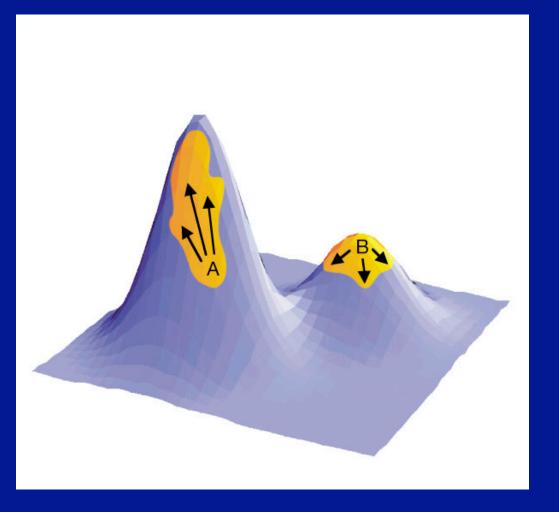
GENETIC ALGORITHMS





2 BOOKS FYI

- Mitchell, M. 1997. An Introduction to Genetic Algorithms.
- Goldberg, D.E. 1989. Genetic algorithms in search, optimization, and machine learning.



A POINT

- Standard optimality models are tactical
- There are many problems in behavioral ecology where the payoff function depends upon the actions of others



A USEFUL ABILITY

• With GA'S we can determine the joint optimum for 2 or more traits i.e. the optimal (or stable) co-adaptive gene complex(es)



ALWAYS KEEP IN MIND

- GA processes are merely analogous to their organic evolutionary counterparts
- GA's are search algorithms that use structured random walks to identify optimal solutions



SOME GA PROJECTS

- Sex allocation decisions in plants Sargent
- Evolution of tolerance Robertson
- Growth polymorphisms under frequency dependent predation McGregor
- Evolution of asexuality Lalonde
- Frequency dependent life history decisions Bouskila
- Optimal signal decay rates Hoffmeister
- Evolution of deceit via mimicry Tyerman
- Malaria-mosquito co-evolution Anderson
- Spatially explicit predator-prey games Hoffmeister
- Evolution of solitary and gregarious parasitoids Vet

3 PARTS TO A GA

- Description of a population of genotypes (strategies) at Gen_x
- A procedure for assigning fitness values to the different genotypes
- A "mating" protocol within which genotypes may exchange information and contribute to Gen_x

THE CHROMOSOME

 Each chromosome (strategy) has one or more pieces that are analogs of genes



PHENOTYPIC VALUE

00010 equals 2
(ie. 0*16 + 0*8 + 0*4 + 1*2 + 0*1)

01001 equals 9
(ie. 0*16 + 1*8 + 0*4 + 0*2 + 1*1)

A QUESTION

- Why not just build a set of strategies 0 through 31 and let them duke it out - asexually (e.g. replicator dynamics)?
- A: The boolean structured chromosome provides for information exchange that facilitates development if novel solutions.

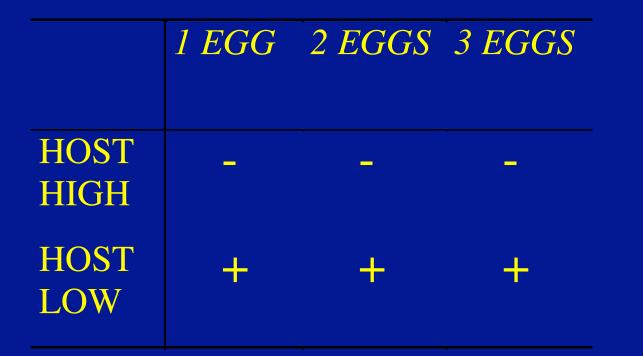


A FACT

• Every chromosome represents a unique strategy



HOW MANY STRATEGIES?



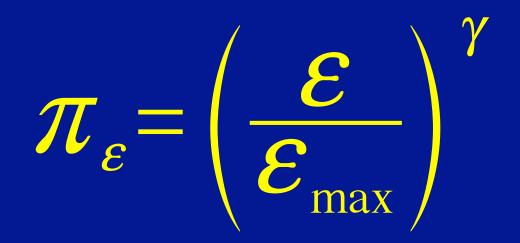
ANSWER $2^3 2^3 = 64$

A PROBLEM?

• If egg loads vary from 1 to 20 then there are there would be about one trillion unique strategies.

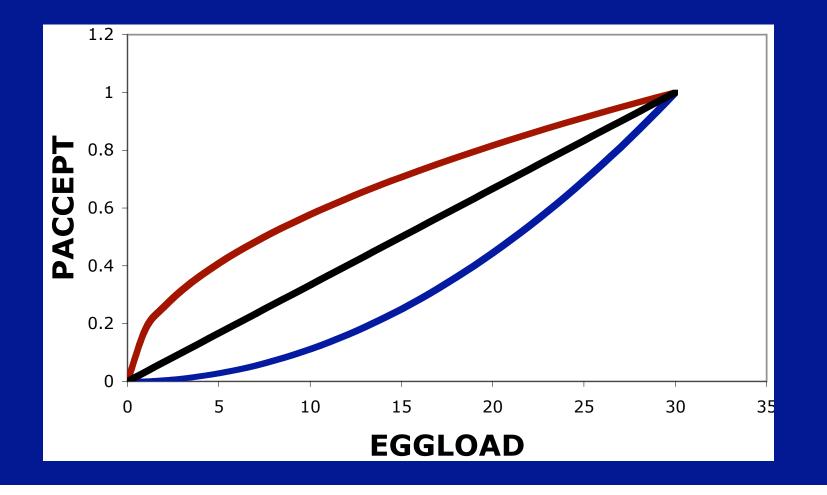


SOLUTION: GENOTYPE TENDENCY



Where: $\varepsilon = eggload$ and $\gamma = genotype$

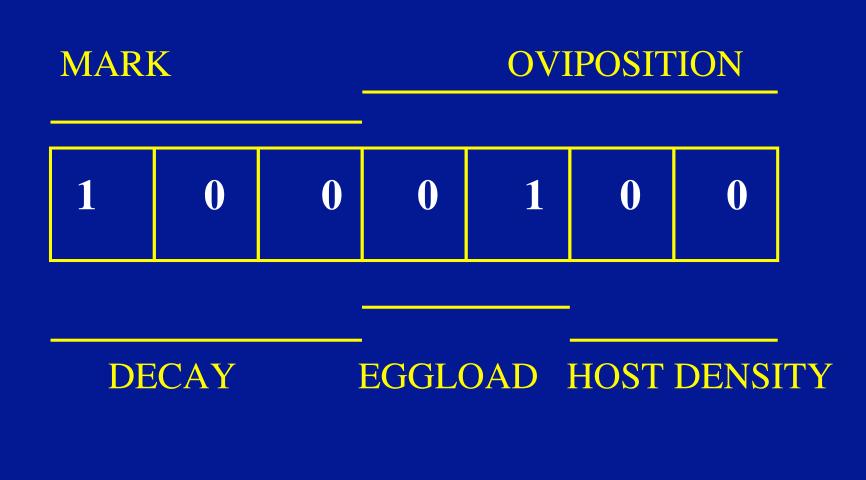
$3\pi f(\varepsilon)$ Reaction Norms



REMEMBER

• You, the modeler, provide the raw materials for "natural selection" to act upon. Be careful not to bound the problem that forces a particular answer.

A CHROMOSOME



SIMULATION: DETERMINE FITNESS

- First, transcribe phenotype from genotype
- Second, play phenotypes in ecological scenario
- Try to employ as few stochastic elements as possible i.e. apply stochasticity when it is at the heart of the problem

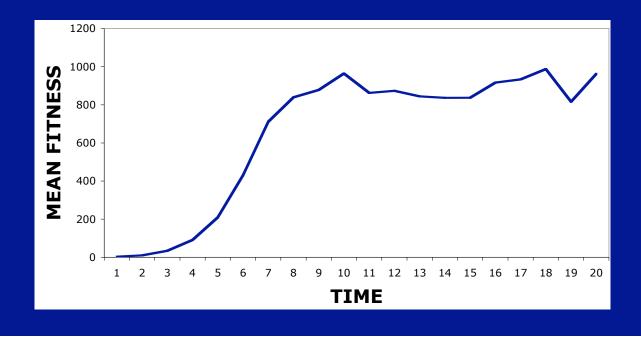
TWO PARAMETERS DETERMINE GENOTYPE FITNESS

- Per capita fitness
- Number of individuals of a given genotype



A FACT

• An evolving population should display increasing mean absolute fitness



MATING PROCEDURE

• Weighted random mate selection

• Crossover and mutation

• Create babies by the pair

WHAT'S SPECIAL ABOUT THE MATING PROCEDURE

• It provides for novel combinations to emerge and for appropriate strategies to dominate

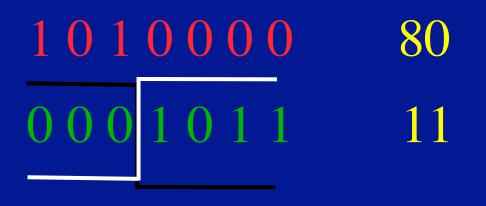


WHO GETS TO MATE?

Imagine 2 genotypes Red and Green. In generation X Red had 60 individuals each with fitness 3.33 (total 200) and Green had 20 with fitness 5.0 (total 100)

Sample with replacement

IMPLEMENTING A CROSSOVER



 1 0 1 1 0 1 1
 91

 0 0 0 0 0 0 0
 0

IMPLEMENTING MUTATIONS

 Position by position, allow for

 mutation with some defined

 probability (e.g. 2%)

 1 0 1 1 0 1 1

 0 0 0 0 0 0 0

 0 0 0 0 0 0 0

SCHEMA CONTEXT

STRATEGY	FITNESS
10100	.9
01100	.6.
10001	.8.5
00011	.3

SCHEMA CONTEXT

 Def'n - a similarity template that is used to group strings that are similar at particular positions



SOME SCHEMA FACTS

- High performance strings will tend to grow exponentially in the population
- Crossovers destroy schemata
- The longer the schemata the more susceptible to crossover e.g. 10 vs 100001
- Short, high performance schema will grow at high rates



• How long should the strings be?



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- How long should the strings be?
- There is no maximum length but longer strings take longer to achieve fixation or stability
- How big should populations be?
- Big populations take longer to evaluate but are less susceptible to stochastic elements



• What should your starting populations look like?



- What should your starting populations look like?
- Normally it is best to start with a random assemblage of strategies (chromosomes)but this should be repeated several times.



 How do you prevent a few high performance (relatively speaking) strategies from highjacking the process?



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- Use scaling factors e.g. set limits on best performers during early stages. The opposite tact can be taken near the end of runs.



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- Employ mean fitness values from groups of runs to gain general inference.
- How many generations?
- Develop criteria for terminating iterations

