AN EPISTEMIC ADVANTAGE OF ACCOMMODATION OVER PREDICTION

Finnur Dellsén

University of Iceland
Inland Norway University of Applied Sciences
University of Oslo

1. Introduction

There are two ways for a piece of data to support a hypothesis. If the hypothesis was designed to fit the data, we say that the hypothesis *accommodates* the data. If the data fits the hypothesis despite not having been designed to do so, we say that the hypothesis *predicts* the data. So the difference between accommodation and prediction comes down to a difference between whether the hypothesis was already built to fit the data (accommodation), or whether this fit between hypothesis and data was instead a happy discovery made after the hypothesis had been constructed (prediction).

But what is the significance of this distinction for whether and how much the data confirms the hypothesis? Philosophers of science have defended a variety of answers to that question, ranging from the view that only predicted data could support a hypothesis (e.g. Giere, 1983, 1984) to the view that there is no epistemic difference between prediction and accommodation (e.g. Keynes, 1921; Howson, 1990). Between these extremes, there are a number of more moderate and widely accepted views, here jointly labelled *weak predictivism* (e.g. Maher, 1988; Lange, 2001; White, 2003; Lipton, 2004; Barnes, 2009). According to these views, the information that a hypothesis predicts rather than accommodates some data is, all other things being equal, symptomatic of some epistemic feature that speaks in favor of the hypothesis. Thus weak predictivists hold that the information that a hypothesis was predicted is an indirect epistemic reason to place more confidence in the hypothesis in so far as this suggests that some such epistemic feature is present in the hypothesis-data pair.

The current paper argues for a form of what I call *weak accommodationism*, viz. that the information that a hypothesis accommodates rather than predicts some data is, all other things being equal, symptomatic of an epistemic feature that speaks in favor of the hypothesis. An outrageous claim, to be sure, especially given the popularity and plausibility of its 'converse' thesis, weak predictivism. But as we shall see, this version of weak accommodationism follows straightforwardly

from plausible assumptions about confirmation, uncertainty, and motivations for data fraud. We shall also see that, appearances perhaps to the contrary, weak accommodationism is not in fact incompatible with weak predictivism, for there may be distinct advantages to prediction that aren't annulled or cancelled by the proposed advantage to accommodation. This, I shall suggest, may partly explain why the accommodation/prediction distinction is generally not deemed as epistemically relevant in science as weak predictivism suggests that it should be. In sum, then, it will be argued that weak accommodationism is true, and furthermore not just compatible with, but indeed complementary to, the 'converse' thesis of weak predictivism.

As we shall see, this argument for weak accommodationism is not merely of theoretical interest. The argument shows that the information that a hypothesis accommodated rather than predicted some data provides an epistemic advantage to the hypothesis via establishing reasons to believe in the integrity of the relevant scientist(s). In this way, the argument of this paper goes against a common sentiment among some philosophers of science according to which scientists who design their hypotheses so as to accommodate existing data are viewed with suspicion, even to the point of being compared to pseudoscientists in the Popperian sense (Barnes, 2009, 240). Instead what emerges is a picture on which prediction and accommodation provide different and complementary epistemic advantages, so that an ideal scientific community would plausibly consist in a mixture of 'predictors' and 'accommodators'. This is especially so in sciences that are politically contested or charged, such as climate science, since even the most ardent skeptics of such sciences cannot reasonably claim that the accommodated data has been manipulated or fabricated in order to artificially support the relevant hypothesis. So, for example, the practice of 'tuning' of climate models to accommodate available data sets (see, e.g., Steele and Werndl, 2013; Frisch, 2015) is not just a perfectly legitimate source of support for such models, but indeed offers an additional reason to place one's confidence in these models and the scientists who develop them.

2. Prediction and Predictivism

As I have indicated already, I will be using the terms 'prediction' and 'accommodation' to mark a distinction in whether a hypothesis supported by some data was *designed* to fit the data. Thus hypothesis H *predicts* data D just in case H fits D but H wasn't designed to fit D; and conversely H *accommodates* D just in case H fits D and H was designed to fit D. In this pair of definitions, I am using the admittedly vague term 'fits' where others often use 'entails'. I prefer the former because a hypothesis will often predict or accommodate data even when the hypothesis doesn't entail the data, as when the hypothesis is inherently statistical and so will at best only assign a certain probability (less than one) to the data.[1] Assuming that you think that accommodation and prediction both carry some evidential weight, you can replace 'fits' with 'confirms' or 'supports' in these definitions. On the other hand, if you think that accommodation (or, alternatively, prediction) is evidentially irrelevant, then you can instead replace 'fits D' with 'would have confirmed H, if H had predicted (accommodated) D'. In this way, 'fits' can be replaced without remainder by other terms commonly used in philosophy of science; but I will continue to use it here to simplify the discussion.[2]

The distinction between prediction and accommodation I am employing here has become known as a *heuristic* distinction, since it concerns whether the data D was *used* (as a heuristic) for designing the

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1. Another type of case in which it would at least be misleading to speak of 'entailment' between hypothesis and data is when the hypothesis only entails the data in conjunction with auxiliary hypotheses whose epistemic status is also at least somewhat uncertain. After all, any proposition entails any other proposition in conjunction with the right premises, but we wouldn't want to say that any proposition either 'predicts' or 'accommodates' any other.
2. I will also simplify the discussion below by using the term 'correct' to refer to the feature of scientific hypotheses for which predicted/accommodated data are meant provide support. I do not intend for this to prejudge the issue of scientific realism versus anti-realism, so those anti-realists who are suspicious of truth or its role in our understanding of evidential support may interpret this term as referring to empirical adequacy or instrumental reliability, for example, rather than truth or approximate truth.

hypothesis H (see, e.g., Zahar, 1973; Worrall, 1978, 1985; Gardner, 1982). In the early literature on prediction and accommodation, by contrast, it was common to employ a *temporal* distinction between prediction and accommodation, where H was said to predict D just in case D fits H and H had been constructed prior to obtaining D — and H was said to accommodate D just in case D fits H and H had not been constructed prior to obtaining D (see, e.g., Popper, 1963; Lakatos, 1970). With the benefit of hindsight, the heuristic distinction is clearly preferable. After all, whatever epistemic benefits there are to prediction will also be present in cases where D was obtained before constructing H but D played no role whatsoever in the construction of H. For example, Einstein is often taken to have predicted the precession of Mercury's perihelion from the general theory of relativity since Mercury's perihelion seemingly played no role in the construction of Einstein's theory — regardless of the fact that the precession of Mercury's perihelion was known well before Einstein's theory. Other ways of drawing the prediction/accommodation distinction have been proposed as well (see, e.g., Barnes, 2009), but following most other recent discussions I will be concerned with the heuristic distinction in what follows.

Predictivism is the general idea that predictions are epistemically superior to accommodation in some way. An extreme form of predictivism, which can rightly be called *naive predictivism*, holds that only predictions can serve to confirm scientific hypotheses.[3] On this view, accommodated data is confirmationally irrelevant. Although naive predictivism seems to have been defended in the past (Giere, 1983, 1984),[4] these arguments have been shown to be fallacious (Howson, 1990; Collins, 1994). Furthermore, naive predictivism would have truly absurd consequences, as the following case illustrates: Suppose H predicted some data set $D_1, ..., D_n$, which thus confirms it at some time t_1; at t_2, H is then modified (never mind why) into another hypothesis H^* so as to

accommodate some additional data D_{n+1} (which may conflict with H or simply lie outside of H's scope) while preserving the previous fit with $D_1, ..., D_n$.[5] According to naive predictivism, H^* could derive no support whatsoever from D_{n+1}, nor could it derive any support from $D_1, ..., D_n$. After all, H^* would have been designed to fit both D_{n+1} and $D_1, ..., D_n$. So, according to naive predictivism, H^* would enjoy no support whatsoever while the clearly less adequate H would be considered strongly supported by $D_1, ..., D_n$.

A somewhat more plausible form of predictivism is *strong predictivism*, which holds that although accommodation and prediction can both confirm hypotheses, "prediction is intrinsically superior to accommodation" (Barnes, 2018, §4). I take this to entail that, if H predicted rather than accommodated D, then D necessarily confirms H more strongly than it would have otherwise (all else being equal). Strong predictivism is widely criticized in the literature (Howson, 1990; Achinstein, 1994; Barnes, 2005b, 2009; Harker, 2006, 2008). The strongest consideration against it may simply be that it places a rather mysterious epistemic significance on how a hypothesis came into existence. Appealing to the genesis of a hypothesis in determining its epistemic status in this way would apparently require us to look beyond any extant account of epistemic justification or evidential support. After all, current theories of epistemic justification typically hold that an empirical proposition is ultimately supported by perceptual foundations (foundationalism), or else logical, probabilistic or explanatory coherence (coherentism); neither of which includes facts about how a hypothesis was designed or constructed. Thus, unless and until a persuasive explanation or argument for why strong predictivism would be true is presented, strong

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3. Barnes (2018) refers to this as 'the null support thesis'.
4. This view is also frequently attributed to Popper (1959), although Popper famously eschews the very idea of inductive confirmation and instead refers to hypotheses that are supported by predictions as 'corroborated'.

5. This is of course a very common type of event in the development of science.

predictivism does not seem promising.[6]

Naturally, then, philosophers tend to advocate more modest theses regarding the epistemic status of prediction versus accommodation. These theses differ in important respects, but they share a common structure and have thus jointly been labelled *weak predictivism*.[7] Weak predictivism holds that the fact that a hypothesis predicts rather than accommodates some data is, all other things being equal, symptomatic of some other epistemic feature that speaks in favor of the hypothesis. Thus weak predictivists hold that it is the likely presence of this other epistemic feature that explains why the information that the hypothesis predicted the data often confirms the hypothesis more strongly than

the information that the hypothesis accommodated the data.[8]

Different versions of weak predictivism then differ in what they identify as the relevant epistemic feature of which prediction is taken to be symptomatic.[9] For example, Maher (1988, 1990, 1993) argues that the information that a hypothesis predicted rather than accommodated data indicates (*ceteris paribus*) that the hypothesis was constructed by a more reliable method, i.e. by a method is more likely to generate correct hypotheses, which in turn increases the probability of the hypothesis. Lange (2001), by contrast, suggests that predicting hypotheses are less likely to consist of arbitrary conjunctions as compared to accommodating hypotheses, and so that predicting hypotheses are superior (*ceteris paribus*) in virtue of being sufficiently unified so as to be capable of being confirmed by past successes. For both Maher and Lange — and indeed for any weak predictivist — there is thus an epistemic feature of hypotheses for which prediction serves as a reliable proxy, all other

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6. Leplin (1997) argues that prediction is superior to accommodation in virtue of the fact that, in cases of prediction, the fit between data and theory cannot be explained without positing that the theory is correct; in cases of accommodation, by contrast, the fit can be explained by citing the way in which the hypothesis was constructed. Therefore, argues Leplin, predicted data allows us to infer the hypothesis via Inference to the Best Explanation (IBE), whereas accommodated data does not. In my view, this argument is not persuasive because the correctness of the hypothesis is not incompatible or even in tension with with its having been constructed to fit the data. Put differently, these are not *competing* explanations (Lipton, 2004, 62-63). Thus, contra Leplin, the fact that the fit between an accommodating hypothesis and the relevant data can be explained by the hypothesis having been constructed to fit the data in no way prevents the correctness of the hypothesis from providing the 'best' explanation among the relevant competing explanations (see Horwich 1982, 112-116; Lipton 2004, 168).

7. I am roughly following the definition of 'weak predictivism' used by authors such as White (2003), Hitchcock and Sober (2004), and Harker (2008). By contrast, Barnes (2009, 2018) prefers a more inclusive definition of 'weak predictivism' which includes the position, advocated by Lipton (2004), that there is a mere *correlation* between prediction and (stronger) confirmation. Barnes refers to this latter type of position as 'thin predictivism', and uses 'tempered predictivism' to refer to what other authors (including myself) call weak predictivism.

8. As an anonymous reviewer points out, a theory evaluator might not know whether the data was accommodated rather than predicted in a given case. In such a case, the theory evaluator would have no grounds for placing more or less confidence in the hypothesis based on the likely presence of the relevant epistemic feature. This shows that, according to weak predictivism, it is not really the *fact* that the hypothesis predicted rather than accommodated the data that confers an epistemic advantage on a hypothesis; rather, it is the *receipt of this information* by those evaluating the theory that confers the advantage. Of course, this opens up the possibility that theory evaluators might receive mistaken, or even intentionally deceitful, information about whether some data was predicted or accommodated. For the purposes of this paper, however, I will set this complication aside in order to focus on what epistemic advantages there are to accommodation versus prediction when, and to the extent that, theory evaluators do indeed know whether the data was predicted or accommodated.

9. Different versions of weak predictivism could also conceivably differ in how strongly they take prediction to be symptomatic for the epistemic feature in question (although this will also presumably depend on the case at hand).

things being equal.[10]

An attentive reader may have noticed that I have described weak predictivists as claiming that prediction is symptomatic of some other epistemic feature of hypotheses *all other things being equal* (or, equivalently, *ceteris paribus*). This qualifier is needed because any reasonable weak predictivism will have to acknowledge that the link between prediction and the relevant epistemic feature is defeasible. Consider, for instance, Maher's weak predictivism: Suppose we knew beforehand that the method by which a hypothesis was constructed was not at all reliable, e.g. that the hypothesis had been generated from a completely random process. Then the information that the hypothesis predicted rather than accommodated some data clearly does not indicate that the hypothesis was constructed by a reliable method. In that case, even by Maher's lights, the information that the data was predicted by the hypothesis doesn't tell us anything about whether the hypothesis is likely to be correct. So in that specific type of case, prediction would not be superior to accommodation on Maher's view. An analogous point holds for Lange's weak predictivism: If we knew already that a hypothesis is a conjunction of utterly arbitrary claims, then the information that the hypothesis predicted rather than accommodated the data cannot successfully indicate that it *isn't* gerrymandered, and so shouldn't boost our confidence in the predicting hypothesis.

It is presumably possible to provide more a informative version of any given weak predictivism by replacing this rather vague qualifier ('all other things being equal'/'*ceteris paribus*') with a precise description of the conditions under which prediction non-defeasibly indicates that the epistemic feature is in place. Indeed, Maher (1988, 276-280) explicitly

provides a list of 12 assumptions from which he derives the result that the information that the hypothesis predicted the data increases the probability that the hypothesis construction method was reliable. These assumptions can effectively be viewed as specifying the conditions under which Maher's thesis holds unqualifiedly. Since Lange does not derive his thesis from probabilistic assumptions, it is harder to identify exactly what conditions would have to be in place for prediction to non-defeasibly indicate that a hypothesis isn't an arbitrary conjunction. Presumably, though, these conditions would rule out — perhaps among other things — situations in which we already know whether, or the extent to which, the hypothesis is a gerrymandered arbitrary conjunction. In general, I assume it would be possible to formulate such specific conditions for any version of weak predictivism — effectively replacing the *ceteris paribus*-qualifier with a more precise description of the range of cases in the thesis is meant to hold unqualifiedly.

I have been dwelling on how to formulate more precise versions of weak predictivism by replacing qualifiers with specific conditions because I shall later suggest that these conditions interact with *other* conditions in ways that illuminate the *overall* epistemic advantage of prediction versus accommodation. In the next two sections, I will be arguing that there are conditions under which the information that a hypothesis accommodated rather than predicted the data indicates that it has a specific epistemic feature. Now, it is perfectly possible for both types of conditions to be satisfied simultaneously, in which case there would be epistemic advantages to both predicting and accommodating the data. To be sure, these epistemic advantages would be different for accommodation and prediction respectively, since prediction and accommodation would be indicative of different epistemic features of the hypothesis. It is of course also possible for the conditions for a given weak predictivism to be satisfied while the conditions for weak accommodationism aren't, in which case prediction would be overall epistemically advantageous. Finally, the converse is also possible, i.e. that the conditions for 'weak accommodationism' are satisfied while the conditions for weak predictivism are not, in which case accommodation

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10. In what follows, I will use Maher's and Lange's views as examples of weak predictivism for the purposes of concretely illustrating how the argument below interacts with various forms of weak predictivism. However, there are of course many other versions of weak predictivism in the philosophical literature (let alone in logical space). For example, Hitchcock and Sober (2004) argue for a version of weak predictivism according to which accommodating hypotheses typically run a greater risk of having been overfitted, which in turn undermines their accuracy in future predictions.

would be overall epistemically advantageous (see section 5).

3. Anti-Fraud Accommodationism

As noted, I will be arguing that the information that a hypothesis accommodated rather than predicted some data is indicative of a epistemic feature that counts in favor of the hypothesis. I have referred to this as 'weak accommodationism', since it is essentially the 'converse' of weak predictivism where 'prediction' and 'accommodation' have switched places.[11] Now, the specific version of weak accommodationism for which I will be arguing holds that, *ceteris paribus*, the information that a hypothesis accommodated rather than predicted some data indicates that the data is more likely to be accurate, which in turn increases the (posterior) probability of the hypothesis. The conditions under which this holds are, roughly, conditions in which one isn't already certain whether the data has been manipulated or fabricated to fit the hypothesis. Since one could conceivably advocate weak accommodationism of a different variety or for different reasons, I shall refer to this specific thesis as *anti-fraud accommodationism*.

My argument for anti-fraud accommodationism proceeds straightforwardly in two distinct steps, corresponding to the structure of the thesis itself. The first step establishes that the information that a hypothesis H accommodated rather than predicted some data D does indeed indicate (*ceteris paribus*) that D is more likely to be accurate. The second step aims to establishes that D being more likely to be accurate increases the probability that H is correct. Let me emphasize that these steps are distinct: the first concerns the connection between a hypothesis being accommodated and the probability of the *data*; the second concerns how this raises the probability of the *hypothesis*. In this section,

I lay out this argument in an informal manner; in the following section I formalize the argument within a Bayesian framework, appealing specifically to the generalization of Bayesian Conditionalization known as Jeffrey Conditionalization. I thus ask formally-inclined readers to bear with me for the time being and interpret the somewhat colloquial argument in this section in light of its later, more precise, formulation.

Although philosophers of science often write as if data can be assumed to be certain and indubitable — the absolute 'given' of scientific reasoning — it should be clear that this is at best a useful idealization. In reality, the data that scientists report may be inaccurate due to a variety of reasons, including honest errors, incompetence, and intentional deception. For a given reported data set, one might of course be more and less optimistic that it is accurate — depending, presumably, on the identity of the scientists, their track record, and the nature of the data. And there is certainly room for reasonable disagreement about how common inaccurate data reporting is in general, and thus how far from the truth is the idealization that data is certain and indubitable. Be that as it may, it would certainly be a mistake of rationality to be absolutely certain of reported data, since that effectively amounts to ruling out beforehand the very possibility that the data is inaccurate for some reason.[12]

The type of inaccurate data that will concern us here is that which is due to deceptive reporting, i.e. to *data fraud*. In particular, two kinds of data fraud will be relevant to the argument below. In data *fabrication*, the relevant data is entirely invented or made up so as to appear to confirm some theory or hypothesis. In one particularly high-profile case of data fabrication, physicist Jan Hendrik Schön was found in 2002 to have manufactured data of several reported semiconductor experiments that never took place. Having published his 'results' in various leading

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11. Some authors use the term 'accommodationism' for the denial of predictivism, i.e. for the view that prediction is not superior to accommodation (Hitchcock and Sober, 2004; Douglas and Magnus, 2013). I am using 'weak accommodiationism' in a quite different — and in some respects stronger — sense, viz. for the view that there is an epistemic advantage to accommodation over prediction.

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12. This point can also be motivated by appealing to the widely accepted thesis of *fallibilism*, i.e. the thesis that one should not be certain of any contingent proposition. In the Bayesian framework, the corresponding condition of *regularity* requires that rational agents assign only non-extreme probabilities (strictly between 0 and 1) to contingent propositions.

journals in his field, Schoen's fabrications were discovered only because he made the mistake of constructing data sets with identical 'noise', i.e. minor disturbances in some of the electrical signals that were supposedly being measured. Another type of data fraud, data manipulation, is when data that has actually been obtained is distorted so as to appear to confirm the relevant hypothesis — either by changing the values of measurements or (more commonly) by excluding measurements that do not fit the hypothesis.[13] One egregious example of data manipulation is Andrew Wakefield's fraudulent study on MMR-vaccination and autism, in which administrating the vaccine was claimed to cause autism in young children. Wakefield was found to have excluded data that didn't fit his hypothesis and to have altered other data, e.g. by claiming that eight of the 12 children investigated had experienced symptoms of autism within three days of the vaccination, when in fact only one child experienced such symptoms.

Cutting across the distinction between fabrication and manipulation is the distinction between *intentional* and *unintentional* data fraud.[14] In the cases mentioned so far, the researchers appear to have reported data that they knew to be inaccurate so as to fit their favored hypotheses. However, there are also well-known cases of inadvertent data fraud, i.e. cases in which scientists have deceived themselves into 'observing' non-existent phenomena or results (Broad and Wade, 1982, 107-126). A particularly striking example is the French physicist René Blondlot's theory of 'N-rays', which Blondlot claimed were a type of radiation analogous to X-rays (Nye, 1980). In 1903, Blondlot claimed to have discovered the presence of N-rays through observing electric sparks jumping between two wires that were (allegedly) slightly brighter than one should otherwise been expected. Blondlot's 'discovery' was widely celebrated among other French scientists and earned him the prestigious Leconte Prize in 1904. Over 40 French scientists subsequently reported that they had 'reproduced' Blondlot's observations, claiming to have also seen the increased brightness reported by Blondlot. Although these scientists couldn't actually have observed this non-existent effect, there is reason to believe that Blondlot himself, and at least some of his followers, did indeed believe themselves to have seen it. If so, this is an example of unintentional data fraud, where the researchers did not just deceive their intended audience but themselves as well.[15]

Now consider what we learn about the likelihood of data fraud when we learn that the relevant data D was either predicted or accommodated by the hypothesis H. When a scientist has used H to predict D, the scientist could have either fabricated or manipulated D so as to make it fit H. Indeed, in many cases the predicting scientist has self-interested reasons to do exactly that, for example because reporting on a prediction that is borne out is generally considered a much more significant result than a failed prediction,[16] or because the scientists has some scientific, financial, or otherwise personal, interest in confirming the hypothesis in question. Returning to our three examples, Schön appears to have fabricated data in order to obtain 'results' that fit with accepted scientific theories on semiconductors and would be publishable in the leading journals in his field; Wakefield had personal and financial ties to private companies that benefitted directly from casting doubt on the safety of traditional MMR-vaccines; and French scientists considered

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13. This is commonly referred to as 'falsification' in the literature on, and guidelines for, scientific misconduct. I have chosen the term 'manipulation' because 'falsification' carries unwanted connotations in philosophy of science (cf. Popper, 1959).
14. Since I define data fraud as the deceptive reporting of inaccurate data, this implies that it is possible to *unintentionally deceive* someone, e.g. in cases where one sincerely communicates a false belief to another person (Adler, 1997). Nothing of substance hangs on this, however. If you think unintentional deception is a conceptual impossibility, you may use the term 'mislead' for what I am calling deception (as is suggested by Carson, 2010, 47), and replace 'deceptive' with 'deceptive or misleading' in my definition of data fraud.

15. Presumably, Blondlot's followers were unwittingly affected by the psychological phenomenon known as *expectancy bias*, where our expectations shape what we take ourselves to perceive (Rosenthal, 1963).
16. Often, nothing statistically significant can be concluded from a failed prediction, and even when something can be concluded it is often much less interesting than the original hypothesis.

Blondlot's 'discovery' of N-rays to be a great triumph of a French scientific community whose reputation was on the decline. In all these cases, the reported data was made to fit pre-conceived hypotheses from which predictions had been derived.

In cases of accommodation, by contrast, there is no operative hypothesis H such that the accommodating scientist could have fabricated or manipulated D in order to fit H. Thus the scientist could not have the type of self-interested reason they have in cases of prediction to manipulate or fabricate D to fit H. This is not to say that it is impossible for a piece of accommodated data to be fraudulent, since a scientist might fabricate or manipulate data for some other reason, e.g. as a form of self-destructive behavior, regardless of whether the data was predicted or accommodated. Moreover, even non-fraudulent data might be inaccurate for various reasons, e.g. because of honest errors in how the data was obtained and registered. So the claim here is not that accommodated data carries no risk of being fraudulent or inaccurate. Rather, the point is that in cases of prediction there is an *additional* risk of the data being fraudulent, and thus inaccurate, due to scientists' own motivations for having their predictions confirm the hypotheses that they have already formulated. A scientist could not possibly have similar motivations for fabricating or manipulating the data to fit the hypothesis in cases of accommodation, since there would be no relevant hypothesis H that the scientist has some stakes in promoting. Indeed, since the hypothesis in question has not yet been formulated when the data is obtained in cases of accommodation, the accommodating scientist can simply alter her hypothesis to fit whatever data she gathers, so the accommodating scientists who is seeking a fit between hypothesis and data can always achieve that in a straightforward, non-fraudulent way.

The relevant upshot here is that data fraud — fabrication and manipulation of data, be it intentional or unintentional — can safely be taken to be considerably less common in cases of accommodation as compared to prediction. That is not necessarily to say that data fraud is common even in cases of prediction; only that it is much more common

than in cases of accommodation. So, all other things being equal, one should be less confident that predicted data is accurate as compared to accommodated data. After all, the chances of predicted data being manipulated or fabricated — and thus inaccurate — are considerably higher than for accommodated data. This contrast in how confident one should be about *the data* in cases of accommodation versus prediction is the epistemic feature that I take accommodation to be an indication of or proxy for. Note that this is not yet to say anything about how confident one should be about the *the hypothesis* in cases of accommodation versus prediction. So it remains to be argued that this epistemic feature of accommodation — that the relevant data is more likely to be accurate in accommodation than in prediction, *ceteris paribus* — makes it more likely that the hypothesis is correct.

That is where the next step of the argument comes in. Informally, this step shows that, all other things being equal, the confidence assigned to a hypothesis in light of some data should be greater to the extent that one assigns greater confidence to the data itself being accurate, provided that the data would indeed confirm the hypothesis if it was accurate. A formal proof of this step will be given shortly, but I'll start by providing the following informal argument. Suppose that by your lights a hypothesis H would be confirmed by some data D, so that if you discovered that D is accurate you would increase your confidence in H. Now suppose that instead of learning that D is definitely accurate, you learn that D is to a certain extent *likelier* to be accurate than you previous thought. Then your confidence in H should be somewhere strictly between what it would be if D was and wasn't definitely discovered to be accurate, since the possibility that D isn't accurate means your confidence should be lower than it would be if you definitely learned that D is accurate while the possibility that D is accurate means it should be higher than what it would be if you definitely learned that D isn't accurate. Similarly, if you learned that D is *even more likely* to be accurate (as compared to the previous case), then your confidence in H should be somewhere strictly between what it should have been in the previous case and what it would have been if you definitely learned

that D is accurate. By the same token, if you learned that D is *less likely* to obtain (as compared to the first case), then your confidence in H should be somewhere strictly between what it should have been in the first case and what it would have been if you didn't learn anything about D. And so forth. The upshot, of course, is that your confidence in H should be proportional to how much you increase your confidence in D in light of what you learn.

With this informal version of the second step in place, I can now summarize the argument for what I am calling *anti-fraud accommodationism*. In the first step, I argued that because scientists have no reason to commit data fraud in cases of accommodation, whereas they unfortunately do have self-interested reasons to do so in cases of prediction (and have been known to do so in such cases), we should place less confidence in the accuracy of predicted data as compared to accommodated data, all other things being equal. In the second step, I then argued that this difference in how much confidence we should place in the data translates into a difference in how confident we should be about the hypothesis that the data is meant to support. From this we can conclude that, all other things being equal, the information that a hypothesis accommodates rather than predicts some data does serves as an indication of an epistemic feature, viz. the likelihood that the data is accurate, that counts in favor of the hypothesis. Since that is what anti-fraud accommodationism asserts, this concludes my (informal) argument.

4. Derivation with Jeffrey Conditionalization

In order to formalize this argument, we must appeal to some formal framework for inductive reasoning. The dominant one is *Bayesianism*, a standard version of which can be viewed as the conjunction of the following three theses: First, perfectly rational agents can be represented as having fine-grained opinions known as *credences*. Second, the credences of such perfectly rational agents satisfy the Kolmogorov axioms of probability, which means that the credences they have at a given time can be represented as (subjective) probabilities. Third, perfectly

rational agents are required to update their credences as they obtain new data in accordance with *Bayesian Conditionalization*, which holds that when you obtain some data, you should set your new credence in any hypothesis equal to your previous credence in that hypothesis conditional on the data.[17] Formally:

Bayesian Conditionalization: When you obtain some data D, your new (subjective) probability for any hypothesis H, $P_n(H)$, should equal your old probability for H *given D*, $P_o(H|D)$:

$$P_n(H) = P_o(H|D)$$

Although Bayesian Conditionalization is a powerful tool, there is an important limitation to this rule that turns out to be crucial to my argument in this paper. What if you do not simply 'obtain' or 'learn' the data D in the intended unqualified sense, but instead merely become more (or less) confident that D holds? Richard Jeffrey (1965) proposed a generalization of Bayesian Conditionalization that handles cases of this sort, a simple version of which can be stated as follows (Jeffrey, 1965,

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17. Note that none of the three theses that jointly constitute this version of Bayesianism say anything about which credences agents should start out with beyond the requirement that these initial credences should satisfy the Kolmogorov axioms. Unfortunately, many sets of initial credences that we would intuitively think of as outrageous satisfy these axioms; and if we do start out with outrageous credences we might very well also end up with outrageous credences once we update them in accordance with Bayesian Conditionalization (although convergence theorems ameliorate this problem in many cases). Indeed, for this reason, many its proponents hold that Bayesanism is merely a bare-bones framework for non-deductive reasoning that will need to be supplemented with substantive assumptions about acceptable probability functions (see, e.g., Howson, 2000; Strevens, 2004). Nothing in what I say below solves or ameliorates this problem; accordingly, I will not assume that probability functions must meet any general constraints beyond the Kolmogorov axioms.

169):[18]

Jeffrey Conditionalization: When your (subjective) probability for some data D changes in any way, your new probability for any hypothesis H, $P_n(H)$, should equal a weighing of your old conditional probabilities $P_o(H|D)$ and $P_o(H|\neg D)$ by your new probabilities for the data, $P_n(D)$ and $P_n(\neg D)$:

$$P_n(H) = P_o(H|D)P_n(D) + P_o(H|\neg D)P_n(\neg D)$$

The idea here is that when there is uncertainty about the data D, one should conditionalize on D to the extent that one has credence in D and on $\neg D$ to the extent that one has credence in $\neg D$.[19]

Since Jeffrey Conditionalization can handle cases in which the data is uncertain, it is arguably superior to Bayesian Conditionalization as a general rule for evidential updating.[20] After all, as we have seen, one should never treat data as absolutely certain. Indeed, the need to use Jeffrey Conditionalization rather than good-old Bayesian Conditional-

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18. What follows is a special case in which the change in one's credences prompted by the learning experience is limited to the partition $\{D, \neg D\}$. In the more general case where the learning experience changes one's credences on the partition $\{D_1, ..., D_n\}$, Jeffrey Conditionalization holds that one's new subjective probability for any proposition H should be:

$$P_n(H) = \sum_{i \leq n} P_o(H|D_i)P_n(D_i)$$

For $n = 2$, this reduces to the simplified version of Jeffrey Conditionalization in the main text.

19. Note that this collapses into Bayesian Conditionalization whenever one becomes certain about the data, since in that case $P_n(D) = 1$ and $P_n(\neg D) = 0$, so the right hand side becomes $P_o(H|D) \times 1 + P_o(H|\neg D) \times 0 = P_o(H|D)$.

20. A well-known criticism of Jeffrey Conditionalization is that after repeatedly updating by this rule one might end up in different epistemic states, depending on the order in which one updates on different pieces of evidence (Levi, 1967). However, Lange (2000) argues that this feature of Jeffrey Conditionalization is a virtue rather than a vice since the character of the evidence will itself depend on the order of updating.

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ization is especially apparent when we contrast accommodation and prediction, since predicted data should (*ceteris paribus*) be treated as more uncertain than accommodated data, due to the fact that scientists have no self-interested reasons to manipulate or fabricate accommodated data whereas they unfortunately often do have such reasons in the case of predicted data. So if we wish to analyze the epistemic significance of accommodation versus prediction, we should clearly prefer Jeffrey Conditionalization, where differences in the certainty of data can be represented, to Bayesian Conditionalization, where such differences have been idealized away. The question, then, is how a rational agent using Jeffrey Conditionalization should update her credences in cases of accommodation versus cases of prediction.

To start, recall that I am seeking to show that accommodation has one important epistemic advantage over prediction, not that accommodation is overall more epistemically advantageous than prediction. Indeed, as I will emphasize in the next section, I am happy to acknowledge that prediction often has epistemic advantages over accommodation, e.g. along the lines suggested by Maher (1988) and Lange (2001). But in order to isolate the specific feature of accommodation that interests me here, I must start by comparing cases of prediction and accommodation in which these advantages to prediction — whatever they may be — are not present.[21] (Recall that proponents of weak predictivism acknowledge that there are such cases, since they concede that prediction is only superior to accommodation when all other things are equal.) Of course, I will not assume that accommodation has any advantages over prediction either, beyond the difference in how probable the data should be taken to be in each type of case. Rather, I will simply restrict the argument to cases in which prediction and accommodation are on a par with regard to how much confirmation is conferred on a hypothesis H by predicted data, D_P versus accommodated data, D_A; and likewise

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21. If this sounds suspicious, compare this approach to how physicists commonly set the effects of various forces to zero in order to isolate the effects of other forces, as when objects are assumed to move on frictionless planes when studying the effects of collisions between such objects.

for their respective negations $\neg D_P$ and $\neg D_A$. Formally:

$$P_o(H|D_A) = P_o(H|D_P)$$
$$P_o(H|\neg D_A) = P_o(H|\neg D_P) \tag{1}$$

I will also restrict the argument to cases in which the hypothesis would be confirmed by the data to some extent, i.e. in which the subjective probability of the hypothesis is higher conditional on the data than on the data's negation. This is just to say that the data, if it were discovered to be accurate, would have some positive epistemic relevance to the hypothesis. To deny this is to say that the data would either be completely irrelevant to the hypothesis, or else disconfirm that hypothesis. Since that is not the sort of case in which the data can be said to 'fit' the hypothesis, I take this condition to follow from the definitions of 'prediction' and 'accommodation'. Formally:

$$P_o(H|D_A) > P_o(H|\neg D_A)$$
$$P_o(H|D_P) > P_o(H|\neg D_P) \tag{2}$$

Finally and most significantly, we represent the fact that one should be less certain about the accuracy of predicted data as compared to accommodated data by an inequality in the (posterior) probabilities assigned to each type of data after obtaining it:[22]

$$P_n^A(D_A) > P_n^P(D_P) \tag{3}$$

In support of this condition, I have argued in the previous section that

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22. Here, and in what follows, $P_n^A(\cdot)$ and $P_n^P(\cdot)$ denote the the posterior probability functions in instances of accommodations and prediction, respectively.

scientists cannot be motivated to manipulate or fabricate data to fit their preferred hypothesis in cases of accommodation, whereas that is unfortunately not so in cases of prediction. Of course, it is still possible that a piece of accommodated data is inaccurate, e.g. due to honest errors or incompetence. But that is equally true of predicted data. The difference is that in the case of predicted data, there is an additional risk of the data being inaccurate due to scientists' own interest in having their predictions confirm the hypotheses they or their colleagues have already formulated. It is this contrast between accommodation and prediction that justifies the third and final condition (although as I discuss below, I do acknowledge that (3) isn't satisfied in certain non-typical cases).

With conditions (1)-(3) in place, a straightforward derivation using Jeffrey Conditionalization can now be given for assigning a higher subjective probability to H in the case of accommodation as compared to prediction:

$$P_n^A(H) > P_n^P(H)$$

A formal proof of this entailment is mathematically straightforward and provided in the Appendix. It should also be easy to see how the proof proceeds at an intuitive level: By Jeffrey Conditionalization, one should roughly speaking update by conditionalizing (i) on D to an extent that matches one's current credence in D, and (ii) on $\neg D$ to an extent that matches one's current credence in $\neg D$. Given (3), one's current credence in D should be higher in cases of accommodation than in cases of prediction, so one should conditionalize to a greater extent on D (and to a lesser extent on $\neg D$) in cases of accommodation than in cases of prediction. By (2), conditionalizing on D raises the probability of H more than conditionalizing on $\neg D$, so — given that all other things are equal, as per condition (1) — it follows that updating by Jeffrey Conditionalization in cases of accommodation raises the probability of H more than it does in otherwise identical cases of prediction.

5. Discussion and Loose Ends

I have argued that, *ceteris paribus*, the information that a hypothesis accommodates rather than predicts some data confers a specific epistemic advantage on the hypothesis in virtue of increasing our rational confidence in the data itself. In this penultimate section, I address two important questions about this thesis: First, how commonly, and under what conditions, is the *ceteris paribus*-clause satisfied in such a way that accommodation *in fact* confers this epistemic advantage on a given hypothesis? Second, assuming that anti-fraud accommodationism and some version of weak predictivism are both true, how (if at all) can one tell, in a given case, whether prediction or accommodation is more epistemically advantageous *all things considered*?

The key to answering the first question is condition (3), according to which accommodated data should be assigned a higher (posterior) probability than predicted data. The justification for this condition was that scientists have self-interested reasons to manipulate or fabricate predicted data, whereas the same isn't true for accommodated data. While I have argued that this is typically the case, there are also cases in which this consideration is defeated. If you already knew for certain whether the data was manipulated or fabricated, then information which bears on whether the relevant scientists *had reasons to* manipulate or fabricate the data shouldn't effect your rational confidence that it was. Consider, in particular, the special case in which you gathered the relevant data yourself. In that case, you can presumably be more-or-less certain that the data wasn't (or was!) manipulated or fabricated, so it would make practically no difference to the probability of the data whether you predicted or accommodated it.[23] Accordingly, the

epistemic advantage of accommodation over prediction to which anti-fraud accommodationism appeals would not be present in cases of this sort.[24]

On the other hand, whenever one isn't already rationally certain whether the data was manipulated or fabricated, then the conditions for there being an epistemic advantage to accommodation over prediction would be satisfied. I think it's fair to say that these conditions will *typically* be satisfied, since it is really only in the special case in which you gathered the data yourself that it would plausibly be rational to be close to absolutely certain that the data hasn't been manipulated or fabricated. According to a recent meta-analysis of various previous surveys on research misconduct, 2% of scientists admit to "fabricating, falsifying or modifying data", and 14% claim to have knowledge of it by their colleagues (Fanelli, 2009). Since these surveys rely on self-reporting of misconduct and knowledge thereof, there is reason to think they underestimate the true extent of data fraud. In any case, these numbers are high enough that it would certainly be a mistake to exclude beforehand the possibility that the predicting scientist has manipulated or fabricated the data they report (except perhaps when that scientist is you). Hence it is fair to say that there is *typically* an epistemic advantage to accommodation over prediction.

Indeed, there is reason to think that scientists are themselves conscious of the possibility that an apparently successful prediction is based on data fraud. Consider, for instance, the controversy over Gregor Mendel's (1866) work on inheritance, in which Mendel proposed and argued for his laws of segregation and independent assortment (Franklin, 2008). The controversy concerns whether the observations reported by Mendel are 'too close' to the frequencies one would expect

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23. Strictly speaking, a perfectly rational Bayesian agent would not assign probability 1 to the data even in that case, since doing so precludes the very possibility of being wrong about this contingent proposition. It is conceivable, after all, that you are misremembering whether you fabricated/manipulated the data. But in cases of this sort, the rationally assigned probability can be taken to be so close to 1 that the epistemic advantage of accommodation would be negligible for most practical purposes.

24. Another type of case in which it might be prudent to regard data as almost certainly accurate is when one knows that the data could very easily be checked by other researchers. In such cases, it would be comparatively foolish for scientists to attempt to 'get away with' publishing fraudulent data. Interestingly, although these types of situations may have been somewhat common in the earliest stages of empirical science, such cases are arguably becoming increasingly rare.

from the laws he proposed. For example, Mendel's laws predicted that certain mutually exclusive phenotypes in peas, e.g. being green versus yellow, would occur with probability ratios of 3:1 in a second generation of breeding. In other words, each pea would be three times more likely to be yellow than green. This would lead us to expect that the observed frequency of dominant to recessive phenotypes will lie somewhere reasonably close to a 3:1 ratio. In fact, Mendel reported an observed frequency of almost exactly that ratio, viz. 3.01:1 (Mendel, 1866, 12).

The fact that the observations Mendel reported fit his theories' predictions so remarkably well aroused skepticism from W.F.R. Weldon, who became convinced that Mendel had manipulated his data (even while acknowledging that Mendel's theories were both important and substantially correct). Another eminent statistician, R.A. Fisher (1936), performed a detailed statistical analysis of Mendel's data and concluded that it provides evidence that "the data of most, if not all, of the experiments have been falsified so as to agree closely with Mendel's expectations" (Fisher, 1936, 132).[25] Whether or not Weldon's and Fisher's accusations are in fact accurate, they show clearly that scientists themselves at least sometimes consider data fraud to be a live possibility in cases of prediction.[26]

The second question I promised to address in this section concerns what the epistemic advantage to accommodation over prediction entails about whether prediction or accommodation is more epistemically advantageous *all things considered*. Suppose — as I believe is plausible

— that some version of weak predictivism is true.[27] Then there are some *ceteris paribus*-conditions under which the information that the data was predicted rather than accommodated confers an epistemic advantage on the corresponding hypothesis. Recall, for example, that in Maher's version of weak predictivism, these conditions specify that one isn't already certain whether the method of hypothesis-construction was reliable. Call any such condition C_P.[28] And call the corresponding condition for anti-fraud accommodationism C_A. In order to answer the question of whether accommodation or prediction is more epistemically advantageous overall in a given case, we consider which of these conditions are satisfied:

1. If neither C_P nor C_A is satisfied, there is no epistemic advantage to either prediction or accommodation, so neither is more epistemically advantageous overall.
2. If C_P is satisfied but C_A isn't, there is some epistemic advantage to prediction but no advantage to accommodation, so prediction is more epistemically advantageous overall.
3. If C_P isn't satisfied but C_A is, there is no epistemic advantage to prediction but some advantage to accommodation, so accommodation is more epistemically advantageous overall.
4. If both C_P and C_A are satisfied, there are (different) epistemic advantages to both prediction and accommodation, and no obvious way to tell which (if either) type of epistemic advantage is stronger.

For our purposes, the most interesting set of cases are those in the third category, where C_A is satisfied but C_P isn't. Whenever one knows that one is dealing with such a case, one should be more confident that the relevant hypothesis is correct if one also knows that it was con-

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25. However, Fisher found it implausible that Mendel had committed fraud himself, so Fisher speculated that the data had been falsified by an assistant (Fisher, 1936, 132).
26. Note also that they seem to have considered this to be a live possibility precisely because Mendel's laws *predict* the actual result that would be obtained. Had the data been gathered independently of constructing the hypothesis, Weldon and Fisher would have had no reason to be suspicious of the data.

27. If no version of predictivism is true, then the answer to the second question would be trivial given how we answered the first question: Accommodation would simply be more epistemically advantageous than prediction whenever the condition outlined in the previous paragraph is satisfied, and otherwise there would be no epistemic difference between the two.
28. Or, if there are more than one such condition, let C_P be the conjunction of these conditions.

structed to accommodate the data than if one knows that the hypothesis was used to predict the data. So in such cases the common thought that prediction is superior to accommodation should not just be rejected but indeed reversed. Suppose for example that Maher's version of weak predictivism is correct (and that other versions of weak predictivism are not). In that case, C_P includes as a necessary condition that one doesn't already know for certain whether the method by which the hypothesis was constructed was reliable. Thus, in any circumstances in which one *does* know for certain whether the method by which the hypothesis was constructed was reliable (so C_P isn't satisfied), but one *doesn't* know for certain whether the data was manipulated or fabricated (so C_A is satisfied), one should prefer the hypothesis to have accommodated rather than predicted the data. The point generalizes to any other version of weak predictivism: Whenever the typicality conditions set forth by the weak predictivist aren't satisfied, but the corresponding typicality condition for anti-fraud accommodationism is satisfied, accommodation is epistemically superior to prediction — not just in one respect, but all things considered as well.

While cases in the third category are thus the most intriguing, cases in the fourth category are the most complicated and difficult to generalize about. For cases in this category, whether prediction or accommodation is overall more epistemically advantageous depends partly on factors other than whether the data was predicted or accommodated. Roughly, this is because whether the epistemic advantage to accommodation outweighs the epistemic advantage(s) to prediction in such cases depends on *the extent to which* a higher probability of accommodated data raises the probability of the hypothesis, which in turn depends on how well the data fits the hypothesis regardless of whether it was

accommodated or predicted.[29] So the extent to which accommodation provides an epistemic advantage over prediction, and thus whether that advantage is overall greater than that of prediction in a given case, depends on factors that are independent of whether the hypothesis was predicted or accommodated. In some cases, these factors will be such that having the hypothesis predict the data will provide more support for the hypothesis; in other cases, accommodated data will provide more support. Thus a further analysis of this category would presumably have to proceed on a case-by-case basis.

Since C_P and C_A are *ceteris paribus*-conditions for weak predictivism and anti-fraud accommodationism respectively, most instances of empirical support will presumably fall under category four. In other words,

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29. To explain, consider a comparison of the posterior probability of the hypothesis H after updating on D in cases of accommodation versus cases of prediction:

$$P_n^A(H) \lessgtr P_n^P(H)$$

Using Jeffrey Conditionalization, we can expand both sides as follows:

$$P_o(H|D_A)P_n^A(D_A) + P_o(H|\neg D_A)P_n^A(\neg D_A)$$
$$\lessgtr P_o(H|D_P)P_n^P(D_P) + P_o(H|\neg D_P)P_n^P(\neg D_P)$$

Now, in so far as there is an epistemic advantage to accommodation in cases that fall into the fourth category above, this manifests itself in a higher value for $P_n^A(D_A)$ than for $P_n^P(D_P)$, and in a lower value for $P_n^A(\neg D_A)$ than for $P_n^P(\neg D_P)$. But the extent to which this affects the comparison between the left and right hand sides depends on the values of the terms to which they are multiplied, i.e. $P_o(H|D_A)$, $P_o(H|D_P)$, $P_o(H|\neg D_A)$, and $P_o(H|\neg D_P)$, respectively. For example, having $P_n^A(D_A)$ be higher than $P_n^P(D_P)$ makes a greater difference to a comparison between $P_n^A(H)$ and $P_n^P(H)$ to the extent that the difference between $P_o(H|D_A)$ and $P_o(H|\neg D_A)$ is greater, since these terms are multiplied together on each side. But the difference between $P_o(H|D_A)$ and $P_o(H|\neg D_A)$ is clearly not solely determined by whether the data was accommodated or predicted by H; rather, it also depends on how likely the data is conditional on *H regardless of whether the data was predicted or accommodated*, i.e. on how well H 'fits' D (e.g. in terms of how many of the data points in a data set are explained by the hypothesis).

there will normally be epistemic advantages to both prediction and accommodation with no obvious way to tell which advantage is stronger. Although it might in principle be possible to estimate which type of advantage is stronger in a given case, it would surely be unrealistic to expect working scientists to even come close to performing such an analysis in practice. This may explain why working scientists do not in fact seem to have preferred prediction over accommodation in many historical cases (Brush, 1989, 1990, 1993, 1994).[30] That is, since any epistemic advantage of prediction over accommodation identified by a given weak predictivism might just as well be outweighed a contrary advantage of accommodation over prediction identified by anti-fraud accommodationism, prediction and accommodation might as well be treated as epistemically on a par for most practical purposes. The exception to this rule would be cases in which it is obvious to scientists themselves that one but not the other of C_P and C_A is satisfied, in which case one would expect scientists to prefer the type of support for which the corresponding condition *is* satisfied.[31]

6. Conclusion

I have argued that there is a respect in which accommodation is typically epistemically superior to prediction. The information that some data was accommodated rather than predicted by a hypothesis typically indicates (*ceteris paribus*) that the data is more likely to be accurate, which in turn increases the probability of the hypothesis by Jeffrey Conditionalization. This is not to deny that there may well be *other* respects in which prediction is epistemically superior to accommodation. If so,

there is no general answer as to which type of empirical support, accommodation or prediction, is epistemically superior all things considered. While it is possible to identify a category of cases in which prediction is always superior all things considered, it is also possible to identify a category in which the reverse is true. Moreover, the largest category of cases is arguably one in which there are advantages to both prediction and accommodation, and in which there is no obvious way to tell which type of advantage happens to be stronger. This goes against the long and venerable tradition in philosophy of science of emphasizing the epistemic potency of prediction as against accommodation.

In closing, I would like to emphasize the potential social implications of these considerations. If my argument is sound, it may be misguided for those who engage with the public about scientific matters to focus exclusively on the predictive support for various scientific theories. Consider, for example, the case of climate science. When the support for anthropogenic climate change is communicated to the public, a great deal of emphasis is often placed on the extent to which climate models with anthropogenic forcings have been predictively successful. There is nothing wrong with pointing to successful predictions, of course, and any sound communication strategy ought to include it. However, a more complete strategy might also emphasize the extent to which these models accommodated data that had been collected previously. After all, support through accommodation cannot plausibly be dismissed as based on fabricated or manipulated data, so even the most ardent climate change deniers cannot reasonably dismiss accommodated data as fraudulent. This suggests that a mixed approach, in which the theory's predictive and accommodative successes are communicated simultaneously, may help to convince some of those who would otherwise remain skeptical.[32]

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30. Interestingly, Brush does find a preference for predicting theories in one case, viz. Mendeleev's periodic table of elements (Brush, 1996). However, Scerri and Worrall dispute even that historical claim (Scerri and Worrall, 2001; Worrall, 2005; Scerri, 2005); see also Brush (2007) and Barnes (2005a; 2009, ch. 3) for replies to Scerri and Worrall.

31. I hope to address the empirical question of whether this expectation is borne out in future work in which working scientists would be queried as to whether prediction or accommodation provides stronger support in different types of cases across categories one through four.

Appendix: Proof of Theorem

Theorem. (1), (2), and (3) jointly entail:

$$P_n^A(H) > P_n^P(H)$$

Proof. First we multiply both sides of (3) with the term $\left(P_o(H|D_A) - P_o(H|\neg D_A)\right)$, which is non-negative according to (2):

$$P_n^A(D_A)\left(P_o(H|D_A) - P_o(H|\neg D_A)\right) \\ > P_n^P(D_P)\left(P_o(H|D_A) - P_o(H|\neg D_A)\right)$$

We then add the term $P_o(H|\neg D_A)$ to both sides:

$$P_o(H|\neg D_A) + P_n^A(D_A)\left(P_o(H|D_A) - P_o(H|\neg D_A)\right) \\ > P_o(H|\neg D_A) + P_n^P(D_P)\left(P_o(H|D_A) - P_o(H|\neg D_A)\right)$$

Algebraic manipulations, omitted here for the sake of brevity, reveal that this is equivalent to:

$$P_o(H|D_A)\,P_n^A(D_A) + P_o(H|\neg D_A)(1 - P_n^A(D_A)) \\ > P_o(H|D_A)\,P_n^P(D_P) + P_o(H|\neg D_A)(1 - P_n^P(D_P))$$

Since $(1 - P_n^A(D_A)) = P_n^A(\neg D_A)$ and $(1 - P_n^P(D_P)) = P_n^P(\neg D_P)$, this

simplifies to:

$$P_o(H|D_A)\,P_n^A(D_A) + P_o(H|\neg D_A)P_n^A(\neg D_A) \\ > P_o(H|D_A)\,P_n^P(D_P) + P_o(H|\neg D_A)P_n^P(\neg D_P)$$

By (1), we can substitute $P_o(H|D_A)$ for $P_o(H|D_P)$, and similarly $P_o(H|\neg D_A)$ for $P_o(H|\neg D_P)$, on the right hand side. This gets us:

$$P_o(H|D_A)\,P_n^A(D_A) + P_o(H|\neg D_A)\,P_n^A(\neg D_A) \\ > P_o(H|D_P)\,P_n^P(D_P) + P_o(H|\neg D_P)\,P_n^P(\neg D_P)$$

By Jeffrey Conditionalization, this is equivalent to $P_n^A(H) > P_n^P(H)$, as desired. $\qquad\square$

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