

Evolutionary Computation

Evolutionary Computing

Evolutionary Computing is a research area within computer science. As the name suggests, it is inspired by Darwin's theory of natural evolution.

In an environment with limited resources, the fittest individuals survive. Also, they have more chances to have offspring.

Evolutive Algorithms Terminology		
Individual	Represents a solution	
Phenotype	The representation of an individual	
Genotype	The representation used for solving the problem	
Gene	A simple value from the genotype	
Fitness	A numeric value that represents the quality of the solution	
Population	It is a group of individuals that recombine and mutate their properties. The initial population is randomly created	
Selection of parents:	The parents must be selected based on their fitness	

The parents inherit their

characteristics to their

Individuals modify their

improve themselves

The fittness, individuals

survive and can live more

characteristics or behavior to

offspring.

time

Evolutive Algorithms Terminology (cont)

Termin-If you know the value of good ation fitness, the algorithm can stop Condition when you find an individual with good fitness

Pseudocode

BEGIN

INI TIALISE population with random candidate solutions; EVA LUATE each

candidate;

REPEAT UNTIL (TERMIN ATION CONDITION is satisfied) DO

1 SELECT

parents;

2 RECOMBINE

pairs of parents;

3 MUTATE the

resulting offspring;

4 EVALUATE

new candid ates;

5 SELECT

indivi duals for the next genera tion;

OD

END

Evolutionary Programming (EP)

Evolutionary Programming (EP)

In the classical example of EP, predictors were evolved in the form of finite state machines.

A finite state machine (FSM) is a transducer that can be stimulated by a finite alphabet of input symbols and can respond in a finite alphabet of output symbols.

It consists of a number of states S and a number of state transitions.

The state transitions define the working of the FSM: depending on the current state and the current input symbol, they define an output symbol and the next state to go to.

Mutation operators to generate new FSMs

The idea was evolving finite state machines (FSMs). There are five generally usable mutation operators to generate new FSMs:

Changing an output symbol

Changing a state transition

Adding a state

Deleting a state

Changing the initial state

Evolutionary Programming Terminology

Repres- entation	Real-valued vectors
Parent selection	Deterministic (each parent creates one offspring via mutation)
Recomb- ination	None
Mutation	Gaussian perturbation
Survivor selection	$(\mu + \mu)$
Specialty	Self-adaptation of mutation step sizes

Particle Swarm Optimization

Particle Swarm Optimization

Inspired by the movement of a flock of birds when searching for food.

Particle Representation

Each particle i represents a solution for the problem. In the time t, it has a position $xi(t) \in \mathbb{R}d$ and a velocity $vi \in \mathbb{R}d$.



Crossover (Repro-

duction)

Mutation

Survival

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Position and Velocity Update

The positions and velocities are updated following the next equations, where Pbest i is the best position where the particle i has been, Gbest is the best location founded until the moment, r1 and \square \square 2 are random numbers between 0 and 1, and w, c1, and c2 are hyper parameters. Those last values can be initialized at 0.9 and gradually reducing it until 0.1.

Genetic Algorithms (GA)

Genetic Algorithms (GA)

John Holland proposed genetic Algorithms in the 1970s. Initially, they were called *"Reproductive Plans."* These algorithms are maybe the most famous of the evolutive algorithms family.

The inspiration comes from the **DNA structure**, which is people's genetic code. All the information is stored in chromosomes that have a lot of genes. Holland's proposal consists of representing the solutions by binary arrays.

Selection of Parents

Roulette
selection

You can imagine a roulette where each section is assigned to an individual. If we have 10 individuals, the roulette is divided into 10 sections. The section size is proportioned to the individual's fitness.

Tournament selection

It consists of randomly choosing k individuals and selecting the fittest one. k represents the tournament size.

Reproduction (crossover or recombination)

1 point	This technique divides the
crossover	parents into two sections
	randomly choosing a crossover
	point.
N point	The parents are divided into
crossover	several sections.
Uniform	For each gene, it copies the
crossover	gene of the first or the second
	parent randomly.

Mutation

Bitwise mutation	Consists of randomly selecting one or several genes and
	changing their values.
Random resetting	Consists of randomly selecting one or several genes and resets its values.
Uniform mutation	It randomly selects one or several genes and chooses a random value between the minimum and maximum values.
Swap mutation	Consists of randomly selecting two elements and swapping their values.

Differential Evolution

Diferencial Evolution (DE)

It is a robust algorithm for solving continuous multidimensional optimization problems. In this algorithm, individuals as seen as vectors.

The novelty is the mutation operator, that uses three individuals for mutate another one, and the mutation depends on the distance

Differential Evolution Example

Video: http://youtu.be/BsfJDg0a0Z4

Differential Evolution Terminology

Repres-	The individuals are repres-
entation	ented as vectors whose
	entries are the variables
	1

values.

Mutation Mutation is the main operation in Differential Evolution. The new individual v i is calculated as follows: $vi = xr1 + F(xr2 - \Box \Box r3)$

Crossover For each variable k of u

 \Box , the value is selected randomly between vi or \Box

 $\Box i$

Selection The selection is performed by

tournament.

Constraint Handling

Disadvantages of Constrains

In general, the presence of constraints will divide the space of potential solutions into two or more disjoint regions, *the feasible region*, containing those candidate solutions that satisfy the given feasibility condition, and the *infeasible region* containing those that do not.

Penalty Functions

Static Relies on the ability to specify a distance metric that accurately reflects the difficulty of repairing the solution, which is obviously problem-dependent, and may also vary from constraint to constraint



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Penalty Functions (cont)

Dynamic

The fitness function used to evaluate the population is a combination of the distance function for constraint i with a death penalty for all solutions violating constraints

Is a distance metric of the infeasible point to the feasible region

Constrains in EA

The presence of constraints implies that not all possible combinations of variable values represent valid solutions to the problem at hand.

Unfortunately, constraint handling is not straightforward in an EA, because the variation operators are typically "blind" to constraints.

There is no guarantee that even if the parents satisfy some constraints, the offspring will satisfy them as well.

Repair Functions

Takes an infeasible point and generates a feasible solution based on it. In some problems, this technique is relatively simple.

In general, defining a repair function may be as complex as solving the problem itself.

Evolution Strategies (ES)

Evolution Strategies (ES)

The goal is to solve *continuous multidime-nsional optimization problems*.

The main characteristic is the **self-adaptation of parameters**. It means that some evolutive algorithm parameters change during the execution.

Those parameters are included in the individual representation and **evolve** at the same time that the solution.

Evolution Strategies Terminology

Individuals' solutions are dual's represented as vectors whose inputs are the values of the entation variables

Mutation The individual's position is

modified by adding a random number, noise, to each entry

Recomb- In ES there are two recombination ination variants

Interm- The values of the parents are ediate averaged.

ination

Discrete One of the parent's values is recomb-randomly chosen with equal chance for either parents

Parent Parent selection in ES is selection completely random, because here the whole population is seen as parent

Survivor (μ, λ) selection, where only Selection the best μ offspring are

selected. $(\mu + \lambda)$ selection, where the best μ individuals (from the union of parents and offspring) are selected

Specialty Self-adaptation of mutation step

Genetic Programming

Genetic Programming (GP)

Automatically solves problems without requiring the user to know or specify the structure of the solution in advance.

The main idea of GP is to evolve a population of computer programs, where individuals are commonly represented as syntax trees.

Elements of a GP individual

Terminals Leave nodes in a syntax tree.

Variables that can be predefined or randomly generated.

Functions Internal nodes in a syntax tree.

Operations

Genetic Programing Terminology

Initial population

Mutation

- 1. Full, where all the trees are randomly created, and all the leaves have the same depth
- 2. **Grow**, each node selects an element randomly from either the function set or the terminal
- Ramped half-and-half
 where half of the population is
 created with the full technique
 and the other half with grow

Selection Tournament Selection

Crossover Classic Crossover

Classic Clossover

Subtree mutation, randomly selects a mutation point in a tree and substitutes the subtree rooted there with a randomly generated subtree



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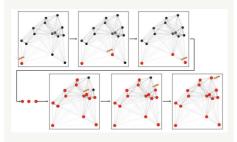


Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO)

Solves problems of finding paths in graphs. It is inspired by the ants' behavior when searching for food. The ants leave pheromones that allow other ants to follow the path to food. The more ants go for a specific path, the more pheromones.

Example



In this algorithm, an artificial ant must simulate a path starting at a specific point. It moves node by node, choosing based on the pheromones of each path.

Ant Colony Terminology

- Cij Path from the node i to the node j
- Tij Pheromones in the path from the node i to the node j
- Nij Heuristic in the path from the node i to the node j
- p Evaporation rate, between 0 and 1

Steps	
First	All the pheromones can be initialized with a small value.
Second	Ants start to move around the graph node by node using the previous equation.
Last	The pheromones must be updated. Ants deposit pheromones to their path proportional to its distance. The pheromones evaporate.

