The **STARK** Framework for **S**patio- **T**emporal Data Analytics on Sp**ark**

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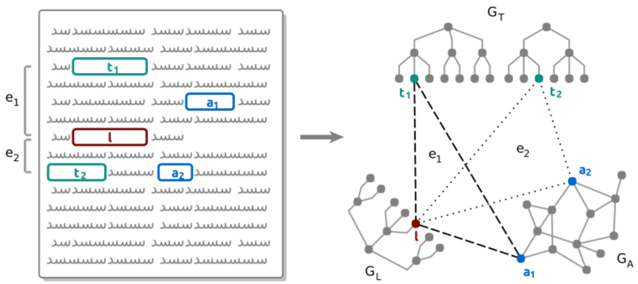
Motivation

- data analytics for decision support
- include spatial and/or temporal information
    - sensor readings from environmental monitoring
    - satellite image data
    - event data
- data sets may be large
  or may be joined with other large data sets

Big Data platforms like Hadoop or Spark don't have
native support for spatial (spatio-temporal) data

What do we want?

event information (extracted from text)



find correlations

fast Big Data platform (Spark/Flink)

easy API/DSL

spatial & temporal aspects

flexible operators & predicates

Outline

1. Existing Solutions
2. STARK DSL
    - Data representation
    - Integration
    - Operators
3. Make it fast
    - Partitioning
    - Indexing
4. Performance evaluation

Existing Solutions

… and why we didn't choose them

- **Hadoop-based**
  - slow
  - long Java programs
  - HadoopGIS, SpatialHadoop, GeoMesa, GeoWave
- **for Spark**
  - GeoSpark
    - special RDDs per geometry type (PointRDD, PolygonRDD) - no mix!
    - unflexible API
    - **crashes & wrong results!**
  - SpatialSpark
    - CLI programs
    - no (documented) API

STARK DSL

Spark Scala API example

```
case class Event(id: String, lat: Double, lng: Double, time: Long)

val rdd: RDD[Event] = sc.textFile( "/events.csv" )
            .map(_.split( ","))
            .map(arr =>  Event(arr(0), arr(1).toDouble, arr( 2).toDouble, arr( 3).toLong)
            .filter(e => e.lat >  10 && e.lat < 50 && e.lng > 10 && e.lng < 50)
            .groupBy(_.time)
```

Problem: Spark does not know about spatial relations: no spatial join!

Goal:

- exploit spatial/temporal characteristics for speedup
- useful and flexible operators
  - predicates
  - distance functions
- integrate analysis operators as operations on RDDs
- seamless integration so that users don't see extra framework

STARK DSL

Data Representation

```
case class STObject(g: GeoType, t: Option[TemporalExpression])
```

- extra class to represent spatial and temporal component
  - time is optional
- defines relation-operators to other instances

```
def intersectsSptl(o: STObject) = g.intersects(o.g)

def intersectsTmprl(o: STObject) =
    (t.isEmpty && o.t.isEmpty ||
        (t.isDefined && o.t.isDefined && t.get.intersects(o.t.get)))


def intersects(t: STObject) = intersectsSpatial(t) && intersectsTemporal(t)
```

$$
\begin{aligned}
\Phi(o,p) \;\Leftrightarrow\quad & \Phi_s(s(o), s(p)) \wedge (\\
& \quad (t(o) = \perp \wedge t(p) = \perp) \vee \\
& \quad (t(o) \neq \perp \wedge t(p) \neq \perp \wedge \Phi_t(t(o), t(p)))
\end{aligned}
$$

STARK DSL

Integration

User program

```
val qry = STObject("POLYGON(...)", Interval(10,20))
val rdd: RDD[(STObject, (Int, String))] = ...

val filtered = rdd.containedBy(qry)
val selfjoin = filtered.join(filtered,  Preds.INTERSECTS)
```

STARK

```
class STRDDFunctions[T](rdd: RDD[(STObject, T)]) {
    def containedBy(qry: STObject) = new SpatialRDD(rdd, qry, Preds.CONTAINEDBY)
}


implicit def toSTRDD[T](rdd: RDD[(STObject, T)]) = new STRDDFunctions(rdd)
```

- we do **not** modify the original Spark framework
- Pimp-My-Library pattern:
  - use *implicit* conversions

STARK DSL

Operations

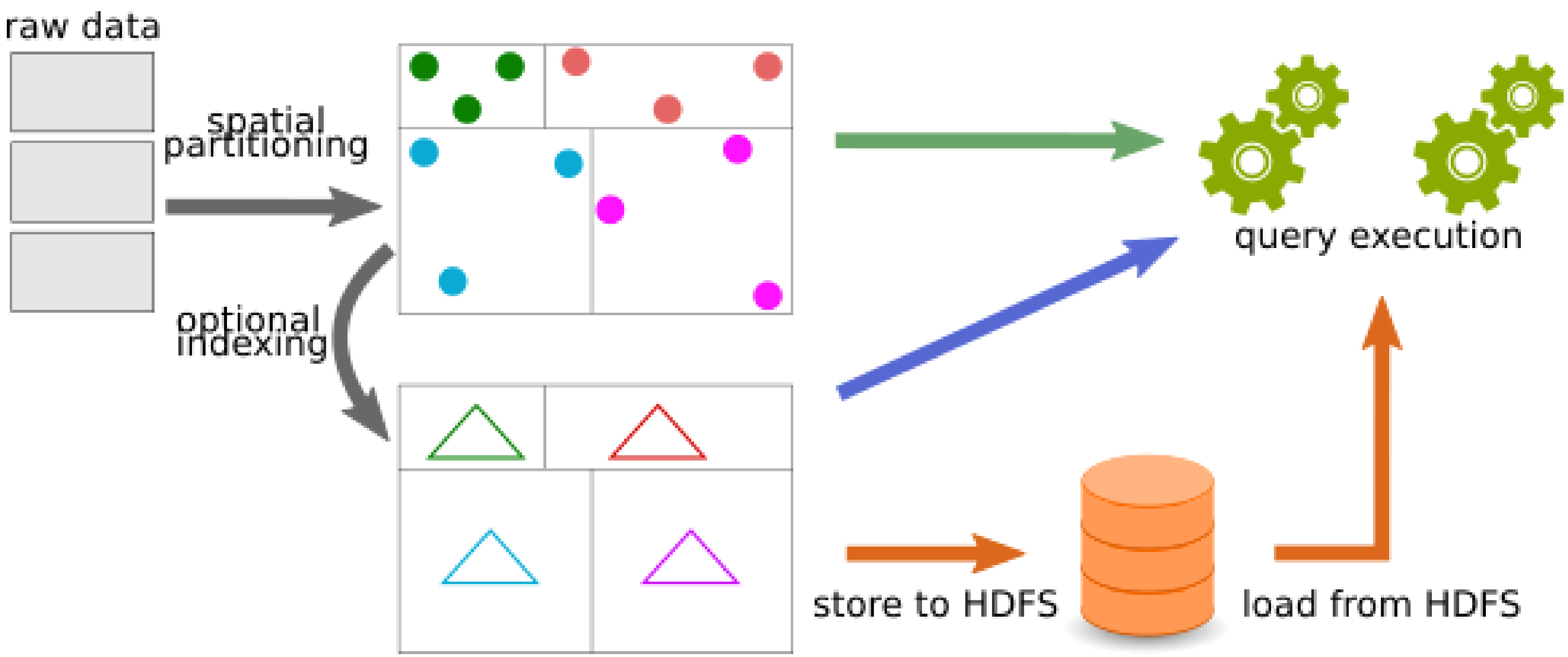
- Predicates
  - *contains*
  - *containedBy*
  - *intersects*
  - *withinDistance*
- can be used for filters <u>and</u> joins
- with and without indexing

- clustering: DBSCAN
- k-Nearest-Neighbor search
- Skyline

- supported by spatial partitioning

Make it fast

Flow



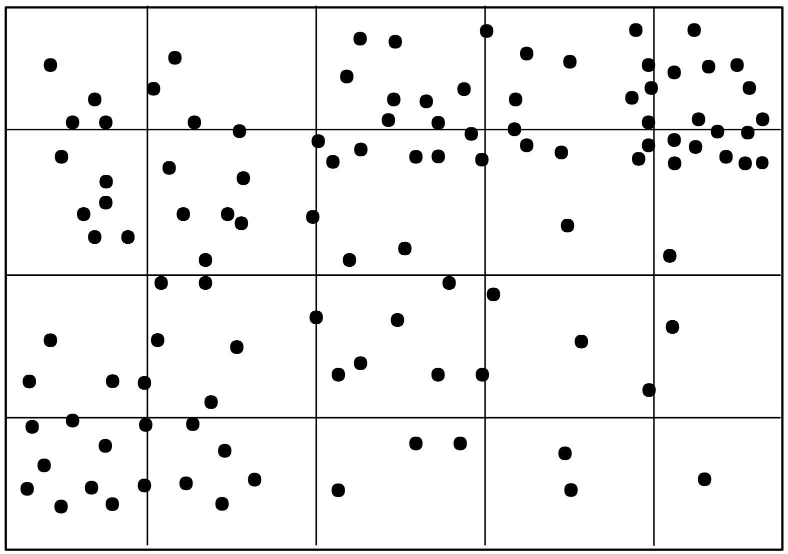
Make it fast

Partitioning

- Spark uses Hash parititioner by default
  - does not respect spatial neighborhood

Fixed Grid Parititoning

- divide space into *n* partitions per dimension
- may result in skewed work balance

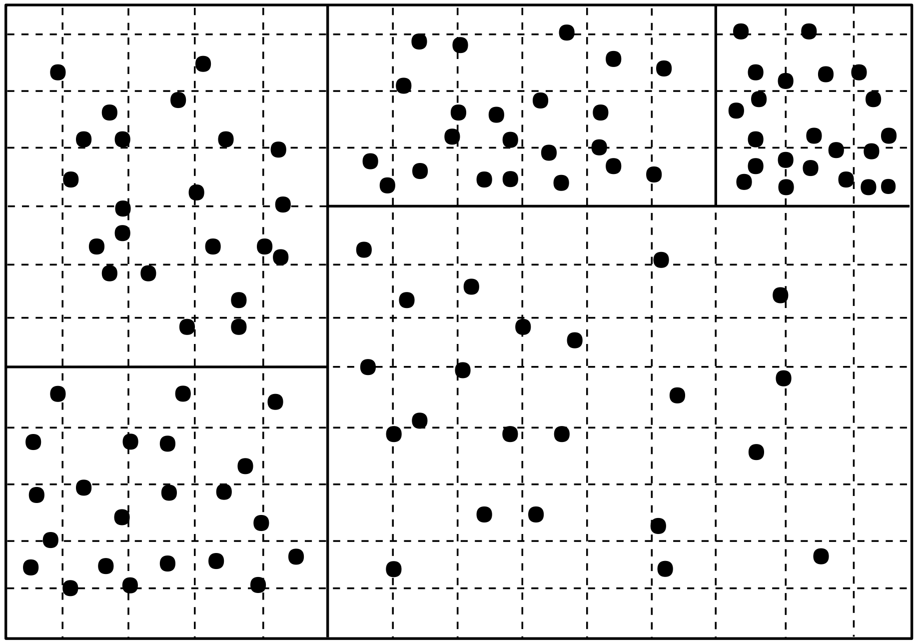


Make it fast

Partitioning

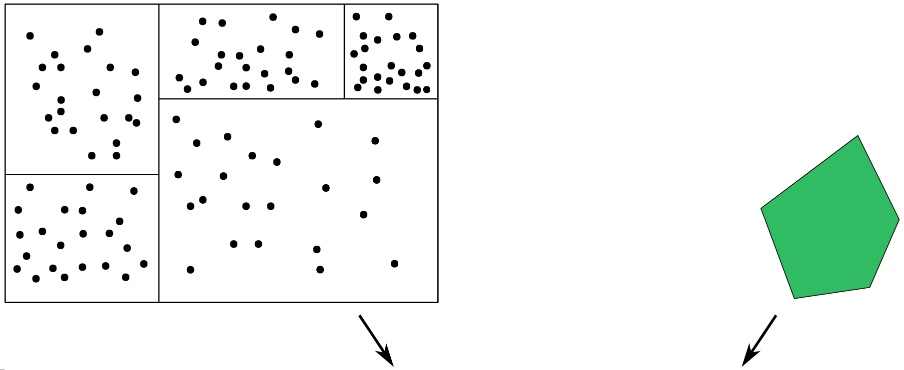
Cost-based Binary Split

- divide space into cells of equal size
- partition space along cells
    - create partitions with (almost) equal number of elements
- repeat recursively if maximum cost is exceeded

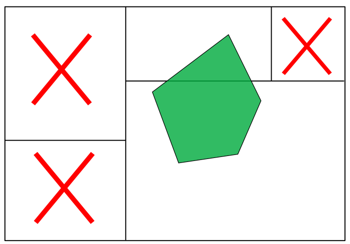


Make it fast

Partition Pruning - Filter

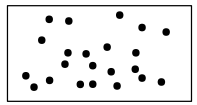


```
SpatialFilterRDD(parent: RDD, qry: STObject, pred: Predicate)
extends RDD {

  def getPartitions = {
```



```
  }

}
```

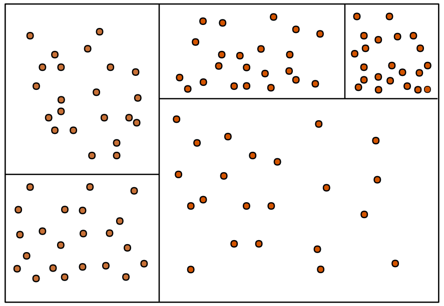
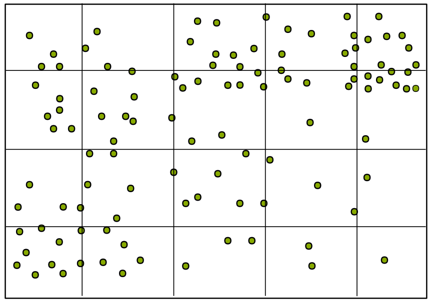
```
def compute(p:
```



```
) = {
for elem in p:
 if(pred(qry,elem))
  yield elem
}
```

Make it fast

Partition Pruning - Join

```
SpatialJoinRDD(left: RDD, right: RDD, pred: Predicate)
extends RDD {

   def getPartitions = {          def compute(p: l, r ) = {
    for l in left.partitions:      for i in l:
     for r in right.partitions:     for j in r:
      if l intersects r:             if pred(i,j):
       yield SptlPart(l,r)            yield(i,j)
   }                              }
}
```

Make it fast

Indexing

Live Indexing

- index is built on-the-fly
- query index & evaluate candidates
- index discarded after partition is complety processed

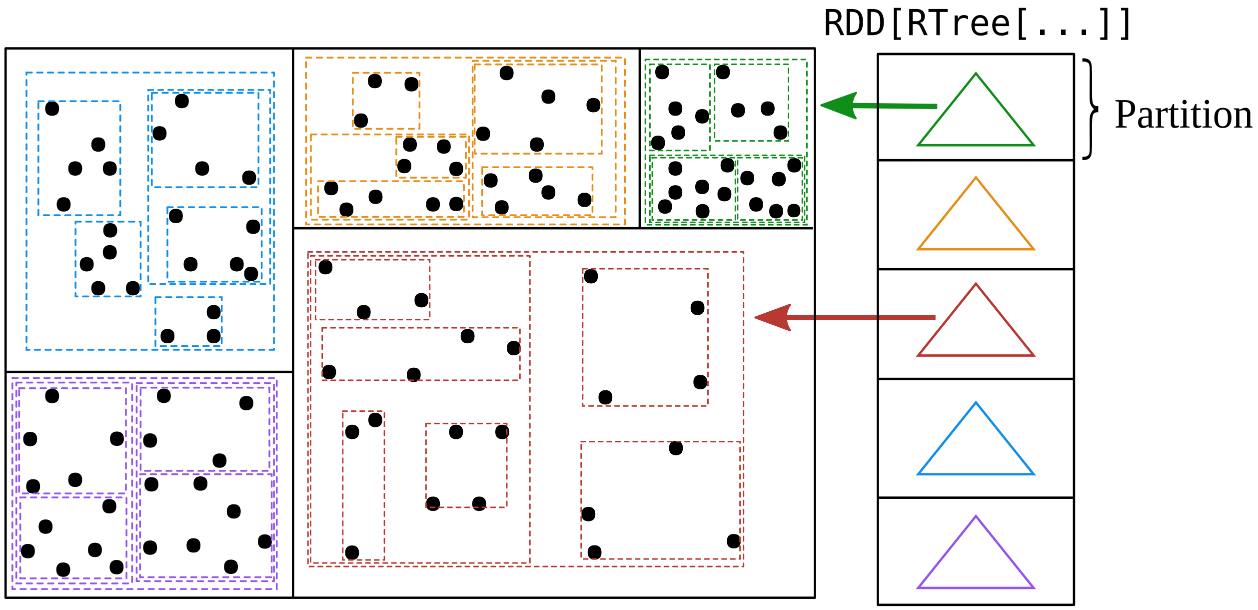
```
def compute(p: Partition) {
    tree = new RTree()
    for elem in p:
        tree.insert(elem)

    candidates = tree.query()
    result = candidates.filter(predicate)
    return result
}
```

Make it fast

Indexing

Persistent Indexing

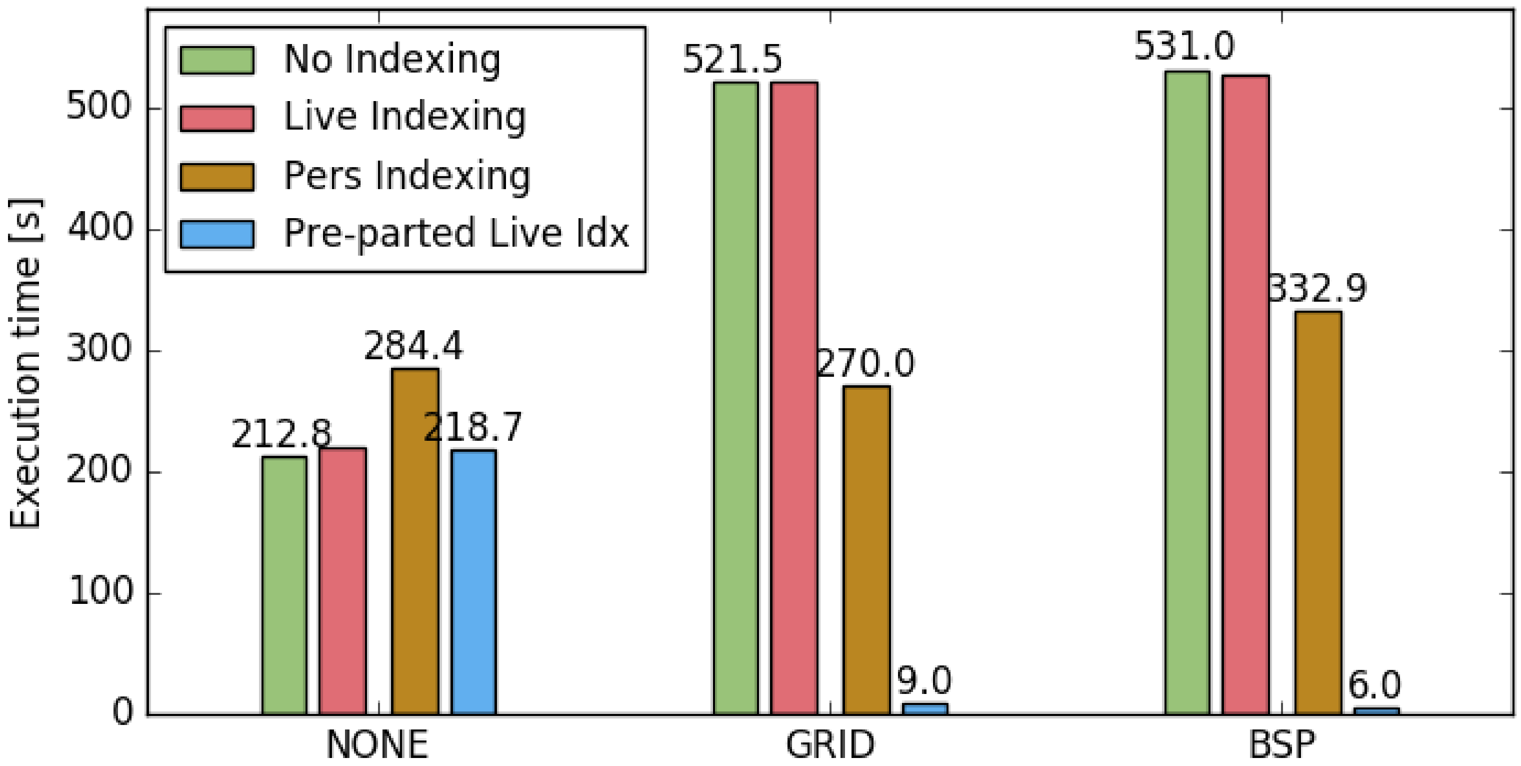
- transform to RDD containing trees
- can be materialized to disk
- no repartitioning / indexing needed when loaded again



Evaluation

Filter

10.000.000 polygons

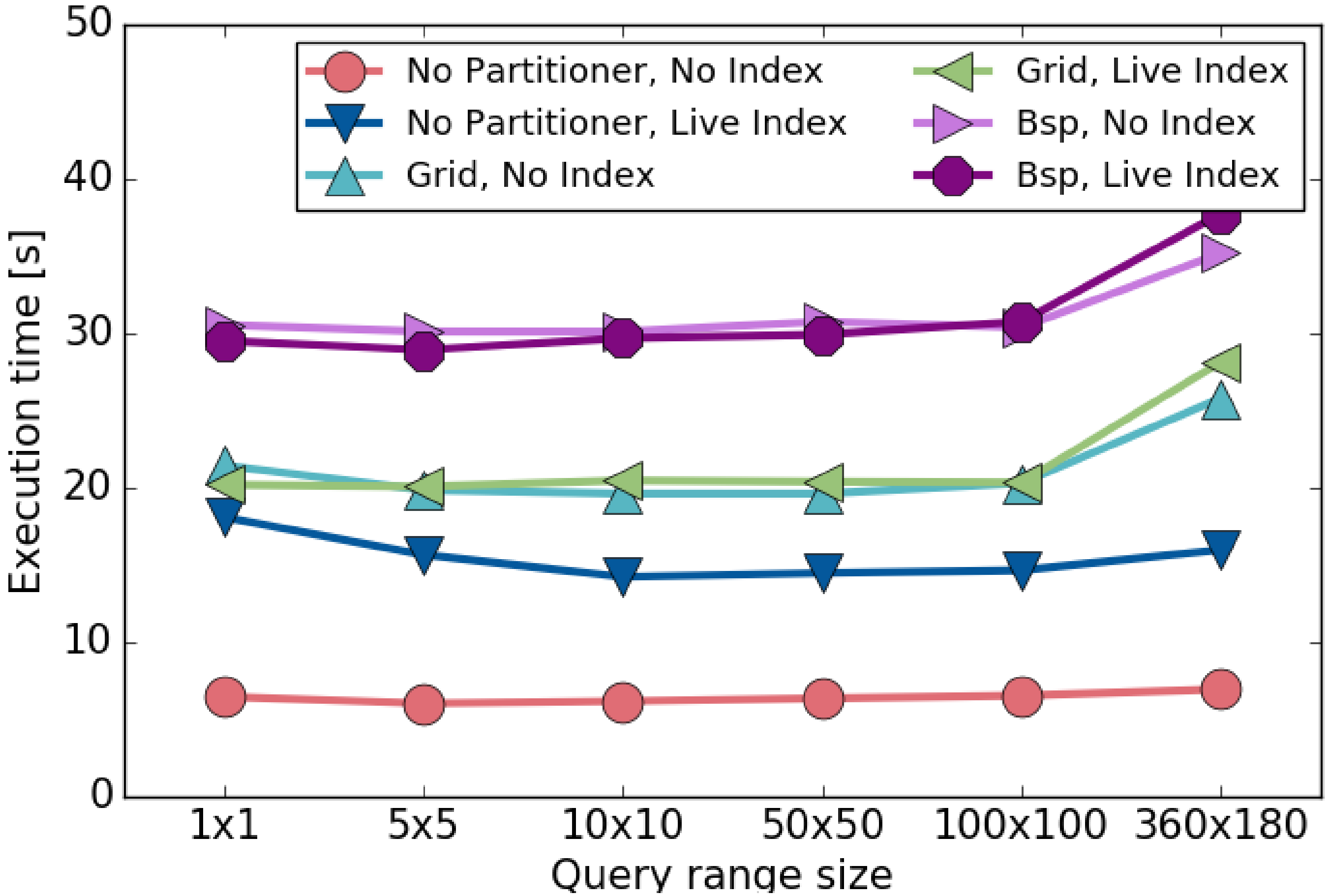


16 Nodes, 16 GB RAM each, Spark 2.1.0

Evaluation

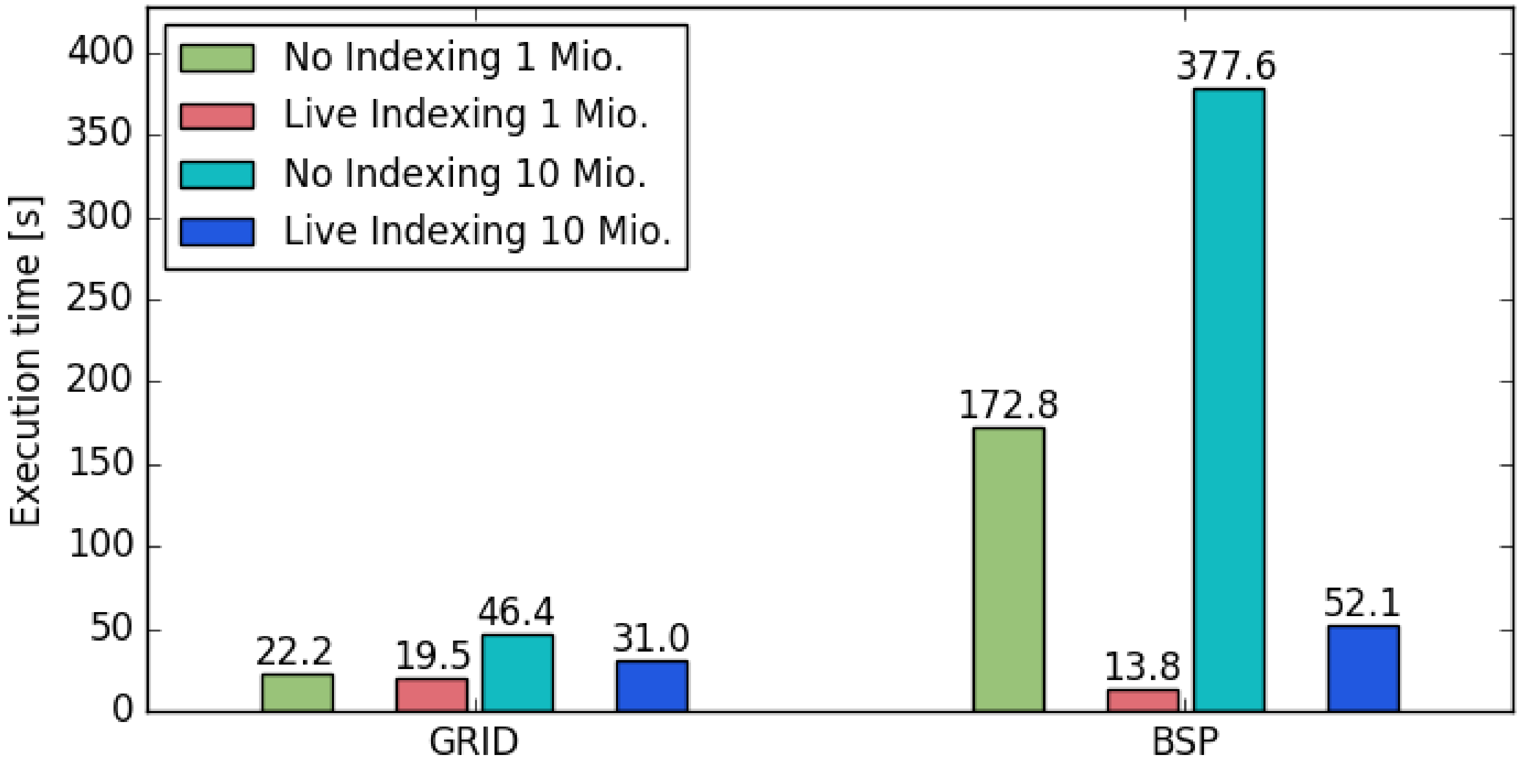
Filter - Varying range size

50.000.000 points



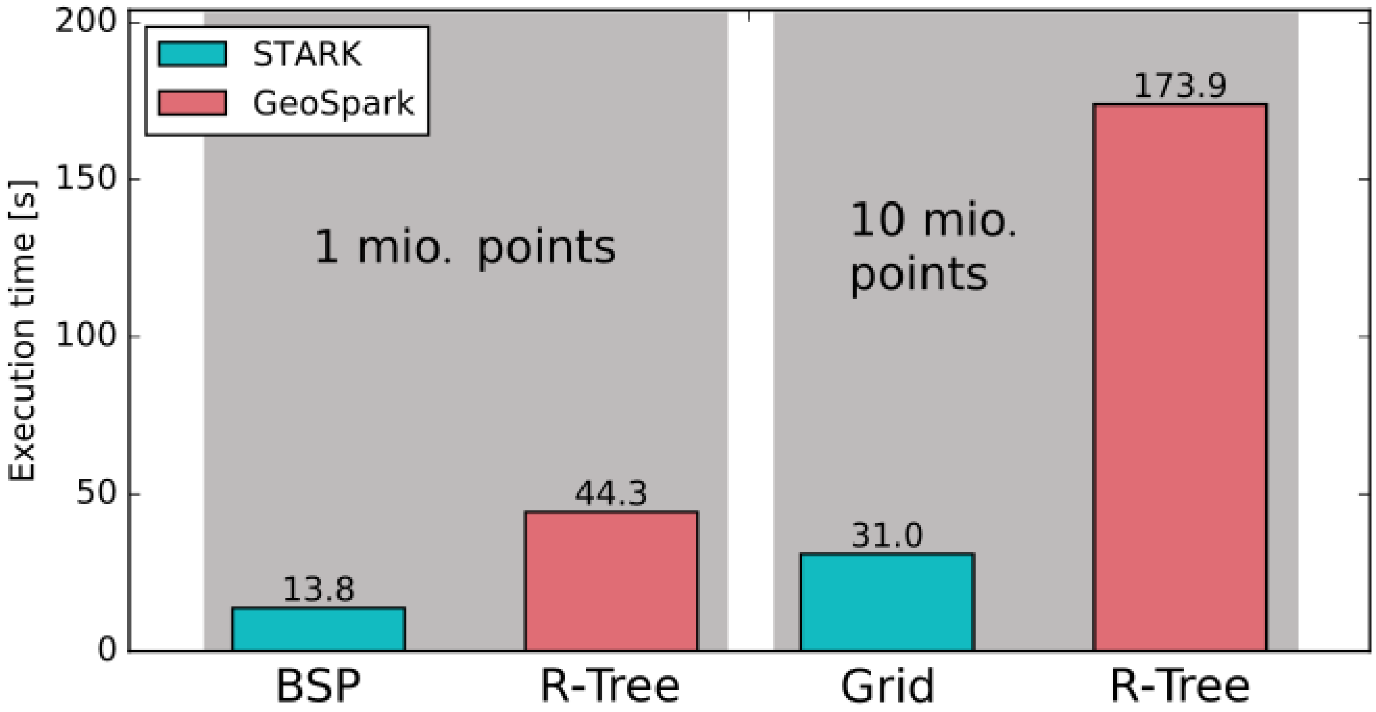
Evaluation

Join



Evaluation

Join



GeoSpark produced wrong results!

- 110.000 - 120.000 result elements missing

Conclusion

- framework for spatio-temporal data processing on Spark
- easy integration into any Spark program (Scala)

- filter, Join, clustering, kNN, Skyline
- spatial partitioning
- indexing

- partitioning / indexing not always useful / necessary
- performance improvement when data is frequently queried

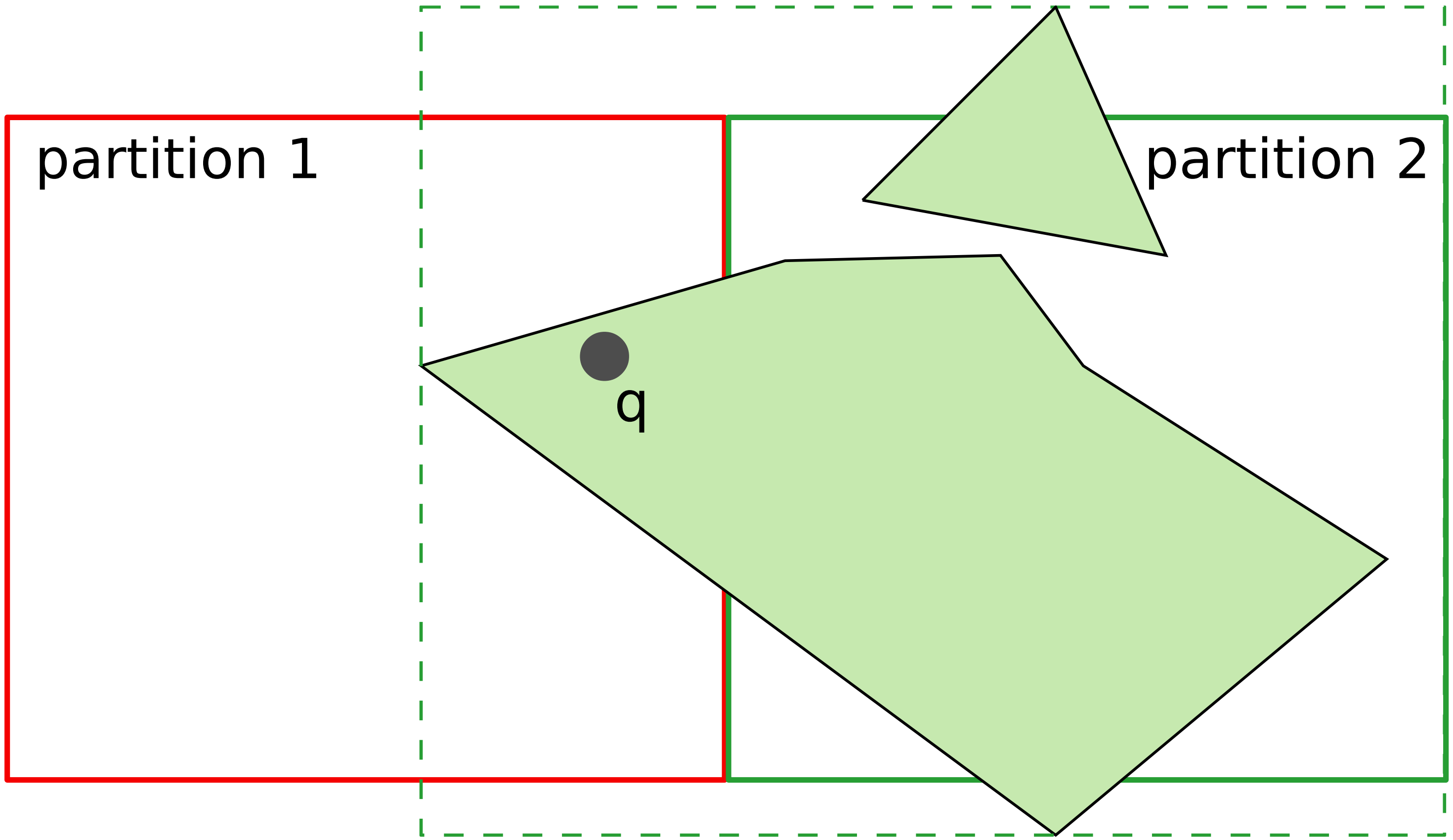
https://github.com/dbis-ilm/stark

Partitioning & Indexing

```
val rddRaw = ...
val partitioned = rddRaw.partitionBy( new SpatialGridPartitioner (rddRaw, ppD=5))
val rdd = partitioned.liveIndex(order= 10).intersects( STObject (...))
```

```
val rddRaw = ...
val partitioned = rddRaw.partitionBy(
                    new BSPartitioner (rddRaw, cellSize= 0.5, cost = 1000*1000))
val rdd = partitioned.index(order= 10)
rdd.saveAsObjectFile( "path" )

val rdd1:RDD[RTree[STObject ,(...)]] = sc.objectFile( "path" )
```

Partition Extent



Clustering

```
val rdd: RDD[(STObject, (Int, String))] = ...
val clusters = rdd.cluster(minPts =  10,
                           epsilon =  2,
                           keyExtractor = {  case (_,(id,_)) => id } )
```

- relies on a spatial partitioning
- extend each partition by epsilon in each direction
  - to overlap with neighboring partitions
- local DBSCAN in each partition
- merge clusters
  - if objects in overlap region belong to multiple clusters => merge clusters