Multi-Strategy Integration for Actionable Trading Agents

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Abstract

Trading agents are very useful for developing and back-testing quality trading strategies to support smart trading actions in the market. However, the existing trading agent research mainly focuses on simple and simulated strategies. As a result, there exists a big gap between academia and business when the developed trading agents are deployed in the real life. Therefore, the actionable capability of developed trading agents is often very limited. In this paper, we introduce approaches for optimizing and integrating multiple classes of strategies for trading agents. Five categories of trading strategies, including 36 types of trading strategies are trained and tested. A strategy integration and optimization approach is proposed to identify golden trading strategy in each category, and finally recommend positions associated with these golden strategies to trading agents. Test in five international markets on ten years of data respectively has shown that the final strategies recommended to trading agents can lead to high benefits while low costs. Concurrent execution of positions recommended by all golden strategies can greatly enhance performance.

Keywords: *trading agent, trading strategy, optimization, integration*

1. Introduction

The concept of trading agent [1] is very useful and increasingly used for evaluating programmed trading techniques and developing automated strategies for buyer and seller software agents in marketplaces. For instance, competitions [2] and simulations have been developed in terms of travel agents, supply chain management agents [2], market design [3]. However, the present trading agent research mainly focuses on problems designed in artificial marketplaces. There are the following issues that prevent the techniques from stepping into real-life markets.

- The first issue is how to design trading strategies that can be used for real-life market trading support. Unfortunately, strategy design and development in existing trading agent research present strong academic favor and sense. Business constraints and expectation [4] are not in the consideration of existing trading agent research.
- The second issue is the actionability of trading agents [6], namely to what extent the trading agents powered by the developed strategies can support both technical significance and business decision making [4] in real-life marketplaces.

To address the above two issues, this paper proposes multi-strategy integration to develop trading strategies for trading agents. Proper trading strategies should increase the benefits while decrease the risk of a trading agent hosting the strategies. Further, the identified trading strategies can not only support real-life trading actions, but satisfy business expectation. We use financial trading agents for stock trading to illustrate the development of multi-strategy integration and actionable trading agents. Seven categories, including 36 types of trading strategies have been developed for stock trading agents. Ten years of historical data from five individual markets are used to evaluate the strategies for actionable trading agents.

2. Trading Strategy Optimization

The objective of trading strategy optimization is to enhance optimal benefits while reduce cost and risk of host trading agents when they take some positions in the market. *Positions* are determined by trading strategies. Good trading strategies encourage trading agents to take those positions with high benefit but low cost.

A trading agent may take one of three *positions* $\{a_1, a_2, \ldots, a_n\}$ in the market:

$$\begin{cases} a = 1, \\ a = 0, or \\ a = -1 \end{cases}$$

Position "-1" indicates a *buy* or *holding buy* action in the market. Position "1" reflects either a *sell* or *holding sell* action. Position "0" indicates *none* actions taken.

We define the concepts "benefit" and "cost" as follows to measure the performance of a trading agent when it takes certain positions in a market.

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Definition 1. Benefit b_s measures the cumulative payoff of a trading agent earned in undertaking positions a_i in price p_i and volume v_i. The positions and its associated prices and volumes are determined by a trading strategy *s*.

$$b_s = \sum a_i \times p_i \times v_i$$

Definition 2. Cost c_s measures the cumulative commission and transaction costs c_i of a trading agent in undertaking position sequences $\{a_1, a_2, \ldots, a_n\}$ determined by a trading strategy *s*.

$$c_s = \sum |a_i| \times c_i \times p_i \times v_i$$

Based on the positions a trading agent may take, the trading strategy optimization is to *increase benefit* while *decrease cost* of a trading agent in the market.

- *Increasing benefit*: increasing benefit is the positive objective of a trading agent when takes a strategy. For instance, a trading agent taking *strategy a* makes more money (higher payoff) than that taking *strategy b* if $b_a > b_b$. There, a trading agent must select trading strategies with highest benefits b_s.

  If $b_a > b_b$
  Then *strategy a* is associated with higher benefits;

- *Decreasing cost*: costs reflect the negative side of a trading agent in conducting a strategy. Controlling and reducing costs is one necessary step in optimizing trading strategies for trading agents. To control costs, a trading agent must select trading strategies with lowest costs c_s.

  If $c_a > c_b$
  Then *strategy a* is associated with higher costs;

Therefore, the aim of trading strategy optimization for trading agents is to select those trading strategies that can guide them to take positions in the market with higher benefits while controlling costs.

3. Multi-Strategy Integration

In real-life trading, trading strategies can be categorized into many classes. To financial experts, different classes of trading strategies indicate varying fundamental principles of the market model and mechanisms. As a result, a trading agent may take serial positions generated by a specific trading strategy, which instantiates a class of trading strategies. It may also take concurrent positions created by multiple trading strategies. We will not discuss multi-strategies taking by a trading agent in this section. Rather, we are interested in identifying a most suitable trading strategy from all available strategies. This leads to the following searching.

Strategy 1. A trading agent identifies and takes the best trading strategy s_o from all parameter combinations of a trading strategy *s*.

To achieve Strategy 1, we can use optimization techniques like Genetic Algorithms [5] to search for the strategy with highest benefit b_s but lowest cost c_s. We won't address it in this paper.

Strategy 2. A trading agent identifies and takes the best trading strategy s_c from a trading strategy class *c*. A trading strategy class may consist of several types of trading strategies.

For instance, double Moving Average *MA* is a common trading strategy. It can further be instantiated into *MA-B*, *MA-C* and *MA-D*, where *B*, *C* and *D* represent different organizational factors and constrained filters considered in the designing the MA strategies. Following the Strategy 2, we need to identify the golden rule of the *MA* family {*MA*, *MA-B*, *MA-C*, *MA-D*}.

Strategy 3. A trading agent identifies and takes the best trading strategy s_{ci} (*ci* is the trading strategy class *i*, *i* = 1, 2, …) from each class *ci*. The agent follows such best strategies from a group of trading strategy classes.

For instance, there are the following trading strategy classes: FR, MA, CB, SR and OBV. For each of them, there exist a few types of instances just like MA discussed above. An agent will discover the golden strategies for them individually, and then follow them to take trading positions concurrently in the market.

The strategy development process is as follows.

Given a trading strategy *a*, a trading strategy class *ci* (*i*=1, 2, …), $a \in ci$, b_a and c_a are the benefit and the cost of a trading agent in executing the strategy *a*,

A. Data preparation:
Separating the source data into two data sets in terms of:
1). Splitting two years of data for training to identify best trading strategies satisfying the Conditions in Section 4;
2). Splitting three years of data including the training data to deploy the identified strategies;
3). Searching optimal strategies as discussed in part B;
4). Sliding the 2-year training and the 3-year deploying data windows one year forward to extract data sets as in 1) and 2), and repeating the operations of searching optimal strategies;

B. Searching optimal strategies:
1). Searching for the strategy instance *a'* of strategy *a* with $\max(b_{a'})$ of its positions;
2). Searching for the strategy *a"* of strategy *a* in its class *ci* with $\max(b_{a''})$ and $\min(c_{a''})$ in class *ci* when its positions are executed;
3). Searching for all strategies a"*1*, a"*2*, … (*i* =1, 2, …) in all strategy classes satisfying conditions in step 2);
4). Generating the positions of a trading agent taking all strategies identified in step 3), respectively;

5). Checking the benefits and costs of a trading agent executing the above positions, and compare to find the strategy with highest benefits while as low as possible cost/benefit ratio;
6). Executing multiple strategies concurrently.

Figure 1 further illustrates the process of a trading agent selecting golden trading strategies from individual strategy class.

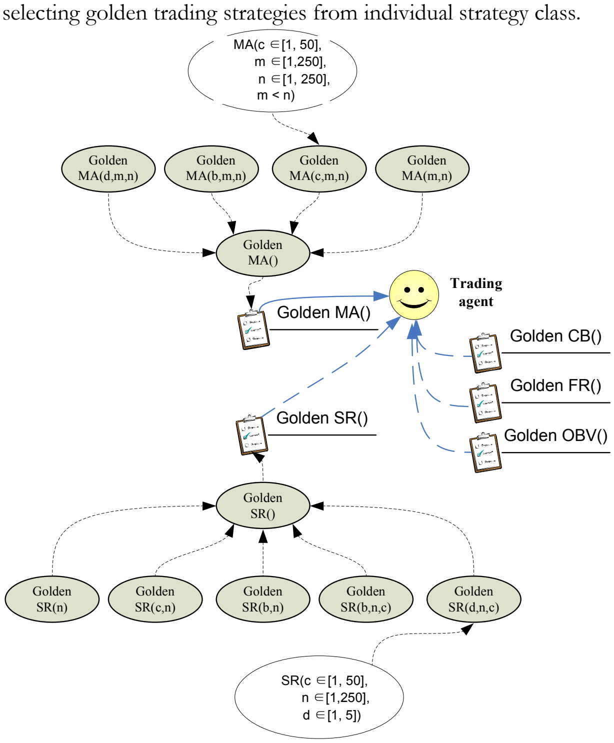

Figure 1. Multi-strategy integration for trading agents

In the following Section 5, we illustrate some of results of using the above strategies in the market data.

4. Trading Agent Actionability

As we have addressed in domain driven data mining [4], a trading strategy is actionable if it satisfies not only technical significance, but also business expectations from both objective and subjective sides. This means that the host trading agent can take those positions recommended by the trading strategies in the market. Here we mainly emphasize the business performance of trading agents following different strategy optimization approaches.

Business performance of stock trading agents is measured in terms of the following aspects. A trading strategy is *actionable* if it satisfies the following two conditions. A trading agent following the actionable trading strategy can take actions in the market.

Condition 1: highest benefit but low cost as possible;
Condition 2: The lowest cost/benefit ratio;

5. Experiments

Experiments of this multi-strategy integration for stock trading agents are conducted as follows:

- Five classes of trading strategies are developed: MA, FR, CB, SR, and OBV as shown in Table 1;
- Five stock markets: ASX, Hongkong, London, New York, and Japan;
- Interday data from 1/1/1997 to 30/12/2006: date, price, volume as shown in Table 2;
- Training data: 2-year sliding window, say 1/1/1997-30/12/1998, 1/1/1998-30/12/1999;
- Deploying data: 4-year sliding window, say 1/1/1997-30/12/2000; see Table 3.

Table 1. Trading strategy base

Class	Types in a class
FR	FR-X, FR-XC, FR-XY, FR-XE
MA	MA-MN, MA-BMN, MA-CMN, MA-DMN
CB	CB-NXC, CB-NXBC
SR	SR-N, SR-NB, SR-NC, SR-NBC, SR-NDC
OBV	OBV-MN, OBV-B, OBV-C, OBV-D

Table 2. Data sample

Date	Price	Volume
2006-12-14	182.6	290244
2006-12-15	183.5	145063
2006-12-18	184.95	126260
2006-12-19	184.6	151536

Table 3. Data partition excerpt

	starting	Train end	Deploy end
Window 1	1/1/1997	30/12/1998	30/12/2000
Window 2	1/1/1998	30/12/1999	30/12/2001
Window 3	1/1/1999	30/12/2000	30/12/2002

Based on the approaches discussed in Sections 2 to 4, we identify the best trading strategies in each type and each class. We then calculate positions associated with these golden strategies (see Table 4 for signals, positions, benefits and costs of trading strategy MA-BMN).

Table 4. Output excerpt of a trading strategy
(Strategy: MA-BMN; Data: 2004)

Date	Price	Sell	Buy	Position	($) Benefit	($) Cost
2004-8-16	3466	-1	0	-1	9200	103
2004-8-17	3480	-1	0	-1	8850	106.5
2004-8-18	3472	-1	0	-1	9150	108.5
2004-8-19	3481	-1	0	-1	8825	110.75
2004-8-20	3494	0	0	-1	8500	114

In searching for golden trading strategy of each strategy type, say MA-BMN, we use GA to find the parameter combinations with highest benefit and lowest cost (as shown in Table 5).

Table 5. Maximal benefits to parameter combinations (excerpt) (Data: 2003; Market: ASX; Strategy: MA-BMN)

Parameter combinations	Benefit ($)	Cost ($)
n = 2; x = 0.010; c = 25; b = 0.001	32350	394.25
n = 5; x = 0.010; c = 75; b = 0.015	18200	268
n = 5; x = 0.010; c = 50; b = 0.001	16900	241.75
n = 2; x = 0.015; c = 25; b = 0.005	16550	256.5
n = 2; x = 0.020; c = 25; b = 0.001	12725	214.5

Trading agent can integrate all golden trading strategies and execute them concurrently in the market. In this case, Table 6 shows the positions recommended by each golden strategy.

Table 6. Trading agent positions recommended by five trading strategy classes (excerpt)
(Strategy class: MA, FR, CB, SR, OBV; Data: Hongkong; Year: 2006)

Date	Position MA	Position FR	Position CB	Position SR	Position OBV
2006-11-16	1	1	0	1	1
2006-11-17	1	1	0	1	1
2006-11-20	1	1	0	1	1
2006-11-21	-1	-1	0	1	1
2006-11-22	-1	-1	0	1	1

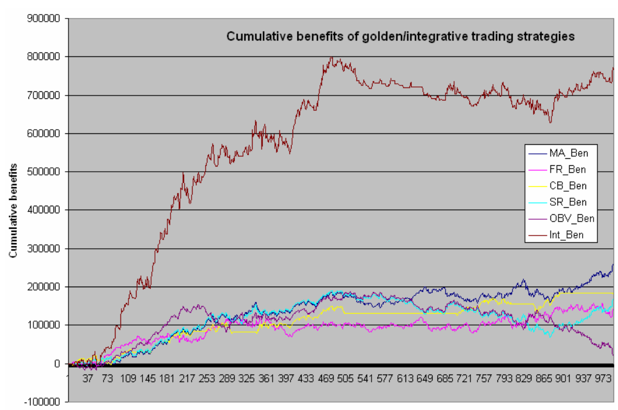

Figure 2. Cumulative benefits of each trading strategies (Year: 2003-2006, Market: Hongkong, Strategies: MA, FR, CB, SR, OBV, and Integrative)

Figures 2 and 3 show the cumulative benefits and cost/benefit ratios of a trading agent taking positions recommended by golden trading strategies as shown in Table 6 in the market, where Int_Ben and Int_Cost are the benefit and cost obtained when a trading agent executes all golden positions concurrently.

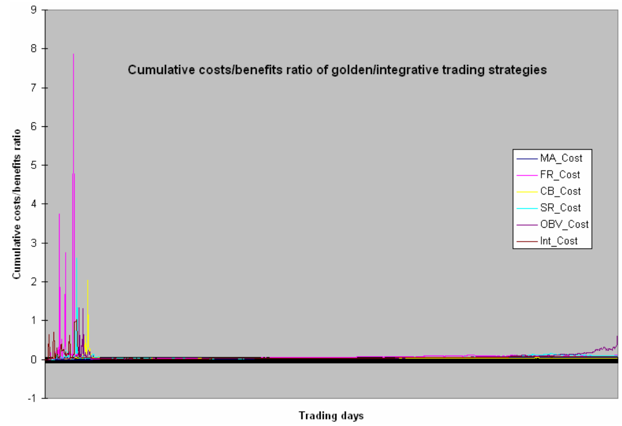

Figure 3. Cumulative cost/benefit ratio of each golden trading strategies (Year: 2003-2006, Market: Hongkong, Strategies: MA, FR, CB, SR, OBV, and Integrative)

A large amount of tests in stock data of five markets have show all golden trading strategies can lead to higher benefits but lower cost/benefit ratios (except FR in the first few days). In particular, concurrent execution of positions from all golden strategies can greatly increase benefits while control very low costs compared to taking positions recommended by an individual strategy only.

6. Conclusions

This paper presents some of our initial work in developing actionable trading strategies for trading agents in stock market. 10 years of five individual market data has been used for the backtesting. A large amount of tests have shown that the identification of golden trading strategies and the concurrent execution of these strategies can greatly increase benefits with low cost. This greatly enhances the actionable capability of trading agents.

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