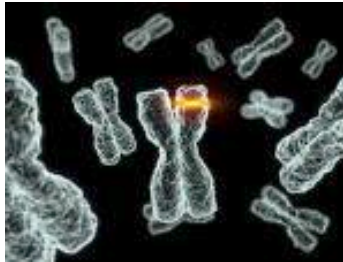


CS 289

Evolutionary Computation



Search, Optimization, Evolution

Problem Solving as Search

- Classic AI way of thinking (e.g McCarthy, Newell and Simon, 1950s)
- Wide domain can be cast this way (planning, theorem-proving, puzzles)
- Methods: optimal/complete search vs local search
- *But Some Problems are Provably Hard (NP-complete, 1973)*
- *And No Search Algorithm is the Best (No Free Lunch Theorem, 1995)*

- Good approach when it is hard to find a solution but *easy to check* if a solution is correct
 - What are some examples?

Brief Timeline

Metropolis algorithm (1953)
 Dartmouth AI conference (1950)
 Genetic Algorithms (John Holland 1970s)
NP-completeness first understood (1973)
 Linear Programming proven to be polynomial time (1979)
 Simulated Annealing (1980s)
 Genetic Programming and Ant Colony Optimization (~1990)
No Free lunch theorem 1995
Evolution: Darwin/Wallace 1859 Mendel 1900 DNA 1953

Casting Problems as Search

F(solution) = objective function to maximize/minimize

$$F(x) = 2^{(-2(x-0.1)/0.9)^2} * ((\sin(5\pi x))^6$$

F(x,y,z) = some complex but differentiable equation (classic optimization)

(e.g. GPS localization: position relative to a set of reference nodes)

F(v1, v2, v3.....vn) = no longer an equation!!!

How well a **neural network with these weights** classifies some images

How well do these **feature detector parameters** capture objects of interest

How well these **1991 stock allocations** would have done in 2012

How well do these allocations **maximize total agent utilities** (class lottery!)

F(circuit/program) = no longer a simple vector/parameter representation!!

How well does this circuit solve the required task?

How well does a robot with this program navigate

F(fruitfly genome A) = how well does this individual survive compared to its buddies

Evolution as a search process over a very complex representation....

Local Search

Local Search

- Many Variants (Hill climbing, Simulated Annealing, K-beam)
- **Exploitation vs Exploration**
- **Representation, Representation, Representation!!**
 - Solution , Objective, Neighborhood function

Evolutionary Computation

Evolutionary Search is a *cooperative local search* method

Based on the belief that

= Evolution is a kind of optimization over a very complex landscape

= The Genotype-Phenotype separation works across all organisms

Key Features (GA/GP)

- Population (Always have many candidate solutions)
- Representation (Genes/Programs; Fitness function)
- Variation (Nbr function = cross-over between solutions!)
- Selection (Choose best solutions across all new candidates)

Simple model: Modern EvoBio looks at much more!

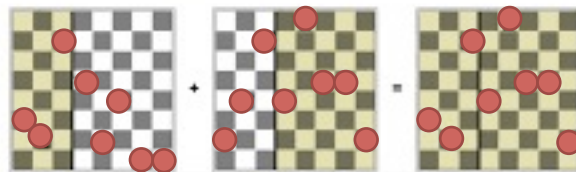
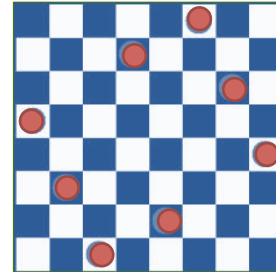
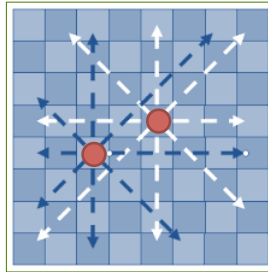
Some “Simple” Examples

- N-queens
- EvoLISA (image compression)
- Evolving Cellular Automata (Crutchfield, Mitchell)
- Next lectures!
 - Evolving Lego bridges (Jordan Pollack’s Lab)
 - Evolving Robot Bodies and Brains (Pollack and Lipson)
 - Evolving Swarm behaviors.

N-Queens Example

On a 8x8 board, place 8 queens, such that they can't kill each other

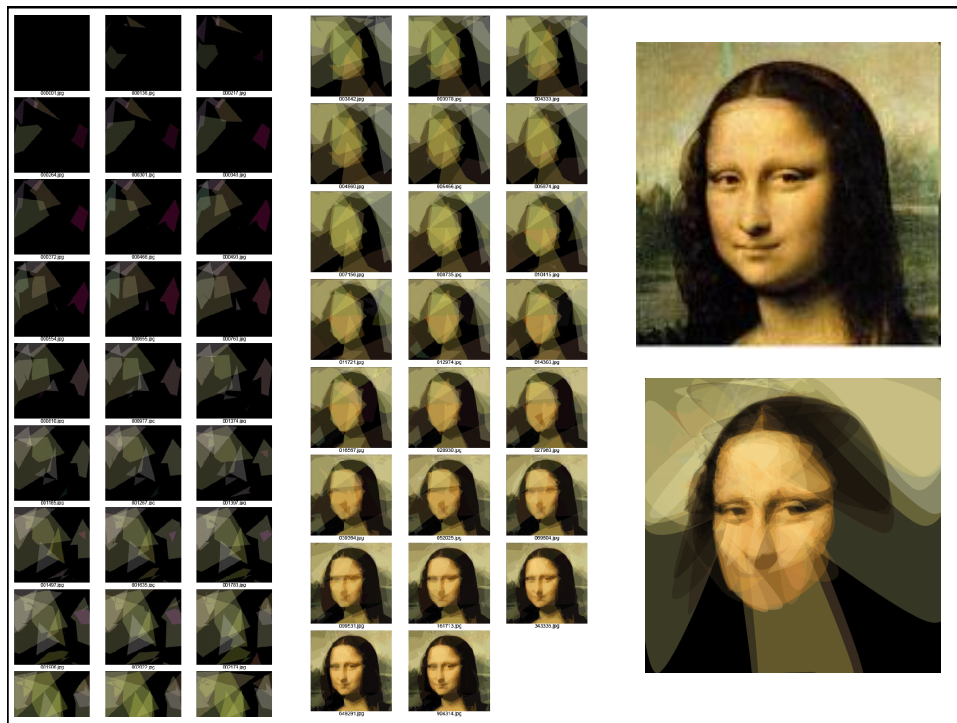
How do we cast this as an evolutionary computation?



EvoLISA

(Roger Asling, 2008)

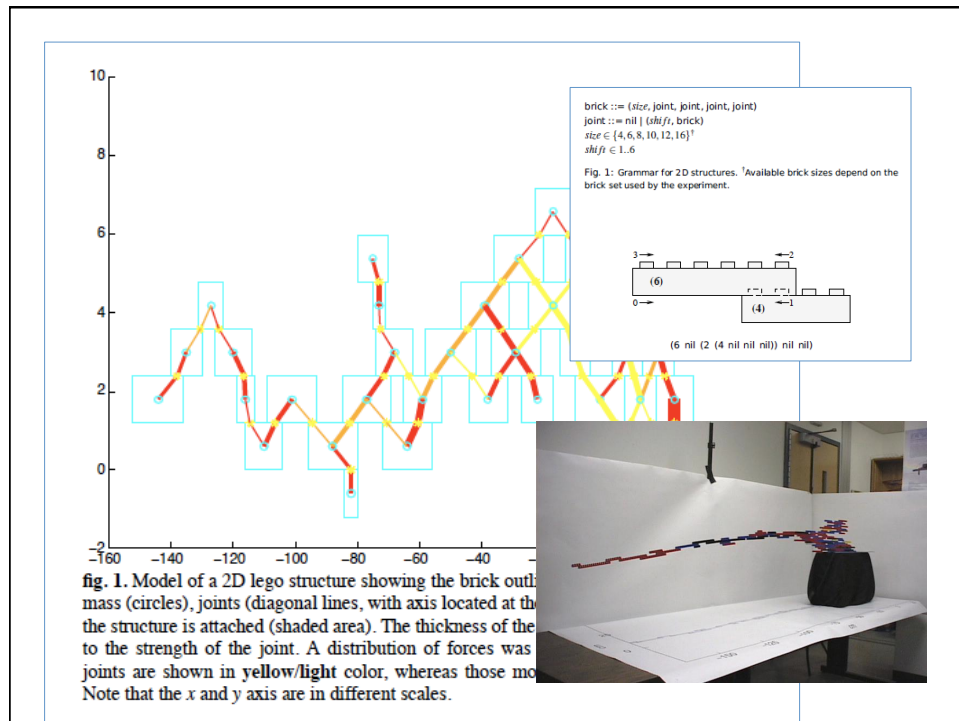
- Image Compression
 - Representation: 50 semi-transparent “polygons”
 - DNA = “vector of attributes”
 - Trying to find the best “DNA” to capture a given image
 - Not obvious how to find the right answer, but relatively easy to evaluate a given answer (how well does it match a given image)
 - Compression: Hard to compress, but easy to decompress!
 - Method: Genetic algorithm
 - Population | Variation | Selection
 - Question: Can we evolve a rep. of Mona Lisa?
 - Lets take a look



Evolving “Architectures” in Lego

(Pablo Funes and Jordan Pollack, ~1999)

- **Next Week’s Topic**
- **EvoCAD**
 - Using evolution as a tool for exploring the design space
 - Fitness function: what is the goal of the structure (or could be human directed evolution)
- **Bridges, Cranes, and other structures**
 - Specific goal (fitness of the structure)
 - Representation: how do I describe the current structure and generate new structures (variation)



Evolving Cellular Automata

(Melanie Mitchell and John Crutchfield 1994)

- Evolving a CA to do “computation”
 - E.g. Density, Synchronization, Pattern formation
- Representation: simple and cool idea
 - “rule table” as a “binary string”

Rule table ϕ :

neighborhood η : 000 001 010 011 100 101 110 111
 output bit: 0 0 0 1 0 1 1 1

Lattice:

Neighborhood $\eta \rightarrow r = 1$

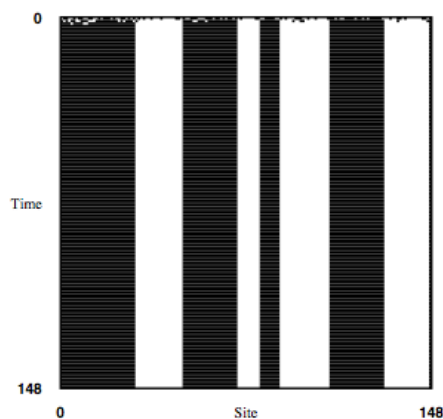
$t = 0$ 1 0 1 0 0 1 1 1 0 1 0

$t = 1$ 0 1 0 0 0 1 1 1 1 0 1

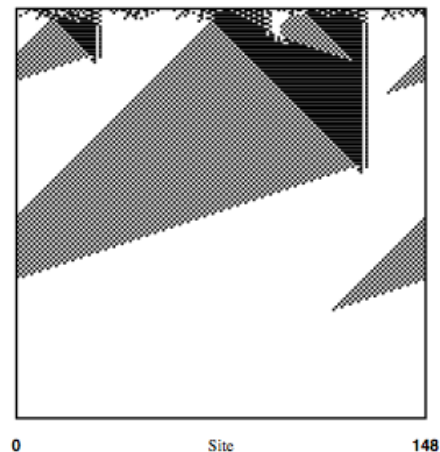
Evolving
Programs!

Implementation Example

- **Problem: Classify Density (if black > $\frac{1}{2}$, then CA turns all black)**
 - Binary Cellular Automata Ring, $N=149$, CA Rule radius $r=3$
 - Claim: no fixed radius rule exists that works for different lattice sizes, but even for a fixed lattice size it is hard to find a rule of low radius (not proven impossible)
- Representation: 128 bit string, population of 100 Candidates
- Variation: Cross-over and Mutation
- Selection: Fitness F100 (performance on 100 randomly generated CAs)
- **How it works**
 - Start with 100 candidate solutions
 - Test fitness F100 for all of them
 - Pick top 20 (elite set)
 - Generate another 80 by cross-over of randomly selected elite parents, do two mutations in each offspring (did not use the roulette wheel)
 - Repeat
- **Interesting Results**
 - Naïve methods: Majority, Expand-block
 - Sophisticated Method: “particle” method
 - Also looked at other “computation” problems (like synchronization)



Majority solution



Evolved “Particle-based” solution

Cooperative Transport

- Ant-inspired Robots = Swarms Bots

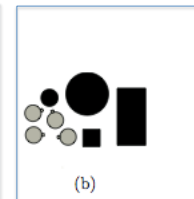
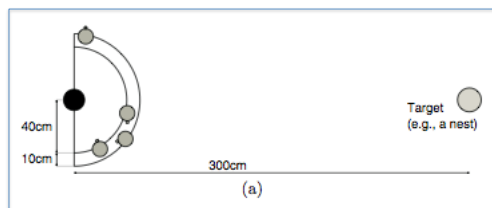
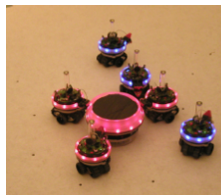
How should they coordinate to move something whose weight and size they don't know apriori?

- Individual Robot Capabilities

- Can see object and goal direction from a distance
 - Don't know weight or size of object
 - Can see other robots ring color, and flash a color themselves
 - Can grip an object (or each other) and move in any direction.

Activity: Find a solution for robots using GAs

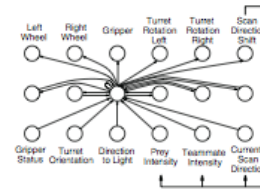
Representation | Variation | Selection



Cooperative Transport

(Roderich Gross, Marco Dorigo, 2004-2006)

- Representation:
 - Neural Network with hidden nodes
- Variation: Perturb Weights
- Selection:
 - Simulation over a random objects
 - **Need a Complex Fitness Function:**
 - Assembly performance (just attaching gets points) and Distance gain



1.12%	2.60%	14.12%	37.96%	0.08%	0.2%
3.64%	0.20%	0.06%	6.56%	12.52%	1.76%
10.56%	0.72%	0.04%	6.52%	1.32%	