

# Likelihood ratio and evidence strength

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The fallacies we considered earlier —such as the base rate fallacy, the prosecutor’s fallacy, and the defense attorney’s fallacy—show how the posterior probability of a hypothesis can be overestimated or underestimated. The posterior probability should reflect all the evidence bearing on the hypothesis, but should not be identified with the probative value or strength of the evidence. It is helpful to distinguish the posterior probability of the hypothesis given the evidence,  $P(H|E)$ , from the extent to which the evidence changes the probability of the hypothesis. This distinction is crucial. A hypothesis may have a high probability given the evidence, even though the evidence reduces the probability of the hypothesis substantially. Or a hypothesis may have a low probability given the evidence, even though the evidence increases the probability of the hypothesis substantially.<sup>1</sup> Measuring strength or probative value of the evidence solely by posterior probabilities leaves out something crucial.

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Another distinction worth making is between the global and local value of the evidence (Di Bello & Verheij, 2018). Let  $E_1, E_2, \dots, E_k$  be the total evidence presented at trial and  $H$  the ultimate hypothesis, say that the defendant is guilty of insider trading. The ultimate hypothesis is usually complex and can be thought of the conjunction of several sub-hypotheses  $H_1, H_2, \dots, H_k$ . The value of the total evidence bearing on the ultimate hypothesis should guide the final decision. But, as a preliminary step, it is useful to evaluate the impact of an individual piece of evidence  $E_i$  on the probability of a specific hypothesis  $H_i$ . When lay witnesses and experts testify at trial, the assessment of the evidential value of their individual testimonies should precede the aggregation of their testimonies into a whole, complex body of evidence.

This chapter articulates a probabilistic account of probative value or evidential strength that is incremental (it tracks changes in probability) and local (it is limited to individual pieces of evidence and specific hypotheses). We will argue that the likelihood ratio is the best measure of evidential value for these purposes. Section 1 explains why the likelihood ratio fares better than another popular measure of evidential strength, the Bayes factor. (Appendix A broadens the discussion to probabilistic measures of confirmation drawing from the literature in formal epistemology, but concludes that these measures are unsuited for the legal setting.) We then offer a couple of illustrations of how likelihood ratios can be fruitfully deployed. Section 2 shows that they allow for a nuanced assessment of the strength of quantitative evidence, for example, DNA match evidence. Section 3 examines how they can help to evaluate eyewitness evidence. This should dispel the impression that likelihood ratios are only suited for explicitly quantitative evidence.

While helpful for evaluating many forms of evidence, likelihood ratios should be deployed with care. They can be hard to interpret in practice, as they depend on the choice of two competing hypotheses, as we discuss in Section 4. In Section 5 we discuss evidential relevance, a topic closely related to that of evidential value.<sup>2</sup> Likelihood ratios may categorize an item of evidence as irrelevant while intuitively the item is relevant. We explain this problem away by insisting that likelihood ratios are *local* measures. The moral is that the value of an item of evidence is to be established both locally (relative to specific hypotheses) and globally (relative to the case as a whole). This suggests the need of formulating a more complex theory. We undertake this task in later chapters.

<sup>1</sup>Here is a more concrete example. Suppose an expert testifies that the blood found at the crime scene matches the defendant’s and it is .5 probable that a person unrelated to the crime would match by coincidence. Absent other evidence to the contrary, it should initially be very likely that the defendant, as anyone else, had little to do with the crime. Say, for illustrative purposes, that the prior probability of the source hypothesis is .01, and let the probability of a match if the suspect is the source be approximately 1. By running Bayes’ theorem, the posterior probability that the defendant is the source comes out to be roughly .17. While the match did not make it very likely that the defendant was the source of the traces, the posterior probability is seventeen times larger than the prior.

<sup>2</sup>An item of evidence is relevant to a hypothesis whenever it positively or negatively supports the hypothesis.

# 1. The likelihood ratio outperforms the Bayes factor

One measure of the strength of evidence is the likelihood of the evidence—the probability of the evidence given the hypothesis of interest,  $P(E|H)$ —divided by the probability of the evidence  $P(E)$ . This measure is often called the *Bayes factor*:

$$BF(E, H) = \frac{P(E|H)}{P(E)}. \quad (BF)$$

The Bayes factor seems a plausible measure of evidential strength as it appropriately deviates from one, its point of neutrality. Since, by Bayes' theorem,  $P(H|E) = BF(H, E) \times P(H)$ , the Bayes factor is greater than one if and only if the posterior probability  $P(H|E)$  is higher than the prior probability  $P(H)$ ,  $P(H) < P(H|E)$ . So  $E$  *positively* supports  $H$  whenever the Bayes factor is greater than one. The greater the Bayes factor (for values above one), the greater the upward shift from prior to posterior probability, the more strongly  $E$  positively supports  $H$ . As expected, the posterior probability of  $H$  given  $E$  could still be low even if the Bayes factor is significantly above one. Conversely,  $E$  *negatively* supports  $H$  whenever the Bayes factor is less than one. The smaller the Bayes factor (for values below one), the greater the downward shift from prior to posterior probability, the more strongly  $E$  negatively supports  $H$ . If  $P(H) = P(H|E)$ , the Bayes factor equals one and the evidence has no impact on  $H$ .

So far so good. Unfortunately, the Bayes factor as a measure of evidential strength suffers from three shortcomings. The first is that it changes depending on the prior probability of the hypothesis. To see why, consider the denominator. It can be unpacked following the law of total probability:

$$P(E) = P(E|H)P(H) + P(E|\neg H)P(\neg H). \quad (1)$$

So the Bayes factor can be written in a longer form:

$$BF(E, H) = \frac{P(E|H)}{P(E|H)P(H) + P(E|\neg H)P(\neg H)}. \quad (2)$$

What should be clear from this formulation is that it depends on the prior probabilities  $P(H)$  and  $P(\neg H)$ . Indeed, suppose  $P(E|H) = 1$  and  $P(E|\neg H) = .1$ . If  $P(H) = .1$ ,  $P(E)$ , the denominator, is .19, and so the Bayes factor is approximately 5.26. If, however,  $P(H) = .2$ , the denominator is .28 and the Bayes factor is approximately 3.57. In fact, a more general look (Figure 1) shows that the prior probability can have larger impact than the likelihood  $P(E|\neg H)$ .

This is a strike against the Bayes factor as a measure of evidential strength in legal fact-finding. For suppose an expert who is testifying in court is tasked with assessing the value of an item of evidence, say a DNA or fingerprint match. This assessment should not depend on the expert's prior convictions about the plausibility of the hypothesis. Further, judges and lay jurors should be in a position to understand the expert's assessment in the same way, even if they assign different prior probabilities to the hypothesis.<sup>3</sup>

A second reason to worry about the Bayes factor is its complexity. To see this, the catch-all alternative hypothesis  $\neg H$  in the denominator can be replaced by a more fine-grained set of alternatives,  $H_1, H_2, \dots, H_k$ , provided  $H$  and these alternatives are exclusive and cover the entire space of possibilities (that is, they form a partition). The denominator becomes:

$$P(E) = P(E|H)P(H) + \sum_{i=1}^k P(E|H_i)P(H_i). \quad (3)$$

Estimating  $P(E)$  now looks quite difficult. It would require one to sift through the entire space of possibilities, as well as coming up with a sensible selection of priors probabilities for the several alternative hypotheses on hand. Whoever is tasked with assessing the strength of evidence—lay jurors, judges, or expert witnesses—might face too great a cognitive burden.

A third reason to hesitate about the Bayes factor comes from an observation by Gillies (1986), also discussed by Branden Fitelson (1999). Consider the hypothesis  $H =$  “the suspect is guilty” and suppose it is a fact that  $E =$  “the suspect killed the victim.” Fact  $E$  does not establish guilt with certainty since

<sup>3</sup>The requirement of prior independence is also in line with an objectivity requirement that the strength of evidence should not vary from one researcher to another (Bickel, 2012).

### Bayes factor as a function of prior and $P(E|\sim H)$ .

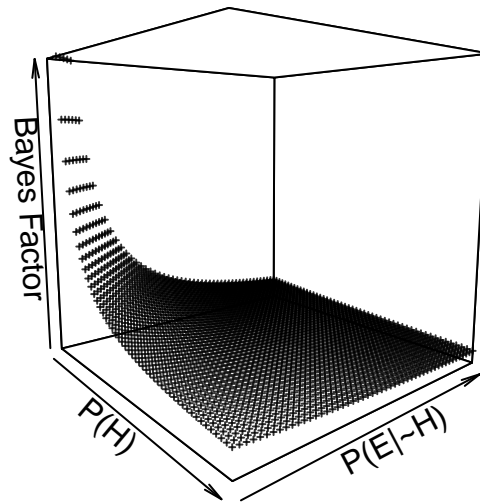


Figure 1: Impact of the prior and likelihood of  $E$  given  $H$  for probabilities in  $(0, 0.05)$  and Bayes Factor restricted to  $(0, 250)$  for visibility.

guilt requires both *actus reus*, the killing, and *mens rea*, the intention. But clearly  $E$  provides positive support for  $H$ . Now consider a composite hypothesis  $H' =$  “the suspect is guilty *and* we live in a simulation built by aliens.” Presumably, the support  $E$  provides for  $H'$  should be weaker than the support it provides for  $H$ . After all, the addition of a far-fetched hypothesis should weaken evidential support. This weakening, however, cannot be captured by the Bayes factor since both  $H$  and  $H'$  deductively entail  $E$ . In general, suppose  $H \models E$  (and so, also,  $H \wedge X \models E$ ). Then both  $P(E|H)$  and  $P(E|H \wedge X)$  equal 1. But this means that  $BF(H, E) = BF(H \wedge X, E) = 1/P(E)$ . So the Bayes factors for the two support relations are equal. This is the problem of irrelevant conjuncts.<sup>4</sup>

So suppose we are after a measure of evidential strength that (i) does not depend on priors, (ii) places no unreasonably heavy cognitive requirements, and (iii) is sensitive to the addition of irrelevant conjuncts. We will argue that a measure that satisfies these desiderata is the likelihood ratio, the ratio between  $P(E|H)$  (the probability of the evidence given the hypothesis is true) and  $P(E|\sim H)$  (the probability of the evidence given the hypothesis is false). Before showing that this measure satisfies the three desiderata, we address a preliminary question. Why use such a ratio in the first place?

For one thing,  $P(E|H)$  by itself is not fine-grained enough. In some cases, this conditional probability may be close to one. For instance, the probability that the blood from the crime matches the accused, if the accused is the source,  $P(\text{blood match}|\text{source})$ , may be close to one. Similarly, the probability that the DNA from the crime scene matches the accused, if the accused is the source,  $P(\text{DNA match}|\text{source})$ , may also be close to one. A quantity such as  $P(E|H)$ , by itself, would make no distinction here, but a DNA match is not on par with a blood type match. The DNA match should be stronger incriminating evidence than the blood type match because a specific DNA profile typically is less common than a specific blood type. This difference can be captured by the other conditional probability  $P(E|\sim H)$ . If the accused is *not* the source, the probability of a blood type match, while relatively small, should be higher than the probability of a DNA profile match. Consequently, the likelihood ratio for the DNA match would be higher than that for the blood match, as expected.<sup>5</sup>

For similar reasons, the strength of evidence cannot be measured by the probability  $P(E|\sim H)$  alone.

<sup>4</sup>The same point can be made using irrelevant hypotheses that are not so far-fetched. For instance, suppose one hypothesis of interest is whether the victim was running in the park on a certain night, and the relevant piece of evidence is her footprints in the park. Perhaps, another hypothesis is whether she had wine at dinner later on. Clearly, whether she did is not obviously relevant to whether she was running in the park beforehand. However, one should be very hesitant to say that the evidential strength of the presence of footprints is the same relative to *she was running in the park* and *she was running in the park and had wine at dinner later on*. But this is what the Bayes factor would commit one to.

<sup>5</sup>Specifically,  $P(\text{DNA match}|\text{source})/P(\text{DNA match}|\sim \text{source}) > P(\text{blood match}|\text{source})/P(\text{blood match}|\sim \text{source})$ .

Consider an example by Triggs & Buckleton (2004). In a child abuse case, the prosecutor offers evidence that a couple's child rocks and that only 3% of non-abused children rock,  $P(\text{child rocks}|\neg\text{abuse}) = .3$ . If it is unlikely that a child who is not abused would rock, that this child rocks might seem evidence of abuse. But this interpretation is mistaken. It could also be that 3% of abused children rock,  $P(\text{child rocks}|\text{abuse}) = .3$ . After all, the two conditional probabilities need not add up to one. If rocking is equally unlikely under either hypothesis, rocking cannot count as evidence of abuse.

So, both the probability of the evidence given the hypothesis and the probability of the evidence given an alternative hypothesis should be part of any good measure of evidential strength (ENFSI, 2015; Royall, 1997; Triggs & Buckleton, 2004). The Bayes factor includes both probabilities, but—as seen before—it falls prey to several difficulties. A more promising measure is the **likelihood ratio**:

$$LR(E, H, H') = \frac{P(E|H)}{P(E|H')}, \quad (LR)$$

where  $H'$  is a hypothesis that is taken to be a competing alternative to  $H$ . If the evidence is more likely given  $H$  than  $H'$ , the ratio would be above one, and if the evidence is more likely given  $H'$  than  $H$ , the ratio would be below one. As with the Bayes factor, support levels correspond to deviations from one. The greater the likelihood ratio (for values above one), the stronger the evidence in favor of  $H$  as contrasted with  $H'$ . The smaller the likelihood ratio (for values below one), the stronger the evidence in favor of the competing hypothesis  $H'$  as contrasted with  $H$ .

Its simplicity makes the likelihood ratio well-suited for presentation in trial proceedings. An expert, for instance, may testify that the blood-staining on the jacket of the defendant is ten times more likely to be seen if the wearer of the jacket hit the victim (prosecutor's hypothesis) rather than if he did not (defense's hypothesis) (CGG Aitken, Roberts, & Jackson, 2010, p. 38). This apparent simplicity, however, can give rise to confusions in the assessment of the evidence, especially if the hypotheses are not stated clearly. In the most straightforward case,  $H'$  is just the negation of  $H$ . But the competing hypotheses  $H$  and  $H'$  need not be one the negation of the other, a point to which we will return.

Let's now examine why the likelihood ratio satisfies our three desiderata. First, unlike the Bayes factor, the likelihood ratio does not depend on the prior probability of the hypothesis. The relationship between likelihood ratio, prior and posterior odds is apparent in the odds version of Bayes' theorem:

$$\frac{P(H|E)}{P(H'|E)} = \frac{P(E|H)}{P(E|H')} \times \frac{P(H)}{P(H')}. \quad (4)$$

If the likelihood ratio is greater (lower) than one, the posterior odds will be greater (lower) than the prior odds of  $H$ . The likelihood ratio, then, is a measure of the upward or downward impact of the evidence on the prior odds of two hypotheses  $H$  and  $H'$ . This fits nicely with the division of labor common in legal fact-finding between experts and decision-makers, judges or lay jurors. A prominent forensic scientist recommends that 'in criminal adjudication, the values of the prior odds and the posterior odds are matters for the judge and jury, in accordance with the normal division of labor in forensic fact-finding' (Colin Aitken & Taroni, 2008, p. 194). Other scholars recommend that experts should 'not trespass on the province of the jury by commenting directly on the accused's guilt or innocence, ... and should generally confine their testimony to presenting the likelihood of their evidence under competing propositions' (CGG Aitken, Roberts, & Jackson, 2010, p. 42).

Second, the likelihood ratio is less cognitively burdensome than the Bayes factor. It does not require one to think about the probability of the evidence in general,  $P(E)$ . Think, for example, of blood match evidence. To calculate the Bayes factor, we need two things:  $P(E|H)$  (which here, say, can be assumed to approximate one) and  $P(E)$  (which is the probability of a blood match under any possible scenarios, whether or not the suspect is the source). Yet, direct and reliable estimation of the probability  $P(E)$  is difficult. One can use the law of total probability from equation (1). This would require, besides an assessment of the conditional probabilities  $P(E|H)$  and  $P(E|\neg H)$ , an assessment of the prior probabilities of  $P(H)$  and  $P(\neg H)$ . Instead, the likelihood ratio would only require an assessment of the conditional probabilities. In this sense, its calculation requires less information.

Finally, unlike the Bayes factor, the likelihood ratio is not susceptible to the problem of irrelevant hypotheses. For suppose  $P(E|H) = P(E|H \wedge X) = 1$ , where  $X$  is an additional hypothesis that is irrelevant to  $H$ . Note that  $LR(E, H) = 1/P(E|\neg H)$ , while  $LR(E, H \wedge X) = 1/P(E|\neg H \vee \neg X)$ . Unlike with the Bayes factor, here the two denominators might differ. For example, suppose a fair coin is tossed three times. Let  $H$  = "two first tosses resulted in two heads," let  $E$  = "at least one of the two first tosses resulted in a head,"

and let  $X$  = “the third toss resulted in heads.” Then  $P(E|H) = 1$ ,  $P(E|\neg H) = 2/3$ ,  $LR(E, H) = \frac{1}{2/3} = 1.5$ . However,  $P(E|H \wedge X) = 1$ ,  $P(E|\neg(H \wedge X)) \approx .71$ , so  $LR(E, H \wedge X) \approx \frac{1}{.71} = 1.4$ . Thus, the support, as measured by the likelihood ratio, can drop by adding a conjunct that is probabilistically irrelevant to the original hypothesis. In fact, this weakening of evidential support by adding an irrelevant conjunct holds in general for the likelihood ratio given sensible assumptions.<sup>6</sup>

All in all, the likelihood ratio outperforms the Bayes factor on several respects. But, of course, there could be other measures of evidential strength that fare even better. Other measures worth considering come from the literature in formal epistemology on confirmation theory. The expression ‘confirmation’ is more common in this literature than ‘strength’ (or value, support). A discussion of these measures, however, would detract us from the main task at hand. We therefore relegate it to Appendix A. The upshot is that two questions should be distinguished. (1) To what extent does a piece of evidence change our beliefs about a given hypothesis? (2) What is the strength (value, support) of a piece of evidence relative to a hypothesis? The two questions overlap to some extent. But the difference is that confirmation depends on prior probabilities, while evidential strength should be kept separate from prior probabilities. Confirmation measures are concerned with (1) rather than (2), and thus they are unsuitable for the evaluation of evidence in trial proceedings.

## 2. Match evidence and error probabilities

The two conditional probabilities that make up the likelihood ratio— $P(E|H)$  and  $P(E|\neg H)$ —should be used in the evaluation of any form of evidence, both quantitative and non-quantitative. This section examines how a DNA match, a widely used form of quantitative evidence, should be evaluated by means of the likelihood ratio. The argument formulated here can be generalized to any ‘match evidence.’ The match can be between genetic profiles, fingerprints, blood types, bite marks, etc.

Consider an expert testimony that there is a genetic, DNA match between the traces at the crime scene and a sample from the defendant. This statement is evidence that the defendant was the *source* of the traces—that the materials found at the scene originated from the defendant. The match can also be evidence that the defendant was present at the scene or committed the crime, but these claims are more questionable, as the chain of inferences is weaker. For simplicity, let us focus on the source hypothesis. The likelihood ratio we should be concerned with is therefore the following:

$$\frac{P(\text{match}|\text{source})}{P(\text{match}|\neg\text{source})}.$$

How strongly does a match favor the hypothesis that the defendant is the source? To answer this question, the simplest analysis relies on the **random match probability**, the probability that a random person, unrelated to the crime, would coincidentally match the crime scene profile. When experts testify about a DNA match, they often only provide the random match probability as an indicator of evidential strength. This probability coincides (roughly) with the denominator of the likelihood ratio, that is, the probability that someone who is not the source would match. What about the numerator? The assumption often made is that the numerator is close to one. Since the random match probability is often an impressively low number, say 1 in 100 million, this is enough to ensure that the likelihood ratio is significantly above one. So the random match probability would ultimately be the only measure of evidential strength.

This analysis, though elegant, lacks precision in at least two respects. First, it assumes that the numerator  $P(\text{match}|\text{source})$  is close to one. But a DNA match need not track with 100% probability the fact that the suspect is the source. There could be false negative matches. In addition—and more importantly—equating the denominator  $P(\text{match}|\neg\text{source})$  with the random match probability ignores the risk of false positive matches. This risk is not negligible (Shaer, 2016). In fact, two distinct sources

<sup>6</sup>Branden Fitelson (2002) proved a general claim about irrelevant conjunctions. Hawthorne & Fitelson (2004) later strengthened this claim. The claim is that, if  $LR(E, H, \neg H) > 1$ ,  $P(E|X \wedge H) = P(E|H)$ , and  $P(X|H) \neq 1$ , then  $LR(E, H, \neg H) > LR(E, H \wedge X, \neg(H \wedge X))$ . Crupi & Tentori (2010) raised a related problem. They point out that if  $LR(E, H) \leq 1$  and  $X$  is confirmationally irrelevant conjunct to  $H$  with regard to  $E$ , then  $E$  will have the same negative or null impact on  $H \wedge X$ , that is  $LR(E, H \wedge X) \leq LR(E, H)$ . They find this counter-intuitive and argue that this can be avoided by switching to the  $Z$  confirmation measure (Crupi, Tentori, & Gonzalez, 2007). As we argue in Appendix A, the  $Z$  measure is prior-sensitive and therefore not fit for our purpose. Further, the phenomenon might not be deeply troubling either. If the likelihood ratio tracks how strongly the evidence supports a hypothesis, it should be no surprise that a more complex hypothesis—one obtained by adding an irrelevant proposition—enjoys a lower support from the same evidence.

of errors are at issue here, a false positive match and a coincidental match. Suppose two individuals—say the perpetrator and the defendant—happen to share the same DNA profile by coincidence. If an expert states that the crime scene sample and the defendant’s sample match, this would be a coincidental match, not a false positive match. This risk of error is captured by the random match probability. But if the two samples do not actually match, and yet the expert says that they do, this would count as a false positive match, not a coincidental match. This risk of error is not captured by the random match probability.

Unlike a coincidental match, a false positive match is often caused by a human error in a number of circumstances (see W. C. Thompson, 2013 for a more exhaustive treatment and multiple examples):

- **Cross-contamination of samples.** For instance, in Dwayne Johnson (2003) samples were accidentally swapped. In Lukis Anderson (2012), the genetic material was carried over by the paramedics. In one case, German police invested a considerable amount of time and effort searching for the so-called Phantom of Heilbronn, whose DNA profile was associated with many crimes. A bounty of EUR 300,000 was placed on her head. It turned out she was an innocent employee involved in the production of cotton swabs used across the country.
- **Mislabeled samples.** For instance, in 2011 the Las Vegas Metropolitan Police Department acknowledged that samples of two men suspected of a 2001 robbery were switched, leading to the exclusion of the perpetrator and four years of incarceration for the other suspect. The mistake came to light only because the perpetrator was later on arrested for another crime.
- **Misinterpretation of test results.** Single-source sample comparison is not easily prone to misrepresentation, but evidence mixtures—often needed in sexual assault cases—are complicated to interpret. For example, Dror & Hampikian (2011) re-examined a 2002 Georgia rape trial in which two forensic scientists had concluded that the defendant could not be excluded as a contributor of the crime traces. The evidence was sent to 17 lab technicians for re-examination. One of them agreed that the defendant could not be excluded as a contributor. Twelve considered the DNA exclusionary, and four found it inconclusive. If the quantity of DNA is limited, there is uncertainty about the number of contributors and about whether any alleles are missing. Ultimately, there is an element of subjectivity in mixed DNA interpretation.

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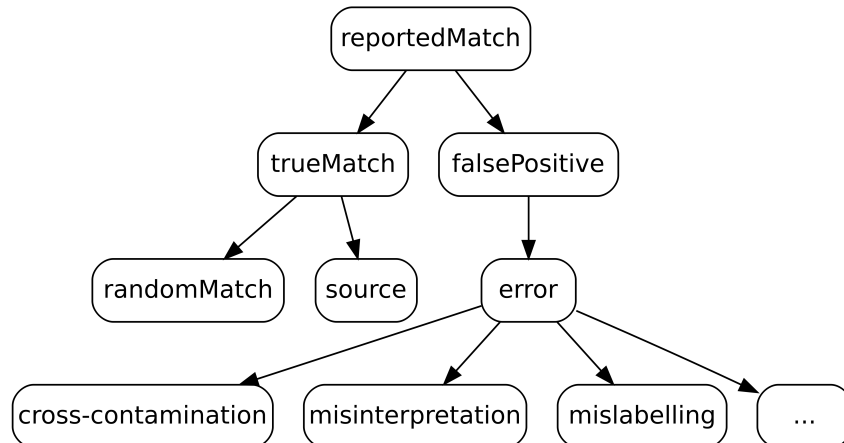


Figure 2: Dependencies between variables in the false positive problem.

To refine the analysis, the risks of false positive and false negative matches should be incorporated into an assessment of a DNA match. This can be done using the likelihood ratio, following Colin



Aitken, Taroni, & Thompson (2003). False positives are usually more worrisome than false negatives as they increase the risk of a mistaken conviction. That is also why we devoted to them more space in the foregoing discussion. But, for the sake of completeness, we will examine both. To this end, we abbreviate:

- $S$  The specimen comes from the suspect (source).
- $R$  A match is reported (reported match).
- $M$  There is a true match (true match).

A true match is the fact that two samples actually carry the same genetic profile, while a reported match is a statement made by an expert that two samples match. A true match will exist not only if the suspect is the source, but also if, even though the suspect is not the source, the profiles are in fact the same due to a random, coincidental match. Similarly, a reported match might arise not only if there is a true match, but also if a false positive error has been made. These possibilities are represented in Figure 2.

In this set-up, the evidence to be assessed is the *reported* match relative to the pair of hypotheses  $S$  and  $\neg S$ . So the likelihood ratio we are after has the form:

$$\frac{P(R|S)}{P(R|\neg S)}.$$

With a few manipulations and assumptions in place, the likelihood ratio can be written as:<sup>7</sup>

$$\frac{P(R|S)}{P(R|\neg S)} = \frac{P(R|M)}{P(R|M)P(M|\neg S) + P(R|\neg M)P(\neg M|\neg S)} \quad (5)$$

Note that, as intended, the numerator  $P(R|M)$  can be different from one, since a false negative reported match can occur (or, which is the same, a true match need not always occur). The denominator reflects the fact that there are two ways misleading evidence can arise: there is a true match and the suspect is not the source (because of a random, coincidental match), or there is no true match, and a false positive error has been made in the identification process.

To make the different sources of error more salient—false negative matches, false positive matches and random or coincidental matches—the likelihood ratio can be written, as follows:

$$\frac{P(R|S)}{P(R|\neg S)} = \frac{1 - FNP}{[(1 - FNP) \times RMP] + [FPP \times (1 - RMP)]} \quad (6)$$

This is the same as the formula above. The expression FNP stands for the false negative probability  $P(\neg R|M)$ , so  $1 - FNP = P(R|M)$ . The expression FPP stands for the false positive probability  $P(R|\neg M)$ . The expression RMP stands for the random match probability  $P(M|\neg S)$ . A false positive or false negative probability track a human error, the possibility that a match may be reported ( $R$ ) even without a true match ( $\neg M$ ) or that a match may *not* be reported ( $\neg R$ ) even with a true match ( $M$ ). The random match probability, instead, tracks a coincidence of nature, the possibility that someone who is not the source ( $\neg S$ ) could still be—coincidentally—a true match ( $M$ ).

Let's now examine the impact of the two error probabilities on the likelihood ratio, holding fixed certain values of the random match probability. Figure 3 shows the impact of the false positive probability

<sup>7</sup>By the law of total probability, the denominator  $P(R|\neg S)$  can be unpacked as  $P(R \wedge M|\neg S) + P(R \wedge \neg M|\neg S)$ . The latter, by the chain rule, is equivalent to  $P(R|M \wedge \neg S)P(M|\neg S) + P(R|\neg M \wedge \neg S)P(\neg M|\neg S)$ . A similar reasoning applies to the numerator. So we have:

$$\frac{P(R|S)}{P(R|\neg S)} = \frac{P(R|M \wedge S)P(M|S) + P(R|\neg M \wedge S)P(\neg M|S)}{P(R|M \wedge \neg S)P(M|\neg S) + P(R|\neg M \wedge \neg S)P(\neg M|\neg S)}$$

Both numerator and denominator can be simplified because a reported match ( $R$ ), given a true match obtains ( $M$ ), is independent of whether the suspect is the source ( $S$ ):

$$P(R|M \wedge S) = P(R|M \wedge \neg S) = P(R|M)$$

$$P(R|\neg M \wedge S) = P(R|\neg M \wedge \neg S) = P(R|\neg M)$$

Finally, in the numerator, let the probability of a true match if the suspect is the source be one:

$$P(M|S) = 1 \text{ so also } P(\neg M|S) = 0.$$

This assumption holds in virtue of the meaning of the statements involved. That the suspect is the source of the crime sample entails, almost analytically, that the two samples must carry the same genetic profile.

FPP (for values between 0 and .05) while the false negative probability FNP is kept to zero. Random match probabilities are assumed to be in the order of  $10^{-9}$  (often reported in the case of two single-source samples over ten or more loci) and  $10^{-3}$  (sometimes obtained by means of less discriminating tests when the comparison involves a mixed sample). Even a small increase in the false positive probability can lower the likelihood ratio dramatically. Interestingly, however, the additional impact of the false negative probability FNP (for values between 0 and .05) is negligible, as shown in Figure 4.

#### Impact of false positive probability on likelihood ratio

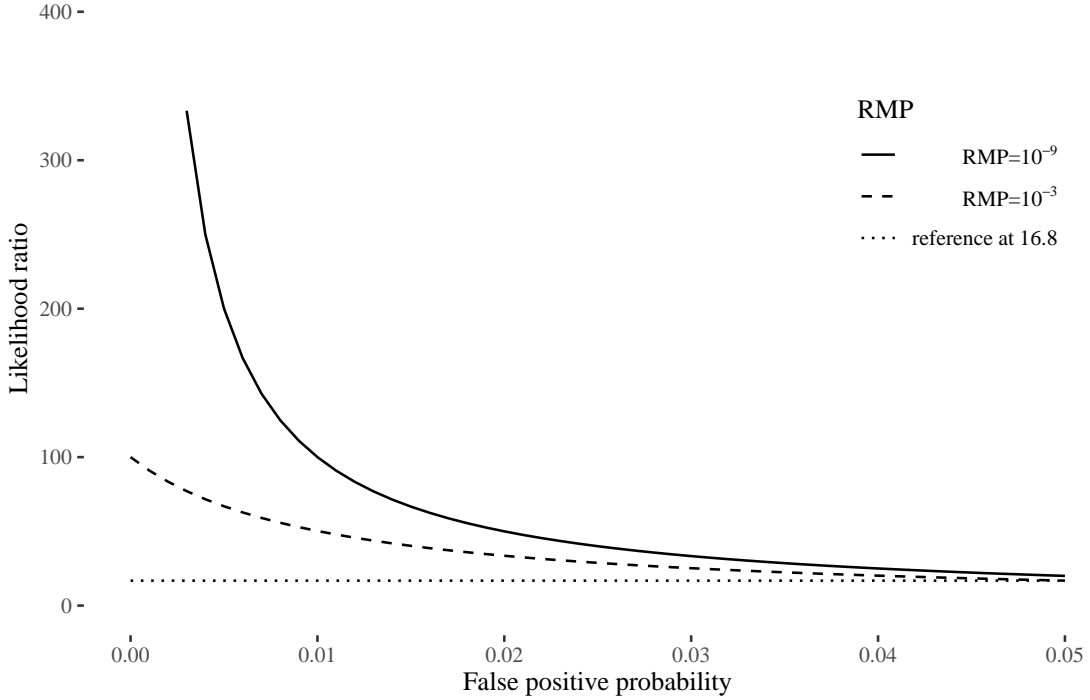


Figure 3: Impact of the false positive probability on the likelihood ratio for two values of RMP. The horizontal reference line is at 16.8, the likelihood reached at  $RMP=10^{-3}$  for  $FPP=0.05$ . At the same value of FPP, the LR for  $RMP 10^{-9}$  is 20.

A similar analysis can be used to study the impact of error probabilities on the value of exculpatory DNA evidence, corresponding to a *negative* (reported) match  $\neg R$ . By replacing  $R$  with  $\neg R$  in formula (5), the likelihood ratio becomes:

$$\frac{P(\neg R|S)}{P(\neg R|\neg S)} = \frac{P(\neg R|M)}{P(\neg R|M)P(M|\neg S) + P(\neg R|\neg M)P(\neg M|\neg S)} \quad (7)$$

$$= \frac{FNP}{FNP \times RMP + [(1 - FPP) \times (1 - RMP)]} \quad (8)$$

Keep in mind that the negative reported match  $\neg R$  is evidence *against* the source hypothesis  $S$  so long as the likelihood ratio is below one. At the extreme, if the false negative probability FNP is zero, the numerator is zero. Thus, the likelihood ratio will be zero, as it should. In such a case, the negative match is completely exculpatory, and the posterior probability that the suspect is the source will also be zero. If the false negative probability is not zero, the likelihood ratio will be greater than zero. The greater the likelihood ratio (for values between 0 and 1), the weaker the value of the exculpatory match. As Figure 5 shows, the likelihood ratio progressively moves away from zero as the false negative error probability increases. Interestingly, however, the impact of the false *positive* probability FPP on the likelihood ratio of exculpatory evidence is essentially null, especially if the random match probability is low (as is usually the case).

So, even a seemingly small error probability trumps the random match probability. If there are good reasons to worry about random matches, there are even better reasons to worry about error probabilities.



## Impact of error probabilities FPP and FNP on likelihood ratio

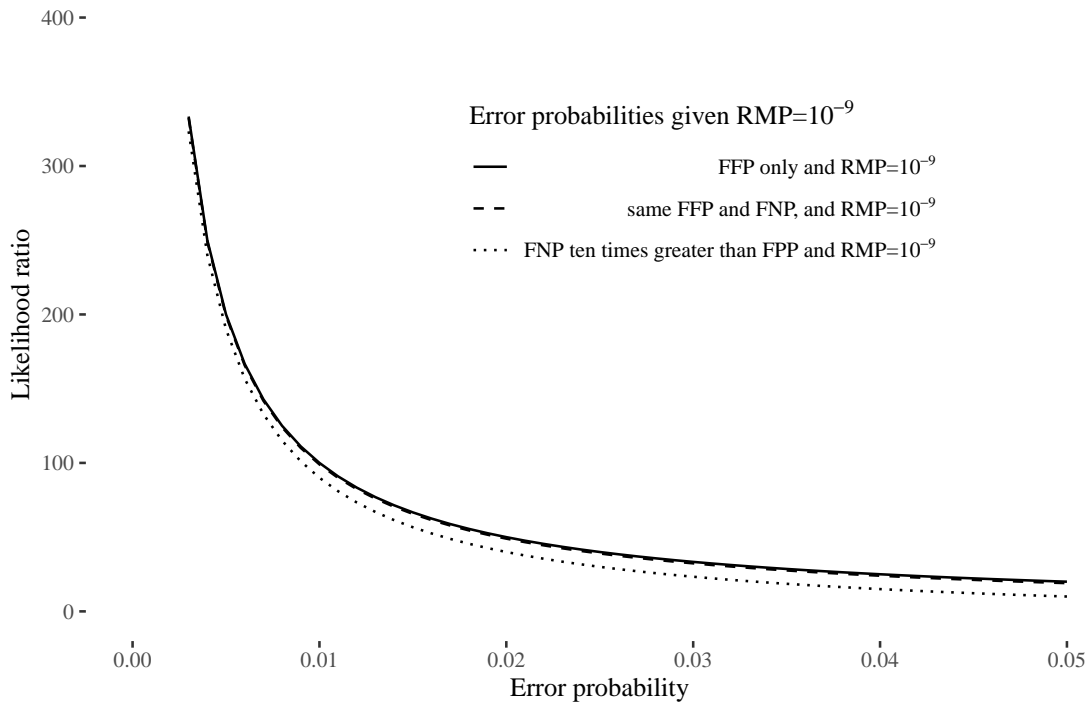


Figure 4: Impact of the false positive probability FPP and false negative probability FNP on the likelihood ratio, assuming  $RMP=10^{-9}$ . For simplicity, the two error probabilities are assumed to be the same. The impact of FNP is negligible.

In addition, this analysis shows which error probabilities we should be concerned about and in which circumstances. The impact of the error probabilities is not uniform, contrary to what one might intuitively think. The false positive probability has a marked impact on the value of incriminating DNA evidence (positive matches), while the false negative probability has a marked impact on the value of exculpatory DNA evidence (negative matches).<sup>8</sup> Conversely, a false negative probability has a negligible impact on the value of incriminating DNA evidence, while a false positive probability has a negligible impact on the value of exculpatory DNA evidence.

But, no doubt, these claims are still rather hypothetical. Unfortunately, no serious attempt has been made to systematically quantify the relevant error probabilities. Sometimes, a lab discovers its own errors and reports them, but this is rare (W. C. Thompson, 2013). Anecdotal information suggest that false positive matches take place more often than coincidental matches would entail, but how often remains unclear (W. C. Thompson, 2013). Regular proficiency tests used in accredited DNA laboratories involve comparison of samples from known sources, but they are criticized for being unrealistically easy (yet, it happens that analysts fail them). Sometimes, corrective action files are made available. They

<sup>8</sup>The impact of false positive and false negative probabilities is not symmetric across positive and negative matches when evidential value is measured by the likelihood ratio. For positive matches, even a small false positive probability can cause the likelihood ratio to drop significantly, as Figure 3 and 4 show. Instead, for negative matches, Figure 5 shows that even a false negative probability as high as 5% has a minor effect on the likelihood ratio, which remains relatively close to zero. But this asymmetry is just an artifact of using the likelihood ratio as a measure of evidential strength. Error probabilities for a positive or negative match affect the posterior probability of the source hypothesis equally strongly. For suppose the random match probability is  $10^{-3}$  and the prior probability of  $S$  is .5. Without taking into account the error probabilities, a positive match would bring the probability of  $S$  from .5 to .99. Instead, taking into account a false positive probability of 0.05, a positive match would bring the probability of  $S$  from .5 to just about .94. What about a negative match? Without taking into account the error probabilities, a negative match would bring the probability of  $S$  from .5 to 0. Instead, taking into account a false negative probability of 0.05, a negative match would bring the probability of  $S$  from .5 to just about .04. Furthermore, a positive match followed by a negative match, each subject to the same error probabilities, would have no impact on the posterior probability of the source hypothesis. All in all, the likelihood ratio should be interpreted carefully, a point to which we will return later in this chapter.

## Negative match: Impact of error probabilities FPP and FNP on likelihood ratio

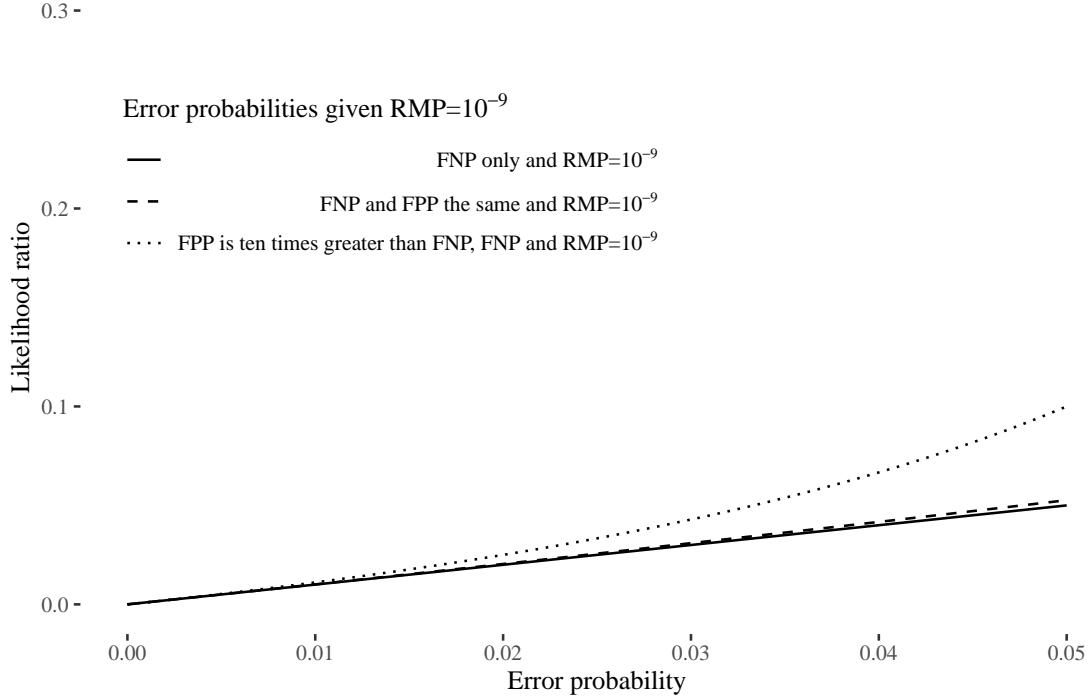


Figure 5: Negative (exculpatory) DNA match. Impact of the false positive probability FPP and false negative probability FNP on the likelihood ratio, assuming a  $RMP=10^{-9}$ . For simplicity, the two error probabilities are assumed to be the same. The impact of FPP is negligible.

usually show relatively few false positive errors.<sup>9</sup> But because of the fragmentary data available, it is premature to conclude there is no reason for concern.

More data should be collected to plug in the right values of false positive and false negative probabilities in the likelihood ratio. These error probabilities should be case-specific, not generic. After all, the objective is to assess the risk of error for *this* match, not a match in general. To this end, numerical data should be collected that are fine-grained enough to document the error probabilities, FPP and FNP, corresponding to scenarios in which specific procedures, safeguards, or protocols are followed. As experts who testify about a match (or lack thereof) are cross-examined at trial, they will testify about the procedures, safeguards and protocols that the laboratory technicians followed in the specific case. This case-specific information could then be combined with performance data about error probabilities under different scenarios. This would yield a case-specific assessment of the value of match evidence.

We conclude this section by noting that other proposals exist in the literature for formulating the likelihood ratio of a genetic match while also incorporating error probabilities, FPP and FNP. Another, more general proposal is due to Buckleton, Bright, & Taylor (2018). But, interestingly, the likelihood ratio of a DNA match used in equations (5) and (7) turns out to be a particular case of this more general approach. This convergence is encouraging. Here we briefly go through the derivation. First, Buckleton and co-authors make the conceptual distinction between the probability that an error occurs,  $P(ERR)$ , and the probability that a match is reported if an error occurs,  $P(R|ERR)$ . Let  $err$  denote the probability of error, and we assume it to be independent of the source hypothesis:

$$err = P(ERR) = P(ERR|S) = P(ERR|\neg S)$$

Separately, let  $k$  denote the probability of a reported match if an error occurs, also assumed to be

<sup>9</sup>For instance, the Santa Clara County district attorney's crime laboratory between 2003 and 2007 caught 14 instances of evidence cross-contamination with staff DNA, three of contamination by unknown person, and six of DNA contamination from other samples, three cases of DNA sample switch, one mistake in which the analyst reported an incorrect result, and three errors in the computation of the statistics to be reported.

independent of whether the source hypothesis is true:

$$k = P(R|ERR) = P(R|ERR, S) = P(R|ERR, \neg S)$$

Now the derivation:

$$\begin{aligned} LR &= \frac{P(R|S)}{P(R|\neg S)} \\ &= \frac{P(R|\neg ERR, S)P(\neg ERR|S) + P(R|ERR, S)P(ERR|S)}{P(R|\neg ERR, \neg S)P(\neg ERR|\neg S) + P(R|ERR, \neg S)P(ERR|\neg S)} \\ &= \frac{1 \times (1 - err) + k \times err}{RMP \times (1 - err) + k \times err} = \frac{1 - err + k \times err}{RMP - err \times RMP + k \times err} \\ &= \frac{1 - (1 - k)err}{RMP \times (1 - err) + k \times err} \end{aligned}$$

M: I don't see why this independence holds

As before, the likelihood ratio is the ratio of the probabilities of a reported match if the suspect is the source and if the suspect is not the source. The numerator  $P(R|S)$  can be split into two possible scenarios: an error has not been made, or an error has been made. Accordingly, the numerator in the second line uses the law of total probability to split  $P(R|S)$  into these two options. Similarly, the numerator  $P(R|\neg S)$  can be split into two cases: the suspect is not the source, but we are dealing with a random match, or the suspect is not the source, and an error has been made. An application of the law of total probability in the denominator mirrors this. The rest of the argument is just rewriting in terms of abbreviations, and algebraic manipulation. The probability of a reported match  $R$  if no error occurs *and* the source hypothesis is false is the random match probability  $RMP$ , so  $P(R|\neg ERR, \neg S) = RMP$ . The probability that a reported match occurs when the source hypothesis is true and no error has made is assumed to be one, so  $P(R|S, \neg ERR) = 1$ .

this bit still needs polishing

Finally, if you think of an error as something that guarantees a mistaken reported match,  $k$  becomes 1 and  $e$  becomes the false positive rate. On this assumption straightforward algebraic manipulation gives:

$$\begin{aligned} \frac{1 - (1 - k) \times err}{RMP \times (1 - err) + k \times err} &= \frac{1 - err + err}{RMP(1 - err) + err} \\ &= \frac{1}{RMP - err \times RMP + err} = \frac{1}{1 + err \times (1 - RMP)} \end{aligned}$$

which is the same as the formula obtained by Colin Aitken, Taroni, & Thompson (2003) if we take  $err$  to be FPP, as we should on the assumption that  $k = 1$ .

### 3. Eyewitness identification and likelihood ratio

So far we paid attention to DNA evidence, a form of quantitative evidence widely used in trial proceedings. But the question arises whether evidence that is not explicitly quantitative, for example, eyewitness testimony, can also be evaluated by means of the likelihood ratio. We show that the answer is affirmative. In fact, there is no sharp divide between quantitative and non-quantitative evidence. A statement in court by an expert witness that the crime scene DNA matches the defendant is qualitative information, but its value is best assessed by means of numerical information, such as error rates and the random match probability. Similarly, a witness testifying 'I saw him!' is qualitative information, but again, its value is best assessed by means of numerical information about the risks of a false identification. As we will show, the likelihood ratio can be of service here.

To start, there is plenty of quantitative data about the risks of a false eyewitness identification. Consider first the statistics about false convictions. The rate of false convictions in death penalty cases in the United States is estimated at about 4% (Gross, O'Brien, Hu, & Kennedy, 2014). How much of this can be attributed to false eyewitness identifications is hard to say exactly, but presumably quite a bit. In fact, a study of 340 exonerations in the years 1989-2003 showed that around 90% of false convictions in rape cases resulted from a false eyewitness identification. This percentage comes close to 100% in rape convictions in which the victim and the defendant were of difference races. In murder cases, 43% of false convictions resulted from a false identification by one or multiple eyewitnesses.

REFERENCE MISSING

Field studies offer a more precise picture. These studies show that, in line-up identifications, eyewitnesses select filler individuals at a rate of 20-24% (Klobuchar, Steblay, & Caligiuri, 2006). That is, around 20-24% of the time, an innocent person in a police line-up is incorrectly identified as the perpetrator. Similarly, a field study in Greater London (Wright & McDaid, 1996) and another study in Sacramento, California (Behrman & Davey, 2001) indicate that the false identification rate is around 20%. Even in experimental settings—where witnesses are less emotionally taxed—eyewitnesses identify a filler individual from a line-up in approximately 20% of the cases (S. G. Thompson, 2007).

In light of these empirical results and similar studies, the justice system has grown suspicious of eyewitness evidence over the last twenty years. This skepticism is welcome, but should not lead to discounting relevant evidence. Some may caution that the risks of mistaken identification should be assessed in the individual circumstances, and that blanket statements that eyewitnesses are unreliable—even when backed up by well-researched statistics—are unhelpful. After all, judges and jurors should make determinations about the reliability of a specific eyewitness identification, not in general.

Cross-examination is often thought to be the tool for an individualized assessment of the risk of error. The evidence law scholar Henry Wigmore in his monumental treatise on the law of evidence famously asserted that ‘cross-examination is greatest legal engine ever invented for the discovery of truth.’ This assertion, however, has been subject to little empirical testing. In fact, empirical studies suggest that cross-examination is ineffective at detecting false identifications. In a series of experiments, subjects were asked to cross-examine eyewitnesses to determine whether they made accurate or mistaken identifications. Subjects showed little or no ability to make such discrimination (Wells & Olson, 2003, p. 285). In another experiment, a representative sample of 48 witnesses was cross-examined. Subjects ( $n = 96$ ) viewing the cross-examination showed little ability to distinguish accurate from false identifications (Lindsay, Wells, & Rumpel, 1981).

reference missing

The ineffectiveness of cross-examination at detecting errors might stem from its reliance on an intuitive, folk assessment of the risks of error, not on well-researched quantitative data. To remedy this, empirical research has identified a few canonical factors that affect the ability of a witness to correctly identify faces. These factors are typically divided into system variables and estimator variables (Behrman & Davey, 2001; Wells & Olson, 2003). The former refer to how the identification took place in a regimented setting, say whether it was a line-up or a show-up;<sup>10</sup> whether the line-up was simultaneous or sequential; whether the witness identified someone prior to the line-up. Instead, estimator variables refer to environmental conditions. The ability of a witness to make correct identifications is impaired by brief exposure, poor visibility (bad lighting or long distance) and a long interval between the first exposure and the moment of recollection. Other estimator variables include race (cross-racial identifications tend to be less reliable), stress (high stress can lead to worse memory), and weapon focus (the presence of a weapon weakens one’s ability to make a correct identification).

A few examples can illustrate how data about estimator and system variables can be incorporated in the likelihood ratio. Consider a recent study about the correlation between distance and eyewitness reliability. It shows that the ratio of correct identifications (hits) to false identifications (false alarms) is 75% to 15% at 0 yard distance; 70% to 20% at 10 yard distance; 65% to 25% at 20 yard distance; 60% to 30% at 30 yard distance; 55% to 35% at 40 yard distance (?). These numbers can be used to fill in the conditional probabilities in the likelihood ratio for an eyewitness identification. Let *id* be the statement that the witness identifies the defendant as the person present at the scene, and let *presence* denote the fact that the witness was actually at the scene. The likelihood ratio of interest would look like this:

add reference

$$\frac{P(id|presence)}{P(id|-presence)}$$

Depending on distance, different numbers can be plugged in the numerator and the denominator. If, for example, the distance is 10 yards, the numerator should be .7 and the denominator .2. Thus, the likelihood ratio would be 3.5, an indication that the eyewitness identification is probative but its value is somewhat limited. This analysis is, of course, rather elementary and it is offered as merely illustrative. More-fine grained quantitative data are needed so that the other estimator variables besides distance can be taken into consideration, such as lighting, stress level, weapon focus, etc.

Research has also tackled the impact of system variables, especially in connection to another factor, witness confidence in the identification. It is a point of contention whether or not confidence is positively

<sup>10</sup> A show-up refers to the observation of a single suspect by a witness in the field, typically at the crime scene. A line-up refers to the presentation of the suspect and several foils, either live or via photographs.

correlated with accuracy. A meta-analysis by Wixted & Wells (2017) offers a nuanced but overall optimistic picture. Their analysis focuses on identifications under *pristine conditions*, which require a certain set-up of system variables. Pristine conditions require, for example, a double-blind line-up containing one suspect and at least five fillers with no resemblance to the suspect. The witness is cautioned that the offender might not be in the line-up and there is no expectation that they identify someone. Needless to say, very few police departments run their line-ups in pristine conditions. But, as it turns out, if the identification occurs under pristine conditions, the high confidence of the witness is strongly predictive of an accurate identification. Most interestingly, witnesses with high confidence under pristine conditions should be around 90% accurate, a rather encouraging figure.<sup>11</sup>

Consider now two scenarios in which an expert is tasked with assessing the value of an eyewitness identification made during a police line-up. In one scenario, suppose the identification conditions are pristine. In line with the research we just discussed, the expert should testify: the probability of the testimony if the suspect was present at the scene— $P(\text{id}|\text{presence})$ —is  $.9 \pm .05$ , and the probability of a false identification— $P(\text{id}|\neg\text{presence})$ —is  $.1 \pm .03$ . In the second scenario, suppose the conditions are not pristine. The expert should testify that the probability of a correct identification is  $.8 \pm .05$  and false identification is  $.2 \pm .05$ . These numbers are taken from the earlier research we cited about a 20-24% filler identification rate in police line-ups. We get two different *ranges* of likelihood ratios,  $lr_1$  and  $lr_2$ . In the first scenario, the minimum and the maximum are as follows:

$$\min(lr_1) = .95/.07 \approx 13.57 \quad \max(lr_1) = .85/.13 \approx 6.53$$

The likelihood ratio is in the range of 6.5-13.5. In the second scenario, the minimum and the maximum are as follows:

$$\min(lr_1) = .85/.2 = 4.25 \quad \max(lr_1) = .75/.3 \approx 2.5$$

So the likelihood ratio is in the range of 2.5-4.25. Figure 6 gives a compact illustration of the strength of an eyewitness identification under the two scenarios.

The examples could continue, but the general point is this. A case-specific assessment of the risks of a false eyewitness identification can be carried out by taking into account estimator and system variables, as well as other relevant factors such as eyewitness confidence. Ideally, properly formatted data about all the factors we discussed could be used to develop a multivariate model. This model would allow an assessment of the risks of error under a variety of relatively well-specified circumstances. We are far from reaching this state of maturity, but even with the current research, an expert who is aware of the literature we have cited and of the specific circumstances of the case could assess the risks of a false identification quantitatively. An untrained jury member unaided by numerical data—even after viewing cross-examination—is unlikely to arrive at a better assessment of the risks of error involved.

We emphasize that the approach we are advocating is continuous with the practice of cross-examination as a tool to detect false identifications. Questions that are routine during cross-examination about time of day, distance, stress level, lighting conditions etc. elicit information about estimator variables as well as system variables. Empirical research will help to determine how much poor visibility, long distance, heightened stress, etc. increase the risk of a false identification. As noted before, the reason why cross-examination is ineffective at detecting mistaken identifications might well be that it does not rely on data about the magnitude of the risks of error under various circumstances. So, by combining numerical information in the likelihood ratio, the effectiveness of cross-examination is likely to improve.<sup>12</sup>

We conclude this section by addressing the question whether an eyewitness identification is stronger or weaker evidence than a DNA match. This is not only a question that is often a source of confusion,

<sup>11</sup>The extent to which initial high confidence under pristine conditions is indicative of accuracy depends on the base rate of target-present lineups. In lab studies the base rate is about 50%, but in real-life circumstances, the best estimate is about 35%.

<sup>12</sup>A word of caution is necessary, however. The mechanics of cross-examination is quite complex. While in general it is meant to elicit further information that should guide the evaluation of the evidence, there are a few different ways the situation might develop, and several argumentative moves that can be made in such a context. On one hand, the additional evidence obtained can *rebutt* the eyewitness evidence, if it supports a hypothesis incompatible with the original one, as might happen when the eyewitness makes a statement contradicting something they have said previously. On the other, the new evidence might *undercut* the eyewitness testimony if it leads to the re-evaluation of the witness's reliability without leading to a new hypothesis, as might happen when the eyewitness provides new evidence about the lighting conditions. This complexity cannot be satisfactorily modeled by using likelihood ratios only. It requires a more sophisticated formalism, Bayesian networks (Di Bello, 2021). We will examine the mechanics of cross-examination in greater detail in another chapter.

M: check and explain these numbers

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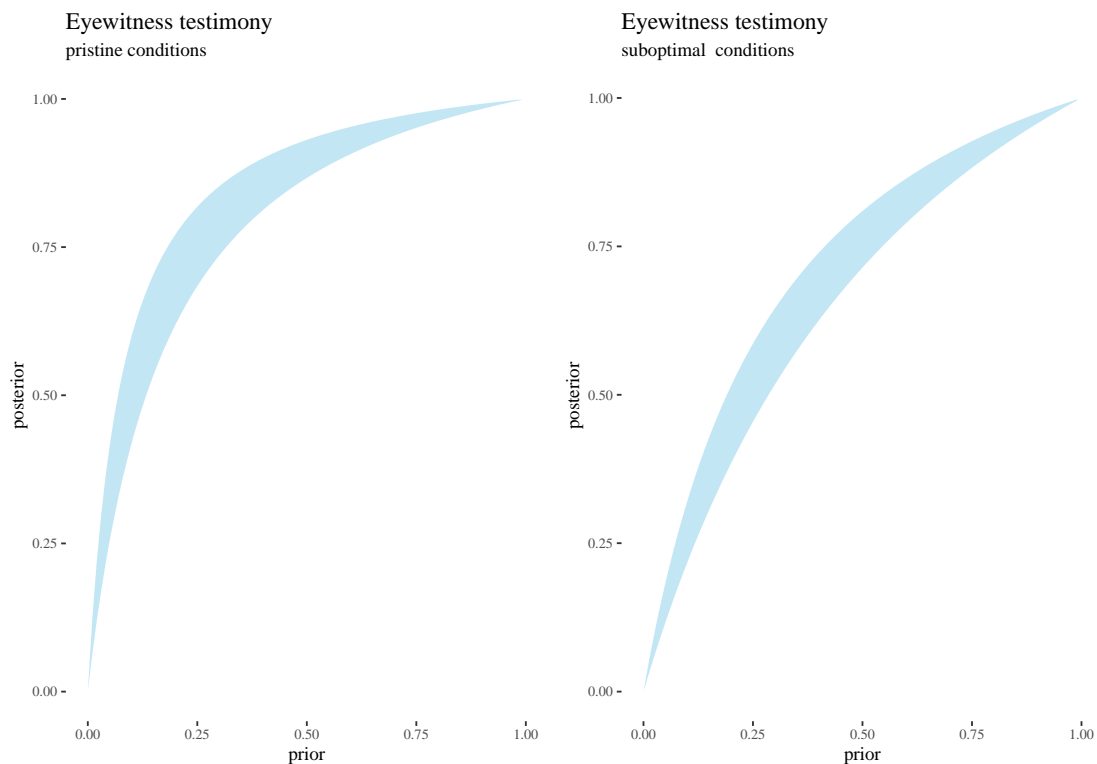


Figure 6: Impact of an eyewitness identification on the prior probability of the presence hypothesis under pristine and non-pristine conditions.

but also a good opportunity to illustrate the applications of what we have learned about match evidence (previous section) as well as eyewitness testimony (this section).

So suppose the eyewitness evidence in a case is exculpatory but there is also an incriminating DNA match. Which should prevail? It is tempting to take a clear-cut position. For example, one could reason that DNA is more reliable and thus should trump eyewitness evidence. Interestingly, an appellate court in New York took a similar stance in *People v. Rush*, 165 Misc. 2d 821 (N.Y. Sup. Ct. 1995). A rape victim identified the defendant from a photograph a few weeks after the event. She also identified the defendant in a line-up two weeks later. At trial, however, she identified a spectator as her assailant, not the defendant. So, the eyewitness evidence was mixed but ultimately exculpatory. On the other hand, the defendant was seen in the vicinity of the crime scene three days prior. A DNA expert testified to a positive match between the crime scene genetic material and the defendant. The expert also testified that the random match probability was 1 in 500 million. Confronted with the question whether to believe the exculpatory eyewitness testimony or the incriminating DNA match, the court wrote:

There can be little doubt, however, that the perils of eyewitness identification testimony far exceed those presented by DNA expert testimony ... This court is, therefore, satisfied that the testimony of even one DNA expert that there is a genetic match between the semen recovered from the victim of a rape and the blood of the defendant, a total stranger, and the statistical probability that anyone else was the source of that semen are 1 in 500 million is legally sufficient to support a guilty verdict.

Such blanket statements are unwarranted. The court framed the question as one of whether a DNA match *alone* can sustain a conviction. It gave no weight to the exculpatory testimony. But, even under this assumption, a random match probability of 1 over 500 million corresponds to a likelihood ratio of 20 (if the false positive error probability is .05) and 99 (if the false positive error probability is .01).<sup>13</sup> Are these numbers enough to convict? Assume the DNA match speaks directly to the hypothesis of guilt, a generous assumption in favor of the prosecution. By Bayes' theorem, if the prior probability of the the guilt hypothesis is about .01, the posterior guilt probability would be .5 (if the false positive

<sup>13</sup>We applied formula (6), assuming a zero false negative probability FNP.



probability is .01) and .16 (if the false positive probability reaches .05). These low numbers do not even take into account the exculpatory testimony. Say the exculpatory testimony is assigned a likelihood ratio of .5. This would bring the posterior guilt probability to .33 and .09 respectively, a far cry from what is needed to convict an individual.<sup>14</sup>

These numbers are merely illustrative, but they convey an important lesson. The random match probability was fairly low, but to exclusively rely on it was a mistake. As the previous section has shown, the false positive probability can have a significant, negative impact on the value of an incriminating match. In addition, it is true that eyewitness testimony is fraught with problems. Its value might be low, especially if the identification was not conducted under pristine conditions. But without further details about estimator or system variables, it is hasty to make sweeping statements that any eyewitness testimony is worthless. This cautionary remark applies even more so to *exculpatory* testimony. The court reasoned that since the balance of the evidence tipped markedly against the accused—because (incriminating) DNA evidence outweighs (exculpatory) eyewitness evidence—this was enough to convict. This is not quite right, however. Even if it has low value, exculpatory eyewitness testimony can in principle weaken an incriminating DNA match and create a reasonable doubt.<sup>15</sup> The value of eyewitness testimony should neither be exaggerated nor underestimated. As suggested in this section, a balanced assessment can be achieved by incorporating—as part of the likelihood ratio—numerical data about the risks of error under different circumstances.

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M: Check calcula-  
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## 4. Hypothesis choice

The argument so far has shown that the likelihood ratio is a fruitful conceptual framework for assessing the strength of the evidence, whether it is match evidence or eyewitness testimony. However, its deployment is not devoid of challenges, and we move to a discussion of how they arise. One major challenge we discuss in this section is the choice of the hypotheses  $H$  and  $H'$  that should be compared in the likelihood ratio. The two hypotheses need not be one the negation of the other, and thus there is quite a bit of leeway in their selection. Generally speaking, they should “compete” with one another—say, in a criminal trial,  $H$  is put forward by the prosecution and  $H'$  by the defense. But this minimal constraint can be a source of confusion.

A stylized case can serve to illustrate the problem. Suppose the prosecutor puts forward the hypothesis that the suspect is the source of the traces found at the crime scene. This hypothesis is well supported by laboratory analyses showing that the defendant genetically matches the traces. The defense, however, responds by putting forward the following *ad hoc* hypothesis: ‘The crime stain was left by some unknown person who happened to have the same genotype as the defendant’ Since the probability of the DNA match given either hypothesis is one, the likelihood ratio equals one (Evetts, Jackson, & Lambert, 2000). The problem generalizes. For any item of evidence and any hypothesis  $H$ , there is an *ad hoc* competing hypothesis  $H^*$  such that  $P(E|H)/P(E|H^*) = 1$ .  $H^*$  is simply a just-so hypothesis, one that is selected only because it explains the evidence just as well as  $H$  does (Mayo, 2018). If no further constraints are placed on the choice of the competing hypotheses—it would seem—no evidence could ever incriminate anyone.

A closer look, however, reveals that this is not a problem for the likelihood ratio, only for how we interpret it. By construction, a genetic match cannot discriminate between hypothesis  $H$  (the crime stain came from the defendant) and  $H^*$  (the crime stain came from someone else who has the same genetic profile as the defendant). They are both equally well-supported by the match. This is just a fact about the world and a fact about how evidence works. The likelihood ratio correctly tracks this fact. The problem here lies elsewhere. One might think that, since the likelihood equals one, the evidence must be worthless. But this would be a mistake. Since the likelihood ratio is relative to a pair of hypotheses, the resulting assessment of the value of the evidence is also relative. Even if the match has no evidential value relative to  $H$  and  $H^*$ , it may have value relative to other hypotheses.

We are dealing with a two-step process here: first, select a pair of hypotheses of interest; and second, assess whether the evidence makes a distinction between the two and to what extent. The likelihood ratio is useful for the second step, not the first. It provides no guidance in choosing the hypotheses. It is a tool to assess the value of the evidence *once* the hypotheses are chosen. The two steps must be spelled

<sup>14</sup>We multiplied the DNA match likelihood ratio by the exculpatory testimony likelihood ratio and then computed the posterior probability with Bayes’ theorem. We examine how to combine different lines of evidence together in another chapter.

<sup>15</sup>A more detailed discussion of standards of proof can be found in Chapter XXX

out clearly and kept separate. If they are not, confusions and misinterpretations of the evidence will occur. A good illustration of this point is the case *R. v. George* (2007 EWCA Crim 2722).

Barry George was accused of murdering TV celebrity Jill Dando. The key piece of incriminating evidence in the case was:

**residue** A single particle of firearm residue was found one year later in George's coat pocket and matched the residue from the crime scene.

The defense argued that, since it was only one particle, there must have been contamination. The experts for the prosecution, however, testified that it was not unusual that a single particle would be found on the person who fired the gun. George was convicted, and his first appeal was unsuccessful.

After the first appeal, Dr. Evett from the Forensic Science Service in the United Kingdom worried that the evidence had not been properly assessed at trial. The jurors were presented with the conditional probability  $P(\text{residue}|H_d)$  of finding the firearm residue in George's coat given the defense hypothesis  $H_d$  (say, that George *did not* fire the gun). This probability was estimated to be quite low, indicating that the evidence spoke against the defense's hypothesis. But the jurors were not presented with the conditional probability  $P(\text{residue}|H_p)$  of finding the same evidence given the prosecutor's hypothesis  $H_p$  (say, that George *did* fire the gun). An expert witness, Mr. Keeley, was asked to provide both conditional probabilities and estimated them to be  $1/100$ , which indicated that the firearm residue had no probative value. After new guidelines for reporting low level of firearm residue were published in 2006, the Forensic Science Service re-assessed the evidence and concluded that it was irrelevant. George appealed again in 2007, and relying on Keeley's estimates, won the appeal.

At first, this case seems a good illustration of how likelihood ratios help to correctly assess the value of the evidence presented at trial. But this reading of the case would be overly optimistic. What were the hypotheses that the expert compared? A close study of the trial transcript shows that Keeley's choice of hypotheses was not transparent and the likelihood ratio based on them was therefore hard to interpret (Fenton, Berger, Lagnado, Neil, & Hsu, 2014). On one occasion, Keeley took the prosecutor's hypothesis to be 'The particle found in George's pocket came from the gun that killed Dando' and the defense hypothesis to be 'The particle on George's pocket was inserted by contamination.' The problem is that the evidence is a logical consequence of either of them, so the conditional probability of the evidence given each of these hypothesis is one. In such case, the likelihood ratio would be one for trivial reasons. The most charitable reading of the trial transcript suggests that the expert had in mind the hypotheses 'George was the man who shot Dando' and 'The integrity of George's coat was corrupted.' But Keeley was never clear that he compared these two hypotheses. Thus, the meaning of the likelihood remains elusive (see Fenton, Berger, Lagnado, Neil, & Hsu, 2014 for further details).

The confusion in the George case stems from the lack of a clear statement of the hypotheses in the likelihood ratio. This lack of clarity can lead one to think that, since the likelihood ratio equals one (for a pair of not well-specified competing hypotheses), the evidence must prove nothing. To avoid this slippage, experts should perhaps only pick hypotheses that are exclusive (they cannot be both true) and exhaustive (they cannot be both false). In this way, the parties would not be able to pick *ad hoc* hypotheses and skew the assessment of the evidence in their own favor. Further, exclusive and exhaustive hypotheses would have likely forced the expert in the George case to be more precise.

But requiring that the hypotheses be always exclusive and exhaustive is not without complications either. Conceptually, it is a good idea to compare a hypothesis with its negation. Practically, this might not be viable, as often there are multiple different ways a hypothesis can turn out to be false. For consider an expert who decides to formulate the defense hypothesis by negating the prosecution hypothesis, say, 'the defendant did *not* hit the victim in the head.' This choice for the defense hypothesis can be unhelpful in assessing the evidence, because the required probabilities are hard to estimate. For instance, what is the probability that the suspect would carry such and such blood stain if he did not hit the victim in the head? This depends on whether he was present at the scene, what he was doing at the time and many other circumstances. As Evett, Jackson, & Lambert (2000) point out, in many real life cases, the choice of a particular hypothesis to be used by the expert in the evaluation of the evidence will depend on contextual factors.<sup>16</sup>

<sup>16</sup> Another practical difficulty is that comparing exclusive and exhaustive hypotheses can be unhelpful for jurors or judges. In a paternity case, for example, the expert should not compare the hypotheses 'The accused is the father of the child' and its negation, but rather, 'The accused is the father of the child' and 'The father of the child is a man unrelated to the putative father' (Biedermann, Hicks, Taroni, Champod, & Aitken, 2014). The choice of the latter pair of competing hypotheses is

The moral is this. The likelihood ratio offers no guidance in how to choose competing hypotheses. Nor should we expect it to do that. Hard and fast rules, such as ‘use only exclusive and exhaustive hypotheses,’ will limit the practical applicability of the likelihood ratio. The mistake consists in overlooking that likelihood ratios are relative to a pair of hypotheses and thus their assessment of the evidence is also relative. As noted at the start of this chapter, we are after a *local* measure of evidential value (strength, support), one that is circumscribed to a certain hypothesis or pair of hypotheses. The likelihood ratio serves this purpose well, but nothing more than that. We elaborate on this point further as we discuss the notion of legal relevance in the next section.

## 5. Relevance and the small-town murder scenario

The Federal Rules of Evidence define relevant evidence as one that has ‘any tendency to make the existence of any fact that is of consequence to the determination of the action more probable or less probable than it would be without the evidence’ (rule 401). As before, we are dealing with a two-step process here: first, select a ‘fact that is of consequence to the determination of the action,’ sometimes called a material fact or hypothesis; and second, assess whether the evidence changes the probability of the material fact or hypothesis. More succinctly, two conditions must be met: (1) materiality and (2) probative value. An item of evidence is relevant if it has probative value for a hypothesis that is material (‘of consequence to the determination of the action’). The likelihood ratio is helpful for assessing probative value, and in fact, it allows for a more fine-grained assessment because it formalizes *degrees* of probative value (or strength, support). We have illustrate how this can be done in the case of match evidence and eyewitness testimony. But the likelihood ratio does not directly address the question of materiality and therefore cannot provide a full account of relevance.

Consider now probative value more closely. Interestingly, the Rules define it in probabilistic language, a fact that has not gone unnoticed (CGG Aitken, Roberts, & Jackson, 2010; Colin Aitken & Taroni, 2004; Lempert, 1977; Lyon & Koehler, 1996; Sullivan, 2019). More specifically, the Rules relies on the idea of a probability change, but do not mention the likelihood ratio. The two are related, however. A piece of evidence changes the probability of hypothesis  $H$  or its negation *if and only if* the likelihood ratio  $P(E|H)/P(E|\neg H)$  is different from one. But note that the comparison here holds between  $H$  and its negation, not just between any two competing hypotheses  $H$  and  $H'$ . When the comparison is between hypotheses that are not one the negation of the other, likelihood ratio and probability change come apart. A piece of evidence may change the probability of a hypothesis—so that  $P(H|E) \neq P(H)$ —even though the likelihood ratio  $P(E|H)/P(E|H')$  equals one. How can that be?

Suppose Fred and Bill attempted to rob a man. The victim resisted, was struck on the head and died. Say  $H_p$  stand for ‘Fred struck the fatal blow’ and  $H_d$  stand for ‘Bill struck the fatal blow.’ The hypotheses are not exhaustive. A missing hypothesis is ‘The man did not die from the blow.’ Suppose  $E$  is the information that the victim had a heart attack six months earlier. The likelihood ratio  $P(E|H_p)/P(E|H_d)$  equals one since  $P(E|H_p) = P(E|H_d)$ . Yet  $E$  reduces the probability of both  $H_p$  and  $H_d$ . This might be confusing, but there is no inconsistency here. If what is material in the case is only whether either Bill or Fred did it, evidence about a heart attack would be irrelevant. The likelihood ratio correctly tracks this fact. On the other hand, if what is material is whether the victim died by natural or human causes, evidence about a heart attack would be relevant. Again, it is paramount not to confuse questions of materiality and questions of probative value.

The distinction between materiality and probative value also helps to deflect the force of a number of counterexamples against the likelihood ratio that we find in the literature. The vignette below was formulated by Ronald Allen and appears in the multi-authored discussion in (Park et al., 2010):

**Small Town Murder.** A person accused of murder in a small town was seen driving to the small town at a time prior to the murder. The prosecution’s theory is that he was driving there to commit the murder. The defense theory is an alibi: he was driving to the town because his mother lives there to visit her. The probability of this evidence if he is guilty equals that if he is innocent, and thus the likelihood ratio is 1 . . . , and under what is suggested as the “Bayesian” analysis, it is therefore irrelevant. Yet, every judge in every trial courtroom . . . would say it is relevant. And so we have a puzzle.

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preferable. Even though the relatives of the accused are potential fathers, considering such a far-fetched possibility would make the assessment of the evidence more difficult than needed.

Counterexamples of this sort abound.<sup>17</sup> The puzzle is that the evidence is intuitively relevant and yet the likelihood ratio would seem to tell otherwise. There are a few things to say in response. First, as noted already, the likelihood ratio provides an account of probative value (strength, support), not relevance (which includes both materiality and probative value). Further, probative value is relative to a specific pair of hypotheses. The likelihood ratio may change depending on the selection of hypotheses.

Rule 401 makes clear that relevant evidence should have ‘any tendency to make the existence of *any fact that is of consequence* [emphasis ours] to the determination of the action more probable or less probable.’ Just because the likelihood ratio equals one for a specific selection of  $H$  and  $H'$ , it does not follow that it equals one for *any* selection of  $H$  and  $H'$  which are of consequence to the determination of what happened. For example, the likelihood ratio of the evidence ‘suspect was seen driving to town’ relative to the pair of hypotheses ‘suspect was in town’ *versus* ‘suspect was not in town’ would be different from one. Whether the suspect was in town at all is presumably of consequence for determining what happened. So the fact that he was seen driving is helpful information for establishing whether or not he was in town, and the likelihood ratio can model this fact.

This discussion makes clear that relevance is a *global, holistic* notion, whereas probative value is a local notion. Legal cases often have a very complex structure. They consist of several pieces of evidence as well as several factual hypotheses to be assessed in light of the evidence. Some may be very all-encompassing, such as the ultimate prosecutor’s hypothesis ‘The defendant is guilty.’ Other hypotheses may be more circumscribed, such as ‘The defendant visited the victim on Sunday.’ Evidence may be probative relative to a hypothesis, and not relative to another. Probative value is a local notion that depends on the circumscribed hypothesis one chooses. Instead, an item of evidence is relevant so long as it can affect the probability of *any* material hypothesis, in one way or another. This underscores the global, holistic nature of relevance.<sup>18</sup> In complex situations, there is no single likelihood ratio that corresponds to a single piece of evidence. Evidence can be relevant so long as it has a probabilistic impact on a sub-hypothesis involved in the case, even without having a recognizable probabilistic impact on the prosecutor’s or defense’s ultimate hypotheses. This agrees with the Federal Rules of Evidence. But to model these complex relationships, we need to move past the likelihood ratio. As we shall see in later chapters, Bayesian networks can make better sense of this holistic perspective. (de Zoete, Fenton, Noguchi, & Lagnado, 2019).

## 6. Conclusions

We have introduced likelihood ratio as a measure of evidential strength, and argued that it is more fit for this purpose in legal contexts than the Bayes Factor (and, in an appendix, than other probabilistic confirmation measure).

Then, we moved to the utility of this notion in theorizing about important factors at play in legal evidence evaluation: false positive probability of DNA evidence, which should be taken more seriously, and in the combining of identifying eyewitness evidence with scientific evidence (and, in appendices on the value of cold-hit DNA matches). Such considerations, while perhaps fail to provide us with precise quantitative estimations, tell us what we do not, but should know: false positive probabilities, and more relevant details of the circumstances of an eyewitness identification. Had such information been available, at least rough quantitative estimates of the weight of joint evidence seem in principle viable, and they seem to be better than mere intuitive judgment of untrained jury members (also, proper considerations of cold-hit matches results in a *prima facie* counter-intuitive result: such matches have higher evidential weight than matches not obtained through a database search, and doubts about their actionability have sources elsewhere than in the mere fact that the matches were obtained through a

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<sup>17</sup> Here is another scenario: Suppose a prisoner and two guards had an altercation because the prisoner refused to return a food tray. The prisoner had not received a package sent to him by his family and kept the tray in protest. According to the defense, the prisoner was attacked by the guards, but according to the prosecution, he attacked the guards. The information about the package sent to the prisoner and the withholding of the tray fails to favor either version of the facts, yet it is relevant evidence (Pardo, 2013).

<sup>18</sup> A complication is that the choice of hypotheses needed to determine relevance might depend on other items of evidence, and so it might be difficult to determine relevance until one has heard all the evidence. This fact—Ronald Allen and Samuel Gross argue in (Park et al., 2010)—makes the probabilistic account of relevance impractical. But, in response, David Kaye points out that deciding whether a reasonable juror would find evidence  $E$  helpful requires only looking at what hypotheses or stories the juror would reasonably consider. Since the juror will rely on several clues about which stories are reasonable, this task is computationally easier than going over all possible combinations of hypotheses (Park et al., 2010).

database search).

R: revised this in light of Sophie's comments.

While, conceptually, likelihood ratio seems to be the right tool for the job of being a local measure of evidential strength, there are some risks to using likelihood ratios in legal evidence evaluation. Likelihood ratios are sensitive of this measure to hypothesis choice. In real-life complex cases multiple hypothesis are available, and proper evidence evaluation needs to go beyond a single likelihood ratio statement. The context of an evidence evaluation and such choices should be made clear and transparent, and proper incorporation of the likelihood ratios in the judging of a whole case requires a more elaborate framework and representation of such complexities. A useful tool fit for this task, we will argue, is Bayesian Network representation.

## A. Confirmation measures

At this point a philosophically minded reader might recall that there is an important notion in the vicinity—that of confirmation—and that there is a vast philosophical literature on probabilistic explication of that notion. Natural questions arise: how is the notion of confirmation related to the notion of evidence strength, and why almost none of the probabilistic explications of confirmation have not been deployed in legal probabilism?

The key question behind the enterprise we are going to take a look at is: when does a piece of evidence confirm a theory, and how are these requirements to be explicated probabilistically to agree with both successful scientific practice and sensible philosophical principles? The hope is that having answered these questions would facilitate both rational reconstructions of various developments in the history of science, and a critical evaluation of various ongoing scientific investigations.

The underlying probabilistic idea is that the level of confirmation of a theory ( $T$ ) by a piece of evidence ( $E$ ) is a function of an agent's degrees of belief. The first stab might be, let's simply identify the confirmation level with  $P(T|E)$ . This, however, is way too quick. Multiple factors come into the assessment of this conditional probability, and two agents can agree on the extent to which  $E$  confirms  $T$  without agreeing on the posterior probability of  $T$  (identified with  $P(T|E)$ ), because the agents might disagree about the prior probability of  $T$  and this might have an impact on the posterior.

Still, some requirements on confirmation measures can be formulated in terms of probabilities. One usual assumption (Sprenger & Hartmann, 2019) is that the level of confirmation is to be a continuous function of  $P(T)$  and  $P(E|T)$  which is non-decreasing in the first argument and non-increasing in the second argument. That is, increasing the prior, should not lower the confirmation level, and increasing the likelihood should not increase the confirmation level. Let's call this condition the *prior-posterior dependence*.<sup>19</sup>

One consequence of the prior-posterior-dependence—called *Final Probability Incrementality* is that confirmation of  $T$  by  $E$ ,  $c(T, E)$  should track the posterior order-wise, that is  $c(T, E) > c(T, E')$  just in case  $P(T|E) > P(T|E')$ .

Another requirement is that there should be a neutral point  $n$  such that  $E$  confirms (disconfirms)  $T$  just in case  $c(T, E) > n$  ( $c(T, E) < n$ ) and is neutral exactly at  $n$ . This is called the *qualitative-quantitative bridge*.

Yet another requirement is *local equivalence*. Theories that are logically equivalent given the evidence should receive equal confirmation from this evidence. Interestingly, all confirmation measures which satisfy prior-posterior dependence, qualitative-quantitative bridge, and local equivalence are strictly increasing functions of  $P(H|E)$ . Such measures are said to explicate confirmation as *firmness of belief*. Moreover, all functions satisfying these three conditions are ordinally equivalent.<sup>20</sup>

However, another notion of confirmation seems often at play. For instance, even if the posterior  $T$  is low, one might still think that a given experiment speaks strongly in favor of  $T$ . And relatedly,  $E$  can lower the posterior of  $T$  while still leading the posterior to be sufficiently high for the firmness confirmation measure to be above the neutrality threshold. Another feature of confirmation as firmness is that if, in this sense,  $T$  confirms  $H$ , then for any  $H'$  that is excluded by  $H$ ,  $T$  disconfirms  $H'$ . But now think of the small town murder scenario we already discussed: the fact that the suspect was seen in town seems to support both the prosecution hypothesis that he committed the murder, and the defense

<sup>19</sup>Some formulations (Crupi, 2015) are a bit more general and include background knowledge  $K$ . In that setting, the corresponding requirement is called *Formality* and takes the confirmation to be a function of  $P(H \wedge E|K)$ ,  $P(H|K)$  and  $P(E|K)$ . For the sake of simplicity, we will suppress the reference to  $K$ , unless required by the context.

<sup>20</sup>Measure  $c$  is ordinally equivalent to measure  $c'$  just in case always  $c(E, T) \geq c(E', T')$  iff  $c'(E, T) \geq c'(E', T')$ .

hypothesis, that he was in town to visit his mother. Confirmation as firmness cannot capture such intuitions, as relevance cannot be captured as a function of the posterior alone.

For such reasons, following the second edition of (Carnap, 1962), it is customary to distinguish another notion in the vicinity: confirmation as increase in firmness of belief. If we replace local equivalence with tautological equivalence  $c(T, \top) = c(T', \top)$ , where  $\top$  is a logical tautology—the idea being that hypotheses are equally supported by empty evidence—we end up with another class of confirmation measures, those meant to capture *probabilistic relevance*. On this approach,  $E$  confirms (disconfirms)  $T$  just in case  $P(H|E) > P(H)$  ( $P(H|E) < P(H)$ ).

Here is a list of key confirmation measures available on the market (Sprenger & Hartmann, 2019), normalized so that they all have neutral points at 0:

$$D(T, E) = P(T|E) - P(T) \quad (\text{Difference})$$

$$Lr(T, E) = \log \left( \frac{P(T|E)}{P(T)} \right) \quad (\text{Log-ratio})$$

$$LL(T, E) = \log \left( \frac{P(E|T)}{P(E|\neg T)} \right) \quad (\text{Log-likelihood})$$

$$K(T, E) = \frac{P(E|T) - P(E|\neg T)}{P(E|T) + P(E|\neg T)} \quad (\text{Kemeny-Oppenheim})$$

$$Z(T, E) = \begin{cases} \frac{P(T|E) - P(T)}{1 - P(T)} & \text{if } P(T|E) \geq P(T) \\ \frac{P(T|E) - P(T)}{P(T)} & \text{if } P(T|E) < P(T) \end{cases} \quad (\text{Generalized entailment})$$

$$S(T, E) = P(T|E) - P(T|\neg E) \quad (\text{Christensen-Joyce})$$

$$C(T, E) = P(E)(P(T|E) - P(T)) \quad (\text{Carnap})$$

$$R(T|E) = 1 - \frac{P(\neg T|E)}{P(\neg T)} \quad (\text{Rips})$$

(Log-likelihood), our good old likelihood ratio, and (Kemeny–Oppenheim) are ordinally equivalent (and no other pair on the list is). The former makes calculations of joint support additive, and the former has the nice feature of ranging from  $-1$  to  $1$  and having  $0$  as a neutral point, so if one accepts the use of likelihood ratio, these two also can be used on some occasions when these additional features are justified. Further grouping and assessment of the confirmation measures for a given purpose is facilitated by the following facts:

- One might require that  $E$  always confirms the disjunction of excluding hypotheses more than one of them just in case it also confirms the other one (*disjunction of alternative hypotheses*). This can happen only if the confirmation measure is a strictly increasing function of the difference measure. Whether this is an intuitive requirement in our context is unclear.
- One might require that confirmation should track likelihood— $c(T, E) > c(T, E')$  (*Law of likelihood*)—just in case  $P(E|T) > P(E'|T)$ . This can happen only if the measure is a strictly increasing function of the Bayes factor. At least in legal applications, the law of likelihood is suspicious, as our example with rocking child abuse victims discussed on page 1 indicates.
- You might wish that confirmation be *contrapositive* ( $c(T, E) = c(\neg E, \neg T)$ ) and *commutative* ( $c(H, E) = c(E, H)$ ). The only measures that satisfy both are relative distance measures, that is, they are strictly increasing functions of the generalized entailment measure.
- One might require that if  $E$  and  $E'$  are conditionally independent given  $T$  and  $\neg T$ , then  $c(T, E)$  should be identical with  $c(T, E|E')$  (the confirmation obtained when  $E'$  is added to the background knowledge). This condition is called *modularity*. This condition holds only if a confirmation measure is a strictly increasing function of the likelihood ratio.

Moreover, if you require strict additivity:  $c(H, E \wedge E') = c(H, E) + c(H, E'|E)$ , the only measure that satisfies the disjunction of alternative hypotheses is the difference measure, the only measure that satisfies the law of likelihood is the log-ratio measure, and the only one that satisfies modularity is the log-likelihood measure.

Some unity can be brought into the picture (Crupi, Tentori, & Gonzalez, 2007) by normalizing by what happens with a measure where logical consequence or exclusion is involved. For instance, if  $E|T$ ,



Measure	Reason not to use
(Difference)	dependence on priors, logical closure failure
(Log-ratio) and (Bayes factor)	satisfies law of likelihood, symmetry, dependence on priors, failure to satisfy logical closure
(Generalized entailment)	dependence on priors, independent conflicting evidence
(Christensen-Joyce)	excluded by final probability incrementality with prior-posterior dependence
(Carnap)	excluded by final probability incrementality with prior-posterior dependence, symmetry, logical closure failure
(Rips)	dependence on priors, failure of logical closure
(Christensen-Joyce)	excluded by final probability incrementality with prior-posterior dependence
(Kemeny-Oppenheim)	none of the above, but unnecessarily complex
(Log likelihood)	none of the above, but logarithms are hard for humans
(Likelihood ratio)	none of the above

Table 1: Reasons not to use various confirmation measures in legal fact-finding applications.

$D(E, T) = P(\neg T)$  and if  $E \vdash T$ ,  $D(E, T) = -P(T)$ . So the normalized version has the form:

$$D_n(E, T) = \begin{cases} D(E, T)/P(\neg T) & \text{if } P(T|E) \geq P(T) \\ D(E, T)/P(H) & \text{otherwise.} \end{cases}$$

Interestingly, analogous normalization of measures other than (Generalized entailment) leads to the same single new Bayesian measure of confirmation: (Generalized entailment). Another reason one might have to like this measure is as follows. Take any  $k > 0$  and say  $v(E, T) = k$  iff  $E \models T$ ,  $v(E, T) = -k$  iff  $E \models \neg T$  and  $v(E, T) = 0$  otherwise. The *logical closure requirement* is that if  $v(E, T) > v(E', T')$ , then  $c(E, T) > c(E', T')$ . It turns out that all measures ordinally equivalent to the listed measures other than (Log-likelihood), likelihood ratio, (Generalized entailment) fail to satisfy this condition and Z, likelihood ratio, (Kemeny-Oppenheim) and (Kemeny-Oppenheim) succeed at satisfying it.

Now, what reasons do we have to not use some of the measures we introduced? First, some insights are obtained by considering the abstract requirements. Crucially, (1) final probability incrementality with prior-posterior dependence exclude (Carnap) and (Christensen-Joyce), (2) (Carnap) and (Log-ratio) have the unintuitive consequence that  $C(T, E) = C(E, T)$  (call this *symmetry*), (3) (Difference), (Generalized entailment), (Log-ratio), (Carnap) and (Rips) depend on the prior of  $T$ , and (4) logical closure requirement excludes many of the measures.

Moreover, there is an issue with Z (Branded Fitelson, 2021). Say  $E$  and  $E'$  are confirmationally independent regarding  $H$  just in case both  $c(T, E|E') = c(T, E)$  and  $c(T, E'|E) = c(T, E')$ . Say  $E$  and  $E'$  are conflicting evidence regarding  $T$  iff  $P(T|E) > P(T)$  while  $P(T|E') < P(T)$ . Branded Fitelson (2021) has proven that any measure ordinally equivalent with Z, however, excludes the fairly intuitive possibility of the existence of confirmationally independent and yet conflicting evidence (he also gives a clear example of such a case).

Last but not least, for legal applications it seems that dependence on the prior probability is undesirable. We propose that at least two conceptual takes on confirmation is available. On one hand, say a scientific community pretty much agrees on the status of a given theory prior to an experiment. Then, after the experiment, it is a legitimate question what impact the experiment has on the status of that theory, and perhaps it makes sense that the prior status of that theory plays a role. On the other hand, in legal context, we would like (1) the expert's assessment not to depend on the expert's prior convictions about the hypothesis, and (2) the expert's statement to mean the same for various agents involved in the fact-finding process, even if they assign different priors to the hypothesis. For this reason, we propose that dependence on priors in legal evidence evaluation is an undesirable feature of a confirmation measure.

Thus, the general picture obtained, pictured in Table 1, seems to suggest that the likelihood ratio is a decent choice for our applications. This, of course, also applies to (Log likelihood) and (Kemeny-Oppenheim), which are ordinally equivalent to likelihood ratio, but the reasons to not use them in a legal context are that (Kemeny-Oppenheim) is conceptually more complex than likelihood ratio, and that thinking in terms of logarithms is not very natural for human agents.

Finally, here is a somewhat abstract, yet important approach to confirmation measures due to (Heckerman, 1988), which constitutes a fairly strong motivation to use likelihood ratio. Suppose you have

R: so here's my account of the Heckerman's result, take a look

background information  $e$ , and consider a hypothesis  $H$  when you obtain a piece of evidence  $E$ . A belief update,  $U(H, E, e)$ , together with your prior stance of  $H$ , should determine your posterior belief in  $H$ . If we denote conditional belief in  $H$  given  $E$ , without assuming it's probabilistic yet, as  $H|E$ , this means that there should be an  $f$  such that:

$$H|Ee = f(U(H, E, e), H|e)$$

where, on this approach,  $H|Ee$ ,  $U(H, E, e)$ , and  $H|e$ , are all real numbers, and  $f$  is required to be continuous in both arguments and monotonically increasing when the other is held constant. Call this the **update requirement**. Bayesian updating is a particular case: the selection of  $H$  and  $e$ , with a joint distribution in the background, determines a function from  $P(H|E)$  to  $P(H|Ee)$ .

Further, assume the **consistency property**: if the arguments are logically equivalent, then belief update yields the same value:

$$[H_1 \Leftrightarrow H_2, E_1 \Leftrightarrow E_2] \Rightarrow U(H_1, E_1, e_1) = U(H_2, E_2, e_2)$$

The next assumption has it that when you update on two items of evidence, the order of updating shouldn't matter and the result should be the same as updating on the joint evidence. The **combination property** requires that there is a function  $g$  that is continuous in both arguments and monotonically increasing in each argument when the other is held constant such that:

$$U(H, E_1 E_2, e) = g(U(H, E_1, e), U(H, E_2, E_1 e))$$

A general result in group theory by Aczel is that any continuous monotonic function of two arguments that satisfies the associativity relation must be additive in some transformed space. In this particular case, the result entails that any update that satisfies the update condition, and the consistency and combination properties is the arithmetic difference of a posterior and prior belief up to an arbitrary monotonic transformation, that is, that there are monotonic functions  $h$  and  $i$  such that:

$$h(U(H, E, e)) = i(H|Ee) - i(H|e)$$

In the probabilistic context, where  $H|E$  is  $P(H|E)$ , the likelihood ratio satisfies the update requirement and has the combination and consistency properties. Accordingly, the transformation that makes it additive is the logarithmic function.

Now, the *independence correspondence property* has it that if  $E_1$  and  $E_2$  are conditionally independent given  $H$  and given  $\neg H$ , then  $U(H, E_2, E_1 e) = U(H, E_2, e)$ . The key result is that any probabilistic update satisfying the independence correspondence must be a monotonic transformation of the likelihood ratio. This means that there is a list of fairly intuitive general conditions on what an update function should behave like which entails that it is just a variant of the likelihood ratio.

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