Algoritmo Genético

e aplicações

Eduardo Dalapicola e Vinicius Arruda

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Introdução

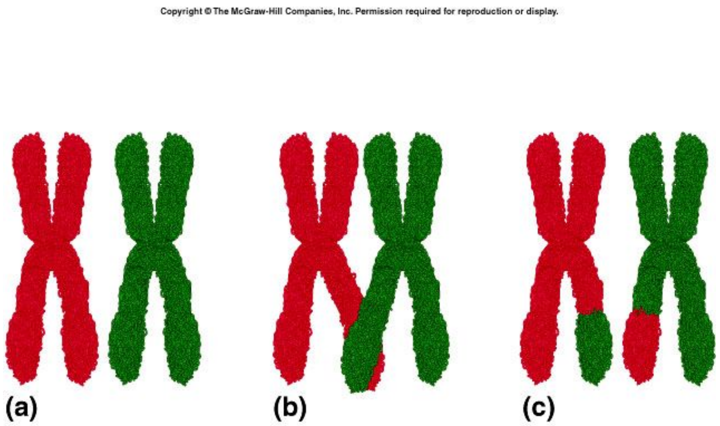
Introdução

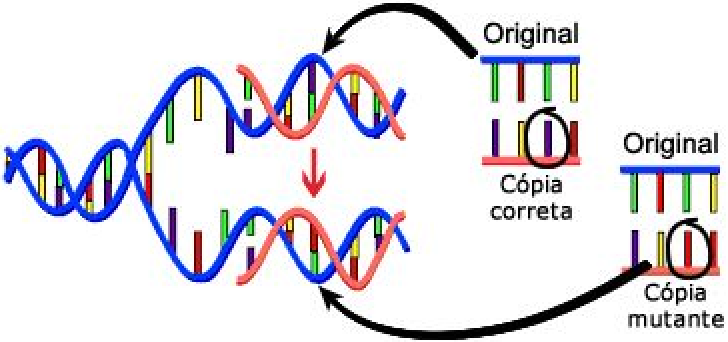
Criou o algoritmo genético na década de 60, o desenvolvendo ao longo da década de 70 e publicando formalmente no livro ***"Adaptation in Natural and Artificial Systems*** (1975, MIT Press)***"*** [1]

John Henry Holland
(1929 - 2015)

Introdução

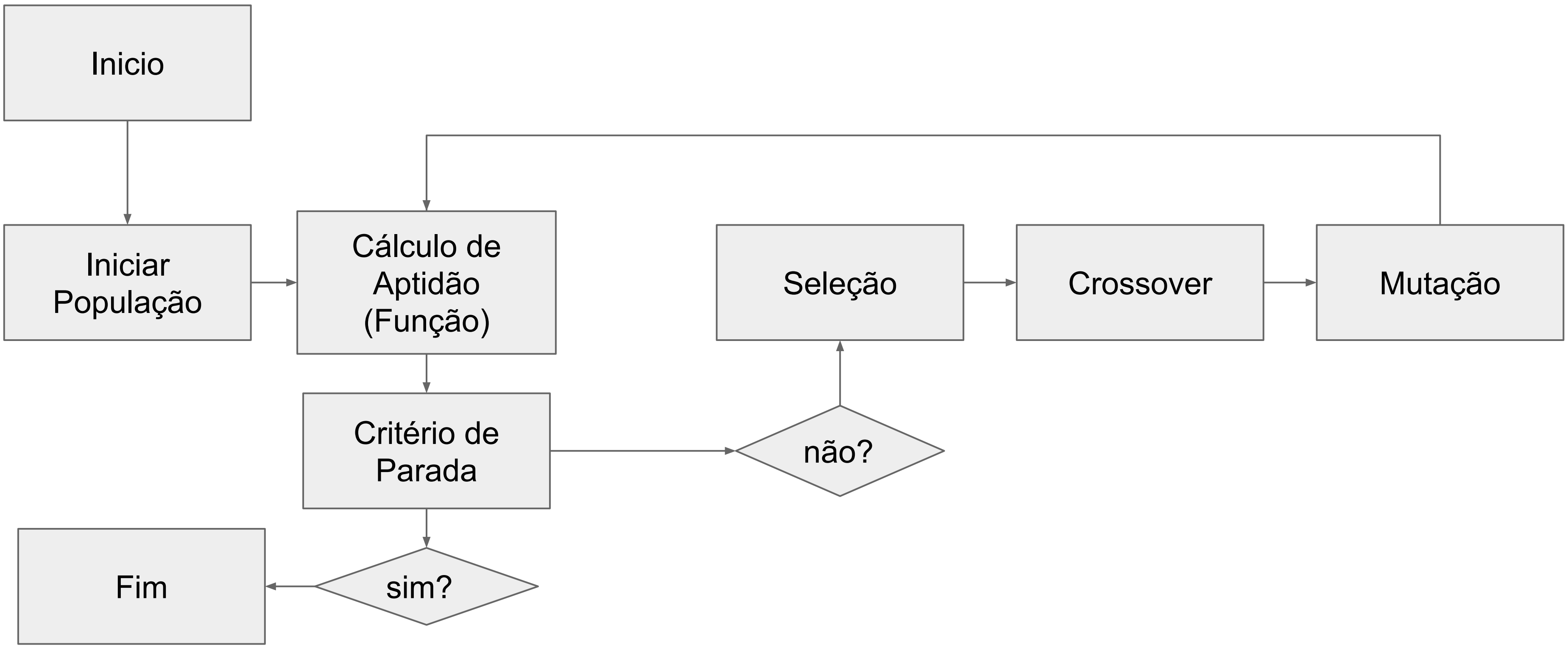
Os Algoritmos Genéticos são uma classe de modelos que são inspirados na teoria de evolução de Darwin. Em que cada instância do seu problema é modelado como um cromossomo.





O Algoritmo

O algoritmo


Inicio
Iniciar População
Cálculo de Aptidão (Função)
Seleção
Crossover
Mutação
Critério de Parada
não?
Fim
sim?

Indivíduo

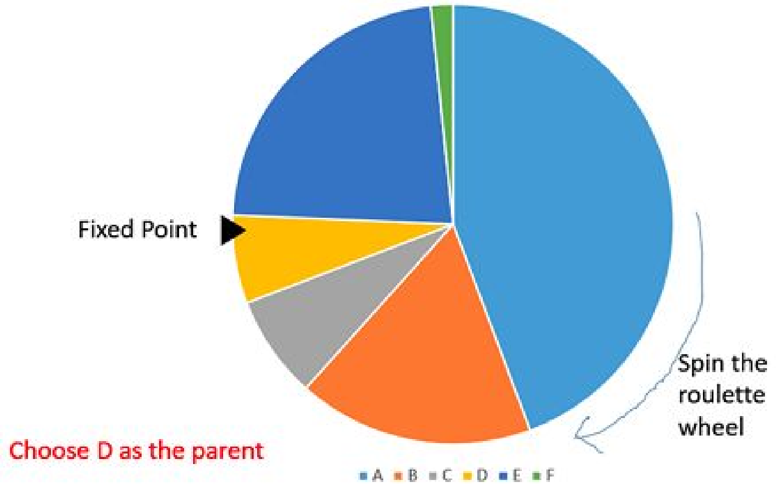
Binário	1	0	1	1	0
Real/Inteiro	0.5	0.9	1.8	9.5	3.8
Permutação	5	2	4	1	3
Abstract Sintax Tree	+	/	*	7.9	3.6
...	...				

Seleção


Antes da seleção
Após a seleção
População final
Nível de resistência
Baixo
Alto

Seleção

Método da Roleta: Indivíduos de maior valor de função ocupam proporcionalmente fatias de maior área. Então essa roleta é girada aleatoriamente e no final escolhemos o indivíduo que é indicado pelo cursor. [2]

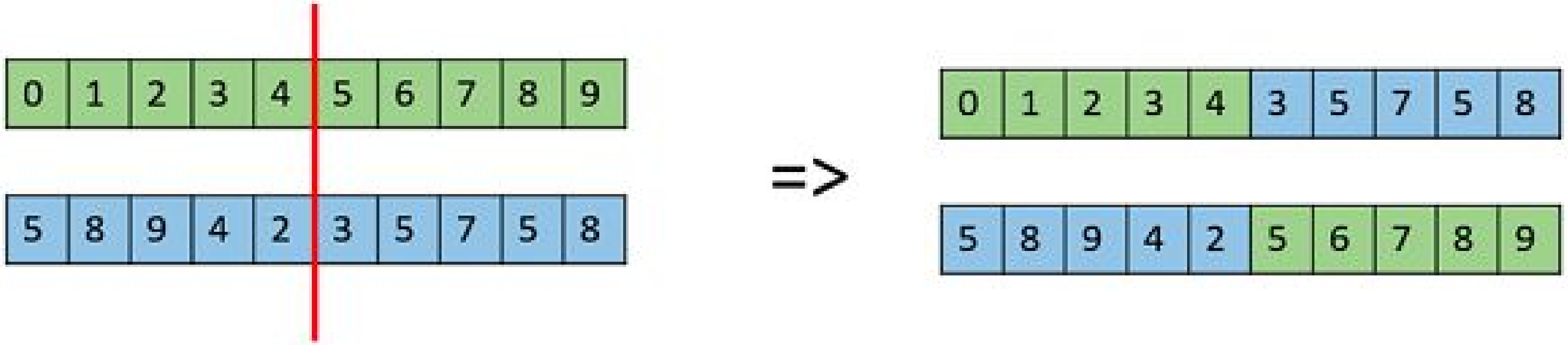


Chromosome	Fitness Value
A	8.2
B	3.2
C	1.4
D	1.2
E	4.2
F	0.3

Crossover

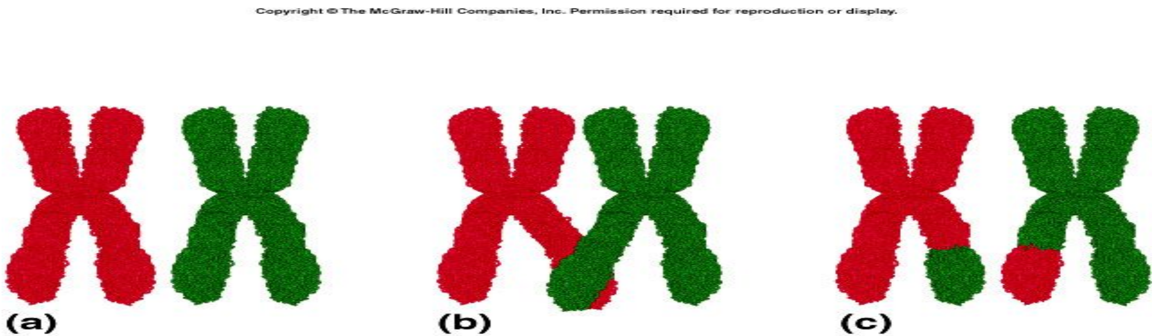
Existem muitos tipos de crossover sendo cada um mais interessante para cada problema.

Um dos mais simples é criar uma lista de parceiros, ou seja, lista de pai e de mães e realizar o cruzamento da seguinte forma [2]:



Crossover

O processo de Crossover é a recombinação de cromossomos do pai e da mãe para a formação de um ou mais indivíduos. Assim o filho terá características da mãe e do pai, mas ainda assim será diferente e possivelmente melhor.



Mutação

Após o crossover ainda pode ocorrer com uma certa probabilidade a mutação na população, é uma sutil mudança nos genes de alguns indivíduos da população. Isso faz com que diversifique a solução escapando assim de mínimos ou máximos locais.

Mutação

Assim como o crossover, a mutação pode ser feita de várias formas:

BIT FLIP:

0	0	1	1	0	1	0	0	1	0	=>	0	0	1	0	0	1	0	0	1	0

SWAP:

1	2	3	4	5	6	7	8	9	0	=>	1	6	3	4	5	2	7	8	9	0

INVERSÃO

0	1	2	3	4	5	6	7	8	9	=>	0	1	6	5	4	3	2	7	8	9

Principais Parâmetros

- Tamanho da População
- Número de Gerações
- Probabilidade de Crossover (60% - 65%)
- Probabilidade de Mutação (0.1% - 5%)

Aplicação

MÍNIMO DE UMA FUNÇÃO

Mínimo de uma função

Crossover

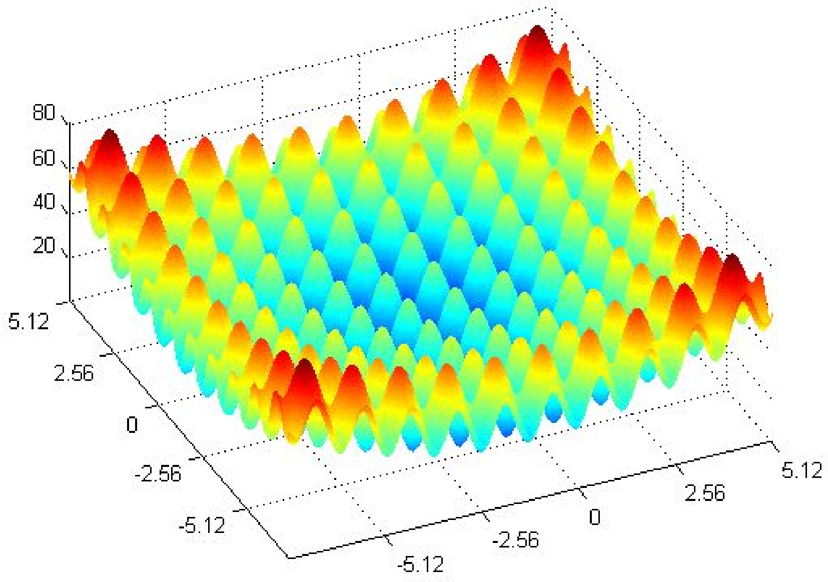
o[i] = **a**·m[i] + (1 - **a**)·f[i]

Mutação

o[i] = **b**·o[i]

Seleção

p = sort(p)[:**y**]



Caixeiro Viajante

Caixeiro Viajante

Caixeiro Viajante

```
[[   0, 2451,  713, 1018, 1631, 1374, 2408,  213, 2571,  875, 1420, 2145, 1972], # New York
 [2451,    0, 1745, 1524,  831, 1240,  959, 2596,  403, 1589, 1374,  357,  579], # Los Angeles
 [ 713, 1745,    0,  355,  920,  803, 1737,  851, 1858,  262,  940, 1453, 1260], # Chicago
 [1018, 1524,  355,    0,  700,  862, 1395, 1123, 1584,  466, 1056, 1280,  987], # Minneapolis
 [1631,  831,  920,  700,    0,  663, 1021, 1769,  949,  796,  879,  586,  371], # Denver
 [1374, 1240,  803,  862,  663,    0, 1681, 1551, 1765,  547,  225,  887,  999], # Dallas
 [2408,  959, 1737, 1395, 1021, 1681,    0, 2493,  678, 1724, 1891, 1114,  701], # Seattle
 [ 213, 2596,  851, 1123, 1769, 1551, 2493,    0, 2699, 1038, 1605, 2300, 2099], # Boston
 [2571,  403, 1858, 1584,  949, 1765,  678, 2699,    0, 1744, 1645,  653,  600], # San Francisco
 [ 875, 1589,  262,  466,  796,  547, 1724, 1038, 1744,    0,  679, 1272, 1162], # St. Louis
 [1420, 1374,  940, 1056,  879,  225, 1891, 1605, 1645,  679,    0, 1017, 1200], # Houston
 [2145,  357, 1453, 1280,  586,  887, 1114, 2300,  653, 1272, 1017,    0,  504], # Phoenix
 [1972,  579, 1260,  987,  371,  999,  701, 2099,  600, 1162,  1200,  504,    0]] # Salt Lake City
```

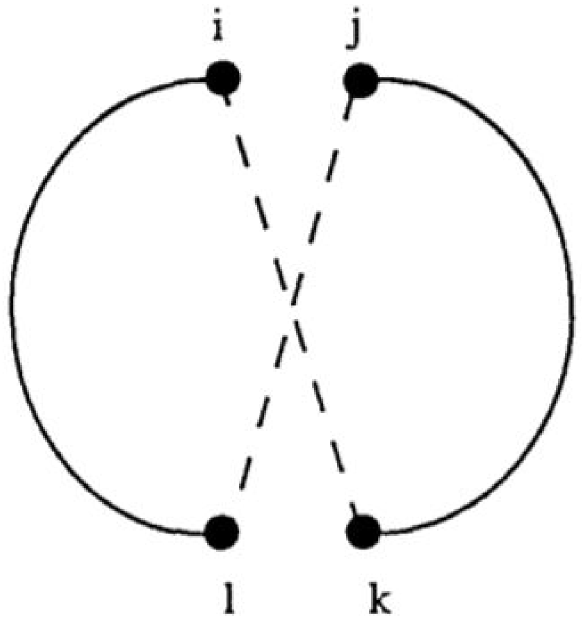
Caixeiro Viajante

```
def individual():
    i = range(0, 13)
    shuffle(i)
    return i
```

```
def fitness(ind):
    cost = 0
    for i in xrange(0, 12):
        cost += city[ind[i]][ind[i+1]]
    cost += city[12][0]
    return cost
```

Caixeiro Viajante

```
def mutate(ind):
    idx1 = randint(0, 12)
    idx2 = randint(0, 12)
    tmp = ind[idx1]
    ind[idx1] = ind[idx2]
    ind[idx2] = tmp
```

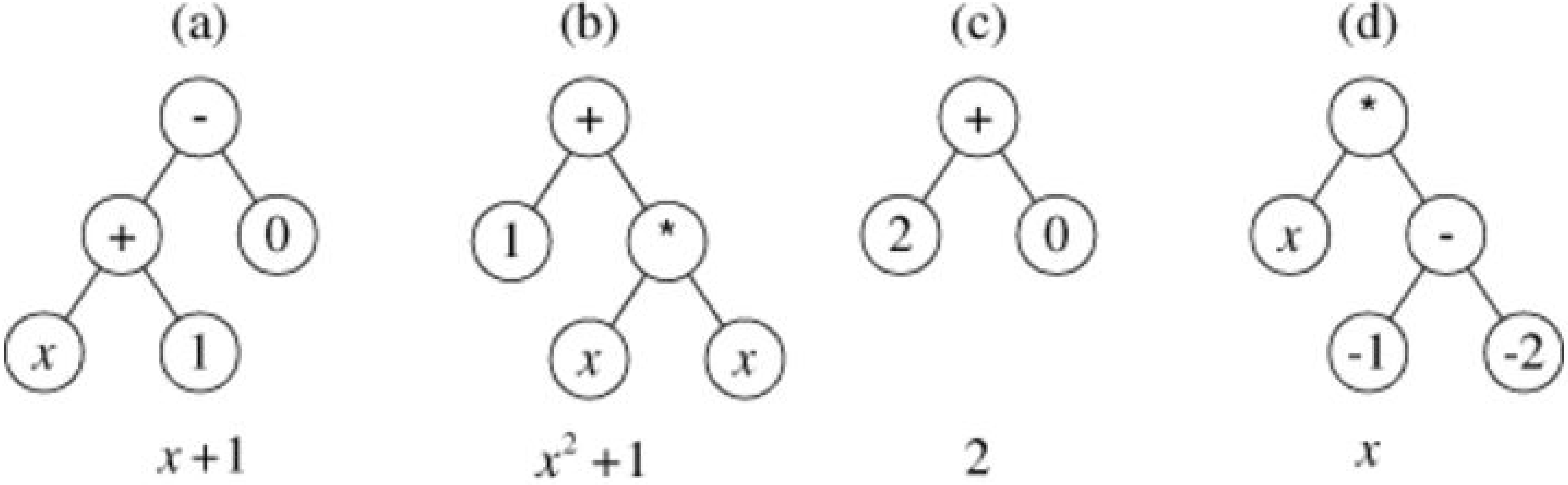


Caixeiro Viajante

```
Order Crossover (OX) [3]

male:              1 2 5 6 4 3 8 7

female:            1 4 2 3 6 5 7 8

offspring:

step 1            - - 5 6 4 - - -

step 2            2 3 5 6 4 7 8 1
```

Programação Genética

Programação Genética



Programação Genética [11]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Programação Genética [11]


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Design

DESIGN (2002)

Antenna Design Using Genetic Algorithms

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Abstract

Antennas are an important component in any wireless system, as they transform a signal that flows through wires into a signal that propagates through space and back again. How well it does this job is a determining factor in how well a

GAs are being applied to many different antenna designs by many different researchers [1]. GAs and other evolutionary computation techniques are very useful in this field for several reasons, including:

- Antenna principles, which are a subset of electromagnetics and founded on Maxwell's equations, are extremely difficult to understand and grasp intuitively.

Design (2006)

Automated Antenna Design with Evolutionary Algorithms

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Al Globus
San Jose State University

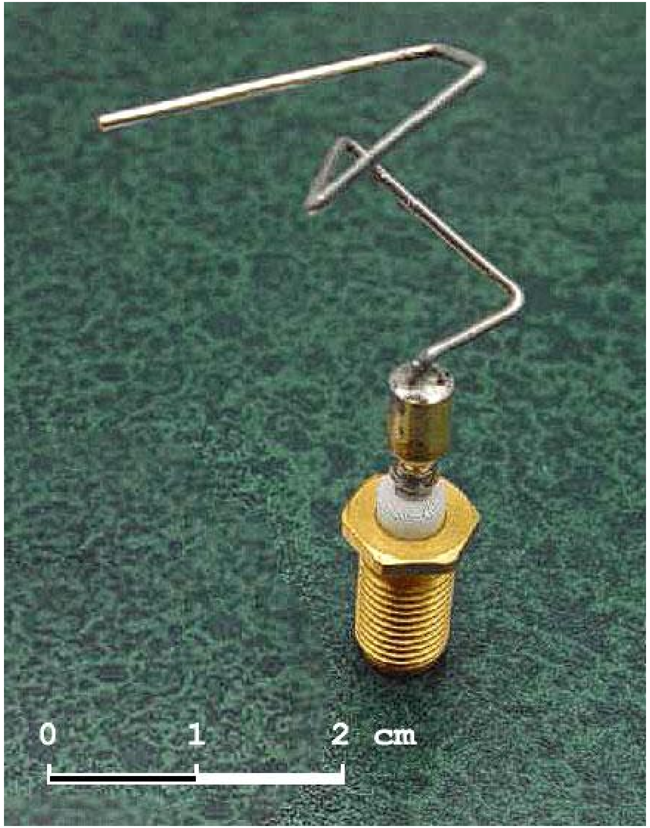
Derek S. Linden
JEM Engineering, 8683 Cherry Lane, Laurel, Maryland 20707

Jason D. Lohn
NASA Ames Research Center, Mail Stop 269-1, Moffett Field, CA 94035

Whereas the current practice of designing antennas by hand is severely limited because it is both time and labor intensive and requires a significant amount of domain knowledge, evolutionary algorithms can be used to search the design space and automatically find novel antenna designs that are more effective than would otherwise be developed. Here we present automated antenna design and optimization methods based on evolutionary algorithms. We have evolved efficient antennas for a variety of aerospace applications and here we describe one proof-of-concept study and one project that produced flight antennas

Design

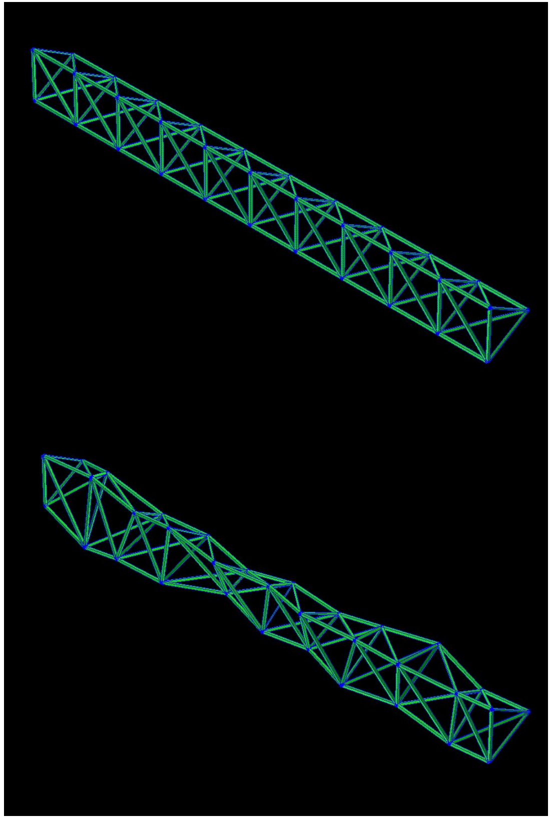
“The 2006 NASA ST5 spacecraft antenna. This complicated shape was found by an evolutionary computer design program to create the best radiation pattern.” [4]

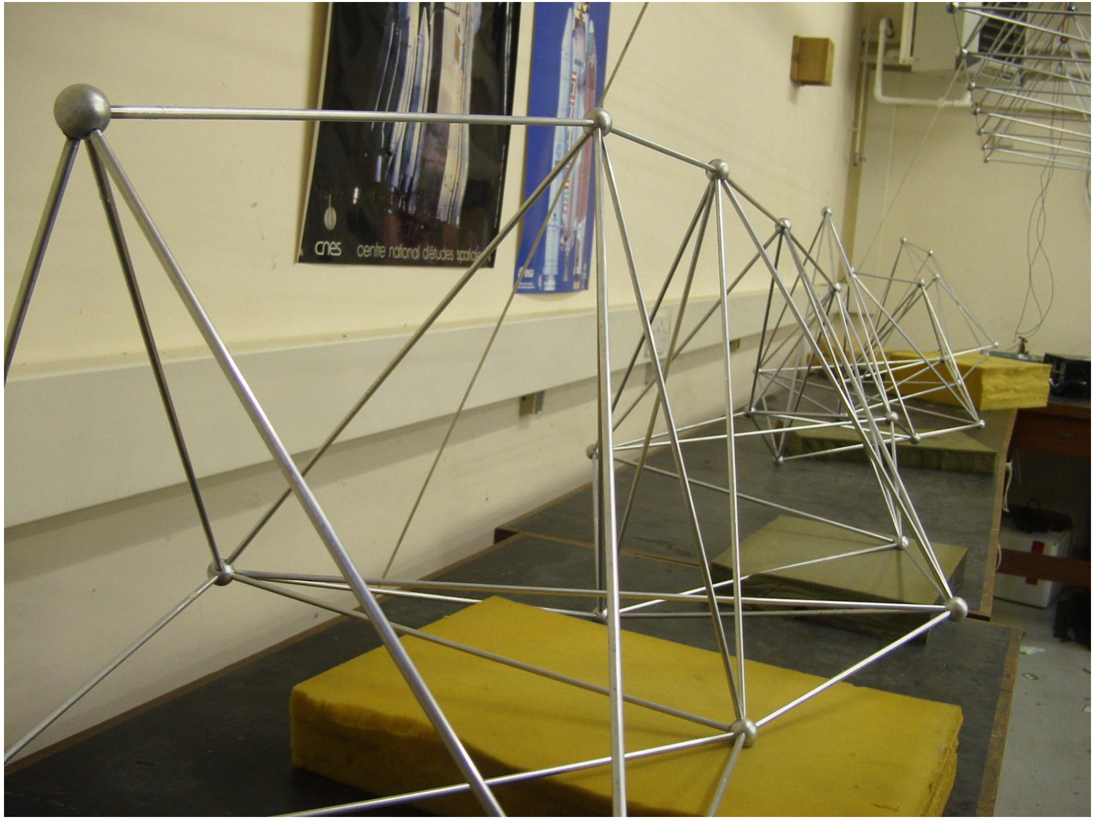


Design

“Design of satellite trusses with enhanced vibration isolation characteristics.” [5]

Design [5]





Sistema de Recomendação

Sistema de recomendação [6]

cromossomo:

filme M = [cor, duração, diretor, ator1, ator2, ator3, diretor, ator1, ator2, ator3, elenco, filme, bilheteria, gêneros, votos_imdb, palavras-chave, num_reviews, classificação_conteúdo, orçamento, ranking_imdb, …]

fitness:

ranking do usuário (*interactive genetic algorithm*)

Sistema de recomendação

seleção:

```
p = sort(p)[:y]
```

crossover:

```
Mo = closer(database, Mm[:idx] + Mf[idx:])
```

mutação:

```
M[r] = random(database, type(M[r]))
```

Sistema de recomendação (2015)

ISSN : 0976-8491 (Online) | ISSN : 2229-4333 (Print)

IJCST Vol. 6, Issue 3, July - Sept 2015

A Hybrid Recommender System using Genetic Algorithm and kNN Approach

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[1]Dept. of Computer Science, Chandigarh University, Gharuan, India

Abstract

Recommender Systems are now popular both commercially and in the research community, where various approaches have been adopted and validated on large scale. In content-based filtering, the systems examine items previously chosen by the actual user, whereas in collaborative filtering, recommendations are based on the information of similar users or items. We also analyzed that recommendations are also influenced by the factors such as age, gender and some other user profile information. In our work both content and collaborative techniques and some demographic information are combined into a hybrid approach, where additional content features are used to improve the accuracy of collaborative filtering. Also we are using the genetic algorithm and k-NN algorithm to provide recommendations to the user. To evaluate precision, recall and F1-measure performance parameters are used.

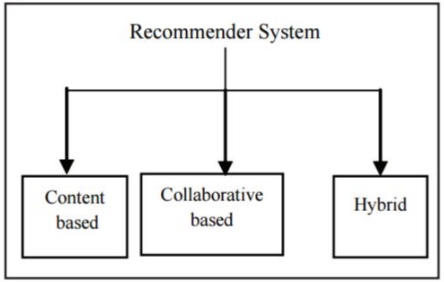

Fig. 1: Classification of Recommender System

In content-based recommendation approach, the system analyze a set of documents or descriptions of items that are previously rated by a user, and create a model or profile of user preferences based on the features of the items rated by that user [4]. The profile is an organized representation of user preferences which is adopted to

Sistema de recomendação (2017)

Research Article

Movie Recommender System using Genetic Algorithm

Jyoti Joshi[1]

Abstract

Recommender systems have become extremely common in recent years, and are utilized in a variety of areas: some popular applications include movies, music, news, books, research articles, search queries, social tags, and products in general. Traditional recommendation techniques in recommender systems mainly use content based or collaborative filtering techniques. These systems only use the product ratings given by the users to predict/recommend new products or items to the user. They do not consider other attributes while generating recommendations for a user.

This article describes a new recommendation system that uses genetic algorithm to learn about the preferences of the users and provides recommendations based on these preferences. This research uses Movie Lens (http://www.movielens.umn.edu) database and the genetic algorithm combines

Sistema de recomendação (2010)

A Recommender System Based on Genetic Algorithm for Music Data

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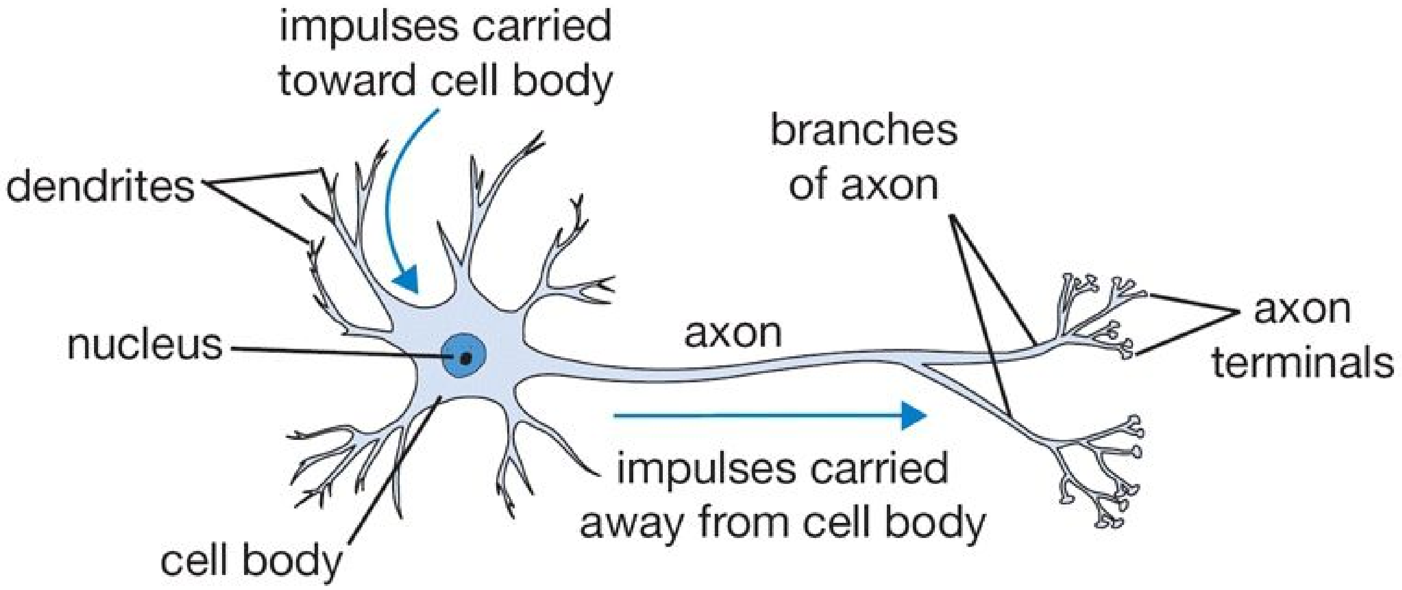
Abstract **– Nowadays, recommender systems are widely implemented in E-commerce websites to assist customers in finding the items they need. A recommender system should also be able to provide users with useful information about the items that might interest them. The ability of promptly responding to changes in user's preference is a valuable asset for such systems. This paper presents an innovative recommender system for music data that combines two**

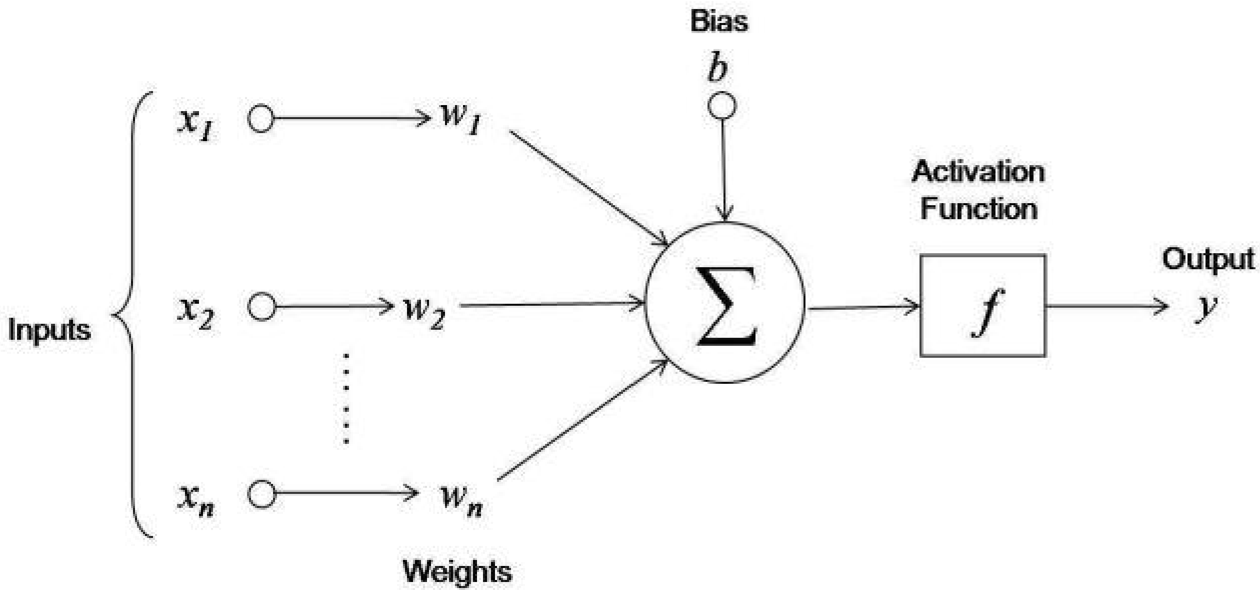
In this paper, we propose a new recommender system for music data by combining the content-based filtering technique with the interactive genetic algorithm. We consider the unique properties of each music track, such as tempo, pitch and chord. We use a music feature extraction tool to analyze these properties. The results of the extraction consist in the database of our proposed system. We expect

Redes Neurais Artificiais

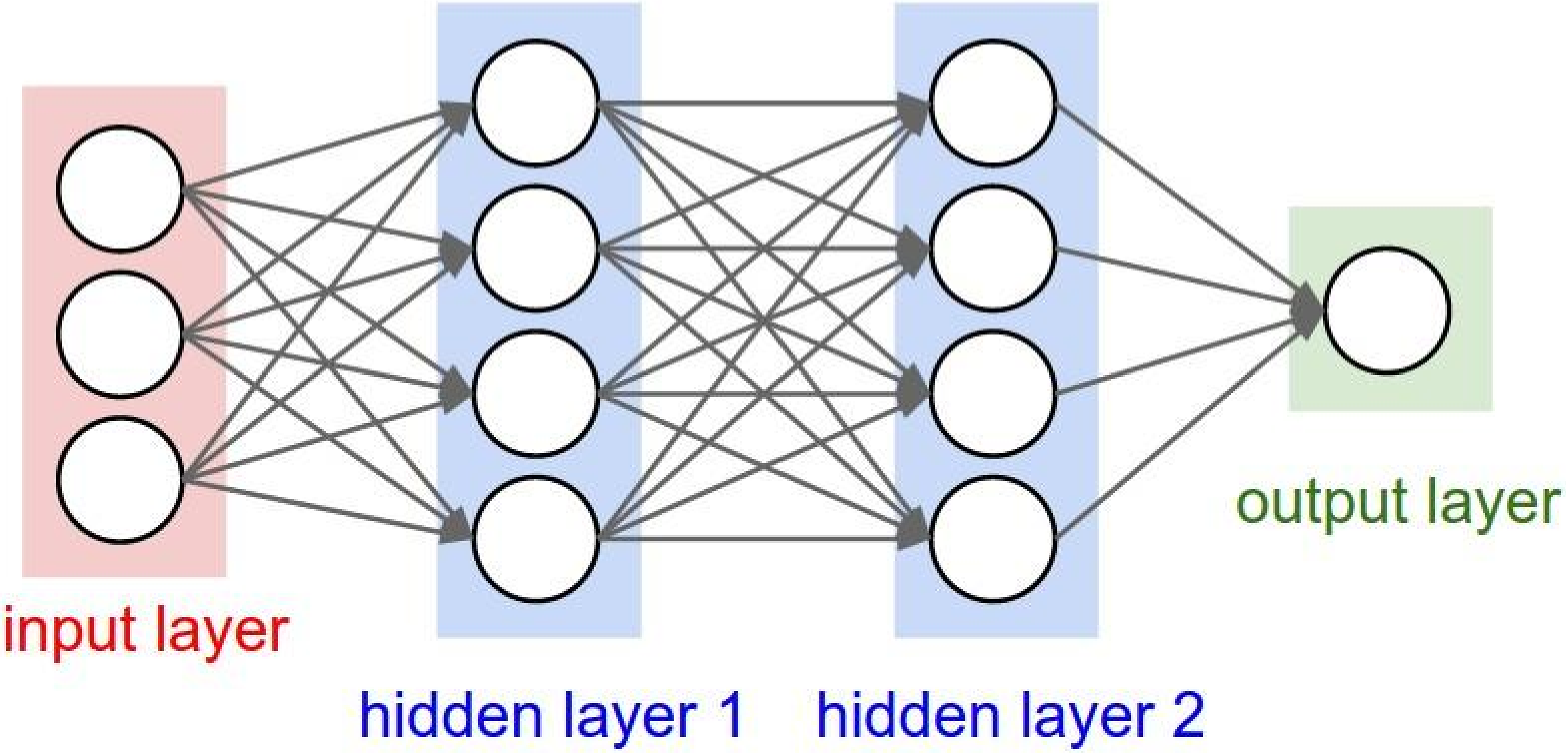
Redes Neurais Artificiais



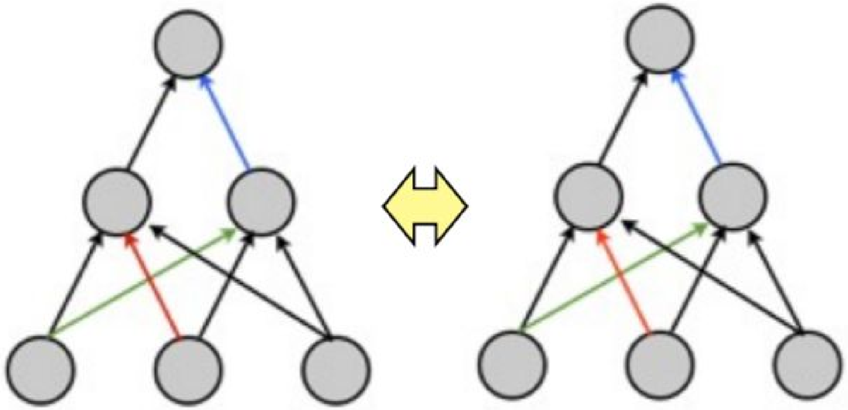
Redes Neurais Artificiais



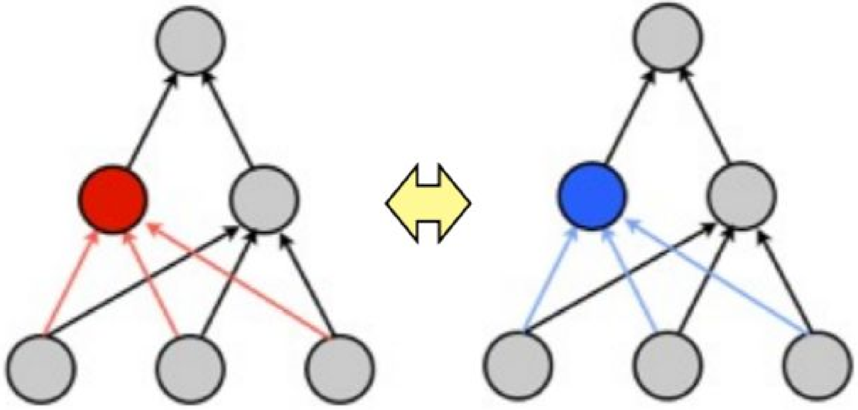
Redes Neurais Artificiais



Redes Neurais Artificiais

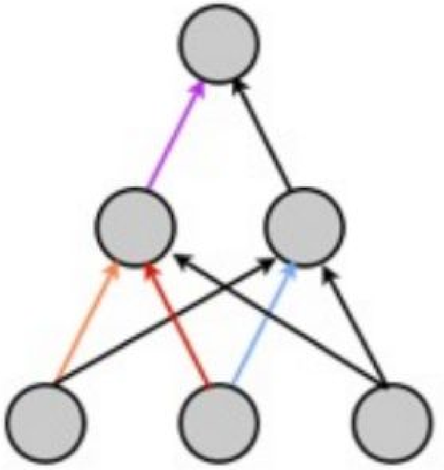


[Crossover-Weights]

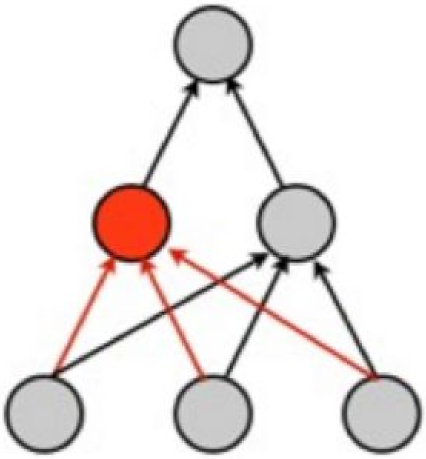


[Crossover-Nodes]

Redes Neurais Artificiais



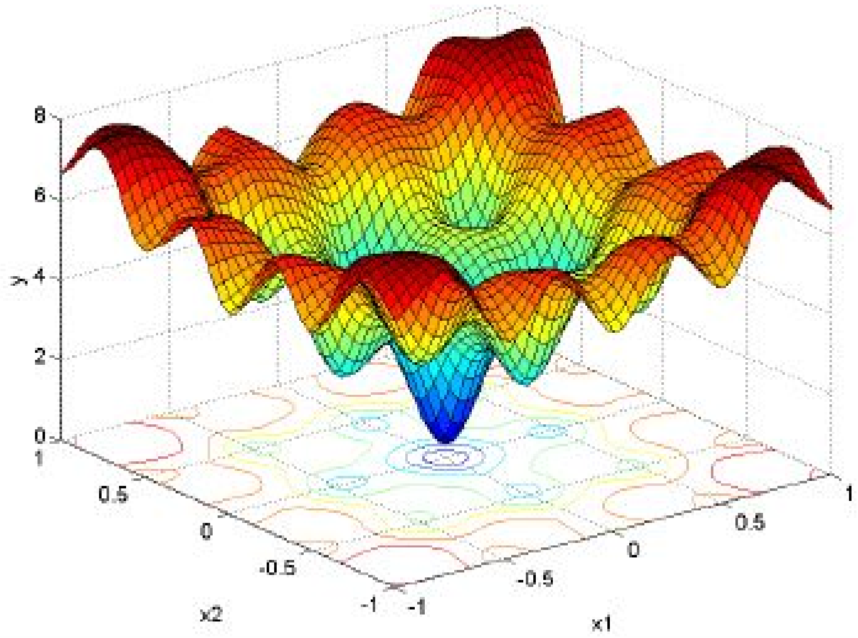
[Mutate-Weights]



[Mutate-Nodes]

Redes Neurais Artificiais

Pode ser utilizado em conjunto com outro algoritmo de treinamento de RNAs.



Redes Neurais Artificiais (2012)

Basic Genetic-Algorithm-Neural-Network (GANN) Pattern with a Self-Organizing Security Example

Paper No. ICCST-2012-42

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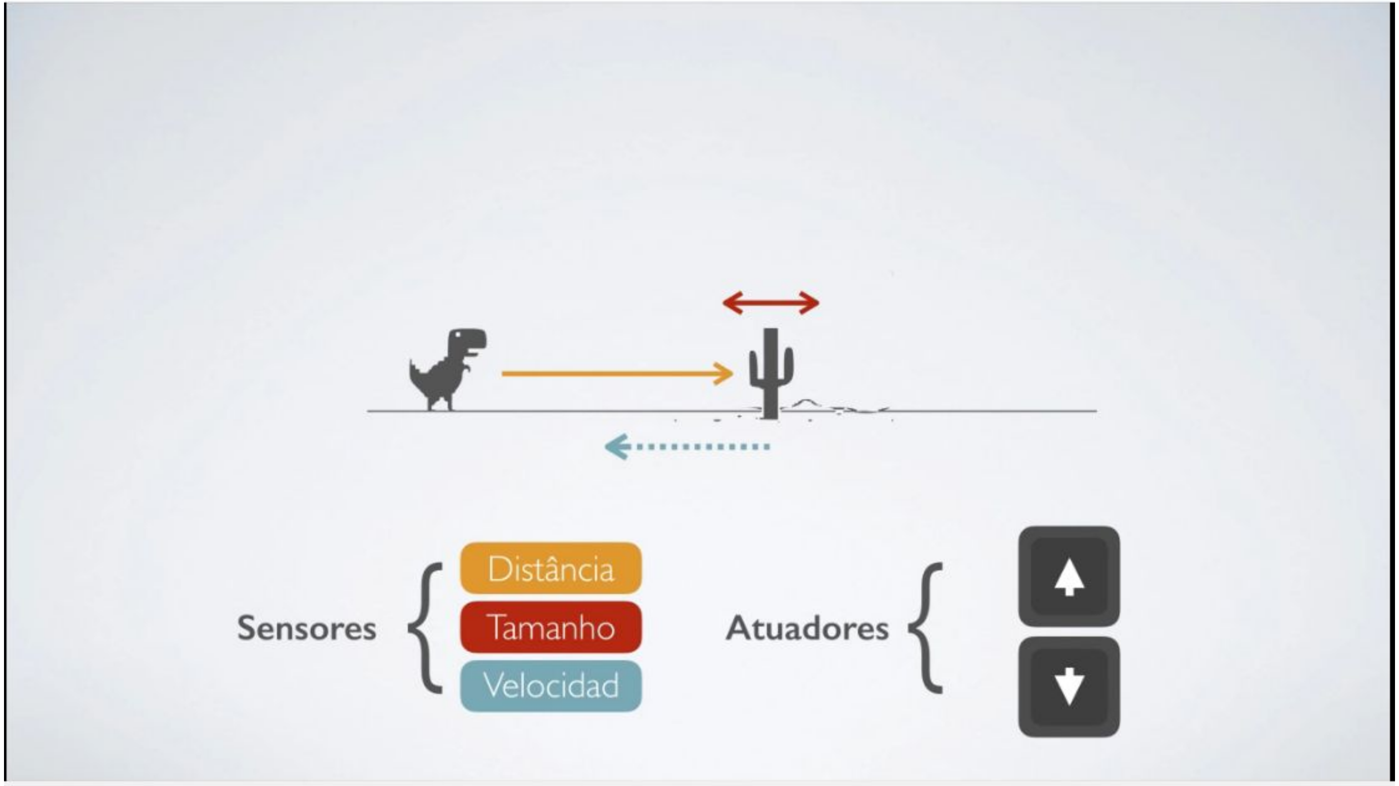
Abstract—The anti-system adversarial community is characterized as a self-organizing system-of-systems, noted collectively for its leadership in rapid evolution and innovative advancement; widening the gap between security cost and security losses. It appears that system security strategy cannot hope to even achieve parity without a comparable self-organizing strategy. Toward that end a project is underway to catalog re-usable patterns of self-organizing security of many

characteristics – but is rather clarifying fine distinctions between the qualifying characteristics and refining the descriptive nature of the pattern form elements.

TABLE I
PATTERN QUALIFICATION SAREPH FILTERS

[S]	**Self-organizing** – with humans embedded in the loop, or with systemic mechanisms.
[A]	**Adapting** to unpredictable situations – with

Redes Neurais Artificiais [7]



Redes Neurais Artificiais [12] (2002)

Evolving Neural Networks through Augmenting Topologies

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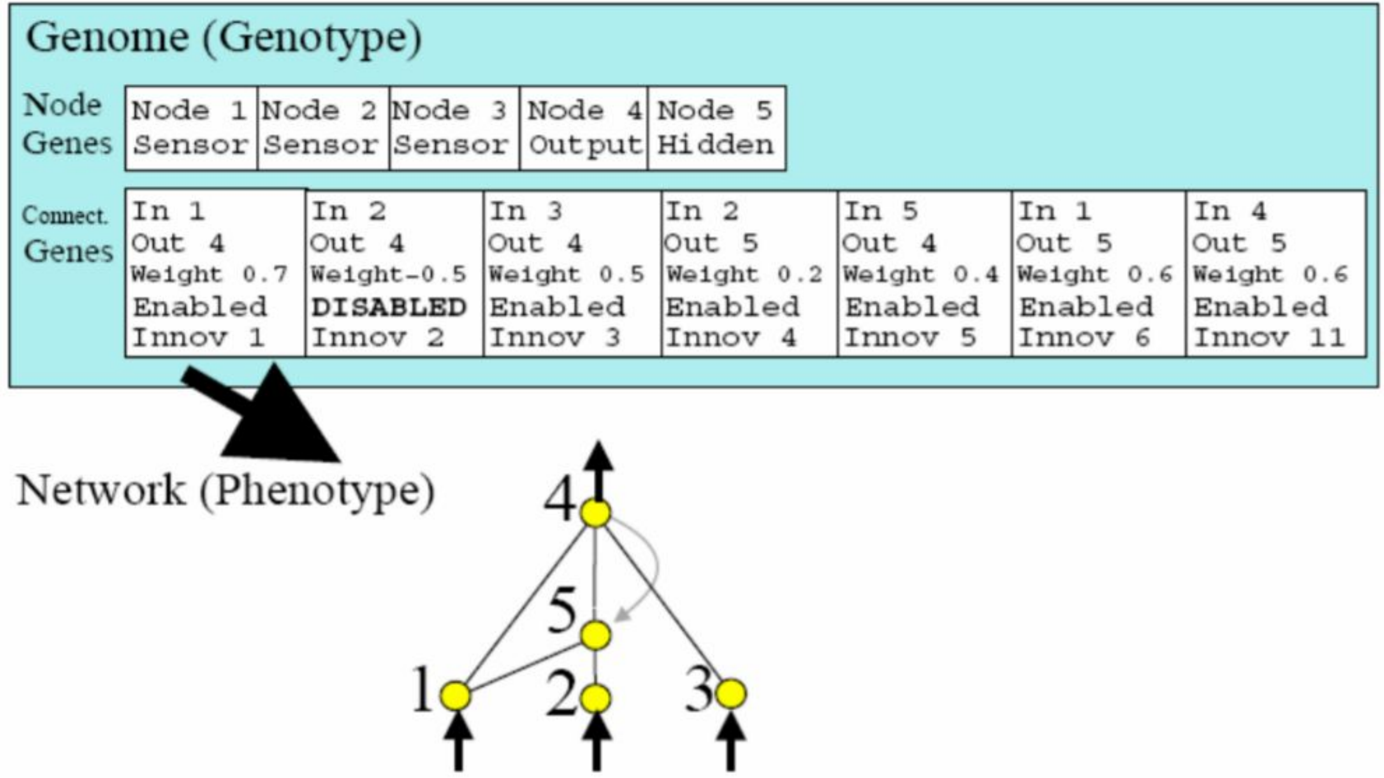
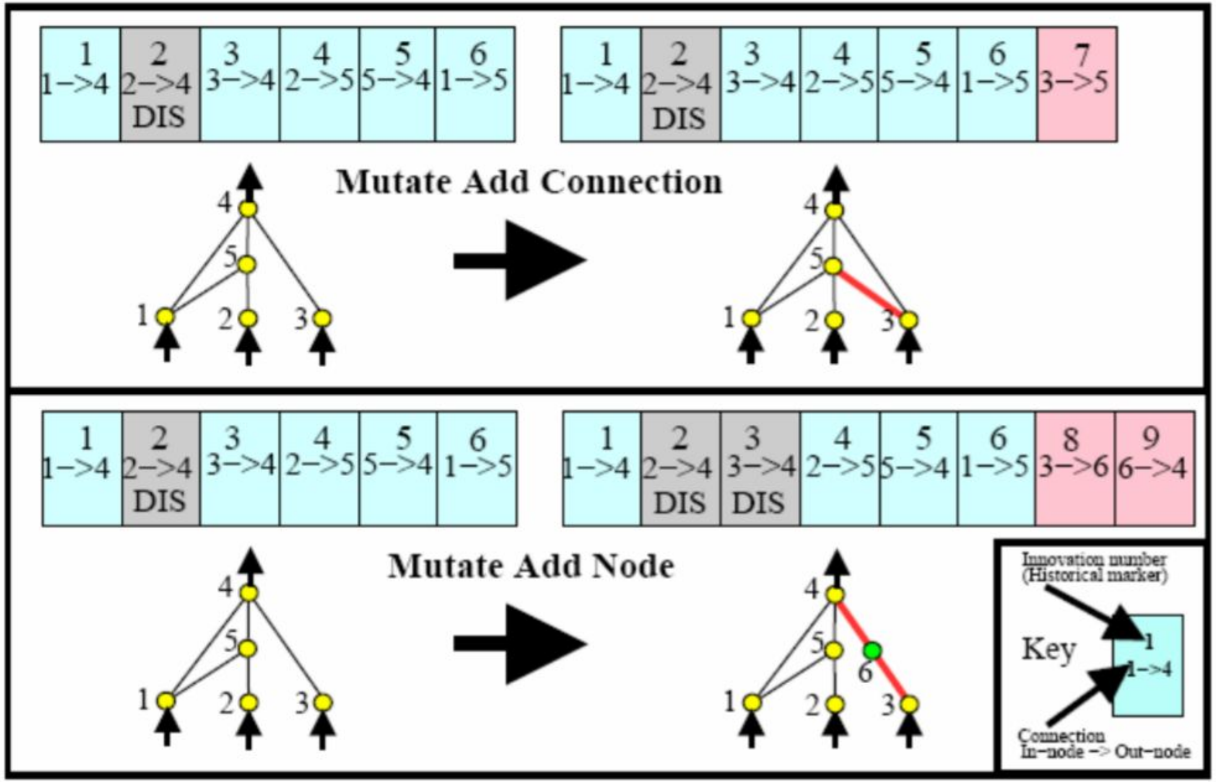
Risto Miikkulainen risto@cs.utexas.edu
Department of Computer Sciences, The University of Texas at Austin, Austin, TX 78712, USA

Abstract

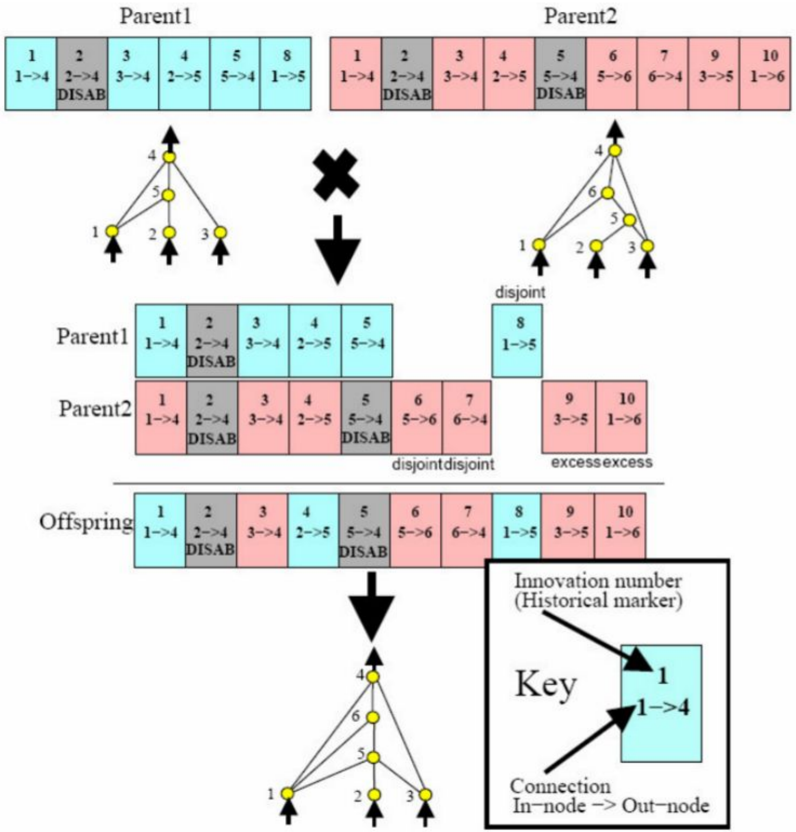
Redes Neurais Artificiais [8][12]



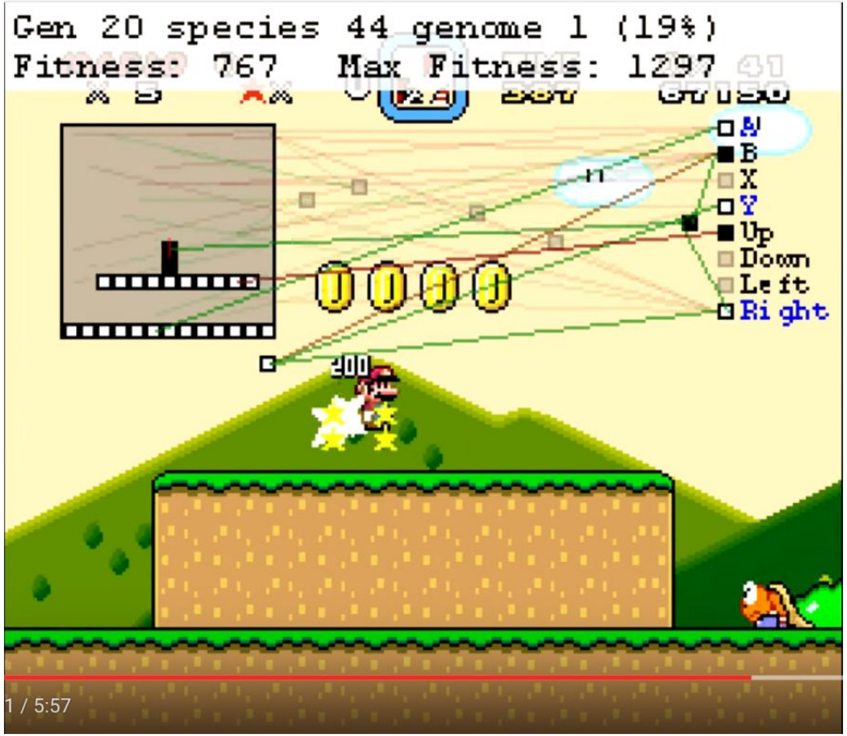
Redes Neurais Artificiais [8][12]

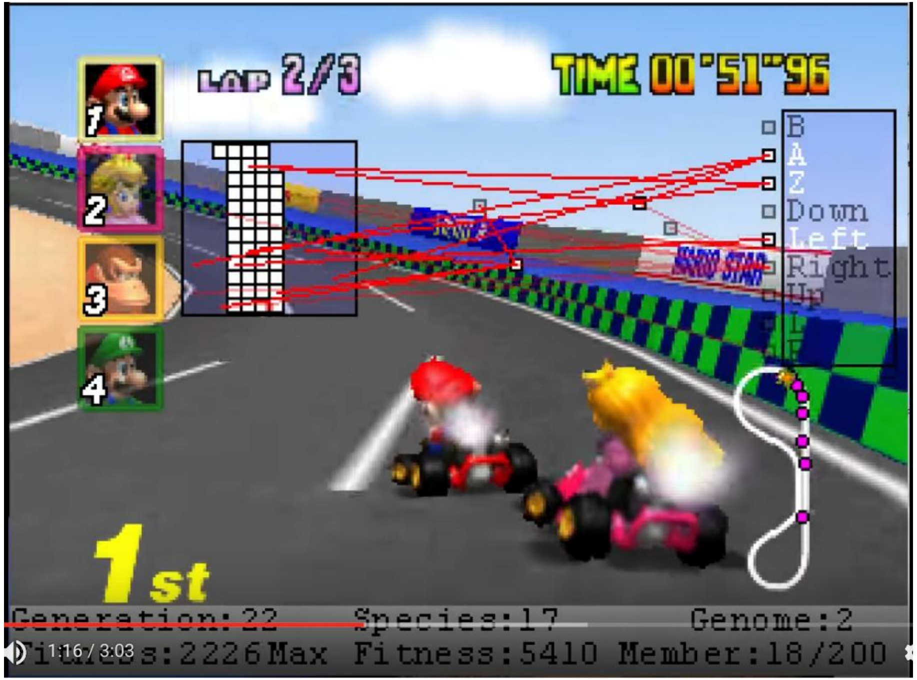


Redes Neurais Artificiais [8][12]



Redes Neurais Artificiais [9][10]





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