

## MSE Algorithms

# L04: Decomposition Methods, Learning Methods: Tabu Search

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# Course Overview

1. Introduction: Basic problems and algorithms
2. Constructive methods: Random building, Greedy
3. Local searches
4. Randomized methods
5. Threshold accepting, Simulated Annealing
- 6. Decomposition methods: Large neighborhood search**
- 7. Learning methods for solution improvement: Tabu search**
8. Learning methods for solution building: Artificial ant systems
9. Methods with a population of solutions: Genetic algorithms

# Lecture 4:

## Decomposition and Learning Methods

**Goal:**

**Know sufficiently many methods to start tackling Santa's Challenge.**

- Decomposition Methods
- Learning Methods: Tabu Search
- Inbetween: Quadratic Assignment Problem (QAP)
- Santa's Challenge



# Recap: Solving Optimization Problems with Meta Heuristics

# Recap: Summary

Meta-Heuristics for Optimization Problem:

1. Use a greedy **Constructive Method** to create an initial solution (e.g. Nearest Neighbour for TSP)
2. Use a **Local Improvement Method** to improve the solution (e.g. 2-opt for TSP)
3. Apply a **Selection Rule** to decide which improving move is taken (e.g. Best Improving Move)
4. Use **Randomized Methods** (e.g. Simulated Annealing) to explore larger search spaces than purely greedy methods



# Decomposition Methods

# Introduction to Decomposition Methods

## Sizes of Problem Instances:

Class	Typical technique	Size (order)
Toy	Complete enumeration	$10^1$
Small	Exact method	$10^1 - 10^2$
Medium	Meta-heuristics	$10^2 - 10^4$ (memory limit $O(n^2)$ )
Large	Decomposition techniques	$10^3 - 10^7$
Very Large	Distributed database	above

## Decomposition techniques/algorithms:

- Very Large Neighbourhood Search (VLNS)
- Popmusic: A generic decomposition technique

# Very Large Neighbourhood Search (VLNS)

## Basic Ideas:

- Start with a reasonable solution
- Neighbourhood size is too large to fully explore (e.g.  $n^k$ ,  $2^n$  or variable size)
- Partially explore the large neighbourhood to find improvements

## Examples:

- **Integer Linear Programming:** Fix the value of a subset (a majority) of variables, solve optimally the sub-problem on the remaining variables. Then repeat with other subsets of fixed variables.
- **Iterated Local Search:** Randomly perturb the best solution so far, and apply an improving method to the perturbed solution
- **Lin-Kernighan algorithm for TSP:** Exchange a variable number (of up to all  $n$ ) edges of a given solution (see next slide).

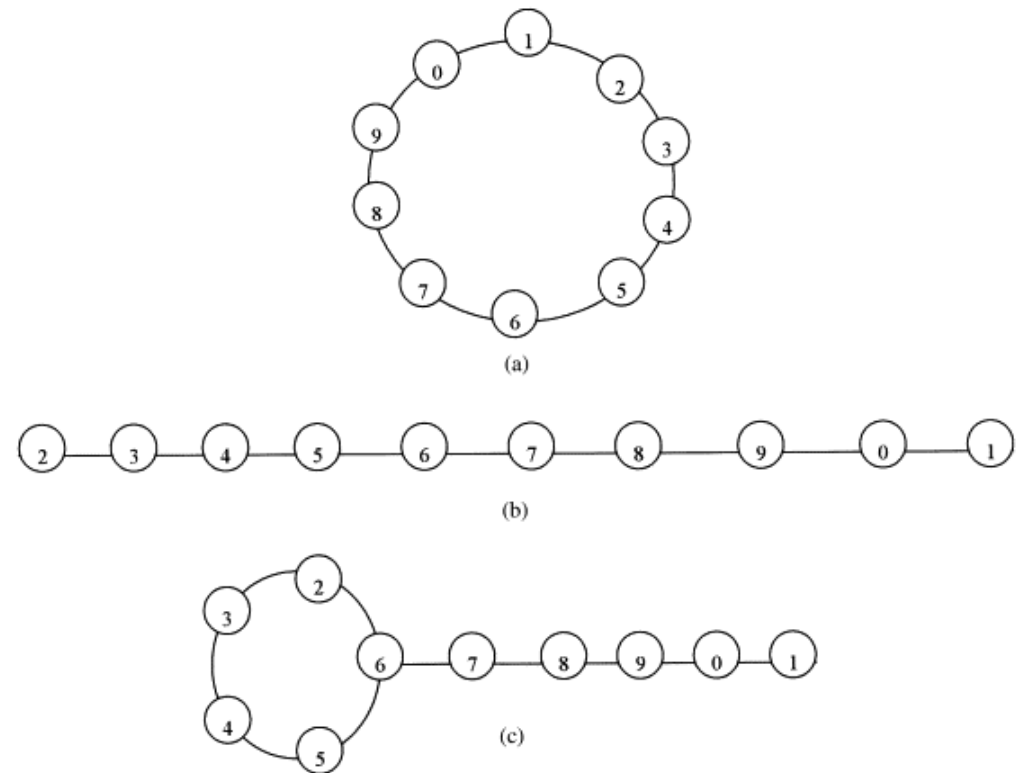
## Overview:

- Ravindra K. Ahuja et al, 2002: "A survey of very large-scale neighborhood search techniques", at [https://dx.doi.org/10.1016/S0166-218X\(01\)00338-9](https://dx.doi.org/10.1016/S0166-218X(01)00338-9)



# Lin–Kernighan algorithm for TSP

- **Basic idea:** Apply a series of pairs of moves to an existing tour as shown in example to the right:
  - (a) initial tour
  - (b) a Hamiltonian path
  - (c) a stem and cycle
- From (b) to (c) the edge (2, 6) is inserted
- From (c) to (b') the edge (5, 6) is removed (and so on)
- Node 1 (right end) stays fixed for the entire series of moves
- Edge insertion moves ((b) to (c)) are guided by a cumulative cost criterion
- Series of moves terminates if no further cost reduction is achievable



Source: [https://dx.doi.org/10.1016/S0166-218X\(01\)00338-9](https://dx.doi.org/10.1016/S0166-218X(01)00338-9)

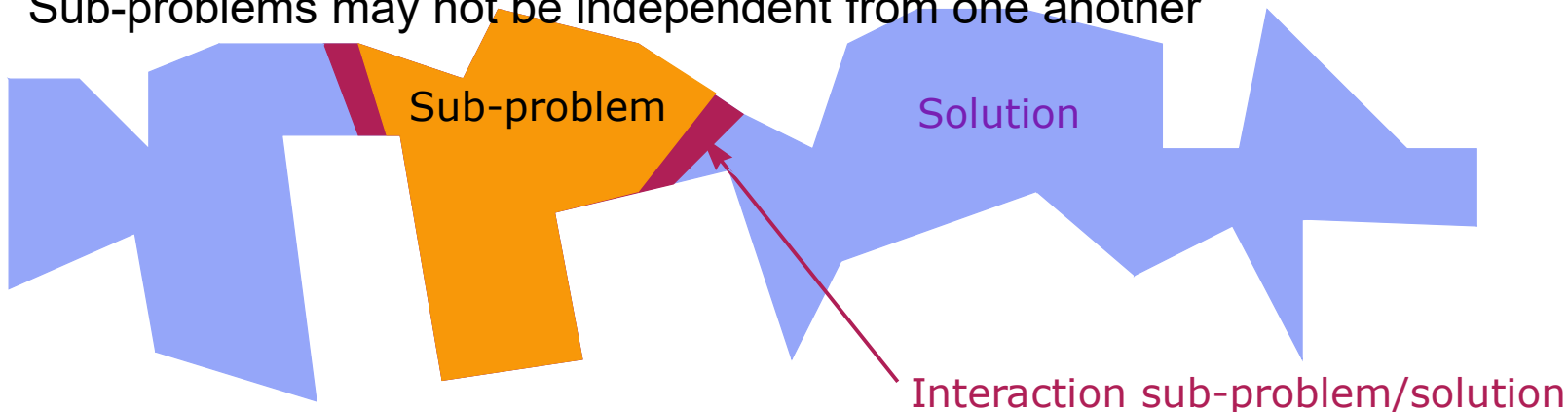
# Meta-Heuristic: Partial Optimization Metaheuristic Under Special Intensification Conditions (POPMUSIC)

## Idea

- Start from an initial solution
- Decompose solution into parts
- Optimize a sub-problem, i.e. several parts of the solution, which are close together (this presumes that there exist a proximity measure between parts and an optimization algorithm for smaller problems of the same kind)
- Repeat, until the optimized portions cover the entire solution

## Difficulty

- Sub-problems may not be independent from one another



# POPMUSIC Algorithm

Solution  $S = s_1 \cup s_2 \cup \dots \cup s_p$  //  $p$  "disjoint" parts  
 $O = \emptyset$  // Set of "already optimized" seed parts  
Parameter  $r$  // Number of "nearest" parts constituting a sub-problem

## **While** $O \neq S$ , **repeat**

1. Choose a seed part  $s_i \notin O$
2. Create a sub-problem  $R$  composed of the  $r$  parts in  $S$  "nearest" of  $s_i$
3. Optimize sub-problem  $R$
4. **If**  $R$  has been improved **then**
  - a) Update  $S$  by the parts of  $R$
  - b) Set  $O = O \setminus R$  // parts in  $R$  are not yet completely optimized
- Else**
  - a') Set  $O = O \cup s_i$  //  $s_i$  is already optimized

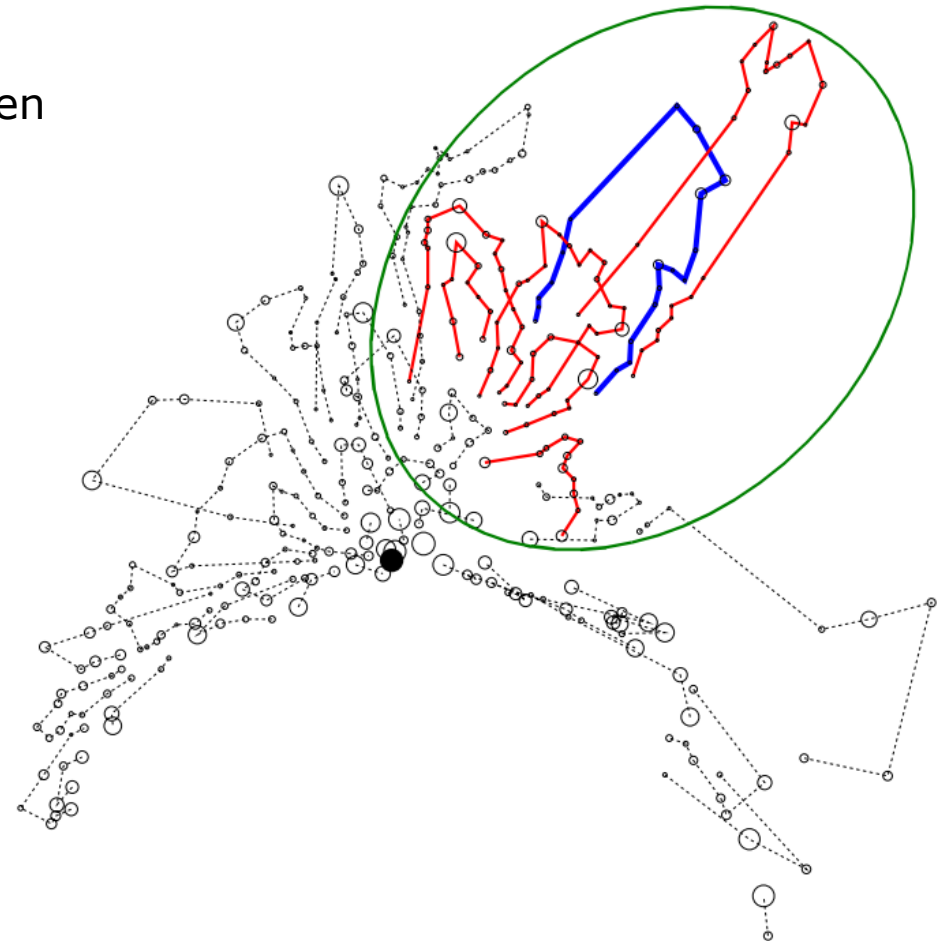
# Choices in POPMUSIC

- Definition of a "part"
- Proximity measure between two parts
- Parameter  $r$ , the number of "nearest" parts to optimize as a sub-problem  $R$
- Optimization procedure for sub-problems  $R$

## Variants:

- Line b): Slower: Set  $O = \emptyset$  instead of  $O = O \setminus R$   $\rightarrow$  *dump all already optimized parts*
- Line a'): Faster: Set  $O = O \cup R$  instead of  $O = O \cup s_i$   $\rightarrow$  *consider all parts in  $R$  as optimized*

- **Part:** Tour of one vehicle
- **Distance between parts:** Distance between centres of gravity
- **Sub-Problem:** A subset of the parts, i.e. a smaller CVRP
- **Optimization process:** E.g. Tabu Search



## **POPMUSIC for TSP:**

How can a "part" and a "sub-problem" be defined for the TSP?

# SOLUTION: POPMUSIC for TSP

## POPMUSIC for TSP:

- Part: A single city  $c$  of the tour
- Distance: The difference of the indices of the two cities in the tour
- Sub-Problem: The  $r$  adjacent cities in the tour, immediately before/after the seed city  $c$
- Solve TSP for the  $r$  cities (e.g. with Exhaustive Search), keeping the first and the last one fixed
- Re-Combination: Re-insert subtour in the existing tour



# Quadratic Assignment Problem

## QAP



# Quadratic Assignment Problem QAP

Given sets of  $n$  *facilities* (also called *activities*) and  $n$  *locations*, the *flows* between facilities and the *distances* between locations, the objective of the **Quadratic Assignment Problem** is to *assign each facility to a location* in such a way as to *minimize the total transportation cost*.

Applications:

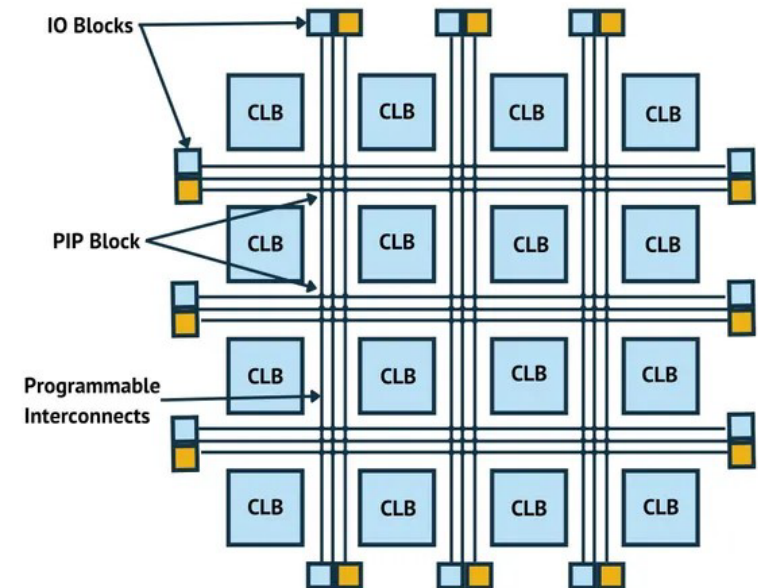
- Number of connections between electronic modules + Possible positions for the placement of the modules in a rack
- Number of connections between logic blocks + Possible positions for the placement of the blocks on a programmable chip (FPGA, see next slide)
- Number of passengers that must change flights + Assignment of flights to the gates at an airport
- Frequency of consecutive appearance of two letters in a language + Time between typing of two successive keys on a keyboard
- Meeting frequency of two employees + Time for walking from one desk to the other

Data Resources: <https://www.opt.math.tugraz.at/qaplib/>

# Quadratic Assignment Problem QAP

## FPGA as an application of QAP:

- The digital circuit to be realized with an FPGA is decomposed into parts (activities), which each fit into a configurable logic block (CLB) of the FPGA (locations).
- The flows between any two activities in this context are the number of interconnects between the corresponding parts used to synthesize the desired digital circuit.
- Since there are only limited interconnect resources on the FPGA, it is crucial to place activities with high interconnect requirements in locations close to each other.



# Formal Definition of QAP

Identifying a permutation matrix  $\mathbf{X}$  of dimension  $n \times n$  (whose elements  $X_{ij}$  are 1 if activity  $j$  is assigned to location  $i$  and 0 in the other cases) such that:

$$\min z = \sum_{i,j=1}^n \sum_{h,k=1}^n d_{ih} f_{jk} X_{ij} X_{hk}$$

Subject to

$$\begin{aligned} \sum_{i=1}^n X_{ij} &= 1 \quad \text{for } j = 1, 2, 3, \dots, n \\ \sum_{j=1}^n X_{ij} &= 1 \quad \text{for } i = 1, 2, 3, \dots, n \\ X_{ij} &\in (0, 1) \quad \text{for } i, j = 1, 2, 3, \dots, n \end{aligned} \tag{1}$$

Where  $d_{ih} \in D$  distance matrix and  $f_{jk} \in F$  flow matrix.

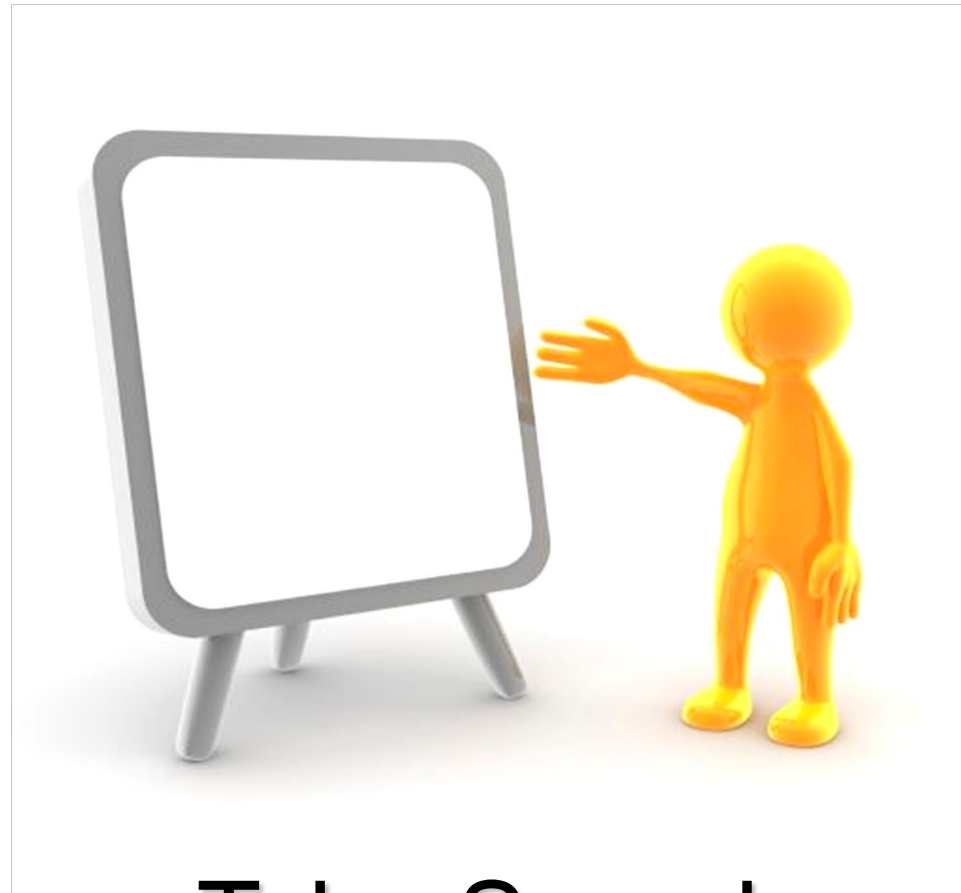
What is a potential neighborhood for the QAP?

What size does the neighborhood have?

# SOLUTION: Neighborhoods for QAP

## Neighborhoods for QAP:

- Swap locations of 2 facilities ("2-exchange neighborhood")  
Size:  $O(n^2)$
- Exchange locations of  $k = 3, 4, \dots$  facilities  
Size:  $O\left(\binom{n}{k} \cdot k!\right) = O(n^k)$  (for  $k \ll n$ )



# Tabu Search

# Basic Idea of Tabu Search

**Basic Algorithm:** E.g. Local Search with Best Improving Move strategy

**Memory:** Solutions visited and/or moves performed

**Use Memory to...**

- Forbid to come back to a solution already visited
- Forbid to perform the reverse of a move
- Penalize moves frequently used
- Force moves never used otherwise

**Wipe Memory:** Remove forbidden (tabu) status after a given number of iterations

**Improvements:** Even a forbidden move can be accepted if it improves best solution so far

**Resources:** Glover & Laguna, "*Tabu Search*" or <https://www.uv.es/rmarti/paper/docs/ts1.pdf>

"Do not revert a move too soon!"

# Meta-Heuristic: Tabu Search

## Data

Initial solution  $s$   
 Utility function to minimize  $f$   
 Set  $M$  of moves that can be applied to any feasible solution  
 Parameters  $t$ ,  $\text{max\_iter}$  : Tabu duration, number of iterations

## Initializations

$T = \emptyset$  // Set of forbidden moves (at most  $t$ )  
 $s^* := s$  // Best solution found

## For $\text{max\_iter}$ iterations repeat

$\text{Value\_best\_neighbour} = \infty$

### For all $m \in M$ , $m \notin T$ repeat

If  $\text{Value\_best\_neighbour} > f(s \oplus m)$  then  
 $\text{Value\_best\_neighbour} = f(s \oplus m)$   
 $\text{Best\_move} = m$

Find best move  $m$

$s = s \oplus \text{Best\_move}$

Replace the oldest move in  $T$  by  $\text{Best\_move}^{-1}$  (or add  $\text{Best\_move}^{-1}$ , if  $|T| < t$ )

If  $f(s^*) > f(s)$  then  
 $s^* = s$

## Return $s^*$



## **Tabu Search for the Knapsack Problem:**

Propose a setting/strategy for a Tabu Search for the Knapsack Problem

# SOLUTION: Tabu Search for Knapsack

## Example of a Tabu Search for Knapsack Problem

- Represent a solution as a bitvector of length  $n$
- Each bit indicates whether the corresponding item is taken or not
- Neighborhood: Flip one item from 0 to 1 or from 1 to 0
- Tabu: Don't flip the same item for the next  $k$  steps again

# Tuning Tabu Search

## If Tabu duration is too low:

- A limited set of solutions is cyclically visited
- Algorithm gets stuck in the neighbourhood of a local minimum

## If Tabu duration is too high:

- Too many solutions forbidden, especially those that can be interesting
- The search remains uphill instead of going down into valleys

## Solution Strategies

- Reactive search:
  - Learn dynamically a good tabu value
  - Increase tabu value if the same solution is visited twice
  - Decrease tabu value if never returned to the same solution for many iterations
- Random tabu duration:
  - After each move, choose tabu duration randomly, e.g.  $t = \lfloor |M| \cdot U(0, 1)^4 + 1 \rfloor$   
where  $U(0, 1)$  is uniformly distributed between 0 and 1,  $M$  is set of possible moves.
  - Effect: Few moves are tabu for a long time, forbidding cycles; most moves are forbidden for very few iterations

# Santa's Challenge

