CSE 417 Dynamic Programming (pt 1) Definition, History, & Simple Examples

UNIVERSITY of WASHINGTON

Reminders

> HW4 is posted: due in one week

– start early!



Outline for Today

- > Motivation & Definition
- > Robot Example
- > History
- > Robot Example 2
- > Extensions



Dynamic Programming: Motivation

Dynamic programming is...

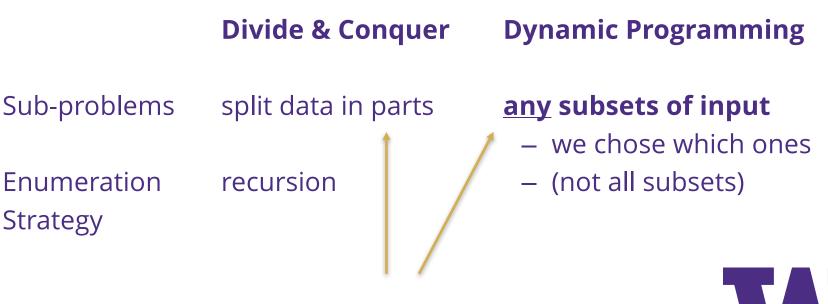
- > most useful algorithm design technique in practice (IMO)
- > more robust to problem changes than techniques discussed so far
- > usually easiest to analyze for run-time performance
- > often easier to implement
 - some could be implemented in Excel
- > ubiquitous in CS
 - more so than greedy or divide & conquer
 - applications are large in number and *importance*

Dynamic Programming: Applications

- > compilers
 - optimal code generation
- > machine learning
 - speech recognition
 - parsing natural language
- > databases
 - query optimization
- > graphics
 - optimal polygon triangulation

- > networking
 - routing
- > practical applications:
 - spell checking
 - file comparison
 - document layout
 - pattern matching
- > many, many more...

Dynamic Programming vs Divide & Conquer



Both apply "optimal substructure": using solution on sub-problems to solve whole problem

Dynamic Programming vs Divide & Conquer

Divide & Conquer

Sub-problems split data in parts

Enumeration recursion Strategy **Dynamic Programming**

any subsets of input

we chose which ones

solve them all

often record in a table

Dynamic Programming: Definition

Dynamic programming approach...

- > describe solution in terms of solution to sub-problems
 - like D&C but consider more general subsets of data
- > solve *every* sub-problem we need
 - once only!
- > Approach is efficient if there aren't too many sub-problems
 - often not trying to get from O(n²) to O(n log n) as in D&C...
 trying to get from impossible to possible
 - number of sub-problems could be large but want n^{O(1)}



Outline for Today

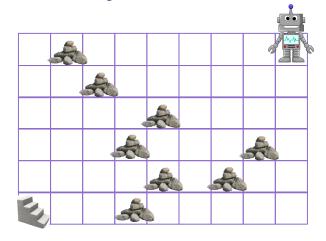
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Example: Broken Robot Path

> Problem: Given an n x m grid where some squares contain rocks, find a path for the robot to get from (n,m) to the exit at (1,1), where the robot only has to move *down or left*.





Example: Broken Robot Path

- > Problem: Given an n x m grid where some squares contain rocks, find a path for the robot to get from (n,m) to the exit at (1,1), where the robot only has to move *down or left*.
- > Problem is too easy so far...
 - Q: how do you solve it efficiently?

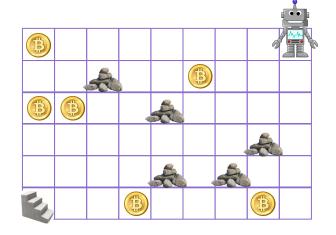


Example: Broken Robot Path

- > Problem: Given an n x m grid where some squares contain rocks, find a path for the robot to get from (n,m) to the exit at (1,1), where the robot only has to move *down or left*.
- > Problem is too easy so far...
 - a shortest path problem
- > Even easier interview question: no rocks
 - problem was to count the number of paths
 - can be solved by dynamic programming, but...



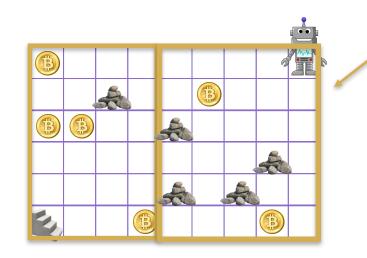
> Problem: Given an n x m grid where squares have rocks or <u>bitcoins</u>, find a path for the robot to get from (n,m) to the exit at (1,1), where the robot only has to move down or left, *maximizing the coins found*!



now an optimization problem

> **Q**: What are the sub-problems?

have to choose these for D&C or DP



Divide & Conquer would split the input into pieces...

Doesn't seem useful...

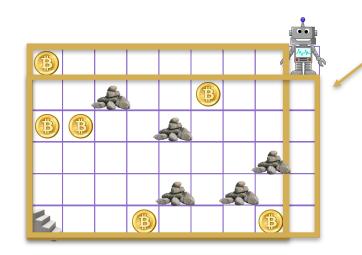
> e.g., right box finds opt
path ending at (5,1)

> solution does not use that

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> **Q**: What are the sub-problems?

DP allows more general choices



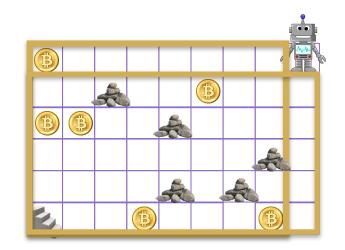
both find paths to (1,1) but with different starts

These are useful...

- > every path from (n,m) steps
 through (n-1,m) or (n,m-1)
- > opt must do one or other

W

- > Q: What are the sub-problems?
 - DP allows more general choices



Optimal path from (n,m) either goes through (n-1,m) or (n,m-1).

- > **Q**: What are the sub-problems?
- > A: Choice of starting point (top-right of rectangle)
 - all rectangles with bottom-left at (1,1)
 - same formula applies to find opt at any (i,j)
- > **Q**: How many sub-problems are there?
- > **A**: nm
 - running time will be nm x time per sub-problem



- > **Q**: What are the sub-problems?
- > A: Choice of starting point
- > Algorithm:
 - allocate a table A with n x m entries
 - record the optimal solution in each spot
 - fill the table in from bottom-left to top-right

no solution below, so opt = left + 1 if coin here

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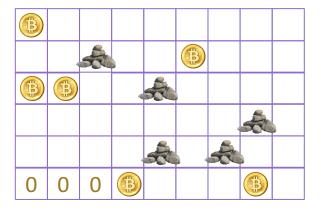
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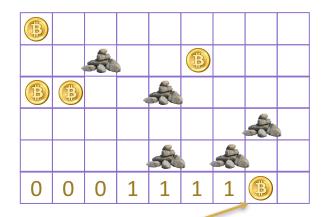
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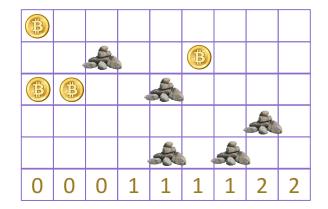
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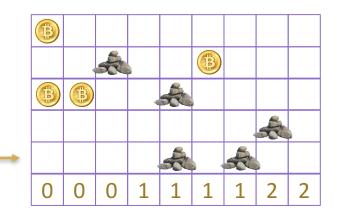
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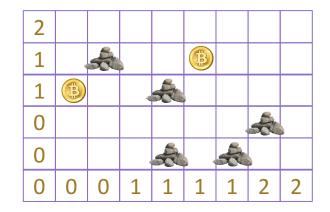


- > **Q**: What are the sub-problems?
- > A: Choice of starting point

no solution to left, so _____ opt = below + 1 if coin here

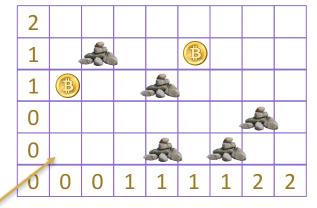


- > **Q**: What are the sub-problems?
- > A: Choice of starting point
- > Algorithm:
 - allocate a table A with n x m entries
 - record the optimal solution in each spot
 - fill the table in from bottom-left to top-right
 - > usually fill in the special (edge) cases first.
 - > many possible orders (row at a time, col at a time, diagonals, etc.)
 - > only rule is bottom & left must be filled in first



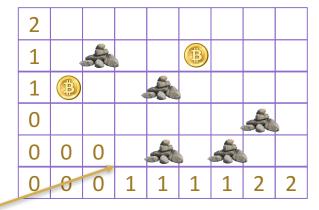


- > **Q**: What are the sub-problems?
- > A: Choice of starting point



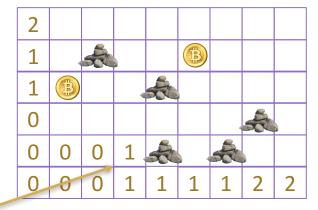
opt here = max(opt left, opt below)
+ 1 if coin here

- > **Q**: What are the sub-problems?
- > A: Choice of starting point



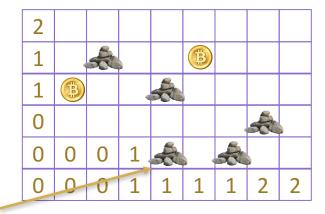
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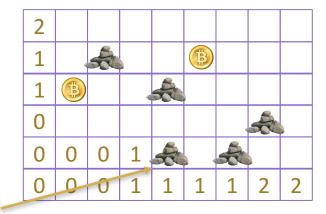
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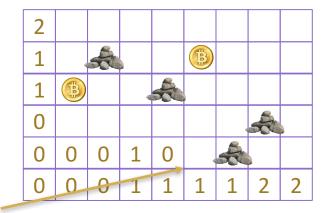


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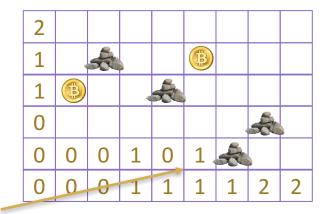


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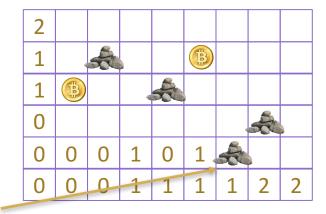


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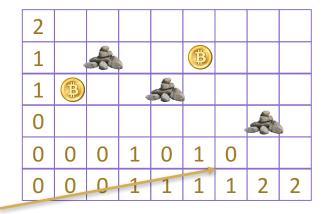


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- > A: Choice of starting point



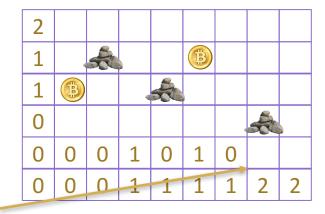


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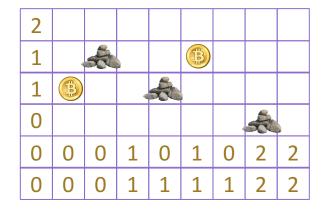


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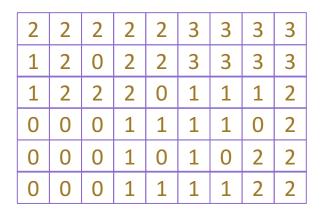
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- > **Q**: What are the sub-problems?
- > A: Choice of starting point

opt here = max(opt le	ot here = max(opt left, opt below)				
+ 1 if coin here					
opt here = 0 if rocks	(or maybe -1?)				





- > **Q**: What are the sub-problems?
- > A: Choice of starting point

> Running time is O(1) per entry opt here = max(opt left, opt below) + 1 if coin here opt here = 0 if rocks

> Total running time is O(nm)

2	2	2	2	2	3	3	3	3
1	2	0	2	2	3	3	3	3
1	2	2	2	0	1	1	1	2
0	0	0	1	1	1	1	0	2
0	0	0	1	0	1	0	2	2
0	0	0	1	1	1	1	2	2



```
int[][] A = new int[n+1][m+1];
                                       for (int i = 2; i \le n; i++) {
                                          for (int j = 2; j <= m; j++) {</pre>
A[1][1] = 0;
                                            if (B[i][i] == COIN)
                                              A[i][j] = 1 +
for (int i = 2; i \le n; i++) {
                                                  max(A[i-1][j], A[i][j-1]);
  if (B[i][1] == COIN)
                                           else if (B[i][j] == ROCK)
    A[i][1] = A[i-1][1] + 1;
                                             A[i][j] = -Infinity;
  else if (B[i][1] == ROCK)
                                            else
    A[i][1] = -Infinity;
                                              A[i][j] = max(A[i-1][j], A[i][j-1]);
  else
                                         }
    A[i][1] = A[i-1][1];
                                        }
}
                                       return A[n][m];
// ... fill in A[1][j] similarly ...
```

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Dynamic Programming: Etimology

- > *programming* : program :: scheduling : schedule
 - think of a program for a concert
 - choice of what to play and when to play it (not just a schedule)
 - same use as "linear programming", "convex programming", etc.
- > *dynamic* means relating to time
 - inventor (Bellman) was looking at problems where index was time
 e.g., our price data in HW4
 - BUT time plays no role in modern user of the word



Dynamic Programming: History

- > Technique invented by Richard Bellman in the 1950s
 - we will see the algorithm when we discuss network flows...
- > At the time, Secretary of Defense did not like math research, so Bellman chose a name that did not sound like math
 - "it is impossible to use the word 'dynamic' in a pejorative sense"
 - "[dynamic programming] was a name not even a Congressman could object to
 - (both quotes from Bellman's autobiography)

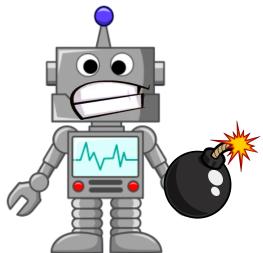


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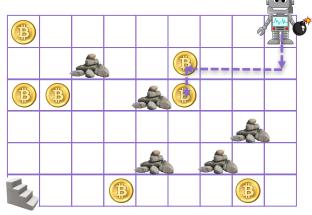
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- > Robot is tired of these rocks in his way!
 - he wants bitcoin!!!
- > Robot buys a bomb he can use to blast rocks
 - only has <u>one</u> bomb
 - has to choose carefully where to use it...

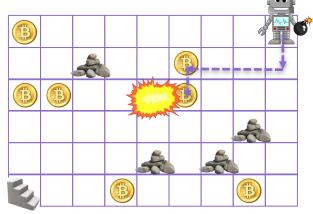


> Problem: Given an n x m grid where squares have rocks or <u>bitcoins</u>, find a path for the robot to get from (n,m) to the exit at (1,1), where the robot only has to move down or left or blast down or blast left (*one time only*), maximizing the coins found.

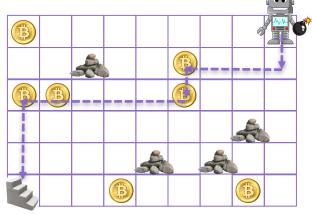




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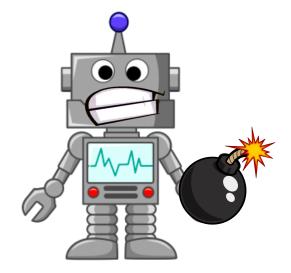


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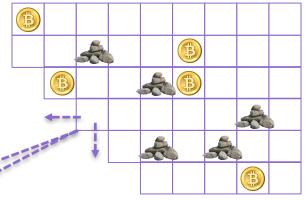
- > **Q**: What are the sub-problems?
- > A: Choice of starting point & whether he still has bomb
- > Can compute this using two tables:
 - one for opt solution with no bomb (saw before)
 - one for opt solution with one bomb left
 - > opt at (i,j) with bomb = max(opt at (i-1,j) with bomb, opt at (i,j-1) with bomb, opt at (i-1,j) using bomb, opt at (i,j-1) using bomb)
 - > opt at (i,j) using bomb = formula for opt at (i,j) without bomb ignoring rocks there



- > **Q**: What are the sub-problems?
- > A: Choice of starting point & whether he still has bomb

BUT re-compute from down & left ignoring any rock here (still O(1) time to compute)

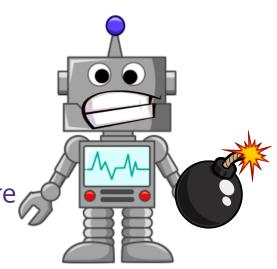
2	2	2	2	2	3	3	3	3
1	2	0	2	2	3	3	3	3
1	2	2	2-	-0-	2	-2	2	2
0	0*	0	1	-1-	1	1	0	2
0	0	0*	1	0	1	0	2	2
0	0	0	1	1	1	1	2	2



can move within one table or jump to the other table...



- > As in the example, it is often easy to accommodate small changes to problem
 - more so than greedy or divide & conquer
- > Only doubles the number of sub-problems here
 - you will see similar situations in future HWs



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Dyn Programming: Counting Solutions

> It is also possible to count solutions.

- > Instead of storing just opt achievable in A[i][j], store the opt achievable and the number of solutions achieving it
 - if left is better, then #opt solutions is #opt solutions from left
 - if down is better, then #opt solutions is #opt solutions from down
 - if both are equal, then #opt solutions is...
 (#opt solutions from left) + (#opt solutions from down)
- > Similar approach works for most DP algorithms



- > Previous algorithm computed <u>value</u> of optimal solution BUT what if we want the solution that is optimal?
- > Can get that from the table as well
 - walk from the end back to the beginning
 - follow along choices that achieve the max score

> Get optimal solution from table of optimal values...

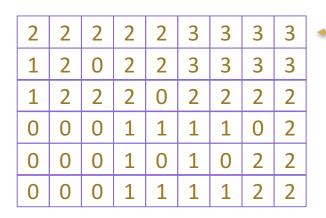


 Table says 3 is possible moving either down or right

Let's go down...

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> Get optimal solution from table of optimal values...

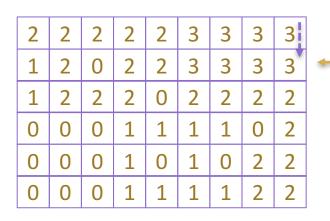
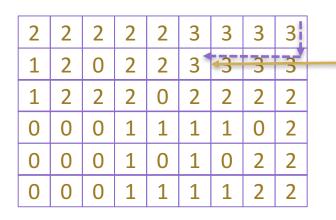


Table says we must go left to get 3...

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> Get optimal solution from table of optimal values...



Now neither solution achieves 3? What?

There's a coin at this spot! Pick it up and look for 2 more, not 3 more.



> Get optimal solution from table of optimal values...

2	2	2	2	2	3	3	3	3
1	2	0	2	2	3	3	3	3
1	2	2	2	0	2	2	2	2
0	0	0	1	1	1	1	0	2
0	0	0	1	0	1	0	2	2
0+	-0-	-0-	1	1	-1	1	2	2



- > Previous algorithm computed <u>value</u> of optimal solution BUT what if we want the solution that is optimal?
- > Can get that from the table as well
 - walk from the end back to the beginning
 - follow along choices that achieve the max score
- > Alternatively, keep track of how you got the value too
 - e.g., in robot, record if max was from down or left
 - requires extra space in the table

