

Elementary Landscape Decomposition of Combinatorial Optimization Problems



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Motivation

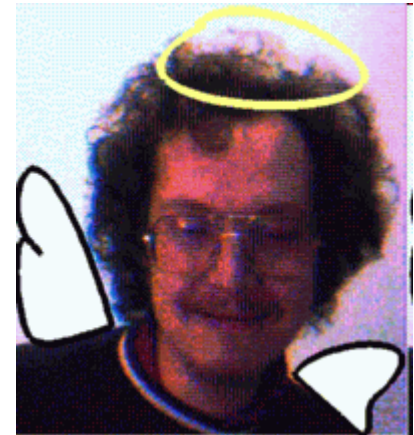
- Landscapes' theory is a tool for **analyzing optimization problems**
- **Peter F. Stadler** is one of the main supporters of the theory

Towards a Theory of Landscapes

Peter F. Stadler

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- 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

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

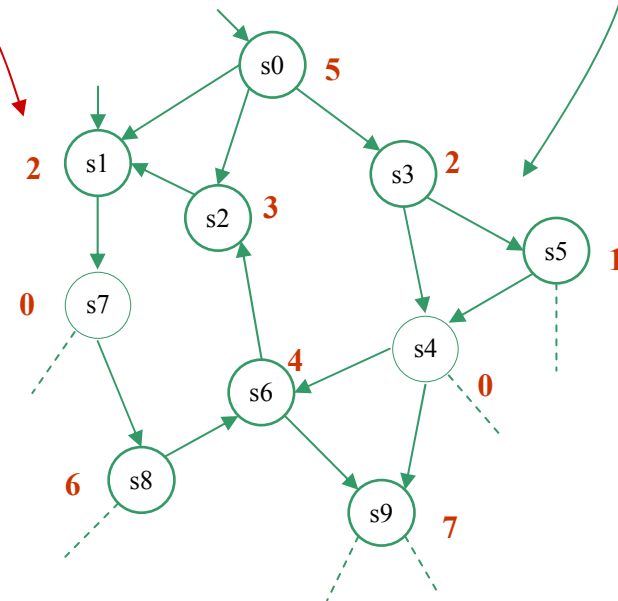
- Solution y is **neighbour of x** if $y \in N(x)$

- **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:

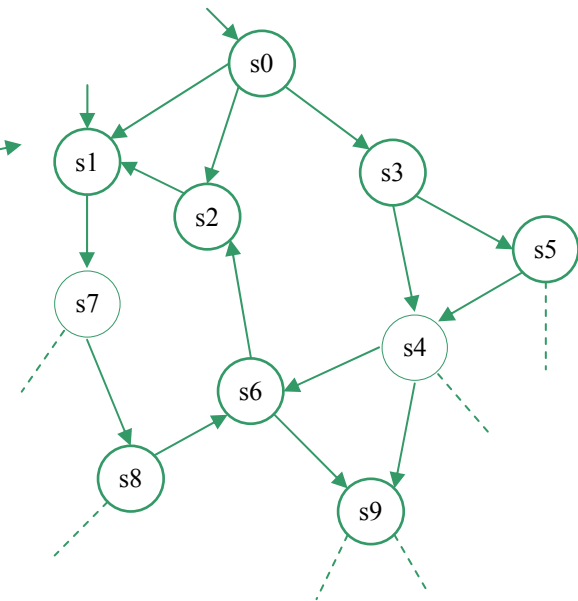
$$\Delta = A - D$$

Depends on the
configuration space

- Elementary function: eigenvector of Δ (plus constant)

$$\Delta(f - b) = \lambda(f - b)$$

Eigenvalue



Elementary Landscapes: Characterizations

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

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

where

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

Depend on the
problem/instance

Linear relationship

- **Grover's wave equation**

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

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

Characteristic constant: $k = -\lambda$

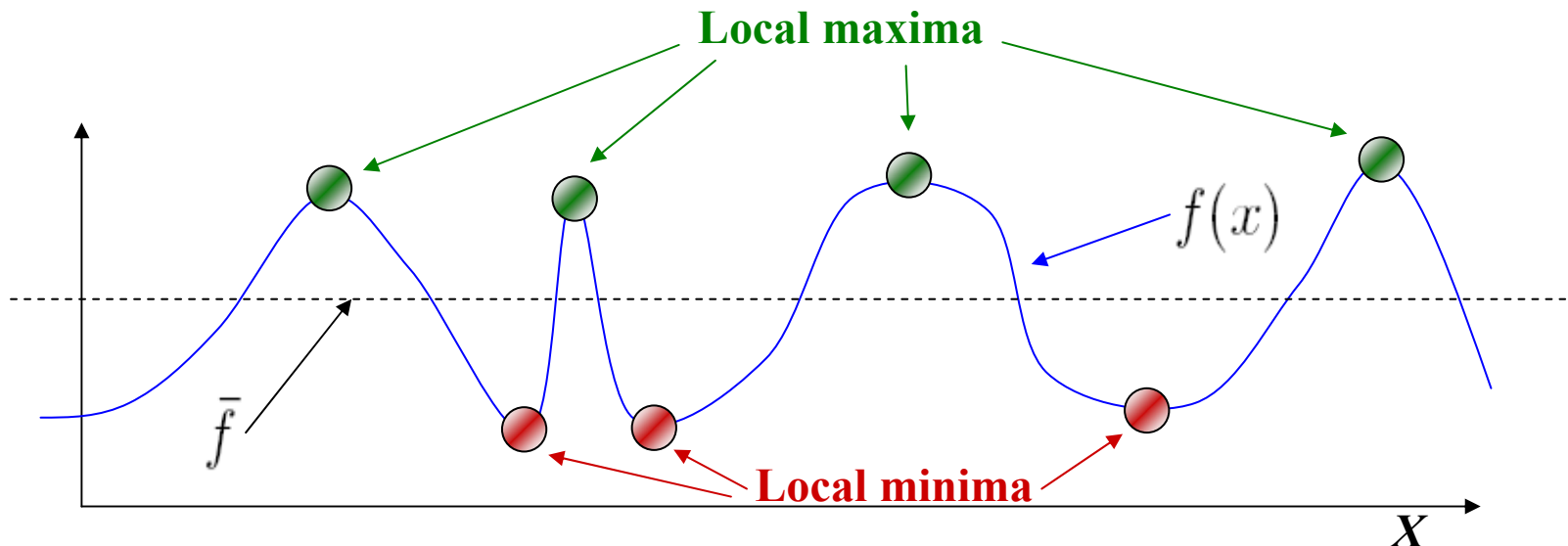
Elementary Landscapes: Properties

- Some **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**

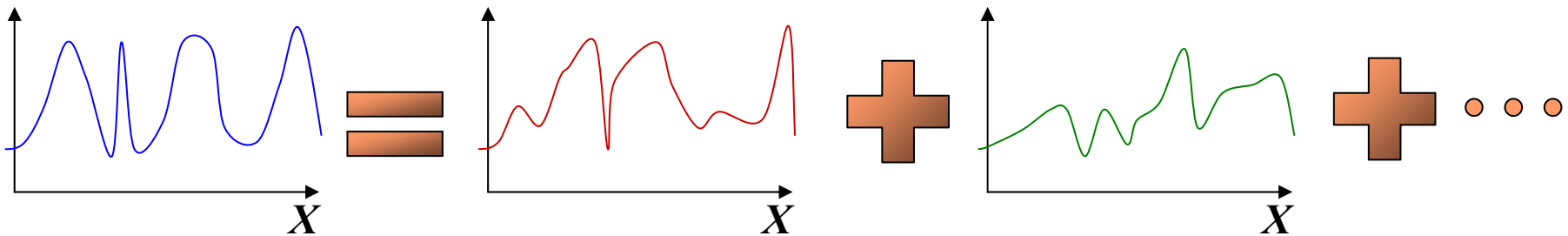


Elementary Landscapes: Examples

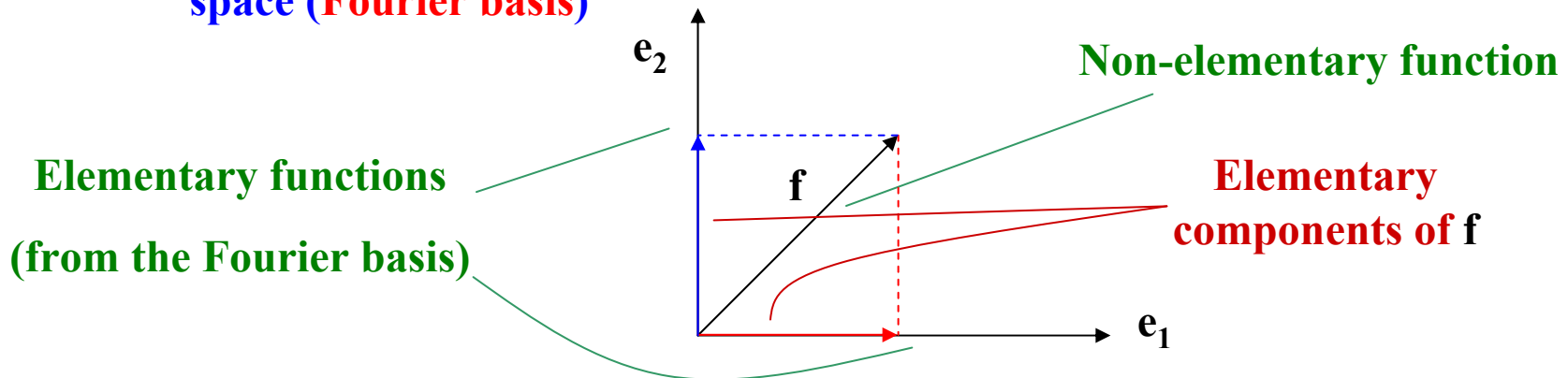
Problem	Neighbourhood	d	k
Symmetric TSP	2-opt	$n(n-3)/2$	$n-1$
	swap two cities	$n(n-1)/2$	$2(n-1)$
Antisymmetric TSP	inversions	$n(n-1)/2$	$n(n+1)/2$
	swap two cities	$n(n-1)/2$	$2n$
Graph α -Coloring	recolor 1 vertex	$(\alpha-1)n$	2α
Graph Matching	swap two elements	$n(n-1)/2$	$2(n-1)$
Graph Bipartitioning	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: Walsh Functions

- If X is the set of **binary strings** of length n and N is the **bit-flip** neighbourhood then a **Fourier basis** is

$$\{\psi_w\} \quad w \in \{0, 1\}^n$$

where

$$\psi_w(x) = (-1)^{\underset{\substack{\uparrow \\ \text{Bit count function} \\ \text{(number of ones)}}}{bc}(w \wedge x)} = \prod_{i=1}^n (-1)^{x_i w_i}$$

Bitwise AND

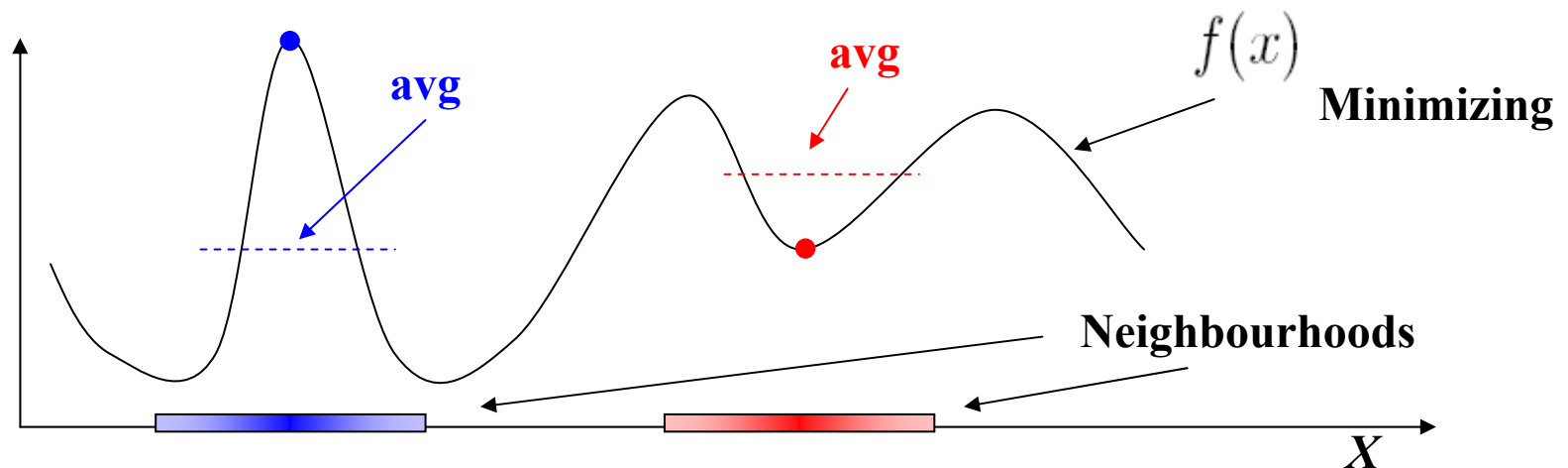
- These functions are known as **Walsh Functions**
- The function with subindex w is **elementary** with $k=2 \ bc(w)$
- In general, decomposing a landscape is **not a trivial task** → **methodology required**

Landscape Decomposition: Examples

Problem	Neighbourhood	d	Components
General TSP	inversions	$n(n-1)/2$	2
	swap two cities	$n(n-1)/2$	2
QAP	swap two elements	$n(n-1)/2$	3
Frequency Assignment	change 1 frequency	$(\alpha-1)n$	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

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...

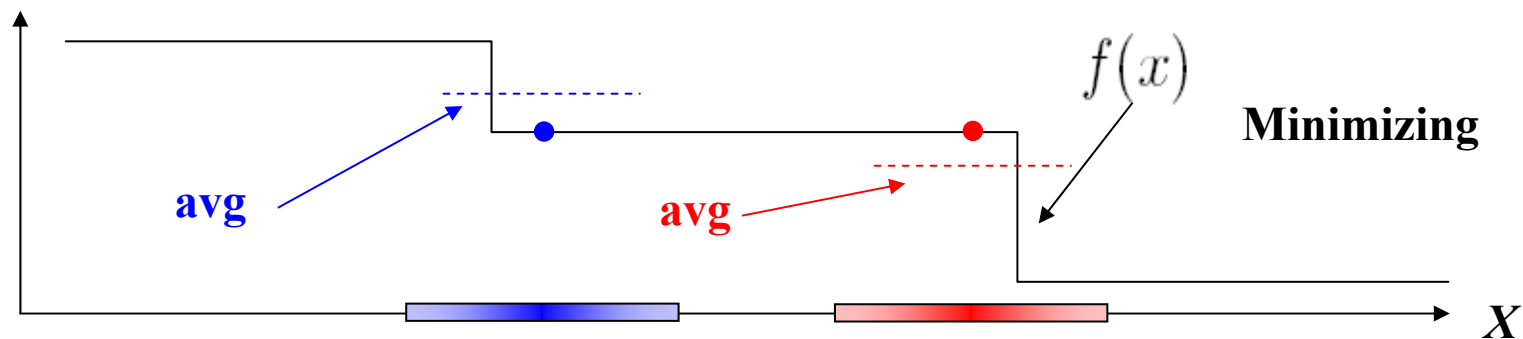
$$\text{avg}_{y \in N(x)} \{f(y)\} = \alpha f(x) + \beta \quad \forall x \in X$$

- 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** is defined as:

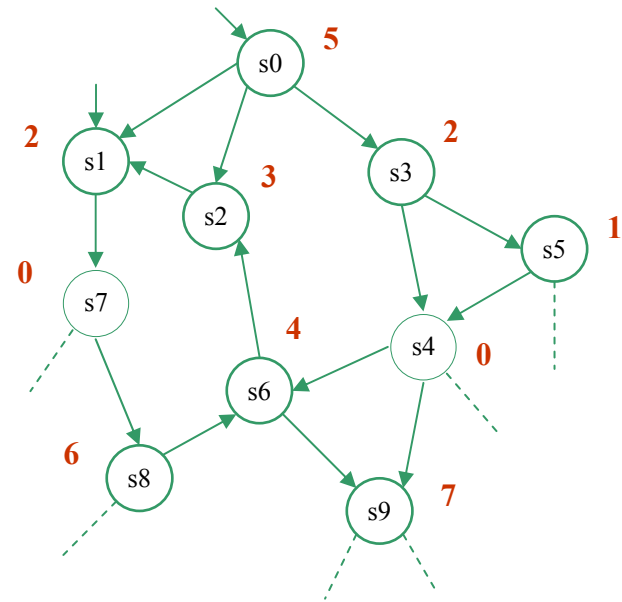
$$l = \sum_{s=0}^{\infty} r(s)$$

- **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

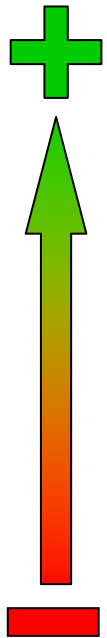


Autocorrelation Length Conjecture

- The **higher** the value of l the **smaller** the number of local optima and the **better** the performance of a local search method
- l is a measure of the **ruggedness** of a landscape

Angel, Zissimopoulos. Theoretical
Computer Science 264:159-172

Length



Ruggedness	Nb. steps (config 1)		Nb. steps (config 2)	
	% rel. error	nb. steps	% rel. error	nb. steps
$10 \leq \zeta < 20$	0.2	50500	0.1	101395
$20 \leq \zeta < 30$	0.3	53300	0.2	106890
$30 \leq \zeta < 40$	0.3	58700	0.2	118760
$40 \leq \zeta < 50$	0.5	62700	0.3	126395
$50 \leq \zeta < 60$	0.7	66100	0.4	133055
$60 \leq \zeta < 70$	1.0	75300	0.6	151870
$70 \leq \zeta < 80$	1.3	76800	1.0	155230
$80 \leq \zeta < 90$	1.9	79700	1.4	159840
$90 \leq \zeta < 100$	2.0	82400	1.8	165610

Autocorrelation and Landscapes

- If f is a sum of elementary landscapes:

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

Fourier coefficients

$$l = \sum_{i \neq 0} \frac{d a_i^2}{k_i \sum_{j \neq 0} a_j^2}$$

- For elementary landscapes:

$$r(s) = \left(1 - \frac{k}{d}\right)^s$$

$$l = \frac{d}{k}$$

- Using the landscape decomposition we can determine *a priori* the performance of a local search method

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**
- It is **not easy** to find a decomposition in the general case

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

Elementary Landscape Decomposition of Combinatorial Optimization Problems

Thanks for your attention !!!

