

# Artificial Life

Lecture 4 : The black art of GA's and making  
it easier

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# This Lecture

- Searchscapes
- Microbial GA (simplifying the implementation)
- Diversity maintenance

# Reading

- Harvey, I. (2009) The Microbial Genetic Algorithm In G. Kamps et al (Eds.) Proceedings of the Tenth European Conference on Artificial Life, Springer LNCS.  
[http://www.cogs.susx.ac.uk/users/inmanh/MicrobialGA\\_ECAL2009.pdf](http://www.cogs.susx.ac.uk/users/inmanh/MicrobialGA_ECAL2009.pdf)

# Population Based Evolutionary Algorithm

*NoGenes, NoIndividuals, NoGenerations*

Initialise population (matrix, *Pop*)

Calculate Fitness (vector, *Fit*)

for  $i=1:NoGenerations$  *%(or for some termination condition)*

    While(*New\_Pop* != Full)

- Select parents proportional to fitness.
- Crossover parents to create children.
- Mutate children.
- Calculate fitness of children *New\_Fit*
- Add children to *New\_Pop*

    end

*Pop* = *New\_Pop*;

*Fit* = *New\_Fit*

end

# Why do GA's work?

- Why is finding a word in a dictionary easy?
- Because it is organised (A..Z), allowing for us to make guesses, and to use those guesses to correct where we look next..

hair  
hall  
hammer  
hamster  
hand  
happy  
hard

hat  
hay  
head  
hear  
heart  
help  
hen

hip  
horn  
horse  
hot dog  
house  
hug

# Patterns in Search Space

- If the words were randomly distributed, you'd struggle!
- So, if a search-space is organised, we can spend less effort searching it...

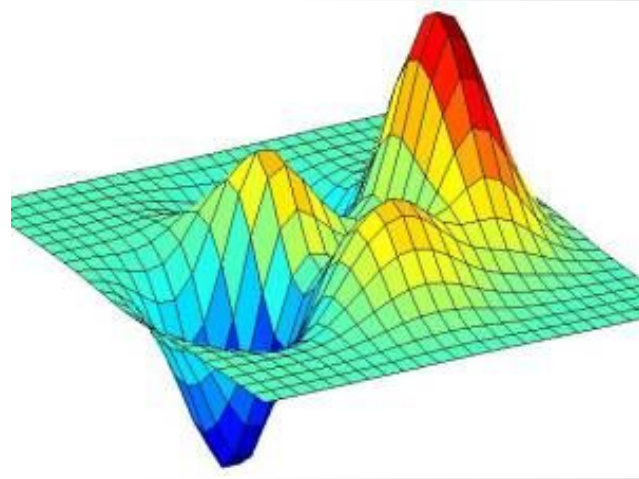
Truck	Grapes	Bulb
Balloon	Blocks	Door
Music	Rectangle	Blocks
Note	Submarine	Rectangle
Octopus	Deer	Guitar
Telephone	Igloo	Engagement Ring
Stop Sign	Dog	Dragon
Apple	Flower	Bee
Tree	Train	Rain
Cat	Wand	Bow and Arrow
Shoe	Light	Star

# Patterns in Search Space

- Genetic algorithms **taking advantages of these kinds of trends in search space**, minimising the number of samples we have to take, by assuming that there are trends or patterns in the search space (think of the Dictionary example)
- In particular, to work effectively GAs require similar genotypes to produce similar phenotypes with similar fitness
- many paths leading from low-fitness genotypes to high-fitness genotypes

# Fitness Landscape

- We can visualise the fitness landscape for a hypothetical 2D (two-gene) problem
- 2-genes (X, Z)
- Height (Y) is how fit that combination of genes is
- Red = high fitness
- Blue = low fitness
- Cyan = average fitness





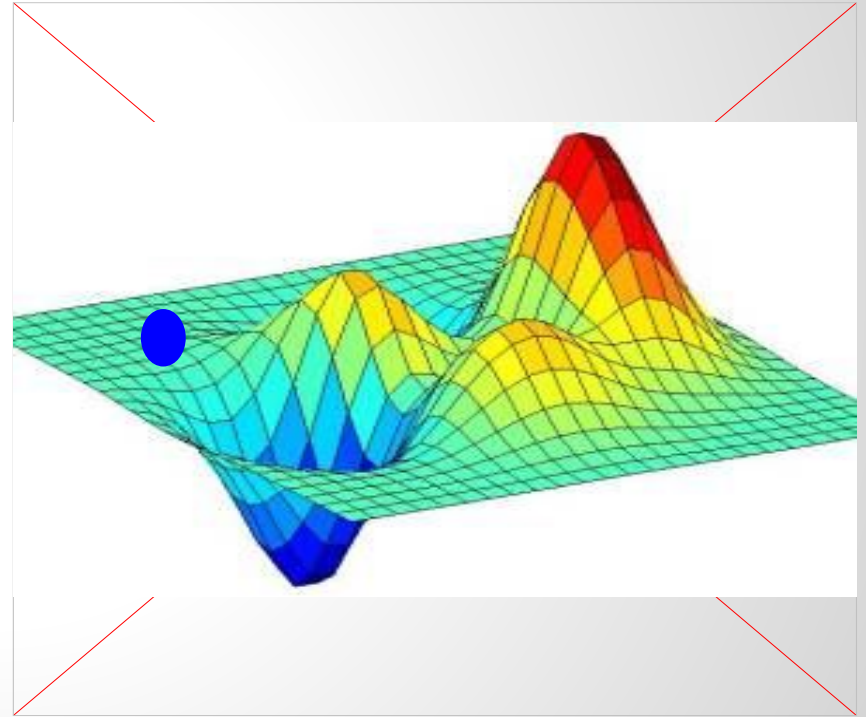
# Mutation as Motion

## Motion

- “Mutation” is sort of like moving through the fitness landscape (different ways to do this..more later)

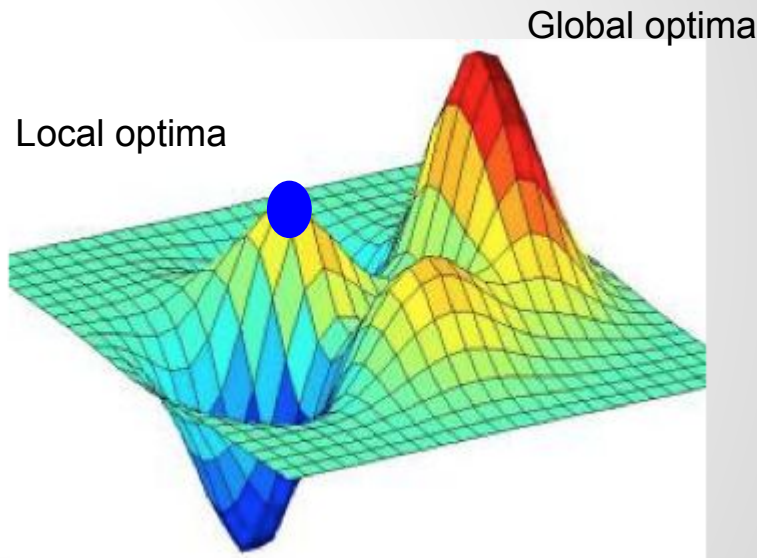
## Distance

- Points that are close together in the fitness landscape are those for which it takes few mutations to move between



# A Simple Hillclimber

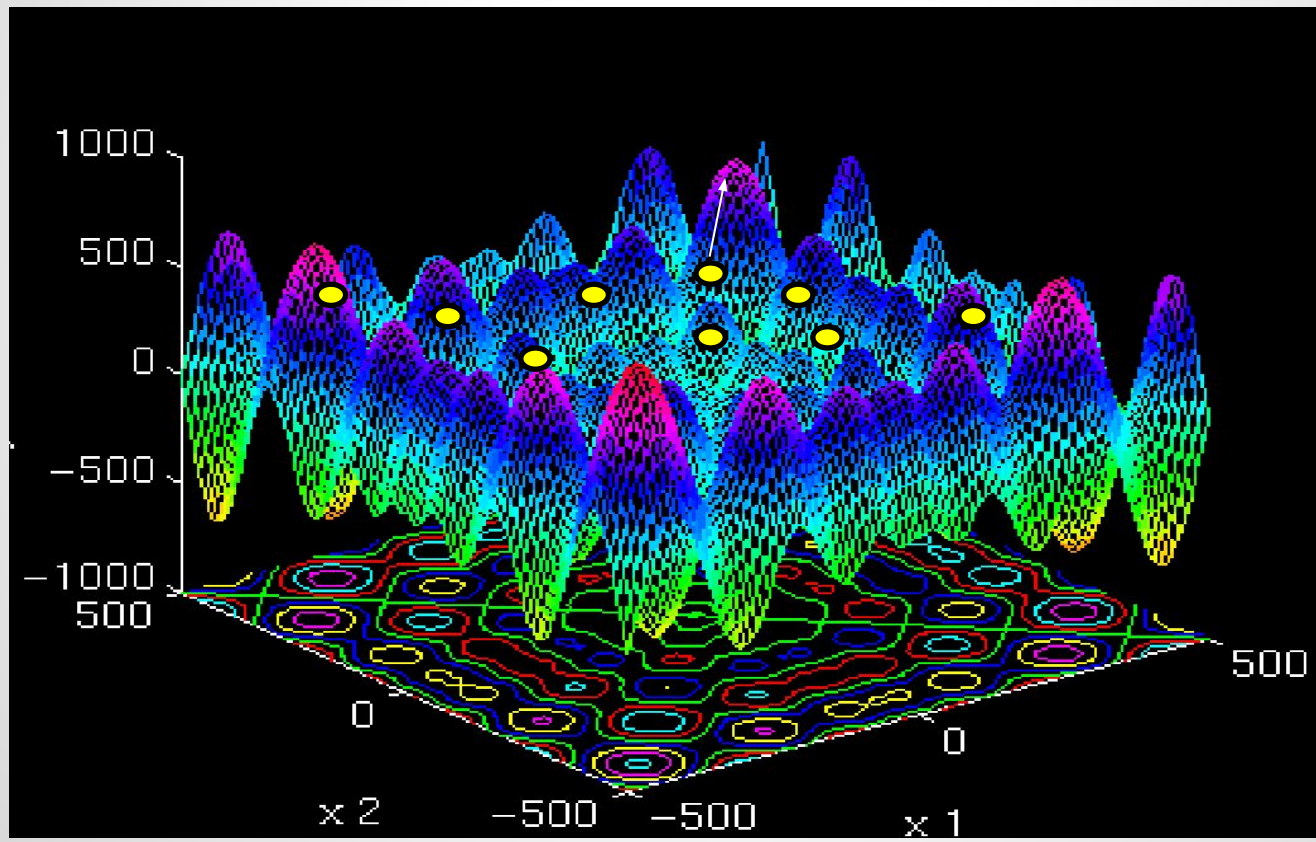
1. Change (mutate)  $a$  by a random amount (small changes more likely)
2. Measure fitness. If it is worse, undo the change.
3. Goto 1



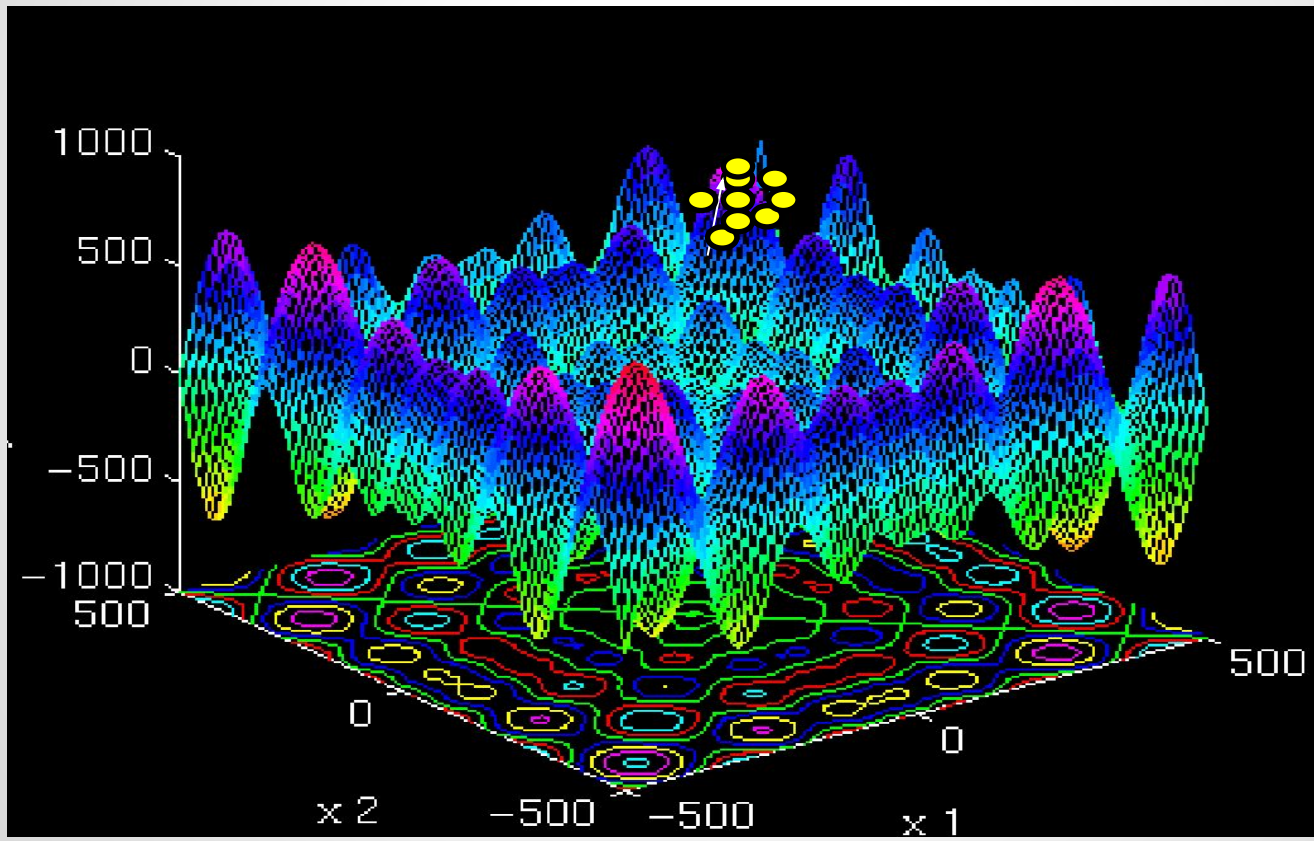
# Benefits of a population

- Evolutionary algorithms
  - Like a hill-climber but with a population
  - Make many random individuals
  - Some individuals might be luckier than others and we can preferentially focus on the better ones
  - Furthermore we can generate new solutions from a bit of one combined with a bit of another (using crossover). See lecture on compositional evolution.

# Benefits of a population



# Benefits of a population



# Diversity Maintenance

- The management of diversity is central to successful GA optimization
- Align with balancing central axioms of evolution
  - HEREDITY - offspring are (roughly) identical to their parents.
  - VARIABILITY - except not exactly the same, some significant variation.
- Mutation increases diversity allowing exploration but destroys heredity inhibiting exploitation
- Crossover tends to decrease diversity too

# Diversity Maintenance: Black Arts

- Population size
  - Too big?
    - waste of time
  - Too small?
    - no useful diversity in population
- Mutation rate
  - Too low?
    - too little innovation
  - Too high?
    - too much destruction

# Population Based Evolutionary Algorithm

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While(*New\_Pop* != Full)

- Select parents proportional to fitness.
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- Mutate children.
- Calculate fitness of children
- Add children to *New\_Pop*

end

*Pop* = *New\_Pop*;

end

- This is much too complicated
- Need two arrays
- Roulette wheel selection is a pain.



# Get rid of roulette wheel selection: Tournament Selection

```
P1=Pop(floor(rand*P+1),:)
```

```
P2=Pop(floor(rand*P+1),:)
```

```
If (fitness(P1)>fitness(P2))
```

```
    Winner = P1;
```

```
    Loser = P2;
```

```
else
```

```
    Winner = P2;
```

```
    Loser = P1;
```

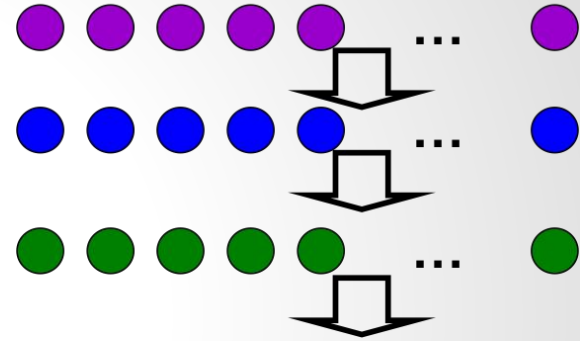
```
end
```

- More generally, pick k individuals and return individual with greatest fitness



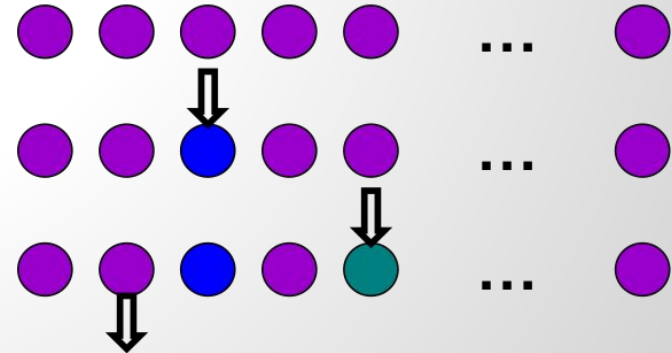
# Get rid of old and new population: Steady State Genetic Algorithm

Instead of a Generational GA,  
replacing all  $n$  at the same  
time

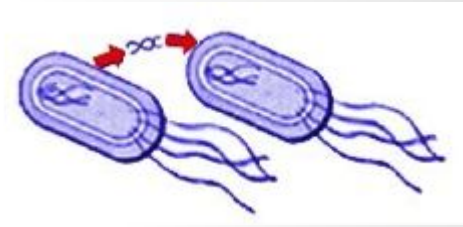
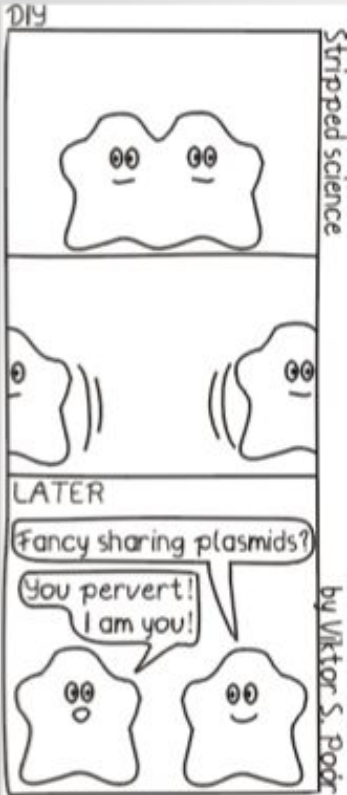


You can just produce one new  
offspring at a time, replacing  
one.

(Repeat  $n$  times for the  
equivalent of one generation)



# Adding Crossover: Microbial Sex



Instead of “Let’s make babies !”

It is

“Want to share some of my genes?”

# Horizontal Gene Transmission

- The movement of genetic material between two organisms. Once incorporated it is then 'vertically' inherited.
  - Only work in organisms with relatively close genetic makeup.
  - Mainly Eukaryotes rather prokaryotes
  - Antibiotic resistance genes on plasmids
- Ochman, Lawrence, and Groisman, Nature 405:299-304

# Microbial Genetic Algorithm – the algorithm

Pick two genotypes at random

- Compare scores -> Winner and Loser
- Go along genotype, at each locus with some prob copy from Winner to Loser (overwrite)
- with some prob mutate that locus of the Loser. So ONLY the Loser gets changed, (giving a version of Elitism for free!)

```
for i=1:NoGenes
    If(rand < Pc)
        Loser(i) = Winner(i);
    end
    if(rand < Pm)
        Loser(i) = flip(Loser(i))
    End
end
```

# Microbial GA (Psuedocode)

*NoGenes, NoIndividuals, NoTournaments*

Initialise population (matrix, *Pop*)

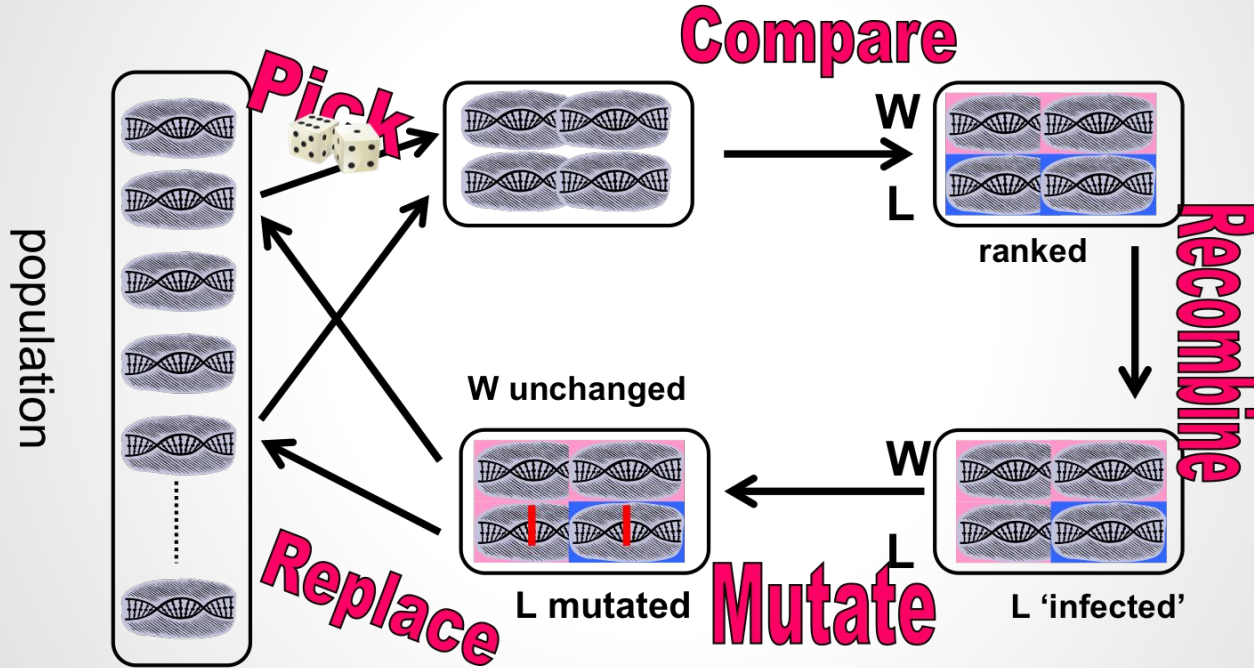
Calculate Fitness (vector, *Fit*)

for  $i=1:NoTournaments$  *%(or for some termination condition)*

- Select two individual and calculate the winner
- Copy the genes of the winner to loser with (probability,  $P_c$ )
- Mutate the Genes of loser (probability,  $P_m$ )

end

# The Microbial GA (diagram)



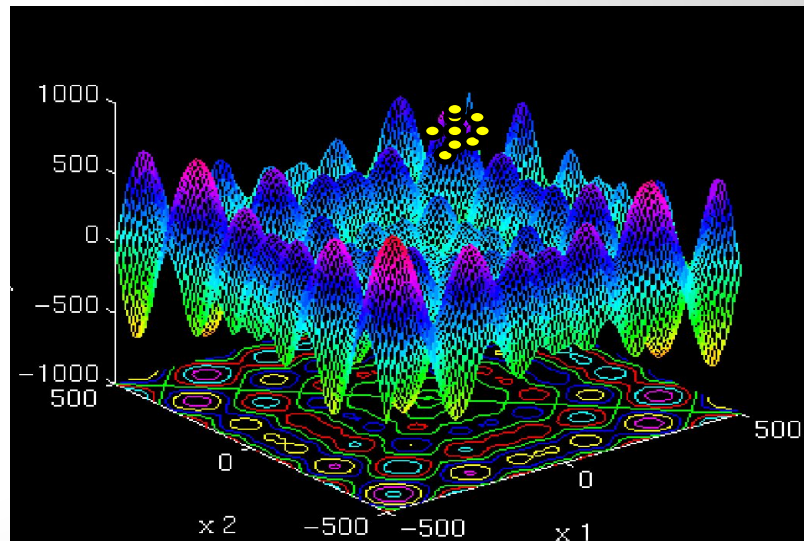
# Computationally, this is quite easy ...

- ... because we can keep all the genotypes in a fixed array and fitness in a single vector.
- Only the Loser's genotype is changed, within the array.
- One cycle round the loop changes one individual,  $n$  cycles is equivalent to a generation.



# Diversity Maintenance

- Multiple populations may search multiple corners – but be different evolutionary runs.
- The diversity tends to collapse very quickly in GA's as the winner begins to dominate
- Maybe you can get the best of both worlds by having multiple sub-populations, with some form of limited breeding between.



# One more trick: Demes, Geographical Breeding

- One way to constrain the interbreeding is to pretend the population is distributed in space, and that they can only reproduce with other individuals near them in that space.

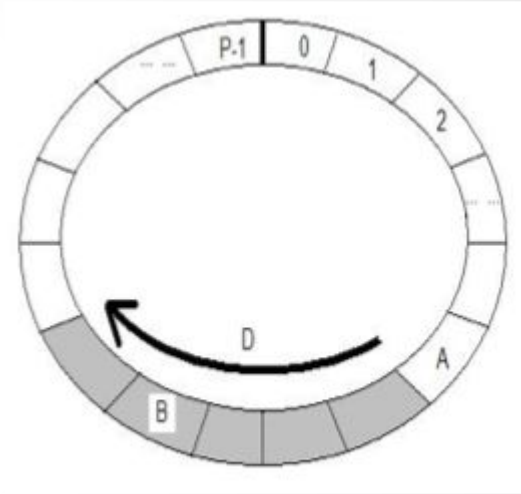


# Genetic material diffuses



# ‘Trivial Geography’

- If the population is not **pan-mictic**, but instead dispersed into (overlapping) demes, we can maintain more diversity across the whole population
- GA people usually use a 2-D geography, but it looks like 1-D (a ring) is good enough.



# Steady State with Demes EA

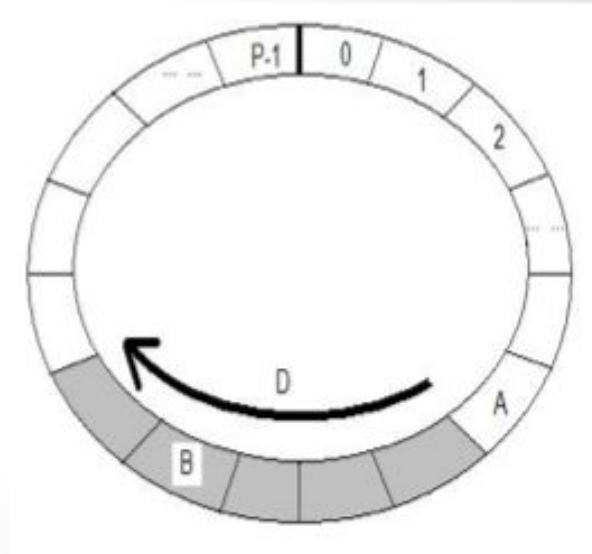
- Initialise P 'individuals'  $\rightarrow$  Pop on a ring
- Until (satisfied or no further improvement)

select the first competitor randomly

- $I1 = \text{rand} * P + 1$
- $P1 = \text{Pop}(I1, :)$

select next from deme size D

- $I2 = (I1 + 1 + \text{floor}(D * \text{rand})) \% \text{NoIndividuals}$
- $P2 = \text{Pop}(I2, :)$



# Combining with Demes

```
void microbial_tournament(void) {
```

```
    int A,B,W,L,i;
```

**Pick +  
Demes**

```
        A=P*rnd();           // Choose A randomly
```

```
        B=(A+1+D*rnd())%P;   // B from Deme, %P..
```

**Compare**

```
        if (eval(A)>eval(B)) {W=A; L=B;}
```

```
        else {W=B; L=A;}     // W=Winner L=Loser
```

```
        for (i=0;i<N;i++) {  // walk down N genes
```

**Recombine**

```
            if (rnd())<REC)   // REComb n rate
```

```
                gene[L][i]=gene[W][i]; // Copy from Winner
```

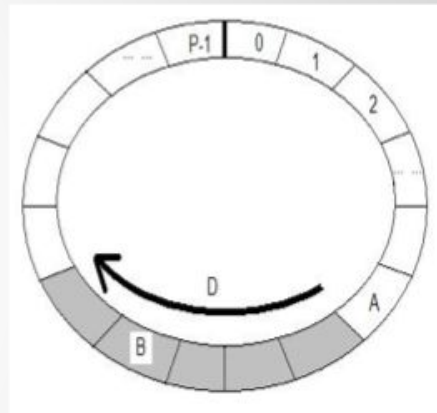
**Mutate**

```
            if (rnd())<MUT)   // MUTation rate
```

```
                gene[L][i]^1; // Flip a bit
```

```
        }
```

```
    }
```



# Elitism for free

- Many people swear by elitism.
- Elitism is the GA strategy whereby as well as producing the next generation through whichever selection, recombination, mutation methods you wish, you also force the direct unmutated copy of best-of-lastgeneration into this generation - 'never lose the best'.

# **Question**

**What difference does elitism make?**



# Recommendation ...

- Steady state GA
- Tournament selection
- Use 1D geographical representation (demes)
- Uniform crossover
- Mutation rate very approx 1 mutation per (non-junk part of) genotype or small creep (1% of range) on real valued genotypes
- Population size usually 30 - 100 or more generally 100 \* number bits of your genotype.

# **Next lecture**

Other optimisation methods and a GA task.