Lecture 12: Dynamic Progamming

CLRS Chapter 15

Outline of this section

- Introduction to Dynamic programming;
  a method for solving optimization problems.

- Dynamic programming vs. Divide and Conquer

- A few examples of Dynamic programming
  - the 0-1 Knapsack Problem
  - Chain Matrix Multiplication
  - All Pairs Shortest Path
  - The Floyd Warshall Algorithm: Improved All Pairs Shortest Path

Recalling Divide-and-Conquer

1. Partition the problem into particular subproblems.

2. Solve the subproblems.

3. Combine the solutions to solve the original one.

Remark: In the examples we saw the subproblems were usually independent, i.e. they did not call the same subsubproblems. If the subsubproblems were *not* independent, then D&C could be resolving many of the same problems many times. Thus, it does more work than necessary!

Dynamic programming (DP) solves every subsubproblem exactly once, and is therefore more efficient in those cases where the subsubproblems are not indepndent.

The Intuition behind Dynamic Programming

Dynamic programming is a method for solving optimization problems.

The idea: Compute the solutions to the subsub-problems *once* and store the solutions in a table, so that they can be reused (repeatedly) later.

Remark: We trade space for time.

0-1 Knapsack Problem

Informal Description: We have n precomputed data files that we want to store, and W bytes of storage available.

File i has two parameters:

size w_i (bytes)

time v_i (minutes); time needed to recompute File i.

Our goal is to use storage space to minimize recomputation time; we want to find a subset of files to store such that

- The files have combined size at most W.
- The total recomputation time of the stored files is as large as possible.

We can not store parts of files, it is the whole file or nothing. (This is why it is called **0-1**.)

How should we select the files?

0-1 Knapsack Problem

Formal description:

Given $W > 0$, and two n-tuples of positive numbers

$$\langle v_1, v_2, \ldots, v_n \rangle \quad \text{and} \quad \langle w_1, w_2 \ldots, w_n \rangle,$$

we wish to determine the subset
$T \subseteq \{1, 2, \ldots, n\}$ (of files to store) that

$$\text{maximizes} \quad \sum_{i \in T} v_i,$$

$$\text{subject to} \quad \sum_{i \in T} w_i \leq W.$$

Remark: This is an optimization problem. The *Brute Force* solution is to try all 2^n possible subsets T.

Question: Is there a better way?

Yes. Dynamic Programming!

General Schema of a DP Solution

Step1: Structure: Characterize the structure of an optimal solution by showing that it can be decomposed into *optimal* subproblems

Step2: Recursively define the value of an optimal solution by expressing it in terms of optimal solutions for smaller problems (usually using min and/or max).

Step 3: Bottom-up computation: Compute the value of an optimal solution in a bottom-up fashion by using a table structure.

Step 4: Construction of optimal solution: Construct an optimal solution from computed information.

Remarks on the Dynamic Programming Approach

- Steps 1-3 form the basis of a dynamic-programming solution to a problem.

- Step 4 can be omitted if only the value of an optimal solution is required.

Developing a DP Algorithm for Knapsack

Step 1: Decompose the problem into smaller problems.

We construct an array $V[0..n, 0..W]$.
For $1 \leq i \leq n$, and $0 \leq w \leq W$, the entry $V[i, w]$ will store the maximum (combined) computing time of any subset of files $\{1, 2, \ldots, i\}$ of (combined) size at most w.

That is

$$V[i, w] = \max \left\{ \sum_{j \in T} v_j \ : \ T \subseteq \{1, 2, \ldots, i\}, \sum_{j \in T} w_j \leq w \right\}.$$

If we can compute all the entries of this array, then the array entry $V[n, W]$ will contain the solution to our problem.

Note: In what follows we will say that T is a *solution* for $[i, w]$ if $T \subseteq \{1, 2, \ldots, i\}$ and $\sum_{j \in T} w_j \leq w$ and that T is an *optimal solution* for $[i, w]$ if T is a solution and $\sum_{j \in T} v_j = V[i, w]$.

Developing a DP Algorithm for Knapsack

Step 2: Recursively define the value of an optimal solution in terms of solutions to smaller problems.

Initial Settings: Set

$V[0, w] = 0$ for $0 \leq w \leq W$, no item
$V[i, w] = -\infty$ for $w < 0$, illegal

Recursive Step: Use

$$V[i, w] = \max(V[i-1, w], v_i + V[i-1, w-w_i])$$

for $1 \leq i \leq n$, $0 \leq w \leq W$.

Correctness of the Method for Computing $V[i, w]$

Lemma: For $1 \leq i \leq n$, $0 \leq w \leq W$,

$$V[i, w] = \max(V[i-1, w], v_i + V[i-1, w-w_i]).$$

Proof: Intuitively, the lemma is correct because if T is an optimal solution for $[i, w]$ then either File i is not in T or File i is not in T.

Formally, we will start by proving that

$$V[i, w] \geq \max(V[i-1, w], v_i + V[i-1, w-w_i]).$$

First we build a solution with $i \notin T$.
Let T be an optimal solution for $[i-1, w]$. This means that $\sum_{j \in T} v_j = V[i-1, w]$, $T \subseteq \{1, 2, \ldots, i-1\}$ and $\sum_{j \in T} w_j \leq w$. The last two statements mean that T *is a solution for* $[i, w]$ so $V[i, w] \geq V[i-1, w]$.

Now build a solution with $i \in T$.
Let T be an optimal solution for $[i-1, w-1]$. This means that $\sum_{j \in T'} v_j = V[i-1, w-w_i]$, $T' \subseteq \{1, 2, \ldots, i-1\}$ and $\sum_{j \in T'} w_j \leq w - w_j$. Now set $T = T' \cup \{i\}$. Then $T \subseteq \{1, 2, \ldots, i\}$ and $\sum_{j \in T} w_j \leq w$ so T *is a solution for* $[i, w]$. Furthermore

$$\sum_{j \in T} v_j = v_i + \sum_{j \in T'} v_j = v_i + V[i-1, w-w_i]$$

so $V[i, w] \geq v_i + V[i-1, w-w_i]$.

Now we prove

$$V[i,w] \leq \max(V[i-1,w], v_i + V[i-1, w-w_i]).$$

Let T be an *optimal solution* for $[i,w]$.
That is, $\sum_{j\in T} v_j = V[i,w]$, $T \subseteq \{1,2,\ldots,i\}$ and $\sum_{j\in T} w_j \leq w$. Again, there are two cases. Either $i \notin T$ or $i \in T$.

If $i \notin T$ then T is a solution for $[i-w,w]$ so

$$V[i,w] = \sum_{j\in T} v_j \leq V[i-1,w].$$

If $i \in T$ then set $T' = T - \{i\}$. Notice that $\sum_{j\in T'} w_j \leq w - w_j$ so T' is a solution for $[i-1, w-w_i]$. This means that $\sum_{j\in T'} v_j \leq V[i-1,w_i]$, and

$$V[i,w] = \sum_{j\in T} v_j = v_i + \sum_{j\in T'} v_j \leq v_i + V[i-1, w-w_i].$$

Combining the two we see that in both cases

$$V[i,w] \leq \max(V[i-1,w], v_i + V[i-1, w-w_i]).$$

In our proof we were a bit sloppy about indices. Note that if $w_i > w$, then $v_i + V[i-1, w-w_i] = -\infty$ so the lemma is always correct.

Developing a DP Algorithm for Knapsack

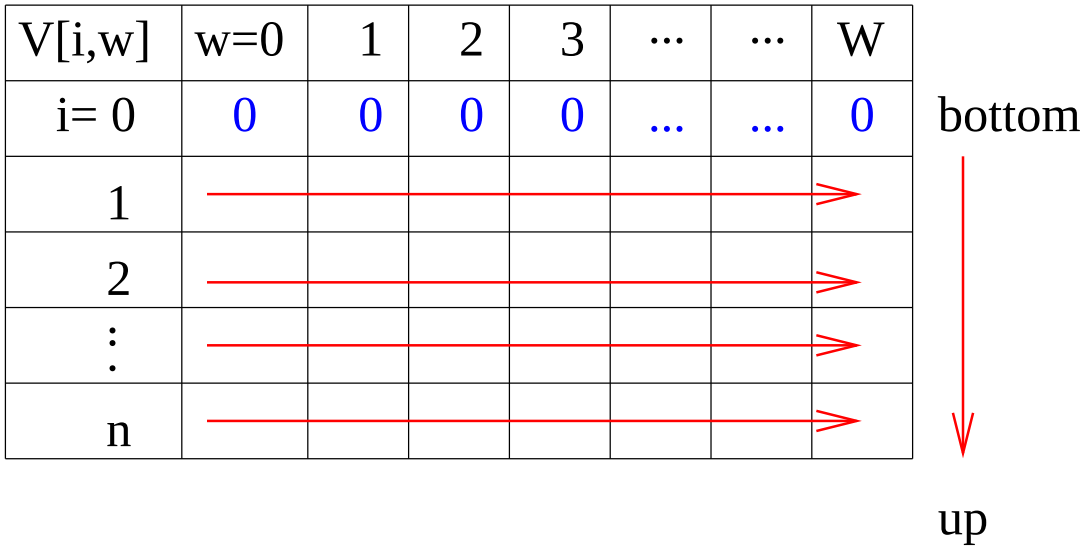
Step 3: Bottom-up computation of $V[i, w]$
(using iteration, not recursion).

Bottom: $V[0, w] = 0$ for all $0 \leq w \leq W$.

Bottom-up computation: Computing the table using

$$V[i, w] = \max(V[i-1, w], v_i + V[i-1, w-w_i])$$

row by row.



Example of the Bottom-up computation

Let $W = 10$ and

i	1	2	3	4
v_i	10	40	30	50
w_i	5	4	6	3

$V[i, w]$	0	1	2	3	4	5	6	7	8	9	10
$i = 0$	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	10	10	10	10	10	10
2	0	0	0	0	40	40	40	40	40	50	50
3	0	0	0	0	40	40	40	40	40	50	70
4	0	0	0	50	50	50	50	90	90	90	90

Remarks:

- The final output is $V[4, 10] = 90$.
- The method described does not tell which subset gives the optimal solution. (It is $\{2, 4\}$ in this example).

The Dynamic Programming Algorithm

```
KnapSack(v, w, n, W)
{
  for (w = 0 to W) V[0, w] = 0;
  for (i = 1 to n)
    for (w = 0 to W)
      if (w[i] ≤ w)
        V[i, w] = max{V[i − 1, w], v[i] + V[i − 1, w − w[i]]};
      else
        V[i, w] = V[i − 1, w];
  return V[n, W];
}
```

Time complexity: Clearly, $O(nW)$.

Constructing the Optimal Solution

- The algorithm for computing $V[i, w]$ described in the previous slide does not record which subset of items gives the optimal solution.

- To compute the actual subset, we can add an auxiliary boolean array $keep[i, w]$ which is 1 if we decide to take the i-th file in $V[i, w]$ and 0 otherwise.

Question: How do we use all the values $keep[i, w]$ to determine the subset T of files having the maximum computing time?

Constructing the Optimal Solution

Question: How do we use the values $keep[i, w]$ to determine the subset T of items having the maximum computing time?

If keep[n, W] is 1, then $n \in T$. We can now repeat this argument for keep[$n - 1, W - w_n$].
If keep[n, W] is 0, the $n \notin T$ and we repeat the argument for keep[$n - 1, W$].

Therefore, the following partial program will output the elements of T:

```
K = W;
for (i = n downto 1)
    if (keep[i, K] == 1)
    {
        output i;
        K = K - w[i];
    }
```

The Complete Algorithm for the Knapsack Problem

```
KnapSack(v, w, n, W)
{
    for (w = 0 to W) V[0, w] = 0;
    for (i = 1 to n)
        for (w = 0 to W)
            if ((w[i] ≤ w) and (v[i] + V[i − 1, w − w[i]] > V[i − 1, w]))
            {
                V[i, w] = v[i] + V[i − 1, w − w[i]];
                keep[i, w] = 1;
            }
            else
            {
                V[i, w] = V[i − 1, w];
                keep[i, w] = 0;
            }
    K = W;
    for (i = n downto 1)
        if (keep[i, K] == 1)
        {
            output i;
            K = K − w[i];
        }
    return V[n, W];
}
```

Dynamic Programming vs. Divide-and-Conquer

The Dynamic Programming algorithm developed runs in $O(nW)$ time.
We started by deriving a recurrence relation for solving the problem

$$\begin{aligned} V[0,w] &= 0 \\ V[i,w] &= \max(V[i-1,w], v_i + V[i-1, w-w_i]) \end{aligned}$$

Question: why can't we simply write a top-down divide-and-conquer algorithm based on this recurrence?
Answer: we could, but it could run in time as bad as $\Theta(2^n)$ since it might have to recompute the same values many times.

Dynamic programming saves us from having to recompute previously calculated subsolutions!

Final Comment

Divide-and-Conquer works Top-Down.

Dynamic programming works Bottom-Up.