Taxonomization of Combinatorial Optimization Problems in Fourier Space

#### Anne Elorza

Advisors: Leticia Hernando and Jose A. Lozano

COPs in Fourier space

Conclusion

## Research area

#### Research area

#### Optimization

 Permutation-based combinatorial optimization problems (COPs)

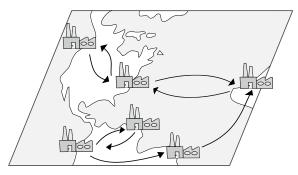
#### Permutation-based COPs

- Quadratic assignment problem (QAP)
- Linear ordernig problem (LOP)
- Traveling salesman problem (TSP)

# Quadratic Assignment Problem

#### Interpretation

A set of n facilities have to be assigned to n locations with the goal of minimizing the cost, which is a function of the flows and distances.



Source: https://www.localsolver.com/docs/last/exampletour/qap.html

# Quadratic Assignment Problem

#### Interpretation

A set of n facilities have to be assigned to n locations with the goal of minimizing the cost, which is a function of the flows and distances.

#### Mathematical definition

Given a distance matrix  $A = [a_{ij}]$  and a flow matrix  $A' = [a'_{ij}]$ , minimize the following objective function:

$$f(\sigma) = \sum_{i=1}^{n} \sum_{j=1}^{n} a_{\sigma(i)\sigma(j)} a'_{ij}.$$

# Linear Ordering Problem

#### Interpretation

Given a matrix A, maximize the sum of the elements above the main diagonal when the rows and columns of A are jointly reordered.

#### Mathematical definition

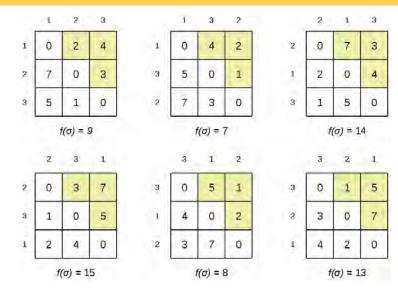
Given a matrix  $A = [a_{ij}]$ , maximize the following objective function:

$$f(\sigma) = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{\sigma(i)\sigma(j)}.$$

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# Linear Ordering Problem: example



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## Linear Ordering Problem

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Given a matrix  $A = [a_{ij}]$ , maximize the following objective function:

$$f(\sigma) = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{\sigma(i)\sigma(j)}.$$

Particular case of the QAP

The LOP is a particular case of the QAP if

$$a'_{ij} = \left\{ egin{array}{cc} 1 & ext{if } i < j \ 0 & ext{otherwise} \end{array} 
ight.$$

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# Traveling Salesman Problem

#### Interpretation

Given *n* cities and the distances between them, find the shortest tour that passes exactly once through all of the cities.



Source: https://blog.essaycorp.com/travelling-salesman-problem/

# Traveling Salesman Problem

#### Interpretation

Given n cities and the distances between them, find the shortest tour that passes exactly once through all of the cities.

#### Mathematical definition

Given a distance matrix  $A = [a_{ij}]$ , minimize the following objective function:

$$f(\sigma) = a_{\sigma(n)\sigma(1)} + \sum_{i=1}^{n-1} a_{\sigma(i)\sigma(i+1)}.$$

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## Traveling Salesman Problem

#### Mathematical definition

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#### Particular case of the QAP

The TSP is a particular case of the QAP if

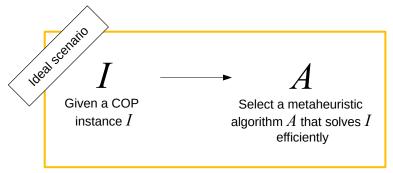
$$a_{ij}' = egin{cases} 1 & ext{if } j = i+1 & ext{or} & (i=n ext{ and } j=1) \ 0 & ext{otherwise} \end{cases}$$

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## Ideal scenario

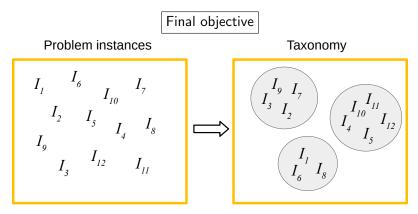
The behaviour of metaheuristic algorithms varies from problem to problem and even from instance to instance



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

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# Taxonomy



Instances that can be solved efficiently by the same algorithms are grouped together

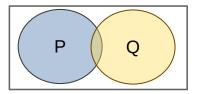
# Initial questions and motivation

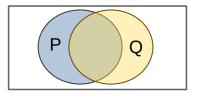
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- Example:

intersection between problems (in terms of objective functions).





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- Is there a framework that puts instances of different problems in the same terms?

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### SOLUTION: USE THE FOURIER TRANSFORM

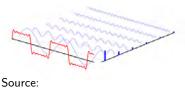
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## **Classic Fourier transform**

#### Fourier coefficients

$$\begin{cases} a_0 = \frac{1}{L} \int_{-L}^{L} f(x) dx \\ a_n = \frac{1}{L} \int_{-L}^{L} f(x) \cos\left(\frac{n\pi x}{L}\right) dx \\ b_n = \frac{1}{L} \int_{-L}^{L} f(x) \sin\left(\frac{n\pi x}{L}\right) dx \end{cases}$$



https://pgfplots.net/fouriertransform/

#### Decomposition of f

$$f(x) = \frac{1}{2}a_0 + \sum_{n=1}^{\infty} a_n \cos\left(\frac{n\pi x}{L}\right) + \sum_{n=1}^{\infty} b_n \sin\left(\frac{n\pi x}{L}\right)$$

#### Base functions

Irreducible representations of the symmetric group.

- Matrix-valued functions.
- The number of irreducible representations of  $\Sigma_n$  is the number of partitions of n.

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#### Partition of n

A partition of a number n is a tuple that sums to n.

Example (n = 5)

Partitions of 5:

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

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Irreducible representations of  $\Sigma_5$ :

 $\rho(\mathbf{5}), \rho(\mathbf{4},\mathbf{1}), \rho(\mathbf{3},\mathbf{2}), \rho(\mathbf{3},\mathbf{1},\mathbf{1}), \rho(\mathbf{2},\mathbf{2},\mathbf{1}), \rho(\mathbf{2},\mathbf{1},\mathbf{1},\mathbf{1}), \rho(\mathbf{1},\mathbf{1},\mathbf{1},\mathbf{1},\mathbf{1}).$ 

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Irreducible representations of the symmetric group.

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Example:  $\rho_{(n)}$  $\rho_{(n)}: \Sigma_n \longrightarrow \mathbb{R}^{1 \times 1}$  is the constant function  $\rho_{(n)}(\sigma) = (1)$ .

#### **Base functions**

Irreducible representations of the symmetric group.

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## Example: $\rho_{(2,1)}$

$$\begin{aligned} \rho_{(2,1)}(1,2,3) &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & \rho_{(2,1)}(1,3,2) = \begin{bmatrix} 1/2 & \sqrt{3}/2 \\ \sqrt{3}/2 & -1/2 \end{bmatrix} \\ \rho_{(2,1)}(2,1,3) &= \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} & \rho_{(2,1)}(2,3,1) = \begin{bmatrix} -1/2 & -\sqrt{3}/2 \\ \sqrt{3}/2 & -1/2 \end{bmatrix} \\ \rho_{(2,1)}(3,1,2) &= \begin{bmatrix} -1/2 & \sqrt{3}/2 \\ -\sqrt{3}/2 & -1/2 \end{bmatrix} & \rho_{(2,1)}(3,2,1) = \begin{bmatrix} 1/2 & -\sqrt{3}/2 \\ -\sqrt{3}/2 & -1/2 \end{bmatrix} \end{aligned}$$

#### Fourier coefficients

Given a function  $f : \Sigma_n \longrightarrow \mathbb{R}$ , the Fourier coefficient associated with partition  $\lambda$  is:

$$\hat{f}_{\lambda} = \sum_{\sigma} f(\sigma) \cdot \rho_{\lambda}(\sigma).$$

The collection of all Fourier coefficients is the Fourier transform of f.

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The collection of all Fourier coefficients is the Fourier transform of f.

Fourier inversion theorem

$$f(\sigma) = \frac{1}{|\Sigma_n|} \sum_{\lambda} d_{\rho_{\lambda}} \operatorname{Tr}[\hat{f}_{\lambda} \cdot \rho_{\lambda}(\sigma)]$$

# Fourier transform over the symmetric group Interpretation

Coefficient  $\hat{f}_{(n)}$ 

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

Directly related to the mean value of f.

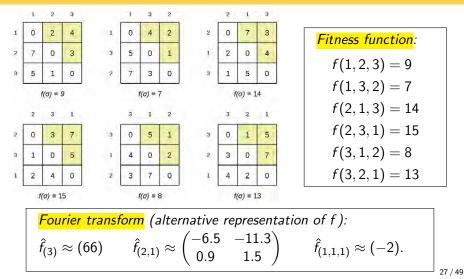
#### Other coefficients

- If f = p (probability),
  - $\hat{p}_{(n-1,1)}$  captures information about first order marginals:  $p(\sigma : \sigma(i) = j)$ .
  - *p̂*<sub>λ</sub> (λ ≠ (n), (n − 1, 1)) captures information about higher order marginals.

COPs in Fourier space

# Characterization of the LOP

#### Example



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# Characterization of the LOP

#### Structure for low dimensions

#### Structure of the example

 $\hat{f}_{(3)}$  and  $\hat{f}_{(1,1,1)}$  are arbitrary, while

$$\widehat{f}_{(2,1)}pprox egin{pmatrix} -6.5 & -11.3 \ 0.9 & 1.5 \end{pmatrix}pprox egin{pmatrix} -6.5 & \sqrt{3} \cdot (-6.5) \ 0.9 & \sqrt{3} \cdot 0.5 \end{pmatrix}.$$

#### Structure when n = 3

 $\hat{f}_{(3)}$  and  $\hat{f}_{(1,1,1)}$  are arbitrary, while

$$\hat{f}_{(2,1)} = \begin{bmatrix} | & | \\ \mathbf{x} & \sqrt{3}\mathbf{x} \\ | & | \end{bmatrix}$$

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# Characterization of the LOP

Structure for low dimensions

Structure when 
$$n = 4$$

• 
$$\hat{f}_{(4)}$$
 is arbitrary
•  $\hat{f}_{(3,1)}$  and  $\hat{f}_{(2,1,1)}$  are rank-1:
$$\hat{f}_{(3,1)} = \begin{bmatrix} | & | & | \\ \mathbf{x} & \sqrt{3}\mathbf{x} & \sqrt{6}\mathbf{x} \\ | & | & | \end{bmatrix} \qquad \hat{f}_{(2,1,1)} = \begin{bmatrix} | & | & | \\ \sqrt{2}\mathbf{y} & \mathbf{y} & \sqrt{3}\mathbf{y} \\ | & | & | \end{bmatrix}$$
•  $\hat{f}_{(2,2)}, \hat{f}_{(1,1,1,1)} = 0$ 

# Characterization of the LOP

Theorem

#### Theorem

If  $f : \Sigma_n \longrightarrow \mathbb{R}$  is the objective function of an LOP instance, then its FT has the following properties:

**1** 
$$\hat{f}_{\lambda} = 0$$
, if  $\lambda \neq (n), (n-1,1), (n-2,1,1)$ .

- **2**  $\hat{f}_{\lambda}$  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.
- **3** For  $\lambda = (n 1, 1), (n 2, 1, 1)$  and a fixed dimension *n*, the proportions among the columns of  $\hat{f}_{\lambda}$  are the same for all the instances.

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# Characterization of the LOP

Reciprocal implication

#### Theorem

If f is an LOP function with non-null (n - 1, 1) and (n - 2, 1, 1)Fourier coefficients, and a function g satisfies the conditions mentioned in the previous theorem, that is,

- 1  $\hat{g}_{\lambda} = 0$ , for  $\lambda \neq (n), (n 1, 1), (n 2, 1, 1)$ .
- **2**  $\hat{g}_{(n-1,1)}$  is 0 or rank-one with the same column proportions as  $\hat{f}_{(n-1,1)}$ .
- **3**  $\hat{g}_{(n-2,1,1)}$  is 0 or rank-one with the same column proportions as  $\hat{f}_{(n-2,1,1)}$ .

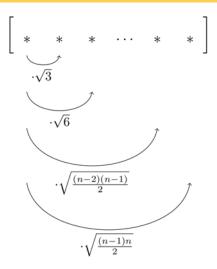
Then, g is the objective function of an LOP instance.

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Conclusion

## Characterization of the LOP

Proportions of coefficient (n-1, 1)

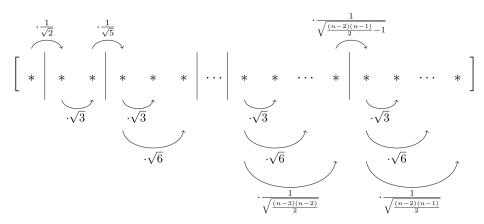


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Conclusion

## Characterization of the LOP

Proportions of coefficient (n - 2, 1, 1)



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# Characterization of the TSP

Structure for low dimensions

#### Structure when n = 4

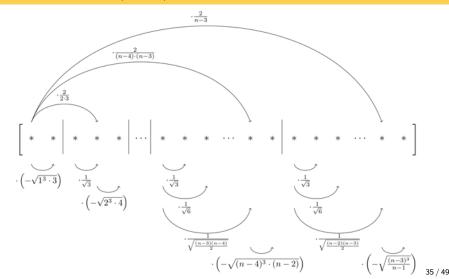
$$\hat{f}_{(2,2)} = \begin{bmatrix} | & | \\ \mathbf{x} & -\frac{1}{\sqrt{3}}\mathbf{x} \\ | & | \end{bmatrix} \qquad \hat{f}_{(2,1,1)} = \begin{vmatrix} | & | & | \\ \mathbf{y} & \sqrt{\frac{1}{2}}\mathbf{y} & \sqrt{\frac{3}{2}}\mathbf{y} \\ | & | & | \end{vmatrix}$$

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Conclusion

## Characterization of the TSP

Proportions of coefficient (n-2,2)

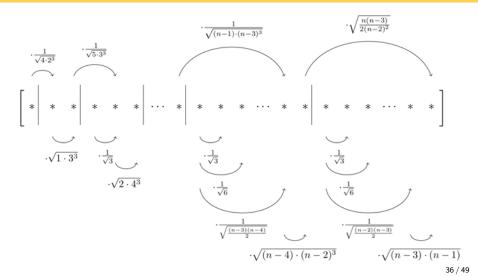


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Conclusion

## Characterization of the TSP

Proportions of coefficient (n-2, 1, 1)



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### Characterization of the QAP

#### Theorem

If  $f : \Sigma_n \longrightarrow \mathbb{R}$  is the objective function of a QAP instance, then its FT has the following properties:

**1** 
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, if  $\lambda \neq (n), (n-1,1), (n-2,2), (n-2,1,1)$ .

**2** 
$$\hat{f}_{\lambda}$$
 has at most rank one for  $\lambda = (n - 2, 2), (n - 2, 1, 1)$ .

- 3  $\hat{f}_{\lambda}$  has at most rank two for  $\lambda = (n 1, 1)$ .
- The reciprocal is also true (proved).

COPs in Fourier space

#### Characterizations: summary

Non-zero Fourier coefficients when n = 5:

COPs	Fourier coefficients							
	(5)	(4, 1)	(3,2)	(3,1,1)	(2,2,1)	(2,1,1,1)	(1,1,1,1,1)	
LOP	~	$\checkmark$		$\checkmark$				
STSP	$\checkmark$		$\checkmark$					
TSP	$\checkmark$		$\checkmark$	$\checkmark$				
QAP	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$				

As n grows, the number of Fourier coefficients grows, but these problems still have at most 4 non-zero coefficients.

COPs in Fourier space

Conclusion

#### Consequences of the characterizations

Intrinsic dimensions of the problems

Number of parameters needed to define the different problems:

COP	Usual representation	Fourier representation
LOP	$n^2 - n$	$\frac{n^2-n}{2}+1$
TSP	n(n-1)	(n-1)(n-2)
STSP	$\frac{n(n-1)}{2}$	$\frac{(n-1)(n-2)}{2}$
QAP	$2(n^2 - n)$	$2(n^2 - n) - 7$

COPs in Fourier space

### Consequences of the characterizations

Intersections between problems

Consider a COP as a set of objective functions, then:

The intersection between the LOP and the symmetric TSP is the set of constant functions.

COPs	Fourier coefficients						
	(n)	( <i>n</i> -1, 1)	( <i>n</i> -2,2)	(n-2,1,1)	( <i>n</i> -2,2,1)		(1,1,,1)
LOP	1	1		$\checkmark$			
STSP	<i>\</i>		$\checkmark$				

### Consequences of the characterizations

Intersections between problems

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COPs	Fourier coefficients						
	(n)	( <i>n</i> -1, 1)	( <i>n</i> -2,2)	(n-2,1,1)	(n-2,2,1)		(1,1,,1)
LOP	1	1		$\checkmark$			
TSP	1		$\checkmark$	$\checkmark$			

COPs in Fourier space

### Consequences of the characterizations

Intersections between problems

Consider a COP as a set of objective functions, then:

- The intersection between the LOP and the symmetric TSP is the set of constant functions.
- The intersection between the LOP and the TSP is the set of constant functions.
- The intersection between the LOP/(symmetric)TSP and the QAP is the LOP/(symmetric)TSP.

COPs in Fourier space

# Breaking down the LOP

Consider the problem composed by those objective functions with a given coefficient equal to 0.

What happens if coefficient (n - 2, 1, 1) is 0?

- The problem is P (proved)
- We implemented a polynomial algorithm

What happens if coefficient (n-1, 1) is 0?

The problem is NP-hard (proved)

Many interesting open questions:

Which is the minimal Fourier representation for a problem to be NP-hard?

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