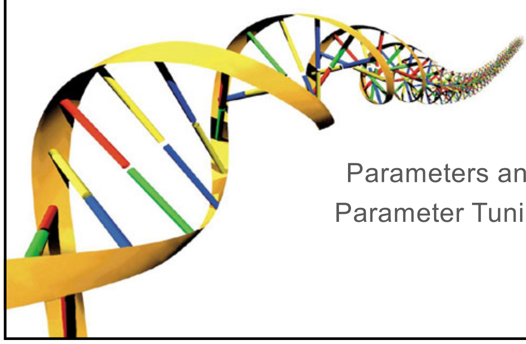
Genetic Algorithms



Parameters and Parameter Tuning

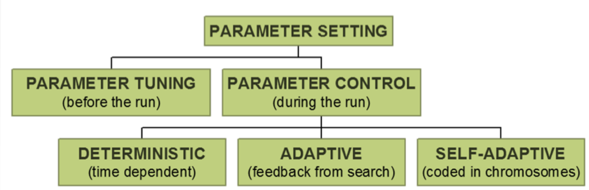
Parameters and Parameter Tuning

- History
- Taxonomy
- Parameter Tuning vs Parameter Control
- EA calibration
- Parameter Tuning
  - Testing
  - Effort
  - Recommendations

Brief historical account

- 1970s/80s “GA is a robust method”
- 1970s + ESs self-adapt mutation stepsize σ
- 1986 meta-GA for optimizing GA parameters
- 1990s EP adopts self-adaptation of σ as ‘standard’
- 1990s papers on changing parameters on-the-fly
- 1999 Eiben-Michalewicz-Hinterding: propose clear taxonomy & terminology

Taxonomy



Parameter tuning

Parameter tuning: testing and comparing different values before the “real” run – part of development

Problems:
- user “mistakes” in settings can be sources of errors or sub-optimal performance
- takes significant time
- parameters interact: exhaustive search is not practical (or even possible, in some cases)
- good values may become bad during the run (at different stages of evolutionary development in the population)

Parameter control

Parameter control: setting values on-line, during the actual run, e.g.
- predetermined time-varying schedule p = p(t)
- using (heuristic) feedback from the search process
- encoding parameters in chromosomes and rely on natural selection

Problems:
- finding optimal p is hard, finding optimal p(t) is harder
- still user-defined feedback mechanism, how to “optimize”?
- when would natural selection work for algorithm parameters?

Notes on parameter control

- Parameter control offers the possibility to use appropriate values in various stages of the search
- Adaptive and self-adaptive control can “liberate” users from tuning → reduces need for EA expertise for a new application
- Assumption: control heuristic is less parameter-sensitive than the EA

BUT

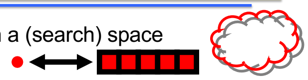
- State-of-the-art is a mess: literature is a potpourri, no generic knowledge, no principled approaches to developing control heuristics (deterministic or adaptive), no solid testing methodology

Historical account (cont’d)

Last 20 years:
- More & more work on parameter control
  - Traditional parameters: mutation and xover
  - Non-traditional parameters: selection and population size
  - All parameters → “parameterless” EAs (what to call these?)
  - Some theoretical results (*e.g.* Carola Doerr)
- Not much work on parameter tuning, i.e.,
  - Nobody reports on tuning efforts behind their published EAs (common refrain: “values were determined empirically”)
  - A handful of papers on tuning methods / algorithms

Parameter – performance landscape

- All parameters together span a (search) space
- One point – one EA instance



- Height of point = performance of EA instance on a given problem
- Parameter-performance landscape or utility landscape for each { EA + problem instance + performance measure }
- This landscape is likely to be complex *e.g.*, multimodal
- If there is some structure in the utility landscape, then perhaps we can do better than random or exhaustive search

The Tuning Problem

- Parameter values determine the success and efficiency of a genetic algorithm
- Parameter tuning is a method in which parameter values determined before a run and remain fixed during
- Common approaches:
  - Convention, *e.g.* mutation rate should be low; xover rate = 0.9
  - Ad hoc choices, *e.g.* let's use population size of 100
  - Limited experimentation, *e.g.* let's try a few values

The Tuning Problem Problems

- Problems with convention and ad hoc choices are obvious
  - Were choices ever justified?
  - Do they apply in new problem domains?
- Problems with experimentation
  - Parameters interact – cannot be optimized one-by-one
  - Time consuming: 4 parameters with 5 values each yields 625 parameter combinations. 100 runs each = 62500 runs just for tuning – to be fair, any tuning method will be time consuming
  - Best parameter values may not be in test set

The Tuning Problem Goal

- Think of design of a GA as a separate search problem
- Then a tuning method is a search algorithm
- Such a tuning method can be used to:
  - Optimize a GA by finding parameters that optimize its performance
  - Analyze a GA by studying how performance depends on parameter values and the problems to which it is applied
- So tuning problem solutions depend on problems to be solved, GA used, and utility function that defines how GA quality is measured

The Tuning Problem Terminology

	Problem Solving	Algorithm Design
METHOD	EA	Tuner
SEARCH SPACE	Solution vectors	Parameter vectors
QUALITY	Fitness	Utility
ASSESSMENT	Evaluation	Test

- Fitness ≈ objective function value
- Utility = ?
  - Mean Best Fitness
  - Average number of Evaluations to Solution
  - Success Rate
  - Robustness, …
  - Combination of some of these

Defining Algorithm Quality

- GA quality generally measured by a combination of solution quality and algorithm efficiency
- Solution quality – reflected in fitness values
- Algorithm efficiency
  - Number of fitness evaluations
  - CPU time
  - Clock-on-the-wall time

Defining Algorithm Quality

- Three generally used combinations of solution quality and computing time for single run of algorithm
  - Fix computing time and measure solution quality
    - Given maximum runtime, quality is best fitness at termination
  - Fix solution quality and measure computing time required
    - Given a minimum fitness requirement, performance is the runtime needed to achieve it
  - Fix both and measure success
    - Given maximum runtime and minimum fitness requirement, run is successful if it achieves fitness requirement within runtime limit

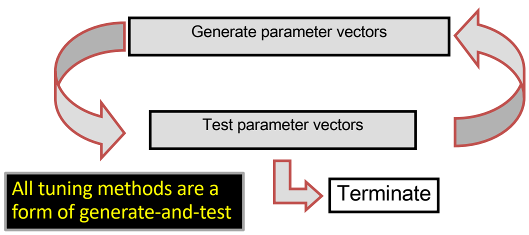
Tuning Methods
Off-line vs. on-line calibration / design

Design / calibration method
- Off-line → parameter tuning
- On-line → parameter control

- Advantages of tuning
  - Easier
  - Most immediate need of users
  - Control strategies have parameters too → need tuning themselves
  - Knowledge about tuning (utility landscapes) can help the design of good control strategies
  - There are indications that good tuning works better than control

Tuning Method
Tuning by generate-and-test

- Generate-and-test is a common search strategy
- Since EA tuning is a search problem itself…
- Straightforward approach:



Generate-and-test
Testing parameter vectors

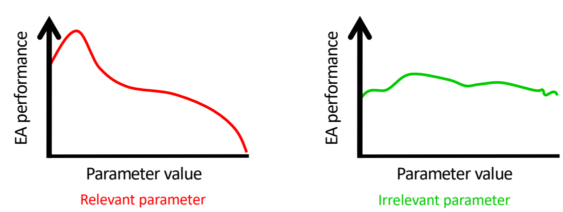
- Run EA with these parameters on the given problem or problems
- Record EA performance in that run *e.g.*, by
  - Solution quality = best fitness at termination
  - Speed ≈ time used to find required solution quality
- EAs are stochastic → repetitions are needed for reliable evaluation → we get statistics, *e.g.*,
  - Average performance by solution quality, speed (MBF, AES)
  - Success rate = % runs ending with success
  - Robustness = variance in those averages over different problems
- Question: how many repetitions of the test (yet another "parameter")

Definitions

- Because GAs are stochastic, single runs don't tell us much about the quality of an algorithm
- Aggregate measures over multiple runs:
  - MBF: Mean Best Fitness
  - AES: Average evaluations to solution
  - SR: Success rate

Generate-and-Test
Numeric parameters

- E.g., population size, xover rate, tournament size, …
- Domain is subset of R, Z, N (finite or infinite)
- Values are well ordered → searchable



Generate-and-test Symbolic parameters

- *E.g.*, xover_operator, elitism, selection_method
- Finite domain, *e.g.*, {1-point, uniform, averaging}, {Y, N}
- Values not well ordered → non-searchable, must be sampled
- A value of a symbolic parameter can introduce a numeric parameter, *e.g.*,
  - Selection = tournament → tournament size
  - Populations_type = overlapping → generation gap
  - Elitism = on → number of best members to keep

What is an EA?

	ALG-1	ALG-2	ALG-3	ALG-4
SYMBOLIC PARAMETERS				
Representation	Bit-string	Bit-string	Real-valued	Real-valued
Overlapping pops	N	Y	Y	Y
Survivor selection	–	Tournament	Replace worst	Replace worst
Parent selection	Roulette wheel	Uniform determ	Tournament	Tournament
Mutation	Bit-flip	Bit-flip	N(0,σ)	N(0,σ)
Recombination	Uniform xover	Uniform xover	Discrete recomb	Discrete recomb
NUMERIC PARAMETERS				
Generation gap	–	0.5	0.9	0.9
Population size	100	500	100	300
Tournament size	–	2	3	30
Mutation rate	0.01	0.1	–	–
Mutation stepsize	–	–	0.01	0.05
Crossover rate	0.8	0.7	1	0.8

What is an EA?

Make a principal distinction between EAs and EA instances and place the border between them by:

- Option 1
  - There is only one EA, the generic EA scheme
  - Previous table contains 1 EA and 4 EA-instances
- Option 2
  - An EA = particular configuration of the symbolic parameters
  - Previous table contains 3 EAs, with 2 instances for one of them
- Option 3
  - An EA = particular configuration of parameters
  - Notions of EA and EA-instance coincide
  - Previous table contains 4 EAs / 4 EA-instances

Tuning effort

- Total amount of computational work is determined by
  - A = number of vectors tested
  - B = number of tests per vector
  - C = number of fitness evaluations per test

Recommendations

- **DO TUNE** your evolutionary algorithm

- Think of the magic constants
- Decide: speed or solution quality?
- Decide: specialist or generalist EA?
- Measure and report tuning effort

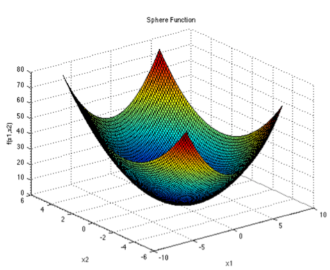
Example study: 'Best parameters'

- Setup:
  - Problem: Sphere Function (see next slide)
  - EA: defined by Tournament Parent Selection, Random Uniform Survivor Selection, Uniform Crossover, BitFlip Mutation
  - Tuner: REVAC spending X units of tuning effort, tuning for speed

- Results: the best EA had the following parameter values
  - Population Size: 6
  - Tournament Size: 4

- Conclusions: *for this problem* we need a high (parent) selection pressure.

Sphere Function (in 3 dimensions)



$$f(\mathbf{x}) = \sum_{i=1}^{d} x_i^2$$

Example study: 'Good parameters'

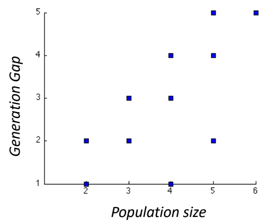
- Setup: same as before

- Results: The 25 best parameters vectors have their values within the following ranges
  - Mutation Rate: [0.01, 0.011]
  - Crossover Rate: [0.2, 1.0]

- Conclusions: *for this problem* the mutation rate is much more relevant than the crossover rate.

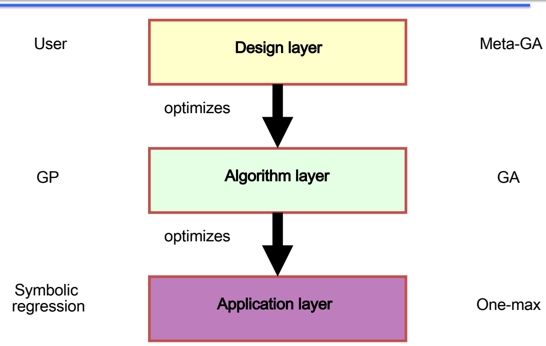
Example study: 'interactions'

- Setup: same as before
- Results: plotting the pop. size and generation gap of the best parameter vectors shows the following

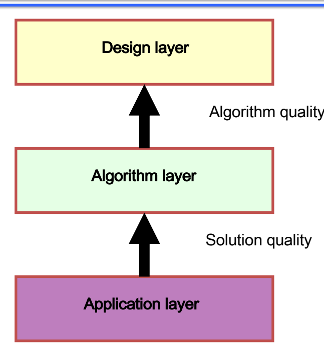


- Conclusions: *for this problem* the best results are obtained when (almost) the complete population is replaced every generation.

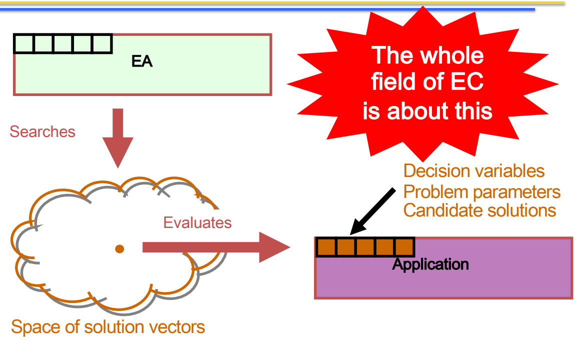
Control flow of EA calibration / design



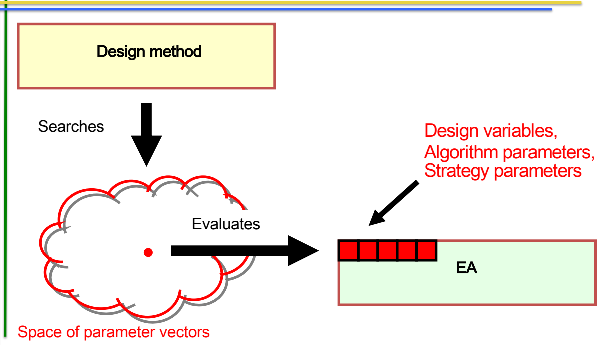
Information flow of EA calibration / design



Lower level of EA calibration / design



Upper level of EA calibration / design

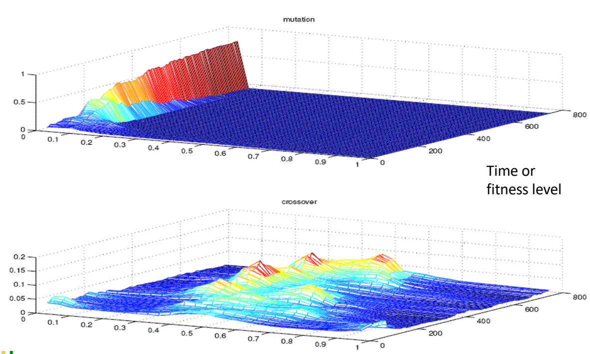


Optimize A = optimally use A

Applicable only to numeric parameters
Number of tested vectors not fixed, A is the maximum (stop cond.)
Population-based search:
- **Initialize with N << A vectors and**
- **Iterate: generating, testing, selecting p.v.'s**

- Meta-EA (Greffenstette '86)
  - Generate: usual crossover and mutation of p.v.'s
- SPO (Bartz-Beielstein et al. '05)
  - Generate: uniform random sampling!!! of p.v.'s
- REVAC (Nannen & Eiben '06)
  - Generate: usual crossover and distribution-based mutation of p.v.'s

EVOLUTION OF DISTRIBUTIONS FOR SCHAFFER'S f_6



REVAC illustration

Optimize B = reduce B

Applicable to symbolic and numeric parameters
Number of tested vectors (A) fixed at initialization
Set of tested vectors can be created by

- regular method → grid search
- random method → random sampling
- exhaustive method → enumeration

Complete testing (single stage) vs. selective testing (multi-stage)

- Complete testing: nr. of tests per vector = B (thus, not optimizing)
- Selective testing: nr. of tests per vector varies, ≤ B
- Idea:
  - Execute **tests in a breadth-first fashion (stages)**, all vectors X < B times
  - Stop testing vectors with statistically significant poorer utility
- Well-known methods
  - ANOVA (Scheffer '89)
  - Racing (Maron & Moore '97)

Optimize A & B

Existing work:

- Meta-EA with racing (Yuan & Gallagher '04)

New trick: sharpening (Smit & Eiben 2009)

- Idea: test vectors X < B times and increase X over time during the run of a population-based tuner

Newest method:

- **REVAC with racing & sharpening = REVAC++**

Which tuning method?

- Differences between tuning algorithms
  - Maximum utility reached
  - Computational costs
  - Number of their own parameters – overhead costs
  - Insights offered about EA parameters (probability distribution, interactions, relevance, explicit model…)
- Similarities between tuning algorithms
  - Nobody is using them
  - Can find good parameter vectors
- Solid comparison is missing – ongoing

Tuning "world champion" EAs

	G-CMA-ES			SaDE		
Tuned by	Avg	St dev	CEC Δ	Avg	St dev	CEC Δ
G-CMA-ES	0.77	0.2	20 %	0.73	0.25	49 %
REVAC++	0.85	0.24	12 %	0.67	0.22	53 %
SPOT	0.76	0.19	22 %	0.73	0.20	49 %
CEC-2005	0.97	0.32	-	1.43	0.25	-

Ranking at CEC 2005

1. CMA-ES
2. SaDE

Ranking after tuning

1. SaDE
2. CMA-ES

Main conclusion: if only they had asked us ….

Tuning vs. not tuning