Abstract

The Penn-Lehman Automated Trading Project is a competition between groups of students to design and implement different algorithms and strategies for automated trading in financial markets and other related environments. In order to provide an environment that can, as accurately as possible, test the effectiveness of these strategies, PLAT makes use of the Penn Exchange Simulator (PXS). This is a software simulator that merges our different agents’ orders (each agent represents some strategy or combination of them) with shares of real-time real-world stock market data. This project is an interesting challenge to embark upon, in light of the fact that it fuses business and computer science together, implementing different algorithms for strategies, which can be used by a trader in any trading market. Four competitions have been held so far to test various trading strategies, in which use has been made of various calculations done by PXS such as each agent’s profit/loss, simulator and external prices, volumes traded etc. Thus, this project is focused on developing agents that can profit in an environment composed of a number of common technical trading strategies.

In our project, we have developed an agent that takes into consideration the continually changing conditions of the market. This agent, the Combination strategy, is a general and risk-averse strategy that aims to take advantage of fluctuating market conditions without ever going into too long or short a position. It is a combination of the Market Making (MM), Momentum (MO) and Reverse strategy (REV).
Related Work

Of recent years, an increasing number of computer scientists are getting involved in various forms of e-commerce, computational markets, algorithmic mechanism design and electronic auctions. In addition, there has been development of platforms and systems in this regard as well. Trading Agent Competition (TAC)\(^1\) is a very successful system that focuses on multicommodity auctions simulations. It is an international forum designed to promote and encourage high quality research into the trading agent problem. Michael Wellman led the team that organized the first years’ competition based on the "travel agent scenario" (called TAC Classic).

In TAC Classic, each entrant to the competition is a travel agent, with the aim of assembling travel packages. Each agent is serving eight clients, who express their preferences for various aspects of the trip. The objective of the travel agent is to maximize the total satisfaction of its clients. A travel package consists of a round trip ticket, hotel reservations, and tickets to specific entertainment events. A model of this scenario is shown on the next page:

\(^1\) More information can be found at [http://www.sics.se/tac/page.php?id=1](http://www.sics.se/tac/page.php?id=1)
Like TAC, PLAT is just another addition to this line of system and competitions. Its primary objective is not just to simulate an environment like that of Wall Street where real traders do ‘actually’ what students try to imitate or improve upon using PXS; it is more of a project whose aim is to develop new, different and principled strategies which can be used to gain big profits under different conditions and environments.

Since three competitions have already been held before ours, there has already been considerable research done in the area of trading strategies, with special emphasis laid on those that use statistical modeling, machine learning, market making, artificial intelligence and technical analysis.

Some agents have performed particularly well in the past PLAT projects. We are now going to give a summary of some of those strategies and comment on their
performance, based on which we will propose how our agent will try to behave differently and more profitably.

The market making strategy has been used before, which makes use of market volatility without predicting the exact direction of the stock price movement. More specifically, a pair of buy and sell orders of the same volume will be placed on a single stock simultaneously. Assuming that the price of the stock will have a lot of fluctuations, the buy price is placed to be slightly lower than the current price and the sell price slightly higher. When the current price goes above the sell price and the order matches, the order is executed. The price should (or assumed to be to) now eventually drop due to the price fluctuations so that the shares can now be bought back at a lower price. This will enable a profit of the product of the gap between the prices and the volume traded. There are of course a number of complications to this strategy, the first of which is the fact that it heavily relies on the price fluctuations throughout the day. If it the prices keep rising or dropping steadily, then huge losses can result. In conjunction with the fact that the profit made on each buy-sell pair is very small (the difference between the pair is made to be small and near the current price so that they can get executed), the losses can easily dominate profits on a bad day. In an attempt to come to terms with these problems, adjusting the volumes being traded according to the price trend, decreasing the price gap etc have been used to minimize losses on a bad day. But all these methods compromise the profits earned by this strategy and can lead to less loss on a bad day and a modest profit on a good day.

Another strategy used by previous participants is the Reverse Strategy. This strategy has earned its name via the fact it does the opposite of what common sense
would tell us to do. When the price is rising, you normally start buying thinking that it will continue rising and so will be able to sell at a higher price and vice versa. But this basic strategy resulted in big losses when tested. So the Reverse Strategy does the reverse: when the current price is greater than the last price, it places a sell order, and when the current price is less than the last price it places a buy order. This is based on almost the same major assumption as that of the market making strategy: there are lots of price fluctuations on a normal trading day. Of course, just as is the case with the market making strategy, if the fluctuations smooth out, this strategy is in danger as well of losing big money.

Both these strategies were tested out in the Feb 2003 PLAT competition. Both of the agents using a strategy each qualified to the second round, where the reverse strategy won and proceeded to the finals. Of course, a lot had to do with the fact that the particular environment was conducive for the reverse strategy to thrive in for that particular competition.

Besides the above-mentioned strategies, others have been implemented as well that use a totally different methodology. For example, the Yahoo Message Client, uses online news to decide how to act in the trading market. Polling Yahoo Finance periodically, it checks to see what the general sentiments are of the general public and based on that executes its transactions. In addition, there are technical analysis agents that use historical data to predict the price movement of a stock, including Moving Average, Channel Breakouts, Momentum and Relative Strength Index.
Technical Approach

All the participants of the PLAT competition are required to use a Linux or Solaris machine to develop and execute agents. According to the specifications, the agent which will be programmed to trade with the Penn Exchange Simulator (PXS), consists of three layers. The topmost level will be the strategy we write. This consists of high-level source code that performs various trading actions by making calls to the underlying agent-shell API. The middle level is the agent-shell API, which performs common actions needed by an automated trader. It includes placing buy or sell orders or informing the automated trader about the market status. The lowest level is the network layer used by the agent-shell API, which enables the agent to communicate with the PXS server to send and/or receive various types of information.

The following steps were undertaken in the technical part of our project:

**STEP 1: Getting comfortable with PLAT, Agents, crux and Strategies:**

**Installing the PLAT-Agent on crux:**

The plat-agent package will be installed to develop strategies on crux by simply typing `/home/pxs/bin/plat-agent-installer`. This in turn will generate a directory named plat-agent. The installer will create a subdirectory named strat inside the plat-agent directory which includes an initial strategy source code and Makefiles, and compile that initial strategy. All strategy development will be done in the plat-agent/strat directory.

**Compiling a strategy:**

A file `strategy.c` is to be used to compile strategies. In its original form it is actually an implementation of a simple automated trading strategy called Static Order.

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2 All technical specifications and further detail can be found at [http://www.cis.upenn.edu/~mkearns/projects/plat.html](http://www.cis.upenn.edu/~mkearns/projects/plat.html)
book Balance. We will use a function updateAgentOrder to compile our own strategies and will pass the following parameters AgentState, MarketState, MarketStatistics, MarketStatistics, Strategy. Then to recompile the strategy we will type in the make command into the AGENT_DIR/plat-agent/strat directory. After compilation, the executable agent mytrader will be created in the AGENT_DIR/plat-agent/strat directory.

**Executing PXS and the agent:**

Once a strategy has been implemented it can be executed by connecting to PXS. PXS is located in /home/pxs/bin, and the command-line for executing the PXS is as follows:

```
```

- `p port_number`: The assigned port number.
- `n stock_name`: The stock name that the simulator processes.
- `h begin_time`: If included the simulator will run in historical mode.
- `e end_time`: If included will tell time of the day which the simulator will end
- `s number_of_agents`: If included the simulator will run in single-threaded mode
- `V`: Simulator will run in verbose mode. That is, in addition to its usual output, it will print out the states of the Island and Simulator queues each iteration.
- `B`: Simulator will output the number of book orders in the Simulator queues after each step of the main algorithm of the simulator.
- `S`: Simulator will print out extra statistical information. This information will include statistics about the number and type of orders in the Simulator queues, number and type
of matches executed by the Simulator, and information about the states of the connected agents.

-T: Will set the real-time frequency at which the Simulator will print its output in live-mode. The default is to print every 3 seconds.

After this command is typed PXS will be invoked and then the agent can be executed by connecting to the PXS.

**STEP 2: Analyzing the Relative Performances of Existing Strategies**

After becoming familiar with the system our next step was to understand under what kind of conditions, e.g. what other strategies, behavior of price movement, volume movement etc, would each of the existing strategies (or agents) do well or poorly. The work on these different aspects of the problem helped define our project and present another strategy, if not the solution, to master the art of profiting in an automated trading environment provided by PXS. Thus our first task included running pairs of all existing strategies along with the background agents and analyzing their performance. A thorough analysis of the reasons behind a strategy’s success or failure provided a solid base for formulating our own strategies.

The strategies included Moving Average, Momentum, Channel Breakout, Relative Strength Index and Market Making. Our goal was to formulate a report based on the outputs which analyzed the relative performance of the five technical strategies and to single out the dominant strategies. A total of seven simulations were run, each simulation representing a different degree of normal distribution. Under these different conditions, the strategies that a strategy was competing against were kept constant. Thus the persistence of the strategy’s performance was evaluated over different distributions.
The indicator of a strategy’s success was taken to be the Simulator Present Value (= Last Price * shares – Cash Spent). Since all strategies must liquidate themselves at the end of the trading period, then when liquidated, the simulator present value tells us the cash spent as well. Otherwise, the simulator present value takes into account the value of the shares as well. So if at the end of the trading day, a strategy is left over with a large amount of shares, then valuing them at the last price could result in a large negative Simulator Present Value if the last price is comparatively lower than its prices at which various quantities of shares were bought. More importantly, if at the end of the trading day, a strategy has resulted in a short position, then the share position is negative and this will be reflected in the Simulator Present Value. Thus, whether a strategy has resulted in a short position or a long position at the end of the trading day or whether complete liquidation was done, these conditions are reflected in the Simulator Present Value. We therefore, used just this variable as the primary indicator for filtering out the most successful strategies.

**Analysis of output:**

Appendix A displays the numerical results of all the strategies under consideration, sorted according to Simulator present value in increasing order. After careful investigation of these results we found that in terms of the Simulator present value, Market Making was the dominant strategy. All the highlighted values are the strategies that are performing the best. We can see the Market Making strategy consistently does the best against all strategies across all distributions.

Now we will attempt to explain the performance of each strategy. Since the market making strategy exploits the price volatility of a stock, rather than predicting the
direction of its movement, the agent will simply put in a pair of buy/sell orders close to the bid/ask at each time interval. This proved to be a more favorable approach with respect to all other strategies.

If we look at the plots, a sample of which is given in the appendix of this paper we can see that across the distributions, each time one particular strategy is paired with the market making strategy we noticed that the former had a sustained decline in their Simulator Present Value plots whereas Market Making strategies showed a steady incline. However, there were two exceptions to this general behavior, RSI performing against Market Making and Market Making performing against Market Making. These results will be explained shortly.

On investigating the Simulator Price for the day plots, we observed that on average, there are many fluctuations in the price of the stock throughout the trading day. Thus, since the market making strategy aims for a neutral share position and has a pair of buy/sell pair close to the bid/ask price, the strategy performed extremely well. If the stock price had actually increased or decreased steadily, only then would have the strategy incurred too large a short or long position if the price did not go back down/up at the end of the trading day. But we observe that the end price of the stock is very near the start price of the stock which provided an ideal environment for the market making strategy.

A Market Making strategy paired with another market making strategy across the distributions always performs well. Infact, they do not differ too much in their relative performance as well. Moreover, we observed that any strategy when paired against the same strategy generally did not differ largely in relative performance and end results.
The Relative Strength strategy paired with the Market Making strategy does not show an overall incline or decline but shows many fluctuations around a constant mean in the Simulator Present Value plots. Furthermore, the numerical results also show that although RSI is not the most dominant strategy it performs far better than the rest against market making and in general as well. This strategy incurs most positive Simulator Present Values and one or two negative values and ranks second in performance, as determined by the numerical results. RSI is really only affected when there are big surges or drops in the stock, and does not inherently analyze the nature of the stock’s fluctuations. But, on average, there are not any huge fluctuations in the stock, but small and many ups and downs. Thus, RSI does not incur any huge high/low Simulator Present Values – rather, it performs ‘safely’.

The rest of the strategies did not perform well on the whole. The Channel Breakout strategy had extreme results whereas the Moving Average and Momentum strategy had varied but poor results. The Moving Average strategy calculates the moving average for a certain time interval specified by us (0 as used for this assignment). Since the moving average is calculated on the basis of historical data and the dates that we used for the simulation was virtual data, the strategy was not effective. The Momentum strategy on the other hand relies more on short-term movements in price. The reasoning behind the strategy is that if there is a change in price in one direction it will hopefully continue in the same direction. We can see the behavior of this strategy by investigating the plots of the Simulator Present Values. In Appendix A (Channel Breakout vs. Momentum strategy) plots indicate a steady decline in the simulator price. In this case, the Momentum strategy has worked relatively much better than the Channel Breakout
strategy. On the other hand, (Moving Average vs. Momentum strategy) plots show price fluctuations. In this case, the Momentum strategy has not worked well in relation to the Moving average strategy due its inherent nature as described above.

The Channel Breakout strategy records the highest and lowest prices for a certain time interval. When the current price goes higher than the highest price recorded, or lower than the lowest price recorded a corresponding buy or sell order is placed in. As stated above we have seen that in most plots we observed that most of them suffered many fluctuations in the simulator price and that the end price of the stock was very close to the start price of the stock. The Channel Breakout strategy works well only when there are historical low/high points and therefore only targets specific environments. (Channel Breakout vs. Relative Strength Index) we observed that the simulator price at some point during the simulation starting plunging down and therefore the Channel Breakout strategy started performing really well as compared to the Relative Strength Index strategy. However, as soon as the trend reversed the Channel Breakout strategy started doing worse. Therefore, the Channel Breakout strategy worked only in conditions of sustained increase or decrease in price.

From the analysis of the outputs above, we can conclude that Market Making is clearly the dominant strategy. All combinations of strategies show that Market Making performs the best against any strategy. The nature of the fluctuations of the stock, which are many and always end with a price that is near to the start price, favors this strategy a great deal. And from the plots of Simulator Price of the day, we were able to see the persistence of this nature of fluctuation and the consequent steady increase in the Simulator Present Value of the stock and the steady decline of it in the competing
strategy. Only RSI managed to compete with Market Making with not a steady decline in profits. The other strategies, Momentum, Channel Breakouts and Moving Average perform dismally against each other as well as RSI and Market Making, for reasons already explained above. When competing against itself, the relative performance of the strategy is about the same. Market Making does well against itself, Moving Average performs with a small Simulator Present Value against itself, and the same is the case with Momentum. Channel Breakout also ends with near negative Simulator Present Value against itself. RSI performs well against itself, though like all the others, its relative performance is the same.

Thus, based on the above, Market Making was felt to be a good strategy to use as a base strategy since overall its performance was the best.

**STEP 3: Implementation of Variant Market Making Strategy:**

**Variant Market Making Strategy:**

From the first assignment we were able to surmise that Market Making seemed to be the most successful strategy in general conditions. However, since Market Making would not necessarily work well under all conditions and different background agents, we initially decided to use a more generalized strategy that attacked as many possible situations. This strategy was a combination of Market Making, Momentum and Moving Average. However, once we were informed about the criterion and the calculation of performance for the competition we were compelled, due to the lack of time, to change our strategy to a simpler one – a modification of the Market Making strategy.

Upon investigation, we realized that in order to improve performance, it was important to clear any short or long positions at the end of the trading day. In order to
avoid penalty, we tried to liquidate the maximum amount of shares at the end of the day and therefore modified the liquidations and the time interval for our strategy. We changed the time at which the strategy should switch from Market Making to liquidating shares to start 30 minutes earlier. This was to serve as an upper hand by starting to liquidate earlier than the other participants and so be able to match as many orders as possible and reduce the penalty of ending up with long/short positions. By starting to liquidate early, we thought we would be able to match an increasing number of our orders on each side and therefore be able to clear our position. Furthermore, we modified the liquidation code such that if we held a short position (currentShare < 0) then we bought back shares for $1001 more than the current price of the particular share. Alternatively, if we held a long position (currentShare > 0) we sold shares for $0.009. The reason driving this change was to make certain that we were not left with any unmatched orders at the end of the trading day. By trying to buyback the shares at a higher value than not only the current price but the original liquidation code (currentPrice + 1000) and selling shares at the lowest possible value (original code value = 0.01) we were trying to ensure that our orders would be placed first in the sell/buy queue and therefore executed and liquidated before any other participants in a similar position.

**Performance:**

We submitted our new strategy for the December 2004 PLAT competition, where it was run in a total of thirteen different simulations. A different background agent was used in each simulation. The symmetric background agent involved symmetric buy and sell distributions, whereas the asymmetric background agent had an asymmetry of the distributions that would, in isolation, cause either an uptrend or downtrend in price. The
real-data background agent was also used, in which the trading was based on historical
data from DELL, MSFT or YHOO from June 2004.

In order to understand our strategy, it is important to understand the constraints of
the environment that our client was presented with, mainly the liquidation penalty.
Firstly, there were no limits on how many buy or sell orders we could place as long as we
liquidated our position completely at the end of the day, given that PXS cannot carry over
the share positions from one trading day to the next. Thus, penalties were imposed on our
client for any short or long positions held at the end of the trading day. Each share that
our client was long at the close of the day was to be valued at 0, so that the penalty was
the price our client paid to buy that share. For each share that our client was short at the
end of the trading day, our profit was to be decreased accordingly. That is, if our client
was \( n \) shares short at the end of the trading day and the closing price of the stock was \( p \),
then our profit/loss was decreased/increased by \( 2 \cdot p \cdot n \) dollars.

A single performance measure, the Sharpe Ratio, was used to evaluate the
different strategies submitted for the competition. The Sharpe Ratio was calculated based
on our client’s profit and loss extending over a period of ten days. Suppose the profits or
losses over the ten days are \( c_1, c_2, c_3, c_4, c_5, \ldots, c_{10} \), where each value can be negative
(loss) or positive (profit). The Sharpe Ratio is then calculated as follows:

\[
\text{Sharpe Ratio} = \frac{\text{Average of } c_1, \ldots, c_{10}}{\text{standard deviation of } c_1, \ldots, c_{10}}
\]

With this background, the results of the competition are below, where X marks our
strategy pitted against the others.

<table>
<thead>
<tr>
<th></th>
<th>brinberg</th>
<th>hashmi</th>
<th>jung</th>
<th>kanon</th>
<th>kumar</th>
<th>ricketts</th>
<th>sohn</th>
<th>veal</th>
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<td>1384</td>
<td>906</td>
<td>625</td>
<td>2607</td>
<td>319</td>
<td>93</td>
<td>1568</td>
<td>-402</td>
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<td>1330</td>
<td>1145</td>
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<td>-13</td>
<td>1203</td>
<td>785</td>
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<td>257</td>
<td>319</td>
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<td>894</td>
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<tr>
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<td>1127</td>
<td>424</td>
<td>2967</td>
<td>461</td>
<td>-358</td>
<td>2130</td>
<td>544</td>
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<tr>
<td>SBG+RSI+X -</td>
<td>383</td>
<td>731</td>
<td>691</td>
<td>364</td>
<td>403</td>
<td>84</td>
<td>-6284</td>
<td>-32</td>
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<td>683</td>
<td>637</td>
<td>690</td>
<td>1854</td>
<td>35</td>
<td>0</td>
<td>0</td>
<td>210</td>
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<tr>
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<td>2328</td>
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<td>1162</td>
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<td>149</td>
<td>4116</td>
<td>128</td>
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<td>-652</td>
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<td>341</td>
<td>-300</td>
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<td>-80344</td>
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<td>-140344</td>
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<td>ABGdown+ALL+X</td>
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<td>-34735</td>
<td>-2432</td>
<td>20723</td>
<td>2456</td>
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<td>10968</td>
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<td>7462</td>
<td>2778</td>
<td>3727</td>
<td>9220</td>
<td>6693</td>
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<tr>
<td>REALBG_msft+X</td>
<td>7783</td>
<td>26525</td>
<td>17857</td>
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<td>2792</td>
<td>25127</td>
<td>6444</td>
<td>15158</td>
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<tr>
<td>REALBG_yhoo+X</td>
<td>8438</td>
<td>16950</td>
<td>12473</td>
<td>13930</td>
<td>-1478</td>
<td>14639</td>
<td>5455</td>
<td>8524</td>
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<tr>
<td>Average</td>
<td>-2650.38</td>
<td>-4101.92</td>
<td>3111.462</td>
<td>4160.231</td>
<td>1122.231</td>
<td>-13186.3</td>
<td>-14172.2</td>
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<td>Standard Deviation</td>
<td>15156.22</td>
<td>26714.51</td>
<td>6031.514</td>
<td>8559.519</td>
<td>1863.102</td>
<td>45969.47</td>
<td>42676.7</td>
<td>4898.587</td>
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<td>Sharpe Ratio</td>
<td>-0.17487</td>
<td>-0.15355</td>
<td>0.515867</td>
<td>0.486036</td>
<td>0.602345</td>
<td>-0.28685</td>
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<td>0.460886</td>
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<tr>
<td>Rank</td>
<td>6</td>
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<td>2</td>
<td>3</td>
<td>1</td>
<td>7</td>
<td>8</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 1: Results before Liquidation Penalty

| brinberg | hashmi | jung | kanon | kuman | ricketts | sohn | veal |
| SBG+CB+X -- after penalty | 1384 | 906 | 625 | 2607 | 319 | 93 | -52921 | -402 |
| SBG+MA+X -- after penalty | -10599 | -102299 | -3967 | 1145 | 373 | -13 | -6294 | 785 |
| SBG+MM+X -- after penalty | 1514 | 510 | -41944 | -204 | 257 | 319 | 0 | 894 |
| SBG+MO+X -- after penalty | -101771 | 1127 | 424 | 2967 | 461 | -358 | -1030 | 544 |
| SBG+RSI+X -- after penalty | 383 | -588922 | -173732 | 364 | 403 | 84 | -494886 | -32 |
| SBG+X+X average -- after penalty | 683 | -24366 | 690 | 1854 | 35 | 0 | 0 | 210 |
| SBG+ALL+X -- after penalty | 3814 | -303836 | 257 | -179804 | 10 | 149 | -297303 | 128 |
| SBG+X1…X8 -- after penalty | -617952 | 0 | -9 | -652 | 399 | -1826529 | -8903 | 8 |
| ABGup+ALL+X -- after penalty | -47114 | -1083067 | -1455 | -12762 | 5784 | -149790 | -160996 | -1767 |
| ABGdown+ALL+X -- after penalty | -20727 | -924684 | -2432 | 20723 | 2456 | -65740 | -615819 | -1393 |
| REALBG_dell+X -- after penalty | -1335989 | -1147287 | -1548461 | -1664944 | 2778 | 3727 | -471720 | 6693 |
| REALBG_msft+X -- after penalty | 7783 | -647570 | -4139 | -117172 | 2792 | 25127 | -46498 | 15158 |
| REALBG_yhoo+X -- after penalty | 8438 | 16950 | -103562 | 13930 | -1478 | 14639 | -23695 | 8524 |
| Average | -162319 | -369426 | -144439 | -273150 | 1122.231 | -153715 | -167697 | 2257.692 |
| Standard Deviation | 391310 | 450925 | 425169.3 | 648866.3 | 1863.102 | 504699.6 | 223798 | 4898.587 |
From the results, it is evident, that our strategy (highlighted) performed at a very low level after the liquidation penalty. Before the liquidation penalty, our strategy competed well in certain environments; earning big profits while it suffered huge losses where the strategy did not perform well. Thus, our strategy was not very risk-averse. Where the environment was conducive to the trading algorithm, it took full advantage of the situation but did not have sufficient barriers in the event of market conditions that were unfavorable to our strategy.

Analyzing first the results before the liquidation penalty, there are a number of points to be taken into consideration. Firstly, with regard to the background agents, our client performed reasonably well with the symmetric and real background agents but failed when it was tested with the asymmetric background agent. Since our strategy was a variant of the Market-Making Strategy, it was structured to perform well in high volatility markets, which is the reason it did very well against the symmetric background agent where the distribution matched the strategy of our client that placed simultaneous buy and sell orders. Based on our investigation of real markets, this high volatility nature of the market was also assumed to be generally true for the real markets- hence our performance was reasonably high against the real background agents as well. However, against the asymmetric background agent that causes either an upward trend or a downward trend in the prices, our strategy failed.

Table 2: Results after Liquidation Penalty

<table>
<thead>
<tr>
<th>Sharpe Ratio</th>
<th>-0.41481</th>
<th>0.81926</th>
<th>-0.33972</th>
<th>-0.42096</th>
<th>0.602345</th>
<th>-0.30457</th>
<th>-0.74932</th>
<th>0.460886</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank</td>
<td>5</td>
<td>8</td>
<td>4</td>
<td>6</td>
<td>1</td>
<td>3</td>
<td>7</td>
<td>2</td>
</tr>
</tbody>
</table>
Against the symmetric background agent, our rank was 3 according to the following calculations:

<table>
<thead>
<tr>
<th>hashmi</th>
<th>brinberg</th>
<th>Jung</th>
<th>kanon</th>
<th>kumar</th>
<th>ricketts</th>
<th>sohn</th>
<th>veal</th>
</tr>
</thead>
<tbody>
<tr>
<td>906</td>
<td>1384</td>
<td>625</td>
<td>2607</td>
<td>319</td>
<td>93</td>
<td>1568</td>
<td>-402</td>
</tr>
<tr>
<td>1072</td>
<td>1398</td>
<td>1330</td>
<td>1145</td>
<td>373</td>
<td>-13</td>
<td>1203</td>
<td>785</td>
</tr>
<tr>
<td>510</td>
<td>1514</td>
<td>1353</td>
<td>-204</td>
<td>257</td>
<td>319</td>
<td>0</td>
<td>894</td>
</tr>
<tr>
<td>1127</td>
<td>1306</td>
<td>424</td>
<td>2967</td>
<td>461</td>
<td>-358</td>
<td>2130</td>
<td>544</td>
</tr>
<tr>
<td>731</td>
<td>383</td>
<td>691</td>
<td>364</td>
<td>403</td>
<td>84</td>
<td>-6284</td>
<td>-32</td>
</tr>
<tr>
<td>637</td>
<td>683</td>
<td>690</td>
<td>1854</td>
<td>35</td>
<td>0</td>
<td>0</td>
<td>210</td>
</tr>
<tr>
<td>2328</td>
<td>3814</td>
<td>257</td>
<td>1162</td>
<td>10</td>
<td>149</td>
<td>4116</td>
<td>128</td>
</tr>
<tr>
<td>0</td>
<td>72</td>
<td>-9</td>
<td>-652</td>
<td>399</td>
<td>341</td>
<td>-300</td>
<td>8</td>
</tr>
</tbody>
</table>

Stdev  | 673.8612 | 1140.757 | 477.6551 | 1288.311 | 171.3971 | 219.4157 | 3028.977 | 441.5549 |
Avg     | 913.875  | 1319.25  | 670.125  | 1155.375 | 282.125  | 76.875   | 304.125  | 266.875  |
Sharpe  | 1.356177 | 1.156469 | 1.402947 | 0.896814 | 1.646031 | 0.350362 | 0.100405 | 0.604398 |
Rank    | 3        | 4        | 2        | 5       | 1        | 7       | 8       | 6       |

Table 3

This is a significantly better rank than that of the overall rank that includes the asymmetric background agent. A similar result was obtained when calculating our rank only with the Real background agent- in fact our rank in this case is 1. Moreover, since the ranking was dependant on the Sharpe ratio which penalizes large standard deviations with respect to the average of the client’s P&L, our ranking reflects this fact. Since our results were substantially positive against the symmetric and real background agents, but low for the asymmetric background agents, our average was compromised and the standard deviation was pumped up, so that our client’s ranking was pulled down.

With regard to the strategies that our client performed against, our client performed the best with the MSFT stock and overall, outdid all the other clients with
respect to its performance against all three real stocks, i.e. MSFT, YHOO and DELL. This reflects the fact that all three stocks experienced market fluctuations during the trading days which was conducive to our strategy performing well.

Against the symmetric background agent, our client has a substantially high profit compared to the other submitted strategies against Moving Average, Momentum, and the combination of all the strategies. This is a reflection of the fact that both Moving Average and Momentum strategies do not take advantage of a symmetric distribution of buy and sell orders, in contrast to our strategy which is a variant of market making and so is tailored for such an environment. Against the other strategies it performs well again (in fact, the profits with all strategies against the symmetric background agent are consistently and substantially higher than Kumar’s, who are ranked 1). However, since there is an observed high standard deviation in the profits, the rank is compromised as explained earlier. Against the real background agent as well, the analysis of the results is similar to that calculated for the symmetric background agent. In fact, the only places where losses are actually incurred are against the asymmetric background agent. Otherwise, there are consistently high profits achieved, but due to the high range of the profits, the Sharpe ratio is pulled down, affecting our rankings. So why is there a high standard deviation with respect to the average in our performance? We will attempt to answer this question shortly.

With regard to the results after the liquidation penalty, our client suffered heavily-its rank dropped by 3 points. There was not enough buffering in our algorithm to guard against the liquidation penalty at the end of the trading day which resulted in heavy losses. As observed from Table 2, there was a significant penalty inflicted upon almost
every simulation. This reflects our algorithms weakness in coping with the liquidation penalty.

Analyzing our strategy, a point to take note is that it is inherently very risk averse. That is, throughout the trading day, our strategy would place buy and sell orders, not taking into account how short or long a position we were acquiring. It was left for the end of the day in the interest of accumulating as much profit as possible during trading. This proved to be fatal however, as at the end of the trading day, there were simply not enough buy or sell orders to be matched in order to liquidate our position effectively. Though withdrawing all our orders would be affected immediately upon closing, there would be simply not enough shares to buy or sell at the end of the day, resulting in high long or short positions. Since this was something that was thought of while planning our strategy, a number of measures were taken such as starting liquidation earlier (this is explained in the earlier section), which was not enough to counteract the deluge of simultaneous liquidation efforts by all the other clients. What was needed, in fact, was a constant awareness of liquidating our position throughout the trading day. This was a result of our client not being as risk averse as the other clients. This leads us to our main problem which we used to tackle in planning our next strategy: setting the level of risk aversion. It helps explain our downfall in the competition, which was based on two main calculations: the high standard deviation with respect to the averages of our profits, and the liquidation penalty.

In comparing our results to the winner of the competition, Kumar, it was interesting to note that it was the most risk-averse client. They were risk averse on two accounts:
Firstly, with regard to the liquidation penalty, there was a constant check on how short or long a position, they had acquired. If the Simulator Present Value became too negative at any one point, there was a mechanism to match buy or sell orders quickly to restore the position. Moreover, rather than starting to liquidate just a half hour before closing time, the liquidation process (of mainly withdrawing orders rather than matching-the latter was taken care of more or less throughout the day) was started much earlier- at 2 30pm rather than 3 pm-the latter was what we had introduced as a modification to the market making strategy. Since Kumar’s strategy took care of liquidation throughout the trading day, and also started liquidation earlier than other strategies, they incurred no liquidation penalties as seen from the results. This was a huge factor in their success, as most clients were affected by this liquidation penalty.

Secondly, there was risk aversion in terms of the number of buy/sell orders placed throughout the day. Since there was no constraint in our strategy to limit the orders, there was ‘free trading’ carried out throughout the day so that if the conditions were favorable, a huge profit would be accumulated and vice versa. Thus, we saw huge profits against the symmetric (specifically against MA and MO which do not fare well in the conditions in which Market Making thrives) and real background agents and huge losses when conditions were not favorable (as observed against the asymmetric background agent). Hence, there was a substantial standard deviation with respect to the average which resulted in a low Sharpe Ratio. Since Kumar’s strategy was careful about its long and short positions as well as the changing market trends, it was more prone to limiting its buy/sell orders. Thus, though their profits never outdid any other client’s profits against a specific strategy, they were limited across a narrow range and never went too negative.
This resulted in a standard deviation that was low and a comparatively high average (no huge losses were suffered), which boosted their Sharpe Ratio and helped their rankings.

**STEP 4: Theorizing the new strategy – the Combination strategy:**

After rigorously analyzing our performance and that of others in the December competition, as well as, taking all possible information gathered from the first report and other investigations, we formulated a new and improved strategy. This strategy is aimed at taking into account maximum possible situations, the different background agents and the technique of calculating performance as given to us. This new strategy is called the Combination strategy. Since a single strategy does not exist that can work optimally for each environment and survive the total market fluctuations in a trading day, we felt that the most consistent approach was to combine the strategies, so that each can cater to the different scenarios for which they are tailored for. As the name suggests the Combination strategy is the combination of the Market Making, Momentum and Reverse strategy. Based on information available to us from the December 2004 PLAT competition and a thorough study of the real market as well as the various trading strategies that exist, we were able to deduce that –

1. The Market Making strategy is most profitable and results in the best performance when there is high price volatility and the market is constantly fluctuating, with the end price close to the start price of the trading day.
2. The Momentum strategy is most profitable and has the best results when there is a clear increasing or decreasing trend in the market, since the strategy itself depends on investigating the trends and placing buy orders if the price is increasing and sell orders if the price is decreasing.
(3) The Reverse strategy is most successful when there is no clear trend in the market and the price is changing in different directions constantly.

We aimed at a more general, risk averse strategy and came up with the following changes and improvements –

Until (a sufficient amount of time to gather price information for the trading day, for example 10.00am):

- Collect all price information: that is, store the prices for the last few minutes in an array of a specified size prices[n].
- Calculate price variance at each interval using the prices array.
- Collect variance information over a period of time: that is if the price information is stored for every 20 minutes.
- Calculate the mean variance using the stored information.
- As long as the position is not too short or too long: (for e.g., currentValue > -500 and currentShare < 10000) that is, as long as the currentValue value is not lower than a chosen negative value or is not larger than a given positive value, then use the Market Making strategy
- If currentValue is not within specified bounds and is negative then liquidate shares by buying back shares at current price. Alternatively, if currentValue is not within bounds and is positive, sell shares at current price.

After 10.00am and before 2:45pm of the current trading day:
- At each time interval re-fill the prices array by storing new price information. With this recalculate price variance.

- Calculate trends by using prices array: that is, if the price is increasing for more than 2n/3 consecutive time intervals then this is an uptrend. If the price is decreasing for more than 2n/3 consecutive time intervals then this is a downtrend. If neither of these cases occurs then there is no clear trend.

- Once again as long as the currentValue value is within specified bounds:
  - If there is a trend then calculate volume of shares to be bought/sold for momentum strategy:
    - If there is a strong uptrend (i.e. there are more than 2n/3 consecutive time intervals for which the price is increasing) then increase the volume of shares to be bought.
    - If there is a strong downtrend (i.e. there are more than 2n/3 consecutive time intervals for which the price is decreasing) then increase the volume of shares to be sold.
  - Else if (there is no trend), we check to see if there has at least been a significant price change in which case we use the Reverse Strategy. We compare the current price to the previous price in the prices array; if there has been a change in prices in any direction, then the reverse strategy will be put into effect. That is, the volume of shares to be sold is increased if the price goes up and
the volume of shares to be bought is increased if the price goes down.

- Else If there is no trend and there are many fluctuations
  (variance: fluctuation from average price) then use the Market Making strategy.
  
  - Control the Market Making strategy such that whenever currentValue becomes negative stop Market Making from executing orders. Re-start the Market Making strategy if there is no trend and the currentValue is positive.

- Once again if the currentShare and currentValue is not within specified bounds and is negative then liquidate shares by buying back shares at current price. Alternatively, if currentValue is not within bounds and is positive, sell shares at current price.

After 2:45: liquidate

- To ensure maximum liquidation, we start withdrawing 20 seconds earlier (to the final liquidation stage) so that the penalty is less during the final liquidation stage. Also, we place buy orders at the current price + 2001 and the sell orders at 0.00099, so that we are ensured maximum execution of our buy/sell orders to effectively liquidate and avoid penalty.

In the above pseudo code there are three values which must be fine tuned by testing. The first value is the size of the array prices, \( n \), which depends on the amount of time for which the price information is to be stored and the time interval to be stored in
each array. That is, for example each cell in the array can contain the price for a time interval of 100 seconds and if the size of the array is 12 then we have price information for every 20 minutes. The more information that is stored and the smaller the intervals the more accurate the trend will be. However, there is a limit after which if the size of the array is increased then it will be hard to identify a clear trend unless it is an extreme situation or extreme change in trend data.

The second value that needs to be tuned is the bounds for the variable currentValue. If the bounds are too strict (that is, the lower bound has a very low absolute value and the upper bound is a low positive number) then risks taken will be minimal so that the volume of shares traded is minimal and therefore will result in a small simulator present value. On the other hand, if the bounds are too lenient (that is, the lower bound has a very high absolute value and the upper bound is a high positive number) then too many risks will be taken and the volume of shares traded will be too high leading to a situation where all share might not be able to be liquidated or matched by orders on the opposite side and ultimately resulting once again in a negative simulator present value. The Combination strategy liquidates whenever the bounds are crossed, which makes it a risk averse strategy and therefore satisfies the competition criterion. That is, since it is liquidating often it will not result in a short or long position and therefore result in a lower or no penalty.

The last value that needs to be fine tuned is the increase of the volume of shares traded along with the threshold value of the change in variance for the Market Making strategy. If the constant added is too small it will not make a significant difference, but if
the constant added is too large then this once again may result in too many shares being traded and a possible negative simulator present value.

This strategy is a more general strategy which performs better in the ever changing market conditions and attacks and takes into consideration more possible situations than the strategy modifyTime. For example, even if there is an extreme situation such as a breakout, that is, there is an extremely strong trend or a historically high/low price trend recorded then the Momentum strategy will make high profits but simply using the Market Making (more along the lines of our old strategy- modifyTime) will result in poor performance. Another improvement is that is also takes into account the affect of different background agents. According to our earlier analysis the Market Making agent works best with the symmetric background agent. However, since the asymmetric background agent causes either an up or down trend in price, the Momentum strategy will work best. Lastly the new strategy is a combination of the Market Making, Momentum and Reverse strategy which handles many possible conditions of the market such as those possible in the real market and hence aims at performing well with the real background agent.

Furthermore, this strategy is not only aimed at improving our own strategy but can also be viewed as an improvement on the winning strategy of the December competition – the Contrarian strategy. It not only takes care of the all the possible situations that the Contrarian strategy takes care of but also has additional bounds and aids to increase performance. The Combination strategy takes into account risk aversion as well as changing volumes in order to trade a larger volume where there is potential, possibly resulting in a larger but positive simulator present value. After examining, the
results of the last competition, it was evident that the Contrarian strategy had a very low risk level and as a result also had very small simulator present values because it was liquidating if the current value went below a certain value. But at the same time, our strategy also aims at trading a larger and proportionate amount where it is possible without increasing any risks by changing the volumes being traded and therefore taking care of the main shortcoming of the Contrarian strategy which is small simulator present values in general. The Combination strategy, apart from the final liquidation stage, also has a wind down stage. This stage starts 20 seconds before the final liquidation stage by withdrawing excess orders. This is done to ensure maximum execution of our buy/sell orders. Thus the Combination strategy, not only aims at making a more risk averse strategy resulting in a smaller penalty but at the same time aims at earning high profits when the opportunity presents itself.

**Conclusion**

In summary, the Combination strategy is designed with as many risk control mechanisms as possible to avoid any penalty for any future competitions. It is also based upon the fact that in the real market it is important to trade larger volumes whenever possible in order to make larger profits.

<table>
<thead>
<tr>
<th>Stock</th>
<th>Open Price</th>
<th>Last Price</th>
<th>Day Change(%)</th>
<th>Day Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>YHOO</td>
<td>$31.94</td>
<td>$31.41</td>
<td>1.75%</td>
<td>32.09 - 31.41</td>
</tr>
<tr>
<td>MSFT</td>
<td>$24.24</td>
<td>$24.28</td>
<td>0.41%</td>
<td>24.47 - 24.20</td>
</tr>
<tr>
<td>DELL</td>
<td>$38.47</td>
<td>$38.38</td>
<td>-0.13%</td>
<td>38.90 - 38.30</td>
</tr>
</tbody>
</table>
The table above is data taken from the Nasdaq market for the day March 27th 2005. The corresponding price graphs for the stocks are included below in Figure A, B and C.

**Fig. A: Price graph for YHOO (March 27th 2005)**

**Fig. B: Price graph for MSFT (March 27th 2005)**
Fig. C: Price graph for DELL (March 27th 2005)

If we apply our analysis to these stocks and graphs, we can see that in

(1) Fig. A there is a clear downtrend.

(2) Fig. B there is no clear trend. However there are many fluctuations, which is also evident from the day change percentage value from the table.

Furthermore, the end price is very close to the start price,

(3) Fig. C, there is no clear trend, but in relation to the values of Fig. B, there are relatively less fluctuations as indicated by day change percentages for each of the stocks and the start price is also relatively not as close to the end price as that of Fig B. Furthermore, the price seems to be constantly changing direction.

We see that Combination strategy, using the above inferences, would tend to use more of the momentum strategy for YHOO stock, more of Market Making strategy for MSFT and Reverse strategy for DELL. However, for all the stocks it will not use only one of the three sub-strategies; it will switch between strategies according to the most current information available. Also, if the time interval for prices array is 100 seconds, that is we
refresh data after every 20 minutes, then it becomes clear that the agent will be able to recognize the fluctuations which occur in every 20 or less minutes in Fig. B. We therefore, have theorized this strategy based mainly on the real market data and set the aim to not sacrifice large profits in the face of minimizing risks. If provided with sufficient historical data, the next step in this project would be to apply reinforcement learning and geometric trends to make a strategy that is less susceptible to market fluctuations and can perform more consistently.

**Technical Challenges**

The principle technical challenge that my partner and I faced was the lack of ‘desired response’ when the new features were implemented. The nature of the results was very unpredictable— in contrast to designing an information system for example. In the PLAT competition, a number of outside agents had to be considered which could make your strategy act in a very unpredictable manner. There was, thus, a very weak correlation between the algorithm and the actual output. However, with a significant amount of testing we were able to estimate the result of our strategies according to the different background agents.

**Resources**

We used a Linux or Solaris machine as an environment to develop and execute agents. An account on crux.cis.upenn.edu was used for the purposes of building the strategies and connecting to PXS. In addition to software, we referenced last years PLAT projects, books on game theory, specifically STRATEGY by Watson and the NASDAQ
Glossary, which were all readily available at the library or online. We also used other software like maple, for drawing graphs and mathematical analysis of the results.