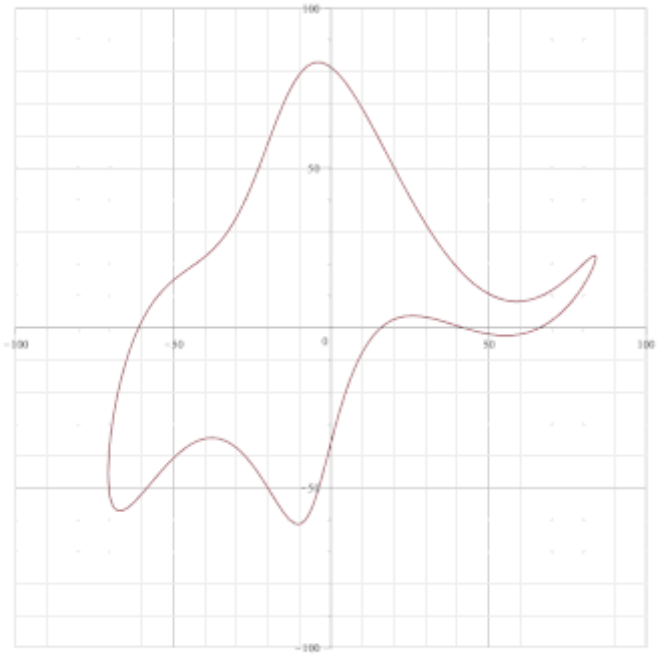
Let's Learn (about) Modeling: Practical Guidelines for the Age of LLM's

Peter Wirtala, CFA | Insurance Strategist & Principal

"With four parameters I can fit an elephant, and with five I can make him wiggle his trunk"

-John von Neumann



With the recent public excitement over LLM's (Large Language Models) and the role they might play in a variety of business applications, it's worth pausing a moment to consider the role of modeling in finance and economics, both positive and negative. Models work best when used in certain ways and within certain limitations, and the prospects for extracting real value from LLM's improve if we calibrate our expectations to the contexts where they make the most sense. We'll present this as a set of guidelines that should help the reader develop their own mental… model of how these tools are best utilized.

1) Models don't create information, they filter it out

When someone hands you a map the first impulse is usually to ignore most of the information and find your current location. The next is typically to find where you're trying to go. Reality is frequently too chaotic or logistically difficult to extract useful information from, so we model it instead. Models are necessarily built on assumptions and simplifications (excepting the map in Jorge Luis Borges' On Exactitude in Science, which expands to the same size as the empire it represents!), because their chief function is to filter out complexity and noise to identify insights useful for decision-making. Practically the defining trait of a useful model is that it's accurate enough on the points you care about, and disregards all else; when all we want to know is whether to turn left or right on Maple Street, we don't need to know where every shrub on the street is located.

Models can lead us to insights or realizations we couldn't have identified in their absence, but this is more akin to wiping the dust off an old book so you can read the cover, than the type of inspiration that generates new ideas. Ultimately models help us discover what was always there, but buried beneath the noise. This is particularly important to keep in mind when interacting with LLM's. Although they seem designed to "create" content, strictly speaking they calculate a probability-weighted semi-randomized prediction of a plausible response to a query, algorithmically assembled from a set of training data. Notwithstanding millions of people having enjoyed the parlor trick of generating remixed images or written works with these systems, many of their most economically valuable applications focus on their utility as filtering/sorting mechanisms: condensing and summarizing large blocks of text, directing customer service requests to the proper resources, streamlining legal or academic research, identifying errors in computer code, analyzing medical data for diagnosis, and (for insurers) analyzing claims data to improve risk assessment and underwriting. In a world awash with data, there's real demand for better tools that lead us to exactly what we're looking for.

2) Models should be simple and focused

Ockham's Razor advises that "entities must not be multiplied beyond necessity". Again, every model is built on simplifying assumptions, which by their nature are less precise than the underlying reality. Most models can tolerate a certain degree of inaccuracy or approximation and still be useful, but as models become more complex and add more hypotheticals and theoreticals and speculative representations, the output inevitably detaches from reality. This is necessarily true, as the more

variables we add the more assumptions we need to make about how they interact with each other (the number of these assumptions grows exponentially relative to the number of variables), and each assumption represents a potential source of error, like how a Jenga tower becomes more fragile with each block moved. Eventually the cumulative error leaking in from a million pinpricks becomes overwhelming and the model's utility collapses. For the many, many regions of life that are too complex to model, this is the reason why: too many assumptions are needed, which introduce too many sources of error. We should be very, very wary of any model that appears to be doing "too much". It is to this kind of predictive hubris that Nobel-winning behavioral economist Daniel Kahneman referred when he said "There are domains in which expertise is not possible".

A model should thus be limited in its aims to be useful. In the 70's Chile attempted to create a semi-automated computer system called Project Cybersyn, empowering a small number of officials to essentially manage the entire economy from a Star Trek-esque control room using telex machines:

While you scarcely need me to tell you this effort proved comically unfruitful and was swiftly abandoned, it remains a cautionary tale about the human impulse to outsource higher- and higher-level decision-making to models and automation. As computers become more powerful and our understanding of markets and economics becomes more sophisticated, surely we can devolve greater responsibility to technology, or so the thinking seems to go. But if anything the opposite is the case, the advantage of better tools is that they let us model narrowly-defined domains more precisely, in areas ranging from geological surveying to aerodynamics to protein folding, even as seemingly-simple questions like "will stocks go up or down this month" remain perennially elusive.

For this reason, it's likely that in the medium term the most valuable LLM's will be those trained on carefully-vetted topical data to address narrowly-prescribed categories of questions like: "how would changing my deductible impact the price of my homeowner's insurance?". By contrast all-purpose chatbots will remain amusing but tough-to-monetize novelties, which brings us to another critical point: as investors we obtain the greatest value from models when they address specific objectives

like asset-liability matching, asset allocation optimization, or assessing risk-based capital impacts, while recognizing that portfolio management fundamentally requires an experienced professional in the driver's seat. Which brings us to…

3) Models are an input to the process, not the process itself

I'm happy to fly on a plane that uses autopilot functionality, but I still want a human pilot sitting in the cockpit. Models can automate and streamline some types of work, but they can't substitute for human judgment and adaptability, especially at tasks where the stakes are high. Moravec's Paradox is the well-established observation that while computers can easily outperform humans at feats of raw calculation, other seemingly-simple tasks related to perceiving and interpreting sensory input (plus many basic motor skills like catching a ball) are extraordinarily difficult for them; computers, like any tools, work best when restricted to the types of tasks they're designed for. Ultimately the utility of models is in their ability to draw out information that improves our decision-making, not to make decisions for us. As investors we may use models to identify candidate trades, but the execution is determined by innumerable idiosyncratic intricacies that evolve from years of professional experience and judgment. While algorithmic trading does exist in the broader industry, its purpose is mainly to maximize transaction speed, and it still requires careful supervision. Actual model-based trading strategies, including those developed by highly-credentialed experts and sponsored by prestigious firms, have a long and infamous history of blowing up with such severity as to threaten the entire economy: the "portfolio insurance" schemes that contributed to the 1987 crash, the fall of Long-Term Capital Management, and of course the 2008 financial crisis with its multitudes of ingeniously re-re-repackaged no-doc MBS/CDS designed around the premise that house prices could only ever go up. Even the "meme stock" retail-trading volatility of early 2021 was driven in part by attempts to exploit programmatic hedging practices of market makers by generating runaway momentum in issues with high outstanding options volume or short interest.

The good news here is that it's unlikely LLM's are about to eliminate the need for huge numbers of skilled workers. Even if they were many times as accurate and sophisticated as they are, there's more to most white-collar work than predicting plausible text strings based on a corpus of past writings. Instead the value is likely to come from reducing laborious manual tasks and making individual workers more productive by improving their ability to navigate large bodies of data efficiently. In fact that description likely encompasses most of how they're used in business today. But those use cases are best served by models trained on carefully circumscribed purpose-built datasets, with their output vetted by humans before being used in real-world applications.

Conclusion

Large Language Models have captured the public imagination with dreams of personalized data concierges that can handle our digital affairs better than we could ourselves, or of fully-automated companies with just a single human sitting atop the pyramid. These, in reality, are among the least-likely outcomes. Models can sometimes do specific things very, very well, but as their scope broadens

their utility rapidly declines. Computer modeling already plays a major role in valuable work ranging from car design to hurricane forecasting to drug development, and LLM's may represent a breakthrough that leads to new discoveries and efficiencies in these data-heavy domains. Certainly, the same is true of fixed income markets, whose size and complexity are such that there's always room for better tools to rapidly identify attractive opportunities and filter them for suitability to unique client objectives and tolerances. But given the ubiquity of the PR and hype that's accompanied recent developments, we should calibrate our expectations of how models can actually add value and improve human decision-making, and of what conversely constitutes clear-cut cases of sci-fi speculations usurping the inherently incalculable intricacy that defines much of the real world.

Peter Wirtala, CFA *is a Principal and AAM's Insurance Strategist with 17 years of investment experience. Peter's responsibilities focus on analysis of client insurance operations and reserves to aid in the development of customized investment solutions. Additionally, he develops ERM-focused asset allocation strategies for clients, conducts peer analysis and NAIC RBC / AM Best BCAR scenario analysis, and prepares educational papers and seminars on key issues facing the insurance industry. Peter also leads AAM's ESG integration effort for clients seeking to incorporate environmental, social, and governance-based principles into their portfolios. Previously he worked for Epic Systems as a Financial Accountant. Peter earned a BBA in Finance from the University of Wisconsin-Madison.*