

Evolutionary Computation: A Unified Approach

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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 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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Present Status:

- wide variety of evolutionary algorithms (EAs)
- wide variety of applications
 - optimization
 - search
 - learning, adaptation
- well-developed analysis
 - theoretical
 - experimental

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Interesting dilemma:

- A bewildering variety of algorithms and approaches:
 - GAs, ESs, EP, GP, Genitor, CHC, messy GAs, ...
- Hard to see relationships, assess strengths & weaknesses, make choices, ...

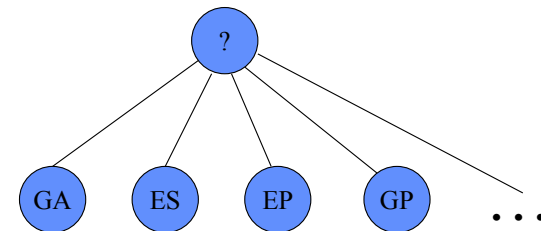
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A Personal Interest:

- 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.

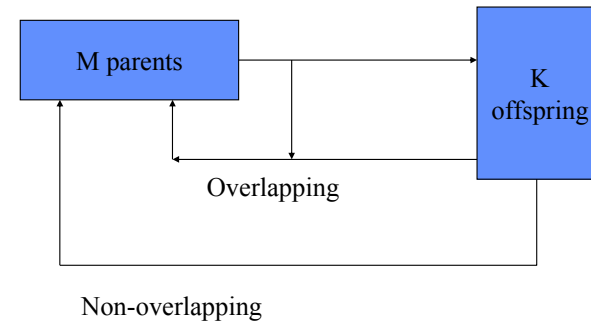
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Instantiate by specifying:

- 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 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:

- **GENITOR: (Whitley)**
 - “steady state” population dynamics
 - $K=1$ offspring
 - overlapping generations
 - parent selection: ranking
 - survival selection: ranking
 - large population sizes
 - high mutation rates

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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:

- **Messy GAs: (Goldberg)**
 - Standard GA population dynamics
 - Adaptive binary representation
 - genes are position-independent

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Other EAs:

- GENOCOP: (Michalewicz)
 - Standard GA population dynamics
 - Specialized representation & operators for real valued constrained optimization problems.

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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

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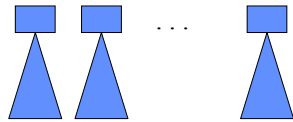
Industrial Example: Evolving NLP Tagging Rules

- Existing tagging engine
- Existing rule syntax
- Existing rule semantics
- Goal: improve
 - development time for new domains
 - tagging accuracy

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Evolving NLP Tagging Rules

- Representation: (first thoughts)
 - variable length list of GP-like trees

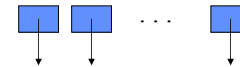


- Difficulty: effective operators

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Evolving NLP Tagging Rules

- Representation: (second thoughts)
 - variable length list of pointers to rules



- Operators:
 - mutation: permute, delete rules
 - recombination: exchange rule subsets
 - Lamarckian: add a new rule

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Evolving NLP Tagging Rules

- Population dynamics:
 - multi-modal: $M > \text{small}$
 - typical: 30-50
 - high operator variance: $K/M > 1$
 - typical: 3-5 : 1
 - parent selection: uniform
 - survival selection: binary tournament

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Evolving NLP Tagging Rules

- So, what is this thing?
 - A GA, ES, EP, ...
- My answer:
 - a thoughtfully designed EA

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Analysis tools:

- Schema analysis
- Convergence analysis
- Markov models
- Statistical Mechanics
- Visualization

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New developments and directions:

- Exploiting parallelism:
 - coarsely grained network models
 - isolated islands with occasional migrations
 - finely grained diffusion models
 - continuous interaction in local neighborhoods

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New developments and directions:

- Co-evolutionary models:
 - competitive co-evolution
 - improve performance via “arms race”
 - cooperative co-evolution
 - evolve subcomponents in parallel

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New developments and directions:

- Exploiting Morphogenesis:
 - sophisticated genotype --> phenotype mappings
 - evolve plans for building complex objects rather than the objects themselves.

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New developments and directions:

- Self-adaptive EAs:

- dynamically adapt to problem characteristics:
 - varying population size
 - varying selection pressure
 - varying representation
 - varying reproductive operators
- goal: robust “black box” optimizer

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New developments and directions:

- Hybrid Systems:

- combine EAs with other techniques:
 - EAs and gradient methods
 - EAs and TABU search
 - EAs and ANNs
 - EAs and symbolic machine learning

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New developments and directions:

- Time-varying environments:

- fitness landscape changes during evolution
- goal: adaptation, tracking
- standard optimization-oriented EAs not well-suited for this.

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New developments and directions:

- Agent-oriented problems:

- individuals more autonomous, active
- fitness a function of other agents and environment-altering actions
- standard optimization-oriented EAs not well-suited for this.

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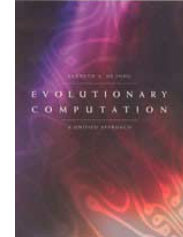
Conclusions:

- 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, 2006



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