CSE 417 Algorithms

Lecture 21, Autumn 2023
Dynamic Programming
Subset Sum etc.

Announcements

- Homework 8: Due Wednesday, Nov 29
- Homework 9: Due Friday, Dec 8
- Dynamic Programming Reading:
  - 6.1-6.2, Weighted Interval Scheduling
  - Path Counting, Paragraphing
  - 6.4 Knapsack and Subset Sum
  - 6.6 String Alignment
    - 6.7* String Alignment in linear space
  - 6.8 Shortest Paths (again)
  - 6.9 Negative cost cycles
    - How to make an infinite amount of money

What is the largest sum you can make of the following integers that is ≤ 20

{4, 5, 8, 10, 13, 14, 17, 18, 21, 23, 28, 31, 37}

What is the largest sum you can make of the following integers that is ≤ 2000

{78, 101, 122, 133, 137, 158, 189, 201, 220, 222, 267, 271, 281, 289, 296, 297, 301, 311, 315, 321, 322, 341, 349, 353, 361, 385, 396 }

Subset Sum Problem

- Given integers $\{w_1,\ldots,w_n\}$ and an integer K
- Find a subset that is as large as possible that does not exceed K
- Dynamic Programming: Express as an optimization over sub-problems.
- New idea: Represent at a sub problems depending on K and n
  - Two dimensional grid

Subset Sum Optimization

Opt[j, K] the largest subset of $\{w_1, \ldots, w_j\}$ that sums to at most K

Opt[j, K] = max(Opt[j – 1, K], Opt[j – 1, K – w_j] + w_j)

Subset Sum Grid

Opt[j, K] = max(Opt[j – 1, K], Opt[j – 1, K – w_j] + w_j)

4																	
3																	
2																	
1																	
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

{2, 4, 7, 10}

Subset Sum Grid

Opt[j, K] = max(Opt[j – 1, K], Opt[j – 1, K – w_j] + w_j)

4	0	2	2	4	4	6	7	7	9	10	11	12	13	14	14	16	17
3	0	2	2	4	4	6	7	7	9	9	11	11	13	13	13	13	13
2	0	2	2	4	4	6	6	6	6	6	6	6	6	6	6	6	6
1	0	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

{2, 4, 7, 10}

Subset Sum Code

```
for j = 1 to n
    for k = 1 to W
        Opt[j, k] = max(Opt[j-1, k], Opt[j-1, k-w_j] + w_j)
```


Knapsack Problem

- Items have weights and values
- The problem is to maximize total value subject to a bound on weght
- Items {I_1, I_2, … I_n}
  - Weights {w_1, w_2, …,w_n}
  - Values {v_1, v_2, …, v_n}
  - Bound K
- Find set S of indices to:
  - Maximize $\sum_{i \in S} v_i$ such that $\sum_{i \in S} w_i$ <= K

Knapsack Recurrence

Subset Sum Recurrence:

Opt[j, K] = max(Opt[j – 1, K], Opt[j – 1, K – w_j] + w_j)

Knapsack Recurrence:

Knapsack Grid

Opt[j, K] = max(Opt[j – 1, K], Opt[j – 1, K – w_j] + v_j)

4																	
3																	
2																	
1																	
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Weights {2, 4, 7, 10} Values: {3, 5, 9, 16}

Knapsack Grid

$Opt[j, K] = \max(Opt[j-1, K], Opt[j-1, K-w_j] + v_j)$

4	0	3	3	5	5	8	9	9	12	16	16	18	18	21	21	24	25
3	0	3	3	5	5	8	9	9	12	12	14	14	17	17	17	17	17
2	0	3	3	5	5	8	8	8	8	8	8	8	8	8	8	8	8
1	0	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Weights {2, 4, 7, 10} Values: {3, 5, 9, 16}

Alternate approach for Subset Sum

- Alternate formulation of Subset Sum dynamic programming algorithm
  - $Sum[i, K]$ = true if there is a subset of $\{w_1, \ldots w_i\}$ that sums to exactly K, false otherwise
  - $Sum[i, K] = Sum[i-1, K]$ **OR** $Sum[i-1, K-w_i]$
  - $Sum[0, 0]$ = true; $Sum[i, 0]$ = false for $i != 0$
- To allow for negative numbers, we need to fill in the array between K_{min} and K_{max}

Run time for Subset Sum

- With n items and target sum K, the run time is O(nK)
- If K is 1,000,000,000,000,000,000,000,000 this is very slow
- Alternate brute force algorithm: examine all subsets: $O(n2^n)$
- Point of confusion: Subset sum is NP Complete

Two dimensional dynamic programming

Subset sum and knapsack

$Opt[j, K] = \max(Opt[j-1, K], Opt[j-1, K-w_j] + w_j)$

$Opt[j, K] = \max(Opt[j-1, K], Opt[j-1, K-w_j] + v_j)$

4	0																
3	0																
2	0																
1	0																
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Reducing dimensions

- Computing values in the array only requires the previous row
  - Easy to reduce this to just tracking two rows
  - And sometimes can be implemented in a single row
- Space savings is significant in practice
- Reconstructing values is harder

Longest Common Subsequence

- $C=c_1 \ldots c_g$ is a subsequence of $A=a_1 \ldots a_m$ if C can be obtained by removing elements from A (but retaining order)
- LCS(A, B): A maximum length sequence that is a subsequence of both A and B

`ocurranec`
`occurrence`

`attacggct`
`tacgacca`

Determine the LCS of the following strings

BARTHOLEMEWSIMPSON

KRUSTYTHECLOWN

String Alignment Problem

- Align sequences with gaps

```
CAT TGA  AT
CAGAT AGGA
```

- Charge δ_x if character x is unmatched
- Charge γ_{xy} if character x is matched to character y

Note: the problem is often expressed as a minimization problem, with $\gamma_{xx} = 0$ and $\delta_x > 0$

LCS Optimization

- $A = a_1a_2\ldots a_m$
- $B = b_1b_2\ldots b_n$

- Opt[j, k] is the length of $LCS(a_1a_2\ldots a_j, b_1b_2\ldots b_k)$

Optimization recurrence

If $a_j = b_k$, Opt[j,k] = 1 + Opt[j-1, k-1]

If $a_j \neq b_k$, Opt[j,k] = max(Opt[j-1,k], Opt[j,k-1])