A GEO-stack for Big Data

Driving Spatial Analysis Beyond the Limits of Traditional Storage

Joana Simões [1]

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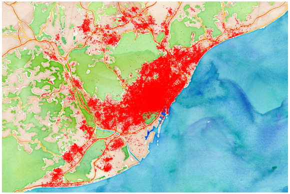
March 9, 2015



Big Data Word Cloud; source:http://olap.com/big-data/

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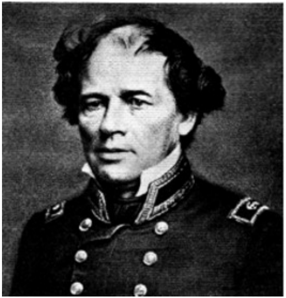
Warning

* This presentation may contain tech talk, such as: databases, clusters, NoSQL.
If you are susceptible to these concepts, you may want to leave the room **now**.
From this point beyond, you are at your own risk! *

The Value of Data

Not a New Idea!

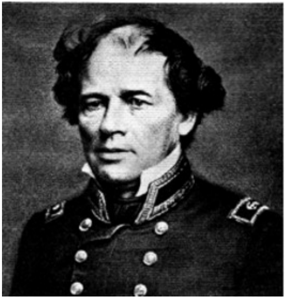
- Matthew Fontaine Maury (1806-1873).



The Value of Data

Not a New Idea!

- Matthew Fontaine Maury (1806-1873).
- Foresaw the hidden value on captain's ships logs, when analysed collectively.
- Used time series data to carry out analysis that would enable him to recomend optimal shipping routes.



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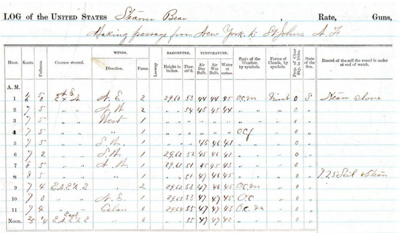
Data Mining, Open-source and Crowd-sourcing



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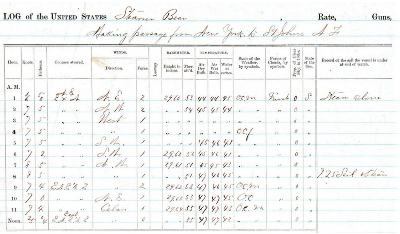

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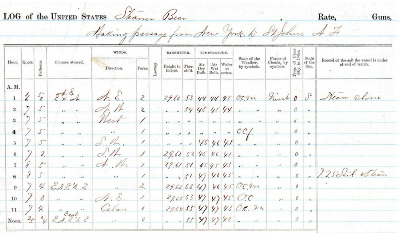

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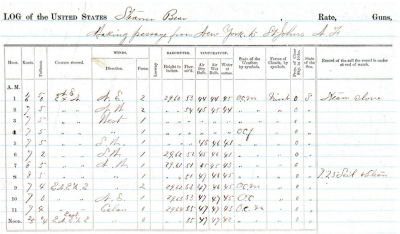
- Collected Data: longitude, latitude, currents, magnetic variation, air and water temperature, general wind direction, etc.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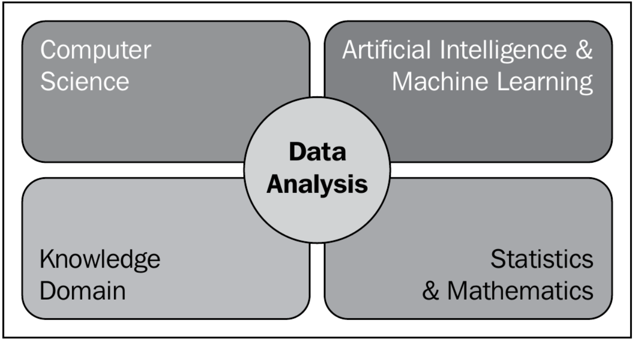
Data Analysis

A multidisciplinary field



Data Analysis

Traditional Stack

- Spreadsheets (e.g.: Excel, OpenOffice)
- RDBMS (e.g.: Oracle, PostgreSQL, MySQL)
- Statistical Packages (e.g.: R, Matlab)
- GIS Packages (e.g.: QGIS)
- Scripting and programming languages (e.g.: Python, Java)
- Libraries

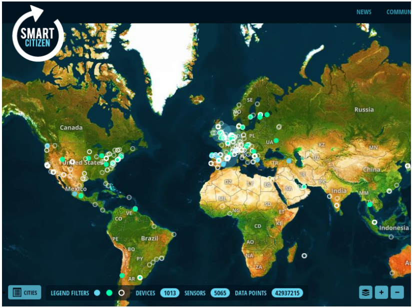
Big Data

What changed in recent years?

- Differences in the way global business and transportation are done have exploded the volume of traditional data sources.
- Widespread increase in data from sensors.

Big Data

Smart Citizen Project

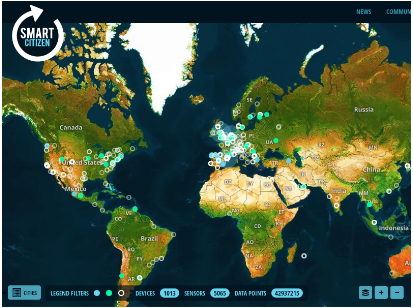


https://smartcitizen.me/

Big Data

Smart Citizen Project

- Platform to generate participatory processes of people in the cities, by connecting data, people and knowledge.



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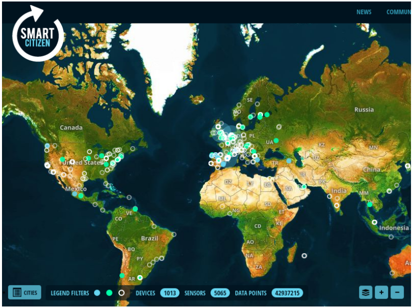

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Smart Citizen Project

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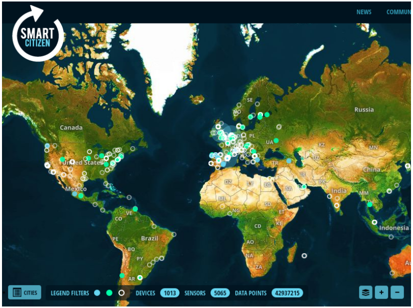
- Relies on the production of objects to connect people with their environment and their city.



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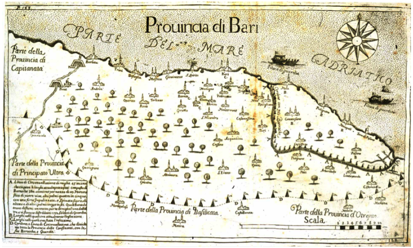

Based on reports, Fillipo Arrieta published maps describing a multi-stage containment plan designed to limit the plague in Bari (1864).

The iLab used the ushahidi platform to collect and display crowd-sorcing information about Ebola in Liberia (2014).

Big Data

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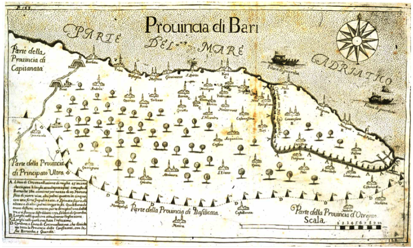

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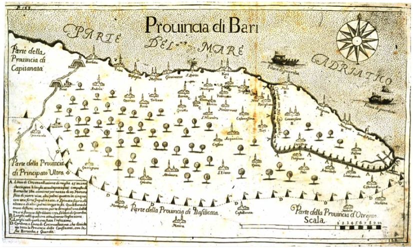
Big Data

- A great deal of this data is actually geo-located (e.g.: satellite navigate coordinates, ip addresses).
- Geography has finally the opportunity to switch from being based on guesses and samples, to become a truly data-driven science.



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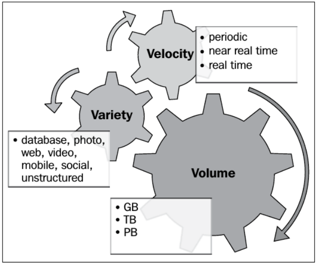

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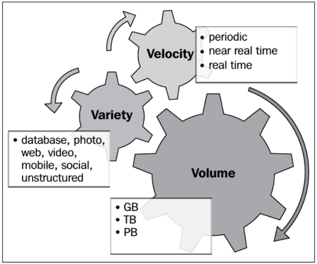
- Volume: Large amounts of data.



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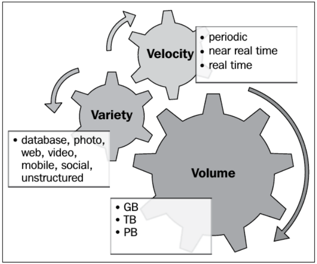
- Volume: Large amounts of data.
- Variety: Different types of structured, unstructured, and multi-structured data.



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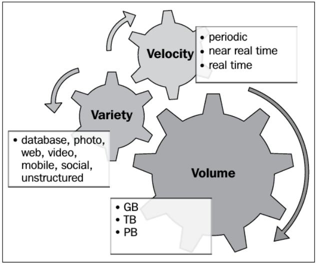
- Velocity: Needs to be analyzed quickly.



Technological Challenges

These characteristics map into challenges:

- Scalability
- Heterogeneity
- Low latency

When the traditional stack is no longer enough, a paradigm shift is required.

RDBMS vs NoSQL

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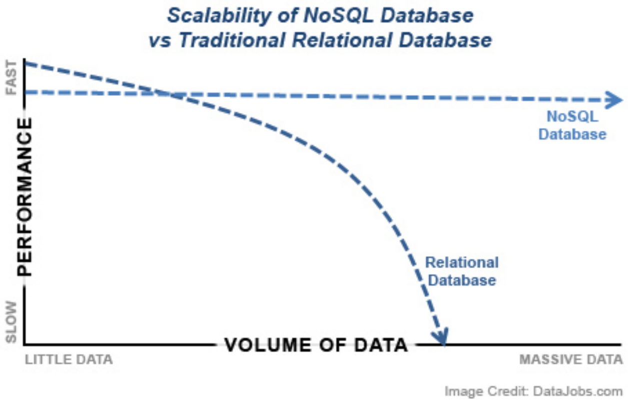
- Advantages: NoSQL databases are simpler, can handle semi-structured and denormalized data and have an higher scalability.
- Disadvantages: loss of abstraction provided by the query optimizer, that increases the complexity of the applications.
- Recently, tools were developed that bring back the full power of SQL language to the NoSQL ecosystem (e.g.: Apache Drill, Hive).

RDBMS vs NoSQL



Examples

cassandra
redis
CouchDB relax
riak
mongoDB
RAVENDB
OrientDB
symas
Neo4j
hadoop
HAZELCAST SOFTWARE
RethinkDB.
HYPERTABLE INC

MapReduce

Programming model for processing and generating large data sets with a parallel, distributed algorithm on a cluster.

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- The framework coordinates the processing, by marshalling the distributed servers, running the tasks and parallel and managing all communications and data between the various parts of the system.
- There are many libraries that implement MapReduce.

A Big Data Approach

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- First ensure that you **really** have, or will have Big Data at some point in the future.
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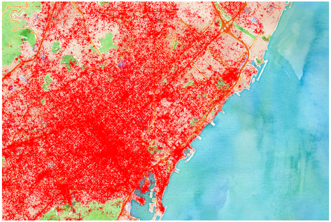
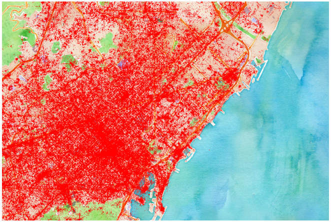
- It is possible to mix & and match.

Analysing geo-located Tweets



Analysing geo-located Tweets

- The purpose of this use case was to analyse the stream of geo-located Tweets, as a sensor for citizen presence.



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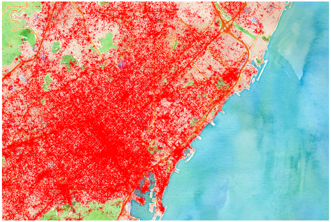

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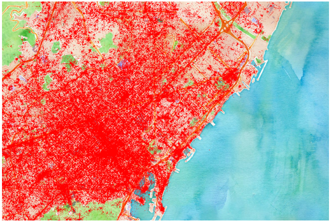

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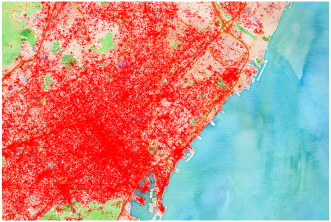
- Continuous stream of data.
- This amount of data is not easily assimilated by the "human-eye", so we decided to create clusters of Tweets.



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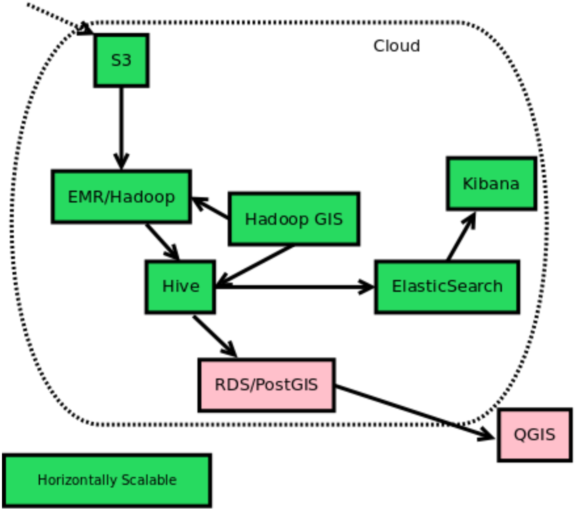
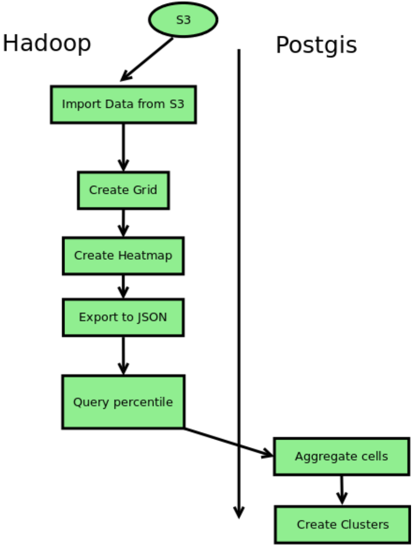
- Strictly, it corresponds to a family of unsupervised machine learning algorithms.
- We wanted to implement this concept using only Hadoop, and apply it to spatial attributes.

Technological Stack

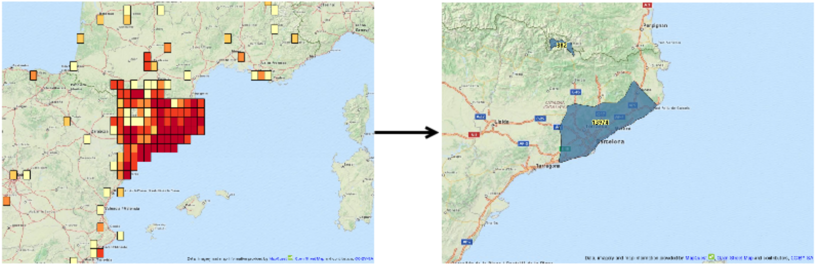


Workflow


S3
Hadoop
Postgis
Import Data from S3
Create Grid
Create Heatmap
Export to JSON
Query percentile
Aggregate cells
Create Clusters

Results

Using this workflow we were able to turn the original raw tweets, first into a density grid, and then into clusters.



As we identified and solved the bottlenecks with the relevant tools, in theory this algorithm is scalable to any Petabytes of data.

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- We are working on the edge of existing technologies; some functions were not implemented yet, and bugs are common.
- Since it is a niche, this is even more true for spatial technologies.
- There are not ready-made solutions: the particular stack and workflow should be compiled for the specific case study.
- this is one stack to solve this problem; it is not the only one, and it may not even be the "best" one;

Acknowledgements

I would like to thank Ellen Friedman (MapR, Apache Mahout, Apache Drill), for her inspiring work on Big Data and Machine Learning.

References

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