Parameter control

Lecture 11

MONASH UNIVERSITY CLAYTON'S SCHOOL OF INFORMATION TECHNOLOGY

Motivation 1

Reading: Eiben& Smith Chapter 8

An EA has many strategy parameters, e.g.

- mutation operator and mutation rate
- crossover operator and crossover rate
- selection mechanism and selective pressure (e.g. tournament size)
- population size

Good parameter values facilitate good performance

Q1 How to find good parameter values ?

Motivation 2

EA parameters are rigid (constant during a run)

BUT

an EA is a dynamic, adaptive process

THUS

optimal parameter values may vary during a run

Q2: How to vary parameter values?

Parameter tuning

Parameter tuning: the traditional way of testing and comparing different values before the “real” run

Problems:

- users mistakes in settings can be sources of errors or sub-optimal performance
- costs much time
- parameters interact: exhaustive search is not practicable
- good values may become bad during the run

Parameter control

Parameter control: setting values on-line, during the actual run, e.g.

- predetermined time-varying schedule $p = p(t)$
- using 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 strategy parameters?

Example

Task to solve:

- min $f(x_1,\ldots,x_n)$
- $L_i \leq x_i \leq U_i$ for $i = 1,\ldots,n$ bounds
- $g_i(x) \leq 0$ for $i = 1,\ldots,q$ inequality constraints
- $h_i(x) = 0$ for $i = q+1,\ldots,m$ equality constraints

Algorithm:

- EA with real-valued representation $(x_1,\ldots,x_n)$
- arithmetic averaging crossover
- Gaussian mutation: $x'_i = x_i + N(0, \sigma)$
- standard deviation σ is called mutation step size

Varying mutation step size: option 1

- Replace the constant σ by a function $\sigma(t)$

$$\sigma(t) = 1 - 0.9 \times \frac{t}{T}$$

- $0 \leq t \leq T$ is the current generation number

Features:

- changes in σ are independent from the search progress
- strong user control of σ by the above formula
- σ is fully predictable
- a given σ acts on all individuals of the population

Varying mutation step size: option 2

- Replace the constant σ by a function σ(t) updated after
- every n steps by the 1/5 success rule (cf. ES chapter):

$$\sigma(t) = \begin{cases} \sigma(t-n)/c & \text{if } p_s > 1/5 \\ \sigma(t-n) \times c & \text{if } p_s < 1/5 \\ \sigma(t-n) & \text{otherwise} \end{cases}$$

Features:

- changes in σ are based on feedback from the search progress
- some user control of σ by the above formula
- σ is not predictable
- a given σ acts on all individuals of the population

Varying mutation step size: option 3

- Assign a personal σ to each individual
- Incorporate this σ into the chromosome: (x1, …, xn, σ)
- Apply variation operators to xi's and σ

$$\sigma' = \sigma \times e^{N(0,\tau)}$$

$$x'_i = x_i + N(0,\sigma')$$

Features:

- changes in σ are results of natural selection
- (almost) no user control of σ
- σ is not predictable
- a given σ acts on one individual

Varying mutation step size: option4

- Assign a personal σ to each variable in each individual
- Incorporate σ's into the chromosomes: (x1, …, xn, σ1, …, σ n)
- Apply variation operators to xi's and σi's

$$\sigma'_i = \sigma_i \times e^{N(0,\tau)}$$

$$x'_i = x_i + N(0,\sigma'_i)$$

Features:

-changes in σ_i are results of natural selection

-(almost) no user control of σ_i

-σ_i is not predictable

-a given σ_i acts on 1 gene of one individual

Example cont'd

- Constraints
  - gi (x) ≤ 0 for i = 1,…,q inequality constraints
  - hi (x) = 0 for i = q+1,…,m equality constraints
- are handled by penalties:
- eval(x) = f(x) + W × penalty(x)
- where:

$$penalty(x) = \sum_{j=1}^{m} \begin{cases} 1 & \textit{for violated constraint} \\ 0 & \textit{for satisfied constraint} \end{cases}$$

Varying penalty: option 1

- Replace the constant W by a function W(t)

$$W(t) = (C \times t)^{\acute{a}}$$

- $0 \leq t \leq T$ is the current generation number

Features:

- changes in *W* are independent from the search progress
- strong user control of *W* by the above formula
- *W* is fully predictable
- a given *W* acts on all individuals of the population

Varying penalty: option 2

- Replace the constant W by W(t) updated in each generation

- $$W(t+1) = \begin{cases} \hat{a} \times W(t) & \textit{if last k champions all feasible} \\ \tilde{a} \times W(t) & \textit{if last k champions all infeasible} \\ W(t) & \textit{otherwise} \end{cases}$$

- $\beta < 1, \gamma > 1, \beta \times \gamma \neq 1$ champion: best of its generation

Features:

- changes in W are based on feedback from the search progress
- some user control of W by the above formula
- W is not predictable
- a given W acts on all individuals of the population

Varying penalty: option 3

- Assign a personal W to each individual
- Incorporate this W into the chromosome: $(x_1, \ldots, x_n, W)$
- Apply variation operators to x_i's and W

- Alert:
- $$\text{eval}((x, W)) = f(x) + W \times \text{penalty}(x)$$
- while for mutation step sizes we had
- $$\text{eval}((x, \sigma)) = f(x)$$
- this option is thus sensitive "cheating" ⇒ makes no sense

Lessons learned from examples

- Various forms of parameter control can be distinguished by:

- primary features:
  - **what** component of the EA is changed
  - **how** the change is made

- secondary features:
  - **evidence/data** backing up changes
  - **level/scope** of change

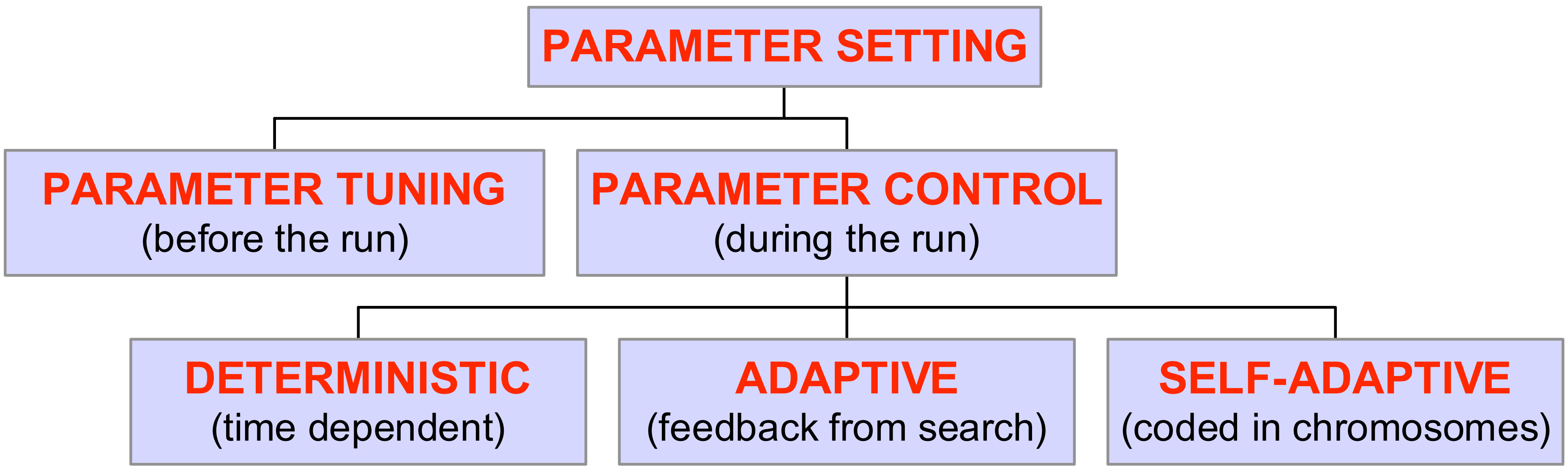
What

- Practically any EA component can be parameterised and thus controlled on-the-fly:
  - representation
  - evaluation function
  - variation operators
  - selection operator (parent or mating selection)
  - replacement operator (survival or environmental selection)
  - population (size, topology)

How

- Three major types of parameter control:
  - deterministic: some rule modifies strategy parameter without feedback from the search (based on some counter)
  - adaptive: feedback rule based on some measure monitoring search progress
  - self-adaptative: parameter values evolve along with solutions; encoded onto chromosomes they undergo variation and selection

Global taxonomy



Evidence informing the change

The parameter changes may be based on:

- time or nr. of evaluations (deterministic control)
- population statistics (adaptive control)
  - progress made
  - population diversity
  - gene distribution, etc.
- relative fitness of individuals created with given values (adaptive or self-adaptive control)

Evidence informing the change

- Absolute evidence: predefined event triggers change, e.g. increase p_m by 10% if population diversity falls under threshold x
- Direction and magnitude of change is fixed
- Relative evidence: compare values through solutions created with them, e.g. increase p_m if top quality offspring came by high mutation rates
- Direction and magnitude of change is not fixed

Scope/level

- The parameter may take effect on different levels:
  - environment (fitness function)
  - population
  - individual
  - sub-individual

Note: given component (parameter) determines possibilities, thus: scope/level is a derived or secondary feature in the classification scheme.

Refined taxonomy

- Combinations of types and evidences
  - Possible: +
  - Impossible: -

	Deterministic	Adaptive	Self-adaptive
Absolute	+	+	-
Relative	-	+	+

Evaluation / Summary

- Parameter control offers the possibility to use appropriate values in various stages of the search
- Adaptive and self-adaptive parameter control
  - offer users "liberation" from parameter tuning
  - delegate parameter setting task to the evolutionary process
  - the latter implies a double task for an EA: problem solving + self-calibrating (overhead)
- Robustness, insensitivity of EA for variations assumed
  - If no. of parameters is increased by using (self)adaptation
  - For the "meta-parameters" introduced in methods