Agent-based Computational Investing Recommender System

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ABSTRACT
The fast development of computing and communication has reformed the financial markets' dynamics. Nowadays many people are investing and trading stocks through online channels and having access to real-time market information efficiently. There are more opportunities to lose or make money with all the stocks information available throughout the World; however, one should spend a lot of effort and time to follow those stocks and the available instant information. This paper presents a preliminary regarding a multi-agent recommender system for computational investing. This system utilizes a hybrid filtering technique to adaptively recommend the most profitable stocks at the right time according to investor's personal favour. The hybrid technique includes collaborative and content-based filtering. The content-based model uses investor preferences, influencing macro-economic factors, stocks profiles and the predicted trend to tailor to its advices. The collaborative filter assesses the investor pairs' investing behaviours and actions that are proficient in economic market to recommend the similar ones to the target investor.

Categories and Subject Descriptors
H.3.3 [INFORMATION STORAGE AND RETRIEVAL] : Information Search and Retrieval - *Information filtering*

Keywords
Recommender system, computational investing, stock market, multi-agent system, hybrid filtering.

1. INTRODUCTION
The rapid evolving development of communication and computing has significantly changed the dynamics of financial markets. These days, people prefer to trade online through the Web rather than using full-service brokerages [2]. Online financial services have provided new opportunities for investors to access real-time data of financial market to trade stocks efficiently. There are more threats or opportunities to lose or make money, with all the available stocks through the World, but merely if one has energy and time to follow the stocks. The stocks' data change continuously, while trading information and news regarding financial status of the companies are instantly available. All these make it difficult to choose the most profitable stocks at the right time and right place.

Volatility modelling and forecasting are critically important to financial market investors. Financial volatility forecasts enable the farsighted investors to adjust their investment portfolios to mitigate investment risk and to modify their investing strategies align with the upcoming market movements [10].

1.1 Agent-based Computational Investing
Agent-based Computational Investing (ACI) is a complex, dynamic and adaptive system where agents are interacting with each other based on rules to process economic data, perceive the environment and take action [12]. Starting from preliminary conditions which is identified by the modeller, computational investing changes over time when its resident agents interact frequently together and learn from each other through the processes of interactions. Therefore, ACI is a bottom-up culture-dish approach to economic systems studies. In a very new research area of agent-based computational economics or investing, researchers utilize computational frameworks to find out the market economies evolution under supervised conditions of experiments [9].

There are some fully automated trading systems, but they are totally automatic and independent from human decisions. These electronic systems are not completely reliable, and it is difficult for investors to let a machine take over their money and trades without their intervention. They prefer to know the procedure and to be involved into the process and the reason of what is being recommended. For this reason we are going to use a recommender system which proposes best stock options available to buy or even sell, but not to be replaced with human judgment and decisions. Therefore, it can attract their trust as well as make them confident about their decisions with letting them know why the system is recommending a specific stock.

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1.2 Recommender Systems

In overall, recommender systems are employed to help people to select and make their choices based on the knowledge which they have [3]. In the beginning, the majority of recommender systems were mainly a basic query-based information retrieval system, which named content-based recommender system. Just like the way that search engines act, they were bringing up those web pages with contents similar to users' queries. Later, a more sophisticated approach was proposed by Goldberg which called collaborative filtering [6]. Collaborative recommender systems accumulate items ratings from other users and make recommendations depending on those ratings. They are widely applied in many fields in academic and commercial context, such as Amazon which uses for proposing books and MovieLens which proposes movies on this basis.

Although collaborative recommender systems are still quite successful, they fail when requested items have no recorded history or when individual preferences are determinant for selection, such as a movie's cast or genre. Additionally, it relies only on other users and the quality recommendation is completely depending on the user rating rather than the information content.

To overcome the limitations of content-based and collaborative approaches, hybrid approaches were proposed to benefit user preferences and content at the same time. Proposed approaches to hybrid system can be classified into two clusters. The first cluster is the linear combination of collaborative and content-based filtering results as is illustrated in Figure 1. As an example, Wasfi [1] developed ProfBuilder which recommends web pages utilizing both collaborative and content-based filters, and each provides a separate recommendation list without merging them to make a combined prediction.

The second cluster combines sequentially the content-based filtering and collaborative filtering as is presented in Figure 2. In this approach, at first, content-based filtering is applied to identify users who have similar interests. Then, a collaborative algorithm is employed to generate predictions.

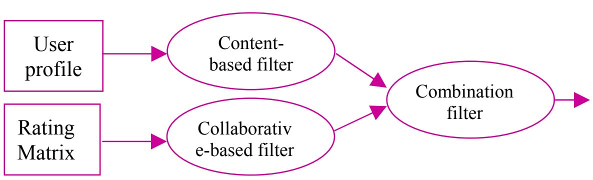

Figure 1. Linear combination in hybrid approach

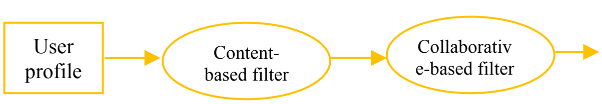

Figure 2. Sequential combination in hybrid approach

2. RELATED WORK AND PROBLEM STATEMENT

In today's stock market, there are huge numbers of competing investments and the prices of stocks change intensely. In such a situation, practitioners try to guide the timing and selection process of investment typically relying on one of two available main frameworks, called technical analysis and fundamental analysis. Technical analysis deals with patterns of price volume for individual stocks. But fundamental analysis is a technique where the stock is studied by itself for its fundamentals such as DIVIDEND YIELD, P/E, PRICE/BOOK VALUE, etc. These traditional techniques enable investors to manage their investment by predicting stocks prices with some tools. So far, experimental studies have adequately shown that stocks price prediction is very non-stationary and time-varying [10], and none of these is sufficient and absolutely superior to the others [7].

Volatility modelling and forecasting of financial time series is regarded as one of the most confronting applications of modern time series forecasting. Financial time series are inherently forceful, noisy and deterministically chaotic [2].

The stock market specialists are not able to come to an agreement regarding whether or not there are strategies which can consistently beat the market. The economic situation, which has been developed since 2008, has made this lack of forecasting precision quite clear. Not even the top financial analysts could predict such a serious economic crisis. Financial markets are too sensitive; and they are affected by so many elements (such as government policies, sanctions, international dependencies, etc.) that it is quite impossible to realize predictions with enough confidence. For example, the Malaysia stock market has experienced a very large drop since September 2011 which is attributed to uncertainties over Malaysia's Election 2013 and a perception of political instability, it is expected to have even greater impact after the election [4]. Past research in this area did not consider any of these influencing elements.

Many high-return projects need long-term commitment of capital. Meanwhile, most of the investors are reluctant to invest in a project for a long period and are not enough confident; therefore less investment goes to the high return project which requires a long-term commitment [12]. This imbalance funding may harm economic growth.

Users mainly are not happy with the recommendations which are not of their interest. This recommendation error is called false positive and it will lower their trusts in the future. So this is the most important error which has not received enough attention from researchers [5].

Moreover, each trader has different style of investment from another investor, some of them are concerned about long term returns and some are more aggressive risk takers. Some may prefer to know what the other investors with the same favour are investing for, or there may be some novice investors who would like to know the professional investor's profile.

As an example, Schelling [8] showed how patterned social behaviour can evolve as the unintentional consequence of repeated local interactions among agents who follow simple behavioural rules. For example, he proves how exclusion by race can arise through local chain reactions if agents have a moderate preference for avoiding small-minority status, since they favour more of their neighbours to have the same race as themselves. Existing systems and services commonly do not take these individual preferences [11].

3. AGENT-BASED COMPUTATIONAL INVESTING RECOMMENDER SYSTEM (ACIRS)

ACIRS has adopted a hybrid approach with combination of collaborative and content-based filtering in a new style which is different with *linear* and *sequential*. As Figure 3 illustrates, it utilizes separated as well as mixed recommendations from both content-based and collaborative filtering. Through content-based filtering, ACIRS recommends stocks relying on *Trend prediction*, *Macro-economic factors* and *User profile*. On the other hand, it is also interested to apply content-based filtering algorithm and to identify users with same interests, then combine with collaborative algorithm to make suggestions.

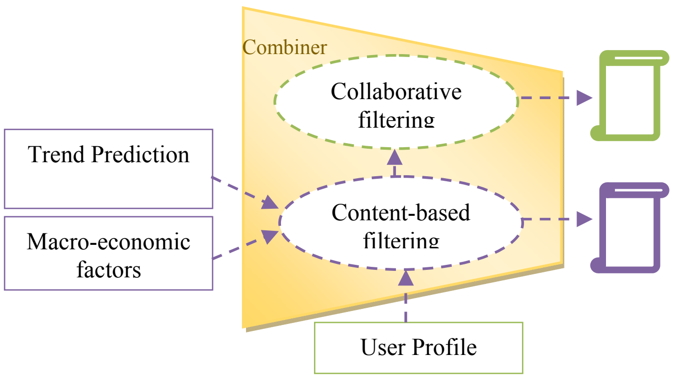

Figure 3. A hybrid approach with new combination

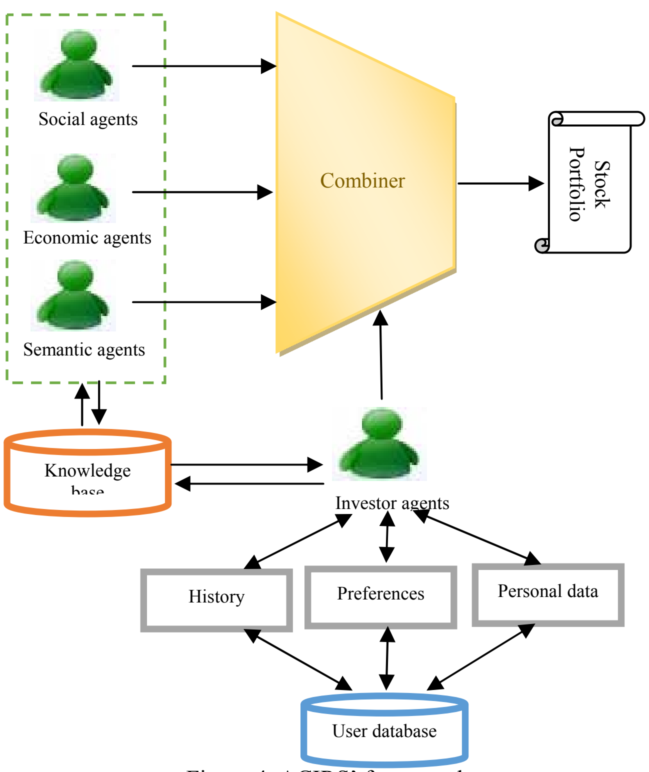

Figure 4. ACIRS' framework

Intelligent agents are the agents who are able to *react* to their environment's changes, have communication and *social ability*, and they are also able to employ computational intelligence to achieve their objectives through *proactive* actions [3].

Agent-based computational investing is defined as the computational investigation of economies which are simulated as autonomous agents interacting in an evolving system. It starts from preliminary condition which is specified by the modeller. Over time, the computational economy grows when its resident agents interact together frequently and learn from each other in these interactions.

The Framework of ACIRS is shown in Figure 4. The ACIRS modeller starts by constructing a stock market trading environment consisting of primary agents. These agents include economic agents (e.g., price trend prediction, companies/producers, intermediaries and so on.), social agents which represent various social and environmental events (e.g., market inter-relations, governmental policies, regulatory, sanctions and so on) and investor agents.

The ACIRS modeller initializes the market state through recognizing the starting attributes belong to the agents. The agent's primary attributes may contain form characteristics, internalized behavioural rules, inner modes of behaviour (comprising communication and learning norms), and knowledge and information of itself and other agents which is stored internally. The market later gets involve over time without more modeller intervention. All consequent events that happen should arise from the historical time-line of agent-agent interactions. To reason and justify the environmental factors and stocks and user priorities, a knowledge-base is needed for semantic agents. The ACIRS' knowledge-base is based on OWL (Web Ontology Language) which is a knowledge representation language for authoring ontologies. It allows sharing and reusing of the information sufficiently in an agent-based system architecture.

For fully automated economic computational models, an investigator may reason to identify a universal learning scheme with appropriate personal tactics of the computational agents which mutually change to fulfil their needs and desired following globally specified goals (e.g., productive efficiency). Whereas, ACIRS already considers users preferences and utilizes their strategies in providing the recommendations. Besides, the user plays the final role in decision making and ordering what to sell or to buy.

4. PROTOTYPE AND EVALUATION

We plan to train the system using Artificial Neural Network machine learning technique and develop a prototype using Object Oriented Programming and Swarm which is an agent-based software library. Another possibility is development of Computational Laboratories (CL) which are pre-built computational frameworks with employing a Graphical User Interface (GUI) that permit systematically experimentation for a domain of particular problem. It also allows a researcher to use a CL to easily evaluate the system sensitivity to changes with various main parameters.

The required data for training and testing is supposed to be collected from Bursa Malaysia, and the data regarding investors is to be collected using a global survey asking about their personal information, interests and behaviours of trading and preferences.

We are going to evaluate the system in a real stock market using several samples of investors and stock. We will compare the ACIRS's recommendations, investors satisfaction and actual purchase or sell of the stocks through a survey.

Open issues: we may not be able to gather all investors' personal details and their attitudes, and it can be done for a small size of users. Another issue is investors' emotions of fear and greed which mainly drive their decision to buy or sell a stock and this is not an emotional intelligent system, so it may alter the evaluation results. Additionally, the macro-economic factors are mainly very difficult to predict precisely, although this system tries to consider them, it may fail to receive and to analyse them on time (real-time), correctly and precisely.

5. CONCLUSION

In this research proposal, we bridged the concept of agent-based computational economics with recommender systems. Recommender systems can address the problem of financial market data overload by reducing the amount of data that investors should examine and recommend the best opportune options to invest. This paper introduced and clarified the potential advantages of application of recommender systems in computational investing through providing a practical system framework. ACIRS uses a new hybrid approach in combination of content-based filtering and collaborative filtering. We plan to develop a prototype and to evaluate the system with real stock market data.

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