Multi-Disciplinary Studies of Probability Perception Contribute to Engineering & Exploiting Predictive Analytic Technologies[1]

Philip M. Sagan, Ph.D.
Sagan Consulting, LLC, Reston VA 20194

Hays W. (Skip) McCormick
Intelligence Community

1 Introduction

Intelligence analysis has historically focused on explaining contemporary events, emphasizing our understanding of existing mysteries and enigmas (Heuer, 1999). Under the impetus of the terrorist attacks of 9/11 (National Commission on Terrorist Attacks Upon the United States, 2004) emphasis has increasingly shifted to anticipating future events based on data collected from a multiplicity of sources, especially the Internet.

This places emphasis on probabilistic estimates of likelihood by systems that combine human expertise with automated technologies that manipulate data beyond unaided human capability to understand and manipulate. Unprecedented emphasis then falls on how humans interpret statements of probability understanding probability as a metric for our lack of certainty an event will occur and ambiguity as to whether it has occurred. How analysts and their customers understand algorithmic combination of data and assign probabilities to future events is essential to addressing interpretation of algorithmic estimates.

2 The Emerging Analytic Environment

In the past Intelligence Community's(IC) data collection systems were like scientific data collection systems: custom engineered from end-to-end as harmonized, coherent systems that meaningfully measured and manipulated data relevant to a well-defined problem. We term data produced by such systems *bespoke data*. [2] This has changed: analysts are increasingly synthesizing *byproduct* data with the IC's traditional bespoke data. Byproduct

[1] This White Paper is based on a study (Sagan, 2015) conducted by the author for an element of the IC concerned with anticipatory intelligence, delivered June, 2015.

[2] We distinguish between bespoke and byproduct data. *Bespoke Data:* through all human history data were created to answer specific questions – they were made to order, bespoke. In contrast *byproduct data* is a term intended to replace *big data* in our lexicon. Byproduct data are automatically created by information technology systems to serve some business or personal objective and are easily repurposed for other, unrelated purposes, like telephony geodata necessary for cell routing repurposed for vehicle navigation.

are thus generally *foreign data* to the systems which are used to analyze them, which means that the assumptions underlying the data (measurement model) are not known.

Driven by the emergence over the last 20 years of a vibrant, global commercial market, the power and pervasiveness of computer and communications technologies have exploded, leading to dramatically reduced *friction* in all sorts of information technology operations. For the first time in human history people have ready, inexpensive, practical access to *tools that amplify the mind* rather than the body. For the first time in history we are using *low-friction* computation tools that create, operate using, and "throw-off" by-product data readily repurposed to ends potentially far-removed from the original intent. This separation of analytical purpose from measurement processes (creation of data) disrupts the historic intellectual integrity of inquiry mediated by professional expertise.

Our techniques for engineering human-machine systems are proven to work when that human expertise is at the heart of data synthesis. Emerging anticipatory analytic systems arguably necessitate a new partitioning and a reassessment of our engineering techniques: novel combination(s), scale, and scope of data mean that tasks that have historically been reserved for humans (in Licklider's model (1960) of human-machine system partitioning) are beyond unaided human cognition. Will analysts using emerging anticipatory analytic systems accept the new partitioning and adopt the products of mind amplifying tools?

3 Impacts on Analysts and Analysis

Dramatic reduction in computational friction is both an opportunity and a threat. It is an opportunity because we can adopt new ways of doing things that could not previously be considered; it is a threat because our corporate culture and (personal) process norms are in transition from those suitable to high friction to one where it is negligible. Fifty years ago, analysts, like scientists or engineers, had to think with extreme care about what data were to be collected, how they were to be analyzed, and how they were to be interpreted. To do anything else was totally infeasible in terms of time and treasure. Now, personal and corporate processes and best practices are rooted in a world that has utterly changed, but our millennia old ways thinking about data and their organization, and our centuries-old way of thinking about mathematical probability are just starting to catch up.

In assessing human understanding of probability there is no unique solution because there is no simple, unique way of describing probability. There are four distinct interpretations of probability that we must consider: relative frequency of occurrence, logical relationship between evidence and belief, subjective degree of belief, and propensity to occur, (Sagan, 2015), (Vick, 2002), (Weisberg, 2014). Just as electromagnetic is sometimes best described as a particle and sometimes as a wave, it benefits us to think of probability in one way, say propensity to occur, at other times in another way, say, subjective degree of belief. However, frequency of occurrence, the original form of probability and what we normally think of as probability, is arguably the least relevant to predictive analysis (Sagan, 2015).

And since the majority, if not the totality, of commonly used statistics are based on the relative frequency interpretation, there is a special challenge for the predictive analysis manager, system engineer, algorithm designer, strategic communications expert, and training expert. This challenge is further complicated because there is a risk of algorithms failing to discriminate spurious or transient correlations from causal connections due to the bring your own data scenario with most byproduct data.

Furthermore, without a clear understanding of how probability is understood by different professions, practitioners and lay people (including the ICs customers), we will be unable to manage the productive use of predictive analytics technology. The roots of these concerns go deep in the history of the analytic community (Kent, 1964). This problem of specifying probability and how we talk about it has continued to receive attention in high-level reports (National Research Council, 2011, p. 36), but more needs to be done since the impacts of low friction computing and byproduct data have yet to be included in the analysis.

4 Open Questions and Recommendations

SBSS disciplines are necessary to understand the broadly defined analytical system (encompassing requirements developer – technology developer – collector – analyst – customer) in the context of the contemporary environment of low-friction computing and byproduct data. Two major problem areas are defined:

1. Understanding and communicating probability, especially when calculated by opaque algorithms operating on byproduct data.

   a. Develop a taxonomy of probability and another of anticipatory (predictive) precision, and combinatoric methods appropriate to different domains and problems that have components where we have varying levels of predictive sophistication and rigor.

   If we do not use words in a consistent and transparent way when discussing probability and anticipation, there will be confusion and, ultimately, disbelief resulting from unmet expectations (Pinker, 2007), (Quine, 1960). Similarly for logical relationship between evidence and belief and subjective degree of belief. We have not previously faced circumstances where we've needed to combine relative frequency and propensity to occur probabilities and so lack widely-accepted, transparent, processes and procedures for how we go about doing so.

   b. Re-assessment of measurement and statistical methods considering low-friction computing and byproduct data combined with bespoke data, especially the use of inferential vs. descriptive statistics.

   Increasingly pervasive low-friction, low-cost computation technologies and the growing availability and importance of byproduct data risk breaking historic links between deep, domain-specific knowledge and understanding of data. Consequently, spurious correlations may be confounded with causal relationships.

2. Understanding, managing, and maintaining vigilance given asynchronous collection of data in anticipation of low frequency, one-time events

   a. Developing methods to communicate to analysts and watch standers the existence of unexpected algorithmically identified targets, and their potential significance.

There is no single dimension to which analysts respond to form a perception of probability of a future event. This is due to the lack of independence of a probability expression from the subject matter of the expression as well as ambiguity in usage of the four usages of "probability." The anticipatory analytic systems analyst works in a highly complex context in general far removed from laboratory research conducted on undergraduate psychology majors, so the direct applicability of research that does not simulate emerging anticipatory analytic environments is unclear.

Government funded vigilance and Signal Detection Theory (SDT) research spanning the past six or seven decades, enabling engineering radar and sonar systems, is a starting point to addressing this issue. Challenges in extending historic vigilance findings include most significantly, the fact that emerging anticipatory analytic systems analysts, unlike radar and sonar operators, have information about the environments they are monitoring independent from what the warning system provides.

b. Understanding the challenges of categorizing signal vs. clutter. vs. noise in byproduct data which is being repurposed to address multiple intelligence issues

SDT can be applied to emerging anticipatory analytic systems operation embodies a signal detection process that can be used to monitor and tune emerging anticipatory analytic systems at a range of granularities. As previously noted (McClelland, 2011), SDT can be applied in assessing human interactions with emerging anticipatory analytic systems and the effectiveness of engineering actions over the entire System Development Life Cycle (SDLC).

5 Relevant SBSS Disciplines

Studies of IC analysts in their actual work environments is required to address the problems identified here, drawing on psychophysics and measurement theory, cognitive psychology, evolutionary psychology, human factors, and Signal Detection Theory. We are now developing "non-invasive" data capture capabilities that will enable this research.

6 References

Heuer, R. J. (1999). *Psychology of Intelligence Analysis.* Center for the Study of Intelligence: Central Intelligence Agency.

Kent, S. (1964). Words of estimative probability. *Studies In Intelligence* (Fall).

Licklider, J. C. (1960). Man-computer symbiosis. *IRE Transactions on Human Factors in Electronics, 4-11*, 4-11.

McClelland, G. H. (2011). Use of Signal Detection Theory as a Tool for Enhancing Performance and Evaluating Tradecraft in Intelligence Analysis. In *Intelligence Analysis: Behavioral and Social Scientific Foundations* (pp. 83-99).

National Commission on Terrorist Attacks Upon the United States. (2004). *The 9/11 Commission Report.*

National Research Council. (2011). *Intelligence Analysis for Tomorrow: Advances from the Behavioral and Social Sciences.* Committee on Behavioral and Social Science Research. Washington, DC:: The National Academies Press.

Pinker, S. (2007). *The Stuff of Thought: Language As a Window Into Human Nature.* New York: Viking.Quine, W. V. (1960). *Word and Object.* Cambridge, Mass: MIT Press.

Sagan, P. M. (2015). *How Humans Understand and Process Probability, Prediction, Inference, Intuition, Confidence, Doubt, and Validation Meta-Information.* Reston, VA: Sagan Consulting, LLC.

Vick, S. G. (2002). *Degrees of belief: subjective probability and engineering judgment.* American Society of Civil Engineers Publications.

Weisberg, H. I. (2014). *Willful Ignorance: The Mismeasure of Uncertainty.* Hoboken, New Jersey: John Wiley & Sons.

7 Selected references from Sagan (2015) Organized By Topic

Psychophysics and Measurement Theory

Green, D. M., & Swets, J. A. (1966). *Signal Detection Theory and Psychophysics.* Huntington, New York: Krieger.

Stevens, S. S. (1951). Mathematics, Measurement and Psychophysics. In S. S. Stevens, *Handbook of Experimental Psychology* (pp. 1-49). New York: John Wiley.

Stevens, S. S. (1975). *Psychophysics.* New York: John Wiley.

Cognitive Psychology

Goff, L. M., & Roediger, H. L. (1998). Imagination inflation for action events: Repeated imaginings lead to illusory recollections. *Memory & Cognition, 26*(1), 20-33.

Fiedler, K. (1988). The dependence of the conjunction fallacy on subtle linguistic factors. *Psychological Research, 50*, 123-129.

Kahneman, D., & Tversky, A. (1973). On the Psychology of Prediction. *Psychological Review, 80*, 237-251. doi:10.1126/science.185.4157.1124

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica, 47*(2), 263-291.

Loftus, E. F., & Palmer, J. C. (1974). Reconstruction of automobile destruction: An example of the interaction between language and memory. *Journal of Verbal Learning & Verbal Behavior, 13,* 585–589. doi:10.1016/s0022-5371(74)80011-3

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, 1124-1131. doi:10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (1981). The Framing of Decisions and the Psychology of Choice. *Science, 211*(4481), 453 - 458. doi:10.1126/science.7455683

<u>Evolutionary Psychology</u>

Cosmides, L., & Tooby, J. (1996). Are humans good intuitive statisticians after all? Rethinking some conclusions from the literature on judgment under uncertainty. *Cognition, 58*(1), 1-73.

Gigerenzer, G. (1994). Why the distinction between single-event probabilities and frequencies is important for psychology (and vice versa). In G. Wright, & P. Ayton, *Subjective Probability* (pp. 129-161). Chichester: Wiley.

Gigerenzer, G. (1996). On narrow norms and vague heuristics: A reply to Kahneman and Tversky. *Psychological Review, 103,* 592-596.

Hertwig, R., & & Gigerenzer, G. (1993). Frequency and single-event judgments. *Unpublished manuscript*.

<u>Human Factors</u>

Holland, J. G. (1958). Human vigilance. *Science, 128*(3315), 61-67. doi:10.1126/science.128.3315.61

Warm, J. S. (1977). Psychological Processes in Sustained Attention. In R. R. Mackie, *Vigilance: theory, operational performance, and physiological correlates:[proceedings](Vol. 3* (pp. 623-644). Plenum.

Wellbrink, J., Zyda, M., & Hiles, J. (2004, April). Modeling Vigilance Performance as a Complex Adaptive System. *The Journal of Defense Modeling and Simulation, 1*(1), 29–42.

<u>Information Theory & Signal Detection Theory</u>

Peterson, W., Birdsall, T., & Fox, W. (1954, September). The Theory of Signal Detectability. *IEEE Transactions on Information Theory, 4*(4), 171-212.

Shannon, C. (1948, July and October). A Mathematical Theory of Communication. *Bell System Technical Journal, 27,* 379-423 and 623-656.