

Simba: Efficient In-Memory Spatial Analytics.

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SIGMOD'16.

Andres Calderon

November 10, 2016

Agenda

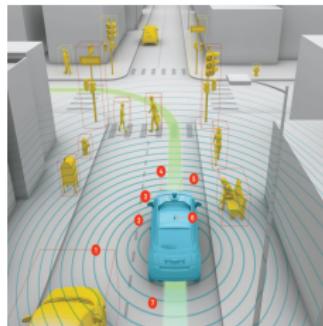
- 1 Background
- 2 Simba Architecture Overview
 - Programming Interface
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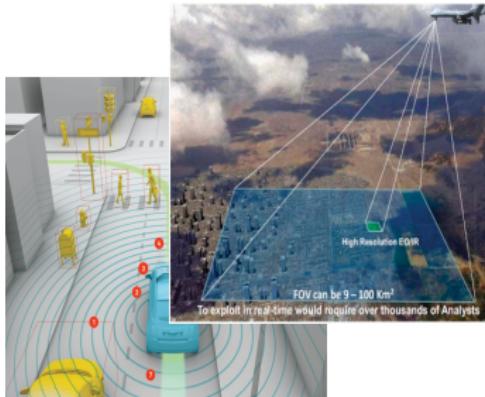
Introduction

- There has been an explosion in the amount of spatial data in recent years...



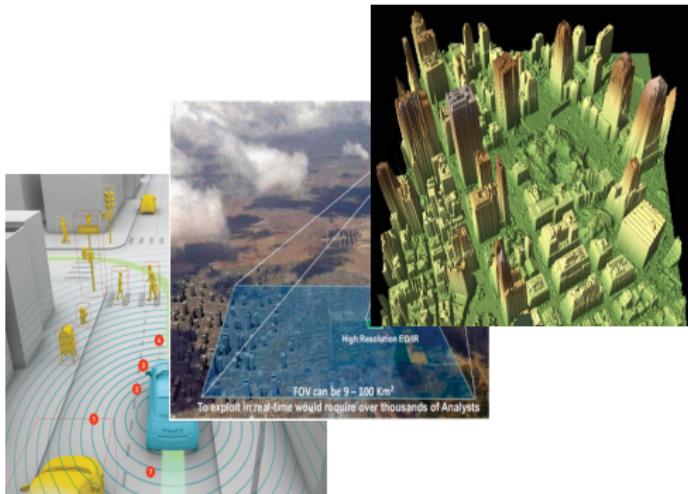
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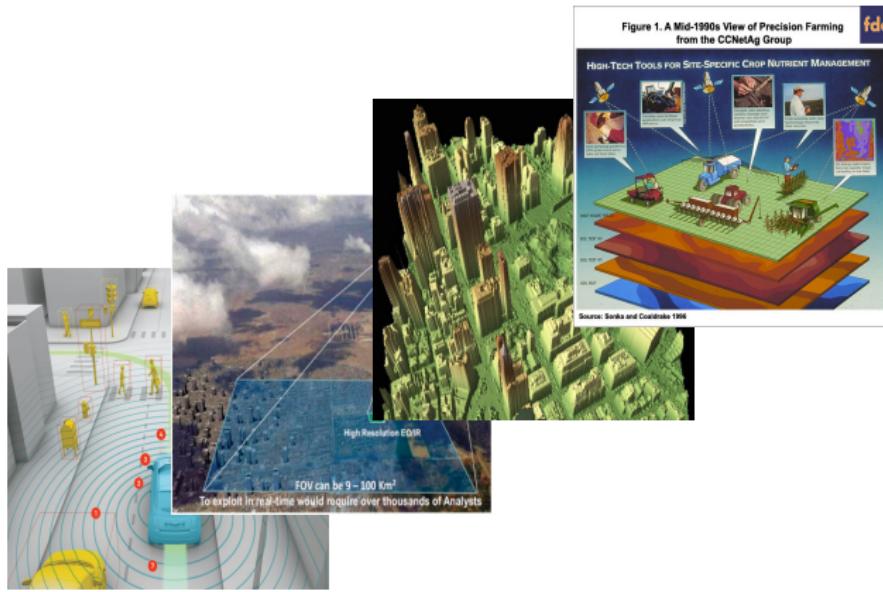
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Introduction

- The applications and commercial interest is clear...



ZigBee®



Introduction

- But remember that “Spatial is Special” ...



Introduction

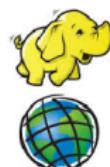
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Hadoop-GIS
Spatial Big Data Solutions



MD-Hbase



geomesa

Introduction

- But remember that “Spatial is Special” ...



Introduction

- Why do we need a new tool???



Introduction

- Problems of Existing Systems...

- Single node database (low scalability)
ArcGIS, PostGIS, Oracle Spatial.
- Disk-oriented cluster computation (low performance)
Hadoop-GIS, SpatialHadoop, GeoMesa.
- No native support for spatial operators
Spark SQL, MemSQL
- No sophisticated query planner and optimizer
SpatialSpark, GeoSpark

Introduction

- Simba: **Spatial In Memory Big data Analytics.**
 - ① Extends Spark SQL to support spatial queries and offers simple APIs for both SQL and DataFrame.
 - ② Support two-layer spatial indexing over RDDs (low latency).
 - ③ Designs a SQL context to run important spatial operations in parallel (high throughput).
 - ④ Introduces spatial-aware and cost-based optimizations to select good spatial plans.

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Introduction

Core Features	Simba	GeoSpark	SpatialSpark	SpatialHadoop	Hadoop GIS
Data dimensions	multiple	$d \leq 2$	$d \leq 2$	$d \leq 2$	$d \leq 2$
SQL	✓	✗	✗	Pigeon	✗
DataFrame API	✓	✗	✗	✗	✗
Spatial indexing	R-tree	R-/quad-tree	grid/kd-tree	grid/R-tree	SATO
In-memory	✓	✓	✓	✗	✗
Query planner	✓	✗	✗	✓	✗
Query optimizer	✓	✗	✗	✗	✗
Concurrent query execution	thread pool in query engine	user-level process	user-level process	user-level process	user-level process
query operation support					
Box range query	✓	✓	✓	✓	✓
Circle range query	✓	✓	✓	✗	✗
k nearest neighbor	✓	✓	only 1NN	✓	✗
Distance join	✓	✓	✓	via spatial join	✓
k NN join	✓	✗	✗	✗	✗
Geometric object	✗ ¹	✓	✓	✓	✓
Compound query	✓	✗	✗	✓	✗

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Spark SQL Overview

Spark SQL is Apache Spark's module for working with structured data.

- Seamlessly mixes SQL queries with Spark programs.
- Connects to any data source the same way.
- Includes a highly extensible cost-based optimizer (*Catalyst*).
- Spark SQL is a full-fledged query engine based on the underlying Spark core.

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Spark SQL Overview

```
# Apply functions to results of SQL queries.
context = HiveContext(sc)
results = context.sql("""
    SELECT
        *
    FROM
        people""")  
names = results.map(lambda p: p.name)  
# Query and join different data sources.
context.jsonFile("s3n://...").registerTempTable("json")
results = context.sql("""
    SELECT
        *
    FROM
        people
    JOIN
        json ...""")
```

Simba Architecture

Simba is an extension of Spark SQL across the system stack.

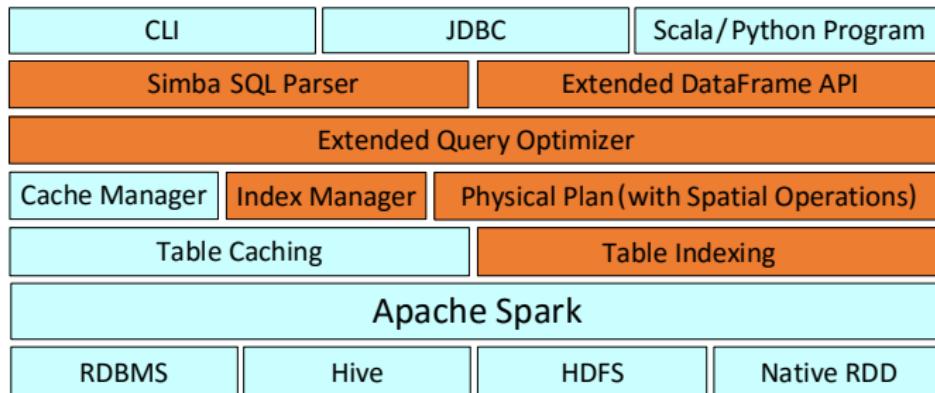


Figure 1: Simba architecture.

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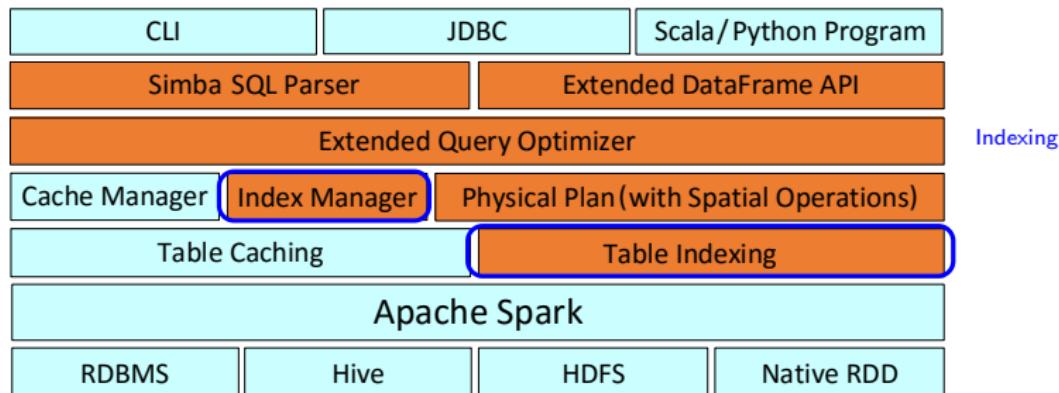


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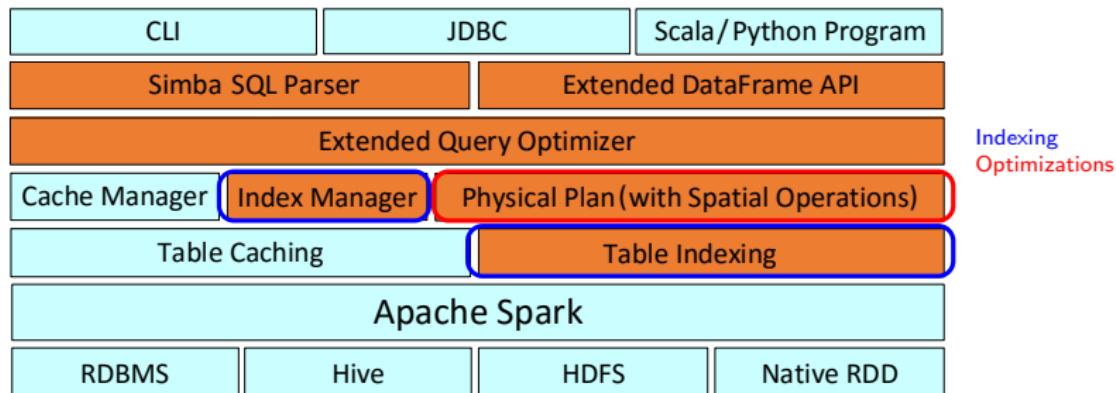


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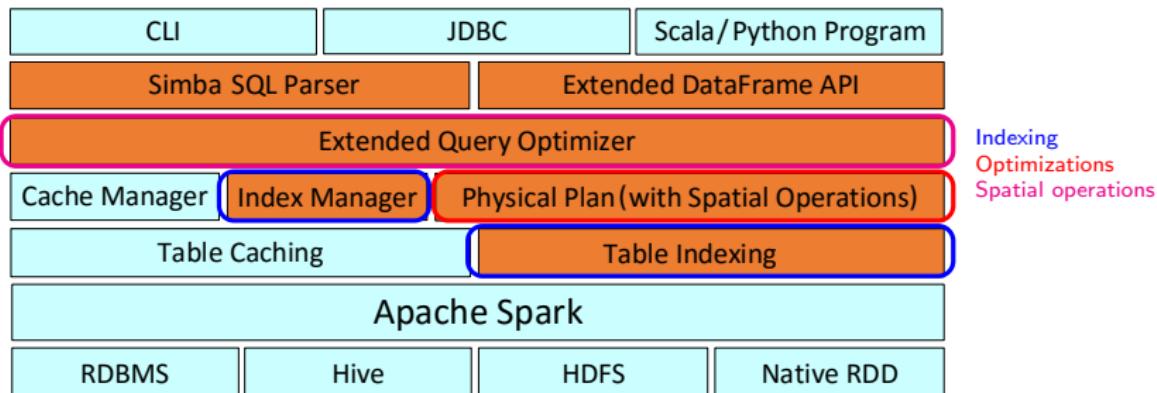


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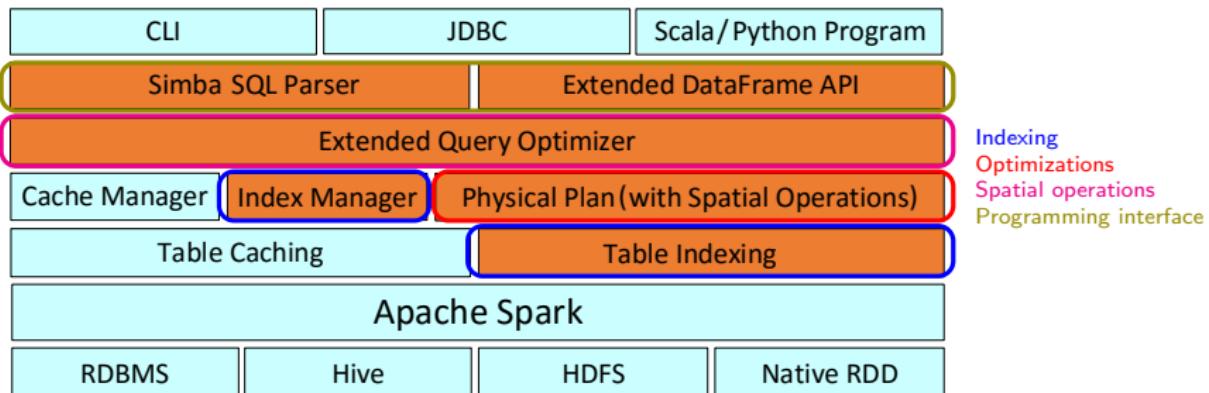
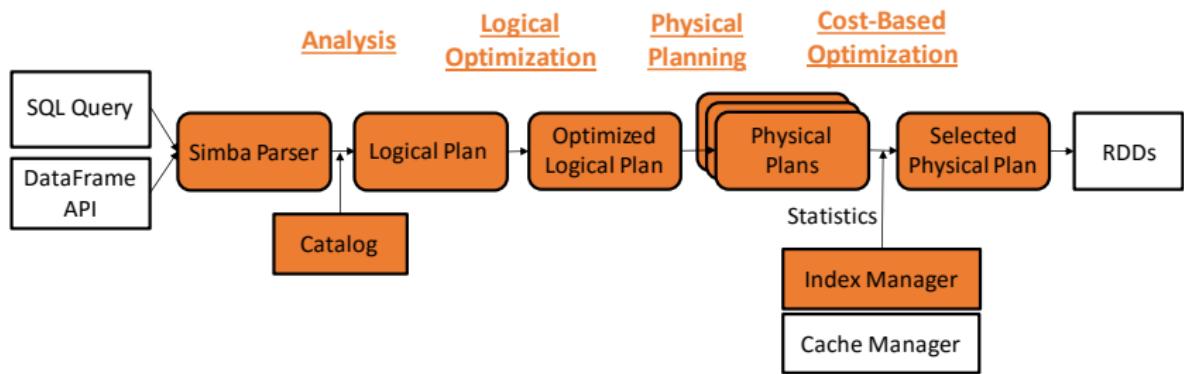


Figure 1: Simba architecture.

Query Load in Simba



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Programming Interface

Support rich query types natively in the kernel...

```
SELECT
    *
FROM
    points
SORT BY
    (x - 2) * (x - 2) +
    (y - 3) * (y - 3)
LIMIT
    5
```



```
SELECT
    *
FROM
    points
WHERE
    POINT(x, y) IN
        KNN(POINT(2, 3), 5)
```

Programming Interface

Achieve something that is impossible in Spark SQL...

```
SELECT
    *
FROM
    queries q
KNN JOIN
    pois p
ON
    POINT(p.x, p.y) IN KNN(POINT(q.x, q.y), 3)
```

Programming Interface

Fully compatible with standard SQL operators...

```
SELECT
    p.id, count(*) AS n
FROM
    pois AS p
DISTANCE JOIN
    restaurants AS r
ON
    POINT(r.lat, r.lng) IN CIRCLE RANGE(POINT(p.lat, p.lng), 200.0)
GROUP BY
    p.id
ORDER BY
    n
```

Programming Interface

Same level of flexibility for DataFrames...

```
pois.distanceJoin(restaurants, Point(pois("lat"), pois("lng")),
                  Point(restaurants("lat"), restaurants("lng")), 3.0)
    .groupBy(pois("id"))
    .agg(count("*").as("n"))
    .sort("n").show()
```

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Table Indexing

- In Spark SQL:
 - Record → Row
 - Table → RDD [Row]
- Spark SQL makes a full scan of RDDs.
 - Inefficient for spatial queries!!!
- Solution: native **two-level** indexing over RDDs

Table Indexing

- IndexRDD

- Pack all Row objects within a RDD partition into an array ($O(1)$ cost for access).
- IPartition data structure:
 - `case class IPartition[Type] (Data: Array[Type], I: Index)`
 - Index can be HashMap, TreeMap or RTree.
- So, by using Type=Row:
 - `type IndexRDD[Row] = RDD[IPartition[Row]]`

Three-Phases Index Construction

• Partition

- Concerns: Partition size, Data locality and Load balancing.
- Partitioner abstract class.
- STRPartitioner (based on Sort-Tile-Recursive algorithm).

• Local Index

- $\text{RDD}[\text{Row}] \rightarrow \text{IndexRDD}[\text{Row}]$.
- Collects statistics from each partition (number of records, partition boundaries, ...).

• Global Index

- Enables to prune irrelevant partitions.
- Can use different types of indexes and keep them in memory.

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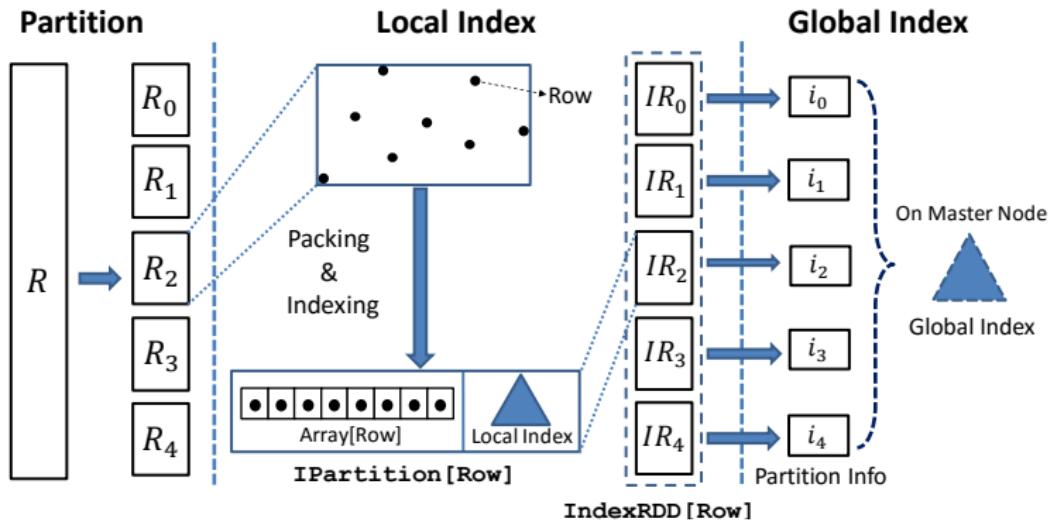
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Two-level indexing strategy



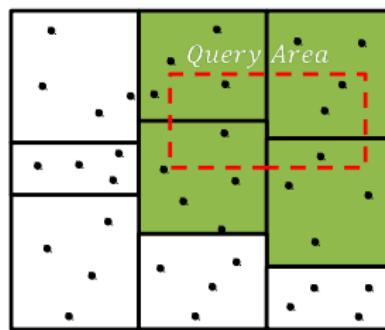
```
CREATE INDEX idx_name ON R(x1, ..., xm) USE idx_type
DROP INDEX idx_name ON table_name
```

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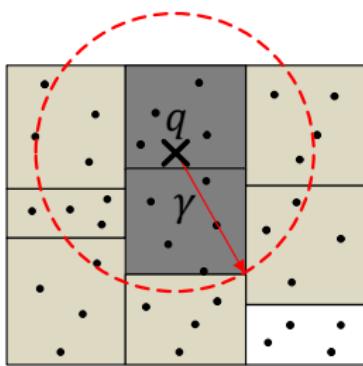
Range Queries

- $\text{range}(Q, R)$
- Two steps: Global filtering + Local processing.

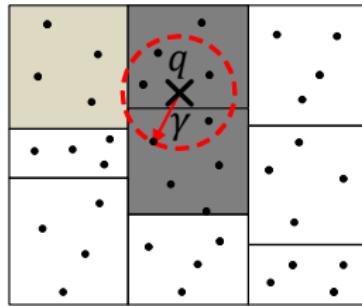


kNN Queries

- $kNN(q, R)$
- Good performance thanks to:
 - Local indexes.
 - Pruning bound that is sufficient to cover global kNN results.



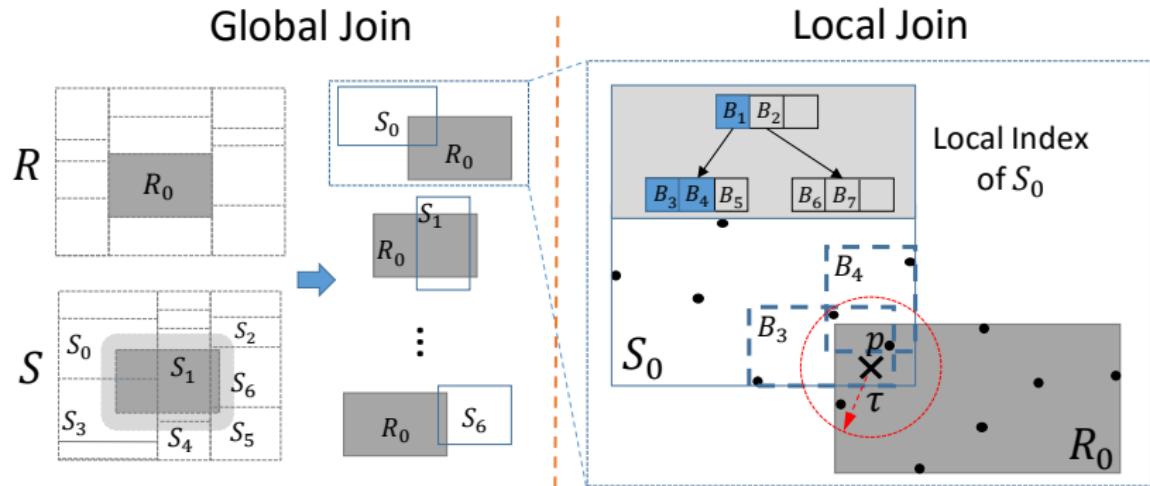
(a) Loose Pruning Bound



(b) Refined Pruning Bound

Distance Join

- $R \bowtie_{\tau} S$
- DJSpark algorithm.



kNN Join

- $R \bowtie_{kNN} S$
- General methodology:
 - ① Producing buckets: R and S are divided into n_1 (n_2) equal-sized blocks.
Every pair of blocks (R_i, S_j) are shuffled to a bucket.
 - ② Local kNN join: Performs $kNN(r, S_j)$ for every $r \in R$
 - ③ Merge: Finds global kNN of every $r \in R$ among its $n_2 k$ local $kNNs$.

kNN Join

- $R \bowtie_{kNN} S$
- Explores several methods:
 - BKJSpark-N: Block nested loop kNN join in Spark.
 - BKJSpark-R: Block R-tree kNN join in Spark.
 - VKJSpark: Voronoi kNN join in Spark.
 - ZKJSpark: z-value kNN join in Spark.
 - RKJSpark: R-tree kNN join in Spark.

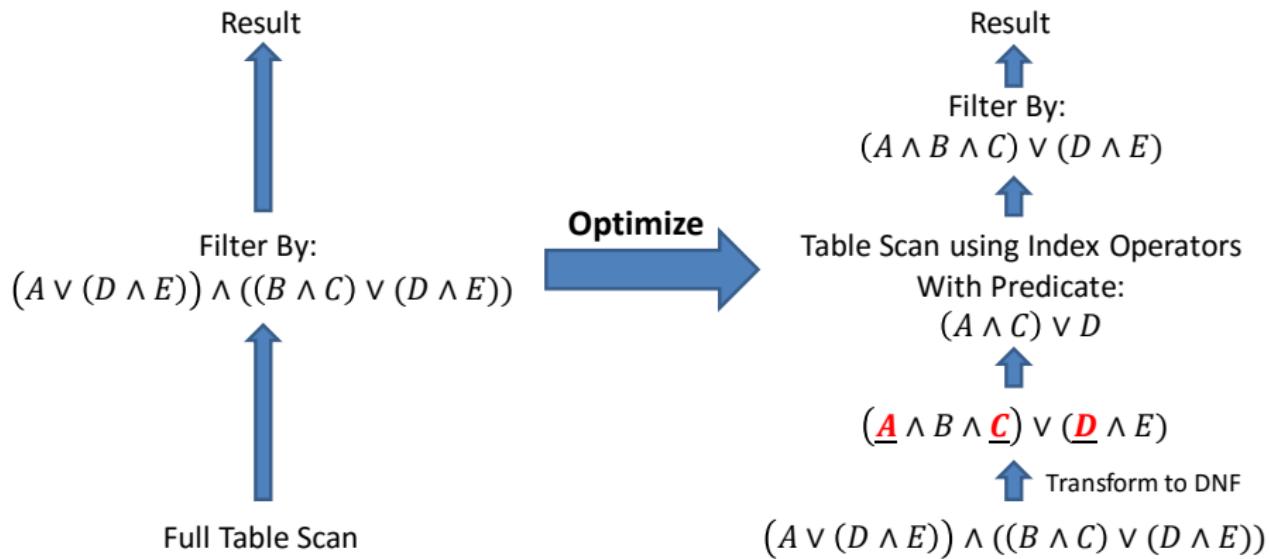
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Query Optimizer

- Index and geometry-awareness optimizations.
- Index scan optimization: for better index utilization.
- Selectivity estimation + Cost-based Optimization.
 - Selectivity estimation over local indexes
 - Choose a proper plan: scan or use index.
- Spatial predicates merging

Query Optimizer



Query Optimizer

- Partition size auto-tuning.
 - Data locality and load balancing through a good partitioner (STR Partitioner).
 - Memory fitness using record-size estimator.
- Broadcast join optimization: small table joins large table.
- Logical partitioning optimization for kNN joins.
 - Provides tighter pruning bounds.

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Setup

- 10 nodes cluster
- Processors: 6-core Intel Xeon E5 (1.6 to 2.0 GHz)
- RAM: 20 to 56 GB.
- Ubuntu 14.04 LTS, Hadoop 2.4.1, Spark 1.3.0

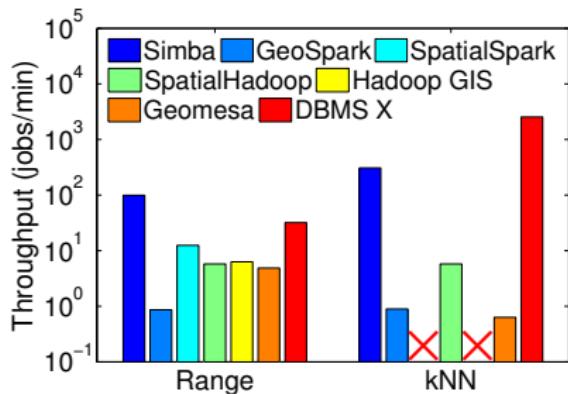
Datasets

- OSM (OpenStreetMap)
 - 2.2 Billion records, 132GB.
 - Five fields: ID, a two-dimensional coordinate and two text information.
- GDEL (Global Data on Events, Language and Tone)
 - 75 Million records
 - Seven attributes: timestamp, three two-dimensional coordinates (start, end and action of the event).
- RC (Synthetic dataset)
 - 1 Million to 1 Billion records, 2 to 6 dimensions.
 - Clusters randomly generated using Gaussian distributions.

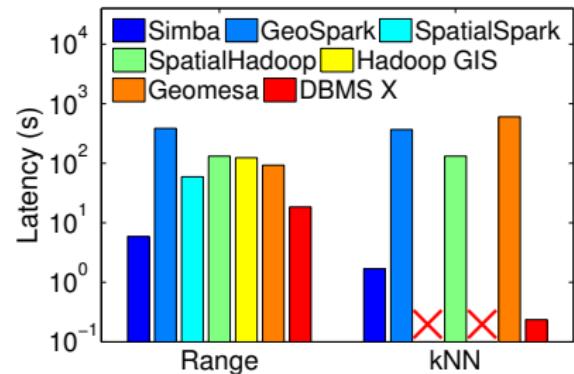
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Range and kNN Operations (OSM)

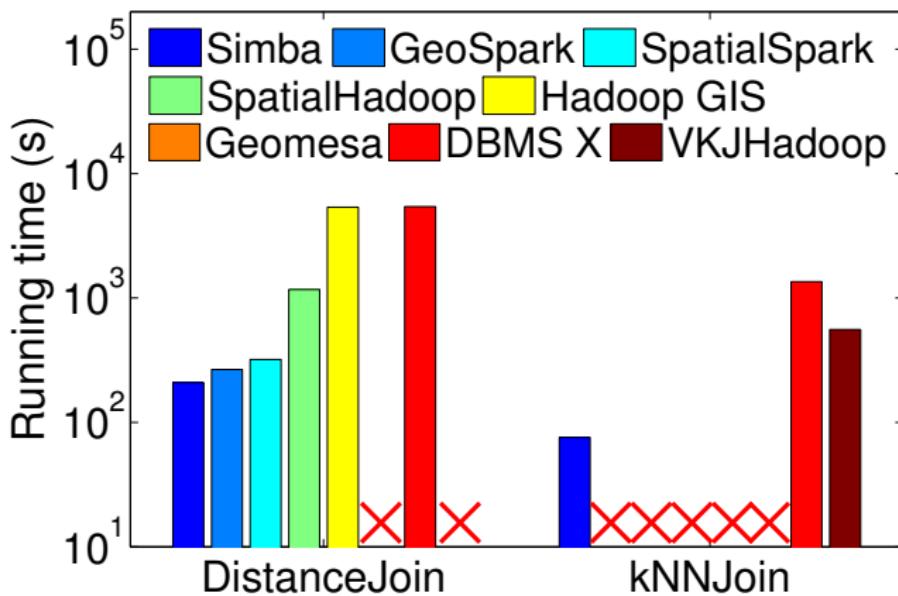


(a) Throughput

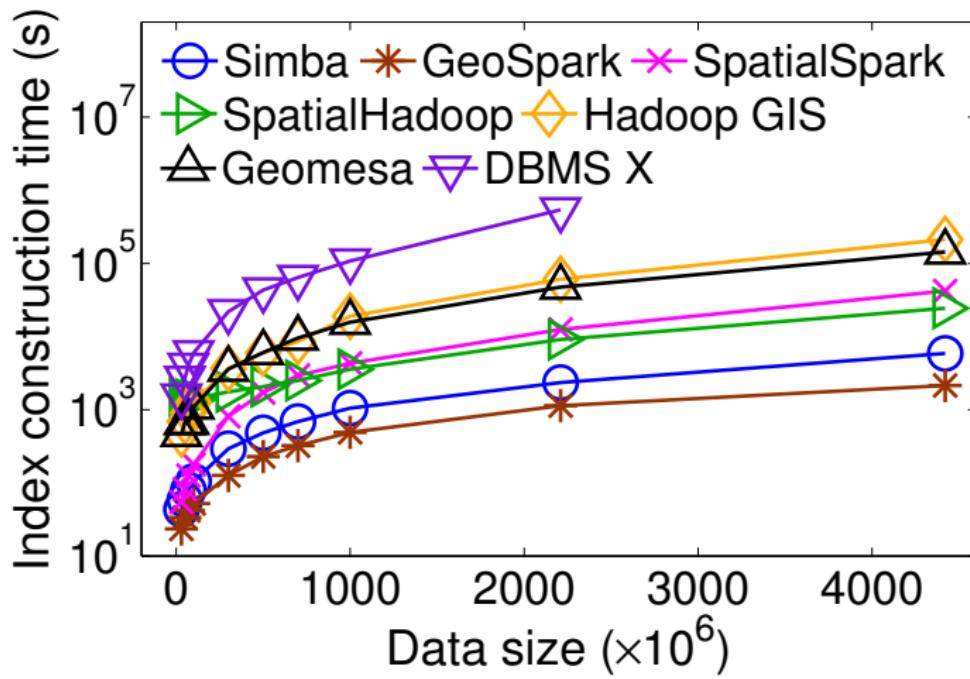


(b) Latency

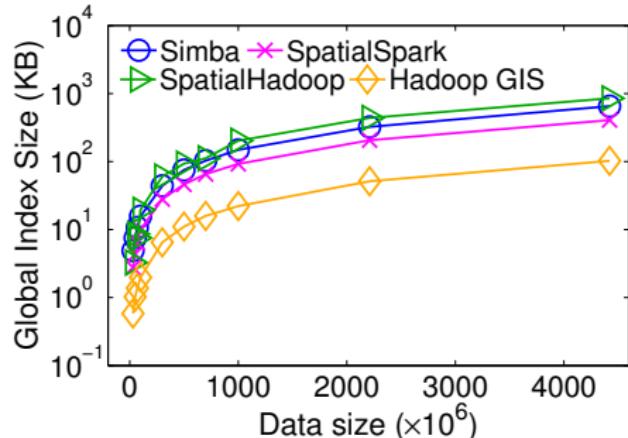
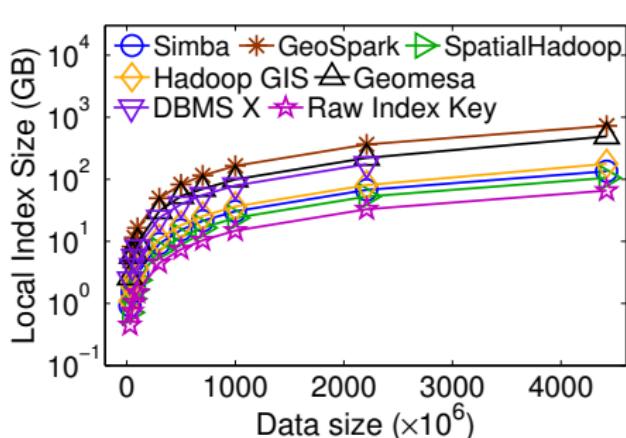
Join Operations (OSM)



Index Construction Time (OSM)



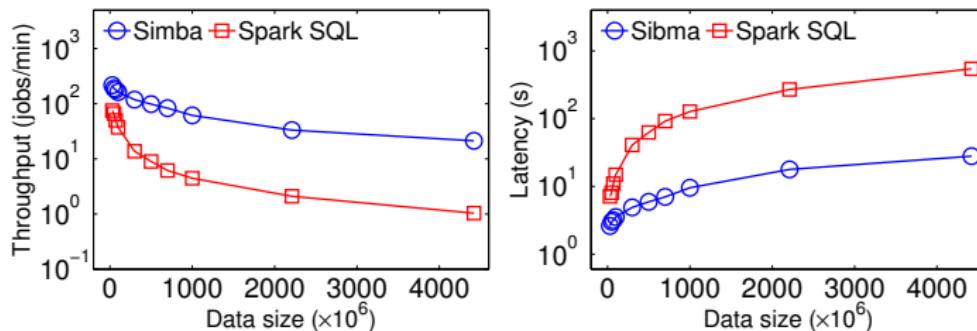
Index Storage Overhead (OSM)



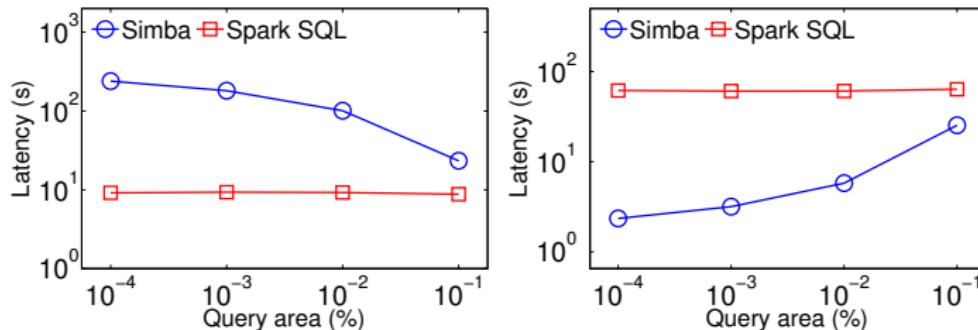
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Range Query Performance (OSM)

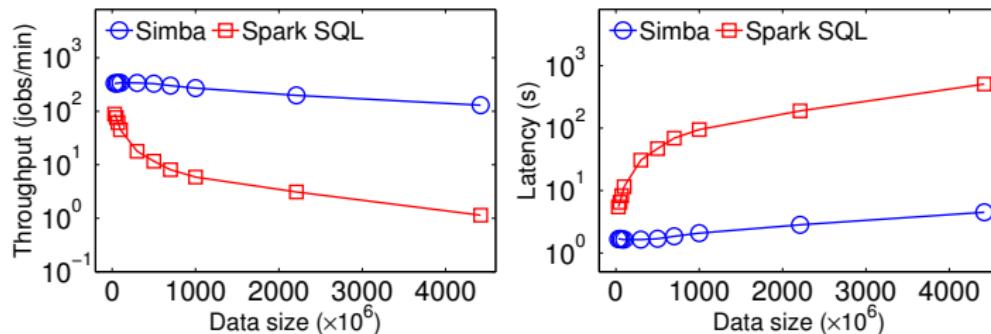


(a) Effect of data size.

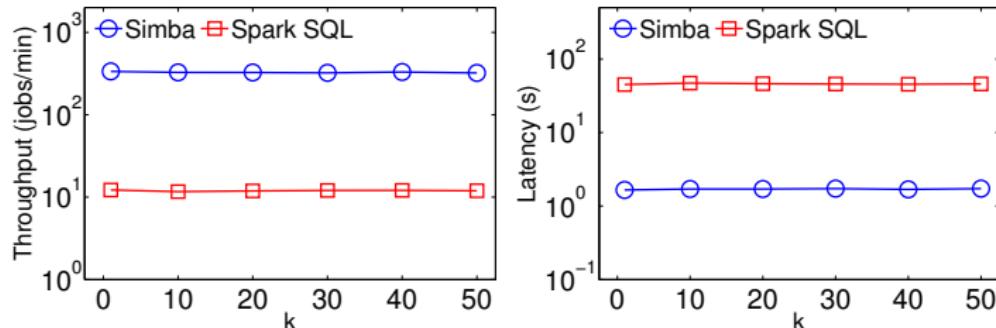


(b) Effect of query area size (percentage of total area).

kNN Query Performance (OSM)

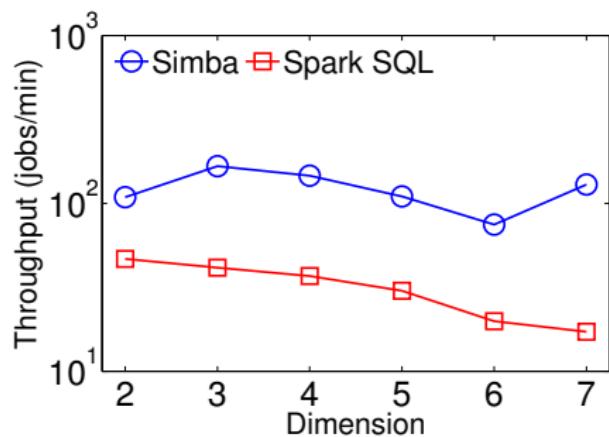


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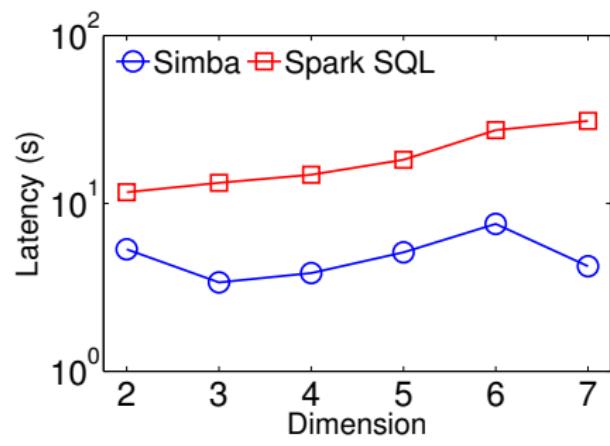


(b) Effect of k .

Range Query Performance (GDELT)

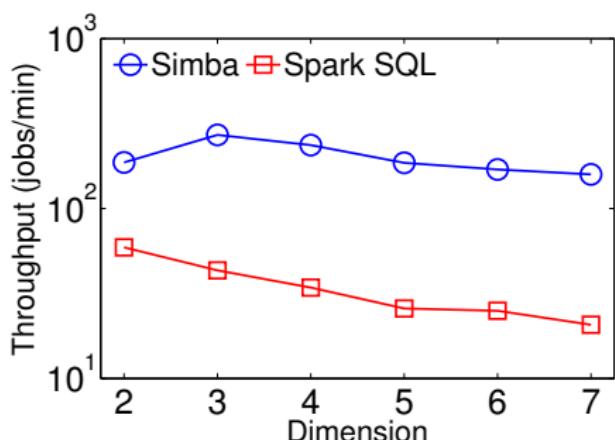


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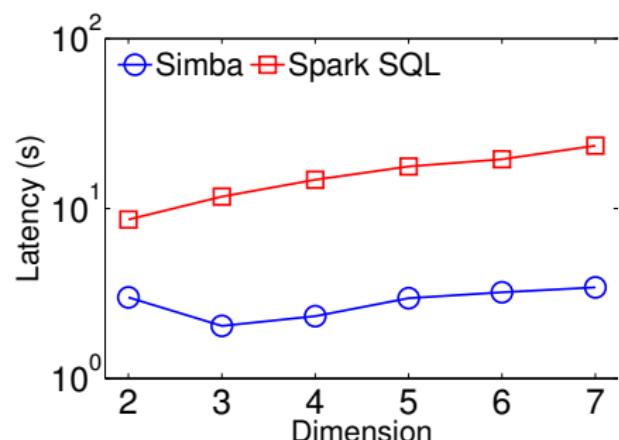


(b) Latency

kNN Query Performance (GDELT)



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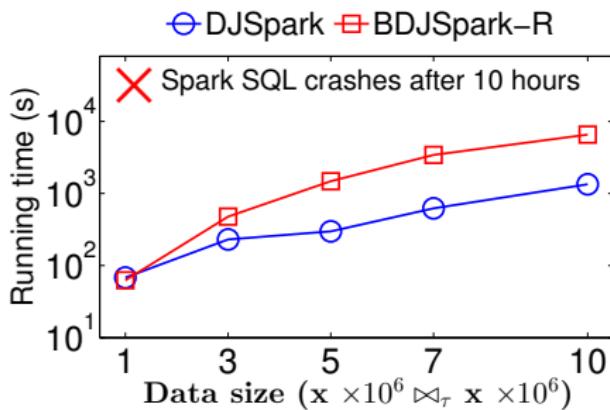


(b) Latency

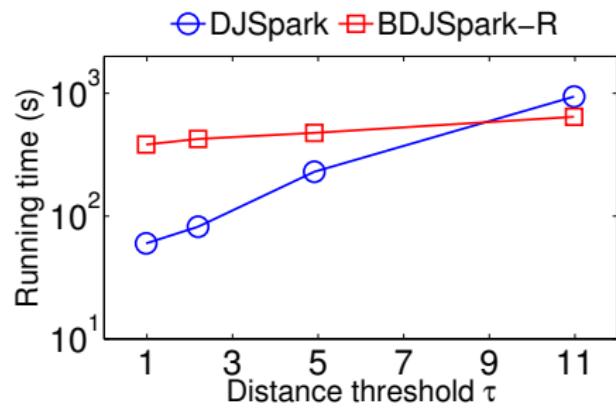
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Distance Join Performance (OSM)

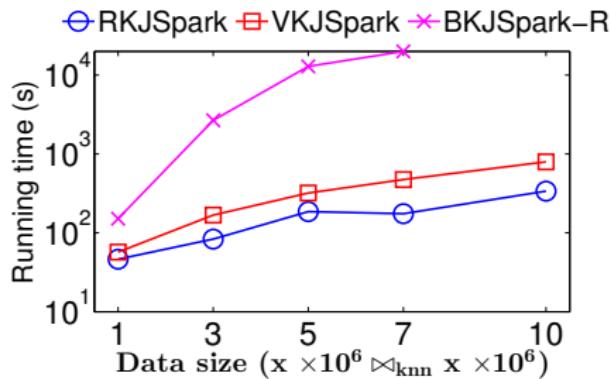


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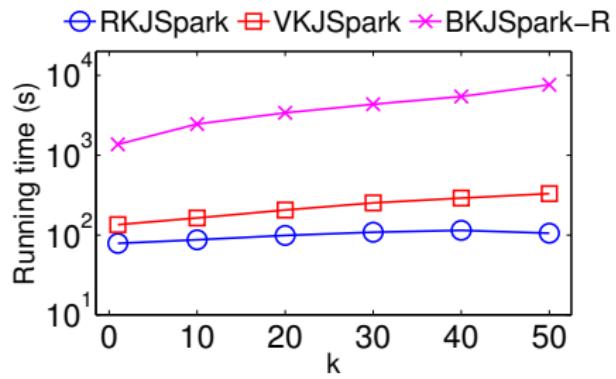


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kNN Join Performance (OSM)

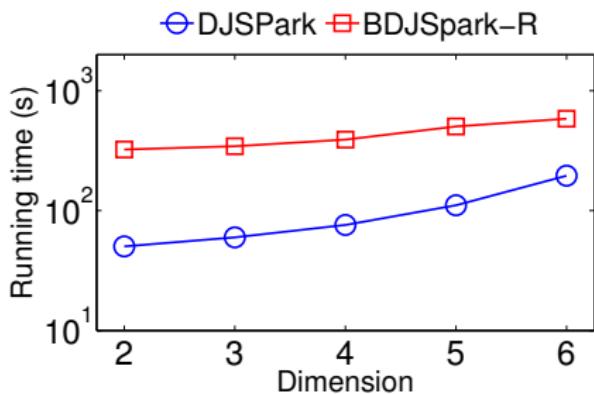


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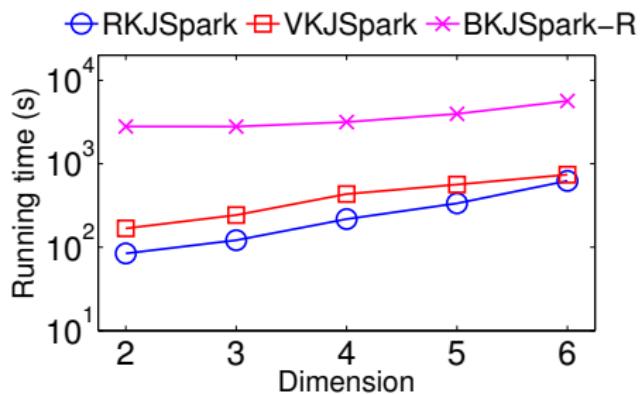


(b) Effect of k .

Join Operations Performance (RC)



(a) Distance join



(b) kNN join

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- Indexing support for efficient query processing.
- Spatial operator implementation tailored towards Spark.
- Spatial and index-aware optimizations.
- User-friendly SQL and DataFrame API.
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Future ideas

- Explore complex spatio-temporal patterns.
- Native support to geometry objects and operations.
- Spatial joins over predicates.

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Thank you!!!

Do you have any question?