

Refresher on Algorithms

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Topics to cover today...

- + Divide and Conquer
- + Dynamic Programming
- + Greedy Approach

Divide and Conquer

Divide

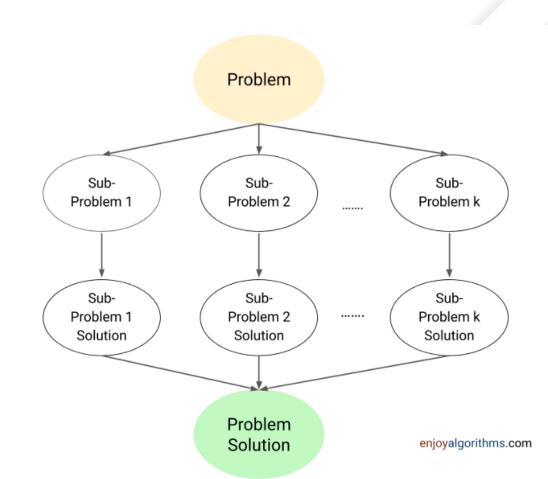
Dividing the problem into smaller sub-problems

Conquer

Solving each sub-problems recursively

Combine

Combining sub-problem solutions to build the original problem solution



Divide and Conquer - Types

+ DAC using one subproblem - Decrease and Conquer

Eg: Binary Search

+ DAC using two subproblems

Eg: Merge Sort

Illustration: Maximum Subarray Sum

+ Given an integer array, find the subarray with the largest sum/return its sum.

```
Input: nums = [-2,1,-3,4,-1,2,1,-5,4]
Output: 6
Explanation: The subarray [4,-1,2,1] has the largest sum 6.
```

```
Input: nums = [1]
Output: 1
Explanation: The subarray [1] has the largest sum 1.
```

+ Not the same as maximum subsequence sum!

Maximum Subarray



Maximum sum

$$= 3+5+1+7+9$$

$$= 25$$

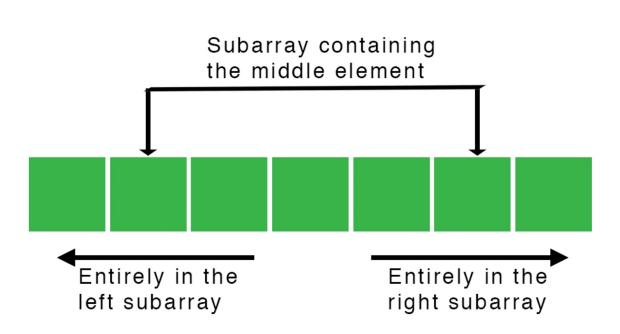
$$= 3-1-1+10$$

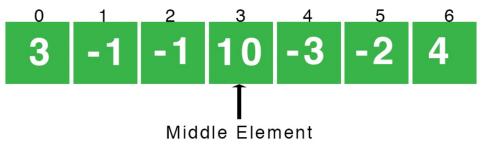
$$= 11$$

Naïve Method: Consider every possible subarray using 2 loops and return the overall maximum.

Time complexity: O(n^2)

Maximum Subarray with DAC





```
Left subarray sum = 0 sum = 0 sum = 0 Start from index 3: Start from index 4: 10 > 0 => sum = 10 -3 < sum(0), sum is 0 10-1=9 < sum(10) -3-2=-5 < sum(0), sum is 0 9-1=8 < sum(10) -5+4=-1 < sum(0), sum is 0 8+3=11> sum => sum = 11
```

Final crossing sum = 11+0=0 from index 0 to 3

Code

 $T(n) = 2T(n/2) + \Theta(n)$

Time: O(nlogn)

Space: O(1)

Dynamic Programming

What is DP?

- + Useful technique for optimization problems
- + Looks through all possible sub-problems and never recomputes the solution to any subproblem
- + Guarantees correctness and efficiency

When can DP be applied?

- + Breaking down an optimization problem into simpler sub-problems (optimal substructure)
- + Storing the solution to each sub-problem so that each sub-problem is solved only once (memoization)

What exactly is a sub-problem?

- + Smaller version of the original problem
- Sub-problems build on each other to obtain the solution to the original problem

Illustration 1: Longest Common Subsequence (LCS)

+ Given two strings s1 and s2 return the length of the longest common subsequence of characters between the two strings (need not be contiguous).

```
Input:
s1 = "ADC"
s2 = "ABCD"

Output: 2
Explanation:
"ADC"
"ABCD"
Both strings share the subsequence "A", "D".
```

Input:

s1 = "DBC"

```
Input:
s1 = "ABCD"
s2 = "ABCD"

Output: 4
Explanation:
"ABCD"
"ABCD"
Both strings share the subsequence "A", "B", "C", "D".
```

```
For example,

lcs('azb', 'aab') = 1 + lcs('az', 'aa') = 1 + max(lcs('az', 'a'), lcs('a', 'aa'))

= 1 + max(max(lcs('az', "), lcs('a', 'a')), 1 + lcs(' ', 'a'))

= 1 + max(1,1) = 2
```

Subproblem decomposition using the DP Table

Find the LCS between AGGTAB and GXTXAYB.

| ▼ | "" | A ▼ | G ▼ | G2 ▼ | T | A3 ▼ | B ▼ |
|-------|----|-----|-----|-------------|---|-------------|------------|
| 11 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| X | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| Т | 0 | 0 | 1 | 1 | 2 | 2 | 2 |
| X | 0 | 0 | 1 | 1 | 2 | 2 | 2 |
| Α | 0 | 1 | 1 | 1 | 2 | 3 | 3 |
| Υ | 0 | 1 | 1 | 1 | 2 | 3 | 3 |
| В | 0 | 1 | 1 | 1 | 2 | 3 | 4 |

Code

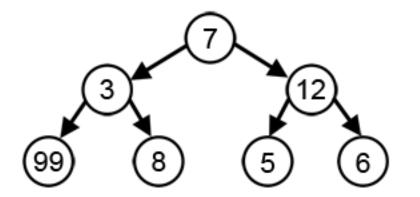
Time: O(mn)

Space: O(mn)

Where m = len(s1), n = len(s2)

Greedy Algorithm

- + An optimization algorithm that prioritizes the optimal choice at each step as it attempts to find the overall optimum to solve the entire problem.
- + An example where it works: Shortest path through a graph
- + An example where it does not work: To reach the largest sum in the graph



Greedy Algorithm

- + When can a greedy algorithm be used?
 - **Greedy choice property:** A global (overall) optimal solution can be reached by choosing the optimal choice at each step.
 - **Optimal substructure:** A problem has an optimal substructure if an optimal solution to the entire problem contains the optimal solutions to the sub-problems.
- + Limitations of Greedy Algorithms:
 - May not be able to find the global optimum because only limited data is considered.
 - Decision at each time step is made based on choices made so far, which may not include all possible future choices.

Illustration: Activity Selection Problem

+ Given N activities with their start time and end time. The task is to find the solution set having a maximum number of non-conflicting activities that can be executed within the given time, assuming only a single activity can be performed at a given time.

Input: start[] = [10, 12, 20}] end[] = [20, 25, 30]

Output: [0, 2]

Explanation: A maximum of two activities can be performed, i.e. Activity 0 and Activity 2[0-based indexing].

Input: start[] = [1, 3, 0, 5, 8, 5] finish[] = [2, 4, 6, 7, 9, 9]

Output: [0, 1, 3, 4]

Explanation: A maximum of four activities can be performed, i.e. Activity 0, Activity 1, Activity 3, and Activity 4[0-based indexing].

The Greedy Choice

Choose activities with the earliest finish time. The earlier you finish, the more time you have for other activities!

+Steps:

- Sort the activities according to their finishing time
- Select the first activity from the sorted array and print it
- Do the following for the remaining activities in the sorted array
 - + If the start time of this activity is greater than or equal to the finish time of the previously selected activity then select this activity and print it



Time: O(nlogn)

Space: O(1)