Mutual Fund Ratings Analysis Using Artificially Intelligent Models

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Abstract

This study investigates the superiority, if any, of the artificial intelligence techniques over the traditional statistical methodologies in identifying potential high/poor rated funds in the mutual fund industry. We want to identify the factors that distinguish five-star mutual funds from one-star mutual funds. The goal is to evaluate the effectiveness of neural network techniques to assist the investor in screening out potential losers in the mutual fund market. The objective of this study is multifold. If we are to believe that investors care about ratings, and there is a great amount of anecdotal evidence that they do, then devising a method to forecast the rating of the mutual funds will be of great interest to individual investors as well as mutual fund managers. Secondly, we want to apply neural network models to differentiate the higher rated mutual funds from the poor rated funds. Thirdly, this study investigates the superiority, if any, of the artificial intelligence techniques over the traditional statistical methodologies in identifying potential high/poor rated funds in the mutual fund industry. Finally, we want to identify the factors that distinguish five-star mutual funds from one-star mutual funds. The goal is to evaluate the effectiveness of neural network techniques to assist the investor in screening out potential losers in the mutual fund market.

1. Introduction

With the tremendous growth of privately managed retirement accounts and the over 10,000 mutual funds now available to investors, mutual fund ratings have never been so popular. As a consequence, many financial publications and financial Internet sites now devote a substantial amount of coverage to rating mutual funds. One, if not the most popular, provider of these mutual fund ratings is Morningstar, Inc. Started in the mid-1980, Morningstar has grown largely as a result of the success of its 5-star rating system. Similar to the ratings of hotels, movies, or restaurants, Morningstar rates mutual funds on a scale of 1 to 5 stars, where 1 star is the worst rating and 5 stars is the best. Due to the rating system's simplicity and the way in which it mimics the ratings of so many other products we buy, the star-rating system has truly become part of accepted lexicon in mutual funds.

Indeed, the Morningstar rating system has become so popular that a fund, which receives a high star rating, is often deemed by the public to have "a good housekeeping seal of approval." In fact, some financial planners report that investors require them to invest only in funds with 4- and 5-star ratings. Given the above, it is not surprising that many people believe investment flows in and out of mutual funds are closely related to the Morningstar star ratings. For example, a recent study by Financial Research Corporation of Boston and reported in the *The Wall Street Journal* found that in 1999, funds with 4 or 5 stars received inflows of $223.6 billion while funds with 3 or fewer stars had outflows of $132 billion.[1] Moreover, the heavy use of Morningstar ratings in mutual fund advertising suggests that mutual fund companies believe that investors care about Morningstar ratings. Indeed, in some cases, the only mention of return performance in the mutual fund advertisement is the *Morningstar star rating.*

The objective of this study is multifold. If we are to believe that investors care about ratings, and there is a great amount of anecdotal evidence that they do, then devising a method to forecast the rating of the mutual funds will be of great interest to individual investors as well as mutual fund managers. Secondly, we want to apply neural network models

[1] Another study reported in the Wall Street Journal (Damato 1996) found that 97 percent of the money flowing into no-load equity mutual funds between January and August 1995 was invested into funds which were rated as 5 or 4 stars; funds with less than 3 stars actually suffered a net outflow during the same period.

to differentiate the higher rated mutual funds from the poor rated funds. Thirdly, this study investigates the superiority, if any, of the artificial intelligence techniques over the traditional statistical methodologies in identifying potential high/poor rated funds in the mutual fund industry. Finally, we want to identify the factors that distinguish five-star mutual funds from one-star mutual funds. The goal is to evaluate the effectiveness of neural network techniques to assist the investor in screening out potential losers in the mutual fund market.

This study is organized into seven parts. Section II reviews previous studies on neural networks in finance. Section III describes the characteristics of the data set used in this study. In addition, section III also details the justification and basis for the methodology used in this study. Section IV discusses the statistical and neural network models used in this study. Section V explains the training of the neural networks. Furthermore, section VI explains the empirical results for mutual fund ratings and prediction using the backpropagation model with adaptive learning. Finally, section VII concludes and summarizes the study.

2. Summary and Conclusion

To assess the performance of neural network and discriminant analysis models in distinguishing potentially "five-star" mutual funds from "one-star" mutual funds, we trained both set of models with a training sample of 500 observations, and tested them with a holdout sample of 250 observations. The neural network models outperformed the discriminant model in identifying poorly rated mutual funds and, therefore, in minimizing the Type I error. Between the two models, the single-layered Backpropagation model with adaptive learning showed substantially better performance in comparison to multiple discriminant analysis in identifying poorly rated mutual funds.

Although the study reported here is far from sufficient to generate any conclusive statements about the applicability of neural network models in general, it does provide some insights into their potentials and limitations. Based on the comparison reported above, the neural network approach offers a comparative alternative to classification techniques especially under the following conditions:

Multi-modal distribution: The nonlinear discrimination function represented by a neural network model provides a better approximation of the sample distribution, especially when the distribution is multi-modal.

Adaptive model adjustment: The neural network models can be easily adjusted in an adaptive manner by modifying network weights and the learning rate. Therefore, neural network models are ableto respond swiftly to changes in the real world.

Robustness: A neural network does not assume any probability distribution or equal dispersion. Further, besides continuity and differentiability, there is no rigid restriction on the use of input/output functions in a neural network. Therefore, simple and universal training (learning) algorithms function independently of the number of inputs. Data having repeated, wrong, or missing value(s) is easily accommodated. The size of input data arrays being considered in parallel is not subjected to any artificially imposed limits. Very large problems can be solved in the absence of the kind of detailed information that is essential to support traditional divide-and-conquer or rule-based approaches. Using neural networks, it is not necessary to first make an analysis based on a detailed knowledge of a problem or a system's internal structure. Thus, neural network models are more robust than the traditional logistics regression model.

3. Limitations And Implications For Researchers And Practitioners

In our study, we evaluated the robustness of neural network models in differentiating excellent rated mutual funds from poorly rated mutual funds by comparing them with the multiple discriminant analysis model. Since the neural network model has performed as well or better than the discriminant analysis model, neural networks may offer a competitive modeling approach for mutual fund ratings. But, there are several limitations that may restrict the use of neural network models for classifications. The following are the limitations of neural network methods:

Network Topology: There is no formal theory to determine optimal network topology for a given classification application. Therefore, decisions such as the appropriate number of layers and the size of the middle layer nodes must be determined using experimentation. In addition, there is a possibility of underfitting or overfitting the network, and the results are sensitive to the selection of learning parameters. Poor results can also occur if the wrong transfer function is selected. Thus, the development and interpretation of neural network models requires more expertise from the user than traditional statistical models.

Computational Efficiency: Training a neural network can be computationally intensive. In our study the computation time of the neural network models was a few minutes to 1 hour on Pentium III mini workstation. On the other hand, all statistical methods took at most half a minute on the same machine.

Symbolic Expression: The discriminant capability of a neural network model is difficult to express in symbolic form. This may not be a serious drawback if one is concerned with predictive accuracy only. However, a neural network is limited if one wants to test the significance of individual inputs.

Explanatory Capability: Neural networks cannot explain how and why they identified a "poor" or “good rated mutual fund. Hence, this inability to explain conclusions may restrict the use of the neural network modeling technique. This is in contrast to expert systems that can provide explanations to the user about how inferences are made.

Finally, in the light of the case analysis carried out, neural networks are a very interesting tool and have great potential capacities that undoubtedly make them attractive to the field of business classification. The following are the implications of this study for the academicians and practitioners:

- Mutual fund rating is a non-trivial and important problem. A better understanding of the causes will have tremendous financial, managerial, and investment consequences. We have presented a general framework for understanding the role of neural networks for this problem. While traditional statistical methods work well for some situations, they may fail miserably when the statistical assumptions are not met.
- Neural network models offer a useful data mining and analytical capability through which financial practitioners can discover meaningful relationships and hidden patterns in the data. Neural network models, unlike the statistical methods, are not constrained by any statistical assumptions about the characteristics of the data. Furthermore, the designer of the network has the flexibility to add any number of layers between the input and output layers or to change the size of the layers (number of hidden neurons) depending on the optimal solution of the problem. Besides, easily available, off-the-shelf neural network software such as Smartlearn, Brainmaker, Neurolab, etc., offer friendly graphical user interfaces to discover meaningful patters in the data.
- In this study we used the existing theoretical neural network models to rate mutual funds. Researchers can further explore the process of designing neural network models to develop new neural network models (combination of the theoretical neural network models) most suitable for the rating of mutual funds.
- Another area of research, researchers and practitioners should focus on is the application of genetic algorithms to the design of network configurations to differentiate between "excellent" rated mutual funds and "poor" rated mutual funds. Genetic algorithms adopt an evolutionary approach where a pool of networks, called the population, is continuously being modified by using genetic operators such as crossover and mutation [Goldberg, 1989]. Each synthesized network, which corresponds to a possible configuration, is evaluated using the backpropagation algorithm. Genetic algorithms have a built-in-bias towards retaining and combining good configurations in the next generation. The evolutionary nature of the algorithm enables the search for good configurations to proceed in a parallel fashion, thus reducing the possibility of trapping in local optimal configuration.
- Our implementation of the neural network models is computer simulation software that runs on a double processor Pentium III workstation. As the intrinsic parallel processing capability of the network was not exploited, the computation time is quite long, especially for the Backpropagation with Levenberg-Marqurdt approximations. Managers should use neural network models etched on silicon to reduce computation time.
- As explained above, neural networks are better for mutual fund ratings only if we are not interested in knowing how a particular conclusion was made. Thus, the limited explanatory capability of neural networks can be improved by linking them with fuzzy logic to form neurofuzzy systems. Therefore, another area for conducting research is the application of neurofuzzy systems to the mutual fund ratings. Fuzzy logic provides a means of combining symbolic and numeric computations in inference processing. The linkage between neural networks and symbolic reasoning can be established through the membership function of fuzzy logic. The membership function measures the degree of possibility of a concept as related to a numeric quantity. A neural network can be used to synthesize a membership function by training it with instances of the relation [Jang, Sun, & Mizutani, 1997].
- For mutual fund ratings, a neural network may represent the membership function of the concept "high risk of poor performance." Such a representation can easily be combined with other symbolic conditions appearing in the rules of an expert system. By utilizing neural networks as frontends in rules definition, one can take advantage of the explanatory capability of expert systems as well as the subsymbolic computational capability offered by neural networks.
- Another area that researchers and practitioners can explore is the design and development of a decision support system that embeds the subjective (judgmental) models and objective (analytic) models to aid the investment analyst/financial planner/fund managers in making a decision on a mutual fund.

- Another area that academicians and practitioners should pursue is the integration of neural networks and statistical techniques. Neural networks have great potential as a forecasting tool. Thus, evaluating the performance of integrating neural networks, with statistical techniques to address finance problems, is likely to provide fruitful opportunities in the future.

Finally, neural networks have shown enough promising features to provide an incentive for more thorough and creative testing. As advancements are made in AI technologies and computer-based related systems, there should be new opportunities to apply neural network technology for finance research.

REFERENCES

Available upon request