

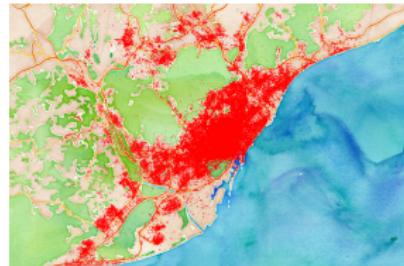
# A GEO-stack for Big Data

Driving Spatial Analysis Beyond the Limits of Traditional Storage

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March 12, 2015



The Value of Data  
The Big Data Revolution  
An Use Case  
Final Remarks



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, cloud, parallelism, scalability.  
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 recommend optimal shipping routes.



# The Value of Data

## Data Mining, Open-source and Crowd-sourcing

Bore.	Bore.	Pounds.	Guns.	WEIGHT.		REARMS.	REARMS.	Rate.	Guns.	
				Direction.	Pounds.	Length.	Height in This Army	For Art. Balls, etc.	Water in Cwt.	Parts of Cannon by Weight.
<b>A. M.</b>										
1.	2	4	85 2	A. S.	2	280.50	44.98	85	100.000	Rank 0 S. Stem above
2.	2	5	-	B. H.	2	-	45	95	85.50	-
3.	2	5	-	Best	1	-	-	-	-	-
4.	2	5	-	-	1	-	-	-	-	8Cf
5.	2	5	-	D. H.	1	-	-	95	95.451	-
6.	2	5	-	D. H.	1	280.50	45.98	95	-	-
7.	2	5	-	A. H.	1	140.00	40.98	95	-	-
8.	2	5	-	-	1	-	51	95	95.87	-
9.	2	4	85 2	-	2	280.50	42.97	95.50	100.000	2250.000 S. stem
10.	2	6	-	A. S.	1	280.50	42.97	95	95.000	-
11.	2	8	"Best"	C. G.	1	280.50	42.97	95	95.000	-
Nom.	2	4	85 2	-	6	-	51	95	95.87	-

# The Value of Data

## Data Mining, Open-source and Crowd-sourcing

- In 1848, Captain Jackson was the first person to try the route recommended by Maury, and as a result he was able to save 17 days on his outbound trip.

Bore. No.	Polaris.	Course steered.	VELOC.		EASTING.		WESTING.		Port of the Cape Horn by approx.	Port of the Cloudy Bay by approx.	Port of the S. E. by approx.	Port of the S. W. by approx.	Port of the N. W. by approx.	Port of the N. E. by approx.	Breadth of the sea all round in miles at end of watch.
			Direction.	Pace.	Lining.	Length.	Right in Tides.	As for Bath.							
<b>A. M.</b>															
1.	2° 4' E. 85° 2'	S. E.	2.	28.0	50.98 98.85	00.222	Rank 0	0	S.	Steam ahead					
2.	2° 5' -	W.	2.	-	58.95 95.95	-	-	-	0	-					
3.	2° 5' -	West	1.	-	-	-	-	-	-	-					
4.	2° 5' -	-	1.	-	-	-	-	-	00f	-					
5.	2° 5' -	S. E.	1.	-	-	58.98 94.91	-	-	-	-					
6.	2° 2' -	S. E.	1.	28.0	52.95 98.91	-	-	-	0	-					
7.	2° 5' -	S. E.	1.	28.0	51.95 98.91	-	-	-	0	-					
8.	2° 5' -	-	1.	-	-	58.95 95.95	-	-	0	-	2250 f. distant				
9.	2° 4' E. 85° 2'	2.	28.0	52.95 98.91	00.222	-	-	-	0	-					
10.	2° 8' -	S. E.	1.	28.0	52.95 98.91	00	-	-	0	-					
11.	2° 8' "East"	Clouds	1.	28.0	52.95 98.91	00.22	-	-	0	-					
Nom.	2° 4' E. 85° 2'	-	1.	-	58.95 95.95	-	-	-	0	-					

# The Value of Data

## Data Mining, Open-source and Crowd-sourcing

- In 1848, Captain Jackson was the first person to try the route recommended by Maury, and as a result he was able to save 17 days on his outbound trip.
- Apart from collecting existing logs, Maury encouraged the collection of more regular and systematic time series, by creating a template.

Date, Month	Latitude	Course steered.	WEATHER.			Rate,	Guns,
			Direction	Fog	Leaving		
1 2 4 85° 2	S.E.	2	28.0 52.94 98.85	00.000	Rank 0	3	Steam ahead
2 2 5 -	W.	2	-	19.95 95.95	-	0	-
3 2 5 -	West	1	-	-	-	0	-
4 2 5 -	-	1	-	-	-	0	-
5 2 5 -	S.W.	1	-	10.96 94.94	-	0	-
6 2 5 -	S.W.	1	28.0 52.95 98.85	-	-	0	-
7 2 5 -	S.W.	1	28.0 52.95 98.85	-	-	0	-
8 2 5 -	-	1	-	19.95 94.95	-	0	-
9 2 4 85° 2	-	2	28.0 52.94 98.85	00.000	-	0	2250 lbs shot
10 2 4 -	S.E.	1	28.0 52.94 98.85	00.000	-	0	-
11 2 4 "East"	Calms	1	28.0 52.94 98.85	00.000	-	0	-
Nom. 2 4 85° 2	-	1	-	19.95 92.95	-	0	-

# The Value of Data

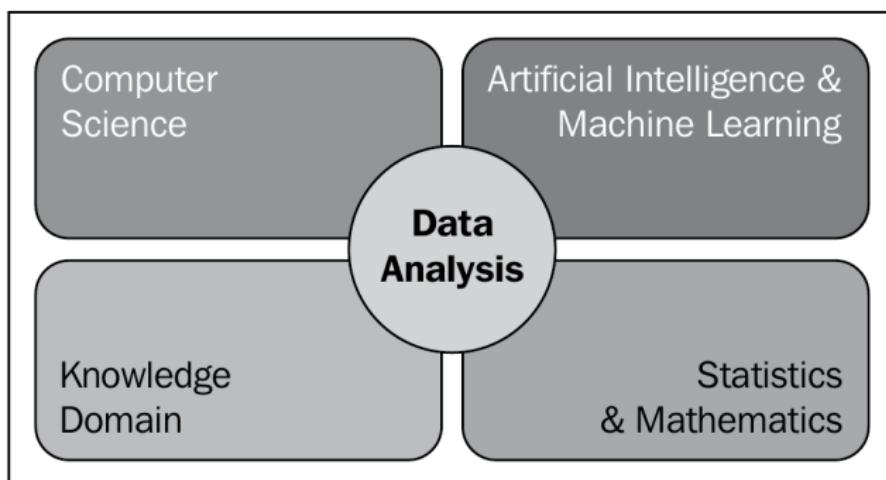
## Data Mining, Open-source and Crowd-sourcing

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- Apart from collecting existing logs, Maury encouraged the collection of more regular and systematic time series, by creating a template.
- Collected Data: longitude, latitude, currents, magnetic variation, air and water temperature, general wind direction, etc.

Bore. Month	Latitude	Course steered.	WEATHER.				Rate,	Guns,
			Direction.	Fog.	Lightning.	Rain.		
1. 6. 4.	59° 8'	S. E.	2.	28.0. 50. 49. 98. 85.	00.000.	Rank. 0.	3.	Steam alone.
2.	5°	-	2.	-	-	-	0.	-
3.	5°	-	1.	-	-	-	0.	-
4.	5°	-	1.	-	-	-	0.	-
5.	5°	-	1.	-	-	-	0.	-
6.	2.	-	1.	-	-	-	0.	-
7.	5°	-	1.	-	-	-	0.	-
8.	5°	-	1.	-	-	-	0.	-
9.	4. 8.	E. S. E.	2.	28.0. 51. 49. 98. 85.	00.000.	Rank. 0.	3.	2250000000.
10.	4. 8.	-	1.	28.0. 51. 49. 98. 85.	00.	-	0.	-
11.	4. 8.	"East."	1.	28.0. 51. 49. 98. 85.	00.000.	-	0.	-
Nom.	4. 8.	E. S. E.	1.	-	-	-	0.	-

# 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

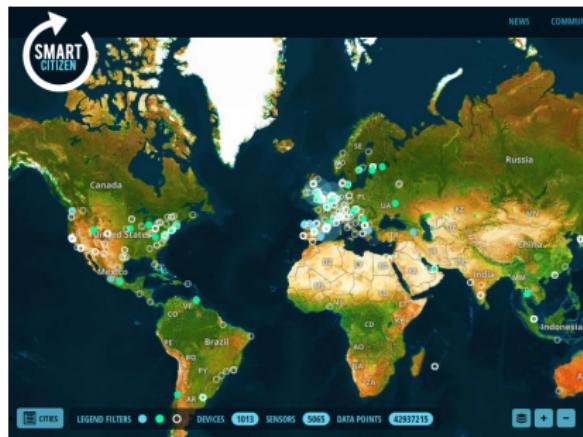


<https://smartcitizen.me/>

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



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## Smart Citizen Project

- Platform to generate participatory processes of people in the cities, by connecting data, people and knowledge.
- Based on geolocation, Internet and free hardware and software for data collection and sharing.
- Relies on the production of objects to connect people with their environment and their city.



<https://smartcitizen.me/>

# Big Data



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-sourcing information about Ebola in Liberia (2014).

# Big Data

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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.



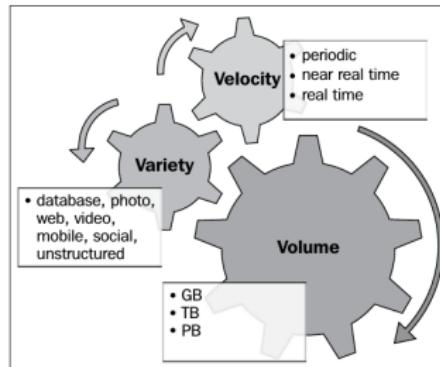
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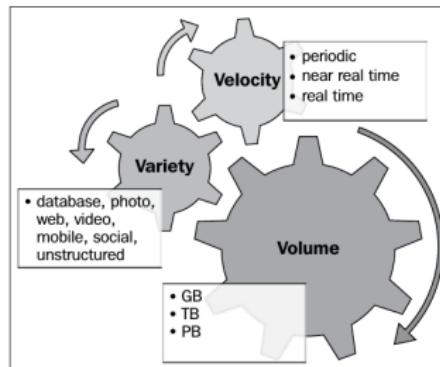
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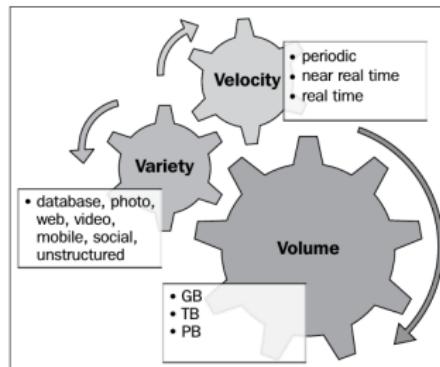
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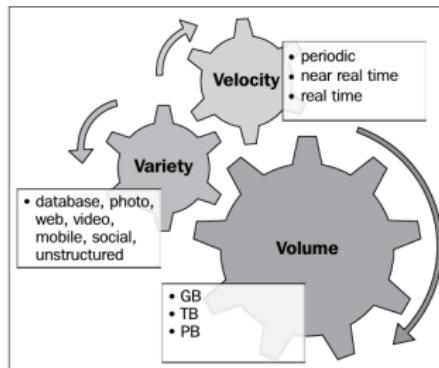
- **Volume:** Large amounts of data.
- **Variety:** Different types of structured, unstructured, and multi-structured data.



# Big Data

## What characterizes Big Data?

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

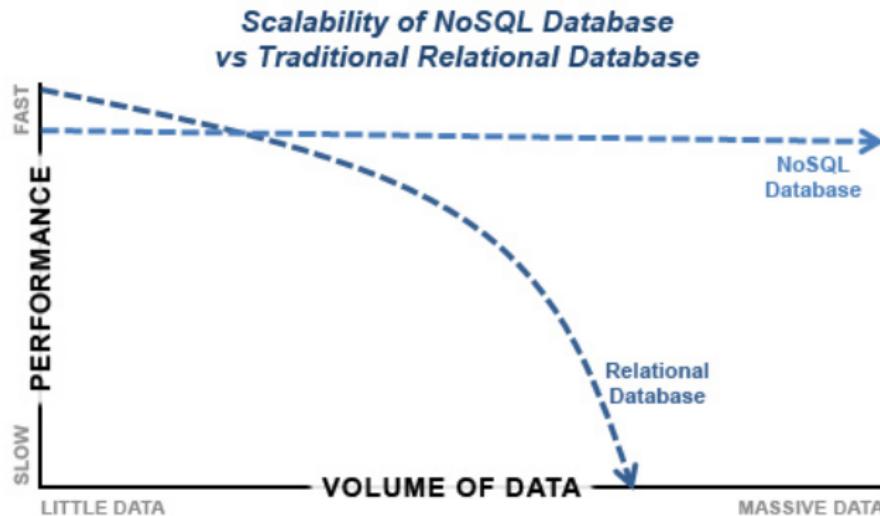


Image Credit: DataJobs.com

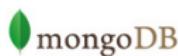
# Examples



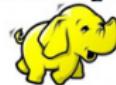
cassandra



redis

CouchDB  
relax

Neo4j

HAZELCAST  
SOFTWARE

RethinkDB.

HYPERTABLE<sup>TM</sup>

# MapReduce

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

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- Map(): performs filtering and sorting.
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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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- It is possible to mix & and match.

## Analysing geo-located Tweets



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- The purpose of this use case was to analyse the stream of geo-located Tweets, as a sensor for citizen presence.
- Number of tweets in Catalunya in around 3 months: +- 6 million.
- Continuous stream of data.
- This amount of data is not easily assimilated by the "human-eye", so we decided to create clusters of Tweets.



# An Use Case

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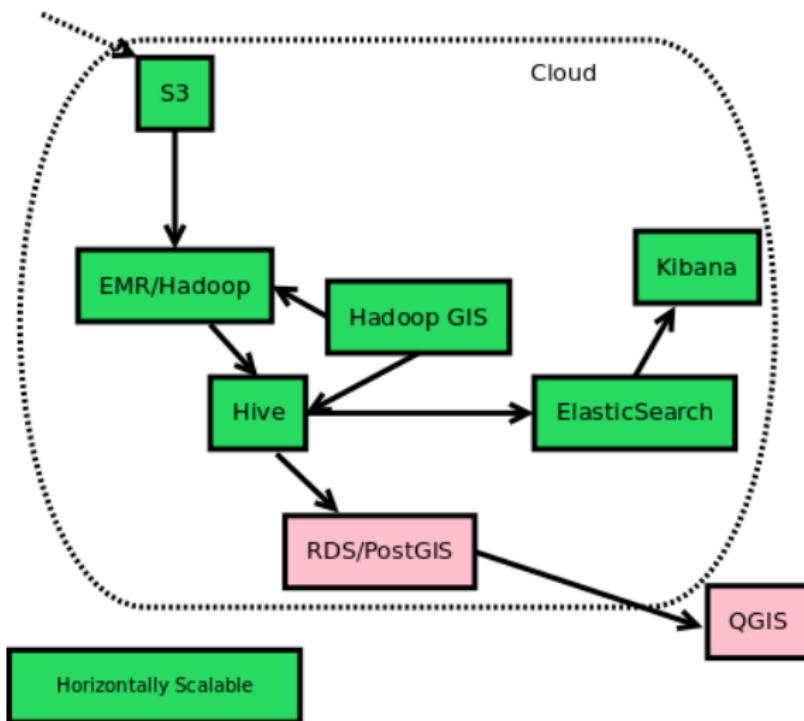
- It is a descriptive data mining technique, often used for dimensionality reduction.
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- Strictly, it corresponds to a family of unsupervised machine learning algorithms.

# An Use Case

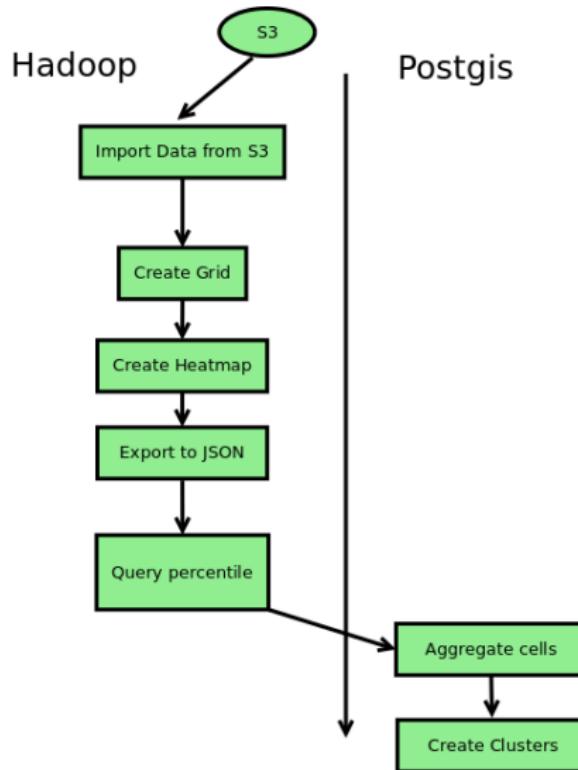
## Clustering

- It is a descriptive data mining technique, often used for dimensionality reduction.
- It groups a set of objects in such a way that objects in the same group are more similar to each other, than to object in other groups.
- 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

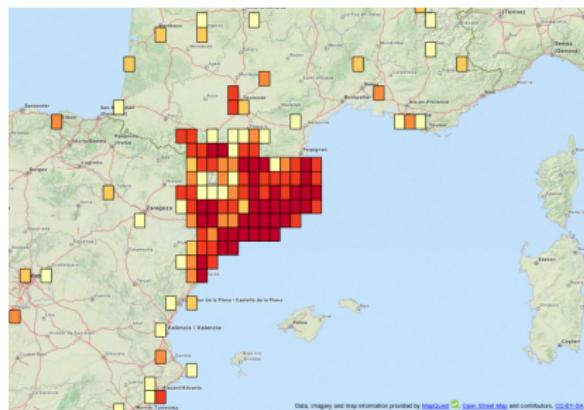


# Workflow



# Results

Using this workflow we were able to turn the original point cloud, into a density grid, and then into clusters.



Clusters expose patterns of presence over time, and can help us to re-define boundaries for the city that are data-driven, rather than administrative.

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- 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.



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# Thank You!



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<http://tinyurl.com/pcmגzxپ>

Next:

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