

Likelihood ratio and decision thresholds

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SAMLE CHAPTER PLAN UPDATE

I am now realizing that perhaps the structure of the chapter could be further broken down into three chapters:

1. A chapter that shows how probabilistic thresholds are good as analytical tools, despite implementation or practical difficulties with them. This chapter would include discussions of expected utility, minimizing errors, signal detection theory, etc. A lot of this stuff is already in the extended version of the SEP entry. So main claim of this chapter is: yes, probabilistic thresholds are not good practically, but they can still be good as analytical tools. Title: "Probability Thresholds as Analytical Models of Trial Decision Making"
2. A chapter that looks at the two theoretical difficulties (naked stats and conjunction paradox, and also problem of priors) and examines whether likelihood ratios are a good way to address these difficulties. This follows the earlier chapter. The point of this chapter is: yes, LR are promising but not as good as we might have thought initially, so we need something better. Title: "Likelihood Ratios as Decision Thresholds"
3. A chapter that finally addresses the two theoretical difficulties, perhaps using Bayesian Networks. This need not be included in the sample chapters we sent out. Title: "Addressing the Proof Paradoxes with Bayesian Networks".

SAMPLE CHAPTER PLAN

In rethinking the sample chapter, we should perhaps stick to a simpler structure, trying to offer a more focused and compelling argument. Right now I think we have too many possible accounts under consideration, and the structure is not very tight or cohesive. It feels more like a literature review, especially the first few sections.

So here is how I proposed we do it:

1. Begin by stating the simplest probabilistic account based on a threshold for the posterior probability of guilt/liability. The threshold can be variable or not. Add brief description of decision-theoretic ways to fix the threshold. (Perhaps here we can also talk about intervals of posterior probabilities or imprecise probabilities.)
2. Formulate two common theoretical difficulties against this posterior probability threshold view: (a) naked statistical evidence and (b) conjunction. (We should state these difficulties before we get into alternative probabilistic accounts, or else the reader might wonder why so many different variants are offered of probabilistic accounts).
R: Yes. That's what I thought.
We might also want to add a third difficulty: (c) the problem of priors (if priors cannot be agreed upon then the posterior probability threshold is not functionally operative). Dahlman I think has quite a bit of stuff on the problem of priors.
3. As a first response to the difficulties, articulate the likelihood ratio account. This is the account I favor in my mind paper. Kaplow seems to do something similar. So does Sullivan. So it's a popular view, worth discussing in its own right. You say that Cheng account is one particular variant of this account, so we can talk about Cheng here, as well.
4. Examine how the likelihood ratio account fares against the two/three difficulties above. One could make an argument (not necessarily a correct one) that the likelihood ratio account can address all

- the two/three difficulties. So we should say why one might think so, even though the argument will ultimately fail. I think this will help grab the reader's attention. This is what I have in mind:
- 4a: the LR approach solves the naked stat problem because $LR=1$ (Cheng, Sullivan) or $L1=unknown$ (Di Bello).
- 4b: the LR approach solves the conjunction problem because – well this is Dawid's point that we will have to make sense of the best we can
- 4c: the LR approach solves the priors problem b/c LR do not have priors.
5. Next, poke holes in the likelihood ratio account:
- against 4a: you do not believe $LR=1$ or $LR=unknown$, so we should talk about this
- against 4b: this is your cool argument against Dawid
- against 4c: do you believe the argument in 4c? we should talk about this
- In general, we will have to talk to see where we stand. As of now, I tentatively believe that the likelihood ratio account can solve (a) and (c), and you seem to disagree with that. Even if I am right, the account is still not good enough because it cannot solve (b).
6. Articulate (or just sketch?) a better probabilistic account overall. Use Bayesian networks, narratives, etc. I am not sure if this should be another paper. That will depend on how much we'll have to say here.

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1 Introduction

After the evidence has been presented, examined and cross-examined at trial, trained judges or lay jurors must reach a decision. In many countries, the decision criterion is defined by law and consists of a standard of proof, also called the burden of persuasion. So long as the evidence against the defendant meets the requisite proof standard, the defendant should be found liable.

In criminal proceedings, the governing standard is ‘proof beyond a reasonable doubt.’ If the decision makers are persuaded beyond a reasonable doubt that the defendant is guilty, they should convict, or else they should acquit. In civil cases, the standard is typically ‘preponderance of the evidence.’ The latter is less demanding than the former, so the same body of evidence may meet the preponderance standard, but not meet the beyond a reasonable doubt standard. A vivid example of this difference is the 1995 trial of O.J. Simpson, who was charged with the murder of his wife. He was acquitted of the criminal charges, but when the family of the victim brought a lawsuit against him, they prevailed. O.J. Simpson did not kill his wife according to the beyond a reasonable doubt standard, but he did according to the preponderance standard. An intermediate standard, called ‘clear and convincing evidence,’ is sometimes used for civil proceedings in which the decision is particularly weighty, for example, a decision whether someone should be committed to a hospital facility.

Not sure if it is clear what you mean by this.

How to define standards of proof—and whether they should be even defined in the first place—remains contentious (Diamond, 1990; Horowitz & Kirkpatrick, 1996; Laudan, 2006; Newman, 1993; Walen, 2015). Judicial opinions offer different, sometimes conflicting, paraphrases of what these standards mean. The meaning of ‘proof beyond a reasonable doubt’ is the most controversial. It has been equated with ‘moral certainty’ or ‘abiding conviction’ (Commonwealth v. Webster, 59 Mass. 295, 320, 1850) or with ‘proof of such a convincing character that a reasonable person would not hesitate to rely and act upon it in the most important of his own affairs’ (US Federal Jury Practice and Instructions, 12.10, at 354, 4th ed. 1987). But courts have also cautioned that there is no need to define the term because ‘jurors know what is reasonable and are quite familiar with the meaning of doubt’ and attempts to define it only ‘muddy the water’ (U.S. v. Glass, 846 F.2d 386, 1988).

To further complicate things, differences between countries and legal traditions exist. The tripartite distinction of proof standards—beyond a reasonable doubt; preponderance; clear and convincing evidence—is common in Anglo-american jurisprudence. It is not universal, however. Different countries may use different standards. France, for example, uses the standard of ‘intimate conviction’ for both civil and criminal proceedings. Judges deciding cases ‘must search their conscience in good faith and silently and thoughtfully ask themselves what impression the evidence given against the accused and the defence’s arguments have made upon them’ (French Code of Criminal Procedure, art. 353). German law is similar. Germany’s Code of Civil Procedure, Sec. 286, states that ‘it is for the court to decide, based on its personal conviction, whether a factual claim is indeed true or not.’

While there are inevitable differences between legal traditions, the question of how strong the evidence should be to warrant a finding of civil or criminal liability has universal appeal. Any system of adjudication whose decisions are informed by evidence will confront this question in one way or another. Not all legal systems will explicitly formulate standards of proof for trial decisions. Some legal systems may specify rules about how evidence should be weighed without formulating decision criteria such as standards of proof. But even without explicit proof standards, the triers of facts, judges or jurors, will have to decide whether the evidence is sufficient to judge the defendant legally liable.

Need to revise this when the chapter is done.

We will not survey the extensive legal literature and case law about proof standards. We will instead examine whether or not probability theory can bring conceptual clarity to an otherwise heterogeneous legal doctrine. This chapter outlines different probabilistic approaches, formulates the most common challenges against them, and offers a number of responses from the perspective of legal probabilism. The legal and philosophical literature has focused on the theoretical and analytical challenges. We will do the same here. We will focus on two key theoretical challenges that have galvanized the philosophical literature: the problem of naked statistical evidence and the conjunction paradox. One reason to choose these two in particular is that it would be desirable to be able to handle basic conceptual difficulties before turning to more complex issues or attempting to implement probabilistic standards of proof in trial proceedings.

2 Probability thresholds

Imagine you are a trier of fact, say a judge or a juror, who is expected to make a decision about the guilt of a defendant who faces criminal charges. The prosecution presents evidence to support its accusation, and the defense offers counterevidence. As a trier of fact, you are confronted with the question whether the totality of the evidence presented at trial warrants a conviction. More specifically, the question is whether the evidence as a whole establishes the defendant's guilt beyond a reasonable doubt.

2.1 The basic idea

Legal probabilists have proposed to interpret proof beyond a reasonable doubt as the requirement that the defendant's probability of guilt, given the evidence presented at trial, meet a threshold (see Bernoulli, 1713; Dekay, 1996; Kaplan, 1968; Kaye, 1979a; Laplace, 1814; Laudan, 2006). On this interpretation, so long as the defendant's guilt is established with a sufficiently high probability, say 95%, guilt is proven beyond a reasonable doubt and the defendant should be convicted. If the probability of guilt does not reach the requisite threshold, the defendant should be acquitted. This interpretation can be spelled out more formally by means of conditional probabilities. That is, a body of evidence E establishes guilt G beyond a reasonable doubt if and only if $P(G|E)$ is above a threshold.

This interpretation is, in many respects, plausible. From a legal standpoint, the requirement that guilt be established with high probability, still short of 100%, accords with the principle that proof beyond a reasonable doubt is the most stringent standard but does not require—as the Supreme Court of Canada put it—‘proof to an absolute certainty’ and thus ‘it is not proof beyond any doubt’ (*R v Lifchus*, 1997, 3 SCR 320, 335). The plausibility of a probabilistic interpretation is further attested by the fact that such an interpretation is tacitly assumed in empirical studies about people's understanding of proof beyond a reasonable doubt (Dhami, Lundrigan, & Mueller-Johnson, 2015). This research examines how high decision-makers set the bar for convictions, say at 80% or 90% probability, but does not question the assumption that standards of proof function as probabilistic thresholds of some kind.

Reliance on probability is even more explicit in the standard ‘preponderance of the evidence’—also called ‘balance of probabilities’—which governs decisions in civil disputes. This standard can be interpreted as the requirement that the plaintiff—the party making the complaint against the defendant in a civil case—establish their version of the facts with greater than 50% probability. The 50% threshold, as opposed to a more stringent threshold of 95% for criminal cases, reflects the fact that preponderance is less demanding than proof beyond a reasonable doubt. The intermediate standard ‘clear and convincing evidence’ is more stringent than the preponderance standard but not as stringent as the beyond a reasonable doubt standard. Since it lies in between the other two, it can be interpreted as the requirement that the plaintiff establish their versions of the facts with, say, 75-80% probability.

2.2 Mixed reactions from legal practitioners

When appellate courts have examined the question whether standards of proof can be quantified using probabilities, they have often answered in the negative. One of the clearest opposition to quantification was formulated by Germany's Supreme Court, the Federal Court of Justice, in the case of Anna Anderson who claimed to be a descendant of the Tsar family. In 1967, the Regional Court of Hamburg ruled that Anderson failed to present sufficient evidence to establish that she was Grand Duchess Anastasia Nikolayevna, the youngest daughter of Tsar Nicholas II, who allegedly escaped the murder of the Tsar family by the Bolsheviks in 1918. (Incidentally, DNA testing later demonstrated that Anna Anderson had no relationship with the Tsar family.) Anderson appealed to Germany's Federal Court, complaining that the Regional Court had set too demanding a proof standard. Siding with the lower court, the Federal Court made clear that ‘[t]he law does not presuppose a belief free of all doubts’, thus recognizing the inevitable fallibility of trial decisions. The Court warned, however, that it would be ‘wrong’ to think that a trial decision could rest on ‘a probability bordering on certainty’ (Federal Court of Justice, February 17, 1970; III ZR 139/67). This decision is all the more interesting as it applies to a civil case. The German court did not think trial decisions could rest on a probability, not even in a civil case.

For criminal cases, Buchak (2014) has persuasively argued that an attribution of criminal culpability is an ascription of blame which requires a full belief in someone's guilt. One is left wondering, however. If a high probability of guilt short of 100% isn't enough but absolute certainty cannot be required either, how else could the standard of proof be met? The question becomes more pressing in civil

cases if we replace ‘guilt’ with ‘civil liability’. Anticipating this worry, Germany’s Federal Court in the Anderson case endorsed a conception of proof standards that acknowledges the inevitable fallibility of trial decisions while at the same time maintaining the need for certainty. The Federal Court wrote that a judge’s decision must satisfy ‘a degree of certainty which is useful for practical life and which makes the doubts silent without completely excluding them’ (Federal Court of Justice, February 17, 1970; III ZR 139/67).

The words of Germany’s Federal Court echo dilemmas that bedeviled early theorists of probability and evidence law. When Jacob Bernoulli—one of the pioneers of probability theory—discusses the requirement for a criminal conviction in his *Ars Conjectandi* (1713), he writes that ‘it might be determined whether 99/100 of probability suffices or whether 999/1000 is required’ (part IV). This is one of the earliest suggestions that the criminal standard of proof be equated with a threshold probability of guilt. A few decades later, the Italian legal penologist Cesare Beccaria in his celebrated treatise *On Crimes and Punishments* (1764) remarks that the certainty needed to convict is ‘nothing but a probability, though a probability of such a sort to be called certainty’ (chapter 14). This suggestive yet—admittedly—quite elusive remark indicates that the standard of decision in criminal trials should be a blend of probability and certainty. But what this blend of probability and certainty should amount to is unclear. At best, it brings us back to paraphrases of proof beyond a reasonable doubt such as ‘moral certainty’ or ‘abiding conviction’.

Not all legal practitioners, however, resist a probabilistic interpretation of standards of proof. Some actually find such interpretation plausible, even obvious. For example, here is Justice Harlan of the United States Supreme Court:

... in a judicial proceeding in which there is a dispute about the facts of some earlier event, the factfinder cannot acquire unassailably accurate knowledge of what happened. Instead, all the factfinder can acquire is a belief of what probably happened. The intensity of this belief – the degree to which a factfinder is convinced that a given act actually occurred – can, of course, vary. In this regard, a standard of proof represents an attempt to instruct the factfinder concerning the degree of confidence our society thinks he should have in the correctness of factual conclusions for a particular type of adjudication.¹

After this methodological premise, Justice Harlan explicitly endorses a probabilistic interpretation of standards of proof, using the expression ‘degree of confidence’ instead of ‘probability’:

Although the phrases ‘preponderance of the evidence’ and ‘proof beyond a reasonable doubt’ are quantitatively imprecise, they do communicate to the finder of fact different notions concerning the degree of confidence he is expected to have in the correctness of his factual conclusions.

2.3 Practical worries

The remarks by Justice Harlan notwithstanding, legal practitioners seem in general quite opposed to quantifying standards of proof probabilistically. This resistance has many causes. One key factor is certainly the conviction that a probabilistic interpretation of proof standards is unrealistic insofar as its implementation would face unsurmountable challenges. How are probabilities—say the probability of someone’s guilt—going to be quantified probabilistically? How will the triers of facts apply probabilistic thresholds? Should the application of the thresholds be automatic—that is, if the evidence is above the requisite threshold, find against the defendant (say, convict in a criminal trial) and otherwise find for the defendant (say, acquit)? The challenge, in general, is to articulate how probabilistic thresholds can be operationalized as part of trial decisions. This is by no means obvious. After all, judges and jurors do not weigh evidence in an explicitly probabilistic manner. Nor do they use probability thresholds to guide their decisions.

To alleviate the force of these worries, the probabilistic interpretation of proof standards can be broken down into two separate claims, what we might call the ‘quantification claim’ and the ‘threshold claim’. In a criminal trial, these claims would look as follows:

QUANTIFICATION CLAIM: a probabilistic quantification of the defendant’s guilt can be given through an appropriate weighing of all the evidence available (that is, of all the evidence against, and of all the evidence in defense of, the accused).

¹In re Winship, 397 U.S. 358, 370 (1970). This is landmark decision by the United States Supreme Court establishing that the beyond a reasonable doubt standard must be applied to both adults and juvenile defendants.

THRESHOLD CLAIM: an appropriately high threshold guilt probability, say 95%, should be the decision criterion for criminal convictions.

Those worried about implementation might reason thusly. If guilt cannot be quantified probabilistically—for example, in terms of the conditional probability of G given the total evidence E —no probabilistic threshold could ever be used as a decision criterion. Since the quantification claim is unfeasible and the threshold claim rests on the quantification claim, the threshold claim should be rejected.

One way to answer this objection is to bite the bullet. Legal probabilists can admit that probabilistic thresholds constitute a revisionist theory. If they are to be implemented in trial proceedings, they will require changes. Jurors and judges will have to become familiar with probabilistic ideas. They will have to evaluate the strength of the evidence numerically, even for evidence that is not, on its face, quantitative in nature. But this response will simply heighten the resistance toward a probabilistic interpretation of proof standards. After all, the likelihood of success of such a program of radical reform of trial proceedings is uncertain. Fortunately, there is a less radical way to respond.

2.4 Idealization

Legal probabilists can admit they are not—at least, not yet—engaged with implementation or trial reform. In fact, the quantification claim can be interpreted in at least two different ways. One interpretation is that a quantification of guilt—understood as an actual reasoning process—can be effectively carried out by the fact-finders. The quantification claim can also be understood as an idealization or a regulative ideal. For instance, the authors of a book on probabilistic inference in forensic science write:

the ... [probabilistic] formalism should primarily be considered as an aid to structure and guide one's inferences under uncertainty, rather than a way to reach precise numerical assessments' (p. xv) [ataroni2006bayesian]

Even from a probabilist standpoint, the quantification of guilt can well be an idealization which has, primarily, a heuristic role.

Just as the quantification claim can be interpreted in two different ways, the same can be said of the threshold claim. For one thing, we can interpret it as describing an effective decision procedure, as though the fact-finders were required to mechanically convict whenever the defendant's probability of guilt happened to meet the desired probabilistic threshold. But there is a second, and less mechanistic, interpretation of the threshold claim. On the second interpretation, the threshold claim would only describe a way to understand, or theorize about, the standard of proof or the rule of decision. The second interpretation of the threshold claim—which fits well with the 'idealization interpretation' of the quantification claim—is less likely to encounter resistance.

Lawrence Tribe, in his famous 1971 article 'Trial by Mathematics', expresses disdain for a trial process that were mechanically governed by numbers and probabilities. He claims that under this scenario judges and jurors would forget their humanizing function. He writes:

Guided and perhaps *intimidated by the seeming inexorability of numbers*, induced by the persuasive force of formulas and the precision of decimal points to perceive themselves as performing a largely mechanical and automatic role, *few jurors ... could be relied upon to recall, let alone to perform, [their] humanizing function* [tribe71].

But this worry does not apply if we interpret the threshold claim in a non-mechanistic way. This is the interpretation we shall adopt in this chapter. To avoid setting the bar for legal probabilism too high, we will not be concerned with practical issues that arise if we wanted to deploy a probabilistic threshold directly. We will grant that, at least for now, successful implementation of such thresholds is not viable. For the time being, probabilistic thresholds are best understood as offering an theoretical, analytical model of trial decisions. The fact that this theoretical model cannot be easily operationalized does not mean that the model is pointless. There are multiple ways in which such a model, even if unfit for direct deployment in trial proceedings, can offer insights into trial decision-making.

2.5 Minimizing expected costs

Here is an illustration of the analytic power of the probabilistic interpretation of proof standards. Standards of proof are usually ranked from the least demanding, such as preponderance of the evidence, to the most demanding, such as proof beyond a reasonable doubt. But why think this way? Can we give a principled justification for the ranking? A common argument is that more is at stake in a criminal

trial than in a civil trial. A mistaken conviction will unjustly deprive the defendant of basic liberties or even life. Instead, a mistaken decision in a civil trial would not encroach upon someone's basic liberties since decisions in civil trials are mostly about imposing monetary compensation. This argument can be made precise by pairing probability thresholds with expected utility theory, a well-established paradigm of rational decision-making used in psychology and economic theory. At its simplest, decision theory based on the maximization of expected utility states that between a number of alternative courses of action, the one with the highest expected utility (or with the lowest expected cost) should be preferred. This theory is general and can be applied to a variety of situations, including civil or criminal trials.

To see how this works, note that trial decisions can be factually erroneous in two ways. A trial decision can be a false positive—i.e. a decision to hold the defendant liable (to convict, in a criminal case) even though the defendant committed no wrong (or committed no crime). A trial decision can also be a false negative—i.e. a decision not to hold the defendant liable (or to acquit, in a criminal case) even though the defendant did commit the wrong (or committed the crime). Let $\text{cost}(CI)$ and $\text{cost}(AG)$ be the costs associated with the two decisional errors that can be made in a criminal trial, convicting an innocent (CI) and acquitting a guilty defendant (AG). Let $P(G|E)$ and $P(I|E)$ be the guilt probability and the innocence probability estimated on the basis of the evidence presented at trial. Given a simple decision-theoretic model (Kaplan, 1968), a conviction should be preferred to an acquittal whenever the expected cost resulting from a mistaken conviction—namely, $P(I|E) \cdot \text{cost}(CI)$ —is lower than the expected cost resulting from a mistaken acquittal—namely, $P(G|E) \cdot \text{cost}(AG)$. That is,

$$\text{convict provided } \frac{\text{cost}(CI)}{\text{cost}(AG)} < \frac{P(G|E)}{P(I|E)}.^2$$

For the inequality to hold, the ratio of posterior probabilities $\frac{P(G|E)}{P(I|E)}$ should exceed the cost ratio $\frac{\text{cost}(CI)}{\text{cost}(AG)}$. So long as the costs can be quantified, the probability threshold can be determined. For example, consider a cost ratio of nine according to which a mistaken conviction is nine times as costly as a mistaken acquittal. The corresponding probability threshold will be 90%. On this reading, in order to meet the standard of proof beyond a reasonable doubt, the prosecution should provide evidence that establishes the defendant's guilt with at least 90% probability, or in formulas, $P(G|E) > 90\%$. The higher the cost ratio, the higher the requisite threshold. The lower the cost ratio, the lower the requisite threshold. For example, if the cost ratio is 99, the threshold would be as high as 99%, but if the cost ratio is 2, the threshold would only be 75%. This model assumes, simplistically, that correct decisions do not bring any positive utility. More complex models are also possible (Dekay, 1996; Laudan, 2016), but the basic idea is the same.

The same line of argument applies to civil cases. Let a false attribution of liability FL be a decision to find the defendant liable when the defendant committed no civil wrong (analogous to the conviction of an innocent in a criminal case). Let a false attribution of non-liability FNL be a decision not to find the defendant liable when the defendant did commit the civil wrong (analogous to the acquittal of a factually guilty defendant in a criminal case). Let $P(L|E)$ and $P(NL|E)$ be the liability probability and the non-liability probability given the evidence presented at trial. So long as the objective is to minimize the costs of erroneous decisions, the rule of decision would be as follows:

$$\text{find the defendant civilly liable provided } \frac{\text{cost}(FL)}{\text{cost}(PN)} < \frac{P(L|E)}{P(NL|E)}.^3$$

If the cost ratio $\frac{\text{cost}(FP)}{\text{cost}(PN)}$ is set to 1, the threshold for liability judgments should equal 50%, a common interpretation of the preponderance standard in civil cases. This means that $P(L|E)$ should be at least 50% for a defendant to be found civilly liable.

The difference between proof standards in civil and criminal cases lies in the different cost ratios. The cost ratio in civil cases, $\frac{\text{cost}(FP)}{\text{cost}(PN)}$, is typically lower than the cost ratio in criminal cases, $\frac{\text{cost}(CI)}{\text{cost}(AG)}$, because a false positive in a criminal trial (a mistaken conviction) is considered a more harmful error than a false positive in a civil trial (a mistaken attribution of civil liability). This difference in the cost ratio can have a consequentialist or a retributivist justification (Walen, 2015). From a consequentialist perspective, the loss of personal freedom or even life can be considered a greater loss than being forced

²This follows from $P(I|E) \cdot \text{cost}(CI) < P(G|E) \cdot \text{cost}(AG)$.

³This follows from $P(NL|E) \cdot \text{cost}(FP) < P(L|E) \cdot \text{cost}(FNL)$

to pay an undue monetary compensation. From a retributivist perspective, the moral wrong that results from the mistaken conviction of an innocent person can be regarded as more egregious than the moral wrong that results from the mistaken attribution of civil liability. This difference in consequences or moral wrongs can be captured by positing a higher cost ratio in criminal than civil cases, $\frac{cost(FP)}{cost(PN)}$.

Justice Harlan of the United Supreme Court draws a clear difference in the cost ratio between criminal and civil litigation:

In a civil suit between two private parties for money damages, for example, we view it as no more serious in general for there to be an erroneous verdict in the defendant's favor than for there to be an erroneous verdict in the plaintiff's favor . . . In a criminal case, on the other hand, we do not view the social disutility of convicting an innocent man as equivalent to the disutility of acquitting someone who is guilty. In *Re Winship* (1970), 397 U. S. 358, 371.

To underscore the differences in the cost ratios, Harlan cites an earlier decision of the United States Supreme Court that emphasizes how a defendant's liberty has a transcending value:

[t]here is always in litigation a margin of error . . . , representing error in factfinding, which both parties must take into account . . . [w]here one party has at stake an interest of transcending value – as a criminal defendant his liberty – . . . this margin of error is *reduced* as to him by the process of placing on the other party [i.e. the prosecutor] the standard of . . . persuading the factfinder at the conclusion of the trial of his guilt beyond a reasonable doubt. *Speiser v. Randall* (1958), 357 U.S. 513, 525-26.

Claims about cost ratios and their magnitude, and claims about differences between criminal and civil cases, can of of course be contested. Some have argued, for example, that the standard of proof in criminal cases should be lower than commonly assumed, and they have done so by offering a different assessment of the cost ratio (CITE LAUDAN – PERHASP LAUDAN'S DERIVATION OF A LOWERE THRESHOLD COULD BE DISCUSSED HERE IN DETAIL AS ANOTHER EXAMPLE OF THE ANALYTICAL POWER OF THE PROBABILISTIC FRAMEWORK). We will not examine this debate here. Rather, the point for now is that probabilistic thresholds, when paired with expected utility theory, provide an analytical framework to justify as well as meaningfully debate the different degrees of stringency necessary for decision criteria—i.e. legal proof standards—in civil or criminal trials. In later chapters, we will examine more in detail how a probability-based analytical framework can help to theorize about the values that should inform trial decisions, such as the minimization of expected costs, the maximization of truth and accuracy, and the fair allocation of the risk of of error. (REFER HERE TO THESE LATER CHAPTERS)

2.6 SUGGESTION

MARCELLO: IF WE END UP DIVIDING THIS CHAPTER INTO TWO OR THREE SEPARATE CHAPTERS, WE COULD CONTINUE THE DISCUSION OF THE ANALYTICAL POWER OF THE PROBABILITSTIC APPROACH MORE IN DETAIL HERE, DRAWING ON SOME OF THE MATERIALS ALREADY IN THE LONGER VERSION OF THE SEP ENTRY.

HERE IS A TENTATIVE IDEA OF WHAT TO DISCUSS:

- (1) SIMPLE EXPECTED UTILITY MODEL (DONE, SEE ABOVE)
- (2) LAUDAN MODEL, THIS IS A MORE COMPLICATED EXPECTED UTILITY MODEL, PARTLY BORROWED FROM LAPLACE (NOT DISCUSSED IN SETP ENTRY)
- (3) SIGNAL DETECTION THEORY MODEL (NOT DISCUSSED ENTRY)
- (4) HAMER MODEL AND KAYE MODEL FOR ERROR MINIMIZATION (DISCUSSED IN THE SEP ENTRY, INTEGRALS, DERIVATIVES, ETC.)
- (5) GOOD AND BAD THINGS ABOUT THESE MODELS, BUT OVERALL THEY SHOW THAT THE PROBABILISTIC FRAMEWORK IS A RICH ANALYTICAL TOOL

3 Theoretical challenges

Let's take stock. We briefly examined difficulties in implementation for probabilistic standards of proof and set those aside. We then offered a few illustrations how probabilistic standards can be used as analytical tools to theorize about decision-making at trial. But even if probabilistic thresholds are used solely as analytical tools, legal probabilists are not yet out of the woods. Even if the practical problems

can be addressed or set aside, theoretical difficulties remain. We will focus on three in particular: the problem of priors; naked statistical evidence; and the difficulty about conjunction, also called the conjunction paradox. The latter two are difficulties that any theory of the standard of proof – not just a probabilistic theory – should be able to address. The first difficulty is peculiar to the probabilistic interpretation of standards of proof. We will examine each difficulty in turn and then examine a promising line of response within legal probabilism based on likelihood ratios instead of posterior probabilities.

3.1 The problem of priors

3.2 Naked statistical evidence

Suppose one hundred, identically dressed prisoners are out in a yard during recreation. Suddenly, ninety-nine of them assault and kill the guard on duty. We know that this is what happened from a video recording, but we do not know the identity of the ninety-nine killers. After the fact, a prisoner is picked at random and tried. Since he is one of the prisoners who were in the yard, the probability of his guilt would be 99%. But despite the high probability, many have the intuition that this is not enough to establish guilt beyond a reasonable doubt. Hypothetical scenarios of this sort suggest that a high probability of guilt, while perhaps necessary, is not sufficient to establish guilt beyond a reasonable doubt.

Perhaps, the resistance in the prisoner scenario lies in the fact that the prisoner was picked at random, and that any prisoner would be 99% likely to be one of the killers. Since the statistics cannot single out the one innocent prisoner, they are bad evidence. But consider this case. Suppose two people enter a department store. There are no other customers in the store. After they exit the store, a member of the staff finds that an item of merchandise is missing. Since no staff member could be culpable—they are strictly surveilled—the culprit must be one of the customers. One of the customers, John, has scored high in a compulsivity test and has been arrested for stealing in department stores several times in the past. The other customer, Rick, has never been arrested for stealing in a department store and shows no sign of high compulsivity. Statistics show that people with a high degree of compulsivity and who have stolen merchandise in department stores before are more likely than others to steal merchandise if they are unsupervised. So John is most likely the culprit. Suppose studies show that people like John, when unsupervised, will steal 99 times out of 100 times. Instead, people like Rick, when unsupervised, will only steal 1 time out of 100 times. So John is 99 times more likely than Rick to have stolen the merchandise. Can these statistics be enough to convict John? Again, it seems not. There is no evidence against him specifically, say, no merchandise was found on him that could link him to the crime. Many would feel uneasy about convicting John despite the fact that, between the two suspects, he is the one who is most likely the culprit.

A similar hypothetical can be constructed for civil cases. Suppose a bus company, Blue-Bus, operates 90% of the buses in town on a certain day, while Red-Bus only 10%. That day a bus injures a pedestrian. Although the buses of the two companies can be easily recognized because they are respectively painted blue and red, the pedestrian who was injured cannot remember the color of the bus involved in the accident. No other witness was around. Still, given the statistics about the market shares of the two companies, it is 90% probable that a Blue-Bus bus was involved in the accident. This is a high probability, well above the 50% threshold. Yet the 90% probability that a Blue-Bus bus was involved in the accident would seem—at least intuitively—insufficient for a judgment of liability against Blue-Bus. This intuition challenges the idea that the preponderance standard in civil cases only requires that the plaintiff establish the facts with a probability greater than 50%.

Confronted with these hypotheticals, legal probabilists could push back. Hypotheticals rely on intuitive judgments, for example, that the high probability of the prisoners's guilt in the scenario above does not amount to proof beyond a reasonable doubt. But suppose we changed the numbers and imagined there were one thousand prisoners of whom nine hundred and ninety-nine killed the guard. The guilt probability of a prisoner picked at random would be 99.9%. Even in this situation, many would insist that guilt has not been proven beyond a reasonable doubt despite the extremely high probability of guilt. But others might say that when the guilt probability reaches such extreme values, values as high as 99.9% or higher, people's intuitive resistance to convicting should subside (Roth, 2010). A more general problem is that intuitions in such hypothetical scenarios are removed from real cases and thus are potentially unreliable as a guide to theorize about standards of proof (Allen & Leiter, 2001; Hedden

& Colyvan, 2019; Lempert, 1986).

Another reason to be suspicious of these hypotheticals is that they seem to amplify biases in human reasoning. Say an eyewitness was present during the accident and testified that a Blue-Bus bus was involved. Intuitively, the testimony would be considered enough to rule against Blue-Bus, at least provided the witness survived cross-examination. We exhibit, in other words, an intuitive preference for judgments of liability based on testimonial evidence compared to judgments based on statistical evidence. This preference has been experimentally verified (Arkes, Shoots-Reinhard, & Mayes, 2012; Niedermeier, Kerr, & Messeé, 1999; Wells, 1992) and exists outside the law (Ebert, Smith, & Durbach, 2018; Friedman & Turri, 2015; Sykes & Johnson, 1999). But testimonial evidence is no less prone to error than statistical evidence. In fact, it may well be more prone to error. The unreliability of eyewitness testimony is well-known, especially when the environmental conditions are not optimal (Loftus, 1996). So are we justified in exhibiting an intuitive preference for eyewitness testimony as opposed to statistical evidence, or is this preference a cognitive bias to avoid?

These reservations notwithstanding, the puzzles about naked statistical evidence cannot be easily dismissed. Puzzles about statistical evidence in legal proof have been around for a while (Cohen, 1977; Kaye, 1979b; Nesson, 1979; Thomson, 1986). Philosophers and legal scholars have shown a renewed interest in both criminal and civil cases (Blome-Tillmann, 2017; Bolinger, 2018; Cheng, 2012; Di Bello, 2019a; Enoch, Spectre, & Fisher, 2012; Ho, 2008; Moss, 2018; Nunn, 2015; Pardo, 2018; Pritchard, 2005; Pundik, 2017; Redmayne, 2008; Roth, 2010; Smith, 2018; Stein, 2005; Wasserman, 1991). Given the growing interest in the topic, legal probabilism cannot be a defensible theoretical position without offering a story about naked statistical evidence.

3.3 Conjunction paradox

Another theoretical difficulty that any theory of the standard of proof should address is the difficulty about conjunction. This difficulty arises when an accusation of wrongdoing, in a civil or criminal proceeding, is broken down into its constituent elements. Suppose the prosecution has to establish both that the defendant caused harm to the victim (call it claim *A*) and that the harmful act was intentional (call it claim *B*). Cohen (1977) argues (p. 66) that common law systems subscribe to a conjunction principle, which assumes that if *A* and *B* are established according to the governing standard of proof, so is their conjunction, and vice versa. If the conjunction principle holds, the following statements must be equivalent, with *S* a generic standard of proof:

Separate	<i>A</i> is established according to <i>S</i> and <i>B</i> is established according to <i>S</i>
Overall	[<i>A</i> and <i>B</i>] are established according to <i>S</i>

More generally, the conjunction principles requires that

$$S[C_1 \wedge C_2 \wedge \dots \wedge C_k] \text{ iff } S[C_1] \wedge S[C_2] \wedge \dots \wedge S[C_k]$$

The conjunction principle is supported by the case law. For example, the United States Supreme Court makes it clear that guilt must be proven beyond a reasonable doubt and also makes clear that the accused [is protected] against conviction except upon proof beyond a reasonable doubt of *every fact* necessary to constitute the crime with which he is charged. In re Winship (1970), 397 U.S. 358, 364.

So, to establish guilt beyond a reasonable doubt simply means to establish each element of the crime according to the requisite standard. This is an application of the conjunction principle in criminal proceedings.

The trouble is that the conjunction principle is false given a probabilistic interpretation of proof standards because the following two statements may come apart:

Seperate	$P(A E) \geq 0.95$ and $P(B E) \geq 95$
Overall	$P(B \wedge A E) \geq 0.95$

Suppose the prosecution manages to present evidence *E* that establishes claims *A* and *B*, separately, to the required probability, say at least 95%. In other words, $P(A|E) \geq 95\%$ and $P(B|E) \geq 95\%$. Has the prosecution met the burden of proof? Since each claim was established to the requisite threshold, guilt should also be established according to the requisite standard, assuming the conjunction principle holds. But even though each claim necessary to sustain the accusation was established according to the requisite probability, the probability of their conjunction – assuming the two claims are independent – is

only $95\% \times 95\% = 90.25\%$, below the required 95% threshold. So guilt was not established according to the requisite standard. It remains unclear whether the prosecution has met the burden of proof or not.

The difficulty about conjunction – the fact that the conjunction principle is false assuming a probabilistic interpretation of the standard of proof – was originally formulated by (Cohen, 1977) and has enjoyed great popularity ever since (???; Allen, 1986; Allen & Stein, 2013; Allen & Pardo, 2019; Haack, 2014; Schwartz & Sober, 2017).

The difficulty about conjunction does not subside if the number of constituent claims increases. If anything the difficulty becomes more apparent. If the prosecution has established three separate claims to 95% probability, their probability – again if the claims are independent – would be about 85%, even further below the 95% threshold. Nor does the difficulty about conjunction subside if the claims are no longer regarded as independent. MARCELLO: CAN WE SAY WHY? HOW DO WE EXPLAIN THIS?

Legal probabilists could reject the conjunction principle. After all, the conjunction principle denies the accumulation of risk. If one is justifiably very sure about the truth of each claim considered separately, one should not be equally sure of their conjunction. Say you have checked each page of a book and found no error whatsoever. So, for each page, you are sure there is no error. Can you, on this basis, be sure that the book as a whole contains no error whatsoever? Not really. As the number of pages grows, the risk you might have missed a mistake increases. It becomes virtually certain that there must be at least one error in the book as a whole, although for each page you are justifiably sure there is no error. The same applies to product quality checks. You may be very sure, for each product you checked, that they are free from defects. But you cannot, on this basis, be sure that all items you checked are free from defects. In fact, since the risk of error accumulates, you should be very sure to have missed at least one defective item. The conjunction principle, instead, would have us deny this basic principle of the accumulation of risk.

The conjunction principle, however, is not so clearly implausible. The example pertaining to risk accumulation all have in common the fact that, as the number of conjuncts increases, the possibility of error becomes more likely and at some point it becomes certain. But in trial proceedings the possibility of error need not become certain as the number of claims increases. It is perhaps best to understand the process of proof as follows. Say there is a piece of evidence E_1 that defeasibly supports a claim C_1 ; E_2 defeasibly supports claims C_2 ; and so up to E_k and C_k . Each of these relationships of evidential support could be defeated by defeaters, D_i . Does the conjunction of $E_1 \wedge E_2 \wedge \dots \wedge E_k$ support the conjunction $C_1 \wedge C_2 \wedge \dots \wedge C_k$? Presumably yes, so long as there is no defeater D_i that undermines one of the relationships of evidential support. This picture seems to capture what intuitively goes on at trial. However, note that while each individual claim C_i could be mistaken in virtue of a defeater D_i , the conjunction $C_1 \wedge C_2 \wedge \dots \wedge C_k$ could be mistaken in virtue of a much larger number of defeaters. So $C_1 \wedge C_2 \wedge \dots \wedge C_k$ is more susceptible to being proved wrong than any individual claim C_i . On the other hand, $C_1 \wedge C_2 \wedge \dots \wedge C_k$ is supported by a much larger body of evidence $E_1 \wedge E_2 \wedge \dots \wedge E_k$ than each individual claim C_i .

Now, for the sake of argument, suppose legal probabilists reject the conjunction principle. How should they then define the standard of proof? They have two options. Each of these options is intuitively unattractive. One option is to require that the prosecution in a criminal case (or the plaintiff in a civil case) establish the claim as a whole – say the conjunction of A and B – to the requisite probability. Call this the *holistic account*. The other option is that the party making the accusation should establish each claim, separately, to the requisite probability. Call this the *atomistic account*.

Going with the atomistic account seems a non-starter. On this account, the prosecution could establish guilt beyond a reasonable doubt without having established guilt with a sufficiently high probability. The atomistic approach would allow convictions in cases where $P(G|E)$ is quite low, just because G is a conjunction of several independent claims that separately satisfy the standard of proof. This is counterintuitive, and even more clearly against the spirit of legal probabilism.

Going with the holistic approach is not without problems either. The proof of $A \wedge B$ would impose an importantly higher requirement on the separate probabilities of the conjuncts. If the conjunction $A \wedge B$ has to be proven with at least 95% probability, the individual conjunction should be established with probability higher than the 95% threshold. This also means that the more conjuncts should be proven with at least 95%, the higher their probability should be. Moreover, what is required exactly for one of them depends on what has been achieved for the other. If I already established that $P(A|E) = 0.8$, I need $P(B|E) \geq 0.635$ to end up with $P(A \wedge B|E) \geq 0.51$. If, however, $P(A|E) = 0.6$, I need $P(B|E) \geq 0.85$ to reach the same threshold. This would mean that standards of proof for a given claim could vary depending on how well a different claim has been argued for and on whether it is a part of a more

complex claim that one is defending, and this does not seem very intuitive. At least, this goes strongly against the equal treatment requirement mentioned already in the introduction. So the holistic option will put seemingly unnecessarily high requirements sensitive to fairly contingent and irrelevant facts on the prosecution, and treat various elements to be proven unevenly. Neither option seems desirable.

4 Likelihood thresholds

4.1 The likelihood strategy

The most natural probabilistic interpretation of proof standards imposes a threshold on posterior probabilities. For example, in criminal cases, the requirement is usually formulated as follows: guilt is proven beyond a reasonable doubt provided $\Pr(G|E)$ is above a suitable threshold, say 95%. The threshold will be lower in civil trials. This interpretation is quite flexible. We should think of it as a family of interpretation rather than a interpretation.

The claim that the defendant is guilty can be replaced by a more fine-grained hypothesis, call it H_p , the hypothesis put forward by the prosecutor, for example, hypothesis that the defendant killed the victim with a firearm while burglarizing

the victim's apartment. H_p can be any hypothesis which, if true, would entail the defendant is guilty (according to the governing law). Hypothesis H_p is a more precise description of what happened that establishes, if true, the defendant's guilt. In defining proof standards, instead of saying that $\Pr(G|E)$ should be above a threshold, a probabilistic interpretation could read: guilt is proven beyond a reasonable doubt provided $\Pr(H_d|E)$ is above a threshold.

Here is another possible variation. Say the defense offers an alternative hypothesis about what happened, call H_d . This may be more common in civil than criminal trial. At any rate, the standard of proof can be defined comparatively as follows. Given a body of evidence E and two competing hypotheses H_p and H_d , the probability $\Pr(H_p|E)$ should be significantly higher than $\Pr(H_d|E)$, or in other words, $\frac{\Pr(H_p|E)}{\Pr(H_d|E)}$ should be above a suitably high threshold. If the threshold is for example 2, $\Pr(H_p|E)$ should be two times $\Pr(H_d|E)$. Note that H_p and H_d need not be one the negation of the other. If they are one the negation of the other, for example, G and I , then $\frac{\Pr(G|E)}{\Pr(I|E)} > 2$ implies that $\Pr(G|E) > 75\%$.

What is common to these variations is that they set a threshold that is based, in one way or another, on the posterior probability given the evidence, such as $\Pr(G|E)$, $\Pr(H_p|E)$, $\frac{\Pr(H_p|E)}{\Pr(H_d|E)}$ or $\frac{\Pr(G|E)}{\Pr(I|E)}$. But focusing on posterior probabilities is not the only approach that legal probabilists can pursue. By Bayes' theorem, the following holds, using G and I as competing hypotheses:

$$\frac{\Pr(G|E)}{\Pr(I|E)} = \frac{\Pr(E|G)}{\Pr(E|I)} \times \frac{\Pr(G)}{\Pr(I)},$$

or using H_p and H_d as competing hypotheses,

$$\frac{\Pr(H_p|E)}{\Pr(H_d|E)} = \frac{\Pr(E|H_p)}{\Pr(E|H_d)} \times \frac{\Pr(H_p)}{\Pr(H_d)},$$

or in words

$$\text{posterior odds} = \text{likelihood ratio} \times \text{prior odds}.$$

A difficult problem is to assign numbers to the prior probabilities such as $\Pr(G)$ or $\Pr(H_p)$, or prior odds such as $\frac{\Pr(G)}{\Pr(I)}$ or $\frac{\Pr(H_p)}{\Pr(H_d)}$.

DISCUSS DIFFICULTIES ABOUT ASSIGNING PRIORS! WHERE? CAN WE USE IMPRECISE PROBABILITIES TALK ABOUT PRIORS – I.E. LOW PRIORS = TOTAL IGNORANCE = VERY IMPRECISE (LARGE INTERVAL) PRIORS? THE PROBLEM WITH THIS WOULD BE THAT THERE IS NO UPDATING POSSIBLE. ALL UPDATING WOULD STILL GET BACK TO THE STARTING POINT. DO YOU HAVE AN ANSWER TO THAT? WOULD BE INTERESTING TO DISCUSS THIS!

Given these difficulties, both practical and theoretical, one option is to dispense with priors altogether. This is not implausible. Legal disputes in both criminal and civil trials should be decided on the basis of the evidence presented by the litigants. But it is the likelihood ratio – not the prior ratio – that offers the best measure of the overall strength of the evidence presented. So it is all too natural to focus on likelihood ratios and leave the priors out of the picture. If this is the right, the question is, how would a probabilistic interpretation of standards of proof based on the likelihood ratio look like? At its simplest, this strategy will look as follows. Recall our discussion of expected utility theory:

$$\text{convict provided } \frac{\text{cost}(CI)}{\text{cost}(AG)} < \frac{\Pr(H_p|E)}{\Pr(H_d|E)},$$

which is equivalent to

$$\text{convict provided } \frac{\text{cost}(CI)}{\text{cost}(AG)} < \frac{\Pr(E|H_p)}{\Pr(E|H_d)} \times \frac{\Pr(H_p)}{\Pr(H_d)}.$$

By rearranging the terms,

$$\text{convict provided } \frac{\Pr(E|H_p)}{\Pr(E|H_d)} > \frac{\Pr(H_d)}{\Pr(H_p)} \times \frac{\text{cost}(CI)}{\text{cost}(AG)}.$$

Then, on this interpretation, the likelihood ratio should be above a suitable threshold that is a function of the cost ratio and the prior ratio. The outstanding question is how this threshold is to be determined.

4.2 Cheng

Here is one way to think about the decision thresholds in terms of likelihoods, stemming from (Cheng, 2012). The idea is to conceptualize juridical decisions in analogy to statistical hypothesis testing. We have two hypotheses under consideration: defendant's H_Δ and plaintiff's H_Π , and we are to pick one: D_Δ stands for the decision for H_Δ and D_Π is the decision that H_Π . On this approach, rather than directly evaluating the probability of H_Π given the evidence and comparing it to a threshold, we compare the support that the evidence provides for these hypotheses, and decide for the one for which the evidence provides better support.

Cheng motivates this approach by the following considerations. Suppose that if the decision is correct, no costs result, but incorrect decisions have their price. Let us say that if the defendant is right and we find against them, the cost is c_1 , and if the plaintiff is right and we find against them, the cost is c_2 :

		Decision	
		D_Δ	D_Π
Truth	H_Δ	0	c_1
	H_Π	c_2	0

Intuitively, it seems that we want a decision rule which minimizes the expected cost. Say that given our total evidence E the relevant conditional probabilities are:

$$p_\Delta = P(H_\Delta|E)$$

$$p_\Pi = P(H_\Pi|E)$$

The expected costs for deciding that H_Δ and H_Π , respectively, are:

$$E(D_\Delta) = p_\Delta 0 + p_\Pi c_2 = c_2 p_\Pi$$

$$E(D_\Pi) = p_\Delta c_1 + p_\Pi 0 = c_1 p_\Delta$$

For this reason, on these assumptions, we would like to choose H_Π just in case $E(D_\Pi) < E(D_\Delta)$. This condition is equivalent to:

$$\begin{aligned} c_1 p_\Delta &< c_2 p_\Pi \\ c_1 &< \frac{c_2 p_\Pi}{p_\Delta} \\ \frac{c_1}{c_2} &< \frac{p_\Pi}{p_\Delta} \end{aligned} \tag{1}$$

Cheng (2012) (1261) insists:

At the same time, in a civil trial, the legal system expresses no preference between finding erroneously for the plaintiff (false positives) and finding erroneously for the defendant (false negatives). The costs c_1 and c_2 are thus equal...

If we grant this assumption, $c_1 = c_2$, (1) reduces to:

$$\begin{aligned} 1 &< \frac{p_{\Pi}}{p_{\Delta}} \\ p_{\Pi} &> p_{\Delta} \end{aligned} \quad (2)$$

That is, in standard civil litigation we are to find for the plaintiff just in case H_{Π} is more probable given the evidence than H_{Δ} , which seems plausible.⁴ Let's call this decision standard **Relative Legal Probabilism (RLP)**.⁵

Here is a slightly different perspective, due to Dawid (1987), that also suggests that juridical decisions should be likelihood-based. The focus is on witnesses for the sake of simplicity. Imagine the plaintiff produces two independent witnesses: W_A attesting to A , and W_B attesting to B . Say the witnesses are regarded as 70% reliable and A and B are probabilistically independent, so we infer $P(A) = P(B) = 0.7$ and $P(A \wedge B) = 0.7^2 = 0.49$.

But, Dawid argues, this is misleading, because to reach this result we misrepresented the reliability of the witnesses: 70% reliability of a witness, he continues, does not mean that if the witness testifies that A , we should believe that $P(A) = 0.7$. To see his point, consider two potential testimonies:

- | | |
|-------|--|
| A_1 | The sun rose today. |
| A_2 | The sun moved backwards through the sky today. |

Intuitively, after hearing them, we would still take $P(A_1)$ to be close to 1 and $P(A_2)$ to be close to 0, because we already have fairly strong convictions about the issues at hand. In general, how we should revise our beliefs in light of a testimony depends not only on the reliability of the witness, but also on our prior convictions.⁶ And this is as it should be: as indicated by Bayes' Theorem, one and the same testimony with different priors might lead to different posterior probabilities.

So far so good. But how should we represent evidence (or testimony) strength then? Well, one pretty standard way to go is to focus on how much it contributes to the change in our beliefs in a way independent of any particular choice of prior beliefs. Let a be the event that the witness testified that A . It is useful to think about the problem in terms of *odds*, *conditional odds* (O) and *likelihood ratios* (LR):

$$\begin{aligned} O(A) &= \frac{P(A)}{P(\neg A)} \\ O(A|a) &= \frac{P(A|a)}{P(\neg A|a)} \\ LR(a|A) &= \frac{P(a|A)}{P(a|\neg A)}. \end{aligned}$$

Suppose our prior beliefs and background knowledge, before hearing a testimony, are captured by the prior probability measure $P_{prior}(\cdot)$, and the only thing that we learn is a . We're interested in what our *posterior* probability measure, $P_{posterior}(\cdot)$, and posterior odds should then be. If we're to proceed with Bayesian updating, we should have:

$$\frac{P_{posterior}(A)}{P_{posterior}(\neg A)} = \frac{P_{prior}(A|a)}{P_{prior}(\neg A|a)} = \frac{P_{prior}(a|A)}{P_{prior}(a|\neg A)} \times \frac{P_{prior}(A)}{P_{prior}(\neg A)}$$

that is,

$$O_{posterior}(A) = O_{prior}(A|a) = \underbrace{LR_{prior}(a|A)}_{\text{conditional likelihood ratio}} \times O_{prior}(A) \quad (3)$$

⁴Notice that this instruction is somewhat more general than the usual suggestion of the preponderance standard in civil litigation, according to which the court should find for the plaintiff just in case $P(H_{\Pi}|E) > 0.5$. This threshold, however, results from (2) if it so happens that H_{Δ} is $\neg H_{\Pi}$, that is, if the defendant's claim is simply the negation of the plaintiff's thesis. By no means, Cheng argues, this is always the case.

⁵We were not aware of any particular name for Cheng's model so we came up with this one. We're not particularly attached to it, and it is not standard terminology.

⁶An issue that Dawid does not bring up is the interplay between our priors and our assessment of the reliability of the witnesses. Clearly, our posterior assessment of the credibility of the witness who testified A_2 will be lower than that of the other witness.

The conditional likelihood ratio seems to be a much more direct measure of the value of a , independent of our priors regarding A itself. In general, the posterior probability of an event will equal to the witness's reliability in the sense introduced above only if the prior is $1/2$.⁷

Quite independently, a similar approach to juridical decisions has been proposed by Kaplow (2014) – we'll call it **decision-theoretic legal probabilism (DTLP)**. It turns out that Cheng's suggestion is a particular case of this more general approach. Let $LR(E) = P(E|H_{\Pi})/P(E|H_{\Delta})$. In whole generality, DTLP invites us to convict just in case $LR(E) > LR^*$, where LR^* is some critical value of the likelihood ratio.

Say we want to formulate the usual preponderance rule: convict iff $P(H_{\Pi}|E) > 0.5$, that is, iff $\frac{P(H_{\Pi}|E)}{P(H_{\Delta}|E)} > 1$. By Bayes' Theorem we have:

$$\begin{aligned}\frac{P(H_{\Pi}|E)}{P(H_{\Delta}|E)} &= \frac{P(H_{\Pi})}{P(H_{\Delta})} \times \frac{P(E|H_{\Pi})}{P(E|H_{\Delta})} > 1 \Leftrightarrow \\ &\Leftrightarrow \frac{P(E|H_{\Pi})}{P(E|H_{\Delta})} > \frac{P(H_{\Delta})}{P(H_{\Pi})}\end{aligned}$$

So, as expected, LR^* is not unique and depends on priors. Analogous reformulations are available for thresholds other than 0.5.

Kaplow's point is not that we can reformulate threshold decision rules in terms of priors-sensitive likelihood ratio thresholds. Rather, he insists, when we make a decision, we should factor in its consequences. Let G represent potential gain from correct conviction, and L stand for the potential loss resulting from mistaken conviction. Taking them into account, Kaplow suggests, we should convict if and only if:

$$P(H_{\Pi}|E) \times G > P(H_{\Delta}|E) \times L \quad (4)$$

Now, (4) is equivalent to:

$$\begin{aligned}\frac{P(H_{\Pi}|E)}{P(H_{\Delta}|E)} &> \frac{L}{G} \\ \frac{P(H_{\Pi})}{P(H_{\Delta})} \times \frac{P(E|H_{\Pi})}{P(E|H_{\Delta})} &> \frac{L}{G} \\ \frac{P(E|H_{\Pi})}{P(E|H_{\Delta})} &> \frac{P(H_{\Delta})}{P(H_{\Pi})} \times \frac{L}{G} \\ LR(E) &> \frac{P(H_{\Delta})}{P(H_{\Pi})} \times \frac{L}{G}\end{aligned} \quad (5)$$

This is the general format of Kaplow's decision standard.

4.3 Likelihood and DAC

But how does our preference for the likelihood ratio as a measure of evidence strength relate to DAC? Let's go through Dawid's reasoning.

⁷Dawid gives no general argument, but it is not too hard to give one. Let $rel(a) = P(a|A) = P(\neg a|\neg A)$. We have in the background $P(a|\neg A) = 1 - P(\neg a|\neg A) = 1 - rel(a)$. We want to find the condition under which $P(A|a) = P(a|A)$. Set $P(A) = p$ and start with Bayes' Theorem and the law of total probability, and go from there:

$$\begin{aligned}P(A|a) &= P(a|A) \\ \frac{P(a|A)p}{P(a|A)p + P(a|\neg A)(1-p)} &= P(a|A) \\ P(a|A)p &= P(a|A)[P(a|A)p + P(a|\neg A)(1-p)] \\ p &= P(a|A)p + P(a|\neg A) - P(a|\neg A)p \\ p &= rel(a)p + 1 - rel(a) - (1 - rel(a))p \\ p &= rel(a)p + 1 - rel(a) - p + rel(a)p \\ 2p &= 2rel(a)p + 1 - rel(a) \\ 2p - 2rel(a)p &= 1 - rel(a) \\ 2p(1 - rel(a)) &= 1 - rel(a) \\ 2p &= 1\end{aligned}$$

First we multiplied both sides by the denominator. Then we divided both sides by $P(a|A)$ and multiplied on the right side. Then we used our background notation and information. Next, we manipulated the right-hand side algebraically and moved $-p$ to the left-hand side. Move $2rel(a)p$ to the left and manipulate the result algebraically to get to the last line.

A sensible way to probabilistically interpret the 70% reliability of a witness who testifies that A is to take it to consist in the fact that the probability of a positive testimony if A is the case, just as the probability of a negative testimony (that is, testimony that A is false) if A isn't the case, is 0.7:⁸

$$P_{prior}(a|A) = P_{prior}(\neg a|\neg A) = 0.7.$$

$P_{prior}(a|\neg A) = 1 - P_{prior}(\neg a|\neg A) = 0.3$, and so the same information is encoded in the appropriate likelihood ratio:

$$LR_{prior}(a|A) = \frac{P_{prior}(a|A)}{P_{prior}(a|\neg A)} = \frac{0.7}{0.3}$$

Let's say that a provides (positive) support for A in case

$$O_{posterior}(A) = O_{prior}(A|a) > O_{prior}(A)$$

that is, a testimony a supports A just in case the posterior odds of A given a are greater than the prior odds of A (this happens just in case $P_{posterior}(A) > P_{prior}(A)$). By (3), this will be the case if and only if $LR_{prior}(a|A) > 1$.

One question that Dawid addresses is this: assuming reliability of witnesses 0.7, and assuming that a and b , taken separately, provide positive support for their respective claims, does it follow that $a \wedge b$ provides positive support for $A \wedge B$?

Assuming the independence of the witnesses, this will hold in non-degenerate cases that do not involve extreme probabilities, on the assumption of independence of a and b conditional on all combinations: $A \wedge B$, $A \wedge \neg B$, $\neg A \wedge B$ and $\neg A \wedge \neg B$.^{9, ~10}

Let us see why the above claim holds. The calculations are my reconstruction and are not due to Dawid. The reader might be annoyed with me working out the mundane details of Dawid's claims, but it turns out that in the case of Dawid's strategy, the devil is in the details. The independence of witnesses gives us:

$$\begin{aligned} P(a \wedge b|A \wedge B) &= 0.7^2 = 0.49 \\ P(a \wedge b|A \wedge \neg B) &= 0.7 \times 0.3 = 0.21 \\ P(a \wedge b|\neg A \wedge B) &= 0.3 \times 0.7 = 0.21 \\ P(a \wedge b|\neg A \wedge \neg B) &= 0.3 \times 0.3 = 0.09 \end{aligned}$$

Without assuming A and B to be independent, let the probabilities of $A \wedge B$, $\neg A \wedge B$, $A \wedge \neg B$, $\neg A \wedge \neg B$ be $p_{11}, p_{01}, p_{10}, p_{00}$. First, let's see what $P(a \wedge b)$ boils down to.

By the law of total probability we have:

$$\begin{aligned} P(a \wedge b) &= P(a \wedge b|A \wedge B)P(A \wedge B) + \\ &\quad + P(a \wedge b|A \wedge \neg B)P(A \wedge \neg B) \\ &\quad + P(a \wedge b|\neg A \wedge B)P(\neg A \wedge B) + \\ &\quad + P(a \wedge b|\neg A \wedge \neg B)P(\neg A \wedge \neg B) \end{aligned} \tag{6}$$

which, when we substitute our values and constants, results in:

$$= 0.49p_{11} + 0.21(p_{10} + p_{01}) + 0.09p_{00}$$

Now, note that because p_{ij} s add up to one, we have $p_{10} + p_{01} = 1 - p_{00} - p_{11}$. Let us continue.

$$\begin{aligned} &= 0.49p_{11} + 0.21(1 - p_{00} - p_{11}) + 0.09p_{00} \\ &= 0.21 + 0.28p_{11} - 0.12p_{00} \end{aligned}$$

⁸In general setting, these are called the *sensitivity* and *specificity* of a test (respectively), and they don't have to be equal. For instance, a degenerate test for an illness which always responds positively, diagnoses everyone as ill, and so has sensitivity 1, but specificity 0.

⁹Dawid only talks about the independence of witnesses without reference to conditional independence. Conditional independence does not follow from independence, and it is the former that is needed here (also, four non-equivalent different versions of it).

¹⁰In terms of notation and derivation in the optional content that will follow, the claim holds if and only if $28 > 28p_{11} - 12p_{00}$. This inequality is not true for all admissible values of p_{11} and p_{00} . If $p_{11} = 1$ and $p_{00} = 0$, the sides are equal. However, this is a rather degenerate example. Normally, we are interested in cases where $p_{11} < 1$. And indeed, on this assumption, the inequality holds.

Next, we ask what the posterior of $A \wedge B$ given $a \wedge b$ is (in the last line, we also multiply the numerator and the denominator by 100).

$$\begin{aligned} P(A \wedge B|a \wedge b) &= \frac{P(a \wedge b|A \wedge B)P(A \wedge B)}{P(a \wedge b)} \\ &= \frac{49p_{11}}{21 + 28p_{11} - 12p_{00}} \end{aligned}$$

In this particular case, then, our question whether $P(A \wedge B|a \wedge b) > P(A \wedge B)$ boils down to asking whether

$$\frac{49p_{11}}{21 + 28p_{11} - 12p_{00}} > p_{11}$$

that is, whether $28 > 28p_{11} - 12p_{00}$ (just divide both sides by p_{11} , multiply by the denominator, and manipulate algebraically).

Dawid continues working with particular choices of values and provides neither a general statement of the fact that the above considerations instantiate nor a proof of it. In the middle of the paper he says:

Even under prior dependence, the combined support is always positive, in the sense that the posterior probability of the case always exceeds its prior probability. . . . When the problem is analysed carefully, the ‘paradox’ evaporates [pp. 95-7]

where he still means the case with the particular values that he has given, but he seems to suggest that the claim generalizes to a large array of cases.

The paper does not contain a precise statement making the conditions required explicit and, *a fortiori*, does not contain a proof of it. Given the example above and Dawid’s informal reading, let us develop a more precise statement of the claim and a proof thereof.

Fact 1. *Suppose that $rel(a), rel(b) > 0.5$ and witnesses are independent conditional on all Boolean combinations of A and B (in a sense to be specified), and that none of the Boolean combinations of A and B has an extreme probability (of 0 or 1). It follows that $P(A \wedge B|a \wedge b) > P(A \wedge B)$. (Independence of A and B is not required.)*

Roughly, the theorem says that if independent and reliable witnesses provide positive support of their separate claims, their joint testimony provides positive support of the conjunction of their claims.

Let us see why the claim holds. First, we introduce an abbreviation for witness reliability:

$$\begin{aligned} \mathbf{a} &= rel(a) = P(a|A) = P(\neg a|\neg A) > 0.5 \\ \mathbf{b} &= rel(b) = P(b|B) = P(\neg b|\neg B) > 0.5 \end{aligned}$$

Our independence assumption means:

$$\begin{aligned} P(a \wedge b|A \wedge B) &= \mathbf{a}\mathbf{b} \\ P(a \wedge b|A \wedge \neg B) &= \mathbf{a}(1 - \mathbf{b}) \\ P(a \wedge b|\neg A \wedge B) &= (1 - \mathbf{a})\mathbf{b} \\ P(a \wedge b|\neg A \wedge \neg B) &= (1 - \mathbf{a})(1 - \mathbf{b}) \end{aligned}$$

Abbreviate the probabilities the way we already did:

$$\begin{aligned} P(A \wedge B) &= p_{11} & P(A \wedge \neg B) &= p_{10} \\ P(\neg A \wedge B) &= p_{01} & P(\neg A \wedge \neg B) &= p_{00} \end{aligned}$$

Our assumptions entail $0 \neq p_{ij} \neq 1$ for $i, j \in \{0, 1\}$ and:

$$p_{11} + p_{10} + p_{01} + p_{00} = 1 \tag{7}$$

So, we can use this with (6) to get:

$$\begin{aligned} P(a \wedge b) &= \mathbf{a}\mathbf{b}p_{11} + \mathbf{a}(1 - \mathbf{b})p_{10} + (1 - \mathbf{a})\mathbf{b}p_{01} + (1 - \mathbf{a})(1 - \mathbf{b})p_{00} \\ &= p_{11}\mathbf{a}\mathbf{b} + p_{10}(\mathbf{a} - \mathbf{a}\mathbf{b}) + p_{01}(\mathbf{b} - \mathbf{a}\mathbf{b}) + p_{00}(1 - \mathbf{b} - \mathbf{a} + \mathbf{a}\mathbf{b}) \end{aligned} \tag{8}$$

Let’s now work out what the posterior of $A \wedge B$ will be, starting with an application of the Bayes’ Theorem:

$$\begin{aligned} P(A \wedge B|a \wedge b) &= \frac{P(a \wedge b|A \wedge B)P(A \wedge B)}{P(a \wedge b)} \\ &= \frac{\mathbf{a}\mathbf{b}p_{11}}{p_{11}\mathbf{a}\mathbf{b} + p_{10}(\mathbf{a} - \mathbf{a}\mathbf{b}) + p_{01}(\mathbf{b} - \mathbf{a}\mathbf{b}) + p_{00}(1 - \mathbf{b} - \mathbf{a} + \mathbf{a}\mathbf{b})} \end{aligned} \tag{9}$$

To answer our question we therefore have to compare the content of (9) to p_{11} and our claim holds just in case:

$$\frac{abp_{11}}{p_{11}ab + p_{10}(a - ab) + p_{01}(b - ab) + p_{00}(1 - b - a + ab)} > p_{11}$$

$$\frac{ab}{p_{11}ab + p_{10}(a - ab) + p_{01}(b - ab) + p_{00}(1 - b - a + ab)} > 1$$

$$p_{11}ab + p_{10}(a - ab) + p_{01}(b - ab) + p_{00}(1 - b - a + ab) < ab \quad (10)$$

Proving (10) is therefore our goal for now. This is achieved by the following reasoning:¹¹

- | | | |
|-----|--|---|
| 1. | $b > 0.5, a > 0.5$ | assumption |
| 2. | $2b > 1, 2a > 1$ | from 1. |
| 3. | $2ab > a, 2ab > b$ | multiplying by a and b respectively |
| 4. | $p_{10}2ab > p_{10}a, p_{01}2ab > p_{01}b$ | multiplying by p_{10} and p_{01} respectively |
| 5. | $p_{10}2ab + p_{01}2ab > p_{10}a + p_{01}b$ | adding by sides, 3., 4. |
| 6. | $1 - b - a < 0$ | from 1. |
| 7. | $p_{00}(1 - b - a) < 0$ | From 6., because $p_{00} > 0$ |
| 8. | $p_{10}2ab + p_{01}2ab > p_{10}a + p_{01}b + p_{00}(1 - b - a)$ | from 5. and 7. |
| 9. | $p_{10}ab + p_{10}ab + p_{01}ab + p_{01}ab + p_{00}ab - p_{00}ab > p_{10}a + p_{01}b + p_{00}(1 - b - a)$ | 8., rewriting left-hand side |
| 10. | $p_{10}ab + p_{01}ab + p_{00}ab > -p_{10}ab - p_{01}ab + p_{00}ab + p_{10}a + p_{01}b + p_{00}(1 - b - a)$ | 9., moving from left to right |
| 11. | $ab(p_{10} + p_{01} + p_{00}) > p_{10}(a - ab) + p_{01}(b - ab) + p_{00}(1 - b - a + ab)$ | 10., algebraic manipulation |
| 12. | $ab(1 - p_{11}) > p_{10}(a - ab) + p_{01}(b - ab) + p_{00}(1 - b - a + ab)$ | 11. and equation (7) |
| 13. | $ab - abp_{11} > p_{10}(a - ab) + p_{01}(b - ab) + p_{00}(1 - b - a + ab)$ | 12., algebraic manipulation |
| 14. | $ab > abp_{11} + p_{10}(a - ab) + p_{01}(b - ab) + p_{00}(1 - b - a + ab)$ | 13., moving from left to right |

The last line is what we have been after.

OPTIONAL CONTENT ENDS

Now that we have as a theorem an explication of what Dawid informally suggested, let's see whether it helps the probabilist handling of DAC.

4.4 Kaplow

On RLP, at least in certain cases, the decision rule leads us to (14), which tells us to decide the case based on whether the likelihood ratio is greater than 1.

¹² While Kaplow did not discuss DAC or the gatecrasher paradox, it is only fair to evaluate Kaplow's proposal from the perspective of these difficulties.

Add here stuff from Marcello's Mind paper about the prisoner hypothetical. Then, discuss Rafal's critique of the likelihood ratio threshold and see where we end up.

4.5 p-value (Cheng?)

5 Challenges (again)

5.1 Likelihood ratio and the problem of the priors

5.2 Dawid's likelihood strategy doesn't help

Recall that DAC was a problem posed for the decision standard proposed by TLP, and the real question is how the information resulting from Fact 1 can help to avoid that problem. Dawid does not mention any decision standard, and so addresses quite a different question, and so it is not clear that 'the paradox' evaporates", as Dawid suggests.

What Dawid correctly suggests (and we establish in general as Fact 1) is that the support of the conjunction by two witnesses will be positive as soon as their separate support for the conjuncts is positive. That is, that the posterior of the conjunction will be higher than its prior. But the critic of probabilism never denied that the conjunction of testimonies might raise the probability of the

¹¹ Thanks to Pawel Pawlowski for working on this proof with me.

¹² Again, the name of the view is by no means standard, it is just a term I coined to refer to various types of legal probabilism in a fairly uniform manner.

conjunction if the testimonies taken separately support the conjuncts taken separately. Such a critic can still insist that Fact 1 does nothing to alleviate her concern. After all, at least *prima facie* it still might be the case that:

- the posterior probabilities of the conjuncts are above a given threshold,
- the posterior probability of the conjunction is higher than the prior probability of the conjunction,
- the posterior probability of the conjunction is still below the threshold.

That is, Fact 1 does not entail that once the conjuncts satisfy a decision standard, so does the conjunction.

At some point, Dawid makes a general claim that is somewhat stronger than the one already cited:

When the problem is analysed carefully, the ‘paradox’ evaporates: suitably measured, the support supplied by the conjunction of several independent testimonies exceeds that supplied by any of its constituents.

[p. 97]

This is quite a different claim from the content of Fact 1, because previously the joint probability was claimed only to increase as compared to the prior, and here it is claimed to increase above the level of the separate increases provided by separate testimonies. Regarding this issue Dawid elaborates (we still use the p_{ij} -notation that we’ve already introduced):

“More generally, let $P(a|A)/P(a|\neg A) = \lambda$, $P(b|B)/P(b|\neg B) = \mu$, with $\lambda, \mu > 0.7$, as might arise, for example, when there are several available testimonies. If the witnesses are independent, then

$$P(A \wedge B|a \wedge b) = \lambda\mu p_{11}/(\lambda\mu p_{11} + \lambda p_{10} + \mu p_{01} + p_{00})$$

which increases with each of λ and μ , and is never less than the larger of $\lambda p_{11}/(1 - p_{11} + \lambda p_{11})$, $\mu p_{11}/(1 - p_{11} + \mu p_{11})$, the posterior probabilities appropriate to the individual testimonies.” [p. 95]

This claim, however, is false.

OPTIONAL CONTENT STARTS

Let us see why. The quoted passage is a bit dense. It contains four claims for which no arguments are given in the paper. The first three are listed below as (11), the fourth is that if the conditions in (11) hold, $P(A \wedge B|a \wedge b) > \max(P(A|a), P(B|b))$. Notice that $\lambda = LR(a|A)$ and $\mu = LR(b|B)$. Suppose the first three claims hold, that is:

$$P(A \wedge B|a \wedge b) = \lambda\mu p_{11}/(\lambda\mu p_{11} + \lambda p_{10} + \mu p_{01} + p_{00}) \quad (11)$$

$$P(A|a) = \frac{\lambda p_{11}}{1 - p_{11} + \lambda p_{11}}$$

$$P(B|b) = \frac{\mu p_{11}}{1 - p_{11} + \mu p_{11}}$$

Is it really the case that $P(A \wedge B|a \wedge b) > P(A|a), P(B|b)$? It does not seem so. Let $\mathbf{a} = \mathbf{b} = 0.6$, $pr = \langle p_{11}, p_{10}, p_{01}, p_{00} \rangle = \langle 0.1, 0.7, 0.1, 0.1 \rangle$. Then, $\lambda = \mu = 1.5 > 0.7$ so the assumption is satisfied. Then we have $P(A) = p_{11} + p_{10} = 0.8$, $P(B) = p_{11} + p_{01} = 0.2$. We can also easily compute $P(a) = \mathbf{a}P(A) + (1 - \mathbf{a})P(\neg A) = 0.56$ and $P(b) = \mathbf{b}P(B) + (1 - \mathbf{b})P(\neg B) = 0.44$. Yet:

$$P(A|a) = \frac{P(a|A)P(A)}{P(a)} = \frac{0.6 \times 0.8}{0.6 \times 0.8 + 0.4 \times 0.2} \approx 0.8571$$

$$P(B|b) = \frac{P(b|B)P(B)}{P(b)} = \frac{0.6 \times 0.2}{0.6 \times 0.2 + 0.4 \times 0.8} \approx 0.272$$

$$\begin{aligned} P(A \wedge B|a \wedge b) &= \frac{P(a \wedge b|A \wedge B)P(A \wedge B)}{P(a \wedge b|A \wedge B)P(A \wedge B) + P(a \wedge b|A \wedge \neg B)P(A \wedge \neg B) + P(a \wedge b|\neg A \wedge B)P(\neg A \wedge B) + P(a \wedge b|\neg A \wedge \neg B)P(\neg A \wedge \neg B)} \\ &= \frac{\mathbf{a}\mathbf{b}p_{11}}{\mathbf{a}\mathbf{b}p_{11} + \mathbf{a}(1 - \mathbf{b})p_{10} + (1 - \mathbf{a})\mathbf{b}p_{01} + (1 - \mathbf{a})(1 - \mathbf{b})p_{00}} \approx 0.147 \end{aligned}$$

The posterior probability of $A \wedge B$ is not only lower than the larger of the individual posteriors, but also lower than any of them!

So what went wrong in Dawid's calculations in (11)? Well, the first formula is correct. However, let us take a look at what the second one says (the problem with the third one is pretty much the same):

$$P(A|a) = \frac{\frac{P(a|A)}{P(\neg a|A)} \times P(A \wedge B)}{P(\neg(A \wedge B)) + \frac{P(a|A)}{P(\neg a|A)} \times P(A \wedge B)}$$

Quite surprisingly, in Dawid's formula for $P(A|a)$, the probability of $A \wedge B$ plays a role. To see that it should not take any B that excludes A and the formula will lead to the conclusion that *always* $P(A|a)$ is undefined. The problem with Dawid's formula is that instead of $p_{11} = P(A \wedge B)$ he should have used $P(A) = p_{11} + p_{10}$, in which case the formula would rather say this:

$$\begin{aligned} P(A|a) &= \frac{\frac{P(a|A)}{P(\neg a|A)} \times P(A)}{P(\neg A) + \frac{P(a|A)}{P(\neg a|A)} \times P(A)} \\ &= \frac{\frac{P(a|A)P(A)}{P(\neg a|A)}}{\frac{P(\neg a|A)P(\neg A)}{P(\neg a|A)} + \frac{P(a|A)P(A)}{P(\neg a|A)}} \\ &= \frac{P(a|A)P(A)}{P(\neg a|A)P(\neg A) + P(a|A)P(A)} \end{aligned}$$

Now, on the assumption that witness' sensitivity is equal to their specificity, we have $P(a|\neg A) = P(\neg a|A)$ and can substitute this in the denominator:

$$= \frac{P(a|A)P(A)}{P(a|\neg A)P(\neg A) + P(a|A)P(A)}$$

and this would be a formulation of Bayes' theorem. And indeed with $P(A) = p_{11} + p_{10}$ the formula works (albeit its adequacy rests on the identity of $P(a|\neg A)$ and $P(\neg a|A)$), and yields the result that we already obtained:

$$\begin{aligned} P(A|a) &= \frac{\lambda(p_{11} + p_{10})}{1 - (p_{11} + p_{10}) + \lambda(p_{11} + p_{10})} \\ &= \frac{1.5 \times 0.8}{1 - 0.8 + 1.5 \times 0.8} \approx 0.8571 \end{aligned}$$

The situation cannot be much improved by taking **a** and **b** to be high. For instance, if they're both 0.9 and $pr = \langle 0.1, 0.7, 0.1, 0.1 \rangle$, the posterior of A is ≈ 0.972 , the posterior of B is ≈ 0.692 , and yet the joint posterior of $A \wedge B$ is 0.525.

The situation cannot also be improved by saying that at least if the threshold is 0.5, then as soon as **a** and **b** are above 0.7 (and, *a fortiori*, so are λ and μ), the individual posteriors being above 0.5 entails the joint posterior being above 0.5 as well. For instance, for **a** = 0.7 and **b** = 0.9 with $pr = \langle 0.1, 0.3, 0.5, 0.1 \rangle$, the individual posteriors of A and B are ≈ 0.608 and ≈ 0.931 respectively, while the joint posterior of $A \wedge B$ is ≈ 0.283 .

OPTIONAL CONTENT ENDS

The situation cannot be improved by saying that what was meant was rather that the joint likelihood is going to be at least as high as the maximum of the individual likelihoods, because quite the opposite is the case: the joint likelihood is going to be lower than any of the individual ones.

OPTIONAL CONTENT STARTS

Let us make sure this is the case. We have:

$$\begin{aligned} LR(a|A) &= \frac{P(a|A)}{P(a|\neg A)} \\ &= \frac{P(a|A)}{P(\neg a|A)} \\ &= \frac{\mathbf{a}}{1 - \mathbf{a}}. \end{aligned}$$

where the substitution in the denominator is legitimate only because witness' sensitivity is identical to their specificity.

With the joint likelihood, the reasoning is just a bit more tricky. We will need to know what $P(a \wedge b | \neg(A \wedge B))$ is. There are three disjoint possible conditions in which the condition holds: $A \wedge \neg B$, $\neg A \wedge B$, and $\neg A \wedge \neg B$. The probabilities of $a \wedge b$ in these three scenarios are respectively $a(1-b)$, $(1-a)b$, $(1-a)(1-b)$ (again, the assumption of independence is important), and so on the assumption $\neg(A \wedge B)$ the probability of $a \wedge b$ is:

$$\begin{aligned} P(a \wedge b | \neg(A \wedge B)) &= a(1-b) + (1-a)b + (1-a)(1-b) \\ &= a(1-b) + (1-a)(b+1-b) \\ &= a(1-b) + (1-a) \\ &= a - ab + 1 - a = 1 - ab \end{aligned}$$

So, on the assumption of witness independence, we have:

$$\begin{aligned} LR(a \wedge b | A \wedge B) &= \frac{P(a \wedge b | A \wedge B)}{P(a \wedge b | \neg(A \wedge B))} \\ &= \frac{ab}{1-ab} \end{aligned}$$

With $0 < a, b < 1$ we have $ab < a$, $1 - ab > 1 - a$, and consequently:

$$\frac{ab}{1-ab} < \frac{a}{1-a}$$

which means that the joint likelihood is going to be lower than any of the individual ones.

OPTIONAL CONTENT ENDS

Fact 1 is so far the most optimistic reading of the claim that if witnesses are independent and fairly reliable, their testimonies are going to provide positive support for the conjunction. And this is the reading that Dawid in passing suggests: “the combined support is always positive, in the sense that the posterior probability of the case always exceeds its prior probability.” (Dawid, 1987: 95) and any stronger reading of Dawid’s suggestions fails. But Fact 1 is not too exciting when it comes to answering the original DAC. The original question focused on the adjudication model according to which the deciding agents are to evaluate the posterior probability of the whole case conditional on all evidence, and to convict if it is above a certain threshold. The problem, generally, is that it might be the case that the pieces of evidence for particular elements of the claim can have high likelihood and posterior probabilities of particular elements can be above the threshold while the posterior joint probability will still fail to meet the threshold. The fact that the joint posterior will be higher than the joint prior does not help much. For instance, if $a = b = 0.7$, $pr = \langle 0.1, 0.5, 0.3, 0.1 \rangle$, the posterior of A is ≈ 0.777 , the posterior of B is ≈ 0.608 and the joint posterior is ≈ 0.216 (yes, it is higher than the joint prior = 0.1, but this does not help the conjunction to satisfy the decision standard).

To see the extent to which Dawid’s strategy is helpful here, perhaps the following analogy might be useful.

Imagine it is winter, the heating does not work in my office and I am quite cold. I pick up the phone and call maintenance. A rather cheerful fellow picks up the phone. I tell him what my problem is, and he reacts:

- Oh, don’t worry.
- What do you mean? It’s cold in here!
- No no, everything is fine, don’t worry.
- It’s not fine! I’m cold here!
- Look, sir, my notion of it being warm in your office is that the building provides some improvement to what the situation would be if it wasn’t there. And you agree that you’re definitely warmer than you’d be if your desk was standing outside, don’t you? Your, so to speak, posterior warmth is higher than your prior warmth, right?

Dawid’s discussion is in the vein of the above conversation. In response to a problem with the adjudication model under consideration Dawid simply invites us to abandon thinking in terms of it and to abandon requirements crucial for the model. Instead, he puts forward a fairly weak notion of support (analogous to a fairly weak sense of the building providing improvement), according to which,

assuming witnesses are fairly reliable, if separate fairly reliable witnesses provide positive support to the conjuncts, then their joint testimony provides positive support for the conjunction.

As far as our assessment of the original adjudication model and dealing with DAC, this leaves us hanging. Yes, if we abandon the model, DAC does not worry us anymore. But should we? And if we do, what should we change it to, if we do not want to be banished from the paradise of probabilistic methods?

Having said this, let me emphasize that Dawid's paper is important in the development of the debate, since it shifts focus on the likelihood ratios, which for various reasons are much better measures of evidential support provided by particular pieces of evidence than mere posterior probabilities.

Before we move to another attempt at a probabilistic formulation of the decision standard, let us introduce the other hero of our story: the gatecrasher paradox. It is against DAC and this paradox that the next model will be judged.

OPTIONAL CONTENT STARTS

In fact, Cohen replied to Dawid's paper (Cohen, 1988). His reply, however, does not have much to do with the workings of Dawid's strategy, and is rather unusual. Cohen's first point is that the calculations of posteriors require odds about unique events, whose meaning is usually given in terms of potential wagers – and the key criticism here is that in practice such wagers cannot be decided. This is not a convincing criticism, because the betting-odds interpretations of subjective probability do not require that on each occasion the bet should really be practically decidable. It rather invites one to imagine a possible situation in which the truth could be found out and asks: how much would we bet on a certain claim in such a situation? In some cases, this assumption is false, but there is nothing in principle wrong with thinking about the consequences of false assumptions.

Second, Cohen says that Dawid's argument works only for testimonial evidence, not for other types thereof. But this claim is simply false – just because Dawid used testimonial evidence as an example that he worked through it by no means follows that the approach cannot be extended. After all, as long as we can talk about sensitivity and specificity of a given piece of evidence, everything that Dawid said about testimonies can be repeated *mutatis mutandis*.

Third, Cohen complains that Dawid in his example worked with rather high priors, which according to Cohen would be too high to correspond to the presumption of innocence. This also is not a very successful rejoinder. Cohen picked his priors in the example for the ease of calculations, and the reasoning can be run with lower priors. Moreover, instead of discussing the conjunction problem, Cohen brings in quite a different problem: how to probabilistically model the presumption of innocence, and what priors of guilt should be appropriate? This, indeed, is an important problem; but it does not have much to do with DAC, and should be discussed separately.

5.3 Problems with Cheng's relative likelihood

How is RLP supposed to handle DAC? Consider an imaginary case, used by Cheng to discuss this issue. In it, the plaintiff claims that the defendant was speeding (S) and that the crash caused her neck injury (C). Thus, H_{Π} is $S \wedge C$. Suppose that given total evidence E , the conjuncts, taken separately, meet the decision standard of RLP:

$$\frac{P(S|E)}{P(\neg S|E)} > 1 \qquad \frac{P(C|E)}{P(\neg C|E)} > 1$$

The question, clearly, is whether $\frac{P(S \wedge C|E)}{H_{\Delta}|E} > 1$. But to answer it, we have to decide what H_{Δ} is. This is the point where Cheng's remark that H_{Δ} isn't normally simply $\neg H_{\Pi}$. Instead, he insists, there are three alternative defense scenarios: $H_{\Delta_1} = S \wedge \neg C$, $H_{\Delta_2} = \neg S \wedge C$, and $H_{\Delta_3} = \neg S \wedge \neg C$. How does H_{Π} compare to each of them? Cheng (assuming independence) argues:

$$\begin{aligned} \frac{P(S \wedge C|E)}{P(S \wedge \neg C|E)} &= \frac{P(S|E)P(C|E)}{P(S|E)P(\neg C|E)} = \frac{P(C|E)}{P(\neg C|E)} > 1 \\ \frac{P(S \wedge C|E)}{P(\neg S \wedge C|E)} &= \frac{P(S|E)P(C|E)}{P(\neg S|E)P(C|E)} = \frac{P(S|E)}{P(\neg S|E)} > 1 \\ \frac{P(S \wedge C|E)}{P(\neg S \wedge \neg C|E)} &= \frac{P(S|E)P(C|E)}{P(\neg S|E)P(\neg C|E)} > 1 \end{aligned} \tag{12}$$

It seems that whatever the defense story is, it is less plausible than the plaintiff's claim. So, at least in this case, whenever elements of a plaintiff's claim satisfy the decision standard proposed by RLP, then so does their conjunction.

Similarly, RLP is claimed to handle the gatecrasher paradox. It is useful to think about the problem in terms of odds and likelihoods, where the *prior odds* (before evidence E) of H_{Π} as compared to H_{Δ} , are $\frac{P(H_{\Pi})}{P(H_{\Delta})}$, the posterior odds of H_{Δ} given E are $\frac{P(H_{\Pi}|E)}{P(H_{\Delta}|E)}$, and the corresponding likelihood ratio is $\frac{P(E|H_{\Pi})}{P(E|H_{\Delta})}$.

Now, with this notation the *odds form of Bayes' Theorem* tells us that the posterior odds equal the likelihood ratio multiplied by prior odds:

$$\frac{P(H_{\Pi}|E)}{P(H_{\Delta}|E)} = \frac{P(E|H_{\Pi})}{P(E|H_{\Delta})} \times \frac{P(H_{\Pi})}{P(H_{\Delta})}$$

[@cheng2012reconceptualizing: 1267] insists that in civil trials the prior probabilities should be equal. Granted this assumption, prior odds are 1, and we have:

$$\frac{P(H_{\Pi}|E)}{P(H_{\Delta}|E)} = \frac{P(E|H_{\Pi})}{P(E|H_{\Delta})} \quad (13)$$

This means that our original task of establishing that the left-hand side is greater than 1 now reduces to establishing that so is the right-hand side, which means that RLP tells us to convict just in case:

$$P(E|H_{\Pi}) > P(E|H_{\Delta}) \quad (14)$$

Thus, (14) tells us to convict just in case $LR(E) > 1$.

Now, in the case of the gatecrasher paradox, our evidence is statistical. In our variant $E = \text{"991 out of 1000 spectators gatecrashed"}$. Now pick a random spectator, call him Tom, and let $\$H_{\Pi} = \text{"Tom gatecrashed"}$. (Cheng, 2012: 1270) insists:

But whether the audience member is a lawful patron or a gatecrasher does not change the probability of observing the evidence presented.

So, on his view, in such a case, $P(E|H_{\Pi}) = P(E|H_{\Delta})$, the posterior odds are, by (13), equal to 1, and conviction is unjustified.

There are various issues with how RLP has been deployed to resolve the difficulties that CLP and TLP run into.

First of all, to move from (1) to (2), Cheng assumes that the costs of wrongful decision is the same, be it conviction or acquittal. This is by no means obvious. If a poor elderly lady sues a large company for serious health damage that it supposedly caused, leaving her penniless if the company is liable is definitely not on a par with mistakenly making the company lose a small percent of their funds. Even in cases where such costs are equal, careful consideration and separate argument is needed. If, for instance, $c_1 = 5c_2$, we are to convict just in case $5 < \frac{P_{\Pi}}{P_{\Delta}}$. This limits the applicability of Cheng's reasoning about DAC, because his reasoning, if correct (and I will argue that it is not correct later on), yields only the result that the relevant posterior odds are greater than 1, not that they are greater than 5. The difficulty, however, will not have much impact on Cheng's solution of the gatecrasher paradox, as long as $c_1 \leq c_2$. This is because his reasoning, if correct (and I will argue that it is not correct later on), establishes that the relevant posterior odds are below 1, and so below any higher threshold as well.

Secondly, Cheng's resolution of DAC uses another suspicious assumption. For (12) to be acceptable we need to assume that the following pairs of events are independent conditionally on E : $\langle S, C \rangle$, $\langle S, \neg C \rangle$, $\langle \neg S, C \rangle$, $\langle \neg S, \neg C \rangle$. Otherwise, Cheng would not be able to replace conditional probabilities of corresponding conjunctions with the result of multiplication of conditional probabilities of the conjuncts. But it is far from obvious that speeding and neck injury are independent. If, for instance, the evidence makes it certain that if the car was not speeding, the neck injury was not caused by the accident, $P(\neg S \wedge C|E) = 0$, despite the fact that $P(\neg S|E)P(C|E)$ does not have to be 0!

Without independence, the best that we can get, say for the first line of (12), is:

$$\begin{aligned} P(S \wedge C|E) &= P(C|E)P(S|C \wedge E) \\ P(S \wedge \neg C|E) &= P(\neg C|E)P(S|\neg C \wedge E) \end{aligned}$$

and even if we know that $P(C|E) > P(\neg C|E)$, this tells us nothing about the comparison of $P(S \wedge C|E)$ and $P(S \wedge \neg C|E)$, because the remaining factors can make up for the former inequality.

Perhaps even more importantly, much of the heavy lifting here is done by the strategic splitting of the defense line into multiple scenarios. The result is rather paradoxical. For suppose $P(H_{\Pi}|E) = 0.37$ and the probability of each of the defense lines given E is 0.21. This means that H_{Π} wins with each of the scenarios, so, according to RLP, we should find for the plaintiff. On the other hand, how eager are we to convict once we notice that given the evidence, the accusation is rather false, because $P(\neg H_{\Pi}|E) = 0.63$?

The problem generalizes. If, as here, we individualize scenarios by boolean combinations of elements of a case, the more elements there are, into more scenarios $\neg H_{\Pi}$ needs to be divided. This normally would lead to the probability of each of them being even lower (because now $P(\neg H_{\Pi})$ needs to be “split” between more different scenarios). So, if we take this approach seriously, the more elements a case has, the more at disadvantage the defense is. This is clearly undesirable.

In the process of solving the gatecrasher paradox, to reach (13), Cheng makes another controversial assumption: that the prior odds should be one, that is, that before any evidence specific to the case is obtained, $P(H_{\Pi}) = P(H_{\Delta})$. One problem with this assumption is that it is not clear how to square this with how Cheng handles DAC. For there, he insisted we need to consider *three different* defense scenarios, which we marked as H_{Δ_1} , H_{Δ_2} and H_{Δ_3} . Now, do we take Cheng’s suggestion to be that we should have

$$P(H_{\Pi}) = P(H_{\Delta_1}) = P(H_{\Delta_2}) = P(H_{\Delta_3})?$$

Given that the scenarios are jointly exhaustive and pairwise exclusive this would mean that each of them should have prior probability 0.25 and, in principle that the prior probability of guilt can be made lower simply by the addition of elements under consideration. This conclusion seems suboptimal.

If, on the other hand, we read Cheng as saying that we should have $P(H_{\Pi}) = P(\neg H_{\Pi})$, the side-effect is that even a slightest evidence in support of H_{Π} will make the posterior probability of H_{Π} larger than that of $\neg H_{\Pi}$, and so the plaintiff can win their case way too easily. Worse still, if $P(\neg H_{\Pi})$ is to be divided between multiple defense scenarios against which H_{Π} is to be compared, then as soon as this division proceeds in a non-extreme fashion, the prior of each defense scenario will be lower than the prior of H_{Π} , and so from the perspective of RLP, the plaintiff does not have to do anything to win (as long as the defense does not provide absolving evidence), because his case is won without any evidence already!

Finally, let us play along and assume that in the gatecrasher scenario the conviction is justified just in case (14) holds. Cheng insists that it does not, because $P(E|H_{\Pi}) = P(E|H_{\Delta})$. This supposedly captures the intuition that whether Tom paid has no impact on the statistics that we have.

But this is not obvious. Here is one way to think about this. Tom either paid the entrance fee or did not. Consider these two options, assuming nothing else about the case changes. If he did pay, then he is among the 9 innocent spectators. But this means that if he had not paid, there would have been 992 gatecrashers, and so E would be false (because it says there was 991 of them). If, on the other hand, Tom in reality did not pay (and so is among the 991 gatecrashers), then had he paid, there would have been only 990 gatecrashers and E would have been false, again!

So whether conviction is justified and what the relevant ratios are depends on whether Tom really paid. Cheng’s criterion (14) results in the conclusion that Tom should be penalized if and only if he did not pay. But this does not help us much when it comes to handling the paradox, because the reason why we needed to rely on E was exactly that we did not know whether Tom paid.

If you are not buying into the above argument, here is another way to state the problem. Say your priors are $P(E) = e$, $P(H_{\Pi}) = \pi$. By Bayes’ Theorem we have:

$$\begin{aligned} P(E|H_{\Pi}) &= \frac{P(H_{\Pi}|E)e}{\pi} \\ P(E|H_{\Delta}) &= \frac{P(H_{\Delta}|E)e}{1 - \pi} \end{aligned}$$

Assuming our posteriors are taken from the statistical evidence, we have $P(H_{\Pi}|E) = 0.991$ and

$P(H_{\Delta}|E) = 0.009$. So we have:

$$\begin{aligned}
 LR(E) &= \frac{P(H_{\Pi}|E)e}{\pi} \times \frac{1-\pi}{P(H_{\Delta}|E)e} \\
 &= \frac{P(H_{\Pi}|E) - P(H_{\Pi}|E)\pi}{P(H_{\Delta}|E)\pi} \\
 &= \frac{0.991 - 0.991\pi}{0.009\pi}
 \end{aligned} \tag{15}$$

and $LR(E)$ will be > 1 as soon as $\pi < 0.991$. This means that contrary to what Cheng suggested, in any situation in which the prior probability of guilt is less than the posterior probability of guilt, RLP tells us to convict. This, however, does not seem desirable.

5.4 Problem's with Kaplow's stuff

Kaplow does not discuss the conceptual difficulties that we are concerned with, but this will not stop us from asking whether DTLP can handle them (and answering to the negative). Let us start with DAC.

Say we consider two claims, A and B . Is it generally the case that if they separately satisfy the decision rule, then so does $A \wedge B$? That is, do the assumptions:

$$\begin{aligned}
 \frac{P(E|A)}{P(E|\neg A)} &> \frac{P(\neg A)}{P(A)} \times \frac{L}{G} \\
 \frac{P(E|B)}{P(E|\neg B)} &> \frac{P(\neg B)}{P(B)} \times \frac{L}{G}
 \end{aligned}$$

entail

$$\frac{P(E|A \wedge B)}{P(E|\neg(A \wedge B))} > \frac{P(\neg(A \wedge B))}{P(A \wedge B)} \times \frac{L}{G} ?$$

Alas, the answer is negative.

OPTIONAL CONTENT STARTS

This can be seen from the following example. Suppose a random digit from 0-9 is drawn; we do not know the result; we are told that the result is < 7 (E = 'the result is < 7 '), and we are to decide whether to accept the following claims:

A	the result is < 5 .
B	the result is an even number.
$A \wedge B$	the result is an even number < 5 .

Suppose that $L = G$ (this is for simplicity only — nothing hinges on this, counterexamples for when this condition fails are analogous). First, notice that A and B taken separately satisfy (5). $P(A) = P(\neg A) = 0.5$, $P(\neg A)/P(A) = 1$ $P(E|A) = 1$, $P(E|\neg A) = 0.4$. (5) tells us to check:

$$\begin{aligned}
 \frac{P(E|A)}{P(E|\neg A)} &> \frac{L}{G} \times \frac{P(\neg A)}{P(A)} \\
 \frac{1}{0.4} &> 1
 \end{aligned}$$

so, following DTLP, we should accept A .

For analogous reasons, we should also accept B . $P(B) = P(\neg B) = 0.5$, $P(\neg B)/P(B) = 1$ $P(E|B) = 0.8$, $P(E|\neg B) = 0.6$, so we need to check that indeed:

$$\begin{aligned}
 \frac{P(E|B)}{P(E|\neg B)} &> \frac{L}{G} \times \frac{P(\neg B)}{P(B)} \\
 \frac{0.8}{0.6} &> 1
 \end{aligned}$$

But now, $P(A \wedge B) = 0.3$, $P(\neg(A \wedge B)) = 0.7$, $P(\neg(A \wedge B))/P(A \wedge B) = 2\frac{1}{3}$, $P(E|A \wedge B) = 1$, $P(E|\neg(A \wedge B)) = 4/7$ and it is false that:

$$\frac{P(E|A \wedge B)}{P(E|\neg(A \wedge B))} > \frac{L}{G} \times \frac{P(\neg(A \wedge B))}{P(A \wedge B)}$$

$$\frac{7}{4} > \frac{7}{3}$$

The example was easy, but the conjuncts are probabilistically dependent. One might ask: are there counterexamples that involve claims which are probabilistically independent?¹³

Consider an experiment in which someone tosses a six-sided die twice. Let the result of the first toss be X and the result of the second one Y . Your evidence is that the results of both tosses are greater than one ($E =: X > 1 \wedge Y > 1$). Now, let A say that $X < 5$ and B say that $Y < 5$.

The prior probability of A is $2/3$ and the prior probability of $\neg A$ is $1/3$ and so $\frac{P(\neg A)}{P(A)} = 0.5$. Further, $P(E|A) = 0.625$, $P(E|\neg A) = 5/6$ and so $\frac{P(E|A)}{P(E|\neg A)} = 0.75$. Clearly, $0.75 > 0.5$, so A satisfies the decision standard. Since the situation with B is symmetric, so does B .

Now, $P(A \wedge B) = (2/3)^2 = 4/9$ and $P(\neg(A \wedge B)) = 5/9$. So $\frac{P(\neg(A \wedge B))}{P(A \wedge B)} = 5/4$. Out of 16 outcomes for which $A \wedge B$ holds, E holds in 9, so $P(E|A \wedge B) = 9/16$. Out of 20 remaining outcomes for which $A \wedge B$ fails, E holds in 16, so $P(E|\neg(A \wedge B)) = 4/5$. Thus, $\frac{P(E|A \wedge B)}{P(E|\neg(A \wedge B))} = 45/64 < 5/4$, so the conjunction does not satisfy the decision standard.

OPTIONAL CONTENT ENDS

Let us turn to the gatecrasher paradox.

Suppose $L = G$ and recall our abbreviations: $P(E) = e$, $P(H_{\Pi}) = \pi$. DTLP tells us to convict just in case:

$$LR(E) > \frac{1 - \pi}{\pi}$$

From (15) we already now that

$$LR(E) = \frac{0.991 - 0.991\pi}{0.009\pi}$$

so we need to see whether there are any $0 < \pi < 1$ for which

$$\frac{0.991 - 0.991\pi}{0.009\pi} > \frac{1 - \pi}{\pi}$$

Multiply both sides first by 0.009π and then by π :

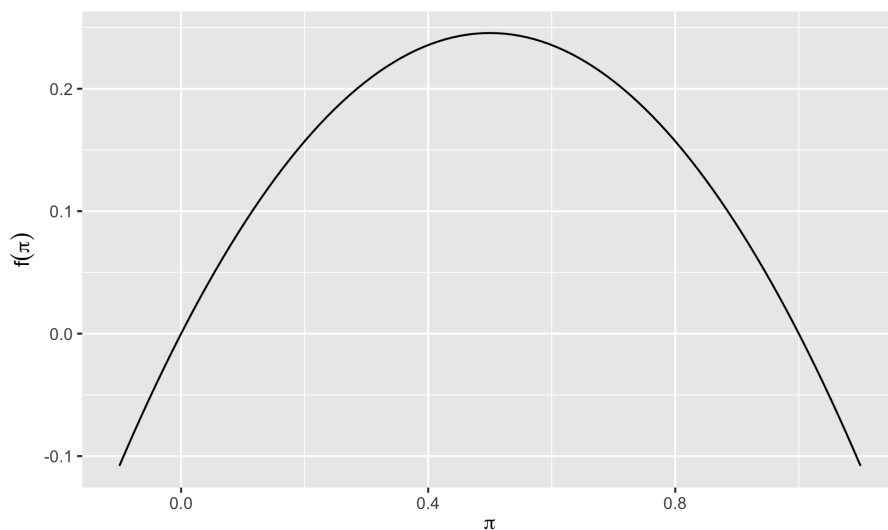
$$0.991\pi - 0.991\pi^2 > 0.09\pi - 0.009\pi^2$$

Simplify and call the resulting function f :

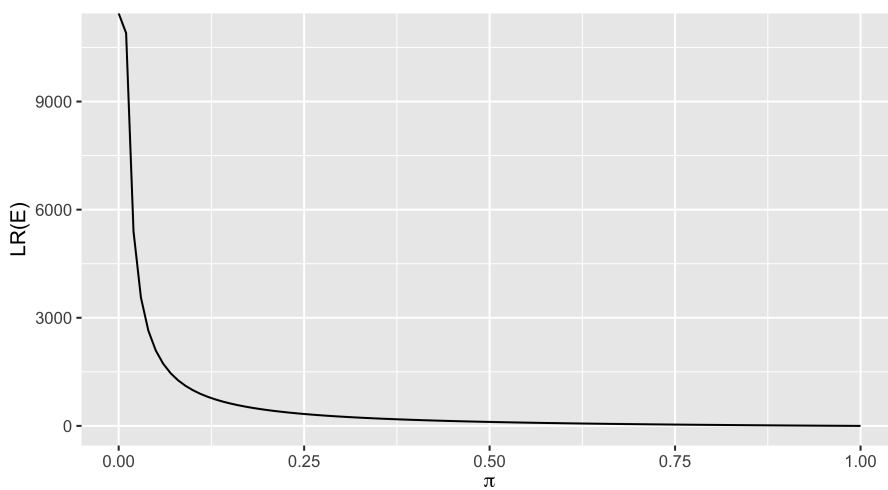
$$f(\pi) = -0.982\pi^2 + 0.982\pi > 0$$

The above condition is satisfied for any $0 < \pi < 1$ (f has two zeros: $\pi = 0$ and $\pi = 1$). Here is a plot of f :

¹³Thanks to Alicja Kowalewska for pressing me on this.



Similarly, $LR(E) > 1$ for any $0 < \pi < 1$. Here is a plot of $LR(E)$ against π :



Notice that $LR(E)$ does not go below 1. This means that for $L = G$ in the gatecrasher scenario DTLP would tell us to convict for any prior probability of guilt $\pi \neq 0, 1$.

One might ask: is the conclusion very sensitive to the choice of L and G ? The answer is, not too much.

OPTIONAL CONTENT STARTS

How sensitive is our analysis to the choice of L/G ? Well, $LR(E)$ does not change at all, only the threshold moves. For instance, if $L/G = 4$, instead of f we end up with

$$f'(\pi) = -0.955\pi^2 + 0.955\pi > 0$$

and the function still takes positive values on the interval $(0, 1)$. In fact, the decision won't change until L/G increases to ≈ 111 . Denote L/G as ρ , and let us start with the general decision standard, plugging

in our calculations for $LR(E)$:

$$\begin{aligned}
LR(E) &> \frac{P(H_{\Delta})}{P(H_{\Pi})} \rho \\
LR(E) &> \frac{1-\pi}{\pi} \rho \\
\frac{0.991-0.991\pi}{0.009\pi} &> \frac{1-\pi}{\pi} \rho \\
\frac{0.991-0.991\pi}{0.009\pi} \frac{\pi}{1-\pi} &> \rho \\
\frac{0.991\pi-0.991\pi^2}{0.009\pi-0.009\pi^2} &> \rho \\
\frac{\pi(0.991-0.991\pi)}{\pi(0.009-0.009\pi)} &> \rho \\
\frac{0.991-0.991\pi}{0.009-0.009\pi} &> \rho \\
\frac{0.991(1-\pi)}{0.009(1-\pi)} &> \rho \\
\frac{0.991}{0.009} &> \rho \\
110.1111 &> \rho
\end{aligned}$$

OPTIONAL CONTENT ENDS

So, we conclude, in usual circumstances, DTLP does not handle the gatecrasher paradox.

6 Probabilistic Thresholds Revised

6.1 Likelihood ratios and naked statistical evidence

6.2 Conjunction paradox and Bayesian networks

7 Conclusions

Where are we, how did we get here, and where can we go from here? We were looking for a probabilistically explicated condition Ψ such that the trier of fact, at least ideally, should accept any relevant claim (including G) just in case $\Psi(A, E)$.

From the discussion that transpired it should be clear that we were looking for a Ψ satisfying the following desiderata:

conjunction closure If $\Psi(A, E)$ and $\Psi(B, E)$, then $\Psi(A \wedge B, E)$.

naked statistics The account should at least make it possible for convictions based on strong, but naked statistical evidence to be unjustified.

equal treatment the condition should apply to any relevant claim whatsoever (and not just a selected claim, such as G).

Throughout the paper we focused on the first two conditions (formulated in terms of the difficulty about conjunction (DAC), and the gatecrasher paradox), going over various proposals of what Ψ should be like and evaluating how they fare. The results can be summed up in the following table:

View	Convict iff	DAC	Gatecrasher
Threshold-based LP (TLP)	Probability of guilt given the evidence is above a certain threshold	fails	fails
Dawid's likelihood strategy	No condition given, focus on $\frac{P(H E)}{P(H \neg E)}$	<ul style="list-style-type: none"> - If evidence is fairly reliable, the posterior of $A \wedge B$ will be greater than the prior. - The posterior of $A \wedge B$ can still be lower than the posterior of any of A and B. - Joint likelihood, contrary to Dawid's claim, can also be lower than any of the individual likelihoods. 	fails
Cheng's relative LP (RLP)	Posterior of guilt higher than the posterior of any of the defending narrations	The solution assumes equal costs of errors and independence of A and B conditional on E . It also relies on there being multiple defending scenarios individualized in terms of combinations of literals involving A and B .	Assumes that the prior odds of guilt are 1, and that the statistics is not sensitive to guilt (which is dubious). If the latter fails, tells to convict as long as the prior of guilt < 0.991 .
Kaplow's decision-theoretic LP (DTLP)	The likelihood of the evidence is higher than the odds of innocence multiplied by the cost of error ratio	fails	convict if cost ratio < 110.1111

Thus, each account either simply fails to satisfy the desiderata, or succeeds on rather unrealistic assumptions. Does this mean that a probabilistic approach to legal evidence evaluation should be abandoned? No. This only means that if we are to develop a general probabilistic model of legal decision standards, we have to do better. One promising direction is to go back to Cohen's pressure against **Requirement 1** and push against it. A brief paper suggesting this direction is (Di Bello, 2019b), where the idea is that the probabilistic standard (be it a threshold or a comparative wrt. defending narrations) should be applied to the whole claim put forward by the plaintiff, and not to its elements. In such a context, DAC does not arise, but **equal treatment** is violated. Perhaps, there are independent reasons to abandon it, but the issue deserves further discussion. Another strategy might be to go in the direction of employing probabilistic methods to explicate the narration theory of legal decision standards (Urbaniak, 2018), but a discussion of how this approach relates to DAC and the gatecrasher paradox lies beyond the scope of this paper.

8 References

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