

Towards Parallel Detection of Movement Patterns in Large Spatio-temporal Datasets

Oral Qualification

Andres Calderon

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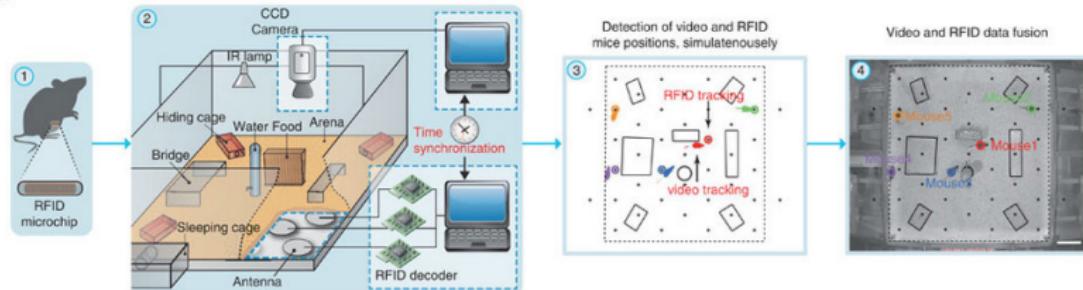
Trajectory datasets

- ▶ Anything that could move (or could be moved), will be tracked...
 - ▶ Sensors, Sensors everywhere...
 - ▶ Smart phones, GPS, RFID, WiFi, Bluetooth, ZigBee, IoT, Satellites, Drones, Surveillance cameras...

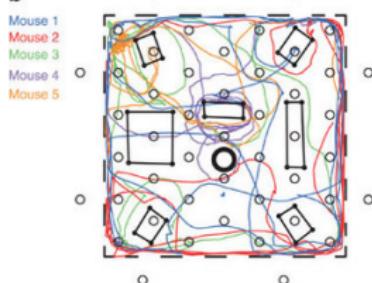
Applications

Tracking social behavior of animal colonies.

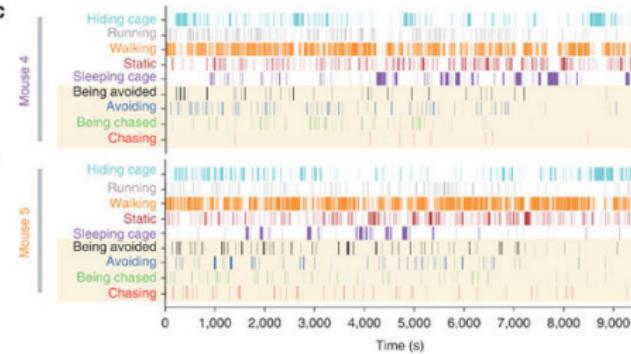
a



b

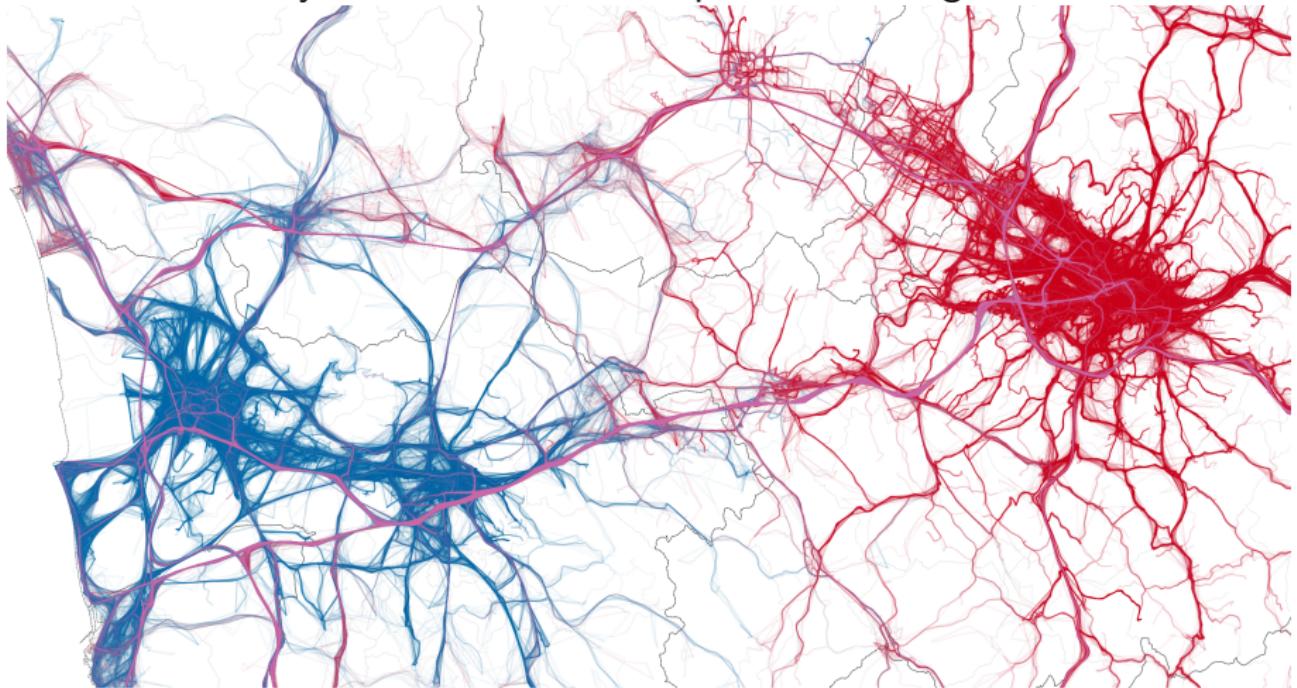


c

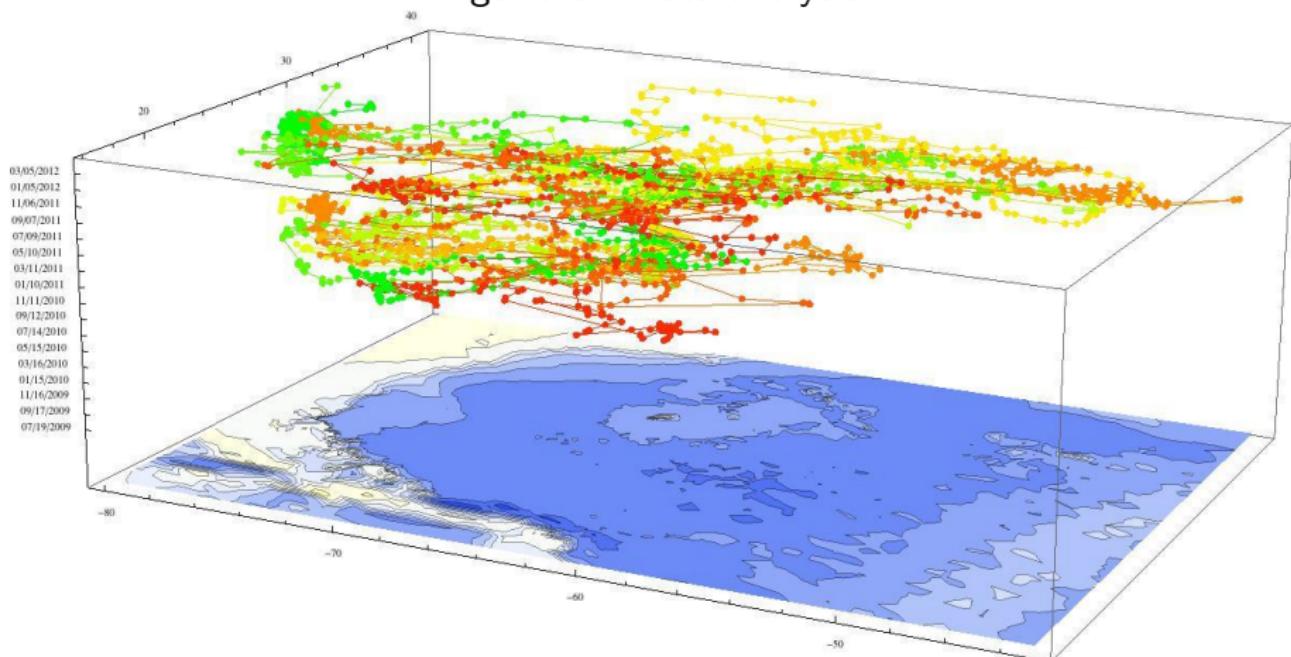


Applications

Are you a returner or an explorer? Ask Big Data.

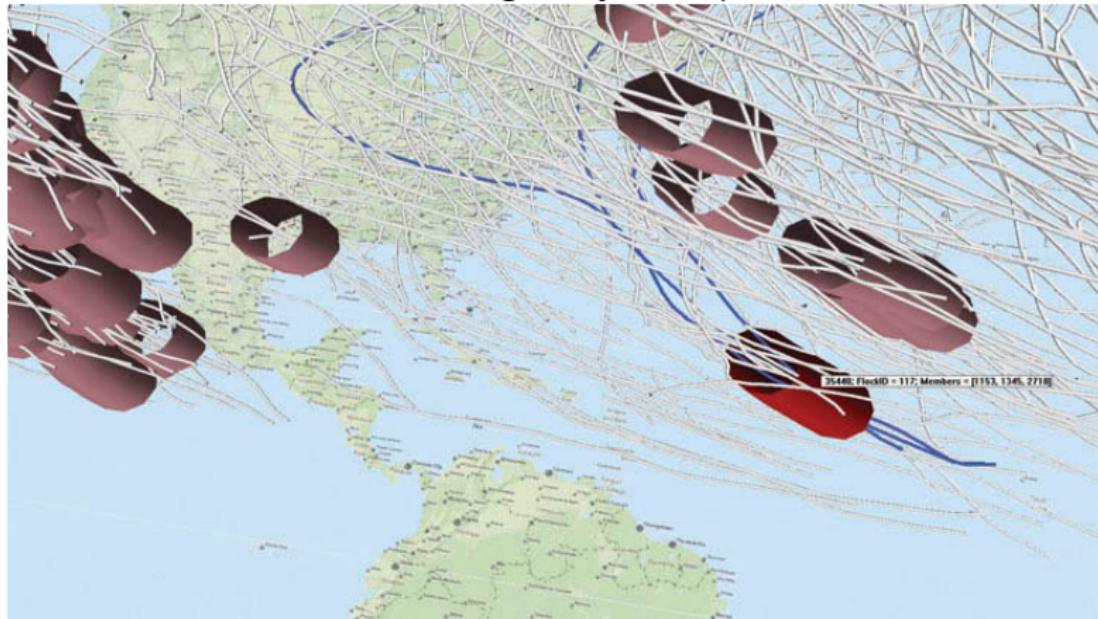


Tiger shark data analysis.



Applications

Visual mining of cyclone paths.



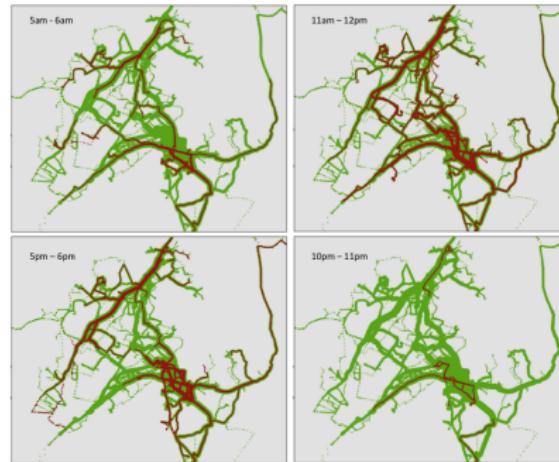
Applications

Bird migration forecast.

Complex movement patterns

Previous works focus on traditional queries:

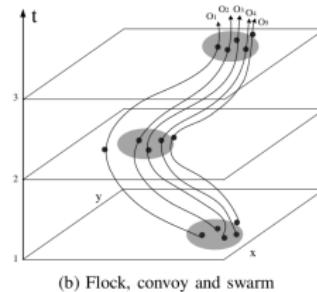
- ▶ Range
- ▶ Nearest Neighbors
- ▶ Similarity



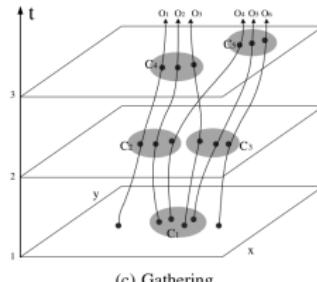
Complex movement patterns

Recent works look for the aggregate behavior:

- ▶ Moving clusters
- ▶ Convoys
- ▶ Flocks
- ▶ Swarms
- ▶ Gatherings



(b) Flock, convoy and swarm



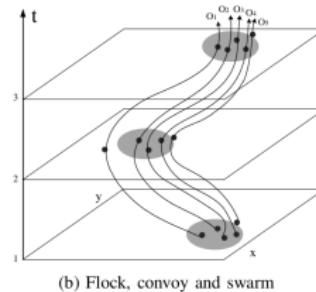
(c) Gathering

(Zheng et al, ICDE'13)

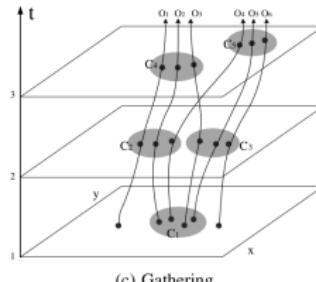
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(c) Gathering

(Zheng et al, ICDE'13)

Outline

Moving flock patterns

Finding candidate disks

Implementation

Experiments

Finding maximal disks

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Experiments

Conclusions and future work

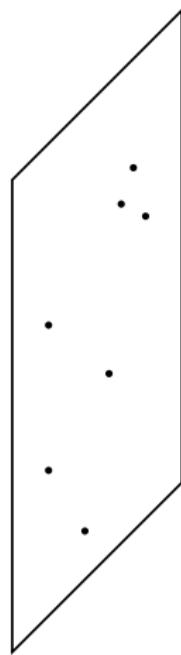
What is a flock???

Definition $((\mu, \epsilon, \delta) - \text{flock})$

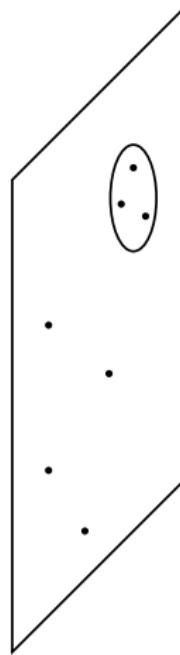
Sets of at least μ objects moving close enough (ϵ) for at least δ time intervals (Benkert et al, 2008).



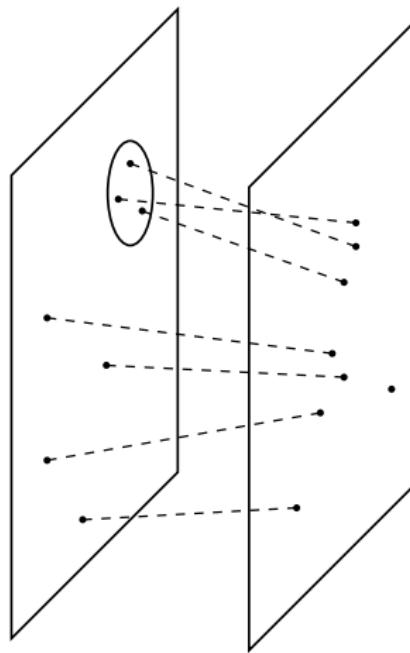
BFE algorithm (Vieira et al, 2009)



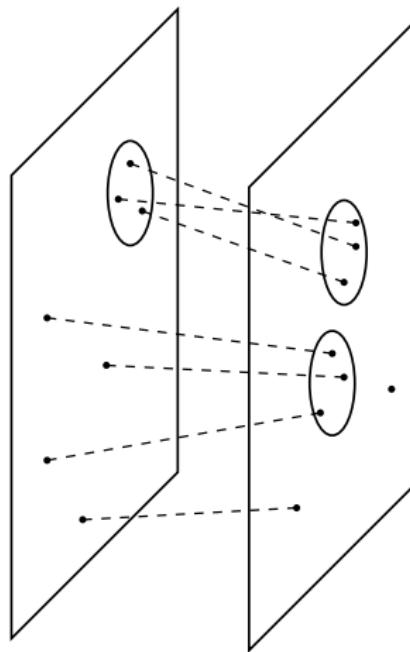
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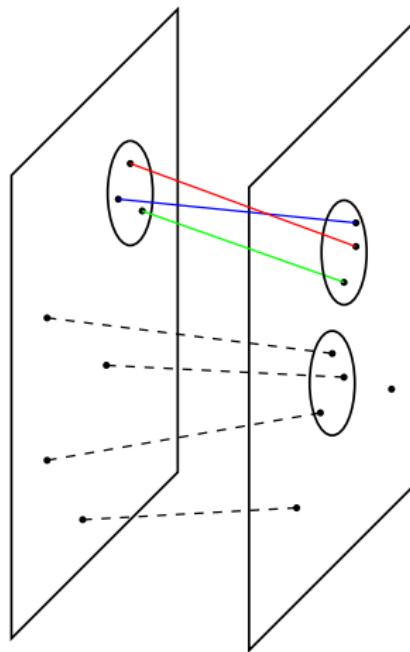
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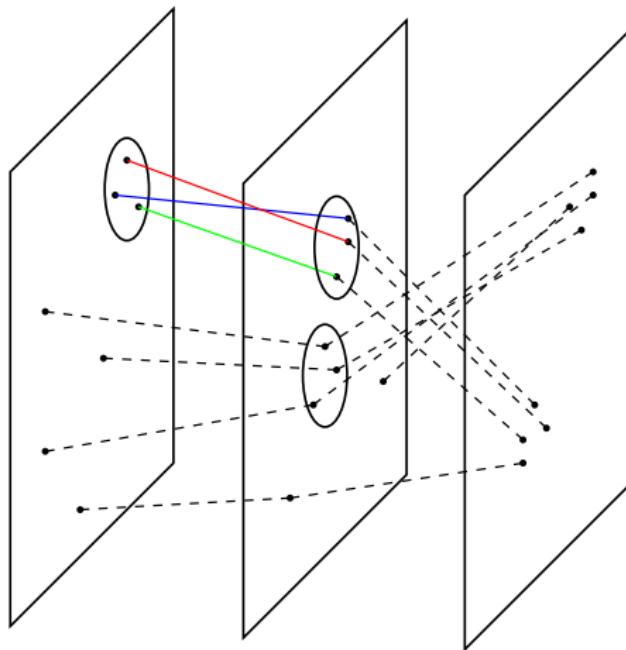
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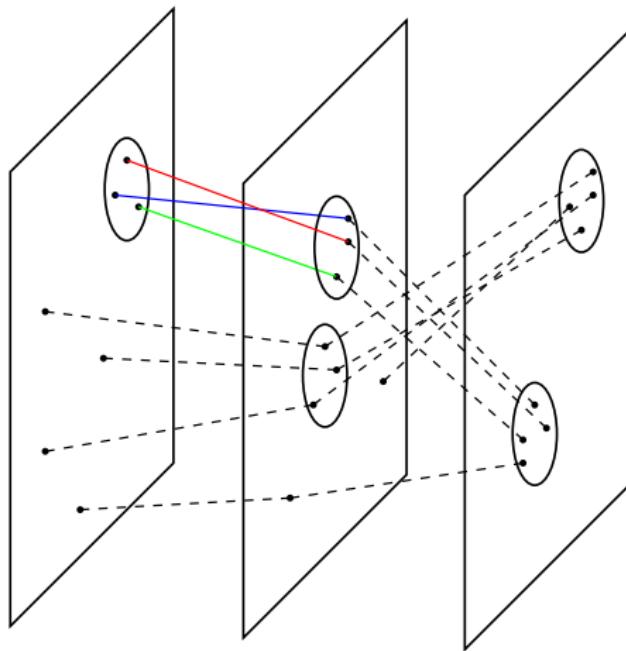
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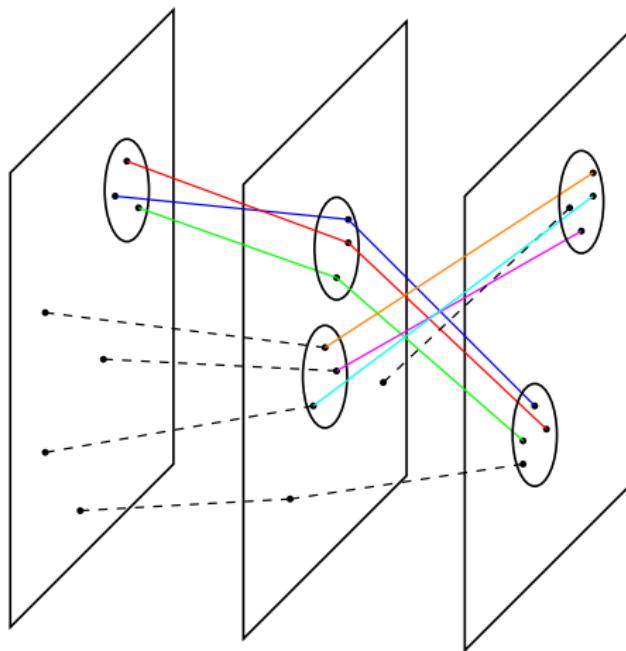
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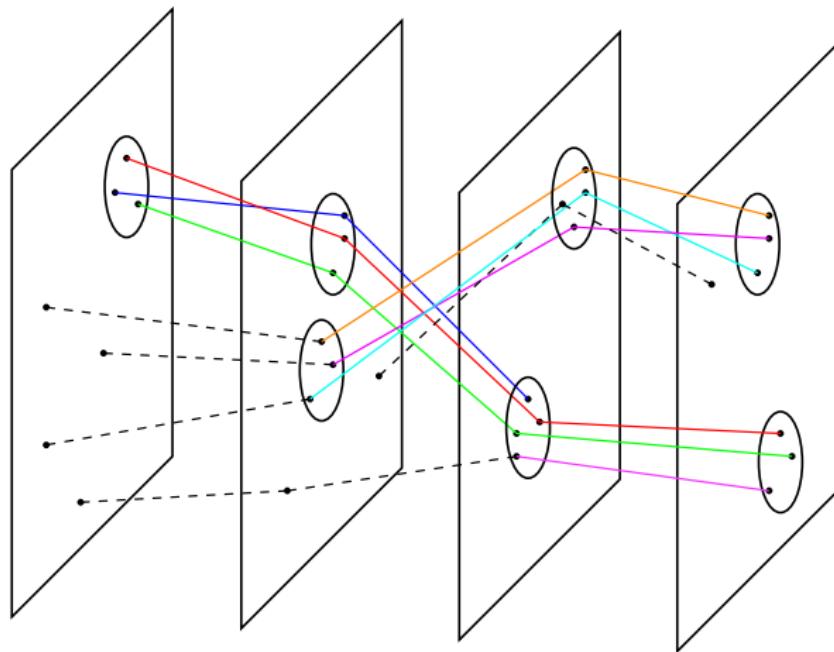
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Motivation

Why is important to focus on flocks and finding disks???

- ▶ Why are moving flock patterns important?
 - ▶ They capture the collective behavior of trajectories as groups.
 - ▶ A general model for other movement patterns.
- ▶ Why is the finding of disks important?
 - ▶ It is no trivial, disks can be at any location.
 - ▶ It has a high complexity ($\mathcal{O}(2n^2)$).
 - ▶ Number of disks can be huge and it can require further filtering.

Contributions

This work focuses on improvements in the two initial parts of the BFE algorithm:

1. Boost the detection of a candidate set of disks through a parallel approach.
2. Apply a frequent pattern approach in order to improve the filtering of disks.

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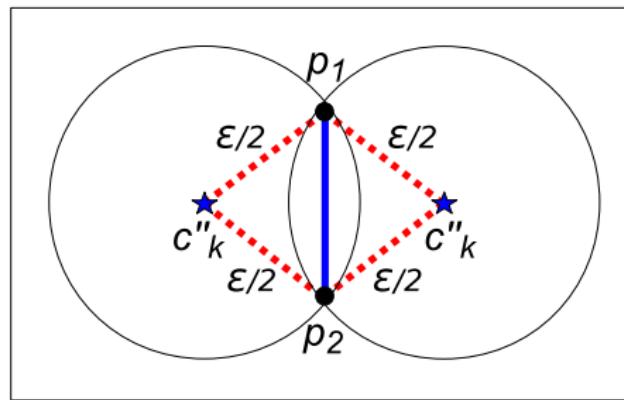
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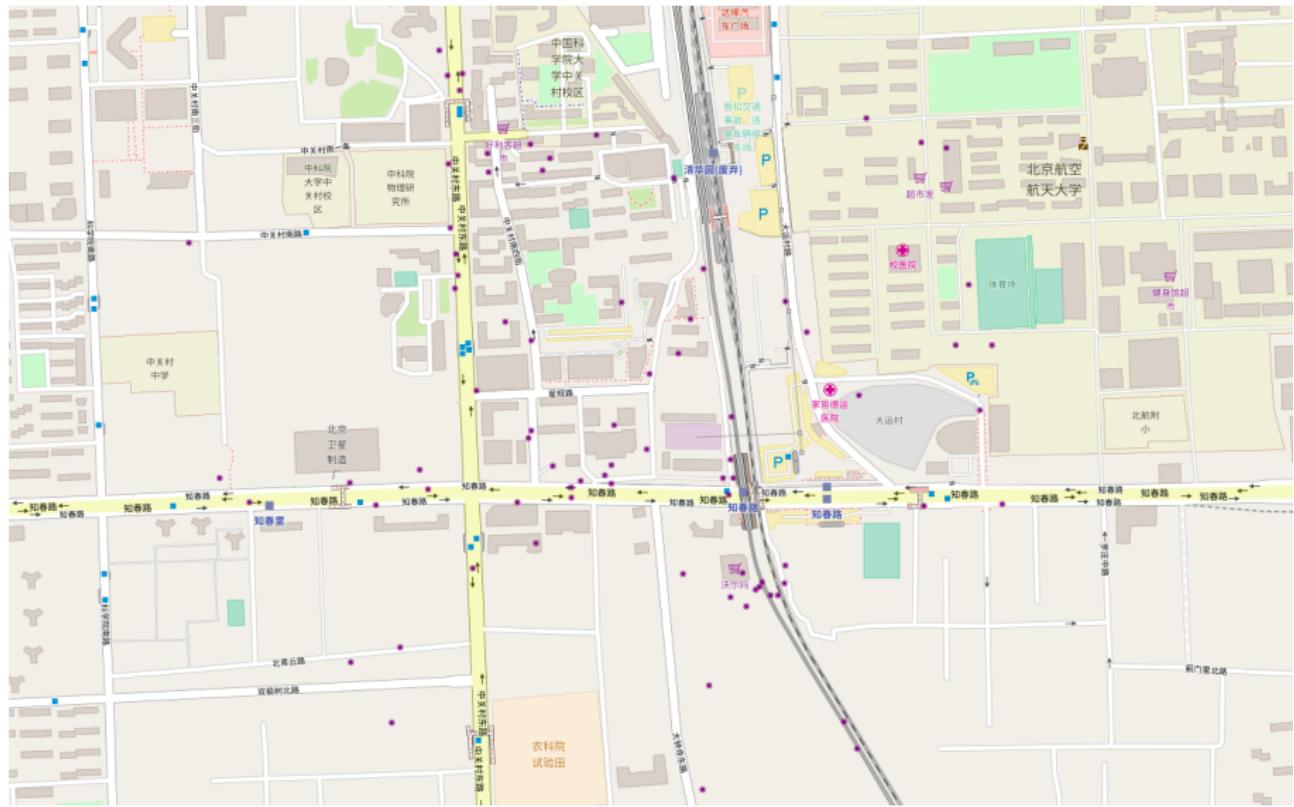
BFE implementation

- ▶ On-Line Discovery of Flock Patterns in Spatio-Temporal Data (Vieira et al, SIGSPATIAL'09).
- ▶ Implementation available at
<https://github.com/poldrosky/FPFlock>.

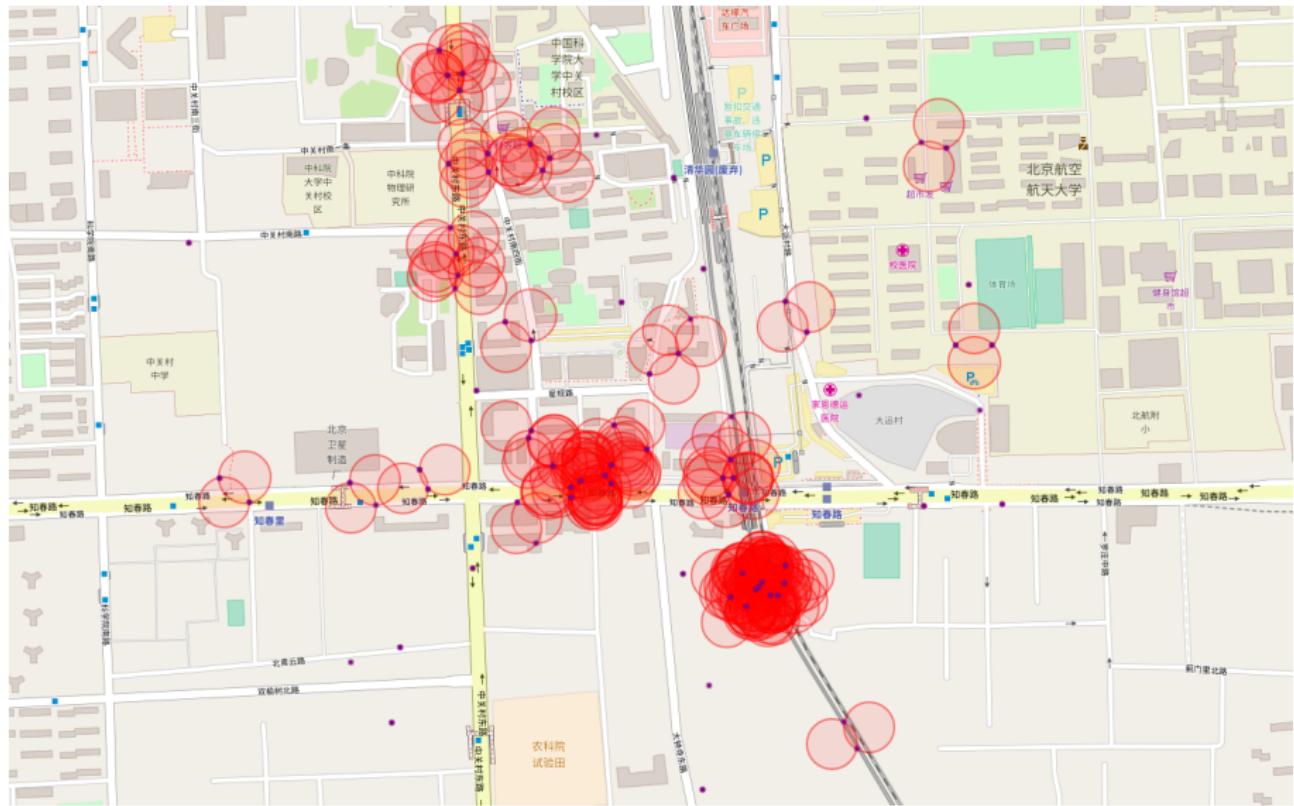
BFE implementation



BFE implementation



BFE implementation



PBFE implementation

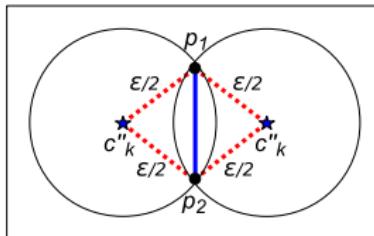
- ▶ Written in Scala using Simba 1.6.3.
 - ▶ Tested by visual inspection and counting number of found disks.
- ▶ Code available at
<https://github.com/aocalderon/PhD/tree/master/Y2Q1/SDB/Project/Code/Scripts/pbfe2>.

PBFE implementation

- ▶ Simba (Xie et al, SIGMOD'16) provides rich spatial operations through both SQL and the DataFrame API.
- ▶ Two-layer spatial indexing, cost-based optimization, open source.
- ▶ DISTANCE JOIN and CIRCLE RANGE operators were the key!!!

PBFE implementation

```
SELECT
    *
FROM
    points p1
DISTANCE JOIN
    points p2
ON
    POINT(p2.x, p2.y) IN CIRCLE RANGE(POINT(p1.x, p1.y), ε)
WHERE
    p1.id < p2.id
```



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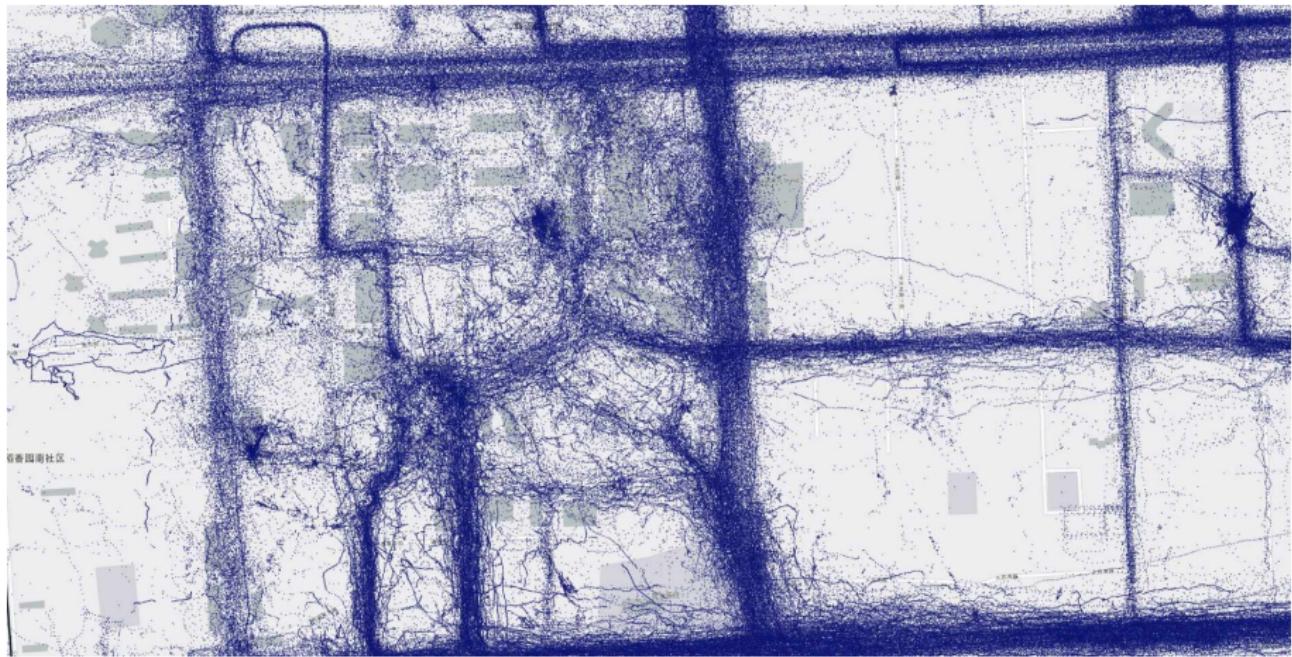
Conclusions and future work

Dataset

- ▶ **Beijing** from Geolife project¹.
 - ▶ 182 users in a period of over three years (from April 2007 to August 2012).
 - ▶ 17,621 trajectories.
 - ▶ ≈18 million points (no duplicates).

¹<http://tinyurl.com/j7t2cao>

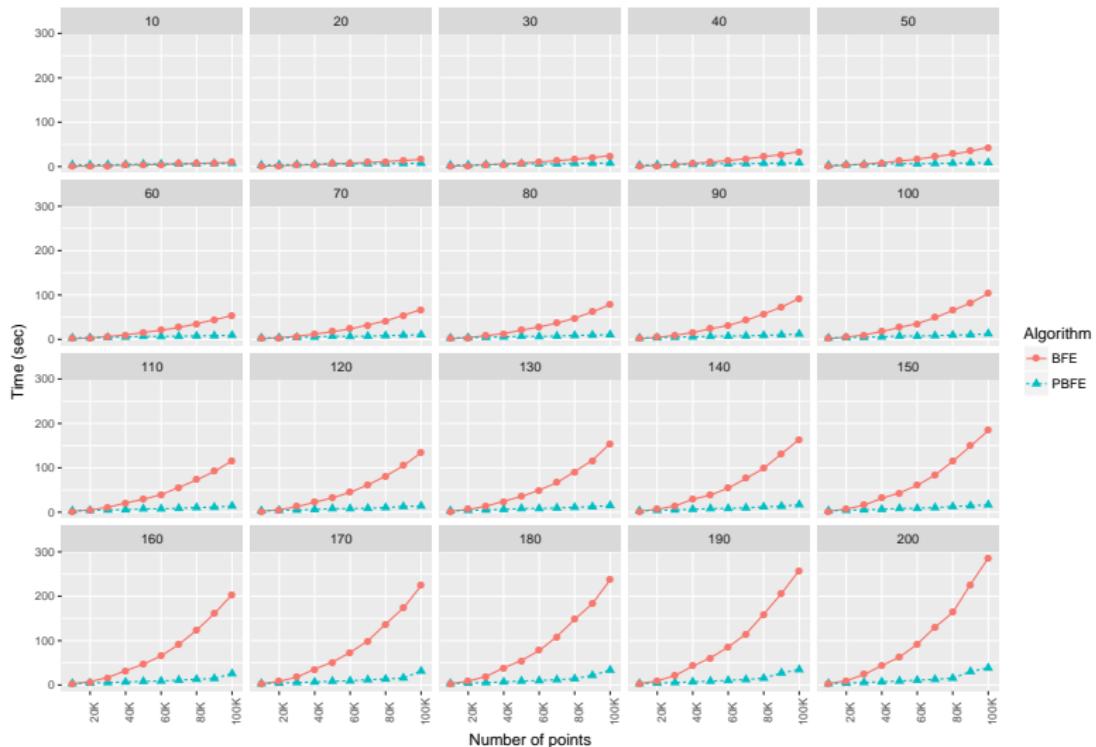
Beijing dataset



Setup

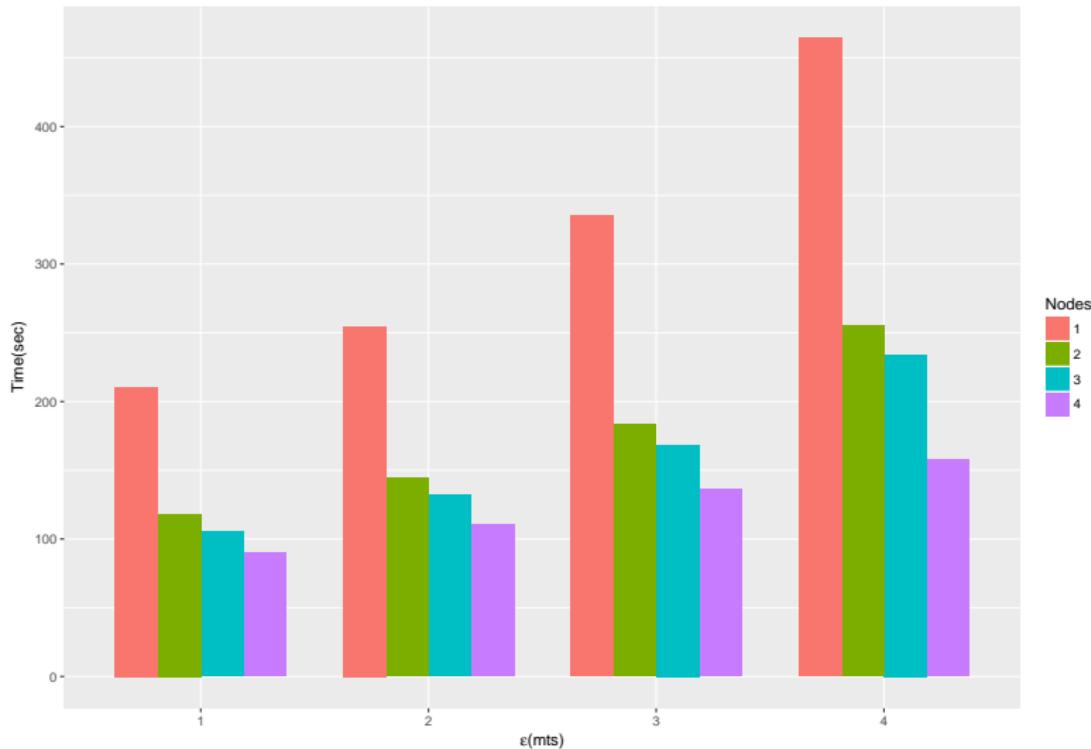
- ▶ Single-node.
- ▶ Processor: 4-core Intel(R) Core(TM) i5-2400S CPU @ 2.50GHz
- ▶ RAM: 8 GB.
- ▶ Ubuntu 16.04 LTS, Simba/Spark 1.6.3.

Execution time

Execution time by ε (radius of disk in mts) in Beijing dataset.

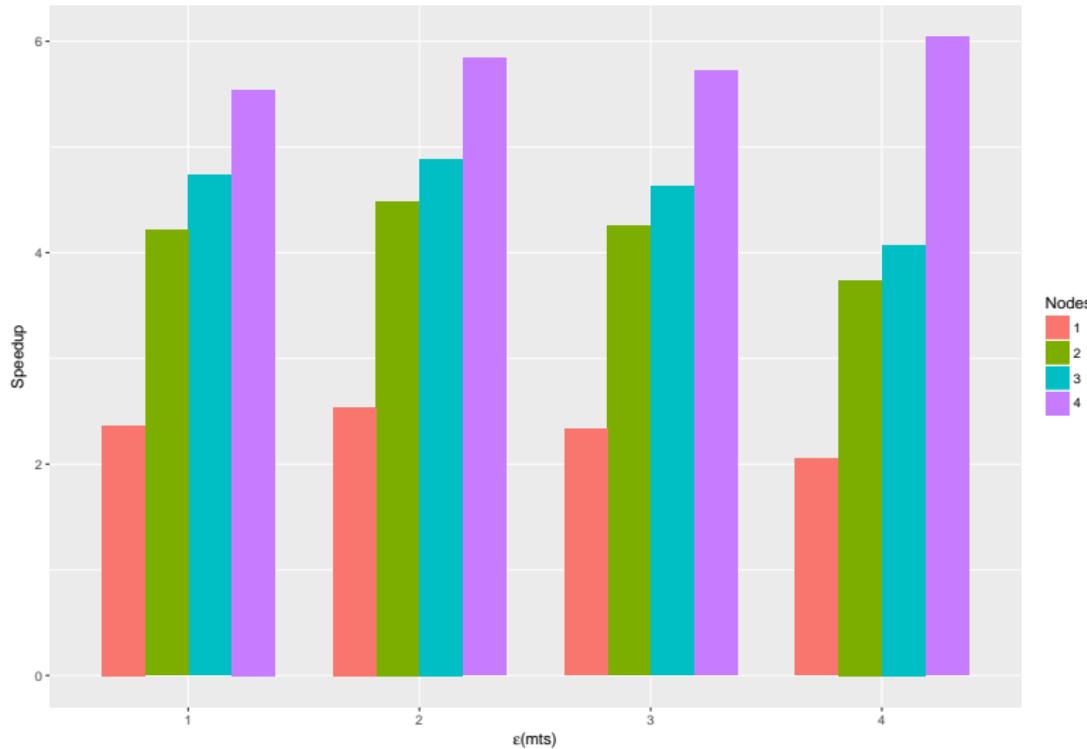
Scaleup

Scaleup in Beijing dataset.



Speedup

Speedup in Beijing dataset.

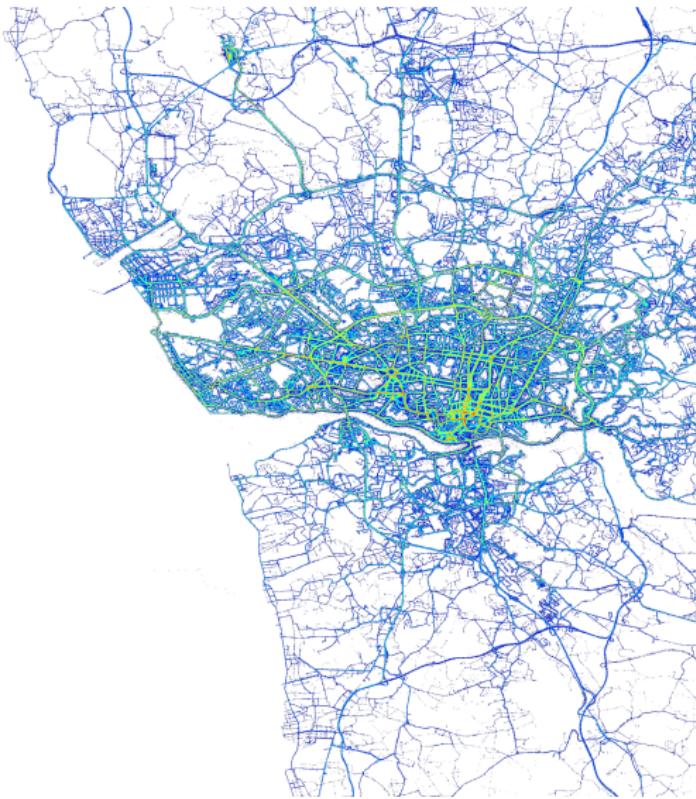


Dataset

- ▶ **Porto** from ECML/PKDD'15 Taxi Trajectory Prediction Challenge².
 - ▶ A complete year (from 01/07/2013 to 30/06/2014).
 - ▶ Trajectories for all the 442 taxis running in the city of Porto, in Portugal.
 - ▶ ≈17.7 million points (no duplicates).

²<http://tinyurl.com/zzbtlt9>

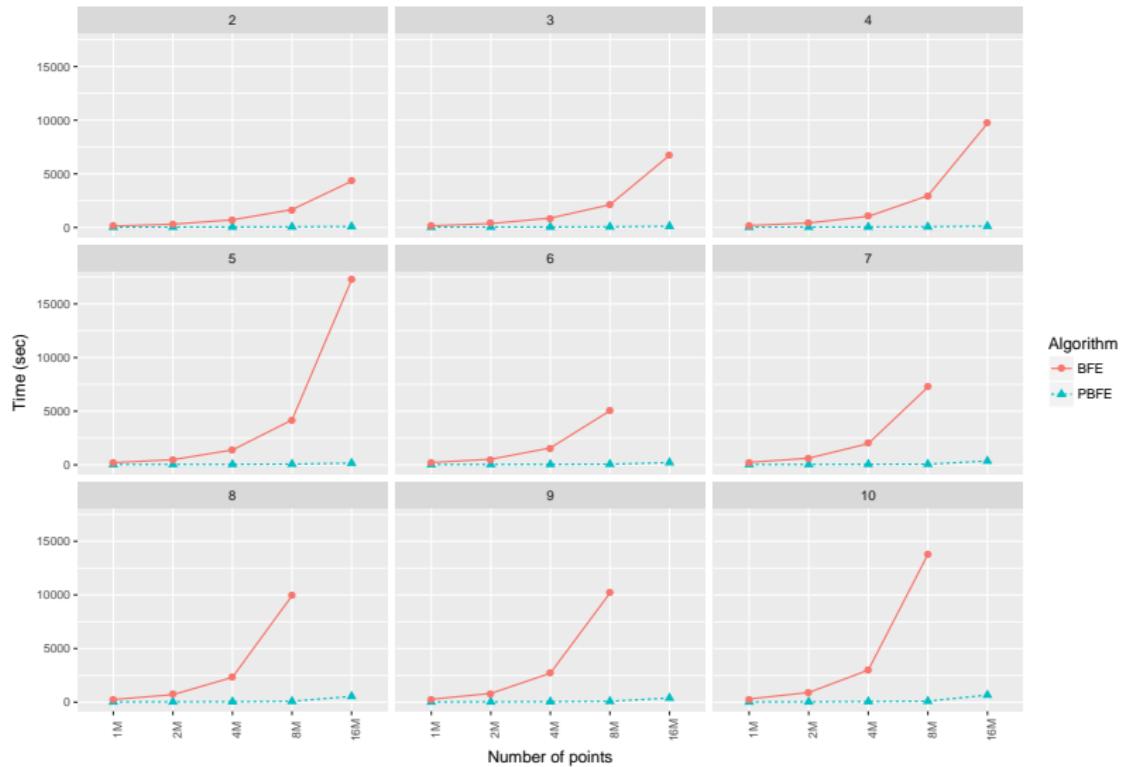
Porto dataset



Setup

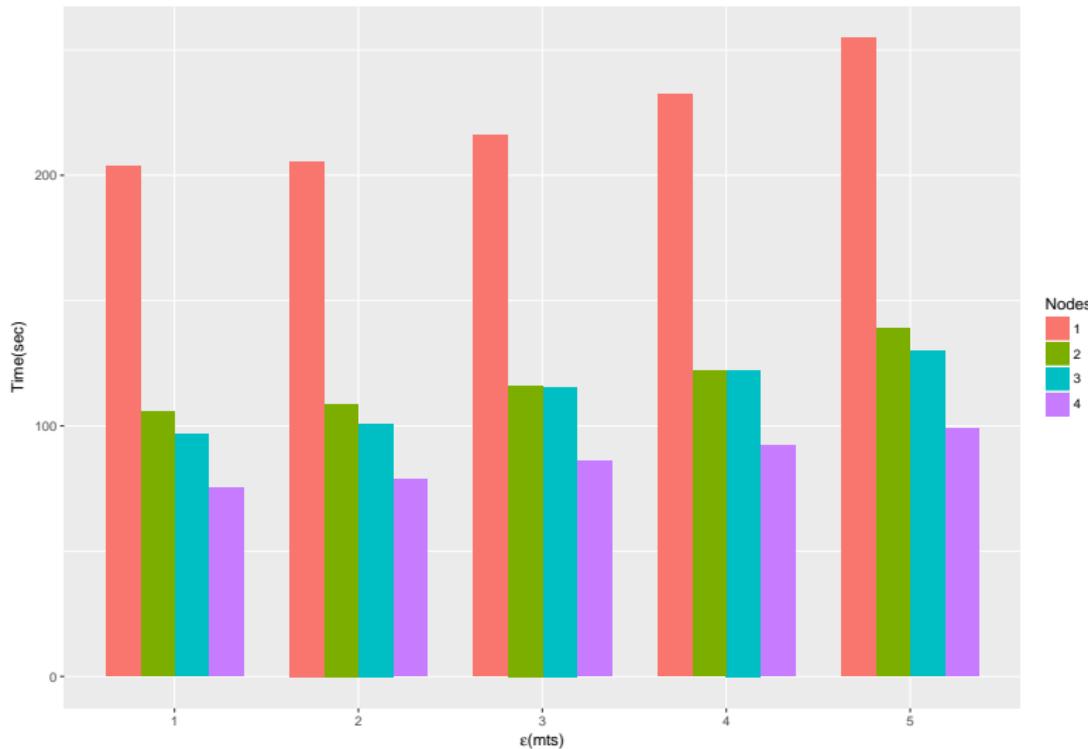
- ▶ 4-node cluster at DBLab.
- ▶ Processors: 8-core Intel(R) Xeon(R) CPU E3-1230 V2 @ 3.30GHz
- ▶ RAM: 15.5 GB.
- ▶ Centos 6.8, Simba/Spark 1.6.3.

Execution time

Execution time by ϵ (radius of disk in mts) in Porto dataset.

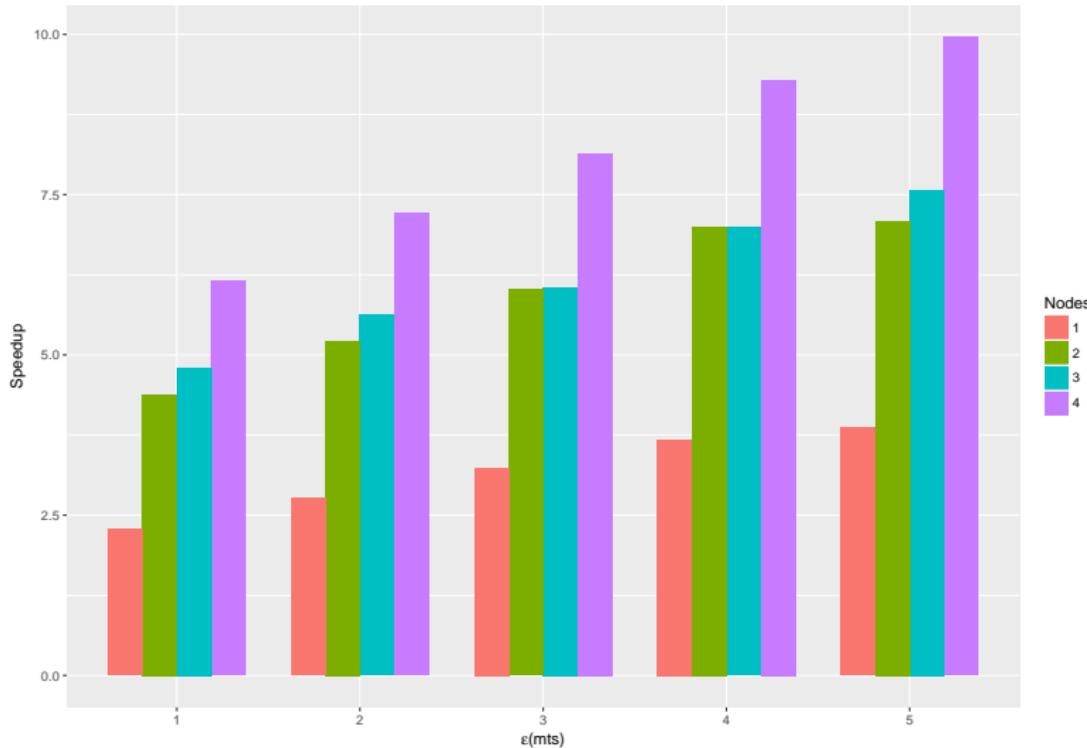
Scaleup

Scaleup in Porto dataset.



Speedup

Speedup in Porto dataset.

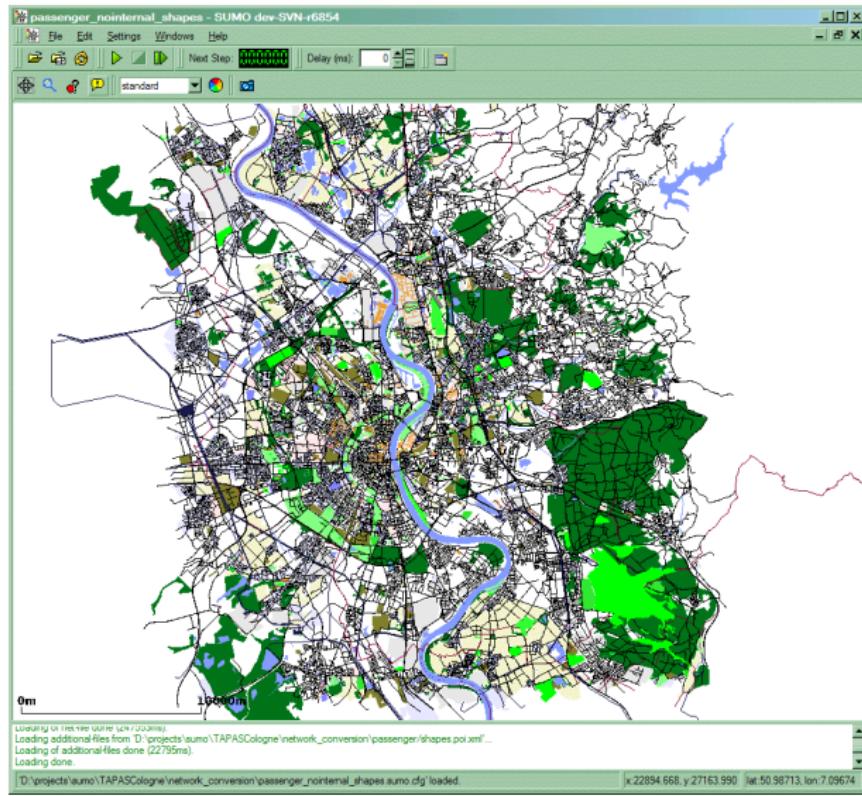


Dataset

- ▶ **Cologne** from the SUMO (Simulation of Urban MObility) project³.
 - ▶ Simulation scenario describing a whole-day traffic in the city of Cologne (Germany).
 - ▶ Data demand based on traveling habits and infrastructure (TAPAS system).
 - ▶ ≈70 million points (no duplicates).

³ <https://tinyurl.com/l9lbw6b>

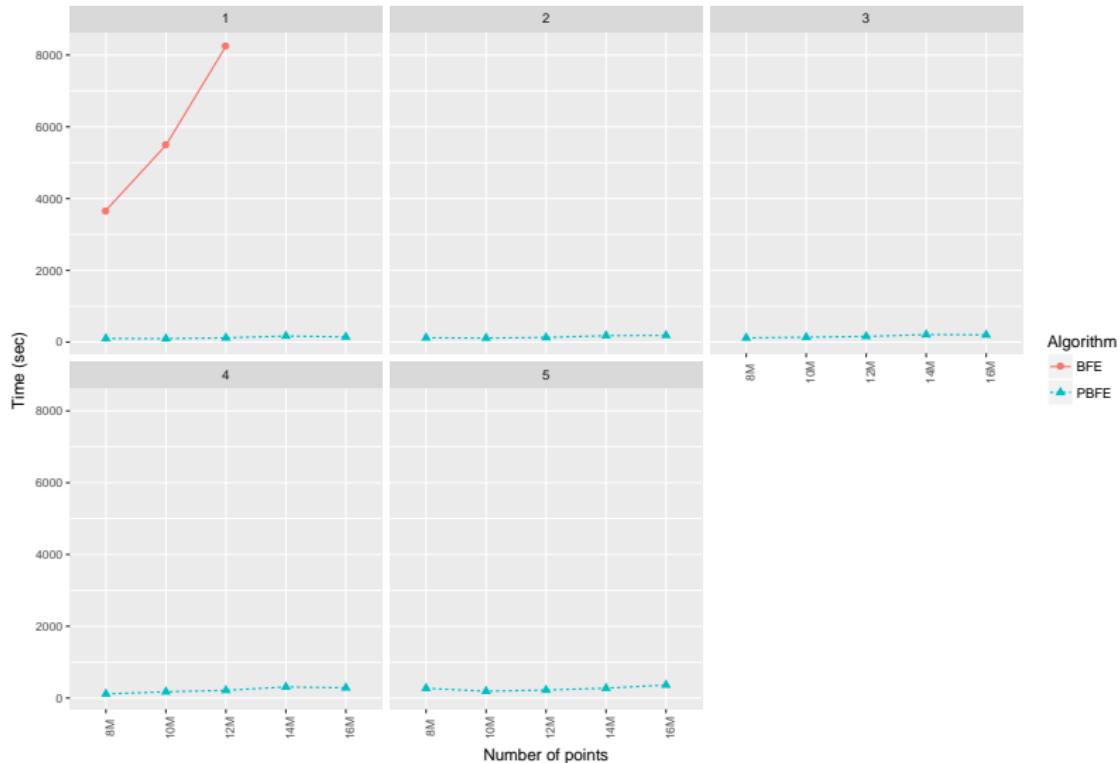
Cologne dataset



Setup

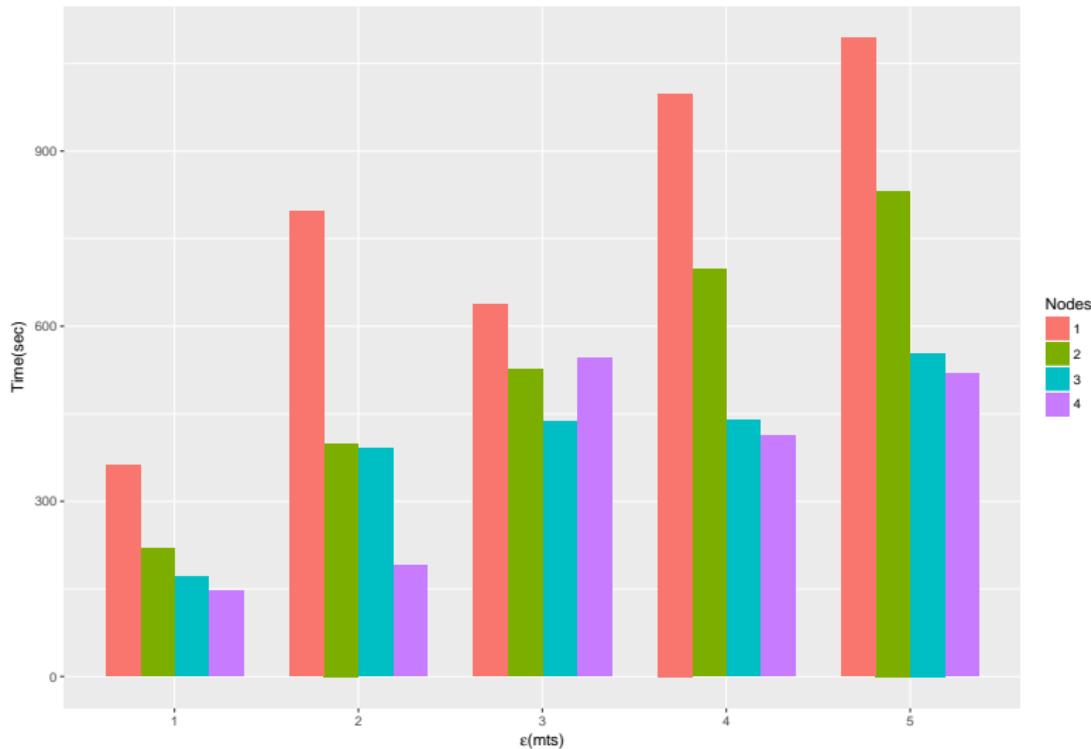
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Execution time by ϵ (radius of disk in mts) in Cologne dataset.

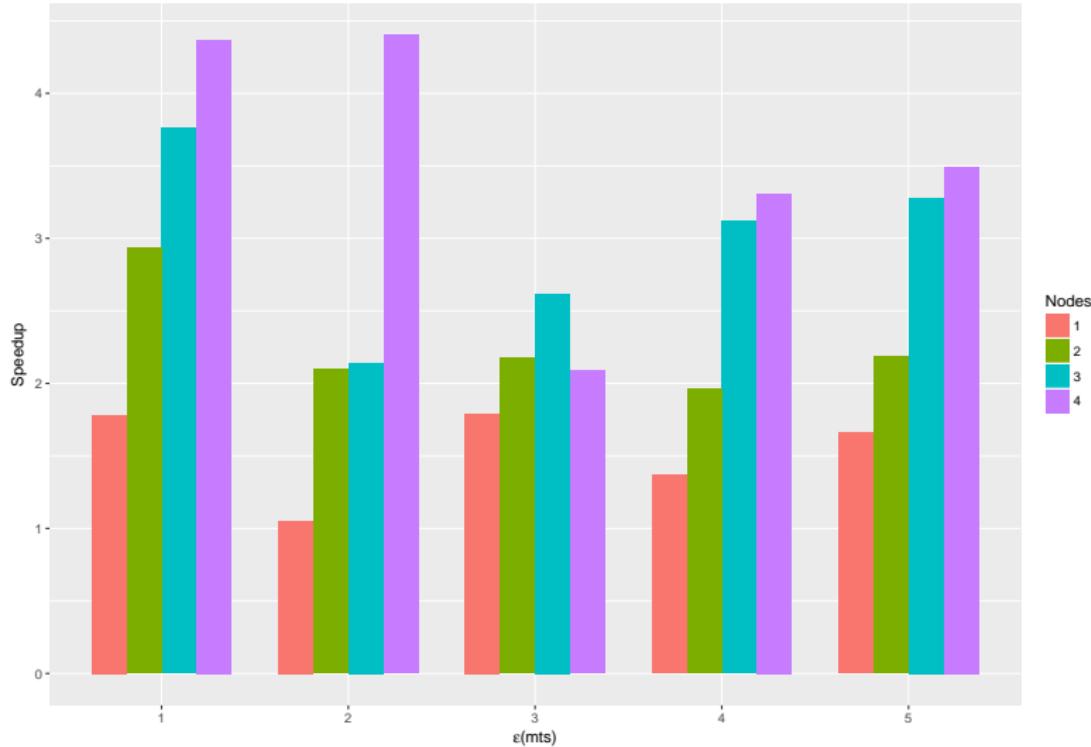
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Speedup

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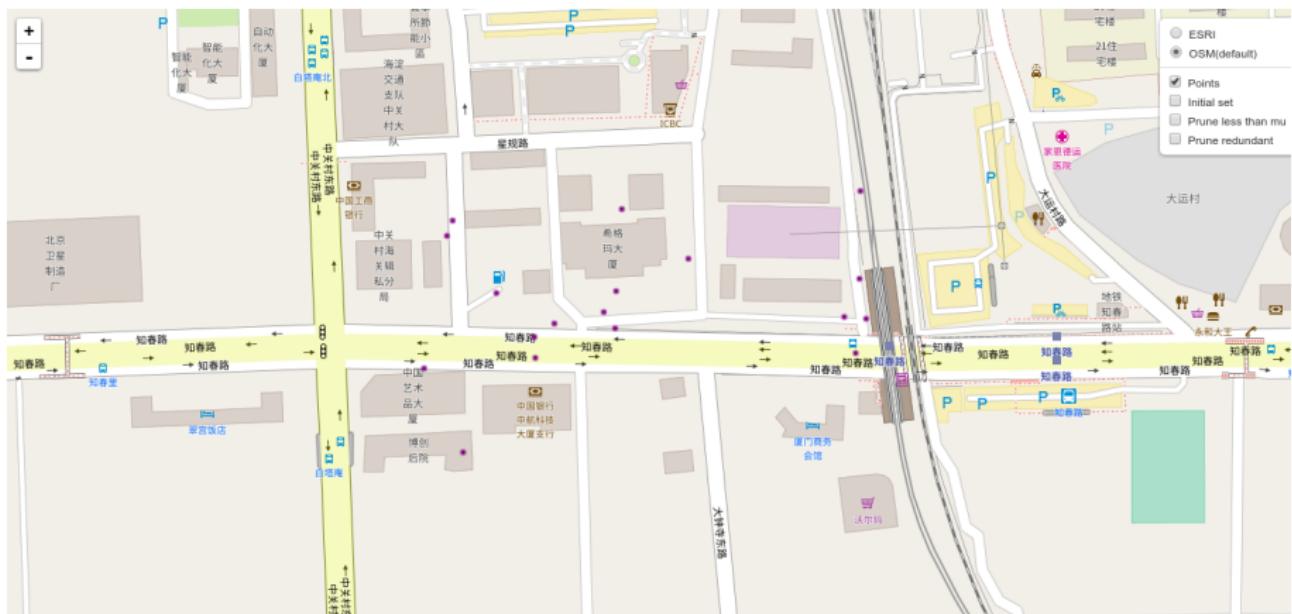
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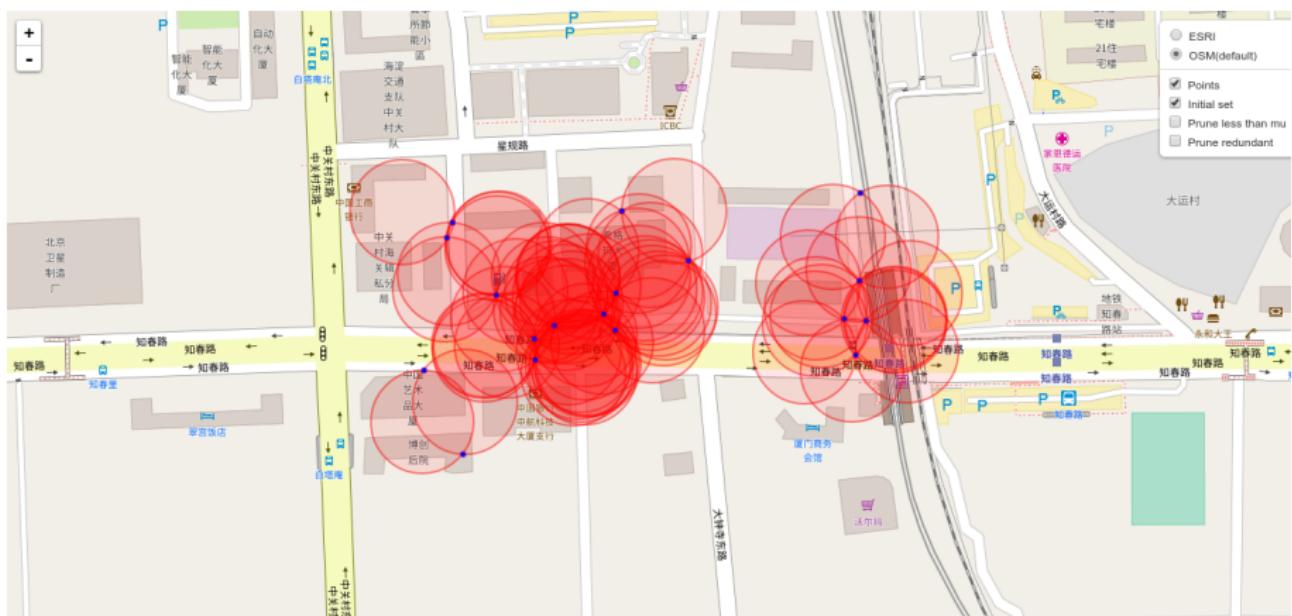
Finding maximal disks

- ▶ The first stage of BFE finds all possible disk locations for each pair of “close enough” points...
- ▶ This candidate set still have redundant and under-the-threshold (μ) disks...
- ▶ BFE uses a simple approach to filter the disks but it can be costly ($O(n^2)$)

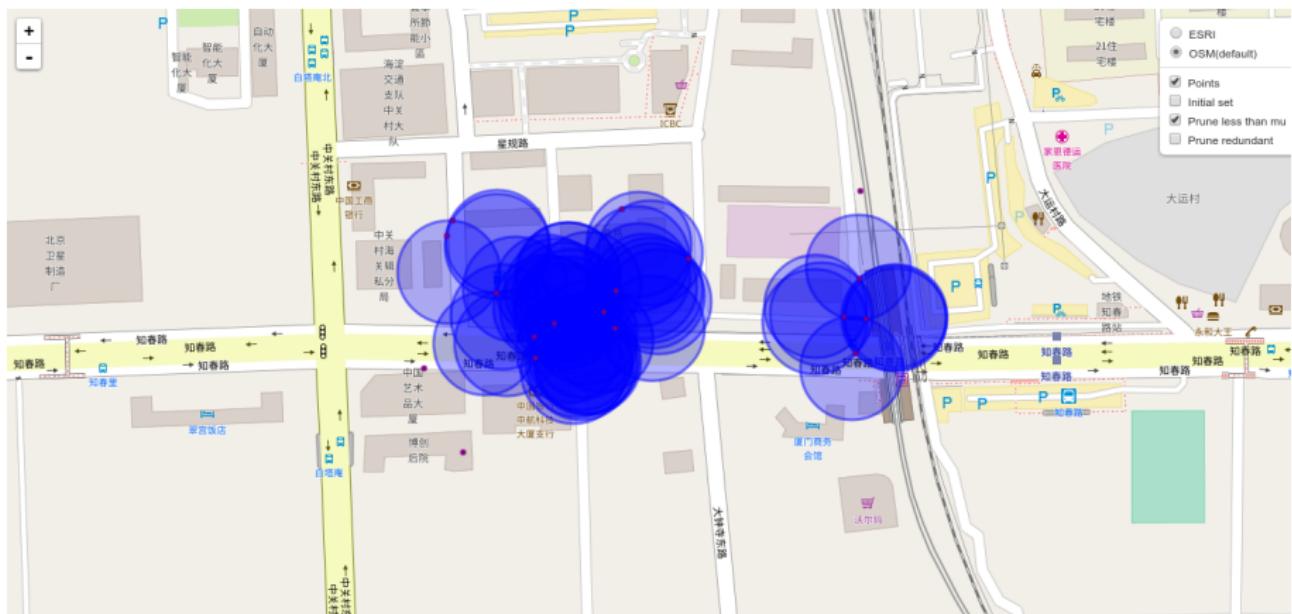
Finding maximal disks



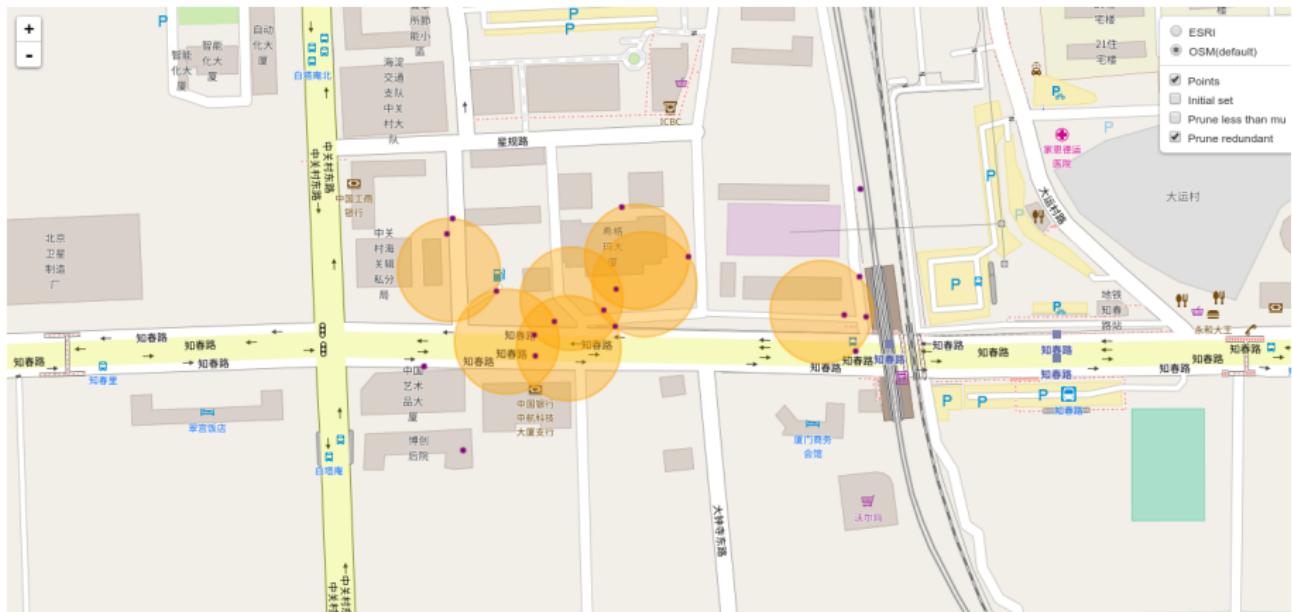
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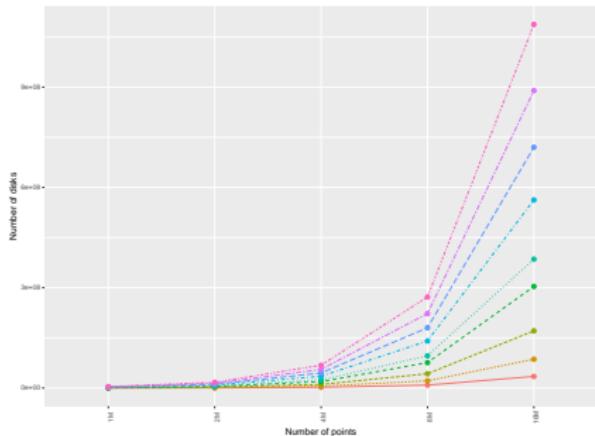
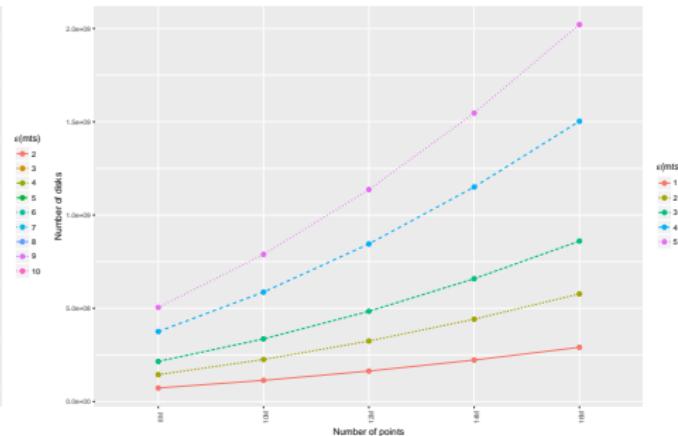
Finding maximal disks



Finding maximal disks



Number of disks can be huge...

Number of disks by ϵ (radius of disk in mts) in Porto dataset.Number of disks by ϵ (radius of disk in mts) in Cologne dataset.

A Frequent/Closed/Maximal pattern example...

Suppose a database D contains 4 transactions:

$$D = \{\langle a_1, a_2, \dots, a_{100} \rangle; \langle a_1, a_2, \dots, a_{100} \rangle; \langle a_{20}, a_{21}, \dots, a_{80} \rangle; \langle a_{40}, a_{41}, \dots, a_{60} \rangle\}$$

With $\text{min_sup} = 2$:

- ▶ $F = \approx 1.27 * 10^{30}$
- ▶ $C = \{\{a_1, a_2, \dots, a_{100} : 2\}; \{a_{20}, a_{21}, \dots, a_{80} : 3\}; \{a_{40}, a_{41}, \dots, a_{60} : 4\}\}$
- ▶ $M = \{\{a_1, a_2, \dots, a_{100} : 2\}\}$

Finding maximal disks using Maximal Pattern algorithms

- ▶ Points enclosed by disks become transactions...
- ▶ Apply well-known algorithms (LCM in this case)...
- ▶ Filter patterns with length less than μ .

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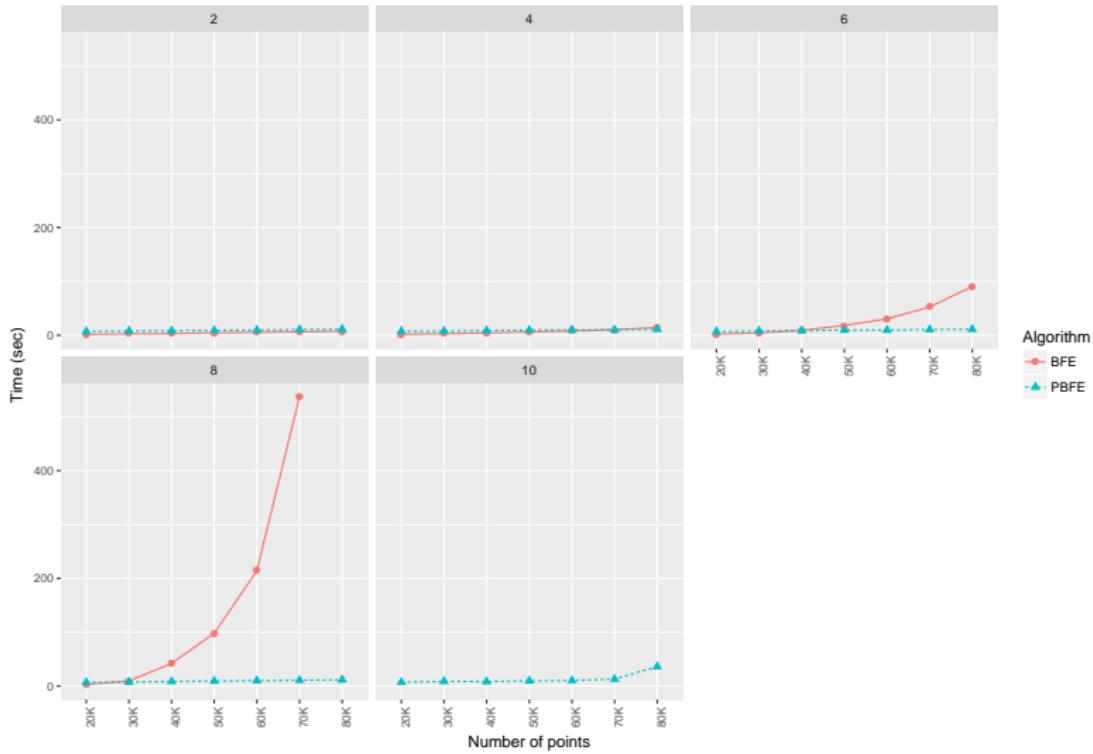
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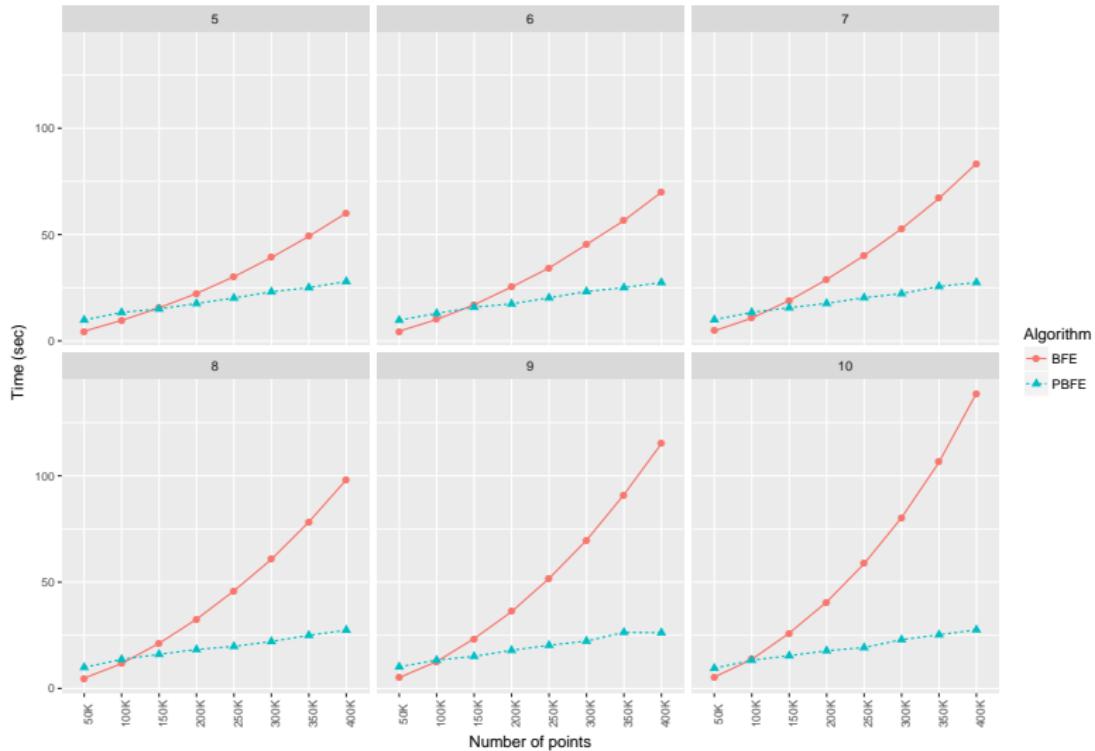
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Porto - Execution time

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- ▶ The finding of a candidate set of disk proves to be scalable and reliable.
- ▶ Execution time improves up to 3 orders of magnitude compared to the sequential code.
- ▶ Good behavior of Scaleup and Speedup metrics.
- ▶ Promising performance for the detection of maximal set of disks.

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- ▶ Work on a parallel strategy to join the sets of valid disks between time intervals.
- ▶ Explore other partition strategies for finding maximal set of disks as alternative to the local-global approach.
- ▶ Test the approach with other spatio-temporal patterns.

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Thank you!!!

Do you have any question?