AA Assignment 1 Report

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We certify that this is all our group's original work. If we took any parts from elsewhere, then they were non-essential parts of the assignment, and they are clearly attributed in our submission. We will show that we agree to this honour code by typing ``Yes": YES.

Experimental Setup
The data is generated randomly, the RandomDataGeneration.java takes a number if parameters, which then outputs Datasets and a command file.

The dataset is generated by filling and array list with Points objects. These objects' use a pre-determined longitude and latitude value, which then gets slowly incremented for every point that is generated, which prevents issues with repeated locations. These points are then stored in an array list, the array list is shuffled, then the points are printed out in an output file.

We tested using different sized datasets as well as different K values based off 1 randomly generated location. The parameters settings we decided to test on is the K-value and dataset size. We hypothesized that by increasing the K- value, the amount of searching by both algorithm increases which increases computation time. We also expect that increasing the dataset size has will have the same effect. Thus, we can then compare how different k values effect computational time vs how the same k-values perform on a larger dataset, then compare the naïve and KD tree implementations.

Scenario 1

We wanted to see the performance distance of finding nearest neighbours as the dataset increases in the two algorithms, thus choose to increase the dataset size to be multiple times larger than the sample data provided. The K-values used were kept constant across the datasets so that the dataset size is the independent variable. According to [7], the optimal k value depends on the dataset which could be large or small. Thus, we tested a range of k values from 2-20 to see how the increase effects the two algorithms.

Scenario 2

For this part, we use the same dataset size as scenario 1. The number of points to be removed then added is the square root of the size of the file, ie for 50000 points, we remove 223 points then add 223 points. Then we performed search again using the same spread of k values. By using the same dataset size, we can compare the knn searches in scenario 1 and see how removing then adding points effect the search time, compared to searching without tampering with the data set.

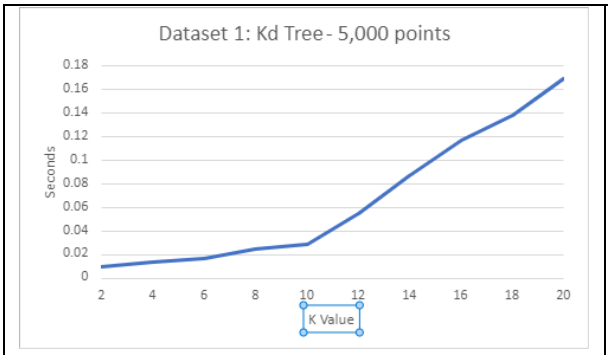
Timing

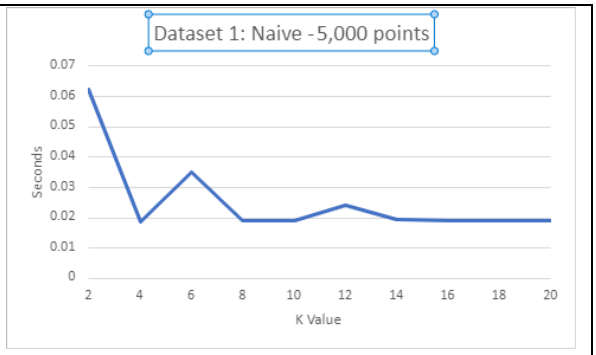
Our timing starts when as the first line inside the called method, it will then end and print out the time it took before the end of the method ie before the “return” statement or be the last 2 lines for a void method. When the command file is run, we will get a printout of how long each method took to run in the console.

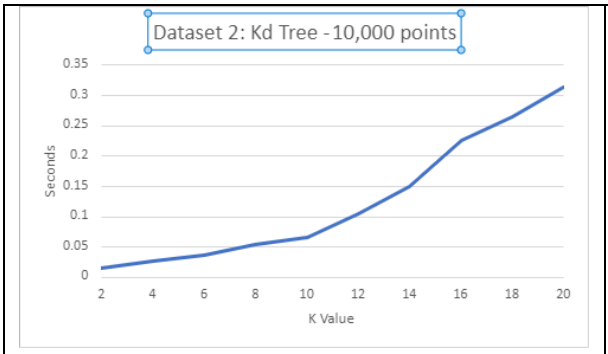
When taking the results, we will run each test for each dataset in both scenarios 5 times, then average the results. The values used in the following graphs are an average of the 5 run times.

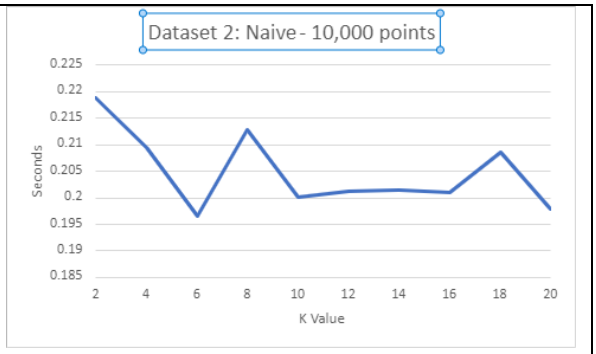
Evaluation

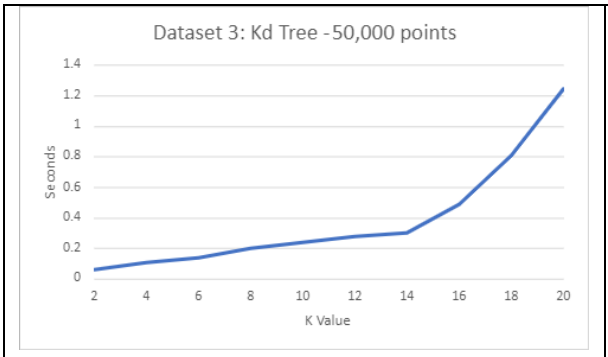
Scenario 1 (k-nearest neighbour searches)

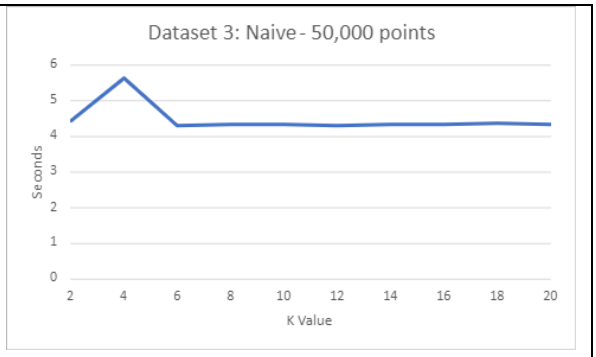












Discussion

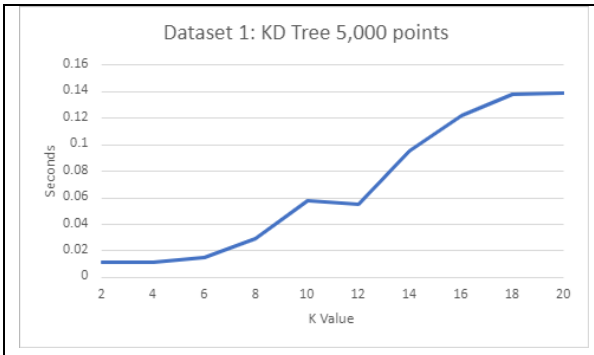
From the results, we can observe similar trends across different data sizes. For the naïve implementation we generally see no change to time used to find the nearest neighbours represented by the k value, even as the k value increases from 2 incrementally by 2 to 20.

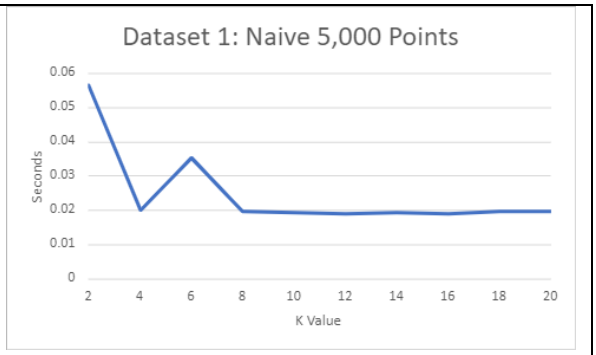
This contrasts the Kd tree implementation, where across the three dataset sizes (5000, 10000 and 50000), as the k value increased, the amount of time increased exponentially.

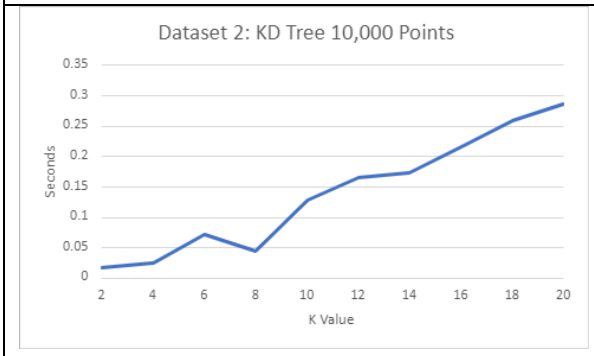
For 5000 points, on average the Naïve method was faster. However, for the 10,000 and 50,000 points, the KD Tree method was faster. In terms of time complexity considering, we used a brute force method and a nested for loop, the time complexity for Naïve implementation is O(n^2). In comparison, the time complexity for KD tree is O(n log n).

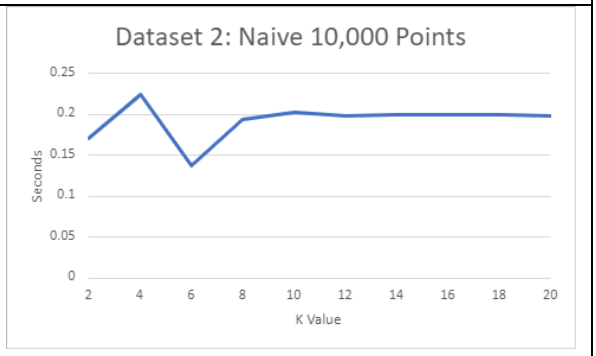
The reason being the KD Tree gets more efficient with more data points, however because we did not have a large enough sample points for the 5,000-point sample this contradicts the popular view of KD Tree being faster than Naïve overall.

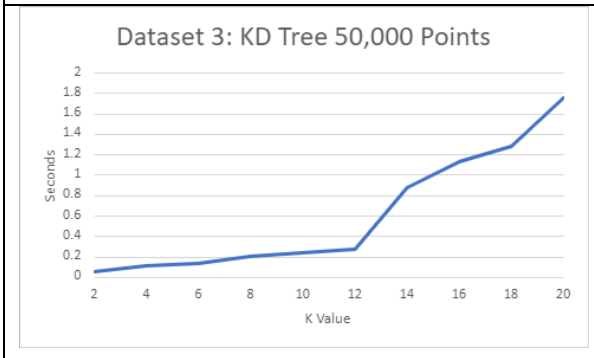
Scenario 2 (Dynamic points set)

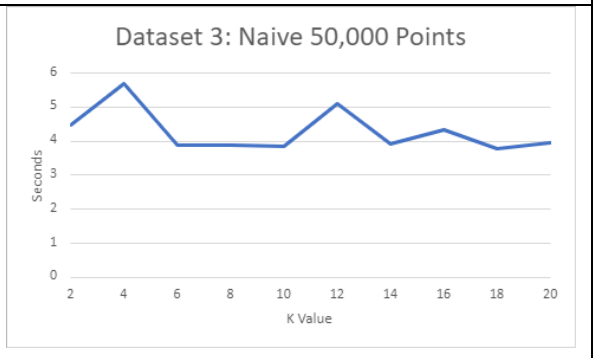












Discussion

In this instance, the behaviour of both algorithms is like scenario 1. KD-Tree took more time to locate Neighbours as the K value increases, whereas Naïve method increases in computational time, decreases then reaches a rough constant.

However, when we deleted points and then added new points, the KD Tree implementation was faster in all three scenarios. The following table shows the total time it took each algorithm to finish the 10 K nearest neighbour searches on each dataset.

Dataset Size	KD Tree – Total Time (seconds)	Naive – Total Time (seconds)
5000	0.6745813	0.2477237
10000	1.3854775	1.919771
50000	6.0597915	42.8504995

As we can see, in a dynamic points list, the KD tree was able to beat the Naïve when there are more than 5000 points. Below that, the Naïve implementation was faster. This is likely because sorting an array list, even by brute force, is quicker to compute, rather than traversing a tree.

However, once there are many data points, the KD Tree becomes significantly faster – around 800% faster in the 50000-point dataset.

Recommendation and Conclusion

Scenario 1

For scenario 1, if you have a smaller sample size like we did in Dataset 1 (5000-point sample - or less), then we would recommend the Naïve implementation, based on our results. Dataset 1 contradicted our hypothesis. However, for larger sample sizes such as Dataset 2 (10,000 points) and Dataset 3 (50,000) points, we would recommend the KD Tree. It is important to note that in most real-world applications which usually contains a lot of data like in Google Maps and would also need to scale with more inputted data, then the KD Tree implementation is the way to go for this scenario,

Scenario 2

Contrastingly, scenario 2 supported our expectations according to our hypothesis and popular opinion. For all Datasets, by increasing the K- value, the amount of searching by both algorithm increases which increases computation time. Also based on our results, increasing the dataset size had the same effect. Conclusively, most real-world application like a GPS, should use KD Tree for this scenario.

Acknowledgement

Thank you to our wonderful and knowledgeable tutors who explained to us these challenging concepts, for which without them, this assignment would not have been possible.

References (~0.5 page)

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- [7] S. Aggarwal, “K-Nearest Neighbors,” *Medium*, Jun. 08, 2020. https://towardsdatascience.com/k-nearest-neighbors-94395f445221 (accessed Sep. 10, 2021).

Appendix

- A copy of the graphs in excel has been provided in the submission in case the graphs used in the report is too small to read.
- Our code is also on Github, in a private repository, please contact us if access is needed.
- https://github.com/Ghost-Recon131/AA-1

- The submitted code does not have code used to time the runtime of each operation in either implementation. Please see the Code-Evaluation branch in our Github Repository.