

Lecture 24

Dynamic Programming: Rod Cutting (contd.), LCS

When to Use Dynamic Programming?

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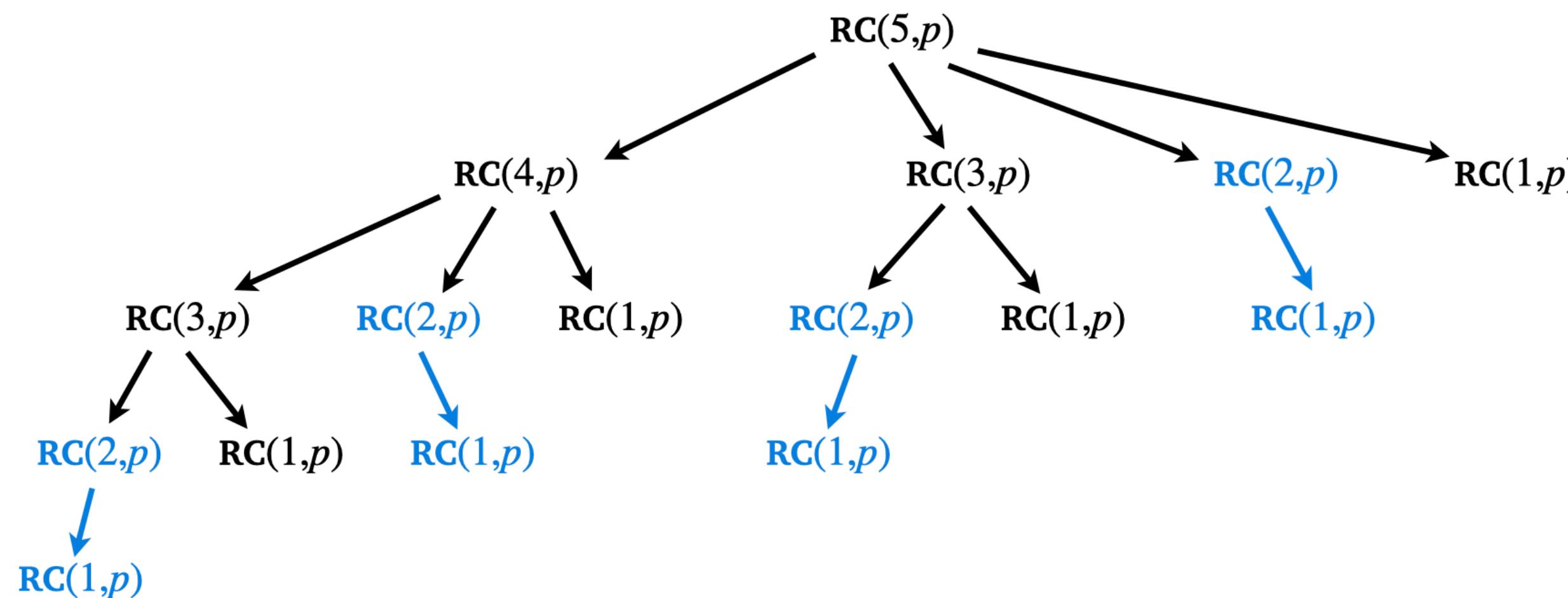
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- Find the **optimal substructure**.
- **Recursively** define the value of optimal solution.
- Compute the value of the optimal solution using an **array**.

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Bottom-Up-RC(n, p):

```
1. profit[1 :  $n$ ] = { $p[1], 0, \dots, 0$ }  
2. for  $j = 2$  to  $n$  ←  
3.   profit[ $j$ ] =  $p[j]$   
4.   for  $i = 1$  to  $j - 1$  ←  
5.     profit[ $j$ ] = Max(profit[ $j$ ],  $p[i] + \text{profit}[j - i]$ )  
6. return profit[ $n$ ]
```

Computing the maximum profit
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Time-Complexity: $O(n^2)$ due to loops of line 2 and 4.

Constructing the Optimal Solution

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How to get optimal cutting not just maximum profit?

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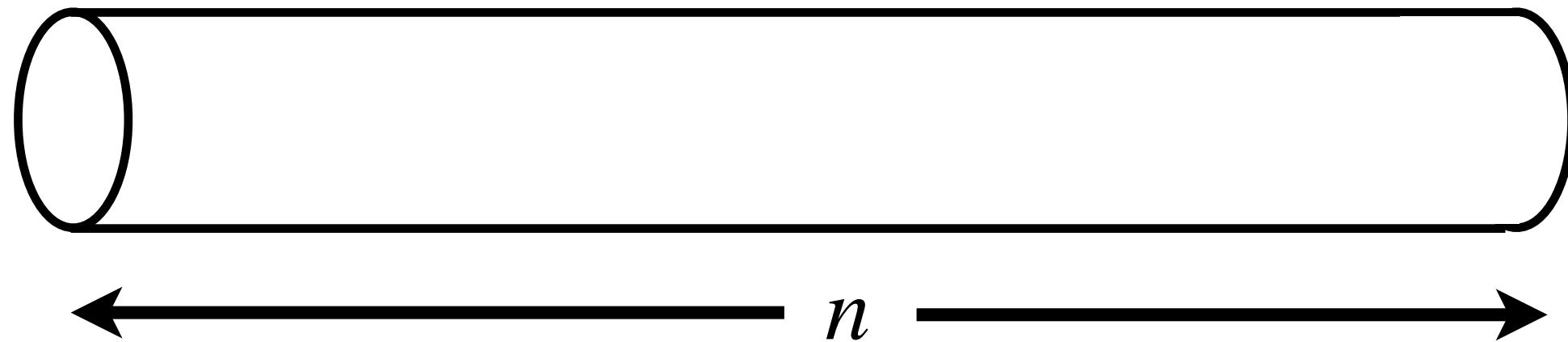
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Repeatedly ask what is the **length of the first cut** in an optimal cutting of the remaining piece.

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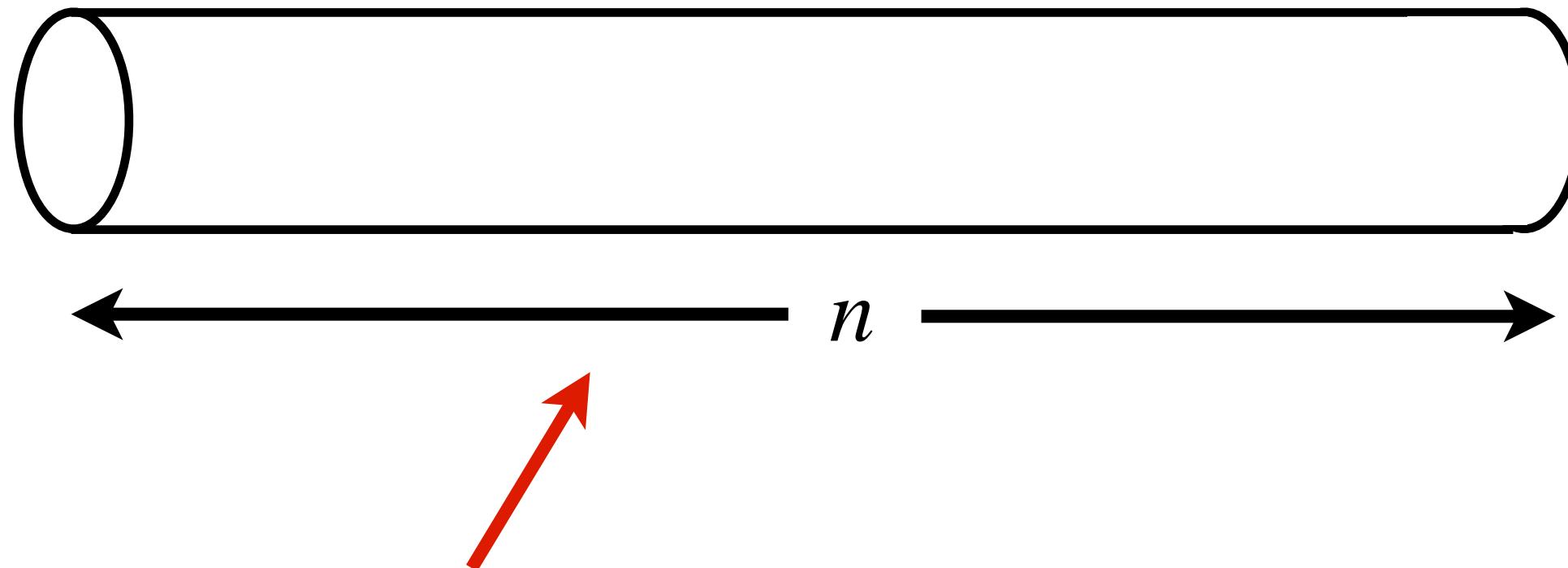
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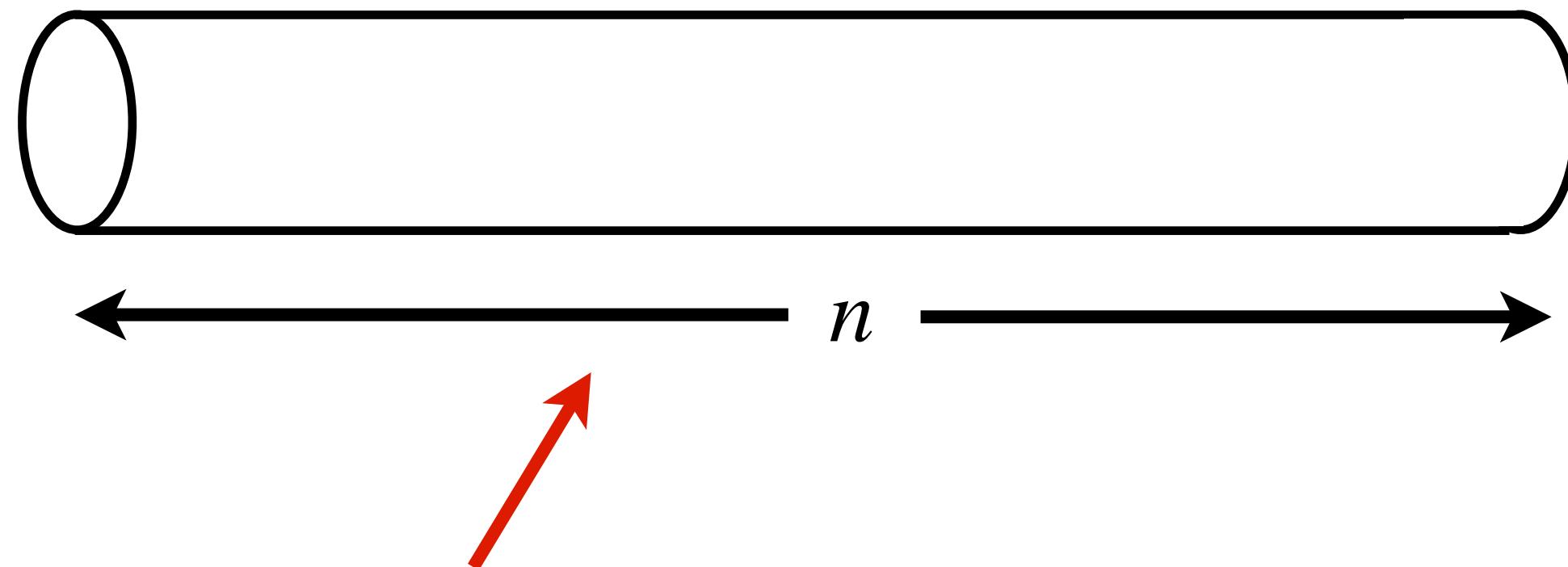


What is the length of the first cut in an n length rod?

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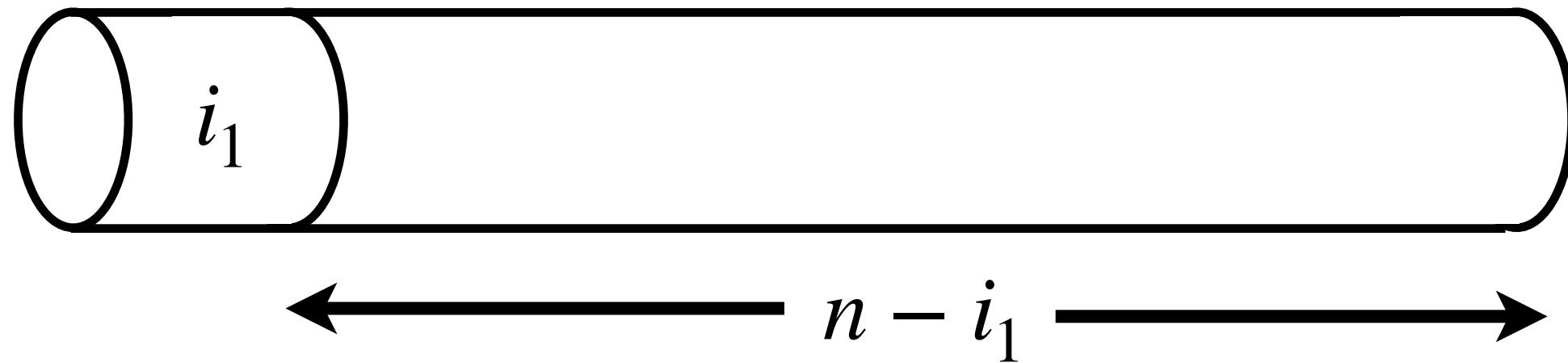


What is the length of the first cut in an n length rod? i_1 .

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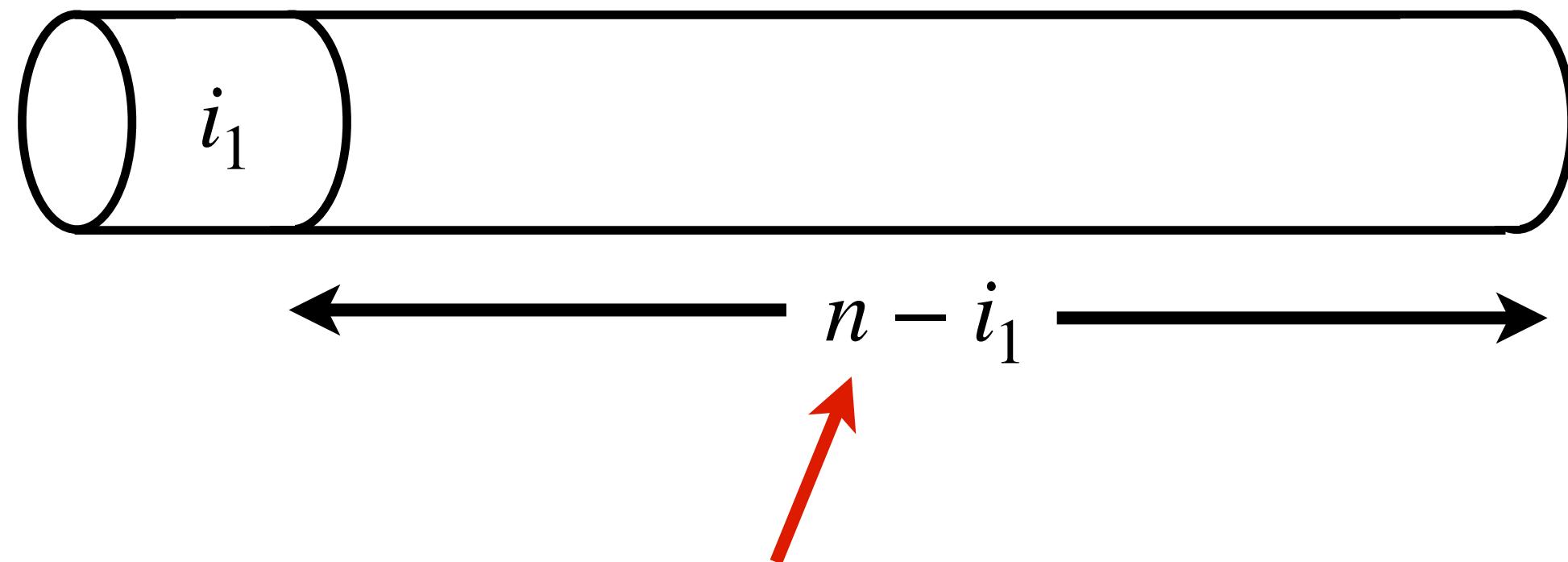
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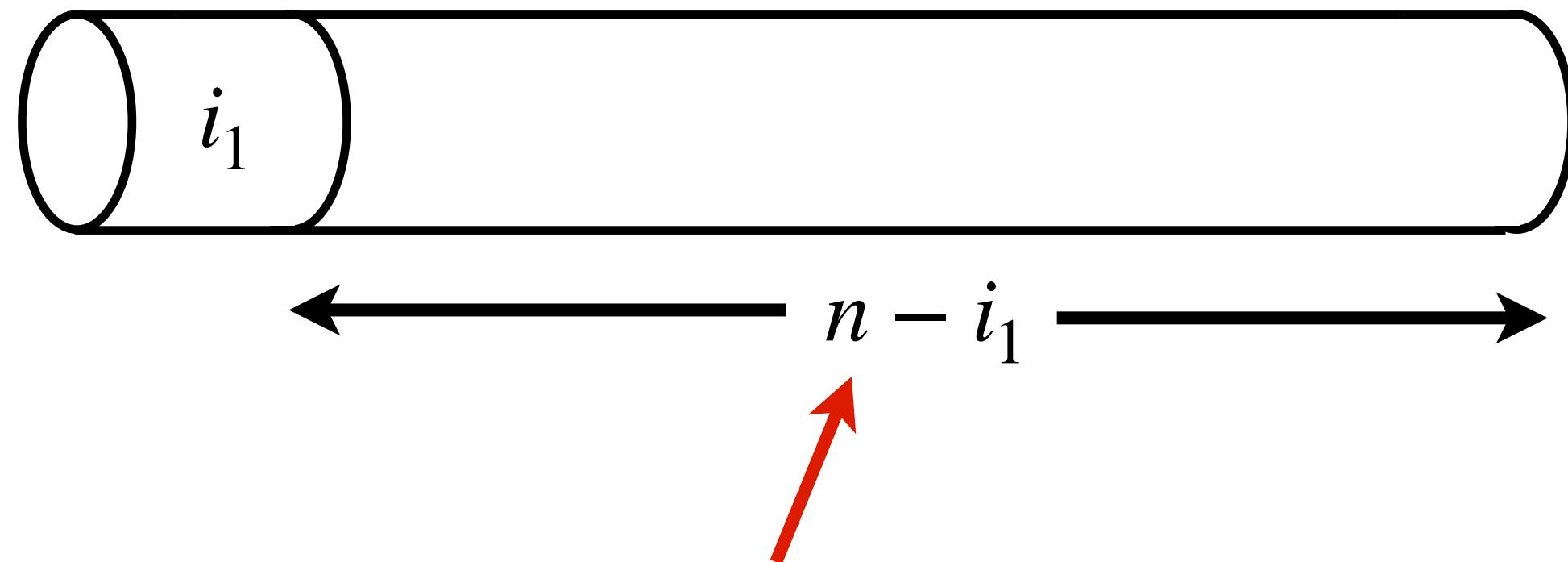


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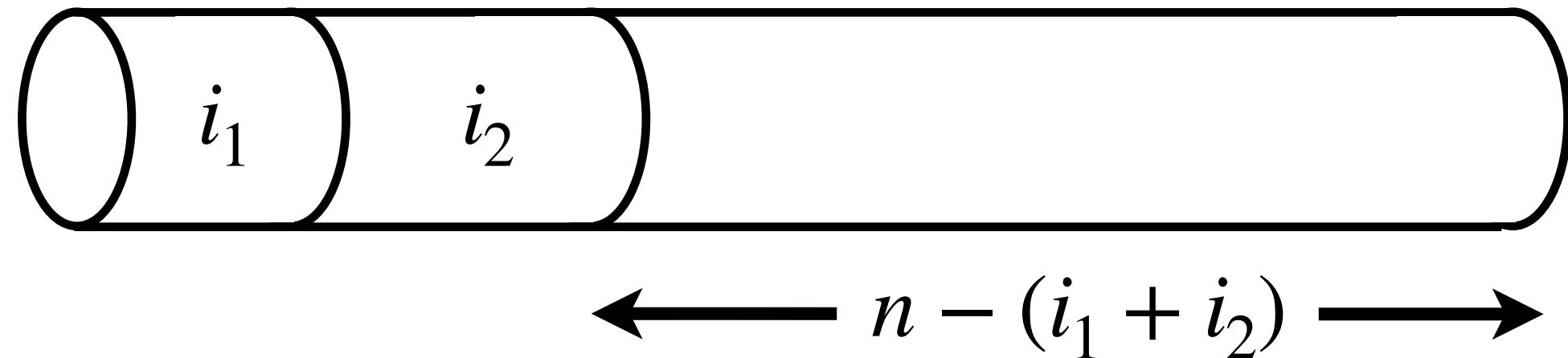


What is the length of the first cut in an $n - i_1$ length rod? i_2 .

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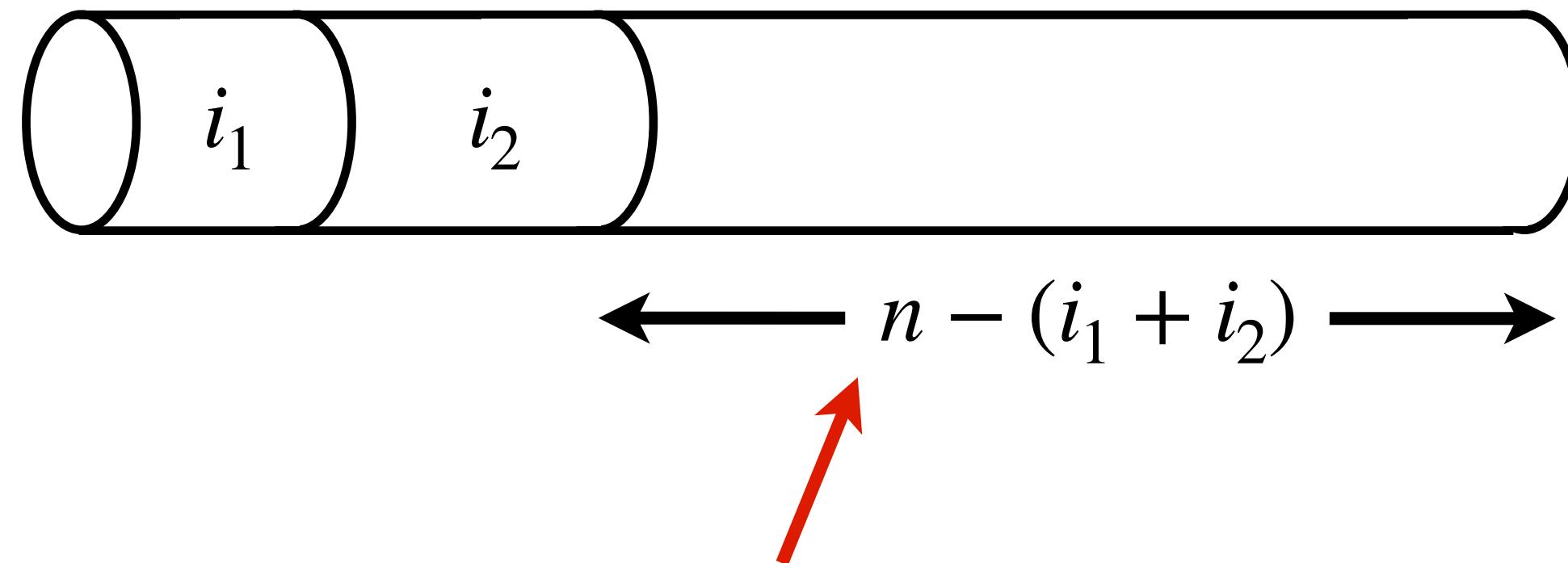
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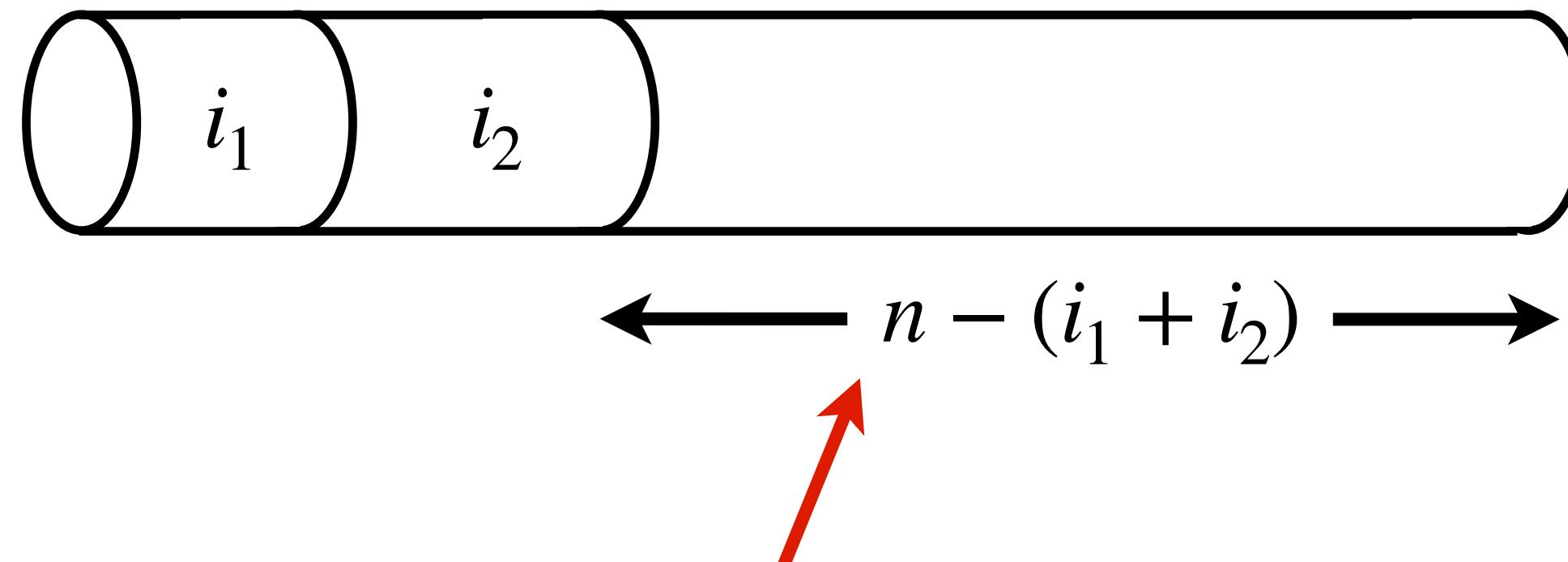


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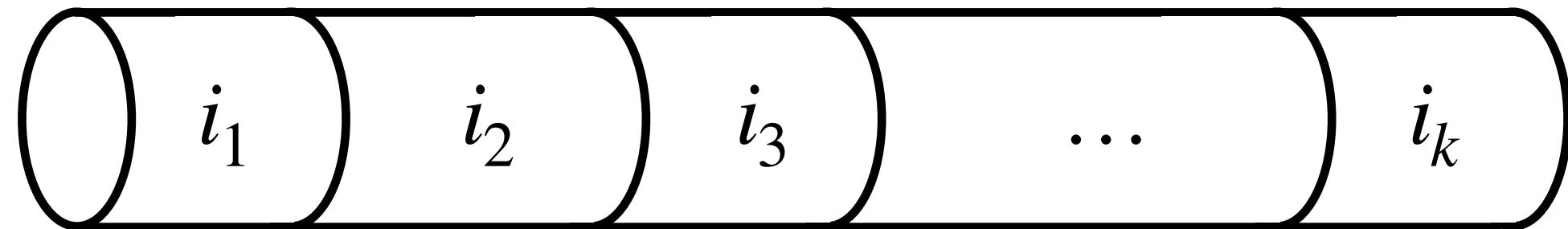


What is the length of the first cut in an $n - (i_1 + i_2)$ length rod? i_3 .

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Optimal cutting of an n length rod.

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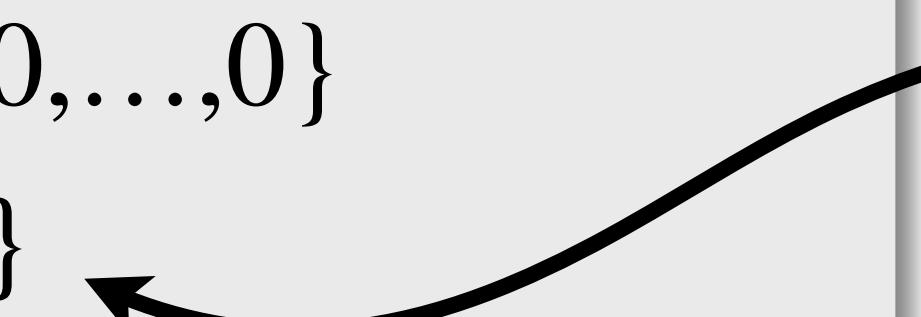
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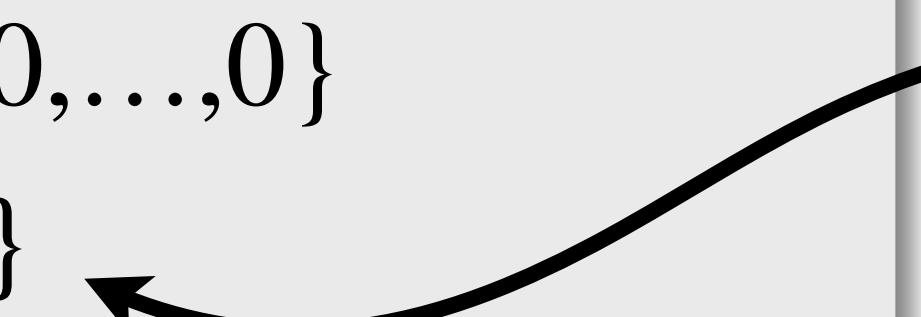
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9. $sol[j] = i$
10. **return** $profit[n]$



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PrintRC(n, sol):

1. **while** $n > 0$

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PrintRC(n, sol):

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PrintRC(n, sol):

1. **while** $n > 0$
2. **print** $sol[n]$
3. $n = n - sol[n]$

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Some subsequences of S are : "mcheco", "m", "iae", "michaelscott", "".

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Input: Two sequences X and Y .

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Some common subsequences of X and Y are: "iit", "dr", "tor".

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Some longest common subsequences of X and Y are: "iitor", "iitdr".

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Application of LCS:

- LCS of two sequences or strings is a measure of how similar they are.
- Used to find similarity of DNAs which can be seen as strings of "A", "C", "G", and "T" characters which represent nucleotides.

Brute Force for LCS

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Brute Force for LCS

BruteForceLCS(X, Y):

1. $lcs = 0$
2. **for** every subsequence x of X Generating all the subsequences takes $O(2^{|x|})$ time.
3. **if** x is a subsequence of Y
4. $lcs = \text{Max}(lcs, |x|)$
5. **return** lcs

Finding Optimal Substructure in LCS

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Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Visakhapatnam".

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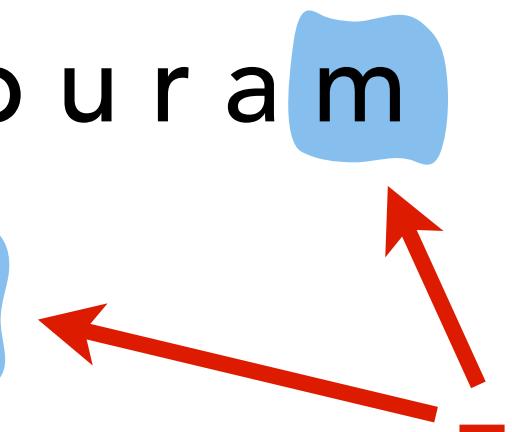
Y = Visakhapatnam

Finding Optimal Substructure in LCS

Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Visakhapatnam".

X = Thiruvananthapuram

Y = Visakhapatnam



Ending characters are same.

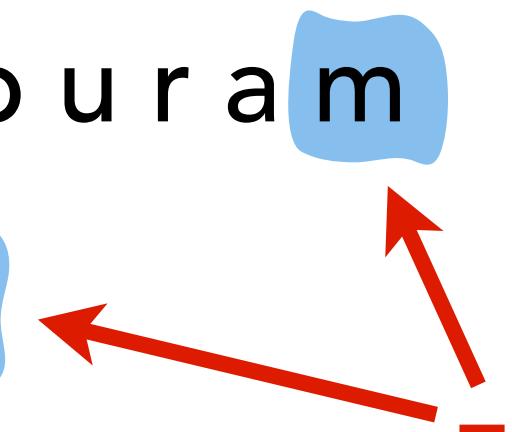
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$\text{LCS}(X, Y) =$



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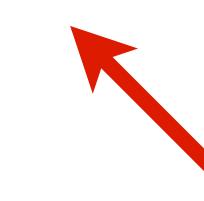
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X = Thiruvananthapuram

Y = Visakhapatnam

$\text{LCS}(X, Y)$ = — — —



What should be the last character in $\text{LCS}(X, Y)$?

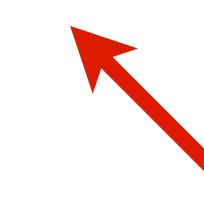
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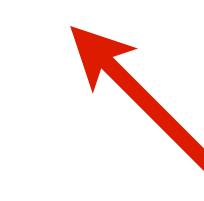
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What should be the last character in $\text{LCS}(X, Y)$?

"m", because if not, we can append "m" at the end of the LCS and get a bigger LCS.

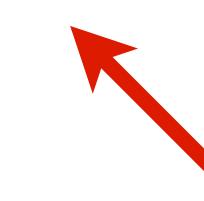
Finding Optimal Substructure in LCS

Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Visakhapatnam".

X = Thiruvananthapuram

Y = Visakhapatnam

$\text{LCS}(X, Y)$ = — — — — $\frac{m}{m}$



What should be the last character in $\text{LCS}(X, Y)$?

"m", because if not, we can append "m" at the end of the LCS and get a bigger LCS.

Finding Optimal Substructure in LCS

Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Visakhapatnam".

X = Thiruvananthapuram ~~X~~

Y = Visakhapatna ~~X~~

$\text{LCS}(X, Y)$ = — — — — m

Finding Optimal Substructure in LCS

Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Visakhapatnam".

$X = \text{Thiruvananthapuram}$ ~~X~~

$Y = \text{Visakhapatna}$ ~~X~~

$\text{LCS}(X, Y) = \underline{\quad \quad \quad \dots \dots \quad \quad \quad} \frac{m}{m}$



What should be the remaining $\text{LCS}(X, Y)$?

Finding Optimal Substructure in LCS

Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Visakhapatnam".

$X = \text{Thiruvananthapuram} \times$

$Y = \text{Visakhapatna} \times$

$\text{LCS}(X, Y) = \underline{\quad \quad \quad \dots \dots \quad \quad \quad} \frac{m}{m}$



What should be the remaining $\text{LCS}(X, Y)$?

Intuition says it should be LCS of "Thiruvananthapuram" and "Visakhapatnam".

Finding Optimal Substructure in LCS

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Claim: Let $X = x_1x_2\dots x_m$ and $Y = y_1y_2\dots y_n$ be two sequences such that $x_m = y_n$. Then,

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Claim: Let $X = x_1x_2\dots x_m$ and $Y = y_1y_2\dots y_n$ be two sequences such that $x_m = y_n$. Then, $Z = \text{LCS}(x_1x_2\dots x_{m-1}, y_1y_2\dots y_{n-1}) + x_m$ will be an LCS of X and Y .

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Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Muzaffarnagar".

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Finding Optimal Substructure in LCS

Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Muzaffarnagar".

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Ending characters are different.

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Y = Muzaffarnagar

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Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Muzaffarnagar".

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Y = Muzaffarnagar

Observation: LCS of X and Y cannot end both "m" and "r":

Finding Optimal Substructure in LCS

Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Muzaffarnagar".

X = Thiruvananthapuram

Y = Muzaffarnagar

Observation: LCS of X and Y cannot end both "m" and "r":

- If it doesn't end with "m", then LCS of X, Y will be:

Finding Optimal Substructure in LCS

Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Muzaffarnagar".

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LCS of "Thiruvananthapura~~X~~" and "Muzaffarnagar".

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Let's try to find LCS of X = "Thiruvananthapuram" and Y = "Muzaffarnagar".

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Claim: Let $X = x_1x_2\dots x_m$ and $Y = y_1y_2\dots y_n$ be sequences such that $x_m \neq y_n$. Then, at least one out of $\text{LCS}(x_1x_2\dots x_{m-1}, y_1y_2\dots y_n)$ and $\text{LCS}(x_1x_2\dots x_m, y_1y_2\dots y_{n-1})$ will be an $\text{LCS}(X, Y)$.