Duo Reges
Capital Management LLC

Exploiting the Gaps in Human-Machine Collaboration

Executive Summary

We believe that the prevalence of model-based trading requires investors to create "model aware" investment strategies. Further return potential lies in actively countering these models, in both their successes and failures. "Models" include direct algorithmic trading, machine learned/AI trading, or implicit models, such as passive, smart beta, factor exposures (including ESG), and crowdsourcing.

- At a minimum, investment decisions need to be made model aware, but to take full advantage, they should actively work with and against model-based investing.
- It is possible to detect and trade against market models through a suite of techniques called **"Counter Machine Learning."**
    - Trading against failures is focused on statistical false positive and false negative errors, as even the best modelers cannot overcome the laws of statistics.
    - Exploiting successes of others in the market takes advantage of the tradeoffs inherent to responsible modeling.
- Human action—the "missing input"—causes many model failures.
- Regulatory actors are not well represented in models. Regulatory intent is typically missed by the market leading to over and under reactions and leaving hints one can successfully exploit creating **regulatory reaction gaps.**
- Behavioral dimensions are critical in folding traditional tools such as technical and fundamental indicators into a model-aware investment process.

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Introduction

In the last decade, investing and capital market structure has been transformed, bringing both rapid innovation and challenges for investors and fiduciaries in managing the twin mandates of risk and return.

The last 30 minutes + closing auction of the US equity trading day have gone from 19% of average daily volume in 2007 to 33.2% of average daily volume in 2018—which has *itself* increased by 62% in dollar volume, while shares traded has fallen 25% over the same time period. Positions have concentrated on larger market capitalization, going from a worldwide average of $731MM in 2007 to $1.6B in 2018 (source: Jefferies).

New investment products and technologies have largely served investors, providing lower costs for all, as well as broad transparency, at the cost of increased correlation among assets and strategies, and magnified risk. Some of this risk is visible, but much of it will continue to unpleasantly come to light in the years ahead.

We have created the seeming impossibility of achieving lower (outperformance) of return, and "balanced" it with increased risk.

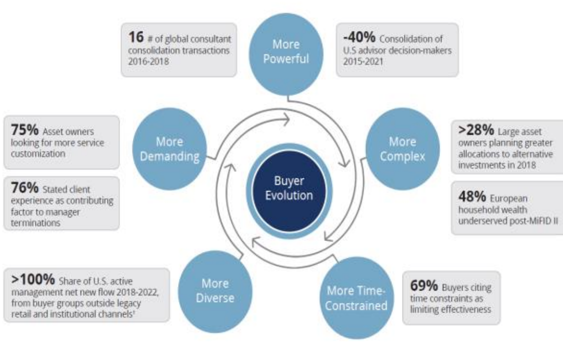

Figure 1 Source: Deloitte/Casey Quirk

More recent changes in distribution technology and research methods have driven deep change into the practice and business of investment management. >100% of US active management net new fund flow 2018-2022 is expected from outside legacy retail and institutional channels. 48% of European household wealth is considered "underserved" by existing institutional products. Asset managers and consultants have focused heavily on data, analytics, and client experience tools as more power has shifted to individual investors, who want tools that help with transparency, customization, cost focus, and innovation (source: Deloitte/Casey Quirk).

To serve these needs, consultants, fiduciaries and others involved in asset allocation have been challenged to improve their due diligence process, using crowdsourcing/social media, technology, and Artificial Intelligence (AI)/Machine Learning (ML). Pensions, endowments, individuals, and other buyers of institutional investment services require transparent, customizable, innovation. However, if someone undercuts the price, the fiduciaries/allocators will watch them leave.

For many institutional investors or consultants, the answer to this challenge has been to give up the liquidity associated with the public markets and seek private market returns. While this a valid approach for a portion of a portfolio, there are aspects of liquidity and public markets that are needed in a portfolio, leading to approaches such as Takahashi and Alexander's (2002) "Yale Model"

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to understand and predict cash flows—or to make private equity behave like public equity. This suggests that public market component will likely need to continue, with enhancements.

To solve this need for liquid public equities, fiduciaries have employed the "Wisdom of Crowds," the creation of natural and synthetic factors, and AI/ML.

Figure 2 Source: McKinsey & Co Analytics in Asset Management

The wisdom of crowds involves indicators such as scraping sentiment or other linguistic signals from discussion forums, changes in paid and free analysis, short interest, and positional crowding. Natural and synthetic factors are the modern extension of the Morningstar “style box” that classified funds into size/strategy approaches. The “factorization” seeks to statistically decompose classic Fama-French factors with ESG/impact investing, or “outcome” factors, with synthetic new factors—sentiment, time horizon, emerging markets, and so on. This creates a systematic deconstruction of the return and risk drivers, to allow cost-effective portfolio construction.

Counter Machine Learning

We are not arguing that these approaches are a problem—or the opposite. These approaches exist and are in effect “models”—systems/processes that represent the world or a part of it, by standardizing and transforming inputs which then produce outputs. Added to that is the growth of adaptive models—AI/ML. These models, most notably the last one, will continue to grow and evolve, begging the question of **how investors and asset managers should adapt?**

Does everyone need to allocate money to model based strategies? At a minimum, everyone’s allocation must be aware of the prevalence of model-centric strategies, just as every pilot needs to be aware that drones are aloft. The smart (and safe) pilots might ponder what it means that they will represent an increasing share of the objects in the skies. Similarly, **asset management strategies need to be at the very least "AI/ML Aware"** even if they do not adopt any specific techniques. Awareness involves being cognizant of what it means for the market that these tools are widespread, and where the tools will fail. The first and second order implications of the markets we have include the increased correlation among markets and greater volatility swings we mentioned, among other implications.

> *The implication is that alpha potential exists in “leaning in” to the prevalence of model-influenced strategies in the market.*

From Model-Aware to Counter-Model Investing

While we posit the only thing that a strategy *needs* to survive in this environment is AI-Awareness, the implication is that alpha potential exists in “leaning in” to the prevalence of model-influenced strategies in the market. We believe that a high potential opportunity space is to focus on the “hard edges” of how humans and machines collaborate, both successfully and unsuccessfully.

As previously mentioned, many things have the characteristics of a model, including factors, technical investing, indexing, as well AI/ML. Many fundamental approaches can be considered models as well. These tools are simply statistics, logic and rules, applied by a computer or a person. Holding human judgment to the end, even the best logic or rules cannot overcome the laws of statistics. We call this focus on directly confronting modeling “Counter Machine Learning.”

Like everything, **machine learning and AI leave tell tale imprints**, some of which show up in public data, such as the order book, or public filings, such as 13F/D/etc. At first glance, this seems impossibly naïve--13Fs/etc. are merely snapshots and can be amazingly misleading. Short positions are excluded, long stock positions might be more than offset by options, shorts on associated debt, and any reasonable turnover makes them very dated snapshots. Before every part of them is dismissed out of hand, we must wonder if there are hidden sources of value. The mental construct we would give you to think about are "recommender systems," also known as collaborative filtering, clustering, or a host of other names, such as those used by Netflix for movies or Amazon for shopping.

There is just as much signal in a person starting a movie or TV show and stopping it at the one hour mark, because that's all the time he or she has, or stopping it because the shoot-'em-up scene is a little more graphic than is pleasant as there is in someone actually finishing a show. "Touching" things creates mathematical entanglement, just as putting a purchase in an online basket and not checking out. This value has been studied in psychology, and provides a systemic window into human-machine collaboration.

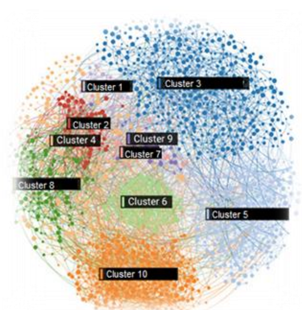


Figure 3 Clustering

Once we have a sense of the securities that interest models, we can use a set of hints to understand the trace of their approaches, and group, or cluster them with mathematically "nearby" approaches. This is the core of the methodology used by the recommender systems previously discussed.

Here again, it might seem naïve to deconstruct the apparent effect of models and reverse engineer the models themselves. First, we focus on groups, or clusters of models, with similar interests. With the high positional crowding and broad availability of data, return drivers are widely and quickly replicated. It is one of the key truths that drive the market conditions we previously discussed. Therefore, two or more completely different theses of investing might in effect net out to the same effect in the market.

Is the goal only to find errors and take advantage of them? Far from it, as we gain just as much intelligence from highly skilled quantitative and discretionary practitioners. We approach a problem more as hackers than builders, trying to find opportunities in their constructs. Highly skilled modelers create uncorrelated opportunities with model failures, helping us build a balanced portfolio. One key ingredient of our counter machine learning approach is to take advantage of model "robustness."

Highly skilled modelers create uncorrelated opportunities with model failures, helping us build a balanced portfolio.

The models that are implemented for trading are different from the originally researched versions because of the focus on robustness, to avoid overfitting and other flaws. This hobgoblin of responsible modeling can sneak unseen into everything, resulting in a beautiful model of yesterday that is useless tomorrow. It shows up as a result of too many variables, or too precise a technique, or too many research "bites at the apple" with a dataset. We think of it as a close cousin to the concept of *alpha decay*, the market and entropy sneaking up on all alpha generators. Overfitting is sneaking up on oneself.

The more responsible and skilled the modeler the more focus on building a robust model, using techniques built for this purpose such as t-distributed stochastic neighbor embedding (tSNE) or principal component analysis (PCA). It is not important that everyone understand or apply these techniques per se, but to be aware that they exist and affect the market.

Avoiding overfitting transforms thousands of variables, factors, fundamentals, alternative data, filters, and other indicators into a smaller handful of synthetic dimensions. This is not costless, as it involves the loss of some mathematical power, akin to taking a photo and saving the thumbnail—one is unable to return to the original screen size without "seeing the pixels," or losing information.

Once this happens, we use this loss of information (a "lossy one-way transformation") to get at the heart of what the cluster was trying to do, using public data, as well as additional proprietary data/specialized decomposition techniques.

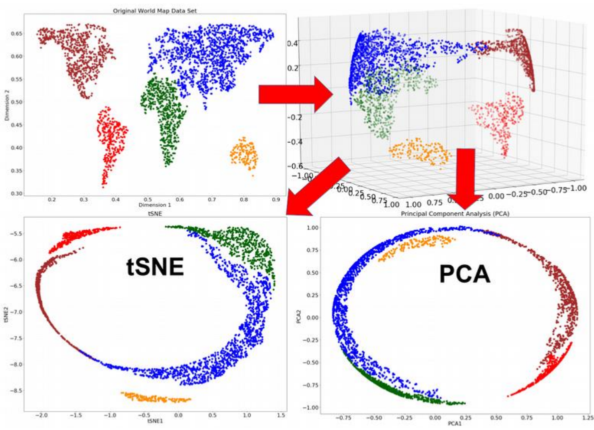


Figure 4 **tSNE, PCA Robustness techniques.**
Source:towardsdatascience.com

This is the first part of our counter machine learning approach—using good modeling technique against itself. **Won't everyone just hide their approach? No, as it is far more efficient to focus on improving model quality or speed than to deploy "cryptographic" techniques designed to hide the transformations of data.** This is already a challenge with massive datasets, especially those including alternative data, which financial machine learning thought leader Marcos Lopez de Prado contends are valuable in proportion to how much they annoy your data infrastructure team (Lopez de Prado, *Advances in Financial Machine Learning*). With a focus on speed, reducing cost, and finding new alpha, it is likely inefficient to "hide," but instead, focus on running models more quickly. That said, even if some actors work diligently on covering their tracks, not everyone will, and imperfect copies help expose the original.

The Confusion Matrix and the Laws of Statistics

The next key element of our "counter machine learning" approach comes from the confusion or error matrix, which spells out predictions vs. reality. Every model or test that tries to sort out signals from noise must deal with this—True Positives and True Negatives come from a system accurately capturing reality. False Positives and False Negatives—forms of error—come from missing reality, as shown in the confusion matrix below.

Confusion Matrix			
		Truth	
		Positive	Negative
Predicted	Positive	**True Positive**	**False Positive**
	Negative	**False Negative**	**True Negative**

Take the best biochemist/physician in the world and have him or her design a pregnancy test and a disease detection test. A pregnancy test is designed with a deliberately high false positive (telling people they are pregnant when they are not) rate, to find 110% of those who might be pregnant. A disease test is designed "closer to the pin," balancing false positives and false negatives (missing those who have the condition). Why the difference? The costs of false positives are dramatically lower for pregnancy tests (perhaps sleepless nights or too much time researching names) than are the costs of false negatives (missed opportunities to manage health during a critical time). For diseases, the costs of a false positive might include patient discomfort, complications from the treatment, and potentially high costs to insurers or patients, as well as displacing those who need medical care.

> *We use this loss of information to get at the heart of what the cluster was trying to do.*

Clustering information then helps detect these failure patterns. Taken together our clusters, decomposition patterns and false positive/false negative errors help us build our counter machine learning model baseline.

The model training and testing took place in specific market contexts, and we must understand what the current market context is, and how it is similar and different. Think of it as diving even deeper than movie and ecommerce recommendations as more characteristics and data are available.

Quantamental Market Context

The market context is comprised of macroeconomic, technical, and company specific industry, long-term outlook, balance sheet, profit, and cash indicators.

Fundamental data, Technical Indicators, and Economics

Views of the value of fundamental data run the spectrum from the value investing belief that they drive the market to technical or efficient market theorists holding that they are useless. We believe in using the **data "quantamentally"—seeking to create distinctions in varying market regimes, sectors, and markets.** In general, we see it as a filter, like moving averages or Kalman filters. While traditionally thought of as technical, we think of it as an injection of fundamental data—cash generation, earnings, balance sheets, and so on.

We think of it as the "future memory" of the market, just as an N-day moving average or exponential moving average, waves, bands, and other indicators suggest a market memory for a security.

We add many sets of fundamental, economic, and technical indicators and expose them to our "counter" artificial neuron, from institutional holders, to short interest, to each of the various moving averages. Our quantamental approach breaks this model into sub models, including applying macroeconomic indicators as they apply by the categorizations previously mentioned.

Regulatory Reaction Gaps

Models, machines with human designers, must interface not just with their designers and users, but must also the broader world. A common characteristic breaks most models, from self driving cars to investment models—people. The interface between humans and the machines they work with is what drives much of technology, from augmented reality to the futuristic mind-machine interface. Why? Bandwidth limitations and error. Both humans and machines can process information dramatically faster than they can share it with each other, and every point of interface, from keyboards to monitors to machine learning recommendations provides opportunity for error, from the statistical error we have discussed to physical errors.

Taken together our clusters, decomposition patterns and false positive/false negative errors help us build our counter machine learning model baseline.

The Missing Input

The complex interface between government regulators and the businesses they regulate is outside most models. By this we do not mean famous political figures making policy pronouncements, or even the FDA approving drug compounds or the Federal Reserve changing interest rates. There are armies of analysts analyzing this, but few decompose the interface between the private sector and the regulatory actions for the alphabet soup of national, state, and local agencies, from the Occupational Safety and Health Administration (OSHA) to the Chemical Safety Board (CSB) to the UK's OfCom to the California Dept. of Food and Ag. to the European Chemicals Agency that regulate commerce.

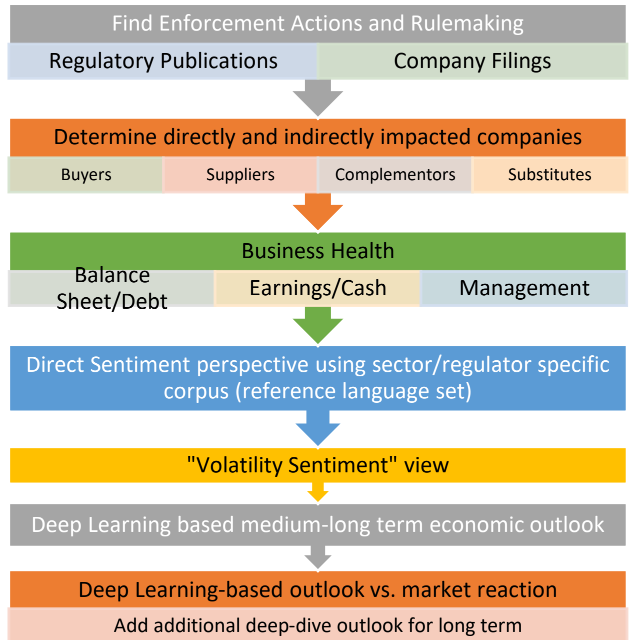
Each of these agencies promulgates many rules. The Federal Register, only covering US Federal agencies, numbered 70,392 pages (source: ballotpedia.org). That excludes the EU, other countries, and state/local agencies, but it also excludes enforcement actions, or fines. These are typically captured in separate memoranda, and if they hit a materiality threshold, corporate filings.

Regulatory Actions as Sparse Datasets

This is a sparse data set—there are not "many" regulatory enforcements actions or rule filings. Even though 70,392 is a large number of pages—with probably 5-7 times that impact including all OECD regulators, it is still an order of magnitude smaller than the amount of data in the financial markets. **We apply prior work done in the ecommerce space, to understand how vendors to a platform respond to more aggressive requirements year-over-year to understand this space.** One does not frequently directly speak with ecommerce customers or suppliers, and traditional sentiment signals, including sarcasm, negation, and stronger language are not widespread in the communications that exist through webforms, some emails, and contact center discussions. One must make inferences through signals such as comparative pricing to competitors, speed of responding to RFPs, and domain specific sentiment tools—a specialized "corpus" or body of language.

Seeking Human-Machine Collaboration Gaps

This set of sparse sentiment and economic measurement tools allows one to apply the same logic to the regulatory space. Our process involves creating a special body of language and related economic impact, by economic sector, country, and regulator. This also allows us to create a related "volatility sentiment," that helps us understand the error bar around our view of economic reaction, and volatility, both to trade derivatives and equities. Our focus is on bounding and comparing error. The goal is to create "smart failure"—the design principle that observes that a broken escalator is a set of stairs, and a broken elevator is at best an afternoon spent in a small room, and therefore, one should focus on making escalators where possible.



Behavioral Factors and Human/Machine Collaboration

The final disjunction or edge between humans and machines involves behavioral economics. Some might think that adding computing, one can reduce human biases. While there are undoubtedly areas in which this is true, it is just as frequently true that modeling tools exacerbate human biases—like the axiom that money or age don't change people, they only make people more of what they already are. For example, it is well documented that machine learning and AI replicate human social biases. This is not to say that model-based investing is worse than traditional, discretionary fundamental or macroeconomic based investing—each has its role, and asset allocations over the last decade heavily lean toward systems and models.

> *Modeling tools exacerbate human biases—like the axiom that money or age don't change people, they only make people more of what they already are.*

To explore these biases, we should understand the key areas in which machines accelerate human biases. *Anchoring* and *Prospect Theory*, taken together represent the first key area of bias. Anchoring involves the use of a psychological or market phenomenon driving how much one is willing to pay for something. George Soros writes of a prevailing market bias and a bias in a security coming together in alignment or conflict and driving a positive or negative run on a stock. A view of cash flow-based value, pegged to history, also creates a modeling anchoring. Where these ideas come into conflict brings together another key concept: loss aversion, the sense that losses hurt more than gains help, and the twin concept of the *hedonic treadmill*, that we quickly acclimate to improvements in our life (or portfolio) and they don't bring as much joy as losing them causes pain.

Together, these constitute our counter-modeling outlook of how volatility "runs," in which volatility becomes one-sided, or too cheap, too expensive for a given stock, bond, ETF, country or sector occur.

Time-Based Portfolios and Intertemporal Biases

Our model creates a portfolio with differing views over time vs. short term market reactions. What drives this view is the well known phenomenon of "intertemporal choice" or discounting and the related concept of the *availability heurist* (also known as "recency bias"), in which people – and the models people created – value recent or near term events much more than those long ago or far into the future. We believe that as we diagnose and describe the clusters that underlie our approach, we try to detect the time horizons they care about, injecting a reliable hard edge to analyze.

Our approach in risk management is to use standard tools around loss prevention, value at risk, and position concentration, but focus even more heavily on keeping return drivers from leaning on the same approach, or "stacking."

Risk Mgmt., Overconfidence and the Peak-End Rule

A final related pair of concepts—*overconfidence* and the *peak-end rule*. Overconfidence usually shows up in both risk management and understanding alpha decay and "recycling."

Our approach in risk management is to use standard tools around loss prevention, value at risk, and position concentration, but focus even more heavily on keeping return drivers from leaning on the same approach, or "stacking." Obviously, this includes position sizing/concentration, but the more important phenomenon is to make sure that as we work our longer running market theses—the ideas that help us focus on key markets and sectors, and regulators—we are not going to the same handful of ideas because they keep working. This is what most modeling does, applying the same set of screens or theories about value over and over, without worrying about too many ideas being aligned. We have seen that effect as more and more markets and securities become correlated, and volatility spikes.

The peak-end rule holds that people—and the models they build--remember the peak of an experience and the last part of it much more than all the interior portions. Duke Professor Dan Ariely speaks of this as a literal "ripping off the band-aid" negotiation he had with nurses as he recovered from serious burns early in life (Ariely, *Predictably Irrational*). The peaks and ends of models show up in the tools of technical, model, and DCF analyses, again creating a time-based bias we seek to exploit.

Conclusion

The growth of model-based investing, including indexing, factor investing, and machine learning/ artificial intelligence have helped investors gain transparency with low cost, but at the expense of increased correlation. To succeed in achieving improved returns, and an improved risk/return relationship, investors should seek to exploit the natural gaps that occur as humans and machines collaborate.

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