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HANDLING UNCERTAINTY IN A COURT OF LAW

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1 Introduction

Many people have difficulty handling uncertainty because the very nature of uncertainty often runs counter to our intuition. By our way of thinking we make errors of logic and our approach is generally wrong. The analysis of uncertainty is not something that lies within most people's experience. Courts are burdened with the task of considering different pieces of evidence, often of different degrees of uncertainty. Eventually the court *somehow* has to weigh up the different pieces of evidence and arrive at a conclusion. And there are right ways and wrong ways of reasoning with uncertainty. People make mistakes when left to their own devices. When it happens in a court of law it can be extremely prejudicial to the defendant.[1]

Recently several court cases grappled with problems of uncertainty and in some instances came to confusing conclusions causing dismay in the forensic scientific community.[2] On 8 February 2011 leading forensic scientists and statisticians issued a "position statement" which was prompted by a controversial judgment in the British Court of Appeal in the case *R v T*.[3] The first point made in the position statement reads as follows:

> "The interpretation of scientific evidence invokes reasoning in the face of uncertainty. Probability theory provides the only coherent logical foundation for such reasoning."[4]

The Board of the European Network of Forensic Science Institutes which is active in 33 countries engaged itself to implement the principles outlined in this position statement. It is feared that the judgment in *R v T* will be "used as a weapon for defending the *status quo* or even a return to pre-scientific notions."[5]

In this paper different manifestations of faulty reasoning concerning uncertainty are discussed. Each section starts with a simplified example which

[1] P Donnelly "Appealing statistics" (2005) 2 *Significance* 46 47.
[2] CEH Berger, J Buckleton, C Champod, IW Evett & G Jackson, "Evidence evaluation: a response to the court of appeal judgment in *R v T* " (2011) 51 *Science & Justice* 43 43-49; M Redmayne, P Roberts, C Aitken & G Jackson "Forensic Science Evidence in Question" (2011) 5 *Crim L Rev* 347 347-356; B Robertson, GA Vignaux & CEH Berger, "Extending the confusion about Bayes" (2011) 74 *Mod L Rev* 444 444-455.
[3] *R v T* [2010] EWCA Crim 2439.
[4] Public Statement by 36 Forensic Scientists and Statisticians "Expressing Evaluative Opinions: A Position Statement" (2011) 51 *Science & Justice* 1 1-2.
[5] Berger et al (2011) *Science & Justice* 49.

illustrates the particular problem. Notation and terminology are explained in the appendix.

2 Transposition of the conditional; the prosecutor's fallacy

Example 1: Consider the two following statements about familiar events.

Statement A: *Given the fact that you have measles. Then the probability* [6] *that you have a headache is 80%.*

Statement A is a statement about a conditional probability. One could reformulate it as follows: the conditional probability that you have a headache, given that you have measles, is 80%. If we write H for the event that you have a headache, and M for the event that you have measles, then we choose to rewrite Statement A in the following way: $P(H|M) = 80\%$. [7]

Statement B: *Given the fact that you have a headache. Then the probability that you have measles is 1%.*

As with Statement A, we rewrite Statement B in the following way: $P(M|H) = 1\%$. The conditional probabilities $P(H|M)$ and $P(M|H)$ are clearly not the same.

Most people readily accept the truth of Statements A and B. People understand headaches and measles. It shows that in general the *transposition of the conditional* can lead to probabilities which are widely different. But strangely enough, we often have difficulty getting our minds around probabilities when (say) *evidence* and *innocence* are the objects under consideration. A typical setting would be the following:

Example 2: At a crime scene a sample of biological material is collected from which a DNA profile of the perpetrator is obtained. Forensic experts estimate that the probability that a randomly chosen person from the population would have the same DNA profile as that of the DNA sample obtained from the crime scene is one in 2 million. (We assume the laboratory work was accurately performed.) Eventually someone is found whose DNA profile matches the DNA profile of the sample obtained at the crime scene. Suddenly this person becomes both suspect and defendant in a criminal case.

Let A and B be the following events:

A: The defendant has the DNA profile of the perpetrator.
B: The defendant is innocent.

As we had done in Example 1, we consider the following two conditional probabilities:

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[6] See appendix (1).
[7] The second entry in the bracket is the condition under which the probability of the first entry is given.

P(A|B) = The probability of *A*, given *B* (ie the probability that the defendant has the DNA profile of the perpetrator, given the fact that he is innocent).

P(B|A) = The probability of *B*, given *A* (ie the probability that the defendant is innocent, given the fact that his DNA profile matches that of the perpetrator).

Failing to distinguish between *P(A|B)* and *P(B|A)* constitutes a serious error in handling uncertainty which could have profound consequences.

People easily come to the mistaken conclusion that the abovementioned ratio of one in 2 million is the probability that the defendant is innocent. This error is called the *prosecutor's fallacy*, a mistake that is often made when probabilities are considered.[8] All that matching DNA profiles tell us is that a person has been found whose DNA profile is the same (or to a high degree the same) as that of a DNA sample found at the crime scene. Although intuitively appealing, it does *not* imply that this individual is the perpetrator. Other evidence is required to prove that. The ratio of one in 2 million refers to the conditional probability *P(A|B)*. We are more concerned with *P(B|A)*.

In the context of Example 2 we may understand the figure one in 2 million as follows: given the present size of the South African population there may be up to 27 people in the country whose DNA profiles match that of the sample found at the crime scene. The advantage of the DNA information is that it narrows down the size of the pool of potential suspects, but usually we do not know who the other people in the pool are. However, the defendant will be a potential suspect. The court should decide on the basis of further evidence whether the defendant is indeed the guilty person among all the other potential suspects. Moreover, if the defendant has close relatives, the number of people in the population whose DNA profiles match that of the sample found at the crime scene may well be greater than 27.

Example 3: On 22 February 2008 *The Guardian* carried a report on the murder trial of Mark Dixie:

> "... Sussex police got a call from the forensics lab: Dixie's DNA was a near-perfect match for the semen discovered on Sally Anne Bowman's body.
>
> 'There was a one in a billion chance it could have belonged to someone else,' said Julie-Ann Cornelius, the senior forensic scientist who gave evidence in the case."[9]

Assuming the senior forensic scientist was accurately quoted, her statement is yet another example of the prosecutor's fallacy. The statement was therefore prejudicial, possibly incorrect, and should not have been made (see part 6).

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[8] CGG Aitken *Statistics and the Evaluation of Evidence for Forensic Scientists* (1995) 36-38; WC Thompson & EL Schumann "Interpretation of Statistical Evidence in Criminal Trials: The Prosecutor's Fallacy and Defence Attorney's Fallacy" (1987) 11 *Law & Hum Behav* 167 181-185.

[9] H Pidd "The boyfriend and first suspect" *The Guardian* (22-02-2008) <www.guardian.co.uk/uk/2008/feb/22/ukcrime.law> (accessed 19-07-2012).

Example 4: In the judgment of the British Court of Appeal in *R v T* we read the following about likelihood ratios:[10]

> "The ratio of two probabilities — the probability of the evidence given that a proposition is true divided by the probability of the evidence given that the alternative proposition is true. ... In the present case it was expressed as the probability that the Nike trainers owned by the appellant had made the marks discovered at the scene divided by the probability that the trainers had not made the marks." [11]

The mistake made in this passage is that of transposing the conditional.[12] The last sentence in this quotation should have read:

> In the present case it was expressed as the probability that the marks discovered at the scene would have been observed if the Nike trainers owned by the appelant had made the marks, divided by the probability that the marks would have been observed if those trainers had not made the marks.

This error occurred at several places in this judgment. Apparently the court confused assessments of the probability of a proposition with the strength of the evidence for the proposition.

3 Database searches

Would our problem of identifying a perpetrator in situations similar to those of part 2 not be solved if we simply searched for a matching DNA profile in a large database of DNA profiles? Perhaps we should consider the following question.

How do we in general determine the probability that two samples with matching DNA profiles came from the same person? These and other related problems are discussed in depth by several authors.[13] But first we need to remind ourselves what is meant by matching DNA profiles.

A DNA molecule is a large molecule consisting of several thousands of millions of pairs of chemical building blocks. It is found in every living organism. Each person's DNA is unique, but it is practically impossible to analyse the entire DNA molecule in order to determine from whom it originated. In practice only a small number of positions (or *loci*) on the large DNA molecule are investigated for chemical variations which may exist from human to human at each *locus*. In this manner a so-called DNA profile is established of the person from whom the DNA originates. If two different DNA samples coincide at all the corresponding *loci*, then we say that we have matching DNA profiles.

In 1994 the American Federal Bureau of Investigation ("FBI") established a database of DNA profiles assembled from various sources, for example forensic material, relatives of missing people, convicted criminals, *et cetera.* The DNA

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[10] See part 6.

[11] *R v T* [2010] EWCA Crim 2439 para 33.

[12] Robertson et al (2011) *Mod L Rev* 449-451.

[13] P Donnelly & RD Friedman "DNA Database Searches and the Legal Consumption of Scientific Evidence" (1999) 97 *Mich L Rev* 931 931-984; Aitken *Statistics and the Evaluation of Evidence for Forensic Scientists* 207-238; K Devlin & G Lorden *The Numbers Behind Numbers* (2007) 89-104.

profiles are based upon information obtained from thirteen specific *loci* on the DNA molecule.

The probability that someone's DNA at one specific *locus* matches a randomly chosen person's DNA configuration at the same corresponding *locus* is known to be on average one in ten (ie $\frac{1}{10}$ or 10%.) It is generally accepted that the DNA configuration at two different *loci* of the DNA molecule are statistically independent of each other. The probability that the DNA profile of a given sample coincides at all thirteen *loci* of the DNA profile of a randomly chosen person in the population would be about $(\frac{1}{10})^{13}$, ie one in 10 million million. Although this figure is known to be fairly reliable, it is not the case with people who are closely related.

Still, the intention was that if two randomly chosen DNA samples corresponded on a large number of *loci* (say thirteen *loci*), then the probability would be extremely small that they would have come from two unrelated people. This is indeed the case, provided the process was performed in accordance with the assumptions (such as that of randomness).

We consider a remarkable example by Devlin and Lorden[14] which reminds us how carefully the results of a database trawl should be handled by courts. A certain state in America has a database of DNA profiles of about 65,000 convicted criminals. This database registers information obtained from the same thirteen *loci* on the DNA molecule as is the case in the database of the FBI. Suppose a "match" is regarded to be coincidental on at least nine *loci*. The probability that the DNA profile of a given sample coincides at nine *loci* with the DNA profile of a randomly chosen person in the population would be about $(\frac{1}{10})^{9}$, ie one in 1000 million.

There are 715 different ways of choosing nine *loci* from thirteen *loci,* hence the probability that a given DNA profile would match a randomly chosen DNA profile from the database at nine *loci,* would be 715 in 1000 million, ie about one in 1.4 million. Again the latter figure is often misunderstood. It does not mean that the sample found at the crime scene has a high probability of originating from the person whose DNA profile in the database matches the DNA profile of the sample (see part 2).

Suppose we choose any DNA profile from the database. Then the probability that a second DNA profile exists in the database which does not match the first DNA profile at nine *loci* equals

$$1 - \frac{715}{10^9}.$$

Therefore the probability that no two entries in the database of 65,000 entries will match at nine *loci* equals

$$(1 - \frac{715}{10^9})^{65000} = 0.95.$$

So the probability that there exist two DNA profiles in the database matching at nine *loci* equals

[14] Devlin & Lorden *The Numbers Behind Numbers* 104.

$$1 - 0.95 = 0.05 \ (= 5\%),$$

ie a probability of about one in 20. Even in this comparatively small database it is quite possible that there would exist several pairs of DNA profiles which coincidentally match.

4 The effect of base-rates

Example 5: At a major athletics championship an athlete is randomly selected to be tested for the use of banned substances. The outcome of the test is positive. It is known that the test gives a true reflection of the actual state of affairs with probability 95%. So the test is quite accurate, but not perfect. It is also known that 1% of the athletes take banned substances. What is the probability that this athlete indeed took a banned substance?

Suppose there are 10,000 athletes. Of these athletes 100 take banned substances (ie 1% of 10,000), and 9,900 (ie 99% of 10,000) do not use banned substances. Of those athletes who do take banned substances the test will be positive in 95% of the cases (ie for 95% of 100 = 95 athletes). Of all those who do not take banned substances the test will be positive in 5% of the cases (ie for 5% of 9,900 = 495 athletes). The latter are sometimes referred to as the "false positive" cases. We may therefore expect about 95 + 495 = 590 athletes testing positive if all athletes were tested. But we showed that only some 95 of them would actually have taken banned substances. So the probability that the selected athlete indeed took a banned substance is

$$\frac{95}{590} = 0.161 \quad (= 16.1\%).$$

People tend to forget that the probability of 95% tells us nothing about the statistical background (ie the base-rate[15]) against which this percentage is taken. One should be aware of arriving at false conclusions by ignoring the pool of potential users of banned substances. As was mentioned in part 2, transposing the conditional leads to wrong conclusions: firstly, there is the conditional probability that the athlete's test is positive, given the event that he took a banned substance. This probability is indeed 95%, but it's not the correct answer to our problem. Then there is the conditional probability that the athlete took a banned substance, given the event that his test is positive. This probability is 16.1%, which is the correct answer. Clearly the athlete cannot be found guilty of taking a banned substance on grounds of the above evidence alone.

Let's approach all the above from a different perspective. Given that the athlete's test is positive, only one of two scenarios is possible. On the one hand we have the possibility that the athlete did not take a banned substance (which is likely, because 99% of athletes do not take banned substances), together with the event that his test is positive (which is unlikely, because the test is 95% reliable). On the other hand we have the possibility that the athlete did take a banned substance (which is unlikely, because only 1% of athletes take banned

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[15] A Tversky & D Kahneman "Evidential Impact of Base Rate" in D Kahneman, P Slovic & A Tversky (eds) *Judgment under Uncertainty: Heuristics and Biases* (1982) 153-160.

substances), together with the event that his test is positive (which is likely, because the test is 95% reliable). We need to find a way of assessing these scenarios.

Fortunately there is a way, and we should thank an eighteenth century clergyman, Thomas Bayes for his remarkable insight. Bayes's theorem automatically takes into account the seemingly intractable combinations of events that are likely, with those that are unlikely. By using Bayes's theorem we also avoid the prosecutor's fallacy. We could well have used Bayes's theorem from the outset. In Example 5 we followed an elementary and commonsensical approach by counting heads, but if we should study those numbers carefully, we would discover that we in fact implicitly used Bayes's theorem (see Example 7). In other more complicated situations the "counting of heads" approach is not advisable.

5 Dependent events

Example 6: Sally Clark lost two babies within a period of fourteen months as a consequence of "cot death", also known as "sudden infant death syndrome" or "SIDS". An eminent paediatrician testified as expert witness at Sally Clark's murder trial[16] that research undertaken in England and Wales established that there was a probability of one in 8,543 that a cot death would occur in a family such as theirs. He claimed that the probability of double cot deaths in the same family would be about one in 73 million (because $8{,}543 \times 8{,}543 = 72{,}982{,}849$). He testified that with such a low probability the cause of the deaths had to be murder. None of this was challenged in court, for the simple reason that in two trials neither the defence lawyers, nor the judges knew how probability works.

The first error of logic is the square. Probabilities cannot be multiplied if the underlying events are statistically dependent events, in which case the figure of one in 73 million is meaningless. There may be unknown evironmental or genetic reasons that predispose certain families to SIDS, in which case a second cot death becomes more likely. Further investigation — unfortunately only after everything was over — revealed[17] that the probability of a double cot death could be around one in 130,000. Still very small, but far removed from the expert witness's one in 73 million.

Secondly, one is tempted to think of the figure of one in 130,000 as the probability of Sally Clark's innocence. This is the prosecutor's fallacy. (The expert witness made a deduction to this effect in court, using the figure one in 73 million.) It is merely the probability that any randomly chosen family may suffer a double cot death (see part 2). It is estimated[18] that the probability of Sally Clark's innocence, given the evidence could be around five in eight (ie 62%).

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[16] *R v Sally Clark* [2000] EWCA Crim 54, [2003] Crim 1020.

[17] H Joyce "Beyond Reasonable Doubt" *Plus Magazine* (1-9-2002) <plus.maths.org/issue21/features/clark> (accessed 19-07-2012); B Lewis "Taking Perspective" (2003) 87 *Math Gazette* 418 422-425; R Hill "Multiple Sudden Infant Deaths – Coincidence or Beyond Coincidence?" (2004) 18 *Paediatric and Perinatal Epidemiology* 320 322.

[18] H Joyce "Beyond Reasonable Doubt" *Plus Magazine* (1-9-2002) <plus.maths.org/issue21/features/clark> (accessed 19-07-2012); B Lewis "Taking Perspective" (2003) 87 *Math Gazette* 418 422-425.

Lastly, an expert witness in court should only testify about the probability of the evidence on which he is an expert. He should not volunteer an opinion concerning innocence or guilt of the defendant, nor should he be asked to do so. The court (ie judge or jury) does that (see part 6).

In 2003 Sally Clark was acquitted at her second appeal after the Royal Statistical Society issued a public statement[19] expressing grave concern over the handling of issues of uncertainty during her first two trials.

6 Using Bayes's theorem

We can no longer avoid Bayes's theorem if we consider the problem mentioned in the first paragraph of this paper: how should a court go about combining the different available pieces of evidence, testimony, *et cetera*, possibly of different degrees of credibility, in order to arrive at the best possible conclusion? We rely on the notation and terminology in the appendix.

Let A and B be any events. For our purposes it is convenient to use the following version of Bayes's theorem[20] which is formulated in terms of the *odds* [21] of the event B:

$$\frac{P(B|A)}{P(\sim B|A)} = \frac{P(B)}{P(\sim B)} \times \frac{P(A|B)}{P(A|\sim B)} .$$

We refer to the term on the left of the equality sign as the "posterior odds of *B*", the first term to the right of the equality sign is referred to as the "prior odds of *B*", and the last term on the right is called the "likelihood ratio".

In words this is often written as follows:

$$\textit{Posterior odds} = \textit{prior odds} \times \textit{likelihood ratio}.$$

For example, suppose A and B are the following events:

A: A certain piece of evidence is placed before the court.
B: The defendant is guilty.

The above equation may conveniently be written as follows:

$$\frac{P(Guilty \mid Evidence)}{P(Innocent \mid Evidence)} = \frac{P(Guilty)}{P(Innocent)} \times \frac{P(Evidence \mid Guilty)}{P(Evidence \mid Innocent)} .$$

In court the opinion of the judge (or jury) about the probability of the defendant's guilt may fluctuate during the course of the proceedings. The reason for this would be the nature and content of successive pieces of evidence

[19] Royal Statistical Society "Royal Statistical Society Concerned by Issues Raised in Sally Clark Case" *Royal Statistical Society* (23-10-2001) <www.rss.org.uk/uploadedfiles/documentlibrary/348.doc> (accessed 19-07-2012).
[20] S Ross *A First Course in Probability* (2010) 72 101; Aitken *Statistics and the Evaluation of Evidence for Forensic Scientists* 41-46.
[21] See appendix (3). We remind that "probability" is easily converted to "odds", and *vice versa*.

brought before the court. Possibly the perception of guilt is greater when the prosecution states its case, than it would be when the defence states its case. By the end of the proceedings the judge (or jury) would hopefully have arrived at a high degree of certainty about the defendant's guilt or innocence.

Bayes's theorem is the tool by means of which the odds of guilt up to a given point in the trial (designated "prior" in the equation) may be revised after a subsequent piece of evidence has been brought forward, and from which the revised odds of guilt (designated "posterior") is obtained. At the start of the trial the initial "prior odds" may for example be taken to be the odds corresponding to a probability of $\frac{1}{n}$, where n is the total number of people estimated to have been in the general vicinity of the crime scene at the time of the crime. All that is needed for each revision is the likelihood ratio of the particular piece of evidence presented. Then the process repeats itself: the odds just obtained becomes the new "prior" odds. Then the latter is revised in a similar way after the next piece of evidence is presented and we obtain a new "posterior" odds, and so on.

It is typically the task of an expert witness to determine the likelihood ratio associated with the particular piece of evidence under consideration. Clear distinction should be drawn between the task of the expert witness, and that of the court. The expert witness's task is limited to the determination of the probability of the evidence on which he is an expert, while the court determines the probability of guilt. An expert witness should not give an opinion concerning guilt or innocence.

Example 7: Using Bayes's theorem we now repeat Example 5. Let A and B be the following events:

A: The athlete's test for banned substances is positive.
B: The athlete is guilty.

Using only the information that any athlete is guilty with probability 1% (or equivalently, probability 0.01) the initial odds of guilt for any athlete is

$$\frac{P(B)}{P(\sim B)} = \frac{0.01}{1-0.01} = \frac{1}{99}.$$

The likelihood ratio of the evidence that the test is positive is

$$\frac{P(A|B)}{P(A|\sim B)} = \frac{0.95}{0.05} = 19.$$

Substituting the above into Bayes's equation gives the posterior odds of the athlete's guilt, namely

$$\frac{P(B|A)}{P(\sim B|A)} = \frac{P(B)}{P(\sim B)} \times \frac{P(A|B)}{P(A|\sim B)} = \frac{1}{99} \times 19 = 0.1919.$$

By appendix (3) the corresponding probability of the athlete's guilt is

$$\frac{0.1919}{1+0.1919} = 0.161 \quad (= 16.1\%).$$

This is the result obtained in Example 5.

Since we now have Bayes's theorem we are able to handle a further complication which would have presented difficulties with the approach we used in Example 5. Suppose the athlete is sent for a *second* test for banned substances. It is known that this test also gives a true reflection of the actual state of affairs with probability 95%. Again the outcome of the test is positive. What is *now* the probability that this athlete indeed took a banned substance?

The second piece of evidence is treated in the manner described in this part. The "prior odds" of guilt is taken to be 0.1919 and the likelihood ratio remains the same (ie 19) since the second test has the same parameters as those of the first test. By Bayes's theorem the new "posterior odds" of guilt equals

$$0.1919 \times 19 = 3.646.$$

By appendix (3) the corresponding probability of the athlete's guilt now is

$$\frac{3.646}{1+3.646} = 0.784 \quad (= 78.4\%).$$

Assuming there is no further evidence in this case it is doubtful if the 78.4% probability of guilt would constitute "guilt beyond reasonable doubt".

Appendix: notation and terminology

As mentioned in the introduction of this paper we use the logic of probability theory, and therefore our terminology is that of probability theory.[22] For example, in our context the nouns *probability*, *odds*, *likelihood* and *possibility* are not synonyms. (Elsewhere the meaning of the word "probabilities" is sometimes different than in this paper.[23])

(1) The *probability* [24] *P(A)* of an event *A* is a measure of the strength of one's conviction of the truth that the event *A* occurs. It is always a number between 0 and 1, or equivalently, a percentage between 0% and 100%. For example, if *A* is the event that heads appear when an unbiased coin is flipped, then we write *P(A)* = 50%, or we write *P(A)* = $\frac{1}{2}$. If for some event *B* we have *P(B)* = 0% we say the event *B* is *impossible*, and if *P(B)* = 100% we say the event *B* is *certain*.

(2) For any event *A*, the *complementary event ~A* of *A* is the event when *A* does *not* occur. For example, if *A* is the event that heads appear when an unbiased coin is flipped, then *~A* is the event that tails appear when an unbiased coin is

[22] Ross *A First Course in Probability* 1-116.
[23] For example, in *National Employer's General Insurance Co Ltd v Jagers* 1984 4 SA 437 (E) 438A-C, 440A-C, 440F-I, 441A-B & 444A the undefined word "probabilities" seems to carry the meaning "events that are more likely to have occurred than not".
[24] Ross *A First Course in Probability* 22-57.

flipped. For any event A we always have $P(A) + P(\sim A) = 1$ (also written $P(A) + P(\sim A) = 100\%$).

(3) Let A be any event with $P(\sim A) > 0$. The *odds* [25] of A (also known as the *relative probability* of A) is the number

$$\frac{P(A)}{P(\sim A)}.$$

Traditionally the gambling industry prefers working with odds rather than working with probability. In general the relationship between the probability x (taken as a number between 0 and 1) and the odds y of an event is the following:

$$y = \frac{x}{1-x}, \qquad \text{alternatively} \qquad x = \frac{y}{1+y}.$$

Using the above we are able to convert probabilities to their corresponding odds, and *vice versa*. For example,

Probability (x):	0	$\frac{1}{100}$	$\frac{1}{10}$	$\frac{1}{4}$	$\frac{2}{5}$	$\frac{1}{2}$	$\frac{3}{5}$	$\frac{4}{5}$	$\frac{99}{100}$	1
Odds (y):	0	$\frac{1}{99}$	$\frac{1}{9}$	$\frac{1}{3}$	$\frac{2}{3}$	1	$\frac{3}{2}$	4	99	∞

SUMMARY

The ability to analyse uncertainty does not reside within most people's experience. Certain fallacies frequently appear. An important example is the so-called prosecutor's fallacy. It is a specific error of logic commonly made when arguments involving probabilities are considered. Since these errors keep happening and people tend to avoid reasoning in terms of probability theory, courts do not always come to the best possible conclusion in matters involving uncertainty. In this paper we discuss different aspects of faulty reasoning concerning uncertainty in legal matters.

[25] Ross *A First Course in Probability* 101.