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Position paper

An argument against presenting interval quantifications as a surrogate for the value of evidence☆

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ABSTRACT

In the various forensic science disciplines, recent analytical developments paired with modern statistical computational tools have led to the proliferation of adhoc techniques for quantifying the probative value of forensic evidence. Many legal and scientific scholars agree that the value of evidence should be reported as a likelihood ratio or a Bayes Factor. Quantifying the probative value of forensic evidence is subjected to many sources of variability and uncertainty. There is currently a debate on how to characterize the reliability of the value of evidence. Some authors have proposed associating a confidence/credible interval with the value of evidence assigned to a collection of forensic evidence. In this paper, we will discuss the reasons for our opinion that interval quantifications for the value of evidence should not be used directly in the Bayesian decision-making process to determine the support of the evidence for one of the two competing hypotheses.

1. Introduction

In order to provide context for the presentation of our views on the reasonableness of using intervals for quantifying the value of evidence, we will discuss the structure of the forensic identification of source problem as we typically encounter it. This includes defining the following elements: the structure of the evidence (Section 2.1), the forensic hypotheses under consideration (Section 2.2), the data generating process for the evidence (Section 2.3), and the various methods of quantifying the value of evidence (Sections 2.4, 3, and 4).

In the introduction paper by Morrison [1], there is a list of different types of uncertainty and variability that may be considered when quantifying the value of evidence. For the purpose of the discussion, we will group together the "intrinsic variability at the source", "variability in sampling the relevant population", and "variability in sampling the known source" into *sampling variability of the sources* and discuss the various issues with interval methods used to capture these types of variability in Section 5.2. We will also consider interval methods used to capture the "variability in the statistical modeling technique employed" which we interpreted to mean the *variability due to numerical techniques* in Section 5.1. Finally, we consider the "variability due to modeling assumptions" and the use of sensitivity analysis (as opposed to intervals) to examine this type of variability in Section 5.3. We recognize that the data generating processes described in this paper can be extended to include "variability in the transfer process" or "variability in the measurement technique employed," although we will not explicitly include these in our discussion.

A major concern that we have with using intervals as surrogates for the value of evidence is whether or not it is possible to obtain an admissible decision rule for deciding between the prosecution and defense hypotheses. This is fundamentally a frequentist concern, and is outside the scope of this discussion under the Bayesian paradigm.

2. Forensic identification of source

2.1. The evidence

In the forensic identification of source problem, the evidence can generally be decomposed into three different subsets of observations. The first subset of the evidence is associated with the population of alternative sources (sometimes called the background database/population) and will be denoted e_a. The second subset of the evidence is associated with the trace material recovered from the crime scene, and typically its source is unknown. This subset will be denoted e_u. The third subset of the evidence is associated

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with control material taken from a known specific source, typically the suspect, and it will be denoted e_s. The collection of all the evidence will be denoted by $e = \{e_a, e_u, e_s\}$.

2.2. The hypotheses

A common question regarding the forensic identification of source problem that is asked is:

"Does the trace material originate from the known specific source or from some other source in the alternative source population?"

Directly related to this question is a set of forensic hypotheses. The first hypothesis is often referred to as the prosecution hypothesis (denoted H_p), and the second is referred to as the defense hypothesis (denoted H_d). For the forensic hypotheses related to the question posed above, H_p states that the trace and the control samples were both generated by the specific source, and H_d states that the trace was not generated by the specific source, but by some other source in the relevant alternative source population.

2.3. Data generating process

The data generating process for the subsets of the evidence described above must be specified in order to ultimately compute the value of evidence. These assumptions will be described in a traditional sampling framework [2], although they will also imply a corresponding set of exchangeability assumptions made under a fully Bayesian framework. The data generating process for the forensic identification of source problems suggests that each subset of the evidence is generated as a random sample from a population which can be modeled with a parametric family of distributions characterized by a (unknown) set of parameters. We will denote the full set of parameters indexing the parametric family of distributions for the entire set of evidence e as θ, and when the values of θ are known, this set of values will be denoted θ_0. Once the parametric family of distributions for each subset of the evidence has been chosen, then the likelihood functions, denoted by f, for the subsets of the evidence have been determined.

For the hypotheses described above, the subsets of the evidence $e = \{e_a, e_u, e_s\}$ are three independent samples drawn in the following way:

1. e_a is constructed by first taking a simple random sample of sources from a given relevant population of alternative sources; then from each sampled source we have a simple random sample. Let θ_a denote the parameters necessary to describe this sampling-induced distribution.
2. e_u is a simple random sample from a single source.
3. e_s is a simple random sample from a given specific source. Let θ_s denote the parameters necessary to describe this sampling-induced distribution.

Under H_p the source of e_u is the specific source from 3. and the sampling distribution of e_u is characterized by the parameters θ_s. This statement in combination with the data generating process described in points 1.–3. above will be denoted M_p. Under H_d, e_u arises from a randomly selected source in the alternative source population and the sampling distribution of e_u is characterized by the parameters θ_a. This statement in combination with the data generating process described in 1. - 3. above will be denoted M_d.

The application of Bayesian methods to these problems requires that the prior probability densities for the parameters be specified; one summarizing our belief about the values of the parameters for the specific source data generating process, $\pi(\theta_s)$, and another summarizing our prior belief about the values of the parameters for the alternative source population data generating process, $\pi(\theta_a)$.

2.4. Quantifying the value of evidence

Under the Bayesian framework, the forensic statistician is tasked with providing the value of evidence that is used to update a prior belief structure concerning the two competing hypotheses. Traditionally, the value of evidence is used to convert the prior odds to posterior odds as follows:

$$\underbrace{\frac{P(H_p|e,I)}{P(H_d|e,I)}}_{\text{Posterior Odds}} = \underbrace{\frac{P(e|H_p,I)}{P(e|H_d,I)}}_{\text{Value of Evidence}} \times \underbrace{\frac{P(H_p|I)}{P(H_d|I)}}_{\text{Prior Odds}}, \tag{1}$$

where e is the realization of the evidence, I is the relevant background information common to both hypotheses, H_p and H_d, and P is some probability measure. The value of evidence is typically known as a "Bayes Factor" in the statistics community and a "likelihood ratio" in the forensic science community [3]. However, we consider the Bayes Factor and likelihood ratio to be two distinct quantities. In particular, when the values of the parameters for the data generating processes are known with certainty, the value of evidence takes the form of the likelihood ratio, which will be described in detail in Section 3. When there is uncertainty concerning the values of the parameters, other strategies need to be used to quantify the value of evidence. One of the commonly used strategies takes the form of the Bayes Factor, described in detail in Section 4.

3. The likelihood ratio

We define the likelihood ratio function as

$$\lambda_{e_u}(\theta) = \frac{f(e_u|\theta, M_p)}{f(e_u|\theta, M_d)}, \tag{2}$$

which is a function of the unknown parameters indexing the data generating process. When there is no uncertainty about the parameters of the data generating process, the likelihood ratio is

$$\lambda_{e_u}(\theta_0) = \frac{f(e_u|\theta_0, M_p)}{f(e_u|\theta_0, M_d)}, \tag{3}$$

and represents a single value of the likelihood ratio function for the specified values of θ. Indeed, the likelihood structure, denoted f, and the values of the parameters, denoted θ_0, for these models need to be known with complete certainty to compute the likelihood ratio [4,5]. The exact form of the likelihood ratio for the identification of source problem described in Section 2 is presented below.

3.1. Specific source likelihood ratio

Under H_p, the unknown source evidence is characterized by the same model and parameters characterizing e_s. Therefore, the numerator of the likelihood ratio, denoted $\lambda_{e_u}(\theta_0)$ below, will be the likelihood of observing e_u given that the value of the parameter θ_s is θ_{s_0}. Similarly, under H_d, e_u is characterized by the same model and parameters as that of e_a. Therefore, the denominator will be the likelihood of observing e_u given that the value of the parameter θ_a is θ_{a_0}. The likelihood ratio

$$\lambda_{e_u}(\theta_0) = \frac{f(e_u|\theta_{s_0})}{f(e_u|\theta_{a_0})}, \tag{4}$$

when it can be determined, is fixed and everyone with comparable beliefs would agree that it is the value of evidence that should be used in Eq. (1). It should be noted that this likelihood ratio is rarely attainable in practice, and some choose to estimate it using various techniques. Typical adhoc methods are based on using maximum likelihood estimates, restricted maximum likelihood estimates, or combining the likelihood ratio function with a posterior distribution for θ to obtain a posterior distribution for the likelihood ratio [6,7]. When it is approximated, it is reasonable to consider whether or not intervals should be used to characterize the various forms of variability and error associated with the approximated quantity. Additionally, when it is approximated, any decision based on the resulting posterior odds will only be approximately "correct" in a logical and coherent sense [5].

4. The Bayes Factor

Instead of estimating the likelihood ratio, it is possible to integrate out the uncertainty on θ using a formal Bayesian quantification of the value of evidence with respect to a given prior belief structure[8]. The Bayes Factor is

$$V(e) = \frac{\int f(e|\theta, M_p) d\Pi(\theta|M_p)}{\int f(e|\theta, M_d) d\Pi(\theta|M_d)} \tag{5}$$

where Π denotes the probability measure corresponding to the subjective prior belief, with density π, described in Section 2.3. A more concise form of the Bayes Factor under the identification of source setting described in Section 2 is given in the following subsection. The form presented below will only involve evaluating the likelihood of the unknown source evidence instead of the entire set of evidence, however, the derivation of this form requires stringent assumptions on the priors for the values of the parameters.

4.1. Specific source value of evidence

Let $\Pi(\theta) = \Pi(\theta_s)\Pi(\theta_a)$ be the probability distribution used to describe the prior belief about θ which will characterize any uncertainty regarding the fixed, but unknown, values of the parameters. Note that we are choosing to restrict the prior distributions on θ_s and θ_a to be *independent of each other*. This means that the belief about the parameters for the alternative source population does not affect the belief about the parameters for the specific source.

$$\begin{aligned} V(e) &= \frac{\int f(e|\theta, M_p) d\Pi(\theta|M_p)}{\int f(e|\theta, M_d) d\Pi(\theta|M_d)} \\ &= \frac{\int f(e_u|\theta_s) f(e_s|\theta_s) d\Pi(\theta_s)}{\int f(e_s|\theta_s) d\Pi(\theta_s)} \times \frac{\int f(e_a|\theta_a) d\Pi(\theta_a)}{\int f(e_a|\theta_a) f(e_u|\theta_a) d\Pi(\theta_a)} \\ &= \int f(e_u|\theta_s) \frac{f(e_s|\theta_s)}{\int f(e_s|\theta_s)\pi(\theta_s) d\theta_s} d\Pi(\theta_s) \bigg/ \int f(e_u|\theta_a) \frac{f(e_a|\theta_a)}{\int f(e_a|\theta_a)\pi(\theta_a) d\theta_a} d\Pi(\theta_a) \\ &= \frac{\int f(e_u|\theta_s) d\Pi(\theta_s|e_s)}{\int f(e_u|\theta_a) d\Pi(\theta_a|e_a)} \end{aligned}$$

The specific source Bayes Factor given below, when it can be exactly evaluated,

$$V(e) = \frac{\int f(e_u|\theta_s) d\Pi(\theta_s|e_s)}{\int f(e_u|\theta_a) d\Pi(\theta_a|e_a)} \tag{6}$$

can be used directly to update the prior odds in Eq. (1).[1] It should be noted that this Bayes Factor is rarely attainable in practice, and it is typically approximated using Markov Chain Monte Carlo (MCMC) and/or other techniques. When using MCMC techniques it is natural to consider the numerical imprecision associated with the approximate value of evidence. Additionally, using an MCMC approximation of the Bayes Factor in Eq. (1) will lead to a decision that is only approximately "correct" in the Bayesian framework.

4.2. Comparing the Bayes Factor to the likelihood ratio

The likelihood ratio function and the Bayes Factor are two distinct strategies designed to handle the uncertainty with the parameters of the data generating process. For a given data generating process, the variability of the resulting value of the likelihood ratio depends on the estimation techniques for θ_0, while the variability between resulting Bayes Factor values will depend upon the use of different prior belief structures and numerical approximations of the integrals.

In most situations, the Bayes Factor is distinct from the likelihood ratio since the construction of the likelihood ratio only involves the data generating process, whereas the construction of the Bayes Factor also involves the prior belief structure. The likelihood ratio is a fixed value of the likelihood ratio function determined by the known parameter values that characterize the relevant background population and the population of traces associated with the specific source. When there is uncertainty about the values of the parameters, the likelihood ratio function can be used to obtain an adhoc approximation of the likelihood ratio.

The Bayes Factor is an alternative method to the approximations based on the likelihood ratio function which accounts for these unknown parameter values under each model independently by integrating the joint likelihood of the evidence with respect to the prior on the unknown parameters. In effect, the Bayes Factor is comparing the marginal "likelihood" of the evidence given the prosecution model with the marginal "likelihood" of the evidence given the defense model. When the values of the parameters are known, then the Bayes Factor (constructed using an appropriate prior on θ) and the likelihood ratio are equal, and both are equivalent to the value of evidence in Eq. (1).

5. Using intervals for quantifying the value of evidence

5.1. Using intervals for capturing variability due to numerical techniques

The error due to the numerical techniques used to compute the value of evidence is an important type of information that should be presented to a decision-maker. For instance, consider the typical situation in which a Monte Carlo integration technique is used to calculate the values of the integrals in the numerator and denominator of Eq. (6), ultimately arriving at an approximated value for the Bayes Factor [9]. The associated Monte Carlo Standard Error (MCSE) for the Bayes Factor is an estimate of the numerical precision in the overall approximated value, and can be controlled by increasing the size of the generated sample in the algorithm. It may be reasonable to consider presenting an interval for the Bayes Factor to the decision-maker that characterizes the numerical imprecision associated with the Bayes Factor. A normal based approximation to this 95% confidence interval would take the form

$$\left[\hat{V} - 1.96\varepsilon, \hat{V} + 1.96\varepsilon\right], \tag{7}$$

where $\hat{V}$ denotes the approximate Bayes Factor and ε denotes the corresponding MCSE. However, we do not recommend presenting this type of interval to a decision-maker. Ideally, this approximated value for the Bayes Factor would not be presented to the decision-maker unless the associated MCSE was sufficiently small, thus ensuring that $\hat{V}$ is a computationally reliable estimate of V. Therefore, we recommend that $\hat{V}$ and the estimate of ε be presented instead of the interval. If the value of

[1] The updated posterior odds can be used to make a statistically admissible decision with respect to an appropriate loss function [4,5].

ε is significantly larger than a tolerance deemed appropriate by a decision-maker, then the decision-maker could choose to request that the statistician recompute the approximate value of evidence in such a way as to obtain a more numerically precise result. To the best of our knowledge, accurately estimating the overall amount of numerical imprecision in a Monte Carlo approximation of the Bayes Factor is an open research problem. However, we still think that it is an important measure of variability that needs to be presented to a decision-maker. We also believe this idea can easily be transferred to other types of numerical techniques as well.

5.2. Concerns about intervals for capturing sampling variability from the sources

There are two types of intervals for capturing sampling variability from the sources that will be discussed in this section, intervals for the Bayes Factor and intervals for the likelihood ratio. First, we will consider the use of intervals for the Bayes Factor. As discussed by Taroni et al. [10], because the Bayes Factor already incorporates the uncertainty associated with the unknown parameters into the final assessment of the evidence, it is clearly redundant to include an interval estimate for the Bayes Factor. Therefore, we agree with this opinion that intervals should not be used to characterize this type of uncertainty associated with the Bayes Factor. Next, we will focus on interval estimates for the likelihood ratio.

Some researchers have suggested using various credible or confidence intervals for the likelihood ratio [11–13]. Some examples of credible intervals include the highest posterior density, equal tails, and approximate normal posterior interval constructions presented in [6,11]. It is unclear whether the entire interval, although informative, can be used in the Bayesian paradigm to make a logical and coherent decision. As we understand the problem, there are three possible single-value representations of the interval that can be considered as surrogates for the value of evidence in the decision process: the endpoint of the interval closer to one, the lower (or upper) endpoint of the interval, or the midpoint of the interval. To thoroughly exhaust the options, we will consider the issues related to each one of these representations in succession (although we admit that there may not be any strong proponents of each of these methods).

First, it can easily be shown that using the lower (or upper) endpoint of the interval as a surrogate for the value of evidence will lead to an incoherent decision process. Next, consider using the endpoint of the interval for the likelihood ratio that is closer to one as a surrogate for the value of evidence. When the bounds on the interval are below one, then this decision rule will be biased in favor of the prosecution. When the bounds on the interval are greater than one, then this decision rule will be biased in favor of the defense. Because using various endpoints of the presented interval results in either an incoherent or a biased decision process, consider using the midpoint of the interval as a surrogate for the value of evidence. A typical way of presenting an interval for the likelihood ratio is to find a point-estimate of the likelihood ratio plus or minus some number of standard errors of the point-estimate [12]. In the context of using a posterior distribution for the likelihood ratio, as mentioned in Section 3, the interval will take the form of the estimate of the mean for this posterior distribution plus or minus some number of posterior standard deviations. Generally, the posterior mean of the likelihood ratio, which is expressed in the equation below, will tend to be very close to the midpoint of any reasonable interval.

$$E(\lambda_{e_u}(\theta)|e_s, e_a) = \int \lambda_{eu}(\theta)\, d\Pi(\theta|e_s, e_a) \tag{8}$$

In general, it is easier to work with the posterior mean of the likelihood ratio than the midpoint of the credible interval.

One of the major concerns we have with using the midpoint of intervals as surrogates for the value of evidence is the relationship between the posterior mean of the likelihood ratio and the Bayes Factor. To illustrate this concern, consider the inequality below, which results from an application of Jensen's inequality, showing the comparison of the posterior mean of the likelihood ratio to the Bayes Factor for the identification of source problem described in Section 2.

$$\begin{aligned}\int \lambda_{e_u}(\theta)d\Pi(\theta|e_s,e_a) &= \int\int \frac{f(e_u|\theta_s)}{f(e_u|\theta_a)}d\Pi(\theta_a|e_a)d\Pi(\theta_s|e_s)\\ &= \int f(e_u|\theta_s)d\Pi(\theta_s|e_s)\int \frac{1}{f(e_u|\theta_a)}d\Pi(\theta_a|e_a)\\ &\geq \int f(e_u|\theta_s)d\Pi(\theta_s|e_s)\frac{1}{\int f(e_u|\theta_a)d\Pi(\theta_a|e_a)}\\ &= V(e)\end{aligned}$$

This result shows that when the posterior mean for the likelihood ratio, which is also a formal estimate of the likelihood ratio, is used to quantify the value of evidence, it will overstate the value of evidence against the suspect. This suggests that if a decision-maker is presented with a credible interval for the likelihood ratio and uses the midpoint of the interval as a surrogate for the value of evidence, the resulting decision will tend to be systematically biased in favor of the prosecution.

Thus, if an interval for the likelihood ratio is solely presented to a decision-maker, any decision based on a single value representation of that interval will be either biased or incoherent. We do not believe that it is appropriate to knowingly present a result that is systematically biased in favor of the prosecution (or in favor of the defense), regardless of the degree of bias. This becomes especially important when the value of many types of evidence are combined into an omnibus value of evidence using tools such as Bayesian networks [14,15], where a systematic bias at each node will compound the overall bias. In conclusion, we do not recommend presenting only an interval for the likelihood ratio to a decision-maker.

5.3. Concerns with intervals for capturing variability due to modeling assumptions

A reasonable question to ask when presented with a value of evidence is, “What is the range of reasonable values for the value of evidence that other experts may present given the same evidence?” Other experts may use a different parametric family for the data generating process, or may use other types of priors for the values of the parameters. How sensitive the value of evidence is to differences in these assumptions tends to fall under the umbrella of sensitivity analysis. To conduct a rigorous formal Bayesian sensitivity analysis, the expert would require some basic knowledge about the priors for the parameters that other experts tend to use (which is likely outside the scope of the relevant expertise of a typical forensic expert). Additionally, we do not suggest presenting intervals to a decision-maker for capturing this type of variability since the results of sensitivity analyses are typically more complex than can be expressed through an interval.

6. Recommendations

Our foremost recommendation is that when presenting forensic evidence to a decision-maker, a single value of evidence needs to be presented from which a logical and coherent decision can be made regarding the two competing hypotheses/models. This single value of evidence can be either a Bayes Factor, a likelihood ratio, or an appropriate approximation of one of these two quantities, but the report needs to explicitly state which quantity is being used.

If the exact Bayes Factor or likelihood ratio cannot be determined for a particular case, then the resulting approximate value of evidence should not be presented as if there is no uncertainty or variability associated with it. If a Bayes Factor is reported, our suggestion is to always present the approximate value of evidence as a single number together with the corresponding estimate of numerical precision to a decision-maker. The first step for the decision-maker should be to use the numerical precision to determine if the value of evidence is reliable, as discussed in Section 5.1. If it is reliable, then the second step should be to make a decision based solely on the value of evidence since any decision based on the value of evidence will be appropriate (i.e. approximately correct).

An interval for the likelihood ratio should not be presented to the decision-maker as a reasonable surrogate for the value of evidence since any decision based on the interval will be either incoherent or biased. First, it is unclear how the interval itself can be used to make a logical and coherent decision under the Bayesian framework. Any decision based on an endpoint of the interval is going to lead to incoherency or bias. Additionally, the midpoint of an interval should not be used as the basis for decision-making since most decisions based on it will be systematically biased against the suspect.

If a sensitivity analysis is required, the results should be reported using a variety of appropriate metrics, as opposed to a single interval for the value of evidence, since these types of analyses are quite complex in nature.

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