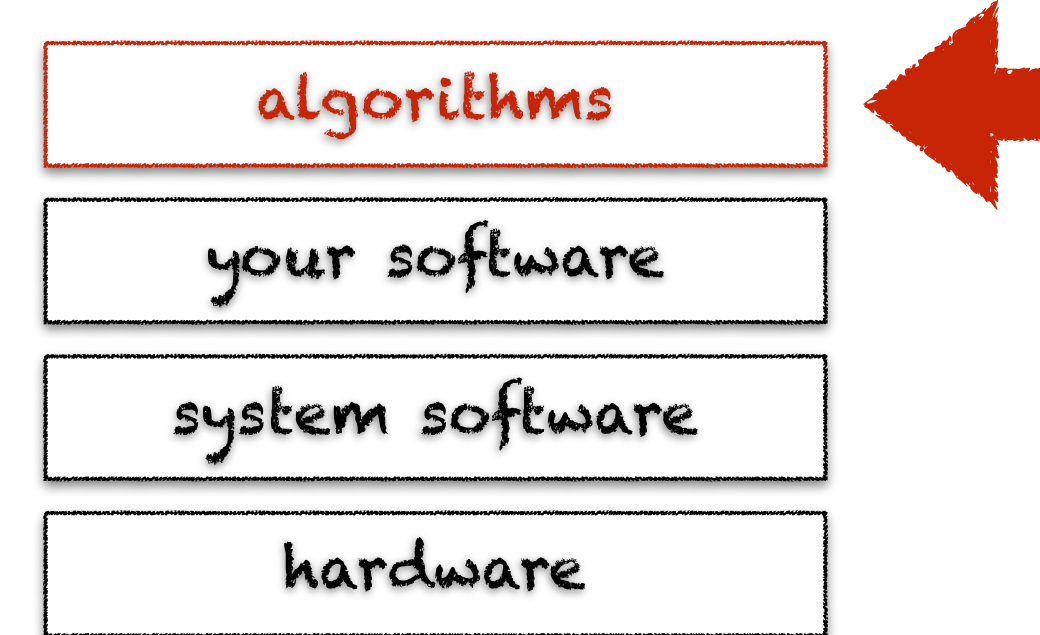




spatial tree algorithms

learning objectives

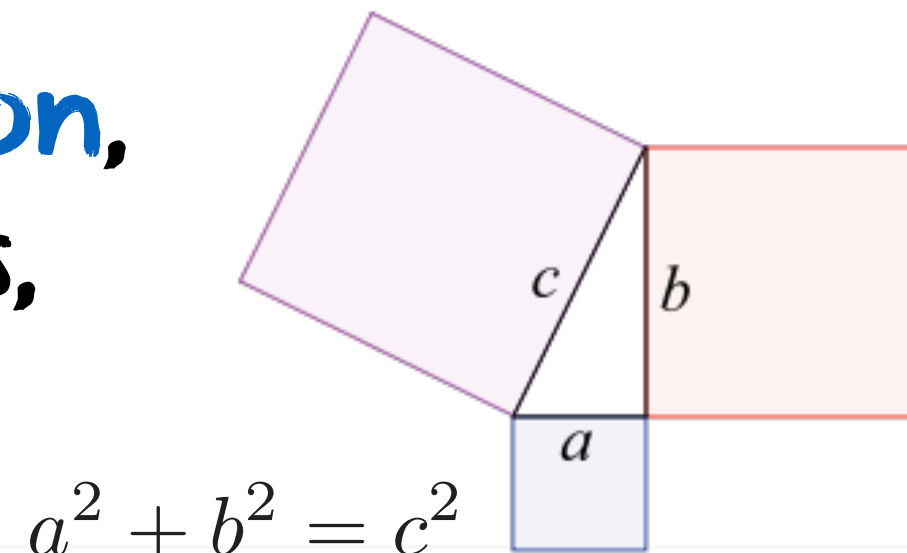


- ♦ learn the characteristics of spatial data
- ♦ learn several spatial indexing data structures
- ♦ learn basic algorithms for using such structures

computational geometry

a branch of computer science focusing on **data structures & algorithms** for solving **geometric problems**

mathematical visualization, e.g., proof without words, mandelbrot sets, etc.



$$a^2 + b^2 = c^2$$

$$z \mapsto z^d + c$$

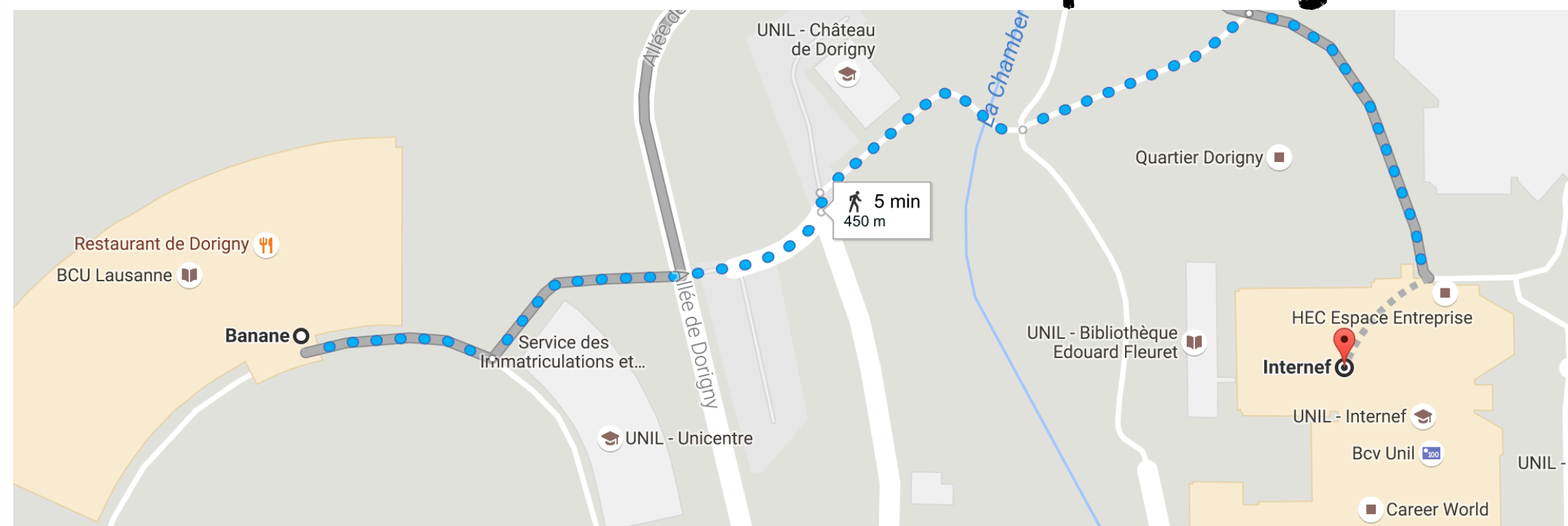


development made possible by **exponential progress in computer graphics**, with multiple applications

computer vision e.g., 3D graphics in games



geographic information systems, e.g., location search & route planning



computer-aided engineering, e.g., mechanical design

computational geometry

what's specific to spatial data?

with 1-dimensional data, natural ordering
implicitly partitions the data, e.g., binary tree

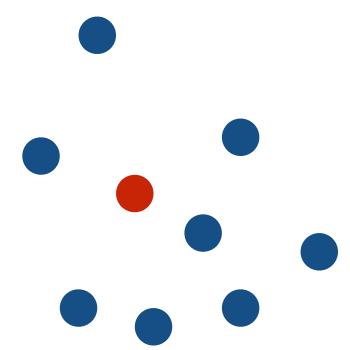
spatial data is intrinsically multidimensional, so there
is no natural ordering of data (e.g., of points)

with 1-dimensional data, the static case is
rather simple and solved by sorting the data

with multidimensional data, the static case is far from
simple and solved by several partitioning techniques

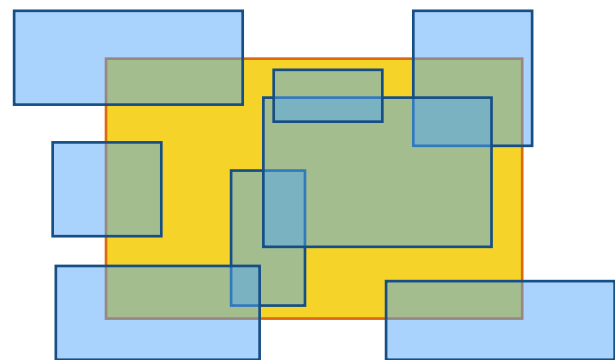
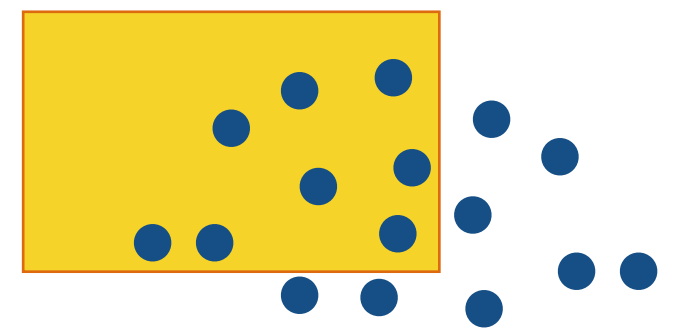
computational geometry

typical problems



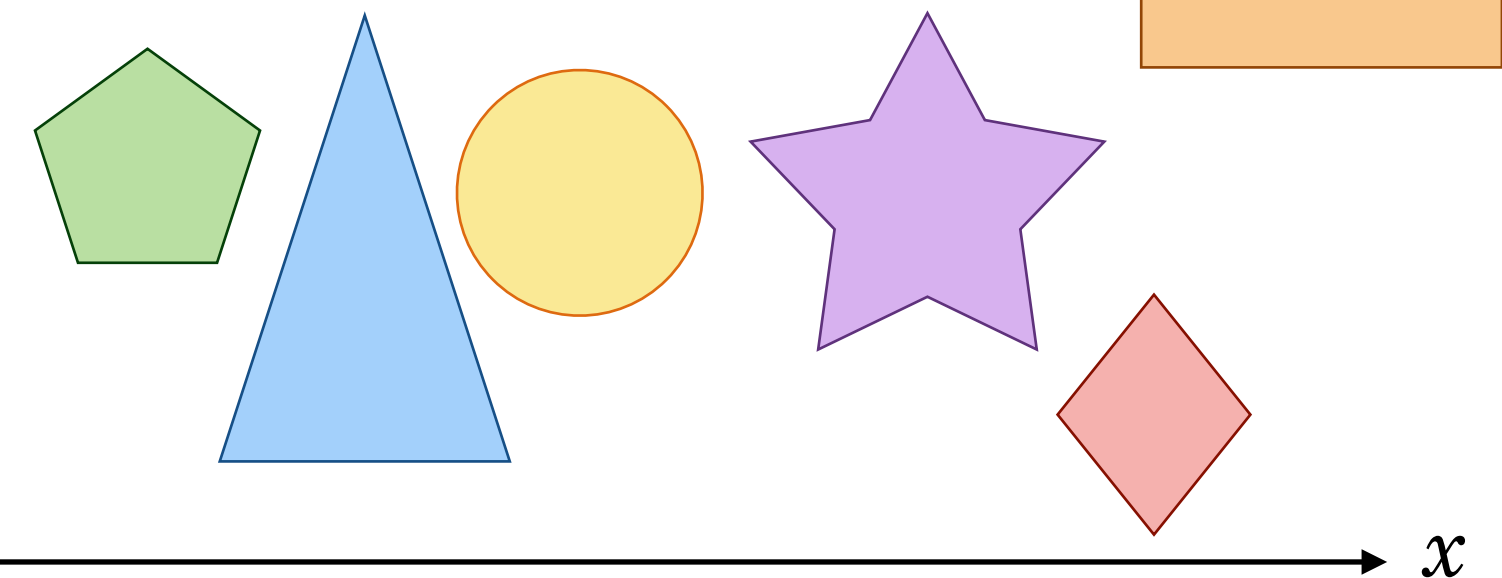
nearest neighbor: given a set of points P , find which one is closest to a target point p_t

range queries: given a set of points P , find the points contained within a given rectangle



intersection queries: given a set of rectangles R , find which rectangles intersect a target rectangle

collision detection: given a set of shapes S , find the intersections between all these shapes



computational geometry

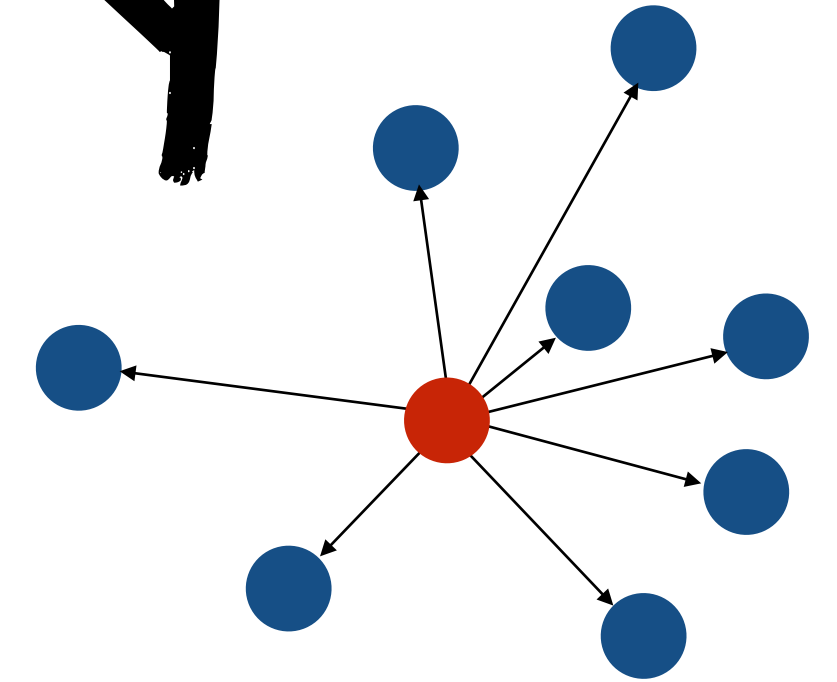
typical approaches

brute-force algorithm

nearest neighbor: given a set of points P , find which one is closest to a target point p_t

Complexity: $O(n)$, with $n = |P|$

```
NEAREST-NEIGHBOR ( $P, p_t$ )  
   $p \leftarrow \text{NIL}$   
   $min \leftarrow \infty$   
  for each  $p_i \in P$   
    if  $\text{distance}(p_i, p_t) < min$   
       $min \leftarrow \text{distance}(p_i, p_t)$   
       $p \leftarrow p_i$   
  return ( $p, min$ )
```



spatial tree structures

they index spatial objects

Complexity: $O(\log n)$, with $n = |P|$

R-trees

quad-trees

kd-trees

R-tree

A. Guttman. *R-trees: A dynamic index structure for spatial searching*.
In Proceedings of the 1984 ACM SIGMOD International Conference on
Management of Data, pages 47–57, New York, NY, USA, 1984. ACM.

a **recursive tree**, where each node has between M and $m = \left\lfloor \frac{M}{2} \right\rfloor$ children, except for the **root which has at least two**

only leaf nodes contain actual spatial object entries, each consisting of the spatial object itself and a **minimum bounding region (mbr)** containing that object, i.e., $object = (shape, mbr)$

internal nodes contain children entries, each consisting of a link to the child node and an **mbr covering all children nodes of that child**, i.e., $node = (child, mbr)$

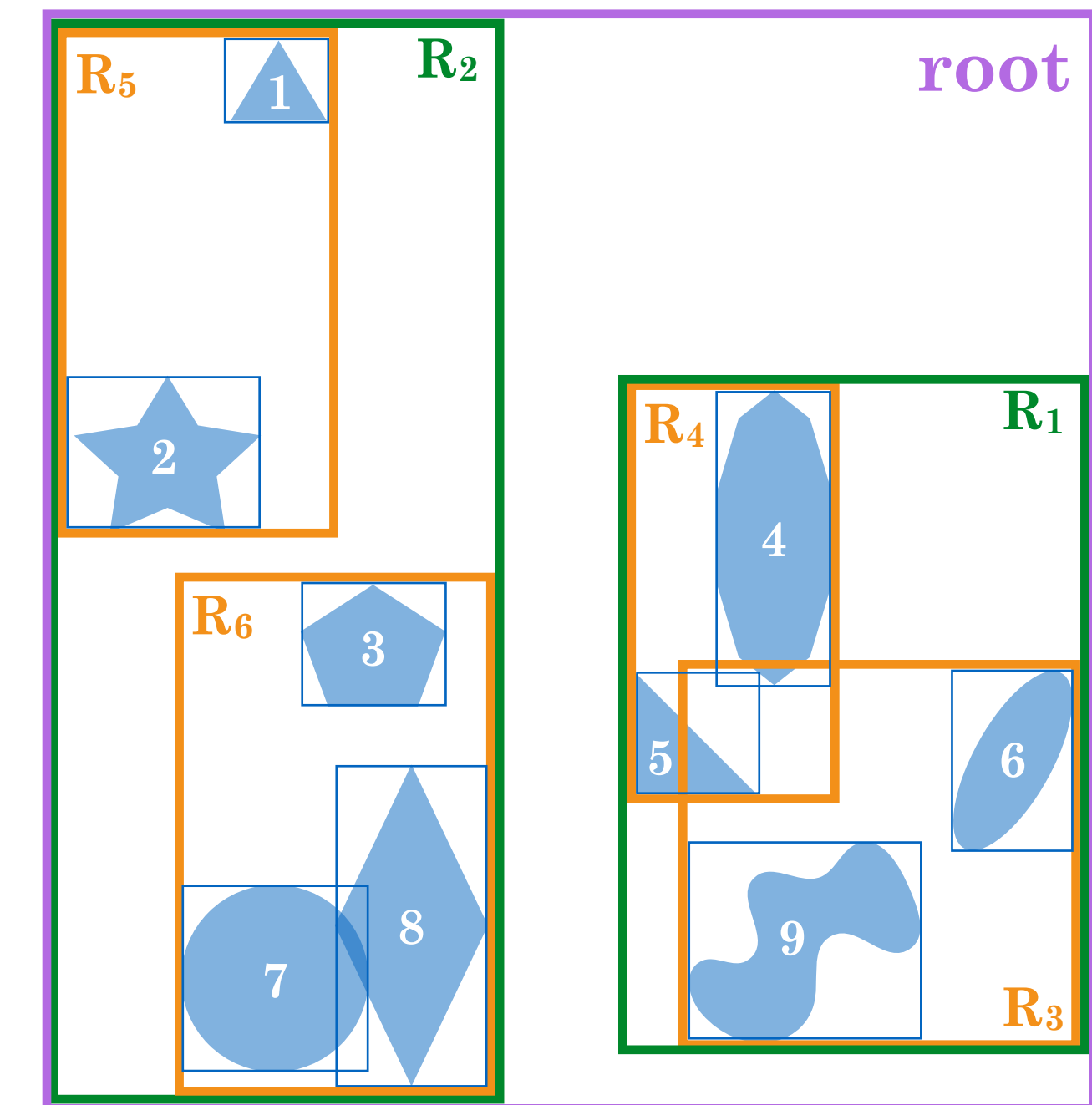
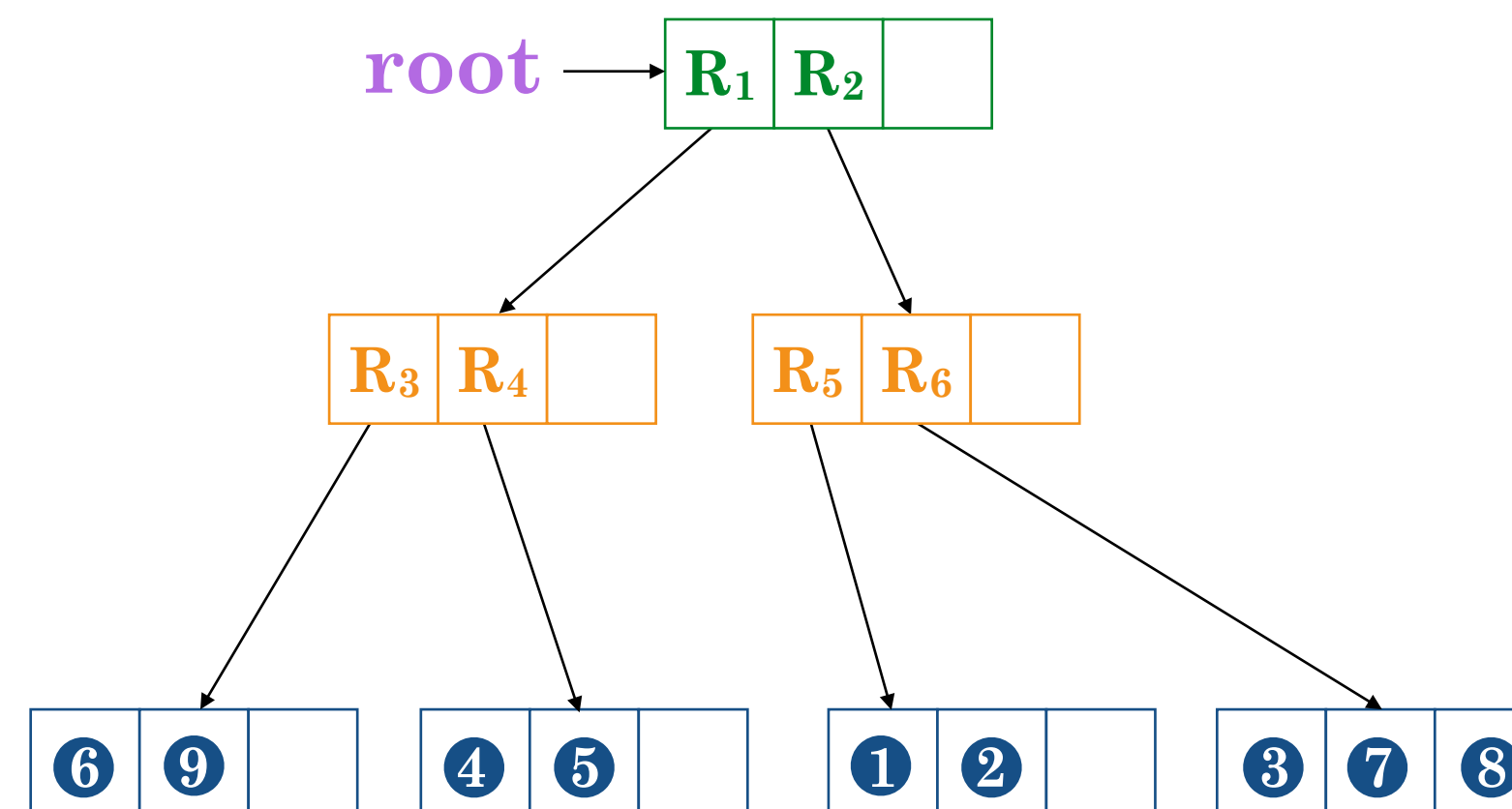
an **minimum bounding region** is typically of the form $mbr = (x_{min}, y_{min}, x_{max}, y_{max})$

all leaves are at the same level, i.e., the tree is **height balanced**

R-tree

only leaf nodes contain actual spatial object entries, each consisting of the spatial object itself and a minimum bounding region (mbr) containing that object, i.e., $object = (shape, mbr)$

internal nodes contain children entries, each consisting of a link to the child node and an mbr covering all children nodes of that child, i.e., $node = (child, mbr)$

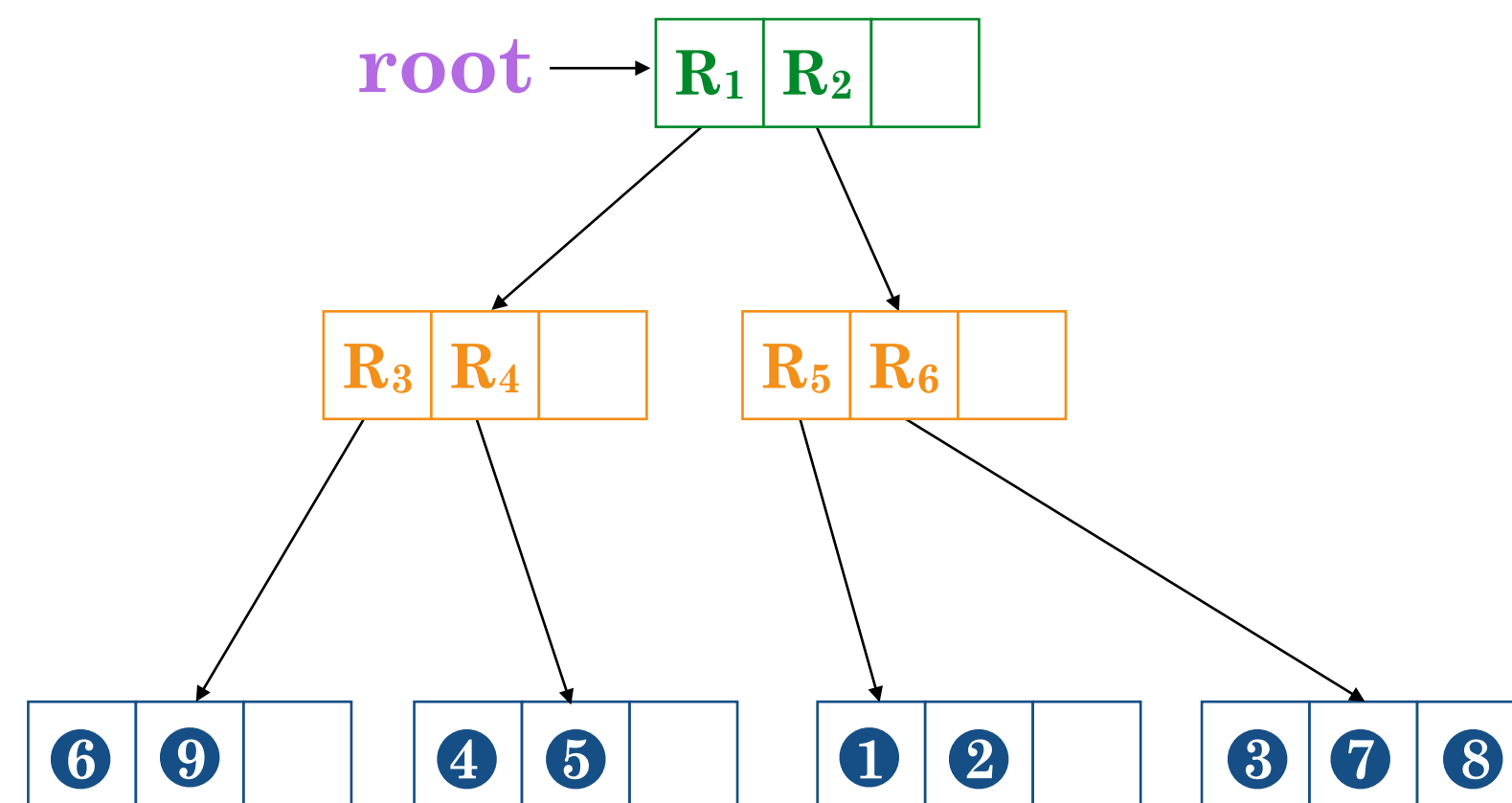


important: the root also contains a minimum bounding box

R-tree

```

INTERSECT (node, region)
  if node.mbr  $\subset$  region
    return { object | object  $\in$  REACHABLE-LEAVES(node) }
  if node is a leaf
    return { object  $\in$  node | object.mbr  $\cap$  region  $\neq \emptyset$  }
  result  $\leftarrow \emptyset$ 
  for each kid  $\in$  node.children
    if kid.mbr  $\cap$  region  $\neq \emptyset$ 
      result = result  $\cup$  INTERSECT (kid.child, region)
  return result
  
```



```

SEARCH (node, shape)
  if node is a leaf
    if  $\exists$  object  $\in$  node : object.shape = shape
      return object
    return NIL
  for each kid  $\in$  node.children
    if shape.mbr  $\subseteq$  kid.mbr
      return SEARCH(kid.child, shape)
  return NIL
  
```

important: the root also contains a minimum bounding box

quad-tree

R. A. Finkel and J. L. Bentley. *Quad trees a data structure for retrieval on composite keys*. Acta Informatica, 4(1):1–9, 1974.

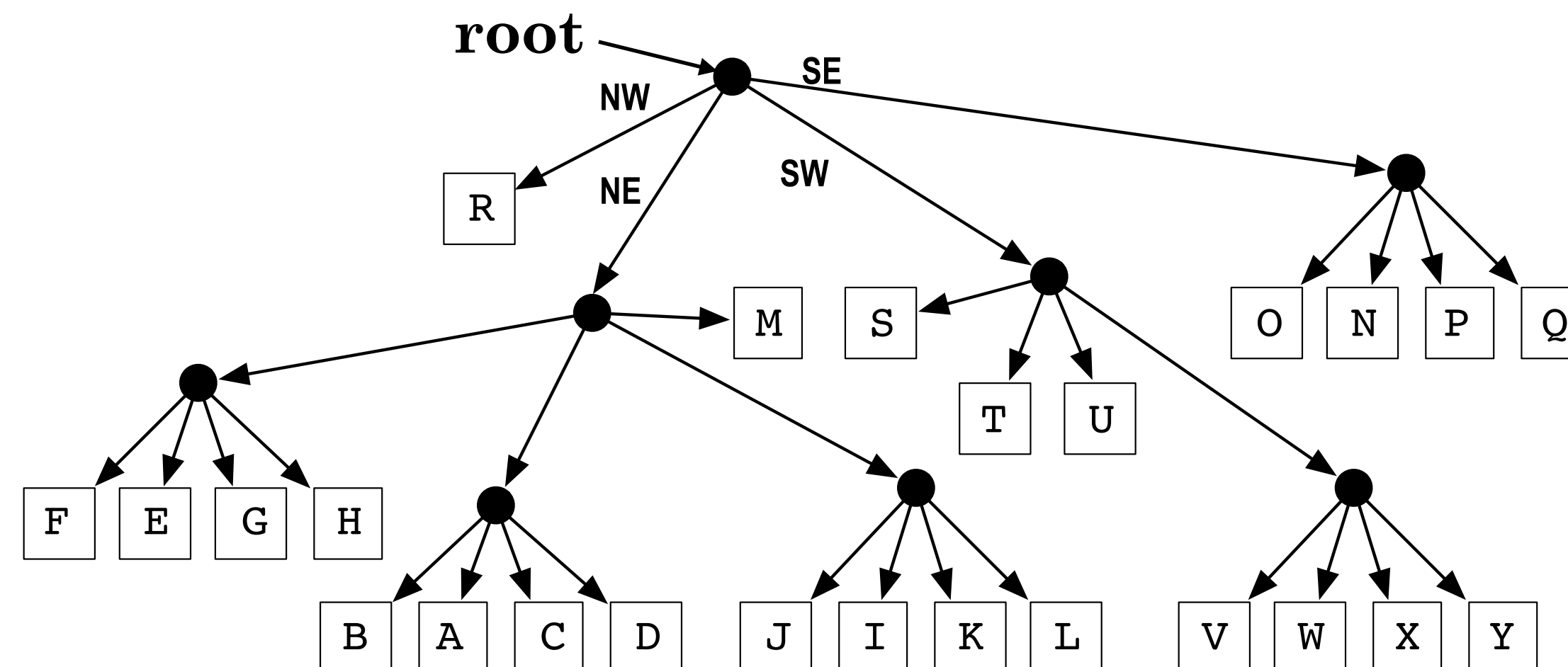
a **recursive tree** where each internal node has **four children**

each node **represents a cell in the geometrical space**, with its children partitioning that cell into an **equally sized subcell**

predefined partitioning with subcells (**quadrants**) named as North West (**NW**), North-East (**NE**), South-West (**SW**) and South-East (**SE**)

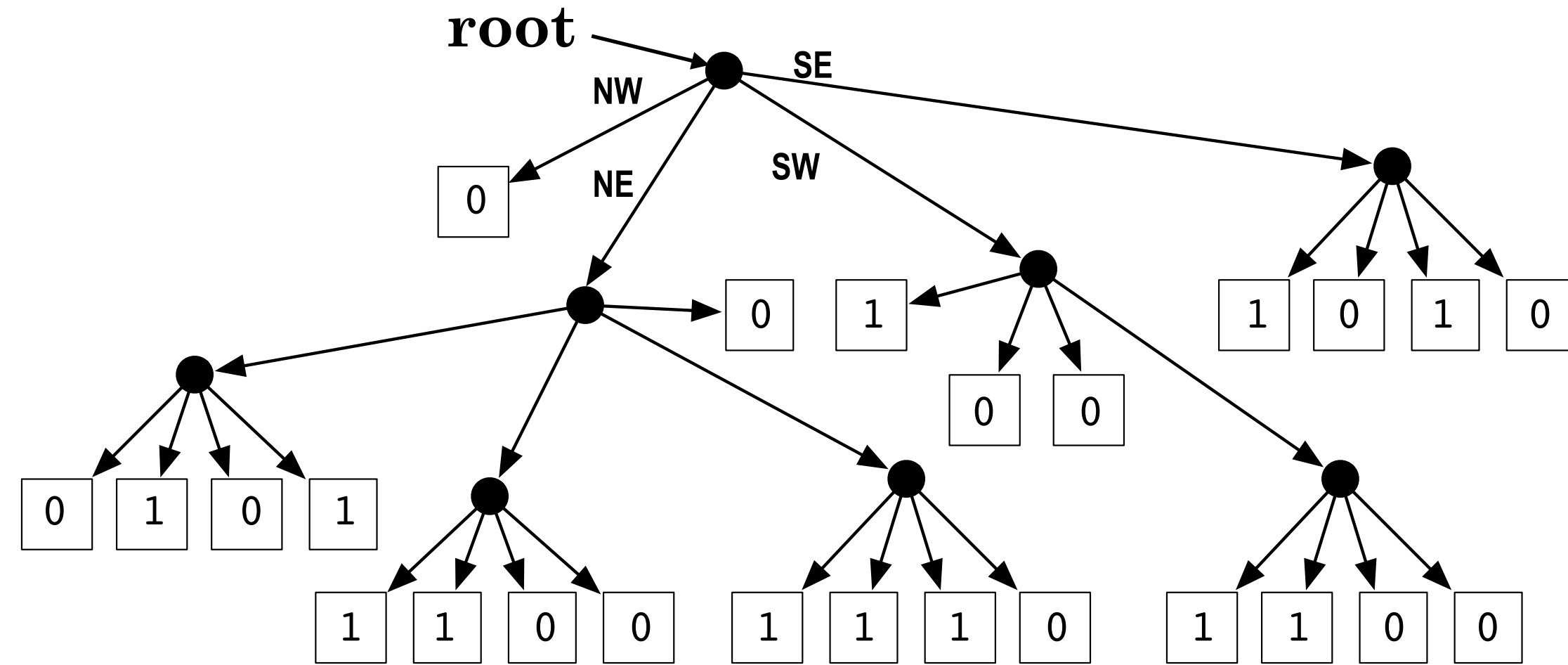
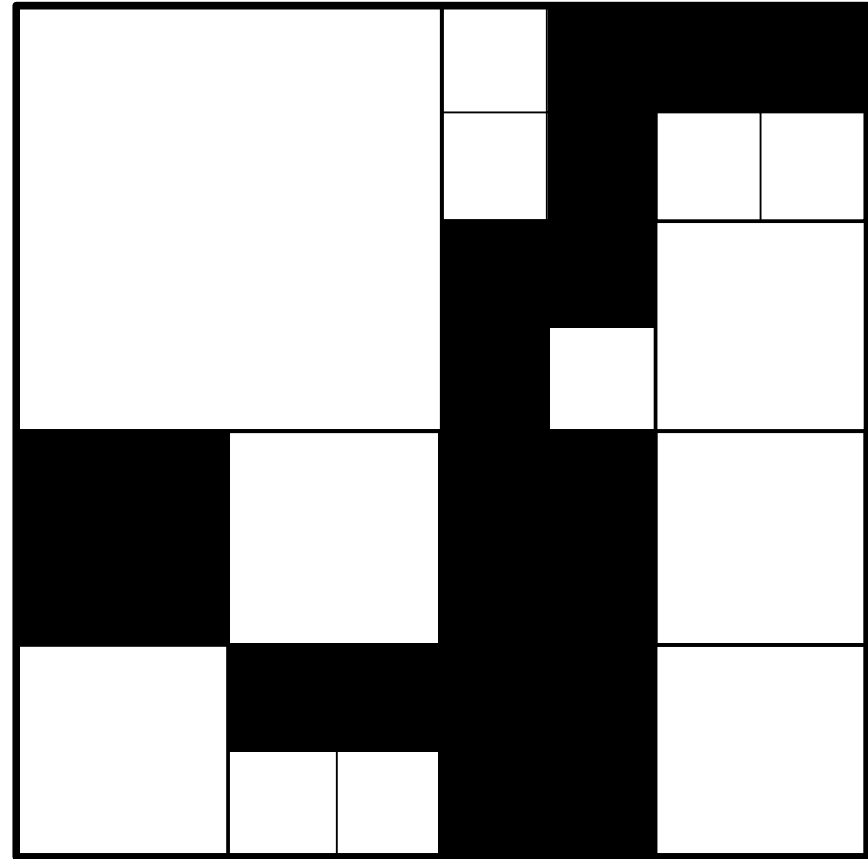
like R-trees, **only leaf nodes store actual geometrical objects**

R		F	E	B	A
		G	H	C	D
		J	I	M	
		K	L		
S	T	O		N	
U	V	W	P		Q
	Y	X			

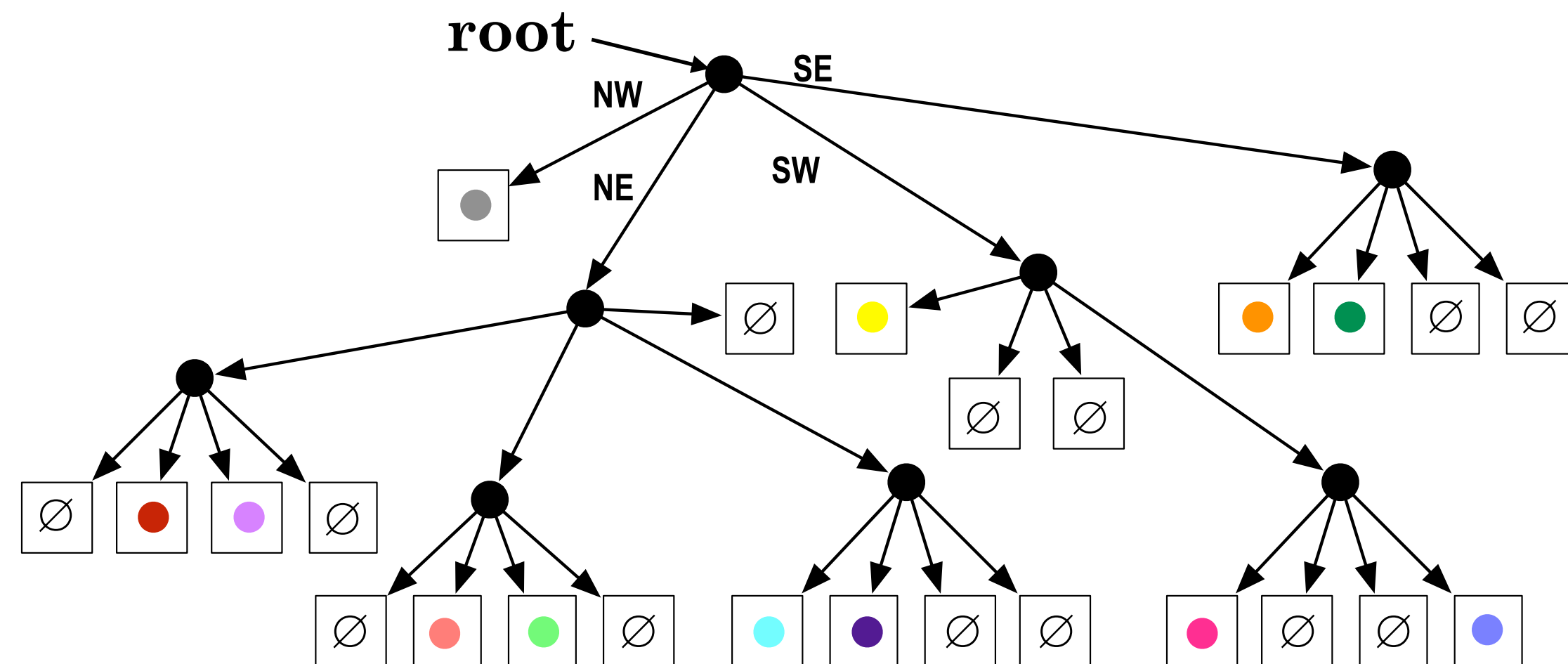
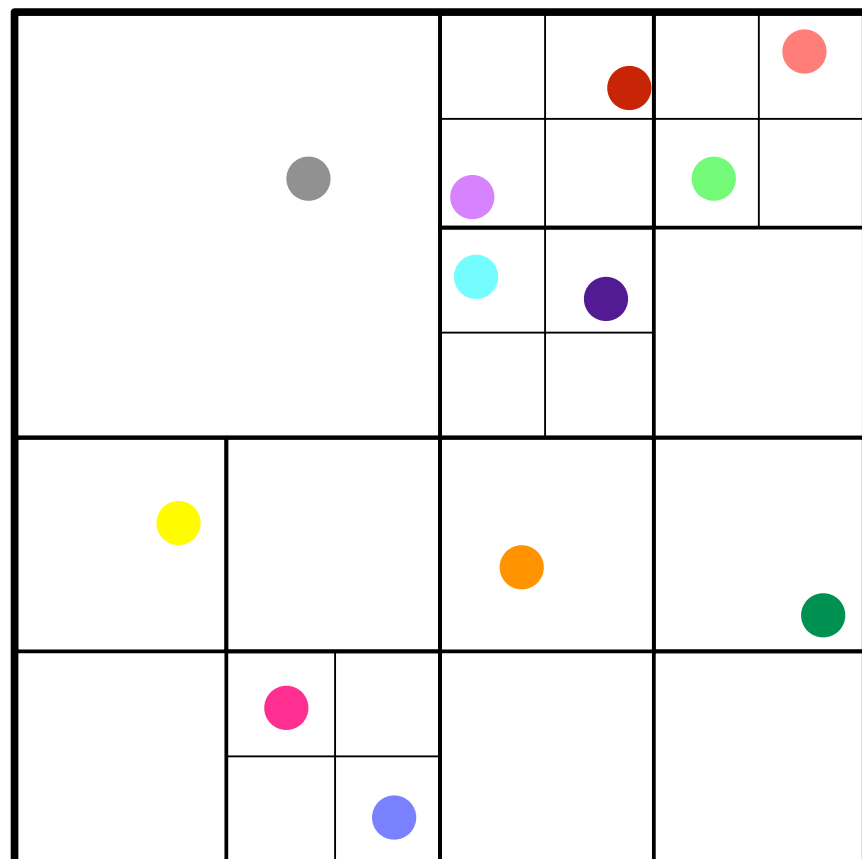


quad-tree

region quad-tree



point-region quad-tree



quad-tree

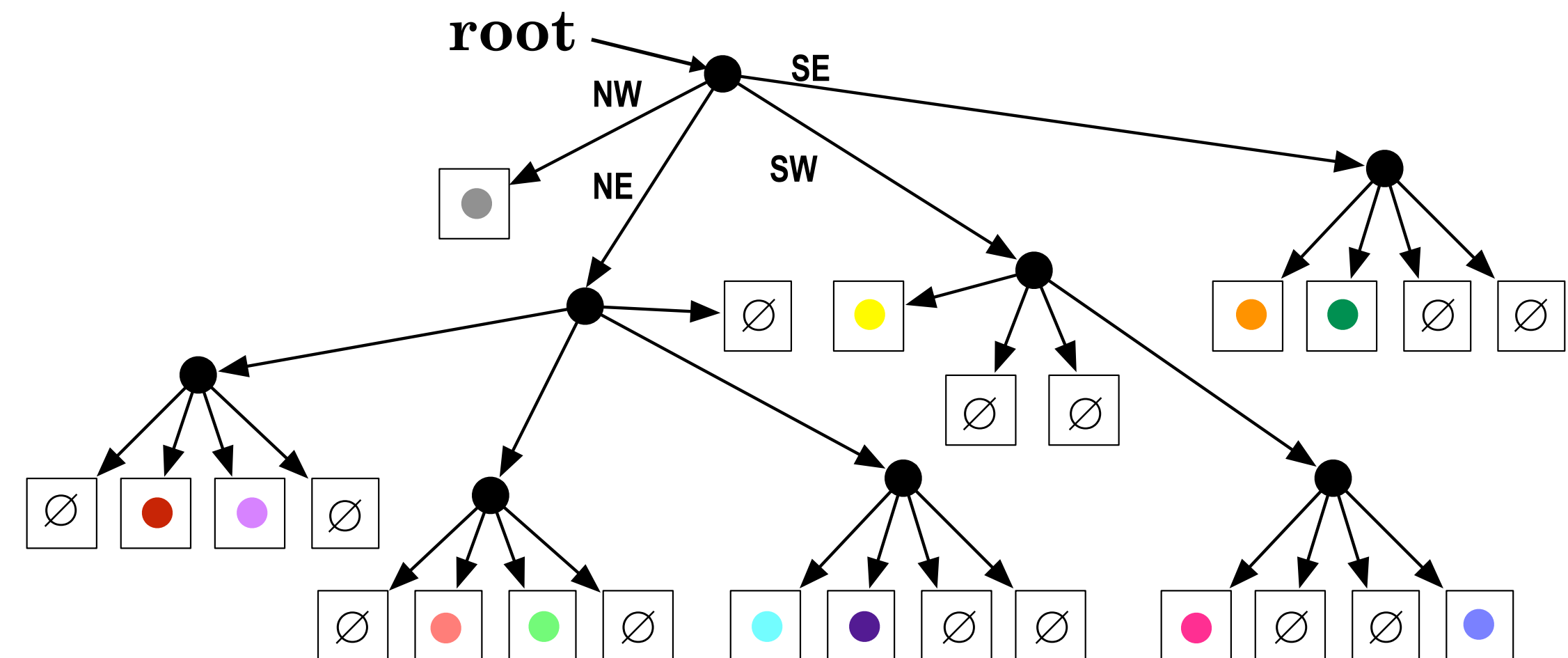
```
ADD (node, point)
  if point  $\notin$  node.cell
    return FALSE
  if node is a leaf
    if node.point = point
      return FALSE
    if node.point = NIL
      node.point  $\leftarrow$  point
    return TRUE
```

```
quadrant  $\leftarrow$  FIND-QUADRANT(node, point)
if node is a leaf
  SUBDIVIDE(node)
return ADD (node[quadrant], point)
```

```
INTERSECT (node, region)
  if node is a leaf
    if node.point  $\in$  region return { node.point }
    return  $\emptyset$ 

  if node.cell  $\subset$  region
    return { node.point | node  $\in$  REACHABLE-LEAVES(node) }

  result  $\leftarrow$   $\emptyset$ 
  for each quadrant  $\in$  { NW, NE, SW, SE }
    if node[quadrant].cell  $\cap$  region  $\neq \emptyset$ 
      result = result  $\cup$  INTERSECT (node[quadrant], region)
  return result
```



kd-tree

J.L. Bentley. *Multidimensional binary search trees used for associative searching*. Commun. ACM, 18(9):509–517, September 1975.

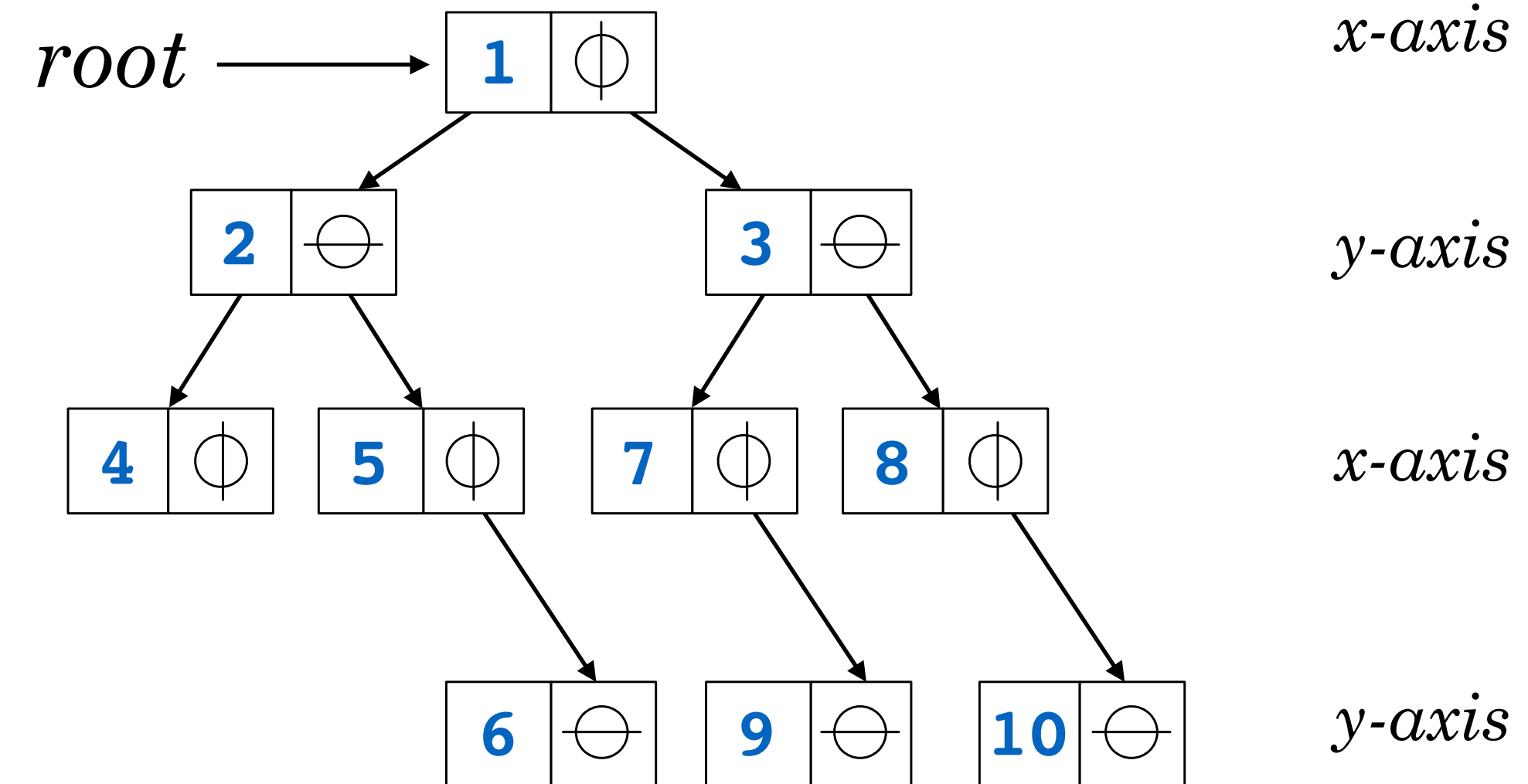
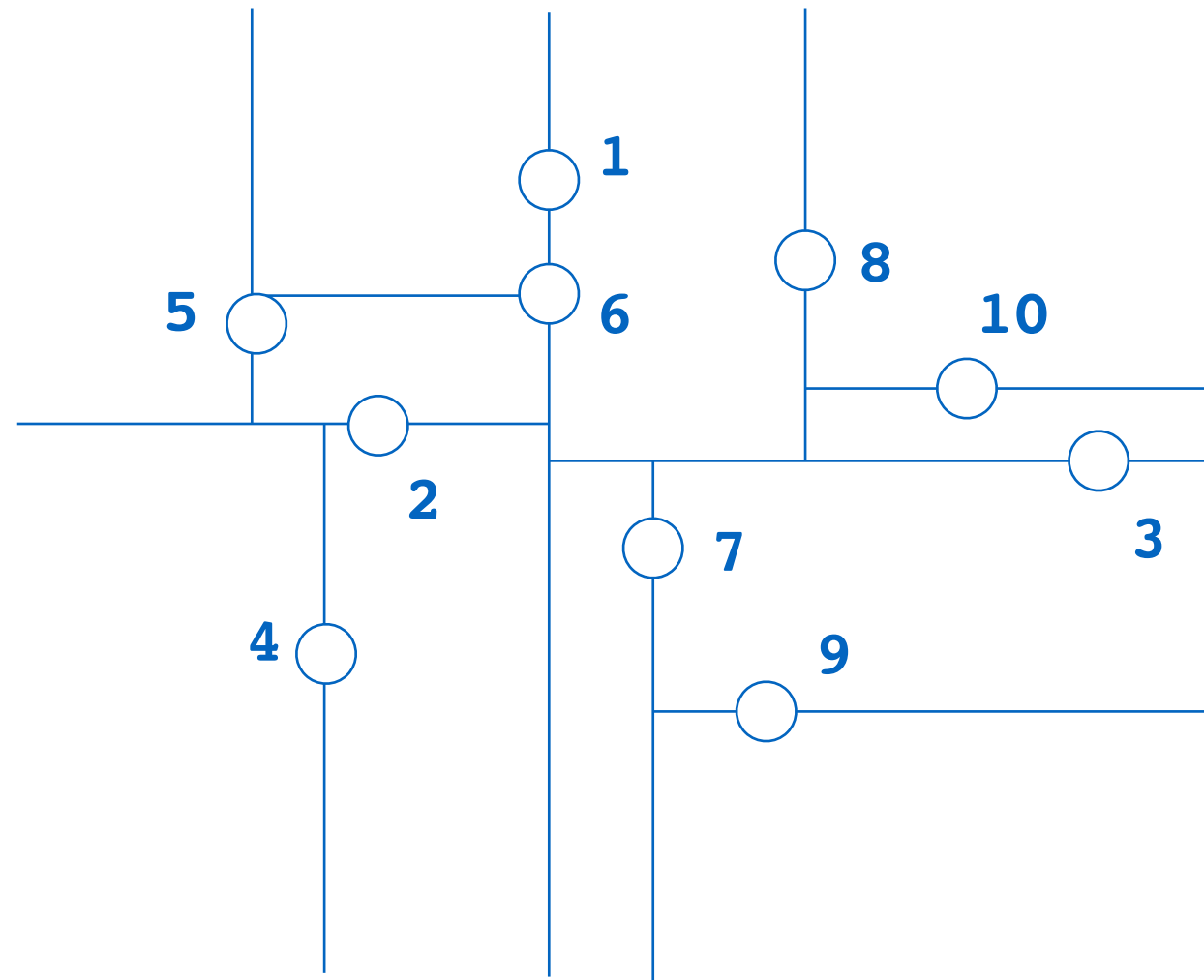
a kd-tree (short for **k-dimensional tree**) is a binary tree in which **every node** is a **k-dimensional point**

in addition, each **internal node divides** the k-dimensional space into two parts known as **half-spaces**

all points in one half space are contained in the **left subtree** of the node and all points in the other half space contained in the **right subtree**

all **nodes at the same level** (height) divide the k-dimensional space according to the **same cutting dimension (axis)**

k-d-tree



Remarks

- Points are stored as k -dimensional arrays
- Each axis corresponds to an index:
 - x -axis corresponds to index 0
 - y -axis corresponds to index 1
 - etc...
- So assuming point $p_i = (x_i, y_i) = (3, 7)$, we have that $p_i = [3, 7]$, $x_i = p[0] = 3$ and $y_i = p[1] = 7$
- In this example, initially $root = \mathbf{NIL}$ and points are inserted as follows:
 - $\text{ADD}(root, p_1, 0)$
 - $\text{ADD}(root, p_2, 0)$
 - $\text{ADD}(root, p_3, 0)$
 - etc...

```

ADD (node, point, cutaxis)
  if node = NIL
    node ← CREATE-NODE
    node.point = point
    return node
  if point[cutaxis] ≤ node.point[cutaxis]
    node.left = ADD(node.left, point, (cutaxis + 1) mod k)
  else
    node.right = ADD(node.right, point, (cutaxis + 1) mod k)
  return node
  
```