Evaluation and reporting of scientific evidence: the impact of partial probability assignments

La valutazione dell'evidenza scientifica: assegnazioni di probabilità parziali

Silvia Bozza, Alex Biedermann, Franco Taroni

Abstract The assessment of the value of scientific evidence can be performed by the derivation of a likelihood ratio, a rigorous concept that provides a measure of the change produced by an item of information in the odds in favor of a proposition as opposed to another. This represents a demanding task with several sources of uncertainty, due for example to elicitation of probabilities or to computational impasses. While use of such a metric is well established and supported by operational standards, opinions about what should be an appropriate way to deal with such sources of uncertainty while presenting expressions of evidential value at trial differ. Some quarters promote positions according to which practitioners should state a range of values for the probabilities of the evidence given competing propositions, and report a range of values for the likelihood ratio. However, such partial probability assignments may not make good use of available information.

Abstract La valutazione del valore delle prove scientifiche può essere eseguita attraverso il rapporto di verosimiglianza, un concetto rigoroso che fornisce una misura del cambiamento prodotto da un elemento di prova nelle probabilità a favore di una proposizione rispetto ad un'altra. Questo rappresenta un compito impegnativo con diverse fonti di incertezza, dovute ad esempio alla necessità di assegnare valori di probabilità o a difficoltà computazionali. Mentre l'uso di tale metrica è ben consolidato e supportato da standard operativi, vi sono opinioni discordanti su quale dovrebbe essere il modo più appropriato per affrontare tali fonti di incertezza

University of Lausanne, School of Criminal Justice, 1015 Lausanne-Dorigny, Switzerland e-mail: franco.taroni@unil.ch



Silvia Bozza

Ca'Foscari University of Venice, Department of Economics, 30121 Venice, Italy University of Lausanne, School of Criminal Justice, 1015 Lausanne-Dorigny, Switzerland e-mail: silvia.bozza@unive.it

Alex Biedermann

University of Lausanne, School of Criminal Justice, 1015 Lausanne-Dorigny, Switzerland e-mail: alex.biedermann@unil.ch

Franco Taroni

mentre si presentano le espressioni del valore probatorio al processo. Seguendo il dibattito in corso, gli esperti forensi sarebbero invitati ad indicare, per ragioni di trasparenza, un intervallo di valori per le probabilità dell'evidenza date le ipotesi di interesse e riportare un intervallo di valori per il rapporto di verosimiglianza. Tuttavia, tali assegnazioni di probabilità parziali potrebbero non fare un buon uso delle informazioni disponibili.

Key words: Likelihood ratio, partial probability assignments, uncertainty.

1 The likelihood ratio framework

Forensic scientists are typically faced to the evaluation of measurements on characteristics of trace evidence. The use of the likelihood ratio as a metric to assess the probative value of forensic traces is largely supported by operational standards and recommendations in forensic disciplines [3]. However, the progress towards more widespread consensus about foundational principles is still fragile and there are different views on how the strength of evidence conclusions should be reported to the court. The assessment of a likelihood ratio may turn out to be a task subjected to various sources of uncertainty, ranging from the problem of eliciting probabilities, to statistical issues related to the model choice, to sensitivity issues related to the choice of a prior distribution, or to even computational impasses that emerge when the marginal likelihoods are not available in closed form and numerical procedures need to be implemented. There is actually an open debate on the topic of whether the precision of forensic likelihood ratios should be measured and how should be reported to the court. A special edition edited by Geoff Morrison has recently been published in Science & Justice ([5] and subsequent papers). From one side, there is a school of thought according to which a forensic expert should report a single value for a likelihood ratio (e.g. [8], [6]). The likelihood ratio being expressed as a ratio of conditional probabilities (or marginal likelihoods whenever the evidence is expressed in terms of continuous measurements) is itself a measure of uncertainty. It represents the best assignment a forensic scientist can provide given data, model and background information. From the other side, it is questioned whether scientists should report interval quantifications as a surrogate for the value of the evidence (e.g. [7]) to acknowledge for uncertainty in likelihood ratio assessment. It is argued that reporting a single value would deprive the legal justice system of essential information needed to assess the reliability of the evidence. This discussion has echoed also in statistical literature, see for example [1].

It must be acknowledged that the discussion took different directions, leading in some cases arguments against the subjectivist interpretation of probabilities or against the Bayesian reasoning scheme, in others starting from different points of view with different interpretations of the same concept of likelihood ratio. It should be emphasized that in reality the fundamental point of this whole discussion is not the defense or not of a subjectivist approach. Nothing prevents, for example, to incorporate 'reassuring' relative frequencies to inform subjective probabilites ([9]). What really matters is finding the thread of the whole discussion, understanding whether to bring uncertainty about the expressions of uncertainty can actually lead to a good use of information taking into account that the ultimate goal must be to help justice.

2 On partial probability assignments

The discussion and related disagreements originate (also) from the fact that presenting a numerical value for probabilities or marginal likelihoods in the numerator and in the denominator of the likelihood ratio may give a false impression of exactitude, as such a precision may be in fact rarely realistic.

Consider the case where the evidence, E_1 , is expressed in terms of a correspondence of genetic profiles between a person of interest and a recovered stain on a crime scene. What is the probability of observing corresponding evidential findings? Should the expert report his uncertainty, or not reporting it could it be misleading to the court? For this reason a forensic scientist may feel the necessity to present a range of values to minimize their personal involvement in the case. Let us therefore admit a partial probability assignment for both the numerator and the denominator of the likelihood ratio, say $Pr(E_1 | H_p) = (l_p, u_p)$, for some $l_p < u_p$, and $Pr(E_1 | H_d) = (l_d, u_d)$, for some $l_d < u_d$, where H_p and H_d designate propositions put forward by the prosecution and the defence, respectively.

On the other hand, a trier of fact could also be vague about their beliefs as to prior odds on the propositions that the person of interest is the source of the crime stain or another unrelated person is the source of that stain. What is the probability associated to the defendant's liability? For this reason, let us admit a partial probability assignment for the prior probability of proposition H_p too, say $Pr(H_p) = (l_h, u_h)$, for some $l_h < u_h$. Suppose now laboratory results are available so that the posterior probabilities of the competing propositions can be computed. For this purpose, it is useful to refer to the example originally sketched out by Frosini in 1989 ([2]) because it is well suited to the forensic issues under discussion. Consider the following partial probability assignments for the probabilities of interest:

$$Pr(H_p) = (0.1, 0.2)$$
; $Pr(E_1 | H_p) = (0.6, 0.8)$; $Pr(E_1 | H_d) = (0.3, 0.5)$

Assuming that values for the prior probabilities and for the likelihoods of the evidence under the competing propositions are uniformly spread over the assigned intervals, several values are randomly generated from each interval and for each realized triplet the posterior probability of the proposition supported by the prosecution is computed. The posterior probability, expressed by means of intervals, is $Pr(H_p | E_1) = (0.12, 0.3)$. The impact of the evidence is to increase vagueness in the probability assignment for the propositions of interest changing the range of the probabilities from (0.1, 0.2) to (0.12, 0.3).

Suppose now that new findings are available, giving rise to new evidence (e.g. in terms of a correspondence between the recovered and control material from a suspect) denoted by E_2 . Following the same line of reasoning, and considering for sake of simplicity the same partial probability assignments for the numerator and the denominator of the likelihood ratio that were assigned to evidence E_1 , a new posterior partial probability assignment is obtained for the prosecution proposition, $Pr(H_p | E_1, E_2) = (0.14, 0.45)$. This process can be reiterated many times. One may easily observe that the range of vagueness, at least initially, increases, though this may be felt counterintuitive as the effect of the evidence should be of reducing the initial size of the range of probabilities on the propositions of judicial interest. Posterior probabilities of the prosecution proposition H_p expressed in terms of partial probability assignments are depicted in Figure 2. Note that the range of probabilities assigned for new available findings E_i is kept fixed, $Pr(E_i | H_p) = (0.6, 0.8)$ and $Pr(E_i \mid H_d) = (0.3, 0.5)$ for i = 1, 2, ..., n. Though the observation of a correspondence between evidential findings will clearly shift the posterior odds versus the prosecution statement, one may observe that the effect of the evidence is to increase prior vagueness, at least until a large amount of findings is available.



Fig. 1 Posterior probabilities proposition H_p expressed in terms of partial probability assignments: Pr(H_p) = (0.1,0.2). Likelihoods are also expressed in terms of partial probability assignments, Pr($E_i | H_p$) = (0.6,0.8) and Pr($E_i | H_d$) = (0.3,0.5), i = 1, ..., 24.

This is clearly a simulated example. In a real case, the assumption of constant partial probability assignments for the likelihoods in the numerator and denominator in correspondence of new available evidence may be felt too restrictive and difficult to defend. Each assignment will reflect the uncertainty of the expert (or experts, whenever there are different laboratories in charge of the analyses of different recovered stains or marks) about a case-specific result. However, it serves the purpose to show in a simple way that the produced effect of such partial probability assignments is counterintuitive and it does not represent the answer the legal system would expect.

3 Conclusions

There may be different levels of resolution for the value of the likelihood ratio. This prompts scientists to elaborate ways to construct intervals or distributions over probabilities and likelihood ratios. It is argued that by reporting a single value, a forensic scientist deprives the legal justice system of essential information needed to assess the reliability of the evidence and this would amount to be highly misleading. However, nothing will be gained if a particular expression for uncertainty is itself obscured by an additional level of uncertainty ([4]). Not only such intervals provide no guidance to recipient of expert information as to how such pairs of values ought to be used, but also but also ranges of posterior probability may be larger than ranges of the corresponding prior probability. The conclusion of the discussion is that, in a given case at hand, forensic scientists ought to offer to a court of justice a given single value for the likelihood ratio. It is obviously desirable that reported likelihood ratios be accompanied with information to help fact-finders understand how and on what bases forensic scientists have reached their conclusions. Reporting a single value does not prevent a scientist, whenever asked, to respond about the strength of their beliefs.

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