



Princeton Competitive Programming

Dynamic Programming II

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Outline

1. Recap of Lecture I
2. Warm Up DP
3. DP on trees
4. The Twin Tower

Recap of Lecture I

What is DP?

Algorithm design technique based on breaking problems into simpler subproblems

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Finding the right subproblem break down is part art part science

Can only be learned by looking at lots of examples

Warm Up DP

Longest Increasing Subsequence

Problem

Given an array a_1, \dots, a_n with n elements, find the length of the longest increasing subsequence.

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Given an array a_1, \dots, a_n with n elements, find the length of the longest increasing subsequence.

- $a = 1, 2, 3$ then $\text{LIS}(a) = 3$, the whole sequence is increasing
- $a = 1, 2, 1, 4, 3, 4$ then $\text{LIS}(a) = 4$, take $[1, 2, 3, 4]$
- $a = 5, 4, 3, 2, 1$ then $\text{LIS}(a) = 1$, take $[1]$

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First possible state:

$\text{dp}(i)$ is the longest increasing subsequence within a_1, \dots, a_i

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It's not clear how to write a recursion on this...

Longest Increasing Subsequence

Another suggestion:

$\text{dp}(i)$ is the longest increasing subsequence within a_1, \dots, a_i that ends at a_i

Longest Increasing Subsequence

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$\text{dp}(i)$ is the longest increasing subsequence within a_1, \dots, a_i that ends at a_i

But now:

$$\text{dp}(i) = \max(1, \max_{\substack{j < i \\ a_j < a[i]}} (1 + \text{dp}(j)))$$


```
public static int lis(int i) {  
    if (dp[i] != -1) {  
        return dp[i];  
    }  
  
    int res = 1;  
    for (int j = 0; j < i; j++) {  
        if (a[j] < a[i]) {  
            res = max(res, 1 + lis(j));  
        }  
    }  
  
    return dp[i] = res;  
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int mx = 0;  
for (int i = 0; i < n; i++)  
    mx = Math.max(mx, lis(i));  
System.out.println(mx);
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What is the time complexity?

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What is the time complexity? It's $O(n^2)$.

DP on trees

Tree Diameter

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Given a tree T of n nodes, calculate longest path between any two nodes

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First things first: root the tree at an arbitrary node

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- The longest path can be entirely on one of the root's subtrees
- The longest path can start in a subtree of root, go through root and end at a different subtree

Tree Diameter

Define:

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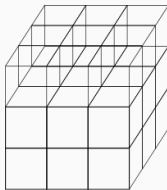
$$\text{longest}(v) = \max\left(\max_{u \text{ child of } v} \text{longest}(u), 1 + \max_{u \text{ child of } v} \text{height}(u) + \text{second max}_{u \text{ child of } v} \text{height}(u)\right)$$

The Twin Tower

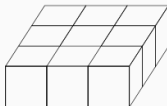
The Twin Tower

Problem

Consider a tower of $3 \times 3 \times n$ blocks, count how many ways there are to tile it using $1 \times 1 \times 2$ blocks.



...



The Twin Tower

Main ideas:

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- Key idea: when we fill the n th layer we might fill some of the $(n - 1)$ th layer, so we define a state like: $\text{dp}(n, S)$ is the number of ways to tile a $3 \times 3 \times n$ tower where the tiles in S are prefilled

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But wait, don't we have to handle a huge number of cases?

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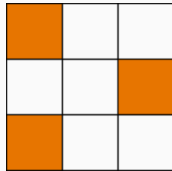
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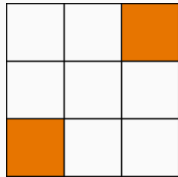
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- $b \& (1 \ll i)$ is 0 if $i \notin S$ and positive otherwise
- $b | (1 \ll i)$ adds i to S , so it is $S \cup \{i\}$

The Twin Tower



$$\begin{array}{r} 100 \\ = 001 \\ 100 \end{array} = 100001100 = 268$$



$$\begin{array}{r} 001 \\ = 000 \\ 100 \end{array} = 001000100 = 68$$

We represent 3×3 tiles as a bitmask like so

Useful functions to use:

```
public static int isNotPresent(int x, int y, int mask) {  
    return (mask & (1 << (y * 3 + x))) == 0;  
}
```

```
public static int add(int x, int y, int mask) {  
    return (mask | (1 << (y * 3 + x)));  
}
```

```
public static int remove(int x, int y, int mask) {  
    return (mask ^ (1 << (y * 3 + x)));  
}
```

```

public static void fill(int maskN, int maskN1, int origMask) {
    if (maskN == (1 << 9) - 1) {
        transition[origMask][maskN1]++;
        return;
    }

    int x = 0, y = 0;
    // find first unused on last layer
    for (int i = 0; i < 3; i++)
        for (int j = 0; j < 3; j++)
            if (isNotPresent(i, j, maskN)) {
                x = i;
                y = j;
                break;
            }

    maskN = add(x, y, maskN);
    // horizontal
    if (x > 0 && isNotPresent(x - 1, y, maskN))
        fill(add(x - 1, y, maskN), maskN1, origMask);
    // vertical
    if (y < 2 && isNotPresent(x, y + 1, maskN))
        fill(add(x, y + 1, maskN), maskN1, origMask);
    // down
    if (isNotPresent(x, y, maskN1))
        fill(maskN, add(x, y, maskN1), origMask);
}

```



```

public static int calc(int n, int mask) {
    //
    // Base Case
    // ????????
    //

    if (dp[n][mask] != -1)
        return dp[n][mask];

    int res = 0;
    for (int i = 0; i < (1 << 9); i++) {
        if (transition[mask][i] == 0) continue;
        res += transition[mask][i] * calc(n - 1, i);
    }

    return dp[n][mask] = res;
}

```

```

public static int calc(int n, int mask) {
    if (n == 0 && mask == 0)
        return 1;
    if (n == 0)
        return 0;

    if (dp[n][mask] != -1)
        return dp[n][mask];

    int res = 0;
    for (int i = 0; i < (1 << 9); i++) {
        if (transition[mask][i] == 0) continue;
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