Genetic Algorithms Overview and Examples

Cse634

DATA MINING

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Genetic Algorithm   Short Overview

- **INITIALIZATION**

- At the beginning of a run of a **Genetic Algorithm** an
- INITIAL POPULATION of *random* chromosomes is created

- The INITIAL POPULATION depends on the nature of the problem, but typically contains several hundreds or thousands of possible chromosomes (possible solutions)

- Often the INITIAL POPULATION covers the entire range of possible solutions (the *search space*)

- Sometimes the solutions (chromosomes) may be "seeded" in areas where optimal solutions are likely to be found

GA Short Overview

- SELECTION
- During each successive generation, a portion of the existing population is **selected** through a *fitness-based* process measured by a **fitness function**
- The fitness function is always problem dependent
- For each new chromosome (solution) to be produced, a pair of "parent" chromosomes is selected from the pool selected previously

GA Short Overview

- The new chromosome (solution) is **produced** by applying **operators** of crossover and mutation
- New parents are **selected** for each new child, and
- **the process** continues **until** a new population of chromosomes (solutions) of appropriate constant size is **generated**
- It is possible to use **other operators** such as regrouping, colonization-extinction, or migration

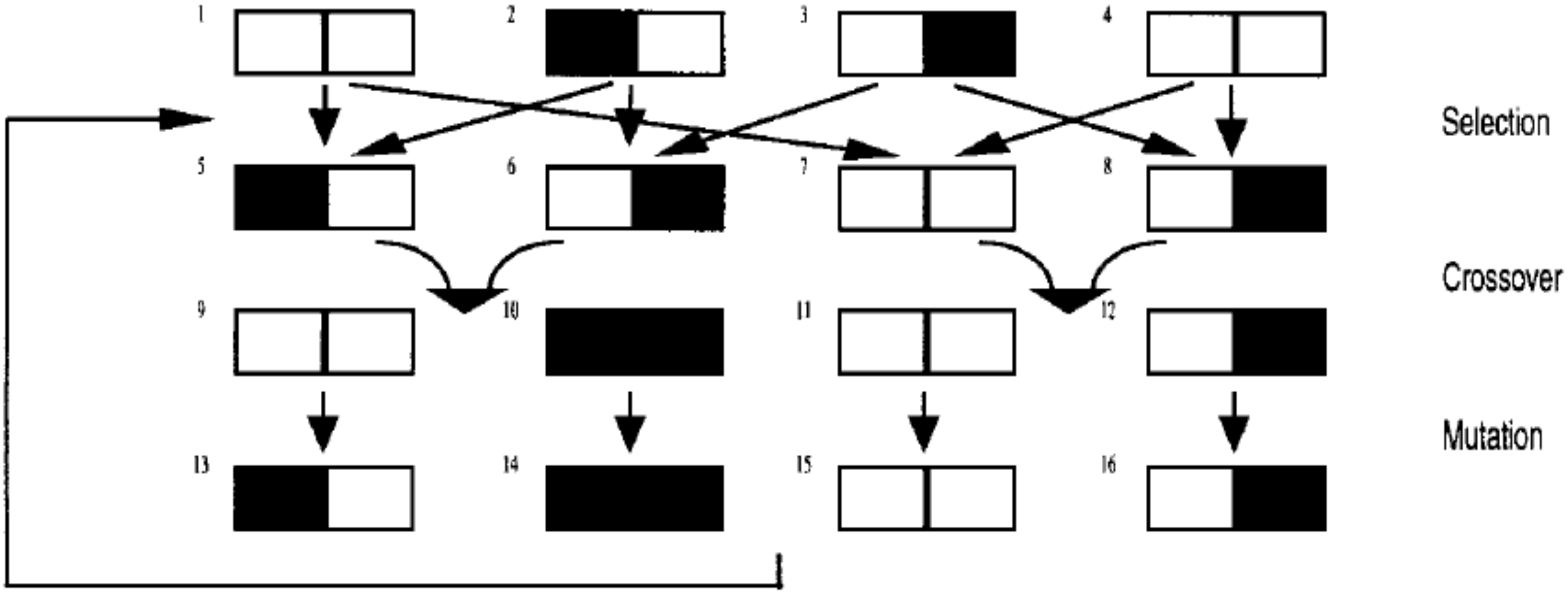
Parameters

- Crossover probability, mutation probability and population size are used often (and tuned) to find reasonable settings for the problem

- A very small mutation rate may lead to genetic drift
- A recombination rate that is too high may lead to **premature convergence** of the genetic algorithm

- A mutation rate that is too high may lead to loss of **good** solutions, unless we employ the elitist selection

One generation of a genetic algorithm, consisting of - from top to bottom - selection, crossover, and mutation stages



Example: Genetic Programming

A program in C

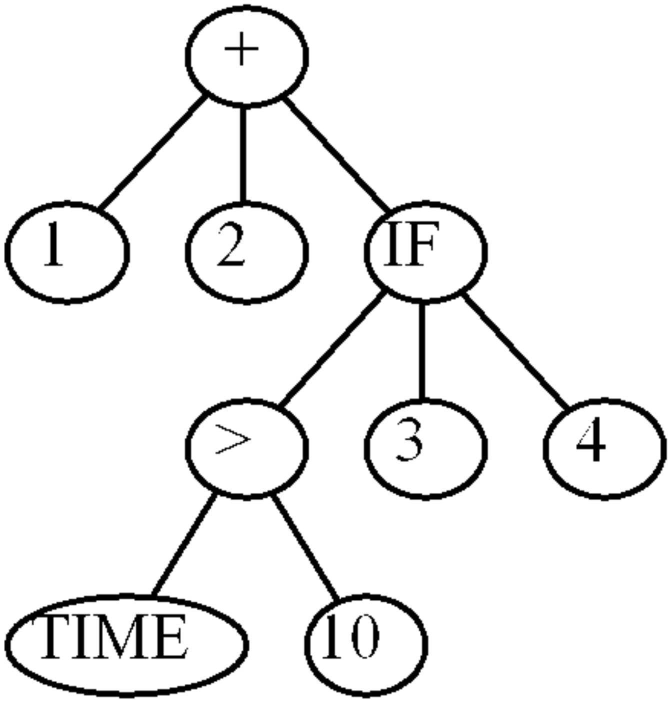
- ```
  int foo (int time)
   {
       int temp1, temp2;
       if (time > 10)
           temp1 = 3;
       else
           temp1 = 4;
       temp2 = temp1 + 1 + 2;
       return (temp2);
   }
  ```

- **Equivalent expression (similar to a classification rule in data mining):**

```
(+ 1 2 (IF (> TIME 10) 3 4))
```

Citation: www.genetic-programming.com/c2003lecture1modified.ppt
```

Program tree



(+ 1 2 (IF (> TIME 10) 3 4))

Citation: www.genetic-programming.com/c2003lecture1modified.ppt

Given data

Input: Independent variable *X*	Output: Dependent variable *Y*
-1.00	1.00
-0.80	0.84
-0.60	0.76
-0.40	0.76
-0.20	0.84
0.00	1.00
0.20	1.24
0.40	1.56
0.60	1.96
0.80	2.44
1.00	3.00

Citation: www.genetic-programming.com/c2003lecture1modified.ppt

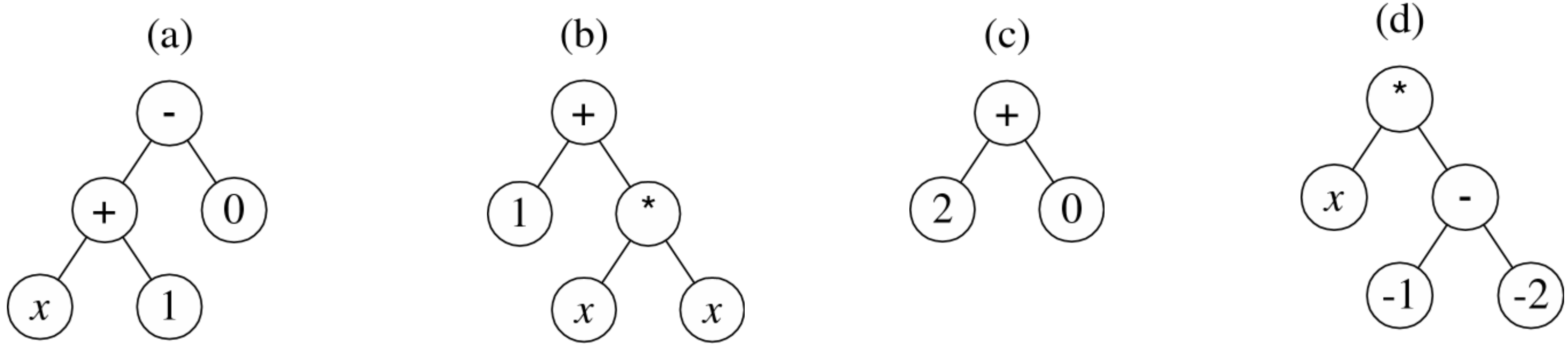
Problem description

	Objective:	Find a computer program with one input (independent variable X) whose output Y equals the given data
1	Terminal set:	`T = {X, Random-Constants}`
2	Function set:	`F = {+, -, *, /}`
3	Initial population:	Randomly created individuals from elements in T and F.
4	Fitness:	$\lvert y_0' - y_0 \rvert + \lvert y_1' - y_1 \rvert + \ldots$ where y_i' is computed output and y_i is given output for x_i in the range [-1,1]
5	Termination:	An individual emerges whose sum of absolute errors (the value of its fitness function) is less than 0.1

Citation: www.genetic-programming.com/c2003lecture1modified.ppt

Generation 0

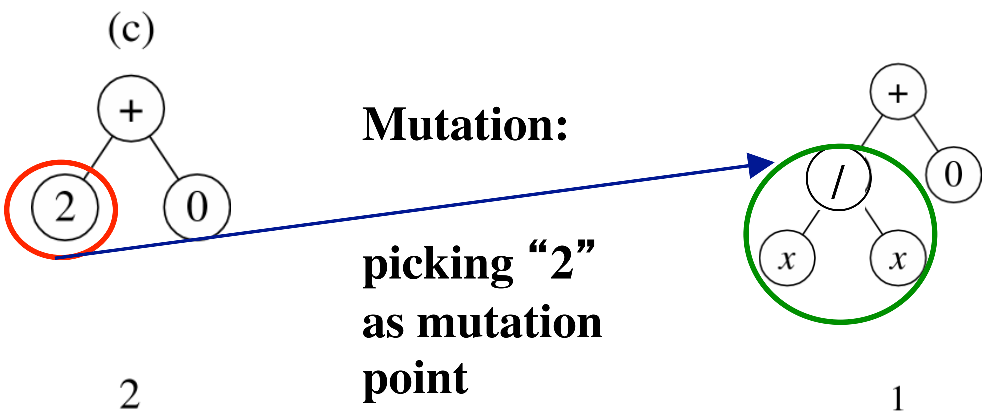
Population of 4 randomly created individuals



$x + 1$ | $x^2 + 1$ | 2 | x

Citation: examples taken from: www.genetic-programming.com/c2003lecture1modified.ppt

Mutation

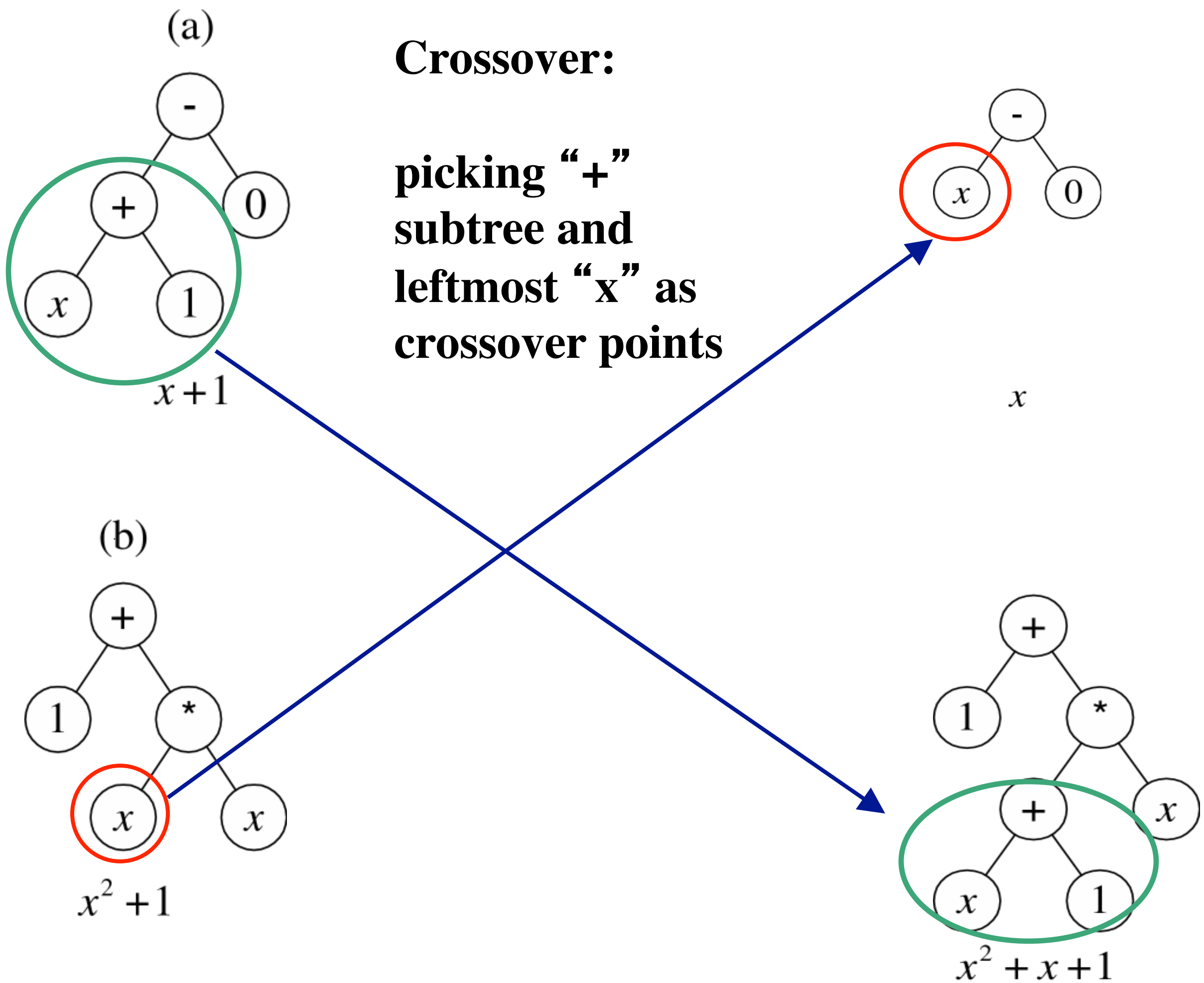


Citation: part of the pictures used as examples are taken from: www.genetic-programming.com/c2003lecture1modified.ppt

Crossover

Crossover:

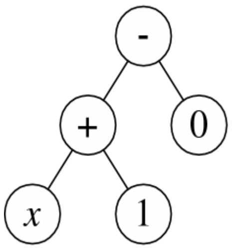
picking "+" subtree and leftmost "x" as crossover points



Citation: example taken from: www.genetic-programming.com/c2003lecture1modified.ppt

Generation 1

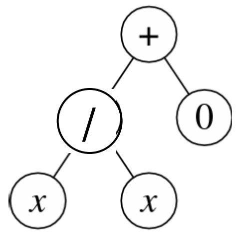
(a)



$x+1$

Copy of (a)

(b)

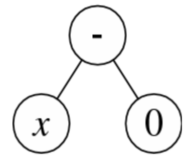


1

Mutant of (c)

picking "2" as mutation point

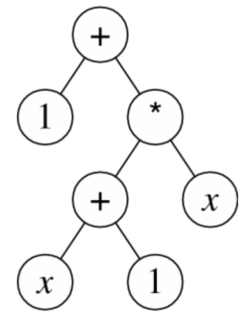
(c)



x

First offspring of crossover of (a) and (b)
picking "+" of parent (a) and left-most "x" of parent (b) as crossover points

(d)



x^2+x+1

Second offspring of crossover of (a) and (b)
picking "+" of parent (a) and left-most "x" of parent (b) as crossover points

Citation: part of the examples is taken from: www.genetic-programming.com/c2003lecture1modified.ppt

X	*Y*	*X+1*	|*X+1-Y*|	*1*	|*1-Y*|	*X*	|*X-Y*|	X^2+X+1	|$X^2+X+1-Y$|
-1.00	1.00	0	1	1	0	-1.00	2	1	0
-0.80	0.84	0.20	0.64	1	0.16	-0.80	1.64	0.84	0
-0.60	0.76	0.40	0.36	1	0.24	-0.60	1.36	0.76	0
-0.40	0.76	0.60	0.16	1	0.24	-0.40	1.16	0.76	0
-0.20	0.84	0.80	0.04	1	0.16	-0.20	1.04	0.84	0
0.00	1.00	1.00	0	1	0	0.00	1	1	0
0.20	1.24	1.20	0.04	1	0.24	0.20	1.04	1.24	0
0.40	1.56	1.40	0.16	1	0.56	0.40	1.16	1.56	0
0.60	1.96	1.60	0.36	1	0.96	0.60	1.36	1.96	0
0.80	2.44	1.80	0.64	1	1.44	0.80	1.64	2.44	0
1.00	3.00	2.00	1	1	2	1.00	2	3	0

	Σ	Σ	Σ	Σ
Fitness:	4.40	6.00	15.40	0.00
				Found!

Example: Classification

Classify customers based on number of children and salary:

Parameter	# of children (NOC)	Salary (S)
Domain	0…10	0…500000
Syntax of atomic expression	NOC = x NOC < x NOC <= x NOC > x NOC >= x	S = x S < x S > x

Classification Rules

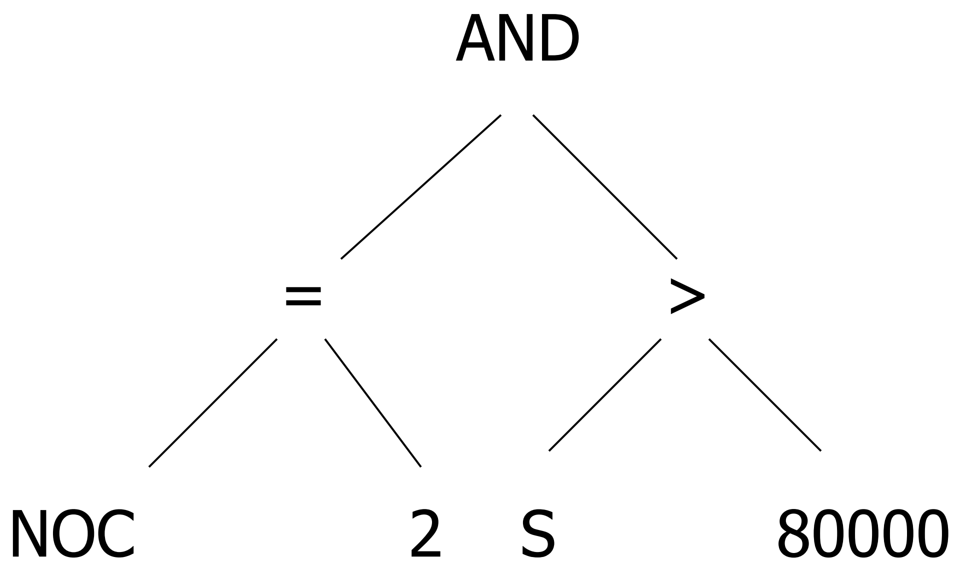
- A classification rule is of the form

IF description THEN class=c_i

Antecedent Consequence

Formula representation

- Possible rule:
  - If (NOC = 2) AND (S > 80000) then GOOD (customer)



Initial data table

Nr. Crt.	Number of children (NOC)	Salary (S)	Type of customer (C)
1	2	> 80000	GOOD
2	1	> 30000	GOOD
3	0	= 50000	GOOD
4	> 2	< 10000	BAD
5	= 10	= 30000	BAD
6	= 5	< 30000	BAD

Initial data represented as rules

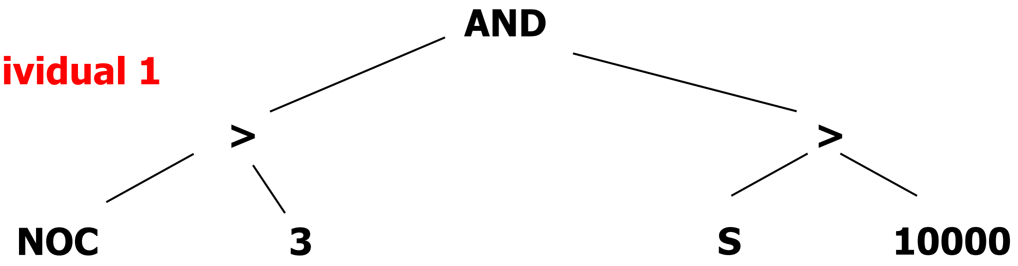
- Rule 1: If (NOC = 2) AND (S > 80000) then C = GOOD
- Rule 2: If (NOC = 1) AND (S > 30000) then C = GOOD
- Rule 3: If (NOC = 0) AND (S = 50000) then C = GOOD
- Rule 4: If (NOC > 2) AND (S < 10000) then C = BAD
- Rule 5: If (NOC = 10) AND (S = 30000) then C = BAD
- Rule 6: If (NOC = 5) AND (S < 30000) then C = BAD

Generation 0

- Population of 3 randomly created individuals:
  - If (NOC > 3) AND (S > 10000) then C = GOOD
  - If (NOC > 1) AND (S > 30000) then C = GOOD
  - If (NOC >= 0) AND (S < 40000) then C = GOOD
- We want to find a more general (if it is possible the most general) characteristic description for class GOOD
- We want to assign predicted class GOOD for all individuals

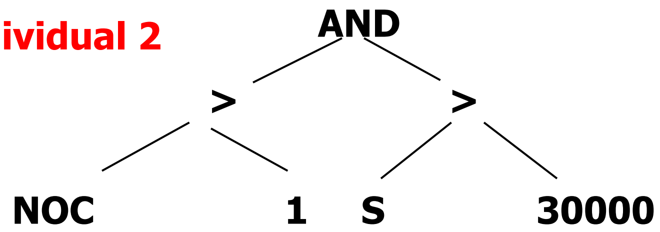
Generation 0

Individual 1



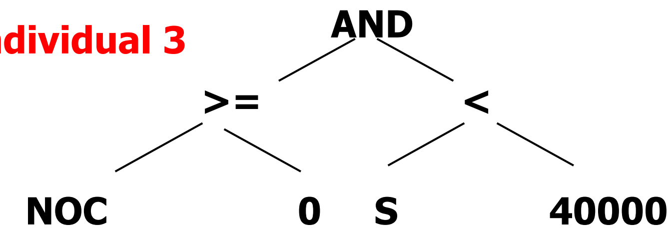
(NOC > 3) AND (S > 10000)

Individual 2



(NOC > 1) AND (S > 30000)

Individual 3



(NOC >= 0) AND (S < 40000)

Fitness function

- For a rule IF A THEN C

CF (Confidence factor) = $\frac{|AUC|}{|A|}$

|A| = number of records that satisfy A

|AUC| = number of records that satisfy A and are in **predicted class** C

Fitness function – Generation 0

Rule 1: If (NOC = 2) AND (S > 80000) then GOOD

Rule 2: If (NOC = 1) AND (S > 30000) then GOOD

Rule 3: If (NOC = 0) AND (S = 50000) then GOOD

Rule 4: If (NOC > 2) AND (S < 10000) then BAD

Rule 5: If (NOC = 10) AND (S = 30000) then BAD

Rule 6: If (NOC = 5) AND (S < 30000) then BAD

Fitness of Individual 1: If (NOC > 3) AND (S > 10000) then GOOD

|A| = 2 (Rule 5 & 6), |AUC| = 0, CF = 0 / 2 = 0

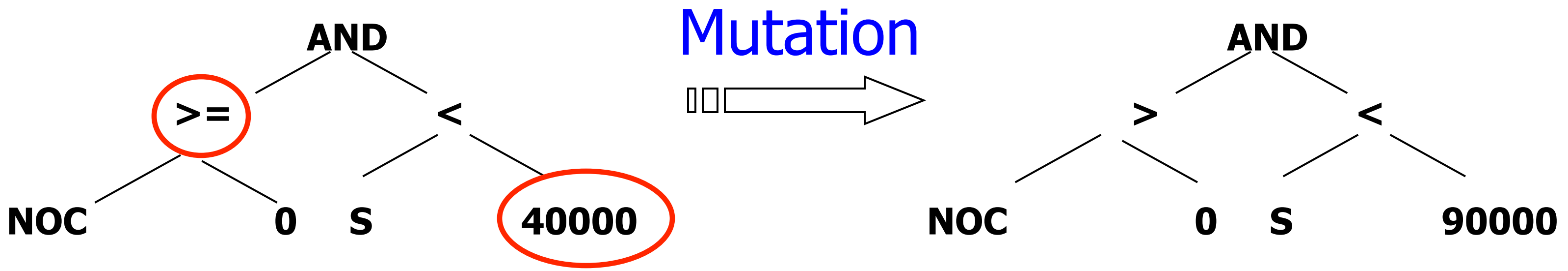
Fitness of Individual 2: If (NOC > 1) AND (S > 30000) then GOOD

|A| = 1 (Rule 1), |AUC| = 1, CF = 1 / 1 = 1 **Best in Gen 0**

Fitness of Individual 3: If (NOC >= 0) AND (S < 40000) then GOOD

|A| = 4 (Rule 2 & 4 & 5 & 6), |AUC| = 1, CF = 1 / 4 = 0.25

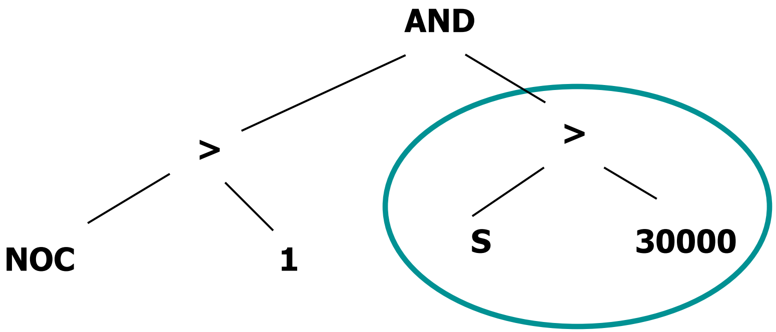
Mutation



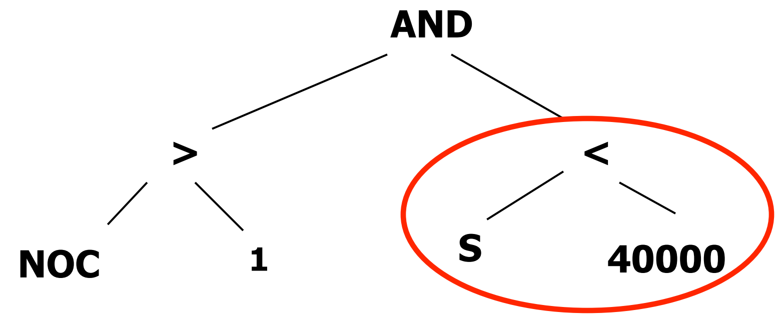
(NOC >= 0) AND (S < 40000)

(NOC > 0) AND (S < 90000)

Crossover

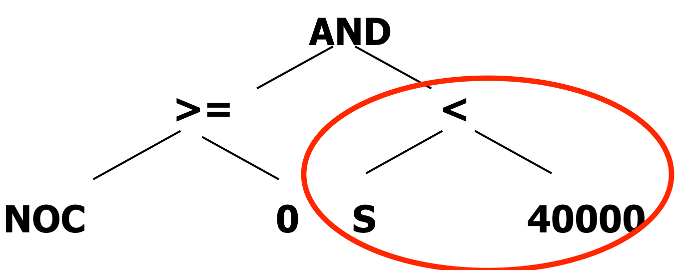


(NOC > 1) AND (S > 30000)

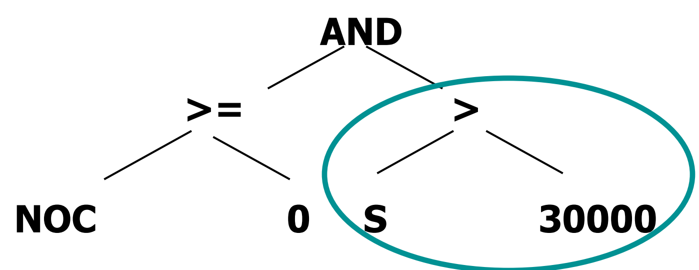


(NOC > 1) AND (S < 40000)

Crossover



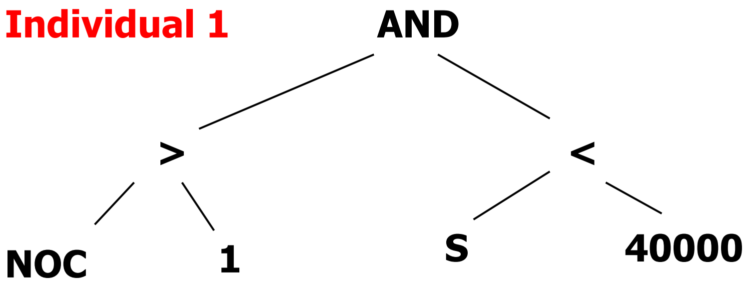
(NOC >= 0) AND (S < 40000)



(NOC >= 0) AND (S > 30000)

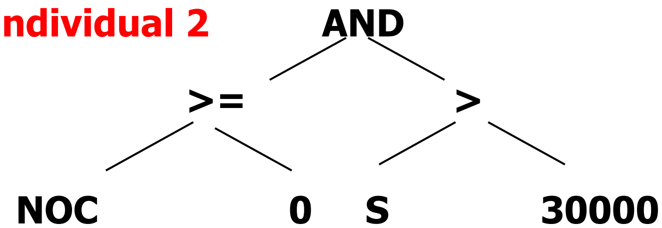
Generation 1

Individual 1



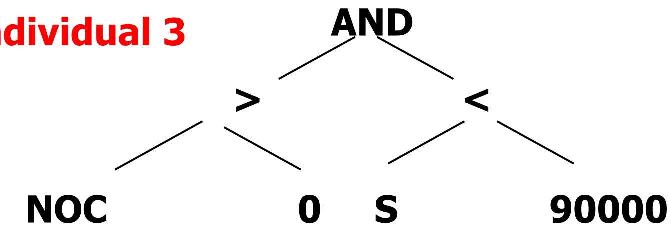
(NOC > 1) AND (S < 40000)

Individual 2



(NOC >= 0) AND (S > 30000)

Individual 3



(NOC > 0) AND (S < 90000)

Fitness function – Generation 1

Rule 1: If (NOC = 2) AND (S > 80000) then GOOD

Rule 2: If (NOC = 1) AND (S > 30000) then GOOD

Rule 3: If (NOC = 0) AND (S = 50000) then GOOD

Rule 4: If (NOC > 2) AND (S < 10000) then BAD

Rule 5: If (NOC = 10) AND (S = 30000) then BAD

Rule 6: If (NOC = 5) AND (S < 30000) then BAD

Individual 1: If (NOC > 1) AND (S < 40000) then GOOD

|A| = 2 (Rule 4 & 5 & 6), |A&C| = 0, CF = 0 / 2 = 0

Individual 2: If (NOC >= 0) AND (S > 30000) then GOOD

|A| = 3 (Rule 1 & 2 & 3), |A&C| = 3, CF = 3 / 3 = 1 **Best in Gen 1**

Individual 3: If (NOC > 0) AND (S < 90000) then GOOD

|A| = 5 (Rule 1 & 2 & 4 & 5 & 6), |A&C| = 1, CF = 1 / 5 = 0.2

GA Rules Problem

- When **GA**s are used for **optimization**, the goal is typically to return a **single value** - the **best solution** found to date

- The entire population ultimately converges to the neighborhood of a **single solution**

- Sometimes **Gas** employ a special method called a **niching method** that makes them **capable** of finding and maintaining **multiple rules**

APPLICATION EXAMPLE

Technical Document of

LBS Capital Management, Inc., Clearwater, Florida

Link: http://nas.cl.uh.edu/boetticher/ML_DataMining/mahfoud96financial.pdf

Forecasting Individual Stock Performance

- GOAL: using historical data of a stock, **predict** relative return for a quarter

Example: If **IBM** stock **is up 5%** after one quarter and the S&P 500 index is **up 3%** over the same period, then **IBM**'s relative return **is +2%**

-The Implementation Example consists of 15 attributes of a stock at specific points in time and the relative return for the stock over the subsequent 12 week time period.

- **200 to 600 (records) examples** were utilized depending on the experiment and the data available for a **particular stock**

GOAL: Combination of rules is required to model relationships among financial variables

Example: **Rule-1 :** IF [P/E > 30] THEN Sell

Rule-2: IF [P/E < 40 and Growth Rate > 40%] THEN Buy

Preliminary Experiments

- For **Preliminary set of experiments**, to predict the return, relative to the market, a Madcap stock was randomly selected from the S&P 400
- 331 examples(records) present in the database of examples of stock X
- 70% of examples (records) were used as a **training set** for the **GA**
- 20% of the examples (records) were used as a stopping set, to decide which population is best
- 10% of the examples (records) were used to measure performance
- **A sample rule** that the GA generated in one of the experiments:

IF [Earning Surprise Expectation > 10% and Volatility > 7%] and […]

THEN **Prediction = Up**

- Same set of experiments were used using **Neural Network** with one layer of hidden nodes using Backpropagation algorithm with the same training, stopping and test sets as that of **GA experiment**

Observations on the Results

- The **GA** correctly predicts the direction of stock relative to the market 47.6% of the time and incorrectly predicts the 6.6% of time and produces no prediction 45%
- Over **half of the time** (47.6% + 6.6%), the GA makes a prediction
- When it **does make a prediction**, GA is correct 87.8% of the time
- The Neural Network **correctly predicts** the direction relative to the market 79.2% of the time and incorrectly predicts direction 15.8% of the time.
- When it **does make a prediction**, the NN is correct 83.4%

Comparison with Neural Networks

- **Advantage** of **GA**'s over **NN**'s:

  1. **GA** has ability to output **comprehensible rules**

  2. **GA** provides rough explanation of the concepts learned by **black-box approaches** such as NN's

  3. **GA** learns rules that are **subsequently used** in a formal **expert system**

- 3. **GA** makes no prediction when data is uncertain as opposed to Neural Network