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Predictive Analytics: An Alternative Perspective

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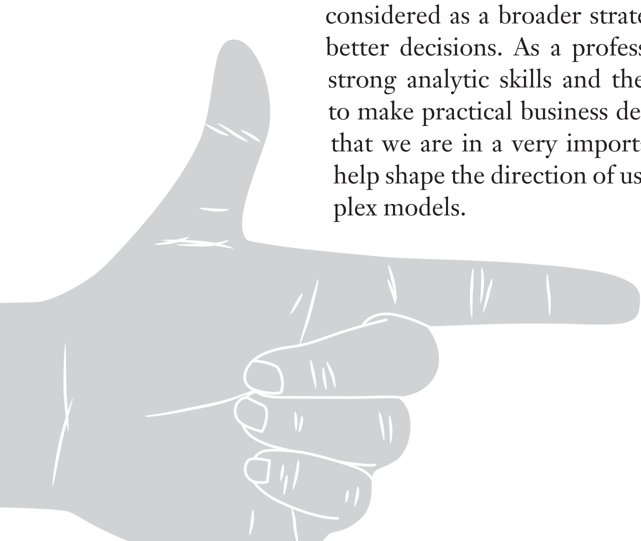
Predictive analytics. The term suggests data, complexity, sophistication, and progress in predicting the future. As suggested by the recent name change in this section, it also represents the general direction of our profession—a move toward more extensive use of data and more complex models. By combining computing power with significantly more data, these analytic processes promise greater accuracy in projecting the future.

There is a great market for this predictive power. Senior managers want to be able to accurately predict the future and set the right expectations for outside stakeholders. Policymakers want to predict the outcomes of policy changes and ensure that these changes are sufficiently funded. IT professionals want to develop a sophisticated infrastructure to help support these data intensive initiatives. Academics want to create even more sophisticated approaches to analyze data. Consultants want to highlight new, but more complex models that have the potential to improve the predictive power over existing models. Considering the many groups advocating for greater complexity, few people stand on the other side of the movement toward more data and greater computing power.

As we move toward more extensive use of predictive analytics and greater complexity, however, I also think that we need to consider the necessary conditions for more sophisticated predictive analytics to be useful and ensure that this tactic is considered as a broader strategy to produce better decisions. As a profession with both strong analytic skills and the responsibility to make practical business decisions, I think that we are in a very important position to help shape the direction of using more complex models.



PREDICTIVE ANALYTICS: THE CONDITIONS NECESSARY FOR A USEFUL ANALYSIS

Before more sophisticated predictive analytics can be proven useful, several conditions should be met before moving to the next step of using a more complex models. These include:

ACCURATE HISTORICAL DATA. Although this obvious step is best characterized by the term "garbage in; garbage out," the potential accuracy of the historical data is often not considered when an analyst makes the next step to introduce a complex model to answer a business question. In many cases, the challenge is that the underlying data is neither completely accurate nor completely wrong, but rather a shade of grey that can be difficult to evaluate. For example, the data could have a selection bias or measurement problem that could impact the accuracy of the model, but the full extent of the impact is difficult to measure. To the full extent possible, an analyst should consider whether these data limitations make a sophisticated data analysis designed to explain subtleties in the data not useful.

A STABLE UNDERLYING SYSTEM WHERE THE HISTORICAL DATA IS A GOOD INDICATOR OF THE EXPECTED EXPERIENCE IN THE PROJECTION PERIOD. If the economic incentives and policies are changing significantly from the historical period to the projection period, the experience and population inherent in the historical data will not necessarily be a good indicator of future performance. The most obvious case of this in our profession has been the pricing development for the Affordable Care Act (ACA). With the change in the underwriting rules and the introduction of income dependent subsidies, the historical experience of a fully underwritten individual population is simply not a good indicator of the future experience for an ACA population. In this case, a sophisticated analysis of the historical data will be much less useful.

THE POTENTIAL ERRORS IN USING A SOPHISTICATED MODELING APPROACH DO NOT OUTWEIGH THE HOPED FOR INCREASE IN ACCURACY. With increased complexity, a model can be become increasingly difficult to understand and more difficult to adequately peer review. The loss of these two important features in a modeling exercise often lead to errors and ultimately decisions that are worse than a model where the results are intuitive and adequately peer reviewed. Although not often explicitly considered, these costs need to be accounted for when moving to a more sophisticated predictive model.

THE PROCESS DOES NOT EASILY LEND ITSELF TO A BIASED ANALYSIS THAT ALLOWS THE RESEARCHER TO PRESENT A PREFERRED OUTCOME. With a more complex analysis, an analyst will have a greater opportunity to "cherry pick" results to present the preferred conclusion in the best possible light. While this problem could be mitigated through adequate review, complex models are much more likely to allow analysts to have this opportunity to skew the final results.

Taken in total, the above conditions are important determinants in whether a complex predictive analytic exercise should be started. Without considering the above factors, we are likely to engage in a costly and time consuming exercise that does little to improve the decision making process and could produce even worse results than a more intuitive approach.

AN ALTERNATIVE APPROACH: GOOD DECISION MAKING

While the term "predictive analytics" has intuitive appeal to many people, its use still needs to produce better decisions that are both accurate and contribute the long term sustainability of the organizations who rely on our estimates. In an effort to highlight a process that produces better decisions rather than a specific tactic—predictive analytics—the following steps outline factors that contribute to better decision-making.

1. CLEARLY DEFINE THE BUSINESS QUESTION AND DEVELOP SEVERAL WORKING HYPOTHESIS THAT COULD CONTRIBUTE TO RESULTS IN THE PROJECTION PERIOD. A clear question with working theories helps focus the analysis and ensure that the research has a well-defined objective.

2. UNDERSTAND ALL ASPECTS OF THE DATA THAT WILL BE USED IN THE ANALYSIS, INCLUDING HOW IT WAS CAPTURED AND ITS POTENTIAL WEAKNESSES. LOOK FOR OTHER DATA SOURCES THAT COULD COMPLIMENT THE DECISION-MAKING PROCESS. Data is the life blood of actuarial analysis and we need to take very seriously its weaknesses as we begin an analysis that presumes that the data are accurate.

3. UNDERSTAND THE SYSTEM BEING PREDICTED AND ENSURE THAT THE HISTORICAL PERIOD DATA CAN ACCURATELY REPRESENT THE EXPECTED RESULTS IN THE PROJECTION PERIOD. While adjustments can be made to the historical experience to better reflect the expected experience in the projection period, more extensive adjustments introduce a greater potential for error in the final estimate. This variability needs to be considered as greater complexity is added to the modeling process.

4. EXHAUST ALL EFFORTS TO ANSWER THE QUESTION WITH SIMPLE DATA ANALYSIS AND QUALITATIVE FACTORS. This high level analysis can help direct the research and ensure that a complex analysis is useful and ultimately passes the high level intuitive test.

5. LOOK TO DISPROVE YOUR THEORY THROUGH ADDITIONAL TESTING OR BY WORKING WITH OTHERS WHO USE ALTERNATIVE APPROACHES. Analysts need to be vigilant about not falling in love with their preferred result and ensure that others adequately test their conclusions.

6. CONSIDER ADDING ADDITIONAL COMPLEXITY THROUGH PREDICTIVE ANALYTICS OR OTHER TECHNIQUES IF MORE SIMPLE TECHNIQUES ARE INADEQUATE AND THE ADDITIONAL COSTS ARE LIMITED. Additional complexity can be costly and the benefits should outweigh the costs.

7. FULLY UNDERSTAND HOW THE RESULTS WILL BE USED AND ENSURE THAT THE RESULTS WILL BE SHOWN IN THE BROADER CONTEXT INCLUDING PRESENTING THE POTENTIAL VARIABILITY ASSOCIATED WITH THE ESTIMATES. We need to be careful to show the likely variability of our estimates and ensure that a point estimate from a highly stable system with less potential volatility is not directly compared with a point estimate from a volatile system.

CONCLUSION

As a profession, our job is to help make the best possible decision with all available information and ensure that our estimates help contribute to the long term sustainability of the institutions that provide health insurance, pensions, and life insurance protection for people at the most vulnerable time of their lives. If a more sophisticated modeling approach or predictive analytics helps contribute to this goal, we should embrace these tactical techniques to help in our mission. That said, predictive analytics is only a potential tactic in a series of steps used to produce the best possible decision. It should not be considered an end in of itself. As our section makes this name change, I hope that we continue to remind ourselves of our broader mission and ensure that our chief goal is to produce better decisions and not necessarily greater technical sophistication. ■

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