Fundamental Sources of Forecast Error and Uncertainty

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When seeking to improve forecast accuracy, it is critical to understand the major sources of forecast error. Unfortunately, this is not something that is typically taught in school. And learning it the hard way can be very expensive. Hence this note.

Broadly speaking, there are four sources of forecast uncertainty and error:

1. An incorrect underlying theory or theories;
2. Poor modeling of a theory to apply it to a problem;
3. Wrong parameter values for variables in a model;
4. Calculation mistakes.

Let's take a closer look at each of these.

<u>Theories</u>

When we make a forecast we are usually basing it on a theory. The problem here is twofold.

First, we often fail to consciously acknowledge the theory that underlies our forecast.

Second, even when we do this, we usually fail to reflect on the limitations of that theory when it comes to accurately forecasting real world results. Here's a case in point: How many economic forecasts have been based on rational expectations and/or efficient market theories, despite their demonstrated weaknesses as descriptions of reality? Or, to cite an even more painful example, in the years before the 2008 Global Financial Crises, central bank policy was guided by equilibrium theories that failed to provide early warning of the impending disaster.

The forecasts we make are actually conditional on the accuracy of the theories that underlie them. In the case of high impact outcomes that we believe to have a low likelihood of occurring, failing to take into account the probability of the underlying theory's accuracy can lead to substantial underestimates of the chance a disaster may occur (see, "*Probing the Improbable: Methodological Challenges for Risks with Low Probabilities and High Stakes*", by Ord et al).

There are three other situations where the role of theory is usually obscured.

The first is forecasts based on intuition. Research has found that accurate intuition is developed through the combination of (a) repeated experience over time; (b) in a system whose structure and dynamics don't change; (c) the receipt of repeated feedback on the accuracy of forecasts; and (d) followed by explicit reflection on this feedback that gradually sharpens intuition.

When we make a forecast based on intuition, we are (usually implicitly) making the assumption that this theory applies to the situation at hand. Yet in too many cases, it does not (e.g., because the underlying system is continually evolving). In these cases, our "intuition" very likely rests on a small number of cases that are easily recalled either because they are recent or still vivid in our memory.

The second is a forecast based on analogies. The implicit theory here is that those analogies have enough in common with the situation at hand to make them a valid basis for a forecast. In too many cases, this is only loosely true, and the resulting forecast has a higher degree of uncertainty that we acknowledge.

The third is a forecast based on the application of machine learning algorithms to a large set of data. It is often said that these forecasts are "theory free" because their predictions are based on the application of complex relationships that were found in the analysis of the training data set.

Yet theory is still very much present, including, for example, those that underlie various approaches to machine learning, and those that guide explanation of the extremely complex process that produced the forecast.

Another theoretical concern with machine learning-based forecasts is the often implicit assumption that either the system that generated the data used to train the ML algorithm will remain stable in the future (which is not the case for complex adaptive social or socio-technical systems like the economy, society, politics, and financial markets), or that it will be possible to continually update the training data and machine learning algorithm to match the speed at which the system is changing.

Models

While theories are generalized approaches to explaining and predicting observed effects, models (i.e., a specification of input and output variables and the relationships between them) apply these theories to specific real world forecasting problems.

This creates multiple sources of uncertainty. The first is the decision about which theory to include in a model, as more than one may apply. RAND's Robert Lempert is a leading expert in this area, who advocates the construction of "ensemble" models that combine the results from applying multiple theories. Most national weather services do the same thing to guide their forecasts. However, ensemble modeling is still far from mainstream.

A second source of uncertainty is the extent to which the implications of a theory are fully captured in a model. A recent example of this was the BBC's 24 February 2020 story, "*Australia Fires Were Worse Than Any Prediction*", which noted they surpassed anything that existing fire models had simulated.

A third source of modeling uncertainty has been extensively researched by Dr. Francois Hemez, a scientist at the Los Alamos and Lawrence Livermore National Laboratories in the United States whose focus is the simulation of nuclear weapons detonations.

He has concluded that all models of complex phenomena face an inescapable tradeoff between their fidelity to historical data, robustness to lack of knowledge, and consistency of predictions.

In evolving systems, models that closely reproduce historical effects often do a poor job of predicting the future. In other words, the better a model reproduces the past, the less accurately it will predict the future, even if its forecasts are relatively consistent.

Hemez also notes that, "while unavoidable, modeling assumptions provide us with a false sense of confidence because they tend to hide our lack-of-knowledge, and the effect that this ignorance may have on predictions. The important question then becomes: 'how vulnerable to this ignorance are our predictions?'"

"This is the reason why 'predictability' should not just be about accuracy, or the ability of predictions to reproduce [historical outcomes]. It is equally important that predictions be robust to the lack-of-knowledge embodied in our assumptions" (see Hemez in "*Challenges in Computational Social Modeling and Simulation for National Security Decision Making*" by McNamara et al).

However, making a model more robust to our lack of knowledge (e.g., by using the ensemble approach) will often reduce the consistency of its predictions about the future.

The good news is that forecast accuracy often can be increased by combining predictions made using different models and assumptions, either by simply averaging them or via a more sophisticated method (e.g., shrinkage, extremizing, etc.).

Parameter Values

The values we place on model variables is the source of uncertainty with which people are most familiar.

As such, many approaches are used to address it, including scenarios and sensitivity analysis (e.g., best, worst, and most likely cases), Monte Carlo methods (i.e., specifying input variables and results as distributions of possible outcomes, rather than point estimates), and systematic Bayesian updating of estimated values as new information becomes available.

However, even when these methods are used important sources of uncertainty can still remain. For example, in Monte Carlo modeling there is often uncertainty about the correct form of the distributions to use for different input variables. Typical defaults include the uniform distribution (where all values are equally possible), the normal (bell curve) distribution, and a triangular distribution based on the most likely value as well as those believed to be at the 10th and 90th percentiles. Unfortunately, when variable values are produced by a complex adaptive system, they often follow a power law (Pareto) distribution, and the use of traditional distributions increases forecast uncertainty.

Another common source of uncertainty is the relationship between different variables. In many models, the default decision is to assume variables are independent, which is often not true.

A final source of uncertainty is that under different conditions, the values of some model input variables may only change with varying time lags, which are rarely taken into account.

Calculations

Researchers have found that calculation errors are distressingly common, and especially in spreadsheet models (e.g., "*Revisiting the Panko-Halverson Taxonomy of Spreadsheet Errors*" by Raymond Panko, "*Comprehensive Review for Common Types of Errors Using Spreadsheets*" by Ali Aburas, and "*What We Don't Know About Spreadsheet Errors Today: The Facts, Why We don't Believe Them, and What We Need to Do*", by Raymond Panko).

While large enterprises that create and employ complex models increasingly have independent model validation and verification (V&V) groups, and while new automated error checking technologies are appearing (e.g., see the ExcelInt add-in), their use continues to be the exception not the rule.

As a result, a large number of model calculation errors probably go undetected, at least until they produce a catastrophic result (usually a large financial loss).

<u>Conclusion</u>

People frequently make forecasts that assign probabilities to one or more possible future outcomes. In some cases, these probabilities are based on historical frequencies – like the likelihood of being in a car accident.

But in far more cases, forecasts reflect our subjective belief about the likelihood of the outcome in question – i.e., "I believe the probability of "X" occurring before the end of 2030 is 25%."

What few people realize is that these forecasts are actually conditional probabilities that contain multiple sources of cumulative uncertainty.

For example, consider the probability of "X" occurring before the end of 2030 is 25% -- conditional upon (1) the probability the theory that underlies my estimate is valid; (2) the probability my model has appropriately applied this theory to the forecasting question at hand; (3) the probability my estimated value or values for the variables in my model are accurate; and (4) the probability I have not made any calculation errors.

Given what we know about these four conditioning factors, it is clear that many of the subjective forecasts we encounter are a good deal more uncertain than we usually realize.

In the absence of the opportunity to delve more deeply into the potential sources of error in a given probability forecast, the best way to improve predictive accuracy is to select and combine multiple forecasts that are made using different methodologies, and/or alternative sources of information.