SOLVING LARGE LOCATION-ALLOCATION PROBLEMS BY CLUSTERING AND SIMULATED ANNEALING

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Introduction

Motivation

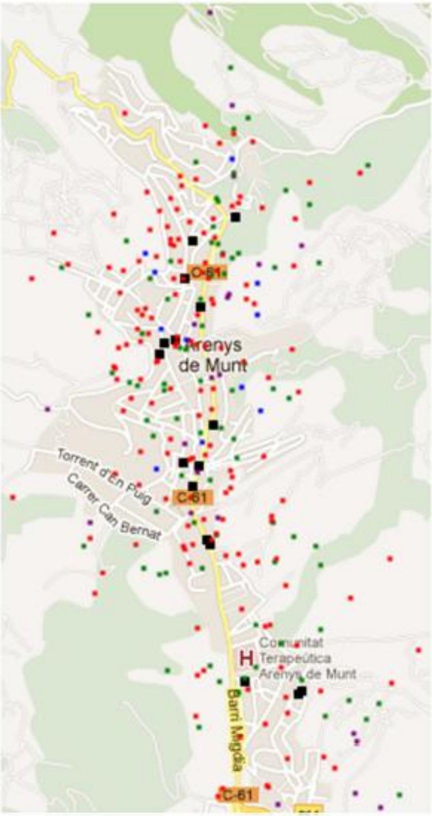
Sport globalization → Simultaneous sport events → Barman decision problem → Automatic decision system

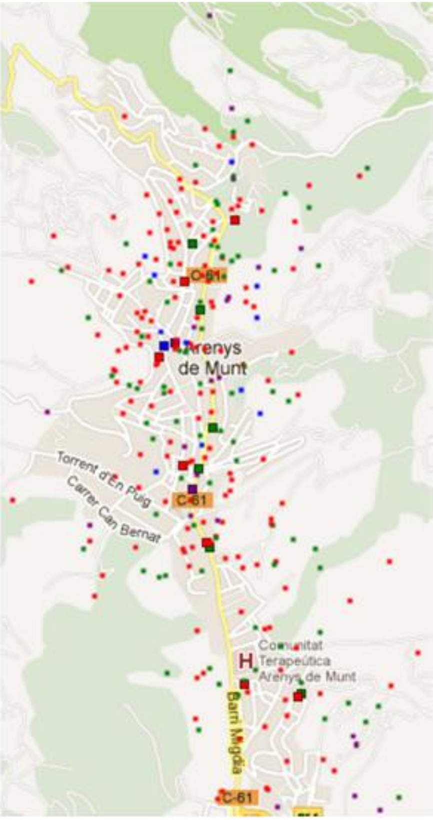
80 people wants match 1
20 people wants match 2

- 10 bars broadcast match 1
  - 8 people/bar
- 8 bars broadcast match 1
  2 bars broadcast match 2
  - 10 people/ bar

Background

- Immobile location-allocation
  - Given a set of facilities with known positions and a demand with known positions, determine the optimal service each facility has to offer
  - Facilities (bars) cannot be moved and their positions are known
  - Each customer desire a single service (match) from a set and it is known
  - Customers' positions are known
  - Complexity → $(N_{matches})^{N_{bars}}$





- Problem dimensionality
  - Most research does not deal with problems of the same complexity/size (the system has to deal with bars from around the world)

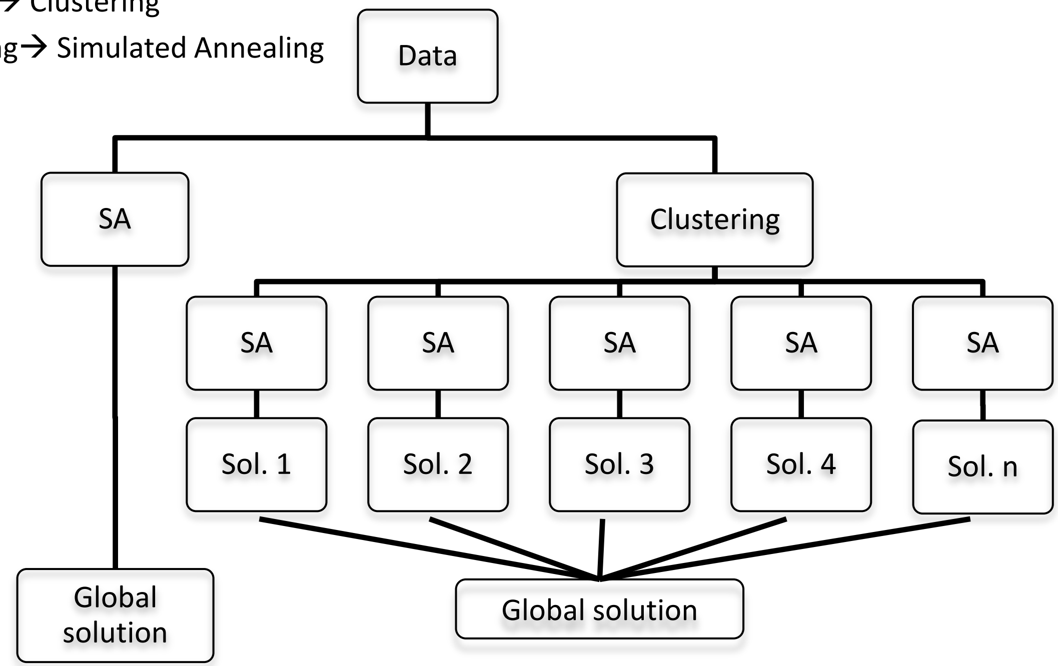
Division of the problem into subproblems

$$k \cdot (N_{matches})^{N_{bars}/k}$$

Objectives

- **Hypothesis**
  - We can approximate the ILA solution by dividing the dataset converting the initial problem into several of easier subproblems.
  - Assumption: geographical distance is a key of the problem and clustering divides the problem according the distance.

- **Objectives**
  - Divide the problem into sub-problems → Clustering
  - Location-allocation (sub)problem solving→ Simulated Annealing
  - Experimental tests



The Model

- Mathematical model

$$\max_{z_{ij}^q}\left\{\sum_{i=1}^{N_{bars}}\sum_{j=1}^{N_{customers}}\frac{z_{ij}^q}{1+d_{ij}^2}\right\}$$

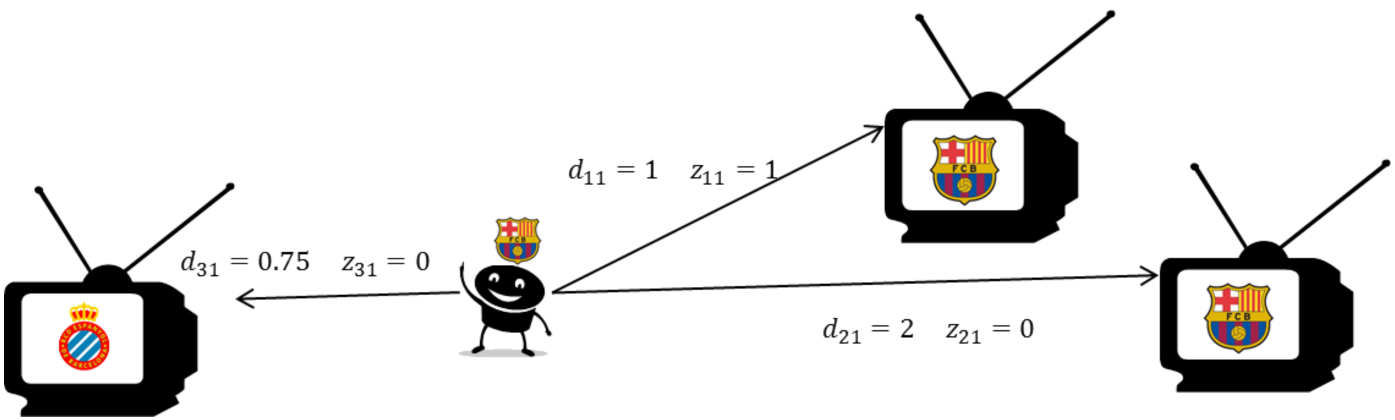
$$z_{ij}^q \in \{0,1\}$$

Subject to

$$\forall_i \quad \sum_{j=1}^{N_{customers}} z_{ij}^q \leq C_i$$

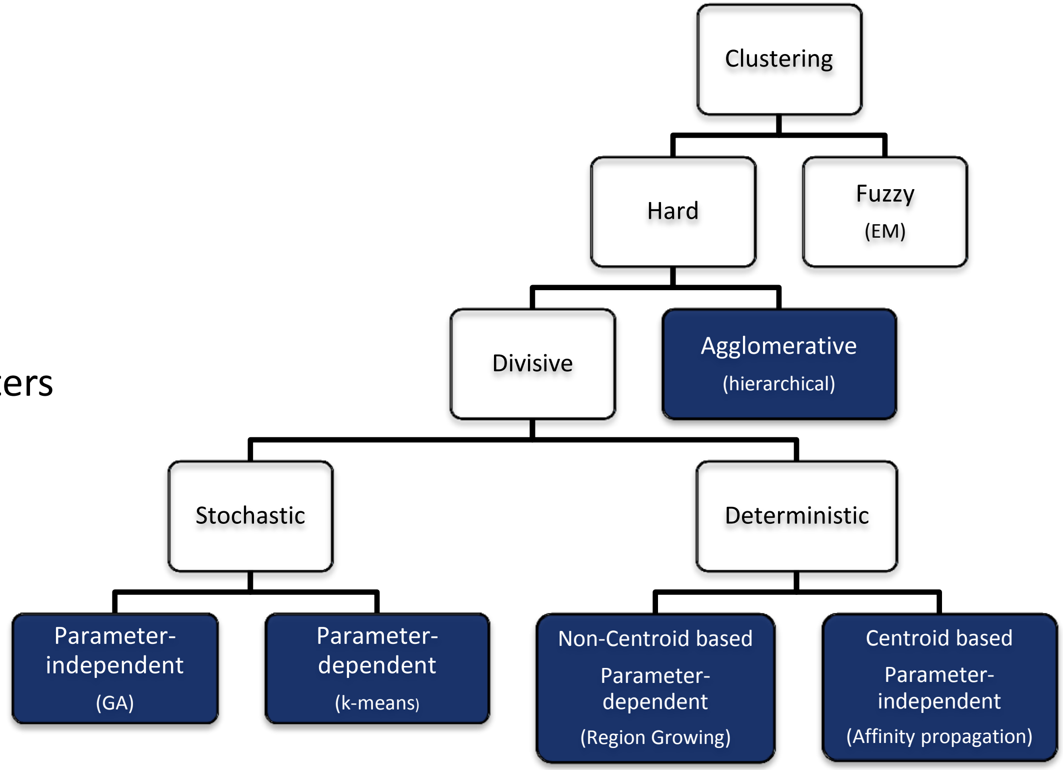
$$\forall_j \quad \sum_{i=1}^{N_{bars}} z_{ij}^q \leq 1$$

$$x_i^q \neq M_j \rightarrow z_{ij}^q = 0, \qquad x_i^q, M_j \in [1, \cdots, N_{matches}]$$



Algorithms

- Division of the problem using different clustering algorithms:
  - Hierarchical clustering
  - K-means
  - Genetic algorithms based clustering
  - Region growing
  - Affinity propagation



- We seek small and separated clusters

Clustering

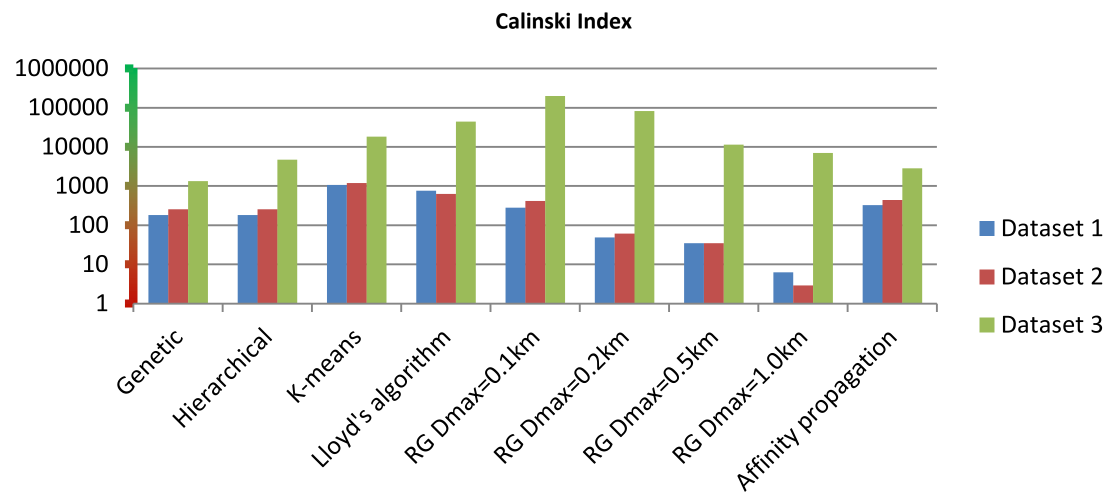
Experimentation Set-up

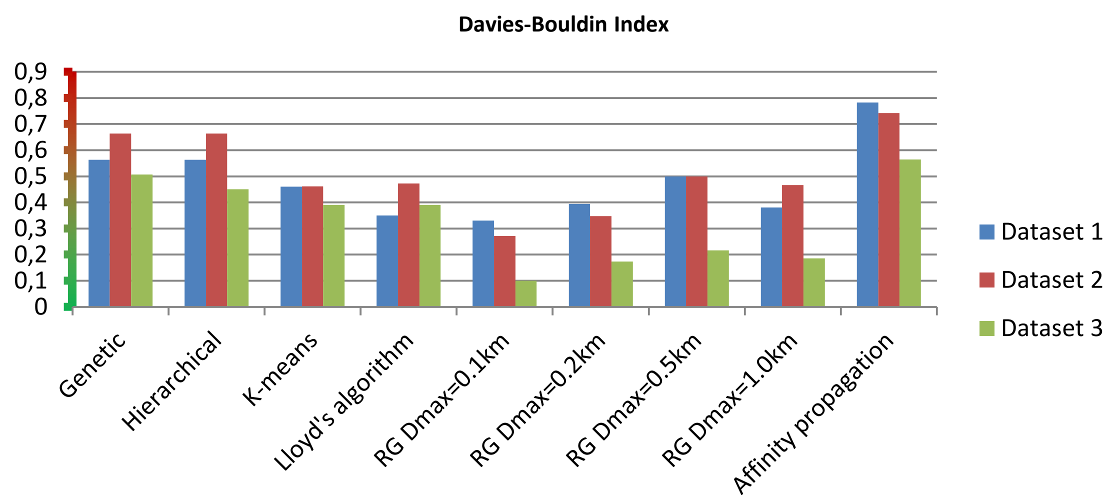
- We have conducted our experiments over different real datasets of bars
- We have simulated the demand
  - Customers are randomly distributed around bars according a Gaussian distribution
  - Each generated customer decides each desired match according to the audiences of the matches
- Here we present the results obtained over three representative datasets
  - Dataset 1: 373 bars and 6676 customers
  - Dataset 2: 458 bars and 8258 customers
  - Dataset 3: 1925 bars and 34954 customers

Clustering

Results

- Different clustering quality results depending on the index.
- Region growing achieves the best results according to both indices

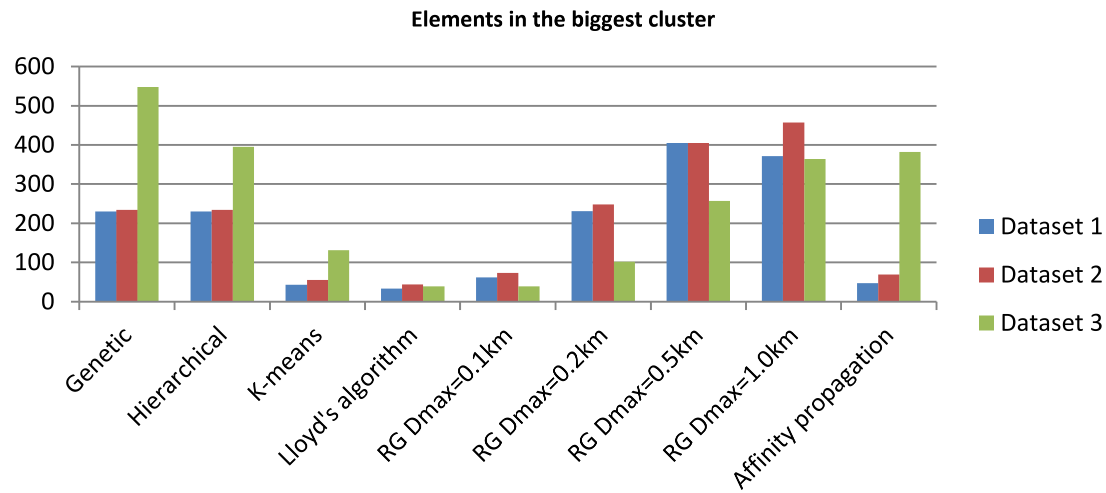


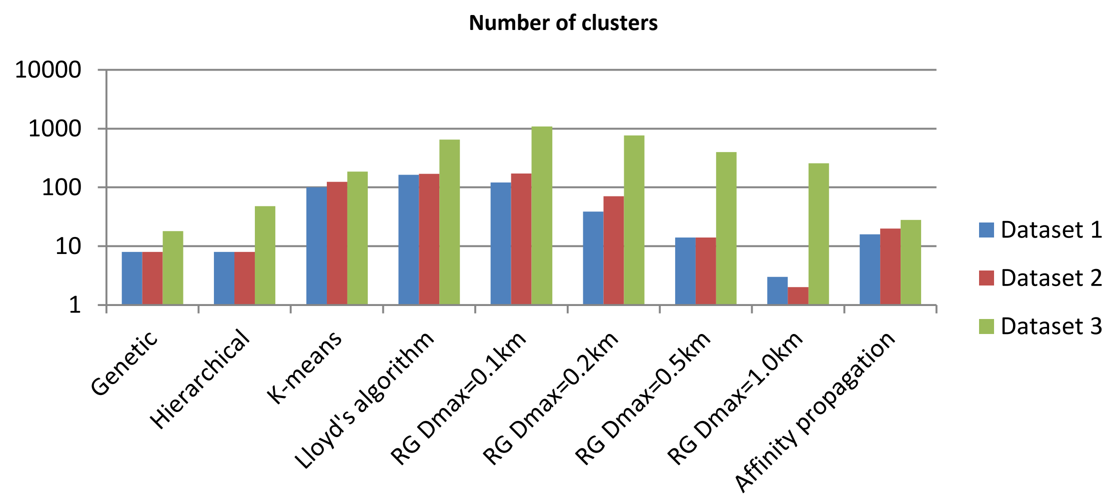


Clustering

Results

- Trade-off between clusters size and number of clusters
- Region growing divides the dataset into a lot of small clusters
- GA, AP, Hier. clust. provide few big clusters
- It is not clear which provide the best partition





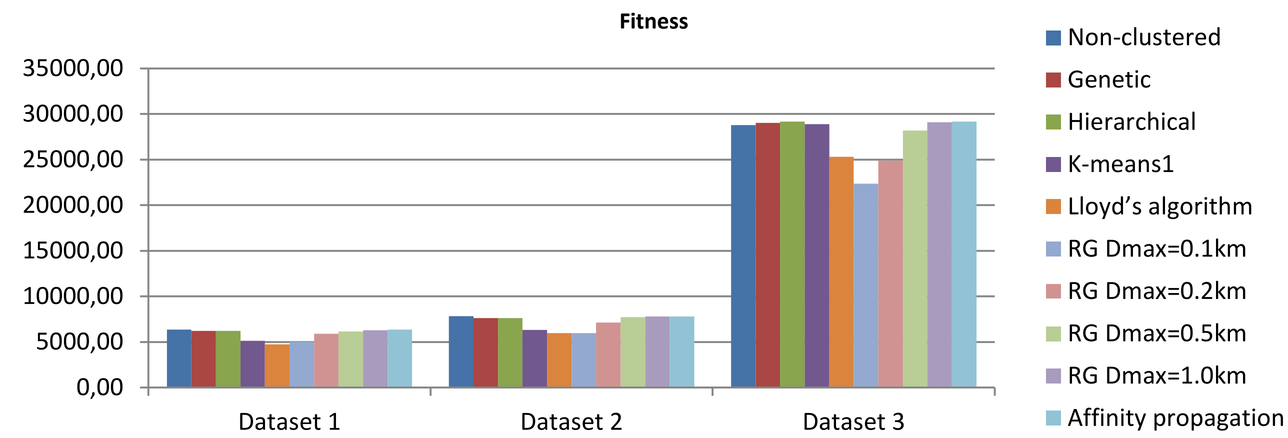
Simulated Annealing

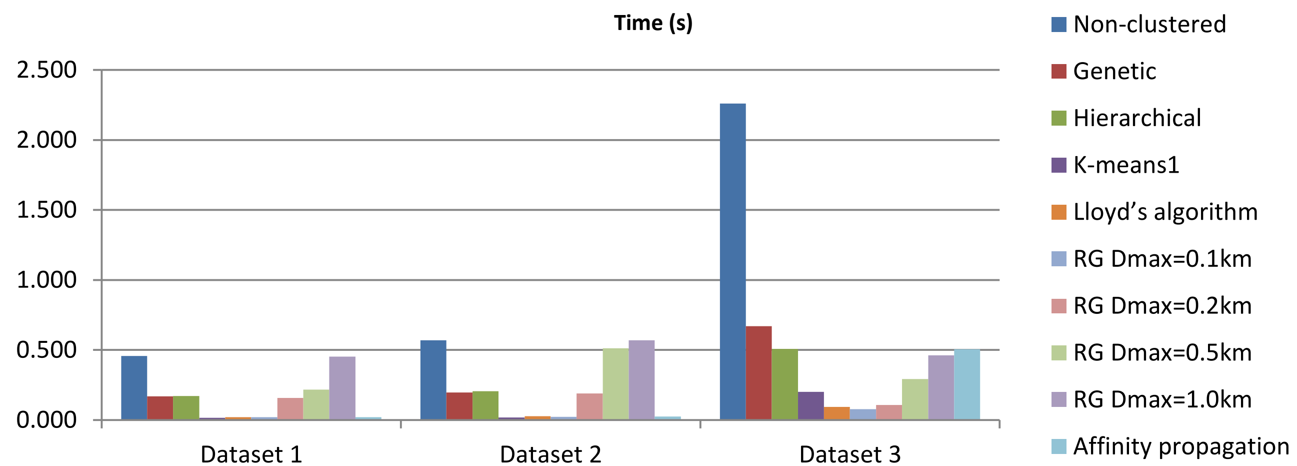
- It does not guarantee the optimal solution but (in practice) it provides near optimal solutions
  - Complete methods are unfeasible due to the number of solutions to be explored
- It has mechanisms to avoid getting stacked on local optimums or flat regions
  - There are many local optimums in the solution space → local search methods would have bad performances
- It does not need any coordinate system to perform the search
  - There is not any coordinate system in the solution space → algorithms such as particle swarm optimization need a coordinate system to guide the search
- It is faster than other heuristic methods like genetic algorithms

Experimentation

ILA Results

- Region growing partition reduces the quality of the final solution
- Algorithms which found few big clusters keep the quality of the final solution
- Clustering highly reduces the elapsed time by SA for seeking the solution





Conclusions

- Formalization of the immobile location-allocation problem
- Development of a new method based on the use of clustering techniques to divide the whole problem
- The use of clustering does not reduce the quality of the solutions
- The use of clustering highly reduces the search time
- Clustering indices such CI or DBI are bad estimators of the quality of the final solutions
- The best results are provided by affinity propagation

Future Work

- Development of a customer position estimator
- Development of a fairness system for bars
- Simplification of the demand allocation process by demand aggregation
- Include cluster permeability for customers

THANK YOU FOR YOUR ATTENTION!

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