

SDS 385: Stat Models for Big Data

Lecture 9: KD trees

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https://psarkar.github.io/teaching

Background

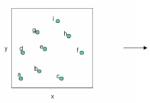
- Has a long history-invented in 1970 by Jon Bentley
- *k* represents the number of dimensions
- Idea is to partition the data spatially, by using only one dimension at any level.
- While searching, this helps pruning most of the search space.

General idea

- Cycle through the dimensions for each level
- Call this cut-dim (cutting dimension)
- Node in tree contains P = (x, y)
- So, to find a point, only need to compare the cutting dimension.

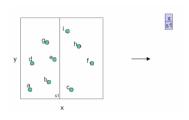
Construct

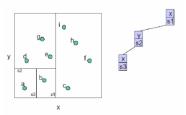
- If there is one point, just form a leaf node
- Otherwise divide the points in half along the cutting axis
 - Find the axis with the widest spread
 - divide in alternative/round robin fashion
- recursively build kdtrees from each half
- Complexity *dn* log *n*

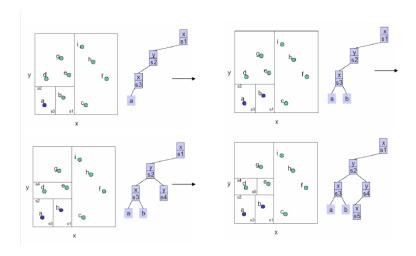


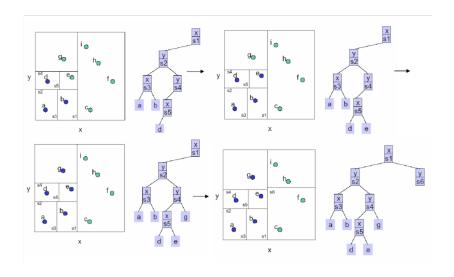
divide perpendicular to the widest spread.

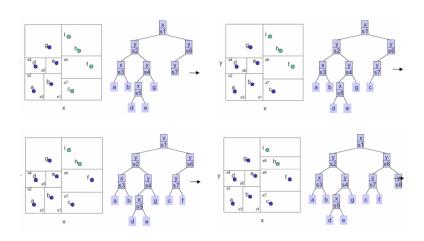












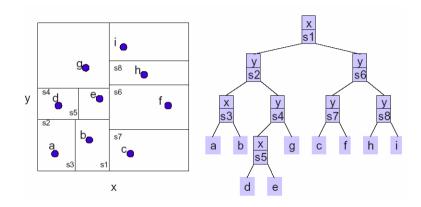
Find point with the smallest element in dimension a

- If cutdim at current node equals a,
 - the min cannot be in the right subtree
 - recurse on the left subtree

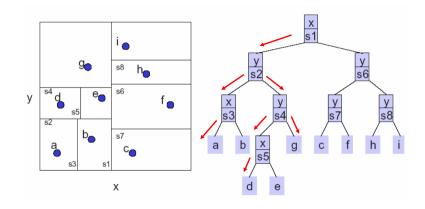
Base case: if there are no left children, stop and return current point.

- Otherwise
 - the min could be in either
 - recurse on both left and right subtrees

Find point with the smallest element in dimension x



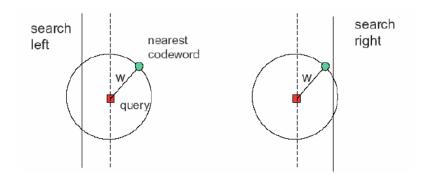
Find point with the smallest element in dimension x



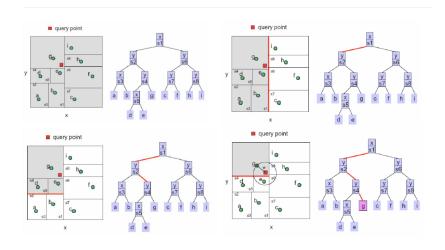
- Given point Q, find the closest point R
- Have to be careful, because its possible that two points are far away in the tree but close in the Eucidean space.
- For each node store a bounding box

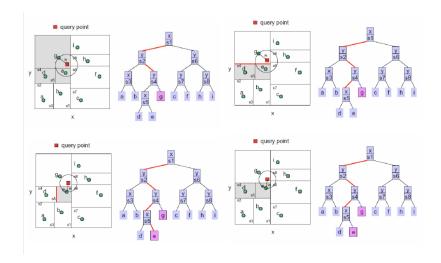
- Given point Q, find the closest point R
- Have to be careful, because its possible that two points are far away in the tree but close in the Eucidean space.
- For each node store a bounding box
- Remember the closest point to Q seen so far (call this R')

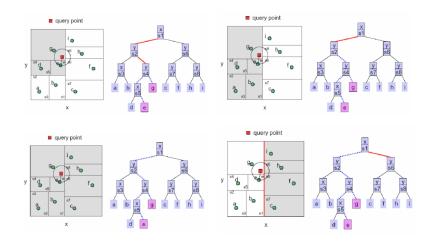
- Given point Q, find the closest point R
- Have to be careful, because its possible that two points are far away in the tree but close in the Eucidean space.
- For each node store a bounding box
- Remember the closest point to Q seen so far (call this R')
- Prune subtrees where bounding boxes cannot contain R'

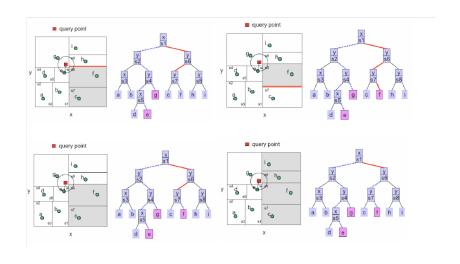


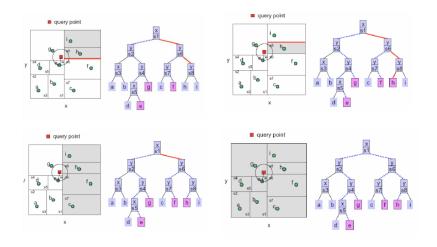
- If circle overlaps with left subtree, search left subtree
- If circle overlaps with right subtree search right subtree
- Has been shown to work in about $O(\log n)$ time.











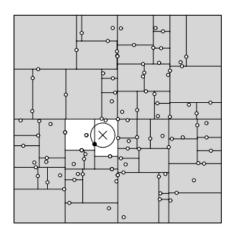


Figure 6.5

Generally during a nearest neighboursearchonly a few leaf nodes need to be inspected.

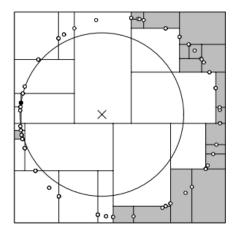


Figure 6.6

A bad distribution which forces almost all nodes to be inspected.

Timing vs tree size

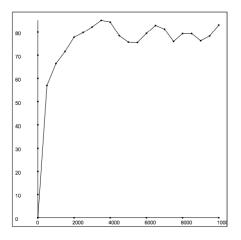


Figure 6.8

Number of inspections against kd-tree size for an eight-dimensional tree with an eight-dimensional underlying distribution.

Timing vs dimensions

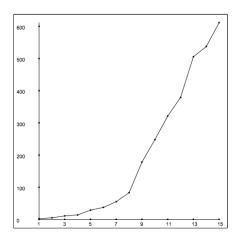
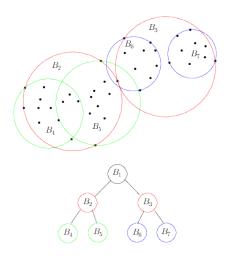


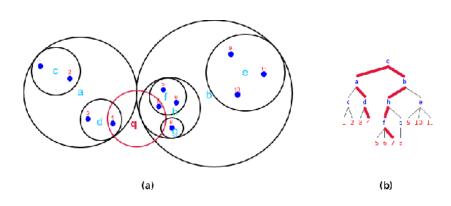
Figure 6.9

Number of inspections graphed against tree dimension. In these experiments the points had an underlying distribution with the same dimensionality as the tree.

Ball trees



Ball tree search



Acknowledgment

- The kdtrees animations were borrowed from
 - Thinh Nguyen's slides
 - Carl Kingsford's slides
- Andrew moore's tutorial