



# **The Soul of Dynamic Programming Formulations and Implementations**

Bowen Yu

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Special Topic for Algorithmic Problem Solving



## What is DP all about

- Advanced technique? 😊
- Transition Function
- Memoization



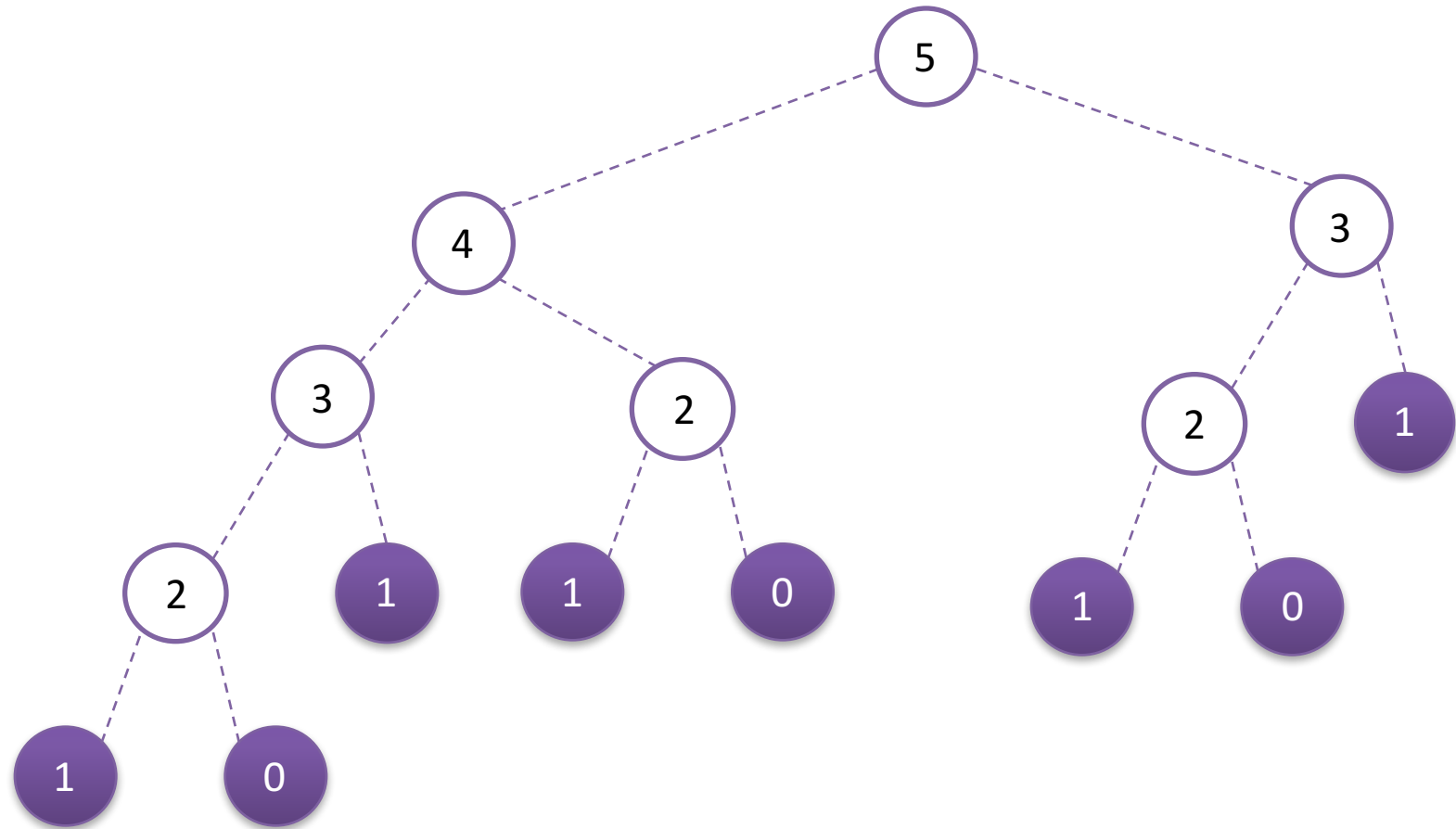
# An example that everyone uses

- Calculate the Fibonacci numbers
- $F(i) = F(i-1) + F(i-2)$

```
30 int fib(int i) {  
31     if (i <= 1) return i;  
32     return fib(i - 1) + fib(i - 2);  
33 }
```



# We know this is slow





# Optimization?

- No need to compute a same value more than once

```
30  int memo[MAXN];  
31  □ int fib(int i) {  
32      if (memo[i] != -1) return memo[i];  
33      if (i <= 1) return memo[i] = i;  
34      return memo[i] = fib(i - 1) + fib(i - 2);  
35  }
```



- Why the -1's?

```
30  int fib[MAXN];
31  void allFibs() {
32      fib[0] = 0;
33      fib[1] = 1;
34      for (int i = 2; i < MAXN; i++) {
35          fib[i] = fib[i - 1] + fib[i - 2];
36      }
37  }
```



# So-called top-down and bottom-up

- Top-down:

- Derive the DP entry dependencies
- Memoize and compute recursively

```
30 int memo[MAXN];
31 int fib(int i) {
32     if (memo[i] != -1) return memo[i];
33     if (i <= 1) return memo[i] = i;
34     return memo[i] = fib(i - 1) + fib(i - 2);
35 }
```

- Bottom-up:

- Compute values in specific order
- No memoization involved

```
30 int fib[MAXN];
31 void allFibs() {
32     fib[0] = 0;
33     fib[1] = 1;
34     for (int i = 2; i < MAXN; i++) {
35         fib[i] = fib[i - 1] + fib[i - 2];
36     }
37 }
```



## Two different DPs?

- Not really.
- They are actually the same computation, as they have exactly the same transitions  $F(i) = F(i-1) + F(i-2)$ .
- We need to get to the soul of DP to actually see them unified.





## Revisiting DP

- ***State*** – an entry of some value of your interest
- ***Transition*** – relations between the states
- ***Order*** – how states get computed

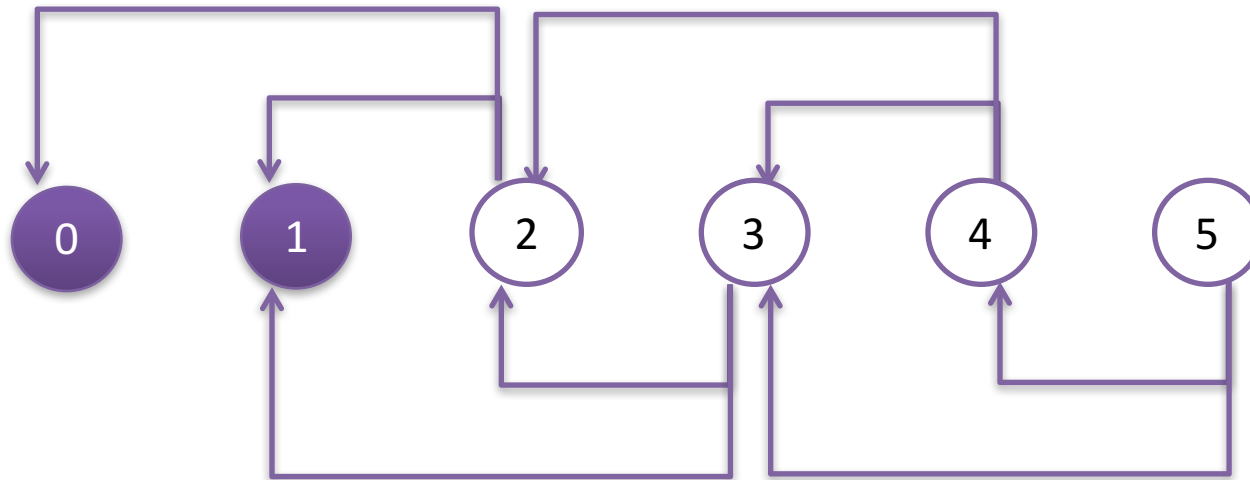


# Fibonacci Sequence

- **State**
  - $\text{Fib}(i)$
- **Transition**
  - $\text{Fib}(i) = \text{Fib}(i - 1) + \text{Fib}(i - 2)$
- **Order?**
  - We always have larger Fibs depending on smaller Fibs.
  - Therefore, we can compute smaller Fibs first before computing larger Fibs.



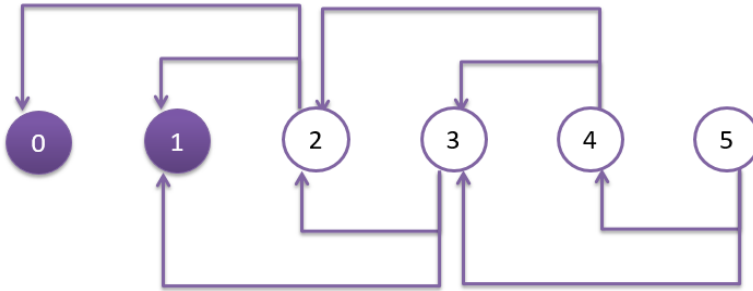
# Thinking on a graph



- This is a ***Directed Acyclic Graph (DAG)***



## How DAG works?



- We can always find a ***topological order*** of a DAG
- The states on the graph can be computed in this topo order, so that when a state is being computed, its dependencies would have already been computed before.
- A DP must have a corresponding DAG (most of the time implicit), otherwise we cannot find a valid order for computation.



# Counting Problem

- Given a set of **N distinct positive** integers:  $v_1, v_2, \dots, v_N$
- How many ways can we compose an **ordered list** with sum  $S$ , by choosing the values from the set?  
(Each value can be chosen multiple times)
- For the discussion purpose, today we:
  - assume all integers values in this lecture are reasonably small so that they fit well in the memory, e.g. in this case  $N \leq 20, v_i \leq 100$ .
  - ignore integer overflows, which are typically handled by modulo arithmetic

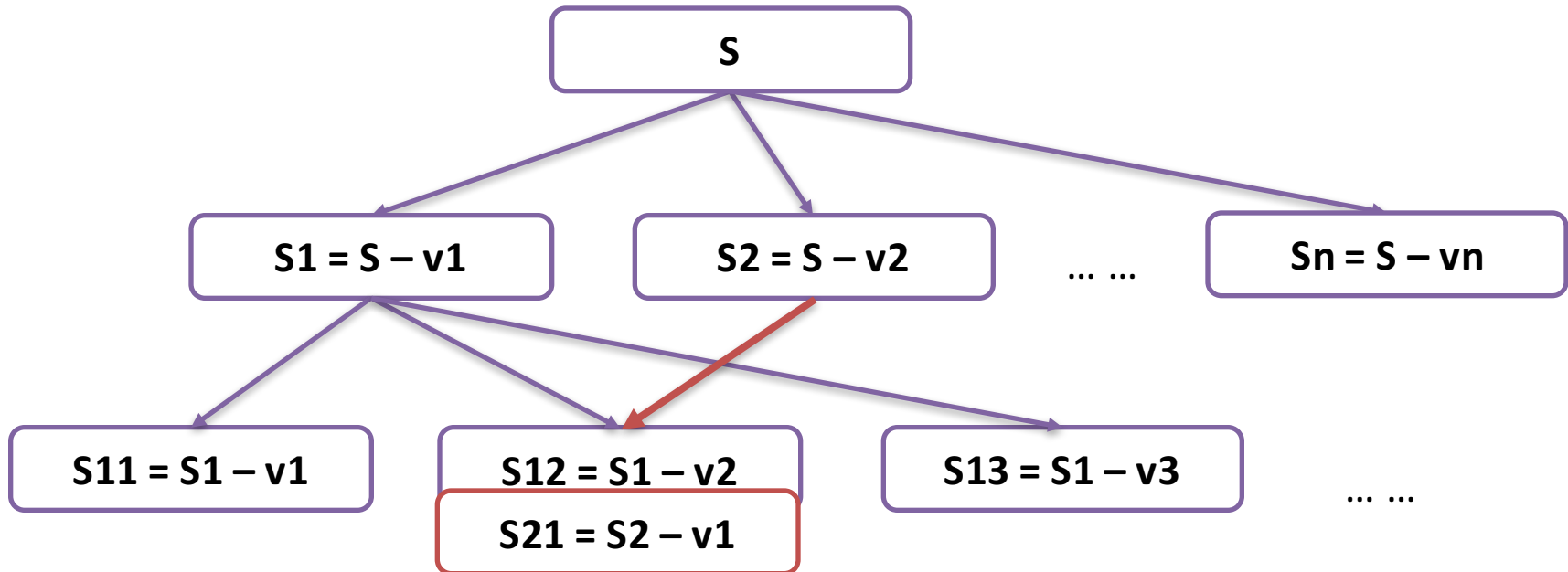


# Counting Problem

- **State**
  - $f(S)$ : the number of ways we can compose sum  $S$
- **Transition**
  - $f(s) = \sum_i f(s - v_i)$
- **Order**
  - In increasing  $S$

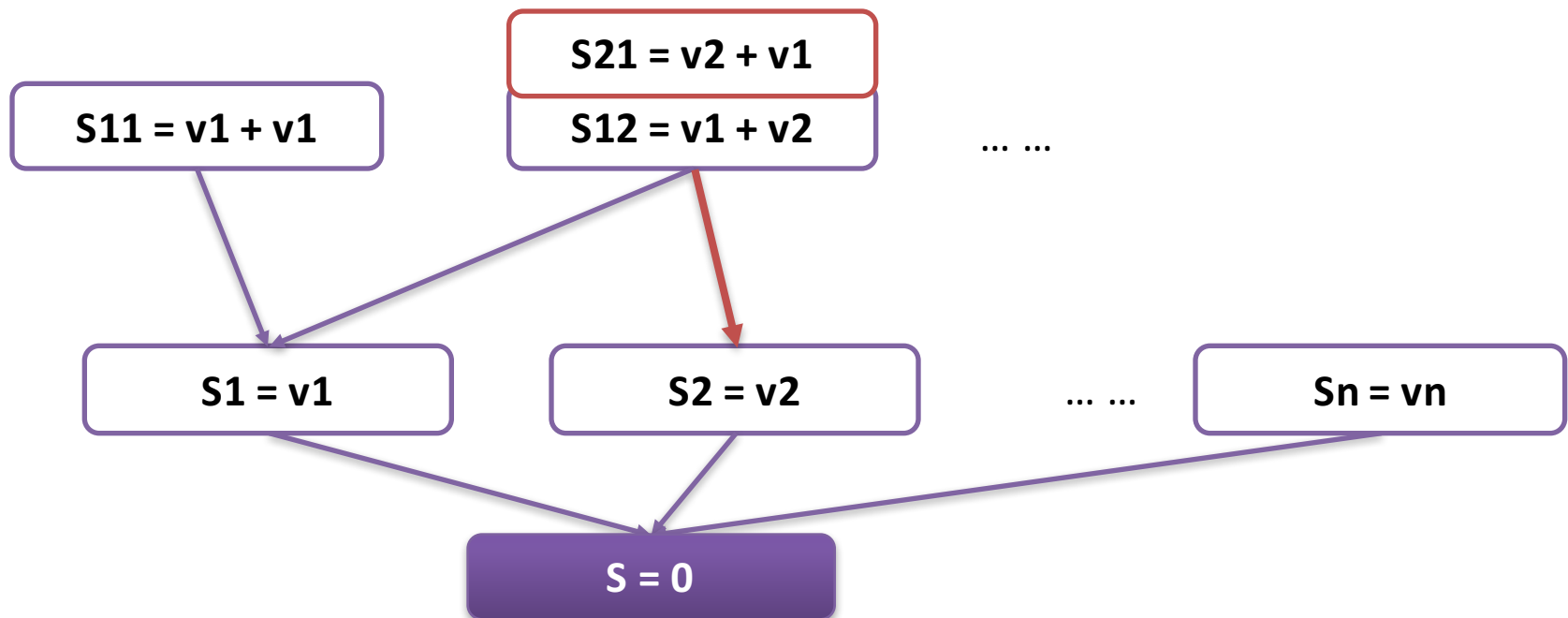


# Counting Problem – DAG (top)





# Counting Problem – DAG (bottom)







# Two implementations

- Top-down

```
30 int N, v[MAXN], dp[MAXS];
31 int count(int S) {
32     if (dp[S] != -1) return dp[S];
33     int ans = 0;
34     for (int i = 0; i < N; i++) {
35         if (S >= v[i]) ans += count(S - v[i]);
36     }
37     return dp[S] = ans;
38 }
```

- Bottom-up

```
30 int N, v[MAXN], dp[MAXS];
31 void count() {
32     dp[0] = 1;
33     for (int S = 1; S < MAXS; S++) {
34         for (int i = 0; i < N; i++) {
35             if (S >= v[i]) dp[S] += dp[S - v[i]];
36         }
37     }
38 }
```

Not much difference ☹



# Two topo-sort algorithms

\* Assuming the graph is DAG

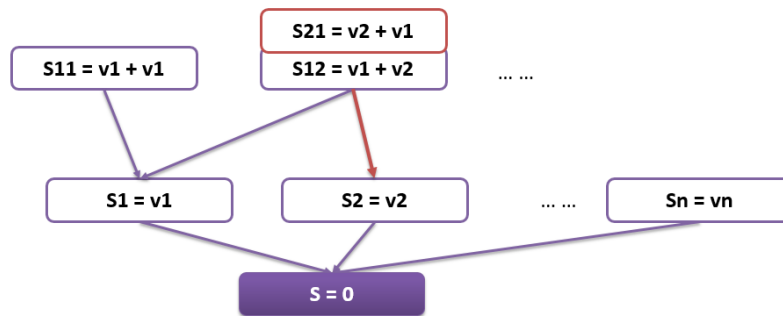
- Queue (Kahn's)
  - Add nodes with in-degree = 0 to the queue
  - Pop nodes out of the queue, decrement their neighbors' in-degrees. Add those new nodes with in-degree = 0 to the queue.
- DFS
  - The current node that completes its DFS has no more outgoing edges and therefore comes first in topo order.
  - Do DP computation in post-order traversal.



# Which one is better?

## Topo-sort and DP

- Use Kahn's algorithm for topo-order: bottom-up DP

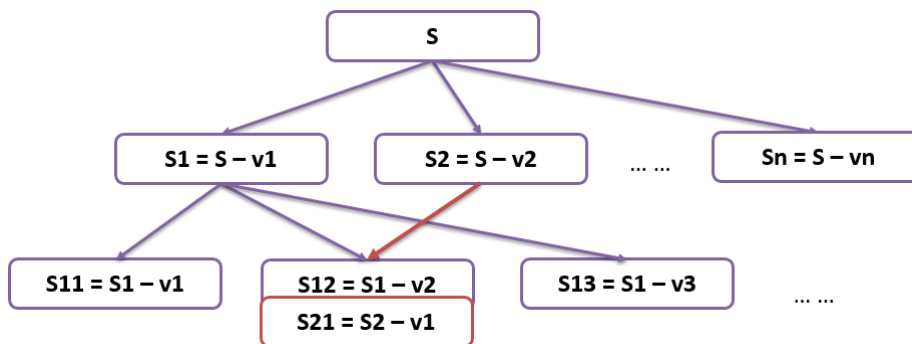


```

30 int N, v[MAXN], dp[MAXS];
31 void count() {
32     dp[0] = 1;
33     for (int S = 1; S < MAXS; S++) {
34         for (int i = 0; i < N; i++) {
35             if (S >= v[i]) dp[S] += dp[S - v[i]];
36         }
37     }
38 }

```

- Use DFS for topo-order: top-down DP



```

30 int N, v[MAXN], dp[MAXS];
31 int count(int S) {
32     if (dp[S] != -1) return dp[S];
33     int ans = 0;
34     for (int i = 0; i < N; i++) {
35         if (S >= v[i]) ans += count(S - v[i]);
36     }
37     return dp[S] = ans;
38 }

```



## Which one is better?

- It depends:
  - If the problem has a clear implicit topo-order (e.g. the Fibonacci Sequence, the counting problem), then bottom-up could be simpler to implement.
  - If the problem has a clear sub-dividing strategy, then top-down could be more intuitive.



# Cutting Sticks

- Given a stick of integer length  $L$ , cut it into multiple segments of integer lengths.
- You are given a list of (length, value) pairs. For every possible length there is an associated value.
- Your task is to maximize your total value after cutting.
- Example:

Length	Value
1	2
2	4
3	7
4	1

Answer with  $L = 4$  is 9.

Cut into 2 segments with lengths 1 and 3.

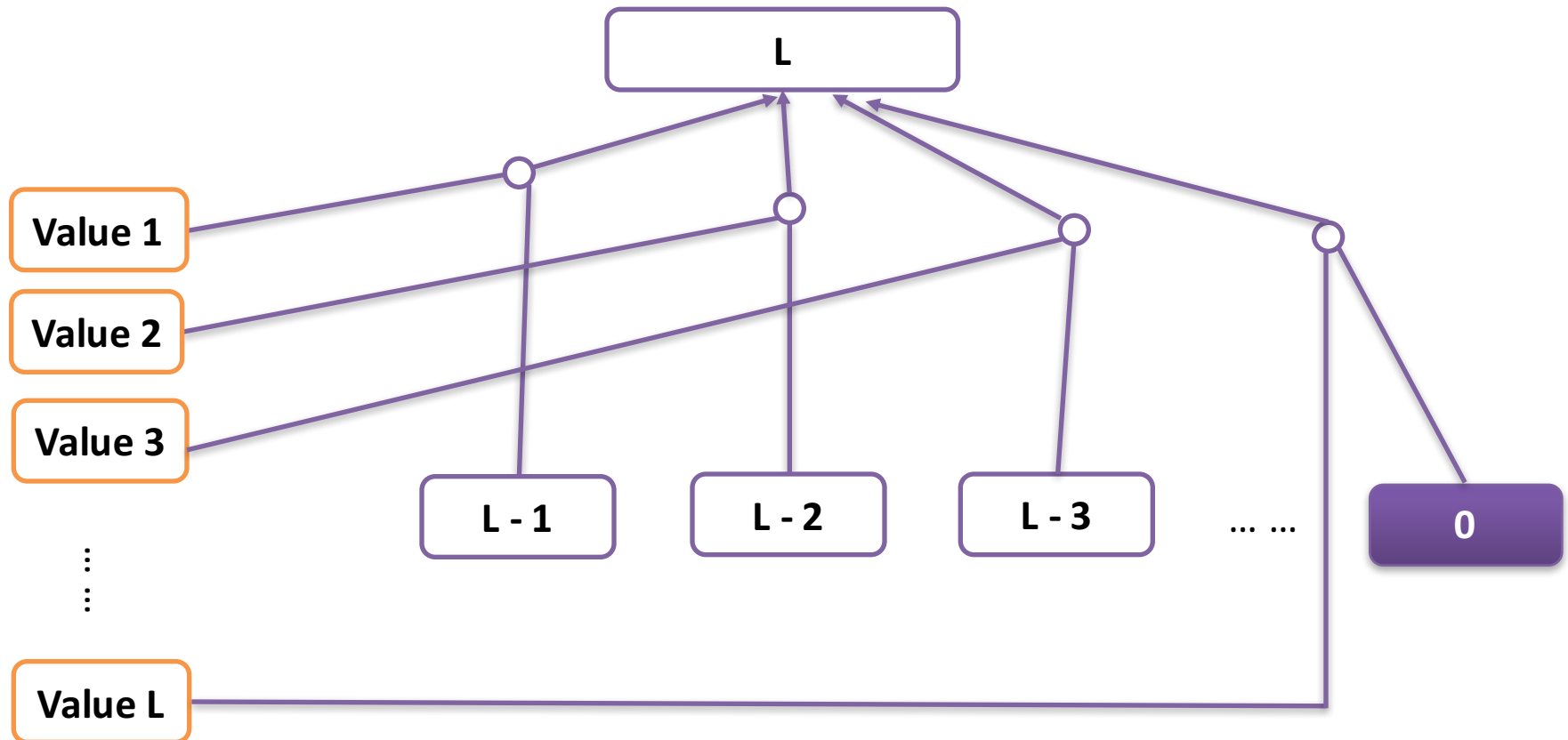


# Cutting Sticks

- **State**
  - $\text{Cut}(L)$ : maximum total value we can get for a stick of length  $L$
- **Transition**
  - $\text{cut}(L) = \max_i \{ \text{value}(i) + \text{cut}(L - i) \}$
- **Order**
  - Larger  $L$  depends on smaller  $L$ 's



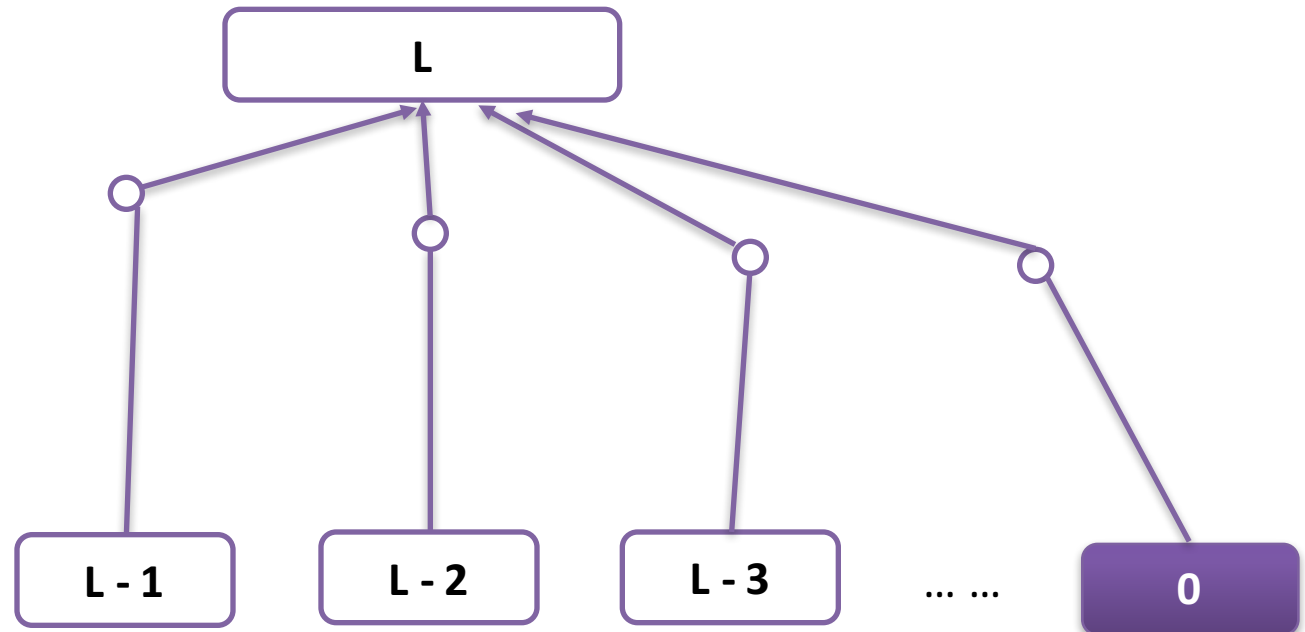
# Cutting Sticks – DAG (top)



\* Note that values are **NOT** states



## Cutting Sticks – DAG (top)



\* Note that values are **NOT** states





## Cutting sticks – top-down implementation

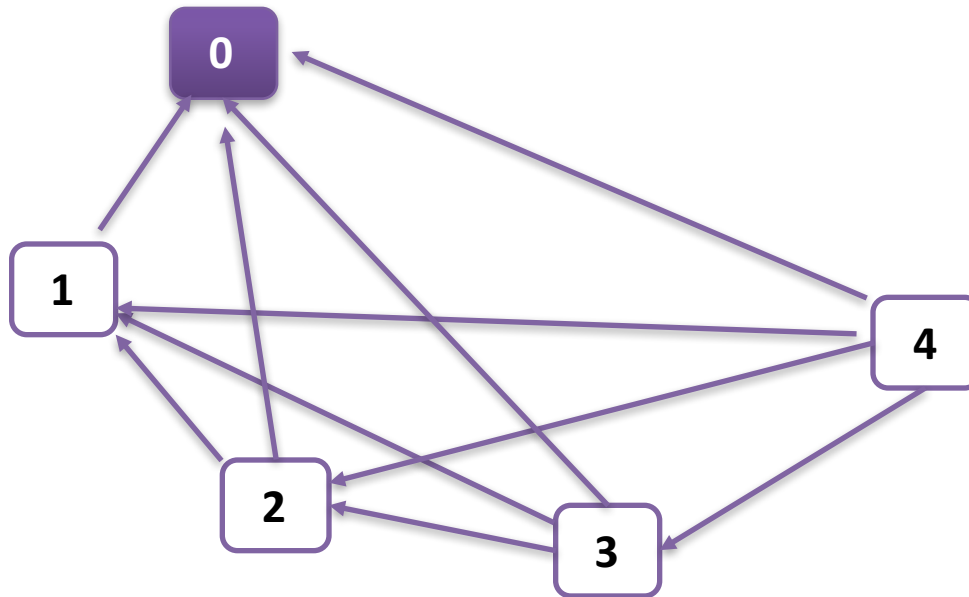
- Because of the action of cutting, it seems that using top-down is more intuitive.

```
30  int value[MAXN], dp[MAXN];
31  int cut(int L) {
32      if (dp[L] != -1) return dp[L];
33      if (L == 0) return dp[L] = 0;
34      int ans = 0;
35      for (int i = 1; i <= L; i++) {
36          ans = max(ans, value[i] + cut(L - i));
37      }
38      return dp[L] = ans;
39  }
```



# Cutting Sticks - DAG

- Actually the DAG is a complete DAG.





## Cutting sticks – bottom-up implementation

- So it could be intuitive too to compute bottom up 😊

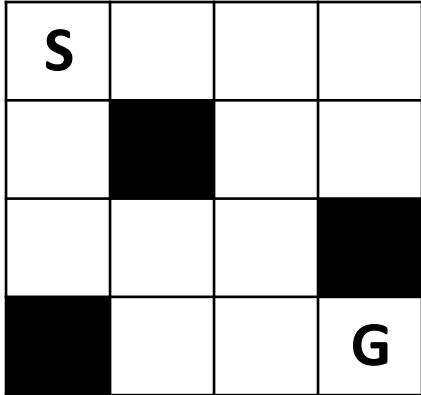
```
31  int value[MAXN], dp[MAXN];
32  void cut() {
33      dp[0] = 0;
34      for (int L = 1; L < MAXL; L++) {
35          for (int i = 1; i <= L; i++) {
36              dp[L] = max(dp[L], value[i] + dp[L - i]);
37          }
38      }
39  }
```

T



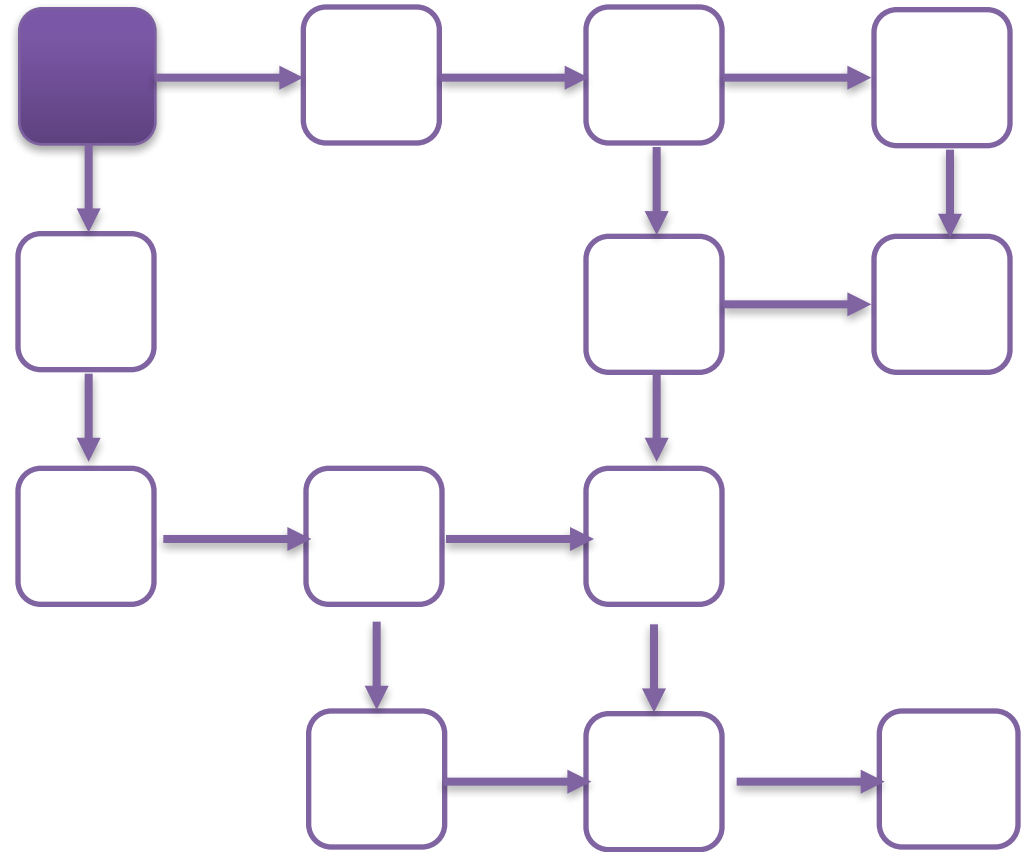
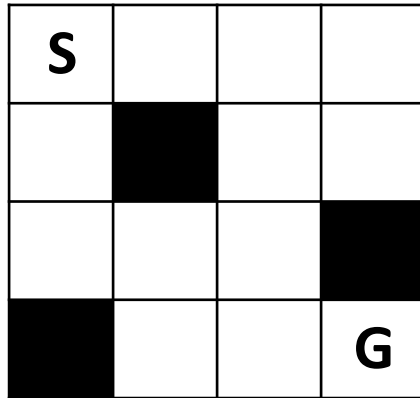
## Why DAG is important

- It helps you ***perceive*** the problem better.
- It helps you find the simplest way to ***implement*** the same DP algorithm.
- It helps you ***determine*** if a problem can be solved by DP.





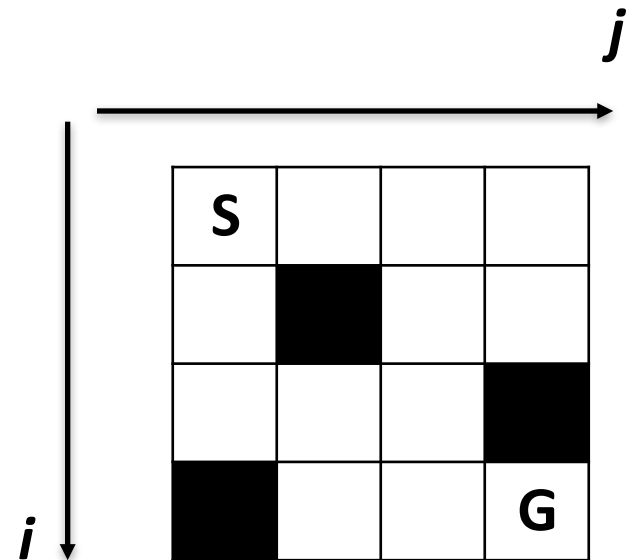
# Perceive – Grid Walking





## Perceive - Grid Walking (cont'd)

- **State**
  - $ways(i, j)$ : number of ways to reach cell  $(i, j)$  from the starting cell
- **Transition**
  - $ways(i, j) = ways(i - 1, j) + ways(i, j - 1)$
  - $ways(i, j) = 0$  if  $(i, j)$  is a blocked cell
- **Order**
  - Right depends on left
  - Bottom depends on top





## Implement – Grid Walking

- The grid map has implicit topology that allows us to get a topo-order simply by iterating  $i$  and  $j$ .

```
30 bool block[MAXN][MAXN];
31 int N, dp[MAXN][MAXN] = {};
32 int walk() {
33     dp[1][1] = 1;
34     for (int i = 1; i <= N; i++) {
35         for (int j = 1; j <= N; j++) {
36             if (block[i][j]) continue;
37             dp[i][j] += dp[i - 1][j];
38             dp[i][j] += dp[i][j - 1];
39         }
40     }
41     return dp[N][N];
42 }
```





## Implement – Grid Walking (cont'd)

- Won't be much work to do top-down either? 😊

```
30  bool block[MAXN][MAXN];
31  int N, dp[MAXN][MAXN];
32  bool out(int i, int j) {
33      return i < 1 || j < 1 || i > N || j > N;
34  }
35  int walk(int i, int j) {
36      if (dp[i][j] != -1) return dp[i][j];
37      if (i == 1 && j == 1) return dp[i][j] == 1;
38      if (block[i][j] || out(i, j)) return dp[i][j] = 0;
39      return dp[i][j] = walk(i - 1, j) + walk(i + 1, j);
40  }
```

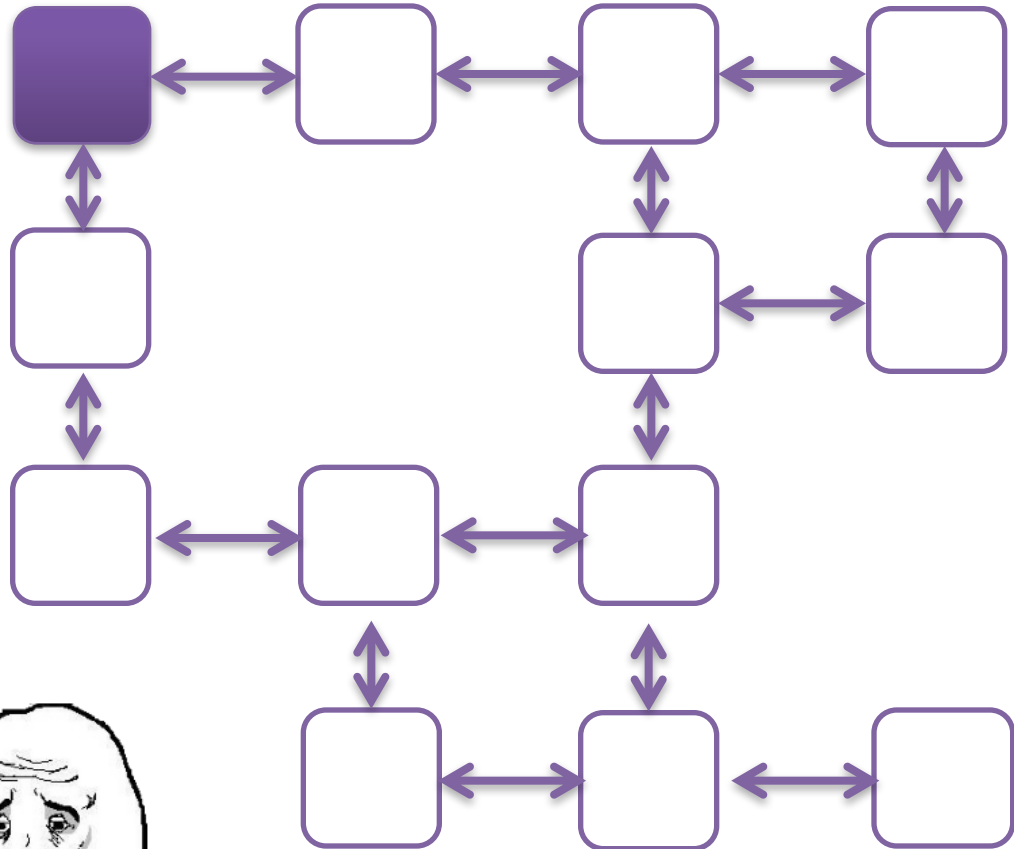
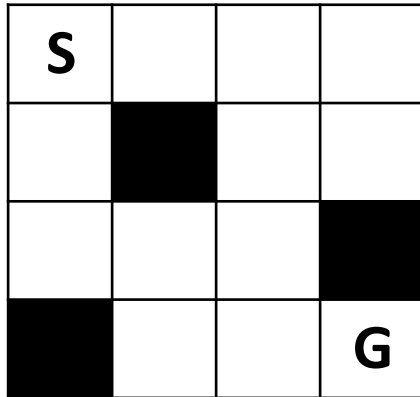


## Determine – Grid Walking

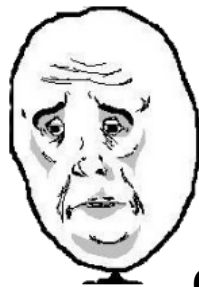
- The previous Grid Walking problem clearly **has** a DAG.
- What if we change the possible walking directions to all four? (up, down, left, right)
- Of course we would have infinite number of ways to reach the goal. Therefore we restrict our walk to take exactly **K** steps.
  - Count how many ways to reach cell  $(i, j)$  from  $(1, 1)$  with exactly  $K$  moves



## Grid Walking 2 – DAG?



Unfortunately this is no longer a DAG and there is NO way to do DP on this.



Okay



# What should we do if it is not a DAG

- Try to make a DAG if you are not given a DAG directly.
- How?
  - Observe where we cannot go back to previous states
  - In other words, observe the monotonicity based on which we can create a DAG

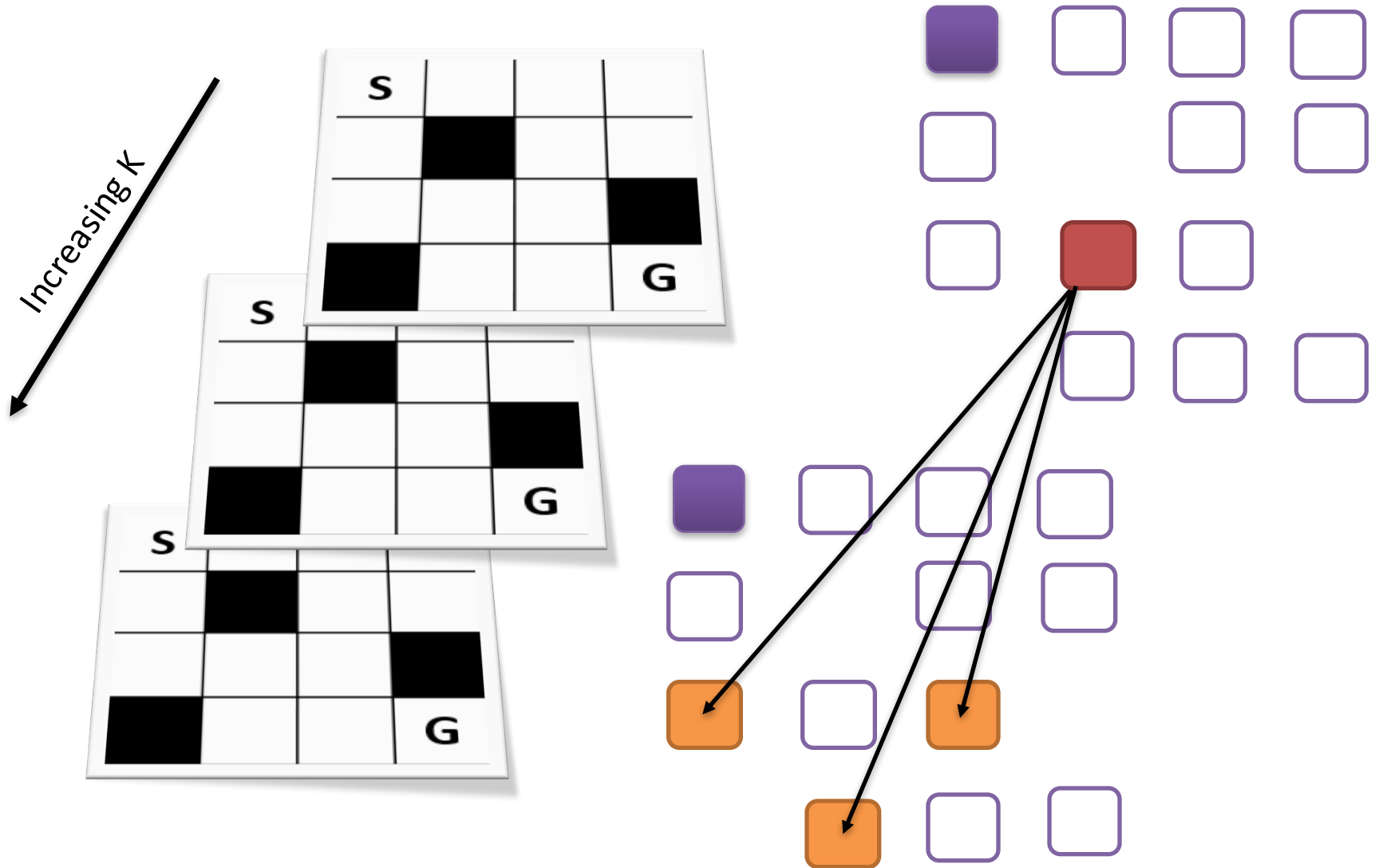


## Grid Walking 2 – DAG creation

- Where we cannot go back
  - After taking  $K$  steps, we can never go back to the states where we have taken  $k < K$  steps.
  - In other words,  $K$  is monotonically increasing.
- Idea: Build a DAG with states  $\text{ways}(i, j, k)$ : the number of ways we can reach cell  $(i, j)$  using **exactly**  $k$  steps.



## Grid Walking 2 - DAG





## How to implement

- Typically, one more dimension in your DP state corresponds to:
  - Top-down: a new argument of your recursive function
  - Bottom-up: a new dimension of your multi-dimensional array



## Grid Walking 2 – Top-down

```
31 bool block[MAXN][MAXN];
32 int N, dp[MAXN][MAXN][MAXK];
33 bool out(int i, int j) {
34     return i < 1 || j < 1 || i > N || j > N;
35 }
36 int walk(int i, int j, int k) {
37     if (dp[i][j][k] != -1) return dp[i][j][k];
38     if (k == 0) return i == 1 && j == 1;
39     if (block[i][j] || out(i, j)) return dp[i][j][k] == 0;
40     return dp[i][j][k] =
41         walk(i + 1, j, k - 1) +
42         walk(i - 1, j, k - 1) +
43         walk(i, j + 1, k - 1) +
44         walk(i, j - 1, k - 1);
45 }
```





## Grid Walking 2 – Bottom-up

```
31  bool block[MAXN][MAXN];
32  int N, dp[MAXN][MAXN][MAXK];
33  void walk() {
34      dp[1][1][0] = 1;
35      for (int k = 1; k < MAXK; k++) {
36          for (int i = 1; i <= N; i++) {
37              for (int j = 1; j <= N; j++) {
38                  if (block[i][j]) continue;
39                  dp[i][j][k] += dp[i + 1][j][k - 1];
40                  dp[i][j][k] += dp[i - 1][j][k - 1];
41                  dp[i][j][k] += dp[i][j + 1][k - 1];
42                  dp[i][j][k] += dp[i][j - 1][k - 1];
43              }
44          }
45      }
46  }
```



# Which one is better? 😊

```
31 bool block[MAXN][MAXN];
32 int N, dp[MAXN][MAXN][MAXK];
33 bool out(int i, int j) {
34     return i < 1 || j < 1 || i > N || j > N;
35 }
36 int walk(int i, int j, int k) {
37     if (dp[i][j][k] != -1) return dp[i][j][k];
38     if (k == 0) return i == 1 && j == 1;
39     if (block[i][j] || out(i, j)) return dp[i][j][k] == 0;
40     return dp[i][j][k] =
41         walk(i + 1, j, k - 1) +
42         walk(i - 1, j, k - 1) +
43         walk(i, j + 1, k - 1) +
44         walk(i, j - 1, k - 1);
45 }
```

```
31 bool block[MAXN][MAXN];
32 int N, dp[MAXN][MAXN][MAXK];
33 void walk() {
34     dp[1][1][0] = 1;
35     for (int k = 1; k < MAXK; k++) {
36         for (int i = 1; i <= N; i++) {
37             for (int j = 1; j <= N; j++) {
38                 if (block[i][j]) continue;
39                 dp[i][j][k] += dp[i + 1][j][k - 1];
40                 dp[i][j][k] += dp[i - 1][j][k - 1];
41                 dp[i][j][k] += dp[i][j + 1][k - 1];
42                 dp[i][j][k] += dp[i][j - 1][k - 1];
43             }
44         }
45     }
46 }
```



## Subtle differences between bottom-up and top-down

- Top-down requires significant stack space while bottom-up uses little.
- Top-down doesn't support the *memory saving trick*.
- It is observed that when a problem has implicit simple DAG, it is faster and neater to code bottom-up.
- Bottom-up may not neatly compute only the necessary states. Sometimes redundant states are involved, resulting in additional computation time.
- Anyway, most of the time it is your call.



# How to get a DP procedure

- Formulate its DAG (either explicitly or implicitly)
  - Determine the states (DAG nodes)
  - Determine the transitions (DAG edges)
  - Determine the order (implicit or explicit DAG topo-sort)
- Think about the computation costs
  - Affordable Memory
  - Affordable Time



# Affordable Memory

- The maximum number of states during computation must fit in the memory limit
  - DP space most commonly is the number of total states. DAG size must not be too large.
  - Memory saving trick: reduce the memory requirement by one more dimension.
- Fibonacci Sequence:
  - We can only work up to  $\text{Fib}(N)$  where  $O(N)$  fits in the memory
- Grid Walking 2:
  - $O(NMK)$  space, as there are  $N * M * K$  nodes in the DAG
  - or  $O(NM)$  if you use the memory saving trick

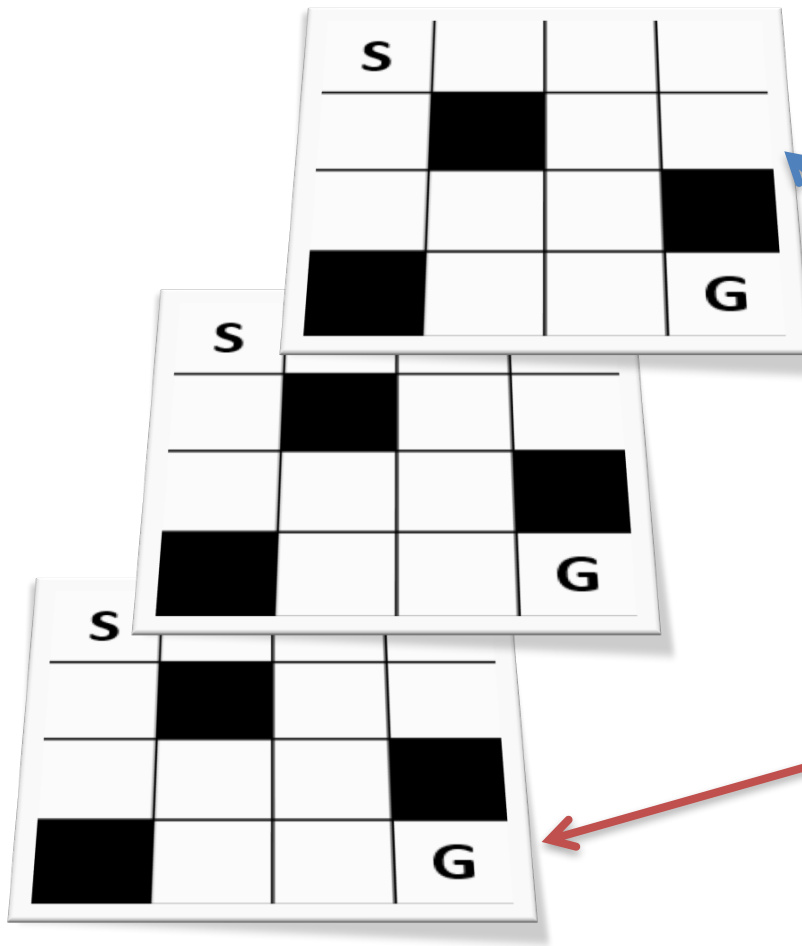


## Memory saving trick

- Simply put: forget about the states if they will no longer be depended on.
  - In other words, let those states be gone forever after they are processed in the topo order.



## Memory saving trick – Grid Walking 2



**this layer** will never  
be used again,

once we reach  
**this layer**



## Implementation – memory saving trick

```
31  bool block[MAXN][MAXN];
32  int N, dp[2][MAXN][MAXN];
33  void walk() {
34      int now = 0, pre;
35      dp[now][1][1] = 1;
36      for (int k = 1; k <= MAXK; k++) {
37          pre = now; now ^= 1;
38          memset(dp[now], 0, sizeof(dp[now]));
39          for (int i = 1; i <= N; i++) {
40              for (int j = 1; j <= N; j++) {
41                  if (block[i][j]) continue;
42                  dp[now][i][j] += dp[pre][i - 1][j];
43                  dp[now][i][j] += dp[pre][i + 1][j];
44                  dp[now][i][j] += dp[pre][i][j + 1];
45                  dp[now][i][j] += dp[pre][i][j - 1];
46              }
47          }
48      }
49  }
```





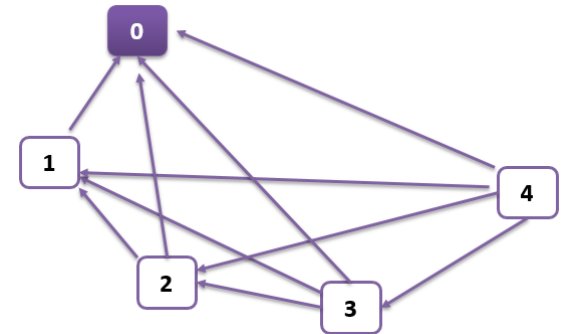
## Affordable Time

- The total computation cost must fit in the Time Limit.
- If the total number of states is  $C$ , then the time complexity would be  $\Omega(C)$ , as every state shall be computed.
- However, it could be more than that, depending on how much time is needed for each state.



## Time needed to compute each state

- Recall the Cutting Sticks problem.
  - We have a complete DAG where each state  $Cut(i)$  depends on every  $Cut(j)$ ,  $j < i$
- In order to compute  $Cut(i)$ , we need to traverse  $i - 1$  states. Therefore we need on average linear time to compute each state. The total time complexity is thus  $O(L^2)$ .





# Online judge scenarios

Problem	Time	Space	Small	Large
Fibonacci Sequence	$O(N)$	$O(N)$	$N \leq 100$	$N \leq 10^7$
Counting Problem	$O(NS)$	$O(S)$	$N \leq 20$ $S \leq 1000$	$N \leq 100$ $S \leq 10^6$
Cutting Sticks	$O(L^2)$	$O(L)$	$L \leq 100$	$L \leq 5000$
Grid Walking	$O(NM)$	$O(NM)$	$N, M \leq 100$	$N, M \leq 5000$
Grid Walking 2	$O(NMK)$	$O(NM)$	$N, M, K \leq 100$	$N, M, K \leq 500$ * Memory saving trick required



## Finding DP states

- A DP problem typically contains important variables that can be used as a dimension of the DP state.
  - Counting Problem: sum  $S$  given
  - Cutting Sticks: stick length  $L$  given
  - Grid Walking 2: number of steps  $K$  given
- More challenging DP questions demand more insights into the computation process, where we may have DP states corresponding not to the problem variables, but to our computation.



# Minimum Balance

- Given  $N$  positive integers  $\{a_1, a_2 \dots a_N\}$ , as a multiset (allowing duplicates), split them into two multisets so that the two multisets have the smallest possible absolute difference.
- Example:
  - $\{1,2,3,4\}$       Answer:  $\text{minDiff} = 0$ , e.g.  $\{1,4\}, \{2,3\}$
  - $\{2,4,5,6\}$       Answer:  $\text{minDiff} = 1$ , e.g.  $\{2,6\}, \{4,5\}$
  - $\{1,1,10\}$       Answer:  $\text{minDiff} = 8$ , e.g.  $\{1,1\}, \{10\}$

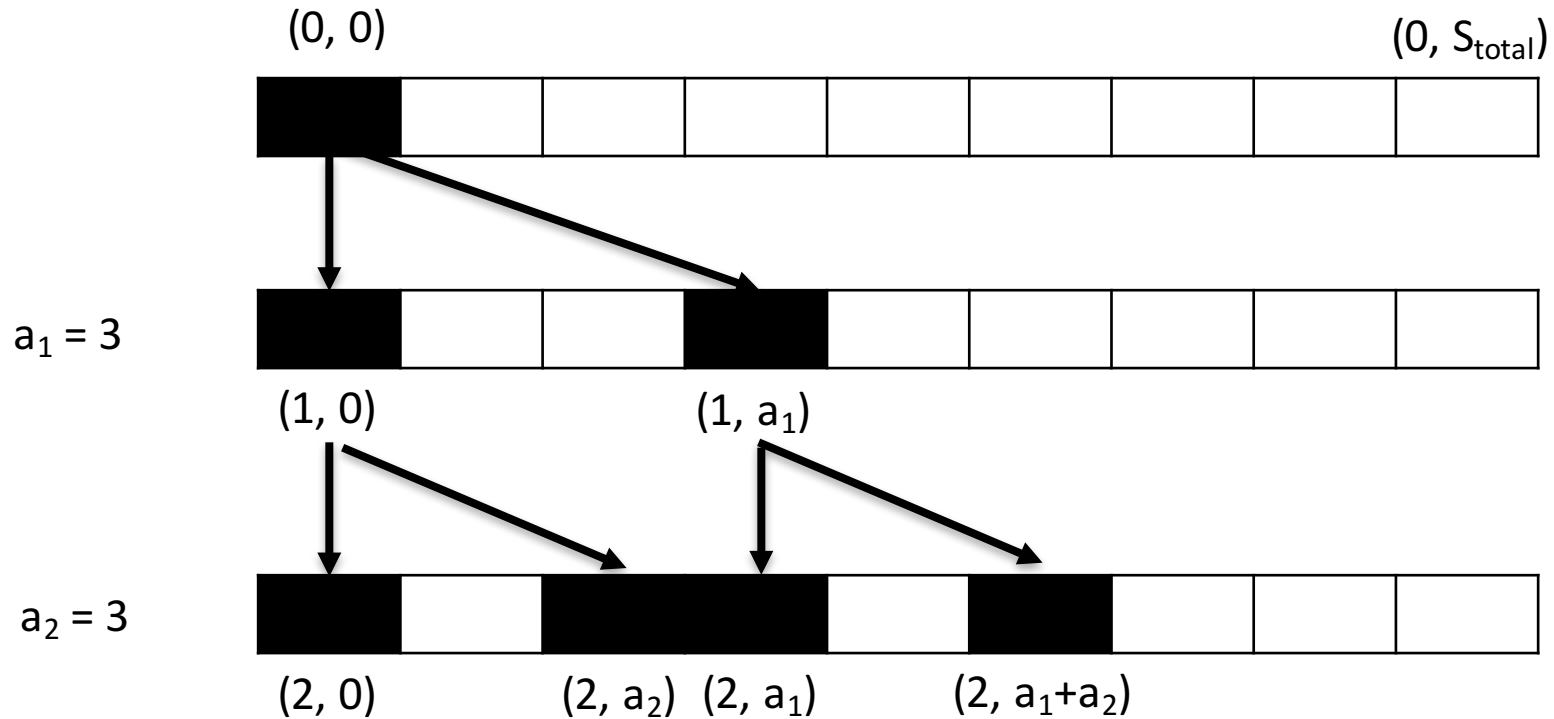


## DP formulation

- **State:**  $\text{possible}(i, S)$ , whether we can find a multiset of integers with sum  $S$ , among the first  $i$  integers.
- Note that  $S$  is not directly given in the problem. But it is closely related to the balance that is asked for.
  - If we know  $\text{possible}(N, S)$  is true, then we can split the integers into two multisets with  $S$  and  $S_{total} - S$ , and their difference is  $|S - (S_{total} - S)|$ .
  - The problem is equivalent to finding the value  $S$  closest to  $S_{total}/2$  so that  $\text{possible}(N, S)$  is true.

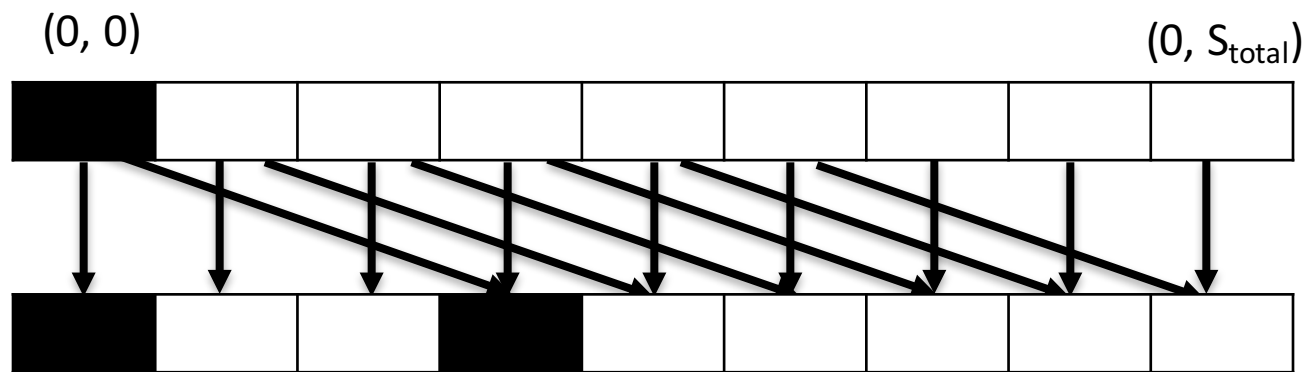


# Minimum Balance - DAG





# Minimum Balance - DAG







# Minimum Balance - Implementation

```
30 bool dp[MAXN][MAXS];
31 int N, Stotal, a[MAXN]; // a[1..N] (1-based)
32 int minBalance() {
33     dp[0][0] = true;
34     for (int i = 1; i <= N; i++) {
35         for (int S = 0; S < MAXS; S++) {
36             dp[i][S] |= dp[i - 1][S];
37             if (S >= a[i])
38                 dp[i][S] |= dp[i - 1][S - a[i]];
39         }
40     }
41     int ans = INF;
42     for (int S = 0; S < MAXS; S++) {
43         if (dp[N][S])
44             ans = min(ans, abs(S - (Stotal - S)));
45     }
46     return ans;
47 }
```



# Lucky Strings

- A string **X** is *lucky* if it contains a lucky character **t**.
- Given the lucky character **t**, count how many lucky strings **X** of length **N** exist ( $|X| = N$ ).
- Strings contain lowercase English letters. For simplicity, we only use the first 3 letters: 'a', 'b', 'c'.



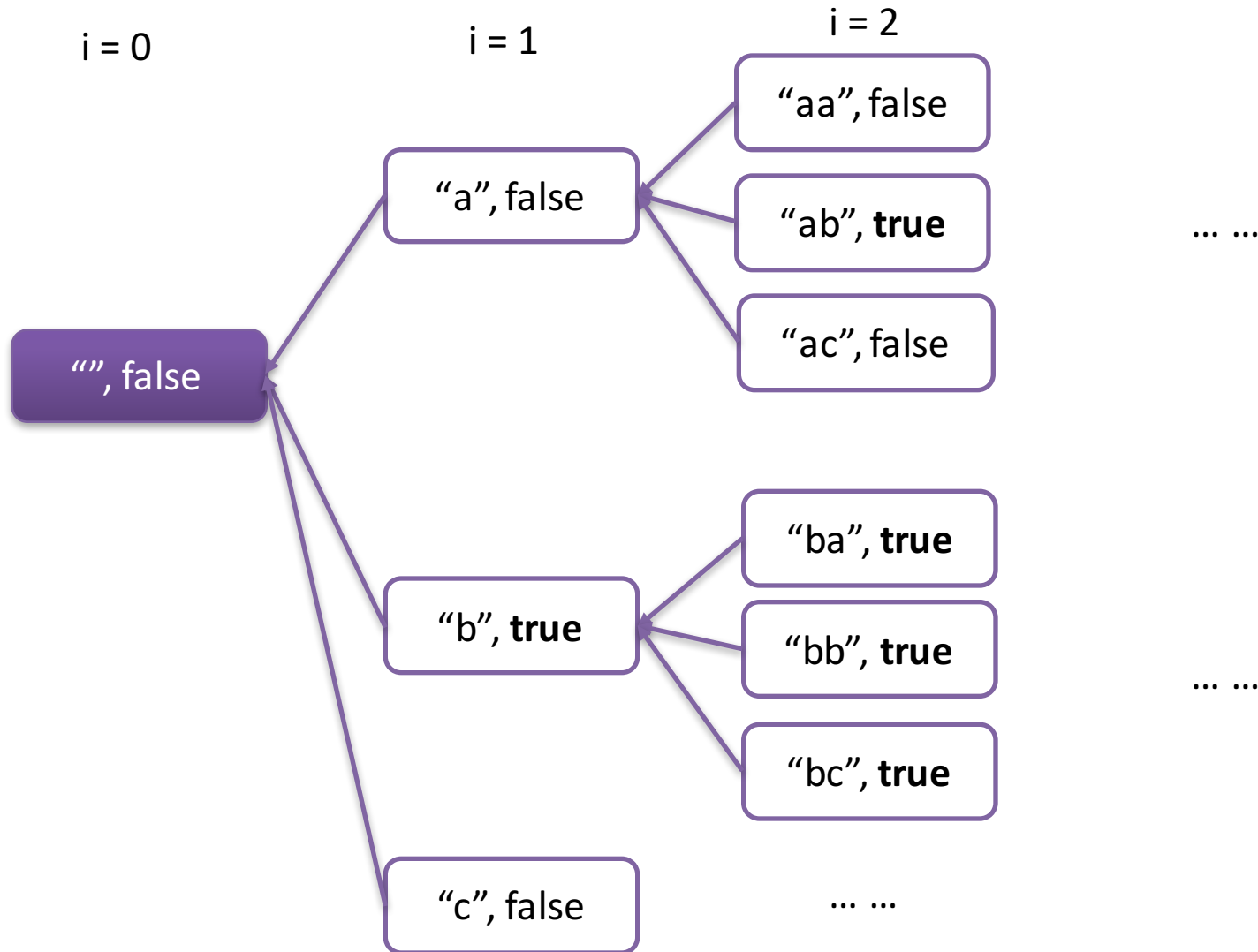
# Lucky Strings – DP Formulation

- **State:**  $\text{count}(i, \text{exist})$ 
  - $i$ : We have written  $i$  letters ( $1 \leq i \leq N$ )
  - $\text{exist}$ : we have already written at least once the lucky character  $c$
- Note that ***exist*** is not directly retrieved from the variables defined by the problem. We come up with it for our computation.



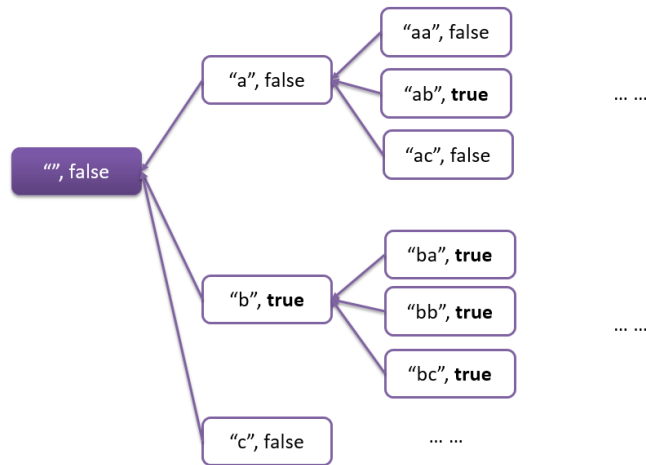
# Lucky String - DAG

Lucky character  $t = 'b'$





# Lucky String - Turn it to code



```
30 int N, dp[MAXN][2];
31 int count() {
32     dp[0][0] = 1;
33     for (int i = 1; i <= N; i++) {
34         for (int exist = 0; exist < 2; exist++) {
35             dp[i][1] += dp[i - 1][exist]; // write 'b'
36             dp[i][exist] += 2 * dp[i - 1][exist]; // write 'a' or 'c'
37         }
38     }
39     return dp[N][1];
40 }
```



## Lucky Strings 2

- A string **X** is *lucky* if it contains a lucky substring **Y**.
- Given the lucky substring **Y**, count how many lucky strings **X** of length **N** exist ( $|X| = N$ ).  $|Y| \leq N$ .
- All letters in **Y** are distinct.



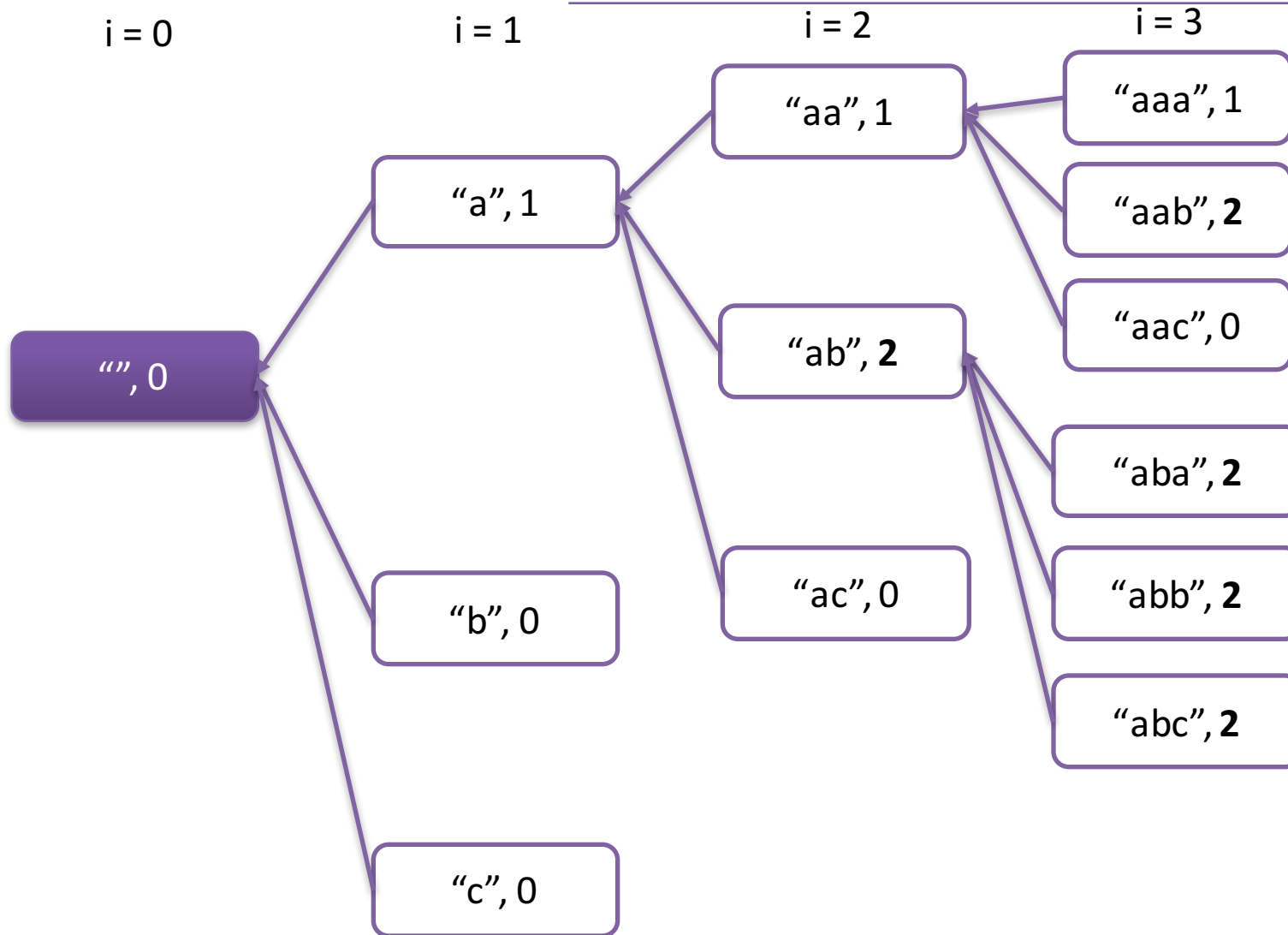
## Lucky Strings 2 – DP Formulation

- **State:**  $\text{count}(i, m)$ 
  - $i$ : We have written  $i$  letters ( $1 \leq i \leq N$ )
  - $m$ : the last  $m$  letters we wrote match the first  $m$  letters of  $Y$ .
    - If  $m = |Y|$ , then it means we have at least written  $Y$  once previously.
- Note that  **$m$**  is not directly retrieved from the variables defined by the problem either. We come up with it to track the substring matching process.



## Lucky Strings 2 - DAG

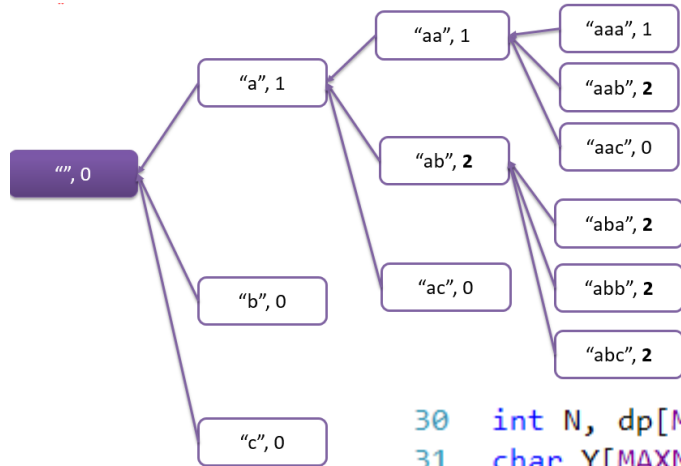
Lucky substring  $Y = "ab"$







# Lucky String 2 - Turn it to code



```
30 int N, dp[MAXN][MAXN];
31 char Y[MAXN];
32 int count() {
33     dp[0][0] = 1;
34     int M = strlen(Y);
35     for (int i = 1; i <= N; i++) {
36         for (int m = 0; m < M; m++) {
37             // write Y[m]
38             dp[i][m + 1] = dp[i - 1][m];
39             // write anything other than Y[0] and Y[m], since we only
40             // have 'a', 'b', 'c', and Y[m] != Y[0], there leaves
41             // one choice left
42             dp[i][0] += dp[i - 1][m];
43             // write Y[0]
44             dp[i][1] += dp[i - 1][m];
45         }
46         dp[i][M] += dp[i - 1][M] * 3; // anything works
47     }
48     return dp[N][M];
49 }
```



## Lucky String 2 - Notice

- **Y has to contain distinct letters.** Otherwise our DP has to be changed.

- Consider  $Y = \text{"abac"}$ .

When  $i = 4$  and  $m = 3$ , if we write 'b', it would be a mismatch.

But the new  $m$  would be 2, instead of 0.

This is because the  $m$  letters we've just written could match some prefix of  $Y$  even when the next letter we are writing doesn't match  $Y[m]$ .

```
30 int N, dp[MAXN][MAXN];
31 char Y[MAXN];
32 int matchHead(int m, int c) {
33     // return the longest length 'len' so that
34     // Y[m-(len-1)..m-1] + c = Y[0..len-1]
35 }
36 int count() {
37     dp[0][0] = 1;
38     int M = strlen(Y);
39     for (int i = 1; i <= N; i++) {
40         for (int m = 0; m < M; m++) {
41             dp[i][m + 1] += dp[i - 1][m]; // write Y[m]
42             for (int c = 0; c < 3; c++) {
43                 if (c == Y[m]) continue;
44                 // write every possible char other than Y[m]
45                 dp[i][matchHead(m, c)] += dp[i - 1][m];
46             }
47         }
48         dp[i][M] += dp[i - 1][M] * 3; // anything works
49     }
50     return dp[N][M];
51 }
```



# Counting in DP – modulo arithmetic

- Answer could grow exponentially.
- $(a + b) \% M = ((a \% M) + (b \% M)) \% M$ 
  - Ensure that  $\sim 2M$  fits in an 32-bit integer.
  - Typically when  $M \sim 10^9$ , the above is satisfied.
- $a * b \% M = ((a \% M) * (b \% M)) \% M$ 
  - Ensure  $M^2$  fits in an integer
  - Typically when  $M \sim 10^9$ , we must use 64-bit integer for the multiplication:  $((\text{long long})a * b) \% M$



- Thinking about the DAG behind DP helps you
  - **Perceive** the problem more clearly
  - See how to **implement** the DP procedure neatly
  - **Determine** if a problem is solvable by DP, or how to solve it by DP.
- Formulate your DP
  - **Think about the DAG:** find states from problem variables, derived dimensions; get transitions
  - **Affordable memory:** check number of states, memory saving trick
  - **Affordable time:** check number of states, computation cost for each state



- Cutting Sticks
  - Compute the maximum sum of values after cutting the original sticks into exactly  $K$  segments.
  - Suppose the stick values are in dollars. Each cut costs you  $D$  dollars. Find the maximum dollars you can achieve after cutting.
- Minimum Balance
  - Suppose  $N$  is even. Find a split into two multisets so that not only the difference between two sums are minimum, but also the two multisets have the same number of integers.
- Lucky String
  - Analyze the complexity requirement for Lucky String and Lucky String 2.
  - Note that the time complexity for Lucky String 2 may additionally include the alphabet size, why?



- Lucky String 2:
  - Remove the constraint of Y's letters being distinct.
  - Naive implementation of *matchHead(m, c)* could work but would give larger time complexity. Use an efficient algorithm that performs *matchHead(m, c)* in  $O(1)$  time.
  - Hint: string matching algorithm
- Grid Walking 2: What if  $N, M \leq 10, K \leq 10^9$ ?
  - We cannot afford any solution that needs  $O(10^9)$  time **OR** space.
  - Still solvable, as an advanced exercise 😊
  - Hint: why should  $N, M$  become smaller, i.e.  $\leq 10$ ?