DPS: A Novel Approach for Efficient Direction-Based Neighborhood Queries

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01

Introduction

Context

Spatial Data Utilization

- Technological advancement and popularization of mobile devices
- Large volume of spatial data generated and consumed
- Various types of applications::
  - Location-based services
  - Route planning
  - Emergency management and control

Large Data Volume

- Needs:
  - Efficient processing
  - Fast and relevant response in various contexts

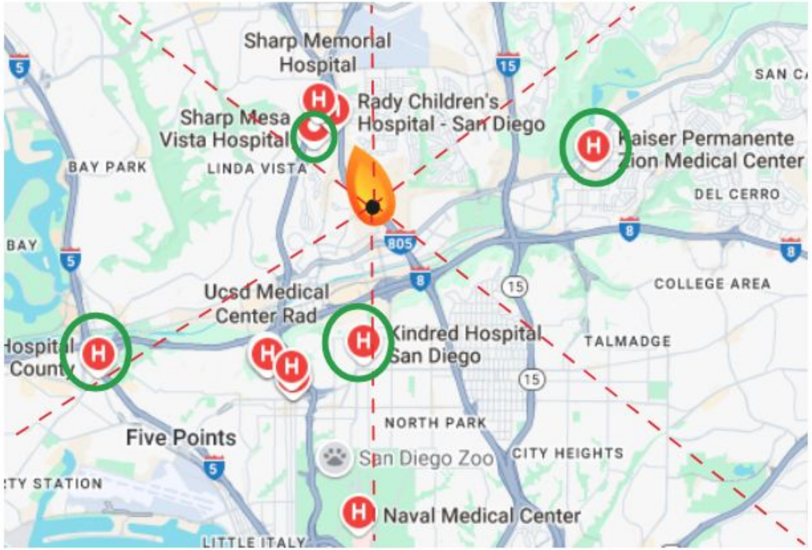
Query Contexts

- Most applications and services use the metric factor as the basis for queries
- Only distance is relevant (KNN)
- Example: Nearest hospital in relation to a person's location

Context

Query Contexts

- The metric condition alone is not always sufficient
- Directional condition is necessary, depending on the context
- Diversity in results
- Example: In a fire situation, searching for hospitals or services:
    - The closest ones might be in a direction inaccessible due to fire or smoke
    - It is desirable to have the closest services returned in different directions



Problem and Motivation

Direction and Distance-Based Neighborhood Queries

- Return the closest objects in different directions around a query point
- Examples in literature:
  - DBS (Direction-Based Surrounder)
  - DNN (Direction-Aware Nearest Neighbor)

DBS and DNN

- Based on **dominance relation**
  - Define dominant objects: those that will be returned in the response
  - Rules based on direction and distance of objects
    - Parameter θ (threshold):
      - The larger θ, the greater the restriction of results
        - Dominant interval is larger
      - The smaller θ, more comparisons performed between objects
        - Longer it takes for the stopping criterion to be reached
  - Aim to ensure **diversity of results**
- Each has its own type of dominance relation

Problem and Motivation

01 — **Computational Efficiency**

- Iterative process
- Dominance relation verified for each object until a stopping condition is reached

02 — **Result Diversity**

DBS: diverse but restricted results
DNN: more diverse results but directionally close to each other in some cases depending on database characteristics

Limitações

Need for Improvements

- Reduction in query execution time
- Consistent diversity regardless of database characteristics

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DPS: Our Novel Approach

Direction Proximity Search (DPS)

DPS Goals

- Reduce processing time
  - Geometric partitioning of the search space that significantly accelerates nearest neighbor retrieval around query point for each partition
- Diverse and consistent results
  - Set of rules that ensures diversity and directional distribution of results regardless of database characteristics and query parameterizations

Three-stage process

Partitioning

Space surrounding the query point is partitioned into geometric regions covering different directional sectors

Processing

Identifies the nearest object to the query point within each partition

Refinement

A dominance relation is established between objects and their respective partitions, guaranteeing that each angular interval of size θ contains at most one object in the final result set

DPS - Partitioning

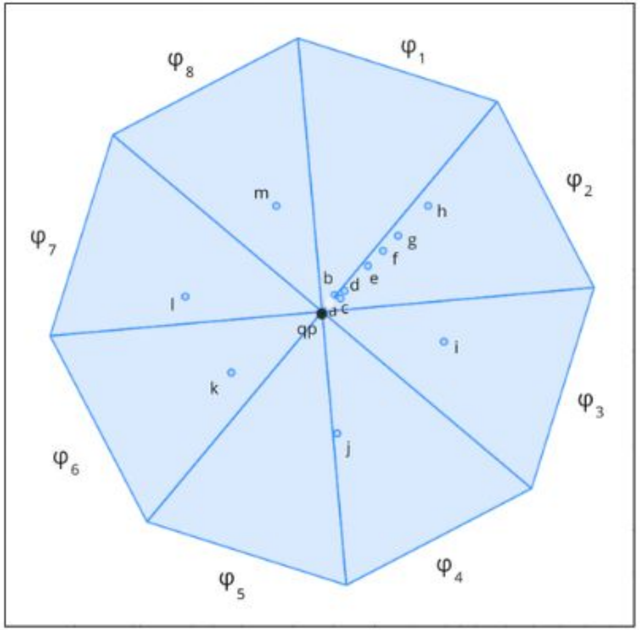
The main objective of this stage is to perform geometric partitioning of the space around the query point.

Algorithm: Partitioning

Require: Query point q, dataset D, angle θ, distance *distMax*, number of partitions n

Ensure: Set of partitions Φ

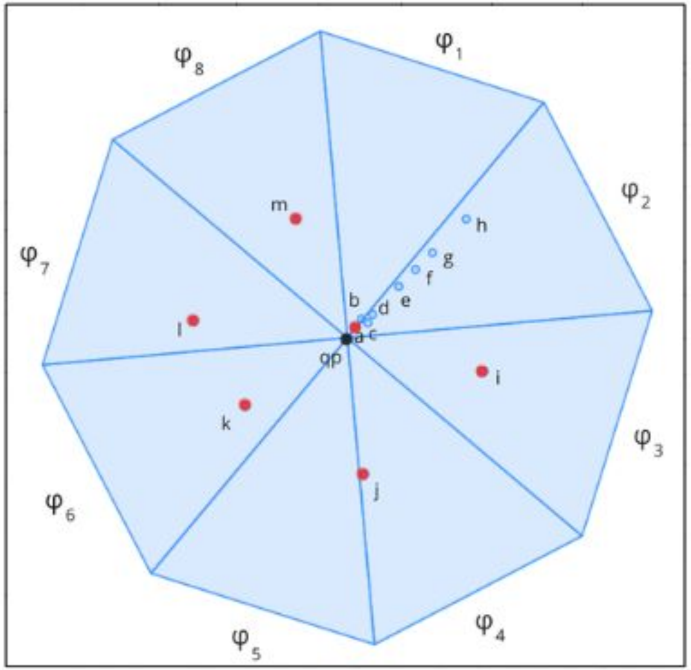
```
// First Partition Construction
NN ← FindNearestNeighbor(q, D)
NN' ← Project(NN, distMax)
v⃗ ← qNN'
ls ← Rotate(v⃗, θ/2)
φ₁ ← CreatePolygon(q, NN', ls)
Φ ← {φ₁}
// Complete Partitioning
for i = 2 to n do
  lprev ← GetUpperBoundary(φᵢ₋₁)
  lnew ← Rotate(lprev, -θ/2)
  φᵢ ← CreatePartition(lprev, lnew)
  Φ ← Φ ∪ {φᵢ}
end for
return Φ
```



DPS - Processing

The objective of this stage is to process each partition simultaneously and return the objects closest to **q**

- Retrieves objects that intersect with the partition
- Returns the object closest to q in each partition



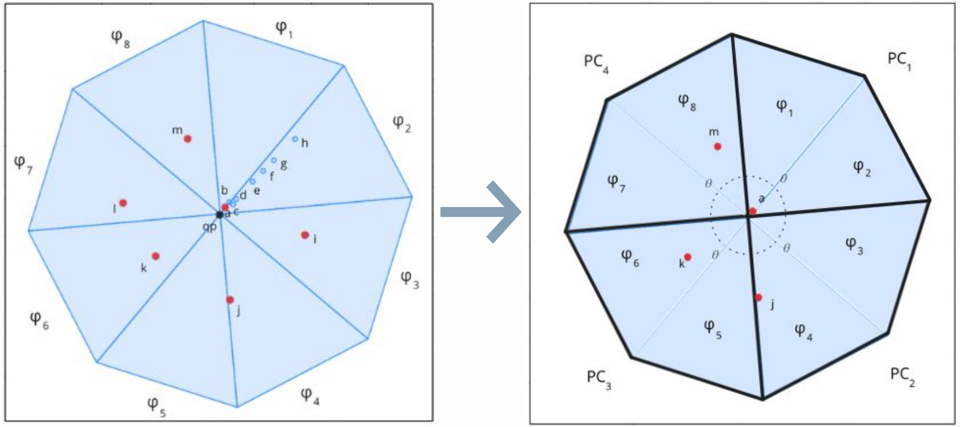
DPS - Refinement

- The objective of this stage is to ensure that the objects found are not directionally close to each other.
- Reduce the number of partitions to guarantee that each θ interval is represented by at most 1 object.

Algorithm: Refinement

Require: Ordered processing list $List_p$
Ensure: Result set R

```
ignored ← ∅
R ← ∅
for each (φᵢ, NNᵢ, distᵢ) in Listₚ do
if φᵢ ∉ ignored then
  R ← R ∪ {NNᵢ}
  adjacent ← GetAdjacentPartitions(φᵢ)
  ignored ← ignored ∪ adjacent
end if
end for
return R
```



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Experimental evaluation

Datasets

Synthetic Datasets

- Spider Generator
- Volumes
  - Small: 20.000
  - Medium: 200.000
  - Large: 2.000.000
- Distributions
  - Uniform
  - Diagonal
  - Gaussian
  - Sierpinski
  - Bit

Real Datasets

- Collected from the OpenStreetMap platform
- Extraction of point-type data from Brazil
- Volumes
  - Small: 22.628
  - Medium: 174.449
  - Large: 3.733.292

Configurations and Parameterizations

Hardware Configurations

- Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz, 12 cores
- 16GB RAM
- SSD 1TB
- Ubuntu 20.04.1 64 bits

Query Parameterization

- Variation of θ (20°, 45°, 60° and 90°)
- Variation of **query point** and **distMax** between synthetic and real databases
- Cache cleaning after each query

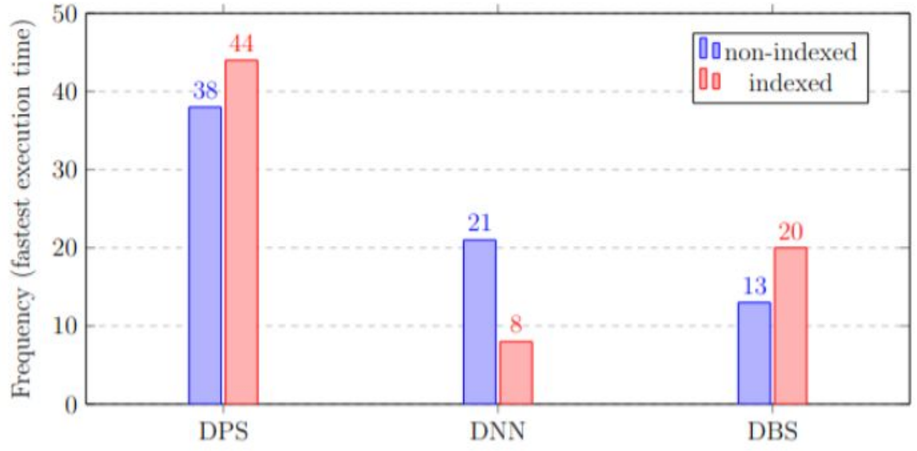
Evaluation process

- Execution of queries on non-indexed databases
- Execution of queries on databases indexed using the PostGIS GiST method (R-Tree variant)
- Results analyzed to identify the best execution times for each type of parameterization
- Comparative analysis of the diversity of objects returned by queries

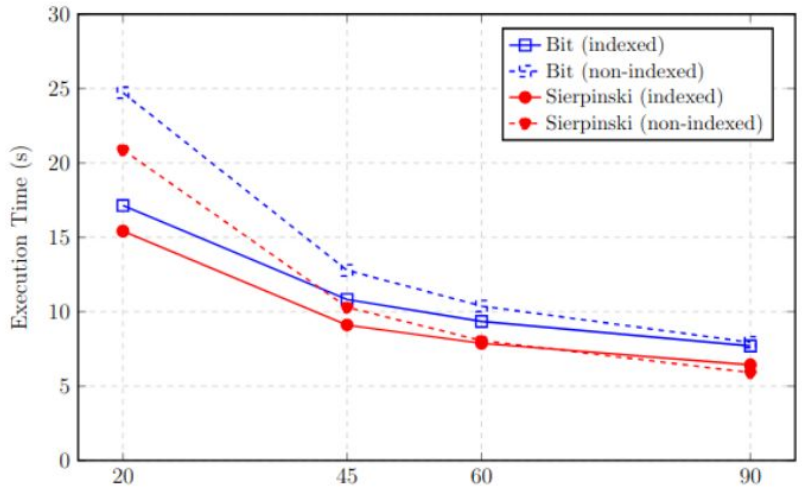
Results

Performance Overview

- Best execution times
  - 52.8% of queries on non-indexed databases
  - 61.1% of queries on indexed databases

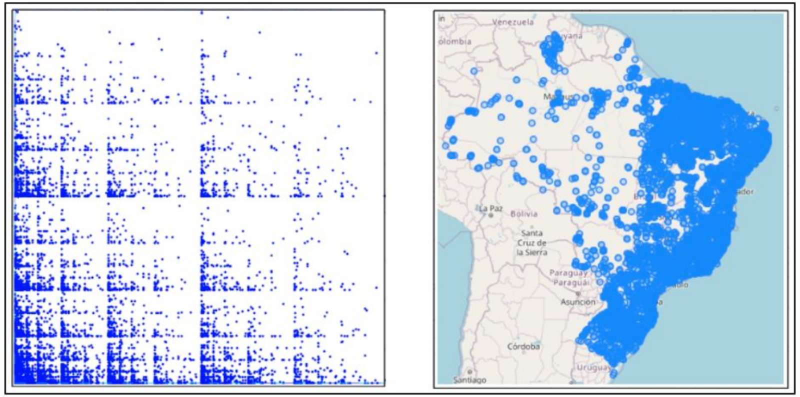


- Execution time for large datasets of Bit and Sierpinski distributions
  - Up to 99.9% improvement in execution time



Results

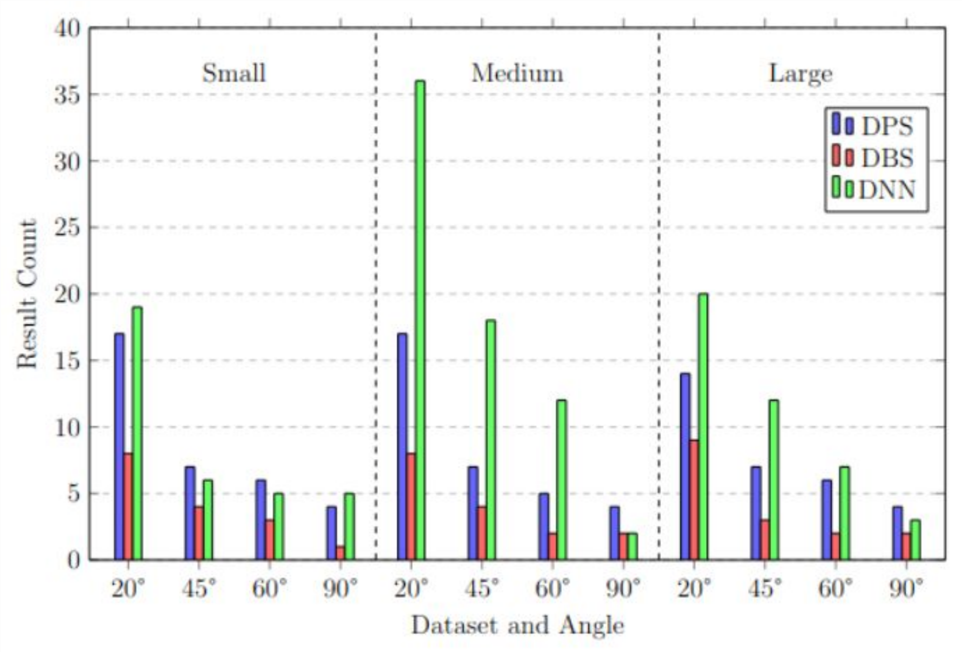
- Real Datasets:
  - Real data has similar pattern as Bit distribution (high direction density)
  - Only 2 cases where it didn't have the best result
  - Best result: Average improvement of 97.3% in execution time for 20-degree angle in medium-sized database



Database Size	Angle	Non-Indexed			Indexed		
		DBS	DNN	DPS	DBS	DNN	DPS
Small	20°	4.37	4.36	**3.14**	4.19	4.22	**1.26**
	45°	2.18	2.13	**1.59**	2.00	2.05	**0.80**
	60°	1.25	**1.24**	1.34	1.13	1.14	**0.78**
	90°	1.28	1.18	**0.87**	1.11	1.19	**0.66**
Medium	20°	187.87	183.04	**4.51**	177.45	182.37	**5.05**
	45°	21.84	21.81	**2.39**	21.30	22.16	**2.51**
	60°	6.04	6.05	**1.92**	5.92	6.01	**2.09**
	90°	**0.78**	**0.76**	1.50	**0.71**	**0.71**	1.63
Large	20°	93.44	98.22	**37.41**	91.63	98.58	**32.13**
	45°	74.59	73.90	**19.06**	72.57	73.02	**19.44**
	60°	33.97	33.85	**15.27**	32.80	32.50	**16.75**
	90°	4.22	**3.97**	11.61	3.52	**3.49**	13.49

Results

- Diversity and consistency of the result set
- One dominant object per θ interval
- Maximum of 360°/θ results:
    - 20° = 18
    - 45° = 8
    - 60° = 6
    - 90° = 4



Results

- **Overall Results:**
  - DPS outperformed DBS and DNN algorithms in 52.8% of queries on non-indexed databases and 61.1% on indexed databases.
  - With Bit and Sierpinski distributions, DPS achieved exceptional performance with 99.9% improvement in execution time on large databases.
  - The algorithm excels in spatial distributions with high object density in specific directions, explaining its superior performance on both synthetic and real-world datasets.
  - DPS showed better performance with smaller angle parameters (20° and 45°) as they impose less strict dominance restrictions.
  - The algorithm consistently maintains that the maximum number of returned objects equals 360°/θ, guaranteeing at most one dominant object per θ interval.

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Conclusion

Conclusion

- We presented DPS (Direction Proximity Search), a geometric partitioning approach for direction-based queries. DPS reduces execution time by up to 99.9% compared to existing methods—completing queries in under 25 seconds that previously took over 24 hours.
- It ensures directional diversity by returning at most one object per θ interval.
- While our experiments focused on geographic datasets, DPS has potential applications in autonomous navigation, IoT networks, and emergency response scenarios.
- Our evaluation was limited to datasets of up to 2 million points, with real-world applications potentially presenting additional challenges.

Future work:

- Intelligent Query Selection: Develop models to automatically choose between DPS, DBS, or DNN based on dataset characteristics and query parameters.
- Scalability Analysis: Evaluate DPS performance with datasets exceeding 10 million objects and identify optimization opportunities.
- Dynamic Environments: Adapt DPS for scenarios with frequently changing data, such as real-time traffic or mobile sensor networks.
- Extended Domains: Explore applications beyond spatial queries, including similarity searches in high-dimensional spaces.