

## 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**>>**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, ...

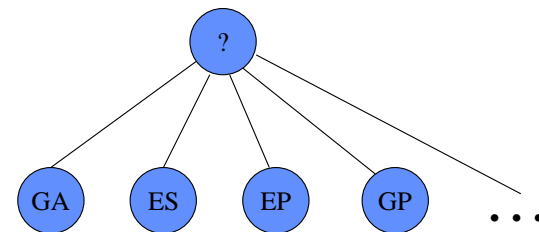
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## A Personal Interest:

- 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.

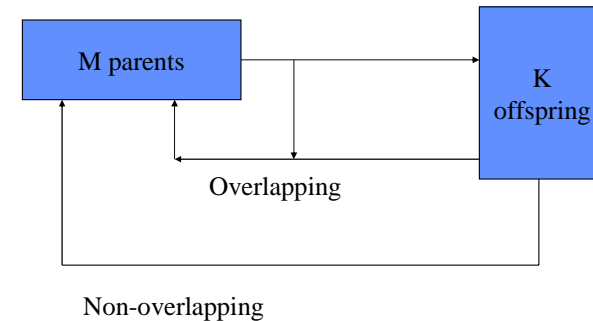
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## Instantiate by specifying:

- 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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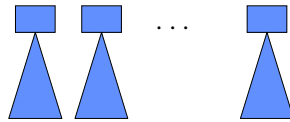
## Industrial Example: Evolving NLP Tagging Rules

- 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

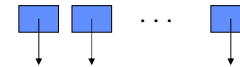


- Difficulty: effective operators

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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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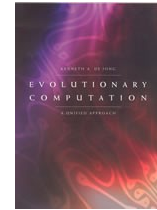
## Conclusions:

- 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](http://www.cs.gmu.edu/~eclab)
  - [www.aic.nrl.navy.mil/galist](http://www.aic.nrl.navy.mil/galist)
- **My book:**
  - Evolutionary Computation: A Unified Approach
    - MIT Press, 2006



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