



Algorithms Theory

14 – Dynamic Programming (3)

Optimal binary search trees

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Method of dynamic programming



Recursive approach: Solve a problem by solving several smaller analogous subproblems of the same type. Then combine these solutions to generate a solution to the original problem.

Drawback: Repeated computation of solutions

Dynamic-programming method: Once a subproblem has been solved, store its solution in a table so that it can be retrieved later by simple table lookup.

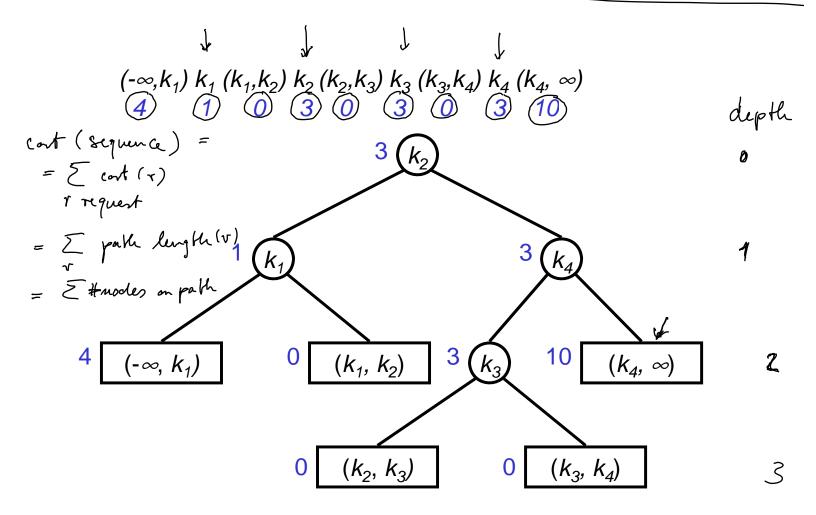
Optimal substructure



Dynamic programming is typically applied to *optimization problems*.

An optimal solution to the original problem contains *optimal* solutions to smaller subproblems.





weighted path length:

$$3 \cdot 1 + 2 \cdot (1+3) + 3 \cdot 3 + 2 \cdot (4+10)$$



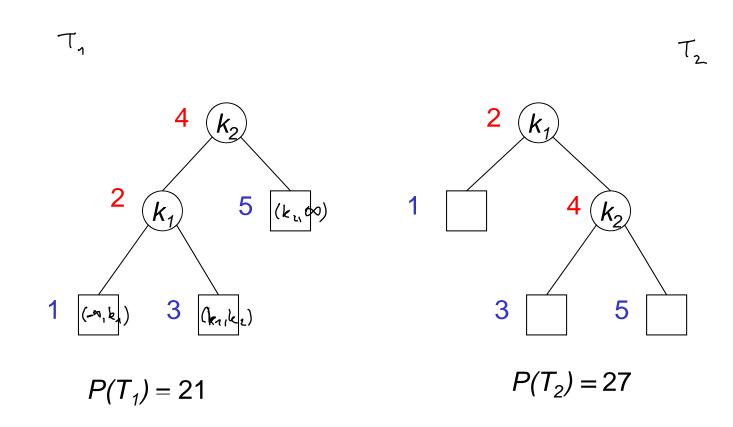
 a_i : (absolute) frequency of requests to key k_i b_j : (absolute) frequency of requests to $x \in (k_j, k_{j+1})$

Weighted path length P(T) of a binary search tree T for S:

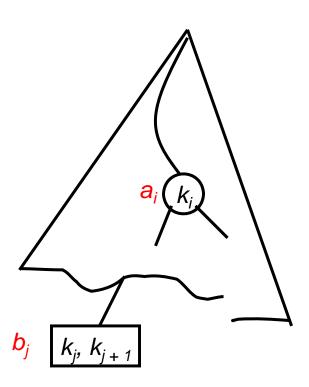
$$P(T) = \sum_{i=1}^{n} (\underbrace{depth(k_i) + 1}) \underbrace{a_i} + \sum_{j=0}^{n} \underbrace{depth((k_j, k_{j+1}))} b_j$$

Goal: Binary search tree with minimum weighted path length P for S.



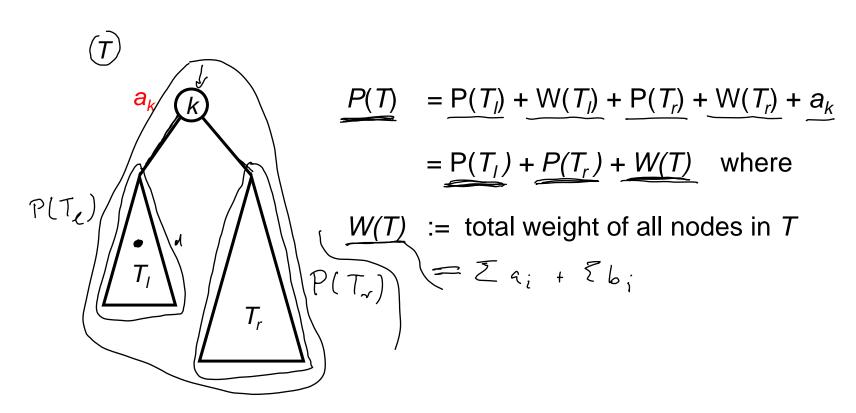






An <u>optimal binary search</u> tree is a binary search tree with <u>minimum</u> weighted path length.





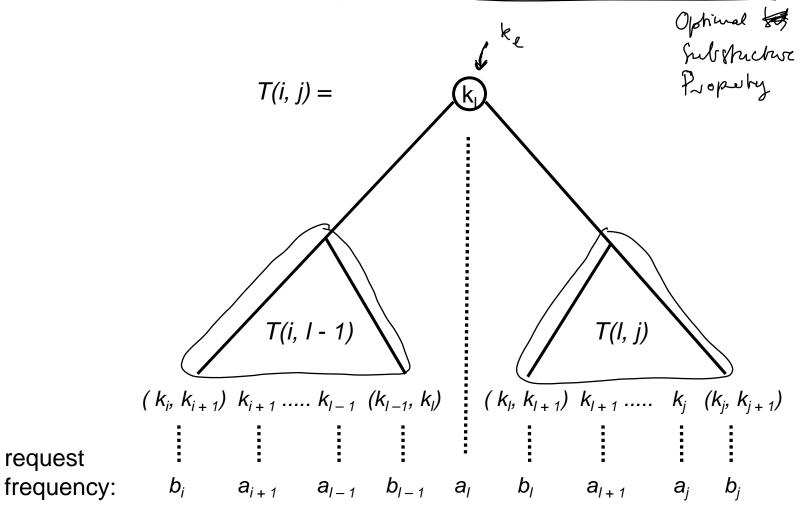
If T is a tree with minimum weighted path length for S, then subtrees T_I and T_r are trees with minimum weighted path length for subsets of S.



Let

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bi ain aj bj
\rightarrow T(i, j): optimal binary search tree for (k_i, k_{i+1}) k_{i+1} \dots k_j (k_i, k_{i+1}),
\rightarrow W(i, j): weight of T(i, j), i.e. W(i, j) = b<sub>i</sub> + a<sub>i+1</sub> + ... + a<sub>j</sub> + b<sub>j</sub>, \omega (T(i,j))
\rightarrow P(i, j): weighted path length of T(i, j).
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10



$$\begin{split} W(i,\,i) &= b_i &, \text{ for } 0 \leq i \leq n \\ &\rightarrow W(i,\,j) = W(i,\,j-1) + a_j + b_j &, \text{ for } 0 \leq i < j \leq n \\ &\searrow b_i + q_{i+1} + \dots + q_{j-1} + b_{j-1} + q_{j} + b_{j} &, \text{ for } 0 \leq i \leq n \end{split}$$

$$P(i,\,i) \equiv 0 &, \text{ for } 0 \leq i \leq n \qquad P(i,i) = b_i \cdot \text{ depth} = \infty \\ P(i,\,j) &= W(i,\,j) + \min \big\{ \underbrace{P(i,\,l-1) + P(l,\,j)}_{i < \ell \leq j} \big\}, \text{ for } 0 \leq i < j \leq n \qquad (*) \end{split}$$

 \rightarrow r(i, j) = the index θ for which the minimum is achieved in (*)



Base cases

Case 1:
$$s = j - i = 0$$

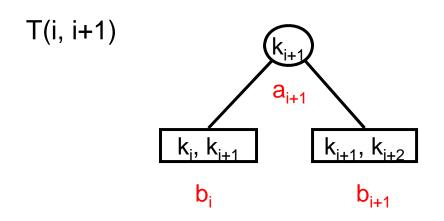
$$T(i, i) = (k_i, k_{i+1})$$

$$W(i, i) = b_i$$

$$P(i, i) = 0, r(i, i) \text{ not defined}$$



Case 2:
$$s = j - i = 1$$



depth
$$P(T(i,i+n))$$

0 $a_{i+n} \cdot (o+n)$

+

1 $b_i \cdot 1 + b_{i+n} \cdot 1$
 $b_i \cdot 1 + b_{i+n} \cdot 1$
 $b_i \cdot 1 + b_{i+n} \cdot 1$

$$W(i, i+1) = b_i + a_{i+1} + b_{i+1} = W(i, i) + a_{i+1} + W(i+1, i+1)$$

 $P(i, i+1) = W(i, i+1)$
 $r(i, i+1) = i+1$

Computing the minimum weighted path length using dynamic programming



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Case 3: s = j - i > 1
for s = 2 to n do
   for i = 0 to (n - s) do
         {j = i + s;}
           <u>determine</u> (greatest) I, i < I \le j, s.t. P(i, I - 1) + P(I, j) is minimal
           P(i, j) = P(i, l-1) + P(l, j) + W(i, j);
          r(i, j) = i;
```

Runing time O(n3)



Define:

$$P(i, j) := \min$$
 weighted path length for $b_i a_{i+1} b_{i+1} \dots a_j b_j$ $W(i, j) := \sup$ of

Then:

$$W(i,j) = \begin{cases} b_i & \text{if } i = j \\ W(i,j-1) + a_j + W(j,j) & \text{otherwise} \end{cases}$$

$$P(i,j) = \begin{cases} 0 & \text{if } i = j \\ W(i,j) + \min_{i < l \le j} \{P(i,l-1) + P(l,j)\} & \text{otherwise} \end{cases}$$

 \rightarrow Computing the solution P(0,n) takes $O(n^3)$ time. and requires $O(n^2)$ space.



Theorem

An <u>optimal binary search</u> tree for n keys and n+1 intervals with known request frequencies can be constructed in $O(n^3)$ time.