Imperial College London

CO202 – Software Engineering – Algorithms **Dynamic Programming**

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Algorithm Design

How to design an (efficient) algorithm?

Structure the problem!*

Make use of algorithmic schemes/design paradigms

- Incremental Approach
- Divide and Conquer (last week)
- Dynamic Programming (this week)
- Greedy Algorithms (next week)

*Take some time and think!

Dynamic Programming Principle

- DP solves problems by combining the solutions to subproblems (similar to Divide and Conquer)
- In D&C subproblems do not overlap: disjoint partitioning
- In DP subproblems overlap: subproblems share subsubproblems
- A DP algorithm solves each subproblem just once and saves its answer in a table, avoiding recomputations

The term "Programming" refers to a **tabular** method, not to writing computer code. DP is typically applied to **optimisation problems**.

Optimisation Problems

Such problems can have many possible solutions

Each solution has a value (e.g. a cost or an energy)

 Optimisation seeks for a solution with the optimal (minimum or maximum) value: an* optimal solution

*Note: there could be several solutions with the same optimal value

Dynamic Programming

When developing a DP algorithm, follow four steps:

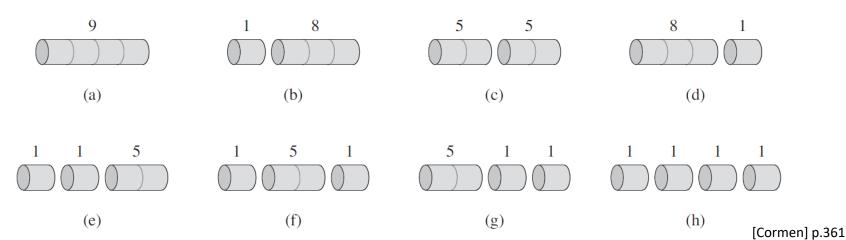
- 1. Characterize the structure of an optimal solution
- 2. Recursively define the value of an optimal solution
- 3. Compute the value of an optimal solution, typically in a bottom-up fashion
- 4. Construct an optimal solution from computed information

Example: Rod Cutting

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

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

Possible cuts for rod of length n=4



Example: Rod Cutting (cont'd)

A rod of length n can be cut up in 2^{n-1} different ways* *we assume only integer-valued cuts are possible

- An optimal solution cuts the rod into k pieces, for some $1 \le k \le n$
- Optimal decomposition is then

$$n = i_1 + i_2 + \dots + i_k$$

Providing maximal revenue

$$r_n = p_{i_1} + p_{i_2} + \dots + p_{i_k}$$

Example: Rod Cutting (cont'd)

Optimal solutions for all $1 \le i \le 10$

Max Revenue	Optimal Decomposition						
$r_1 = 1$	1=1 (no cuts)						
$r_2 = 5$	2 = 2 (no cuts)						
$r_3 = 8$	3=3 (no cuts)						
$r_4 = 10$	4 = 2 + 2						
$r_5 = 13$	5 = 2 + 3						
$r_6 = 17$	6 = 6 (no cuts)						
$r_7 = 18$	7 = 1 + 6 or 7 = 2 + 2 + 3						
$r_8 = 22$	8 = 2 + 6						
$r_9 = 25$	9 = 3 + 6						
$r_{10} = 30$	10 = 10 (no cuts)						

Recursive Rod Cutting

The maximum revenue r_n can be determined by considering the revenues for shorter rods:

$$r_n = \max(p_n, r_1 + r_{n-1}, r_2 + r_{n-2}, \dots, r_{n-1} + r_1)$$

or more compact (with $r_0 = 0$)

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

The rod-cutting problem exhibits **optimal substructure**: optimal solutions to a problem incorporate optimal solutions to related subproblems.

Recursive Rod Cutting (cont'd)

Top-down Implementation

What is the running time of the CUT-ROD algorithm?

$$T(n) = 2^n$$

Bad, bad...really bad!

Recursive Rod Cutting (cont'd)

Exponential running time of CUT-ROD

OD
$$T(n) = \begin{cases} 1, & \text{if } n = 0 \\ 1 + \sum_{j=0}^{n-1} T(j), & \text{if } n > 0 \end{cases}$$

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

$$T(0) = 1 = 2^0$$

Holds.

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

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

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

$$=2T(n)$$

$$= 2(2^n)$$

$$= 2^{n+1}$$

Extract T(n) from the summation

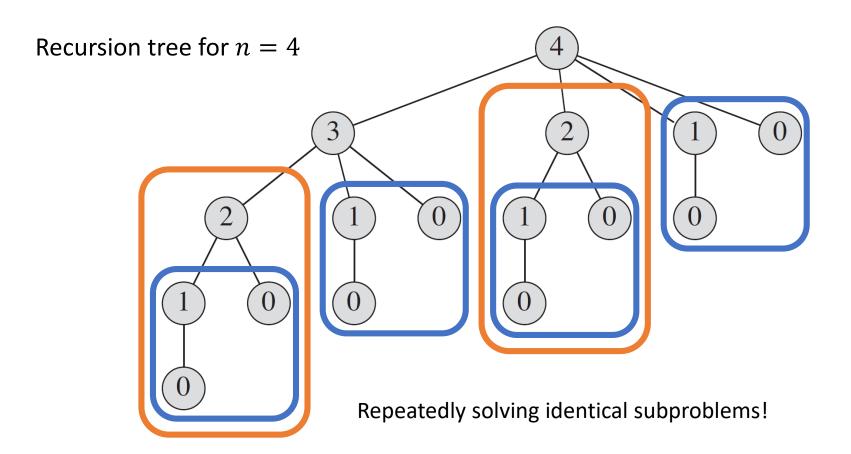
Get twice the same term

Insert assumption

Done.

Inefficiency of Recursive Rod Cutting

Why is CUT-ROD so inefficient?



[Cormen] p.364

The Dynamic Programming Approach

- Subproblems are solved once, and solutions are saved
- If we encounter a subproblem again, just look up the solution
- Dynamic programming uses additional memory, often yielding a time-memory trade-off
- Two strategies for implementing a DP algorithm:
 - 1. Top-down with memoization*
 - 2. Bottom-up

^{*}Note: not a typo, memoization comes from memo.

Top-Down with Memoization

```
MEMOIZED-CUT-ROD(p,n)
 1: let r[0..n] be a new array
2: for i = 0 to n
3: r[i] = -\infty
4: return MEMOIZED-CUT-ROD-AUX(p,n,r)
MEMOIZED-CUT-ROD-AUX(p,n,r)
                                     CUT-ROD(p,n)
 1: if r[n] \ge 0
                                      1: if n == 0
                                      2: return 0
2: return r[n]
 3: if n == 0
                                      4: for i = 1 to n
4: q = 0
                                      5: q = max(q, p[i] + CUT-ROD(p,n-i))
                                      6: return q
 5: else
6: q = -\infty
7: for i = 1 to n
 8: q = max(q, p[i] + MEMOIZED-CUT-ROD-AUX(p,n-i,r)
9: r[n] = q
10: return q
```

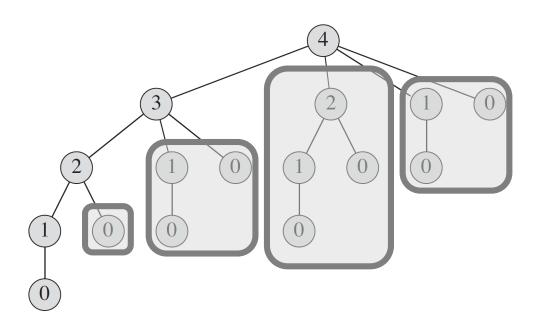
Bottom-Up Version of Rod Cutting

```
BOTTOM-UP-CUT-ROD(p,n)
1: let r[0..n] be a new array
2: r[0] = 0
3: for j = 1 to n
4:
   q = -∞
5: for i = 1 to j
           q = \max(q, p[i] + r[j-i])
6:
7: r[j] = q
8: return r[n]
```

What is the running time of BOTTOM-UP-CUT-ROD?
$$T(n) = n^2$$

Memoization

- Memoization allows us to make top-down recursive algorithms as efficient as bottom-up approaches
- A memoized recursive algorithm maintains an entry in a table for the solution to each subproblem



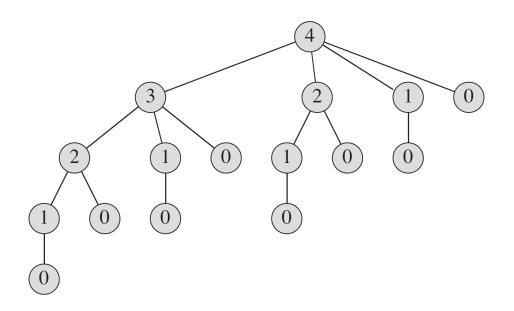
Top-down vs. Bottom-up

Top-down with memoization and bottom-up have the same asymptotic running time

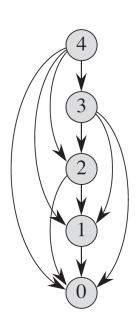
- Bottom-up is usually more efficient by a constant factor because there is no overhead for recursive calls
- Bottom-up might benefit from optimal memory access
- Top-down can avoid to compute solutions of subproblems that are not required
- Top-down implementation is closer to the natural, recursive definition of the problem

Subproblem Graphs

Rod cutting with n=4



Recursion Tree



Subproblem Graph

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[Cormen] p.364 [Cormen] p.367

Dynamic Programming

Reconstructing a Solution

Compute not only the maximum revenue, but also record the solution (i.e. the cut off pieces)

i	0	1	2	3	4	5	6	7	8	9	10
r[i]	0	1	5	8	10	13	17	18	22	25	30
s[i]		1	2	3	2	2	6	1	2	3	10

Print a Solution

Print the list of piece sizes for an optimal decomposition of a rod of length \boldsymbol{n}

```
PRINT-CUT-ROD-SOLUTION(p,n)

1: (r,s) = EXTENDED-BOTTOM-UP-CUT-ROD(p,n)

2: while n > 0

3: print s[n]

4: n = n - s[n]
```

Key Elements of Dynamic Programming

When should we consider DP?

 Optimal substructure: Optimal solution to a problem contains optimal solutions to subproblems

 Overlapping subproblems: The space of subproblems must be "small". Subproblems are solved over and over, rather then generating new subproblems

Longest Common Subsequence (LCS)

Consider the following two strands of DNA

A strand of DNA is a string over the finite set {A, C, G, T}, standing for bases adenine, cytosine, guanine, and thymine.

$$S_1 = ACCGGTCGAGTGCGCGGAAGCCGGCCGAA$$

$$S_2 = GTCGTTCGGAATGCCGTTGCTCTGTAAA$$

How similar are these two strands?

One way of defining similarity is to look for bases that appear in same order, but not necessarily consecutively

$$S_3 = GTCGTCGGAAGCCGGCCGAA$$

Formal Definition of Subsequence

Given a sequence

$$X = \langle x_1, x_2, \dots, x_m \rangle$$

Another sequence

$$Z = \langle z_1, z_2, \dots, z_k \rangle$$

is a **subsequence** of X if there exists a strictly increasing sequence $\langle i_1, i_2, ..., i_k \rangle$ of indices of X such that for all j = 1, 2, ..., k we have $x_{i_j} = z_j$.

Example: $Z = \langle B, C, D, B \rangle$ is a subsequence of $X = \langle A, B, C, B, D, A, B \rangle$ with corresponding index sequence $\langle 2, 3, 5, 7 \rangle$.

Common Subsequence

Given two sequences X and Y, then the sequence Z is a **common subsequence** if it is a subsequence of X and Y.

Example: $X = \langle A, B, C, B, D, A, B \rangle$ and $Y = \langle B, D, C, A, B, A \rangle$ then $Z = \langle B, C, A \rangle$ is a common subsequence. What is the LCS?

The LCS Problem

Given two sequences X and Y, find a maximum-length common subsequence. We will solve this using DP!

Reminder: Dynamic Programming

When developing a DP algorithm, follow four steps:

- 1. Characterize the structure of an optimal solution
- 2. Recursively define the value of an optimal solution
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Brute-force: Enumerate all subsequences of X and check each whether it is also a subsequence of Y. Impractical!

Definition of prefix: The *i*th prefix of X, for i=0,1,...,m, is defined as $X_i=\langle x_1,x_2,...,x_i\rangle$ with X_0 being the empty sequence

Optimal substructure of LCS (Theorem):

- 1. If $x_m = y_n$, then $z_k = x_m = y_n$ and Z_{k-1} is LCS of X_{m-1} and Y_{n-1}
- 2. If $x_m \neq y_n$, then $z_k \neq x_m$ implies that Z is LCS of X_{m-1} and Y
- 3. If $x_m \neq y_n$, then $z_k \neq y_n$ implies that Z is LCS of X and Y_{n-1}

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$$X_7 = \langle A, B, C, B, D, A, B \rangle$$

$$Y_6 = \langle B, D, C, A, B, A \rangle$$

$$Z_4 = \langle B, C, A, B \rangle$$

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$$X_{1} = \langle A, B, C, B, D, A, B \rangle$$

$$Y_{0} = \langle B, D, C, A, B, A \rangle$$

$$Z_{0} = \langle B, C, A, B \rangle$$

Optimal substructure of LCS (Theorem):

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

- 1. If $x_m = y_n$, then $z_k = x_m = y_n$ and Z_{k-1} is LCS of X_{m-1} and Y_{n-1}
- 2. If $x_m \neq y_n$, then $z_k \neq x_m$ implies that Z is LCS of X_{m-1} and Y
- 3. If $x_m \neq y_n$, then $z_k \neq y_n$ implies that Z is LCS of X and Y_{n-1}

Proof: (Part 1)

1) If $z_k \neq x_m$, then we could append $x_m = y_n$ to Z and get an LCS with k+1, which is a contradiction to Z being LCS of X and Y.

The prefix Z_{k-1} with length k-1 is LCS of X_{m-1} and Y_{n-1} . Suppose there is LCS W that is greater than k-1, then appending $x_m=y_n$ to W produces an LCS with length >k, which is a contradiction.

Optimal substructure of LCS (Theorem):

Given $X = \langle x_1, x_2, \dots, x_m \rangle$ and $Y = \langle y_1, y_2, \dots, y_n \rangle$ 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 Z_{k-1} is LCS of X_{m-1} and Y_{n-1}
- 2. If $x_m \neq y_n$, then $z_k \neq x_m$ implies that Z is LCS of X_{m-1} and Y
- 3. If $x_m \neq y_n$, then $z_k \neq y_n$ implies that Z is LCS of X and Y_{n-1}

Proof: (Part 2 & 3)

- 2) If $z_k \neq x_m$, then Z is a common subsequence of X_{m-1} and Y. If there were a common subsequence W of X_{m-1} and Y with length > k, then W would also be a common subsequence of X_m and Y, which is a contradiction with Z being LCS of X and Y.
- 3) The proof is symmetric to (2).

LCS - Step 2: Recursive Solution

There are two cases:

- 1. If $x_m = y_n$, find LCS of X_{m-1} and Y_{n-1} and append $x_m = y_n$
- 2. Otherwise, solve two subproblems
 - a) Find LCS of X_{m-1} and Y
 - b) Find LCS of X and Y_{n-1}

Whichever LCS is longer, it is also an LCS of X and Y

Overlapping-subproblems property:

In order to find LCS of X and Y we may need to find LCSs of X and Y_{n-1} and X_{m-1} and Y. Each of these subproblems has the subsubproblem of finding LCS of X_{m-1} and Y_{n-1} .

LCS - Step 2: Recursive Solution (cont'd)

Let c[i,j] be the length of an LCS of sequences X_i and Y_j

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

LCS - Step 3: Computing a Solution (Bottom-up)

```
LCS-LENGTH(X,Y)
 1: m = X.length
2: n = Y.length
3: let b[1..m,1..n] and c[0..m,0..n] be new tables
4: for i = 1 to m
                                                 # initialize first column
 5: c[i,0] = 0
6: for j = 0 to n
                                                 # initialize first row
7: c[0,j] = 0
8: for j = 1 to n
   for i = 1 to m
9:
10:
            if x_i == y_i
                                                 # case 1
11:
               c[i,j] = c[i-1,j-1] + 1
12:
               b[i,j] = 
13:
           elseif c[i-1,j] \ge c[i,j-1]
                                                 # case 2a
               c[i,j] = c[i-1,j]
14:
15:
               b[i,j] = \uparrow
16:
           else
                                                 # case 2b
17:
               c[i,j] = c[i,j-1]
               b[i,j] = \leftarrow
18:
19: return c and b
```

LCS - Step 4: Construct a Solution

```
PRINT-LCS(b,X,i,j)
 1: if i == 0 or j == 0
 2: return
 3: if b[i,j] == \
4: PRINT-LCS(b,X,i-1,j-1)
 5: print x_i
6: elseif b[i,j] == ↑
       PRINT-LCS(b,X,i-1,j)
8: else
9: PRINT-LCS(b,X,i,j-1)
```

Approximate String Matching

How similar are SUNNY and SNOWY?

- LCS has length 3: SNY
- LCS Distance: How many operations does it need to transform one string into the other? Allowed operations are DELETE and INSERT



Distance: 4

Levenshtein Distance



Allowed operations are DELETE, INSERT and REPLACE

S	U	N	N	-	Υ
S	-	N	0	W	Υ

Distance: 3

$$d[i,j] = \begin{cases} \max(i,j), & \text{if } i = 0 \text{ or } j = 0 \\ d[i-1,j] + 1 \\ d[i,j-1] + 1 \\ d[i-1,j-1] + \mathbf{1}_{(x_i \neq y_j)} \end{cases}, \text{ otherwise}$$

Levenshtein Distance (cont'd)

```
LEV-DISTANCE(X,Y)
1: m = X.length
2: n = Y.length
3: let d[0..m,0..n] be new table
4: for i = 1 to m
5: d[i,0] = i
6: for j = 0 to n
7: d[0,j] = j
8: for j = 1 to n
9: for i = 1 to m
10:
           c = x_i == y_i ? 0 : 1
11:
           d[i,j] = min(d[i-1,j] + 1, d[i,j-1] + 1, d[i-1,j-1] + c)
12: return d[m,n]
```

Conclusions

 DP is a powerful algorithm design technique that can sometimes reduce exponential running time to polynomial (e.g. rod cutting, LCS, ...)

- DP is employed in many applications
 - Bioinformatics (computational genomics, DNA matching)
 - Spell checker (via approximate string matching)
 - Time series analysis (speech recognition)
 - Economics

References

Books

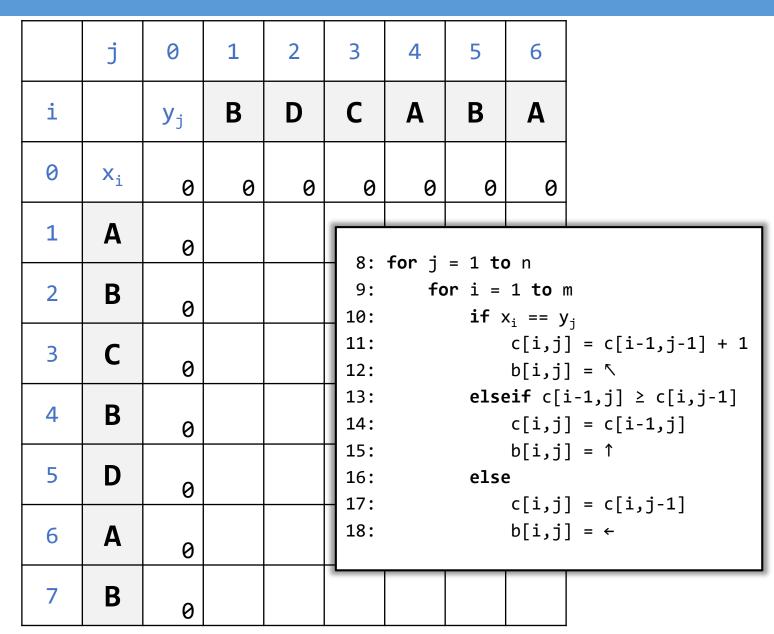
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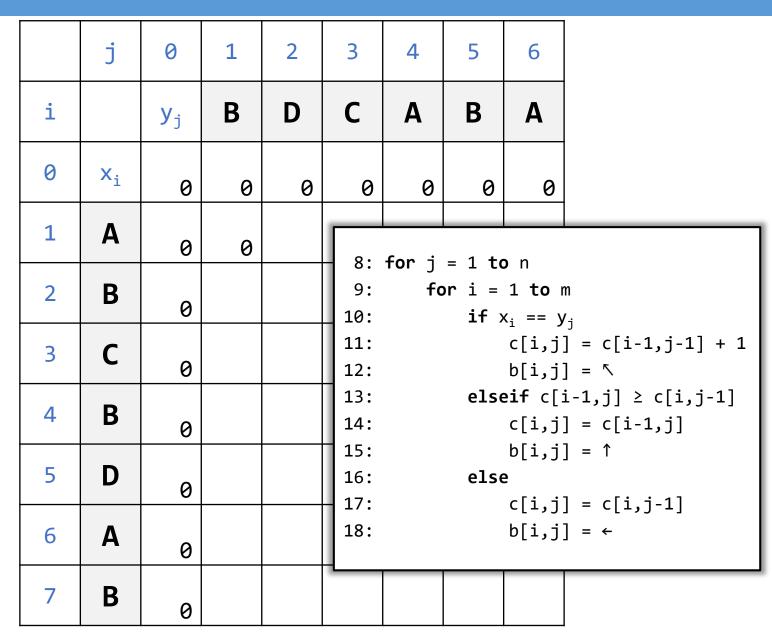
Online

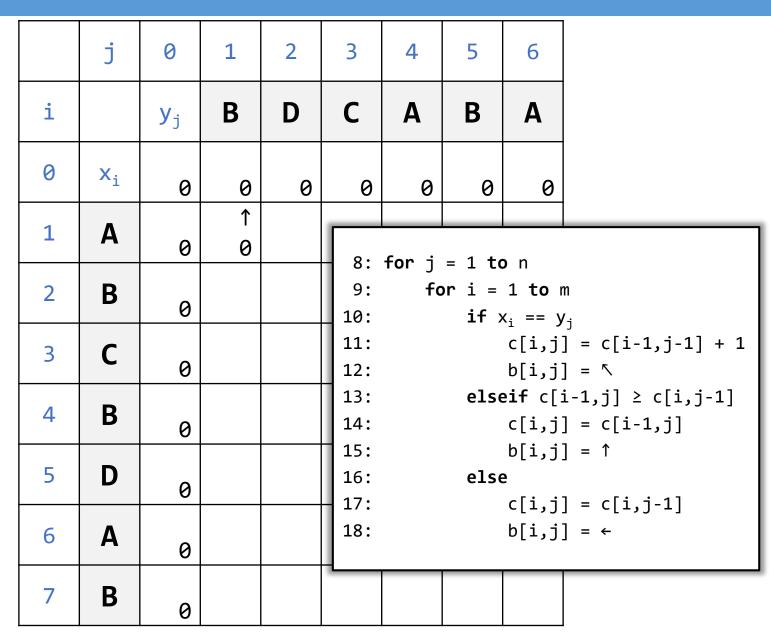
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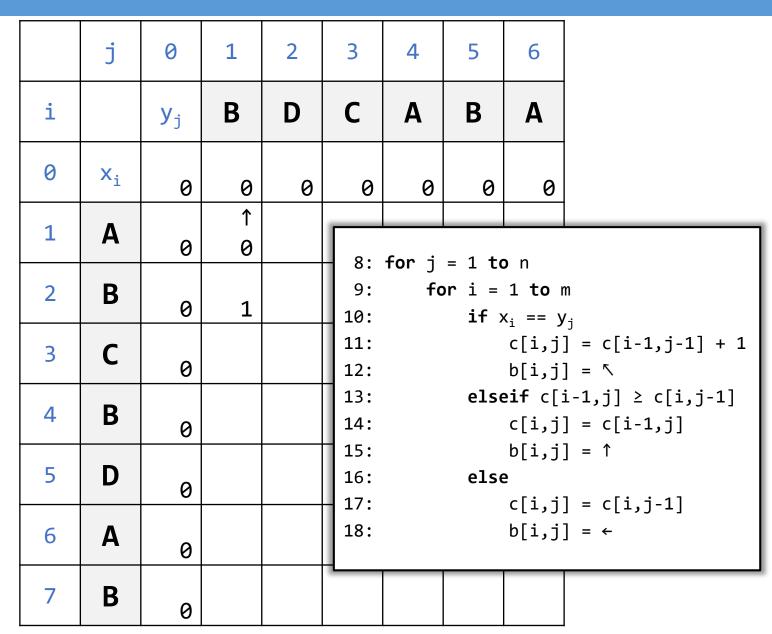
CO202 – Software Engineering – Algorithms Dynamic Programming - Exercises

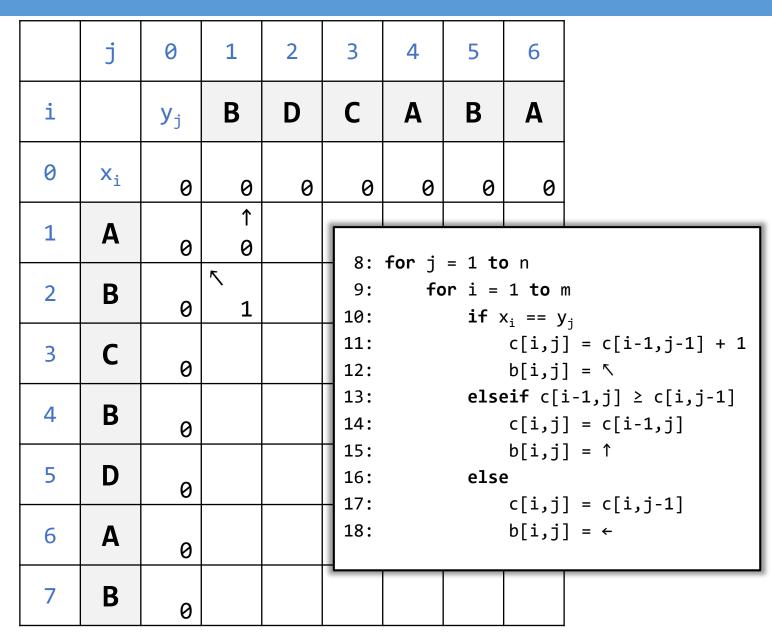
	j	0	1	2	3	4	5	6
i		Уj	В	D	С	Α	В	Α
0	Xi							
1	Α							
2	В							
3	С							
4	В							
5	D							
6	Α							
7	В							

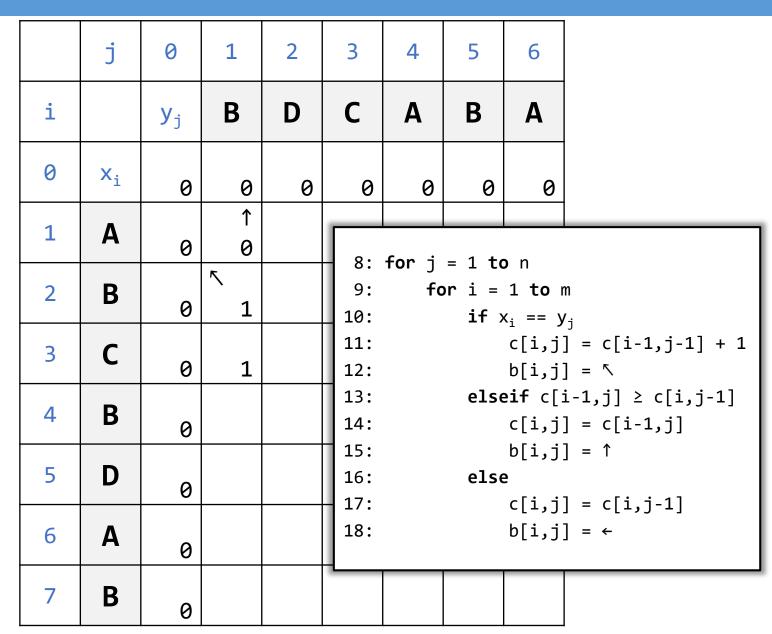


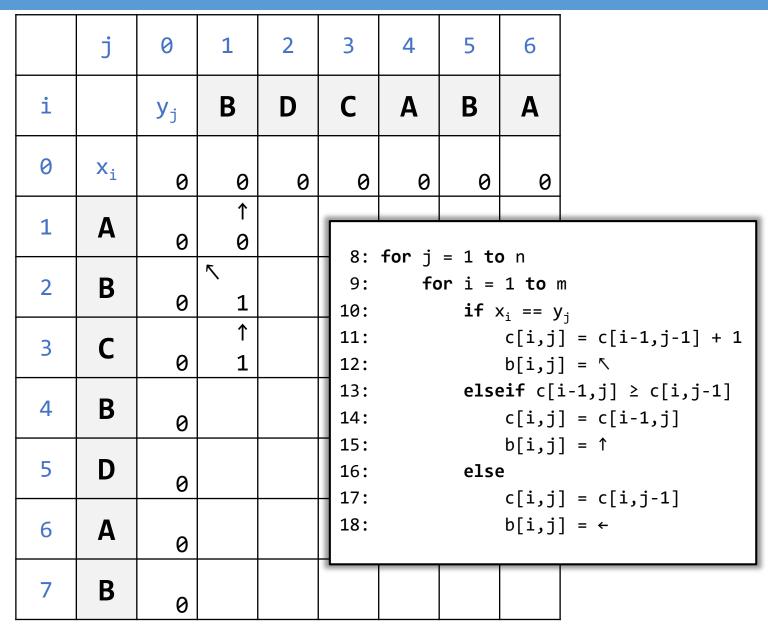












	j	0	1	2	3	4	5	6	7	8	9
i		Уj	E	M	Р	I	R	I	С	Α	L
0	Xi										
1	I										
2	М										
3	Р										
4	E										
5	R										
6	I										
7	Α										
8	L										

	_	_									
	j	0	1	2	3	4	5	6	7	8	9
i		Уj	E	М	Р	I	R	I	С	Α	L
0	Xi	0	1	2	3	4	5	6	7	8	9
1	I	1									
2	M	2									
3	P	3									
4	E	4									
5	R	5									
6	I	6									
_	_							-			

```
8: for j = 1 to n

9: for i = 1 to m

10: c = x<sub>i</sub> == y<sub>j</sub> ? 0 : 1

11: d[i,j] = min(d[i-1,j] + 1, d[i,j-1] + 1, d[i-1,j-1] + c)
```

		_	_								
	j	0	1	2	3	4	5	6	7	8	9
i		Уj	E	М	Р	I	R	I	С	Α	L
0	Xi	0	1	2	3	4	5	6	7	8	9
1	I	1	R 1								
2	М	2									
3	Р	3									
4	E	4									
5	R	5									
6	I	6									
_								_			

```
8: for j = 1 to n

9: for i = 1 to m

10: c = x<sub>i</sub> == y<sub>j</sub> ? 0 : 1

11: d[i,j] = min(d[i-1,j] + 1, d[i,j-1] + 1, d[i-1,j-1] + c)
```

	j	0	1	2	3	4	5	6	7	8	9
i		у _j	E	M	Р	Ι	R	Ι	С	Α	L
0	Xi	0	1	2	3	4	5	6	7	8	9
1	Ι	1	R 1								
2	М	2	R D 2								
3	Р	3									
4	E	4									
5	R	5									
6	I	6									
_											

```
8: for j = 1 to n

9: for i = 1 to m

10: c = x<sub>i</sub> == y<sub>j</sub> ? 0 : 1

11: d[i,j] = min(d[i-1,j] + 1, d[i,j-1] + 1, d[i-1,j-1] + c)
```

	j	0	1	2	3	4	5	6	7	8	9
i		Уj	E	М	Р	I	R	I	С	Α	L
0	Xi	0	1	2	3	4	5	6	7	8	9
1	I	1	R 1								
2	М	2	R D 2								
3	Р	3	R D 3								
4	E	4									
5	R	5									
6	I	6									
_								-			

```
8: for j = 1 to n

9: for i = 1 to m

10: c = x<sub>i</sub> == y<sub>j</sub> ? 0 : 1

11: d[i,j] = min(d[i-1,j] + 1, d[i,j-1] + 1, d[i-1,j-1] + c)
```

											-
	j	0	1	2	3	4	5	6	7	8	9
i		Уj	E	М	Р	Ι	R	I	С	Α	L
0	Xi	0	1	2	3	4	5	6	7	8	9
1	I	1	R 1								
2	М	2	R D 2								
3	Р	3	R D 3								
4	Е	4	K 3								
5	R	5									
6	I	6									
								-			

```
8: for j = 1 to n

9: for i = 1 to m

10: c = x<sub>i</sub> == y<sub>j</sub> ? 0 : 1

11: d[i,j] = min(d[i-1,j] + 1, d[i,j-1] + 1, d[i-1,j-1] + c)
```

		j	0	1	2	3	4	5	6	7	8	9
j	Ĺ		Уj	E	М	Р	I	R	I	С	Α	L
6	9	Xi	0	1	2	3	4	5	6	7	8	9
1	L	I	1	R 1								
2	2	М	2	R D 2								
3	3	Р	3	R D 3								
4	1	E	4	K 3								
5	5	R	5	D 4								
6	5	I	6									
									7			

```
8: for j = 1 to n

9: for i = 1 to m

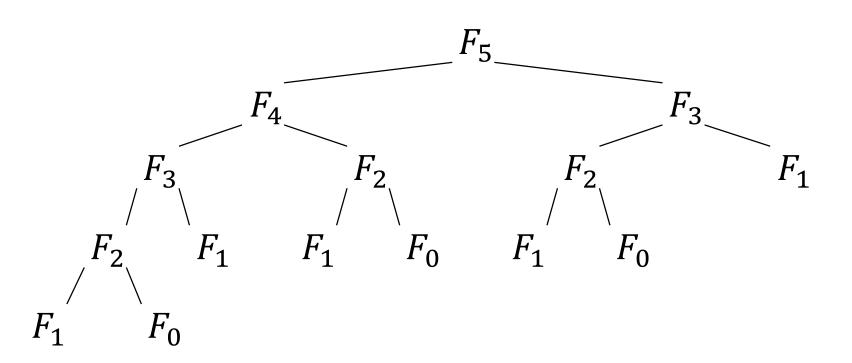
10: c = x<sub>i</sub> == y<sub>j</sub> ? 0 : 1

11: d[i,j] = min(d[i-1,j] + 1, d[i,j-1] + 1, d[i-1,j-1] + c)
```

Exercise 3: Fibonacci Sequence

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

$$F(n) = \begin{cases} 0, & \text{if } n = 0 \\ 1, & \text{if } n = 1 \\ F(n-1) + F(n-2), & \text{otherwise} \end{cases}$$



Exercise 3: Fibonacci Sequence

```
NAÏVE-FIBONACCI(n)
1: if n == 0
2: return 0
3: if n == 1
4: return 1
5: return NAÏVE-FIBONACCI(n-1) + NAÏVE-FIBONACCI(n-2)
```

Running time of NAÏVE-FIBONACCI:

$$T(n) = O(2^{0.694n})$$

Exercise 3: Fibonacci Sequence

```
0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, ...
BOTTOM-UP-FIBONACCI(n)
                                                  F(n) = \begin{cases} 0, & \text{if } n = 0 \\ 1, & \text{if } n = 1 \\ F(n-1) + F(n-2), & \text{otherwise} \end{cases}
 1: if n == 0
 2: return 0
 3: let f[0..n] be a new array
 4: f[0] = 0
 5: f[1] = 1
 6: ?
 8: ?
```

What is the running time of BOTTOM-UP-FIBONACCI?

if n = 0

Exercise 4: Coin Change Problem

Coin change is the problem of finding the least number of coins for a given amount of money.

For example, the UK coin set contains the following coins:

- 1p, 2p, 5p, 10p, 20p, 50p, £1, £2, and £5 (very uncommon).
- For £2.82, the optimal change is £2, 50p, 20p, 10p, 2p.

1. Write a mathematical recurrence equation that determines the least number of coins.

2. Devise a pseudo-code, bottom-up dynamic programming algorithm coin_change(n,coins).

Exercise 5: Fibonacci Challenge

D&C Fibonacci Revisited

Naïve:

$$F(n) = \begin{cases} 0, & \text{if } n = 0 \\ 1, & \text{if } n = 1 \\ F(n-1) + F(n-2), & \text{otherwise} \end{cases}$$

Let's rewrite Fibonacci

$$F(n) = F(2k) = F(k)^2 + 2F(k)F(k-1)$$
 for even n
 $F(n) = F(2k-1) = F(k)^2 + F(k-1)^2$ for odd n

$$F(n) = \begin{cases} 0, & \text{if } n = 0 \\ 1, & \text{if } n = 1 \end{cases}$$

$$F([n/2])^2 + 2F([n/2])F([n/2] - 1), & \text{if } n \ge 2 \text{ and } n \text{ is even}$$

$$F([n/2])^2 + F([n/2] - 1)^2, & \text{if } n \ge 2 \text{ and } n \text{ is odd}$$

Exercise 5: Fibonacci Challenge

D&C Fibonacci Revisited

```
F(n) = \begin{cases} 0, & \text{if } n = 0 \\ 1, & \text{if } n = 1 \end{cases}
F([n/2])^2 + 2F([n/2])F([n/2] - 1), & \text{if } n \ge 2 \text{ and } n \text{ is even}
F([n/2])^2 + F([n/2] - 1)^2, & \text{if } n \ge 2 \text{ and } n \text{ is odd}
```

```
DC-FIBONACCI(n)
1: if n == 0 || n == 1
2:    return n
3: else
4: ?
```

What is the running time?