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Communicating forecasts: The simplicity of simulated experience

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ABSTRACT

It is unclear whether decision makers who receive forecasts expressed as probability distributions over outcomes understand the implications of this form of communication. We suggest a solution based on the fact that people are effective at estimating the frequency of data accurately in environments that are characterized by plentiful, unbiased feedback. Thus, forecasters should provide decision makers with simulation models that allow them to experience the frequencies of potential outcomes. Before implementing this suggestion, however, it is important to assess whether people can make appropriate probabilistic inferences based on such simulated experience. In an experimental program, we find that statistically sophisticated and naïve individuals relate easily to this presentation mode, they prefer it to analytic descriptions, and their probabilistic inferences improve. We conclude that asking decision makers to use simulations actively is potentially a powerful – and simplifying – method to improve the practice of forecasting.

1. Introduction

The predictions of forecasting models are often represented by probability distributions over potential outcomes – and sometimes by just the mean and variance of a distribution. An important issue, however, is whether consumers of forecasts (e.g., decision makers) understand the implications of the uncertainty implicit in the forecasts communicated in this manner. In this paper we address this issue and make a concrete suggestion. Instead of using forecasting models to provide probability distributions over outcomes, the forecasters should provide the intended recipients with simulation models that allow them to observe possible outcomes through a process of what we call simulated experience. Since this is a radical suggestion, we outline below the underlying rationale as well as summarizing a research program that addresses an issue that is key to our proposal: Can people make accurate probabilistic inferences on the basis of simulated experience?

A considerable amount of literature examines people's ability to understand probabilistic statements. For example, in a recent discussion Budescu, Por, and Broomell (2012) review difficulties due inter alia to context, the roles people play in the communication process, the extent to which uncertain events are or are not precisely defined, and whether uncertainties are expressed numerically in probabilistic format or verbally (e.g., using words such as "likely"). A revealing study by Gigerenzer, Hertwig, van den Broek, Fasolo, and Katsikopoulos (2005) clearly demonstrates that interpretations of numerical probabilistic forecasts and the events with which they are associated are ambiguous. The participants variously interpreted a forecast expressed as "a 30% chance of rain tomorrow" as implying rain in 30% of the region, 30% of the time, or 30% of days like the one in question. The authors cite one respondent who stated "Thirty percent means that if you look up to the sky and see 100 clouds, then 30 of them are black" (Gigerenzer et al., 2005, p. 626).

The respondents in Gigerenzer et al.'s (2005) study were members of the general public and thus one might not expect them to be familiar with probabilistic reasoning. However, it is not clear that experts understand the probabilistic implications of forecasts or forecasting models in the domains of their professional activity. For instance, studies have demonstrated that medical doctors and judges have difficulty in interpreting appropriately crucial statistical information regarding test results and evidence. One example is the inability of gynecologists to infer correctly the probability of breast cancer based on the way mammography results are conveyed (Gigerenzer, Gaissmaier, Kurz-Milcke, Schwartz, & Woloshin, 2007).

In a recent study (Soyer & Hogarth, 2012), we surveyed economics scholars employed at universities around the world. We asked the respondents to consider a simple regression model that captured the relation between a costly input variable, X, and a desirable outcome variable, Y. We presented the estimated parameters of the model in a standard format used in economics journals, which typically involves number of observations, mean and standard deviation of the dependent variable, regression coefficients and standard errors, t-statistics, and R^2. We solicited probabilistic inferences from the respondents, thereby testing whether they understood the implications

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of the forecasting model. For instance, one question asked how many additional inputs of X are necessary to make an individual 90% sure of obtaining a positive Y. Most respondents failed to answer this question correctly. No difference in answers occurred between versions of the question that varied the statistical fit of the underlying regression model–between $R^2 = 0.25$ and $R^2 = 0.50$. In other words, the respondents demonstrated limited understanding of the uncertainty implicit in the model's predictions. They identified the uncertainty in the model that affected the parameter estimates, but ignored the uncertainty about the dependent variable (Y) conditional on stated values of the independent variable (X).

In short, when faced with forecasts, or models from which predictions can be derived, many people have difficulty in comprehending the level of uncertainty implicit in the information they have been given. This issue is true both of those who are naïve and sophisticated in statistical modeling, although clearly the latter should be able to deal more competently with many problems that would baffle the former.

The present paper deals with the issue of how to present forecasts to decision makers so that they understand the uncertainty implicit in outcomes. Specifically, we propose providing decision makers with models that they can use to simulate outcomes. In other words, we suggest a mechanism whereby their understanding of the uncertainties implicit in the forecasts reflects their own simulated experience. The rationale for this method is based on identifying how people encode data naturally and thus what is simple for them.

We first discuss how people make predictive judgments in everyday life and when predictions are or are not likely to be accurate. We argue that experience has a crucial role in learning and forming judgments. Moreover, the environments where learning takes place can be characterized as either kind or wicked (Hogarth, 2001, 2010). In particular, kind environments provide decision makers with clear, unbiased, and veridical feedback. In contrast, wicked environments involve deficient feedback that can lead people astray in their perceptions and create systematic biases in their judgments.

To assess the feasibility of simulation as a communication tool, it is important to establish whether people can make appropriate probabilistic inferences on the basis of simulated experience and their levels of comfort and trust in doing so. We therefore describe an experimental research program in which we investigated these issues. We find that people make accurate probabilistic forecasts in kind environments, that is, they express appropriate levels of uncertainty in judgment. Moreover, they show more trust in their opinions based on simulated experience than in their intuitive guesses made without the aid of the tool. Finally, we discuss our results in the larger context of forecasting in the social and economic domains.

2. Issues concerning intuitive forecasts

Asking how accurate people's forecasts are in everyday life and what discriminates success from failure are appropriate starting points. Numerous studies document errors in predictive judgment in a variety of settings. This issue has been investigated, for example, from the viewpoints of clinical psychology (Dawes, Faust, & Meehl, 1989), forecasting and planning (Hogarth & Makridakis, 1981), economic and political forecasting (Tetlock, 2005), and other areas of decision making (Armstrong, 2001; Kahneman, Slovic, & Tversky, 1982). Humans, according to this literature, are just not very good at making accurate predictive judgments.

We need to look at this picture, however, in the context of three important issues. The first is that the literature documents deficient judgments largely in domains that are a product of how society is organized in the present as opposed to those to which humans have adapted across time (Simon, 1996). Contrast the complexity of modern economic and social life with the demands made of humans as hunter-gatherers.

Second, phenomena vary on the extent to which they are predictable (see also, Hammond, 1996; Kahneman & Klein, 2009). For example, the size, and timing of large earthquakes are, to the best of current knowledge, unpredictable (Buchanan, 2001; Silver, 2012). And the cause does not lie in deficiencies in forecasting methods so much as the nature of the geological processes that produce earthquakes. Of course, the predictability of certain phenomena is open for discussion and scientists need to establish levels of predictability. However, perhaps one should not blame the forecasts so much as those who are willing to believe them (see Armstrong, 1980, on the "seersucker" theory)?

The third contextual point is the simple fact that humans do make many forecasts every day and survive! Consider, for instance, the sheer number of predictive judgments you make while driving a car or navigating your way along a crowded street. Most of the time, you avoid accidents, do not bump into people, or avoid putting your foot in what dogs have left on the sidewalk.

To understand how good people's predictions are and to improve them, it is necessary to understand when they are and are not accurate and why.

3. The importance of kind environments

Many human predictive tasks are continuous as opposed to discrete in nature. That is, instead of making a judgment at time_0 that will be accurate or otherwise at time_1, we modify our judgment at time_0 using information (feedback) that we receive before time_1. This process allows us to make an appropriate adjustment. As a specific example, imagine that you wish to leave the room where you are currently located and exit by a specific door. Clearly, you make a judgment (prediction) as to the path you will take to reach the door. However, that judgment does not need to be precise because as you approach the door you can adjust your path using information you had not previously considered (e.g., to avoid some objects on the floor). Our contention is that this kind of process – rough directional judgments with adjustments made to allow for new information – characterizes much judgmental and predictive activity (for example, in addition to moving around in the environment, consider social interactions we have with other people, or how you predict the various tasks that you accomplish on a daily basis).

The point is that much natural predictive activity involves *continuous* (as opposed to *discrete*) tasks (Hogarth, 1981). Initial judgments imply short-term actions with low commitment, and corrective feedback is available to keep the system on track. Interestingly, success in these tasks does not depend on precise judgments or the use of much computation. Figs. 1 and 2 formalize these ideas.

In Fig. 1, the decision maker is at point A and wishes to hit the target D but can err between B and C. Provided she is facing in the right direction, her chances of hitting the target at random are equal to the angle α (BAC) divided by 180. Moreover, if she uses the cues L and M, she can

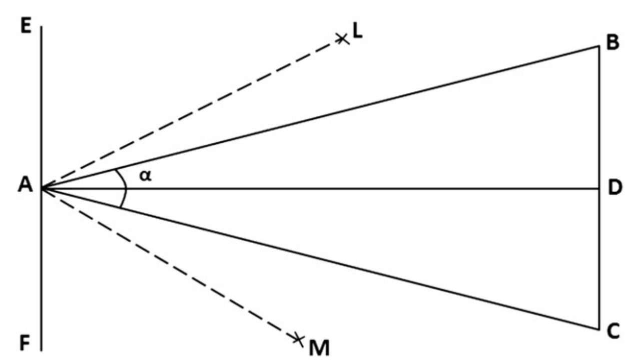

Fig. 1. Diagram of a judgmental task. (The person positioned at point A wants to hit the target D and can err between B and C.) From Hogarth (1981, Fig. 1, p. 200). Copyright © 1981 by the American Psychological Association.