

CMSC 420 - 0201 - Fall 2019

Lecture 13

Point Quadtree and kd-Trees



Overview

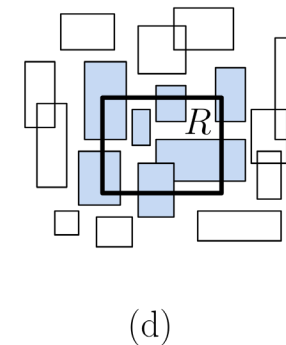
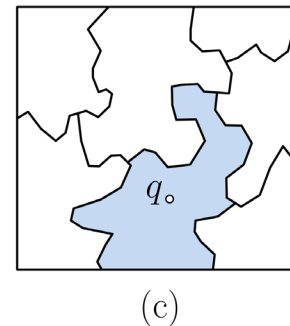
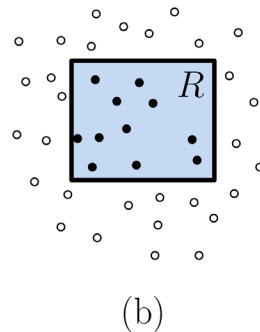
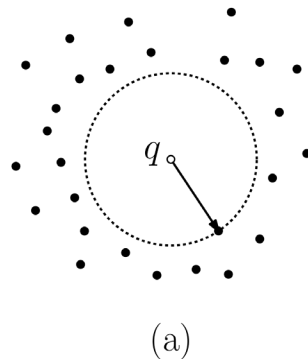
- So far, we have studying data structure for 1-dimensional search problems
- Many data structure problems involve data in multi-dimensional spaces:
 - Spatial databases, automated cartography (maps), and navigation
 - Computer graphics
 - Robotics and motion planning
 - Solid modeling and industrial engineering
 - Particle and fluid dynamics
 - Molecular dynamics in computational biology
 - Machine learning
 - Image processing, pattern recognition, computer vision



Geometric Queries

Examples

- **Nearest-neighbor searching** - Find the closest point to a given query point q
- **Range searching** - Report/Count the points lying within a query region R
- **Point location** - Find the region of a subdivision (map) containing a query point q
- **Intersection searching** - Find all the objects that overlap a given query object R
- **Ray shooting** - Find the first (if any) object hit by shooting a ray from a point p



Geometric Queries

Similarities and differences

- Multi-dimensional data structures **borrow** many concepts from 1-dimensional search structure
 - Tree-based structures based on **hierarchical partitions**
 - Maintaining **balance** $O(\log n)$ height
 - Use **key/splitters** to navigate the search space
- Many **differences** as well
 - There is no natural **total order** in geometric space.
 - What does it mean to say one point is **smaller** than another?



Geometric Data

Point Representation

- A point in a d -dimensional space is represented by a **d-vector** of reals:

$$p = (p_1, p_2, \dots, p_d)$$

- In Java, this could be represented by a **d-element array**

```
float[] p = new float[d];
```

- While in linear algebra, indexing is from $1 \dots d$, in Java indexing is from $0 \dots d - 1$

- A set of n points can be represented as a **2-dimensional array**:

```
float[][] P = new float[n][d];
```



Geometric Data

Point Representation

- A better approach is to encapsulate points in a class structure

```
public class Point {  
    private float[] coord;           // coordinate storage  
  
    public Point(int dim) { /* construct a zero point */ }  
    public int getDim() { return coord.length; }  
  
    public float get(int i) { return coord[i]; }  
    public void set(int i, float x) { coord[i] = x; }  
  
    public boolean equals(Point other) { /* compare with another point */ }  
    public String toString() { /* convert to string */ }  
}
```

Point Quadtree

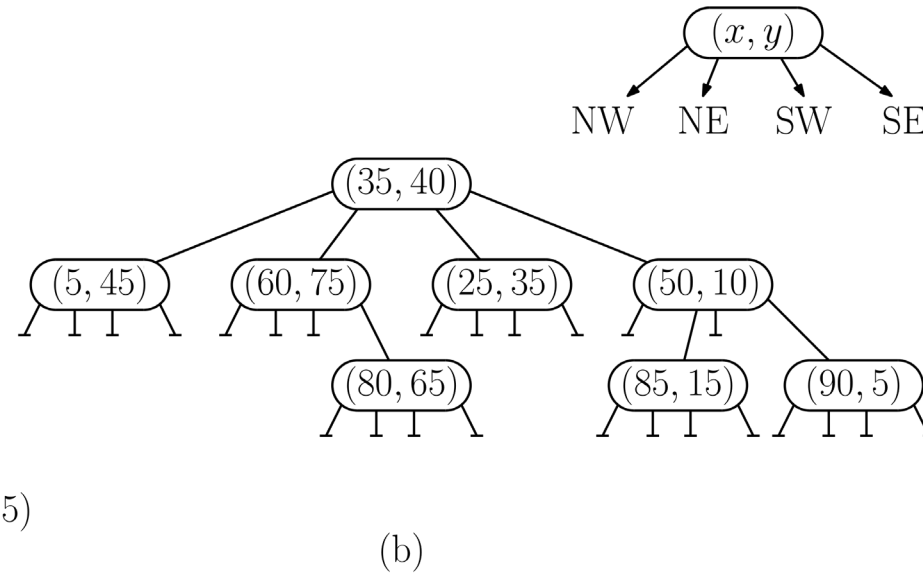
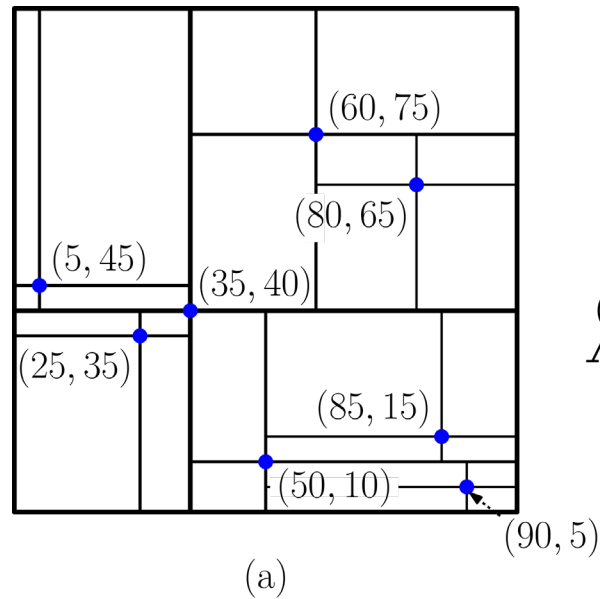
A Natural Generalization of Binary Search Trees

- How do we **generalize** a 1-dimensional tree to d -dimensional space?
- **Partition tree:**
 - Each node is associated with a **region of space** (e.g., a rectangle), its **cell**
 - Each internal node contains a **splitter**, which **subdivides** space into smaller regions
 - Data may be stored in the nodes (as the splitters) or in external nodes (as in extended binary search trees)
- **Point Quadtree:**
 - Each node stores a **point** (both **data** and **splitter**)
 - 2-dimensions: Horizontal and vertical lines through point subdivide cell into **4 quadrants**
 - d -dimensions: d axis-parallel hyperplanes passing through the point subdivide space into 2^d (generalized) **orthants**
 - Each node has 2^d (possibly null) **children**

Point Quadtree

A Natural Generalization of Binary Search Trees

- In 2D, quadrants are labeled NW, NE, SW, and SE
 - Example: (35,40), (50,10), (60,75), (80,65), (85,15), (5,45), (25,35), (90,5)
- To locate a point, we descend from the root, visiting the appropriate child



Point kd-Tree

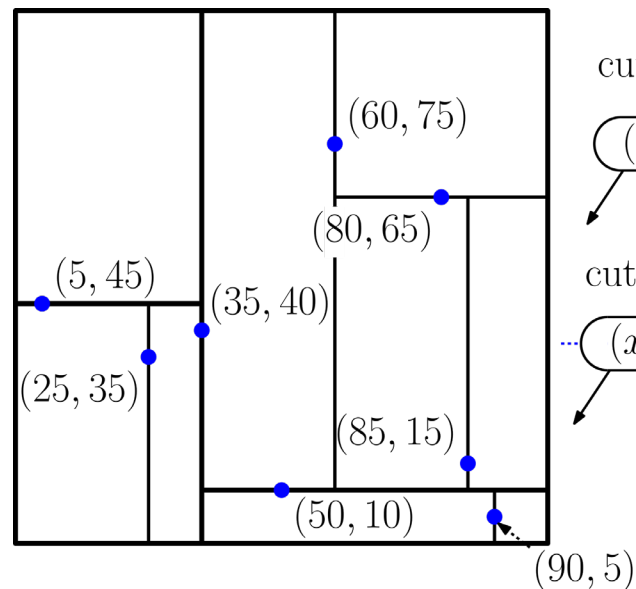
A Binary Partition Tree

- The point quadtree works fine in low-dimensional space, but does not scale well to high dimensional space. For example, in $d = 20$ space, each node has a fanout of $2^d \approx 1,048,576$
- **Idea:** Let's just split **one dimension at a time**
- **Point kd-tree:**
 - Each node stores a **point** (both data and splitter)
 - And an index i , $0 \leq i \leq d - 1$, the **cutting dimension**
 - For any point $x = (x_0, \dots, x_{d-1})$:
 - If $x_i < p_i$, x goes in the **left subtree**
 - If $x_i \geq p_i$, x goes in the **right subtree**
 - **Cutting dimension** varies by level (e.g., `p.child.cutDim = (p.cutDim+1)%dim`)

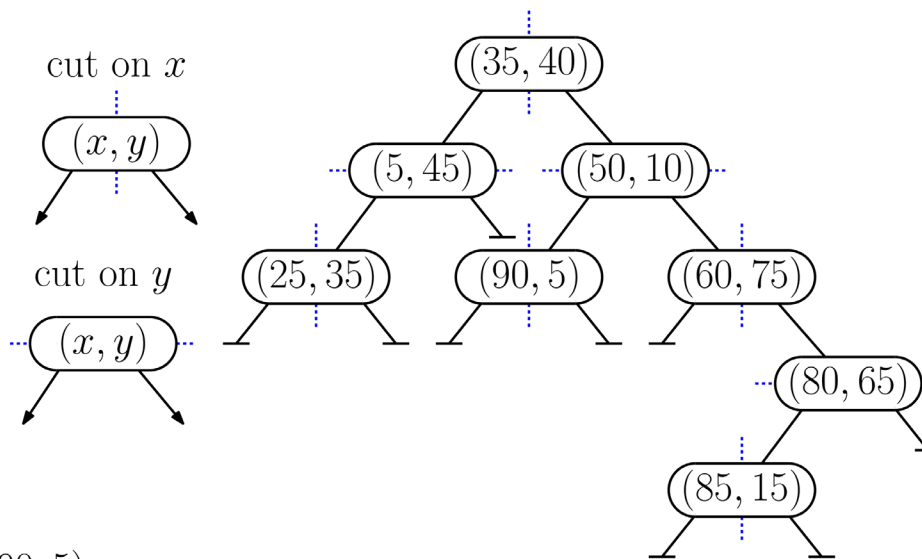
Point kd-Tree

A Binary Partition Tree

- Example: $(35,40)$, $(50,10)$, $(60,75)$, $(80,65)$, $(85,15)$, $(5,45)$, $(25,35)$, $(90,5)$
- Cutting dimension **alternates** between x and y



(a)



(b)

Point kd-Tree

Node structure

```
class KNode { // node in a kd-tree
    Point point; // splitting point
    int cutDim; // cutting dimension
    KNode left; // children
    KNode right;

    KNode(Point point, int cutDim) { // constructor
        this.point = point;
        this.cutDim = cutDim;
        left = right = null;
    }

    boolean inLeftSubtree(Point x) { // is x in left subtree?
        return x.get(cutDim) < point.get(cutDim);
    }
}
```

Point kd-tree

Point insertion

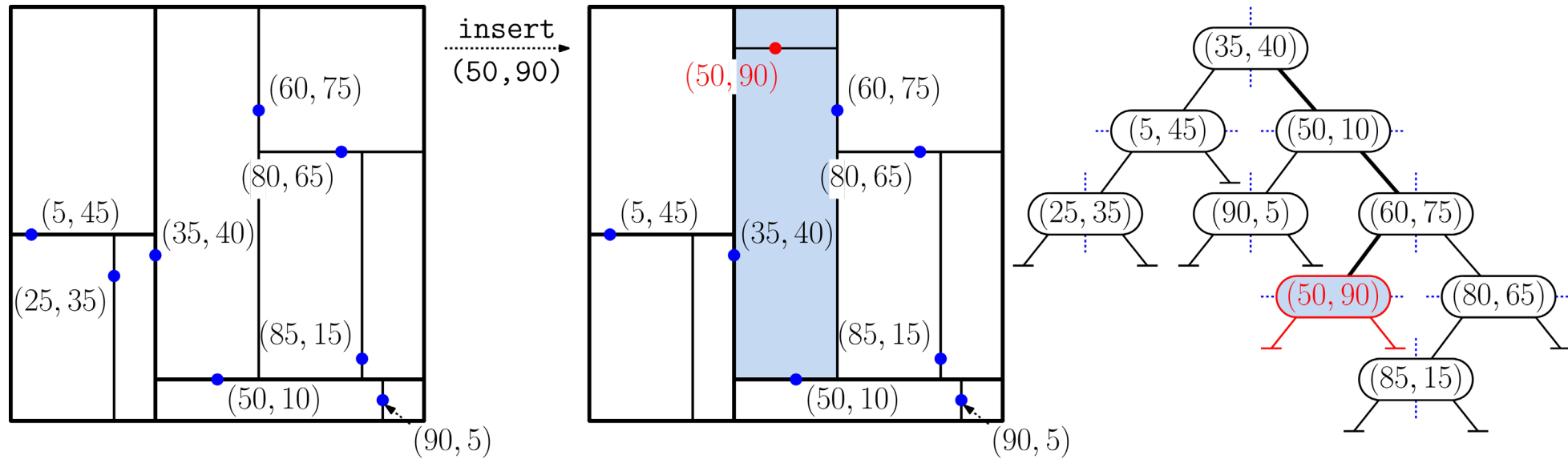
- To insert a point, descend the tree to find the leaf cell containing the point
- Create a new cell and assign its cutting dimension

```
KDNode insert(Point x, KDNode p, int cutDim) {
    if (p == null) { // fell out of tree
        p = new KDNode(x, cutDim); // create new leaf
    } else if (p.point.equals(x)) {
        throw Exception("duplicate"); // duplicate data point!
    } else if (p.inLeftSubtree(x)) { // insert into left
        p.left = insert(x, p.left, (p.cutDim + 1) % x.getDim());
    } else { // insert into right
        p.right = insert(x, p.right, (p.cutDim + 1) % x.getDim());
    }
    return p;
}
```

Point kd-Tree

Point insertion

- $\text{Insert}(50, 90)$:



Point kd-tree

Point deletion

- Deletion is more **complicated** - Need a **s** node
- How to choose the replacement?
 - Can't just take the **inorder successor** (inorder doesn't make geometric sense)
 - Depends on the current **cutting dimension** i
 - Want the point of the right subtree with the **minimum i coordinate** $p[i]$
- **Utility:** Select the point with the smaller i th coordinate

```
Point minAlongDim(Point p1, Point p2, int i) { // return smaller point on dim i
    if (p2 == null || p1[i] <= p2[i])
        return p1;
    else
        return p2;
}
```

Point kd-tree

Utility for finding replacement nodes

- **Utility:** Find the point that minimizes i th coordinate in subtree p
 - if ($p.\text{cutDim} == i$):
 - The subtrees are **ordered** by the i th coordinate
 - Look recursively in p 's **left subtree**, if it exists
 - If not, take **$p.\text{point}$**
 - if ($p.\text{cutDim} != i$):
 - The subtrees are **ordered arbitrarily** with respect to i
 - Compute the **minima** from p 's **left** and **right** subtrees recursively
 - Use `findMin` to select the **overall minimum** from left-min, right-min, and $p.\text{point}$



Point kd-tree

Utility for finding replacement nodes

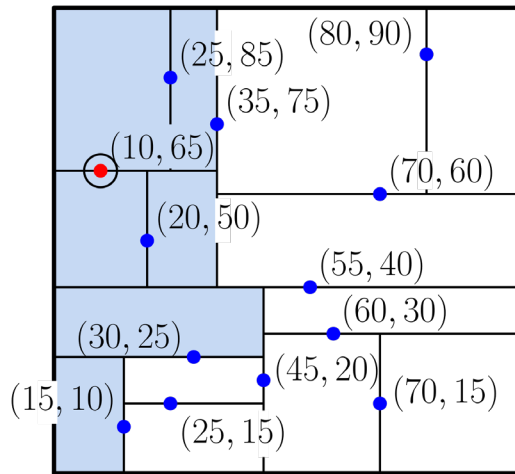
- **Utility:** Find the point that minimizes i th coordinate in subtree p

```
Point findMin(KDNode p, int i) { // get min point along dim i
    if (p == null) { // fell out of tree?
        return null;
    }
    if (p.cutDim == i) { // cutting dimension matches i?
        if (p.left == null) // no left child?
            return p.point; // use this point
        else
            return findMin(p.left, i); // get min from left subtree
    } else { // it may be in either side
        Point q = minAlongDim(p.point, findMin(p.left, i), i);
        return minAlongDim(q, findMin(p.right, i), i);
    }
}
```

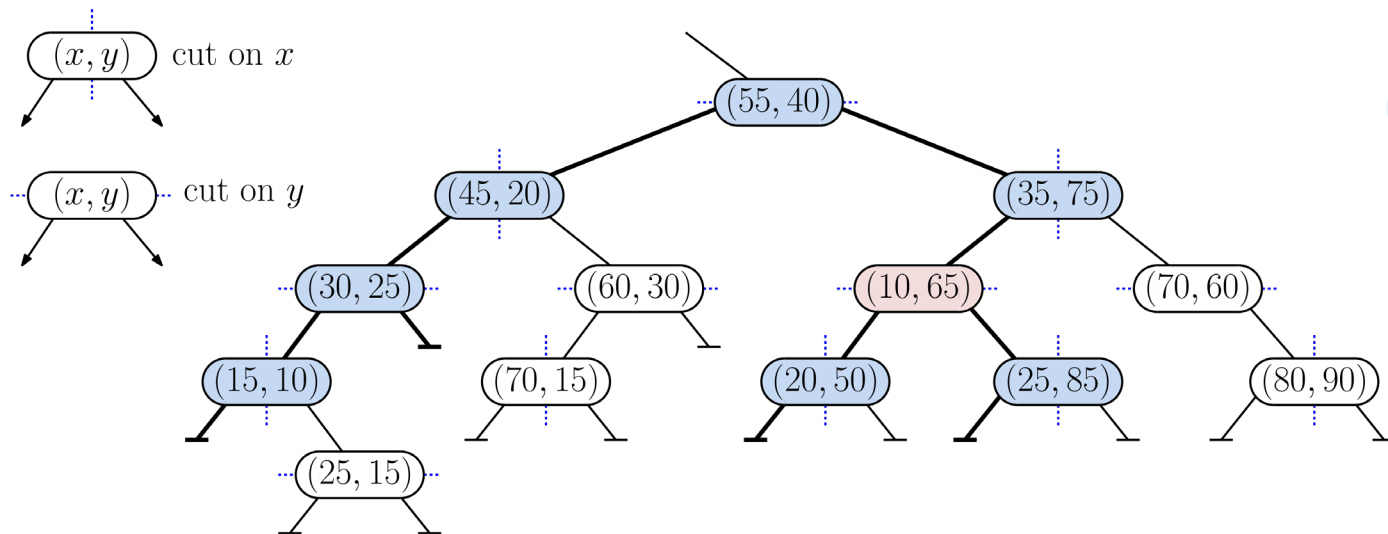

Point kd-tree

Utility for finding replacement nodes

- Example: Find minimum along x
 - If cut dim = x : Try **left** child (or p itself)
 - If cut dim = y : Try **both** children



(a)



(b)

Point kd-tree

Point deletion

- **Overview:** Delete x from subtree p
 - `if (p == null):`
 - Fell out of the tree - **Error: attempt to delete nonexistent point!**
 - `else:`
 - If both of p 's children are null - Simply **unlink** p (return null)
 - If p 's right child exists:
 - Invoke `findMin(p.right, p.cutDim)` to compute replacement node
 - Copy its contents to p
 - Recursively delete the replacement node from $p.right$
 - `Else:`
 - **Tricky!**



Point kd-tree

Point deletion

- **Overview:** Delete x from subtree p , where p has a left child but no right child:
 - In the 1D case, we just **unlinked** p
 - But this has the effect of promoting p 's child **up a level**
 - The cutting dimensions **no longer cycle** from parent to child. (Do we care? Suppose we do)
 - How about picking the **maximum point in p 's left subtree?**
 - Our tie-breaking rule assumed that points in the left subtree have coordinates **strictly smaller** than the splitter
 - This will cause problems if there are **duplicate coordinates** in p 's left subtree
 - **Final answer (very sneaky!)**
 - Compute the **minimum** from p 's **left subtree** as replacement (But it's on the **wrong side!**)
 - Make the left subtree the **new right subtree**. (Amazingly, this works!)

Point kd-tree

Point deletion

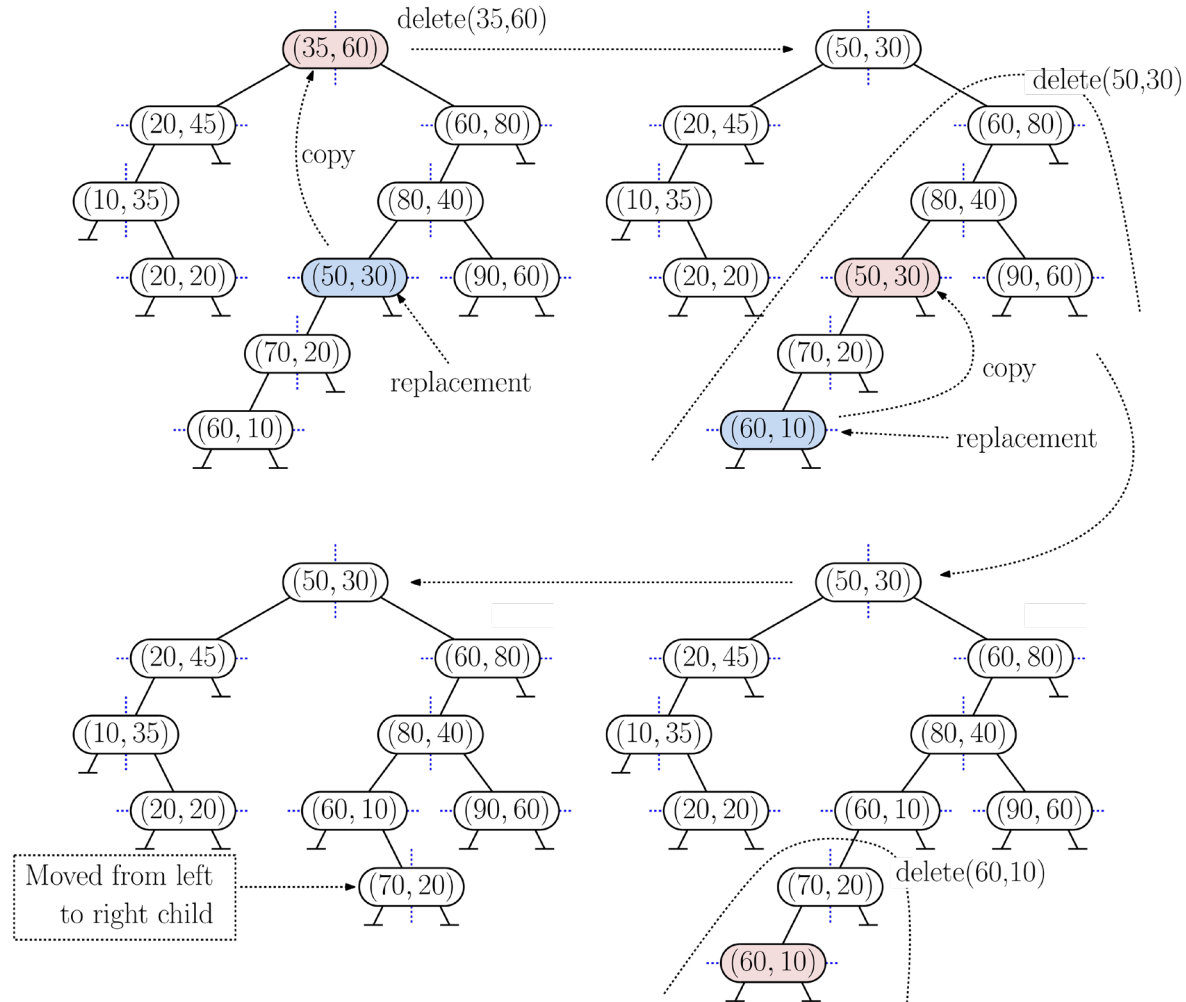
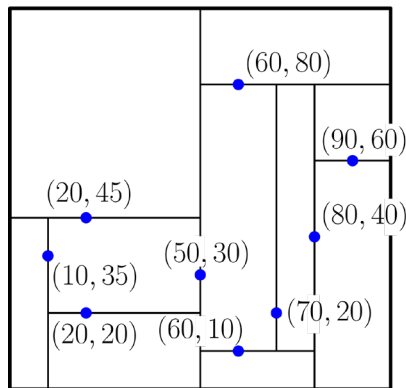
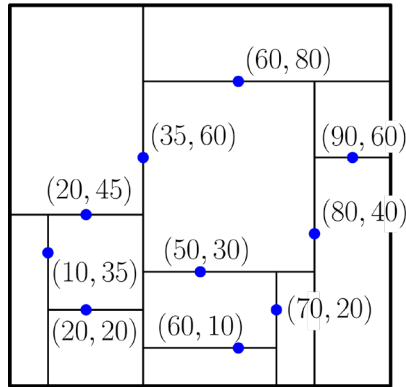
```
KDNode delete(Point x, KDNode p) {
    if (p == null) {
        throw Exception("point does not exist");
    } else if (p.point.equals(x)) {
        if (p.right != null) {
            p.point = findMin(p.right, p.cutDim);
            p.right = delete(p.point, p.right);
        } else if (p.left != null) {
            p.point = findMin(p.left, p.cutDim);
            p.right = delete(p.point, p.left);
            p.left = null;
        } else {
            p = null;
        }
    } else if (p.inLeftSubtree(x)) {
        p.left = delete(x, p.left);
    } else {
        p.right = delete(x, p.right);
    }
    return p;
}
```

// fell out of tree?
// found it
// take replacement from right
// take replacement from left
// move left subtree to right!
// left subtree is now empty
// deleted point in leaf
// remove this leaf

// delete from left subtree
// delete from right subtree

Point kd-tree

Point deletion - Example



Point kd-tree

Analysis

- Analogous to unbalanced binary search trees
 - Storage space linear in n , the number of points
 - All dictionary operations (insert, delete, find) take time proportional to tree's height
 - **Theorem:** If n points are inserted in **random order**, the expected height of the kd-tree is $O(\log n)$
 - I'd **conjecture** that deletion suffers from the same systematic bias, which would lead to heights of \sqrt{n} after long sequences of random insertions and deletions, but I know of no results from the literature

Summary

- Geometric Search
 - Point representation
- Point Quadtree
- Point kd-Trees
 - Node representation (point and cutting dimension)
 - Insertion
 - Deletion
 - FindMin utility
 - Sneaky trick to compute replacement nodes
 - Analysis: $O(\log n)$ time assuming random insertions

