

Introduction to Competitive Programming

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- › Dynamic programming
- › Non classical DP problems

Dynamic Programming

The most challenging problem-solving technique...

A tastes of DP

› UVa 11450 – Wedding shopping

- Given $1 \leq C \leq 20$ classes of garments
 - › e.g. shirt, belt, shoe
- Given $1 \leq K \leq 20$ different models for each class of garment
 - › three shirts, two belts, four shoes, ..., each with its own price
- Task: Buy **just one** model of **each class** of garment
- Our budget $1 \leq M \leq 200$ is limited
 - › We cannot spend more money than it.
 - › But we want to spend the maximum possible.
- What is our maximum possible spending?
- Output “no solution” if this is impossible.

Demonstration

- › Budget $M=100$
- › $C=3, K=3$
 - Best solution is 75.

Model Garment	0	1	2	3
0	8	6	4	
1	5	10		
2	1	3	3	7
C=3	50	14	23	8

Demonstration

- › Budget $M=20$
- › $C=2, K=3$
 - Best solution is 19.
 - › Alternative answers are possible!
- › Budget $M=5$
 - No Solution!

Model Garment	0	1	2	3
0	4	6	8	
1	5	10		
2	1	3	5	5

Model Garment	0	1	2	3
0	6	4	8	
1	10	6		
2	7	3	1	7

Greedy solution?

- › What if we buy the most expensive model for each garment which still fits our budget?
- › Counter example:
 - $M=12$
 - Greedy algorithm produces: No solution! (uh oh~)
 - The correct answer is 12!
 - › More than one answer is present.

Model Garment	0	1	2	3
0	6	4	8	
1	<input data-bbox="749 1133 823 1188" type="text" value="?"/>	5	10	
2	1	5	3	5

Complete search

- › What is the potential **state** of the problem?
 - g (which garment?)
 - id (which model?)
 - $money$ (money left?)
- › Answer:
 - $(money, g)$ or $(g, money)$
- › Recurrence (recursive backtracking function):

`shop(money, g)`

`if (money < 0) return -INF`

`if (g == C) return M - money`

`return max(shop(money - price[g][model], g + 1),`

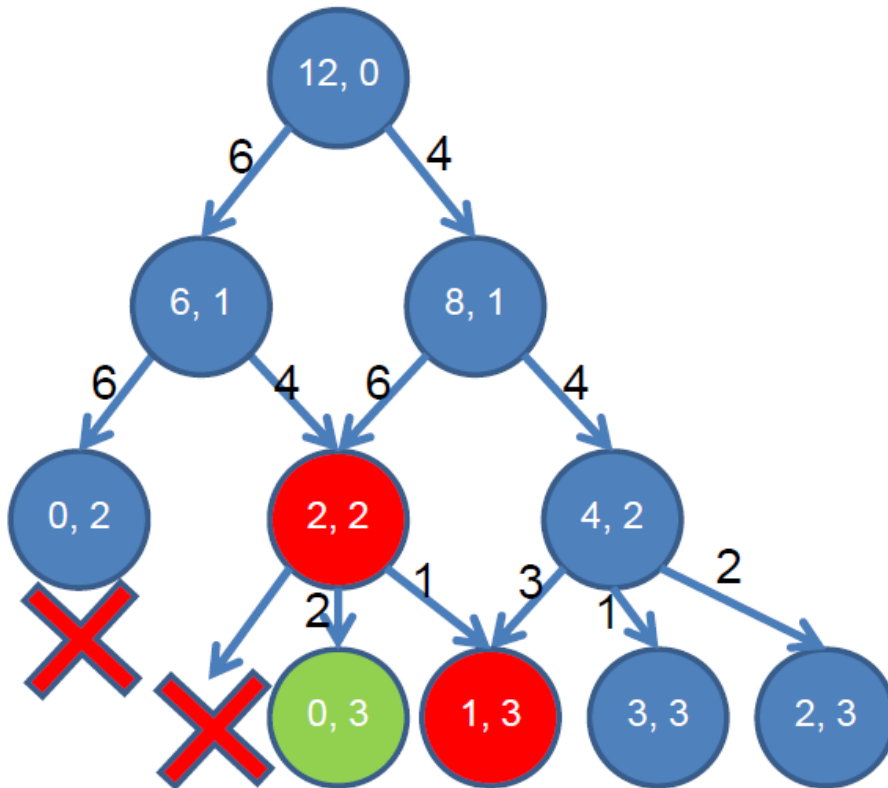
`∀model ∈ [1..K]`

Complete search

- › Extreme analysis when $M = 200$, 20 models, and 20 garments.
 - Time complexity is 20^{20} (3 second TLE!)

Overlapping sub problems

- › Observe the 20^{20} search space, you can find **many overlapping sub problems**.
 - Many routes lead to the same state.



Model Garment	0	1	2
0	6	4	
1	4	6	
2	1	2	3

Dynamic programming

- › DP = Dynamic Programming
 - Programming here is not writing computer code, but a “**tabular method**”!
 - › **Table** method
- › **A programming paradigm that you must know!**
 - and hopefully, master...

Dynamic programming

- › Use DP when the problem exhibits:
 - Optimal sub structure.
 - › Optimal solution to the original problem contains optimal solution to sub problems.
 - This is **similar** as the requirement of **Greedy algorithm**
 - If you can formulate complete search recurrences, you can solve it.
 - Overlapping sub problems:
 - › Number of **distinct sub problems** are actually “small”.
 - › But they are **repeatedly computed**.
 - › This is **different** from **Divide and Conquer**.

Dynamic programming

- › There are two ways to implement DP:
 - Top-Down.
 - Bottom-Up.
- › Top-Down (Demo):
 - Recursion as per normal + **memoization table**
 - › It is just a simple change from backtracking (complete search) solution!

Turn recursion into memoization

Initialize memo table in main function (use 'memset')

```
return_value recursion(params/state) {  
    if this state is already calculated,  
        simply return the result from the memo table  
    calculate the result using recursion(other_params/states)  
    save the result of this state in the memo table  
    return the result  
}
```

Dynamic programming (Top-Down)

› For our example:

```
shop(money, g)
```

```
  if (money < 0) return -INF
```

```
  if (g == C) return M - money
```

```
  if (memo[money][g] != -1) return memo[money][g];
```

```
  return memo[money][g] = max(shop(money -  
    price[g][model], g + 1),  $\forall$  model  $\in$  [1..K])
```

What if optimal solution(s) are needed

```
print_shop(money, g)
    if (money < 0 || g == C) return
    for each model  $\in$  [1..K]
        if shop(money - price[g][model], g + 1) ==
            memo[money][g]
            print "take model = " + model +
                " for garment g = " + g
            print_shop(money - price[g][model], g + 1)
            break
```


Dynamic programming (Bottom-Up)

- › Another way: Bottom-Up:
 - Prepare a table that has size equals to the number of distinct states of the problem.
 - Start to fill in the table with base case values.
 - Get **the topological order** in which the table is filled
 - › Some topological orders are natural and can be written with just (nested) loops!
 - Different way of thinking compared to Top-Down DP
- › Notice that both DP variants use “table”!

Dynamic programming (Bottom-Up)

- › Start with with table **can_reach** of size $20(g) * 201(\text{money})$
 - The state (money, g) is reversed to (g, money) so that we can process bottom-up DP loops in row major fashion.
 - Initialize all entries to 0 (false).
 - Fill in the first row with money left (column) reachable after buying models from the first garment ($g = 0$)
 - Use the information of current row g to update the values at the next row $g + 1$.

Dynamic programming (Bottom-Up)

		Money																				
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
gg	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0
	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Model Garment	0	1	2	3
0	4	6	8	
1	5	10		
2	1	3	5	5

Dynamic programming (Bottom-Up)

		Money																				
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
bg	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0
	1	0	0	1	0	1	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Model Garment	0	1	2	3
0	4	6	8	
1	5	10		
2	1	3	5	5

Dynamic programming (Bottom-Up)

		Money																				
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
bg	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0
	1	0	0	1	0	1	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
	2	0	1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0

Red arrows indicate dependencies from row 1 to row 2 and from row 0 to row 1:

- Row 1, Col 3 → Row 2, Col 2
- Row 1, Col 5 → Row 2, Col 4
- Row 1, Col 6 → Row 2, Col 5
- Row 1, Col 7 → Row 2, Col 6
- Row 1, Col 8 → Row 2, Col 7
- Row 1, Col 9 → Row 2, Col 8
- Row 1, Col 10 → Row 2, Col 9
- Row 1, Col 11 → Row 2, Col 10
- Row 1, Col 12 → Row 2, Col 11
- Row 1, Col 13 → Row 2, Col 12
- Row 1, Col 14 → Row 2, Col 13
- Row 1, Col 15 → Row 2, Col 14
- Row 1, Col 16 → Row 2, Col 15
- Row 1, Col 17 → Row 2, Col 16
- Row 1, Col 18 → Row 2, Col 17
- Row 1, Col 19 → Row 2, Col 18
- Row 1, Col 20 → Row 2, Col 19
- Row 0, Col 12 → Row 1, Col 11
- Row 0, Col 14 → Row 1, Col 13
- Row 0, Col 16 → Row 1, Col 15
- Row 0, Col 18 → Row 1, Col 17
- Row 0, Col 20 → Row 1, Col 19

Model Garment	0	1	2	3
0	4	6	8	
1	5	10		
2	1	3	5	5

Top-down or Bottom-up?

› Top-down

- Pro:
 - › Natural transformation from normal recursion.
 - › Only compute sub problems when necessary.
- Cons:
 - › Slower if there are many sub problems due to recursive call overhead.
 - › Use exactly $O(\text{states})$ tables size. (Could cause MLE)

› Bottom-up

- Pro:
 - › Faster if many sub problems are visited: no recursive calls!
 - › Can save memory space (?)
- Cons:
 - › Maybe not intuitive for those inclined to recursion.
 - › If there are X states, bottom up visits/fills the value of all these X states.

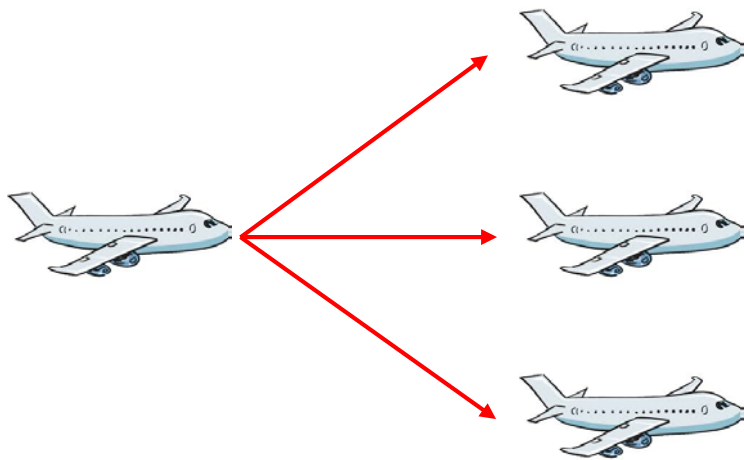
Solving UVa 10337 – Flight planner

- › UVa 10337 – Flight planner
 - Unit: 1 mile altitude and 1 (x100) miles distance.
 - Given wind speed map.
 - Fuel cost: {Climb: +60, Hold: +30, Sink: +20} – wind speed $wsp[alt][dis]$.
 - Compute min fuel cost from (0,0) to (0,x = 4)!

Solving UVa 10337 – Flight planner

› Wind table:

- Tailwind: -1 unit of fuel.
- Headwind: +1 unit of fuel.



1	1	1	1	1	9
1	1	1	1	1	8
1	1	1	1	1	7
1	1	1	1	1	6
1	1	1	1	1	5
1	1	1	1	1	4
1	1	1	1	1	3
1	1	1	1	1	2
1	9	9	1	1	1
1	-9	-9	1	1	0
0	1	2	3	4	(x100)

Of course, level 1

- › First guess:
 - Do complete search/brute force/**backtracking**
 - Find *all possible* flight paths and pick the one that yield the minimum fuel cost!

Complete search

› Recurrence of the Complete Search

- **fuel** (al t, di s) =
 $\min(60 - \text{wsp}[\text{al t}][\text{di s}] + \text{fuel}(\text{al t} + 1, \text{di s} + 1),$
 $30 - \text{wsp}[\text{al t}][\text{di s}] + \text{fuel}(\text{al t}, \text{di s} + 1),$
 $20 - \text{wsp}[\text{al t}][\text{di s}] + \text{fuel}(\text{al t} - 1, \text{di s} + 1))$
- Stop when we reach final state (base case):
 - › al t=0 and di s=X, i.e. **fuel** (0, X) =0
- Prune infeasible states (also base cases):
 - › al t<0 or al t>9 or di s>X!, i.e. return INF*

› Answer of the problem is **fuel** (0, 0) .

Complete Search Solutions

SOLUTION 1

1	1	1	1		9
1	1	1	1		8
1	1	1	1		7
1	1	1	1		6
1	1	1	1		5
1	1	1	1		4
1	1	1	1		3
1	1	1	1		2
1	9	9	1		1
1	→ -9	→ -9	→ 1	→	0
0	1	2	3	4	(x100)

$$29 + 39 + 39 + 29 = \mathbf{136}$$

SOLUTION 2

1	1	1	1		9
1	1	1	1		8
1	1	1	1		7
1	1	1	1		6
1	1	1	1		5
1	1	1	1		4
1	1	1	1		3
1	1	1	1		2
1	9	9	1		1
1	→ -9	→ -9	↗ 1 ↘		0
0	1	2	3	4	(x100)

$$29 + 39 + 69 + 19 = \mathbf{156}$$

Complete Search Solutions

SOLUTION 3

1	1	1	1		9
1	1	1	1		8
1	1	1	1		7
1	1	1	1		6
1	1	1	1		5
1	1	1	1		4
1	1	1	1		3
1	1	1	1		2
1	9	9	1		1
1	→ -9	→ -9	→ 1	→	0
0	1	2	3	4	(x100)

$$29+69+11+29=\mathbf{138}$$

SOLUTION 4

1	1	1	1		9
1	1	1	1		8
1	1	1	1		7
1	1	1	1		6
1	1	1	1		5
1	1	1	1		4
1	1	1	1		3
1	1	1	1		2
1	9	9	1		1
1	→ -9	→ -9	→ 1	→	0
0	1	2	3	4	(x100)

$$59+11+39+29=\mathbf{138}$$

Complete Search Solutions

SOLUTION 5

1	1	1	1		9
1	1	1	1		8
1	1	1	1		7
1	1	1	1		6
1	1	1	1		5
1	1	1	1		4
1	1	1	1		3
1	1	1	1		2
1	9	9	1		1
1	-9	-9	1		0
0	1	2	3	4	(x100)

$$29+69+21+19=138$$

SOLUTION 6

1	1	1	1		9
1	1	1	1		8
1	1	1	1		7
1	1	1	1		6
1	1	1	1		5
1	1	1	1		4
1	1	1	1		3
1	1	1	1		2
1	9	9	1		1
1	-9	-9	1		0
0	1	2	3	4	(x100)

$$59+21+11+29=120(\text{OPT})$$

Complete Search Solutions

SOLUTION 7

1	1	1	1		9
1	1	1	1		8
1	1	1	1		7
1	1	1	1		6
1	1	1	1		5
1	1	1	1		4
1	1	1	1		3
1	1	1	1		2
1	9	9	1		1
1	-9	-9	1		0
0	1	2	3	4	(x100)

$$59+21+21+19=\mathbf{120(OPT)}$$

SOLUTION 8

1	1	1	1		9
1	1	1	1		8
1	1	1	1		7
1	1	1	1		6
1	1	1	1		5
1	1	1	1		4
1	1	1	1		3
1	1	1	1		2
1	9	9	1		1
1	-9	-9	1		0
0	1	2	3	4	(x100)

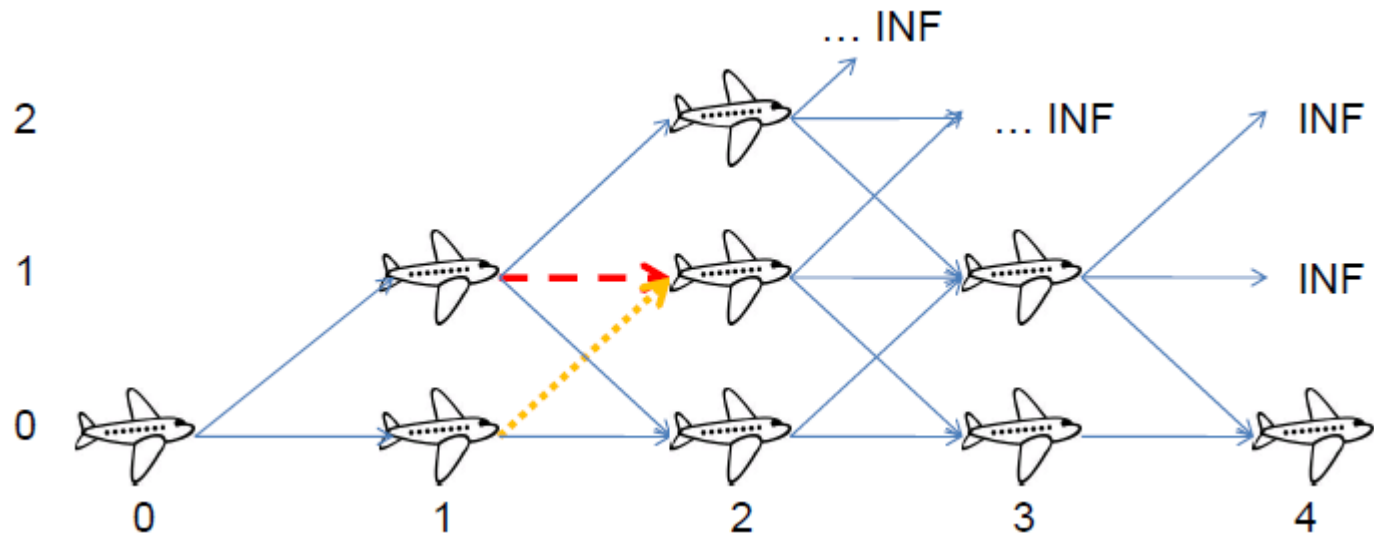
$$59+51+19+19=\mathbf{148}$$

Complete search

- › How large is the search space?
 - Max distance is 100,000 miles.
 - Each distance step is 100 miles.
 - That means we have **1,000** distance columns!
 - › Note: this is an example of “**coordinate compression**”
 - Branching factor per step is 3... (climb, hold, sink).
 - That means complete search can end up performing 3^{1000} operation.

Overlapping sub problem issue

- › In simple 3^{1000} Complete Search solution, you should have observe **many overlapping sub problems!**
 - Many ways to reach coordinate (alt, dis).



DP solution

› Recurrence of the Complete Search

$$\begin{aligned} - \text{fuel}(\text{alt}, \text{dis}) = \\ \min(60 - \text{wsp}[\text{alt}][\text{dis}] + \text{fuel}(\text{alt} + 1, \text{dis} + 1), \\ 30 - \text{wsp}[\text{alt}][\text{dis}] + \text{fuel}(\text{alt}, \text{dis} + 1), \\ 20 - \text{wsp}[\text{alt}][\text{dis}] + \text{fuel}(\text{alt} - 1, \text{dis} + 1)) \end{aligned}$$

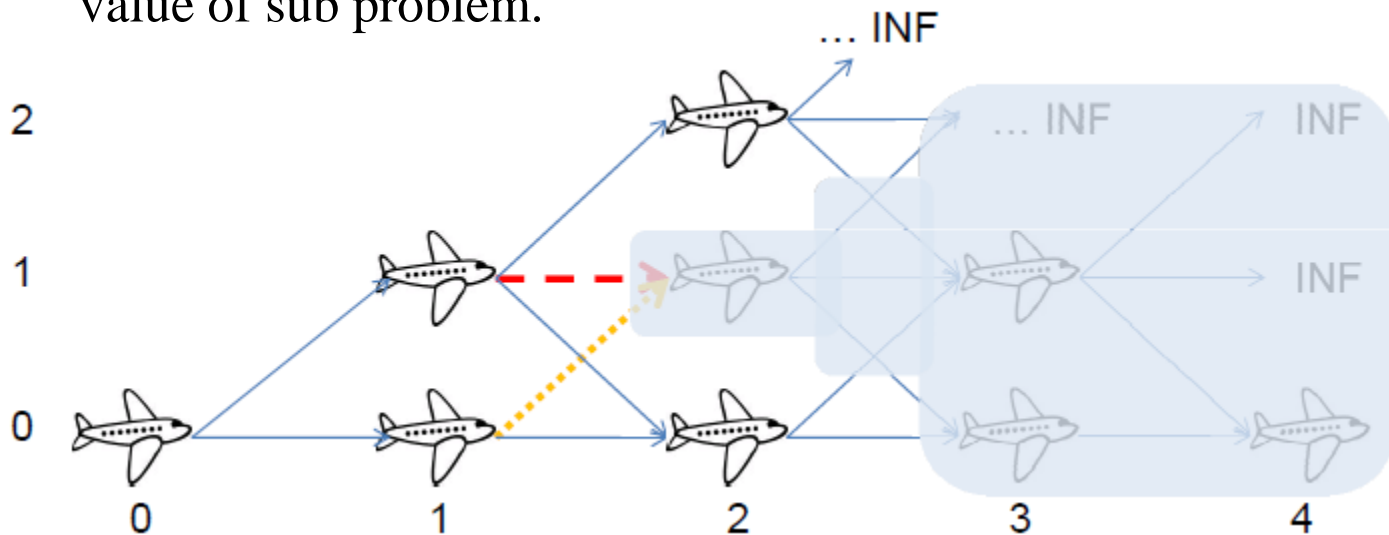
› Sub-problem fuel(alt, dis) can be **overlapping!**

- There are only 10 alt and 1,000 dis = **10,000** states
- A lot of time saved if these are not re-computed!
- Exponential 3^{1000} to polynomial 10×1000 !

DP solution (Top-down)

- › Create a 2-D table of size $10 \times (\frac{X}{100})$.
 - Save spaces.
 - Set “-1” for unexplored sub problems (**memset**)
 - Store the computation value of sub problem.

2	-1	-1	-1	∞	∞
1	-1	-1	40	19	∞
0	-1	-1	-1	29	0
	0	1	2	3	4



DP solution (Bottom-up)

- › Memory saving tip:
 - Reduce the 2 dimensional array by keeping 2 recent columns.
 - Time complexity unchanged!

2	∞	∞			
1	∞	59			
0	0	29			
	0	1	2	3	4

2	∞	∞	110		
1	∞	59	80		
0	0	29	68		
	0	1	2	3	4

2	∞	∞	110	131	
1	∞	59	80	101	
0	0	29	68	91	
	0	1	2	3	4

2	∞	∞	110	131	-
1	∞	59	80	101	-
0	0	29	68	91	120
	0	1	2	3	4

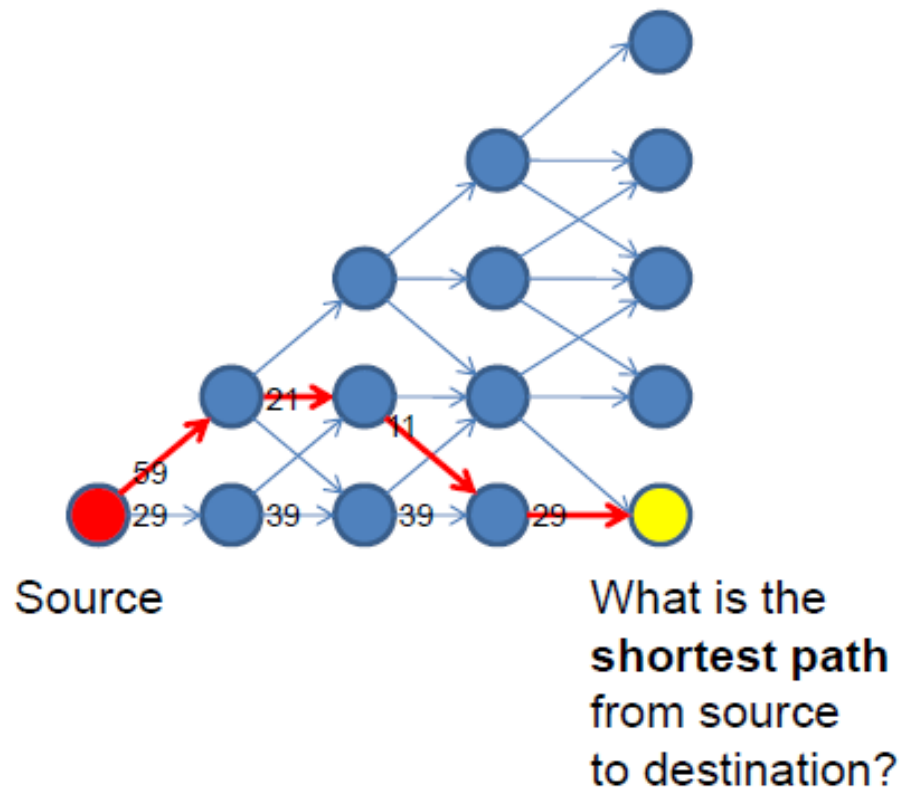
If optimal solution(s) are needed

- › Although not often, sometimes this is asked!
- › As we build the DP table, record which option is taken in each cell!
 - Usually, this information is stored in different table.
 - Do recursive scan(s) to output solution.
 - › Sometimes, there are more than one solutions!

Remodel the problem

- › Shortest path problem!
 - Model the problem as a **DAG**.
 - Vertex is each position in the unit map.
 - Edges connect vertices reachable from vertex $(a_l t, d_i s)$, i.e. $(a_l t+1, d_i s+1)$, $(a_l t, d_i s+1)$, $(a_l t-1, d_i s)$
 - › Weighted according to flight action and wind speed!
 - › Do not connect infeasible vertices.
 - $a_l t < 0$ or $a_l t > 9$ or $d_i s > X$

Visualization of the DAG



Shortest path problem

- › The problem: find the **shortest path** from vertex $(0, 0)$ to vertex $(0, X)$ on this DAG...
- › $O(V + E)$ solution exists!
 - V is just $10 \times \left(\frac{X}{100}\right)$
 - E is just $3V$.
- › Thus this solution is as good as the DP solution!

Non classical dynamic programming problems

Oh man...

Non classical DP problems

- › Not the pure form (or simple variant) of 1D/2D Max Sum, LIS, 0-1 Knapsack/Subset Sum, Coin Change, TSP where the DP **states** and **transitions** can be “memorized”.
- › Requires **original* formulation** of DP states and transitions.
- › Throughout this lecture, we will talk mostly in *DP terms*
 - **State** (to be precise: “*distinct* state”)
 - **Space Complexity** (i.e. the number of distinct states)
 - **Transition** (which entail overlapping sub problems)
 - **Time Complexity** (i.e. num of distinct states * time to fill one state)

The Cutting sticks problem

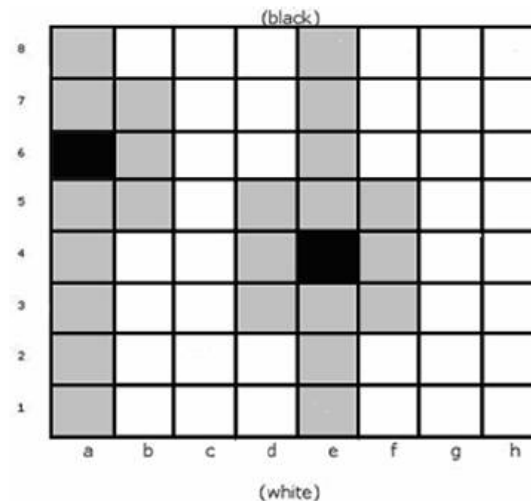
- › UVa 10003 – Cutting sticks
- › State: index (l, r) where $l, r \in [0..n + 1]$ and $l < r$
 - Q: Why these two parameters?
- › Space Complexity: $O(n^2)$ distinct states
- › Transition: Try all possible cutting points i between l and r .
 - i.e. cut (l, r) into (l, i) and (i, r) with cost $(A[r] - A[l])$
- › Time Complexity: There are $O(n)$ possible cutting points, thus overall $O(n^2 \times n) = O(n^3)$

DP on DAG

- › Dynamic Programming (DP) has a close relationship with (usually implicit) Directed Acyclic Graph (DAG).
 - The **states** are the **vertices** of the DAG.
 - Space complexity: Number of vertices of the DAG.
 - The **transitions** are the **edges** of the DAG.
 - › Logical, since a recurrence is always **acyclic**.
 - Time complexity: Number of edges of the DAG.
 - Top-down DP: Process each vertex just once via **memorization**.
 - Bottom-up DP: Process the vertices in **topological order**.
 - › Sometimes, the topological order can be written by just using simple (nested) loops.

The injured queen problem

- › Like N -queens problem, but the queens are “injured” (can only attack the current column but acts as king otherwise)
- › With some of K ($0 \leq K \leq N$) injured queens positions have been predetermined, count how many possible arrangements of the other $(N - K)$ queens so that no two queens attack each other?



DP on math problems

- › Some well-known mathematic problems involves DP.
 - Some combinatorics problem have recursive formulas which entail overlapping subproblems.
 - › e.g. those involving Fibonacci number, $f(n) = f(n - 1) + f(n - 2)$.
 - Some probability problems require us to search the entire search space to get the required answer.
 - › If some of the sub problems are overlapping, use DP, otherwise, use complete search.
 - Mathematics problems involving **static** range sum/min/max!
 - › Use dynamic tree DS for dynamic queries.

Dice throwing problem

- › Throw N common 6-sided dice. ($1 \leq N \leq 24$)
- › What is the probability that the sum of all thrown dices is at least x ? ($0 \leq x \leq 150$)
- › Basic probability = $\frac{\text{\#Events}}{\text{Sample space}}$
 - Sample space = 6^n
 - How to compute #Events?

Dynamic programming issues

- › Potential issues with DP problems:
 - They may be disguised as (or looks like) non DP
 - › It looks like greedy can work but some cases fails...
 - problem looks like a shortest path with some constraints on graph, but the constraints fail *greedy* SSSP algorithm!
 - They may have subproblems but not overlapping
 - › DP does not work if overlapping subproblems not exist
 - Anyway, this is still a good news as perhaps Divide and Conquer technique can be applied.

Dynamic programming issues

- Optimal substructures may not be obvious.
 - › Find correct “states” that describe problem.
 - Perhaps extra parameters must be introduced?
 - › Reduce a problem to (smaller) sub problems (with the same states) until we reach base cases
- There can be more than one possible formulation.
 - › Pick the one that works!

DP problems in ICPC

- › The number of problems in ICPC that must be solved using DP are growing!
 - At least one, likely two, maybe three per contest...
- › These new problems are **not** the classical DP!
 - They require deep thinking...
 - Or those that look solvable using other (simpler) algorithms but actually must be solved using DP.
 - Do not think that you have “mastered” DP by only memorizing the classical DP solutions!

DP problems in ICPC

- › In 1990ies, mastering DP can make you “king” of programming contests...
 - Today, it is a must-have knowledge...
 - So, get familiar with DP techniques!
- › By mastering DP, your ICPC rank is probably:
 - from top \sim [25-30] (solving 1-2 problems out of 10)
 - › Only easy problems.
 - to top \sim [15-20] (solving 3-4 problems out of 10)
 - › Easy problems + brute force + DP problems.

Be a problem setter

One who sets a trap should know how to disarm one...

Be a problem setter

› Problem solver:

- Read the problem.
- Think of a good algorithm.
- Create a solution.
- Create tricky I/O test case.
- WA/TLE: debug!
- AC!

› Problem setter:

- Write a **good** problem.
- Write a **good** solution.
 - › The correct/best one.
 - › The incorrect/slower ones.
- Set a good I/O test case.
- Set problem setting (mem/time).

› A problem setter must think from a different angle!

- By setting good problems, you will simultaneously be a better problem solver!

Problem setter tasks

- › Write a good problem:
 - Options:
 - › Pick an algorithm, then find problem/story or
 - › Find a problem/story, then identify a good algorithm for it (**hard**).
 - Problem description must not be ambiguous.
 - › Specify input constraints.
 - › English!
 - › Easy one: longer story.
 - › Hard one: shorter story.
- › Write good solutions:
 - **Must be able to solve your own problem!**
 - › To set hard problem, one must increase his own programming skill!
 - Use the **best** possible algorithm with lowest time complexity (or memory complexity).
 - › Use the inferior ones that barely works to set the WA/TLE/MLE parameters.

Problem setter tasks

- › Set a good secret I/O:
 - Tricky test case to check WA verses AC.
 - › Boundary cases!
 - Large test case to check TLE/MLE verses AC.
 - › Use input generator to generate large test case.
 - › Pass this large test case to our solution.
- › Set problem settings:
 - Time limit:
 - › Usually 2~3 times the timings of your own best solutions.
 - › Java is slower than C++!
 - Memory Limit.
 - Problem Name:
 - › Avoid revealing the algorithm in the problem name.

Be a contest organizer

- › Contest organizer tasks:
 - Set problems of *various* topic.
 - › Better set by >1 problem setter.
 - Must balance the difficulty of the problem set
 - › Try to make it fun.
 - › Each team solves some problems.
 - › Each problem is solved by some teams.
 - › No team solve all problems.
 - › Every teams must work until the end of contest.