

Evolutionary Computation: A Unified Approach

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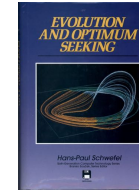
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Historical roots:

- **Evolution Strategies (ESs):**

- developed by Rechenberg, Schwefel, etc. in 1960s.
- focus: real-valued parameter optimization
- individual: vector of real-valued parameters
- reproduction: Gaussian “mutation” of parameters
- M parents, $K \gg M$ offspring

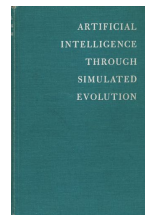


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Historical roots:

- **Evolutionary Programming (EP):**

- Developed by Fogel et al in 1960s
- Goal: evolve intelligent behavior
- Individuals: finite state machines
- Offspring via mutation of FSMs
- M parents, M offspring

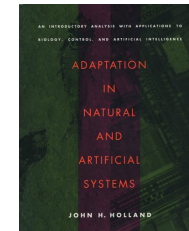


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Historical roots:

- **Genetic Algorithms (GAs):**

- developed by Holland in 1960s
- goal: robust, adaptive systems
- used an internal “genetic” encoding of points
- reproduction via mutation and recombination of the genetic code.
- M parents, M offspring



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By the year 2000:

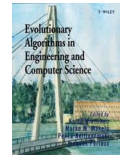
- A variety of evolutionary algorithms (EAs)
- A variety of applications:
 - optimization
 - search
 - learning, adaptation
- A variety of analysis tools:
 - theoretical
 - experimental



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Interesting dilemma:

- Lots of new and difficult application opportunities.
- A bewildering variety of algorithms and approaches:
 - GAs, ESs, EP, GP, ...
- Hard to see relationships, assess strengths & weaknesses, make choices, ...



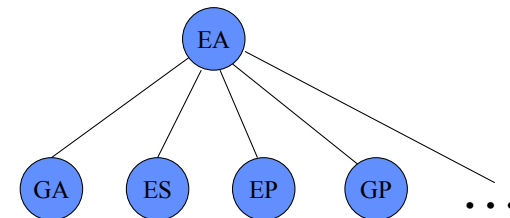
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A Personal Interest:

- Develop a general framework that:
 - Helps one compare and contrast approaches.
 - Encourages crossbreeding.
 - Facilitates intelligent design choices.

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Viewpoint:



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Starting point:

- Common features
- Basic definitions and terminology

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Common Features:

- Use of Darwinian-like evolutionary processes to solve difficult computational problems.
- Hence, the name:

Evolutionary Computation

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Key Element: An Evolutionary Algorithm

- Based on a Darwinian notion of an evolutionary system.
- Basic elements:
 - a population of “individuals”
 - a notion of “fitness”
 - a birth/death cycle biased by fitness
 - a notion of “inheritance”

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An EA template:

1. Randomly generate an initial population.
2. Do until some stopping criteria is met:
 - Select individuals to be parents (biased by fitness).
 - Produce offspring.
 - Select individuals to die (biased by fitness).
 - End Do.
3. Return a result.

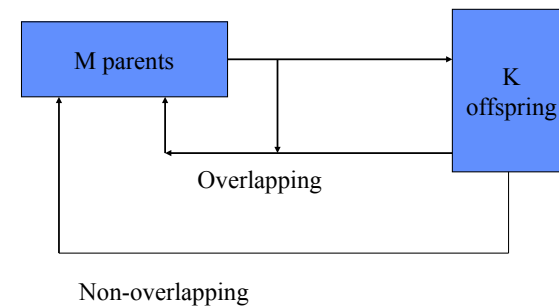
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Instantiate by specifying:

- Population dynamics:
 - Population size
 - Parent selection
 - Reproduction and inheritance
 - Survival competition
- Representation:
 - Internal to external mapping
- Fitness

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EA Population Dynamics:



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Population sizing:

- Parent population size **M**:
 - degree of parallelism
- Offspring population size **K**:
 - amount of activity w/o feedback

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Population sizing:

- Examples:
 - **M**=1, **K** small: early ESs
 - **M** small, **K** large: typical ESs
 - **M** moderate, **K**=**M**: traditional GAs and EP
 - **M** large, **K** small: steady state GAs
 - **M** = **K** large: traditional GP

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Selection pressure:

- Overlapping generations:
 - more pressure than non-overlapping
- Selection strategies (decreasing pressure):
 - truncation
 - tournament and ranking
 - fitness proportional
 - uniform
- Stochastic vs. deterministic

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Reproduction:

- Preserve useful features
- Introduce variety and novelty
- Strategies:
 - single parent: cloning + mutation
 - multi-parent: recombination + mutation
 - ...
- Price's theorem:
 - fitness covariance

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Exploitation/Exploration Balance:

- Selection pressure: exploitation
 - reduce scope of search
- Reproduction: exploration
 - expand scope of search
- Key issue: appropriate balance
 - e.g., strong selection + high mutation rates
 - e.g., weak selection + low mutation rates

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Representation:

- How to represent the space to be searched?
 - **Genotypic** representations:
 - universal encodings
 - portability
 - minimal domain knowledge

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Representation:

- How to represent the space to be searched?
 - **Phenotypic** representations:
 - problem-specific encodings
 - leverage domain knowledge
 - lack of portability

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Fitness landscapes:

- Continuous/discrete
- Number of local/global peaks
- Ruggedness
- Constraints
- Static/dynamic

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The Art of EC:

- Choosing problems that make sense.
- Choosing an appropriate EA:
 - reuse an existing one
 - hand-craft a new one

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EC: Using EAs to Solve Problems

- What kinds of problems?
- What kinds of EAs?

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Intuitive view:

- Parallel, adaptive search procedure.
- Useful global search heuristic.
- A paradigm that can be instantiated in a variety of ways.
- Can be very general or problem specific.
- Strong sense of fitness “optimization”.

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Evolutionary Optimization:

- **Fitness:** function to be optimized
- **Individuals:** points in the space
- **Reproduction:** generating new sample points from existing ones.

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Useful Optimization Properties:

- Applicable to continuous, discrete, mixed optimization problems.
- No *a priori* assumptions about convexity, continuity, differentiability, etc.
- Relatively insensitive to noise.
- Easy to parallelize.

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Real-valued Param. Optimization:

- High dimensional problems
- Highly multi-modal problems
- Problems with non-linear constraints

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Discrete Optimization:

- TSP problems
- Boolean satisfiability problems
- Frequency assignment problems
- Job shop scheduling problems

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Multi-objective Optimization:

- Pareto optimality problems
- A variety of difficult industrial problems

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Properties of standard EAs:

- **GAs:**
 - universality encourages new applications
 - well-balanced for global search
 - requires mapping to internal representation

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Properties of standard EAs:

- **ESs:**
 - well-suited for real-valued optimization.
 - built-in self-adaptation.
 - requires significant redesign for other application areas.

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Properties of standard EAs:

- **EP:**
 - well-suited for phenotypic representations.
 - encourages domain-specific representation and operators.
 - requires significant design for each application area.

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Other EAs:

- **GP: (Koza)**
 - standard GA population dynamics
 - individuals: parse trees of Lisp code
 - large population sizes
 - specialized crossover
 - minimal mutation

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Other EAs:

- **CMA-ESs: (Hansen et al)**
 - **C**ovariance **M**atrix **A**daptation
 - ES variation to deal with parameter interactions
 - Maintains/updates matrix used to help generate useful offspring.

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Other EAs:

- **(m,k)EAs: (Wegener et al)**
 - Combines ES dynamics with GA representation and operators:
 - Binary representations
 - Bit-flip mutation
 - Applied to discrete optimization problems
 - Simplicity yields strong convergence proofs

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Other EAs:

- Differential Evolution: (Storn & Price)
 - Specifically for continuous function optimization
 - $K=1$ offspring
 - overlapping generations
 - parent selection: deterministic
 - 1 offspring via crossover with a 3-parent combo
 - survival selection: parent vs. offspring

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Other EAs:

- Messy GAs (Goldberg)
- Genitor (Whitley)
- Genocop (Michalewicz)
- CHC (Eschelman et al)
- Geometric Semantic GP: (Moraglio et al)
- Gene Expression Programming (Ferreira)
- Neuroevolution (Stanley)
- ...

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Designing an EA:

- Choose an appropriate representation
 - effective building blocks
 - semantically meaningful subassemblies
- Choose effective reproductive operators
 - fitness covariance

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Designing an EA:

- Choose appropriate selection pressure
 - local vs. global search
- Choosing a useful fitness function
 - exploitable information

Result: a well-designed EA

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The Present ...

- New applications pressing state of the art.
- Unified view of “simple EAs” is not sufficient.
- Principled extensions are required.

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Broader Problem domains:

- **Objects to be evolved:**
 - Parameter values
 - Non-linear structures
 - Variable-size structures
 - Executable programs
- **Goals:**
 - Optimization (single, multiple objectives)
 - Adaptation (tracking, tuning)
 - Learning (induction, prediction)

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Example: Evolving NLP Tagging Rules

- **Given:**
 - Existing tagging engine
 - Existing rule syntax
 - Existing rule semantics
- **Goal:**
 - Improve development time for new domains. by evolving tagging rule sets.
 - Improve tagging accuracy.

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Example: Adaptive Testing

- **How to validate complex systems?**
 - Prove theorems?
 - Develop test suites?
 - Hire test engineers?
- **Interesting alternative:**
 - Use EAs to **search scenario spaces**.
 - Scenario's fitness related to the difficulties it creates.
 - **Testing autonomous vehicle controllers**

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Example: Evolving agent behavior

- Evolve interesting/robust behavior for:
 - Web crawlers
 - Teams of robots
 - Stock market trading programs
 - War games: semi-automated forces
 - ...

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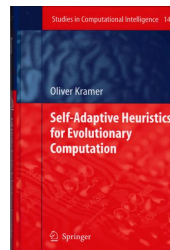
To Repeat ...

- Unified view of “simple EAs” is not sufficient.
- Principled extensions are required.

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EC extensions:

- Reduced knob twiddling:
 - To “get it right” we:
 - vary population size
 - vary selection pressure
 - vary representation
 - vary reproductive operators
 - Far better to have:
 - Principled choices
 - Self-adapting mechanisms



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EC extensions:

- Automated EA Design:
 - Meta-heuristics
 - Hyper-heuristics
 - ...



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EC extensions:

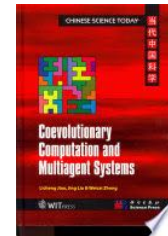
- Exploiting parallelism:
 - Low hanging fruit: parallel evaluation
 - Tougher challenges:
 - coarsely grained network models
 - isolated islands with occasional migrations
 - finely grained diffusion models
 - continuous interaction in local neighborhoods



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EC extensions:

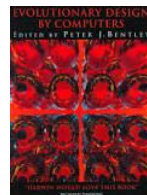
- Understanding co-evolutionary models:
 - Competitive co-evolution
 - improve performance via “arms race”
 - Cooperative co-evolution
 - evolve subcomponents in parallel
 - Agent-oriented models



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EC extensions:

- Evolutionary Design:
 - Exploring design spaces
 - Exploiting morphogenesis:
 - Sophisticated genotype --> phenotype mappings
 - Evolve plans for generating objects
 - Evolutionary art, music, ...



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EC extensions:

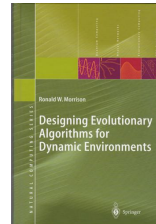
- Understand multi-objective optimization better:
 - Standard feature of industrial problems.
 - Goal: find a set of non-dominated alternatives.
 - Considerable progress already.
 - Need a deeper theoretical understanding.



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EC extensions:

- Understand time-varying environments better:
 - Fitness landscape changes during evolution
 - Goal: adaptation, tracking
 - Considerable progress already
 - Need deeper theoretical understanding



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EC extensions:

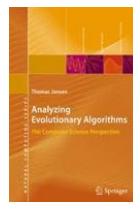
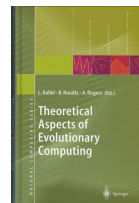
- Agent-oriented problems:
 - Individuals more autonomous, active
 - Fitness is a function of other agents and environment-altering actions
 - E.g.,
 - Evolutionary Robotics
 - HIV evolution
 - Evolution of cooperation



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EC extensions:

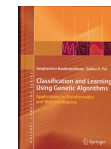
- Need stronger analysis tools:
 - Markov models
 - Statistical mechanics
 - Evolutionary game theory
 - Test problem generators
 - Visualization



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EC extensions:

- Need better hybrid systems:
 - Memetic algorithms: EAs and local search
 - EAs and ANNs
 - EAs and machine learning
 - EAs and agent-based models
 - ...



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The Future ...

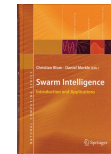
- Continuing development of extensions
- Expanding contact with other communities:
 - Heuristic search
 - AI
 - Optimization
 - Automated design
 - ...

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Broader picture:

“Natural Computation”

- Computational models inspired by nature:
 - Evolutionary computation
 - Simulated annealing
 - Ant colony optimization
 - Particle swarm optimization
 - Artificial neural networks
 - Artificial immune systems
 - ...

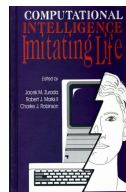
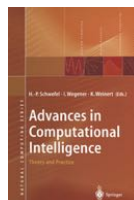


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Broader picture:

“Computational Intelligence”

- Preferred by many over “Artificial Intelligence”
 - Evolutionary computation
 - Fuzzy systems
 - Artificial neural networks
 - ...



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Conclusions:

- Powerful tool for your toolbox.
- Complements other techniques.
- Best viewed as a paradigm to be instantiated, guided by theory and practice.
- Success a function of particular instantiation.

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More information:

- Journals:
 - Evolutionary Computation (MIT Press)
 - Trans. on Evolutionary Computation (IEEE)
 - Genetic Programming & Evolvable Hardware
- Conferences:
 - GECCO, CEC, PPSN, FOGA, ...
- Internet:
 - www.cs.gmu.edu/~eclab
- My book:
 - Evolutionary Computation: A Unified Approach
 - MIT Press

