

Dynamic Programming and Greedy: Review

Examples in lectures and labs

Dynamic programming:

- Playing a board game
 - Rod cutting
 - Knapsack
 - Pharmacist
 - Fibonacci
 - Longest TRUE interval
 - LCS (longest common subsequence)
 - Optional: Robbing a house
 - Optional: Playing a game
 - This week: Longest increasing subsequence
 - This week: Unbounded knapsack
 - Optional Skis and skiers
- Handwritten annotations: $1D (i)$ points to the first two items; $2D \rightarrow \text{subproblem } (i, j)$ with w, i above it points to Knapsack and Pharmacist; max partial sum with a downward arrow points to Longest TRUE interval; $O(n)$ points to Longest increasing subsequence.

Greedy:

- Activity selection
- Guarding a museum
- A different pharmacist problem (all bottles have same cost)
- Optional: Matching points on a line
- Optional: Greedy skis and skiers

1 Rod cutting

- The problem: Given a rod of length n and a table of prices $p[i]$ for $i = 1, 2, 3, \dots, n$, determine the maximal revenue obtainable by cutting up the rod and selling the pieces.
- Notation and choice of subproblem: We denote by $\text{maxrev}(x)$ the maximal revenue obtainable by cutting up a rod of length x . To solve our problem we call $\text{maxrev}(n)$.
- Recursive definition of $\text{maxrev}(n)$:

```

maxrev( $x$ )
    if ( $x \leq 0$ ): return 0
    For  $i = 1$  to  $n$ : compute  $p[i] + \text{maxrev}(x - i)$  and keep track of max
    RETURN this max

```

- Correctness: see notes.
- Dynamic programming solution, top-down with memoization:
We create a table of size $[0..n]$, where $\text{table}[i]$ will store the result of $\text{maxrev}(i)$. We initialize all entries in the table as 0. To solve the problem, we call $\text{maxrevDP}(n)$.

```

maxrevDP( $x$ )
    if ( $x \leq 0$ ): return 0
    IF  $\text{table}[x] \neq 0$ : RETURN  $\text{table}[x]$ 
    For  $i = 1$  to  $n$ : compute  $p[i] + \text{maxrevDP}(x - i)$  and keep track of max
     $\text{table}[x] = \text{max}$ 
    RETURN  $\text{table}[x]$ 

```

- Dynamic programming, bottom-up:

```

maxrevDP_iterative( $x$ )
    create  $\text{table}[0..n]$  and initialize  $\text{table}[i] = 0$  for all  $i$ 
    for ( $k = 1; k \leq n; k++$ )
        for ( $i = 1; i \leq k; i++$ )
            set  $\text{table}[k] = \text{max}\{\text{table}[k], p[i] + \text{table}[k - i]\}$ 
    RETURN  $\text{table}[n]$ 

```

- Analysis: $O(n^2)$
- Computing full solution:

2 0 – 1 Knapsack

- The problem: We are given a knapsack of capacity W and a set of n items; an each item i , with $1 \leq i \leq n$, is worth $v[i]$ and has weight $w[i]$ pounds. Assume that weights $w[i]$ and the total weight W are integers. The goal is to fill the knapsack so that the value of all items in the knapsack is maximized.
- Notation and choice of subproblem: Denote by *optknapsack*(k, w) the maximal value obtainable when filling a knapsack of capacity w using items among items 1 through k . To solve our problem we call *optknapsack*(n, W).
- Recursive definition of *optknapsack*(k, w):

```

optknapsack( $k, w$ )
  if ( $w \leq 0$ ) or ( $k \leq 0$ ): return 0 //basecase
  IF ( $weight[k] \leq w$ ): with =  $value[k] + \text{optknapsack}(k - 1, w - weight[k])$ 
  ELSE:  $with = 0$ 
  without = optknapsack( $k - 1, w$ )
  RETURN max { with, without }

```

- Correctness: see notes.
- Dynamic programming solution, top-down with memoization: We create a table $table[1..n][1..W]$, where $table[i][w]$ will store the result of *optknapsack*(i, w). We initialize all entries in the table as 0. To solve the problem, we call *optknapsackDP*(n, W).

```

optknapsackDP( $k, w$ )
  if ( $w \leq 0$ ) or ( $k \leq 0$ ): return 0
  IF ( $table[k][w] \neq 0$ ): RETURN  $table[k][w]$ 
  IF ( $w[k] \leq w$ ):  $with = v[k] + \text{optknapsackDP}(k - 1, w - w[k])$ 
  ELSE:  $with = 0$ 
   $without = \text{optknapsackDP}(k - 1, w)$ 
   $table[k][w] = \max \{ with, without \}$ 
  RETURN  $table[k][w]$ 

```

- Dynamic programming, bottom-up:

optknapsackDP_iterative

```
create table[0..n][0..W] and initialize all entries to 0
for ( $k = 1; k < n; k++$ )
    for ( $w = 1; w < W; w++$ )
        with =  $v[k] + table[k - 1][w - w[k]]$ 
        without =  $table[k - 1][w]$ 
         $table[k][w] = \max \{ \text{with}, \text{without} \}$ 
RETURN  $table[n][W]$ 
```

- Analysis: $O(n \cdot W)$
- Computing full solution:

3 Pharmacist

- The problem: A pharmacist has W pills and n empty bottles. Bottle i can hold $p[i]$ pills and has an associated cost $c[i]$. Given W , $p[1..n]$ and $c[1..n]$, find the minimum cost for storing the pills using the bottles.
- Notation and choice of subproblem: Denote by $MinPill(i, j)$ the minimum cost obtainable when storing j pills using bottles among 1 through i . To solve our problem we call $minPill(n, W)$.
- Recursive definition of $minPill(i, j)$:

```

minPill( $i, j$ )
    if ( $j \leq 0$ ): return 0 //no pills left
    IF ( $i == 0$  and  $j > 0$ ): return  $\infty$  //have pills, but no bottles, sol not possible
    with =  $c[i] + minPill(i - 1, j - p[i])$ 
    without =  $minPill(i - 1, j)$ 
    RETURN  $\min \{ \text{with, without} \}$ 

```

- Correctness:
- Dynamic programming solution, top-down with memoization: We create $table[1..n][1..W]$, where $table[i][j]$ will store the result of $minPill(i, j)$. We initialize all entries in the table as 0. To solve the problem, we call $minPillDP(n, W)$.

```

minPillDP( $i, j$ )
    if ( $j \leq 0$ ): return 0 //no pills left
    IF ( $i == 0$  and  $j > 0$ ): return  $\infty$  //have pills, but no bottles, sol not possible
    IF ( $table[i][j] \neq 0$ ): RETURN  $table[i][j]$ 
    with =  $c[i] + minPillDP(i - 1, j - p[i])$ 
    without =  $minPillDP(i - 1, j)$ 
     $table[i][j] = \min \{ \text{with, without} \}$ 
    RETURN  $table[i][j]$ 

```

- Dynamic programming, bottom-up:

minPill_iterative

create $table[0..n][0..W]$ and initialize all entries to 0

for ($i = 1; i < n; i++$)

 for ($j = 1; j < W; j++$)

 with = $c[i] + table[i - 1][j - p[i]]$

 without = $table[i - 1][j]$

$table[i][j] = \min \{ \text{with, without} \}$

RETURN $table[n][W]$

- Analysis: $O(n \cdot W)$
- Computing full solution:

4 Longest True interval

- The problem: Suppose we are given an array $A[1..n]$ of booleans. We want to find the longest interval $A[i..j]$ such that every element in the interval is true – in other words, $A[i], A[i + 1], \dots, A[j]$ are all true.
- Notation and choice of subproblem: Denote by $G(x)$ to be the length of the longest suffix¹ of $A[1..x]$ that is all true. In other words, $G(x)$ is the largest integer l such that $A[x - l + 1], A[x - l + 2], \dots, A[x]$ are all true, or 0 if $A[x]$ is false.
- Recursive definition of $G(x)$:

```

G(x)
  IF (x == 1): return A[1]
  else
    IF A[x] == False: return 0 else return 1 + G(x - 1)

```

- Correctness:
- Dynamic programming solution, top-down with memoization: We create $table[0..n]$, where $table[i]$ will store the result of $G(i)$. We initialize all entries in the table as 0. To solve the problem, we call $G_DP(0), G_DP(1), G_DP(2), \dots$ to fill the table and then return the max element in this table.

```

G_DP(x)(x)
  IF (x == 1): return A[1]
  else
    IF (table[x] != 0): RETURN table[x]
    IF A[x] == False: answer = 0 else answer = 1 + G_DP(x - 1)
    table[x] = answer
  return answer

```

- Dynamic programming, bottom-up:
- Analysis: $O(n)$ ←
- Computing full solution:

¹An array $B[1..m]$ is a suffix of an array $A[1..n]$ if $A[n - k] = B[m - k]$ for $0 \leq k < m$

5 LCS

- The problem: Given two arrays $X[1..n]$ and $Y[1..m]$, find their longest common subsequence.
- Notation and choice of subproblem: Denote by $c(i, j)$ the length of the LCS of X_i and Y_j , where X_i is the array consisting of the first i elements of X , and Y_j is the array consisting of the first j elements of Y . To solve the problem, we call $c(n, m)$
- Recursive definition of $c(i, j)$:

```

c(i, j)
  IF (i == 0 or j == 0): return 0
  else
    IF  $X[i] == Y[j]$ : return  $1 + c(i - 1, j - 1)$ 
    Else: return  $\max\{c(i - 1, j), c(i, j - 1)\}$ 

```

- Correctness:
- Dynamic programming solution, top-down with memoization: We create $table[0..n][0..m]$, where $table[i][j]$ will store the result of $c(i, j)$. We initialize all entries in the table as 0 and call $c_DP(n, m)$.

```

c_DP(i, j)
  IF (i == 0 or j == 0): return 0
  else
    IF ( $table[i][j] \neq 0$ ): RETURN  $table[i][j]$ 
    IF  $X[i] == Y[j]$ : answer  $1 + c\_DP(i - 1, j - 1)$ 
    Else: answer =  $\max\{c(i - 1, j), c\_DP(i, j - 1)\}$ 
     $table[x] = answer$ 
  return answer

```

- Dynamic programming, bottom-up:
- Analysis: $O(m \cdot n)$
- Computing full solution: