V. Evolutionary Computing

A. Genetic Algorithms
Read Flake, ch. 20
Genetic Algorithms

• Developed by John Holland in ‘60s
• Did not become popular until late ‘80s
• A simplified model of genetics and evolution by natural selection
• Most widely applied to optimization problems (maximize “fitness”)
Assumptions

• Existence of fitness function to quantify merit of potential solutions
  – This “fitness” is what the GA will maximize

• A mapping from bit-strings to potential solutions
  – best if each possible string generates a legal potential solution
  – choice of mapping is important
  – can use strings over other finite alphabets
Outline of Simplified GA

1. Random initial population $P(0)$

2. Repeat for $t = 0, \ldots, t_{\text{max}}$ or until converges:
   a) create empty population $P(t + 1)$
   b) repeat until $P(t + 1)$ is full:
      1) select two individuals from $P(t)$ based on fitness
      2) optionally mate & replace with offspring
      3) optionally mutate offspring
      4) add two individuals to $P(t + 1)$
Fitness-Biased Selection

- Want the more “fit” to be more likely to reproduce
  - always selecting the best
    $\Rightarrow$ premature convergence
  - probabilistic selection $\Rightarrow$ better exploration
- Roulette-wheel selection: probability $\propto$ relative fitness:
  \[
  \Pr\{i \text{ mates}\} = \frac{f_i}{\sum_{j=1}^{n} f_j}
  \]
Crossover: Biological Inspiration

- Occurs during meiosis, when haploid gametes are formed
- Randomly mixes genes from two parents
- Creates genetic variation in gametes

(fig. from B&N Thes. Biol.)
GAs: One-point Crossover

parents

offspring
GAs: Two-point Crossover

parents

offspring
GAs: $N$-point Crossover

parents

offspring
Mutation: Biological Inspiration

- **Chromosome mutation** ⇒
- **Gene mutation**: alteration of the DNA in a gene
  - inspiration for mutation in GAs
- In typical GA each bit has a low probability of changing
- Some GAs models rearrange bits

(fig. from B&N Thes. Biol.)
The Red Queen Hypothesis

• *Observation*: a species probability of extinction is independent of time it has existed

• *Hypothesis*: species continually adapt to each other

• Extinction occurs with insufficient variability for further adaptation

“Now, *here*, you see, it takes all the running *you* can do, to keep in the same place.”
— *Through the Looking-Glass and What Alice Found There*
Demonstration of GA:
Finding Maximum of Fitness Landscape

Run Genetic Algorithms — An Intuitive Introduction
by Pascal Glauser
<www.glauserweb.ch/gentore.htm>
Demonstration of GA: Evolving to Generate a Pre-specified Shape (Phenotype)

Run Genetic Algorithm Viewer
<www.rennard.org/alife/english/gavgb.html>
Eaters Seeking Food

• Eaters are FSMs
• Have internal state (memory): 0..15.
• Can sense one square ahead.
• It can see one of four different things: an Eater, a plant, a blank space, or a wall.
• On basis of the above, can change state and:
  – 1. Move forward one square
  – 2. Move backwards one square
  – 3. Turn in place 90 degrees to the left
  – 4. Turn in place 90 degrees to the right.
• If lands on a square with food, it eats it.
Demonstration of GA: Eaters Seeking Food

http://math.hws.edu/eck/js/genetic-algorithm/GA.html
Morphology Project
by Michael “Flux” Chang

• Senior Independent Study project at UCLA
  – users.design.ucla.edu/~mflux/morphology

• Researched and programmed in 10 weeks

• Programmed in Processing language
  – www.processing.org

Note: Safari works, but perhaps not other browsers!
Genotype $\Rightarrow$ Phenotype

- Cells are “grown,” not specified individually
- Each gene specifies information such as:
  - angle
  - distance
  - type of cell
  - how many times to replicate
  - following gene

- Cells connected by “springs”

- Run **phenome**:  
  <users.design.ucla.edu/~mflux/morphology/gallery-sketches/phenome>
Complete Creature

• Neural nets for control (**blue**)
  – integrate-and-fire neurons
• Muscles (**red**)
  – Decrease “spring length” when fire
• Sensors (**green**)
  – fire when exposed to “light”
• Structural elements (**grey**)
  – anchor other cells together
• Creature embedded in a fluid
• Run <users.design.ucla.edu/~mflux/morphology/gallery/sketches/creature>
Effects of Mutation

- Neural nets for control (blue)
- Muscles (red)
- Sensors (green)
- Structural elements (grey)
- Creature embedded in a fluid
- Run

<users.design.ucla.edu/~mflux/morphology/gallery.sketches/creaturepack>
• Population: 150–200
• Nonviable & nonresponsive creatures eliminated
• Fitness based on speed or light-following
• 30% of new pop. are mutated copies of best
• 70% are random
• No crossover
Gallery of Evolved Creatures

- Selected for speed of movement
- Run
  <users.design.ucla.edu/~mflux/morphology/gallery/sketches/creaturegallery>
Karl Sims’ Evolved Creatures (1994)
Winner of The Virtual Creatures Competition, GECCO, 2016
Why Does the GA Work?

The Schema Theorem
A schema is a description of certain patterns of bits in a genetic string.
The Fitness of Schemata

• The schemata are the **building blocks** of solutions

• We would like to know the average fitness of all possible strings belonging to a schema

• We cannot, but the strings in a population that belong to a schema give an estimate of the fitness of that schema

• Each string in a population is giving information about all the schemata to which it belongs (**implicit parallelism**)

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Effect of Selection

Let $n =$ size of population

Let $m(S,t) =$ number of instances of schema $S$ at time $t$

String $i$ gets picked with probability $\frac{f_i}{\sum_j f_j}$

Let $f(S) =$ avg fitness of instances of $S$ at time $t$

So expected $m(S,t + 1) = m(S,t) \cdot n \cdot \frac{f(S)}{\sum_j f_j}$

Since $f_{av} = \frac{\sum_j f_j}{n}$, $m(S,t + 1) = m(S,t) \cdot \frac{f(S)}{f_{av}}$
Exponential Growth

• We have discovered:
  \[ m(S, t+1) = m(S, t) \cdot \frac{f(S)}{f_{av}} \]

• Suppose \( f(S) = f_{av} (1 + c) \)

• Then \( m(S, t) = m(S, 0) (1 + c)^t \)

• That is, exponential growth in above-average schemata
Effect of Crossover

• Let $\lambda =$ length of genetic strings
• Let $\delta(S) =$ defining length of schema $S$
• Probability $\{\text{crossover destroys } S\}$:
  \[ p_d \leq \frac{\delta(S)}{(\lambda - 1)} \]
• Let $p_c =$ probability of crossover
• Probability schema survives:
  \[ p_s \geq 1 - p_c \frac{\delta(S)}{\lambda - 1} \]
Selection & Crossover Together

\[ m(S, t + 1) \geq m(S, t) \frac{f(S)}{f_{av}} \left[ 1 - p_c \frac{\delta(S)}{\lambda - 1} \right] \]
Effect of Mutation

• Let $p_m = \text{probability of mutation}$

• So $1 - p_m = \text{probability an allele survives}$

• Let $o(S) = \text{number of fixed positions in } S$

• The probability they all survive is
  
  \[(1 - p_m)^{o(S)}\]

• If $p_m \ll 1$, $(1 - p_m)^{o(S)} \approx 1 - o(S) p_m$
Schema Theorem:
“Fundamental Theorem of GAs”

\[ m(S, t + 1) \geq m(S, t) \frac{f(S)}{f_{av}} \left[ 1 - p_c \frac{\delta(S)}{\lambda - 1} - o(S) p_m \right] \]
The Bandit Problem

• Two-armed bandit:
  – random payoffs with (unknown) means $m_1, m_2$ and variances $\sigma_1^2, \sigma_2^2$
  – optimal strategy: allocate exponentially greater number of trials to apparently better lever

• $k$-armed bandit: similar analysis applies

• Analogous to allocation of population to schemata

• Suggests GA may allocate trials optimally
Goldberg’s Analysis of Competent & Efficient GAs
Paradox of GAs

• Individually uninteresting operators:
  – selection, recombination, mutation

• Selection + mutation ⇒ continual improvement

• Selection + recombination ⇒ innovation
  – fundamental to invention: generation vs. evaluation

• Fundamental intuition of GAs: the three work well together
Race Between Selection & Innovation: Takeover Time

- Takeover time $t^* = \text{average time for most fit to take over population}$
- Transaction selection: population replaced by $s$ copies of top $1/s$
- $s$ quantifies selective pressure
- Estimate $t^* \approx \ln n / \ln s$
Innovation Time

• Innovation time $t_i = \text{average time to get a better individual through crossover \& mutation}$

• Let $p_i = \text{probability a single crossover produces a better individual}$

• Number of individuals undergoing crossover $= p_c n$

• Number of probable improvements $= p_i p_c n$

• Estimate: $t_i \approx 1 / (p_c p_i n)$
Steady State Innovation

• Bad: $t^* < t_i$
  – because once you have takeover, crossover does no good

• Good: $t_i < t^*$
  – because each time a better individual is produced, the $t^*$ clock resets
  – *steady state innovation*

• Innovation number:

$$I_v = \frac{t^*}{t_i} = p_c p_i \frac{n \ln n}{\ln s} > 1$$
Feasible Region

- Selection pressure
- Crossover probability
- Drift boundary
- Schema theorem boundary
- Mixing boundary
- Cross-competition boundary
- Successful genetic algorithm
Other Algorithms Inspired by Genetics and Evolution

• Evolutionary Programming
  – natural representation, no crossover, time-varying continuous mutation

• Evolutionary Strategies
  – similar, but with a kind of recombination

• Genetic Programming
  – like GA, but program trees instead of strings

• Classifier Systems
  – GA + rules + bids/payments

• and many variants & combinations…
Additional Bibliography
