

# Balanced Trees

## Part Two

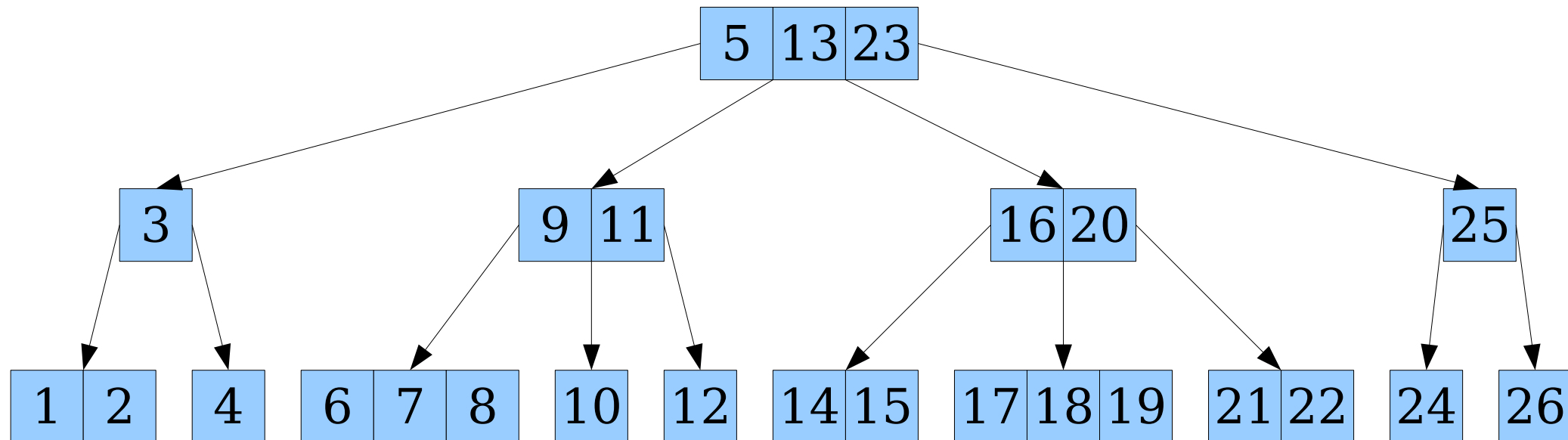
# Outline for Today

- ***Red/Black Trees***
  - Using our isometry!
- ***Tree Rotations***
  - A key primitive in restructuring trees.
- ***Augmented Binary Search Trees***
  - Leveraging red/black trees.

Recap from Last Time

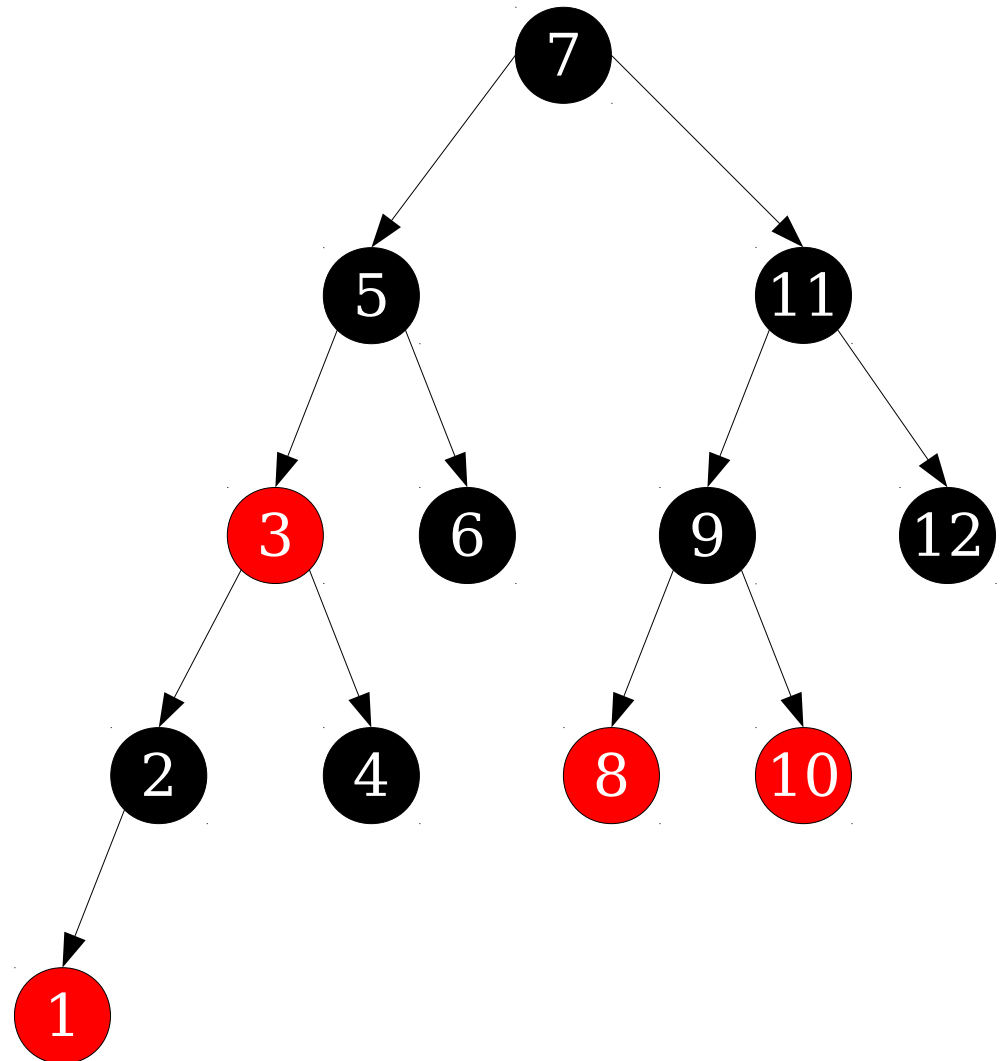
# 2-3-4 Trees

- A **2-3-4 tree** is a multiway search tree where
  - every node has 1, 2, or 3 keys,
  - any non-leaf node with  $k$  keys has exactly  $k+1$  children, and
  - all leaves are at the same depth.
- To insert a key, place it in a leaf. If out of space, split the leaf and kick the median key one level higher, repeating this process.



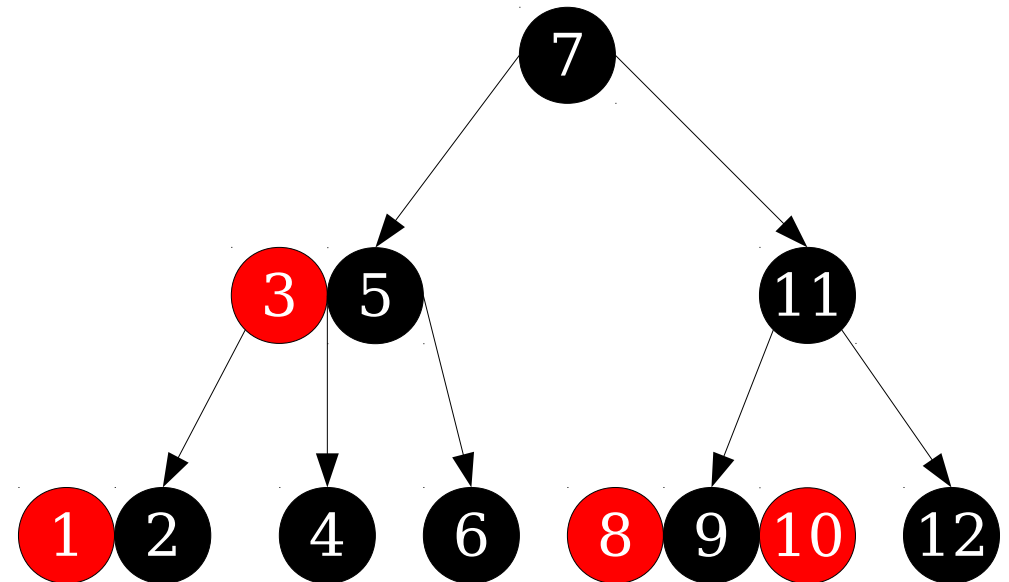
# Red/Black Trees

- A **red/black tree** is a BST with the following properties:
  - Every node is either red or black.
  - The root is black.
  - No red node has a red child.
  - Every root-null path in the tree passes through the same number of black nodes.



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  - Every root-null path in the tree passes through the same number of black nodes.
- After we hoist red nodes into their parents:
  - Each “meta node” has 1, 2, or 3 keys in it. (No red node has a red child.)
  - Each “meta node” is either a leaf or has one more child than key. (Root-null path property.)
  - Each “meta leaf” is at the same depth. (Root-null path property.)



***This is a  
2-3-4 tree!***

New Stuff!

# Data Structure Isometries

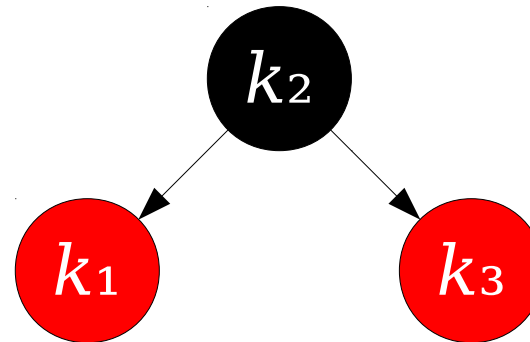
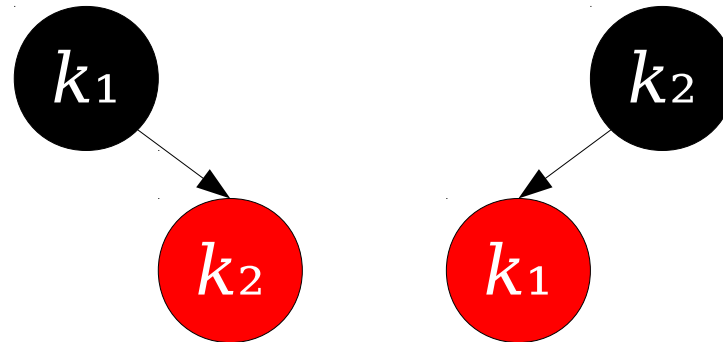
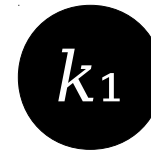
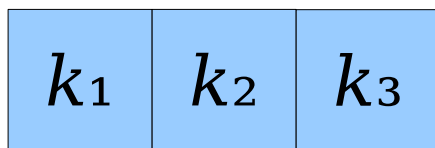
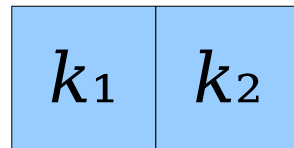
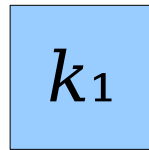
- Red/black trees are an ***isometry*** of 2-3-4 trees; they represent the structure of 2-3-4 trees in a different way.
- That gives us some really easy theorems basically for free.
- ***Theorem:*** The maximum height of a red/black tree with  $n$  nodes is  $O(\log n)$ .
- ***Proof idea:*** Pulling red nodes into their parents forms a 2-3-4 tree with  $n$  keys, which has height  $O(\log n)$ . Undoing this at most doubles the height of the tree. ■-ish

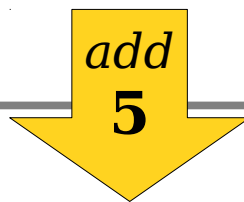
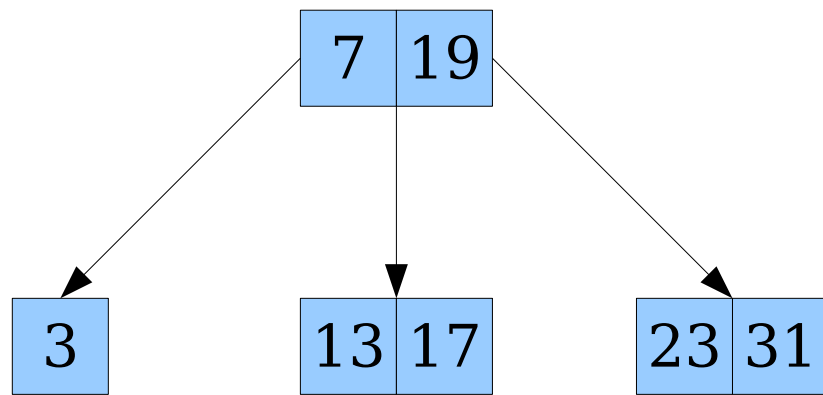
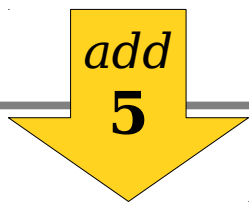
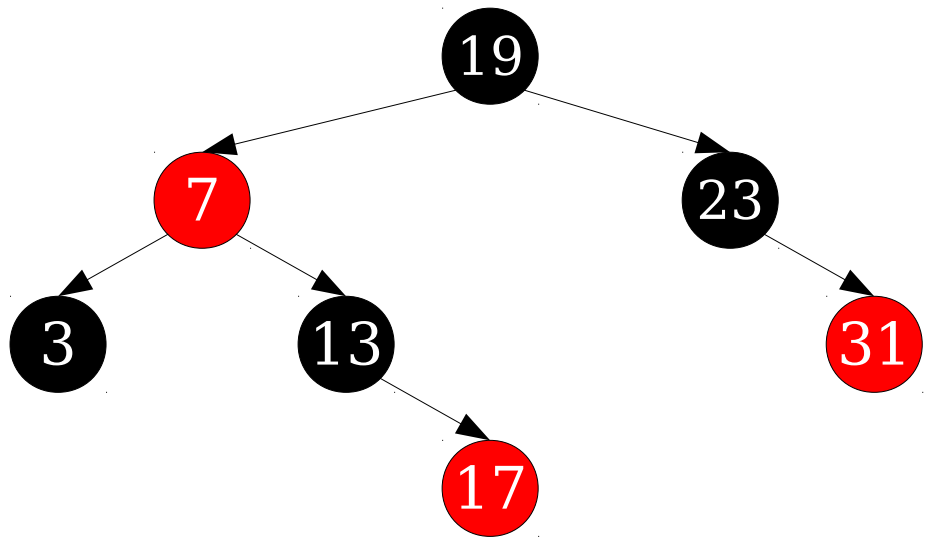


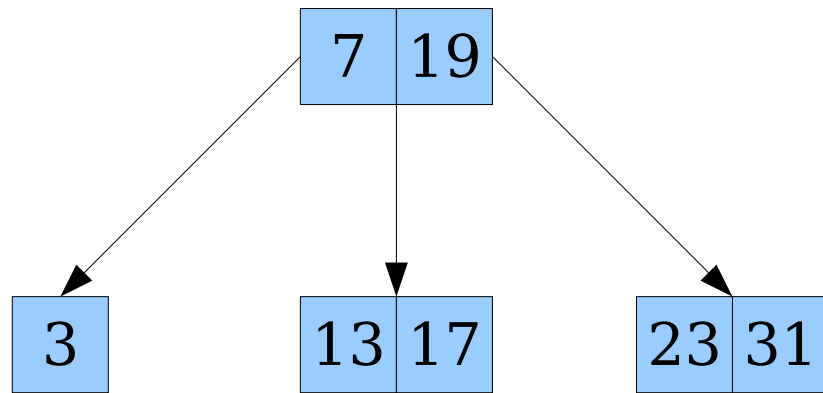
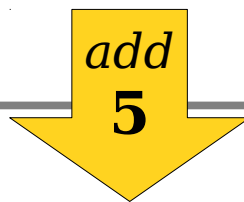
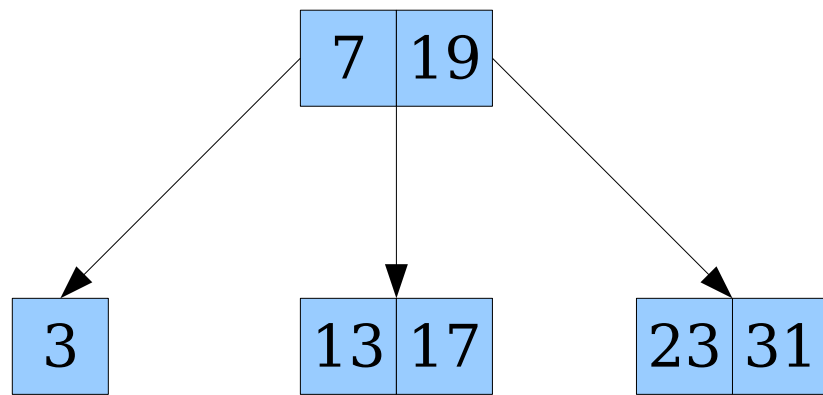
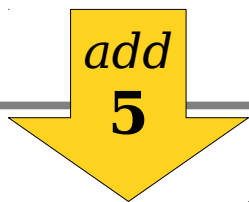
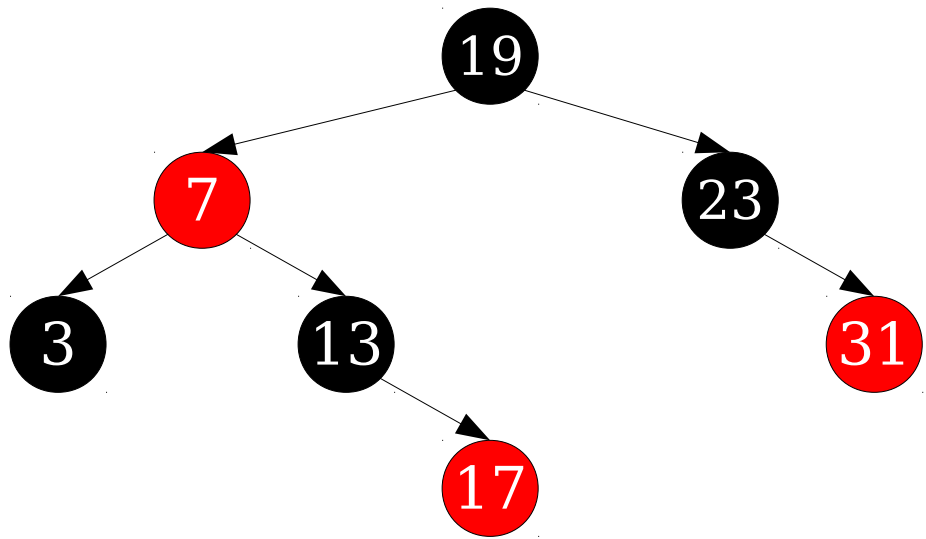
# Exploring the Isometry

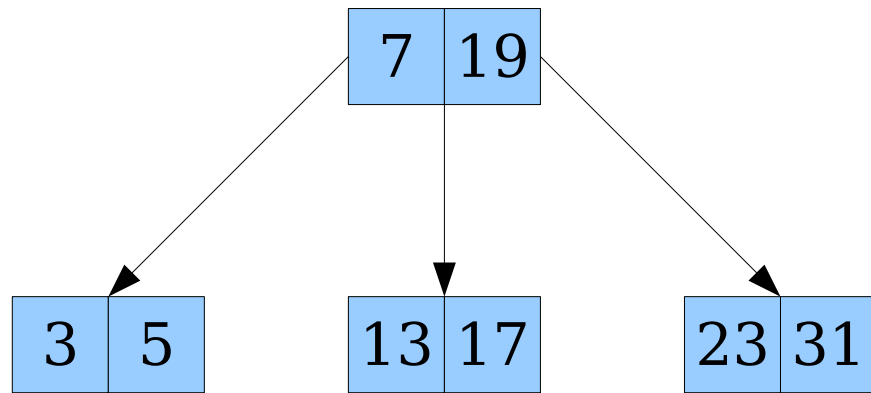
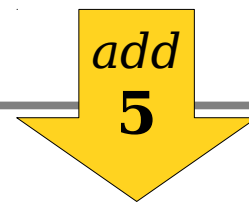
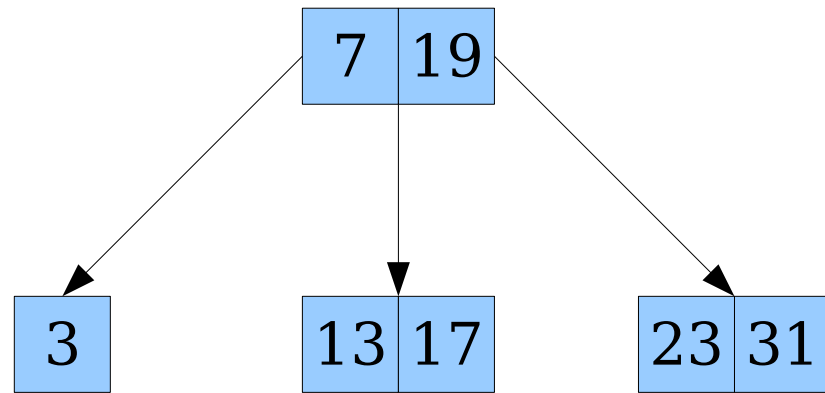
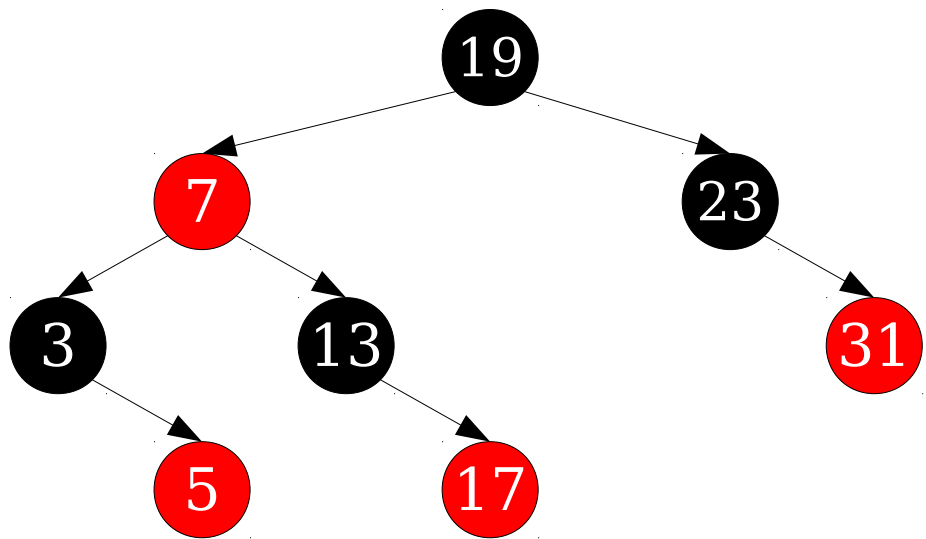
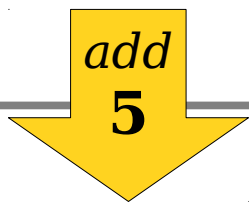
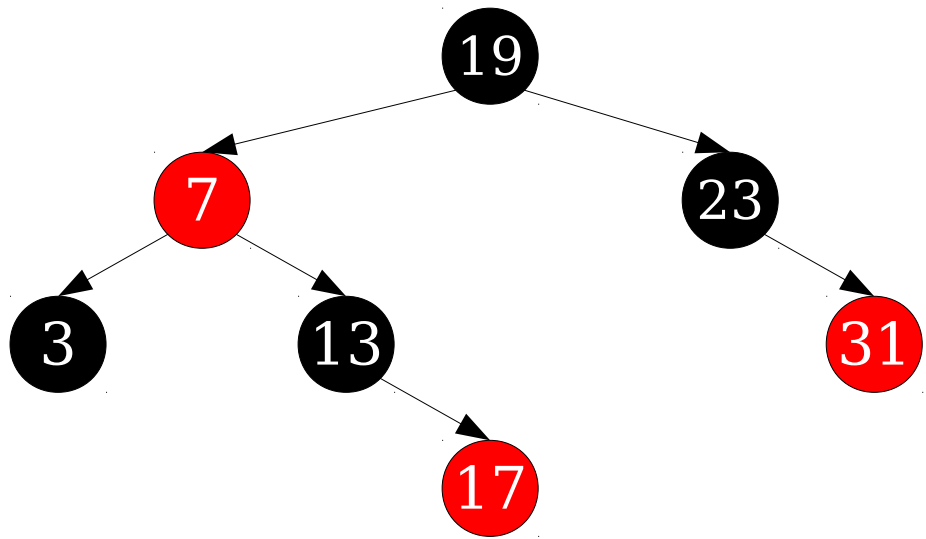
- Nodes in a 2-3-4 tree are classified into types based on the number of children they can have.
  - **2-nodes** have one key (two children).
  - **3-nodes** have two keys (three children).
  - **4-nodes** have three keys (four children).
- How might these nodes be represented?

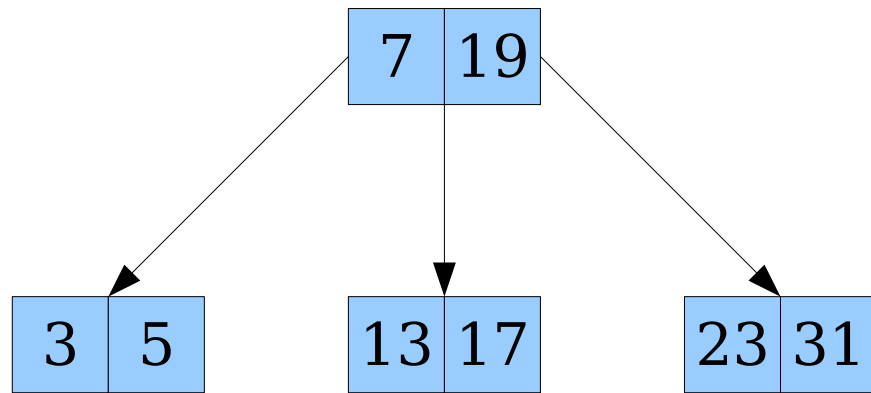
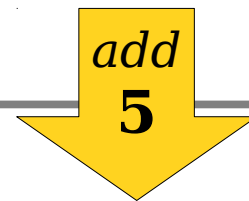
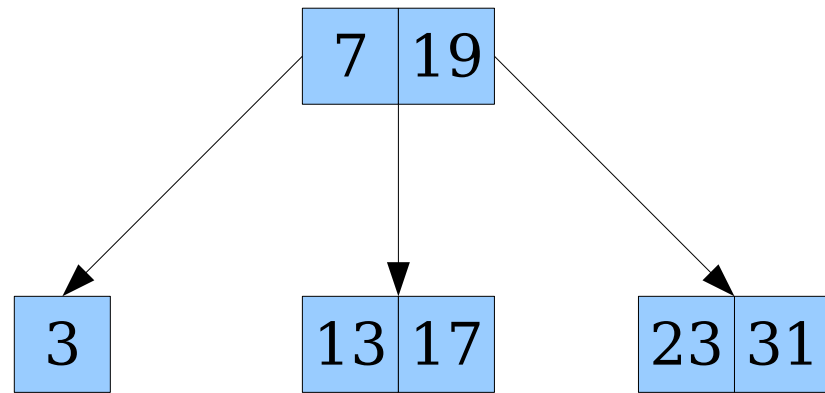
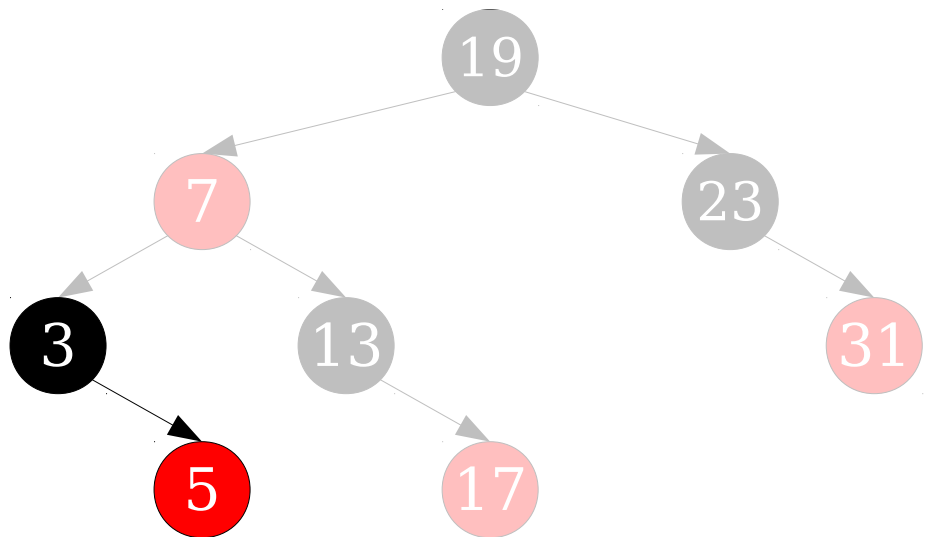
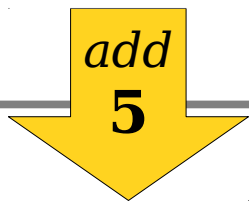
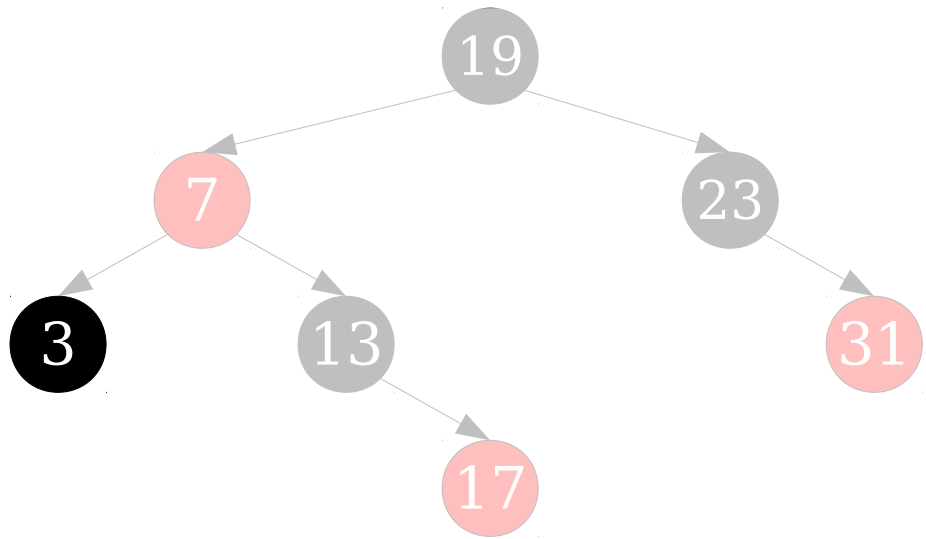
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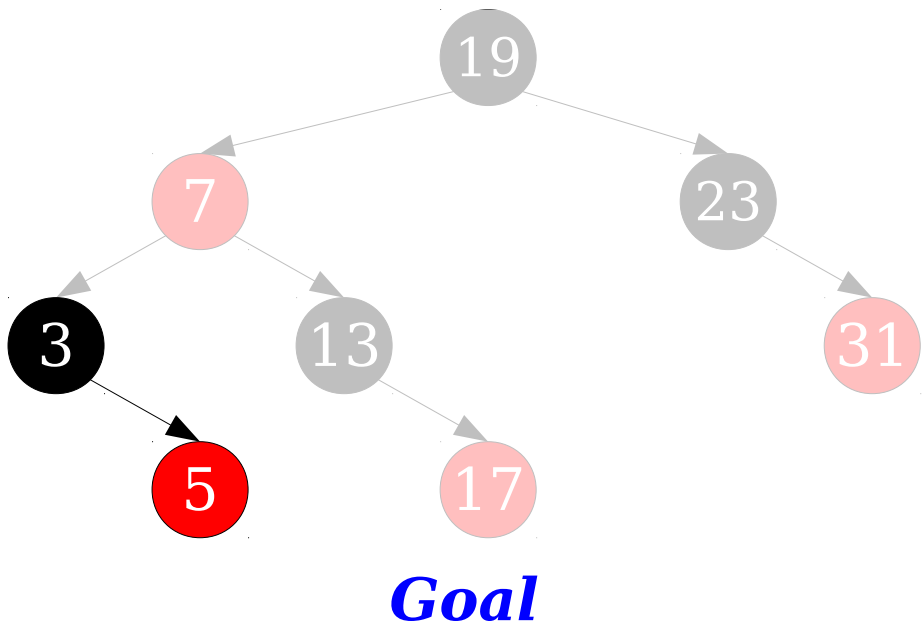
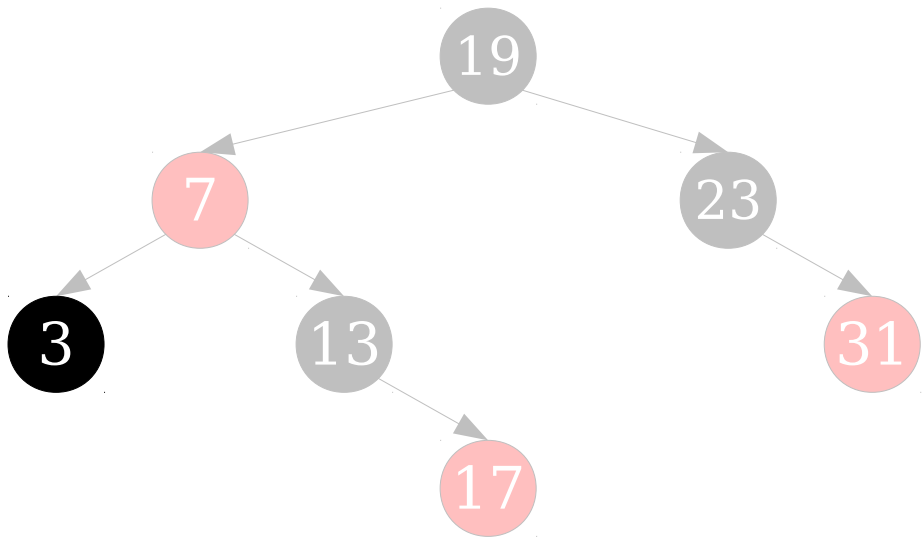


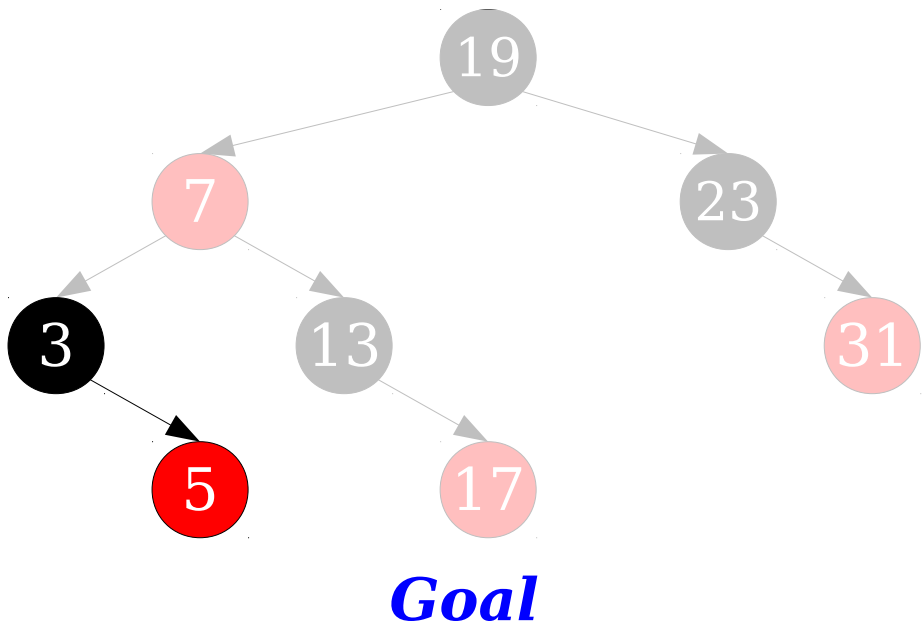
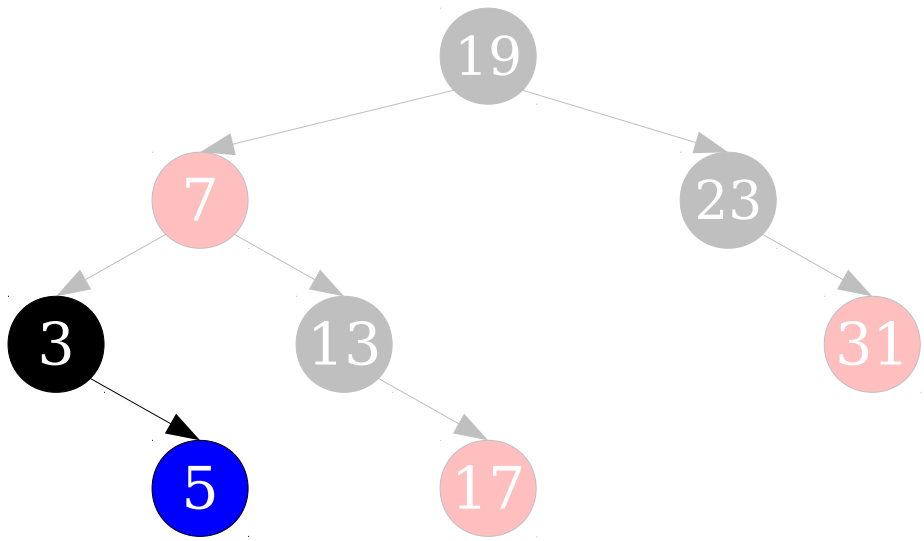




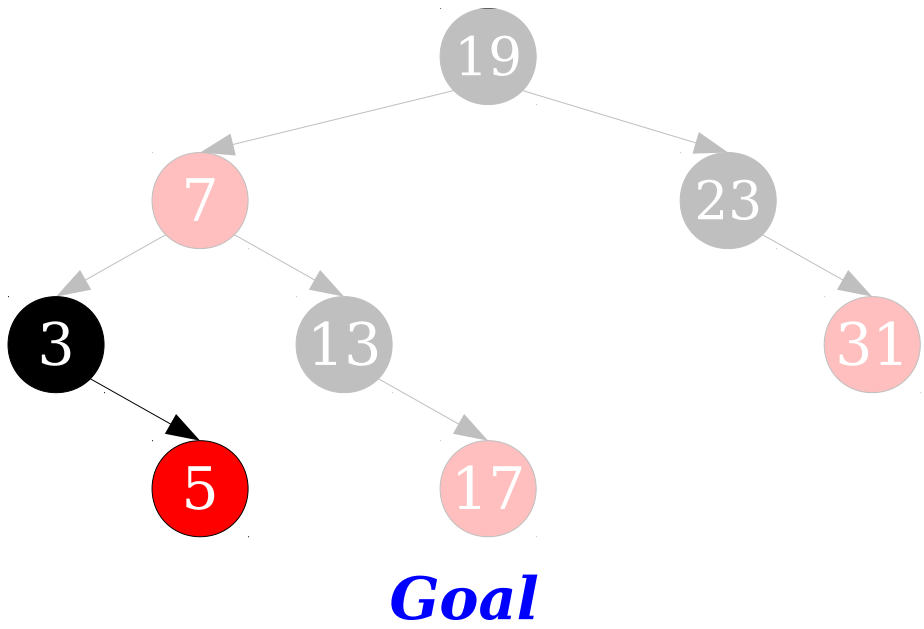
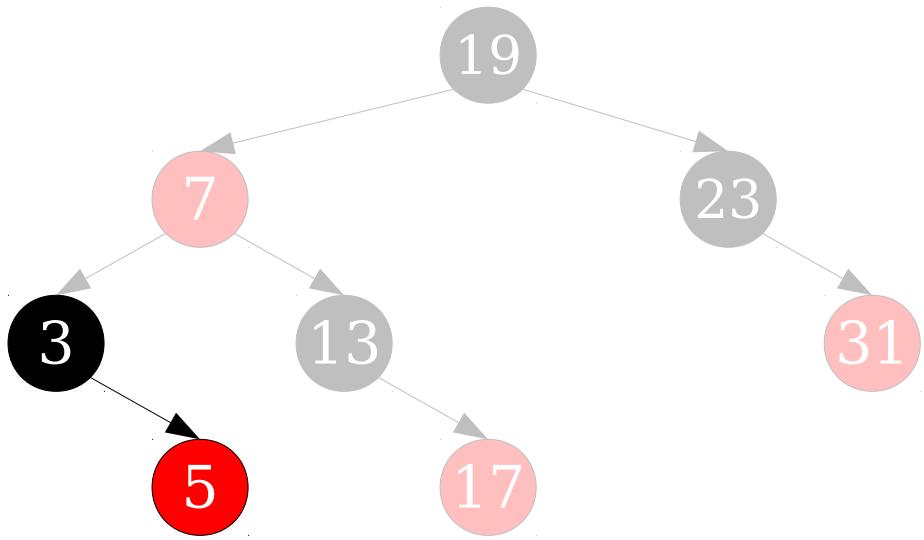


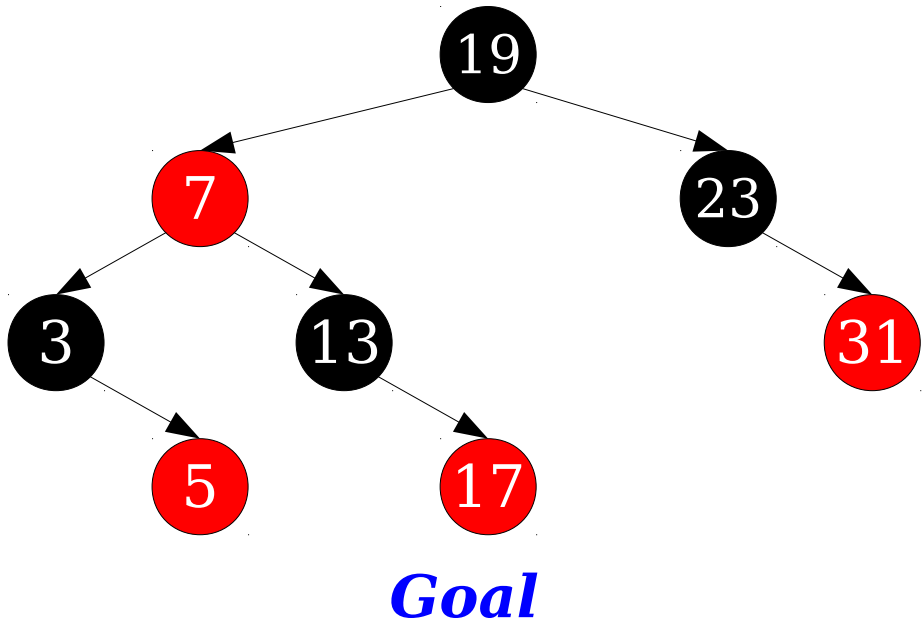
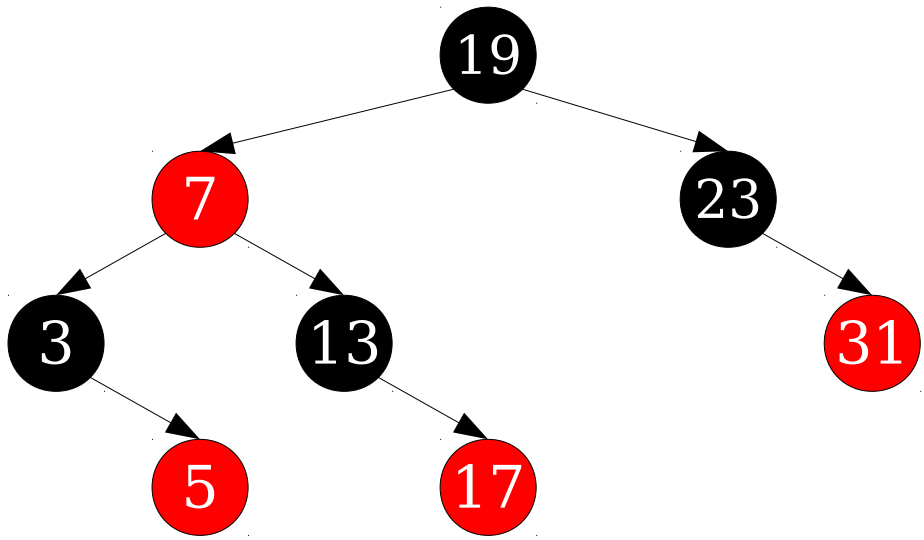


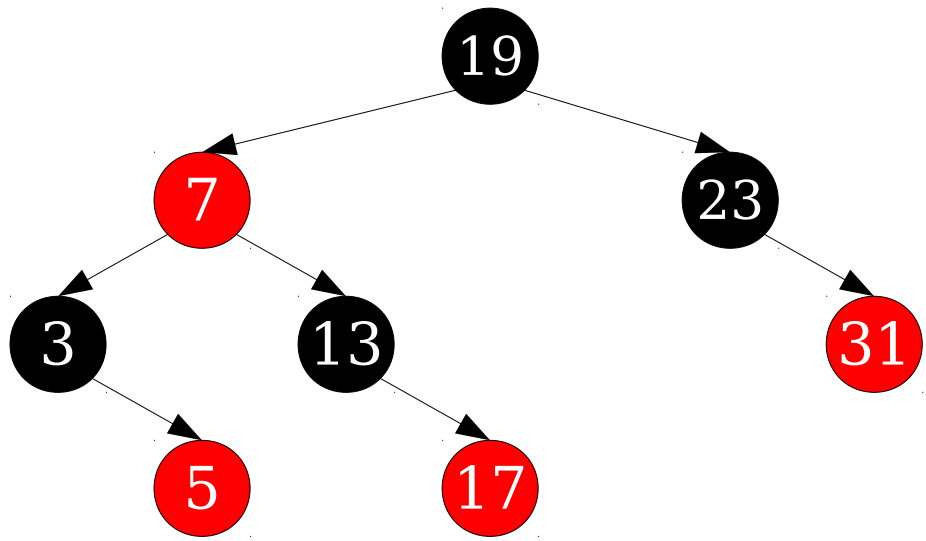


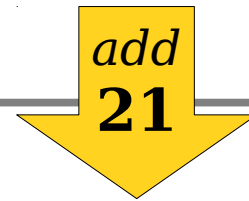
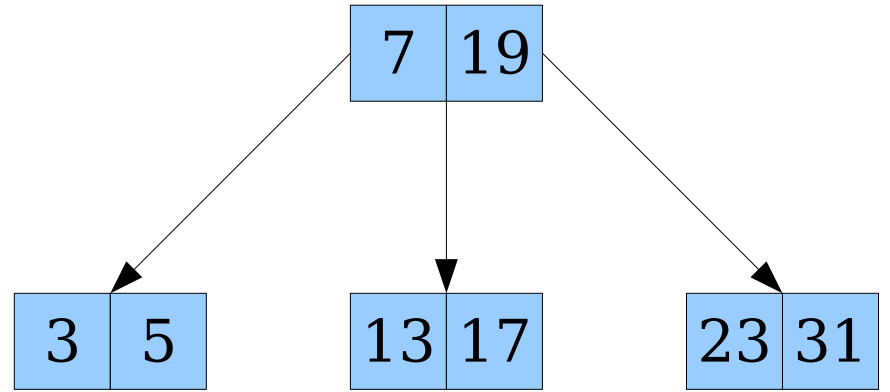
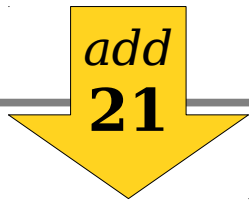
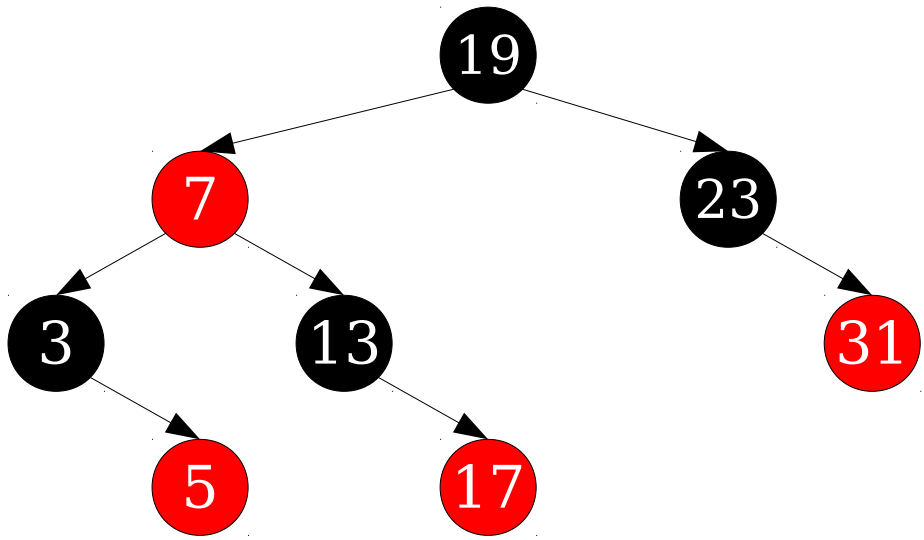


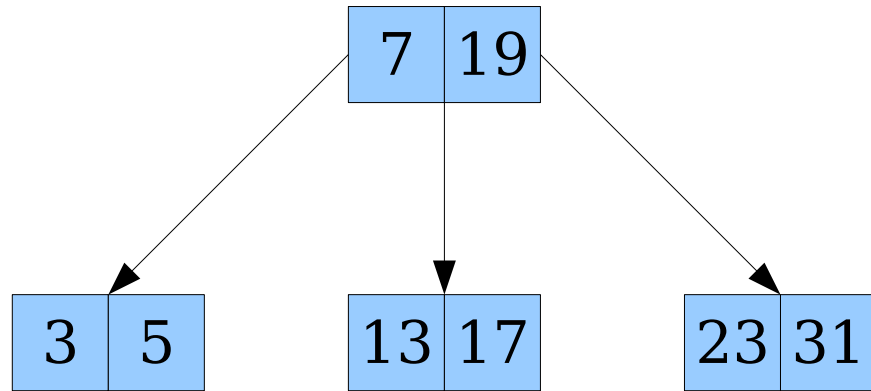
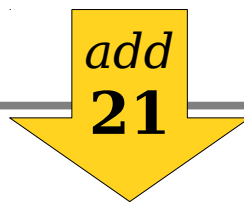
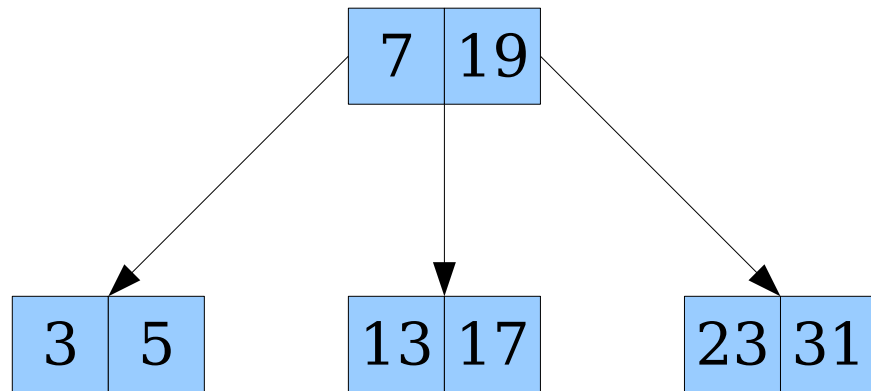
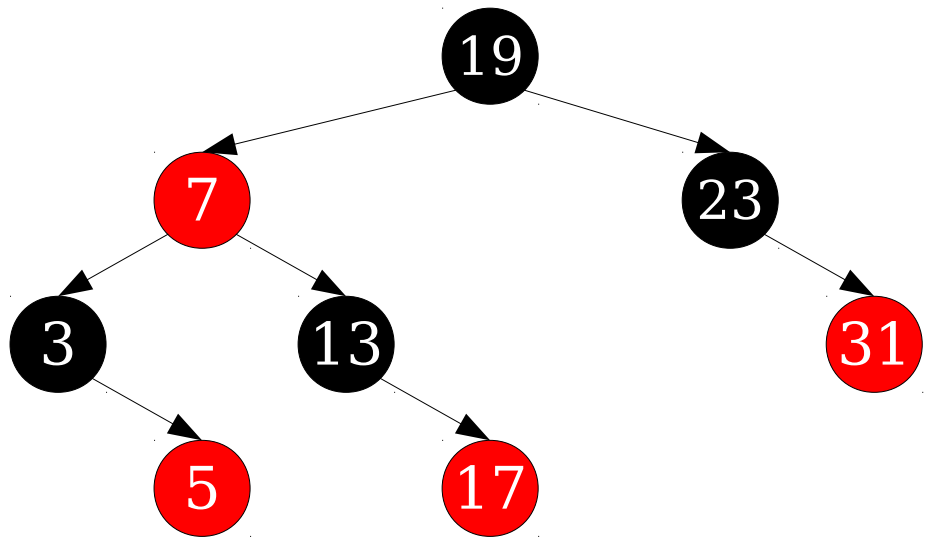


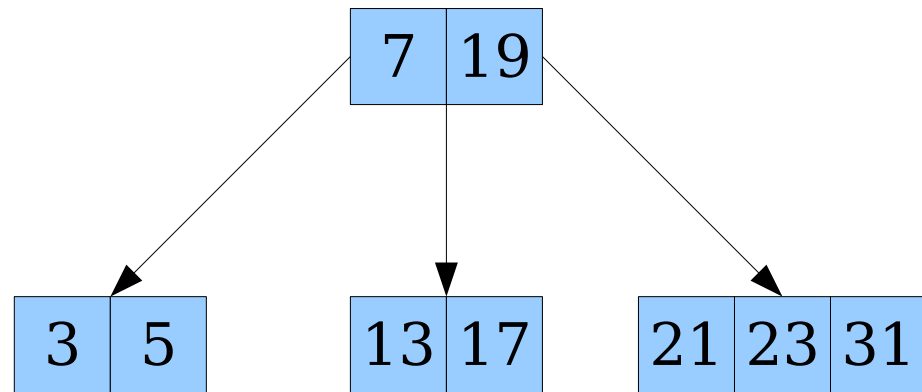
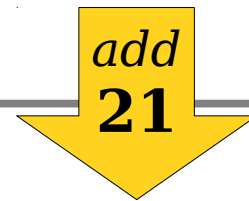
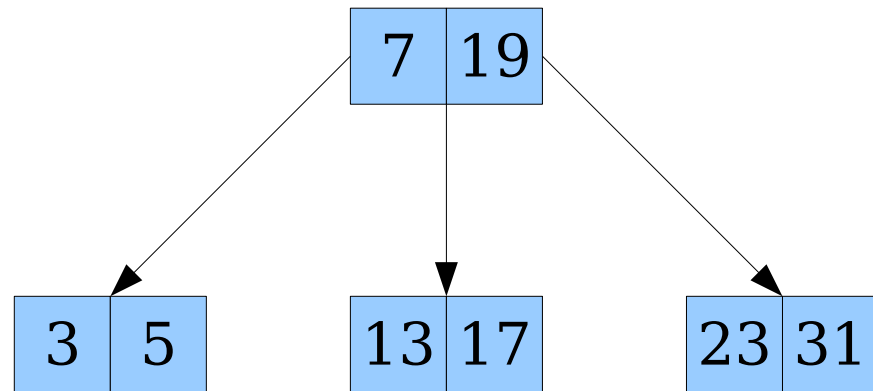
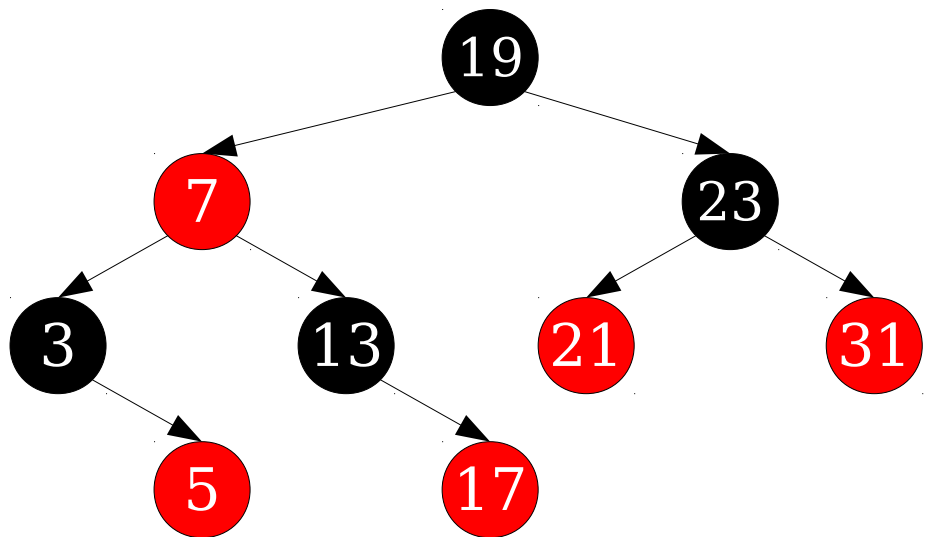
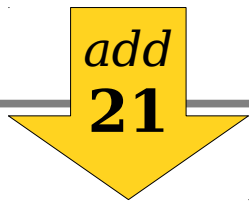
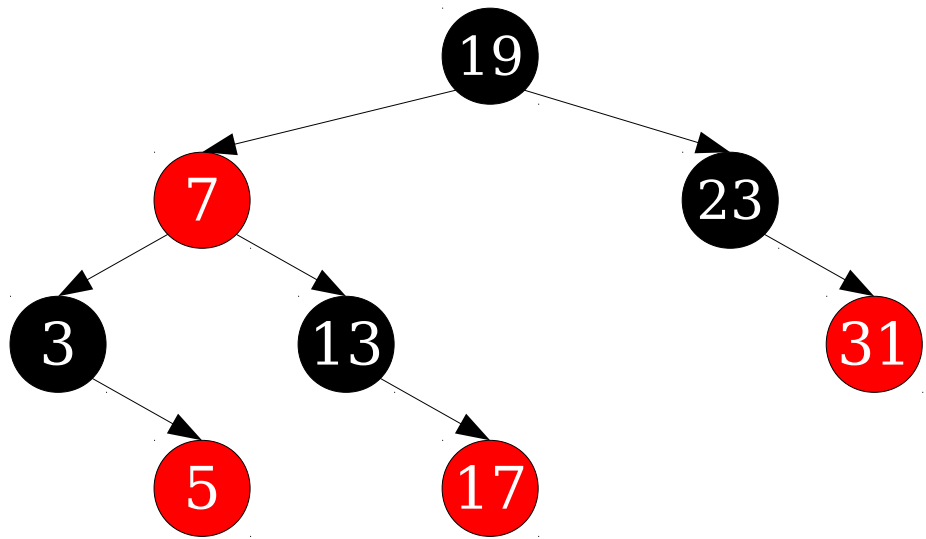


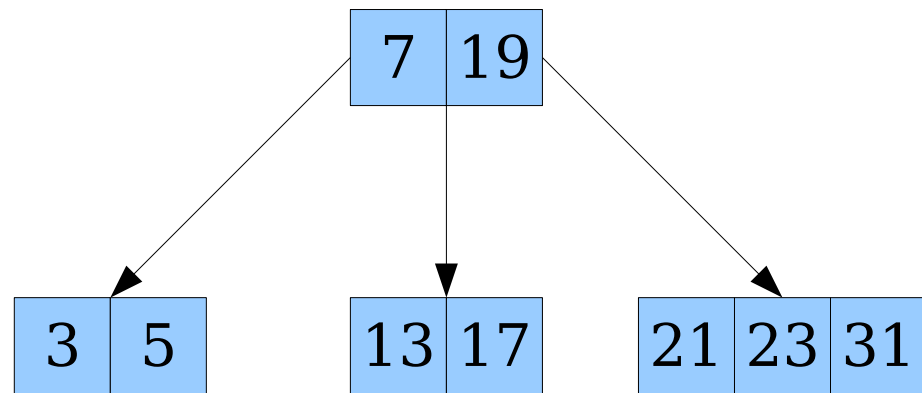
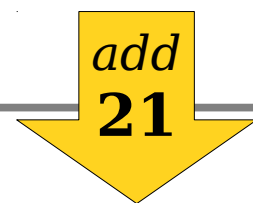
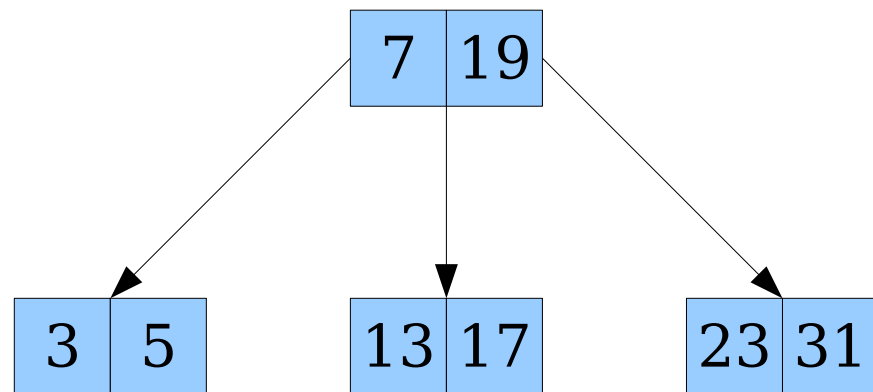
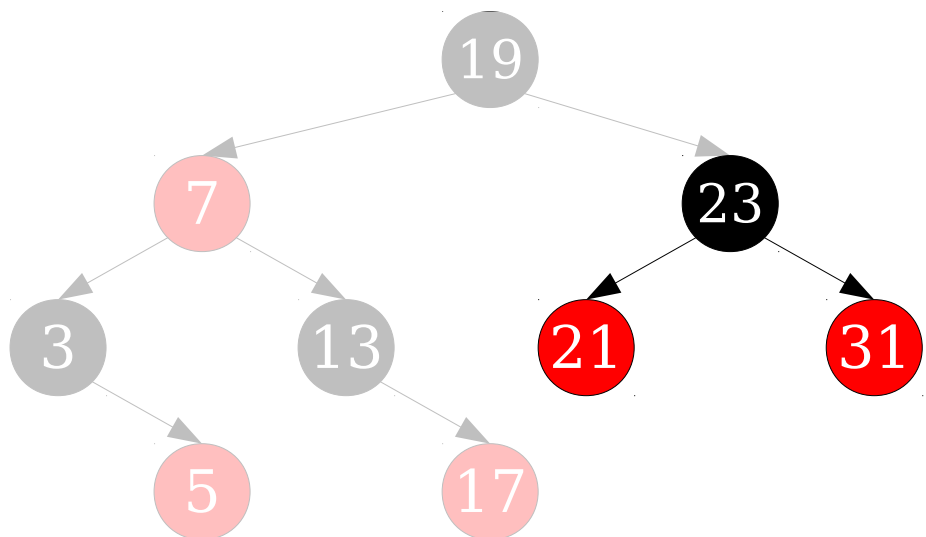
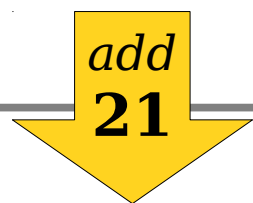
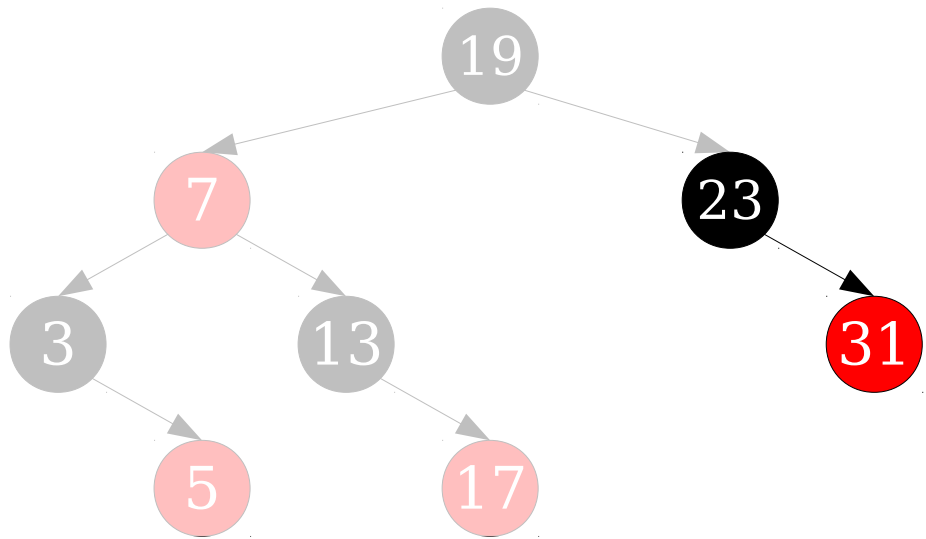


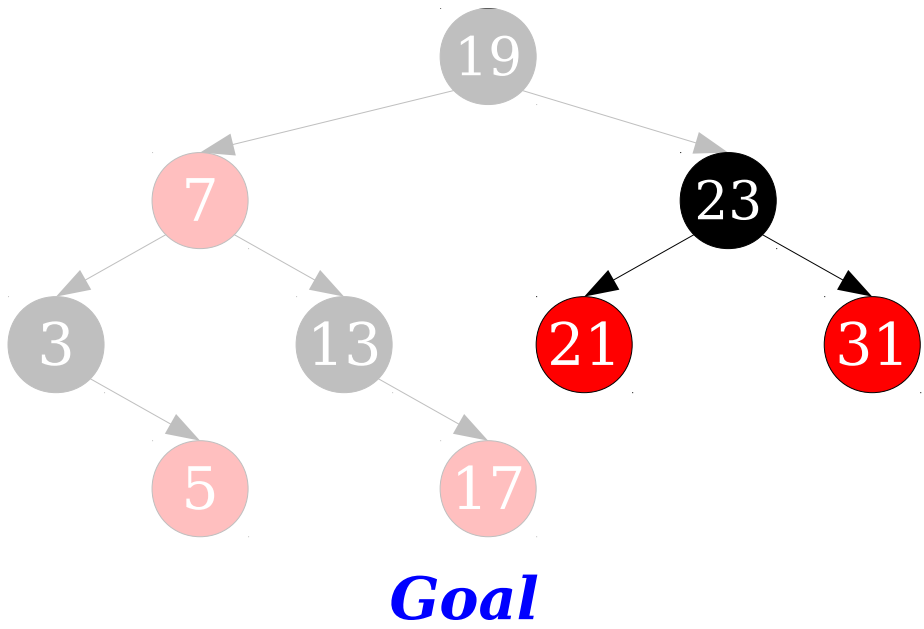
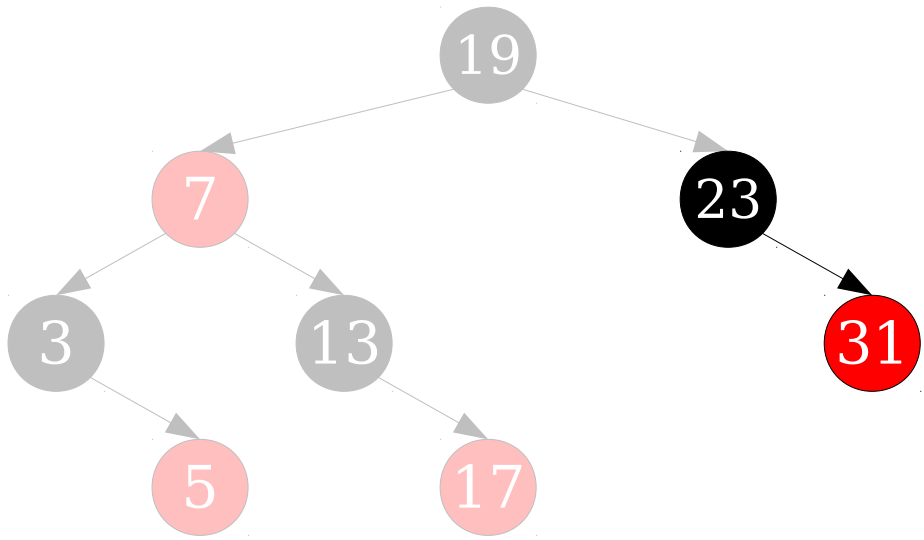




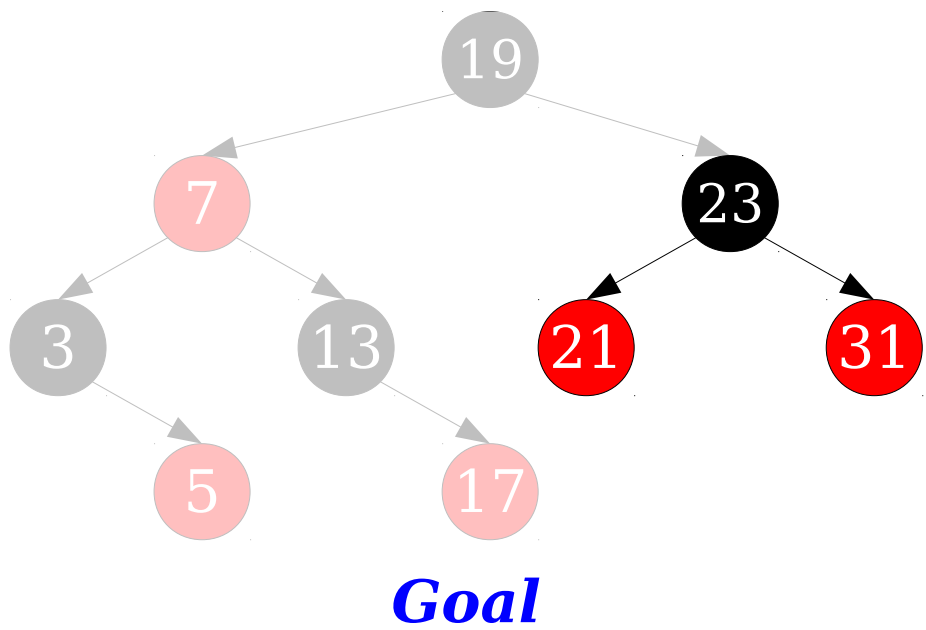
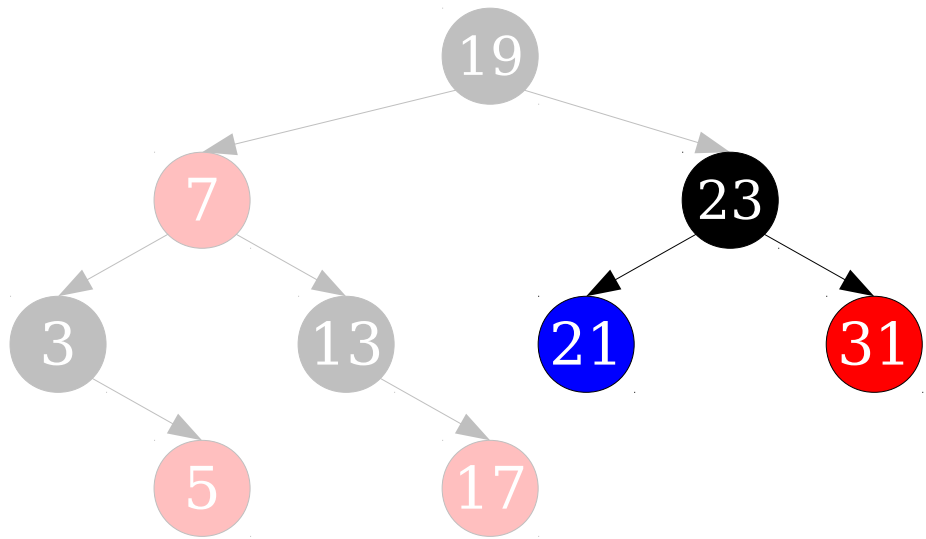


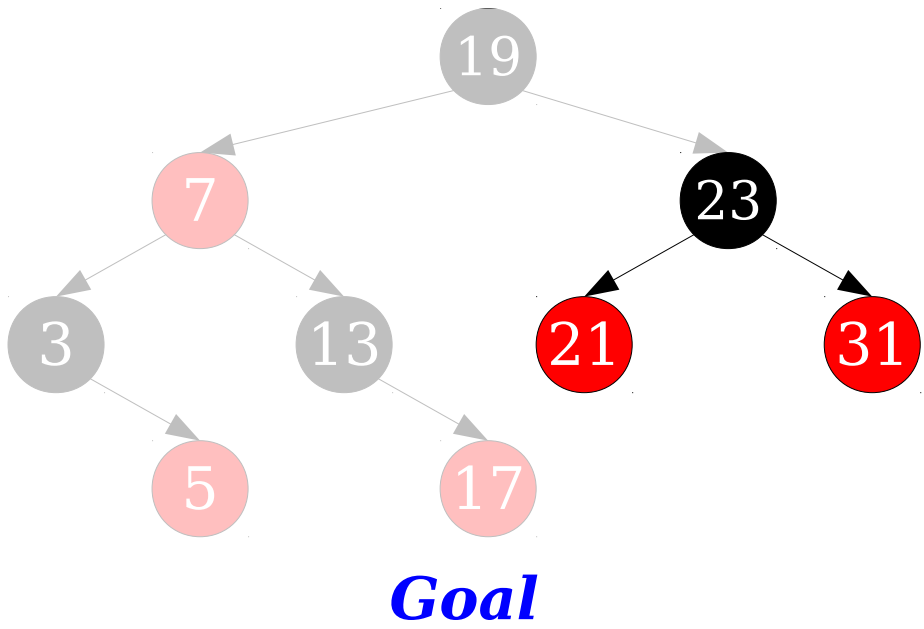
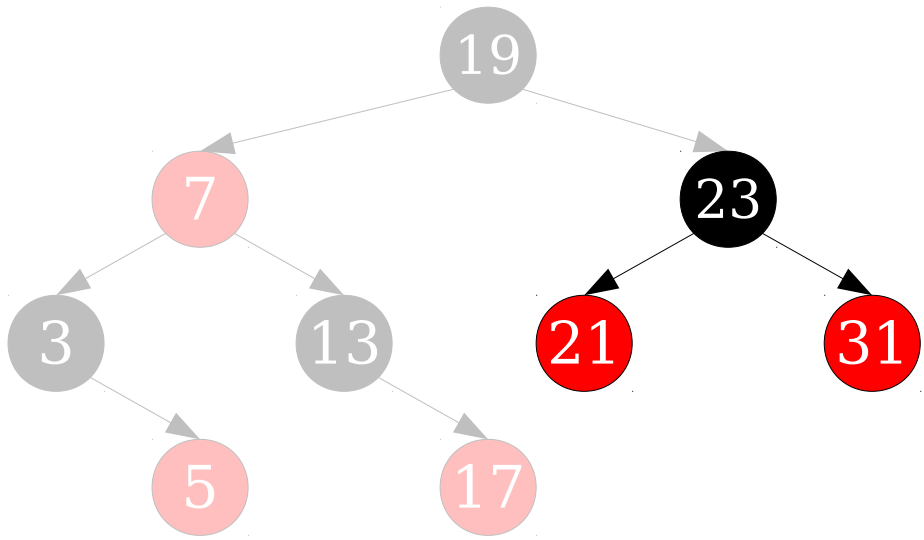


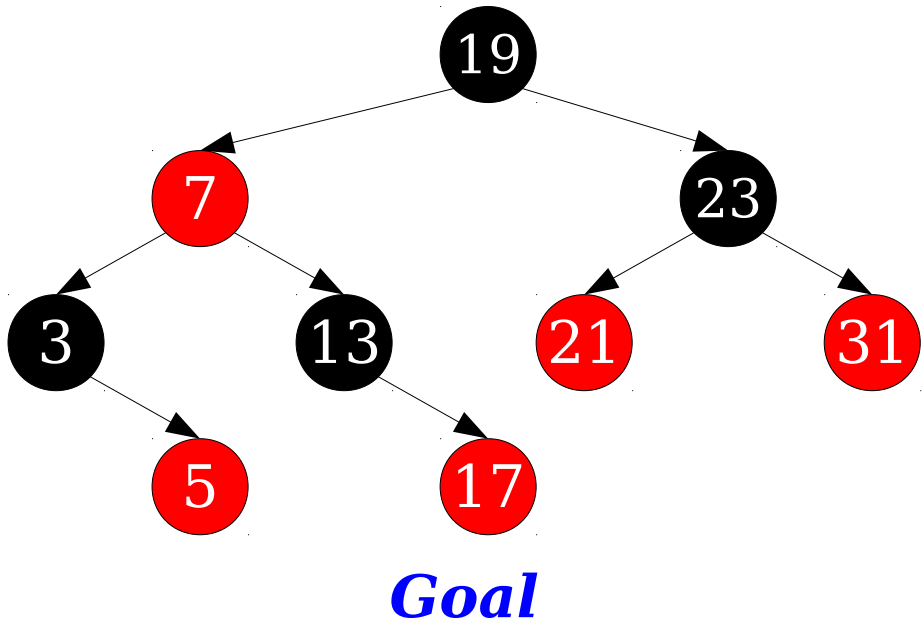
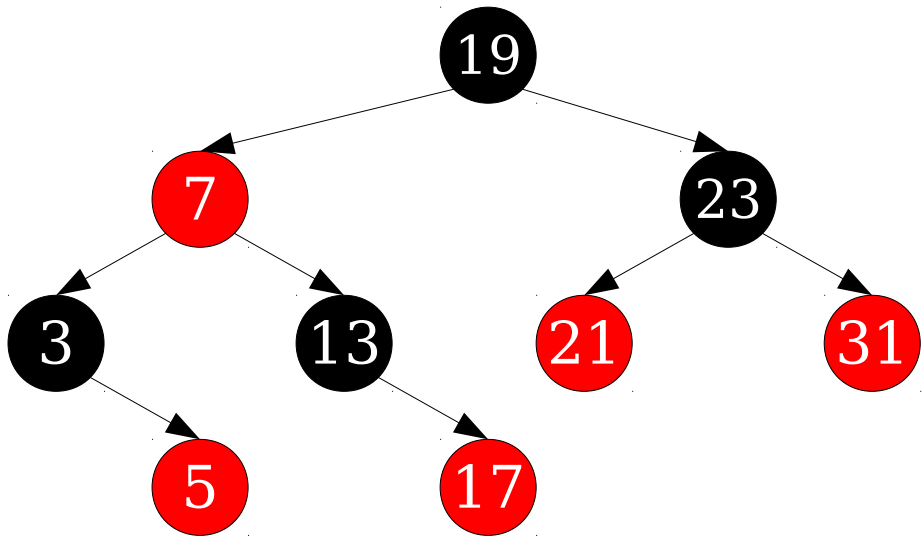






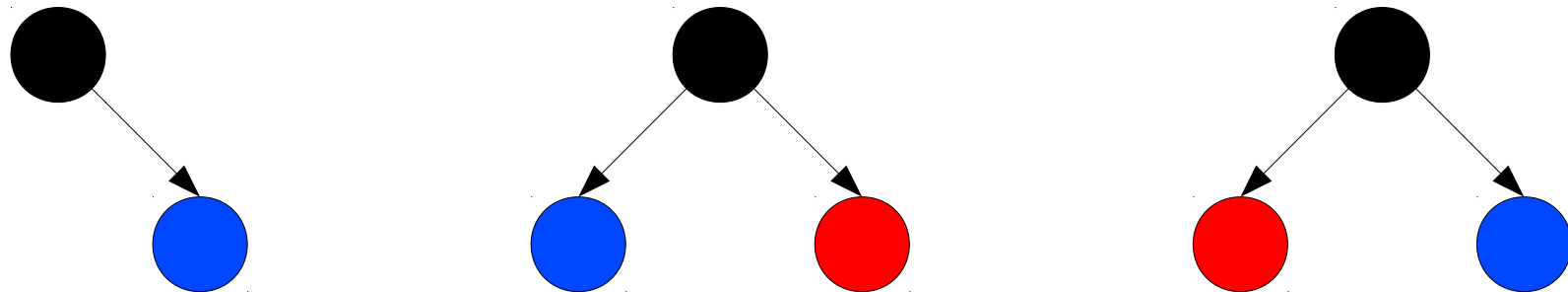


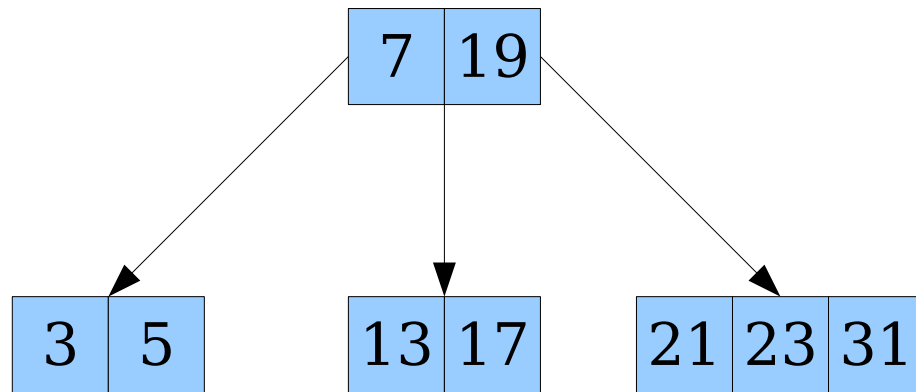
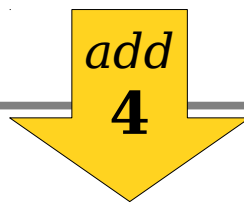
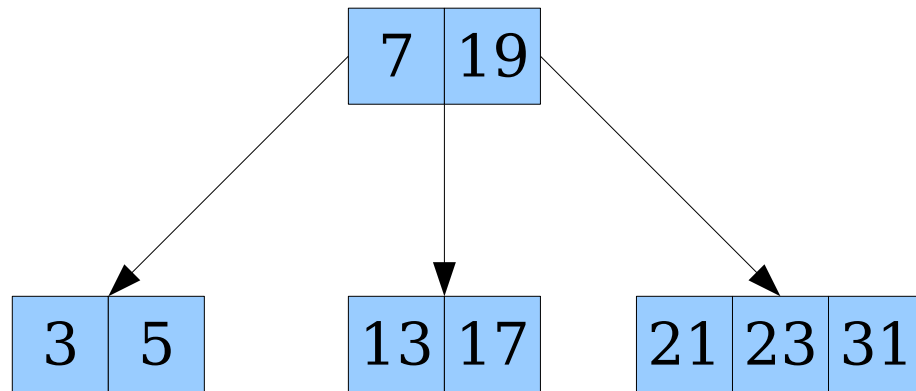
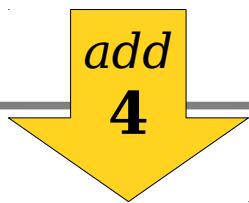
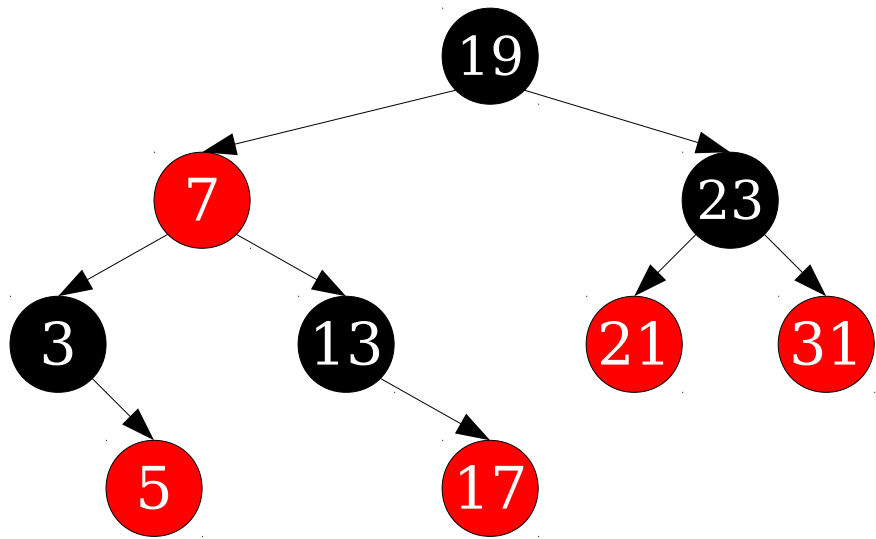


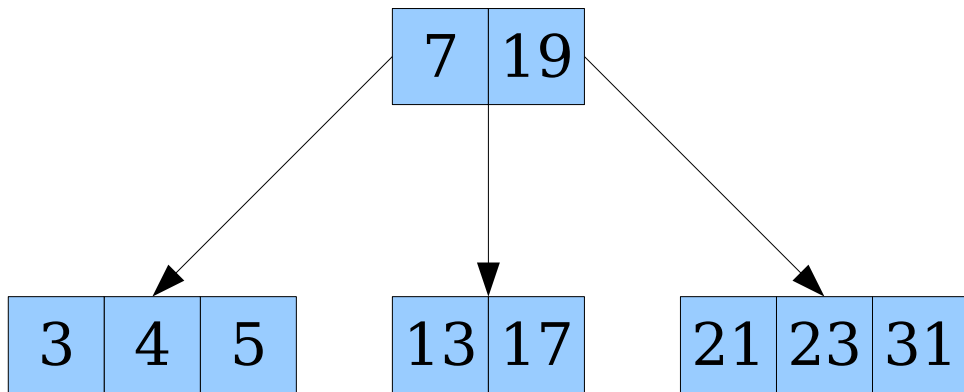
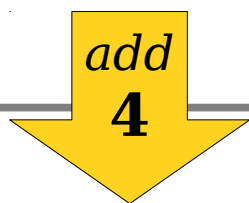
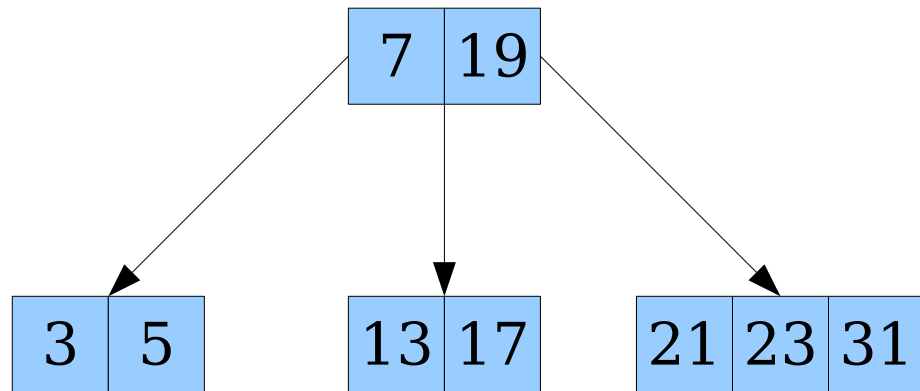
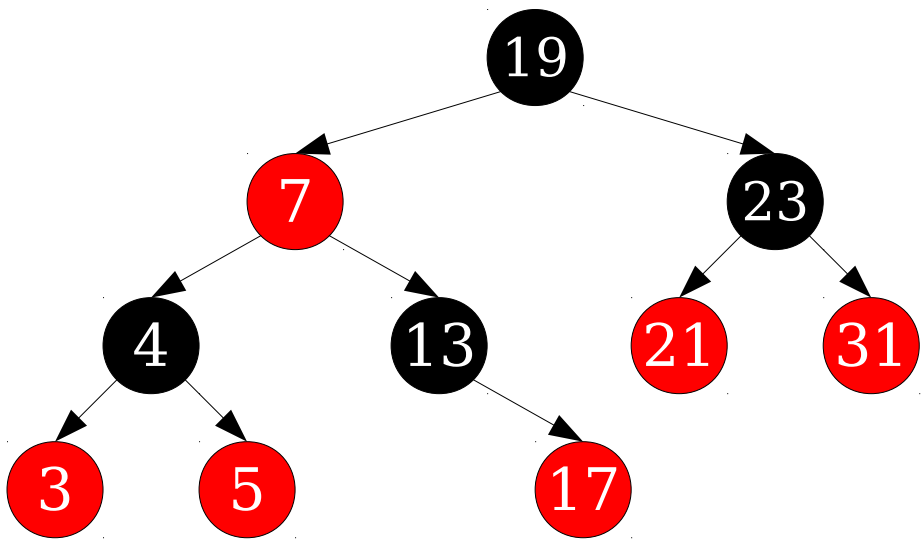
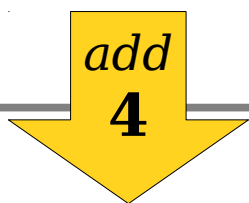
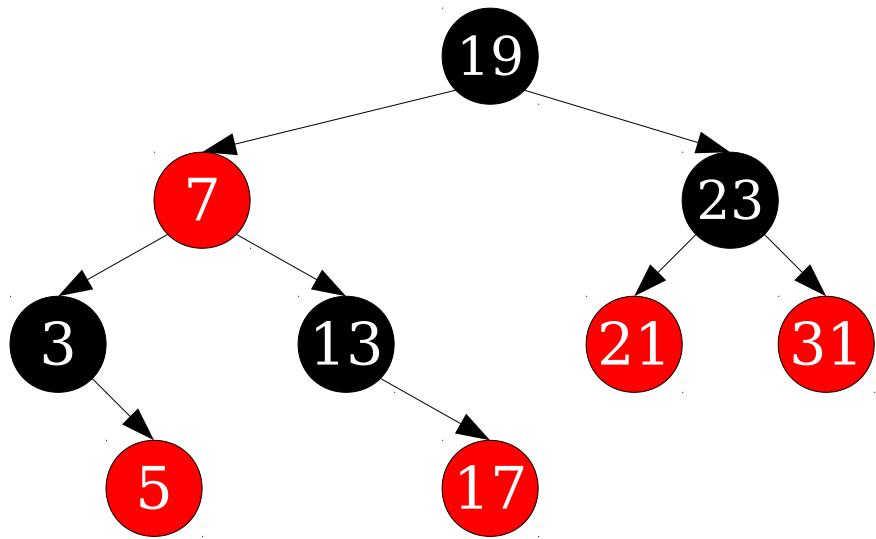


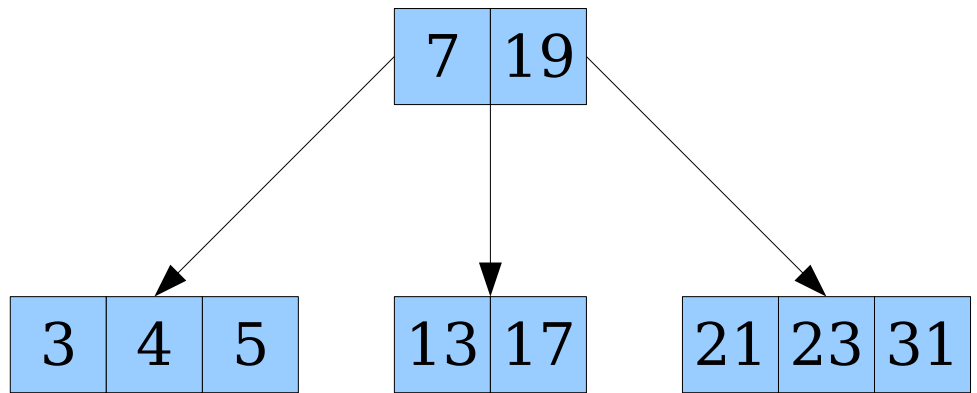
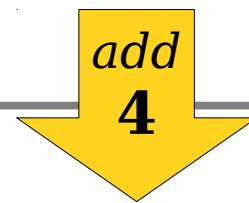
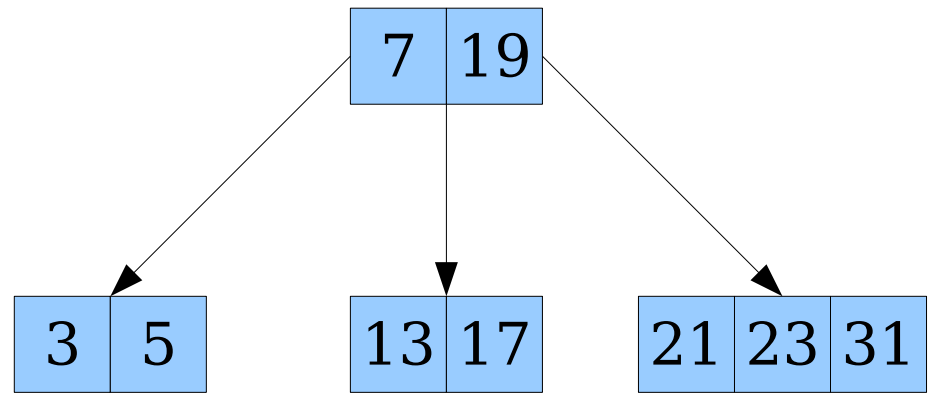
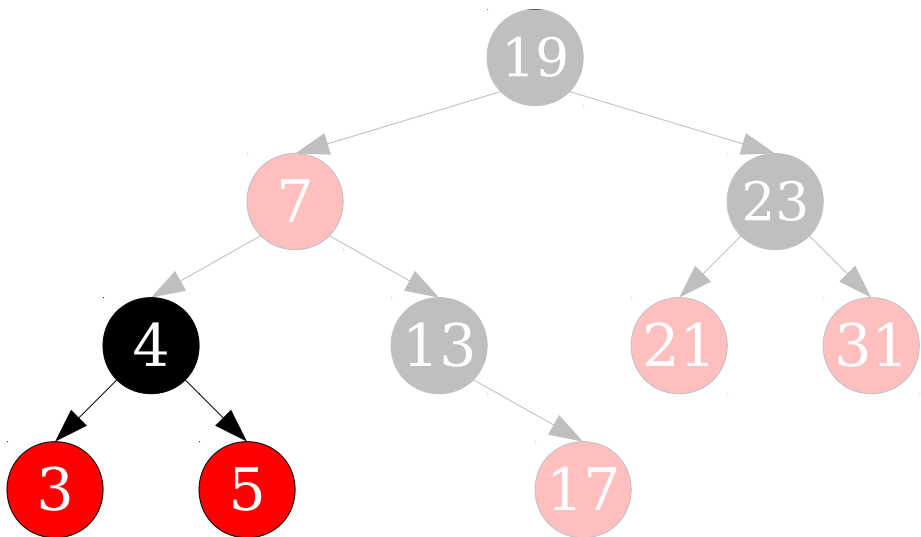
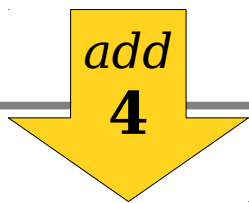
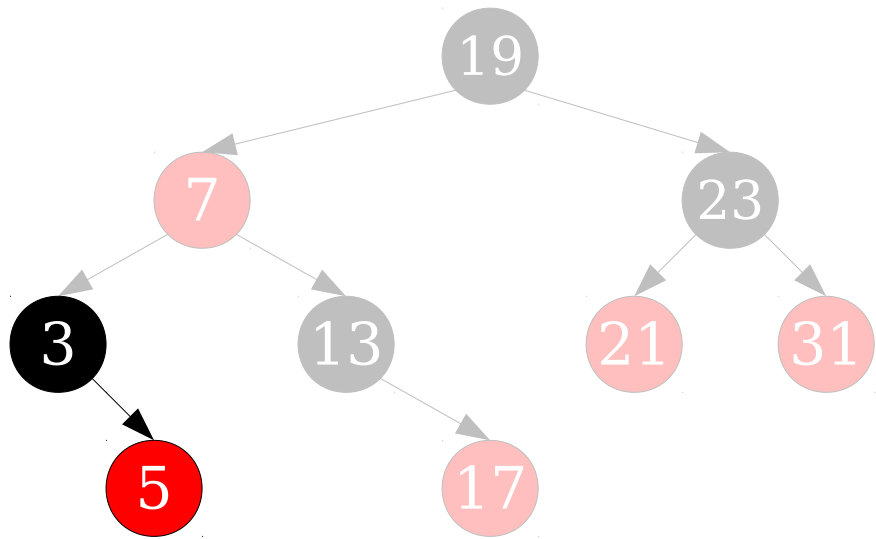
# Red/Black Tree Insertion

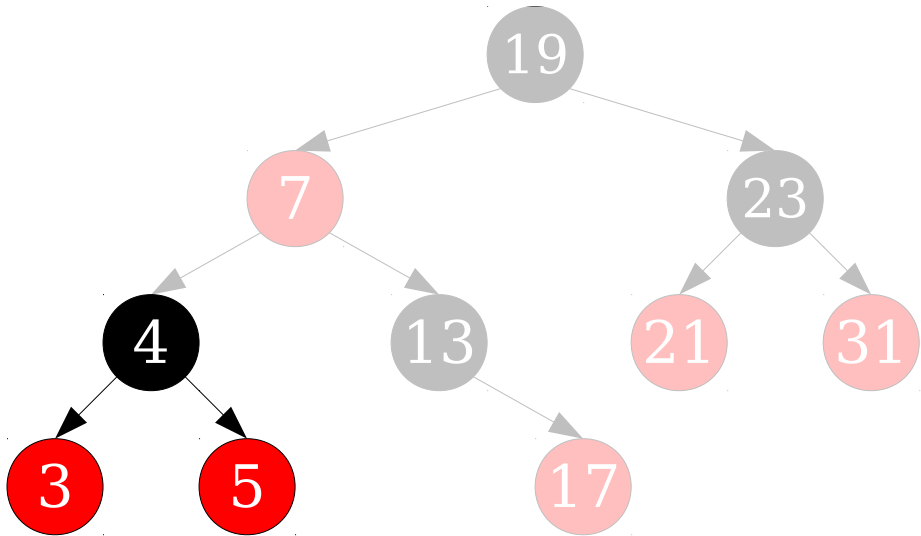
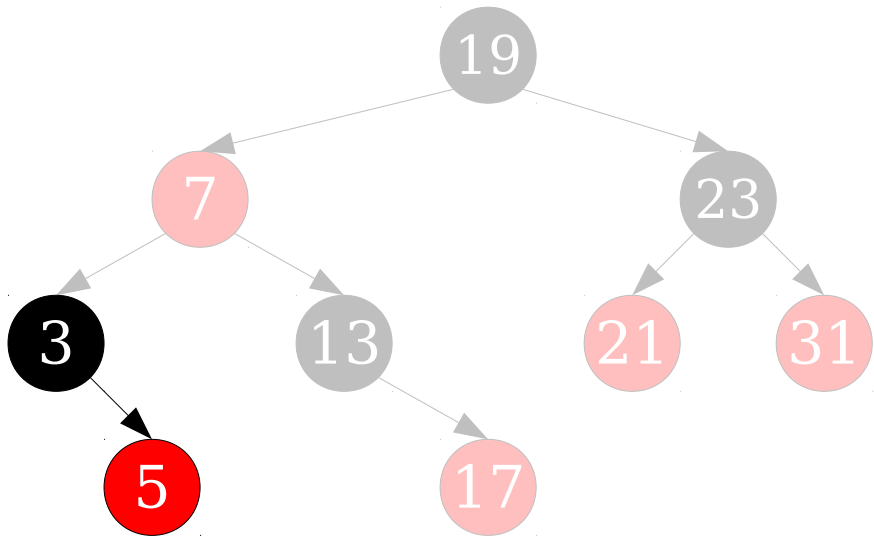
- **Rule #1:** When inserting a node, if its parent is black, make the node red and stop.
- **Justification:** This simulates inserting a key into an existing 2-node or 3-node.





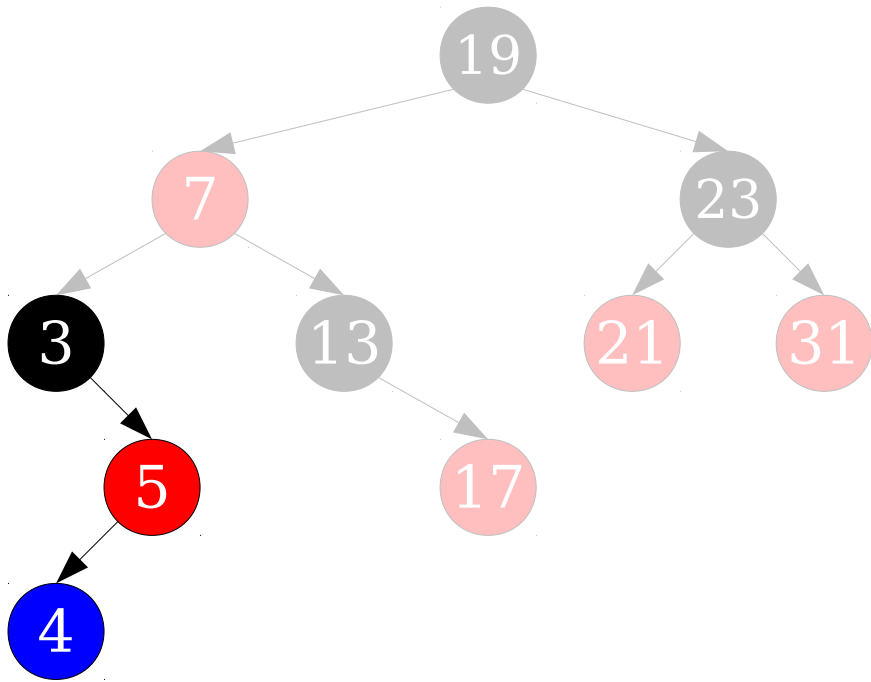




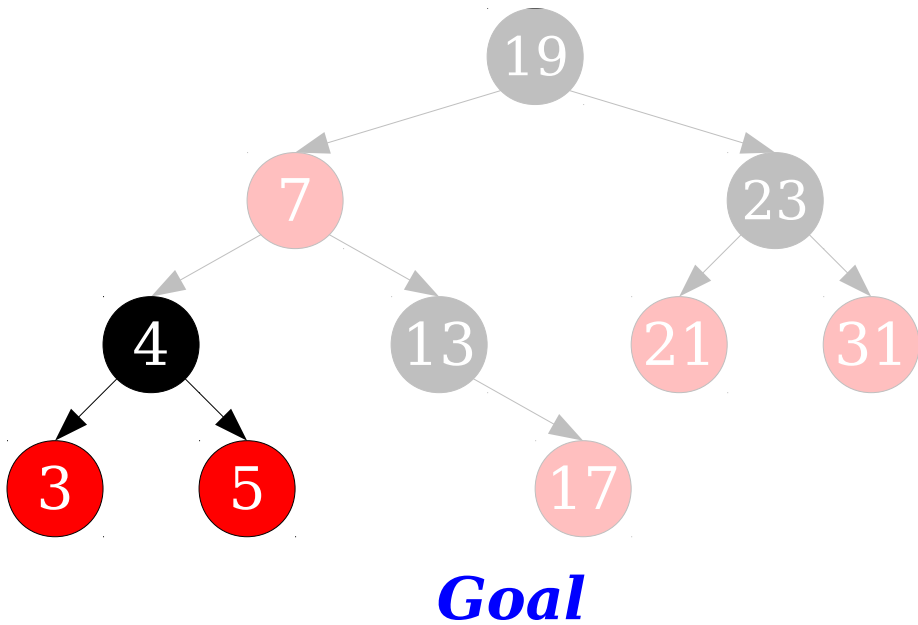


***Goal***

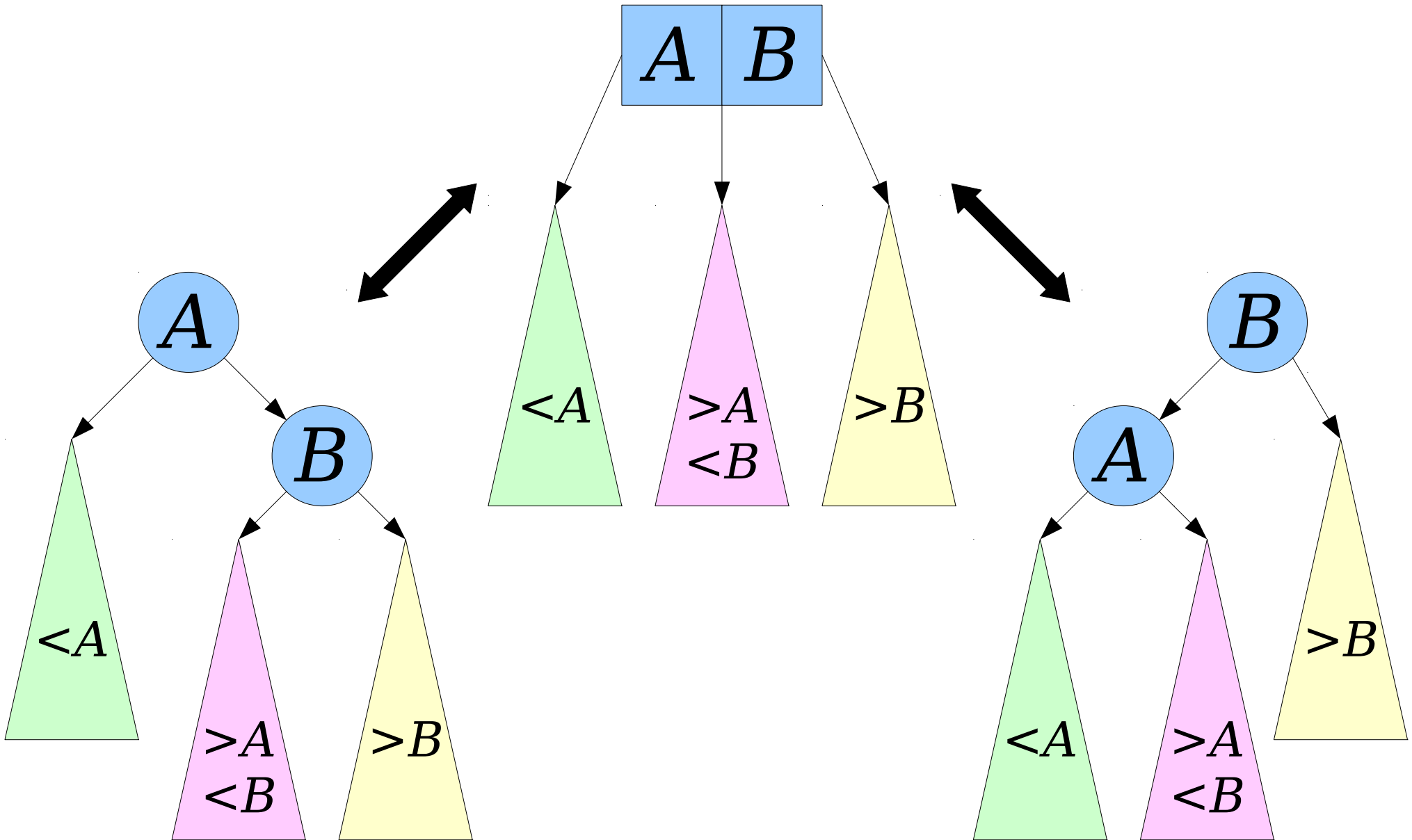




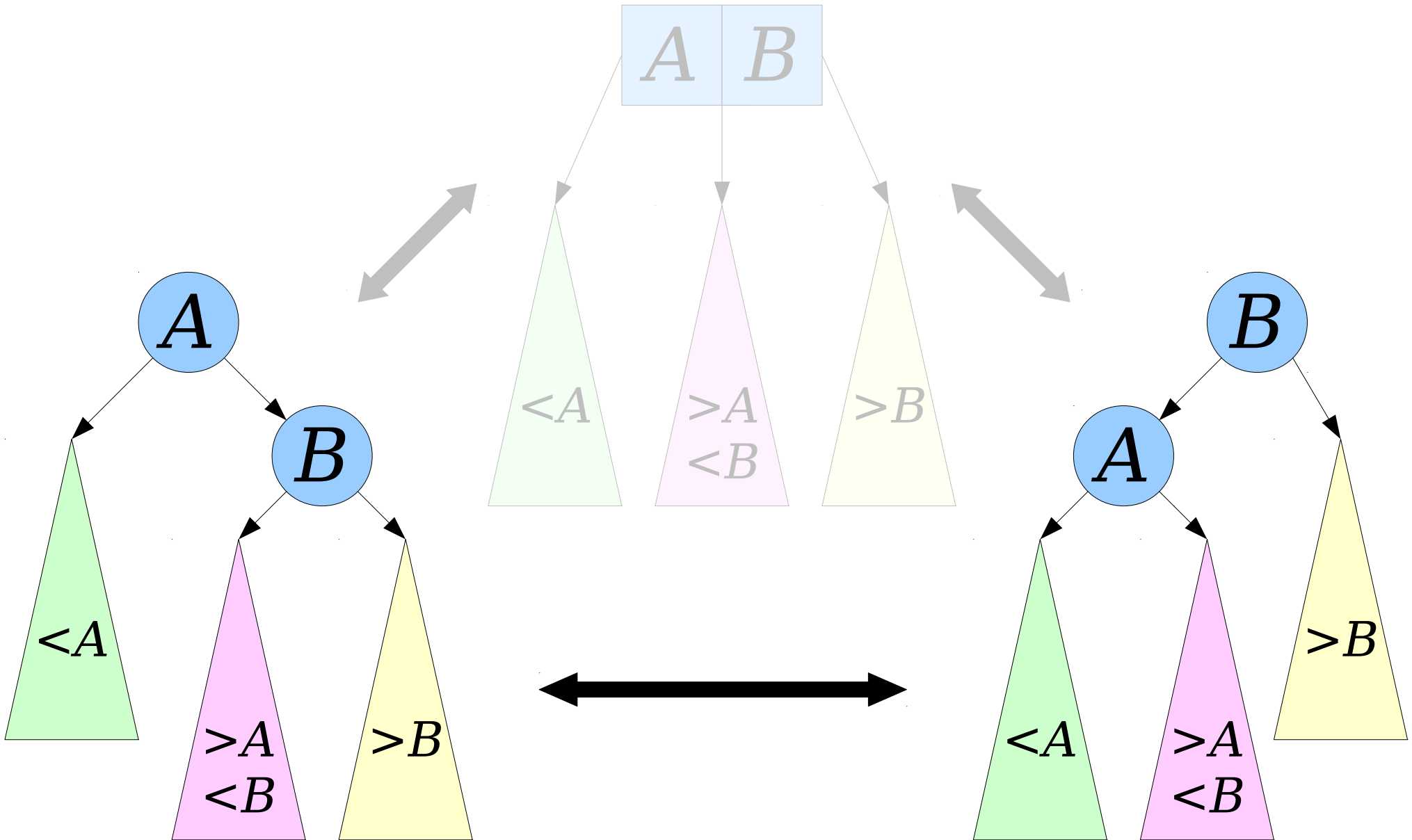
We need to move nodes around in a binary search tree. How do we do this?

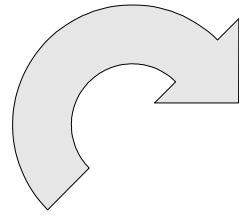
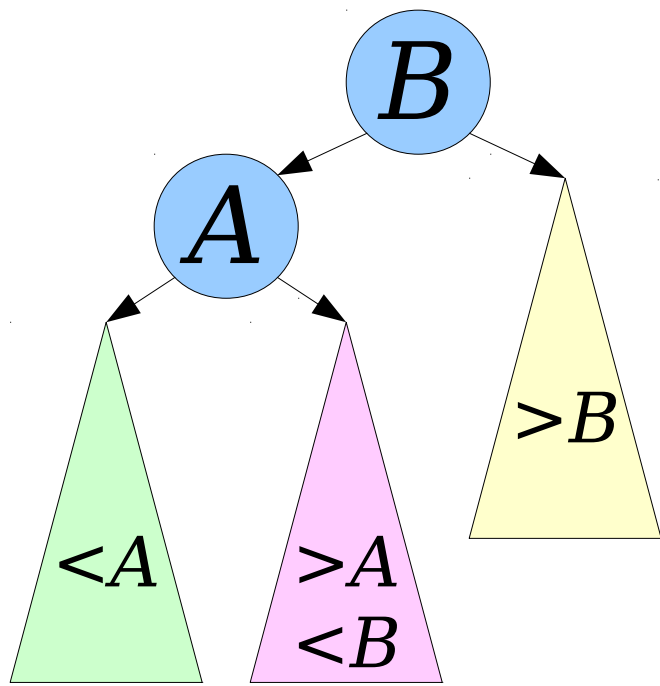


# Tree Rotations

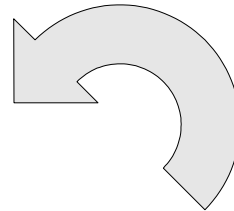
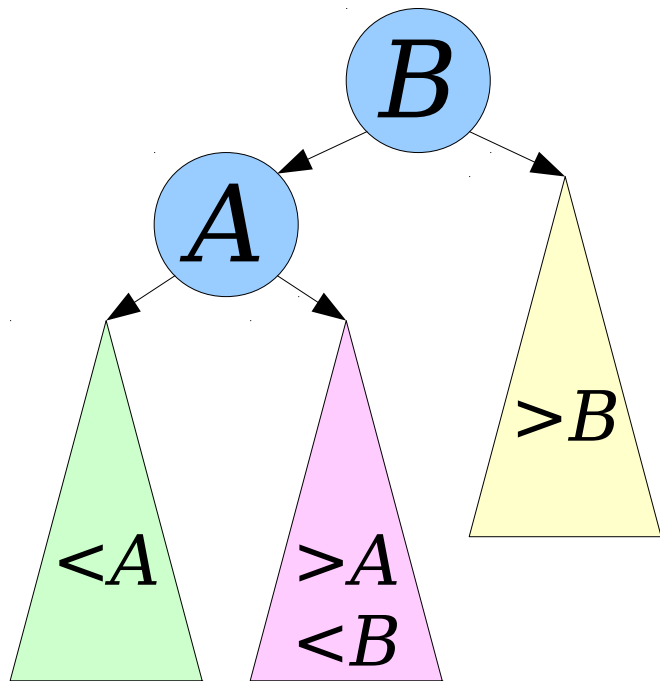
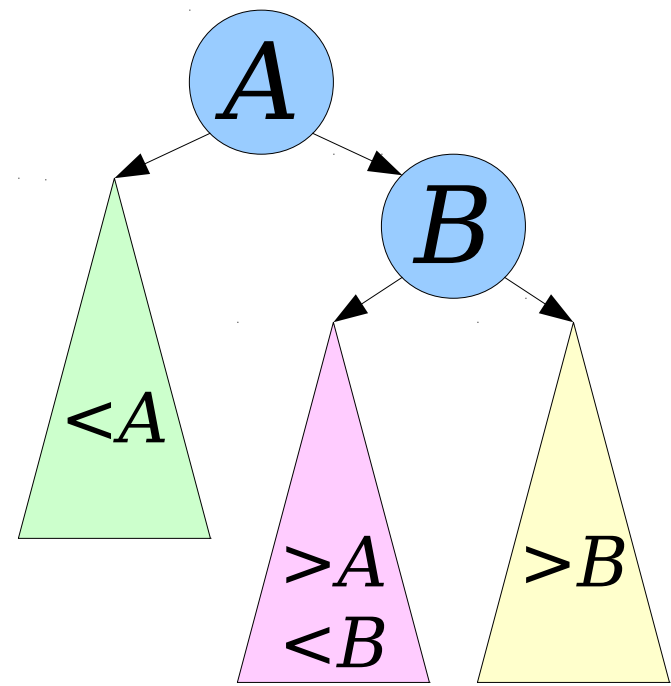


# Tree Rotations

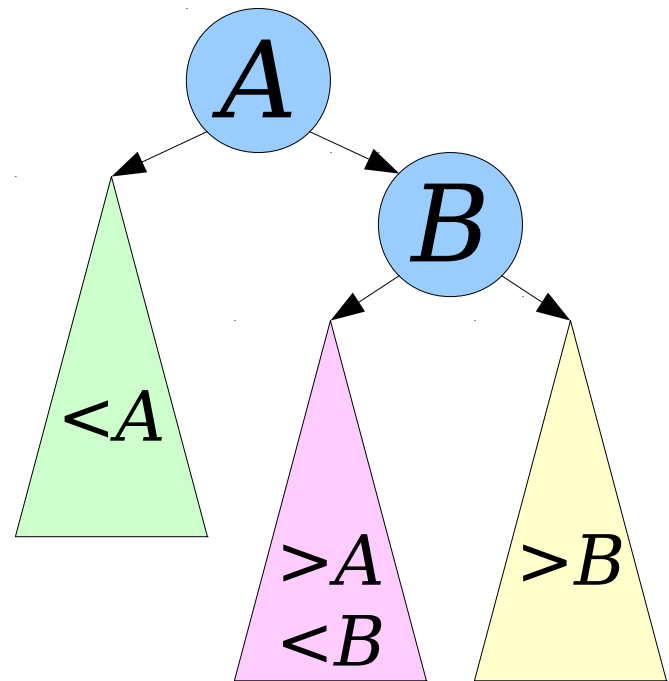


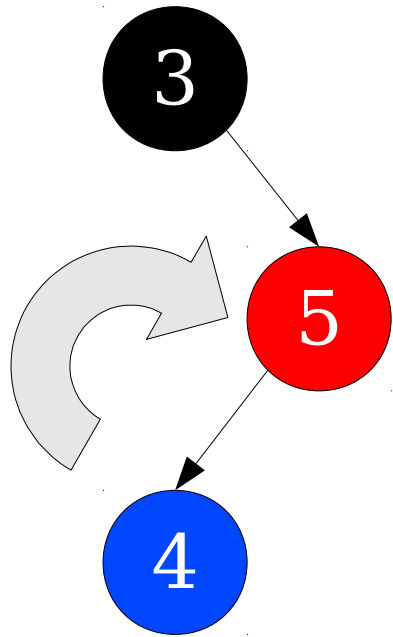


*Rotate  
Right*

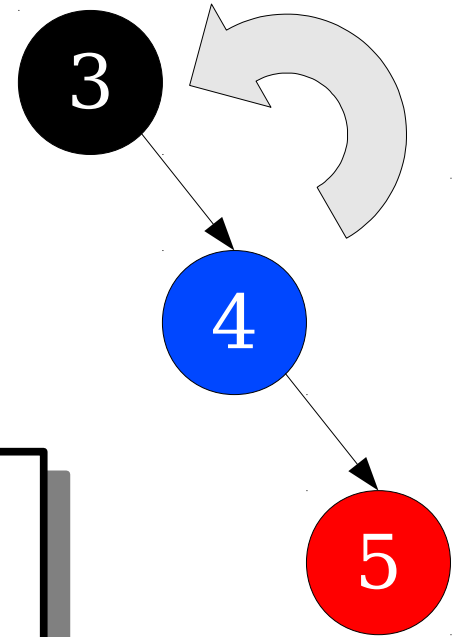


*Rotate  
Left*





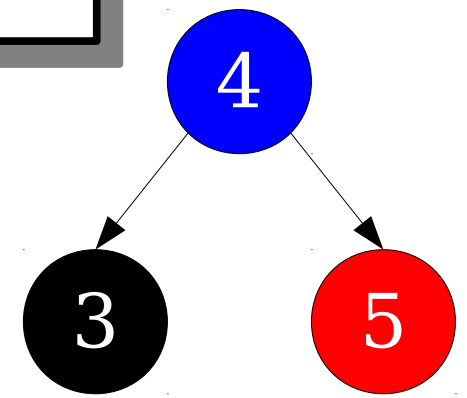
apply rotation



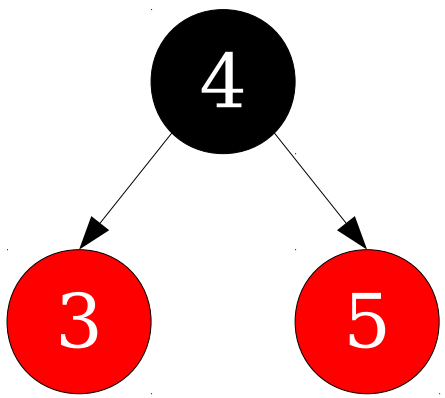
This applies any time we're inserting a new node into the middle of a "3-node" in this pattern.

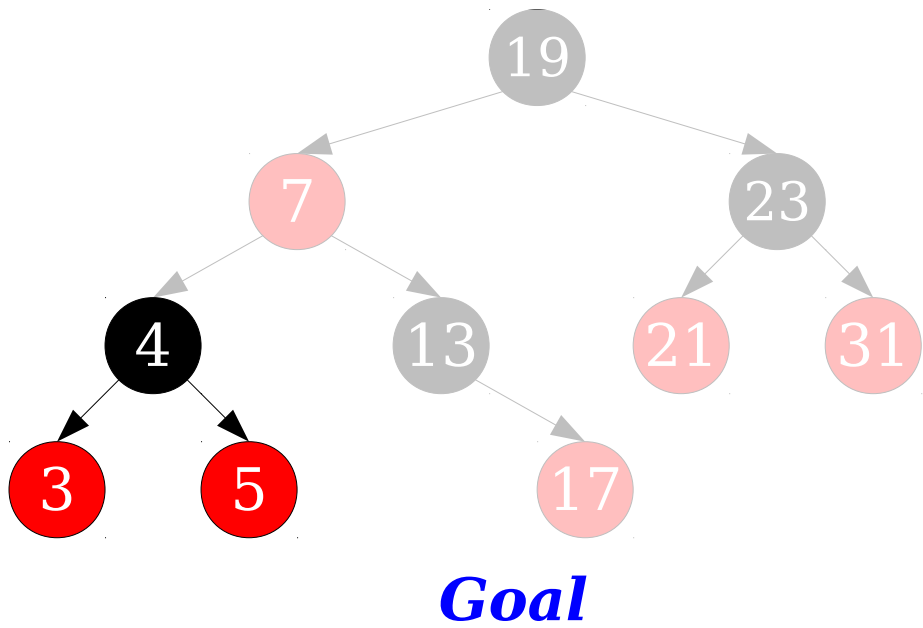
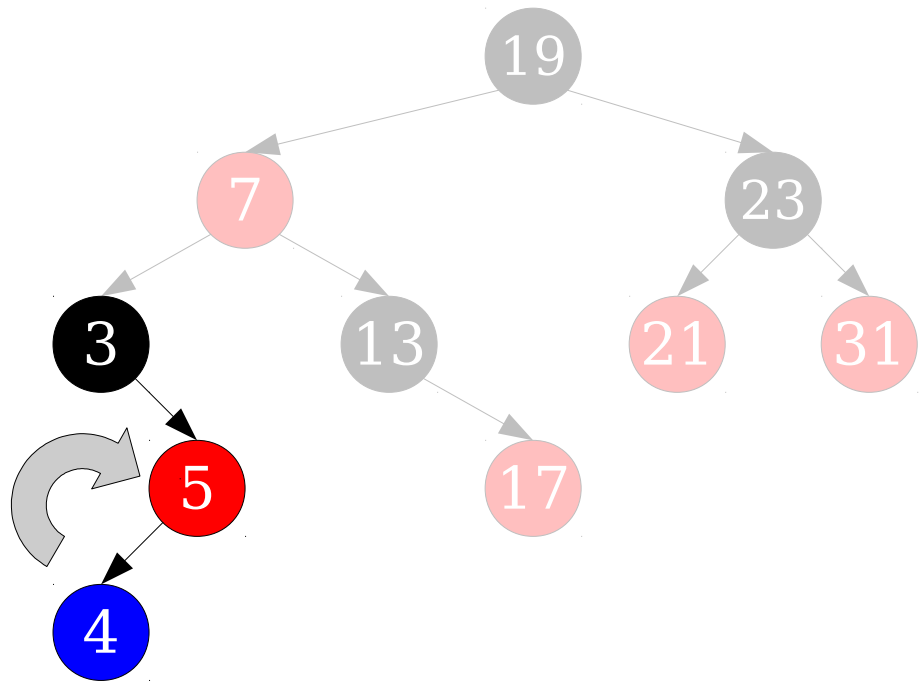
By making observations like these, we can determine how to update a red/black tree after an insertion.

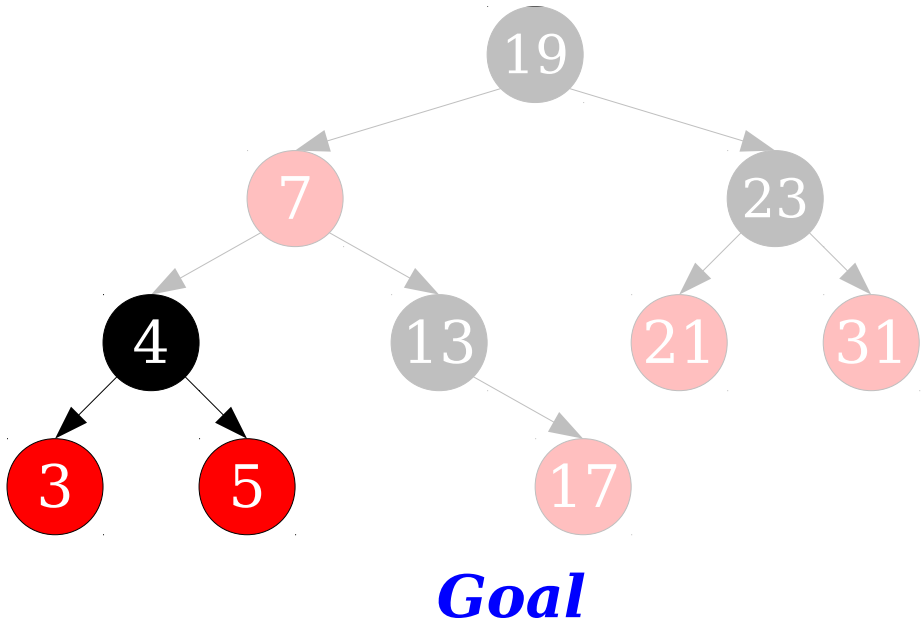
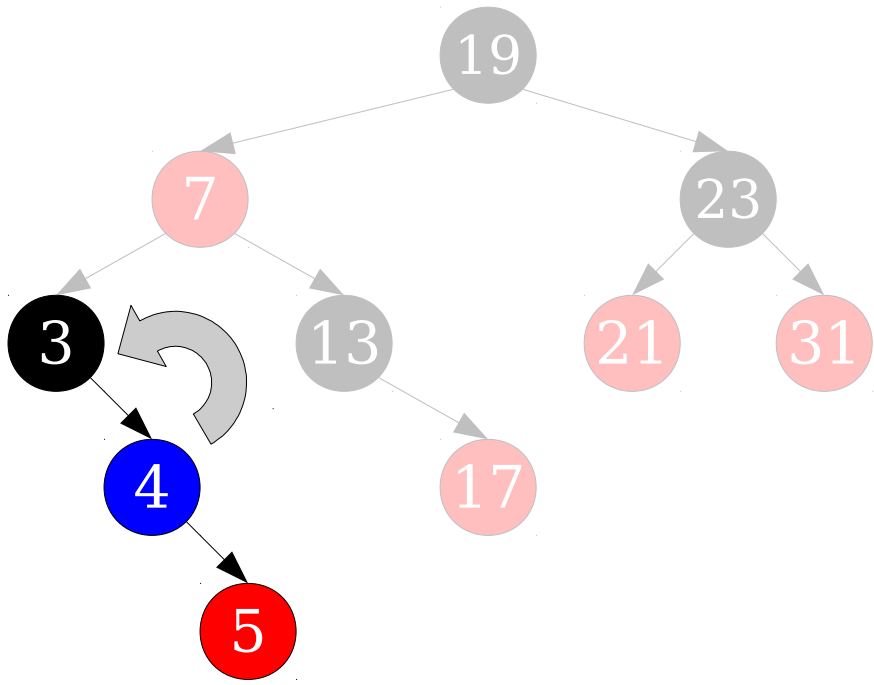
apply rotation

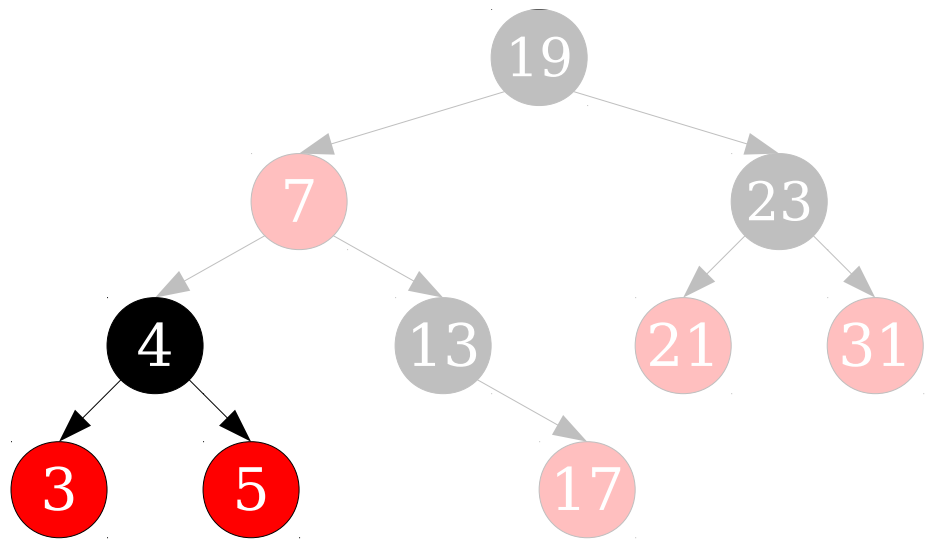
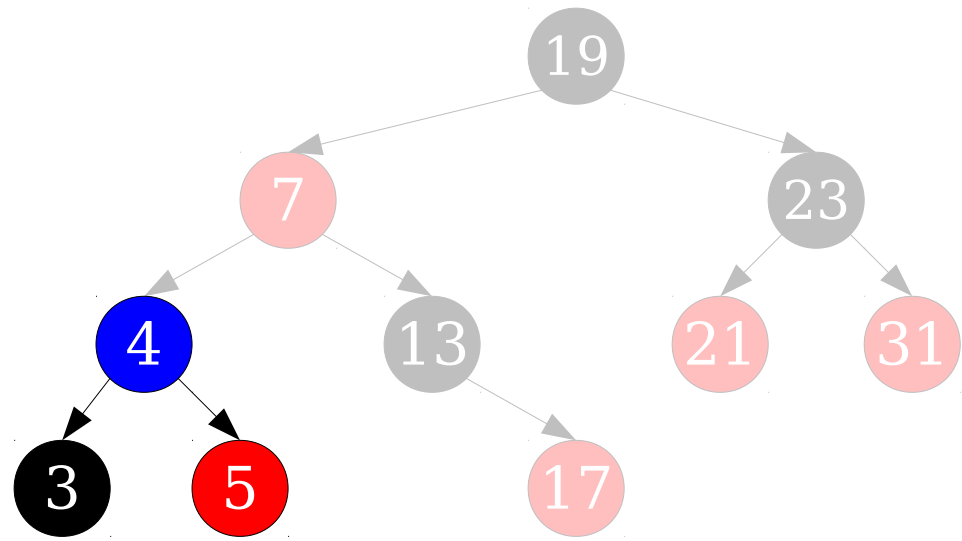


change colors



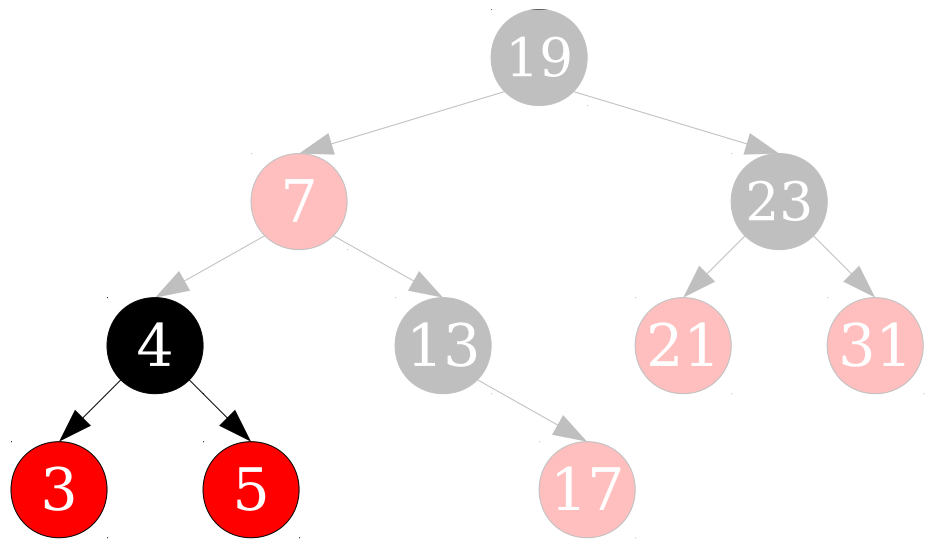
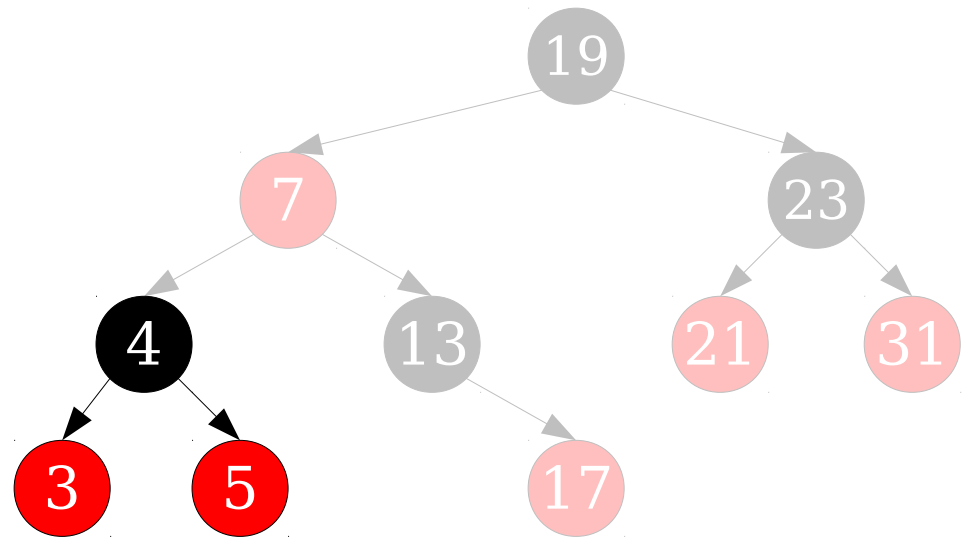




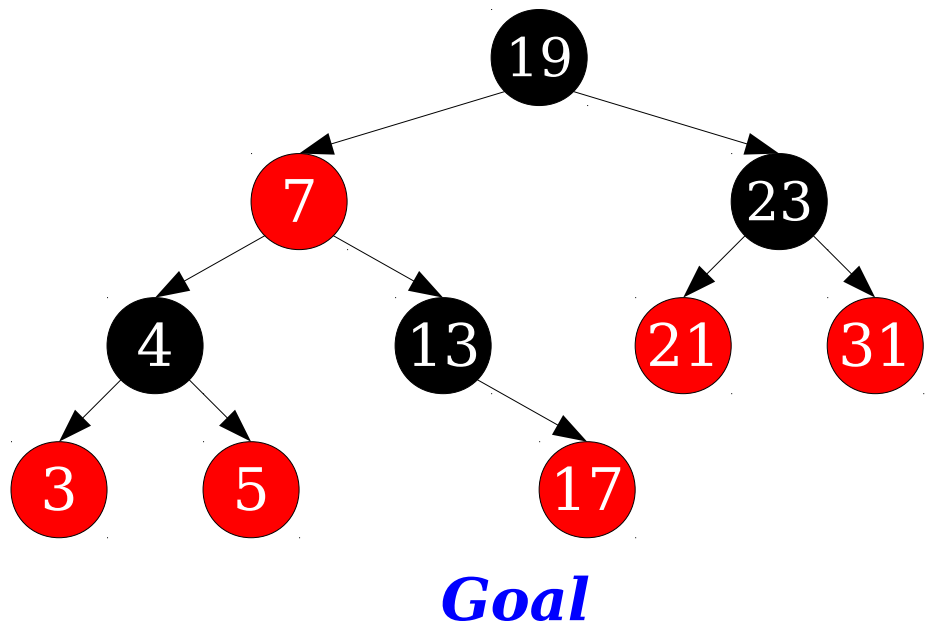
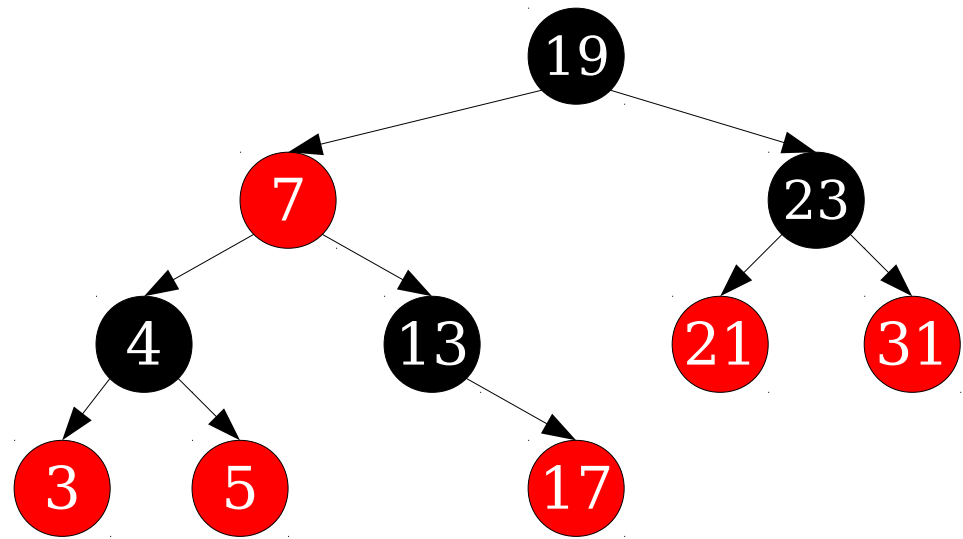


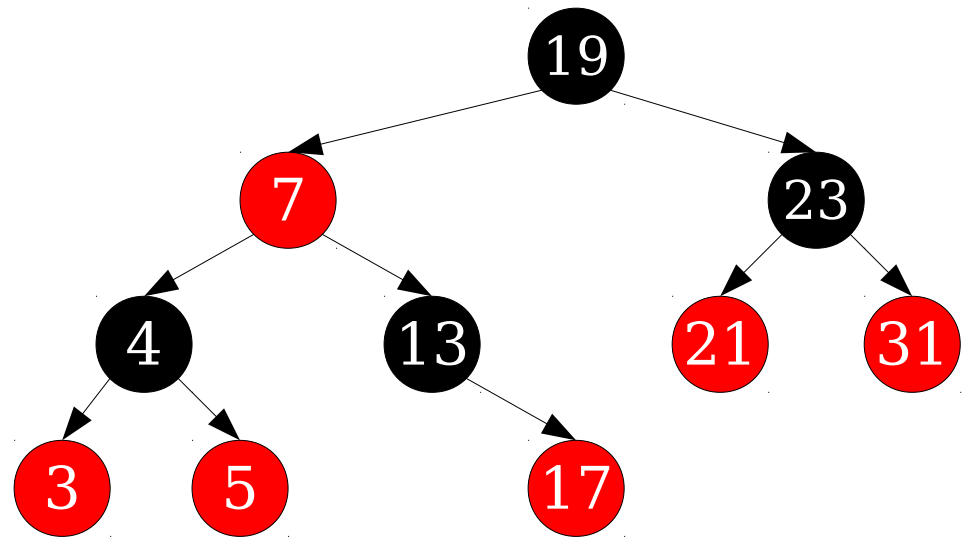
***Goal***

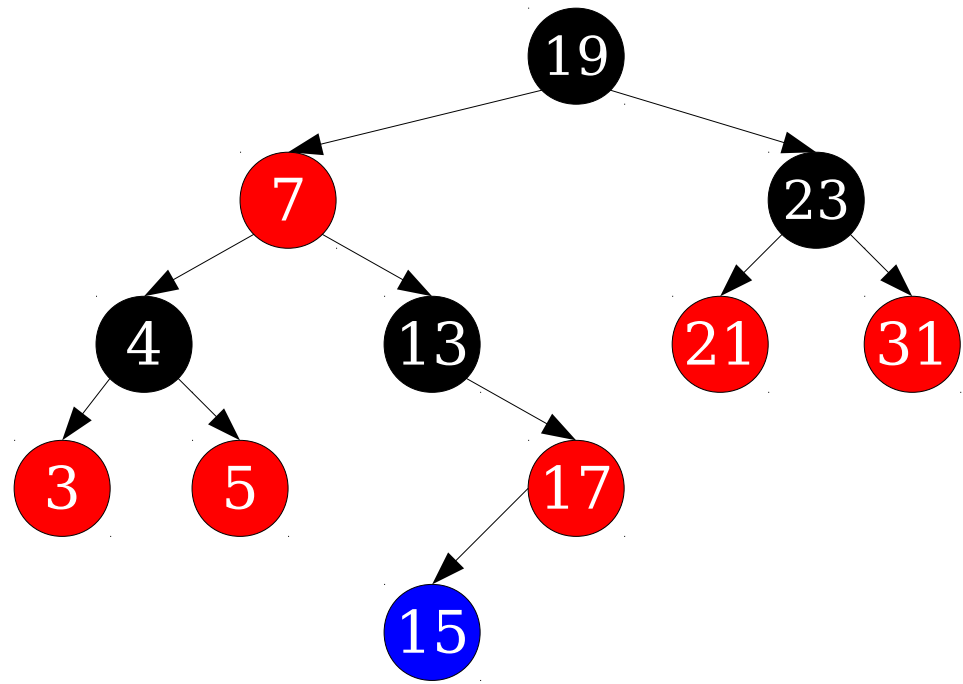


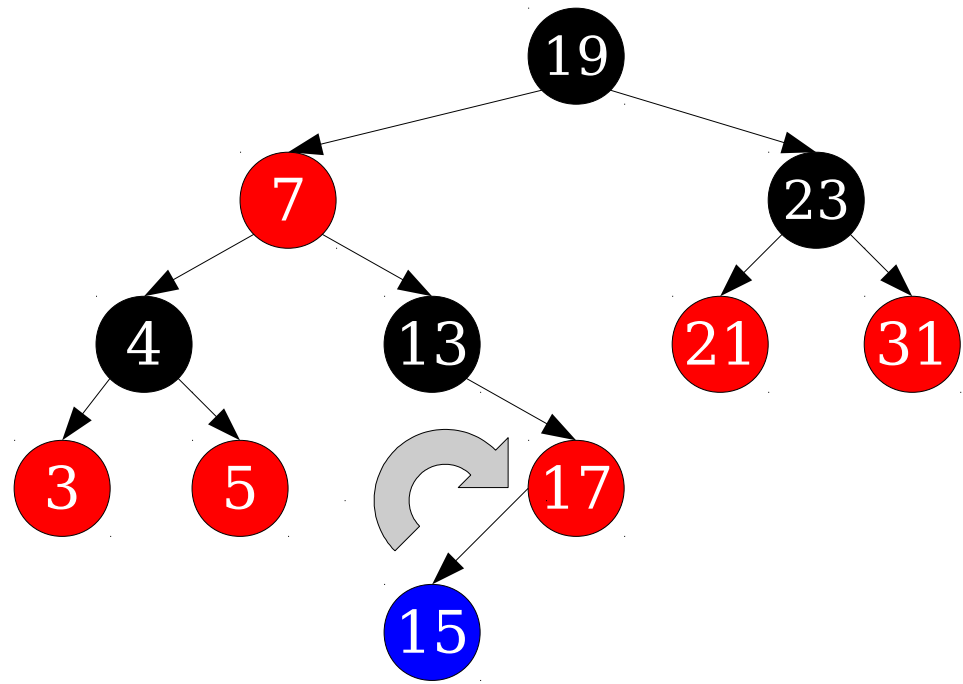


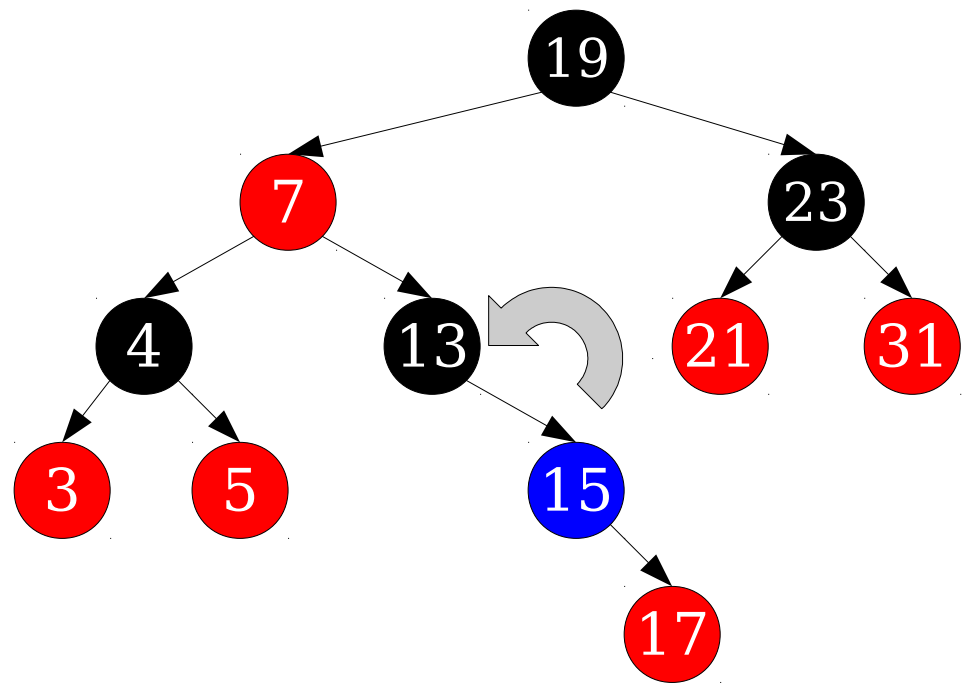
***Goal***

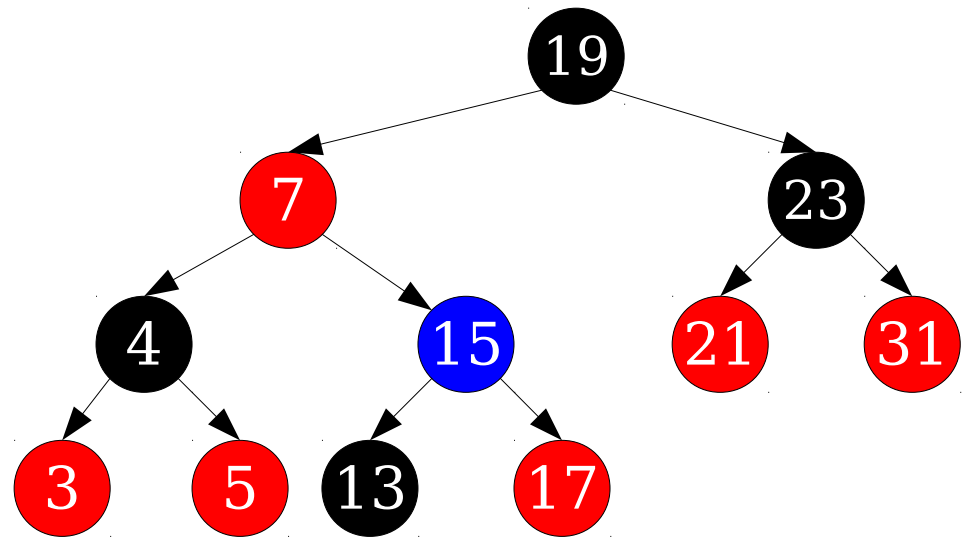


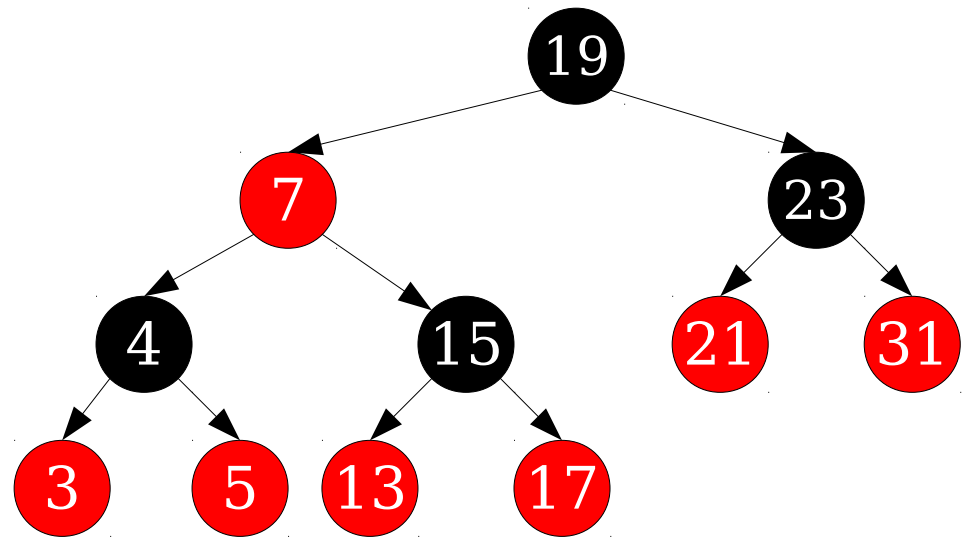




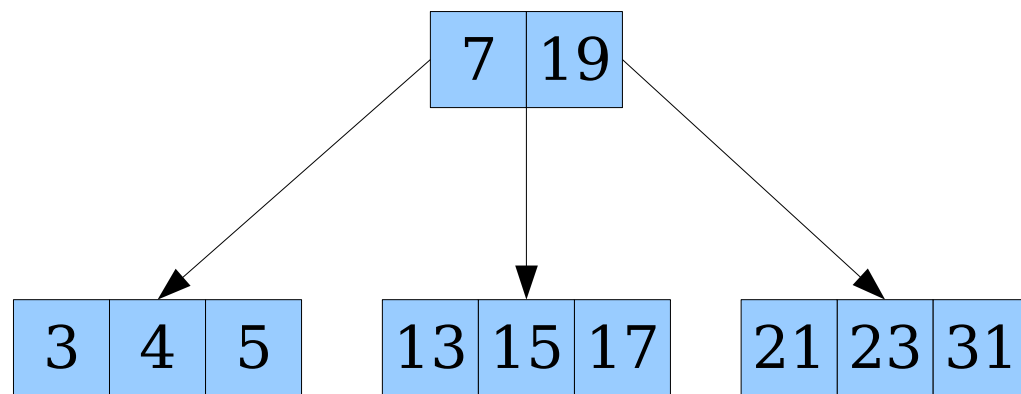
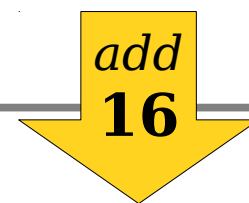
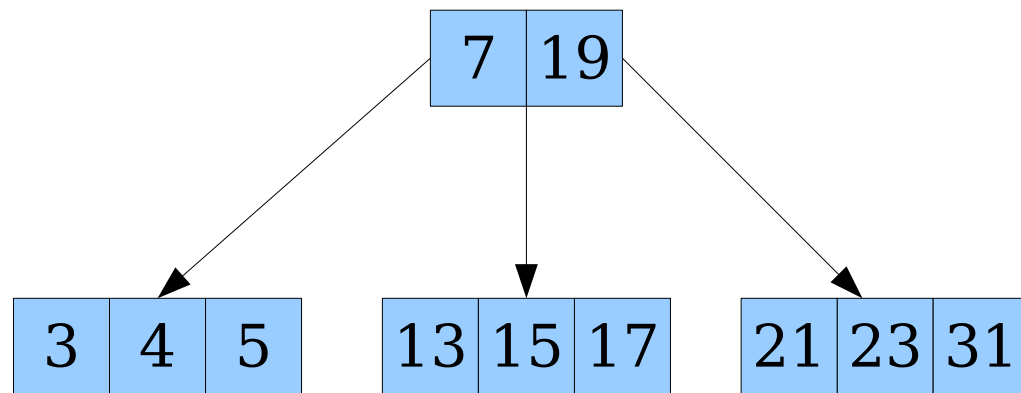
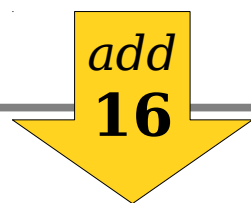
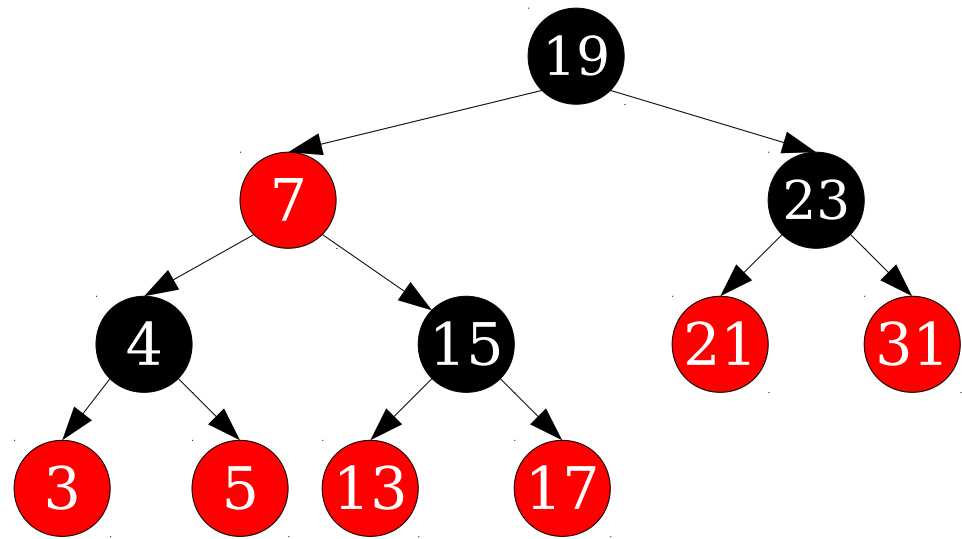


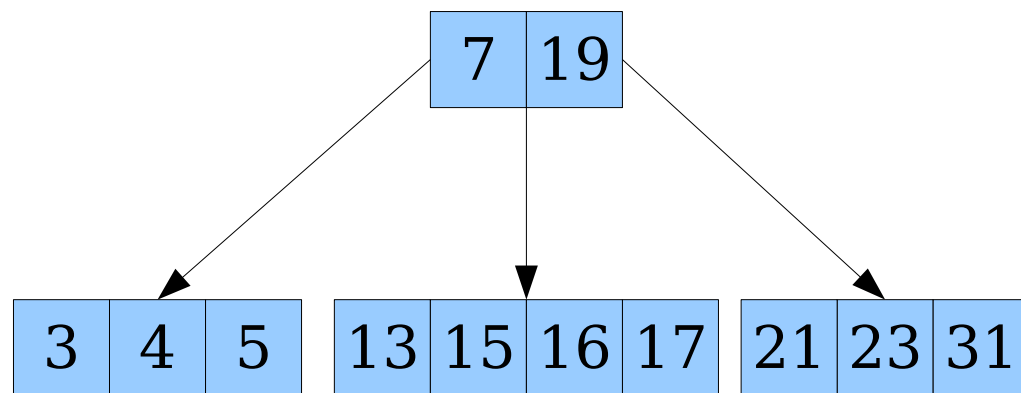
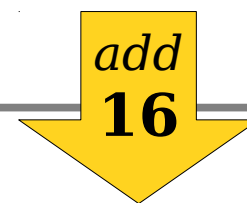
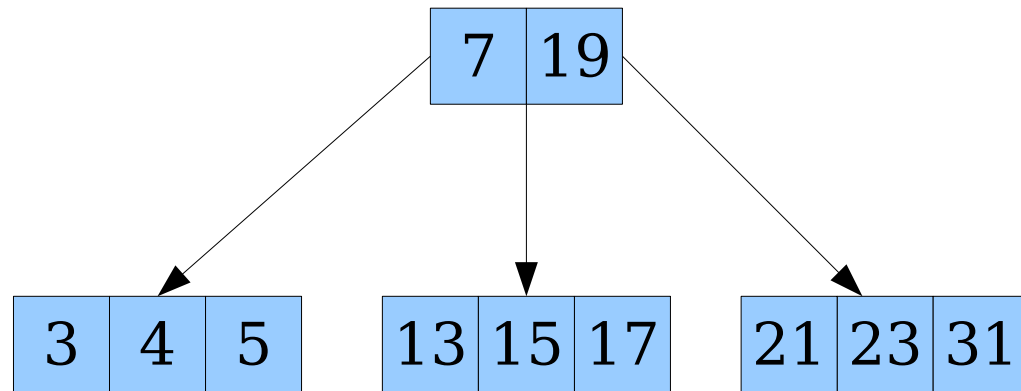
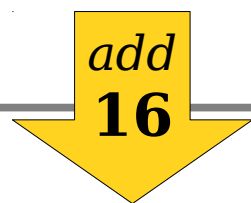
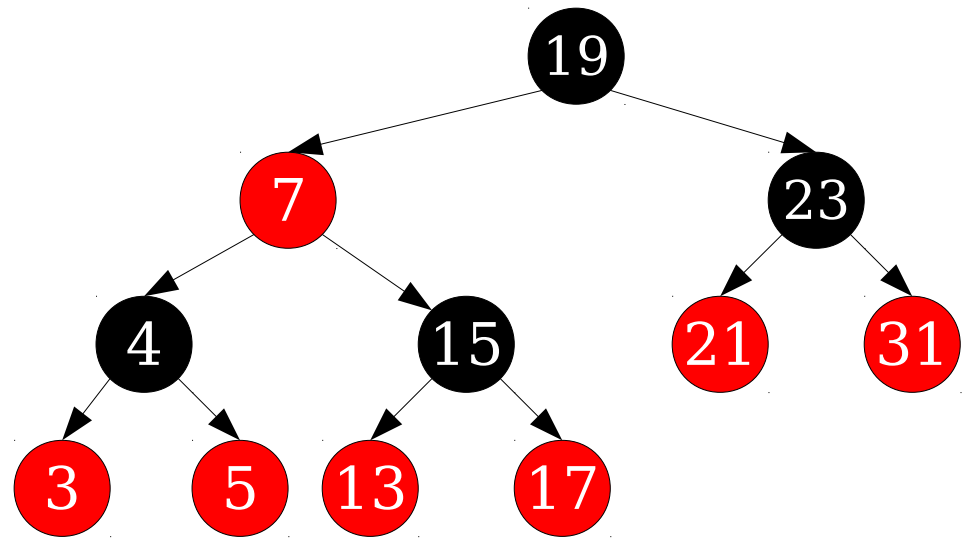


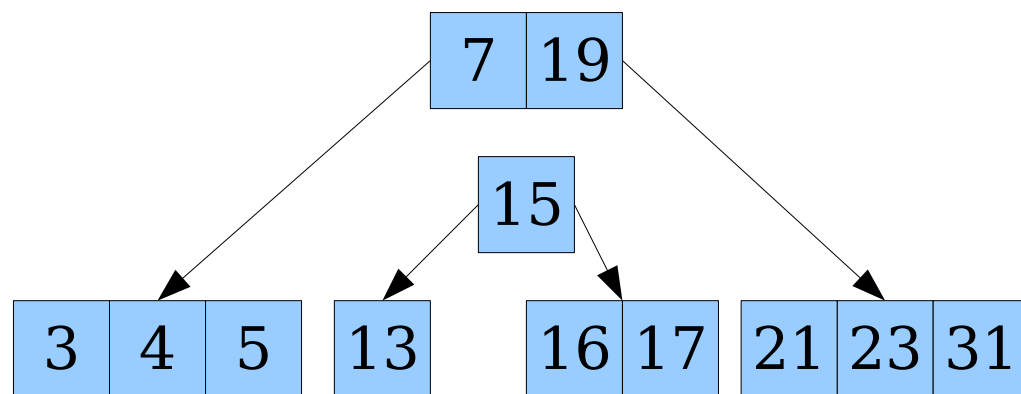
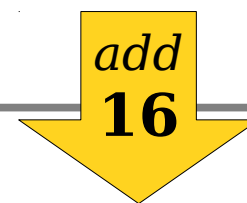
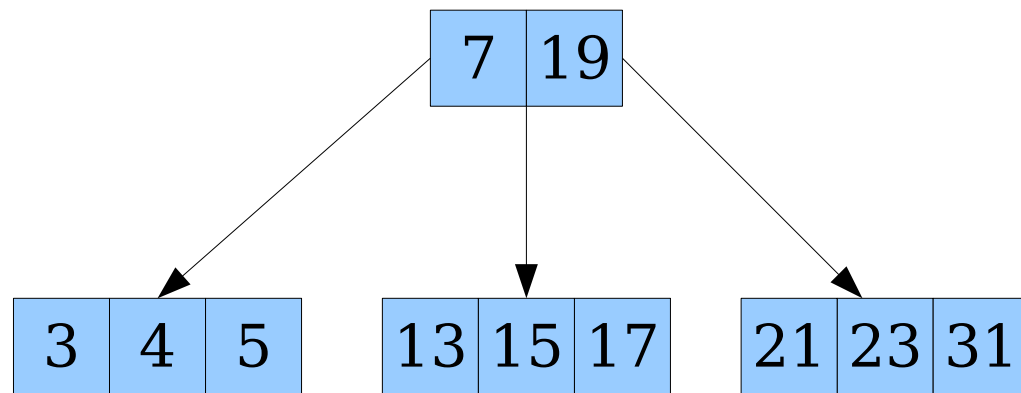
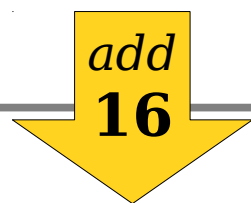
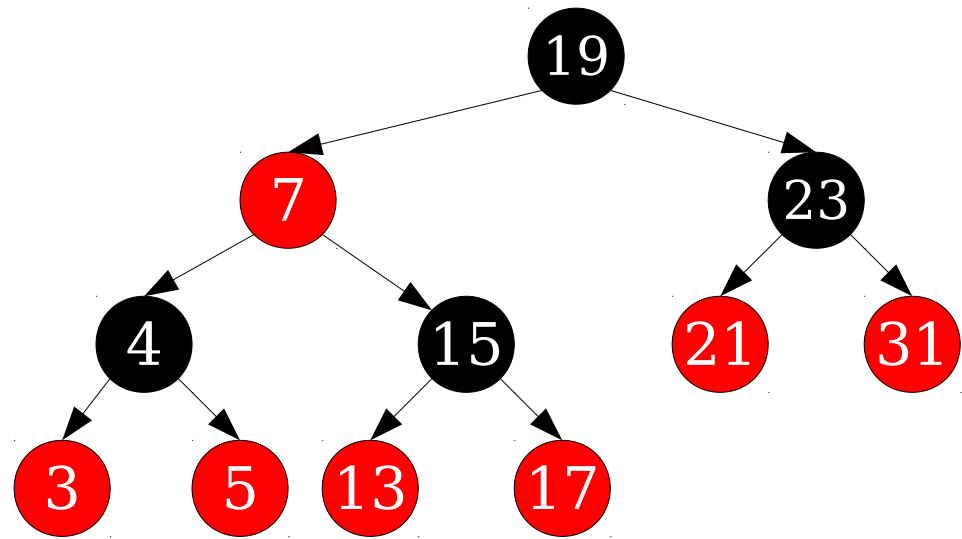


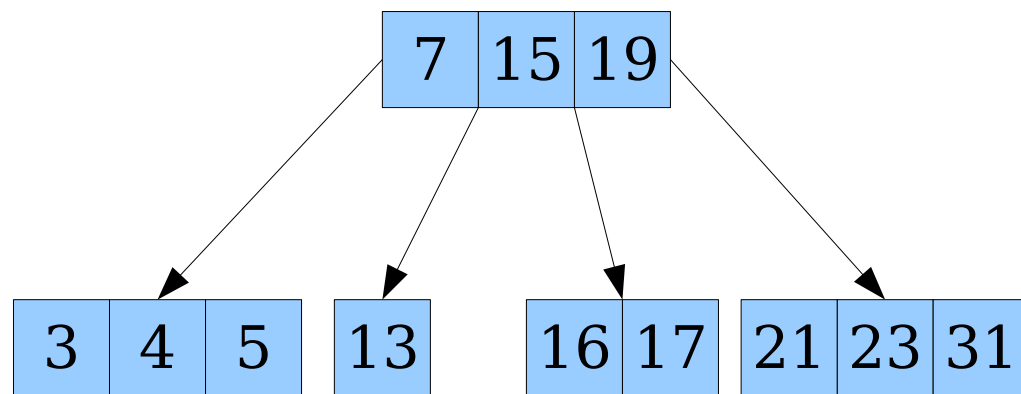
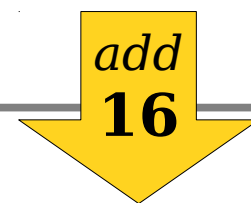
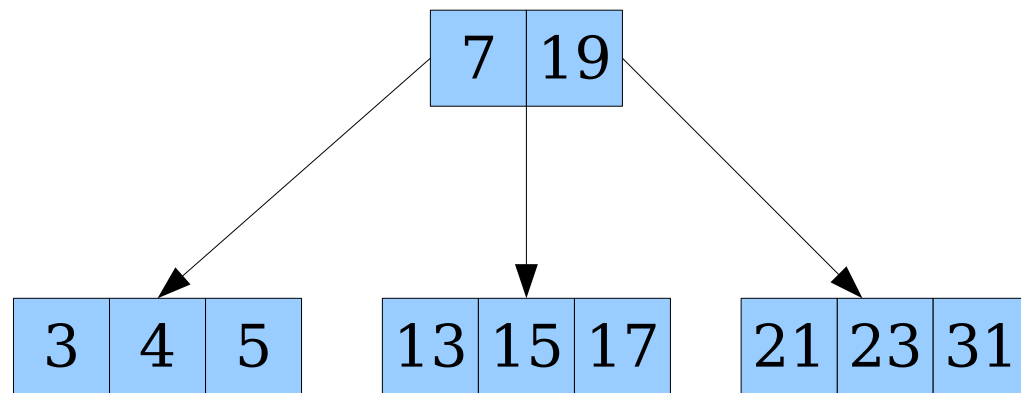
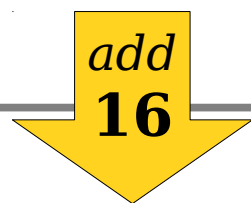
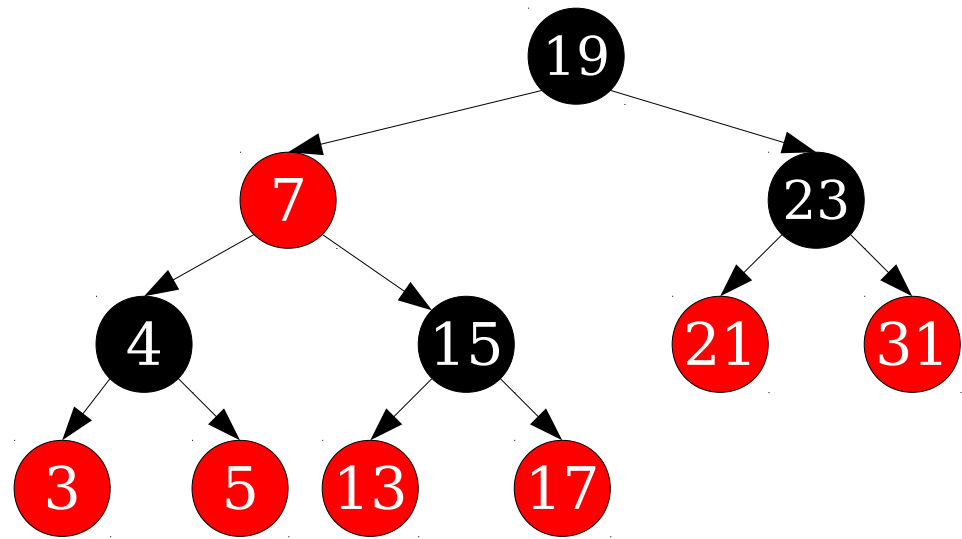


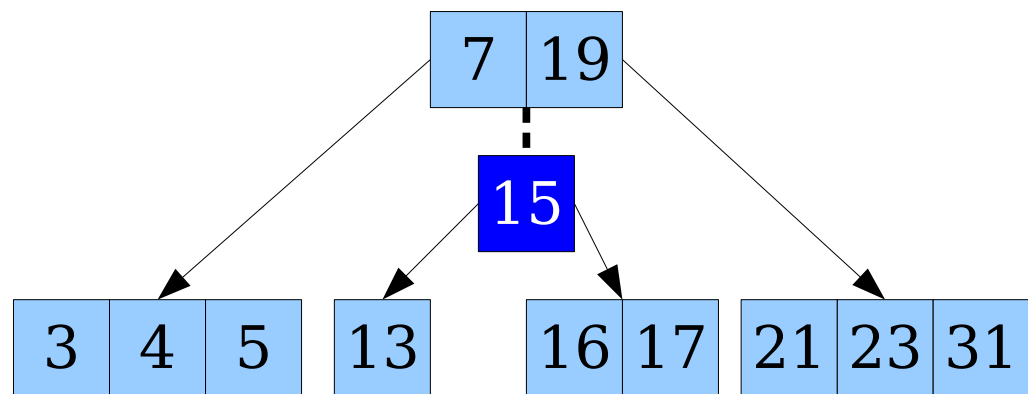
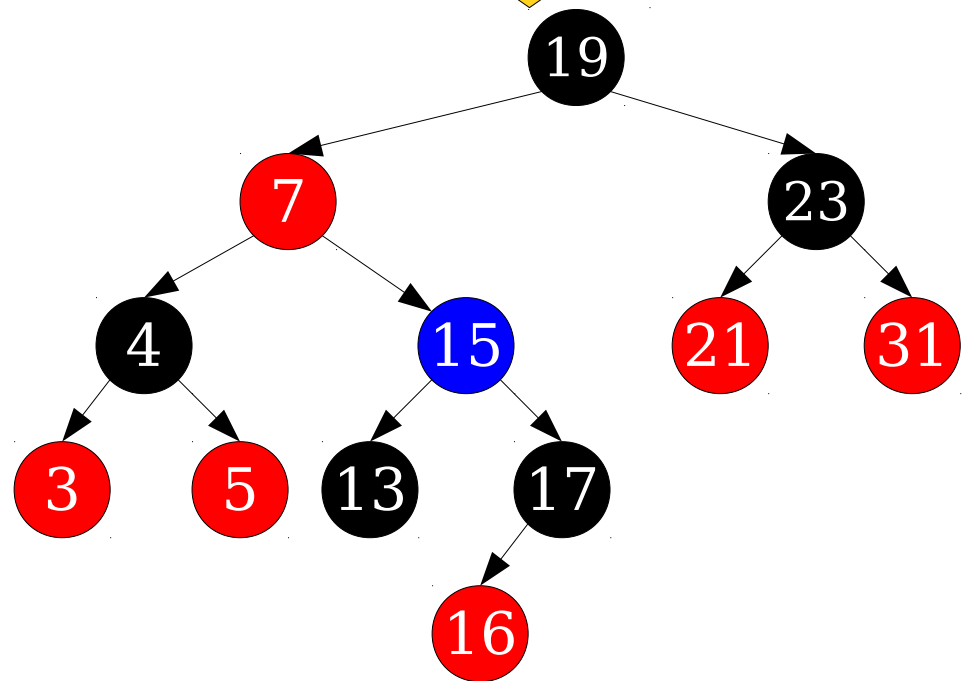
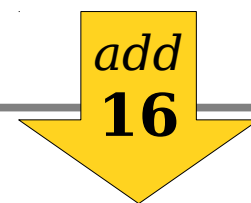
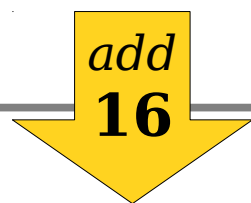
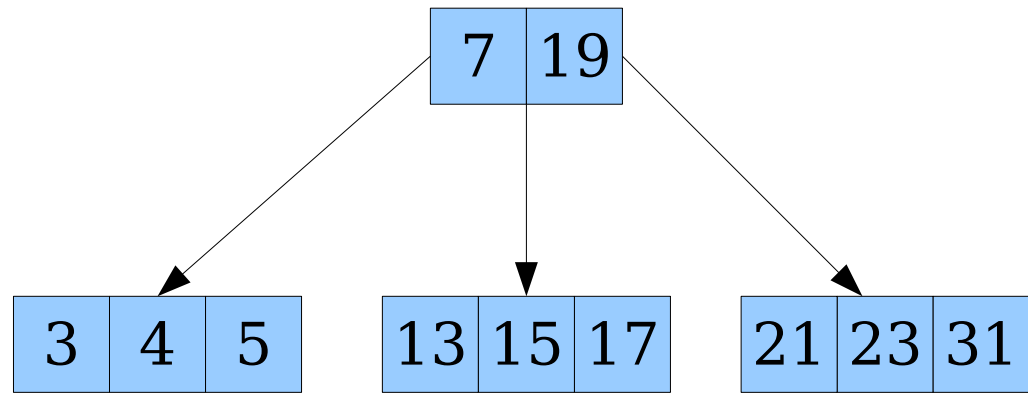
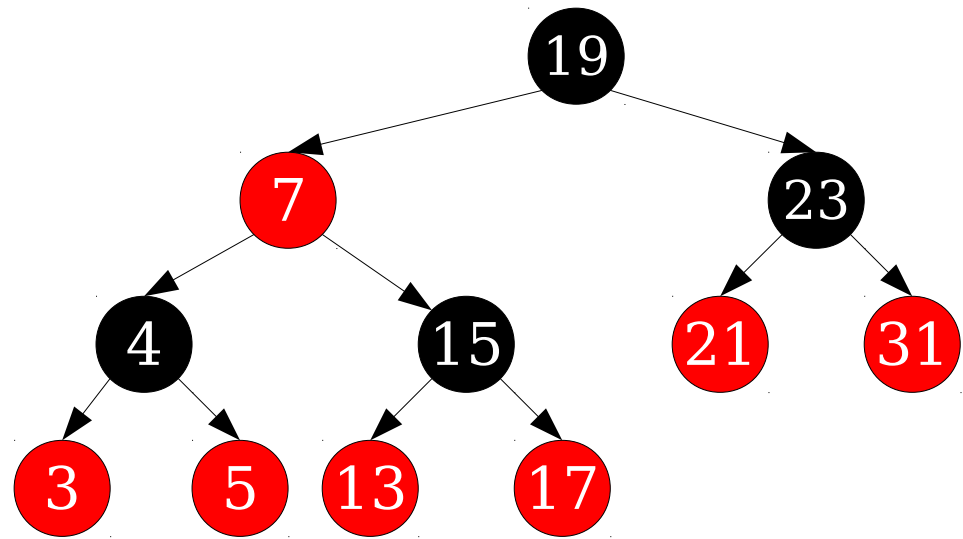


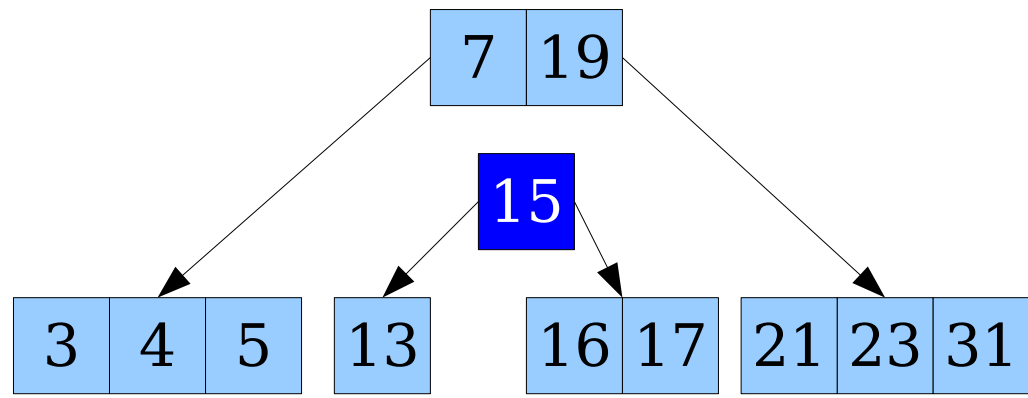
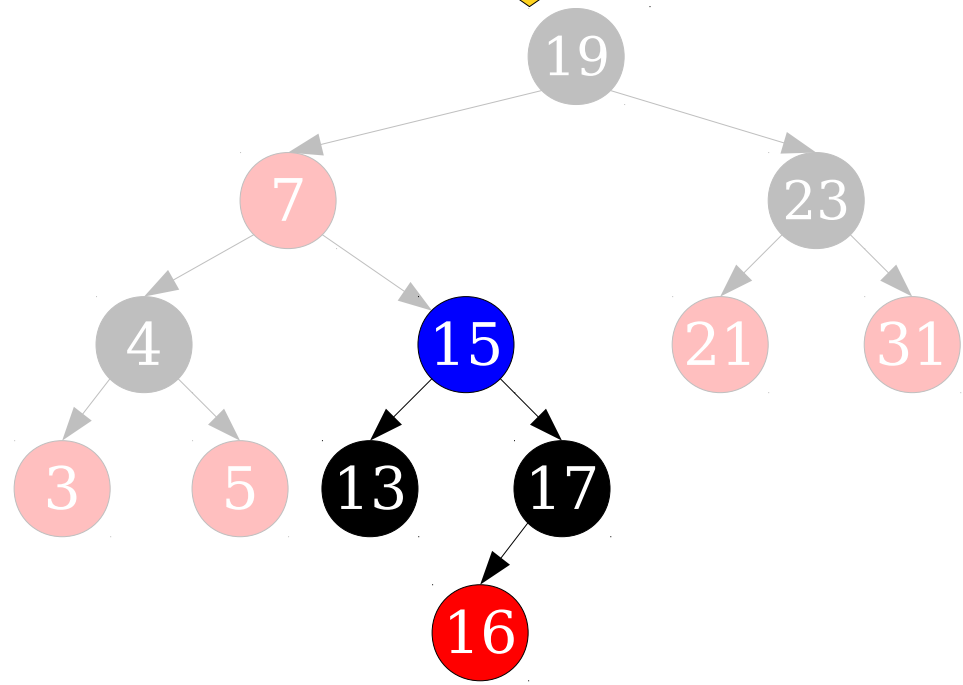
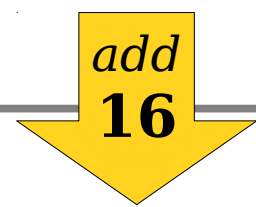
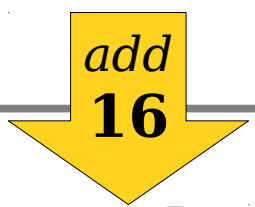
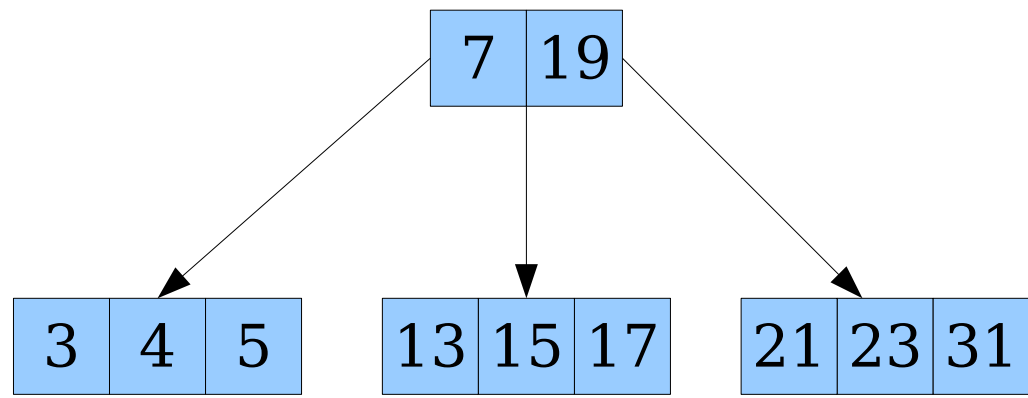
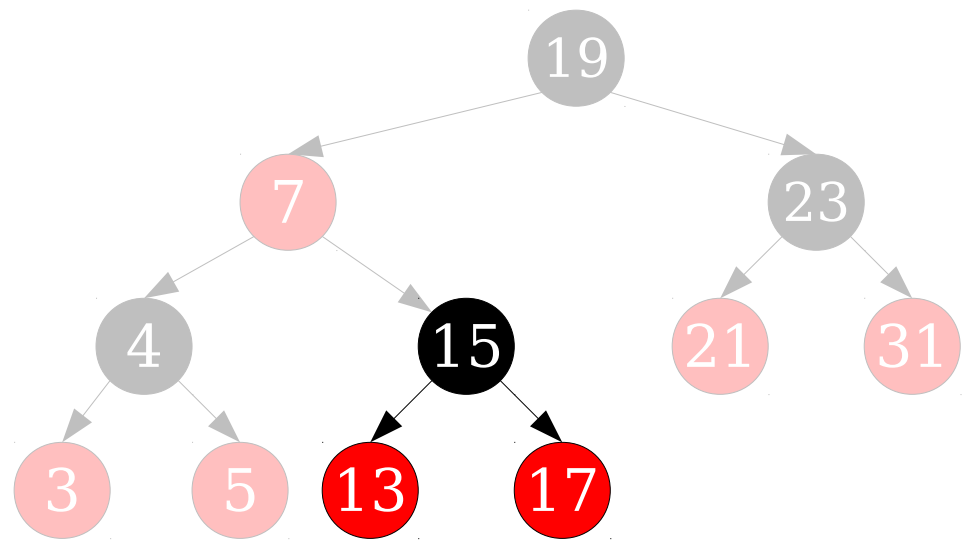


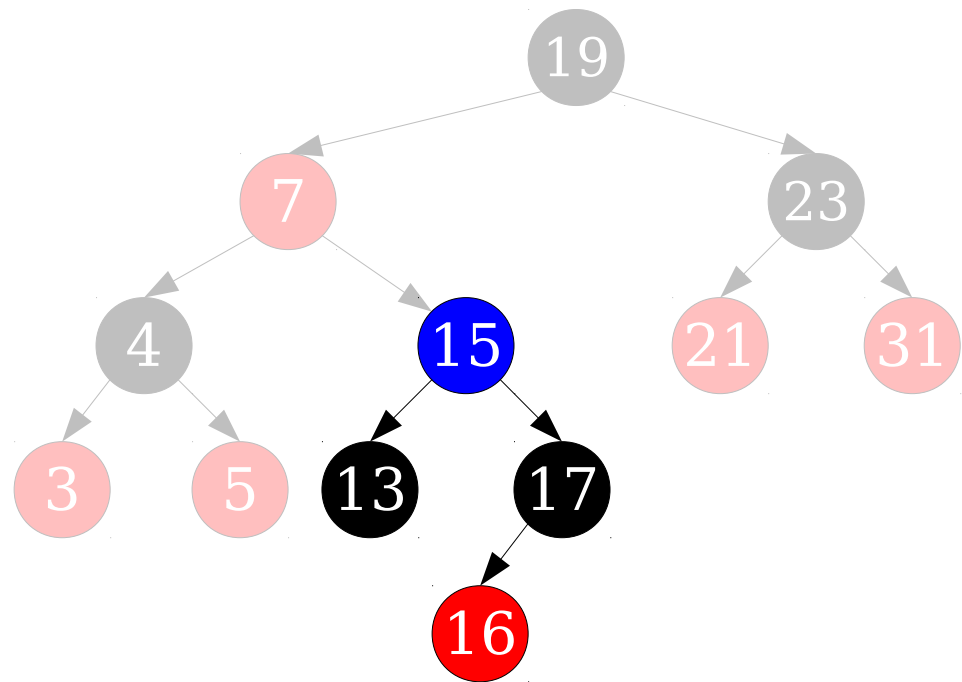
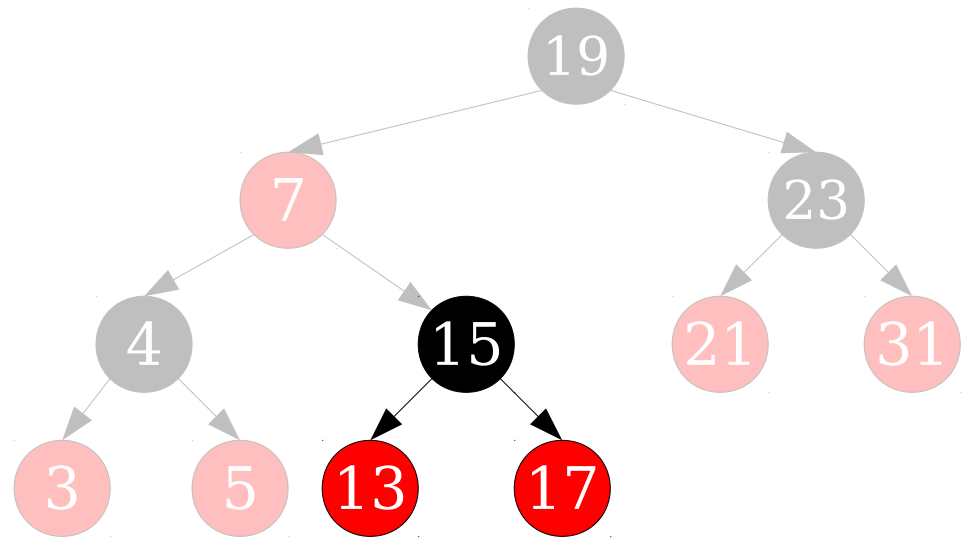


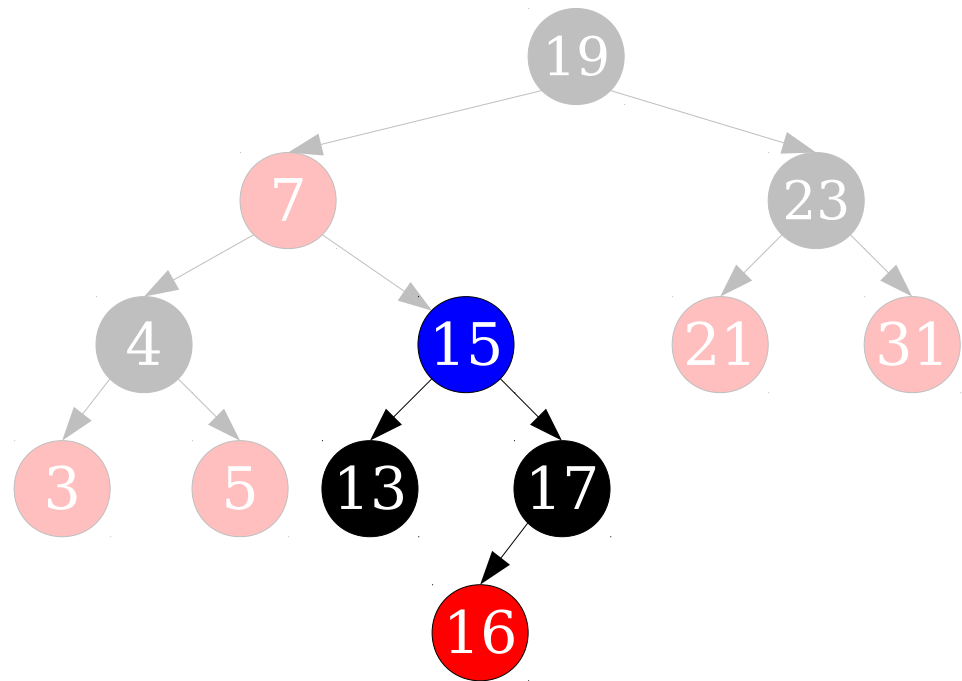
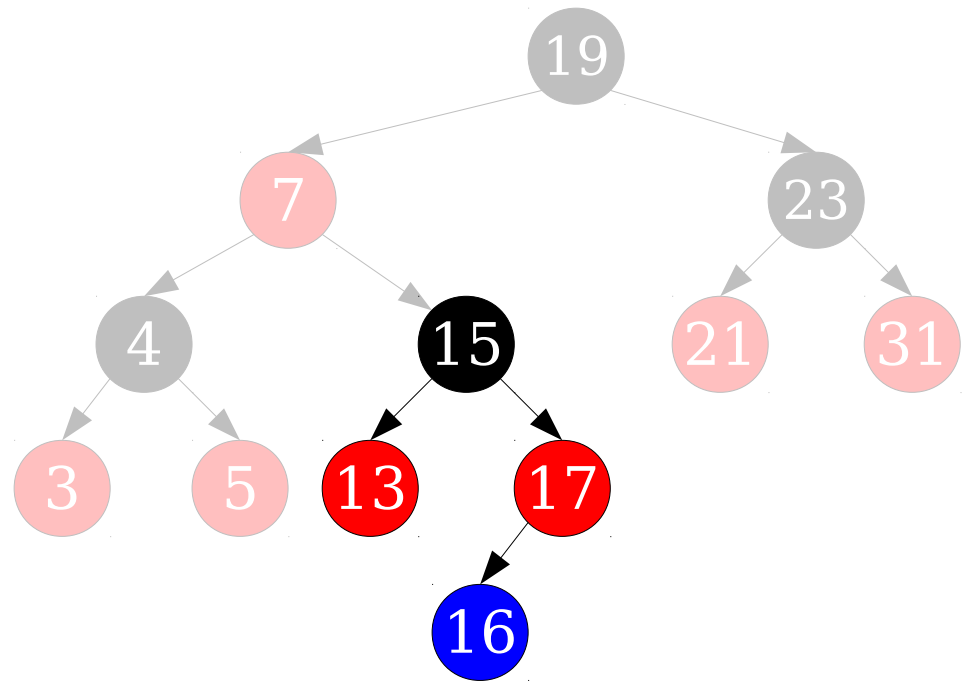




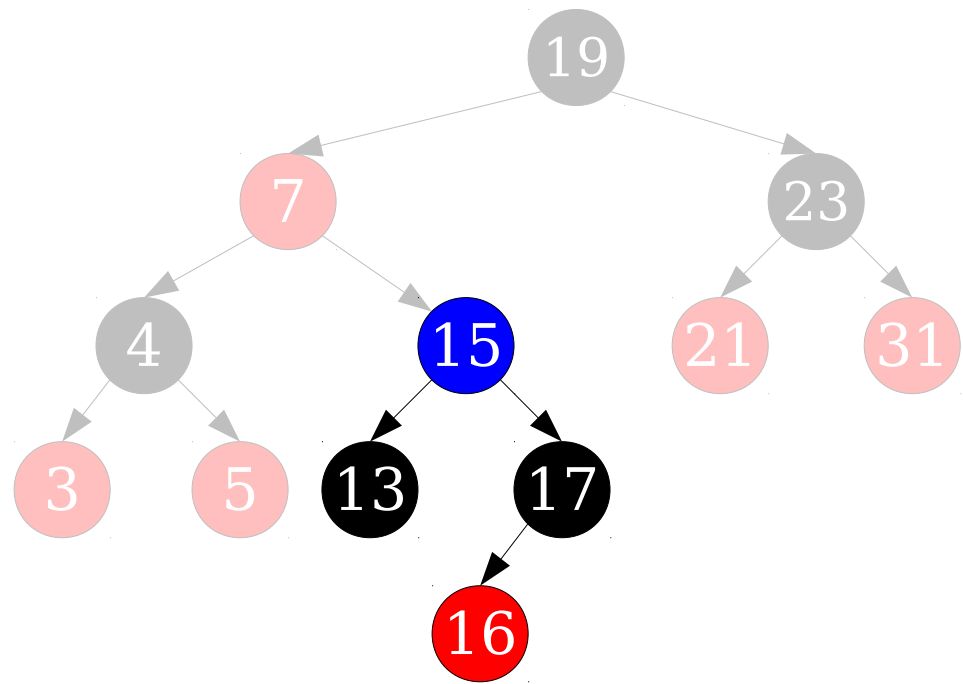
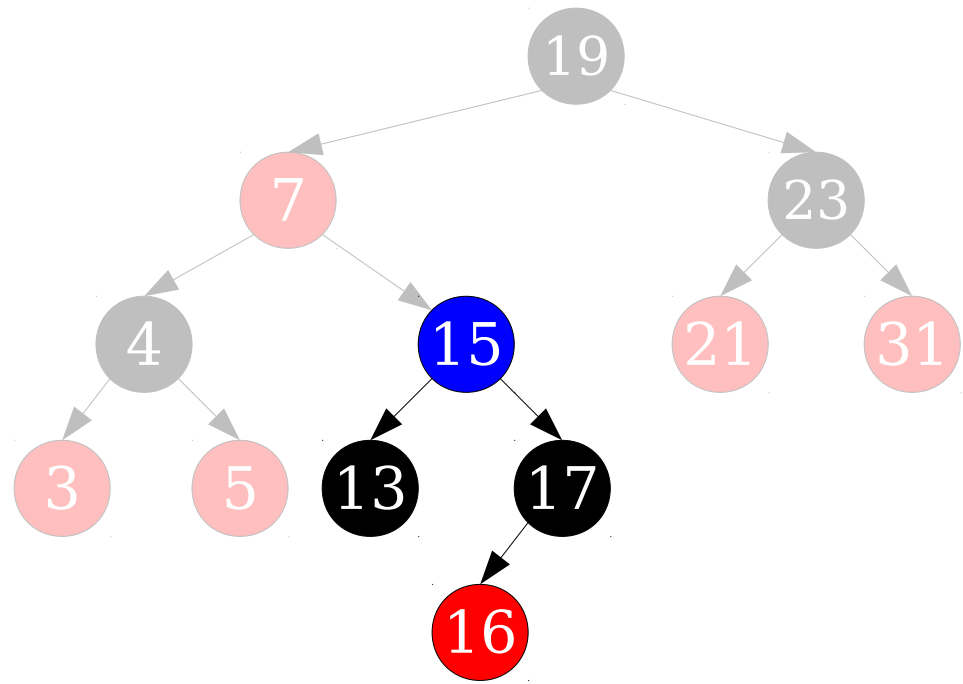


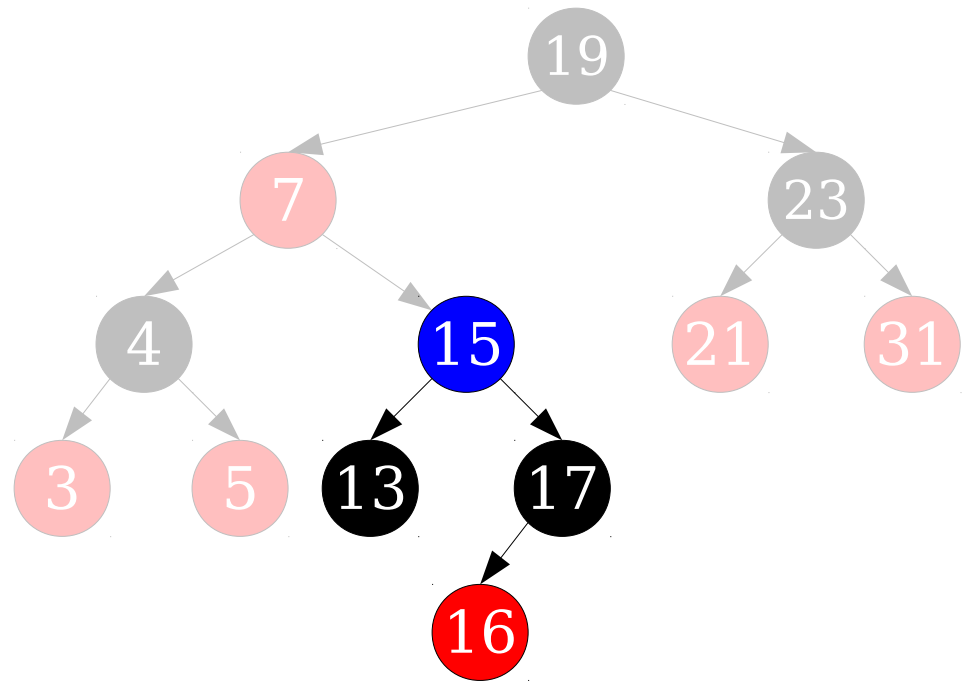


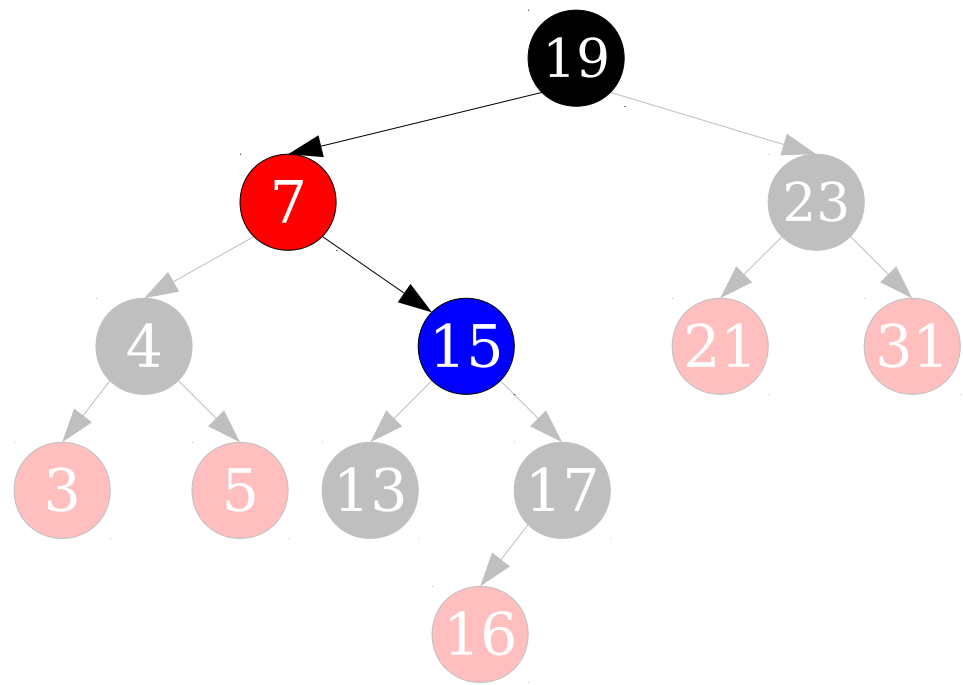


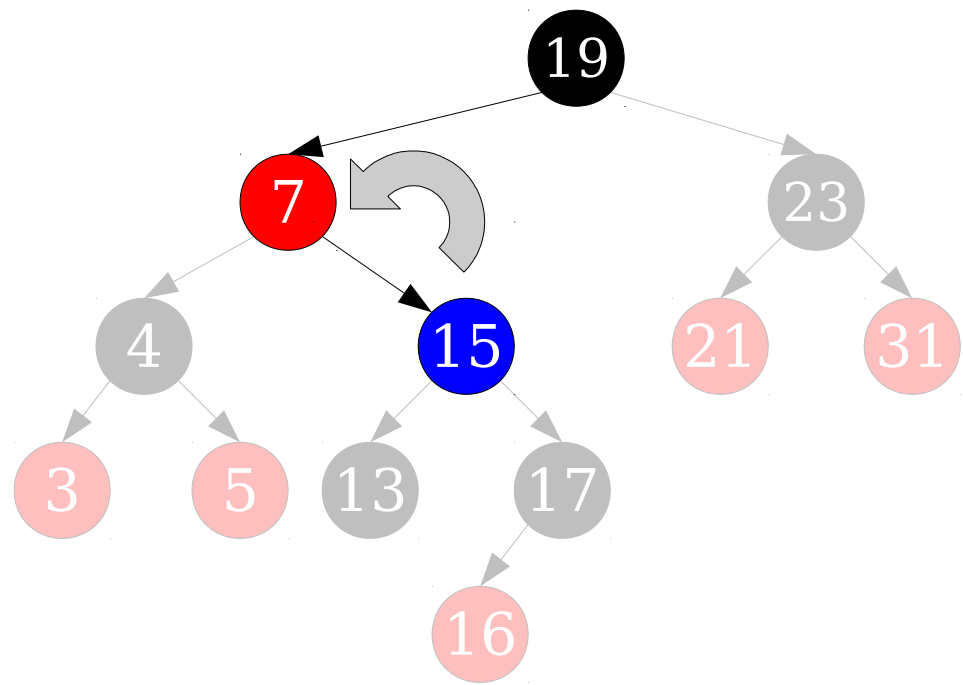


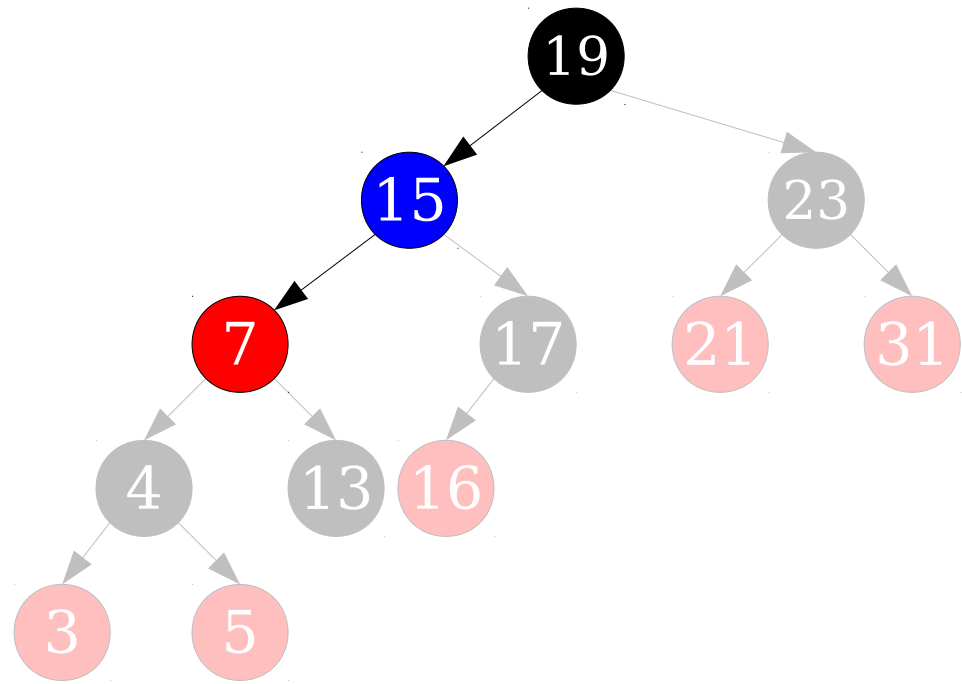


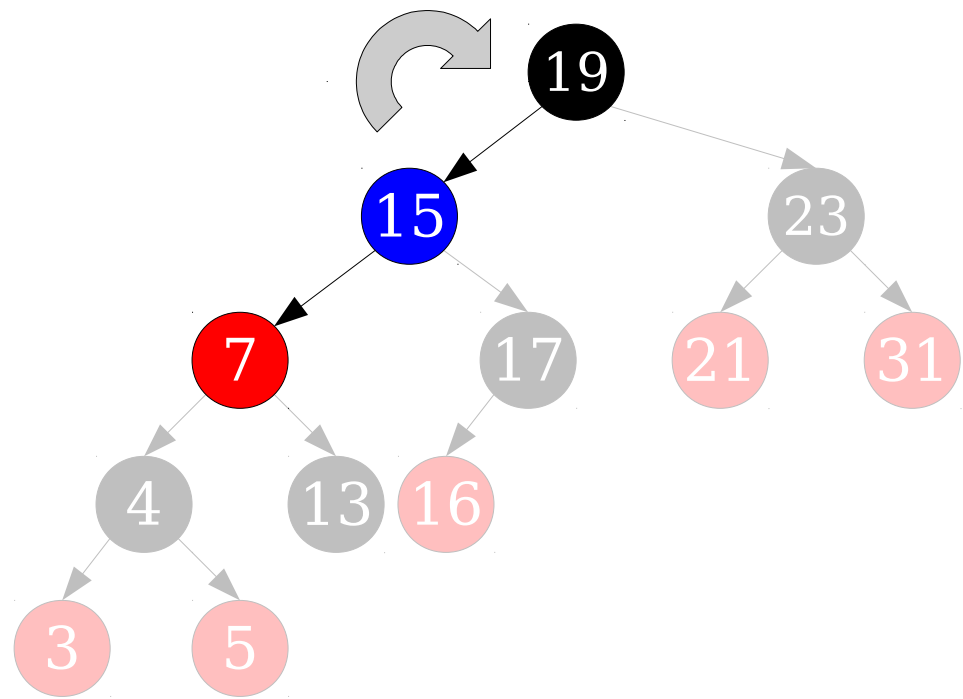


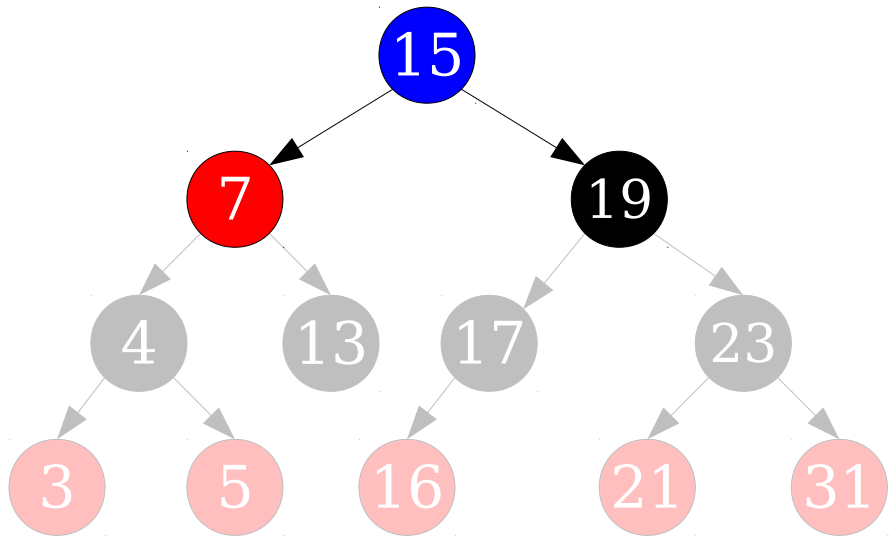


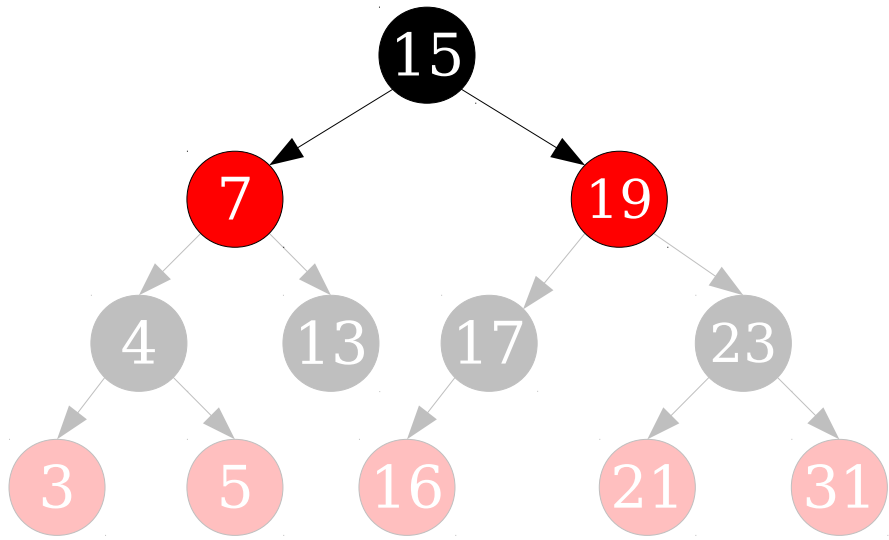




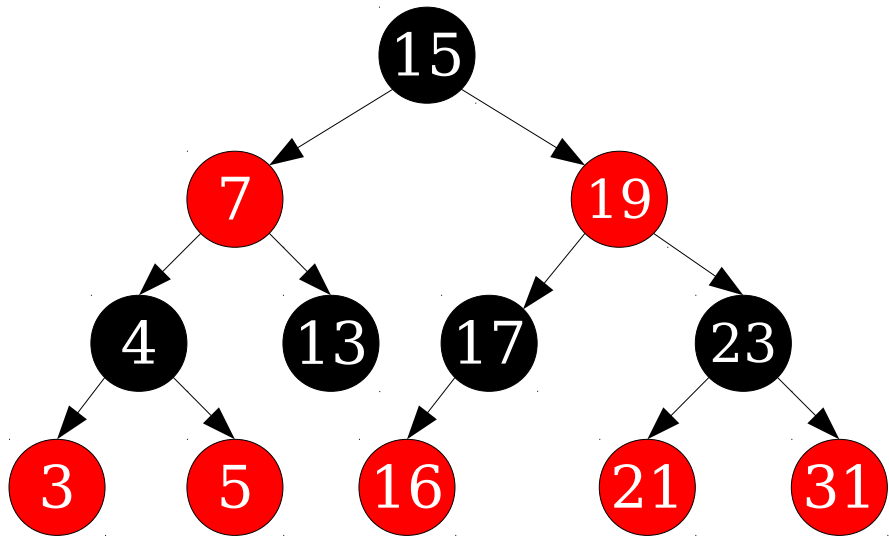












# Building Up Rules

- The complex rules on red/black trees make perfect sense if you connect it back to 2-3-4 trees.
- There are lots of cases to consider because there are many different ways you can insert into a red/black tree.
- ***Main point:*** Simulating the insertion of a key into a node takes time  $O(1)$  in all cases. Therefore, since 2-3-4 trees support  $O(\log n)$  insertions, red/black trees support  $O(\log n)$  insertions.
- The same is true of deletions.

# My Advice

- **Do** know how to do B-tree insertions and searches.
  - You can derive these easily if you remember to split nodes.
- **Do** remember the rules for red/black trees and B-trees.
  - These are useful for proving bounds and deriving results.
- **Do** remember the isometry between red/black trees and 2-3-4 trees.
  - Gives immediate intuition for all the red/black tree operations.
- **Don't** memorize the red/black rotations and color flips.
  - This is rarely useful. If you're coding up a red/black tree, just flip open CLRS and translate the pseudocode. ☺

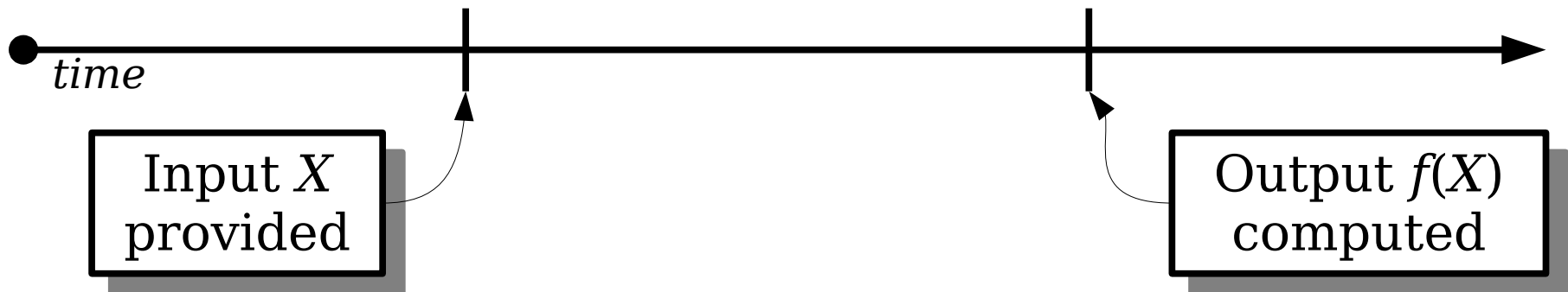
# Dynamic Problems

# Classical Algorithms

- The “classical” algorithms model goes something like this:

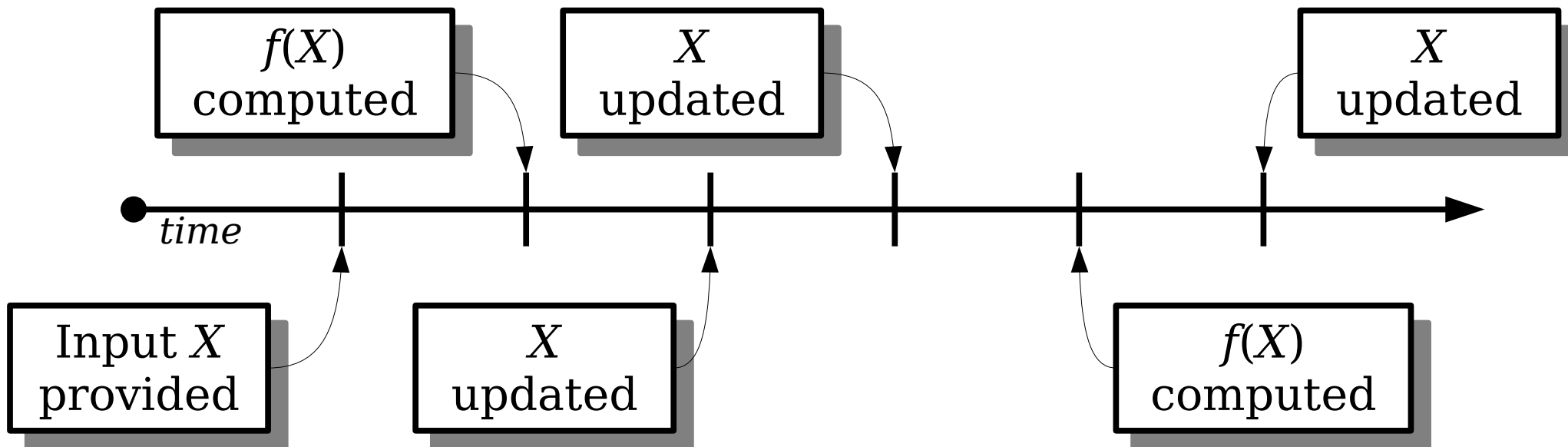
*Given some input  $X$ , compute some interesting function  $f(X)$ .*

- The input  $X$  is provided up front, and only a single answer is produced.



# Dynamic Problems

- ***Dynamic versions*** of problems are framed like this:  
*Given an input  $X$  that can change in fixed ways, maintain  $X$  while being able to compute  $f(X)$  efficiently at any point in time.*
- These problems are typically harder to solve efficiently than the “classical” static versions.



# Dynamic Selection

- The **selection** problem is the following:  
*Given a list of distinct values and a number  $k$ , return the  $k$ th-smallest value.*
- In the static case, where the data set is fixed in advance and  $k$  is known, we can solve this in time  $O(n)$  using quickselect or the median-of-medians algorithm.
- **Goal:** Solve this problem efficiently when the data set is changing – that is, the underlying set of elements can have insertions and deletions intermixed with queries.

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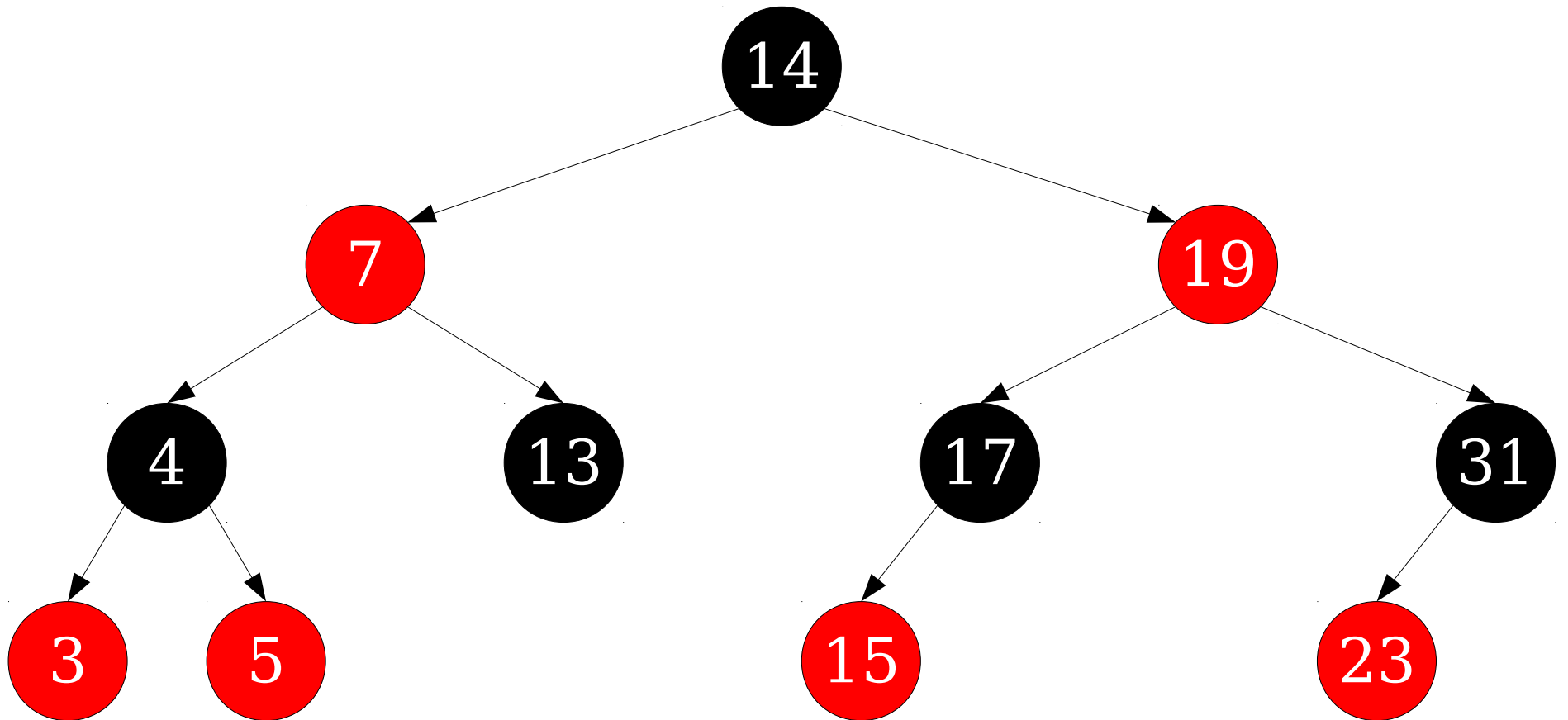
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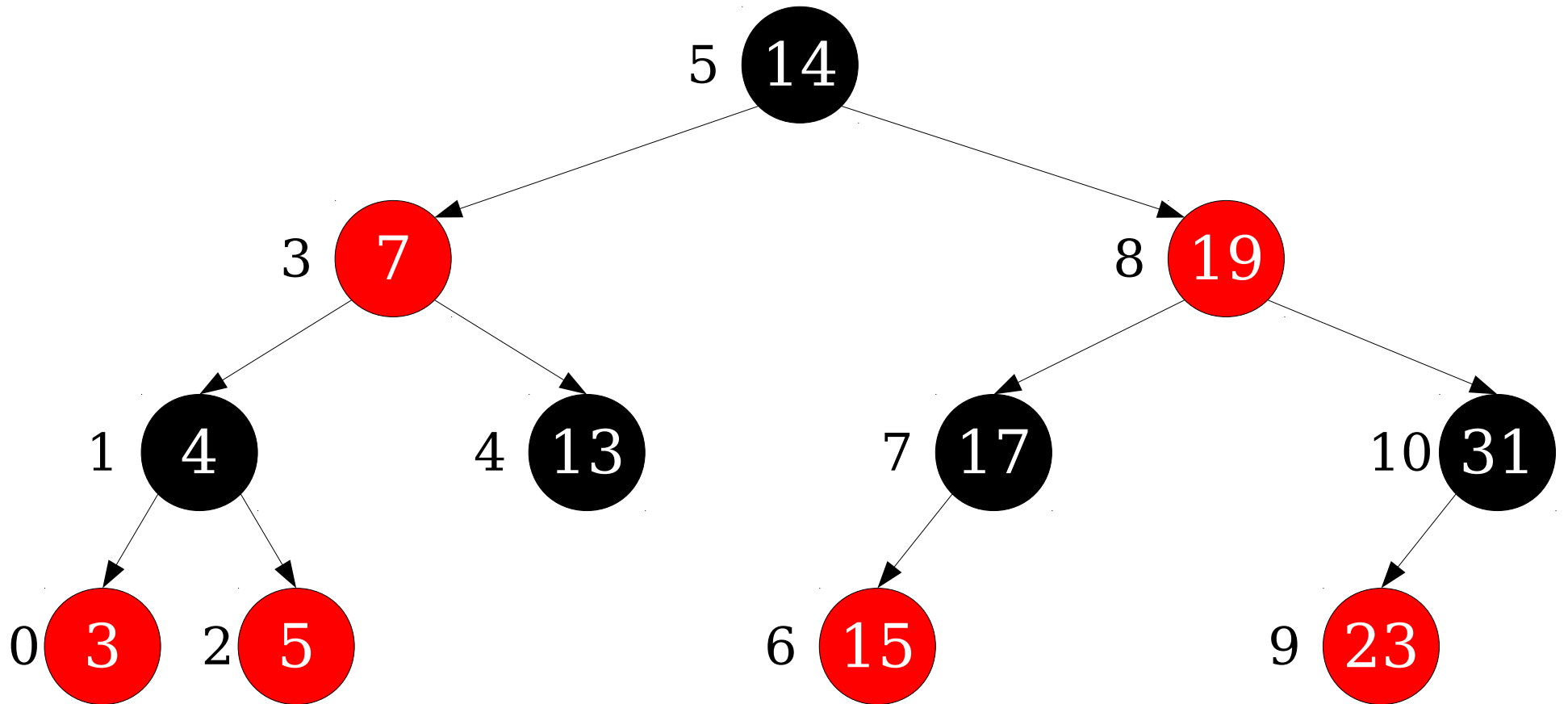
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# Dynamic Selection

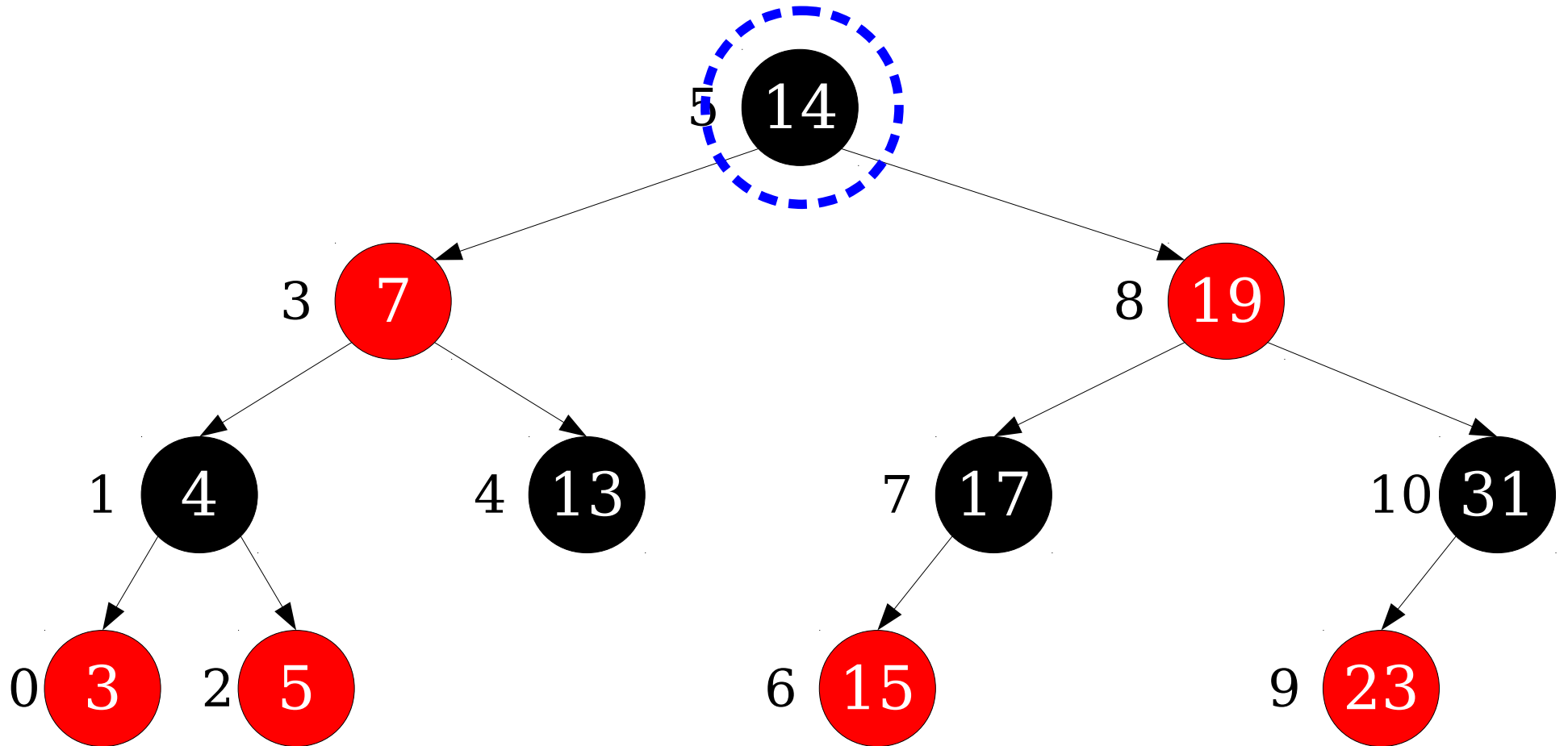




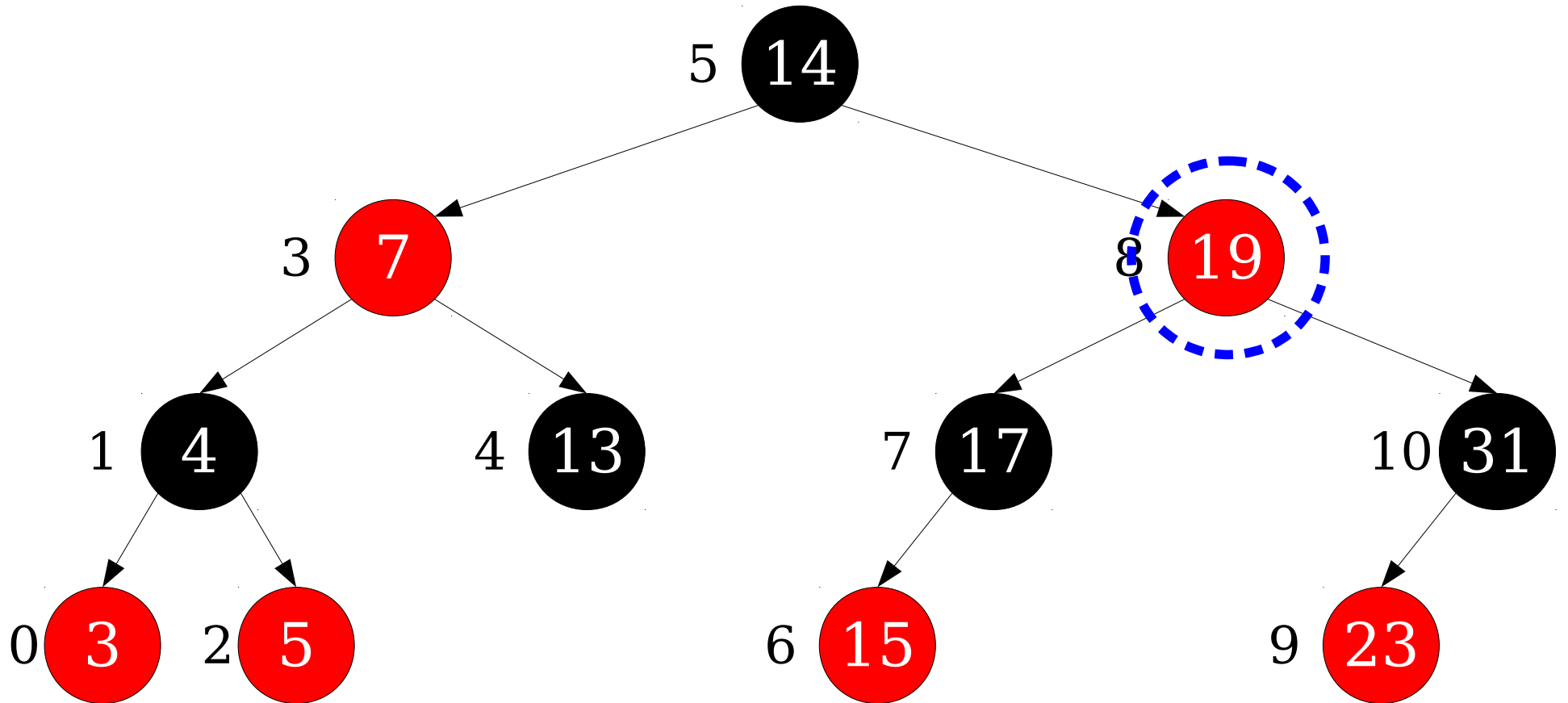
# Dynamic Selection



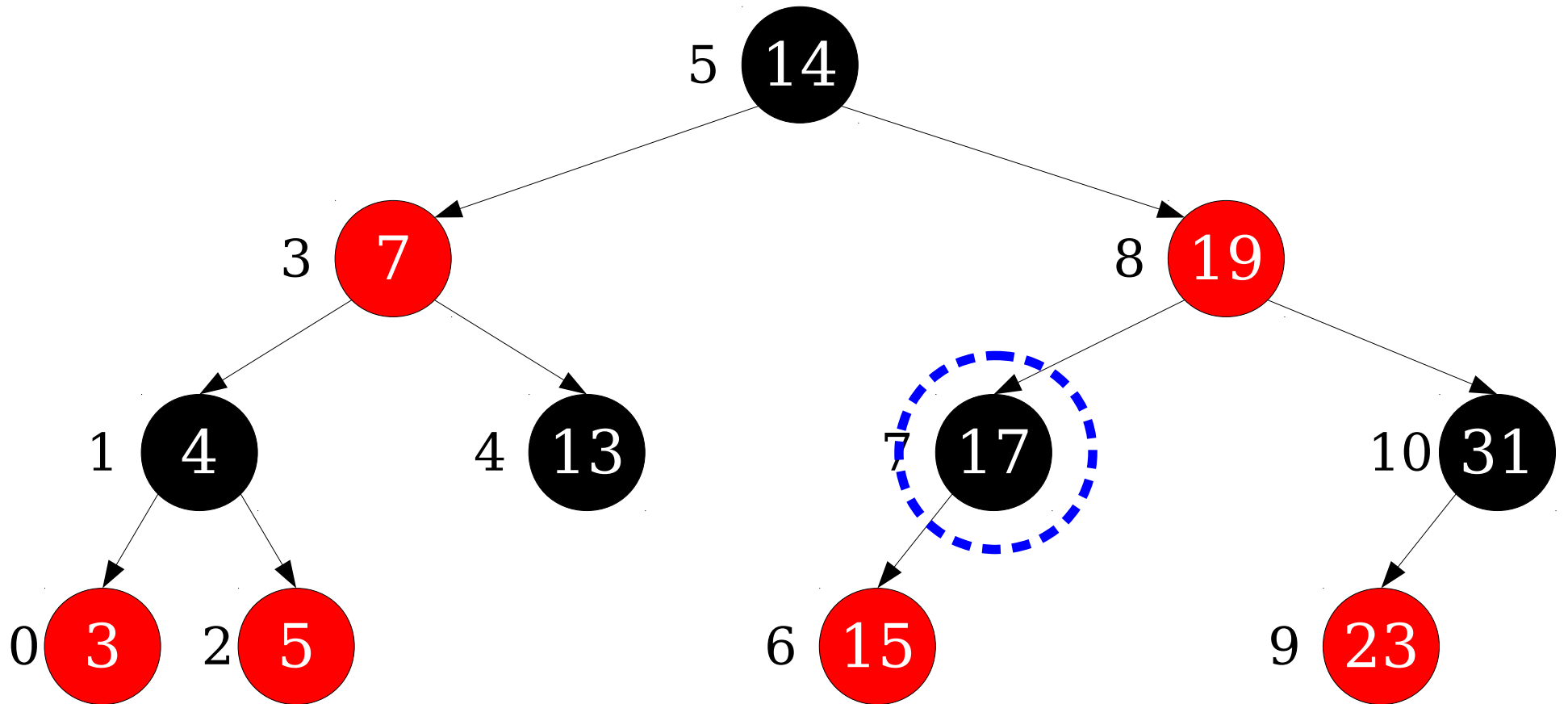
# Dynamic Selection



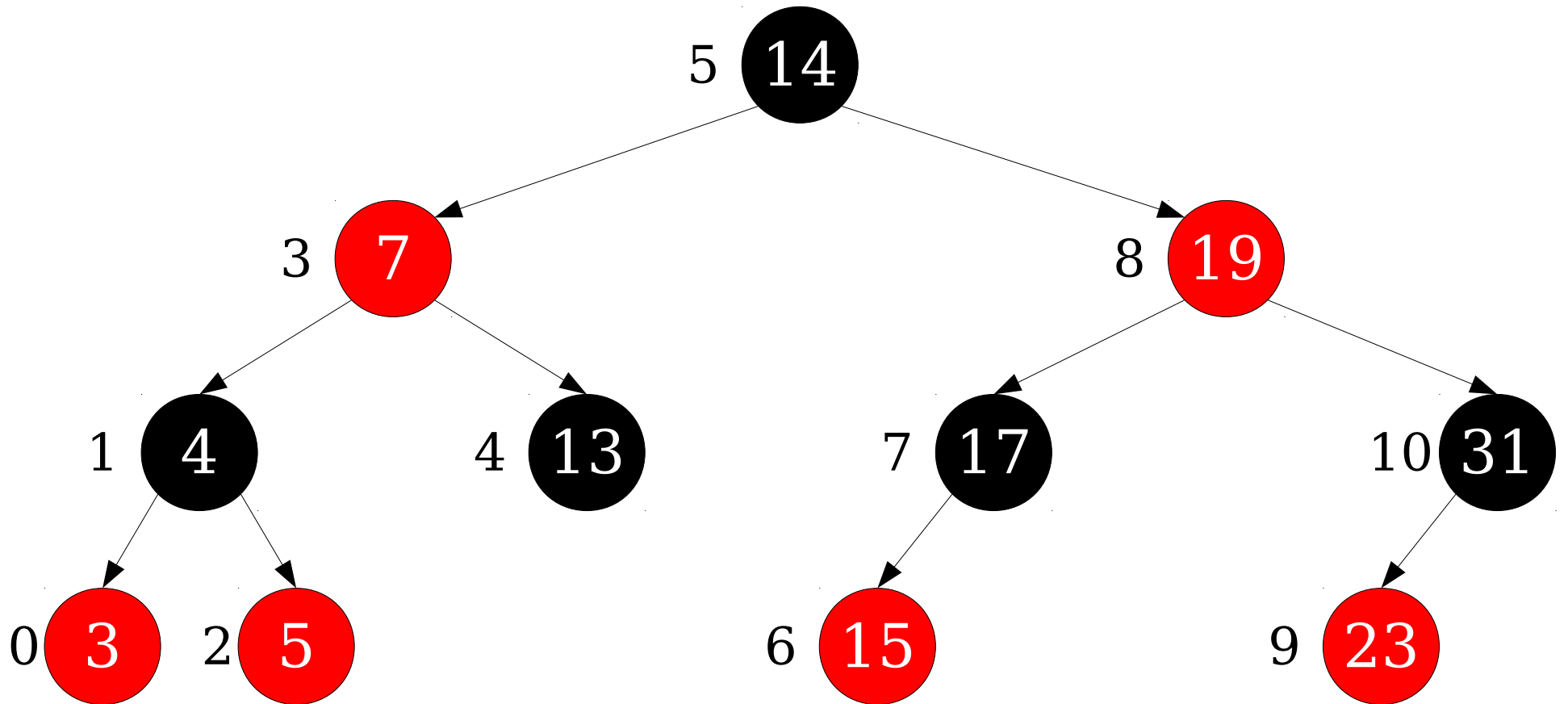
# Dynamic Selection



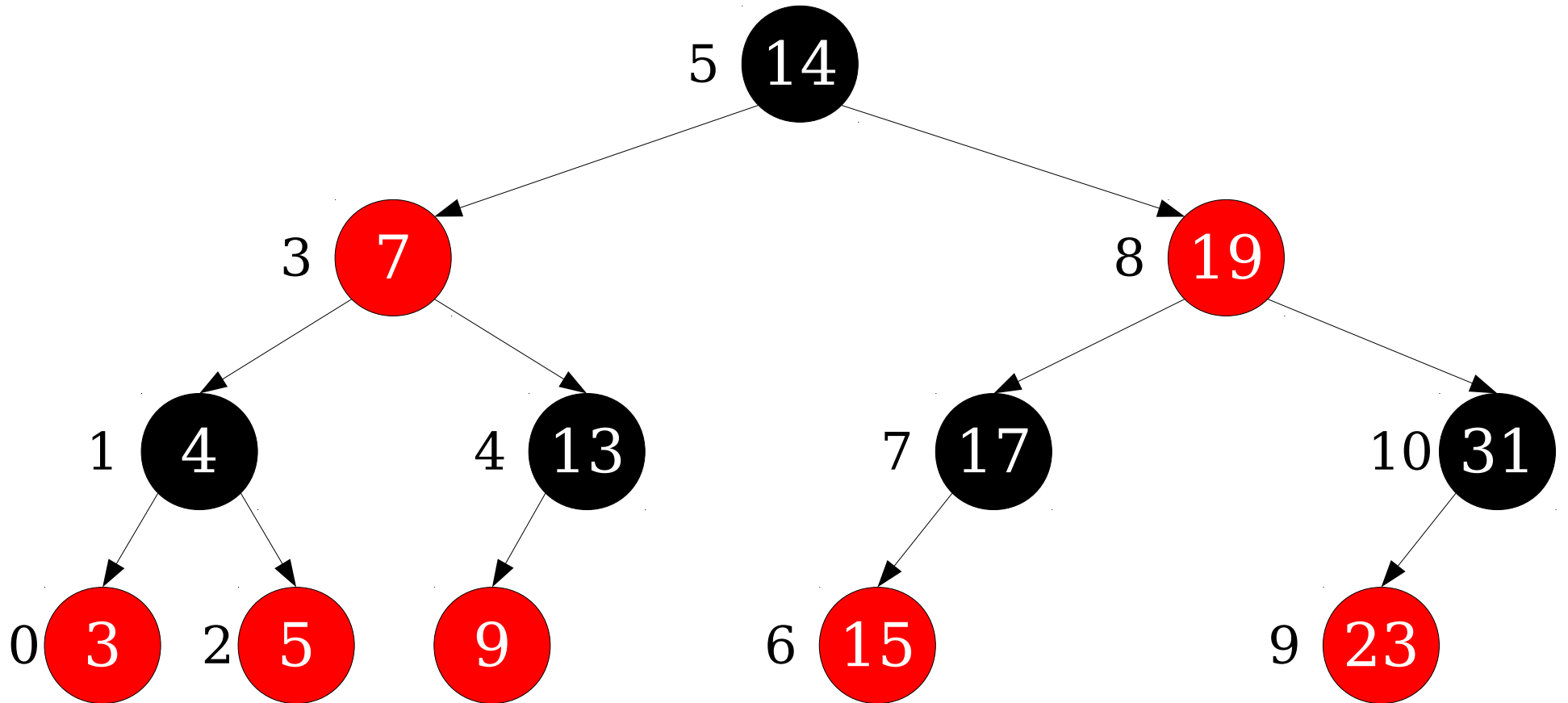
# Dynamic Selection



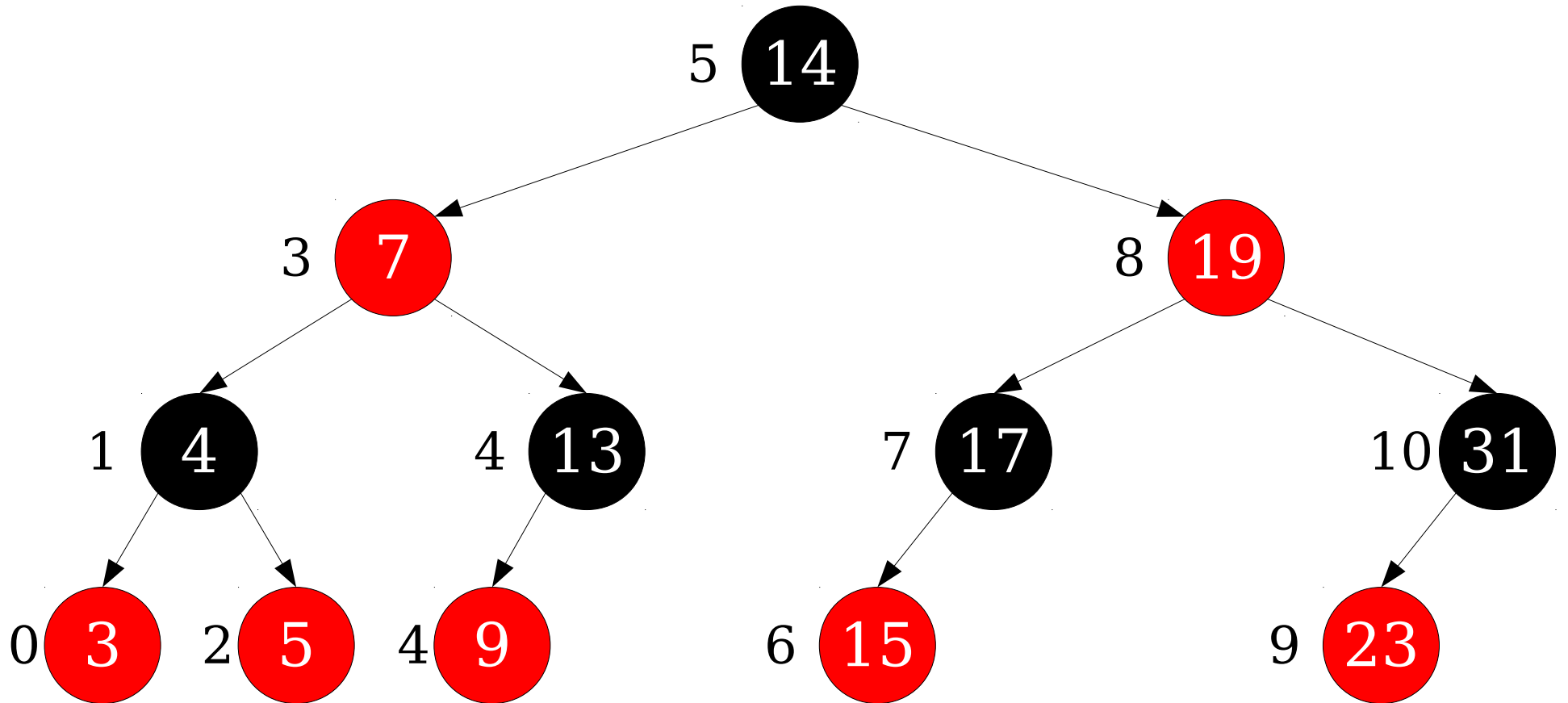
# Dynamic Selection



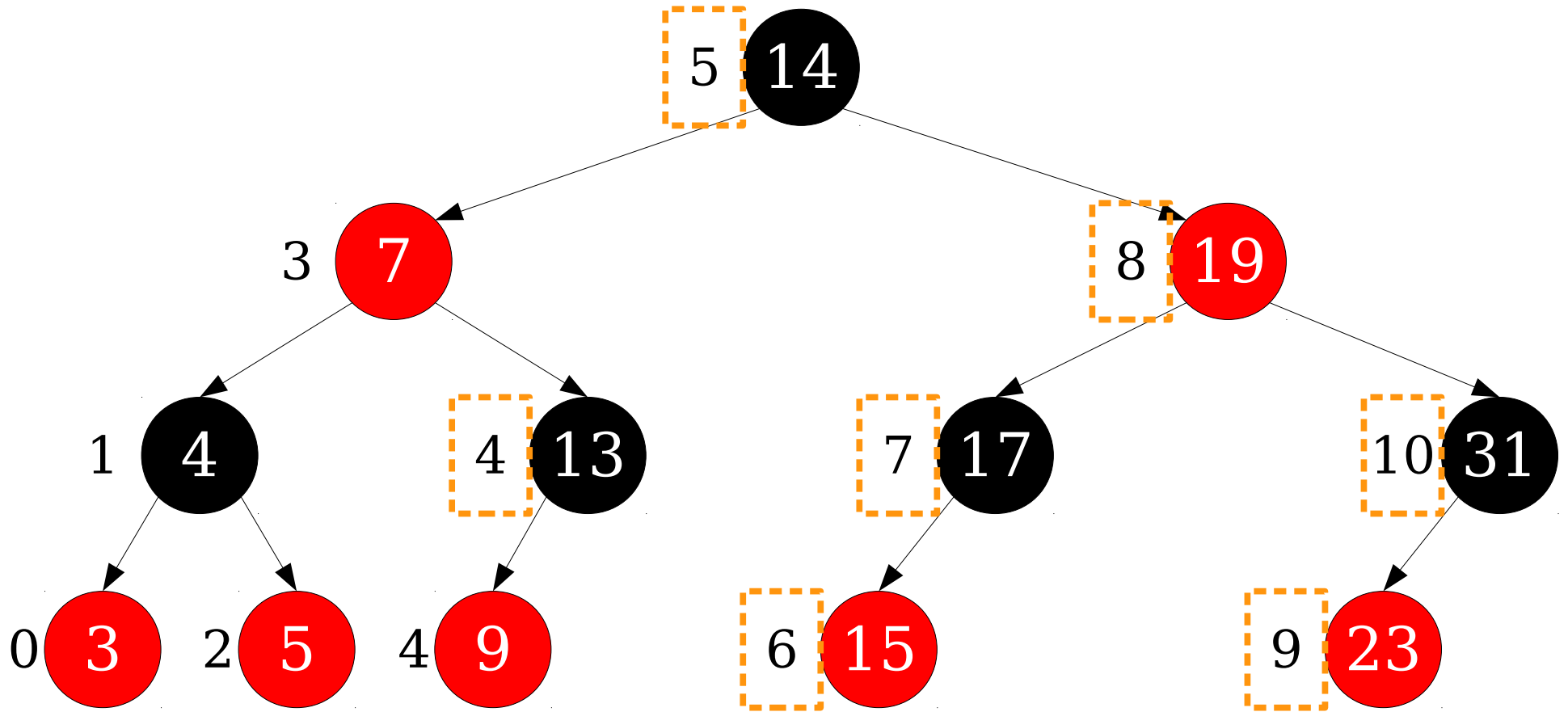
# Dynamic Selection



# Dynamic Selection

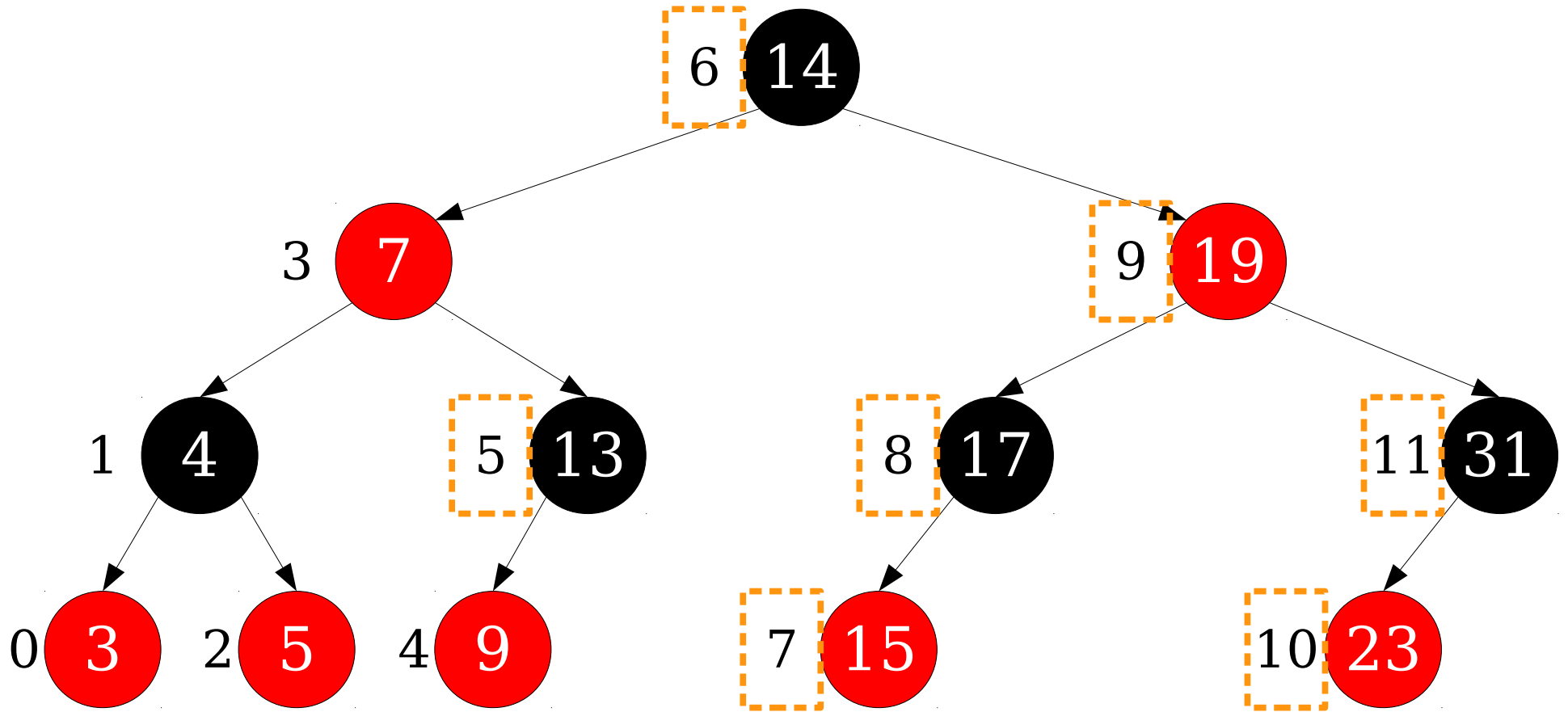


# Dynamic Selection

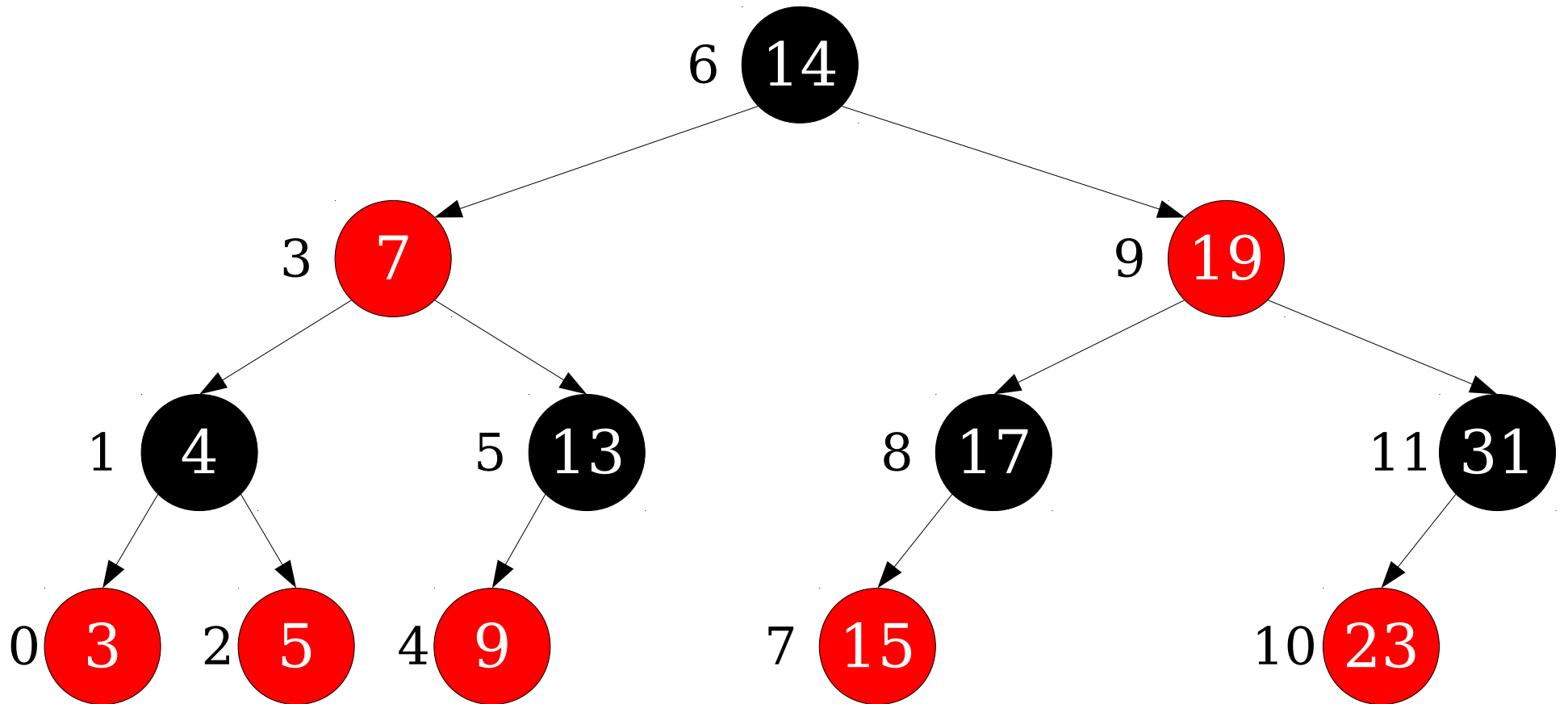




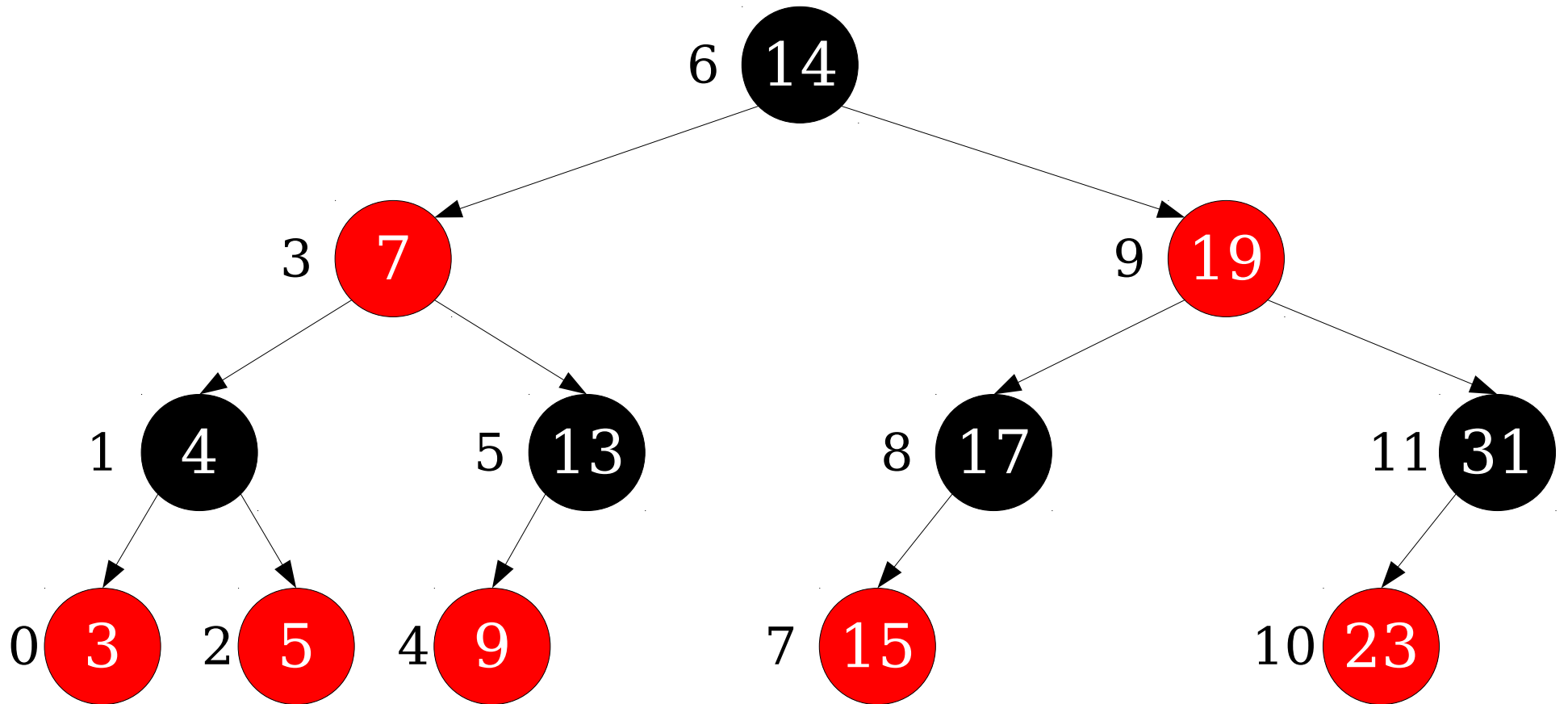
# Dynamic Selection



# Dynamic Selection



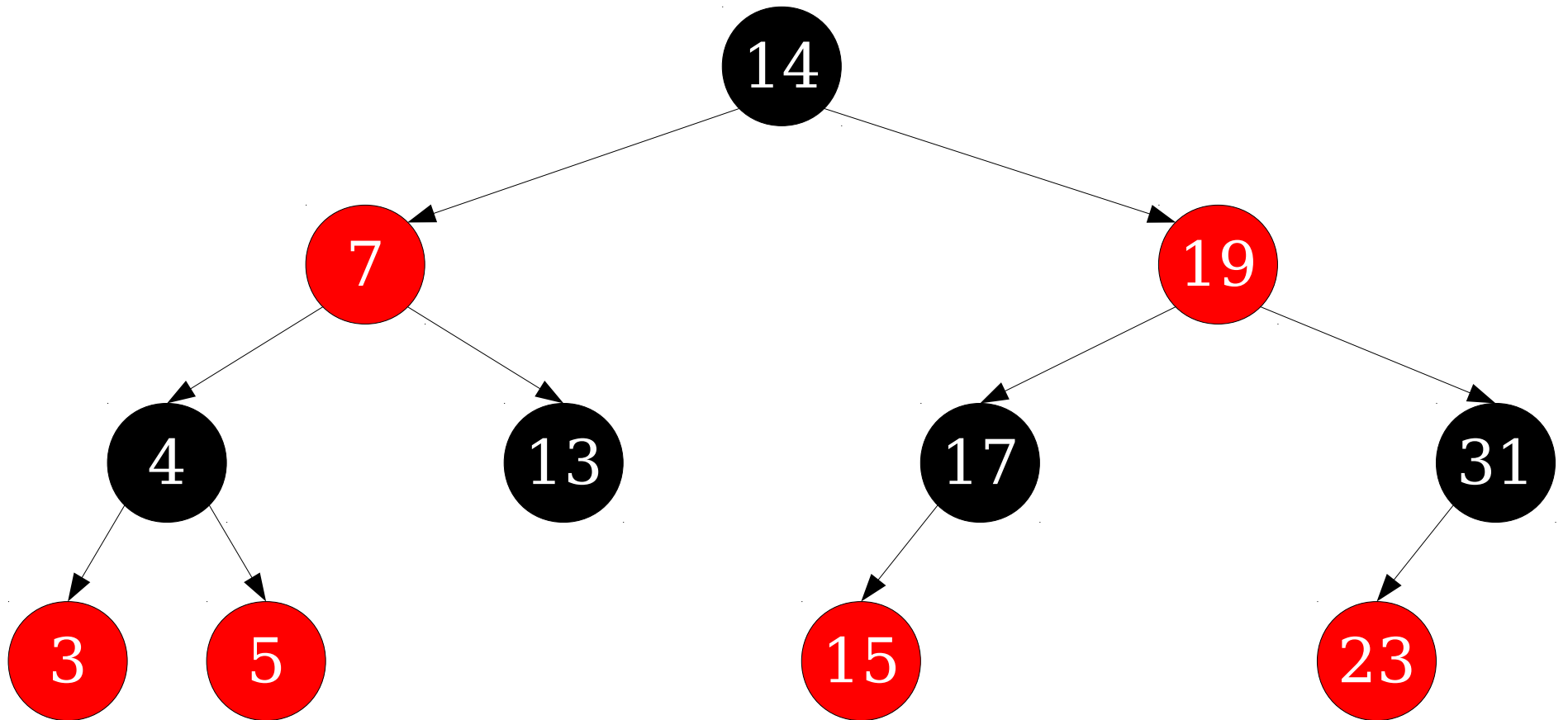
# Dynamic Selection



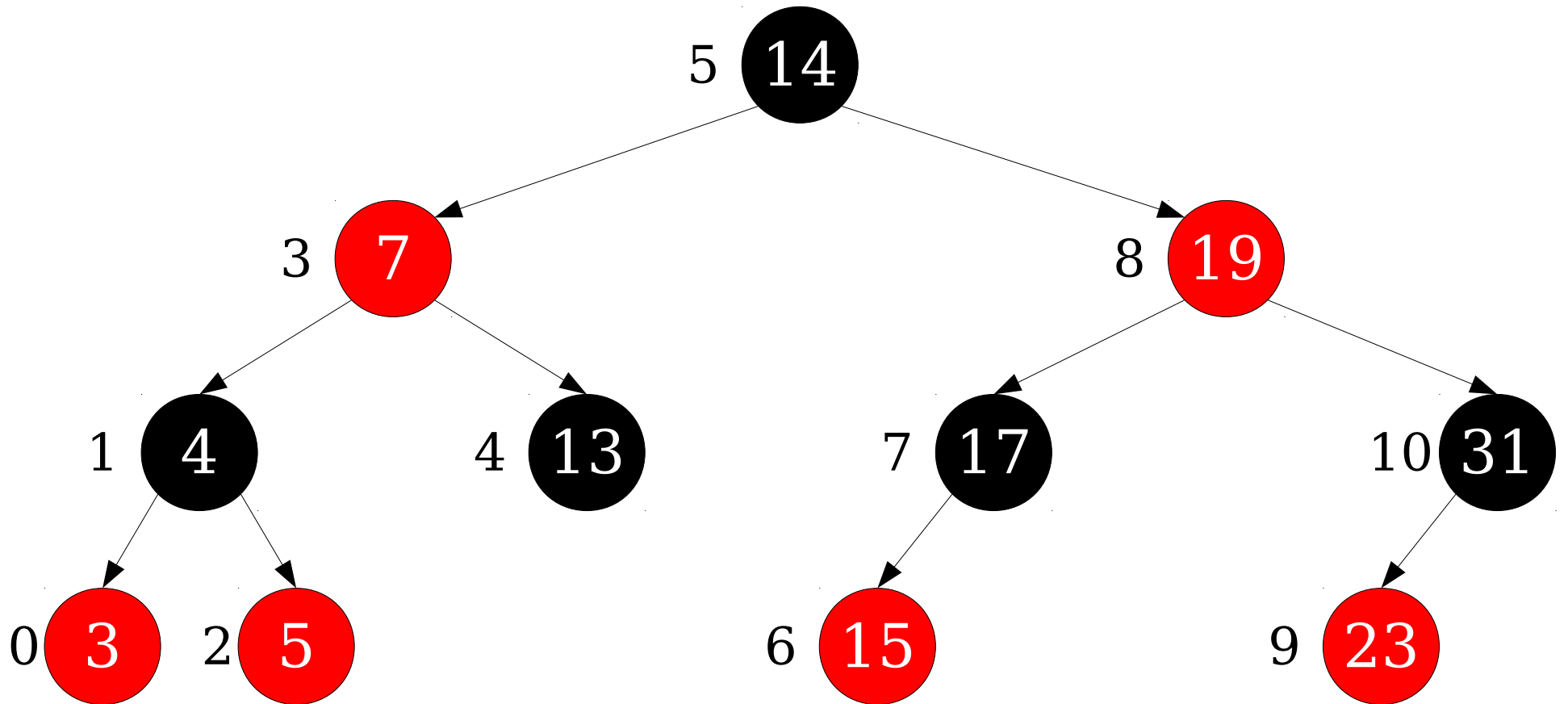
**Problem:** After inserting a new value, we may have to update  $\Theta(n)$  values.

This is inherent in this solution route. These numbers track *global* properties of the tree.

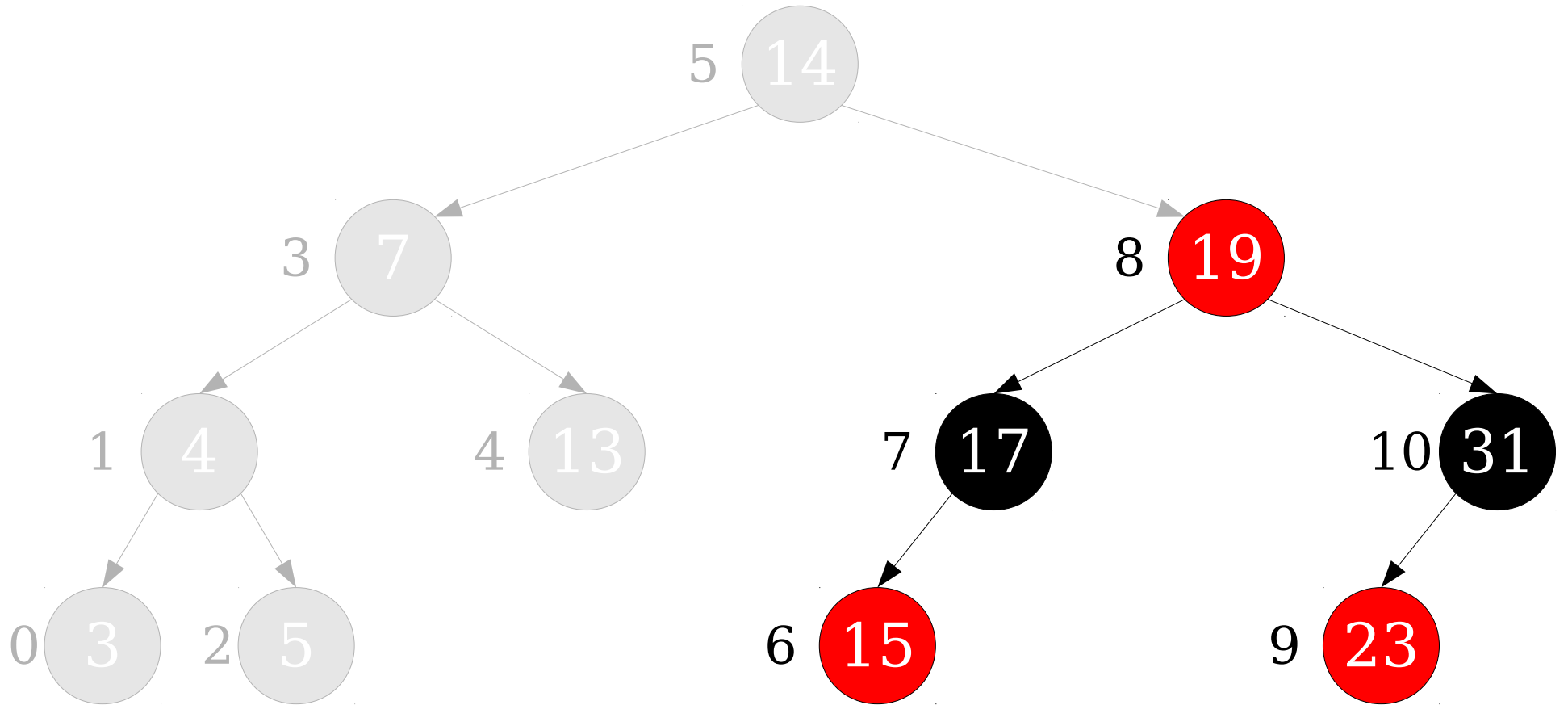
# Dynamic Selection



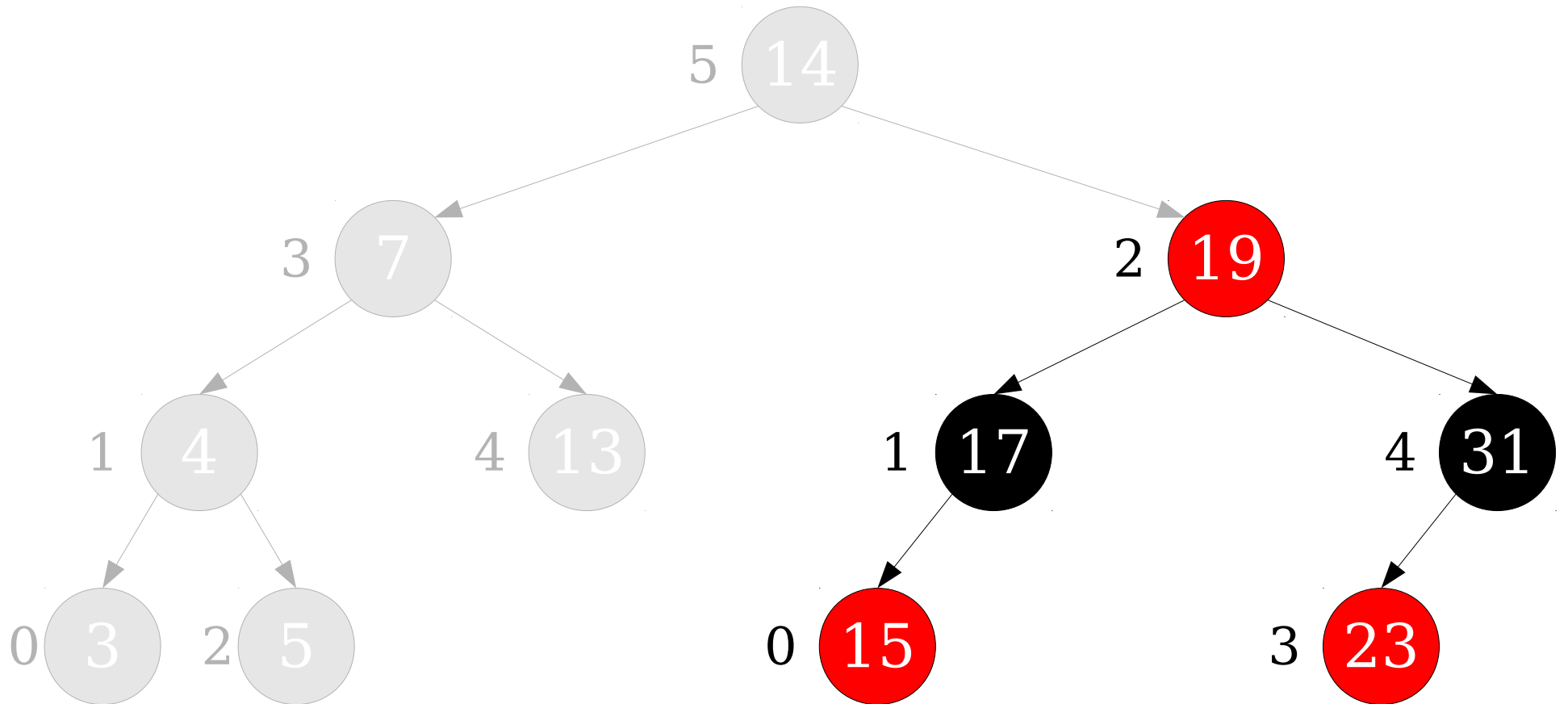
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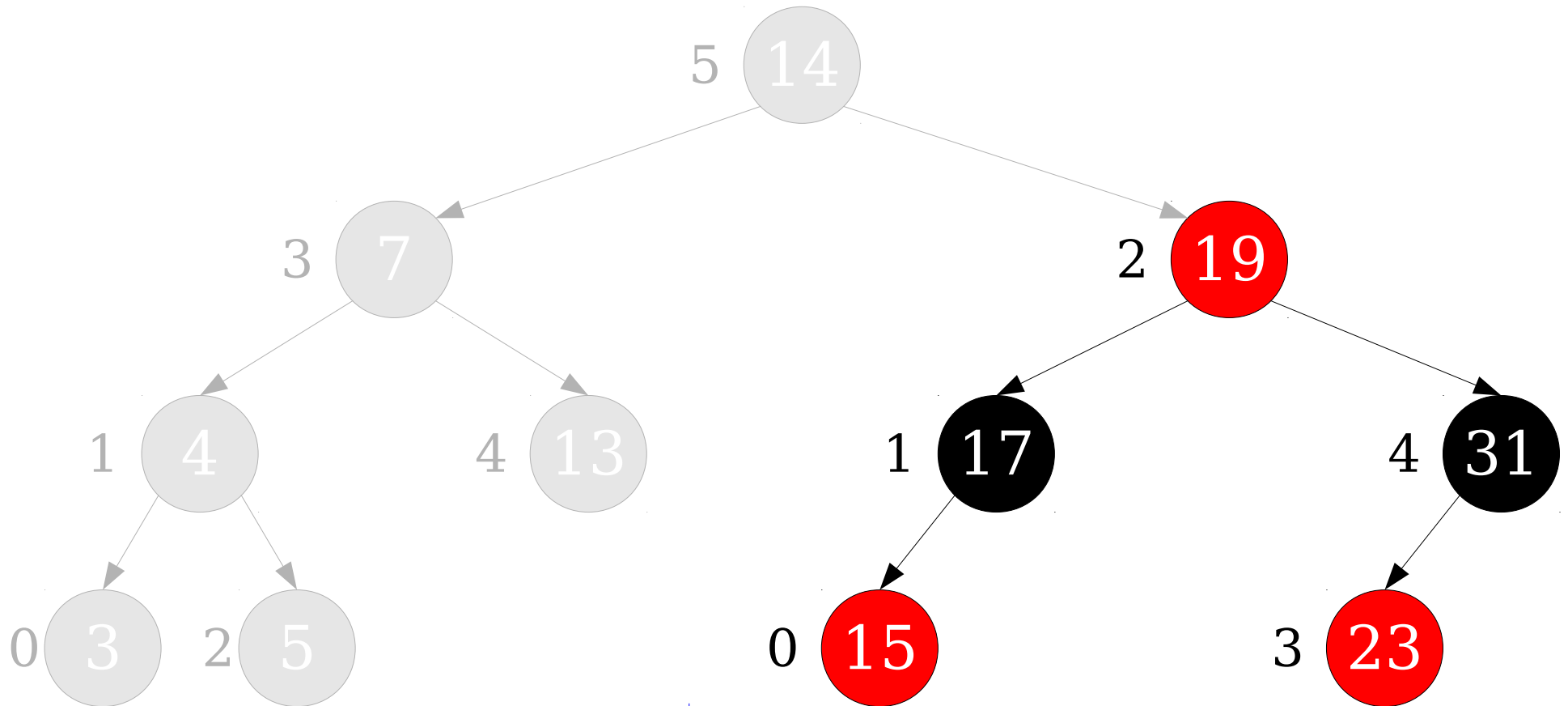
# Dynamic Selection



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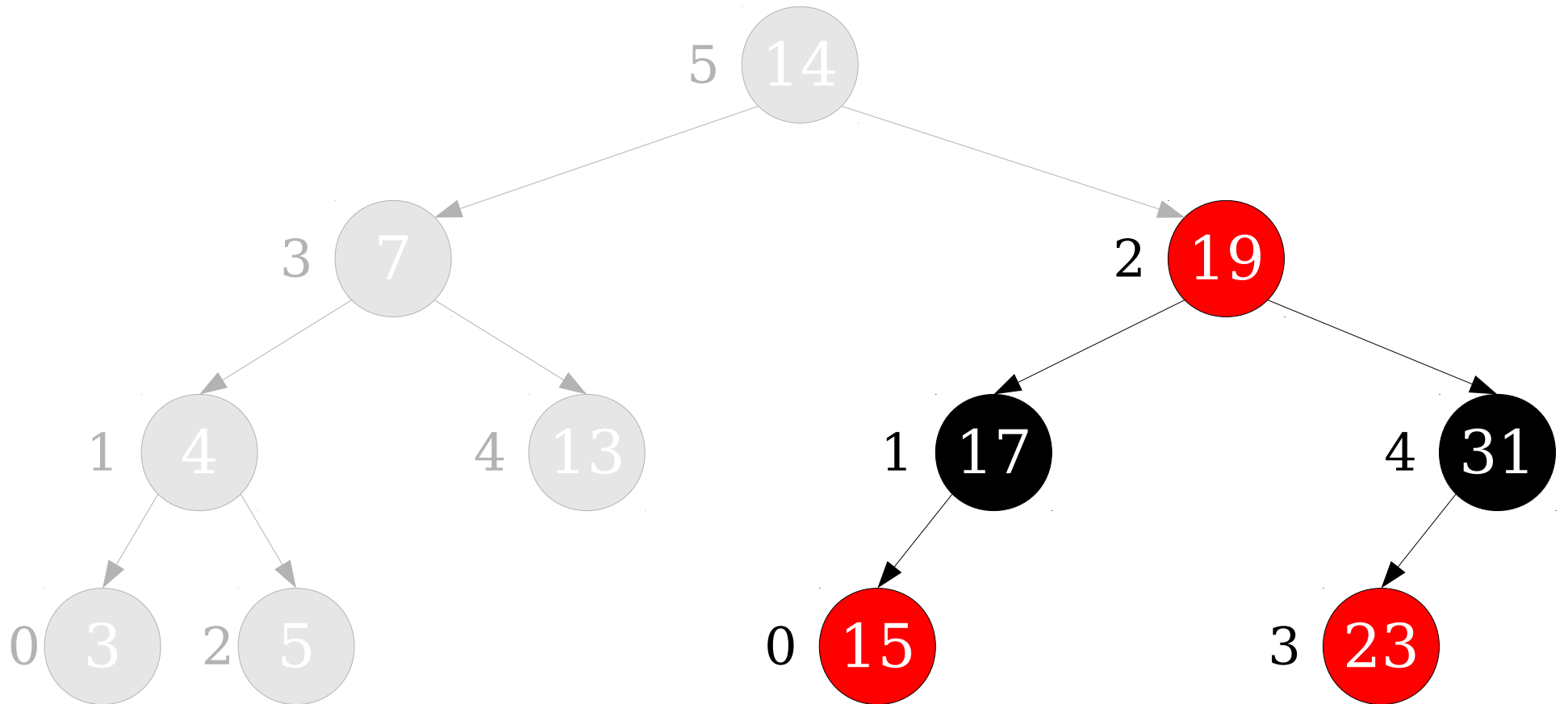
# Dynamic Selection



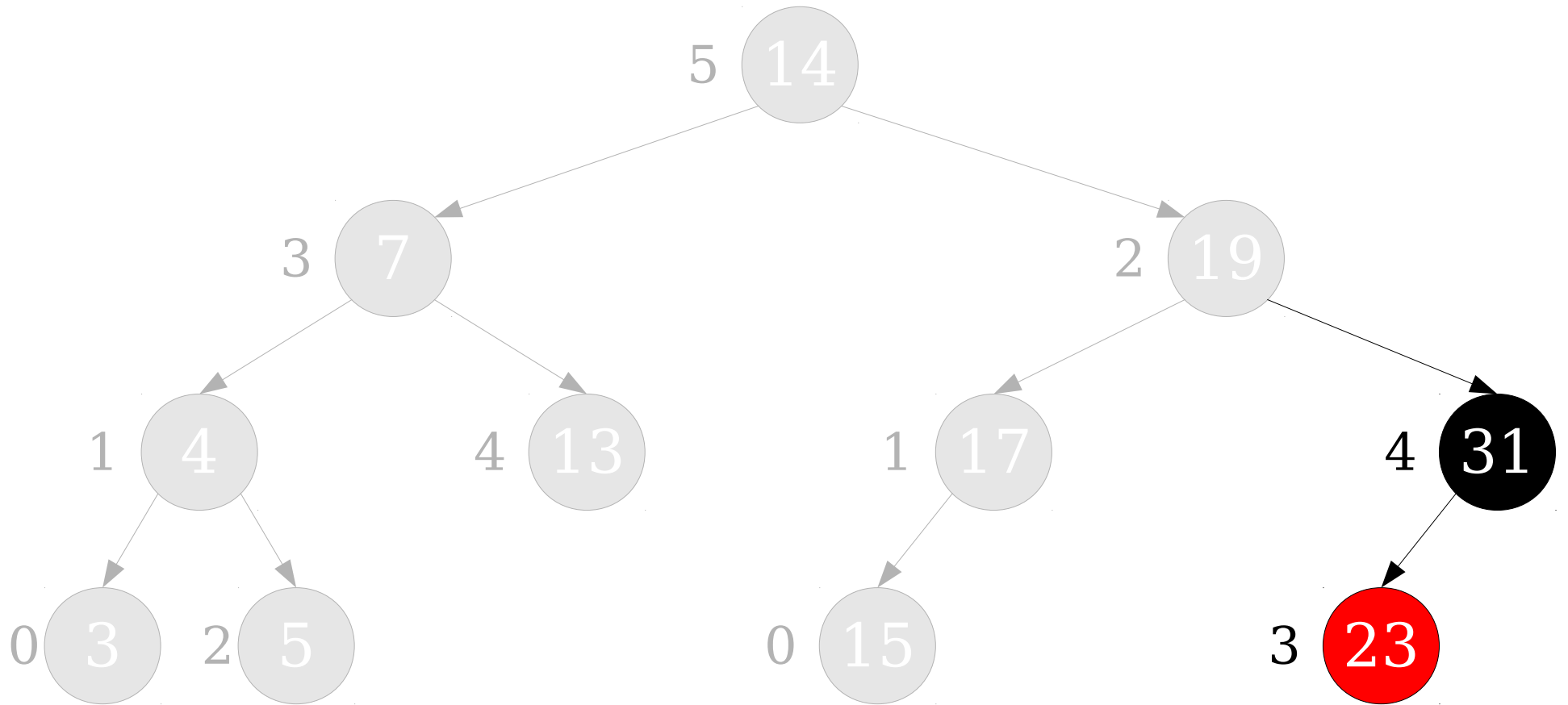
If new nodes are added to the left subtree, the numbers on the right don't need to update.



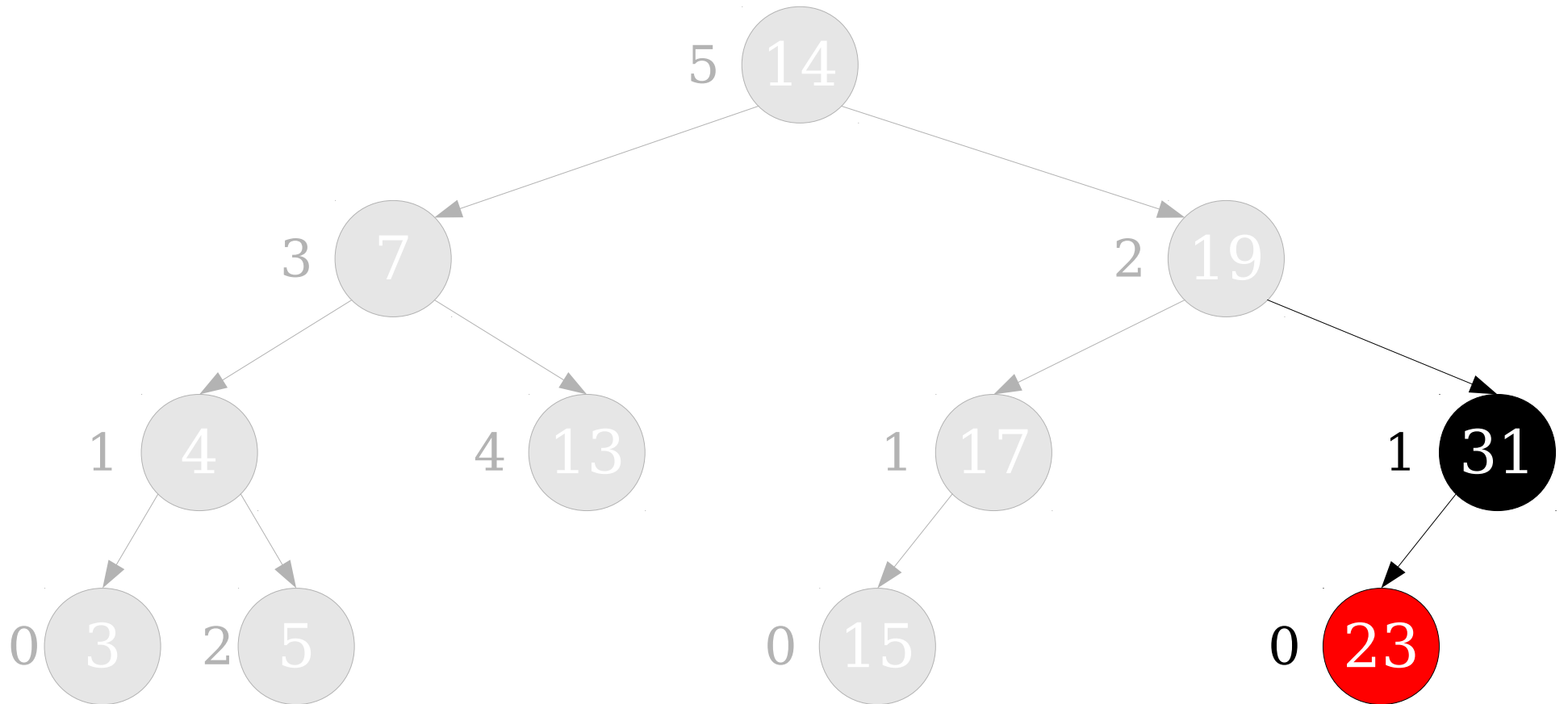
# Dynamic Selection



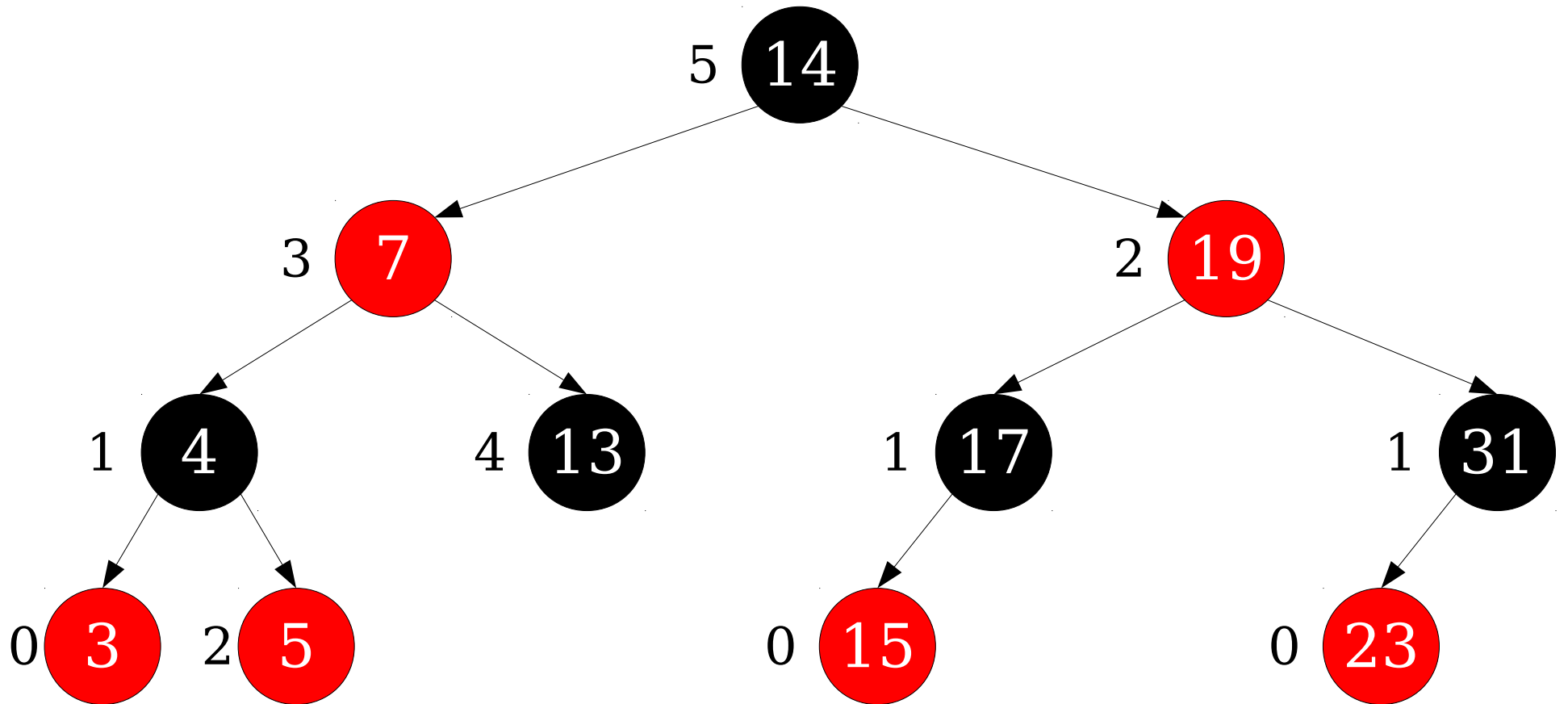
# Dynamic Selection



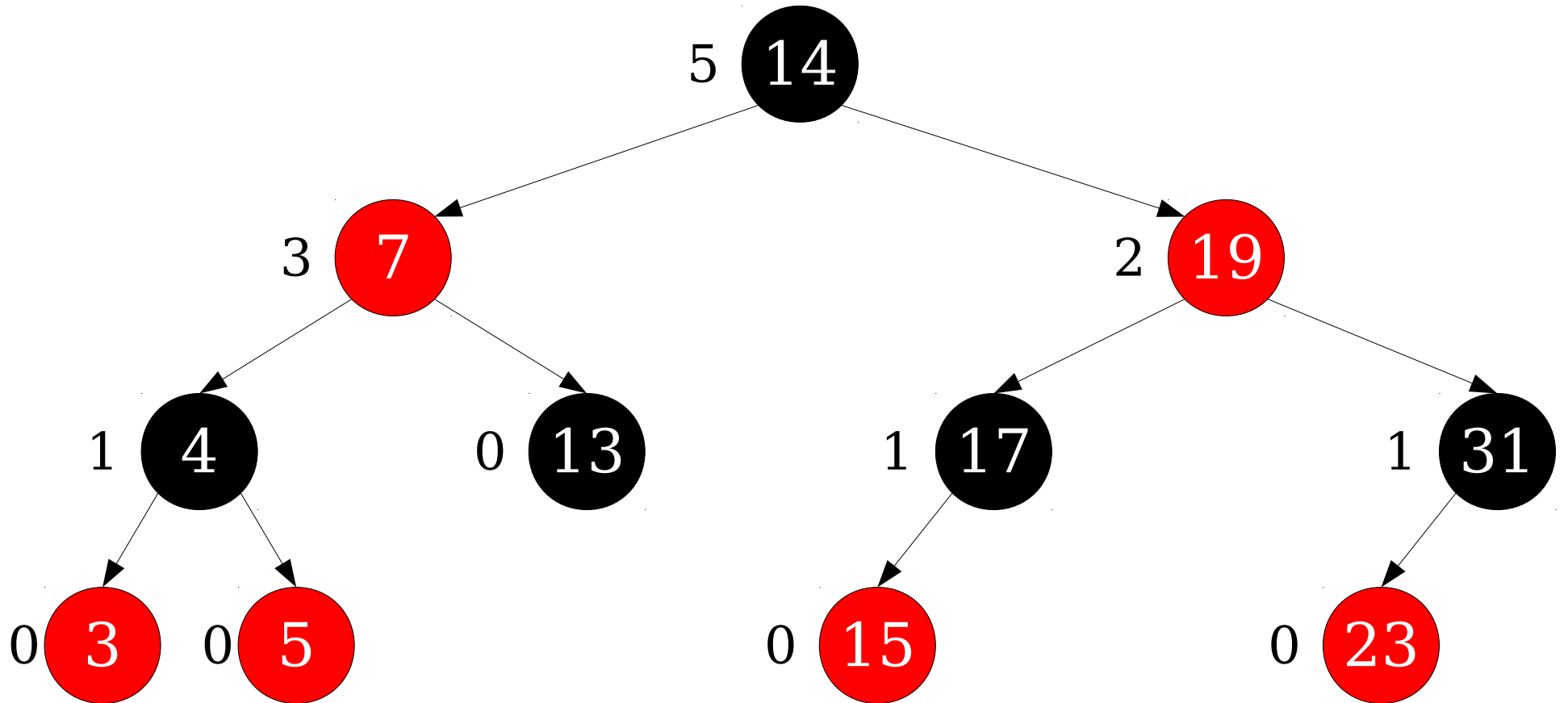
# Dynamic Selection



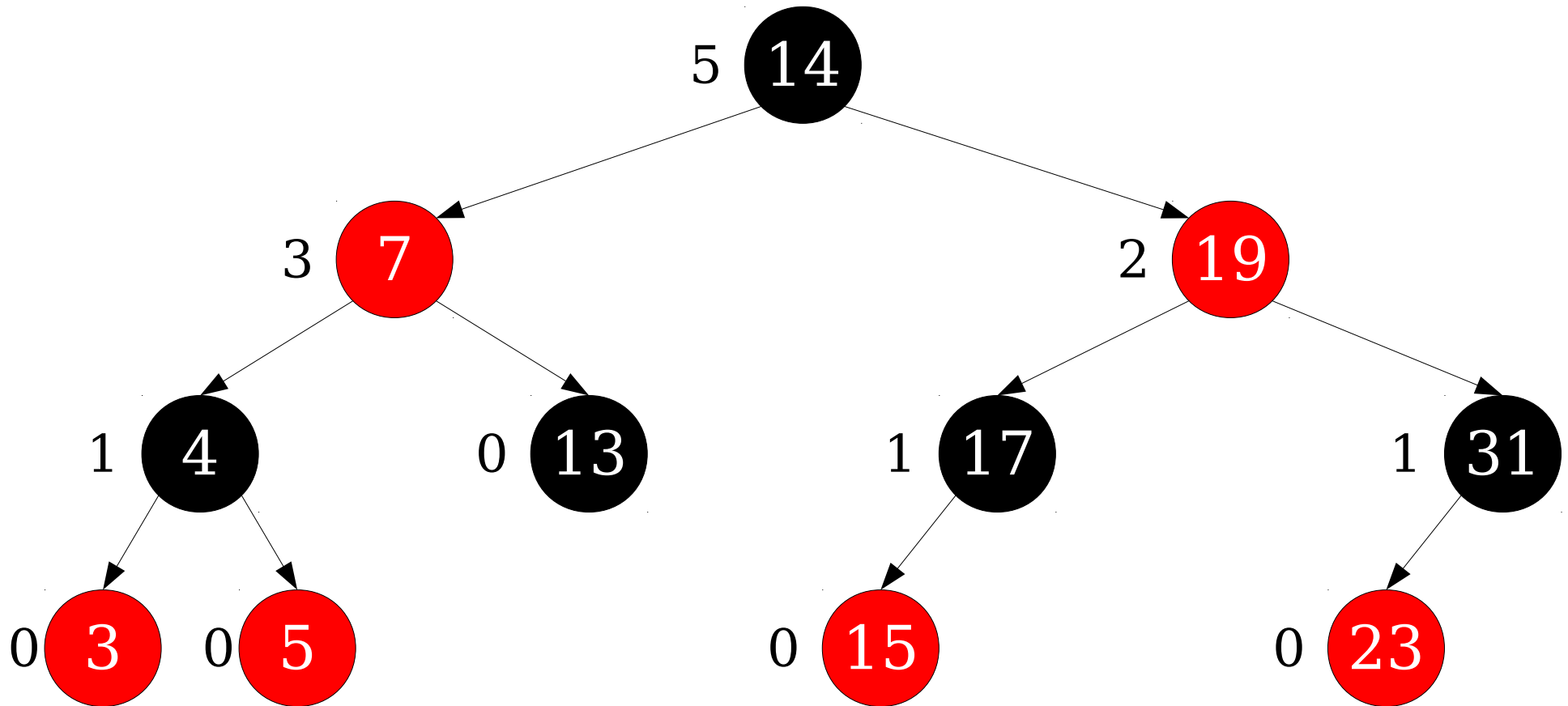
# Dynamic Selection



# Dynamic Selection



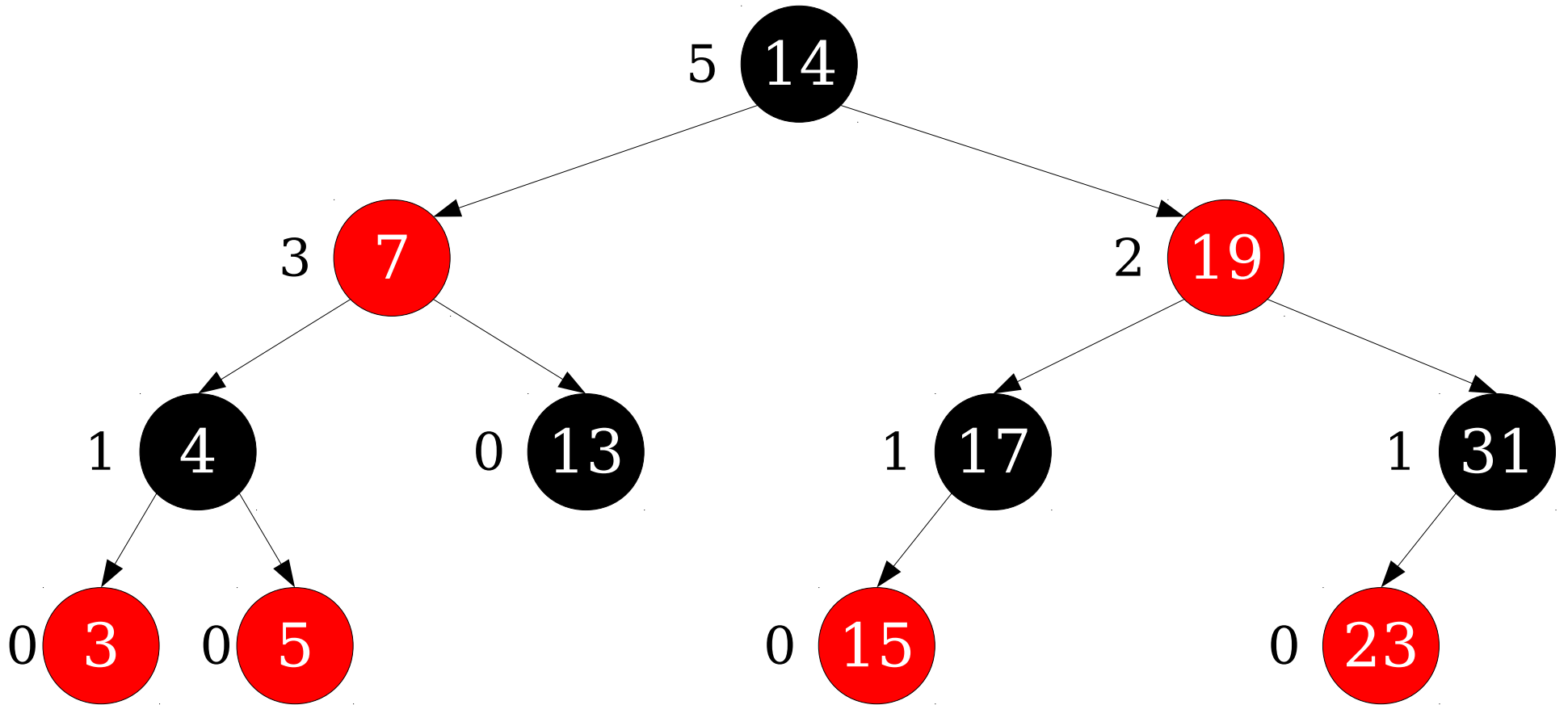
# Dynamic Selection



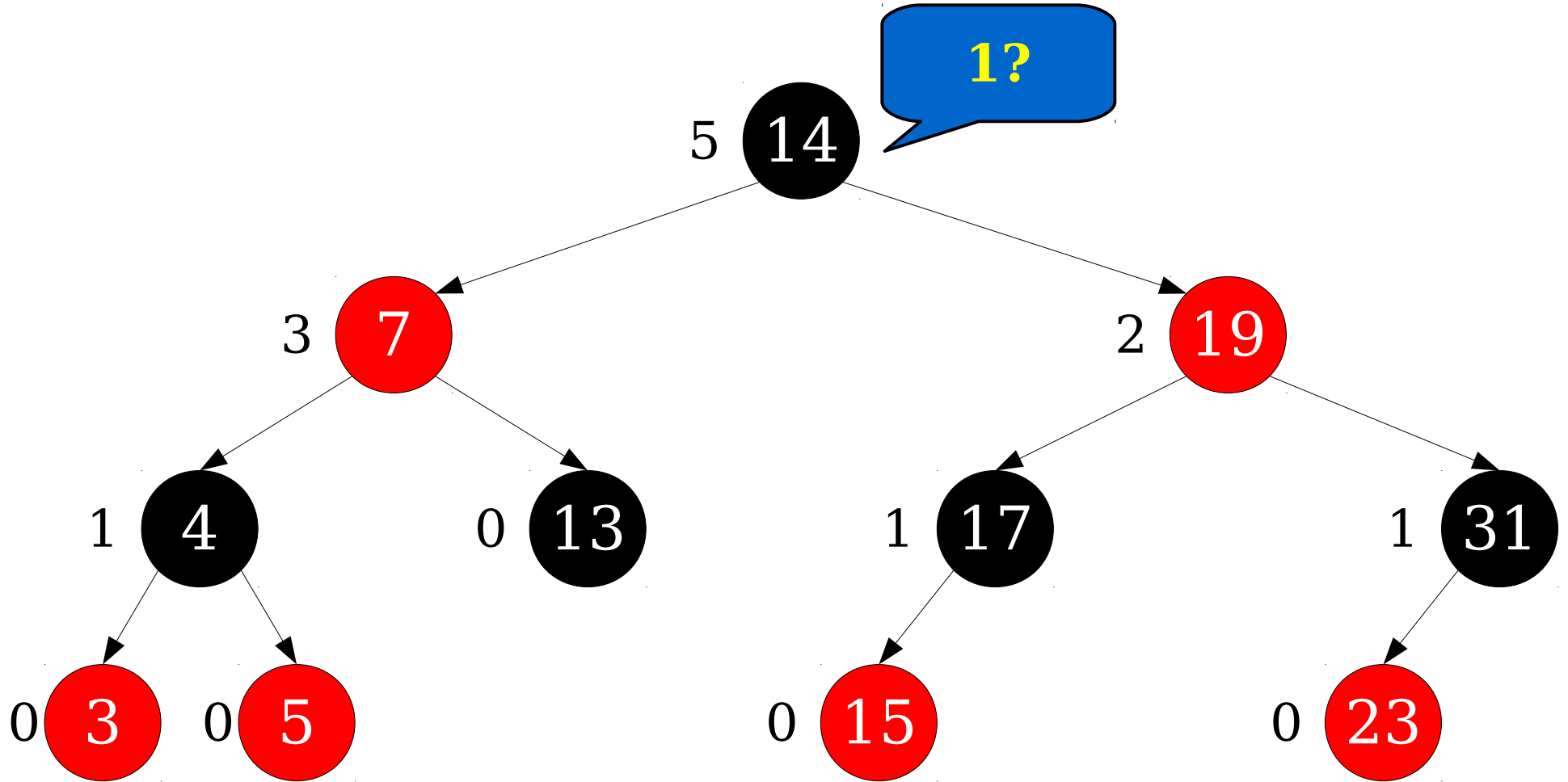
**Mechanically:** Number each key so that it only stores its order statistic in the subtree rooted at itself.

**Operationally:** Annotate each key with the number of keys in its left subtree.

# Dynamic Selection

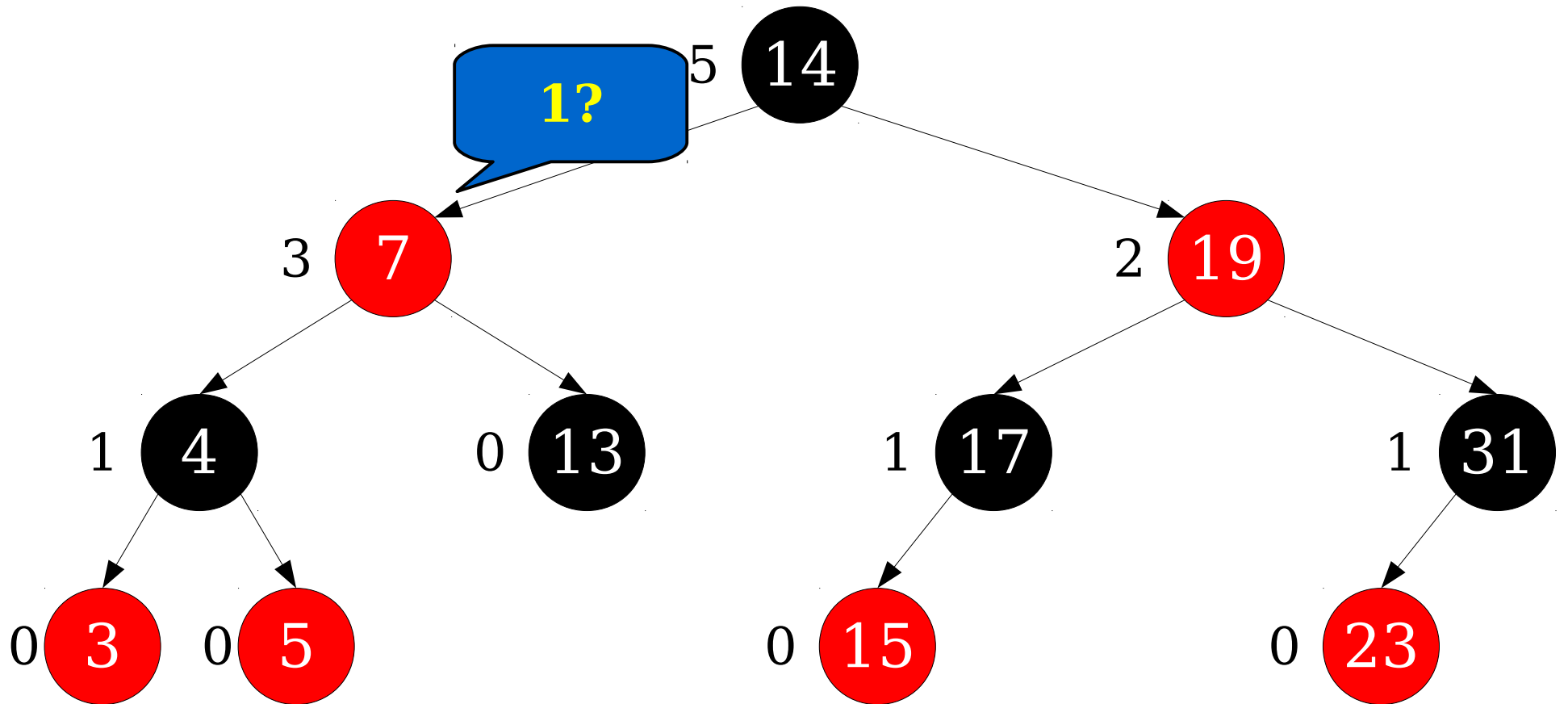


# Dynamic Selection

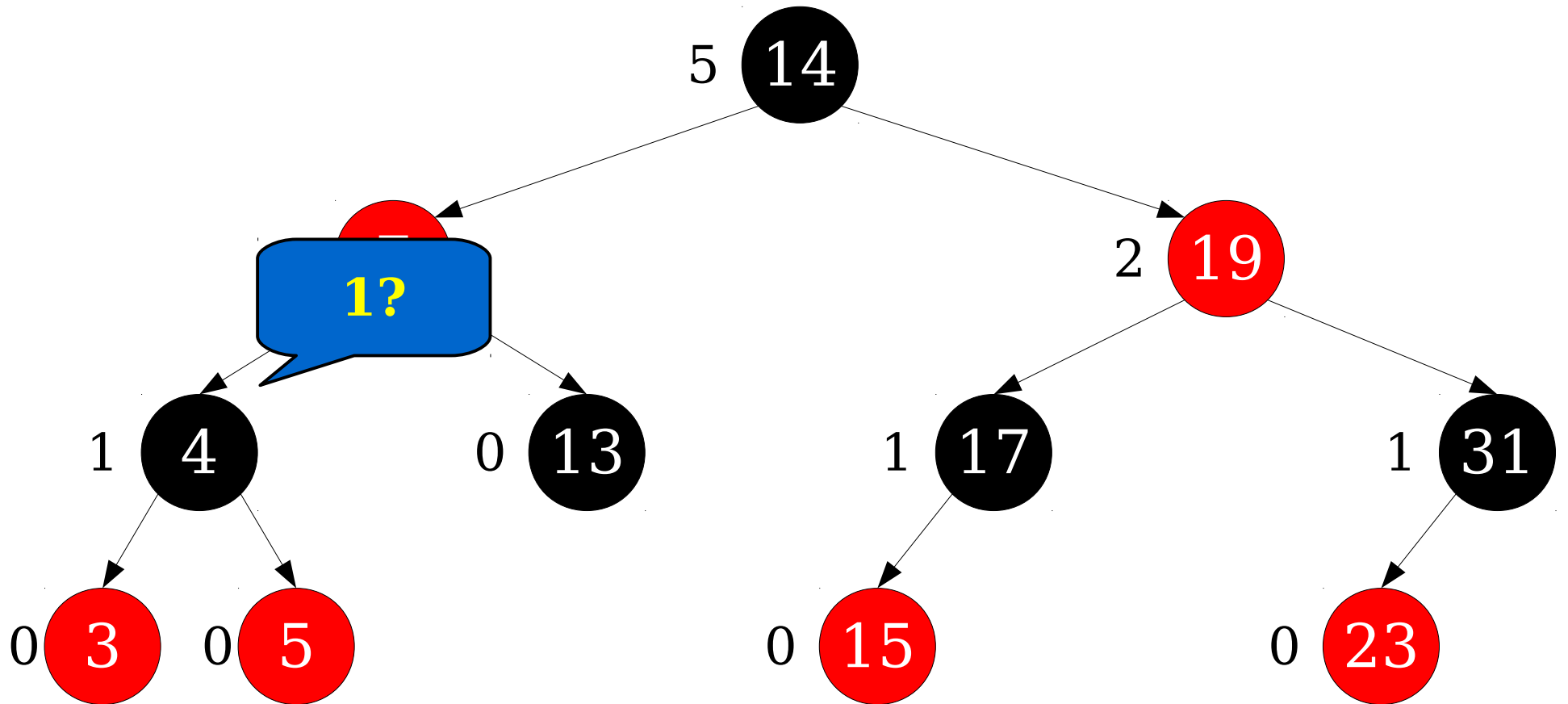




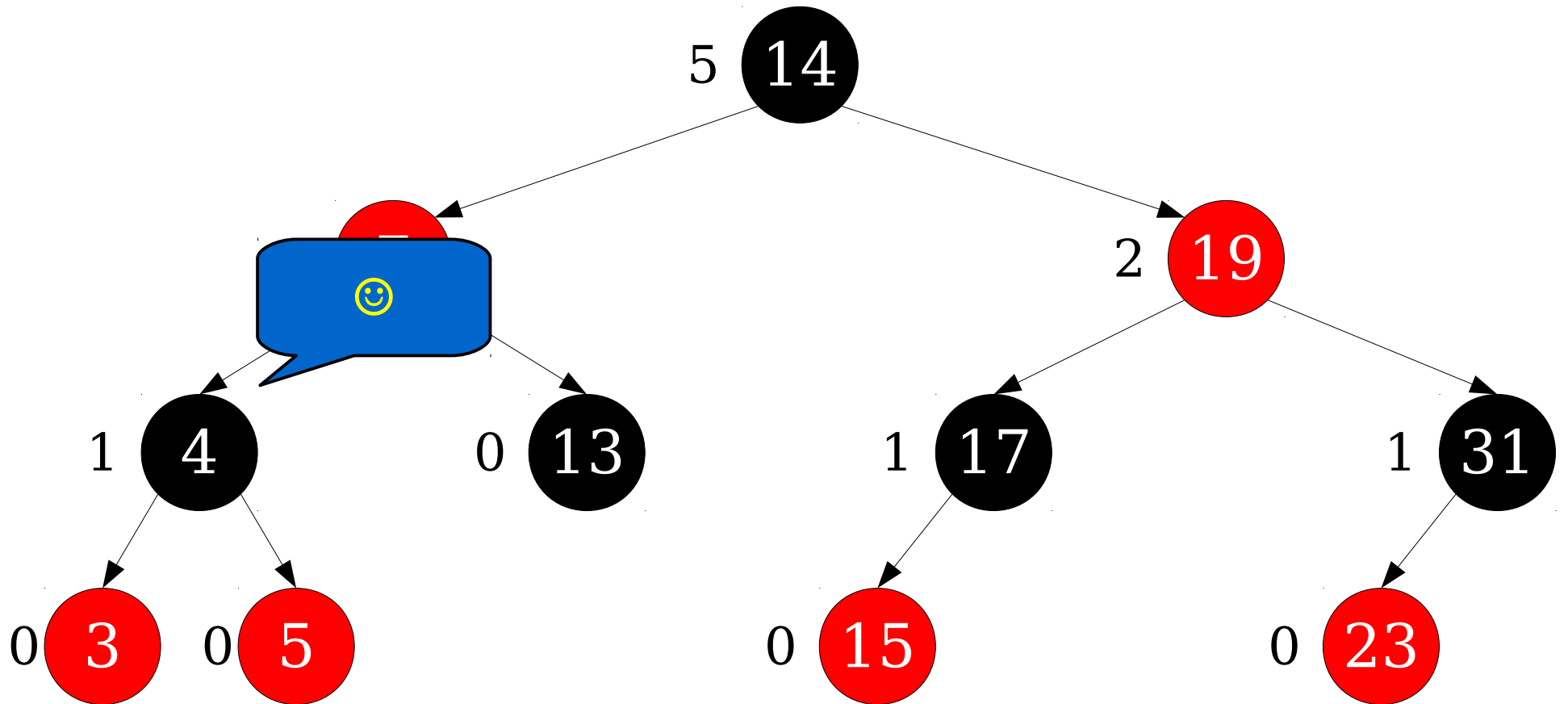
# Dynamic Selection



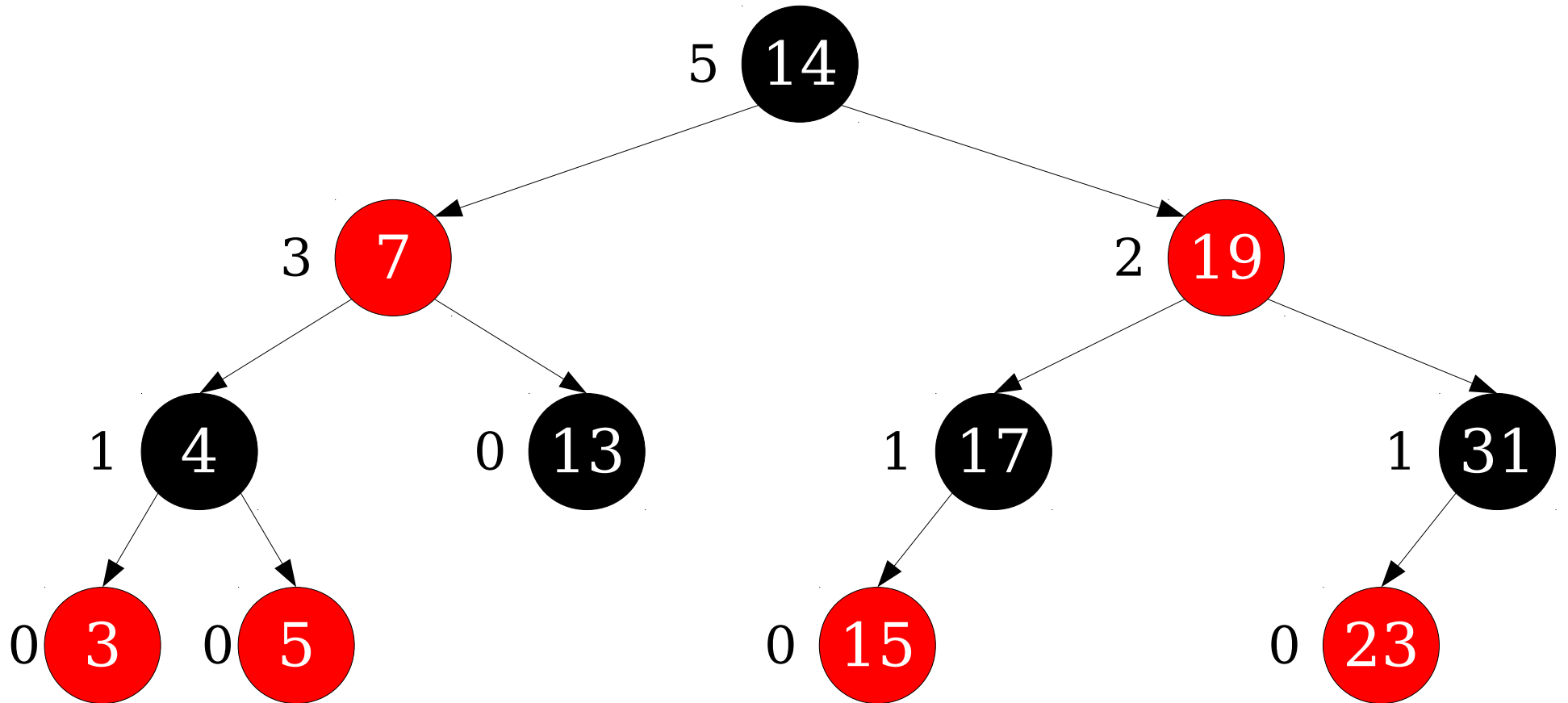
# Dynamic Selection



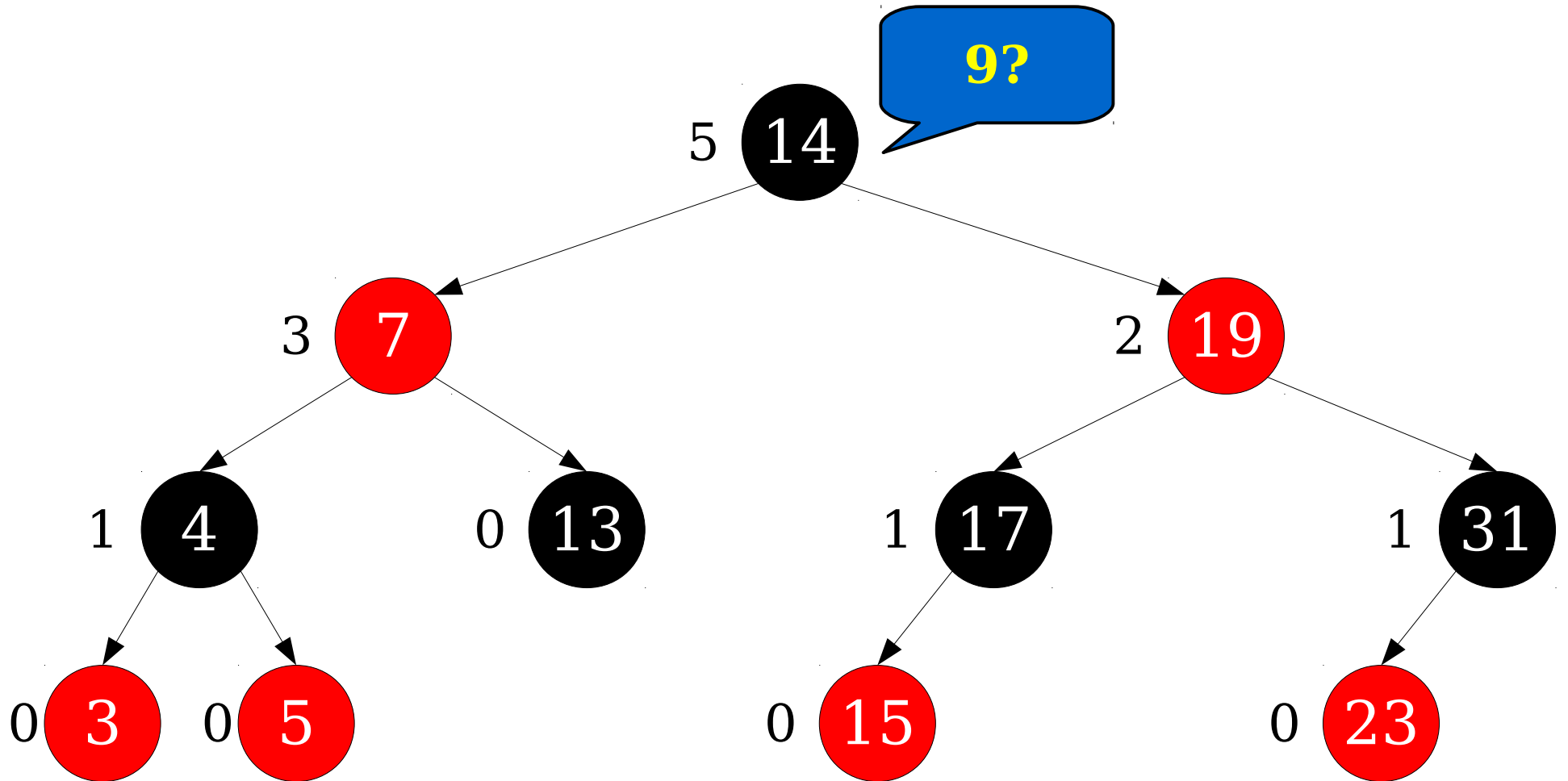
# Dynamic Selection



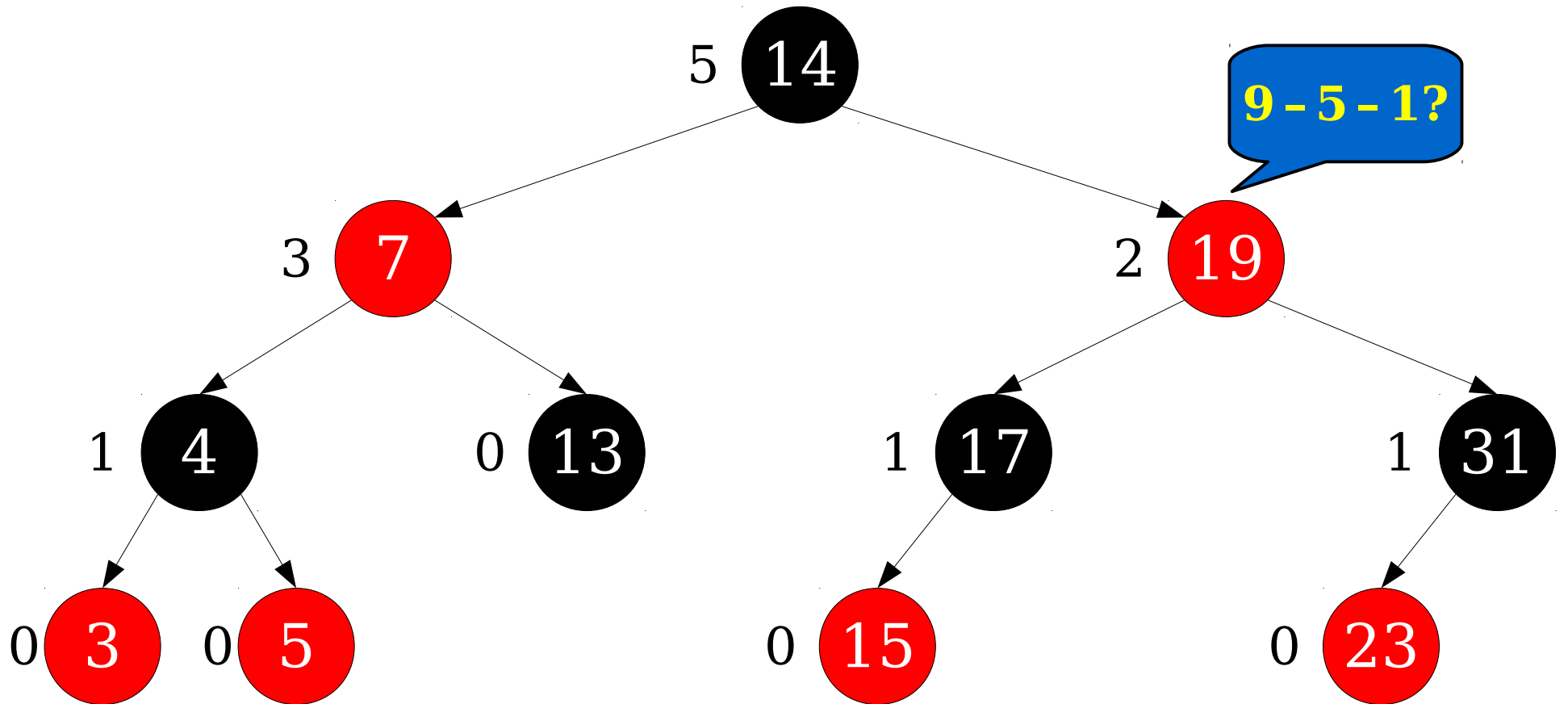
# Dynamic Selection



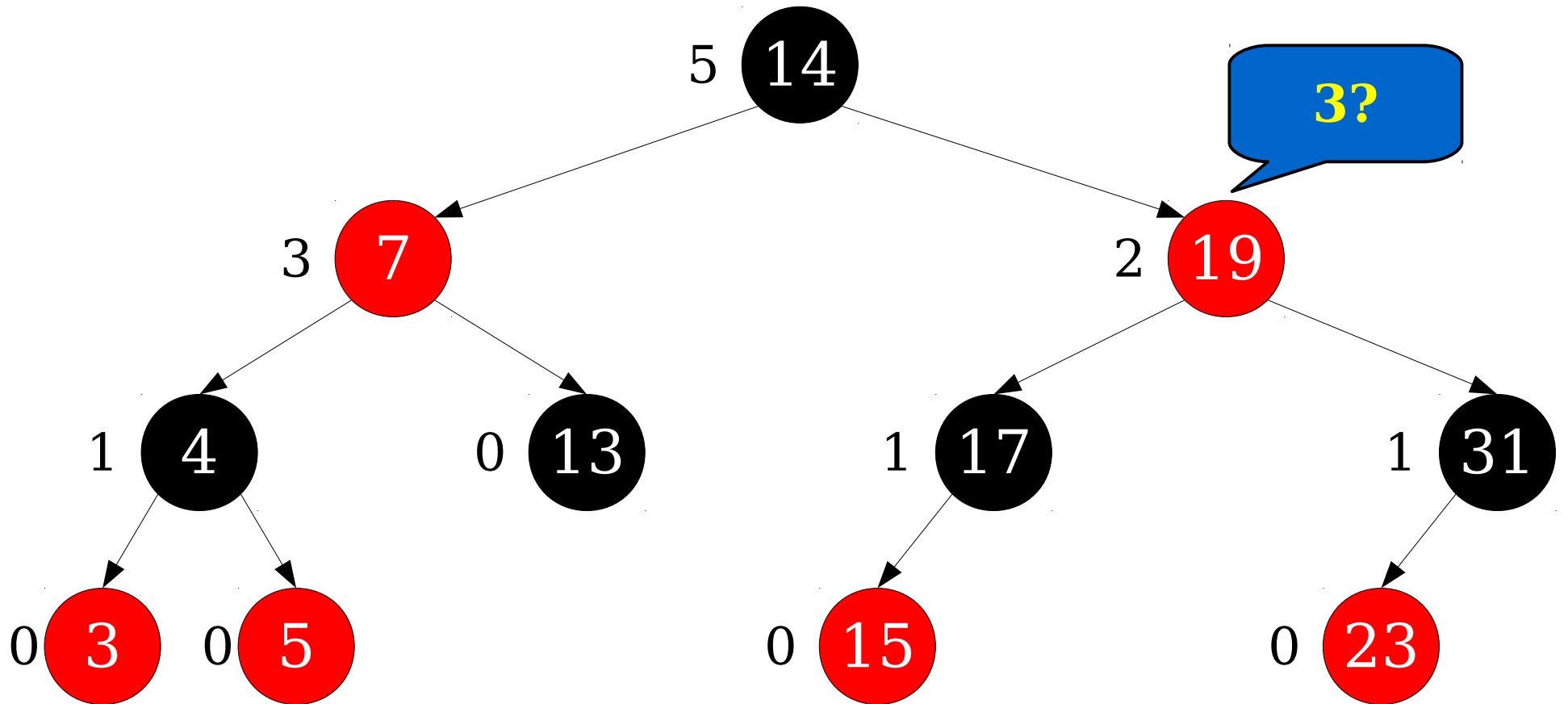
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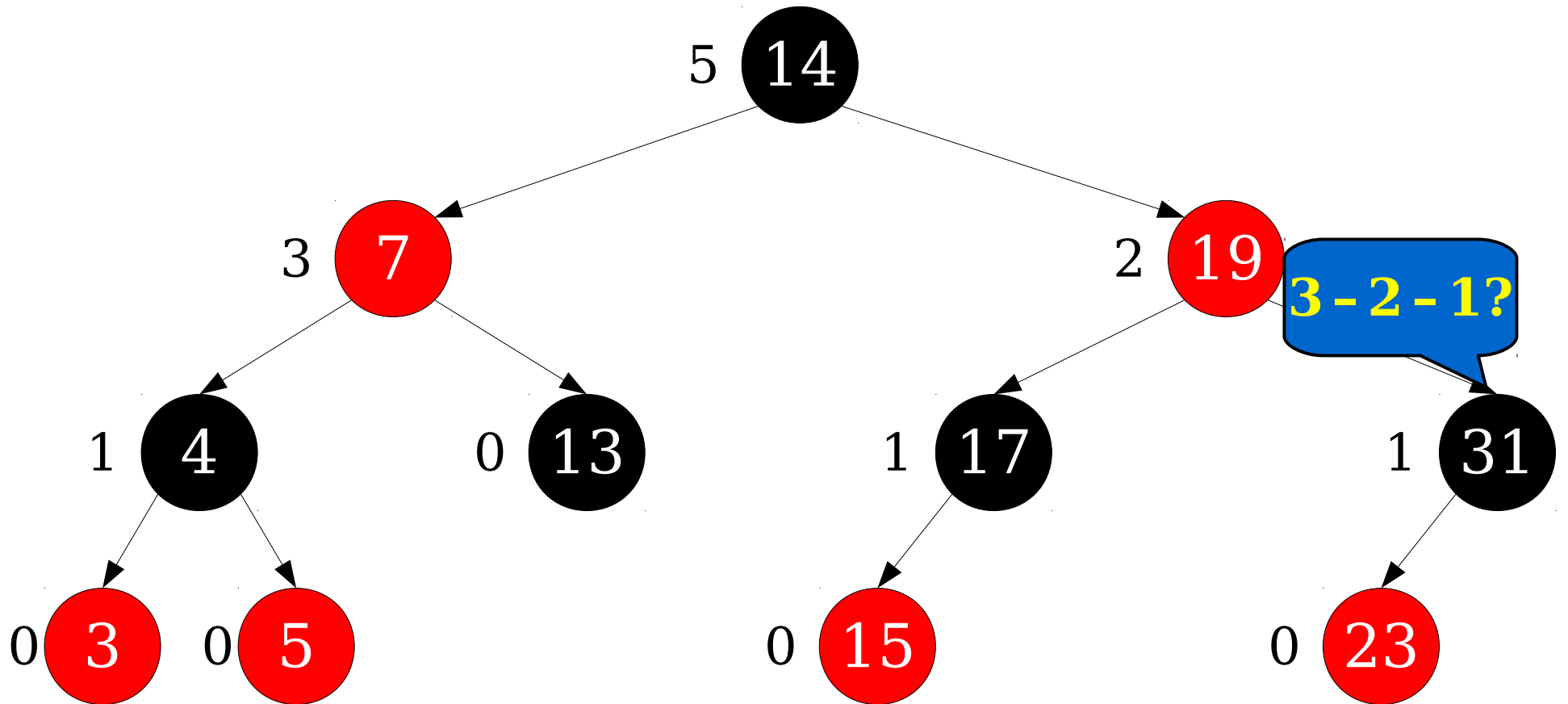
# Dynamic Selection



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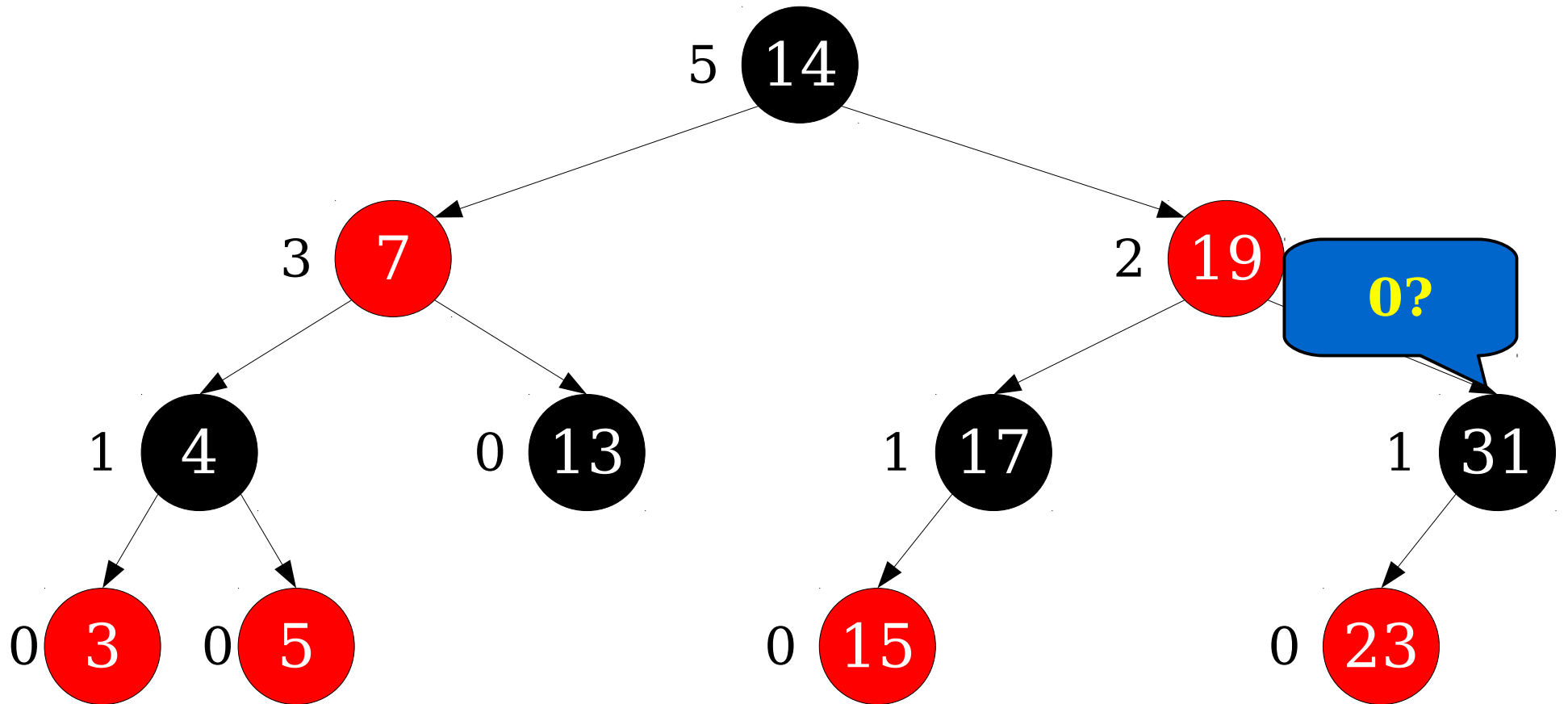


# Dynamic Selection

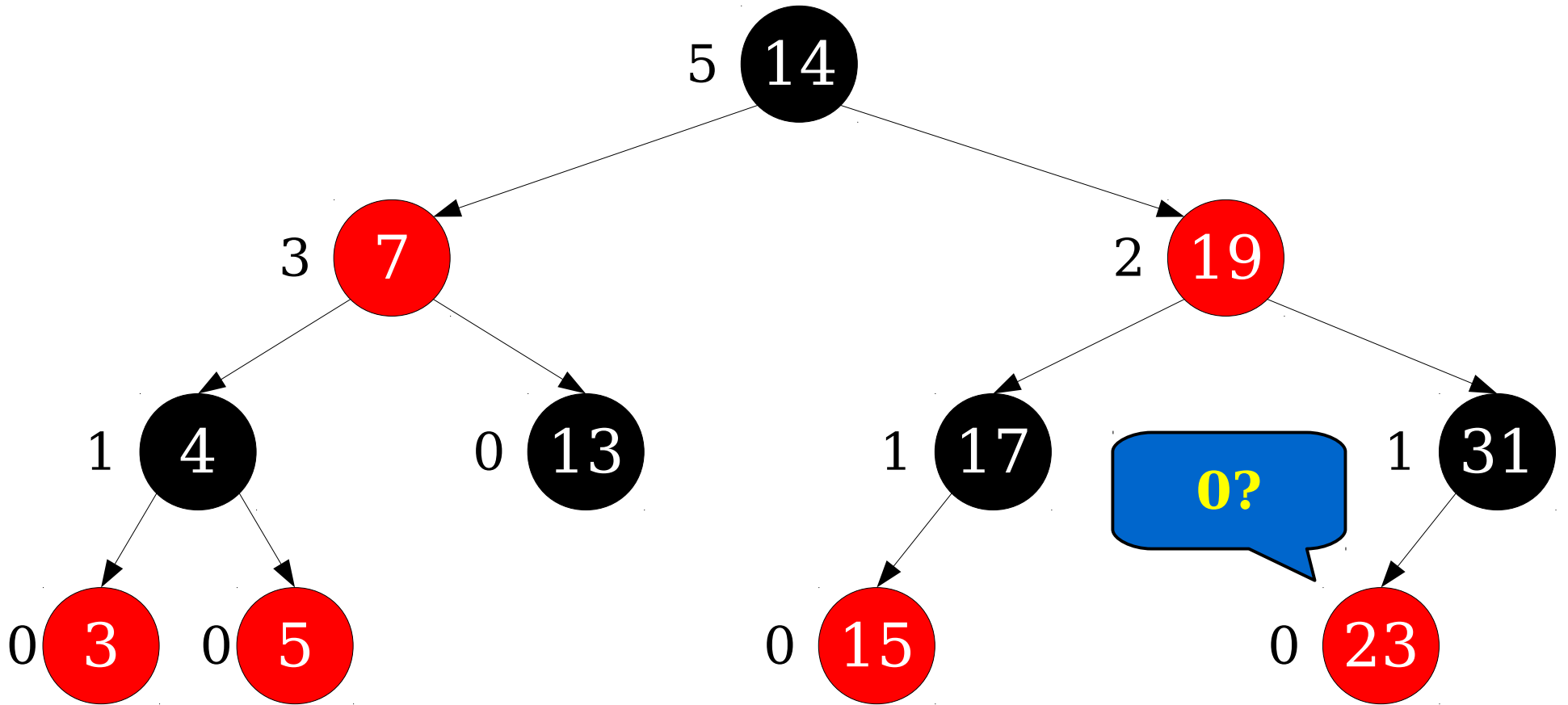




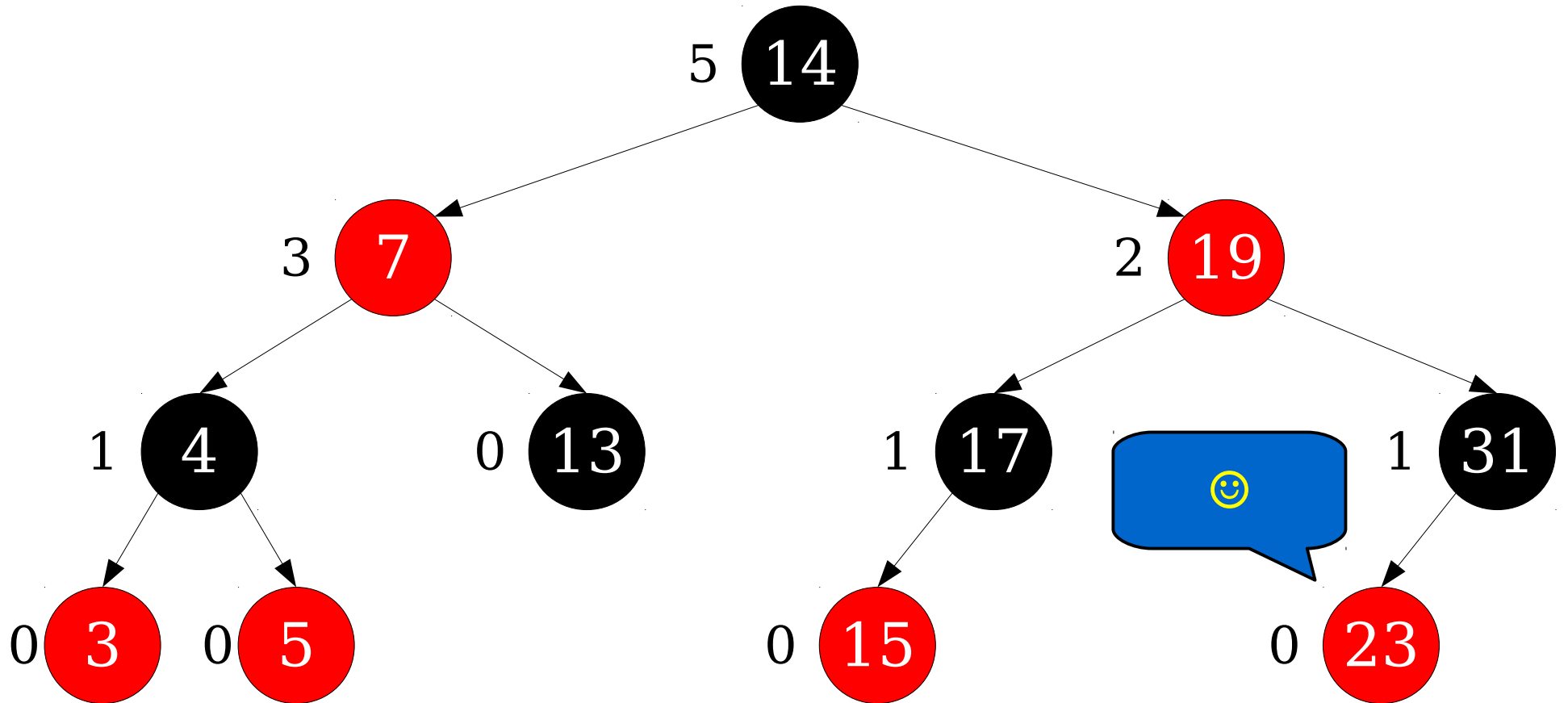
# Dynamic Selection



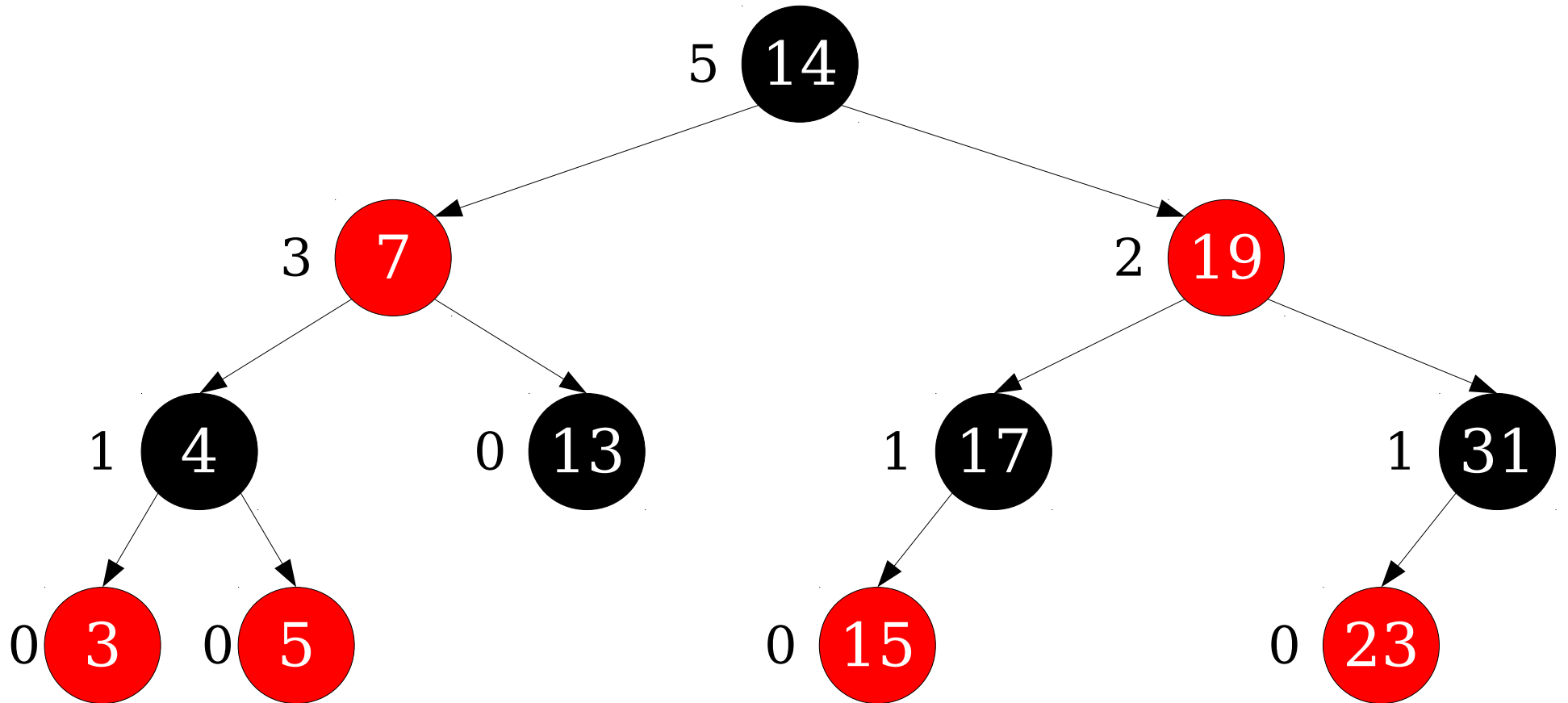
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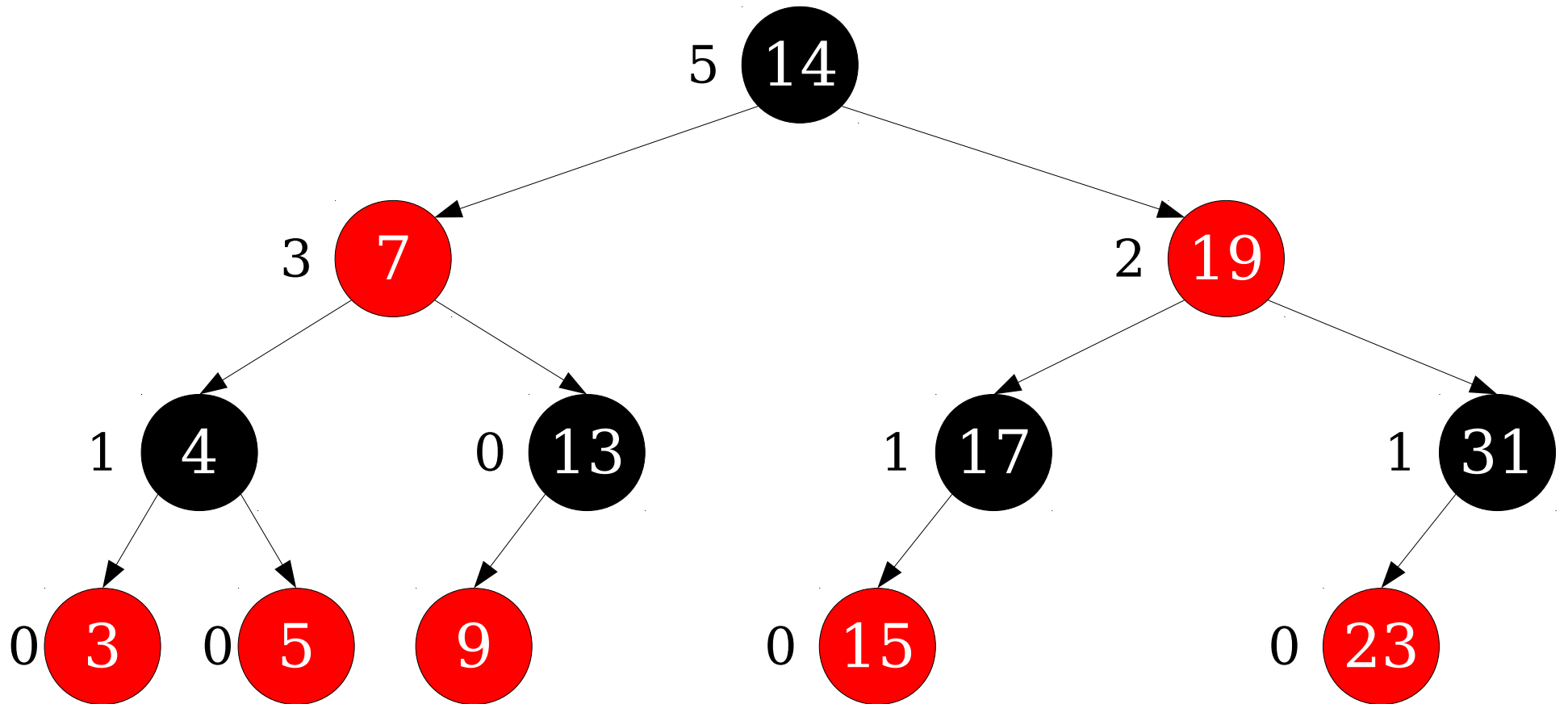
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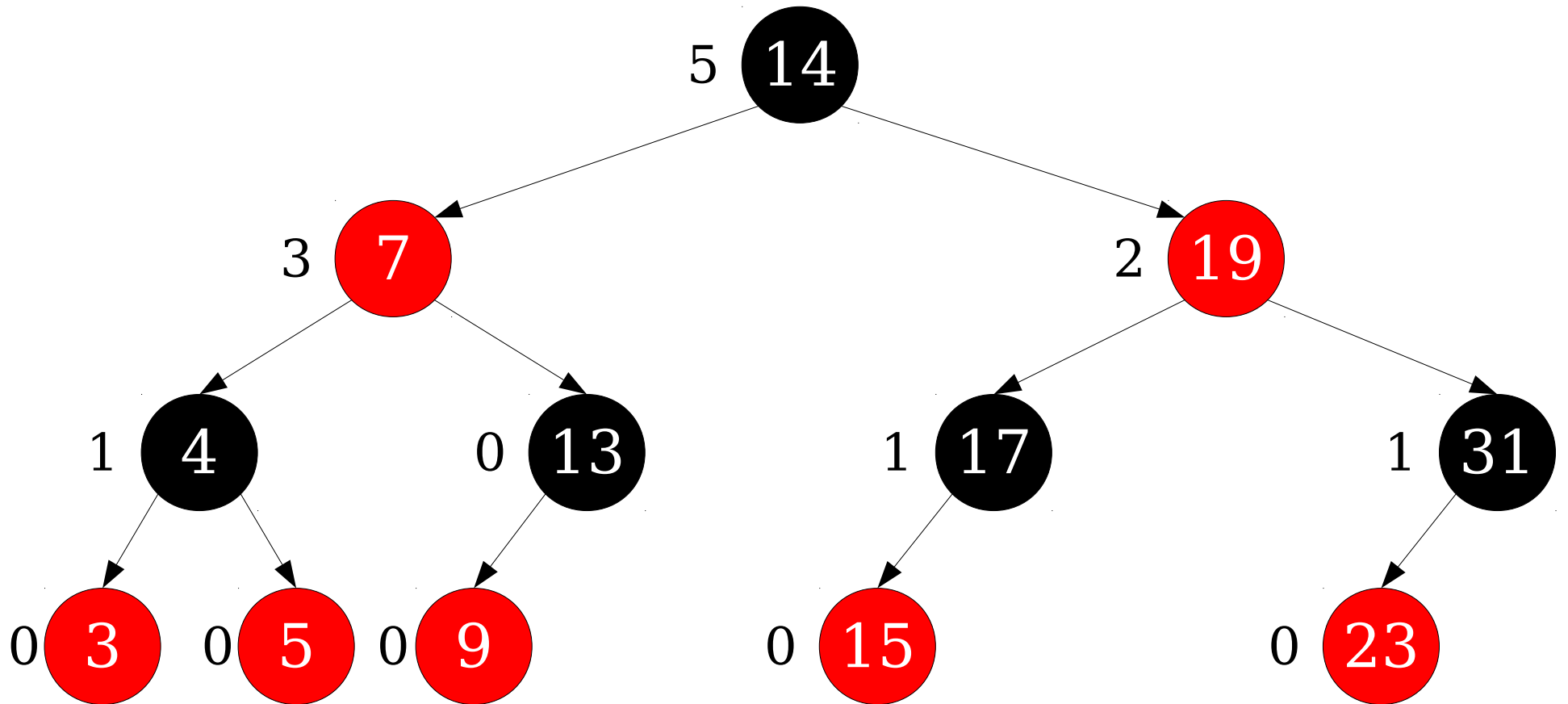
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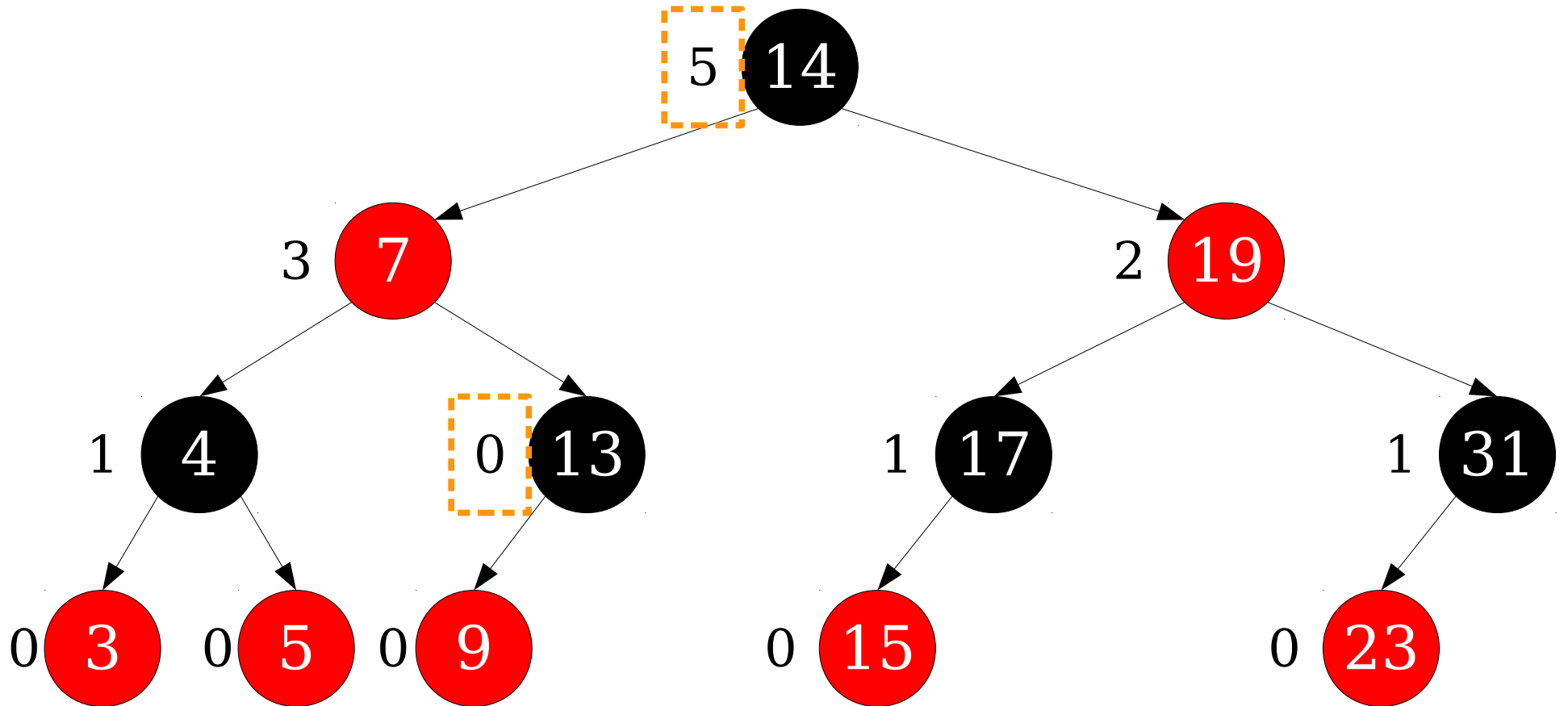
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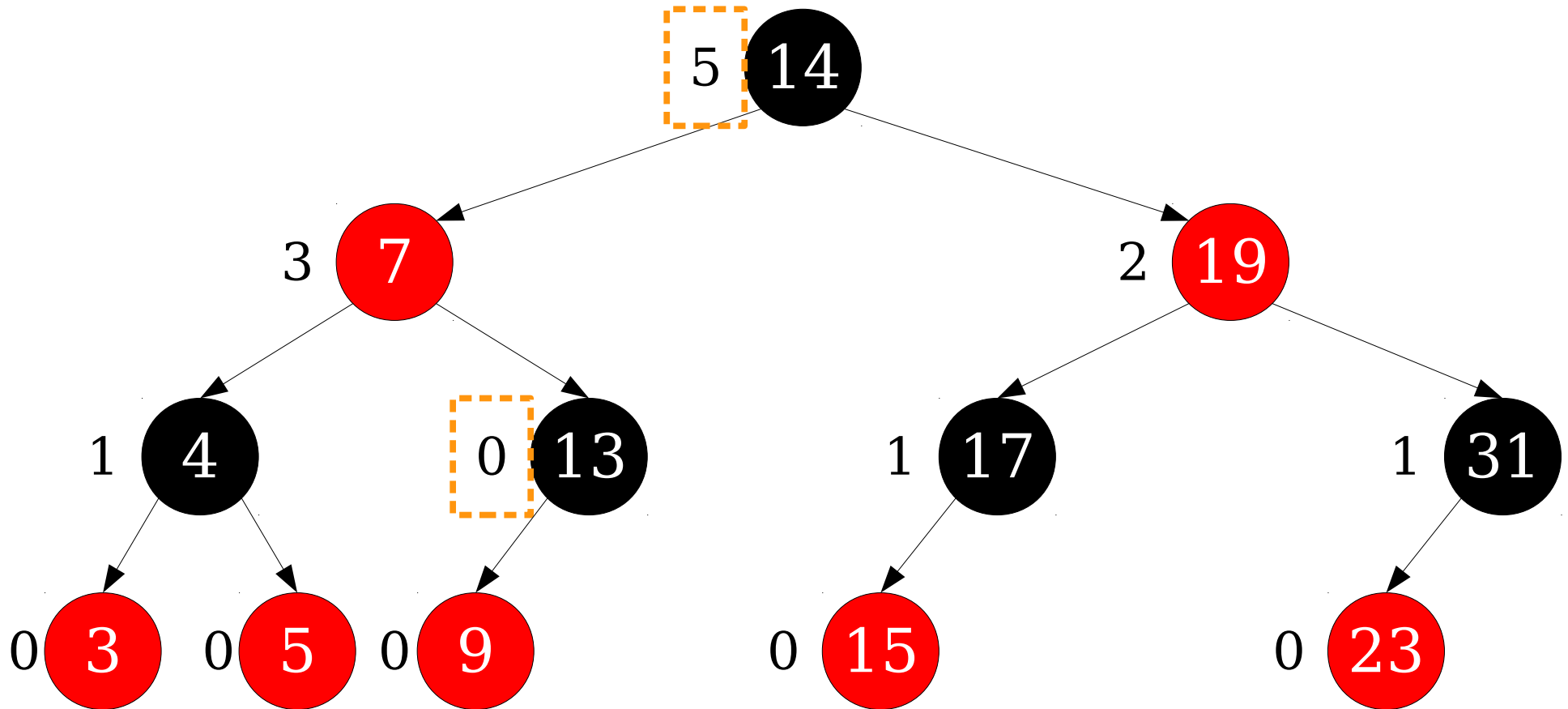
# Dynamic Selection



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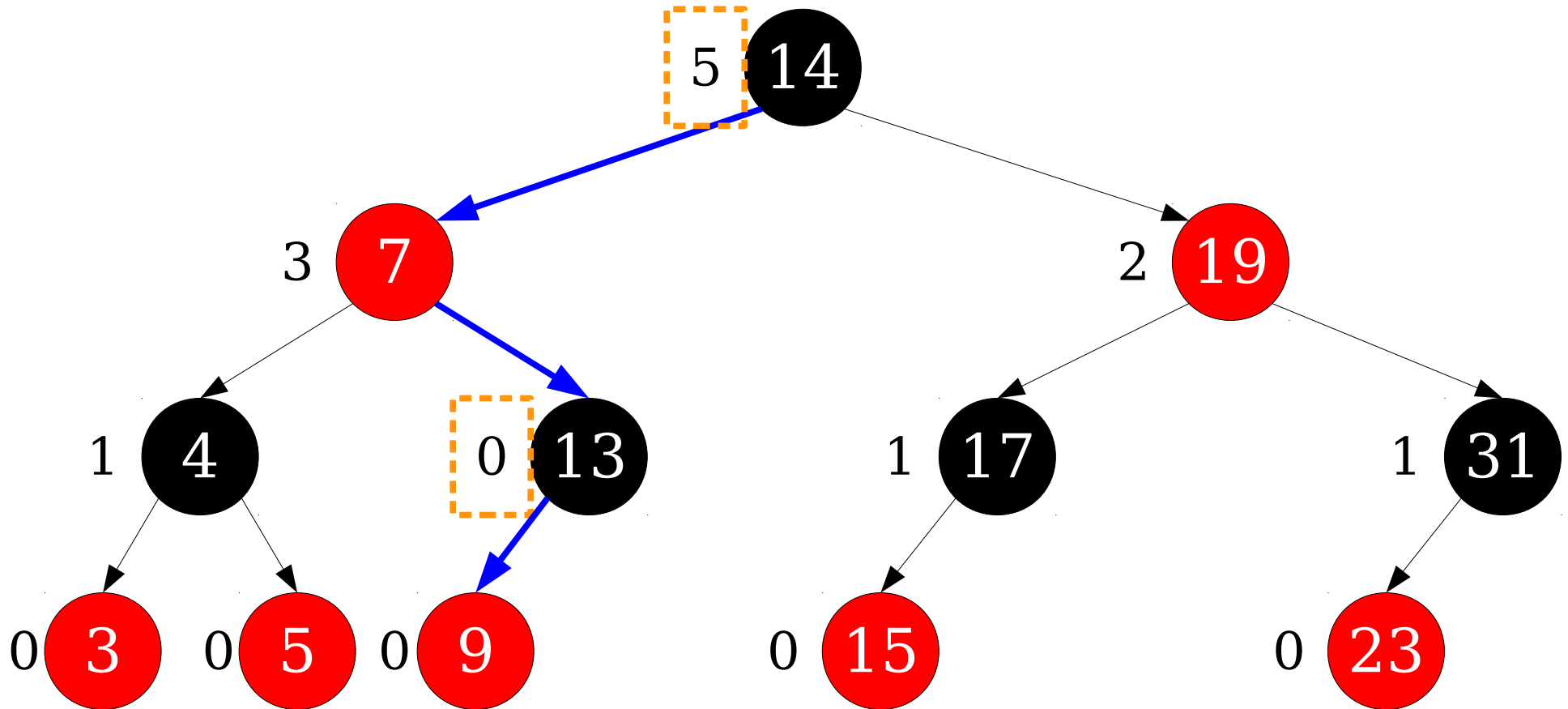
# Dynamic Selection



We only update values on nodes that gained a new key in their left subtree. And there are only  $O(\log n)$  of these!

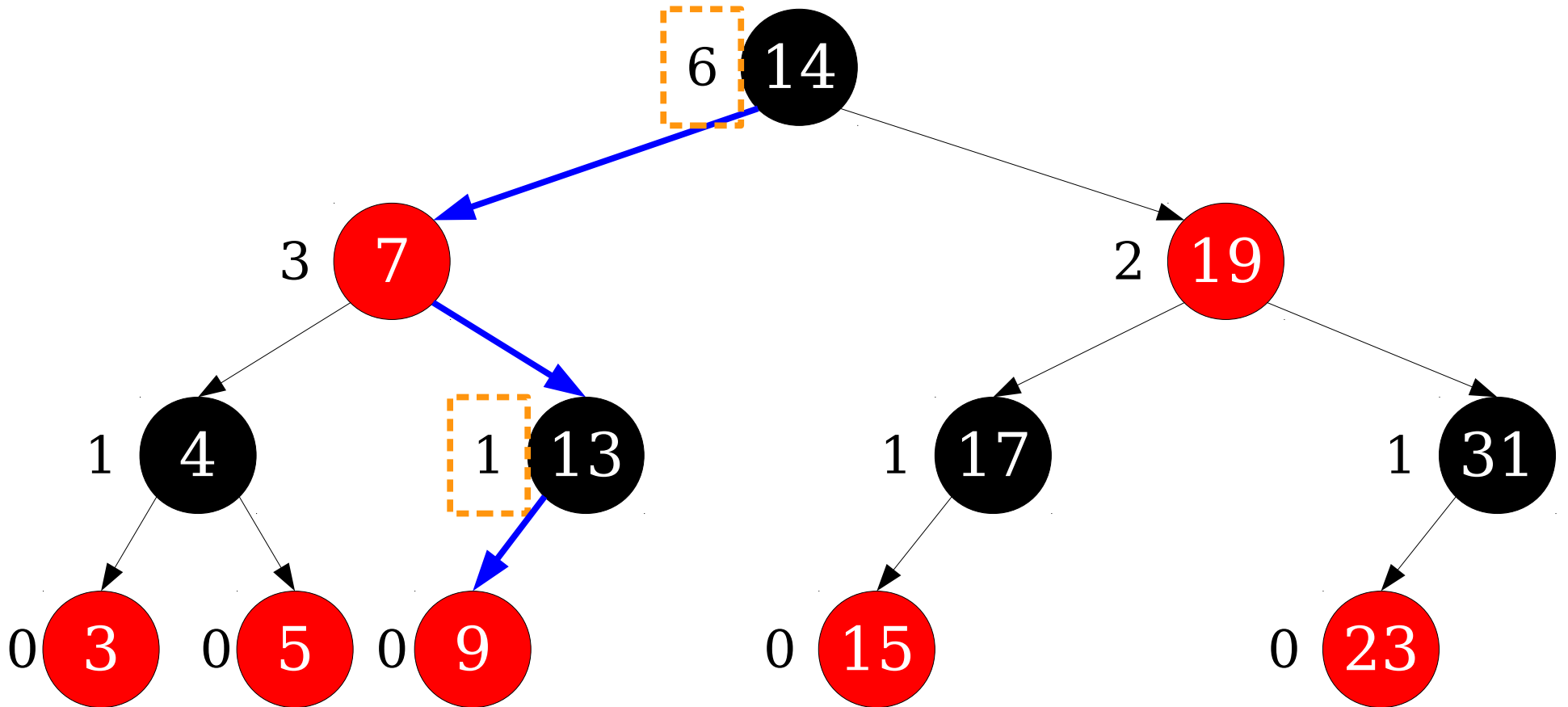


# Dynamic Selection



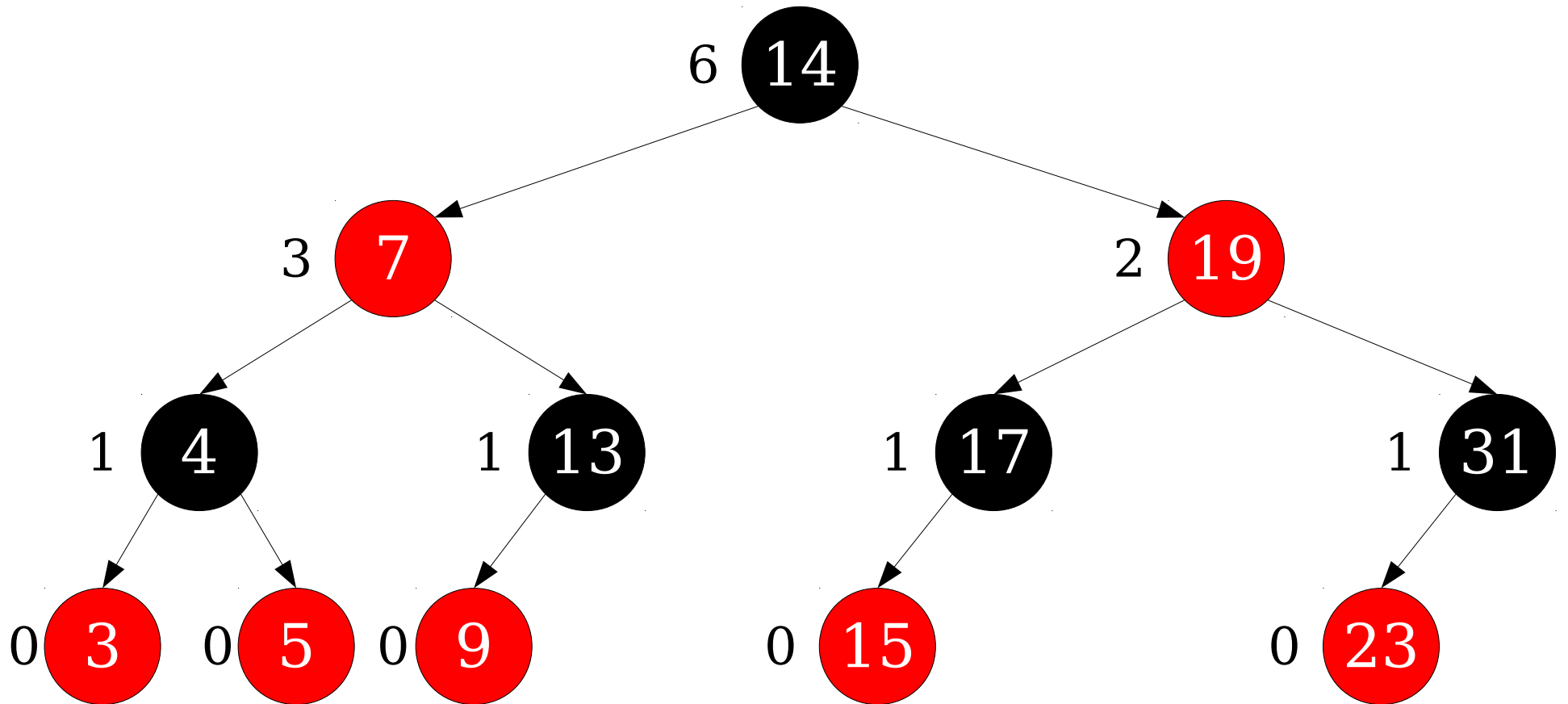
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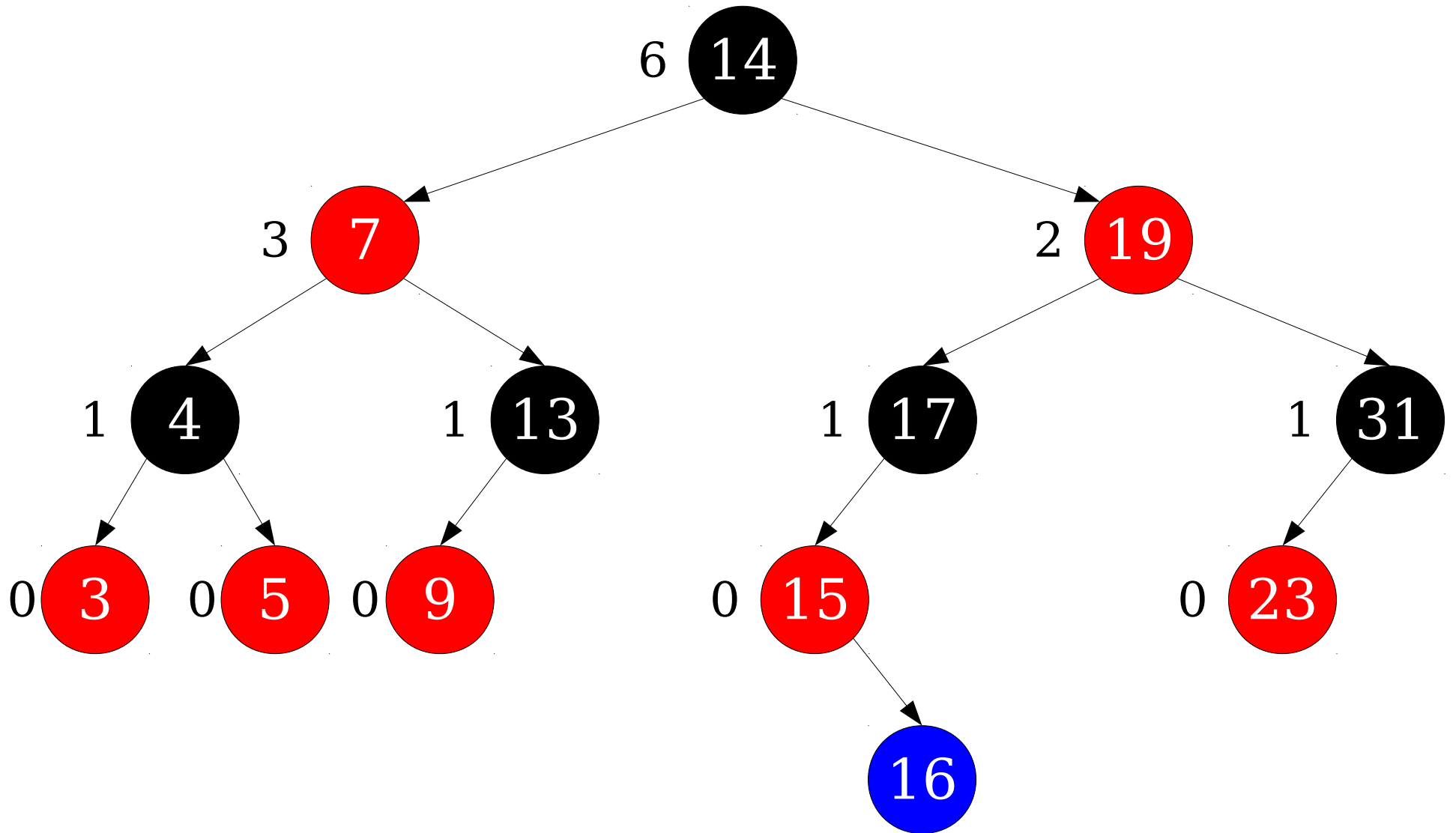


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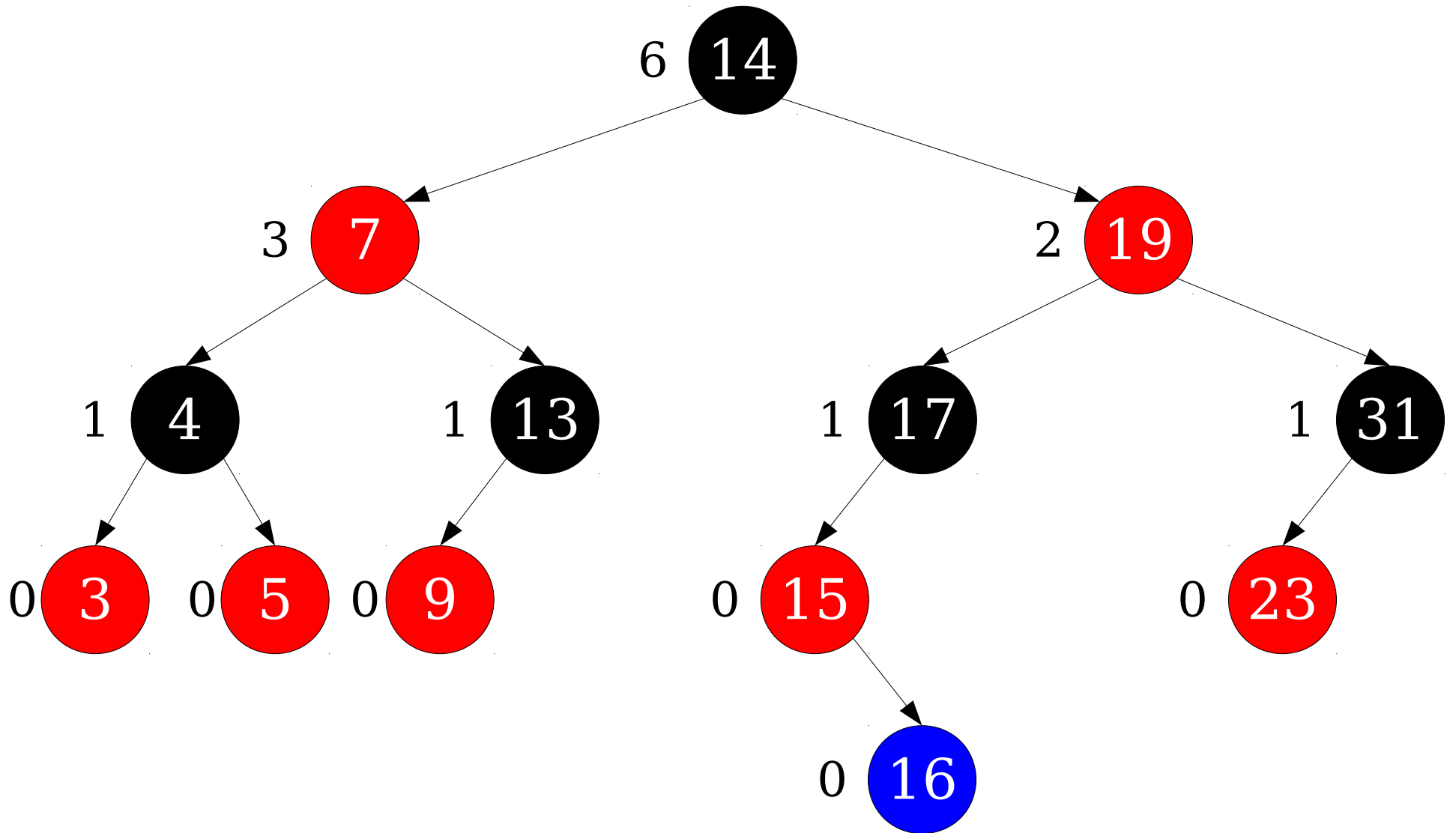
# Dynamic Selection



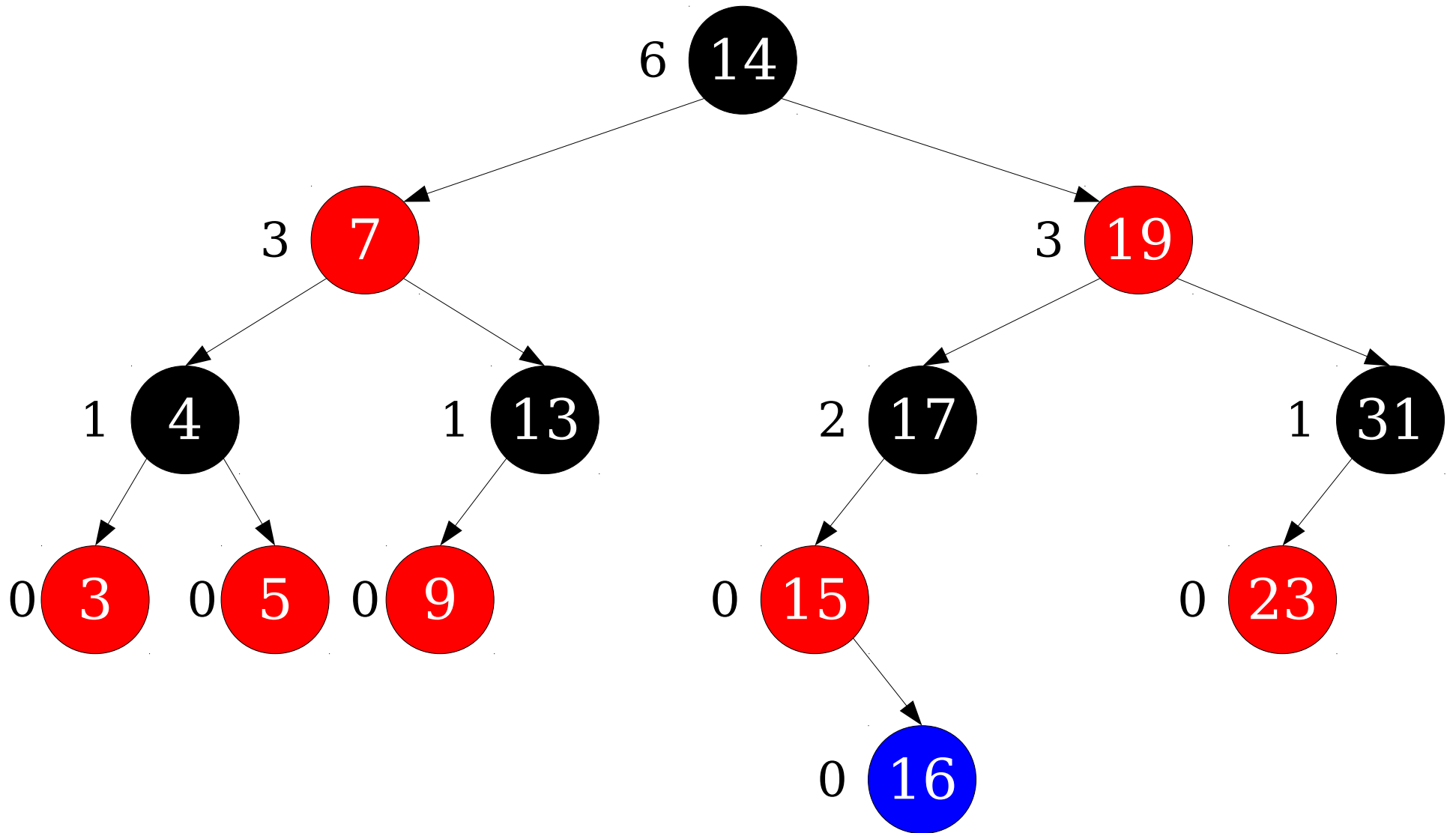
# Dynamic Selection



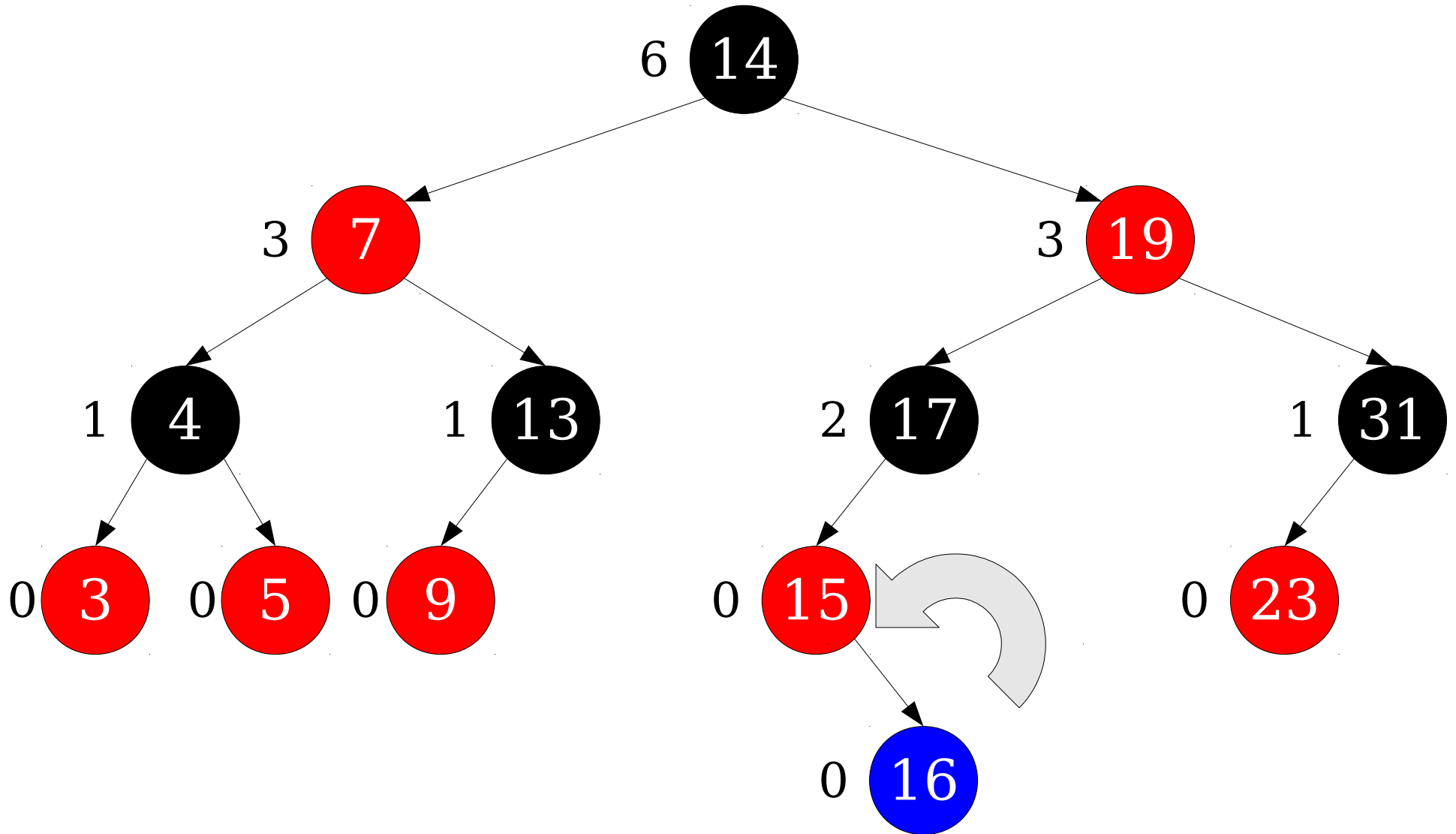
# Dynamic Selection



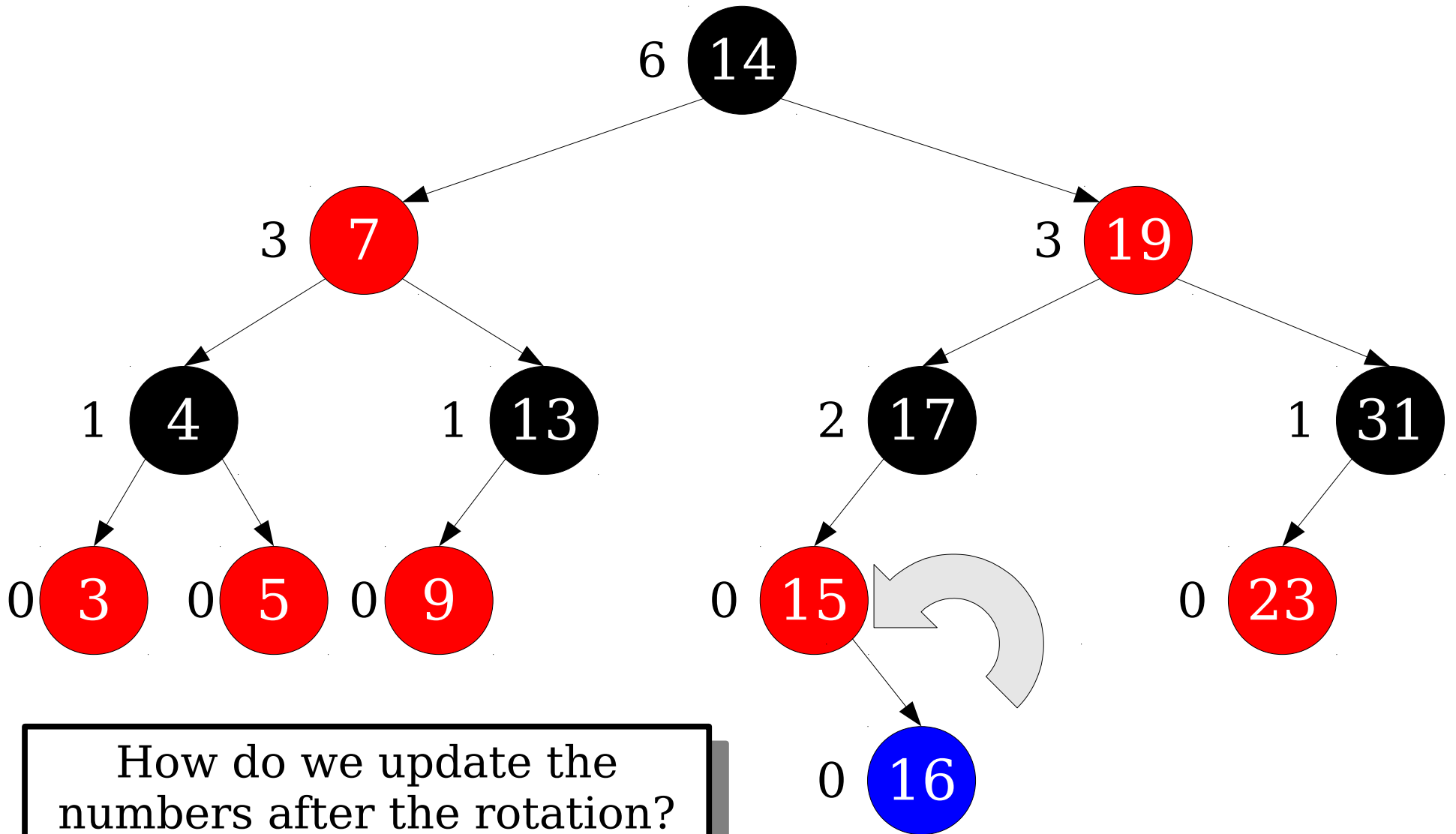
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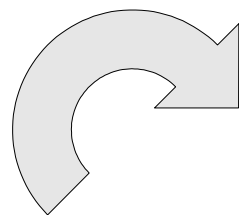
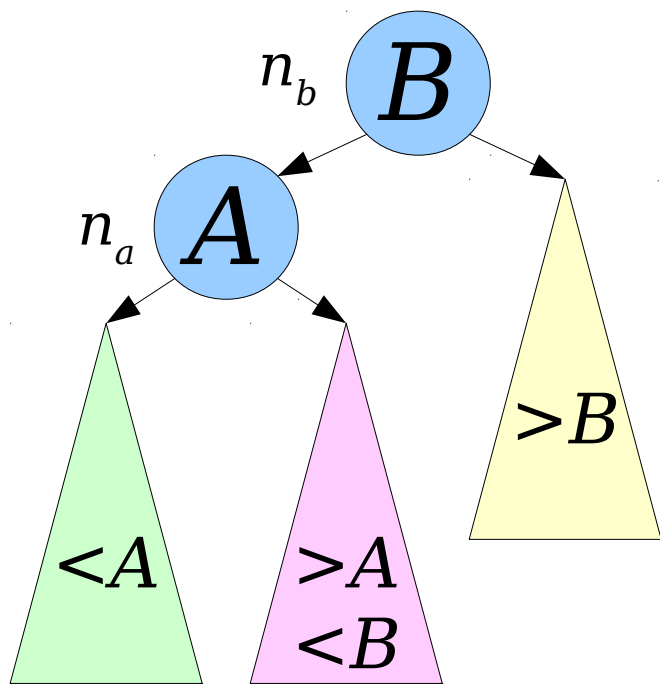
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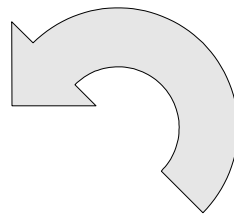
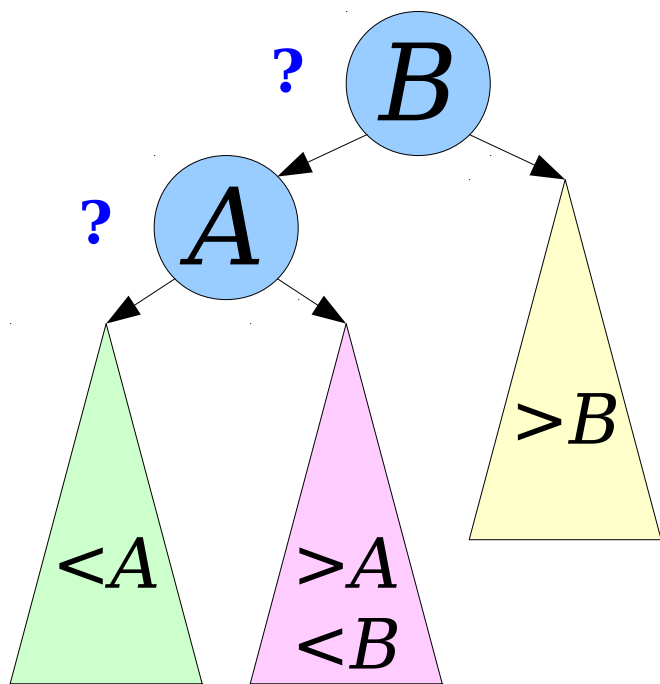
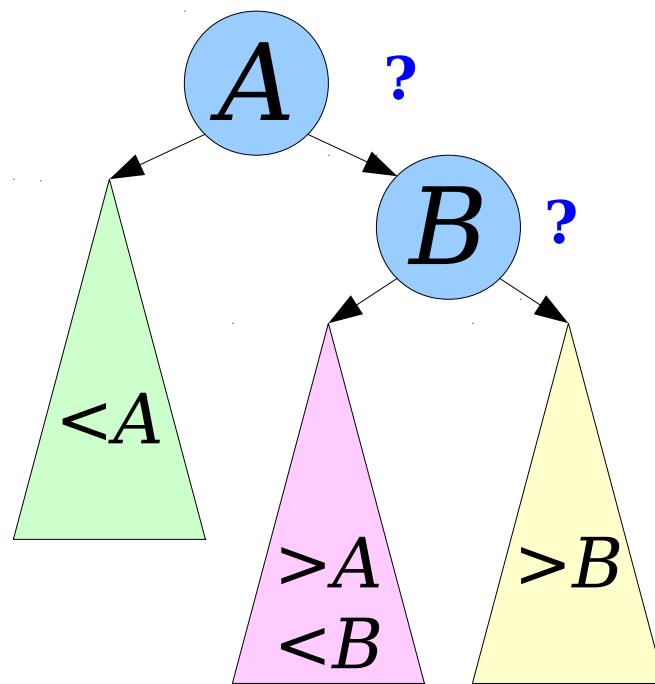
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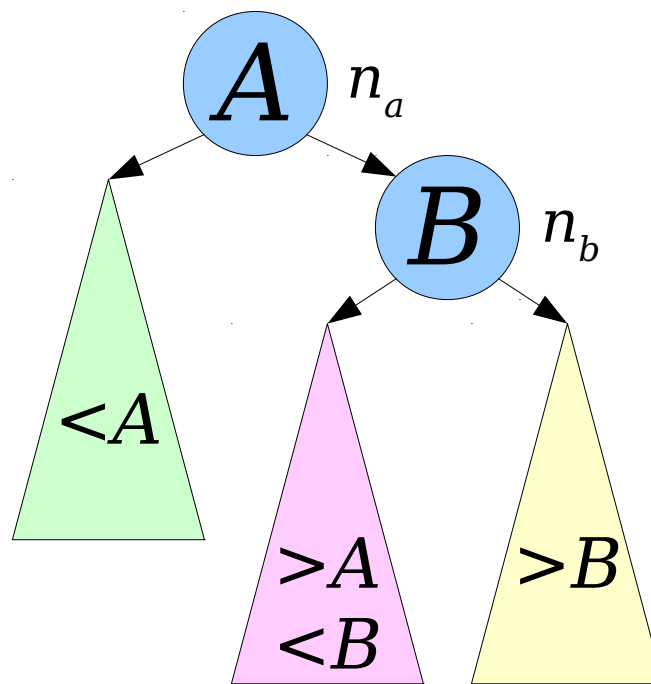


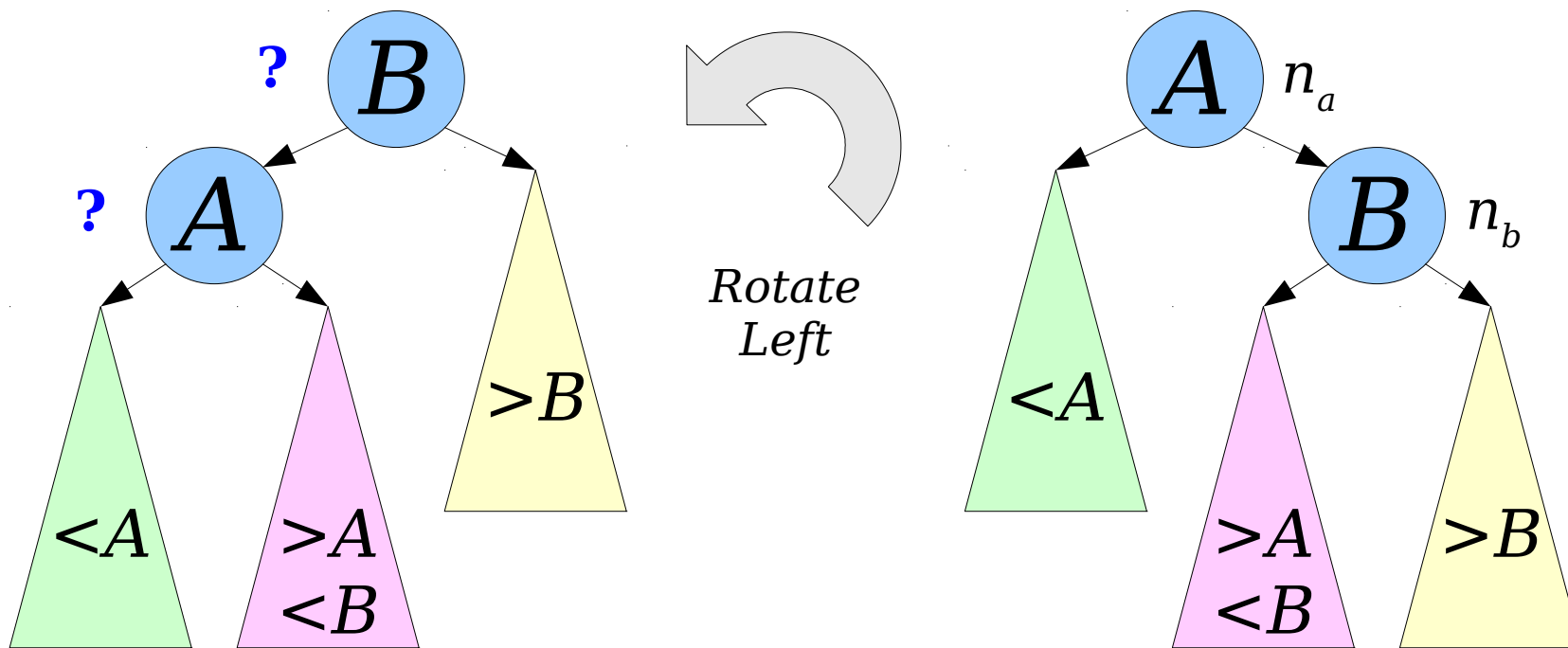
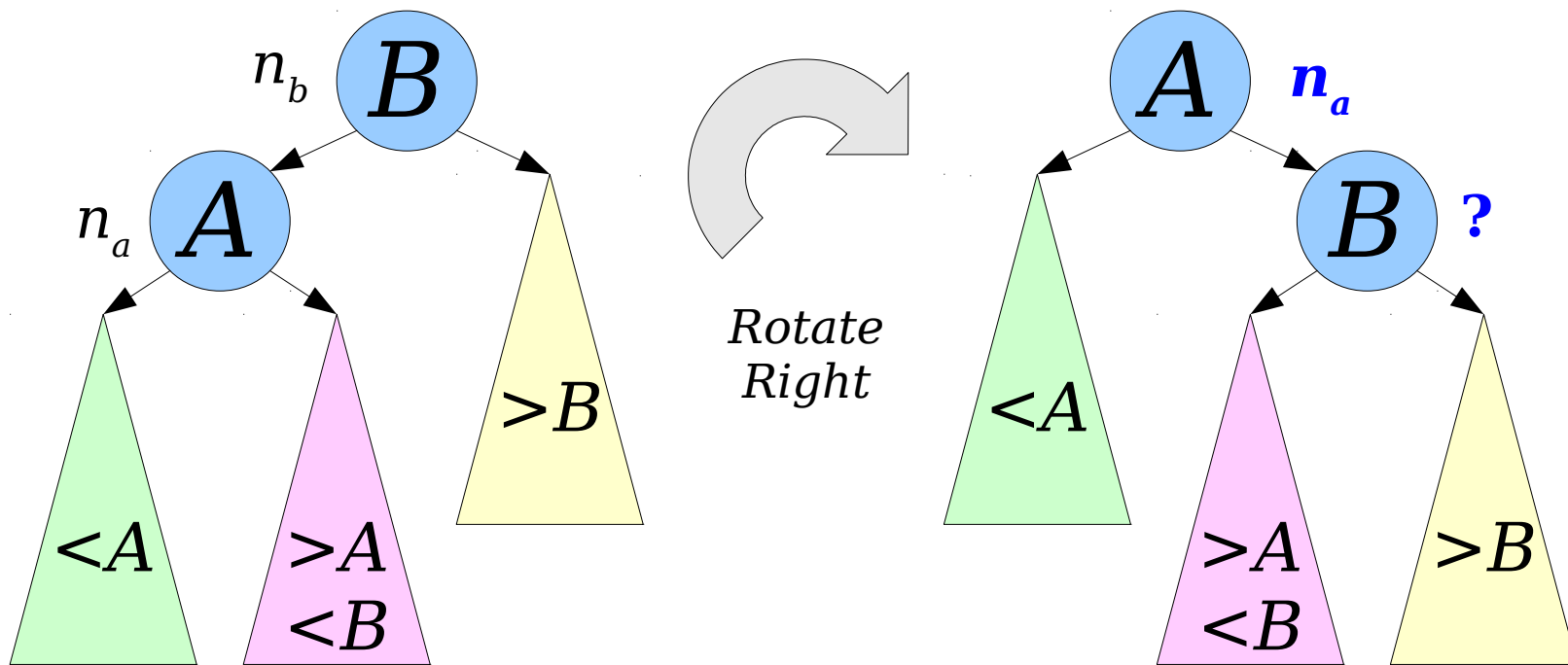


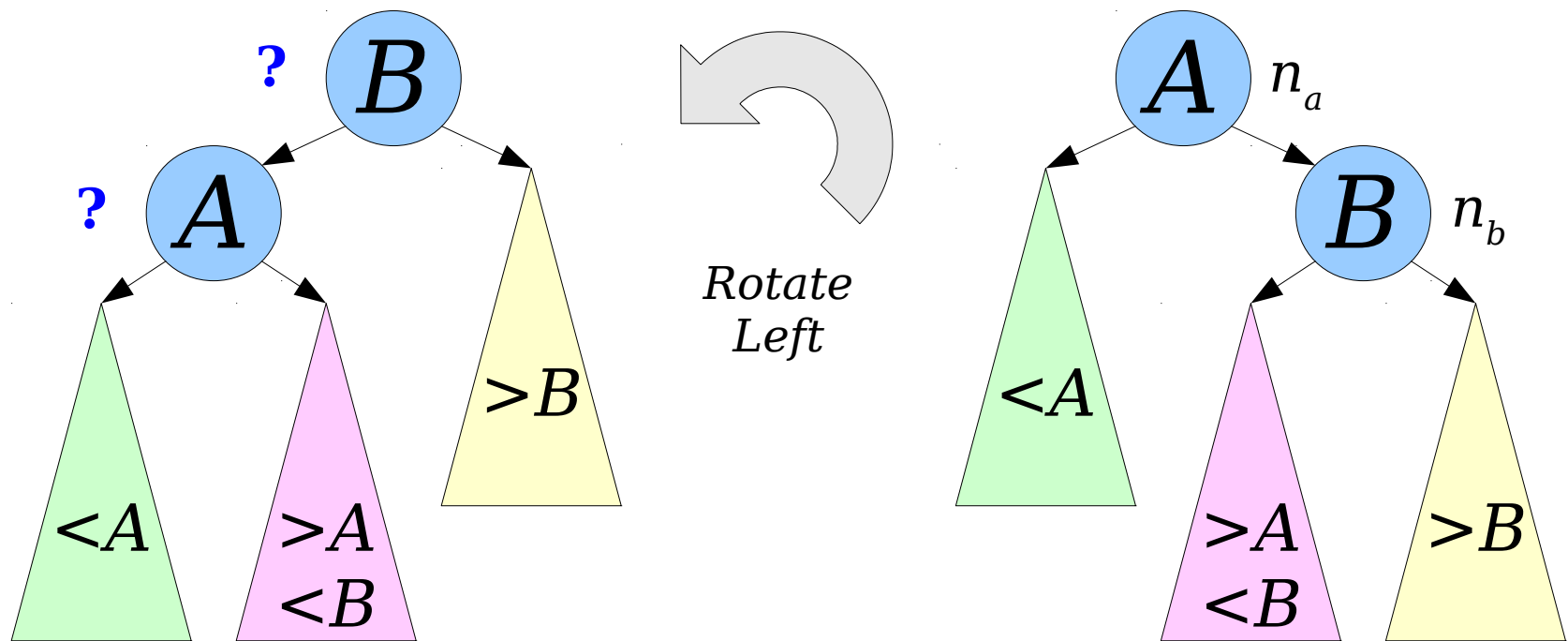
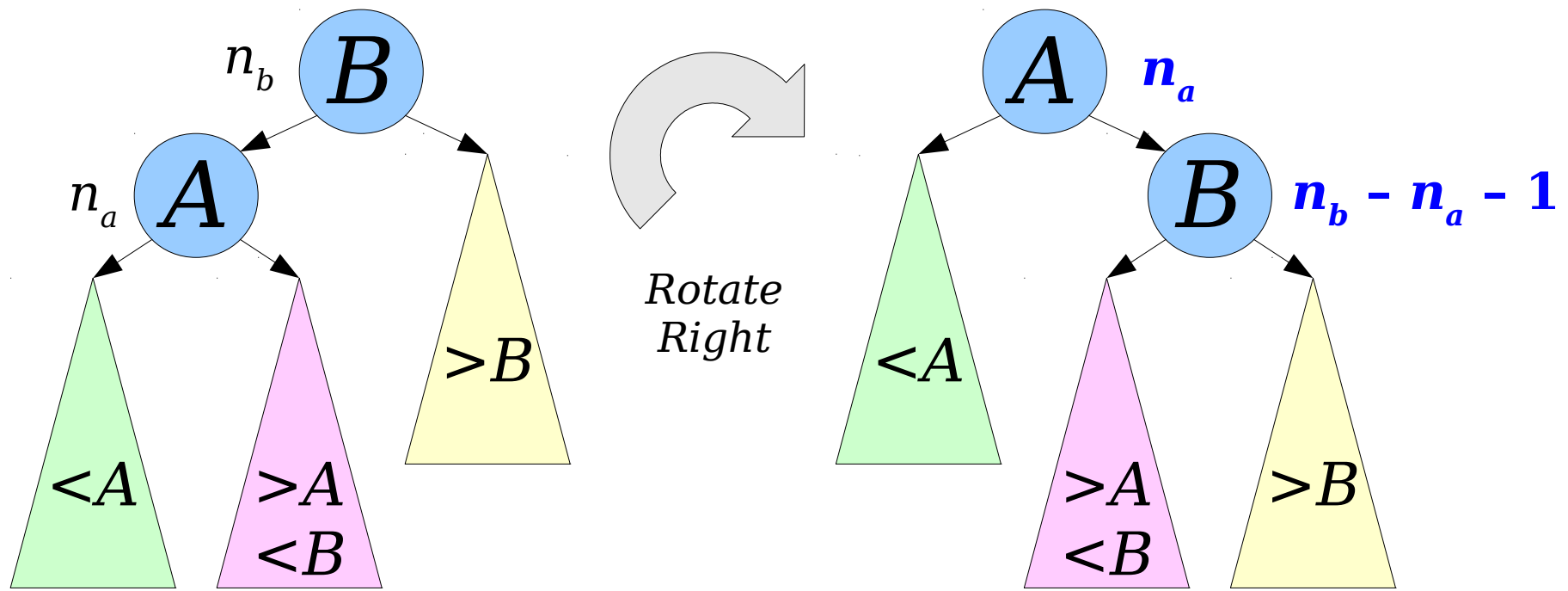
Rotate  
Right

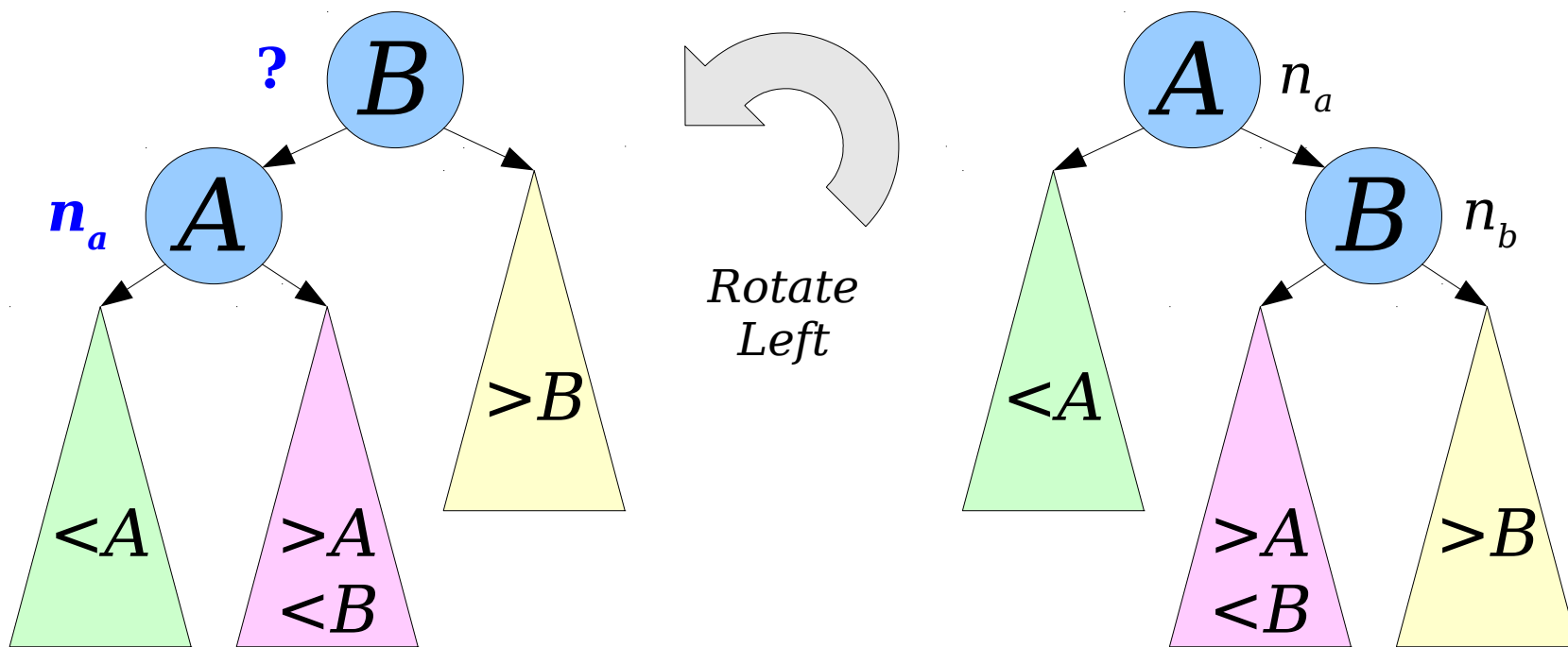
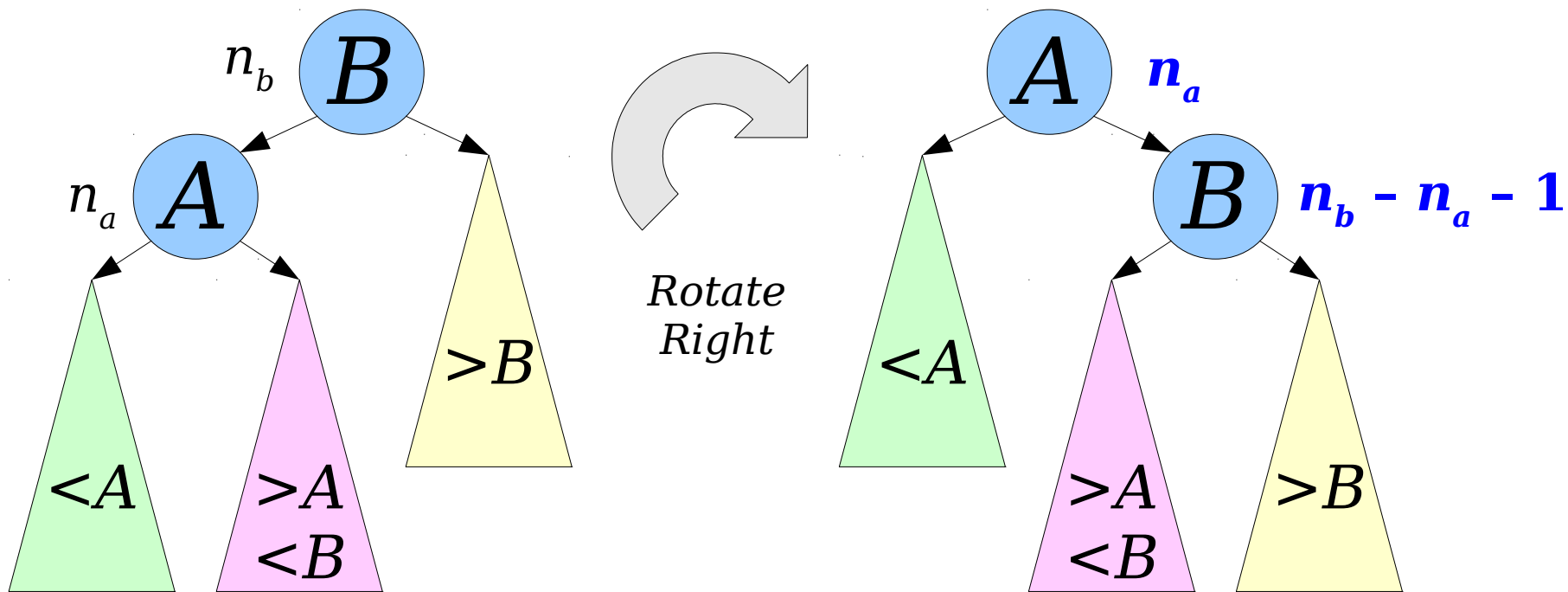


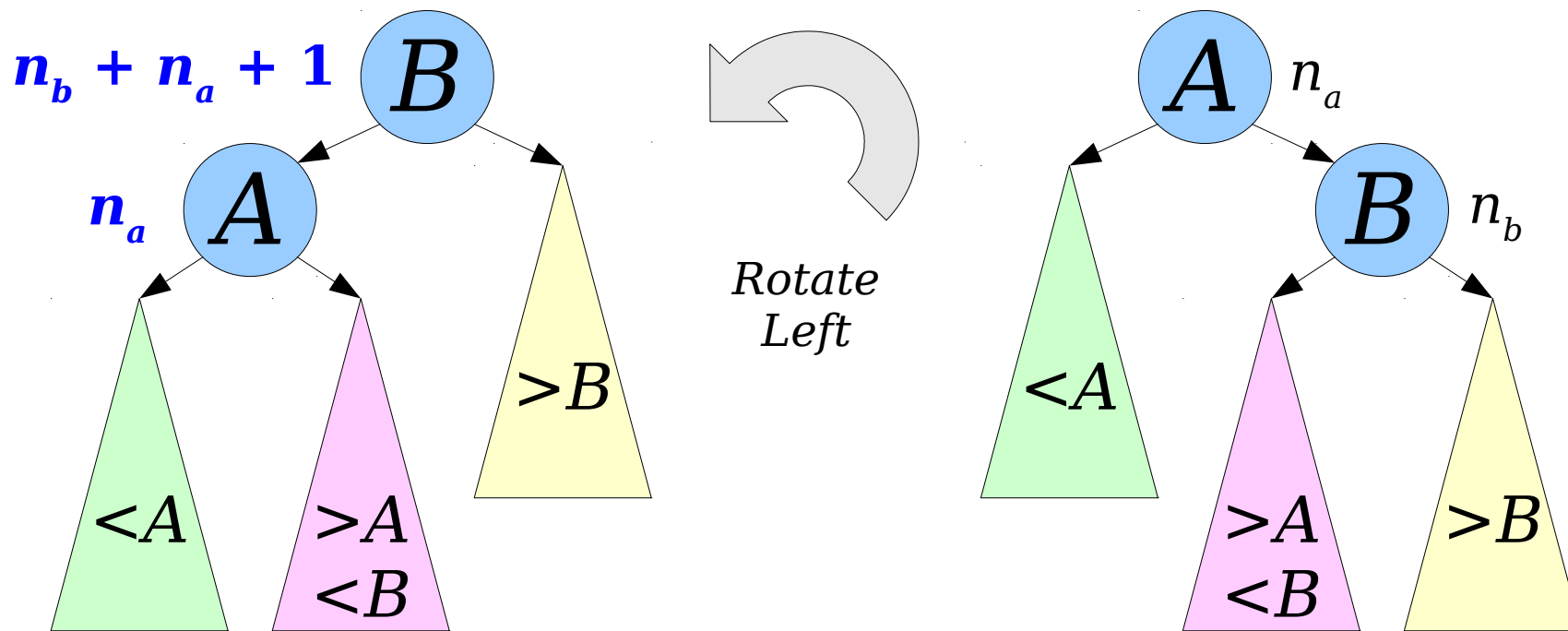
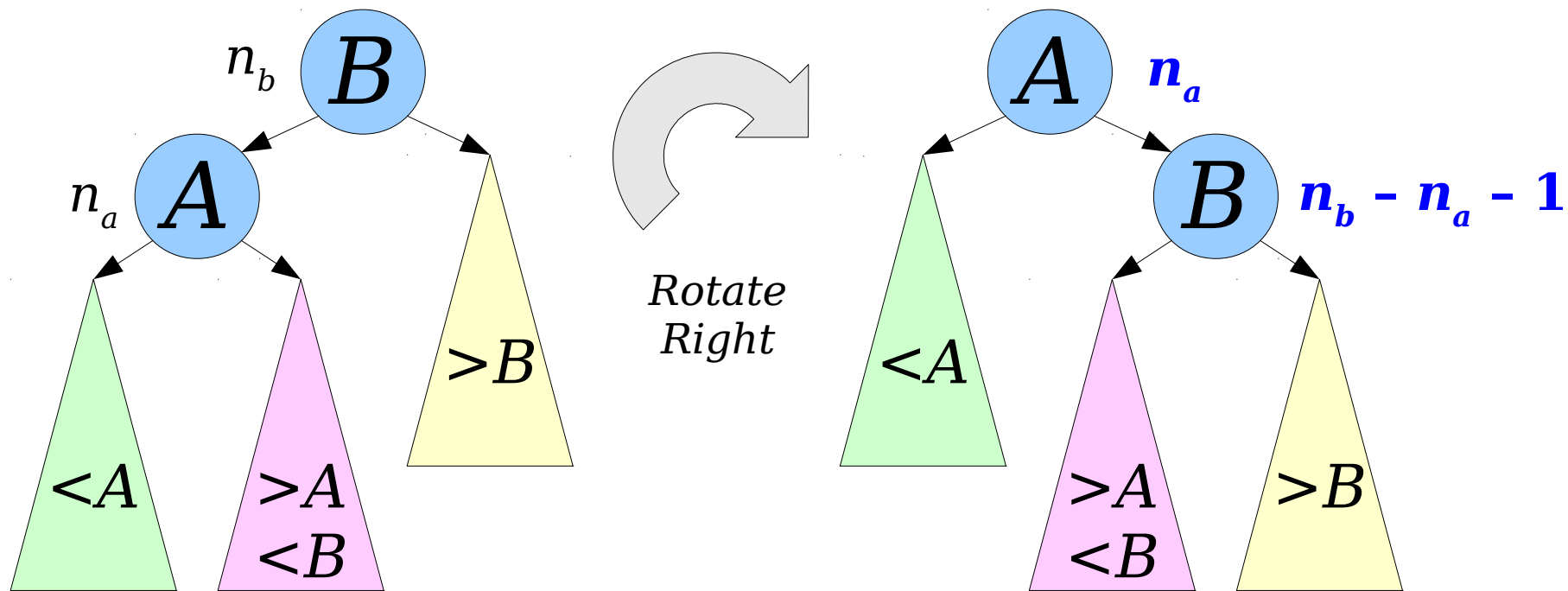
Rotate  
Left



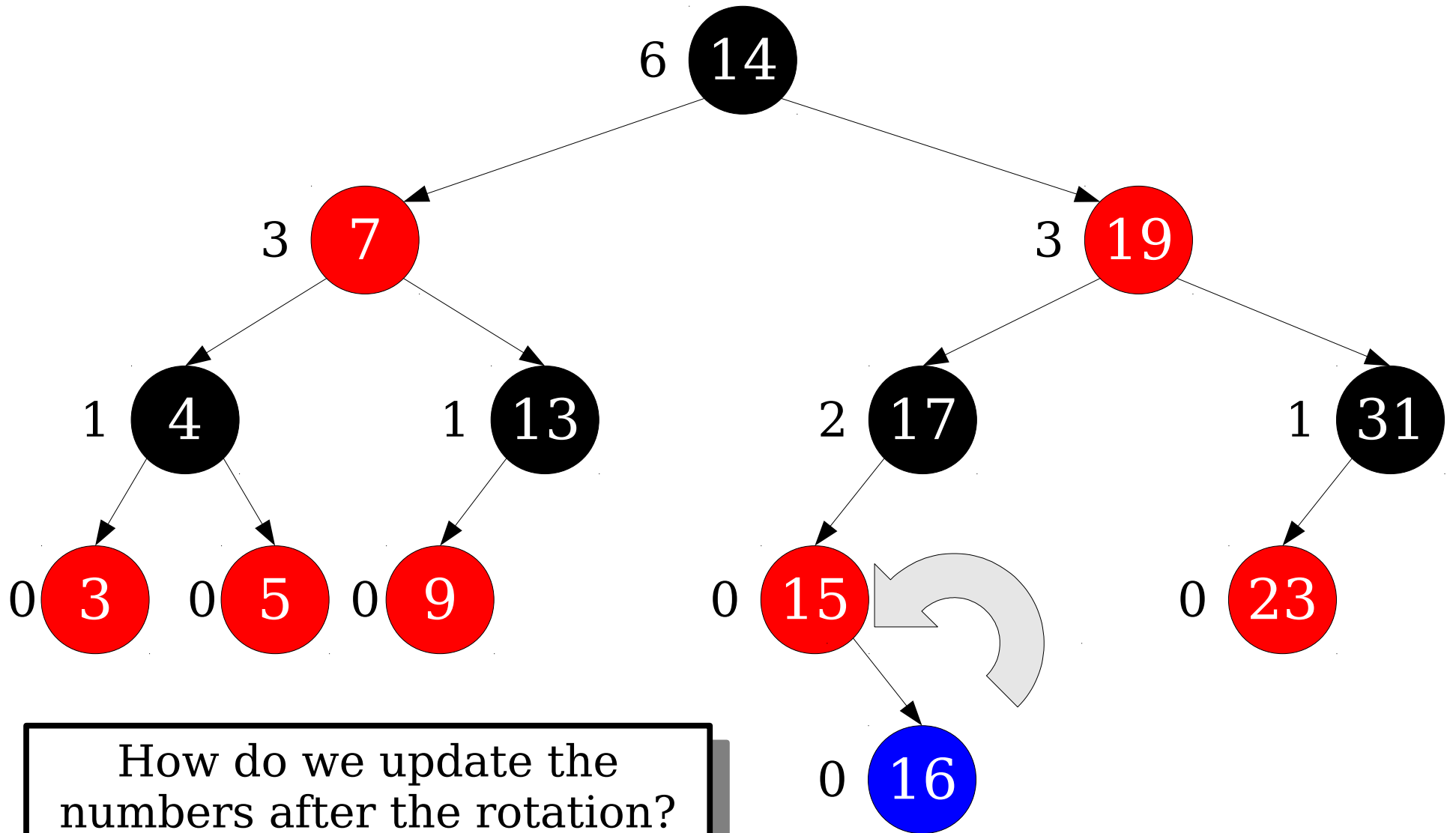




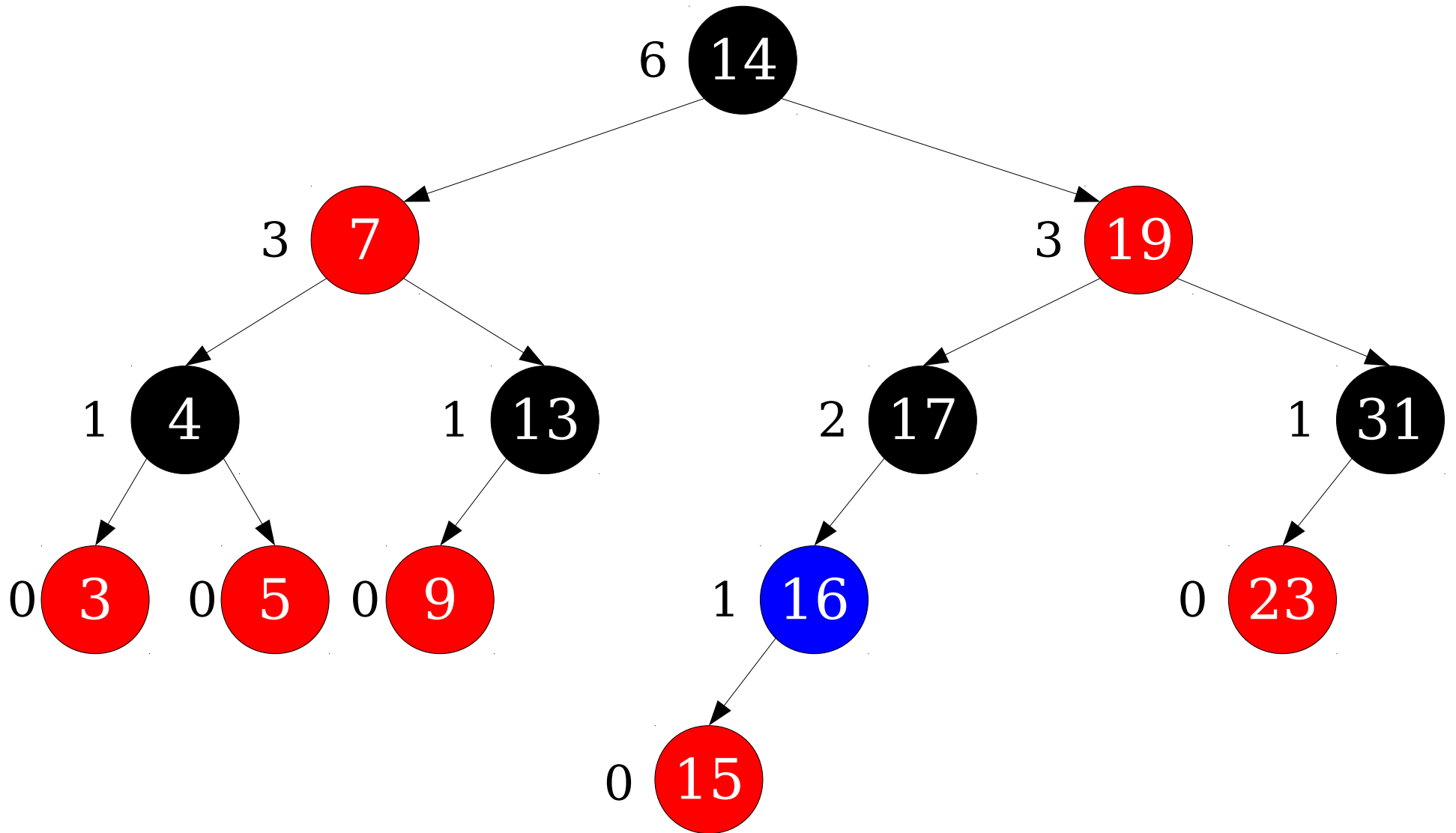




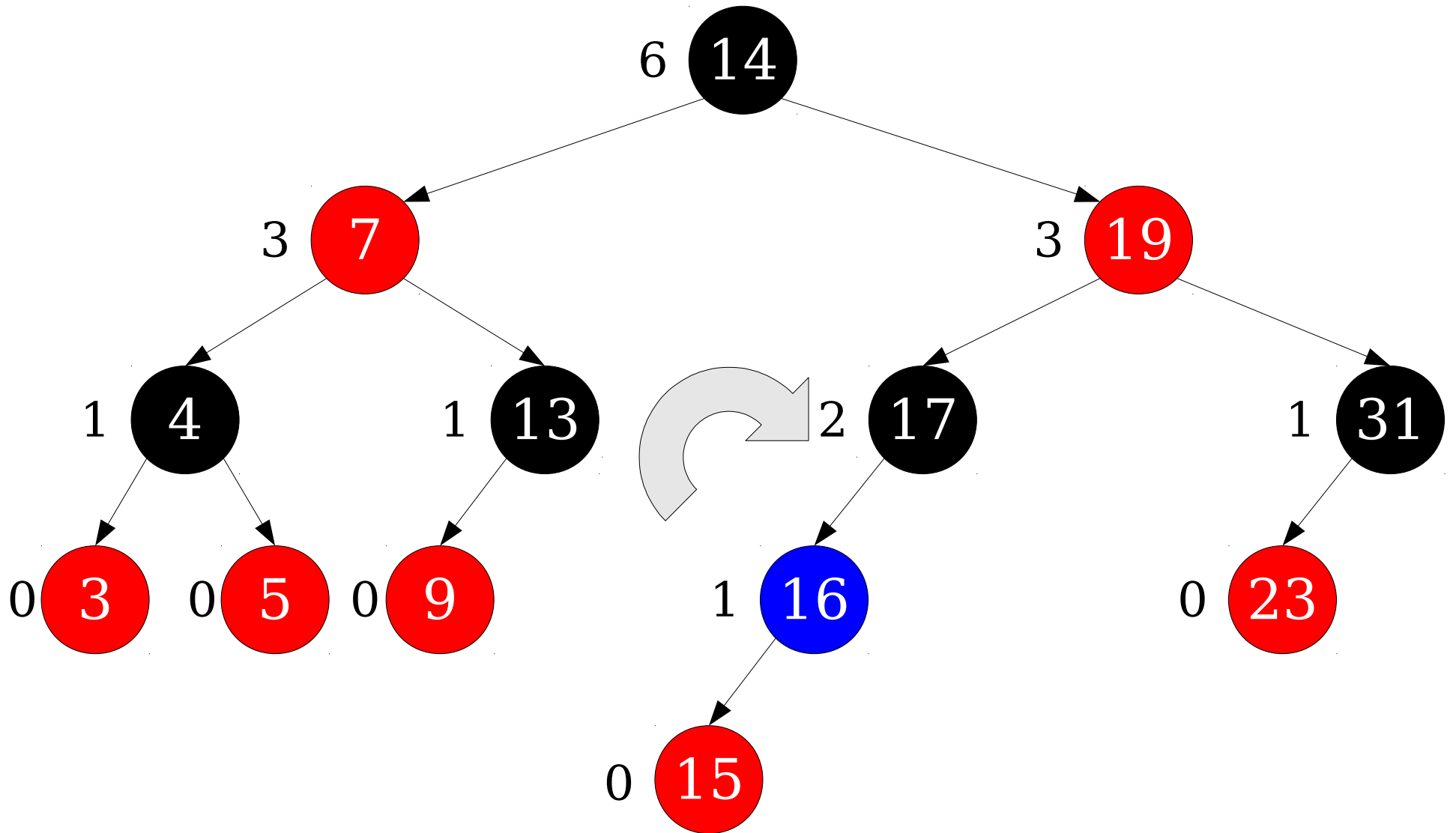
# Dynamic Selection



# Dynamic Selection

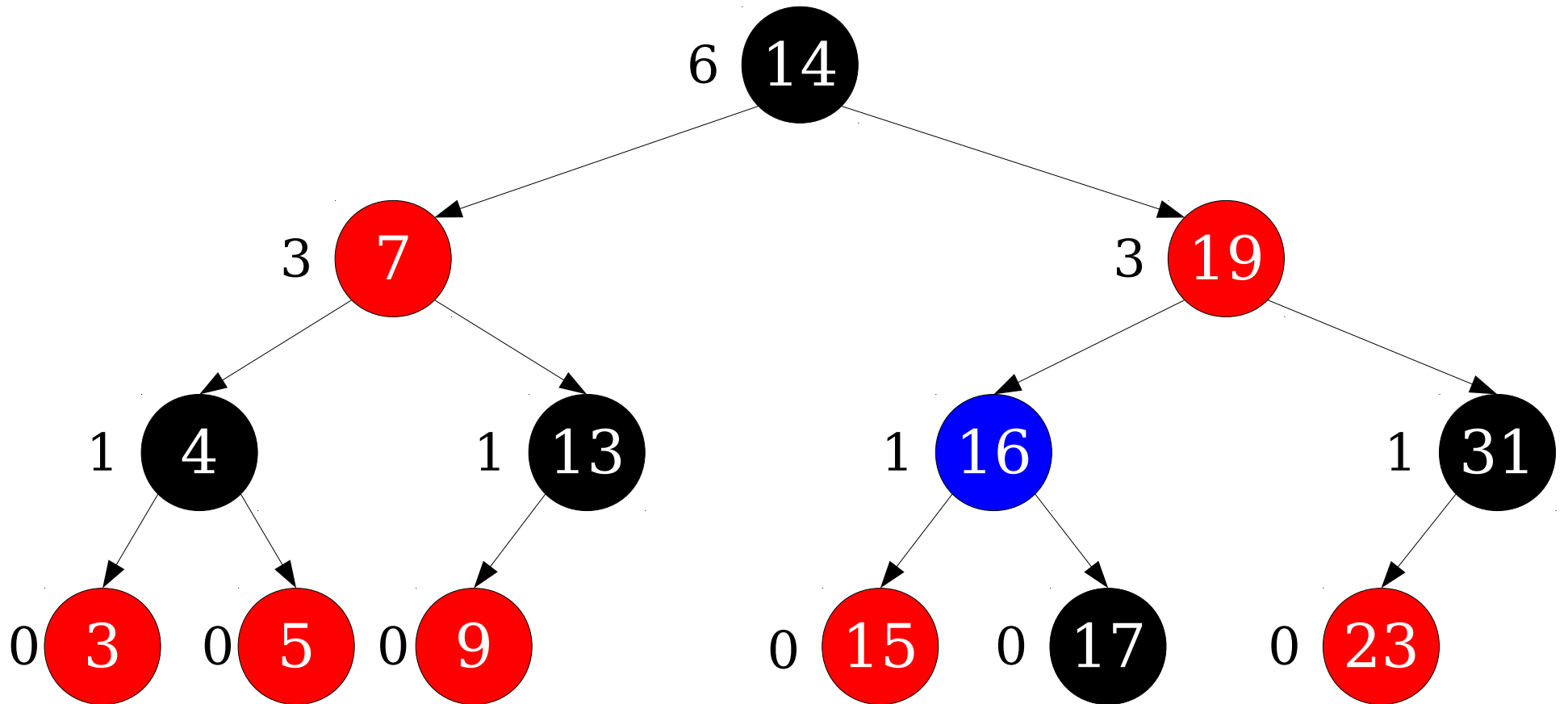


# Dynamic Selection

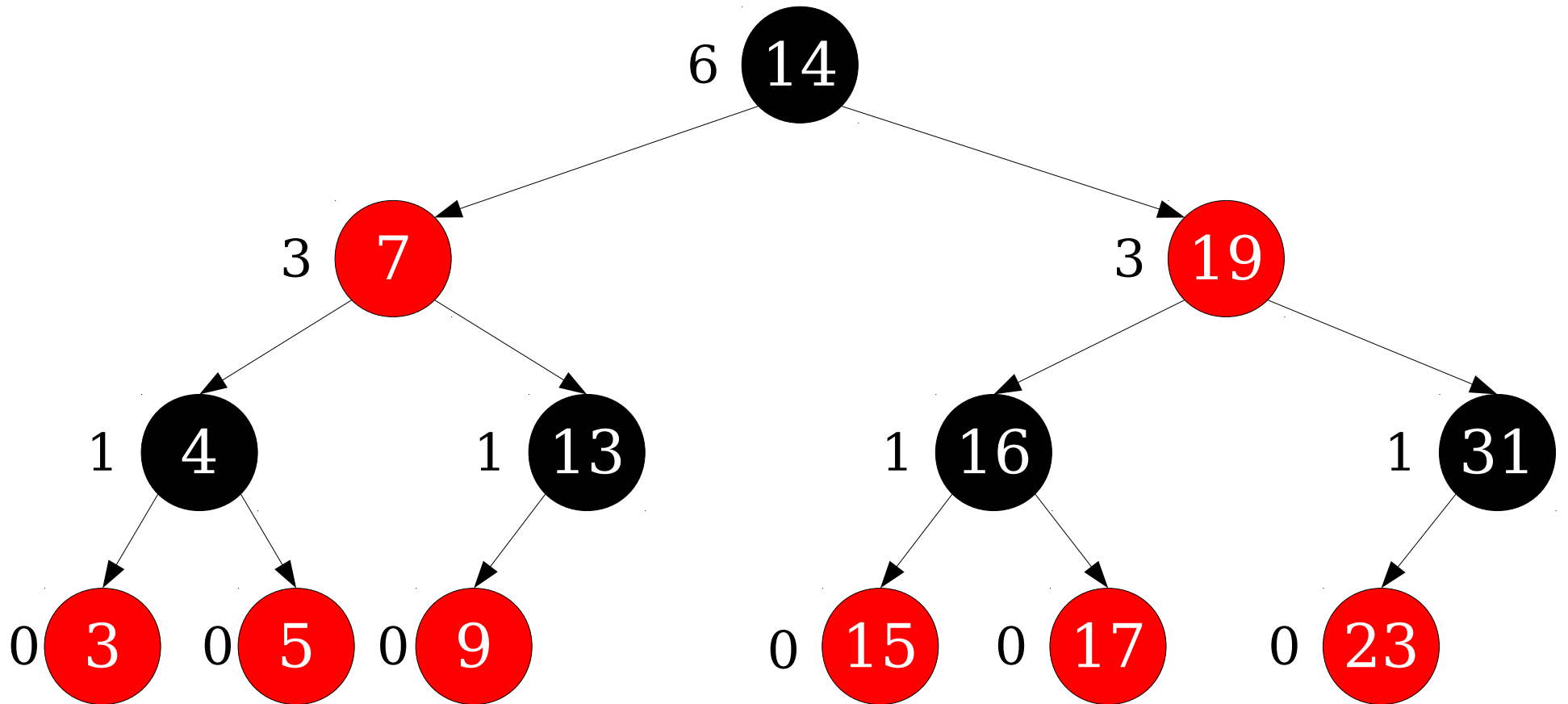




# Dynamic Selection



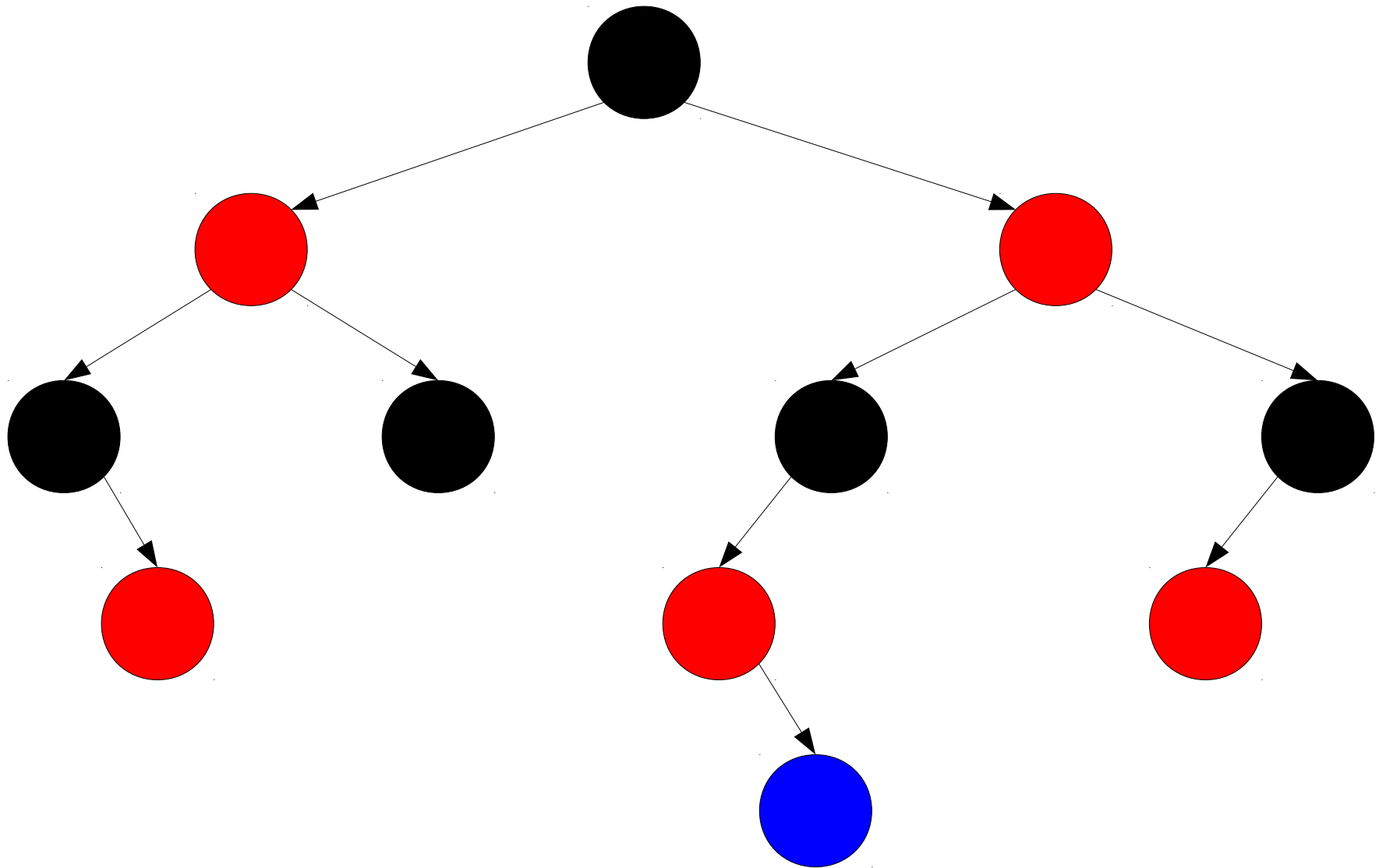
# Dynamic Selection



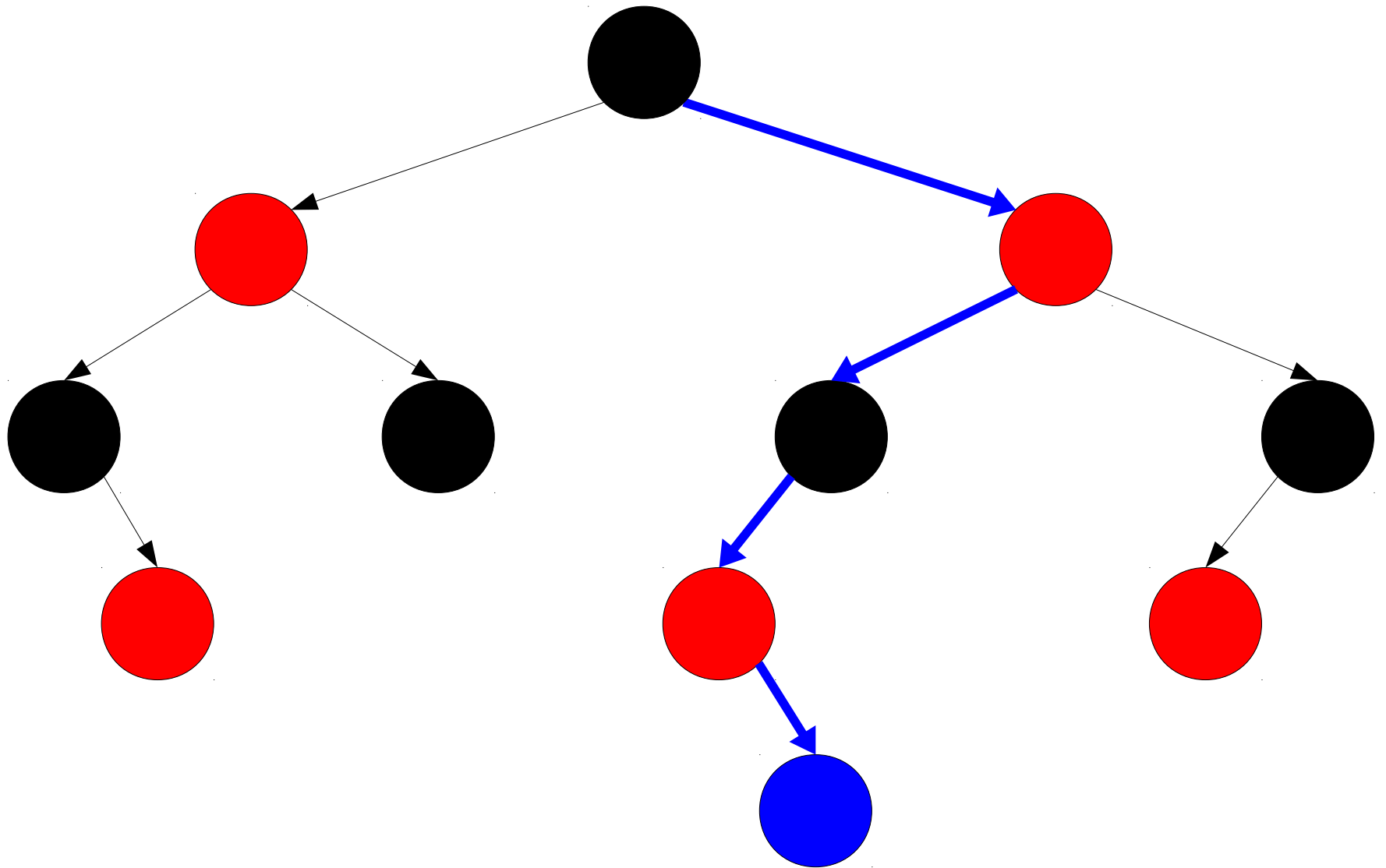
# Order Statistic Trees

- This modified red/black tree is called an ***order statistics tree***.
  - Start with a red/black tree.
  - Tag each node with the number of nodes in its left subtree.
  - Use the preceding update rules to preserve values during rotations.
  - Propagate other changes up to the root of the tree.
- Only  $O(\log n)$  values must be updated on an insertion or deletion and each can be updated in time  $O(1)$ .
- Supports all BST operations plus ***select*** (find  $k$ th order statistic) and ***rank*** (given a key, report its order statistic) in time  $O(\log n)$ .

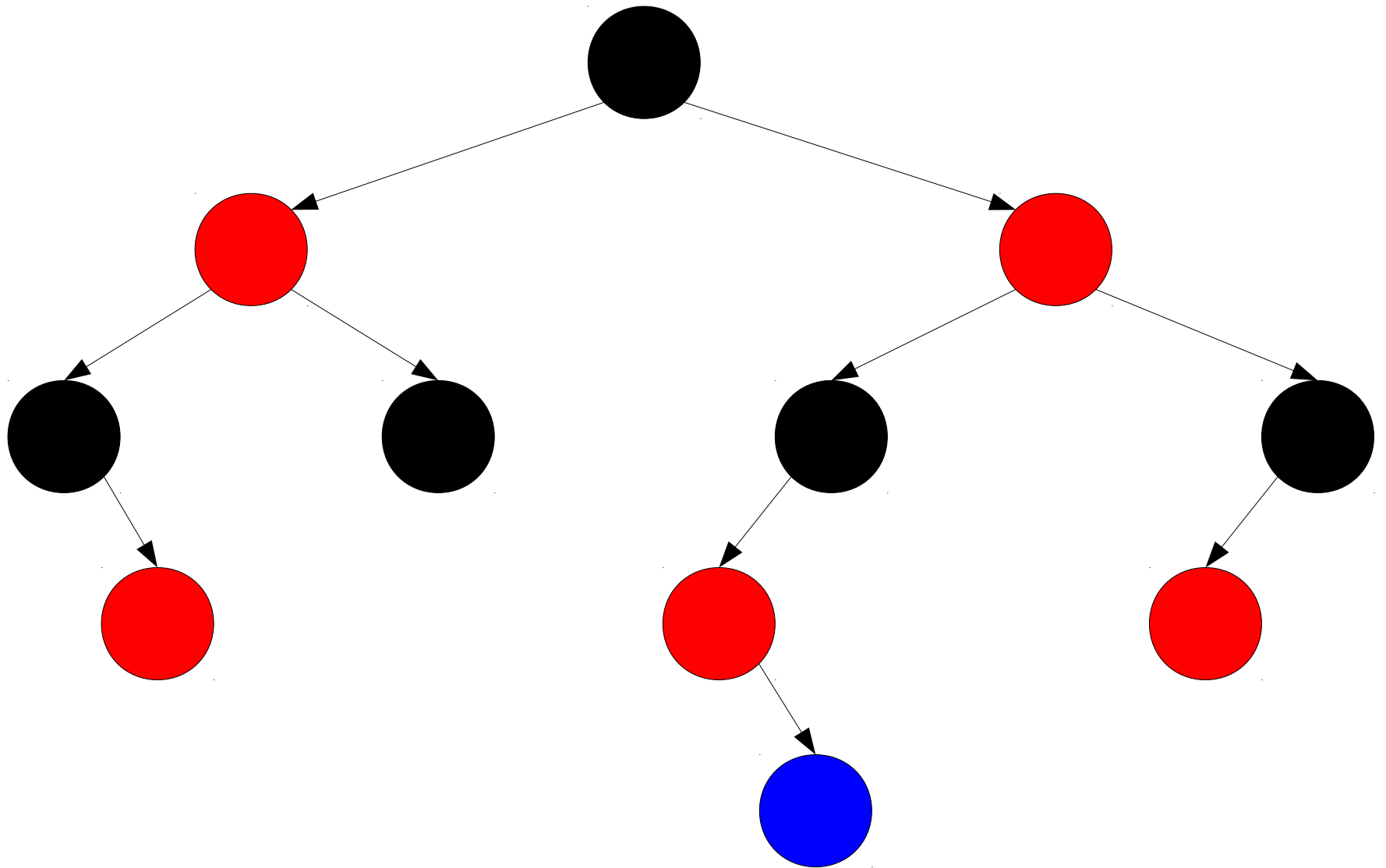
# Generalizing our Idea



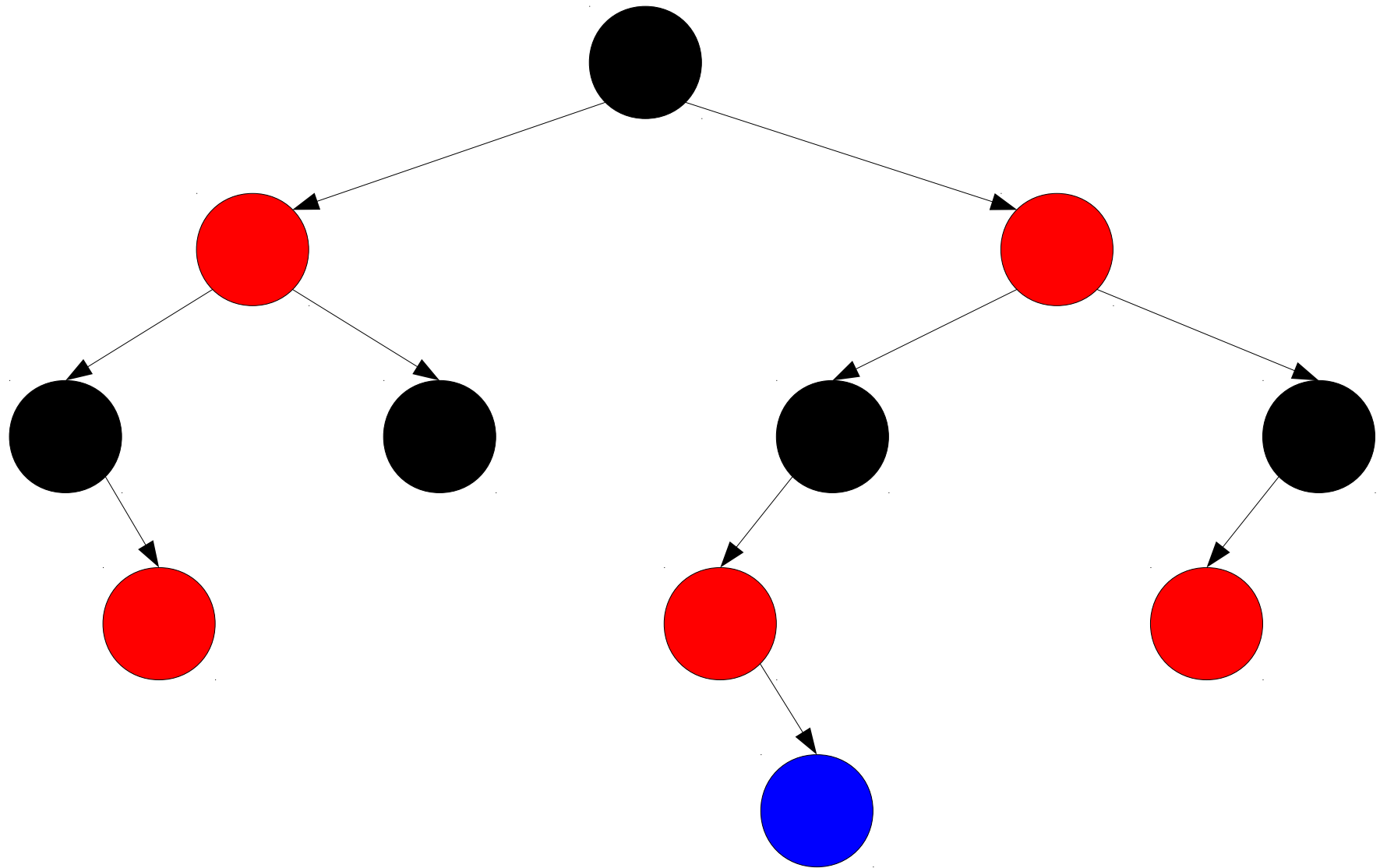
Edits to values are localized along the access path.



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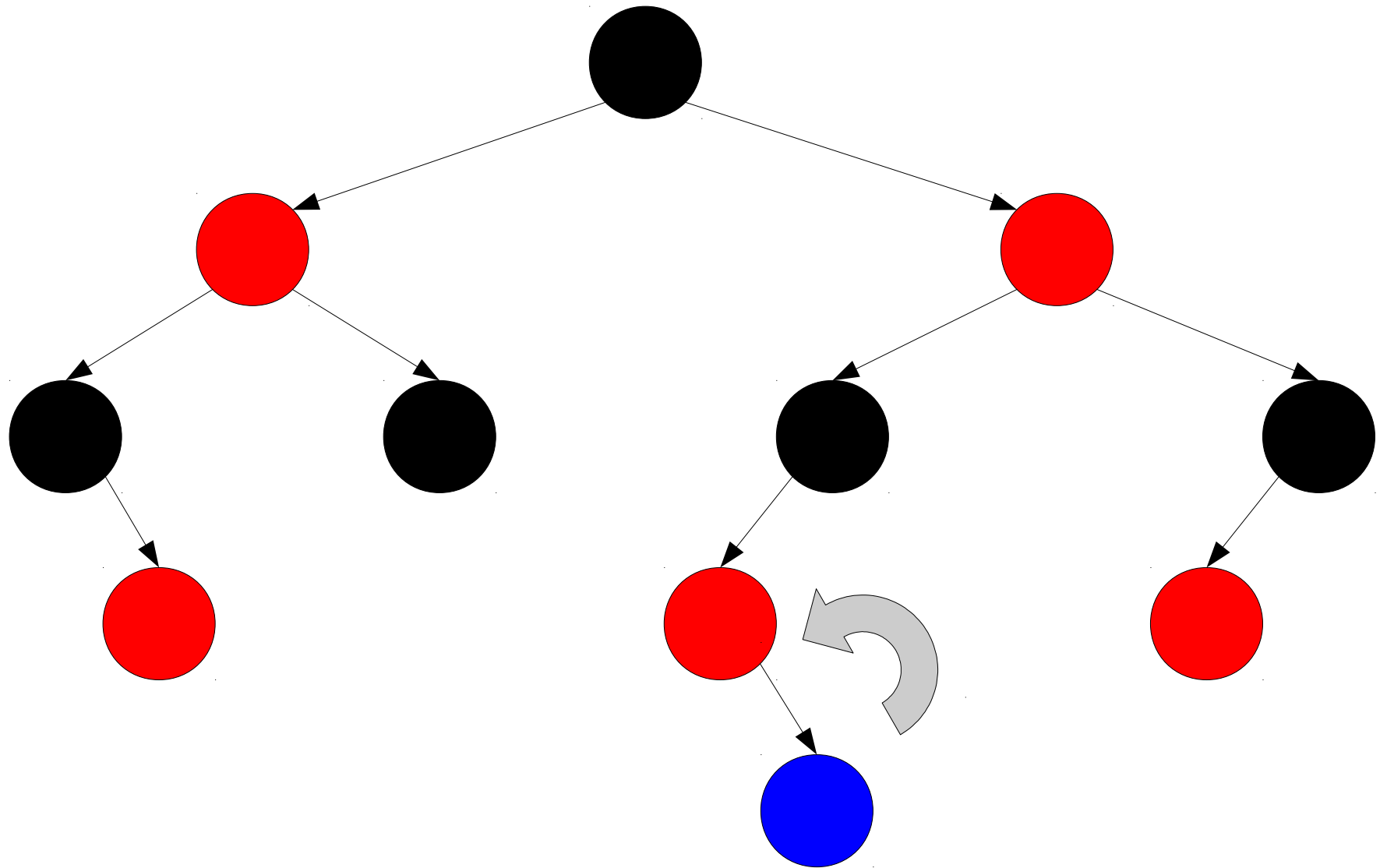


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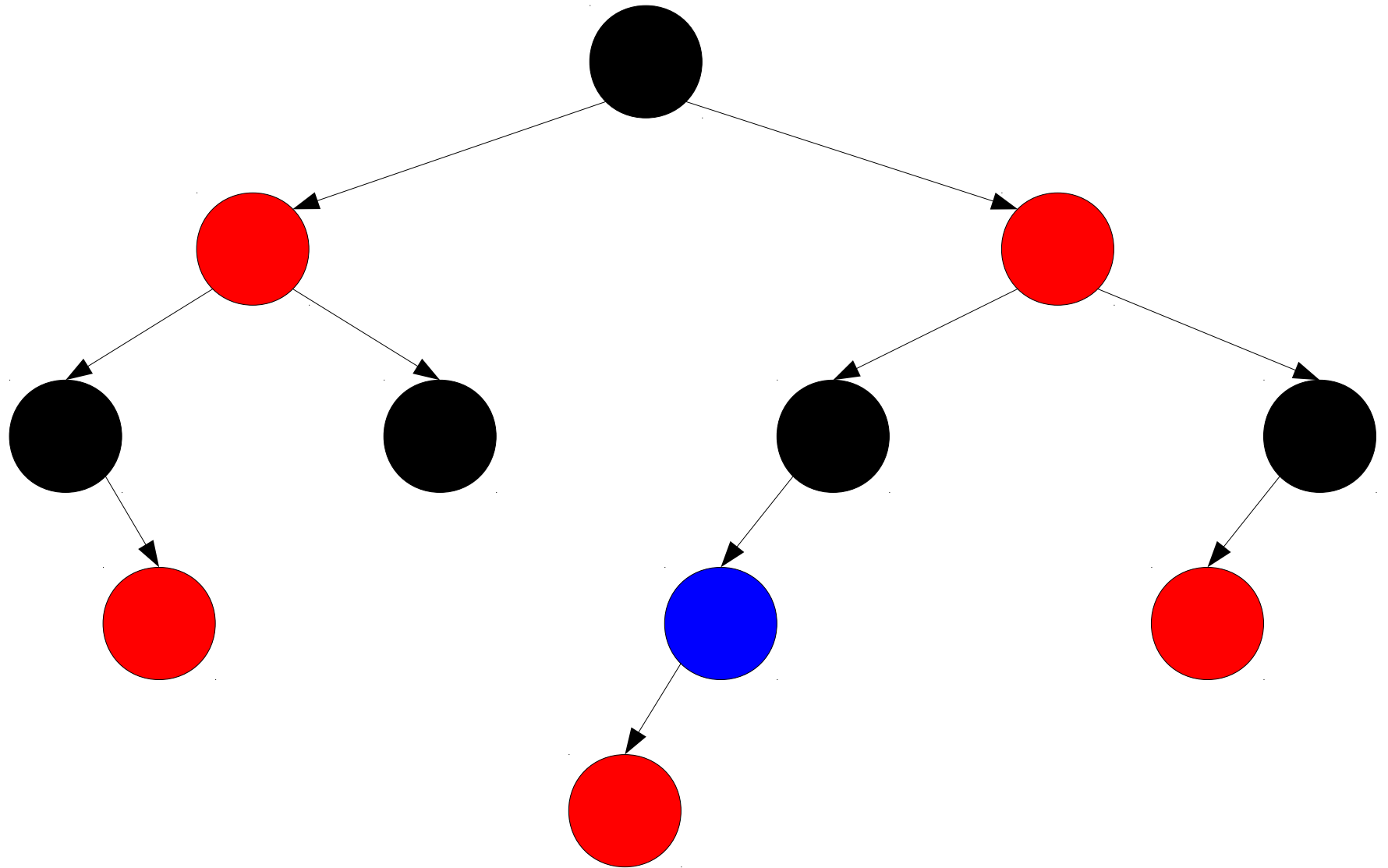


Edits to values are localized along the access path.  
We can recompute values after a rotation.

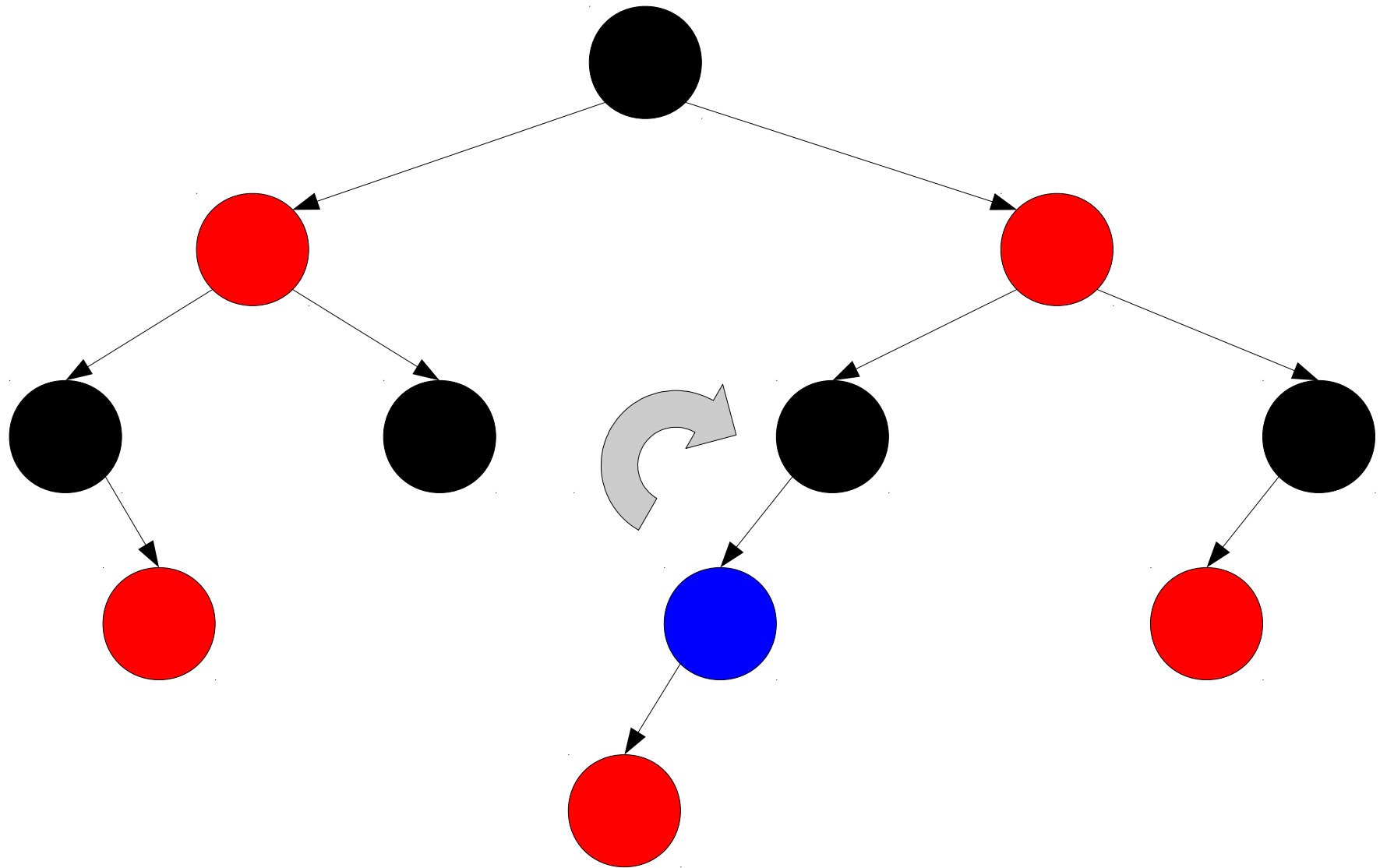




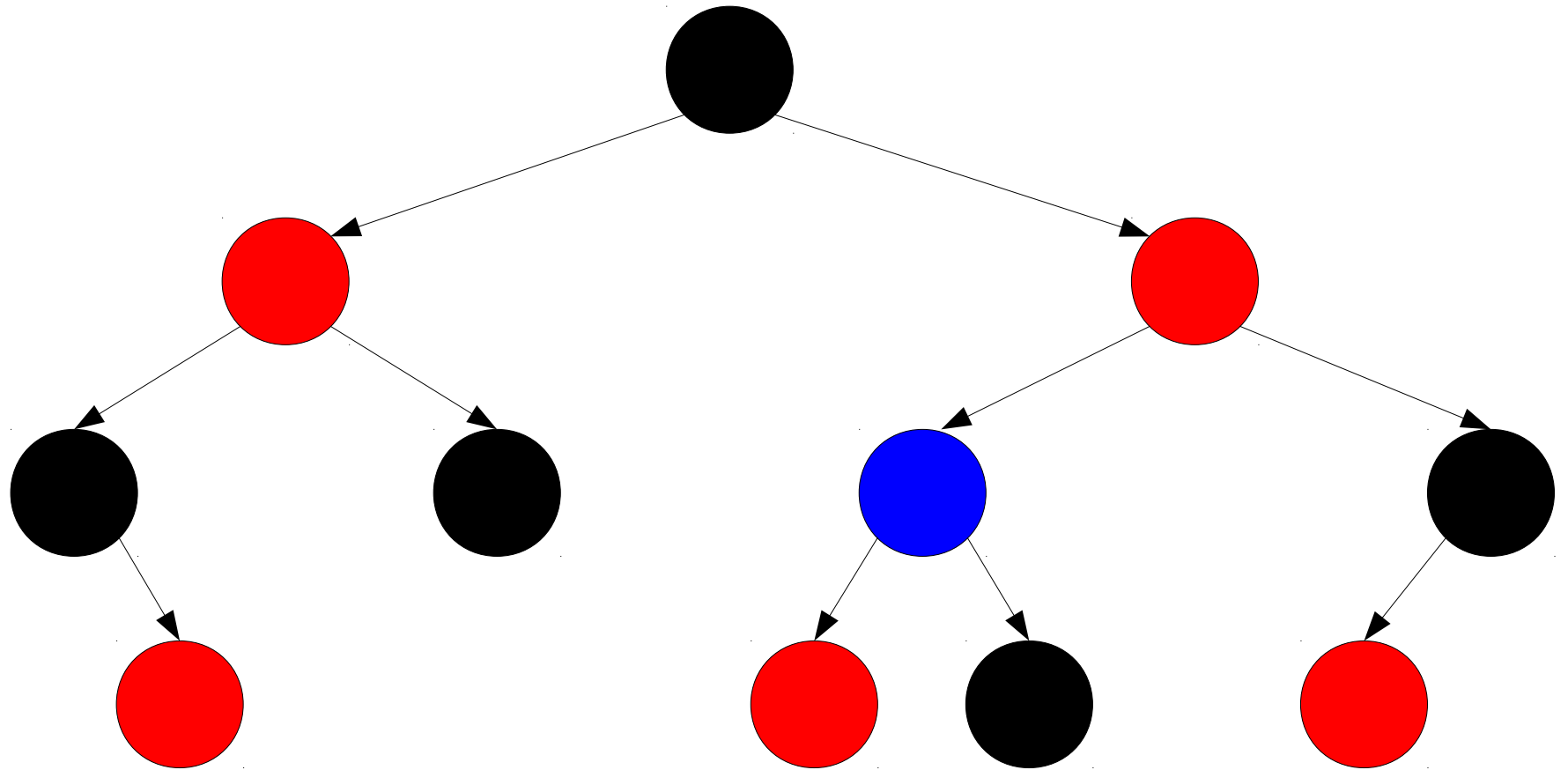
Edits to values are localized along the access path.  
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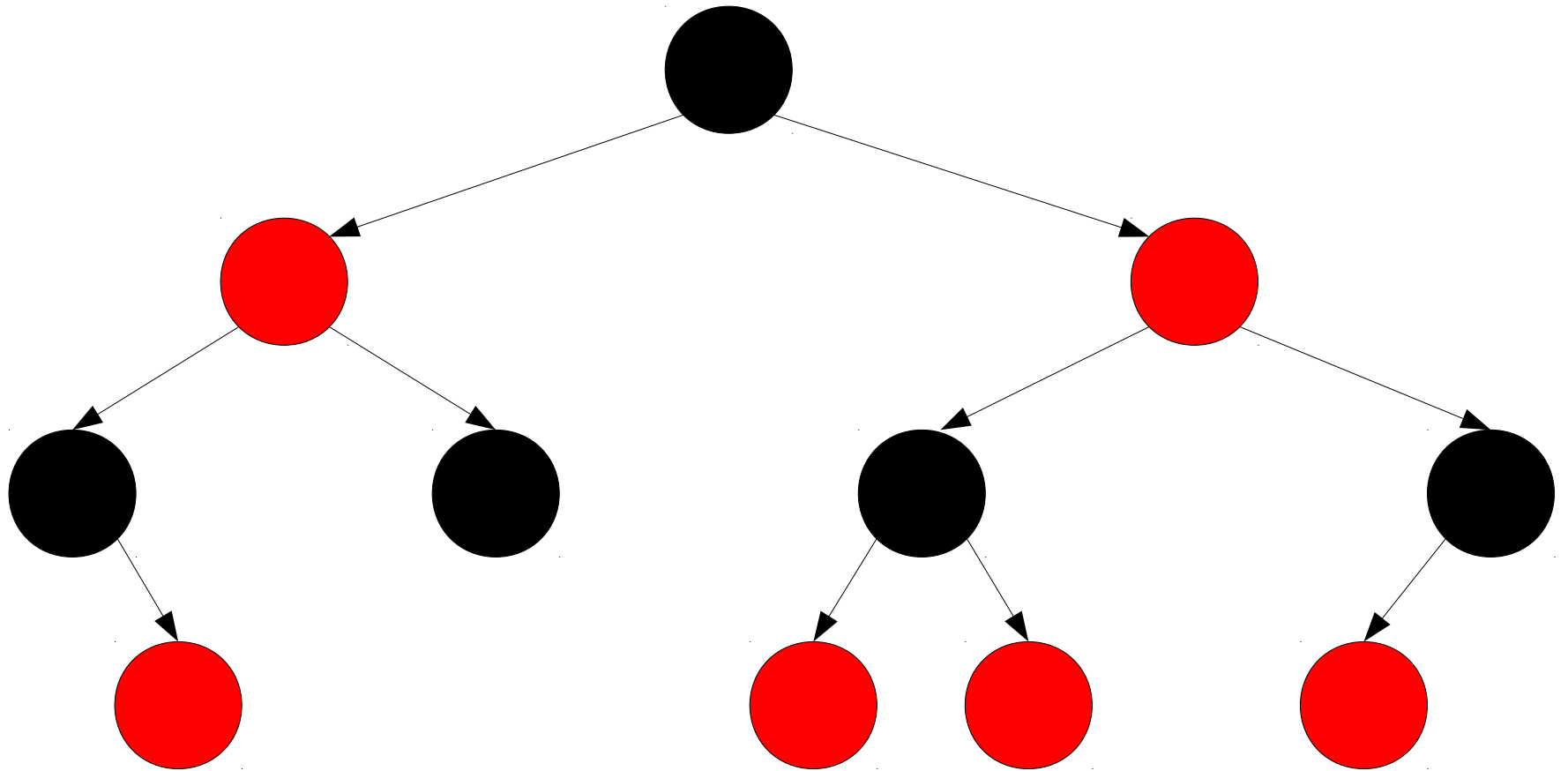
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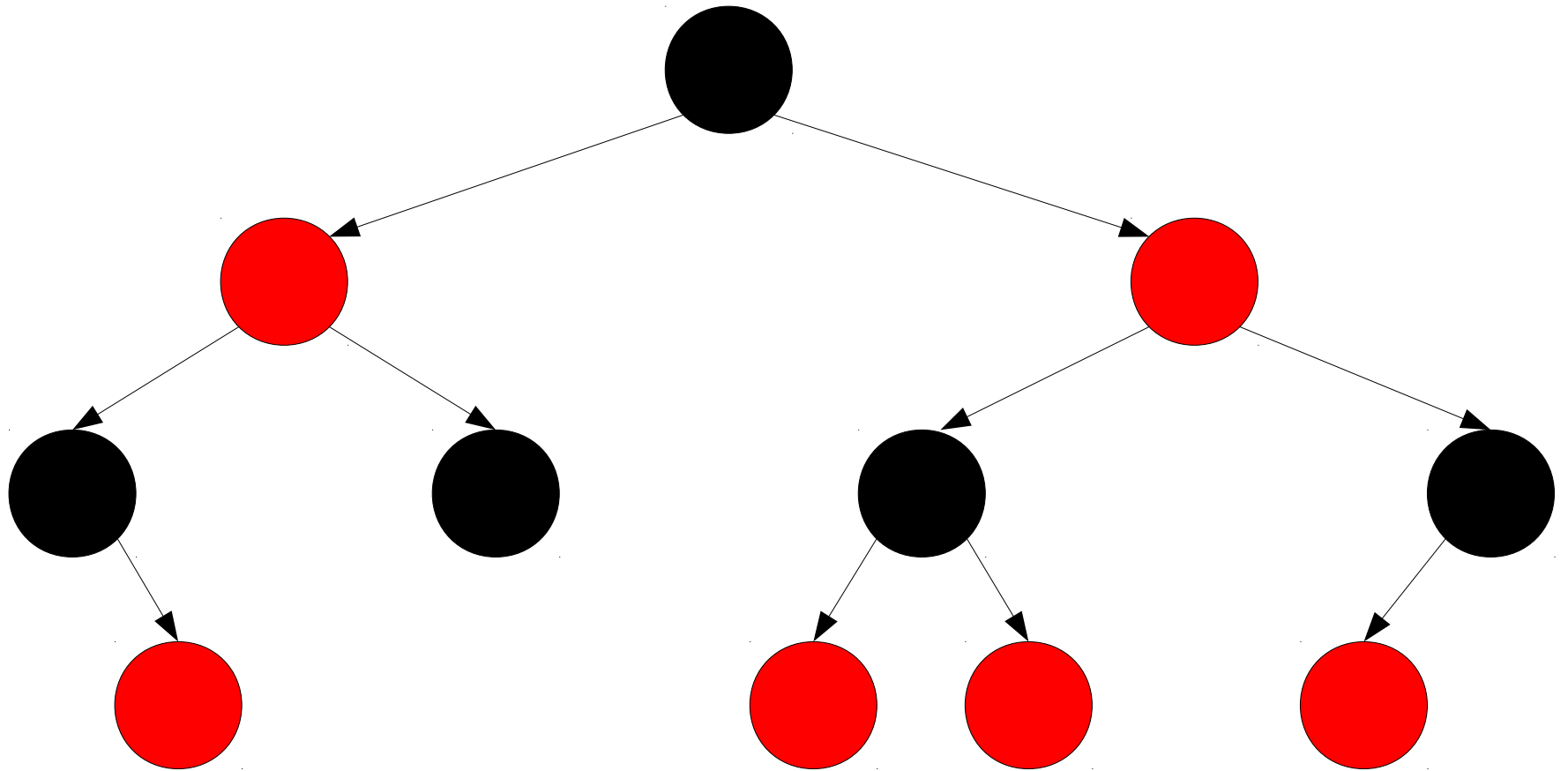
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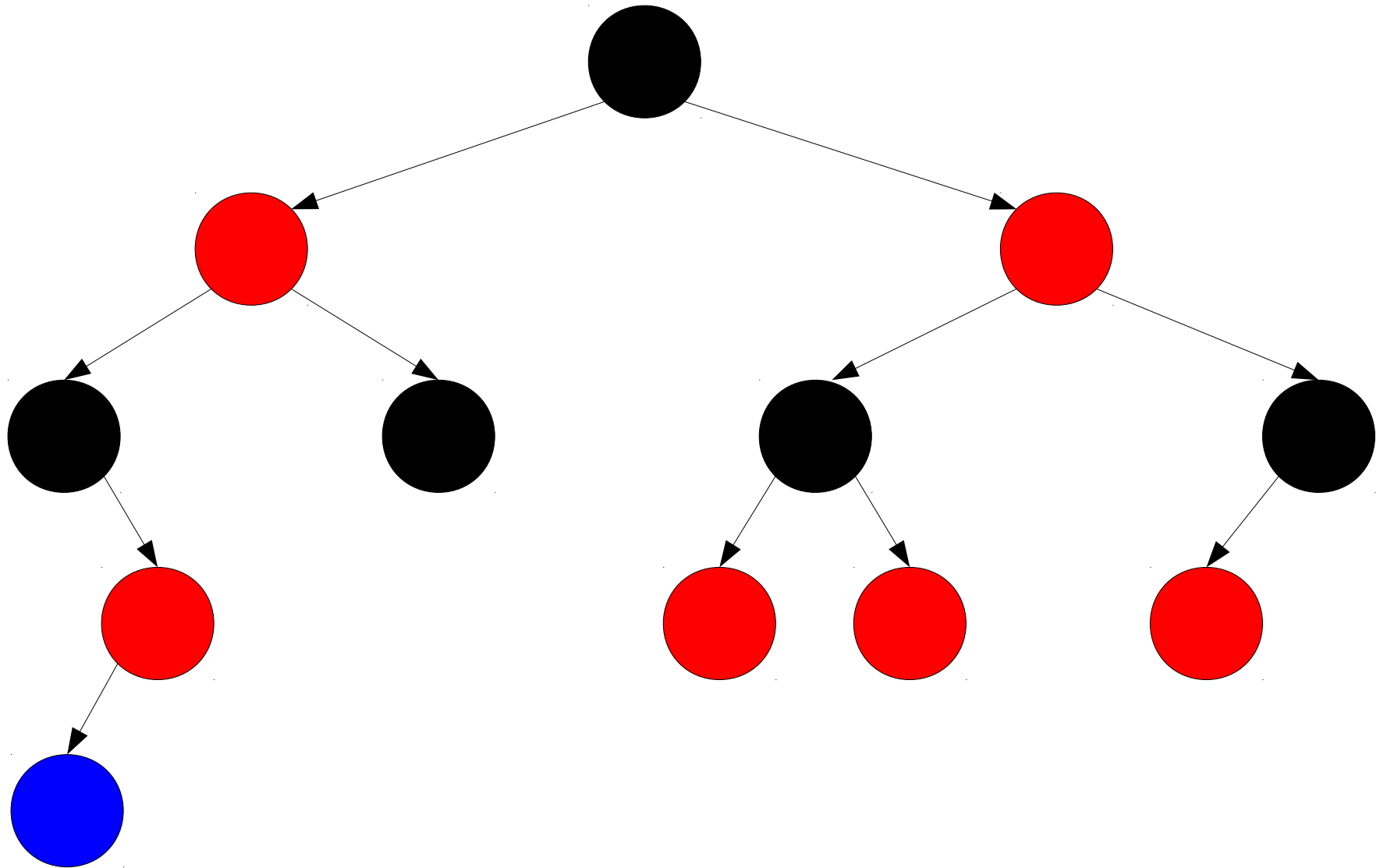
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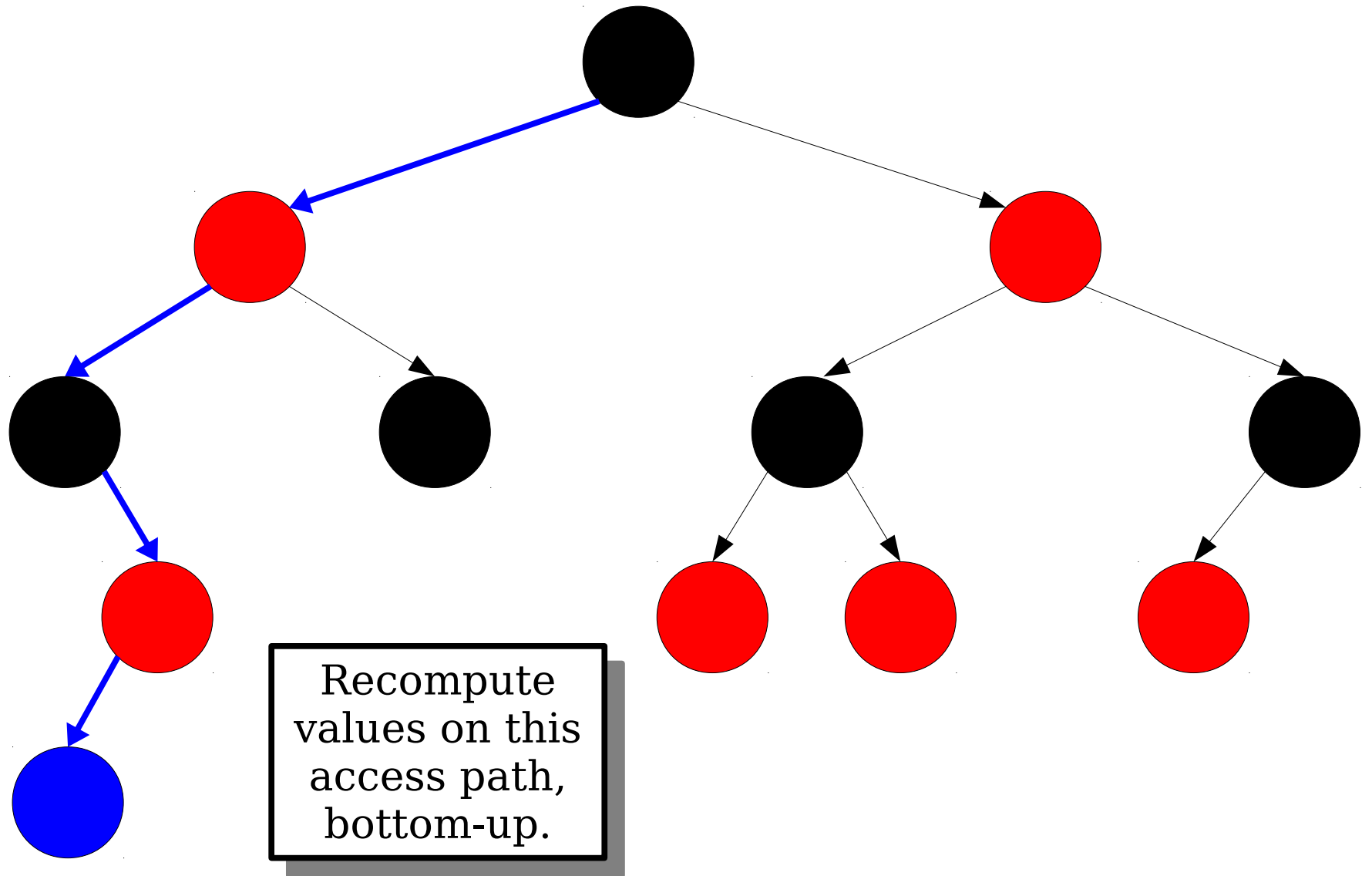
Edits to values are localized along the access path.  
We can recompute values after a rotation.



Imagine we cache some value in each node that can be computed just from (1) the node itself and (2) its children's values.

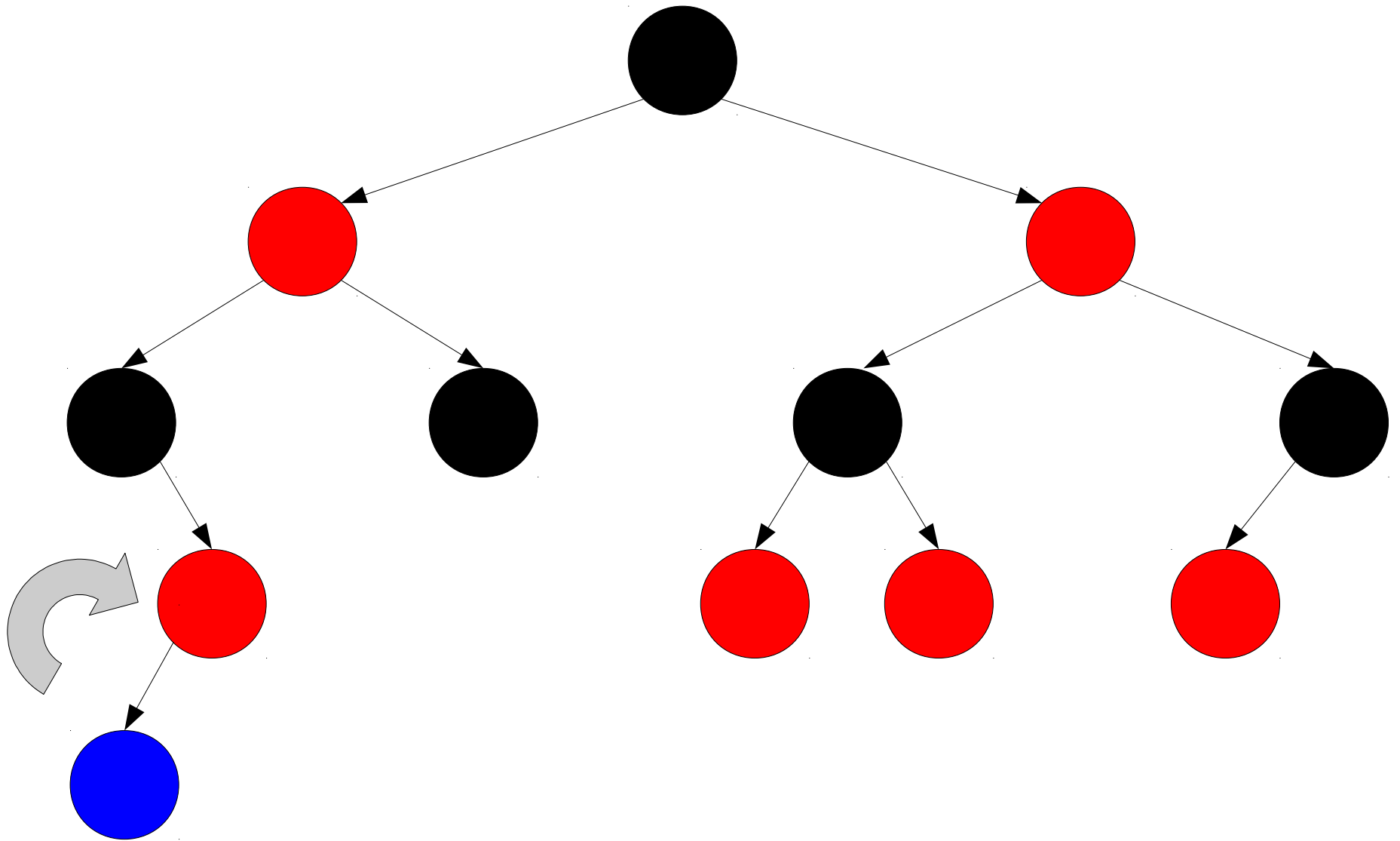


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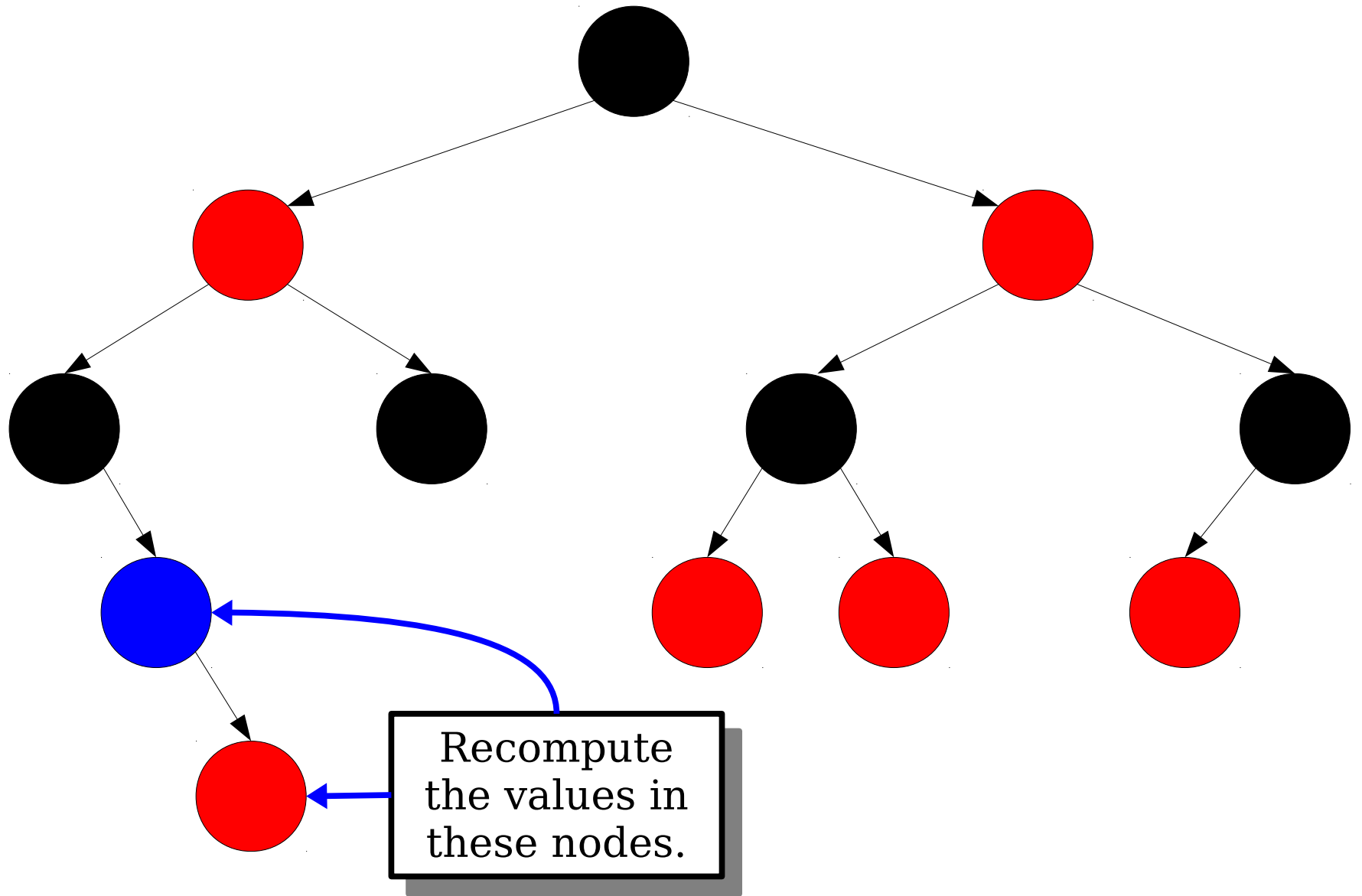


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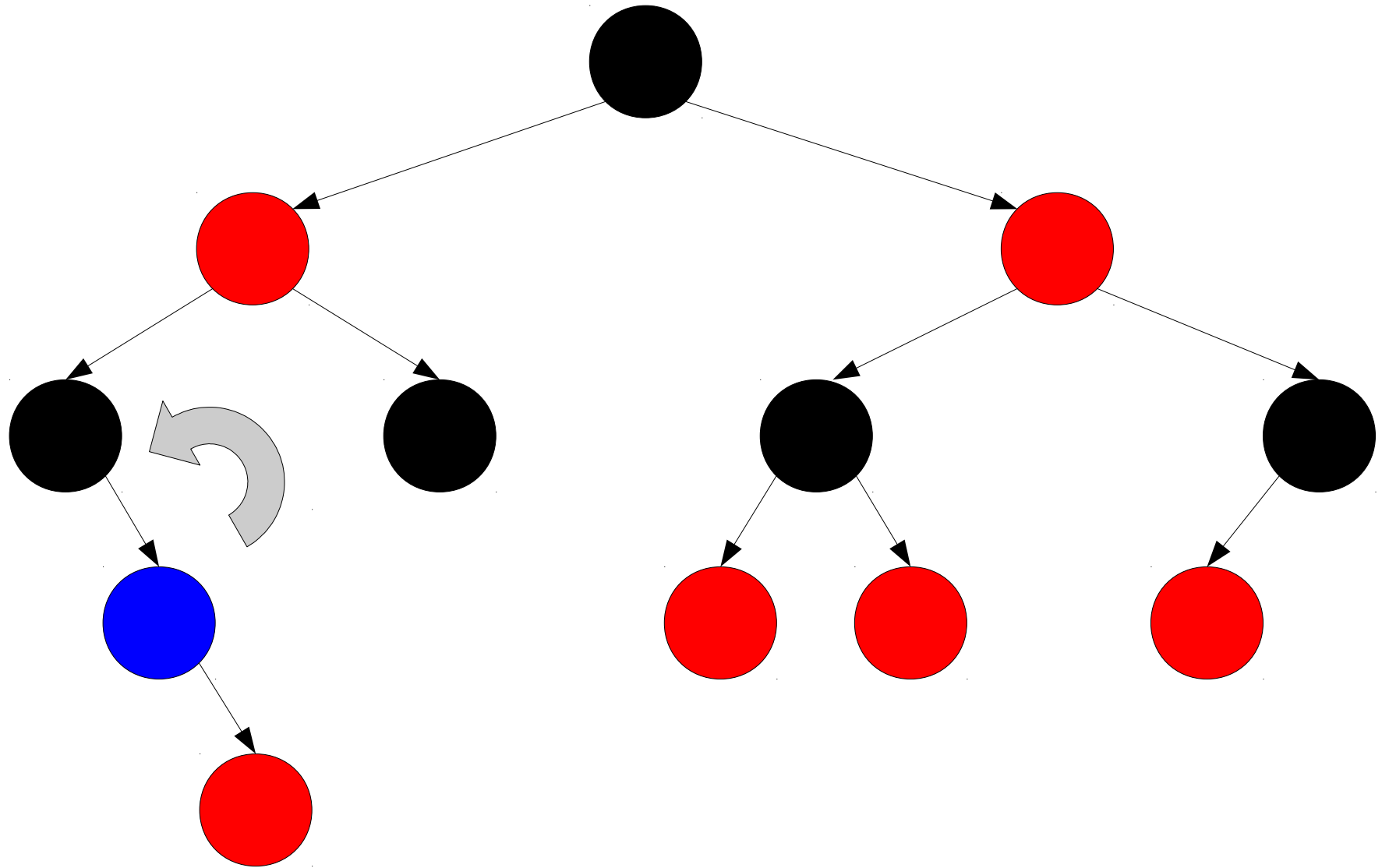




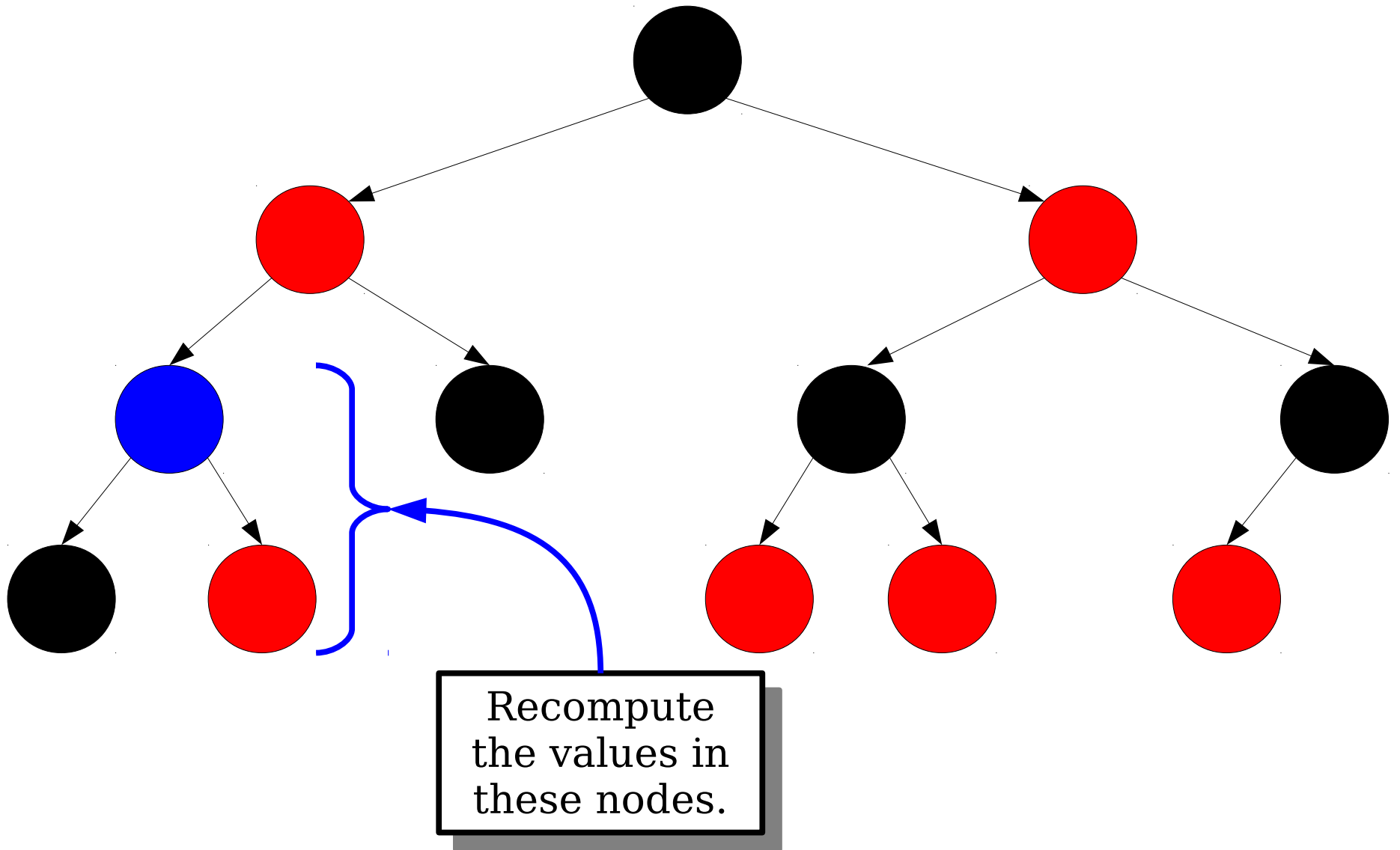
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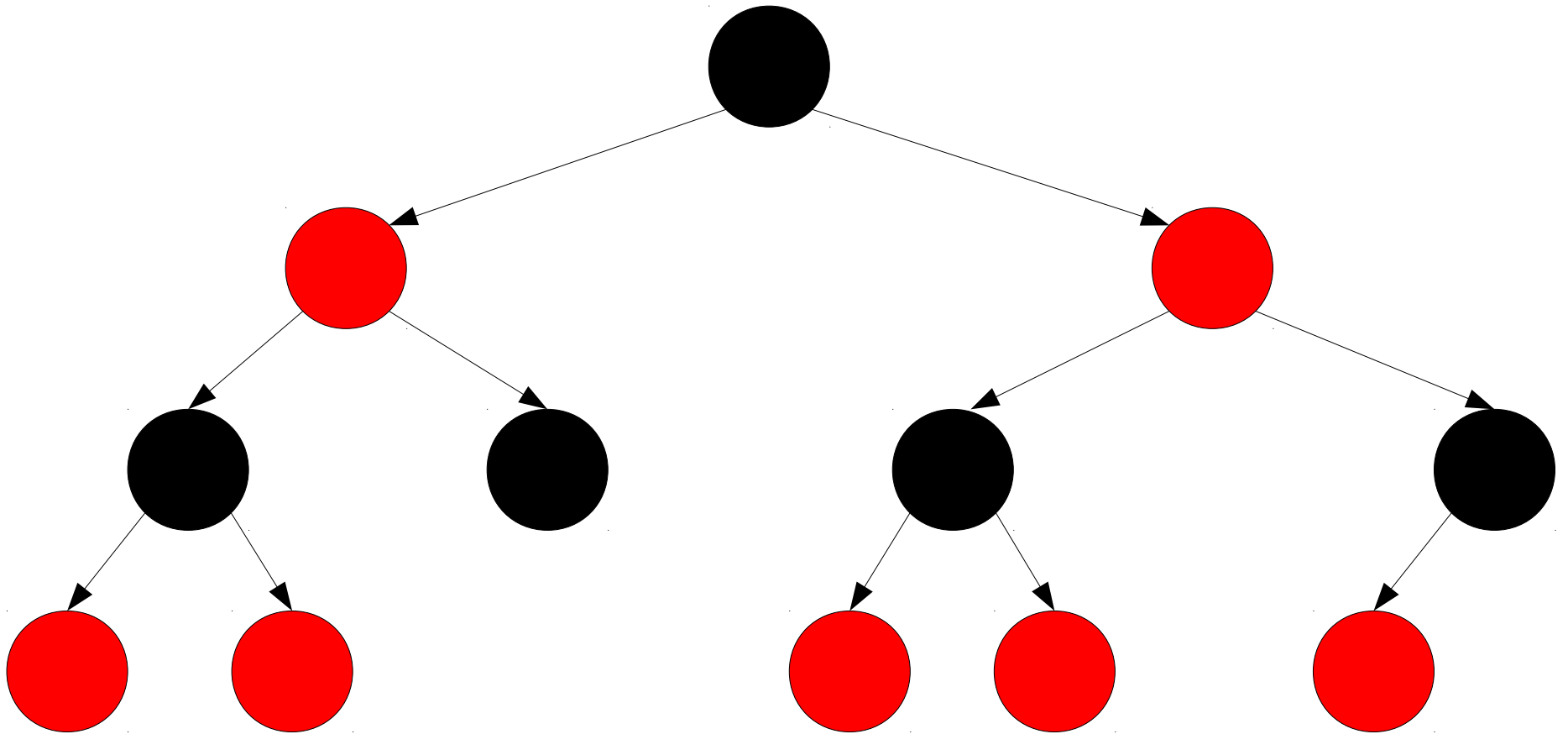
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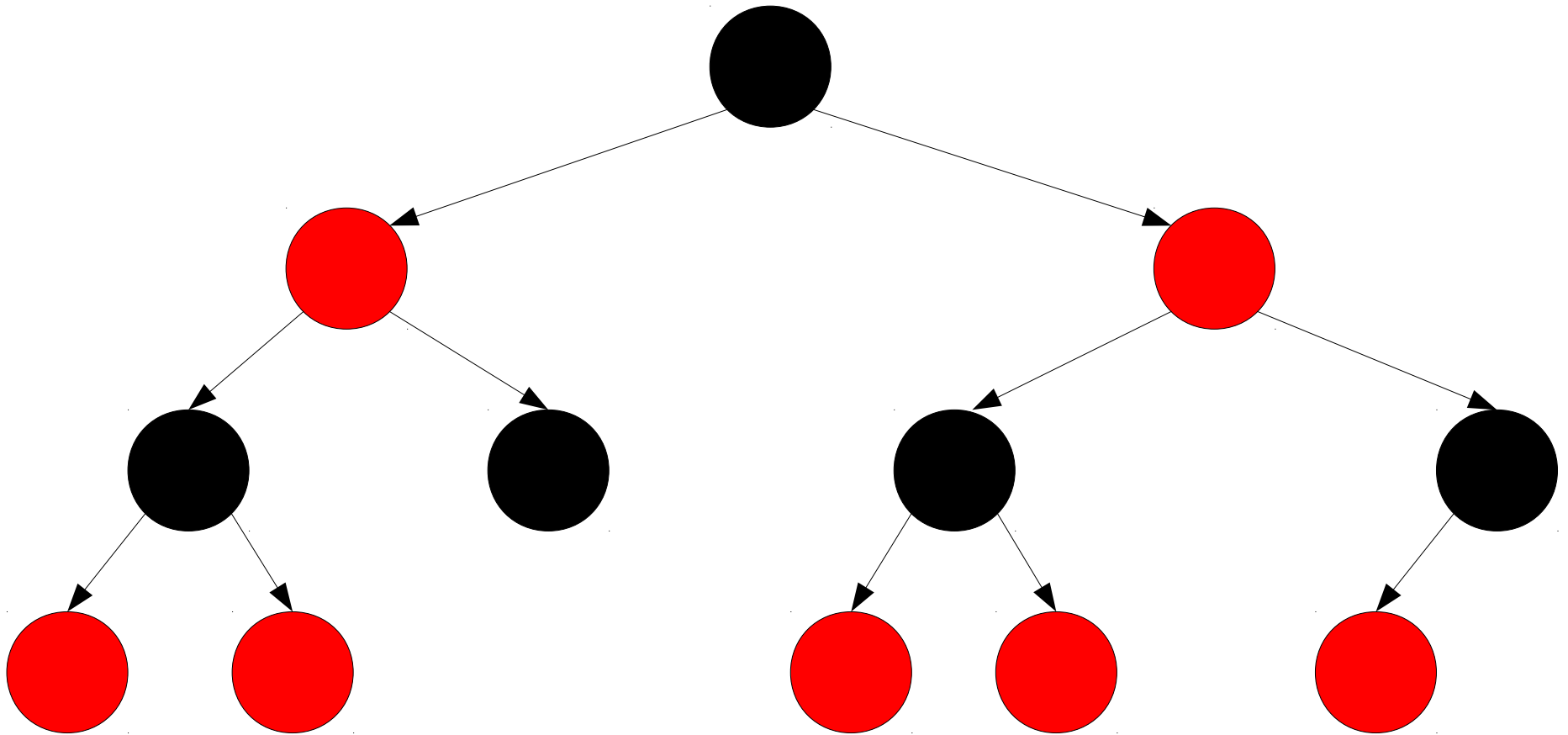
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**Theorem:** Suppose we want to cache some computed value in each node of a red/black tree. Provided that the value can be recomputed purely from the node's value and from its children's values, and provided that each value can be computed in time  $O(1)$ , then these values can be cached in each node with insertions, lookups, and deletions still taking time  $O(\log n)$ .

Example: ***Hierarchical Clustering***

# 1D Hierarchical Clustering

**20**

**42**

**44**

**60**

**66**

**71**

**86**

**92**

**100**

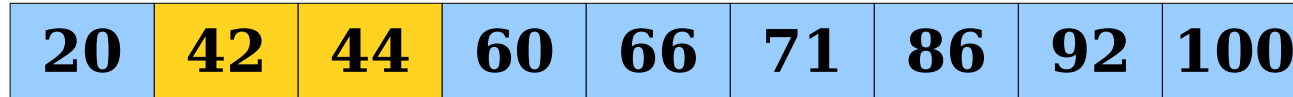


# 1D Hierarchical Clustering

<b>20</b>	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>
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<b>20</b>	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>
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# 1D Hierarchical Clustering

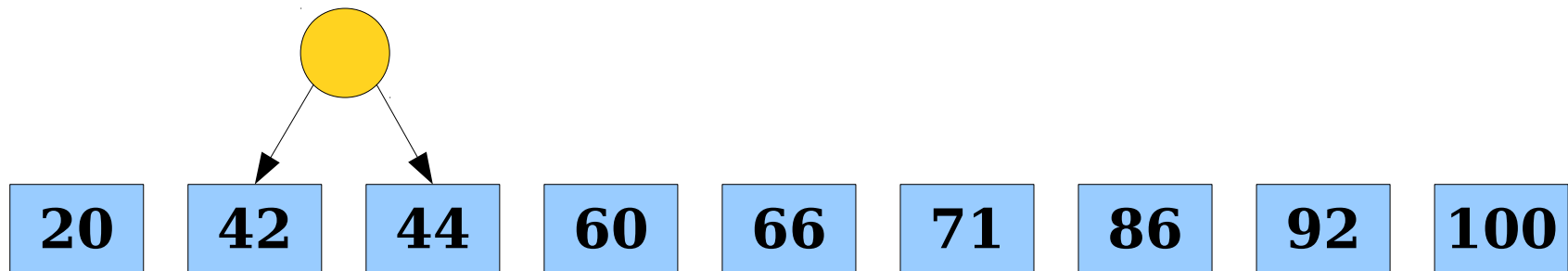
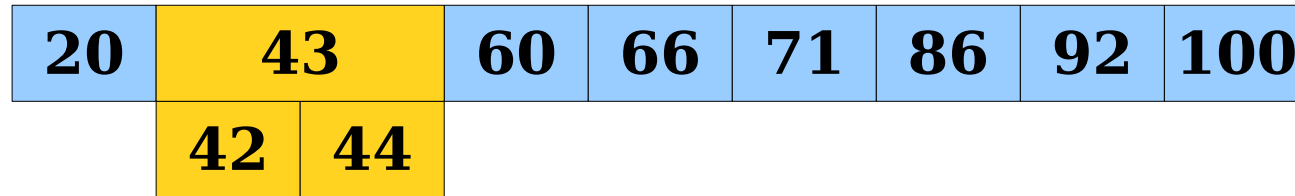


# 1D Hierarchical Clustering

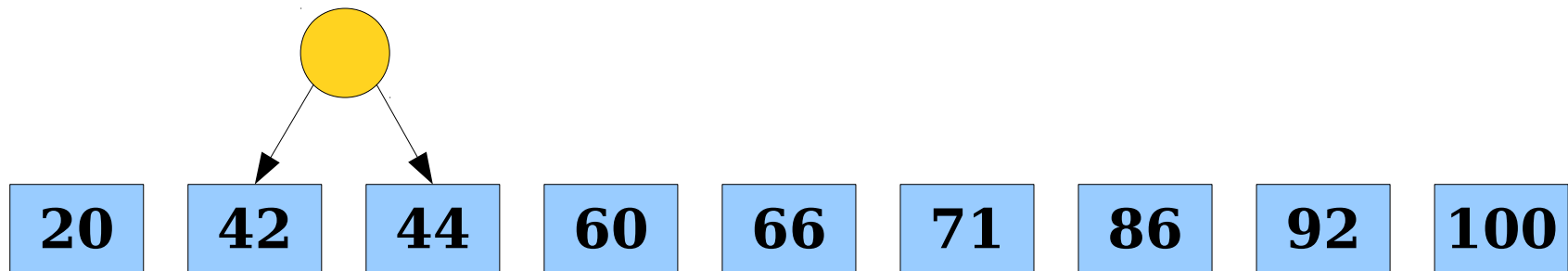
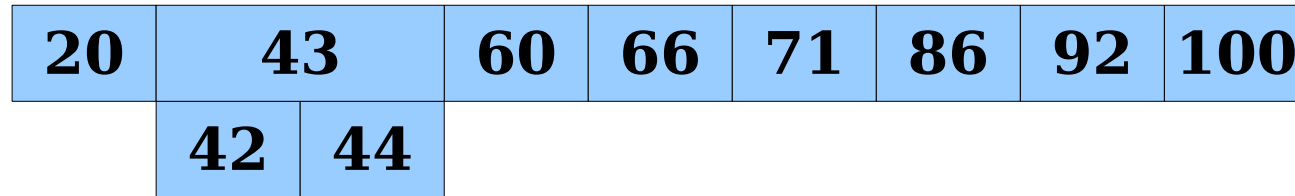
20	43	60	66	71	86	92	100
	42	44					

20	42	44	60	66	71	86	92	100
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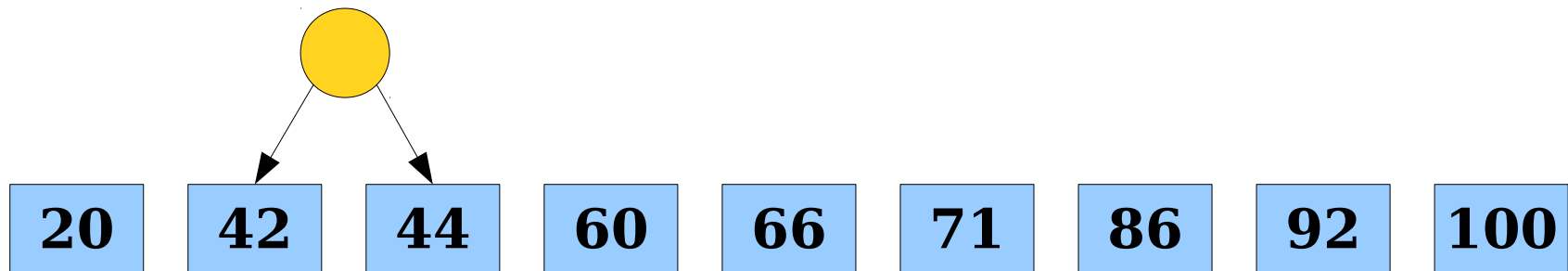
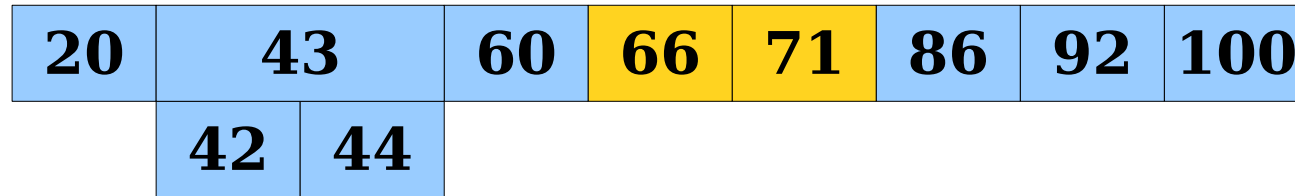
# 1D Hierarchical Clustering



# 1D Hierarchical Clustering

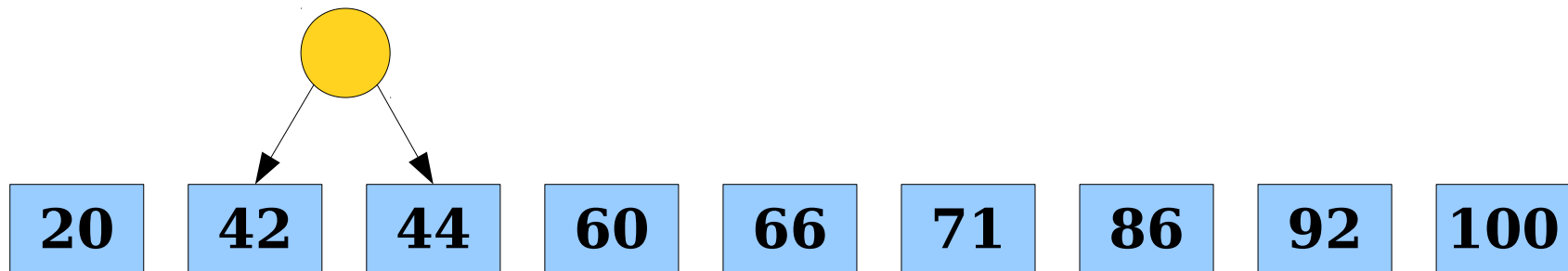


# 1D Hierarchical Clustering



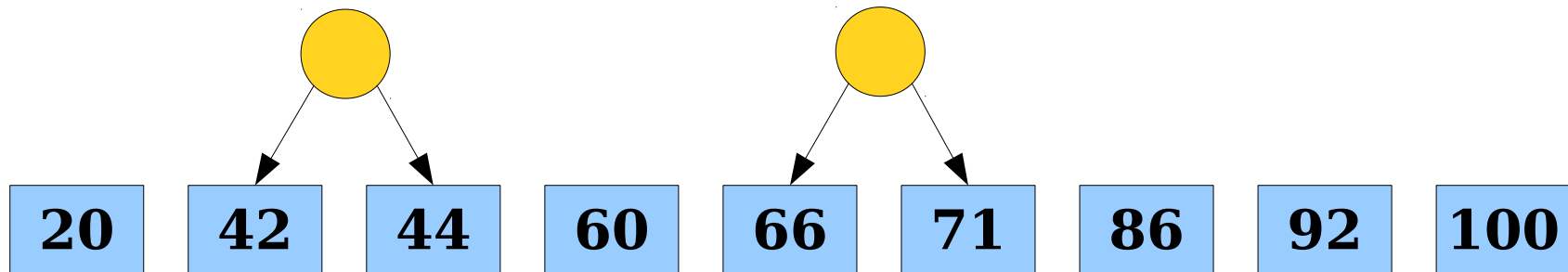
# 1D Hierarchical Clustering

20	43		60	68.5	86	92	100
	42	44		66	71		



# 1D Hierarchical Clustering

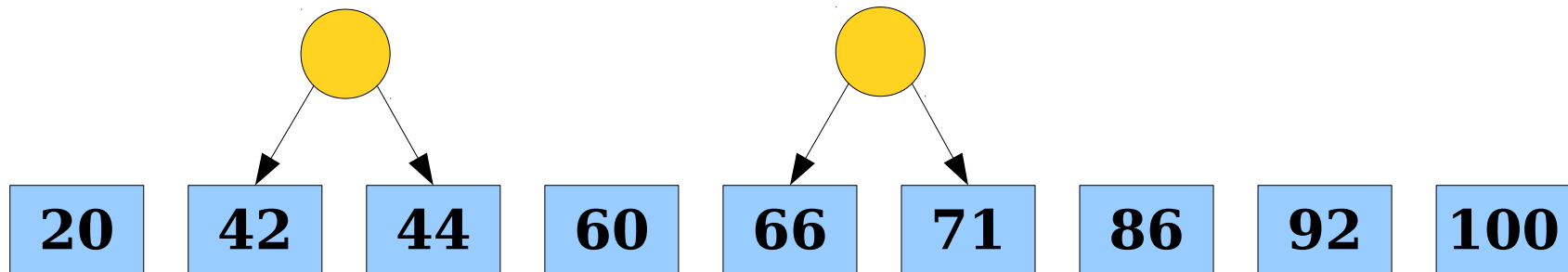
<b>20</b>	<b>43</b>		<b>60</b>	<b>68.5</b>		<b>86</b>	<b>92</b>	<b>100</b>
	<b>42</b>	<b>44</b>		<b>66</b>	<b>71</b>			



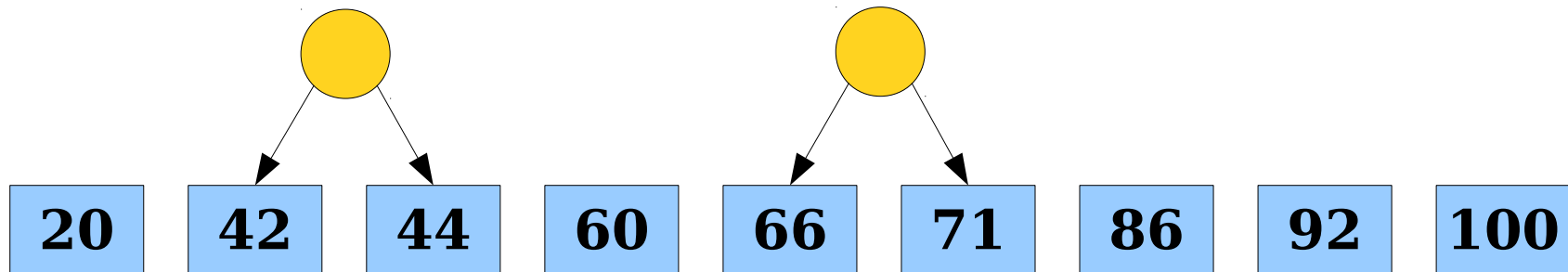
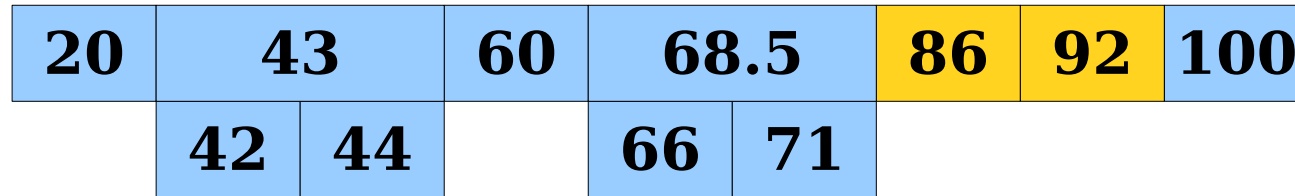


# 1D Hierarchical Clustering

<b>20</b>	<b>43</b>		<b>60</b>	<b>68.5</b>		<b>86</b>	<b>92</b>	<b>100</b>
	<b>42</b>	<b>44</b>		<b>66</b>	<b>71</b>			

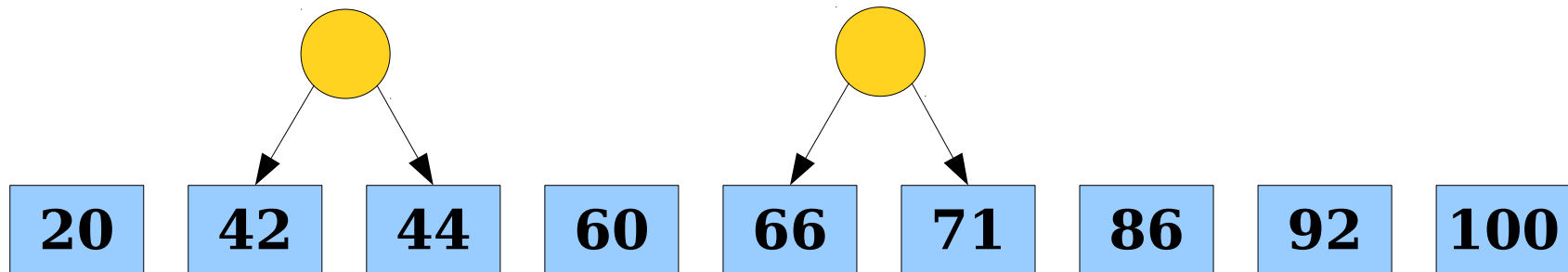


# 1D Hierarchical Clustering



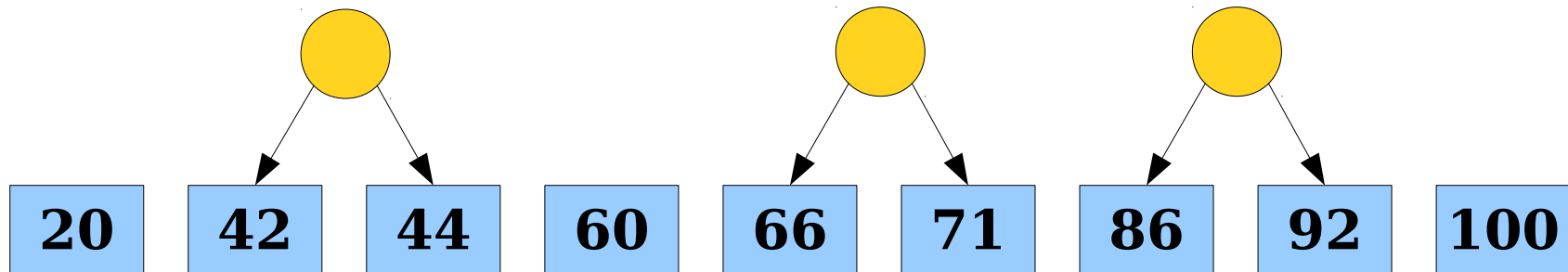
# 1D Hierarchical Clustering

<b>20</b>	<b>43</b>		<b>60</b>	<b>68.5</b>		<b>89</b>		<b>100</b>
	<b>42</b>	<b>44</b>		<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	



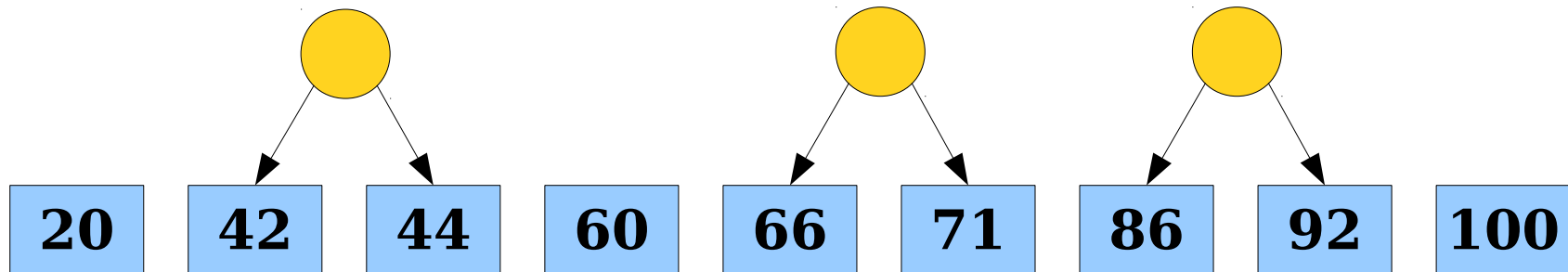
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<b>20</b>	<b>43</b>		<b>60</b>	<b>68.5</b>		<b>89</b>		<b>100</b>
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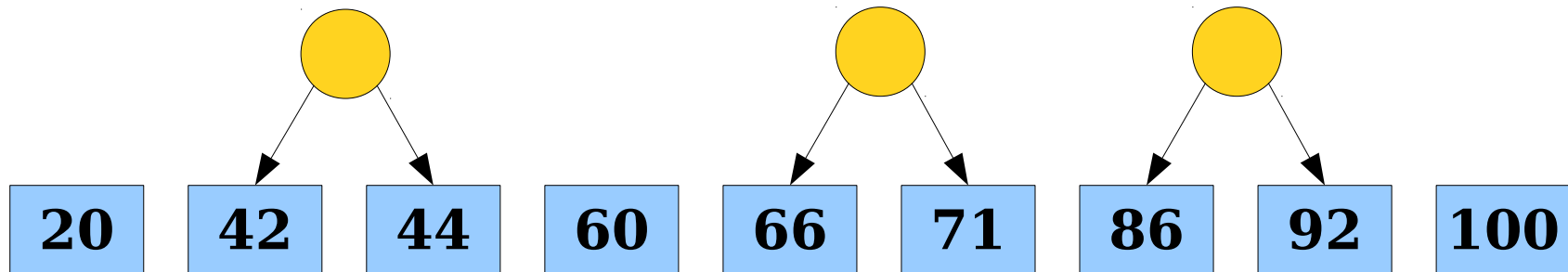
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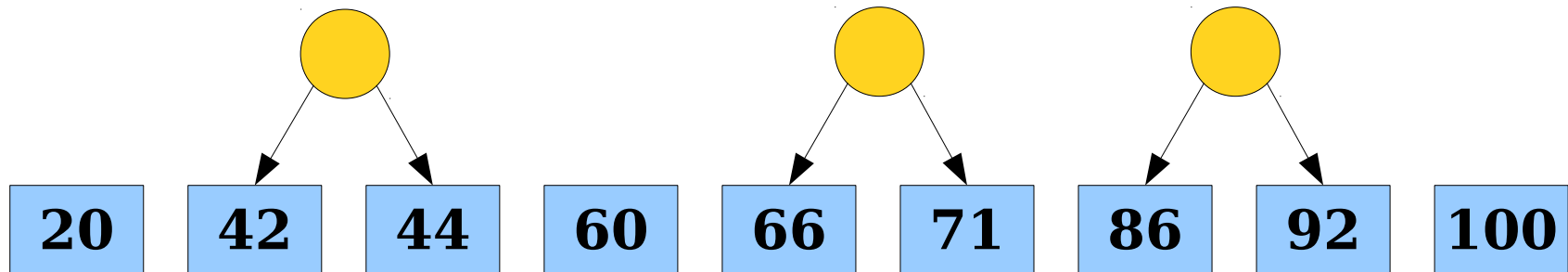
# 1D Hierarchical Clustering

<b>20</b>	<b>43</b>		<b>60</b>	<b>68.5</b>		<b>89</b>		<b>100</b>
	<b>42</b>	<b>44</b>		<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	



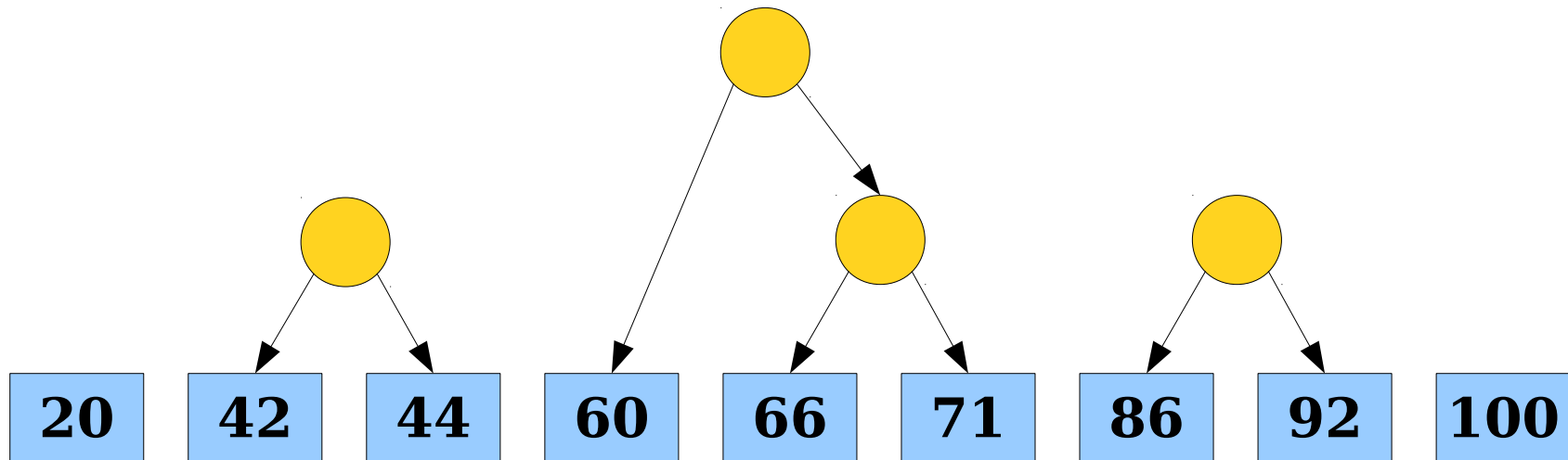
# 1D Hierarchical Clustering

<b>20</b>	<b>43</b>	<b>65.67</b>			<b>89</b>	<b>100</b>	
	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>



# 1D Hierarchical Clustering

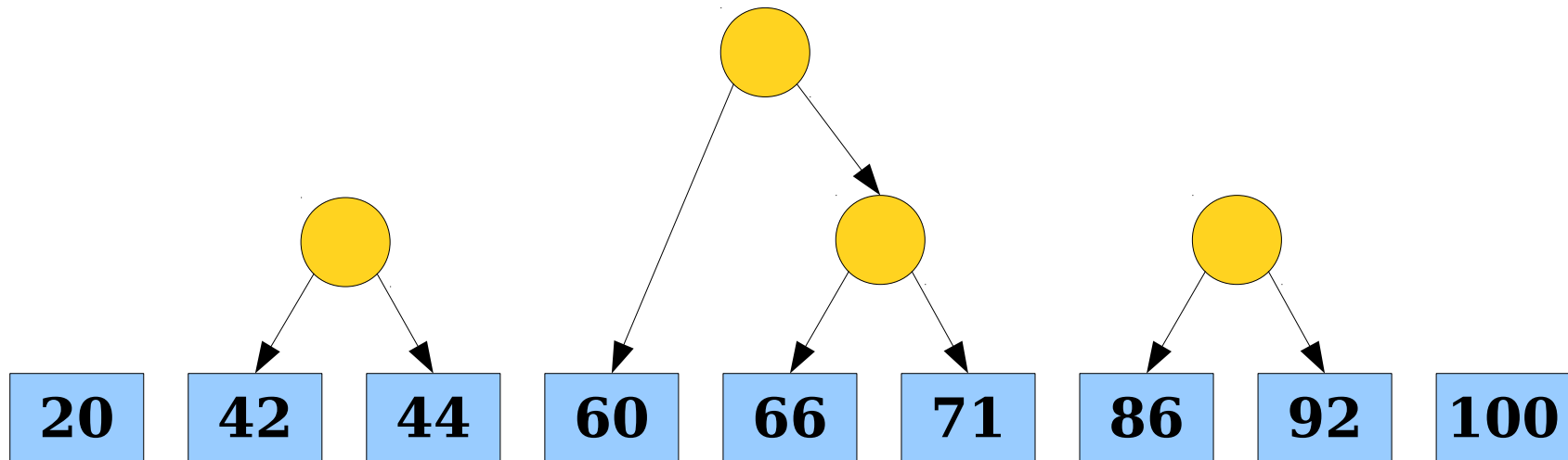
<b>20</b>	<b>43</b>	<b>65.67</b>			<b>89</b>	<b>100</b>	
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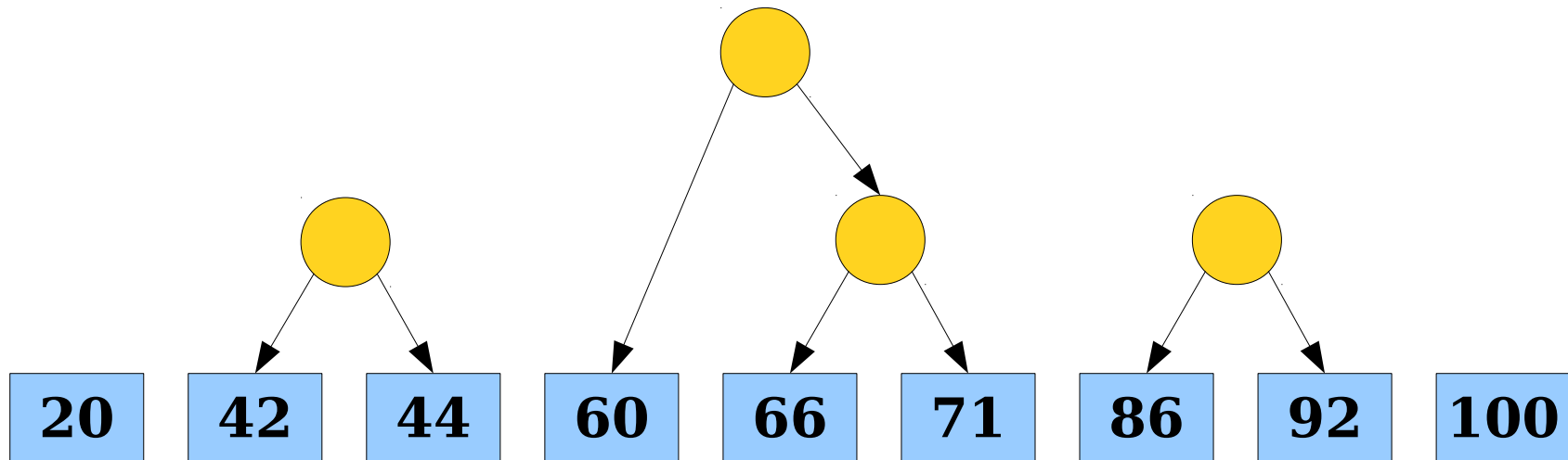
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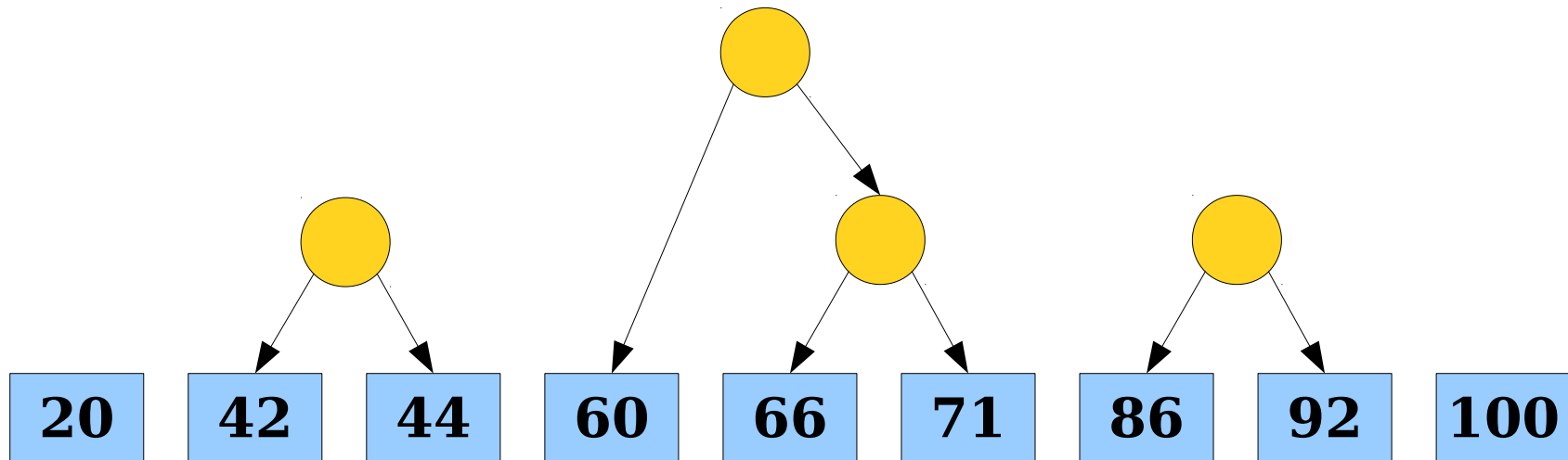
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<b>20</b>	<b>43</b>		<b>65.67</b>			<b>89</b>		<b>100</b>
	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	



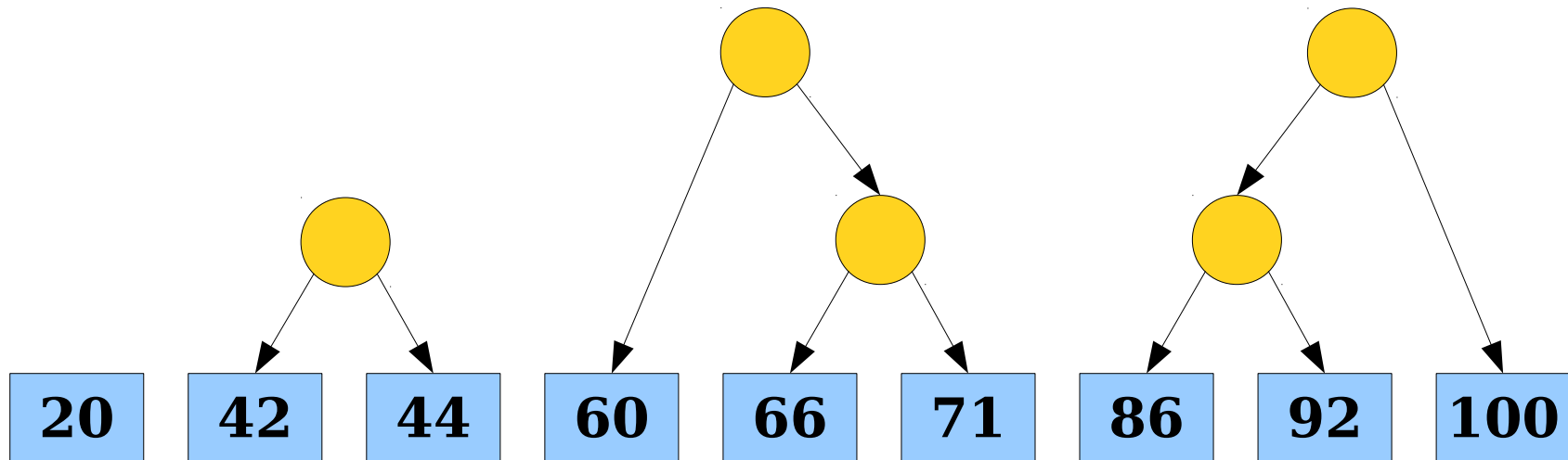
# 1D Hierarchical Clustering

<b>20</b>	<b>43</b>		<b>65.67</b>			<b>92.67</b>		
	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>



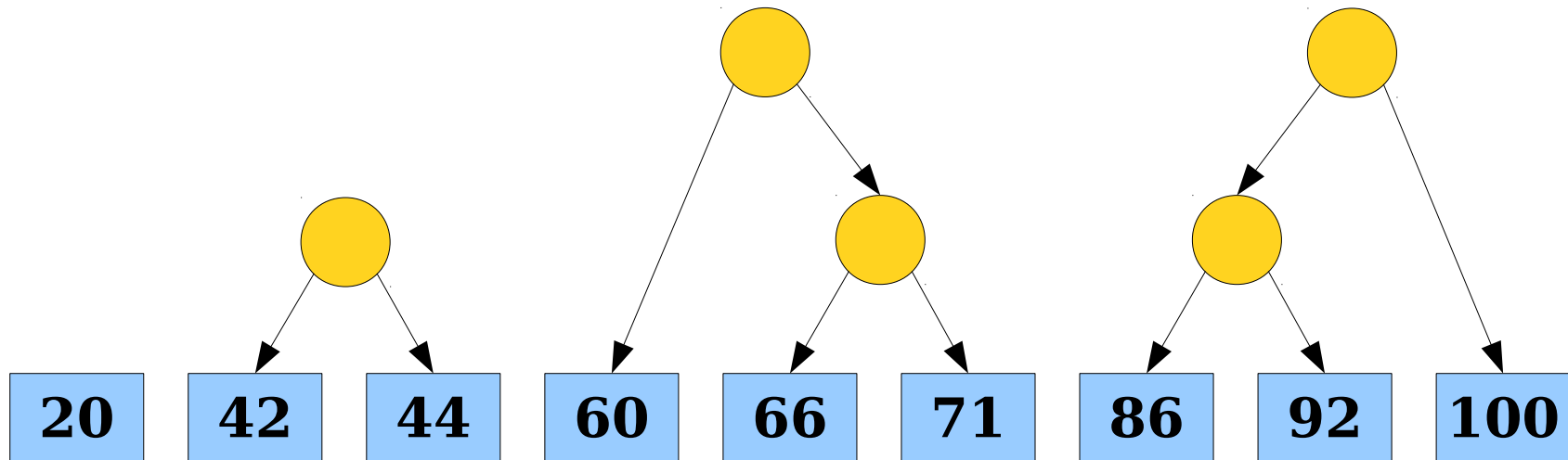
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<b>20</b>	<b>43</b>		<b>65.67</b>			<b>92.67</b>		
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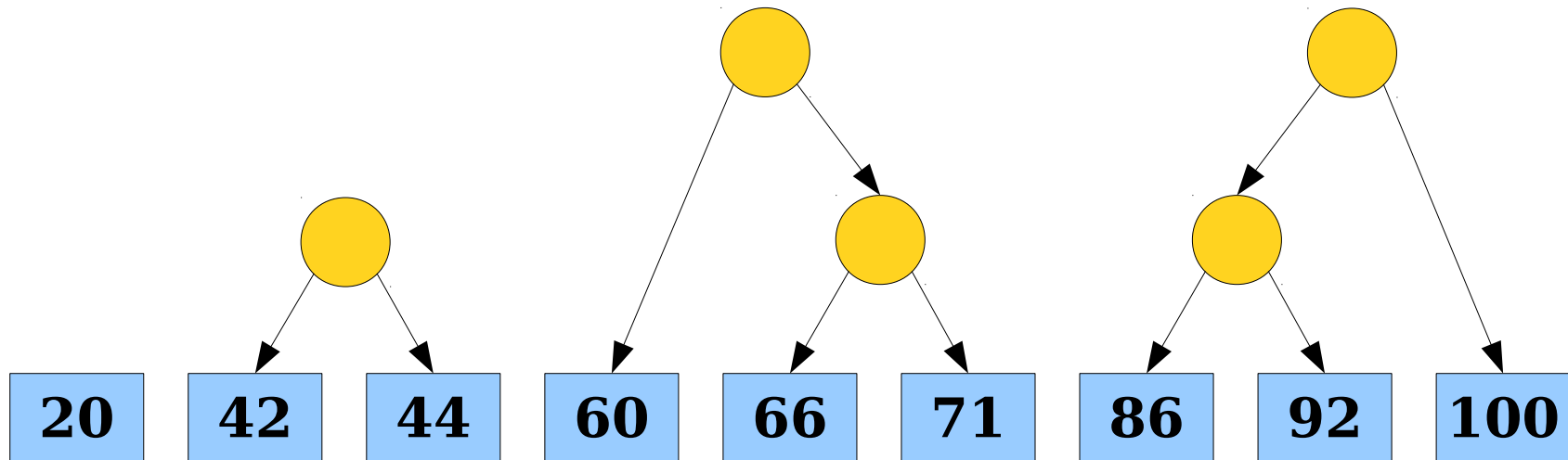
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<b>20</b>	<b>43</b>		<b>65.67</b>			<b>92.67</b>		
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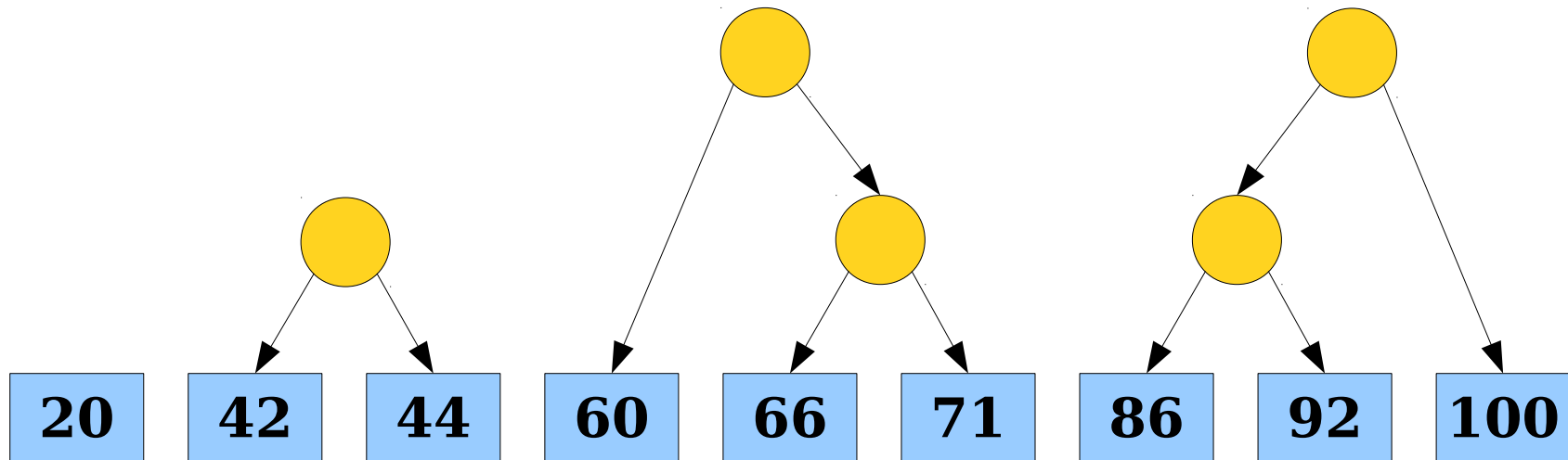
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<b>20</b>	<b>43</b>		<b>65.67</b>			<b>92.67</b>		
	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>



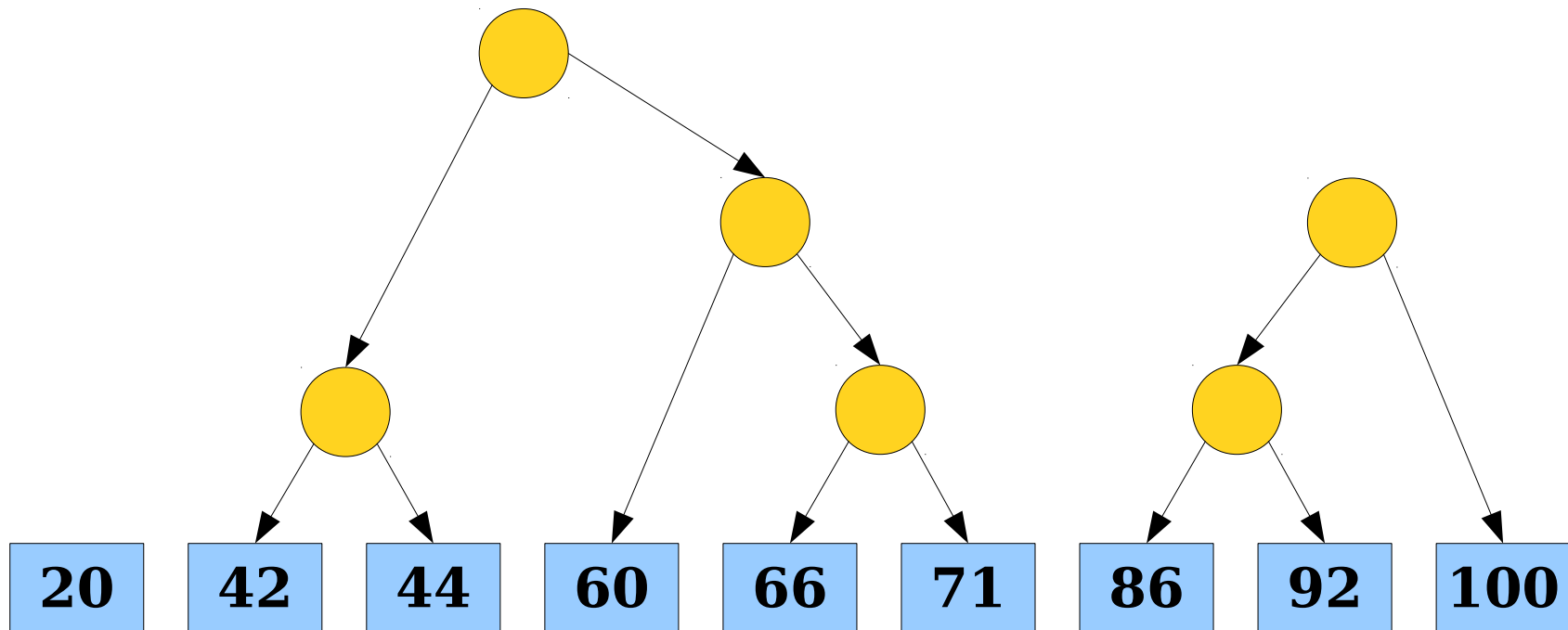
# 1D Hierarchical Clustering

<b>20</b>	<b>56.6</b>					<b>92.67</b>		
	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>



# 1D Hierarchical Clustering

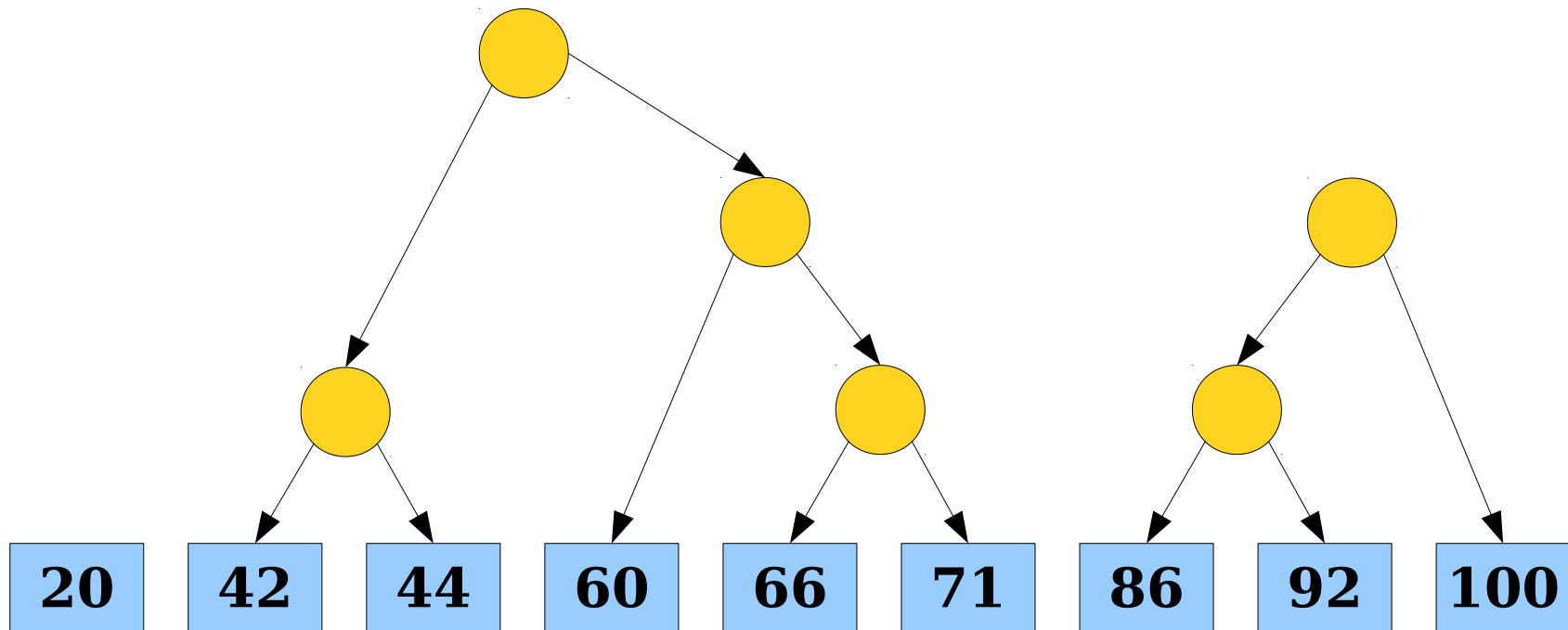
<b>20</b>	<b>56.6</b>					<b>92.67</b>		
	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>





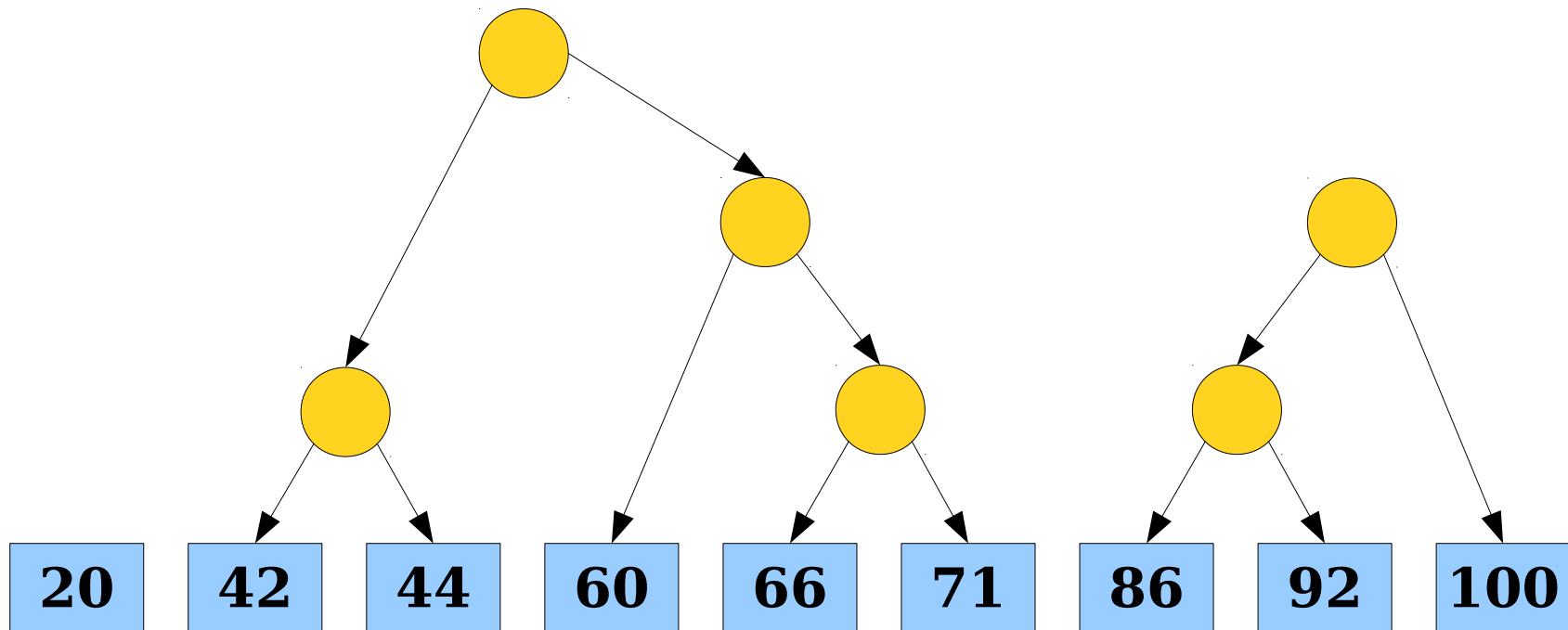
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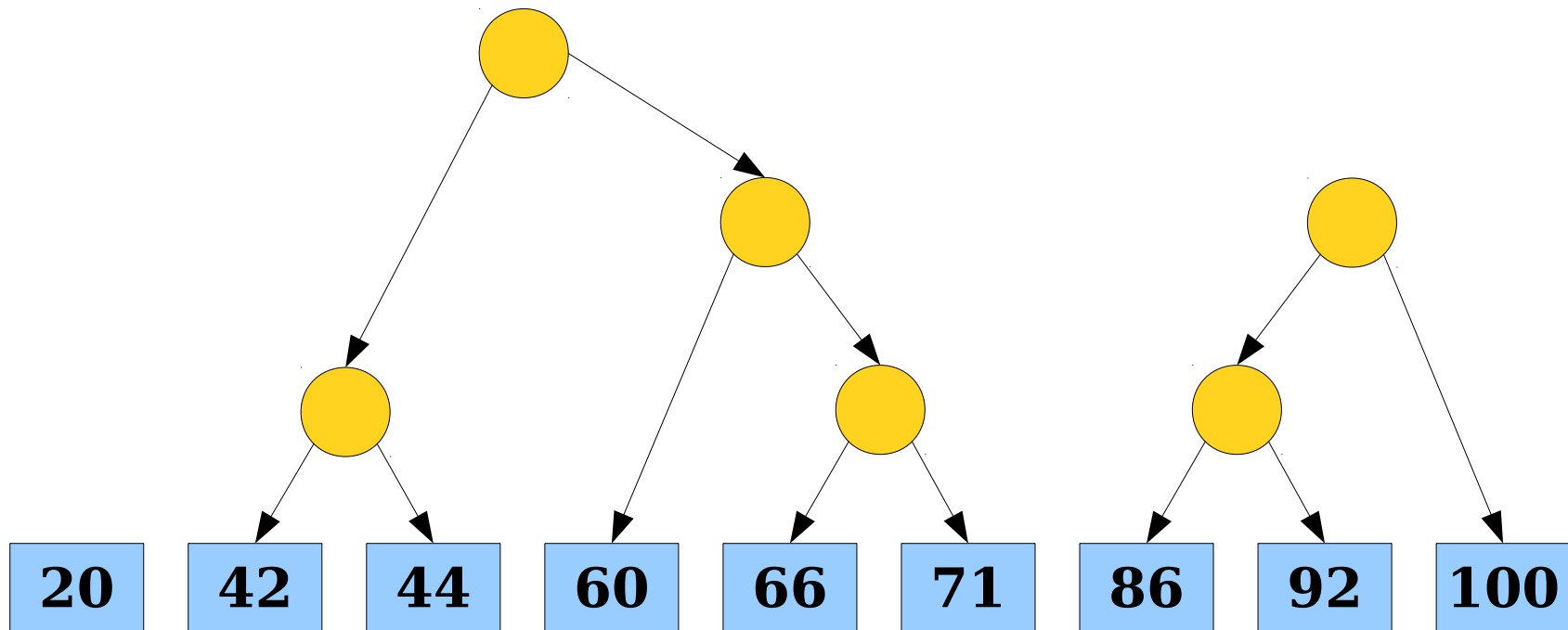
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<b>20</b>	<b>56.6</b>					<b>92.67</b>		
	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>



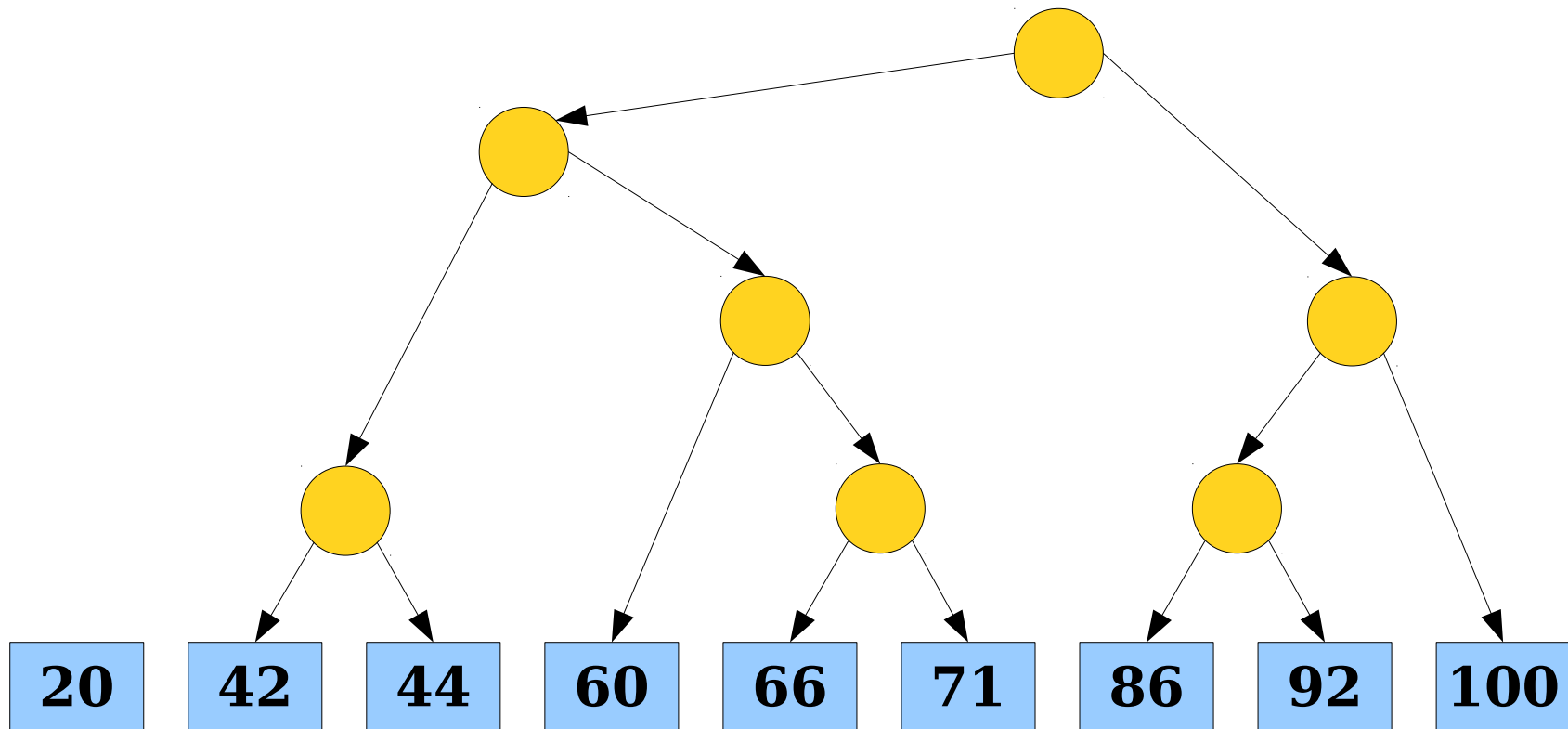
# 1D Hierarchical Clustering

<b>20</b>	<b>70.13</b>							
	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>



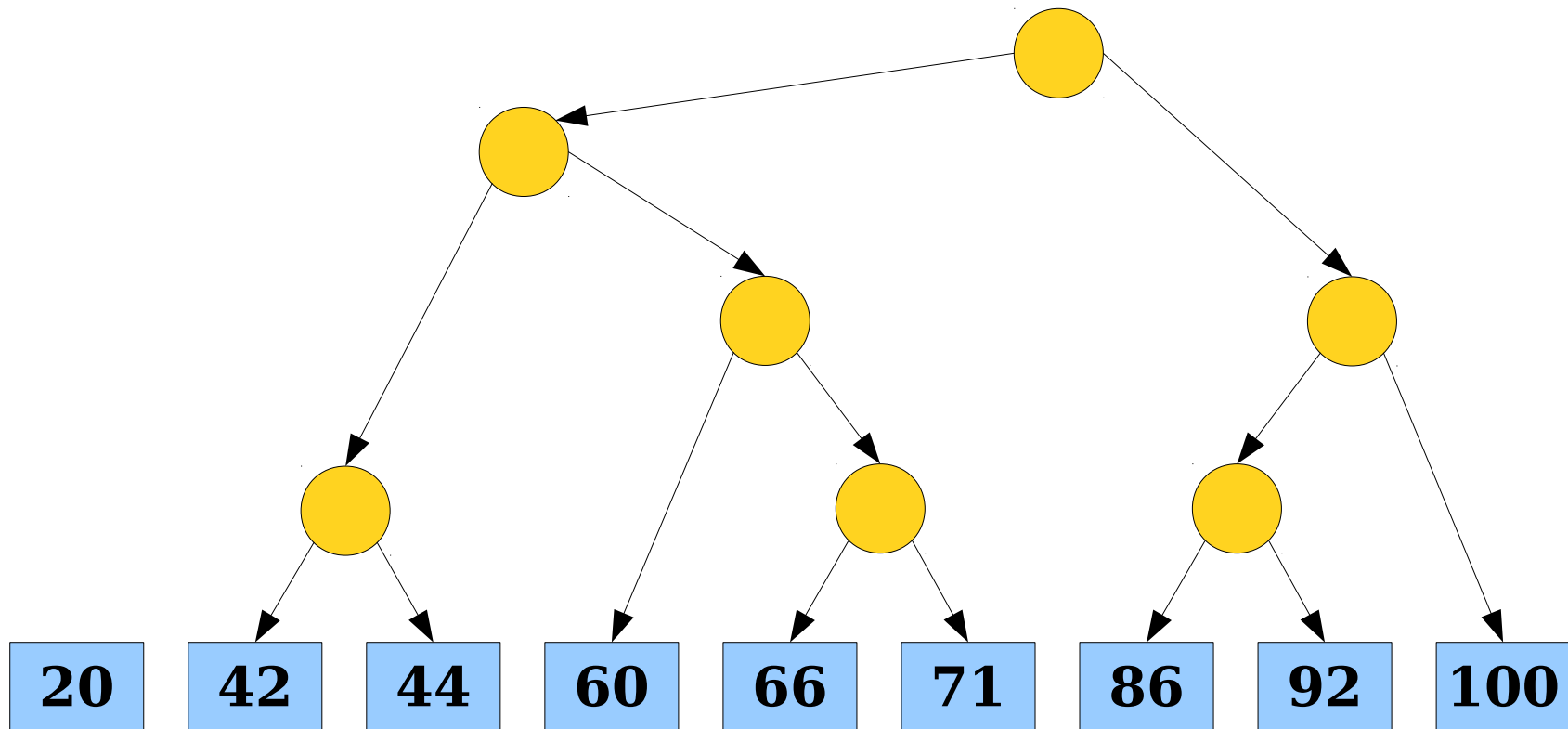
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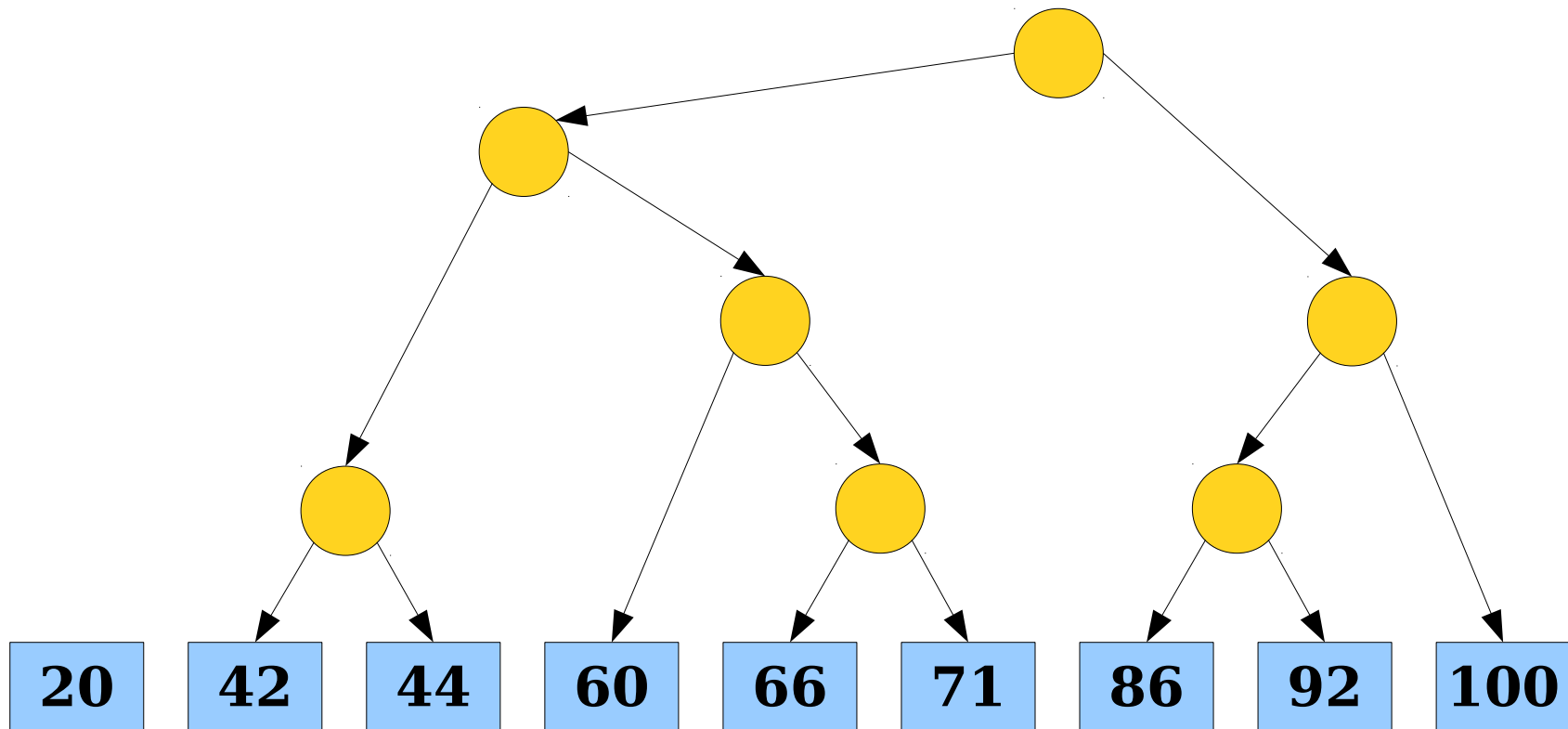
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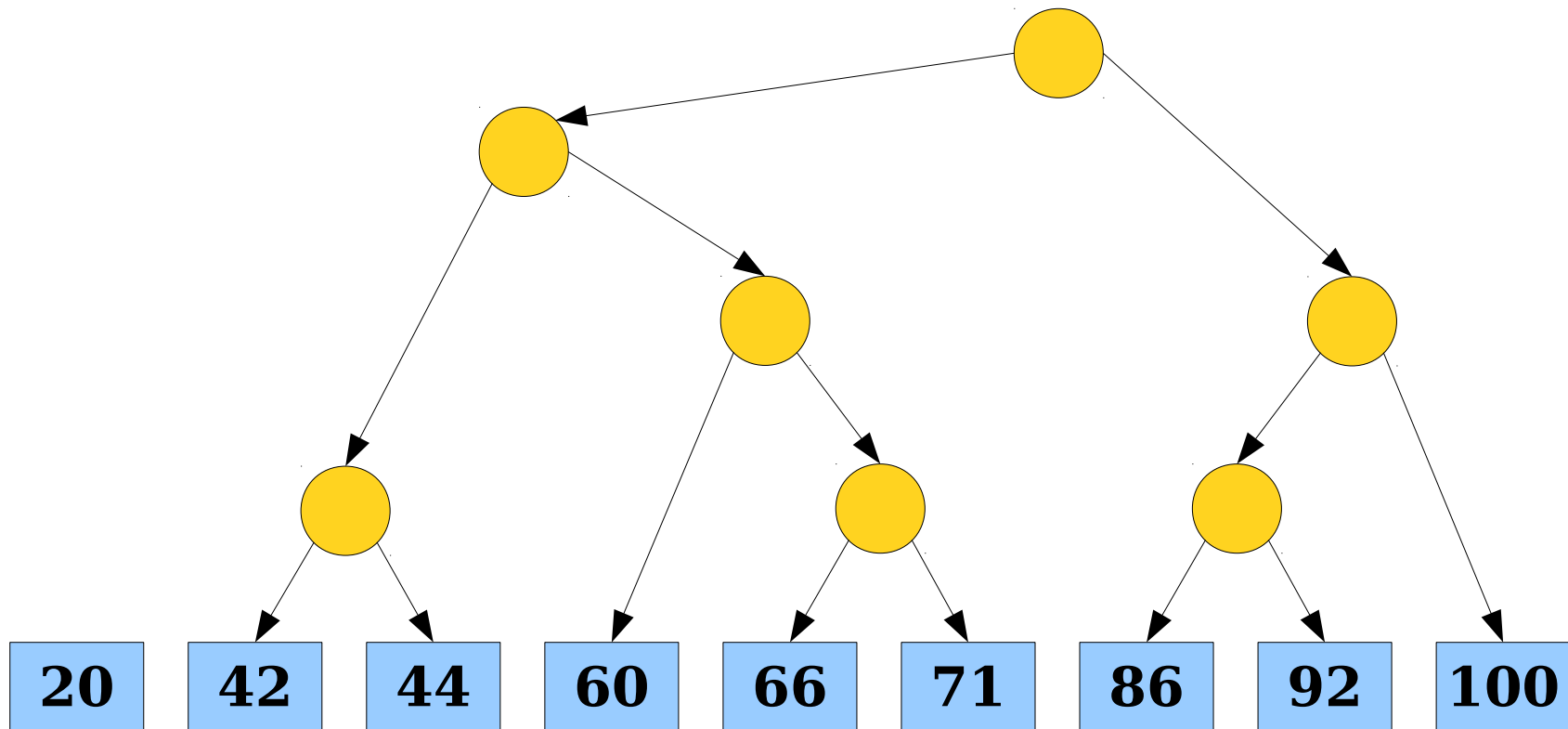
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	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>



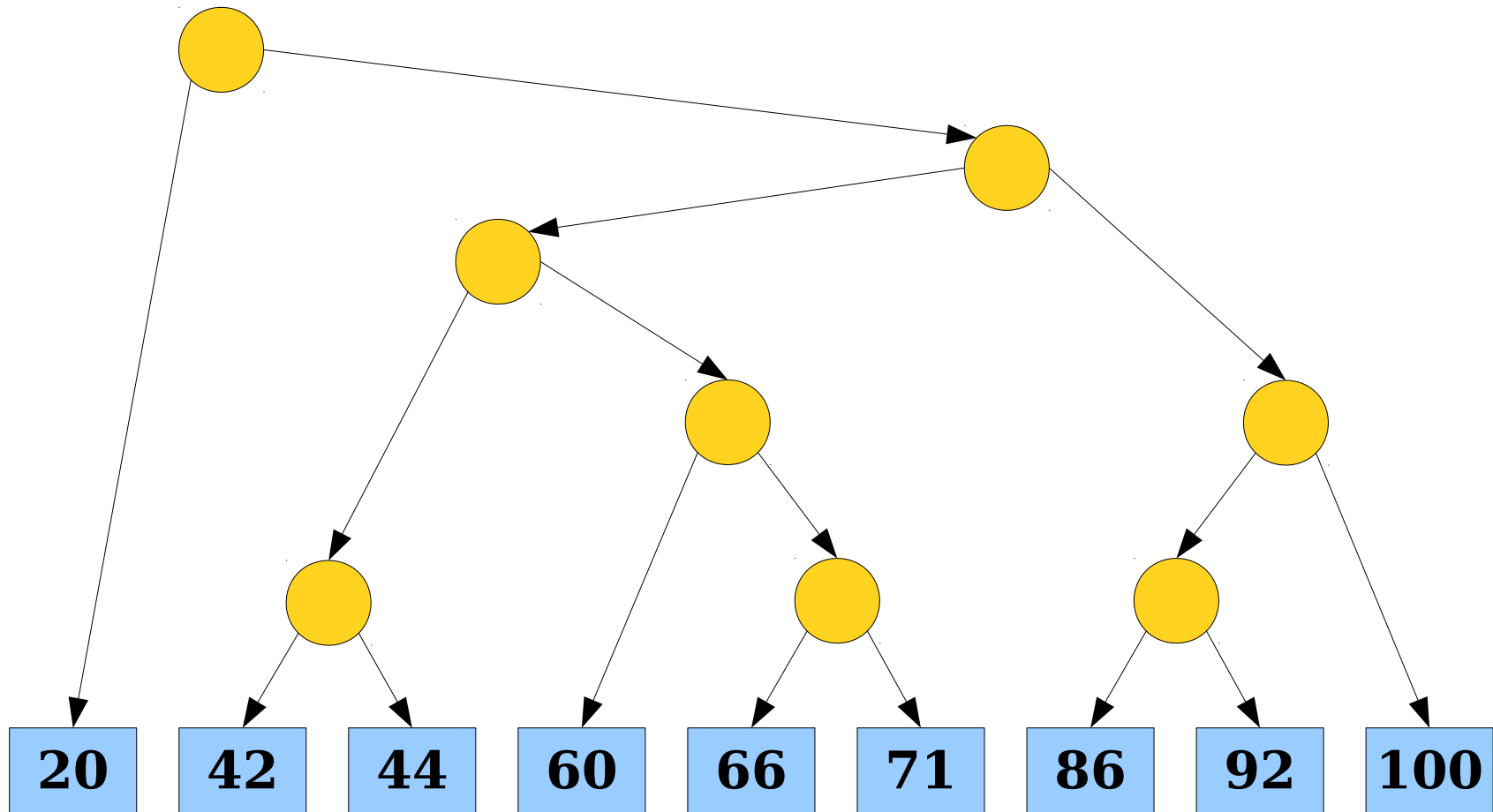
# 1D Hierarchical Clustering

<b>64.56</b>								
<b>20</b>	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>



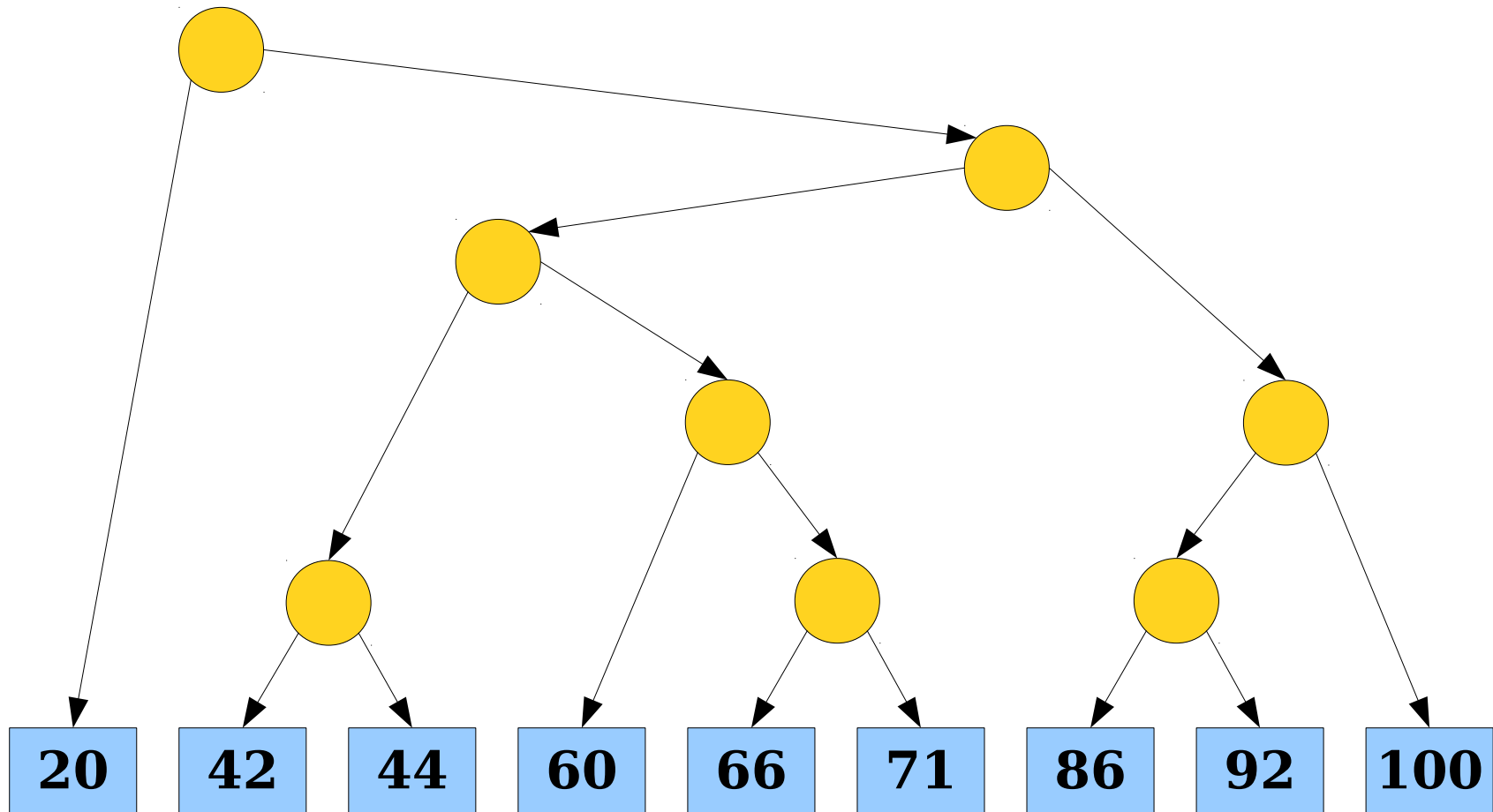
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<b>20</b>	<b>42</b>	<b>44</b>	<b>60</b>	<b>66</b>	<b>71</b>	<b>86</b>	<b>92</b>	<b>100</b>



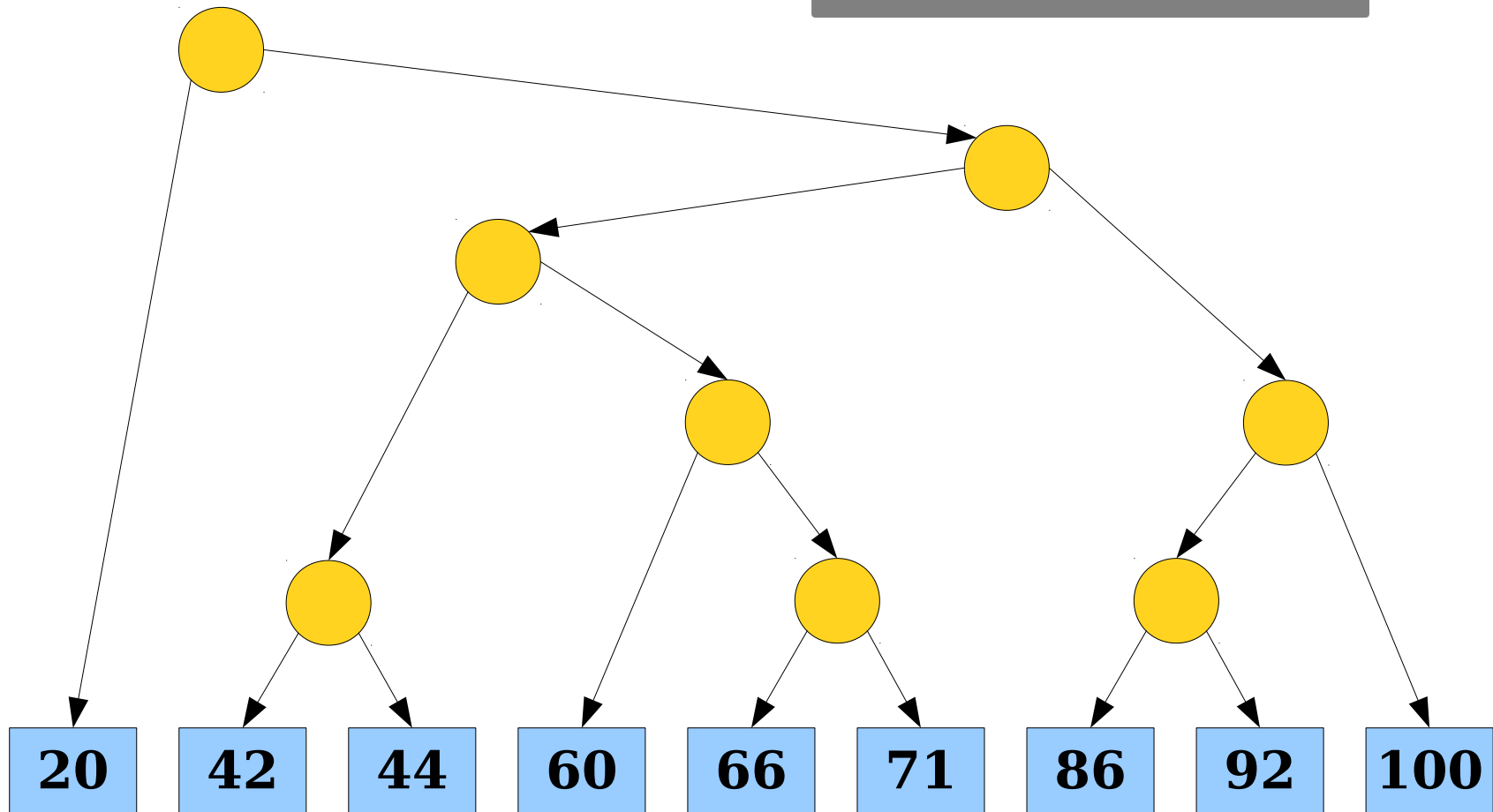


# 1D Hierarchical Clustering



# 1D Hierarchical Clustering

This tree is called a *dendrogram*.



# Analyzing the Runtime

- How efficient is this algorithm?
  - Number of rounds:  $\Theta(n)$ .
  - Work to find closest pair:  $O(n)$ .
  - Total runtime:  $\Theta(n^2)$ .
- Can we do better?

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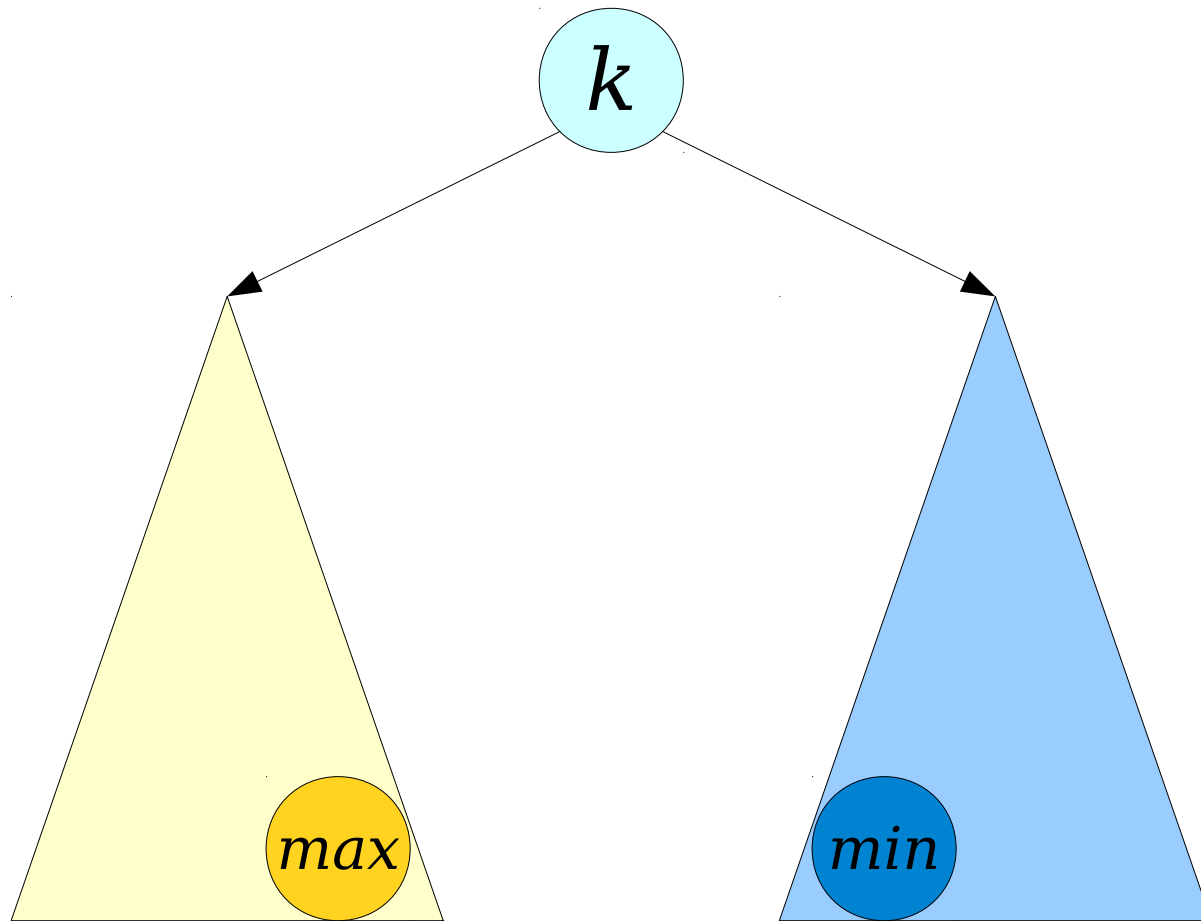
# Dynamic 1D Closest Points

- The ***dynamic 1D closest points problem*** is the following:

Maintain a set of real numbers undergoing insertion and deletion while efficiently supporting queries of the form “what is the closest pair of points?”

- Can we build a better data structure for this?

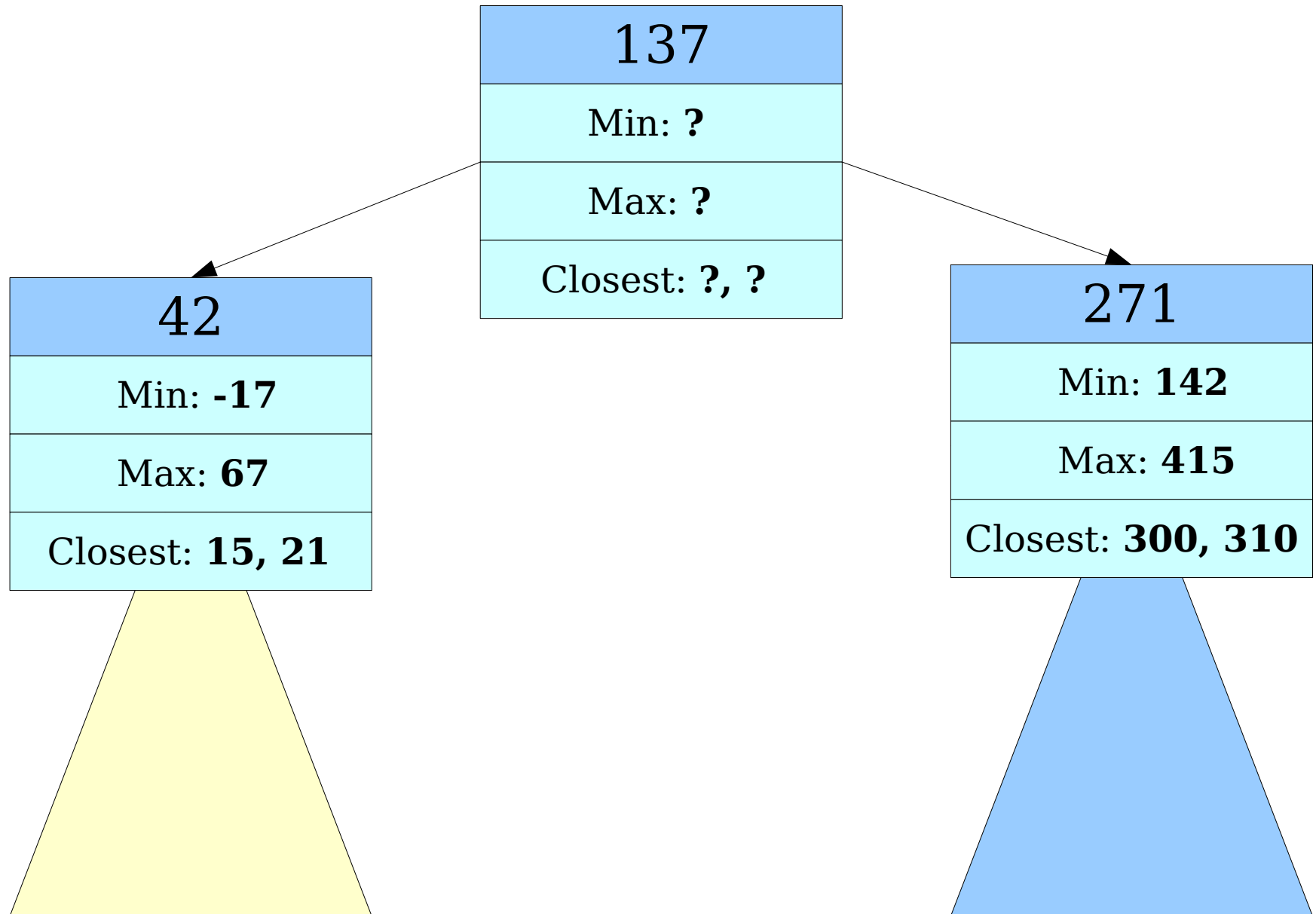
# Dynamic 1D Closest Points



# A Tree Augmentation

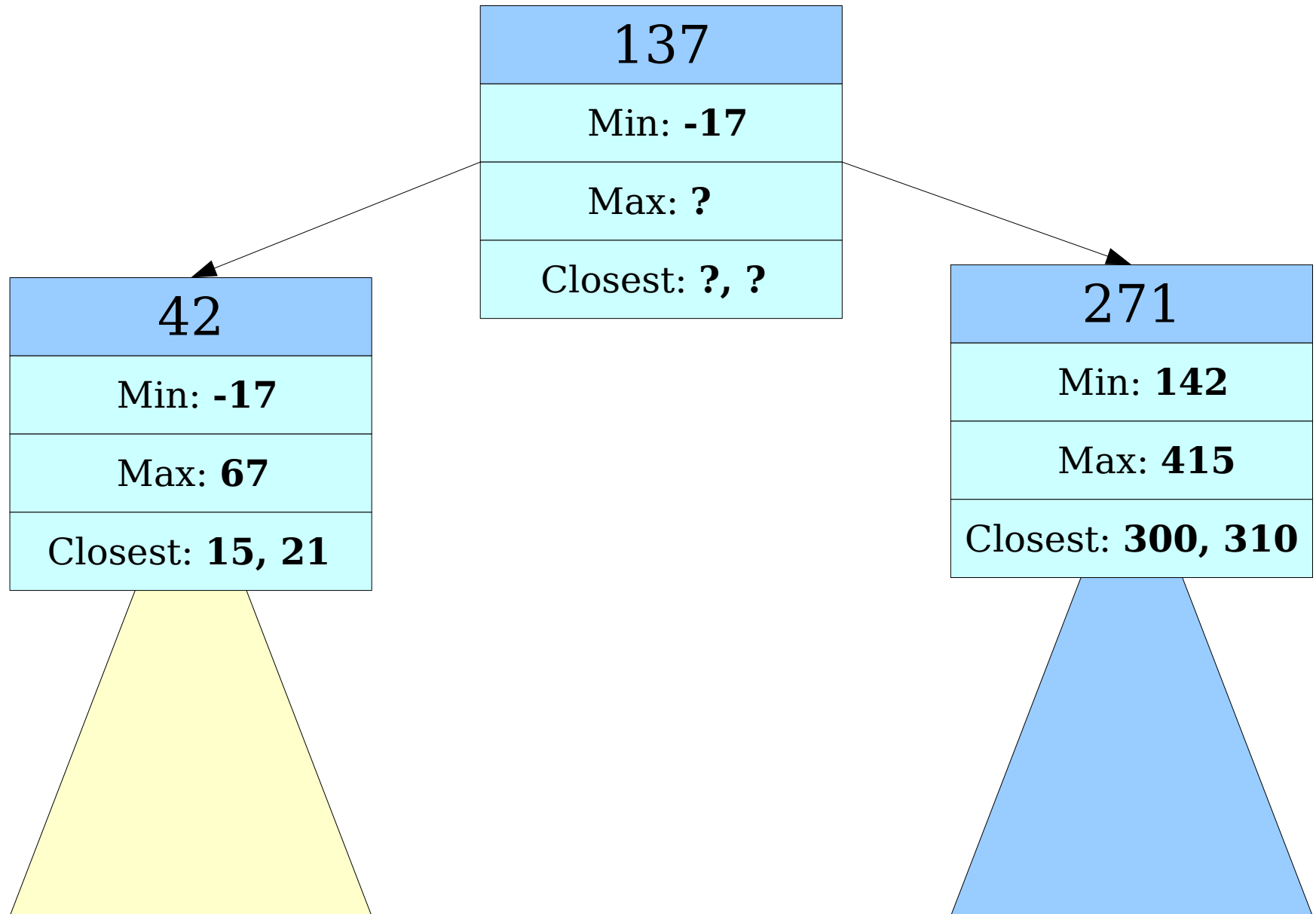
- Augment each node to store the following:
  - The maximum value in the tree.
  - The minimum value in the tree.
  - The closest pair of points in the tree.
- **Claim:** Each of these properties can be computed in time  $O(1)$  from the left and right subtrees.
- These properties can be augmented into a red/black tree so that insertions and deletions take time  $O(\log n)$  and “what is the closest pair of points?” can be answered in time  $O(1)$ .

# Dynamic 1D Closest Points

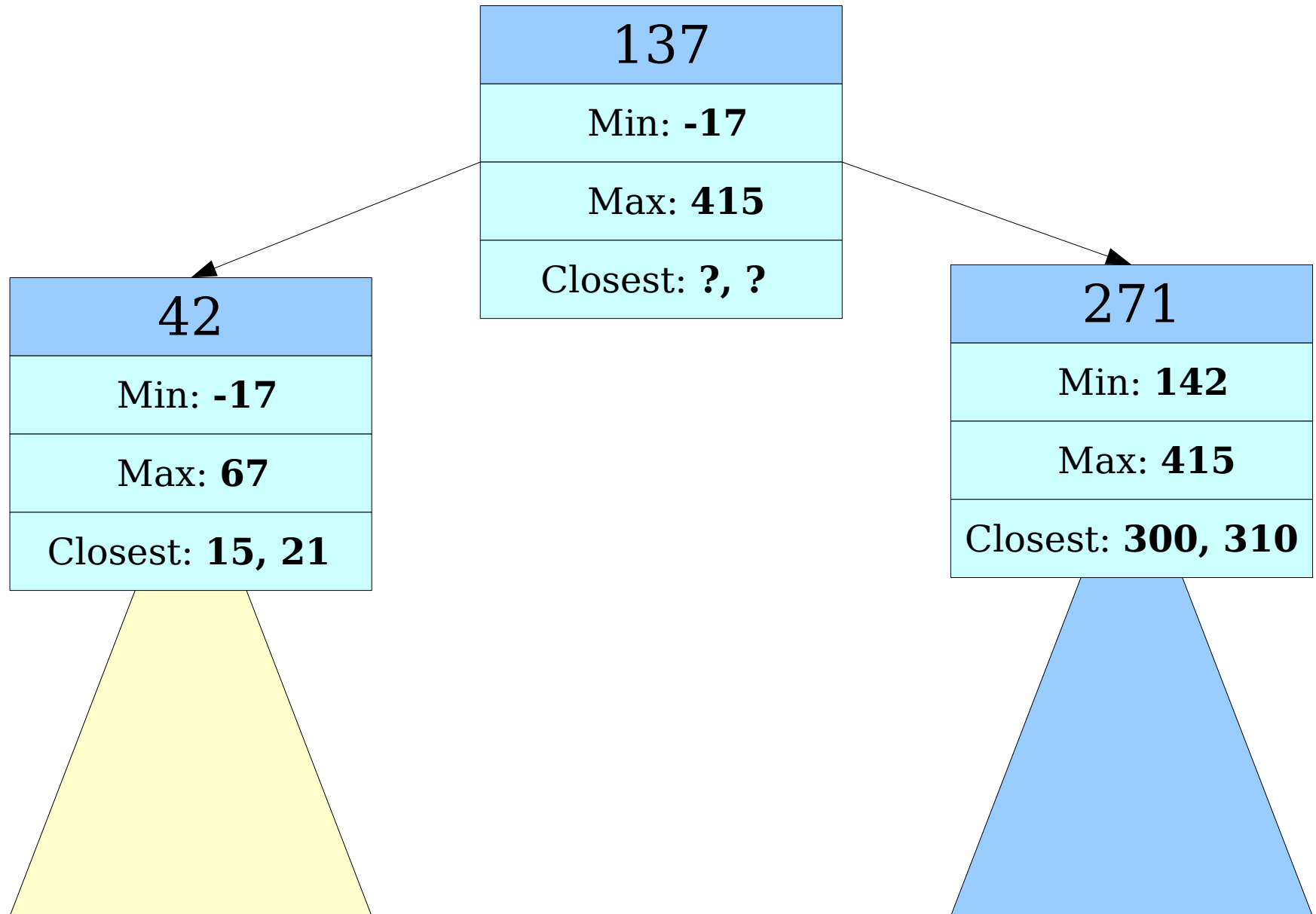




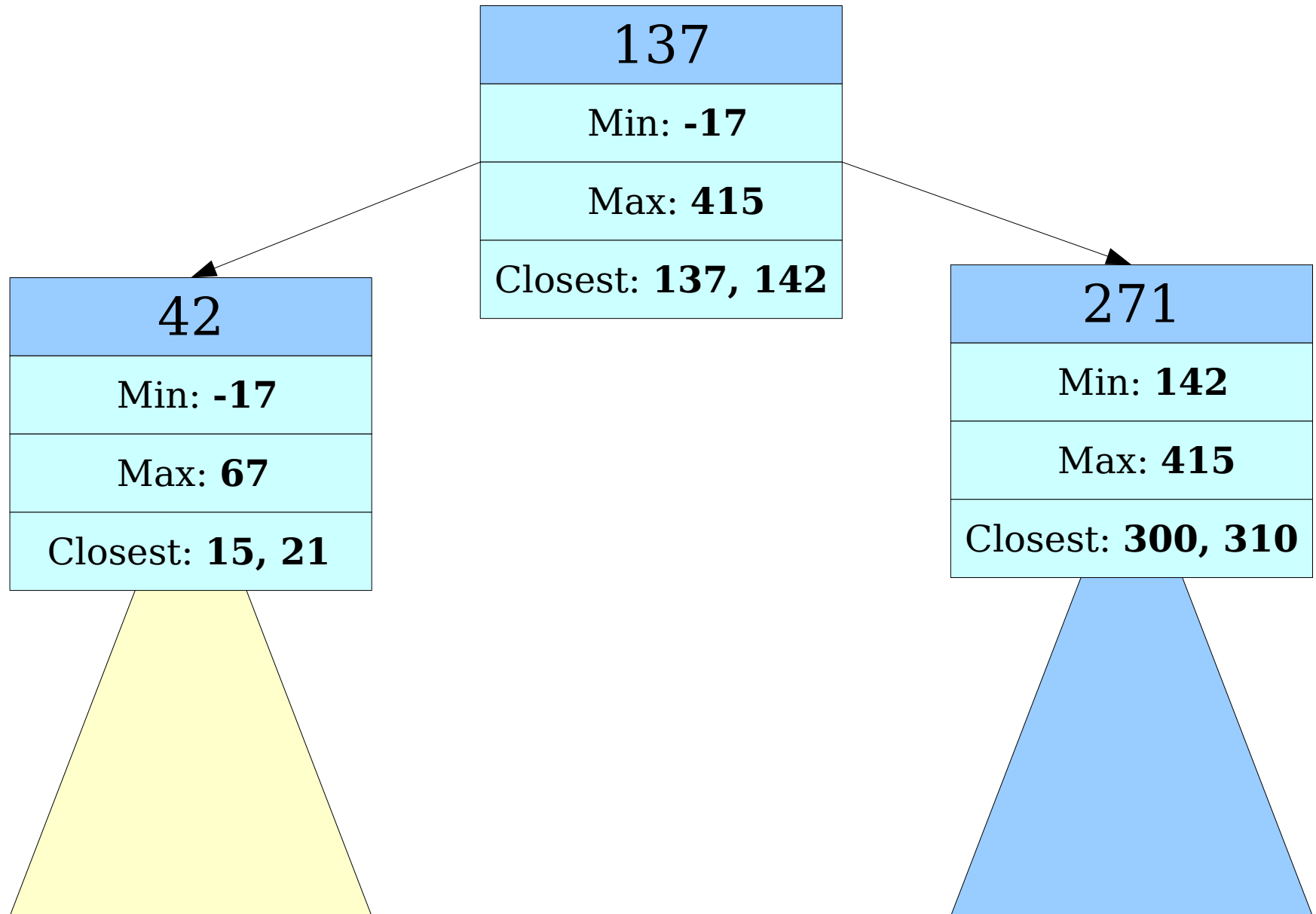
# Dynamic 1D Closest Points



# Dynamic 1D Closest Points



# Dynamic 1D Closest Points



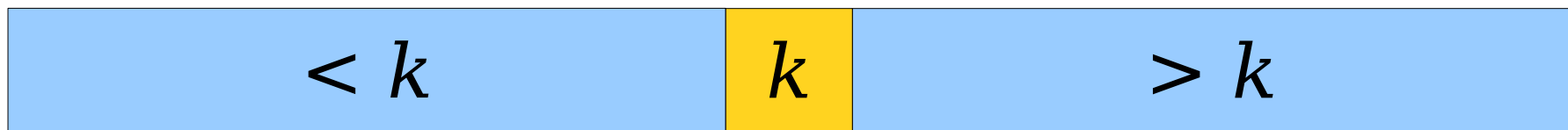
# Some Other Questions

- How would you augment this tree so that you can efficiently (in time  $O(1)$ ) compute the appropriate weighted averages?
- ***Trickier:*** Is this the fastest possible algorithm for this problem?
  - What if you're guaranteed that the keys are all integers in some nice range?

# A Helpful Intuition

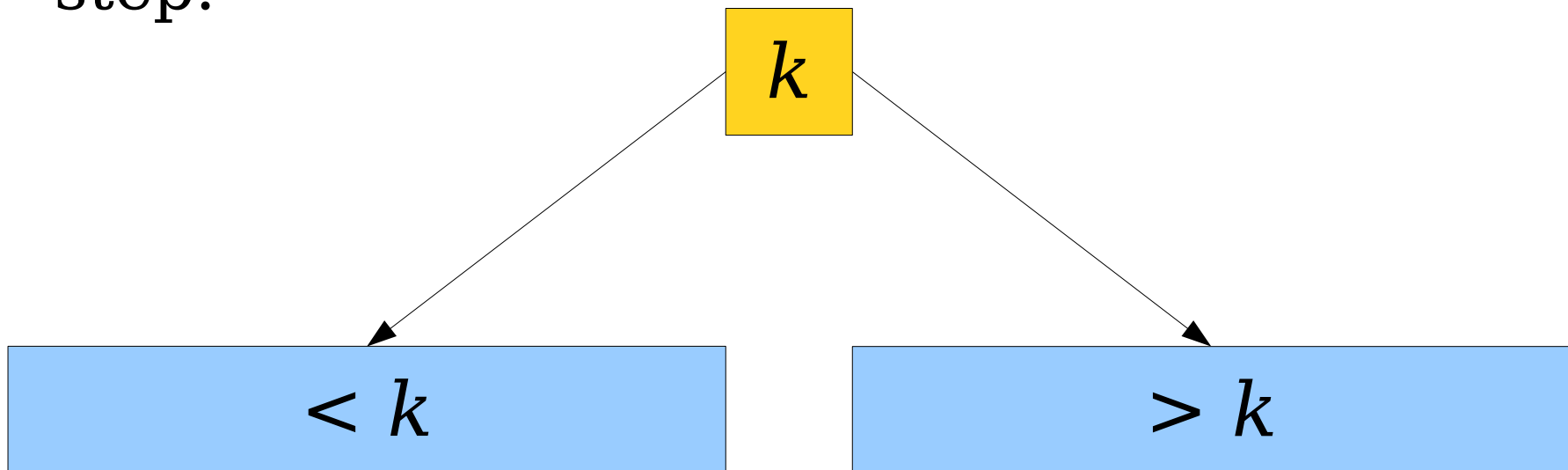
# Divide-and-Conquer

- Initially, it can be tricky to come up with the right tree augmentations.
- ***Useful intuition:*** Imagine you're writing a divide-and-conquer algorithm over the elements and have  $O(1)$  time per “conquer” step.



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# Next Time

- ***Amortized Analysis***
  - Lying about runtime costs in an honest manner.
- ***Frameworks for Amortization***
  - How can we think about assigning costs?
- ***Some Applications***
  - Building queues and handling red/black tree deletions