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Blue pill or red pill? Common myths in quantitative strategy research

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ABSTRACT: Quantitative signal research has been one of the most challenging missions in finance, for mistakes are easily made and rewards are scarce. The Pareto principle and Matthew effect of accumulated advantage applies well in the asset management industry as any other fields, if not more so. What are the common myths researchers encounter? How do experienced portfolio managers tackle these problems? We present typical myths in trading signal explorations, discuss why they come into being and point out potential solutions for those interested.

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1 Introduction

In the world depicted in the critically acclaimed movie 'The Matrix', you take the blue pill and the story ends, you wake up in your bed and believe whatever you want to believe - falsehood, security, happiness and the blissful ignorance of illusion. However, if you take the red pill, you will be offered knowledge, freedom, adversity, with the brutal truth of reality.

Do you get a funny feeling that the entire market is moving against you all the time? Why does it always move in the opposite direction against my bets? Why doesn't the whales just let go of my tiny thousand-dollar position? Why does everybody else claim to make a hell of profit, and I always seem to be the compromised?

First of all, this is largely a psychological effect in consequence of evolution - humans are born to be risk averse. You are actually doing better than you think, and just happen to magnify the result from bad bets instinctly. You are not alone, all portfolio managers and traders are facing the same conundrum - market drawdowns bring us far more negative feelings and memories than rallies. They affect your trading decisions if you don't keep them under control. This is an important reason many individual investors buy high and sell low at wrong times. The best way to fight against it is to persevere in a systematic, working strategy and keep improving it year after year.

However, it would have been too easy if that's the full story. Aside from psychology, the construction of trading strategies are easily swamped in a few common myths. These are hazadous zones even experienced and successful fund managers must tread carefully. We discuss in this article the typical mistakes researchers make in developing new strategies, and ways to cope with them properly. Section 2-7 discuss the symptoms, reasons and solutions to overfitting, forward-looking bias, selection bias, reliability in consolidated prices, issues in intraday candlesticks and transaction costs, respectively, followed by concluding remarks and open brainstorm in Section 8.

This article is intended for generic readers with all backgrounds, and the scope goes beyond just cryptos.

2 Overfitting

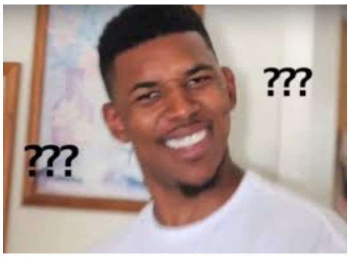
You took a crypto and analyzed it with a few common indicators, conducted fine-tuning in a large, multi-dimentional parameter space and determined the best set. But when you applied this set on simulated or live trading, the signal vanished or diminished significantly.

Thus Spoke Katula: Simple predictors like technical indicators are usually limited in predictive power. When you optimize them along backtests, a default assumption is made: these indicators are informative and valuable. This is however not always true and should be examined closely and proactively. Moreover, even if the indicator offers guidance for market signals, one must avoid overfitting, as it brings overly optimistic results far from truth.

Solution: Select appropriate indicators with systematic rules. Good strategies are usually based on a straightforward and reasonable vision neither too complex nor too simple. It is usually difficult to find good strategies out of publicly available data such as price and volume. Fit the data conservatively, or look for signals with artificial intelligence or machine learning techniques. These advanced methodologies are better means to search for needles in the big data heystack. We noticed a trend lately that top IT talents joined renowned high frequency shops or hedge funds. As AI technology progresses, the financial markets become more and more efficient, and professionals have been setting and pushing a bar on alpha research beyond the reach of most entheusiasts outside quantitative or coding backgrounds. If you are interested to develop your skills toward machine learning in your spare time, the testbase on Kaggle is a good entry point to get started.

3 Forward looking bias

You found the top cap underlyings, checked their historical performances and discovered a few nice patterns. Perfect! And you started to construct your trading strategies. But the signals with great historical performances behaved quite differently in live trading.



Thus Spoke Katula: Do your historical data contain information from the future? Any quantitative research requires or favors point-in-time data. We can't emphasize more about its importance. This means all data used in backtests should be available or readily attainable upon every timestamp. When you select today's top cap underlyings for historical backtests, an implicit assumption is made that you knew about their future success, but that wasn't necessarily true back then. According to our previous statistics in Ref. [1], most top cap crypto dropouts failed to beat Bitcoin. If you select the universe point-in-time, the results would be quite different.

Another type of implicit forward looking bias has to do with data vendor's backfill methodology. For instance, a vendor established their business in 2015 and provides data since 2011. It is critical to find out how they obtained data between 2011 and 2015: did they collect them real-time, purchase them elsewhere, or simply backfill by certain rules? Simple price-volume and cap data are likely fine, but complex ones such as news, sentiments, rankings, company fundamentals must be collected and posted point-in-time to be trustworthy, as they are easily modified ex post to meet certain expectations, intentionally or not. Smart and experienced vendors collect and package their point-in-time data for a higher price. The backfilled data usually carry some hindsight, which compromises their reliability to a good extent.

Solution: Document all information and data collections with accurate timestamps. Construct your strategy on real-time data readily obtainable on each timestamp. Backfill with conservative estimates, and avoid capturing any information from the future at any point of time.

4 Selection bias

After careful preparation over a while and lots of trials and errors, you identified 100 systematic strategies. Some of them were based on single names, some multiple. They all varied in research methodologies, but all made sense in some ways and performed well in backtests. You ran them in simulated trading and combined them as appropriate, but were shocked after some period of time - their out-of-sample behaviors turned out very different from historical performance, and the combined strategy seemed almost flat!

Thus Spoke Katula: How many times did you trial for a tradable strategy? The issue arised from the number of trials you conducted and errors you disposed of. If you tried 100 times, found half of them profitable and picked the best 10, be warned. Strategy research is a cruel domain. Unlike the realm of scientific discoveries and inventions where single and repeatable experiment proves or disproves everything, if you don't do it right, your result is mostly likely a statistical fluctuation. We present a straightforward example here. Let's generate 100 time series for daily rates of return out of a standard normal distribution. Their cumulative P&L over the last 4 years are shown in Fig. 1.

Intuition and commonsense from statistics tell us, the final returns of these 100 'strategies' follow the standard normal distribution too. We take the first 3 years as in-sample, and the last year as out-of-sample, correponding to the left and right areas beside the vertical splitters. Now we pick the top 10 in-sample performers in returns (circled in red) and combine them with equal weights. Fig. 2 shows the combined portfolio performance. We see the strategy performs well in the first 3 years as selected and expected (in-sample, left of vertical red line), but poorly in the last year (out-of-sample, right of vertical red line). The reason is straightforward. We generated these time series out of random numbers, and

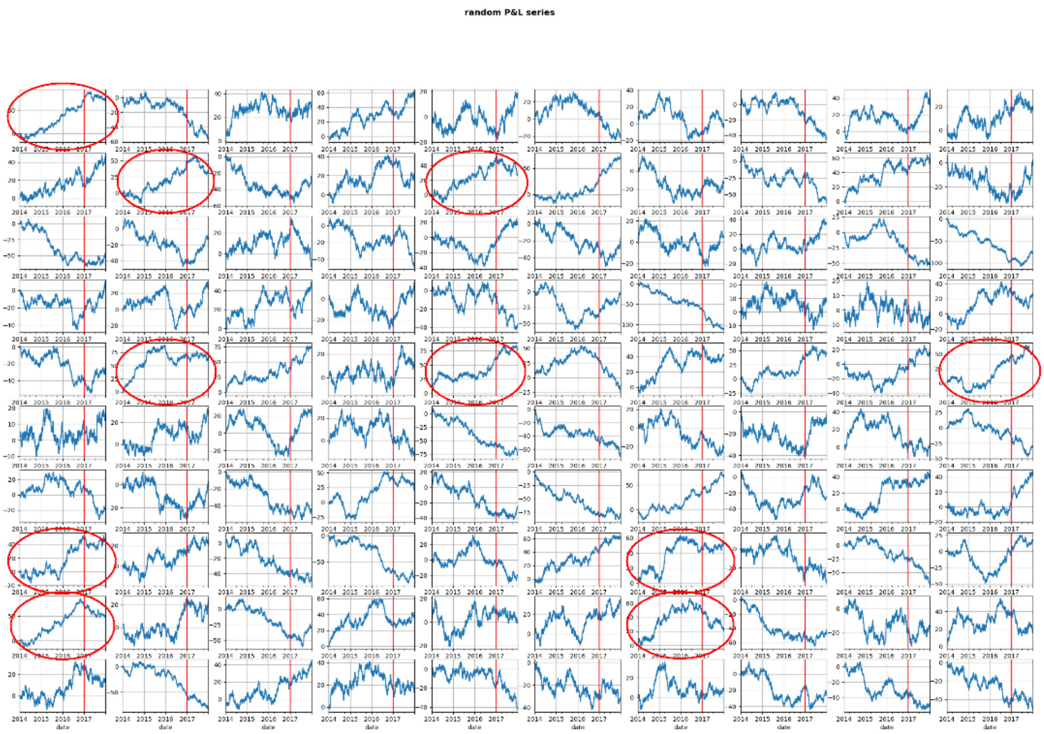


Figure 1. The cumulative P&L out of 100 time series of random daily rates of return, generated from a standard normal distribution. The in-sample and out-of-sample stay to the left and right of verticle lines, respectively. The circled are top 10 performers over in-sample returns.

the simulated trading in out-of-sample is but the mean of 100 random series as well. By the law of large numbers, the more 'strategies' involved as such, the more horizontal and straight the cumulative P&L would be out-of-sample. It is also easy to verify this directly from Fig. 1, that the chance to profit is about 50% in the full ensemble, either in-sample or out-of-sample, and also about 50% out-of-sample for the top 10 in-sample picks circled in red. Now you see how easy it is to pick ambiguous strategies among a large number of time series out of trial-and-error. Many of them are inevitably statistical fluctuations and not really applicable, let alone those appear to make sense, but actually do not for reasons one isn't aware of due to limited understanding or resources.

When your research advances to a certain stage, you would realize that the effective distinction of true strategies and random series is the divide between excellent fund managers and the crowd, either in strategy picking or talent hiring. An independent trading team in a quantitive fund relies heavily on the portfolio managers (PM) and quant researchers. The PMs decide final positions based on multiple quant models, and take responsibilities on the P&L. The researchers are responsible in proposing alpha or beta models without taking capital risks. Their ratio is typically 1:3 to 1:10, and the de facto divide between them is the ability and experience to select and invest tradable strategies. This is a challenging

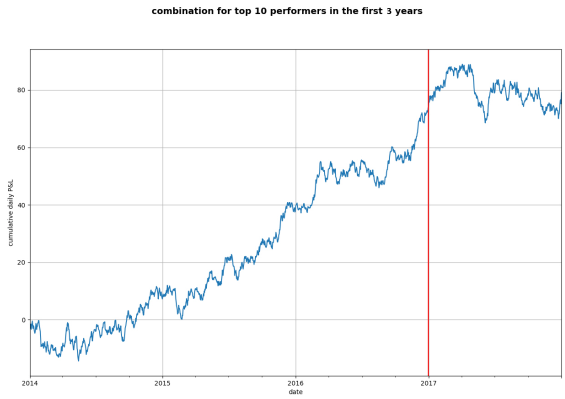


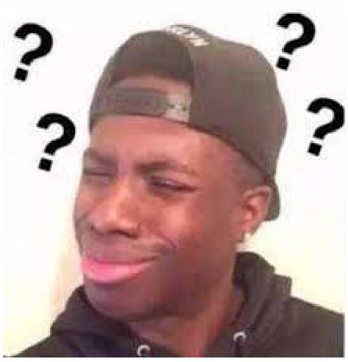
Figure 2. The cumulative P&L of the equal weight combination on the top 10 in-sample performers in returns.

task all hedge funds pay dear resources to accomplish, and quite likely tougher than most people think.

Solution: Develop strategies backed by economical, financial or value-investing principles and avoid overly complex research methods. Lower your expectations. Admit and assume that all new strategies could perform differently in and out-of-sample. Paper trade for some time before any massive capital allocation. Size up prudently and gradually. The time it requires to paper trade is contingent on the out-of-sample performance - shorter if pretty good and vice versa.

5 Executability of consolidated prices

You analyzed data on Coinmarketcap, found some interesting pattern, developed some strategies and paper traded them for several months. The out-of-sample looked good and cleared, no problem! But when you started live trading, the P&L achieved ended up quite different.

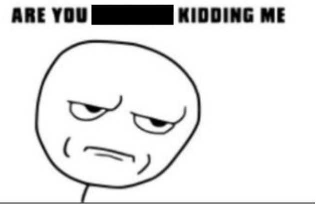


Thus Spoke Katula: If your strategy is somewhat sentitive to the prices, that's usually because a relatively high trading frequency results in higher turnover. It is perfectly fine, but did you ever wonder if the data you backtested upon might not be as reliable as you thought? Coinmarketcap and most websites offer consolidated prices, i.e. a weighted mean price across multiple exchanges, usually by liquidity but sometimes other factors weigh in too. However, the consolidated price isn't necessarily tradable in specific exchanges especially if your volume is high.

Solution: Trade less if you can, and use the actual data from the exchange for backtests. The length of such data is usually not long, and consolidated prices are still needed beyond a certain point, but one can at least try to confirm the recent performances with available data from the exchange. The result is usually worse than your backtest, intraday trading in particular.

6 Reliability of interval prices

An expert in big data analysis, you found the volatility in cryptos much stronger than the stock market and feature distinctive patterns. You went ahead and built a machine learning based strategy on 5-minute prices. The performance was strong historically and out-of-sample, but diminished a great deal, flattened out or went south in live trading.



Thus Spoke Katula: The shorter the candlesticks the less reliability, even a different exchange could give you distinct results. As all roads lead to Rome, there are 5 ways to define a 5-minute interval, one can start from the first, second, third, fourth and fifth minute. If your strategy works on one of them and performs poorly on some others, there could be implicit overfitting. Moreover, the longer it takes to compute signals, the more uncertainty in live trading. Since the order book depth and slippage vary across different exchanges, the backtested and executed prices could be quite different.

Solution: Use different ways to construct your candlesticks, and test performances separately for intraday strategies in particular. Beware and stay alert if you can't profit in the worst scenario.

7 Transaction costs

Your historical backtest soared straight up! Exhilarated and motivated, you tested the strategy live for a couple of days and the performance went straight down?

Thus Spoke Katula: You may or maynot include the transaction costs in massive back-tests, but the bottom line is to keep your eyes wide open on the turnovers. There is a big difference in costs between monthly and daily rebalancing, for which reason most alphas or signals seem to exist before cost but evaporate after. Also, the total cap and volume in the crypto market aren't big enough for now, and lack of liquidity means the bid and ask spread is insufficient to estimate the transaction costs. One must calculate the executable prices with an in-depth order book on your capital size, or equivalently, estimate the capacity of your strategy based on the average liquidity of cryptos involved.

Solution: Trade less often and trade small. Estimate the transaction costs as accurate as possible. A conservative methodology and defensive mindset go a long way.

8 Conclusion and brainstorm

We reviewed the common myths, possible reasons and potential solutions in quantitative strategy researches. This is however a lightweight overview intended mainly for readers without a financial background in the buy side.

Now that you have a better idea in quant research, let's work on a few interesting open questions and brainteasers. Don't be surprised if you ran into some of these in a quant interview, crypto or not!

1. All bubbled market participants are entheusiastic about the hunt for the next hundredfold underlyings, crypto markets in particular. What are the potential myths in those predictions? What if one attempts to predict tens of cryptos separately over the course of weeks? Assuming faithful without further modification, are those historical snapshots or analysis on single-name predictions trustworthy? What is it to gain if one keeps doing so?

2. If you make predictions often, and many readers referenced your suggestions to trade (not necessarily a strict copy), what happens? Will they believe you if you are an ordinary predictor? And can you come up with predictive methods with almost 100% success rate under certain circumstances? No cheating of course. Hint: what if you offer an entry point without an exit point in a highly volatile (even better, growing) market like the cryptos?

3. Why is auditable or verifiable track record so important? Why do professional hedge funds always emphasize 'past performance is not indicative of future results'? Why do they accept capital from accredited investors only?

4. Does it help if a fund issues decentralized tokens? Any pros and cons? What use cases can you imagine? How would you price the tokens? Would it be higher than the redemption price the fund offers (if applicable)? Why? Should a crypto fund raise fiat or cryptocurrencies? What standard(s) should they be based upon in P&L reports and settlements? Does it differ between a mutual fund and a hedge fund?

5. How would you pick a competent fund manager to invest with? In other words, if you are the CEO, how would you pick adequate and qualified portfolio managers and quants to work for you?

References

[1] K. Lamperouge, *founder of cryptosmartbeta.com*, https://cryptosmartbeta.com/fallen-angels/, 2018.