

B. Genetic Algorithms

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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")

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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

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Outline of Simplified GA

1. Random initial population $P(0)$
2. Repeat for $t = 0, \dots, t_{\max}$ 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 $P(t + 1)$

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Fitness-Biased Selection

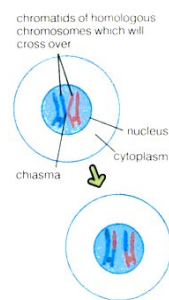
- Want the more "fit" to be more likely to reproduce
 - always selecting the best
⇒ premature convergence
 - probabilistic selection ⇒ better exploration
- Roulette-wheel selection: probability \propto relative fitness:

$$\Pr\{i \text{ mates}\} = \frac{f_i}{\sum_{j=1}^n f_j}$$

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Crossover: Biological Inspiration

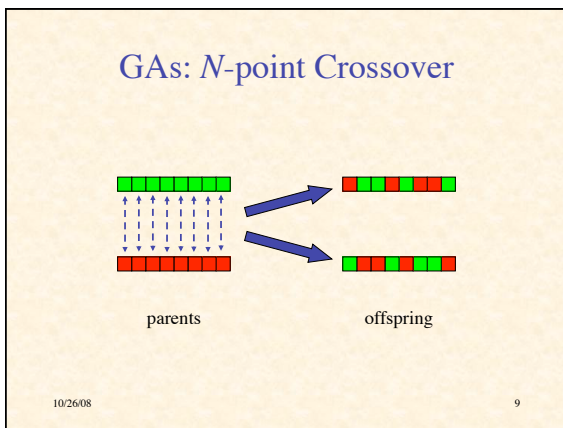
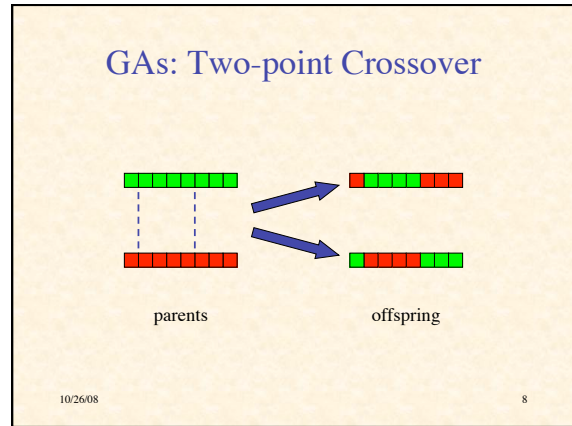
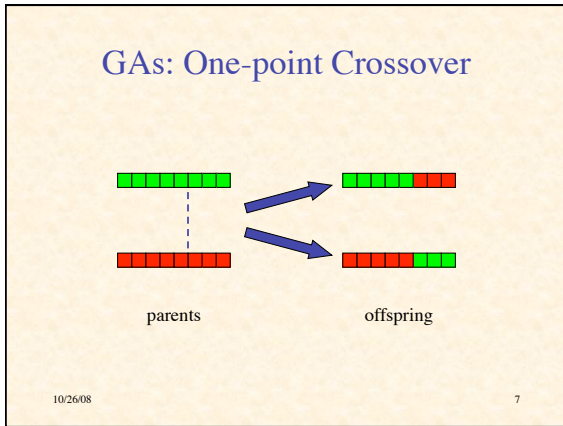


- Occurs during meiosis, when haploid gametes are formed
- Randomly mixes genes from two parents
- Creates genetic variation in gametes

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(fig. from B&N Thes. Biol.)

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Mutation: Biological Inspiration

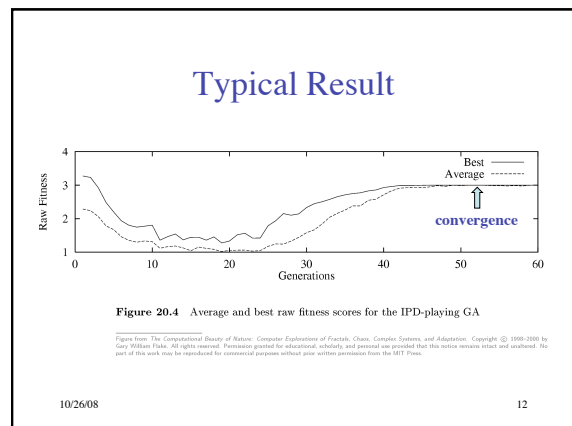
- **Chromosome mutation** ⇒
- **Gene mutation:** alteration of the DNA in a gene
 - inspiration for mutation in GAs
- In typical GA each bit has a low probability of changing
- Some GAs rearrange bits

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Example: GA for IPD

- Genetic strings encode strategy
 - for first round
 - based on self's & opponent's action on r previous rounds
 - hence $2^{2r} + 1$ bits
- E.g., for $r = 1$:

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The Red Queen Hypothesis



“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*

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- *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

Reading

- Read Flake, ch. 17, “Competition & Cooperation”

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Demonstration of GA: Finding Maximum of Fitness Landscape

[Run Genetic Algorithms — An Intuitive Introduction](#)
by Pascal Glauser
<www.glauserweb.ch/gentore.htm>

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Demonstration of GA: Evolving to Generate a Pre-specified Shape (Phenotype)

[Run Genetic Algorithm Viewer](#)
<www.rennard.org/alife/english/gavgb.html>

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Demonstration of GA: Eaters Seeking Food

<http://math.hws.edu/xJava/GA/>

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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

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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

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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

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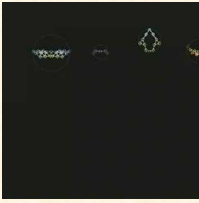
Effects of Mutation

- 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

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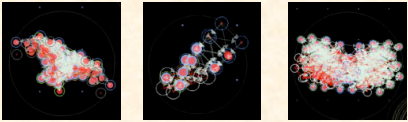
Evolution

- 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



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Gallery of Evolved Creatures



- Selected for speed of movement
- Run
users.design.ucla.edu/~mflux/morphology/gallery/sketches/creaturegallery

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Why Does the GA Work?

The Schema Theorem

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Schemata

A **schema** is a description of certain patterns of bits in a genetic string

a schema describes many strings
a string belongs to many schemata

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

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Exponential Growth

- We have discovered:
 $m(S, t+1) = m(S, t) \cdot f(S) / f_{av}$
- 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

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Effect of Crossover

- Let λ = length of genetic strings
- Let $\delta(S)$ = defining length of schema S
- Probability {crossover destroys S }:
 $p_d \leq \delta(S) / (\lambda - 1)$
- Let p_c = probability of crossover
- Probability schema survives:

$$p_s \geq 1 - p_c \frac{\delta(S)}{\lambda - 1}$$

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Selection & Crossover Together

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

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Effect of Mutation

- Let p_m = probability of mutation
- So $1 - p_m$ = probability an allele survives
- Let $o(S)$ = number of fixed positions in S
- The probability they all survive is $(1 - p_m)^{o(S)}$
- If $p_m \ll 1$, $(1 - p_m)^{o(S)} \approx 1 - o(S)p_m$

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Schema Theorem: “Fundamental Theorem of GAs”

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

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The Bandit Problem

- Two-armed bandit:
 - random payoffs with (unknown) means m_1, m_2 and variances σ_1, σ_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

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Goldberg’s Analysis of Competent & Efficient GAs

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Paradox of GAs

- Individually uninteresting operators:
 - selection, recombination, mutation
- Selection + mutation \Rightarrow continual improvement
- Selection + recombination \Rightarrow innovation
 - fundamental to invention:
generation vs. evaluation
- Fundamental intuition of GAs: the three work well together

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Race Between Selection & Innovation: Takeover Time

- Takeover time t^* = 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 $t^* \approx \ln n / \ln s$

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Innovation Time

- Innovation time t_i = average time to get a better individual through crossover & mutation
- Let p_i = probability a single crossover produces a better individual
- Number of individuals undergoing crossover = $p_c n$
- Probability of improvement = $p_i p_c n$
- Estimate: $t_i \approx 1 / (p_c p_i n)$

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Steady State Innovation

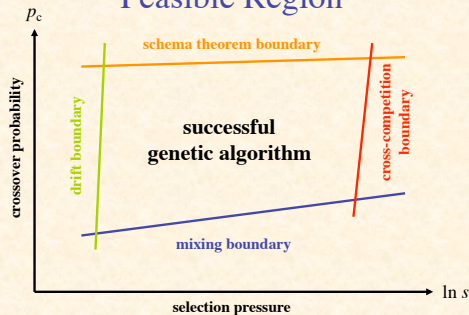
- Bad: $t^* < t_i$
 - because once you have takeover, crossover does no good
- Good: $t_i < t^*$
 - because each time a better individual is produced, the t^* clock resets
 - *steady state innovation*
- Innovation number:

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

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Feasible Region



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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...

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Additional Bibliography

1. Goldberg, D.E. *The Design of Innovation: Lessons from and for Competent Genetic Algorithms*. Kluwer, 2002.
2. Milner, R. *The Encyclopedia of Evolution*. Facts on File, 1990.



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