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INTEGRATING GENETIC ALGORITHM AND RULE BASED SYSTEMS

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ABSTRACT
Genetic algorithms may be considering from two different points of view: as global optimization procedure and learning procedure. As global optimization procedure they analyze parallel search space and are able to escape from local extreme. They are also applicable if target value is not known in advance or cannot be defined. This paper is presenting an example of genetic algorithms where the expected results are a set of efficient frontiers and decision maker chooses acceptable values among possible solutions. The outcomes of implementing genetic algorithm are inputs into knowledge base which helps decision maker to make final judgment. The paper also includes the software solution for genetic algorithms. The integration of genetic algorithms and rule based systems has shown satisfactory development and applicable power.
Key words: genetic algorithms, rule based systems, risk management, portfolio.

1. INTRODUCTION
Genetic algorithms are stochastic search methods that intend to mimic the natural biological evolution. They are explained in detail in many books and papers but the applicability and understandability simulation software of genetic algorithm in field of economy is not yet at satisfactory level. This paper has the goal to provide a clear and accessible presentation of genetic algorithm in economic applications. The best individuals of population in generation are preserved in knowledge base in the form of facts. Rule based system may consider the fittest individuals in each one generation and provides decision maker valuable and usable conclusions. Experimental results based on such ideas of integrating genetic algorithms and rule based systems enable decision makers to be flexible in their judgment. In comparison to neural networks, which use back propagation algorithm for modification, the weights among neurons according to error (the difference between a target output and the target produced by network) the genetic algorithm do not need such kind of supervision. This is an important advantage of genetic algorithms because in many cases the target is not known in advance or cannot be defined and one has to consider learning without supervision. In such cases the genetic algorithms are applicable, as they do not need a continuous presence of targets [1].

2. GENETIC ALGORITHMS CHARACTERISTICS
Genetic algorithm is a search algorithm based on well-known law of natural selection. In their focus is Darwinian Theory of survival and reproduction of the fittest individuals in the population to natural laws. Genetic algorithms [1] have four important characteristics:
Parameters. Parameters are optimization objects of genetic algorithms. The basic goal of optimization is to find out the best combination of parameters for solving some problem.

Parallelism. Genetic algorithms consider simultaneously points distributed in various regions of the definition field. The standard optimization algorithms consider only one point at a time.
Fitness function. The only information needed for genetic algorithm is any kind of objective function.
Transitional rules. The exploration of the space is based on stochastic and not on monotonic hill climbing. So the algorithm escapes the dangerous to be trapped in local extreme (maximal or minima).

2.1. Rule based systems and genetic algorithms

Rule based systems are computers programs that represent the knowledge by production rules: IF <condition> THEN <action>. Expert systems are rule based because those contain stored knowledge in the form of production rules [5].The format that a knowledge engineer uses to capture the knowledge is called a knowledge representation. The most popular knowledge representation is the production rule (also called the if-then rule).
The knowledge typically comes from a series of conversations between the developer of the expert system and one or more experts. But extract knowledge from expert and transform it in form of production rules is often very tedious task. A peculiarity of the idea to integrate genetic algorithm and rule based expert systems is to avoid only one source of knowledge. Knowledge into expert systems comes as an output from genetic algorithms. The judgment of discovered knowledge will be performed by building rule based expert systems. On conceptual level the integration of genetic algorithms and rule based systems illustrates the next figure:

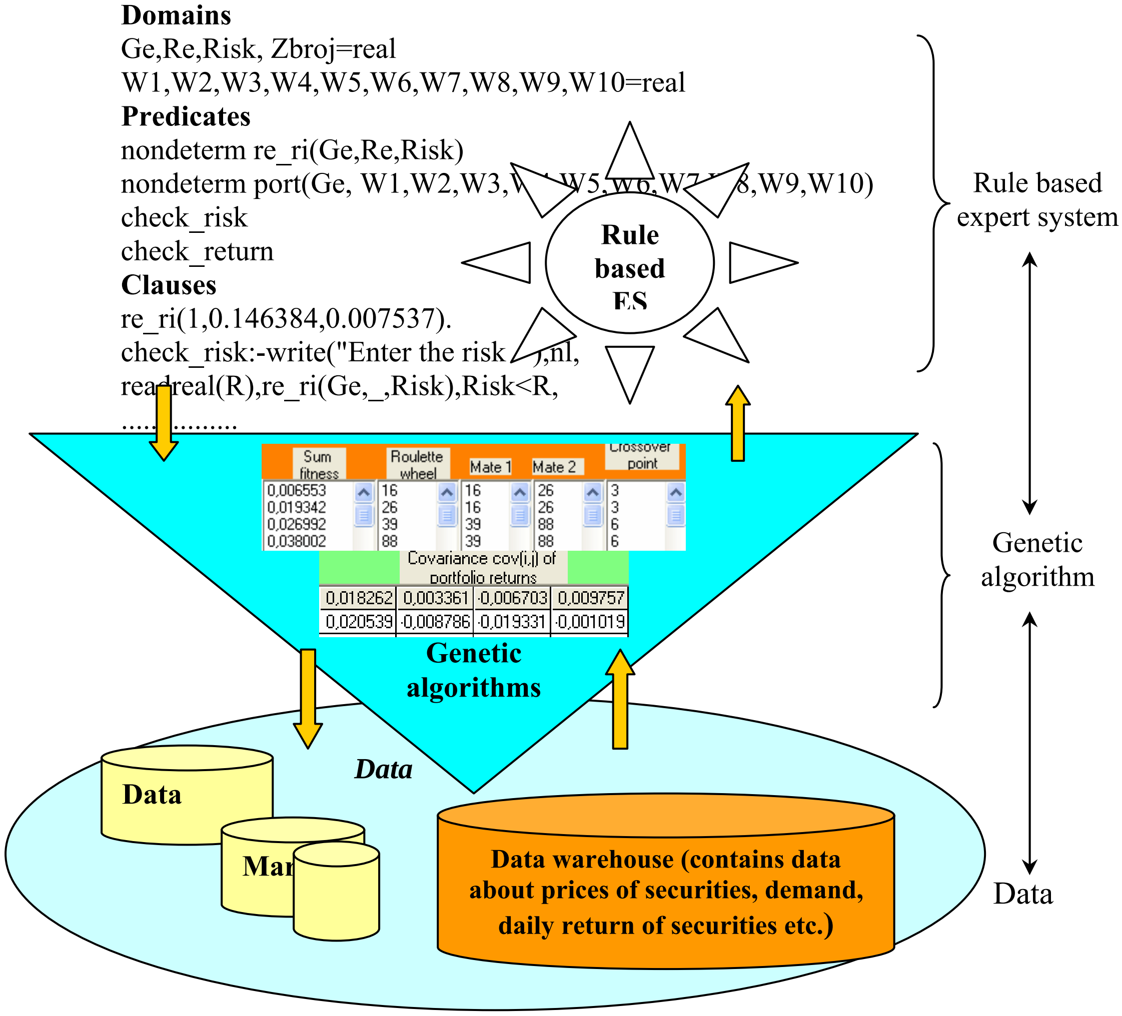

Figure 1. The Conceptual model of integration genetic algorithm and rule based systems

The first step in integrating genetic algorithms and rule based expert systems is building up the logical data model and its physical implementation in any data base management system. Database stores data concerning various types of objects: securities, bonds, returns of securities, demand etc. Using this data, fitness function and selection, crossover and mutation genetic algorithm finds out the weights (proportions) of portfolios that generate the best relationship of returns and risk in each one and all generations. The outcomes of genetic algorithm set up the knowledge rule (facts) in rule based systems. Inference rules incorporated in inference engine of rule based expert systems identify all portfolios that have expected risk equal or less the acceptable risk rate to decision maker.

3. PORGES – INTEGRATED GENETIC ALGORITHM AND RULE BASED EXPERT SYSTEM FOR PORTFOLIO OPTIMIZATION

Portfolio optimization of securities is very complex and challenging task. Successful solution is not possible without integration knowledge from different scientific disciplines. Especially may be stressed economic knowledge which tends to maximize portfolio returns and minimize investment risk at the same time. In mathematical sense the problem is solving by quadratic programming.

3.1. Portfolio optimization

The main input data in portfolio optimization model are expected return of portfolio and variance of expected return of securities in portfolio. In real situation investors have at disposal one, two, three or hundreds of securities. The investor has information about expected return of each one security in portfolio Ri and variance of return σ_i^2. Using σ_i^2 is possible to calculate the covariance matrix σ_{ij} (or correlation coefficient ρ_{ij}). That is well known Markowitz theory about portfolio structure and represents the key point of contemporary portfolio theory. In mathematical form targets are:

$$\min \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij} \qquad \text{.... (1)}$$

$$\sum_{i=1}^{n} w_i R_i \geq E$$

$$\sum_{i=1}^{n} w_i = 1,\ w_i \geq 0, \qquad i = 1,2,...,n$$

where are: Ri = expected return of i-th security, w_i = weight of i-th security in portfolio, σ_i^2 = return variance of i-th security, σ_{ij} = covariance between i-th and j-th securities, E= expected return of portfolio. The first step in building the PORGES system is selection of securities that will constitute the portfolio. Therefore the system monitors the securities returns in the last fifty periods (period may be day, week or month). Portfolio is consisting from ten securities with highest returns in the last fifty periods. Data model stores data about daily stock prices on that will be calculated monthly average.

The return of portfolio is calculated by function $R_p = \sum_{i=1}^{n} w_i R_i$ .... (2) and investment risk by formula $\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}$ ...(3). Fitness function [2] $f = \dfrac{\sum_{i=1}^{n} w_i R_i}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}}$ ... (4) tends to maximize the ratio between expected portfolio returns and risk.

After 1000 generations the genetic algorithms records for each one generation the best ratio between return and risk of portfolios.

3.2. Integrating genetic algorithms and knowledge base

Knowledge base is consisting of declarative rules that state all the facts and relationships about stock return, risk and generation of portfolio. There are two types of declarative rules in PORGES represented in Visual Prolog:

Domains
Ge,Re,Risk=real; port=real*
Predicates
nondeterm re_ri(Ge,Re,Risk);
nondeterm portfolio(Ge, W1,W2,W3,W4,W5,W6,W7,W8,W9,W10); check_risk;

Rule **nondeterm re_ri(Ge,Re,Risk)** states the generation of population (Ge), portfolio return (Re) and risk (variable Risk). Rule **nondeterm portfolio(Ge, W1,W2,W3,W4,W5,W6,W7,W8,W9,W10)** stores data about generation(Ge) and stock weights in portfolio (W1, W2,…,W10). The rule **check_risk** is used in clause:
check_risk:-write("Enter the risk "), nl, readreal(R),re_ri(Ge,_,Risk),Risk<R,
portfolio(Ge, W1,W2,W3,W4,W5,W6,W7,W8,W9,W10),
write ("The next portfolio is proposing: "), nl,
write(W1, "; ",W2,"; ",W3,"; ",W4,"; ",W5,"; ",W6,"; ",W7,"; ",W8,"; ",W9,"; ",W10), fail.
This rule finds out all portfolios in 1000 generations which satisfy condition Risk<R (where the expected risk is less then the investors acceptable risk). One dialog with rule based expert system PORGES is:
Enter the acceptable risk rate (as decimal number):
0.00907 (this means that the investor is ready to accept risk rate 9.07% or less)
The next portfolio is proposing:
0.0486; 0.1477; 0.0803; 0.0152; 0.1538; 0.0811; 0.1249; 0.144; 0.0756; 0.1289
The next portfolio is proposing:
0.0275; 0.1506; 0.0637; 0.0242; 0.1587; 0.1133; 0.1509; 0.1195; 0.0785; 0.1131
The next portfolio is proposing:
0.0275; 0.1506; 0.0637; 0.0242; 0.1587; 0.1133; 0.1509; 0.1195; 0.0785; 0.1131
The next portfolio is proposing:
0.0275; 0.1506; 0.0637; 0.0242; 0.1587; 0.1133; 0.1509; 0.1195; 0.0785; 0.1131
The next portfolio is proposing:
0.0275; 0.1506; 0.0637; 0.0242; 0.1587; 0.1133; 0.1509; 0.1195; 0.0785; 0.1131
no
The goal of integration of genetic algorithm and rule based system is achieved. Finally decision makers obtain benefits of diversification by investing in one of the proposed portfolios. Among different portfolios the investor will choose one because all of them offer the expected risk less then acceptable.

4. CONLUSION

In this paper is clearly presented the approach of selection efficient portfolio by integrating natural method in form of genetic algorithm and rule based expert systems. It is developed and implemented originally software solution that proposes to investor the proportions (weights) of each stock in portfolio. The software stores information about the best population individuals in each generation. This information is input (facts) in knowledge base of rule based system. According to decision maker readiness to accept a risk rate rule based component in PORGES proposes stock weights in portfolio.

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