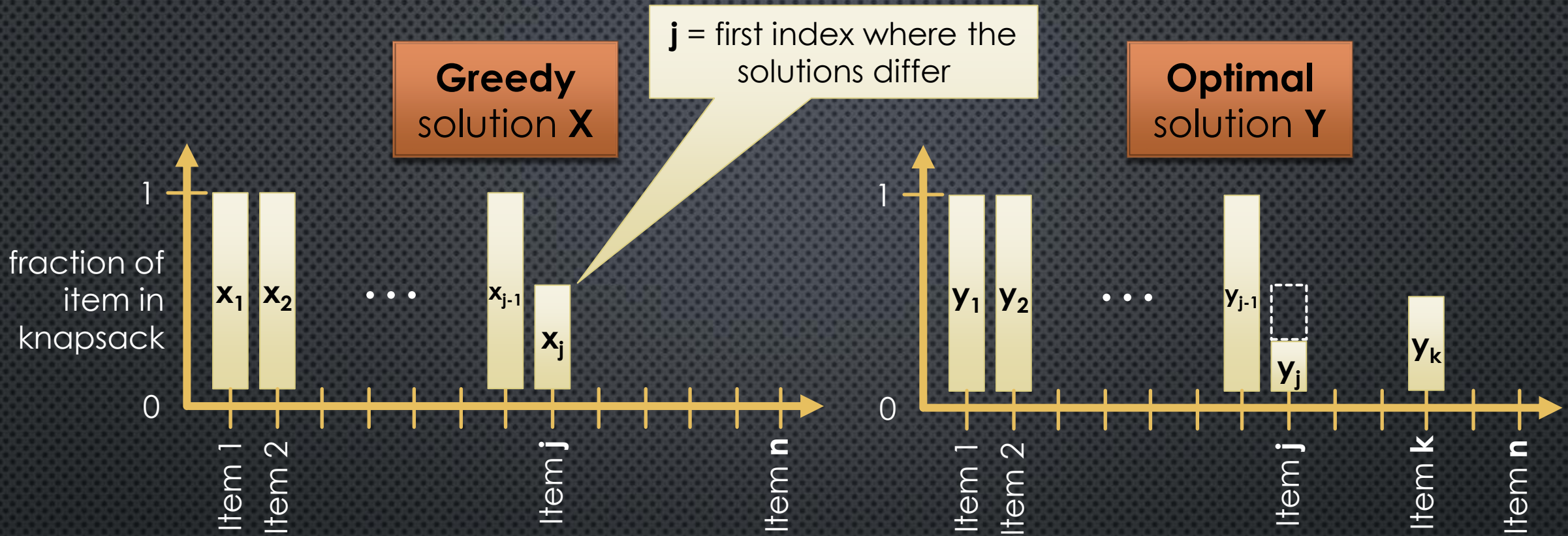


Must exist $k > j$ such that $y_k > 0$

But, by our **sort order**, **item j is worth more** (per unit of weight) than **item k**!

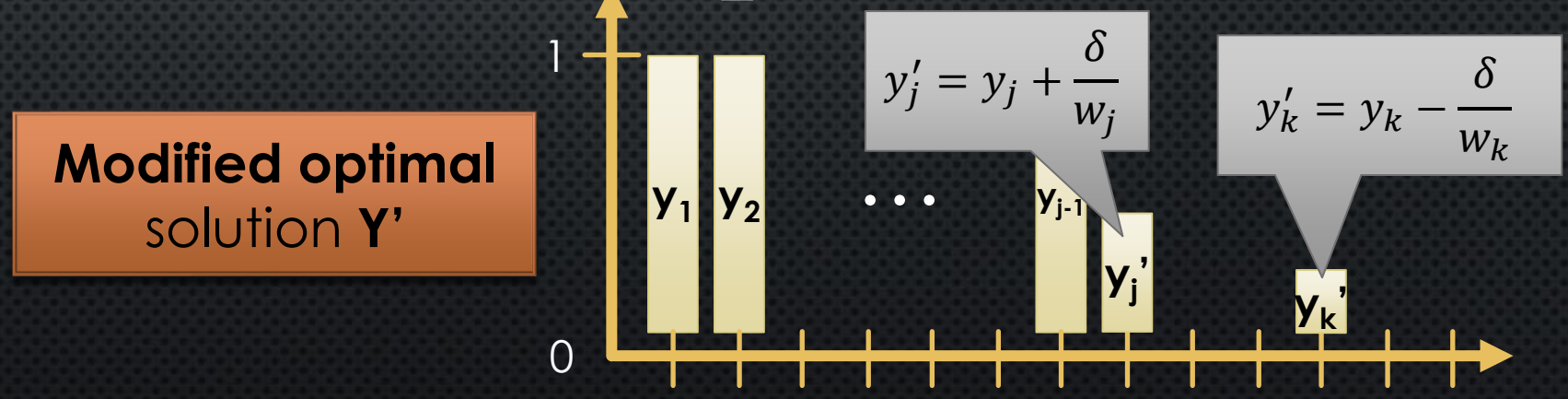
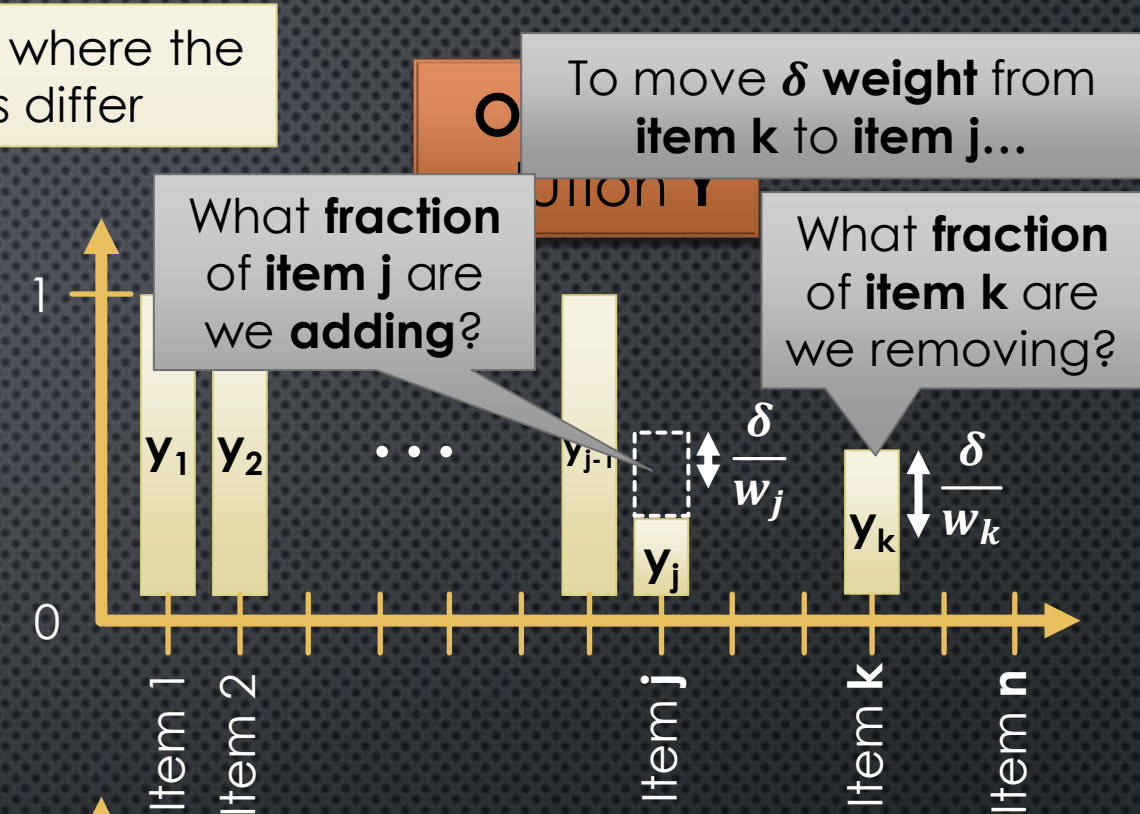
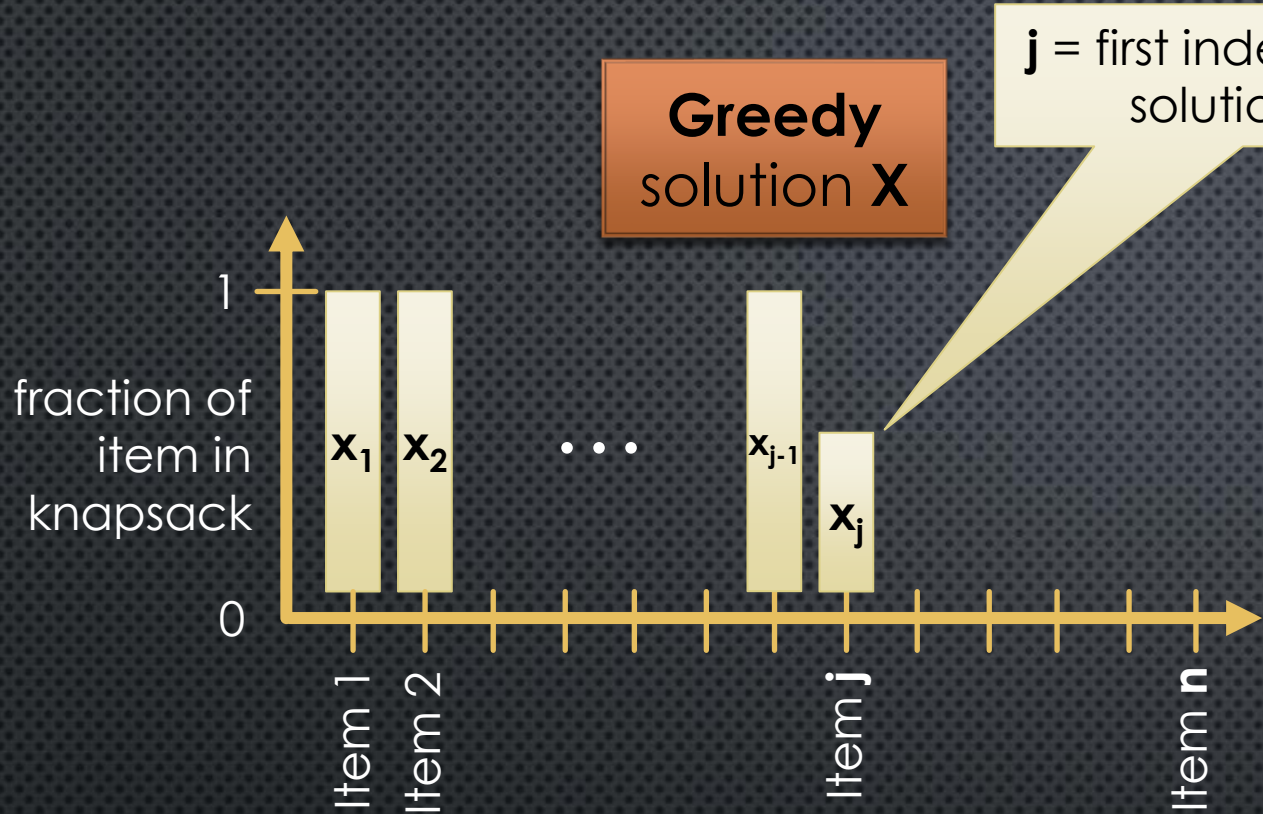
Remove some of item **k** and **replace** it with some of item **j**?

How much of item **k** should we remove?

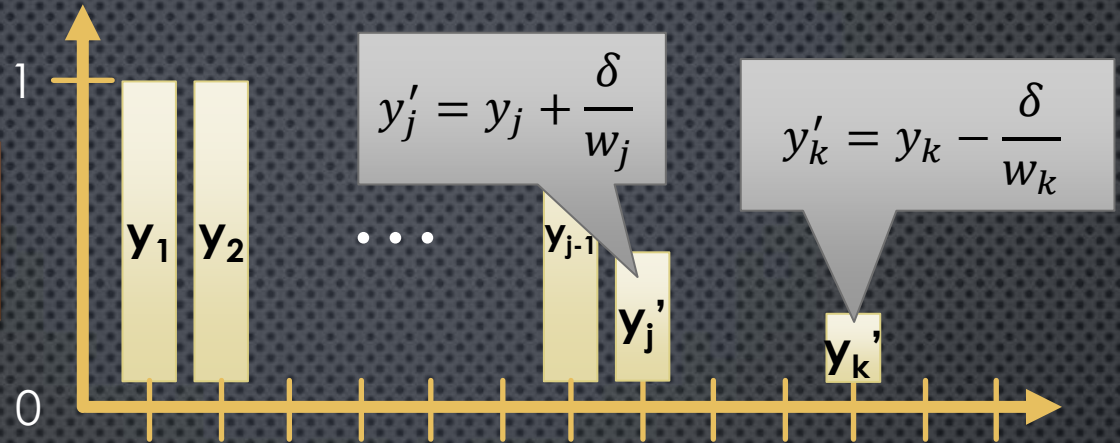


Since item j is worth **more per unit weight**, replacing **even a tiny amount** of item k with item j will improve the solution

So, we remove an infinitesimal $\delta > 0$ of weight of item k , and add δ weight of item j



Modified optimal solution Y'



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 $\text{weight}(Y') \leq M$

FEASIBILITY OF Y'

- To show Y' is feasible, we show $y'_k \geq 0, y'_j \leq 1$ and $weight(Y') \leq M$
- 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 δ to be smaller than this **positive number**
 - Therefore, it is possible to choose positive δ s.t. $y'_k \geq 0$

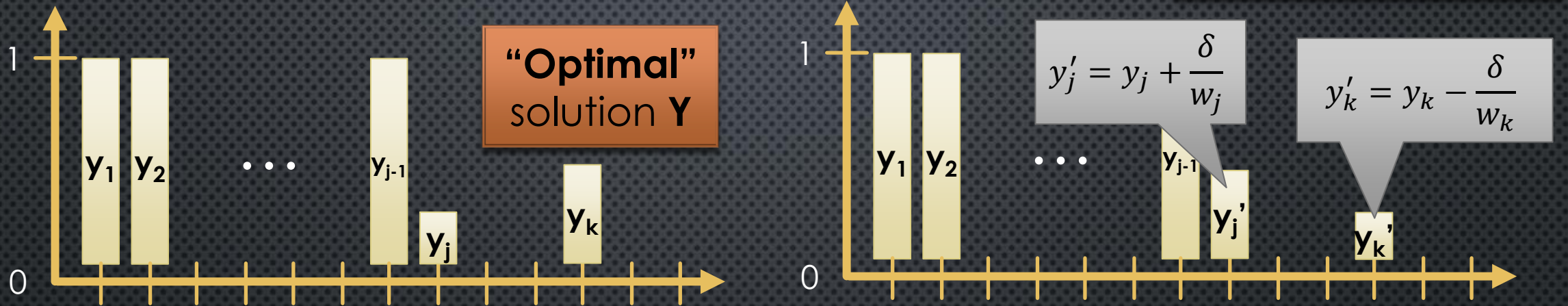
Existence proof, but a
non-constructive one

FEASIBILITY OF Y'

- To show Y' is feasible, we show $y'_k \geq 0, y'_j \leq 1$ and $weight(Y') \leq M$
- 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 δ to be smaller than some **positive number**

FEASIBILITY OF Y'

- Finally, we show $weight(Y') \leq M$



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

SUPERIORITY OF Y'

- Finally we compute $profit(Y')$

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

(Fraction of item j **added**)
× (profit for item j)

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

(Fraction of item k **removed**)
× (profit for item k)

- 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 $\delta \left(\frac{p_j}{w_j} - \frac{p_k}{w_k} \right) > 0$

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

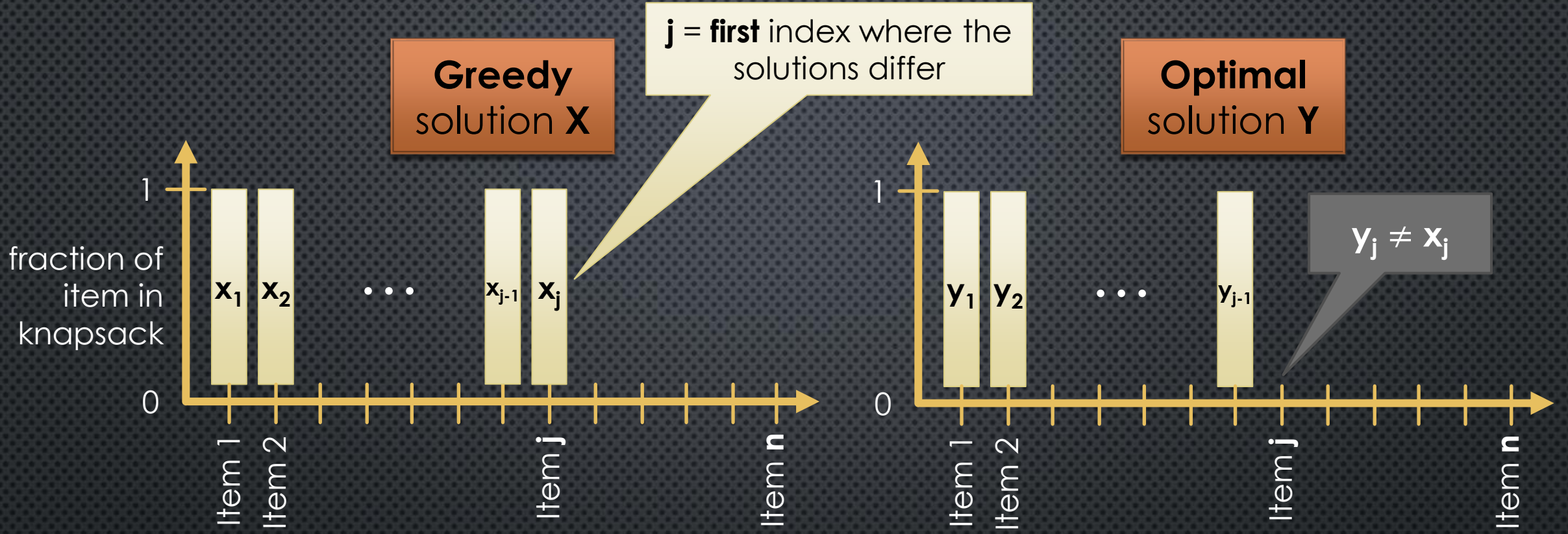
- Since we can choose $\delta > 0$, we have $profit(Y') > profit(Y)$.

Covering the next 9
slides is homework!

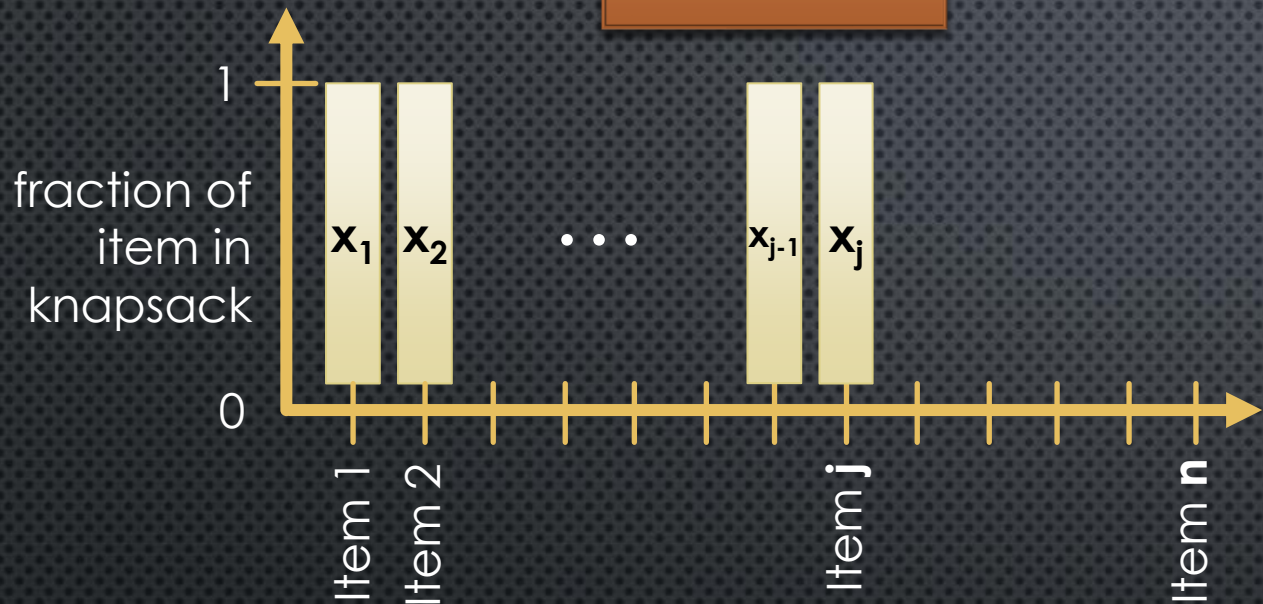
WHAT IF ELEMENTS DON'T HAVE
DISTINCT PROFIT/WEIGHT RATIOS?

OPTIMALITY PROOF WITHOUT DISTINCTNESS

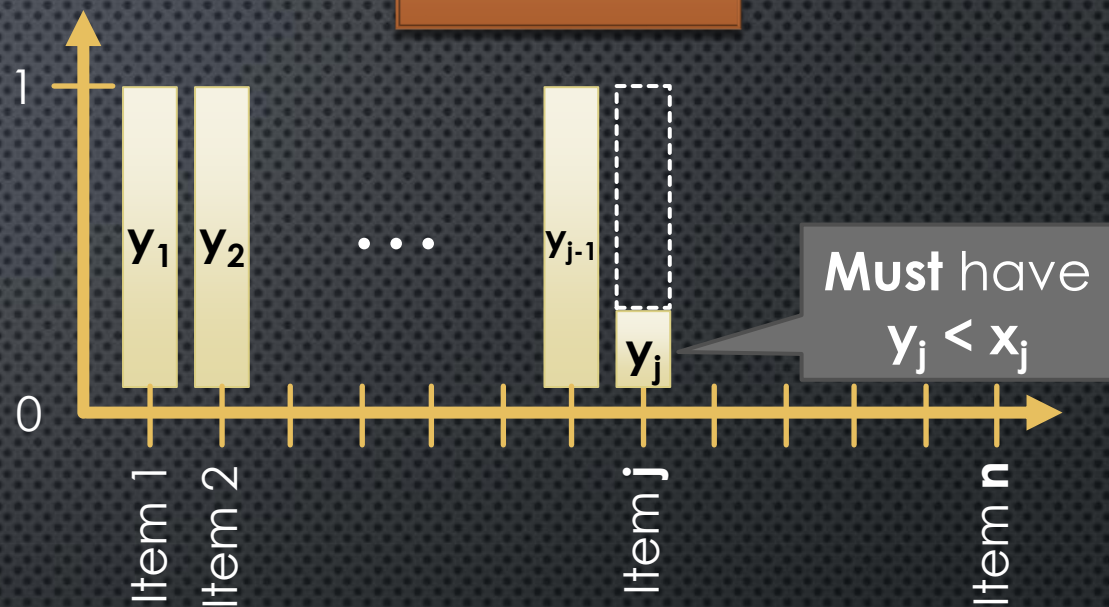
- There may be many optimal solutions
- **Key idea:** Let Y be an optimal solution that **matches X on a maximal number of indices**
- **Observe:** if X is really optimal, then $Y = X$
- Suppose not for contra
 - We will modify Y , preserving its optimality, but making it match X on **one more index**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



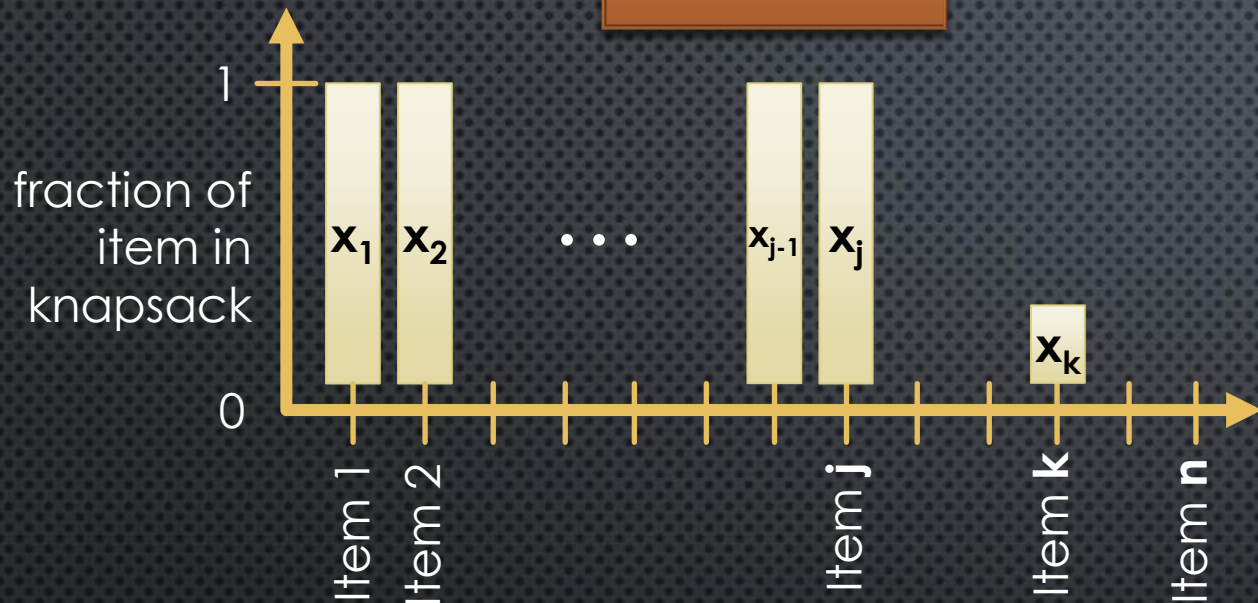
**Greedy
solution X**



**Optimal
solution Y**



Greedy solution X

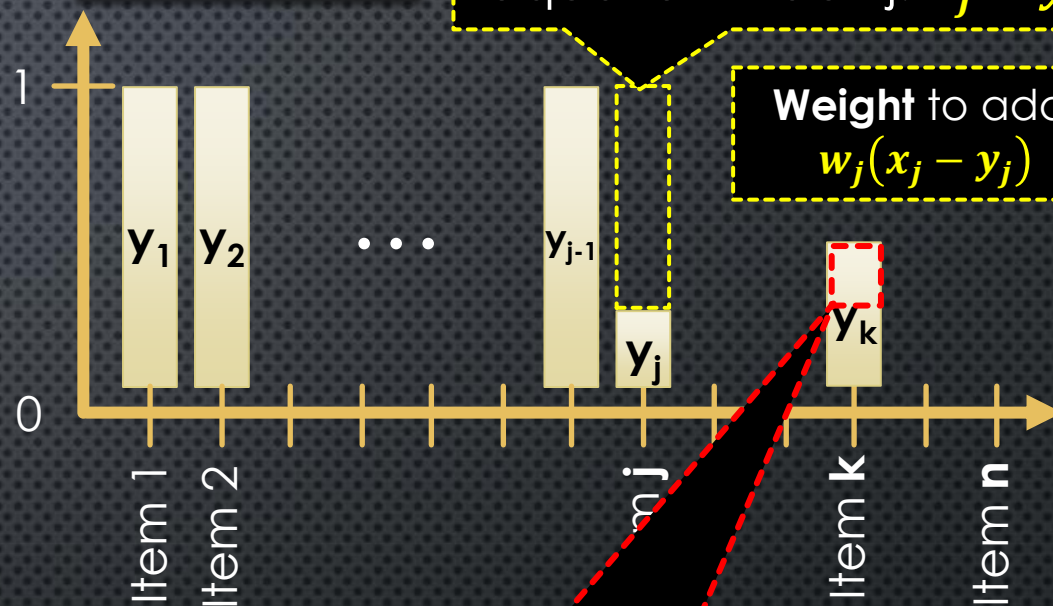


Must exist $k > j$ such that $y_k > x_k$ because weight of X and Y must be the same

Remove some **weight δ** of item **k** and **add** the same weight of item **j**

With the goal of making the solutions **equal on index k or index j**

Optimal solution Y



Fraction we should **add** to j to make solutions equal on index j : $x_j - y_j$

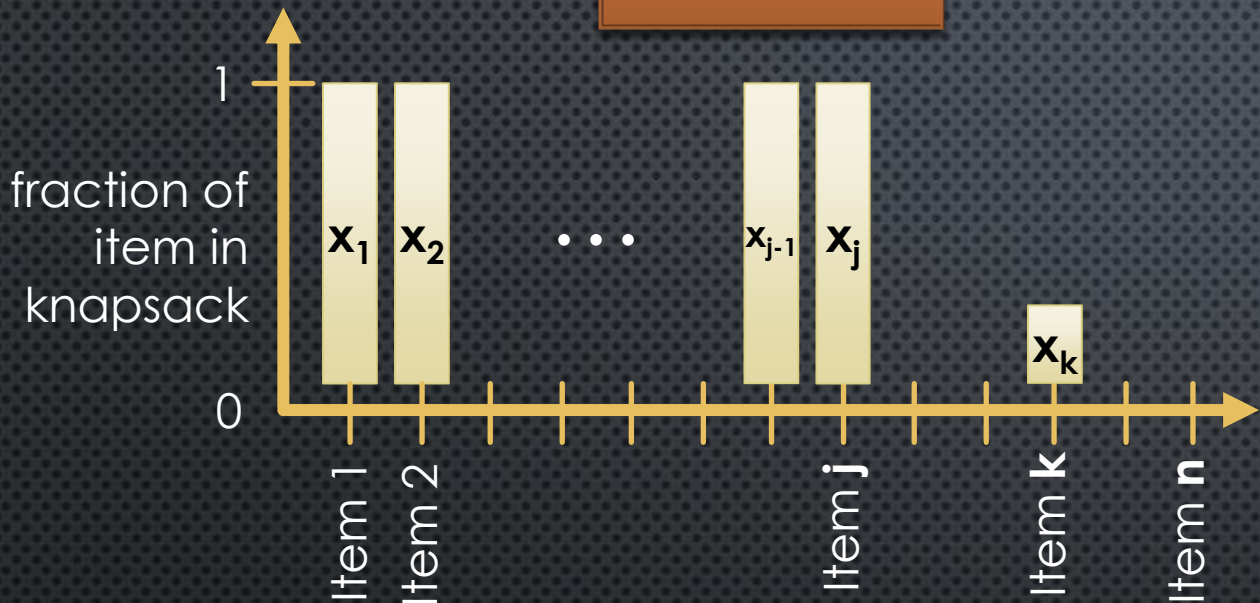
Weight to add: $w_j(x_j - y_j)$

Fraction we should **remove** from k to make solutions equal on index k : $y_k - x_k$

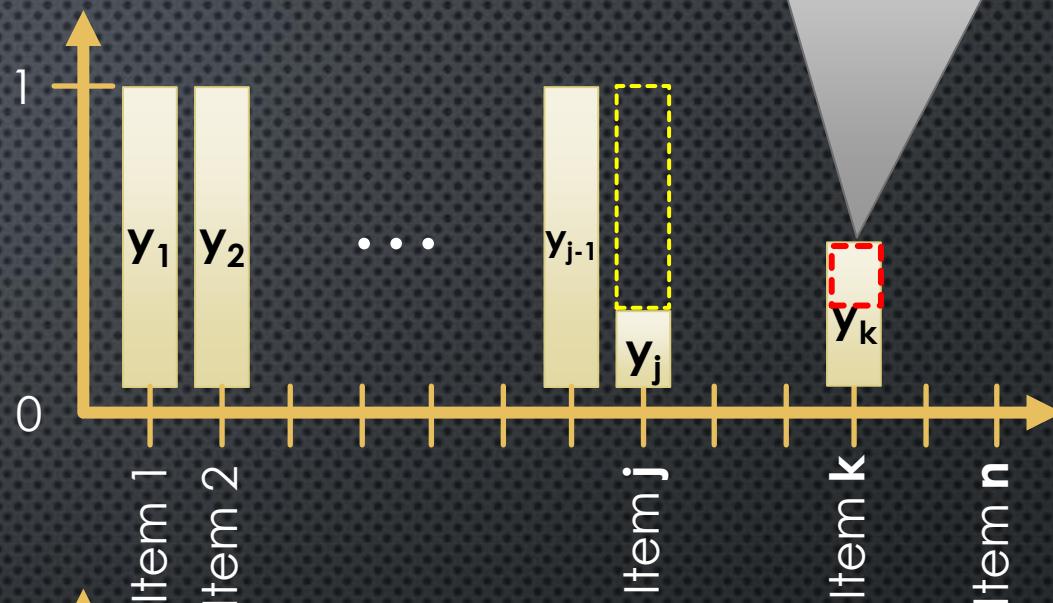
Weight to remove: $w_k(y_k - x_k)$

Let $\delta = \min\{w_j(x_j - y_j), w_k(y_k - x_k)\}$
Observe $\delta > 0$

Greedy solution X

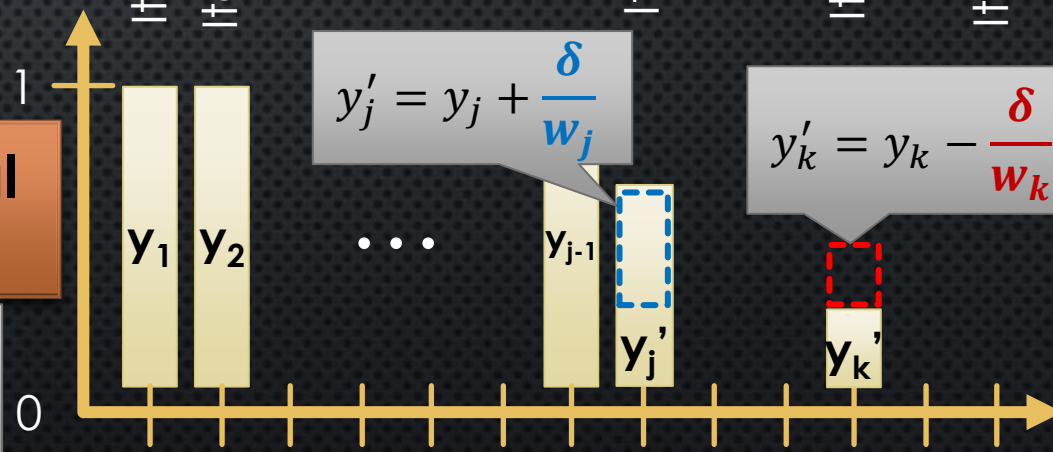


Optimal solution Y



Suppose $\delta = w_k(y_k - x_k)$

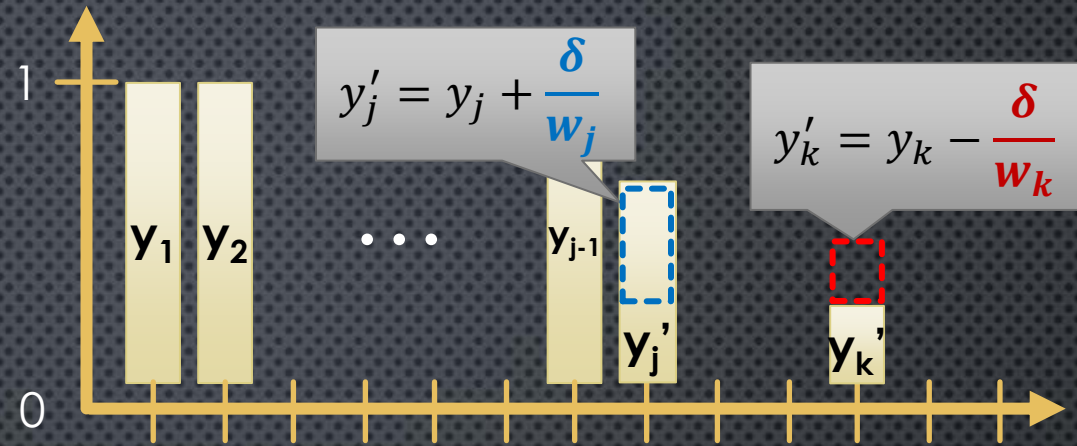
Modified optimal solution Y'



In this case, since $\delta = w_k(y_k - x_k)$, we end up with $y_k' = x_k$

If δ were $w_j(x_j - y_j)$, we would have $y_j' = x_j$

Modified optimal solution Y'



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

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

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 δ 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 δ)
 - and $w_j(x_j - y_j) \leq w_j(1 - y_j)$ (by feasibility of X , i.e., $x_j \leq 1$)

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!

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