Journal of Applied Research in Memory and Cognition 4 (2015) 221–228

Contents lists available at ScienceDirect

Journal of Applied Research in Memory and Cognition

journal homepage: www.elsevier.com/locate/jarmac

Original Article

Providing information for decision making: Contrasting description and simulation

Robin M. Hogarth [a,*], Emre Soyer [b]

[a] Universitat Pompeu Fabra, Department of Economics & Business, Barcelona, Spain
[b] Ozyegin University, Faculty of Business, Istanbul, Turkey

ARTICLE INFO

Article history:
Received 17 October 2013
Accepted 22 January 2014
Available online 30 January 2014

Keywords:
Decision making
Uncertainty
Description
Experience
Simulation
Story telling

ABSTRACT

Providing information for decision making should be like telling a story. You need to know, first, what you want to say; second, whom you are addressing; and third, how to match the message and audience. However, data presentations frequently fail to follow these simple principles. To illustrate, we focus on presentations of probabilistic information that accompany forecasts. We emphasize that the providers of such information often fail to realize that their audiences lack the statistical intuitions necessary to understand the implications of probabilistic reasoning. We therefore characterize some of these failings prior to conceptualizing different ways of informing people about the uncertainties of forecasts. We discuss and compare three types of methods: description, simulation, and mixtures of description and simulation. We conclude by identifying gaps in our knowledge on how best to communicate probabilistic information for decision making and suggest directions for future research.

1. Introduction

Upon arriving in continental Europe in the early 13th century, Fibonacci convinced people that the Hindu-Arabic numerical system was superior to Roman numerals for making calculations, maintaining quantitative records and conveying information. His work essentially transformed the language in which analyses were conducted and communicated and thereby contributed significantly to both science and everyday life (Savage, 2009). Better understanding of quantitative analyses eventually led to better judgments and decisions.

We propose that providing information to help people make decisions can be likened to telling stories. First, the provider – or story teller – needs to know what he or she wants to say. Second, it is important to understand characteristics of the audience as this affects how information is interpreted. And third, the provider must match what is said to the needs of the audience. Moreover, when it comes to decision making, the provider should not tell the audience what to do. Instead, the latter should draw its own conclusions. That is, as in a well-crafted story, the audience should be free to interpret the outcomes without being told the "message" directly (i.e., what to do).

In this paper, we argue that our story telling metaphor does not capture how information is typically presented for decision making in applied settings. However, the metaphor captures principles that can improve decision makers' understanding of the situations they face and their satisfaction with the alternatives they select.[1] Our aim is to highlight and provide a perspective about these principles, given possible methods of communicating information for decision making. We consider the standard method of description and use it as a benchmark to discuss the benefits and weaknesses of an alternative approach: providing experience through simulations. Finally, we reflect on possible hybrid techniques that merge descriptions and simulations. To make our ideas concrete, we concentrate here on the presentation of information about uncertainty associated with taking different actions. However, we believe that the principles apply across a wide range of types of problems.

Our interest in this issue was stimulated by a survey we conducted of how economists interpret the results of regression analysis (Soyer & Hogarth, 2012). In this study, academic economists from prestigious universities answered questions about making decisions in light of the results of a simple regression analysis. The economists were given the outcomes of the regression

* Corresponding author. Tel.: +34 935422561.
E-mail addresses: robin.hogarth@upf.edu (R.M. Hogarth), emre.soyer@ozyegin.edu.tr (E. Soyer).

[1] We emphasize that we use the term "story" in a metaphorical manner. Most forecasts are, of course, not stories in that they lack characters and plots that evolve across time. However, both forecasts and stories require transmitting information in an accessible manner.

http://dx.doi.org/10.1016/j.jarmac.2014.01.005

analysis in a typical, tabular format and the questions involved interpreting the probabilistic implications of specific actions given the estimation results. Hence, the participants had available all the information necessary to provide correct answers, but in general they failed to do so. Although their answers were influenced by the uncertainties concerning the model's regression coefficients, they tended to ignore the uncertainty involved in predicting the dependent variable conditional on values of the independent variable. As such they vastly overestimated the predictive ability of the model. Our survey also involved another group of similar economists who only saw a bivariate scatterplot of the data. These economists were accurate in answering the same questions.

Now academic economists typically do not use the results of regression analysis for decision making purposes and thus perhaps our survey was "unfair". However, since these economists were statistical experts (econometricians), their poor performance raises the issue of what people really understand when they consult data provided for decision making. Second, that one group made accurate answers after only seeing a scatterplot suggests that such displays could be used for better decision making. However, it is not clear that this suggestion would be accepted because, despite the accuracy of their answers, members of this group complained bitterly that they did not have enough information to answer the questions adequately.

As an exercise in providing information for decision making, our survey was a failure. The story did not match with the audience. In particular, the story in this case (regression results) was engineered by the analyst, whose principal aim is typically not to be understood (in terms of improving judgments and decisions) but just to be heard (published). If nothing else, our study showed that different *descriptions* of the same information, lead people to draw different conclusions – a phenomenon that has been documented many times in the literature (Hogarth, 1982).

2. Probabilistic forecasts – issues and challenges

In this paper, we consider the communication of probabilistic forecasts. In essence, this means that the analyst provides the decision maker with a probability distribution over possible future outcomes of a variable of interest. These can cover many different types of applications. Consider, for example, simple forecasts involving the weather (e.g., "Will it rain tomorrow?") as opposed to more complicated issues such as effects of climate change (Budescu, Por, & Broomell, 2012). In the economic domain, one can envisage forecasts involving sales and inventories, as well as outcomes of investments. In politics, probabilistic forecasts can cover elections, trading disputes, and so on.

We emphasize this range of applications because analysts and decision makers may have quite different conceptions when they consider a description of a decision making situation. In particular, the meaning of probability is not clear to many in that it does not necessarily map into people's experience. For example, imagine that a decision maker is told that the probability of rain tomorrow is 0.3. Now, let's assume it does not rain the next day. How should she interpret the meaning of the forecast? Was it correct or incorrect? Our bemused decision maker is not sure because rain could only occur or not occur and a single trial cannot reveal whether a 0.3 probability estimate is appropriate (Lopes, 1981). On the other hand, for a statistically sophisticated analyst, the 0.3 estimate can be interpreted as a personal "degree of belief" (supported intellectually by a Bayesian betting paradigm) or as the limit of a long-run relative frequency (imagining many days when the weather conditions were identical, i.e., as a frequentist statistician).

Given these issues, should analysts simply forget about numerical estimates and instead use verbal statements that describe feelings of uncertainty? Indeed, several studies show that verbal expressions of probability (e.g., phrases such as "unlikely", "almost certain", and so on) can be relatively effective (see, e.g., Budescu & Wallsten, 1985). However, verbal expressions do not have exactly the same meaning for different people and it is problematic to generalize from these results.

A further problem in providing forecasts in the form of probabilities to statistically naïve decision makers is that the latter may make assumptions of which the analysts are unaware. In a revealing study, Gigerenzer, Hertwig, van den Broek, Fasolo, and Katsikopoulos (2005) asked people what they thought was meant by weather forecasts of the form "the probability of rain tomorrow is 30%". There was a wide range of different interpretations including the possibility of having rain during 30% of the day and 30% of the region receiving rain during that day.

At one level, these interpretations are amusing. However, it can be argued that the statement the respondents were asked to interpret was ambiguous. What is missing is clarification of how one would know whether or not it had rained on the morrow. Lacking this insight, it is possible for people to have several interpretations even if statistical experts would not think of them. Statements of probabilities of events should be accompanied by operational definitions such that the occurrence or non-occurrence of the events cannot be disputed. For example, if a person makes a bet conditional on the occurrence of the event, he or she should not subsequently be able to avoid responsibility by changing the definition of the event.[2]

Finally, people may differ not only in statistical expertise but also expertise concerning the issue at hand, e.g., meteorologists know much more about the weather than non-meteorologists. What is unclear is whether such substantive expertise affects the ability to interpret probabilistic forecasts.

3. Human information processing: strengths and weaknesses

We assume that, prior to providing probabilistic forecasts, the analysts have made the appropriate analyses. This being said, we now consider some human strengths and weaknesses in information processing since it is important to understand the factors that help and hinder people in the task of interpreting information.

Although research in psychology and neuroscience can lead one to marvel at the capacity of the human mind, from our perspective, there are limitations. In particular, limits on processing capacity restrict our ability to "take in" all the information that may be relevant to a problem. At any point in time, we can only perceive a small fraction of what is actually in our visual field. Thus, anything that attracts attention is important and the reality in which we operate is bound by this attentional filter. Indeed the literature is replete with examples of how minor shifts in the presentation of information can change a person's conclusions (Einhorn & Hogarth, 1981; Hogarth, 1982). To overcome such problems, through experience people have developed skills in seeking specific information in particular situations so that attention can be guided appropriately. Indeed, this lies at the heart of expertise (Ericsson & Smith, 1991).

A second limitation is that people often fail to consider relevant information precisely because it does not form part of the information presented and they lack the ability to recognize this fact. Consider publication bias (Ioannidis, 2005). Academic publications make information part of the public domain; easily reachable by all consumers of knowledge. If certain analyses (those that find

[2] This betting criterion was originally suggested by Bruno de Finetti.

statistically significant effects) are more likely to be published than others (those that fail to find effects), then the story, that is, the conclusion from the available evidence is as biased as the evidence on which it is based. Imagine, for instance, a physician contemplating whether to prescribe a certain drug. Say, among the 20 publications that contain valid tests of the drug's effectiveness, 17 demonstrate positive results. The verdict seems clear (17 vs. 3). If, however, there are also 15 unpublished manuscripts with valid tests, of which 13 show no effects, the story now changes (19 vs. 16) and the decision becomes harder (for cases on selective publication, see Goldacre, 2013; and Turner, Matthews, Linardatos, Tell, & Rosenthal, 2008).

Another important dimension is the distinction between whether the information is presented at once – as in the typical description of a problem – or whether it has been acquired across time. As an example of the latter, imagine deciding between two restaurants that are well known to you. In essence, you already have estimates of "how good" both restaurants are based on past experiences. Moreover, for each the estimates are based on aggregating your experiences across time. That is, your estimates are based on *sequential* updating of the impressions of your different visits as opposed to accumulating all the impressions at one time. Indeed, with a sequential updating process, all that you need to remember is your last overall impression.

In short, limits on information processing are not so important when dealing with what we call sequential data. Indeed, numerous studies have demonstrated that people are remarkably effective at extracting aggregate frequencies from single events that they have previously experienced and encoded sequentially (Hasher & Zacks, 1979, 1984; Zacks & Hasher, 2002).[3] Moreover, this appears to be a well-developed skill in that it shows little variation across the life cycle and is used in many different tasks. The fact that it has been observed in several non-human species also suggests that it is well anchored in evolution. From our perspective, it is important because it shows the type of task environment in which humans can overcome processing capacity constraints.

In summary, although subject to attentional shifts, human information processing reacts accurately to information observed sequentially across time. However, the system is deficient in that it operates too "literally". Many studies have shown that people treat the data they see as representative of the processes that generate them, that is, they are "naïve" statisticians (Juslin, Winman & Hansson, 2007; Peterson & Beach, 1967). As a consequence, people make inferential errors due, inter alia, to "small sample" effects and the failure to realize that samples can be biased in different ways. Indeed, this failure to recognize and correct for biases has been labeled a lack of "meta-cognitive" ability (Fiedler, 2000; Fiedler, Brinkmann, Betsch, & Wild, 2000).

Clearly, lack of meta-cognitive ability coupled with the inability to take account of missing data means that people's judgments are often defective. Moreover, they are typically unaware of this fact. In *Thinking Fast and Slow*, Kahneman (2011) discusses the notion of WYSIATI (acronym for "what you see is all there is"), i.e., the tendency of humans to base their judgments predominantly on the information that is readily available. Moreover, humans are inclined to consider such available yet potentially biased information as the whole story. Recognizing these issues, many attempts have been made to help people make more accurate judgments.

[3] To illustrate, consider being asked how many times you have been to the cinema in the last three months. Most people can answer this question (albeit not always completely accurately) despite the facts that (a) they did not know they were going to be asked this particular question, and (b) when they attended the cinema they did not make a conscious effort to record the frequency of their visits. Of course, we do not claim that people have perfect memory. Survey researchers, for example, have documented several patterns of systematic distortions (see, e.g., Bradburn, Rips, & Shevell, 1987).

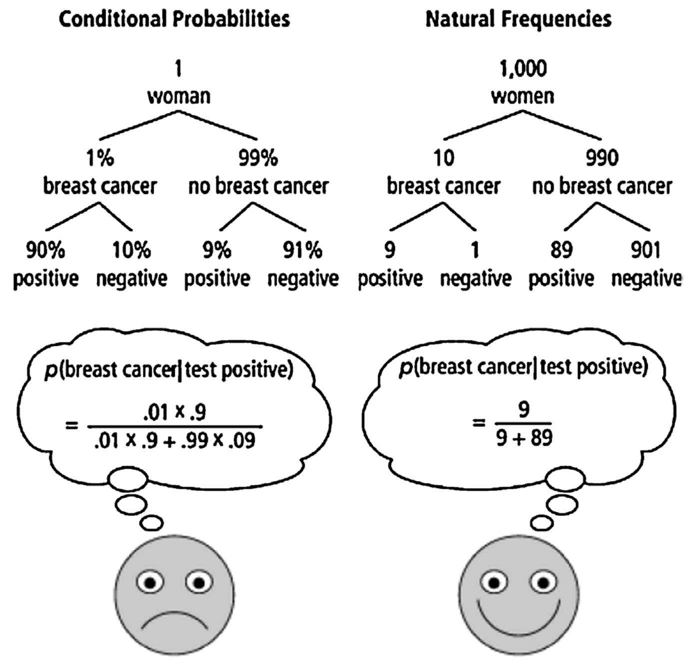


Fig. 1. Two ways of calculating the probability that a woman who tests positive in mammography screening actually has breast cancer (positive predictive value). The left side illustrates the calculation with conditional probabilities, and the right side with natural frequencies. The four probabilities at the bottom of the left tree are conditional probabilities, each normalized on base 100. The four frequencies at the bottom of the right tree are natural frequencies. The calculation using natural frequencies is simpler (smiling face) because natural frequencies are not normalized relative to base rates of breast cancer, whereas conditional probabilities (or relative frequencies) are, and need to be multiplied by the base rates (the formula to calculate the positive predictive value is known as Bayes's rule).

4. Varieties of decision aids

Almost all decision aids involve changing how problems are described to help people make "better" decisions. The range of aids varies from complex decision analytic techniques (involving decision trees, multi-attribute utility functions, and so on) to simply reframing problems in order to direct attention in particular ways. The latter approach is particularly interesting in that it combines psychological insights of how people process information with an understanding of the tasks they face.

A good example is the work of Gigerenzer and Hoffrage (1995) who explored how to help people make so-called Bayesian updating inferences. Imagine, for instance, assessing the probability of having a particular disease given a positive test result. The typical presentation used in the description of these problems provides the component probabilities that should be combined by Bayes' theorem, i.e., the prior probability of having the disease and the sensitivity and specificity of the test. Most people, however, are quite confused about how to combine this information correctly. Gigerenzer and Hoffrage argued that such confusion was not surprising given that people's experience is not in the form of these component probabilities but can be more accurately represented by frequency data. Thus, if problems were described in terms of "natural frequencies" people would both understand the data better and be able to perform the necessary calculations more easily – see Fig. 1.

That people can learn to do Bayesian calculations using the natural frequency method has been well documented (Gigerenzer, Gaissmaier, Kurz-Milcke, Schwartz, & Woloshin, 2007; Sedlmeier &

Gigerenzer, 2001). However, this is but one solution to one specific type of inferential problem.

More recently, Thaler and Sunstein (2008) highlighted changing the manner in which decision problems are described in a popular book entitled *Nudge*. Their main argument is that there is often considerable leeway in how choices are described. Thus, decisions can be improved if a third party redefines problems and tells the story in an alternative way. One striking example involves helping people to invest more in pension plans by committing to save out of future increases in salary as opposed to reducing current salary (Thaler & Benartzi, 2004). Since many pension plans are underfunded, such "nudges" are important.

The implication of this approach is that in creating a nudge somebody has to know what is "good" for the decision maker and this can raise ethical issues that Thaler and Sunstein (2008) recognize. Indeed, they describe their approach as *libertarian paternalism*. That is, although one problem presentation format has been chosen "paternalistically" for the decision maker (at least one has to be chosen), people are still "free" to make their own choices and can change the problem format if they want.

5. An alternative approach

Recent work in the psychology of judgment and decision making has highlighted the fact that the information humans use for decision making can be conceptualized as having two distinct sources (Hertwig, Barron, Weber, & Erev, 2004; Hertwig & Erev, 2009). On the one hand, people acquire information about judgment and decision problems through *description* of the particulars of the situations involved. This is exactly the case of the Bayesian inference problems of Gigerenzer et al. (2007) described above and the work of Thaler and Sunstein (2008).

On the other hand, people also learn about the specific features of problems through *experience* of past instances. For example, imagine the owner of a supermarket who wonders how many customers will enter the store on a particular day of the week. Whereas the owner could have some description of this problem, he or she undoubtedly has had *experience* of this situation from the past and can call upon this experience to estimate the number of customers.

In brief, people can learn about the characteristics of judgment and decision problems through description or experience and, of course, mixtures of the two. Most decision aiding has focused on exploring effects of different problem descriptions and, as has been shown, is important because human judgments and decisions are so sensitive to different aspects of descriptions. At the same time, this very sensitivity is problematic in that different types of judgments and decisions seem to need different solutions (even though some concepts such as "loss aversion" have found wide applicability). There is a need to find methods with more general application.

We suggest exploiting the well-recognized human ability to encode frequency information. That is, we consider the possibility of transforming problems so that people learn about them through experience as opposed to description. We argue that since decision and judgment problems involve outcomes (i.e., gains, losses, estimates, etc.), being able to describe a problem also implies having the information necessary to build a simulation model that can be used to generate "outcomes" through a process that we call "simulated experience".

6. Experience vs. description

From the viewpoint of storytelling, simulated experience essentially allows a decision maker to live actively through a decision situation as opposed to being presented with a passive description. A simple example would be the problem of estimating the probability of obtaining, say a sum of four, when two dice are cast. This situation can be described by providing the structure and parameters of the problem (two six sided dice, identical shapes, having dots on each side representing numbers from one to six), such that the correct answer can be calculated (analytical approach). Alternatively, an experiential approach could be taken, casting the dice many times and observing the prevalence of a certain outcome (sum of four) among many successive trials (experiential approach).

Table 1
Presentation of a regression analysis: Sample statistics and estimation results.

Sample statistics	Sample mean	Standard deviation
Change in income	8.4	7.9
Investment 1	11.1	5.8
Investment 2	9.6	5.2

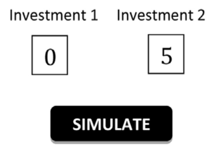
Estimation results (dependent variable: *change in income*)	Coefficient estimate	Standard error
Constant	−0.1	0.15
Investment 1	0.5	0.20*
Investment 2	0.3	0.05*
R^2	0.21	
Number of observations (n)	1000	

(Data originally reported in Hogarth & Soyer, 2011, Fig. 5, p. 445).
* Statistical significance at 95% confidence level.

In this particular example, the description is easy to understand and the analytical approach would produce a precise and accurate answer. The experiential approach, on the other hand, would be time consuming, lead to a less precise response and require the physical availability of two dice. However, imagine what would happen if the problem were more complicated. For example, consider the task of estimating the probability that the product of the outcomes is larger than eight when one of the dice has four sides instead of six. Now, relative to an analytical approach, basing judgments on experience would start to become easier and less error prone due to lack of expertise in probability theory. Parenthetically, we note that the difference between resolving problems that have been described as opposed to experienced is related to Brunswik's (1952) distinction between the use of cognition and perception. In the former, people can be quite accurate in their responses but they can also make large errors. In the latter, they are unlikely to be highly accurate but errors are likely to be small.

Both Lejarraga (2010) and Hogarth and Soyer (2011) suggest that as the complexity of problems grows, experiential approaches lead to improvements in judgments and decisions. In such cases, people also trust their experiences more than their analytical intuitions. Consider, for instance, a scenario where decision makers can make two possible investments and then have to judge the probability of different possible consequences of their actions, such as ending up losing money, earning more or less than a certain amount, or earning more than someone who did not make any investments. When a regression analysis is conducted to determine the yields of the investments, the description of the outputs would usually include two tables, one with descriptive statistics and other with estimation results (see Table 1).

Alternatively, a simulation can be built based on the estimated model to allow users to enter their decisions (investments) and observe model predictions as outcomes (see Fig. 2). A comparison of judgments using these two approaches reveals that, regardless of statistical sophistication, simulated experience leads to more accurate perceptions about the uncertainties. Description, on the other hand leads to an illusion of predictability, where the uncertainty is underestimated due to the characterization of results



Investment 1	Investment 2	Simulated Change in income
3	5	**4**
3	5	**9**
0	5	**0**
0	5	**2**
0	5	**-3**
0	5	**9**
0	5	**-5**

Fig. 2. Simulation interface for an estimated investment model. Each time the SIMULATE button is clicked, a predicted outcome (the change in income) is shown based on both the user's inputs (investment choices) and the estimated parameters of the model.

mainly through the average coefficient estimates. Hence, simulated experience provides a useful way of communicating such probability estimates (Armstrong, 2012; Hogarth & Soyer, 2011; Hogarth & Soyer, in press-a, in press-b). In order to identify when this approach should be preferred to description, however, we need to discuss the pros and cons of simulation methodology in the context of judgment and decision making.

7. Advantages of simulated experience

Let us first consider the advantages.

7.1. Simulation technology

There are no technological barriers to simulating complex processes. Just a decade ago, building simulations and using them was a difficult and slow endeavor. Today, the technology allows for the construction of simulations for virtually any decision scenario and can function quite rapidly.

7.2. Ease of use

Our investigations show that people relate easily to the task of simulating sequential outcomes and interact seamlessly with simulations. Moreover, as problems grow more complex, they prefer their experiential intuitions over their analytical calculations.

7.3. Statistical knowledge

Simulated experience can be employed even when the decision maker has limited knowledge of statistics. For instance the description in Table 1 is foreign to anyone not familiar with regression analysis. On the other hand, a simulation based on such results can be used by anyone who has previously operated a calculator or a simple spreadsheet.

7.4. Freedom of choice

If the experience produced by the simulation is kind (i.e., abundant, unbiased and immediate, Hogarth, 2001, 2010) then the experiential approach provides the decision maker with a complete picture of the outcomes of a process rather than a frame that nudges her to a particular choice. Clearly, simulated experience needs a simulation to be built (by a third party or in some cases even the decision maker) but this is not a particular statement of the problem that has been selected by somebody else in the guise of libertarian paternalism.

7.5. Active participation in the decision process

Relatedly, simulated experience makes sure that, by building the simulation or simply by sampling experience, decision makers actively participate in the decision making process. This can lead to increased understanding of the relation between their actions and the consequent outcomes.

8. Disadvantages of simulated experience

Simulated experience also has some disadvantages and provides several challenges for future research.

8.1. Sample size

Simulated experience allows decision makers to determine the number of trials they wish to experience. Hence, sample size becomes an important factor in the precision of judgments. This leads to asking what affects people's choice of sample size and what constitutes the optimal number of observations (Hertwig & Pleskac, 2010).

8.2. Rare events

The literature on the so-called "decision-experience gap" suggests that whereas Kahneman and Tversky's (1979) description-based prospect theory implies overweighting of small probabilities, decisions based on experience are consistent with underweighting (Hertwig et al., 2004). By definition, rare events will not be experienced often in simulations with the consequence that decision makers might not pay much attention to these when making judgments and decisions. One way to overcome this problem would be to use conditional simulations. For example, consider a Bayesian updating problem. If the simulation is built for incidents conditional on a certain prior event, then the rare outcomes would be more visible (e.g., the probability of having a disease, given a positive result in a medical test; or the possibility of a loss beyond a certain amount, given the occurrence of a natural disaster).

8.3. Risk attitudes

Some research has shown that the effect of simulated experience, as opposed to description, is less risk aversion in choice. Kaufmann, Weber, and Haisley (2013) argued that, for investment portfolio choices, such risk attitudes are more in line with rational choice theory. However, since people may have legitimate reasons to have different risk attitudes for single as opposed to repeated choices, the issue of how risk attitudes are affected by simulation experience needs to be investigated.

8.4. Statistical sophistication

Simulated experience does not require statistical sophistication on the part of the user. Thus, its benefits are larger in contexts where the analysis is complicated and hard to describe to someone with limited prior knowledge in statistics. However, the user still needs to be introduced to the simulation interface and trained in its operation. One key issue is sample size (see also above). In our experiments, statistically sophisticated people sampled consistently more information, which, in turn, led to better judgments. Simulation training should include information on the law of large numbers.

8.5. Trust in the model

Users should trust the models they use for simulated experience. At present, little is known about the determinants of such trust. The same, of course, is also true for descriptions. Future research should therefore illuminate the conditions under which people trust descriptions and explanations by experts as well as experiences based on simulations. In terms of user satisfaction, recent analyses by Goldstein, Johnson, and Sharpe (2008) and Kaufmann et al. (2013) suggest that sampling increases both comprehension and satisfaction about decisions under uncertainty.

8.6. Simulation building

The method of simulated experience requires both a simulator based on the underlying decision situation and a user-friendly interface. Although popular spreadsheet software, such as MS Excel, can provide viable bases for such simulations, one still needs some proficiency in programming to build a reliable decision tool. To solve this, a platform of simulations can be created that includes a set of simulations for a variety of relevant situations. Moreover, such a platform might also incorporate modules that users can transform and combine to create custom simulations. For instance, different modules might allow users to select from a variety of model specifications (e.g., distributions with fat tails, skewed distributions, etc.).

8.7. Knowledge transfer

This paper discusses the simulated experience methodology as a means to communicate information to decision makers and we have limited our discussions to matters of presentation. However, a weakness of simulation technology could be that the decision maker does not gain insight into the problem structure that can be generalized. On the other hand, in our experiments we observed that, when able to consult both a description and a simulation, people's analytical calculations improved (Hogarth, Mukherjee, & Soyer, 2013; Hogarth & Soyer, 2011). Their experiences provided a means to check the accuracy of their analysis.

9. Simulated experience instead of description

Description is typically the default mode of providing information for decision making. Thus, when should it be replaced by simulated experience? Our discussion on experience vs. description highlights two major shortcomings of every description. First, it always involves a frame, and thus different descriptions might lead to different perceptions and decisions. Second, for some problems that incorporate uncertainties or complex structures, descriptions might be hard to construct or obscure a crucial part of the story. Simulated experience essentially takes description out of the picture; hence it should substitute descriptions in situations where these shortcomings are prevalent.

9.1. Uncertainties

Describing uncertainties inherent in a decision situation is difficult. Examples include situations where outcomes are subject to regression toward the mean or when a variable is a complex function of many independent variables and prediction errors.

In a series of experiments we have found that in scenarios similar to that described in Table 1, descriptions lead people to overestimate the predictability of the dependent variable. The main reason behind this illusion of predictability is that description frames the question mainly around average effects (Hogarth & Soyer, 2011; Soyer & Hogarth, 2012). More importantly, our results suggest that augmenting the description with experience, e.g., letting decision makers experience simulated outcomes *on top of* a description, does not lead to better perceptions. This is because people are used to relying primarily on descriptions. It was only when we eliminated the description and constrained the decision makers to *only* visualize simulated outcomes that their judgments improved.

9.2. Complex structures

In problems with complex probabilistic structures, descriptions may not only be hard to decipher, they could also mislead one's analysis of the situation. Consider for instance the birthday problem (i.e., What is the probability that two or more people have the same birthday in a group of *N* people?) and the famous Monty Hall problem. Research has repeatedly shown that attempts to solve these problems analytically lead to biased answers largely because people find it difficult to understand the problem structures (Hogarth & Soyer, 2011).

In these situations, decision makers can be provided with simulations that let them live through the problems many times (learning the birthdays of multiple groups of *N* people in the birthday problem, and selecting one door among three in the Monty hall problem). In this way, users learn about the outcome probabilities through experience, *without* resorting to any bias-prone analyses. Similarly, simulations have been shown to be useful for mitigating base rate neglect (Hayes, Newell, & Hawkins, 2013), and assessing probabilities of success in competitions (Hogarth et al., 2013).

10. Hybrid approaches

In our experiments, participants often showed discontent when they lacked access to descriptions, even when such access biased their judgments. Hence, advocating for the abolition of descriptions in certain situations is not realistic. Also, considering that both description and simulation have advantages and disadvantages it is important to investigate where these methods might be used *together* for optimal storytelling.

10.1. Graphs

One tool that merges descriptions with simulation is a graph of simulated outcomes that result from the described model. Such a plot would follow the description of the problem and include individual level data (simulated or real) that makes visible the uncertainty inherent in the outcomes. Advances in computing technology have facilitated the way we design and use graphical illustrations. Recent research shows that in relevant situations, such as medical decision making, depicting individual data through interactive graphics that allow decision makers to visualize simulated outcomes help probabilistic understanding (Ancker, Chan, & Kukafka, 2009; Ancker, Weber, & Kukafka, 2011). Moreover, news media and online communities make use of a broad selection of diagrams and infographics to inform their readers about a wide variety of statistics (for a comprehensive review and examples of such approaches, see Spiegelhalter, Pearson, & Short, 2011).

Although plotting individual level data is increasingly convenient and straightforward, a survey we conducted of applied economics publications in prestigious academic journals reveals that approximately only 40% of the analyses that can provide scatter plots actually do so (Soyer & Hogarth, 2012). Moreover, a part of these displays are limited to mainly showing average trends.

Fig. 3 shows how providing simulated outcomes at the individual level in graphs would lead to better perceptions of uncertainty. In all three figures, the straight line depicts the estimated average relation between variables *X* and *Y*, which is one-to-one and the same in all three cases. The difference between Fig. 3a and b is due to different levels of uncertainty at the individual level; the predictability of *Y* from *X* is lower in the former due to larger variation at the individual level. Finally, in Fig. 3c uncertainty at the individual

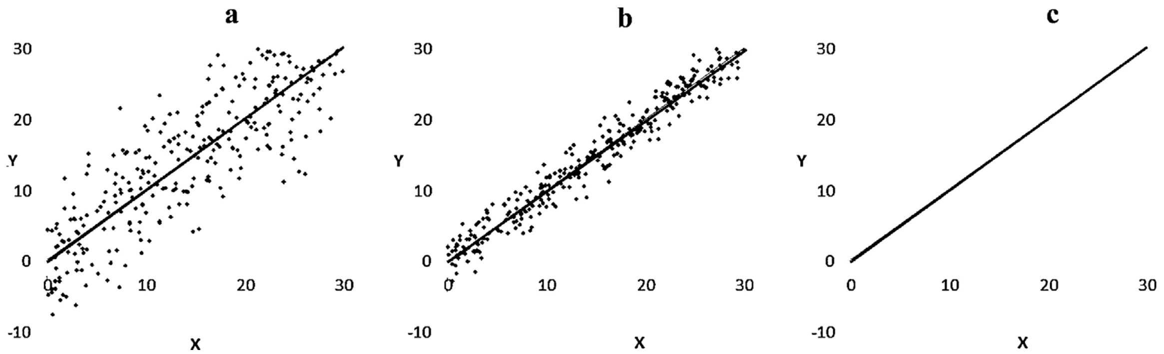


Fig. 3. (a–c) The average effect of *X* on *Y* (the straight line). (a and b) Simulated individual observations (*n* = 300). In the scenario depicted in (a), the variance of the uncertainty of Y conditional on values of *X* is larger than that of the scenario depicted in (b). (c) does not depict such uncertainty.

level is hidden and the graph only displays the estimated average effect.

A weakness of this visual approach is that it oversimplifies the analysis by reducing the whole story to a graph between two variables. Most of the analyses in applied work involve multiple variables and factors that interact in complex fashion to produce the outcomes. However, we argue that the presence of even a simple plot showing the predicted outcomes given different levels of an independent variable conditional on the mean vales of the remaining control variables would help the decision maker avoid developing an illusion of predictability.

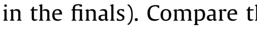
10.2. Add-on simulations

When used for decision making, presenting results in the form illustrated in Table 1 leads to illusions of predictability. Moreover, the importance of this finding is accentuated by the fact that this presentation method is prevalent in most scientific studies, and especially in applied economics. Publications in these domains might therefore consider featuring online simulations to accompany articles that have decision making or prediction implications. Such simulations would be based on the estimated model and allow people to live through the problem many times by sequentially observing potential outcomes given their inputs. Moreover, this would not disrupt the content of the description. Indeed, these add-on simulations would constitute a much needed bridge between scientific analyses and decision making activities.

10.3. Sparklines

In their creator Edward Tufte's words, sparklines are "small, high-resolution graphics usually embedded in a full context of words, numbers, images. (They) are datawords: data-intense, design-simple, word-sized graphics" (Tufte, 2006, p. 47). In other words, sparklines are within-text-plots that replace words when conveying statistical information. These plots usually have no numbers or axes on them. Their purpose is to make the data and its distribution readily available for quick and easy inspection.

Such items are still not employed in academic or popular writings, even though they provide genuine insights about the data, without requiring discussion about their statistical properties through a separate table or visual display. Consider the following two examples:

1. "The Lakers' 2004 season was their last with Shaq, when they reached the NBA finals and lost to Detroit (note the last 3 losses which sealed their fate in the finals). Compare those days of glory with their abysmal  2005 performance, with only 2 wins in the last 21 games" (top, gray lines represent wins, bottom, black ones represent losses, Gheorghiu, 2005).
2. People show difficulty in judging the chances of success in competitions. Whereas the probabilities of winning are distributed  , the judgments reveal that decision makers act as if they are  (Soyer & Hogarth, in preparation).

This result suggests that an efficient methodology to present information to decision makers would include a combination of description and simulation.

11. Discussion or "back to storytelling"

We have discussed how information gathered by an analyst is communicated to parties who will use it for decision making. Although our initial observations result from casual empiricism, our general contention is that such information is not always communicated satisfactorily. Moreover, we contend that much could be gained by respecting norms of good storytelling. At a minimum, this involves knowing: (1) precisely what one wants to say, that is, the message; (2) relevant characteristics of the decision maker, that is, the audience; and (3) how to match the message to the audience. In general, the analyst should not be telling the decision maker what to do but instead provide information that allows the decision maker to reach his or her own conclusions.

As a specific example, we focused on probabilistic information that accompanies forecasts. As noted, this encompasses a wide range of activities ranging from simple weather forecasts to outcomes of medical procedures, financial decisions, climate change, and so on. We pointed out that many people have deficient notions of probabilistic reasoning. For example, there is much ignorance about the meaning of probability and what conclusions can be drawn from data. We also noted that, although limited as information processors, humans are adept at estimating the frequencies of events they have experienced sequentially. However, they tend to treat samples as "representative" and lack "meta-cognitive" ability to correct for biased observations.

To date, attempts to help people understand probabilistic forecasts or reasoning (i.e., to match message and audience) have mainly involved *describing* problems in alternative ways (Gigerenzer & Hoffrage, 1995; Thaler & Sunstein, 2008). Instead, we suggest building on people's ability to understand and encode frequency data by having them *experience* simulated outcomes or, what we call "simulated experience". Importantly, this requires that the decision maker plays an active role in the communication process. Moreover, in all the cases that we have examined, such simulated experience does meet the criteria of good storytelling described above.

The use of simulated experience to inform decision makers of the probabilistic implications of predictions is in its infancy. Above, we outlined different conceptual and methodological challenges that still need to be resolved. In our view, good storytelling will involve both description and simulation, thereby harnessing the advantages of both. At a more general level, the challenge we face is to develop understanding of when information should be presented as description, experience, or both. For example, we know that complexity favors experience over description but we need to be able to define boundary conditions.

Finally, following Fibonacci's advice to adopt the Hindu-Arabic numerical system, humans have progressed substantially in their ability to encode, store, and manipulate data. Indeed, the current explosion of "big data" owes much to having an appropriate numerical system and much will be gained by those who can interpret this new trove of information. However, since interpretation will always be a human activity, future progress will depend on how we cope with this bottleneck. We suggest that exploiting people's ability to process simulated experience is one way to enhance the use of intuition in organizational decision making.

Conflict of interest

The authors declare that there are no conflicts of interest.

Acknowledgments

The authors thank Sam Savage, the editors, Gary Klein, Mitra Galesic, and an anonymous reviewer for their constructive comments. Hogarth gratefully recognizes the financial support of the Spanish Ministerio de Economía y Competitividad (Grant ECO2012-35545).

References

Ancker, J. S., Chan, C., & Kukafka, R. (2009). Interactive graphics for expressing health risks: Development and qualitative evaluation. *Journal of Health Communication*, *14*(5), 461–475.

Ancker, J. S., Weber, E. U., & Kukafka, R. (2011). Effects of game-like interactive graphics on risk perceptions and decisions. *Medical Decision Making*, *31*(1), 130–142.

Armstrong, J. S. (2012). Illusions in regression analysis. *International Journal of Forecasting*, *28*, 689–694.

Bradburn, N. M., Rips, L. J., & Shevell, S. K. (1987). Answering autobiographical questions: The impact of memory and inference on surveys. *Science*, *236*(4798), 157–161.

Brunswik, E. (1952). *The conceptual framework of psychology*. Chicago, IL: University of Chicago Press.

Budescu, D. V., Por, H.-H., & Broomell, S. B. (2012). Effective communication of uncertainty in the IPCC reports. *Climate Change*, *113*, 181–200.

Budescu, D. V., & Wallsten, T. S. (1985). Consistency in interpretation of probabilistic phrases. *Organizational Behavior and Human Decision Processes*, *36*, 391–405.

Einhorn, H. J., & Hogarth, R. M. (1981). Behavioral decision theory: Processes of judgment and choice. *Annual Review of Psychology*, *32*, 53–88.

Ericsson, K. A., & Smith, J. (Eds.). (1991). *Toward a general theory of expertise: Prospects and limits*. New York, NY: Cambridge University Press.

Fiedler, K. (2000). Beware of samples! A cognitive-ecological sampling approach to judgment biases. *Psychological Review*, *107*, 659–676.

Fiedler, K., Brinkmann, B., Betsch, T., & Wild, B. (2000). A sampling approach to biases in conditional probability judgments: Beyond base rate neglect and statistical format. *Journal of Experimental Psychology: General*, *129*, 399–418.

Gheorghiu, G. (2005). *Sparkplot: Creating sparklines with matplotlib*. Agile Testing [web log]. Retrieved from http://agiletesting.blogspot.co.uk/2005/04/sparkplot-creating-sparklines-with.html

Gigerenzer, G., & Hoffrage, U. (1995). How to improve Bayesian reasoning without instructions: Frequency formats. *Psychological Review*, *102*, 684–704.

Gigerenzer, G., Gaissmaier, W., Kurz-Milcke, E., Schwartz, L. M., & Woloshin, S. (2007). Helping doctors and patients make sense of health statistics. *Psychological Science in the Public Interest*, *8*, 53–96.

Gigerenzer, G., Hertwig, R., van den Broek, E., Fasolo, B., & Katsikopoulos, K. V. (2005). A 30% chance of rain tomorrow: How does the public understand probabilistic weather forecasts? *Risk Analysis*, *25*(3), 623–629.

Goldacre, B. (2013). *Bad pharma: How drug companies mislead doctors and harm patients*. Random House Digital, Inc.

Goldstein, D. G., Johnson, E. J., & Sharpe, W. F. (2008). Choosing outcomes versus choosing products: Consumer-focused retirement investment advice. *Journal of Consumer Research*, *35*, 440–456.

Hasher, L., & Zacks, R. T. (1979). Automatic and effortful processes in memory. *Journal of Experimental Psychology: General*, *108*, 356–388.

Hasher, L., & Zacks, R. T. (1984). Automatic processing of fundamental information: The case of frequency occurrence. *American Psychologist*, *39*, 1372–1388.

Hayes, B. K., Newell, B. R., & Hawkins, G. E. (2013). Causal model and sampling approaches to reducing base rate neglect. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.), *Proceedings of the 35th annual conference of the Cognitive Science Society* August, (pp. 567–572).

Hertwig, R., & Erev, I. (2009). The description–experience gap in risky choice. *Trends in Cognitive Sciences*, *13*, 517–523.

Hertwig, R., Barron, G., Weber, E. U., & Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science*, *15*, 534–539.

Hertwig, R., & Pleskac, T. J. (2010). Decisions from experience: Why small samples? *Cognition*, *115*, 225–237.

Hogarth, R. M. (2001). *Educating intuition*. Chicago: The University of Chicago Press.

Hogarth, R. M. (2010). Intuition: A challenge for psychological research on decision making. *Psychological Inquiry*, *21*(4), 338–353.

Hogarth, R. M. (Ed.). (1982). *Question framing and response consistency: New directions for methodology of social and behavioral science, No. 11*. San Francisco, CA: Jossey-Bass.

Hogarth, R. M., & Soyer, E. (2011). Sequentially simulated outcomes: Kind experience vs. non-transparent description. *Journal of Experimental Psychology: General*, *140*, 434–463.

Hogarth, R. M., & Soyer, E. (in press-a). Communicating forecasts: The simplicity of simulated experience. *Journal of Business Research* (in press-a).

Hogarth, R. M., & Soyer, E. (in press-b). Improving judgments and decisions by experiencing simulated outcomes. In V. Reyna (Ed.), *Neuroeconomics, judgment and decision making*. New York, NY: Psychology Press (in press-b).

Hogarth, R. M., Mukherjee, K., & Soyer, E. (2013). Assessing the chances of success: Naïve statistics versus kind experience. *Journal of Experimental Psychology: Learning Memory, and Cognition*, *39*, 14–32.

Ioannidis, J. P. A. (2005). Why most published research findings are false. *PLoS Medicine*, *2*, 696–701.

Juslin, P., Winman, A., & Hansson, P. (2007). The naïve intuitive statistician: A naïve sampling model of intuitive confidence intervals. *Psychological Review*, *114*, 678–703.

Kahneman, D. (2011). *Thinking, fast and slow*. New York, NY: Farrar, Strauss and Giroux.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*, 263–292.

Kaufmann, C., Weber, M., & Haisley, E. (2013). The role of experience sampling and graphical displays on one's investment risk appetite. *Management Science*, *59*, 323–340.

Lejarraga, T. (2010). When experience is better than description: Time delays and complexity. *Journal of Behavioral Decision Making*, *23*, 100–116.

Lopes, L. L. (1981). Decision making in the short run. *Journal of Experimental Psychology: Human Learning and Memory*, *7*, 377–385.

Peterson, C. R., & Beach, L. R. (1967). Man as an intuitive statistician. *Psychological Bulletin*, *68*, 29–46.

Savage, S. L. (2009). *The flaw of averages: Why we underestimate risk in the face of uncertainty*. Hoboken, NJ: John Wiley & Sons, Inc.

Sedlmeier, P., & Gigerenzer, G. (2001). Teaching Bayesian reasoning in less than two hours. *Journal of Experimental Psychology: General*, *130*, 380–400.

Soyer, E., & Hogarth, R. M. (2012). The illusion of predictability: How regression statistics mislead experts. *International Journal of Forecasting*, *28*, 695–711.

Soyer, E., & Hogarth, R. M. (2014). *What are the odds of winning? A model and possible heuristics*. Manuscript in preparation.

Spiegelhalter, D., Pearson, M., & Short, I. (2011). Visualizing uncertainty about the future. *Science*, *333*(6048), 1393–1400.

Thaler, R. H., & Benartzi, S. (2004). Save More Tomorrow™. Using behavioral economics to increase employee saving. *Journal of Political Economy*, *112*, S164–S187.

Thaler, R. H., & Sunstein, C. R. (2008). *Nudge: Improving decisions on health, wealth, and happiness*. New Haven, CT: Yale University Press.

Tufte, E. R. (2006). *Beautiful evidence* (Vol. 23) Cheshire, CT: Graphics Press.

Turner, E. H., Matthews, A. M., Linardatos, E., Tell, R. A., & Rosenthal, R. (2008). Selective publication of antidepressant trials and its influence on apparent efficacy. *New England Journal of Medicine*, *358*(3), 252–260.

Zacks, R. T., & Hasher, L. (2002). Frequency processing: A twenty-five year perspective. In P. Sedlmeier, & T. Bestch (Eds.), *Etc.: Frequency processing and cognition* (pp. 21–36). New York, NY: Oxford University Press.