Review of Gerhard Schurz, *Hume’s Problem Solved: The Optimality of Meta-Induction*

Gerhard Schurz’s new book is an ambitious attempt to solve Hume’s problem of induction by techniques developed in computational learning theory. The book advances two major theses. The first is negative: We have no epistemic justification of the reliability of induction (Chs. 2-4), where “reliable” means truth-preserving with high probability. The negative thesis motivates Schurz to investigate the weaker claim: We have an epistemic justification of the optimality of induction (Ch. 5-8), where “optimal” means no worse than any alternative method. In other words, we cannot tell whether induction is reliable or not, but if any prediction method is reliable, then induction is. So, we have good reason to use induction for prediction. This line of support for induction is familiar since Reichenbach (1938), but in light of the problems of Reichenbach’s proposal (Sec. 5.3), Schurz defends the positive thesis of optimality in two steps. First, Schurz argues a priori that the method of meta-induction he describes is optimal in all possible worlds (Chs. 5-7). This is the main part of the book, where he draws on insights from computational learning theory. Schurz then combines the a priori result with the observation that object-induction has been more successful than other methods, to argue a posteriori that object-induction is optimal (Ch. 8). I will fill out below some details of these points, and note one concern about the optimality approach.

Schurz’s negative thesis, to be more precise, is that we have no non-circular epistemic justification of the reliability of induction in the sense (“narrow sense”) of making a prediction based on the observed regularity. Central to his negative thesis is the charge of circularity, e.g. the higher order justification of induction based on its past success assumes, tacitly, the reliability of induction for which the observed regularity relied on is the past success of induction. Some Bayesians may object to the charge of circularity here because by the axioms of the probability calculus the hypothesis is confirmed (the probability of the hypothesis goes up) by the observation entailed by the hypothesis.1 The hypothesis that all emeralds are green, for example, is confirmed (its probability goes up) by the observations of green emeralds, where there is no epistemic circularity. Schurz’s response to this objection is a version of the tacking problem (Sec. 4.1). The general hypothesis that all emeralds are green is a conjunction: All observed emeralds are green and all non-observed emeralds are green. This conjunction is confirmed by the observation of green emeralds only because the first conjunct is confirmed by the observation while the second conjunct tacked onto it remains unconfirmed. So, the Bayesian argument for the general hypothesis does not justify an inductive prediction. Indeed, the observation of green emeralds also confirms the anti-inductive general hypothesis: All observed emeralds are green and all non-observed emeralds are not green. So, we need justification for using the inductive general hypothesis, instead of the anti-inductive general hypothesis, in making a prediction.

It should be noted here that Schurz distinguishes the problem of language-dependence introduced by Goodman (1955) from Hume’s problem of induction (Secs. 1.2, 4.2). Schurz therefore grants that the anti-inductive prediction is indeed anti-inductive, setting aside the challenge that it is inductive relative to an alternative language. Hume’s problem remains in

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1 Assuming that the hypothesis is non-contradictory and the prior probability of the observation is less than one.
Schurz’s view because we still need to defend the inductive prediction against the challenge of the anti-inductive prediction. Induction is, of course, more “intuitive” and in much better accord with “common sense” than anti-induction, but that is irrelevant to epistemic justification. An epistemic justification of induction, as Schurz sees it, requires that we establish truth-conduciveness of induction (Sec. 2.2).

In light of the negative thesis on reliability, Schurz retreats to the claim of optimality. The formal framework of his argument for the optimality of meta-induction is “the prediction game” (Sec. 5.5). A prediction game consists of a stream of events and a set of prediction methods (“players”). Each event in the stream has a value in the interval [0, 1] and each player predicts the value of the next event (e_{n+1}) based on the stream of n events observed so far. For the purpose of exposition, I will describe here a case where the event is binary {0, 1} and the prediction is probabilistic: Each player in the game distributes the probability over {0, 1} for the next event based on the stream of 0’s and 1’s observed so far. The lower is the probability assigned to the true event value, 0 or 1, the greater is the “loss”. The bar is set high for the optimality claim: An optimal prediction method must be at least as good as any other method in all prediction games. The straight rule of extrapolation (which distributes the probability based on the observed frequency ratio) fails to meet the requirement because the stream of events in some games are misleading and the set of players to compete may even include a clairvoyant. Indeed, no substantive (object-level) prediction method can meet the requirement.

The solution is meta-induction that makes a prediction based on the performance of the players in the set. The simplest form of meta-induction is “Imitate the Best” (ITB) that makes (at each point in the stream) the same prediction as the most successful player (at that point) makes (Sec. 6.1). If the set contains a clairvoyant player with an impeccable record, then ITB makes the same prediction as she does. There is a problem, though. The best player in some prediction games keep changing, e.g. two players may be alternately the best for some stream of events. ITB then keeps changing the player to imitate, so as to match their performance. However, the ITB prediction lags behind and is never as good as the best player at any point. So, Schurz turns to “multiple-favorite” meta-induction, of which his preferred version is “attractivity-weighted meta-induction” (AW). The procedure is as follows: Ignore poorly performing players in the set, and take the weighted average of the predictions made by the better-performing players, where the weights are determined by their performance so far. If a particular player has been performing better than others in the set, AW assigns a high weight (but not the whole weight as in ITB) to that player’s prediction in assigning the probability for the next event. This strategy may seem no better than ITB: We can easily think of a prediction game in which the best player (so far) makes a better prediction for the next event than AW does. Indeed, AW is not optimal with regard to the prediction of the next event. Schurz’s point, however, is that AW is long-run optimal and short-run near optimal (Sec. 5.7). It is long-run optimal in that as the stream gets longer and longer to infinity, its performance score approaches the value no worse than any player in the set. It is short-run near optimal in that even though it is not optimal in short run, its amount of “regret” (how much worse it performs than the best player in the set) has a sufficiently small upper bound. The retreat to long-run optimality and short-run near optimality may be disappointing to some, but they are still significant results in light of the high bar set for optimality—its prediction must be at least as good as any other method in all prediction games.

There is one more step Schurz needs to take to solve Hume’s problem. AW itself (or any meta-inductive method) is not the prediction method we commonly use in our inductive practice. So, Schurz combines the optimal meta-induction with the past success of object-induction to
argue a posteriori that induction as we practice it is optimal (Sec. 8.1). This part of the book only presents an outline without extended elaboration, and some questions remain. For example, meta-induction is not higher-order induction to choose a prediction method, but a way of making a prediction by consulting predictions of various methods. So, the claim to establish is that given the past success of object-induction, the optimal meta-induction makes the same prediction that object-induction makes. However, since AW makes a prediction by the weighted average, it may not make the same prediction as object-induction does even if the latter has a very good track record. The prediction by AW still depends in part on the other players in the set. For example, if one of them is an anti-inductivist whose “subversion” point is yet to come, and thus has a track record as good as object-induction so far, AW must assign equal weights to two predictions, one by the object-inductivist and the other by the anti-inductivist. Indeed, if the anti-inductivist is among the players, we cannot say that object-induction has been more successful than other methods.

There may be answers to questions of this kind on specific points, but there is also a general concern about the optimality approach. Suppose, as Schurz claims, we have no epistemic justification of the reliability of induction, but only its optimality. The fact remains that induction has been mostly reliable. Of course, we cannot defend our belief in its future reliability by simply citing its past reliability, but the fact calls for an explanation: Why has induction been mostly reliable? The optimality of induction falls short of explaining its past reliability. The point is not that we cannot defend the reliability hypothesis by inference to the best explanation. We cannot because the reliability of anti-induction can also explain the past reliability of induction. The point, rather, is that if there really is no reason to believe in the reliability of induction, we are left with a mystery. Each time we used induction in the past, we had no good reason (let’s suppose) to believe it would be reliable, but somehow induction turned out to be mostly reliable. There is a related problem about justification. The optimality may be enough for us to keep using induction, but it does not fully justify our current epistemic practice, viz. if we only have an epistemic justification of the optimality of induction, then we should be less confident of our inductive predictions than we commonly are. For example, we should make it a habit to prepare a fall back plan in anticipation of prediction failure. The optimality thesis, if correct, may still be considered a solution to Hume’s problem in that it justifies the use of induction, but it fails to explain the past reliability of induction, and we lack a full justification of our current epistemic practice.

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References