

THEORETICAL NOTES

Finding Useful Questions: On Bayesian Diagnosticity, Probability, Impact, and Information Gain

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Several norms for how people should assess a question's usefulness have been proposed, notably Bayesian diagnosticity, information gain (mutual information), Kullback–Liebler distance, probability gain (error minimization), and impact (absolute change). Several probabilistic models of previous experiments on categorization, covariation assessment, medical diagnosis, and the selection task are shown to not discriminate among these norms as descriptive models of human intuitions and behavior. Computational optimization found situations in which information gain, probability gain, and impact strongly contradict Bayesian diagnosticity. In these situations, diagnosticity's claims are normatively inferior. Results of a new experiment strongly contradict the predictions of Bayesian diagnosticity. Normative theoretical concerns also argue against use of diagnosticity. It is concluded that Bayesian diagnosticity is normatively flawed and empirically unjustified.

Keywords: optimal experimental design, decision theory, information gain, Bayesian diagnosticity, value of information

In word learning, medical diagnosis, job interviews, and scientific hypothesis testing, choice of questions (experiments, tests, queries) is critical. Whether people can identify useful questions, and what exactly constitutes a useful question, are central problems in theories of human cognition. Popper's (1959) falsificationist philosophy of science and Inhelder and Piaget's (1955/1958) experimental research inspired Wason's (1960, 1966) 2-4-6 task, which was designed to be a miniature scientific problem. Wason (1960) suggested that success on that task required "a willingness to attempt to falsify hypotheses" (p. 139). However, many subjects had difficulty devising tests to falsify their working hypotheses, a pattern sometimes called *confirmation bias* (Wason & Johnson-Laird, 1972, as cited in Mynatt, Doherty, & Tweney, 1977, as

reviewed by Klayman, 1995). Many recent researchers have distanced themselves from the falsificationist view and have suggested that *differentiation* of plausible hypotheses is normatively a better goal than *falsification* of the working hypothesis. Several of these researchers have described evidence-acquisition situations in a probabilistic framework (Baron, 1981, as cited in Baron, 1985, pp. 130–167; Fischhoff & Beyth-Marom, 1983; Oaksford & Chater, 1994, 2003; Skov & Sherman, 1986; Trope & Bassok, 1982, 1983).

An advantage of the probabilistic approach is the ability to differentiate the following components:

1. A *probabilistic belief model* with a set of hypotheses, a prior probability of each, and a set of possible questions (or experiments, queries, or tests) to differentiate among them;
2. A *sampling norm* to quantify the expected usefulness of each possible question, relative to a probabilistic belief model; and
3. A method to update beliefs according to a test's outcome.

In models of sequential tasks, in which the first question's answer is known before the second question is asked, an additional component, to check whether a stopping criterion has been reached, is also needed. (Similar accounts appear in Box & Hill, 1967; Fischhoff & Beyth-Marom, 1983; Over & Jessop, 1998; and Zimmerman, 2000.) Most experimental research in this area (see Table 1) assesses the adaptiveness of information-gathering behavior by considering whether people choose highly useful queries, as identified by a particular sampling norm. The goal of the present article is to illuminate differences among sampling norms (Component 2)

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Table 1
Sampling Norms and Probabilistic Information-Gathering Tasks

Sampling norm	Task	No. of hypotheses	Reference	Article type
Diagnosticity, log diagnosticity	Medical diagnosis	2	Good and Card (1971); Card and Good (1974)	Theory
	Introvert vs. extravert	2	Bassok and Trope (1983–1984); Trope and Bassok (1982, 1983)	Experiment
	Planet Vuma	2	Skov and Sherman (1986); Slowiaczek, Klayman, Sherman, and Skov (1992)	Experiment
	Hypothesis testing	2	Klayman and Ha (1987)	Theory
	Selection task, causal conditionals	2	Evans and Over (1996); Over and Jessop (1998)	Theory
	Covariation assessment	2	McKenzie and Mikkelsen (in press)	Review, experiment
Information gain, Kullback–Liebler distance	Hypothesis testing	2	Klayman (1987)	Theory
	Selection task	2	Oaksford and Chater (1994, 2003)	Review, theory
		2	Oaksford, Chater, and Grainger (1999)	Experiment
		2, 3	Hattori (2002)	Theory
	Selection task, causal conditionals	2	Over and Jessop (1998)	Theory
	2-4-6 task	2	Ginzburg and Sejnowski (1996)	Experiment
	Eye movement: reading	various	Legge, Klitz, and Tjan (1997); Legge, Hooven, Klitz, Mansfield, and Tjan (2002)	Theory
	Reduced array selection task	2	Oaksford and Chater (1998); Oaksford, Chater, Grainger, and Larkin (1997)	Experiment
	Number concept task	millions	Nelson, Tenenbaum, and Movellan (2001)	Experiment
	Alien mind reading	2, 18	Steyvers, Tenenbaum, Wagenmakers, and Blum (2003)	Experiment
Eye movement: shape learning	n/a	Walker Renninger, Coughlan, Verghese, and Malik (2005)	Experiment	
Probability gain, probability correct	2-4-6 task	3	Baron (1985)	Theory
	Urns and poker chips	5	Baron (1985)	Theory
	Medical diagnosis	3	Baron, Beattie, and Hershey (1988)	Experiment
	Eye movement: visual search	85	Najemnik and Geisler (2005)	Experiment
Impact (absolute change)	Eyewitness identification	2	Wells and Lindsay (1980); Wells and Olson (2002)	Theory
	Hypothesis testing	2	Klayman and Ha (1987)	Theory
	Selection task, Hempel's paradox	2	Nickerson (1996)	Theory

by holding constant both probability belief models (Component 1) and the method of belief updating (Component 3).

In this article, the intuitive scientist metaphor as outlined above is used as a descriptive model of human cognition, and Bayes's (1763) theorem is used to update beliefs. Use of normative models as descriptive models, or to facilitate development of descriptive models, is a familiar research strategy (Anderson's, 1990, 1991, rational analysis; Baron, 2004; Brunswik's, 1952, molar analysis; Marr, 1982; McKenzie, 2003; Oaksford & Chater, 2001; Peterson & Beach, 1967; Viswanathan et al., 1999). However, Kuhn (1989, 2000) discussed both the usefulness and limitations of the normative intuitive scientist metaphor as a descriptive model of human cognition. It has also been suggested that humans change their beliefs to a lesser extent than predicted by Bayes's theorem, perhaps by using a *conservative* Bayesian form of belief revision (Edwards, 1968). Setting these issues aside enables the present article to focus on the relative normative and descriptive justification of several sampling norms in the psychological literature, each of which explicitly describes what makes a question (experiment, query, or test) useful.

From a mathematical standpoint, the method of belief revision (Bayesian or other) and the choice of sampling norm (to assess possible questions' expected usefulness) are completely independent of each other. This notwithstanding, some researchers have implied that Bayesian diagnosticity is the only theoretically (normatively) defensible, or the only Bayesian, sampling norm. For instance, Slowiaczek, Klayman, Sherman, and Skov (1992) stated "according to Bayes's theorem, the diagnosticity [usefulness] of an answer or datum, D, depends on the likelihood ratio" (p. 393), in other words, on that answer's Bayesian diagnosticity. (Similar statements appear in Bassok & Trope, 1983–1984, p. 200; Beyth-Marom & Fischhoff, 1983, p. 1193; Doherty, Chadwick, Garavan, Barr, & Mynatt, 1996, p. 644; and Fischhoff & Beyth-Marom, 1983, pp. 240–241.) Evans and Over (1996) stated log diagnosticity would be "much more satisfactory as a normative standard" than information gain (p. 358). Good (1975) simply said Bayesian diagnosticity "was central to my first book and occurred also in at least 32 other publications. . . . What I say thirty-three times is true" (pp. 52–53).

Yet several norms have been proposed for evaluating the usefulness of a question (or test or experiment) in probabilistic evidence-gathering situations. Prominent proposals include information gain, Kullback–Liebler (KL) distance, impact (absolute change), probability gain (minimal error), Bayesian diagnosticity, and log diagnosticity (see Table 1). The literature to date, however, does not make clear (a) what norms best describe human behavior, (b) when the norms disagree, or (c) whether some norms are theoretically (normatively) better motivated than others.

The rest of this article is structured as follows. Each sampling norm is explicitly defined below. (Appendix A provides a more intuitive scenario and example calculations.) Prior experimental evidence-acquisition research is reanalyzed to examine the extent to which earlier researchers' conclusions depend on the sampling norm used. New simulations demonstrate that the sampling norms can disagree with each other and that this disagreement occurs in a variety of statistical environments. Further simulations identify particularly strong cases of disagreement among norms. Those limiting cases are used to attempt to design a definitive experiment, to address whether diagnosticity and log diagnosticity are plausible descriptive psychological models of human intuitions. Finally, theoretical objections to diagnosticity and log diagnosticity are discussed, and important issues for future research are outlined.

The Sampling Norms

There is a conceptual distinction between *disinterested* utility functions for evidence acquisition and *situation-specific* utility functions for situations with unique reward structures (Baron & Hershey, 1988; Box & Hill, 1967; Chater, Crocker, & Pickering, 1998; Chater & Oaksford, 1999; Kirby, 1994; Lindley, 1956). Disinterested utility functions are useful for information gathering, where no immediate action is required; Chater et al. (1998) likened them to pure scientific research. Situation-specific utility functions are appropriate when making the best decision is more important than believing the correct hypothesis. However, the same mathematical framework can be used in both cases (Raiffa, 1968; Savage, 1954, pp. 105–119). Each norm discussed in this article—diagnosticity, log diagnosticity, information gain, KL distance, probability gain, and impact—can be thought of as a subjective utility function for evidence acquisition. The norms give different definitions of an individual *answer's* usefulness. However, all of the norms define a *question's* usefulness as the *expected usefulness* of its possible answers, averaged according to the probability of each possible answer occurring.

A technical definition of each norm is given below. Appendix A provides a more intuitive treatment, in the context of the Vuma probability model, with example calculations and further discussion. In this article's notation, capital letters represent random variables; lowercase letters represent specific values that those random variables can take. Q is a question, query, test, or experiment whose results are unknown; q_j are specific answers or experiment results; C is the unknown category or hypothesis; and c_i are particular categories or hypotheses.

Bayesian Diagnosticity

Good (1950, 1975, 1983) introduced the concept of diagnosticity. He called an answer's diagnosticity the "weight of evidence" and a question's diagnosticity the "expected weight of evidence." Explicit use of the term *diagnosticity* in this context appeared at least as early as Edwards (1968, pp. 25–27).¹ Diagnosticity relates to the likelihood ratio of particular data given two categories:

$$\text{diagnosticity}(q_j) = \max\left(\frac{P(q_j|c_1)}{P(q_j|c_0)}, \frac{P(q_j|c_0)}{P(q_j|c_1)}\right) \text{ and}$$

$$\text{diagnosticity}(Q) = \sum_{q_j} P(q_j) \times \text{diagnosticity}(q_j),$$

¹ *Pseudodiagnosticity* articles (Beyth-Marom & Fischhoff, 1983; Doherty et al., 1996; Doherty, Mynatt, Tweney, & Schiavo, 1979; Doherty, Schiavo, Tweney, & Mynatt, 1981; Maggi, Butera, Legrenzi, & Mugny, 1998) also use diagnosticity as a sampling norm. In a typical experiment, subjects are given d_1 and d_2 (where d refers to datum) and try to determine whether h_1 or h_2 (where h refers to hypothesis) is correct. They may select two of four possible pieces of information: $P(d_1 | h_1)$, $P(d_1 | h_2)$, $P(d_2 | h_1)$, or $P(d_2 | h_2)$. The normatively correct behavior, which makes it possible to calculate posterior probabilities, is to select $P(d_1 | h_1)$ and $P(d_1 | h_2)$, or $P(d_2 | h_1)$ and $P(d_2 | h_2)$. Subjects frequently make other selections, which is nonnormative irrespective of the sampling norm used. Unfortunately, these empirical data do not discriminate the relative plausibility of different sampling norms as descriptive models.

where $\max(a, b)$ denotes the larger of a and b .

Log₁₀ Diagnosticity

The set of researchers using log diagnosticity is virtually the same as the set of researchers using diagnosticity. Some researchers first introduce diagnosticity, then use log diagnosticity for their calculations, without addressing whether those sampling norms may disagree, or giving a rationale for preferring one or the other (Evans & Over, 1996; McKenzie & Mikkelsen, in press). But their expectations are not equivalent: A question’s diagnosticity cannot be derived from its log diagnosticity or vice versa. Base 10 (i.e., *log₁₀ diagnosticity*) will be used in this article; constant positive multiples convert among bases. Specifically,

$$\begin{aligned} \log_{10} \text{diagnosticity}(q_j) &= \log_{10} \max\left(\frac{P(q_j|c_1)}{P(q_j|c_0)}, \frac{P(q_j|c_0)}{P(q_j|c_1)}\right) \\ &= \text{abs}\left(\log_{10} \frac{P(q_j|c_1)}{P(q_j|c_0)}\right) \end{aligned}$$

and

$$\log_{10} \text{diagnosticity}(Q) = \sum_{q_j} P(q_j) \times \log_{10} \text{diagnosticity}(q_j).$$

It should be emphasized that the two above formulations of an answer q_j ’s \log_{10} diagnosticity, one taking the maximum of two likelihood ratios and the other taking an absolute log likelihood ratio, are identical. Diagnosticity and log diagnosticity are both infinite for an answer q_j that eliminates a category (hypothesis) by setting its posterior probability to 0. The descriptive psychological claim is that such an answer, or a question Q with some probability of it, is infinitely useful.

Information Gain

One way to measure a question’s usefulness is by quantifying its expected reduction in uncertainty, or information gain, with respect to the true hypothesis or category. Lindley (1956), Box and Hill (1967), and Fedorov (1972) quantified this idea explicitly, using Shannon’s (1948) entropy to measure uncertainty. Good (1950, pp. 74–75) also alluded to the possibility of using a sampling norm based on Shannon entropy. Baron (1985, pp. 150–151; citing Marschak, 1974) suggested that using information gain would be appropriate in rare situations only, such as when maximizing data transmitted through a telephone line. Outside the realm of cognitive tasks, information gain has been used to model development of visual neurons (Ruderman, 1994; Ullman, Vidal-Naquet, & Sali, 2002) and auditory neurons (Lewicki, 2002), and to set camera parameters in computer vision (Denzler & Brown, 2002). This article measures information with base 2 logarithms (*bits*); one bit equals $\log_2 2 = 0.6931$ *nats* of information. The information gain in Q is the *mutual information* between C and Q (Cover & Thomas, 1991):

$$I(C, Q) = H(C) - H(C|Q), \text{ where}$$

$$H(C) = \sum_{c_i} P(c_i) \times \log_2 \frac{1}{P(c_i)}, \text{ the initial entropy in } C,$$

$$H(C|Q) = \sum_{q_j} P(q_j) \times H(C|q_j),$$

the *conditional entropy* in C given Q , and,

$$H(C|q_j) = \sum_{c_i} P(c_i|q_j) \times \log_2 \frac{1}{P(c_i|q_j)},$$

the entropy in C given a particular answer q_j .

Kullback–Liebler (KL) Distance

A question’s usefulness could also be quantified as the amount that its answer is expected to *change* one’s beliefs. KL distance (Cover & Thomas, 1991; Kullback & Liebler, 1951) provides one means to measure the change from prior beliefs about the true category, C , to posterior beliefs after a particular question is answered:

$$KL \text{ distance}(q_j) = \sum_{c_i} P(c_i|q_j) \times \log_2 \frac{P(c_i|q_j)}{P(c_i)} \text{ and}$$

$$KL \text{ distance}(Q) = \sum_{q_j} P(q_j) \times \sum_{c_i} P(c_i|q_j) \times \log_2 \frac{P(c_i|q_j)}{P(c_i)}.$$

In this article, KL distance and information gain are equivalent, because they give identical measures of a *question’s* usefulness (Oaksford & Chater, 1996). (Table A1 illustrates that they give different statements of the usefulness of particular *answers*.)

Probability Gain

Baron (1981, as cited in Baron, 1985) suggested this norm as a special case of Savage’s (1954, chap. 6, pp. 105–119) analysis of the value of observations, in which the inquirer assigns the same utility to any correct guess and lower, equal utility to any incorrect guess. Assuming that the most probable category is chosen after a question’s answer is obtained, one can calculate how much asking a particular question improves the expected probability of making a correct guess, the question’s *probability gain*. Maximizing probability gain is equivalent to minimizing probability of error, a common criterion in computer science, as well as to maximizing probability of making a correct decision. Specifically,

$$\text{probabilityGain}(q_j) = \max_{c_i} P(c_i|q_j) - \max_{c_i} P(c_i) \text{ and}$$

$$\text{probabilityGain}(Q) = \left(\sum_{q_j} P(q_j) \times \max_{c_i} P(c_i|q_j)\right) - \max_{c_i} P(c_i).$$

Impact (Absolute Change)

Impact is based on the idea that answers q_j that change beliefs are useful. In this respect, impact is similar to KL distance; however, it is based on a different measure of belief change. Wells and Lindsay (1980), Klayman and Ha (1987, pp. 219–220), and Nickerson (1996), discussing belief models with two hypotheses, suggested measuring a particular answer’s impact on an individual hypothesis as $\text{abs}[P(\text{hypothesis} | \text{answer}) - P(\text{hypothesis})]$ or, in present notation, $\text{abs}[P(c_i | q_j) - P(c_i)]$, where *abs* denotes absolute value. (Wells and Lindsay, 1980, and Wells and Olson, 2002,

Table 2
Selected Properties of Several Sampling Norms

Property	Diagnosticity	Log diagnosticity	Information gain	Kullback–Liebler distance	Probability gain	Impact
Usefulness(q_1) finite			Yes	Yes	Yes	Yes
Usefulness(q_1) ≥ 0	Yes	Yes		Yes		Yes
Usefulness(q_1 and q_2) = Usefulness(q_1) + Usefulness(q_2)			Yes		Yes	

Note. Usefulness(q_1) denotes the usefulness (utility) of the answer q_1 . Blank cells indicate absence of the corresponding property.

termed their sampling norm *information gain*. However, in present terminology, their sampling norm would be called *impact*.) If a belief model contains exactly two hypotheses, as Nickerson noted, then a particular answer has the same impact on each hypothesis. The present article generalizes impact to situations with multiple categories or hypotheses:

$$impact(q_j) = \frac{1}{n} \sum_{c_i} abs[P(c_i|q_j) - P(c_i)],$$

where n is the number of categories c_i , and

$$impact(Q) = \sum_{q_j} P(q_j) \frac{1}{n} \sum_{c_i} abs[P(c_i|q_j) - P(c_i)].$$

Slowiaczek et al. (1992, p. 402) reported that many subjects used the *heuristic* strategy of asking about the feature with the maximal difference in feature probabilities, $abs[P(\text{feature} | c_1) - P(\text{feature} | c_2)]$. It is presently shown that this strategy is not merely heuristic, but exactly implements impact.² If prior probabilities of two hypotheses are equal, impact and probability gain are identical. Several models in the literature meet this condition (Nickerson, 1996; Oaksford & Chater, 1994, 1998, 2003; Skov & Sherman, 1986; Slowiaczek et al., 1992). (After an answer has been obtained, posterior probabilities of two hypotheses—which become priors for purposes of evaluating successive questions—will in general no longer be equal.)

Properties of the Sampling Norms

The psychological plausibility of claiming that subjective utility is infinite is questionable, so it is of interest to note whether each norm is finite. Similarly, it has been argued (Evans & Over, 1996) that it is psychologically implausible that an answer that changes beliefs can have negative utility. It is thus useful to note which norms are nonnegative. Finally, is the usefulness of obtaining two pieces of data (answers q_1 and q_2) simultaneously the sum of the usefulness of obtaining each datum separately? Intuitively, it seems that if two data in effect cancel each other out, such that posterior beliefs after obtaining both of them are the same as prior beliefs, those data were useless.³ Under which sampling norms is this the case? Table 2 lists which of these properties each sampling norm satisfies.

Prior Research and the Descriptive Plausibility of Each Norm

Most research that assesses people’s faculties at identifying useful questions has used a single sampling norm to calculate each

question’s usefulness. This raises the possibility that using other normative models would result in different conclusions. To what

² A proof of the equivalence of the heuristic feature difference maximization strategy and the impact sampling norm appears below. There are two categories, c_1 and c_0 , and a question Q with possible answers q_1 and q_2 . If $P(q_1 | c_1) > P(q_1 | c_0)$, then $impact(Q)$

$$\begin{aligned} &= [P(q_1) \times impact(q_1)] + [P(q_2) \times impact(q_2)] \\ &= \{P(q_1) \times abs[P(c_1 | q_1) - P(c_1)]\} + \{P(q_2) \times abs[P(c_1 | q_2) - P(c_1)]\}, \\ &\quad \text{because there are two } c_i, \\ &= \{P(q_1) \times [P(c_1 | q_1) - P(c_1)]\} + \{P(q_2) \times [P(c_1) - P(c_1 | q_2)]\}, \\ &\quad \text{because } P(q_1 | c_1) > P(q_1 | c_0), \\ &= [P(q_1) \times P(c_1 | q_1)] - [P(c_1) \times P(q_1)] \\ &\quad + [P(c_1) \times P(q_2)] - [P(q_2) \times P(c_1 | q_2)] \\ &= [P(c_1) \times P(q_1 | c_1)] - [P(c_1) \times P(q_1)] \\ &\quad + [P(c_1) \times P(q_2)] - [P(c_1) \times P(q_2 | c_1)] \\ &= P(c_1) \times [P(q_1 | c_1) - P(q_1) + P(q_2) - P(q_2 | c_1)] \\ &= P(c_1) \times \{P(q_1 | c_1) - P(q_1) + [1 - P(q_1)] - [1 - P(q_1 | c_1)]\}, \\ &\quad \text{because } P(q_1) = 1 - P(q_2) \text{ and } P(q_2 | c_1) = 1 - P(q_1 | c_1), \\ &= 2 \times P(c_1) \times [P(q_1 | c_1) - P(q_1)] \\ &= 2 \times P(c_1) \times \{P(q_1 | c_1) - [P(c_1) \times P(q_1 | c_1)] - [P(c_0) \times P(q_1 | c_0)]\}, \\ &\quad \text{by Law of Total Probability,} \\ &= 2 \times P(c_1) \times \{[(1 - P(c_1)) \times P(q_1 | c_1)] - [P(c_0) \times P(q_1 | c_0)]\} \\ &= 2 \times P(c_1) \times \{[P(c_0) \times P(q_1 | c_1)] - [P(c_0) \times P(q_1 | c_0)]\}, \\ &\quad \text{because } P(c_0) = 1 - P(c_1), \\ &= 2 \times P(c_1) \times P(c_0) \times [P(q_1 | c_1) - P(q_1 | c_0)]. \end{aligned}$$

By a similar derivation, if $P(q_1 | c_1) > P(q_1 | c_0)$, then

$$impact(Q) = 2 \times P(c_1) \times P(c_0) \times [P(q_1 | c_0) - P(q_1 | c_1)].$$

In both cases,

$$impact(Q) = 2 \times P(c_1) \times P(c_0) \times abs[P(q_1 | c_0) - P(q_1 | c_1)].$$

³ Nick Chater (personal communication, February 10, 2005) raised this final issue.

Table 3
New Analysis of Features Used by Skov and Sherman (1986) and Slowiaczek et al. (1992)

Feature	% of gloms, fizes with each feature	Information gain, Kullback–Liebler distance	Probability gain, impact	Diagnosticity	Log ₁₀ diagnosticity
Low usefulness					
A, B	48, 52; 52, 48	0.001	.020	1.083	0.035
C, D, E, F	28, 32; 32, 28; 68, 72; 72, 68	0.001	.020	1.084	0.035
Medium usefulness					
G, H, I, J	15, 45; 45, 15; 55, 85; 85, 55	0.080	.150	1.982	0.276
K, L	34, 66; 66, 34	0.075	.160	1.941	0.288
High usefulness					
M, N, O, P	10, 50; 50, 10; 50, 90; 90, 50	0.147	.200	2.760	0.388
Q, R	26, 74; 74, 26	0.173	.240	2.846	0.454

Note. Skov and Sherman (1986) used all of the features in this table. Slowiaczek et al. (1992) used only the low usefulness features C, D, E, and F and the high usefulness features M, N, O, and P. Multiple features, for example, Features A and B, appear on the same line if all sampling norms agree that those features are equally useful. Semicolons separate features. For example, 48% of gloms and 52% of fizes have Feature A; 52% of gloms and 48% of fizes have Feature B.

degree do earlier researchers' conclusions about people's sensitivity to questions' usefulness depend on the specific sampling norm used? This section considers several belief models, each with specific hypotheses, prior probabilities, and available questions. For each belief model, the usefulness of each question is computed using diagnosticity, information gain–KL distance, probability gain, and impact. Because “the complexity of any real decision problem defies complete explicit description” (Savage, 1954, p. 107), the probability models below reflect simplified experimental tasks. For instance, Baron, Beattie, and Hershey (1988) studied a simple case of medical diagnosis. Extension of that analysis to actual medical decision making is not straightforward (Baron, 1996; Cohen, 1996), although value of information analyses have proven useful in medicine (Yokota & Thompson, 2004). Nor is it straightforward to predict how subjects will interpret an experimental task (McKenzie, Wixted, & Noelle, 2004). On Wason's (1966, 1968) selection task, there are several proposed probability models. An evenhanded approach, for the present article, is to exactly implement the original researchers' belief model, in each experiment considered.

Two-Category, Binary-Feature Tasks

Skov and Sherman (1986) and Slowiaczek et al. (1992, Experiments 3a and 3b) designed a task to be a case of miniature

scientific inference but in which appropriateness of a particular belief model was clear. Subjects were told the distribution of gloms and fizes, the two types of creatures on planet Vuma, and the distribution of various binary features within gloms and fizes. Subjects were asked to indicate which features they would ask about, to determine whether a novel creature was a glom or fizo. Skov and Sherman and Slowiaczek et al. used diagnosticity or log diagnosticity to measure the usefulness of questions. In Skov and Sherman's experiment, as many as five high-diagnosticity questions could be chosen: 68% of the 66 subjects chose five high-diagnosticity questions; an additional 18% chose four high-diagnosticity questions. In Slowiaczek et al.'s Experiment 3a, a single question was selected; 98% of subjects (196 of 199) chose a high-diagnosticity question.

Do Skov and Sherman's (1986) or Slowiaczek et al.'s (1992, Experiment 3a) results depend on using diagnosticity or log diagnosticity to measure the usefulness of questions? In the present analysis, each question's usefulness was calculated using information gain–KL distance, probability gain, impact, diagnosticity, and log diagnosticity. All norms agree with Skov and Sherman's high > medium > low ordering and with Slowiaczek et al.'s high > low ordering of the usefulness of each question (see Table 3). This corroborates the earlier findings that people tend to select reasonable questions. But neither experiment's behavioral results

Table 4
New Analysis of the Usefulness of Features Used by Slowiaczek et al. (1992, Experiment 3b)

Type of feature	% of gloms, fizes with each feature	Information gain, Kullback–Liebler distance	Probability gain, impact	Diagnosticity	Log ₁₀ diagnosticity
Extreme	90, 55; 45, 10	0.1177	.1750	2.4239	0.3347
Nonextreme	65, 30; 30, 65	0.0905	.1750	2.0792	0.3175

Note. Semicolons separate features. For example, 95% of gloms and 55% of fizes have one of the extreme features; 45% of gloms and 10% of fizes have the other extreme feature. Both Planet Vuma and medical diagnosis scenarios were used.

differentiate the relative plausibility of the sampling norms under consideration as descriptive models.

Slowiczek et al. (1992, Experiment 3b) also sought to address whether people prefer questions with extreme feature probabilities; for example, wearing a hula hoop (Hula), present in 90% of gloms and 55% of fizos, versus drinking iced tea (Drink), found in 65% of gloms and 30% of fizos. The intent was to hold usefulness constant while modifying the extremity of feature probabilities (see Table 4) in a pair of questions. Unfortunately, the stimuli confounded extremity with several sampling norms, such that the questions with more extreme feature probabilities also had higher diagnosticity, log diagnosticity, and information gain–KL distance. Impact and probability gain were indifferent between the two questions in each pair. Slowiczek et al.'s behavioral results were that on average, the feature with higher diagnosticity, log diagnosticity, and information gain–KL distance was chosen around 60% of the time (chance would be 50%). It is difficult to make strong inferences about the sampling norms from this result.

Medical Diagnosis

Baron et al. (1988, Experiments 4, 5, and 6) asked subjects to rate the usefulness of several medical tests. The task instructions described a situation in which probability gain would be the most obviously justifiable measure.⁴ Only one test could be conducted before diagnosing and treating the disease. Diseases were described abstractly as Diseases A, B, and C; their prior probabilities were 0.64, 0.24, and 0.12, respectively. Thus, the diseases were presumably equally problematic, if untreated, and equally treatable. Subjects were given the conditional probabilities that each of several tests would come out positive or negative, given each disease.⁵

Subjects rated each test's usefulness on a 0–100 scale, "where 0 means the test is worthless and should not be done and 100 means the test would remove all doubt about which disease the patient has" (Baron et al., 1988, p. 101). Baron et al. (1988) found that subjects were generally sensitive to the relative usefulness of each test, as measured with probability gain. However, subjects consistently gave positive ratings to some tests that were useless, as calculated by probability gain. Baron et al. referred to this tendency as information bias.

Could the idea that subjects were making use of a sampling norm besides probability gain better explain Baron et al.'s (1988) data? To address this possibility, I computed the probability gain, impact, and information gain–KL distance of each test (see Tables 5 and 6). Impact and information gain–KL distance agree with subjects that some zero probability gain tests are useful (Tests 3–8 in Experiment 4). In other words, if impact or information gain were to be deemed appropriate normative models of this task, information bias would largely disappear. Overall, however, although subjects' ratings correlate highly with each sampling norm, there is no clear pattern wherein a particular sampling norm best accounts for responses (see Table 7).

The Abstract Selection Task

In a typical version of this task, introduced by Wason (1966, 1968), a subject is shown the top faces of four cards, showing A, 2, K, and 3. The subject is asked what cards would need to be

flipped to falsify the rule that "If a card has an A on one side, it has a 2 on the other side." Wason (1966, 1968) intended the selection task to be a deductive logical task, in which the 2 card and the K card would be useless. But very few subjects (seldom 10%) select just the A and 3 card (Stanovich & West, 1998); most subjects do select the 2 card, which Wason (1966, 1968) took to be a mistake. Over several decades of subsequent study involving around 1,000 experimental subjects, the ordering of the most frequently selected cards has been $A > 2 > 3 > K$ (Oaksford & Chater, 1994).

Oaksford and Chater (1994, 1998, 2003) introduced probabilistic, rather than logical, models of the selection task and proposed that subjects choose cards to maximize information gain⁶ with respect to their beliefs, rather than to falsify a particular hypothesis. There has been extensive debate about this approach (Almor & Sloman, 1996; Evans & Over, 1996; Laming, 1996; Oaksford & Chater, 1996, 1998, 1999; Over & Jessop, 1998), and other probabilistic models have also been proposed (e.g., Hattori, 2002; Kirby, 1994; Klauer, 1999). However, novel predictions have been tested behaviorally (e.g., Oaksford, Chater, & Grainger, 1999), in turn improving the model. Oaksford and Chater's (2003) belief model includes two hypotheses: a *dependence hypothesis*, that every card with an A on one side does have a 2 on the other side, and an *independence hypothesis*, that A, K, 2, and 3 are assigned independently, with the constraint that each card has a letter on one side and a number on the other side. The model requires four parameters: probability of the dependence hypothesis, overall $P(A)$, overall $P(2)$, and probability of an error under the dependence hypothesis, under which A is paired with 3. The general constraints specified by Oaksford and Chater (1994, 2003) are that As and 2s be *rare* and that the combination of parameters lead to a valid probability distribution under the dependence hypothesis (Over & Jessop, 1998, explicitly specified these constraints). Among other results, Oaksford and Chater (1994, 2003) found that the ordering of the information gain of each card, $A > 2 > 3 > K$, matched card selection frequencies.

Would sampling norms other than information gain provide similar results? Oaksford and Chater's (2003) model was implemented here, fixing $P(\text{dependence hypothesis}) = .50$, $P(\text{error}) = .10$, $P(A) = .22$, and $P(2) = .27$. Each norm gave the same ordering (see Table 8), suggesting that at this level of analysis, the model does not differentiate the sampling norms under consider-

⁴ If reducing the number of possible diseases improves treatment, irrespective of the true disease, probability gain might not be uniquely justified. Shanks, Tunney, and McCarthy (2002), on a two-arm bandit task that did not involve active sampling, found that some subjects did seek to maximize average winnings. One could imagine a modified task that includes asking questions, where probability gain is uniquely compatible with the goal of maximizing average winnings.

⁵ In Experiment 5, joint probabilities of each disease and each test, for instance that 32% of patients have Disease 1 and a positive result from Test A, were given. A set of conditional probabilities uniquely implies a set of joint probabilities and vice versa.

⁶ Some research on the abstract selection task (Hattori, 2002; Oaksford & Chater, 1998, 2003) has reported information gain values scaled to sum to 1. The present article reports nonnormalized values; normalized values give the same ordering.

Table 5
Reanalysis of Experiment 4 in Baron et al. (1988)

Test	1	2	3	4	5	6	7	8	9	10
P(positive disease)										
Disease A	.75	0	.75	.50	.50	.50	.50	.25	1.00	.50
Disease B	.75	1.00	1.00	1.00	0	0	1.00	0	0	.50
Disease C	.75	0	1.00	0	0	1.00	1.00	0	0	.50
Subjects' ratings	21	61	40	34	26	26	48	25	75	9
Usefulness										
Probability gain	0	.200	0	0	0	0	0	0	.240	0
Information gain	0	0.795	0.115	0.350	0.264	0.350	0.264	0.115	0.943	0
Impact	0	.243	.077	.141	.154	.141	.154	.077	.307	0

Note. Prior probabilities of Diseases A, B, and C were .64, .24, and .12, respectively. Subjects' ratings and the conditional probabilities of a positive test given each disease are adapted from Table 4 in "Heuristics and Biases in Diagnostic Reasoning: II. Congruence, Information, and Certainty," by J. Baron, J. Beattie, and J. C. Hershey, 1988, *Organizational Behavior and Human Decision Processes*, 42, p. 102. Copyright 1988 by Elsevier. Adapted with permission.

Table 6
Reanalysis of Experiments 5 and 6 in Baron et al. (1988)

Test	1	2	3	4	5	6	7	8	9	10	11
P(positive disease)											
Disease A	.50	1.00	.81	0	1.00	0	0	1.00	0	1.00	1.00
Disease B	.50	1.00	0	1.00	.50	1.00	.50	0	0	0	1.00
Disease C	.50	0	0	0	0	1.00	0	1.00	1.00	0	1.00
Subjects' ratings											
Experiment 5	—	42	56	64	41	69	44	65	42	64	—
Experiment 6	—	64	62	75	52	75	41	69	56	79	—
Usefulness											
Probability gain	0	.120	.118	.240	.120	.240	.120	.240	.120	.240	0
Information gain	0	0.529	0.550	0.795	0.555	0.942	0.289	0.795	0.529	0.943	0
Impact	0	.141	.245	.243	.205	.307	.122	.243	.141	.307	0

Note. Prior probabilities of Diseases A, B, and C were .64, .24, and .12, respectively. Baron et al. (1988) stated that most subjects rated Tests 1 and 11 zero. However, Baron et al. did not report subjects' ratings of those tests, which is indicated by dashes. Subjects' ratings and the conditional probabilities of a positive test given each disease are adapted from Table 5 in "Heuristics and Biases in Diagnostic Reasoning: II. Congruence, Information, and Certainty," by J. Baron, J. Beattie, and J. C. Hershey, 1988, *Organizational Behavior and Human Decision Processes*, 42, p. 106. Copyright 1988 by Elsevier. Adapted with permission.

Table 7
New Analysis of Correlations Between Three Sampling Norms and Subjects' Average Ratings in Baron et al.'s (1988) Study

Sampling norm	Experiment		
	4	5	6
Probability gain	.84	.91	.83
Information gain	.89	.86	.94
Impact	.89	.88	.81

Note. Correlations exclude Tests 1 and 11, in Experiments 5 and 6, for which Baron et al. (1988) did not report subjects' ratings. Pearson product-moment corrections were used. A similar pattern, with slightly lower correlation values, results if Spearman rank correlation coefficient is used.

Table 8
New Analysis of Each Card's Usefulness on the Selection Task

Sampling norm	A (P)	2 (Q)	3 (not-Q)	K (not-P)
Information gain, Kullback-Liebler distance	0.324	0.200	0.066	0.040
Probability gain, impact	.315	.257	.095	.089
Diagnosticity	4.980	3.120	2.001	1.548
Log ₁₀ diagnosticity	0.664	0.493	0.191	0.162

Note. Each card's (A, 2, 3, and K) usefulness was calculated with respect to Oaksford and Chater's (2003) belief model, with P(dependence hypothesis) = .50, P(error) = .10, P(A) = .22, and P(2) = .27. The terms in parentheses (P, Q, not-Q, and not-P) refer to presence or absence of the logical antecedent (P) or consequent (Q).

Table 9
New Analysis of McKenzie and Mikkelsen's (in press) Covariation Assessment Model

Observation	Information gain, KL distance	Probability gain, impact	Diagnosticity	Log ₁₀ diagnosticity	Log ₂ diagnosticity
Cell A	0.38	.35	5.50	0.74	2.46
Cell B	0.08	.17	2.00	0.30	1.00
Cell C	0.08	.17	2.00	0.30	1.00
Cell D	0.0005	.01	1.06	0.02	0.08

Note. McKenzie and Mikkelsen's (in press) model describes answers' (q_j), rather than questions' (Q), usefulness, illustrating the variety of tasks in which explicit sampling norms may be calculated. Particular answers' information gain and Kullback–Liebler (KL) distance are not necessarily the same, although they are in this case.

ation.⁷ Would other parameter settings strongly differentiate the norms? If $P(\text{error}) = 0$, both diagnosticity and log diagnosticity rate the A and 3 cards as infinitely useful. This is because if $P(\text{error}) = 0$, each of these cards offers a chance of eliminating the dependence hypothesis, which diagnosticity and log diagnosticity consider infinitely useful. Diagnosticity and log diagnosticity are indifferent to the relative probability of eliminating a hypothesis when selecting the A or 3 card in this case. If $P(\text{error}) = .01$, diagnosticity rates the A and 3 cards as most useful; log diagnosticity rates the A and 2 cards as most useful. To summarize, if subjects believe $P(\text{error})$ is very low, diagnosticity and/or log diagnosticity contradict abstract selection task data. Information gain and impact–probability gain maintain the $A > 2 > 3 > K$ ordering when $P(\text{error}) = .01$ or 0. A further note is that Evans and Over (1996) objected to information gain per se but not to Oaksford and Chater's (1994) probability model. Present results show that a sampling norm as intuitive as probability gain or impact could be used.

Covariation Assessment

How are variables related to each other? Inhelder and Piaget's (1955/1958) studies set a foundation for research in several areas.⁸ This section focuses on covariation assessment (Inhelder & Piaget, 1955/1958; McKenzie, 1994; Peterson & Beach, 1967; Smedslund, 1963). A typical task involves two binary variables: X (e.g., glom or not) and Y (hulaWorn or not). Each individual observation falls in one cell of a matrix with four cells: Cell A, glom wearing a hula hoop; Cell B, glom not wearing a hula hoop; Cell C, fizo wearing a hula hoop; or Cell D, fizo not wearing a hula hoop. Subjects frequently are shown a matrix with counts of the number of individuals in each of those four cells. Which cell's observations are the most informative with respect to the goal of determining whether the variables X and Y covary? Most normative models treat the four cells as equally useful. Yet over several experimental manipulations (reviewed in McKenzie & Mikkelsen, in press), subjects treat Cell A as most useful and Cell D as least useful, with Cell B and Cell C in between: $A > (B \approx C) > D$. This differential evaluation has been considered suboptimal.

McKenzie and Mikkelsen (in press) proposed that subjects may be approaching covariation assessment tasks as inferential tasks and using their prior beliefs to interpret the tasks. For instance, subjects may have the goal of finding out which of two hypotheses (h) is true: h_1 , that there is a moderate correlation between X and Y , or h_0 , that X and Y are independent. Each hypothesis specifies the probability that an observation will fall in each of Cells A–D.

Presence of X (glom) and Y (hulaWorn) are each rare (10% probability under both h_1 and h_0) in the model, corresponding to several researchers' findings that subjects usually assume rarity in related tasks (Anderson & Sheu, 1995; McKenzie, Ferreira, Mikkelsen, McDermott, & Skrable, 2001; McKenzie & Mikkelsen, 2000; Oaksford & Chater, 2003). McKenzie and Mikkelsen (in press) calculated the log₂ diagnosticity of an observation in each cell, relative to their probability model. McKenzie and Mikkelsen's (in press) model gave the ordering $A > (B = C) > D$, providing a rational explanation of one of the main covariation assessment research findings. In the present analysis, McKenzie and Mikkelsen's (in press) probability model was implemented,⁹ and each cell's usefulness was calculated, relative to information gain, KL distance, probability gain, impact, diagnosticity, and log diagnosticity. All sampling norms agree on the $A > (B = C) > D$ ordering (see Table 9). This result bolsters McKenzie

⁷ The present analysis fixed $P(\text{dependence hypothesis}) = .50$ and $P(\text{error}) = .10$, like Oaksford and Chater (2003). But whereas Oaksford and Chater (2003) optimized $P(A)$ and $P(2)$ to fit data from each of several dozen experiments in the literature, the present analysis fixed $P(A) = .22$ and $P(2) = .27$ to match the mean best fit parameters reported by Oaksford and Chater (2003). For each experiment, Oaksford and Chater (2003) used a logistic function to transform the information gain of each card into a probability of selection, as proposed by Hattori (2002). A further step in analysis of the selection task would be to replicate Oaksford and Chater's (2003) optimizations, finding the best fit parameters of $P(A)$ and $P(2)$ for each sampling norm, for each of the several dozen experiments Oaksford and Chater (2003) fit. Those results, for instance goodness of fit in each experiment and number of experiments in which a model is rejected, could potentially speak to the relative descriptive plausibility of each sampling norm, even without overt disagreements on the ordering of the cards' usefulness.

⁸ In one of Inhelder and Piaget's (1955/1958) studies, subjects experimented with string length, weight on the string, and so forth to learn what variables control the movement of a pendulum. Scientific reasoning research (Klahr, 2000; Kuhn, 1989, 2002; Kuhn, Amsel, & O'Loughlin, 1988, pp. 161–183; Wason, 1960; Zimmerman, 2000) frequently uses similarly rich tasks. Another related area is contingency, the degree to which one variable predicts another variable's occurrence later in time (Allan, 1993; Anderson & Sheu, 1995; Jenkins & Ward, 1965).

⁹ McKenzie and Mikkelsen (in press) did not specify prior probabilities of h_1 and h_0 . The diagnosticity and log diagnosticity of an observation (answer q_j) is independent of priors; for example, log₂ diagnosticity(A) = 2.46, irrespective of whether $P(h_1) = P(h_2) = .5000$, or $P(h_1) = .9999$ and $P(h_2) = .0001$. As the other norms are sensitive to priors, equal priors of h_1 and h_0 were used.

and Mikkelsen's (in press) conclusion that subjects' behavior is justifiable but does not provide evidence against any sampling norm as a descriptive model of subjects' behavior.

Do the Sampling Norms Ever Disagree?

The previous section showed that the sampling norms under consideration behave similarly with respect to several probability belief models. This result corroborates previous researchers' frequent finding that subjects are sensitive to questions' and answers' usefulness. However, this result does not directly address when the sampling norms make contradictory claims. Simulations were therefore conducted to address the frequency and pervasiveness in different environments of disagreements among the sampling norms.

Simulation 1.0: Multiple Features

How often do any of the norms disagree with each other, and does the number of features relate to the frequency of disagreement? To address this question, I simulated the Vuma scenario (described in the above review of Skov & Sherman, 1986; Slowiczek et al., 1992; and in Appendix A) with $P(\text{glom}) = P(\text{fizo}) = .50$ and random feature probabilities such as $P(\text{hulaWorn} \mid \text{glom})$. (*Random probabilities* denotes pseudorandom numbers independently sampled from a uniform distribution between 0 and 1, inclusive.) Ten thousand random trials were run for each number of features between 2 and 20. Each trial was analyzed to determine whether there was disagreement among diagnosticity, log diagnosticity, information gain–KL distance, and probability gain–impact on the relative usefulness of each feature. Number of disagreements increased monotonically with the number of features. Disagreements occurred in 7% of 2-feature trials, a majority of 6-feature trials, and more than 99% of 15-feature trials.

Simulations 1.1–1.3: Several Environments

Is the existence of disagreements among sampling norms restricted to a particular environment?¹⁰ In each simulation, 1,000,000 random trials were generated. Simulation 1.1 used random feature probabilities and random prior probabilities. Simulation 1.2 used equal prior probabilities and random feature probabilities. Simulation 1.3 considered an environment where both features were *rare* (feature probabilities between 0 and .5), as subjects in hypothesis-testing tasks usually assume (Anderson & Sheu, 1995; McKenzie et al., 2001; McKenzie & Mikkelsen, 2000; Oaksford & Chater, 2003) but was otherwise identical to Simulation 1.1. Results showed that in each simulation, every possible type of pairwise disagreement (where one norm prefers Hula and another norm prefers Drink) occurred. Likewise, each simulation produced cases of disagreement with and without extreme feature values: having a feature probability close to 0 or 1 is not necessary for a disagreement to occur. In Simulations 1.1 and 1.3, where $P(\text{glom})$ was random, sometimes both questions had zero probability gain. Simulation 1.3 (rare features) had results similar to Simulation 1.1. Together, these simulations show that in a variety of environments, using one norm leads to asking different questions than using another norm. Some cases of disagreement were qualitatively stronger than others, an issue addressed below.

Simulation 2: Cases of Strongest Disagreement

Could identification of cases of strong disagreement elucidate the differences among the sampling norms? This section describes a simulation to search for limiting cases.

Method

A simulation automatically searched for cases of high pairwise disagreement strength (DStr; see Appendix B) between diagnosticity, log diagnosticity, information gain–KL distance, probability gain, and impact. Each optimization used fixed prior probabilities, specified by $P(\text{glom})$, and began with random feature probabilities, in which the two norms being compared disagreed about which feature was more useful. Optimizations to maximize the pairwise disagreement in all 10 pairs ($5 \text{ choose } 2 = 10$) of norms were run, for each $P(\text{glom})$ between .500 and .995, in increments of .005. The optimization procedure was allowed to find feature probabilities of 0, any number between .0001 and .9999, or 1. Each trial was repeated 10 times; feature probabilities in the trial with the highest DStr were recorded.

Results and Discussion

Figure 1 shows the maximum obtained DStr as a function of $P(\text{glom})$ for each pair of norms. A surprising result, considering that some researchers have used diagnosticity and log diagnosticity interchangeably, is the consistently high disagreement between diagnosticity and log diagnosticity (dashed line at top of figure). In each of the trials in this particular optimization, diagnosticity's claims were strongly suboptimal with respect to all other sampling norms; log diagnosticity agreed with information gain–KL distance, probability gain, and impact. In all other optimizations where very high disagreement (DStr near 100) was observed, diagnosticity and log diagnosticity agreed with each other in each trial but were suboptimal with respect to all other norms. In these trials, diagnosticity and log diagnosticity were unduly influenced by the occasional presence of a certainty-inducing answer, which occurred because a feature probability was 1 or 0. Information gain–KL distance, probability gain, and impact had only moderate degrees of disagreement with each other, suggesting that they may be more closely related to each other (three lines in middle and bottom of figure).

Representative cases of disagreement are discussed below; Appendix B shows how patterns change as a function of $P(\text{glom})$. (Additional results are included in the supplementary material, which is available on the Web at <http://dx.doi.org/10.1037/0033-295X.112.4.979.supp>.) In most of the individual cases discussed below, $P(\text{glom}) = .70$; this prior led to high DStr in most optimizations (see Figure 1 and Appendix B). Where multiple optimizations, for example, probability gain versus diagnosticity and probability gain versus log diagnosticity, produced essentially identical feature probabilities, those optimizations are discussed simultaneously.

Log₁₀ Diagnosticity Versus Diagnosticity

The following example is representative of the results presented in Table B1: $P(\text{glom}) = .7000$, $P(\text{hulaWorn} \mid \text{glom}) = .9987$,

¹⁰ Methods and results are briefly described here; complete details on the design of the simulations and results are included in the supplementary material, which is available on the Web at <http://dx.doi.org/10.1037/0033-295X.112.4.979.supp> and at <http://www.jonathandnelson.com>.

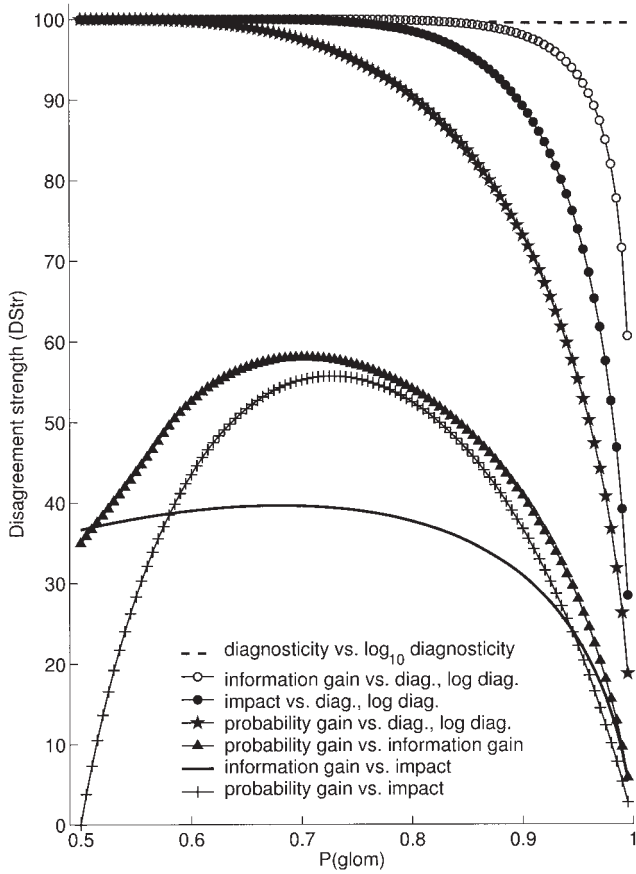


Figure 1. Simulation 2 results: strength of limiting cases of disagreement between pairs of sampling norms for different prior probabilities. diag. = diagnosticity; glom = type of creature on planet Vuma.

$P(\text{hulaWorn} \mid \text{fizo}) = .0013$, $P(\text{drinksTea} \mid \text{glom}) = 0.0001$, and $P(\text{drinksTea} \mid \text{fizo}) = .6203$ (DStr = 99.68). Diagnosticity rates the Drink feature as much more useful than Hula; \log_{10} diagnosticity rates Hula as much more useful than Drink. Testing the Hula feature leads to probability 0.9987 of correct guess (it has remaining uncertainty 0.0137 bit); testing the Drink feature leads to probability .8860 of correct guess (it has remaining uncertainty 0.4763 bit). Similar examples were observed in other limiting cases of disagreement between diagnosticity and \log_{10} diagnosticity. In all of these cases, using diagnosticity to select questions is strongly suboptimal with respect to probability of correct guess (probability gain), reduction in uncertainty (information gain), and absolute change in beliefs (impact).

Information Gain Versus Diagnosticity, Information Gain Versus Log₁₀ Diagnosticity, Impact Versus Diagnosticity, and Impact Versus Log₁₀ Diagnosticity

If a question has any possibility of completely eliminating a hypothesis, then even if that possibility is extremely remote, diagnosticity and log diagnosticity regard that question as infinitely useful. The following example is representative of the results presented in Table B2, for information gain versus diagnosticity:

$P(\text{glom}) = .7000$, $P(\text{hulaWorn} \mid \text{glom}) = .0001$, $P(\text{hulaWorn} \mid \text{fizo}) = .9999$, $P(\text{drinksTea} \mid \text{glom}) = .0001$, and $P(\text{drinksTea} \mid \text{fizo}) = .0000$. Hula leads to 99.99% probability of correct guess (it has probability gain .2999) and to uncertainty 0.0014 bit (it has information gain 0.8799 bit). Drink gives no improvement in probability of correct guess (it has probability gain zero) and almost no reduction in uncertainty (it has information gain 0.00004 bit). Yet the Drink question, with probability 7 in 100,000, results in the drinksTea answer, which provides conclusive evidence that the creature is a glom. Diagnosticity and log diagnosticity therefore consider the Drink question to be infinitely¹¹ useful. Probability gain, information gain–KL distance, and impact all strongly prefer the Hula question. Essentially identical results occurred throughout the optimizations in which information gain or impact was contrasted with diagnosticity or log diagnosticity.

Probability Gain Versus Diagnosticity and Probability Gain Versus Log₁₀ Diagnosticity

The following example is representative of the results presented in Table B3, for probability gain versus diagnosticity: $P(\text{glom}) = .7000$, $P(\text{hulaWorn} \mid \text{glom}) = .0001$, $P(\text{hulaWorn} \mid \text{fizo}) = .9999$, $P(\text{drinksTea} \mid \text{glom}) = .0914$, and $P(\text{drinksTea} \mid \text{fizo}) = .0000$ (DStr = 97.48). Hula has probability gain .2999; Drink has probability gain 0. Hula has information gain .8799; Drink has information gain .0343. Yet the Drink feature has infinite diagnosticity and \log_{10} diagnosticity. In all cases of these optimizations, diagnosticity and \log_{10} diagnosticity agreed with each other and were suboptimal with respect to information gain, impact, and probability gain. These optimizations' results are similar in some respects to the previous example comparing information gain and diagnosticity. However, probability gain is zero for a wider range of feature probabilities than information gain and impact. In the present optimization, that tends to result in more variable feature probabilities in the question that diagnosticity and \log_{10} diagnosticity prefer. (Had the present example contrasted information gain with diagnosticity, $P[\text{drinksTea} \mid \text{glom}]$ would have been expected to be .0001, rather than .0914.)

Information Gain Versus Probability Gain

Recall that information gain generally prefers features with an extreme feature probability, especially features with an extreme feature probability given the working hypothesis. By contrast, probability gain prefers features with an extreme feature probability given the working hypothesis but not extreme feature probabilities in general. In this optimization, information gain preferred a feature with an extreme feature probability given the alternate hypothesis, for example, $P(\text{hulaWorn} \mid \text{fizo}) \approx 0$ or 1. Probability gain preferred a feature in which the more extreme of the two feature probabilities was paired with the more working hypothesis

¹¹ Strict formalists may state that diagnosticity(Drink) is undefined. But clearly,

$$\lim_{P(\text{drink} \mid \text{fizo}) \rightarrow 0^+} \text{diagnosticity}(\text{Drink}) = \infty.$$

This difficulty stems from the definitions of diagnosticity and log diagnosticity. Features, like $P(\text{hasDNA} \mid \text{human})$, can have probability 0 or 1.

Table 10
Feature Probabilities for Each Question in the Experiment

Species	Drink	Gurgle	Harmonica	Hula
Gloms	30%	70%	1%	99%
Fizos	0.01%	30%	99%	100%

(glom). The following example is representative of the results presented in Table B4: $P(\text{glom}) = .7000$, $P(\text{hulaWorn} | \text{glom}) = .5714$, $P(\text{hulaWorn} | \text{fizo}) = .0000$, $P(\text{drinksTea} | \text{glom}) = .9525$, and $P(\text{drinksTea} | \text{fizo}) = .5587$ (DStr = 58.04). Hula had probability gain zero; Drink had probability gain .0991. Information gain, however, was greater for Hula (0.2813 bit) than for Drink (0.1577 bit). Impact agreed with probability gain when $P(\text{glom})$ was between .50 and .58, and with information gain for more extreme values of $P(\text{glom})$. In most cases, the feature preferred by information gain offered the possibility of a certain result and was favored by diagnosticity and log diagnosticity.

Information Gain Versus Impact

Information gain has a preference for extreme feature probabilities, especially extreme feature probabilities given the working hypothesis (glom where $P[\text{glom}] > 1/2$). If feature difference is held constant, then impact has no preference among features with extreme feature probabilities given the working or alternate hypothesis, or without extreme feature probabilities altogether. This optimization gave each feature preferred by information gain (Hula) probability of 1 or 0 given the working hypothesis. Compared with the Hula features, the Drink features were given less extreme feature probabilities overall. To further minimize their information gain, the Drink features are asymmetric in the sense that the relatively extreme feature probability was paired with the alternate hypothesis (fizo). The following example is representative of the results presented in Table B5: $P(\text{glom}) = .7000$, $P(\text{hulaWorn} | \text{glom}) = 1.0000$, $P(\text{hulaWorn} | \text{fizo}) = .6247$, $P(\text{drinksTea} | \text{glom}) = .2770$, and $P(\text{drinksTea} | \text{fizo}) = .7791$ (DStr = 39.57). Information gain was 0.2213 for Hula and 0.1604 for Drink; impact was .1576 for Hula and .2109 for Drink. Probability gain was .1126 for Hula and .0398 for Drink. In this optimization, probability gain agreed with impact when $P(\text{glom})$ was between .50 and .58 and with information gain for more extreme $P(\text{glom})$ values.

Impact Versus Probability Gain

Probability gain and impact are identical if $P(\text{glom}) = P(\text{fizo}) = .50$ but otherwise can disagree. Impact is a constant multiple of feature

Table 11
Usefulness of Each Question in the Experiment, as Calculated by Each Norm

Sampling norm	Drink	Gurgle	Harmonica	Hula
Diagnosticity	451.36	2.33	99.00	Infinite
Log_{10} diagnosticity	0.65	0.37	2.00	Infinite
Information gain, Kullback–Liebler distance	0.17	0.12	0.92	0.01
Probability gain, impact	.15	.20	.49	.01

difference, for fixed $P(\text{glom})$, and always prefers the question with maximal difference in feature probabilities. For impact's preferred feature (Hula), the optimization appears to have maximized feature difference, subject to the constraint that the feature should have probability gain approximately zero. This was achieved by making the most extreme feature probability conditional on the alternate hypothesis, for example, $P(\text{hulaWorn} | \text{fizo}) \approx 0$ or 1. For the feature that probability gain prefers, the optimization found features with lower feature difference than the corresponding feature preferred by impact but in which an extreme feature probability was conditioned on the working hypothesis, for example, $P(\text{drinksTea} | \text{glom}) \approx 0$ or 1, so as to maximize probability gain. The following example is representative of the results presented in Table B6: $P(\text{glom}) = .7000$, $P(\text{hulaWorn} | \text{glom}) = .5714$, $P(\text{hulaWorn} | \text{fizo}) = 0$, $P(\text{drinksTea} | \text{glom}) = 1.0000$, and $P(\text{drinksTea} | \text{fizo}) = .6966$ (DStr = 55.25). Hula has impact 0.2400; Drink has impact 0.1274. Hula has probability gain 0; Drink has probability gain 0.0910. In each trial of this optimization, information gain agreed with impact.

An Experiment to Separate Sampling Norms

Given that people may choose queries in a noisy manner (Hattori, 2002), an experiment to identify what norms best predict human queries should use cases of strong disagreement among norms. This section reports an experiment whose design was based on cases of maximal possible disagreement among the sampling norms, given equal priors, as identified by Simulation 2 (see Appendix B).

Method

Subjects were undergraduate students in an introduction to cognitive science class at the University of California, San Diego ($N = 151$) who participated as part of class requirements. All subjects gave informed consent. A planet Vuma scenario was used; subjects were asked to rate the possible questions from most to least useful for determining whether a novel Vumian was a glom or fizo. Prior probabilities of glom and fizo were equal.¹² Tables 10 and 11 give the feature probabilities of each question and each norm's calculation of each question's usefulness. A sample stimulus is given in Appendix C. The order of features with particular feature probabilities and the order of features' labels (Drink, Gurgle, etc.) both varied across subjects.

Results and Discussion

Three subjects were excluded for not ranking all features. One subject gave all queries equal rank. Correlations between that subject's data and each sampling norm are set to 0 in the analyses. The most common pattern (32% of subjects) was an exact match to information gain–KL distance. The next most common pattern (27%) was an exact match to probability gain–impact. No responses matched

¹² A pilot experiment with unequal prior probabilities of glom and fizo was conducted. Several subjects indicated that they had forgotten that priors were not equal when rating the questions. Because of this possible confound, and because of the default assumption that priors are equal (Fox & Rottenstreich, 2003), equal prior probabilities were used. Impact and probability gain are identical in this two-category, equal-prior-probability case.

Table 12
Experiment Results

% of subjects	No. of subjects	Pattern	Description	Pattern correlation with			
				Information gain, KL distance	Probability gain, impact	Diagnosticity	Log diagnosticity
32	48	Harmonica > Drink > Gurgle > Hula	Information gain, KL distance	1.00	.80	-.40	-.20
27	40	Harmonica > Gurgle > Drink > Hula	Probability gain, impact	.80	1.00	-.80	-.40
18	26	Drink > Harmonica > Gurgle > Hula	Close to information gain	.80	.40	-.20	-.40
5	8	Harmonica > Drink = Gurgle > Hula	Average information, probability gain	.95	.95	-.63	-.32
18	26	Other patterns, 1-3 responses each	Various patterns	.26	.20	.04	.21
0	0	Hula > Drink > Harmonica > Gurgle	Diagnosticity	-.40	-.80	1.00	.80
0	0	Hula > Harmonica > Drink > Gurgle	Log diagnosticity	-.20	-.40	.80	1.00
100	148	Aggregate results	Various patterns	.78	.69	-.41	-.22

Note. The Spearman rank correlation coefficient, with correction for ties, was used. Mean correlations are given for rows that aggregate multiple patterns of response rankings. *KL* denotes Kullback-Liebler.

diagnosticity or log diagnosticity. Table 12 summarizes frequent ordering patterns along with each pattern's Spearman rank correlation coefficient with information gain, probability gain, diagnosticity, and log diagnosticity.

Two analyses were conducted. The first analysis addressed whether the number of responses consistent with each norm was consistent with assigning Rank Orders 1-4 at random. The probability of exactly matching a particular norm by chance, under this null hypothesis, is $1/4! = 1/24$. The number of subjects matching a particular norm, under this null hypothesis, is approximately normally distributed ($M = 6.17$, $SD = 2.43$). (Standard deviation is derived from the binomial variable with parameter $1/24$ and $n = 148$.) Significantly more subjects gave rankings in accord with information gain, $t(147) = 17.2$, $p < .0001$, and probability gain, $t(147) = 13.9$, $p < .0001$, than expected under the null hypothesis. No subjects responded according to diagnosticity or log diagnosticity, less than expected under the null hypothesis, each $t(147) = -2.53$, $p = .012$. The second analysis consisted of all 148 responses' Spearman rank correlation coefficient with each sampling norm (see Table 11, bottom row). Average correlation with information gain-KL distance was .78, with probability gain-impact was .69, with log diagnosticity was -.22, and with diagnosticity was -.41. These results strongly contradict claims that people choose queries according to diagnosticity or log diagnosticity.

The other norms make relatively similar predictions and are not strongly differentiated from each other here. However, some points may be noted. Information gain-KL distance had the largest number of exact matches. Probability gain and impact, which made the same predictions (because of equal priors), were second. Subjects were not asked to explain their choices in this experiment. However, several pilot subjects reported using the feature difference strategy in a scenario with unequal priors, which corresponds to impact. (Slowiaczek et al., 1992, found a similar result in a scenario with equal priors.) If the feature difference strategy is consistently used, even by a subset of subjects, then impact is a necessary component of a descriptive theory of human questions.

Theoretical Problems With Bayesian Diagnosticity and Log Diagnosticity

It is possible that an inquirer's subjective sense of queries' usefulness might correspond to diagnosticity or log diagnosticity. But that seems unlikely and normatively ill advised, in part for the following reasons.

Disregard for Priors if Features Are Symmetric

Intuitively, it seems that if the inquirer already knows the true category or hypothesis, for instance, because all creatures are known to be gloms, no question is useful (Lindley, 1956, p. 987), but if the inquirer is highly uncertain, many questions are useful. Consider the symmetric feature probability case, where $P(\text{hulaWorn} \mid \text{glom}) = 1 - P(\text{hulaWorn} \mid \text{fizo})$. Diagnosticity and \log_{10} diagnosticity rate the Hula question as equally useful, irrespective of whether gloms comprise 1%, 20%, 50%, or 99.9999% of the creatures on Vuma. The other sampling norms recognize that if the true category is known in advance, every question is useless. This disregard for prior knowledge, in cases with symmetric feature probabilities, is an undesirable yet unavoidable consequence of using diagnosticity or log diagnosticity.

Oversensitivity to Occasional Certainty: Features With Multiple Values

This article focused on a situation with binary features. What if answers (features) could take three or more values q_j ? Perhaps a single fizo has a hard time hearing "Do you drink iced tea?" because of an injury to its auditory system, and answers "maybe" if a question is not clear. If occurrence of the maybe answer makes it certain that the creature is a fizo, then diagnosticity and log diagnosticity rate the question as infinitely useful. This holds even if the maybe answer is rare, occurring with a probability of

Table 13
Natural Environment Feature Distribution

Gender	Skirt (or dress)		Glasses			Beard		Earrings		Hair	
	No	Yes	None	Sun	Yes	Yes	No	Yes	No	Short	Long
% of males	100	0	67	6	27	16	84	2	98	93	7
% of females	98	2	83	3	14	0	100	47	53	47	53

Note. About 51% of individuals were male. When hair completely obscured the ears, the ears were classified as not having earrings.

Table 14
Natural Environment Feature Usefulness Values

Sampling norm	Skirt (or dress)	Glasses	Beard	Earrings	Hair
Information gain, Kullback–Liebler distance	0.010	0.025	0.084	0.235	0.634
Probability gain	.010	.065	.062	.220	.420
Impact	0.010	0.080	0.080	0.225	0.430
Diagnosticity	Infinite	1.412	Infinite	7.056	13.296
Log ₁₀ diagnosticity	Infinite	0.093	Infinite	0.532	1.123

1/1,000,000. The other norms are not unduly influenced by a certainty-inducing answer with rare occurrence.¹³

Log Diagnosticity Can Be Normatively Inferior to Diagnosticity

Let $P(\text{glom}) = .99$, $P(\text{hulaWorn} \mid \text{glom}) = .99$, $P(\text{hulaWorn} \mid \text{fizo}) = .50$, $P(\text{drinksTea} \mid \text{glom}) = .97$, and $P(\text{drinksTea} \mid \text{fizo}) = .50$. Probability gain is zero for both questions. Log diagnosticity prefers Drink, which is suboptimal with respect to diagnosticity, information gain–KL distance, and impact. There are a range of cases like this in which diagnosticity and log diagnosticity contradict each other. In each of these cases, log diagnosticity makes the normatively inferior (as judged by information gain–KL distance, impact, and diagnosticity) claim.

Multiple Hypotheses–Categories

Fischhoff and Beyth-Marom (1983, p. 243) stated that diagnosticity was defined in situations with multiple hypotheses, although they did not provide an operational definition; Oaksford and Chater (2003, p. 309) stated the contrary. A literature review conducted for the present article failed to produce a single example calculation of a query’s diagnosticity in a situation with more than two hypotheses. However, for the sake of argument, an operational definition is provided here. Note that what has been called the diagnosticity of a question, Hula, could just as easily be called the *pairwise diagnosticity* of Hula with respect to whether a creature is a glom or fizo, and denoted as $\text{diagnosticity}_{\text{glom}\&\text{fizo}}(\text{Hula})$. Now suppose that jervas, in addition to gloms and fizos, reside on Vuma. Define $\text{diagnosticity}^{++}$ as the average of each pairwise diagnosticity:

$$\text{diagnosticity}^{++}(\text{Hula}) = \frac{1}{3} \times [\text{diagnosticity}_{\text{glom}\&\text{fizo}}(\text{Hula}) + \text{diagnosticity}_{\text{glom}\&\text{jervu}}(\text{Hula}) + \text{diagnosticity}_{\text{fizo}\&\text{jervu}}(\text{Hula})].$$

(Generalization to cases with more than three categories and definition of \log_{10} $\text{diagnosticity}^{++}$ are straightforward.) How would $\text{diagnosticity}^{++}$ perform? To explore this issue, I computed the $\text{diagnosticity}^{++}$ of the medical tests from Experiments 4–6 in Baron et al. (1988). Results showed that with the exception of those tests that can never change beliefs, irrespective of their outcome (and that all norms agree are useless), every test has infinite $\text{diagnosticity}^{++}$. $\text{Diagnosticity}^{++}$ makes absurd claims in this case and in every case where each test has nonzero probability of eliminating a hypothesis.

Does It Matter?

In the real world, would using diagnosticity or log diagnosticity actually be problematic? Suppose one’s task was to identify the gender of a passerby, by inquiring about one of several features of interest: whether the person has a beard, is wearing a dress, is wearing earrings, and so forth. Statistics were gathered from one natural environment, the University of California, San Diego, campus in the afternoon, with each of about 500 passersby classified according to their gender (51% were male; 49% female) and several features (see Tables 13 and 14). What features are most useful, according to each sampling norm? The Hair length feature has maximal information gain–KL distance, probability gain, and impact. Asking about Hair length leads to 93% probability of correctly categorizing gender. The Skirt and Beard features have infinite diagnosticity and log diagnosticity, because 0% of men wore skirts and 0% of women had beards. Asking about Skirt or Beard leads, respectively, to only 52% or 59% probability of a correct guess. Although the wearsSkirt and hasBeard answers provide 100% certainty of the person’s gender in this popu-

¹³ A further note is that reinforcement learning researchers (Kearns & Singh, 2002, p. 211) have found that learning an unknown probability model within a finite time is not possible if rewards can be infinite.

lation, those answers are infrequent. For a person, or seeing robot, to use diagnosticity or log diagnosticity to select queries in this natural environment would be exceptionally inefficient, with respect to all the other sampling norms. The other norms make reasonable claims and differ from each other only slightly. A related note is that Najemnik and Geisler (2005) compared information gain-based ideal observers and probability correct-based ideal observers in simulation of a visual search task. The two types of ideal observers behaved similarly, and achieved similar performance (Jiri "George" Najemnik, personal communication, May 17, 2005).

General Discussion

Diagnosticity and log diagnosticity lack several useful properties that the other norms each possess, including (a) sensitivity to prior probabilities: If there is minimal uncertainty, no question has high usefulness; (b) being finite; and (c) equal applicability in situations with 2, 3, or 1,000,000 hypotheses or categories. Because diagnosticity and log diagnosticity lack these important properties, contradict this article's experimental results, and appear unnecessary to explain other empirical data, there appears to be no further purpose for them in normative or descriptive theories of evidence acquisition.

In many evidence-gathering situations where there is no particular external coercion to shape behavior, more than one sampling norm might reasonably apply. Several researchers have explicitly made this point (Baron, 1985; Klayman, 1987; Klayman & Ha, 1987; McKenzie, 2003; Oaksford & Chater, 2003; Over & Jessop, 1998; Slowiaczek et al., 1992). Theoretical claims that human evidence seeking is adaptive (or that it is biased) would be bolstered by showing that multiple sampling norms agree on what questions are most useful.

A further issue is whether people actually use normative, versus heuristic, utilities. Various heuristic *confirmatory* or *positive test* strategies have been proposed (Devine, Hirt, & Gehrke, 1990; Gorman, Stafford, & Gorman, 1987; Klayman & Ha, 1987, 1989; Skov & Sherman, 1986; Slowiaczek et al., 1992; all reviewed in Klayman, 1995). In some situations, strategies that reduce memory load (Costa-Gomes, Crawford, & Broseta, 2001) might also be used. These and other possibilities, including the sampling norms of the present article, could be combined to form very flexible heuristic models. Most empirical data might then appear to be better fit by a heuristic model than by a sampling norm, but only because of the heuristic model's greater complexity. To avoid overfitting, future research comparing simple sampling norms with flexible heuristic models could explicitly balance model complexity with descriptive accuracy (Pitt, Myung, & Zhang, 2002).

Geman and Jedynak (2001) described situations in which looking only one step into the future, as done in this article, results in having to ask more questions on average than would be required if an optimal sequence of questions was planned in advance (also see Chernoff, 1959, 1972; Klauer, 1999). Unfortunately, planning an optimal series of questions requires knowledge of the individual features' conditional dependence on each other, given the true category. For example, if a particular glom drinks gasoline, is he more likely to breathe fire than the average glom? Most tasks have not specified this information, or have not obtained sequences of questions, and are therefore unable to address whether subjects' queries are sensitive to class-conditional dependencies. In a review of work on perceptual information integration (not involving active sampling), Movellan and McClelland (2001) found that people

made appropriate use of features' level of class-conditional dependence. Whether people's queries make use of these intricate statistical relationships is an important issue for future research.

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(Appendixes follow)

Appendix A

Example Calculations of Each Sampling Norm

Each sampling norm will be discussed in the context of the planet Vuma scenario (Skov & Sherman, 1986; Slowiaczek et al., 1992). The task is to discover whether a novel creature is a *glom* or *fizo*, by asking whether it possesses a particular binary feature, such as wearing a hula hoop or not, or drinking iced tea or not. The probability belief model is specified with five parameters. These parameters are listed here, together with specific example values: the *prior probability* that an individual creature is a *glom*, $P(\text{glom}) = .7$, and four *feature probabilities*, $P(\text{hulaWorn} \mid \text{glom}) = .1$, $P(\text{hulaWorn} \mid \text{fizo}) = .9$, $P(\text{drinksTea} \mid \text{glom}) = .3$, and $P(\text{drinksTea} \mid \text{fizo}) = .5$. [Two aspects of the present notation should be noted: Random variables, such as the question *Hula*, are capitalized. Specific values taken by random variables, such as the answer *hulaNotWorn*, are lowercase, with inner caps.] Questions are answered truthfully; Bayes’s (1763) theorem is used to update beliefs. For instance, if a hula hoop is worn,

$$P(\text{glom} \mid \text{hulaWorn}) = \frac{P(\text{hulaWorn} \mid \text{glom}) \times P(\text{glom})}{P(\text{hulaWorn})} = \frac{.1 \times .7}{.34} \approx .21,$$

where by the Law of Total Probability,

$$P(\text{hulaWorn}) = [P(\text{hulaWorn} \mid \text{glom}) \times P(\text{glom})] + [P(\text{hulaWorn} \mid \text{fizo}) \times P(\text{fizo})] = [.1 \times .7] + [.9 \times .3] = .34.$$

(All knowledge to date becomes prior knowledge when calculating the usefulness of subsequent questions; for instance, if features have class-conditional dependencies, obtained answers may change feature probabilities in addition to $P(\text{glom})$ and $P(\text{fizo})$, as the General Discussion considers.) Is the Drink or Hula question more useful in this example? Each sampling norm gives its own means of calculating an individual answer’s usefulness. However, all norms discussed in this article define a question’s usefulness as the *expected usefulness* of the individual answers. For example,

$$\text{usefulness}(\text{Hula}) = [P(\text{hulaWorn}) \times \text{usefulness}(\text{hulaWorn})] + [P(\text{hulaNotWorn}) \times \text{usefulness}(\text{hulaNotWorn})].$$

Equations for the *hulaWorn* answer and the *Hula* question follow; specific values for the sample questions are given in Table A1.

Diagnosticity

$$\text{diagnosticity}(\text{hulaWorn}) = \max \left(\frac{P(\text{hulaWorn} \mid \text{glom})}{P(\text{hulaWorn} \mid \text{fizo})}, \frac{P(\text{hulaWorn} \mid \text{fizo})}{P(\text{hulaWorn} \mid \text{glom})} \right),$$

Table A1
Example Questions’ and Answers’ Usefulness as Calculated by Each Sampling Norm

Question and answer	Diagnosticity	Log ₁₀ diagnosticity	Information gain	KL distance	Probability gain	Impact
Hula	9.000	0.954	0.456	0.456	.200	.336
hulaWorn (<i>p</i> = .34)	9.000	0.954	0.148	0.752	.094	.494
hulaNotWorn (<i>p</i> = .66)	9.000	0.954	0.615	0.303	.255	.255
Drink	1.496	0.173	0.026	0.026	.000	.084
drinksTea (<i>p</i> = .36)	1.667	0.222	-0.099	0.044	-.117	.117
doesn’tDrink (<i>p</i> = .64)	1.400	0.146	0.096	0.016	.066	.066

Note. $P(\text{glom}) = .7$, $P(\text{wearsHula} \mid \text{glom}) = .1$, $P(\text{wearsHula} \mid \text{fizo}) = .9$, $P(\text{drinksTea} \mid \text{glom}) = .3$, and $P(\text{drinksTea} \mid \text{fizo}) = .5$. Individual answers can have negative information gain or probability gain, as *drinksTea* illustrates. Each question’s usefulness is nonnegative, irrespective of which sampling norm is used. The *Drink* question has probability gain exactly zero because it does not improve probability of correct guess. Information gain and Kullback–Liebler (KL) distance are equivalent when evaluating questions, but not individual answers, as shown.

where $\max(a, b)$ denotes the larger of *a* and *b*, and

$$\text{diagnosticity}(\text{Hula}) = [P(\text{hulaWorn}) \times \text{diagnosticity}(\text{hulaWorn})] + [P(\text{hulaNotWorn}) \times \text{diagnosticity}(\text{hulaNotWorn})].$$

Log₁₀ Diagnosticity

$$\log_{10} \text{diagnosticity}(\text{hulaWorn}) = \log_{10} \max \left(\frac{P(\text{hulaWorn} \mid \text{glom})}{P(\text{hulaWorn} \mid \text{fizo})}, \frac{P(\text{hulaWorn} \mid \text{fizo})}{P(\text{hulaWorn} \mid \text{glom})} \right) \text{ and}$$

$$\log_{10} \text{diagnosticity}(\text{Hula}) = [P(\text{hulaWorn}) \times \log_{10} \text{diagnosticity}(\text{hulaWorn})] + [P(\text{hulaNotWorn}) \times \log_{10} \text{diagnosticity}(\text{hulaNotWorn})].$$

Information Gain

The information gain of the answer *hulaWorn* is as follows:

$$\text{information gain}(\text{hulaWorn}) = H(\text{Species}) - H(\text{Species} \mid \text{hulaWorn}),$$

where $H(\text{Species})$, the uncertainty (entropy) about the true species before the answer is obtained:

$$H(\text{Species}) = \left[P(\text{glom}) \times \log_2 \frac{1}{P(\text{glom})} \right] + \left[P(\text{fizo}) \times \log_2 \frac{1}{P(\text{fizo})} \right],$$

and $H(\text{Species} \mid \text{hulaWorn})$, the uncertainty (entropy) about the true species after the answer is obtained:

$$H(\text{Species} \mid \text{hulaWorn}) = \left[P(\text{glom} \mid \text{hulaWorn}) \times \log_2 \frac{1}{P(\text{glom} \mid \text{hulaWorn})} \right] + \left[P(\text{fizo} \mid \text{hulaWorn}) \times \log_2 \frac{1}{P(\text{fizo} \mid \text{hulaWorn})} \right].$$

The information gain of the *Hula* question, $I(\text{Hula}, \text{Species})$, the mutual information between *Hula* and *Species*:

$$I(\text{Hula}, \text{Species}) = H(\text{Species}) - H(\text{Species} \mid \text{Hula}),$$

where the conditional entropy, $H(\text{Species} \mid \text{Hula})$, is

$$H(\text{Species} \mid \text{Hula}) = [P(\text{hulaWorn}) \times H(\text{Species} \mid \text{hulaWorn})] + [P(\text{hulaNotWorn}) \times H(\text{Species} \mid \text{hulaNotWorn})].$$

Kullback–Liebler (KL) Distance

$$KL \text{ distance}(\text{hulaWorn}) = \left[P(\text{glom} \mid \text{hulaWorn}) \times \log_2 \frac{P(\text{glom} \mid \text{hulaWorn})}{P(\text{glom})} \right] + \left[P(\text{fizo} \mid \text{hulaWorn}) \times \log_2 \frac{P(\text{fizo} \mid \text{hulaWorn})}{P(\text{fizo})} \right].$$

$$KL \text{ distance}(\text{Hula}) = [P(\text{hulaWorn}) \times KL \text{ distance}(\text{hulaWorn})] + [P(\text{hulaNotWorn}) \times KL \text{ distance}(\text{hulaNotWorn})].$$

Probability Gain

$$\text{probabilityGain}(\text{hulaWorn}) = \max [P(\text{fizo} \mid \text{hulaWorn}), P(\text{glom} \mid \text{hulaWorn})] - \max [P(\text{glom}), P(\text{fizo})].$$

$$\text{probabilityGain}(\text{Hula}) = P(\text{CorrectGuess} \mid \text{Hula}) - P(\text{CorrectGuess}),$$

where

$$P(\text{CorrectGuess}) = \max [P(\text{glom}), P(\text{fizo})], \text{ and}$$

$$P(\text{CorrectGuess} \mid \text{Hula}) = \{P(\text{hulaWorn}) \times \max [P(\text{glom} \mid \text{hulaWorn}), P(\text{fizo} \mid \text{hulaWorn})]\} + \{P(\text{hulaNotWorn}) \times \max [P(\text{glom} \mid \text{hulaNotWorn}), P(\text{fizo} \mid \text{hulaNotWorn})]\}.$$

Impact

From the definition in the text,

$$\text{impact}(\text{hulaWorn}) = \frac{1}{2} \times \{\text{abs}[P(\text{glom} \mid \text{hulaWorn}) - P(\text{glom})] + \text{abs}[P(\text{fizo} \mid \text{hulaWorn}) - P(\text{fizo})]\}.$$

However, because $P(\text{fizo} \mid \text{hulaWorn}) = 1 - P(\text{glom} \mid \text{hulaWorn})$, and $P(\text{fizo}) = 1 - P(\text{glom})$,

$$\text{impact}(\text{hulaWorn}) = \text{abs}[P(\text{glom} \mid \text{hulaWorn}) - P(\text{glom})].$$

If a probability model has two categories, the impact of a question is a constant multiple of the difference in feature probabilities (see Footnote 2 in the text):

$$\text{impact}(\text{Hula}) = 2 \times P(\text{glom}) \times P(\text{fizo}) \times \text{abs}[P(\text{hulaWorn} \mid \text{glom}) - P(\text{hulaWorn} \mid \text{fizo})].$$

Appendix B

Limiting Cases of Disagreement Between Norms

This appendix gives several limiting cases of disputes between each pair of norms, as obtained in Simulation 2. Each optimization shows results for several prior probabilities, to illustrate the systematic relationship of feature probabilities to the prior $P(\text{glom})$. Each of Tables B1, B2, B3, B4, B5, and B6 gives results for an optimization comparing one pair of norms. Tables are organized such that one norm prefers the “Hula” question and the other norm prefers the “Drink” question, as noted.

Precise Definition of Disagreement Strength (DStr) and Preference Strength

DStr is defined to be high when one norm strongly prefers one particular question and another norm strongly prefers the other question. DStr, therefore,

requires a measure of each individual norm’s strength of preference between Drink and Hula. The absolute value of the difference in usefulness of Hula and Drink, as measured by each norm, was computed in each of 100,000 random trials, in which $P(\text{glom})$, $P(\text{wearsHula} \mid \text{glom})$, and so forth were all random probabilities. For probability gain, cases where both features had probability gain zero and were therefore tied were excluded; no other ties occurred. Endpoints to the distributions underlying each norm’s strength of preference were added where they exist. In a novel trial, a particular norm’s degree of preference is quantified as a percentile of the set of 100,000 previously observed differences in the usefulness of Hula and Drink. Linear interpolation was used so that DStr would be continuously valued. DStr is the geometric mean (the square root of the product) of two norms’ strengths of (contrary) preferences.

Table B1
Log Diagnosticity (Prefers Hula) Versus Diagnosticity (Prefers Drink)

P(glom)	wearsHula		drinksTea		DStr	Strength of each norm’s preference:				
	% gloms	% fizos	% gloms	% fizos		Diagnosticity	Log diagnosticity	Information gain	Probability gain	Impact
.50	99.90	0.10	53.66	0.01	99.66	−99.70	99.62	99.16	87.06	88.50
.60	99.90	0.10	0.01	62.76	99.68	−99.78	99.58	97.45	69.45	79.14
.70	99.87	0.13	0.01	62.03	99.68	−99.65	99.70	95.87	58.12	74.63
.80	0.17	99.82	0.01	76.77	99.61	−99.80	99.41	82.60	27.90	45.30
.90	99.85	0.21	29.73	0.01	99.51	−99.56	99.47	93.94	52.86	65.41
.995	99.86	0.16	68.27	99.99	99.50	−99.64	99.33	33.17	2.62	5.58

Note. Preference strength of 100 indicates maximal preference for the Hula question, −100 indicates maximal preference for the Drink question, and 0 indicates indifference between Hula and Drink. DStr = disagreement strength.

(Appendixes continue)

Table B2
Information Gain (Prefers Hula) Versus Diagnosticity (Prefers Drink)

P(glom)	wearsHula		drinksTea		DStr	Strength of each norm's preference				
	% gloms	% fizes	% gloms	% fizes		Diagnosticity	Log	Information	Probability	Impact
							diagnosticity	gain	gain	
.50	99.99	0.01	100.00	99.99	100.00	-100.00	-100.00	100.00	100.00	100.00
.60	99.99	0.01	0.01	0.00	100.00	-100.00	-100.00	100.00	99.43	100.00
.70	0.01	99.99	0.01	0.00	99.99	-100.00	-100.00	99.98	95.02	99.77
.80	99.99	0.01	99.99	100.00	99.83	-100.00	-100.00	99.67	81.74	96.98
.90	0.01	99.99	0.01	0.00	97.98	-100.00	-100.00	96.01	53.42	79.56
.995	99.99	0.01	99.99	100.00	60.64	-100.00	-100.00	36.77	3.53	8.08

Note. Results for impact versus diagnosticity, information gain versus log diagnosticity, and impact versus log diagnosticity are not presented separately, because each of those optimizations produced feature probabilities that were virtually identical to the results for information gain versus diagnosticity. Disagreement strength (DStr) values for information gain versus log diagnosticity were essentially identical to those for information gain versus diagnosticity. DStr values for impact versus diagnosticity, and impact versus log diagnosticity, follow a qualitatively similar pattern; those values can be approximated from the strengths of each norm's preference in this table. Preference strength of 100 indicates maximal preference for the Hula question, -100 indicates maximal preference for the Drink question, and 0 indicates indifference between Hula and Drink.

Table B3
Probability Gain (Prefers Hula) Versus Diagnosticity (Prefers Drink)

P(glom)	wearsHula		drinksTea		DStr	Strength of each norm's preference				
	% gloms	% fizes	% gloms	% fizes		Diagnosticity	Log	Information	Probability	Impact
							diagnosticity	gain	gain	
.50	0.01	99.99	0.00	0.01	100.00	-100.00	-100.00	100.00	100.00	100.00
.60	0.01	99.99	86.87	100.00	99.72	-100.00	-100.00	99.99	99.43	99.75
.70	0.01	99.99	9.14	0.00	97.48	-100.00	-100.00	99.95	95.02	99.19
.80	0.01	99.99	49.48	100.00	90.41	-100.00	-100.00	97.86	81.74	74.60
.90	0.01	99.99	87.77	100.00	73.09	-100.00	-100.00	95.42	53.42	74.51
.995	0.01	99.99	16.43	0.00	18.78	-100.00	-100.00	36.15	3.53	6.81

Note. Results for probability gain versus log diagnosticity are not given separately because they were indistinguishable from results for probability gain versus diagnosticity. Preference strength of 100 indicates maximal preference for the Hula question, -100 indicates maximal preference for the Drink question, and 0 indicates indifference between Hula and Drink. DStr = disagreement strength.

Table B4
Information Gain (Prefers Hula) Versus Probability Gain (Prefers Drink)

P(glom)	wearsHula		drinksTea		DStr	Strength of each norm's preference				
	% gloms	% fizes	% gloms	% fizes		Diagnosticity	Log	Information	Probability	Impact
							diagnosticity	gain	gain	
.50	0.00	31.44	28.91	71.09	34.94	100.00	100.00	37.42	-32.61	-35.75
.60	66.67	100.00	87.51	56.42	52.55	100.00	100.00	51.87	-53.24	8.71
.70	57.14	0.00	95.25	55.87	58.04	100.00	100.00	63.38	-53.15	45.89
.80	75.00	0.00	1.58	46.12	54.07	100.00	100.00	64.94	-45.02	55.54
.90	11.11	100.00	99.69	51.39	40.80	100.00	100.00	58.39	-28.50	45.21
.995	0.50	100.00	0.00	50.21	5.81	0.00	0.00	18.27	-1.82	4.07

Note. Preference strength of 100 indicates maximal preference for the Hula question, -100 indicates maximal preference for the Drink question, and 0 indicates indifference between Hula and Drink. DStr = disagreement strength.

Table B5
Information Gain (Prefers Hula) Versus Impact (Prefers Drink)

P(glom)	wearsHula		drinksTea		DStr	Strength of each norm's preference				
	% gloms	% fizos	% gloms	% fizos		Diagnosticity	Log	Information	Probability	Impact
							diagnosticity	gain	gain	
.50	67.72	100.00	28.80	71.26	36.64	100.00	100.00	39.16	-31.13	-34.28
.60	100.00	65.60	71.53	25.70	38.98	100.00	100.00	41.76	7.81	-36.39
.70	100.00	62.47	27.70	77.91	39.57	100.00	100.00	44.08	41.96	-35.52
.80	100.00	58.88	73.13	17.29	37.66	100.00	100.00	44.03	46.14	-32.21
.90	100.00	53.76	75.23	11.06	30.92	100.00	100.00	40.42	28.70	-23.65
.995	0.00	54.84	15.95	98.86	5.59	100.00	100.00	13.30	1.98	-2.35

Note. Preference strength of 100 indicates maximal preference for the Hula question, -100 indicates maximal preference for the Drink question, and 0 indicates indifference between Hula and Drink. DStr = disagreement strength.

Table B6
Impact (Prefers Hula) Versus Probability Gain (Prefers Drink)

P(glom)	wearsHula		drinksTea		DStr	Strength of each norm's preference				
	% gloms	% fizos	% gloms	% fizos		Diagnosticity	Log	Information	Probability	Impact
							diagnosticity	gain	gain	
.505	1.98	0.00	0.07	1.19	3.78	100.00	100.00	8.81	-3.97	3.60
.60	33.33	0.00	0.00	17.27	43.49	0.00	0.00	49.13	-40.20	47.03
.70	57.14	0.00	100.00	69.66	55.25	0.00	0.00	59.21	-49.93	61.12
.80	25.00	100.00	0.00	40.66	52.48	0.00	0.00	59.99	-45.77	60.18
.90	88.89	0.00	0.00	47.59	36.71	0.00	0.00	55.25	-29.44	45.78
.995	0.50	100.00	0.00	45.82	2.75	0.00	0.00	19.70	-1.68	4.44

Note. Impact and probability gain are identical when there are two equiprobable hypotheses. There is therefore no case of disagreement between those norms in the Vuma scenario when P(glom) = .50. Cases of slight disagreement are observed when P(glom) = .505, included here. Preference strength of 100 indicates maximal preference for the Hula question, -100 indicates maximal preference for the Drink question, and 0 indicates indifference between Hula and Drink. DStr = disagreement strength.

Appendix C

Sample Stimulus From Vuma Experiment

Imagine you are visiting the planet Vuma. There are 1 million creatures on Vuma; 50% of them are Gloms, and 50% are Fizos. All creatures are invisible to the human eye, so you cannot learn about them by looking at them, but only by asking them questions.

Suppose you have just met a creature from Vuma. Your job is to tell which of the two kinds of creatures it is. The table below [see Table C1] gives information about the percent of Gloms, and the percent of Fizos, with certain characteristics. (The characteristics are listed in a random order.)

Imagine that to help you find out the identity of the creature, you could ask it *one* yes or no question, about one of its characteristics. For instance, if "swims fast" were a characteristic, you could ask "Do you swim fast?" The creature answers truthfully.

Considering the information given, which of the possible questions would be most useful to help you learn whether the creature is a Glom or Fizo? Please rank the questions below, putting a "1" in the box beside the most useful question, a "2" in the box beside the next-most-useful question, and so on. If two questions are equally useful, give them the same rank.

Table C1
Table Given to the Subjects in the Experiment

Species	Characteristic			
	Drinks tea	Wears a hula hoop	Plays harmonica	Gurgles a lot
Proportion of gloms	30%	99%	1%	70%
Proportion of fizos	0.01%	100%	99%	30%

Note. Subjects indicated their rankings of each feature in the following format:

Question	Rank
Do you drink tea?	<input type="text"/>
Do you wear a hula hoop?	<input type="text"/>
Do you play harmonica?	<input type="text"/>
Do you gurgle a lot?	<input type="text"/>

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