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Fuzzy logic-based portfolio selection with particle filtering and anomaly detection

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ABSTRACT

This paper proposes a new knowledge-based system (KBS) featuring fuzzy logic (FL) with particle filtering and anomaly detection to create high-performance investment portfolios. In particular, our FL system selects a portfolio with fine risk-return profiles from a number of candidates by integrating multilateral performance measures. The candidates consist of various portfolios based on multiple time-series models estimated by a particle filter with anomaly detectors. In an out-of-sample numerical experiment with a dataset of international financial assets, we demonstrate our KBS successfully generates a series of selected portfolios with satisfactory investment records.

1. Introduction

It is well-recognized both in academia and industry that financial markets are highly complex and non-linear systems with large noise, which are affected by economic, political, geopolitical and psychological factors. Therefore, in the analysis of financial investment problems, machine learning (ML) techniques based on sophisticated computer science are widely used since they are effective to deal with non-linearity and uncertainty (e.g., [1]).

Fuzzy logic (FL) is considered to be one of the ML techniques, which is applied with great success in financial investment problems. Especially, fuzzy set theory, introduced by Zadeh [2], is utilized in portfolio optimization problems since it enables to represent imperfect knowledge or ambiguity for the future asset return. For example, although a mean-variance (MV) portfolio [3] has been one of the most famous strategies, there is a well-known serious problem that the direct MV optimization amplifies the effects of estimation errors (e.g., [4]). Consequently, many researchers introduce the fuzziness in portfolio optimization problems from various perspectives (e.g., [5–22]).

On the other hand, fuzzy logic systems (e.g., [23,24]) are effective to construct knowledge-based systems (KBS) for trading strategies with technical and fundamental analysis (e.g., [25–32]). In trading practice, domain expert knowledge is often expressed in the linguistic form, which can be incorporated into trading strategies through IF-THEN rules of FL systems.

This paper proposes a new knowledge-based system (KBS), particularly expert system (ES) featuring fuzzy logic (FL) to create a high-performing portfolio. Specifically, our ES consists of three stages: estimation, portfolio simulation and FL-based selection. That is, we first estimate expected return and volatility with several time-series models, and then calculate MV optimal portfolio weights based on these predictors with several types of anomaly detectors and different levels of risk-averseness. Finally, our FL system, by combining multiple investment criteria, evaluates the historical performances of each simulated MV portfolio and selects the best one. Here, we employ a variety of performance measures which are practically well-known to investment experts such as hedge fund managers.

Although each previous research has presented a state-of-the-art investment scheme, it may have some difficulties in adapting to frequent or/and drastic changes in market conditions. Differently, our approach does not rely on a single scheme, but selects the most appropriate one under the current market environment among various options. Consequently, our proposed system creates high performance over a period that includes different market conditions.

In the estimation step, we introduce state space models to obtain the estimates of expected return and volatility for MV portfolio construction. State space models are commonly used in

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various fields to represent the dynamic dependence between the latent state and observed variables. Their dynamics are described as stochastic processes called system and observation models. Moreover, applying filtering methods, we can partially observe latent state variables with noises through the observation model.

In the current work, we regard expected return and volatility as state variables, which are observed with noise as asset return. For model estimation, we resort to a particle filtering (PF) method applicable to non-linear and non-Gaussian models (e.g., [33,34]). PF is an on-line estimation algorithm to time-series data under the state-space representation of models, which takes much less computational time than repeated implementation of off-line algorithms with sliding windows.

In particular, we assume an exponential moving average (EMA) and generalized EMA as system models. The former is often used both in investment practice and previous ML researches (e.g., [35–38]), and the latter is introduced in Nakano et al. [39] to obtain marginally better predictions based on EMA.

In addition, we exploit three anomaly detection (AD) methods to refine investment universe [39]. Since we can obtain the model likelihoods or the distributions of state variables for each time step, PF is easily combined with on-line detection schemes. In our investment problem, realized asset returns sometimes largely deviate from the models, whence it is inappropriate to implement predictions. Hence, by excluding the assets for which anomalies are detected from investment universe (i.e. trading assets), we can enhance portfolio performance.

Our investment universe consists of international equities, REITs and bonds with cash. Besides, we employ various investment criteria, i.e., compound return (CR), standard deviation (SD), downside deviation (DD), maximum drawdown (MDD), Sharpe ratio (ShR), Sortino ratio (SoR) and Stering ratio (StR), which enable multilateral assessment.

Lastly, we briefly summarize the motivation, contribution and implication of our work.

(i) Motivation:
The motivation of our work is how to select the best investment decision from numerous possible options under the situation that we cannot know it in advance. For instance, in the current work, we employ a mean-variance portfolio among various investment strategies. Then, we must estimate means and variances of asset returns, which involves choosing a statistical model and its parameters from rich variations. Besides, it is necessary to decide investment assets before portfolio construction. In addition, we cannot always determine a crisp parameter value (risk aversion parameter) in mean-variance analysis, which further diversifies the possible options.

(ii) Contribution:
Our contribution is to propose an effective solution to this problem by introducing a fuzzy system at the final stage of an investment process, which is a new perspective in FL-based portfolio construction. In particular, we develop an ES featuring FL system which is able to integrate each investor's performance measures to select the best investment decision from various possible options. Importantly, since performance measures are the most essential and critical investment objectives for investors, this specification is expected to directly link to high performance.

(iii) Implication:
The applicability of our FL system is quite broad. Namely, we use a FL system at the last stage of investment decision processes, i.e. performance evaluation, which is the reason why our approach is extensively applicable.
Especially, although the current paper focuses on a mean-variance portfolio, our FL system can incorporate any strategies into the possible options. For instance, we are able to employ the investment strategies appearing in the previous works, that is, fuzzy rule-based technical/fundamental trading (Section 2.2) or extension of Markowitz model with fuzzy logic (Section 2.3). We will show an example in Section 4.3.

The remainder of this paper is organized as follows. Section 2 summarizes related works. Section 3 presents composition of our ES: PF-based estimation with AD scheme, MV portfolio simulation and FL-based selection. Section 4 shows the results of out-of-sample numerical experiments. Finally, Section 5 concludes.

2. Related works

In this section, we shortly review previous works for application of fuzzy set theory to three financial investment topics, that is, time-series prediction, technical/fundamental trading and modern portfolio theory.

2.1. Application to financial time-series prediction

FL is frequently used to develop KBSs for financial time-series prediction due to its general applicability. For example, Korol [40] builds a fuzzy system for forecasting exchange rates based on various economic factors such as GDP and inflation, which achieves lower mean absolute percentage error than other statistical models and artificial neural network approaches.

Cai et al. [41] develop a new fuzzy time series forecasting model. Particularly, they exploit ant colony optimization to promote the forecasting performance. Further, the auto-regression method is adopted to make better use of historical information. The new model combined with these techniques is shown to be more effective than existing models through the application to Taiwan capitalization weighted stock index.

Hadavandi et al. [42] construct a stock price forecasting expert system based on genetic fuzzy systems and artificial neural networks. More precisely, after step-wise regression analysis determines factors having most influence on stock prices, they divide raw data into multiple clusters by self-organizing map neural network. Then, each cluster is fed into genetic fuzzy systems with the ability of rule base extraction and database tuning.

Singh and Borah [43] develop a new high-order fuzzy time-series model, where artificial neural network based architecture is exploited for defuzzification. In particular, they discuss the importance on "lengths of intervals" for time-series and introduce a repartitioning discretization approach. Their methodology is validated with daily temperature data and stock price data.

2.2. Application to technical/fundamental trading

Since fuzzy IF-THEN rules are helpful to quantitatively express expert knowledge for technical and fundamental trading, various researchers have applied FL systems to this field. As a pioneering work, in 1991, Kosaka et al. [27] propose a framework for fuzzy rule-based technical trading, which is illustrated by single stock data.

Simutis [30] develops a computer software for fuzzy logic-based stock trading with evolutionary programming methods, where technical and fundamental information is exploited to produce buy/sell signal. The system with datasets of US stock markets shows high performance over two year investment period (1996–1998).