We'll be starting shortly!

To help us run the workshop smoothly, please kindly:

- Switch off screen sharing and mute your microphone
- Submit all questions using the Q&A function
- If you have an urgent request, please use the "Raise Hand" function

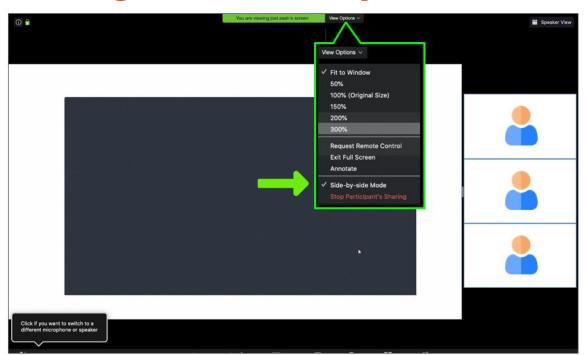
Thank you!







Using Zoom: People & Slides



Side-By-Side Mode

- When sharing screen (slide share)
- With small thumbnails of people on the sidebar

STEPS:

- 1. View Options
- 2. Side-By-Side Mode







DP: Speaker Notes

Overall Talking Points: What, Why, How

- introduce concepts
- contextualize concepts with examples
- up to **YOU** to practice! (especially for DP, this is the only way to master)
- 1. Overview Dynamic Programming(DP): What and Why
 - a. Definition:
 - i. "Solving Problems by incrementally solving for and re-using solutions of its subproblems"
 - ii. A category of algorithms that solves certain types of problems
 - iii. Two Defining Properties:
 - 1. **Optimal** Substructure: F(final) = G(F(small)...)
 - 2. Overlapping Subproblems: Can get significant speed-up from brute force
 - b. Motivation:
 - i. When applicable, often lead to performant solutions(correct solutions, no TLE: 'time limit exceeded')
 - ii. goto reason #i, more weapons in your algo toolbox :D
 - c. Example: Fibonacci Sequence
- 2. Solving Problems with DP
 - a. Problem Solving Approaches (your choice, but take note of the difference):
 - i. Top-Down: Recursion (exhaustive search + memoization)
 - ii. Bottom-Up: Tabulation (building a table)
 - iii. Top-Down vs Bottom-Up:
 - 1. Most the problems could be solved by either





Introduction to Dynamic Programming

Liang Qiao, Rocket Academy

Slides: https://tinyurl.com/y7pf7vkn

Register: https://rocketacademy.co/scl-slides



Overview

- 1. What is dynamic programming (DP)
- 2. Why/When to use dynamic programming (DP)
- 3. Problem solving approaches of DP
- 4. Problem solving strategy







Goal: Be able to solve basic DP problems





What is Dynamic Programming?

- "Solving Problems by incrementally solving for and re-using solutions of its subproblems"
- 2. Two Defining Properties:
 - a. Optimal Substructure: F(final) = G(F(small)...)
 - b. Overlapping Subproblems







Introducing Fibonacci Sequence

$$f_n = f_{n-1} + f_{n-2}$$

0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89 ...

Question: how to write program to produce fib(n) where n is the index?

Rocket Academy



Introducing Fibonacci Sequence

```
def fib(n):
    if n == 0 or n == 1:
        return n
    return fib(n-1) + fib(n-2)
```

What's the time complexity? (you could answer in chat)





Naive Fibonacci: time complexity

Recurrence:

```
T(n) = T(n-1) + T(n-2)
>= 2*T(n-2) >= 2*2*T(n-2-2)
>= 2*2*2*T(n-2-2-2) so on and so forth ...
>= 2^(n/2)
```

Exponential is NOT Good! Too SLOW! Rocket Academy



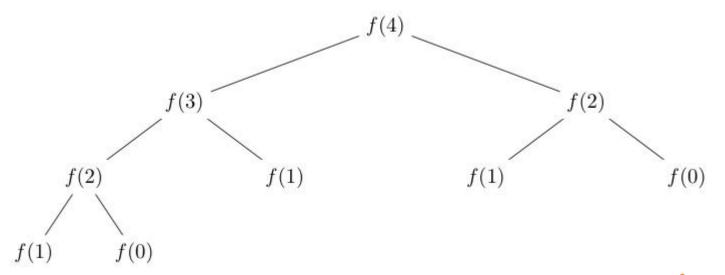
Why Dynamic Programming?







Speeding up Fibonacci Sequence









Speeding up Fibonacci Sequence

```
def solve fib(n):
  memo = \{\}
  def fib(n):
    if n in memo:
      return memo[n]
    if n == 0 or n == 1:
      return n
    memo[n] = fib(n-1) + fib(n-2)
    return memo[n]
  return fib(n)
```

Now it's linear time complexity O(n)!





Dynamic Programming Fibonacci: time complexity O(n)!

$$T(n) = T(n-1) + T(n-2)$$
>= $T(n-1) + O(1)$ <- Why?
>= $[T(n-2)+T(n-3)] + O(1)$
>= $T(n-2) + O(1)*2$
>= $T(n-3) + O(1)*3$
>= ...
>= $T(n-n) + O(1)*n$

>= O(n) <- Fast Enough!





Speeding up Fibonacci Sequence: Iterative approach

```
def solve_fib(n):
    if n == 0 or n == 1:
        return n
    fib = [0] * (n+1)
    fib[1] = 1
    for i in range(2, n+1):
        fib[i] = fib[i-1]+fib[i-2]
```

Why linear time complexity O(n)?





Speeding up Fibonacci Sequence: Iterative approach

```
def solve fib(n):
  if n == 0 or n == 1:
    return n
  fib n2, fib n1 = 0, 1
  for i in range(n-1):
    fib = fib n2 + fib n1
    fib n2, fib n1 = fib n1, fib
  return fib
```

Why linear time complexity O(n)?





Recall: What is Dynamic Programming

- "Solving Problems by incrementally solving for and re-using solutions of its subproblems"
- 2. Two Defining Properties:
 - a. Optimal Substructure: F(final) = G(F(small)...)







Problem Solving with Dynamic Programming

- Problem Solving Approaches:
 - a. Top-down: Recursion + Memoization
 - b. Bottom-up: Tabulation
- 2. Problem Solving Strategy







Speeding up Fibonacci Sequence

```
def fib_topdown(n):
    memo = {}

    def fib(n):
        if n in memo:
            return memo[n]
        if n == 0 or n == 1:
            return n
        memo[n] = fib(n-1) + fib(n-2)
        return memo[n]

    return fib(n)
```

```
def fib_bottomup(n):
   if n == 0 or n == 1:
      return n

fib_n2, fib_n1 = 0, 1
   for i in range(n-1):
      fib = fib_n2 + fib_n1
      fib_n2, fib_n1 = fib_n1, fib
   return fib
```





Problem Solving Approaches

Top-down

More intuitive, because of **recursion + memo**

VS



Bottom-up

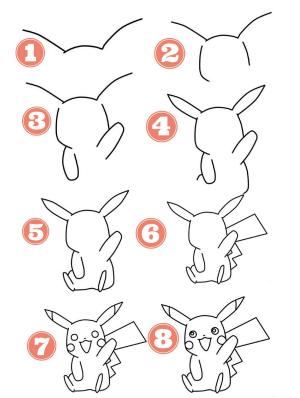
More efficient, and easier to optimize for space complexity







Problem Solving Strategy: steps to follow









Problem Solving Strategy: top down

- Step 1: Recognize DP Problems
 - weak signal: problems asking for min / max / total number / if solution exists
 - 2. strong signal: two defining properties of DP
- ii. Step 2: Find the brute force solution (recursion)
- iii. Step 3: Apply memoization (save the result for reuse)

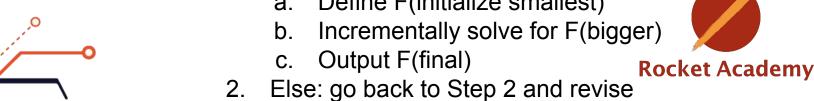






Problem Solving Strategy: bottom up

- Step 1: Recognize DP Problems
 - 1. weak signal: problems asking for min / max / total number / if solution exists
 - strong signal: two defining properties of DP
- ii. Step 2: Define Subproblem: F(small)
- Step 3: Define Recurrence: F(big) = G(F(small)...) iii.
 - If works:
 - Define F(initialize smallest)





Longest Increasing Subsequence

Given input: n numbers: x1, x2, ... xn Task: find the length of longest increasing subsequence.

e.g 0, 8, 4, 12, 2, 10, 6, 14, 1, 9, 5, 13, 3, 11, 7, 15

Ans: 6 0, 8, 4, 12, 2, 10, 6, 14, 1, 9, 5, 13, 3, 11, 7, 15





Top-down: Longest Increasing Subsequence

arr	0	8	4	12	2	10	6	14	1	9	5	13
LIS	1	2	2	3	?							

- i. Step 2: Find the brute force solution (recursion)
- ii. Step 3: Apply memoization (save the result for **reuse**)







Top-down: Longest Increasing Subsequence

```
def solve_lis(arr, i, prev):
   if i == len(arr):
      return 0
   excl i = solve lis(arr, i + 1, prev)
   incl i = 0
   if arr[i] > prev:
      incl i = 1 + solve lis(arr, i + 1, arr[i])
   return max(incl_i, excl_i)
   time complexity?
```

Rocket Academy

Top-down: Longest Increasing Subsequence

```
def solve(arr):
                                            time complexity?
    memo = \{\}
    def solve lis(arr, i, prev):
        if i == len(arr):
             return 0
        if (i, prev) in memo:
             return memo[(i, prev)]
        excl i = solve lis(arr, i + 1, prev)
        incl i = 0
        if arr[i] > prev:
             incl i = 1 + solve lis(arr, i + 1, arr[i])
        memo[(i, prev)] = max(incl i, excl i)
        return memo[(i, prev)]
    return solve lis(arr, 0, 0)
                                               Rocket Academy
```

Bottom-up: Longest Increasing Subsequence

arr	0	8	4	12	2	10	6	14	1	9	5	13
LIS	1	2	2	3	?							

i. Step 2: Define Subproblem:

LIS(i) = length of the longest increase subsequence

ii. Step 3: Define Recurrence: F(big) = G(F(small)...)

How to express LIS(i) with LIS(i-1) or LIS(smallers)?

- 1. If works:
 - a. Define F(initialize smallest)
 - b. Incrementally solve for F(bigger)
 - c. Output F(final)
- 2. Else: go back to Step 2 and revise







Bottom-up: Longest Increasing Subsequence

arr	0	8	4	12	2	10	6	14	1	9	5	13
LIS	1	2	2	3	?							

i. Step 2: Define Subproblem:

LIS(i) = length of the longest increase subsequence, that end with arr(i)

- ii. Step 3: Define Recurrence: F(big) = G(F(small)...)
 How to express LIS(i) with LIS(i-1) or LIS(smallers)?
 LIS(n) = max(1+LIS(i) for i from 1..n-1)
 - 1. If works:
 - a. Define F(initialize smallest)
 - b. Incrementally solve for F(bigger)
 - c. Output F(final)
 - 2. Else: go back to Step 2 and revise







Bottom-up: Longest Increasing Subsequence

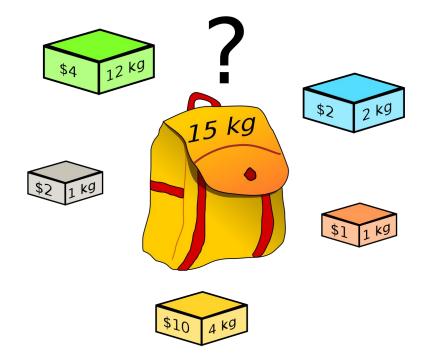
```
def solve lis(arr):
                                   time complexity?
   n = len(arr)
   lis = [1]*n
   for i in range(1, n):
      for j in range(0, i):
         if arr[i] > arr[j]:
            lis[i] = max(lis[i], lis[j]+1)
   return max(lis)
```







0-1 Knapsack Problem









Longest Common Subsequence

0,1, 2, 9, 6, 1, 9, 5, 11, 7, 15, 7 0, 8, 4, 12, 2, 10, 6, 14, 1, 9, 5, 13, 3, 11, 7, 15

Ans: 0, 2, 6, 9, 11, 15.







Edit Distance

0,1, 2, 9, 6, 1, 9, 5, 11, 7, 15, 7 0, 8, 4, 12, 2, 10, 6, 14, 1, 9, 5, 13, 3, 11, 7, 15

Ans: 0, 2, 6, 9, 11, 15.







More Examples: LIS, Knapsack, LCS, Edit Distance

- 1. Longest Increasing Subsequence (LIS)
- 2. Knapsack problems
- 3. Longest Common Subsequence (LCS)
- 4. Edit Distance
- More on https://leetcode.com/





More Learning Resources on DP

- Introduction to Algorithm (MIT)
- 2. <u>Introduction to Graduate Algorithm</u> (Georgia Tech)
- 3. <u>Dynamic Programming</u> (Stanford)







Summary

- 1. What is dynamic programming (DP)
- 2. Why/When to use dynamic programming (DP)
- 3. DP problem solving approaches (topdown vs bottomup)
- 4. Problem solving strategy (steps i, ii, iii)







Now Practice Practice and Practice!











Introduction to Dynamic Programming

Liang Qiao, Rocket Academy

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Register: https://rocketacademy.co/scl-slides



Your Feedback Matters!

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