GeoFlink: A Framework for the Real-time Processing of Spatial Streams

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Abstract—Apache Flink is an open-source system for the scalable processing of batch and streaming data. Flink does not natively support efficient processing of spatial data streams, which is the requirement of many applications dealing with spatial data. Besides Flink, other scalable spatial data processing platforms including GeoSpark, Spatial Hadoop, GeoMesa and Parallel Secondo do not support streaming workloads and can only handle static/batch workloads. Hence this work presents GeoFlink, which extends Apache Flink to support spatial data types, index and continuous queries. To enable efficient processing of continuous queries, GeoFlink currently supports spatial range, spatial $k$NN and spatial join queries. An extensive experimental study on real spatial data streams show that GeoFlink achieves several orders of magnitude higher query performance than other ordinary distributed approaches.

Index Terms—

I. INTRODUCTION

With the increase in the use of GPS-enabled devices, spatial data is omnipresent. Such data includes people movement data, vehicles trajectory data, animals tracking data, geotagged social media data to name a few. Many applications require real-time processing of spatial data, for instance, to guide people to safety in a disaster. This entails real-time processing of billions of tuples per second. Existing spatial data processing frameworks for instance PostGIS [1] and QGIS [2] are not scalable to handle such huge data and throughput requirements, while scalable platforms like Apache Spark [3], Apache Flink [4], Apache Samza [5] and Apache Storm [6] do not natively support spatial data processing and randomly distribute incoming data to available nodes without considering its spatial data proximity, resulting in increased querying cost.

Beside these, there exist a few solutions to handle large scale spatial data, for instance Hadoop GIS [7]. Spatial Hadoop [8], GeoSpark [9], Parallel Secondo [10] and GeoMesa [11], however they are only suitable for static/batch processing and cannot handle real-time spatial streams. Hence this work presents GeoFlink, which extends Apache Flink to support distributed and scalable processing of spatial data streams. Namely, GeoFlink extends Apache Flink to support spatial data types, spatial index and spatial queries.

To enable the real-time processing of spatial data streams, a lightweight grid-based index is introduced. Unlike static data, stream tuples arrive and expire at a high velocity and hence tree-based spatial indexes are not suitable for it owing to their high maintenance cost [12]. In fact the grid-based index used in this work is logical in the sense that it only assigns a grid ID to the incoming streaming tuples or moving objects and based on the grid ID the objects are processed, pruned and distributed across the cluster nodes. We do not physically store the objects in the data structure, hence no update is required as we receive an updated object location. Furthermore, given Flink’s key-based data distribution, the grid-based index is quite effective in distributing dynamic spatial data streams across the distributed cluster nodes by keeping in view the spatial data proximity as discussed in Section VII.

Many database operators are blocking, i.e., they require the entire input before an output can be generated. For example, the aggregation and join operators require processing of the entire dataset before outputting the correct result. Since the data streams are continuous and infinite, we can never see it entirely. Therefore windows are used to bound and execute different operations on data streams. Apache Flink [4] supports many different types of windows, which causes the continuous queries output to be generated periodically, i.e., hourly, daily, weekly, etc., or for some fixed number of tuples. Similarly, the GeoFlink operators i.e., spatial range, spatial $k$NN and spatial join queries, are also window-based. The grid-based GeoFlink queries are evaluated against the respective ordinary Apache Flink’s distributed queries. To summarize, the following key contributions are made in this paper:

• The core of GeoFlink, which extends Apache Flink to
support spatial data types, index and continuous queries.
- Grid-based spatial data index for the efficient spatial queries’ processing and effective data partitioning across the cluster nodes.
- Optimized grid-based spatial range, spatial kNN and spatial join queries.
- An extensive experimental study on real spatial data streams to show that GeoFlink achieves several orders of magnitude higher query performance than the ordinary distributed approaches.

The rest of the paper is organized as follows: Section II presents the related work. Section III briefly discusses the Flink programming model and its limitations. In Section IV the proposed GeoFlink architecture is presented. Section V presents the grid index used in GeoFlink. Sections VI and VII detail the Spatial Stream and the Spatial Queries layers of GeoFlink. In Section VIII detailed experimental study is presented while Section IX concludes our paper and highlights a few future directions.

II. RELATED WORK

Existing spatial data processing frameworks like ESRI ArcGIS [13], PostGIS [1] and QGIS [2] are built on relational DBMS and are therefore not scalable to handle huge data and throughput requirements. Authors in [14] extend SQL by integrating spatio-temporal data as abstract data types into already exiting data models and present STQL (Spatio-temporal Query Language), which enables querying moving objects. The authors describe the moving objects as geometries changing continuously over time. The authors present a DBMS data model and query language capable of handling such time-dependent geometries. Their model focuses on moving points (cars, planes, animals, people) and moving regions (storms, people, temperature zones, high or low pressure areas).

Beside these, there exist a few solutions to handle large scale spatial data, for instance Hadoop GIS [7], Spatial Hadoop [8], GeoSpark [9], Parallel Secondo [10] and GeoMesa [11], however they are only suitable for static/batch processing and cannot handle real-time spatial streams. Among the above mentioned spatial data processing frameworks, GeoSpark is closest to our work. GeoSpark is a spatial data management and processing framework, which extends the core engine of Apache Spark and SparkSQL to support spatial data types, indexes and geometrical operations. However, it does not support continuous processing of spatio data streams [9] as we do.

Large-scale real-time computation in the order of millions and billions of tuples is only possible with the help of state-of-the-art distributed and horizontally scalable big data processing platforms like Apache Spark [3] and Apache Flink [4]. These distributed batch and streaming platforms are built to handle large throughputs and dynamically changing data, however, do not natively support spatial data processing and hence do not support spatial data types, spatial indexes and meaningful spatial data distribution (which takes into account the spatial proximity of data) across the cluster nodes.

A number of researchers, both from academia and industry, have put efforts to extend the above mentioned scalable platforms for the processing of spatial data. SpatialSpark [15] leverages Apache Sparsks broadcast mechanism to provide partitions based on broadcast space. GeoSpark [9] processes spatial data by extending Sparsks native Resilient Distributed Dataset (RDD) to create Spatial RDD (SRDD) along with a Spatial Query Processing layer on top of the Spark API to run spatial queries on these SRDDs. For efficient spatial query processing, GeoSpark creates a local spatial index (Grid, R-tree) per RDD partition rather than a single global index. For re-usability, the created index can be cached on main memory and can also be persisted on secondary storage for later use. However, the index once created cannot be updated, and must be recreated to reflect any change in the dataset due to the immutable nature of RDDs.

LocationSpark [16], GeoMesa [11] and Spark GIS [17] are a few other spatial data processing frameworks developed on top of Apache Spark. All these frameworks, like the GeoSpark, are scalable however can only handle static/batch datasets and do not support real-time stream processing as we do in GeoFlink.

To support real-time queries, Apache Spark introduces Spark Streaming that relies on micro-batches to address latency concerns and mimic streaming computations. Latency is inversely proportional to batch size however, the experimental evaluations in [18] show that as the batch size is decreased to very small to mimic the real-time streams, Apache Spark is prone to system crashes and exhibits lower fault tolerance. Furthermore, even with the micro-batching technique, Spark only approaches near real-time results at best, as data buffering latency still exists however miniscule.

Other distributed streaming platforms worth considering are Apache Samza [5] and Apache Storm [6]. Performance comparison by Fakrudeen et al. [18] reveal that both the Storm and Samza demonstrate a lower throughput and reliability than Apache Flink [4]. Indeed F. Zhang et al. [9] mentions that the architecture of their spatial querying framework could demonstrate a higher throughput if implemented on Apache Flink.

To support real-time processing of spatial data streams, Zhang et al. [19] extend Apache Storm. They proposed and implemented distributed spatial indexing for efficient continuous spatial query processing. The grid index in their work consists of a primary index (of the grid cells) and a secondary index (of the individual cell objects). The secondary index is tree-based and physically stores the moving objects and must be updated as the object moves or updated. In contrast, the grid index in GeoFlink is logical, in the sense that it only assigns a grid ID to the incoming streaming tuples or moving objects and based on the grid ID the objects are processed, pruned and distributed across the cluster nodes. We do not physically store the objects in any data structure, hence no update is required as we receive an updated object location. Hence enabling GeoFlink to achieve higher query throughput.

In light of the above discussed works, this paper presents GeoFlink, a distributed and scalable framework for real-time
processing of spatial data streams. To enable efficient spatial query processing and effective spatial data distribution across the cluster nodes, a light-weight logical grid-based index is proposed.

III. Flink Dataflow Programming Model and Its Limitations to Support Spatial Data

Apache Flink uses the following two data collections to represent data in a program: 1) DataSet: Represents a static and finite collection of tuples, 2) DataStream: Represents a continuous and infinite/unbounded collection of tuples. However, the DataTypes used in Flink’s DataSet API are also streams internally. A Flink program has 3 basic building blocks: 1) Source, 2) Transformations and 3) Sink. Conceptually a stream is a (potentially never-ending) flow of data records, and a transformation is an operation that takes one or more streams as input, and produces one or more output streams as a result. When executed, Flink programs are mapped to streaming dataflows, consisting of streams and transformation operators. Each dataflow starts with one or more sources and ends in one or more sinks. The dataflows resemble arbitrary Directed Acyclic Graphs (DAGs), however special forms of cycles are permitted via iteration constructs [20]. By its very definition dataflow processing offers lower latency with the price of lower fault tolerance. To address the need for fault tolerance, Flink provides distributed check-pointing and program resumption mechanism upon failure while maintaining its exactly once semantics. Thus, for real-time analytics use cases a natural choice is to use Apache Flink.

In a Flink’s streaming program, one can refer to different notions of time: 1) Event Time is the time when an event was created. It is usually described by a timestamp in the events. 2) Ingestion Time is the time when an event enters the Flink dataflow at the source operator. 3) Processing Time is the local time at each operator that performs a time-based operation. Aggregates on streams (counts, sums, etc.), are scoped by windows, such as "count over the last 5 minutes", or "sum of the last 100 elements", since it is impossible to count all elements in a stream, because streams are in general infinite (unbounded). Windows can be time driven (example: every 30 seconds) or data driven (example: every 100 elements). One typically distinguishes different types of windows, such as tumbling windows (no overlap), sliding windows (with overlap), and session windows (punctuated by a gap of inactivity). When using windows, output is generated based on the complete window contents as the window moves.

Flink’s DataStream API enables transformations like filter, map, reduce, keyby, aggregations, window, etc. on unbounded data streams of data and provides seamless connectivity with data sources and sinks like Apache Kafka (source/sink), Apache Cassandra (sink), etc. [20]. While many operations in a dataflow simply look at one individual event at a time, some operations remember information across multiple events (for example window operators). These operations are called stateful.

Programs in Flink are inherently parallel and distributed. During execution, an operator is divided into one or more subtasks (operator instances) which are independent of one another and execute in different threads that may be on different machines or containers. The number of an operator’s subtasks depends on the amount of its parallelism. A user can define the parallelism of each operator or set the maximum parallelism globally for all operators. Flink parallelism depends on the number of available task slots, where a good default number of task slots is equivalent to the number of CPU cores.

In Flink, keys are responsible for the data distribution across the task slots or operator instances. All the tuples with the same key are guaranteed to be processed by a single operator instance. In addition, many of Flink’s core data transformations like join, groupBy, reduce and windowing require the data to be grouped on keys. Keying operations are enabled by the keyBy operator, which logically partitions stream tuples with respect to their keys. Intelligent key assignment ensures uniform data distribution among operator instances and hence leverages the performance offered by parallelism.

Streams can transport data between two operators in a one-to-one (or forwarding) pattern, or in a redistributing pattern. One-to-one streams preserves partitioning and order of elements, while redistributing streams change the partitioning of streams. Each operator subtask sends data to different target subtasks, depending on the selected transformation. By default each operator preserves the partitioning and order of the operator before it, thus preserving the source parallelism. While keying operations causes data reshuffling and distribution overhead, data forwarding may cause a load imbalance and even idling of cores that are not in use, thus not fully leveraging computation power of the entire cluster as shown in Figure III. Therefore, in order to guarantee efficient execution of queries, one must find the right balance between data redistribution and data forwarding. Furthermore, as parallel instances of operators cannot communicate with each other, data locality per instance must be ensured by the user.
As intelligent grouping/keying of data is application or data specific, for the effective grouping of spatial data in this work, a grid-index based data grouping and distribution is proposed. Using this distribution, all the spatial objects belonging to a particular grid cell is assigned the same key and hence is directed to the same operator’s instance. This ensures that the spatially close objects are being processed by the same operator instance and hence enables effective pruning and spatial query processing as discussed in Section VII.

IV. GEOFLINK ARCHITECTURE

Figure 2 shows the proposed GeoFlink architecture. Users can register queries to the GeoFlink system through a Scala/Java API. The API allows the users to use Java or Scala programming languages to write custom spatial queries. In order to execute Spatial Range, Spatial kNN or Spatial Join queries on the incoming data streams, a stream need to be translated into spatial data stream. Users can do so by calling the respective operation of the spatial library. At the time of writing this paper, GeoFlink supports only point spatial object, however we are working on its extension for other spatial objects including line and polygon. The query output is available to the end user via a variety of sinks including Apache Kafka, files, sockets and external systems. The GeoFlink architecture has two important layers, i.e., 1) Spatial Stream Layer and 2) Real-time Spatial Query Processing Layer.

A. Spatial Stream Layer

This layer is responsible for converting the incoming data stream(s) into spatial data stream(s). Apache Flink treats incoming data stream as ordinary text stream and its direct processing by Flink can be inefficient. GeoFlink converts the incoming data stream into spatial data stream by keeping in view the geometrical properties of spatial objects, i.e., point object, line object, polygon object, etc. This layer assigns cell ID(s) to spatial objects based on Grid-based index (refer Sec. V) for the efficient distribution and processing of incoming data stream.

B. Real-time Spatial Query Processing Layer

This layer enables the execution of spatial queries over spatial data streams. GeoFlink currently supports the most widely used spatial query operators, i.e., spatial range, spatial kNN and spatial join. The users can use Java or Scala programming languages (Scala/Java API) to write custom spatial queries. This layer makes extensive use of the grid-based index for the efficient processing of spatial queries by pruning the objects which cannot be part of the query output and by uniformly distributing data across the distributed operator instances. The query output is available to the end user via a variety of sinks including Apache Kafka, files, sockets and external systems.

V. GEOFLINK GRID INDEX

The index structures for the spatial data can be classified into broad categories, i.e., 1) Tree-based, and 2) Grid-based. The tree-based index structures supports efficient query processing, however its update cost is high, as in the case of node addition, removal or update, the tree needs to be rebalanced and sometimes the whole tree needs to be restructured. On the other hand, a simple structure of grid-based index enables quick updates, however it cannot answer queries as efficiently as the tree-based index [21][22]. Since GeoFlink is meant to support streaming applications with very high update rates, the maintenance cost of the index employed has to be as small as possible. To this end, grid-based index seems to be a natural choice for GeoFlink.

A grid-based index [23] is a space-partitioned structure where a predefined area is divided into equal-sized cells of some fixed length l, as shown in Figure 3. Geometrical objects with coordinates within the boundaries of the grid cell(s) belong to that particular cell(s). Each grid cell is identified by a unique key or ID and all the objects whose coordinates lie within the boundaries of the grid cell c is assigned the same cell key.

The grid index used in this work is aimed at pruning unnecessary objects during spatial queries execution and to help in the uniform distribution of spatial objects across the distributed cluster nodes. The grid index (G) is constructed by partitioning the 2D space given by its boundary (MinX, MinY), (MaxX, MaxY) into square shaped cells of length l. Here we assume that G boundary is known as it can be estimated easily based on the geographical location of the data stream.

Let \( C_{x,y} \in G \) be a grid cell with x and y indices x and y, respectively, then \( L_1(C_{x,y}), L_2(C_{x,y}), ..., L_n(C_{x,y}) \) denote its neighbouring layers, where \( L_1(C_{x,y}) \) is given by:

\[
L_1(C_{x,y}) = \{ C_{u,v} | u = x \pm 1, v = y \pm 1, C_{u,v} \neq C_{x,y} \}
\]
The grid-based index used in this work is logical, that is, it denotes the concatenation operator. For instance, a grid $G$ is given by a boundary $(\text{Min}X, \text{Min}Y), (\text{Max}X, \text{Max}Y) = (0, 0), (50, 50)$. For a stream tuple $s$ with coordinates $(25, 42)$ and $n = 3$, its key $s$ given by: $x\text{Index} = 2 = 002$, $y\text{Index} = 4 = 004$, $s\text{key} = 002004$.

The grid-based index used in this work is logical, that is, it only assigns a key (cell ID) to incoming streaming tuples or moving objects and based on the key, the tuples are processed, pruned and distributed across the cluster nodes. Beside the assignment of a key to streaming tuples, no physical data structure is needed, hence no update is required when a stream tuple expires or an updated object location is received. This makes our grid-based index fast and memory efficient.

VI. SPATIAL STREAM LAYER

Spatial streams in GeoFlink are distributed streams where each tuple represents a spatial object. For the effective distribution of data streams that take into account the spatial proximity of data so to speed up spatial query processing across the GeoFlink cluster nodes, grid-based index is used.

A. Spatial Stream Indexing

Spatial indexes like R-tree, Quad-tree and KDB-tree can significantly speed-up spatial query processing, however their maintenance cost is high especially in the presence of heavy insertions and deletions.

Since GeoFlink is meant to support streaming applications with very high update rates, tree-based index is not a good choice. Instead we need a spatial index which can support efficient query processing and uniform data distribution across the distributed cluster nodes. Therefore, GeoFlink uses a very light and update-efficient grid based index as discussed in Section VI.

One problem with the grid-based index is that it requires data boundaries for its construction. Since a stream is dynamic and infinite, its boundaries cannot be known in advance however, it can be easily estimated based on the geographical location of the sensors generating the data streams in case of fixed sensors or if the data stream is being generated by moving objects, it can be estimated by utilizing the loose bounds of the area or city of the objects. For instance, assuming that we are aware of the city of the data stream source(s), we can use the city’s geographical boundaries for the grid-index creation. A GeoFlink Java API example of constructing the grid-based index is given below.

```java
UniformGrid uGrid = new UniformGrid(GridSize, MinX, MaxX, MinY, MaxY)
```

where GridSize of 50 generates a grid index of 50x50 cells, with the bottom-left (MinX, MinY) and top-right (MaxX, MaxY) coordinates, respectively.

B. Spatial Objects Support

GeoFlink currently supports CSV and GeoJSON input formats from Apache Kafka and Point type spatial object, however we are working on its extension to support other input formats and spatial object types including line and polygon.

GeoFlink users need to make an appropriate Apache Kafka connection by specifying the topic name and bootstrap server(s). Once the connection is established, the user can construct spatial stream using the GeoFlink Java/Scala API. A GeoFlink Java API example of constructing a spatial stream from GeoJSON stream is as follows.
C. Spatial Stream Partitioning

Effective partitioning of data across distributed cluster nodes plays a vital role in efficient query processing. As discussed in Section III, Apache Flink `keyBy` transformation logically partitions a stream into disjoint partitions in such a way that all the tuples with the same key are assigned to the same partition or to the same operator instance. Internally, the `keyBy` transformation is implemented using hash partitioning.

To enable effective partitioning in GeoFlink, which takes into account the incoming data’s spatial proximity, grid indexing is used. GeoFlink assigns a grid cell ID (`key`) to each incoming stream tuple based on its spatial location. Since all spatially close tuples belong to a single grid cell, they are assigned the same key. GeoFlink uses the key as the `keyBy` operator’s key to enable effective stream distribution across the distributed operator instances. The grid index creation is discussed in Section VI-A, whereas the key assignment is done as part of the spatial objects creation as discussed in Section VI-B. Stream partitioning is further discussed in Section VII.

VII. REAL-TIME SPATIAL QUERY PROCESSING LAYER

The real-time spatial query processing layer of GeoFlink provides support for all the basic spatial operators which are required by any spatial data processing and analysis applications. The supported queries/operations include spatial range query, spatial kNN query and spatial join query. All the queries discussed in this section make use of aggregation window and are continuous in nature, i.e., they generate window-based continuous results on the continuous data stream. Namely, one output is generated per window aggregation.

To reduce spatial query execution cost and to distribute the spatial data effectively across the cluster nodes, GeoFlink makes use of the grid index structure. One traditional and a very effective way to reduce the computation cost is to prune out the objects which cannot be part of the query result. Given a cell $C_{x,y} \in G$ containing a query object, we define the following layers for the sake of effective pruning, where a layer is made up of grid cells as discussed in Section V.

- **Guaranteed Layers** ($L_g(C_{x,y})$): The objects in this layer are guaranteed to be part of the query result.
- **Candidate Layers** ($L_c(C_{x,y})$): The objects in this layer may or may not be the part of the query result and hence require distance evaluation.
- **Non-neighbouring Layers** ($L_n(C_{x,y})$): The objects in this layer cannot be part of the query result and hence can be safely pruned.

The cells in the layers $L_g(C_{x,y})$, $L_c(C_{x,y})$ and $L_c(C_{x,y})$ are disjoint. In the following, we call the objects belonging to the $L_g(C_{x,y})$, $L_c(C_{x,y})$ and $L_n(C_{x,y})$ layers as the guaranteed neighbours, candidate neighbours and non-neighbours, respectively. Since most of the spatial queries deal with the spatial data effectively across the cluster nodes, GeoFlink

A. Spatial Range Query

**Definition 1** ($r$-neighbours): Geometrical objects that lie within the radius $r$ of the query point $q$.

Let $l$, $q$ and $r$ denote a grid cell length, a query point, and the query radius, respectively. Assuming that a cell $C_{x,y}$ contains a query point $q$ as shown in Figure 3, then the layers $L_g(C_{x,y})$ and $L_c(C_{x,y})$ are given as follows:

$$L_g(C_{x,y}) = \left\lfloor \frac{r}{l \sqrt{2}} \right\rfloor - 1$$

$$L_c(C_{x,y}) = \left\lfloor \frac{r}{l} \right\rfloor - L_g(C_{x,y})$$

The layers other than $L_g(C_{x,y})$ and $L_c(C_{x,y})$ are the non-neighbouring layers, i.e., $L_n(C_{x,y})$.

**Algorithm 1** and **Figure 7** details the different phases of the grid-based range query. GeoFlink receives data streams from a distributed messaging system, for instance, Apache Kafka.
Algorithm 1 Spatial Range Query

Input: $S_{in}$: Spatial data stream, $q$: query object, $r$: Query radius, $G$: Spatial grid index
Output: $S_{out}$: Spatial stream containing objects that satisfy the range query predicate

1: Get $C_q$ using $q.key$; \{$C_q$ denotes the cell containing $q$\}
2: Compute $L_g(C_q)$ and $L_c(C_q)$ using Equations 1 and 2 respectively.
3: for each $s \in S_{in}$ do
   4:     if $s \in L_g(C_q)$ then
   5:         $s$ is a guaranteed $r$-neighbour($q$) and is added to $S_{out}$
   6:     else if $s \in L_c(C_q)$ then
   7:         $s$ is a candidate neighbour and is added to $S_{candid}$
   8:     end if
9: end for
10: Shuffle $S_{candid}$ to balance the load across cluster nodes
\{Refine Phase\}
11: for each $s \in S_{candid}$ do
12:     if $s \in r$-neighbour($q$) then
13:         Add $s$ to $S_{out}$ \{$s \in r$-neighbour($q$) is computed using distance function\}
14: end if
15: Return $S_{out}$
16: end for

[27] Provided the right configuration, the binding between stream source cluster and Apache Flink cluster enables the uniform distribution of incoming stream across the Flink cluster nodes. Given the query point $q$, each GeoFlink node computes the $L_g(C_q)$ and $L_c(C_q)$ sets, where $C_q$ denotes the cell containing $q$. The algorithm consists of two main phases, i.e., the filter phase and the refine phase. The filter phase prunes out the input spatial stream ($S_{in}$) tuples which are not part of $L_g(C_q)$ or $L_c(q)$. As a result of filtering, majority of tuples are pruned out, while a few are sent to the output stream ($S_{out}$) and the remaining candidate neighbours ($S_{candid}$) require refine phase. After the filter phase, a small shuffling is done to rebalance the data stream. Finally in the refine phase, $S_{candid}$ are checked for the $r$-neighbour($q$) using the actual distance function.

To execute a spatial range query via GeoFlink Java/Scala API SpatialRangeQuery method of the RangeQuery class is used. We first create a query point and then pass it to the SpatialRangeQuery method along with the spatial data stream and other required parameters.

```
// Create a query point q
Point queryPoint = new Point (qLongitude, qLatitude, uGrid);

// Register a spatial range query
DataStream<Point> outputStream = RangeQuery . SpatialRangeQuery (pointStream, queryPoint, radius, windowSize, windowSlideStep, uGrid);
```

where $pointStream$ is a spatial point data stream,
that of the naive approach. However, after the first iteration, the distance of the \(k\)th nearest neighbour from \(q\), \(d_k\), is sent back to the filter phase. The filter phase uses the \(d_k\) to estimate the candidate neighbouring layers \(L_c(q)\) in the next iteration and hence can prune the non-neighbouring objects in the non-neighbouring layers \(L_n(q)\). To maximize the chances of obtaining at least \(k\)NN from every window/iteration, the \(d_k\) is multiplied with a constant factor \(\alpha\), where \(\alpha > 1\). The execution continues in a similar fashion, with the feedback being sent back after every iteration and thus enabling the updates of the \(L_c(q)\) and \(L_n(q)\) continuously.

### Algorithm 2 Spatial kNN Query

**Input:** \(S_{in}\): Spatial data stream, \(q\): query object, \(k\): number of nearest neighbours required, \(\alpha\): Multiplication factor, \(G\): Spatial grid index

**Output:** \(S_{out}\): Spatial stream containing the \(k\)NN objects with respect to \(q\)

1. \(L_c(q) = m\) \(\{m\}:\) Max. number of grid layers \(\{\text{Filter Phase}\}\)
2. for each \(s \in S_{in}\)
3. if \(s \in L_c(q)\) then
4. \(s\) is a candidate neighbour and is added to \(S_{candid}\)
5. end if
6. end for
7. Shuffle \(S_{candid}\) to balance the load across the cluster nodes \(\{\text{Refine Phase}\}\)
8. for each \(s \in S_{candid}\)
9. if \(s\) is a \(k\)NN then
10. Add \(s\) to \(S_{pre-out}\)
11. end if
12. end for
13. Merge and sort \(k\)NNs (\(S_{pre-out}\)) from all the cluster nodes to obtain the combined \(k\)NN and add the results to the \(S_{out}\)
14. \(d_k = \text{dist}(q, k^{th} \text{NN})\) \(\{k^{th} \text{NN denotes the } k^{th} \text{ nearest neighbour}\}\)
15. Update \(L_c(q)\) using \(k^{th}\)NN for the next iteration and send it back to the Filter Phase; \(L_c(q) = \left\lceil \alpha \cdot d_k \right\rceil\)
16. Return \(S_{out}\)

To execute a spatial \(k\)NN query via the GeoFlink Java/Scala API SpatialKNNQuery method of the KNNQuery class is used.

```java
// Create a query point q
Point queryPoint = new Point(qLongitude, qLatitude, uGrid);

// Register a spatial kNN query
DataStream <PriorityQueue<Tuple2<Point, Double>>> outputStream = KNNQuery.
SpatialKNNQuery(spatialStream, queryPoint, k, windowSize, windowSlideStep, uGrid);
```

where \(k\) denotes the number of points required in the \(k\)NN output. Please note that the output stream is a stream of priority queue which is a sorted list of \(k\)NNs with respect to the distance from the query point \(q\). The query output is generated continuously for each window slide based on the \(windowSize\) and \(windowSlideStep\).

### Algorithm 3 Spatial Join Query

**Input:** \(S1\): Spatial ordinary data stream, \(S2\): Spatial query data stream, \(q\): query object, \(r\): Query radius, \(G\): Spatial grid index

**Output:** \(S_{out}\): Joined spatial stream

1. for each \(q \in S2\) do
2. Get \(C_q\) using \(q\).key; \(\{C_q\} denotes the cell containing \(q\}\)
3. Compute \(L_q(C_q)\) and \(L_c(C_q)\) using Equations 1 and 2 respectively.
4. \(S2' = \text{Replicate} S2\), such that each \(q \in S2'\) is assigned keys from the sets \(L_q(C_q)\) and \(L_c(C_q)\);
5. end for
6. Distribute \(S1\) and \(S2'\) across the cluster nodes based on their keys
7. for each \(q \in S2'\) do
8. for each \(s \in S1\) do
9. if \(s\) lies in \(L_q(C_q)\) then
10. \(s\) is a guaranteed neighbour and is added to \(S_{out}\)
11. else if \(s \in L_c(C_q)\) then
12. \(s\) is a candidate neighbour and is added to \(S_{candid}\)
13. end if
14. end for
15. end for
16. for each \(q \in S2'\) do
17. for each \(s \in S_{candid}\) do
18. if \(s \in r\text{-neighbour}(q)\) then
19. Add \(s\) to \(S_{out}\)
20. end if
21. end for
22. end for
23. end for
24. Return \(S_{out}\)

### C. Spatial Join Query

Spatial join is an expensive operation, where each tuple of a query stream must be checked against every tuple of an ordinary stream. To achieve this using the naive approach, low rate stream (query stream) is replicated across all the cluster nodes whereas the high rate stream (ordinary stream) is divided across the cluster nodes. However, this involves expensive distance computations and heavy shuffling of stream tuples. Definition 4 formally defines the spatial join.

**Definition 4:** [Spatial Join Query] Given two streams \(S1\) (ordinary stream) and \(S2\) (query stream), a radius \(r\) and window parameters, spatial join query returns all the points in \(S1\) that lie within the radius \(r\) of \(S2\) points for each aggregation window.
To reduce the number of distance computations by pruning ordinary stream tuples which cannot be part of the query result and to reduce data shuffling, we made use of grid index. Since the grid index takes into account the spatial proximity of spatial objects, a number of objects can be filtered out resulting in efficient join processing.

Figure 6 gives an overview of the GeoFlink spatial join. The grid-based spatial join consists of the following three phases: 1) Replication phase, 2) Filter phase, and 3) Refine phase. Let $S_1$ and $S_2$ denote the ordinary stream and the query stream, respectively. Given the spatial join query radius $r$, the replication phase computes the $L_g(C_q)$ and $L_c(C_q)$ of each $C_q | q \in S_2$, where $C_q$ denotes the cell containing query $q$. Next, the query points are replicated in such a way that each replicated point is assigned a cell ID (key) from the set $L_c(C_q)$. We denote the replicated query stream by $S_2'$. Next, we make use of the Apache Flink’s key-based join to join the two stream. Flink’s key-based join enables the tuples from the two joining streams with the same key to land on the same operator instance, hence enabling effective joining by filtering out the tuples which cannot be part of the join result. Hence, we join $S_1$ with $S_2'$ on keys. This causes the join to be executed only between the query point $q \in S_1$ and the ordinary stream points which belong to the cells in $L_c(C_q)$ in the refine phase. The $S_1$ objects which belong to the cells in $L_g(C_q)$ are guaranteed to be part of the join output and hence can be added to the output stream. Algorithm 3 lists the main steps of the spatial join query.

To execute a spatial join query via the GeoFlink Java/Scala API SpatialJoinQuery method of the JoinQuery class is used. The query output is generated continuously for each window slide based on the windowSize and windowSlideStep.

```java
// Create a query stream
DataStream<Point> queryStream = SpatialStream(
    geoJSONQryStream, "GeoJSON", uGrid);
// Register a spatial join query
DataStream<Tuple2<String, String>> outputStream =
    JoinQuery.SpatialJoinQuery(spatialStream, queryStream, radius, windowSize, windowSlideStep, uGrid);
```

VIII. EXPERIMENTAL EVALUATION

This section presents the detailed experimental evaluation of GeoFlink. In particular, we evaluated the throughput of GeoFlink for the three spatial queries, i.e., Spatial Range, Spatial kNN and Spatial Join.

A. Data streams

For performance evaluation of GeoFlink, a real dataset, Microsoft T-Drive trajectory data [28], containing GPS trajectories of 10,357 taxis during the period of February 2 to 8, 2008 in Beijing city is used. The total number of points(tuples) in the dataset is 17 million and the total distance of the trajectories is around 9 million kilometres. Each tuple consists of a taxi ID, datetime, longitude and latitude. The dataset is loaded into the Apache Kafka [27] system and is supplied as a distributed data stream to the GeoFlink cluster.

B. Environment

For the experiments, Apache Kafka and Apache Flink clusters are used. The clusters are deployed on AIST AAIC cloud [29], where each VM has 128 GB memory and 20 CPU cores and each core uses Intel skylake 1800 MHz processor. Table II shows the deployment details of each cluster. All the VMs are operated using Ubuntu 16.04 LTS.
Fig. 7. Spatial range query

Fig. 8. Spatial kNN query
The section presents the evaluation results of the three queries discussed in Section VII. We compared the grid-based implementation of GeoFlink queries with the respective naive approaches, which are discussed in Section VII. For fair comparison, efforts are made to distribute the data stream uniformly across the cluster nodes however the respective naive approaches lack the grid-based pruning. The evaluation is presented in terms of the system throughput, which can be defined as the maximum number of stream tuples which can be processed by the system per second. Unless otherwise stated, following default parameter values are used in the experiments: grid size: 150 x 150 cells, query radius r: 400 meters, window size: 10 seconds, window slide: 5 seconds and k: 10. Each experiment is performed three times and the average values are reported in the graphs. To construct the grid, the end-user needs to provide the approximate/loose boundaries of the data stream. For instance, in the case of the T-Drive data stream in this work we made use of the following rectangular boundary in terms of longitudes and latitudes, which covers Beijing city: bottom-left = 115.50000, 39.60000, top-right = 117.60000, 41.10000. Simple Euclidean distance is used for the distance computation.

### C. Evaluation

Figure 7 compares system throughput of our cell-based approach with the naive approach for the spatial range query by varying different parameters. The system throughput of the cell-based approach is far higher compared to the naive approach for all the variation of the parameters, which is mainly due to the effective grid-based pruning. In Figure 7(a) throughput of the cell-based approach is comparatively lower for the grid size 50 x 50. This is because at this grid size, each individual cell size is quite large, hence resulting in poor

### TABLE I

| Cluster          | # Nodes | Memory | Version |
|------------------|---------|--------|---------|
| Apache Flink     | 4<sup>a</sup> | 128 GB | 1.9.1   |
| Apache Kafka     | 3<sup>b</sup> | 128 GB | 2.3.0   |

<sup>a</sup> 1 Job Manager and 3 Task Managers
<sup>b</sup> 1 Zookeeper and 2 Broker Nodes
pruning. On the other hand very small cell sizes also result in lower throughput as can be observed from the grid sizes 200 x 200 and 250 x 250, which is due to the fact that the small cell sizes increases the number of cells exponentially, whose processing incurs higher processing cost hence reducing the system throughput. In Figure 7(b) we varied the query radius. Since the increase in query radius results in bigger query evaluation set, the throughput decreases with the increase in the query radius, however the decrease is significant in the naive approach compared to the cell-based approach. This is again due to the strong pruning capability of the cell-based approach. In Figures 7(c) and 7(d), the window size and slide step are varied. Increasing window size results in a decrease in the throughput which is quite obvious however, again the decrease is less significant in the cell-based approach proving the effectiveness of the grid-based approach. On the other hand, increasing the window slide step in Figure 7(d) results in an increase in the system throughput, because larger slide step means less overlapping computation as the window slides. This results in the decrease in the number of distance computations and hence increase in the system throughput.

In Figure 8 we evaluated the kNN query by varying different parameters. For the cell-based kNN evaluation, the α value is set to 1.5. Although the throughput of the cell-based approach is comparatively better than the naive approach in all cases, the difference is not significant. This is due to the fact that the kNN cell-based approach utilizes a feedback approach rather than direct pruning as in the case of the range query. Hence, pruning is not as good as in the case of the range query. Furthermore, implementation of the iterative/feedback approach incurs an additional operator in the cell-based approach resulting in the reduced throughput. The variation of parameters has more or less the same effect on the processing of the kNN query as in the case of the range query. The only new parameter in the kNN query is k, in Figure 8(b). Increasing the parameter k decreases the system throughput because for the larger k values, the system needs to maintain bigger priority queues to keep the kNN sorted. Since the proposed grid-based kNN can prune a large number of objects and require far less distance computations compared to the naive approach, our approach will be more beneficial when expensive distance computations are used, for instance, the road distance computation.

Figure 9 evaluates the spatial join query by varying different parameters. From the figure, the throughput of the cell-based join query is comparatively far higher than the naive approach, and in most cases more than the double. This is because the join query involves multiple query points, which means that the naive approach now needs to deal with a large number of points and distance computations. However, in case of the grid-based approach, majority of the non-neighbours can be pruned out and the join query requires far less number of distance computations. The trends in the variation of the parameters including grid size, query radius, window size and window join are essentially the same as that of the previous queries. The Figure 9 includes variation in the query stream arrival rate as an additional evaluation. The increase in the query stream arrival rate results in the reduced system throughput, which is obvious as with the increase in the number of query points, more computations are needed. However, this reduction is quite significant in the naive approach compared to the cell-based approach, proving the effectiveness of the cell-based approach.

IX. Conclusion and Future Work

This work presents GeoFlink which extends Apache Flink to support spatial data types, index and continuous queries. To enable the efficient processing of continuous spatial queries and the effective data distribution among the Flink cluster nodes, a grid-based index is introduced. The grid index enables the pruning of spatial objects which cannot be part of a spatial query result and thus can guarantee efficient query processing, similarly it helps in preserving the spatial data proximity resulting in effective data distribution.

GeoFlink currently supports spatial range, spatial kNN and spatial join queries on geometrical point data type. Extensive experimental study proves that GeoFlink’s grid-based approach can significantly improve the system throughput by pruning a large number of data points. As a future direction, we are working on GeoFlink’s extension to support line and polygon data types and other complex query operators.

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