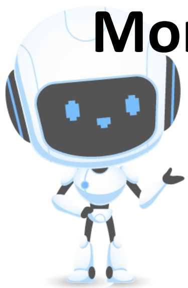

More Info than You Probably Wanted About what goes into OVTLYR

The Wisdom of Crowds

In 1906, British scientist Sir Francis Galton attended a farmers' fair where a contest was being held to guess the weight of an ox. Contestants ranged from professional livestock ranchers to inexperienced villagers. None of them guessed the correct answer, but when Galton averaged the nearly 800 guesses not only was the average better than any single entry – including those of cattle experts – it was also within 1lb of the 1198lb animal (99.92% accurate).

This is the "wisdom of crowds" phenomenon, where large groups offering independent diversity of thought may arrive at a more accurate estimate than even industry experts. As Aristotle pointed out in book III of *Politics*:

> "It is possible that the many, no one of whom taken singly is a sound man, may yet, taken all together, be better than the few, not individually but collectively."

The Foolishness of Herds

Not all crowds are wise. In James Surowiecki's 2004 book The Wisdom of Crowds 5 key elements are necessary to differentiate between wise (and otherwise) crowds:

1. Diversity of opinion.
2. Independence.
3. Decentralization.
4. Aggregation.
5. Trust.

Unfortunately, groups attempting to work collectively have a tendency to revert into herd mentalities, where an individual deemed an expert in the field is, either explicitly or implicitly, designated the "leader" of the herd. This hierarchy quickly dismantles the key elements of a wise crowd, as the group differs to the opinions of the leader to their own detriment.

Expert Opinions

We love our experts, from the mechanics who fix our cars to the doctors who fix our bodies. Although we can generally rely on experts in favor of novices to solve readily apparent problems (a mechanic could far more efficiently rebuild an engine block than I could), trouble arises if the problem being solved is of a subjective nature (look up a few of your favorite shows on Rotten Tomatoes and see what the critics think of your viewing choices). It's even worse once we start asking for predictions of the future.

When it comes to the most significant issues – finances, health, etc. – we crave certainty of the future above all else. We expect our experts to provide that certainty, but these expectations are often unmet. CXO Advisory Group conducted a study of nearly 70 well-known financial experts and their forecasts between 2005-2012. The mean and weighted accuracy of over 6,500 total forecasts were both just north of 47%, and less than 40% of these influential and highly respected experts maintained an average accuracy equal to or greater than 50%... less than 2 out of 5 were as good or better than a coin toss. Similar studies on the predictions of large financial institutions rather than individuals have revealed even less appealing outcomes.

This sort of predictive shortcoming transcends industries to varying degrees in which those requiring frequent or crucial (or both) predictions suffer the most. The argument is held by some that alternative motives may drive experts to give an opinion which aligns with their incentives, and this may occur to some small extent. However, according to Johns Hopkins, medical error accounts for over a quarter-million deaths in the U.S. per year, making it the third-leading cause of death. Certainly, there are not 251,000 annual instances – or even a meaningful fraction thereof – in which a doctor kills a patient for their own benefit.

The takeaway is that, although one person may be highly trained and skilled in a given area – far more so than a novice – individuals are simply bad at making predictions.

How does a Group Predict Better than Experts?

The short answer is: no one really knows yet. There are some areas we can explore to help first identify what can lead individuals astray, and how group efforts might mitigate those risks in much the same way diversification of assets can reduce the risk of holding a portfolio.

(Ir)rationality

Generally, people are not rational. They are *efficient*. The vast majority of our day-to-day choices are decided heuristically, where we rely on the outcomes of previous decisions and their similarity to the one currently being made. For example, you may check traffic reports before your first day of work in a large, unfamiliar city, but soon you will develop a reliable pattern that – outside of a major catalyst, say, a blizzard – eventually becomes "your" route. When approaching a red traffic light, you don't stop to consider the low probability of receiving a citation for blowing through it. You don't even think about the high price to pay for potentially causing a major accident, because you've already solved that problem in your head long ago. And so, you stop. When reading the word "blink," over 75% of readers will physically blink (were you one?), but they probably didn't do so after a thoughtful consideration of the rational merits of blinking at that time.

Blink again. Building on over 200,000 years of human survival, heuristic thought is estimated to be exponentially faster, more efficient, than rational thought, and without it we would be able to complete only a fraction of our daily tasks. These mental shortcuts also allow us to build upon prior information, saving us from repeating elementary decisions as we process more complex problems. However, we become error prone when heuristics and various forms of cognitive biases permeate areas requiring deeper analytical thought.

Psychologist and Nobel Memorial Prize in Economic Sciences winner Daniel Kahneman explores the depths of fast, heuristic logic and slower, methodical reasoning in his 2011 book Thinking, Fast and slow.

Cognitive Biases

As of today, there are over 200 identified, categorized forms of cognitive bias, roughly half of which can have a direct impact on the actions of a market participant. A fraction of those not only can have a powerful affect in terms of outcomes, but are also highly prevalent amongst most everyone you meet (including those you may find yourself trading against).

Contrarianism

"Buy when markets are fearful and sell when they're greedy," we all know the quote. The trouble is that "fearful" markets – when there are many more sellers than buyers driving prices lower as investors flee – are by definition lacking buyers to support valuations. It is natural for people to capitulate to the crowd, and likewise very difficult to oppose the overwhelming majority, especially in the face of falling prices in real time, where the sellers appear to be right. But this contrarianism is exactly what is required in order to "buy low and sell high."

To make matters more challenging, constant contrarianism has proven extremely detrimental to financial health. Consider being short the SPY (or some other broad index) and long the VIX (volatility index) over any considerable period of time: There may be brief instances when this yields a gargantuan payday like during the financial crisis of 2008, but generally this would be a painful position to hold.

The key to effective, selective contrarianism is to recognize opportunities where the majority have devolved into states of fearful panic or greedy euphoria, differentiating those from situations where there is reasonable justification and proportional changes to an asset's value (even if you disagree with the change). This is orders of magnitude easier said than done. For a deeper dive, Adrian Iliopoulos leads a fascinating dissection of contrarianism in this article.

Game Theory

Game theory is the mathematical study of strategy involving two or more rational contestants (who can be either cooperative or non-cooperative), each with multiple choices or sequences of choices. In modern use, the term “game theory” has become something of a catch-all phrase for the science of logical decision-making, but it’s worth questioning how logical people’s actions actually are.

It’s nearly impossible to talk about game theory without mentioning mathematician and Nobel Prize winner John Nash, famous for the Nash equilibrium and portrayed by Russell Crowe in the 1998 film *A Beautiful mind*. He proposed that when no player can increase their expected return by changing strategies while all others’ strategies remain constant, then equilibrium is achieved (this video has a quick introduction with examples). However, both the Nash equilibrium and later Rationalizability (Bernheim & Pearce) require rational participants.

It is possible to simultaneously have a completely rational desired outcome – to “win,” or in the case of investing to capture a greater return – while also taking irrational measures to achieve that goal, like a military victory attributed to doing what the enemy never expected. Have you ever watched people playing tic-tac-toe, and one of the players makes an obviously foolish move? What about situations where the obviously foolish move still resulted in – perhaps even fundamentally caused – victory?

Not every game is as simple as tic-tac-toe. When interacting with markets, the logical, rational choice is seldom readily apparent, and as we’ve already explored, participants are frequently hindered by an assortment of cognitive biases. These biases are left to fill the voids created by the lack of a clearly preferable option, influencing outcomes tick-by-tick, day-by-day, year after year, even if you make no changes to your portfolio, because even inaction is a choice.

Efficient Markets

Efficient Market Hypothesis is the theory that all known information related to an asset is reflected in the asset’s current price by way of the immediate repositioning of rational market participants. Therefore, the current price is always “correct.” In today’s world, it’s true that information arbitrage moves at near-zero latency. As the joke goes, by the time you hear about a hot stock tip, it’s already too late. However, a correct current price can have little relevance weeks or months into the future. This is the nature of speculation, where wins and losses are attributed to luck according to EMH, but there are obvious cases of broader irrationalities leading to market inefficiencies. Nobel laureates Eugene Fama and Richard Thaler discuss this in greater detail in this Chicago Booth Review from 2016.

As you've probably guessed by now, another leading criticism of EMH is the dependence on participant rationality. So, what does it look like when some market participants – perhaps even the overwhelming majority – behave in seemingly rational ways while others "go rogue?"

Our internal research as well as that of many other entities reflect similar findings: markets with higher liquidity, and thus greater price discovery, have lesser deltas between top and bottom quartile performance, sometimes approaching but never achieving zero. This would suggest market efficiency is better understood as a distribution variable, not a constant state. Simply, illiquid asset classes like venture capital and private equity exhibit less efficient markets (platykurtic distribution), whereas highly-liquid large cap public equities are much more efficient… but never perfectly so (leptokurtic distribution).

What about Technicals?

Market efficiency is often highly contested by proponents of technical analysis. At Ovtlyr, we consider technical analysis to be a rudimentary form of behavioral analysis. In a recent test, 74 (we stopped there because the results were so uniform, but we encourage you to try the following experiment for yourself) large cap stocks totaling over 2,300 combined years of public data – all constituents of the S&P 500 and most likely to demonstrate highly efficient pricing – were subjected to a MACD strategy as outlined by Fidelity. Across these assets in a long-only capacity, the average exposure (days holding / total market days) was just north of 60% while capturing 37.45% of returns relative to buying and holding over the entire duration, giving the strategy a 62.24% effectiveness compared to buy & hold.

The natural response among some at this point would be to decry the strategy as too simplistic, or applied to the wrong assets, "I only act on the MACD when it's in alignment with [some other indicator] and not within 3 business days of a lunar eclipse…" perhaps these arguments are correct (we've personally seen some convincing cases), perhaps not, but the nature of the argument is fundamentally immaterial here. The purpose of using this methodology was due to its ubiquity. We specifically wanted a metric and assets seen by many market participants in order to effectively compare the same strategy against complete and blind randomness.

We constructed a random-walk generator, cumulatively adding or subtracting each successive day based on the distribution of outcomes from our real-world sample, then standardized the distribution to nullify drift, and ran it for an equivalent number of years a thousand times over. When the same MACD strategy was applied to the average of our 1,000 iterations the exposure was approximately equal but captured only 1.01% of returns relative to buy & hold from the same data (1.68% effectiveness).

In other words, the strategy was exponentially more effective when participants could see and react to the changing data than when they could not.

So then, why do we call technical analysis a "rudimentary form" of behavioral analysis? People typically rely on technical analysis as a way to bypass their own biases. When the decisions are made according to mathematical standards applied to chance, there is no place for *your* biases, but that doesn't eliminate biases. Instead, it simply replaces your own with those of the herd following similar metrics… people don't use technicals because they work, they work (*when* they work) because people use them.

How does OVTLYR fit in?

The purpose of OVTLYR is to create the best possible environment to refine and engage the wisdom of crowds without imparting "noise" from additional biases or herd-like behaviors.

Our process consumes both publicly available and non-personally identifiable data relevant to covered assets using a unique classification system to generate consolidated psychographic distributions, which can then be used to identify the propensities of an array of cognitive biases. The presence (or lack) of these biases are treated as variables to correct for irrationality within a deep game theory tensor. This model produces a discrete directional (appreciation/depreciation) probability, which is charted as an oscillator where low values represent overly "fearful" markets and higher values represent increasingly "greedy" ones.

After a prediction has been made, OVTLYR tracks each asset's adjusted price action to identify correlations between what's seen in the behavioral model and what's realized on the market. These are displayed as a confirming heatmap, where red zones indicate price pullbacks with corroborating behavioral data and similarly blue zones represent run-ups.

As with any AI architecture, there's a ton of math involved in our system. However, no traditional technical indicators or fundamental financial values are used in this process, as including them may inadvertently lead our members who rely on these sources to factor them into their considerations more than once.

Because no data should be interpreted in a vacuum, we are happy to provide additional information such as financial fundamentals and breaking news to help provide context to the behavioral analytics.

TL/DR:

We build on data from the bottom-up so that you can have a top-down view of when markets have been too fearful or too greedy.

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