

Why lawyers hate math

(and should get comfortable with numbers)

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“There is no math on the LSAT” is a common refrain of counsel faced with a numbers problem. Many of us have an aversion, even an allergy, to anything math-like. I ascribe two reasons to this numerophobia. The first is the obvious one: Most come to law from the arts and humanities side of the educational ledger. We left math when we left high school.

The other reason is subliminal. Numbers suggest an objective truth that is at odds with law’s inherent, often intentional subjectivity. Legal language is littered with amorphous lingo: “reasonably foreseeable,” “reasonable probability,” “more likely than not.” Numbers imply a certainty that is alien to the unpredictability of litigation in particular.

Because the language we use feeds our thought processes, lawyers tend to think in an abstract way about probabilities – those related to the facts of a case, and those that might influence its outcome. The former would include the likelihood that a DNA sample is a match for an accused, while the latter concerns how the accused not testifying may influence the jury. Putting numbers to these ideas seems foreign, but doing so will help us understand, predict and present our cases.

Litigation is not chess

We often liken litigation to a game of chess. We strategize about our plan of attack, and the moves our opponent might make and how to defend them. The analogy sounds good, but it is all wrong. Litigation is nothing like chess. Chess is a closed system. On any given chessboard, there are a fixed number of available moves. The only variables in a chess game are the players and which of the allowed moves they decide to make. A player who makes the best available move at each turn will not lose.

In contrast, a perfect trial strategy cannot neutralize the number of variables in a courtroom. Yes, a trial is governed by rules – those relating to procedure and evidence. However, along with the unknowns surrounding our opponent’s strategy, we have limited, sometimes minimal control over what witnesses might say and the inevitable surprises that trials bring. Most importantly, a trial is not decided by objective criteria like, for example, the relative importance of chess pieces. Trial decisions turn on often unsettled legal principles and the beliefs and values of a sometimes mercurial judicial third party, or parties in the case of a jury matter.

In *Thinking in Bets*, former professional poker player Annie Duke contrasts chess with poker, the latter involving not only the skill of its players but also the luck of the cards they draw. Duke likens poker to game theory and its requirement for making decisions with incomplete information.¹ If poker is like game theory, a



trial’s additional uncertainties make it like game theory mixed with chaos theory. Sometimes the best you can do is plan for battle and watch for falling shrapnel. Having a plan is key, however. And the fact that we cannot always predict what will happen does not mean we cannot assess probabilities and adjust our plan accordingly.

Translating vague language into numbers

Our jurisprudence has embraced non-committal language. The “tests” courts have developed for everything from criminal culpability to contractual obligations to tortious liability turn on amorphous concepts like “reasonableness,” which can often mean whatever a judge (or jury) wants it to mean. Perhaps the best example of this flexibility is loss of chance in tort. A plaintiff must show that the chance lost was “significantly real” and “above mere speculation”² – except in medical negligence cases, where she must meet the “more likely than not” or “greater than 50 percent” threshold.³

There is a lot of wiggle room in those standards.

University of Pennsylvania psychology professor Philip Tetlock suggests that an aversion to numerical precision is a product of evolution. When our ancestors foraged the savannah for food, they needed to be wary of predators. If they heard rustling in the tall grass, they had time to process at most three possibilities: (1) It's a lion, so run like hell; (2) It's nothing, carry on foraging; or (3) It might be nothing but it also might be a lion, so stay focused – and ready to run like hell. If our ancestors stopped to assess whether the likelihood of a lion in the tall grass was closer to 60 percent or 80 percent, they risked becoming that lion's lunch.⁴

We left the savannah long ago, but evolutionary habits die hard, and not just for lawyers. In the 1950s, famed Central Intelligence Agency analyst Sherman Kent proposed replacing the ambiguous language in intelligence briefings with the numerical measurements that appear in the following table.⁵

Certainty	General area of possibility
100%	Certain
93% (+ or - 6%)	Almost certain
75 % (+ or - 12%)	Probable
50% (+ or - 10%)	Chances about even
30% (+ or - 10%)	Probably not
7% (+ or - 5%)	Almost certainly not
0%	Impossible

In other words, saying an outcome was “probable” would mean it had a 63 to 87 percent likelihood of happening. Stating that an outcome would probably not occur would mean a likelihood of 20 to 40 percent. Kent's concern was fuelled by the inconsistency with which agents interpreted words like “probable” and “unlikely,” but the CIA balked at forgoing soft language for hard numbers. Kent's opponents said that words have inherent poetry whereas using numbers would make intelligence analysts sound like bookmakers. Kent replied: “I'd rather be a bookie than a [expletive] poet.”⁶

We face a similar struggle when clients ask us to estimate the chance of success in percentages. Using language like “likely” or “maybe” must bug clients. I am reminded of President Harry Truman famously asking for a one-armed economist because he was tired of hearing “on the other hand.”⁷ But even as people interpret subjective terms like “might” and “likely” differently, they tend to interpret anything above a 65 percent probability as an endorsement that an event *will* occur, such that if it does not, your advice will be deemed “wrong.”⁸ So expressing expectations numerically to clients may be unwise.

Using numbers to better assess our cases

Even if we choose to keep our numerical predictions to ourselves, just making them has two benefits for the advocate. The first is that it will improve our own assessments of likely success. Tetlock's research shows that the more granular we make our forecasts, the more accurate they tend to be.⁹ This is because granularity tends to follow focused consideration. A trial success prediction of “60 percent” is often one we pick out of the air. A prediction of “63 percent” suggests we have spent time looking at the variables involved: how witnesses will be received, the impact of the chosen venue, the trial judge's predilections. It also suggests we have separated epistemic uncertainty – that which we do not know, but is

theoretically knowable – from unknowable, aleatory uncertainty.

The second benefit of making numerical assessments is that it forces us to drill down on often hidden aspects of our cases, such as the educational history of our witnesses and the depth of an expert's statistical analysis. Though we routinely overlook these peripheral issues in favour of the big, obvious ones, the secret to victory often lies in the organization of the non-obvious.¹⁰

Using numbers to better understand our cases

Speaking of statistics, they are not as objective as they seem. According to McGill University neuroscientist Daniel Levitin, statistics are not facts, but interpretations. People gather statistics. People choose what to count, how to count and how to share their results.¹¹ When we think numerically, we can avoid the trap of being swayed by statistics.

Consider a medical malpractice claim wherein a plaintiff has a mastectomy on her doctor's recommendation, but later learns the cancer diagnosis was a false positive. Was it appropriate for the doctor to recommend surgery? That depends on the probabilities and how the doctor assessed them. About a decade ago, German psychologist Gerd Gigerenzer gave groups of physicians, including gynecologists, the following statistics:

- The probability that a woman has breast cancer is 1 percent;
- If a woman has breast cancer, the probability that she tests positive is 90 percent; and
- If a woman does not have breast cancer, the probability that she nevertheless tests positive is 9 percent.

Gigerenzer then asked the doctors the best estimate for the probability that a 50-year-old woman with a positive mammogram has breast cancer: 1 percent, 10 percent, 81 percent or 90 percent. Only 19 percent of doctors got the right answer: 10 percent.¹² Sixty percent of doctors thought that the right answer was 81 percent or 90 percent, meaning they overestimated the probability by *eight or nine times*. The standard of care – based on the conduct of a reasonable and prudent similarly situated physician¹³ – might in this case be low.

A way to avoid the confusion that plagued Gigerenzer's doctors is to input percentages into a chart of Bayesian probabilities, named after 18th-century English statistician Thomas Bayes. The chart would look like the one that follows.

Has cancer	Tests positive		Total
	Yes	No	
Yes	9	1	10
No	89	901	990
	98	902	1000

Eighty-nine of 1,000 test positive, but only nine of those testing positive have cancer. $Nine \div 98 \times 100 = 9.2$ percent, meaning that 10 percent was the best estimate.

Another example. Consider an accused in a murder trial whose DNA is a match for that found on the victim. The forensics expert testifies that the probability of a match if the accused was not at the scene is 0.05 percent. That is pretty compelling, and much more compelling than saying there are 1,464 other people in Toronto that are also a match.¹⁴

The DNA example shows that understanding probabilities can help us cut through statistics that seem more authoritative than they

really are. Yes, most car accidents occur close to home, but that is because we drive more in the area around where we live.¹⁵ Four out of five dentists do recommend Colgate, but that does not mean they necessarily recommend Colgate over other brands – the underlying survey allowed dentists to recommend more than one brand, prompting the UK Advertising Standards Authority to rule these ads misleading.¹⁶


Probabilistic thinking also lets us easily grasp how people can be both below and above average, and how the median wage across a population can rise even as the median wage falls for every subgroup (e.g., high school graduate, university graduate). The former relates to the measure chosen to assess “average”¹⁷ as well as the comparator group. The latter is called Simpson’s paradox,

and is solved by recognizing that the number of people in each subgroup is not fixed. For example, the median wages of university graduates can decline even as the number of university graduates earning higher wages than other subgroups increases.¹⁸

Using numbers to better persuade

The other side of not being fooled by numbers is to use people’s instinctive impression of statistics to better persuade them. We can present the DNA example above in terms of a minute percentage rather than the actual (larger-seeming) numbers. We can rely on the “average” of lost sales that best suits our argument. Put more simply by football and science writer Gregg Easterbrook: “Torture numbers, and they’ll confess to anything.”¹⁹

If these concepts seem foreign, it is because we are not conditioned to think this way. Many of us chose law because we did not want to deal with numbers or a system with fixed boundaries. One of the great attractions of law is that its boundaries are fluid and we can change the equation by attacking it in a new way.

But an understanding of probabilities is not trigonometry. It is basic arithmetic mixed with the kind of critical thinking every advocate should employ. As legendary investor Charlie Munger told a 1994 business school audience at the University of Southern California: “If you don’t get this elementary, but mildly unnatural, mathematics of elementary probability into your repertoire, then you go through a long life like a one-legged man in an asskicking contest.”²⁰ 

Notes

1. Annie Duke, *Thinking in Bets* (New York: Penguin Random House, 2018), 20–21.
2. *Trillium Motor World Ltd v Cassels Brock & Blackwell LLP*, 2017 ONCA 544, at paras 260–273.
3. *Cottrelle v Gerrard* (2003), 67 OR 3d 737 (CA) at paras 36–38.
4. Philip E Tetlock and Dan Gardner, *Superforecasting: The Art and Science of Prediction* (New York: Broadway Books, 2015), 137–138.
5. “Words of Estimative Probability,” Sherman Kent and the Board of National Estimates: Collected Essays, originally classified Confidential and published in the fall 1964 number of Studies in Intelligence; online: <<https://www.cia.gov/library/center-for-the-study-of-intelligence/csi-publications/books-and-monographs/sherman-kent-and-the-board-of-national-estimates-collected-essays/6words.html#ft8>>.
6. Jack Davis, “Sherman Kent and the Profession of Intelligence Analysis” (2002) 1(5) The Sherman Kent Center for Intelligence Analysis, Occasional Papers; online: <<https://www.cia.gov/library/kent-center-occasional-papers/vol1no5.htm>>.
7. Buttonwood, “One-Armed Economists: How Is the Humble Investor to Cope When Expert Opinion Is Divided?” *The Economist* (7 June 2010); online: <<https://www.economist.com/buttonwoods-notebook/2010/06/07/one-armed-economists>>.
8. Tetlock and Gardner, *supra* note 4, 58 and 140.
9. *Ibid.*, 145–146.
10. This quote is almost always attributed to Roman Emperor Marcus Aurelius, but there is doubt about its source; online: <<https://www.quora.com/What-is-the-primary-source-of-the-supposedly-Aurelius-quote-‘The-secret-of-all-victory-lies-in-the-organization-of-the-non-obvious’>>>.
11. Daniel Levitin, *A Field Guide to Lies* (Toronto: Random House Penguin Canada, 2016), 3.
12. Gerd Gigerenzer, “Helping Doctors and Patients Make Sense of Health Statistics: Towards an Evidence-Based Society,” Proceedings of the Eighth International Conference on Teaching Statistics (ICOTS8, July 2010), Ljubljana, Slovenia. Voorburg, The Netherlands: International Statistical Institute; online: <https://iase-web.org/documents/papers/icots8/ICOTS8_PL3_GIGERENZER.pdf>.
13. *Crits v Sylvester*, [1956] OR 132 (CA), at 143, aff’d, [1956] SCR 991.
14. This is based on the 2017 population of 2,929,886, as reported on the City of Toronto website. If the chance of a match among the population is 0.05 percent, there are 1,465 matches in the city. These calculations do not exclude extremely young or old individuals, who would normally be ruled out.
15. Levitin, *supra* note 11, 116.
16. David Derbyshire, “Colgate Gets the Brush Off for ‘Misleading’ Ads,” *The Telegraph* (17 January 2007); online: <<https://www.telegraph.co.uk/news/uknews/1539715/Colgate-gets-the-brush-off-for-misleading-ads.html>>.
17. An “average” can be (1) the mean, the total number divided by the number of inputs in the set; (2) the median, the middle number in the set; or, (3) the mode, the most frequently occurring number in the set.
18. For a further discussion, see Hector Macdonald, *Truth* (London: Transworld Publishers, 2018), 99–102.
19. Though this quote is a common internet meme, its source is a mystery. The only citation available online is to a November 1999 *New Republic* article entitled “Our Warming World,” which does not appear to exist. Easterbrook did write a November 1999 article for the *New Republic* called “Warming Up,” but that article does not contain the subject quote.
20. Charlie Munger, “A Lesson on Elementary Worldly Wisdom”; online: <<https://fs.blog/a-lesson-on-worldly-wisdom>>.