

Elementary Landscape Decomposition of the Quadratic Assignment Problem



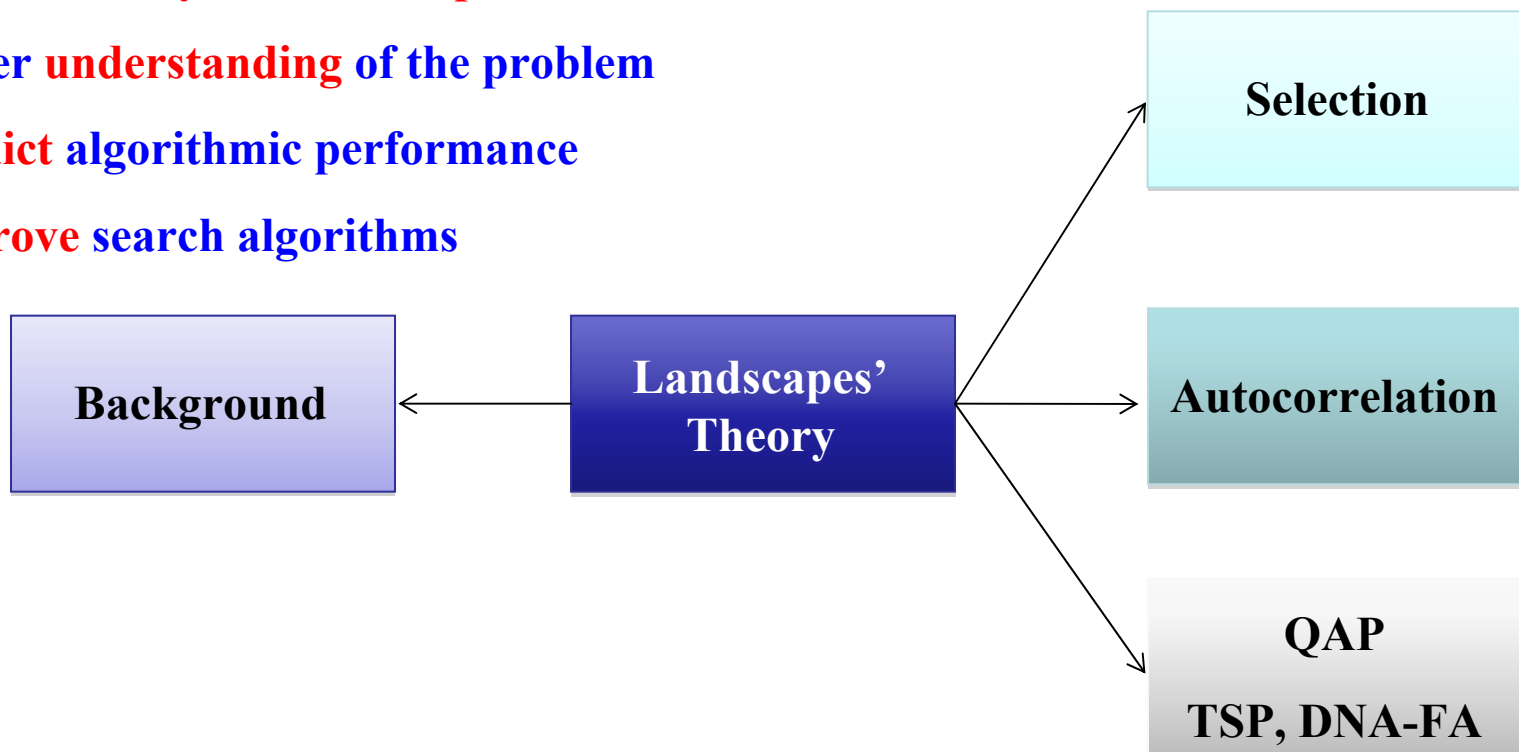
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UNIVERSIDAD DE MÁLAGA



Francisco Chicano, Gabriel Luque, and Enrique Alba

Motivation

- Landscapes' theory is a tool for **analyzing optimization problems**
- Applications in Chemistry, Physics, Biology and **Combinatorial Optimization**
- Central idea: **study the search space to obtain information**
 - **Better understanding** of the problem
 - **Predict** algorithmic performance
 - **Improve** search algorithms



Landscape Definition

- A **landscape** is a triple (X, N, f) where

- X is the solution space
- N is the neighbourhood operator
- f is the objective function

The pair (X, N) is called
configuration space

- The **neighbourhood operator** is a function

$$N: X \rightarrow \mathcal{P}(X)$$

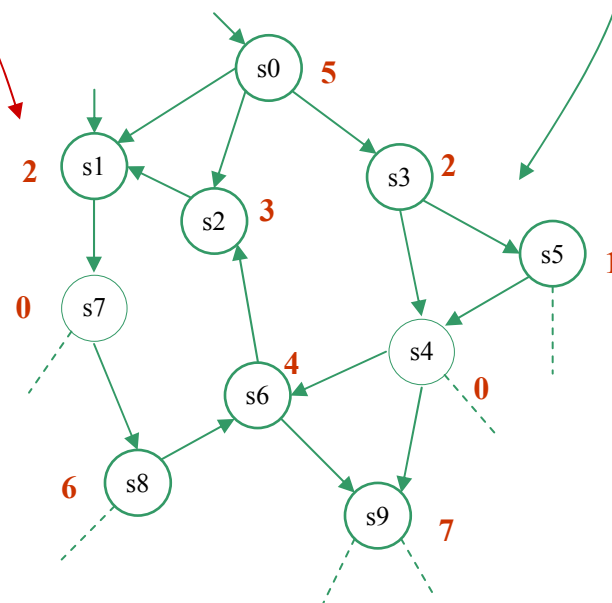
- Solution y is **neighbour of x** if $y \in N(x)$

- **Regular and symmetric neighbourhoods**

- $d = |N(x)| \quad \forall x \in X$
- $y \in N(x) \Leftrightarrow x \in N(y)$

- **Objective function**

$$f: X \rightarrow R \text{ (or } N, Z, Q)$$



Elementary Landscapes: Formal Definition

- An **elementary function** is an **eigenvector** of the graph Laplacian (plus constant)

Adjacency matrix

$$A_{xy} = \begin{cases} 1 & \text{if } y \in N(x) \\ 0 & \text{otherwise} \end{cases}$$

Degree matrix

$$D_{xy} = \begin{cases} |N(x)| & \text{if } x = y \\ 0 & \text{otherwise} \end{cases}$$

- **Graph Laplacian:**

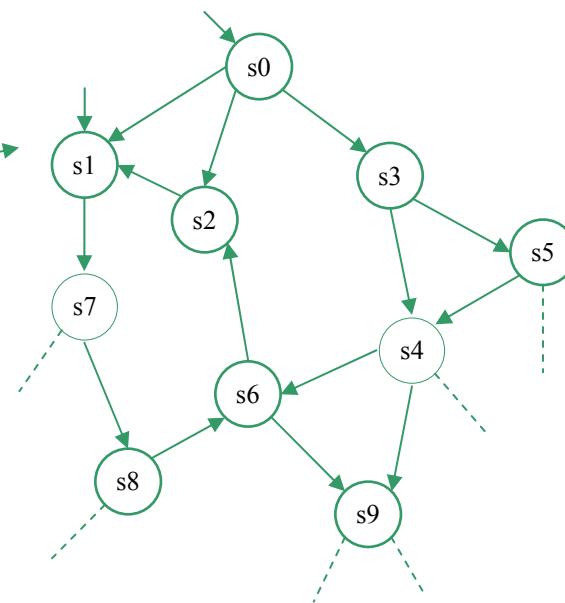
$$\Delta = A - D$$

Depends on the
configuration space

- **Elementary function: eigenvector of Δ (plus constant)**

$$\Delta \times (\vec{f} - b) = \lambda \cdot (\vec{f} - b)$$

Eigenvalue



Elementary Landscapes: Characterizations

- An **elementary landscape** is a landscape for which

$$\text{avg}_{y \in N(x)} \{f(y)\} = \alpha f(x) + \beta \quad \forall x \in X$$

Depend on the
problem/instance

where

$$\text{avg}_{y \in N(x)} \{f(y)\} \stackrel{\text{def}}{=} \frac{1}{d} \sum_{y \in N(x)} f(y)$$

Linear relationship

- **Grover's wave equation**

$$\text{avg}_{y \in N(x)} \{f(y)\} = f(x) + \frac{k}{d} (\bar{f} - f(x)) \quad \forall x \in X$$

$$\bar{f} = \frac{1}{|X|} \sum_{y \in X} f(y)$$

$$\alpha = 1 - \frac{k}{d} \quad \beta = \frac{k}{d} \bar{f}$$

Characteristic constant: $k = -\lambda$

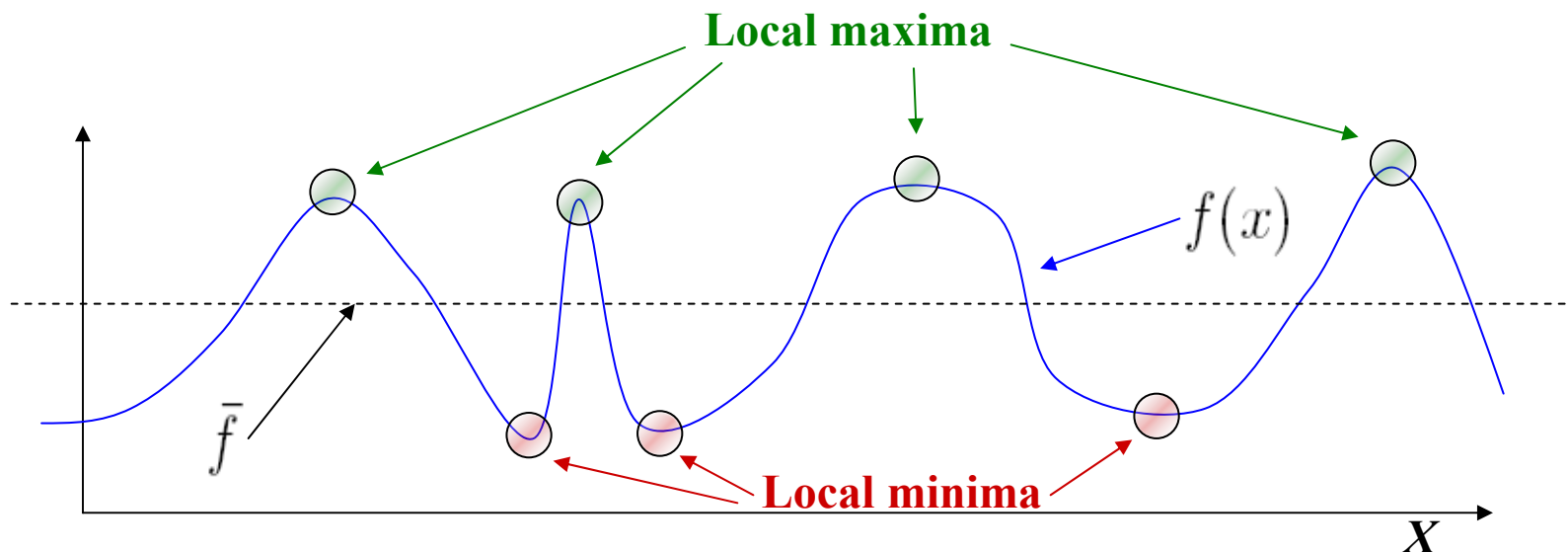
Elementary Landscapes: Properties

- Several **properties of elementary landscapes** are the following

$$f(x) < \min \left\{ \text{avg}\{f(y)\}_{y \in N(x)}, \bar{f} \right\} \quad \text{or} \quad f(x) > \max \left\{ \text{avg}\{f(y)\}_{y \in N(x)}, \bar{f} \right\}$$

where $f(x) \neq \bar{f}$

- **Local maxima and minima**

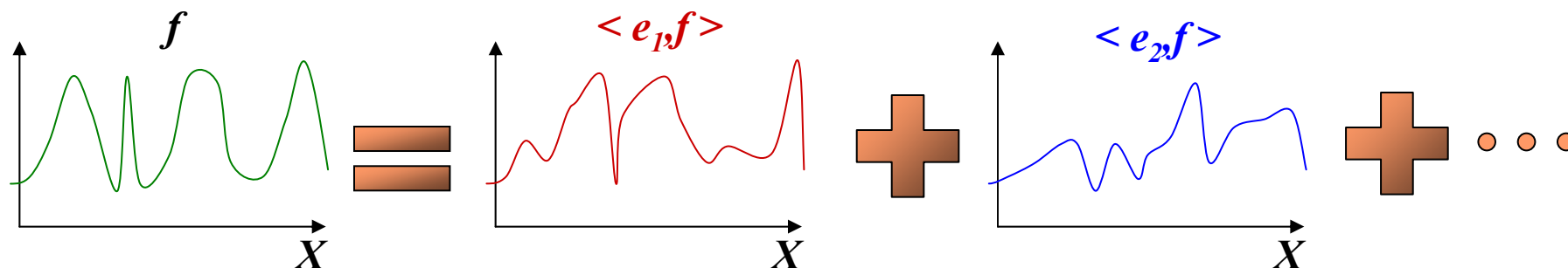


Elementary Landscapes: Examples

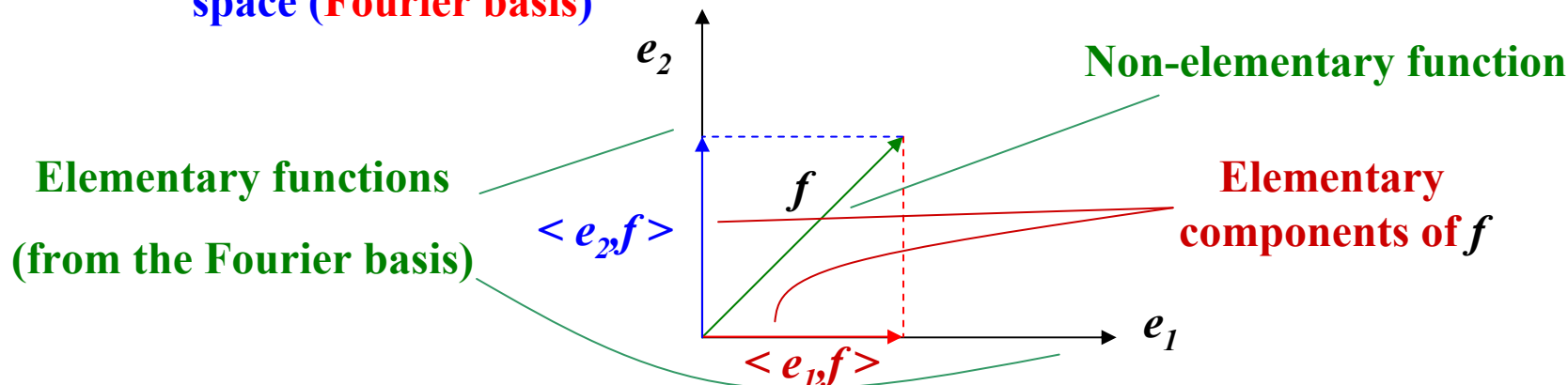
Problem	Neighbourhood	d	k
Symmetric TSP	2-opt	$n(n-3)/2$	$n-1$
	swap two cities	$n(n-1)/2$	$2(n-1)$
Antisymmetric TSP	inversions	$n(n-1)/2$	$n(n+1)/2$
	swap two cities	$n(n-1)/2$	$2n$
Graph α -Coloring	recolor 1 vertex	$(\alpha-1)n$	2α
Graph Matching	swap two elements	$n(n-1)/2$	$2(n-1)$
Graph Bipartitioning	Johnson graph	$n^2/4$	$2(n-1)$
NEAS	bit-flip	n	4
Max Cut	bit-flip	n	4
Weight Partition	bit-flip	n	4

Landscape Decomposition

- What if the landscape is **not elementary**?
- Any landscape can be written as the **sum of elementary landscapes**



- There exists a set of **eigenfunctions of Δ** that form a basis of the function space (**Fourier basis**)

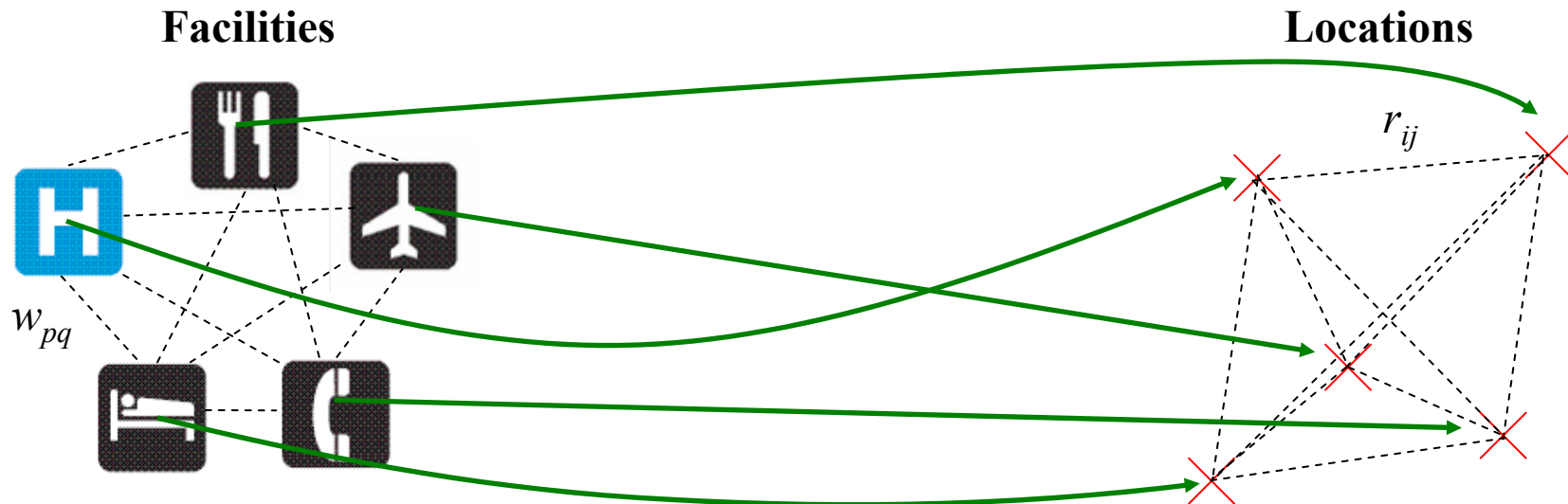


Landscape Decomposition: Examples

Problem	Neighbourhood	d	Components
General TSP	inversions	$n(n-1)/2$	2
	swap two cities	$n(n-1)/2$	2
Subset Sum Problem	bit-flip	n	2
MAX k-SAT	bit-flip	n	k
NK-landscapes	bit-flip	n	$k+1$
Radio Network Design	bit-flip	n	max. nb. of reachable antennae
Frequency Assignment	change 1 frequency	$(\alpha-1)n$	2
QAP	swap two elements	$n(n-1)/2$	3

Quadratic Assignment Problem: Definition

- A **QAP** instance is composed of **n facilities** and **n locations**



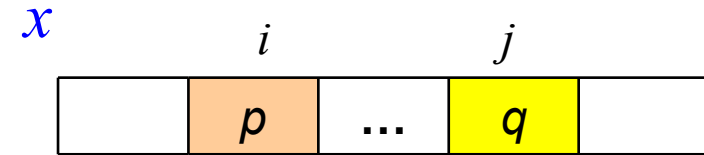
- A **distance** r_{ij} is specified between each pair of locations
- A **flow** w_{pq} is specified between each pair of facilities
- The problem consists in assigning the facilities to the locations **minimizing cost**

$$f(x) = \sum_{i,j=1}^n r_{ij} w_{x(i)x(j)} \quad \text{where } x \text{ is a permutation (solution)}$$

Quadratic Assignment Problem: Decomposition

- **Auxiliary φ functions**

$$\phi_{(i,j),(p,q)}^{\alpha,\beta,\gamma,\varepsilon,\zeta}(x) = \begin{cases} \alpha & \text{if } x(i) = p \wedge x(j) = q \\ \beta & \text{if } x(i) = q \wedge x(j) = p \\ \gamma & \text{if } x(i) = p \oplus x(j) = q \\ \varepsilon & \text{if } x(i) = q \oplus x(j) = p \\ \zeta & \text{if } x(i) \neq p, q \wedge x(j) \neq p, q \end{cases}$$



- **The Ω functions are defined after the φ functions**

$$\Omega_{(i,j),(p,q)}^1 \stackrel{\text{def}}{=} \phi_{(i,j),(p,q)}^{n-3,1-n,-2,0,-1}$$

Characteristic constant

$$k_1 = 2n$$

$$\Omega_{(i,j),(p,q)}^2 \stackrel{\text{def}}{=} \phi_{(i,j),(p,q)}^{n-3,n-3,0,0,1}$$

$$k_2 = 2(n-1)$$

$$\Omega_{(i,j),(p,q)}^3 \stackrel{\text{def}}{=} \phi_{(i,j),(p,q)}^{2n-3,1,n-2,0,-1}$$

$$k_3 = n$$

Quadratic Assignment Problem: Decomposition

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$$\Omega_{(i,j),(p,q)}^3 \stackrel{\text{def}}{=} \phi_{(i,j),(p,q)}^{2n-3,1,n-2,0,-1}$$

$$k_3 = n$$

Quadratic Assignment Problem: Decomposition

- Using the **swap neighborhood**, the fitness function can be decomposed into three elementary components:

$$f_{c1}(x) = \sum_{\substack{i, j, p, q = 1 \\ i \neq j \\ p \neq q}}^n r_{ij} w_{pq} \frac{\Omega_{(i,j),(p,q)}^1(x)}{2n} \quad k_1 = 2n$$

$$f_{c2}(x) = \sum_{\substack{i, j, p, q = 1 \\ i \neq j \\ p \neq q}}^n r_{ij} w_{pq} \frac{\Omega_{(i,j),(p,q)}^2(x)}{2(n-2)} \quad k_2 = 2(n-1)$$

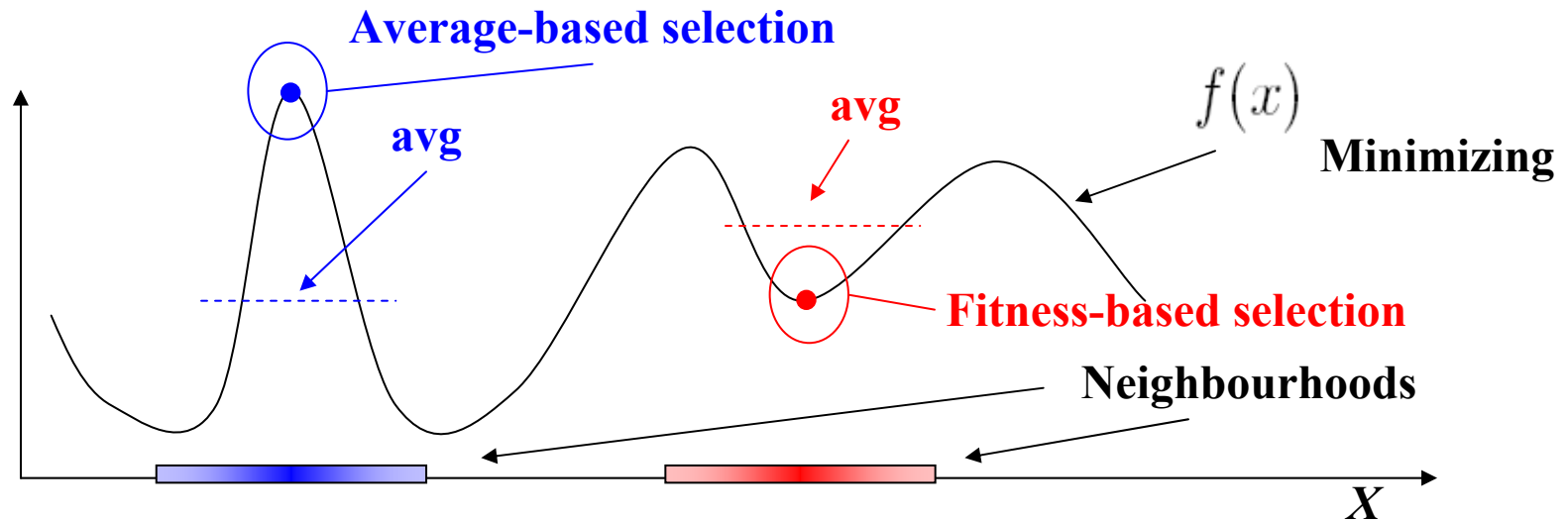
$$f_{c3}(x) = \sum_{\substack{i, j, p, q = 1 \\ i \neq j \\ p \neq q}}^n r_{ij} w_{pq} \frac{\Omega_{(i,j),(p,q)}^3(x)}{n(n-2)} + \sum_{i,p=1}^n r_{ii} w_{pp} \delta_{x(i)}^p \quad k_3 = n$$

Kronecker's delta

$$f(x) = f_{c1}(x) + f_{c2}(x) + f_{c3}(x)$$

New Selection Strategy

- Selection operators usually take into account the **fitness value** of the individuals



- We can improve the selection operator by selecting the individuals according to the **average value in their neighbourhoods**

New Selection Strategy

- In **elementary landscapes** the traditional and the new operator are the same!

Recall that...

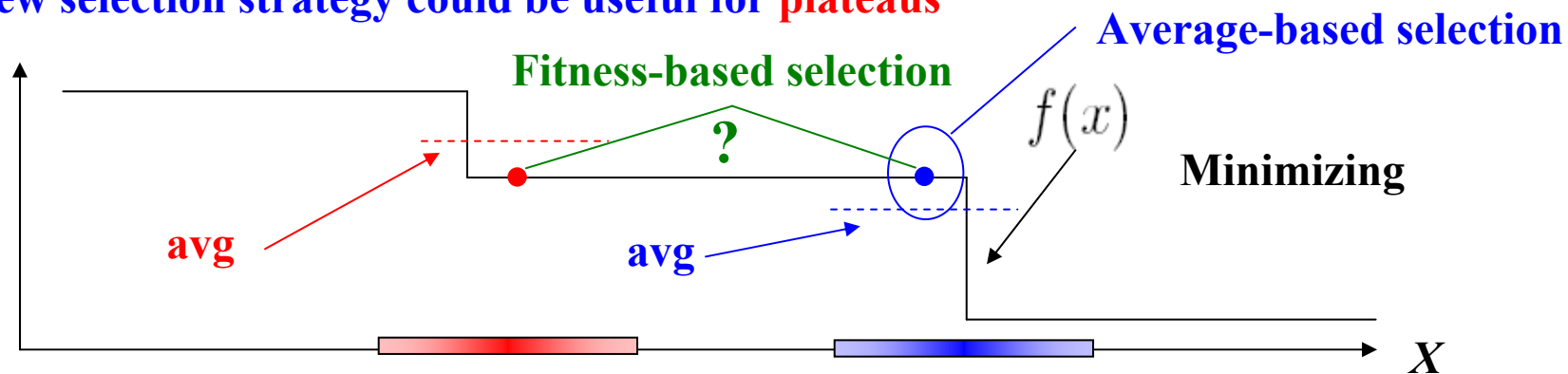
$$\text{avg}_{y \in N(x)} \{f(y)\} = \alpha f(x) + \beta \quad \forall x \in X$$

- However, they are not the same in **non-elementary landscapes**. If we have n elementary components, then:

$$\text{avg}_{y \in N(x)} \{f(y)\} = \alpha_0 + \alpha_1 f(x) + \sum_{i=2}^n \alpha_i f_i(x) \quad \forall x \in X$$

Elementary components

- The new selection strategy could be useful for **plateaus**



Autocorrelation

- Let $\{x_0, x_1, \dots\}$ a simple **random walk** on the configuration space where $x_{i+1} \in N(x_i)$
- The random walk induces a **time series** $\{f(x_0), f(x_1), \dots\}$ on a landscape.
- The **autocorrelation function** is defined as:

$$r(s) = \frac{\langle f(x_t) f(x_{t+s}) \rangle_t - \langle f \rangle^2}{\langle f^2 \rangle - \langle f \rangle^2}$$

- The **autocorrelation length and coefficient**:

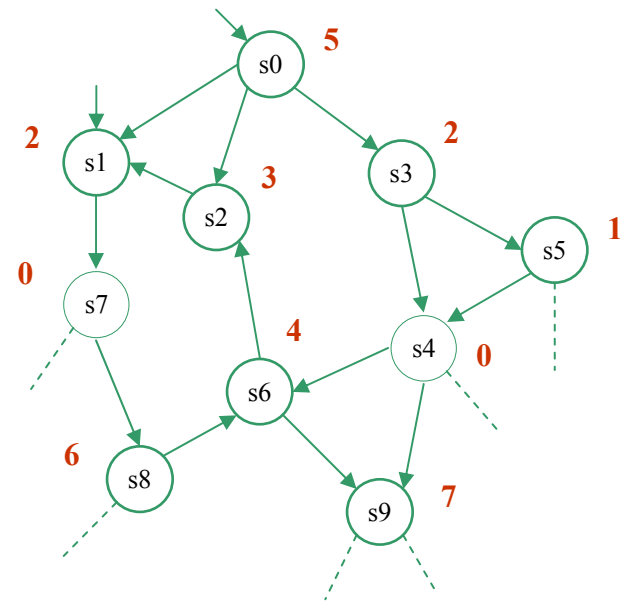
$$l = \sum_{s=0}^{\infty} r(s) \quad \xi = \frac{1}{1 - r(1)}$$

- **Autocorrelation length conjecture:**

The number of local optima in a search space is roughly

$$M \approx |X| / |X(x_0, l)|$$

**Solutions
reached from x_0
after l moves**



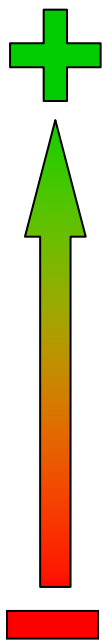
Autocorrelation Length Conjecture

- The **higher** the value of l and ξ the **smaller** the number of local optima
- l and ξ is a measure of **ruggedness**

Angel, Zissimopoulos. Theoretical
Computer Science 263:159-172 (2001)

Ruggedness	SA (configuration 1)		SA (configuration 2)	
	% rel. error	nb. of steps	% rel. error	nb. of steps
$10 \leq \zeta < 20$	0.2	50,500	0.1	101,395
$20 \leq \zeta < 30$	0.3	53,300	0.2	106,890
$30 \leq \zeta < 40$	0.3	58,700	0.2	118,760
$40 \leq \zeta < 50$	0.5	62,700	0.3	126,395
$50 \leq \zeta < 60$	0.7	66,100	0.4	133,055
$60 \leq \zeta < 70$	1.0	75,300	0.6	151,870
$70 \leq \zeta < 80$	1.3	76,800	1.0	155,230
$80 \leq \zeta < 90$	1.9	79,700	1.4	159,840
$90 \leq \zeta < 100$	2.0	82,400	1.8	165,610

Length
Coefficient



Autocorrelation and Landscapes

- If f is a sum of elementary landscapes:

Fourier coefficients

$$r(s) = \sum_{i \neq 0} \frac{a_i^2}{\sum_{j \neq 0} a_j^2} \left(1 - \frac{k_i}{d}\right)^s \qquad l = \sum_{i \neq 0} \frac{d a_i^2}{k_i \sum_{j \neq 0} a_j^2}$$

- Summing all the squared coefficients with the same k_i :

$$r(s) = \sum_i W_i \left(1 - \frac{k_i}{d}\right)^s \qquad \xi = \frac{d}{\sum_i W_i k_i} \qquad l = d \sum_i \frac{W_i}{k_i}$$

where

$$W_i = \frac{\overline{f_{ci}^2} - \overline{f_{ci}}^2}{\overline{f^2} - \overline{f}^2}$$

Autocorrelation for QAP

- Using the landscape decomposition we can compute l and ξ

$$\xi = \frac{n(n-1)}{(4-2W_3)n-4W_2} \qquad l = \frac{(1+W_3)(n-1)+W_2}{4}$$

- The **bounds** for these parameters are:

$$\frac{n-1}{4} \leq \xi \leq \frac{n-1}{2} \qquad \frac{n-1}{4} \leq l \leq \frac{n-1}{2}$$

- We designed an $O(n^2)$ algorithm for this computation (optimal complexity)
- We computed l and ξ for all the instances in the **QAPLIB**

Autocorrelation for QAP

- Using the landscape decomposition we can compute l and ξ

$$\xi = \frac{1}{4}$$

Instance	ξ	l	Instance	ξ	l
bur26a	11.825	12.130	esc32b	8.000	8.000
bur26b	11.727	12.073	esc32c	8.000	8.000
bur26c	12.109	12.291	esc32d	8.000	8.000
bur26d	12.050	12.258	esc32e	8.000	8.000
bur26e	12.032	12.248	esc32f	8.000	8.000
bur26f	11.962	12.208	esc32g	8.000	8.000
bur26g	12.323	12.407	esc32h	8.000	8.000
bur26h	12.296	12.392	esc64a	16.000	16.000
chr12a	3.096	3.171	had12	3.743	4.000
chr12b	3.201	3.346	had14	4.319	4.000
chr12c	3.044	3.079	had16	4.405	4.000
chr15a	3.917	4.049	had18	5.084	4.000
chr15b	4.126	4.388	had20	4.000	4.000
chr15c	3.843	3.920	kra30a	4.000	4.000
chr18a	4.585	4.658	kra30b	4.000	4.000
chr18b	4.632	4.742	lipa25	5.000	5.000
chr20a	5.105	5.195			
chr20b	5.035	5.067			
chr20c	5.260	5.450			

$$1) + W_2$$

- The bounds for

$$\frac{n-1}{4}$$

$$l \leq \frac{n-1}{2}$$

- We designed

- We computed

computation (optimal complexity)

in the QAPLIB

Subproblems of QAP: TSP and DNA-FA

- **TSP** is a particular case of QAP with **two elementary components** (f_{c1} and f_{c2})

$$f(x) = \sum_{i=1}^{n-1} w_{x(i)x(i+1)} + w_{x(n)x(1)} \quad r_{ij} = \begin{cases} 1 & \text{if } j = (i \bmod n) + 1 \\ 0 & \text{otherwise} \end{cases}$$

- **The autocorrelation parameters are:** $\xi = \frac{n(n-1)}{4(n-W_2)}$ $l = \frac{n-1+W_2}{4}$

- **DNA Fragment Assembly** is a technique to reconstruct an original DNA sequence a large number of fragments

Alba, Luque, Khuri, CEC 2005:57-65

- **Two fitness functions** are possible and both define QAP subproblems

$$F1(x) = \sum_{i=1}^{n-1} w_{x(i)x(i+1)} \quad r_{ij} = \delta_i^{j-1}$$

$$F2(x) = \sum_{i=1}^n \sum_{j=1}^n |i-j| \cdot w_{x(i)x(j)} \quad r_{ij} = |i-j|$$



Conclusions & Future Work

Conclusions

- Elementary landscape decomposition is a **useful tool** to understand a problem
- The decomposition can be used to **design new operators**
- We can exactly determine the **autocorrelation functions**
- We present the **decomposition for QAP** (permutation representation)

Future Work

- **Methodology** for landscape decomposition
- Search for **additional applications** of landscapes' theory in EAs
- Design **new operators and search methods** based on landscapes' information
- Analyze **other problems**

Elementary Landscape Decomposition of the Quadratic Assignment Problem



Thanks for your attention !!!

