Evolutionary Programming

Lecture 5

MONASH UNIVERSITY CLAYTON'S SCHOOL OF INFORMATION TECHNOLOGY

EP quick overview

Reading: Eiben& Smith Chapter 5

- Developed: USA in the 1960's
- Early names: D. Fogel
- Typically applied to:
  - traditional EP: machine learning tasks by finite state machines
  - contemporary EP: (numerical) optimization
- Attributed features:
  - very open framework: any representation and mutation op's OK
  - crossbred with ES (contemporary EP)
  - consequently: hard to say what "standard" EP is
- Special:
  - no recombination
  - self-adaptation of parameters standard (contemporary EP)

EP technical summary tableau

Representation	Real-valued vectors
Recombination	None
Mutation	Gaussian perturbation
Parent selection	Deterministic
Survivor selection	Probabilistic (μ+μ)
Specialty	Self-adaptation of mutation step sizes (in meta-EP)

Historical EP perspective

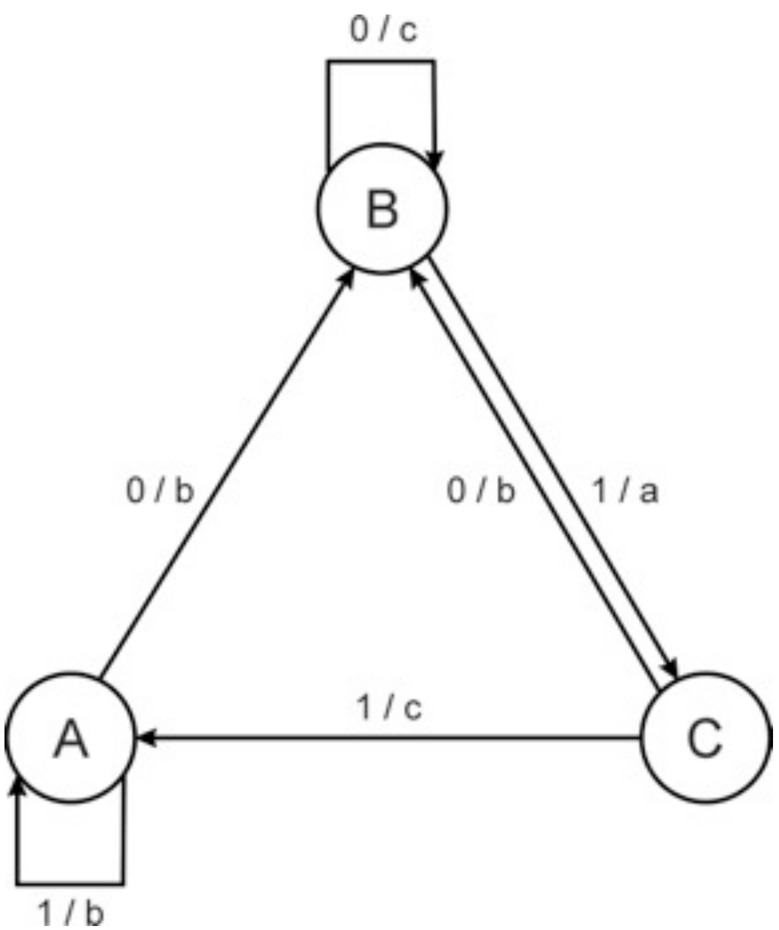
- EP aimed at achieving intelligence
- Intelligence was viewed as adaptive behaviour
- Prediction of the environment was considered a prerequisite to adaptive behaviour
- Thus: capability to predict is key to intelligence

Prediction by finite state machines

- Finite state machine (FSM):
  - States S
  - Inputs I
  - Outputs O
  - Transition function $\delta : S \times I \rightarrow S \times O$
  - Transforms input stream into output stream
- Can be used for predictions, e.g. to predict next input symbol in a sequence

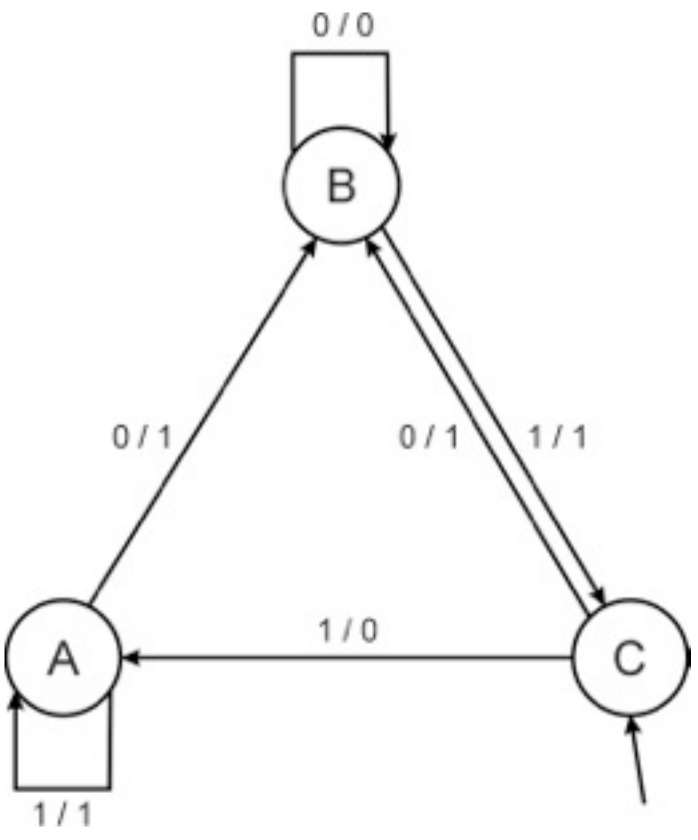
FSM example

- Consider the FSM with:
  - S = {A, B, C}
  - I = {0, 1}
  - O = {a, b, c}
  - δ given by a diagram



FSM as predictor

- Consider the following FSM
- Task: predict next input
- Quality: % of $in_{(i+1)} = out_i$
- Given initial state C
- Input sequence 011101
- Leads to output 110111
- Quality: 3 out of 5



Introductory example:

- $P(n) = 1$ if n is prime, 0 otherwise
- $I = \boldsymbol{N} = \{1,2,3,\ldots, n, \ldots\}$
- $O = \{0,1\}$
- Correct prediction: $out_i = P(in_{(i+1)})$
- Fitness function:
  - 1 point for correct prediction of next input
  - 0 point for incorrect prediction
  - Penalty for “too many” states

Introductory example:

- Parent selection: each FSM is mutated once
- Mutation operators (one selected randomly):
  - Change an output symbol
  - Change a state transition (i.e. redirect edge)
  - Add a state
  - Delete a state
  - Change the initial state
- Survivor selection: $(\mu+\mu)$
- Results: overfitting, after 202 inputs best FSM had one state and both outputs were 0, i.e., it always predicted “not prime”

Modern EP

- No predefined representation in general
- Thus: no predefined mutation (must match representation)
- Often applies self-adaptation of mutation parameters
- In the sequel we present *one EP variant*, not the canonical EP

Representation

- For continuous parameter optimisation
- Chromosomes consist of two parts:
  - Object variables: $x_1,\ldots,x_n$
  - Mutation step sizes: $\sigma_1,\ldots,\sigma_n$
- Full size: $\langle x_1,\ldots,x_n, \sigma_1,\ldots,\sigma_n \rangle$

Mutation

- Chromosomes: $\langle x_1,\dots,x_n, \sigma_1,\dots,\sigma_n \rangle$
- $\sigma_i' = \sigma_i \bullet (1 + \alpha \bullet N(0,1))$
- $x'_i = x_i + \sigma_i' \bullet N_i(0,1)$
- $\alpha \approx 0.2$
- boundary rule: $\sigma' < \varepsilon_0 \Rightarrow \sigma' = \varepsilon_0$
- Other variants proposed & tried:
  - Lognormal scheme as in ES
  - Using variance instead of standard deviation
  - Mutate σ-last
  - Other distributions, e.g, Cauchy instead of Gaussian

Recombination

- None
- Rationale: one point in the search space stands for a species, not for an individual and there can be no crossover between species
- Much historical debate "mutation vs. crossover"
- Pragmatic approach seems to prevail today

Parent selection

- Each individual creates one child by mutation
- Thus:
  - Deterministic
  - Not biased by fitness

Survivor selection

- P(t): μ parents, P′(t): μ offspring
- Pairwise competitions in round-robin format:
  - Each solution x from P(t) ∪ P′(t) is evaluated against q other randomly chosen solutions
  - For each comparison, a "win" is assigned if x is better than its opponent
  - The μ solutions with the greatest number of wins are retained to be parents of the next generation
- Parameter q allows tuning selection pressure
- Typically $q = 10$

Example application: the Ackley function (Bäck et al '93)

- The Ackley function (here used with n =30):

$$f(\bar{x}) = -20 \cdot \exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$$

- Representation:
  - $-30 < x_i < 30$ (coincidence of 30's!)
  - 30 variances as step sizes
- Mutation with changing object variables first !
- Population size $\mu = 200$, selection with $q = 10$
- Termination : after 200000 fitness evaluations
- Results: average best solution is $1.4 \cdot 10^{-2}$

Example application: evolving checkers players (Fogel'02)

- Neural nets for evaluating future values of moves are evolved
- NNs have fixed structure with 5046 weights, these are evolved + one weight for "kings"
- Representation:
  - vector of 5046 real numbers for object variables (weights)
  - vector of 5046 real numbers for σ's
- Mutation:
  - Gaussian, lognormal scheme with σ-first
  - Plus special mechanism for the kings' weight
- Population size 15

Example application: evolving checkers players (Fogel'02)

- Tournament size q = 5
- Programs (with NN inside) play against other programs, no human trainer or hard-wired intelligence
- After 840 generation (6 months!) best strategy was tested against humans via Internet
- Program earned "expert class" ranking outperforming 99.61% of all rated players