

# Simba: Efficient In-Memory Spatial Analytics.

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Andres Calderon

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# Agenda

- 1 Background
- 2 Computational Geometry Operations
  - Union
  - Skyline
  - Convex Hull
- 3 Experiments
- 4 Conclusions

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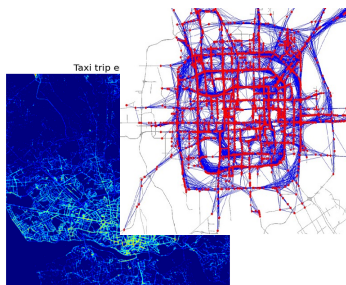
# Introduction

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



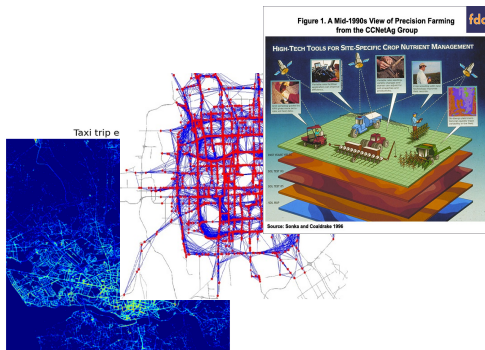
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- But remember that “Spatial is Special” ...



Hadoop-GIS  
*Spatial Big Data Solutions*



MD-Hbase



SECONDO

SpatialSpark  
GeoSpark

GeoTrellis



# Introduction

- Why do we need a new tool???





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- Simba: **S**patial **I**n **M**emory **B**ig data **A**alytics.
  - Extends Spark SQL with important spatial operations.
  - Offers simple APIs for both SQL and DataFrame.
  - Support two-layer spatial indexing over RDDs (low latency).
  - Designs a SQL context to run spatial queries in parallel (high throughput).
  - Introduces spatial-aware and cost-based optimizations to select good spatial plans.

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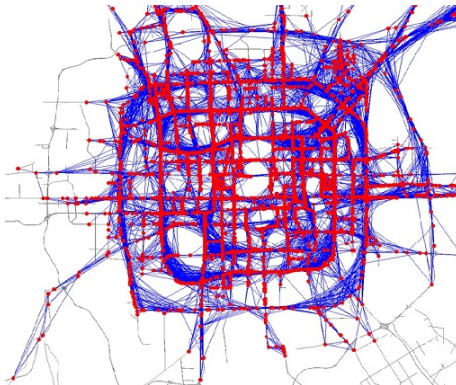
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# Setup

- Cluster of 25 nodes:
  - HDD from 50GB to 200GB.
  - RAM from 2GB to 8GB.
  - Processors 2.2GHz to 3GHz
- Single machine:
  - HDD 2TB.
  - RAM 16GB.
  - Processor 3.4GHz.

# Datasets

- Real datasets (from OpenStreetMap):
  - OSM1: 164M polygons, 80GB.
  - OSM2: 1.7B points, 52GB.
- Synthetic dataset:
  - SYNTH: 3.8B points, 128GB.
  - Five different distributions.



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# Conclusions

- This paper introduced CG\_Hadoop as a scalable and efficient MapReduce library.
- Focused on 5 fundamental computational geometry problems...
  - Polygon union, Skyline, Convex hull, Farthest and Closest Pairs.
- Provided versions for Apache Hadoop and SpatialHadoop systems.
- Distributed approach speed up performance.
- Spatial partitioning allows early pruning which make it even more efficient.
- Achieve up to 29x and 260x better performance.

# Future ideas

- Working on more complex operations, for example motion patterns.
- Explore ports to new distributed platforms such as Spark or Simba.

# Thank you!!!

Do you have any question?