8-16-1996

Expert Systems for Security Analysis

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1.0 Introduction

The aim of security analysis is to determine whether there are securities that are under-priced or over-priced relative to their intrinsic value - thus providing an opportunity for an investor to gain. Two common approaches to stock selection are known as the top-down and the bottom-up approach. In the first approach the investor proceeds with an analysis of the economy and the capital markets, screens the industry or sectors and finally arrives at individual securities. In the bottom-up approach the investor makes stock selections without reference to environmental factors. The construction of a portfolio of securities enables an investor to eliminate non-systemic or security-specific risk. The Markowitz portfolio diversification model [Markowitz, 52] is a quadratic programming model that minimizes risk given a level of expected return. Security analysis techniques are broadly classified into fundamental methods and technical methods. While the first class focuses on variables impacting the (business) issuer of securities, technical methods are based on trading parameters such as price and market volume.

2.0 Areas of Application

A large number of expert systems have been implemented for portfolio management applications. Detailed information on most systems is difficult to come by since developers seek to maintain their competitive edge through proprietary techniques. The basic sub-tasks in managing a portfolio are:

Elicitation of customer goals (targeted risk level and return); Selection of asset classes; Choice of industry/sectors to invest in; Picking of specific stocks in chosen sectors; Timing entry into and exit from a stock; Trading; Risk management (hedging) and Credit line management.

Since portfolio management is an ongoing task, it also involves continuous evaluation of changes that will have an impact on the security and reacting to these changes.

Application areas and characteristics of some of the expert systems cited in academic literature are shown in the table.

Invest [Heuer, 1988]	Selects specific securities matching customer objectives	Frame based system, uses frame matching
KFolio[Lee, 1989, 1990]	Creates portfolio with targeted risk/return parameters	Hybrid system; rule based stock grading with optimization
SAP [Madhavan, 1994]	Provides recommendations on a given security	Case-based and goal-based reasoning
Marketmind/Quantex [Leinweber, 1994]	Tracking of indicators and execution of trades	Production rules based
Le Courtier [Humpert, 1988]	Advice on stock purchase and portfolio distribution	Rule based system with heuristic constraint satisfaction
Folio [Cohen, 1983]	Optimal portfolio based on math programming and rules	Rule based with linear optimization
[Braun, 1987]	Identify market trends using induced rules	Rule induction

ESTA [Karakoulos, 1994]	Technical Analysis	Rule based
Splendors [Kaiser, 1991]	'Real-time' portfolio management	Object oriented paradigm with agent architecture
[Tam 1991]	Induces rules to screen stocks from a sample database	Rule induction

[Bouwman, 1983] describes one of the early systems to apply expert knowledge to financial analysis based on a study of human decision making behavior. Various systems such as [Buta, 1994] have been developed for bond-rating, an application in which corporate bonds are classified into different risk classes. A large number of commercial trading systems such as [Tradestation, 1995] have been developed. Most of these focus on technical parameter based trading rules operating on real-time data feeds.

Some of the commercial systems [Keyes, 1992] include Paine-Webber's AI-based hedging advisor, Washington Square Advisors' Watchdog investment monitoring system, Institutional Equity Managers' Portfolio selection system and Morgan Stanley's Expert Tick to review stockmarket quotations.

[Hutchinson, 1994] proposes that the criteria of performance, construct validity, reliability, integration and cost-benefit be used in the evaluation on financial applications using artificial intelligence.

An analysis of various systems suggests a number of weaknesses such as use of rules that are highly time specific and use of historic information on security returns for portfolio construction. Model-based reasoning systems have typically used associative models (non-causal), where symptoms are used to generate hypotheses. [Hart, 1986] suggests the application of qualitative reasoning models to the financial assessment task. This involves applying constraints to construct qualitative causal models.We believe that the large number of variables to be modeled with possibly no stable relationships (unlike physical systems) limit the applicability of this approach. Classification type systems have been built using a number of approaches (rule-based, induction rule-based, neural-net based, case-based) but most of them operate on historic data, which really forms only part of the analysis. The real problem confronting the practitioner is how to forecast the future. Rule-based systems tend to be forward-chaining, reasoning forward from customer data. This approach helps to restrict the analysis to the domain of securities the customer would be more interested in and can help to cut down the search, but this approach tends to overlook security-specific issues that distinguish securities in the same class. It has also been recognized that rule-based systems do not perform well at representing and exploiting causality.

3.0 Domain related issues

Though a large number of commercial systems have been developed, there has not been much academic research in this area. The discipline of portfolio management does not have strong scientific underpinnings unlike other areas like technology and medicine. Even experts in this area rely on limited and imperfect knowledge, which itself changes over time. Security performance is a complex variable that is affected by numerous other variables (virtually any news event may impact stock prices) and therefore is difficult to analyze or model. Also, information that can be used to profit usually comes from uncertain events. One of the common objections to rule-based systems for this task has been the large and dynamic knowledge base required. [Fogler, 1995] asserts that the power and sophistication of computers and algorithms will make markets more efficient and hence harder to outperform. One of the of positive features of the domain is the availability of historic data for 'backtesting' or evaluation of the knowledge base. The need for expert systems in the domain of security analysis and trading stems from growing trading volumes, development of electronic exchanges, integration of markets around the world and increased surveillance by regulators. These factors pose the need for analysts and traders to cope with increasing amount of information and yet react in constrained time. Expert systems could therefore be used to take over part of the information analysis role and enable better and quicker decision making. [Leinweber, 1988] suggests that the financial community can best use expert systems to extend conventional analytic techniques and to reduce the 'cognitive overload'.

4.0 Proposal for a DSS with an expert component

We propose a Decision Support System (DSS) for portfolio management with an expert component that will perform the role of a securities analyst (SECAN). [Turban, 1993] has suggested gains in capabilities of expert systems and an improvement in functionality and efficiency of information systems through the embedding of an expert system. The basic purpose of SECAN will be to come up with a list of securities that conform to an investor's risk profile and preferences, analyze these against the background of macroeconomic, industry and business conditions and finally suggest investment decisions.

An analysis of past systems has highlighted the need to limit the comprehensiveness of the expert system component and involve the decision maker in making decisions with ambiguous data where many different inferences could be supported. Another insight gained is to use model-based representations that allow causality to be represented and allow for changes to be accommodated. Object-based representations also need to be incorporated as the domain of securities is naturally hierarchical and such a representation would ease development and addition of new knowledge.

1. This DSS focuses on a long-term investment strategy as opposed to a short-term trading strategy.

2. A simple formulation for the fundamental analysis component is difficult without making some simplifying assumptions. We recognize this in allowing for the analyst to bring his/her subjective judgment to bear on the task and to look for additional information.

Architecture

- Forward chaining (data-directed) from customer data to select a class of securities that would be of interest.

- Backward chaining (goal-directed) rule-based system to analyze a particular stock. - Certainty factors will be used along with the rules to handle uncertainty. Explanations will be attached to rules to permit reasoning to be displayed to a user

Frames for - economy (macro-economic variables)

- sector (Growth, competitive variables)

- security classes (security features)

- securities (company financial and

operating data)

- Frames for investor profiles

- Model based system for projections

Year1 earnings model, economy model & sector model

Year2 Year 3 ....

Math programming model based on Markowitz specification.

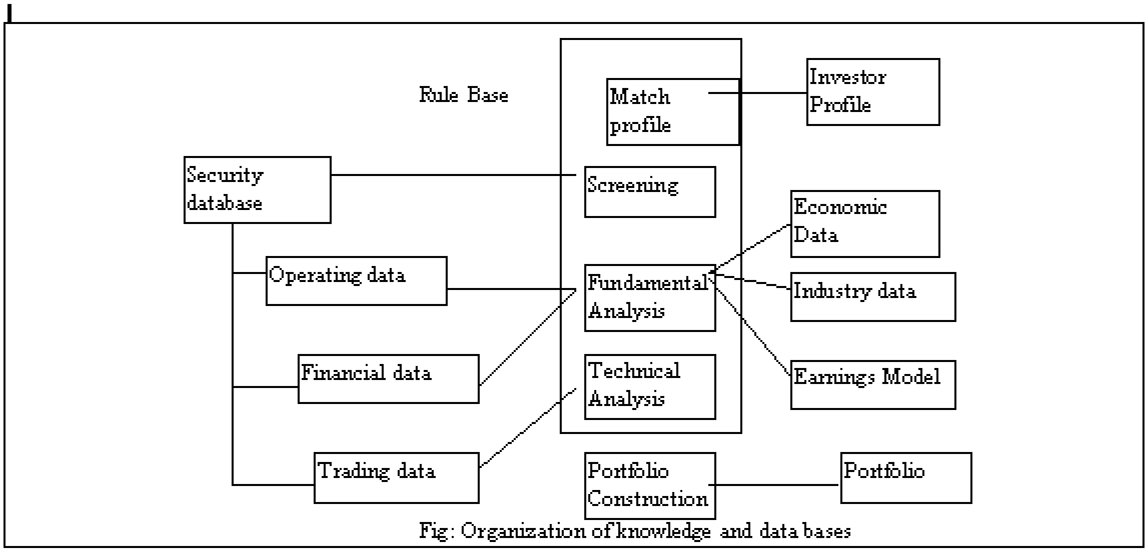


Fig: Organization of knowledge and data bases

5.0 Problem Solving Technique

Evaluate investor preferences

Investor preferences and risk profile are first ascertained through responses to questions about age, risk-taking ability, earnings and expenses profile, expected cash flows, past investments and demographics. Based on these, the investor is assigned to a risk class and a distribution of assets is arrived at. Securities are classified into various classes based on expected risk-return characteristics and earnings stream. A rule induction system could be used for the classification. In this step, based on investor profile, get a list of securities (asset-class) to be analyzed.

The kinds of knowledge this system needs to have is :

How do investor profiles correspond to desirable security choices.

for example,

(1) If

investor is highly risk-averse

then

security-classes <-- low-beta stocks, fixed income securities

portfolio: Assign equities a low proportion of the portfolio

(2) If

investor expects to require funds in near-term

then

security-classes<-- Securities with short term maturities

(3) If

investor prefers regular returns to capital appreciation

then

security-classes<-- High dividend securities, fixed income securities

The investment amount is determined and the allocation to the various asset classes is made at this stage.

Evaluate Securities in the preferred class

The process of analyzing the list of securities takes two steps. In the first step, securities are subjected to screening rules based on specified fundamental and technical parameters. In the second step the shortlisted securities are intensively analyzed to predict future performance.

Screen the list

The screening rules are based on parameters used by expert analysts to judge security performance.

For example a set of rules might include the following criteria:

market_capitalization > $ 100 mn

Debt_equity_ratio < 1.00

Earnings_per_share_growth > 10%

Dividend_payout < 50%

Current_ratio > 1.00

Accounts_receivable_turnover > 5.00

Current_price < Moving_average_10_days

These parameters would be calculated based on current and historic financial and trading information.

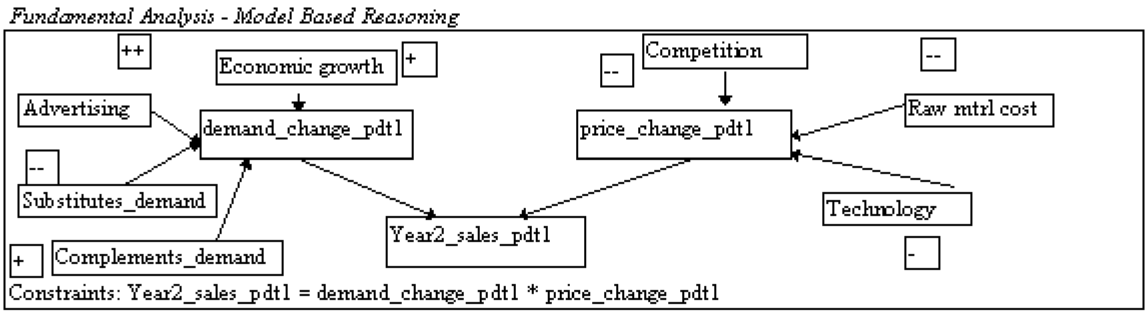
Evaluate individual securities

For each security in the shortlist, use goal-directed reasoning to get an investment decision. The goal state causes the invocation of two different set of rule bases - fundamental and technical. A stock will be recommended if it performs 'well' on both criteria. The security will be evaluated on different dimensions and overall attractiveness will be assessed based by its grade on those dimensions and the importance of the dimensions.

Fundamental Analysis - Model Based Reasoning

A three year future-earnings model for the company will be created. Current earnings will be used as a base and the model will capture the impact of economic changes, industry changes, product introductions, product life cycle effects, competitive changes etc. A spreadsheet-like interface will be provided to the user with default values. This module will function in a decision support mode and provide inputs for the analyst with a certainty-level. The analyst can then use these inputs or appropriately modify them to reflect additional information. We recognize that it is virtually impossible to capture all the kinds of factors which can have an impact and therefore the system cannot entirely replace an expert.

A fragment of the model is shown:



Constraints: Year2_sales_pdt1 = demand_change_pdt1 * price_change_pdt1

The model asserts (for example) that a positive change in economic growth will lead to higher sales for the product.

demand_change_pdt1 <-- d(economic_growth)

The system will extract information from the databases to build up the earnings model with default values. On the basis of available information about projected scenarios it will build up a consistent future earnings profile. The use of qualitative reasoning to support the process needs to be investigated.

The aim of the system will be to provide inputs to the analyst about the variables which can impact the parameter under consideration (sales-growth for a product) and the level and direction of the impact. .

The type of variables that will be considered include product introduction, competitor entry and exits, economic growth acceleration/slowdown and price structure changes.

On the basis of the projected net earnings for the forecasted period, the security value will be arrived at and a judgment about the whether the security is under or over-valued will be made.

Technical Analysis - Rule based

This module will be used to get the timing of the investment right. It has been noted [Tam, 1991] that a combination of technical and fundamental analysis provides better results compared to only one technique being used. A rule-base will be generated based on knowledge of technical analysis experts. This will then be applied to trading data for the stock to arrive at the decision.

Construct a portfolio based on a mathematical programming approach

The stocks that appear to be undervalued (based on fundamental analysis) and for which technical analysis indicates a bullish strategy will be considered for inclusion in the portfolio. The portfolio will be constructed using the Markowitz model.

Knowledge Acquisition

The system requires a security analyst's knowledge to be available for incorporation in the technical and fundamental rule-bases. The kind of cues used by a technical analyst to analyze price trends need to be provided. The kind of fundamental variables and the way they affect security fundamentals also need to be provided to build the association model.

The knowledge of the system is captured in the form of generic rules and information likely to change over time is encoded as facts that are linked to a continually updated database.

Implementation

The proposed system can be implemented using expert system shell libraries. A typical shell (such as M4) supports the use of rules, procedures, certainty factor algebra, object data structures and interface to spreadsheet and database software. This would allow various components of the system to be integrated together.

[Note : References and a longer version of the paper available upon request from the author]