Magellan – Spark as a Geospatial Analytics Engine

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DATA SCIENCE AND ENGINEERING AT SCALE
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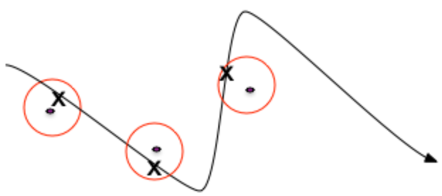
Who Am I?

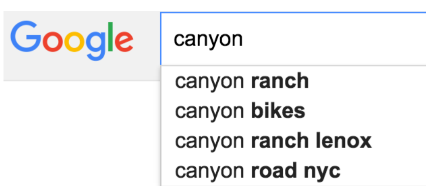
- Apache Spark PMC Member
- Hortonworks Architect, Spark + Data Science
- Prior to HWX, Principal Research Scientist @ Yahoo Labs (Large Scale Machine Learning)
  - Login Risk Detection, Sponsored Search Click Prediction, Advertising Effectiveness Models, Online Learning, …

What is Geospatial Analytics?

How do pickup/ dropoff neighborhood hotspots evolve with time?



Correct GPS errors with more Accurate landmark measurements

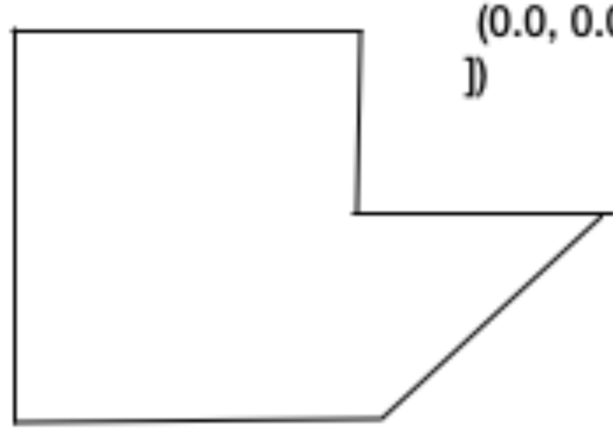


Incorporate location in IR and search advertising

Do we need one more library?

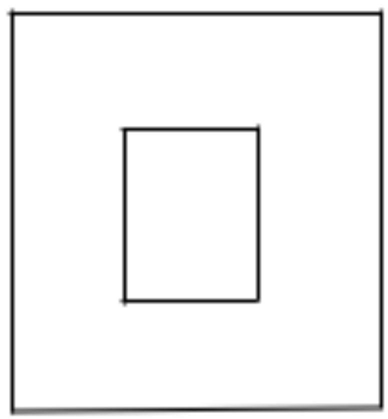
- Spatial Analytics at scale is challenging
  - Simplicity + Scalability = Hard
- Ancient Data Formats
  - metadata, indexing not handled well, inefficient storage
- Geospatial Analytics is not simply BI anymore
  - Statistical + Machine Learning being leveraged in geospatial
- Now is the time to do it!
  - Explosion of mobile data
  - Finer granularity of data collection for geometries
  - Analytics stretching the limits of traditional approaches
  - Spark SQL + Catalyst + Tungsten makes extensible SQL engines easier than ever before!

Introduction to Magellan



```
Polygon = (
  [],
  [(0.0, 0.0),(1.0, 0.0),
   (2.0, 1.0),(1.0, 1.0),
   (1.0, 2.0),(0.0, 2.0),
   (0.0, 0.0)
  ])
```

Introduction to Magellan



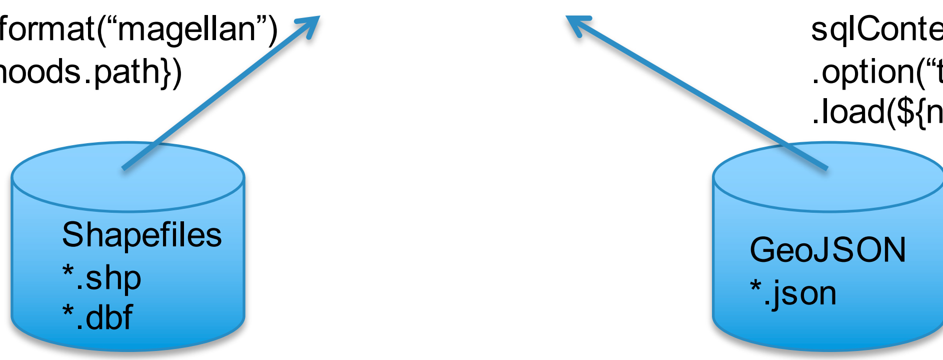
```
Polygon = (
  [0, 5],
  [(0.0, 0.0),(1.0, 0.0),
   (1.0, 2.0),(0.0, 2.0),
   (0.0, 0.0),
   (0.3, 0.3),
   (0.6, 0.3),
   (0.6, 0.9),
   (0.3, 0.9),
   (0.3, 0.3)
  ])
```

Introduction to Magellan

polygon	metadata
([0], [(-122.4413024, 7.8066277), …])	neighborhood -> Marina
([0], [(-122.4111659, 37.8003388), …])	neighborhood -> North Beach

sqlContext.read.format("magellan")
.load(${neighborhoods.path})

sqlContext.read.format("magellan")
.option("type", "geojson")
.load(${neighborhoods.path})



Introduction to Magellan

polygon	metadata
([0], [(-122.4413024, 7.8066277), …])	neighborhood -> Marina
([0], [(-122.4111659, 37.8003388), …])	neighborhood -> North Beach

polygon	metadata
([0], [(-122.4111659, 37.8003388), …])	neighborhood -> North Beach

```
neighborhoods.filter(
 point(-122.4111659, 37.8003388)
 within
 'polygon
).show()
```

Shape literal

Boolean Expression

Introduction to Magellan

polygon	metadata
([0], [(-122.4111659, 37.8003388), …])	neighborhood-> North Beach
([0], [(-122.4413024, 7.8066277), …])	neighborhood-> Marina

point
(-122.4111659, 37.8003388)
(-122.4343576, 37.8068007)

```
points.join(neighborhoods).
  where('point within 'polygon).
  show()
```

point	polygon	metadata
(-122.4343576, 37.8068007)	([0], [(-122.4111659, 37.8003388), …])	neighborhood-> North Beach

Introduction to Magellan

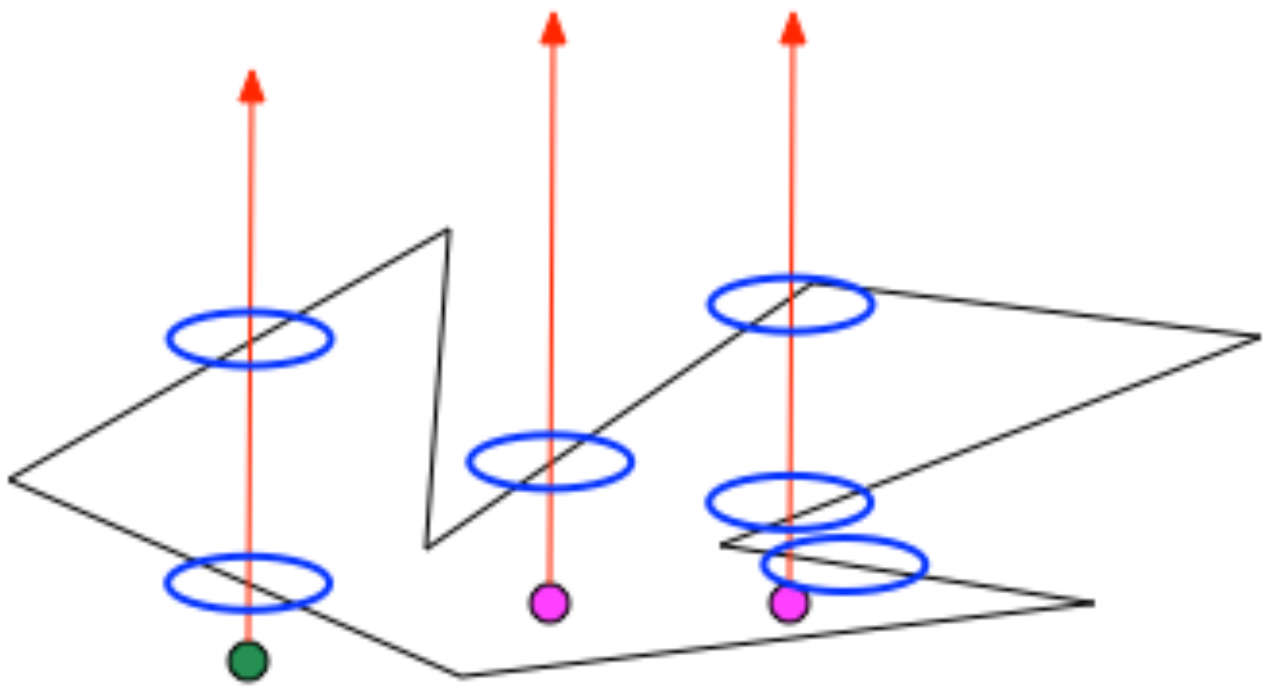
polygon	metadata
([0], [(-122.4111659, 37.8003388), …])	neighborhood -> North Beach
([0], [(-122.4413024, 7.8066277), …])	neighborhood -> Marina

→

point	polygon	metadata
(-122.4343576, 37.8068007)	([0], [(-122.4111659, 37.8003388), …])	neighborhood -> North Beach

```
neighborhoods.filter(
  point(-122.4111659, 37.8003388).buffer(0.1)
  intersects
  'polygon
).show()
```

‘point within ‘polygon



the join

- Inherits all join optimizations from Spark SQL
  - if neighborhoods table is small, Broadcast Cartesian Join
  - else Cartesian Join

Status

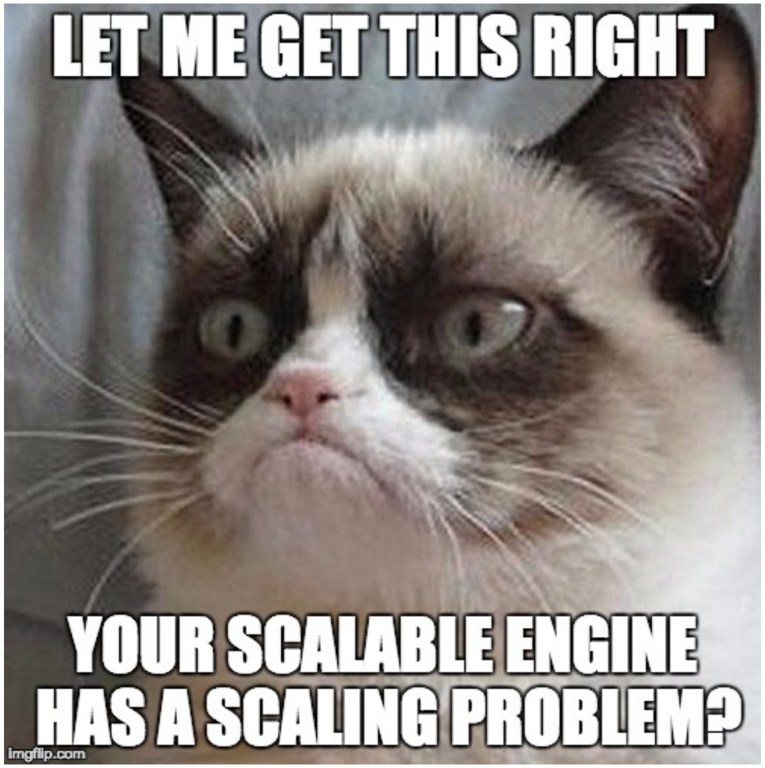
- Magellan 1.0.3 available as Spark Package.
- Scala
- Spark 1.4
- Spark Package: Magellan
- Github: https://github.com/harsha2010/magellan
- Blog: http://hortonworks.com/blog/magellan-geospatial-analytics-in-spark/
- Notebook example: http://bit.ly/1GwLyrV
- Input Formats: ESRI Shapefile, GeoJSON, OSM-XML
- Please try it out and give feedback!

What is next?

- Magellan 1.0.4
  - Spark 1.6
  - Python
  - Spatial Join
  - Persistent Indices
  - Better leverage Tungsten via codegen + memory layout optimizations
  - More operators: buffer, distance, area etc.

the join revisited

- What is the time complexity?
  - m points, n polygons (assume average k edges)
  - l partitions
  - O(mn/l) computations of 'point within 'polygon
  - O(ml) communication cost
  - Each 'point within 'polygon costs O(k)
  - Total cost = O(ml) + O(mnk/l)
  - O(m√n√k) cost, with O(√n√k) partitions


LET ME GET THIS RIGHT
YOUR SCALABLE ENGINE
HAS A SCALING PROBLEM?
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Optimization?

- *Do we need to send every point to every partition?*
- *Do we need to compute 'point in 'neighborhood for each neighborhood within a given partition?*

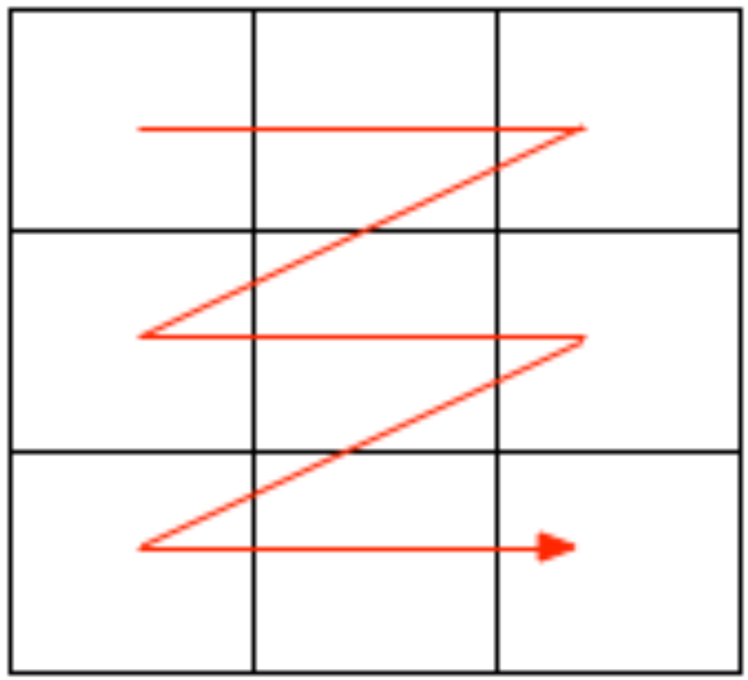
2d indices

- Quad Tree
- R Tree
- Dimensional Reduction
  - Hashing
  - PCA
  - Space Filling Curves

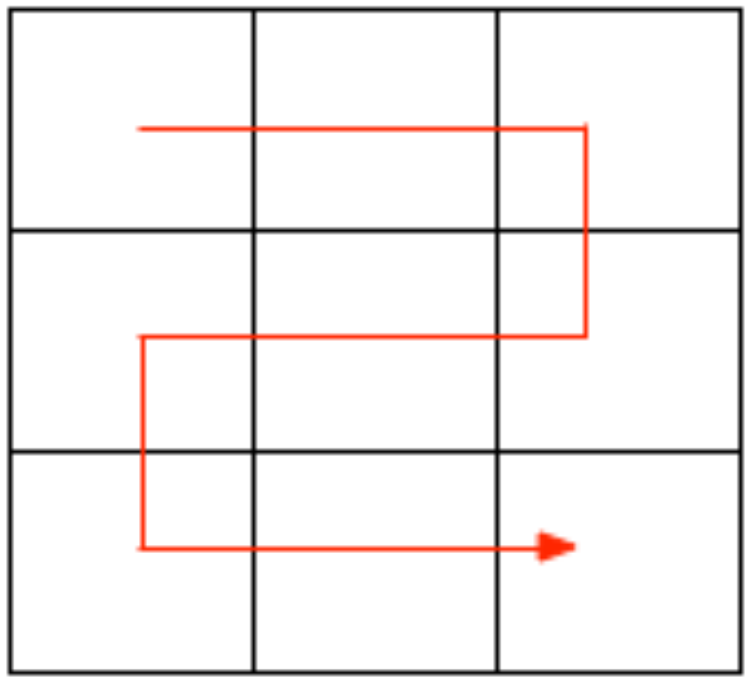
dimensional reduction

- What does a good dimensional reduction look like?
  - (Approximately) preserve nearness
  - enable range queries
  - No (little) collision

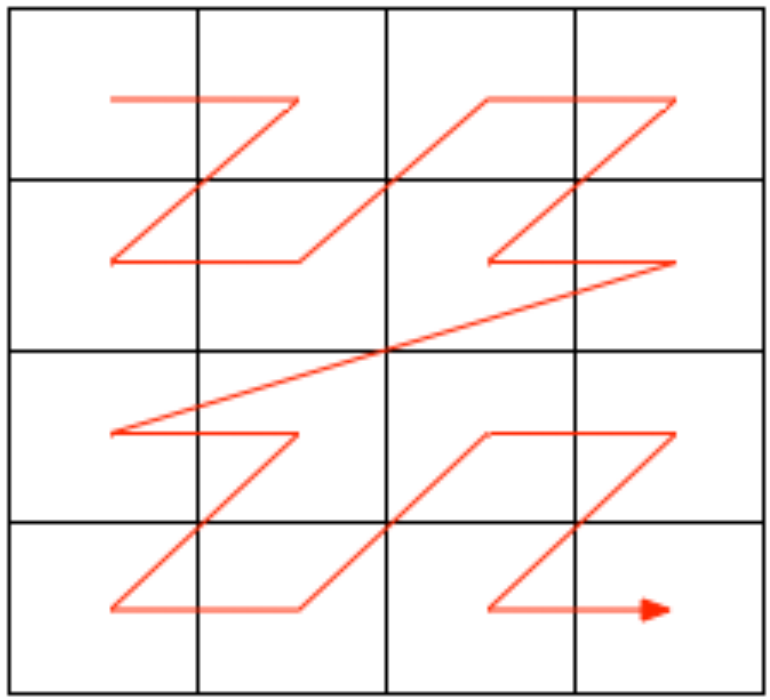
row order curve



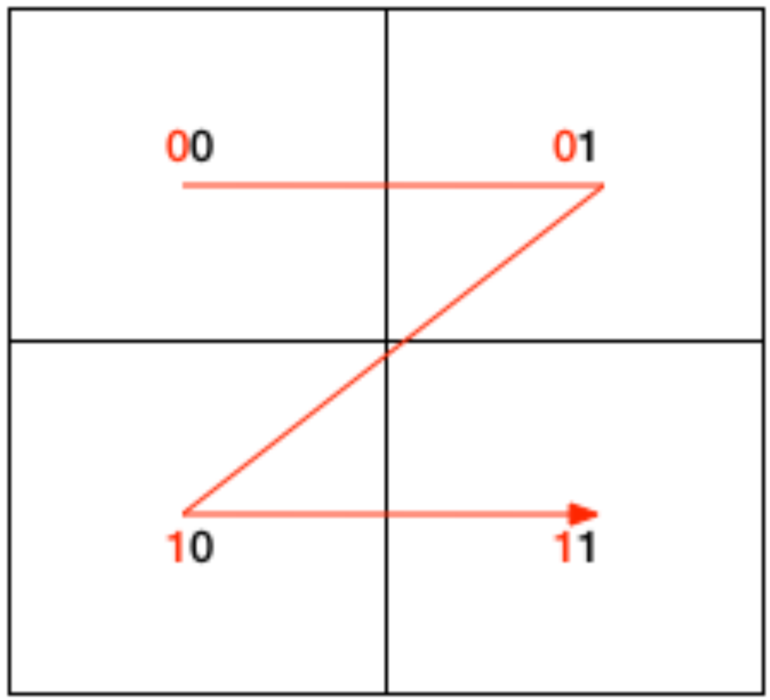
snake order curve



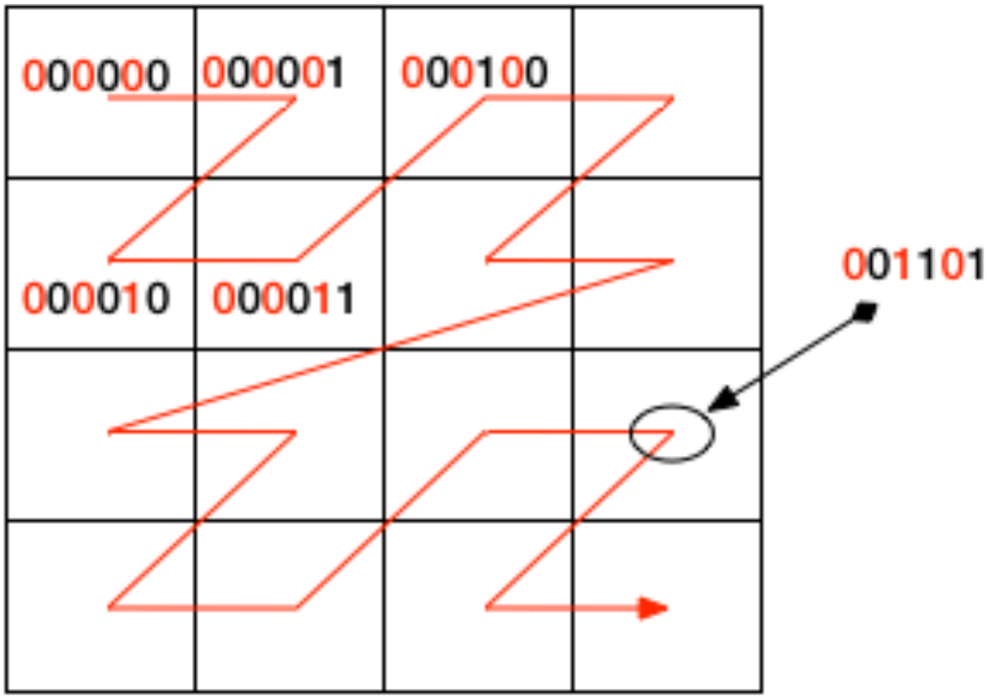
z order curve



Binary Representation



Binary Representation



properties

- Locality: Two points differing in a small # of bits are near each other
  - converse not necessarily true!
- Containment
- Efficient construction
- Nice bounds on precision

geohash

- *Z order curve with base 32 encoding*
- *Start with world boundary (-90,90) X (-180, 180) and recursively subdivide based on precision*

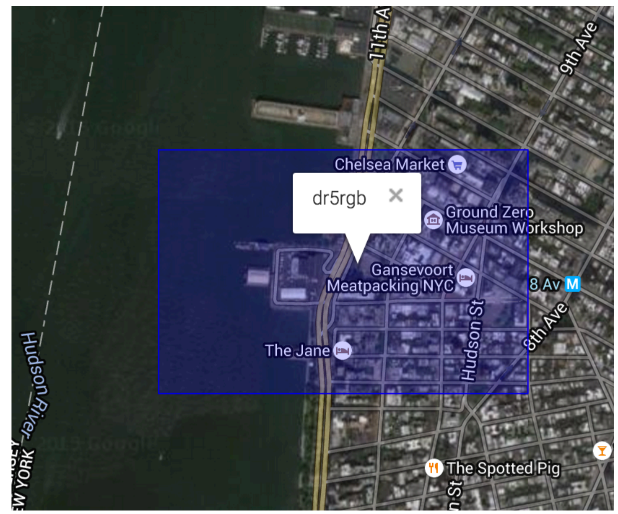
encode (-74.009, 40.7401)

- 40.7401 is in [0, 90) => first bit = 1
- 40.7401 is in [0, 45) => second bit = 0
- 40.7401 is in [22.5, 45) => third bit = 1
- …
- do same for longitude

answer = dr5rgb

decode dr5rgb

- Decode from Base 32 -> Binary
  - 01100 10111 00101 01111 01010
- lat = 101110001111, long = 0100101111000
- Now decode binary -> decimal.
  - latitude starts with 1 => between 0 - 90
  - second bit = 0 => between 0 - 45
  - third bit = 1 => between 22.5 - 45
  - …



An algorithm to scale join?

- Preprocess points
  - *For each point compute geohash of precision p covering point*
- Preprocess neighborhoods
  - *For each neighborhood compute geohashes of precision p that intersect neighborhood.*
- Inner join on geohash
- Filter out edge cases

Implementation in Spark SQL

- Override Strategy to define SpatialJoinStrategy
  - Logic to decide when to trigger this join
    - Only trigger if geospatial queries
    - Only trigger if join is complex: if n ~ O(1) then broadcast join is good enough
  - Override BinaryNode to handle the physical execution plan ourselves
    - Override execute(): RDD to execute join and return results
  - Stitch it up using Experimental Strategies in SQLContext


JOIN IMPLEMENTATION TOO SLOW
LEVERAGED SPATIAL INDICES AND CATALYST TO FIX IT
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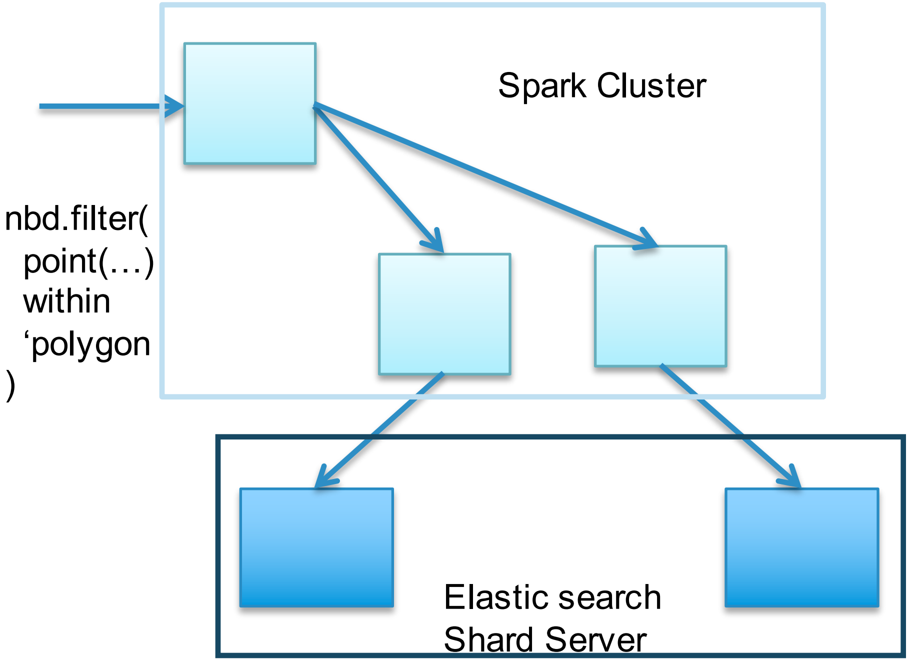
Persistent Indices

- Often, the geometry dataset does not change… eg. neighborhoods
- Index the dataset once and for all?

Persistent Indices

- Use Magellan to generate spatial indices
  - *Think of geometry as document, list of geohashes as words!*
- Persist indices to Elastic Search
- Use Magellan Data Source to query indexed ES data
- Pushdown geometric predicates where possible
  - *Predicate rewritten to IR query*

Overall architecture




```
curl –XGET 'http://…' –d '{
  "query" : {
     "filtered" : {
       "filter" : {
         "geohash" : ["dr5rgb"]
        }
     }
  }
}'
```


That's all Folks!

THANK YOU.

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