Machine Learning for Market Microstructure and High Frequency Trading [*]

Michael Kearns[†] Yuriy Nevmyvaka[‡]

1 Introduction

In this chapter, we overview the uses of *machine learning* for high frequency trading and market microstructure data and problems. Machine learning is a vibrant subfield of computer science that draws on models and methods from statistics, algorithms, computational complexity, artificial intelligence, control theory, and a variety of other disciplines. Its primary focus is on computationally and informationally efficient algorithms for inferring good predictive models from large data sets, and thus is a natural candidate for application to problems arising in HFT, both for trade execution and the generation of alpha.

The inference of predictive models from historical data is obviously not new in quantitative finance; ubiquitous examples include coefficient estimation for the CAPM, Fama and French factors [5], and related approaches. The special challenges for machine learning presented by HFT generally arise from the very fine granularity of the data — often microstructure data at the resolution of individual orders, (partial) executions, hidden liquidity, and cancellations — and a lack of understanding of how such low-level data relates to actionable circumstances (such as profitably buying or selling shares, optimally executing a large order, etc.). In the language of machine learning, whereas models such as CAPM and its variants already prescribe what the relevant variables or "features" are for prediction or modeling (excess returns, book-to-market ratios, etc.), in many HFT problems one may have no prior intuitions about how (say) the distribution of liquidity in the order book relates to future price movements, if at all. Thus *feature selection* or *feature engineering* becomes an important process in machine learning for HFT, and is one of our central themes.

Since HFT itself is a relatively recent phenomenon, there are few published works on the application of machine learning to HFT. For this reason, we structure the chapter around a few case studies from our own work [6, 14]. In each case study, we focus on a specific trading problem we would like to solve or optimize; the (microstructure) data from which we hope to solve this problem; the variables or features derived from the data as inputs to a machine learning process; and the machine learning algorithm applied to these features. The cases studies we will examine are:

- **Optimized Trade Execution via Reinforcement Learning [14].** We investigate the problem of buying (respectively, selling) a specified volume of shares in a specified amount of time,

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[†] Department of Computer and Information Science, University of Pennsylvania. Email:mkearns@cis.upenn.edu

[‡] Department of Computer and Information Science, University of Pennsylvania. Email:yuriy.nevmyvaka@gmail.com

with the goal of minimizing the expenditure (respectively, maximizing the revenue). We apply a well-studied machine learning method known as *reinforcement learning* [16], which has roots in control theory. Reinforcement learning applies state-based models that attempt to specify the optimal action to take from a given state according to a discounted future reward criterion. Thus the models must balance the short-term rewards of actions against the influences these actions have on future states. In our application, the states describe properties of the limit order book and recent activity for a given security (such as the bid-ask spread, volume imbalances between the buy and sell sides of the book, and the current costs of crossing the spread to buy or sell shares). The actions available from each state specify whether to place more aggressive marketable orders that cross the spread or more passive limit orders that lie in the order book.

- **Predicting Price Movement from Order Book State.** This case study examines the application of machine learning to the problem of predicting directional price movements, again from equities limit order data. Using similar but additional state features as in the reinforcement learning investigation, we seek models that can predict relatively near-term price movements (as measured by the bid-ask midpoint) from market microstructure signals. Again the primary challenge is in the engineering or development of these signals. We show that such prediction is indeed modestly possible, but it is a cautionary tale, since the midpoint is a fictitious, idealized price; and once one accounts for trading costs (spread-crossing), profitability is more elusive.
- **Optimized Execution in Dark Pools via Censored Exploration [6].** We study the application of machine learning to the problem of Smart Order Routing (SOR) across multiple dark pools, in an effort to maximize fill rates. As in the first case study, we are exogenously given the number of shares to execute, but while in the first case we were splitting the order across time, here we must split it across venues. The basic challenge is that for a given security at a given time, different dark pools may have different available liquidity, thus necessitating an adaptive algorithm that can divide a large order up across multiple pools to maximize execution. We develop a model that permits a different distribution of liquidity for each venue, and a learning algorithm that estimates this model in service of maximizing the fraction of filled volume per step. A key limitation of dark pool microstructure data is the presence of *censoring*: if we place an order to buy (say) 1000 shares, and 500 are filled, we are certain exactly only 500 were available; but if all 1000 shares are filled, it is possible that more shares were available for trading. Our machine learning approach to this problem adapts a classical method from statistics known as the Kaplan-Meier Estimator in combination with a greedy optimization algorithm.

Related Work. While methods and models from machine learning are used in practice ubiquitously for trading problems, such efforts are typically proprietary, and there is little published empirical work. But the case studies we examine do have a number of theoretical counterparts that we now summarize.

Algorithmic approaches to execution problems are fairly well studied, and often applies methods from the stochastic control literature [2, 8, 7, 3, 4]. These papers seek to solve problems similar to ours — execute a certain number of shares over some fixed period as cheaply as possibly – but approach it from another direction. They typcially start with an assumption that the underlying "true" stock price is generated by some known stochastic process. There is also a known impact function that specifies how arriving liquidity demand pushes market prices away from this true value. Having this information, as well as time and volume constraints, it is then possible to compute the optimal strategy explicitly. It can be done either in closed form or numerically (often using dynamic programming, the basis of reinforcement learning). The main difference between this body of work and our approach is our use of real microstructure data to learn feature-based optimized control policies. There are also interesting game-theoretic variants of execution problems in the presence of an arbitrageur [12], and examinations of the tension between exploration and exploitation [15].

There is a similar theoretical dark pool literature. Some work [10] starts with the mathematical solution to the optimal allocation problem, and trading data comes in much later for calibration purposes. There are also several extensions of our own dark pool work [6]. In [1], our framework is expanded to handle adversarial (i.e. not i.i.d.) scenarios. Several brokerage houses have implemented our basic algorithm and improved upon it. For instance, [13] adds time-to-execution as a feature and updates historical distributions more aggressively, and [11] aims to solve essentially the same allocation/order routing problem, but for lit exchanges.

2 High Frequency Data for Machine Learning

The definition of high frequency trading remains subjective, without widespread consensus on the basic properties of the activities it encompasses, including holding periods, order types (e.g. passive versus aggressive), and strategies (momentum or reversion, directional or liquidity provision, etc.). However, most of the more technical treatments of HFT seem to agree that the data driving HFT activity tends to be the most granular available. Typically this would be microstructure data directly from the exchanges that details every order placed, every execution, and every cancellation, and that thus permits the faithful reconstruction (at least for equities) of the full limit order book, both historically and in real time. [1] Since such data is typically among the raw inputs to an HFT system or strategy, it is thus possible to have a sensible discussion of machine learning applied to HFT without committing to an overly precise definition of the latter — we can focus on the microstructure data and its uses in machine learning.

Two of the greatest challenges posed by microstructure data are its scale and interpretation. Regarding scale, a single day's worth of microstructure data on a highly liquid stock such as AAPL is measured in gigabytes. Storing this data historically for any meaningful period and number of names requires both compression and significant disk usage; even then, processing this data efficiently generally requires streaming through the data by only uncompressing small amounts at a time. But these are mere technological challenges; the challenge of interpretation is the more significant. What systematic signal or information, if any, is contained in microstructure data? In the language of machine learning, what "features" or variables can we extract from this extremely granular, lower-level data that would be useful in building predictive models for the trading problem at hand?

This question is not special to machine learning for HFT, but seems especially urgent there. Compared to more traditional, long-standing sources of lower-frequency market and non-market data, the meaning of microstructure data seems relatively opaque. Daily opening and closing prices generally aggregate market activity and integrate information across many participants; a missed earnings target or an analyst's upgrade provide relatively clear signals about the performance of a particular stock or the opinion of a particular individual. What interpretation can be given for a single order placement in a massive stream of microstructure data, or to a snapshot of an intraday order book — especially

[1] Various types of hidden, iceberg and other order types can limit the complete reconstruction, but does not alter the fundamental picture we describe here.

considering the fact that any outstanding order can be cancelled by the submitting party any time prior to execution? [2]

To offer an analogy, consider the now-common application of machine learning to problems in natural language processing (NLP) and computer vision. Both of them remain very challenging domains. But in NLP, it is at least clear that the basic unit of meaning in the data is the word, which is how digital documents are represented and processed. In contrast, digital images are represented at the pixel level, but this is certainly not the meaningful unit of information in vision applications — objects are, but algorithmically extracting objects from images remains a difficult problem. In microstructure data, the unit of meaning or actionable information is even more difficult to identify, and is probably noisier than in other machine learning domains. As we proceed through our case studies, proposals will be examined for useful features extracted from microstructure data, but it bears emphasizing at the outset that these are just proposals, almost certainly subject to improvement and replacement as the field matures.

3 Reinforcement Learning for Optimized Trade Execution

Our first case study examines the use of machine learning in perhaps the most fundamental microstructre-based algorithmic trading problem, that of optimized execution. In its simplest form, the problem is defined by a particular stock, say AAPL; a share volume V; and a time horizon or number of trading steps T. [3] Our goal is to buy [4] exactly V shares of the stock in question within T steps, while minimizing our expenditure (share prices) for doing so. We view this problem from a pure agency or brokerage perspective: a client has requested that we buy these shares on their behalf, and the time period in which we must do so, and we would like to obtain the best possible prices within these constraints. Any subsequent risk in holding the resulting position of V shares is borne by the client.

Perhaps the first observation to make about this optimized trading problem is that any sensible approach to it will be *state-based* — that is, will make trading and order placement decisions that are conditioned on some appropriate notion of "state". The most basic representation of state would simply be pairs of numbers (v, t) indicating both the volume $v \leq V$ remaining to buy, and the number of steps $t \leq T$ remaining to do so. To see how such a state representation might be useful in the context of microstructure data and order book reconstruction, if we are in a state where v is small and t is large (thus we have bought most of our target volume, but have most of our time remaining), we might choose to place limit orders deep in the buy book in the hopes of obtaining lower prices for our remaining shares. In contrast, if v is large and t is small, we are running out of time and have most of our target volume still to buy, so we should perhaps start crossing the spread and demanding immediate liquidity to meet our target, at the expense of higher expenditures. Intermediate states might dictate intermediate courses of action.

While it seems hard to imagine designing a good algorithm for the problem without making use of this basic (v, t) state information, we shall see that there are many other variables we might profitably add to the state. Furthermore, mere choice of the state space does not specify the details of how we should act or trade in each state, and there are various ways we could go about doing so. One

[2] A fair estimate would be that over 90 per cent of placed orders are cancelled.

[3] For simplicity we shall assume a discrete-time model in which time is divided into a finite number of equally spaced trading opportunities. It is straightforward conceptually to generalize to continuous-time models.

[4] The case of selling is symmetric.

traditional approach would be to design a policy mapping states to trading actions "by hand". For instance, basic VWAP [5] algorithms might compare their current state (v, t) to a schedule of how much volume they "should" have traded by step t according to historical volume profiles for the stock in question, calibrated by the time of day and perhaps other seasonalities. If v is such that we are "behind schedule", we would trade more aggressively, crossing the spread more often, etc.; if we are "ahead of schedule", we would trade more passively, sitting deeper in the book and hoping for price improvements. Such comparisons would be made continuously or periodically, thus adjusting our behavior dynamically according to the historical schedule and currently prevailing trading conditions. In contrast to this hand-designed approach, here we will focus on an entirely learning-based approach to developing VWAP-style execution algorithms, where we will learn a state-conditioned trading policy from historical data.

Reinforcement Learning (RL) [16], which has its roots in the older field of control theory, is a branch of machine learning explicitly designed for learning such dynamic state-based policies from data. While the technical details are beyond our scope, the primary elements of an RL application are as follows:

- The identification of a (typically finite) state space, whose elements represent the variable conditions under which we will choose actions. In our case, we shall consider state spaces that include (v, t) as well as additional components or features capturing order book state.

- The identification of a set of available actions from each state. In our application, the actions will consist of placing a limit order for all of our remaining volume at some varying price. Thus we will only have a single outstanding order at any moment, but will reposition that order in response to the current state.

- The identification of a model of the impact or influence our actions have, in the form of execution probabilities under states, learned from historical data.

- The identification of a reward or cost function indicating the expected or average payoff for taking a given action from a given state. In our application, the cost for placing a limit order from a given state will be any eventual expenditures from the (partial) execution of the order.

- Algorithms for learning an optimal policy — that is, a mapping from states to actions — that minimizes the empirical cost (expenditures for purchasing the shares) on training data.

- Validation of the learned policy on test data by estimating its out-of-sample performance (expenditures).

Note that a key difference between the RL framework and more traditional predictive learning problems such as regression is that in RL we learn directly how to *act* in the environment represented by the state space, not simply predict target values.

We applied the RL methodology to the problem of optimized trade execution (using the choices for states, actions, impact and rewards indicated above) to microstructure data for several liquid stocks. Full historical order book reconstruction was performed, with the book simulation used both for computing expenditures in response to order executions, and for computing various order book features that we added to the basic (v, t) state, discussed below.

[5] *Volume Weighted Average Price*, which refers to both the benchmark of trading shares at the market average per share over a specified time period, and algorithms which attempt to achieve or approximate this benchmark.

As a benchmark for evaluating our performance, we compare resulting policies to *one-shot* submission strategies and demonstrate the benefits of a more dynamic, multi-period, state-based learning approach. [6] One-shot strategies place a single limit order at some price p for the entire target volume V at the beginning of the trading period, and leave it there without modification for all T steps. At the end of the trading period, if there is any remaining volume v, a market order for the remaining shares is placed in order to reach the target of V shares purchased. Thus if we choose the buying price p to be very low, putting an order deep in the buy book, we are effectively committing ourselves to a market order at the end of the trading period, since none of our order volume will be executed. If we choose p to be very high, we cross the spread immediately and effectively have a market order at the beginning of the trading period. Intermediate choices for p seek a balance between these two extremes, with perhaps some of our order being executed at improved prices, and the remaining liquidated as a market order at the end of trading. One-shot strategies can thus encompass a range of passive and aggressive order placement, but unlike the RL approach, do not condition their behavior on any notion of state. In the experiments we now describe, we describe the profitability of the policies learned by RL to the *optimal* (expenditure minimizing) one-shot strategy on the training data; we then report test set performance for both approaches.

The potential promise of the learning approach is demonstrated by Figure 1. In this figure, we compare the test set performance of the optimal one-shot strategy, and the policies learned by RL. To normalize price differences across stocks, we measure performance by *implementation shortfall* — namely, how much the average share price paid is greater than the midpoint of the spread at the beginning of the trading period; thus, lower values are better. In the figure, we consider several values of the target volume and the period over which trading takes place, as well as both a coarser and finer choice for how many discrete values we divide these quantities into in our state space representation (v, t). In every case we see that the performance of the RL policies is significantly better than the optimal one-shot. We sensibly see that trading costs are higher overall for the higher target volumes and shorter trading periods. We also see that finer-grained discretization improves RL performance, an indicator that we have enough data to avoid overfitting from fragmenting our data across too large a state space.

Aside from the promising performance of the RL approach, it is instructive to visualize the details of the actual policies learned, and is possible to do so in such a small, two-dimensional state representation. Figure 2 shows examples of learned policies, where on the x and y axes, we indicate the state (v, t) discretized into 8 levels each for both the number of trading steps remaining and the inventory (number of shares) left to purchase, and on the z axis, we plot the action learned by RL training relative to the top of the buy book (ask). Thus action Δ corresponds to positioning our buy order for the remaining shares at the bid *plus* Δ. Negative Δ are orders placed down in the buy book, while positive Δ enters or crosses the spread.

The learned policies are broadly quite sensible in the manner discussed earlier — when inventory is high and time is running out, we cross the spread more aggressively; when inventory is low and most of our time remains, we seek price improvement. But the numerical details of this broad landscape vary from stock to stock, and in our view this is the real value of machine learning in microstructure applications — not in discovering "surprising" strategies per se, but in using large amounts of data

[6] In principle we might compare our learning approach to state-of-the-art execution algorithms, such as the aforementioned VWAP algorithms used by major brokerages. But doing so obscures the benefits of a principled learning approach in comparison to the extensive hand-tuning and optimization in industrial VWAP algorithms, and the latter may also make use of exotic order types, multiple exchanges, and other mechanisms outside of our basic learning framework. In practice, a combination of learning and hand-tuning would likely be most effective.

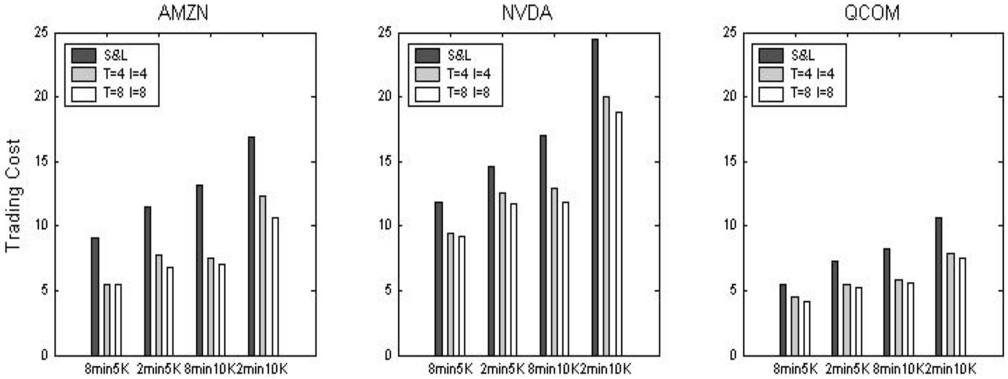

FIGURE 1: Test set performance for optimal one-shot (black bars, leftmost of each triple) and RL policies (gray and white bars, middle and rightmost of each triple) on stocks AMZN, NVDA and QCOM, as measured by implementation shortfall (trading costs). The x-axis labels indicate the target volume to buy and the trading period; while the legends indicate the resolution of discretization in the RL state space for v (target volume divided into I levels, from lowest to highest) and t (trading divided into T discrete steps, equally spaced throughout the trading period).

to optimize, on a per-stock basis, the fine-grained details of improved performance, in this case for execution. We also note that all of the learned policies choose to enter or cross the spread in all states (positive Δ), but this is likely an artifact of the relatively large target volumes and short trading periods we have chosen for such high-liquidity stocks; for smaller volumes, longer periods and lower liquidity, we should expect to see some states in which we sit down in the order book.

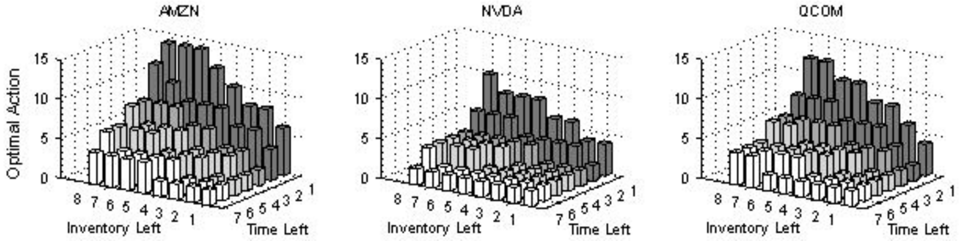

FIGURE 2: Sample policies learned by RL. The state (v, t) is indicated on the x and y axes as discrete levels of inventory remaining v and number of trading steps or time remaining t. Actions indicate how far into or across the spread to reposition the order for the remaining volume. Lower indices on the x and y values indicate lower values for the features.

So far we have made minimal use of microstructure information and order book reconstruction, which has been limited to determining the prices we obtain for executions and their impact on the market book. But the opportunity and challenge of machine learning typically involves the search for improved features or state variables that allow the learned policy to condition on more information and thus improve performance. What are natural order book-based state variables we might add to (v, t) in this quest? While the possibilities are manyfold, here we list some plausible choices for features that might be relevant to the optimized execution problem:

- **Bid-Ask Spread:** A positive value indicating the current difference between the bid and ask prices in the current order books.

- **Bid-Ask Volume Imbalance:** A signed quantity indicating the number of shares at the bid minus the number of shares at the ask in the current order books.
- **Signed Transaction Volume:** A signed quantity indicating the number of shares bought in the last 15 seconds minus the number of shares sold in the last 15 seconds.
- **Immediate Market Order Cost:** The cost we would pay for purchasing our remaining shares immediately with a market order.

Along with our original state variables (v, t), the features above provide a rich language for dynamically conditioning our order placement on potentially relevant properties of the order books. For instance, for our problem of minimizing our expenditure for purchasing shares, perhaps a small spread combined with a strongly negative signed transaction volume would indicate selling pressure (sellers crossing the spread, and filling in the resulting gaps with fresh orders). In such a state, depending on our inventory and time remaining, we might wish to be more passive in our order placement, sitting deeper in the buy book in the hopes of price improvements.

We ran a series of similar train-test experiments using the RL methodology on our original state (v, t) augmented with various subsets of the order book features described above. [7] The results are summarized in Table 1, which shows, for each of the features described above, the percentage reduction in trading cost (implementation shortfall) obtained by adding that feature to our original (v, t) state space. Three of the four features yield significant improvements, with only bid-ask volume imbalance not seeming especially useful. The final row of the table shows the percentage improvement obtained by adding all three of these informative features, which together improve the (v, t) state by almost 13%.

Feature(s) Added	**Reduction in Trading Cost**
Bid-Ask Spread	7.97%
Bid-Ask Volume Imbalance	0.13%
Signed Transaction Volume	2.81%
Immediate Market Order Revenue	4.26%
Spread + signed Volume + Immediate Cost	12.85%

TABLE 1: Reduction in implementation shortfall obtained by adding features to (v, t).

It is again informative to examine not only performance, but also what has been learned. This is clearly more difficult to visualize and summarize in a 5-dimensional state space, but we can get some intuition by projecting the policies learned onto subsets of 2 features. Like Figure 2, Figure 3 shows a visualization plotting a pair of feature values, discretized into a small number of levels, against the action learned for that pair of values, except now we are averaging across the other three features. Despite this projection or averaging, we can still see that sensible, intuitive policies are being learned. For instance, we see that we place more aggressive (spread-crossing) actions whenever the spread is large or the immediate cost of purchasing our remaining shares is low. In the first case, larger spreads simply force us to be more aggressive to initiate executions; in the second, a bargain is available. When both conditions hold simultaneously, we bid most aggressively of all.

[7] All features are normalized in a standard way by subtracting the historical mean value and expressing the value in units of historical standard deviations.

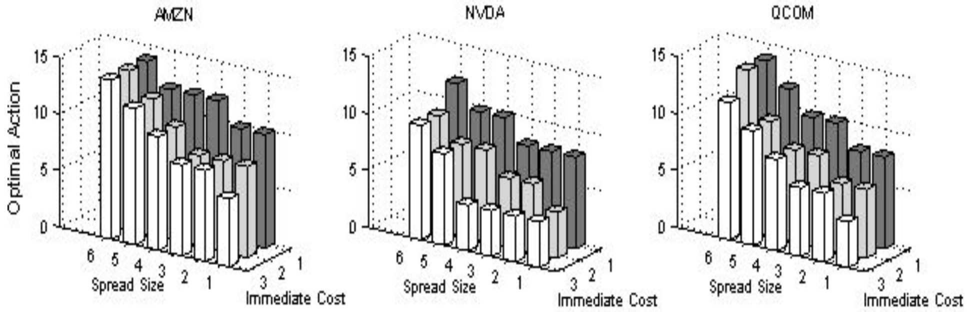

FIGURE 3: Sample policies learned by RL for 5-feature state space consisting of (v, t) and three additional order book features, projected onto the features of spread size and immediate cost to purchase remaining shares. Lower indices on the x and y values indicate lower values for the features.

4 Predicting Price Movement from Order Book State

The case study of Section 3 demonstrated the potential of machine learning approaches to problems of pure execution: we considered a highly constrained and stylized problem of reducing trading costs (in this case, as measured by implementation shortfall), and showed that machine learning methodology could provide important tools for such efforts.

It is of course natural to ask whether similar methodology can be fruitfully applied to the problem of generating profitable state-based models for trading using microstructure features. In other words, rather than seeking to reduce costs for executing a *given* trade, we would like to learn models that themselves profitably decide *when* to trade (that is, under what conditions in a given state space) and *how* to trade (that is, in which direction and with what orders), for alpha generation purposes. Conceptually (only) we can divide this effort into two components:

- The development of features that permit the reliable *prediction* of directional price movements from certain states. By "reliable" we do not mean high accuracy, but just enough that our profitable trades outweigh our unprofitable ones.

- The development of learning algorithms for *execution* that capture this predictability or alpha at sufficiently low trading costs.

In other words, in contrast to Section 3, now we must first find profitable predictive signals, and then hope they are not erased by trading costs. As we shall see, the former goal is relatively attainable, while the latter is relatively difficult.

It is worth remarking that for optimized execution in Section 3, we did not consider many features that directly captured recent directional movements in execution prices; this is because the problem considered there exogenously imposed a trading need, and specified the direction and volume, so momentum signals were less important than those capturing potential trading costs. For alpha generation, however, directional movement may be considerably more important. We thus conducted experiments employing the following features:

- **Bid-Ask Spread:** Similar to that used in Section 3.

- **Price:** A feature measuring the recent directional movement of executed prices.

- **Smart Price:** A variation on mid-price where the average of the bid and ask prices is weighted according to their inverse volume.
- **Trade Sign:** A feature measuring whether buyers or sellers crossed the spread more frequently in recent executions.
- **Bid-Ask Volume Imbalance:** Similar to that used in Section 3.
- **Signed Transaction Volume:** Similar to that used in Section 3.

We have thus preserved (variants of) most of the features from our optimized execution study, and added features that capture directional movement of both executed prices, buying/selling pressure, and bid-ask midpoint movement. All of the features above were normalized in a standard fashion by subtracting their means, dividing by their standard deviations, and time-averaging over a recent interval. In order to obtain a finite state space, features were discretized into bins in multiples of standard deviation units. [8]

In order to effect the aforementioned separation between predicting directional movement, and capturing such movements at in a cost-efficient way, in our first studies we make deliberately optimistic execution assumptions that isolate the potential promise of machine learning. More specifically, we consider just two idealized classes of actions available to the learning algorithm: buying 1 share at the bid-ask midpoint and holding the position for t seconds, at which point we sell the position, again at the midpoint; and the opposite action, where we sell at the midpoint and buy t seconds later. In the first set of experiments we describe, we considered a short period of $t = 10$ seconds. It is important to note that under the assumption of midpoint executions, one or the other of the two actions is always profitable — buying and selling after t seconds if the midpoint increased, and the reverse action if it decreased. This will no longer hold when we consider more realistic execution assumptions.

The methodology can now be summarized as follows:

- For each of 19 names, [9] order book reconstruction on historical data was performed.
- At each trading opportunity, the current state (the value of the six microstructure features described above) was computed, and the profit or loss of both actions (buy then sell, sell then buy) is tabulated via order book simulation to compute the midpoint movement.
- Learning was performed for each name using all of 2008 as the training data. For each state $\vec{x}$ in the state space, the cumulative payoff for both actions across all visits to $\vec{x}$ in the training period was computed. Learning then resulted in a *policy* π mapping states to action, where $\pi(\vec{x})$ is defined to be whichever action yielded the greatest training set profitability in state $\vec{x}$.
- Testing of the learned policy for each each name was performed using all 2009 data. For each test set visit to state $\vec{x}$, we take the action $\pi(\vec{x})$ prescribed by the learned policy, and compute the overall 2009 profitability of this policy.

[8] Experiments can also be performed using continuous features and a parametric model representation, but are beyond the scope of the current article.

[9] Tickers of names examined are AAPL, ADBE, AMGN, AMZN, BIIB, CELG, COST, CSCO, DELL, EBAY, ESRX, GILD, GOOG, INTC, MSFT, ORCL, QCOM, SCHW, YHOO.

Perhaps the two most important findings of this study are that learning consistently produces policies that are profitable on the test set, and that (as in the optimized execution study), those policies are broadly similar across stocks. Regarding the first finding, for all 19 names the test set profitability of learning was positive. Regarding the second finding, while visualization of the learned policies over a six-dimensional state space is not feasible, we can project the policies onto each individual feature and ask what the relationship is between the feature and the action learned. In Figure 4, for each of the 19 policies and each of the six state features, we plot a bar showing the correlation between the value of the feature and the action learned, where by convention we assign a value of +1 to buying then selling, and -1 to selling then buying. For virtually every feature, we see that the sign of the correlation is the same across all policies. As in the optimized execution study, however, the numerical values of the correlations vary significantly across names. This again speaks to the strengths of a learning approach — the policies are all "sensible" and qualitatively similar, but the learning performs significant quantitative optimization on a name-specific basis.

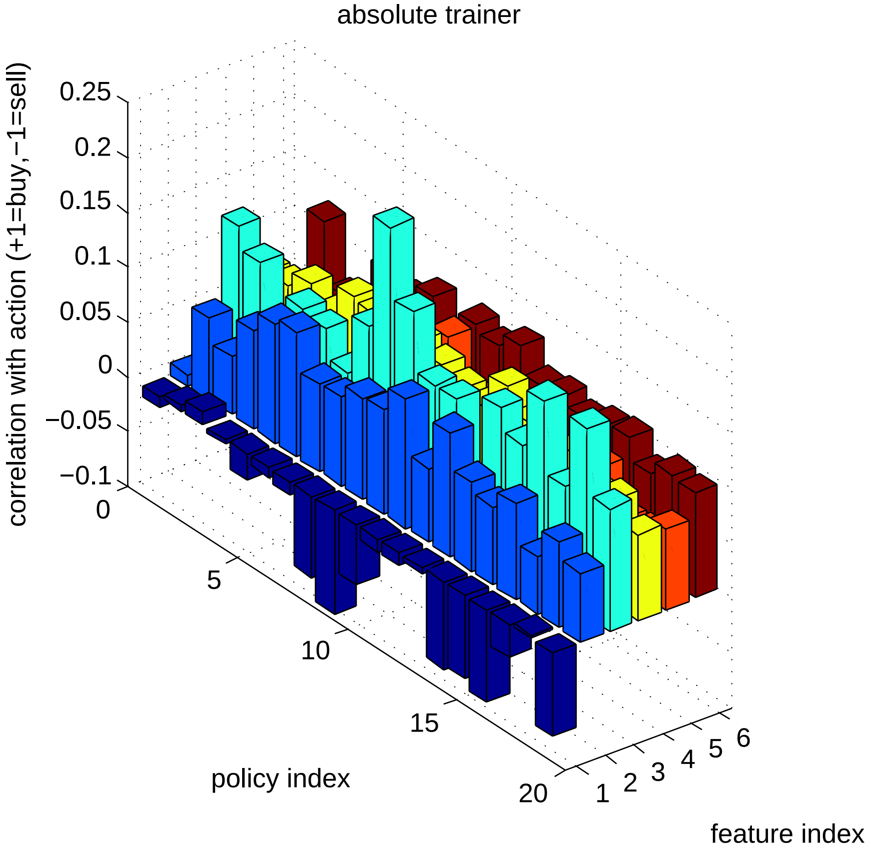

FIGURE 4: Correlations between feature values and learned policies. For each of the six features and 19 policies, we project the policy onto just the single feature compute the correlation between the feature value and action learned (+1 for buying, -1 for selling). Features indices are in the order Bid-Ask Spread, Price, Smart Price, Trade Sign, Bid-Ask Volume Imbalance, Signed Transaction Volume.

What have these consistent policies learned? Figure 4 reveals that, broadly speaking, we have learned momentum-based strategies: for instance, for each of the four features that contain directional information (Price, Smart Price, Trade Sign, Bid-Ask Volume Imbalance, and Signed Transaction Volume), higher values of the feature (which all indicate either rising execution prices, rising midpoints, or buying pressure in the form of spread-crossing) are accompanied by greater frequency of buying in the learned policies. We should emphasize, however, that projecting the policies onto single features does not do justice to the subtleties of learning regarding interactions between the features. As just one simple example, if instead of conditioning on a single directional feature having a high value, we condition on several of them having high values, the correlation with buying becomes considerably stronger than for any isolated feature.

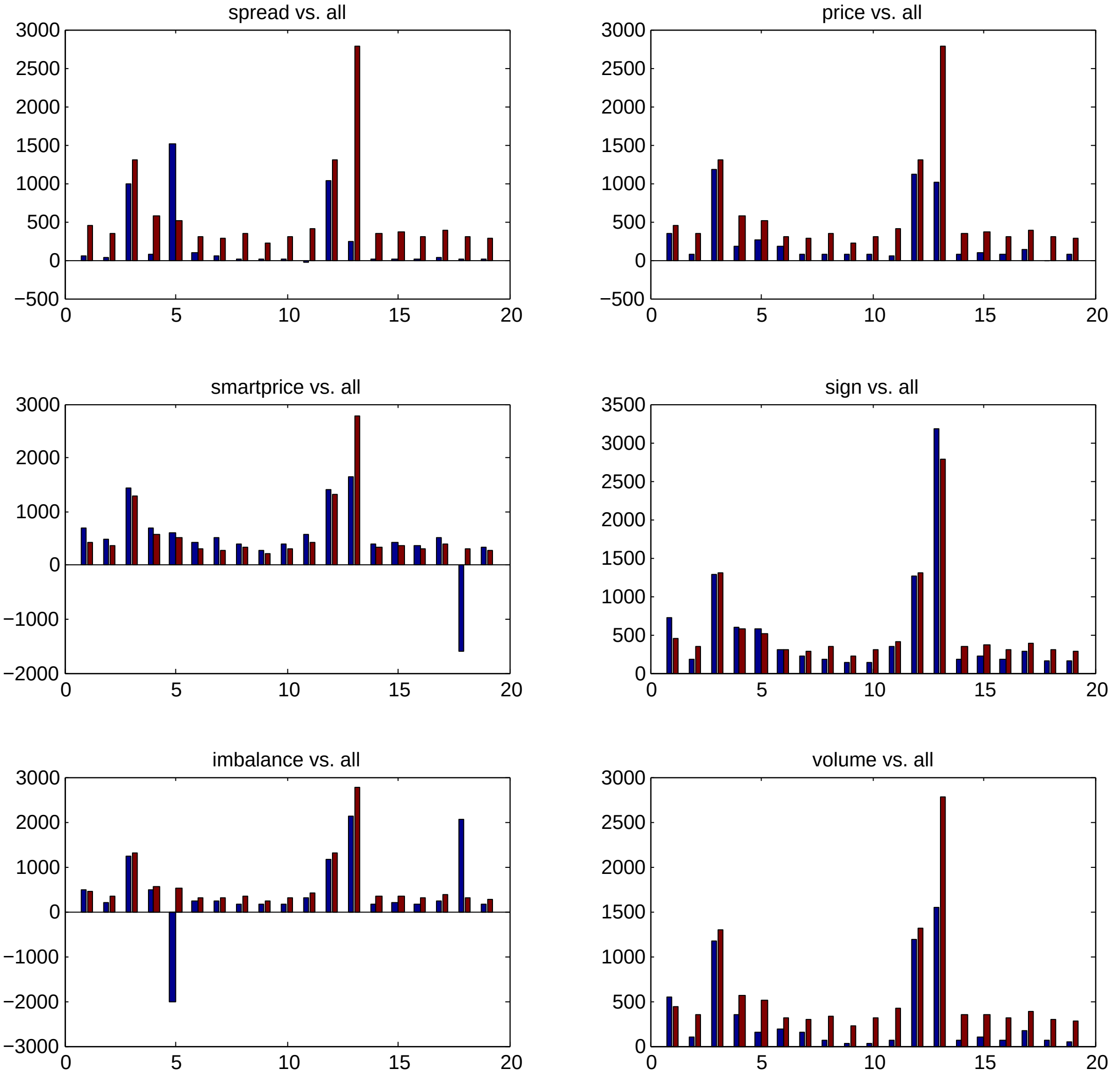

FIGURE 5: Comparison of test set profitability across 19 names for learning with all six features (red bars, identical in each subplot) versus learning with only a single feature (blue bars).

As we did for optimized execution, it is also instructive to examine which features are more more or less informative or predictive of profitability. In Figure 5 there is a subplot for each of the six features. The red bars are identical in all six subplots, and show the test set profitability of the policies learned for each of the 19 names when all six features are used. The blue bars in each subplot show the test set profitability for each of the 19 names when only the corresponding single feature is used. General observations that can be made include:

- Profitability is usually better using all six features than any single feature.
- Smart Price appears to be the best single feature, and often is slightly better than using all features together, a sign of mild overfitting in training. However, for one stock using all features is considerably better, and for another doing so avoids a significant loss from using Smart Price only.
- Spread appears to be the less useful single feature, but does enjoy significant solo profitability on a handful of names.

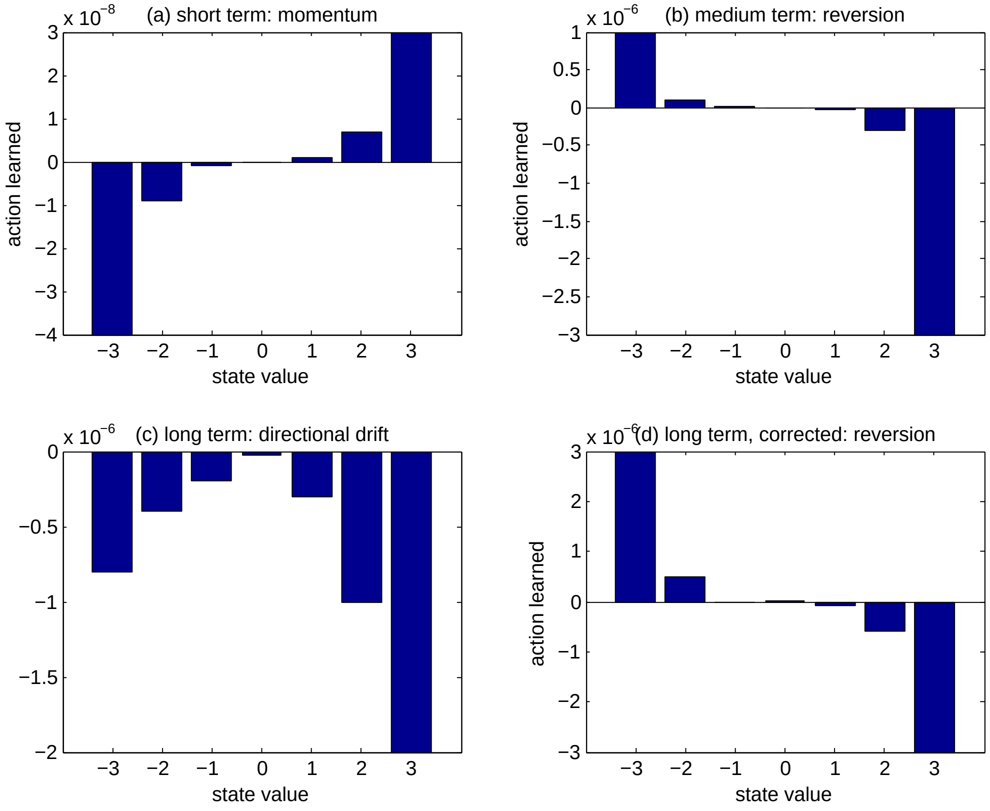

FIGURE 6: Learned policies depend strongly on timescale. For learning with a single feature measuring the recent directional price move, we show the test set profitability of buying in each possible state for varying holding periods.

While we see a consistent momentum relationship between features and actions across names, the picture changes when we explore different holding periods. Figure 6 illustrates how learning discovers different models depending on the holding period. We have selected a single "well-behaved" stock [10] (DELL) and plot *value functions* – which measure the test-set profits or losses — of a buy

[10] The results we describe for DELL, however, do generalize consistently across names.

order in each possible state of a single-feature state space representing recent price changes. [11] Note that since executions take place at the midpoints, the value functions for selling are exactly opposite those shown. We show the value function for several different holding periods.

Over very short holding periods (see Figure 6(a)), we see fairly consistent momentum behavior: for time periods of milliseconds to seconds, price moves tend to continue. At these time scales, buying is (most) profitable when the recent price movements have been (strongly) upwards, and unprofitable when the price has been falling. This echoes the consistency of learned multi-feature momentum strategies described above, which were all at short holding. Features that capture directional moves are positively correlated with future returns: increasing prices, preponderance of buy trades, and higher volumes in the buy book all forecast higher returns in the immediate future.

We see a different pattern, however, when examining longer holding periods (dozens of seconds to several minutes). At those horizons, (see Figure 6(b)), our learner discovers *reversion strategies*: buying is now profitable under recent downward price movements, and selling is profitable after upward price movements. Again, these results are broadly consistent across names and related features.

A desirable property of a "good fit" in statistical learning is to have models with features that partition the variable that they aim to predict into distinct categories. Our short-term momentum and longer-term reversion strategies exhibit such behavior: in the momentum setting, the highest values of past returns predict the highest future returns, and the most negative past returns imply the most negative subsequent realizations (and vice-versa for reversion). Furthermore, this relationship is monotonic, with past returns near zero corresponding to near-zero future returns: in Figure 6(a) and (b) the most pronounced bars are the extremal ones. We lose this desirable monotonicity, however, when extending our holding period even further: in the range of 30 minutes to several hours, conditioning on *any* of our chosen variables no longer separates future positive and negative returns. Instead, we end up just capturing the overall price movement or directional drift – as demonstrated in Figure 6(c), the expected value of a buy action has the same (negative) sign across all states, and is distributed more uniformly, being roughly equal to the (negative) price change over the entire training period (divided by the number of training episodes). Thus since the price went down over the course of the training period, we simply learn to sell in every state, which defeats the purpose of learning a dynamic state-dependent strategy.

The discussion so far highlights the two aspects that one must consider when applying machine learning to high frequency data: the nature of the underlying price formation process, and the role and limitations of the learning algorithm itself. In the first category, a clean picture of market mechanics emerges: when we look at price evolution over milliseconds to seconds, we likely witness large marketable orders interacting with the order book, creating directional pressure. Over several minutes, we see the flip side of this process: when liquidity demanders push prices too far from their equilibrium state, reversion follows. On even longer time scales, our microstructure-based variables are less informative, apparently losing their explanatory power.

On one hand, it may be tempting to simply conclude that for longer horizons microstructure features are immaterial to the price formation process, but longer holding periods are of a particular interest to us. As we have pointed out in our HFT profitability study [9], there is a tension between shorter holding periods and the ability to overcome trading costs (specifically, the bid-ask spread). While the direction of price moves is easiest to forecast over the very short intervals, the magnitude of these predictions – and thus the margin that allows one to cover trading costs – grows with holding

[11] As usual, the feature is normalized by subtracting the mean and binned by standard deviations, so -3 means the recent price change is 3 standard deviations below its historical mean, and +3 means it is three standard deviations above.

periods (notice that the scale of the y axis, which is measuring profitability, is 100 times larger in Figure 6(b) than in Figure 6(a)). Ideally, we would like to find some compromise horizon, which is long enough to allow prices to evolve sufficiently in order to beat the spread, but short enough for microstructure features to be informative of directional movements.

In order to reduce the influence of any long-term directional price drift, we can adjust the learning algorithm to account for it. Instead of evaluating the total profit per share or return from a buy action in a given state, we monitor the *relative* profitability of buying in that state versus buying in *every* possible state. For example, suppose a buy action in state S yields 0.03 cents per trade on average; while that number is positive, suppose *always* buying (that is, in every state) generates 0.07 cents per trade on average (presumably because the price went up over the course of the entire period), therefore making state s relatively less advantageous for buying. We would then assign $-0.04 = 0.03 - 0.07$ as the value of buying in that state. Conversely, there may be a state-action pair that has negative payout associated with it over the training period, but if this action is even more unprofitable when averaged across all states (again, presumably due to a long-term price drift), this state-action pair be assigned a positive value. Conceptually, such "adjustment for average value" allows us to filter out the price trend and hone in on microstructure aspects, which also makes learned policies perform more robustly out-of-sample. Empirically, resulting learned policies recover the desired symmetry, where if one extremal state learns to buy, the opposite extremal state learns to sell – notice the transformation from Figure 6(c) to Figure 6(d), where we once again witness mean reversion.

While we clearly see patterns in the short-term price formation process and are demonstratively successful in identifying state variables that help predict future returns, profiting from this predictability is far from trivial. It should be clear from the figures in this section that the magnitude of our predictions is in fractions of a penny, whereas the tightest spread in liquid US stocks is one cent. So in no way should the results be interpreted as a recipe for profitability: even if all the features we enumerate here are true predictors of future returns, and even if all of them line up just right for maximum profit margins, one still cannot justify trading aggressively and paying the bid-ask spread, since the magnitude of predictability is not sufficient to cover transaction costs. [12]

So what can be done? We see essentially three possibilities. First, as we have suggested earlier, we could hold our positions longer, so that price changes are larger than spreads, giving us higher margins. However, as we have seen, the longer the holding period, the less directly informative market microstructure aspects seem to become, thus making prediction more difficult. Second, we could trade with limit orders, hoping to avoid paying the spread. This is definitely a fruitful direction, where one jointly estimates future returns and the probability of getting filled, which then must be weighed against adverse selection (probability of executing only when predictions turn out to be wrong). This is a much harder problem, well outside of the scope of this article. And finally, a third option is to find or design better features that will bring about greater predictability, sufficient to overcome transaction costs.

It should be clear now that the overarching theme of these suggested directions is that the machine learning approach offers no easy paths to profitability. Markets are competitive, and finding sources of true profitability is extremely difficult. That being said, what we have covered in this section is a framework for how to look for sources of potential profits in a principled way – by defining state spaces, examining potential features and their interplay, using training-test set methodology, imposing sensible value functions, etc – that should be a part of the arsenal of a quantitative professional, so that we can at least discuss these problems in a common language.

[12] Elsewhere we have documented this tension empirically at great length [9].

5 Machine Learning for Smart Order Routing in Dark Pools

The studies we have examined so far apply machine learning to trading problems arising in relatively long-standing exchanges (the open limit order book instantiation of a continuous double auction), where microstructure data has been available for some time. Furthermore, this data is rich — showing the orders and executions for essentially all market participants, comprising multiple order types, and so on — and is also extremely voluminous. In this sense these exchanges and data are ideal testbeds for machine learning for trading, since (as we have seen) they permit the creation of rich feature spaces for state-based learning approaches.

But machine learning methodology is also applicable to recently emerging exchanges, with new mechanisms and with data that is considerably less rich and voluminous. For our final case study, we describe the use of a machine learning approach to the problem of Smart Order Routing (SOR) in dark pools. Whereas our first study investigated reinforcement learning for the problem of dividing a specified trade across *time*, here we examine learning to divide a specified trade across *venues* — that is, multiple competing dark pools, each offering potentially different liquidity profiles. Before describing this problem in greater detail, we first provide some basic background on dark pools and their trade execution mechanism.

Dark pools were originally conceived as a venue for trades in which liquidity is of greater concern than price improvement — for instance, trades whose volume is sufficiently high that executing in the standard lit limit order exchanges (even across time and venues) would result in unacceptably high trading costs and market impact. For such trades, one would be quite satisfied to pay the "current price" — say, as measured by the bid-ask midpoint — as long as there were sufficiently liquidity to do so. The hope is that dark pools can perhaps match such large-volume counterparties away from the lit exchanges.

In the simplest form of dark pool mechanism, orders simply specify the desired volume for a given name, and the direction of trade (buy or sell); no prices are specified. Orders are queued on their respective side of the market in order of their arrival, with the oldest orders at the front of the queue. Any time there is liquidity on both sides of the market, execution occurs. For instance, suppose at a given instant the buy queue is empty, and the sell queue consists of two orders for 1000 and 250 shares. If a new buy order arrives for 1600 shares, it will immediately be executed for 1250 shares against the outstanding sell orders, after which the buy queue will contain the order for the residual 350 shares and the sell queue will be empty. A subsequent arrival of a buy order for 500 shares, followed by a sell order for 1000 shares, will result in an empty buy queue and the residual sell order for 150 ($= 1000 - 350 - 500$) shares. Thus at any instant, either one or both of the buy and sell queues will be empty, since incoming orders are either added to the end of the non-empty queue, or cause immediate execution with the other side. In this sense, all orders are "market" orders, in that they express a demand for immediate liquidity.

At what prices do the executions take place, since orders do not specify prices? As per the aforementioned motivation of liquidity over price (improvement), in general dark pool executions take place at the *prevailing prices in the corresponding lit (limit order) market for the stock in question* – for instance, at the midpoint of the bid-ask spread, as measured by the National Best Bid and Offer (NBBO). Thus while dark pools operate separately and independently of the lit markets, their prices are strongly tied to those lit markets.

From a data and machine learning perspective, there are two crucial differences between dark pools and their lit market counterparts:

- Unlike the microstructure data for the lit markets, in dark pools one has access only to one's own order and execution data, rather than the entire trading population. Thus the rich features measuring market activity, buying and selling pressure, liquidity imbalances, etc. that we exploited in Sections 3 and 4 are no longer available.

- Upon submitting an order to a dark pool, all we learn is whether our order has been (partially) executed, not how much liquidity might have been available had we asked for more. For instance, suppose we submit an order for 10,000 shares. If we learn that 5,000 shares of it have been executed, then we know that only 5,000 shares were present on the other side. However, if all 10,000 shares have been executed, then any amount larger than 10,000 might have been available. More formally, if we submit an order for V shares and S shares are available, we learn only the value $\min(V, S)$, not S. In statistics this is known as *censoring*. We shall see that the machine learning approach we take to order routing in dark pools explicitly accounts for censored data.

These two differences mean that dark pools provide us with considerably less information not only about the activity of other market participants, but even about the liquidity present for our own trades. Nevertheless, we shall see there is still a sensible and effective machine learning approach.

We are now ready to define the SOR problem more mathematically. We assume that there are n separate dark pools available (as of this writing $n > 30$ in the United States alone), and we assume that these pools may offer different liquidity profiles for a given stock — for instance, one pool may be better at reliably executing small orders quickly, while another may have a higher probability of executing large orders. We model these liquidity profiles by probability distributions over available shares. More precisely, let P_i be a probability distribution over the non-negative integers. We assume that upon submitting an order for V_i shares to pool i, a random value S_i is drawn according to P_i; S_i models the shares available on the other side of the market of our trade (selling if we are buying, buying if we are selling) at the moment of submission. Thus as per the aforementioned mechanism, $\min(V_i, S_i)$ shares will be executed. The SOR problem can now be formalized as follows: given an overall target volume V we would like to (say) buy, how should we divide V into submissions $V_1, \ldots, V_n$ to the n dark pools such that $\sum_{i=1}^{n} V_i = V$, and we *maximize* the (expected) number of shares we execute?

As an illustration of how a real distribution of liquidity looks, consider Figure 7, which shows submission and execution data for a large brokerage to a U.S. dark pool for the stock DELL. Each point in the scatterplot corresponds to a single order submitted. The x value is the volume submitted to the pool, while the y value is the volume executed in the pool in a short period of time (on the order of several seconds). All points lie below the diagonal $y = x$ since we never execute more than we submitted. The left plot shows all submission data, while the right plot zooms in on only the smaller orders submitted. We see that while the larger orders — say, those exceeding 20,000 shares — rarely result in even partial execution, the smaller orders (right plot, 1000 shares and smaller) routinely result in partial or full execution. It is empirically the case that such distributions will indeed differ from one dark pool to another, thus suggesting that effective solutions to the SOR problem will divide their orders across pools in an asymmetric fashion.

In our formalization of the SOR problem, *if* we had complete knowledge and descriptions of the distributions P_i, it can be shown [6] there is a straightforward algorithmic solution. In order to maximize the fraction of our V shares that are executed, we should determine the allocations V_i in the following fashion. Processing the shares sequentially (strictly for the purposes of the algorithm),

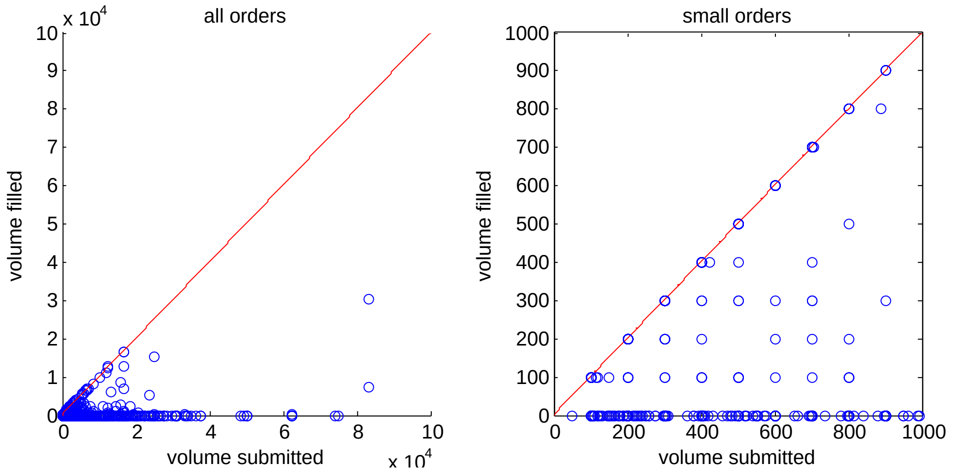

FIGURE 7: Sample submission and execution data for DELL from a large brokerage firm orders to a U.S. dark pool. The x axis shows the volume submitted, and the y value the volume executed in a short period following submission. Points on the diagonal correspond to censored observations.

we allocate the conceptually "first" share to whichever pool has the highest probability of executing a single share. Then inductively, if we have already determined a partial allocation of the V shares, we should allocate our "next" share to whichever pool has the highest *marginal* probability of executing that share, *conditioned* on the allocation made so far. In this manner we process all V shares and determine the resulting allocation V_i for each pool i. We shall refer to this algorithm for making allocations under known P_i the *greedy* allocation algorithm. It can be shown that the greedy allocation algorithm is an optimal solution to the SOR problem, in that it maximizes the expected number of shares executed in a single round of submissions to the n pools. Note that if the submission of our V shares across the pools results in partial executions leaving us with $V' < V$ shares remaining, we can always repeat the process, resubmitting the V' shares in the allocations given by the greedy algorithm.

The learning problem for SOR arises from the fact that we do *not* have knowledge of the distributions P_i, and must learn (approximations to) them from only our own, censored order and execution data — that is, data of the form visualized in Figure 7. We have developed an overall learning algorithm for the dark pool SOR problem that learns an optimal submission strategy over a sequence of submitted volumes to the n venues. The details of this algorithm are beyond the current scope, but can be summarized as follows:

- The algorithm maintains, for each venue i, an approximation $\hat{P}_i$ to the unknown liquidity distribution P_i. This approximation is learned exclusively from the algorithm's own order submission and execution data to that venue. Initially, before any orders have been submitted, all of the approximations $\hat{P}_i$ have some default form.

- Since the execution data is censored by our own submitted volume, we cannot employ basic statistical methods for estimating distributions from observed frequencies. Instead, we use the *Kaplan-Meier estimator* (sometimes also known as the *product limit* estimator), which is the maximum likelihood estimator for censored data [6] . Furthermore, since empirically the execution data exhibits and overwhelming incidence of no shares executed, combined with occasional executions of large volumes (see Figure 7), we adapt this estimator for a parametric model for the $\hat{P}_i$ that has the form of a power law with a separate parameter for zero shares.

- For each desired volume V to execute, the algorithm simply behaves as if its current approximate distributions $\hat{P}_i$ are in fact the true liquidity distributions, and chooses the allocations V_i according to the greedy algorithm applied to the $\hat{P}_i$. Each submitted allocation V_i then results in an observed volume executed (which could be anything from zero shares to a censored observation of V_i shares).

- With this fresh execution data, the estimated distributions $\hat{P}_i$ can be updated, and the process repeated for the next target volume.

In other words, the algorithm can be viewed as a simple repeated loop of optimization followed by re-estimation: our current distributional estimates are inputs to the greedy optimization, which determines allocations, which result in executions, which allow us to estimate improved distributions. It is possible, under some simple assumptions, to prove that this algorithm will rapidly converge to the optimal submission strategy for the unknown *true* distributions P_i. Furthermore the algorithm is computationally very simple and efficient, and variants of it have been implemented in a number of brokerage firms.

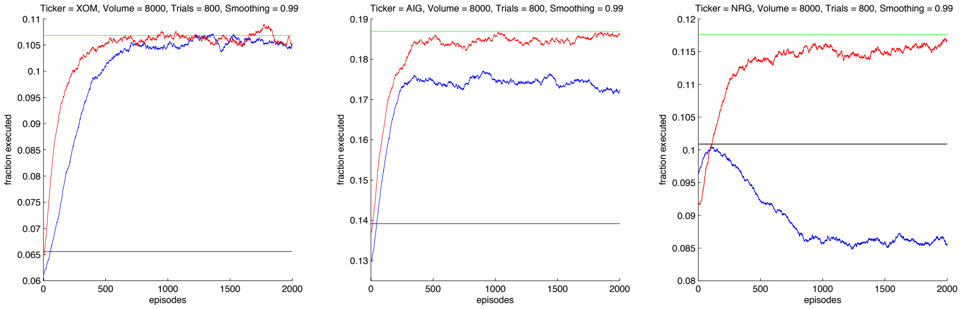

FIGURE 8: Performance curves for our learning algorithm (red) and a simple adaptive heuristic (blue), against benchmarks measuring uniform allocations (black) and ideal allocations (green).

Some experimental validation of the algorithm is provided in Figure 8, showing simulations derived using the censored execution data for four U.S. dark pools. Each subplot shows the evolution of our learning algorithm's performance on a series of submitted allocations for a given ticker to the pools. The x axis measures time or trials for the algorithm — that is, the value of x is the number of rounds of submitted volumes so far. The y axis measures the total fraction of the submitted volume that was executed across the four pools; higher values are thus better. The red curves for each name show the performance of our learning algorithm. In each case performance improves rapidly with additional rounds of allocations, as the estimates $\hat{P}_i$ become better approximations to the true P_i.

As always in machine learning, it is important to compare our algorithm's performance to some sensible benchmarks and alternatives. The least challenging comparison is shown by the black horizontal line in each figure, which represents the expected fraction of shares executed if we simply divide every volume V equally amongst the pools — thus there is no learning, and no accounting for the asymmetries that exist amongs the venues. Fortunately we see the learning approach quickly surpasses this sanity-check benchmark.

A more challenging benchmark is the horizontal green line in each subplot, which shows the expected fraction of shares executed when performing allocations using the greedy algorithm applied to the *true* distributions P_i. This is the best performance we could possibly hope to achieve, and we see that our learning algorithm approaches this ideal quickly for each stock.

Finally, we compare the learning algorithm's performance to a simple adaptive algorithm that is a "poor man's" form of learning. Rather than maintaining estimates of the complete liquidity distribution for each venue i, it simply maintains a single numerical weight w_i, and allocates V proportional to the w_i. If a submission to venue i results in any shares being executed, w_i is increased; otherwise it is decreased. We see that while in some cases this algorithm can also approach the true optimal, in other cases it asymptotes at a suboptimal value, and in others it seems to outright diverge from optimality. In each case our learning algorithm outperforms this simple heuristic.

6 Conclusions

In this article we have presented both the opportunities and challenges of a machine learning approach to HFT and market microstructure. We have considered both problems of pure execution, over both time and venues, and predicting directional movements in search of profitability. These were illustrated via three detailed empirical case studies. In closing, we wish to emphasize a few "lessons learned" common to all of the cases examined:

- Machine learning provides no easy paths to profitability or improved execution, but does provide a powerful and principled framework for trading optimization via historical data.
- We are not believers in the use of machine learning as a black box, nor the discovery of "surprising" strategies via its application. In each of the case studies, the result of learnings made broad economic and market sense in light of the trading problem considered. However, the numerical optimization of these qualitatitve strategies is where the real power lies.
- Throughout we have emphasized the importance and subtlety of feature design and engineering to the success of the machine learning approach. Learning will never succeed without informative features, and may even fail with them if they are not expressed or optimized properly.
- All kinds of other fine-tuning and engineering are required to obtain the best results, such as the development of learning methods that correct for directional drift in Section 4.

Perhaps the most important overarching implication of these lessons is that there will always be a "human in the loop" in machine learning applications to HFT (or any other long-term effort to apply machine learning to a challenging, changing domain). But applied tastefully and with care, the approach can be powerful and scalable, and is arguably necessary in the presence of microstructure data of such enormous volume and complexity as confronts us today.

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References

[1] A. Agarwal, P. Bartlett, and M. Dama. Optimal Allocation Strategies for the Dark Pool Problem. *Technical Report, arXiv.org*, 2010.

[2] D. Bertsimas and A. Lo. Optimal Control of Execution Costs. *J. Financial Markets*, 1(1), 1998.

[3] J. Bouchaud, M. Mezard, and M. Potters. Statistical Properties of Stock Order Books: Empirical Results and Models. *Quantitative Finance*, 2:251–256, 2002.

[4] R. Cont and A. Kukanov. Optimal Order Placement in Limit Order Markets. *Technical Report, arXiv.org*, 2013.

[5] E. Fama and K. French. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of financial economics*, 33(1):3–56, 1993.

[6] K. Ganchev, M. Kearns, Y. Nevmyvaka, and J. Wortman. Censored Exploration and the Dark Pool Problem. *Communications of the ACM*, 53(5):99–107, 2010.

[7] O. Guant, C.A. Lehalle, and J.F. Tapia. Optimal Portfolio Liquidation with Limit Orders. *Technical Report, arXiv.org*, 2012.

[8] I. Kharroubi and H. Pham. Optimal Portfolio Liquidation with Execution Cost and Risk. *SIAM Journal on Financial Mathematics*, 1(1), 2010.

[9] A. Kulesza, M. Kearns, and Y. Nevmyvaka. Empirical Limitations on High Frequency Trading Profitability. *Journal of Trading*, 5(4):50–62, 2010.

[10] S. Laruelle, C.A. Lehalle, and G. Pages. Optimal Split of Orders Across Liquidity Pools : A Stochastic Algorithm Approach. *SIAM Journal on Financial Mathematics*, 2(1), 2011.

[11] C. Maglaras, C. C. Moallemi, and H. Zheng. Optimal Order Routing in a Fragmented Market. *Working paper*, 2012.

[12] C. C. Moallemi, B. Park, and B. Van Roy. Strategic Execution in the Presence of an Uninformed Arbitrageur. *Journal of Financial Markets*, 15(4):361391, 2012.

[13] JP Morgan. Dark Matters Part 1: Optimal Liquidity Seeker (JP Morgan Electronic Client Solutions). May 2012.

[14] Yuriy Nevmyvaka, Yi Feng, and Michael Kearns. Reinforcement Learning for Optimized Trade Execution. In *Proceedings of the 23rd international conference on Machine learning*, pages 673–680. ACM, 2006.

[15] B. Park and B. Van Roy. Adaptive Execution: Exploration and Learning of Price Impact. *Technical Report, arXiv.org*, 2012.

[16] Richard S. Sutton and Andrew G. Barto. *Reinforcement Learning: An Introduction*. MIT Press, 1998.