

# Lecture 12: Spatial Partitioning, KD Trees

CS 6017 – Data Analytics and Visualization

MASTER OF SOFTWARE DEVELOPMENT (MSD) PROGRAM

J. DAVISON DE ST. GERMAIN

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# Lecture 13 – Topics

2

- Spatial Partitioning
  - KD Tree



# Miscellaneous

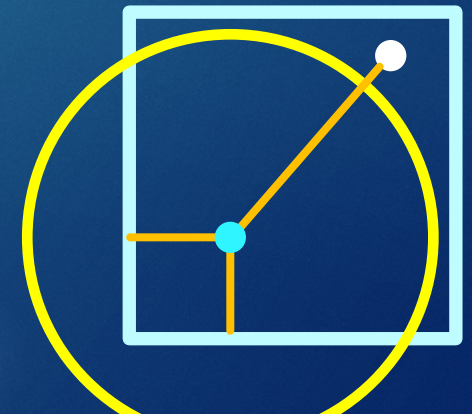
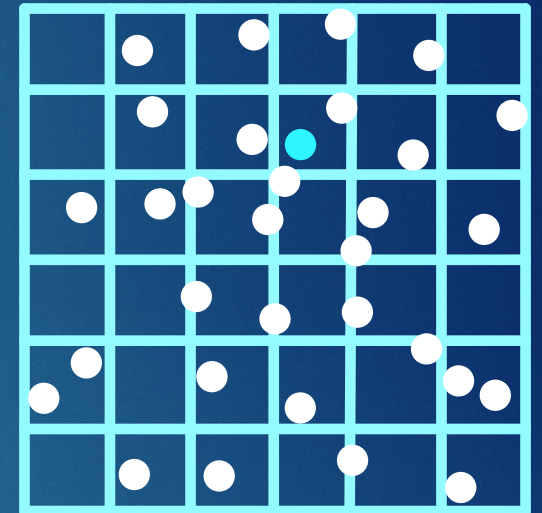
- Questions?
- Remember, HW3 is due Tuesday.



# Spatial Partitioning – Uniform Grid

4

- “Training” → Put (data / training) points in the correct grid cell.
  - What do the white points represent? Why do we do all this?
- **Range Query**
  - Find all points within a radius from the test point.
  - Find the cell(s) that overlap the test point / radius and test all points in those cells.
- **KNN Query**
  - K closest points
  - How to do this?
    - Find query point cell and check all points there.
    - If  $\text{len}(\text{result}) < K$  or distance to worse point  $>$  distance to adjacent cell
      - move out one cell in appropriate directions
- The Good: Works great for uniformly distributed points / cache friendly.
- The Bad: Number of cells can become very large as the number of dimensions (of the data) increases.

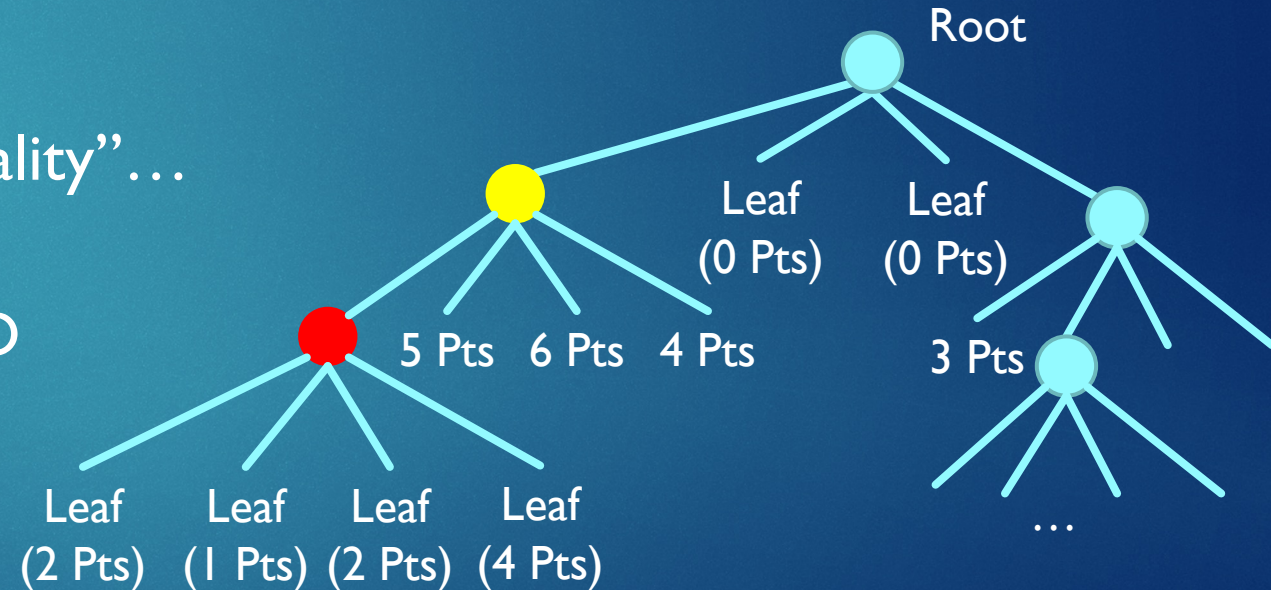
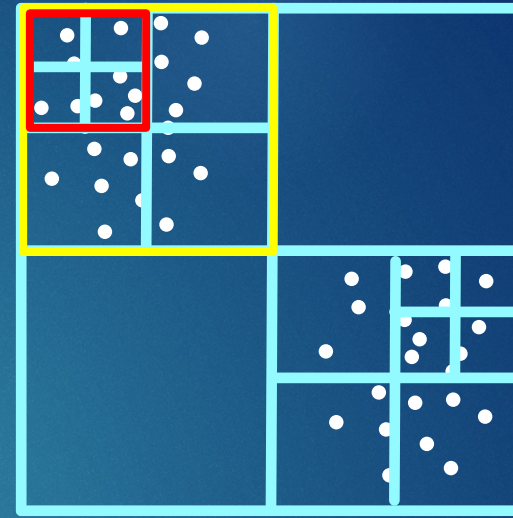




# Quad Tree

5

- Reason for Quad Tree over Uniform Grid?
  - Addresses the “clumped” (non-uniform) data distribution.
- Oct Tree in 3D
- Fix # of splits to 2
- Suffers from the “curse of dimensionality”...
  - # children ==  $2^{\text{dim}}$
  - So (usually) only used in 2D and 3D
- Note: Could tweak data structure to split in median of points (instead of just in the middle of the cells) in order to “always” divide the number of points evenly.





# KD Tree (K-Dimension Tree)

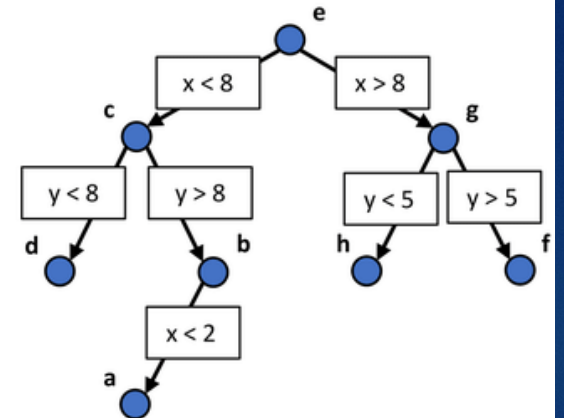
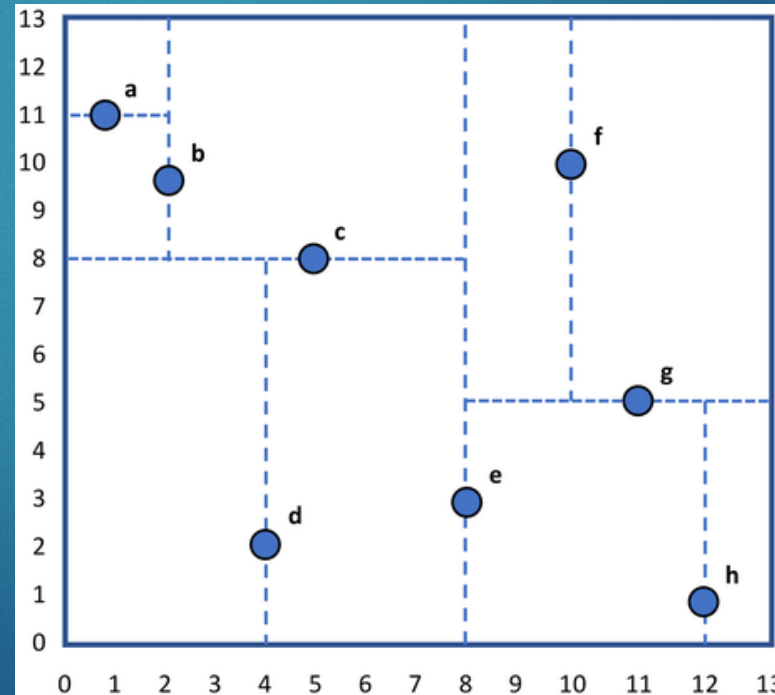
- K (here) specifies the number of dimensions
  - Not related to KNN
- A “generalization” of BSTs for multiple dimensions
- KD Tree == BST, where at each level we split using a different *dimension* of the data.



# Approach Three: KD Tree

7

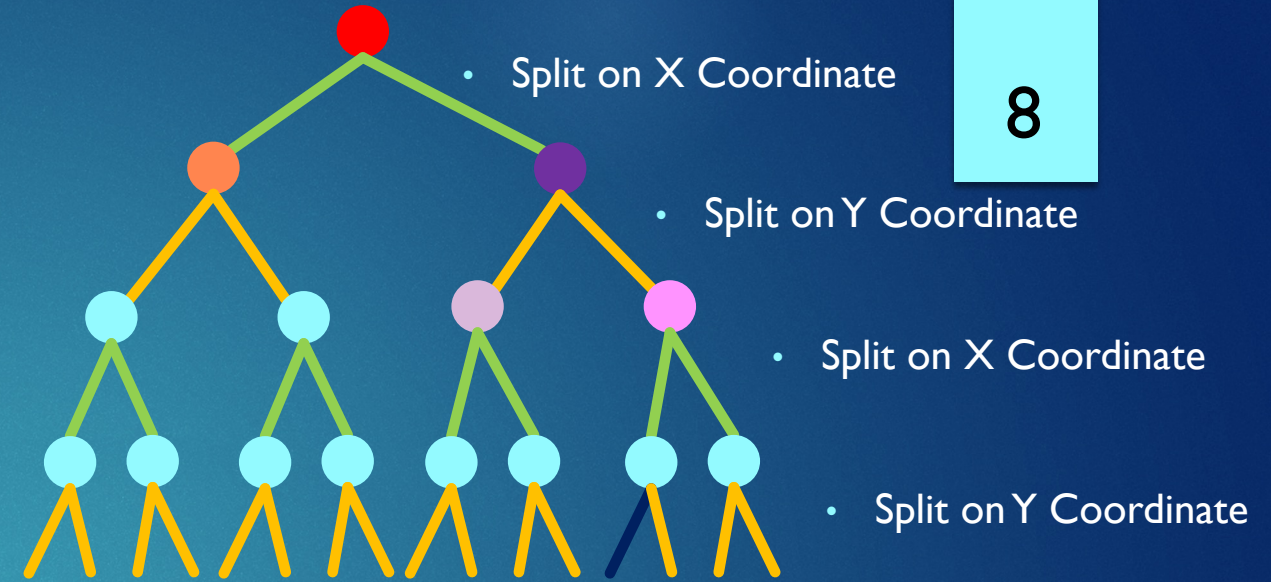
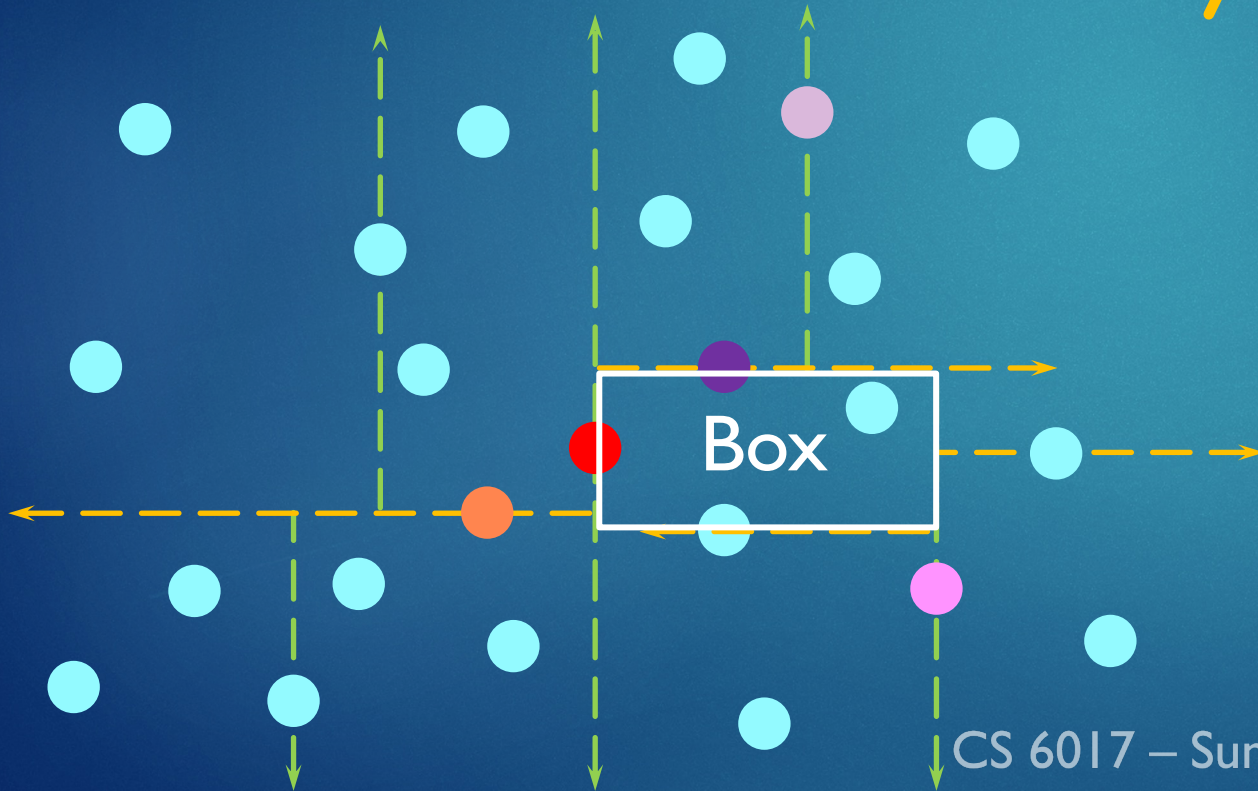
- Generalization of a BST to many "keys"
- Each node stores the median of it's subtree according to one of the dimensions (x, y, z, etc)
- Each time we go down one level, we move to the next dimension (if I split by x, my children split by y)
- Each node stores a point and the dimension it splits by





# Building the KD Tree

- Right: BST (visualization)
- Left: Spatial Display (visualization)
  - Note: all levels are not complete



- Split on X Coordinate
- Split on Y Coordinate
- Split on X Coordinate
- Split on Y Coordinate
- How is space partitioned using the KD Tree? What are the “shapes” of the children?
  - Each line (chopping of space) creates a new “box” (easier to see at lower levels of the tree)
  - Every time we sub-divide, we are moving in one of the “sides” of the box.
- Height of KNN Tree?
  - It turns out to be a balanced BST
  - $\log N \leftarrow$  Notice *dimension* not here...
  - However, the bigger the # of dimensions, the larger the “volume” of the (N-dimensional) box



# KD Tree Construction

- `KdTree( Point[] points )`
  - `root = new Node( points )`
- Data that a Node needs to store?
  - Node left, right
  - Point `split_point`
  - *Dimension* `split_dimension`
- XNode
  - YNode left, right
  - Point `split_point`
- YNode
  - XNode left, right
  - Point `split_point`
- Advantages
  - Can't accidentally have two X splits in a row.
  - Compiler checks for this.
- Disadvantages (as a S/W Dev?)
  - Duplicating some code...
  - Can fix this by templating the Node
- `Node!0`  $\leftarrow$  XNode
- `Node!1`  $\leftarrow$  YNode
- `Node!2`  $\leftarrow$  ZNode



# Node Constructor

- Node( Point [] points )
  - split\_point = ?
  - // Find middle point based on split dimension
  - // Store middle point
  - // Group smaller points and bigger points
  - // Create children nodes using (corresponding) points. (Recurring)
  - left = new Node( left half of points )
  - right = new Node( right half of points )
  - // Base case?
    - // length( points ) == 1



# Finding the Middle Value / Partitioning

II

- How long does it take to partition a list of numbers into the smaller half and the larger half?
  - Method 1:
    - We know the median value, thus partitioning is:
      - $O(n)$
  - Method 2: We don't know the median value...
    - Sort:  $O(n \log n)$
    - Get median:  $O(1)$
    - Total:  $O(n \log n)$
  - Method 3: We don't know the median value...
    - Use a smart person's algorithm... 😊
    - Thus:  $O(n)$
- [Quick Median \(i-programmer.info\)](http://i-programmer.info)
- [Quickselect – Wikipedia](https://en.wikipedia.org/wiki/Quickselect)
- [std::nth\\_element - cppreference.com](http://cppreference.com/std/nth_element)
- [topN - multiple declarations - D Programming Language \(dlang.org\)](http://dlang.org/topN-multiple-declarations.html)



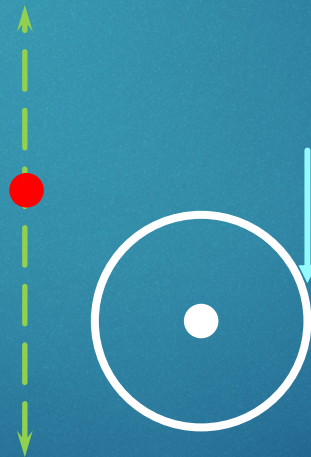
# KD Tree Range Query

```
KdTree::rangeQuery( query_pt, radius )  
    return root.rangeQuery( query_pt, radius )  
Node::rangeQuery( query_pt, radius )  
    if node.p is close to query_pt  
        add to list  
    if necessary recurse left  
    if necessary recurse right
```

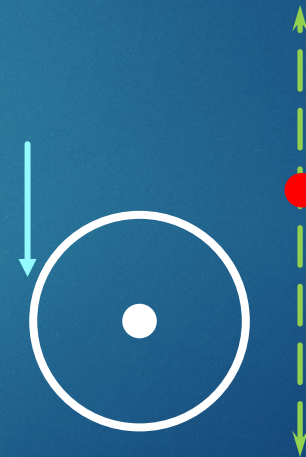


# Which Children to Recurse Into?

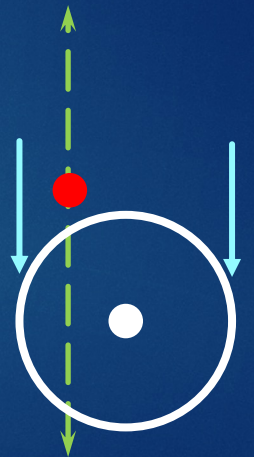
- Three cases... (Split point in red, query point in white)
  - Note: case 3 is covered by handling case 1 and case 2
- Do I need to recurse Right?
  - Look at the point + radius // Right side of circle
- Do I need to recurse Left?
  - if  $\text{query\_point.x} - \text{radius} < \text{split\_point.x}$  // ie: The left side of circle
- Recurse both directions?
  - Handled above.
- Above tests use the X coordinate, but if this is a Y node, we would just use ".y"
  - Note, set up so left is always <.



- Case 1
- Look Right



- Case 2
- Look Left



- Case 3
- Look Both



# KNN Query For KD Tree

14

- Review – What did we do for the Quad Tree?
  - for each child
    - if  $\text{list\_size} < K$  or  $\text{closestPointInAABB}(pt)$  is closer than worst in list
      - recurse
- For KD Tree:
  - check point in node
  - // Left Check:
    - if  $\text{list\_size} < K$  or distance from left child to  $p$  is closer than the worst point in list
      - recurse left
- Need to know the bounding box of left child
  - Could store, or (easier) can compute as we traverse (see next slide)

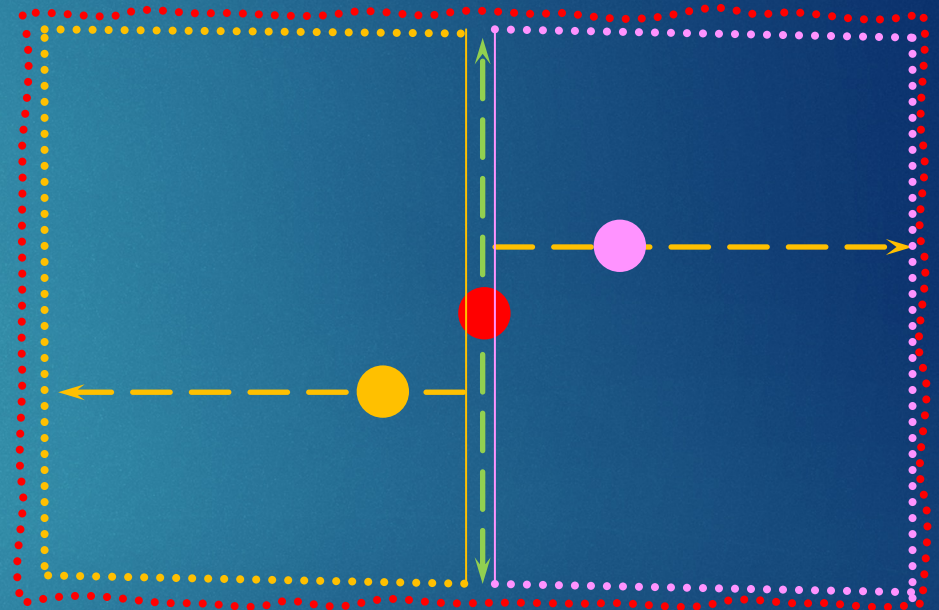


# KNN Query

15

```
KdTree::KnnQuery( query_pt, K )  
    return root.KnnQuery( query_pt, K, box )
```

- What is the bounding box of a (sub)tree?
- Root:
  - `box == infinite AABB`
  - Left Child?
    - `left_aabb = parent's aabb`
    - `left_aabb.right = root.x`
  - Right Child
    - `right_aabb.left = root.x`
  - Note: we might denote “left” as `x_min`, etc...
  - “Cutting off” (making smaller) one side of the box each time we recurse to a child node.





# HW 4 – Spatial Data Structures

16

- We provide the uniform grid implementation as an example for you.
- You will implement Quad Tree and KD Tree.
- We will be doing timing studies on our implementations.
- Going to implement this in “D”. [Ben’s favorite language]
- Providing:
  - bucket\_knn.d – Implementation of uniform grid
  - dumb\_knn.d – A very naïve implementation of KNN with no grid.
  - common.d – A lot of general utilities.
- Look at unit test blocks for some examples.
- Two-week assignment – aim to have data structures implemented by week 1, then use week 2 to do analysis.



~ Fin ~