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The Actuarial Profession and Complex Models: Knowing the Limits of Our Knowledge

By Kurt Wrobel

In very simple terms, actuaries are in the business of predicting future liabilities associated with financial products. In attempting to quantify this future cost, we use historical experience and then make adjustments to account for expected changes in unit cost and utilization to estimate future liabilities. And, in keeping with our professional standards, we follow the best statistical methods available to impartially predict future costs. As I will highlight in this article, I believe that gradual changes in the business environment have made this impartial prediction process much more difficult for our profession, but still possible to achieve. Following the initial discussion, I will outline some steps that we can follow to ensure a more rational and productive approach to data analysis.

The Problem: So What Has Changed?

Over the past several years, we have seen changes in the business environment that have impacted our ability to ensure that our organizations make appropriate decisions based on the available data, including:

- Easy access to data and the growth of software packages that allow more sophisticated data analysis and the appearance of more sophisticated data analysis.
- Increasing expectation for the usefulness of data as popularized by several books and movies.
- The degree of dislocation and change in our economy has made historical data less useful in predicting future results.

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Easy Access to Data and Software Tools

With the remarkable progress in software and access to data, companies have effectively democratized data analysis across large organizations giving access to a significant number of individuals with less intensive statistical training and without the same degree of professionalism applied to impartial data analysis. In many respects, this can be a real positive for a company. The actuarial profession certainly does not have a lock on the appropriate use of data in a business environment and a company could benefit from more people analyzing data. That being said, the increased democratization of data analysis has a serious downside as less sophisticated individuals present data analytics. Although the problem can take on many forms, I have highlighted some of the more challenging problems.

Presentation of data with little or no credibility. This is an issue that is self-evident to most actuaries. Throughout my career, I have consistently seen people draw inferences from data that lacked almost any credibility. Alternatively, in response to a concern about credibility, someone will ask about a specific break point where the data suddenly becomes credible rather than think about the underlying distribution associated with different population sizes. For example, the stylized chart on page 17 highlights the distribution of medical loss ratios at different underlying membership levels using a simulation process.

As highlighted above, the distribution of potential outcomes becomes more tightly centered around the mean as membership increases, but there is not a specific break point where the data suddenly become credible. In addition, a single observed loss ratio with a small membership base provides little information on what the true underlying mean would be if the simulation were run numerous times.

Mistaking correlation with causation. As we have all learned in basic statistics, correlation does not necessarily imply causation. Some interesting examples include:

- A win for the Redskins in their last home game prior to Election Day coincides with the incumbent party being reelected.
- Greater sun spot activity produces an increase in the stock market or GDP.

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- When a team from the old NFL wins the Super Bowl, the stock market will rise.

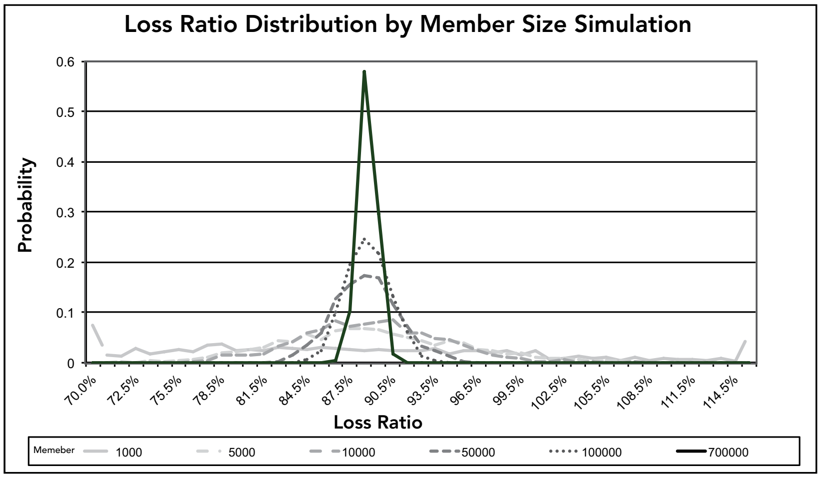
- U.S. stock markets are weakest following the election of a new president

The problem, of course, is that less sophisticated people will present and draw inferences without adequately controlling for other variables that could be driving the underlying causation.

Biased data mining. Without the same degree of professionalism and commitment to impartiality, some data analysts will sift through data to find specific data points that will support their particular position. For example, in a linear regression, an analyst could engage in "regression fishing" where several regressions are run with numerous explanatory variables with only the most favored result—as measured by the strength of the fit—presented. By not accounting for the inherent biases associated with running several regressions to find the best fit, the conclusions drawn from a partial presentation of the facts are biased and inaccurate.

Narrative bias. While biased data mining involves the abuse of statistics to develop a particular conclusion *before* the prediction, the narrative bias problem represents conclusions or "sound bites" drawn *after* an event has occurred. In this case, a data analyst or commentator will draw a conclusion to the perceived event that is consistent with the broader story he wants to tell to the organization. The problem is that the perceived event was likely the result of a complex model that could have just as likely produced this or several outcomes.

In a simple example of this problem, one could think of someone drawing inferences on why a random throw of the two dice produced a particular result—say a three—after the roll has occurred. While actuaries or more sophisticated analysts may attribute this result to an event that could have occurred given the distribution of possible outcomes, less



sophisticated analysts may attempt to explain this result with an elaborate explanation. In a business environment, this story will typically support a particular business policy that they had been advocating.

This problem is especially troublesome for actuaries. Using the dice example, while we could have correctly said that the most likely outcome was a seven and that we would expect an entire distribution of outcomes, we could be perceived as incorrect in our prediction and our reputation compromised because the most likely event did not occur. With the perception then created that the actuarial prediction was incorrect, this could then provide an opportunity for someone else to introduce their own simplifying narrative on why a particular event occurred. Using the dice example, someone could say that their lucky rabbit's foot or dice throwing technique produced the three and that the actuary who predicted the seven did not adequately account for their abilities. As a result, in the next prediction cycle, the story now becomes that the actuary should better account for their skill or luck in throwing the dice. Continuing with the story, if the next throw of the dice produces a more likely result—say a seven—then nothing will be heard from data analysts who criticized the prior prediction. Of course, if another three is produced, the criticism will be immediate and our prediction abilities questioned once again.

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Increasing Expectations for the Usefulness of Data

We live in a business world that has come to increasingly worship data analysis and its potential to answer important business questions. In many respects, this represents an effective strategy. We have seen many companies (Capital One) and even sports team (the Oakland As) effectively deploy strategies to dramatically improve results. (Admittedly, I wrote an article several years ago discussing *Moneyball* and its potential applications to the actuarial profession.) While the media and business books have popularized the potential uses of data with compelling narratives, they have not adequately highlighted the limitations associated with data analysis—particularly as it applies to complex models that attempt to predict future human behavior.

A simple comparison between predicting the average height in a large population and predicting the price movement in the stock market provides an extreme example of the problem. For example, If we have physical data on a large number of Americans (including height, weight, and demographic data), we have a number of statistical techniques that would allow us to accurately predict the height of another large population. In this case, the data analysis works largely because we are predicting a biological attribute that is more limited and less complex. The price movement in the stock market, on the other hand, is driven by a wide range of factors that make prediction and the deployment of mathematical models much more difficult. One only needs to look at the hubris of many technical analysts who have attempted and ultimately failed to predict future stock market movements. As chronicled in the book *When Genius Failed*, the catastrophic failure of the Long Term Capital Management hedge fund and their two Nobel Prize winning economist advisors provides a clear example of this problem.

ULTIMATELY, THE BASIS OF OUR WORK DEPENDS ON APPLYING SOPHISTICATED STATISTICAL TECHNIQUES TO HISTORICAL DATA TO MAKE PREDICTIONS ABOUT THE FUTURE.

The above example highlights the problem associated with worshipping data analysis in all situations. While it is absolutely appropriate to use and expect significant prediction power in some situations (predicting height in a population, quantifying the value of baseball players, segmenting credit card customers), assuming that this approach will be equally effective in predicting more complex models is simply not appropriate. In saying this, I'm not suggesting that models or analysis should not be employed, but I am suggesting that the analysis should clearly highlight the prediction limitation and the potential for a wide range of factors to impact results. As I will highlight in the last section, I also believe that business decisions dependent on complex environments should be more holistic and less dependent on the simple results from a model.

Environmental Change

Ultimately, the basis of our work depends on applying sophisticated statistical techniques to historical data to make predictions about the future. To the extent historical data no longer accurately represents a given phenomenon—human behavior in utilizing services, for example—even the most sophisticated data analysis will not adequately predict the future. As a result, unless we can quantify this change in future behavior, the models built up using this historical data will inherently produce inaccurate predictions.

By most measures, we are now in an economic and regulatory environment that is much different than our historical experience. Considering the dislocation and severity of our economic challenges along with the enormous change in health care regulation, the historical data and experience is not sufficiently robust to account for all the factors that could impact human behavior. Although we still need to employ sophisticated modeling and attempt to quantify behavior in this new environment, we also need to acknowledge that our prediction accuracy will not be the same as our historical pricing accuracy.

Consistent with this, we need to provide quantitative and *qualitative* opinions of the potential distribution around an expected outcome. In addition to highlighting the potential variation, this process also helps maintain our reputation if an unforeseen event or change does occur.

A Proposed Response to the Problem

First and foremost, we need to approach data analysis with humility and a certain degree of skepticism when attempting to predict the future of complex systems (stock price changes, future GDP growth, election results, human behavior in utilizing services in an environment with significant economic change). We need to openly acknowledge that predicting the future is difficult and subject to an infinite number of unforeseen events and changes that could impact results. Consistent with this view, we also need to openly acknowledge the limits of our statistical predictions and provide both quantitative and qualitative analysis in outlining potential outcomes. As part of our qualitative discussion, we need to consider the broader business strategy and have a philosophy toward expected changes in human behavior. While this approach may run against the grain of those worshiping data and its potential to solve business questions, I believe this provides an honest appraisal of data and its implications that underpin our profession. This approach also helps maintain our credibility if an unforeseen event or change does occur that impacts our results.

In addition to acknowledging our limits, I also think that the most common pitfalls to data analysis need to be openly discussed including presenting data with almost no credibility, mistaking correlation with causation, biased data mining, the problems with developing a narrative bias, and presenting data without proper caveats.

In considering the challenges in our profession, I can't help but think of a famous quote from the economist Friedrich Hayek: "The curious task of economics is to demonstrate to men how little they really know about what they can imagine they can design." Like economists, in addition to making unbiased predictions about the future using actuarially sound statistical techniques, I also think our profession has an obligation to clearly articulate the limits and potential variation in our predictions of complex systems. ▼

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