

Algorithm Design and Analysis

Dynamic Programming (Again)

Roadmap for today

- More *dynamic programming*

Key element #1: Memoization

Memoization: Don't solve the same problem twice

```
function fib(int n) {  
  if n <= 1 then return 1  
  else return fib(n-1) + fib(n-2)  
}
```



dictionary<int,int> *memo*

```
function fib(int n) {  
  if n <= 1 then return 1  
  if n is in not in memo then {  
    memo[n] = fib(i-1) + fib(i-2)  
  }  
  return  
}
```

Key element #2: Optimal substructure

Optimal substructure: Break the problem into smaller versions of itself (recursively), and build the solution to the bigger problem by combining the answers to the smaller (sub-)problems

Examples:

- $LCS(i,j)$ = Length of the LCS between $S[\dots i]$ and $T[\dots j]$
- $V(k,B)$ = Maximum value subset of items $1 \dots k$ with total weight $\leq B$
- $W(v)$ = Max-weight independent set of the subtree rooted at v

“Recipe” for dynamic programming

1. *Identify a set of optimal subproblems*

- Write down a clear and unambiguous definition of the subproblems.

2. *Identify the relationship between the subproblems*

- Write down a recurrence that gives the solution to a problem in terms of its subproblems

3. *Analyze the required runtime*

- *Usually* (but not always) the number of subproblems multiplied by the time taken to solve a subproblem.

4. *Select a data structure to store subproblems*

- *Usually* just an array. Occasionally something more complex.

5. *Choose between bottom-up or top-down implementation*

6. *Write the code!*



Mostly focus on these steps

Problems!

Traveling Salesperson Problem (TSP)

Definition (TSP) Given a complete, directed, weighted graph, we want to find a minimum-weight cycle that visits every vertex.

Traveling Salesperson Problem (TSP)

$$C(S, t) = \left\{ \right.$$

Traveling Salesperson Problem (TSP)

Analysis: TSP can be solved in $O(n^2 2^n)$ time

Data structure: How do we store the subproblems??

All-pairs shortest paths

Definition (APSP) Given a directed, weighted graph, compute the length of the shortest path between every pair of vertices.

All-pairs shortest paths

$$D(u, v, k) =$$

$$D(u, v, 0) = \left\{ \right.$$

All-pairs shortest paths

Analysis: APSP uses $O(n^3)$ time and $O(n^3)$ space

That's a **lot** of space. Can we improve this?

All-pairs shortest paths

Optimization:

$$D[u][v] = \text{base case from earlier} \rightarrow D(u, v) = \begin{cases} 0, & \text{if } u = v \\ w(u, v), & \text{if } (u, v) \in E \\ \infty, & \text{otherwise} \end{cases}$$

```
for k = 1 to n do  
  for u = 1 to n do  
    for v = 1 to n do
```

All-pairs shortest paths

Analysis: **Floyd-Warshall** runs in $O(n^3)$ time and $O(n^2)$ space

Why does it work?

Longest Increasing Subsequence

Definition (LIS) Given a sequence of numbers a_1, a_2, \dots, a_n , find the length of the longest strictly increasing subsequence. i.e., find indices i_1, i_2, \dots, i_k such that $a_{i_1} < a_{i_2} < \dots < a_{i_k}$ for the largest possible k

Longest Increasing Subsequence

$$L(i) = \left\{ \begin{array}{l} \text{...} \end{array} \right.$$

Longest Increasing Subsequence

Analysis: LIS can be solved in $O(n^2)$

Faster? Seems a bit slow...

$$1 + \max_{\substack{0 \leq j < i \\ a_j < a_i}} L(j)$$

Longest Increasing Subsequence

Optimizing with range queries

```
n = size(a)
b = sorted(a)
LIS = SegTree(n+1, 0)
for i in 1 to n - 1 {
    rank =
    LIS.Assign(
}
return
```

Take-home messages

- Breaking a problem into subproblems is hard. *Common patterns:*
 - Can I use the first k elements of the input?
 - Can I restrict an integer parameter (e.g., knapsack size) to a smaller value?
 - On trees, can I solve the problem for each subtree? (Tree DP)
 - Can I store a subset of the input? (TSP subproblems)
 - Can I remember the most recent decision? (Previous vertex in TSP)
- Many techniques are useful to **optimize** a DP algorithm:
 - Can I remove redundant subproblems to save space? (Floyd-Warshall)
 - Can I use a fancier data structure than an array? (LIS with SegTree)