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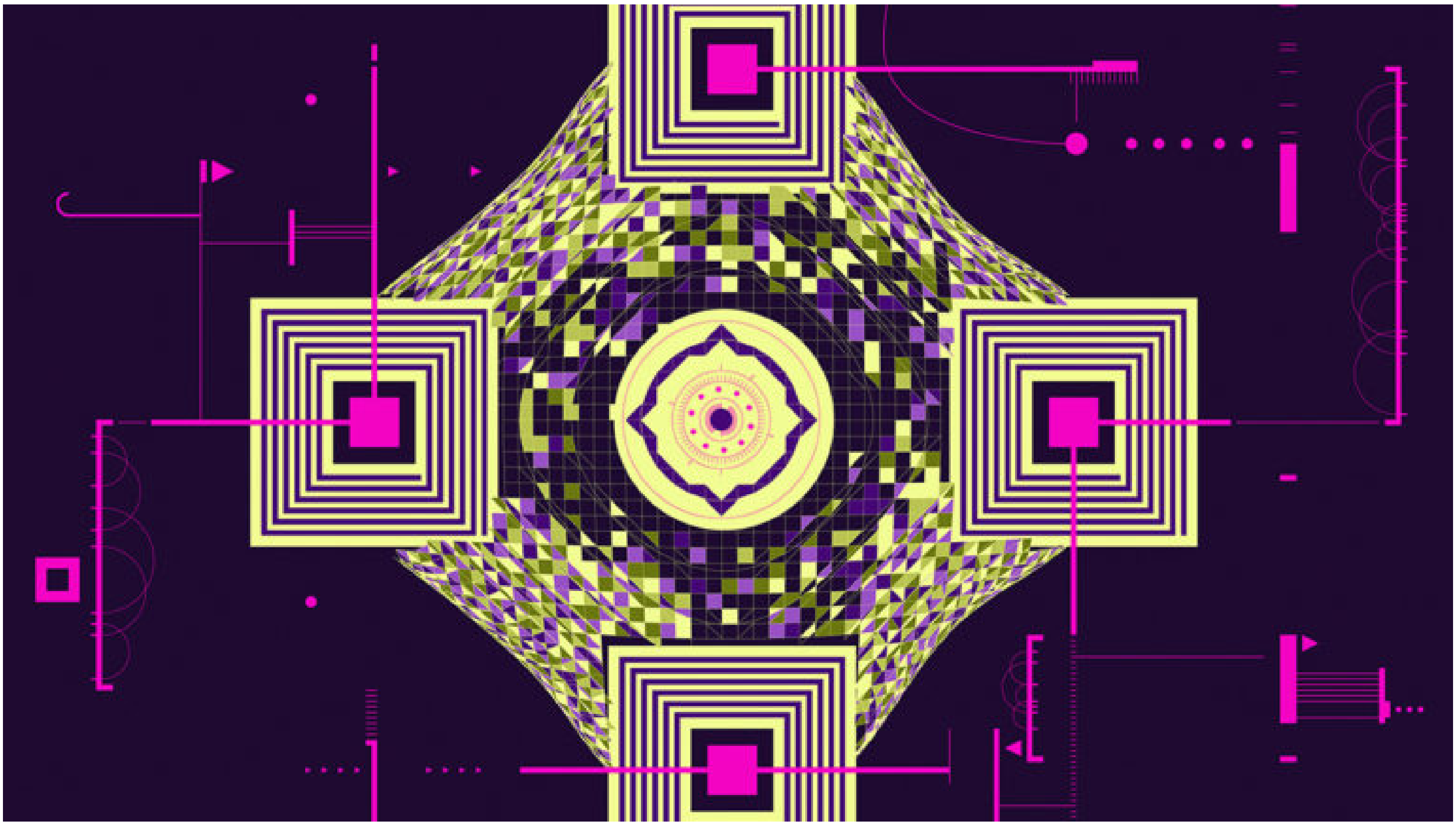
FINANCIAL MARKETS

# Big Data and Machine Learning Won’t Save Us from Another Financial Crisis

by Stephen Blyth

SEPTEMBER 18, 2018



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Ten years on from the financial crisis, stock markets are regularly reaching new highs and volatility levels new lows. The financial industry has enthusiastically and profitably embraced big data and computational algorithms, emboldened by the many triumphs of machine learning. However, it is imperative we question the confidence placed in the new generation of quantitative models, innovations which could, as William Dudley warned, “lead to excess and put the [financial] system at risk.”

Eighty years ago, John Maynard Keynes introduced the concept of irreducible uncertainty, distinguishing between events one can reasonably calculate probabilities for, such as the spin of a roulette wheel, and those which remain inherently unknown, such as war in ten years' time. Today, we face the risk that investors, traders, and regulators are failing to understand the extent to which technological progress is — or more precisely is *not* — reducing financial uncertainty.

Two areas are of particular concern. First, there are many unsettling parallels between the recent advances in machine learning and algorithmic trading and the explosive growth of financial engineering prior to the crisis. Secondly, we cannot draw comfort simply from more data and greater computing power: statistical theory shows that big data does not necessarily prevent big trouble.

Like today, finance in the 1990s and early 2000s attracted many of the sharpest quantitative minds, who produced remarkable theoretical and methodological advances. Like today, financial engineering around the millennium brought great commercial success: the mathematical tools developed by derivative desks built businesses, boosted profits and delivered superior investment returns. I lived that era in New York, part of a dynamic, entrepreneurial world of advanced probabilistic modeling and unprecedented computational power. We were taming financial uncertainty, or so we believed.

The financial crisis exposed that mindset as a "quant delusion," an episode which we may now be at risk of repeating. Many modeling assumptions, such as correlations between asset prices, were shown to be badly flawed. Furthermore, foundational underpinnings of quantitative finance — for example, elementary logical bounds on the prices of securities — broke down. It also became clear that quants had grossly mis-specified the set of possible outcomes, and had calculated conditional probabilities of events, subject to the world staying more or less as they had known it. They made decisions that were exposed as nonsensical once apparently impossible events occurred.

Importantly, there was also a proliferation of what statistician Arthur Dempster has termed "proceduralism": the rote application of sophisticated techniques, at the expense of qualitative reasoning and subjective judgment, leading to illogical outcomes. An example: banks often adopted different models to price different derivative contracts, leading to an identical product being given two unequal prices by the same institution.

An influx of quantitative talent; rapid technical advances; surging profits: today's world of quantitative finance echoes that of the millennium. Proceduralism may be even more prevalent now, fueled by the broad success of algorithms and associated competitive pressures to adopt them; and by the regulatory push to validate or "attest to" models, whose results are then vested with unrealistic credibility.

Yes, with bigger data and greater computing power than ten years ago, we can now explore ever larger sets of possible outcomes. But we still do not know to what degree our calculated conditional probabilities differ from actual probabilities. We still do not know which of our assumptions will break down. In fact, as our algorithms become more complex, as with deep learning, it is becoming more difficult to identify gaps in logic that may be embedded within algorithms, or to comprehend when models might badly fail.

Machine learning can be very effective at short-term prediction, using the data and markets we have encountered. But machine learning is not so good at inference, learning from data about underlying science and market mechanisms. Our understanding of markets is still incomplete.

And big data itself may not help, as my Harvard colleague Xiao-Li Meng has recently shown in "Statistical Paradises and Paradoxes in Big Data." Suppose we want to estimate a property of a large population, for example, the percentage of Trump voters in the U.S. in November 2016. How well we can do this depends on three quantities: the amount of data (the more the better); the variability of the property of interest (if everyone is a Trump voter, the problem is easy); and the quality of the data. Data quality depends on the correlation between the voting intention of a person and whether that person is included in the dataset. If Trump voters are less likely to be included, for example, that may bias the analysis.

Meng shows that data quality dominates data quantity in remarkable ways. For example, suppose we polled 1% of U.S. voters, approximately 2.3 million people, and that the probability of a Trump voter accurately responding is just 0.1% lower than a non-Trump voter. Then the big dataset provides a *less* reliable estimate of the overall percentage of Trump voters than a simple random sample of just 450 people, where responses are accurate.

The lesson for finance is stark. If our dataset, however large, is in a minimal but systematic way not representative of the population, big data does not preclude big problems. Those who revert to a proceduralist approach of throwing complex algorithms and large datasets at challenging questions are particularly vulnerable. Who can tell how non-representative our data today is in terms of representing the future? Yes, we may never again assume house prices cannot fall simultaneously in every state, but we do not know what other assumptions are implicitly being made.

More than ever, judgment — necessarily subjective and based on experience — will play a significant role in moderating over-reliance on and misuse of quantitative models. The judgment to question even the most successful of algorithms, and to retain humility in the face of irreducible uncertainty, may prove the difference between financial stability and the "horrific damage" of another crisis.

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