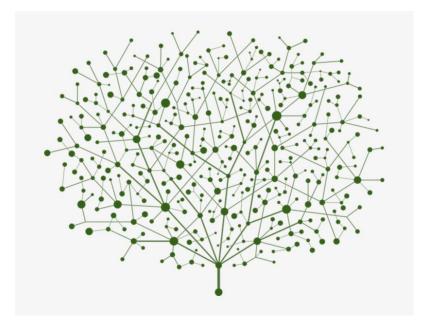
CSC 212 Final Project K-D Tree

Team Members

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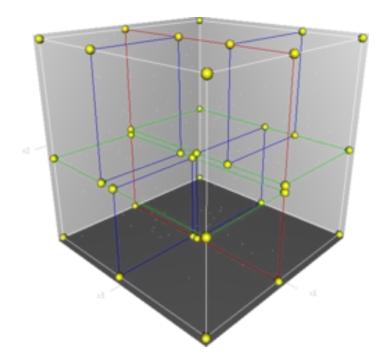
https://github.com/raymondturrisi/CSC212-Final-Project

9 December 2020



Outline

- Introduction to K-D Trees
- 2. Theory
- 3. Analysis
- 4. Implementation
- 5. Application
- 6. Conclusion





Intro (1.1)

- K-Dimensional Trees
 - Developed in the 1970's, first notably discussed in Dr. Jon Louis Bentley's paper on the investigation of multidimensional divide-and-conquer techniques, in "Divide and Conquer in Multidimensional Space" which was published in 1975 [1].

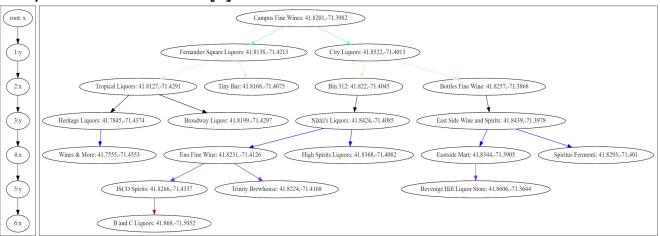


Fig. 1: 2-D KD Tree with local location data.



Intro (1.2)

- Building a K-D Tree
 - Like the BST, the K-D Tree traverses the tree to the left and right based on if the new member's current dimension is less than or greater than the observed nodes dimension.
 - Unlike the BST, it offers dimensionality, making branching decisions based not only on size relation, but also the observed dimension based on the depth from the root node
 - Keywords:
 - Depth, d
 - Dimensions, *k*
 - Discriminator, i

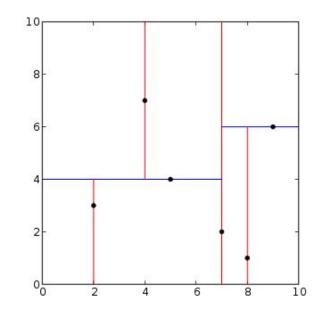


Fig. 2: X-Y plane partitioned by K-D Tree's members.



Intro (1.3)

Building a K-D Tree, cont. (Example)

$$\{(293, 267), (271, 98), (372, 260), (337, 156)\}$$
 $i = d\%K, i \in [0, K]$

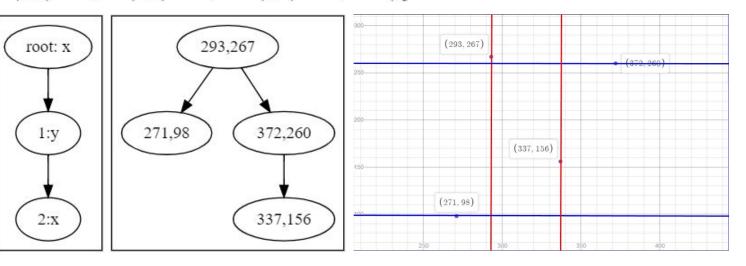


Fig. 3: Construction of a K-D Tree when K = 2, within an X-Y plane.



Theory (2.1)

- K-D Tree has the basic structure of a Binary Tree
- Basic Operations in have the same complexity

Table 1: Time and Space Complexity for Standard Functions

Algorithm	Average	Worst Case
Space	$\Theta(n)$	$\Theta(n)$
Search	$\Theta(log_2n)$	$\Theta(n)$
Insert	$\Theta(log_2n)$	$\Theta(n)$
Delete	$\Theta(log_2n)$	$\Theta(n)$



Theory (2.2)

- Three methods for building a balanced K-D Tree with the following complexities:
 - Heap/Merge sort: Θ(n log^2(n))
 - Median of Medians: Θ(n log(n))
 - Pre-sorted by dimension: Θ(k n log(n))
- We constructed our balancing algorithm with the median of medians algorithm as it offered the best complexity Θ(n)
- Median of Medians Recurrence Relation:
 T(n) = cn/5 + T(n/5) + cn + T(7n/10)

$$\Theta(n) = cn$$

$$\Theta(n) = n$$

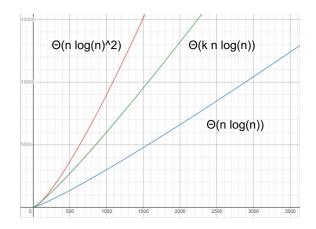


Fig. 4: Graph of asymptotic complexities as n approaches infinity.



Theory (2.3)

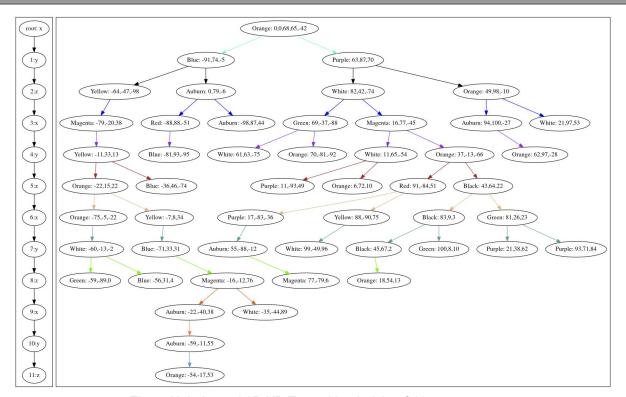


Fig. 5: Unbalanced 2D KD Tree with a height of 11.



Theory (2.4)

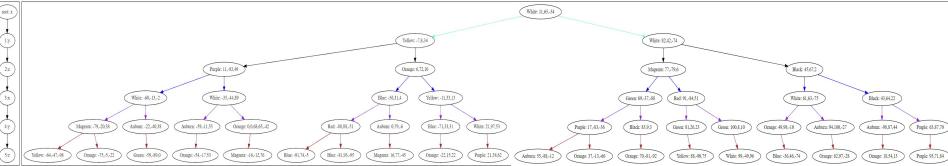


Fig. 6: Balanced 2D KD Tree with a height of 5.

- Balanced Tree Height: 5
 - \circ Constructed in $\Theta(n \log(n))$
- Un-Balanced Tree Height: 11
 - \circ Constructed in $\Theta(\log(n))$
- Big implications for efficiency of future operations
 - Search
 - Insert
 - Nearest Neighbors Approximation



Theory (2.5)

Constructing a Balanced Tree

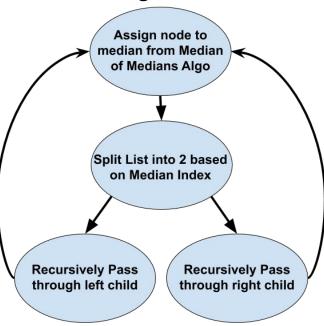


Fig. 7: Diagram of median of medians recurrence .



Algorithm performance (3.1)

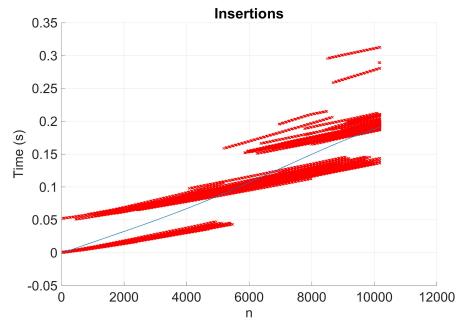


Fig. 8: Data on an unbalanced KD Trees performance in insertions.

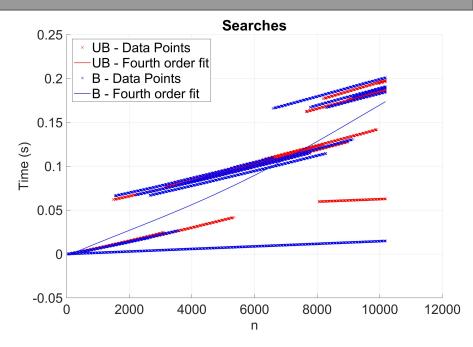


Fig. 9: Data on an unbalanced and balanced KD Trees performance in searching an existing tree.



AP - Nearest Neighbors (3.2)

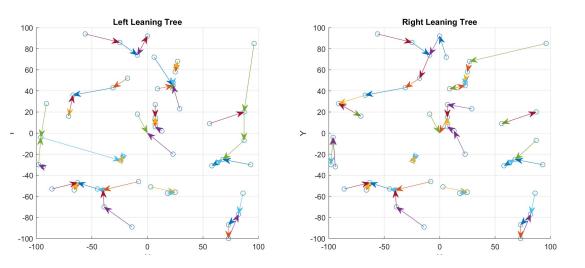


Fig. 10: Nearest Neighbors algorithm, approximated, on KD trees with left and right leaning biases.

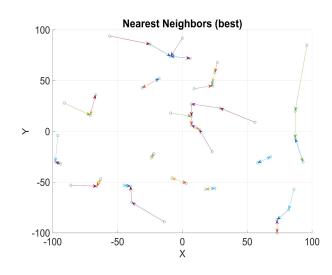


Fig. 11: Nearest Neighbors algorithm, best ()



Nearest Neighbors (3.3)

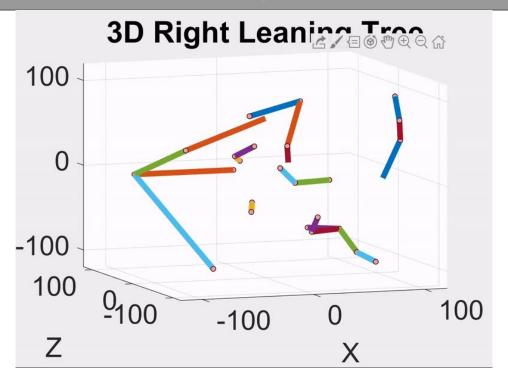


Fig. 12: Nearest Neighbors algorithm, fast, on a 3D right leaning K-D Tree



Nearest Neighbors (3.4)

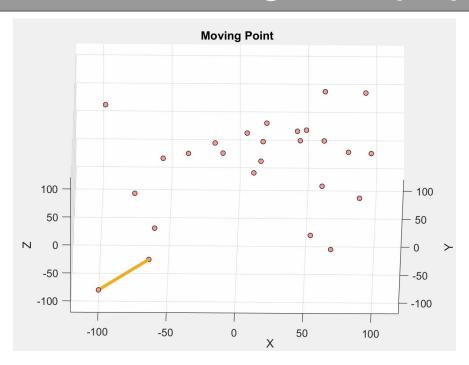


Fig. 13: Nearest Neighbors algorithm, approximated, on a point moving through 3D space



Implementation (4.1)

Implementation in C++

- Fully templated K-D Tree class for to easy deployment on existing classes, requiring small modifications
 - KDTree.hpp
 - Inserts, searches, nearest neighbors, and balancing constructor with Median of Medians
 - Nodes.hpp
 - Median.hpp
 - dataStructs.hpp
 - KDTree_Key class
 - DefaultLocation class

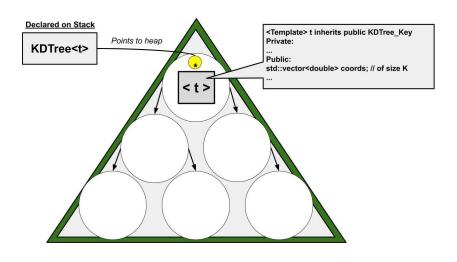


Fig. 14: K-D Tree C++ Class implementation diagram.

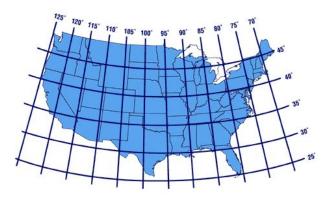


Application (5.1)

Motivation

- Find nearest location (coffee shop, theater, etc.)
- Instantiate a 2-dimensional tree
 - Dimension 1: Longitude
 - o Dimension 2: Latitude







Application (5.2)

Retrieving location data:

- Python
- Used Yelp application programming interface (API), retrieve data from Yelp's servers using HTTP
- Results
 - o 10,000 locations: RI, CT, MA
 - Comma separated value format (CSV)



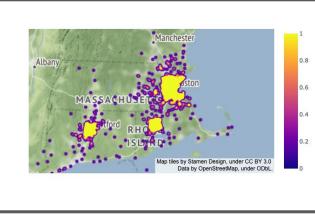


Fig. 15: Representation of our location data set. Shows geographical coverage and density of location data.



Application (5.4)

 User inputs longitude, latitude and an option for what type of location they want to search for



Fig. 16: Demonstration of our team's location-finding application.



Application (5.5)

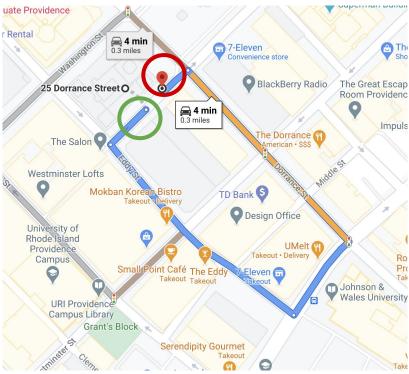
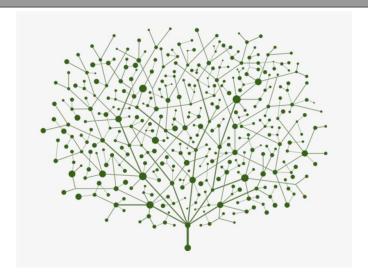


Fig. 17: The results of the demonstration in the previous slide. Circled in green is the longitude latitude passed as input, and circled in red is

Conclusions



Questions?

References

[1] J. L. Bentley and M. I. Shamos, Divide-And-Conquer In Multidimensional Space. Proceed-ings of the Eighth Annual ACM Symposium on Automata and Theory of Computing.

