19. Dynamic Programming CPSC 535

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Dynamic Programming

- Dynamic programming: pattern for solving problems with a divide-and-conquer structure and overlapping subproblems
- Note: "programming" does not refer to coding
- Similar to divide-and-conquer
 - Recall: merge sort, closest pair
- Only applies to a narrow category of problems
- But offers huge speed-ups in those rare cases
 - ▶ often exponential → fast polynomial

Designing Dynamic Programming Algorithms

Suggested process to design a dynamic programming algorithm:

- 1. Characterize the structure of an optimal solution (i.e. data type)
- Recursively define the value of an optimal solution (like divide-and-conquer)
- Design pseudocode that computes the value of an optimal solution
 - ▶ Either bottom-up, or with memoization
- 4. (If desired, next class) Design pseudocode that constructs an optimal solution based on information computed in step 3.

Rod Cutting Problem

rod cutting problem

input: integer rod length $n \ge 0$ and a table of prices p_1, \ldots, p_n **output:** maximum revenue obtainable by cutting the rod into pieces of length $\le n$

(Above computes a *value* of a solution, to compute an actual *solution* change the **output** to:)

output: a list of rod-lengths in [1, n] that add up to exactly n and maximize revenue

Greedy Doesn't Work

- Tempting to try a greedy heuristic
 - e.g. pick the length with the best unit price p_i/i
- But greedy algorithms for this problem are not correct
- Problem definition makes no guarantee that
 - ightharpoonup prices p_i obey common-sense properties
 - e.g. larger pieces are more valuable than smaller ones
 - e.g. buying in bulk is a better deal
 - e.g. small scraps like p_1 are nearly worthless
- In general, problems that benefit from dynamic programming cannot be solved correctly by greedy methods
- If you design a greedy alg., onus is on you to prove correctness
- Tip: if a problem is framed as dynamic programming, don't even bother with greedy approaches

Baseline: Exhaustive Search

- ▶ Baseline idea: try every way of dividing length *n* into smaller pieces
- $\triangleright \approx 2^n$ candidates
- \triangleright $O(2^n)$ time
- extremely slow

1. Characterize Solution

- recall: p_i = price of a rod of length i
- ▶ a solution is a sequence of rod-lengths $S = \langle i_1, i_2, \dots, i_k \rangle$ such that $\sum_i i_i = n$ and the total revenue

$$\sum_{j} p_{i_j}$$

is maximized

define

 r_i = the **maximum revenue obtainable** from a rod of length i

• the **optimal value** is r_n

2. Recursive Definition of an Optimal Solution

- ▶ Each piece must have length ≥ 1 , so each $i_i \in [1, n]$
- Given original length n, we could make one cut to form: $1 + (n-1), 2 + (n-2), 3 + (n-3), \ldots, n+0$ (last entry means to keep the rod whole; no cut)
- ▶ These produce revenue $p_1 + r_{n-1}, p_2 + r_{n-2}, p_3 + r_{n-3}, \dots, p_n + r_0$
- Goal is to maximize revenue
- So $r_n = \max(p_1 + r_{n-1}, p_2 + r_{n-2}, p_3 + r_{n-3}, \dots, p_n + r_0)$ i.e.

$$r_n = \max_{1 \le i \le n} (p_i + r_{n-i})$$

Aside: Recursive Top-Down Algorithm

```
    function CUT-ROD(p[0..n], n)
    if n = 0 then
    return 0
    end if
    q = -∞
    for i = 1 to n do
    q = max(q, p[i] + CUT-ROD(p, n - i))
    end for
    return q
    end function
```

Overlapping subproblems: ex. CUT-ROD(p, 2) will be computed many times **Slow;** $O(2^n)$ time

Enter Dynamic Programming

- Problem: top-down recursion recomputes the same values over and over
- Solution: use a table (array) to cache these solutions
- For each x, evaluate

CUT-ROD(p, x)

only once

- Time/space trade-off
 - table takes extra space
 - saves a lot of time
 - ▶ exponential → polynomial

Memoization and Bottom-Up

- Two fine approaches for caching subsolutions
- Memoization: use an array or hash table T, where
 T[i] = solution for input i, or dummy value if undefined
- CUT-ROD is still recursive, but has a base case to reuse T[i] instead of evaluating the function body
- Bottom-Up: solve subproblems from smallest to largest
- ▶ Initialize T[0], T[1], ..., T[n] in an interative loop
- Mostly a matter of preference
- Some programming languages support automatic memoization (ex. Racket)

3. Pseudocode for **Memoized** Dynamic Programming Alg.

```
1: function MEMOIZED-CUT-ROD(p[0..n], n)
       Create empty hash map H
       return CUT-ROD-REC(p, n, H)
4: end function
5: function CUT-ROD-REC(p[0..n], n, H)
6:
       if H.CONTAINS-KEY(n) then
7:
          return H[n]
      end if
8:
9.
      if n = 0 then
10:
          return 0
11: end if
12:
       a = -\infty
       for i = 1 to n do
13:
          q = \max(q, p[i] + \text{CUT-ROD-REC}(p, n - i, H))
14:
15:
       end for
       H[n] = q
16:
17:
       return a
18 end function
```

3. Pseudocode for **Bottom-Up** Dyn. Prog. Alg.

```
1: function BOTTOM-UP-CUT-ROD(p[0..n], n)
       Create new array r[0..n]
      r[0] = 0
3:
                                                            base case
 4:
    for j = 1 to n do

    □ general cases bottom-up

 5:
           q = -\infty
 6:
           for i = 1 to j do \triangleright only references initialized elements
               q = \max(q, p[i] + r[j - i])
 7:
           end for
8:
           r[j] = q
9:
       end for
10:
       return r[n]
11:
12: end function
```

Analysis

- ▶ BOTTOM-UP-CUT-ROD: clearly $\Theta(n^2)$ b/c nested for loops
- MEMOIZED-CUT-ROD:
 - Less clear, but $\Theta(n^2)$ expected time
 - Cache hit (H contains n): $\Theta(1)$ expected time
 - Cache miss: $\Theta(n)$ expected time due to for loop
 - Observe: each miss happens at most once
 - Total time at most

$$\sum_{i=0}^{n} \Theta(i) \in \Theta(n^2)$$

- ▶ Same $\Theta(n^2)$ efficiency; memoized version is expected
- ▶ **Huge** speedup: $O(2^n) \longrightarrow \Theta(n^2)$
- ▶ Modest $\Theta(n)$ space complexity for table

What's Next

- Computing a solution (list of rod-lengths)
- Maximizing over two indices
- Longest common subsequence problem