Calculating Spatial Distance Histograms For 3D Points

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Abstract—Complex aggregates are functions offered by database management systems to do rigorous calculations without redundancy in code. Database management systems such as PostgreSQL offers users the ability to implement and integrate additional complex aggregates. The project goal was to compute the spatial histogram in 3D space. We used 3D spatial distance histogram implementation and generated a quadtree index of the points. Result of the SDH query was stored into a table.

I. INTRODUCTION

Aggregation is the formation of a number of things into a cluster such as adding all values of a column to find the sum. Database management systems (DBMS) such as PostgreSQL supports such complex aggregates to help the user perform complex analytical task with their SQL server. PostgreSQL currently supports various aggregates such as SUM, MAX, MIN, AVG, and COUNT. If a aggregate is not supported, PostgreSQL provides the ability for users to implement their own aggregate function in a compatible language such as C and integrate it into the codebase.

A. Problem Statement

A spatial distance histogram (SDH) is the histogram of distances between all pairs of particles in the system [2]. While the current codebase handles SDH queries for a set of 2D points, our task is to extend the complex aggregates in another language to handle a set of 3D points and integrate it into the codebase.

II. METHODOLOGY

In this section, we will discuss how to integrate with PostgreSQL, how quadtrees can be used for indexing and the algorithm behind SDH.

A. PostgreSQL Integration

PostgreSQL allows users to extend functionality by creating custom attributes to complement the database server such as custom types, aggregate functions and general purpose functions. Moreover, while the PostgreSQL source code is written in the C language, we have the freedom of using any external language that can be integrated into the source code including the procedural language provided by PostgreSQL themselves called plpgsql. We have made use of these to create external functions in both C as well as plpgsql.

At a high level, the custom source code is dynamically loaded via shared library object files which are OS specific. As long as the absolute path to these . so files are provided or they are available in the dynamic library path, these files can be referenced inside a database session in PostgreSQL using SQL functions. PostgreSQL provides some much needed abstractions in the form of C macros to aid in retrieving user data such as arguments to a function or data inside of SQL tables.

1) Custom Type: We start with creating a custom type called Point3D to store our 3 dimensional data. Point3D is defined as follows:

```
typedef struct Point3D
{
    double x;
    double y;
    double z;
} Point3D;
```

As can be seen from the interface, each coordinate is stored as a double numeric type. All other custom functions that we have are created on top of Point3D.

2) Custom Functions: We have a general purpose function named distance3d to calculate the euclidean distance between any 2 given Point3Ds.

We also have the aggregate function SDH that populates the histogram and stores each bucket as its own row.

B. QuadTrees/Octrees

QuadTree is a tree like data structure which has exactly four children. It's used to store 2D points that can be traversed efficiently in logarithmic time [3]. QuadTrees are commonly used to index geographical data by partitioning two-dimensional space into four quadrants and recursively subdividing it until all points are mapped. Octrees are an extension of quadtrees, octrees have eight children and are often used to partition three-dimensional spaces and store 3D points, such as images. For our uses, since we are just calculating the distance of a spatial histogram, a quad tree is more than enough to store the data.

C. Spatial Distance Histogram Calculation

For our project, we went with the brute force method [4],[1] as shown in Algorithm 1.

```
Algorithm 1: Spatial Distance Histogram
  Input: Set of 3D points
  Output: Set of distances of 3D points between
            buckets in a histogram
1 arr = Set of 3D points
2 histogram = list of buckets
3 for i \in numSamples do
      for j \in numSamples do
4
          x_1, y_1, z_1 = arr[i]
5
          x_2, y_2, z_2 = arr[j]
          dist = euclidean distance between
 7
           (x_1, y_1, z_1) and (x_2, y_2, z_2)
          h_n os = |dist/bucketWidth|
 8
          histogram[h_n os].distCount++
      end for
10
11 end for
12 return histogram
```

III. RESULTS

For the calculation of the SDH query, we were able to create a list of 3d points and stream them into the table such as shown on Fig. 1.

Once the 3d point table was populated, it was passed into the SDH custom aggregate that goes row by row to calculate the point-to-point distances and update the histogram distribution count as per Algorithm 1. The resulting SDH is shown on Fig. 2.

IV. FUTURE WORK

Since the scope of the project was small, we had to implement the ideas that were feasible while discarding the rest for a later time. Some of the future work that we could do is has the 3D point accept any datatype, on top that we would also like to be able to pass in a whole set of 3D points at once rather than one at a time. From the SDH standpoint, another future work is to implement the faster method [2] of SDH instead of the brute force method. The faster algorithm on top of doing a full scale octree instead of quadtree for indexing would speed up performance of the whole program.

While researching the SDH problem, we found an external library call PostGIS which makes solving the SDH problem easier for future integration. PostGIS is a spatial database extender for PostgreSQL object-relational database. It adds support for geographic objects allowing location queries to be run in SQL. What made PostGis useful is that it had an implementation of SDH that was more robust and adaptable to different scenario.

```
select * from points:
          p
(-63.91,0.51,-20.28)
(57.07,-72.7,-1.19)
(-35.25,12.16,41)
(-23.34,48.44,31.09)
(36.1,-75.22,-1.79)
(-63.71,94.41,-65.74)
(-73.5,58.67,-71.96)
(-21.95,84.23,-60.07)
(-37.91,-5.07,63.12)
(-55.53,94.17,-78.86)
(-33.87,27.29,50.7)
(99.98.68.64.4.55)
(-96.53,55.92,-68.24)
(-26.1,44.95,37.59)
(74.76,-28.64,-92.08)
(-55.42,-96.73,21.5)
(-54.24,25.24,-48.78)
(5.59, -74.44,81.68)
(15.06,-16.35,34.61)
(7.36,-64.62,61.37)
(91.58, -36.22, 26.51)
(93.26,-16.11,51.45)
(88.85,91.26,-74.16)
(55.9,61.25,-91.26)
(-50.65, -73.45, -10.38)
(45.87,-33.76,-42.62)
(15.5,60.82,-9.2)
(30.75,-10.43,24.18)
```

Fig. 1. Table storing 3d points

V. CONCLUSION

Overall this project was nourishing in what it set for us to do and how to accomplish it. In the pursuit of implementing a complex aggregates, we learned the inner workings of PostgreSQL codebase. Since the codebase was highly modularized, it was simple to see how to plug in our complex aggregate implementation. We learned how to dynamically link a function with the source code and we learned a little bit about the complexity of indexing in a DBMS. Some of the problems however were mostly in project requirement. Since the project description wasn't very clear, there was some confusion as to what a spatial distance histogram was since we never learned it in class, how the SDH query gets tested,

i	count
-	Count
	1 11
0	
1	
2	
3 4 5	
4	106 153
2	
6	1 159
7	217
8	255
9	292
10	284
11	327
12	331
13	321 365
14	
15	340
16	359
17	331 292
18	
19	231
20	164
21	136
22	1 107
23	49
24	35
25	24
26	11
27	7 1
28	
(29 rows)	

Fig. 2. Table showing the output of the SDH for 100 sample 3D points with a bucket width of 100

and what are the expected results. Another issue we had is that the description said there was an initial SDH codebase that handled 2D points but that wasn't provided beforehand nor was it in PostgreSQL codebase so we had to do some investigation to find it. However once those were cleared up, we had no issue doing the project.

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