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A Review of Nate Silver's *The Signal and the Noise: Why So Many Predictions Fail – but Some Don't*

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The book *The Signal and The Noise; Why So Many Predictions Fail - But Some Don't* is, as its name implies, a book about predictions in a wide range of fields including weather, sports-betting, elections, and economic predictions. Rather than focus solely on the mathematics of prediction in each field, it places just as much emphasis on the role of people that make predictions. Thus, the book is about the human process of making predictions, the many factors that affect their accuracy, and how these factors interact with each other. Silver's (2012) approach highlights that because the person making predictions is an indispensable part of the prediction process, the fallibility of people leads to the fallibility of predictions. He takes great care to describe approaches to mitigating these biases and describes them thoroughly in the context of prediction.

The primary guidance given to the book-reviewers for this volume was to give a mathematics education perspective on the books we reviewed. Thus, this review begins with why I think mathematics educators might be interested in what I interpret to be the overarching theme of the book, humanizing the mathematics of prediction. I then shift to discussing more specific lessons I learned from Silver (2012) and how they are supported empirically in the book. I conclude with some suggestions for how this book might be utilized by mathematics educators.

Humanizing Mathematical Practice in Mathematics Education

As mathematics educators, it is useful to have our eyes on the mathematical practice that occurs past the walls of the classrooms we study and teach in. Our students, particularly

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those who go into mathematics intensive careers, benefit from our knowledge of what skills and ways of thinking will benefit them in those careers. Luckily many mathematics education researchers find themselves in and around mathematics departments where we have access to professional mathematicians. Studying these mathematicians is a part of mathematics education research (e.g., Weber & Mejía-Ramos, 2011; Kontorovich, 2016). However, there are people who don't necessarily self-identify as mathematicians who have mathematics intensive careers. Although I'm familiar with research that studies professional users of mathematics (e.g., Roth, & Bowen, 2001), Silver's (2012) book helped me realize that much of my images of mathematics intensive careers were previously limited to images of academics such as mathematicians, biologists and physicists. This book helped humanize some of the people who have mathematics intensive careers outside academia and helped me understand the kinds of problems (both mathematical and non-mathematical) they struggle with. It helped highlight some of the nuances behind what people that use mathematics do and the pressures that influence their work.

I assume that Silver's (2012) book will benefit other mathematics educators in similar ways to how it helped me. However, I do not want to overstate what I know about the practices of my colleagues. Mathematics educators studying the practices of other mathematics educators is still a burgeoning field of study (e.g., Kontorovich, 2015).

Silver's Approach to Humanizing Mathematical Prediction

Studying mathematicians and other academic users of mathematics is not uncommon in mathematics education research (e.g., Kontorovich, 2016; Weber & Mejía-Ramos, 2011; Roth, & Bowen, 2001). So it was tempting for me to conceptualize Silver (2012) as a study of expert users of mathematics outside the confines of academia. However, the approach is quite different in that it treats the human's subjects as people. In other words, it humanizes them. The primary means by which prediction is humanized in this book is through narratives about the people involved in prediction. These narratives help the reader get to know the people that make predictions, what their motivations are, what their data look like, what broader (scientific) theories they base their predictions on and importantly how these factors affect the accuracy of their predictions. It bears mentioning that mathematics educators have taken an interest in the practices of mathematicians (e.g., Kontorovich, 2016; Weber & Mejía-Ramos, 2011; Weber *et al.*, 2013) and other professional users of mathematics (e.g., Roth & Bowen, 2001). However, this work tends to focus on some specific aspect of practice such as how mathematicians read a proof (Weber *et al.*, 2013) or how scientists interpret graphs (Roth & Bowen, 2001). Silver (2012) takes a far more holistic almost ethnographic approach. He discusses who the people making predictions are, and how their individual personalities interface with the pressures of their craft.

Each chapter focuses on a different type of prediction: elections, earthquakes, weather, hurricanes, economic predictions, poker, sports betting, and terrorism. Consistent with Silver's human centered approach each chapter begins with a thick description of an expert involved in prediction, how they look, what their role is, their demeanor, and their surroundings. The chapter delves deep into what prediction looks like in some specific field and how that's evolved over time. If focuses on how experts approach their predictions and what factors account for predictive success and failures within their field. In the chapters where the field of prediction is something the author, Nate Silver, has expertise in, namely elections and poker, the narrative turns autobiographical in nature.

Each of the sub-fields discussed in the book are not treated in isolation. The book is structured to contrast the causes of predictive failures in one field with the causes of predictive successes in another. In drawing these parallels between the various fields, Silver builds up a robust image of what makes a good prediction which can be used beyond the fields discussed in the book. This creates a broad framework for judging which predictions are likely to come to fruition, and which others are little more than blind stabs in the dark (which also occasionally come true). It also helps to illustrate how advances in science and technology have caused incremental increases in the accuracy of prediction. This is not done without acknowledging the roles people play in these predictions. Silver (2012) takes time to touch upon theories regarding what personality traits tend to align with good predicting. Though these have some face validity, there is little in the way of empirical evidence for these theories, at least not within the pages of the book.

My Main Takeaways from the Book

My main takeaways from the book are the following insights (each of these include examples discussed in more detail in the book):

One

The goal of the person making a prediction is not always to make the most accurate prediction possible. Predictions are often made for a particular audience and have consequences. The consequences for certain kinds of predictions and the needs and perspectives of the audience have an influence on the predictions.

In some fields, making predictions that the consumers of those predictions are happier with, is more important than the accuracy of those predictions. The book contains some great examples to illustrate this phenomenon in the context of weather prediction. The audience for weather predictions of the type seen on the local news is the general public, which itself is not particularly mathematically literate. A consequence of this is that certain predictions are periodically misinterpreted by the public. Namely, predicting a 50% chance of rain, even if the model indicates that there is in fact a 50% chance of rain, is interpreted by the public as indecisive. To deal with this, weather forecasters often bump 50% predictions to either 40% or 60%. This overtly makes such predictions less accurate, while simultaneously increasing public trust in the predictions. A similar example occurs when there is a low chance of rain, say 5%. These are often bumped to 20% since, no rain when rain was predicted is interpreted more favorably than the converse. Since weather predictions in commercial news outlets are subject to the pressures of what consumers of news want, the meteorologists succumbing to these pressures in exchange for some amount of accuracy is natural. It is a consequence of the people making the predictions succumbing to the pressure of the people receiving them.

Two

Accurate predictions: (a) are based around a sound (scientific) theory, (b) have quality data relevant to the theory, and (c) require sufficient computing resources available to apply the model implied by the theory to the data. The absence of any of the three factors implies poor predictions. Though their presence does not guarantee accuracy.

An example of good theory without good data can be seen in earthquake prediction. The prediction of the dates, locations and intensities in which earthquakes will occur is considered by the United States Geological Society to be currently impossible. In fact, not a single occurrence of an earthquake being accurately predicted is known to exist. There is a well-developed scientific theory of plate tectonics which explains why and how earthquakes occur and ample computing power available for this predictive endeavor. However, tectonic plates are so deep underground that the necessary measurements to make such predictions accurately are unavailable. This lack of accurate data means that all the best geologists are currently able to do is predict the long-term frequency and intensity of earthquakes. This means building codes in earthquake prone areas can be meaningfully implemented, but no planning that involves knowing when an earthquake will happen can occur.

An example of a prediction problem where theory is lacking involves predicting stock market crashes. The core issue with economic predictions is that the nature of the economy, what products are bought and sold, who sells them, who buys them and the behaviors of investors are constantly changing. There is plenty of data available and companies willing to spend money on the computer power to analyze it. The core issue at hand is that the relationship between the many economic variables is in a constant state of flux, with new variables continually emerging. So, the system is too chaotic to predict accurately. Compounding this issue, is that the economic predictions themselves influence the market, meaning that a prediction can circumvent itself once it is published since investors respond to it.

The need for a computing power for accurate prediction is well illustrated in the book by the predictions of the US National Weather Service. Unlike the news outlet's weather predictions discussed above, the national weather service does not publish data directly to the public, so is not subject to the pressures discussed above. The core results of computational fluid dynamics (the mathematics used to predict the weather) have existed since the late 1960's. However, even though the mathematics used to compute the weather has not changed significantly since then, the average error of weather reports has steadily decreased since the 1970's. The meteorologist interviewed in Silver (2012) attributes this progress to progressively more accurate data and progressively faster super computers.

Three

Even when there is good theory indicating which model to use, accurate data, sufficient computing resources, human beings still play an important role in the prediction process. One persistent issue with weather prediction is a result of chaos theory. That is, that small fluctuations in data may lead to vastly different predictions in the long term. In fact, even though ten-day forecasts are fairly normal in public facing weather predictions, only the first four-five days of the forecast hold actual predictive value. The remaining five-days are included to improve perceptions of the accuracy of the initial days of the forecast. The forecasters at the national weather service are intimately aware of the kinds of errors in models that tend to occur because of chaos theory. It thus becomes necessary to readjust some aspects of the predictions manually. Since these types of errors are intrinsic to all mathematical models, the human-computer hybrid predictions are actually more accurate than would be possible with either the computer or human in isolation.

The points above are explored much more thoroughly in the book, each with far more examples than can fit in this short review.

How This Book Can Be Useful to Mathematics Educators.

Now that I have given the reader some sense of what to expect from the book, it is worth shifting back to who might get what from reading it. I began this review by implying that this might be a useful read for mathematics educators, particularly those interested in better understanding what mathematically intensive careers outside of academia look like. However, I believe a more general tertiary mathematics education audience would also appreciate this book as it provides some useful *knowledge at the mathematical horizon* (Zazkis & Mamolo, 2011). In particular, for tertiary mathematics educators teaching upper division mathematics courses there is a fairly short timeframe between when their students are in their classroom and when they will be expected to be real-world users of mathematics. Knowing more about the kinds of environments that some of these students will work in and the types of things that might make them better practitioners of their chosen careers might leave some mathematics educators better equipped to prepare tertiary students.

Finally, the book itself might be a good one to recommend to students pursuing an applied math track. Students who might potentially be involved in making predictions for a living would get a broad introduction into what that might involve from this book. Additionally, Silver (2012) provides useful advice for those interested in exploring their own (for profit) predictive endeavors; the fields where the predictions have good data but lower quality available predictions are the ripest for aspiring predictors. I know, personally, I have a list of books I periodically recommend to students and I'm adding Silver (2012) to the list.

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