

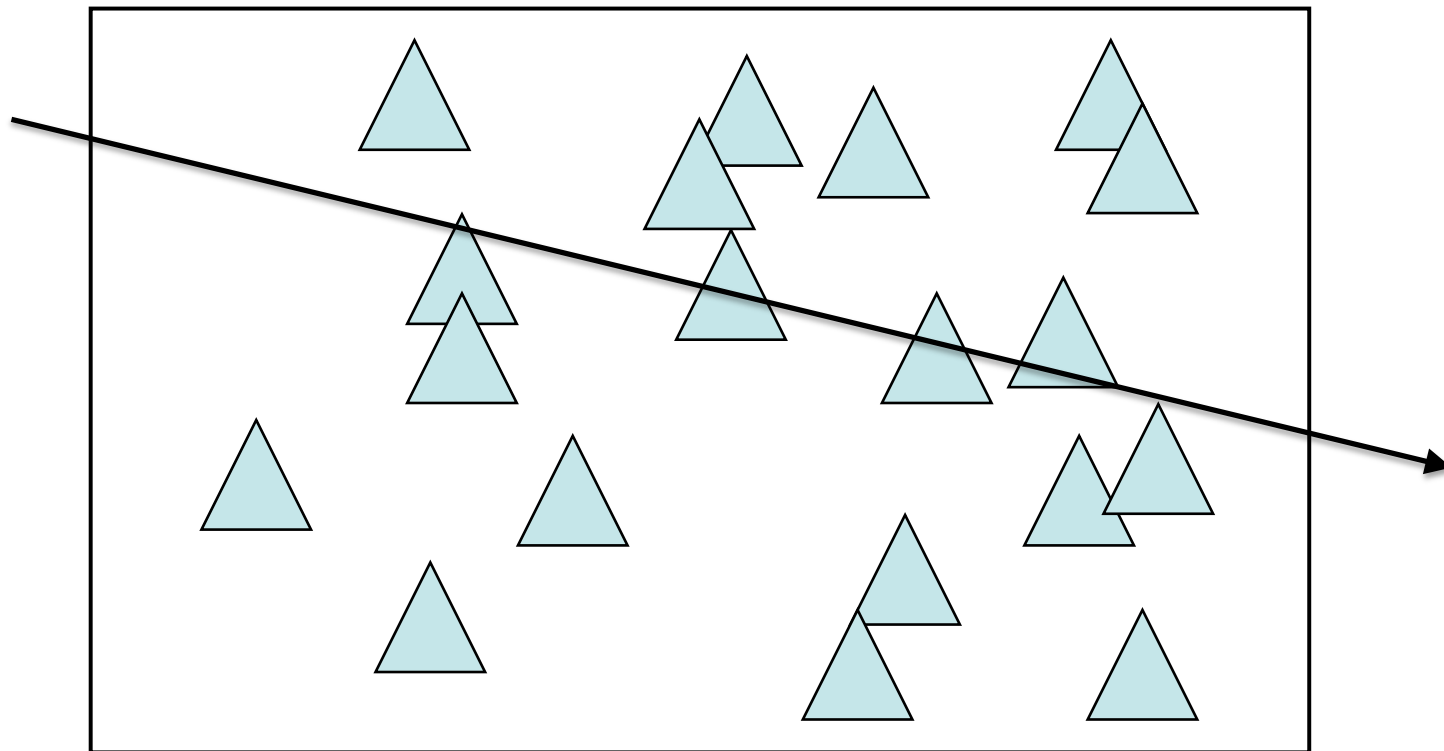


Acceleration Structure for Ray Tracing

K-D Tree Traversal

Motivation

- **Locate the primitives that intersect with a ray, FAST!** (Avoid brute-force approach)

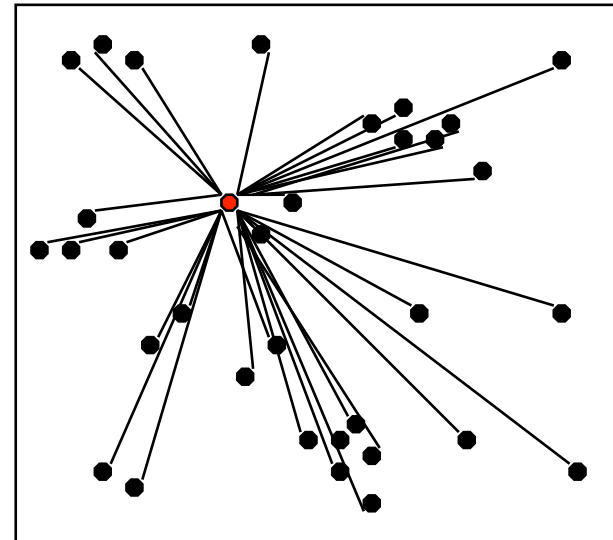


Background

- **Similarity search or nearest neighbor search**
- **Applications:**
 - Statistics
 - Content-based retrieval
 - Data-mining and Pattern recognition
 - Geographic information system (GIS)
 - where is the closest post office
 - Graphics

Naïve Approach

- Given a query point X.
- Scan through each point Y
- Takes $O(N)$ time for each query!



33 Distance Computations

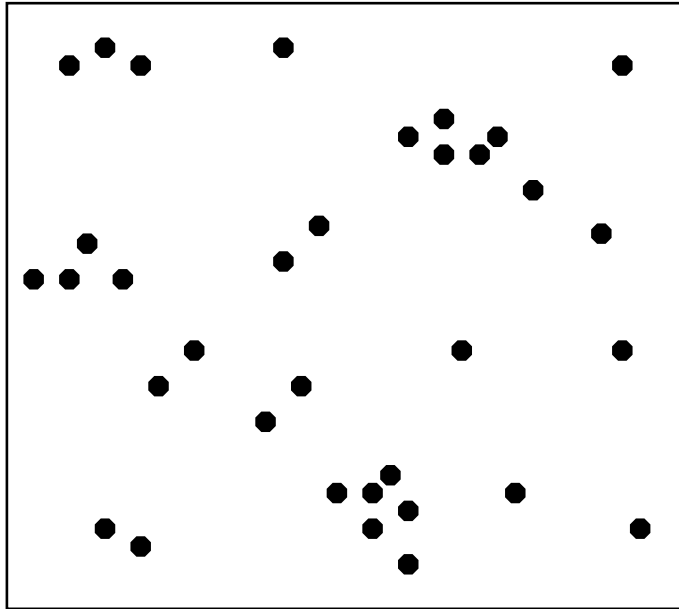
Acceleration: Spatial Index Structure

- **We can speed up the search for the nearest neighbor:**
 - Examine nearby points first.
 - Ignore any points that are further than the nearest point found so far.

K-D Tree

- **k-d tree is a multidimensional binary search tree.**
- **Recursively partitions points into axis aligned boxes. One axis at a time.**

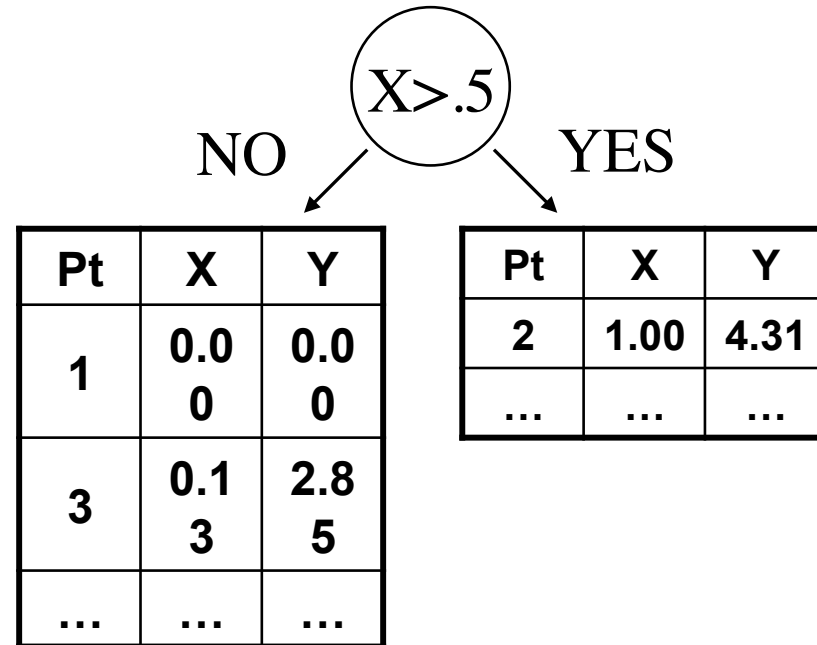
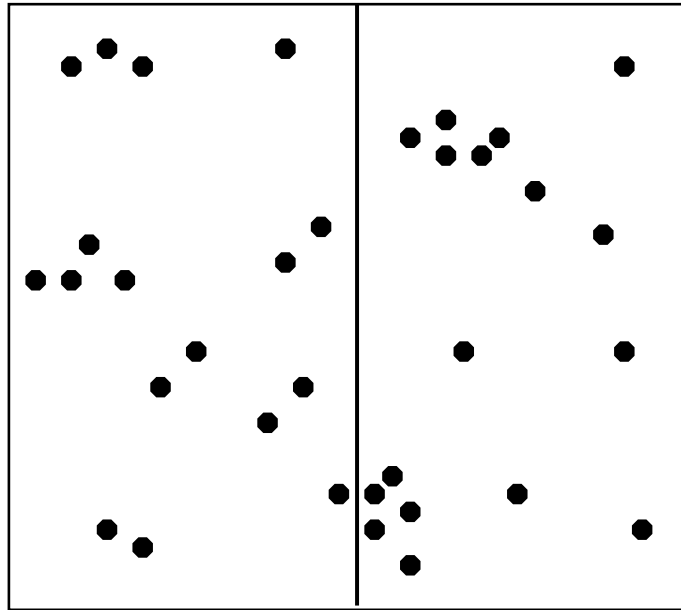
KD-Tree Construction



Pt	X	Y
1	0.00	0.00
2	1.00	4.31
3	0.13	2.85
...

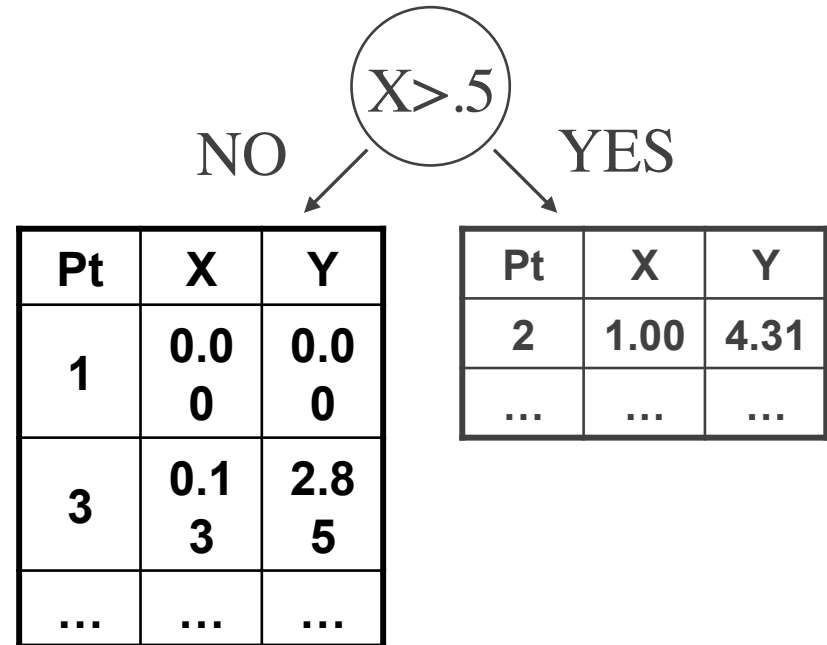
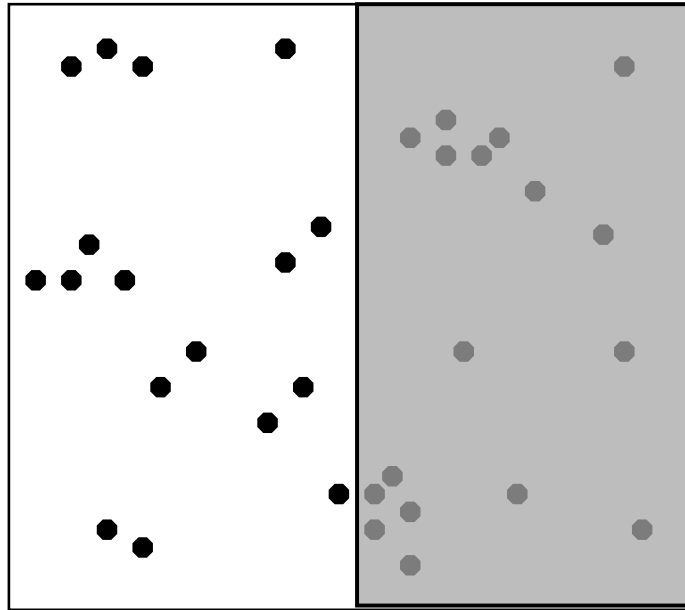
We start with a list of n-dimensional points.

KD-Tree Construction



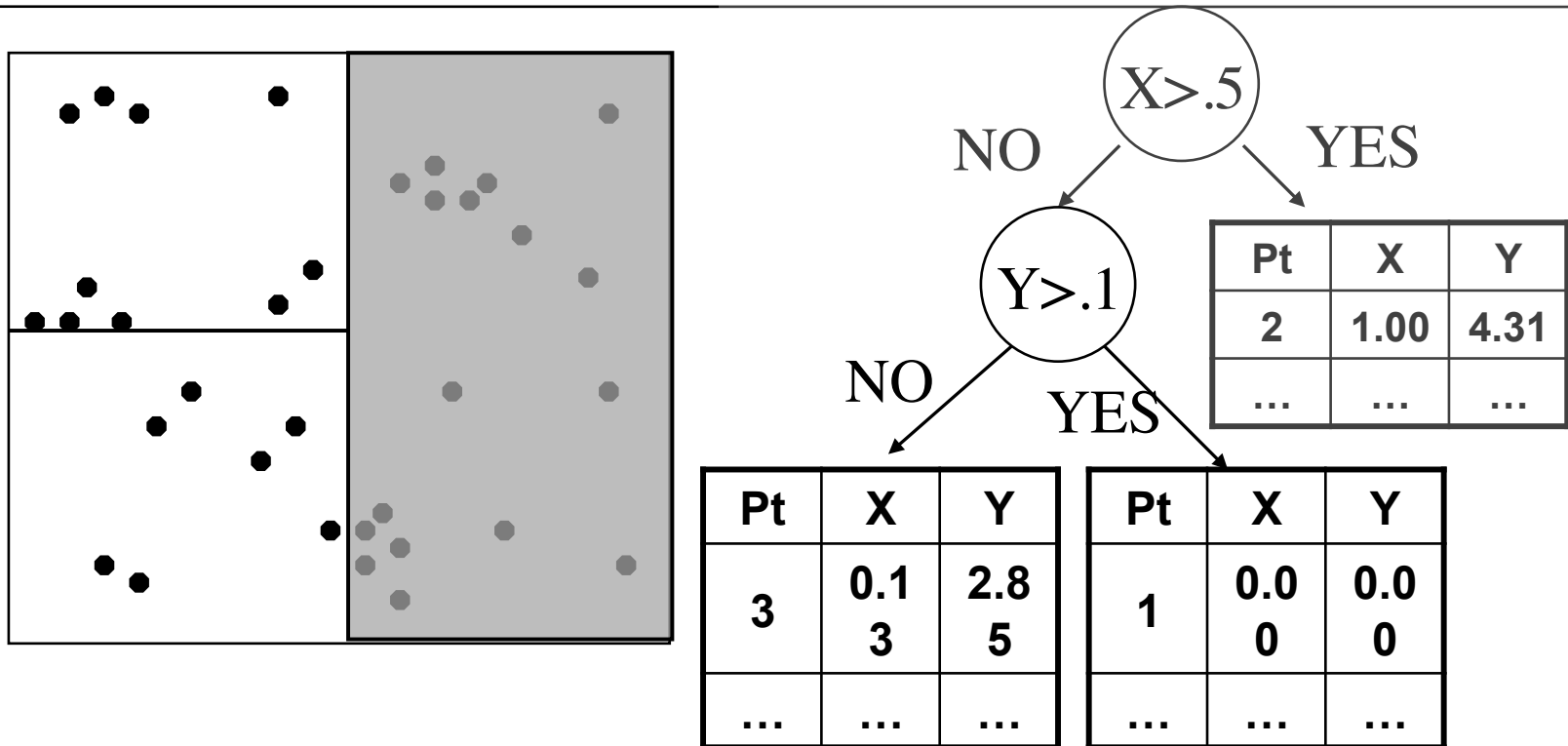
We can split the points into 2 groups by choosing a dimension X and value V and separating the points into $X > V$ and $X \leq V$.

KD-Tree Construction



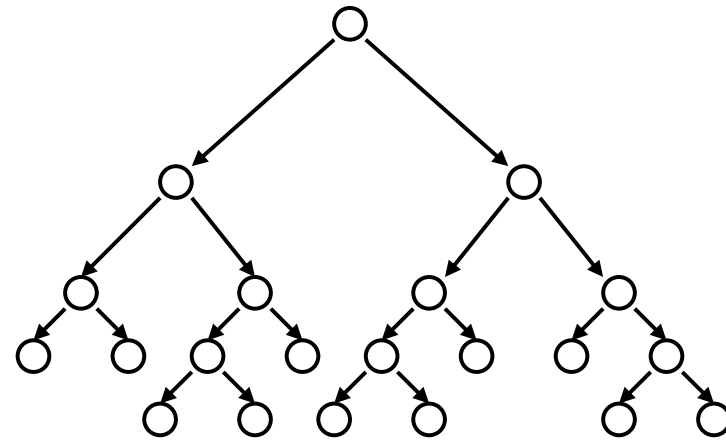
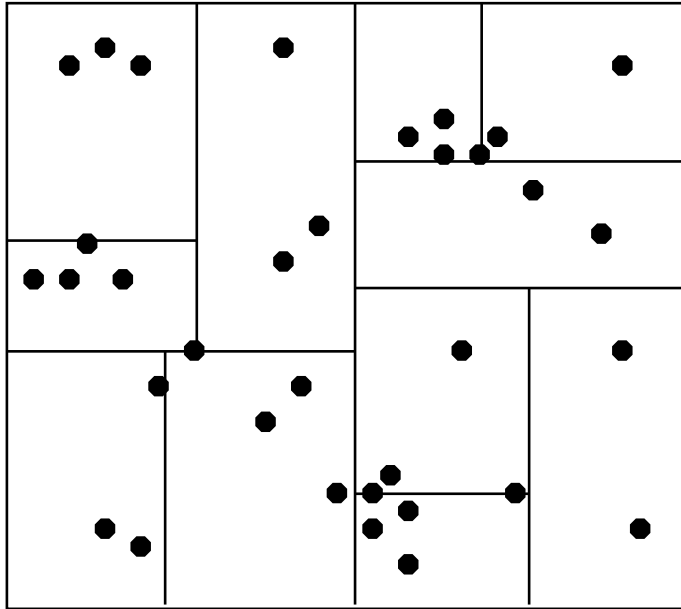
We can then consider each group separately and possibly split again (along same/different dimension).

KD-Tree Construction



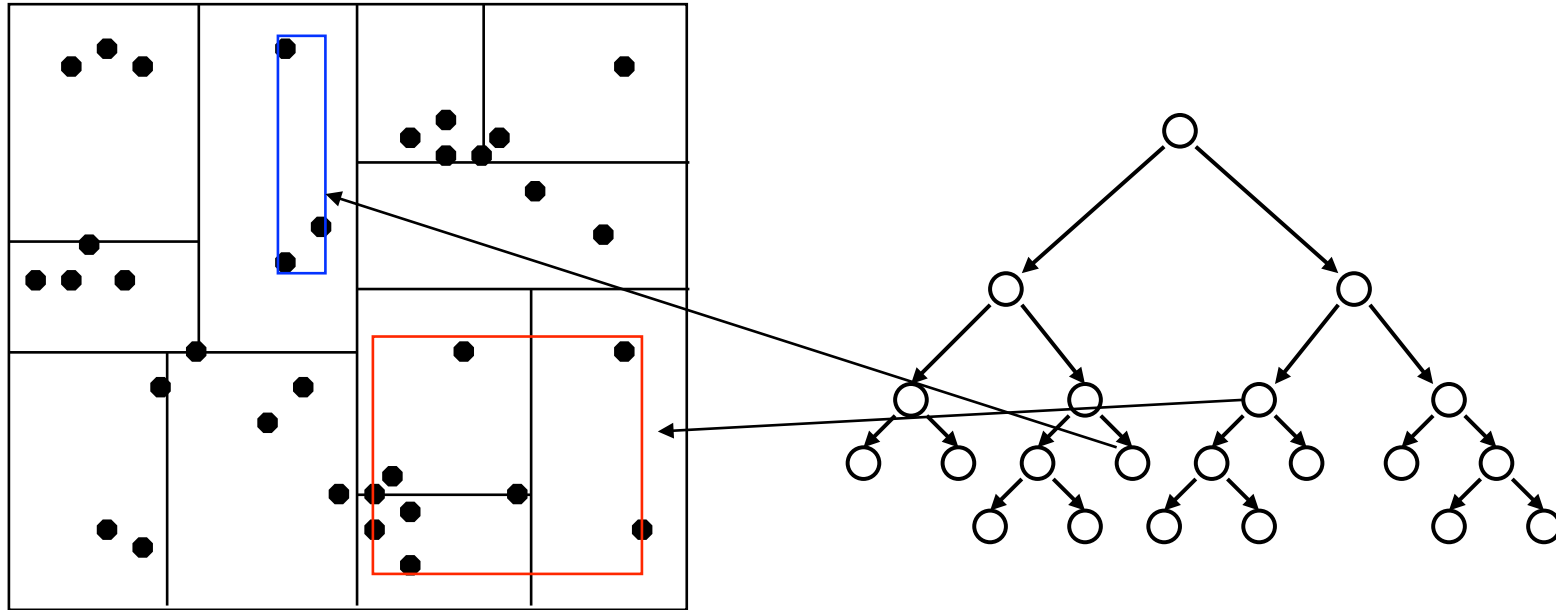
We can then consider each group separately and possibly split again (along same/different dimension).

KD-Tree Construction



We can keep splitting the points in each set to create a tree structure. Each node with no children (leaf node) contains a list of points.

KD-Tree Construction

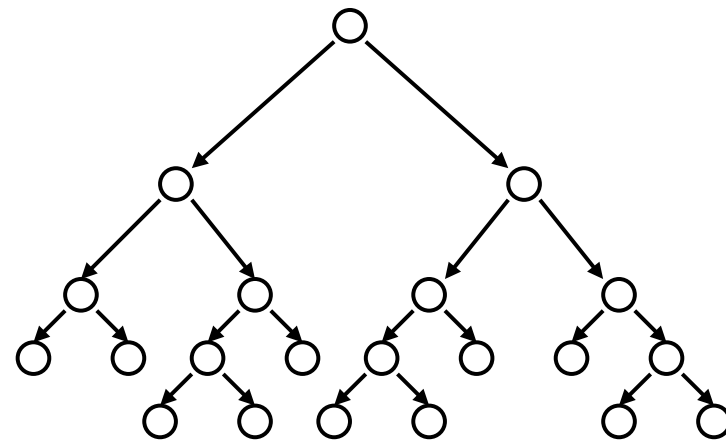
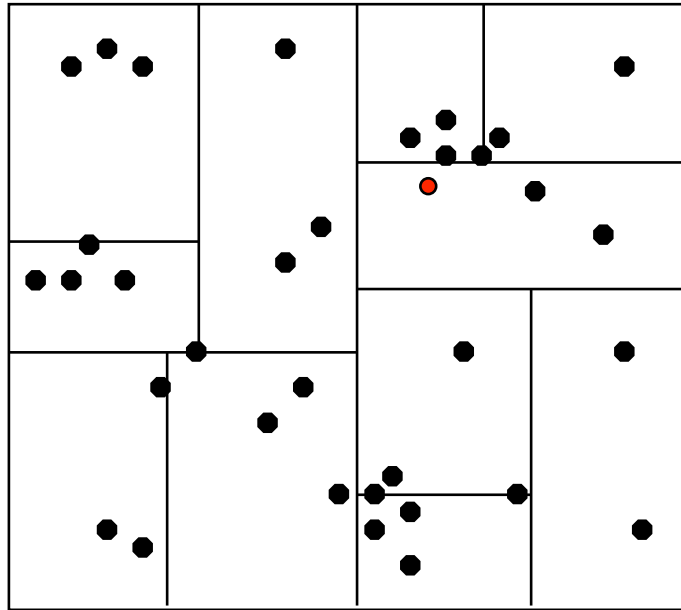


We will keep around one additional piece of information at each node. The (tight) bounds of the points at or below this node.

KD-Tree Construction

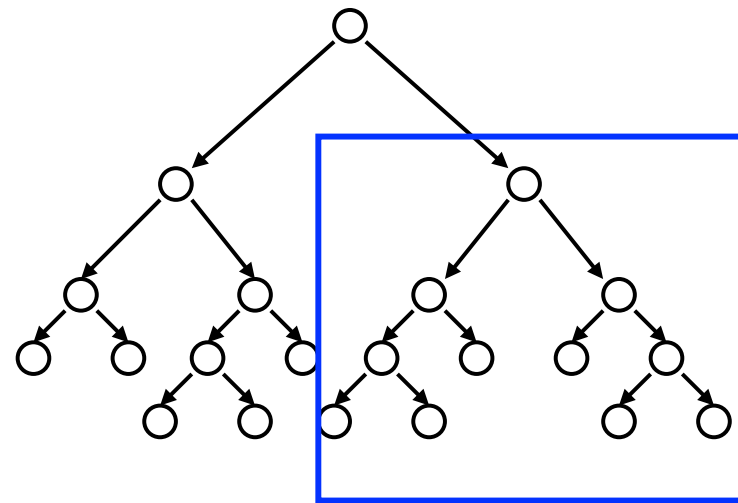
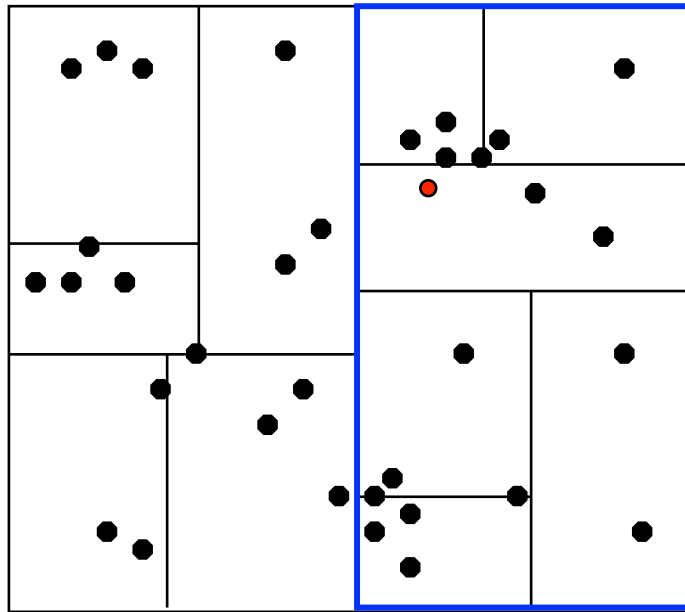
- Use heuristics to make splitting decisions:
- Which dimension do we split along?
Widest
- Which value do we split at? **Median of value of that split dimension for the points.**
- When do we stop? **When there are fewer than m points left OR the box has hit some minimum width.**

Nearest Neighbor with KD Trees



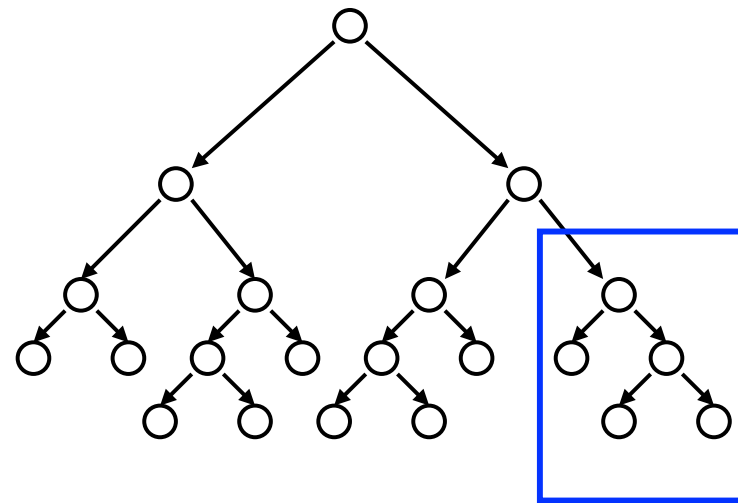
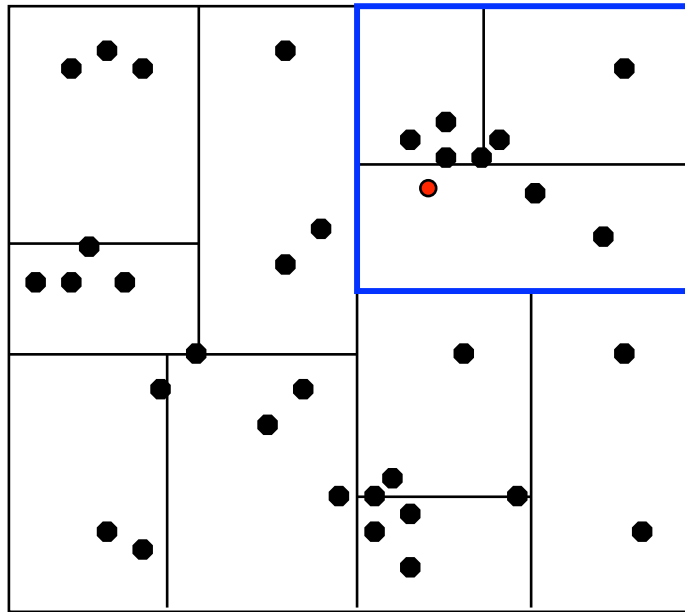
We traverse the tree looking for the nearest neighbor of the query point.

Nearest Neighbor with KD Trees



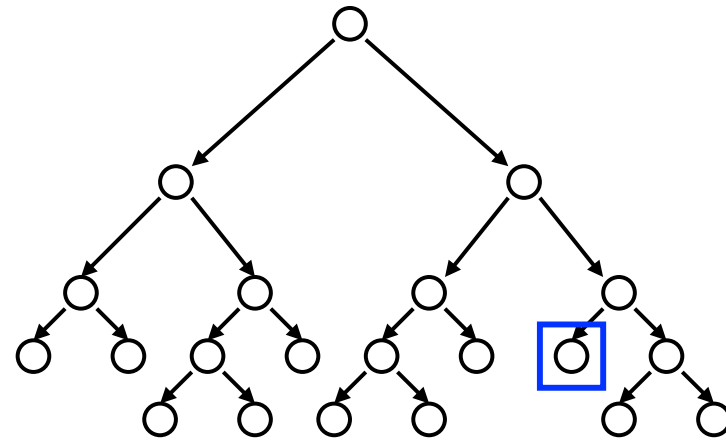
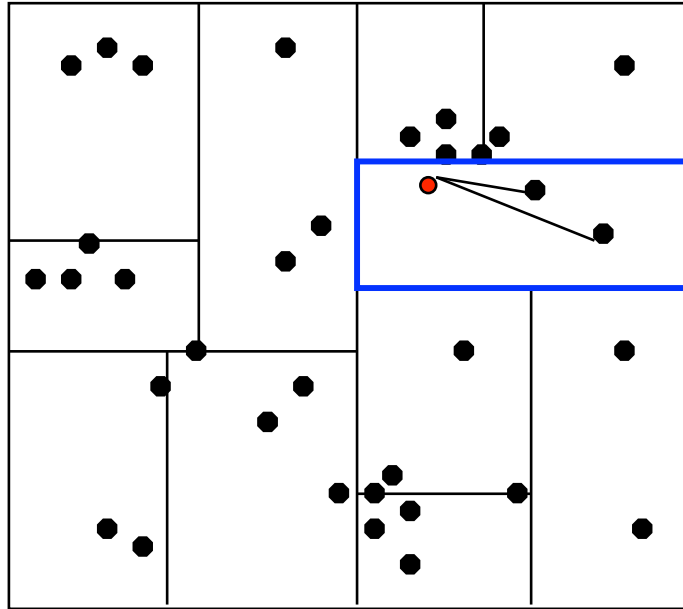
Examine nearby points first: Explore the branch of the tree that is closest to the query point first.

Nearest Neighbor with KD Trees



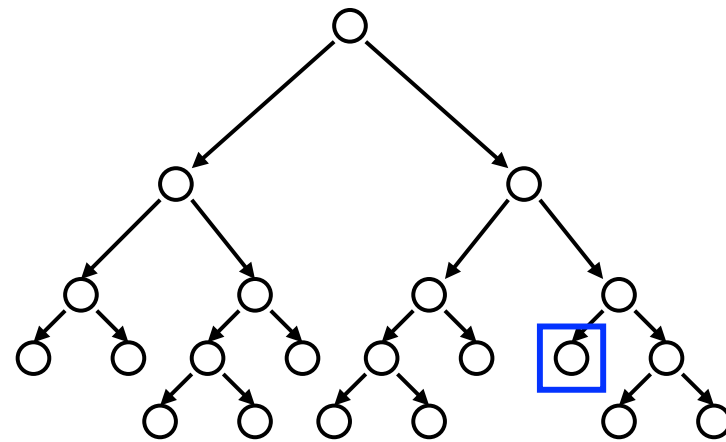
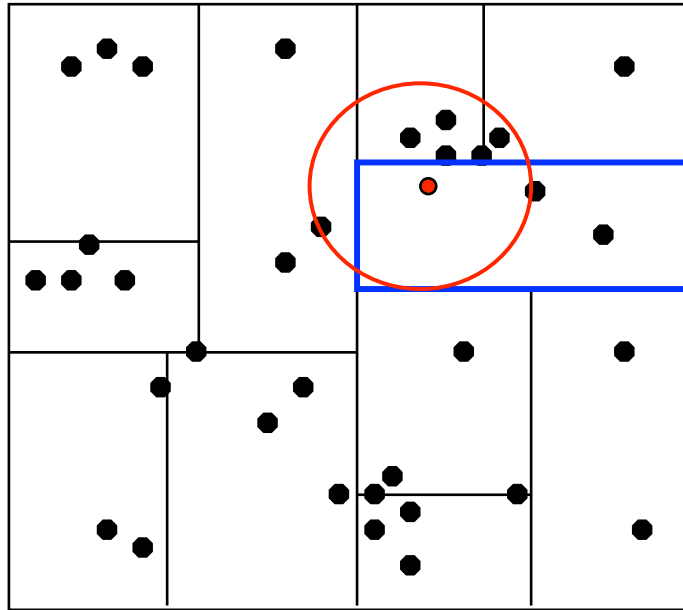
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Nearest Neighbor with KD Trees



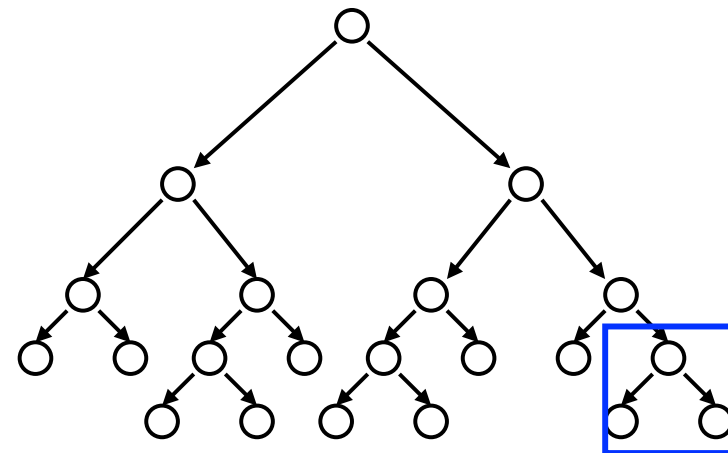
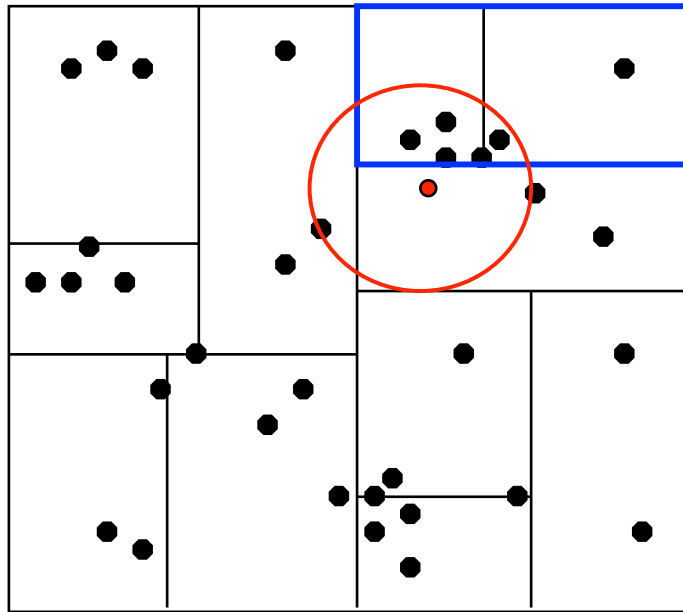
When we reach a leaf node: compute the distance to each point in the node.

Nearest Neighbor with KD Trees



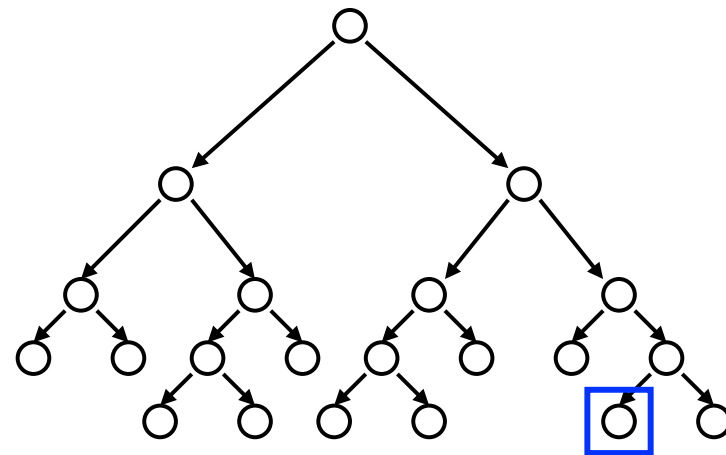
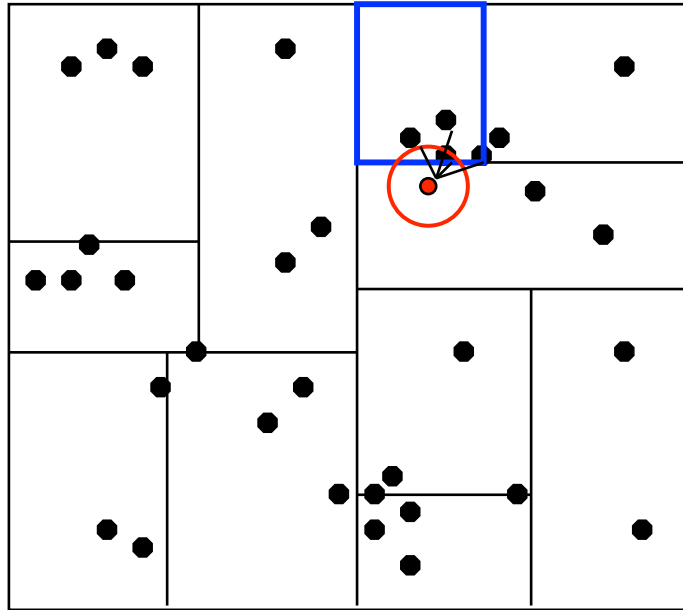
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Nearest Neighbor with KD Trees



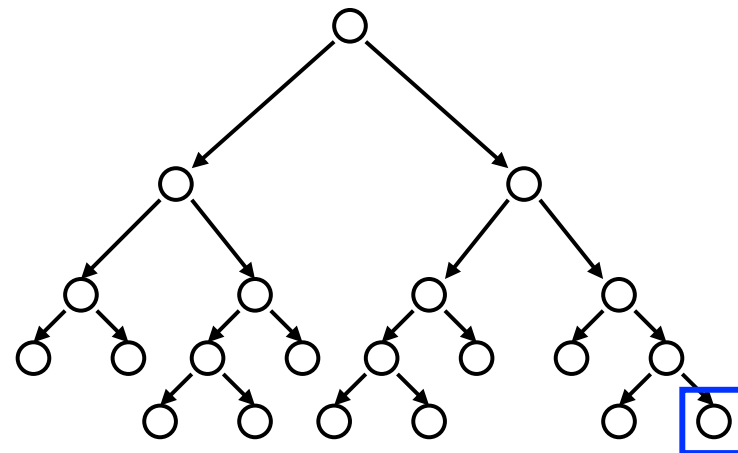
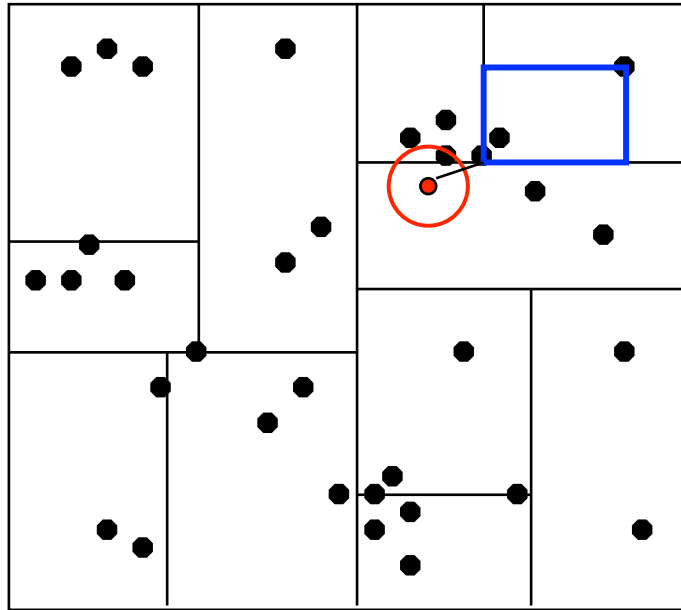
Then we can backtrack and try the other branch at each node visited.

Nearest Neighbor with KD Trees



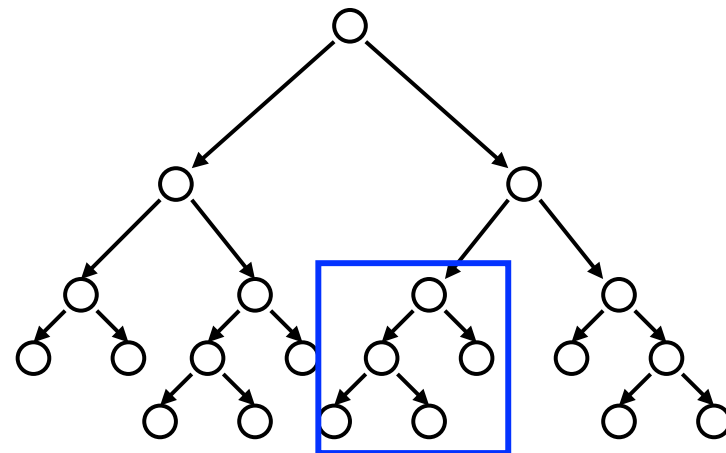
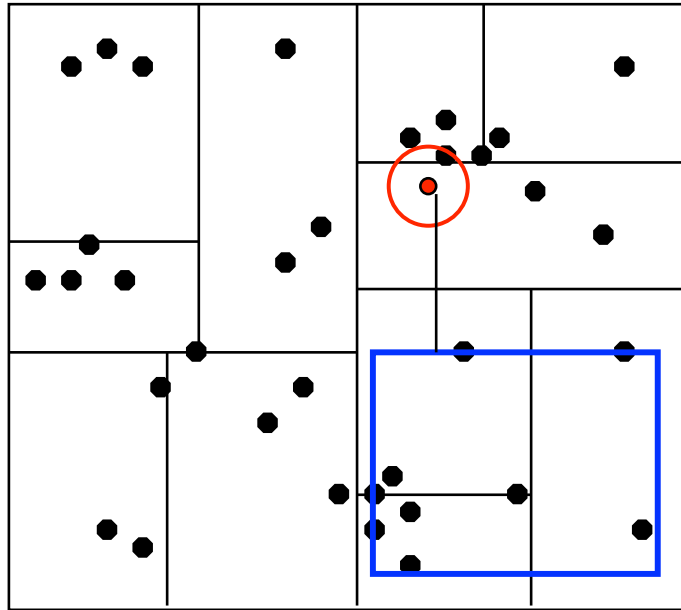
Each time a new closest node is found, we can update the distance bounds.

Nearest Neighbor with KD Trees



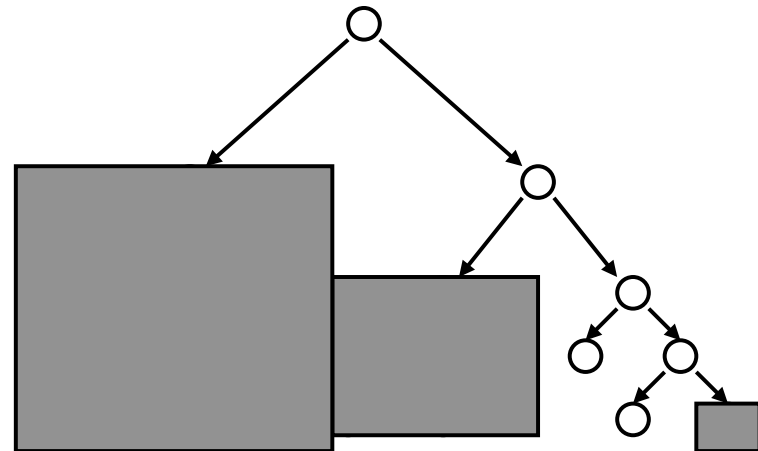
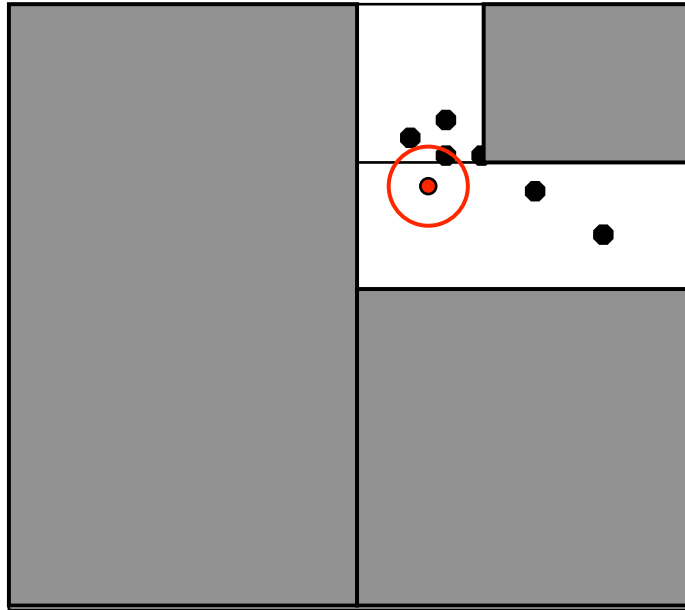
Using the distance bounds and the bounds of the data below each node, we can prune parts of the tree that could NOT include the nearest neighbor.

Nearest Neighbor with KD Trees



Using the distance bounds and the bounds of the data below each node, we can prune parts of the tree that could NOT include the nearest neighbor.

Nearest Neighbor with KD Trees

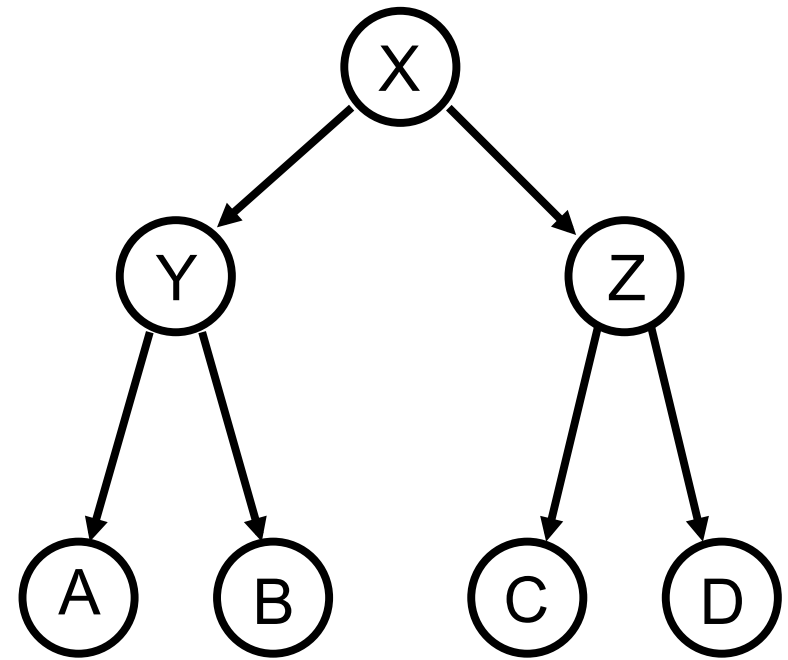
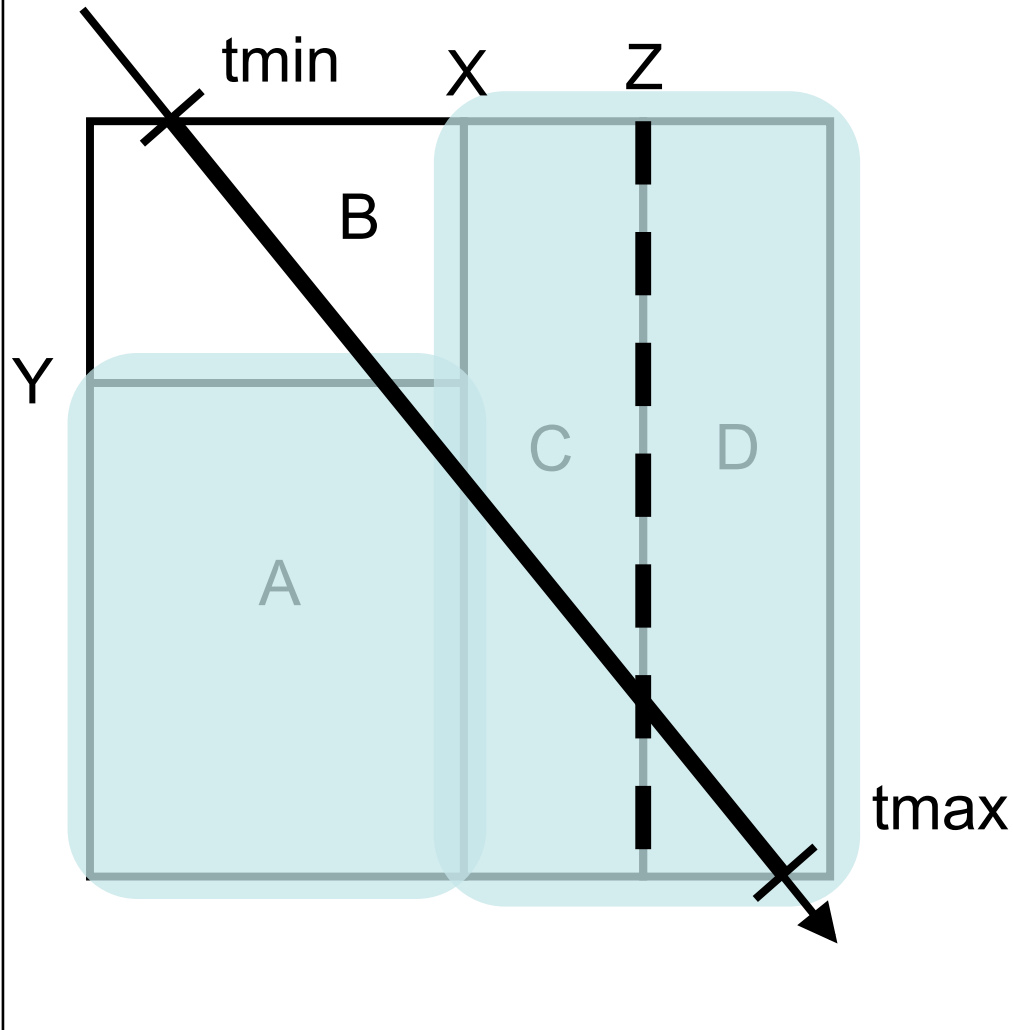


Using the distance bounds and the bounds of the data below each node, we can prune parts of the tree that could NOT include the nearest neighbor.

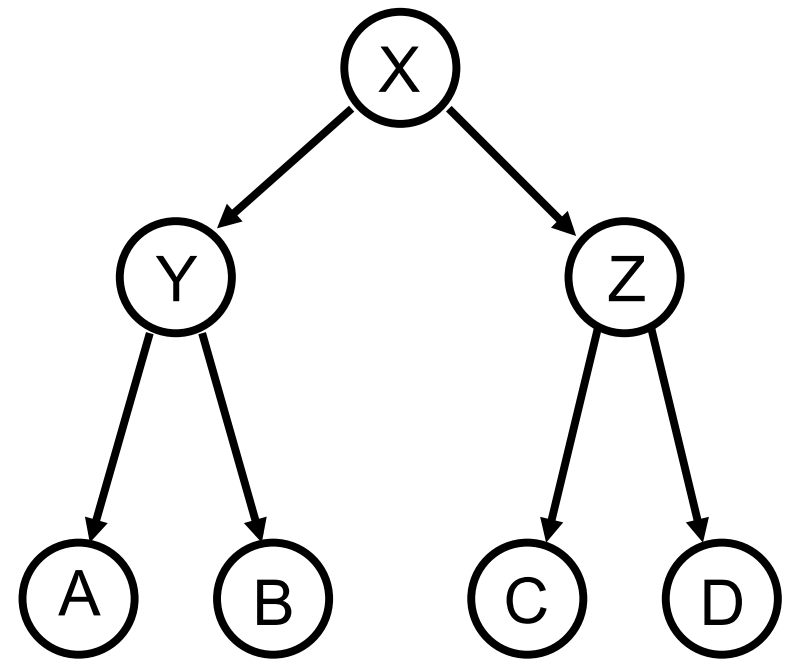
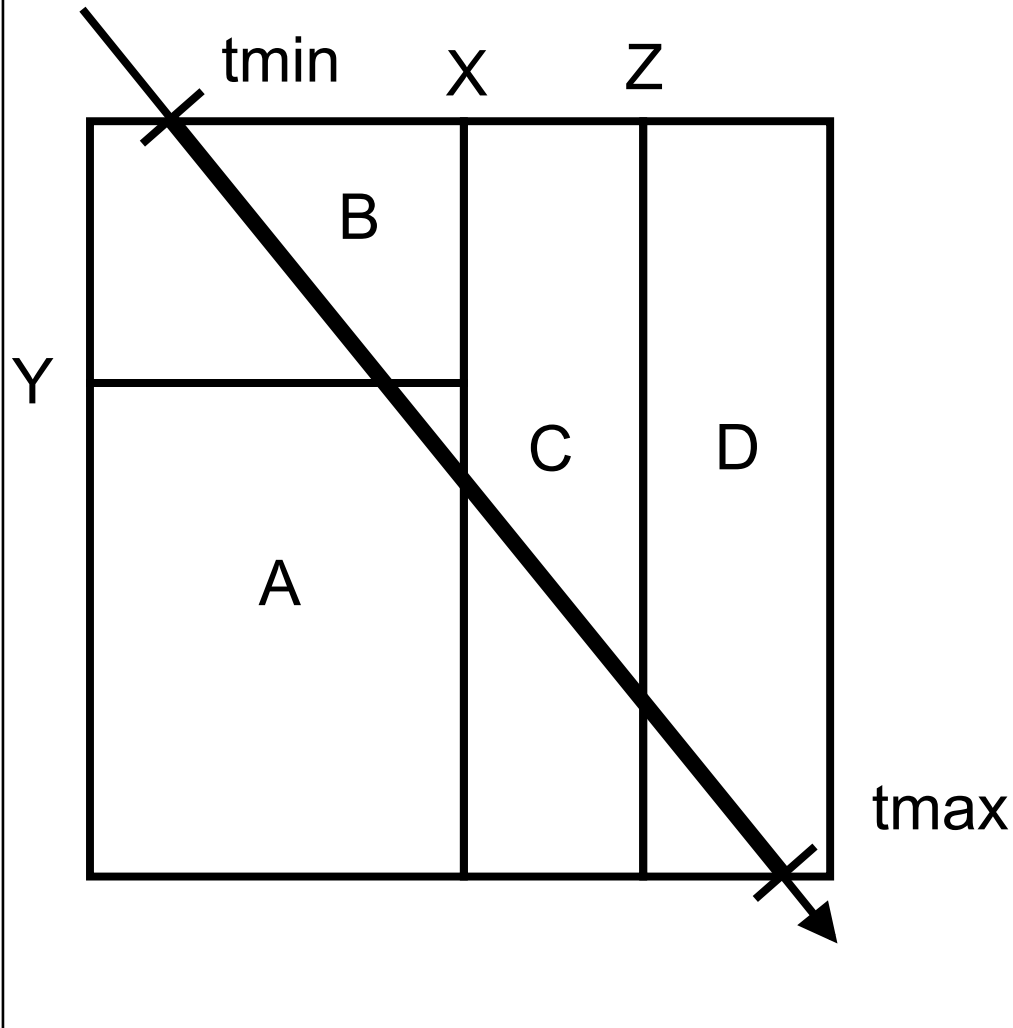
KD-Tree in Ray Tracing

- **Query: given a ray $r(t)$, find the primitives that intersected with the ray**

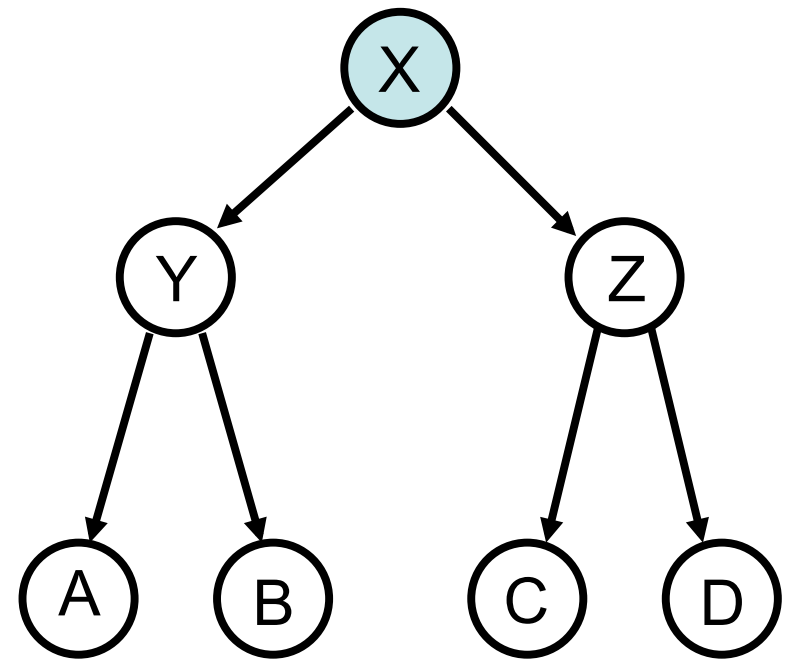
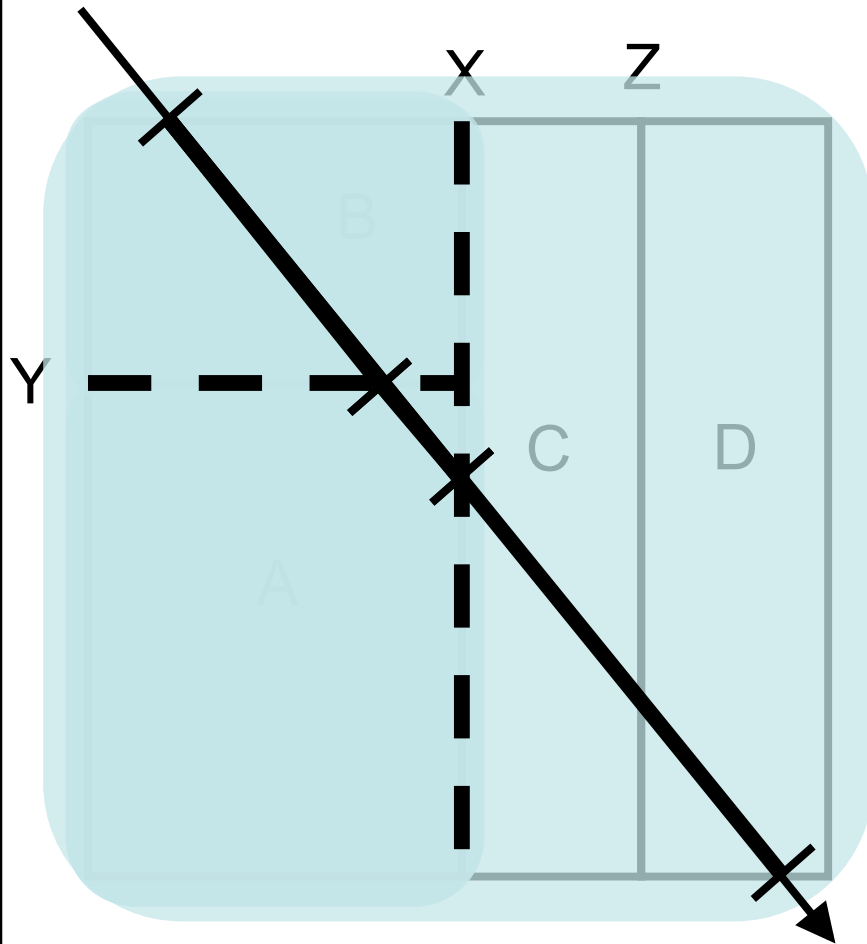
KD-Tree in Ray Tracing



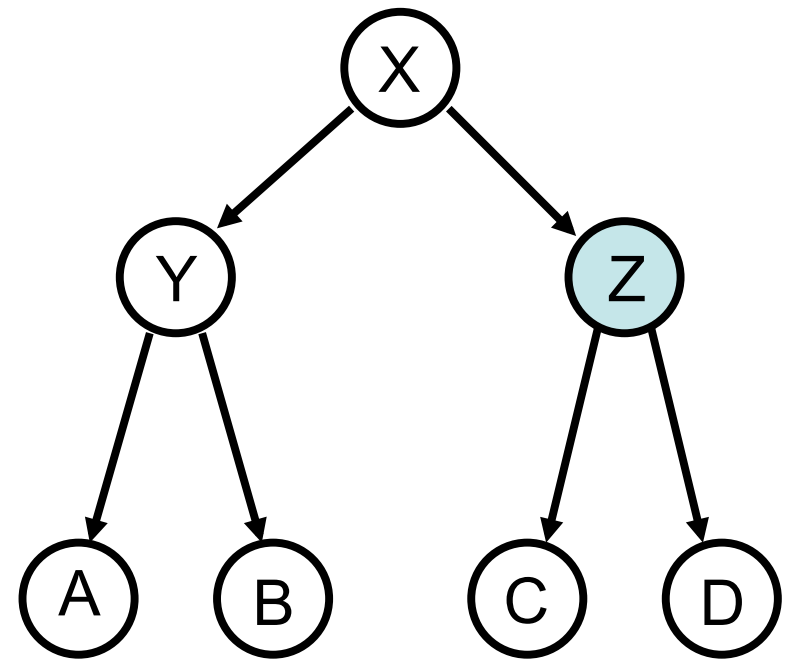
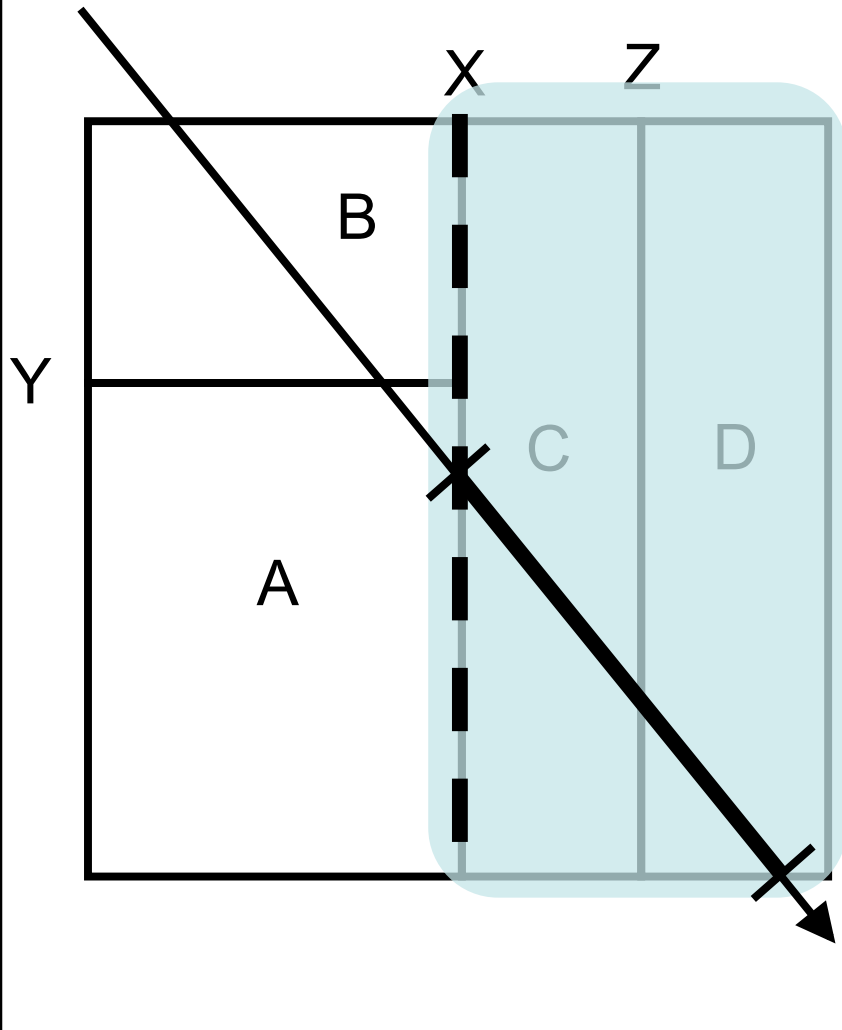
KD-Tree in Ray Tracing



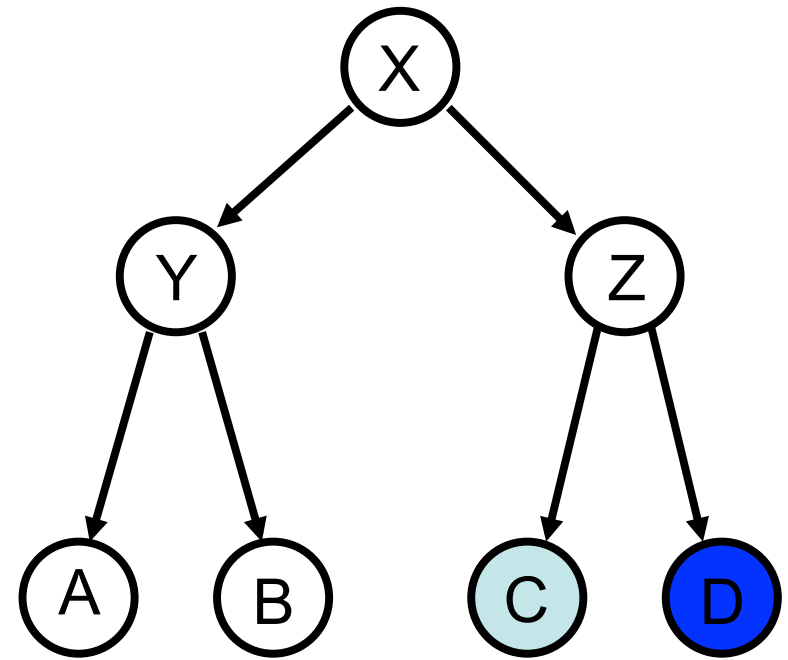
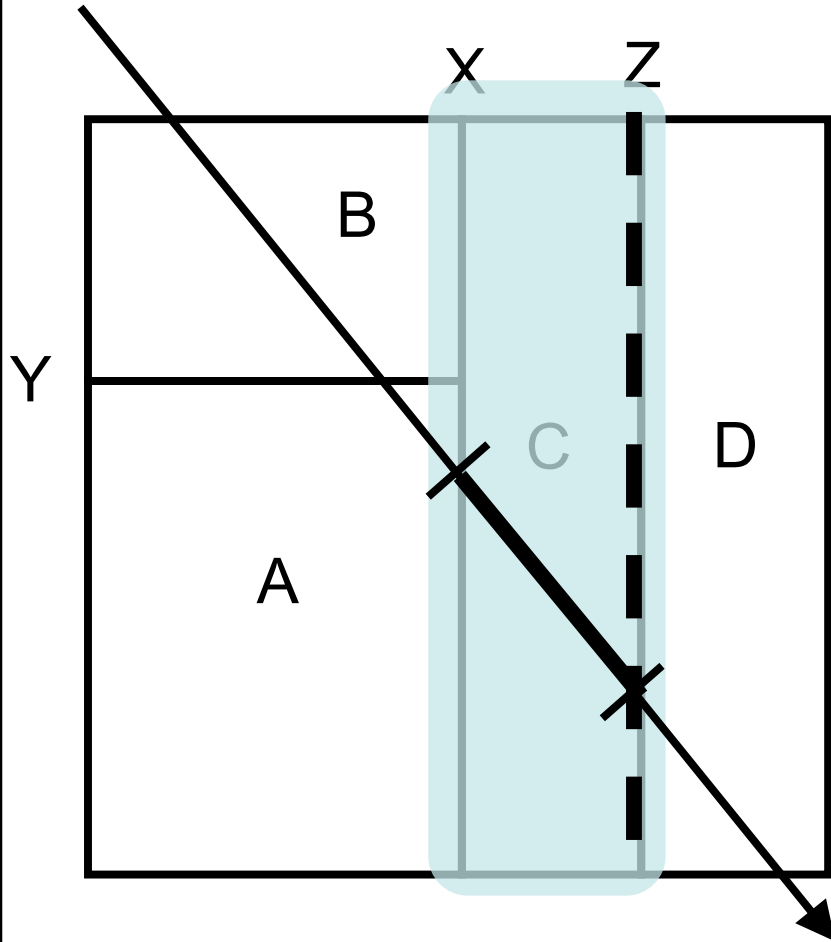
KD-Tree Traversal



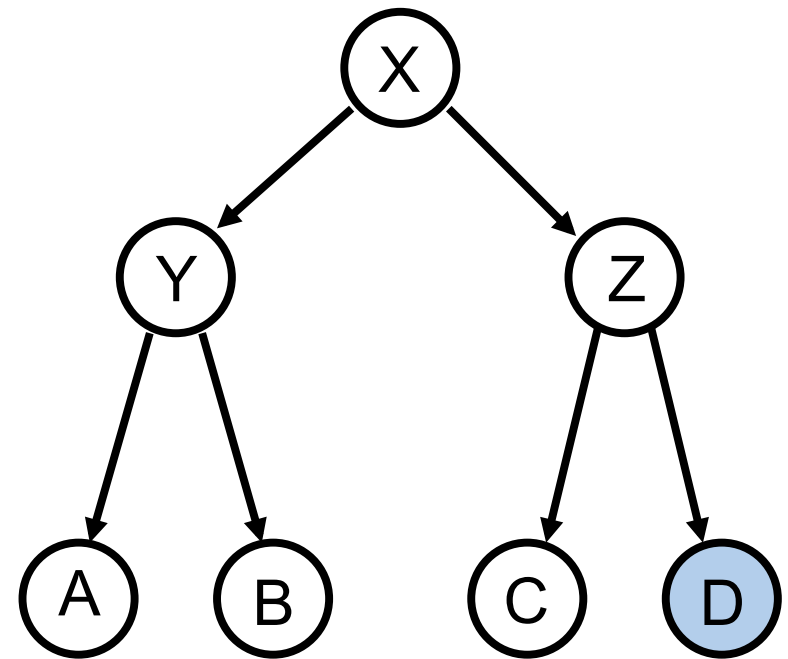
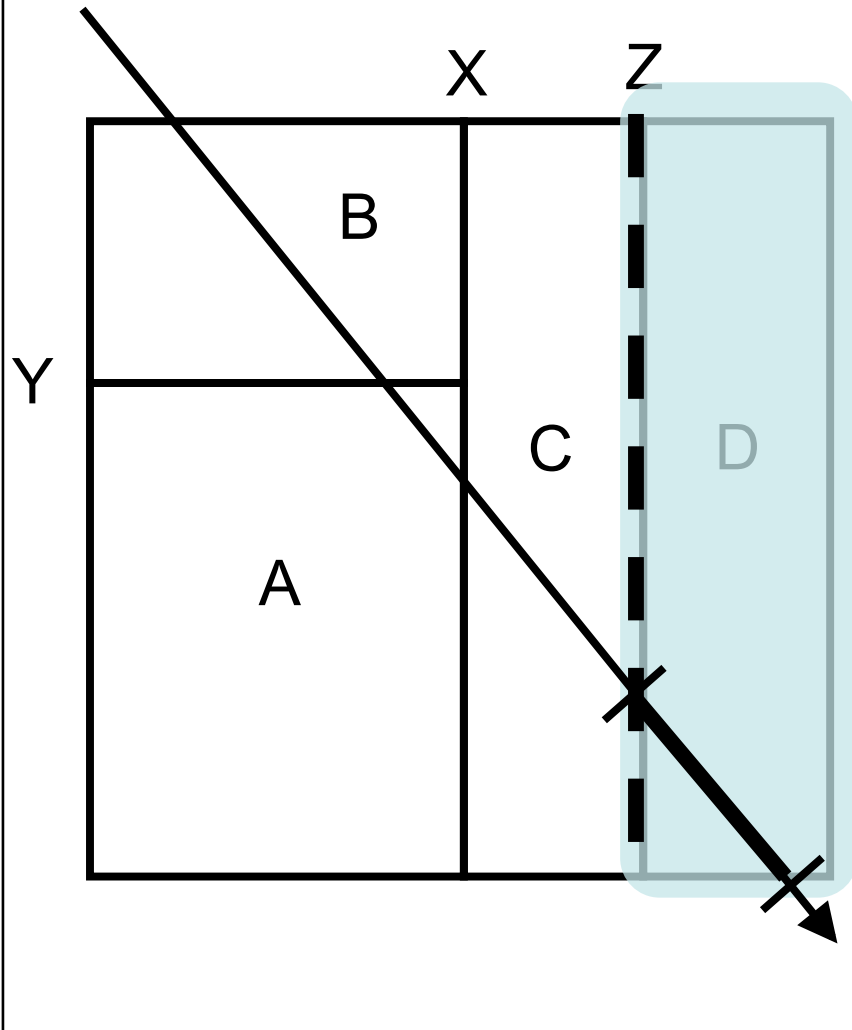
KD-Tree Traversal



KD-Tree Traversal



KD-Tree Traversal



Advantages of kD-Trees

➤ Adaptive

- Can handle the “Teapot in a Stadium”
 - Octree is not.

➤ Compact

- Relatively little memory overhead
- 8 bytes only (function as BSP-tree, not more compact)

➤ Cheap Traversal

- One FP subtract, one FP multiply

Fast Ray Tracing w/ kD-Trees

- **Adaptive**
- **Compact**
- **Cheap traversal**

Building kD-trees

➤ **Given:**

- axis-aligned bounding box (“cell”)
- list of geometric primitives (triangles?) touching cell

➤ **Core operation:**

- pick an axis-aligned plane to split the cell into two parts
- sift geometry into two batches (some redundancy)
- recurse
- termination criteria!

“Intuitive” kD-Tree Building

- **Split Axis**
 - Round-robin; largest extent
- **Split Location**
 - Middle of extent; median of geometry (balanced tree)
- **Termination**
 - Target # of primitives, limited tree depth

“Hack” kD-Tree Building

- **Split Axis**
 - Round-robin; largest extent
- **Split Location**
 - Middle of extent; median of geometry (balanced tree)
- **Termination**
 - Target # of primitives, limited tree depth
- **All of these techniques stink.**

“Hack” kD-Tree Building

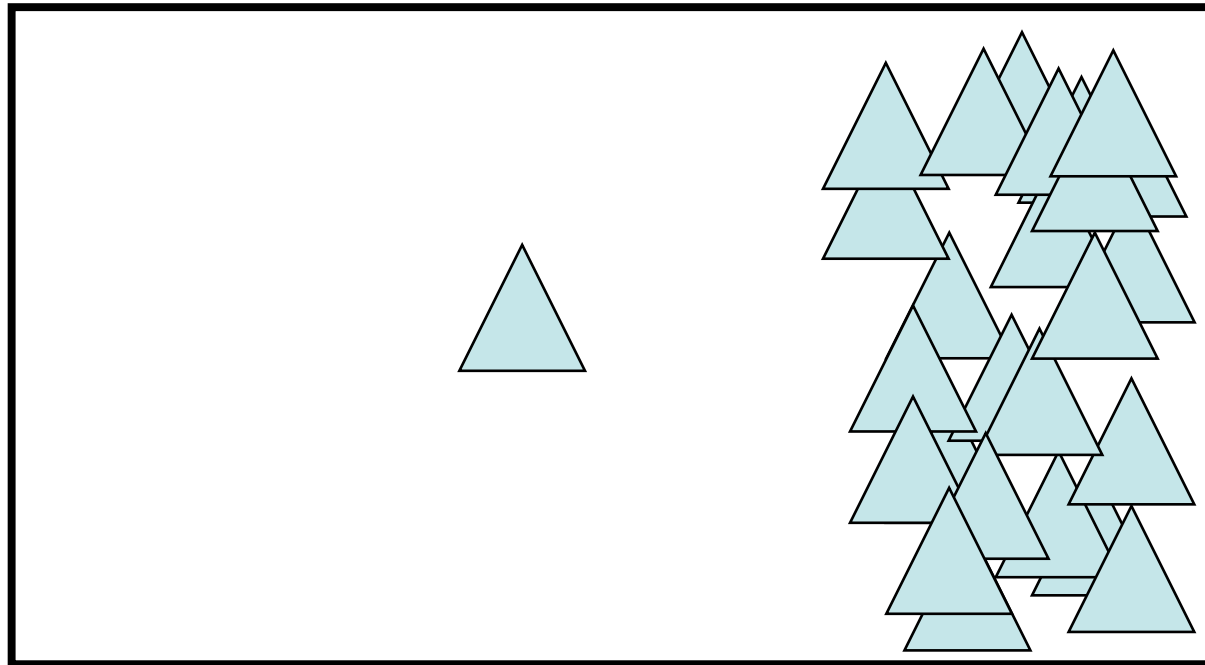
- **Split Axis**
 - Round-robin; largest extent
- **Split Location**
 - Middle of extent; median of geometry (balanced tree)
- **Termination**
 - Target # of primitives, limited tree depth
- **All of these techniques stink. Don't use them.**

Building good kD-trees

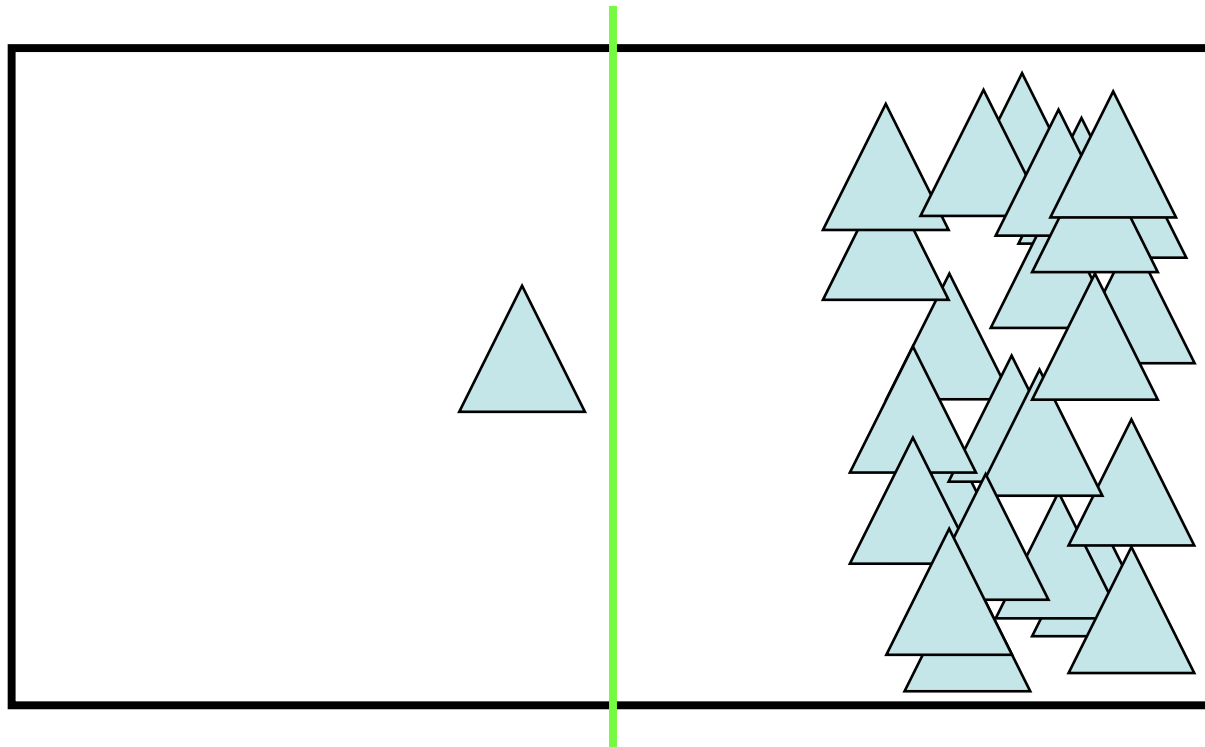
- **What split do we really want?**
 - Clever Idea: The one that makes ray tracing cheap
 - Write down an expression of cost and minimize it
 - *Cost Optimization*
- **What is the cost of tracing a ray through a cell?**

$$\text{Cost}(\text{cell}) = C_{\text{trav}} + \text{Prob}(\text{hit L}) * \text{Cost}(\text{L}) + \text{Prob}(\text{hit R}) * \text{Cost}(\text{R})$$

Splitting with Cost in Mind

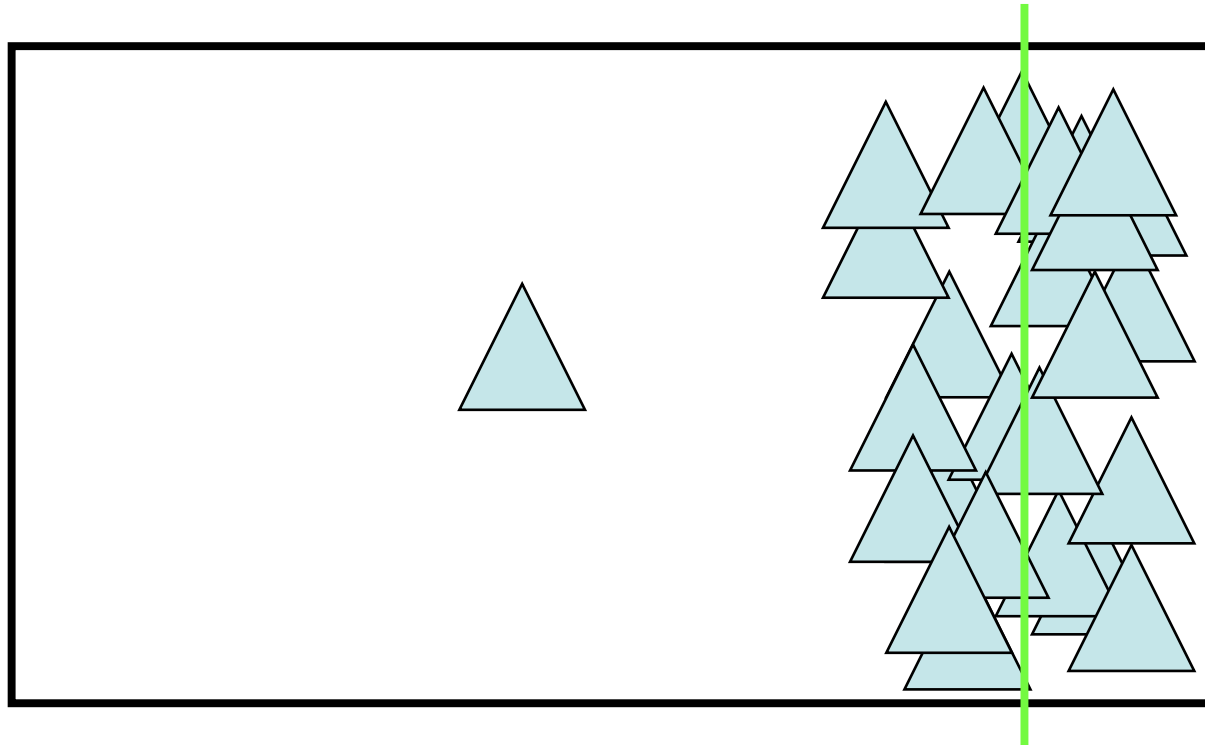


Split in the middle



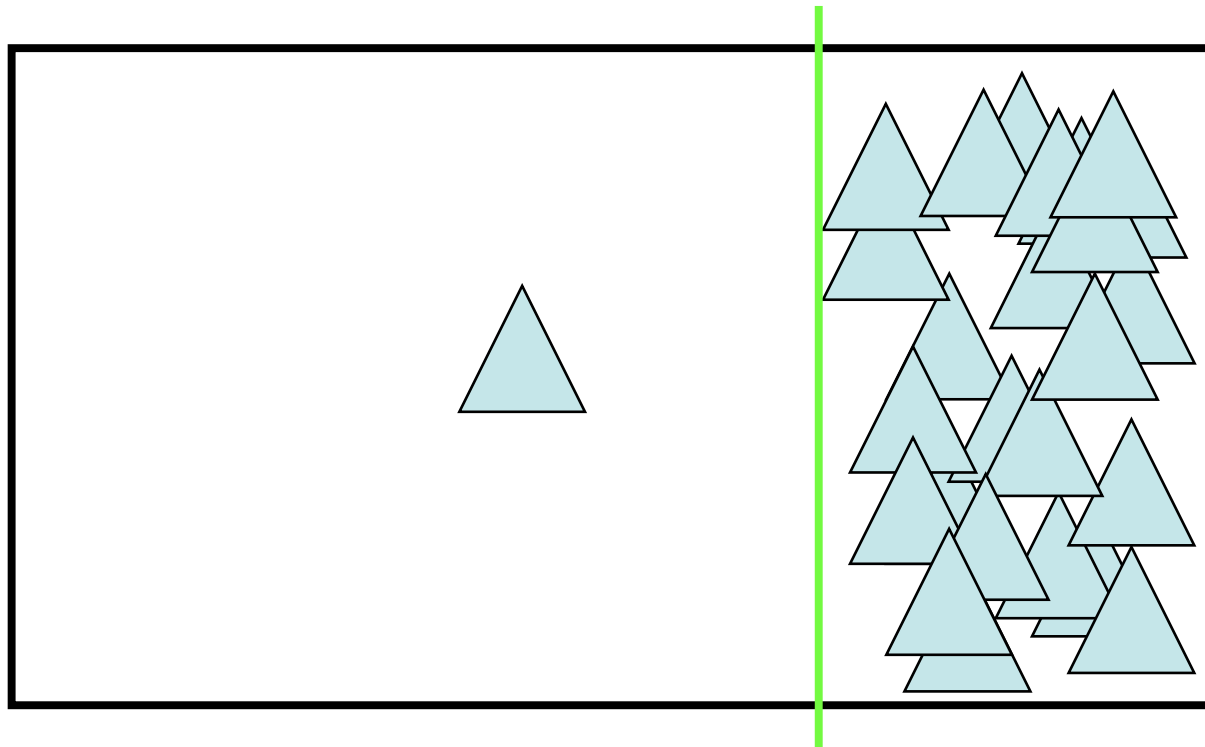
- Makes the L & R probabilities equal
- Pays no attention to the L & R costs

Split at the Median



- Makes the L & R costs equal
- Pays no attention to the L & R probabilities

Cost-Optimized Split



- Automatically and rapidly isolates complexity
- Produces large chunks of empty space

Building good kD-trees

- **Need the probabilities**
 - Turns out to be proportional to surface area
- **Need the child cell costs**
 - Simple triangle count works great (very rough approx.)

$$\begin{aligned}\text{Cost}(\text{cell}) &= C_{\text{trav}} + \text{Prob}(\text{hit L}) * \text{Cost}(\text{L}) + \text{Prob}(\text{hit R}) * \text{Cost}(\text{R}) \\ &= C_{\text{trav}} + \text{SA}(\text{L}) * \text{TriCount}(\text{L}) + \text{SA}(\text{R}) * \text{TriCount}(\text{R})\end{aligned}$$

Termination Criteria

- **When should we stop splitting?**
 - Use the cost estimates in your termination criteria
- **Threshold of cost improvement**
 - Stretch over multiple levels
- **Threshold of cell size**
 - Absolute probability so small there's no point

Building good kD-trees

- **Basic build algorithm**
 - Pick an axis, or optimize across all three
 - Build a set of “candidates” (split locations)
 - BBox edges or exact triangle intersections
 - Sort them or bin them
 - Walk through candidates or bins to find minimum cost split
- **Characteristics you’re looking for**
 - “stringy”, depth 50-100, ~2 triangle leaves, big empty cells

Fast Ray Tracing w/ kD-Trees

- **adaptive**
 - build a cost-optimized kD-tree w/ the surface area heuristic
- **compact**
- **cheap traversal**

What's in a node?

- **A kD-tree internal node needs:**
 - Am I a leaf?
 - Split axis
 - Split location
 - Pointers to children

Compact (8-byte) nodes

- **kD-Tree node can be packed into 8 bytes**
 - Leaf flag + Split axis
 - 2 bits
 - Split location
 - 32 bit float
 - Always two children, put them side-by-side
 - One 32-bit pointer

Compact (8-byte) nodes

- **kD-Tree node can be packed into 8 bytes**
 - Leaf flag + Split axis
 - 2 bits
 - Split location
 - 32 bit float
 - Always two children, put them side-by-side
 - One 32-bit pointer
- **So close! Sweep those 2 bits under the rug...**

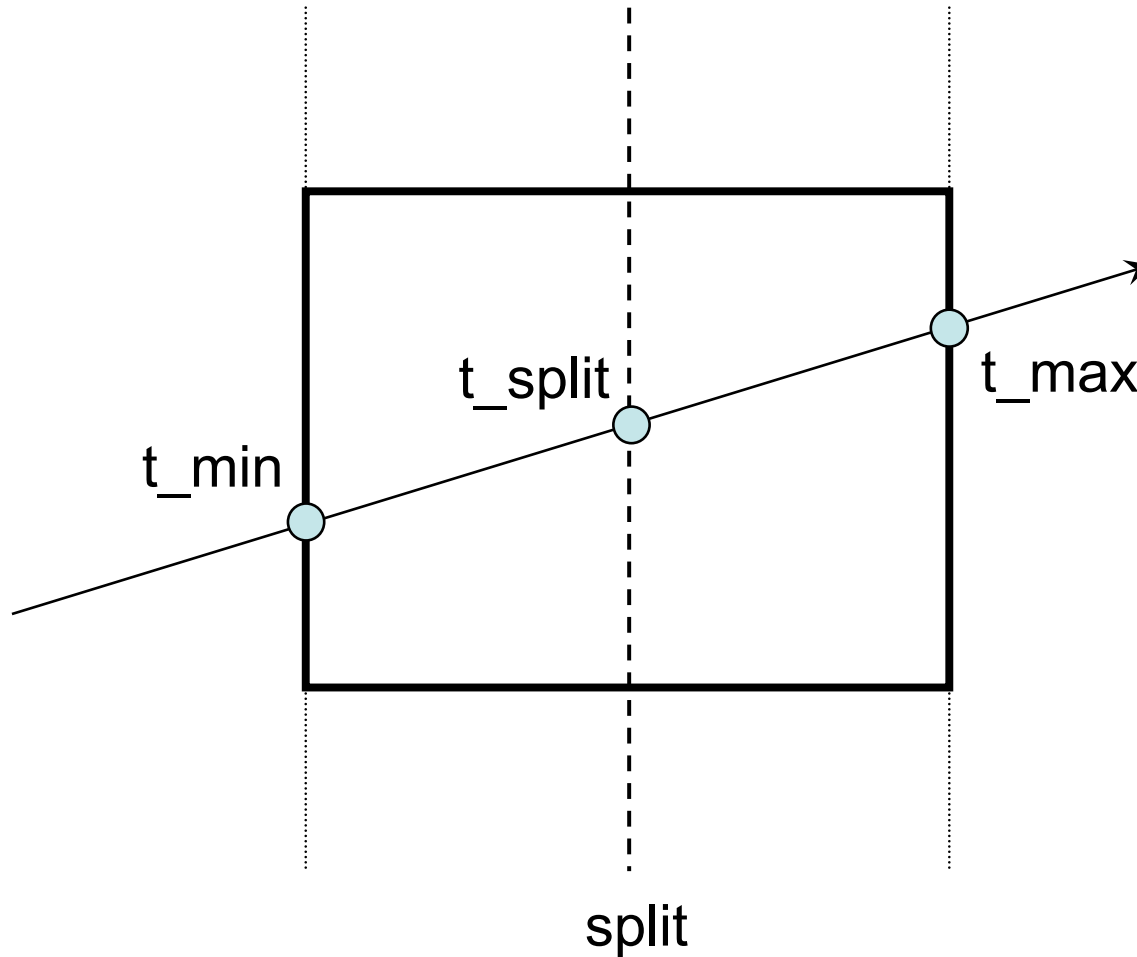
No Bounding Box!

- **kD-Tree node corresponds to an AABB**
- **Doesn't mean it has to *contain* one**
 - 24 bytes
 - 4X explosion (!)

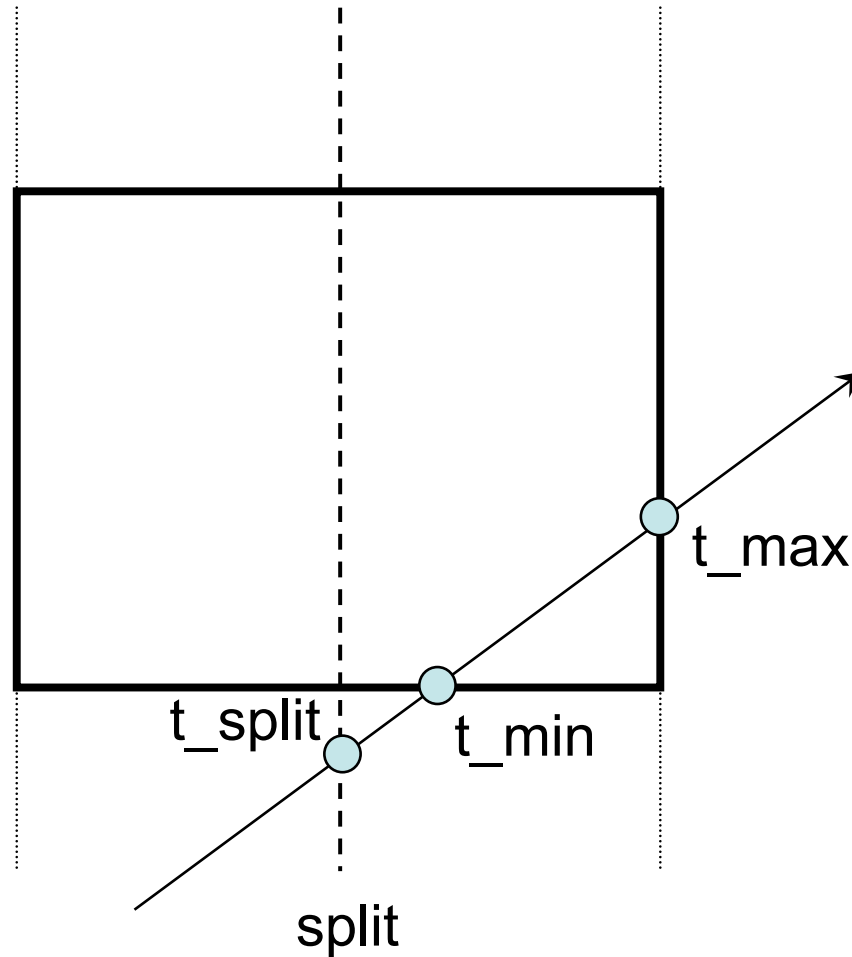
Fast Ray Tracing w/ kD-Trees

- **adaptive**
 - build a cost-optimized kD-tree w/ the surface area heuristic
- **compact**
 - use an 8-byte node
 - lay out your memory in a cache-friendly way
- **cheap traversal**

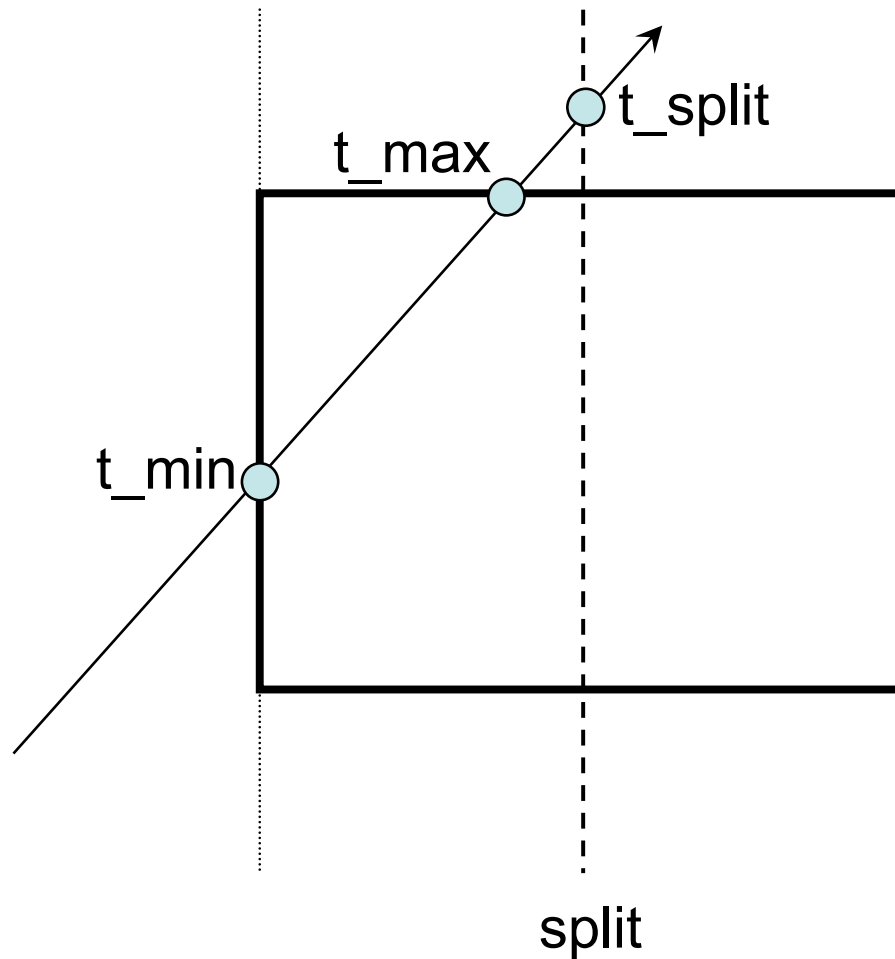
kD-Tree Traversal Step



kD-Tree Traversal Step



kD-Tree Traversal Step



kD-Tree Traversal Step

**Given: ray P & iV (1/V), t_min, t_max,
split_location, split_axis**

**t_at_split = (split_location - ray->
P[split_axis]) * ray_iV[split_axis]**

**if t_at_split > t_min
 need to test against near child**

**If t_at_split < t_max
 need to test against far child**

Optimize Your Inner Loop

- **kD-Tree traversal is the most critical kernel**
 - It happens about a zillion times
 - It's tiny
 - Sloppy coding *will* show up
- **Optimize, Optimize, Optimize**
 - Remove recursion and minimize stack operations
 - Other standard tuning & tweaking

kD-Tree Traversal

```
while ( not a leaf )
    tsplit = ( split_location - ray->P[split_axis] )
             * ray_iV[split_axis]
    if tsplit <= tmin
        continue with far child // hit either far child or none
    if tsplit >= tmax
        continue with near child // hit near child only
    // hit both children
    push (far child, tsplit, tmax) onto stack
    continue with (near child, tmin, tsplit)
```


Reference

- **Slides from Siggraph 2005 course on “Ray Tracing Performance” by Gordon Stoll**
- **Slides from “KD-Tree Acceleration Structures for a GPU Raytracer” by Tim Foley and Jeremy Sugerman**