# PROBLEM DECOMPOSITION IN METAHEURISTICS



Éric Taillard

HEIG-VD, University of Applied Sciences of Western Switzerland

# SUMMARY OF THE LECTURE

#### **Introduction**

Metaheuristic components

Few combinatorial problems interesting for decomposition methods p-median, map labelling, vehicle routing, location-routing Small and large instances

# **Building a large initial solution**

Delaunay triangulation *p*-median with capacity

# **Improving large solutions**

LNS

**POPMUSIC** 

# METAHEURISTIC COMPONENTS

# Problem modelling, objective and utility functions

Mono-optimization, Multiobjective optimization, Classification

#### **Constructive methods**

Random building

Greedy constructive methods

#### **Local searches**

Neighbourhood structure

Neighbourhood limitation (candidate list) and extension (ejection chain)

# **Decomposition methods**

Domain decomposition

**Building** method

Improvement methods ⇒ LNS, POPMUSIC

#### **Learning mechanisms**

Learning to model ⇒ Hyper-heuristics

Learning to build ⇒ GRASP, Artificial ants

Learning to improve ⇒ Tabu Search

Learning with solutions ⇒ Genetic algorithms, particle swarm, path relinking

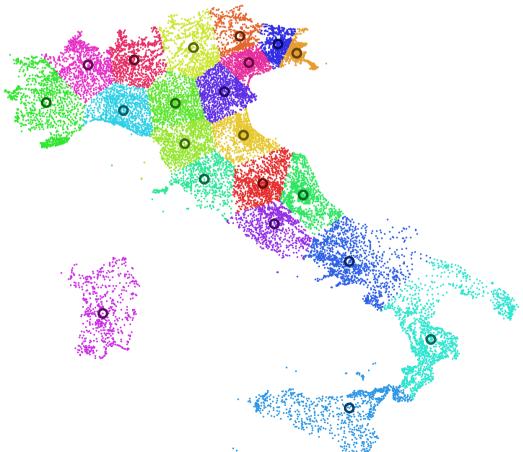
# THE P-MEDIAN PROBLEM

#### Given:

*n* elements  $\in I$  with distance matrix  $D = (d_{ij})$  between them

#### Find:

p central elements  $\{c_1, ..., c_p\} \in I$  minimizing  $\sum_{i=1}^n min_{j=1, ..., p}(d_{i, c_j})$ 



# MAP LABELLING

Yverdon Yverdon Xverdon Xverdon Labelling Max stable Lausanne Lausanne Lausanne Yverdon \_ausanne

Other problem that can be modelled like this: assigning flight levels and departure times of aeroplanes.

# CAPACITATED VEHICLE ROUTING PROBLEM

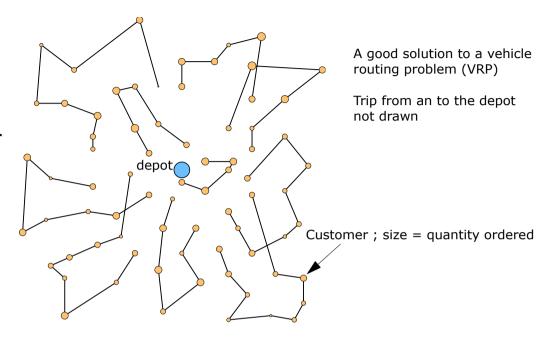
#### Given:

*n* customers and 1 depot

 $q_i$ : quantity ordered by customer i

Distances between each pair of customer and between depot and customer

Q: vehicle capacity



#### Find:

Set of tours such that:

Each tour starts from and comes back to the depot

Each customer appears exactly once in the set of tours

The sum of the quantities ordered by the customer on any tour  $\leq Q$ 

+ eventually other constraints on the tour length, time windows, multiple depots, etc.

#### **Objective:**

Minimize the total length performed by the vehicle

# LOCATION-ROUTING PROBLEM

#### Given:

*n* customers

*m* potential depots locations

 $q_i$ : quantity ordered by customer i

Travel costs between each pair of customers and between depots and customers

D: Depot opening cost

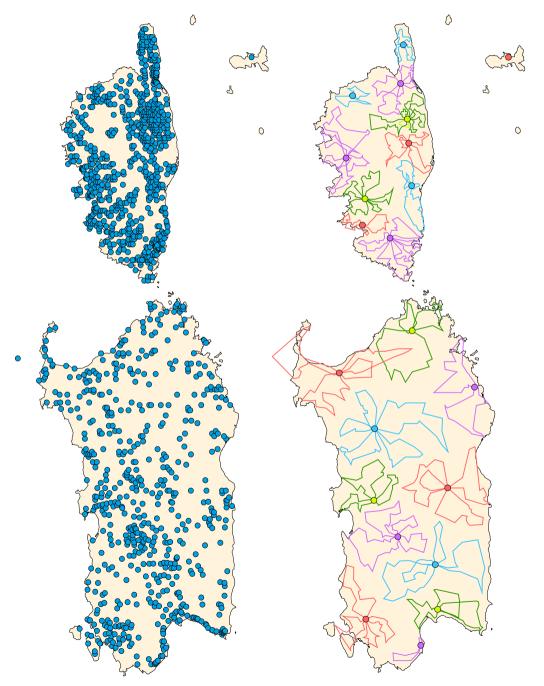
Q: vehicle capacity

#### Find:

Subset of depots to open
Set of tours verifying VRP constraints

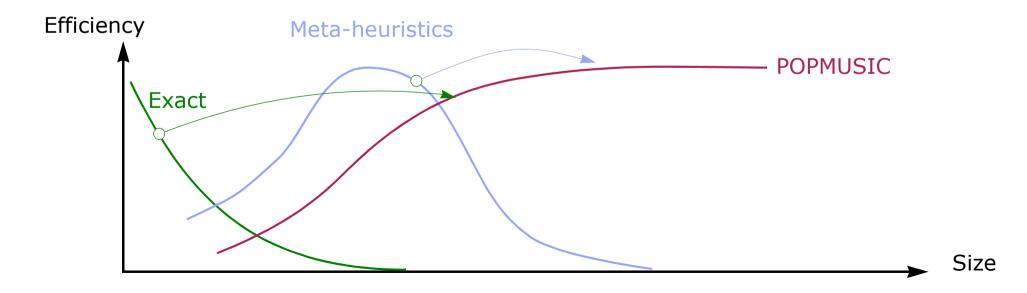
# **Objective:**

Minimize the total costs



# CLASSIFICATION OF PROBLEM SIZE

Class	Typical technique	Size (order)	
Toy	Complete enumeration	10 <sup>1</sup>	
Small	Exact method	$10^1 - 10^2$	
Medium	Meta-heuristics	$10^2 - 10^4$	Memory limit $O(n^2)$
Large	Decomposition techniques	$10^3 - 10^7$	Time limit $O(n^{3/2})$
Very Large	Distributed database	above	



# DOMAIN DECOMPOSITION

#### Part of problem modelling

Difficult to generalize

Frequently used for small problems with several embedded subproblems

#### **Example 1: Location-routing**

Find number and position of depots to open

Solve a multi-depot vehicle routing problem

# **Example 2: Location-routing**

Find a TSP tour on all customers ⇒ Concorde TSP solver

Split the TSP tour into sub-paths with sum of customer demands  $\leq Q \Rightarrow$  Dynamic programming

Group the customers of a sub-path into a single super-customer

Find number and position of depot ⇒ Uncapacitated warehouse location

# **Example 3: Map labelling**

Generate several label positions for each object

Build and solve the maximum weight stable set problem

# Building an initial solution: Greedy constructive method

#### Idea

Build a solution, element by element, by adding systematically the most appropriate element This works optimally for a number of problems (optimum spanning trees, matroids)

# A solution is composed of elements $e \in E$

TSP, Steiner tree: Edges

Nodes

Colouring: Vertex with a given colour

Edge orientation

QAP: Element at a given position

The method starts with a solution s empty or trivial

An incremental cost function c(e, s) that measures (empirically) the quality of adding element e on partial solution s must be defined

Adding an element generally implies restrictions for the next elements to add

# GREEDY CONSTRUCTIVE METHOD

```
= minimal partial solution
                                                                      // Generally : \emptyset
                                           // Set of elements that can be added to s
R = E
```

# Repeat

Evaluate c(s, e) for each  $e \in R$ Choose e' optimizing c(s, e)Set  $s = s \cup \{e'\}$ 

Remove from R all elements that cannot be added to s any more **Until** s is a complete solution

# **Example for the TSP: Nearest neighbour heuristic**

 $s = \{1\}$ 

R: set of cities not yet visited (+ city 1, if all cities already visited)

c(s, e) = length of the edge going from the last city of s to city e

# **Complexity analysis:**

Number of main loop **Repeat...Until**: n

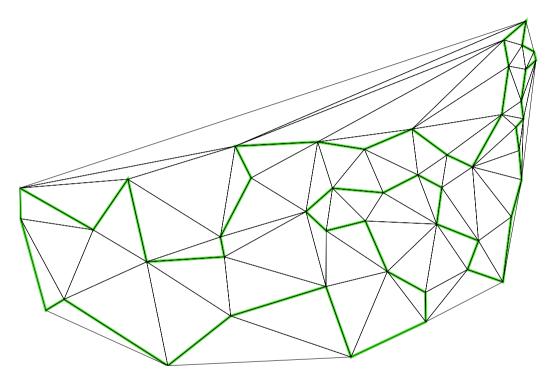
Number of evaluation of c(s, e) at  $k^{th}$  iteration : n - k

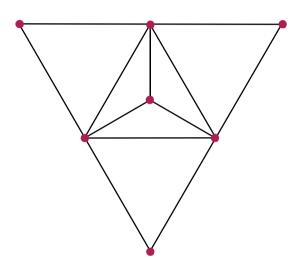
Total :  $O(n^2)$ 



# N LOG N GREEDY CONSTRUCTIVE METHOD FOR EUCLIDEAN TSP

Build a Delaunay triangulation  $\Rightarrow$   $O(n \log n)$  algorithm,  $\sim 6n$  remaining edges Build a TSP tour on the Delaunay





Non Hamiltonian Delaunay

#### ⇒ Best insertion

s = Tour on 2 cities (e.g. 1-2-1, closest cities, most distant cities)

R: Set of cities not yet visited

Next city *e* to insert: randomly chosen in *R* 

c(s, e) = Minimum insertion cost of city e between 2 cities of partial tour s

Choose the smallest  $c(s, e) \Rightarrow O(\log n)$  if done while building the Delaunay

# LOCAL SEARCH TEMPLATE

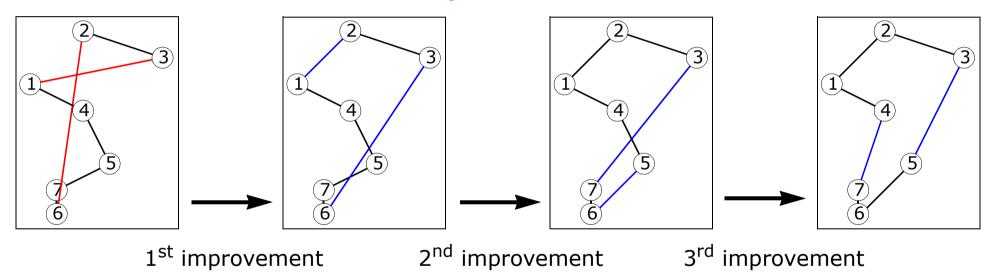
Start with a given solution (obtained e.g. with a constructive method)

Repeat

Try to find a modification that improves the solution If such a modification is found, perform it

While An improvement is found

#### **Example for the TSP**



# **Example of modification:**

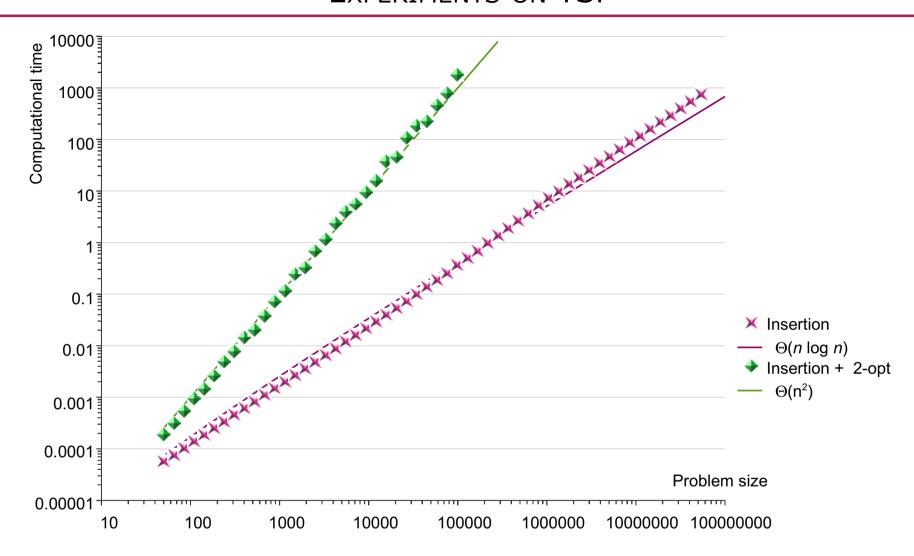
Replace 2 edges of the tour by 2 others (2-opt neighbourhood)

# **Neighbourhood size**





# EXPERIMENTS ON TSP



#### **Questions:**

How to generate a solution for non Euclidean problems in less than  $O(n^2)$ ? How improve a solution in less than  $O(n^2)$ ?

# BUILDING A SOLUTION TO LARGE INSTANCES VIA PROBLEM DECOMPOSITION

# PERTINENCE OF PROBLEM DECOMPOSITION

# **Hypothesis**

Large problem instances but moderate dimension

- $\Rightarrow$  2 elements close to a third one are also close
- $\Rightarrow$  2 elements far away cannot be both close to a third one

Distant elements are not directly connected together in reasonable solutions

Reasonable solutions are composed of sets with about *C* elements (independent of problem size)

Example: The number of letters a postman can deliver in a day does not depend on the total number of people living in the country

# TEMPLATE FOR PROBLEM DECOMPOSITION

# **Input**

n elements, function d(i, j) measuring the proximity between elements i and j

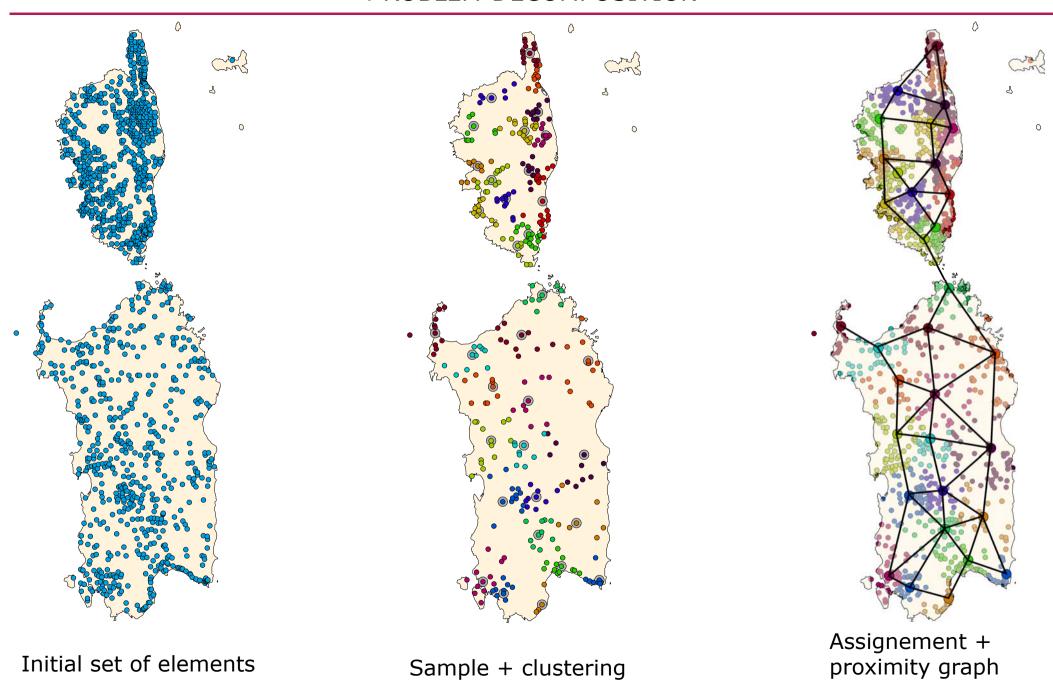
# **Body**

- 1 Create a random sample E of  $20\sqrt{n}$  elements
- 2 Solve a relaxation of a p-median with capacity with  $p=\sqrt{n}$  on E
- 3 Assign each of the n elements to its closest among the p centres  $\Rightarrow \sqrt{n}$  clusters with  $\sim \sqrt{n}$  elements each
- 4 Build a proximity graph G on the centres  $\Rightarrow c_i$  and  $c_j$  are neighbours if: there is an element assigned to  $c_i$  which second closest centre is  $c_j$

#### Output

 $\sim \sqrt{n}$  clusters, proximity graph G

# PROBLEM DECOMPOSITION



#### FAST HEURISTIC FOR P-MEDIAN WITH CAPACITY

#### Goal:

Decomposing a set  $E = \{1, ..., n\}$  into p clusters  $C_1, ..., C_p$  with  $\sim n/p$  elements each

#### **Notation**

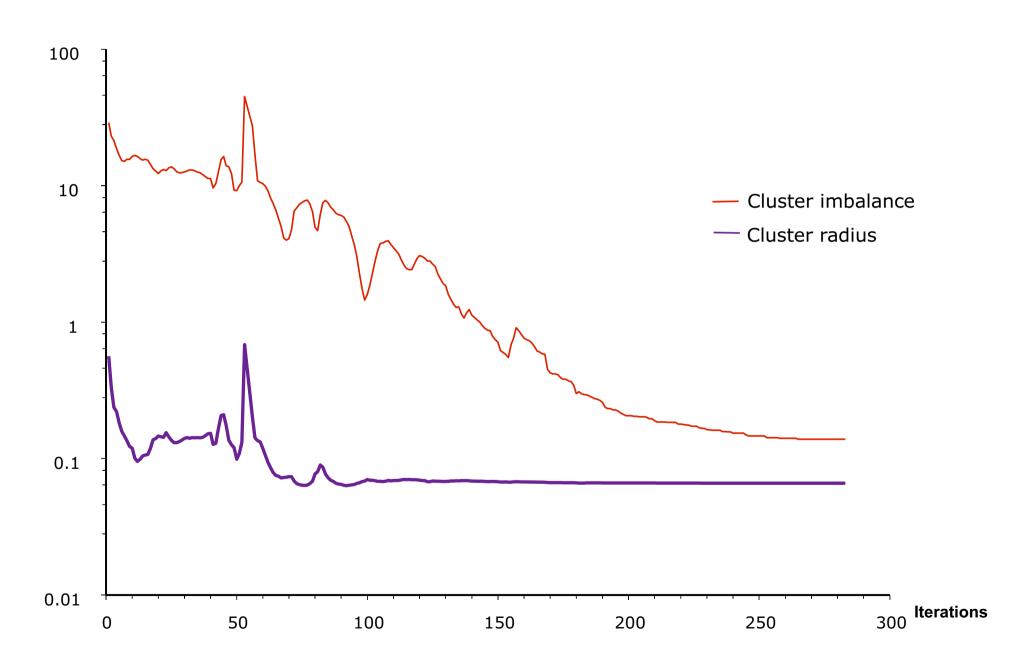
 $\lambda_i$ : penalty of centre j

```
1 Randomly choose p centres c_1, ..., c_p among the n entities 2 f=1.0; \lambda_j=0; j=1, ..., p; 3 for 234 iterations do 4 Allocate entities of E to the closest centre with penalty (Create clusters C_1, ..., C_p) 5 for j=1, ..., p do Find the best position of centre c_j among entities of C_j if Current solution improves best known then Memorize current solution as best known f \leftarrow 0.98 \cdot f 10 for j=1, ..., p do \lambda_j \leftarrow \lambda_j + f (average distance of elements to centre) \cdot (p \cdot |C_j|/n-1)
```

# **Complexity**

$$\Theta(n \cdot p + n^2/p) \Rightarrow \Theta(n^{3/2})$$
 if  $p$  in  $\Theta(\sqrt{n})$ 

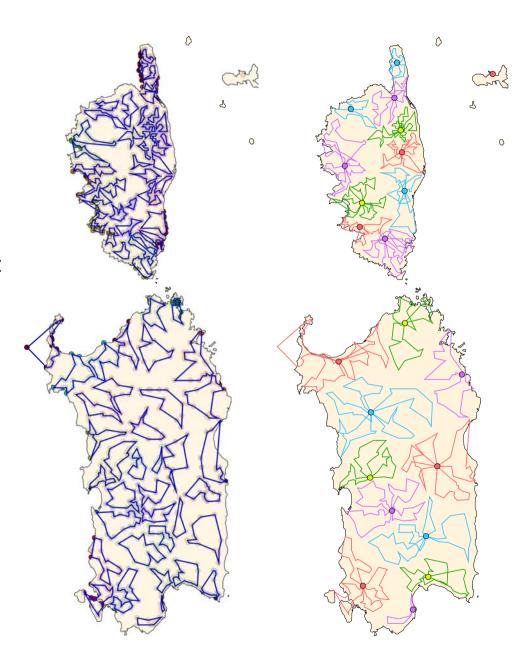
# EVOLUTION OF SUM OF DISTANCES AND SIZE VARIATION OF CLUSTERS



# APPLICATION TO LOCATION-ROUTING

Decomposition of clusters into smaller clusters that satisfy +/- vehicle capacity

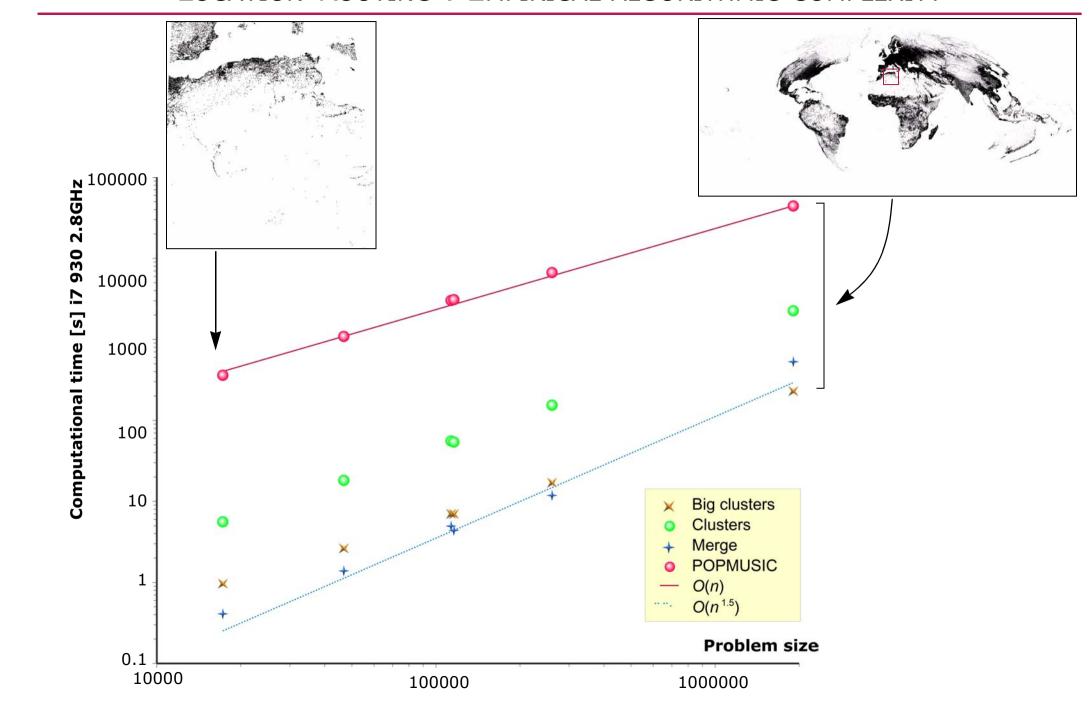
Building independent vehicle tours



Finding depot location

Connexion of TSP tours on depots

# LOCATION-ROUTING: EMPIRICAL ALGORITHMIC COMPLEXITY



# **E**XERCISE

You have an O(1) « distance » function d(i,j) for computing the distance between cities i and j You have an  $O(n^2)$  greedy procedure  $\mathbf{G}$  for building a TSP tour

You have an  $O(n^{3/2})$  procedure  $\mathbf{P}$  for decomposing a set of n entities into  $\sqrt{n}$  clusters of  $\sim \sqrt{n}$  entities

How to get a TSP solution in  $O(n^{3/2})$ 

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# SOLUTION IMPROVEMENT OF LARGE INSTANCES

Large neighbourhood search (LNS)

Popmusic: a generic decomposition technique

# **Applications**

Clustering

VRP, location-routing

Cartographic labelling

# LARGE NEIGHBOURHOOD SEARCH (LNS)

#### Idea

In an enumeration method for integer or mixed integer linear programming

Fix the value of a subset (a majority) of variables

Solve optimally the sub-problem on the remaining variables

Repeat with other subsets of fixed variables

#### **Evolution**

Destroy a portion (free variables) of the solution
Try to rebuild the solution by keeping fixed variables
Repeat with other portions

Iterated local search

Randomly perturb the best solution known

Apply an improving method with penalties

Repeat after having modified the penalties

# LNS FOR THE VRP (SHAW 1998)

#### **Generate an initial solution**

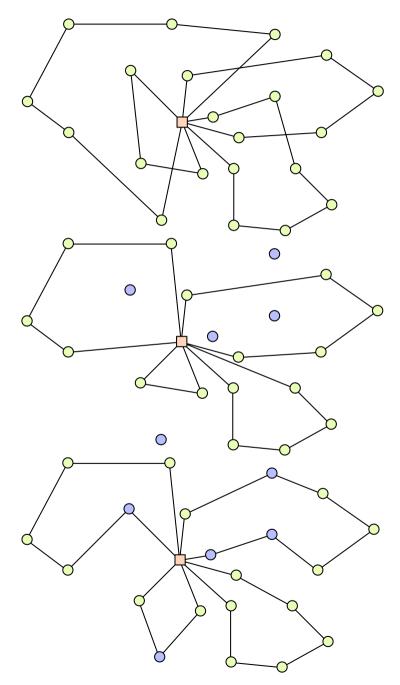
# **Destroy mechanism**

Select a random customer and few close customers "close" : Euclidean distance + random component

# **Repair method**

Optimal or heuristic re-insertion (with constraint programming)

- ⇒ Applied to small-medium problem instances only
- ⇒ No preoccupation on algorithmic complexity
- $\Rightarrow$  Destroy + repair = reoptimize a portion of the solution



# POPMUSIC GENERAL IDEA

Start from an initial solution

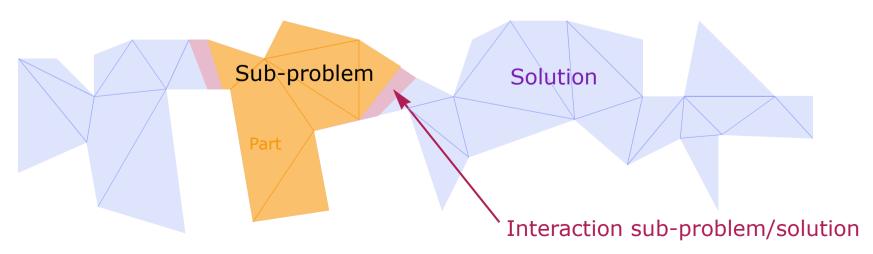
# **Decompose solution into parts**

**Optimize a portion (several parts) of the solution** 

Repeat, until the optimized portions cover the entire solution

# **Difficulty**

Sub-problems are not necessarily completely independent one another



# POPMUSIC FOR CLUSTERING

#### Part:

Elements belonging to a cluster

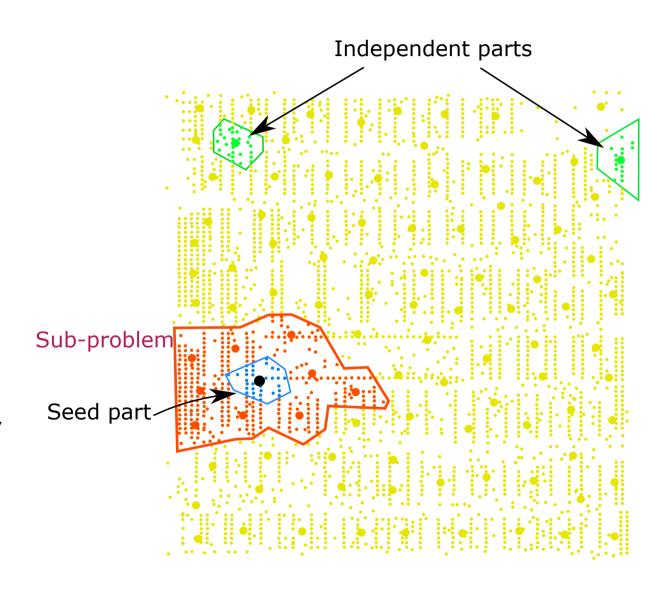
#### Distance:

Average dissimilarity between elements of different groups,

Distance between centres

# **Optimization process:**

Improving method based on candidate list, relocation of a centre, stabilizing solutions (CLS)



# POPMUSIC TEMPLATE

# **Input**

```
Solution S = s_1 \cup s_2 \cup ... \cup s_p
                                                                      // p disjoint parts
O = \emptyset
                                                    // Set of "optimized " seed parts
While 0 \neq S, repeat // Parts may still be used for creating sub-problems
   1. Choose a seed part s_i \notin O
                                                                         //r: parameter
   2. Create a sub-problem R composed of the r " closest " parts \in S from s_i
   3. Optimize sub-problem R
   4. If R improved then
          Set O \leftarrow O \setminus R
      Else
          Set 0 \leftarrow 0 \cup s_i
```

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# **POPMUSIC CHOICES**

# How to get an initial solution

cf. above

**Definition of a part** 

# **Distance** between two parts

# **Seed part choice**

Random, O managed as a stack, ...

Parameter r

Depends on optimization procedure capability

**Optimization procedure** 

Exact method, matheuristic, metaheuristic

Variants:

Slower:

set  $O \leftarrow \emptyset$  instead of set  $O \leftarrow O \setminus R$ 

Faster:

set  $O \leftarrow O \cup R$  instead of set  $O \leftarrow O \cup s_i$ 

# RELATED CONCEPTS

**Candidate list, strongly determined and consistent variables (Glover)** 

"Chunking" (Woodruff)

Large neighbourhoods (Shaw)

**VDNS (Hansen & Mladenovic)** 

**Decomposition methods** 

# POPMUSIC FOR VRP (TAILLARD 1993, ...)

#### Part:

Vehicle tour

# **Distance between parts:**

Polar distance between centres of gravity

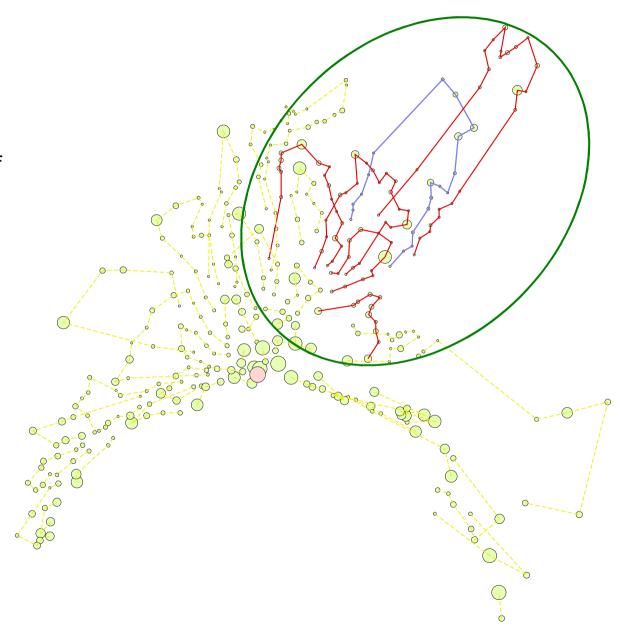
A sub-problem is a smaller VRP

# **Optimization process:**

Basic tabu search

# **Particularity:**

Many simultaneous optimization processes, treating all tours at each iterations



# POPMUSIC FOR LOCATION-ROUTING (ALVIM & TAILLARD 2012)

#### Part:

Vehicle tour

# **Distance between parts:**

Minimal distance between customers of different tours

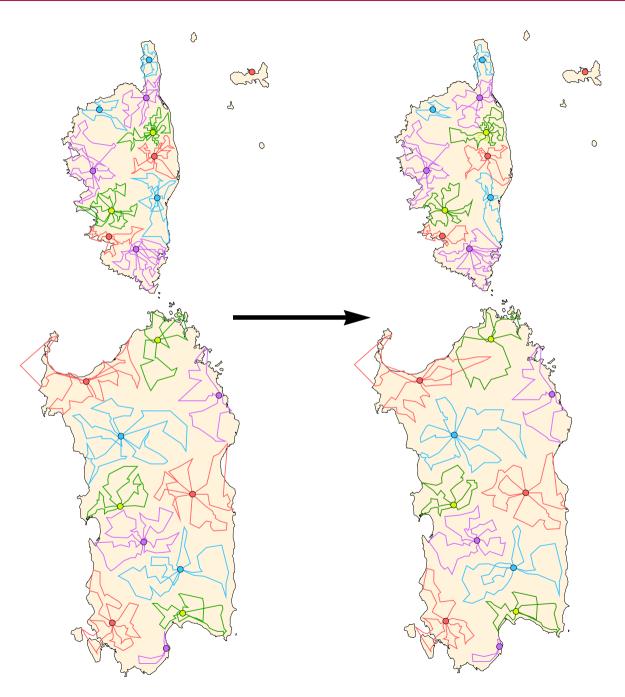
A sub-problem is a smaller MDVRP

# **Optimization process:**

Basic tabu search for MDVRP

# **Particularity:**

No depot relocation



# POPMUSIC CHOICES FOR MAP LABELLING

#### Part:

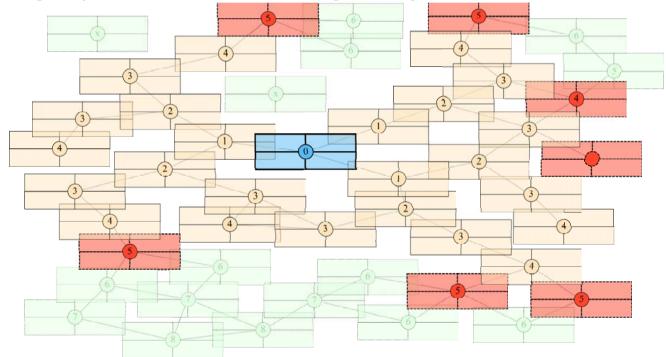
Object to label

# **Distance between parts:**

Minimum number of edges needed to connect parts

Vertex ≡ object

Edge 3 possible conflict in labelling the objects associated to vertices connected

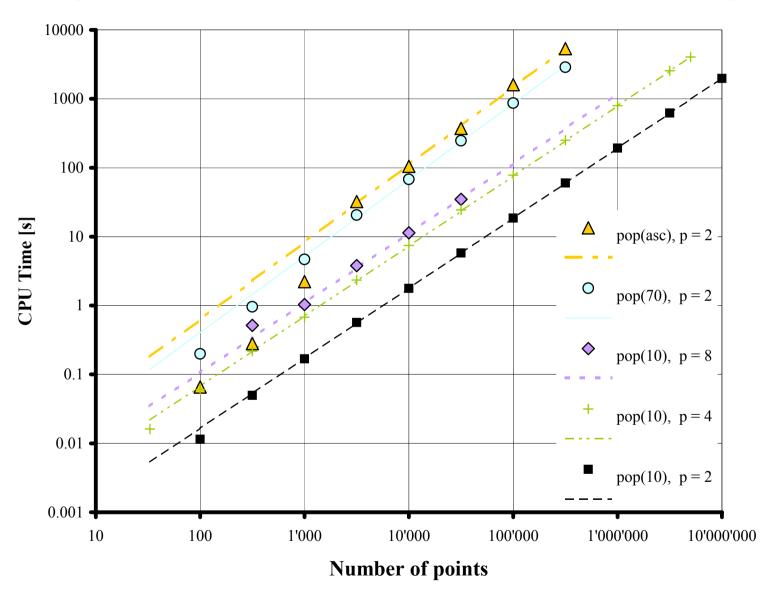


# **Optimization process:**

Tuned taboo search (Yamamoto, Camara, Nogueira Lorena, 2002), local search with ejection chains

# NUMERICAL RESULTS

Uniformly generated problem instances, between 30% and 90% of labels without overlap



The complexity grows typically quasi-linearly with problem size

# **CONCLUSIONS**

# **POPMUSIC** complexity

Can be implemented in  $O(n^{3/2})$ 

Main difficulty: generating an initial solution, finding the r closest parts

⇒ Solved with proximity graph

#### **POPMUSIC options and parameter**

Natural stopping criterion

Must have an optimization process for sub-problems

Heuristic

Exact ⇒ Matheuristic

A single parameter *r*, for defining sub-problem size

⇒ Easy to tune: sub-problem size must meet best efficiency of optimization process

#### **POPMUSIC drawback**

Definition of part and sub-problem dependent on problem under consideration

# **F**UTURE

# **Application to higher dimensional instances**

Up to now: Map labelling 2D, Location-routing  $2^{1/2}D$ , MDVRPTW 3D What happens for higher dimensions?

# **Application to other problems**

Testing different definitions for parts

# **Study of different options**

Definition of distance between parts

Management of non-optimized parts

# **Parallel implementations**