

Algorithms and datastructures I

Lecture 13: dynamic programming

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Dynamic programming



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Fib(n) (with memoization)

1. If $T[n]$ is defined: return $T[n]$.
2. If $n \leq 1$: $T[n] \leftarrow n$.
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Fib(n) (without recursion)

1. $T[0] \leftarrow 0, T[1] \leftarrow 1$
2. For $k = 2, \dots, n$: $T[k] \leftarrow T[k-1] + T[k-2]$
3. Return $T[n]$.
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Grand plan:

1. Start with a recursive algorithm
2. Determine repeated invocations
3. Add a table (cache) memoizing the results
4. Determine an order of filling the cache avoiding the recursion

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Recall: Floyd-Washall algorithm

Let G be a graph with vertices $V = \{1, 2, \dots, n\}$.

Instead of distances from a given vertex v_0 we want to compute **distance matrix** D such that $D_{i,j} = d(i, j)$.

Definition

Let D^k be a matrix such that $D_{i,j}^k$ is the length of shortest path from i to j such that all internal vertices are in $\{1, 2, \dots, k\}$.

Floyd-Washall Algorithm

Input: Matrix of length of edges D^0

1. For $k = 0, \dots, n - 1$
2. For $i = 1, \dots, n$
3. For $j = 1, \dots, n$
4. $D_{i,j}^{k+1} = \min(D_{i,j}^k, D_{i,k+1}^k + D_{k+1,j}^k)$

Output: Matrix of distances D^n

Time complexity $\Theta(n^3)$.

Memory complexity can be reduced by $\Theta(n^2)$ by modifying matrix “in place”

(it holds that $D_{k+1,j}^{k+1} = D_{k+1,j}^k$ and $D_{i,k+1}^{k+1} = D_{i,k+1}^k$).

Walks in Manhattan

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Edit $((x_1, \dots, x_m), (y_1, \dots, y_n), i, j)$

1. If $i > n$: return $m - j + 1$.
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4. If $x_i \neq y_j$: $l_r \leftarrow l_r + 1$.

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6. $l_i \leftarrow$ Edit $((x_1, \dots, x_m), (y_1, \dots, y_n), i, j + 1) + 1$.
7. Return $\min(l_r, l_d, l_i)$.

Optimal search trees



Donald E. Knuth

Definition

Given set of elements x_1, x_2, \dots, x_n and weights w_1, w_2, \dots, w_n the **optimal search tree** is a binary search tree minimizing

$$\sum_{i=1}^n w_i F(x_i)$$

where $F(x_i)$ is the number of vertices visited by $\text{Find}(x_i)$.

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$\text{OptTree}((x_1, \dots, x_n), (w_1, \dots, w_n), i, j)$

1. If $i > j$: return 0.
2. $W \leftarrow w_i + \dots + w_j$
3. $C \leftarrow +\infty$
4. For $k = 1, \dots, j$:
5. $C_\ell \leftarrow \text{OptTree}((x_1, \dots, x_n), (w_1, \dots, w_n), i, k-1)$
6. $C_r \leftarrow \text{OptTree}((x_1, \dots, x_n), (w_1, \dots, w_n), k+1, j)$
7. $C = \min(C, C_\ell + C_r + W)$
8. Return C .

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OptTree $((x_1, \dots, x_n), (w_1, \dots, w_n), i, j)$ (Knuth 1971)

1. For $i = 1, \dots, n+1$: $T[j, i-1] \leftarrow 0$
2. For $\ell = 1, \dots, n$, $i = 1, \dots, n-\ell+1$
3. $j \leftarrow i + \ell - 1$
4. $W \leftarrow w_i + \dots + w_j$
5. $T[i, j] \leftarrow +\infty$
6. For $k = 1, \dots, j$:
7. $C \leftarrow T[j, k-1] + T[k+1, j] + W$
8. If $C < T[i, j]$: $T[i, j] \leftarrow C, K[i, j] \leftarrow k$

Optimal search trees

$w_1 = 1$
$w_2 = 10$
$w_3 = 3$
$w_4 = 2$
$w_5 = 1$
$w_6 = 9$

T	0	1	2	3	4	5	6
1	0	1	12	18	24	28	52
2	-	0	10	16	22	26	50
3	-	-	0	3	7	10	25
4	-	-	-	0	2	4	16
5	-	-	-	-	0	1	11
6	-	-	-	-	-	0	9
7	-	-	-	-	-	-	0

K	1	2	3	4	5	6
1	1	2	2	2	2	2
2	-	2	2	2	2	2
3	-	-	3	3	3	6
4	-	-	-	4	4	6
5	-	-	-	-	5	6
6	-	-	-	-	-	6



