

Evaluating the Impact Of Spatial Features Of Mobility Data and Index Choice On Database Performance

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Abstract

The growing number of moving Internet-of-Things (IoT) devices has led to a surge in moving object data, powering applications such as traffic routing, hotspot detection, or weather forecasting. When managing such data, spatial database systems offer various index options and data formats, e.g., point-based or trajectory-based. Likewise, dataset characteristics such as geographic overlap and skew can vary significantly. All three significantly affect database performance. While this has been studied in existing papers, none of them explore the effects and trade-offs resulting from a combination of all three aspects.

In this paper, we evaluate the performance impact of index choice, data format, and dataset characteristics on a popular spatial database system, PostGIS. We focus on two aspects of dataset characteristics, the degree of overlap and the degree of skew, and propose novel approximation methods to determine these features. We design a benchmark that compares a variety of spatial indexing strategies and data formats, while also considering the impact of dataset characteristics on database performance. We include a variety of real-world and synthetic datasets, write operations, and read queries to cover a broad range of scenarios that might occur during application runtime.

Our results offer practical guidance for developers looking to optimize spatial storage and querying, while also providing insights into dataset characteristics and their impact on database performance.

Keywords

spatial, benchmark, postGIS, performance, index

1 Introduction

Spatial data has become integral to modern applications due to the evergrowing amount of Internet-of-Things (IoT) devices. These devices produce geospatial information used in services such as real-time traffic-aware routing, incident hotspot detection, and weather updates and predictions, with various other use cases existing [16, 17, 22, 24]. Building such applications requires informed decisions regarding the technology stack, especially regarding data storage factors.

Spatial indexes enhance query performance in spatial databases by enabling efficient querying of spatial data [1, 27, 43]. These structures provide a way to quickly locate spatially co-located data points and vectors, while also enabling filtering of irrelevant data points. Some systems offer a single default index, while others, such as PostGIS, support multiple types, each with unique trade-offs between query speed, index creation time, and maintenance costs.

Moving object data is an important subset of spatial data, showing the movement of multiple objects over time. Such data can be stored in different formats, such as discrete points or trajectories [31, 37, 42]. While purpose-built systems for trajectories exist, general-purpose solutions such as PostGIS remain widely used due to their flexibility and ecosystem compatibility.

Choosing an optimal index and format for both spatial data and moving object data is non-trivial, as not all indexes are equally effective for all datasets and query types [26]. This is important to consider however, as the data format can impact the possible queries, the granularity of the query response, and the performance of the database. Performance may also vary depending on the characteristics of the data, such as spatial distribution and amount of data overlap, which can be difficult to determine a priori.

This paper investigates how spatial data characteristics, data format, and index choice impact database performance using PostGIS as a prototype database platform for our evaluation. We construct an application-driven benchmark using both synthetic and real-world spatial datasets with varying data distributions and degrees of overlap. We provide novel approximation methods to determine the degree of skew and overlap, which scale for large datasets by providing a constant time complexity using an approximation method. Our benchmark includes both read and write evaluations to fully regard the impact of dataset properties, index choice, and data format on database performance. Based on our results, we provide guidance for developers seeking to make informed storage decisions tailored to their use case.

Our key contributions are as follows:

- We develop novel, tunable approximation methods to assess overlap and distribution properties of trajectory-based datasets (§3).

- We design a benchmark for comparing data formats, data characteristics, and index types using both real-world and synthetic datasets in PostGIS, analyzing their impact on read and write performance (§4.1).
- We provide practical recommendations which index type and data format to choose depending on one’s dataset characteristics (§4.4).

2 Background and Related Work

In this section, we provide a background on moving object data, relevant storage and indexing strategies, and highlight key related work that guides our paper.

Moving Object Data

Moving object data is a category of spatial data that captures the position of objects over time enables mobility-based applications, such as traffic prediction, route planning, and fleet management [11, 12, 25]. Typically, this data originates from GPS sensors, producing a sequence of point observations. A trajectory represents a continuous path constructed by linking these points, for example, tracing a bicyclist’s commute [23].

Trajectories can be stored in different formats, such as storing individual points, segments of a trajectory (each with its own entry), or storing the full trajectory as a single object. Each format offers trade-offs: Storing trajectory segments allows for more fine-grained analysis, while whole-trajectory storage simplifies representation and storage at the cost of query flexibility. Figure 1 illustrates how these formats differ from one another.

Some databases provide interpolation features to support trajectory-based queries while storing data in a point-based format, with MobilityDB being a notable example [44].

Spatial Indexing Strategies

Spatial Indexes exist to support efficient querying of spatial data. These include R-Trees, QuadTrees, Generalized Search Trees (GiST), Block Range Indexes (BRIN), space-filling curves, and many more. Each of these have trade-offs in terms of data structure, dimensionality, and query performance. Many of these indexes rely on bounding boxes such as the Minimum Bounding Rectangle (MBR) to quickly filter irrelevant data points. A summary of common index types is shown in Table 1, however many more exist to also include other attributes such as time [14, 33]. Systems exist that implement custom indexing and storage techniques for trajectory data [2, 8, 21].

Factors Affecting Performance

Several features of trajectory data affect database performance, which includes the storage format, spatial distribution of data (data skew), and the degree of spatial overlap (intersections). Storage format influences how efficiently queries can be processed. For example, segmenting trajectories may enable better indexing but increase complexity. Data skew refers to uneven distribution of data over space, such as traffic clustering in urban areas. This may lead to an imbalance in indexing structures and performance degradation. Intersections refer to overlapping spatial objects, and while related, they are distinct from skew. High skew does not necessarily imply high intersection, as we show in §3. For instance, delivery vehicles often operate in dense urban zones (high skew) without frequent overlap due to route optimization.

Studies have addressed both phenomena. Chen et al. proposed specialized representations and intersection algorithms for 3D spatial data [6]. Others explored detecting skew in systems such as SpatialHadoop [4, 40].

The Role of Representative Datasets

Benchmarking indexing performance requires realistic, diverse datasets. Using only one dataset, as is often done, fails to account for performance variations due to data characteristics

For example, Zhang et al. demonstrate how data skew can be exploited to optimize queries [41]. Publicly available datasets like the Piraeus AIS maritime dataset provide ample real-world data (over 240 million records) for this purpose [34].

Related Work

A wide range of research has investigated spatial indexes and benchmarks. Nguyen et al. demonstrated the benefit of using spatial indexes with trajectories in PostGIS, but only evaluated GiST and ignored other strategies, and also only considered a single data format [27]. Additionally, the work focuses on a road network, which is not representative of moving object data in general.

Chen et al. benchmarked several indexes outside of a database, with synthetic car trajectory data [5]. However, they did not include real-world datasets or assess data formats.

Xu et al. proposed GMOVbench, a benchmark for multimodal trajectory data, but again relied on synthetic datasets and did not explore storage alternatives [39].

BerlinMOD introduced a mobility benchmark focusing on spatiotemporal queries and data generation [10]. Its contribution lies in query categorization, not in evaluating index or storage format impact.

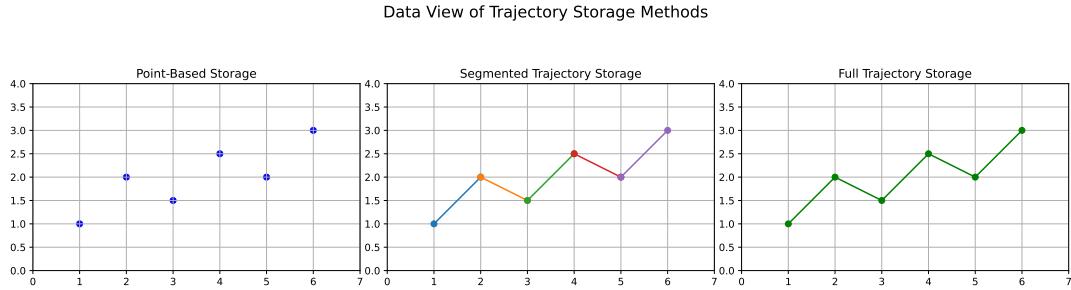


Figure 1: Moving Object Data can be stored in various formats, such as simply storing the point data. One can also store segments of the trajectory separately (each color represents a separate entry in the database), or store the entire trajectory as one object.

Index Type	R-Tree	BRIN	GiST	SP-GiST	Space-Filling Curves
Summary	Partitions points and spatial data in vector format based on their minimum bounding rectangle across a balanced tree structure	Relies on data being sorted by the queried attribute to optimally function due to dividing a table into block ranges	Uses a generalized R-Tree approach to function for multiple data types	Relies on an underlying QuadTree; Designed for space partitioned data (not necessarily spatial data)	Maps multiple dimensions of the dataset (do not have to be spatial/temporal) to a singular continuous curve
Commonly used for	Spatial data	Any data that can be sorted by the queried attribute	Various use cases	Spatially partitioned data	Multidimensional data
Used/Evaluated/ Adapted in	[3, 13, 43]	[36, 38]	[15, 29, 30]	[1, 29]	[19, 20, 35]

Table 1: Each of these indexing strategies has its own advantages and disadvantages, which can be used to determine the best index for a specific use case. The related work mentioned in the table is not exhaustive, but provides a good overview.

TrajStore proposed a specialized trajectory storage format and indexing mechanism [8]. While valuable, its architecture differs from widely-used systems like PostGIS.

3 Approach

Previous research has shown that certain indexes are better suited for overlapping and non-overlapping data, and that data distribution can also impact the performance of a database depending on the index [9, 28]. Developers therefore should be interested in their dataset characteristics to make an informed decision on which index to use.

In this section, we describe our benchmarking approach, while highlighting dataset features that we consider when selecting representative datasets for our evaluation. We provide novel approximation methods to quantify overlap and distribution in a dataset, which can be used as a guideline for developers to choose the appropriate index for their data.

Assessing the Impact of Data Skew and Overlap

Real datasets, while sharing common characteristics, can differ greatly in terms of data skew and overlap. Data such as urban cycling data is often more evenly distributed across the city; however, when including all data from a country, a large skew may be present.

Intersections and Overlaps. Intersections refer to two vectors or trajectories intersecting at one or more points, while overlaps refer to these trajectories occupying the same space for a larger amount of distance besides a single point. A simple example would be a 4-way street crossing: Two bicycles going in perpendicular directions have intersecting paths, while two going in the same direction overlap. In spatial databases that use MBR-based indexing strategies however, these two terms come together due to the way indexes are

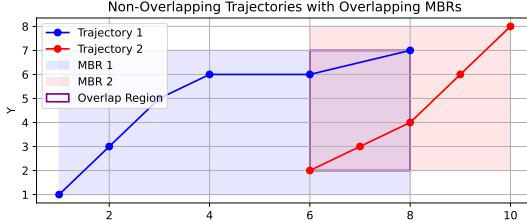


Figure 2: Trajectory 1 and 2 have overlapping minimum bounding rectangles, but do not intersect.

structured. As mentioned in the previous section, MBRs help quickly filter irrelevant data when running queries and allow for faster query responses. When regarding two trajectories for a possible intersection, the system first checks these MBR structures for an overlap, leading to the interchangeable use of the two words in this context. Figure 2 shows how both actually intersecting and non-intersecting data can have overlapping MBRs.

Determining the Global Overlap Coefficient. The amount of overlap in a dataset is crucial for the choice of the most suitable index, as some indexes perform better when data is space partitioned [1]. Given a trajectory t and another trajectory t' , we can determine if they overlap in matters of bounding box based-indexing by checking if their MBRs overlap. Using this, we can turn our trajectory data into a graph to use an existing graph metric to determine the amount of overlap in our dataset. We can represent each trajectory in our dataset as a node in a graph. If the MBR of two trajectories overlap, we create an edge between those nodes. An example of how the trajectory data is converted to a graph can be seen in Figure 3. A graph representation of our data enables us to apply graph density measures to quantify the trajectory overlap. The graph density sets the number of total edges in relation to the number of all *possible* edges. Given a set of nodes V and edges E , the density of a graph can be calculated as follows:

$$D = \frac{2|E|}{|V|(|V| - 1)}$$

Going back to our way of converting trajectories to overlaps, density in our case reflects the amount of overlapping trajectories in relation to the total amount of possible overlaps. A high density (i.e. closer to 1) indicates that a high degree of trajectories overlap with one another, while a low value (closer to 0) indicates the opposite. The general graph approach is not without its problems, especially with highly overlapping data: Generating a graph data structure from large trajectory datasets, containing millions or billions of instances, is computationally not feasible. We thus propose an

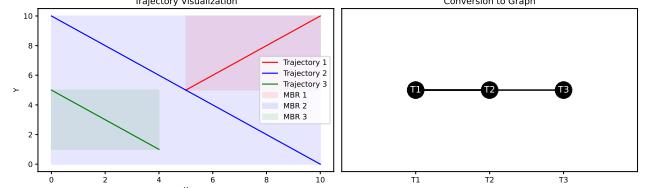


Figure 3: Traj. 1's MBR is overlapping with Traj. 2 and 3, while Traj. 2 and 3 are not overlapping. In graph form, each trajectory is a node and possesses an edge to overlapping trajectories. The GOC of this dataset would then be 2/3.

approximation to allow developers a fast estimation of their dataset characteristics. Given a dataset of m trajectories:

- We take n randomly selected trajectories from our dataset.
- We apply our approach to the selected trajectories and calculate the density of the graph.
- We repeat this process p times and take the median of all approximated densities.

This allows for a constant time complexity of $O(n * p)$ instead of $O(m^2)$ for all graph sizes, where we can choose n and p based on the desired accuracy of our approximation. In the rest of the paper, we refer to this metric as the global overlap coefficient (GOC) of a dataset.

Adapting Average Nearest Neighbor to Trajectories. The graph density, while suitable for evaluating overlap, does not cover the skew of a dataset. Data in some scenarios can be highly clustered without overlapping, which our density coefficient would not be able to detect. We therefore need an alternative approach to evaluate the distribution of our dataset. For point patterns, a common way to evaluate data distribution is using the average nearest neighbor (ANN) approach [7, 32]. Here we determine the average distance of each point to its nearest neighbor. The result is compared to the expected value of a dataset with a uniform distribution. The observed distance can be calculated as follows:

$$D_O = \frac{\sum_{i=1}^n d_i}{n}$$

where d_i is the distance of point i to its nearest neighbor, and n is the total amount of points in the dataset. The expected distance in a uniformly distributed dataset with n points can be calculated as:

$$D_E = \frac{0.5}{\sqrt{n/A}}$$

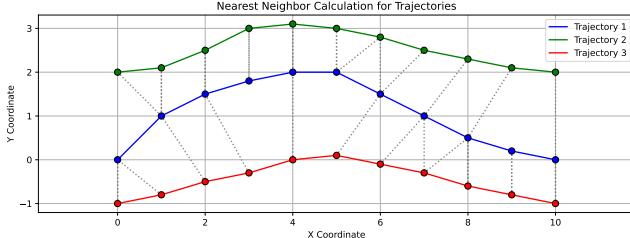


Figure 4: These simplified trajectories show how we can apply ANN to trajectories. With a small number of trajectories, exactly calculating this value is still realistic. Including a large amount of trajectories necessitates an approximation to finish the calculation in a reasonable time. Our ANN approximation excludes points from the own trajectory.

where A is the area of the bounding box of the dataset. The ANN is simply the ratio of the two values:

$$ANN = \frac{D_O}{D_E}$$

A value of < 1 indicates a clustered distribution, while a value of > 1 indicates a distributed dataset. The larger the value, the more distributed the dataset is. When applying this to trajectories, the idea does not hold up well: The distance between trajectories is the closest possible distance of the two, which is not indicative of their actual distribution. Two trajectories may intersect at one point, but be very far apart otherwise and still have a distance of 0. We can however still use the ANN idea if we convert our trajectories into multiple points. In this paper, we rely on the update frequency of the trajectory to convert trajectories, meaning that every time a sensor updates its position, we create a point in our dataset. Figure 4 shows how such a nearest neighbor approach would look like in a trajectory dataset, while immediately highlighting an issue: Given a large amount of trajectories, which in turn is transformed into an even larger amount of points, the ANN approach is too computationally expensive to be used in a reasonable time frame. We can again approximate the value by relying on a sampling strategy. Given a dataset containing m trajectories, each with k points, we use the following approach:

- We take a random point from a random trajectory.
- We calculate the nearest neighbor of this point, and store the distance.
- We repeat this process n times, sum up the stored distances, and divide by n to get the average distance.
- We scale this value by multiplying it with $(m * k) / n$ to get an approximation of D_O .
- We again repeat this process p times and take the median of all results.

This allows us to reduce the time complexity to $O(n * p)$, where we can choose n and p based on the desired accuracy of our approximation instead $O((m * k)^2)$ for all dataset sizes.

Covering all Bases with Representative Datasets. We include real-world datasets from a variety of use cases, such as cycling data, aviation data, and ship trajectory (AIS) data. However, when we want to evaluate the impact of skew and overlap on database performance, a broader combination of datasets is required. Various approaches to dataset generation are possible and have been implemented in a variety of papers [10, 18]. By implementing the following dataset generation strategies, we can cover a broad range of use cases and data distributions:

- Randomly generating trajectories within a bounding box.
- Evenly distributing trajectories within a bounding box, where we lay a raster over the bounding box and place trajectory starting points at the center of each cell.
- Enable a hotspot-based approach of trajectories, where trajectories mostly exist within hotspots and form clusters.
- Provide the same hotspot-approach with overlaps to other hotspots (as could be found in car traffic).

We run our benchmark against all mentioned datasets, and evaluate the impact of dataset features on database performance using them. All included datasets can be found in Table 2, where important data features are highlighted. Data sets are stored in two different formats: Line-based data can still differ in its storage format, as we could store the entire trajectory as a single object, or store each segment of the trajectory separately. These two approaches have trade-offs, with the segmented approach allowing for more fine-grained querying and analysis, while the trip as a whole reduces the entire trip to a single row in the database, which could lead to a change in performance. Therefore, both formats are included in our benchmark. A point-based approach reduces the amount of possible queries without prior conversion to a trajectory (at least within PostGIS and using real-world datasets), which led us to omit this format.

4 Evaluation

In this section, we evaluate database performance using both the synthetic and real-world datasets, and regard the impact of data format, index choice, and dataset characteristics in both read and write scenarios.

4.1 Experiment Design

We include different read query types in our evaluation to cover a broad range of real-world applications.

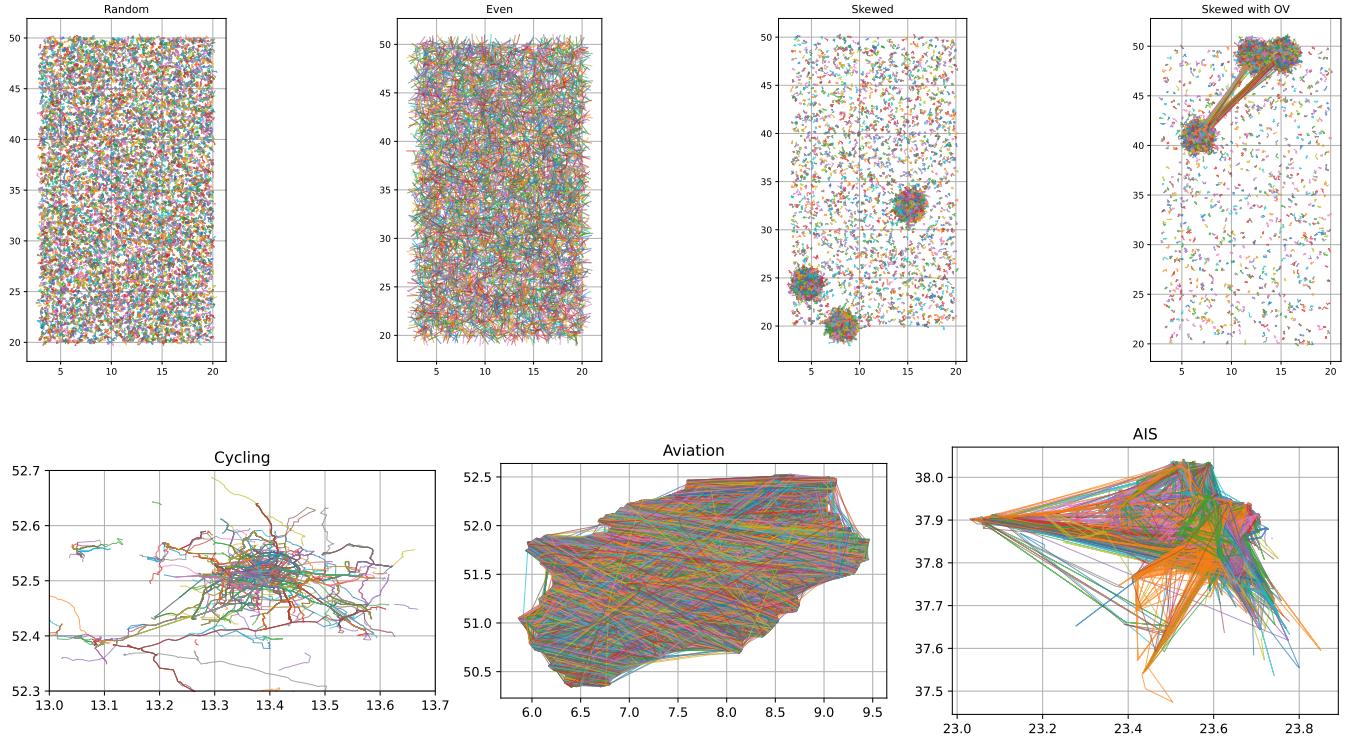


Figure 5: We include 7 different datasets in our evaluation, with 4 synthetic and 3 real-world datasets. The real-world datasets are from the SimRa project, the Deutsche Flugsicherung, and the Piraeus AIS dataset.

Dataset	Description	# Trajectories	GOC	ANN
Random (Random)	Random trajectories	3,000,000	0.0032	27.053
Evenly Distributed (Even)	Evenly distributed trajectories	3,000,000	0.0036	27.310
Skewed (Skewed)	Clustered data, where a high percentage of trajectories are centered around hotspots	3,000,000	0.048	16.477
Skewed with Overlap (Skewed with OV)	Clustered data, where a high percentage of trajectories are centered around hotspots, and a degree of trajectories travel to other hotspots	3,000,000	0.0553	12.963
SimRa (Cycling)	Cycling trajectory data from Berlin	4,387	0.106	5.052
Deutsche Flugsicherung (Aviation)	Flight trajectory data from Northrhine-Westphalia	215,908	0.201	0.698
Piraeus AIS Dataset (AIS)	AIS ship data from a research maritime dataset.	2,719	0.392	0.996

Table 2: We include synthetic and real-world datasets to cover a variety of data patterns that might occur in various use cases. We calculate GOC and ANN using our approximation method where appropriate, doing 10 iterations of 10000 samples each. Each dataset consists of 30,000,000 segments, which are distributed across the listed number of trajectories. The name in parentheses is the name used in our evaluation.

- How many other trajectories does a given trajectory overlap with (*Intersection* query)?
- What trajectories are partially/completely within a specified polygon (*Contains* query)?
- What are my K nearest neighbors to a given trajectory (*KNN* query)?
- How many trajectories are within a specific distance of a given trajectory (*Proximity* query)?

We additionally evaluate the three different write operations that can be performed (*Insert*, *Update*, and *Delete*), as they cover basic application scenarios and index choice may impact performance here as well. For our write operations, we insert either a single trajectory or 100 trajectories into the database. Regarding the update and delete scenarios, we either adjust a single trajectory or 1% of the dataset in a batch operation.

Each of these queries is run with 50 unique configurations. Using a *Contains* and a single *Insert* query as an example: During each of the configurations, the bounding box of the polygon in which trajectories are queried is unique and a randomly generated trajectory is inserted into the database within a specified polygon. The SUT is therefore subjected to 50 different benchmark configurations for each query type. We take further considerations into account here, such as filtering polygons which return no results using rejection sampling, and ensuring that the bounding box is within the area of the dataset. Each of these experiments is run against each dataset in every unique combination of index type and data format that we include in this paper. Each dataset is included in two formats, a segmented and non-segmented version, and three different index types are included in the evaluation (GiST, SP-GiST, and BRIN). As SP-GiST is specifically designed for space partitioned data, our assumption is that datasets with low overlap will benefit from this index type. The segmented version of the dataset is created by splitting the trajectory using the update frequency of the dataset.

To fairly compare the impact of spatial features and data format, our dataset size is fixed across all datasets. We always include 30, 000, 000 segments of trajectories across each dataset to ensure that we can fairly evaluate the impact of overlap/distribution. The key difference in datasets is how these are distributed across single entire trajectories, and how they are distributed across their respective bounding boxes.

4.2 Experiment Setup

All of our experiments were run on a 8-core Intel Xeon 4310 CPU with 32GB of RAM, with the database being run as a single instance. The SUT uses PostGIS 3.5.0 and PostgreSQL 16.8, with the database being run on a single instance. During

initialization, we deploy all datasets to the SUT, with index creation happening before the evaluation.

4.3 Experiment Results

We first evaluate the read performance of our datasets using a variety of queries, and afterwards run write experiments, where we run separate insert, update, and delete benchmark runs. Within each part, we evaluate the impact of data format, index choice, and dataset characteristics.

4.3.1 Read Performance. We ran three experiment repetitions, but due to the high amount of results, we will focus on one run. The other runs were similar in their results.

Impact of Spatial Index Choice. Results from our evaluation show GiST and SP-GiST to be the best performing index types for our read queries, with GiST outperforming SP-GiST especially in the non-segmented format. This was the likely result, as the larger bounding boxes resulting from the non-segmented format do not allow for efficient space partitioned indexing of our data, which is the main advantage of SP-GiST. Figure 6 shows the performance of the different index types across all datasets and query types, with the segmented data on the left and the non-segmented data on the right. For trajectory data in PostGIS, BRIN performed poorly across all datasets and query types. The trajectory format makes it inefficient to use BRIN, and while it may be beneficial for point data in some cases, our results show that one should likely not use BRIN when working with trajectory data.

Impact of Data Format and Characteristics. Figure 7 highlights the performance difference for all query types for both formats using GiST, as it was the best performing index type overall. Our results show a split between the two formats, with all of our high GOC datasets performing better with the segmented format, while the low GOC datasets benefitted from the non-segmented format.

This lead us to further investigate the relation between GOC and the average speedup from relying on the non-segmented format when using GiST as an index type when averaging across all query types. Figure 8 shows the relation between GOC and average speedup across all query types when using GiST as an index type, with the dotted line indicating a possible regression between values. We find that the lower the GOC of a dataset, the better the performance of the non-segmented format, with the high GOC datasets performing better with the segmented format across most query types. Further research here is required to determine the exact relation between GOC and performance, with one idea being to determine the elbow method for the GOC values to determine a threshold where the non-segmented format is beneficial.

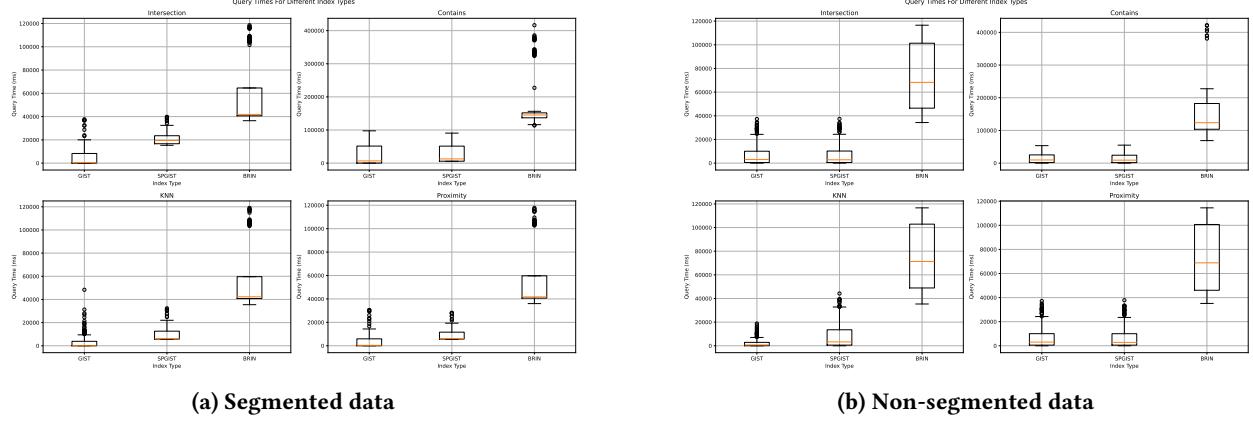


Figure 6: On average, GiST outperforms SP-GiST, especially in the segmented formats, however there are scenarios where SP-GiST does provide an advantage. If designing a general purpose application able to handle a variety of queries, GiST is the better choice. BRIN performed poorly across all datasets and query types, and should likely not be used for trajectory data.

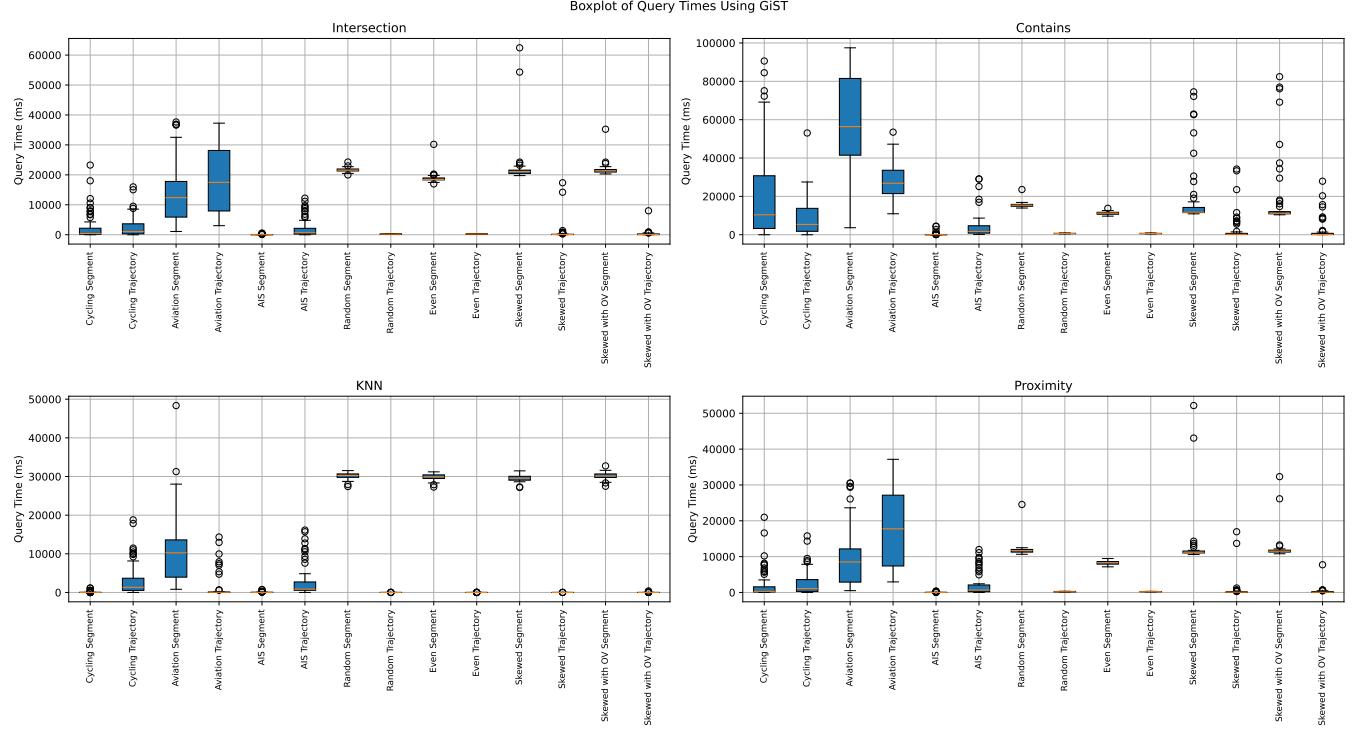


Figure 7: The GOC of a dataset here seems to be a good indicator whether the non-segmented format has any benefit at all, with our low GOC datasets showing performance benefits for the non-segmented format, while the ones with a higher GOC experience better performance with the segmented format. The *Contains* query type is the only one where the non-segmented format performs better across almost all datasets.

While our ANN coefficient is able to provide insights into the distribution of the data, it does not seem to impact performance in our evaluation regarding the read performance

overall. Regardless, we believe that it is a valuable addition and could potentially provide insights into performance when relying on other databases or indexing strategies.

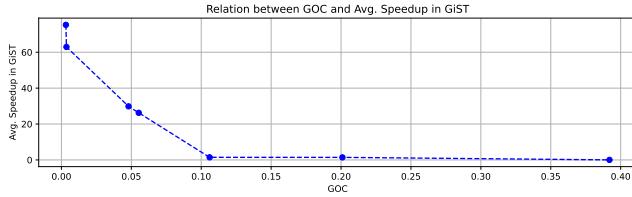


Figure 8: In our evaluation, datasets with a lower GOC benefitted heavily from using the non-segmented format when averaging across all query types. Higher GOC datasets received little to no speedup, with AIS data even performing better when using the segmented format. We were not able to determine a significant correlation however.

4.3.2 Write Performance. Our write experiments highlight how data format plays a large role in database performance across all three types of write operations, while also showing that BRIN can provide an advantage in some cases.

Impact of Index Choice. Figure 9 shows the performance of the different index types across all datasets and query types, with the singular operations on the left and the batch operations on the right. Our results show that BRIN is the best performing index type for most write operations, however the benefit is not as pronounced as it was negative for read operations. As its benefit are inconsistently spread across write operations, we believe that it is not a good choice for trajectory data in PostGIS unless an application is heavily write focused. SP-GIST was outperformed by GiST in nearly all of our cases, however it sometimes provides a small advantage in datasets with low overlap. In single insert scenarios, SP-GIST was able to outperform GiST on average in all datasets, however the performance difference was negligible.

Impact of Data Format and Characteristics Impact. When regarding the impact of data format on write performance, we found that the segmented format lacked behind the non-segmented trajectory in nearly all of our comparisons. This is as expected, due to the fact that each operation on a segmented trajectory requires the database to perform the operation on multiple rows, whether it be inserting a trajectory in a segmented format or deleting/updating an existing one. The difference is not as pronounced in our insert operations, as we do not insert a percentage of the dataset, but a fixed number of trajectories.

4.4 Summary of Findings & Recommendations for Developers

When specifically regarding the impact of GOC and ANN on write performance, we focus on the segmented format, as the number of segments is fixed here across all datasets.

Insert operations, where a bounding box is used to insert new trajectories, show that the GOC may have an impact on performance, as our higher GOC datasets performed noticeably worse than the lower GOC datasets. However, these are not in ascending order, and we were not able to determine a correlation between GOC and performance.

While we still believe that trajectory ANN to be an important metric, it did not impact performance in our evaluation. When relying on another indexing strategy and database, it may be beneficial to include ANN in the evaluation again to regard a possible correlation with performance.

Our results show that GiST remains the dominant choice when wanting to index spatial trajectory data in PostGIS, as it outperforms or performs similarly to SP-GIST in nearly all cases, while outperforming it in nearly all scenarios with non-segmented data. When developers are deciding how to store their data, we provide the following recommendations based on our results: When storing non-segmented data, GiST remains the optimal choice within the scope of our evaluation, as it outperforms SP-GIST in all cases.

When implementing a segmented data format, both index types perform similarly, with SP-GIST performing slightly better in some cases. These cases are however not tied to the degree of overlap in the data.

Our findings show that the higher the GOC of your data, the less of a benefit it is to store data in a non-segmented format. When using GiST, High GOC datasets benefit only slightly and in some cases even suffer from the non-segmented format. For those datasets, we recommend using the segmented format, as it provides better performance and a higher level of detail.

While adapting ANN to trajectories provides novel insights into a dataset, we did not find a correlation between ANN and performance. While other experiments may show a relationship here, our results indicate that data skew does not impact performance when using trajectory-based data.

When running a write-heavy workload, the non-segmented format provides advantage as it allows for faster writes across all datasets. While BRIN indexes are a good choice if one only considers write performance, its poor read performance likely makes it unsuitable for most applications.

If expecting a mix of read and write queries, we recommend evaluating the GOC of your data to determine the optimal data format for performance, and relying on GiST as the index type. Our assumption was that SP-GIST would prove a better choice in scenarios where data is equally distributed across the observed area, as it was specifically designed for cases where data is spatially partitioned. However, results show that at least for trajectory data in PostGIS, this is not the case. Regarding write performance, both index types perform similarly in most cases, with BRIN having an advantage in most scenarios. The GOC seems to be a good

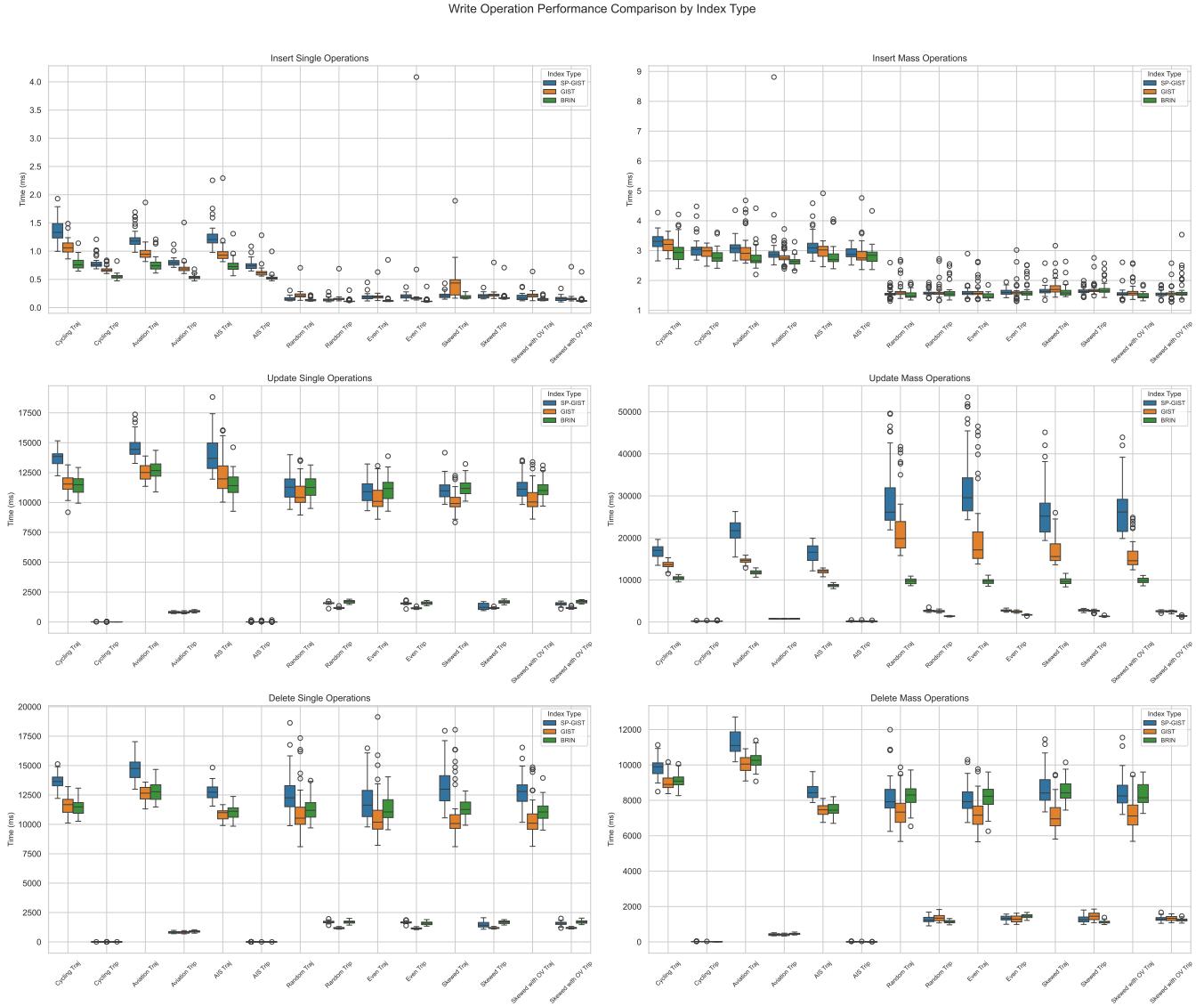


Figure 9: BRIN is usually the best performing index type for most write operations. SP-GiST was outperformed by GiST in nearly all of our cases, however, it sometimes provides a small advantage in datasets with low overlap. Of note is the noticeably better performance in our low GOC datasets for insert operations.

indicator whether the non-segmented format has any benefit at all, while the ANN coefficient did not seem to impact performance in our evaluation.

5 Discussion & Future Work

In this section, we discuss limitations of our evaluation and suggest future work to address these.

While MobilityDB could be considered a more suitable system under test (SUT) due to its focus on mobility data,

we chose PostGIS as it is more widely used, and our evaluation is limited to spatial queries. MobilityDB, despite its spatiotemporal capabilities, does not introduce novel spatial indexing strategies and offers no significant advantage in purely spatial scenarios without temporal aspects. Future work should consider extending the evaluation to spatiotemporal queries, in which case MobilityDB or similar databases would be more appropriate.

We focus on GiST, SP-GiST, and BRIN indexes, as these are the primary spatial indexing methods available in PostGIS. While additional strategies such as space-filling curves or

alternative indexing approaches could offer further insights, initial tests showed negligible benefit or poor performance compared to the selected methods. Future evaluations could explore these approaches in different database systems that offer a broader range of indexing options.

Our benchmark includes diverse datasets and query types to ensure general applicability. Nevertheless, certain edge cases and access patterns may not be fully represented. While we normalize datasets by segment count to ensure fairness, this may unintentionally bias the results. We mitigate this by using multiple configurations and repeating experiments. Future work could expand the dataset range and normalization strategies to further reduce bias.

6 Conclusion

In this paper, we regarded the performance of a popular spatial database and how the choice of index, data format, and dataset characteristics impact the performance of a database, as these factors have been shown to impact the performance of a database in previous work but have not been considered together in detail.

For this, we designed novel approximation methods to determine the degree of skew and overlap in a dataset, which can be used to determine key data characteristics. We use these in combination with a self-designed benchmark to evaluate the performance of a popular spatial database, using both synthetic and real-world datasets. Our findings showed that especially data format and index choice can have a strong impact both on read and write performance, with data characteristics possibly influencing a possible speedup to be gained when relying on a specific data format. While we did not find a correlation for our ANN coefficient and performance, we believe that it provides a novel insight into trajectory distribution and may be useful for further research with other benchmark configurations. Future work should focus on extending our benchmark to further databases and indexing strategies to regard if data characteristics impact the performance of other databases and indexing strategies, while also including further datasets.

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