## Where Intuition Goes Wrong

## Quote of the day:

"It ain't what you don't know that gets you into trouble. It's what you know that just ain't so."
-- Mark Twain

Readings for next time

Paper assignment
intuition: the ability to understand something immediately, without the need for conscious reasoning

Intuition is sometimes highly accurate. One such area covers matters closely linked to survival, where our distant ancestors had to make split-second decisions.

Some examples:

- Reading facial emotions. People can do this quickly, and there is broad (though far from perfect) agreement across individuals and societies on what a person's face indicates.
- Sizing up dangers like spoiled food or wild animals.

However, our intuition often fails in other areas, such as understanding scientific concepts (Andrew Shtulman, Scienceblind).


We can have intuitions that are culturally shaped and hence unquestioned, but which might not always be accurate (Sheena lyengar and choice).

## Our intuition is also faulty when it comes to understanding probability.

Let's examine your strings of 200 coin flips.

How did I know (within a range of uncertainty) who actually flipped a coin 200 times and who made up the results? Let's look at two kinds of statistics.

Descriptive statistics. Constructed to describe a set of data. Examples include the mean, median, mode, range, and standard deviation. For the 200 flips, another useful statistic is the count of the longest string of either heads or tails.

Inferential statistics. Constructed to infer from a set of data to a larger population, process, or phenomenon. Science relies far more on inferential than descriptive statistics.

Using inferential statistics, I examined your results and inferred whether or not you cheated. For 200 coin flips, here is the cumulative distribution function for the longest string of either heads or tails:

| 3 | 1 in a million |
| :--- | :--- |
| 4 | 1 in a thousand |
| 5 | $4 \%$ |
| 6 | $21 \%$ |
| 7 | $46 \%$ |
| 8 | $68 \%$ |
| 9 | $83 \%$ |
| 10 | $91 \%$ |
| 11 | $95 \%$ |
| 12 | $97 \%$ |

A longest string of 5 is suspicious, 4 is extremely suspicious, and with a longest string of 3 , I'm virtually certain that you made up the data.

The same reasoning applies on the high side (strings of 12 or greater), but someone making up the data will normally miss on the low rather than the high side. Why?

Because they commit the gambler's fallacy: the belief that one or more results of a random process affect the subsequent results. Typically, people expect balancing and underestimate the probability of long strings.

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|  |  |  |  |  |  |  |
|  | 12 | 2112 |  |  | 12 |  |
|  | 1511 W\% | $\square$ |  |  | , |  |

On August 18, 1913 at the Monte Carlo Casino in Monoco, black came up on the roulette table 26 times in a row. Continually thinking that red was "due," desperate betters lost millions of francs.
hot hand fallacy: the belief that a person who has experienced success on a probabilistic event has a greater chance of success on additional attempts. The hot hand fallacy is the opposite of the gambler's fallacy.

The earliest research on professional basketball, examining both shots and free throws, found no evidence of a hot hand. Later research managed to detect a hot hand, though the effect size was tiny-far smaller than most fans would expect.

People often make an error related to the gambler's fallacy, called the clustering illusion. It is the tendency to find in random data a pattern or cluster, which people interpret as meaningful. They mistakenly assume that a random process will not give rise to a pattern.

Example: when Apple first released its iPod with its randomizing (shuffle) function, some users fell for the clustering illusion and complained. Paradoxically, to make people think the shuffile function is random, Apple had to make it non-random.

Our evolutionary history can explain why people so often fall for the clustering illusion. Among our distant ancestors, it was more dangerous to fail to notice a real pattern than to falsely discover a pattern that doesn't actually exist.

## Texas sharpshooter fallacy, a variant of the clustering illusion:

a person finds a pattern or cluster within random data and then claims to have expected it all along. Normally this is a form of self-delusion rather than intentional deception.

How can we know whether a pattern could have easily arisen by chance? We use inferential statistics to calculate the range of likely possibilities from a purely random process. If the results are outside that range, you infer that a systematic process is at work.

It can be complicated to find the right test statistic for a given situation. Conceptually, though, the problem is simple: you figure out whether it's unlikely that chance alone could have led to your data.

When conducting scientific research, you should develop your hypothesis first and then test it on data. When you peek at the data first, you can easily commit the Texas sharpshooter fallacy.

Another variant of the clustering illusion is pareidolia, the tendency to interpret a random pattern within an image or sound as significant. A common example of pareidolia is finding faces in natural phenomena.




The Virgin Mary in a grilled cheese sandwich. Sold for \$28,000 on eBay.

An example that pulls these fallacies together: the controversy over backmasking (putting messages in songs that could only be understood when playing the record backwards.)


Christian groups in the 1980s claimed that backmasking was rampant and reflected the hand of Satan.
Connected to the larger moral panic over (nonexistent) Satanic ritual abuse. In reality, if you listen to enough songs backward, a small percentage will appear to have words amongst the gibberish.

## An example:

## httos://www.youtube.com/watch?v=rYOWxgSXdEE

## httos://www.youtube.com/watch?v=Gv6-ZAM5gds

The backmasking controversy showed a combination of the clustering illusion, pareidolia, the Texas sharpshooter fallacy, and expectancy effects (to be covered next time).

> Besides the area of probability, our intuition is often inaccurate when it comes to understanding the causes of behavior-our own and other people's.

Example 1: in explaining why other people behave as they do, we place too much weight on their personalities and not enough on the situations in which they find themselves (the "fundamental attribution error")

Stanley Milgram study on obedience (1963). Would you be willing to administer increasingly intense shocks to someone as part of a learning experiment?

In the actual study, when the learner was in another room, $65 \%$ of participants were willing (though often with resistance) to go to the highest level of shocks.

Why? Because of the situation-an authority figure told participants to continue, participants could hear but not see the victim, and the shocks increased gradually.

John Darley and C. Daniel Batson study on helping behavior (1973). Participants were seminary students. Would they stop to help a man slumped in a doorway, head down, eyes closed, and coughing?

Personality characteristics had no predictive power for who would help. Neither did the content of the speech (on either the Good Samaritan or on jobs for seminary graduates).

A key aspect of the situation, however, mattered greatly. Students were far less likely to help if they were in a hurry (10\%) than not in a hurry (63\%).

Example 2: we overestimate the extent to which other people notice us, a phenomenon known as the "spotlight effect"

Thomas Gilovich et al. study (2000). Would others notice the picture (Barry Manilow) on a particular student's t-shirt?


Subjects thought 47\% of the other students would notice, but only $23 \%$ actually did.

Thus, we have seen today that our intuitions are often wrong about scientific concepts, probability, and the causes of our own and other people's behaviors.

