Visualizing Geolocated Tweets

A Spatial Data Mining Approach

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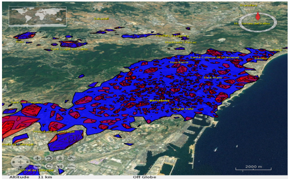

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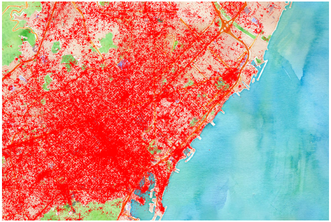
- Due to its willingness in sharing data, Twitter has been a prime *playground*, for researchers and practitioners around the world.

Some Context

- Users on Twitter generate over 400 million tweets everyday.



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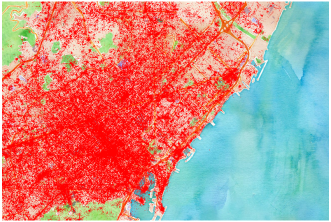

Some Context

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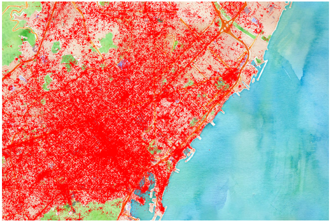
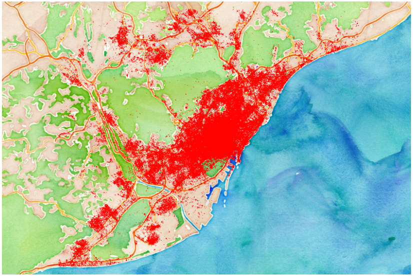
- Approximately 1% of all Tweets published on Twitter are geolocated.
- This (*Big*?) amount of data is not easily assimilated by the "human-eye".



Motivation

How to assimilate these large datasets and extract some relevant information?



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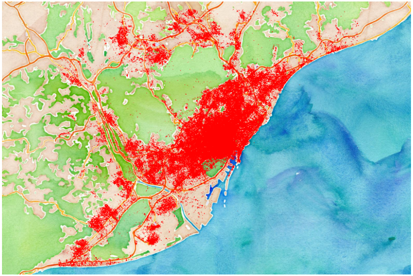
- Technological Challenge + **Representation Challenge**.



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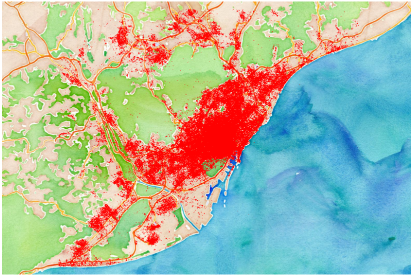
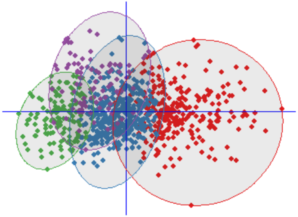


Clustering

- Unsupervised, descriptive, method.



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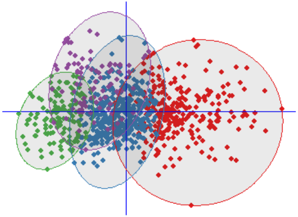

Clustering

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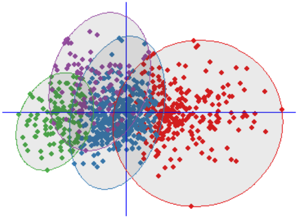
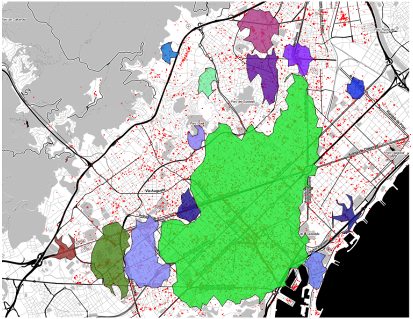
- Widely used due to its segmentation and summarization features.
- Identifies groups of objects, which are similar between them, and distinct from the rest.



DBSCAN



DBSCAN

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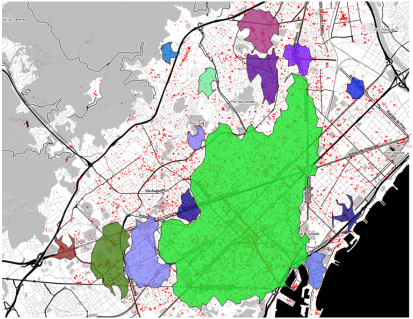

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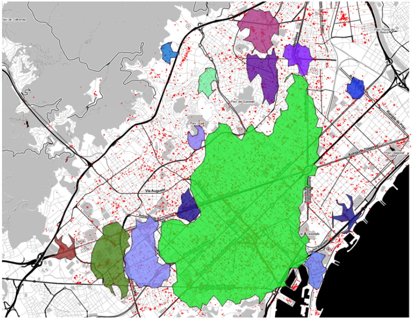

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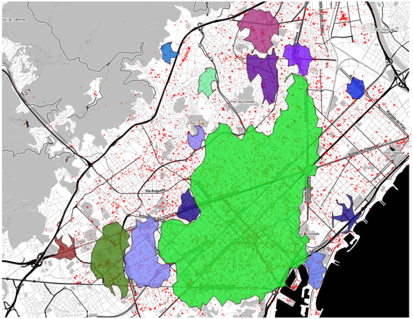

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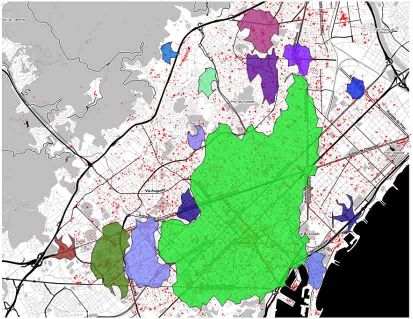
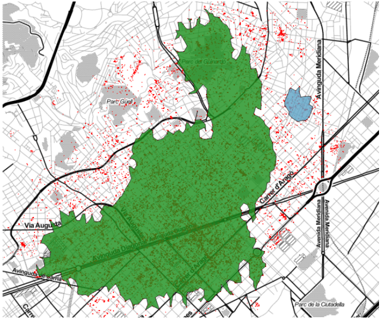
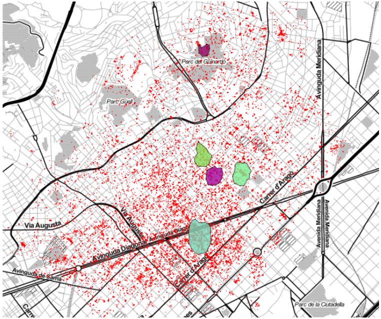
- A *dense-region* is defined by global parameters:
    - epsilon: neighbourhood radius.
    - minPts: minimum number of points required to form a dense region.



The Bottleneck: Global Parameters



Less strict combination of parameters



Strict combination of parameters

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- Larger epsilon, lower minpts: larger clusters that include a great part of the points, but it fails to expose the details of the highly dense zones in the city centre.

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- Larger epsilon, lower minpts: larger clusters that include a great part of the points, but it fails to expose the details of the highly dense zones in the city centre.
- Lower epsilon, larger minpts: detects these highly dense zones, but leaves out other *potential* clusters that are less dense, in the city outskirts.

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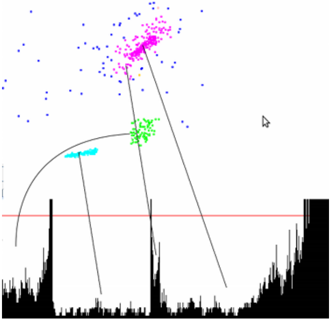
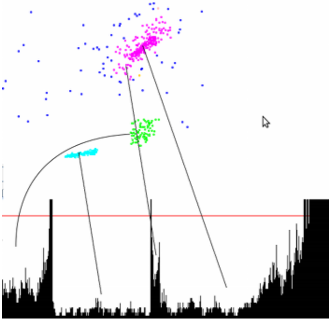
- It does **not** produce a strict partition of the data.

OPTICS (cont.)

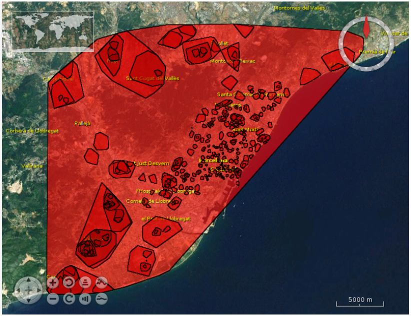


OPTICS (cont.)

- In the ordering clusters appear as *valleys*, separated by *noise regions*(peaks).

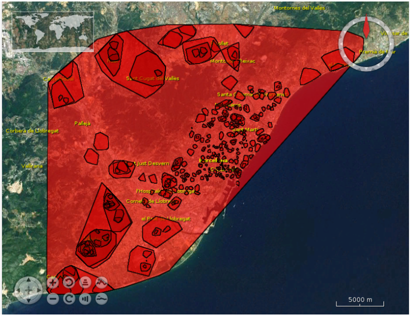


Opticsxi: detecting Clusters



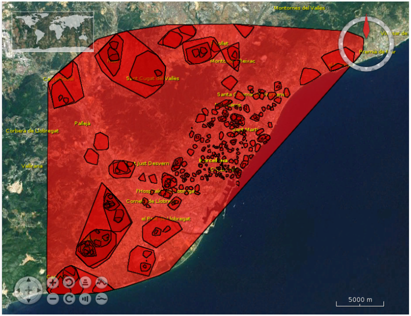
Opticsxi: detecting Clusters

- We can define the *start* and *end* of a cluster, based on a threshold (xi).



Opticsxi: detecting Clusters

- We can define the *start* and *end* of a cluster, based on a threshold (xi).
- Hierarchical partition.



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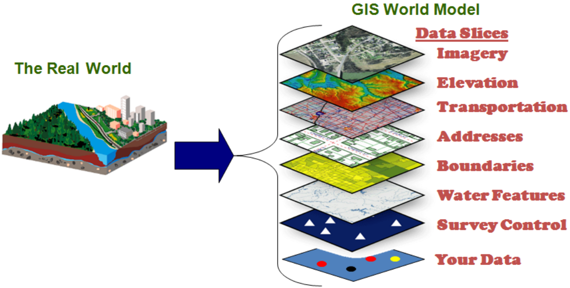

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NASA WW

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    - OpenGL.

Cluster Explorer

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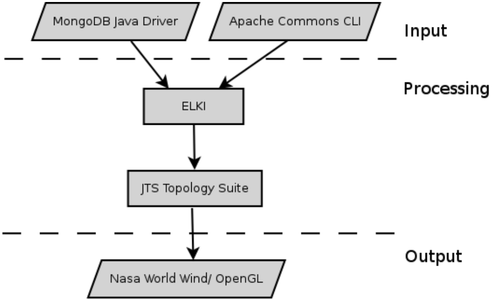

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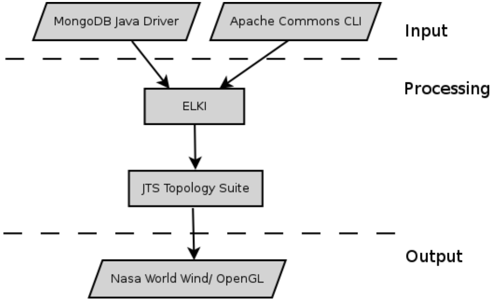
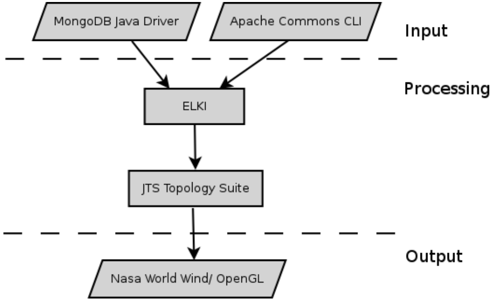


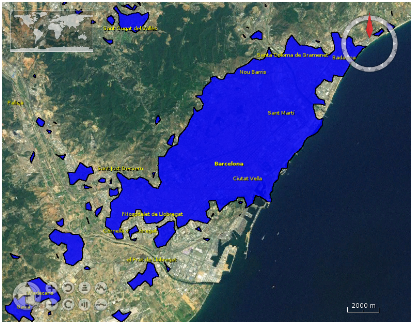
Cluster Explorer

- Java App based on FOSS.
- Generates clusters based on DBSCAN, OPTICSxi (or both).
- Displays the results on a virtual globe.

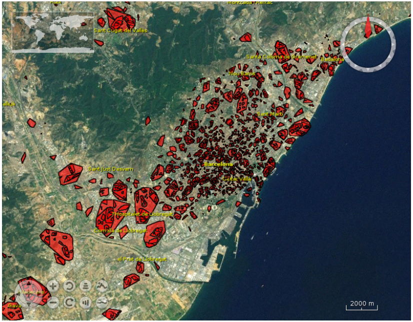


A Case Study

A set of geo-located Tweets in the city of Barcelona, over a period of five days

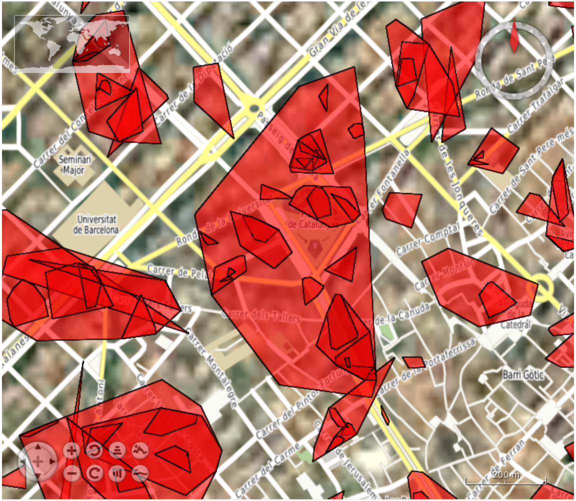


DBSCAN run



OPTICSxi run

GIS and the value of Location-Analysis (cont.)



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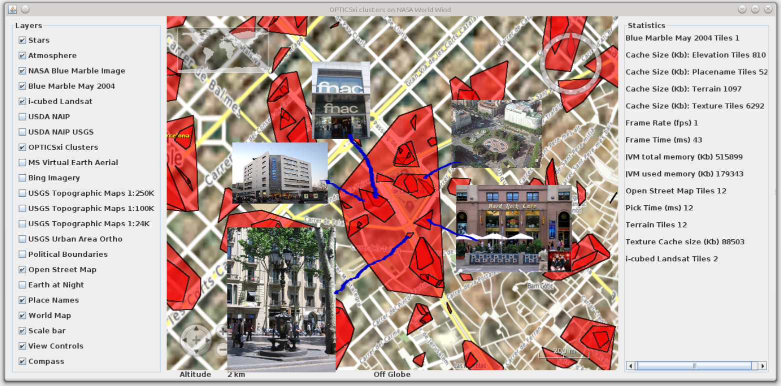

GIS and the value of Location-Analysis (cont.)

Identified clusters (hierarchical level):

- Plaza de Catalunya cluster (L1)
- Triangle Shopping Centre (L2)
- FNAC shop (L3)
- Hard rock cafe (L2)
- Central gardens (L2)

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- Combining machine learning and GIS, can be a promising approach in the field of spatial data mining.
- The reproducibility of this approach is encouraged by the use of FOSS technologies.

Thank You for Listening!

This presentation is available at:
`http://tinyurl.com/nd29g3f`