



Scalable Data Science

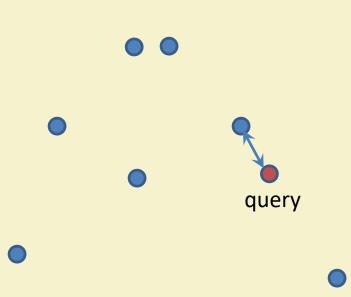
Lecture 11: Near Neighbors

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Finding Near Neighbors



Given a set of data points and a query

Can we find what is the nearest datapoint to the query?

- K-nearest neighbors
- d(p, query) < r

Applications

Numerous

- Finding near duplicate webpages / articles
- Finding similar images in search
- Clustering
- Nearest neighbour classifier
- Variants
 - all pairs near neighbors



Naïve solution?

- Naïve scan
 - -O(nd) time for each query

- Can we calculate and store the Voronoi partition of the pointset?
 - Will give the exact answer if possible
 - needs $n^{d/2}$ storage for n points in d dimensions



Space Partitioning trees

- Basic idea
 - Recursively partition the space
 - Given the query, prune the dataset using the created partition tree
 - All depends on how to partition



Kd-trees

- Works "well" for "low to medium" dimensions
- Initially proposed by Bentley 1970
- Originally, k was #dimensions
- Idea: each level of the tree uses a single dimension to partition



Algorithm

- Each level has a cutting dimension
- Cycle through the dimensions
- At every step, choose the point which is the median along that dimension, create an axis-aligned partition



Example





Complexity

- Space taken = O(n)
- Nearest neighbour search:
 - Defeatist search: only search the child that contain the query point
 - Descending search: maintain the current near neighbour and distance to it.
 Visit one or both children depending on whether there is intersection
 - Priority search: Maintain a priority queue of the regions depending on distance.
 - Can potentially take O(n)



Variants

- Several variants of space partitioning trees possible
 - Random Projection tree chooses a unit direction at random for every node
 - PD tree uses the principal eigenvector of the covariance matrix
 - 2-Mean tree: partition the data into 2 clusters, find the hyperplane that bisects the line connecting them



Possible intuition to analyze

- Does the partitioning algorithm adapt to "intrinsic dimension"?
 - i.e. if the data has some low-dimensional structure
 - E.g. if the data has "intrinsic dimension" d, then all cells O(d) levels below a cell C
 has at most ½ the diameter of C



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- Definition of "intrinsic dimension" is not obvious
 - Ex: covariance dimension is d if the d largest eigenvalues of covariance matrix account for $1-\epsilon$ fraction of trace
- Can be shown that RP, PD trees adapt to this dimension, but k-D tree does not



Summary

- Nearest neighbour question
- Number of algorithms for low dimensional data based on space partitioning trees
 - Some of the adapt to the intrinsic dimensionality of data



References:

- Primary references for this lecture
 - Foundations of multidimensional and metric data structures, H. Samet. Morgan Kaufman 2006.
 - "Which space partitioning trees adapt to Intrinsic Dimension", Verma, Kpotfe, Dasgupta UAI 2009.



Thank You!!

