

Lecture 29

Greedy: Activity-Selection Problem (contd.), MST

Greedy Algorithm for Activity-Selection

Greedy Algorithm for Activity-Selection

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Let's try to find $A_{0,12}$ using greedy choices!

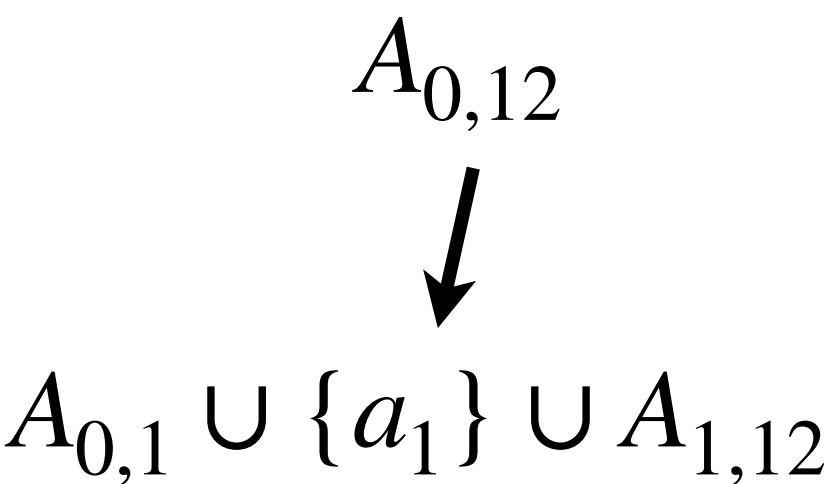
Greedy Algorithm for Activity-Selection

$A_{0,12}$



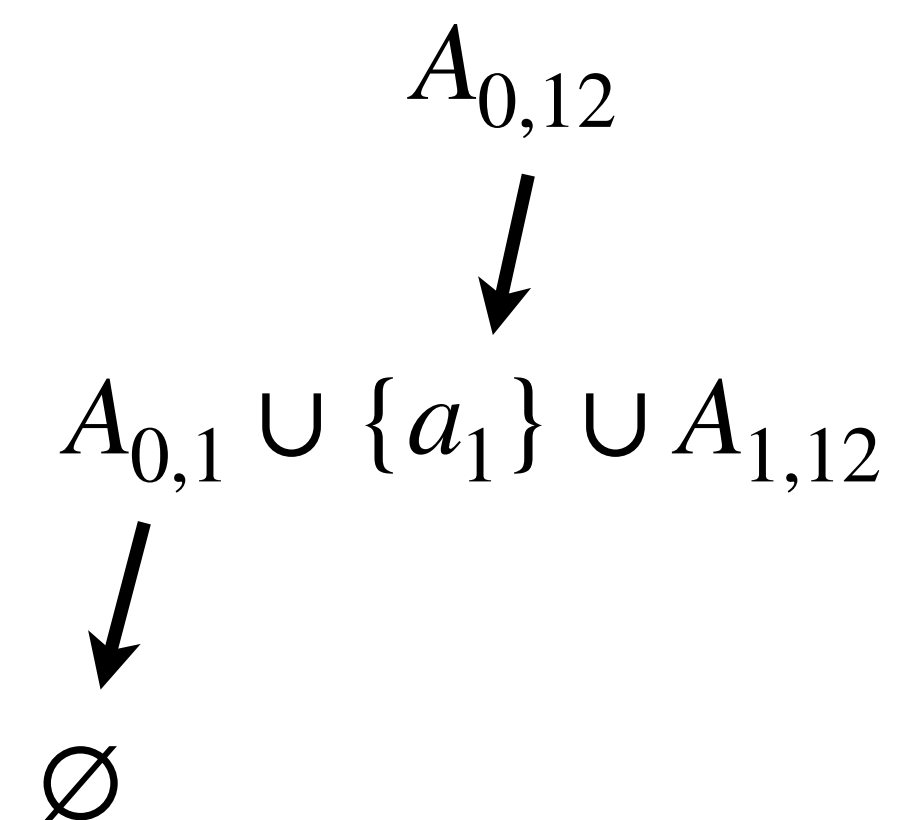
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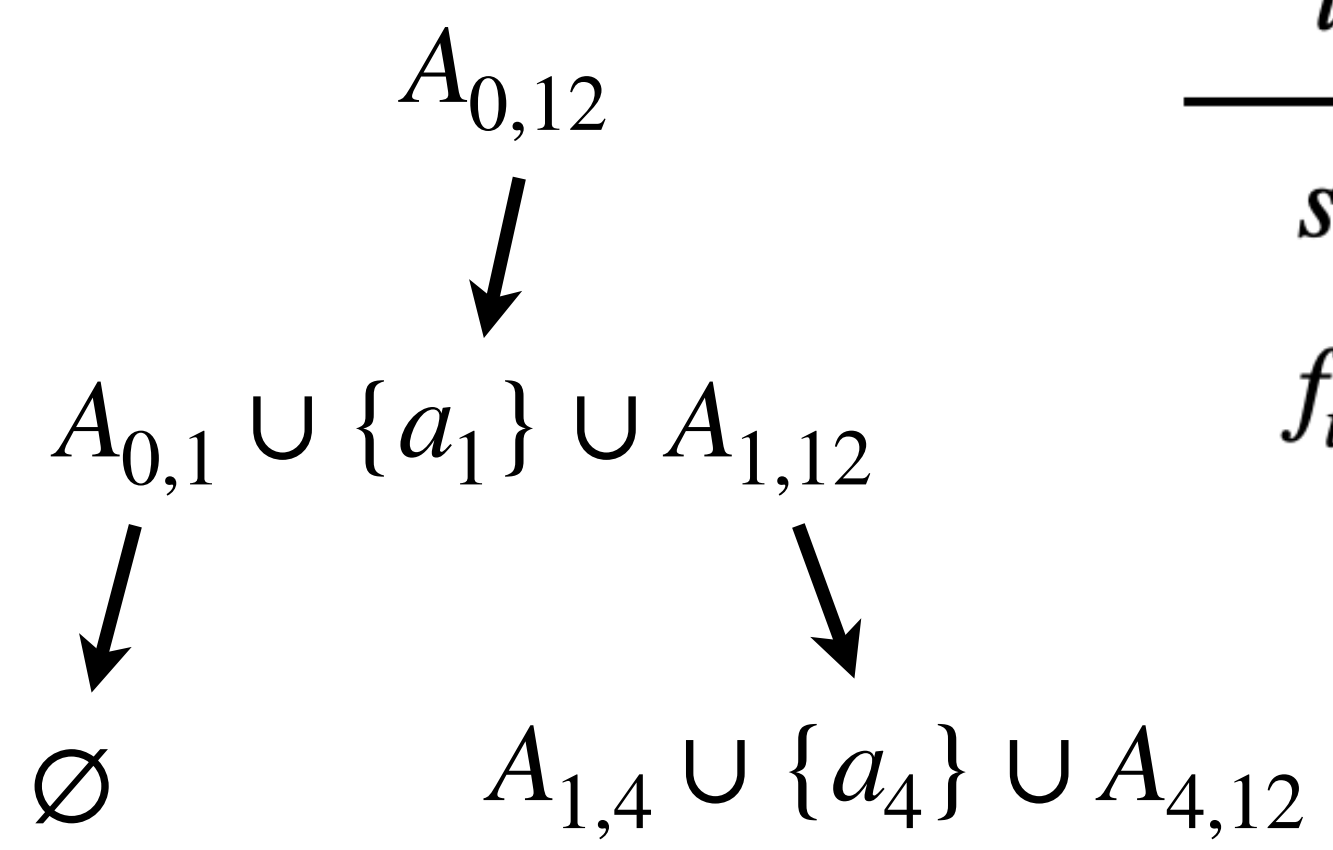
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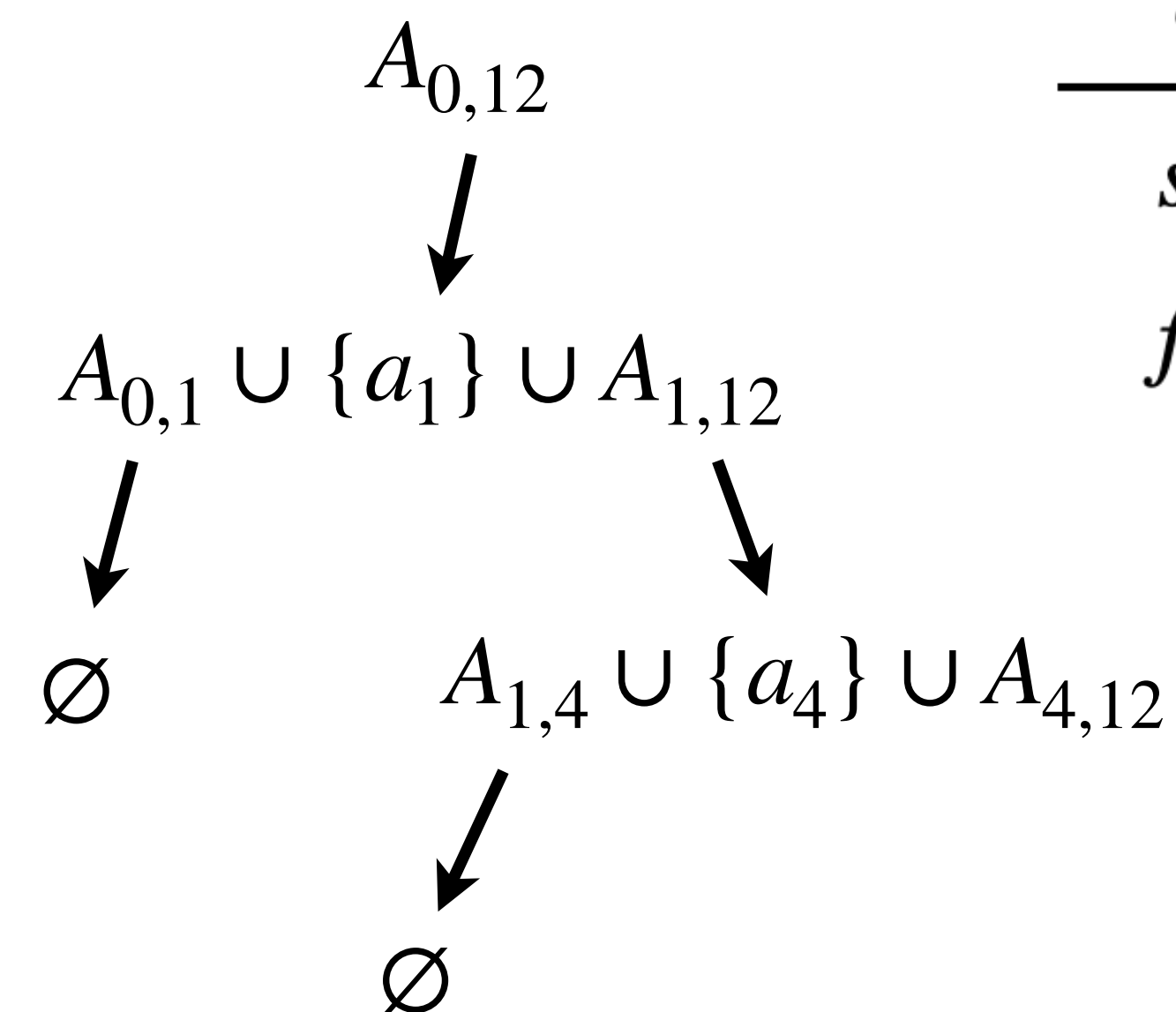
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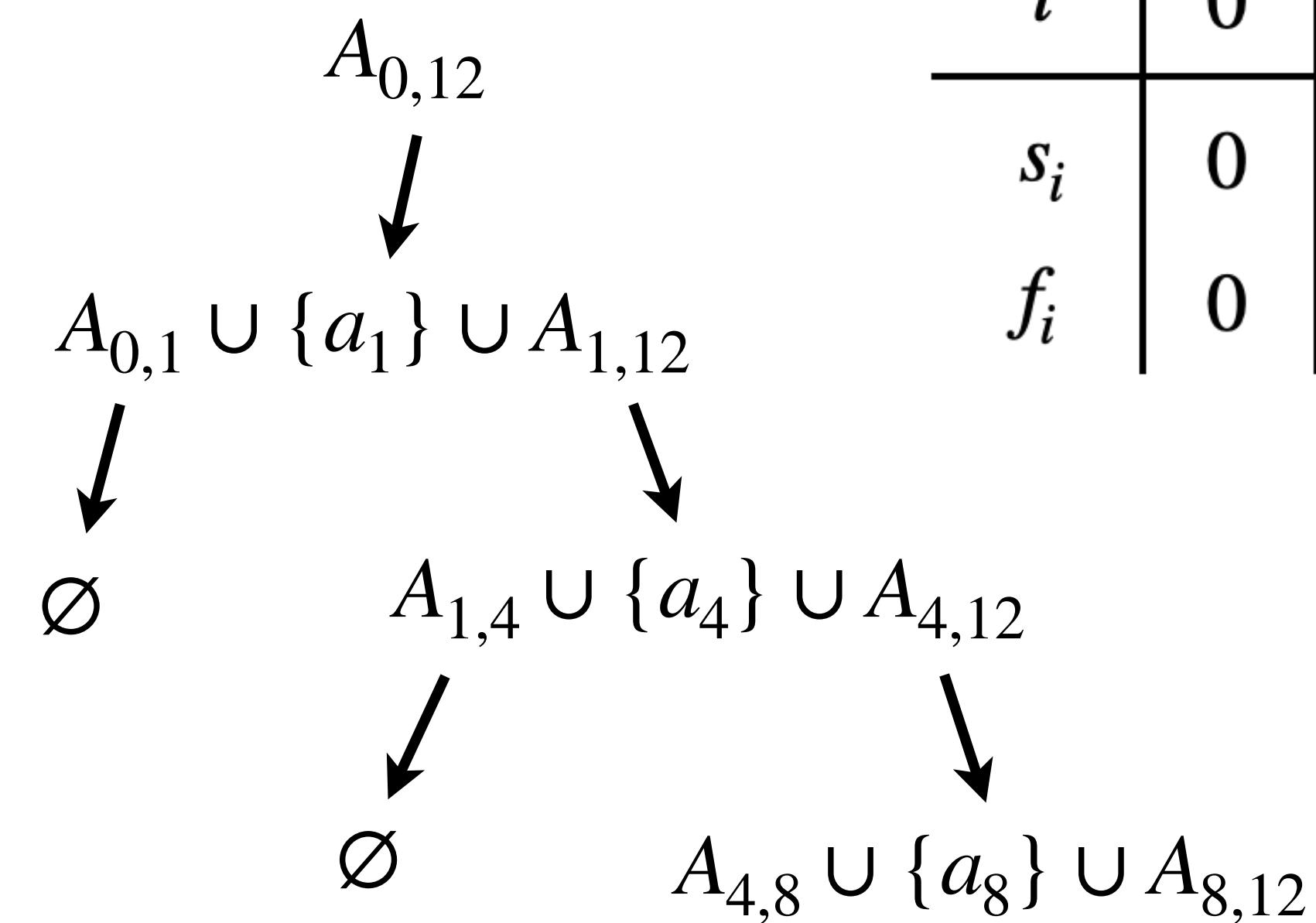
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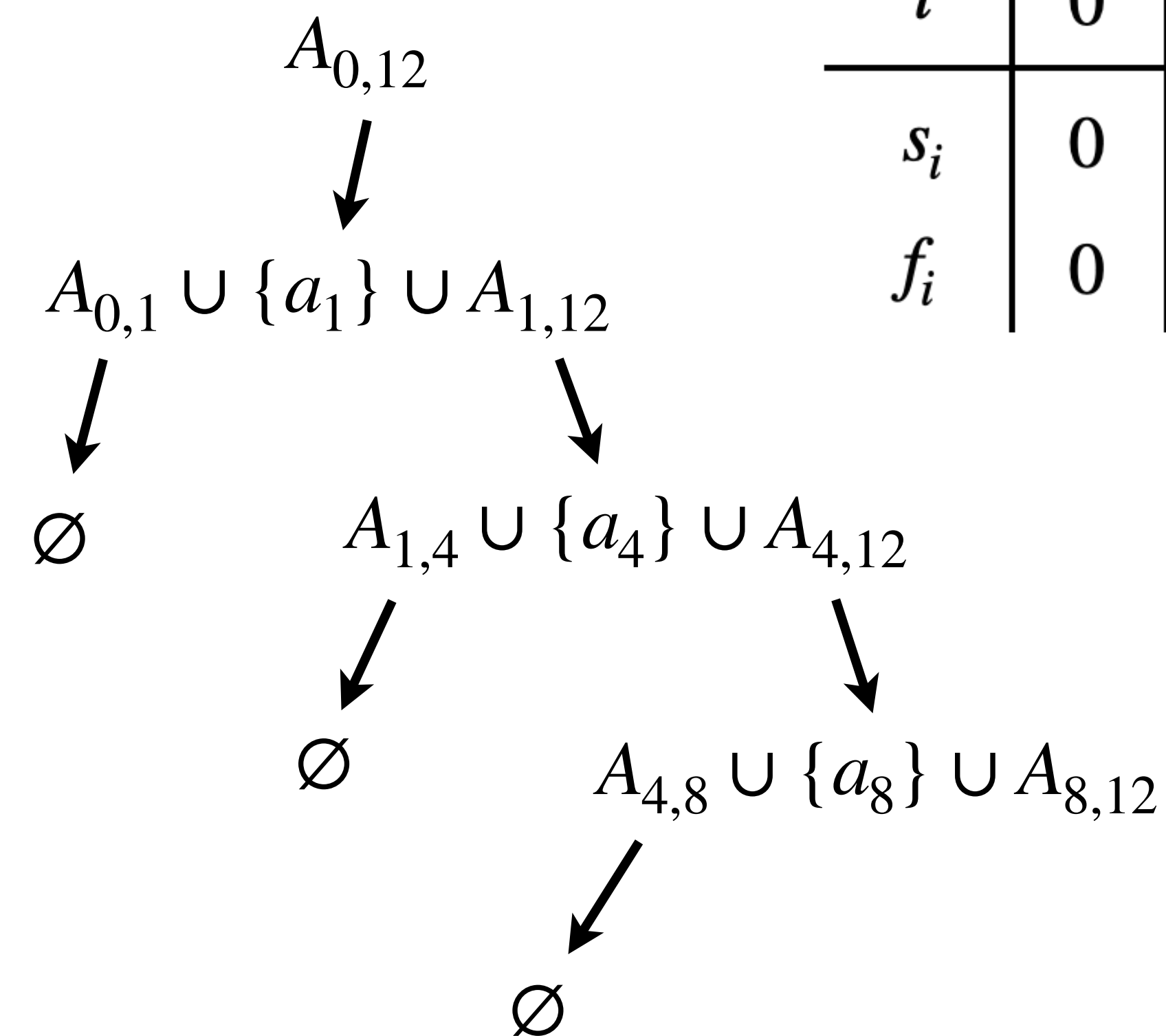
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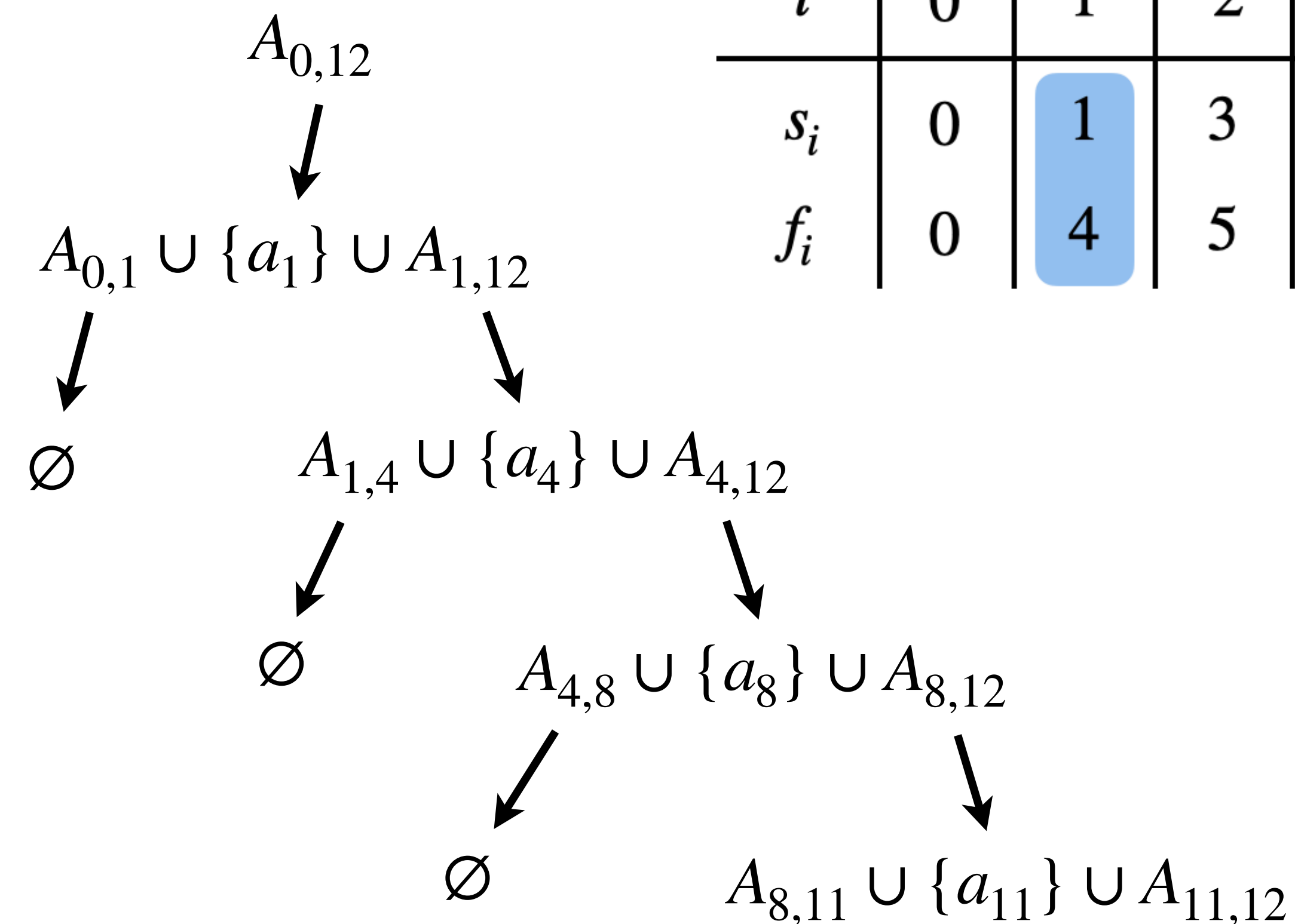
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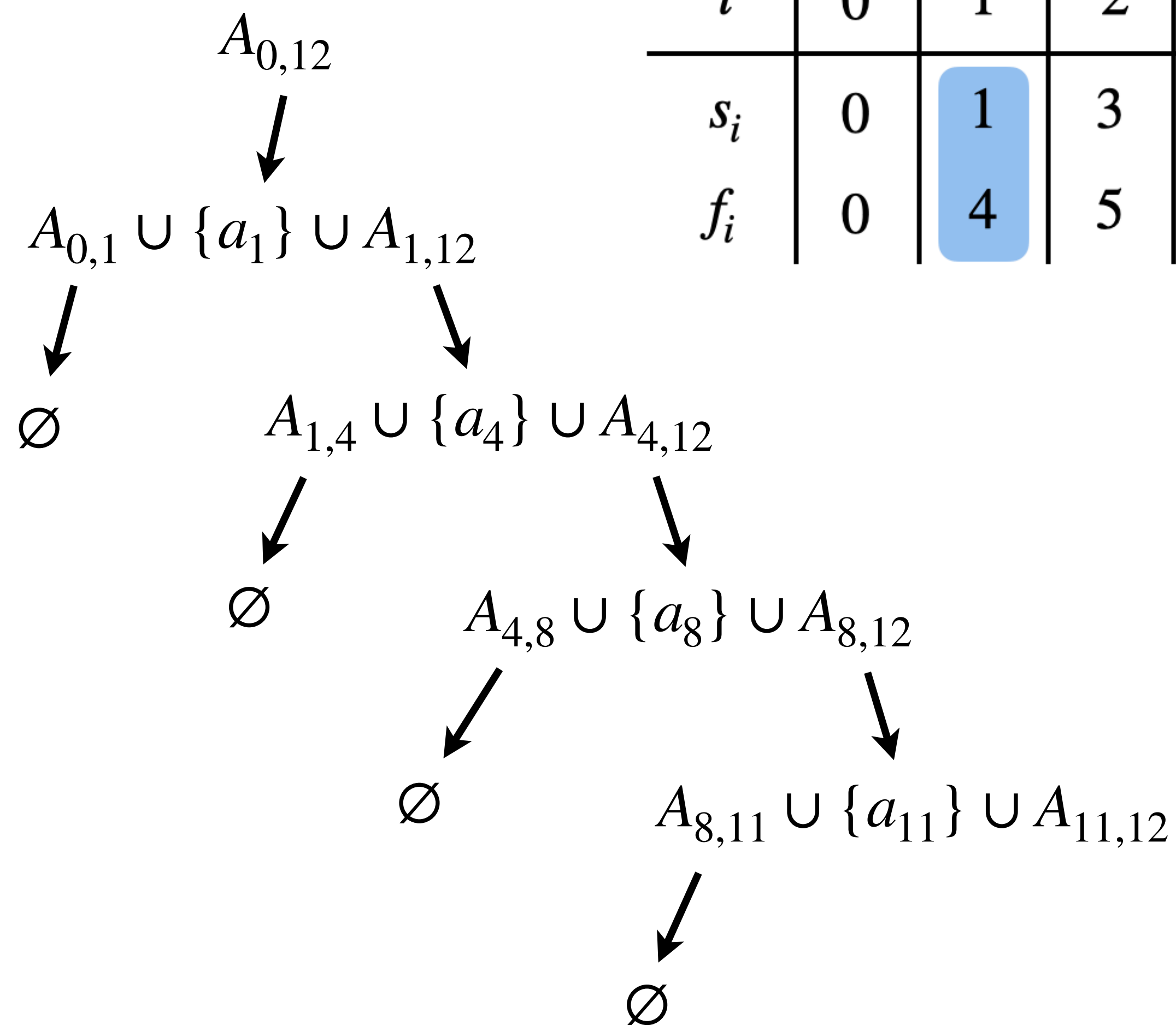
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Greedy Algorithm for Activity-Selection

$$A_{0,12}$$
$$A_{0,1} \cup \{a_1\} \cup A_{1,12}$$



\emptyset

$$A_{1,4} \cup \{a_4\} \cup A_{4,12}$$



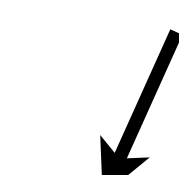
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$$A_{4,8} \cup \{a_8\} \cup A_{8,12}$$

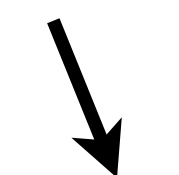


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$$A_{8,11} \cup \{a_{11}\} \cup A_{11,12}$$



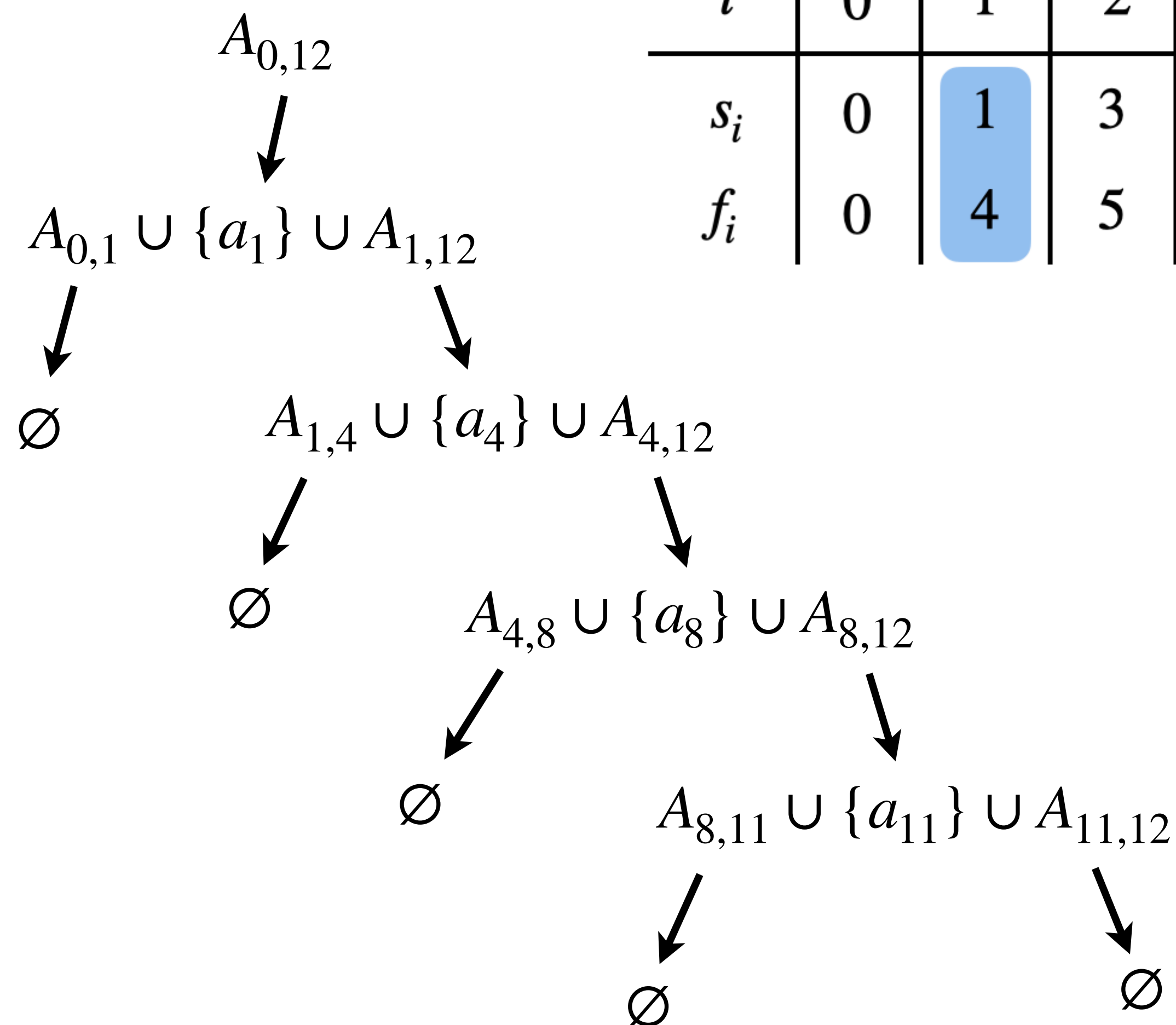
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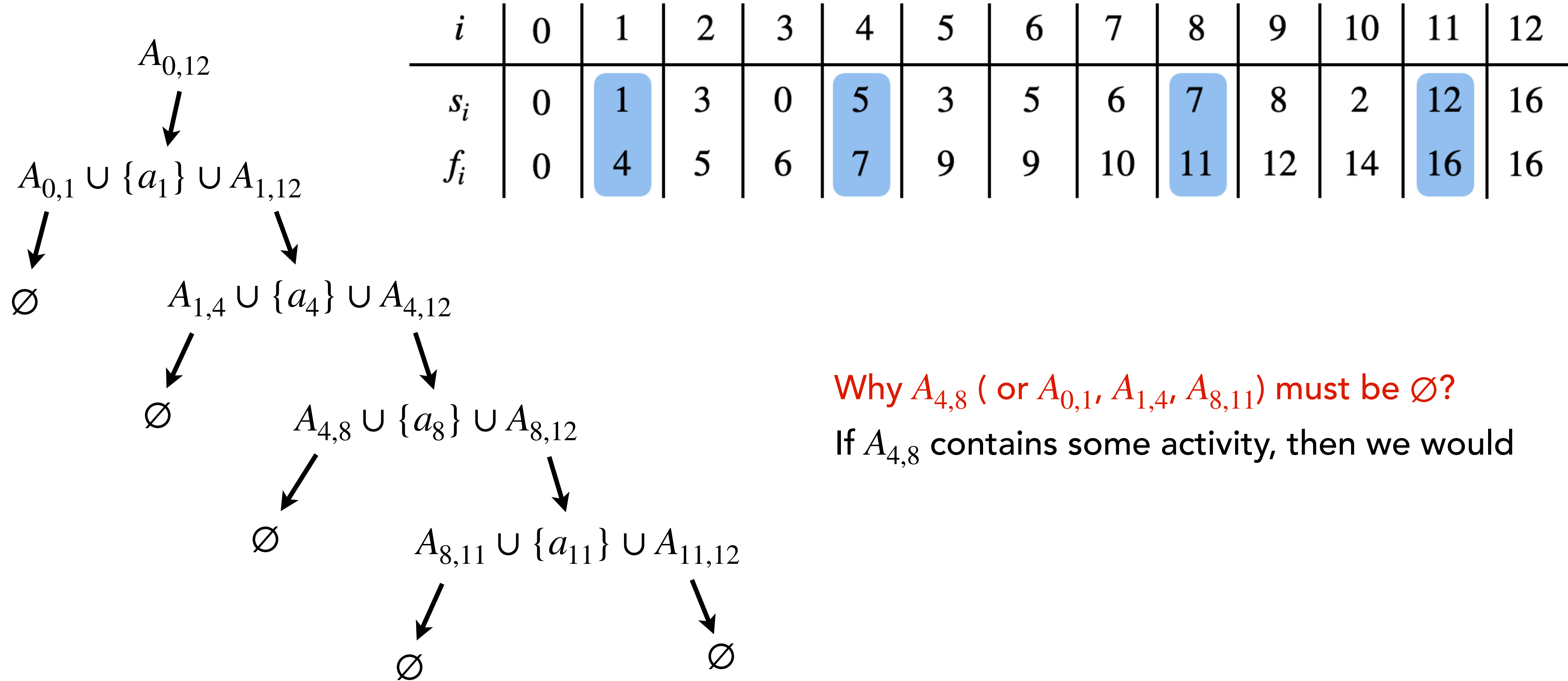
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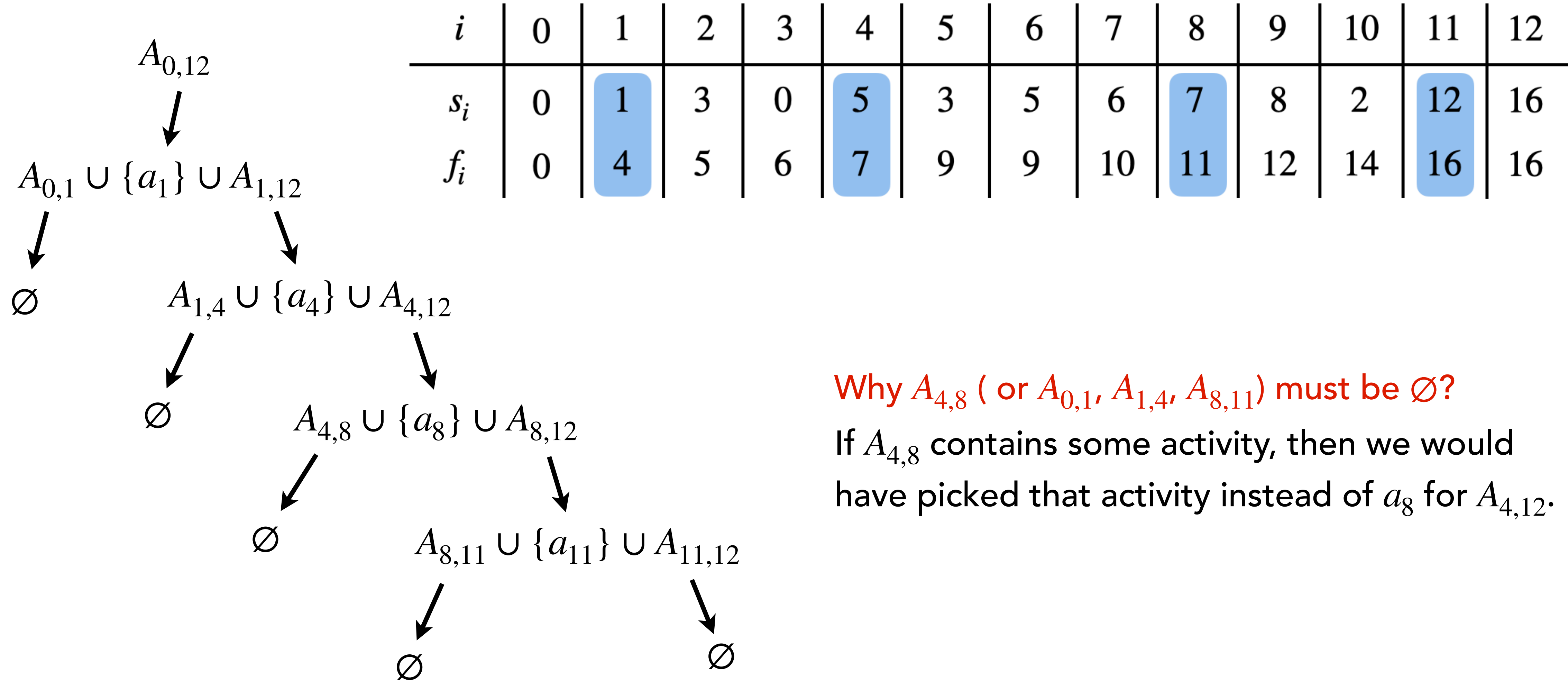
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Why $A_{4,8}$ (or $A_{0,1}$, $A_{1,4}$, $A_{8,11}$) must be \emptyset ?

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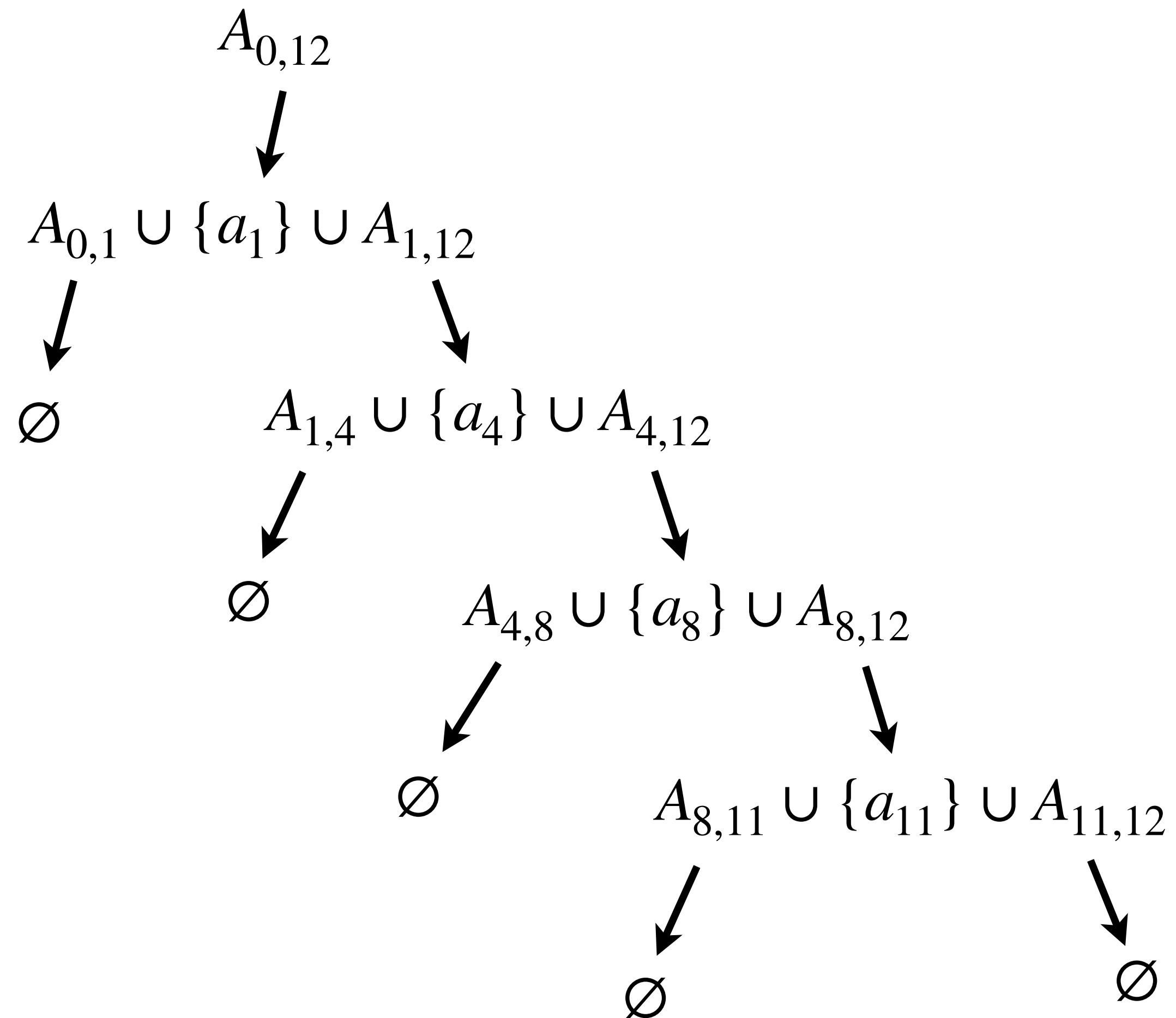
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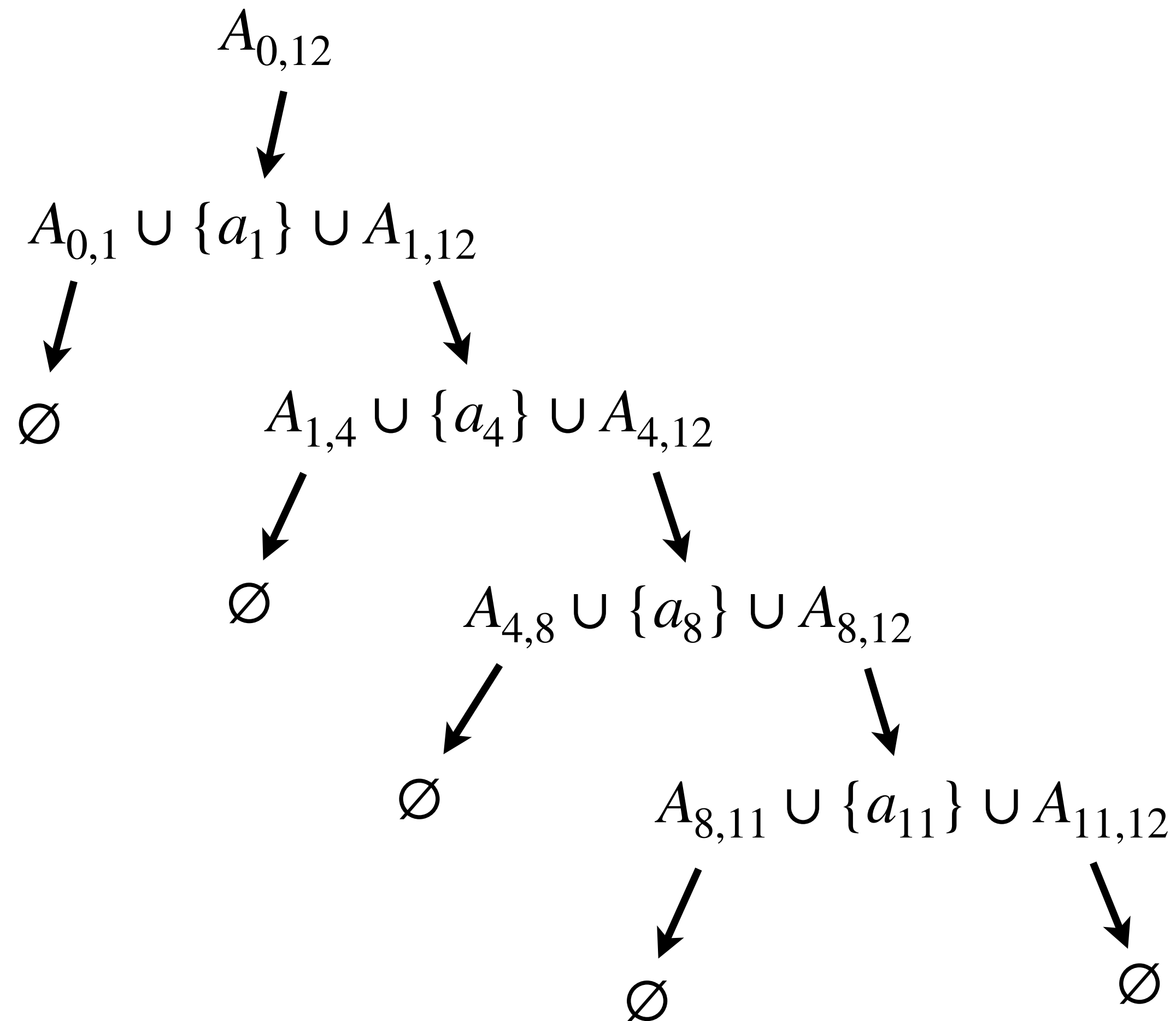
If $A_{4,8}$ contains some activity, then we would have picked that activity instead of a_8 for $A_{4,12}$.

Greedy Algorithm for Activity-Selection



Greedy Algorithm for Activity-Selection

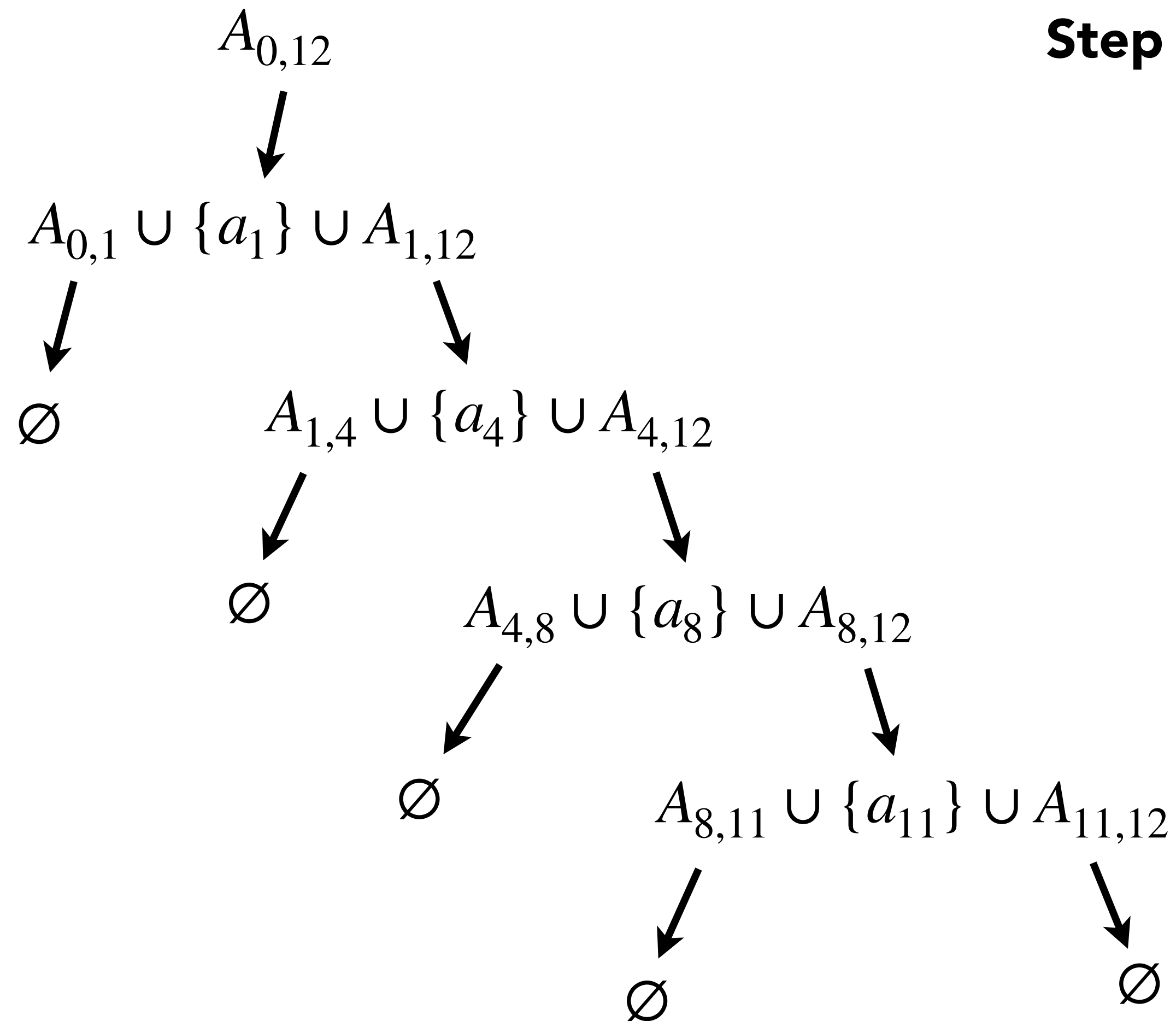
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Greedy Algorithm for Activity-Selection

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Step 1: Pick a_1 .

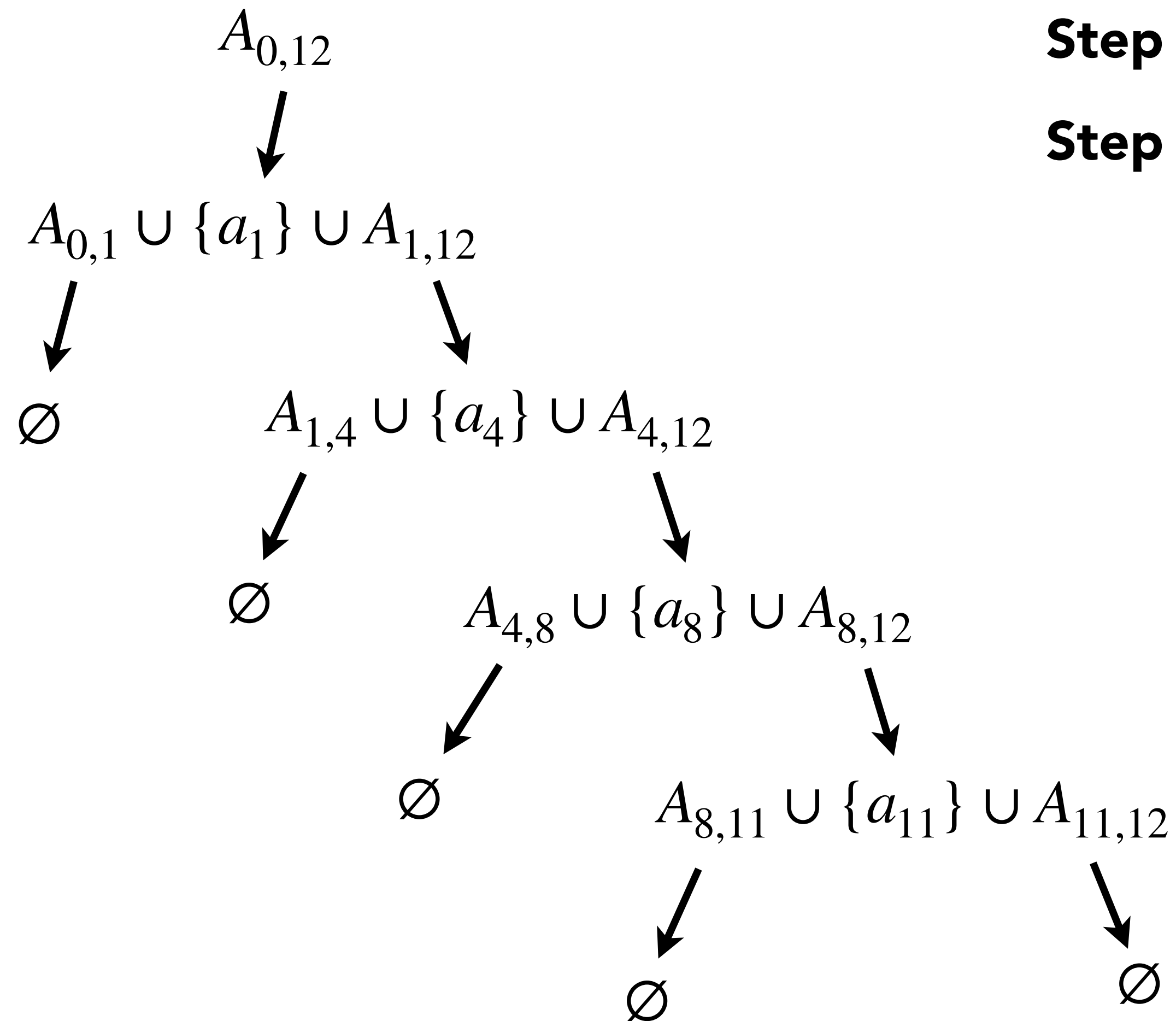


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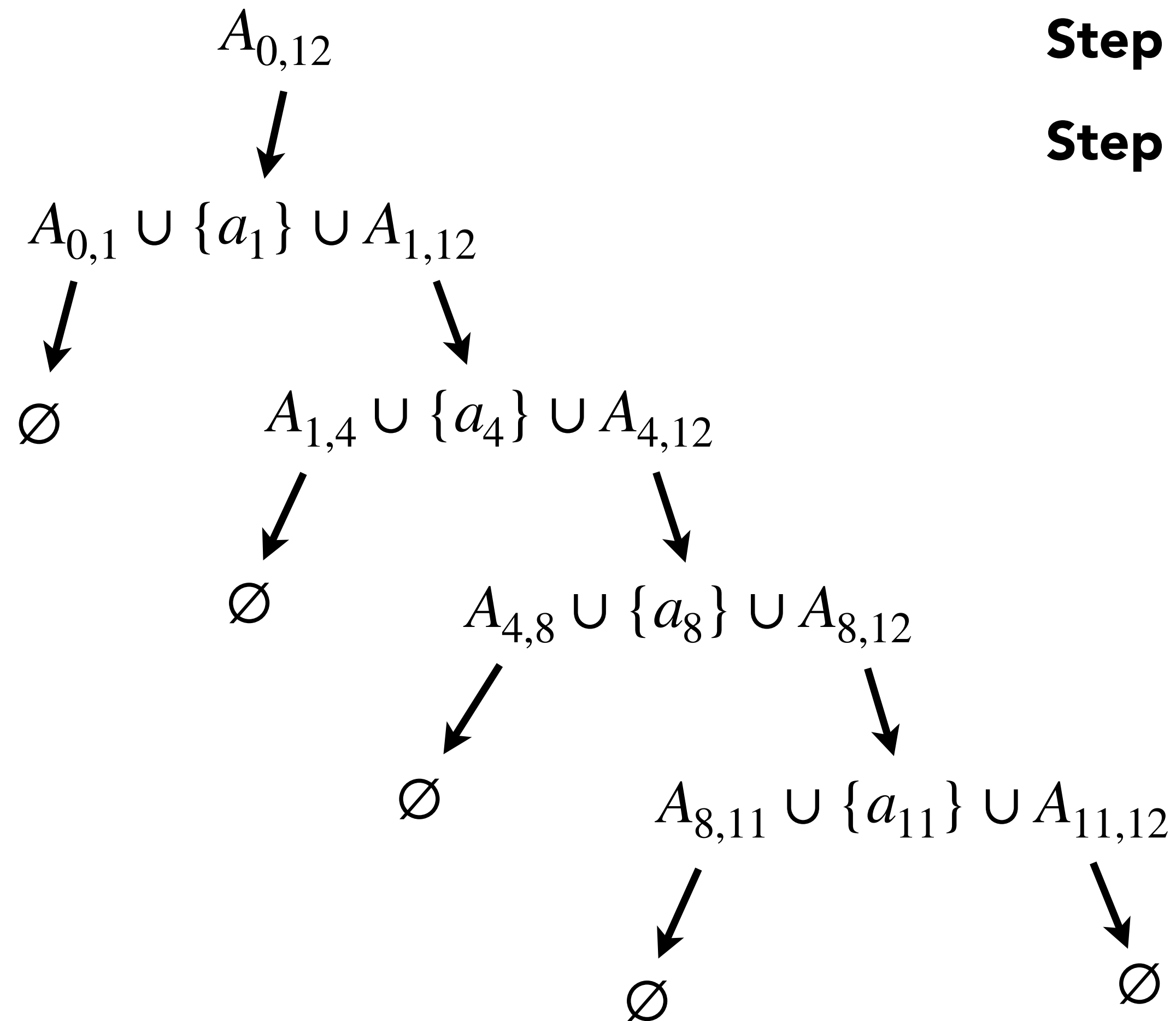


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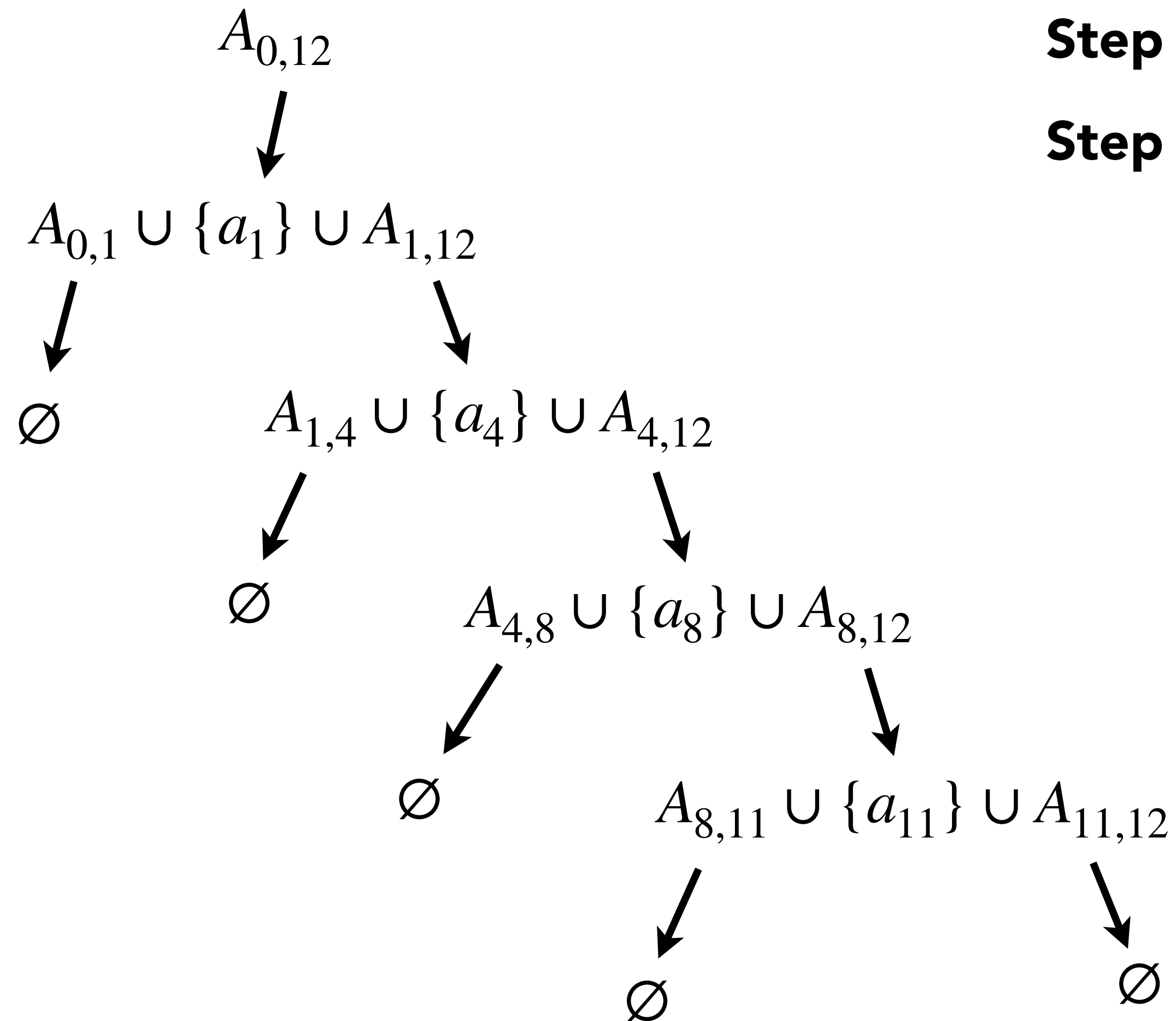


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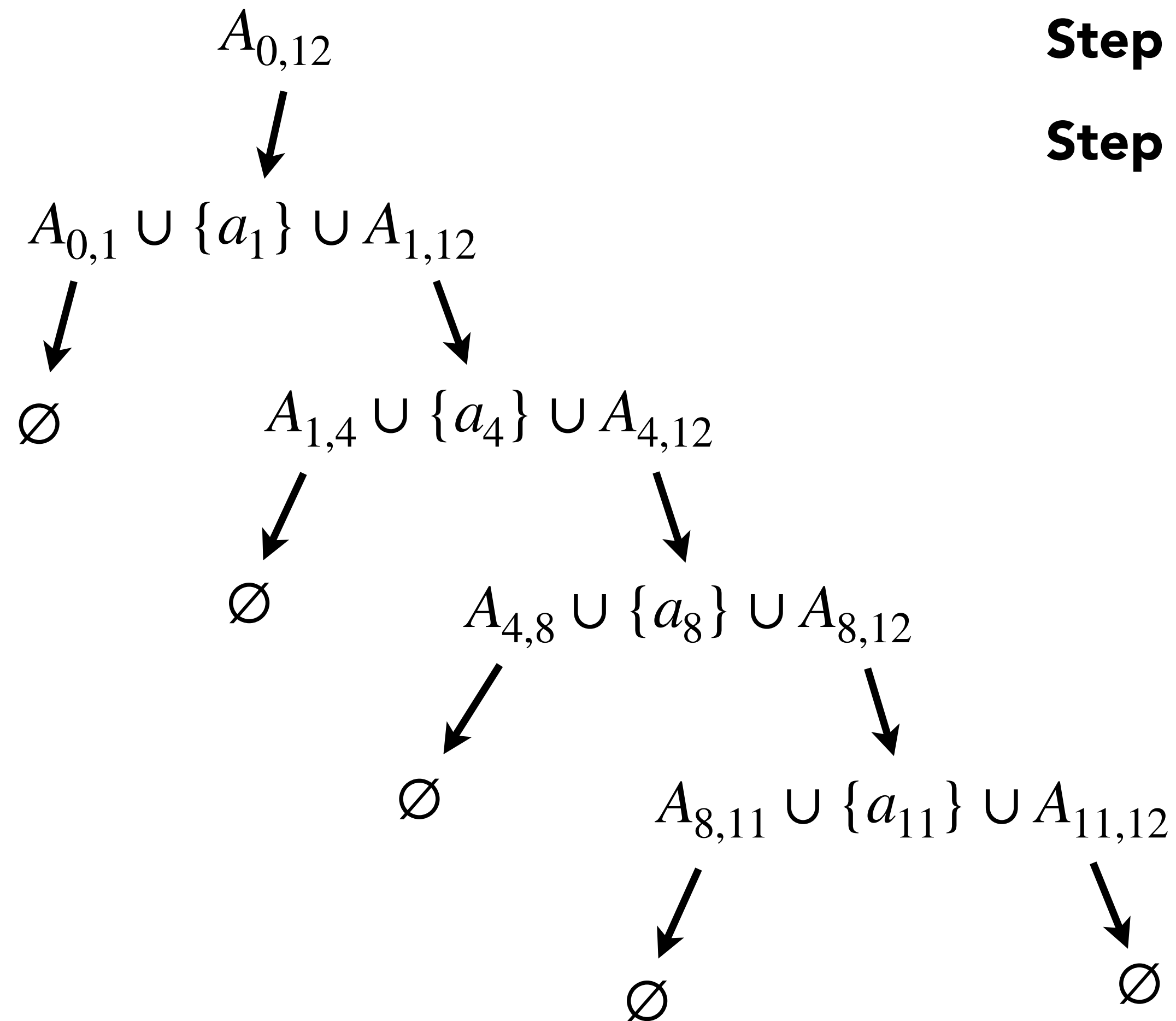


Greedy Algorithm for Activity-Selection

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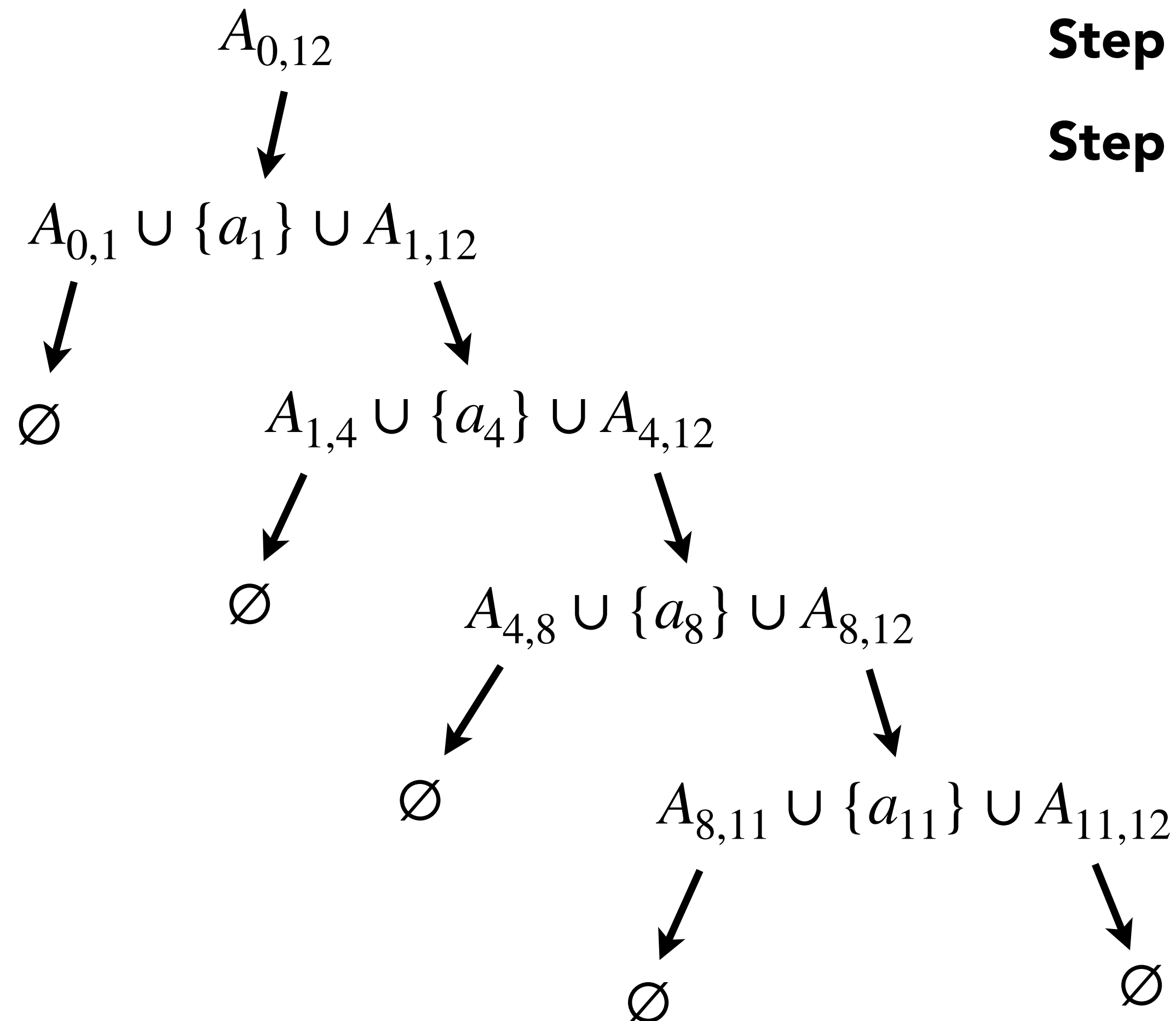
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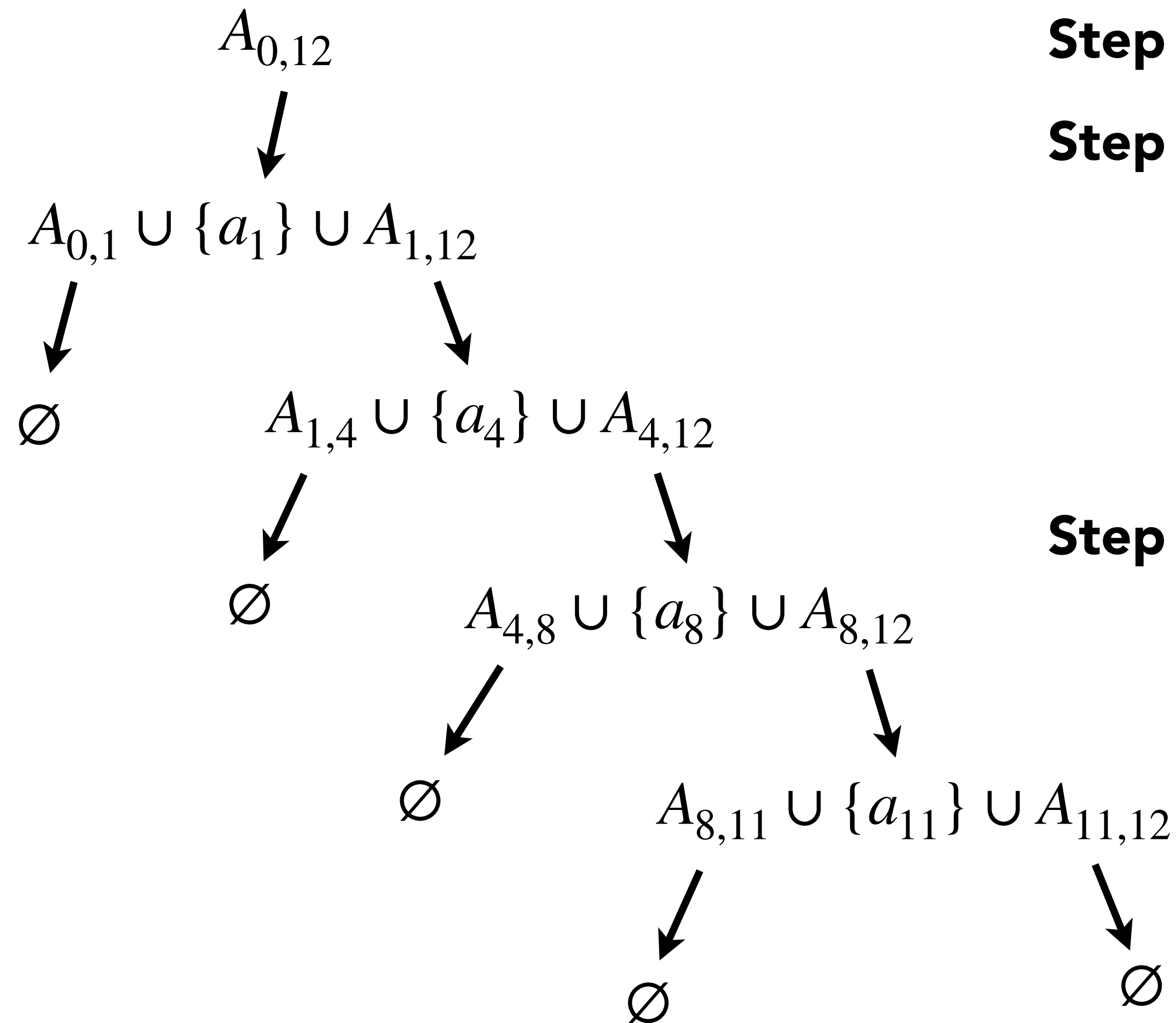
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Step 3: Go to **Step 2**, if you can.



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Activity-Selection($s, f, n + 2$)

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Start and finish time of $n + 2$ activities (with dummy activities a_0 and a_{n+1})



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Time Complexity: $\Theta(n)$

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Earliest finishing activity in $S_{i,j}$ will be part of some $A_{i,j}$.

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Note: In practice, one can directly present a greedy algorithm, skipping the above steps..

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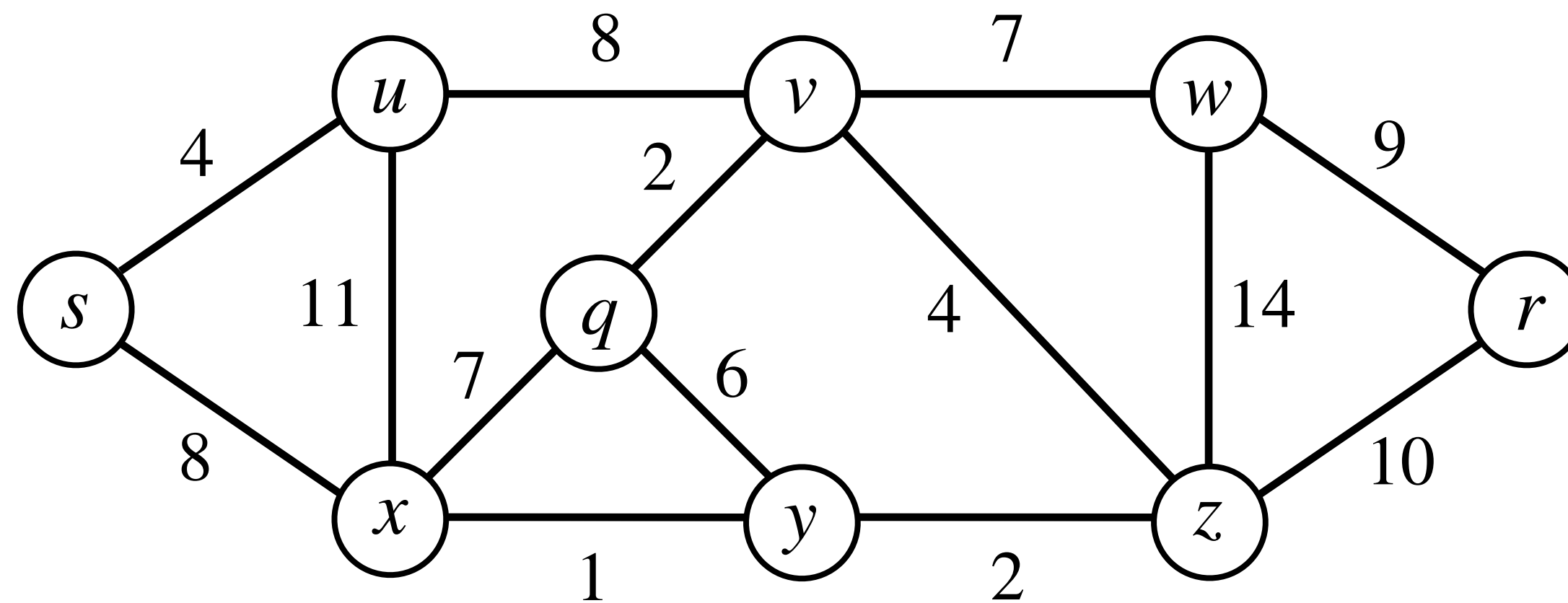
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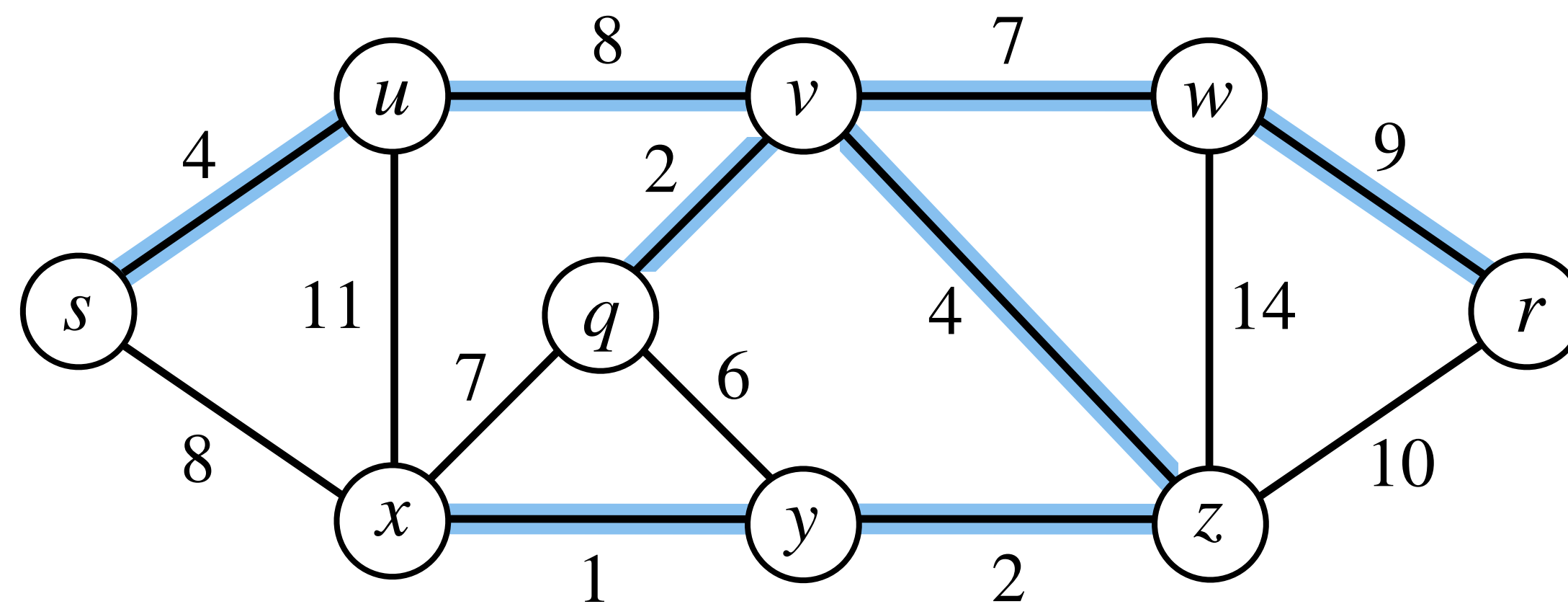
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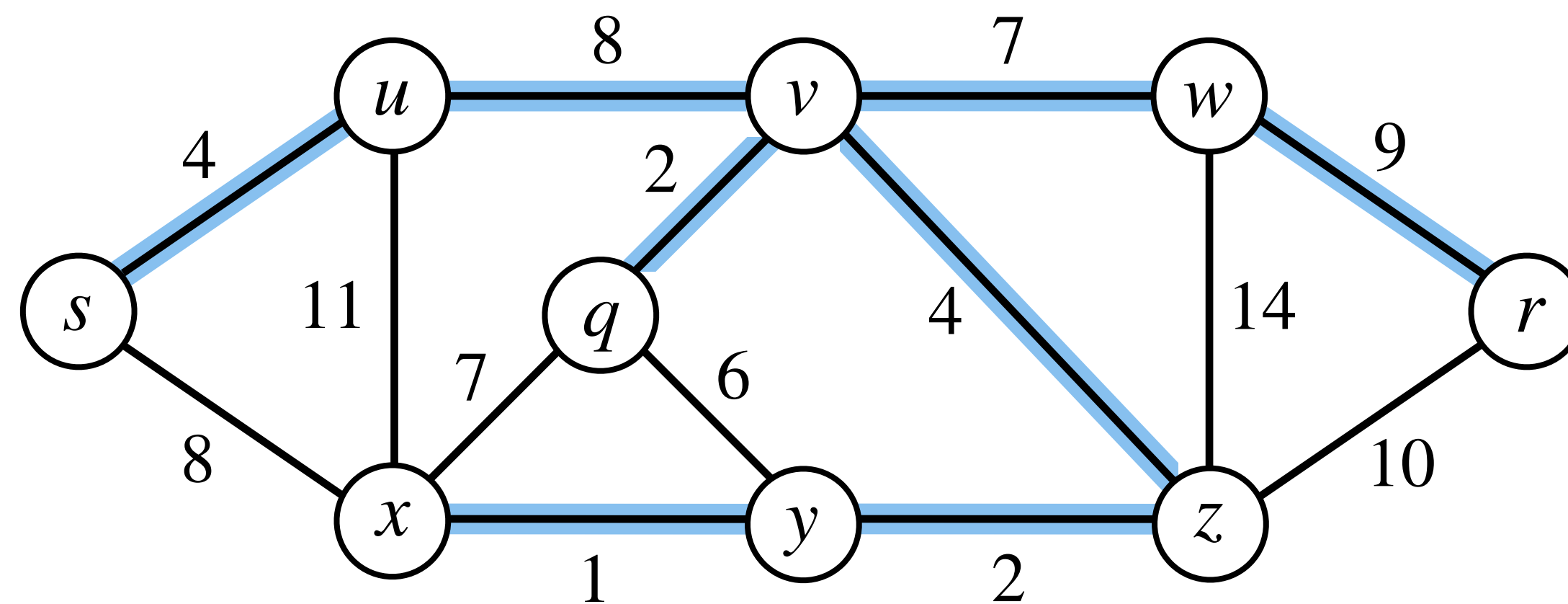
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Note: We will represent an MST as a set of edges.

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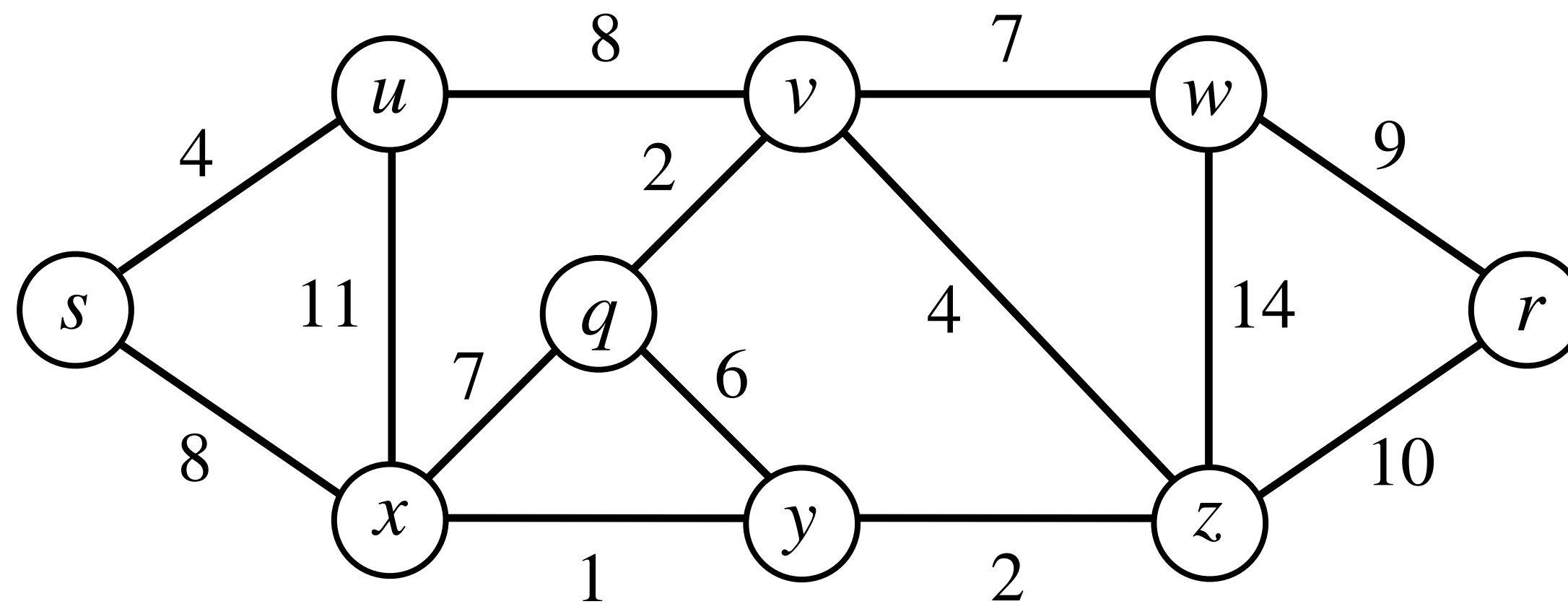
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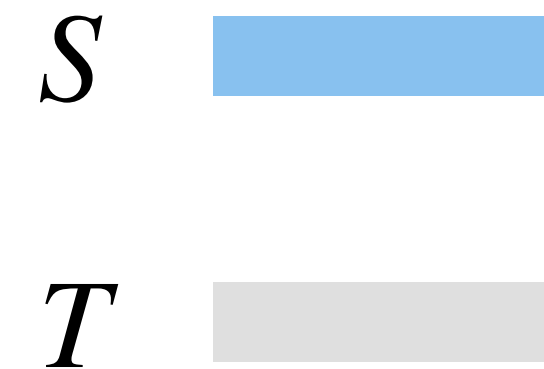
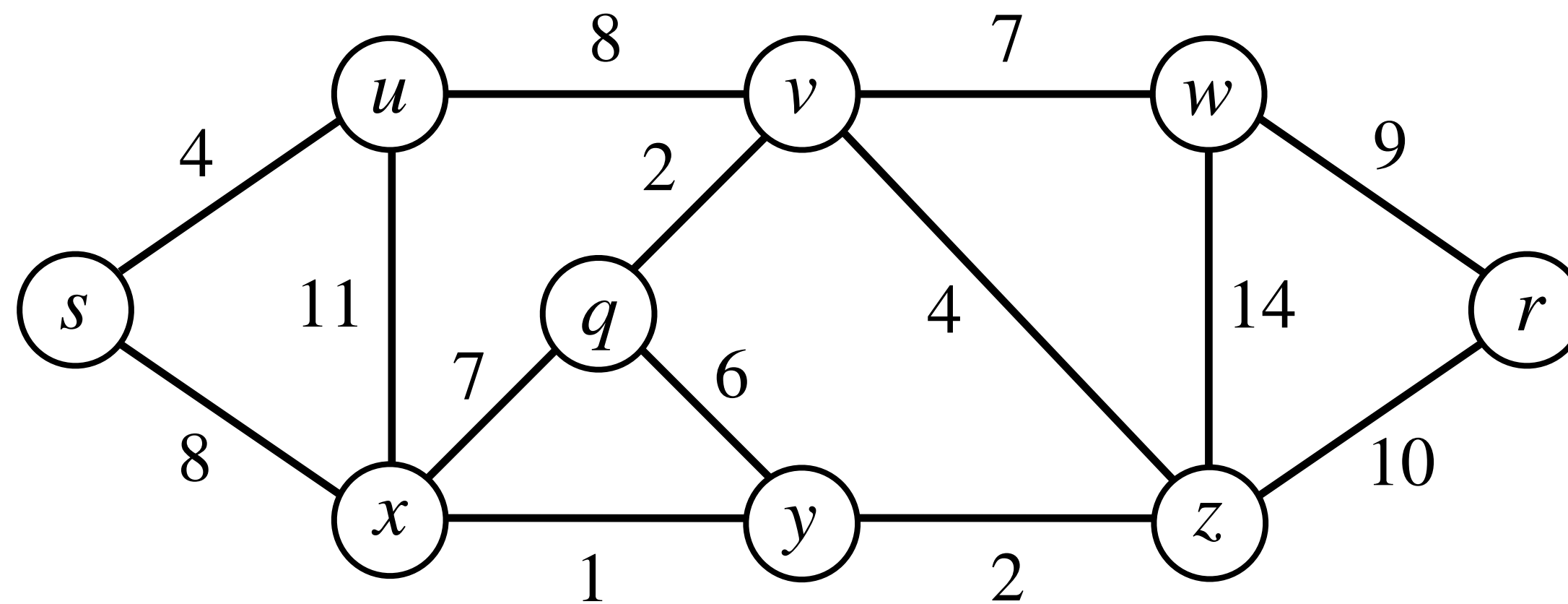


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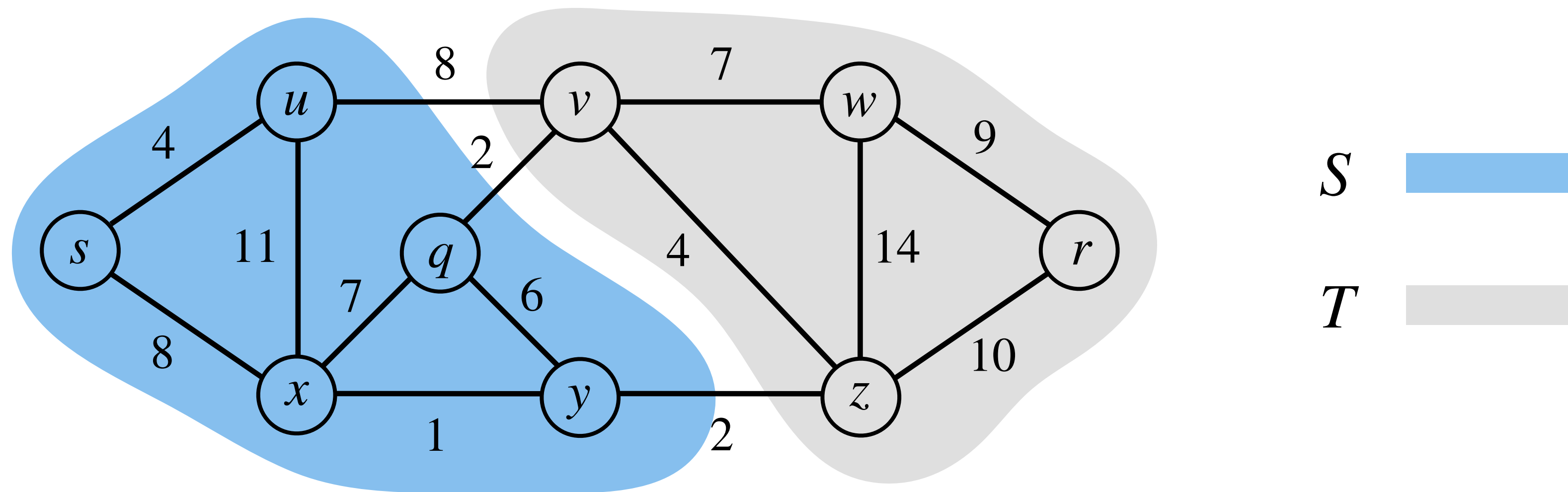


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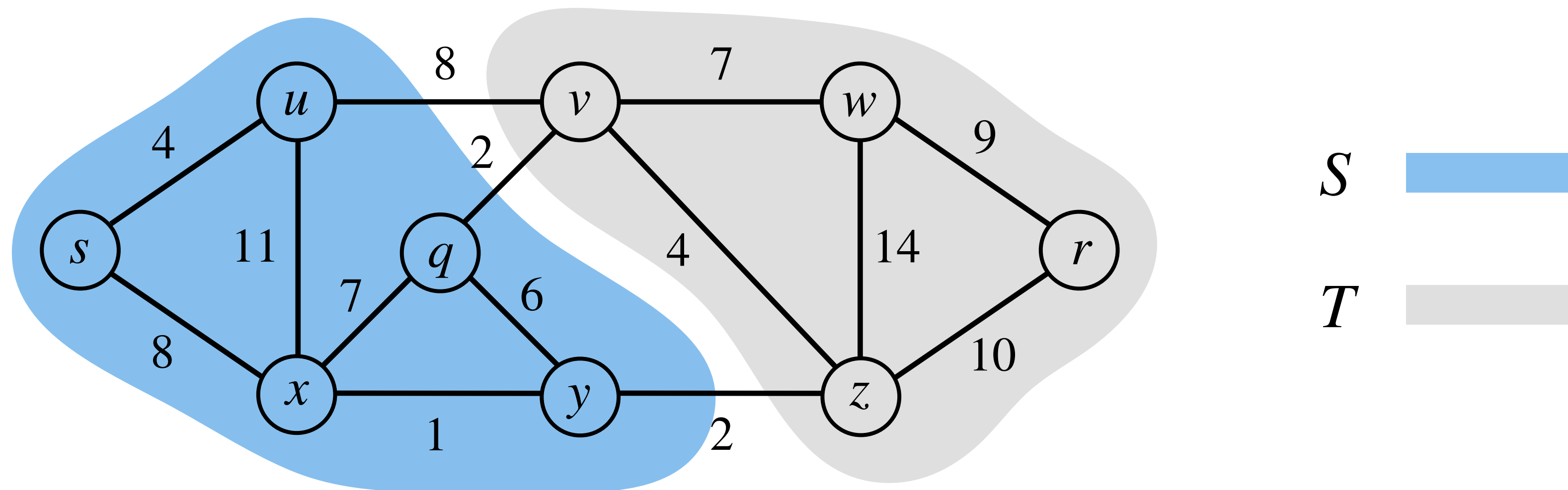


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The **cut-set** for cut (S, T) is $\{ \{u, v\}, \{q, v\}, \{y, z\} \}$

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Proof: On the next slide.

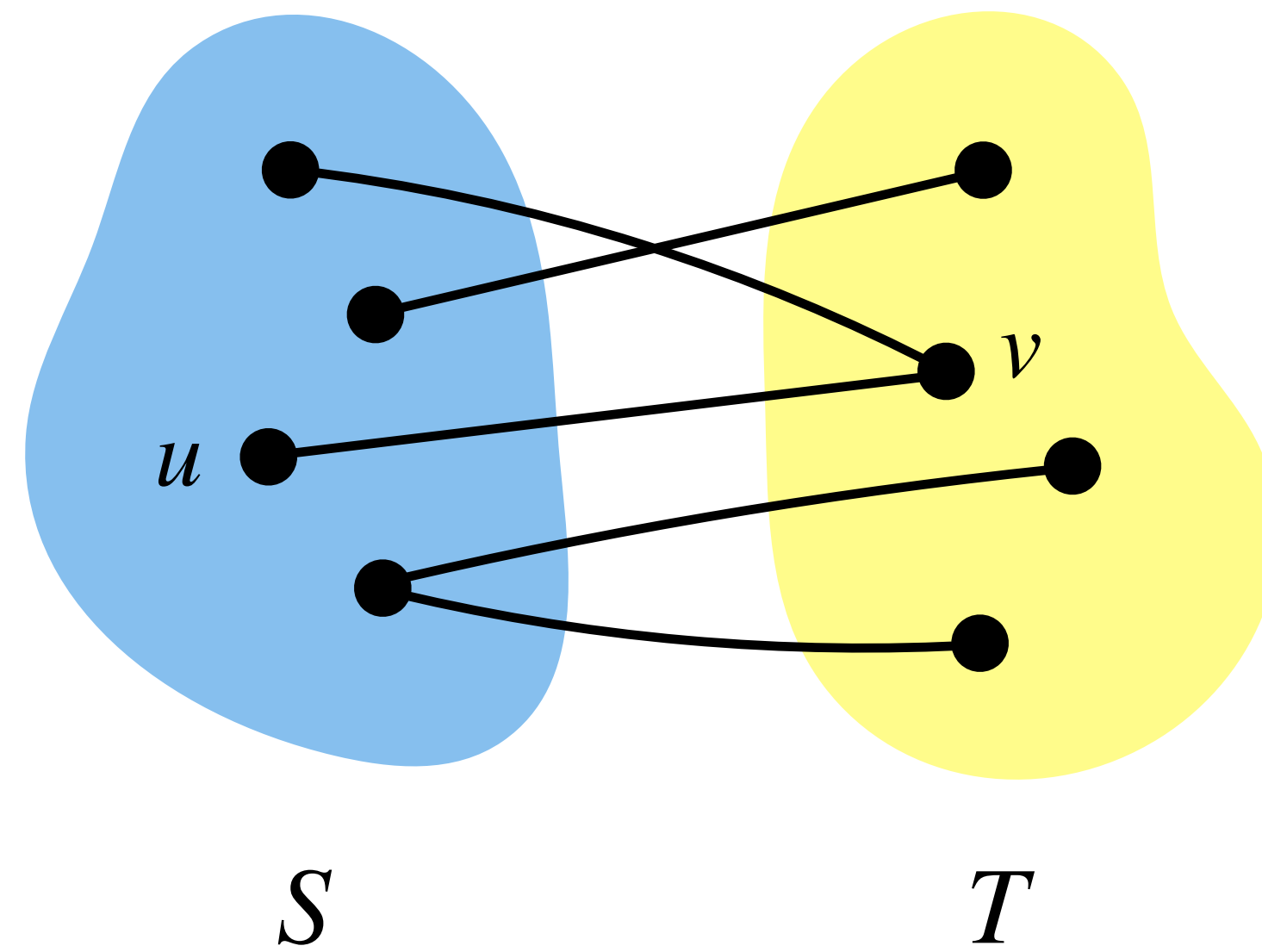
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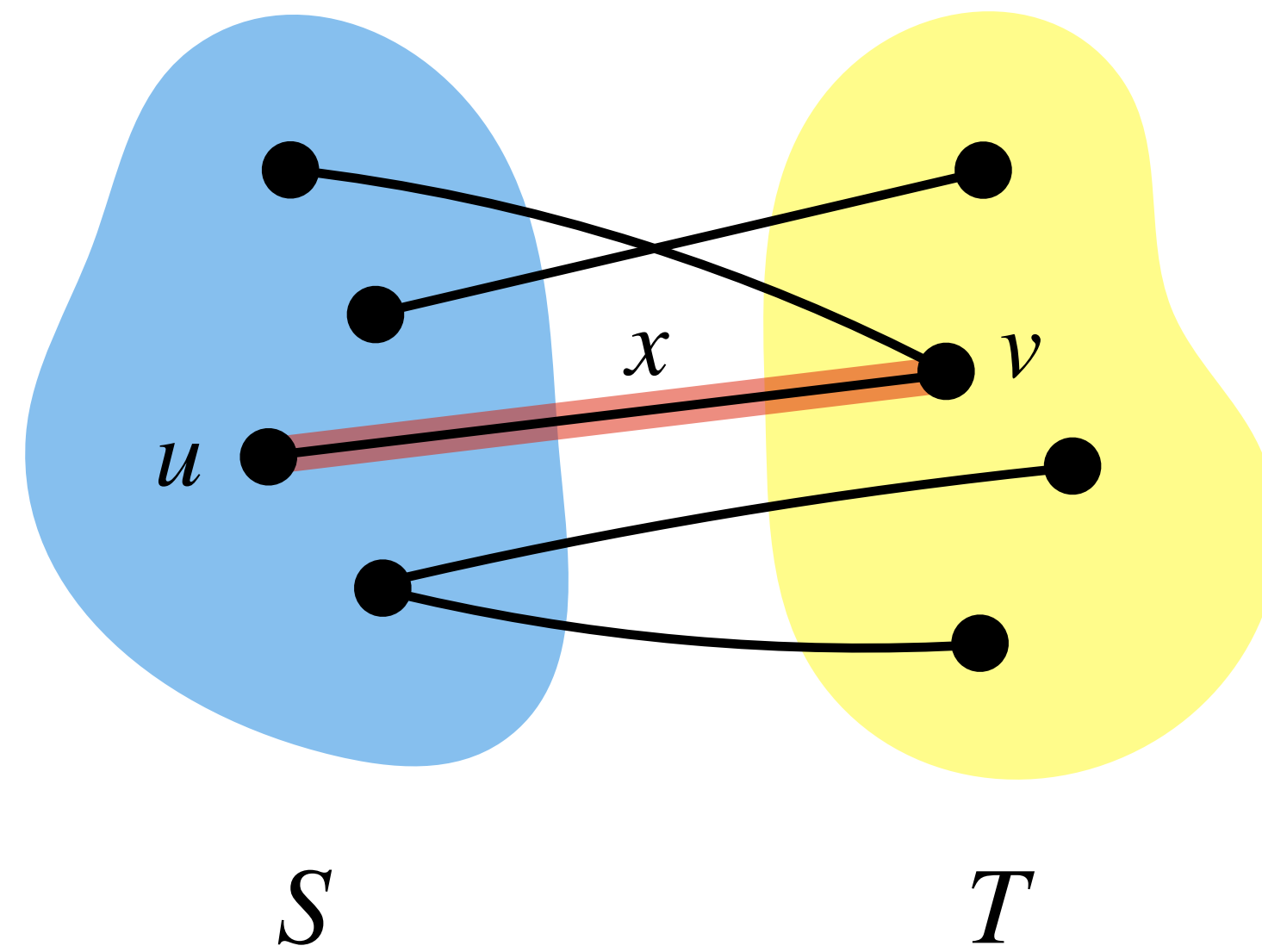
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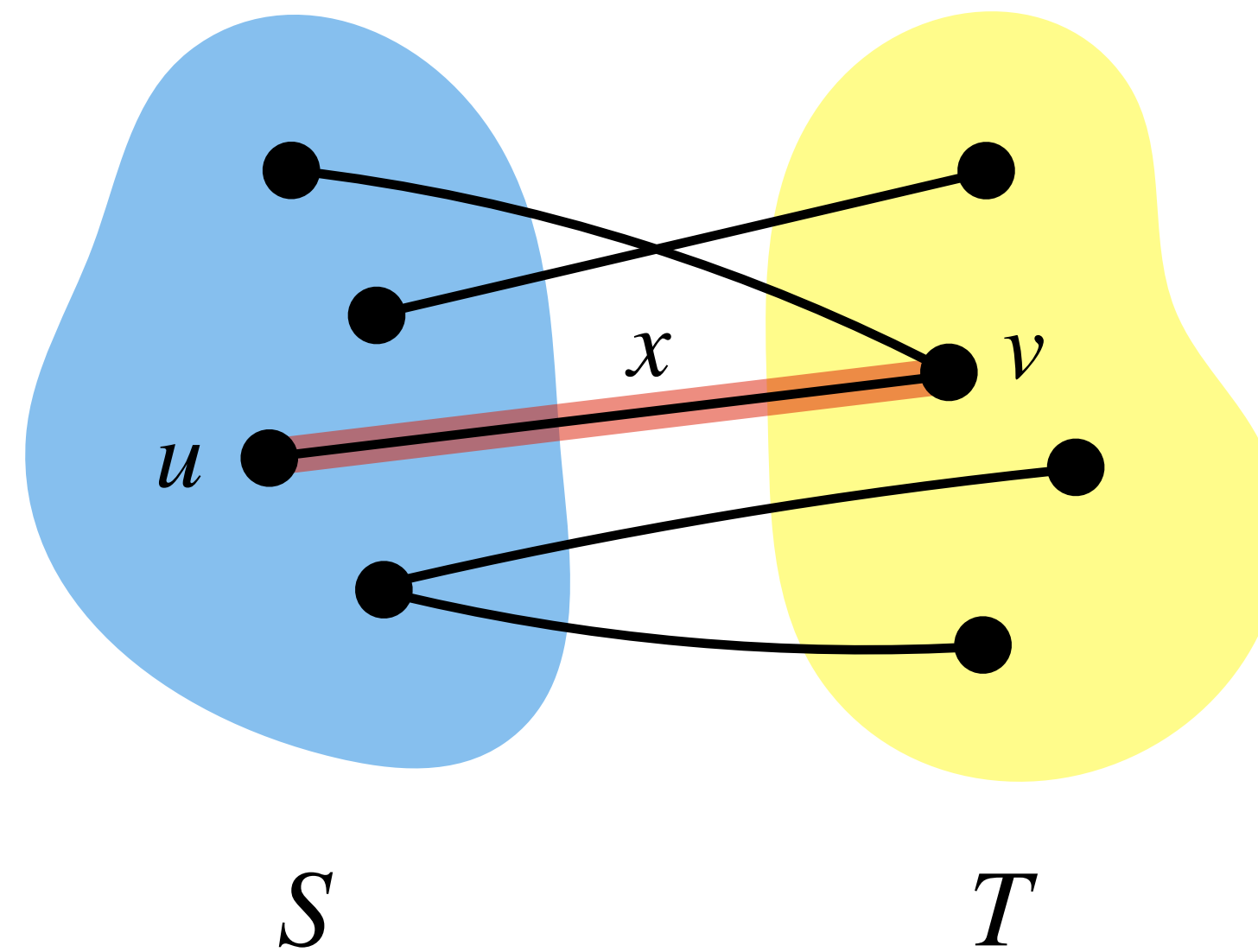
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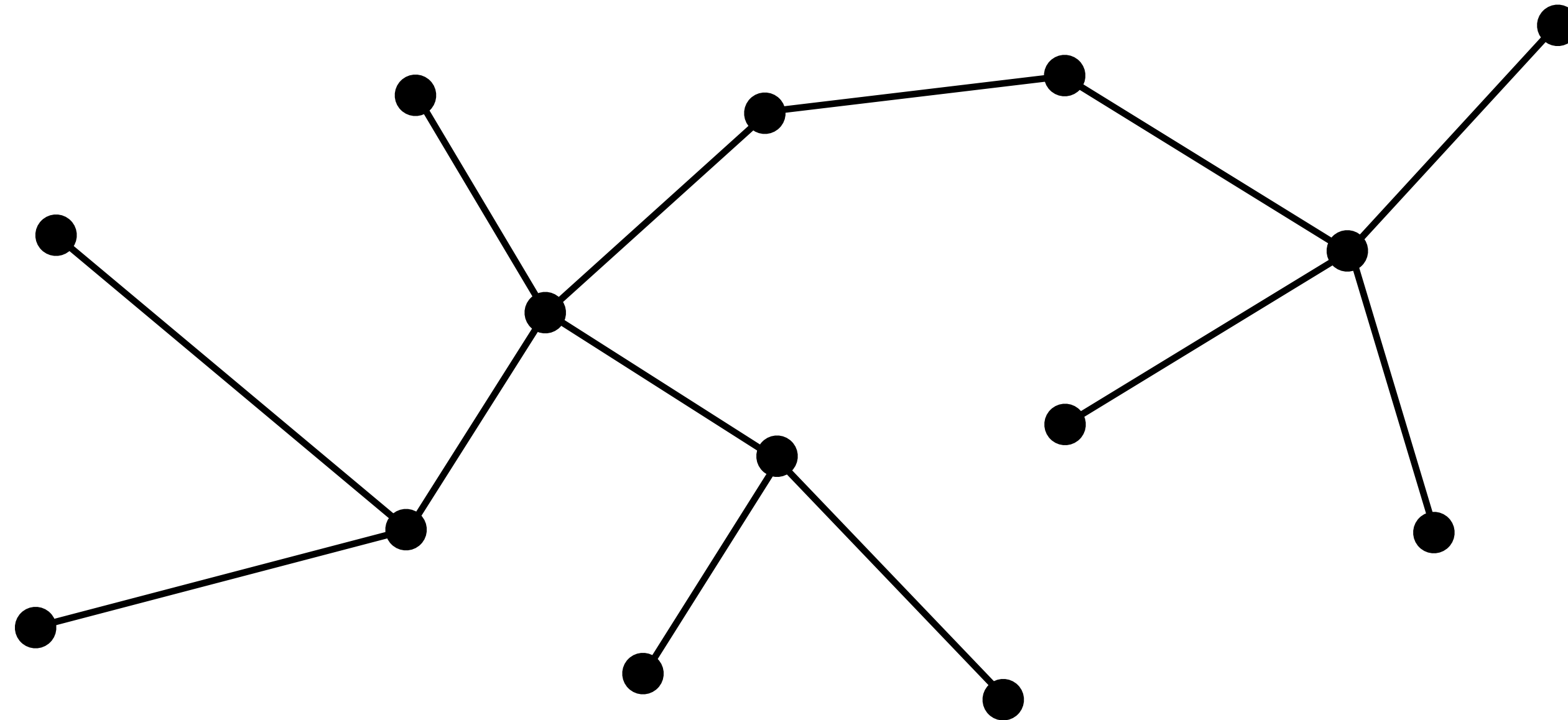
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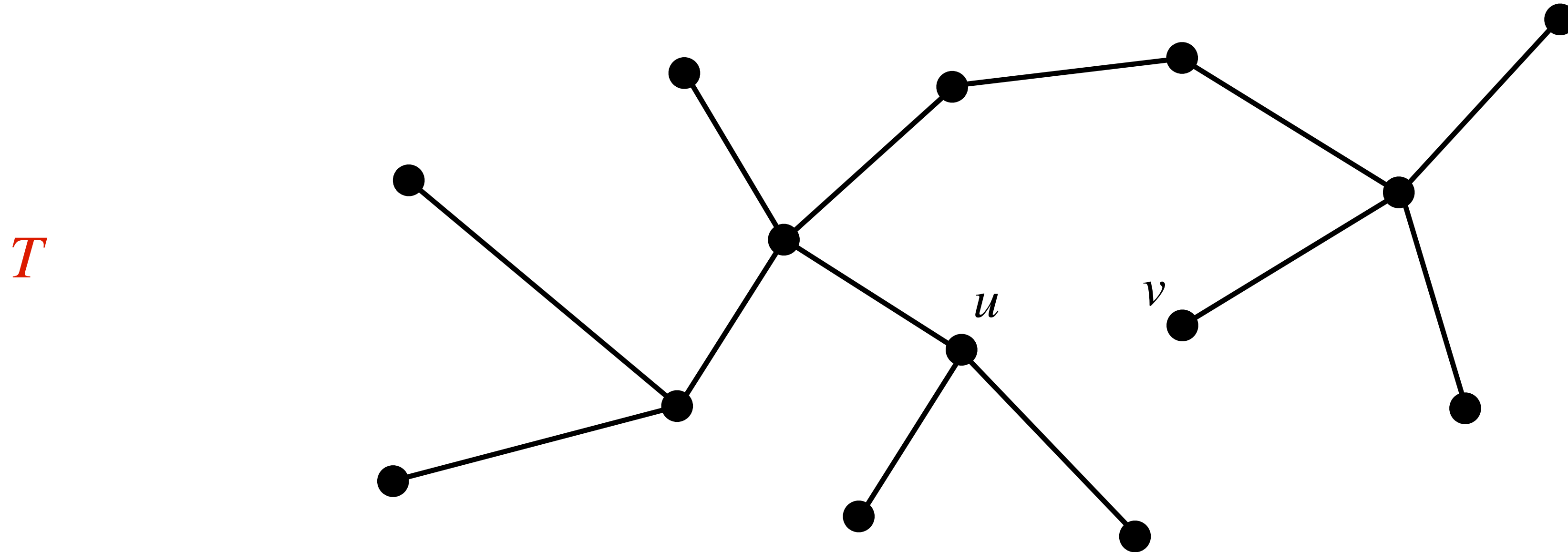
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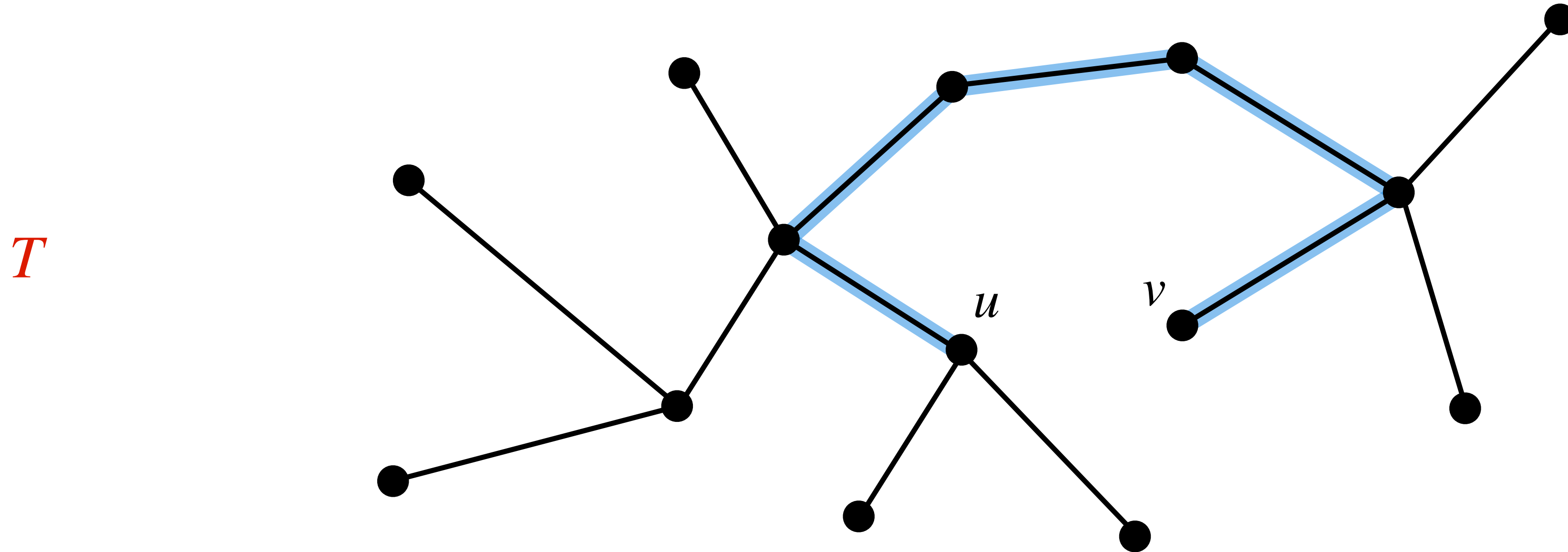
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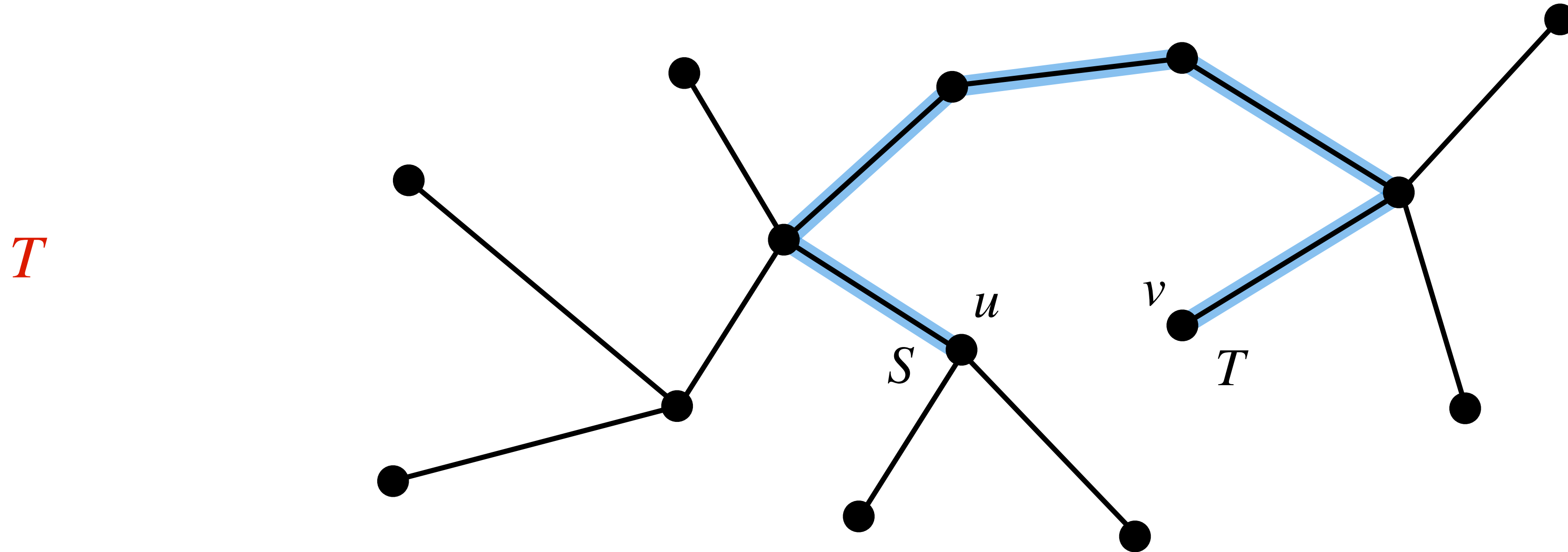
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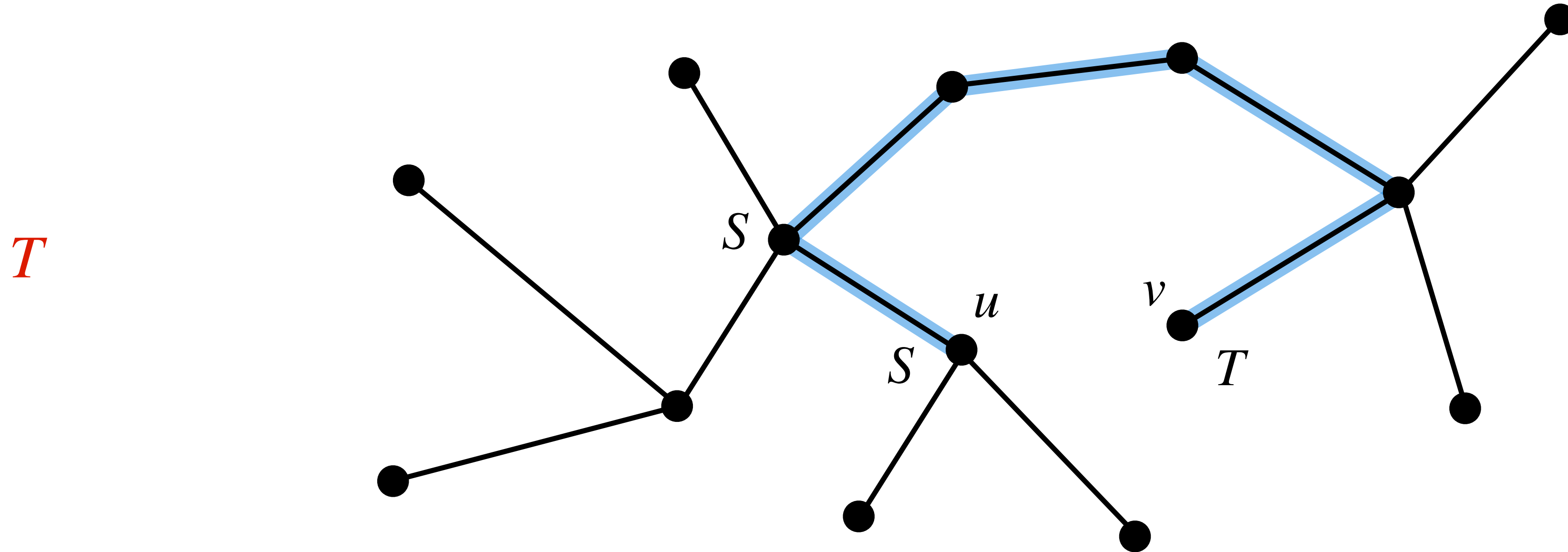
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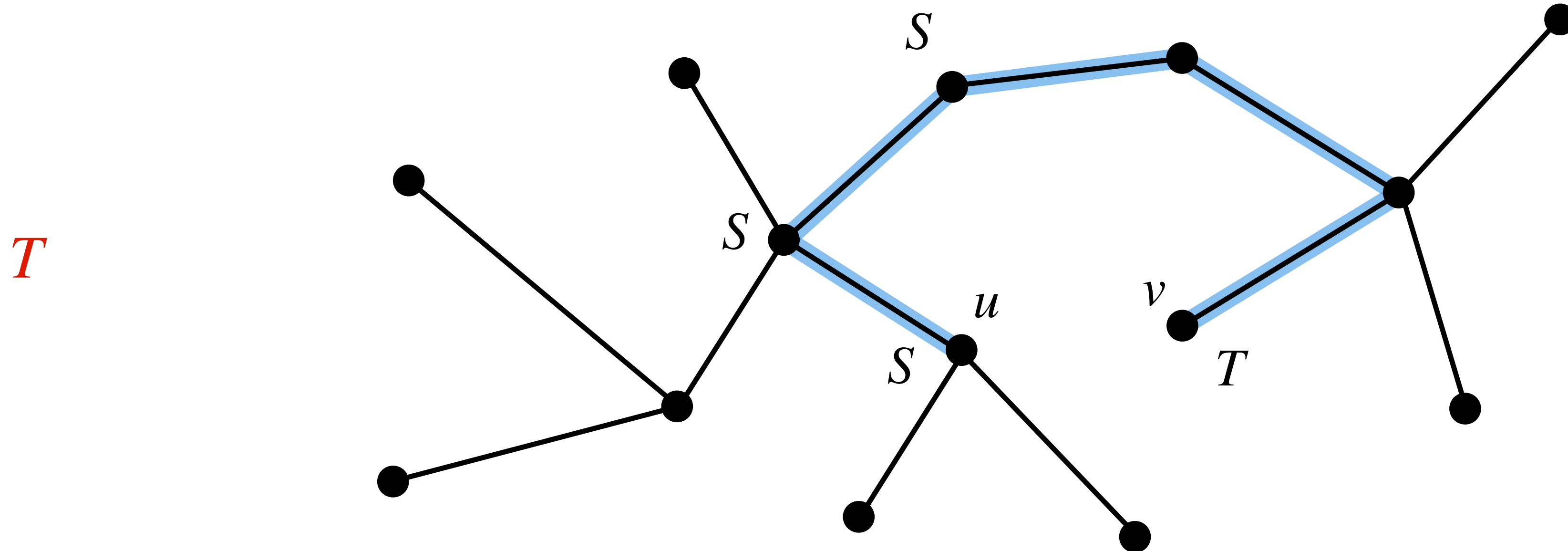
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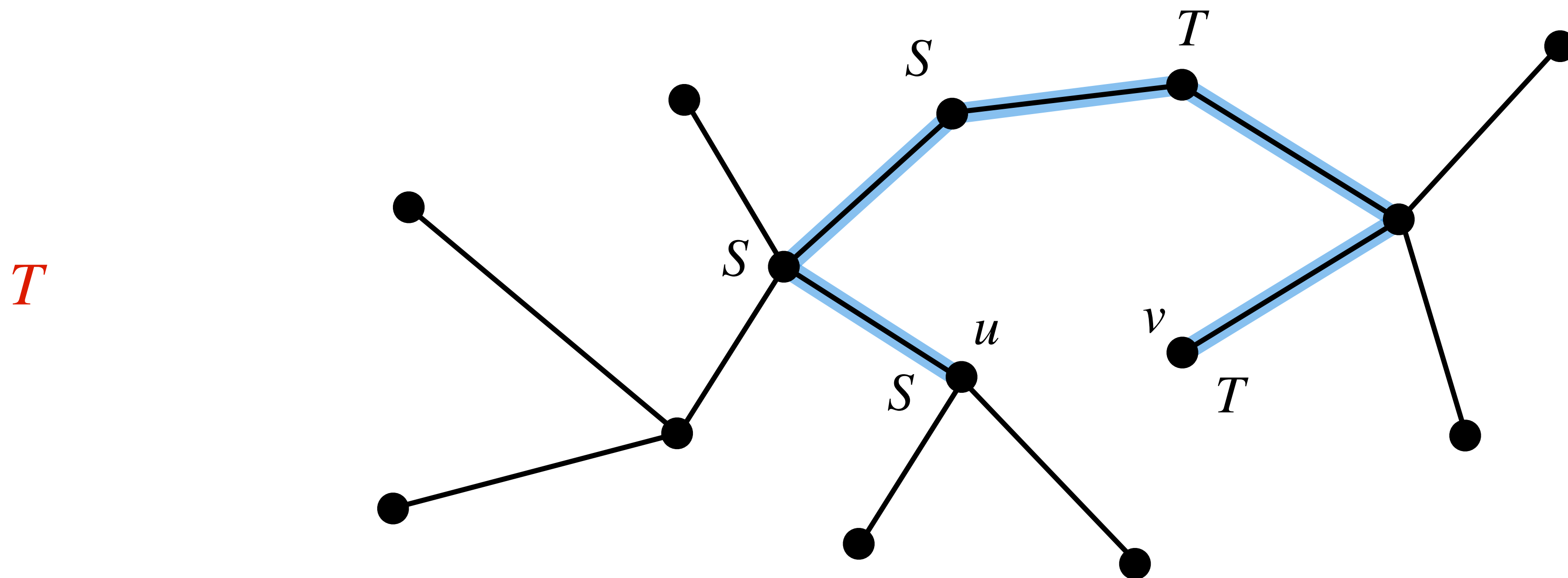
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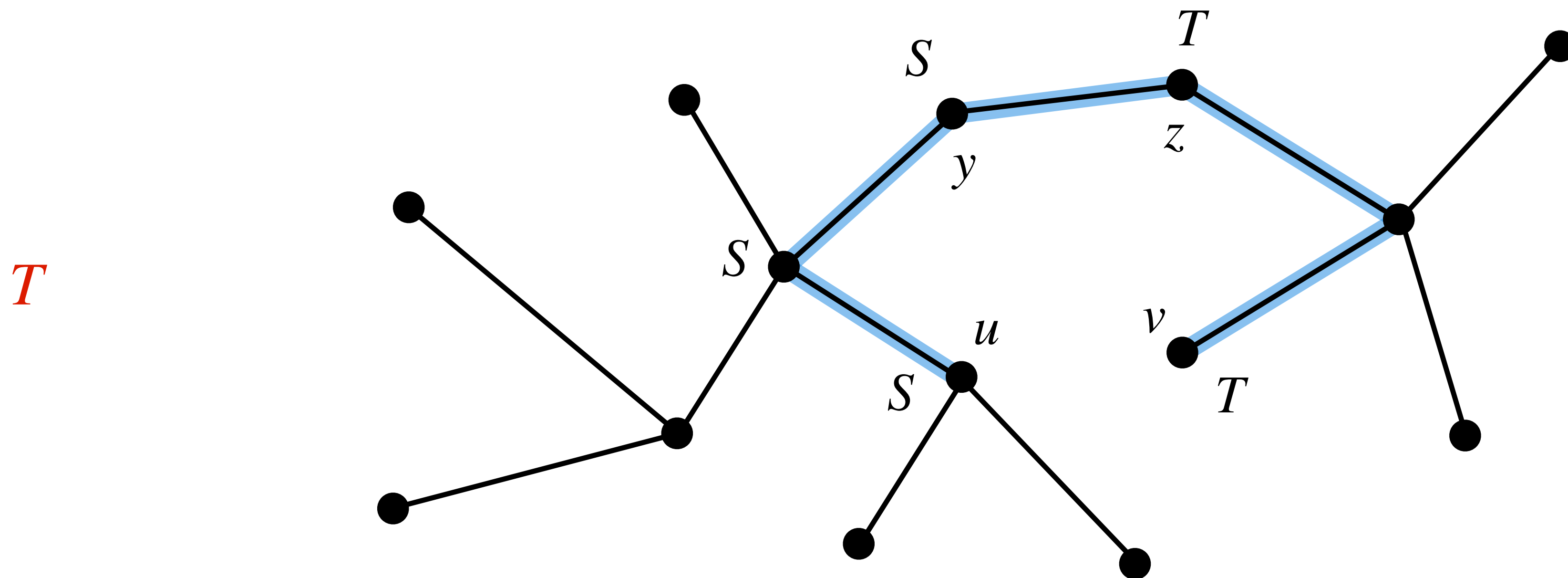
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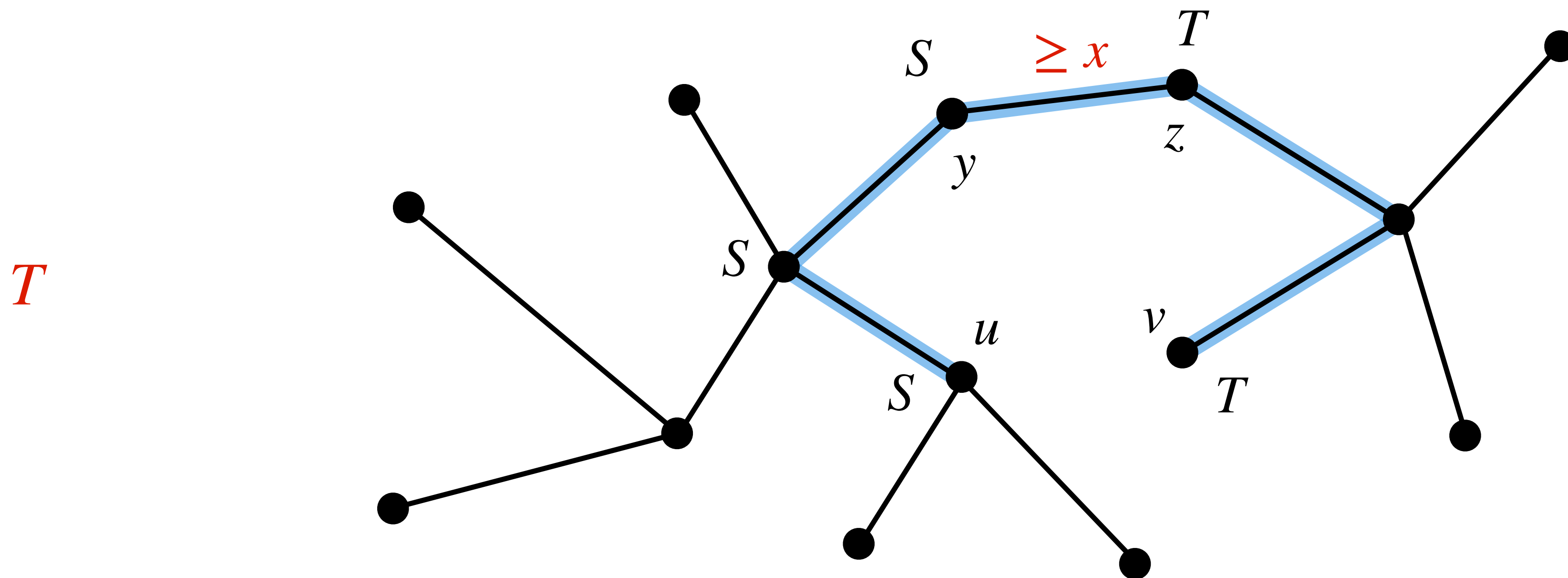
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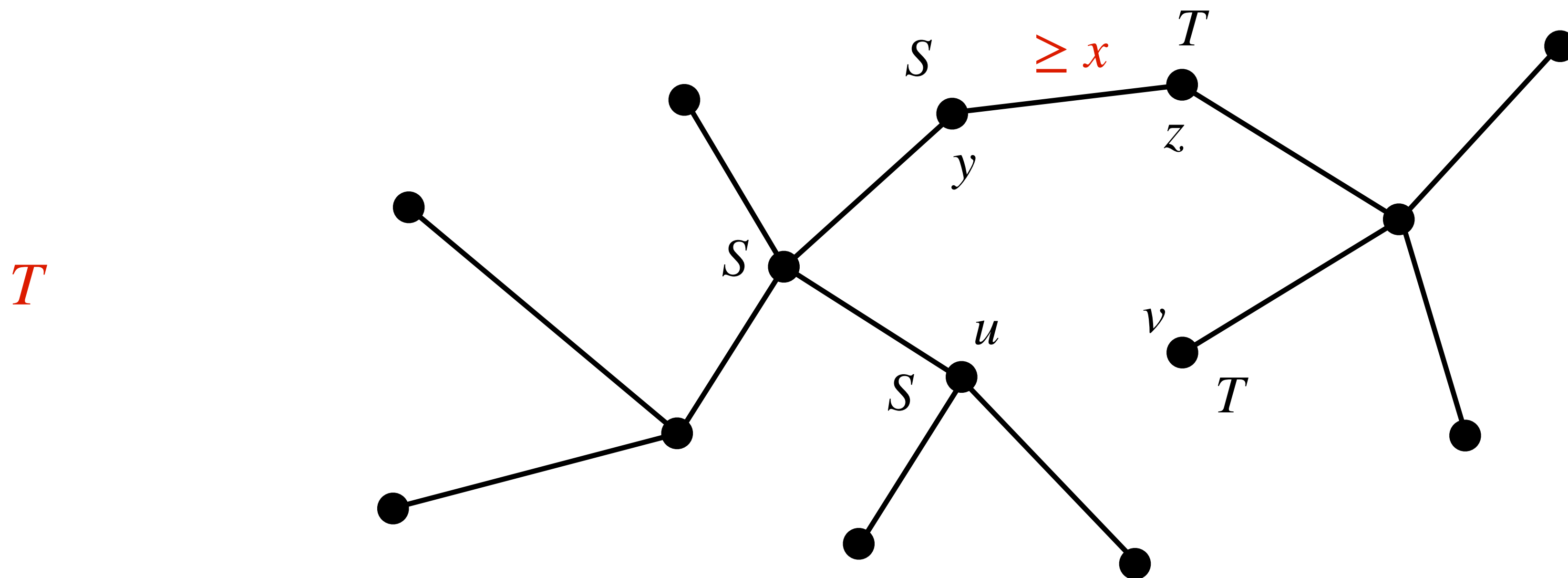
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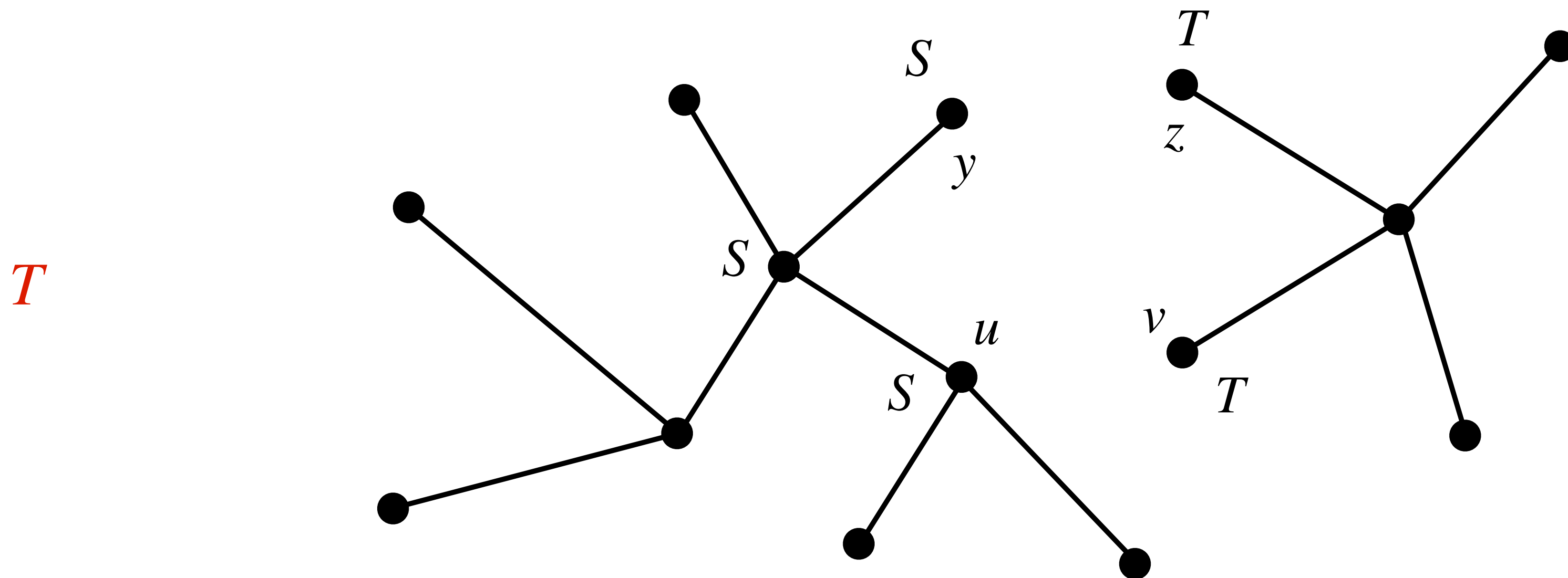
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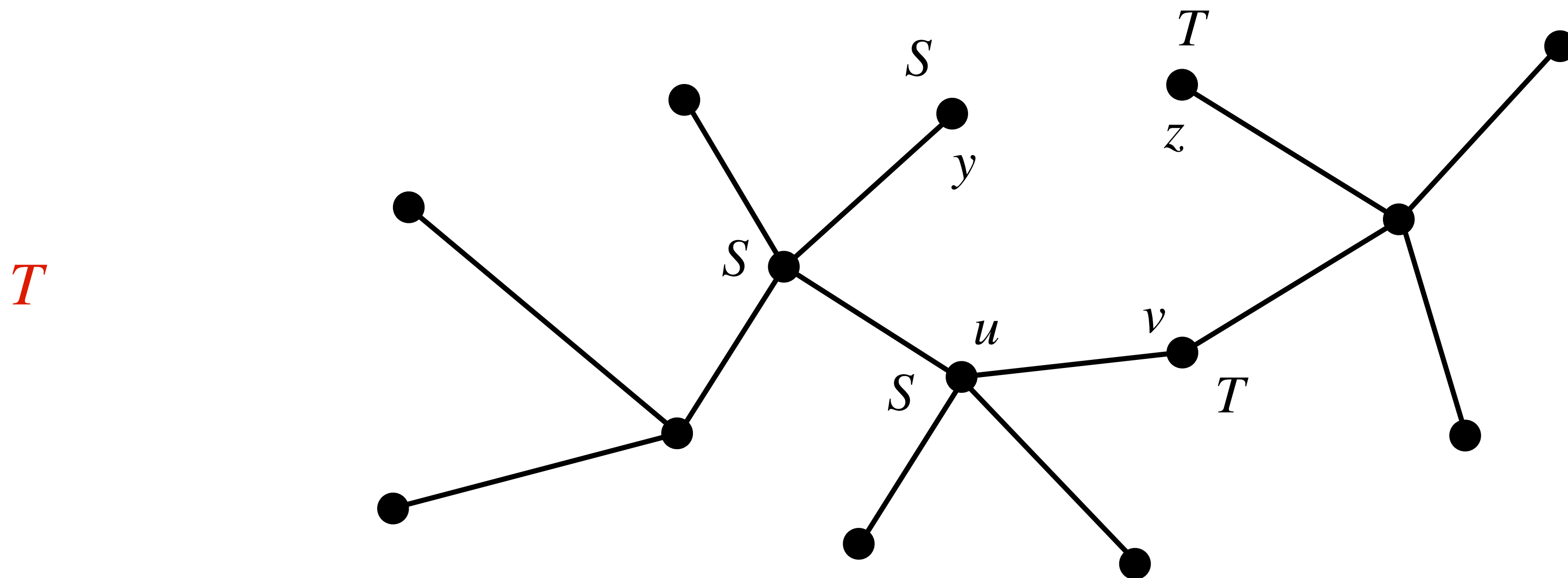
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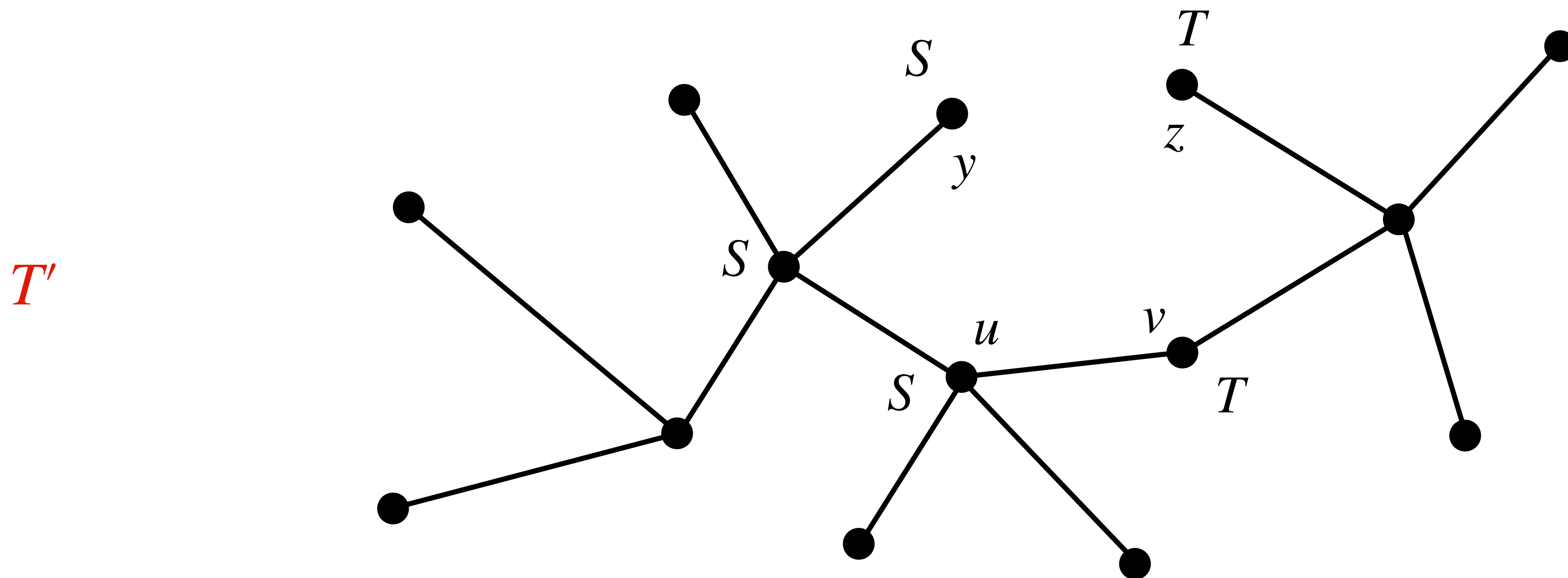
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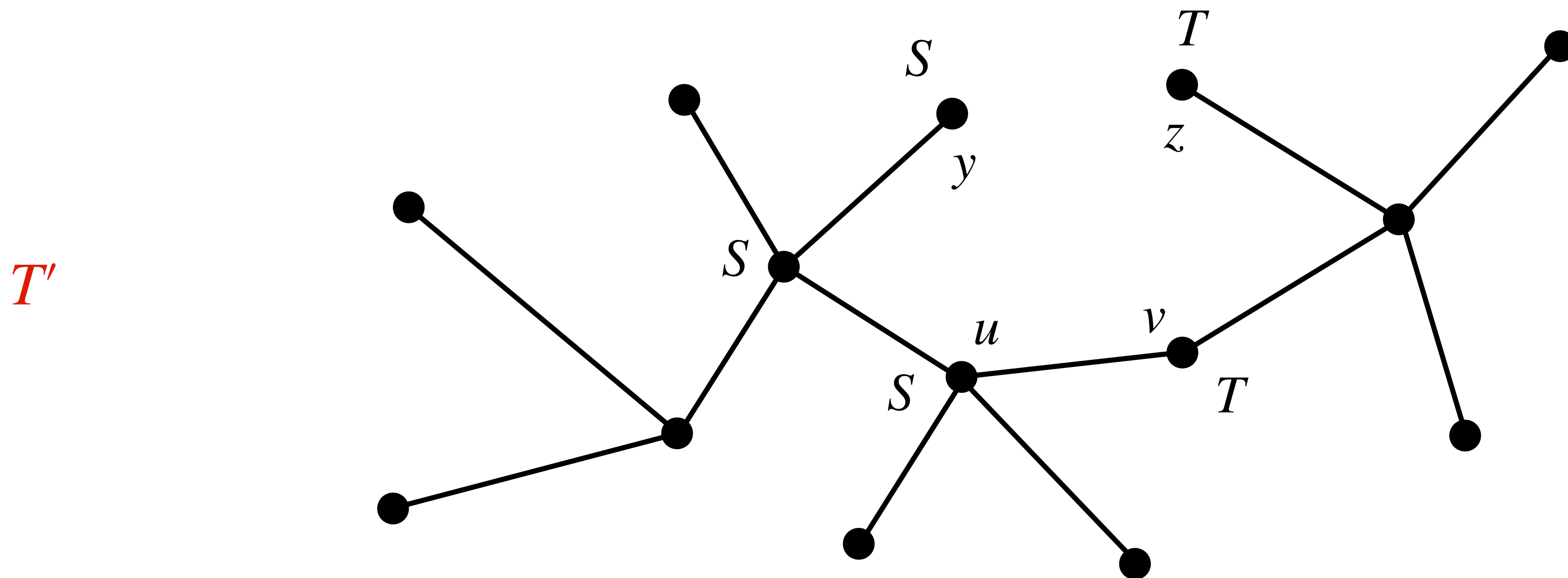
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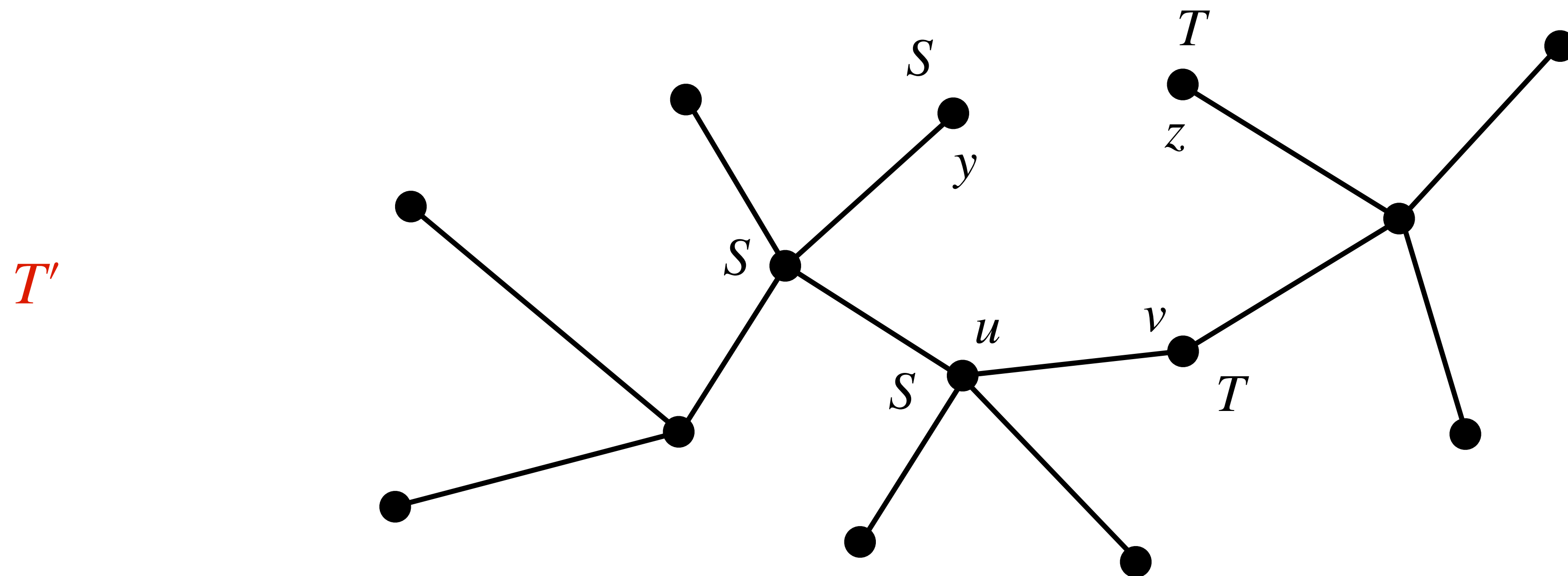


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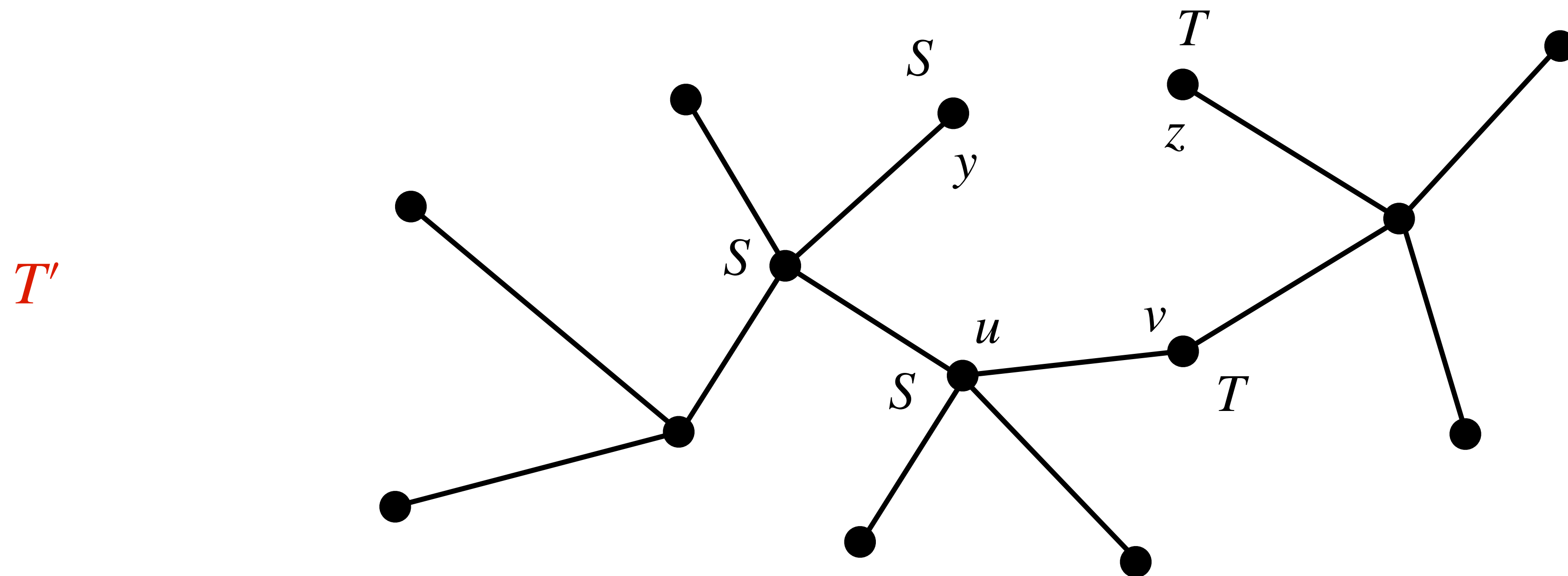
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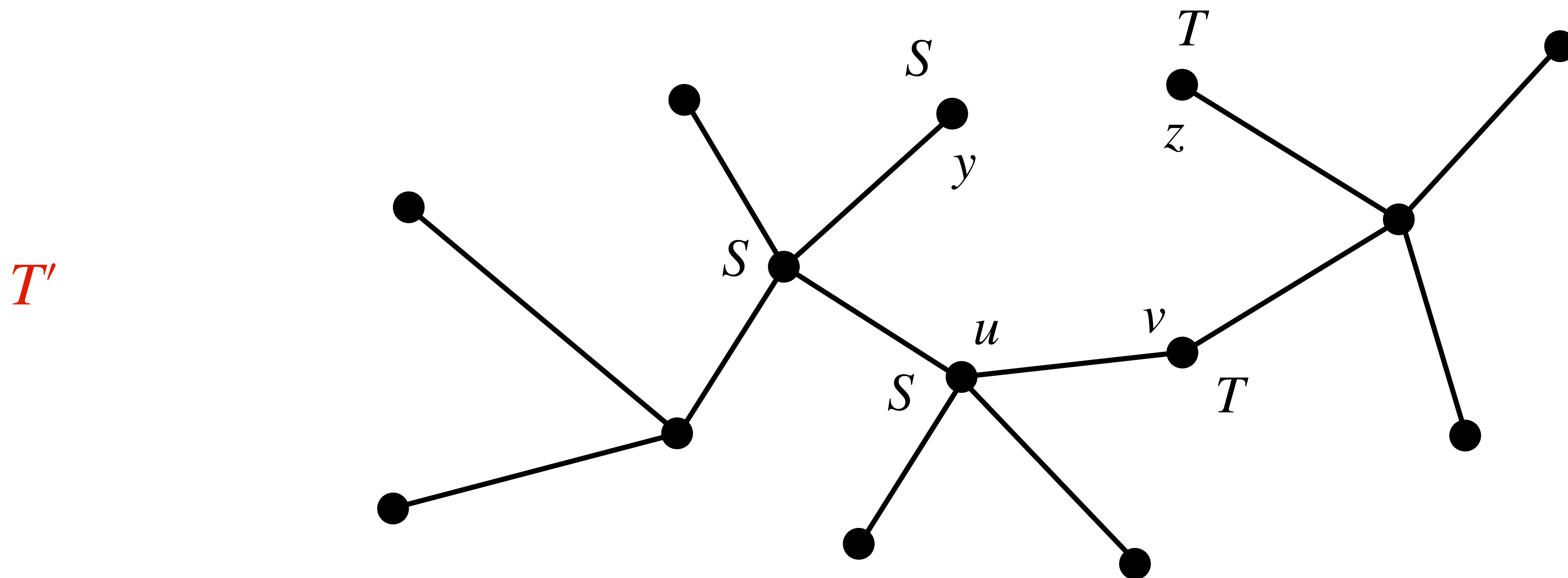
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