

# Discrete Optimization

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# Heuristics and approximation algorithms

Sometimes, an exact approach is **very difficult** to finalize or **computationally too expensive**.

## Heuristics

A **heuristic** is an algorithm whose running time is reasonable and that is likely to give a **good feasible solution** most of the time for a given class of problems.

A **meta-heuristic** is a heuristic that is generic and only some parts of the heuristic must be defined in a **problem-specific** way.

## Approximation algorithms

An **approximation algorithm** is a problem-specific algorithm that runs in **polynomial time** and such that its outcome has a worst-case **guarantee** compared to the optimal solution.

## Simple greedy heuristics for the TSP

- **Nearest neighbor** : Pick a city, take the **closest remaining city** in the tour
- **Greedy** (Kruskal-like) : Sort the edge costs, pick all edges in **nondecreasing order** without creating a subtour or a degree 3 node
- **Nearest insertion** : Start from the cheapest edge, and insert in the tour the **closest node** to the tour.
- **Farthest insertion** : Same except that we insert the **farthest** node in the **cheapest** way.

## Local search

Consider the problem

$$\begin{array}{ll}\min & c(x) \\ \text{subject to} & x \in \mathcal{F}\end{array}$$

Idea :

Start from a given feasible solution  $x$ .

Define a neighborhood  $N(x)$  of  $x$ .

Pick  $y \in N(x)$ .

If  $c(y) < c(x)$ , then  $x := y$  is the new incumbent.

Repeat until some convergence criterion is reached.

## Local search

Fundamental question : define a **neighborhood**.

**Examples** : TSP : 2-opt, 3-opt, matching neighborhood  
 $k$ -opt for binary optimization.

**Issue** : One is often trapped in a local minimum.

## Very-large neighborhood search

In this framework, the idea is to define a **very large neighborhood** and to rely on generic solver or known well-solved problems to deal with it.

**Example** : If we want to solve an MIP

$$\begin{array}{ll}\min & c^x \\ \text{s.t.} & Ax \leq b \\ & x \in \{0, 1\}^n\end{array}$$

From a given solution  $x^*$ , we can define a large neighborhood by splitting the variable set into two and **fixing alternatively** each set of variables.

Each subproblem is then solved using a branch-and-bound algorithm.

This is also very popular to combine with **constraint programming**.

In all these methods, it is important to know the **structure** of the problem for the heuristic to make sense.

## Feasibility pump

This is an MIP-based method to find good **feasible solutions**.

We want to solve

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & Ax \leq b \\ & x \in \{0, 1\}^n \end{aligned}$$

1. Solve the LP relaxation. Let  $x^*$  be an optimal solution.
2. For  $T$  iterations, do the sequence (2. - 3.)  
Round  $x^*$  componentwise to the nearest integer :  $\tilde{x}_j = \lfloor x_j^* \rfloor$ .
3. Solve minimize  $\sum_{j=1}^n |x_j - \tilde{x}_j|$  subject to  $x \in LP$ .

# Simulated annealing

Metaheuristic based on local search that tries to escape from local minima.  
Inspired by physical analogy.

## Simulated annealing algorithm

- **Start** with  $x \in \mathcal{F}$  and an initial temperature  $T$
- **Repeat** until some convergence criterion is reached
- **Pick** randomly  $y \in N(X)$
- **If**  $c(y) < c(x)$ , **then**  $x := y$
- **If**  $c(y) > c(x)$ , **then accept**  $x := y$  with probability  $e^{(c(x)-c(y))/T}$
- **Decrease** the temperature  $T$



## Simulated annealing

Let  $A = \sum_{z \in \mathcal{F}} e^{-c(z)/T}$  and

$$\pi(x) = \frac{e^{-c(x)/T}}{A}.$$

### Theorem

Assume that the Markov chain  $x(t)$  is irreducible, then the unique steady distribution of the Markov chain is the vector with components  $\pi(x), x \in \mathcal{F}$ .

## 3/2-approximation algorithm for TSP

- Compute a **minimum spanning tree**  $T$ .
- Let  $S$  be the set of nodes with **odd degree** in  $T$ .  
Compute a min cost matching  $M$  of the nodes in  $S$
- All nodes in  $T \cup M$  have even degree, create a closed walk using all edges in  $T \cup M$ .  
Shortcut the closed walk to form a tour.

# Approximation algorithms

## Scheduling with precedence constraints

We have  $n$  jobs with processing times  $p_i$  and weights  $w_i$ .

We want to schedule the jobs on a **single machine** and respect the **precedence constraints** while minimizing

$$\sum_i w_i C_i$$

where  $C_i$  is the **completion time** of job  $i$ .

## Formulation

$$\min \sum_i w_i C_i$$

$$\text{s.t. } \sum_{i \in S} p_i C_i \geq \frac{1}{2} \sum_{i \in S} p_i^2 + \frac{1}{2} \left( \sum_{i \in S} p_i \right)^2 \quad S \subset V$$

$$C_j \geq C_i + p_j \quad \text{if } i \text{ precedes } j$$

# Rounding algorithm

## Deterministic rounding algorithm

- **Solve** the linear programming relaxation  
Obtain  $C^*$
- **Sort** the  $C_i^*$  in increasing order and create a feasible schedule by using the **same order**.  
(The precedence constraints will be automatically satisfied)

## Theorem

Let  $Z_H$  be the weighted completion time of the schedule produced by the algorithm, and  $Z_{LP}$  the value of the relaxation. Then

$$\frac{Z_H}{Z_{LP}} \leq 2.$$

*Proof* : Let us assume  $C_1^* \leq C_2^* \leq \dots \leq C_n^*$ .

The completion time of job  $j$  is  $\bar{C}_j = \sum_{k=1}^j p_k$ .

$$\begin{aligned} C_j^* \sum_{k=1}^j p_k &\geq \sum_{k=1}^j p_k C_k^* \text{ since } C_j^* \geq \dots \geq C_1^* \\ &\geq \frac{1}{2} \sum_{k=1}^j p_k^2 + \frac{1}{2} \left( \sum_{k=1}^j p_k \right)^2 \\ &\geq \frac{1}{2} \left( \sum_{k=1}^j p_k \right)^2 \end{aligned}$$

and thus

$$C_j^* \geq \frac{1}{2} \sum_{k=1}^j p_k = \frac{1}{2} \bar{C}_j.$$

# Approximation schemes

- A family of algorithms  $\mathcal{A}_\epsilon$  is a **polynomial time approximation scheme (PTAS)** if for every  $\epsilon > 0$ ,  $\mathcal{A}_\epsilon$  is an  $\epsilon$ -approximation algorithm and its running time is polynomial for fixed  $\epsilon$ .
- If  $\mathcal{A}_\epsilon$  is a PTAS and its running time is also polynomial in  $1/\epsilon$ , then it is a **fully polynomial time approximation scheme (FPTAS)**

# The bin packing problem

$n$  items with sizes  $s_1, \dots, s_n$ .

Find the minimum number of bins needed to **pack them**.

## The first fit algorithm

Let  $j$  be the **first bin** in which item  $i$  **fits**.

Place item  $i$  in bin  $j$ .

It is an asymptotic approximation scheme.

## Proposition

$$z_H \leq 2Z_{IP} + 1$$

## Proposition

If we can approximate the bin packing problem with approximation ratio  $\alpha < 3/2$ , then  $P = NP$ .