4.5 Survivorship bias

This a logic flaw that is pernicious because it can be so hard to spot. Survivorship bias is commonly seen in popular journalism but, mercifully, far less in scientific work since the scientific method usually shields us from it. However, it is important to be aware of it any clinical research setting, particularly when designing studies.

To illustrate the effects of this bias, imagine that a few months before September 11 2001, US aviation authorities bring in a rule requiring that commercial aircraft flight decks be inaccessible during a flight, rendering impossible the terror attack on the World Trade Centre and Pentagon*. Imagine also that an international pandemic prevention team rapidly identified an infectious new coronavirus in bats in central China and within a week produced a diagnostic test and enforced a short lockdown in towns nearby, blocking its spread. In both of these scenarios history would be changed, but later we might complain about inconvenient restriction of movement for aircraft captains or question the huge cost of a pandemic preparedness, since 'nothing' had happened. These illustrate some of the traps and consequences of Survivorship bias – we cannot see things that do not happen, but which might have happened.

What exactly is this bias?

Defining this bias in simple terms is not easy. We can formally describe it as failing to see things that do not survive a selection process; we thus fall for the bias when we see only those things surviving selection and assume they are representative of the whole. However, this type of definition of Survivorship bias is not very helpful as it does not convey why the bias is so often invisible, which is the real problem. Often (as in the scenarios above) it is because we are only dimly aware that a selection process even exists. In other cases it is complicated by other mental biases such as Hindsight bias, where we think that things that occurred in the past necessarily had to happen. It may be more helpful to work through illustrating examples.

So what examples might help?

Examples from popular journalism displaying Survivorship bias are everywhere, such as discussing the great strategies of successful people in a field (such as wealth accumulation or finance) without considering those people who followed the exactly the same strategies but who failed. The latter group are hard to see since they tend to exit the arena. Clearly, adopting a strategy based on such incomplete data is dangerous as it leads to over-optimism about the strategy.

For another example, we admire the beautiful and functional buildings built in the past without considering that any ugly and badly constructed building were demolished years ago. Most ancient Roman dwellings, for all we know, may have been horrible. Historians by the nature of their work are highly subject to Survivorship bias as they study documents and artefacts that have survived the years; they cannot easily study what might have been or what was lost.

A slightly happier story can be seen in the introduction steel helmets in world war one trenches. When French Adrian and British Mark 1 steel helmets were worn there was an increase in soldiers being treated for serious head wounds, and it was widely supposed that this was due to some defect in helmet design. In fact careful analysis of the data by army medical staff showed that it was because of improved survival of soldiers hit on the head. That is, soldiers without steel helmets tend not to survive to be treated for head wounds. This illustrates that the logic error arises from the perspective of the data-gatherer who only notices the increases in head wounds, but it also shows how this bias can be overcome.

Lastly, there is the apocryphal but entertaining story of the scammers who sent weekly messages predicting stock market up or down movements to potential investors. To half they sent predictions of up, the other half predictions of down. If the market went down they sent no more messages to those who received a prediction of up; to the remainder, half were sent new (random) messages predicting up and half predicting down. And so process repeated. This continued until most investors were dropped. By this time a few investors had had a long run of correct predictions and with such 'proof' of the scammers competence, sent them money. The trap was the newly impoverished investor's perspective: they could not see they were a survivor of a random selection process.

Where does this bias crop up in clinical research?
The most obvious is in publication bias, where only exciting positive trial results are published and we cannot see the unpublished negative results. This can be dealt with using the techniques of trial pre-registration and of systematic review and meta-analysis. When designing a study we must be alert to how survivorship bias may affect outcomes, for example if a subset of a group under study may systematically drop out over time. Hypothesis construction may be based on datasets where outcome evidence may be missing or biased; it is not necessarily fatal to have a flawed basis for the project hypothesis (since it will be tested), but it will affect weighting of priorities and funding justifications, and may lead to time wasted.

Survivorship issues can crop up whenever a selection or stratification step is made in data analyses. Interpretation of clinical outcomes becomes a problem if some outcomes are not recorded, so cannot be seen. This is classified as a study design flaw and is well understood in clinical trials; it is dealt with by the technique of censoring.

How can a researcher minimise or avoid this bias?
Half the battle is simply to recognise that it can occur, and it is useful to think about where it might happen in your work – which is really the point of an article like this. It can be an example of an unknown unknown, that is, a problem that we are not aware could exist so we are completely blind to it. That being the case the way to tackle this is by adopting a routine strategy to detect it, such as checking if all participants entering a trial have an outcome that is recorded.

Another approach using data is to construct a prediction model which can then be cross-validated on other datasets. This can reveal the presence of biases, including survivorship.

*Example taken from Nassim Nicholas Taleb's book "The Black Swan".

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