A Robo-Advisor Design using Multiobjective RankNets with Gated Neural Network Structure

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Abstract—With rapid developments in deep learning and financial technology, a customized robo-advisory service based on novel artificial intelligence techniques has been widely adopted to realize financial inclusion. This study proposes a novel robo-advisor system that integrates trend prediction, portfolio management, and a recommendation mechanism. A gated neural network structure combining three multiobjective RankNet kernels could rank target financial products and recommend the top-n securities to investors. The gated neural network learns to choose or weigh each RankNet for incorporating the most important partial network inputs, such as earnings per share, market index, and hidden information from the time series. Experimental results indicate that the recommendation results of our proposed robo-advisor based on a gated neural network and multiobjective RankNets can outperform existing models.

Keywords—learning preferences, rankings, deep learning

I. INTRODUCTION

Investment consultants develop trading strategies, design novel products through financial engineering, and provide investors with practical recommendations on portfolio management. Thus, they play an important role in financial markets. With rapid developments in artificial intelligence, deep learning techniques such as long short-term memory, attention learning, transfer learning, and reinforcement learning are widely being used to perform the abovementioned tasks and are being applied to financial technology innovation and novel robo-advisor services. This study combines the concept of recommendations and the applications as described above to propose a stock recommendation system based on the advanced learning to rank technique to model interactions between financial products in the whole market. This system can serve as an efficient and effective robo-advisor.

The main contributions of this study can be summarized as follows: (1) We propose a stock recommendation system that uses the advanced learning to rank technique to learn the interaction of each stock. (2) We introduce a multi-objective RankNets and a gated neural network to our framework. Investors can focus on both historical time-series data and other market information such as the market index and financial information.

II. RELATED WORKS

The learning to rank technique that combines ranking problems with a deep learning mechanism has become popular in recent years. The learning to rank technique was introduced in a study that proposed new general ranking functions by using genetic programming [1]. Subsequently, various applications of this technique have been proposed. For recommendation tasks, Cheng [2] proposed a network architecture that combined width and depth characteristics and used the ranking method to recommend users to the app. Tang [3] proposed a knowledge distillation technique called ranking distillation for learning to rank problems. The abovementioned approaches are mainly of three types: pointwise, pairwise, and listwise [4]. In a pointwise approach, each object is considered a learning instance. In a pairwise approach, a pair of objects is considered a learning instance. In this study, we use a pairwise method with a large number of feature sets.

III. PROPOSED METHOD

This study proposes a ranking-based recommendation framework that combines the mechanisms of learning to rank and gated neural network, as shown in Figure 1. The inputs of this framework are the average market information, *Market*; historical transaction data of companies *A* and *B*, $Co._{[A,B]}$; and extra financial information of *Co.A* and *Co.B*, *Fin.* $S_{[A,B]}$ represents the scores from the RankNet model scoring function. $P_{[A,B]}$ is the probability that *Co.A* outperforms *Co.B*. The framework automatically learns not only the interaction of time-series data but also market information through the feature extractor, which observes historical records over the past few days and captures learnable patterns in these data. Then, all candidate stocks are ranked using the proposed model. Each ranking model in the network represents different extra market information, such as market index and financial information of the company that investors concentrate on; furthermore, the gated neural network is used to learn the weights of each network.

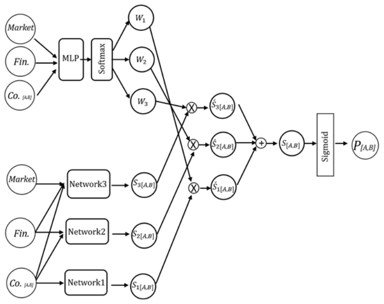

Fig.1. Gated network used to recommend top-n stocks.

A. Deep RankNet for Recommendation System

In our framework, we adopt the deep RankNet model for pairwise ranking. This approach differs from the traditional neural network framework. RankNet considers query-stock representation pairs. RankNet applies cross entropy as a loss function to minimize the loss between the predicted probabilities and the true probabilities calculated from labels and updates the network parameter to obtain the optimal scoring function. In our proposed model, we construct a gated network model to observe whether combining several different networks to automatically learn the weight of each network output realizes better performance than one RankNet model.

B. Gated Neural Network

Our network inputs include information of importance to investors, such as the market trend, stock price, and company information. We use multiobjective RankNets with a gated neural network. Weights are calculated as given by equation (1). ϖ_i is the weight of the i^{th} network; σ_1 is the sigmoid function; x_1, x_2, and x_3 respectively represent $Taiex$, $Co.$, and $Fin.$; $\omega_{1,j}$, $\omega_{2,j}$, and $\omega_{3,j}$ respectively represent the weight of $Taiex$, $Co.$, and $Fin.$ in the j^{th} hidden layer; and b_i represents the network bias. Then, the output before the substract layer is the SoftMax weighted average of the upper models' outputs.

$$\varpi_i(Market, Co., Fin.) = \frac{e\sum_{j=1}^{J}\sigma_1\left(x_1\omega_{1,j}, x_2\omega_{2,j}, x_3\omega_{3,j}+b_i\right)\omega_{j,i}+b_i}{\sum_{i=1}^{I} e\sum_{j=1}^{J}\sigma_1\left(x_1\omega_{1,j}, x_2\omega_{2,j}, x_3\omega_{3,j}+b_i\right)\omega_{j,i}+b_i} \quad (1)$$

In our study, the gated neural network uses related information to learn the weight of the upper models, which is the most important for our target. In summary, we suggest that this gated neural network will provide higher accuracy for solving our problem.

IV. Experimental Results

A. Dataset Description

We use two datasets—Taiwan 50 index and Taiwan mid-cap 100 index—and the total number of stocks is 150. Further, we take minute data from Jan. 2017 to Sep. 2017 for training and test on Apr. 2017 to Dec. 2017. 141 stocks remained for treatment and control groups in the final dataset used for the experiments.

B. Gated Network Recommendation Experiment

In the previous experiment, the performance of model 2 with a deep RankNet structure was better than that of other models. Below, we introduce each gated neural network with different data as weights in this experiment and present the experiment results in Figure 2 and Table 1, including (1) Gated1: $Co._{[A,B]}$, (2) Gated2: $Co._{[A,B]}$ and $Fin.$, (3) Gated3: $Co._{[A,B]}$ and $Market$, (4) Gated4: $Market$ and $Fin.$, and (5) Gated5: $Co._{[A,B]}$, $Fin.$, and $Market$.

TABLE I. PERFORMANCE EVALUATION OF GATED NETWORKS

Date	4/7	5/5	6/6	6/30	7/28	8/25	9/22	10/20	11/17	AVG.
Gated1	-0.0191	-0.0066	0.0094	0.0008	0.0121	0.0064	-0.0107	-0.0123	0.0128	0.0005
Gated2	-0.0046	0.0085	0.0131	-0.0146	0.018	0.0048	-0.0043	-0.0032	0.0165	0.0047
Gated3	-0.0217	-0.004	0.0098	-0.0016	0.0118	0.0168	-0.0091	-0.0004	0.0201	0.0044
Gated4	-0.0117	0.0067	0.0085	-0.0042	0.0135	0.0001	-0.0097	-0.0022	0.0095	0.0024
Gated5	-0.0388	0.0031	0.0025	-0.0127	-0.0001	0.0069	-0.0074	-0.0124	0.0238	0.0017
A+Fin.	-0.0076	-0.0017	0.0056	-0.007	0.0138	0.0089	-0.0053	-0.0126	0.0253	0.0038
Market	-0.023	0.0018	0.0041	-0.0076	0.0075	0.0099	-0.0088	-0.002	0.0154	0.0021

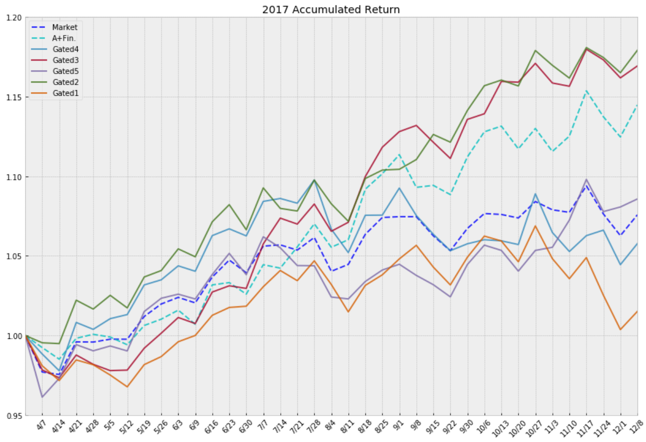

Fig.2. Gated network recommendation experimental results for networks with different input data.

Baseline: We set the market performance and the best performance of the previous experiment as our baseline for comparisons with all experimentally tested networks.

V. Conclusion

Robo-advisors have become popular in the financial industry, and artificial intelligence technology is being used widely to implement them. This study proposes a novel model that combines the concepts of trend prediction, port-folio management, and recommendations to recommend the top-20 stocks. An analysis of the experimental results indicates that our proposed gated neural network model can control the weight of a RankNet model effectively by adopting different gated structures, and it performs better than other networks implemented using deep RankNet recommendation.

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