



# COMP 4752

## Computational Intelligence

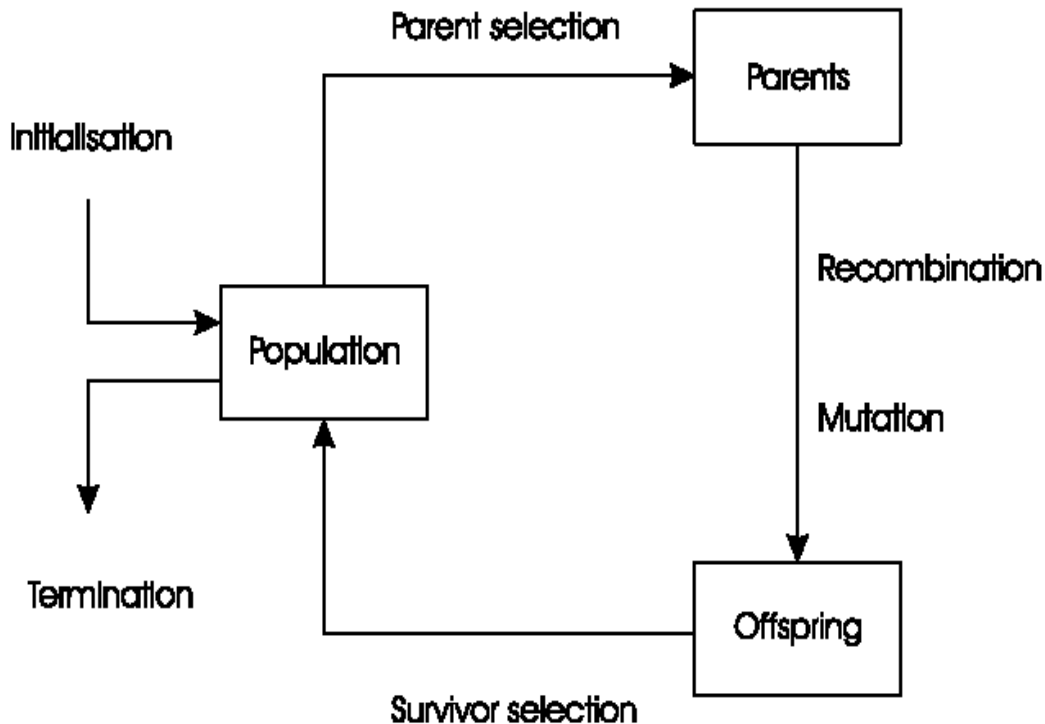
### **Lecture 18**

#### Evolutionary Algorithms

# Recap: EC Metaphor

1. **Population** of **individuals** exists in an **environment** with limited resources
2. Competition for those resources causes selection of fitter individuals that are **better adapted**
3. Those individuals reproduce to form new generation of individuals through **recombination** and **mutation**
4. New individuals have **fitness** evaluated, high fitness individuals chosen to reproduce, pass on good traits
5. Over time, natural selection causes **fitness to rise**

# Evolutionary Algorithms



# Evolutionary Algorithms

1. INITIALIZE population w/ random individuals
2. REPEAT UNTIL (termination condition)
3.     EVALUTE population / individual fitness
4.     SELECT parents with high fitness
5.     COMBINE parents to form offspring
6.     MUTATE resulting offspring
7.     NEXT POP = select from [pop,offspring,parents]

# Main Components of an EA

- Representation (definition of individuals)
- Evaluation / Fitness Function
- Population (Size, Shape)
- Parent Selection Mechanism
- Variation Operators (Recombination / Mutation)
- Survivor Selection Mechanism (Replacement)

# Representations

- Candidate solutions (individuals) exist in phenotype space
  - Phenotype = Actual Solution Candidate
- They are encoded in chromosomes, exist in genotype space
  - Genotype = Representation of Phenotype
  - Encoding: Phenotype  $\rightarrow$  Genotype
  - Decoding: Genotype  $\rightarrow$  Phenotype (1 to 1)
- In order to find global optimum, every possible solution must be represented in genotype space

# Representation Example

Phenotype

5	3			7				
6			1	9	5			
	9	8					6	
8				6				3
4			8		3			1
7				2				6
	6					2	8	
			4	1	9			5
				8			7	9

Genotype

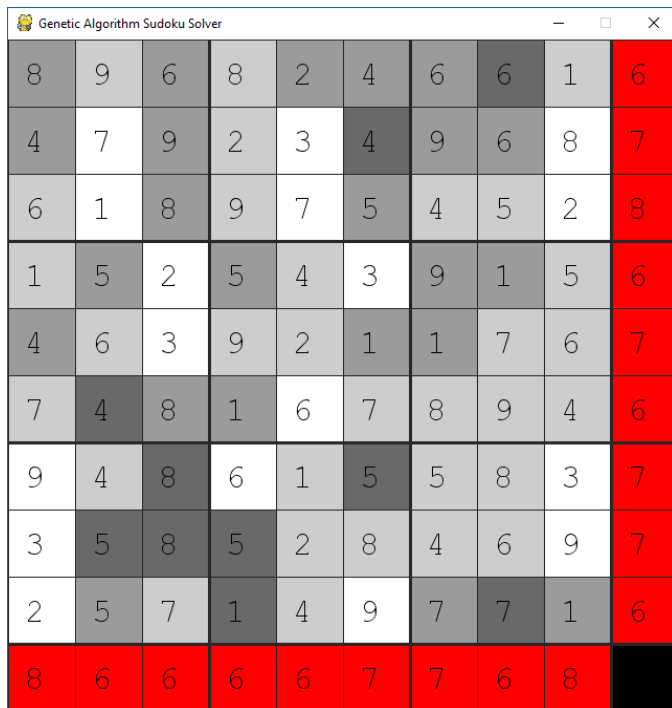
[5,3,0,0,7,0,0,0,0,...0,7,9]

# Evaluation (Fitness) Function

- Represents the requirements that the population should adapt to
- Assigns a real-values fitness to each phenotype with forms the basis for selection
  - More fine-grained different values, the better
- Typically we talk about fitness being maximized
  - Some problems may be minimization



# Example Fitness Function



8	9	6	8	2	4	6	6	1	6
4	7	9	2	3	4	9	6	8	7
6	1	8	9	7	5	4	5	2	8
1	5	2	5	4	3	9	1	5	6
4	6	3	9	2	1	1	7	6	7
7	4	8	1	6	7	8	9	4	6
9	4	8	6	1	5	5	8	3	7
3	5	8	5	2	8	4	6	9	7
2	5	7	1	4	9	7	7	1	6
8	6	6	6	6	7	7	6	8	

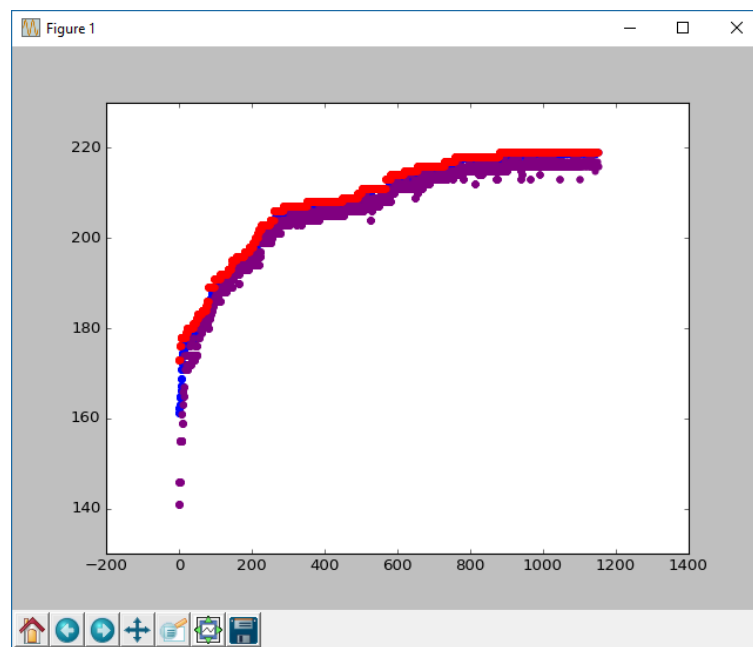
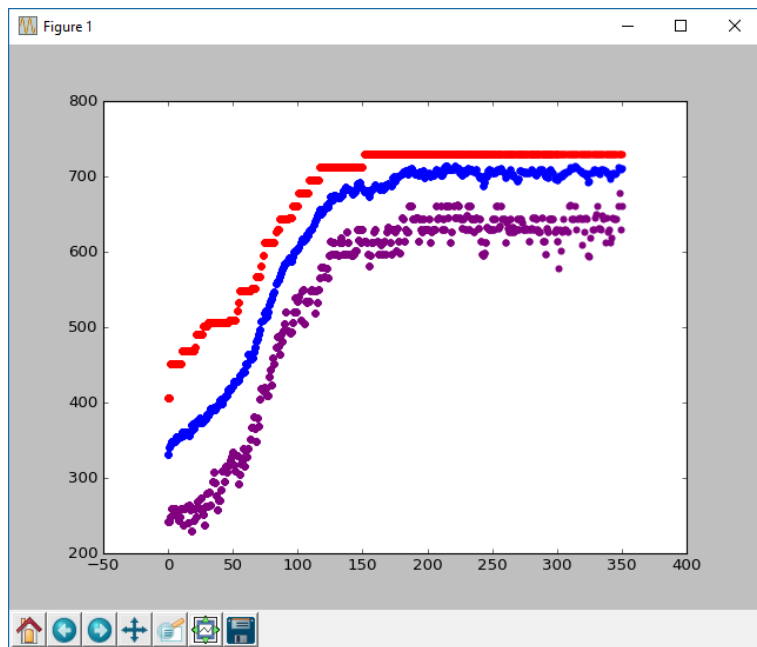


8	9	5	4	9	1	6	3	7	8
5	7	4	2	3	6	9	1	8	9
6	1	3	8	7	5	4	5	2	8
1	9	2	7	8	3	2	4	5	8
4	6	3	9	5	2	1	7	6	8
7	8	5	1	6	4	3	9	4	8
9	4	1	6	1	7	5	8	3	8
3	7	6	5	2	8	4	6	9	8
2	5	8	3	4	9	7	2	1	8
9	7	7	9	9	9	8	9	9	

# Population

- Holds (representation of) possible solutions
- Usually has a fixed size
- Some sophisticated EAs assert a special structure on the population (grid, etc)
- Selection operators usually take whole population into account (current generation)
- Diversity of population refers to the number of different fitnesses / phenotypes / genotypes

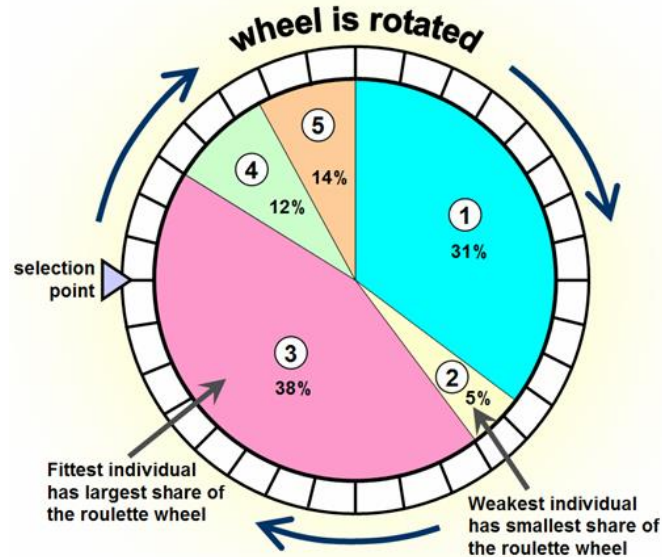
# Population Diversity



# Parent Selection Mechanism

- Assigns variable probabilities of individuals as parents depending on their fitnesses
- Usually Probabilistic
  - High quality solutions more likely to reproduce (be a parent) but not guaranteed
  - Worst candidate usually has non-zero chance
- Stochastic nature can help escape local optima

# Example Parent Selection



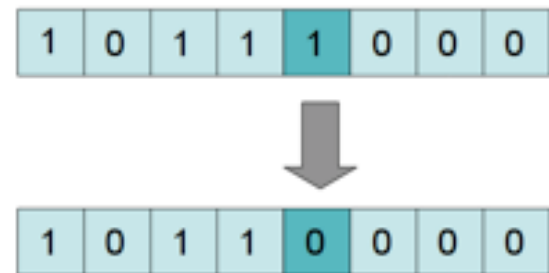
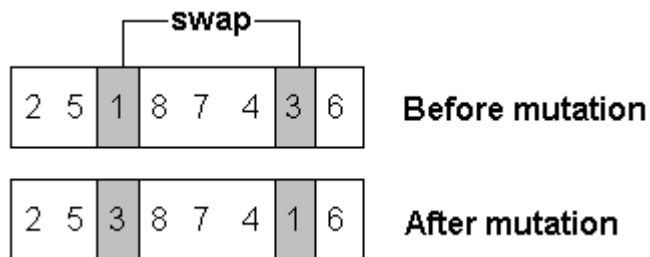
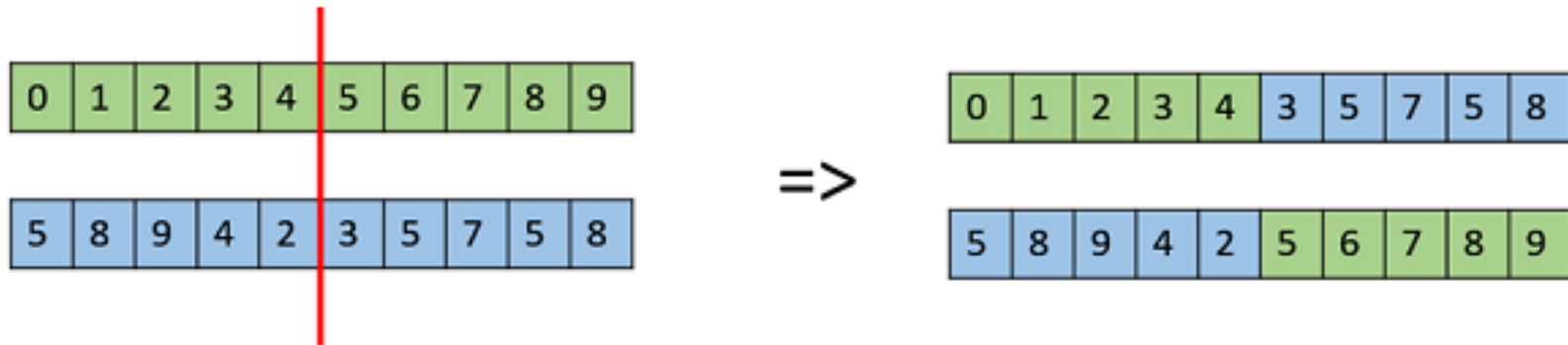
# Roulette Wheel Selection

1. **roulette\_select**(population)
2.     pop\_fitness = [fit(p1), fit(p2), ..., fit(pn)]
3.     max = sum(pop\_fitness)
4.     pick = random(0, max)
5.     current = 0
6.     **for** i in len(population):
7.         current += pop\_fitness[i]
8.         **if** (current > pick): **return** population[i]

# Variation Operators

- Role is to generate new candidate solutions
  - From parents to children (offspring)
- Usually divided into two types according to their number of inputs:
  - Mutation Operator (1 input)
  - Recombination Operator ( $> 1$  input)
  - 2 Inputs = Crossover
- Most EA use both recombination and mutation

# Crossover / Mutation





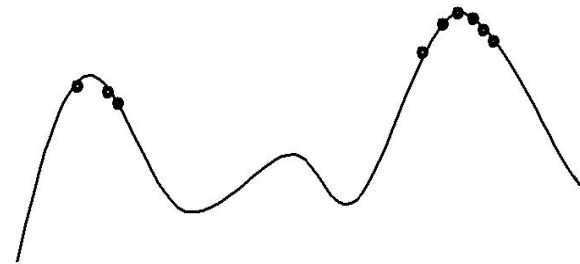
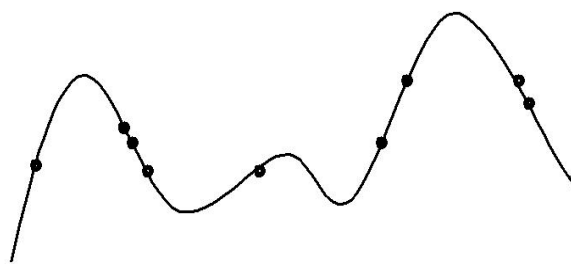
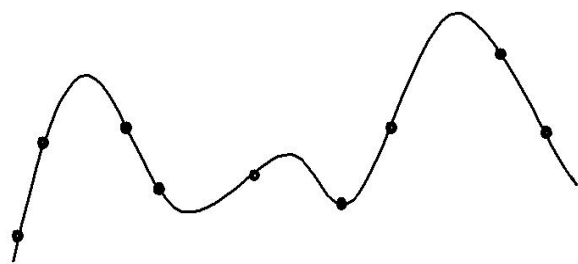
# Survivor Selection

- Also called environmental selection
- Most EA use a fixed population size, and need a way of going from (parents + offspring) to next generation
- Often Deterministic
  - Fitness Based (rank all and select)
  - Age Based (prefer offspring)
  - Elitism (best n always live)

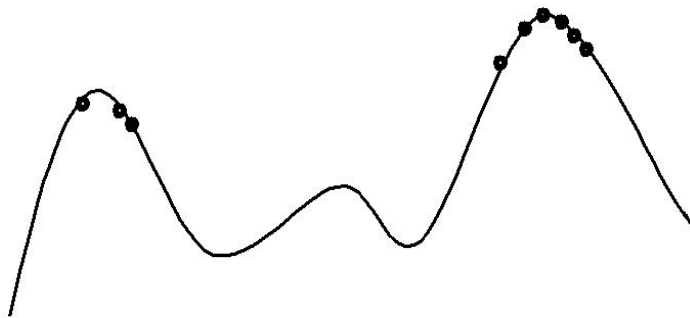
# Initialization and Termination

- Initialization usually done randomly
  - Need to ensure even mixture of candidates
  - Can include existing solutions, heuristics
- Termination Condition
  - Reach some known / desired fitness
  - Reach a generation limit
  - Reach a minimum diversity
  - Reach a generation limit of no improvement

# Typical Behaviour of an EA



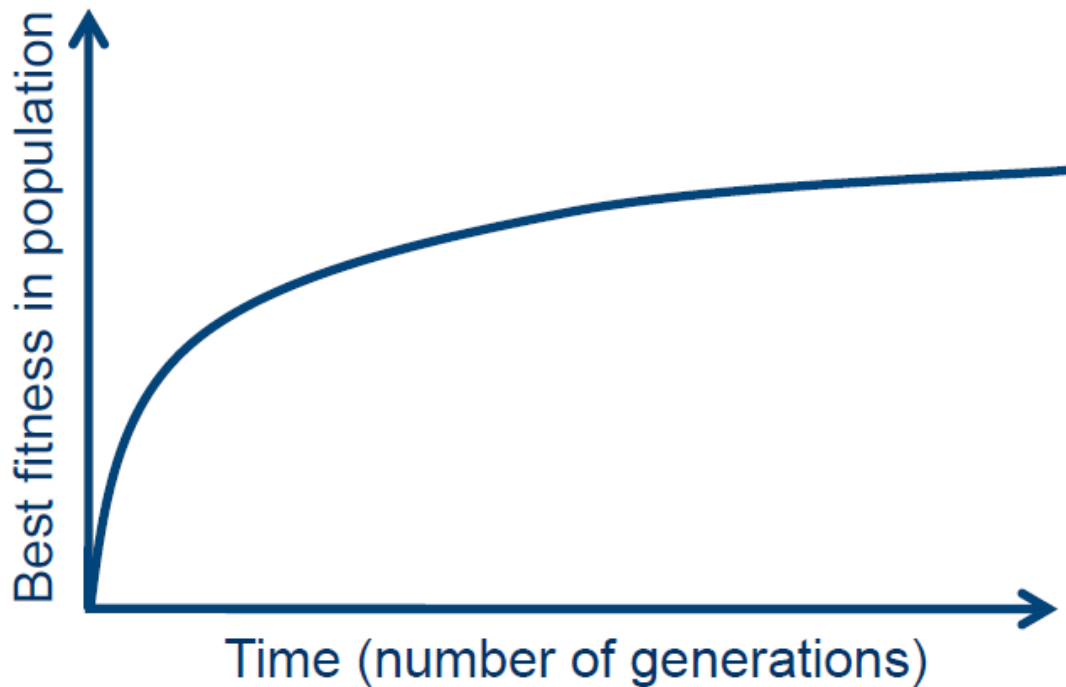
# Local Maxima



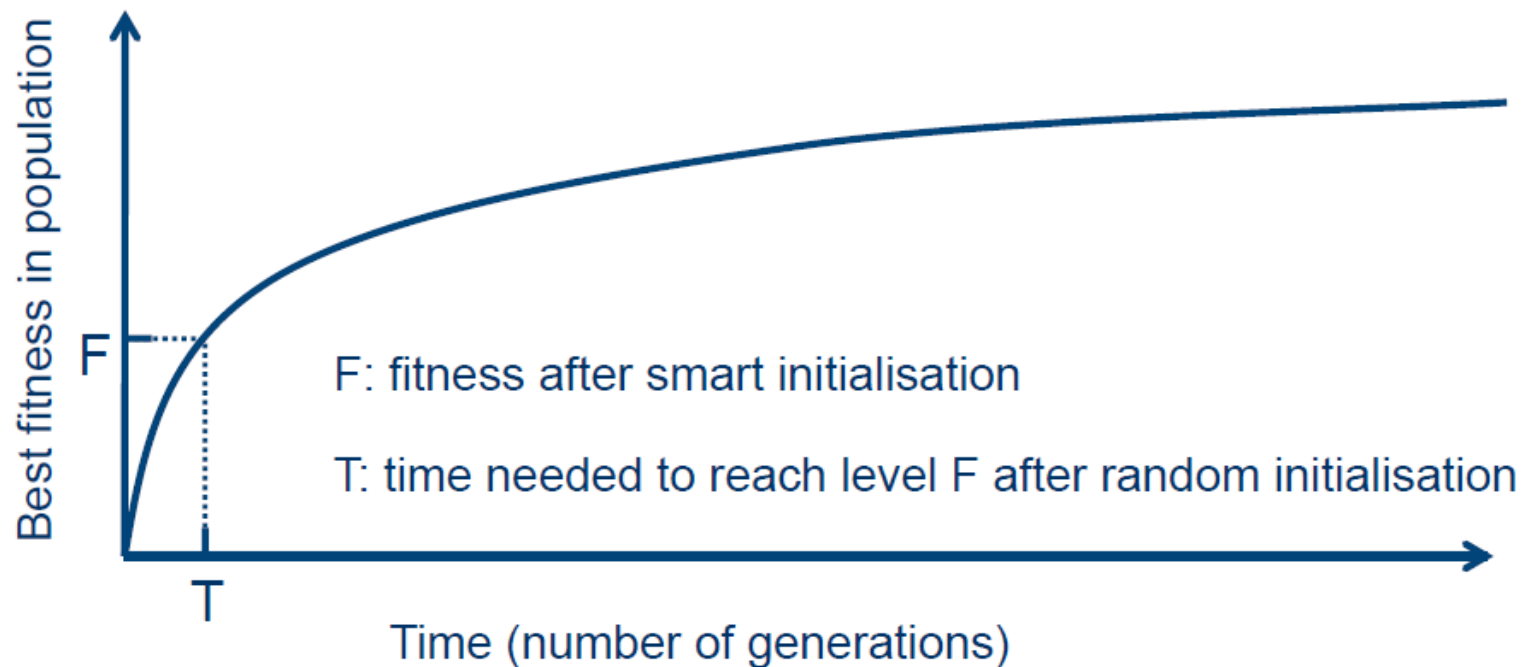
Genetic Algorithm Sudoku Solver

2	6	7	9	4	3	5	8	1	9
5	8	4	1	6	7	2	3	9	9
1	9	3	8	5	2	6	4	7	9
4	7	8	3	9	5	1	6	2	9
9	5	2	4	1	6	8	7	3	9
6	3	1	2	7	8	9	5	4	9
3	2	9	6	8	4	7	1	5	9
7	4	6	5	1	9	3	2	8	9
8	1	5	7	2	3	4	9	6	9
9	9	9	9	8	8	9	9	9	

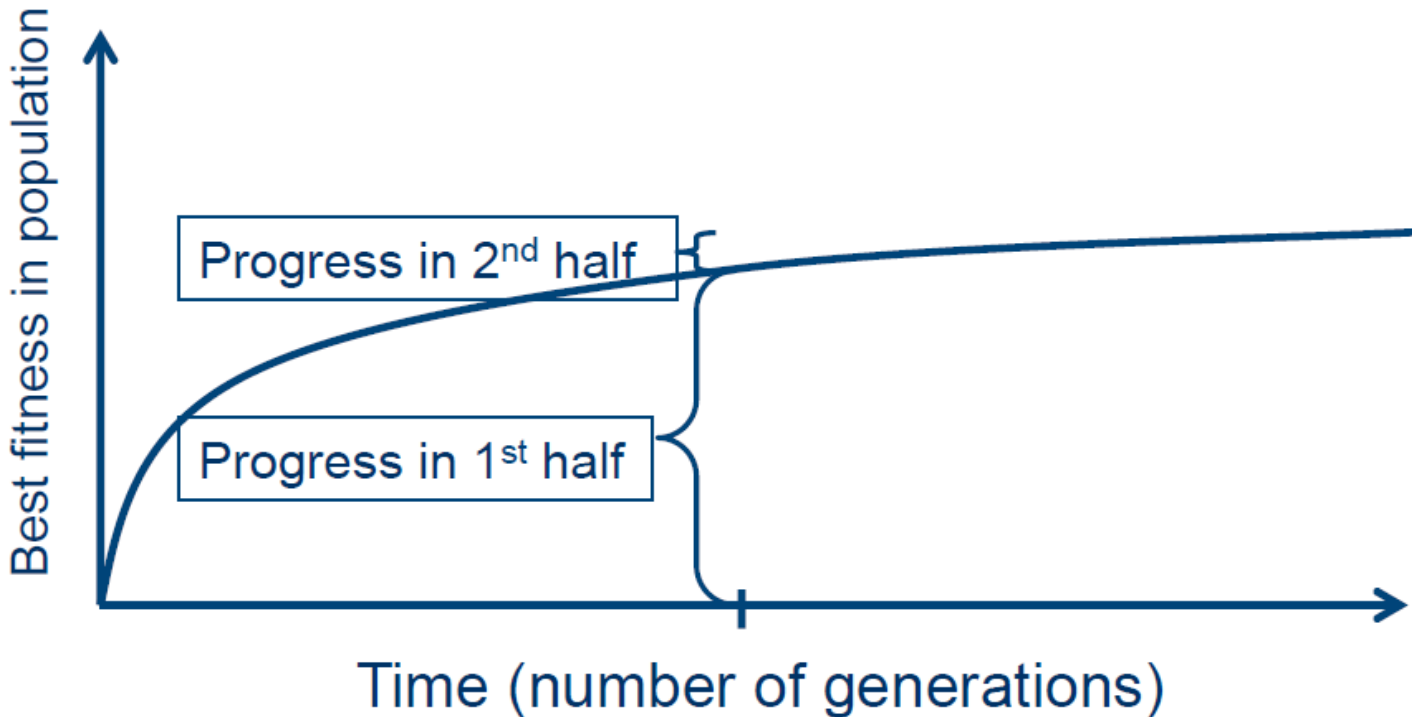
# Typical GA Run



# Smart vs. Random Initialization



# Running Time vs. Fitness



# Evolutionary Algorithms

1. INITIALIZE population w/ random individuals
2. REPEAT UNTIL (termination condition)
3.     EVALUTE population / individual fitness
4.     SELECT parents with high fitness
5.     COMBINE parents to form offspring
6.     MUTATE resulting offspring
7.     NEXT POP = select from [pop,offspring,parents]