Measures of Epistemic Utility and the Value of Experiments[1]

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Abstract

Measures of epistemic utility have been used to model the epistemic decisions of truth seekers in general and scientists in particular. (See, for example, Levi's *Gambling With Truth*.) Such models of epistemic decisions invariably assign different epistemic utilities to different *courses of epistemic action* that a truth seeker can choose between. For example, such a model might assign different epistemic utilities to the truth seeker accepting, suspending judgement on, or rejecting a true hypothesis. In this paper, I defend a model that assigns different epistemic utilities directly to different *degrees of belief* that a truth seeker might have in a true hypothesis. Interestingly, on this "degrees of belief" model of epistemic decisions, there are plausible counter−examples to Carnap's "principle of total evidence" (in particular, to the claim that performing experiments is always epistemically valuable).

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1. Measuring epistemic utility

Many philosophers (see, e.g., Hempel 1960, 462−469; Levi 1967; Maher 1993; Kaplan 1996) have tried to apply decision theory to epistemology in general and to the epistemic practices of scientists in particular. In particular, measures of *epistemic utility* have been used to model the decisions of individuals who are interested in achieving purely epistemic goals (e.g., acquiring true beliefs). For example, such measures have been used to model a scientist's decision about whether to accept, suspend judgement on, or reject a scientific hypothesis (see, e.g., Levi 1962; Rescher 1976). However, such measures can also be used to model other epistemic decisions. For example, such measures can be used to model a scientist's decision about which experiments she should perform in her search for truth.

I begin this paper with a description of the standard decision theoretic model of a scientist's decision about whether to accept, suspend judgement on, or reject a hypothesis. I will refer to this model as the *ASR model of epistemic decisions*. Whereas the ASR model assigns different epistemic utilities to different *courses of epistemic action* that a truth seeker can choose between, I propose an extension of the ASR model that assigns different epistemic utilities directly to different *degrees of belief* that a truth seeker might have. I will refer to this model as the *DB model of epistemic decisions*. The DB model is suggested by the work of Paul Horwich (1982, 127−129) and the work of Alvin Goldman (1999, 87−100, 115−123).[2] I argue that the DB model provides a better model of a truth seeker's decision about which experiments to perform than do the

2 The term "DB model" is suggested by Goldman's term "DB scheme" (1999, 88). Even though they do not explicitly use the term, Horwich's "error in a probability valuation" (1982, 127) and Goldman's "veritistic value" (1999, 87) are measures of epistemic utility.

"courses of epistemic action" models of epistemic decisions. Finally, I discuss the surprising fact that, on the DB model, there are plausible counter−examples to I. J. Good's theorem (1967) that performing experiments is always valuable.

2. The ASR model of epistemic decisions

Suppose that a particular truth seeker, TS, is interested in whether or not a particular substance, XYZ, is an acid. Let *h* be the hypothesis that XYZ is an acid. In the ASR model (cf. Levi 1962, 55−56), we assume that TS has three available courses of epistemic action. She can accept the hypothesis *h*, she can suspend judgement on *h*, or she can reject *h*. The possible states of the world are that *h* is true or that *h* is false. Accepting a true hypothesis (or rejecting a false hypothesis) has the maximum epistemic utility (1). Rejecting a true hypothesis (or accepting a false hypothesis) has the minimum epistemic utility (0). The epistemic utility of suspending judgement on a true hypothesis (or a false hypothesis) is somewhere in between (*k*). We also assume that TS has a certain initial degree of belief in *h*. Finally, as with any decision problem, TS should choose the course of action with the highest expected utility.

	***h* is true**	***h* is false**
Accept *h*	1	0
Suspend judgement on *h*	*k*	*k*
Reject *h*	0	1

The parameter *k* is TS's "degree of caution" (Levi 1962, 56). It is a measure of TS's attitude toward risk in this epistemic decision. That is, it tells us how much risk of error she is willing to run in order to have a definitive conclusion about the acidity of XYZ. The larger the value of *k*, the greater her interest in avoiding error (i.e., the more *risk averse* she is with respect to acquiring true beliefs). The smaller the value of k, the greater her interest in "relief from agnosticism" (Levi 1967, 76) (i.e., the more *risk seeking* she is with respect to acquiring true beliefs).

In addition to allowing us to determine whether or not TS should accept a hypothesis, this model allows us determine which experiments—if any—TS should perform in order to acquire true beliefs. In particular, this model allows us to determine if performing a particular experiment (e.g., a litmus test on XYZ) can be expected to yield an increase in epistemic utility (and to determine the magnitude of that increase). In order to make this determination, we calculate the (expected) *epistemic value* of performing the experiment. This calculation is based on standard work on the *value of information* (see, e.g., Good 1967; Rosenkrantz 1977, 4−11).

First, we determine the expected epistemic utility of deciding to accept, suspend judgement on, or reject h without performing an experiment. In other words, we determine the expected epistemic utility of making the decision on the basis of the evidence that TS has already acquired. Second, we determine the expected epistemic utility of making the decision after performing the experiment.[3] (In calculating this value, we assume that TS *conditionalizes* on new evidence.) The epistemic value of performing the experiment is the difference between these two values. Finally, under the assumption that she is solely concerned with acquiring true beliefs, TS should perform the available experiment which has the highest epistemic value.

3 In order to calculate the expected epistemic utility of deciding after performing the experiment, we calculate the expected epistemic utilities of deciding after getting each of the possible results of the experiment. These expected epistemic utilities are then weighted according to the subjective probabilities that TS assigns to getting each of these results.

The ASR model can also be used to provide support for Rudolf Carnap's "principle of total evidence" (1947, 138). In particular, under the assumption that she is solely concerned with acquiring true beliefs, it is possible to prove that it is always better for TS to perform some experiment than to perform no experiment (see Good 1967). In other words, the epistemic value of performing an experiment is always positive.[4] Good proved this theorem with respect to *pragmatic* utilities, but the proof goes through equally well for *epistemic* utilities (cf. Maher 1990, 116).

3. The DB model of epistemic decisions

4 Strictly speaking, Good's theorem states that the epistemic value of performing an experiment is never negative. The epistemic value will be zero in some circumstances (see section 5 below). Also, the theorem only states that an experiment always has positive epistemic value *from the perspective of the truth seeker*. Another individual (who is better informed) may be in a position to predict that TS will end up in a worse epistemic state as a result of performing a particular experiment (see Good 1974, 341). Finally, the theorem has now been extended to cases where TS does not become absolutely certain of any particular piece of new evidence (see Graves 1989).

There are a number of ways in which the ASR model can be extended (such that the ASR model becomes a special case). For example, Nicholas Rescher (1976, 93−95) has proposed an extension of the ASR model in which the two hypotheses can have different degrees of *informativeness*. So, for example, the epistemic utility of accepting *h* if it is true might be twice the epistemic utility of rejecting *h* if it is false. Also, Isaac Levi (1967, 56−90) has proposed an extension of the ASR model in which there can be any finite number of hypotheses.[5] However, in describing the DB model, I will continue to make the simplifying assumptions that there are only two available hypotheses (namely, *h* and ~*h*) and that they each have the same degree of informativeness (namely, 1).

The ASR model explicitly assigns different epistemic utilities to three different courses of action that TS can choose between. However, on the assumption that TS chooses the course of action with the highest expected utility, the ASR model can be used to determine the expected epistemic utility of any particular degree of belief that TS might have in a given hypothesis. For example, as long as TS has a degree of belief in *h* that is greater than *k*, she will decide to accept *h*. If TS accepts *h*, she will end up with either an epistemic utility of 1 if *h* is true or an epistemic utility of 0 if *h* is false. So, if her degree of belief in *h* is 0.9 (and *k* is less than 0.9), her expected epistemic utility is 0.9 (= 0.9·1 + 0.1·0).

In general, TS's expected epistemic utility (EEU) with respect to *h* can be viewed

5 Unlike the ASR model, the DB model assigns different epistemic utilities to an infinite number of different epistemic states. However, Isaac Levi (1980, 45−50) has also proposed an extension of the ASR model in which there can be an *infinite* number of hypotheses. This model assigns different epistemic utilities to an infinite number of different courses of epistemic action.

as a weighted average of two functions from degrees of belief to epistemic utilities. In particular, the epistemic utility of a particular degree of belief in *h* if *h* is true (EU_h) and the epistemic utility of that very same degree of belief in *h* if *h* is false ($EU_{\sim h}$) are weighted according to TS's confidence in the truth of *h* (i.e., using that very same degree of belief in *h*). In other words, $EEU(p) = p(h) \cdot EU_h(p) + p(\sim h) \cdot EU_{\sim h}(p)$ where *p* is TS's subjective probability function.

In the case of the ASR model, the two epistemic utility functions are step functions. For example, Figure 1 is the epistemic utility function if *h* is true and $k = 0.8$; Figure 2 is the epistemic utility function if *h* is false.[6] The DB model simply generalizes this to functions in general. For example, Horwich and Goldman consider linear epistemic utility functions that assign an epistemic utility of α to a degree of belief of α in a true hypothesis (see Figure 3). If $EU_h(p) = p(h)$ and $EU_{\sim h}(p) = p(\sim h)$, then the epistemic utility of a degree of belief of 0.9 in *h* is 0.9 if *h* is true and 0.1 if *h* is false. Thus, the expected epistemic utility of a degree of belief in *h* of 0.9 is 0.82 ($= 0.9 \cdot 0.9 + 0.1 \cdot 0.1$).

Figure 1

Figure 2

Figure 3 – $EU_h(p) = p(h)$

In fact, there are many possible shapes that the two epistemic utility functions

6 In all the graphs in this paper, the X−axis is TS's degree of belief in *h* and the Y−axis is epistemic utility.

might take other than step functions and linear functions. For example, the epistemic utility functions might be concave (see Figure 4). In this case, true belief has declining marginal epistemic utility. In other words, TS is risk averse when it comes to acquiring a more accurate belief about the acidity of XYZ. Conversely, if the epistemic utility function is convex, then TS is risk seeking.

Figure 4 – $EU_h(p) = 2 \cdot p(h) - p(h)^2$

Even though the DB model greatly expands the number of possible epistemic utility functions, there *are* some constraints on these functions. In the ASR model, the epistemic utility of accepting a particular true hypothesis must be at least as great as the epistemic utility of suspending judgement on that true hypothesis and the epistemic utility of suspending judgement on that true hypothesis must be at least as great as the epistemic utility of rejecting that true hypothesis (see, e.g., Figure 1). In the DB model, the analogous constraint is that the epistemic utility function must be increasing. In other words, if α is greater than β, then the epistemic utility of a degree of belief of α in a particular true hypothesis must be at least as great as the epistemic utility of a degree of belief of β in that same hypothesis.

I should also note that the epistemic utility functions for different hypotheses may be different. The ASR model assumes that TS's attitude toward risk is the same for both of the hypotheses, but it need not be. Just as one hypothesis may be more informative than another, TS may be more risk averse with respect to one hypothesis than with respect to another. In other words, some answers to the question under investigation may be (epistemically) riskier than others.

Finally, I should note that, unlike the ASR model, the DB model does not model TS's decision about whether to accept, suspend judgement on, or reject *h* (i.e., her decision about which course of epistemic action to choose). In the DB model, the expected epistemic utility of TS's degree of belief in *h* is simply her estimate of the epistemic utility of the epistemic state that she is currently in. TS does not use this estimate to decide what degree of belief in *h* that she should adopt; she simply has the degree of belief in *h* that she currently has.[7] However, this estimate *is* relevant to her decision about which experiments to perform. Just as in the ASR model, the epistemic value of performing the experiment is the difference between the expected epistemic utility of performing the experiment and the expected epistemic utility of not performing the experiment. And just as in the ASR model, TS should perform experiments that are expected to move her to a degree of belief in *h* that has a higher epistemic utility than the degree of belief in *h* that she currently has.

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7 In particular, TS cannot simply choose to adopt the degree of belief in *h* that has the highest expected epistemic utility given her current degree of belief in *h*. This would lead to some bizarre consequences. For example, when her epistemic utility function is linear, she would—as Patrick Maher (1990, 112−113) points out—always choose to adopt a degree of belief in *h* of either 1 or 0. However, the fact that TS cannot simply choose to adopt a degree of belief is why the assumptions needed to prove Good's theorem are not satisfied by the DB model.

4. Objections to epistemic utility

Several philosophers (see, e.g., Jeffrey 1956; Rosenkrantz 1977; Kaplan 1996) have criticized the kind of application of decision theory to epistemology that is exemplified by the ASR model and the DB model. So, before I make the case for the DB model in particular, I want to consider three standard objections to the ASR model—and to any extension of the ASR model.

The first objection is that there is no way to assign *purely epistemic* utilities to the possible outcomes in the ASR model (see Jeffrey 1956, 242). In particular, we seem to have to take into consideration the practical consequences of the various courses of action in order to make the necessary utility assignments. However, while it is not immediately clear how to assign purely epistemic utilities to the possible outcomes in any given epistemic context, this project does not appear to be hopeless. There are plausible constraints on the assignment of epistemic utilities that are independent of pragmatic utilities. For example, the epistemic utility of accepting a true hypothesis should be greater than the epistemic utility of rejecting it. This is so despite the fact that the pragmatic utility of accepting a true hypothesis might very well be less than the pragmatic utility of rejecting it in some circumstances.

In addition, many epistemologists (most notably, René Descartes) seem to think that a truth seeker's degree of risk aversion should be extremely high in most epistemic contexts. For example, according to David Hume, "there is a degree of doubt, and caution, and modesty, which, in all kinds of scrutiny and decision, ought for ever to accompany a just reasoner" (1965, *Enquiry*, Section XII, 164).

The second objection is that, while the ASR model captures TS's desire to avoid error and to maximize the informativeness of the hypotheses that she accepts, there are many other important epistemic goals—such as simplicity, explanatory power, verisimilitude, and justification—that truth seekers often wish to achieve (see Kaplan 1996, 122). However, these two particular epistemic goals are especially important and it is of interest to determine how truth seekers can go about achieving them. In addition, at least some of these other epistemic goals (e.g., simplicity and explanatory power) might be incorporated into a single measure of the informativeness of hypotheses.

The third objection is that accepting and rejecting hypotheses is not part of the legitimate role of a scientist (see Jeffrey 1956, 245). The legitimate role of the scientist is simply to assign *degrees of confidence* to hypotheses. However, even if acceptance is "epiphenomenal" (Rosenkrantz 1977, 242), models of epistemic decisions can still—as I will argue below—play an important epistemological role. In particular, such models can help us determine which experiments TS should perform in order to acquire true beliefs. In fact, the ability of the DB model to model this particular decision better than the ASR model provides a large part of the motivation for this particular extension of the ASR model.

5. The case for the DB model

In this section, I make the case that the DB model is an extremely attractive model of epistemic decisions. First, while greater epistemic utility is assigned to higher degrees of belief in a true hypothesis on the ASR model, there is no *a priori* reason to think that epistemic utility might not increase smoothly rather than in discrete jumps. In other words, any increase in TS's degree of belief in the truth about the acidity of XYZ would seem to be epistemically valuable. Also, while Horwich and Goldman both restrict their attention to epistemic utility functions that are linear, there is no reason to think that epistemic utility functions are always risk neutral (cf. Levi 1962, 56). The DB model allows epistemic utility to increase smoothly and models a wide range of attitudes toward risk.

Second, since the ASR model is a fairly plausible model of epistemic decisions, it is an argument in favor of the plausibility of the DB model that the two models have similar consequences. As I will show below, there are many striking similarities between the consequences of the two models. Even so, there are some cases in which the consequences of the two models are rather different. However, as I will argue below, in these cases, the consequences of the DB model are preferable.

In addition to the fact that epistemic utility increases monotonically on both models, there are other important similarities between the ASR model and the DB model. For example, with the ASR model, Levi defined a family of step functions where the parameter *k* ranges from 0 to 1 and is a measure of TS's attitude toward risk. But it is also possible to define families of continuous functions where *k* ranges from 0 to 1 and is a measure of TS's attitude toward risk. One such family of continuous functions is defined by the following formula:

$$\mathrm{EU}_h(p) = p(h)^{\log_{½} k}$$

For both the step functions and these continuous functions, the larger the value of *k*, the more risk averse TS is.[8] For a fixed value of *k*, the continuous function is a smooth approximation of the step function (see, e.g., Figure 5).[9] Also, *k* is the expected epistemic utility when TS is maximally uncertain about the acidity of XYZ (i.e., when TS has a degree of belief in *h* of 0.5).

Figure 5

In addition, the consequences of the ASR model are strikingly similar to the consequences of the DB model using this family of continuous functions. For example, for a fixed value of *k*, TS's expected epistemic utility calculated using the continuous function is a smooth approximation of TS's expected epistemic utility calculated using the ASR model (see, e.g., Figure 6). Similarly, for a fixed value of *k*, the epistemic value of performing an experiment that will tell TS for sure whether or not *h* is true (i.e., the epistemic value of *perfect information*) calculated using the continuous function is a smooth approximation of the epistemic value calculated using the ASR model (see, e.g., Figure 7).

Figure 6

Figure 7

Even so, there are differences between the two models with respect to the value of performing experiments. However, these differences seem to count in favor of the DB model. For example, the ASR model leads us to seriously underestimate the epistemic

8 Kenneth Arrow (1974, 94) gives the standard measure of the degree of risk aversion of continuous utility functions.

9 In Figures 5, 6, and 7, *k* is 0.8.

value of performing an experiment for truth seekers who are extremely eager to eliminate uncertainty (i.e., who are risk seeking with respect to acquiring true beliefs). In fact, the epistemic value of performing an experiment remains the same for all values of *k* less than 0.5.[10] As a result, the ASR model accurately models decisions about which experiments to perform only for truth seekers who are risk neutral or risk averse.[11]

The DB model, however, accurately models the decisions about which experiments to perform for very risk seeking truth seekers. On the DB model, the epistemic value of performing an experiment continues to increase as the value of *k* approaches 0. For example, Figure 8 is a graph of the epistemic value of perfect information when *k* = 0.2. (The smooth graph is the epistemic value on the DB model.)

Figure 8

Another difference between the two models shows up when we consider the epistemic value of performing experiments that only provide TS with *imperfect information* about the acidity of XYZ. In the ASR model, in order for performing an experiment to be valuable, it has to be possible for the results of the experiment to lead TS to adopt a new course of action. For example, one of the possible results of an experiment might lead her to accept that XYZ is an acid when she was initially inclined

10 This is a result of the fact that, when *k* is less than 0.5, TS is either going to decide to accept the hypothesis or to reject it; suspending judgement on the hypothesis is never an attractive option.

11 This limitation of the ASR model would not count against the ASR model if there were conclusive reasons to think that epistemic utility functions should never be risk seeking. But even if there is such a constraint on epistemic utility functions, this limitation would not count in favor of the ASR model since it is a simple matter to add this constraint to the DB model (e.g., we might simply require that epistemic utility functions not be convex).

to suspend judgement on this hypothesis. However, it is not always possible for experiments that only provide imperfect information to lead TS to adopt a new course of action.

Performing such an experiment is only valuable when TS's initial degree of belief in the hypothesis is sufficiently close to the threshold between acceptance and suspension of judgement (or to the threshold between suspension of judgement and rejection). As a result, there are typically two spikes on the graph of the epistemic value of performing an experiment that provides imperfect information (see, e.g., Figure 9).[12] What is especially troubling about this aspect of the ASR model is that there is often no epistemic value to performing an experiment when TS is maximally uncertain about the acidity of XYZ.

Figure 9

In the DB model, however, the epistemic value of performing an experiment is a smooth curve that is typically positive for all possible degrees of belief in h and is typically highest when TS is maximally uncertain about h (see, e.g., Figure 8). This seems to be a much more plausible picture of the epistemic value of performing an experiment.

6. Performing experiments is not always valuable

Even so, there is at least one consequence of the DB model that is somewhat

12 In Figure 9, k is 0.8 and the experiment is three times more likely to report that h is true (false) when it is true (false) than when it is false (true).

troubling. In particular, Good's theorem does not hold in the DB model. That is, there are cases where the epistemic value of performing an experiment is negative. Now, Horwich (1982, 127−129) did prove that the epistemic value of performing an experiment is always positive when the epistemic utility functions are linear.[13] In other words, as long as TS is risk neutral, it is always (epistemically) valuable to perform an experiment.

When the epistemic utility functions can be any increasing functions, however, it is possible for the epistemic value of performing an experiment to be negative.[14] In other words, there are circumstances where TS herself will be able to predict that she will end up in a worse epistemic state as a result of performing an experiment. One scenario in which performing an experiment has negative epistemic value occurs when TS is risk averse with respect to *h* such that $EU_h(p) = 2 \cdot p(h) - p(h)^2$ and risk seeking with respect to ~*h* such that $EU_{\sim h}(p) = p(\sim h)^2$. Using these two epistemic utility functions, Figure 10 is a graph of the epistemic value of performing an experiment that is three times more likely to report that *h* is true (false) when it is true (false) than when it is false (true).

Figure 10

13 This result also follows as a simple corollary to a theorem proved independently by Goldman (1999, 121) in collaboration with Moshe Shaked.

14 Roger Rosenkrantz (1977, 10−11) gives an example (in a "courses of action" model) where it is supposed to be better for a decision maker not to perform an experiment that is not very reliable. As Rosenkrantz shows, the expected utility of performing this experiment is negative. However, since the expected utility of not performing the experiment is even lower in his example, the value of performing the experiment is still positive. As a result, his example is not a counter−example to Good's theorem.

This negative epistemic value of performing the experiment is primarily a result of TS's risk aversion. The results of an experiment that provides imperfect information can move TS further toward the truth or further away from the truth. However, if the experiment is fairly reliable, she will think that it is much more likely that she will be moved further toward the truth. Even so, if she is fairly risk averse, the possible epistemic benefits of being moved further toward the truth can be outweighed—as they are in this particular scenario—by the possible epistemic costs of being moved further away from the truth.

In this particular scenario, the magnitude of the negative epistemic value is very small and the epistemic value is only negative for a small range of initial degrees of belief in *h* (in particular, when TS is already fairly sure that XYZ is an acid).[15] Even so, it is very strange consequence of the DB model that the epistemic value of performing an experiment can be negative at all. It seems to be a reasonable condition on models of epistemic decisions that the epistemic value of performing an experiment never be negative. In fact, this is one of the "rationality conditions" that William Goosens (1976, 96) claims that an adequate measure of epistemic utility must meet.

There are at least two possible reactions to this particular scenario.[16] On the one hand, we might continue to maintain that the epistemic value of performing an experiment must never be negative. In that case, further plausible constraints on the shapes of epistemic utility functions in the DB model need to be found in order to rule

15 There is negative epistemic value even if TS is equally risk averse with respect to both hypotheses as long as one hypothesis is somewhat more informative than the other.
16 Another possible reaction would be to conclude that conditionalization on new evidence is not a good idea if it is expected to lead to a decrease in epistemic utility.

out this scenario.[17] On the other hand, it is not clear to me that the aforementioned epistemic utility functions might not be appropriate in some epistemic contexts. If they are appropriate in some contexts, then we have to conclude that there are at least a few circumstances under which truth seekers should decide that it is a bad idea to perform an experiment.

But either way, more work needs to be done on identifying possible further constraints on epistemic utility functions—in general and with respect to particular hypotheses. As I noted above, many epistemologists seem to think that epistemic utility functions should be risk averse. Is this the case for all hypotheses? Or might epistemic utility functions be risk seeking for some hypotheses? Also, might an epistemic utility function be risk averse for some degrees of belief in a true hypothesis and risk seeking for others? Finally, if epistemic utility functions are often risk averse, does the degree of risk aversion remain constant, decrease, or increase with higher degrees of belief in a true hypothesis?[18]

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17 Even if the epistemic value of performing an experiment must never be negative, this does not necessarily count in favor of the ASR model as long as such constraints on the epistemic utility functions in the DB model are found.

18 With regard to the utility of wealth, utility functions are often risk averse. However, the degree of risk aversion usually decreases as wealth increases (see Arrow 1974, 96). It is not clear whether *epistemic* utility functions should share this property.

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