

Taxonomization of combinatorial optimization problems

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Dream: Optimal Optimization

Given a problem, tell me the **best** algorithm for it!!!

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Given an **instance** of a problem, tell me the best algorithm for it

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Given an **instance** of a problem, tell me the best algorithm for it

Taxonomize problems and instances

Taxonomize algorithms

Outline of the presentation

- 1 Functions as permutations
- 2 The Fourier transform on the symmetric group: where combinatorial optimization problems meet

Taxonomization

- The most common taxonomy: P vs NP-complete
- More advanced: parameterized complexity

Challenges

- Problems have disparate definitions: distances, flows, etc..
- There are infinite number of functions

Infinite number of functions

The space of permutations

- Most heuristic algorithms do not use $f(x)$ but its ranking
- These algorithms behave the same in two functions f and g such that for all x and y if $f(x) > (<)f(y)$ then $g(x) > (<)g(y)$

Taxonomization

Any function can be seen as a permutation of the solutions

$f(\mathbf{x})$	\mathbf{x}
0	(1, 0, 1)
1	(1, 0, 0)
2	(0, 1, 1)
7	(1, 1, 0)
13	(0, 0, 1)
22	(1, 1, 1)
40	(0, 1, 0)
100	(0, 0, 0)

$g(\mathbf{x})$	\mathbf{x}
15	(1, 0, 1)
25	(1, 0, 0)
53	(0, 1, 1)
69	(1, 1, 0)
93	(0, 0, 1)
122	(1, 1, 1)
140	(0, 1, 0)
200	(0, 0, 0)

Taxonomization

Any function can be seen as a permutation of the solutions

$f(\mathbf{x})$	\mathbf{x}	ranking
0	(1, 0, 1)	1
1	(1, 0, 0)	2
2	(0, 1, 1)	3
7	(1, 1, 0)	4
13	(0, 0, 1)	5
22	(1, 1, 1)	6
40	(0, 1, 0)	7
100	(0, 0, 0)	8

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The space of permutations

- Any injective function $f : \Omega \rightarrow \mathcal{R}$ can be considered as a permutation of the numbers $\{1, 2, \dots, m\}$ with $|\Omega| = m$
- Expansion of a combinatorial optimization problem \mathcal{P} :

$$E_m(\mathcal{P}) \subset \Sigma_m$$

Interesting questions

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 $E_m(\mathcal{P}) \cap E_m(\mathcal{Q})$

Interesting questions

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 $E_m(\mathcal{P}) \cap E_m(\mathcal{Q})$
- Some rankings could be efficiently solved for some algorithms. Therefore knowing the rankings that can be produced by a problem could give us an idea of the goodness of an algorithm for that particular problem

Even more interesting questions?

- Is there a problem (with a closed form expression for the objective function) able to generate all the possible permutations depending on a **polynomial** number of parameters?

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- Is there a problem (with a closed form expression for the objective function) able to generate all the possible permutations depending on a **polynomial** number of parameters?
- Given two problems \mathcal{P} and \mathcal{Q} , assume that \mathcal{P} is defined using a number of parameters r and \mathcal{Q} with r' such that $r > r'$. Let's also assume that $|E_m(\mathcal{P})| < |E_m(\mathcal{Q})|$. Is it possible to reparameterized \mathcal{P} with a lower number of parameters?

Example: Linear ordering problem

Definition

Given a matrix $B = [b_{ij}]_{n \times n}$ of numbers, find a **simultaneous** permutation σ of the rows and columns of B , such that the sum of the elements above the main diagonal is maximized:

$$\sigma^* = \arg \max_{\sigma} f(\sigma) = \sum_{i=1}^{n-1} \sum_{j=i+1}^n b_{\sigma_i \sigma_j}$$

Equivalently, the sum of the elements below the main diagonal is minimized

Example: Linear ordering problem

	1	2	3	4	5
1	0	16	11	15	7
2	21	0	14	15	9
3	26	23	0	26	12
4	22	22	11	0	13
5	30	28	25	24	0

$$\sigma = (1, 2, 3, 4, 5)$$

$$f(\sigma) = 138$$

	2	3	1	4	5
2	0	14	21	15	9
3	23	0	26	26	12
1	16	11	0	15	7
4	22	11	22	0	13
5	28	25	30	24	0

$$\sigma' = (2, 3, 1, 4, 5)$$

$$f(\sigma') = 158$$

	5	3	4	2	1
5	0	25	24	28	30
3	12	0	26	23	26
4	13	11	0	22	22
2	9	14	15	0	21
1	7	11	15	16	0

$$\sigma^* = (5, 3, 4, 2, 1)$$

$$f(\sigma^*) = 247$$

Example: Linear ordering problem

	5	3	4	2	1
5	0	25	24	28	30
3	12	0	26	23	26
4	13	11	0	22	22
2	9	14	15	0	21
1	7	11	15	16	0

$$\sigma^* = (5, 3, 4, 2, 1)$$

$$f(\sigma^*) = 247$$

- If $\sigma^* = (5, 3, 4, 2, 1)$ is the optimum then $\text{Reverse}(\sigma^*) = (1, 2, 4, 3, 5)$ is the worst
- If σ is the k -th best, then $\text{Reverse}(\sigma)$ is the k -th worst

Example: Linear ordering problem

	5	3	4	2	1
5	0	25	24	28	30
3	12	0	26	23	26
4	13	11	0	22	22
2	9	14	15	0	21
1	7	11	15	16	0

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(1 2 3)

(2 1 3)

(2 3 1)

(1 3 2)

(3 1 2)

(3 2 1)

Example: Linear ordering problem

Conclusions

- The linear ordering problem can only create functions that are symmetric with respect to the operation *Reverse*
- It is possible to bound the number of possible functions (permutations) it can generate:

$$|E_n!(LOP)| \leq 2^{n/2} \frac{n!}{2}$$

- When n increases:

$$\lim_{n \rightarrow \infty} \frac{|E_n!(LOP)|}{|\Sigma_n!|} \leq \lim_{n \rightarrow \infty} \frac{2^{n/2} \frac{n!}{2}}{(n!)!} = 0$$

Example: Asymmetric TSP

Non-reverse cyclic ranking

- The ATSP generates a partial ranking of solutions
- Each solution has at least $n - 1$ solutions with the same objective function value
- Example ($n=4$):

(1 2 3 4)	(4 1 2 3)	(3 4 1 2)	(2 3 4 1)
(4 1 3 2)	(2 4 1 3)	(3 2 4 1)	(1 3 2 4)
...

LOP \cap ASTP

$$\begin{array}{ccc}
 & \text{LOP} & \\
 & & \text{ATSP} \\
 A = & \begin{pmatrix} 0 & 4 & 1,5 & 0,5 \\ 1 & 0 & 9,5 & 0 \\ 2 & 4 & 0 & 8,5 \\ 3 & 2,5 & 3,5 & 0 \end{pmatrix} & D = \begin{pmatrix} 0 & 1,7 & 7,1 & 8,5 \\ 8 & 0 & 1,6 & 7 \\ 6 & 9 & 0 & 1,5 \\ 1 & 2 & 8 & 0 \end{pmatrix}
 \end{array}$$

$$|E_n!(LOP) \cap E_n!(ATSP)| \leq 2^{(n-1)!/2} \cdot \left(\frac{(n-1)!}{2}\right)!$$

L. Hernando, A. Mediburu and J.A. Lozano. *Characterising the Rankings Produced by Combinatorial Optimisation Problems and Finding their Intersections*. GECCO 2019.

Example: quadratic assignment problem

Quadratic Assignment Problem

Given two matrices of distances and flows $D = [d_{ij}]$ and $F = [f_{kl}]$ respectively calculate the permutation that maximises:

$$f(\sigma) = \sum_{i=1}^n \sum_{j=1}^n f_{ij} d_{\sigma(i)\sigma(j)}$$

Problems

- We could not find any regularity in the functions ranking
- For $n = 3$ all the permutations are obtained
- For $n = 4$, the space of functions $(4!)!$ is too big

Solution: Fourier Transform of the Symmetric Group???

Outline of the presentation

- 1 Functions as permutations
- 2 The Fourier transform on the symmetric group: where combinatorial optimization problems meet

Representation of a group

They are the equivalent to the sin/cos in the real line

A representation of a group Σ_n is a map $\rho : \Sigma_n \rightarrow R^{d_\rho \times d_\rho}$ such that $\forall \sigma_1, \sigma_2 \in \Sigma_n, \rho(\sigma_1 \sigma_2) = \rho(\sigma_1) \cdot \rho(\sigma_2)$

$$\rho(\sigma) = \begin{bmatrix} \rho_{11}(\sigma) & \rho_{12}(\sigma) & \cdots & \rho_{1d_\rho}(\sigma) \\ \rho_{21}(\sigma) & \rho_{22}(\sigma) & \cdots & \rho_{2d_\rho}(\sigma) \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{d_\rho 1}(\sigma) & \rho_{d_\rho 2}(\sigma) & \cdots & \rho_{d_\rho d_\rho}(\sigma) \end{bmatrix}$$

Examples of representations

Trivial representation

$$\rho_{(n)} : \Sigma_n \longrightarrow R^{1 \times 1} \quad \text{such that} \quad \rho_{(n)}(\sigma) = 1$$

First-order permutation representation

map σ to its permutation matrix: $[\tau_{(n-1,1)}(\sigma)]_{ij} = 1 \{\sigma(j) = i\}$

$$\tau_{(2,1)}(\varepsilon) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \tau_{(2,1)}(1,2) = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \tau_{(2,1)}(2,3) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

New representations

Equivalence

Given an invertible matrix C we can define a new representation departing from ρ_1 :

$$\rho_2(\sigma) = C^{-1} \cdot \rho_1(\sigma) \cdot C$$

Direct Sum

$$\rho_1 \oplus \rho_2(\sigma) \triangleq \left[\begin{array}{c|c} \rho_1(\sigma) & 0 \\ \hline 0 & \rho_2(\sigma) \end{array} \right]$$

Irreducible Representations

The Fourier Transform

Given a function $f : \Sigma_n \rightarrow \mathbb{R}$ and ρ a representation. The Fourier transform of f at ρ is:

$$\hat{f}_\rho = \sum_{\sigma} f(\sigma) \rho(\sigma)$$

The collection of Fourier Transforms at all irreducible representations of Σ_n form the Fourier Transform of f

Fourier Inversion Theorem

$$f(\sigma) = \frac{1}{|G|} \sum_{\lambda} d_{\rho_\lambda} \text{Tr} \left[\hat{f}_{\rho_\lambda}^T \cdot \rho_\lambda(\sigma) \right]$$

where λ indexes over the collection of irreducibles of Σ_n

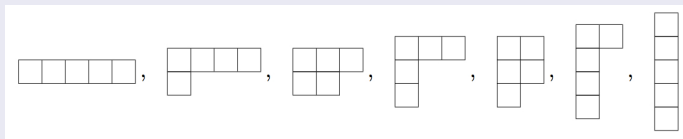
Irreducible representations

Partitions of n

Tuples of numbers that sum to n :

(5) , $(4,1)$, $(3,2)$, $(3,1,1)$, $(2,2,1)$, $(2,1,1,1)$, $(1,1,1,1,1)$

Ferrers diagrams:



Irreducible representations are indexed by the partitions of n .

Fourier transform of LOP

Theorem

If $f : \Sigma_n \rightarrow \mathbb{R}$ is the objective function of a Linear Ordering Problem and $\lambda \vdash n$ is a partition, then the Fourier coefficients of f have the following properties:

- 1 $\hat{f}_\lambda = 0$ if $\lambda \neq (n), (n-1, 1), (n-2, 1, 1)$
- 2 \hat{f}_λ has at most rank one for $\lambda = (n-1, 1), (n-2, 1, 1)$.
Having rank one is equivalent to the fact that the matrix columns are proportional. For the mentioned partitions and a fixed dimension n , the proportions among the columns of \hat{f}_λ are the same for all the instances.

Conjecture

The opposite is also true

Fourier transform of the asymmetric TSP

Theorem

If $f : \Sigma_n \rightarrow \mathbb{R}$ is the objective function of a Traveling Salesman Problem and $\lambda \vdash n$ is a partition, then the Fourier coefficients of f have the following properties:

- 1 $\hat{f}_\lambda = 0$ if $\lambda \neq (n), (n-2, 2), (n-2, 1, 1)$
- 2 \hat{f}_λ has at most rank one for $\lambda = (n-2, 2), (n-2, 1, 1)$. In addition, for the mentioned partitions and a fixed dimension n , the proportions among the columns of \hat{f}_λ are the same for all the instances.

Conjecture

The opposite is also true

Consequences

Reparameterization

- LOP: $n(n-1) \rightarrow 1 + (n-1) + \frac{(n-1)(n-2)}{2}$
- ATSP: $n(n-1) \rightarrow 1 + \frac{n(n-3)}{2} + \frac{(n-1)(n-2)}{2}$

Final remarks

- Many open questions, low number of answers
 - Which rankings/functions can be generated with some non-zero Fourier coefficients?
 - QAP: for $n = 4$ not all rankings can be generated
- We have settle up the first step in the process of taxonomization of combinatorial optimization problems

Collaboration

- Anne Elorza (UPV/EHU), Leticia Hernando (UPV/EHU)
- Josu Ceberio (UPV/EHU), Alex Mediburu (UPV/EHU)
- Roberto Santana (UPV/EHU)

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