



Algorithmic Methods for Mathematical Models

COURSE PROJECT

Facultat d'Informàtica de Barcelona
Master in Innovation and Research in Informatics

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- Fall 24
- Barcelona, December 10, 2024



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Problem Statement : Inputs & Outputs

► Inputs

- D is the number of departments in the faculty.
- $n[1..D]$ is the array of size D , department p has exactly a number $n[p]$ of participants in the commission.
- N is the total number of faculty members.
- $d[1..N]$ the department of i will be denoted by $d[i]$.
- $m[1..N][1..N]$ is a $N \times N$ matrix where each element $m[i][j]$ is the compatibility between members i and j . The diagonal of the compatibility matrix consists of 1's.

► Outputs

- The solution (if one exists) with optimal objective value.
- The selection of faculty members, represented by the array $x[1..N]$,

$$x[i] = \begin{cases} 1 & \text{indicates that faculty member } i \text{ is selected for the commission,} \\ 0 & \text{indicates that faculty member } i \text{ is not selected.} \end{cases}$$

Integer Linear Programming Model

► Objective Function

$$\text{maximize} \left(\frac{1}{\text{numberOfPairs}} \sum_{i=1}^N \sum_{j=i+1}^N m[i][j] \cdot x[i] \cdot x[j] \right)$$

► Constraints

► Department Participation

$$\sum_{\substack{i=1 \\ d[i]=p}}^N x[i] = n[p], \quad \forall p \in \{1, \dots, D\}, \quad i \in \mathbb{Z}$$

► Zero Compatibility

$$x[i] + x[j] \leq 1, \quad \forall i, j \in \{1, \dots, N\} \text{ such that } m[i][j] = 0$$

► Conflict Mediation

$$x[i] + x[j] \leq 1 + \sum_{\substack{k=1 \\ m[i][k]>0.85, m[k][j]>0.85}}^N x[k], \quad i, j, k \in \{1, \dots, N\}$$

Heuristic algorithms

Greedy Constructive Algorithm

Algorithm 3 Greedy Construction Algorithm

Input: D, n, N, d, m

Output: partial_solution

```
1: partial_solution  $\leftarrow \emptyset$ 
2: dep_participantN[d]  $\leftarrow 0, \forall d \in \{1, \dots, D\}$ 
3: compatibilities  $\leftarrow \text{sort}(N, \sum m[i][j], \text{DESC})$ 
4: for member in compatibilities do
5:   department  $\leftarrow d[\text{member}]$ 
6:   if dep_participantN[department] < n[department - 1] then
7:     if  $\forall \text{other} \in \text{partial\_solution}, m[\text{member}][\text{other}] > 0$  and
        $\forall \text{other} \in \text{partial\_solution}, (m[\text{member}][\text{other}] \geq 0.15 \text{ or } \exists k \in \text{partial\_solution}, m[\text{member}][k] > 0.85 \wedge m[k][\text{other}] > 0.85)$  then
8:       partial_solution  $\leftarrow \text{partial\_solution} \cup \{\text{member}\}$ 
9:       dep_participantN[department]  $\leftarrow \text{dep\_participantN}[\text{department}] + 1$ 
10:  if  $|\text{partial\_solution}| = \sum n$  then
11:    break
12: if  $|\text{partial\_solution}| < \sum n$  then return INFEASIBLE
13: return partial_solution
```

Heuristic algorithms

Greedy Constructive and Local Search Procedure

Algorithm 4 Local Search Algorithm

Input: $D, n, N, d, m, \text{solution}$

Output: $\text{best_solution}, \text{best_objective}$

```
1:  $\text{best\_solution} \leftarrow \text{solution}$ 
2:  $\text{best\_objective} \leftarrow \text{calculate\_objective}(m, \text{best\_solution})$ 
3:  $\text{is\_improved} \leftarrow \text{True}$ 
4: while  $\text{is\_improved}$  do
5:    $\text{is\_improved} \leftarrow \text{False}$ 
6:   for each  $i$  in  $\text{best\_solution}$  do
7:      $\text{current\_member} \leftarrow \text{best\_solution}[i]$ 
8:      $\text{current\_department} \leftarrow d[\text{current\_member}]$ 
9:     for each  $j$  in  $\{0, \dots, N - 1\}$  do
10:      if  $j$  in  $\text{best\_solution}$  or  $d[j] \neq \text{current\_department}$  then
11:        continue
12:       $\text{new\_solution} \leftarrow \text{best\_solution}$ 
13:       $\text{new\_solution}[i] \leftarrow j$ 
14:      if  $\text{is\_feasible}(D, n, N, d, m, \text{new\_solution})$  then
15:         $\text{new\_objective} \leftarrow \text{calculate\_objective}(m, \text{new\_solution})$ 
16:        if  $\text{new\_objective} > \text{best\_objective}$  then
17:           $\text{best\_solution} \leftarrow \text{new\_solution}$ 
18:           $\text{best\_objective} \leftarrow \text{new\_objective}$ 
19:           $\text{is\_improved} \leftarrow \text{True}$ 
20:        break
21: return  $\text{best\_solution}, \text{best\_objective}$ 
```

Heuristic algorithms

GRASP

Algorithm 5 GRASP Main Function

Input: $D, n, N, d, m, \text{iterations}, \alpha$

Output: $\text{best_solution}, \text{best_objective}$

```
1:  $\text{best\_solution} \leftarrow \text{None}$ 
2:  $\text{best\_objective} \leftarrow -\infty$ 
3: for  $k = 1$  to  $\text{iterations}$  do
4:    $\text{initial\_solution} \leftarrow \text{GreedyConstructionGRASP}(D, n, N, d, m, 0 \text{ if } i = 1 \text{ else } \alpha)$ 
5:   if  $\text{initial\_solution} = \text{INFEASIBLE}$  then
6:     continue
7:    $(\text{local\_best\_sol}, \text{local\_best\_obj}) \leftarrow \text{LocalSearch}(D, n, N, d, m, \text{initial\_sol})$ 
8:   if  $\text{local\_best\_obj} > \text{best\_objective}$  then
9:      $\text{best\_sol} \leftarrow \text{local\_best\_sol}$ 
10:     $\text{best\_obj} \leftarrow \text{local\_best\_obj}$ 
11: return  $(\text{best\_solution}, \text{best\_objective})$ 
```

Algorithm 6 Greedy Construction with GRASP

Input: D, n, N, d, m, α

Output: partial_solution or **None**

```
1:  $\text{partial\_solution} \leftarrow \emptyset$ 
2:  $\text{dep\_participantN}[d] \leftarrow 0, \forall d \in \{1, \dots, D\}$ 
3:  $\text{compatibilities}[i] \leftarrow \sum m[i], \forall i \in \{1, \dots, N\}$ 
4:  $\text{candidates} \leftarrow \text{sort}(N, \text{compatibilities}[i], \text{DESC})$ 
5: while  $|\text{partial\_solution}| < n$  and  $\text{candidates} \neq \emptyset$  do
6:    $\text{max\_compatibility} \leftarrow \text{compatibilities}[\text{candidates}[0]]$ 
7:    $\text{min\_compatibility} \leftarrow \text{compatibilities}[\text{candidates}[-1]]$ 
8:    $\text{RCL} \leftarrow \{\text{member} \in \text{candidates} \mid \text{compatibilities}[\text{member}] \geq \text{max\_compatibility} - \alpha \cdot (\text{max\_compatibility} - \text{min\_compatibility})\}$ 
9:    $\text{selected\_member} \leftarrow \text{random.choice}(\text{RCL})$ 
10:   $\text{dept} \leftarrow d[\text{selected\_member}]$ 
11:  if  $\text{dep\_participantN}[\text{dept}] < n[\text{dept} - 1]$  then
12:    if  $\forall \text{others} \in \text{partial\_solution}, m[\text{member}][\text{others}] > 0$  and
       $\forall \text{others} \in \text{partial\_solution}, (m[\text{member}][\text{others}] \geq 0.15 \text{ or } \exists k \in \text{partial\_solution}, m[\text{member}][k] > 0.85 \wedge m[k][\text{others}] > 0.85)$  then
13:       $\text{partial\_solution} \leftarrow \text{partial\_solution} \cup \{\text{member}\}$ 
14:       $\text{dep\_participantN}[\text{dept}] \leftarrow \text{dep\_participantN}[\text{dept}] + 1$ 
15:     $\text{candidates} \leftarrow \text{candidates} - \{\text{selected\_member}\}$ 
16: if  $|\text{partial\_solution}| < \sum n$  then
17:   return INFEASIBLE
18: else
19:   return  $\text{partial\_solution}$ 
```

Tuning the alpha parameter

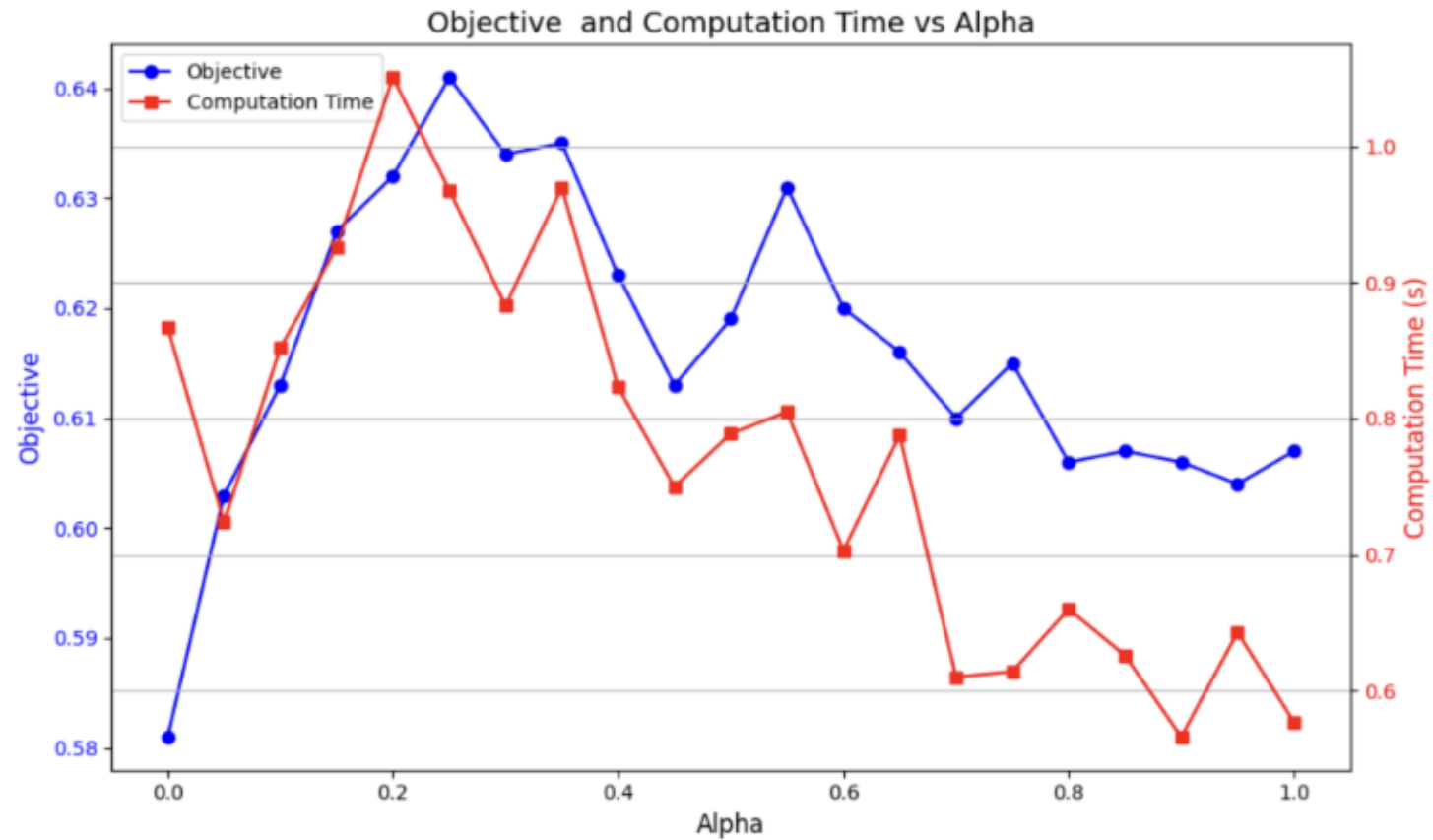


Figure 1: Objective and Computation Time vs Alpha

Performance

