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

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

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

Present Status:

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

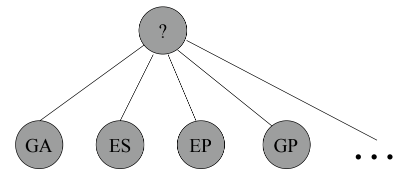
Interesting dilemma:

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

A Personal Interest:

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

Viewpoint:



Starting point:

- Common features
- Basic definitions and terminology

Common Features:

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

Evolutionary Computation

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”

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.

Instantiate by specifying:

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

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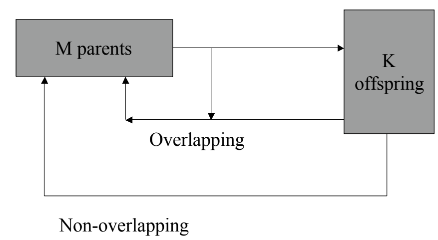
EA Population Dynamics:



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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

Representation:

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

Representation:

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

Fitness landscapes:

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

The Art of EC:

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

EC: Using EAs to Solve Problems

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

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”.

Evolutionary Optimization:

- fitness: function to be optimized
- individuals: points in the space
- reproduction: generating new sample points from existing ones.

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

Real-valued Param. Optimization:

- high dimensional problems
- highly multi-modal problems
- problems with non-linear constraints

Discrete Optimization:

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

Multi-objective Optimization:

- Pareto optimality problems
- a variety of industrial problems

Properties of standard EAs:

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

Properties of standard EAs:

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

Properties of standard EAs:

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

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

Other EAs:

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

Other EAs:

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

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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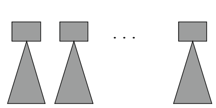
Evolving NLP Tagging Rules

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



- Difficulty: effective operators

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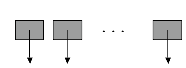
Evolving NLP Tagging Rules

- 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 > small
    - typical: 30-50
  - high operator variance: K/M > 1
    - typical: 3-5 : 1
  - parent selection: uniform
  - survival selection: binary tournament

Evolving NLP Tagging Rules

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

Analysis tools:

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

New developments and directions:

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

New developments and directions:

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

New developments and directions:

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

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

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

New developments and directions:

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

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.

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.

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
  - www.aic.nrl.navy.mil/galist
- New book:
  - Evolutionary Computation: A Unified Approach
    - Kenneth De Jong, MIT Press, 2004-2005