

CSE 331: Algorithms & Complexity “Dynamic Programming”

Prof. Charlie Anne Carlson (She/Her)

Lecture 28

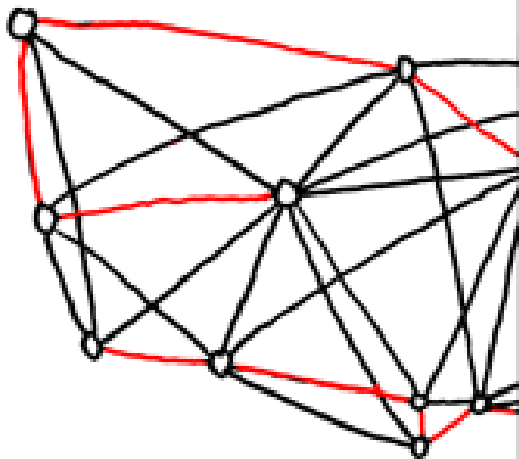
Monday Nov 7th, 2025



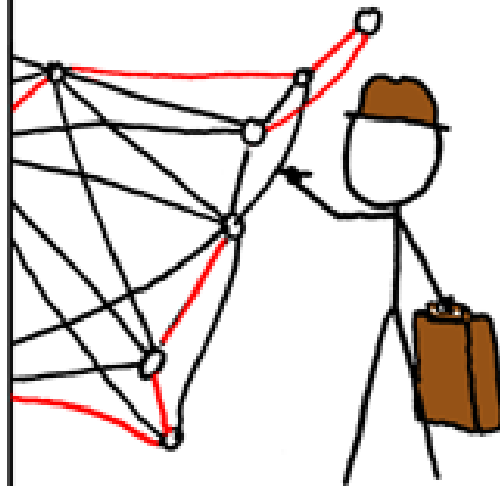
University at Buffalo®



BRUTE-FORCE
SOLUTION:
 $O(n!)$



DYNAMIC
PROGRAMMING
ALGORITHMS:
 $O(n^2 2^n)$



SELLING ON EBAY:
 $O(1)$

STILL WORKING
ON YOUR ROUTE?

SHUT THE
HELL UP.



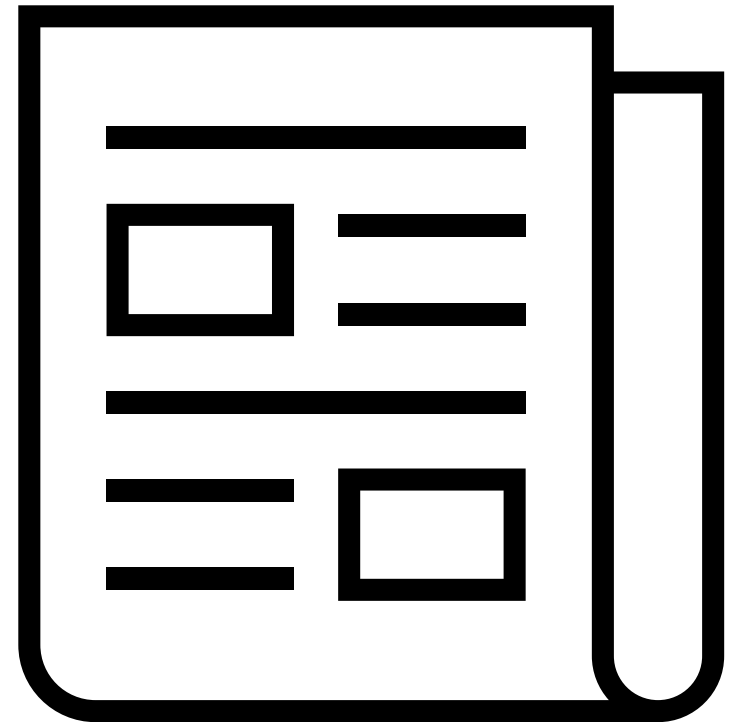
Schedule

1. Course Updates
2. Weighted Interval Scheduling
3. Memoization
4. Dynamic Programming



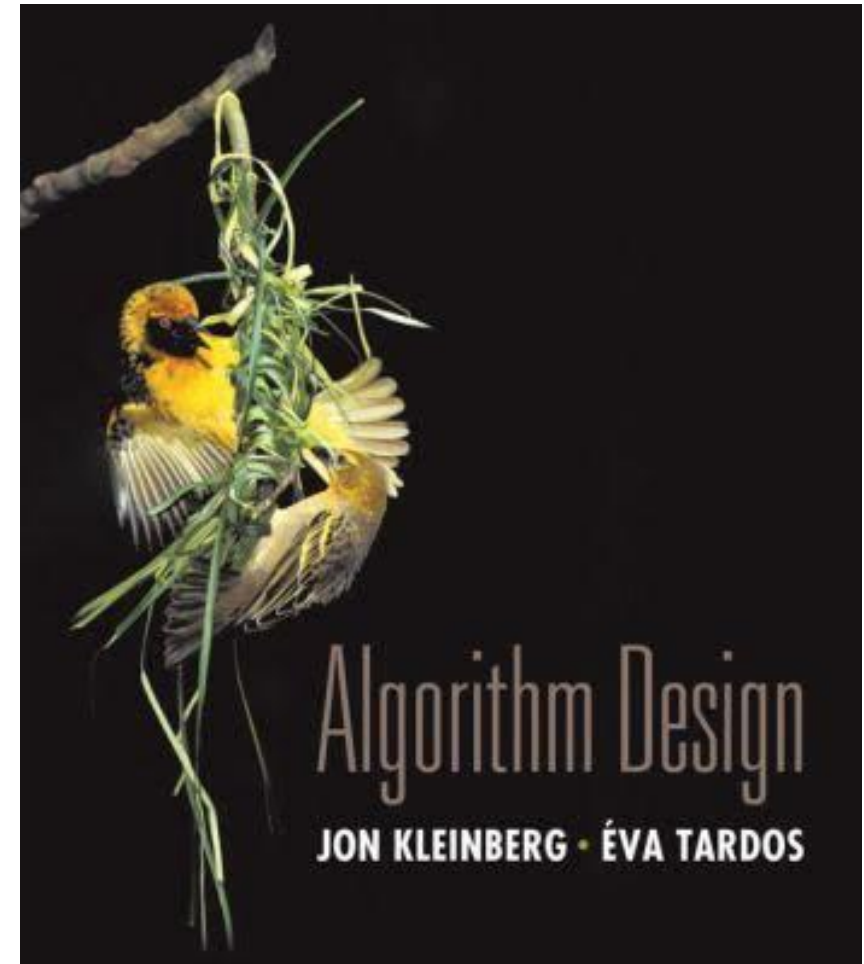
Course Updates

- HW 6 Out
 - Autolab Up
 - Due November 11th
- Group Project
 - Code 3 Due November 24th
 - Reflections 3 Due December 1st
- Check Piazza for Google Form Review Link (before Friday)
- Next Quiz is December 1st



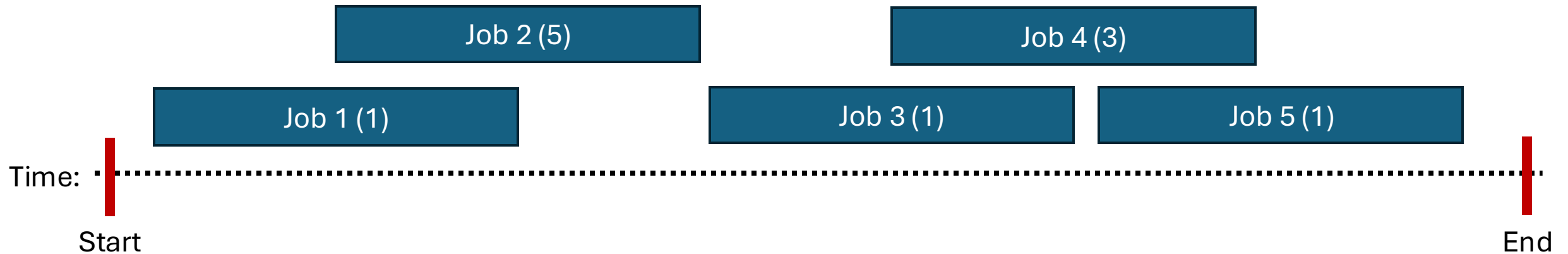
Reading

- You should have read:
 - Started 6.1
 - Started 6.2
- Before Next Class:
 - Finish 6.1
 - Finish 6.2



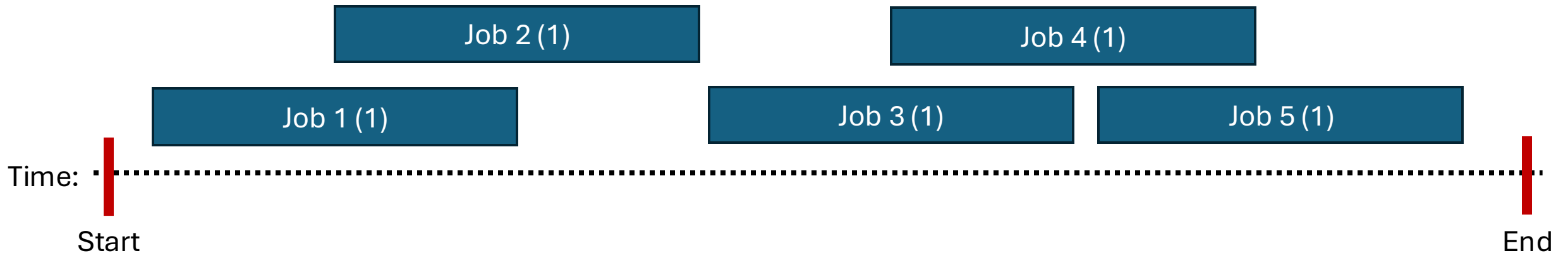
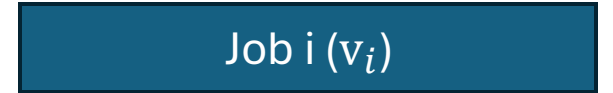
Weighted Interval Scheduling

- **Input:** A list of n jobs L
 - Each job i has a start time s_i and finish time f_i
 - Two jobs are “compatible” if they don’t overlap
 - Each job i has a weight v_i
- **Goal:** Find the max-weight subset of mutually compatible jobs.



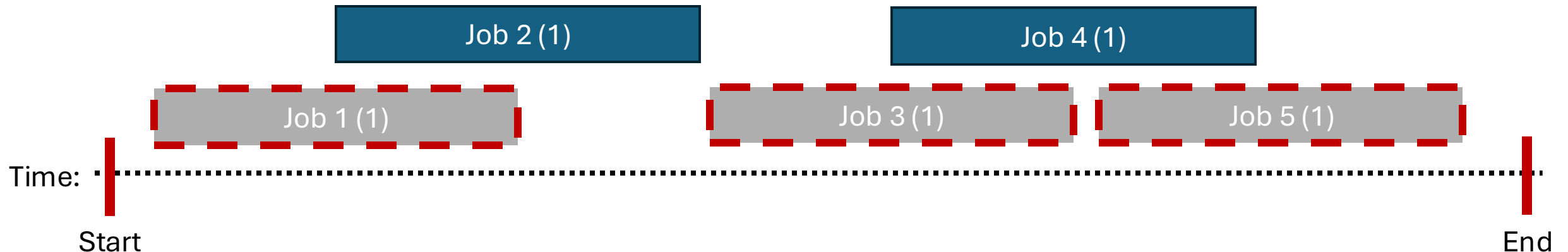
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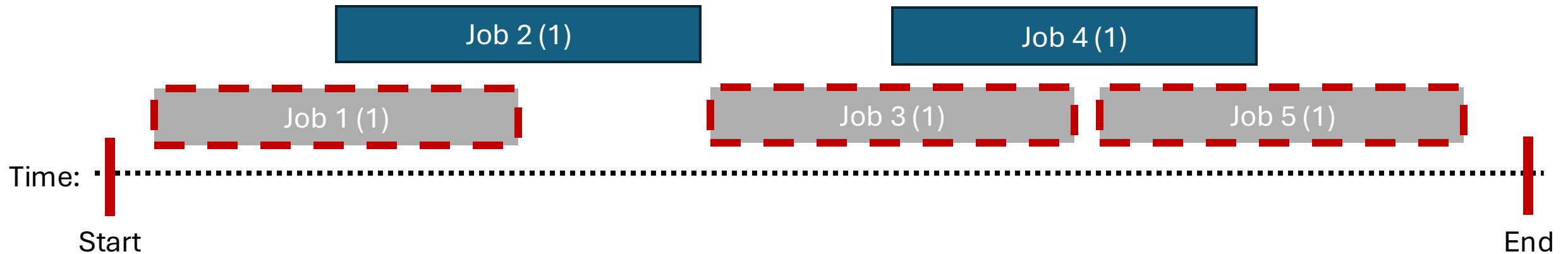
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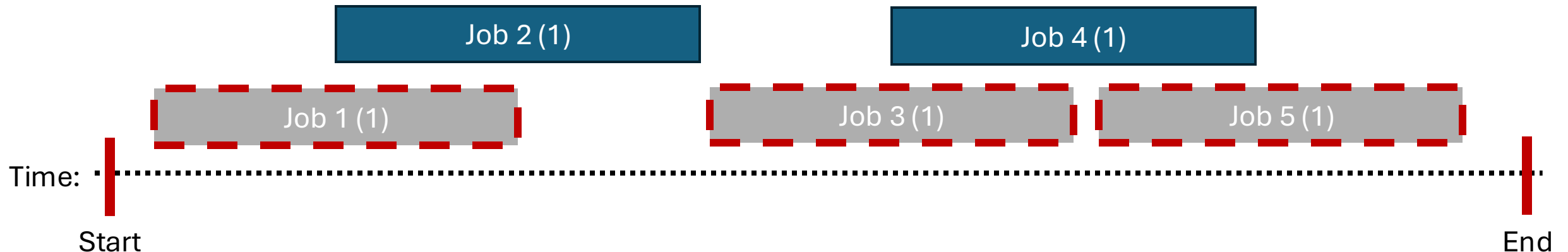
Unweighted Case

- **Question:** What algorithm do we use to find the maximum weight subset when the weight of each job is 1?



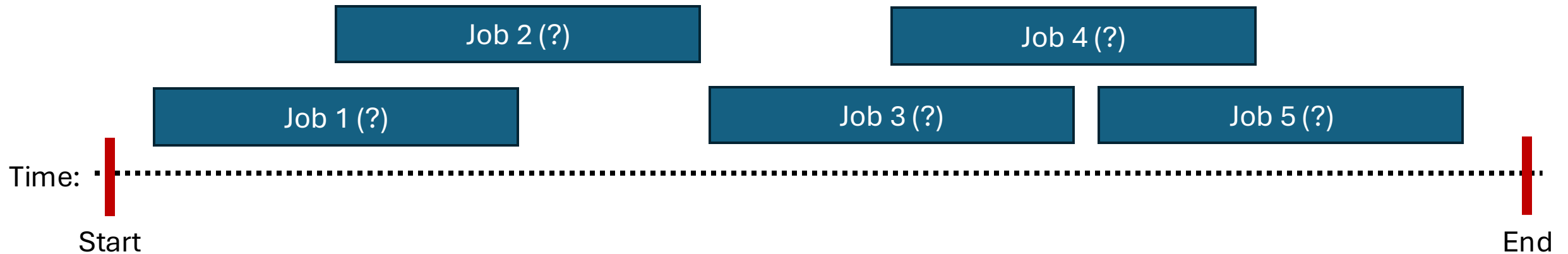
Unweighted Case

- **Question:** What algorithm do we use to find the maximum weight subset when the weight of each job is 1?
- **Answer:** We use a greedy algorithm where we scan from left to right and always take the next job to finish.



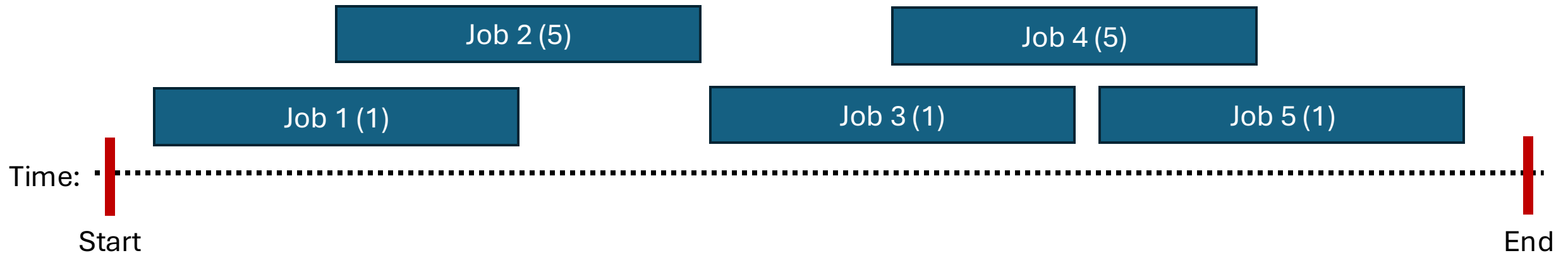
Weighted Case

- **Question:** Does this greedy algorithm work for other weights?



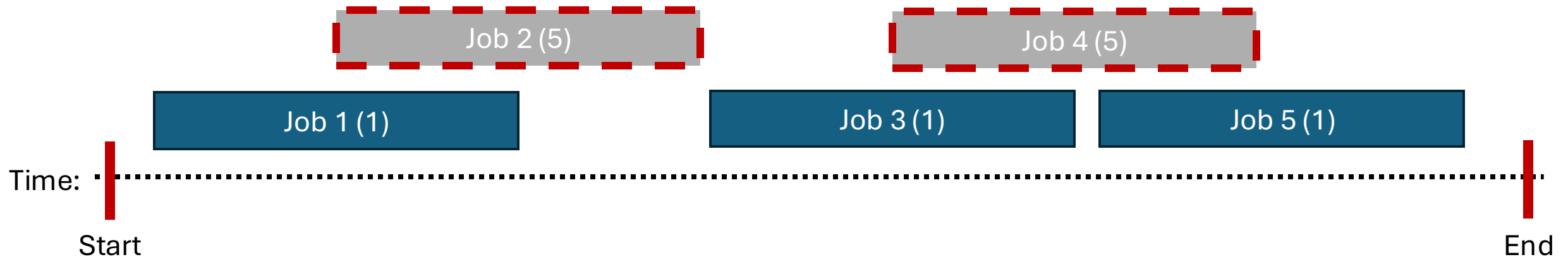
Weighted Case

- **Question:** Does this greedy algorithm work for other weights?
- **Answer:** No, there could be a situation where the number of jobs isn't the thing to maximize.



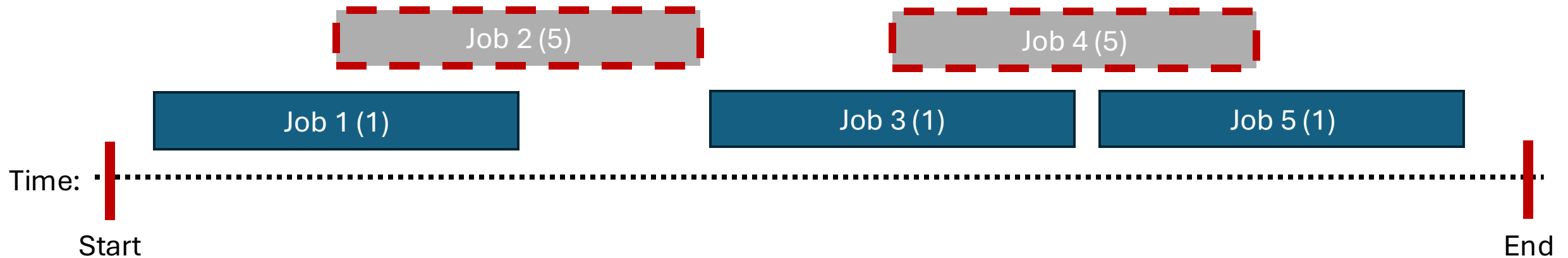
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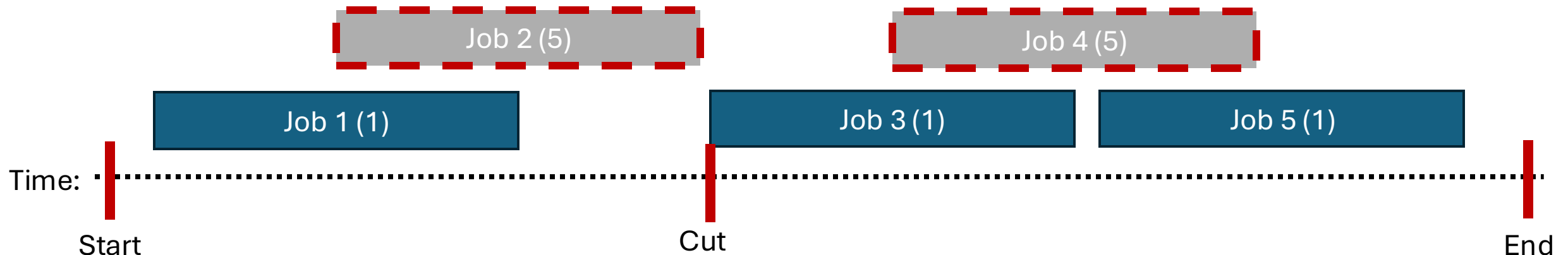
Divide & Conquer Approach

- **Question:** How would divide and conquer work for this problem?



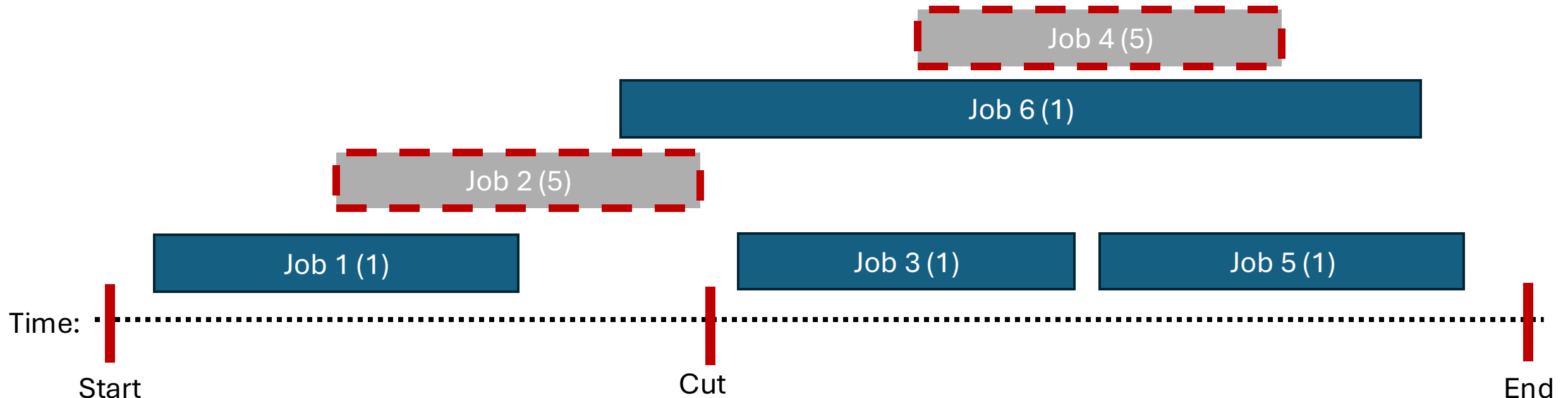
Divide & Conquer Approach

- **Question:** How would divide and conquer work for this problem?
- **Answer:** You might try to split the time in half or even put half of the jobs in both halves.



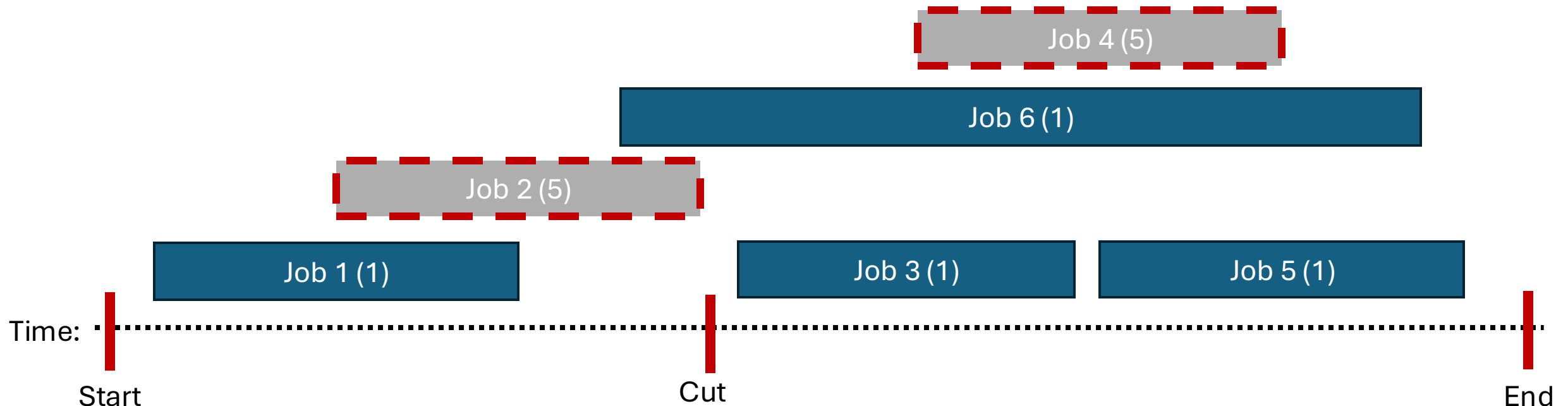
Divide & Conquer Approach

- **Question:** How would divide and conquer work for this problem?
- **Answer:** You might try to split the time in half or even put half of the jobs in both halves.
 - However, some problems may not split as easily...



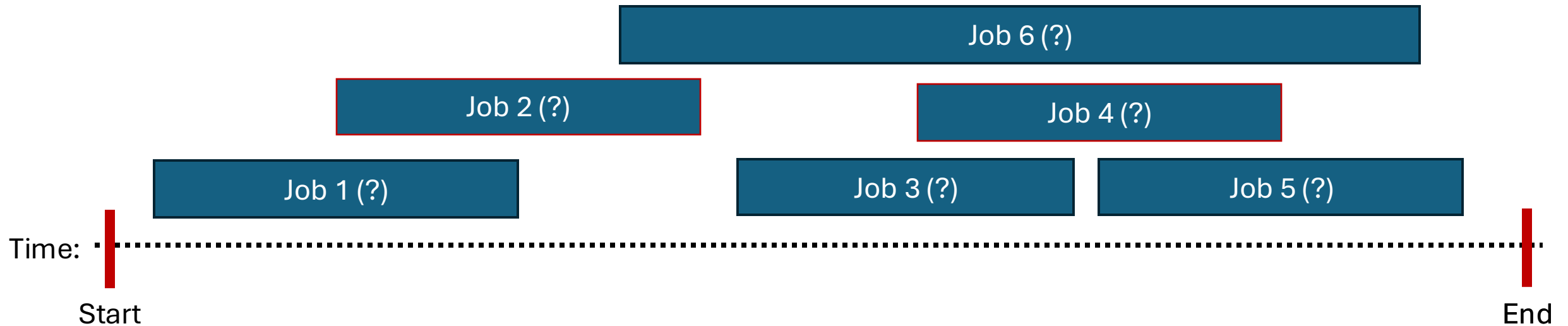
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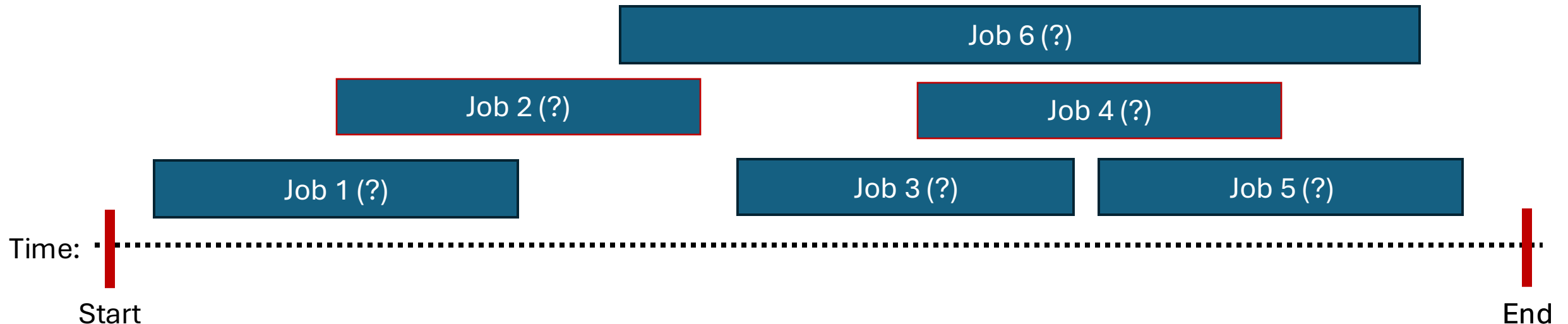
Divide & Conquer Approach

- **Question:** Consider an arbitrary instance with optimal solution OPT. What do we know about job 1?



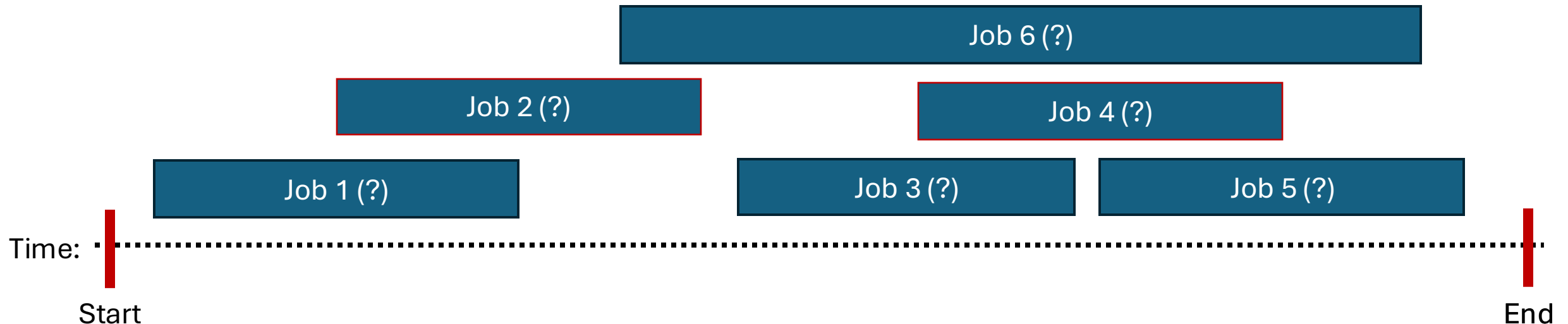
Binary Choice

- **Question:** Consider an arbitrary instance with optimal solution OPT. What do we know about job 1?
- **Answer:** It is either in OPT or it is not.



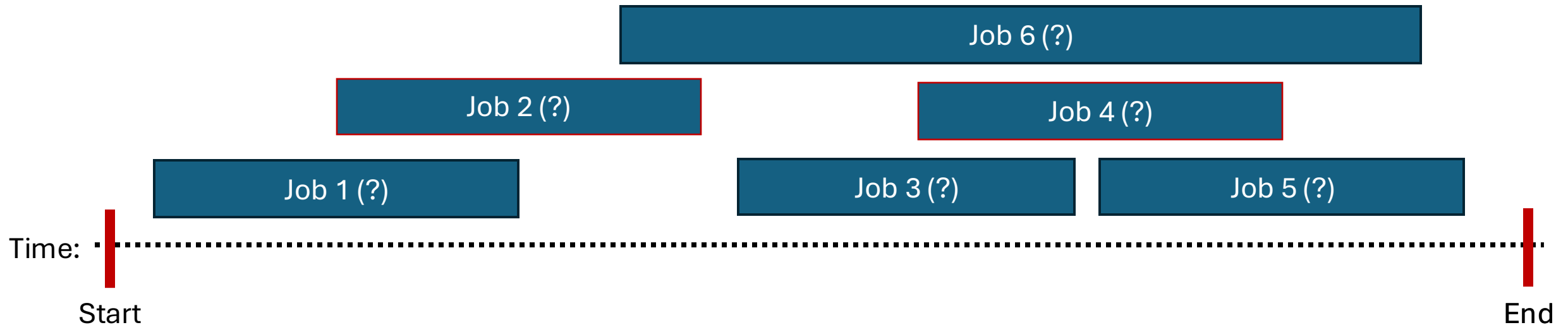
Binary Choice

- In a greedy algorithm we are assuming about if job 1 is in the optimal solution.
 - Our greedy rule doesn't work anymore if we don't know the weight.
- **Question:** Why not try both options?



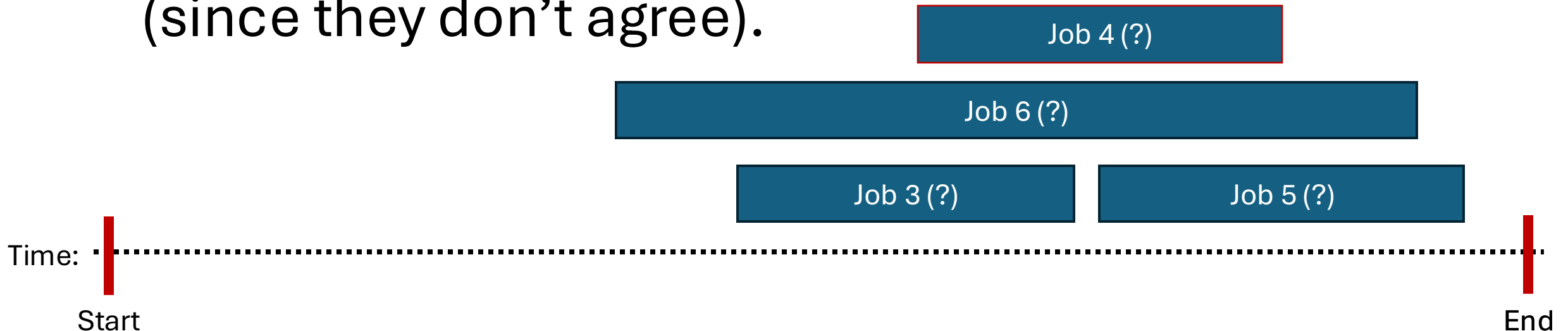
Binary Choice

- Suppose I gave you the hint that Job 1 was in OPT.
- **Question:** What do you need to do to find the rest of OPT?



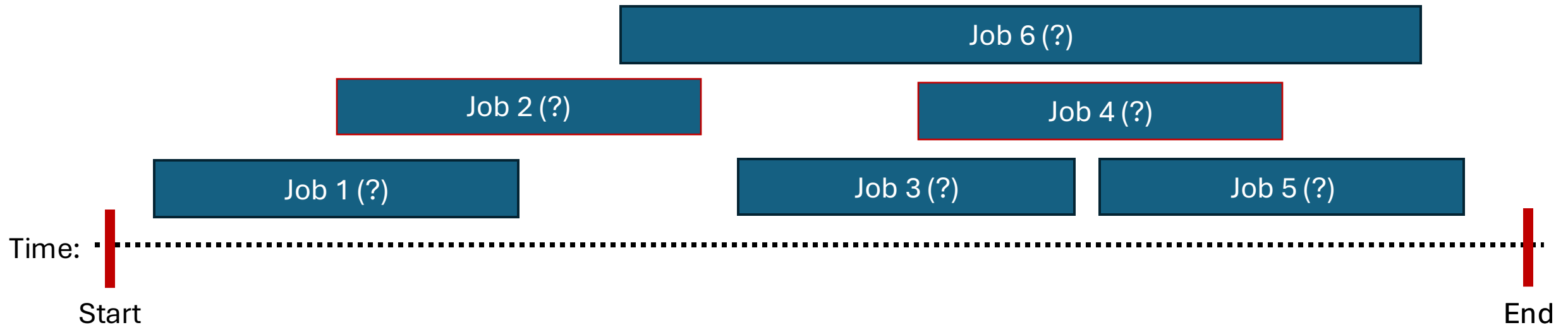
Binary Choice

- Suppose I gave you the hint that Job 1 was in OPT.
- **Question:** What do you need to do to find the rest of OPT?
- **Answer:** Recurse on a job without Job 1 or Job 2 (since they don't agree).



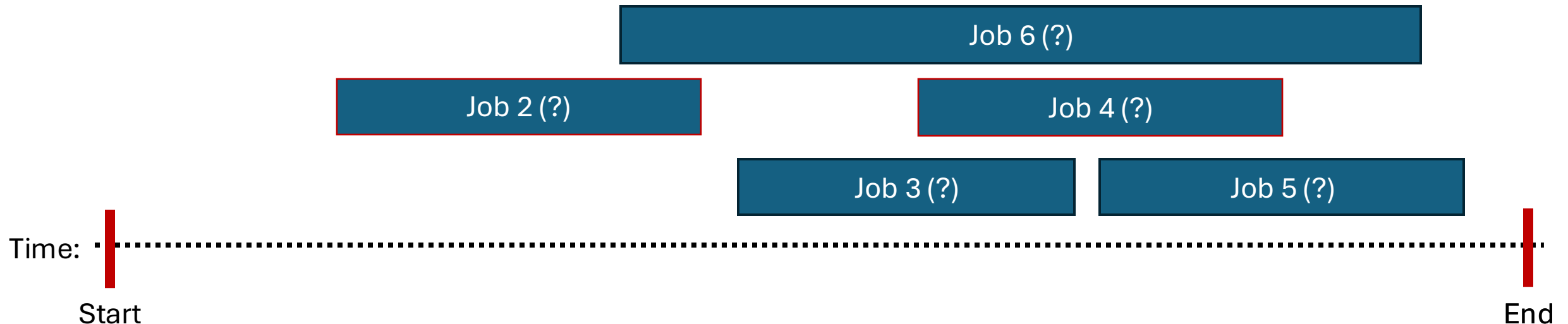
Binary Choice

- Suppose I gave you the hint that Job 1 was in OPT.
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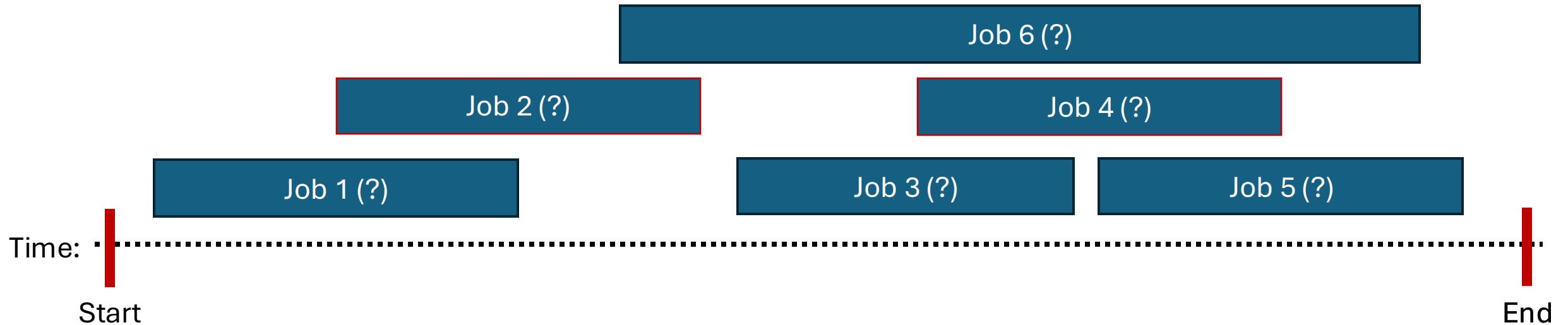
Binary Choice

- Suppose I gave you the hint that Job 1 was not in OPT.
- **Question:** What do you need to do to find the rest of OPT?
- **Answer:** Recurse on a job without Job 1.



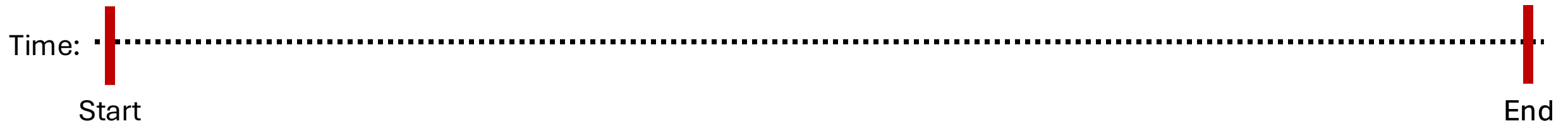
Binary Choice

- **Observation:** In both cases, we found a smaller instance of the problem to consider!



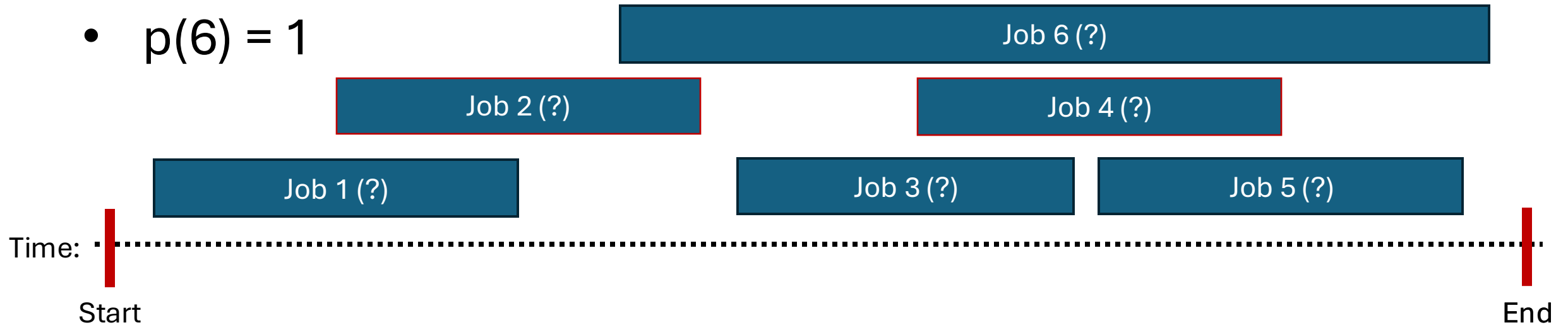
Binary Choice

- Assume our list of n jobs are sorted by finish times.
- For all $j \in [n]$,
 - Let S_j be the optimal solution on the first j jobs.
 - Let $\text{OPT}(j)$ be the value of that solution.
 - Let $p(j)$ be largest i such that $i < j$ and Job i is computable with Job j .
 - Let $p(j) = 0$ if no jobs exist.



Binary Choice

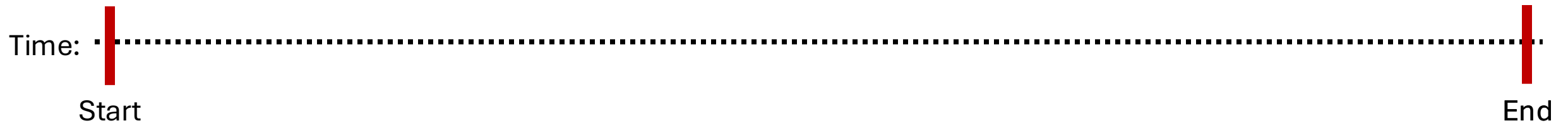
- $p(1) = 0$
- $p(2) = 0$
- $p(3) = 2$
- $p(4) = 2$
- $p(5) = 3$
- $p(6) = 1$



Binary Choice

- Now we can write

$$OPT(j) = \max\{(v_j + OPT(p(j))), OPT(j - 1)\}$$

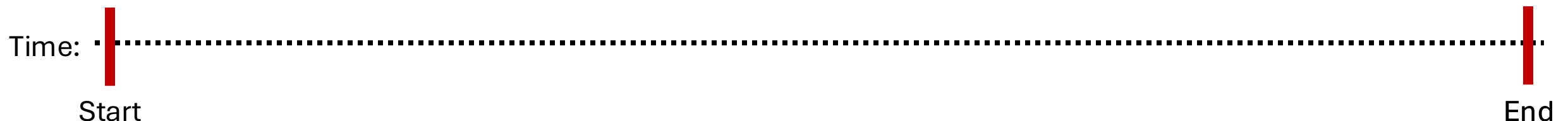


Binary Choice

- Now we can write

$$OPT(j) = \max\{(v_j + OPT(p(j))), OPT(j - 1)\}$$

English: The optimum solution for the first j jobs either uses Job j or it does not. The maximum of these two choices is the optimum.



Binary Choice

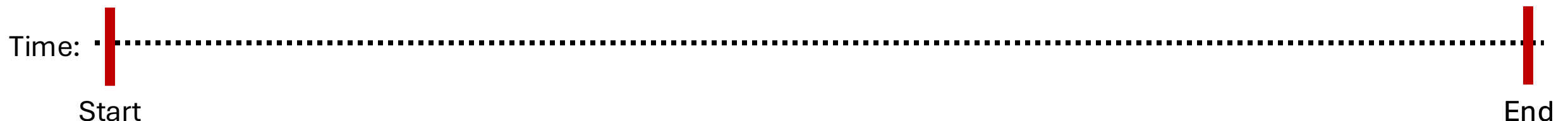
- Now we can write

We take Job J.

We consider the next job.

$$OPT(j) = \max\{(v_j + OPT(p(j))), OPT(j - 1)\}$$

English: The optimum solution for the first j jobs either uses Job j or it does not. The maximum of these two choices is the optimum.



Binary Choice Algorithm

Brute-Force(L) :

Sort L by job finish times.

Compute $p[i]$ for each i using binary search.

Return Compute-Opt(n)

Compute-Opt(j) :

If ($j == 0$) :

Return 0

else:

Return $\text{Max}(\text{Compute-Opt}(j-1), v[j] + \text{Compute-Opt}(p[j]))$

Time:

Start

End

Question: What is the runtime?

Brute-Force(L) :

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Time:

Start

End

Question: What is the runtime?

Brute-Force(L) :

Sort L by job finish times.

Compute $p[i]$ for each i using binary search.  $O(n \log(n))$

Return Compute-Opt(n)

Compute-Opt(j) :

If ($j == 0$) :

Return 0

else:

Return $\text{Max}(\text{Compute-Opt}(j-1), v[j] + \text{Compute-Opt}(p[j]))$

Time: 

Start

End

Answer: Could be exponential

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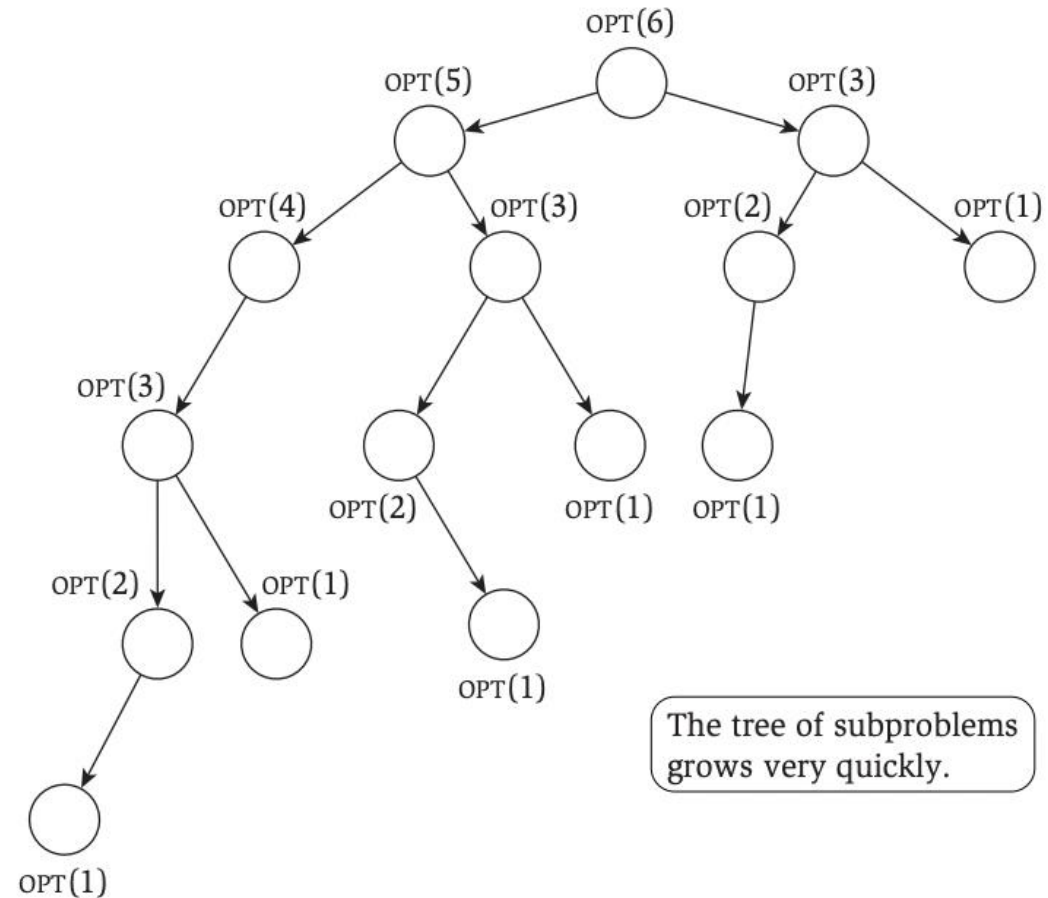
Time:

Start

End

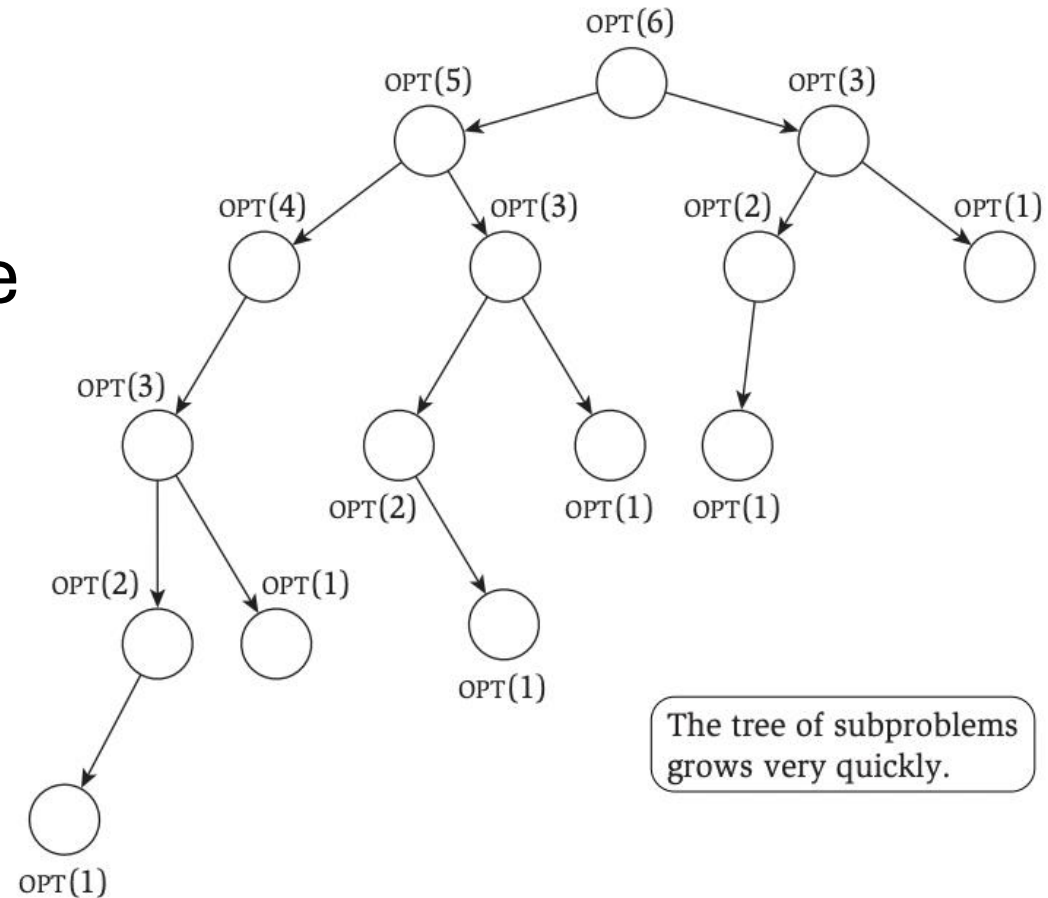
Recursion Tree

- For each $\text{OPT}(i)$ we draw an arrow to the subproblems we need to solve to solve it.
- It is possible that the tree has linear depth, and each internal node has two children.
- Notice that some problems appear more than once!



Memoization

- Notice that some problems appear more than once!
- What if our algorithm never computed the answer to the same subproblem more than once?
- Let's keep track of our answers using an array.



DYNAMIC

"IT'S IMPOSSIBLE TO USE THE WORD 'DYNAMIC' IN THE PEJORATIVE SENSE...THUS, I THOUGHT 'DYNAMIC PROGRAMMING' WAS A GOOD NAME."

— RICHARD BELLMAN, EXPLAINING HOW HE PICKED A NAME FOR HIS MATH RESEARCH TO TRY TO PROTECT IT FROM CRITICISM (EYE OF THE HURRICANE, 1984)

ENTROPY

"YOU SHOULD CALL IT 'ENTROPY'... NO ONE KNOWS WHAT ENTROPY REALLY IS, SO IN A DEBATE YOU WILL ALWAYS HAVE THE ADVANTAGE."

— JOHN VON NEUMANN, TO CLAUDE SHANNON, ON WHY HE SHOULD BORROW THE PHYSICS TERM IN INFORMATION THEORY (AS TOLD TO MYRON TRIBUS)

DYNAMIC ENTROPY

SCIENCE TIP: IF YOU HAVE A COOL CONCEPT YOU NEED A NAME FOR, TRY "DYNAMIC ENTROPY."

Remember Remember

Brute-Force(L) :

Sort L by job finish times.

Compute $p[i]$ for each i using binary search.

Global $M = []$, $M[0] = 0$

Return Compute-Opt(n)

M-Compute-Opt(j) :

If j not in M :

$M[j] = \text{Max}(M\text{-Compute-Opt}(j-1), v[j] + M\text{-Compute-Opt}(p[j])$

Return $M[j]$

Time:

Start

End

Memoization Runtime

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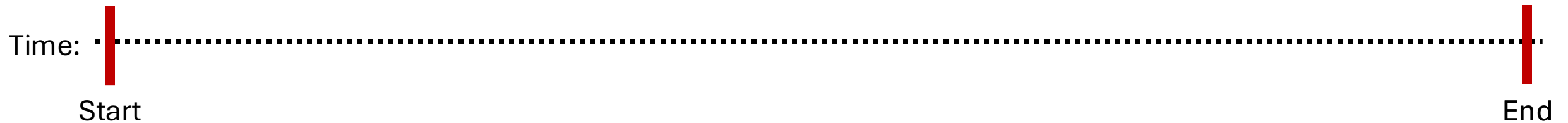
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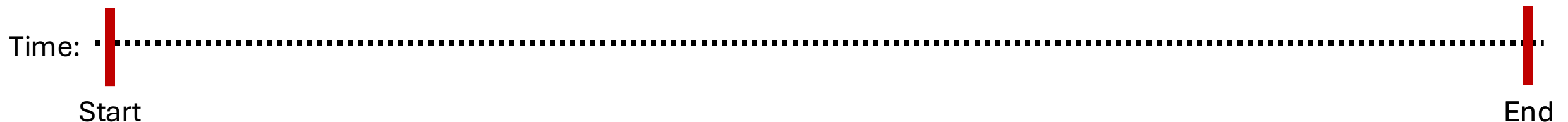
Memoization Runtime

- We will show that the runtime is $O(n \log(n))$.
 - The preprocessing takes $O(n \log(n))$ time.
 - The M-Compute-Opt(n) call takes $O(n)$ time.



Memoization Runtime

- The M-Compute-Opt(n) call takes $O(n)$ time.
 - To bound the runtime, we will introduce a "progress measure". Namely, we will track how many entries in M are uninitialized.
 - Each time we initialize an entry of M , we make two recursive calls which takes constant time.
 - Since M will only have at most $O(n)$ entries, it follows that the runtime is at most $O(n)$ as desired.



Top-Down Dynamic Programming

Brute-Force(L) :

Sort L by job finish times.

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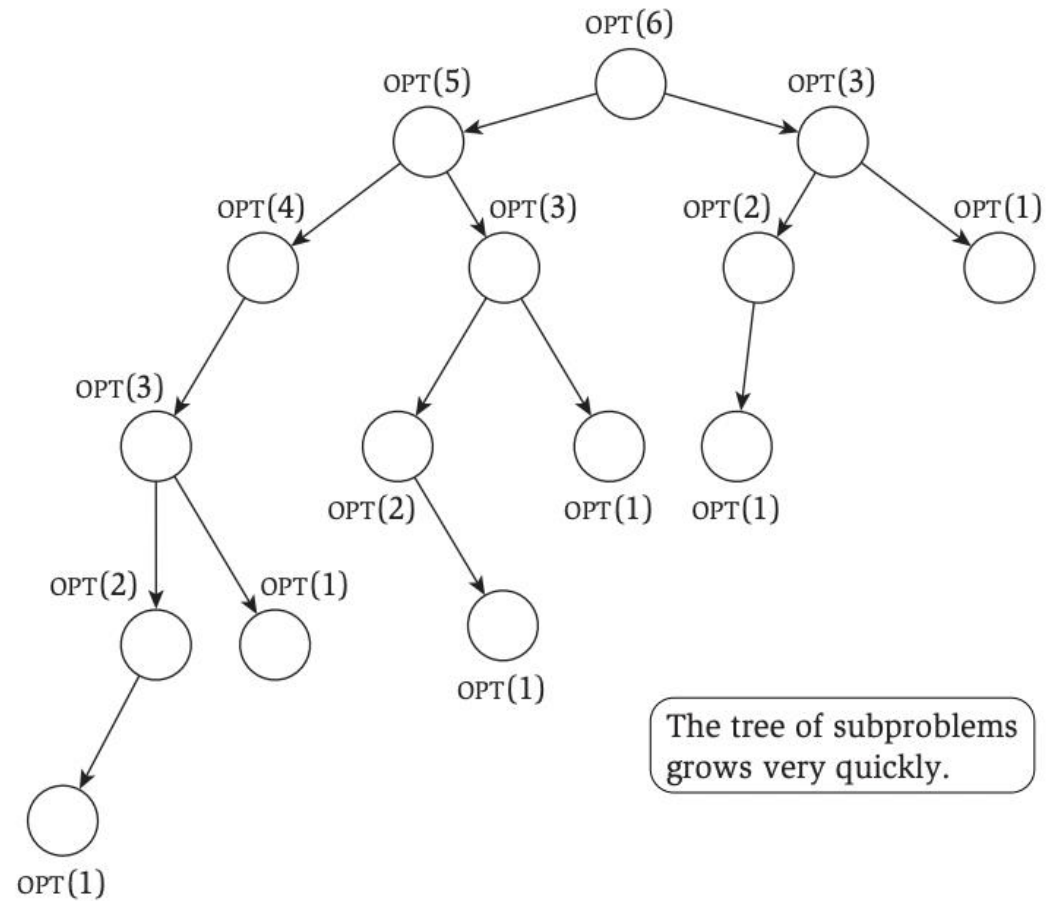
Return $M[j]$

Time:

Start

End

Top-Down Dynamic Programming



Next Time

- Recover Optimal Solutions
- Bottom-Up Dynamic Programming
- Process of coming up with Dynamic Programming algorithm.