

Or consider a medical example of how variance is important: There may be two conditions with equal average prognoses—say, advanced AIDS and advanced liver cirrhosis—but doctors may offer “Do Not Resuscitate” orders to AIDS patients at much higher rates. It’s tempting to conclude that doctors are more eager to avoid resuscitating AIDS patients, perhaps for discriminatory reasons. But the real reason may be that the variance in survival in the AIDS group is much higher and there may be many more patients in that group who will die imminently. The doctors may be oriented to this fact rather than to the average survival of the two groups; they may reason that they can wait to offer DNR orders to the cirrhosis patients.

A familiarity with variance would also allow us to make sense of the famously controversial hypothesis regarding why there are more male math professors at major universities: The mean overall math aptitude among men and women might be the same, but the variance in men might be higher. If so, this would mean that there are more men at the very bottom of the distribution (and, indeed, boys are roughly three times more likely to be mentally disabled than girls) but also that there are more men at the upper end of the distribution.

When we focus mainly on the mean, we miss the chance to observe interesting and important things about the world. And a restricted view has adverse practical as well as scientific implications. Do we want a richer, less equal society? Do we want educational programs to increase the equality of test scores, or the average? Will a cancer drug that makes some patients live longer and kills others sooner still be preferred by patients even if it has no effect on average survival? To really understand the relevant tradeoffs, we must acquire not only the tools but also the vision to focus on variance.

STANDARD DEVIATION

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The notion of standard deviation has confused hordes of scientists; it’s time to retire it from common use and replace it with the more effective one of mean deviation. Standard deviation, STD, should be left to mathematicians, physicists, and mathematical statisticians deriving limit theorems. There’s no scientific reason to use it in statistical investigations in the age of the computer, as it does more harm than good—particularly with the growing class of people in social science mechanically applying statistical tools to scientific problems.

Say someone just asked you to measure the “average daily variations” for the temperature of your town (or the stock price of a company, or the blood pressure of your uncle) over the past five days. The five changes are: (-23, 7, -3, 20, -1). How do you do it?

Do you take every observation, square it, average the total, then take the square root? Or do you remove the sign and calculate the average? For there are serious differences between the two methods. The first produces an average of 15.7, the second 10.8. The first is technically called the root mean square deviation. The second is the mean absolute deviation, MAD. It corresponds to “real life” much better than the first—and to reality. In fact, whenever people make decisions after being supplied with the standard-deviation number, they act as if it were the expected mean deviation.

It's all due to a historical accident. In 1893, the great Karl Pearson introduced the term "standard deviation" for what had been known as "root mean square error." The confusion started then; people thought it meant "mean deviation." The idea stuck. Every time a newspaper has attempted to clarify the concept of market "volatility," it has defined it verbally as mean deviation yet produced the numerical measure of the (higher) standard deviation.

But it's not just journalists who fall for the mistake. I recall seeing official documents from the Department of Commerce and the Federal Reserve partaking of the conflation, even regulators in statements on market volatility. What's worse, Daniel Goldstein and I found that a high number of data scientists (many with PhDs) also get confused in real life.

It all comes from bad terminology for something nonintuitive. By a psychological bias Danny Kahneman calls "attribute substitution," some people mistake MAD for STD because the former is easier to come to mind.

(1) MAD is more accurate in sample measurements and less volatile than STD since it's a natural weight, whereas standard deviation uses the observation itself as its own weight, imparting large weights to large observations, thus overweighing tail events.

(2) We often use STD in equations but really end up reconvertng it in the process into MAD (say, in finance, for option pricing). In the Gaussian world, STD is about 1.25 times MAD—that is, the square root of $(\pi/2)$. But we adjust with stochastic volatility where STD is often as high as 1.6 times MAD.

(3) Many statistical phenomena and processes have "infinite variance" (say, the popular Pareto 80/20 rule) but have finite, and very well behaved, mean deviations. Whenever the mean exists, MAD exists. The reverse (infinite MAD and finite STD) is never true.

(4) Many economists have dismissed infinite-variance models, thinking these meant "infinite mean deviation." Sad, but true. When the great Benoit Mandelbrot proposed his infinite variance models fifty years ago, economists freaked out because of the conflation.

It is sad that such a minor point can lead to so much confusion. Our scientific tools are way too far ahead of our casual intuitions, which starts to be a problem with science. So I close with a statement by Sir Ronald A. Fisher: "The statistician cannot evade the responsibility for understanding the process he applies or recommends."

And the probability-related problems with social and biological science do not stop there: There are bigger problems with researchers using statistical notions out of a can without understanding them and babbling "n of 1" or "n large," or "This is anecdotal" (for a large Black Swan-style deviation), mistaking anecdotes for information and information for anecdote. The majority use regression in their papers in "prestigious" journals without quite knowing what it means and what claims can—and cannot—be made from it. Because of little check from reality and lack of skin-in-the-game, coupled with a fake layer of sophistication, social scientists can make elementary mistakes with probability yet continue to thrive professionally.