

Comparing Artificial Intelligence Systems for Stock Portfolio Selection

Extended Abstract

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Abstract

The goal of an artificial intelligence decision support system is to provide the human user with an optimized decision recommendation when operating under uncertainty in complex environments. The particular focus of our discussion is the investment domain – the goal of investment decision-making is to select an optimal portfolio that satisfies the investor's objective, or, in other words, to maximize the investment returns under the constraints given by investors. The investment domain contains numerous and diverse information sources, such as expert opinions, news releases and economic figures, and so on. This presents the potential for better decision support, but poses the challenge of building a decision support agent for selecting, accessing, filtering, evaluating, incorporating information from different sources, and for making final investment recommendations. In this study we compare three most popular artificial intelligence systems for portfolio selection. We found that the artificial intelligence systems outperform human portfolio manager and market in 1997 and 2000.

Investment Problems

The investment domain, like many other domains, is a dynamically changing, stochastic and unpredictable environment. Take the stock market as an example; there are

more than two thousand stocks available from which portfolio manager or individual investor may select. This poses a problem of filtering all those available stocks to find the ones that are worth investment. There are also vast amounts of information available that will affect the market to some degree. All above is making extremely difficult for human portfolio manager to create the investment portfolio without relying on any tools.

Related Work

We explored the way to reduce the complexity of the investment decision deliberation that might cause the investor to lose money under urgent situations, and, at the same time, to provide the highest quality investment recommendations possible. .

For portfolio management, there is related work by Sycara, et al. [5] that focused on using distributed agents to manage investment portfolios. Their system deployed a group of agents with different functionality and coordinated them under case-based situations. They modeled the user, task and situation as different cases, so their system activated the distributed agents for information gathering, filtering and processing based on the given case. Their approach mainly focused on portfolio monitoring issues and has no mechanism to deal with uncertainty and urgency factors. Our system on the other hand reacts to the real-time market situation and gathers the relevant information as needed. Other related research on portfolio selection problems has received considerable attention in both financial and statistics literature [1, 2, 3, 4, 6].

Experiment Setting for Investment Portfolio Selection

In the experiments we ran, we selected three commonly use artificial intelligence systems – Bayesian network system, C5.0 Rule base system and a feed forward neural network system as illustrated in figure1. We selected eight financial ratio data from the S&P

500 companies as the input factors to all three systems. The training data is collected from the Compustat database from the period of 1987 to 1996. To test the performance, we used the date from 1997 and 2000 and let all three systems made the decision recommendation on which of the S&P 500 companies to be included in the investment portfolio.

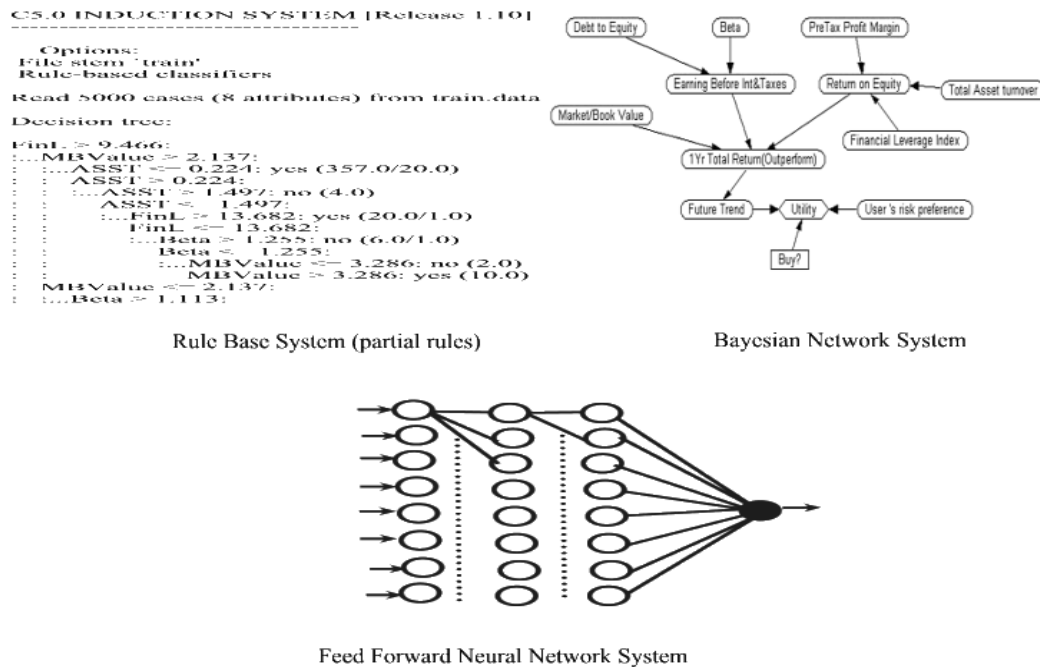


Figure 1. Three artificial intelligence systems for portfolio selection.

Experiment Result

We compared the performance of all three systems, Bayesian network, C5.0 and back-propagation neural network. We trained all three systems with the same training data and tested them with the same testing data. On the 1997 test data, Bayesian network system obtains its one year total return performance of 38.16154% when the portfolio contains the 156 selected companies. And the top 108 companies ranked by expected utility produce an

average one-year total return of 42.8264, almost twice the average of the S&P500's return and is better than the leading index fund Vanguard Index 500 which produced a 32% return for 1997.

The neural network failed to converge due to the large variation of the training data. The C5.0, the successor of the C4.5, did produce some interesting results. The C5.0 selected 218 out of the 500 companies and the average one-year total return for that portfolio is 38.90556. The C5.0 slightly outperformed the Bayesian network on 1997 data.

We also compared the performance of our system and the C5.0 using the data from year 2000 to demonstrate systems' performance in a modest year. The S&P 500 produced a negative return of -9% that year and the Vanguard index 500 fund were also in the negative territory of -8% return. Bayesian network system on the other hand produced a return of 12.23% and the C5.0 produced a return of 11.69%. In this case not only Bayesian network system outperform the market and the leading index fund, it also outperform the C5.0 algorithm.

Conclusion

We conducted some performance analysis with all three systems. We compared the two systems that was able to trained given the financial data – the Bayesian network and the C5.0 rule base system. Both systems outperform the leading mutual fund by a significant margin in 1997. We also ran the systems with the data from an under-perform year (2000); both the S&P 500 and the leading mutual fund produced a negative return for that year. Both systems on the other hand produced a positive return and outperforms the leading mutual fund and the S&P 500 index by a large margin.

Bayesian network system uses the influence diagram as the decision model; the structural information of the influence diagram plays an important role on the performance of

our system. We obtained the structural information from the domain expert and the information represents what the expert's opinion on the causal relationships among the nodes. From the experiment results we ran on an under-perform year, we can see that the Bayesian network system works better than C5.0 in a more general situation. This is due to the background information given by the domain expert when constructing the network.

Given the above analysis, we could conclude that by using a artificial intelligence system for portfolio selection has performance edge over the human portfolio manager and the market. The systems we selected for this study are only three among numerous artificial intelligence systems available. We would like to conduct further study to better qualify and quantify various artificial intelligence systems for use in the portfolio selection domain.

References

- [1] P. H. Algoet and T. M. Cover. Asymptotic optimality and asymptotic equipartition properties of log-optimum investment. *The Annals of Probability*, pages 876-898, 1991.
- [2] T. M. Cover. Universal portfolios. *Mathematical Finance*, vol. 1, pages 1-29, 1991.
- [3] T. M. Cover and D. H. Gluss. Empirical Bayes stock market portfolios. *Advances in Applied Mathematics*, vol. 7, pages 170-181, 1986.
- [4] T. M. Cover and E. Ordentlich. Universal portfolio with side information. *IEEE Transactions on Information Theory*, pages 348-363, March 1996.
- [5] K. P. Sycara and K. Decker. Intelligent Agents in Portfolio Management. *Agent Technology*, Springer-Verlag, 1997.
- [6] R. R. Trippi and J. K. Lee. Artificial Intelligence in Finance and Investing. Irwin, 1996.