

# K-D Trees and Quad Trees

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Lecture 12

# Range Queries

- Think of a range query.
  - “Give me all customers aged 45-55.”
  - “Give me all accounts worth \$5m to \$15m”
- Can be done in time \_\_\_\_\_.
- What if we want both:
  - “Give me all customers aged 45-55 with accounts worth between \$5m and \$15m.”

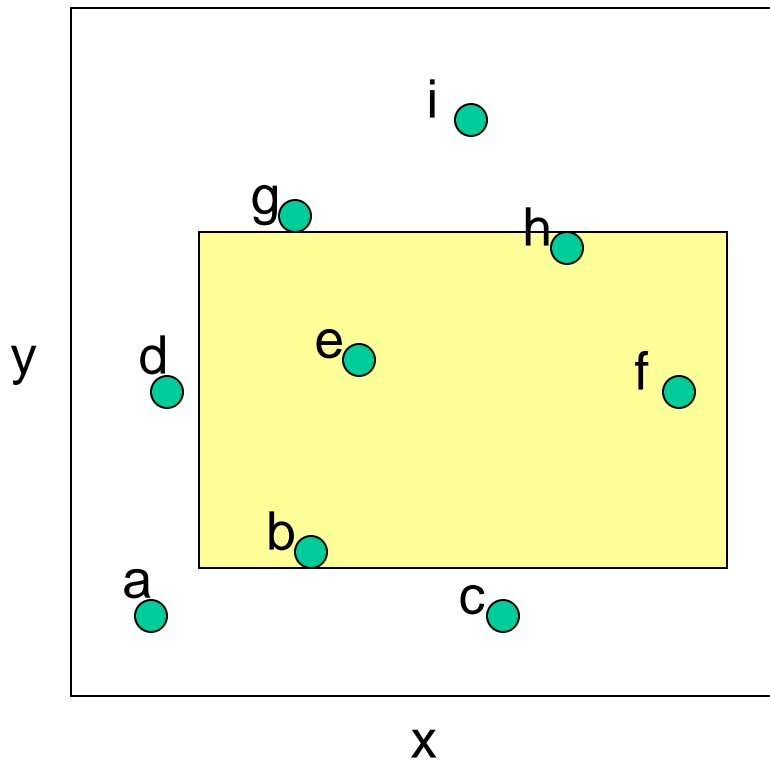
# Geometric Data Structures

- Organization of points, lines, planes, etc in support of faster processing
- Applications
  - Map information
  - Graphics - computing object intersections
  - Data compression - nearest neighbor search
  - Decision Trees - machine learning

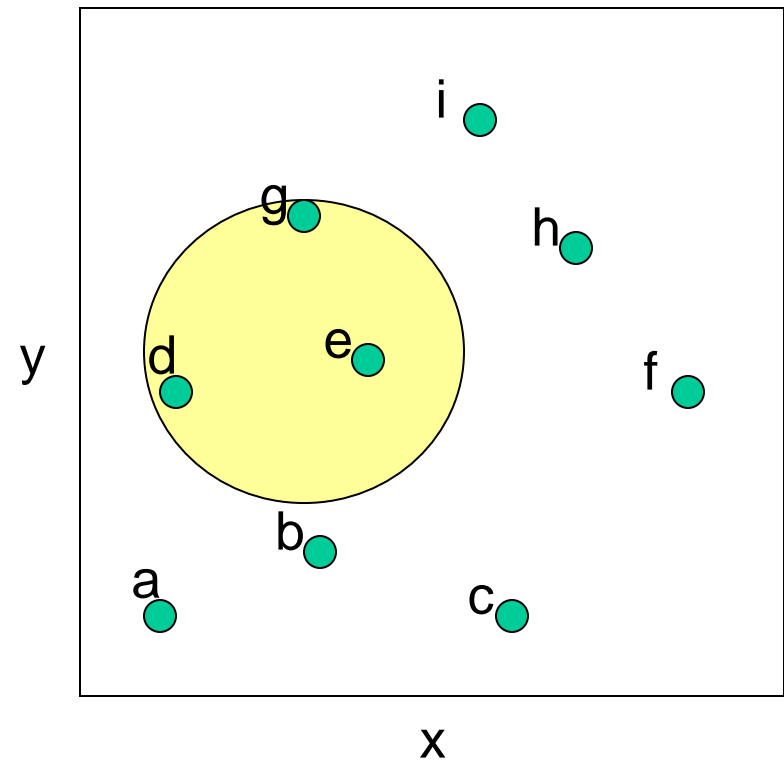
# k-d Trees

- Jon Bentley, 1975, while an undergraduate
- Tree used to store spatial data.
  - Nearest neighbor search.
  - Range queries.
  - Fast look-up
- k-d tree are guaranteed  $\log_2 n$  depth where  $n$  is the number of points in the set.
  - Traditionally, k-d trees store points in d-dimensional space which are equivalent to vectors in d-dimensional space.

# Range Queries

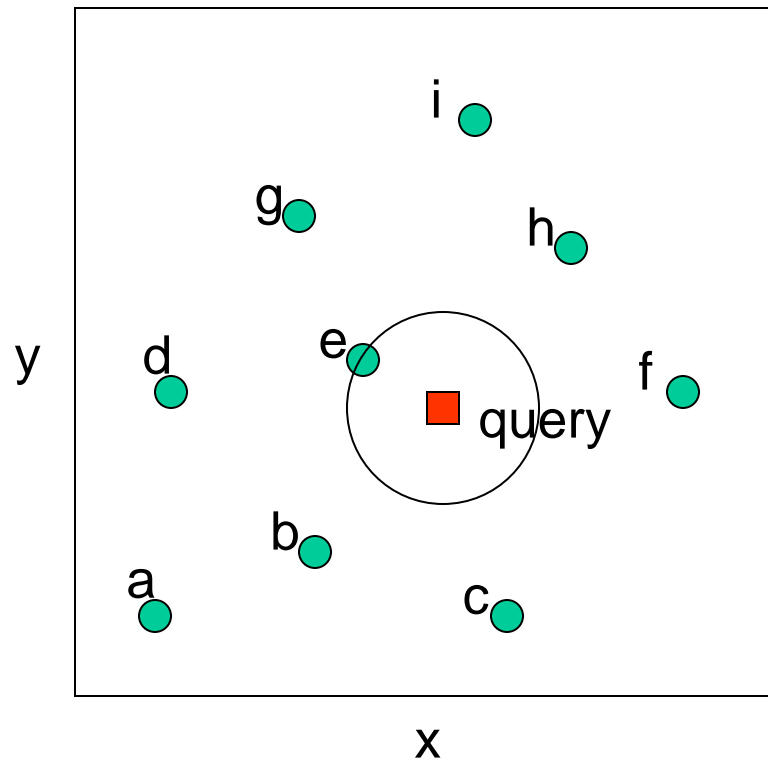


Rectangular query



Circular query

# Nearest Neighbor Search

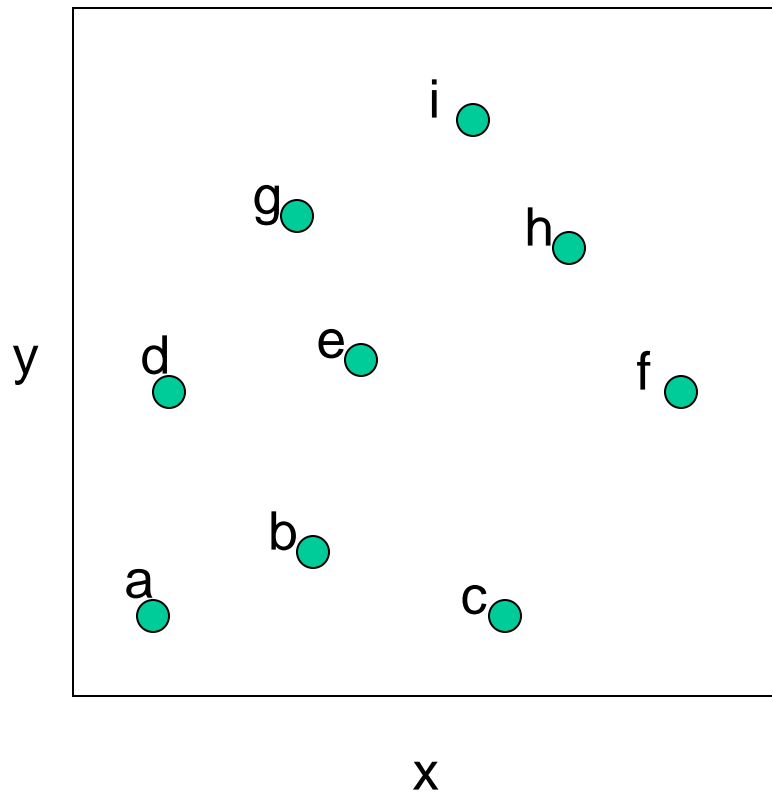


Nearest neighbor is e.

# k-d Tree Construction

- If there is just one point, form a leaf with that point.
- Otherwise, divide the points in half by a line perpendicular to one of the axes.
- Recursively construct k-d trees for the two sets of points.
- Division strategies
  - divide points perpendicular to the axis with widest spread.
  - divide in a round-robin fashion (book does it this way)

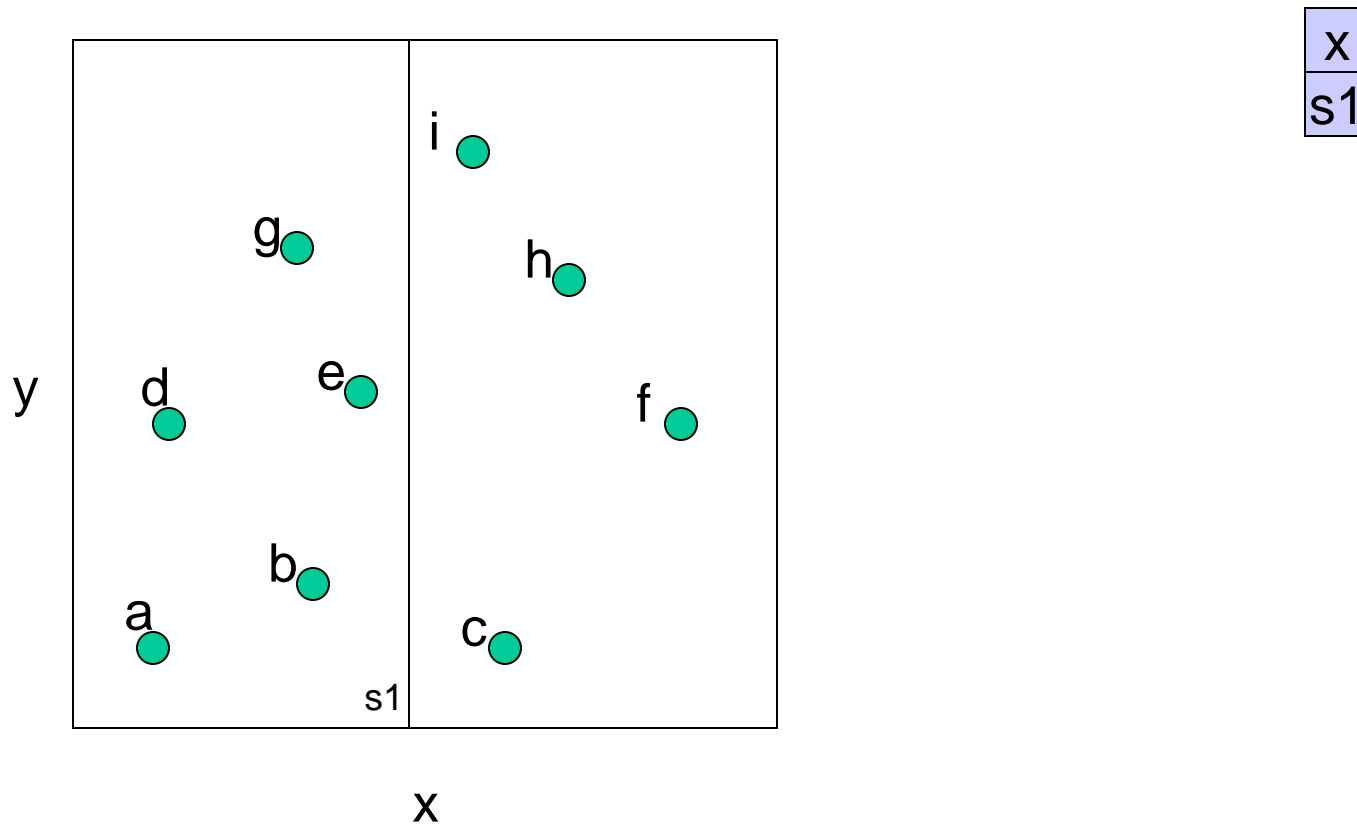
# k-d Tree Construction (1)



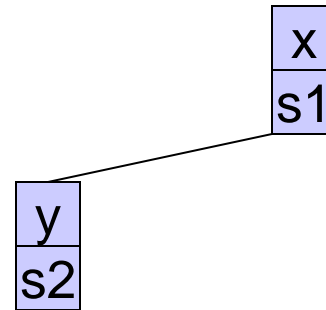
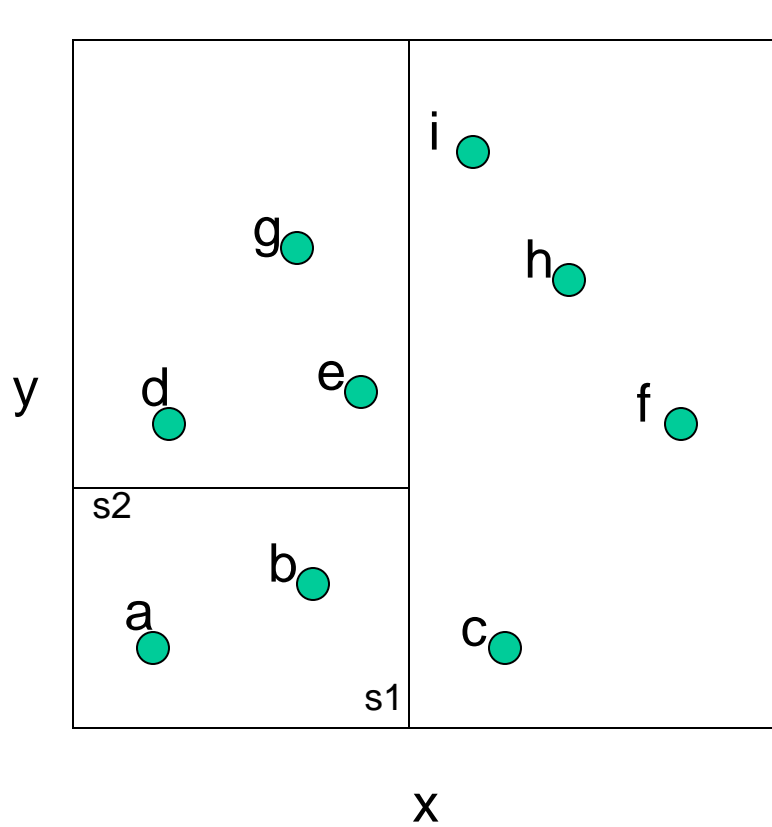
divide perpendicular to the widest spread.



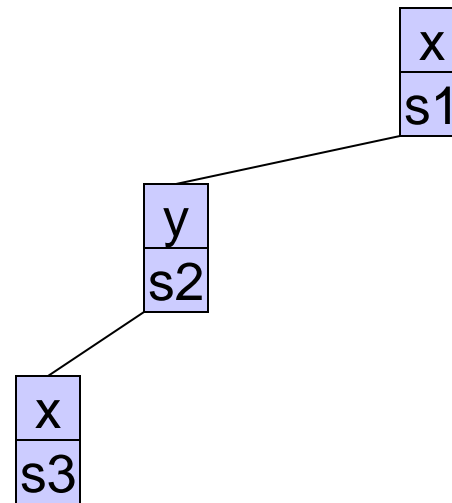
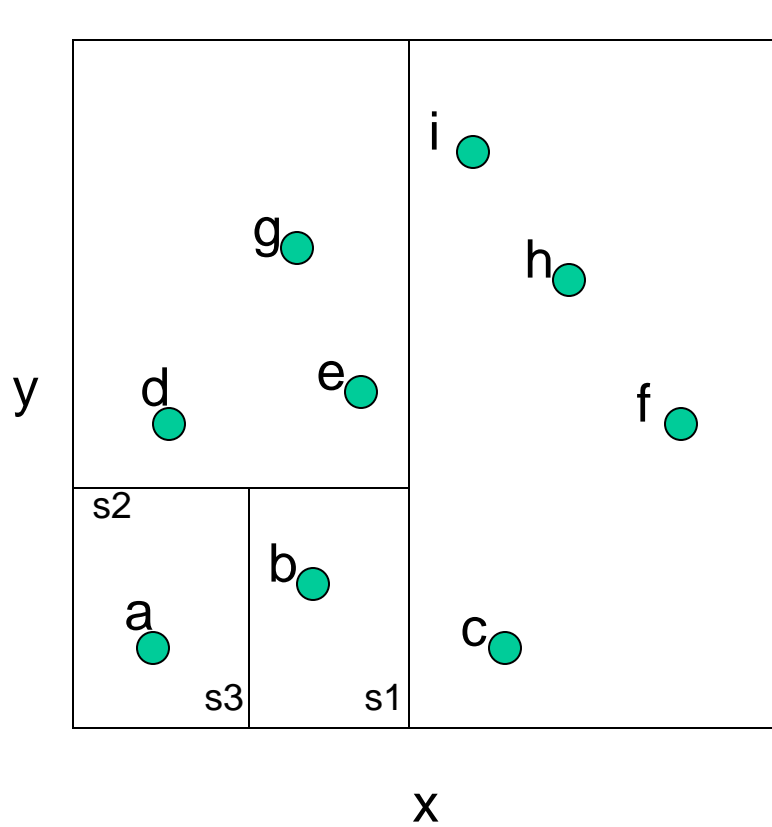
# k-d Tree Construction (2)



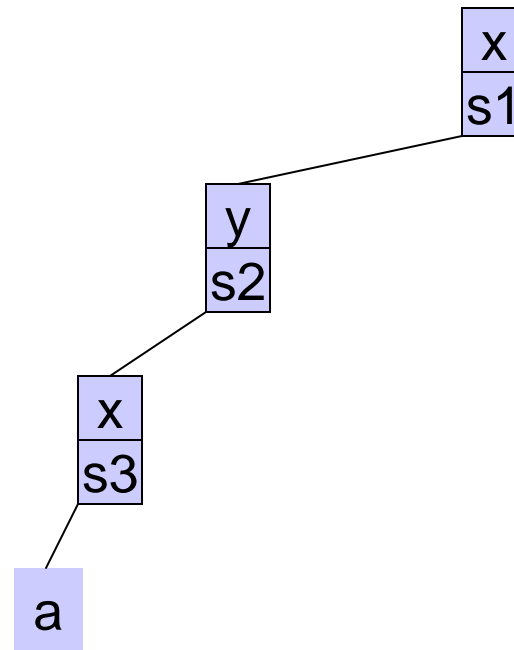
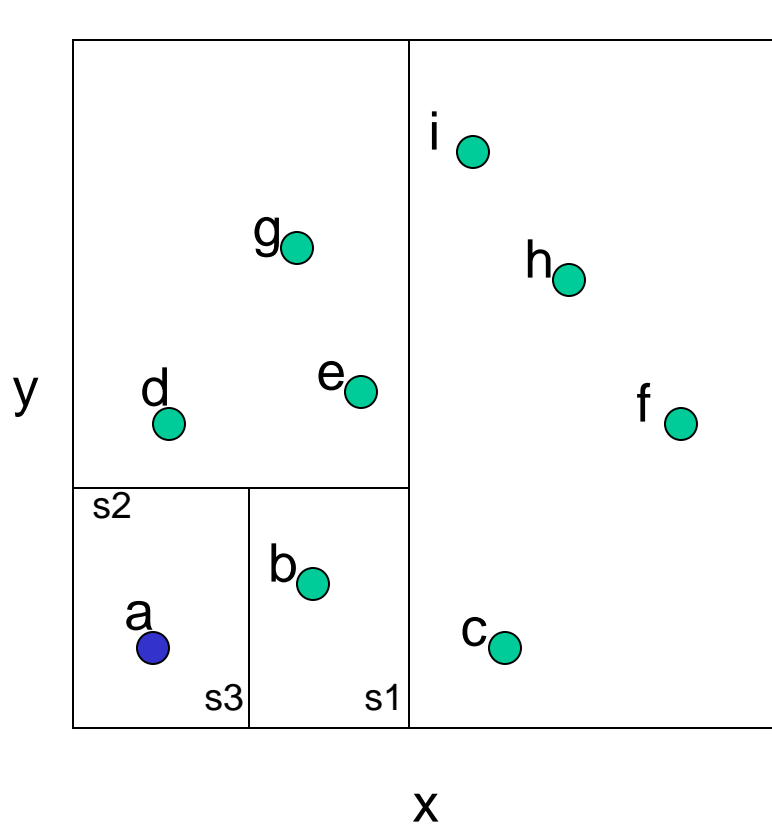
# k-d Tree Construction (3)



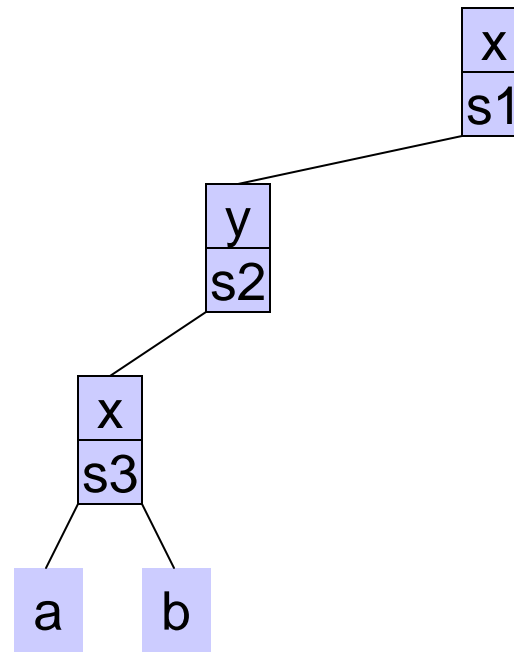
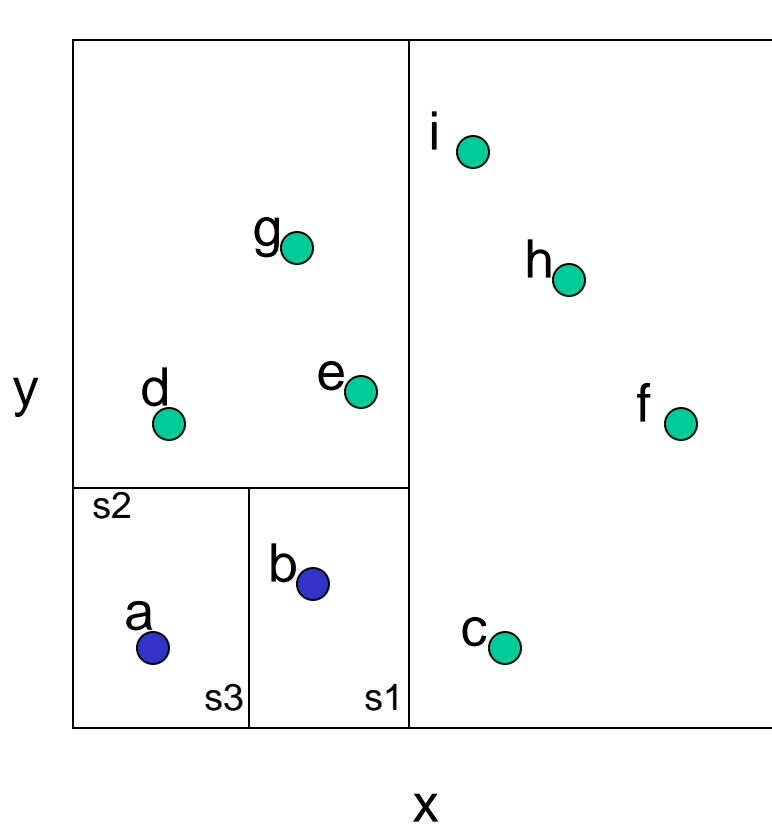
# k-d Tree Construction (4)



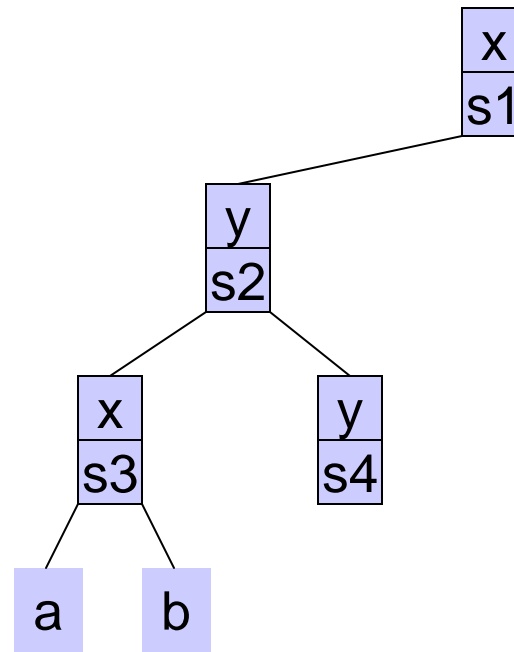
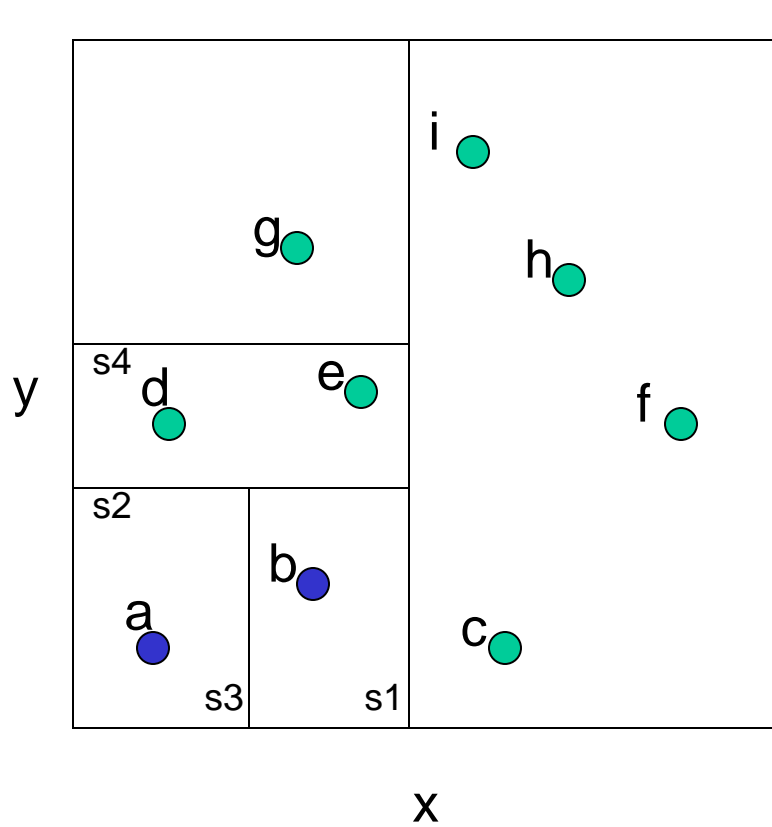
# k-d Tree Construction (5)



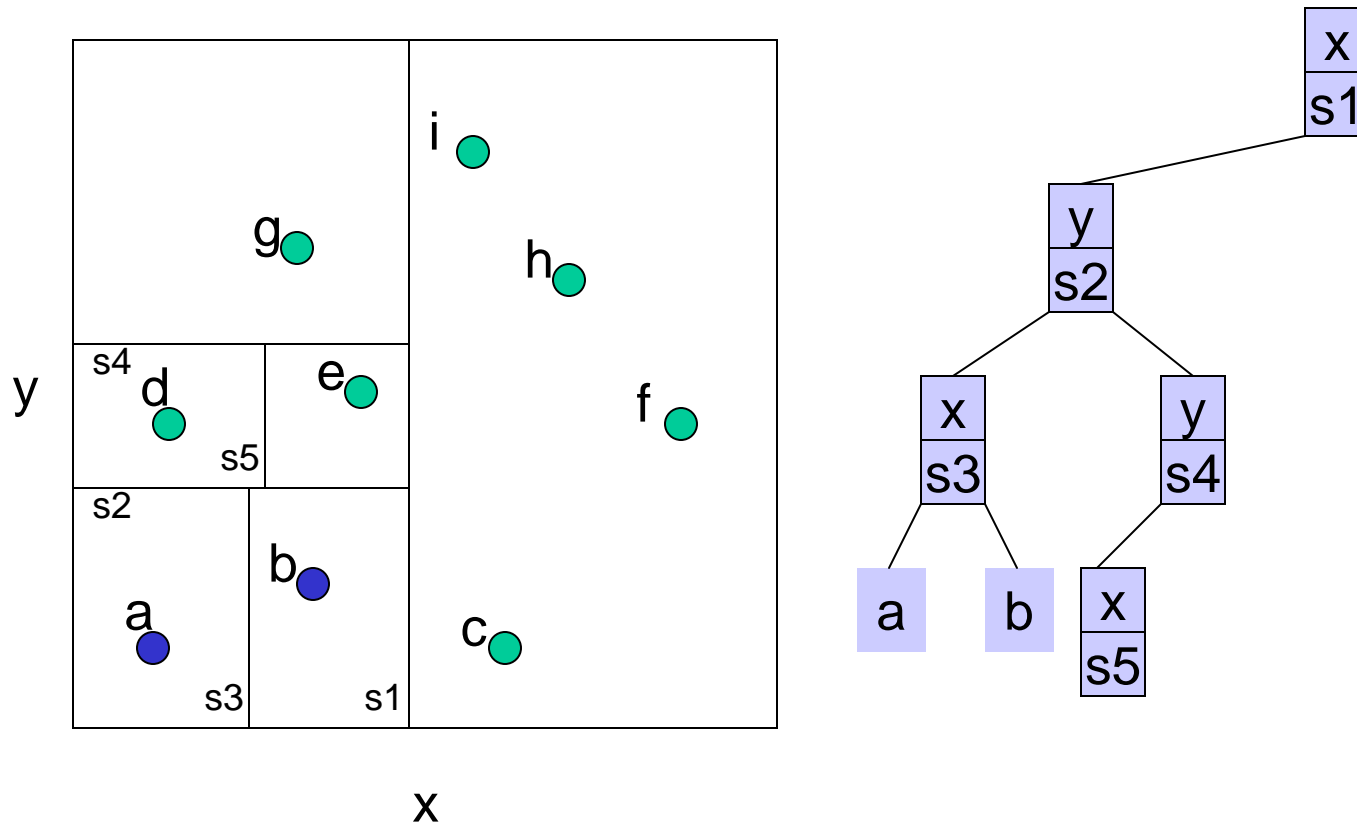
# k-d Tree Construction (6)



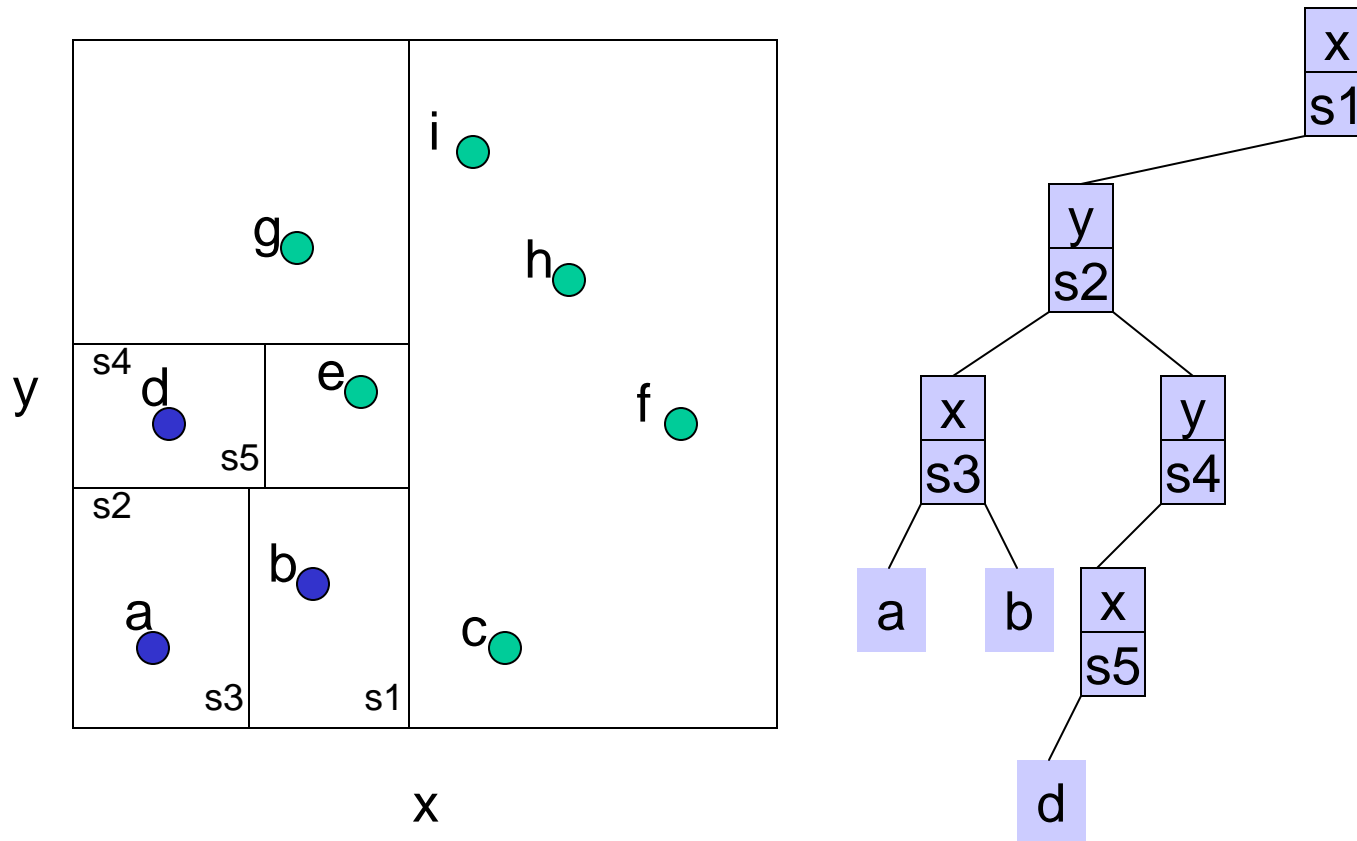
# k-d Tree Construction (7)



# k-d Tree Construction (8)

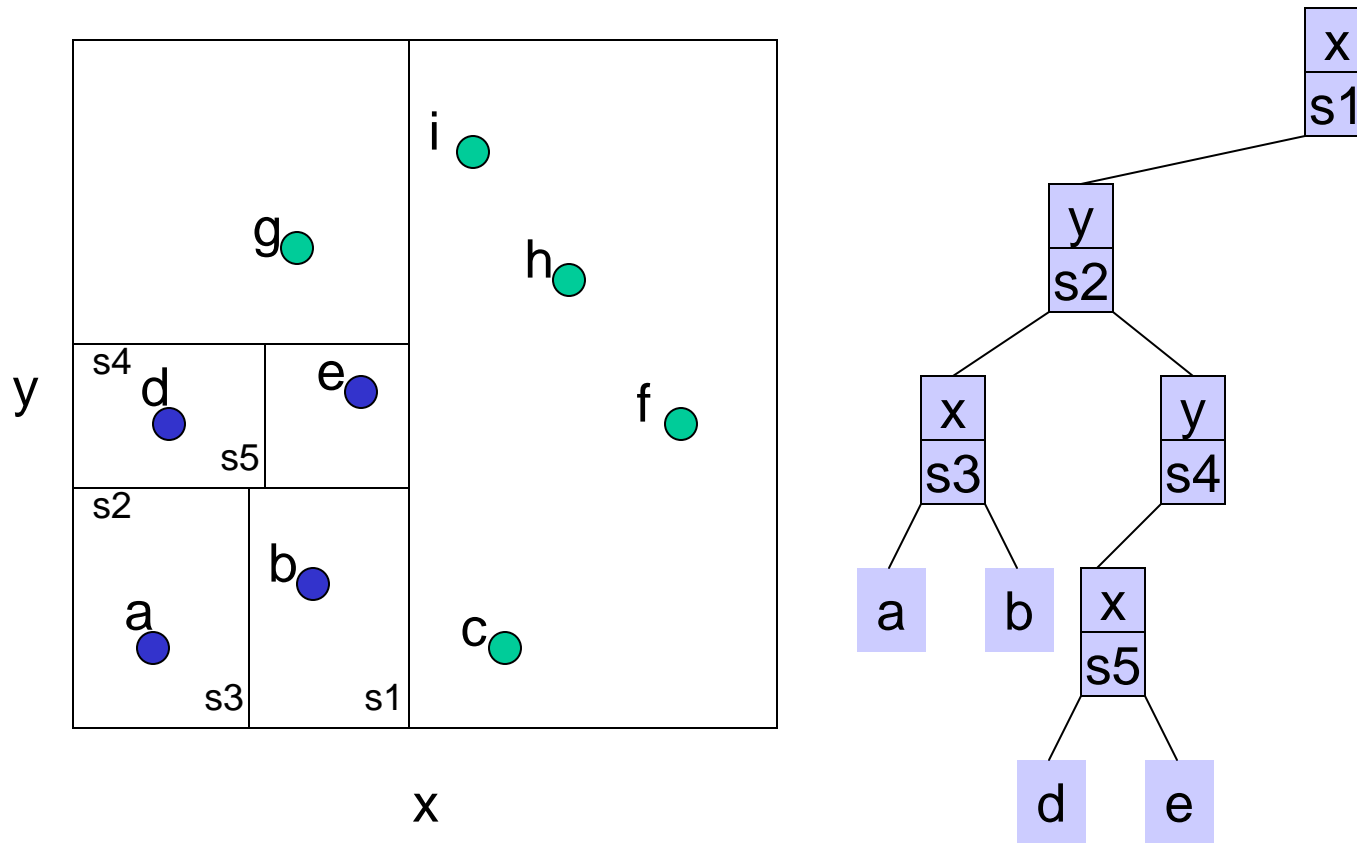


# k-d Tree Construction (9)

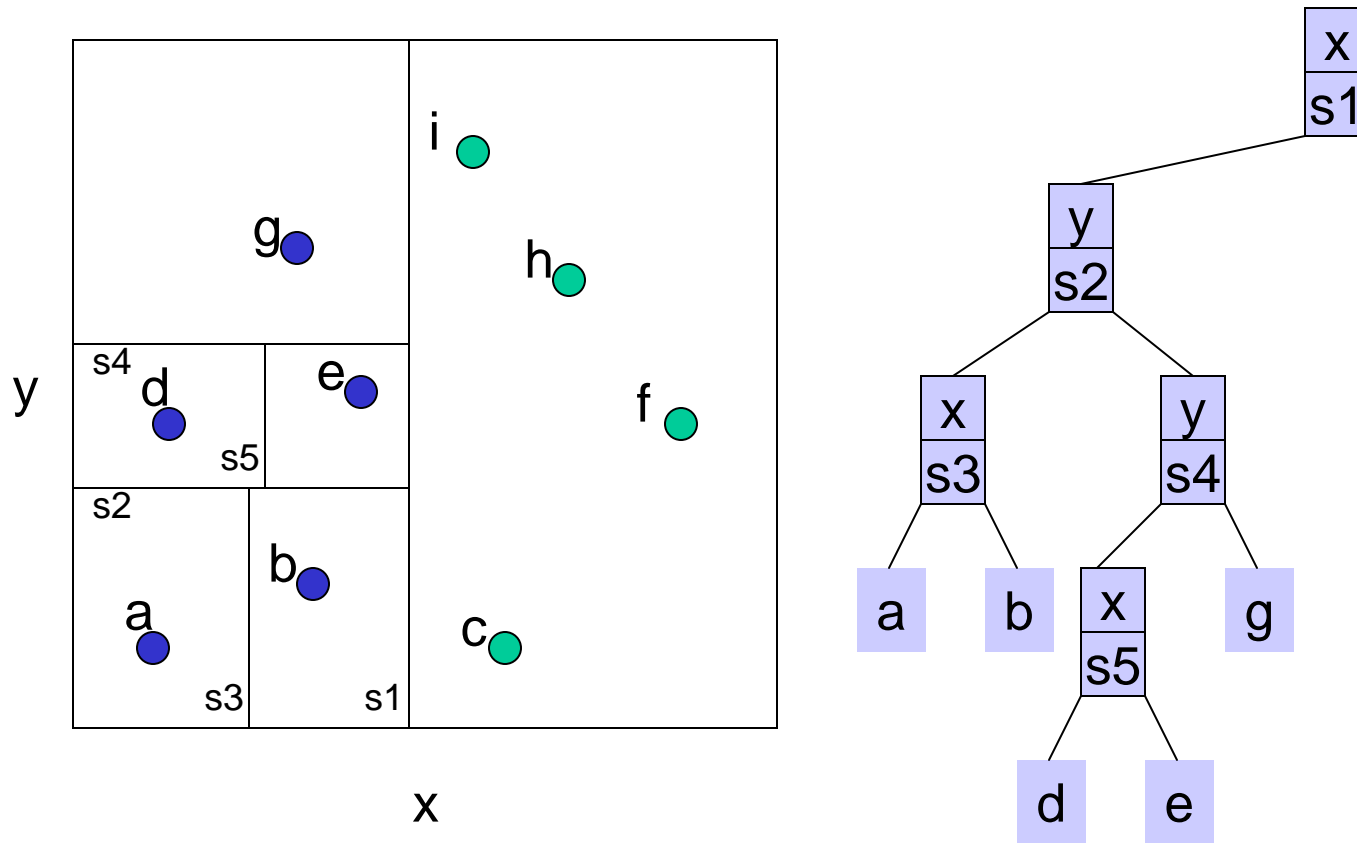




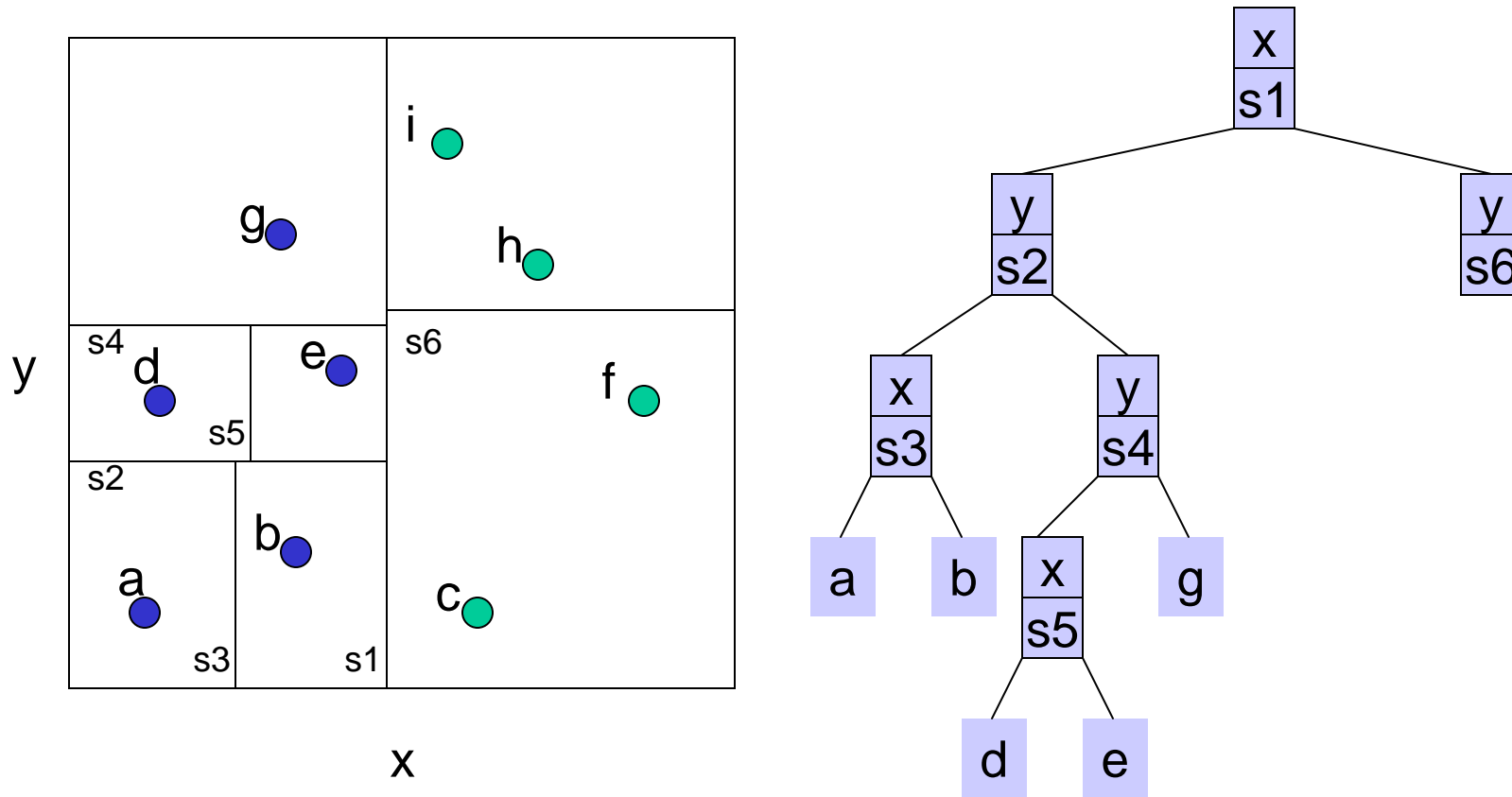
# k-d Tree Construction (10)



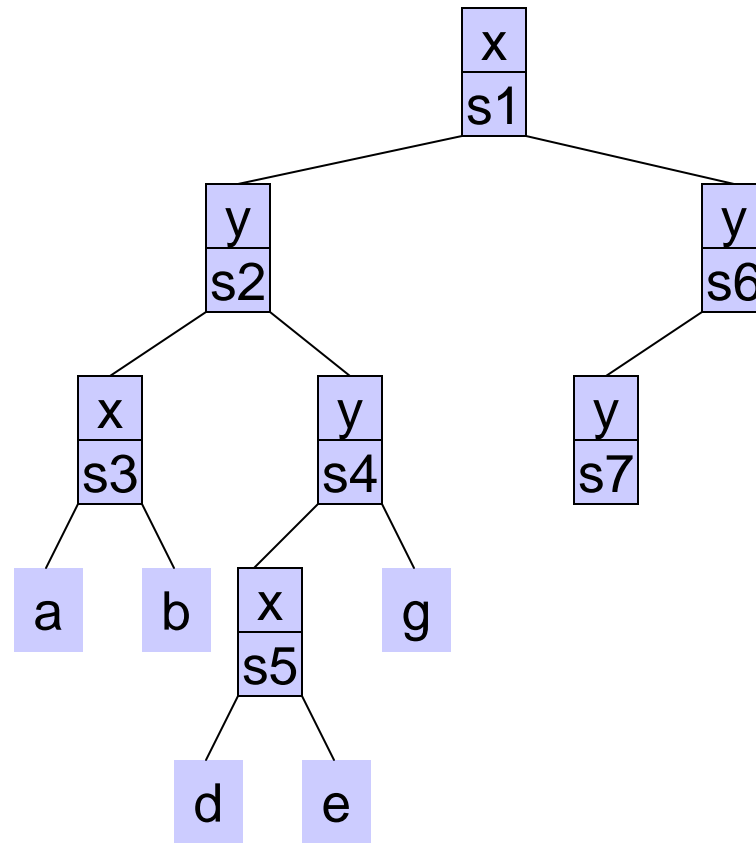
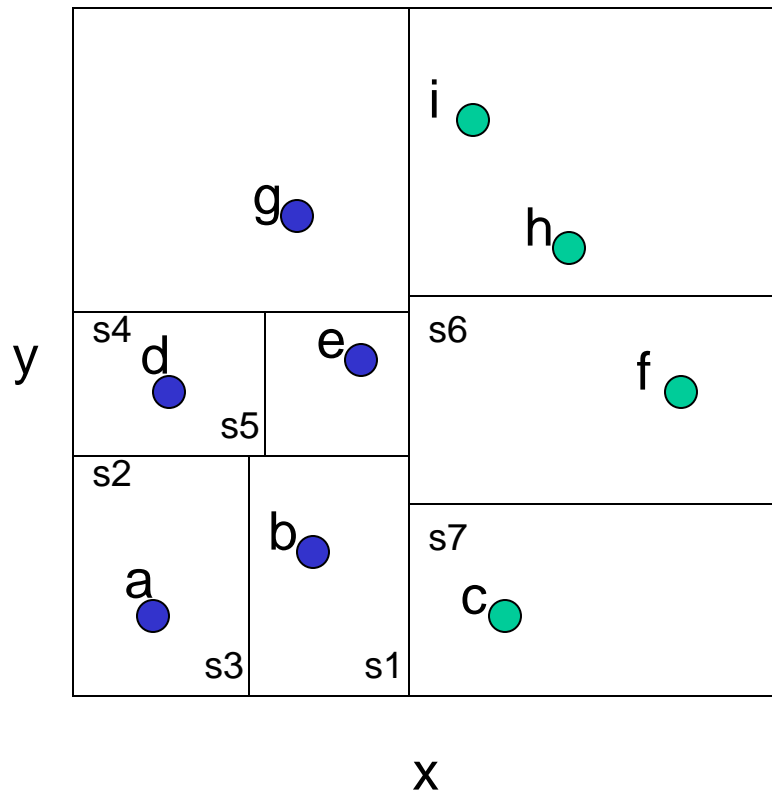
# k-d Tree Construction (11)



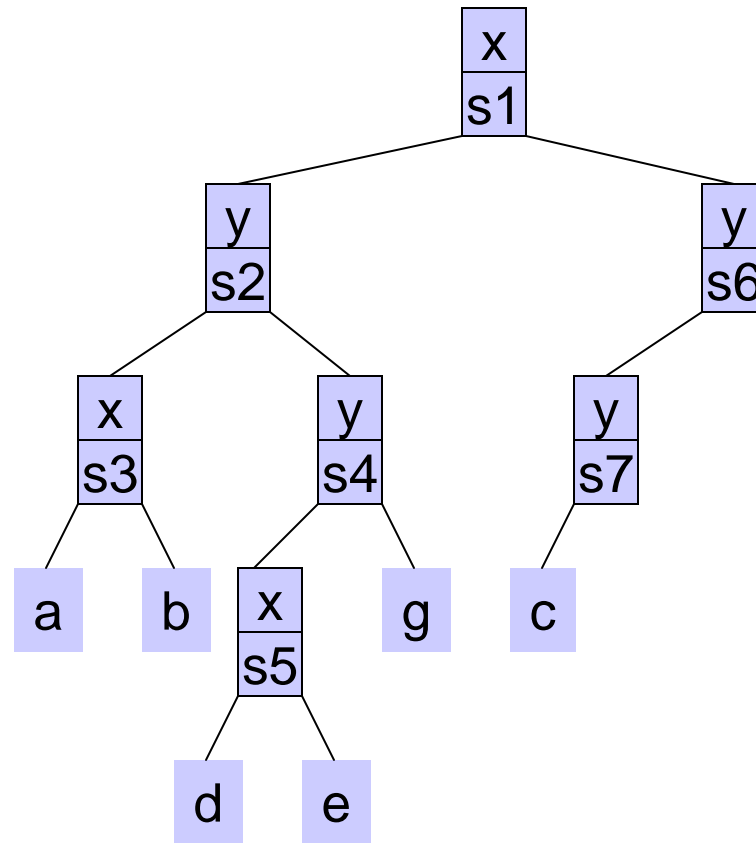
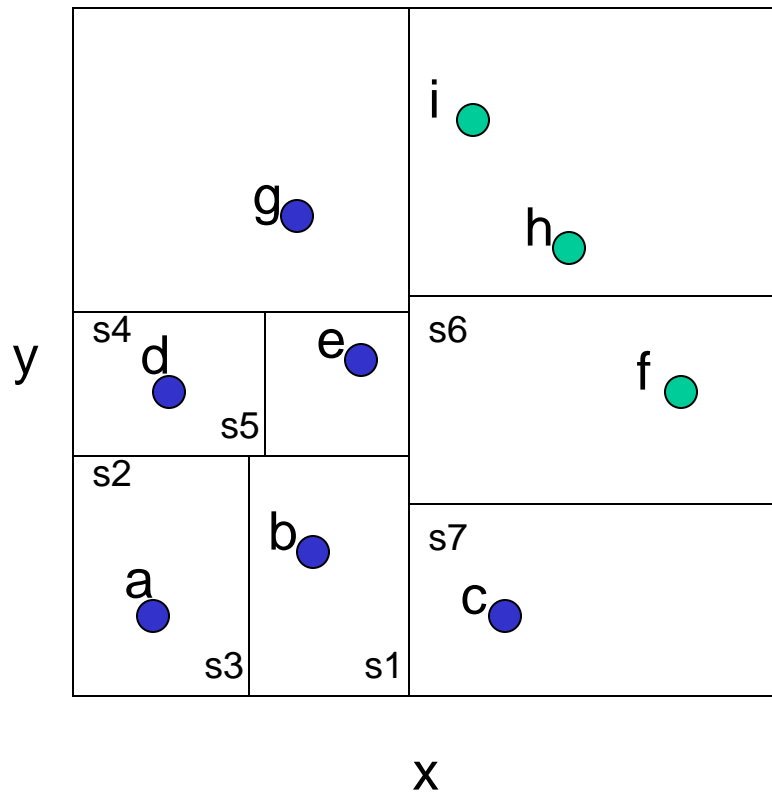
# k-d Tree Construction (12)



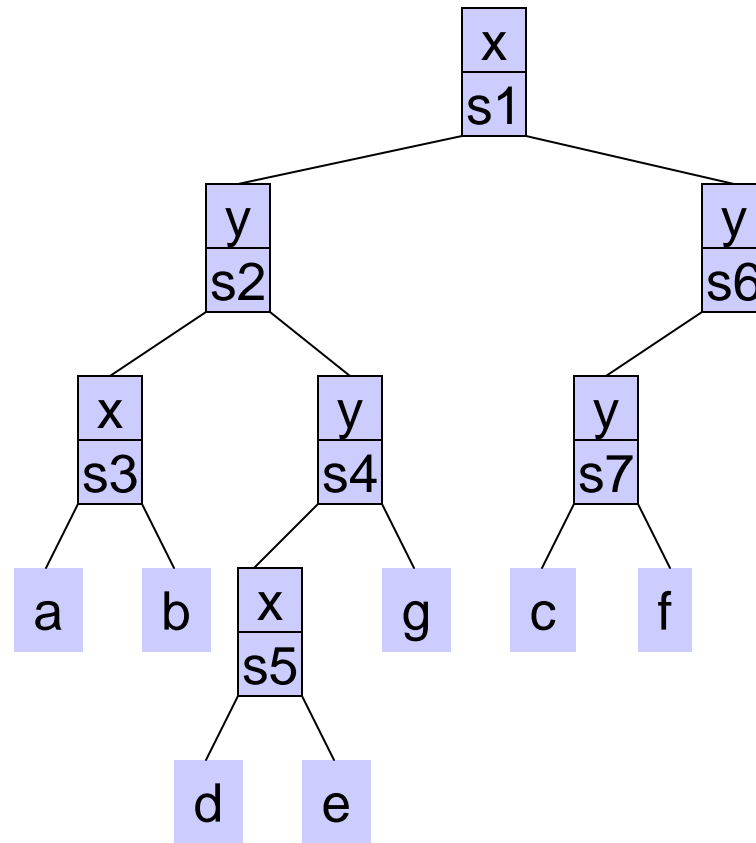
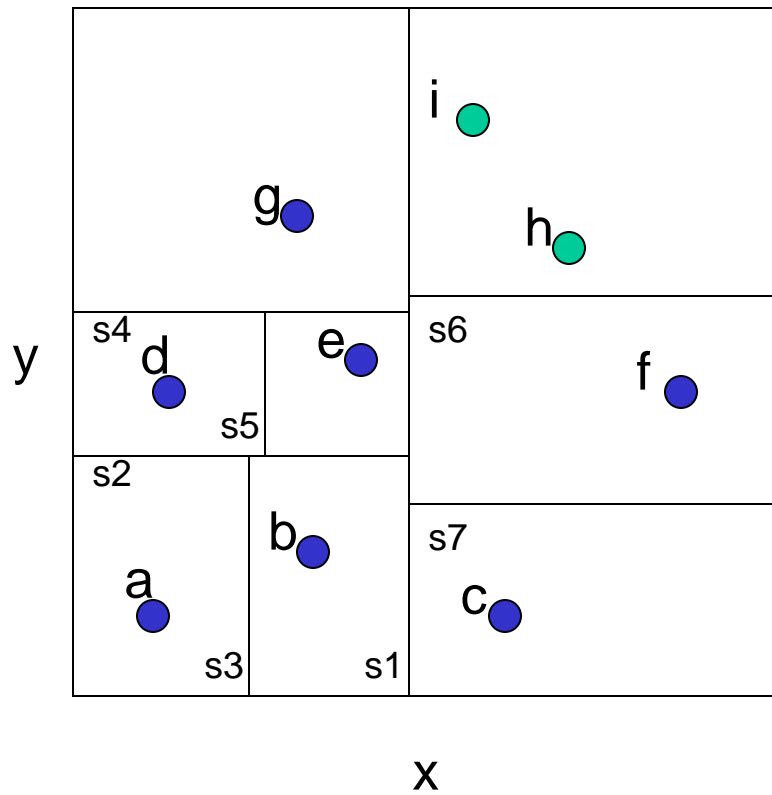
# k-d Tree Construction (13)



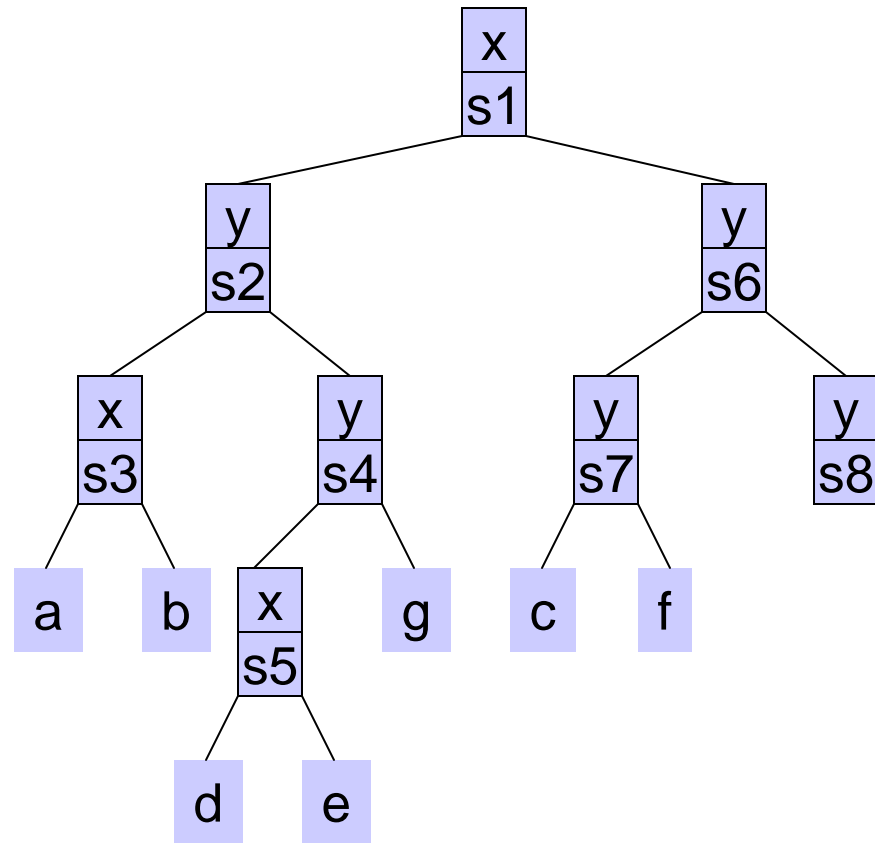
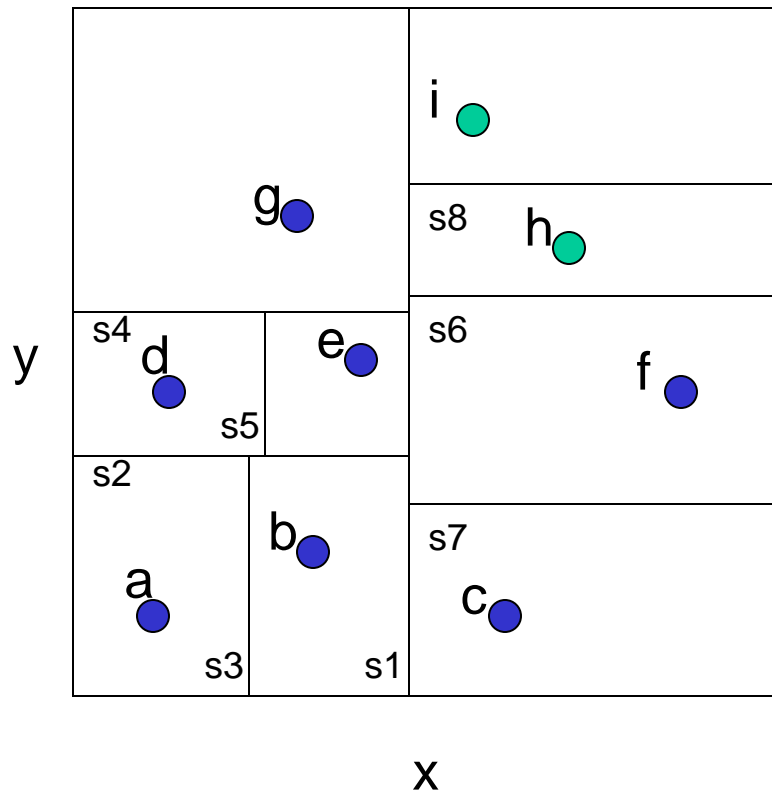
# k-d Tree Construction (14)



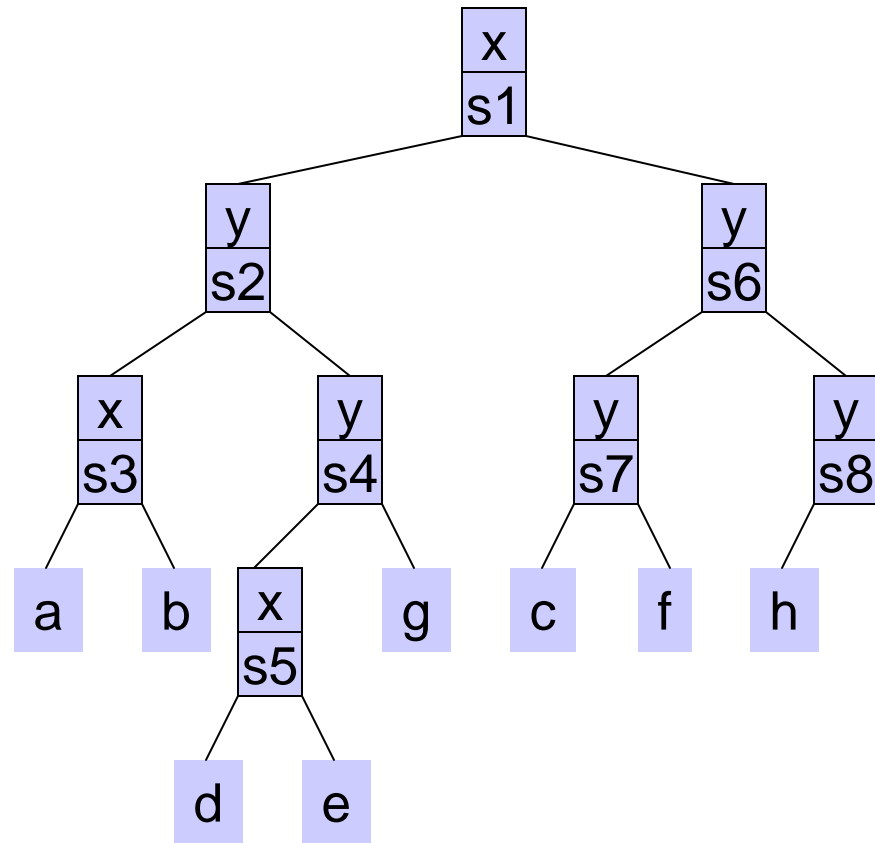
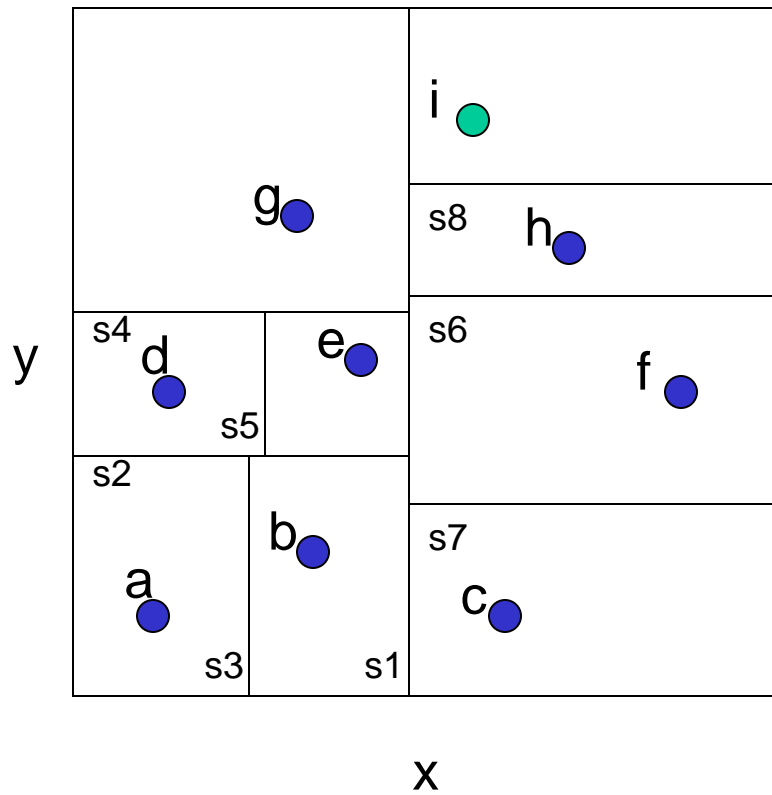
# k-d Tree Construction (15)



# k-d Tree Construction (16)

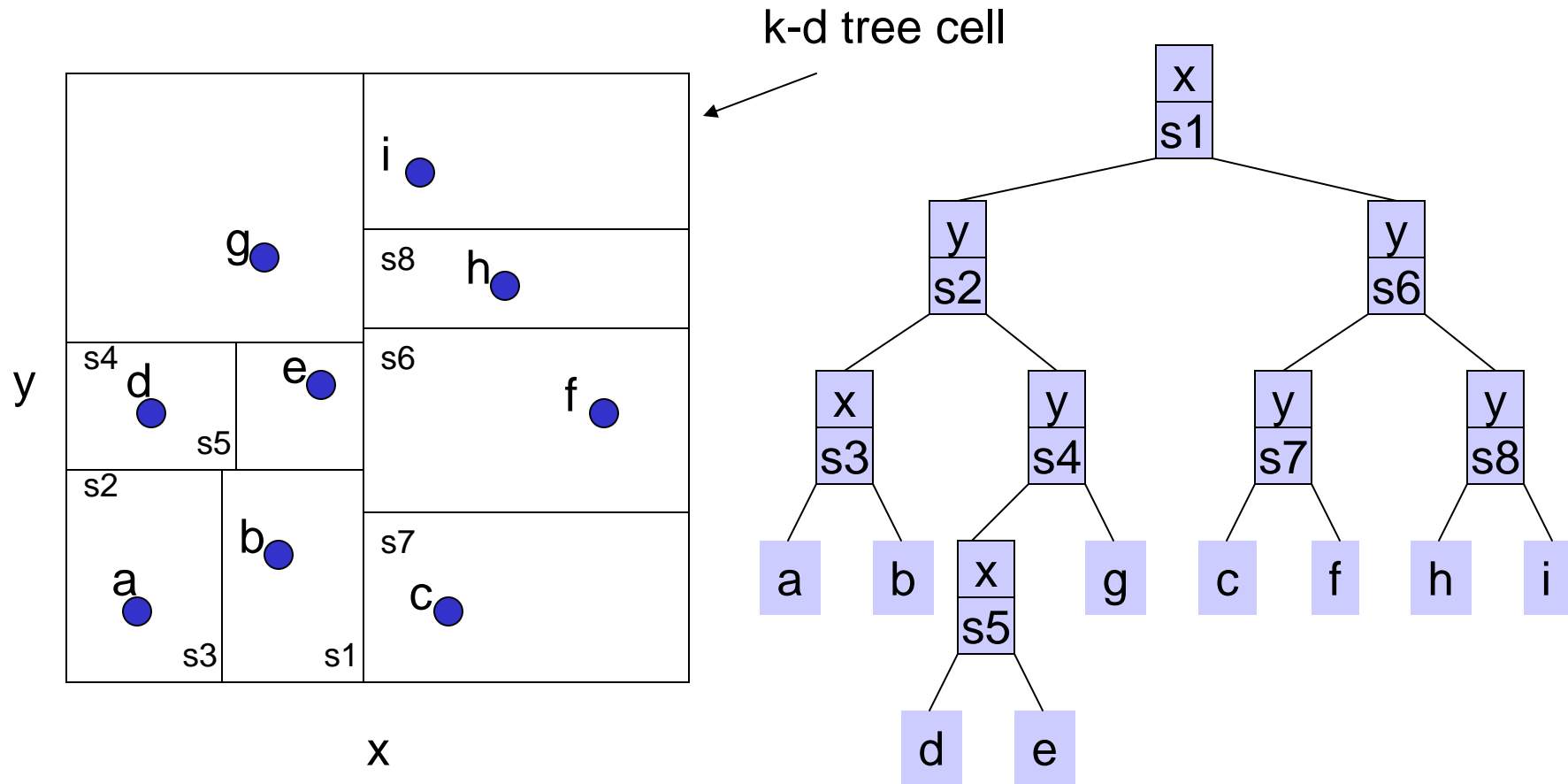


# k-d Tree Construction (17)

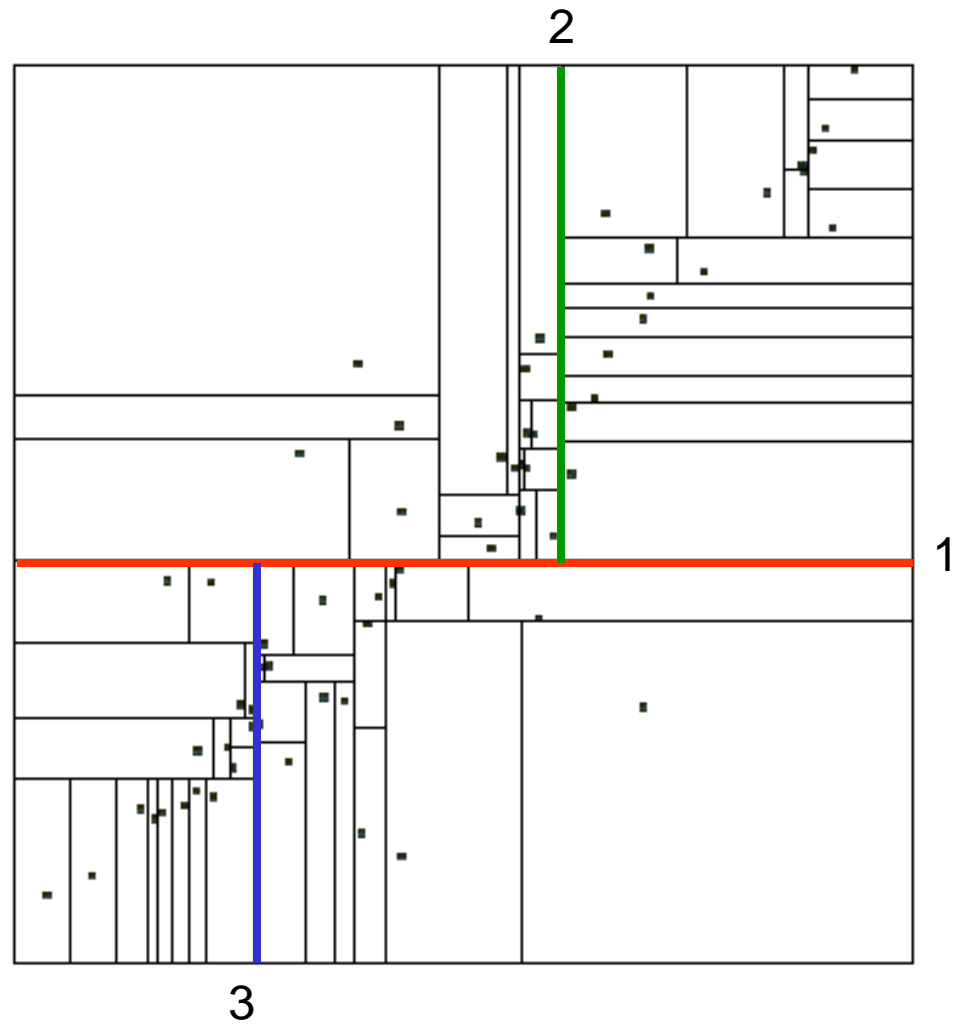




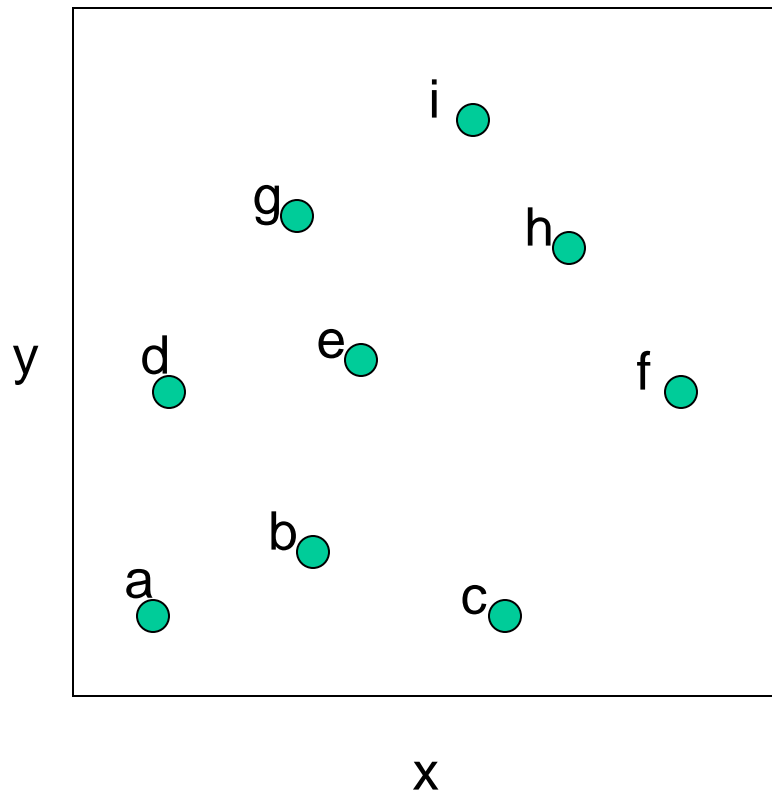
# k-d Tree Construction (18)



# 2-d Tree Decomposition



# k-d Tree Splitting

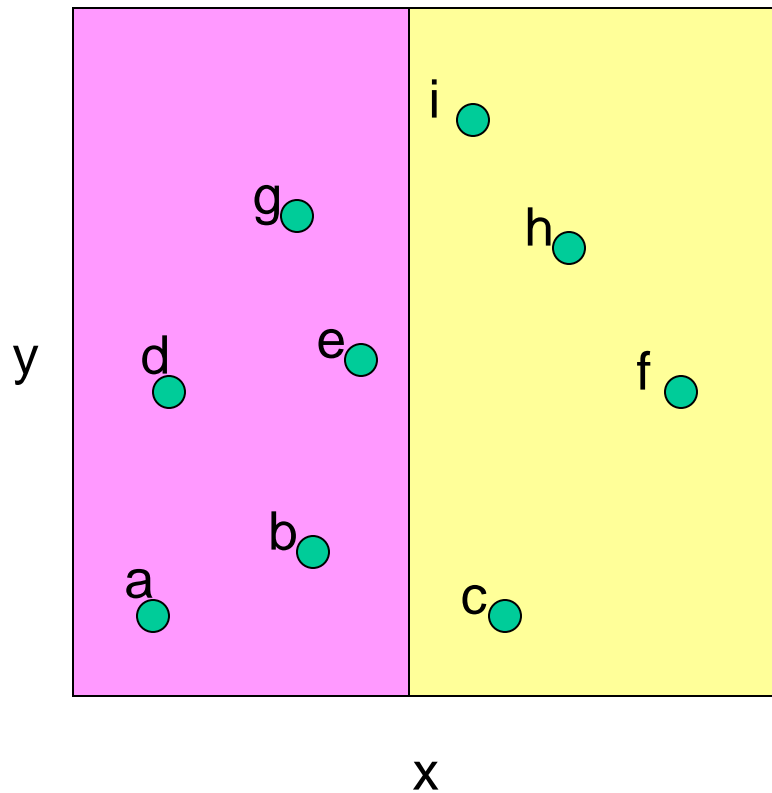


sorted points in each dimension

	1	2	3	4	5	6	7	8	9
x	a	d	g	b	e	i	c	h	f
y	a	c	b	d	f	e	h	g	i

- max spread is the max of  $f_x - a_x$  and  $i_y - a_y$ .
- In the selected dimension the middle point in the list splits the data.
- To build the sorted lists for the other dimensions scan the sorted list adding each point to one of two sorted lists.

# k-d Tree Splitting



sorted points in each dimension

	1	2	3	4	5	6	7	8	9
x	a	d	g	b	e	i	c	h	f
y	a	c	b	d	f	e	h	g	i

indicator for each set

	a	b	c	d	e	f	g	h	i
	0	0	1	0	0	1	0	1	1

scan sorted points in y dimension  
and add to correct set

y	a	b	d	e	g	c	f	h	i
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# k-d Tree Construction Complexity

- First sort the points in each dimension.
  - $O(dn \log n)$  time and  $dn$  storage.
  - These are stored in  $A[1..d, 1..n]$
- Finding the widest spread and equally divide into two subsets can be done in  $O(dn)$  time.
- We have the recurrence
  - $T(n, d) \leq 2T(n/2, d) + O(dn)$
- Constructing the k-d tree can be done in  $O(dn \log n)$  and  $dn$  storage

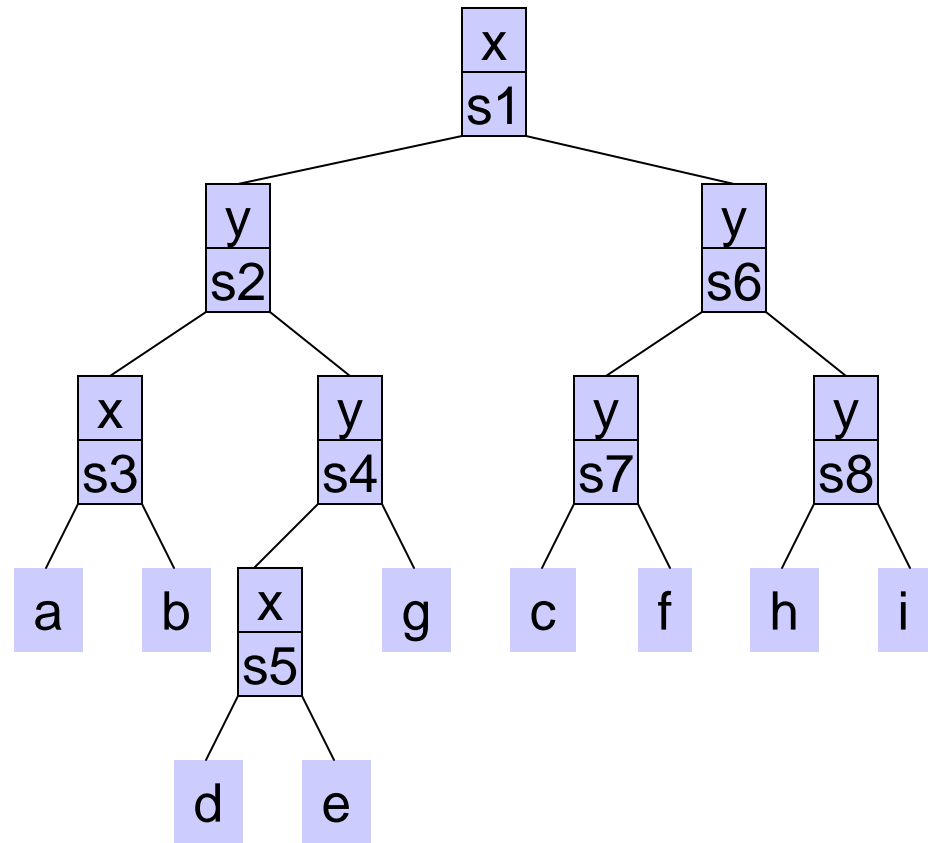
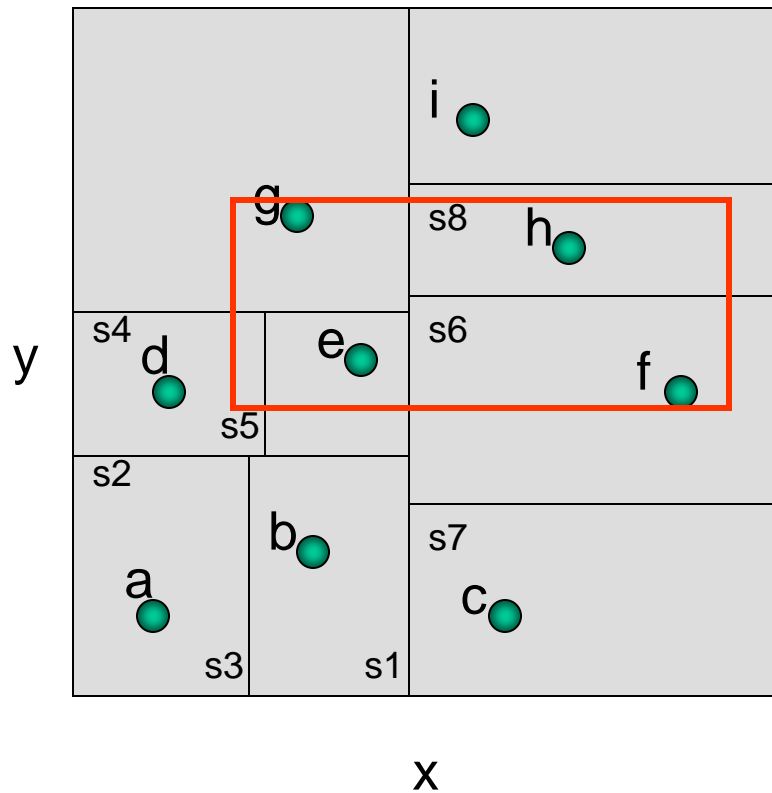
# Node Structure for k-d Trees

- A node has 5 fields
  - axis (splitting axis)
  - value (splitting value)
  - left (left subtree)
  - right (right subtree)
  - point (holds a point if left and right children are null)

# Rectangular Range Query

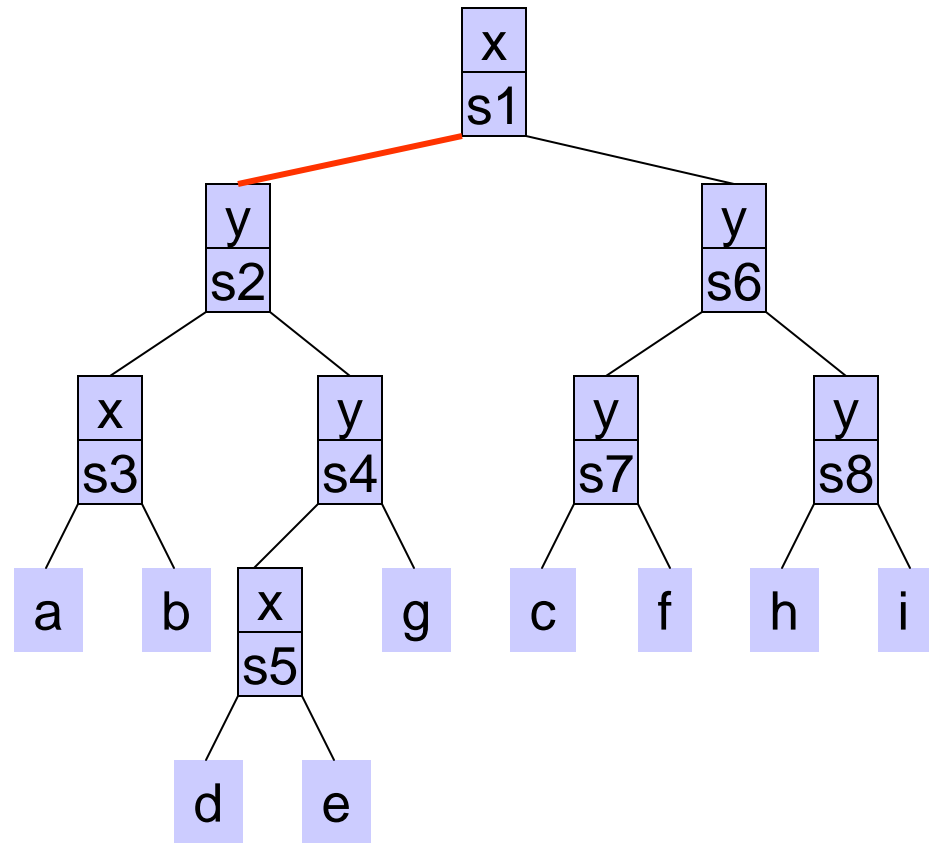
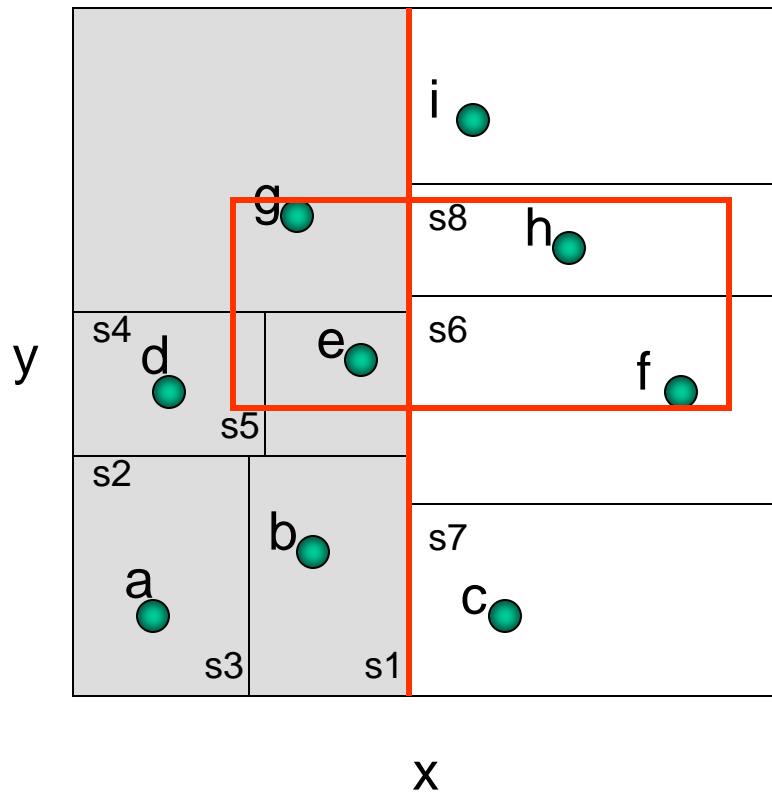
- Recursively search every cell that intersects the rectangle.

# Rectangular Range Query (1)

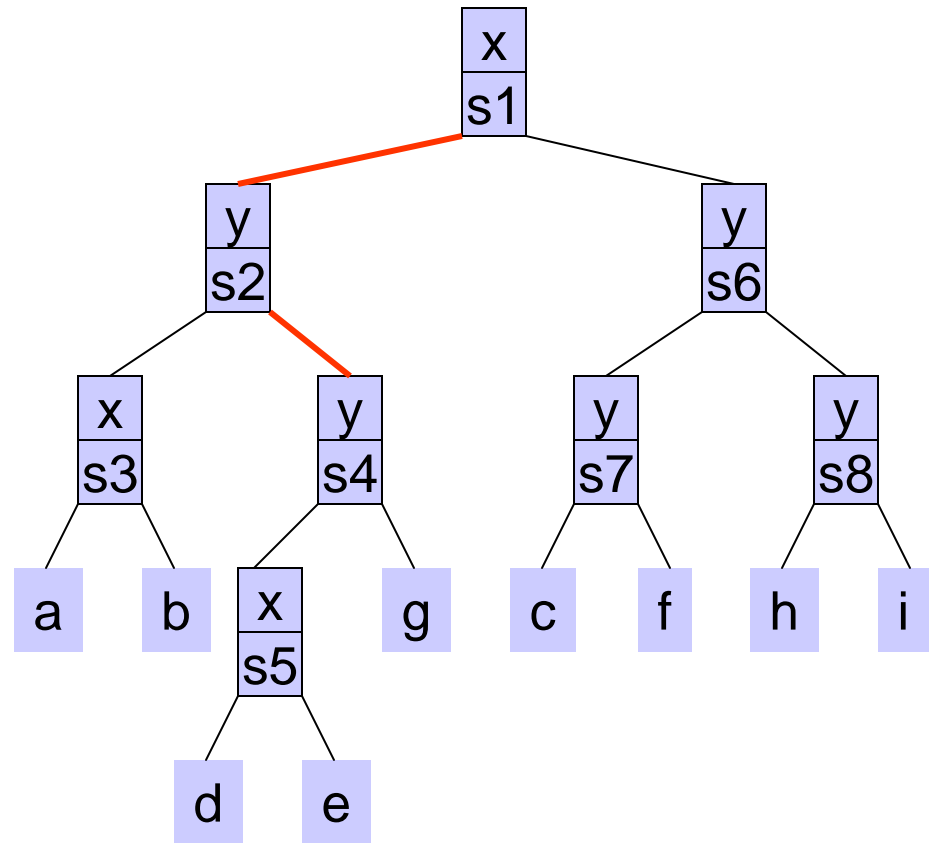
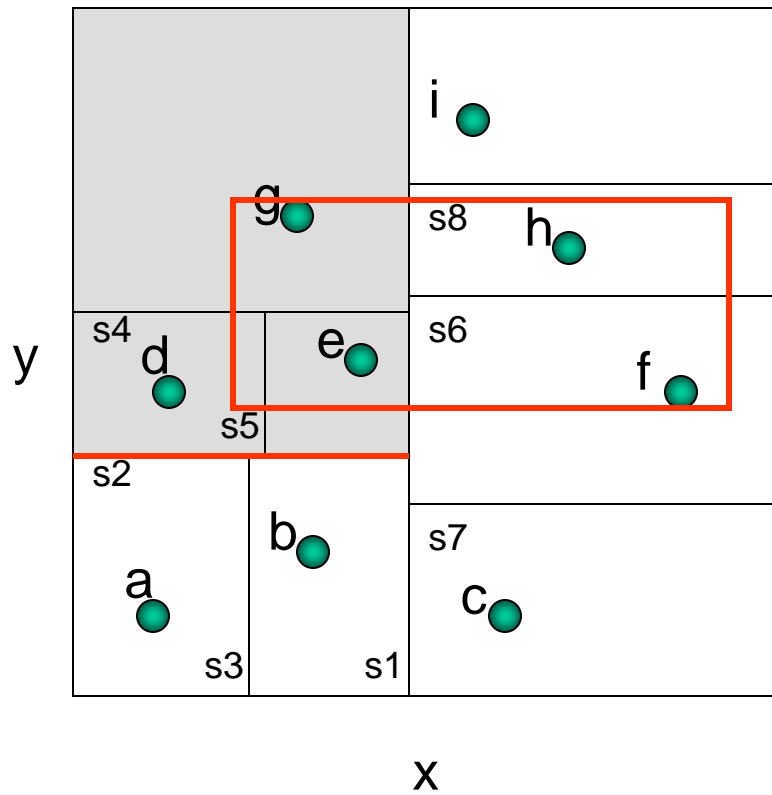




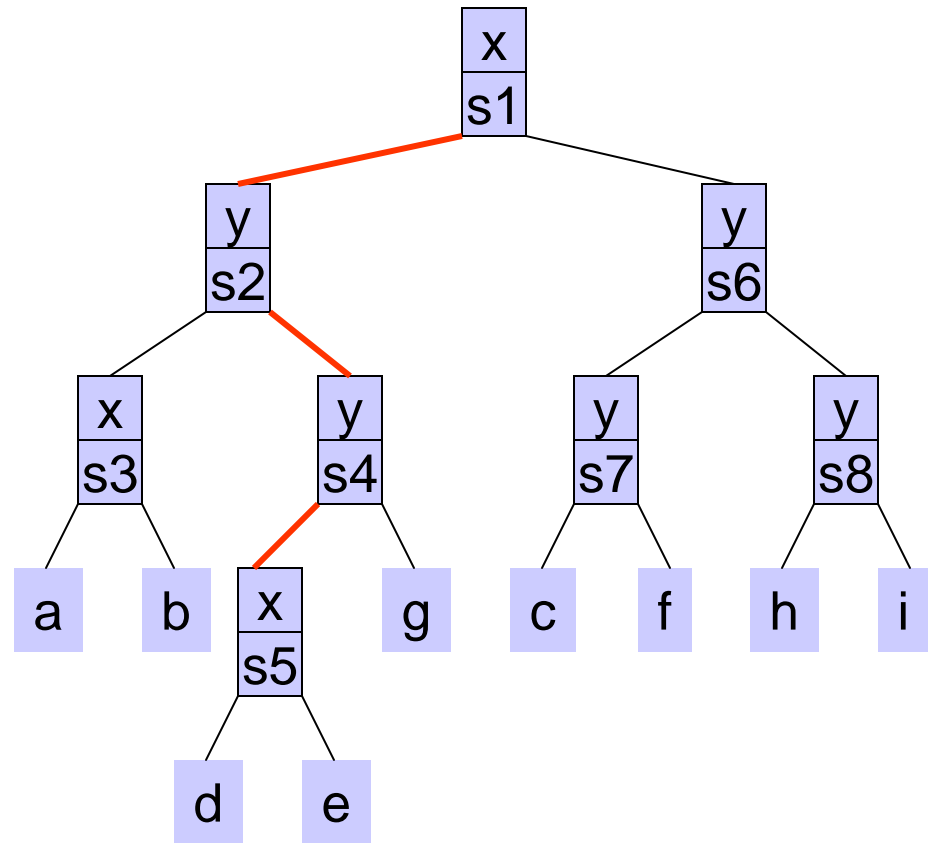
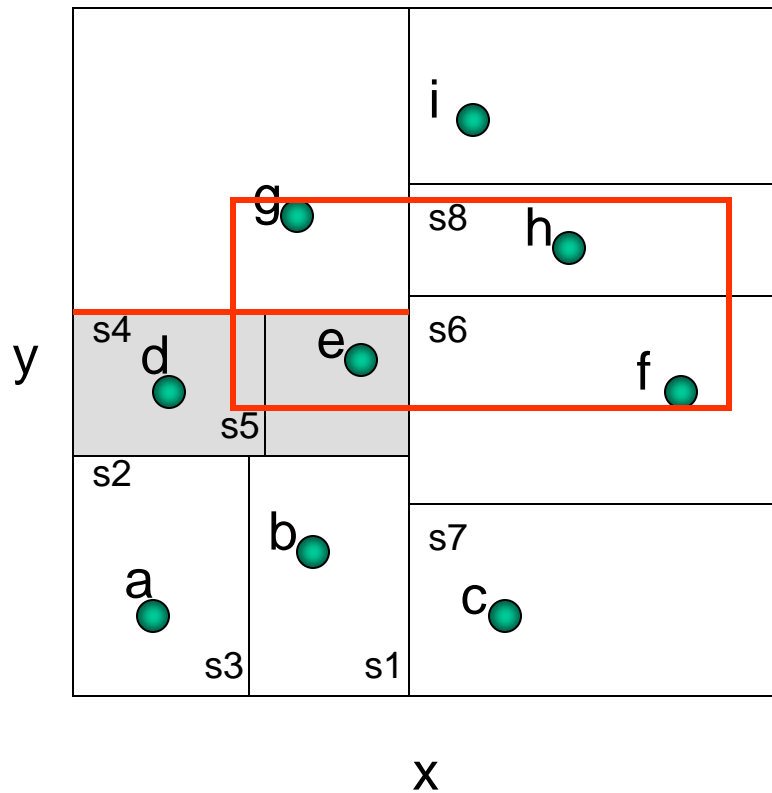
# Rectangular Range Query (2)



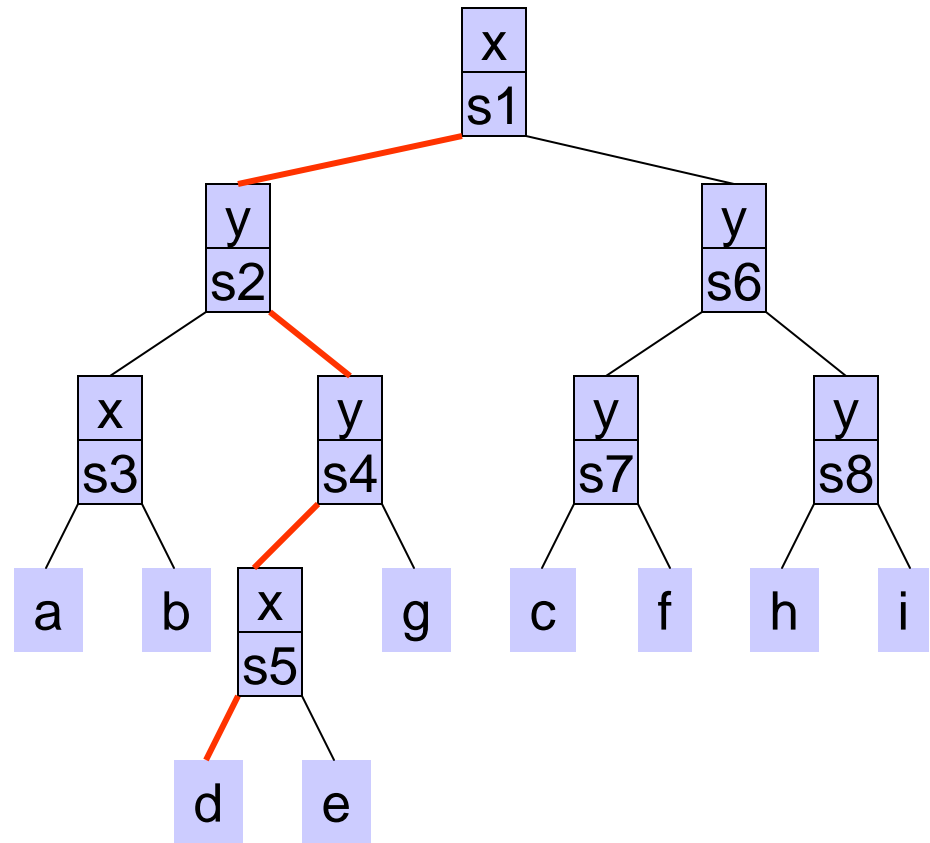
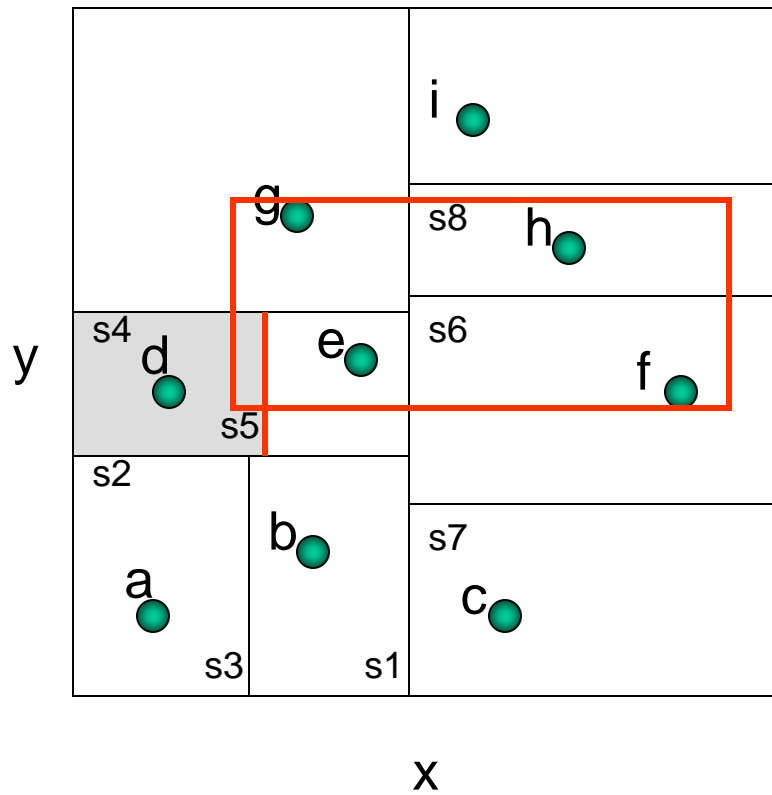
# Rectangular Range Query (3)



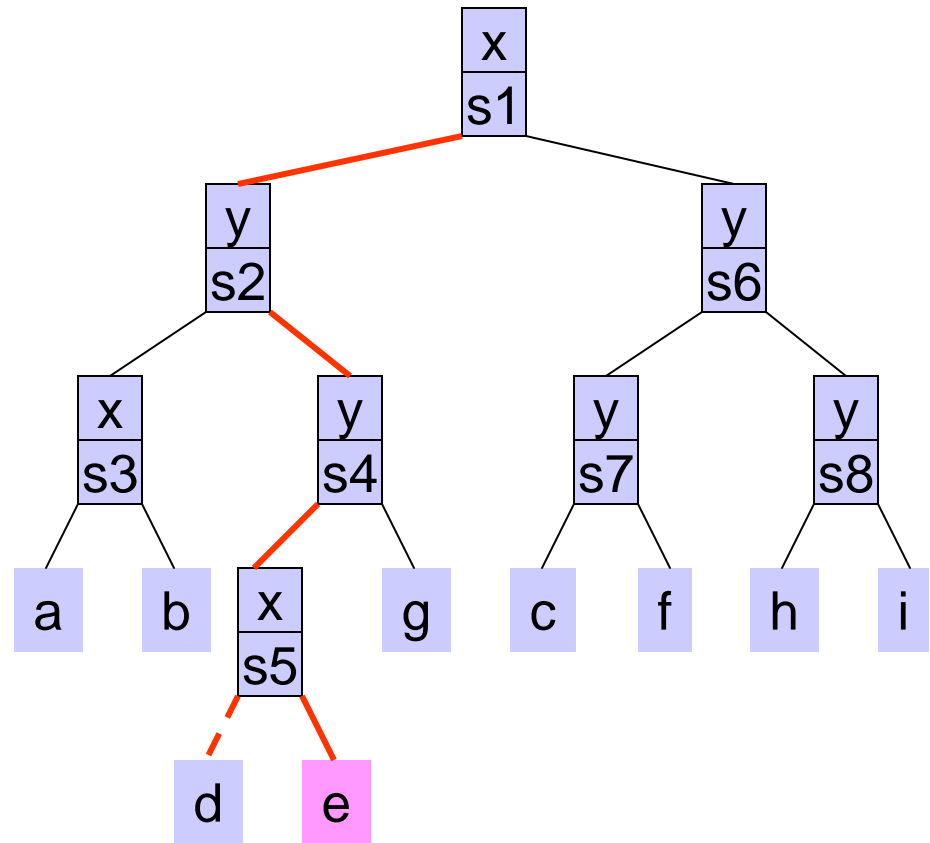
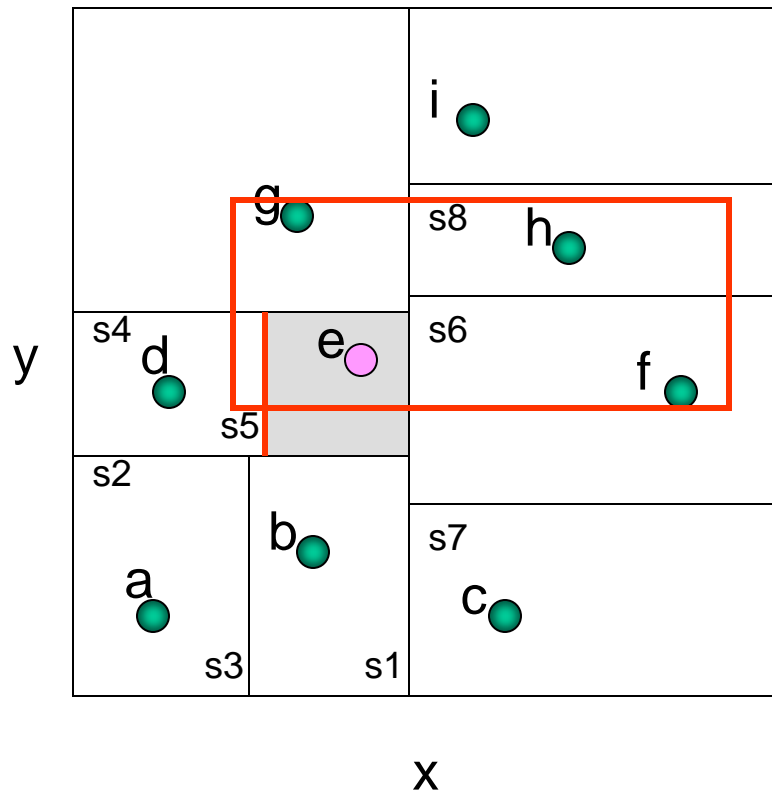
# Rectangular Range Query (4)



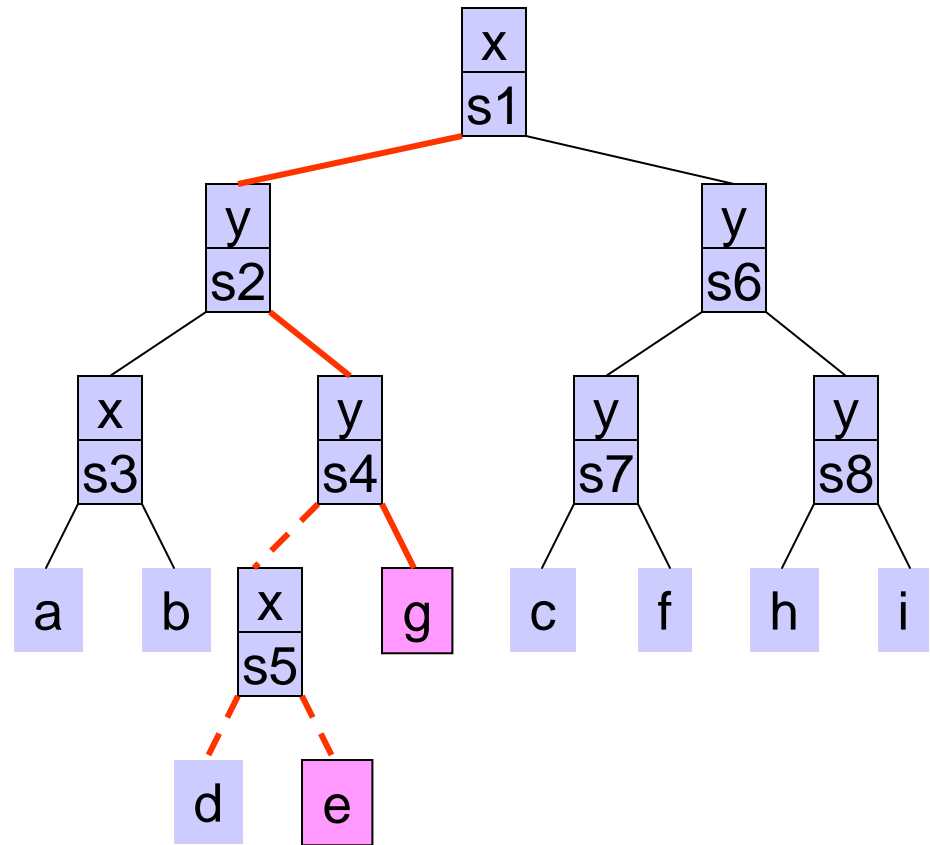
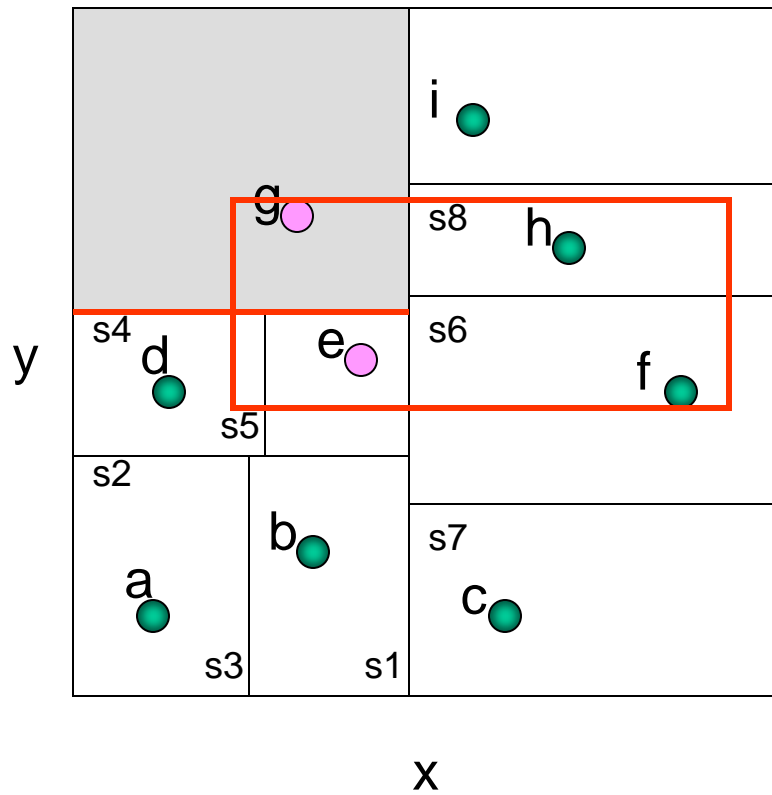
# Rectangular Range Query (5)



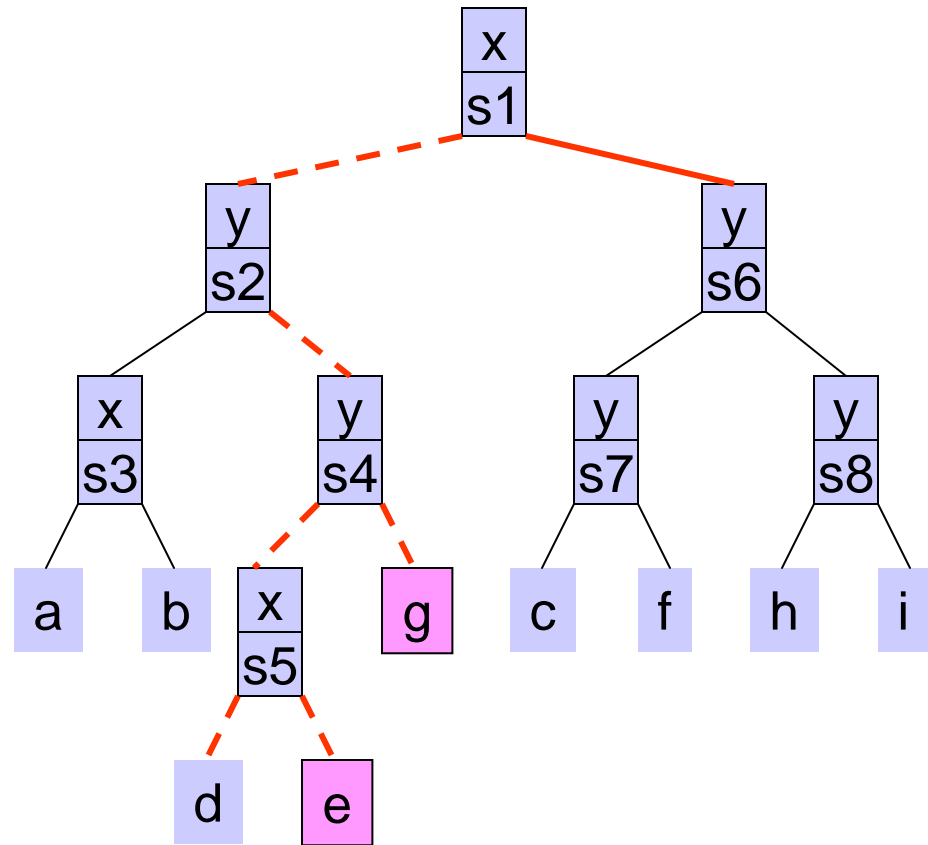
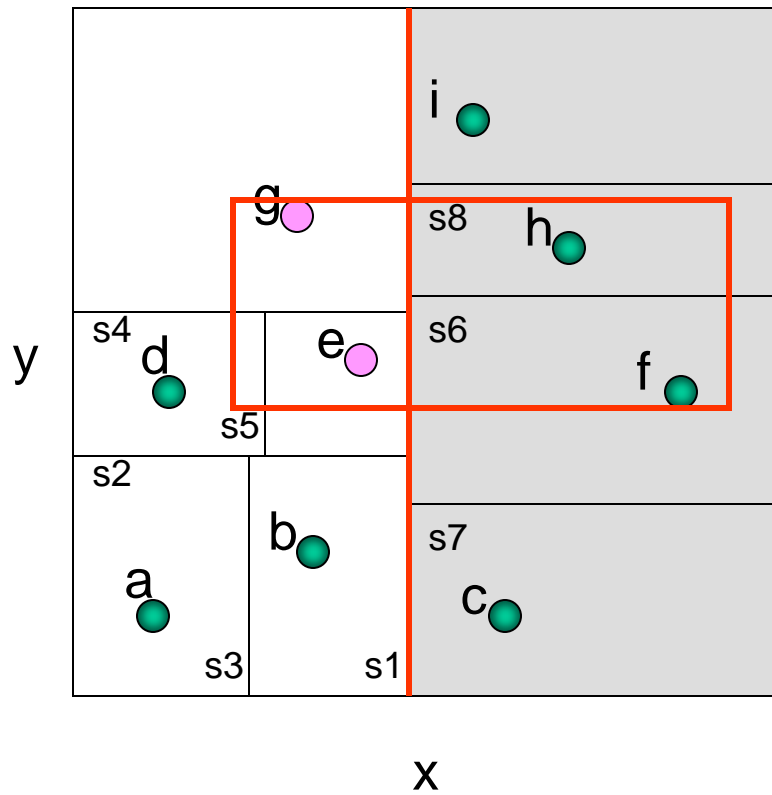
# Rectangular Range Query (6)



# Rectangular Range Query (7)



# Rectangular Range Query (8)



# Rectangular Range Query

```
print_range(xlow, xhigh, ylow, yhigh :integer, root: node pointer) {
  Case {
    root = null: return;
    root.left = null:
      if xlow ≤ root.point.x and root.point.x ≤ xhigh
      and ylow ≤ root.point.y and root.point.y ≤ yhigh
      then print(root);
    else
      if(root.axis = "x" and xlow ≤ root.value ) or
      (root.axis = "y" and ylow ≤ root.value ) then
        print_range(xlow, xhigh, ylow, yhigh, root.left);
      if (root.axis = "x" and xlow > root.value ) or
      (root.axis = "y" and ylow > root.value ) then
        print_range(xlow, xhigh, ylow, yhigh, root.right);
  }}
}}
```

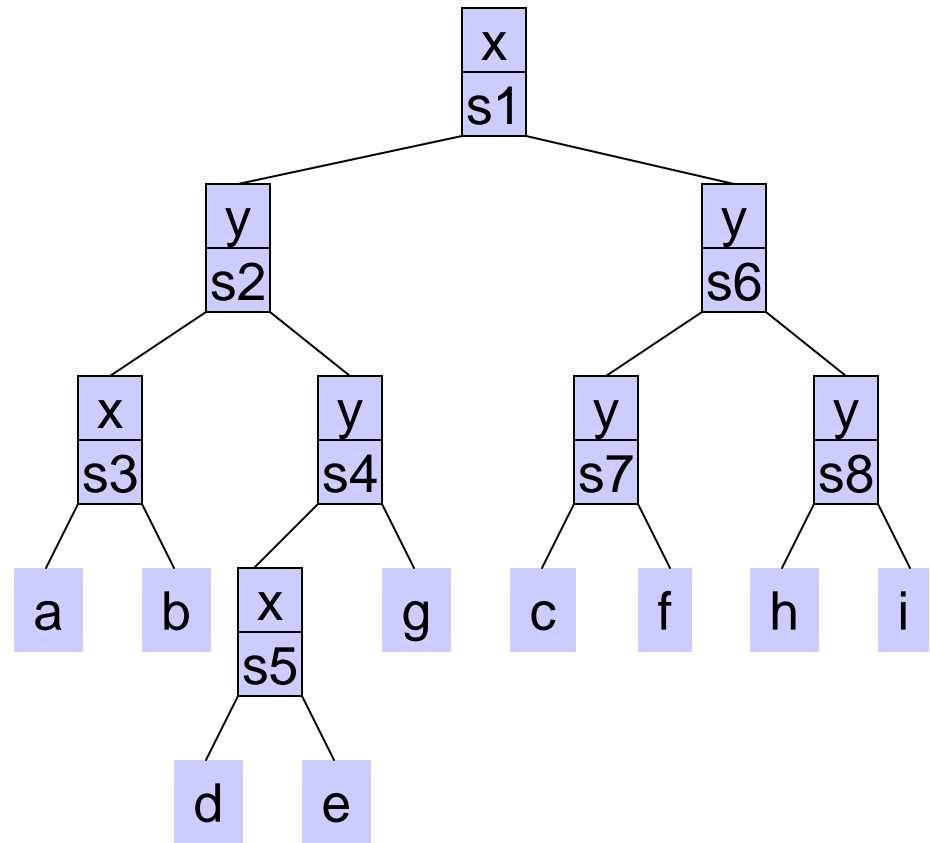
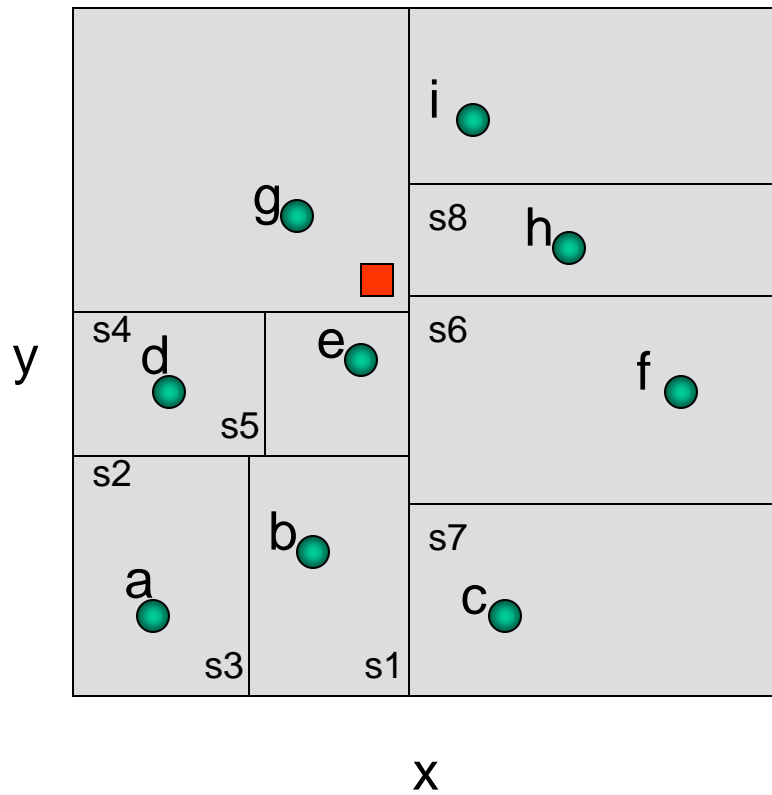


# k-d Tree Nearest Neighbor Search

- Search recursively to find the point in the same cell as the query.
- On the return search each subtree where a closer point than the one you already know about might be found.

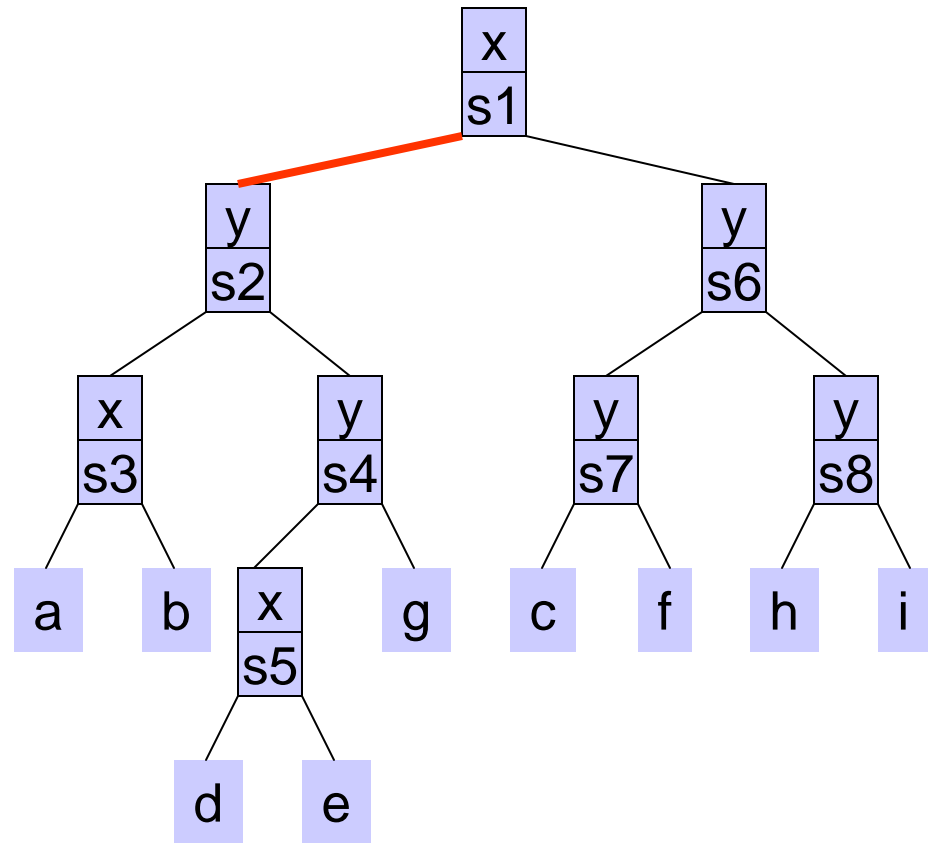
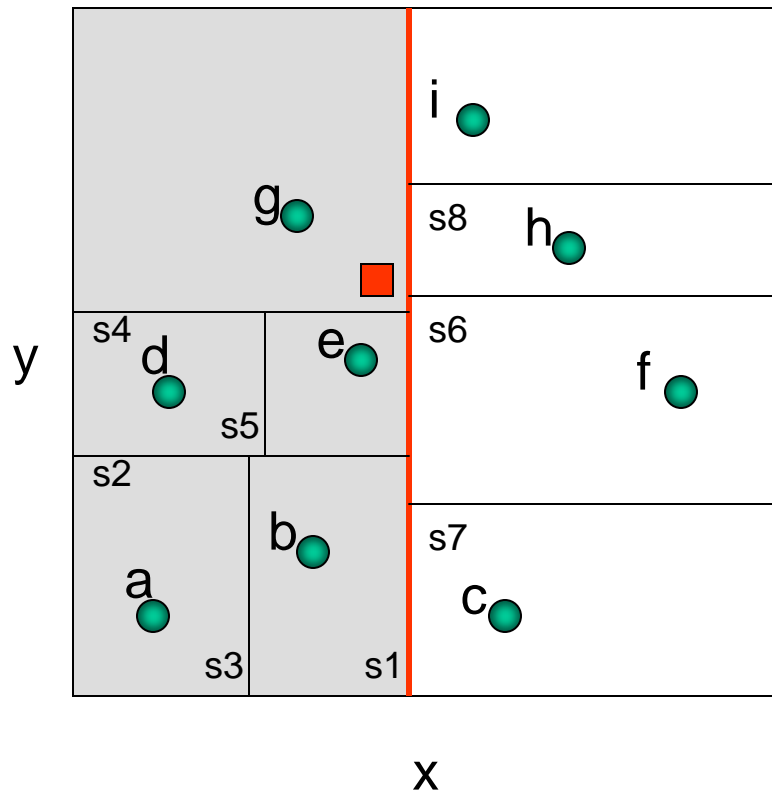
# k-d Tree NNS (1)

■ query point



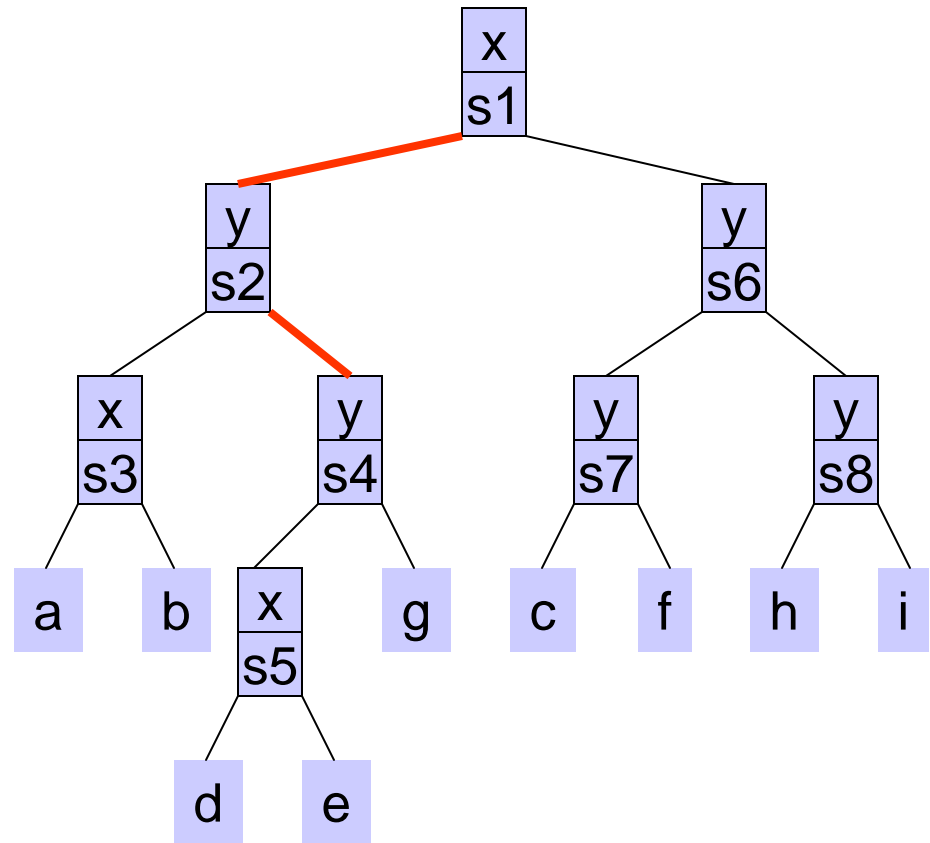
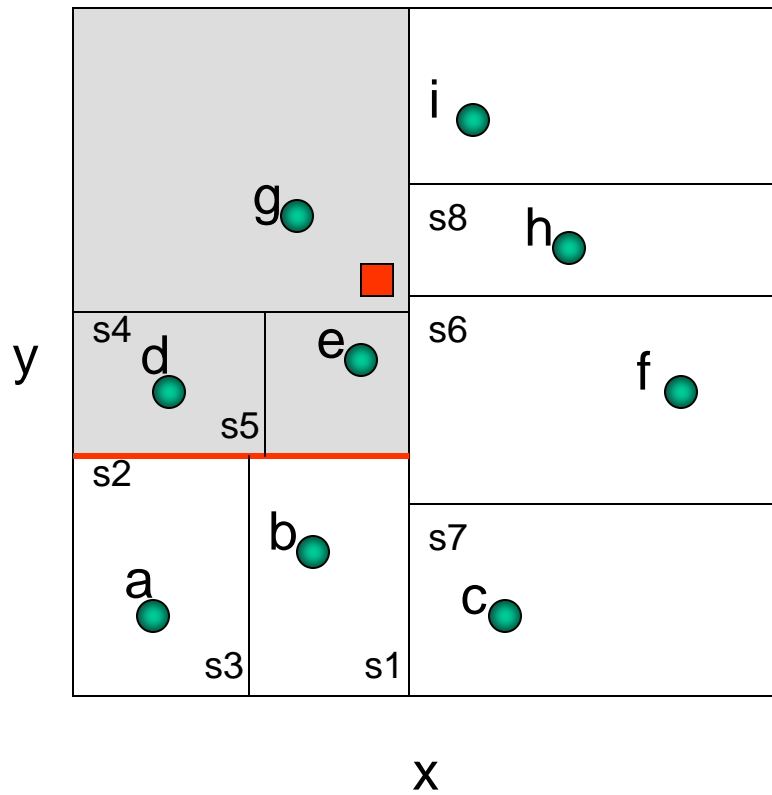
# k-d Tree NNS (2)

■ query point



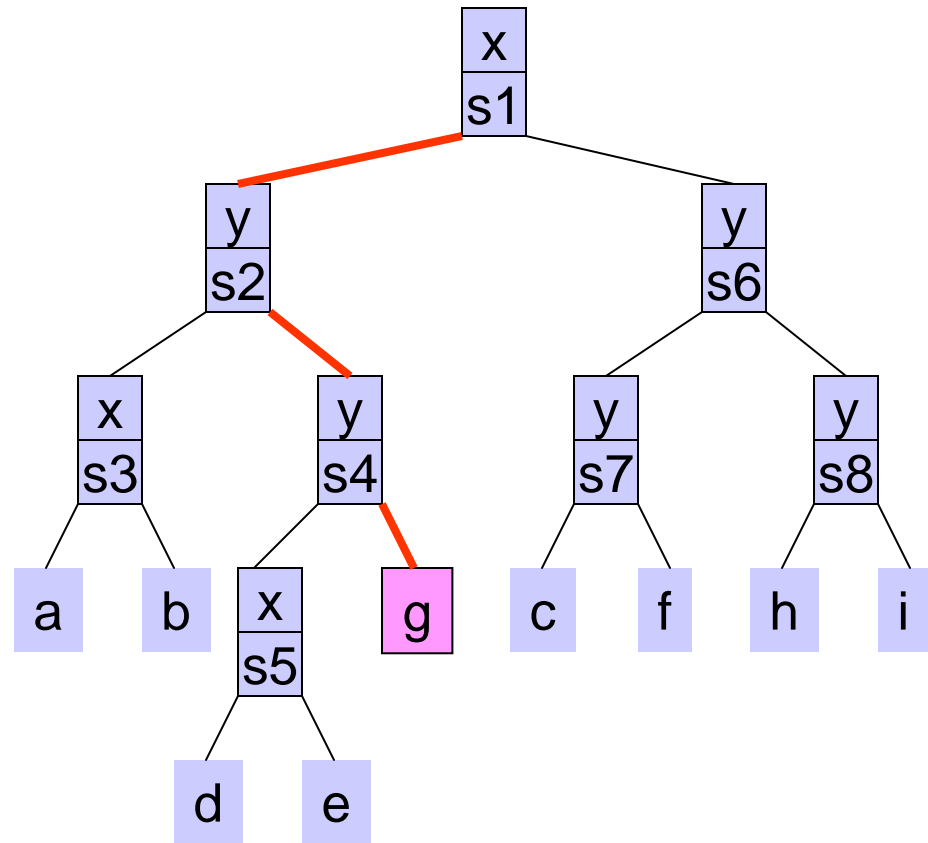
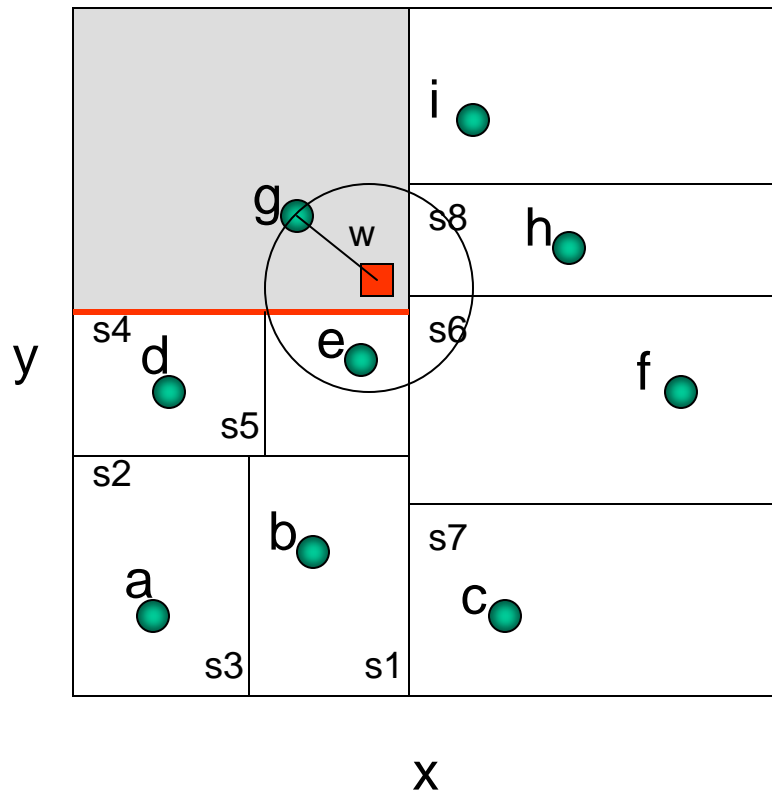
# k-d Tree NNS (3)

■ query point



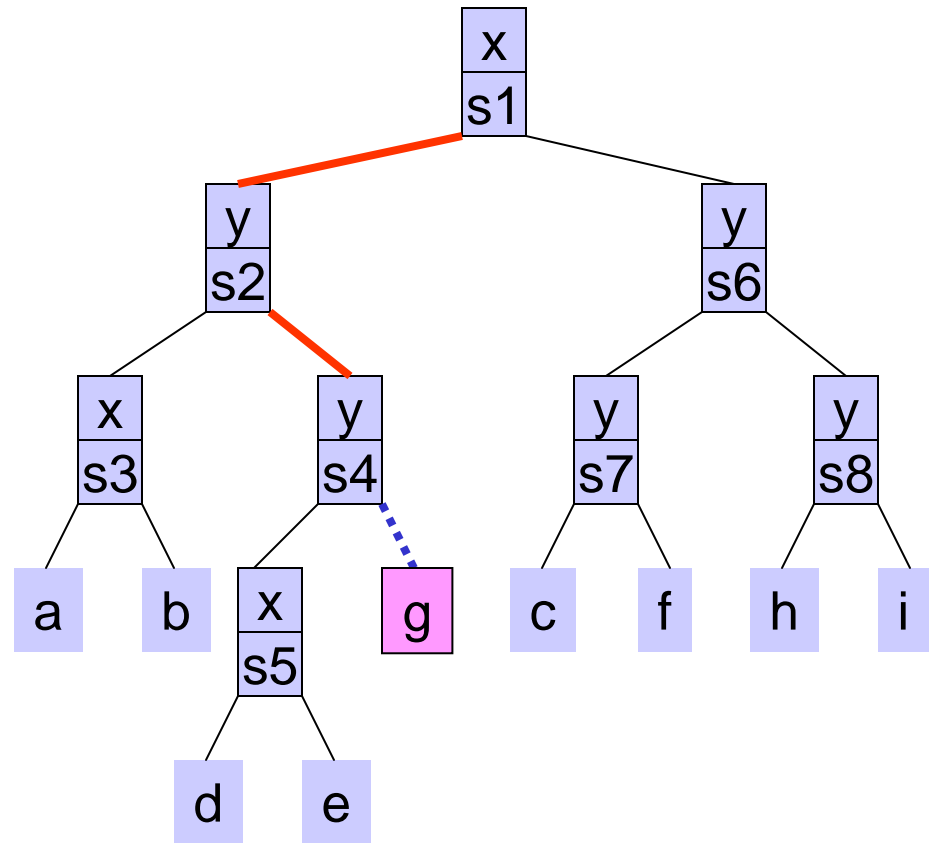
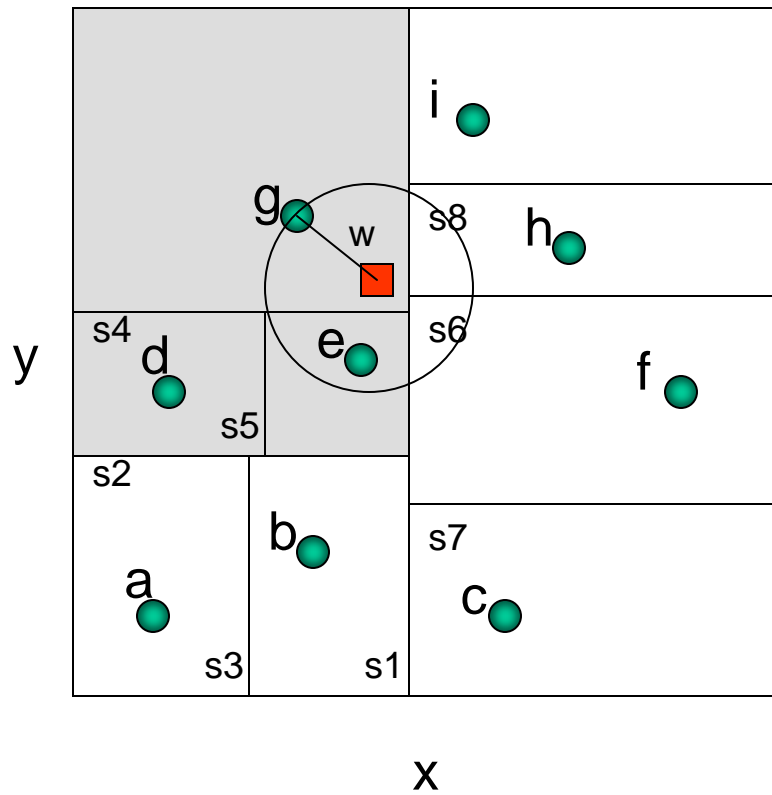
# k-d Tree NNS (4)

■ query point



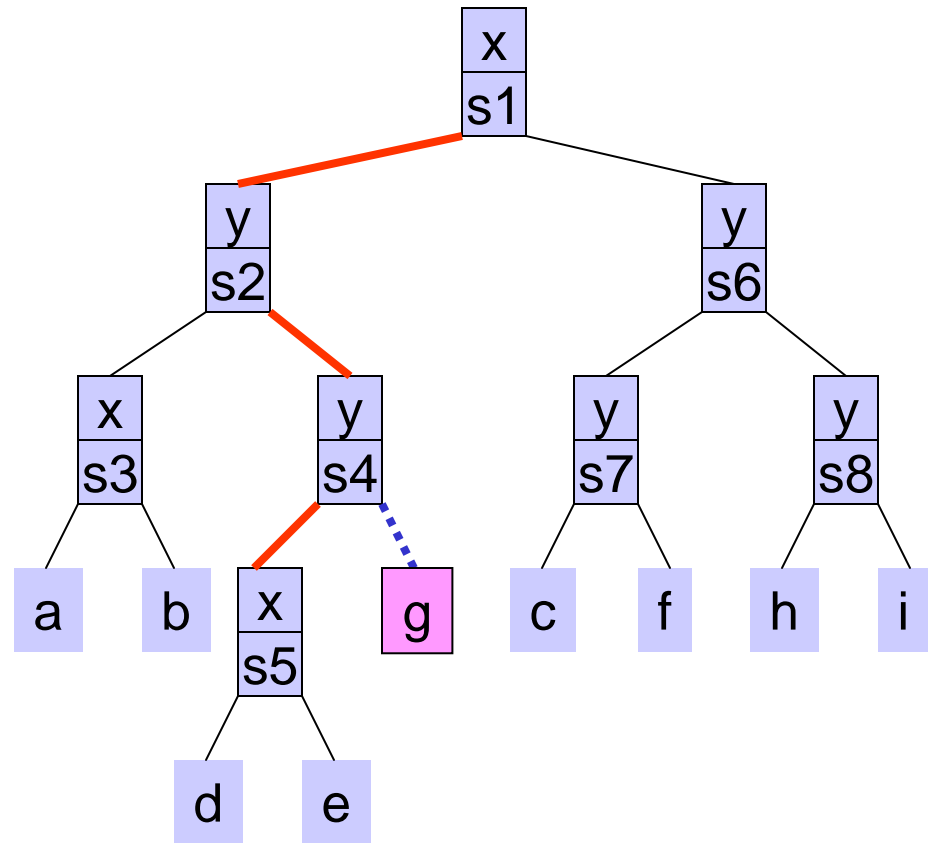
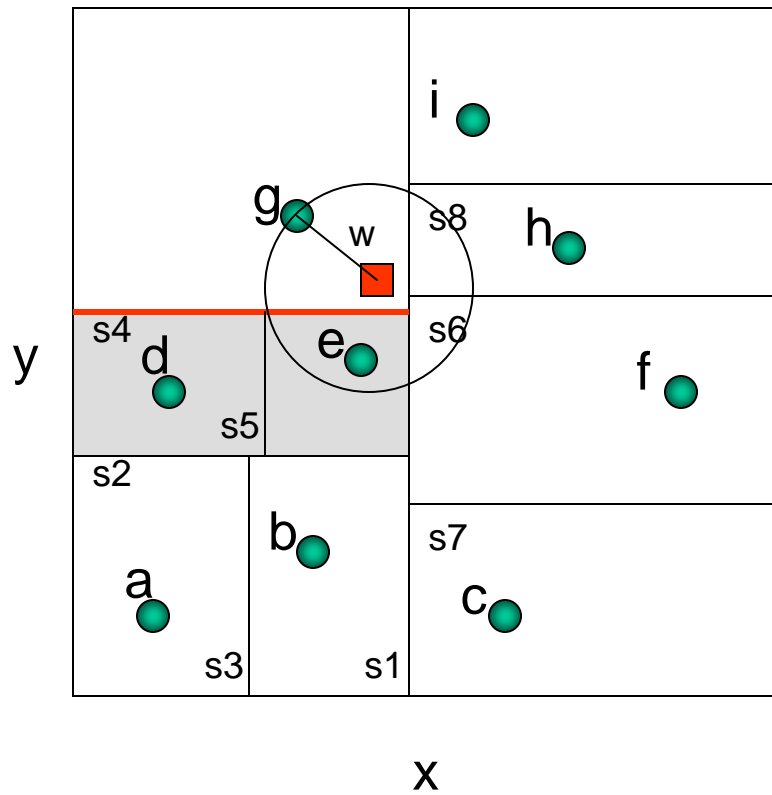
# k-d Tree NNS (5)

■ query point



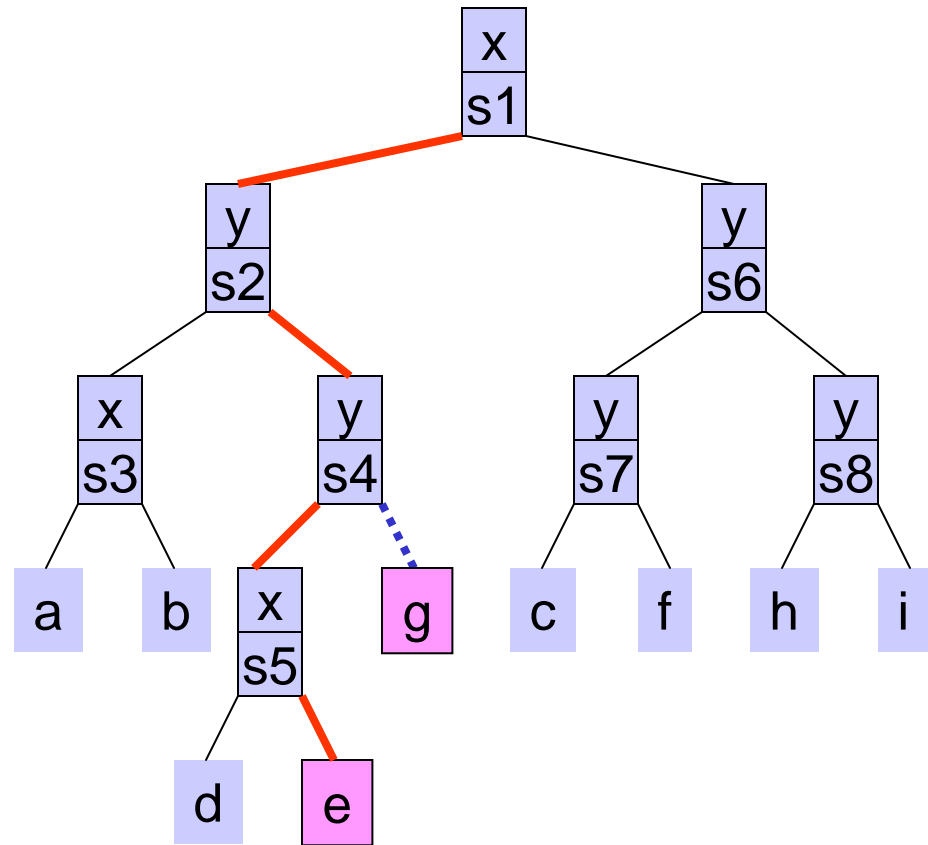
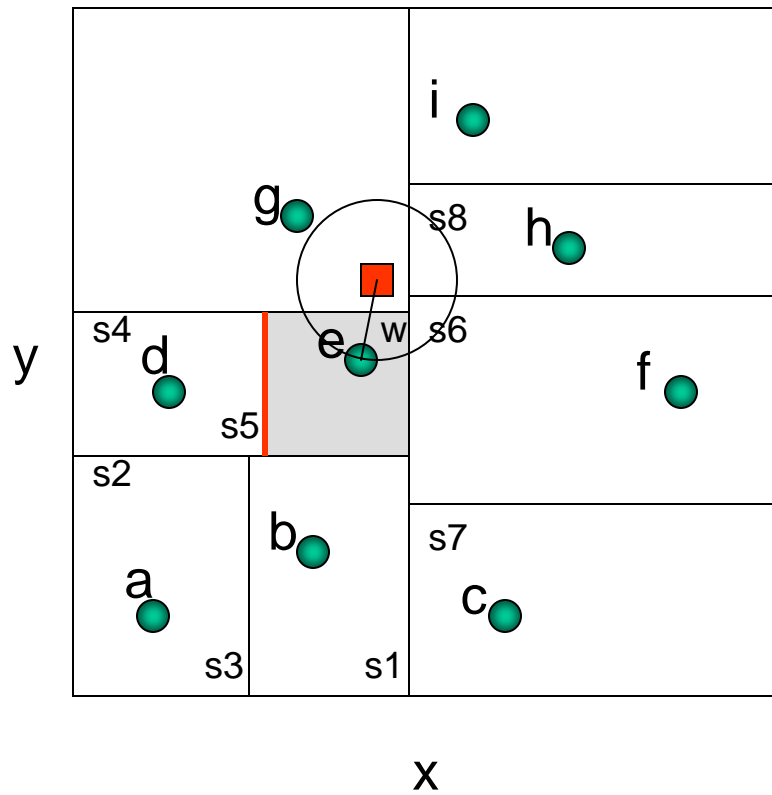
# k-d Tree NNS (6)

■ query point



# k-d Tree NNS (7)

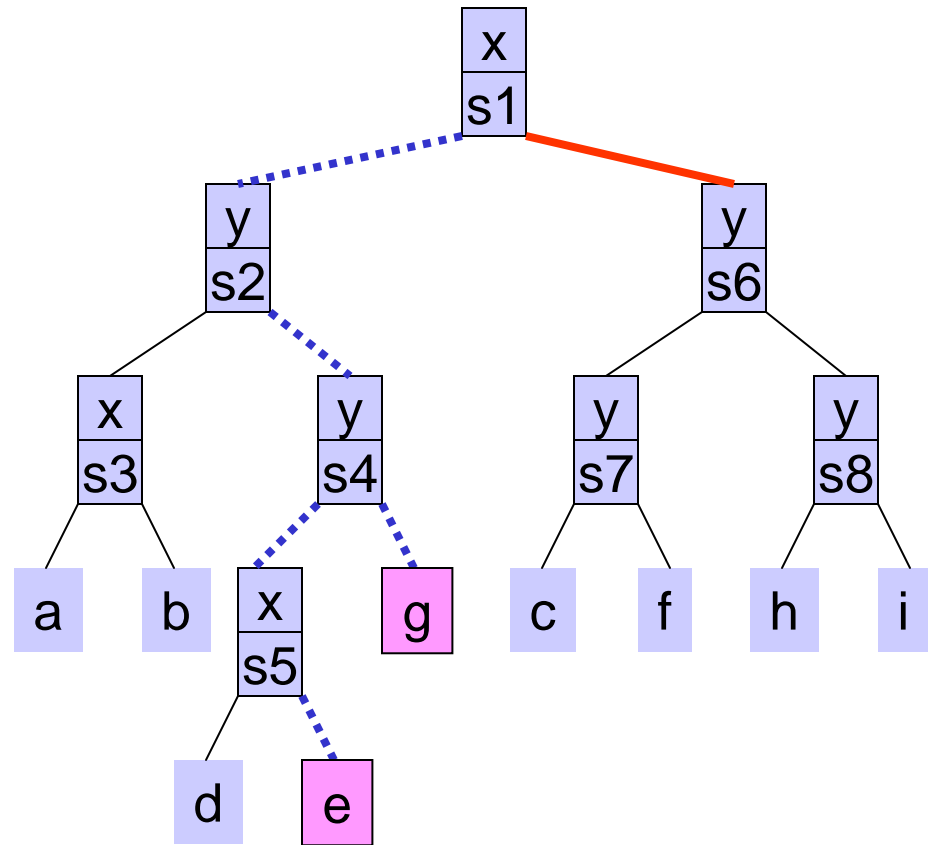
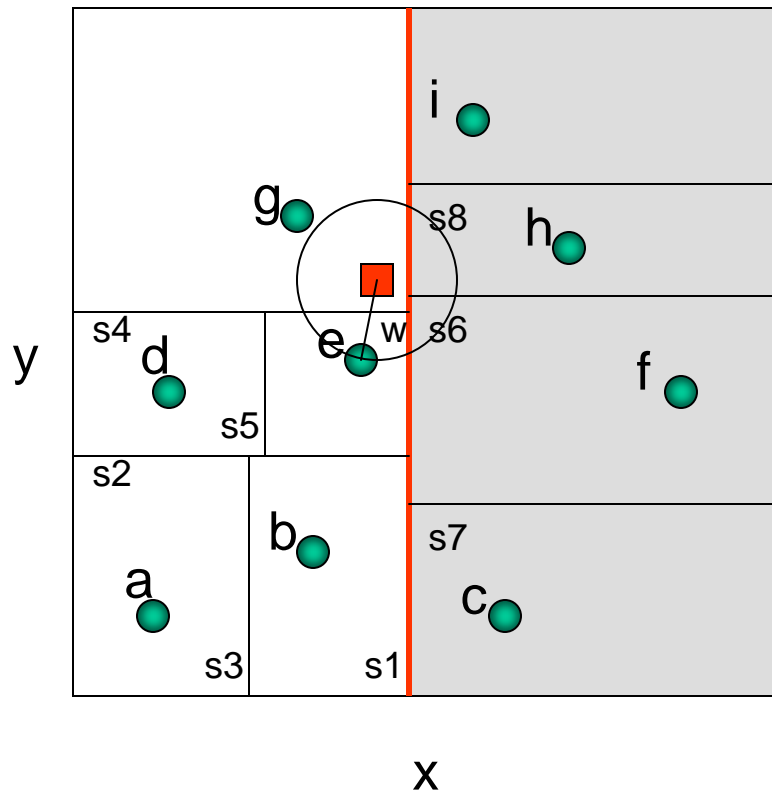
■ query point





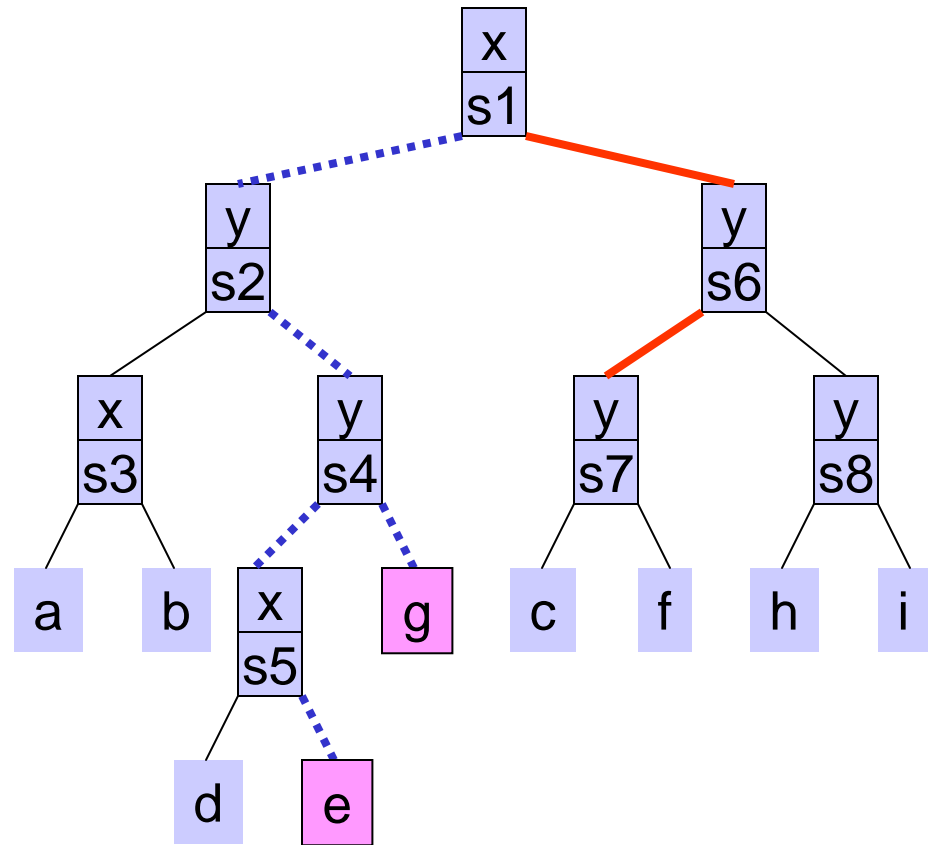
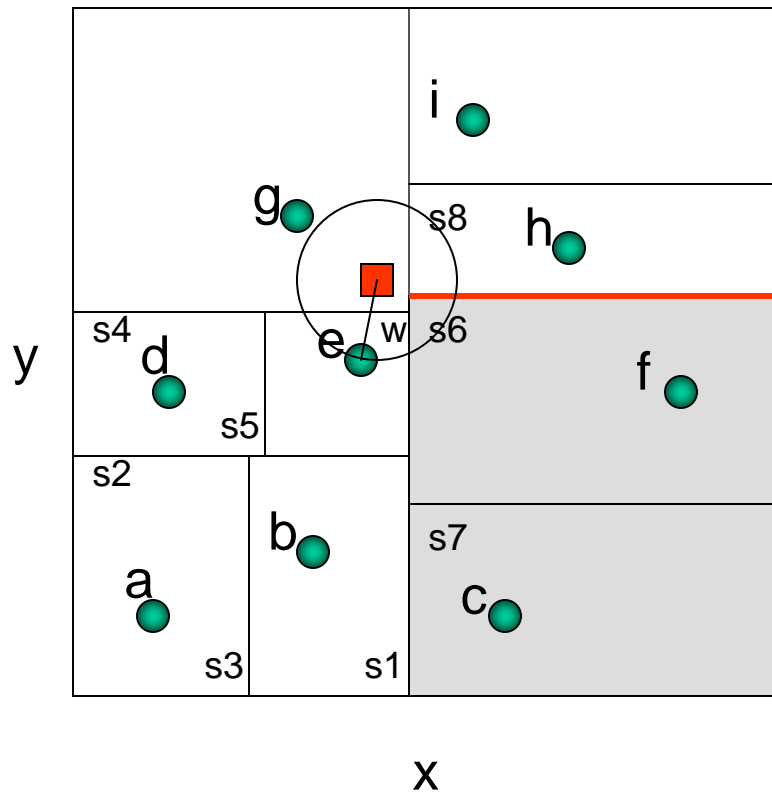
# k-d Tree NNS (10)

■ query point



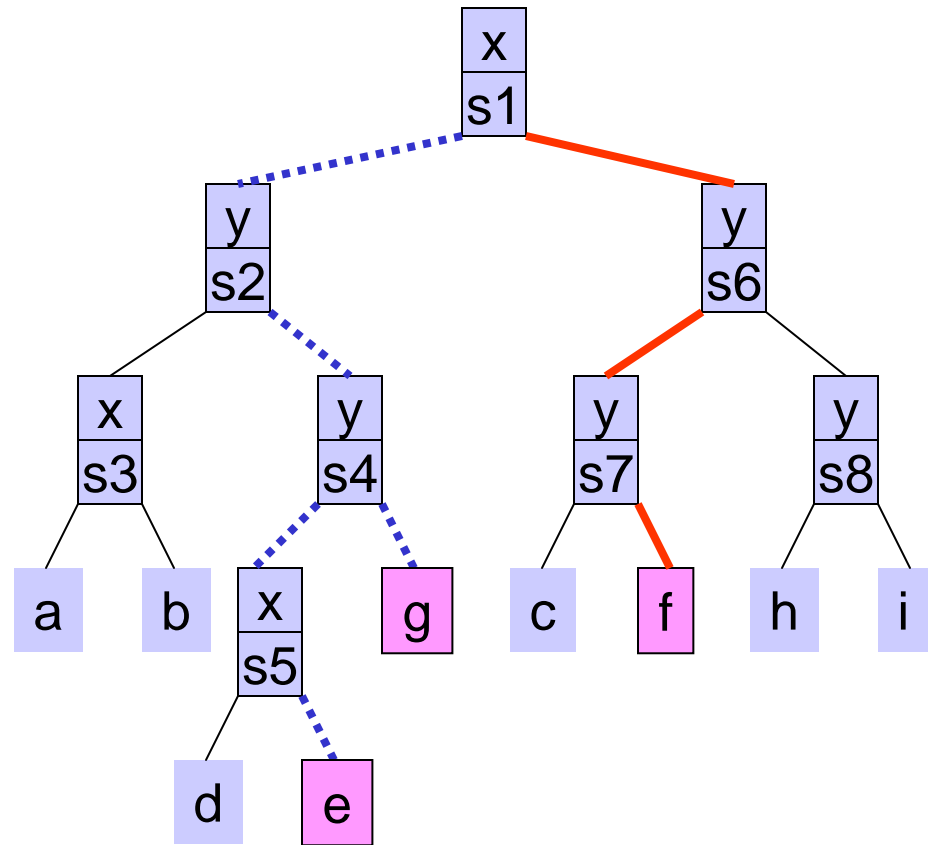
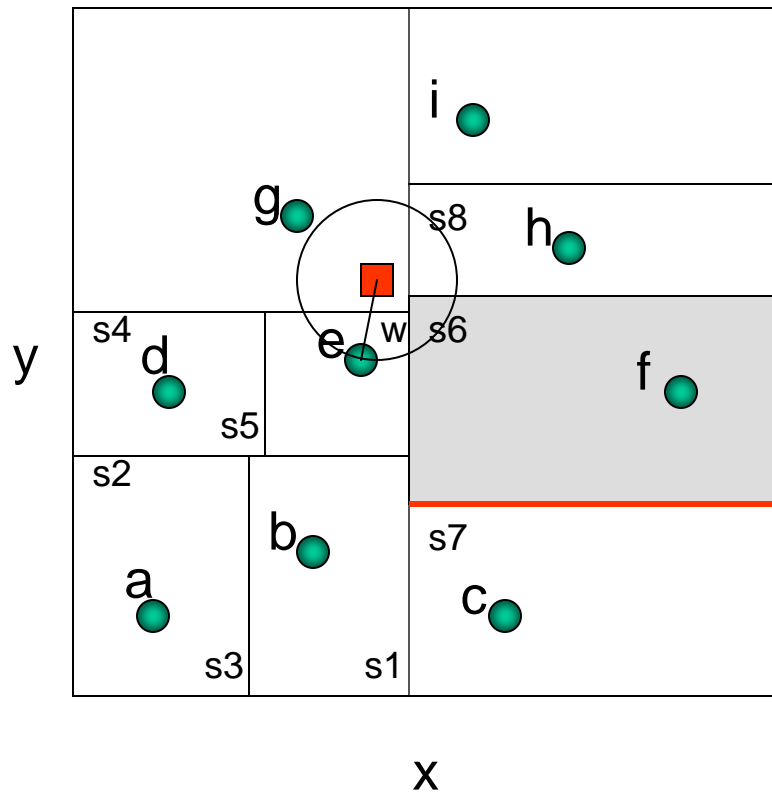
# k-d Tree NNS (11)

■ query point



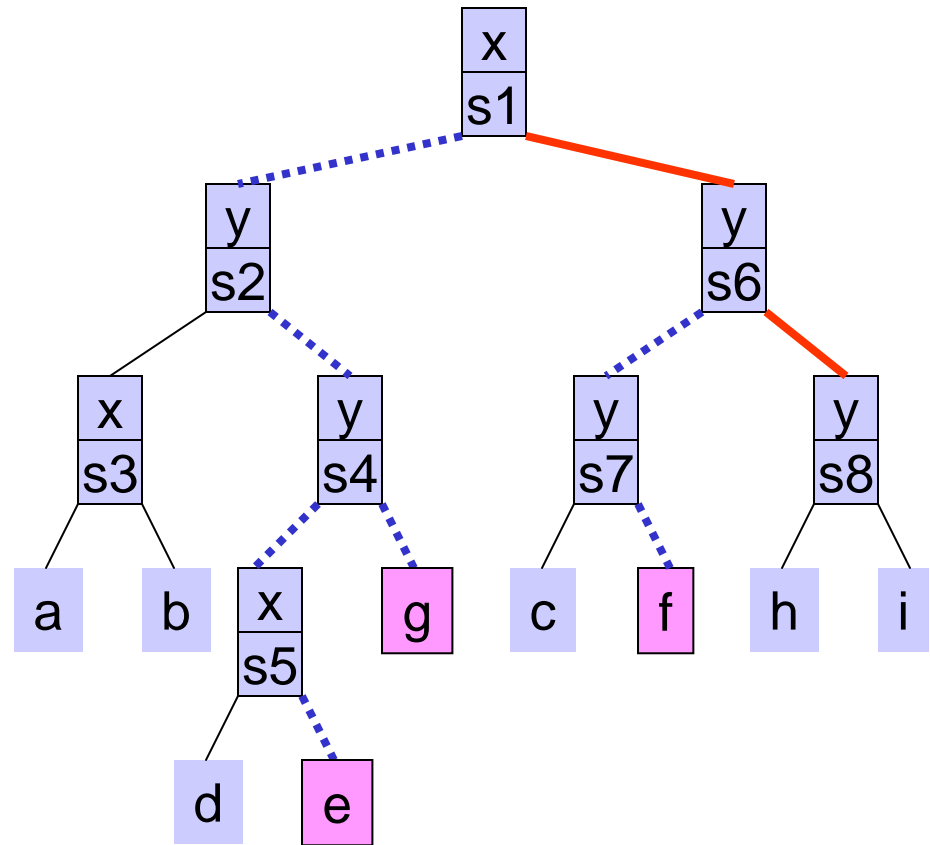
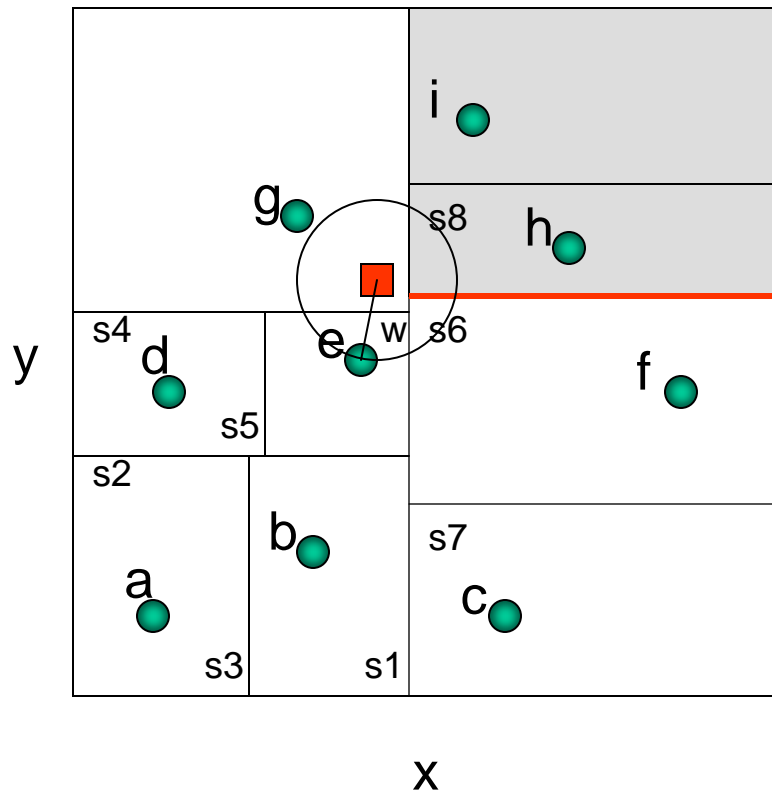
# k-d Tree NNS (12)

■ query point



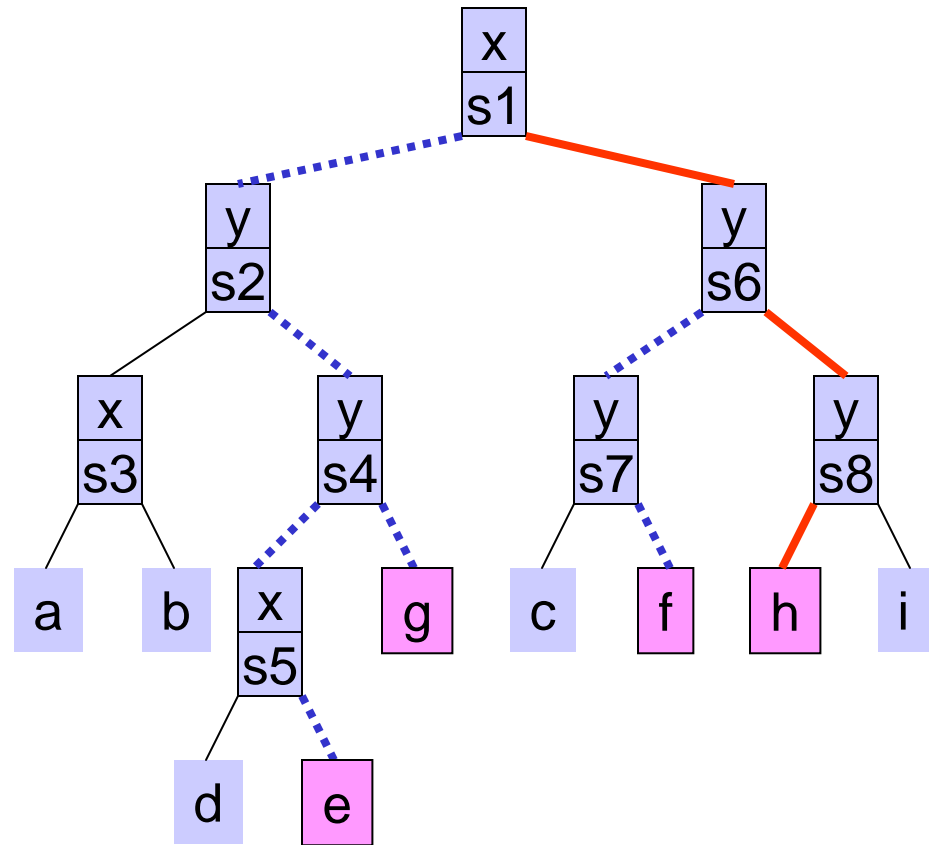
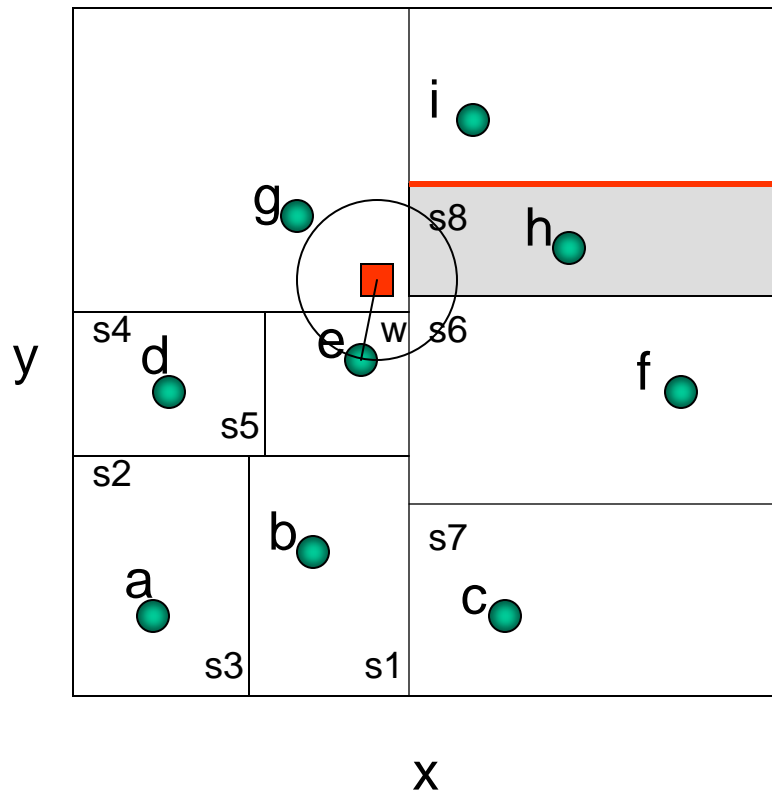
# k-d Tree NNS (13)

■ query point



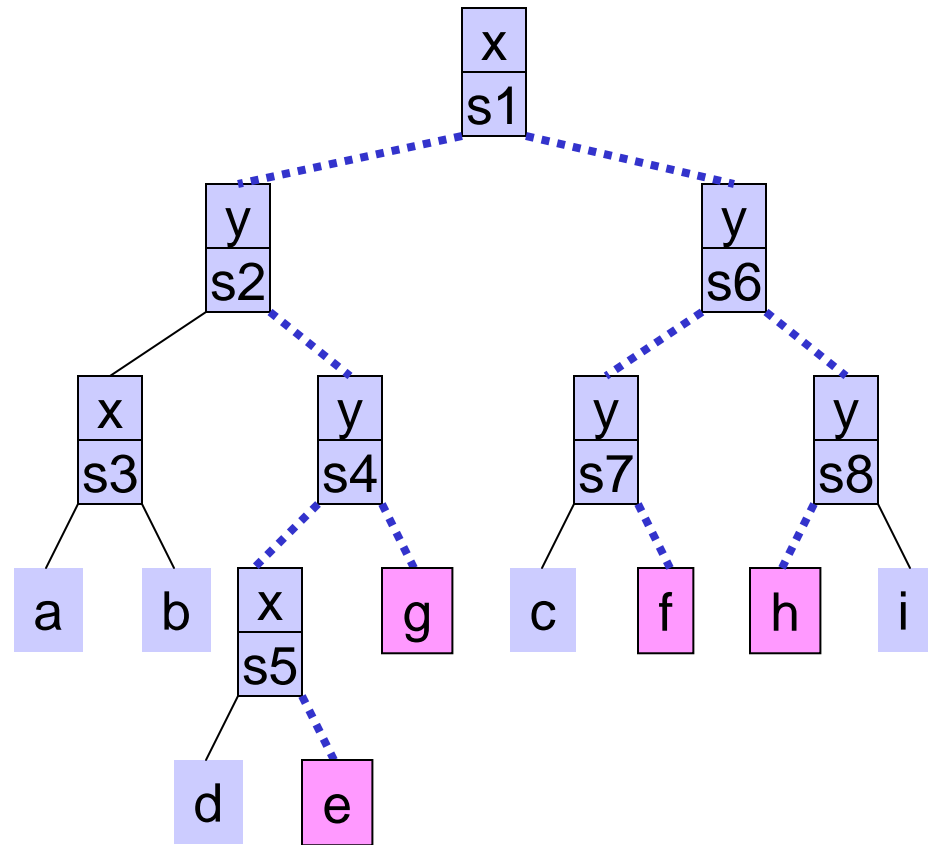
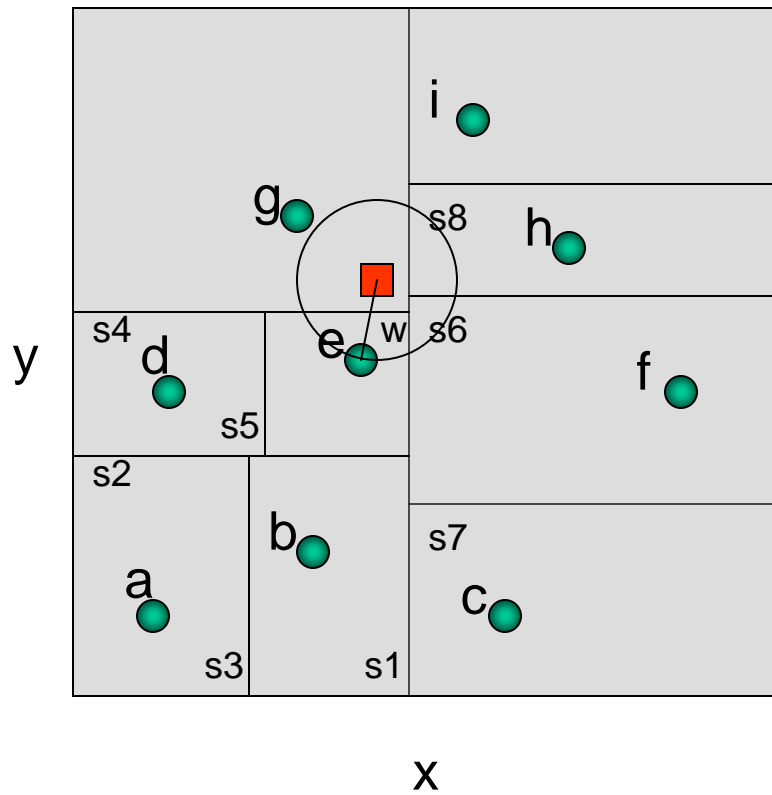
# k-d Tree NNS (14)

■ query point



# k-d Tree NNS (15)

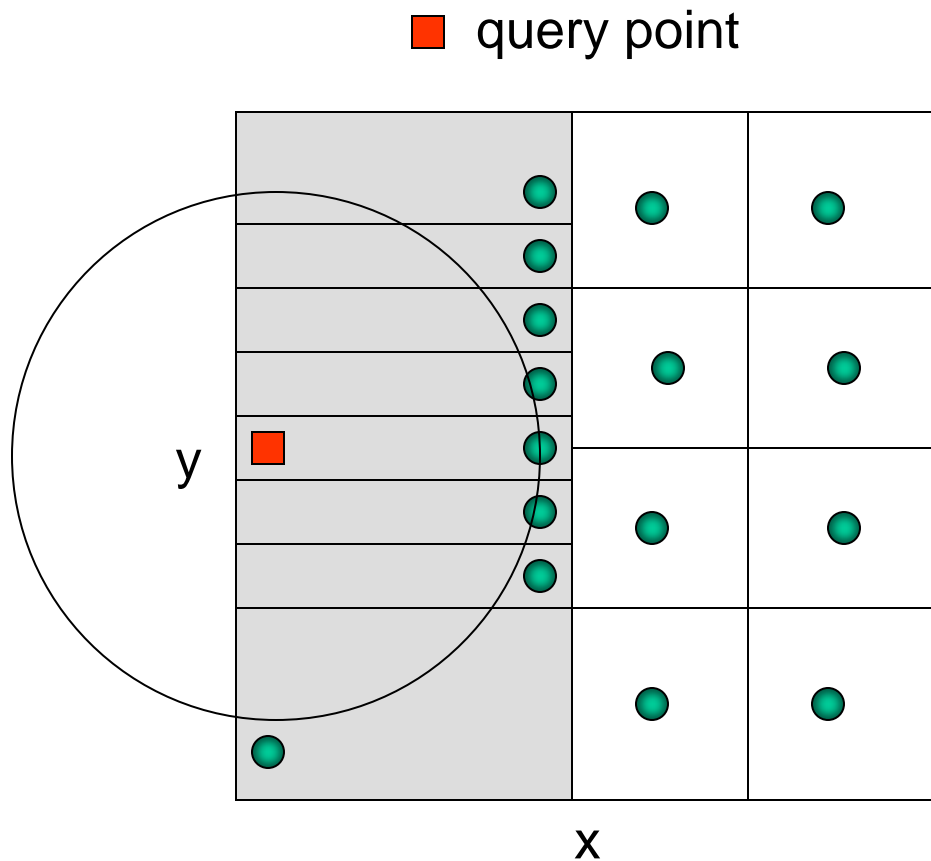
■ query point



## Notes on k-d NNS

- Has been shown to run in  $O(\log n)$  average time per search in a reasonable model.
- Storage for the k-d tree is  $O(n)$ .
- Preprocessing time is  $O(n \log n)$  assuming  $d$  is a constant.

# Worst-Case for Nearest Neighbor Search

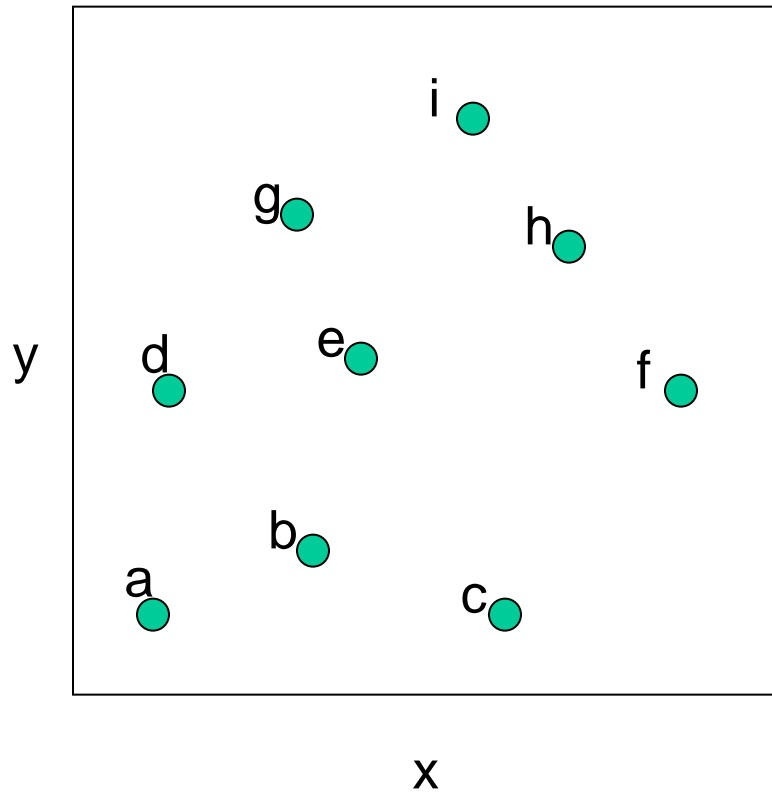


- Half of the points visited for a query
- Worst case  $O(n)$
- But: on average (and in practice) nearest neighbor queries are  $O(\log N)$



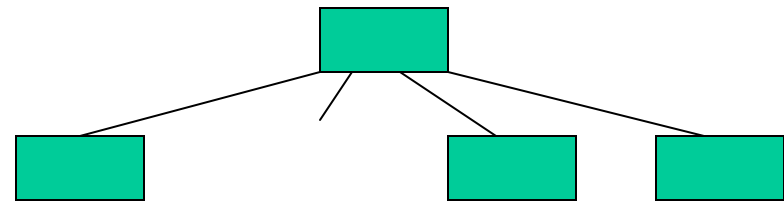
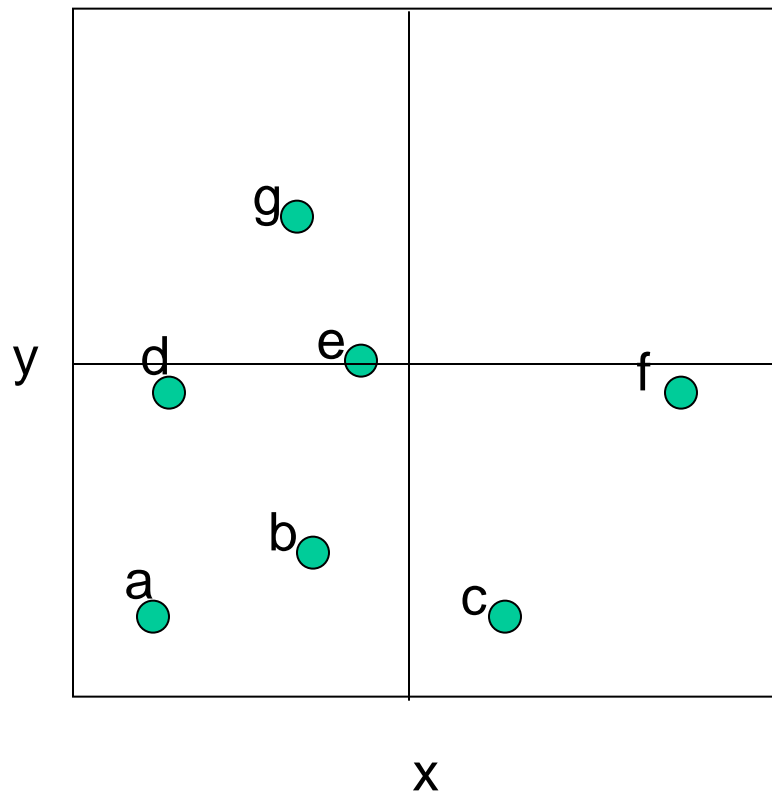
# Quad Trees

- Space Partitioning



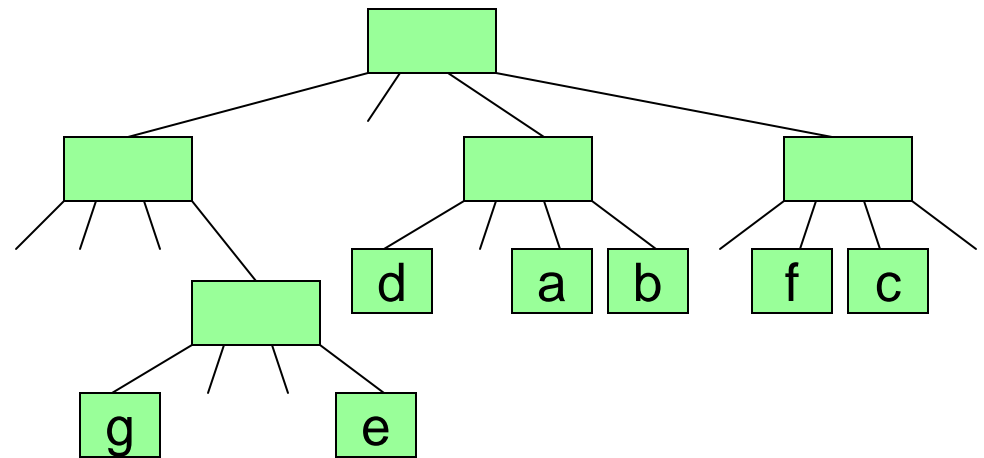
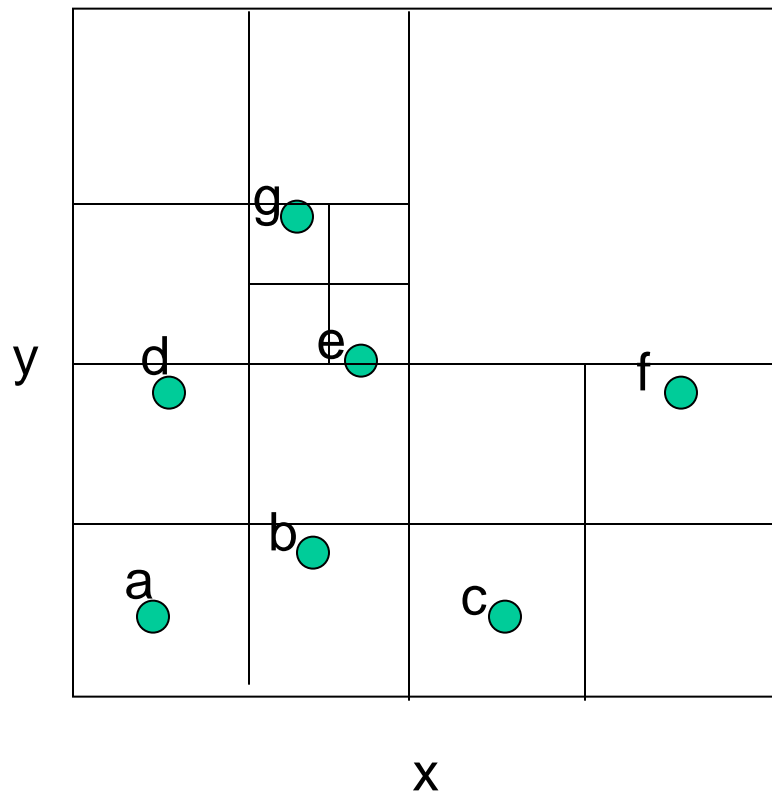
# Quad Trees

- Space Partitioning

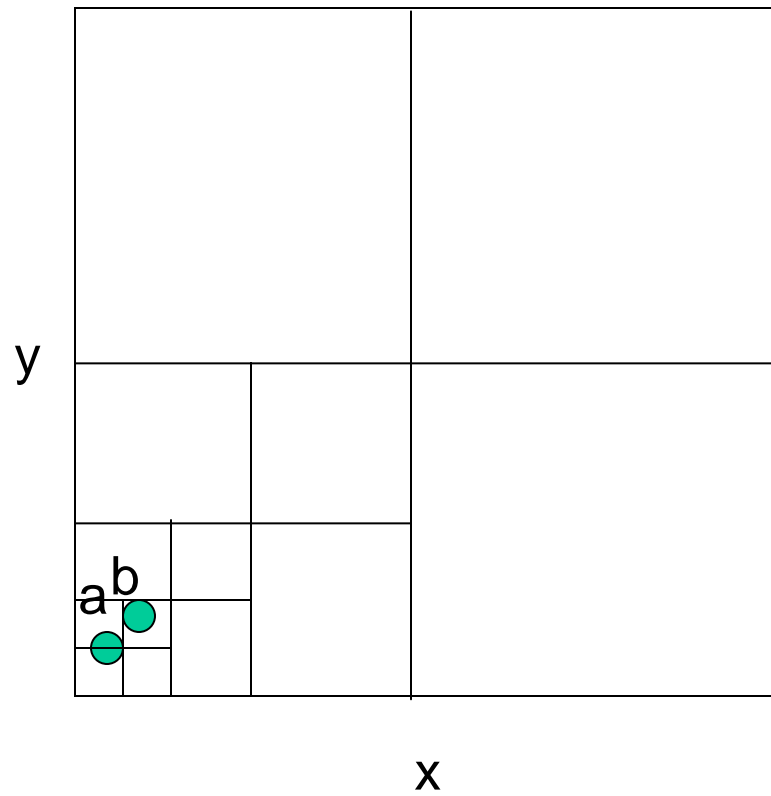


# Quad Trees

- Space Partitioning



# A Bad Case



# Notes on Quad Trees

- Number of nodes is  $O(n(1 + \log(\Delta/n)))$  where  $n$  is the number of points and  $\Delta$  is the ratio of the width (or height) of the key space and the smallest distance between two points
- Height of the tree is  $O(\log n + \log \Delta)$

# K-D vs Quad

- k-D Trees
  - Density balanced trees
  - Height of the tree is  $O(\log n)$  with batch insertion
  - Good choice for high dimension
  - Supports insert, find, nearest neighbor, range queries
- Quad Trees
  - Space partitioning tree
  - May not be balanced
  - Not a good choice for high dimension
  - Supports insert, delete, find, nearest neighbor, range queries

# Geometric Data Structures

- Geometric data structures are common.
- The k-d tree is one of the simplest.
  - Nearest neighbor search
  - Range queries
- Other data structures used for
  - 3-d graphics models
  - Physical simulations