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Object detection with the DBScan algorithm
Programming Assignment P2 (10%)
CSI2110 Fall 2022

***This project is individual;* P2 is due December 5 by 23:59**

Late penalty : -30% from 1 min to 24 hours late.

Problem Description

In P1, you created a program that detects objects (clusters of points in fact) in a scene captured by a LiDAR (a laser scanner). This has been done using the DBSCAN algorithm. In the second part of this programming assignment, we will try to improve the efficiency of this algorithm.

But what is the runtime complexity of DBSCAN? Basically, you have to go over all N points of the set and for each point you must search its neighborhood; the current neighborhood search is O(N) since we have to go over all points to find the ones at a distance less than eps. Therefore the global complexity of DBSCAN is $O(N^2)$; note that this is true only if the average number of neighbors per point is small compared to N.

Your Task

To improve the efficiency of the DBSCAN algorithm, we will create a new NearestNeighbors class with a new rangeQuery method. This class is structured as follows:

- The NearestNeighbors class that includes
  - a constructor that accepts a List of Point3D
    - `NearestNeighbors(List<Point3D>)`
  - a rangeQuery method that finds the nearest neighbors of a 3D point
    - `public List<Point3D> rangeQuery(Point3D p, double eps)`

Our objective is to use an abstract data type called k-d tree in order to obtain a better runtime complexity for the neighborhood search. The k-d tree partitions a point set using a binary tree representation. There will be two programming steps:

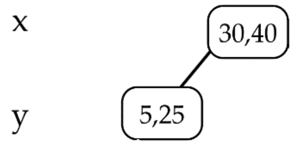
1. *Building the k-d tree by inserting all points in this binary tree. This will be done in the constructor of the new NearestNeighborsKD class.*
2. *Finding the neighbors of a given point by searching in the binary k-d tree that should have a depth of O(logN). This will be done in the rangeQuery method.*

1. Building the k-d tree

The k-d tree will be built from the point cloud contained in the files given to you. Since these are 3D point, your k-d tree will be a 3-d tree. You will read the point cloud csv file and store the point in a List<Point3D> as you did before. You will then construct the NearestNeighborsKD instance by passing the list of points to the constructor inside which the binary tree will be built.

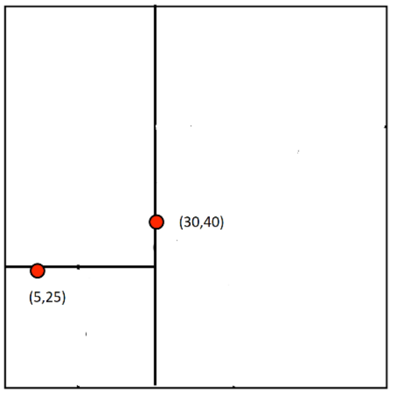
K-d trees have been invented by Jon Bentley in the 1970s. They are used to store spatial data on which quick search operations can be done. A k-d tree is a kind of binary search tree that splits a point set through comparisons done against <u>one</u> dimension at each level. For simplicity, we show an example that uses 2-dimensional points (x,y). In this case, the first level of the tree will use the x-dimension, the second level uses the y-dimension, the third level the x-dimension, the fourth the y-dimension etc.

Like for the case of binary search tree, the first element that is inserted becomes the root of the tree. For example, let's say that the point (30,40) is inserted in our 2-d tree. The next points to be inserted will be compared to this point at the root but using only the x-dimension. All points with an x-coordinate smaller or equal to 30 will go to the left of the tree, the ones greater than 30 will go to the right. Therefore, if we insert point (5,25), this one will become the left child of the tree.

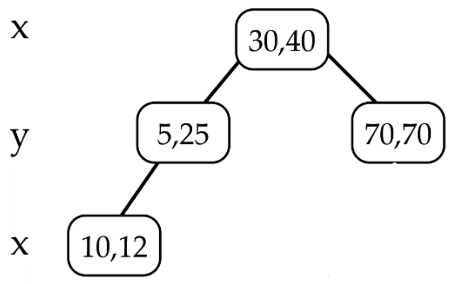


When points to be inserted will reach this second node, they will be compared using, this time, the y-coordinate, if this one is smaller or equal to 25, then the point will go to the left, if not it will go to the right.

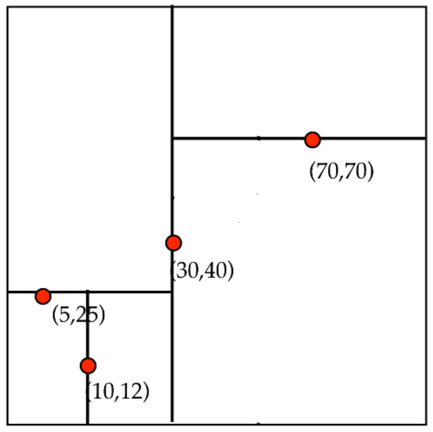
Now, if we look at the space of points, this means that with the first node we have split the space of points into 2 partitions: the points with an x-coordinate smaller than 30, and the ones with an x-coordinate greater than 30. Because of the second point inserted, the left partition has been further split into 2 sub-partitions, along the vertical axis this time, with 25 as the splitting value. This is illustrated by the following 2D space of points.



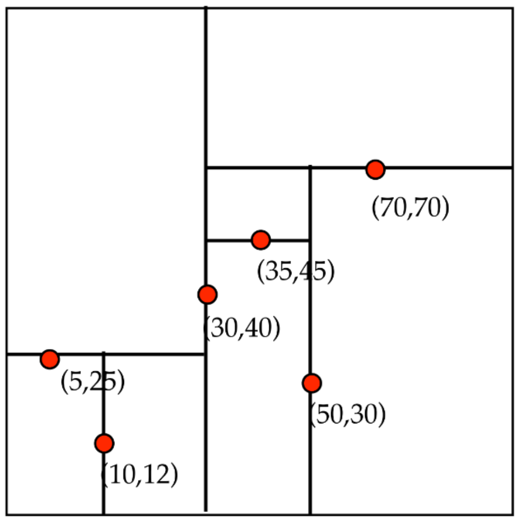
Each time we insert a new point, the space of point, one of the partitions is split along the axis that corresponds to the tree level where the point has been inserted (always alternating between x and y). Let's see what happen if we insert points (10,12) and (70,70). The 2-d tree will be as follows:

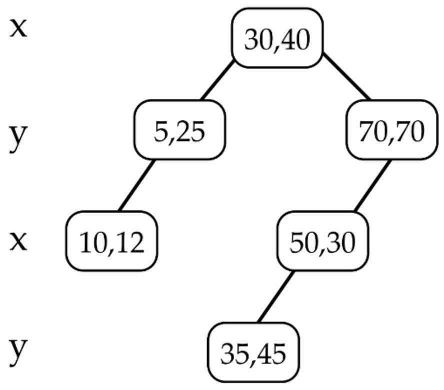


which partitions the 2D space as follows:



And the process continues until all points have been inserted. Here we add two more points:





Remember that in the case of 3D points, you will alternate between x, y and z-coordinates.

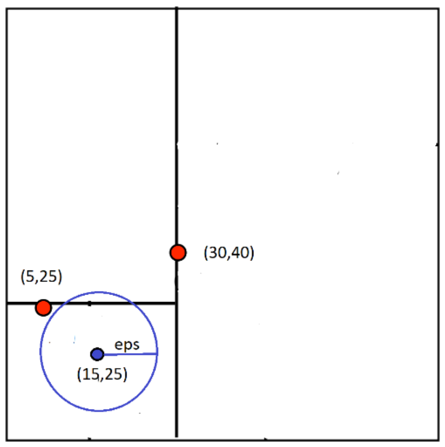
2. Finding the neighbors of a point

You will have to create a new rangeQuery method that will be called by your initial rangeQuery method.

Again, for simplicity, we now explain how to do the search using a 2-d tree example. Going back to the example we show, we know that, at the root of the tree, the space of points has been divided into two partitions, the ones having an x-coordinate smaller and greater than 30. Now suppose you are looking for the neighbors of a query point (15, 20) with an eps value of 10.

- The first thing to do is to check if the point stored at this node is a neighbor: the distance between (15,20) and (30,40) is greater than 10 so (30,40) is not a neighbor of query point (15,20) so we do not add it to the list of neighbors.
- The next step is to continue the search inside the k-d tree. We do this by comparing the x-coordinates of the query point and the node point. Since 15+10=25 is smaller than the cut value of 30, we know that all neighbors of point (15,20) have to be on the left part of the tree. We can therefore recursively search the neighbors from the left sub-tree which leads us to the (5,25) node.
- The distance between the query point (15,20) and the point (5,25) is also greater than 10, so this point is not a neighbor of point (15,20).
- As we did before, we must now check in which sub-partition we should continue to search for the neighbors of (15,20). At this level, the cut value is the y-coordinate of the node point (5,25). Since 20-10=10 is smaller than the cut value 25, we have to search for neighbors in the left sub-tree. But we also have 20+10=30 greater than 25, so neighbors can also be present in the right subtree. In this case, we must therefore search in both sub-trees.

This process is illustrated below where we see that the neighbors of the query point have to be inside the drawn circle. We must search inside all partitions that intersects with this circle.



Programming the k-d tree

You must create the KDnode inner class with the following attributes:

- point: the Point3D associated with this node
- axis: the splitting axis (x, y, or z) represented by integers 0, 1 or 2
- value: the splitting value (the coordinate value of the splitting axis)
- left: a reference to the left node (or null)
- right: a reference to the right node (or null)

To facilitate your programming, you should add to the Point3D class, created in Part 1, the following get method that returns the value of a specific coordinate

-
  ```
  public double get(int axis)   // axis is 0 for x,
                                // 1 for y, 2 for z
  ```

The KDtree class that contains the tree structure. Inserting in this tree is like inserting in a binary search tree except that the coordinate used for splitting alternates from level to level.

```
public class KDtree {

  public class KDnode {

     public Point3D point;
     public int axis;
     public double value;
     public KDnode left;
     public KDnode right;

     public KDnode(Point3D pt, int axis) {
       this.point= pt;
       this.axis= axis;
       this.value= pt.get(axis);
       left= right= null;
     }
  }

  private Node root;

  // construct empty tree
  public KDtree() {

     root= null;
  }

     ...
```

The new NearestNeighborsKD class will have the same basic methods as the one created in part 1, that is:

- a constructor that accepts a List of Point3D
```
NearestNeighborsKD(List<Point3D>) // that creates a k-d tree
                                  // from the list of points
```
- a rangeQuery method that finds the nearest neighbors of a 3D point
```
// this method will call a new method searching a the k-d tree
public List<Point3D> rangeQuery(Point3D p, double eps) {
     List<Point3D> neighbors;
     rangeQuery(p, eps, neighbors, kdtree.root());
     return neighbors;
}
```
- A KDtree instance will be embedded into this class. The constructor of the `NearestNeighborsKD` class will create this tree instance and add all points to this tree:
```
NearestNeighborsKD(List<Point3D> list) {

     kdTree = new KDTree();
     List<Point3D> neighbors;
     for (Point3D p : list) {
          kdTree.add(p); // the add method should call the
                         // insert method given in pseudo-code
     }

     // plus possibly other initializations
}
```

- The search for neighbors in the k-d tree is done by the following class (called by the original rangeQuery method). The pseudo-code of this recursive method is given in the next section.
```
private void rangeQuery(Point3D p, double eps,
                         List<Point3D> neighbors, KDnode node)
```

Note:
There is several variants of the k-d tree representations. This one is among the simplest but does not guarantee to produce a balanced tree so it has a worst case search complexity of O(N).

Algorithms

```
insert(P : Point, node : KDnode, axis : integer) {

     if (node == null)
          node = new KDNode(P, axis)
     else if (P.get(axis) <= node.value)
          node.left = insert(P, node.left, (axis+1) % DIM)
     else
          node.right = insert(P, node.right, (axis+1) % DIM)

     return node
}


rangeQuery(P : Point, eps : double, N : list, node : KDnode) {

     if (node == null)
          return

     if (distance(P, node.pt) < eps)
          N.add(node.pt)

     if (P.get(node.axis) - eps <= node.value)
          rangeQuery(P, eps, N, node.left)

     if (P.get(node.axis) + eps > node.value)
          rangeQuery(P, eps, N, node.right)

     return
}
```

Experiments

To perform the experimental part of this assignment, you must have the following 2 classes:

- `NearestNeighbors`: that finds the nearest neighbors of a point though a simple linear search (see part 1)
- `NearestNeighborsKD`: that finds the nearest neighbors of a point using k-d trees.

1. Experiment 1: Validation

Using the point list contained in the file `Point_Cloud1.csv`, find the nearest neighbors of the following points using an eps value of `0.05`:

```
1. (-5.429850155, 0.807567048,   -0.398216823)
2. (-12.97637373, 5.09061138,    0.762238889)
3. (-36.10818686, 14.2416184,    4.293473762)
4. (3.107437007,  0.032869335,   0.428397562)
5. (11.58047393,  2.990601868,   1.865463342)
6. (14.15982089,  4.680702457,   -0.133791584)
```

For each of these query points, create a text file containing the neighbors. You perform this search using both approaches (linear and k-d tree). Name the file using the point number (1 to 6) and the method used (lin vs kd). For example, the file containing the neighbors of the first query point should be named:

`pt1_lin.txt` and `pt1_kd.txt`

If your two classes work well, both methods should produce the same list of neighbors but not necessarily in the same order.

2. Experiment 2: Computational time

For each of the three point cloud files (1 to 3) provided, you will compute the time required (in ms) to find the neighbors of every 10 points in a file, using the eps value `0.5` (i.e. in the case of Point_Cloud1.csv, you will find the neighbors of the 10th point in the file, the 20th, the 30th until the 29630th point, the 1st point being the point (0,0,0)). Important: you compute the time to execute the method `rangeQuery`, not the time required to build the k-d tree.

```
long startTime = System.nanoTime();
nn.rangeQuery(point, eps);
long endTime = System.nanoTime();

long duration = (endTime - startTime)/1000000 // in milliseconds.
```

We want the average time to find these neighbors for each file and for each method (linear and k-d tree). Hopefully, the k-d tree method should be faster…

3. Experiment 3: Integration to DBScan

Now we would like to compare the computational speed of DBScan using `NearestNeighborsKD` instead of the linear neighbor search implemented in P1; we expect the former to be faster than the latter.

Compute the runtime of your DBScan program created in part 1, then replace the `NearestNeighbors` class by the `NearestNeighborsKD` class and compute again the total runtime. Perform this comparison for the three point cloud files provided.

Submission

For this assignment P2, you have to submit the following items:

- **All your Java classes in a zip file**, in particular
  - the `NearestNeighborsKD` class
  - the `KDTree` class
  - and three classes containing the main method required to perform experiment 1, 2 and 3.

- **A report in PDF format**
- For experiment 1, you must provide:
  - The `Exp1` class containing the `main` method for running experiment 1. This class should be run by specifying, the method used for searching (lin or kd), the parameter value (eps), the point cloud filename and the query point:

```
java Exp1 lin 0.05 Point_Cloud_1.csv -5.42985 0.80756 -0.39821
```

    The program should display number of neighbors found and the list of neighboring points (one per line).
  - In the report, a description of the results you obtained and the tests you made to confirm that both methods give the same results.
  - The 12 files `pt1_lin.txt`, `pt1_kd.txt` to `pt6_lin.txt`, `pt6_kd.txt` in a subdirectory called `exp1`.
- For experiment 2, you must provide:
  - The `Exp2` class containing the `main` method for running experiment 2. This class should be run by specifying, the method used for searching (lin or kd), the parameter value (eps), the point cloud filename and the step parameter for the query points.

```
java Exp2 kd 0.5 Point_Cloud1.csv 10
```

    The program should display the average compute time to find neighbors from the list of points.

  - In the report, a description of the results you obtained. Comment on the compute times you obtained, are they what you expected?
- For experiment 3, you must provide:
  - The `Exp3` class containing the `main` method for running experiment 3. This class should simply run the DBScan as in part 1 but, this time, using the new NearestNeighborsKD class. In addition, the program should display the total runtime (including all steps: file reading, tree construction, queries, etc.).
  - In the report, provide a comparison between the runtime of the DBScan program for the three provided files and for the two methods. Comment on the results you obtained (are they the same for both methods) and on the compute times you obtained, are they what you expected?
  - Note that experiment 3 worth only 10%, so if you have not been able to complete part 1 of this assignment, simply explain in the report why you are not able to run this last experiment and your assignment will be marked on 90%.

Marking grid

k-d tree construction	20%
k-d tree search	20%
NearestNeighborsKD class	10%
Quality of programming (structures, organisation, etc)	10%
Quality of documentation (report, comments and headers)	10%
Validation test	10%
Computational time experiment	10%
Integration to DBScan	10%

All your files must include a header that includes your name and student number. All the files must be submitted in a single zip file.