

Exact Algorithms

Sommer Term 2020

Lecture 2. Branching Algorithms and Satisfiability

Based on: [Exact Exponential Algorithms: §2]

Further discussions: [Parameterized Algorithms: §3; specifically §3.2]

(slides by J. Spoerhase, Th. van Dijk, S. Chaplick, and A. Wolff)

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- Other names:
Backtracking, search-tree algorithms, ...

General Form

- **Branching Rules:**

Choose a small part of the solution and solve a corresponding subproblem for each choice

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- **Specification:**

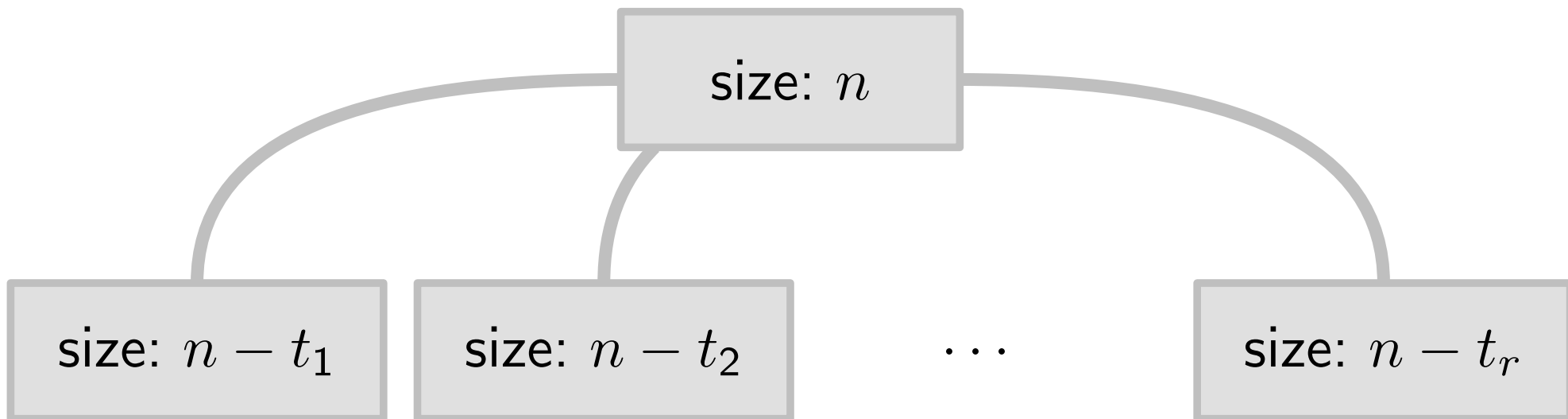
Often only calculates the optimal value.

Branching Vectors

- Apply a branching rule b to an instance I of size n .

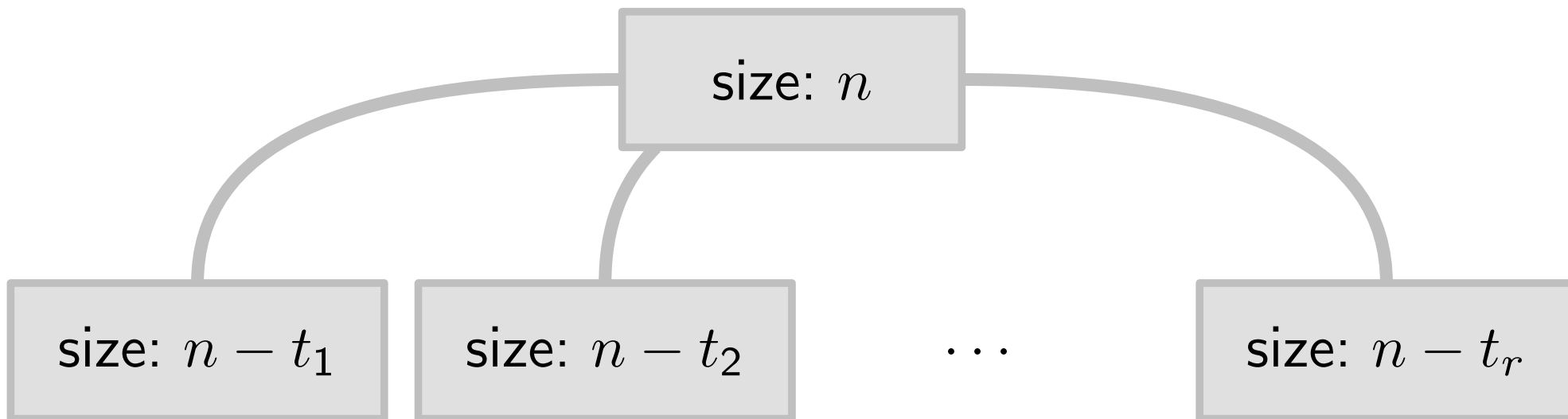
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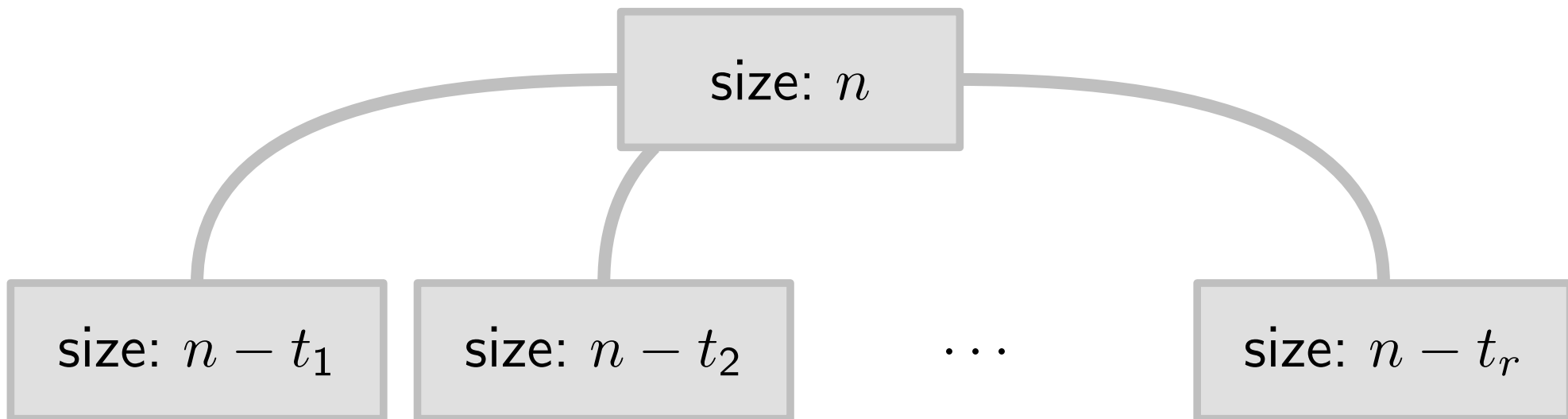
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Recurrence: $T(n) \leq T(n - t_1) + T(n - t_2) + \dots + T(n - t_r)$

Theorem on Branching Vectors

Thm. Let b be a branching rule with vector (t_1, t_2, \dots, t_r) .
Then the runtime of an algorithm executing b is $O^*(\alpha^n)$,
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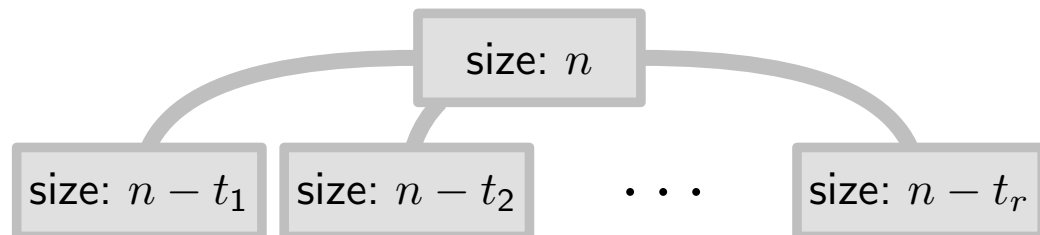
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- Often irrational.

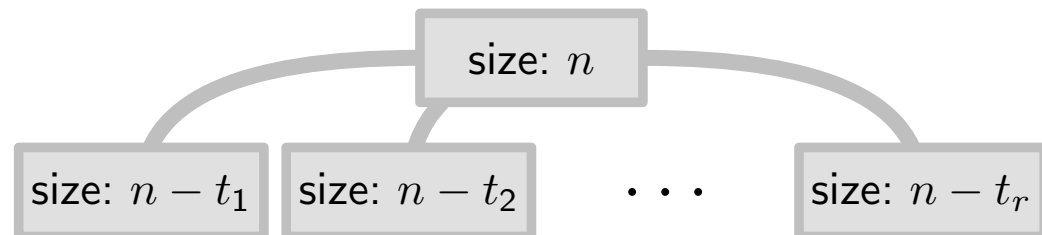
Properties of $\tau(\cdot)$



Thm. Let $r \geq 2$ and, for $i = 1, \dots, r$, let $t_i > 0$. Then:

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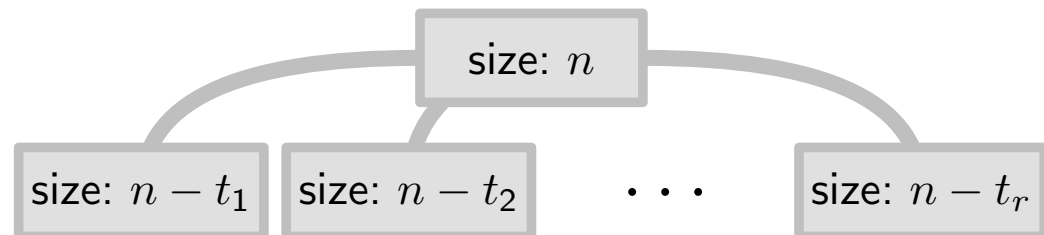
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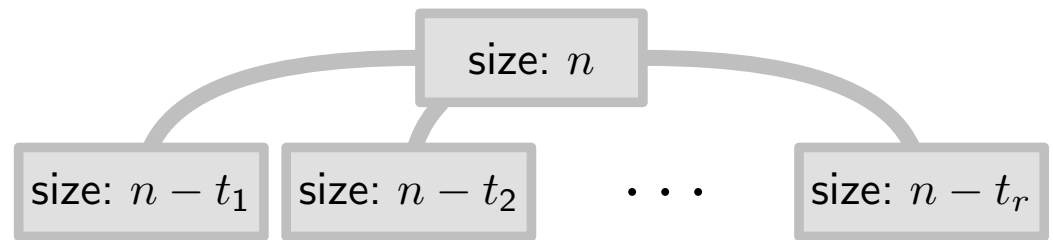
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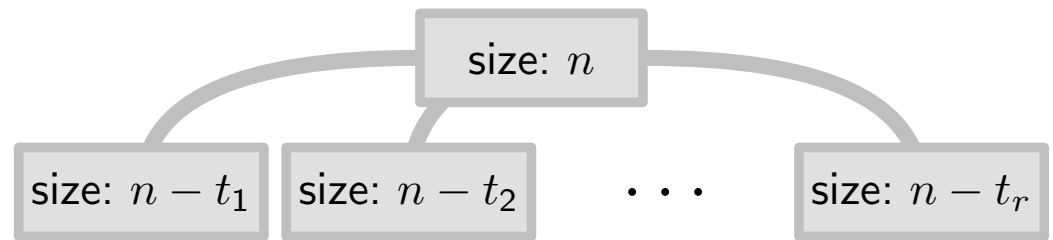
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Lemma. For $i, j, k > 0$, the following **balancing properties** apply:

- (i) $\tau(k, k) \leq \tau(i, j)$ if $i + j = 2k$,
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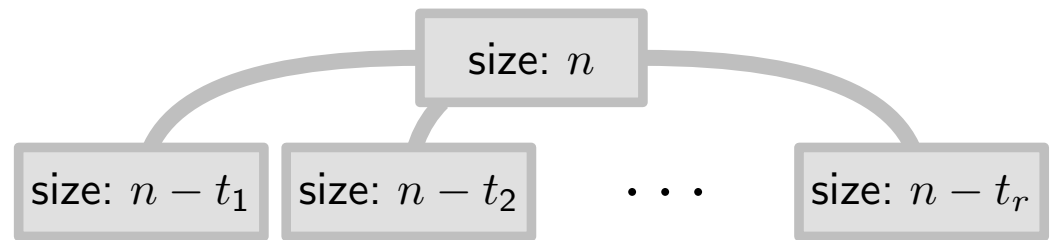
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E.g.:

$$\tau(1, 1) = 2$$

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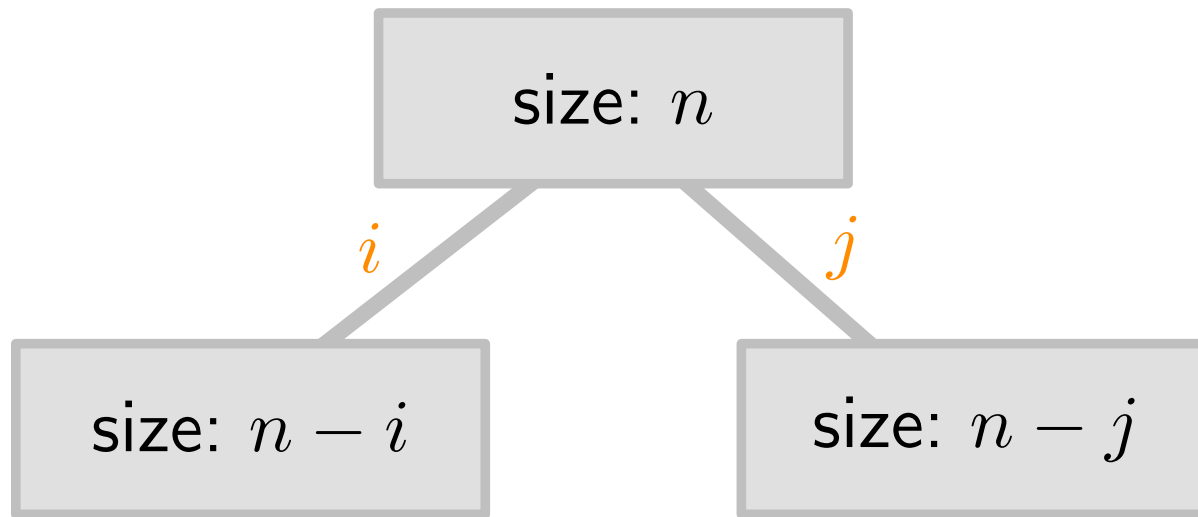
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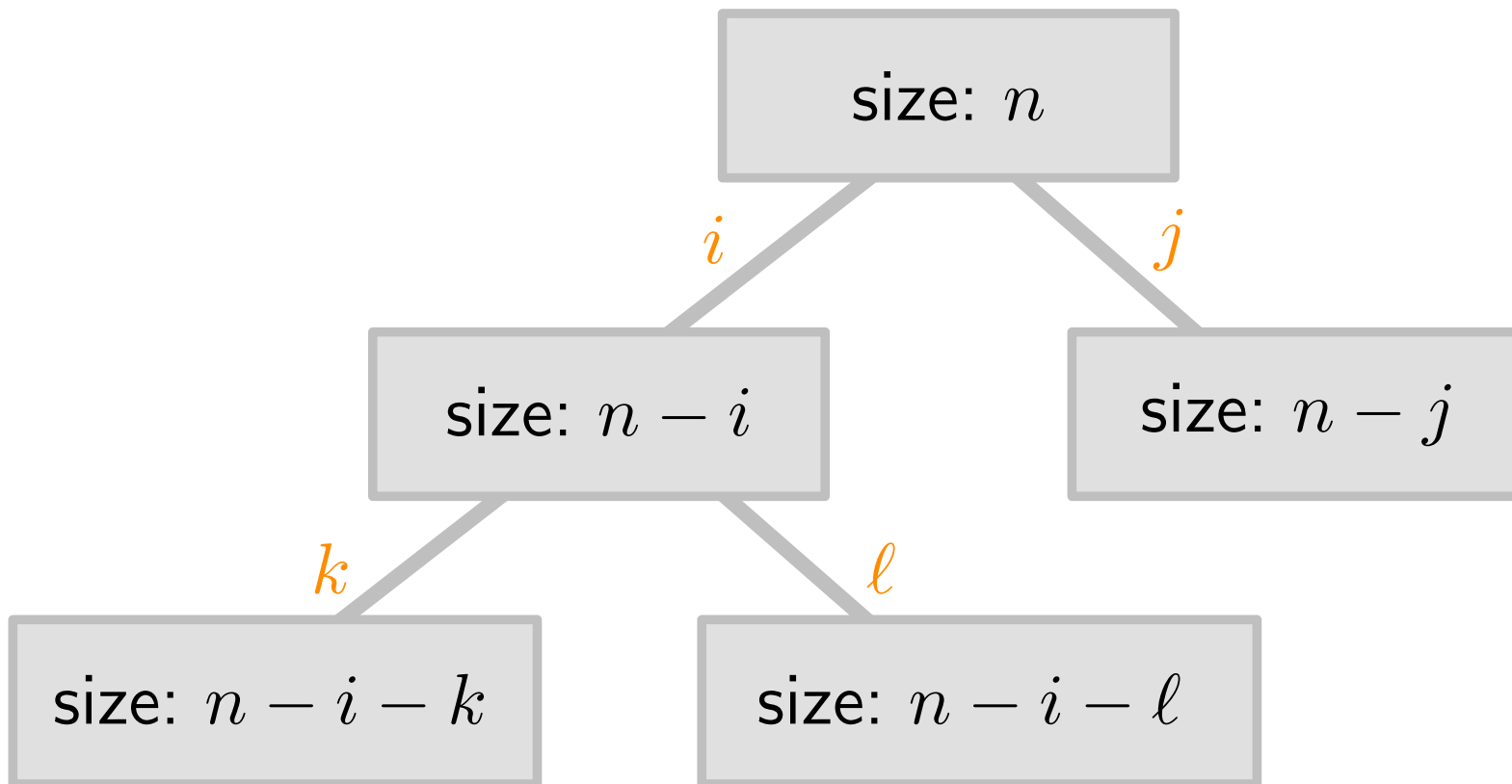
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$$\begin{array}{ll} \tau(1, 1) = 2 & \tau(3, 3) = \sqrt[3]{2} < 1.26 \\ \tau(1, 2) = \frac{1+\sqrt{5}}{2} < 1.62 & \tau(2, 4) < 1.272 \\ & \tau(1, 5) < 1.3248 \end{array}$$

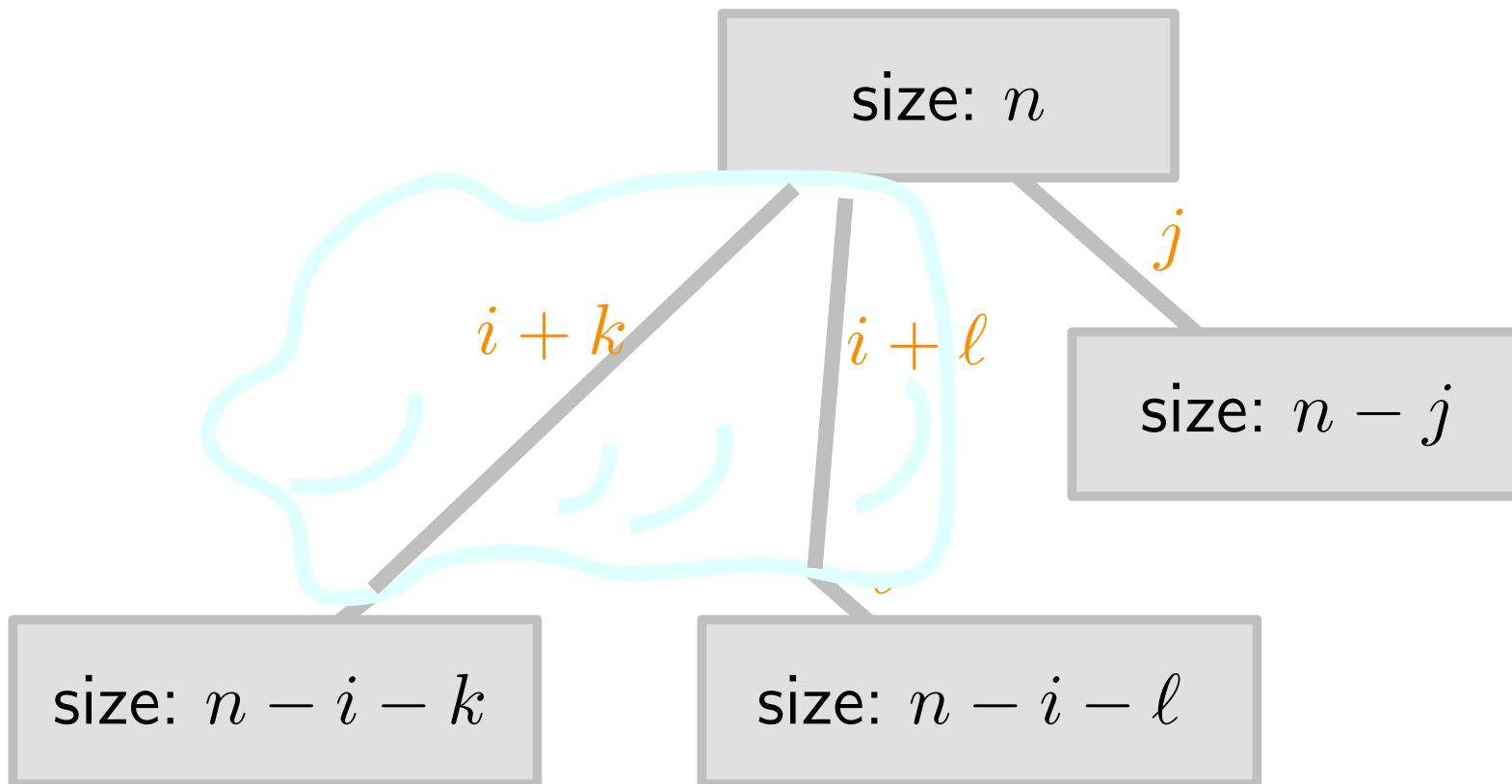
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Branching-Vector: $(i + k, i + l, j)$

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k -SAT: Each clause has $\leq k$ literals.

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Properties of Reduced Formulas

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A First Algorithm for k -SAT

Algorithm k -SAT-v1(F)

if F is empty **then**

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pick clause $c = (\ell_1 \vee \ell_2 \vee \dots \vee \ell_q)$ from F , where $q \leq k$

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- If t is *not* an autark, then $F[t]$ contains a clause of length $\leq k - 1$.

An Improved k -SAT Algorithm

Algorithm k -SAT-v2(F)

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□