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, …

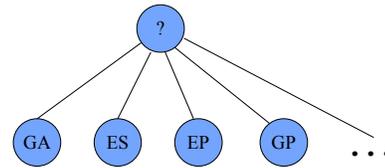- Hard to see relationships, assess strengths & weaknesses, make choices, ...

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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).
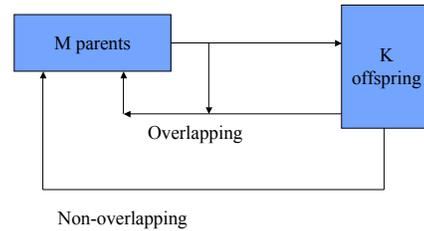
   End Do.

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:

Non-overlapping

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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
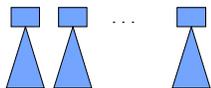 – exploitable information

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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
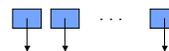

- Difficulty: effective operators

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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 > 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
  - www.aic.nrl.navy.mil/galist
- New book:
  - Evolutionary Computation: A Unified Approach
    - Kenneth De Jong, MIT Press, 2006

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