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Difficulties in Making Claims to Knowledge in Social Science

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ABSTRACT: *This paper looks at the difficulties faced in making a knowledge claim, especially in social science. A knowledge claim is defined here as a justified belief, that would be open to change in the light of new evidence. The discussion is based on claims defined by two distinct types of knowledge. Claims can be envisaged as "fully descriptive" or more "generally descriptive", and they can be causal or not. Each type is commonly used in social science. But each requires different philosophical assumptions. Fully descriptive claims merely summarise any data observed. This is the easiest and safest kind of claim, but even these might suffer from non-random errors and inaccuracies. However, their biggest limitation is sometimes their lack of any wider purpose. Generally descriptive claims are often more useful, and involve statements about as yet unobserved data hypothesised on the basis of a fully descriptive claim. Here we meet Hume's problem of induction. These claims have two parts – fully descriptive and inductive - and the inductive part cannot seemingly be justified by logic, inferential statistics, Carnap's inductive probabilities, or even necessarily by Popper's falsification process. The third type, causal claims, are also usually general claims. This paper summarises a model, based on the work of Mill, Bradford-Hill, and others, of what a plausible causal claim entails. But it still has all of the problems emerging from the first two types of claim, and adds a further problem created by our inability to assess causes directly. The paper concludes by suggesting how social science can proceed most safely in practice, and in terms of theoretical explanations, by avoiding being misled by false claims to knowledge, and reporting research findings with tentative care and judgement.*

Key words*: Causal claims, Claims to knowledge, Descriptive claims, Hempl's Paradox, Philosophy of social science.*

1. Introduction to the Nature of Knowledge Claims

This paper is about the rather shaky empirical and logical foundations of claims to knowledge in social science. The paper starts with a preliminary consideration of the role of "truth". It then introduces a typology of three kinds of claims to knowledge and the logical difficulties that each of these face, and possible solutions to those difficulties, before drawing out some proposed implications for the conduct and understanding of social science. It is concerned primarily with claims based on empirical evidence.

Traditionally, it has been assumed that knowledge of the kind represented by social science claims has to be true, in order to be knowledge (Nagel 2014). If a claim is not true then it cannot be knowledge, by definition. However, the only things that we can be relatively certain are true are actually tautologies. These true statements are derived from formal logic or maths, based on deduction (Locke 1979). Deduction, or deriving logical inferences from assumed foundation statements, contain no new information. The term information here is linked to uncertainty, and is measured in terms of how much uncertainty the information reduces (Shannon and Weaver 1949). All of the information in a deduction comes from the initial assumptions, and is simply revealed or clarified by the subsequent logical process.

For example, consider a classical syllogism such as:

All objects A have characteristic B
This is an object A
Therefore, this has characteristic B

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The claim that a specific example of object A has characteristic B contains no information that is not also in the premise – that All objects A have characteristic B. If the premise is true then the conclusion is necessarily true.

However, if this kind of argument is converted into real-life (not logic/maths) it then involves claims about the real world, and so the lack of information in the conclusion is quite not so clear. For example:

All Greeks are human
Alicia is a Greek
Therefore, Alicia is a human

In this syllogism, two things have to be true for the conclusion to be true, and both are now no longer logical or mathematical statements but claims about the real world. Of course, if things like Greek, Alicia and human are defined so that the claims are tautologous, then the apparently real world terms are just being used as mathematical symbols like A and B. Otherwise, claims like all Greeks are human, or Alicia is a Greek, are claims to knowledge about the real world. The latter is a specific descriptive claim, requiring a clear understanding of who Alicia is, and what it means to be Greek. The former claim is more general. It requires a clear understanding of what it means to be Greek, and to be human. But over and above those, the claim requires enough evidence for a general proposition – that all Greeks are human. This could be established, for example, by knowing or observing the nature of all Greeks.

How is it possible to tell whether either kind of statement is true? For some commentators there is no such thing as truth, even as an ideal. For example, "realities are discursive; that is, there is no direct access to a reality 'outside' discourse" (Maclure 2003, p.180). Research, according to these accounts, is merely the deconstruction of meaning rather than a search for the truth, or for practicality (what works). But surely it would be a category mistake to say that some social science research descriptions are not meant to be imagined as "true", else why should we be concerned with them? Denying the possibility that there is any means of judging knowledge claims to be more or less true would make research a pointless activity (Gomm 2004).

Truth, according to Howe (1988), is a normative concept. It is what works in practice, and for the present, because that is how we recognise its truth (see the later section on causation). Where research has been testable, and has practical consequences, a kind of evolutionary natural selection might have led, over time, to this universality of approach. This kind of science, in general terms, is the best way of knowing about the world (Thompson 2025). Research findings, and the models based on them, represent a simplified description of real-world systems that assist us with calculations and predictions. They do not represent complete truths, and are good and useful only in so far as they enable us to make appropriate decisions or improve the performance of a system or process (West and Harrison 1997).

According to the tracking theory of knowledge, proposed by Nozick (1981) and others, we can only be said to know something if that something is factually true, we correctly believe it to be true, and that if it were not true then we would not believe it any longer. However, if we remove the idea of 100% factual truth, the best we can do is to imagine knowledge to be something for which we have a justifiable belief - as long as we would change that belief if new evidence or an argument emerged to make it no longer justified. The truth would be our best bet about something on the basis of all existing evidence. Perhaps it is better envisaged as a conditional probability. We believe something to be true on the basis of something else we already believe to be true, to a greater or lesser extent.

1.1. A Simple Typology of Research Claims

Treating truth as justified but alterable belief, this paper looks in turn at a simple typology of three distinct kinds of claims to knowledge, as used in social science (and elsewhere).

- *Fully descriptive* claims based on a knowingly limited set of observations or data points, where the claims concern only those data points. A simple example might be reporting interview data from a number of participants, not intended to represent a wider population of possible participants. The claim Alicia is a Greek (above) is another example. These claims are historical, about things that have already taken place or been observed, and do not try to predict the future.

- *Generally descriptive* claims are based on a limited set of observations, just like fully descriptive claims. But here the observations are intended to be used to make a more general claim to knowledge.

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A common example might be the attempt to generalise the findings from a sample of participants to a wider population of cases not participating in the research. The claim that all Greeks are human (above) might be another example. Such claims are based on historical or observed evidence, but go beyond that and so are harder to establish as "true".

- *General causal claims* will also be general claims, based again on a limited set of observations. They add a further conceptual element to general claims, by claiming that some observations were created (or modified, influenced or impacted) by other observations. An example might be the proposition that gaining a particular educational qualification tends to lead to a higher-paid job. Such claims make assumptions about unseen cases, and are also predictive about what will happen in the future.

There can also be causal claims about a limited or one-off situation, that are not intended to be either general or predictive. An example might be when a historian talks about what caused the Great Depression of the 1930s. But such claims are not common in social science, and cannot be assessed in the same way as general causal claims.

Each type of claim requires more than the one above it, not only in terms of evidence but mostly in terms of the assumptions needed to justify them. Each type of claim is therefore increasingly hard to justify. However, they all have several aspects in common. All start with some observations (or data points of any kind). These observations are the "facts" which underpin each claim. They are an attempt to portray something valid about the "stuff" which makes up the world we are trying to research. But in social science these "facts" would not actually be 100% factual, because the observations could be biased, mistaken, misunderstood, mis recorded or misreported.

The paper discusses each of these claims further, and the problems that can be faced when making them. In doing so, it looks at the correspondence (or not) between research claims and our glimpse of an external reality.

1.2. Fully Descriptive Claims

Fully descriptive claims can be useful in social science. Examples include descriptive summaries of population data. They are usually (even if disguised) in a format comparing the number of observations with a certain characteristic (denoted throughout as nC) to the total number of observations made (n). They can be about unique events (e.g. this thing observed is a raven), about the relative number of cases or proportions (e.g. 58% of respondents in this survey reported being employed), and they can be comparisons across groups, (e.g. in a survey more of the employed, than the unemployed, had degrees), or over space or time (e.g. this problem has been getting worse).

For such fully descriptive claims, the n matters. Claims tend to be more substantive and convincing with larger n. For example, "15% of 100 ravens are not black" is more substantive than "this thing is a raven", but less than "15% of 1,000 ravens are not black". And like all empirically-founded claims, they are more trustworthy when the data collection is clear, independent, replicable and so on (Gorard 2024). All research is like a warranted argument (Gorard 2013a). If the reported observation claims were not true how else can we explain their appearance? If we cannot find a better explanation then we accept the descriptive claim, at least for the time being. Done properly this warrant could provide a justified belief in the claim.

Such simple descriptions can help define an issue or problem, they can set the context for a more general study, and sometimes they can be powerful in their own right. For example, fully descriptive claims can expose injustice or document suffering. The term statistics derives from simple descriptive portrayal of numeric "facts" about the state, such as levels of poverty, ill health, and infant mortality. This approach can lay bare a problem or the level of inequality, in a way that is hard for politicians and others to ignore. It can be invaluable, and has been so in the past. Nevertheless, it is just a start. Even with such political arithmetic, readers are quickly moved to ask whether these figures are equally true everywhere, why they arise, and what should be done to ameliorate them. These more complex but interesting questions cannot be answered by fully descriptive claims.

Therefore, perhaps the major problem with most fully descriptive claims is why anyone would want to make them. Simply describing the characteristics or experiences of a limited number of cases is not usually useful. Readers would immediately want to know if these findings are special or permanent or true more widely. They would want to know the usefulness of the findings. Research is more than story-telling. In practice, fully descriptive claims are more like journalism or novel-writing, reporting what happened, or who

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said what, only partially, and often with little rigour. Such claims are of little greater interest for social science.

Also, in any reasonably large set of observations there will be errors. A key point to note here is that people have no reason to assume that these errors will be "random" in nature (randomness is discussed further below). Bias, by definition, is not a chance occurrence. Research has long suggested that misrecording or misreporting data is not random, and tends to favour the prior beliefs of the researcher. This means that researchers have no easy, or even technically complex way, of estimating the scale and impact of such errors, let alone of correcting them. Care and judgement are needed, but something like inferential statistics cannot help (see next section). There is no randomisation or probability to assess (Gorard 2021).

Even fully descriptive claims usually involve more than the observations themselves. There will be some kind of analysis as well. To continue an example above, maybe the researcher will report how many interview participants responded in a particular way, or whether participants with a specific characteristic responded more frequently in a particular way. The count of participants itself may be in error. Any form of analysis can be conducted wrongly in practice, or misapplied to the context. And the more complex the analysis is the more likely it is to be in error, and the more any initial errors in the data will propagate (Gorard 2013b). And just like errors in the original observations, any subsequent analytical errors will not be random in nature. A mistake in counting or in classification cannot be addressed or even identified by any process predicated on randomisation. These problems, and many more, will arise for any empirical claim. Care, simplicity (parsimony, see below), and transparent judgement are the main ways to deal with them.

One can try to minimise the problems with any observed data, and there is a wide literature on how to do so. It might help if the observations were automated, replicated, made by people who were unaware of the purpose of the research (blinded), made by people with no vested interest in the results, checked for the "reliability" of several observers, collected about the same phenomena in different ways, and so on. Failure to consider such assistance suggests that the observer is really only interested in what they think is going on, and not concerned that others are persuaded by the "truth" of their account (to have justified belief).

Aside from errors in data collection, bias caused by missing data, and mistakes in analysis (all of which are possible in any evidence), such descriptions can be deemed "factual". They simply report what was observed (or believed to have been observed). They should do so fully, and transparently, so that readers can check the accuracy of every claim.

1.3. Generally Descriptive Claims

Generally descriptive claims go beyond the data that they are based on, to make statements at least partly about data or cases that have not been observed. They might suggest patterns or rules about cases from which no evidence has been collected. A hypothetical example might be the claim that "all ravens are black" (or more realistically for social science perhaps, most ravens are black). In order to prove definitively the statement that all ravens are black through observation we would need to see all ravens (and to know that we had seen all ravens). The numerator (number of black ravens) and the denominator (number of all ravens) must be exactly the same. Barring errors, this would be a fully descriptive (population) claim rather than a generalisation. This is not very realistic for many research purposes, where we would hardly ever know how many cases there were in a population nor whether we have really observed them all. But. as Hume (1962) and others have noted, without seeing all ravens we cannot prove that all ravens are black. This is the problem of induction.

By definition therefore, a generally descriptive claim must be based on observing fewer than all ravens (or whatever). This gives the claim two components - an empirical fully descriptive basis, and an inductive part. The empirical part is how many ravens (n) have been observed and how many of these had the characteristic C (or nC) – the characteristic of being black, for example. For the universal positive statement to be true, n must equal nC, otherwise it has been falsified.

The inductive part is the extension of the empirical report about some number of observed ravens all (or mostly) being black, to the claim of "all" (or most) possible ravens being black. This part is not empirical, and cannot be empirical for any n less than the total number of ravens (or whatever). How can the inductive part of a general claim be justified, given that it cannot be empirical (by definition)? Note that the same problems arise even for the apparently weaker claim that "most ravens are black". This still supposes knowledge of all

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ravens, and claims that more than half are black. If not all ravens have been observed, then "most ravens are black" is still an inductive claim.

The rest of this section considers a range of ways that commentators have tried to solve the problem of induction, starting with statistical generalisation, then looking at Carnap's inductive probabilities. The later comes up against Hempel's paradox, and this section considers ways of resolving the paradox in a kind of Bayesian solution, and others. This involves the work of Popper.

1.3.1. Inferential Statistics

One widespread approach used in attempting to justify the inductive part of a claim involves the use of inferential statistics (significance tests, standard errors and related constructs). However, using traditional inferential statistics to make more generalisable claims involves making several unrealistic assumptions (Gorard 2021). We can only use these techniques when the cases involved have been fully randomised – either through random selection from a known wider population, or by random allocation of a population to two or more groups. Neither situation applies to the examples used so far, and both are very unusual in social science (due to non-response, attrition and other forms of missing data). Anyway, if we knew the wider population of ravens, or non-black things, for example, in order to be able to select a random sample from it, then we would often only need to count the population. No generalisation would be needed. If we do not know the wider population then we cannot randomise cases from it.

The kinds of probabilities involved in inferential statistics are anyway only those that might apply to an ideal game of chance. If we know that a six-sided die is unbiased then we can state that the probability of rolling a 2 in one attempt is 1/6. We can say that the probability of getting two 2s in a row is 1/36 etc. Put another way, if we know everything relevant about a situation like this then we can easily calculate the probability of any specific set of observed occurrences. But this is never the case in real-life research. And the reverse is not possible. We cannot use a specific set of occurrences that we observe to tell us about everything else relevant (Hume 1962). Rolling a 2 in one attempt with a die does not tell us whether the die is unbiased.

Anyway, the whole approach makes no sense in attempting to justify the inductive part of claim. Imagine we were trying to assess the likelihood that all ravens were black. Observing just one non-black raven makes any statistical analysis redundant. So, we must assume that all observations so far have been of black ravens. We already know that the claim "no ravens are black" is false, because we have observed at least some black ravens. Therefore, we also know that some ravens are black. Again, no inferential statistics are needed. If we "test the hypothesis" that all ravens are black, then the p-value for however many black ravens have been observed will always be very large. Here the inferential statistics approach is useless.

If instead we want to test the idea that "most ravens are black" we would need to specify a precise figure for what "most" means in order to compute a p-value. The p-value we get will depend on the figure we choose to represent the notion of most. We know that if we "test" the claim that all but one of very many ravens were black, then the p-value of obtaining all black observations of ravens in a limited sample will still be very high – almost as high as if we assumed all ravens were black. If all but one raven is black then any raven you spot is very likely to be black. And conversely the probability of observing a non-black raven is very low. Both probabilities depend on knowing exactly how many ravens there are from the outset. The p-value tells us nothing that our, otherwise arbitrary, assumption does not do already. We are no closer to knowing if indeed all but one raven is black, or more or less. The same kind of conclusion would be so, whatever the precise figure used for the initial assumption. The calculation is entirely tautological and yields no more information. It is just another, less accessible, way of restating the initial assumption.

An analyst could use something like the principle of indifference to decide on the key initial (but arbitrary) assumption for inferential statistics, about the likelihood of the initial hypothesis being true before collecting new evidence. For example, in the absence of any knowledge to the contrary they might assume that one of two possible outcomes was equally likely (50% or equipoised). The initial assumption might be about whether a specified hypothesis (all ravens are black) were true or not. However, this 50% likelihood will not be true in a real-life situation, even with no prior knowledge, and in most real-life situations there will be at least some prior evidence. Traditional inferential statistical analysis simply ignores such prior evidence and eschews any context in an anti-scientific way.

Carnap (1955) has anyway demonstrated that the principle of indifference is difficult to apply, and can be misleading. If we have no knowledge, the principle states, we assume that all outcomes are equally probable.

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But what does this really mean? For example, imagine a large bag of marbles of three colours (blue, red and yellow). We do not know how many marbles there are of each colour. If our assumption is that the first ball will be blue, then by the principle of indifference the hypotheses B that the ball will be blue and its inverse B' that the ball will not be blue are evens. There is then a 50% chance of a blue ball and a 50% chance of either red or yellow. On the other hand, a hypothesis that the first ball will either be blue or red means that this outcome is 50% likely and so there is a corresponding 50% chance of yellow. But no marbles have been selected yet. And making up a hypothesis cannot affect the number of marbles of each colour. Using the principle of indifference quickly leads us to clear contradictions.

Perhaps more importantly, the principle assumes that we know from the outset how many possible outcomes there are. We may not know this, even if we think we do. If there are more options in reality than are catered for in setting up initial equipoise probabilities then those probabilities will be wrong. So, the principle of indifference does not work as intended.

Added to this is the problem that even if social science researchers knew the full population, they would rarely, if ever, have a set of fully randomised cases in real-life due to missing data – non-response, attrition and so on. And randomness is a mathematical necessity for undertaking the computations involved in inferential statistics. But the real killer blow is that even if a social scientist actually had an ideal set of randomised cases and knew everything necessary about the population, they could then only compute the probability of their specific set of observations occurring, given the initial assumptions about their general claim. Therefore, they still cannot use inferential statistics to test their general claim. They cannot use the statistical result to assess whether their claim is true, how likely it is to be true, or how likely it is to have arisen by chance (Gorard 2021).

Inferential statistics do not work to help establish general claims. Frequency statistics, comparisons, and modelling (not inferential statistics) can be used, of course, but only with fully descriptive claims – whether these fully descriptive claims are stand-alone, or form the basis for a more general or even a causal claim. However, none of these approaches can help to justify the inductive part of a general claim.

1.3.2. Inductive Probability

Commentators have long concluded that conditional probabilities of the kind represented by inferential statistics are not needed anyway (Jeffreys 1948). For them, everything needed for social science claims can be expressed in terms of what Carnap (1955) called inductive probabilities. This is perhaps what most early statisticians intended statistics to be, until Fisher and others devised what they envisaged as a more precise statistical probability approach.

Carnap (1955) and others have tried to create a coherent way of computing the likelihood of an inductive statement being true, based on additional evidence emerging. This is different to wanting a larger n for a fully descriptive claim in order for the claim to be taken more seriously. Instead, an inductive probability computation is based on the assumption that every new observation changes the likelihood of an inductive claim by a specific and calculable amount.

Imagine a general claim H that all observations of X have the characteristic Y, with pXY (the probability of X having characteristic Y) as the prior or unconditional probability of H being true. Imagine also that H is "resistant" to the complete generalisation that all X have characteristic Y, by a constant value known as lamda. Here lamda could entail a range of factors, but it is usually and mostly taken to represent the size of the population, and therefore how big n would have to be to have made a general claim fully descriptive. However, it could also be represented as the amount of information that would be needed to reduce uncertainty about the claim (Shannon and Weaver 1949). According to Carnap's inductive method, the posterior probability of all X having characteristic Y in light of new evidence E (or pXY|E) is equal to:

$$\frac{\text{(the new number of observations with characteristic Y + lamda.pXY)}}{\text{(the total number of observations+lamda)}}$$

For example, if the prior probability of H were 0.5 (based on the principle of indifference, above) then the formula would be:

$$\frac{\text{(nY+lamda/2)}}{\text{(n+lamda)}}$$

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In this example, if lamda were 0 then the inductive probability of H would be the number of observations of X with characteristic Y over the number of observations of X (or nY/n). This could be the simple proportion of black ravens, for example. Using a lamda of 0 (assuming no resistance to generalisation) would be what is termed the frequentist approach in statistics – to ignore the resistance of the claim to generalisation, and always to assume a prior probability of exactly 0.5 (above). New evidence thus completely over-rides any prior knowledge in a clearly unjustified way (Gorard 2002a).

As lamda rises, the inductive probability of H tends towards pXY (the prior or unconditional probability of all X also being Y). With high lamda the impact of each new observation is less, but never zero. For example, if pXY is 0.5 and lamda is 1,000, then the probability of H after one new observation of XY is 501/1,001, or around 0.5005. This is only just a bit bigger than the unconditional probability, without new evidence, of 0.5.

If pXY is 0.1 at the outset, and lamda is 10, then one observation of X with characteristic Y changes the probability of H after this new evidence to around 0.182 (2/11). A further observation of the same kind would change pXY|E to 0.256 (2.82/11). After a sequence of 10 observations of X with characteristic Y, then the probability of H after this new evidence would be 0.55 (11/20). How helpful is this in justifying inductive claims?

1.3.3. Hempel's Paradox

Before considering the value and validity of such inductive probabilities any further, we discuss what is required of new evidence for a universal general claim, by looking at the ramifications and suggested resolutions of what has been termed Hempel's paradox. The key issue is to determine how large n and nC would be in Carnap's formula above. We have so far assumed that nC is simply the number of black ravens observed, for example. But the equivalence criterion (as discussed below) suggests that something like nC could be much larger in reality, and this would make a substantial difference to the calculation of any inductive probability.

Figure 1 represents the example of a generally descriptive claim that "all ravens are black". It is a universal set with four marked subsets. A is everything that is black but not a raven (b.(not r)). B is everything that is black and a raven (b.r). C is everything that is a raven and not black ((not b).r). And D is everything that is not black and not a raven ((not b).(not r)). A, B, C and D can be used to refer to these subsets (for any similarclaim).

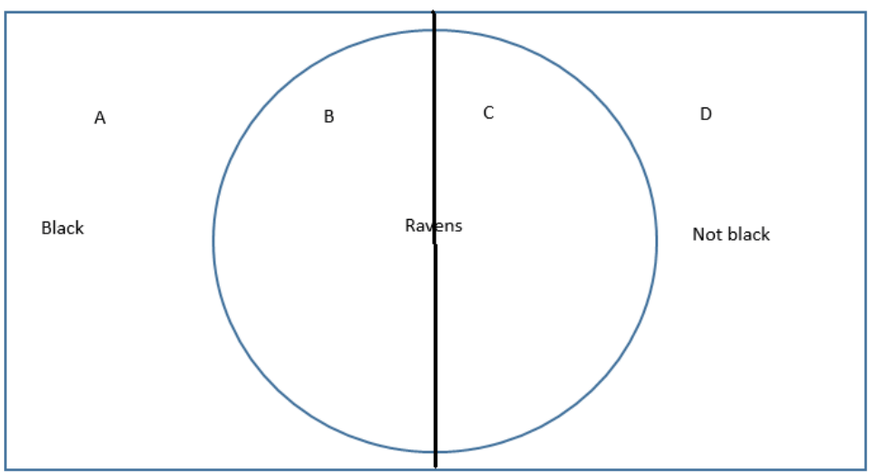


Figure 1. Venn diagram illustrating a general claim.

If it were true, the statement "all ravens are black" would mean that C must be empty (there are no non-black ravens). The statement has no immediately obvious implications for A (other things can also be black) or for D (other things can still be not black, even if all ravens are black). It is more ambiguous whether the statement has any necessary implications for B. If there are ravens, then they must be black and so included in subset B. But on one interpretation, there could be no ravens, and B could be empty. Here the statement is

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interpreted more precisely as being "if there are such things as ravens then they would all be black" (or mostly black).

It seems that observing (or gathering evidence of) a case in each of these four subsets would have different implications for the statement "all ravens are black". Observing a black non-raven (A) appears to make no difference to any other subset. It seemingly neither confirms nor denies the statement. Observing a black raven (B) would seem to provide some evidence or confirmation for the general claim, but makes no difference otherwise. Observing a non-black raven (C) would falsify the general statement (all ravens are black). What difference does observing a non-black non-raven (D) make? At first sight, to take a standard example, observing a green apple appears to be irrelevant to the claim that "all ravens are black".

However, if we consider the statement that "all ravens are black" (or if something is a raven it is black) more closely, this is logically equivalent to the statement "if something is not black it is not a raven". Whenever the first statement is true then the second is also true, and *vice versa*. If the second statement is false then the first is also false, and *vice versa*. We consider observation of a black raven to be evidence for the first statement, and therefore it must also be evidence of the second statement. But it then follows that observation of a green apple (for example) which is evidence for the second statement also provides some evidence for the first statement - that all ravens are indeed black.

This is what has been termed Hempel's Raven Paradox (Hempel 1945a, 1945b). In logic, apparently, observing anything that is not a raven and not black provides the same kind of evidence for the statement that "all ravens are black" as the observation of a black raven. This sound incorrect, because we would not normally agree that seeing a green apple told us anything about the colour of ravens. How can we resolve this?

Maher (1999) phrases this problem in terms of three plausible sounding principles. The first has been termed Nicod's condition (Nicod 1930). Given no other context, observing an object X that has characteristic Y is treated as confirmatory evidence that all X are also Y. The second principle, termed the equivalence condition, is that where evidence confirms a claim, then the same evidence also confirms any proposition that is logically the same as that claim. The final plausible principle (Nicod's criterion) is that, given no other context, observing something that is neither X nor Y provides no evidence on whether all X are also Y. Green apples are, at first sight, deemed irrelevant to whether all ravens are black.

It is clear that these principles lead to a contradiction, and cannot all be true. The first two together imply that green apples are some kind of evidence for the claim that all ravens are black. The last one denies this. Which, if any, of them are right or wrong? Can we assess the truth of each claim using relative frequencies?

1.3.4. Is There A "Bayesian" Solution?

In real-life, as researched by social scientists, we might assume that subset D in Figure 1 is bigger than subset A. There are, in effect, more non-black things than black things in the world. Both A and D will be bigger than both B and C. Only a small fraction of the things in the world are ravens. And we might also assume that B is bigger than C. Even if not all ravens are black, many patently are. So in terms of scale: D>A>B>C. This relative frequency of cases in each part of Figure 1 could help to resolve the paradox.

For the moment, we are only concerned with subsets B and D. An observation in A apparently makes no difference to whether C is empty (but see below), and an observation in C settles that C is not empty. Only an observation in B or D could otherwise alter our belief that all of subset B.C is in B, but without settling the matter absolutely. In traditional philosophy of knowledge only the observation of ravens would be allowed to either confirm or falsify the statement that "all ravens are black". The observation of other things of any colour are deemed to make little or no difference (Nicod's criterion, above).

We might assume that the number of ravens in the world, while perhaps large, remains finite. So, it could be argued that observing one more black raven takes us one step closer to proving conclusively that all ravens are black (where nC/n is closer to 1). However, the number of things that are not black and not ravens is much larger than the number of ravens. In this case, observing a green apple might indeed have an implication for the truth of the statement about ravens but the increase in evidence would be correspondingly much smaller than that provided by observing a black raven (Good 1960). This coincides with common sense, and seems to resolve the apparent paradox. A thing that is not a raven provides some small confirmation by not being a raven of the kind/colour that would falsify the claim that all ravens are black. Or more simply, it reduces the number of things that, before observation, could have been ravens, and so the number of ravens that could

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have been not black. It therefore slightly increases our confidence that all ravens are black, but not by as much as observing an actual black raven. This argument could be a called a "Bayesian solution", based on the relative estimated frequency of items in each subset.

This argument relies on relative frequencies, probabilities or similar numeric values. But Hintikka (1970) suggested that the solution does not lie in relative frequencies. They considered the general claim that "all men are tall", which they said was logically the same as "all short people are women" (or more strictly all short people are not men). Allowing an individual's sex to be binary in this way for the purposes of Hintikka's illustration, the equivalence condition means that observing a short non-man provides confirmation that all men are tall. This example, Hintikka claims, is not like "all ravens are black" where we assume that there are more black things than ravens, and this relative frequency affects our understanding of the paradox. In the absence of clear knowledge that there are many fewer men than short people, we still find it hard to accept that observing a short non-man is evidence that all men are tall. The solution to the raven paradox is therefore apparently not about the relative frequency of observing each term in the claim.

However, the number of "things" that are not ravens and not black might reasonably be so large as to be infinite, so that counting them would be a "super task". If so, then observing one more of these would make no (or little) difference to the statement that all ravens are black (*Swinburne 1971)*. If so, Nicod's criterion stands, the paradox remains, and Bayesian solutions do not work. Observing a non-black non-raven cannot help confirm than all ravens are black. The equivalence criterion appears false. How can that be?

1.3.5. Resolving the "Paradox" Otherwise

A lot of debate about the paradox centres on the relevance of having additional background knowledge to the claim or not. Imagine we knew that we could be in one of two possible universes. In one there would be a million birds overall, including 100 ravens all of which are black. In the other universe there would be a million birds and 1,000 ravens of which 999 were black. Observing a black raven is much more likely in the second universe. Therefore, observing a black raven would, oddly, be evidence of living in a universe where not all ravens were black. According to this example by Good (1967), maybe it is Nicod's condition that is wrong. The paradox only seems solid in the absence of further knowledge. Perhaps evidence does not affect our inductive probability as we imagine, or maybe not at all. See also Maher (1999), who rejects the whole idea of a Bayesian resolution based on relative frequencies.

Other examples have been suggested to make a similar point about Nicod's condition. For example, if we make the claim that "all humans are less than 3 metres tall" because we have never observed anyone much more than 2 metres tall, then observing someone 2.9 metres tall may make us more likely to reject our initial claim. Here, observing someone 2.9 metres might make the claim that "all humans are less than 3 metres tall" weaker even though the new observation ostensibly supports it (i.e. 2.9 is less than 3).

Another way of resolving the apparent paradox might be to imagine that there was no such thing as ravens – that subsets B and C are both empty. It is then not clear that the second step (the equivalence condition) makes sense. The condition would then say, anything that is not black is not also something that does not exist. This is surely the same as the tautology that anything that exists is not something that does not exist. However, this attempt at resolution is not useful for two reasons. We do have evidence that ravens exist. And anyway ravens are merely meant to be a simple and scientifically neutral example of any object, event, or thing that we are interested in.

Strawson (1952) claims that any proposition of the format "all X are also Y", assumes from the outset that there is such a thing as X (and presumably Y). This would make the resolution above impossible. However, it may suggest a different solution. If "all X are also Y" presupposes that X exist then it cannot be logically and completely the same as "all non-Y things are not X" which does not explicitly assume that X exists. If the two statements really have this different implication, then the equivalence criterion does not apply here. Testing the two claims would presumably involve different actions in research terms.

There are several variations of this idea that the two propositions deemed equivalent in the equivalence condition are actually subtly different. Observing a black raven would falsify the claim that "no ravens are black" (a universal negative claim), in the same way that observing a non-black raven would falsify the universal affirmative claim that "all ravens are black". However, observing a non-black non-raven does not falsify the claim that "no ravens are black". Therefore, observing a black raven might provide crucially

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different information to observing a non-black non-raven (Scheffler and Goodman 1972). This, in turn, would make the equivalence condition false.

The equivalence condition can also lead to a seeming contradiction. Consider the claims that "all ravens are white" and "all ravens are black". They are contradictory. Yet the equivalence condition states that observing a non-black non-raven like a green apple provides support for the claim that "all ravens are black". By the same equivalence a green apple also provides support for the contradictory claim that "all ravens are white" because a green apple is a non-white non-raven. The equivalence condition takes us into strange territory. It is probably best ignored.

1.3.6. Returning to Inductive Logic

As noted so far, there are both philosophical and practical problems to face in using the inductive probability approach outlined previously. It is not clear exactly what the resistance constant lamda is in any context, and indeed whether it is anything more than the size of the relevant population. It is also not clear what the prior probability should be (the same issue arises for all so-called "Bayesian" models). Carnap's formula never allows for all cases to be observed, because it takes no account of the population size, meaning that if all ravens have been observed and all were black then the probability of all ravens being black would still seemingly remain less than 1. It also seems that n must always equal nC. It is impossible for nC to be greater than n (there cannot be more black ravens than there are ravens). But it is also impossible for nC to be less than n, because the observation of even one non-black raven immediately negates or falsifies the claim that all ravens are black. The issue then ceases to be one about probability or likelihood (if it ever was).

However, the biggest obstacle to the kind of inductive probability proposed by Carnap and others is that it fails to overcome longstanding objections to the "logic" of induction (Hume 1962). We are dealing with a general claim that has two elements – the empirical part (nC/n), and an inductive part that goes beyond the evidence to state that all future observations will be the same as all past observations. Each new piece of evidence E which is relevant to our claim H, must alter the probability of H given E (H!E) so that it is greater than the unconditional probability of H. This means that p(H|E)>p(H). But the empirical part of H will be directly confirmed by E, while it is not clear that the inductive part is changed at all, or if so how it is changed. Popper (1992) argued that the part of the claim that is empirically-founded is supported by any new evidence purely deductively. It is clear that observing a new black raven increases the number of black ravens that have been observed. But it relates only to that sub-part of a general claim that is actually fully descriptive. Meanwhile, according to Popper, the part of H that is not deductively supported by new evidence remains unchanged (Popper and Miller 1983). Statistical probability cannot handle induction, and is irrelevant to it. In fact then, there is no role for probability of any kind. The first part of the claim is handled deductively/descriptively, and the second part remains a problem for the logic of all social scientific claims.

1.3.7. Claims Like - Most Ravens Are Black

Another relatively simple attempted resolution to Hempel's paradox might be to consider that the claim "all ravens are black" is unrealistic. A weaker alternative claim would be "most ravens are black" or, as Gaifman (1979) puts it, "nearly all ravens are black". Now the paradox is not as clear. "Nearly all ravens are black" is not the strict equivalent of "nearly all non-black things are not ravens". Not in the same way that all ravens are black is the same as all non-black things are not ravens. If we substitute "nearly all" for "all" in the phrasing of the paradox, perhaps the paradox disappears, or at least it weakens enough to allow a loophole.

However, in almost all other respects a move from universal claims like "all ravens are black" to considering more particular claims like "most ravens are black" does not help with induction. We would still need either to observe all ravens, and note that more than half were black, or we would need to know exactly how many ravens there were, and to observe as many as needed (more than half) to know that most were black. Both of these would lead to fully descriptive claims. To make a general claim about "most" is no easier in practice or principle than to make a claim about "all".

Note that this is very different from fully descriptive claims such as "some ravens are black" or more accurately "at least one raven is black". These might require only one observation in order to be fully proven. Rather than say that claims based on "most" are really universal in nature, as Aristotle would, even though they are very like them, it is more accurate to express them as generally descriptive claims rather than fully descriptive ones.

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In real-life research, we are in a situation analogous to having a very large bag of marbles, of which we do not know how many there are, what colours they might be, or how many there would be of each colour. If we shake the bag and blindly remove one marble at random and it is blue, what does this tell us about the remaining marbles in the bag? Not a great deal it seems. It does not help to decide whether any, most, or all of the other marbles are blue (or not). Therefore, it cannot help us estimate either the frequentist or inductive probability of the remaining marbles being blue (or not). Nor does it really help to have withdrawn several other marbles previously. For any large number of marbles in the bag, removing one more offers the same lack of knowledge about the remaining ones as when we withdrew the first one (Gorard 2021).

We can build up a collection of observed marbles, by taking more out of the bag. This is like the empirical part of any claim. The more observations we have the stronger any pattern (or perhaps lack of pattern) will be in the observed marbles. But these fully descriptive observations are necessarily silent on the colour of the marbles remaining in the very large bag. Speculation about the remaining contents of the bag is like the inductive part of a general claim. It is not based on evidence – marbles outside the bag do not tell us about the contents of the bag. Nor is speculation deductive in any way, so we cannot use a *modus tollens* form of argument to help, for example.

If the probability of the remaining marbles being blue (or whatever) depended on how many have already been observed, compared to how many there are altogether, as it is made to in inductive probability calculations, then we would need to know more about the population than we generally do know in social science research. If the equivalence condition is valid, then the denominator in any real-life situation is infinite (or so large as makes no diffrence). If the nominator is the number of black ravens observed so far, then the denominator is far greater than the number of possible ravens. It would include also the number of all non-black things. If the denominator is infinite then each new observation cannot affect the proportion of objects seen.

1.3.8. Does Falsification Help?

If one wants to make a more general claim to knowledge – taking a Popperian example – that all swans are white, then observing one white swan is not enough to sustain the claim. Even 100 or one million observations are not enough. Replicating observations in this way does not seem to help establish the general claim (as with the bag of marbles). All one can truly do, even after observing one million white swans, is to make the fully descriptive claim that one million swans are white. And, as above, even this claim is not absolutely clear, because of the possibility of misclassifying, misrecording and so on. Any more general claim would have to be tentative unless or until one has seen and judged the colour of all swans. And how would one know, in practice, that they had seen all swans?

In the same way as in Popper's example, all of our claims based on research data are limited (even where they have been replicated and peer-reviewed). They must be seen as tentative. Concerning induction however, the replication of our results is not actually that important. One can see many white swans without the claim that all swans are white being true, and a research "finding" can be replicated many times and still be wrong. Hume (1962) introduced this "skeleton in the cupboard of philosophy" - that the process of inductive reasoning has no logical foundation. Yet induction has often been used as the chief criterion of demarcation between what is considered "science" and what is not.

Popper (2002) suggested a way around this, by highlighting the notion of falsification. This kind of testability, he said, is the true difference between science and all else. One cannot, for example, conclude with logical certainty that all swans are white merely from repeated observation of white swans (induction). But one can falsify the claim that all swans are white by just one observation of a non-white swan. Thus, progress comes chiefly from falsifying theories not from further confirmation of them. This is an attractive idea. But is it true that Popper's falsification evades the use of induction?

In formal logic, the statements "A entails B" and "Here is an A which is not B" form a contradiction. Neither can be said to falsify the other because one would not know which, if any, of the statements was true. One only knows that both cannot be true. There is no logical justification for saying that the example of "A which is not B" means that "A entails B" is false, or *vice versa*. Since A and B are ideal terms we do not attempt to tinker with them and overcome the contradiction. Contradiction is not the same as falsification.

The idea of falsification arises from the fact that these nouns and adjectives are not logical entities. They are names for real-world things, and in that real world there is bias, misclassifying and so on. In the real

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world, where A and B become swan and white, one can at least consider the possibility that only one of the propositions is falsified by the contradiction. This is what Popper does without making this step explicit. He then states that it is clear which proposition is wrong - so clear that the alternative is usually dismissed as merely playing with words (Thouless 1974). But perhaps this supposed clarity is, like induction, actually only a habit of mind.

In the example, Popper proposes that we change the definition of swan to include the possibility that some swans are not white, and does not even bother to argue against the alternative. Nevertheless, the other way out of the contradiction is equally logical. We could change the definition of black to exclude the possibility of being applied to swans. Thus, the thing that looks like a black swan is actually not a swan because it is black. The choice is between changing our definition of swan or of black. In this example, people prefer changing the definition of the least familiar term, and black is a much more familiar term than swan. If the same is true in every example of falsification then what seems like a logical argument for falsification is actually an appeal to the same non-logical phenomenon of familiarity that underlies induction. When observation leads us to question a belief because it brings two beliefs into contradiction people tend to stick with the most familiar of the two concepts. This suggests that Popper's notion of falsification does not actually eliminate inductive logic at all (see also Goodman 1973). Familiarity breeds certainty in a way that appears logically unjustified.

Take another example of a claim – that all doors are rectangular in shape. Many doors are rectangular, partly because people can control their shape. But some are not – perhaps in igloos, or the International Space Station. There will also be cases of different shapes that we are not sure are doors. The problem, as with the "bias" in falsification, lies in the use of words. Words are not like the categorical, algebraic or logical variables A, B etc. Our name categories, like door or swan, are imposed on things that could really be continuously variable in nature. One might, in theory, line up everything in the world, in order of "doorness", and somewhere there would be examples that are genuinely hard to classify (maybe some kinds of windows). We all know this. As Russell (1903) and others have shown, putting things into clearly delineated sets may not work. So, the induction problem is not one of knowledge *per se* but stems mostly from language and the imposition of categories.

1.3.9. Summary of Descriptive Claims

"Generally descriptive" claims have all of the same problems as fully descriptive claims, but they are also problematic in making statements about observations that have not been made (and that might never be made). They require something like induction. Although describing a sample in fully descriptive work has some technical problems, it is a relatively simple process in terms of logic. However, going beyond the sample to make assumptions about cases not in the sample has a much shakier logical foundation.

Inferential statistics cannot help. If one already knew how many marbles there were of each colour in a bag, then one could easily compute the probability of obtaining any combination of colours when sampling from the bag. However, without already knowing what is in the bag, revealing a subset of marbles does not permit one even to say what the probability was of those marbles being revealed – let alone compute the probability of the next marble from the bag being revealed as blue (or any other colour). The sample of marbles does not reveal what colour the other marbles in the bag are. It says nothing about the remaining contents of the bag.

To apply the marble analogy to research, if we already know what is in the bag then we do not need to do the research to find out. And if we do not know what is in the bag then we can only find out by taking out every single marble. It may seem, therefore, that generally descriptive claims can be made about populations, where the entire population is observed (or otherwise has data collected about it). In a sense, this is true. But we prefer to envisage this as being an extreme example of fully descriptive work. There is no generalisation beyond the cases actually observed. In any case, social science population data will nearly always be incomplete due to non-response, dropout, or simply missing values about some existing cases. And the problems of miscounting etc. apply to population data as much as they do to anything else.

1.4. The Nature and Habit of Causal Claims

The final type of claim, causal ones, are even more problematic than descriptions. Causes and effects are ideas used to describe a firm impression that people have about the way the world works. Events and processes have a regularity and time sequence that offer both an explanation for why things occur, and even a

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way of controlling them. Social science, perhaps more than other fields, is pervaded by what Abbot (1998, p.149) called 'an unthinking causalism", which appears to be worsening over time (Robinson et al. 2007). Correlations, patterns and even just perceptions and opinions are routinely presented by researchers in very definitive causal terms. We all need to be clearer about what it means to make the strong claim that something causes something else.

Hume (1962) described cause and effect as an immutable habit of mind – people are pre-disposed to see regularities in their environment and ascribe something like causation to them. This may have been a valuable evolutionary heuristic when time was short and a quick decision was needed. But it can lead to mistakes and superstition in the longer term. Across his different writings Hume seemed to be somewhat ambivalent about causation (Coventry 2008). On the one hand, as a "matter of fact", all that one has to support the existence of causation is the observed regularities of nature. One cannot use Hume's "relation of ideas" to deduce causation logically from any such available facts or regularities. But Hume also suggested that causal claims are, and must be, testable propositions about knowledge.

Causes cannot be deduced just from observing effects (Blalock 1964). Seeing a light bulb going off does not, by itself, allow the observer to deduce whether it has been switched off, or there is a power failure, or the bulb is broken, for example (Salmon 1998). Similarly, effects can rarely, if ever, be deduced simply by observing their possible causes. Who would have thought before experiencing it that striking a flint could create a fire, for example? How could we tell what an unknown switch might turn on?

Potentially, causal models are also very complex. Any event could be the effect of a large number of contributing causes. All of these causes might be needed to create the effect, but be insufficient in isolation. All causes might work only within a given context, or only in combination (Emmet 1984). A fire needs oxygen, flammable material, and ignition (a flame). One can say that the flame causes the fire, but it does not do so alone, and a variety of causes could be sufficient to create the effect, with none of them strictly necessary. One might start a fire with a lighter, a match, a flint, or a magnifying glass. Also, any cause or combination of causes could have more than one effect. Starting a fire causes combustion of the flammable material, but it also causes heat and light, among other things.

These issues are all problematic for Hume's idea of cause and effect as having a constant conjunction. If C is caused by both A and B in combination, then the correlation between A and C in isolation may be zero. The same thing arises for B and C in isolation. We may therefore be unable to predict exactly what the effects of a set of causes might be, because of the complexity of their interaction. Instead, one might predict their effects in probabilistic terms, or after controlling for everything else. An example of a *ceteris paribus* causal model could be the erosion of a river bank caused by a meandering river (Corbi and Prades 2000). There is no doubt that the river bank will erode over time even though it is not possible to be precise about the exact pattern it will form. This is reasonable, but makes it hard to test any causal model in practice.

There have been many attempts, since Hume, to describe the elements needed to establish a strong causal claim. For Mill (1882) a cause has three key elements. It should be clearly related to the effect (correlated through observation in a descriptive claim), it must precede the effect, and there must be no plausible alternative explanations for the effect other than the cause.

The first of these elements, the association of the putative cause and its effect, is certainly a *sine qua non*. Commentators might say that a correlation is not the same as causation, but not having a correlation between the cause(s) and its purported effect surely means that neither is the cause of the other. So, one can test a causal claim by falsification, to the extent that one can assess a correlation as part of a fully descriptive claim (see above).

Of course, assessing such a correlation may not be easy in practice. In some of the natural sciences one might clone cells, or find identical particles. Hume considered billiard balls, which are also similar to each other, and may be envisaged as interchangeable. In social science, however, one cannot usually expose the same people or organisations both to a research process and not. This means that the results of causal research in social science is not generally clear-cut. People might use statistical approaches to express the nature of causal models, and this may lead others to imagine them as being probabilistic (Goldthorpe 2001). But actually, they reflect the limitation of our understanding and ability to control, and not necessarily the reality of the world (Shafer 1996).

Viewing causation as a stable association between two phenomena, as Mill and Hume do, also creates several problems. It is clearly wrong to suggest that a singular event cannot have a cause or causes, but there

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can be no repeated association between singular events – such as the onset of the Second World War. In a sense, all events are singular in terms of time, place, context, and the actors involved. Mill's criteria are best understood as describing how one can identify causes, and are not necessarily characteristics of all cause:effect sequences. Where one can observe or repeat very similar situations, such as striking a billiard ball in Hume's account, it is much easier to test a proposed causal model than when faced with a complex causal question about a one-off process, such as what caused the outbreak of the Second World War.

In both classical and operant conditioning, it has been shown that the association of two things leads the conditioned subject to behave in the presence of one thing as though it implied the presence of the other (Skinner 1971). Skinner's pigeons "learnt" to pull a lever which had always accompanied the release of a pellet of food in the past. The conditioned subjects do this whether the lever is mechanically releasing the pellet or not – for a time at least. To an observer, the pigeons seem to behave as though the lever is a cause. In intermittent reinforcement schedules, where the pellet appears on only some occasions, this behaviour is even stronger – it will take more examples of no pellet after pulling the lever to un-condition the subject than it would if the pellet had previously always appeared.

Further, Skinner's accidental reinforcement schedule is a powerful reminder of the dangers of allowing causal models to be based only on association. In accidental reinforcement schedules, providing pellets at random tends to reinforce whatever behaviour the subject was involved in at the time. That behaviour is then more likely to be repeated by the subject, and so more likely to coincide with the next random arrival of a pellet. It is a kind of confirmation bias. The more the pigeons perform the ritual the more likely it is that food will randomly follow one of the performances. This continuously reinforces the ritual. Eventually, the subject repeats an endless superstitious ritual of one behaviour, only intermittently reinforced by the arrival of a pellet, so making the apparent association resistant to un-conditioning. The response becomes self-fulfilling.

These findings suggest that the kind of imagined probabilistic causation, commonly reported in social science, will paradoxically be an even stronger habit of mind than Hume's constant conjunction idea. And this is so, even though it is actually more likely to be an erroneous association than a constant conjunction would be, partly because of the complexity of deciding whether a purported cause that is only sometimes "effective" is actually a cause at all. And partly because it may be accidental (a superstition). Our task as researchers is to identify and avoid such superstitions as far as possible.

Mill's second element is also problematic. It is not necessarily true that a cause must precede an effect. The two can be contemporaneous. Some observations which are seemingly in a temporal sequence may actually be reciprocal (Hagenaars 1990). One can accept causes simultaneous with their effects, such as where a ball rests on a cushion, and the cushion is causing the ball not to drop further (Mackie 1974). If we drop two balls into a bowl, we can model the final resting places of both balls mathematically, but we cannot use this to decide which ball is "causing" the other to be displaced from the centre of the bowl. The events are surely mutually determined (Garrison 1993). Mathematical statements or systems of equations can describe such systems but they cannot express either intention or causality. They can be used to show that systems are, or are not, in equilibrium, and to predict the actual change in the value of one variable if another variable is changed. However, it is important to recall that this prediction works both ways. If $y=f(x)$ then there will be a complementary function such that $x=f'(y)$. Which variable is the dependent one (on the left-hand, predicted side) is purely arbitrary. Nothing in mathematics, logic, or statistical analysis can overcome this limitation.

In fact, all one can say, with some conviction, is that our present models do not permit a reverse sequence of causation. The effect cannot come before its ultimate cause. Student attainment at age 16 cannot cause their attainment at age 11, in any real sense (but see Gorard 2013a).

Mill's third element is the need for an explanation of the causal model. It is correct that such an explanation must be the simplest and most plausible. A causal explanation describes a process that shows how the cause could generate the effect. A good explanation must be easy to test, and must make the fewest assumptions necessary to provide a mechanism linking cause and effect. The proposed effect must be capable of change, and it must be capable of being changed by the proposed cause (de Vaus 2001). A good example is the clear relationship between smoking and lung cancer. The statistical conjunctions and the observations from laboratory trials with animals were explained by the isolation of carcinogens in the smoke, and the pathological evidence from diseased lungs. These combined to create an explanatory theory.

However, it is not clear that an explanation is essential to a causal claim. It is possible to switch a light on and off without understanding how it works. The fact that it does work is part of what shows that the switch is

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the cause of the light going on and off. This suggests that the explanatory mechanism is the least important part of any causal model. If it is clear that altering the presence or strength of a potential cause works in the sense of changing an effect, then it matters less if the mechanism is fully understood or not. And, of course, even the most convincing possible explanation is of little consequence if the potential cause has no discernible effect in practice.

Bradford-Hill (1966), and others working on the links between smoking and lung cancer, proposed a somewhat tougher set of scientific conditions than Mill, for the identification of a causal link. Some of these are clarifications of Mill's elements, establishing rules for how and when Mill's elements will have been established. For example, the first element, correlation, must be found in different studies, led by different researchers, using different methods and differing cases. This additional specification is good practice, but is not a philosophical component of a causal model. In addition, Bradford Hill tried to address the lack of constant association in some contexts, by saying that the frequency of association between the cause and effect must be substantial compared to the frequency of either X or Y in isolation. They no longer have to be constantly conjoined. This is an appropriate rule, but it does make the identification of causes harder (as with intermittent reinforcement).

Mill's sequence element is divided into two parts by Bradford-Hill. So, a cause must be able to predict the effect (as discussed above). And the cause must come before the effect (but see limitations of this idea for contemporaneous events, above).

The third element is again the requirement for a coherent, plausible, workable mechanism explaining how the cause can influence the effect. But it should also be widely "agreed" and "consistent with prior knowledge". Again, these additional requirements sound sensible for practice (or in a legal case), but again they do not form part of the actual logic of causes. Something could be correctly identified as a cause by only one person, or incorrectly identified by many. And that identification might create a scientific revolution that is not consistent with what was assumed to be prior "knowledge". Also missing from the Bradford-Hill account is the "elimination of sensible alternative explanations". This elimination can be through robust testing of all possible explanations, or it can be based on an argument such as that the best explanation is the most parsimonious one. Plausibility alone is not enough for a theory.

Bradford-Hill adds a fourth element in two parts. There must be a reduction in the effect after removing or reducing the cause. And there must be an increase in the cause after the introduction of, or increase in, the cause. This is useful. It adds a requirement that deliberate variation in the appearance or strength of the cause must yield a change in the effect. Put another way, one must not consider a causal model established unless it has been robustly tested (though an experimental design or similar) on several occasions. However, it still assumes the idea of a constant conjunction, and that the effect has only one cause. Neither is necessarily true.

A key point is not whether one can explain why a cause has an effect, but whether it can be demonstrated to have an effect at all. Causation can best be viewed via the impact of an intervention. Does the proposed causal model work in practice, under controlled and rigorously evaluated conditions? Since causes are not susceptible to direct observation, but what they cause is effects, then at least those effects must be observable (like a light coming on, when the switch is pressed). We need evidence that controlled interventions have altered the level or presence of the potential cause, and so produced changes in the purported effect that cannot be explained in any other way.

Gorard (2002b, 2013a, 2021) reformulated all of these elements into a simplified model of causal evidence for social science, consisting of four main criteria. These criteria do not require constant conjunction. They allow cause and effect to appear at the same time (but not with the cause after the effect). They include the need for intervention studies. And they insist that the explanation must be warranted by the full body of evidence available. Note that causes will exist even if they are not known about. These criteria concern what we would need to know in order to state justifiably that a causal model exists.

For X (a possible cause) and Y (a possible effect) to be in a causal relationship:

1. X and Y must be repeatedly associated (correlated). This association must be strong and clearly observable. It must be replicable, and it must be specific to X and Y.
2. X and Y must proceed in a suitable sequence. X must always precede or appear with Y (where both appear), and the appearance of Y must be safely predictable from the appearance of X.

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3. It must have been repeatedly demonstrated that an intervention to change the strength or appearance of X clearly changes the strength or appearance of Y. Of course X may not be the true proximal cause of Y, and may only have an impact on Y via an intermediary process or event.

And possibly:

4. It helps to have a coherent mechanism to explain the causal link. This mechanism must be the simplest available without which the evidence cannot be explained. Put another way, if the proposed mechanism were not true then there must be no simpler or equally simple way of explaining the evidence for it. However, this criterion is unlike the other three. The former are relatively objective or descriptive "facts" about the world, while the latter is more about our understanding of those facts.

In this formulation, a causal model cannot be for a specific event because of the need for replication of the impact of an intervention, and the repeated observations needed to establish any correlation. A causal claim cannot be only descriptive of existing data because it must be replicable. Because of the emphasis on replication, and the need for repeated association and interventions, a causal claim can be taken more seriously when both the number of such repetitions and the number of total attempts are large. The numbers of attempts and successes matter, and this is independent of the types of data being collected as evidence.

1.4.1. Summary of Causal Claims

Causation is not something that can be observed directly. It is not even, like the unobserved cases in a general claim, something that could ever be observed. Instead, it is concept used to try and explain regularity in findings. Again, it should not really need to be stated that one cannot demonstrate or prove the existence of a causal model underlying observations through any technical or probabilistic means, such as inferential statistics.

Causation is always only ever a hypothetical construct, but it is one that underpins all social science research. It is of course possible to envisage a world without causation, but that would be a world in which research was pointless. It is also possible to envisage a world in which there was sometimes causation and sometimes not, but that would be unparsimonious. There can be no direct evidence that observations are either caused, or somehow just random events that might seem patterned, in the same way as there are sequences in a table of random numbers (Arjas 2001). Either explanation fits the facts. So, using either as an explanation for observed phenomena involves making an assumption not contained in any data. To use both to explain observations involves making two assumptions, and is therefore unparsimonious. It is hard enough to establish whether causes exist or not. To allow them to exist alongside unrelated phenomena would make most social scientific propositions completely untestable (Gorard 2013a).

We therefore assume that social science is interested in causation, and that causation will be built on something like the four principles above (especially repeated interventions), which have emerged from centuries of philosophical, legal and practical considerations.

2. Discussion

2.1. Summary

This paper considers three different types of claims to knowledge - "fully descriptive", "generally descriptive" and causal claims. These are all common in social science, and each type of claim requires more assumptions than the previous one. After discussing their methodological and logical foundations, this paper describes some of the limitations in the nature of these three claims.

Fully descriptive claims can suffer from non-random errors and inaccuracies in observations, and analysis. Otherwise, fully descriptive claims are based solely on evidence, and so are the easiest to justify. They can have powerful impacts, but in practice are often more trivial in nature.

Generalised claims stem from fully descriptive ones, and so have the same issues. In addition, generally descriptive claims can also be questioned because of the long-standing problem of induction. No satisfactory solution has been found to this problem.

Finally, causal claims are the most problematic of the three. While widely assumed, causation cannot be observed directly. Making more general claims, including causal ones, involves going beyond the available evidence and so such claims are harder to justify. Causal claims must also be general ones in social science, and so the paper focuses on universal general claims. These claims have two components, an empirical part and an inductive part.

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Neither part can be addressed through inferential statistics. None of the problems identified in this paper relating to each kind of knowledge claim is genuinely probabilistic in nature. From the early discussion about errors in collecting and assembling data to the lack of a logical foundation for causal claims, the kind of uncertainty introduced in all knowledge claims cannot be addressed by significance tests (or confidence intervals, and related paraphernalia).

There is no obvious Bayesian solution based on relative frequencies. The problem is not really about probabilities at all, and increasing the available evidence any further can only confirm the first component of a general or causal claim. Nor can we use the seemingly more promising approach of Carnap's inductive probabilities, once the paper has discussed possible resolutions of Hempel's paradox about general claims.

According to Russell (1996 pp. 649-700), Hume "proved that pure empiricism is not a sufficient basis for science" nor, by implication, for social science. But Russell also conceded that if we just overlook this problem enough to allow the principle of induction to hold, then scientific research makes sense. We can still make (tentative) general and causal claims while also suggesting that our claims are based on evidence. However, this is a big "if". Russell admits that it is hard to formulate a valid argument why this one concession to non-empirical non-deductive faith should be made, but all others rejected.

Nevertheless, it is consistent for anyone conducting social science research to assume that causation exists, else why would they bother to do the research? Researchers are logically and ethically required to accept that causation is a real possibility. If we genuinely reject the idea of causation then research, and trying to improve social conditions, become pointless. Research can only make sense if researchers can make a difference (i.e. have an effect). However, our preference for causation (invisible and without form) is still little more than a kind of religious belief.

Popper (2002) famously suggested that the problem of induction is solved by a focus on falsification. All claims are tentative. The best tentative claims are those most easily exposed to being falsified. They should be unambiguously expressed, parsimonious, and yield testable propositions. This testability, and the possibility of being surprised by a new finding, are at the heart of good social scientific claims. We can make apparent progress in social science, as in many other fields, by testing claims to "destruction" to see if they survive. The lack of logical or empirical foundation for induction behoves all researchers to be sceptical of all claims – their own and others.

2.2. The Role of Theory

Theory helps us to decide what and how we research. It helps us to measure and explain. It can be crucial in the transfer of research findings to new settings, and an important end-product of research. Above all, theories are cheap. They allow us to consider alternative positions simultaneously, to make progress in parallel, and to accept failure without great cost. A theory is a tentative explanation, used for as long as it usefully explains or predicts real-world events, not an end in itself. As soon as theory itself becomes an obstacle to what or how research is conducted then it becomes worse than useless. Above all, theories must be subject to testing and then discarded whenever they consistently do not match up to empirical observation. Theories will always be under-determined by the evidence on which they rest, since any finite number of observations can be explained by a potentially infinite number of theories.

It is clear that theory or explanation is the least important element of a causal claim (or indeed any claim). If two items are unrelated to each other then neither can be the cause of the other. If the apparent effect appears before the apparent cause then the causal claim is considered wrong. If varying the cause never produces a change in the apparent effect then the causal claim is wrong. But the explanation is not about what is true. It is about people's understanding of what is true. Just as a cause can exist without anyone noticing it, so a cause can exist even if no one understands how it works. The fact that it works (or at least appears to work) is enough. Theory is often playing catch up, in trying to explain new findings, as well as sometimes generating new ideas to test.

The simplest explanation of any observation(s) is the best, not because it is proven or more likely, but because it is easier to test than any more complex ones. Adding needless elements to the explanation makes it confusing. Explanations must be trimmed down to the minimum needed, and this also makes them easier to test. This needs for simplicity leads to a warranting principle (Gorard 2002). Before drawing a conclusion, we need see whether the observations (data/evidence) can be explained at least as well by any simpler conclusion.

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2.3. Care In Making/Establishing Claims

Given the rather unsatisfactory nature of all knowledge claims, the best way to help avoid being misled lies in care and good judgement. All claims are clearly contingent. A claim that is unfalsifiable is useless and may be damaging. Transparency of data and analysis help. It can help others understand how the data was assembled and its flaws, and to judge whether the research is the best bet for them to act on for the present.

There is no point at all in trying to establish whether an invalid or untrue claim is then more generally true. It has not even been established as a valid fully descriptive claim. Generalisation is something that is only relevant once a secure claim has been established. As discussed, there is no way of knowing for certain whether a secure finding is also true of other cases not involved in the research (whether, indeed, all swans are white). Attempted falsification, in imaginative ways, might help but as we have illustrated there are problems even in that. And, as above, statistical analysis must be silent on this.

Moving from merely descriptive claims to causal ones introduces more barriers to security. This means that the move in research from one to the other should start only with the securest claims and ensure that a similar regard to the safety of findings is applied to every stage.

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