

# Dynamic Programming (2)

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# Credits

- Introduction to Algorithms, Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest, Clifford Stein
- Dynamic Programming: Weighted Interval Scheduling, CMSC 451: Lecture 10, by Dave Mount

# Longest Common Subsequence

# THE LOCH NESS MONSTER?

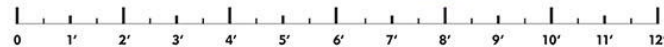
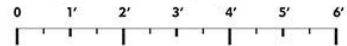
Of the common theories associated with the 1,000 or so sightings of something swimming in the water at Loch Ness, the environmental DNA data obtained suggests at least one theory remains plausible.

Eels returned the largest proportion of DNA from the 250 water samples taken throughout Loch Ness.

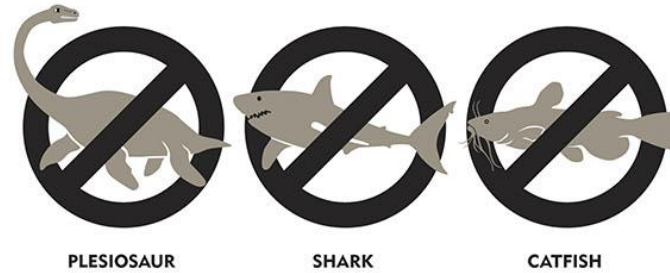
Typically not gigantic, could an extremely large European eel be the creature people have seen moving "like a torpedo" in the water? The data obtained suggests this may be possible, although no eel of the size described in some accounts has ever been caught or found.

Infrequent visitors such as seals and possibly sturgeons may account for some sightings, but wakes, standing waves and logs are the basis of most.

LARGEST-KNOWN EUROPEAN EEL



A LOCH NESS EEL?



- Biological applications often need to compare the DNA of two (or more) different organisms.
- A strand of DNA consists of a string of molecules called bases, where the possible bases are adenine, cytosine, guanine, and thymine. Representing each of these bases by its initial letter, we can express a strand of DNA as a string over the 4-element set **{A, C, G, T}**.
- For example, the DNA of one organism may be
$$S_1 = \text{ACCGGTCGAGTGCGCGGAAGCCGGCCGAA}$$
- and the DNA of another organism may be
$$S_2 = \text{GTCGTTCGGAATGCCGTTGCTCTGTAAA}$$
- One reason to compare two strands of DNA is to measure of how closely related the **two organisms** are.

- A way to measure the similarity of strands  $S_1$  and  $S_2$  is by finding a third strand  $S_3$  in which the **bases** in  $S_3$  appear in each of  $S_1$  and  $S_2$ .
- These bases must **appear in the same order**, but **not necessarily consecutively**. The **longer** the strand  $S_3$ , the **more similar**  $S_1$  and  $S_2$  are.
- We call this notion as "The longest common subsequence". In our example,

•  $S_1 =$  ACCGGTCGAGTGCGCGGAAGCCGGCCGAA

•  $S_2 =$  GTCGTTCGGAATGCCGTTGCTCTGTAA

- The longest common subsequence, or  $S_3$ , is:

GTCGTCGGAAGCCGGCCGAA

- Given two sequences  $X$  and  $Y$ , a sequence  $Z$  is a **common subsequence** of  $X$  and  $Y$  if  $Z$  is a subsequence of both  $X$  and  $Y$ .
- If  $X = \langle A, B, C, B, D, A, B \rangle$  and  $Y = \langle B, D, C, A, B, A \rangle$ , then  $\langle B, C, A \rangle$  is a common subsequence of both  $X$  and  $Y$  that has length **three**.

The longest-common-subsequence (LCS) problem:

Given two sequence  $X$  and  $Y$ , find a **maximum-length** common subsequence of  $X$  and  $Y$ .

- **Brute-Force Approach:** enumerate all subsequences of  $X$  and check each subsequence to see if it is also a subsequence of  $Y$ , while keeping track of the longest subsequence found.
- There are  $2^n$  subsequences of  $X$  with  $n$  items. So the brute-force solution is **exponential** in the number of items in  $X$ .
- LCS can be efficiently solved using Dynamic Programming.

### Notation:

Given a sequence  $X = \langle x_1, x_2, \dots, x_m \rangle$ , we define the  **$i$ -th prefix** of  $X$ , for  $i = 0, 1, 2, \dots, m$ , as  **$\text{pref}(X, m)$**   $= \langle x_1, x_2, \dots, x_m \rangle$ .

For example, if  $X = \langle A, B, A, C, D, B \rangle$ , then  **$\text{pref}(X, 4)$**   $= \langle A, B, A, C \rangle$  and  **$\text{pref}(X, 0)$**   $= \langle \rangle$ .



## Step 1: a theorem (Optimal Substructure of an LCS)

Let  $X = \langle x_1, x_2, \dots, x_m \rangle$  and  $Y = \langle y_1, y_2, \dots, y_n \rangle$  be sequences, and let  $Z = \langle z_1, z_2, \dots, z_k \rangle$  be any LCS of  $X$  and  $Y$ .

1. If  $x_m = y_n$ , then  $z_k = x_m = y_n$  and  $\text{pref}(Z, k - 1)$  is an LCS of  $\text{pref}(X, m - 1)$  and  $\text{pref}(Y, n - 1)$ .
2. If  $x_m \neq y_n$  and  $z_k \neq x_m$ , then  $Z$  is an LCS of  $\text{pref}(X, m - 1)$  and  $Y$ .
3. If  $x_m \neq y_n$  and  $z_k \neq y_n$ , then  $Z$  is an LCS of  $X$  and  $\text{pref}(Y, n - 1)$ .

In general, an LCS of two sequences contains within it an LCS of prefixes of the two sequences.

## Exercise:

Use "proof by contradiction" to show the truth of the optimal substructure of LCS!

## Step 2: a recursive solution for LCS

Suppose  $c(i, j)$  be the length of an LCS of the sequences  $\text{pref}(X, i)$  and  $\text{pref}(Y, i)$ .

$$c(i, j) = \begin{cases} 0 & i = 0 \text{ or } j = 0 \\ c(i - 1, j - 1) + 1 & i, j > 0 \text{ and } x_i = y_j \\ \max\{c[i, j - 1], & c[i - 1, j]\} & i, j > 0 \text{ and } x_i \neq y_j \end{cases}$$

If want to find an LCS between  $X = \langle x_1, x_2, \dots, x_m \rangle$  and  $Y = \langle x_1, x_2, \dots, x_n \rangle$ , then call  $c(m, n)$

## Step 2: a recursive solution for LCS

Suppose  $c(i, j)$  be the length of an LCS of the sequences  $\text{pref}(X, i)$  and  $\text{pref}(Y, j)$ .

If  $x_i = y_j$  then you need to find an LCS of  $\text{pref}(X, i - 1)$  and  $\text{pref}(Y, j - 1)$ .  
Appending  $x_i = y_j$  yields an LCS of  $\text{pref}(X, i)$  and  $\text{pref}(Y, j)$


$$c(i, j) = \begin{cases} 0 & i = 0 \text{ or } j = 0 \\ c(i - 1, j - 1) + 1 & i, j > 0 \text{ and } x_i = y_j \\ \max\{c[i, j - 1], & c[i - 1, j]\} & i, j > 0 \text{ and } x_i \neq y_j \end{cases}$$

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## Step 2: a recursive solution for LCS

Suppose  $c(i, j)$  be the length of an LCS of the sequences  $\text{pref}(X, i)$  and  $\text{pref}(Y, j)$ .

If  $x_i \neq y_j$  then you need to solve **two subproblems!** Whichever of these two LCSs is longer is an LCS of  $\text{pref}(X, i)$  and  $\text{pref}(Y, j)$

$$c(i, j) = \begin{cases} 0 & i = 0 \text{ or } j = 0 \\ c(i - 1, j - 1) + 1 & i, j > 0 \text{ and } x_i = y_j \\ \max\{c[i, j - 1], c[i - 1, j]\} & i, j > 0 \text{ and } x_i \neq y_j \end{cases}$$


If want to find an LCS between  $X = \langle x_1, x_2, \dots, x_m \rangle$  and  $Y = \langle x_1, x_2, \dots, x_n \rangle$ , then call  $c(m, n)$

**Step 2:** a recursive solution has the **overlapping-subproblems**

To find an LCS of **X** and **Y**, you might need to find the LCSs of **X** and **pref(Y,n-1)** and of **pref(X,m-1)** and **Y**.

Each of these subproblems has the subsubproblem of finding an LCS of **pref(X,m-1)** and **pref(Y,n-1)**.

$$c(i, j) = \begin{cases} 0 & i = 0 \text{ or } j = 0 \\ c(i - 1, j - 1) + 1 & i, j > 0 \text{ and } x_i = y_j \\ \max\{c[i, j - 1], c[i - 1, j]\} & i, j > 0 \text{ and } x_i \neq y_j \end{cases}$$

If want to find an LCS between  $X = \langle x_1, x_2, \dots, x_m \rangle$  and  $Y = \langle x_1, x_2, \dots, x_n \rangle$ , then call  $c(m, n)$

### Step 3: a DP solution (bottom-up version)

There are only  $\Theta(mn)$  distinct subproblems.

- The following LCS-LENGTH procedure takes two sequences  $X = \langle x_1, x_2, \dots, x_m \rangle$  and  $Y = \langle y_1, y_2, \dots, y_n \rangle$  as inputs, along with their lengths.
- It stores  $c(i, j)$  values in a table  $c[0:m, 0:n]$  whose entries are computed in **row-major** order.
- The procedure also maintains the table  $b[1:m, 1:n]$  to help in constructing an optimal solution (step 4).

## Step 3: a DP solution (bottom-up version)

**LCS-LENGTH(X, Y, m, n):**

let  $b[1:m, 1:n]$  and  $c[0:m, 0:n]$  be new matrix

for  $i = 1$  to  $m$ :

$c[i, 0] = 0$

for  $j = 0$  to  $n$ :

$c[0, j] = 0$

for  $i = 1$  to  $m$ :

//iterate the matrix in row-major order

    for  $j = 1$  to  $n$ :

        if  $X_i = Y_j$  then

$c[i, j] = c[i-1, j-1] + 1$

$b[i, j] = \nwarrow$

        else if  $c[i-1, j] \geq c[i, j-1]$  then

$c[i, j] = c[i-1, j]$

$b[i, j] = \uparrow$

        else

$c[i, j] = c[i, j-1]$

$b[i, j] = \leftarrow$

return  $c$  and  $b$

The running time is  $\Theta(mn)$



# Example

Create the table/matrix when computing an LCS of  $X = \langle A, B, C, B, D, A, B \rangle$  and  $Y = \langle B, D, C, A, B, A \rangle$

		j	0	1	2	3	4	5	6
				B	D	C	A	B	A
i		0	0	0	0	0	0	0	0
1	A	0	↑0	↑0	↑0	↖1	←1	↖1	
2	B	0	↖1	←1	←1	↑1	↖2	←2	
3	C	0	↑1	↑1	↖2	←2	↑2	↑2	
4	B	0	↖1	↑1	↑2	↑2	↖3	←3	
5	D	0	↑1	↖2	↑2	↑2	↑3	↑3	
6	A	0	↑1	↑2	↑2	↖3	↑3	↖4	
7	B	0	↖1	↑2	↑2	↑3	↖4	↑4	

## Step 4: Print a solution using the table b

```
PRINT-LCS(b, X, i, j):    // initial call: PRINT-LCS(n,X,m,n)
    if i == 0 or j == 0 then
        return []
    if b[i,j] == "↖" then
        return PRINT-LCS(b, X, i-1, j-1) + [xi]    // same as + [yj]
    else if b[i,j] == "↑" then
        return PRINT-LCS(b, X, i-1, j)
    else
        return PRINT-LCS(b, X, i, j-1)
```

The running time is  $\Theta(m + n)$

# Rod Cutting Problem

# The summary so far

- Weighted Interval Scheduling, Knapsack, LCS
  - There are  $n$  subproblems
  - Two cases: e.g., include  $j$  or don't include  $j$
- Rod Cutting Problem (what we're going to see)
  - There are  $n$  subproblems
  - Many cases ...

## Rod Cutting

Given a rod of length  $n$  inches and a table of prices  $p_i$  for  $i = 1, 2, \dots, n$ , determine the maximum revenue  $r_n$  obtainable by cutting up the rod and selling the pieces.

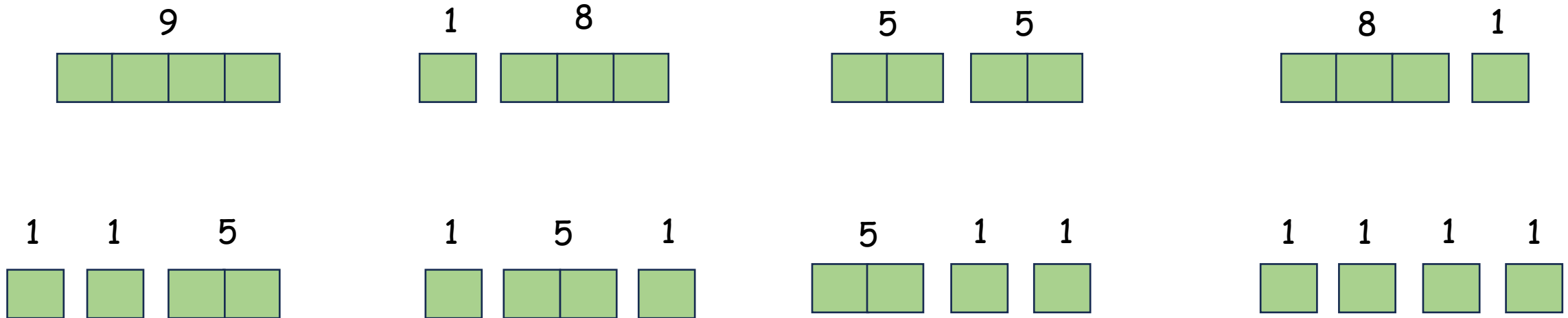
If the price  $p_n$  for a rod of length  $n$  is large enough, an optimal solution might require no cutting at all.

## Rod Cutting

Consider the case when  $n = 4$ , and the following price table for rods:

Length $i$	1	2	3	4	5	6	7	8	9	10
Price $p_i$	1	5	8	9	10	17	17	20	24	30

There are 8 possible ways of cutting up a rod of length 4:



## Rod Cutting

We can determine the optimal revenue  $r_i$  for  $i = 1, \dots, 10$  by inspection:

$r_1 = 1$  from solution  $r_1 = p_1$  (no cuts)

$r_2 = 5$  from solution  $r_2 = p_2$  (no cuts)

$r_3 = 8$  from solution  $r_3 = p_3$  (no cuts)

$r_4 = 10$  from solution  $r_4 = r_2 + r_2$

$r_5 = 13$  from solution  $r_5 = r_2 + r_3$

$r_6 = 17$  from solution  $r_6 = p_6$  (no cuts)

$r_7 = 18$  from solution  $r_7 = r_1 + r_6$  or  $r_7 = r_2 + r_2 + r_3$

$r_8 = 22$  from solution  $r_8 = r_2 + r_6$

$r_9 = 25$  from solution  $r_9 = r_3 + r_6$

$r_{10} = 30$  from solution  $r_{10} = p_{10}$  (no cuts)

## Rod Cutting

We can determine the optimal revenue  $r_i$  for  $i = 1, \dots, 10$  by inspection:

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$r_8 = 22$  from solution  $r_8 = r_2 + r_6$

$r_9 = 25$  from solution  $r_9 = r_3 + r_6$

$r_{10} = 30$  from solution  $r_{10} = p_{10}$  (no cuts)

**This exhibits optimal substructure!**

In General, 
$$r_n = \max\{p_n, r_1 + r_{n-1}, r_2 + r_{n-2}, r_{n-1} + r_1\}$$

$$r_n = \max\{p_i + r_{n-i} : 1 \leq i \leq n\}$$



# Rod Cutting

## Recursive Implementation

$$r_n = \max\{p_i + r_{n-i} : 1 \leq i \leq n\}$$



$$\text{CUT-ROD}(p, n) = \max\{p_i + \text{CUT-ROD}(p, n-1) : 1 \leq i \leq n\}$$

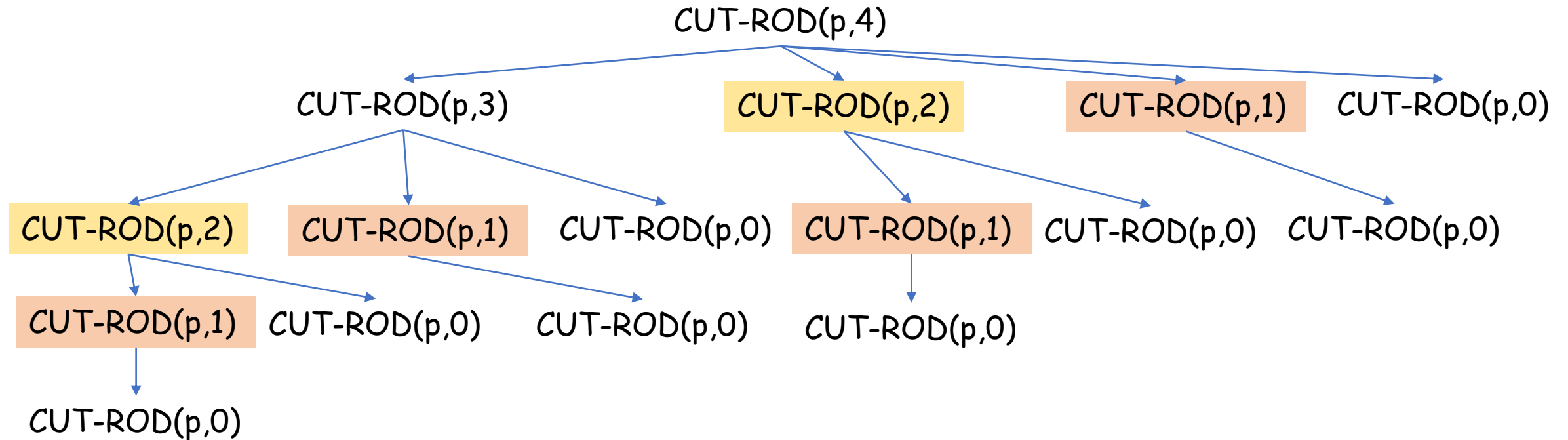
```
CUT-ROD(p, n):  
  if n == 0 then  
    return 0  
  q = - INF  
  for i = 1 to n:  
    q = max {q, p[i] + CUT-ROD(p, n - i)}  
  return q
```

Running Time:

$$T(n) = 1 + \sum_{j=0}^{n-1} T(j) = 2^n$$

# Rod Cutting

Overlapping Subproblems? Let's inspect the recursion tree:



# Rod Cutting

## DP solution (bottom-up)

A subproblem of size  $i$  is "smaller" than a subproblem of size  $j$  if  $i < j$ . Thus, the procedure solves subproblems of sizes  $j = 0 \dots n$  in that order.

```
CUT-ROD(p, n):  
  let r[0:n] be a new array      // to save the results of subproblems  
  let s[1:n] be a new array      // the optimal size of the first piece to cut off (for reconstruction)  
  r[0] = 0  
  for j = 1 to n:  
    q = -INF  
    for i = 1 to j:  
      temp = p[i] + r[j - i]  
      if q < temp then  
        q = temp  
        s[j] = i  
  r[j] = q  
  return r and s
```

**Exercise:**

Running time =  $\Theta(?)$

## Rod Cutting

### Reconstructing a solution

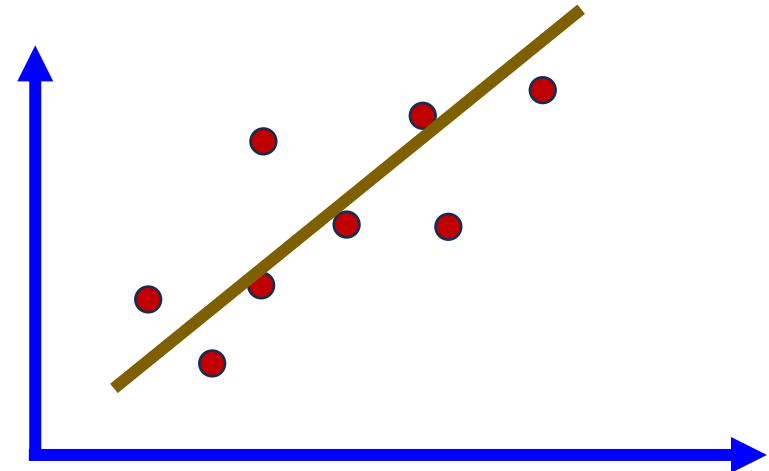
```
PRINT-CUT-ROD-SOLUTION(s, n):  
    solution = []  
    while n > 0:  
        solution = solution + [s[n]]  
        n = n - s[n]  
    return solution
```

# Segmented Least Squares

# Ordinary Least Squares (OLS)

- It's a foundational problem in statistics and numerical analysis.
- Given  $n$  points in the plane:  $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$
- Find a line  $y = ax + b$  that minimizes the sum of the squared errors:

$$= \sum_{i=1}^n (y_i - ax_i - b)^2$$



# Least Squares Solution

Use your calculus knowledge and least squares are achieved when:

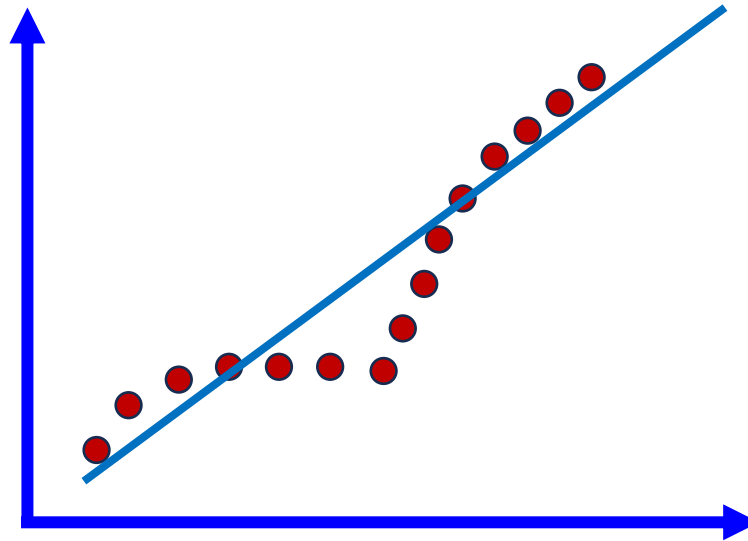
$$a = \frac{n \sum_{i=1}^n x_i y_i - (\sum_{i=1}^n x_i)(\sum_{i=1}^n y_i)}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2}$$

$$b = \frac{\sum_{i=1}^n y_i - a \sum_{i=1}^n x_i}{n}$$

If you encapsulate this formula as a subroutine, what is the **running time**?

# Least Squares

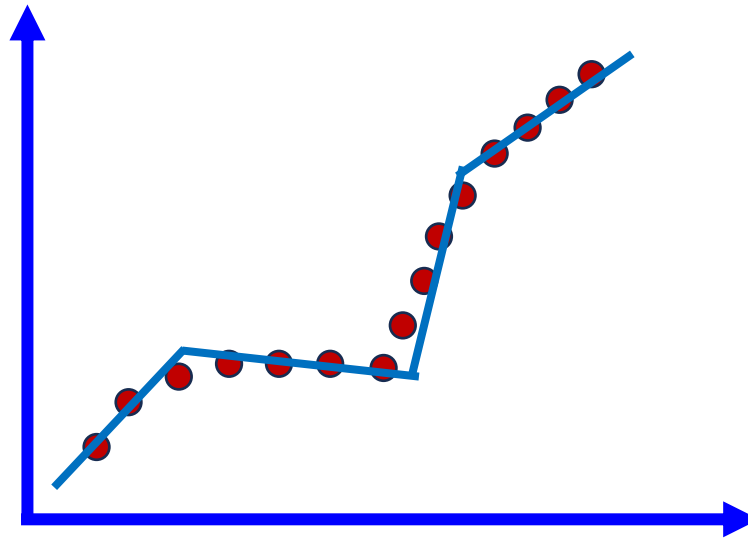
We sometimes think that a single line is just not enough.





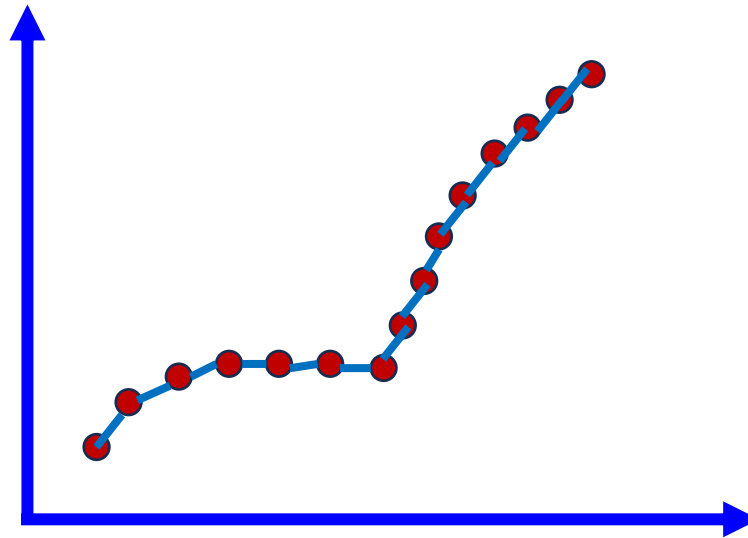
# Segmented Least Squares

Given  $n$  points in the plane:  $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$  with  $x_1 < x_2 < \dots < x_n$ , find sequence of lines that fits well.



# Segmented Least Squares

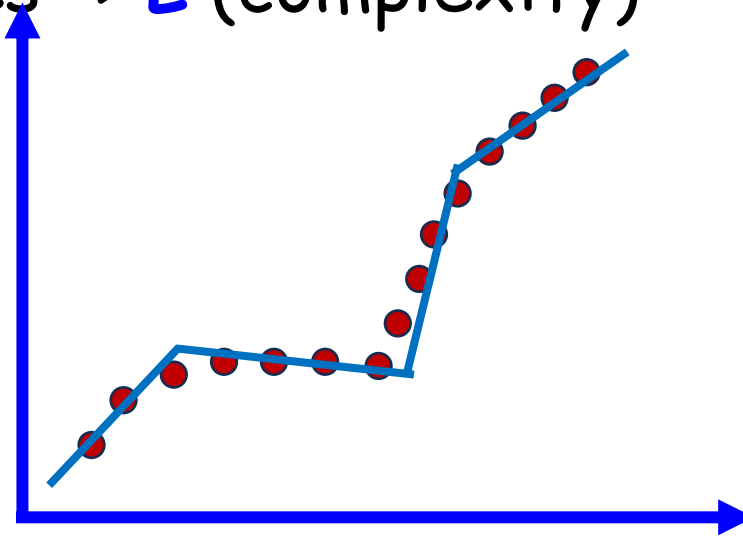
**Too many lines:** perfect solution, but too complex (prone to overfitting)



# Segmented Least Squares

**Goal:** Find a sequence to minimize some combination of

- The total error from each segment  $\rightarrow$  **err** (fitness)
- The number of lines  $\rightarrow$  **L** (complexity)



Trade-off function:

$$\text{cost} = \text{err} + cL,$$

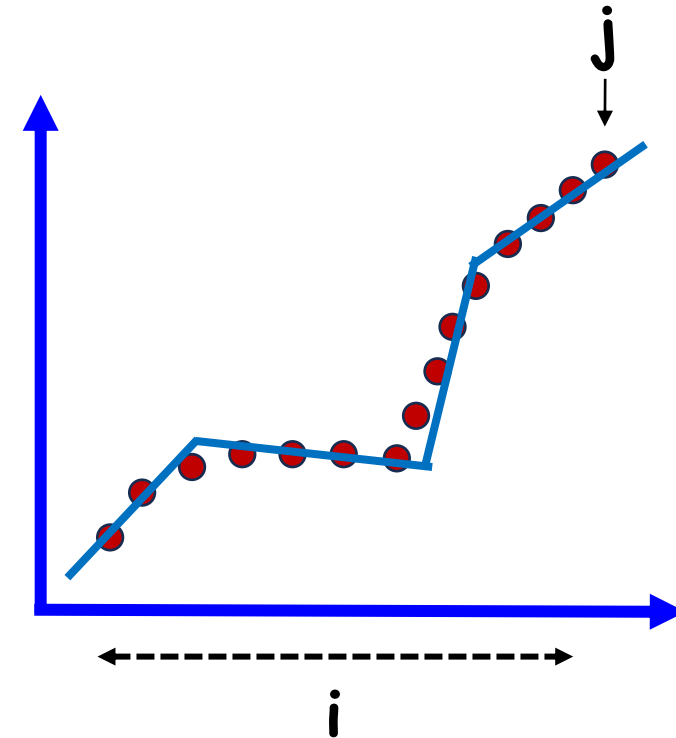
For some constant  $c > 0$

# Segmented Least Squares

- $OPT(j)$  = minimum cost for points  $p_1, p_2, \dots, p_j$
- $e(i, j)$  = minimum sum of squared errors for points  $p_i, p_{i+1}, \dots, p_j$

$$Cost = e(i, j) + c + OPT(i - 1)$$

$$OPT(j) = \begin{cases} 0 & j = 0 \\ \min_{1 \leq i \leq j} \{e(i, j) + c + OPT(i - 1)\} & j > 0 \end{cases}$$



Segmented-LS( $n, p_1, \dots, p_n, c$ ):  
  **let**  $M[0:n]$  be a new array  
  **let**  $e[1:n, 1:n]$  be a new matrix

$M[0] = 0$

**for**  $j = 1$  **to**  $n$ :

**for**  $i = 1$  **to**  $j$ :

    compute least square error  $e[i,j]$  for the segment  $p_i, \dots, p_j$

**for**  $j = 1$  **to**  $n$ :

$M[j] = \text{INF}$

**for**  $i = 1$  **to**  $j$ :

$\text{temp} = e[i,j] + c + M[i-1]$

**if**  $\text{temp} < M[j]$  **then**

$M[j] = \text{temp}$

What is the running time?