Optimal trading? In what sense?

Market Microstructure in Practice 3/3

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① Optimal Trading and the Principal-Agent Problem

2 Monitoring Trading Algorithms: A Machine Learning Viewpoint



This session is smaller than the others. We will have talks during the week on optimal trading scheme. We will just focus on few aspects:

- ► The Principal-Agent problem for optimal trading; and potential robust architecture for optimal trading;
- Something unusual: realtime monitoring of trading algorithms .



① Optimal Trading and the Principal-Agent Problem



Monitoring Trading Algorithms: A Machine Learning Viewpoint



- The Principal-Agent problem is raised when someone (the Agent) acts on behalf of someone else (the Principal);
- ► How to guarantee the alignment of interest of the Agent and the Principal?
- Very often the Principal gives accurate instructions and constraints to his Agent, typically in terms of risk taking.
- For trading we have seen the benchmarks (VWAP, TWAP, IS, etc) are used by the user of the algorithm to specify a style of trading. It is typically a kind of risk the Agent can or cannot take on behalf of the Principal.
- Market makers or prop. shops (the purpose of the whole firm is to make money by trading and nothing else) usually do not have to face to the P-A problem.
- One global optimization is better than two optimizations: one by the Buy Side, and the other by the Sell Side.



Going back to different participants and the roles inside each of them:

- ► The portfolio manager build a portfolio. Did he took into account: (1) the intraday market impact, (2) the daily impact? [Garleanu and Pedersen, 2013]
- ► He send the instructions to his **dealing desk**, which often acts as a supplier to the portfolio manager.
- The Dealing desk take the responsibility to send fractions of these instruction to different trading venues and brokers, with associated **Benchmarks**.
- ► The broker trades on behalf of the dealing desk, executing the portfolio manager instructions.
- How to measure the performance of each step?
- How to insure information goes backward too: from the broker to the dealing desk, from the dealing desk to the portfolio manager? This should implement a continuous improvement scheme.

One important task is performed by the dealing desk and the broker: the TCA (Transaction Costs Analysis).



A Principal-Agent problem inside trading algorithms?



In a lot of optimal trading schemes, the control is not the interaction with the orderbook (i.e. send a market order or a limit order), but something smoother, like the participation rate or a trading intensity.

Even if the control is the price to post orders (like in [Bayraktar and Ludkovski, 2012] or [Guéant et al., 2012]), in practice some risk controls have to be added (see [Labadie and Lehalle, 2014] for some details).

Moreover when the trading algorithm is monitored and piloted by a trader, the algorithm is constrained to use parameters easy to understand by a human operator.





In [Bouchard et al., 2011], we proposed to model a trading algorithm in two layers:

- one, implementing a stochastic control scheme, takes care of the scheduling part of the trading logic;
- for this strategic layer, the control is to launch *trading robots*, having random properties (market impact, average price, etc) with known laws;
- these trading robots can adjust their behaviour taking into account the fast fluctuations of liquidity.
- In terms of latency, it allows the strategic layer to be up to 5 minutes away to the trading venues; the *tactics* (i.e. the robots), can be co-located. They report their advances to the strategic layer who adjust his decisions.





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Monitor? what for?



Each trader monitors 150 to 700 trading algorithms.

- algorithms reacts to realtime feeds,
- ► estimates,
- market state.

Algo have "meta parameters" that can be tuned by traders.

An algo (should not but) can have unexpected behaviours (bad logic, bad programming, unexpected inputs).



Knight Capital Reports Net Loss After Software Error

By Whitney Kisling | Oct 17, 2012 5:58 PM GMT+0200 | 0 Comments 🛎 Email 🔂 Print

Knight Capital Group Inc. (KCG) reported a quarterly loss of \$389.9 million on bigger-than-estimated costs from the software error that nearly pushed it into bankruptcy.

The third-quarter net loss was \$6.30 a share, the widest since at least 2001, and compared with profit of 29 cents a year earlier, based on a statement today from Knight and data compiled by Bloomberg. The loss related to its Aug. 1 computer malfunction was \$457.6 million, wider than the \$440 million previous preported. Knight said.

A technology error Aug. 1 bombarded equity exchanges with erroneous orders, leading Knight, one of the largest traders of

U.S. shares by volume, to the brink of insolvency as customers routed orders elsewhere and the shares plunged 75 percent in two days. The Jersey City, New Jersey-based company is now more than 70 percent owned by the companies that balled it out with a \$400 million cash influsion the following week. Almost all customers have come back to the firm, Chief Executive Officer Thomas Joyce said today on a conference call with analysts.

Source: Bloomberg news

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What's this? 27

The 1st of Aug 2012, it is assumed an issue in the deployment of a new version of Knight's software suite conducted them to bankruptcy.

Knight Capital was one of the four market makers on the Nyse. They have been bought by Getco few months later.

It took them 45 min to understand what append and shut their systems down.



Bloomberg

A Print Back to story

Goldman's Options Error Shows Peril Persists After Knight

By Nikolaj Gammeltoft and Alex Barinka - Aug 21, 2013

For all the efforts to shore up electronic markets in the aftermath of one of America's biggest trading catastrophes, yesterday's options malfunction by Goldman Sacha (GS) Group Inc. shows the dangers haven't gone away.

A programming error caused the first to send unintentional atock options orders in the first minutes of trading, pushing projects on docerss of a contract to a oddine schedule control of the sense Stach, the fifth-largest U.S. bank by assets, word 'be known until exchanges determine which contracts should be canceled, said the person, who requested amounty because the information is private.

Investors who for about the increasing dominance of electronic exchanges asy the error at Goldman Sacha, which generated about half to revenue from trading lar quarter, shows that were breakdown as incrivable. A year asy Kajida Cajida Graphia Graphin. Nava pauhod to third of hankrupty by at trading breakdown, and Chinese regulators are investigating broker. Forefight (60;768) Securities Co. After 5;8 billion of incorrect by orders are the Sanghad Composite Tokeu va boot or percent in two minimes last week.

Source: Bloomberg news

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Knight Capital was one of the four market makers on the Nyse. They have been bought by Getco few months later.

It took them 45 min to understand what append and shut their systems down.

Same kind of issue one year later for Goldman Sachs on options market.





The 6th of May 2010, prices dropped on wall street by 10% in 10 minutes

Most probably: the trading algorithms (and specially the market making ones) run for liquidity as a reaction to the large sell of E-mini contracts by an institutional investor.

Circuit breakers did not react as expected.





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Circuit breakers did not react as expected.



What kind of interactions with the trader?



A typical (Bloomberg) screen

Trading algorithms are parametrized via:

- A benchmark, specifying the risk profile allowed (VWAP to follow the usual liquidity profile, PoV to follow the current liquidity profile in realtime, TWAP to be agnostic and conservative, Implementation Shortfall to be fast and price reactive, or Liquidity Seeking to be liquidity reactive), or a combination with switch / cases.
- A set of hard constraints (avoid a given type of trading pools, no more late than ..., or no more ahead than ...).
- Some meta parameters like: aggressiveness, speed, "pegging" on other instruments.

The trader can modify them or call the initiator of the metaorder to give him advices (it is part of the *execution service* provided by intermediaries).



- ► In [Azencott et al., 2014] we define some efficiency criteria Y_t (like performance) and some potential explanatory variables X^t_t,...,X^N_t (like a sector, an increase of volatility, a change in liquidity).
- On the fly (for instance every five minutes), we will **build predictors** $\phi(X) = \mathbb{E}(Y|X)$ of the current performance of all the trading algorithms of a trader using the sector, the volatility level, the liquidity, etc.
- ► The variables succeeding to explain bad performances will be said to be the **causes of bad performance**. That for, we will define the *predicting power* $\pi(t)$ of each variable X^i .



Performances and explanatory variables



- We use the PnL (in bid ask spread) as a performance criterion;
- We use market descriptors: volatility (risk), bid-ask spread (liquidity), and momentum (directionality);
- We renormalize them using their scores (i.e. their empirical likelihood);
- We add patterns: price trends, price jumps and volume peaks.





Scoring increases the "contrast" of the figure.





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- > To be fast and take into account the number of possible predictors given the number of data,
- ▶ at each *t*, we select the 5% worst performances (i.e. *Y* is now zero or one) and try to explain them
- using two-sided binary predictors:

$$\phi(x) = egin{cases} 0 & ext{if } x \in [\theta^-, \theta^+] \ 1 & ext{otherwise} \end{cases}$$

• we choose the thresholds $(\theta^-(i), \theta^+(i))$ to obtain the best possible predictor for each X^i .

(



Generic Optimal Randomized Predictors

Fix a random vector $\mathbb{X} \in \mathbb{R}^N$ of explanatory factors and a target binary variable *Y*. Let $0 \le v(x) \le 1$ be any Borel function of $x \in \mathbb{R}^N$ such that $v(\mathbb{X}) = \Pr(Y = 1 \mid X)$ almost surely. For any Borel decision function $\phi \in \Phi$, define the predictive power of the randomized predictor \hat{Y}_{ϕ} by $\pi(\phi) = Q(\mu, \mathbb{P}^1(\phi), \mathbb{P}^0(\phi))$, where *Q* is a fixed continuous and increasing function of the probabilities of correct decisions $\mathbb{P}^1, \mathbb{P}^0$. Then there exists $\psi \in \Phi$ such that the predictor \hat{Y}_{ϕ} has maximum predictive power

 $\pi(\psi) = \max_{\phi \in \Phi} \pi(\phi)$

Any such optimal Borel function $0 \le \psi(x) \le 1$ must almost surely verify, for some suitably selected constant $0 \le c \le 1$.

(1)
$$\psi(X) = 1 \text{ for } v(X) > c ; \quad \psi(X) = 0 \text{ for } v(X) < c.$$

Meaning that our two-sided predictors are not bad at all when it comes to do something simple. Moreover we have confidence intervals too (see in the paper).



Influence of explanatory variables

We define the influence of \mathfrak{X} a subset of explanatory variables as the **predictive power** of the best predictor:

 $\mathcal{I}_t(\mathfrak{X}, Y) = \pi(\psi) = \max_{\phi \in \Phi} \pi(\phi).$

Remind we do not use the past of the variables X (except to build their *score* and for the *pattern matching* detectors).

We just rely here on the **joint distribution** of (Y, X) over all the instrument currently traded. It means we will use the states of all algorithms to try to establish a relation, now, between bad performances and variables of interest.

At the end of this process:

- ► at each update,
- ▶ we build optimal predictors and combinations of predictors explaining at most current bad performances.
- Implicitly we selected hyperplanes in the space of combinations of our explanatory variables separating trading algos with good perf. vs. bad ones.
- ► Some subsets of predictors are good (i.e. they allow hyperplanes to be efficiently positioned), others are not.
- This allows us to identify variables currently influencing the performances. They are said to be the causes of bad performances.
- ► We present to the trader the summarized information: "sort by this variable if you want to understand what is happening to your algos".



Seen from one trading algo



- ► top: the explanatory variable.
- ► bottom: the performance.
- The performance quantile is in dotted red; around update 40 this algo is 3 times among the 5% worst performers;
- on update 41, the spread score is selected by the good predictors to be used: θ⁻ = 0, θ⁺ ≃ 70%.



Seen from one trading algo



- ► top: the explanatory variable.
- ► bottom: the performance.
- The performance quantile is in dotted red; around update 40 this algo is 3 times among the 5% worst performers;

 around update 32, the volume score is selected to predict bad perf. of other algos.



Seen from one trading algo



- ► top: the explanatory variable.
- ► bottom: the performance.
- The performance quantile is in dotted red; around update 40 this algo is 3 times among the 5% worst performers;

 the volatility score is selected at update 42, but the associated predictors says it is ok for this algo.



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During this talk we have explore two aspects of optimal trading:

- The Principal-Agent problem, or how to conciliate the interests of the end user of the algo (i.e. the issuer of the metaorder) and the actions of the trading algorithm (the kind of risk it will take or not). And we have seen this kind of problem arise inside the life cycle of the trading algorithm itself.
- I opened the topic of algo trading to machine learning and big data , even further than what we did with Laruelle and Pagès in our two joint papers ([Laruelle and Pagès, 2012] and [Pagès et al., 2011] ; see also [Kearns and Nevmyvaka, 2013]).
 I hope I convinced you TCA is a wonderful field of applications for ML.



We went together trough the following questions:

- Part 1. The last few years, we have seen the emergence of continuous trading on equity markets, it had (unexpected) consequences as a deep modification of the role of market makers. Will any market evolve to the same state, or will some markets stay in a different, less liquid one, forever?
- Part 1. The concept of intermediation is at the core of the functioning of the financial system, could we use our tools to shed light on the system itself?
- Part 2. The big question in modelling is how mechanical and informational effects mix to move the price? To my eyes, too many models today embed the answer to this question ex ante, hence they cannot provide an answer.
- Part 2. As usual in control: the specification of the utility function and the accuracy of the parameters of the models are of importance. Do we have enough specifications? Do we know what to do when the signal over noise ratio is bad? My answer to this second question is to switch from stochastic control to machine learning.
- Part 3. We questioned the role of the specification of the utility function: what would a multi-scale architecture for an optimal trading system?
- Part 3. Practitioners use machine learning in optimal trading and microstructure more than it appears, where are the theoretical papers?

In terms of future directions of research, the only point I could add is to note that if you put some of these questions together, you often obtain a mean field game, or at least a differential game...



And more...



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