



Evolutionary Algorithms for Complex Designs of Experiments and Data Analysis

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outline

Complex Design of Experiments: High Dimensionality and High Throughput (HDHT)

Intelligent data: the evolutionary perspective

Statistical models in the evolution: the <u>Statistical Evolutionary Experimental Designs (SEEDS)</u> involving small sets and low dimensional data





refers to the immense volume of data that are continuously generated in any area of research, from Biology, to Material Science, Economics, Finance or Environment.

Data are growing in

- *size,* for the huge number of data provided by the great technological advances (high Throughput);
- *dimensions,* for the very large number of variables that investigators consider in developing research;
- **complexity**, for the high level of connectivity that characterizes these data sets.

From such "**Big Data**", how can investigators extract information, how can they find meaning and connections?

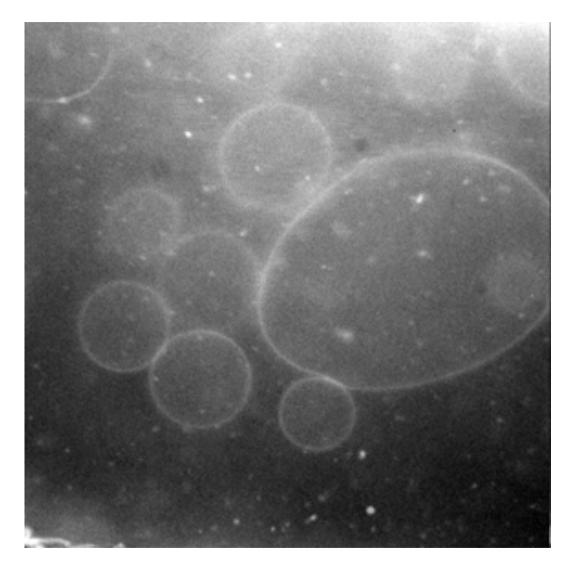
experimentation



High Throughput Robot







Protolife Laboratory, Martin Hanczyc, EU - PACE project

Q: in HDHT settings how do we *design* the experiments?

how many and which factors should be considered in the investigation;

how many and which levels for each factor,

which interactions among factors; *which network* of interaction

which experimental technology and laboratory protocols to employ.

The Statistical Design of Experiments

and the challenge of high dimensional data.

When the number of variables increases the number of experimental points to be explored increases exponentially

Developments in: *Feature selection and Dimensionality reduction: Tibshirani , Donoho, Johnstone and Titterington;* Li, Cook, Fan, Li *Fractional Factorial Design, Response surface,* Jones, Myers Uniform Design: Lin, Sharpe, and Winker

Evolution, as a search engine in HDHT

The idea is to learn from Nature: how Nature solves complex and complicated problems?

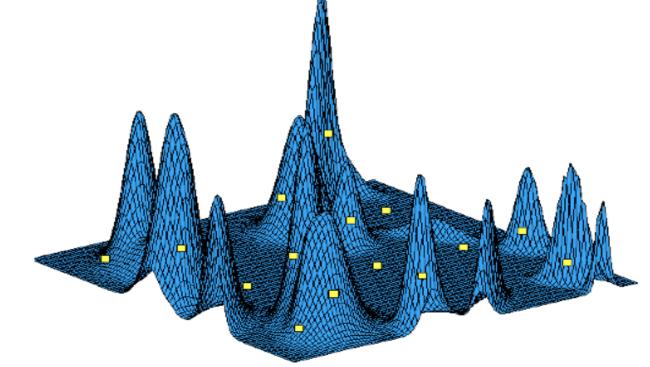
Living systems evolve through generations, learning, adapting, changing in a particular environment and according to a particular target.

The search in huge spaces can then be realized adopting the **Darwinian paradigm of evolution**

The Evolutionary Design

The design of an experiment

is a set of experimental points in a multidimensional space where to ...look for uncovering information on the target of the problem

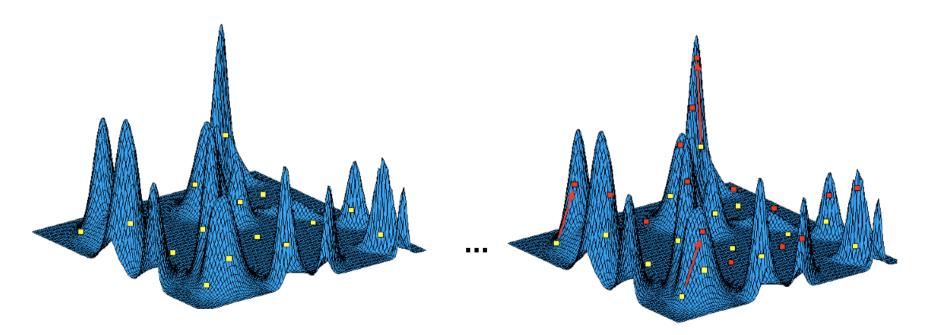


A small, low dimensional, set of sites where to collect information ${\scriptstyle 10}$

The Evolutionary Design

The design can then be represented as a *population of solutions that can learn, adapt* and then *evolve* through generations.

It is not of an *a priori* choice.



How to build the evolutionary design?

The problem:

- Let $X = \{x_1, \ldots, x_p\}$ be the set of experimental factors, with $x_k \in L_k$, where L_k is the set of the levels for factor k, k = 1, ..., p.
- The experimental space, represented by Ω , is the product set $L_1 \times L_2$, ..., $\times L_p$.
- Each element of Ω , namely ω_r , r = 1, ..., N, *is a candidate solution*, and the experimenter is asked to

find ω_{T}^{*} the best combination,

the combination with the maximum (minimum) response value (optimization problem).

Evolution with a Genetic Algorithm, GA

A GA

is an iterative, population-based search procedure.

In designing experiments

the GA evolves a population of experimental points,

which are evaluated in their environment and

transformed under genetic operators,

to generate a new population experimental points,

... emulating Nature in generating new solutions.

The GA design

An initial *very small set* of experimental points, **D**¹, with different structure composition, is chosen in a random way

Randomness (instead of just prior knowledge) allows the exploration of the space in areas not anticipated by prior knowledge but where interesting new information may reside.

each element of D¹, is a vector of symbols from a given alphabet (binary or decimal or other), is a candidate solution to be tested.

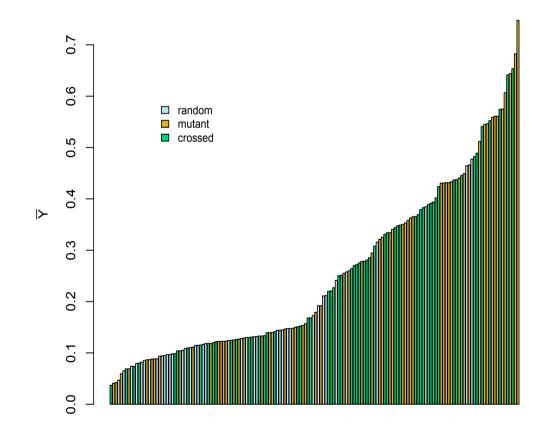
The GA design

Experimenting D¹, we learn which are the best solutions and their compositions and
with a set of genetic operators (selection, recombination, mutation, ecc..) we can build the successive generations of solutions, i.e. the successive design.

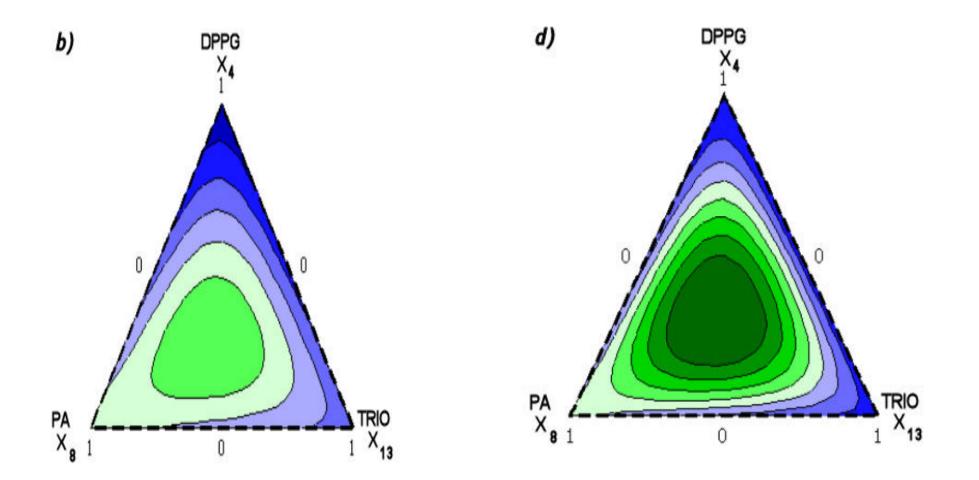
 $D^{1} \leftarrow \text{Randomly select an initial design from } \Omega$ Conduct the experiment testing each member of D^{1} and derive its fitness function value while termination conditions not met do $D^{1}_{1} \leftarrow \text{Select } (D^{1})$ $D^{1}_{2} \leftarrow \text{Recombine } (D^{1}_{1})$ $D^{1}_{3} \leftarrow \text{Mutate } (D^{1}_{2})$ $D^{2} \leftarrow \dots$

Conduct the experimentation testing each member of D_{3}^{1} endwhile

Results from the GA design on **real** experiments



Contour plots

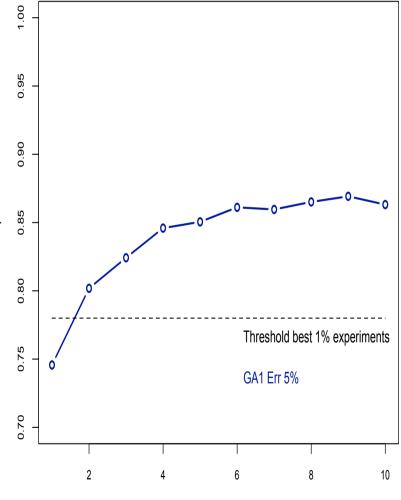


Forlin, Poli, De March, Packard, Serra, 2008, Chemometrics.

Simulated experiments

Behaviour of the average T as a function of the generations in 500 simulations (MGA) 1.00 0.8 0.95 0.7 06.0 0.6 0.85 ⊩ ⊩ 0.5 0.80 0 0.75 0. 4 GA1 Err 5% 0 0.70 0.3 2 2 4 6 8 10

Behavior of the best solution as a function of the generations in 500 simulations (ENN)



Generation

Generation

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Statistical models in the evolution? Can statistical models make a difference in the evolutionary process?

At any generation of experiments, we can build *statistical models* on the dataset and uncover information not considered by the genetic operators.

This *information* can then be embedded in the generating process of the next generation of experiments, providing "more intelligent data"

Finding information and communicating it...

The Statistical Evolutionary Experimental Design

A simulation platform for comparing different evolutionary procedures where *models* lead the evolution of the design.

The Model Based Genetic Algorithm Design (MGA)

The Evolutionary Neural Networks Design (ENN)

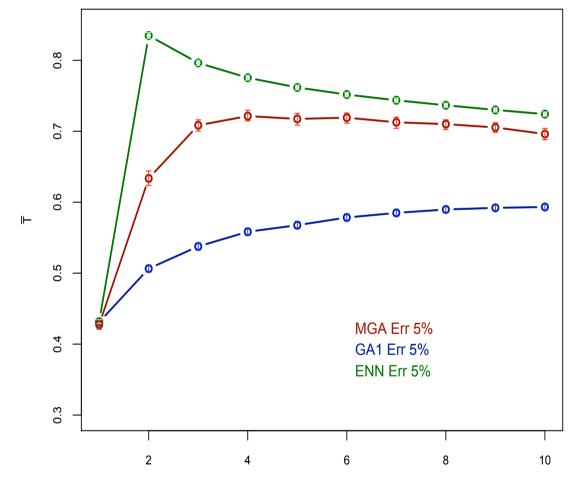
The Evolutionary Bayesian Network Design (EBN)

and Ant Colony Design

Particle Swarm Design

The average experimental response

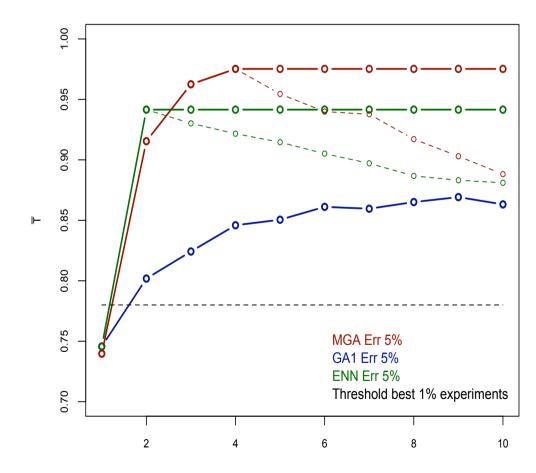
Behaviour of the average T as a function of the generations in 500 simulations (MGA)



Generation

The best experimental response

Behavior of the best solution as a function of the generations in 500 simulations (ENN)



Generation

Proportion of the best experiments in the class of the 1% best experiments

0.7 0.6 59.5 % MGA Err 5% Proportion of the best experiments 0.5 47.6 % GA1 Err 5% ENN Err 5% 0.4 0.3 0.2 12.4 % 0.1 0.0 2 8 10 4 6

Proportion of the best experimetns with T> t p and p=.99 (MGA)

Generation

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Conclusions

The evolutionary approach can successfully address the problem of HDHT

The statistical models can lead the evolutionary process generating "more intelligent data"

The Statistical Evolutionary Experimental Designs (SEEDS) can derive designs which are

cheap,

fast

and effective.

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