Modelling Complex Systems

Genetic Algorithms

This lecture is adapted slides of David Sumpter and Yu Liu

Final Stretch

- ▶ Thur 14th Lab cancelled.
- Mon 18th 1-4pm Lab 6
- Tue 19th 1-4pm start Final Proj
- Sun 31st May: deadline for Labs 5 & 6
- Mon 25th 1-4pm, Tue 26th 3-5pm Final Proj discussion with groups
- 7th June: deadline for final project

Resit period - opportunity to resit each Lab separately.



Evolution

- Evolution solves "problems"
- But there is no specific problem needed to be solved, only one general problem: increasing fitness

We have specific problems

Evolution

• e.g., **eye**

- Large solution space
- Open-ended
- Natural selection (adaptation):
 - 1. reproduction
 - 2. mutation
 - 3. competition (e.g., limited resources)

Genetic Algorithm (GA)

- Large solution space, hard to check every possibility
- Not open-ended (should stop)
- Natural selection in computer:
 - 1. reproduction?
 - 2. mutation?
 - 3. competition?



Genetic Algorithm (GA)

- John Henry Holland, 1970s
- Computer programs that evolve over generations to find (some of) the "fittest" out of a very large number

Basic GA Recipe

- 1. Define a format (a string) to represent different strategies.
 We call one strategy as one chromosome.
- 2. Give a population of some random chromosomes

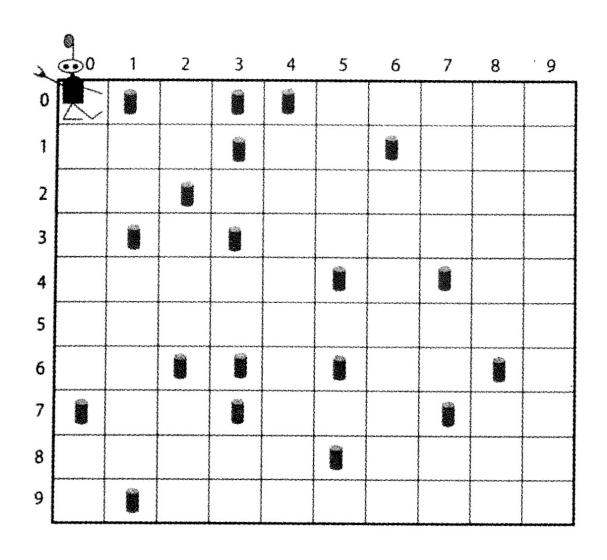
- > 3. Calculate each chromosome's fitness
- ▶ 4. Evolution: cross-over and mutate
- ▶ 6. Repeat from step 3 for enough generations

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	9	Action			
North	East	South	West	Here	Action
-	-	-	-	-	Move north
-	-	-	-	can	Move east
-	-	-	-	wall	Pick up can
-	-	-	can	-	Move
•••••					
wall	-	can	wall	-	Stay still
•••••					
wall	wall	wall	wall	wall	Move east



	9	Action			
North	East	South	West	Here	Action
-	-	-	-	-	0
-	-	-	-	can	1
-	-	-	-	wall	6
-	-	-	can	-	4
•••••					
wall	-	can	wall	-	5
•••••					
wall	wall	wall	wall	wall	1



- \rightarrow 3^5 = 243 situations
- Move north
 Move east
 Move south
 Move west
 Move randomly
 Stay still
 Pick up can



 \rightarrow 3^5 = 243 situations

- Each chromosome is a string of 243 digits, each of which is between 0 and 6.
- There are 6^243 = 1.23e189 possible chromosomes.

Move north
 Move east
 Move south
 Move west
 Move randomly
 Stay still
 Pick up can

23300323421630343530546006102562515114162260435654334066511514 15650220640642051006643216161521652022364433363346013326503000 40622050243165006111305146664232401245633345524126143441361020 150630642551654043264463156164510543665346310551646005164



GA Evolving Robot: Measure Fitness

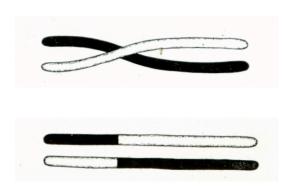
- Given a finite time, the number of cans it picks up.
- The minimum time to pick all cans up.
- Pick up can correctly +10; Try to pick up but no can -1; Crash to the wall -5; Otherwise 0.

The fitness should be an average measured in many cases (e.g., 100 cases)

23300323421630343530546006102562515114162260435654334066511514 15650220640642051006643216161521652022364433363346013326503000 40622050243165006111305146664232401245633345524126143441361020 150630642551654043264463156164510543665346310551646005164



GA Evolving Robot: Cross-Over



- 1. Define a format (a string) to represent different strategies.
 We call one strategy as one chromosome.
- 2. Give a population of some random chromosomes

- > 3. Calculate each chromosome's fitness
- ▶ 4. Evolution: cross-over and mutate
- ▶ 6. Repeat from step 3 for enough generations

- 1. Define a format (a string) to represent different strategies.
 We call one strategy as one chromosome.
- 2. Give a population of some random chromosomes (200)

- 3. Calculate each chromosome's fitness (100 random cases)
- ▶ 4. Evolution: cross-over and mutate
- 6. Repeat from step 3 for 1000 generations

GA Evolving Robot

▶ 4. Evolution: cross-over and mutate

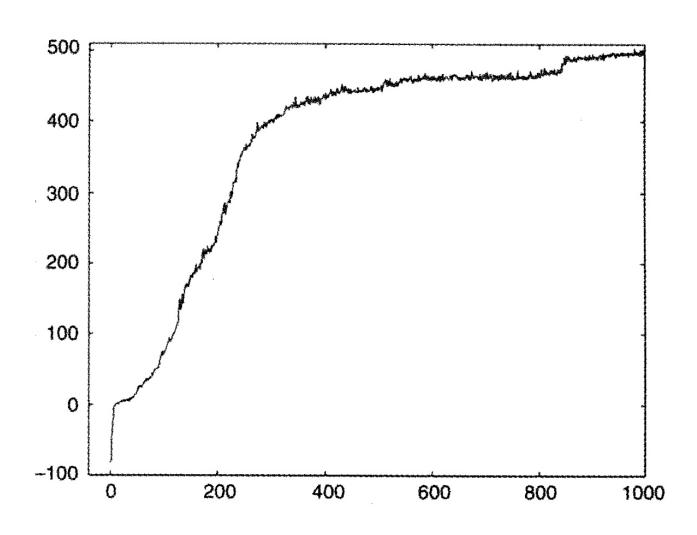
- > 4.1 Randomly select chromosome A and B based on their fitness
- ▶ 4.2 Randomly select a position and cross-over
- \blacktriangleright 4.3 By small probability (e.g., p = 0.05), mutate one gene
- ▶ 4.4 Repeat from 4.1 until you get 200 chromosomes

GA Evolving Robot

What parameters do we have in this case?

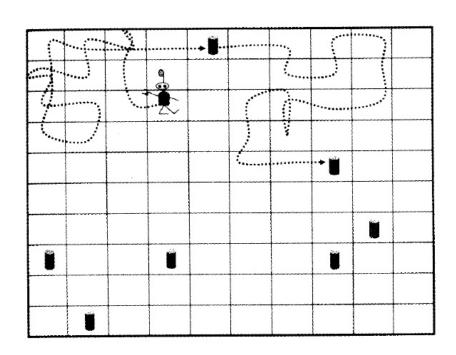
- ▶ 1. fixed population of chromosomes (200)
- 2. number of repeats to calculate average fitness (100)
- ▶ 3. mutation rate per chromosome (0.05)
- ▶ 4. number of generations (1000)

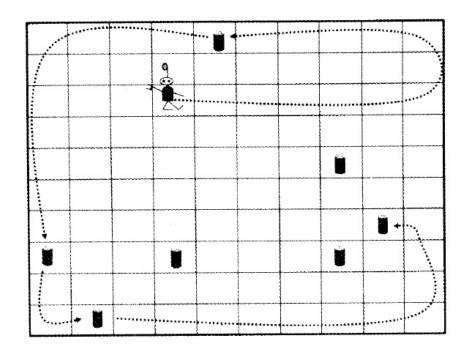




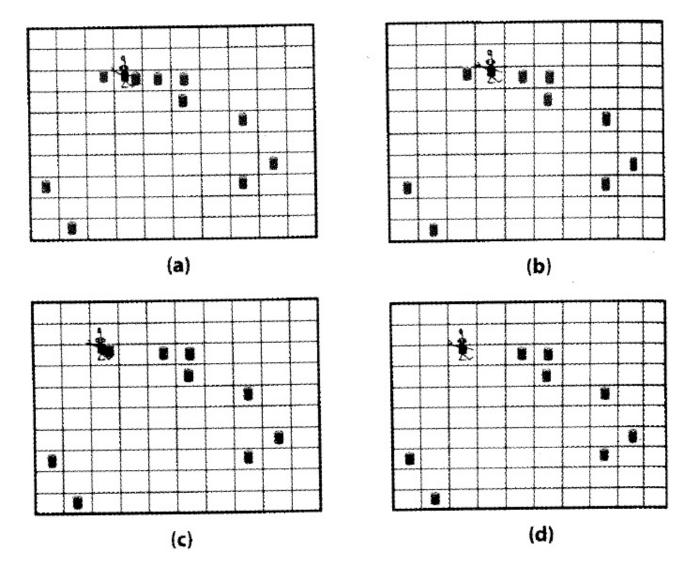




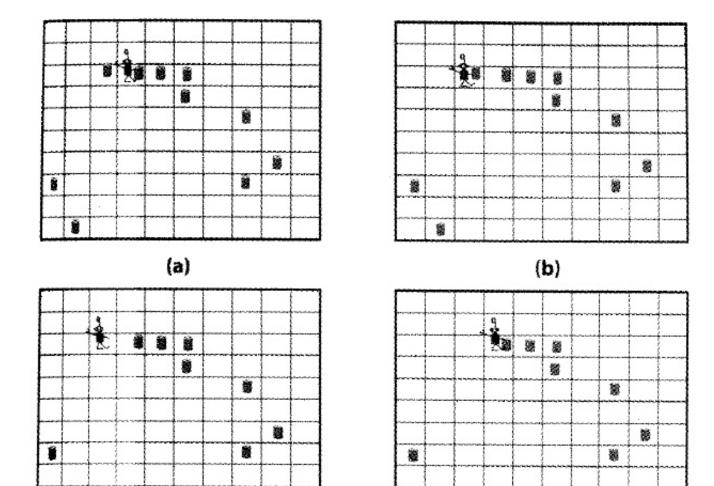




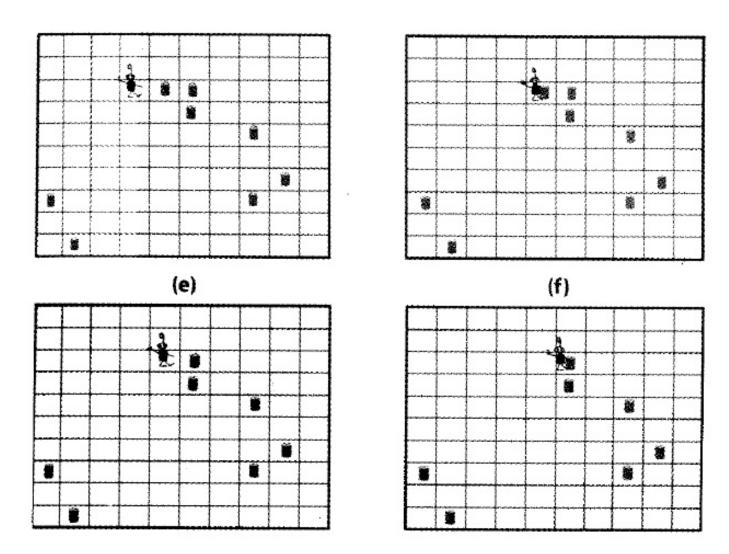






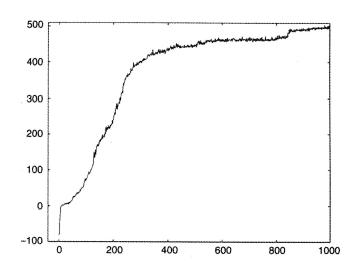












- Independent good genes are easy to appear.
- Cooperative genes are difficult to appear but also very important.

- Why does GA work?
- A balance between selection, mutation and cross-over.
- ▶ 1. Low mutation rate make sure that 1) genes are not easy to be wiped out (both good and bad genes), and 2) there is chance of good innovations.
- ▶ 2. Good strategies can always be made of groups of good gene modulars. The cross-over can assemble modulars.
- 3. Selection picks the good genes and good gene modulars.



GA Cellular Automata Computer

▶ Tell whether there are more black grids or not, based on local information.



GA Cellular Automata Computer

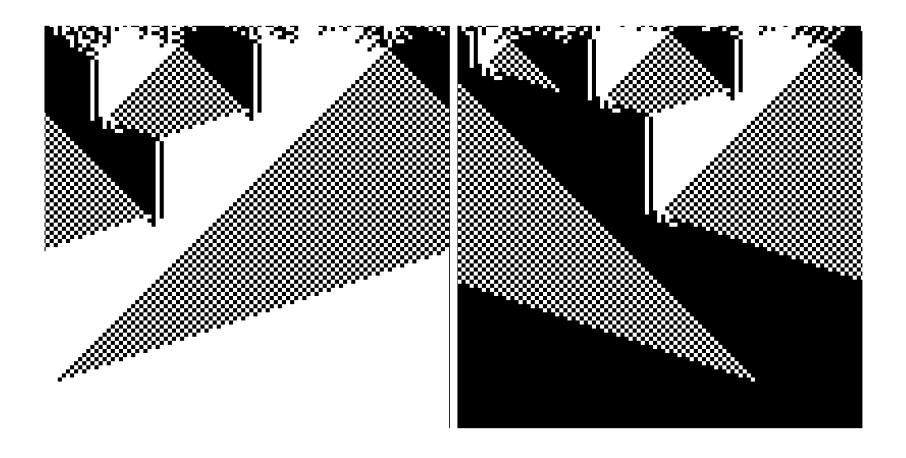
Given a string of 0 and 1, tell whether there are more 1s or not, based on local information.

2⁵ = 32 situations;
 Each situation has 2 possible actions, so there are
 2³² = 4.295e9 strategies.



GA Cellular Automata Computer

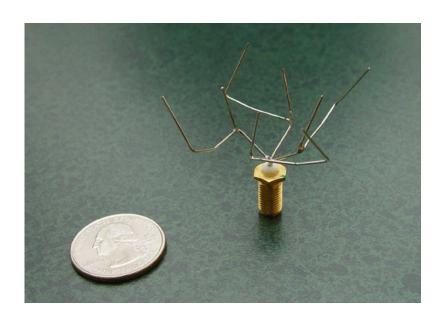
• Given a string of 0 and 1, tell whether there are more 1s or not, based on local information.





Comments On GA

- Automated design (e.g., Shape of the plane, antenna)
- Analyse satellite images
- Animations in film (e.g., horses in The Lord of the Rings III)
- Develop new drugs
- Protein folding
-



Comments On GA

- GA always cannot get the best solution (there may be not a best solution), but can be good enough.
- Biological evolution is open-ended, while we define an end for GA.
- For biological evolution, the whole solution space is not fixed; while for GA generally, the whole solution space is actually fixed.



GAVs Machine Learning

- The common part is the ability to learn or 'fit' to data for predictions.
- Both have a fitness function to determine how well the algorithm is performing
- GA is an example of reinforcement learning
- ▶ GA group of algorithms, rather than a single algorithm.
- Update rules from group of algorithms to group of algorithms in GA, very different to how one updates algorithms in other machine learning contexts.
- Nice example of reinforcement learning, (but not a GA!) is: arxiv:1707.02286



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