

Second-order Probabilism: Expressive Power and Accuracy

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Abstract. Rational agents are often uncertain about the truth of many propositions. To represent this uncertainty, it is natural to rely on probability theory. Two options are typically on the table, precise and imprecise probabilism, but both fall short in some respect. Precise probabilism is not expressive enough, while imprecise probabilism suffers from belief inertia and the impossibility of proper scoring rules. We put forward a novel version of probabilism, higher-order probabilism, and we show that it outperforms existing alternatives.

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1 Introduction

As rational agents, we are uncertain about the truth of many propositions since the evidence we possess about them is often fallible. To represent this uncertainty, it is natural to rely on probability theory. Two options are typically on the table: precise and imprecise probabilism. Precise probabilism models an agent's state of uncertainty (or credal state) with a single probability measure: each proposition is assigned one probability value between 0 and 1 (a sharp credence). The problem is that a single probability measure is not expressive enough to distinguish between intuitively different states of uncertainty rational agents may find themselves in (§2). To avoid this problem, a *set* of probability measures, rather than a single one, can be used to represent the uncertainty of a rational agent. This approach is known as imprecise probabilism. It outperforms precise probabilism in some respects, but also runs into problems of its own, such as belief inertia and the impossibility of defining proper scoring rules (§3).

To make progress, this paper argues that the uncertainty of a rational agent is to be represented neither by a single probability measure nor a set of measures. Rather, it is to be represented by a higher-order probability measure, more specifically, a probability distribution over parameter values interpreted as probabilities. The theory we propose is not mathematically novel, but addresses many of the problems that plague both precise and imprecise probabilism (§4 and §5). It also fares better than existing versions of probabilism when the probability of multiple propositions, dependent or independent, is to be assessed (§6 and 7).

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2 Precise probabilism

Precise probabilism holds that a rational agent's uncertainty about a proposition is to be represented as a single, precise probability measure. Bayesian updating regulates how the prior probability measure should change in light of new evidence that the agent learns. The updating can be iterated multiple times for multiple pieces of evidence considered successively. This is an elegant and simple theory with many powerful applications. Unfortunately, representing our uncertainty about a proposition in terms of a single, precise probability measure runs into a number of difficulties.

Precise probabilism fails to capture an important dimension of how our fallible beliefs reflect the evidence we have (or have not) obtained. A couple of stylized examples featuring coin tosses should make the point clear. Here is the first:

No evidence v. fair coin You are about to toss a coin but have no evidence about its bias. You are completely ignorant. Compare this to the situation in which you know, based on overwhelming evidence, that the coin is fair.

On precise probabilism, both scenarios are represented by assigning a probability of .5 to the outcome *heads*. If you are completely ignorant, the principle of insufficient evidence suggests that you assign .5 to both outcomes. Similarly, if you know for sure the coin is fair, assigning

.5 seems the best way to quantify the uncertainty about the outcome. The agent's evidence in the two scenarios is quite different, but precise probabilities fail to capture this difference.

And now consider a second scenario:

Learning from ignorance You toss a coin with unknown bias. You toss it 10 times and observe *heads* 5 times. Suppose you toss it further and observe 50 *heads* in 100 tosses.

Since the coin initially had unknown bias, you should presumably assign a probability of .5 to both outcomes if you stick with precise probabilism. After the 10 tosses, you again assess the probability to be .5. You must have learned something, but whatever that is, it is not modeled by precise probabilities. When you toss the coin 100 times and observe 50 heads, you learn something new as well. But your precise probability assessment will again be .5.

These examples suggest that precise probabilism is not appropriately responsive to evidence. Representing an agent's uncertainty by a precise probability measure can fail to track what an agent has learned from new evidence. Precise probabilism assigns the same probability in situations in which one's evidence is quite different: when no evidence is available about a coin's bias; when there is little evidence that the coin is fair (say, after only 10 tosses); and when there is strong evidence that the coin is fair (say, after 100 tosses). In fact, analogous problems also arise for evidence that the coin is not fair. Suppose the rational agent starts with a weak belief that the coin is .6 biased towards heads. They can strengthen that belief by tossing the coin repeatedly and observing, say, 60 heads in 100 tosses. But this improvement in their evidence is not mirrored in the .6 probability they are supposed to assign to *heads*.¹

These problems generalize beyond cases of coin tossing. It is one thing not to know much about whether a proposition is true, for example, whether an individual is guilty of a crime. It is another thing to have strong evidence that favors a hypothesis and equally strong evidence that favors its negation, for example, strong evidence favoring the guilt hypothesis and equally strong evidence favoring the hypothesis of innocence. Despite this difference, precise probabilism would recommend that a probability of .5 be assigned to both hypotheses in either case. Here, too, precise probabilities fail to be appropriately responsive to the evidence.

In addition, evidence can accumulate in a way that does not require changing our initial probability assignments. Suppose that, at first, one's overall evidence favors *A* over *B*. So the probability assigned to *A* should be greater than that assigned to *B*. Next, the agent acquires new evidence. The total quantity of evidence has increased, but suppose this larger body of evidence overall still favors *A* over *B*. So no change in the probabilities seems required. Still, something has changed about the agent's state of uncertainty towards *A* and *B*: the quantity of evidence on which the agent can make their assessment whether *A* is more probable than *B* has become larger. And yet, this change in the quantity of overall evidence is not reflected in the precise probabilities assigned to the propositions *A* and *B*.²

add reference about sweetening in footnote

¹Here is another problem for precise probabilism. Imagine a rational agent who does not know the bias of the coin. For precise probabilism, this state of uncertainty should be represented by a .5 probability assignment to the *heads*. Next, the agent learns that the bias towards heads, whatever the bias is, has been slightly increased, say by .001. The addition of this new information is called *sweetening* in the philosophical literature (Hare, 2010). This sweetening should now make the agent bet on heads: if the probability of *heads* was initially .5, it must now be slightly above .5. But, intuitively, the new information should leave the agent equally undecided about betting on heads or tails. After sweetening, the agent still does not know much about the actual bias of the coin.

²The distinction here is sometimes formulated in terms of the *balance* of the evidence (that is, whether the evidence available tips in favor a hypothesis or another) as opposed to its *weight* (that is, the overall quantity of evidence regardless of its balance); see Keynes (1921) and James M. Joyce (2005) among others.

3 Imprecise probabilism

What if we give up the assumption that probability assignments should be precise? Imprecise probabilism holds that a rational agent's credal stance towards a hypothesis is to be represented by a set of probability measures, typically called a representor \mathbb{P} , rather than a single measure P . The representor should include all and only those probability measures which are compatible with the evidence (more on this point later).³ It is easy to see that modeling an agent's credal state by sets of probability measures avoids some of the shortcomings of precise probabilism. For instance, if an agent knows that the coin is fair, their credal state would be represented by the singleton set $\{P\}$, where P is a probability measure that assigns .5 to *heads*. If, on the other hand, the agent knows nothing about the coin's bias, their credal state would be represented by the set of all probabilistic measures, since none of them is excluded by the available evidence. Note that the set of probability measures does not represent admissible options that the agent could legitimately pick from. Rather, the agent's credal state is essentially imprecise and should be represented by means of the entire set of probability measures.

So far so good. But, just as precise probabilism fails to be appropriately evidence-responsive in certain scenarios, imprecise probabilism runs into similar difficulties in other scenarios.

Even v. uneven bias: You have two coins and you know, for sure, that the probability of getting heads is .4, if you toss one coin, and .6, if you toss the other coin. But you do not know which is which. You pick one of the two at random and toss it. Contrast this with an uneven case. You have four coins and you know that three of them have bias .4 and one of them has bias .6. You pick a coin at random and plan to toss it. You should be three times more confident that the probability of getting heads is .4. rather than .6.

The first situation can be easily represented by imprecise probabilism. The representor would contain two probability measures, one that assigns .4. and the other that assigns .6 to the hypothesis 'this coin lands heads'. However imprecise probabilism cannot represent the second situation. Since the probability measures in the set are all compatible with the agent's evidence, no probability measure can be assigned a greater (higher-order) probability than any other.⁴

These examples show that imprecise probabilism is not expressive enough to model the scenario of uneven bias. Defenders of imprecise probabilism might concede this point but prefer their account for reasons of simplicity. They could also point out that imprecise probabilism models scenarios that precise probabilism cannot model, for example, a state of complete lack of evidence. In this respect, imprecise probabilism outperforms precise probabilism in expressive power, and also retains theoretical simplicity. But this is not quite true as imprecise

³For the development of imprecise probabilism, see Keynes (1921); Levi (1974); Gärdenfors & Sahlin (1982); Kaplan (1968); James M. Joyce (2005); Fraassen (2006); Sturgeon (2008); Walley (1991). Bradley (2019) is a good source of further references. Imprecise probabilism shares some similarities with what we might call interval probabilism (Kyburg, 1961; Kyburg Jr & Teng, 2001). In interval probabilism, precise probabilities are replaced by intervals of probabilities. On imprecise probabilism, instead, precise probabilities are replaced by sets of probabilities. This makes imprecise probabilism more general, since the probabilities of a proposition in the representor set do not have to form a closed interval.

⁴Other scenarios can be constructed in which imprecise probabilism fails to capture distinctive intuitions about evidence and uncertainty; see, for example, (Rinard, 2013). Suppose you know of two urns, GREEN and MYSTERY. You are certain GREEN contains only green marbles, but have no information about MYSTERY. A marble will be drawn at random from each. You should be certain that the marble drawn from GREEN will be green (G), and you should be more confident about this than about the proposition that the marble from MYSTERY will be green (M). For each $r \in [0, 1]$ your representor will contain a P with $P(M) = r$. But then, it also contains one with $P(M) = 1$. This means that it is not the case that for any probability measure P in the representor set, $P(G) > P(M)$, that is, it is not the case that a rational agent should be more confident of G than of M . This is counter-intuitive.

probabilism suffers from several shortcomings that do not affect precise probabilism.

The first shortcoming has not received extensive discussion in the literature, but it is fundamental. Recall that, for imprecise probabilism, an agent's state of uncertainty is represented by those probability measures that are *compatible* with the agent's evidence. The question is, how should the notion of compatibility be understood here? Perhaps we can think of compatibility as the fact that the agent's evidence is consistent with the probability measure in question. But mere consistency wouldn't get the agent very far in excluding probability measures, as too many probability measures are consistent with most observations and data. Admittedly, there will be clear-cut cases: if you see the outcome of a coin toss to be heads, you reject the measure with $P(H) = 0$, and similarly for tails. Another class of cases might arise while randomly drawing objects from a finite set where the objective chances are known. But clear-cut cases aside, what else? Data will often be consistent with almost any probability measure.⁵

A second, related problem for imprecise probabilism is known as belief inertia. Precise probabilism offers an elegant model of learning from evidence: Bayesian updating. Imprecise probabilism, at least *prima facie*, offers an equally elegant model of learning from evidence, richer and more nuanced. It is a natural extension of the classical Bayesian approach that uses precise probabilities. When faced with new evidence E between time t_0 and t_1 , the representor set should be updated point-wise, running the standard Bayesian updating on each probability measure in the representor:

$$\mathbb{P}_{t_1} = \{P_{t_1} | \exists P_{t_0} \in \mathbb{P}_{t_0} \forall H [P_{t_1}(H) = P_{t_0}(H|E)]\}.$$

The hope is that, if we start with a range of probabilities that is not extremely wide, point-wise learning will behave appropriately. For instance, if we start with a prior probability of *heads* equal to .4 or .6, then those measures should be updated to something closer to .5 once we learn that a given coin has already been tossed ten times with the observed number of heads equal 5 (call this evidence E). This would mean that if the initial range of values was $[.4, .6]$ the posterior range of values should be narrower.

Unfortunately, this narrowing of the range of values becomes impossible whenever the starting point is a complete lack of knowledge, as imprecise probabilism runs into the problem of belief inertia (Levi, 1980). This problem arises in situations in which no amount of evidence could lead the agent to change their belief state, according to a given modeling strategy. Consider a situation in which you start tossing a coin knowing nothing about its bias. The range of possibilities is $[0, 1]$. After a few tosses, if you observed at least one tail and one head, you can exclude the measures assigning 0 or 1 to *heads*. But what else have you learned? If you are to update your representor set point-wise, you will end up with the same representor set. For any sequence of outcomes that you can obtain and any probability value in $[0, 1]$, there will exist a probability measure (conditional on the outcomes) that assigns that probability to *heads*. Consequently, the edges of your resulting interval will remain the same. In the end, it is not clear how you are supposed to learn anything if you start from complete ignorance.⁶

⁵Probability measures can be inconsistent with evidential constraints that agents believe to be true. Mathematically, non-trivial evidential constraints are easy to model (Bradley, 2012). They can take the form, for example, of the *evidence of chances* $\{P(X) = x\}$ or $P(X) \in [x, y]$, or *structural constraints* such as “ X and Y are independent” or “ X is more likely than Y .” These constraints are something that an agent can come to accept outright, but only if offered such information by an expert whom the agent completely defers. Besides these idealized cases, it is unclear how an agent could come to accept such structural constraints upon observation. There will usually be some degree of uncertainty about the acceptability of these constraints.

⁶Here is another example of belief inertia by Rinard (2013). Suppose all the marbles in the urn are green (H_1), or exactly one-tenth of the marbles are green (H_2). Your initial credence about these hypotheses is completely uncertain, the interval $[0, 1]$. Next, you learn that a marble drawn at random from the urn is green (E). After conditioning on this evidence, you end up with the same spread of values for H_1 that you had before learning E . This result holds no matter how many green marbles are drawn. This is counterintuitive: if you keep drawing green marbles, the hypothesis that all marbles are green should become more probable.

Some downplay the problem of belief inertia. After all, if you start with knowing truly nothing, then it is right to conclude that you will never learn anything. Joyce (2010) writes:

You cannot learn anything in cases of pronounced ignorance simply because a prerequisite for learning is to have prior views about how potential data should alter your beliefs (p. 291) (James M. Joyce, 2010)

The upshot is that uniform priors should not be used and that imprecise probabilism gives the right results when the priors are non-vacuous. **Moss CITE** arrives at the same conclusion by drawing the following parallelism. If contingent propositions should not be assigned probabilities of 0 or 1 whenever these extreme values are unrevisable, then by the same token the uniform interval $[0, 1]$ should not be used for imprecise probabilities whenever it is impervious to revision.⁷ The challenge, however, is to explain in a principled manner which types of priors a rational agent is justified in assigning and why. What is the reason not to assign uniform priors except that they are unrevisable and thus cause belief inertia? While it is true that one cannot learn anything in a state of complete ignorance, the scenarios giving rise to belief inertia are not like that. The agent knows that the coin is two-sided, that the bias of the coin does not change from one toss to the next, etc. As we will soon see, uniform priors are not necessarily unrevisable and can be a starting point for learning. This suggests that the problem lies with imprecise probabilism, not with uniform priors as such.

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Finally, even setting aside belief inertia, imprecise probabilism faces a third major problem that does not arise for precise probabilism. As it turns out, it is impossible to define proper scoring rules for measuring the accuracy of a representor. Workable scoring rules exist for measuring the accuracy of a single, precise probability measure, such as the Brier score. These rules measure the distance between a rational agent's probability measure and the actual value. A requirement of scoring rules is that they be *proper*: any rational agent will expect their own probability measure to be more accurate than any other. After all, if an agent thought a different probability measure was more accurate, they should switch to it. Proper scoring rules are then used to formulate accuracy-based arguments for precise probabilism. These arguments show (roughly) that, if your precise measure follows the axioms of probability theory, no other non-probabilistic measure is going to be more accurate than yours whatever the facts are. Can the same be done for imprecise probabilism? It cannot. Impossibility theorems demonstrate that no proper scoring rules are available for representor sets (Seidenfeld, Schervish, & Kadane, 2012). So, as many have noted, the prospects for an accuracy-based argument for imprecise probabilism look dim (Campbell-Moore, 2020; Mayo-Wilson & Wheeler, 2016). Moreover, as shown by Schoenfield (2017), if an accuracy measure satisfies certain plausible formal constraints, it will never strictly recommend an imprecise stance, as for any imprecise stance there will be a precise one with at least the same accuracy.

4 Higher-order probabilism

Let us take stock. Imprecise probabilism is more expressive than precise probabilism. It can model the difference between a state in which there is no evidence about a proposition (or its negation) and a state in which the evidence for and against a proposition is in equipoise. However imprecise probabilism has its own expressive limitations, for example, it cannot model the case of uneven bias. In addition, imprecise probabilism faces difficulties that do not affect precise probabilism: the notion of compatibility between a probability measure and the

⁷ Another strategy is to say that, in a state of complete ignorance, a special updating rule should be deployed. Elkin (2017) suggests the rule of *credal set replacement* that recommends that upon receiving evidence the agent should drop measures rendered implausible, and add all non-extreme plausible probability measures. This, however, is tricky. One needs a separate account of what makes a distribution plausible from a principled account of why one should use a separate special update rule when starting with complete ignorance.

evidence is too permissive; belief inertia makes it impossible for a rational agent to learn via Bayesian updating; and no proper scoring rules exist for imprecise probabilism. In this section, we show that higher-order probabilism overcomes the expressive limitations of imprecise probabilism without falling prey to any such difficulties.

Proponents of imprecise probabilism already hinted at the need to rely on higher order probabilities. For instance, Bradley compares the measures in a representor to committee members, each voting on a particular issue, say the true chance or bias of a coin. As they acquire more evidence, the committee members will often converge on a chance hypothesis.

...the committee members are “bunching up”. Whatever measure you put over the set of probability functions—whatever “second order probability” you use—the “mass” of this measure gets more and more concentrated around the true chance hypothesis. (Bradley, 2012, p. 157)

But such bunching up cannot be modeled by imprecise probabilism alone: a probability distribution over chance hypotheses is needed.⁸ That one should use higher-order probabilities has also been suggested by critics of imprecise probabilism. For example, Carr (2020) argues that sometimes evidence requires uncertainty about what credences to have. Carr, however, does not articulate this suggestion more fully; does not develop it formally; and does not explain how her approach would fare against the difficulties affecting precise and imprecise probabilism. We now set out to do precisely that.

The central idea of higher-order probabilism is this: a rational agent’s uncertainty is not single-dimensional and thus cannot be mapped onto a one-dimensional scale such as the real line. Uncertainty is best modeled by the shape of a probability distribution, sometimes even over the parameters that are best construed as probabilities themselves. In some straightforward cases of narrow and symmetric distributions, we can get away with using point estimates, but such approximations will fail to be useful in more complex cases. Stated more formally, a rational agent’s state of uncertainty (or credal stance) towards a proposition X is not represented by a single probability value $P(X)$ between 0 and 1, but by a probability density $f(P(X))$, where the first-order probability of X is the parameter in question and is treated as a random variable. Crucially, this representation is general. While the examples used so far may not indicate this, the first-order probability of X is not restricted to chance hypotheses or the bias of a coin. The probability density $f(P(X))$ assigns a second-order probability (density) to all possible first-order probabilities $P(X)$.⁹

Since f is discretized, can we just say distribution?

How should these second-order probabilities be understood? It is helpful to think of higher-order probabilism as a generalization of imprecise probabilism. Imprecisers already admit that some probability measures are compatible and others incompatible with the agent’s evidence at some point. Compatibility is a coarse notion; it is an all-or-nothing affair. But, as seen earlier, evidence can hardly exclude a probability measure in a definitive manner except in clear-cut cases. Just as it is often a matter of degrees whether the evidence supports a proposition, the notion of compatibility between evidence and probability measures can itself be a matter of degrees. In this picture, the evidence justifies different values of first-order probability to various degrees. So, second-order probabilities express the extent to which the first-order probabilities are supported by the evidence.

This higher-order approach at the technical level is by no means novel. Bayesian probabilistic programming languages embrace the well-known idea that parameters can be stacked and depend on each other (Bingham et al., 2021). But, while the technical machinery has been

⁸In a similar vein, James M. Joyce (2005), in a paper defending imprecise probabilism, explicates the notion of weight of evidence using a probability distribution over chance hypotheses. Oddly, representor sets play no central role in Joyce’s account of the weight of evidence.

⁹For computational ease, we will use a higher-order density that is discretized and ranges over 1000 first-order probabilities.

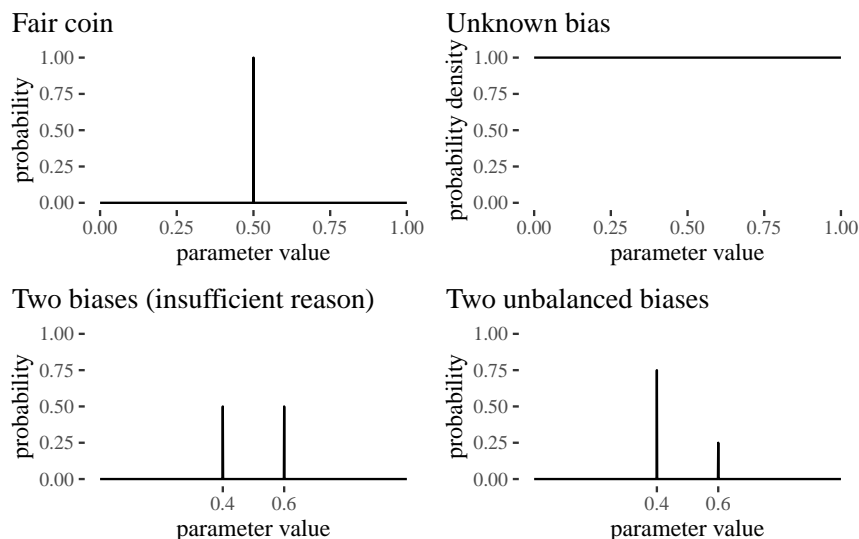


Figure 1: Examples of higher-order distributions for a few scenarios problematic for both precise and imprecise probabilism.

around for a while, it has not been deployed by philosophers to model a rational agent’s uncertainty or credal state. Because of its greater expressive power, higher-order probabilism can represent uncertainty in a more fine-grained manner, as illustrated in Figure 1. In particular, the uneven coin scenario in which the two biases of the coin are not equally likely—which imprecise probabilism cannot model—can be easily modeled within high-order probabilism by assigning different probabilities to the two biases.

An agent’s uncertainty could—perhaps, should—sometimes be represented by a single probability value. Higher-order probabilism does not prohibit that. For example, there may well be cases in which an agent’s uncertainty is aptly represented by the expectation.¹⁰ But this need not always be the case. If the probability distribution is not sufficiently concentrated around a single value, a one-point summary will fail to do justice to the nuances of the agent’s credal state.¹¹ For example, consider again the scenario in which the agent knows that the bias of the coin is either .4 or .6 but the former is three times more likely. Representing the agent’s credal state with the expectation $.75 \times .4 + .25 \times .6 = .45$ would fail to capture the agent’s different epistemic attitudes towards the two biases. The agent believes the two biases have different probabilities, and is also certain the bias is *not* .45.

Besides its greater expressive power in modeling uncertainty, higher-order probabilism does not fall prey to belief inertia. Consider a situation in which you have no idea about the bias of a coin. You start with a uniform distribution over $[0, 1]$ as your prior. Observing any non-zero number of heads will exclude 0 and observing any non-zero number of tails will exclude 1 from the basis of the posterior. The posterior distribution will become more centered as the observations come in. This result is a straightforward application of Bayesian updating. Instead of plugging sharp probability values into the formula for Bayes’s theorem, the factors to be multiplied in the theorem will be probability densities (or ratios of densities as needed). Figure 2 illustrates—starting with a uniform prior distribution—how the posterior (beta) distribution

¹⁰The expectation is usually defined as $\int_0^1 x f(x) dx$. In the context of our approach here, x is the first-order probability of a given proposition and f is the density representing the agent’s uncertainty about x .

¹¹This approach lines up with common practice in Bayesian statistics, where the primary role of uncertainty representation is assigned to the whole distribution. Summaries such as the mean, mode standard deviation, mean absolute deviation or highest posterior density intervals are only succinct ways of representing uncertainty.

changes after successive observations.¹²

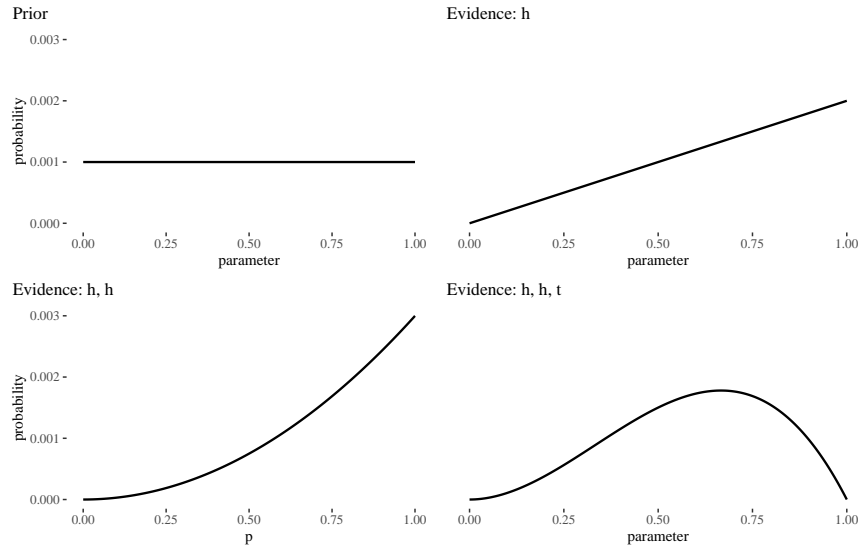


Figure 2: As observations of heads, heads and tails come in, extreme parameter values drop out of the picture and the posterior is shaped by the evidence.

The impossibility of defining proper scoring rules was another weakness of imprecise probabilism. This is a significant shortcoming, especially because proper scores do exist for precise probabilism. Fortunately, one can show that there exist proper scoring rules for higher-order probabilism. We defend this claim in the next section. The argument, however, will be more formal and can be skipped upon first reading.

5 Proper scores

A scoring rule or inaccuracy score quantifies the distance (inaccuracy) between a probability distribution and the true state of the world. A desirable property that any such score should have is strict propriety. In the precise case, let $I(p, w)$ be an inaccuracy score of a probability distribution p relative to the true state $w \in W$. The score $I(p, w)$ is strictly proper if, for any other probability distribution q different from p , the following holds:

$$\sum_{w \in W} p(w)I(p, w) < \sum_{w \in W} q(w)I(p, w).$$

That is, the expected inaccuracy of p from the perspective of p itself should always be smaller than the expected inaccuracy of p from the perspective of another distribution q . Other common requirements are: the score $I(p, w)$ should be a function of the probability distribution p

¹² Assuming independence and constant probability for all the observations, learning is modeled the Bayesian way.

You start with some prior density p over the parameter values. If you start with a complete lack of information, p should be uniform. Then, you observe the data D which is the number of successes s in a certain number of observations n . For each particular possible value θ of the parameter, the probability of D conditional on θ follows the binomial distribution. The probability of D is obtained by integration. That is:

$$\begin{aligned} p(\theta|D) &= \frac{p(D|\theta)p(\theta)}{p(D)} \\ &= \frac{\theta^s(1-\theta)^{(n-s)}p(\theta)}{\int (\theta')^s(1-\theta')^{(n-s)}p(\theta') d\theta'}. \end{aligned}$$

and the true state w (extensionality); and the score should be a continuous function around p (continuity). Well-known results demonstrate that the Brier score is an extensional score for precise probabilities that is both proper and continuous.¹³

Can similar results be established for imprecise probabilities? The answer is likely to be negative since several hurdles exist. First, a plausible scoring rule for imprecise probabilities cannot be easily found. Suppose an imprecise forecast assigns the $[\cdot 8, \cdot 9]$ interval to the outcome that it would rain tomorrow, where the true state is ‘rain’. Would the $[\cdot 6, \cdot 99]$ interval be more accurate since its $\cdot 99$ upper bound is closer to the true state? Intuitively, the $[\cdot 6, \cdot 99]$ interval should not be more accurate, otherwise, the trivial interval $[0, 1]$ would always be more accurate than any other interval. To remedy this problem, a plausible inaccuracy score for imprecise probabilities could be directly proportional to the Brier score computed using the side of the interval closer to the true state, but inversely proportional to the size of the interval.¹⁴

Still, even if a well-behaved score for imprecise probabilities can be found, a second hurdle remains. Recall that the notion of expected inaccuracy is needed to establish strict propriety. Unfortunately, expected inaccuracy cannot be easily defined for imprecise probabilities. Let $I([p_-, p_+], w)$ be an inaccuracy score for the interval $[p_-, p_+]$. What is its expected inaccuracy from the perspective of the interval $[p_-, p_+]$ itself, or from the perspective of another interval $[q_-, q_+]$? There is no standard answer to this question. After all, $I([p_-, p_+], w)$ cannot be multiplied by $[p_-, p_+]$, in the way in which $I(p, w)$ can be multiplied by $p(w)$. And if the notion of expected inaccuracy is not defined, the question of whether an imprecise inaccuracy score can be proper is ill-defined. Perhaps the expected inaccuracy of the interval $[p_-, p_+]$ can be evaluated from the perspective of the precise probabilities p_- or p_+ at the edges.¹⁵ But now the impreciser would face another problem. If the expected inaccuracy of the interval $[p_-, p_+]$ is evaluated from the perspective of the precise probabilities at the edges, finding a proper inaccuracy score that is also continuous turns out to be impossible (Seidenfeld et al., 2012).

Despite the difficulties that plague imprecise probabilism in defining scoring rules that are proper, here we put forward an intuitively plausible scoring rule for higher-order probabilities that is both proper and continuous. Building on existing work on this topic (Hersbach (2000), Pettigrew (2012), Gneiting & Raftery (2007)), the higher-order scoring rule we propose is based on a well-known measure of divergence between probability distributions, the Kullback-Leibler (KL) divergence, which is defined as follows:

$$D_{\text{KL}}(p||q) = \sum_x p(x) \log \left(\frac{p(x)}{q(x)} \right)$$

where x ranges over all hypotheses under consideration (i.e. the elements of the sample space). This is a standard information-theoretic measure of divergence of p from q from the perspective of p .¹⁶ In our particular case, we will be dealing with a finite array of evenly spaced hypotheses $\theta_1, \dots, \theta_n$ about what the true chance is (this is our discretization). Each particular hypothesis $\theta_k \in [0, 1]$ is associated with an omniscient distribution tracking the true state of the world

¹³The Brier score is defined as the squared distance between the true state and the probability forecast, or formally, $(p(x) - V(x, w))^2$, where $p(x)$ is the probability forecast and $V(x, w)$ determines if a proposition obtains at w ($V(x, w) = 1$) or not ($V(x, w) = 0$). If, for example, the proposition ‘rain’ obtains at w , the forecast ‘rain with $\cdot 9$ probability’ would be more accurate at w than the forecast ‘rain with $\cdot 8$ probability’. If, on the other hand, the proposition ‘not rain’ obtained at w , the latter forecast would be more accurate.

¹⁴If the score increases when the Brier score (thus defined) increases or when the size of the interval increases, this would block the result that the $[0, 1]$ interval is always the most accurate; see Seidenfeld et al. (2012).

¹⁵So the expected inaccuracy of $I_w([p_-, p_+])$ would equal $\sum_{w \in W} p_-(w)I([p_-, p_+], w)$ or $\sum_{w \in W} p_+(w)I([p_-, p_+], w)$.

¹⁶In the continuous case, we would need to use the so-called differential KL divergence.

Is the formal statement of Brier score in the footnote correct?

Looks alright, don't remove comment, will pay attention when reading the section at some point.

(i.e. the true chance being θ_k). We denote it by $Ind^k(\cdot)$ so that $Ind^k(\theta_i)$ is 1 if $i = k$ and 0 otherwise. We write Ind_i^k instead of $Ind^k(\theta_i)$.

With this notation, we can now formulate our notion of the inaccuracy of a probability distribution p if the true hypothesis is θ_k . It's the KL divergence between p and Ind^k .

$$I_{DK}(p, \theta_k) = D_{KL}(Ind_k || p)$$

As shown in the appendix, this boils down to $-\log_2 p_k$.

For instance, imagine the possible outcomes being the chance hypotheses $\theta_1, \theta_2, \dots, \theta_n$ about the true bias of a coin. If, for example, the true bias of the coin is .6 and the higher-order distribution p assigns .8 to this bias, the higher-order inaccuracy score of p would be $-\log .8$. Notice that, on this approach, two distributions p and q which assign the same probability to the true chance hypothesis will have the same inaccuracy score even though they might differ in the probabilities they assign to other chance hypotheses. So the shape of the distribution does not matter for the inaccuracy score; it does matter for expected inaccuracy, as we will soon see.

We will now give a higher-level description of the proof of strict propriety of the scoring rule I_{DK} . The first step is to define the score's expected inaccuracy, as follows:

Score's EI
or EI of p
from the
persp. of q?

$$EI_{DK}(p, q) = \sum_{k=1}^n p_k I_{DK}(q, \theta_k)$$

As shown in the appendix, this is identical to the cross-entropy $H(p, q)$. In particular, if we measure EI_{DK} of p from the perspective of p this further boils down to $H(p)$, so the entropy of p .

The only missing part now is Gibb's inequality, according to which $H(p, q) \geq H(p)$ with identity holding only if $p = q$ (we elaborate on why this holds in the appendix as well). Therefore the inaccuracy of a distribution from its perspective will always be the lowest, which goes along the principle of strict propriety. ¹⁷

To see that the proposed account of expected inaccuracy works as intended, consider a variation of a scenario by Schoenfield (2017). A rational agent is invited to engage in a bet by an opponent who has a representative bag of coins coming from a factory where the distribution

¹⁷KL divergence is not the only possible score for higher-order probabilities. Another approach relies on the Cramer-Von-Mises measure (CRPS). In the discretized version, it is defined as follows:

$$D_{CM}(p, q) = \sum_x |P(x) - Q(x)|^2,$$

where P and Q are the cumulative distributions corresponding to the probability distribution p and q . Looking at cumulative densities ensures that all densities are considered on the same scale. (In the continuous case, this measure is defined as the area under the squared Euclidean distances between the corresponding cumulative density functions. That is, $D_{CM}(p, q) = \int_0^1 |P(x) - Q(x)|^2 dx$.) If q plays the role of the true distribution, the CRPS measure can be turned into an inaccuracy measure that closely resembles the Brier score. The inaccuracy of p with respect to the true state θ_k is defined, as follows:

$$I_{CRPS}(p, \theta_k) = \sum_{i=1}^n |P(x) - Ind_i^k|^2$$

Finally, Cramer-Von-Mises can also be used to define the expected inaccuracy, analogously to the case of KL-divergence. However, for reasons that will soon become clear, we believe that KL divergence is a more natural higher-order inaccuracy measure.

of bias among the coins produced, the true generative process, is known. It is a mixture of two normal distributions centered at .3 and at .5, both with a standard deviation of .05. The opponent randomly selects one of the coins in the bag and flips it. The rational agent who knows this set-up may form a number of higher-order credal states in response to this information. Consider three such credal states, out of many options: first, a faithful bimodal distribution centered at .3 and .5; second, a unimodal distribution centered at .4; third, a wide bimodal distribution centered at .2 and .6. The three options are depicted in Figure 3.

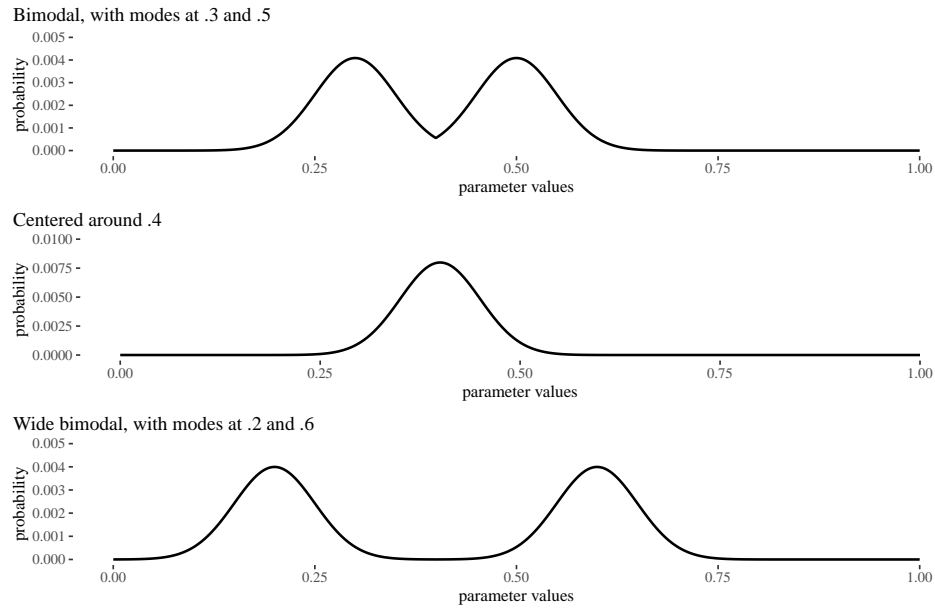


Figure 3: Three distributions in a vague EMS scenario. The distributions are built from normal distributions with standard deviation .05, the bimodal ones are joint in the middle. All of them have expected values $\approx .4$.

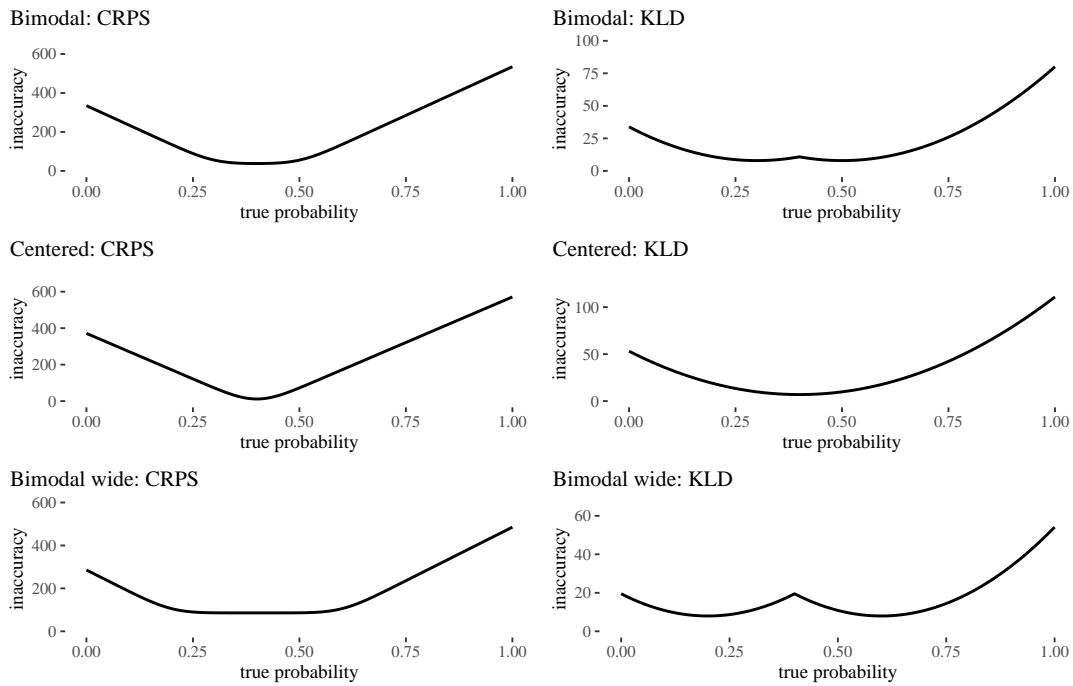


Figure 4: CRPS and KL divergence based inaccuracies relative to n true chance hypotheses for the three distributions, faithful bimodal, centered unimodal and wide bimodal.

	CRPS			KLD		
	bimodal	centered	wide bimodal	bimodal	centered	wide bimodal
bimodal	64.670	78.145	88.380	8.577	10.655	11.336
centered	41.657	28.181	85.911	9.239	7.690	15.627
wide bimodal	137.699	171.719	113.989	11.541	19.231	8.689

Table 1: Expected inaccuracies of the three distributions from their own perspective and that of the other distributions. Each row corresponds to a perspective.

The accuracy scores of these higher-order distributions are in Figure 4. Each point in the graph reflects the accuracy score calculated relative to a possible omniscient distribution corresponding to the values of θ , the true bias of the coin. The expected inaccuracies of the three distributions from their own perspective, as well as from the perspective of the other distributions, are in Table 1. The results are as intended: from their own perspective, the distributions see themselves as the least inaccurate. The strict propriety of the scoring rule is verified.¹⁸

Even though they all recommend themselves, the three distributions are by no means equivalent. The faithful bimodal is the one that best reflects the true generative process, while the others less so. How does the KL-based inaccuracy score capture the fact that the wide bimodal seems more adequate than the others? This is apparent by looking at the inaccuracy score relative to two chance hypotheses H_3 , where the true chance is 0.3, and H_5 , where the true chance is 0.5. You can find the inaccuracies for them in Table 2. To make sure that this favorable out-

¹⁸One important difference transpires between using CRPS and KLD. Notice how for chance hypotheses between the actual peaks the inaccuracy remains flat. This seems to be an artifice of choosing a squared distance metric. If instead we go with a more principled, information-theory-inspired KL divergence, inaccuracy in fact jumps a bit for values in between the peaks for the bimodal distributions, which seems intuitive and desirable. This seems to be a reason to prefer KL-based inaccuracy scores.

NL: Distribution, not a value representing a coin's bias?

Why just those two, and not also .4, another possible true chance hypothesis? The uni-modal has a better score of .4. This seems ad hoc.

come isn't due to not using pointed credences, we can redo the calculations using the pointed version. In the pointed version, all the focus is on 0.4, or the weight is evenly divided between 0.3 and 0.5, or between 0.2 and 0.6. As anticipated, when we consider inaccuracy, both of these setups recommend the faithful bimodal distribution (Table 3).

	CRPS		KLD	
	H3	H5	H3	H5
bimodal	55.475	55.378	7.935	7.935
centered	72.281	72.090	9.836	9.825
wide bimodal	86.230	86.223	10.871	10.882

Table 2: CRPS and KLD inaccuracies of the three distributions with respect to the two hypotheses. On both inaccuracy measures the bimodal distribution dominates the other two.

	CRPS		KLD	
	H3	H5	H3	H5
pointed bimodal	49.75	49.75	1.00	1.00
pointed centered	100.00	100.00	16.61	16.61
pointed wide bimodal	99.75	99.75	16.61	16.61

Table 3: CRPS and KLD inaccuracies of the three-pointed distributions with respect to the two hypotheses.

Key to the result of strict propriety is summing over all possible chance hypotheses. But the precise probabilist might insist that this is unnecessary. There are ultimately only two possible first-order level outcomes, heads and tails, and thus also only two possible chance hypotheses (or omniscient distributions), one that places all weight on heads and the other that places all weight on tails. On this view, the accuracy score I_{KL} of a distribution p , should only take two possible values, $I(p, \text{heads})$ and $I(p, \text{tails})$, where ‘tails’ or ‘heads’ is one of the two omniscient distributions. Thus, expected inaccuracy would be calculated as follows:

$$EI_{\text{binary}}(p, q) = I(p, \text{heads}) \times q(\text{heads}) + I(p, \text{tails}) \times q(\text{tails}).$$

Instead of calculating inaccuracy relative to all possible chance hypotheses about the coin's bias, expected inaccuracy would result from the sum of the two inaccuracy scores weighted by the probabilities of the two outcomes. To be sure, the three distributions considered so far do not provide the probabilities of the outcome ‘heads’ or ‘tails’ directly. They assign probabilities to different values of coin bias, but it is natural enough to take the expected values of these distributions, which equals .4 for all three. Table 4 displays the relevant inaccuracy scores as well as the expected inaccuracy scores. Note that since the probability of heads or tails is the same on all the distributions, those are expected values from the perspective of each of the measures; changing the perspective in this example doesn't change the expected inaccuracy.

This approach to expected inaccuracy runs into trouble. As it turns out, the expected KL-inaccuracy score recommends the wide bimodal distribution as the most accurate (or least inaccurate), and the KL divergence from the omniscient measure makes the same recommendation. This is counterintuitive because the faithful bimodal seems the most evidence-responsive. The unimodal distribution, while centering on the expected value, gets the chances wrong, and the

Not sure this last part is needed.

Just multiplying by the probability of the outcome?

wide bimodal has its guesses too close to the truth values and too far from the known chances. But there is a further problem. While the wide bimodal distribution expects itself to be the least inaccurate, the other distributions also expect the wide bimodal to be the least inaccurate. In this setting, then, strict propriety fails. since some distributions recommend others as less inaccurate, whatever the true state of the world.

distribution	CRPS1	CRPS0	KLD1	KLD0	ExpCRPS	ExpKLD
bimodal	534.7305	334.9305	80.06971	33.90347	414.8505	52.36997
centered	571.2192	371.4192	110.84220	53.13440	451.3392	76.21752
wide bimodal	485.4052	285.6177	54.13433	19.50965	365.5340	33.35974

Table 4: CPRS and KLD inaccuracies of the three distributions to the TRUE and FALSE omniscient functions, with expected inaccuracies, calculated using the shared point estimates of the probabilities of heads and tails.

What are we to make of this result? The same expected value of .4 is used in the calculations of the expected inaccuracies on the assumption that there are two possible outcomes with respect to which expected inaccuracy is calculated. This approach, however, runs against the spirit of our enterprise. If expected values are often not good representations of a rational agent's uncertainty, it should not be surprising that relying on them fails to deliver plausible expected accuracy scores. By reducing each of the distributions' stances towards heads to a single point value .4, key information is washed away. As emphasized earlier, rather than measuring inaccuracy relative to two omniscient distributions that peak at either 0 or 1 and averaging using expected values of the distributions, we should instead utilize a set of n potential true probability hypotheses. We then compute all the inaccuracies with respect to each of these n values represented by possible omniscient distributions (or true chance hypotheses) and determine the expected inaccuracy scores using the entire distributions rather than relying solely on the expected values of the distributions. As we have seen, this approach delivers the result of strict propriety we were looking for.¹⁹

take a look
at fn

6 Conjunctions

Let us take stock. In some circumstances, assigning sharp probabilities to events is justified. In others, it is less so, for example, when the bias of a coin is unknown, or when there is evidence that a coin could have a number of biases. In such cases, imprecise probabilities model uncertainty better than precise ones. But imprecise probabilities also fall short in their own way, for example, when the biases of a coin are not equally likely given the evidence available. Higher-order probabilities are better able to model these more complex scenarios. They also avoid many of the problems of imprecise probabilities, such as belief inertia and the difficulty of finding proper scoring rules.

One limitation of the discussion so far, however, is that we only looked at assessing probabilities of individual events, say whether a coin would come up heads or tails. But, of course, rational agents may need to assign probabilities to multiple events, for example, the conjunction of two events. Suppose I am holding two coins, and I have information about their respective

¹⁹What if we abandon this focus on true distributions being "pointy" and allow them to be any distributions whatsoever? Then we have a bit of work to do to make sure the framework is coherent and the semantics is well-defined (this is possible, as illustrated by the work of Dorst (2022b)). However we do that, if we then take KL divergence to the true distribution as an inaccuracy measure, since $\log(1)$ is 0, whatever the weights, any distribution will expect itself to be the least inaccurate, as expected inaccuracy calculation for a distribution and itself will always involve multiplying by zero.

biases. What is, then, the probability that they both come up, say, heads? In the precise case, the answer is straightforward: assuming independence, it is enough to multiply the individual probabilities. But what happens in the imprecise case? And how to proceed with higher-order probabilities? Once again, we will see that in assessing probabilities for conjunctions of events higher-order probabilities fare better than precise and imprecise ones.

To fix ideas, we will go through a stylized legal example. We selected this example also to illustrate that higher-order probabilities can be useful beyond cases of coin tossing, though anything we say here does apply to coin tossing. Here is some preliminary background. In a murder case, the police recover two items of so-called match evidence: first, hair found at the crime scene matches the defendant's hair; and second, the fur of the defendant's dog matches the fur found in a carpet wrapped around one of the bodies.²⁰ Clearly, these two matches constitute evidence against the defendant. The most obvious explanation is that the defendant visited the crime scene and contributed both traces. The alternative explanation is that the matches are a coincidence. Maybe another person visited the scene and happened to have the same hair type and a dog with the same fur type. How likely would that be? If the probability of this happening is low, the two matches would be strong incriminating evidence; if it is not low, they would be weak incriminating evidence. Trial experts usually provide coincidental match probabilities (also called random match probabilities). They express the likelihood that, by coincidence, a random person (or a random dog) who is not a contributor would still match. These are the probabilities we are looking for.

It is customary to rely on database frequencies to assess the coincidental match probabilities, for example, by counting how many matches are found in a sample of the human population or the canine population. Suppose the matching hair type occurs 0.0253 times in a reference database, and the matching dog fur type occurs 0.0256 times in a reference database (more on how these numbers are calculated soon). These frequencies give the individual coincidental probabilities. To assess the probability of the two coincidental matches happening jointly, it is enough to multiply the individual probabilities:

$$P(\text{dogMatch}|\neg\text{contributor}) \times P(\text{hairMatch}|\neg\text{contributor}) = 0.0253 \times 0.0256 = 6.48 \times 10^{-4}$$

Multiplication is allowed on the assumption that the coincidental matches are independent events.²¹ The resulting joint probability is very small. The two matches, combined, are strong evidence against the defendant, or so it would appear.

This is the story told by the precise probabilist. But this story misses something crucial. As it happens, the coincidental match probability for hair evidence is based on 29 matches found in a sample database of size 1,148, while the coincidental match probability for the dog evidence is based on finding 2 matches in a smaller database of size 78. The relative frequencies are about .025 in both cases, but the two samples differ in size. The smaller the sample, the greater the uncertainty about the probabilities. So, for individual pieces of evidence, simply reporting the exact numbers makes it seem as though the evidential value of the hair and fur matches is the same, but actually, it is not.²² In the aggregate, multiplying the coincidental match probabilities further washes away this difference.

A better alternative is easily available: take into account higher-order uncertainty. Figure 5 (upper part) depicts higher-order probability distributions of different coincidental match prob-

²⁰The hair evidence and the dog fur evidence are stylized after two items of evidence in the notorious 1981 Wayne Williams case (Deadman, 1984b, 1984a).

²¹To put it more carefully, the two matches are independent conditional on the hypothesis that the defendant is not a contributor.

²²The probabilities in the Wayne Williams case on which our running example is based were 1/100 for the dog fur, and 29/1148 for Wayne Williams' hair. Probabilities have been slightly but not unrealistically modified to be closer to each other in order to make a conceptual point: the same first-order probabilities, even when they sound precise, may come with different degrees of second-order uncertainty.

abilities given the sample data—the actual number of matches found in the sample databases. As expected, some coincidental probabilities are more likely than others, and since the sizes of the two databases are different, the distributions have different spreads: the smaller the database the greater the spread, the greater the uncertainty about the coincidental probability. In light of this, Figure 5 (lower part) depicts the probability distribution for the joint coincidental match probabilities associated with both hair and fur evidence. The mathematics here is straightforward: once the higher-order distributions are known, simply multiply them to obtain the higher-order distribution of the joint coincidental match probabilities.

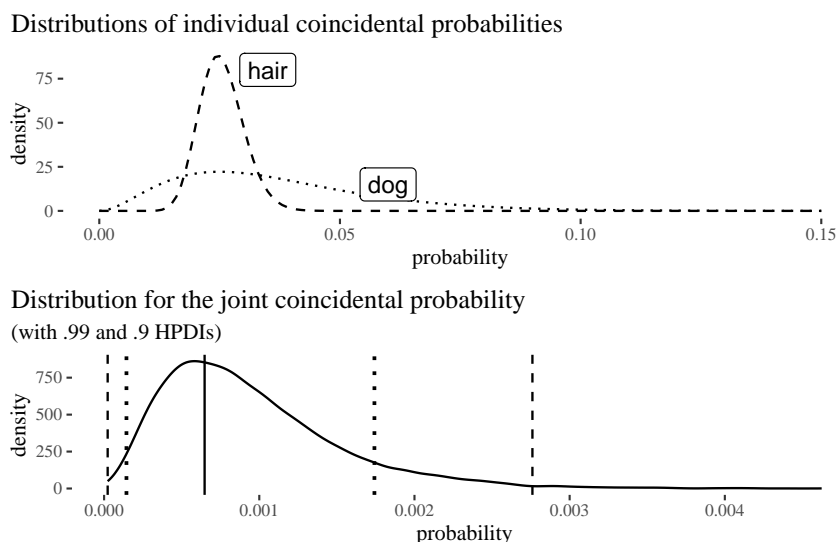


Figure 5: Beta densities for individual items of evidence and the resulting joint density with .99 and .9 highest posterior density intervals, assuming the sample sizes as discussed and independence, with uniform priors.

The precise probabilist might insist that our best assessment of the first-order coincidental match probabilities is still the relative frequency of matches found in the database, whether large or small. All things considered, our best assessment of the match probabilities for both fur and hair evidence should be about .025, based on the relative frequencies 2/78 and 29/1,148. After all, if we were to bet whether a dog or a human picked at random would have the matching fur or hair type, our odds should be .025 no matter the size of the database. This argument has some bite for individual events. In fact, the expected values of the coincidental probabilities for hair and match evidence—based on the higher-order distributions in Figure 5 (upper part)—still end up being about .025. If, as the precise probabilist assumes, first-order probabilities are all we should care about, going higher-order would seem a needless complication.

This line of reasoning, however, breaks down when evaluating conjunctions of events. What should our betting odds be for the proposition that a human and a dog, both picked at random, would have the matching fur and hair type in question? For the precise probabilist, the answer is straightforward: on the assumption of independence, multiply the .025 individual match probabilities and obtain a joint match probability of 6.48×10^{-4} . The higher-order probabilist will proceed differently. In assessing first-order match probabilities, they will retain information about higher-order uncertainty as much as possible. This can be done in two steps: first, aggregate the higher-order distributions for the two-match probabilities and obtain a higher-order distribution for the joint match probability (see Figure 5); next, to obtain our best assessment of the first-order joint match probability, take the expected value of this latter distribution. Interestingly, the higher-order probabilist will assign 9.38×10^{-4} to the joint

coincidental match probability, a value greater than what the precise probabilist would assign.

So, the higher-order and precise probabilist will disagree about the betting odds for the proposition that a human and a dog, both picked at random, would have the matching fur and hair type in question. The disagreement will become even starker as a larger number of independent items of evidence are evaluated.²³ Who should be trusted? Since the higher-order probabilist takes into account more information—that is, the higher-distributions—there is good reason to think that the higher-order probabilist should be trusted more than the precise probabilist.

Consider now how the imprecise probabilism fares in these cases. It will also run into its own problems when assessing probabilities of multiple events in conjunction. Recall that the probability measures in the representor set are those compatible with the evidence. The problem is that almost any coincidental match probability will be compatible with any sample data²⁴ So the appropriate interval would be $[0,1]$ for both coincidental match probabilities, and the same for the conjunction. This result would make it impossible to learn anything.

But now suppose we rely on reasonable ranges of coincidental match probabilities, for example, $(.015, .037)$ $(.002, .103)$, for hair and fur match evidence respectively.²⁵ As expected, the range is wider for dog fur match evidence than hair match evidence: the uncertainty about the dog fur match probability is greater since the sample database was smaller. This is a good feature of the interval approach, unavailable to the precise probabilist. Now, what to do to assess the joint uncertainty? The most natural strategy is to focus on what happens at the edges of the two intervals. Reasoning with representor members at the edges of the intervals will yield the most extreme probability measure the impreciser is committed to, the worst-case and best-case scenarios. Following this strategy yields a new range for the joint match probabilities: $(.00003, .003811)$.²⁶ This interval does not seem to be particularly informative, but the bigger problem is that relying on ranges for the match probabilities leaves the impression that any value in the interval is just as good as any other. Perhaps we should pick the middle value as representative of the interval. To see why this will not work, consider again Figure 5 (lower part) which depicts the probability distribution for the joint match probability. This distribution is not symmetric. So the most likely value and the bulk of the distribution do not lie in the middle between the edges. So, only relying on the edges—or taking central values

²³Consider the simple case of independent items of evidence whose individual match probabilities are .025. For three, five and seven items of evidence, the joint match probabilities would be: 1.25×10^{-4} , 3×10^{-7} and 8×10^{-10} (for the precise probabilist); 5.34×10^{-4} , 1.68×10^{-5} and 9.999×10^{-7} (for the higher-order probabilist, based on small databases of size 20); and 1.08×10^{-4} , 2×10^{-7} and 6×10^{-10} (for the higher-order probabilist, based on larger databases of size 20,000).

²⁴Think by analogy to coin tossing: even a coin that has a .99 bias toward tails could come up heads on every toss. This series of outcomes is unlikely but possible. Similarly, a hair type that has a match probability extremely small could still be found several times in a sample population.

²⁵These are 99% credible intervals starting with uniform priors. A 99% credible interval is the narrowest interval to which the expert thinks the true parameter belongs with probability .99. For a discussion of what credible intervals are, how they differ from confidence intervals, and why confidence intervals should not be used, see Kruschke (2015).

²⁶Redoing the calculations using the upper bounds of the two intervals, .037 and .103, yields the following:

$$P(\text{dogMatch} \wedge \text{hairMatch} | \text{—contributor}) = .037 \times .103 = .003811.$$

This number is around 5.88 times greater than the original, precise estimate. Given this number, the two matches are much weaker evidence for the contributor hypothesis than previously thought. The calculation for the lower bounds, .015 and .002, yields the following:

$$P(\text{dogMatch} \wedge \text{hairMatch} | \text{—contributor}) = .015 \times .002 = .00003$$

This number is around 0.46 times lower than the original estimate. Given this number, the two matches are much stronger evidence for the contributor hypothesis than previously thought.

as representative—can lead to overestimating or underestimating the probabilities at play.²⁷

All in all, precise and imprecise probabilism does not fare well in assessing the probabilities of conjunction of independent events. In the case of individual events, this problem is not readily apparent, but when the probabilities of multiple events are assessed, the divergence between higher-order probabilism and the other versions of probabilism becomes significant. Insisting that all we should care about are first-order probabilities will not work if the values of the first-order probabilities are not assessed in light of all the information available. What precise and imprecise probabilities are ultimately guilty of is neglecting useful information.

One final clarification is in order. While the examples we have used in this section involve match probabilities based on samples of different sizes, the problem we are highlighting is not confined to differences in sample size or match probabilities; it is broader than that. Probabilities can be subject to higher-order uncertainty for other reasons, for example, when they are derived from a probability model that has little support, or when the sample size is unrepresentative. The general point of this section is that, these higher-order uncertainties may be compounded while assessing the probabilities of events in conjunction. It would be a mistake to ignore them, even if all we cared about were first-order probabilities.

7 Bayesian networks

We looked at simple cases of conjunctions in which the events in question were probabilistically independent. But realistic scenarios are much more complex. Think, for example, of two witnesses testifying in a trial about two propositions, say the defendant's whereabouts and the defendant's motive. These two propositions are likely probabilistically dependent. In these more complex cases, precise probabilism relies on Bayesian networks. The graphical part of a Bayesian network consists of nodes and arrows. Arrows between nodes visually represent relationships of probabilistic dependence between different hypotheses and items of evidence, each corresponding to a node in the network. The numerical part of a Bayesian network describes the strengths of these dependencies. On a purely formal level, the numerical part consists of probability tables that are filled in with precise prior probabilities (for nodes without incoming arrows) or conditional probabilities (for nodes with incoming arrows). Equipped with these input probabilities, the network can run the calculations about the output probabilities of interest.²⁸ We might be interested, for example, in the probability of a hypothesis given several items of evidence, while keeping track of dependencies between them. In the standard formulation, Bayesian networks run on precise probabilities but can be extended to handle imprecise and higher-order probabilities. This is the topic of this section.

As an illustration, let us start with a Bayesian network developed by Fenton & Neil (2018). The network in Figure 6 represents the key items of evidence in the infamous British case *R. v. Clark* (EWCA Crim 54, 2000). Sally Clark, the mother of two sons, witnessed her first son die in 1996 soon after birth. Her second son died in similar circumstances a few years later in 1998. These two consecutive deaths raised suspicion. One hypothesis about the cause of death is that Sally murdered her children. An alternative explanation is that both children died of Sudden Infant Death Syndrome (SIDS). At trial, however, the pediatrician Roy Meadow

Why is a node for death missing in the network? That seems necessary as part of the evidence, no?

²⁷The calculations for the joint interval assume that because the worst- or best-case probability for one event is x and the worst- or best-case probability for another independent event is y , the worst- or best-case probability for their conjunction is xy . However, this conclusion does not follow if the margin of error (credible interval) is fixed. Just because the probability of an extreme value x for one variable X is .01, and so it is for the value y of another independent variable Y , it does not follow that the probability that those two independent variables take values x and y simultaneously is the same. In general, it is impossible to calculate the credible interval for the joint distribution based solely on the individual credible intervals corresponding to the individual events.

²⁸The calculations can quickly get out of hand, so software exists to perform the calculations automatically.

testified that the probability that a child from a family like the Clark's would die of SIDS was quite low, 1 in 8,543. Assuming probabilistic independence between the two events, the probability of both children dying of SIDS becomes extremely low. It equals the product of the two probabilities, approximately 1 in 73 million. Based on this low probability and signs of bruising on the bodies, Sally Clark was convicted of murder. The conviction was reversed on appeal thanks to new evidence, specifically, signs of a potentially lethal disease found in one of the bodies.

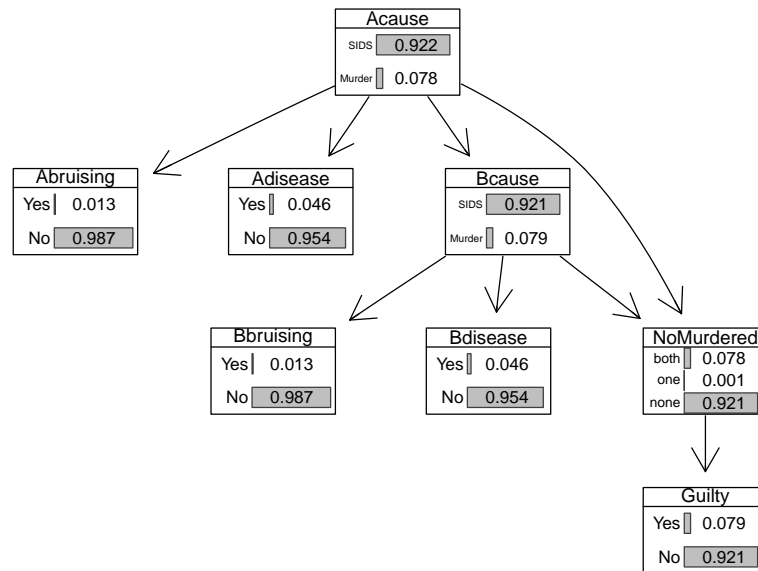


Figure 6: Bayesian network for the Sally Clark case, with marginal prior probabilities.

Much has been written about Sally Clark by philosophers and statisticians. The discussion has often focused on whether Meadow was allowed to assume, as he did, that the two SIDS deaths would be independent events. The assumption of independence delivered the low probability of 1 in 73 million by multiplying 1 in 8,543 by itself. Another much-discussed point was this: even if it was unlikely that two consecutive SIDS deaths would occur, it does not follow it was likely that Sally murdered her children.²⁹ A Bayesian network helps to avoid these mistakes. It also helps to view the case holistically. The two consecutive deaths were an important piece of evidence, but other evidence was also important, including signs of bruising and signs of a lethal disease as they were discovered during the appeal process.

Unfortunately, Bayesian networks, in their standard formulation, inherit the shortcomings of precise probabilism. The choice of the input probabilities should be precise, and it is often unclear where the values come from or whether they are justified. Consider, for example, the probability that a death by SIDS would occur. How sure are we that this probability equals, exactly, 1 in 8,543? The figure Meadow used is a sample-based frequency. How big was that sample? How representative? Other input probabilities need to be entered in the network to carry out the calculations, for example, the probability that a mother would kill her son, or the probability that signs of bruising would be found given the hypothesis that Sally was trying to murder her child, and so on. There will be uncertainty about these probabilities since they are based on sample frequencies or expert elicitation.

²⁹One could reason that, since 1 in 73 million is a low probability, the alternative explanation, that Sally murdered her children, should be likely. But that a mother would do such a thing is also unlikely, perhaps even less likely than 1 in 73 million.

The standard response to these concerns is to invoke *sensitivity analysis*: a range of plausible values is tested. Say we are interested in the output probability that Sally is guilty. The network is updated by the known facts—the items of evidence—following standard Bayesian conditionalization. The input probabilities in the network are then assigned a range of possible values to see how they impact the output probability of Sally’s guilt. Sensitivity analysis is another variant, perhaps more rudimentary, of the interval approach we considered earlier. In fact, Bayesian networks for reasoning with intervals and imprecise probabilities already exist.³⁰ But, as discussed earlier, imprecise probabilism, the interval approach and sensitivity analysis ignore the shape of the underlying distributions. They do not distinguish between probability measures (or point estimates) in terms of their plausibility, even though some will be more plausible than others. Moreover, if the sensitivity analysis is only guided by the values at the edges of the interval, these extremes will often play an undeservedly strong role.

add references to imprecise BNs; see footnote.

These concerns can be addressed by recourse to higher-order probabilities. In a precise Bayesian network, each node is associated with a probability table determined by a finite list of numbers (precise probabilities). In an imprecise Bayesian network, each node is associated with a table determined by an interval of numbers. But suppose that, instead of precise numbers or intervals of numbers, we have distributions over the possible numbers to enter into the probability tables.³¹ An example of such a higher-order Bayesian network for the Sally Clark case is represented in Figure 7.

The higher-order Bayesian network helps to investigate the impact of different items of evidence on Sally Clark’s probability of guilt (see Figure 8). The starting point is the prior distribution for the Guilt node (first graph). Next, the network is updated with evidence showing signs of bruising on both children (second graph). Next, the assumption that both children lack signs of potentially lethal disease is added (third graph). Finally, we consider the state of the evidence at the time of the appellate case: signs of bruising existed on both children, but signs of lethal disease were discovered only in the first child. Interestingly, in the strongest case against Sally Clark (third graph), the median of the posterior distribution is above .95, but the uncertainty around that median is still quite wide.³² This underscores the fact that relying on point estimates can lead to overconfidence.

³⁰One can use uniform sampling with Bayesian networks to approximate the impreciser’s commitments (Caprio et al., 2024). Another approach is to rely on probabilistic programs with the restriction that the variables corresponding to probabilities are sampled from uniform distributions corresponding to the representor set. A critical survey of approaches along these lines shows that, in complex reasoning situations, “the imprecision of inferences increases rapidly as new premises are added to an argument” (Kleiter, 1996).

³¹The densities of interests can then be approximated by (1) sampling parameter values from the specified distributions, (2) plugging them into the construction of the BN, and (3) evaluating the probability of interest in that precise BN. The list of the probabilities thus obtained will approximate the density of interest. In what follows we will work with sample sizes of 10k.

³²The lower limit of the 89% Highest Posterior Density Intervals (HPDI) is at .83.

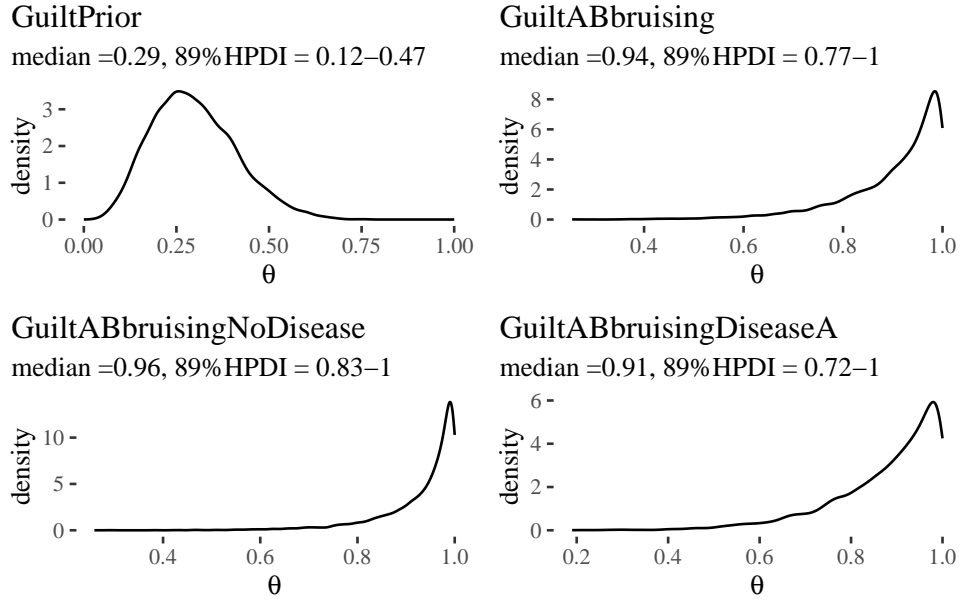


Figure 8: Impact of incoming evidence in the Sally Clark case.

8 Conclusion

We have argued that higher-order probabilism outperforms both precise and imprecise probabilism. It is able to model scenarios that the other two cannot model, for example, the case of uneven bias. In addition, higher-order probabilism does not fall prey to difficulties peculiar to imprecise probabilism, such as belief inertia and the lack of proper scoring rules. We have also identified a novel set of problems for precise and imprecise probabilism, mostly stemming from the question of how to evaluate, in the aggregate, the probabilities of multiple propositions. Here again, higher-order probabilism fares better.

Some might dislike the idea of going higher-order for a number of reasons, for example, unnecessary complexity. This is a line taken by Bradley, who refuses to go higher-order for the following reason:

Why are sets of probabilities the right level to stop the regress at? Why not sets of sets? Why not second-order probabilities? Why not single probability functions? This is something of a pragmatic choice. The further we allow this regress to continue, the harder it is to deal with these belief-representing objects. So let's not go further than we need. 131-132

We have shown that given the difficulties of precise and imprecise probabilism, we are not going further than we need in using higher-order probabilities. The pragmatic concerns one might have are at best unclear.

We should underscore that, mathematically, we do not propose anything radically new. Concepts from the Bayesian toolkit that can model higher-order uncertainty already exist. Our suggestion is that they have been under-appreciated in formal epistemology and should be more widely used. This is not to say that there is no need for any novel technical work. For example, we still need a proper accuracy argument in defense of higher-order probabilism. Will an agent who relies on higher-order probabilities accuracy-dominate one who relies on just first-order probabilities? We leave this as an open question. Another concern is the lack of clear semantics for higher-order probabilities. While a more elaborate account is beyond the scope of this paper, the answer should gesture at a modification of the framework of probabilistic

frames (Dorst, 2022b, 2022a). Start with a set of possible worlds W . Suppose you consider a class of probability distributions D , a finite list of atomic sentences q_1, \dots, q_2 corresponding to subsets of W , and a selection of true probability hypotheses C (think of the latter as omniscient distributions, $C \subseteq D$, but in principle this restriction can be dropped if need be). Each possible world $w \in W$ and a proposition $p \subseteq W$ come with their true probability distribution, $C_{w,p} \in D$ corresponding to the true probability of p in w , and the distribution that the expert assigns to p in w , $P_{w,p} \in D$. Then, various propositions involving distributions can be seen as sets of possible worlds, for instance, the proposition that the expert assigns d to p is the set of worlds w such that $P_{w,p} = d$.³³

Appendix: the strict propriety of I_{kl}

The fact that I_{KL} is strictly proper as applied to second-order probabilities is not very surprising. However, in the existing literature, the proof is not usually explicitly given, and some of the pieces are not present in the philosophical literature. So we tried to include the whole chain of thought, warning that some of these results are already known and all we did was making the proofs more presentable, and pointing out new elements in the reasoning. Let us start with a definition of concavity.

Definition 1 (concavity). *A function f is convex over an interval (a, b) just in case for all $x_1, x_2 \in (a, b)$ and $0 \leq \lambda \leq 1$ we have:*

$$f(\lambda x_1 + (1 - \lambda)x_2) \leq \lambda f(x_1) + (1 - \lambda)f(x_2)$$

A function f is concave just in case:

$$f(\lambda x_1 + (1 - \lambda)x_2) \geq \lambda f(x_1) + (1 - \lambda)f(x_2)$$

A function f is strictly concave just in case the equality holds only if either $\lambda = 0$ or $\lambda = 1$.

For us it is important that if a function is twice differentiable on an interval, then it is (strictly) concave just in case its second derivative is non-positive (negative). In particular, as $(\log_2(x))'' = -\frac{1}{x^2 \ln(2)}$, \log_2 is strictly concave over its domain.³⁴

Lemma 1 (Jensen's inequality). *If f is concave, and g is any function of a random variable, $\mathbb{E}(f(g(x))) \leq f(\mathbb{E}(g(x)))$. If f is strictly concave, the equality holds only if $g(x) = \mathbb{E}g(x)$, that is, if $g(x)$ is constant everywhere.*

Proof. For the base case consider a two-point mass probability function. Then,

$$p_1 f(g(x_1)) + p_2 f(g(x_2)) \leq f(p_1 g(x_1) + p_2 g(x_2))$$

follows directly from the definition of concativity, if we take $\lambda = p_1$, $(1 - \lambda) = p_2$, and substitute $g(x_1)$ and $g(x_2)$ for x_1 and x_2 .

Now, suppose that $p_1 f(g(x_1)) + p_2 f(g(x_2)) = f(p_1 g(x_1) + p_2 g(x_2))$ and that f is strictly concave. That means either $(p_1 = 1 \wedge p_2 = 0)$, or $(p_1 = 0 \wedge p_2 = 1)$. Then either x always takes value x_1 , in the former case, or always takes value x_2 , in the latter case. $\mathbb{E}g(x) = p_1 g(x_1) + p_2 g(x_2)$, which equals $g(x_1)$ in the former case and $g(x_2)$ in the latter.

³³There is at least one important difference between this approach and that developed by Dorst. His framework is untyped, which allows for an enlightening discussion of the principle of reflection and alternatives to it. In this paper, we prefer to keep this complexity apart and use an explicitly typed set-up.

³⁴I line with the rest of the paper, we'll work with log base 2. We could equally well use any other basis.

Now suppose Jensen's inequality and the consequence of strict convexity holds for $k - 1$ mass points. Write $p'_i = \frac{p_i}{1-p_k}$ for $i = 1, 2, \dots, k - 1$. We now reason:

$$\begin{aligned}
\sum_{i=1}^k p_i f(g(x_i)) &= p_k f(g(x_k)) + (1 - p_k) \sum_{i=1}^{k-1} p'_i f(g(x_i)) \\
&\leq p_k f(g(x_k)) + (1 - p_k) f\left(\sum_{i=1}^{k-1} p'_i g(x_i)\right) && \text{by the induction hypothesis} \\
&\leq f\left(p_k g(x_k) + (1 - p_k) \sum_{i=1}^{k-1} p'_i g(x_i)\right) && \text{by the base case} \\
&= f\left(\sum_{i=1}^k p_i g(x_i)\right)
\end{aligned}$$

Notice also that at the induction hypothesis application stage, we know that the equality holds only if $p_k = 1 \vee p + k = 0$. In the former case $g(x)$ always takes value $x_k = \mathbb{E}g(x)$. In the latter case, p_k can be safely ignored and $\sum_{i=1}^k p_i g(x_i) = \sum_{i=1}^{k-1} p'_i g(x_i)$ and by the induction hypothesis we already know that $\mathbb{E}g(x) = g(x)$. □

In particular, the claim holds if we take $g(x)$ to be $\frac{q(x)}{p(x)}$ (were both p and q are probability mass functions), and f to be \log_2 . Then, given that A is the support set of p , we have:

$$\sum_{x \in A} p(x) \log_2 \frac{q(x)}{p(x)} \leq \log_2 \sum_{x \in A} p(x) \frac{q(x)}{p(x)}$$

Moreover, the equality holds only if $\frac{q(x)}{p(x)}$ is constant, that is, only if p and q are the same pmfs. Let's use this in the proof of the following lemma.

Lemma 2 (Information inequality). *For two probability mass functions p, q , $D_{\text{KL}}(p, q) \geq 0$ with equality iff $p = q$.*

Proof. Let A be the support set of p , and let q be a probability mass function whose support

is B .

$$\begin{aligned}
-D_{\text{KL}}(p, q) &= -\sum_{x \in A} p(x) \log_2 \frac{p(x)}{q(x)} && \text{(by definition)} \\
&= \sum_{x \in A} p(x) - (\log_2 p(x) - \log_2 q(x)) \\
&= \sum_{x \in A} p(x) (\log_2 q(x) - \log_2 p(x)) \\
&= \sum_{x \in A} p(x) \log_2 \frac{q(x)}{p(x)} \\
&\leq \log_2 \sum_{x \in A} p(x) \frac{q(x)}{p(x)} && \text{by Jensen's inequality} \\
&\text{(and the equality holds only if } p = q) \\
&= \log_2 \sum_{x \in A} q(x) \\
&\leq \log_2 \sum_{x \in B} q(x) \\
&= \log(1) = 0
\end{aligned}$$

□

Observe now that D_{KL} can be decomposed in terms of cross-entropy and entropy.

Lemma 3 (decomposition). $D_{\text{KL}} = H(p, q) - H(p)$.

Proof.

$$\begin{aligned}
D_{\text{KL}}(p, q) &= \sum_{p_i} (\log_2 p_i - \log_2 q_i) \\
&= -\sum_{p_i} (\log_2 q_i - \log_2 p_i) \\
&= -\sum_{p_i} \log_2 q_i - \sum_{p_i} -\log_2 p_i \\
&= \underbrace{-\sum_{p_i} \log_2 q_i}_{H(p, q)} - \underbrace{-\sum_{p_i} \log_2 p_i}_{H(p)}
\end{aligned}$$

□

With information inequality this easily entails Gibbs' inequality:

Lemma 4 (Gibbs' inequality). $H(p, q) \geq H(p)$ with identity only if $p = q$.

We are done with our theoretical set-up, which is already common knowledge, except presented in an orderly manner in one place. Now we present our argument for the claim that the above entails the propriety of I_{KL} . First, let's systematize the notation. Consider a discretization of the parameter space $[0, 1]$ into n equally spaced values $\theta_1, \dots, \theta_n$. For each i the 'true'

second-order distribution if the true parameter indeed is θ_i —we’ll call it the indicator of θ_i —which is defined by

$$Ind^k(\theta_i) = \begin{cases} 1 & \text{if } \theta_i = \theta_k \\ 0 & \text{otherwise} \end{cases}$$

We will write Ind_i^k instead of $Ind^k(\theta_i)$.

Now consider a probability distribution p over this parameter space, assigning probabilities p_1, \dots, p_n to $\theta_1, \dots, \theta_n$ respectively. It is to be evaluated in terms of inaccuracy from the perspective of a given ‘true’ value θ_k . The inaccuracy of p if θ_k is the ‘true’ value, is the divergence between Ind^k and p .

$$\begin{aligned} I_{KL}(p, \theta_k) &= D_{KL}(Ind^k || p) \\ &= \sum_{i=1}^n Ind_i^k (\log_2 Ind_i^k - \log_2 p_i) \end{aligned}$$

Note now that for $j \neq k$ we have $Ind_j^k = 0$ and so $Ind_j^k (\log_2 Ind_j^k - \log_2 p_j) = 0$. Therefore we continue:

$$= Ind_k^k (\log_2 Ind_k^k - \log_2 p_k)$$

Further, $Ind_k^k = 1$ and therefore $\log_2 Ind_k^k = 0$, so we simplify:

$$= -\log_2 p_k$$

Now, let’s think about expected values. First, what is the inaccuracy of a distribution q as expected by p , $EI_{DK}(p, q)$?

$$\begin{aligned} EI_{DK}(p, q) &= \sum_k k = 1^n p_k I_{DK}(q, \theta_k) \\ &= \sum_{k=1}^n p_k \sum_{i=1}^n Ind_i^k (\log_2 Ind_i^k - \log_2 q_i) \\ &= \sum_{k=1}^n p_k Ind_k^k (\log_2 Ind_k^k - \log_2 q_k) \\ &= \sum_{k=1}^n p_k (-\log_2 q_k) \\ &= -\sum_{k=1}^n p_k \log_2 q_k = H(p, q) \end{aligned}$$

How can we measure the expected inaccuracy of p from its perspective?

$$EI_{DK}(p, p) = -\sum_k k = 1^n p_k \log_2 p_k = H(p)$$

References

9 Evidence aggregation: the simple case - SET ASIDE FOR BOOK

Rational agents are often tasked with aggregating pieces of evidence and assessing their value relative to a hypothesis. In this and the next section, we examine the question of how multiple items of evidence should be evaluated together. This question raises novel difficulties for both precise and imprecise probabilism. We show how higher-order probabilism can handle them.

For the precise probabilist, a natural measure of the value of the evidence is the likelihood ratio. This ratio is relative to a pair of competing hypotheses, say H and its negation $\neg H$ (though the two hypotheses need not be one the negation of the other). Relative to these hypotheses, the likelihood ratio of a single piece of evidence E is the probability of E given H divided by the probability of E given $\neg H$, or in short, $\frac{P(E|H)}{P(E|\neg H)}$. Degrees of evidential value (or support, strength) can be expressed as follows:

the higher $\frac{P(E|H)}{P(E|\neg H)}$ (if greater than one), the more strongly E supports H .

The value of the evidence increases whenever $P(E|H)$ increases or whenever $P(E|\neg H)$ decreases. The higher $P(E|H)$, the better the evidence at tracking H (a true positive); the lower $P(E|\neg H)$, the better the evidence at avoiding $\neg H$ (a true negative). If the probability of E is the same given hypothesis H as given its negation, that is, the likelihood ratio equals one, the evidence would have no value for H .

Likelihood ratios can also be used for assessing the value of multiple pieces of evidence in the aggregate, again relative to a pair of hypotheses of interest. In the simplest case (for more complex cases, see the next section), multiple items of evidence all bear on the same hypothesis. Then, to obtain their combined evidential value, it is enough to multiply their individual likelihood ratios.

$$\frac{P(E_1 \wedge E_2 \dots E_k | H)}{P(E_1 \wedge E_2 \dots E_k | \neg H)} = \frac{P(E_1 | H)}{P(E_1 | \neg H)} \times \frac{P(E_2 | H)}{P(E_2 | \neg H)} \times \dots \times \frac{P(E_k | H)}{P(E_k | \neg H)}$$

The equality holds provided E_1, E_2, \dots, E_k are probabilistically independent conditional on hypothesis H and its negation. Think, for example, at several diagnostic tests performed by independent laboratories or independent witnesses in a trial testifying about the same issue.

To see how likelihood ratios can be deployed, it is worth working through a specific case. In a murder case, the police recover two items of trace evidence, both against the defendant. First, hair found at the crime scene matches the defendant's hair; call this evidence 'hair.' Second, the fur of the defendant's dog matches the fur found in a carpet wrapped around one of the bodies; call this evidence 'fur.'³⁵ The two matches favor the hypothesis that the defendant (and the defendant's dog) must be the source of the crime traces; call this hypothesis 'source'. If the two matches are independent lines of evidence (conditional on the source hypothesis and its negation), their likelihood ratios can be multiplied:

$$\frac{P(\text{fur} \wedge \text{hair} | \text{source})}{P(\text{fur} \wedge \text{hair} | \neg \text{source})} = \frac{P(\text{fur} | \text{source})}{P(\text{fur} | \neg \text{source})} \times \frac{P(\text{hair} | \text{source})}{P(\text{hair} | \neg \text{source})}$$

So far so good. But how do we fill in the precise probabilities? The numerators can be equated to one: if the defendant is a contributor, the laboratory will declare a match for sure. This is a simplification, but it will do for our purposes. To fill in the denominators, a trial expert will provide so-called match probabilities. They express the likelihood that, by coincidence,

³⁵The hair evidence and the dog fur evidence are stylized after two items of evidence in the notorious 1981 Wayne Williams case (Deadman, 1984b, 1984a).

a random person (or a random dog) who is not a contributor would still match. The match probabilities are approximated by counting how many matches are found in a representative sample of the human population (or the canine population). Suppose the matching hair type occurs 0.0253 times in a reference database, and the matching dog fur type occurs 0.0256 times in a reference database (more on how these numbers are calculated soon). These frequencies can fill in the match probabilities. Putting everything together:

$$\frac{P(\text{dog}|\text{source})}{P(\text{dog}|\neg\text{source})} \times \frac{P(\text{hair}|\text{source})}{P(\text{hair}|\neg\text{source})} = \frac{1}{0.0252613} \times \frac{1}{0.025641} = 1543.862069$$

The resulting ratio is large. The two matches, combined, strongly favor the source hypothesis.

This is the story about evidence aggregation told by the precise probabilist. But this story misses something crucial. As it happens, the match probability for hair evidence is based on 29 matches found in a sample database of size 1148, while the match probability for the dog evidence is based on finding two matches in a smaller database of size 78. The relative frequencies are about .025 in both cases, but the two samples differ in size. The smaller the sample, the greater the uncertainty about the match probabilities. So, for individual pieces of evidence, simply reporting the exact numbers makes it seem as though the evidential value of the matches is the same, but actually, it is not.³⁶ In the aggregate, multiplying the individual likelihood ratios further washes away this difference.

A better alternative is easily available: the evaluation of multiple items of evidence should take into account higher-order uncertainty. Figure 5 (upper part) depicts higher-order probability distributions of different match probabilities given the sample data—the actual number of matches found in the sample databases. As expected, some random match probabilities are more likely than others, and since the sizes of the two databases are different, the distributions have different spreads: the smaller the database the greater the spread, the greater the uncertainty about the match probability. In light of this, Figure 5 (lower part) depicts the probability distribution for the joint match probability associated with both items of match evidence, hair and fur evidence. The aggregate value of the two pieces of match evidence, then, is given by a distribution over possible likelihood ratios. The shape of this distribution conveys the degree of higher-order uncertainty about the value of the aggregate evidence. **Marcello (Rafal/Nikodem to add): Can we have a formula for how the two matches are combined in the higher-order approach? In precise probabilism, you multiply the individual LRs, in higher-order probabilism, what do we do formally? Can we also have a distribution of likelihood ratios? What happens if both the numerator and denominator in the LR are distributions?**

add distributions of LRs figure

³⁶The match probabilities in the Wayne Williams case on which our running example is based were 1/100 for the dog fur, and 29/1148 for Wayne Williams' hair. Match probabilities have been slightly but not unrealistically modified to be closer to each other in order to make a conceptual point: the same first-order probabilities, even when they sound precise, may come with different degrees of second-order uncertainty.

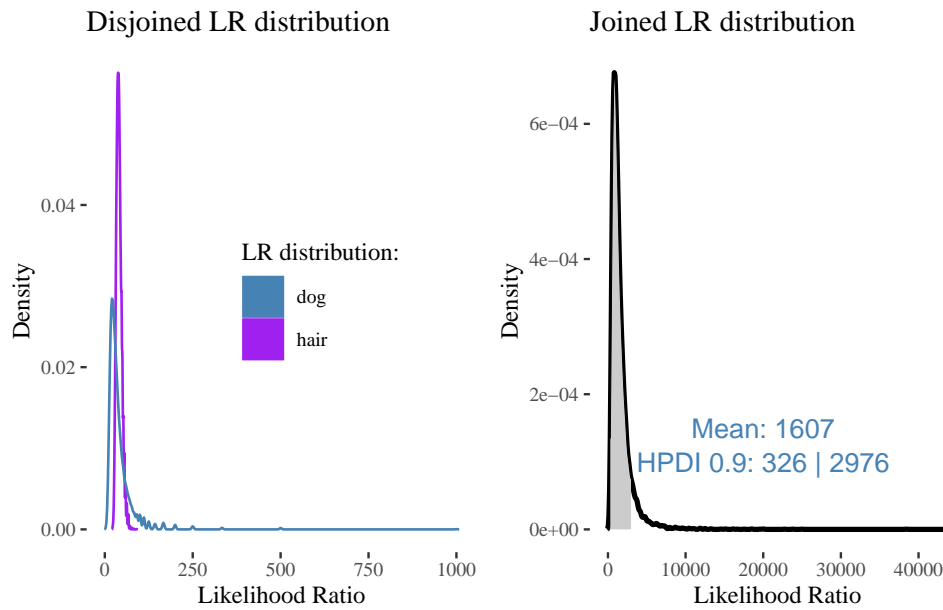


Figure 9: Distributions of dog and hair likelihood ratios and the resulting joint likelihood ratio. Created with the samples from beta distributions. Shaded area on the second one represents HPDI with 0.9 credibility.

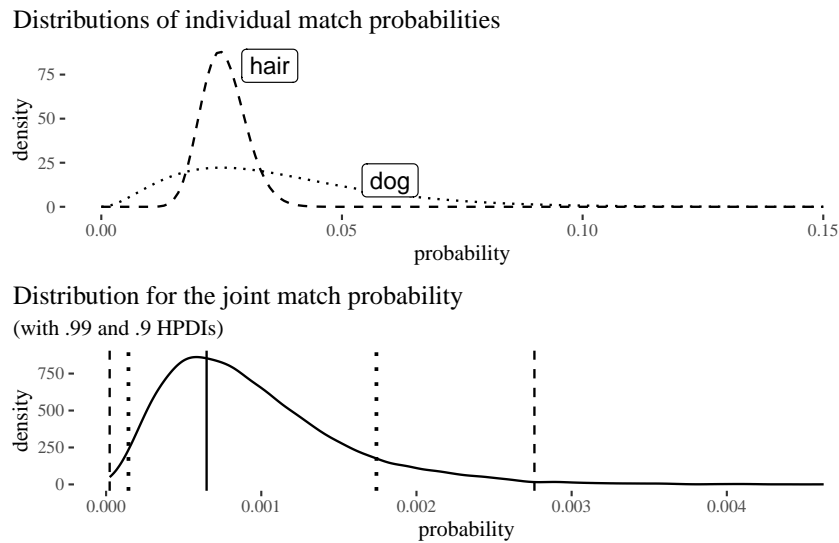


Figure 10: Beta densities for individual items of evidence and the resulting joint density with .99 and .9 highest posterior density intervals, assuming the sample sizes as discussed and independence, with uniform priors.

The precise probabilist might insist that the value of the evidence—one item or multiple items of evidence—is naturally captured by a precise likelihood ratio. In our running example, this ratio equals one over the first-order match probability, and our best assessment of this first-order probability is still the relative frequency of matches found in the database, whether large or small. If this is right, our best assessment of the match probabilities for both fur and hair evidence should be about .025, based on the relative frequencies 2/78 and 29/1148. If we were to bet whether a dog or a human picked at random would have the matching fur or hair type, our odds should be .025 no matter the size of the database. This argument has some bite when

evaluating single items of evidence. In fact, the expected values of the match probabilities for hair and match evidence—based on the higher-order distributions in Figure 5 (upper part)—still end up being about .025. If, as the precise probabilist assumes, first-order probabilities are all we should care about, going higher-order would seem a needless complication.

This line of reasoning, however, breaks down when evaluating two or more items of evidence. What should our betting odds be for the proposition that a human and a dog, both picked at random, would have the matching fur and hair type in question? For the precise probabilist, the answer is straightforward: on the assumption of independence, it is enough to multiply the .025 individual match probabilities and obtain a joint match probability of 6.4772626×10^{-4} . The higher-order probabilist will proceed differently. In assessing first-order match probabilities, they will retain information about higher-order uncertainty as much as possible. This can be done in two steps: first, aggregate the higher-order distributions for the two-match probabilities and obtain a higher-order probability distribution for the joint match probability (see Figure 5); next, to obtain our best assessment of the first-order joint match probability, take the expected value of this latter distribution. The higher-order probabilist will assign 9.381365×10^{-4} to the joint match probability, a value greater than what the precise probabilist would assign.

So, the higher-order and precise probabilist will disagree about the betting odds for the proposition that a human and a dog, both picked at random, would have matching fur and hair type. The disagreement will become even starker as a larger number of independent items of evidence are evaluated.³⁷ Who should be trusted? Since the higher-order probabilist takes into account more information—that is, the higher-distributions—there is good reason to think that the higher-order probabilist should be trusted more than the precise probabilist.³⁸

Imprecise probabilism will also run into its own problems when assessing the value of aggregate evidence. Recall that the probability measures in the representor set are those compatible with the evidence. The problem is that almost any random match probability will be compatible with any sample data—with any number of matches found in a reference database. This point should be familiar from the earlier discussion. Think by analogy to coin tossing: even a coin that has a .99 bias toward tails could come up heads on every toss. This series of outcomes is unlikely but possible. Similarly, a hair type that has a match probability extremely small could still be found several times in a sample population. So, it is not clear how to proceed if one takes seriously the binary notion of compatibility. Imprecise probabilism is too permissive because almost any match probability will be compatible with the data.

Another option for the imprecise probabilist is to rely on reasonable ranges of match probabilities. Suppose these ranges are (.015,.037) (.002, .103), for hair and fur evidence respectively in our original case.³⁹ As expected, the range is wider for dog fur match evidence than

³⁷Consider the simple case of independent items of evidence whose individual match probabilities are .025.

For three, five and seven items of evidence, the joint match probabilities would be: 1.25×10^{-4} , 3.125×10^{-7} and 7.8125×10^{-10} (for the precise probabilist) and 5.3363868×10^{-4} , 1.6754185×10^{-5} and 9.9986742×10^{-7} (for the higher-order probabilist, based on small databases of size 20).

³⁸As a further illustration of this point, consider a couple of variations of our running example. First, suppose the match probabilities associated with two matches are both set to .05 since they are based on the following relative frequencies: one match occurs in a dog fur database and one match occurs in a human hair database, where both databases are small, say of size 20. By multiplying the individual $1/.05$ likelihood ratios associated with the two matches, their evidential value against the defendant would seem quite strong: $1/.05 \times 1/.05 = 400$. However the match probabilities are based on frequencies resulting from small databases, so their evidential value should be rather weak. Precise probability here seems to exaggerate the aggregate value of the evidence. Following higher-order probabilism, the joint likelihood ratio would be 237.8675988, a significantly smaller value. On the other hand, if the same .05 match probabilities were based on larger databases, the evidential value of the two matches should be correspondingly greater, but precise probabilism would make no difference. If, for example, 1,000 hair and fur matches are found in databases of size 20,000, the higher-order probabilist would assign 441.2059925 to the joint likelihood ratio, a much greater value than before. This outcome agrees with our intuitions.

³⁹These are 99% credible intervals starting with uniform priors. A 99% credible interval is the narrowest interval

hair match evidence: the uncertainty about the dog fur match probability is greater since the sample database was smaller. This is a desirable feature of the interval approach. Now, to assess the joint uncertainty, it is enough to focus on what happens at the edges of the two intervals. Reasoning with representor members at the edges of the intervals will yield the most extreme probability measure the impreciser is committed to, the worst-case and best-case scenarios. We end up with a new range for the joint match probabilities, (.00003, .003811).⁴⁰ The corresponding likelihood ratios could be as high as 3.333333×10^4 or as low as 262.3983. The two matches could be much stronger or much weaker evidence than previously thought.

Using plausible ranges for the match probabilities leaves the impression that any value in the interval is just as good as any other. Perhaps we should pick the middle value as representative of the interval. However, relying on the entire interval or the middle value will misrepresent the evidence. To see why, consider again Figure 5 (lower part) which depicts the probability distribution for the joint match probability. Interestingly, this distribution is not symmetric. So the most likely value (and the bulk of the distribution, really) does not lie in the middle between the edges. Therefore, only relying on the edges—or taking central values as representative of the interval—can lead to overestimating or underestimating the probabilities at play.⁴¹

Another problem in taking intervals as representative of the value of the evidence is that they will tend to widen as more items of evidence are evaluated. The size of the likelihood ratio interval was initially 39.64 (hair evidence) and 490.29 (fur evidence). After aggregating the two items of evidence, the likelihood ratio interval widened to 3.3070935×10^4 . The size of the match probability interval was initially -0.022 (hair evidence) and -0.101 (fur evidence). After aggregating the two items of evidence, the match probability interval narrowed to -0.003781. Posterior interval (starting with 1:1 prior odds) was initially 0.0209015 (hair evidence) and 0.0913857 (fur evidence). After aggregating the two items of evidence, the posterior interval narrowed to 0.0037665.

All in all, precise and imprecise probabilism does not fare well in modeling the value of evidence in the aggregate. Instead, the evaluation of multiple items of evidence should take into account higher-order uncertainty (as illustrated in Figure 5). Whenever probability distributions for the probabilities of interest are available (and they should be available for match evidence and many forms of scientific evidence whose reliability has been studied), those distributions should be reported for assessing the value of the evidence. This approach avoids hiding actual aleatory uncertainties under the carpet. It also allows for a more balanced assess-

LR intervals widen but match and posterior probability intervals do not? How does that work? How can we claim that uncertainty increases?

to which the expert thinks the true parameter belongs with probability .99. For a discussion of what credible intervals are, how they differ from confidence intervals, and why confidence intervals should not be used, see Kruschke (2015).

⁴⁰Redoing the calculations using the upper bounds of the two intervals, .037 and .103, yields the following:

$$P(\text{dog} \wedge \text{hair} | \neg \text{source}) = .037 \times .103 = .003811.$$

This number is around 5.88 times greater than the original estimate. Given this number, the two matches are much weaker evidence for the source hypothesis than previously thought. The calculation for the lower bounds, .015 and .002, yields the following:

$$P(\text{dog} \wedge \text{hair} | \neg \text{source}) = .015 \times .002 = .00003$$

This number is around 0.46 times lower than the original estimate. Given this number, the two matches are much stronger evidence for the source hypothesis than previously thought.

⁴¹The calculations for the joint interval assume that because the worst- or best-case probability for one event is x and the worst- or best-case probability for another independent event is y , the worst- or best-case probability for their conjunction is xy . However, this conclusion does not follow if the margin of error (credible interval) is fixed. Just because the probability of an extreme value x for one variable X is .01, and so it is for the value y of another independent variable Y , it does not follow that the probability that those two independent variables take values x and y simultaneously is the same. In general, it is impossible to calculate the credible interval for the joint distribution based solely on the individual credible intervals corresponding to the individual events.

ment of the evidence, whereas using point values or intervals may exaggerate or underestimate the value of the evidence.

A couple of clarifications are in order. First, the problem we are highlighting is not confined to match evidence. Say an eyewitness testifies against the defendant: they saw the defendant near the crime scene at the relevant time. To assess the value of this testimony, one should know something analogous to the match probability: if the defendant was not there, how probable is it that the witness would still say the defendant was there? Or suppose a medical test for a disease turns out positive. Here again, to assess the evidential value of the positive test, one should know how probable it is that the test would still turn out positive even when a patient is actually negative. And so on. These false positive probabilities are usually derived from sample-based frequencies in surveys or experiments: how often witnesses misidentify people; how often tests misdiagnose; etc. So, depending on the sample size, the false positive probabilities will have different degrees of uncertainty, and the latter should be taken into account when evaluating eyewitness testimonies, diagnostic test results, and many other forms of evidence. At the same time—and this is the second clarification—this discussion is not meant to suggest that the problem we are highlighting is confined to differences in sample size; it is broader than that. Probabilities can be subject to uncertainty for other reasons, for example, when they are derived from a probability model for which there is little support, or when the sample size is large but unrepresentative. So, in short, the problem of higher-order uncertainty is widespread and goes beyond match evidence and questions of sample size.

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