Artificial intelligence approaches to convex market strategies

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September 3, 2020

Introduction

Axinoss Ltd, founded in 2019 and based in the greater Helsinki area in Finland is a research and development organization for AI-powered algorithmic trading and risk taking strategies towards successful long-term capital management. In this article we outline the background for our current philosophical framework on approaching the problem of capturing alpha in the complex environment of dynamic markets, our strategy for avoiding ruin and enabling long-term, profitable capital management. This is a non-technical overview, intended for a larger audience. For a more, in-depth technical overview for the curious, please contact our research department at *research@axinoss.com* or visit our website at *www.axinoss.com*.

1 Background

Axinoss was founded on the basic idea that the models describing successful capital management strategies should be 1) data driven and 2) end-to-end 3) long-term and 4) optimal. Should there exist a successful strategy, it should emerge directly from the data and without human intervention and in a way that survives in the future, producing optimal gains. Such a model would not require explicit human design for boundary conditions, parameter tuning or other factors that risk introducing bias to the outcome. Alas, one of the biggest obstacles for long-term automated capital management is the lack of quantifiable knowledge the current strategy produces about itself. Human devised, static, rule based systems work - until they don't, prompting the development of new strategies. In some cases this insight comes *late*, sometimes too late, leading to the subsequent collapse of the fund and loss of assets in their entirety - or in other words, *ruin*.

The problems many hedge funds, algorithmic trading companies and capital management firms face arise from that a) static models cannot account for the evolving Nth degree dynamics of the markets b) the theoretical background traditionally used for describing market dynamics is inherently flawed. Additionally, the traditional methods for evaluating the potential success of a strategy, such as backtests, don't necessarily tell anything about the future performance, especially so if excessive human intervention is introduced in the design process (again, bias). On the other hand, a strategy that's developed on top of the flawed theoretical framework will most certainly be extremely fragile and at constant risk of ruin (there are plenty of historical examples of this).

The latter point is easy to see. The traditional economic modelling approaches assume that market returns are at the very least approximately Gaussian distributed and build the mathematics on top of this assumption for price dynamics, volatility dynamics, options pricing and risk management. This premise leads to extremely fragile models that massively underestimated the probability of *catastrophic* events, such as the multiple market crashes we have experience in the last 100 years.

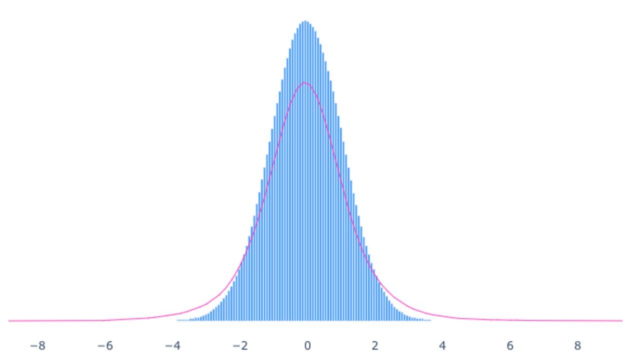

Figure 1: *The assumption of Gaussian distributed market dynamics (blue) does not hold empirically, as the true distribution is long-tailed, often fat-tailed and conditionally skewed (red)*

In fact, a single observation outside the expected scope of Gaussian dynamics (6, 8, even 15-sigma events) during the entire lifetime (including future) of the human economic system is sufficient to falsify the entire theoretical basis.

The true (and empirical) behavior of market dynamics is neither *Gaussian*, nor *Mediocristanian*-stable in any other sense, but instead complex, wildly random and highly unstable, *Extremistanian*. The empirical distribution of market returns exhibits long tails, sometimes fat tails and high skew, wild randomness, an elevated probability for extreme events as well as fractality at every scale. All factors that lead to unavoidable ruin under fragile assumptions.

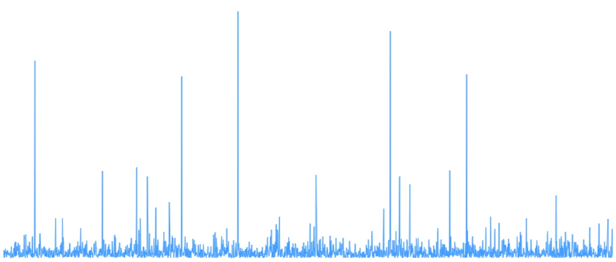

Figure 2: *Example of wild randomness in the volatility dynamics of the cryptocurrency markets. To assume Gaussian (=mild) randomness is to misrepresent the problem to such degree as to render any further decision making, strategy and risk management entirely useless.*

Furthermore, market dynamics *evolve* over time, so for any system that intends to survive optimally in that complex environment must evolve with the market (what was optimal before is probably not optimal anymore). Interestingly, it can be shown that market dynamics evolve *towards approximately Gaussian* given infinite timescale (towards maximum entropy) but from a survival perspective at the present moment, that is neither here nor there due to ergodicity (market participants that hold fragile assumptions will not survive to the end). This calls for dynamic approaches, strategies and rules that evolve over time and hence, survive in the long-term.

Such a system must be 1) *convex to model error*, benefiting from unpredictable extreme events 2) *able to prove its optimality* by quantifying its own knowledge. It is these premises that our risk taking approach is based on.

2 Our approach

In recent years, deep learning has had a tremendous success in areas where human-designed rule based systems fail, due to the ability to capture complex non-linear dynamics. This value proposition has been the main source of motivation for Axinoss' approach since the beginning, but the topic has remained largely unexplored in the financial industry.

In fact, the value proposition is so attractive, that the internet is littered with naïve examples on how to use deep neural networks for market prediction. One Google search reveals dozens of articles on attempts at predicting next-day returns using LSTM networks. Unfortunately, all of these approaches fall prey to the same, extremely basic errors, which is why none of them work. Additionally, there are numerous research papers on this topic, some of them useful, most of them useless (making similar errors elsewhere). It turns out it's not completely obvious *how* the recent advances in deep learning could be helpful in this industry, which is why its potential has been largely ignored.

Technically, it holds that any complex system with Nth order non-linear dynamics can be described as first order linear dynamics, given some boundary conditions and non-linear state augmentation. This is precisely how we approach the problem and how AI becomes beneficial. By leveraging deep learning, the non-linearities of market dynamics can be captured in a state augmentation, on top of which simple, dynamic rules for maximal long-term profit (survival) can emerge. For daily automated trading, the problem reduces down to estimating the odds of some market events, computing the exposure and applying risk management. The end rules need not to be complicated if a state augmentation is sufficiently accurate and exposure to tail risk is properly managed. No matter how complex a model, the probability of a tail event itself cannot be "measured" but *exposure to risk* can be, which is why it's possible to capture excess return in the markets.

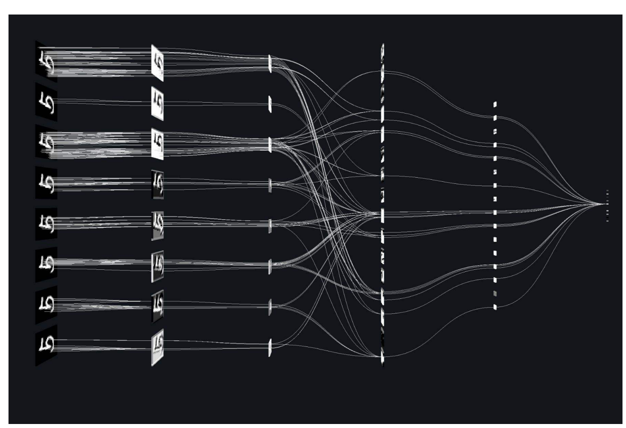

Figure 3: *How can deep learning be leveraged in capital management?*

2.1 Capturing alpha

Our approach to capturing alpha in the markets is quite simply the following: we identify *fragilities* in the market structure by capturing its dynamics using non-linear state augmentation and then optimally exploit those fragilities with dynamic, evolutionary rules (that have emerged from survival). Convexity to payoffs is at the heart of our method, meaning that the most alpha is captured by the strategies that are inherently *antifragile* in nature (they benefit from model error and extreme events, instead of collapsing). Generally our exposure is small, payoff is massive. Being wrong often doesn't matter if being right pays big. We benefit directly from high volatility.

3 Algorithms

Currently, our most successful approaches to capturing the non-linearities of market dynamics are our 'AlphaHedge' and 'AlphaGen' algorithms. In short, 'a-Hedge' learns to model the technical fragility of a position, conditioned on the current market state, allowing us to estimate price breaks and the probability of liquidation levels in discrete time. 'a-Gen' is a generative neural network that learns the spatial distribution of price dynamics, and can lend itself to a similar strategy. More importantly, it captures the full conditional distribution, including volatility. 'Conditional' meaning here, that the output of both algorithms is conditioned on the present market state (up to some temporal sample size), which allow them to capture the possible skew. 'a-Gen' directly learns to synthesize the spatial price distribution (and hence, volatility), which allows us to very accurately price options and compute odds for future states, producing an edge. Using 'a-Gen' we are able to compute the statistical odds of billions of different outcomes in the market, which is equivalent to having millions of years of historical data as reference.

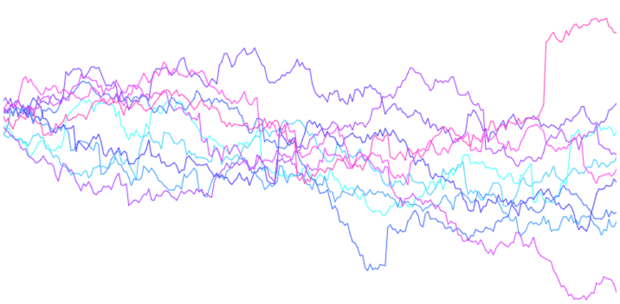

Figure 4: *Examples of synthetic samples generated using 'a-Gen' for XBT price dynamics*

The benefit over traditional Monte-Carlo forward simulation is that 'a-Gen' doesn't make any initial assumptions about the underlying distribution. It is therefore fully agnostic to whatever market one wishes to model, irrespective of current state and maturity. It converges very closely to the true empirical distribution of the market (by EMD metric), allowing it to capture any potential a) technical patterns b) volatility clustering c) mean-reverting behavior and so on. Computing the statistical odds for conditional scenarios allows us to identify structural fragilities and apply optimal betting strategy on the outcomes.

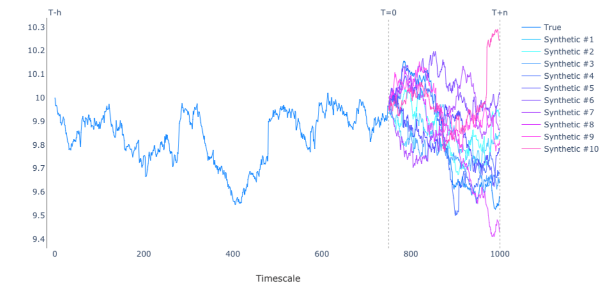

Figure 5: *Examples of conditional outcomes generated using 'a-Gen'*

Additionally, as a by-product, 'a-Gen' produces a state augmentation (a vector representation of the captured non-linear dynamics, which can be used for clustering, dimensionality reduction and so on) as well as measures its own error - in other words knowing what it doesn't know. The model error for any given market state can lend itself to adjustments on optimal decision making.

Our decision making systems are either based on a) the statistical odds computed from synthetic scenarios and log-growth maximization of capital (simple) b) reinforcement learning from state augmentation (complex, differentiable rules) or c) a population of simple heuristics that have genetically evolved to survive the markets (ability to describe non-differentiable rules). All of these these methods achieve the same thing, but in a different way and the specifics where each method work best is an active research area at Axinoss.

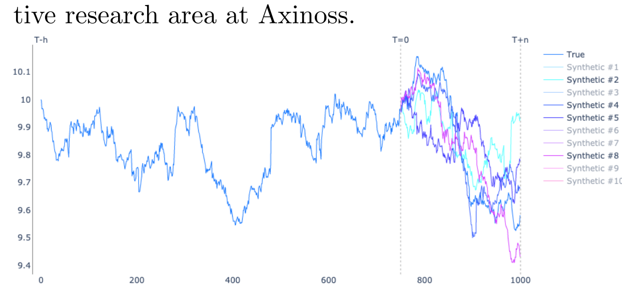

Figure 6: *Making no assumptions about the underlying distribution and learning from the data produces better estimates than traditional approaches*

4 Risk approach

Successful algorithmic trading is really only about 1) finding a way to estimate the odds of some outcomes 2) risk management by proper bet sizing on the odds. The former is solved by good understanding of the market dynamics but the latter, more importantly, is partly a mathematical problem, partly a philosophical one (owing to the unavoidable error in the former and the inherent randomness of the market system).

A mathematical framework already exists for maximizing long-term capital growth, given odds of outcomes and is widely applied but the philosophical framework by which one chooses to operate divides organizations in this industry into three groups 1) fragile 2) robust 3) anti-fragile. We choose the latter as it's the only way to operate that guarantees long-term survival under complex dynamics. Additionally, we exploit the fact that market structure is fractal, and as such there always exists enough opportunities to benefit and generate profit. Our edge comes precisely from the fact that other market participants choose to be fragile.

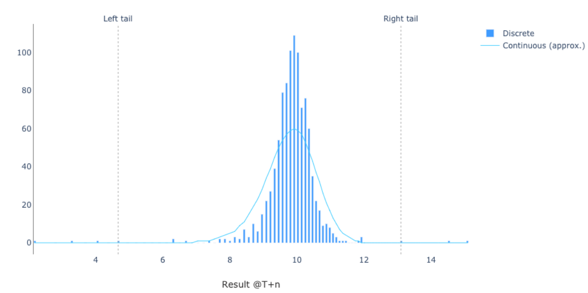

Figure 7: *Our approach benefits from high-impact tail events. Fragile market participants risk a permanent ruin, which is why they might be unable to operate in some markets.*

Convexity to payoffs simply means that your downside is capped and upside is (near) unlimited. The opposite of that is concavity, which is the de-facto for fragile market participants. In practise, our strategy involves taking a lot of small losses and rarely a profit. However, when a profit scenario plays out, the payoff is so large that even a long series of losses is rendered utterly insignificant in proportion to the outcome*.

How can we guarantee long-term success? The answer is again, *antifragility* and 'entropy advantage'. In technical terms, whoever assumes Gaussian market dynamics will always have an informational disadvantage as it is the maximum entropy distribution for an unbounded real valued range of outcomes. As long as there are *some* market participants that hold this view, there will be an edge for operators such as Axinoss.

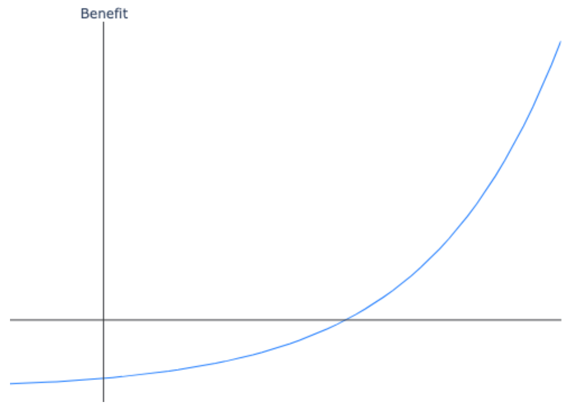

Figure 8: *Convex response to events produces disproportionally large* ***payoff*** *as the event size increases. High impact, rare events are welcome.*

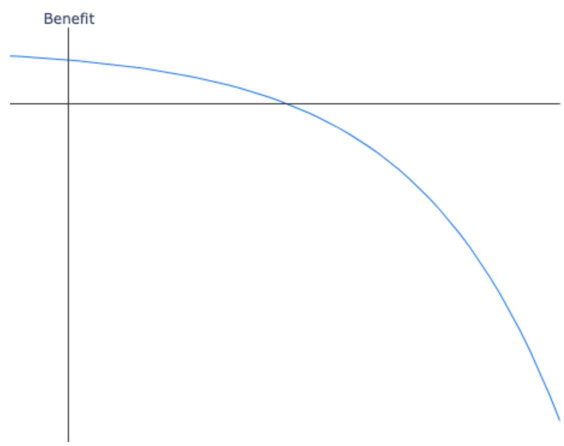

Figure 9: *Concave response to events produces disproportionally large* ***harm*** *as the event size increases. High impact, rare events are unwelcome (possibly deadly)*

1. *Mediocristan* simple outcomes	2. *Mediocristan* complex outcomes
3. *Extremistan* simple outcomes	4. *Extremistan* complex outcomes

Figure 10: *Antifragility allows us to operate in the fourth quadrant, where traditional methods fail*

**Some people prefer to call our style of operations 'Black Swan funds'. Black Swan is a name given to extremely rare, unpredictable, high-impact events. Due to the fractal nature of the markets the so called 'rare-events' that benefit our strategy are really not all that rare, depending on scale.*

5 Current operations

Our framework is completely agnostic to in which market one chooses to operate, but since our strategy directly benefits from high volatility, we mainly operate in markets where extreme events are abundant. The cryptocurrency markets are a relatively new (and extremely inefficient) market, at the very beginning of its evolution cycle. There is a tremendous amount of illiquidity and information asymmetry in the cryptomarkets, causing high volatility and unpredictable gaps. However, the market is mature enough, such that various instruments - including complex derivatives, already exist allowing us to operate and scale efficiently. Our technical platform includes integrations to high volume crypto exchanges such as BitMEX and Deribit. Future scaling or strategic interest from Axinoss' partners might require integrations to more traditional market operators, but presently there's no incentive for us for that.