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RESEARCH ARTICLE

An intelligent market making strategy in algorithmic trading

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Abstract Market making (MM) strategies have played an important role in the electronic stock market. However, the MM strategies without any forecasting power are not safe while trading. In this paper, we design and implement a two-tier framework, which includes a trading signal generator based on a supervised learning approach and an event-driven MM strategy. The proposed generator incorporates the information within order book microstructure and market news to provide directional predictions. The MM strategy in the second tier trades on the signals and prevents itself from profit loss led by market trending. Using half a year price tick data from Tokyo Stock Exchange (TSE) and Shanghai Stock Exchange (SSE), and corresponding Thomson Reuters news of the same time period, we conduct the back-testing and simulation on an industrial near-to-reality simulator. From the empirical results, we find that 1) strategies with signals perform better than strategies without any signal in terms of average daily *profit and loss* (*PnL*) and *sharpe ratio* (*SR*), and 2) correct predictions do help MM strategies readjust their quoting along with market trending, which avoids the strategies triggering stop loss procedure that further realizes the paper loss.

Keywords algorithmic trading, market making strategy, order book microstructure, news impact analysis, market simulation

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1 Introduction

A market maker refers to a bank or brokerage company that participates in market nearly all the trading time and quotes (bid and ask prices) for other stock buyers and sellers. When people enter the market and want to trade a stock, market makers are always there and provide liquidity. In doing so, they are literally "making a market" for the stock [1]. With the development of the algorithmic trading, the job of making market is progressively transitioned to automated computer programs. In particular, the market making (MM) strategy has been playing an increasingly important role in the real market. Due to the fast speed and high accuracy, the MM strategy has become the key proprietary algorithmic trading strategy. The MM strategy is doing the job of specialists who quote for other traders, place passive or aggressive orders in an order book, and dynamically readjust their quotes and orders following market conditions and the strategy's own logic.

The profit of the MM strategy mainly comes from the bouncing of stock prices. When the prices change within a small range, orders frequently hit either strategy's buy or sell orders, which gives the strategy an amount of chances to capture the bid-ask spread and make profit. However, MM strategies without any forecasting signal are not safe while trading. There are two main risks on MM. The first one refers to informed traders or information asymmetry. Since the MM strategy does not have 100% perfect information, there are always traders with faster or better information who could game with the MM strategy. This risk is especially severe for illiquid stocks, where the strategy needs to detect and identify whether the order is sent by an informed trader or not and set larger bid-ask spread to compensate the risk [2][1]. The second one is inventory imbalance or adverse selection led by market trending. As illustrated by [3], when market price is trending, the MM strategy with no pre-trending action will accumulate risky inventory which brings loss to the strategy in the worst case. Since the MM strategy is a fully automatic program that both makes trading decisions to provide liquidity, as well as takes actions to balance inventory and handle risks, how to build an intelligent MM strategy has been an attractive research issue on algorithmic trading.

There are many research papers in literature about MM strategy [2,4–7]. To formulate, the proposed strategies could be considered as a mapping from the strategy's current state θ_t and the market condition to the strategy's action in next step a_{t+1},

$$f(\theta_t, p_t) \mapsto a_{t+1}. \quad (1)$$

The market condition p_t refers to events extracted from price series. The strategy has to consider θ_t and p_t, and takes corresponding action a_{t+1}. Different from their approaches, we add one more information source into MM strategy's information set, which is news event. And Formula (1) is changed to

$$f(\theta_t, p_t, n_t) \mapsto a_{t+1}, \quad (2)$$

where $n_t \in N$ is the news data set.

In this paper, we develop a trading signal generator and a MM strategy, aiming at adaptively and progressively integrating multiple market information sources to improve the performance of the strategy. The first tier is a trading signal generator. We employ support vector machines (SVMs), a successful nonparametric classifier, to classify patterns of the order book and market news titles into either *positive*, *neutral*, or *negative* categories. The second tier is the trading strategy. The predictions provided by the first tier are fed into the MM strategy, where the strategy will then trade on these signals. We back-tested this MM strategy with half a year real market tick prices and news on a near-to-reality simulator. Experimental results show that the average daily *profit and loss* (*PnL*) improves when the strategy has the help of signals, and correct signals help the strategy quote along the market trending and avoid the strategy triggering stop loss utility in many cases.

The rest of this paper is organized as follows. Section 2 is a brief literature review. Section 3 first shows our system architecture, and then illustrates in detail how to generate trading signals from two information sources, and finally explains the logic and work flow of the MM strategy. Section 4 describes the back-testing setup and simulation results. Section 5 gives our conclusion and describes our future work.

2 Related work

There are many works on MM strategy analysis. In our proposed two-tier framework, there are mainly two research issues. The first one is the signal generator, while the second one is the trading strategy. In this section, we will briefly introduce the current methodologies about these two issues.

2.1 Trading signal generation

Mining signals from market prices and news articles have been studied in many previous works. For the mining of price signals, Kim [8] used SVM to predict index prices and claimed that the performance of SVM was better than back-propagation neural networks. Similar result could be found from the work of Cao and Tay [9, 10]. They applied SVM to predict S&P 500 daily prices and also found that SVM had better performance based on the metrics of normalized mean square error and mean absolute error. Huang et al. [11] used SVM to predict price directional movement of NIKKEI 225 index. After comparing SVM with linear discriminant analysis, quadratic discriminant analysis and back-propagation neural networks, they drew the same conclusion.

Market news, which is traditionally processed by human investors, has become an emerging and important information source for machine learning models while forecasting. The basic motivation is to analyze the statistical relationship between word patterns and market responses. Fung et al. [12] classified news articles into categories and predicted newly released news articles' directional impact based on the trained model. AZFinText system, built by Schumaker and Chen [13–16], was also able to give directional forecast of prices.

One recent work shows that it would be better to use two types of market information together [17]. Multi-kernel SVM (MKSVM) is employed, and one sub-kernel handles the information set of market prices while the other sub-kernel deals with the instances of market news. Sub-kernels' weights are learnt according to the predictability, and final

[1] How to detect and identify orders' properties is beyond the scope of this paper. Interested readers can refer to the references listed.

predictions are made by MKSVM. The experimental results show that combination of information sets gives higher classification accuracy.

However, due to the small number of pieces of news reported each day, most of the intra-day trading opportunities (signals generated by prices only) are lost if the strategy only trades when news appears. For example, on December 28, 2007, there are three pieces of news about 0005.HK (HSBC). On the same day, there are hundreds of samples of order book snapshots if we sample at one minute interval. If a strategy only trades on the signals generated when both news and prices are available, which has three times on December 28, 2007, the strategy will miss most other signals that could be solely extracted from order book when there is no news reported. In order to fully use the trading opportunities, it would be better to let prices and news be modeled separately, and combine the two signals within the logic of a trading strategy.

2.2 MM strategy

Theoretical MM strategies have been proposed in many previous works. Othman and Sandholm [4] ran an automated market maker on the Gates Hillman Prediction Market (GHPM) which was designed and built to predict the opening day of the Gates and Hillman Centers. Chen et al. [18] analyzed the strategic behaviors in a Fisher market and proved that Leontief market had incentive ratio of 2. Abernethy et al. [19] proposed a general framework for the design of security markets over combinatorial of infinite state of outcome spaces. Othman et al. [5] constructed a market maker that was sensitive to market liquidity. Brahma et al. [2] proposed a Bayersian market maker for binary outcome (or continuous 0–1) markets that learned from the informational content of trades. Bu et al. [20, 21] studied the strategies and arbitrage opportunities in auction and pari-mutual market. Das and Magdon-Ismail [6] studied the profit-maximization problem of a monopolistic market maker who set two-sided prices in an asset market. One theoretical analysis of market maker behavior was proposed by Chakraborty and Kearns [7]. They considered the characteristics of market prices — mean reversion, and showed that the MM strategy made profit on mean reverting stochastic processes.

There are several differences between our MM strategy and those strategies reviewed:

1) The major difference is that we do not make any assumption on whether strategy is trading with informed traders or noise traders [2,5] which is the first kind of risks as described in Section 1. In contrast, we use supervised machine learning algorithms to directly mine the trading signals from two different information sources, i.e., order books and news, and incorporate the directional predictions to guide the MM strategy.

2) Our strategy is designed for real stock market instead of either prediction market [4] or stock market with synthetically generated price series [2, 5, 7, 19].

The market rules, such as tick size (i.e., the minimum increment/decrement when a buyer/seller bids/offers), trading hours (i.e., market open time, lunch break and market close time), price limit (i.e., the highest/lowest price that a buyer/seller can bid/offer) etc., are different from the virtual markets, and all these rules need to be considered while implementing the strategy. The whole system is further backtested with real market data.

3 An intelligent MM strategy

In this section, we firstly show an overall system architecture of the trading platform, and then we introduce the work flow of the MM strategy. As shown in Fig. 1, the whole platform is composed of four parts:

- **In-memory database** Due to the fast speed of high frequency trading (HFT), an in-memory database is used because of its specifically designed utility for speeding up transactions. For example, market quote has many price levels, and on each price level's change, data feeds need to construct a snapshot and publish data. The in-memory database stores the quote data in an incremental way and refills the unchanged price levels with the most recent values within a short time. In this way, the database not only saves memory usage but also saves the transaction time.
- **Signal generator** The signal generator publishes the signals modeled and mined by machine learning models. Section 3.1 explains in details the approach that is used in our system to generate trading signals.
- **Trading strategy** The MM strategy is the core of the system. It places orders depending on the market conditions and its own trading logic. Notice that there is a spare machine in the box, which is used for on-line fail-over in case the main strategy instance crashes.
- **Simulator** Commercial simulators use historical tick data and simulate the market environment. Different from the agent-based simulator, simulators used in our system do not make any assumption on the behaviors of market players. The MM strategy's performance is evaluated on the simulators.

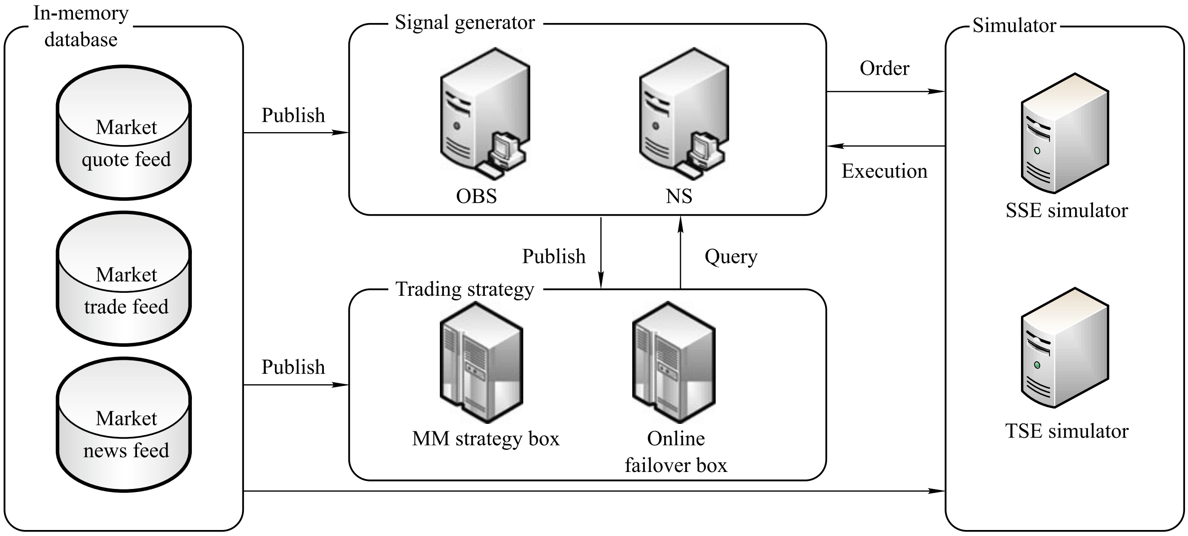

Fig. 1 Architecture of the trading platform. The platform has four components: 1) in-memory database; 2) signal generator; 3) trading strategy and 4) simulator

As mentioned above, the main part of our MM strategy process is composed of two components: signal generator and trading strategy. In the following, we will show the detailed information about these two components.

3.1 Signal generator

Order book information and market news articles are modeled separately in signal modeling. We will refer to them as order book signal (OBS) and news signal (NS) in the rest of this paper.

As shown in Fig. 2, the order book is first sampled regularly and frequently to get the snapshots of the order book. The series of the snapshots are then translated into order book signals (the construction detail is discussed in Section 3.1.1). Different from the numerical order book snapshots, textual news articles are segmented and represented by Vector Space Model [22] (the processing detail is discussed in Section 3.1.2). All the samples (instances) are then aligned with price series by their time stamps. Since we are going to predict the future price movement, all the instances are labeled by short-term price returns. We then use SVMs to learn from the information within historical prices and news title pieces, respectively, and try to provide the strategy[2)] with signals that indicate market momentum.

As explained in Section 1, our proposed approach uses two SVMs to model two different kinds of information sources respectively. This approach could make use of the sources, as well as overcome the disadvantage that limited number of signals is generated while integrating two information

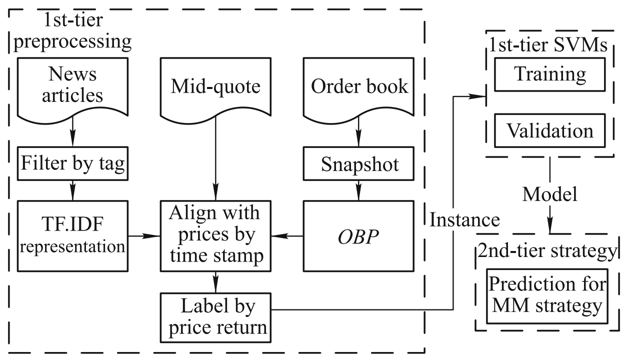

Fig. 2 The first tier consists the preprocessing and the supervised learning approach for order book and news articles; the second tier consists the MM strategy using the model and signals from the first tier

sources of different frequencies in a single model. As reviewed in Section 2, the SVM is the state-of-the-art machine learning algorithm that has been reported to have superior prediction performance comparing to many others, such as back-propagation neural network [8, 11], extreme learning machine [23] etc. This is why we choose SVMs as the prediction algorithm in the first tier of the framework.

3.1.1 OBS modeling

Traditional technical indicators, such as *exponential moving average* (*EMA*), *moving average convergence divergence* (MACD), *relative strength index* (*RSI*) etc., are much more familiar to market players. However, those indicators are designed for a daily basis strategy, and they might not be as sensitive to market movement as expected while translating to intra-day tick data. Modern exchanges usually use order book and double auction rule to match players' orders. The

2) When there is no ambiguity, we use the term "MM strategy" and "strategy" interchangeably in the rest of the paper.

information of order book, such as bid price (price at buy side), ask price (price at sell side), bid size and ask size etc., is broadcasted to investors. We consider such information more useful and be able to provide more accurate insights of market movement.

The order book is constructed by two priority queues. At each time point, we can get a snapshot of the order book, including bid_1 to bid_n, ask_1 to ask_n, and queue sizes at each level, as shown in Fig. 3. Suppose we sample the historical data at a determined frequency (e.g., 1 minute), the snapshots of all sampling time points will form a time series, and each entry in the series is an object with structure (order book snapshot). We denote the series as S, and each snapshot as s_i, where subscript i indexes the order of the snapshots in the series, i.e., $S = \{s_0, s_1, \ldots, s_n\}$.

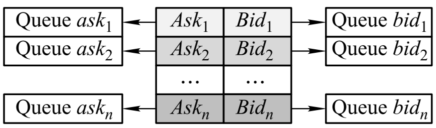

Fig. 3 Order book buy side and sell side queues. Prices decrease from bid_1 to bid_n and increase from ask_1 to ask_n. The price difference between bid_1 and ask_1 is termed as bid-ask spread, and measured by number of tick-size. The arrow links the orders in each queue, by the priority of their limit price and submission time

Raw data series such as S is not useful, since changes at each order book level is nearly random because of the investors' new submission of limit order, order cancelation and even order replacement supported by some markets. As a consequence, we need to summarize S and translate it into more informational indicators.

Order book pressure (*OBP*) [3] is constructed to summarize the dynamic shape of the order book. Figure 4 gives an intuition of the indicators. At time point t, if the total size of

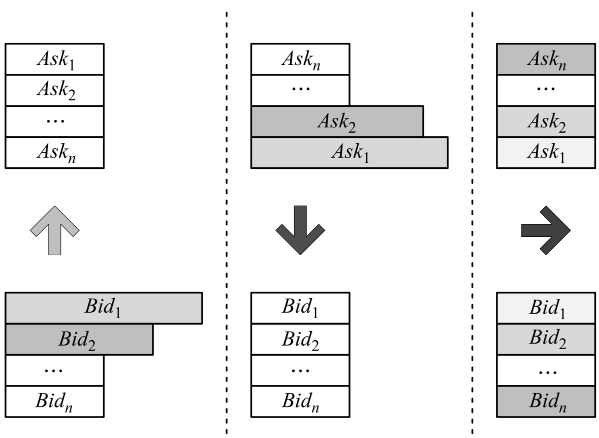

Fig. 4 *OBP*. The size of the box indicates the queue size at that level

orders at sell side is bigger than the size at buy side by a threshold, we expect the mid quote ($mid = (bid_1 + ask_1)/2$) to go down in the near short period, and vice versa; if the queue size difference is within upper and lower thresholds, we expect that the mid quote will not change.

To formalize *OBP*, we have

$$OBP(n, l) = \frac{\sum_{\tau=0}^{n} \sum_{j=1}^{l} BidSize_{j,t-\tau}}{\sum_{\tau=0}^{n} \sum_{i=1}^{l} AskSize_{i,t-\tau}}, \tag{3}$$

where $AskSize$ denotes the queue size at sell side and $BidSize$ denotes the queue size at buy side. Specifically, $OBP(n, l)$ is to measure the ratio between ask queue size and bid queue size, where argument l controls the number of order book levels used, and n controls the number of history order book snapshots used.

3.1.2 NS modeling

Another type of signal comes from market news pieces. News pieces are reported by journalists who are monitoring the market. News agencies, such as Bloomberg, Dow Jones and Thomson Reuters etc., edit and publish news articles for investors to use. Those pieces of news capture the event in the market and try to reach investors at the first place. For NS, real-time Reuters news title is used in this paper, which reports things that have happened or events that are happening inside and outside market. Among many categories of news titles, market players are more interested in the ones that are related to finance, which have already been tagged with specific tags ("FIN") by Reuters to help extract them out from the database. Since the Reuters news is commonly believed to be timely updated and broadcasted, we assume that market events are timely reported, and the news impact could be immediately captured and analyzed.

Following traditional text mining approach (as shown by the left part in Fig. 2), each news title is represented by a vector $\langle word_1, \ word_2, \ \ldots \rangle$. It is observed that the news title is always a short sentence and the main information is contained in one or several short phrases, e.g., $\langle noun, verb \rangle$ pair (such as "prices rise") and $\langle verb, noun \rangle$ pair (such as "beats estimates"). Based on these observations, we add bi-gram[3)] to the feature lists.

Each news title is labeled by the sign of point-to-point price return, namely, up/neutral/down. SVM is trained on the training data set and generates a tuned model as news signal

[3)] A bi-gram is every sequence of two adjacent words.

source. In the testing period, when out-of-sample news pieces come in, SVM will give predictions.

3.2 Trading strategy

The MM strategy, which is quite different from execution strategies, such as direct market access (DMA), volume weighted average price (VWAP) etc., is a strategy that does full time trading, quoting on both buy and sell sides, managing bid-ask spread, and keeping its inventory from bankruptcy. Similar to human specialist, the MM strategy initially quotes at market open and dynamically changes the quotes. Naturally, the key jobs for a MM strategy are 1) how to manage orders (quotation), and 2) how to manage risk (balance cash and stocks).

Our MM strategy is an event-driven computer program whose work flow is shown in Fig. 5. It places two equal sized passive limit orders on each side of the order book (bid_1 and ask_1, or level 1 in short), waiting for other order flows to come in and hit either side. When market condition changes and signals could give correct prediction, the MM strategy will adjust its quotes by manipulating pre-placed orders by cancelation and new submission.

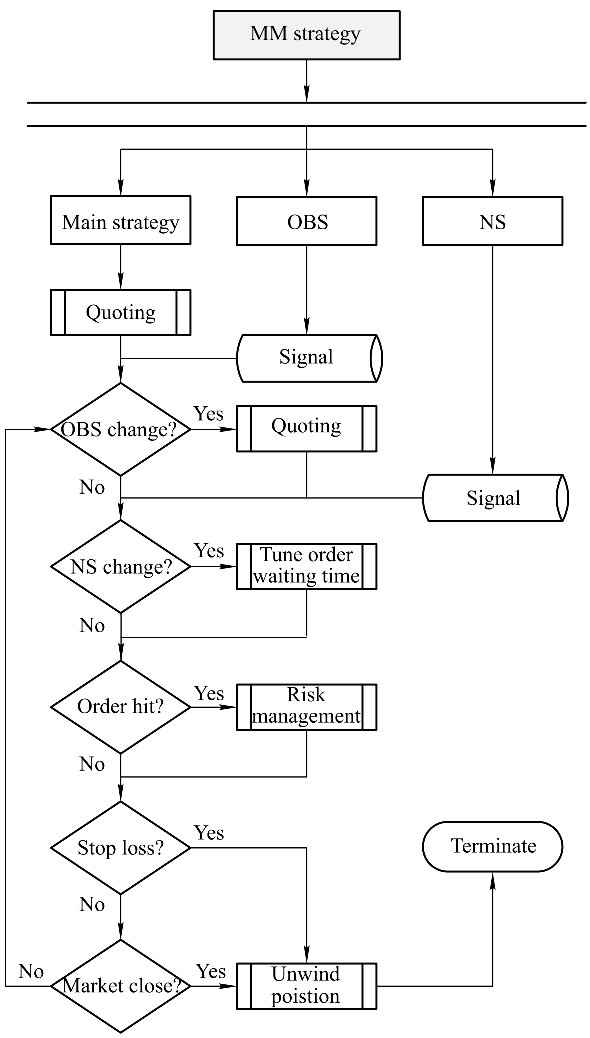

Fig. 5 Work flow of MM strategy

To be specific, the strategy's logic could be summarized by the actions on the following four events:

(1) **Liquidation trigger** Our MM strategy is designed for single day trading. It does not carry any inventory into the next trading day, which means the strategy avoids the overnight risk. At the end of trading hour (i.e., at market close), the strategy will unwind all the positions it is holding, no matter whether the position is making profit or losing money.

(2) **Stop loss trigger** This is a key risk management facility in the strategy. A threshold for stop loss is predefined. If inventory's value (realized and unrealized) is less than the threshold, the strategy will stop MM and exit market. There are some other risk management facilities using different measurements. Easley et al. [24, 25] proposed the trading volume based indicator that measures the toxicity of the order flow. VPIN (Volume-synchronized probability of informed trading) calculates the distribution of the trading volume based on volume-clock. They claimed in their analysis that VPIN could be considered as an "early warning" for the trading strategies. Using the data around the "Flash Crash"[4)], they illustrated the effectiveness of VPIN. However, as they said, "the liquidity problem was slowly developing in the hours and days before the collapse". It is useful for other kind of trading strategies, such as trend following strategies, as a hedge tool. But the uncertainty about the exit time point is not practical for the market makers, especially those with licenses, since they are supposed to be in the market every day, and they cannot stop trading for hours or even days. Stop-loss trigger, on the other hand, is a traditional and practical risk management facility that is used to get the strategy out of the market immediately when situation is "bad enough" for the trading strategy. Since the focus of this paper is to mine directional signals from order book and news to help the trading strategy, we only use simple stop loss trigger and do not unfold the discussion of other risk management facilities.

(3) **One side hit** When either the buy side or sell side is hit by the market order flow (hit by a trade), the MM strategy will trigger the following actions: 1) records the

4) May 6, 2010

fills/partial-fills in inventory, 2) calculates waiting time for the un-hit order, and 3) adjusts quoting and places two new limit orders when waiting time is over. Take hit of buy side order for example, inventory is changing form zero to non-zero since it records that one buy order got hit. Since the strategy is risk neutral, the stock position is risky if market price is trending down, and the sell order waiting in the order book could not be sold at a price higher than the buy price. To get rid of this inventory risk and make money, the strategy needs to unwind this position at a higher (than buy price) price level. However, this expectation could only be achieved when the market is holding still or trending up, which means that market should not be against our inventory. Therefore, risk is translated to order's waiting time. The longer the waiting time is, the more risky it will be. If the strategy has the ability to take higher risk, the waiting time of order could be longer, and vice versa. The upper bound of the waiting time is determined by signals prediction time horizon.

(4) **Signal change** If the signal sign changes, the strategy will 1) cancel previous two limit orders, 2) adjust quoting, and 3) place two new limit orders.

Assume we have already trained classifiers which can predict the future of an asset using order book information and news respectively, i.e., within next T_{OBP} time period and next T_n, respectively, it tells the price movement will 1) go up, 2) go down, or 3) stay still. Suppose the best bid and ask prices at time t are p_t^b and p_t^a. The quoting formula for our market maker at time $t+1$ is:

$$p_{t+1}^{b|a} = p_t^{b|a} + (sign_{OBP} \times \mu + sign_n \times \eta) \times TickSize, \quad (4)$$

where μ is a scalar factor that determines the number of ticks the quoting formula is going to increase/decrease the bid/ask levels when OBP signal changes. For different stocks, μ may be different and should be determined and calibrated using the historical data specifically, as shown in Section 4. η is calculated by

$$\eta = \sigma \times \sqrt{\frac{T_{OBP}}{T_n}}, \quad (5)$$

where σ is the daily volatility of prices. When Brownian process is assumed, and T_n is usually longer than T_{OBP}, η needs to be scaled by the square root of the ratio of the time lengths. And the final price that is set into the PRICE field of FIX protocol (Financial Information eXchange[5]), PRICE is the 44th field of a FIX message.) is rounded to the nearest allowed limit price.

Imagine that the price is trending up and signal correctly gives a positive prediction, according to Eq. (4), p_{t+1} would be $p_t + (\mu + \eta) \times TickSize$ which is greater than p_t. It means that the strategy will quote more aggressive bid price and more passive ask price than time t. Conversely, if the price is trending down, signal correctly gives negative signal, the strategy will quote more passive bid price and pull down ask bar by $(\mu + \eta)$ ticks to place more aggressive ask price. There will be no change of quote if the signal is neutral. The reason why tick size appears in Eq. (4) is that for a specific market, e.g., Tokyo Stock Exchange (TSE), equities use variant tick sizes instead of consistent tick size, which enlarges the tick size when the price is high and shrinks the tick size while the price is low[6].

It could be observed that the proposed MM strategy has two advantages: 1) the signal generators are working in separate threads, which will speed up the responding speed of the strategy; 2) unlike the strategies reviewed in Section 2, this strategy does not either calculate the distribution of the informed/noise traders, or calculate the probability of the trade that is initiated by an informed or a noise trader. Since most of the time, people cannot have the ground truth to verify the assumption. In contrast, the proposed strategy integrates the signals mined from two kinds of real historical data by a nonparametric machine learning model. As long as the signals are tuned to be more accurate, the strategy could avoid risks and place the orders in right positions.

4 Experimental setup and back-testing simulation

As illustrated in the previous section, the performance of the strategy relies on the quality of signals. In this section, we first represent the setup of different signals and then simulate our strategy on historical data.

4.1 Experiment universe

The main principles that determine which markets/stocks are included into the experiment universe depend on two factors:

- **High v.s. low stamp duty** Real markets charge investors stamp duties. Different markets' stamp duties may have different values by different rules. Since the stamp duty will consume part of the investors' profit, investors would

[5] www.fixprotocol.org
[6] TSE tick size rules can be found here: http://www.tse.or.jp/english/faq/list/stockprice/p_e.html

prefer the market with low stamp duty to make more profits.

- **Liquid v.s. illiquid stocks** The MM strategy prefers stocks that are liquid, since liquid stocks are easier to trade than illiquid stocks. The main profit of the MM strategy comes from the bid-ask spread. The more times of the buy-sell/short-buy round trades happen, the strategy will thus make more profits. On the other side, the liquid stocks are easier for simulator to simulate. Since the long queuing effect in the order book of illiquid stock, i.e., orders in the queue of illiquid stocks will wait a long time to get filled, the current simulator we use will overestimate the fill rate for the illiquid stocks[7]. To illustrate this point, we include both liquid and illiquid stocks in the experiment universe for comparison.

We have three candidate markets: TSE, Hong Kong Stock Exchange and Shanghai Stock Exchange (SSE). The first two markets are mature markets and the last one is an emerging market. We want to test the strategy in both mature and emerging markets. Based on the principles, among the mature markets, we choose TSE since TSE has lower stamp duty, and among the emerging markets we choose SSE.

The back-testing period starts from July 2011 to January 2012, which lasts about six months and covers the inactive and active trading seasons of 2011. We select one stock from TSE, Toyota Motor Corp. (7203.T), and one other stock from SSE, China Minsheng Banking Corp. Ltd. (600016.SS)[8]. 7203.T and 600016.SS are quite liquid names with small bid-ask spread, which is appropriate for market making strategy. We also include one illiquid stock, Mizuho Financial Group Inc. (8411.T), for comparison, which illustrates the queuing effect in the order books of the illiquid stocks. Reuters news is used in the experiment. As 7203.T and 8411.T are constituents of .N225 (NEKKEI 225 index) and 600016.SS is a constituent of .CSI300 (CSI 300 index), we include news titles relevant to 7203.T, 8411.T, .N225, 600016.SS, and .CSI300 for news signal setup.

4.2 OBS setup

Before training SVM for OBSs, we need to decide the length of the training period, parameters calibration method and training samples' labeling.

As shown in Fig. 6, we use a rolling window for training: window size N is fixed and the window's right edge advances one day each time whilst discards one day on the left side; training is executed daily, and a new model is generated for the next day's prediction. Since market microstructure changes along with time, it is obvious that market microstructure is much more consistent within a short period of time than a longer one. Non-stationary context requires a model to adopt recent-historical data for training, and this short memory would have relatively consistent statistical property in order to make the learning model to have more generality in the following trading day.

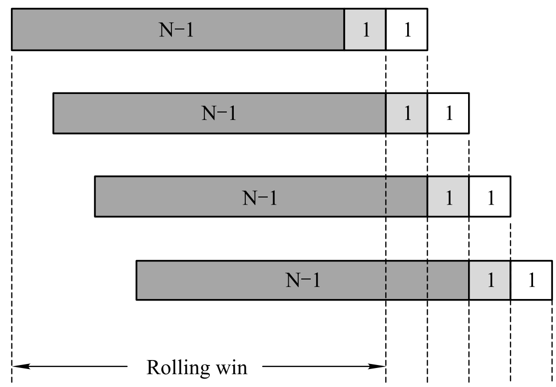

Fig. 6 MM strategy rolling window mode. Window size is N. $N-1$ days are used for training, and 1 day is used for validation. The 1 day in white box is the real trading day (testing)

We manually conduct several trials of back-testing with different rolling window sizes: 3 months, 1 month, 14 days and 1 day. In the preliminary running, we find that 3 months and 1 day training periods are not appropriate because they either cumulate too many training instances (3 months) or include too few (1 day). We find that 14 days for order book data and 1 month for news data have proper training time and consume affordable memory usage. Therefore, N for OBS is set as 14 days in our experiment. Comparing with method that uses bigger proportion of data set to train a model and applies the model to the rest samples, rolling window mode could use fresh memory to generate model each day and use that model for one day only. The disadvantage of this mode is longer computation time, which is multiple times than the single model approach.

SVM with RBF kernel has two parameters to tune, γ and C. γ is the width of Gaussian kernel and C is the penalty parameter. We calibrate γ and C on the training set, which iterates γ from 0.001 to 1 000 by the formula $\gamma = 10^I, I \in \{-3, -2, -1, 0, 1, 2, 3\}$, and chooses C from 1 to 20 with step

[7] The simulator uses the market standard tick data that is published by the exchange. The tick data contains the information about the price levels and queue length, but does not contain any information within the queue, e.g., what is the size or position of each order in the queue. Therefore, the simulator cannot calculate the exact fill rate of the simulated order.

[8] RIC code is used.

size 1. This two-dimension grid search of parameter combinations would iterate 7×20 times. However, only calibrating parameters on the training set may cause an over-fitting issue, which makes the model have good performance on the training set but poor performance on an unseen test set. To overcome this issue and balance the bias and variance, we pick the last day from the rolling window as the validation set. The model is trained by rolling the training set excluding validation day, and performance is evaluated on the validation set. Parameter combination with the best performance on the validation set is reserved. This method ensures that the model has relatively good generality for future use.

Besides SVMs' parameters, OBS has two other parameters (shown in Eq. (3)): 1) OBS built-up time n and 2) order book level l. Tick data is aggregated and sampled in minutes in the experiment. Built-up time indicates how many historical snapshots will signal use to calculate the signal value. Order book level means how many bid/ask levels will signal use to calculate the signal value. For instance, suppose current time is t_0, $OBP(5,1)$ uses the last five minutes order book level 1 information to calculate the signal value at t_0. In our available data, we could get at most five levels. Fortunately, parameters of signal do not need to calibrate, since SVM could take a vector of *OBP*s with different parameters as input features. We select built-up time from $\{1, 2, 3, 5, 10, 15\}$ minutes and order book level from 1 to 5. Therefore we form a vector of $6 \times 5 = 30$ *OBP* features.

Training instances should be labeled before use in the classification. Point-to-point return, which calculates price change ratio at two time points t_0 and $t_{0+\Delta}$, is a good choice. However, since tick price is not continuous (due to tick size), point-to-point return needs to be further translated into tick change, otherwise it would be hard for the strategy to determine the orders' limit price. In our experiment, if mid quote price's increment in one minute exceeds μ ticks, where μ is selected specific to each stock, instance is then labeled as positive, and vice versa; if mid price's change does not exceed μ ticks, instance is labeled as neutral. μ is calibrated among several candidates, finally determined by the accuracy improvement level of the model comparing with benchmark (random signal, flip coin).

For each instance, it is classified into either positive, neutral or negative class. The benchmark makes guesses on prediction by randomly picking up positive, neutral or negative based on label's prior distribution in the training data set. Assume the distribution of three classes in the training data set is P_1, P_0 and P_{-1}, where $P_1 + P_0 + P_{-1} = 1$, then the accuracy of benchmark will be $P_1^2 + P_0^2 + P_{-1}^2$. It is worth noting that when μ becomes greater, more instances will fall into neutral class, which implies that the distribution of three classes is highly imbalanced and P_0 is much greater than P_1 and P_{-1}. In this case, the accuracy will become arbitrarily high. One extreme case is that if μ covers the biggest price change in training samples, then accuracy would equal 100%. Based on the discussion, it is apparent that we do not need to calibrate too large values for μ. To determine μ, we calculate the learning effects[9)] as shown in Tables 1 and 2. For 7203.T, $\mu = 2$ is the best[10)] and for 600016.SS, we choose $\mu = 3$.

Table 1 Learning effects at different μ for 7203.T

7203.T	1 tick	2 ticks
Benchmark /%	33.34	65.78
SVM Model /%	38.10	75.40
Learning effect /%	4.76	9.62
Learning effect /%	14.28	14.62

Table 2 Learning effects at different μ for 600016.SS

600016.SS	1 tick	2 ticks	3 ticks	4 ticks	5 ticks	10 ticks
Benchmark /%	35.19	37.72	55.13	73.20	90.06	99.04
SVM model /%	37.72	42.97	64.85	81.94	93.99	99.42
Learning effect /%	2.53	5.25	9.72	8.74	3.93	0.38
Learning effect /%	7.19	13.92	17.63	11.94	4.36	0.38

4.3 NS setup

To set up news signal, we also need to define the built-up time, training method and labeling.

As OBS, we adopt a rolling window mode for NS. The window size is 30 days which is longer than OBS (the number of news instance is less than OBS, so we choose a longer rolling window size than OBS). All the news titles are represented by $tf \times idf$ vector [22]. Different from OBS, words in news are filtered and selected automatically by using Information Gain [26] (select 20% as our dictionary). This dictionary is updated each day along with model training.

Model's training also uses the grid search approach. The only difference is that instead of selecting last one day as the validation set, we use 10-fold cross-validation to calibrate model's parameters. Although cross-validation is not applicable to OBS due to the "look-into-the-future" issue, news articles are considered as independent from each other and cross-validation would not become an issue here. This has been pointed out by some previous researchers [16].

9) Learning effect is defined as the prediction accuracy increment comparing to the random draw baseline.

10) The highest μ equals to 2 because 1) in practice, 7203.T prices rarely change beyond 2 ticks; 2) 14.62% improvement is a convincing and significant value.

We label each piece of news with the sign of next n minutes point-to-point tick change, thus each news is tagged as positive if the return is positive and vice versa. We use .CSI300 and .N225 indices, and calibrate point-to-point return for the next 30, 60 and 120 minutes, which is longer than OBS. Results are shown in Table 3. We find that 60 minutes led to better performance for both 7203.T and 600016.SS (600016.SS performs also well at 30 minutes), and performance at 120 minutes is lower than expected and .CSI300 has fewer qualified news titles at that time length.

Table 3 Calibration of news signal prediction time horizon

	30 min (Correct/total)	60 min (Correct/total)	120 min (Correct/total)
.N225&7203.T	50.24%	55.56%	45.32%
	(206/410)	(170/306)	(92/203)
.CSI300&600016.SS	52.67%	53.73%	50.00%
	(69/131)	(36/67)	(1/2)

4.4 Simulation

In order to compare the performance of MM strategy, we include two benchmarks and conduct five groups of simulations. The first benchmark is MM strategy without any signal (naive signal), which means that the strategy does not make prediction on price change. In another word, it uses the same signal *neutral* from the market open to market close. The other benchmark is MM strategy with random signal. Random signal is generated by flipping a coin, either 1, 0 or -1 with equal possibility. It is expected that random signal will hurt the strategy and lower the performance. Besides the two benchmarks, we have another three simulations which are "strategy with only OBS", "strategy with only NS" and "strategy with both OBS and NS". Thus, we have five groups of simulations.

To evaluate the performance, we record each day's *PnL/Trade* for MM strategy over all the back-testing days. We then calculate the *sharpe ratio* (*SR*) whose formula is

$$SR = \frac{\mathrm{avg}(PnL/Trade)}{\mathrm{dev}(PnL/Trade)}. \quad (6)$$

SR measures the profitability with the risk. If *SR* is greater than 1, the strategy is making profit; if *SR* is less than 1, the strategy is not profitable.

Tables 4 and 5 represent the simulation results of 7203.T and 600016.SS over trading days from July 27, 2011 to January 20, 2012. The currency unit for 7203.T is Japanese Yen, and for 600016.SS is Chinese Yuan.

From Tables 4 and 5, we can see that the strategy with either OBS or NS has higher score on average daily *PnL* than benchmark strategies do. While looking at *SR* column, we find that the strategy with OBS or NS has higher *SR* than the strategy with naive signal, and the strategy with both OBS and NS has even higher score than the strategy with only one of them. This observation is consistent both for 7203.T and 600016.SS. Besides, the strategy with random signal has lower score (<1) than the strategy with naive signal, which is exactly what we have expected.

Table 4 Results of 7203.T, from 2011-07-27 to 2012-01-20

7203.T	Max	Min	Avg	Dev	*SR*
Random signal	281.481 5	–1 060.000 0	46.879 5	51.706 8	0.906 6
Naive signal	143.761 0	–666.667 0	45.314 8	36.273 9	1.249 2
OBS	143.056 4	–270.833 0	56.573 0	26.196 2	2.159 6
NS	135.290 4	–171.429 0	56.416 9	23.231 9	2.428 4
OBS and NS	123.353 9	–186.667 0	60.060 6	17.851 1	3.364 5

Table 5 Results of 600016.SS, from 2011-07-27 to 2012-01-20

600016.SS	Max	Min	Avg	Dev	*SR*
Random signal	1.736 5	–0.400 9	0.892 3	0.181 2	4.924 4
Naive signal	1.354 0	–0.366 7	0.997 8	0.171 4	5.821 2
OBS	1.373 1	0.488 9	1.002 5	0.130 8	7.761 4
NS	1.502 9	0.488 9	1.013 1	0.138 1	7.334 6
OBS and NS	1.435 5	0.488 9	1.014 9	0.128 6	7.795 6

To compare the performance of strategy on liquid and illiquid stocks, we add one more stock, 8411.T, into our universe. Table 6 presents the calibration of μ and the learning effect for 8411.T, and Table 7 presents the simulation results for 8411.T. From the results, we can see that

- The random signal hurts the performance of the MM strategy. In the *SR* column, the value of the random signal benchmark is much lower than the other four models.
- The performance for the other four models are very similar. Since 8411.T has a wide bid-ask spread, and the mid quote rarely changes throughout the whole day trading, naive signal which always gives *neutral* prediction is good enough for the strategy and it "predicts" correctly most of the time.
- The *SR* for 8411.T is much higher than 7203.T and 600016.SS. This does not mean that running the MM strategy on 8411.T can have much higher return than 7203.T. As mentioned before, 8411.T is an illiquid stock, and the order in the bid/ask queue needs to wait for a long time to get filled. In practice, the MM strategy cannot have many buy-sell round trades each day for 8411.T. The fill rate of illiquid stocks is overestimated in the simulator because the simulator cannot properly simulate the long queuing time with the current market tick data

quality.[11] However, this bias does not affect the comparison between the models.

Table 6 Learning effects at different μ for 8411.T

8411.T	1 tick	2 ticks
Benchmark /%	76.72	99.67
SVM model /%	82.42	99.90
Learning effect /%	5.70	0.23
Learning effect /%	7.43	0.23

Table 7 Results of 8411.T, from 2011-07-27 to 2012-01-20

8411.T	Max	Min	Avg	Dev	*SR*
Random signal	100.221 2	96.648 0	99.592 4	0.476 2	209.142 3
Naive signal	100.000 0	97.140 0	99.776 0	0.368 8	270.519 2
OBS	100.000 0	97.140 0	99.778 0	0.368 8	270.519 5
NS	100.000 0	97.140 0	99.776 0	0.368 8	270.519 3
OBS and NS	100.000 0	97.140 0	99.779 6	0.368 8	270.519 5

4.5 Case study

Besides the comparison on *SR*, we also compare the performance of MM strategies with different signal combinations on the daily apple-to-apple basis. To be specific, we will show cases in the simulation and dig into the trading days in this subsection.

If we draw the curves of daily *PnL* (naive version and OBS+NS version), as shown in Fig. 7, we could explicitly see that most parts of the curves coincide except for several spikes. From Fig. 7, we find one valuable thing about signals that they save the strategy from triggering stop loss while the market is trending. Take the day marked by circle for example, "strategy with naive signal" triggered stop loss in the morning while "strategy with OBS and NS" successfully avoided the loss and completed following MM. When

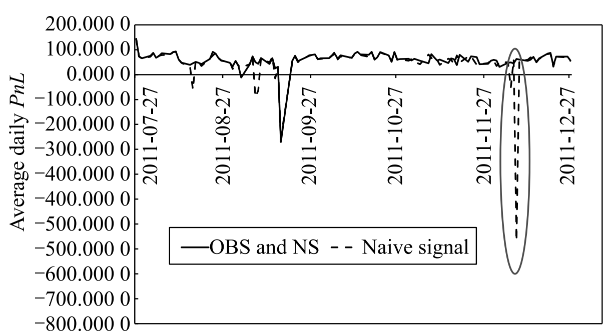

Fig. 7 Average daily *PnL* comparison between "strategy with OBS and NS" and "strategy with naive signal". For most of the days, there is not much difference between the two curves. Circle-marked place (December 21, 2011) has a spike for "strategy with naive signal", which is a big loss on that day. While "strategy with OBS and NS" survives from that loss

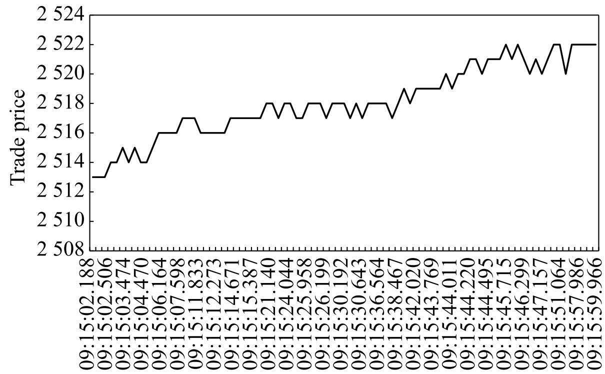

Fig. 8 Trade prices for stock 7203.T on December 21, 2011, from 09:15:00.000 to 09:16:00.000. Despite the bouncing of trade prices, stock price moves up about JNY 8

we trace back the trade prices of that day (2011-12-21) and plot them in Fig. 8, we find at 09:15:02.000, stock price was trending up and the OBS at 09:15:00.000 indicated the price is going up by μ ticks.

5 Conclusion and future work

In this paper, we have proposed a two-tier framework which includes a trading signal generator using information from order book microstructure and market news titles, and an event-driven MM strategy trading on the signals. We model the dynamics of *OBP* and market news textual patterns, and use SVMs to classify and translate them into usable trading signals. Our MM strategy adjusts its quoting prices along with these signals. We conduct back-testing by using the real market tick data from TSE and SSE, and the simulation results show that during the half a year testing, this strategy has good performance with higher *PnL* and *SR* than benchmarks.

Our MM strategy gives positive results in the TSE and SSE simulators. In the future, there are still some issues to be considered.

- Firstly, due to the execution issue that is affected by the queuing in the real order book, there is still a gap between such an experimental strategy and a real trading one. In practical trading, long queuing time will delay the finish time of buy-sell (or short-buy) round trades, which further increases the strategy's inventory carrying risk when its one side order got hit, and decreases strategy's profitability.
- Secondly, our strategy currently uses OBS and NS to guide the quotation. There are many other signals[12] that

[11] This is not an issue for liquid stocks since their fill rate is very fast.

[12] The other signals constructed from market microstructure, such as VPIN and the signals modeling each side of the order book instead of modeling the order book imbalance etc., are worth of being investigated and incorporated into strategies in the future.

could be analyzed and included for the strategy's use.

In the future study, we would like to investigate more on the order book queuing theory and try to make the strategy more practical. One possible approach is to establish the stochastic relationship between the incoming flow (investors' new orders) and outgoing flow (investors' cancel orders and market fill orders), and estimate the queuing time by the stochastic process. Regarding the second issue, we will do a further study on how to combine different signals and make the strategy more effectively trade when more signals are constructed based on the market microstructure.

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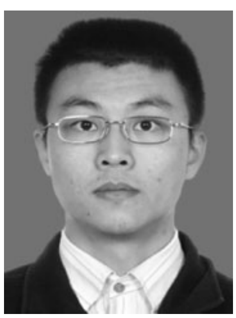

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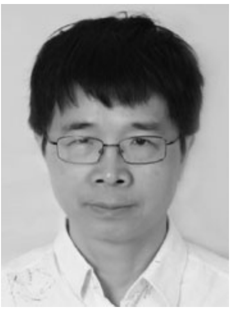

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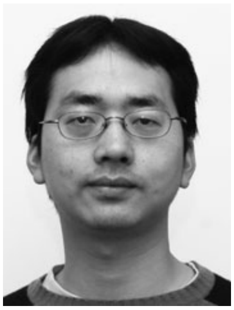

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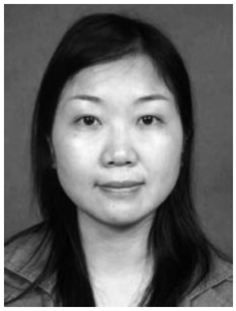

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