

Awareness Growth in Bayesian Networks

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1 Introduction

Learning is modeled in the Bayesian framework by the rule of conditionalization. This rule posits that the agent's new degree of belief in a proposition H after a learning experience E should be the same as the agent's old degree of belief in H conditional on E . That is,

$$P^E(H) = P(H|E),$$

where $P()$ represents the agent's old degree of belief (before the learning experience E) and $P^E()$ represents the agent's new degree of belief (after the learning experience E).

Both E and H belong to the agent's algebra of propositions. This algebra models the agent's awareness state, the propositions taken to be live possibilities. Conditionalization never modifies the algebra and thus makes it impossible for an agent to learn something they have never thought about. This forces a great deal of rigidity on the learning process. Even before learning about E , the agent must already have assigned a degree of belief to any proposition conditional on E . This picture commits the agent to the specification of their 'total possible future experience' (Howson 1976, *The Development of Logical Probability*), as though learning was confined to an 'initial prison' (Lakatos, 1968, *Changes in the Problem of Inductive Logic*).

But, arguably, the learning process is more complex than what conditionalization allows. Not only do we learn that some propositions that we were entertaining are true or false, but we may also learn new propositions that we did not entertain before. Or we may entertain new propositions—without necessarily learning that they are true or false—and this change in awareness may in turn change what we already believe. How should this more complex learning process be modeled by Bayesianism? Call this the problem of awareness growth.

Critics of Bayesianism and sympathizers alike have been discussing the problem of awareness growth under different names for quite some time, at least since the eighties. This problem arises in a number of different contexts, for example, new scientific theories (Glymour, 1980, *Why I am not a Bayesian*; Chihara 1987, *Some Problems for Bayesian Confirmation Theory*; Earman 1992, *Bayes of Bust?*), language changes and paradigm shifts (Williamson 2003, *Bayesianism and Language Change*), and theories of induction (Zabell, *Predicting the Unpredictable*).

A proposal that has attracted considerable scholarly attention is Reverse Bayesianism (Karni and Viero, 2015, *Probabilistic Sophistication and Reverse Bayesianism*; Wenmackers and Romeijn 2016, *New Theory About Old Evidence*; Bradely 2017, *Decision Theory with A Human Face*). The idea is to model awareness growth as a change in the algebra while ensuring that the probabilities of the propositions shared between the old and new algebra remain fixed under suitable constraints.

Let \mathcal{F} be the initial algebra of propositions and let \mathcal{F}^+ the algebra after the agent's awareness state has grown. Both algebras contain the contradictory and tautologous propositions \perp and \top , and they are closed under connectives such as disjunction \vee , conjunction \wedge and negation \neg .

Denote by X and X^+ the subsets of these algebras that contain only basic propositions, namely those without connectives. **Reverse Bayesianism** posits that the ratio of probabilities for any basic propositions A and B in both X and X^+ —the basic propositions shared by the old and new algebra—remain constant through the process of awareness growth:

$$\frac{P(A)}{P(B)} = \frac{P^+(A)}{P^+(B)},$$

where $P()$ represents the agent’s degree of belief before awareness growth and $P^+()$ represents the agent’s degree of belief after awareness growth.

Reverse Bayesianism is an elegant theory that manages to cope with a seemingly intractable problem. As the awareness state of an agent grows, the agent would prefer not to throw away completely the epistemic work they have done so far. The agent may desire to retain as much of their old degrees of beliefs as possible. Reverse Bayesianism provides a simple recipe to do that. It also coheres with the conservative spirit of conditionalization which preserves the old probability distribution conditional on what is learned.

Unfortunately, Reverse Bayesianism is not without complications. Steele and Stefánsson (2021, Belief Revision for Growing Awareness) argue that Reverse Bayesianism, when suitably formulated, can work in a limited class of cases, what they call *awareness expansion*, but cannot work for *awareness refinement* (more on this distinction later). Their argument rests on a number of ingenious counterexamples.

We contend, however, that their counterexamples have limited applicability and thus constitute an overall weak argument against Reverse Bayesianism (§ 2). Still, we share Steele and Stefánsson’s skepticism and provide a better counterexample (§ 3). At the same time, we carve out a class of cases in which Reverse Bayesianism still holds, and these include not just cases of expansion but also some cases of refinement (§ 4). Our critique of Reverse Bayesianism is thus more fine-grained than Steele and Stefánsson’s. Ultimately, we conjecture that the problem of awareness growth cannot be tackled in an algorithmic manner because subject-matter structural assumptions are necessary (§ 5). We rely on the theory of Bayesian networks at several key junctures in our argument.

2 Counterexamples?

We begin by rehearsing two of the ingenious counterexamples to Reverse Bayesianism by Steele and Stefánsson. One example targets awareness expansion and the other awareness refinement. The difference between expansion and refinement is intuitively plausible, but it can be tricky to pin down formally. A rough characterization will suffice here. Suppose, as is customary, propositions are interpreted as sets of possible worlds, where the set of all possible worlds is the possibility space. An algebra of propositions thus interpreted induces a partition of the possibility space. Refinement occurs when the new proposition added to the algebra induces a more fine-grained partition of the possibility space. Expansion, instead, occurs when the new proposition shows that the existing partition was not exhaustive.

The first counterexample by Steele and Stefánsson targets cases of awareness expansion:

FRIENDS: Suppose you happen to see your partner enter your best friend’s house on an evening when your partner had told you she would have to work late. At that point, you become convinced that your partner and best friend are having an affair, as opposed to their being warm friends or mere acquaintances. You discuss your suspicion with another friend of yours, who points out that perhaps they were meeting to plan a surprise party to celebrate your upcoming birthday—a possibility that you had not even entertained. Becoming aware of this possible

explanation for your partner's behaviour makes you doubt that she is having an affair with your friend, relative, for instance, to their being warm friends. (Steele and Stefánsson, 2021, Section 5, Example 2)

Initially, the algebra only contains the hypotheses 'my partner and my best friend met to have an affair' (*Affair*) and 'my partner and my best friend met as friends or acquaintances' (*Friends/acquaintances*). The other proposition in the algebra is the evidence, that is, the fact that your partner and your best friend met one night without telling you (*Secretive*). Given this evidence, *Affair* is more probable than *Friends/acquaintances*:

$$P(\textit{Affair}|\textit{Secretive}) > P(\textit{Friends/acquaintances}|\textit{Secretive}). \quad (>)$$

When the algebra changes, a new hypothesis is added which you had not considered before: your partner and your best friends met to plan a surprise party for your upcoming birthday (*Surprise*). Given the same evidence, *Friends/acquaintances* is now more likely than *Affair*:

$$P^+(\textit{Affair}|\textit{Secretive}) < P^+(\textit{Friends/acquaintances}|\textit{Secretive}). \quad (<)$$

This holds assuming that hypothesis *Surprise* is more likely than the hypothesis *Affair*:

$$P^+(\textit{Surprise}|\textit{Secretive}) > P^+(\textit{Affair}|\textit{Secretive}),$$

and, in addition, that *Surprise* implies *Friends/acquaintances*. After all, in order to prepare a surprise party, your partner and best friend have to be at least acquaintances.

The conjunction of (>) and (<) violates Reverse Bayesianism. But, as Steele and Stefánsson admits, Reverse Bayesianism can still be made to work with a slightly different—though quite similar in spirit—condition, called **Awareness Rigidity**:

$$P^+(A|T^*) = P(A),$$

where T^* corresponds to a proposition that picks out, from the vantage point of the new awareness state, the entire possibility space before the episode of awareness growth. In our running example, the proposition $\neg\textit{Surprise}$ picks out the entire possibility space in just this way. And conditional on $\neg\textit{Surprise}$, the probability of *Affair* does not change. Thus,

$$P^+(\textit{Affair}|\textit{Secretive} \& \neg\textit{Surprise}) > P^+(\textit{Friends/acquaintances}|\textit{Secretive} \& \neg\textit{Surprise}).$$

Awareness Rigidity is vindicated. Reverse Bayesianism—the spirit of it, not the letter—stands.

This is not the end of the story, however. Steele and Stefánsson offer another counterexample that also works against Awareness Rigidity, this time targeting a case of refinement:

MOVIES: Suppose you are deciding whether to see a movie at your local cinema. You know that the movie's predominant language and genre will affect your viewing experience. The possible languages you consider are French and German and the genres you consider are thriller and comedy. But then you realise that, due to your poor French and German skills, your enjoyment of the movie will also depend on the level of difficulty of the language. Since it occurs to you that the owner of the cinema is quite simple-minded, you are, after this realisation, much more confident that the movie will have low-level language than high-level language. Moreover, since you associate low-level language with thrillers, this makes you more confident than you were before that the movie on offer is a thriller as opposed to a comedy. (Steele and Stefánsson, 2021, Section 5, Example 3)

Initially, you did not consider language difficulty. So you assigned the same probability to the hypotheses *Thriller* and *Comedy*. But learning that the owner is simple-minded made you think that the level of linguistic difficulty must be low and the movie most likely a thriller rather than a comedy (perhaps because thrillers are simpler—linguistically—than comedies). So, against Reverse Bayesianism, MOVIES violates the condition $\frac{P(\textit{Thriller})}{P(\textit{Comedy})} = \frac{P^+(\textit{Thriller})}{P^+(\textit{Comedy})}$.

The counterexample also works against Awareness Rigidity. It is not true that $P(\textit{Thriller}) = P^+(\textit{Thriller}|\textit{Thriller} \vee \textit{Comedy})$. Note that this counterexample is a case of refinement. First, you categorize movies by just language and genre, and then you add a further category, level of difficulty. So the proposition which picks out the entire possibility space should be the same before and after awareness growth, for example, $\textit{Thriller} \vee \textit{Comedy}$. In cases of awareness growth by refinement, then, Awareness Rigidity mandates that all probability assignments stay the same. But MOVIES does not satisfy this requirement.

This is all well and good, but how strong of a counterexample is this? Steele and Stefánsson consider an objection:

It might be argued that our examples are not illustrative of ... a simple growth in awareness; rather, our examples illustrate and should be expressed formally as complex learning experiences, where first there is a growth in awareness, and then there is a further learning event ... In this way, one could argue that the awareness-growth aspect of the learning event always satisfies Reverse Bayesianism

Admittedly, MOVIES can be split into two episodes. In the first, you entertain a new variable besides language and genre, namely the language difficulty of the movie. In the second episode, you learn something you did not consider before, namely that the owner is simple-minded. Could Reverse Bayesianism still work for the first episode, but not the second? Steele and Stefánsson do not address this question explicitly, but insist that no matter the answer both episodes are instances of awareness growth. We agree with them on this point. Awareness growth is both *entertaining* a new proposition not in the initial awareness state of the agent and *learning* a new proposition. Nonetheless, we should still wonder. Is the second episode (learning something new) necessary for the counterexample to work together with the first episode (mere refinement without learning)?

Suppose the counterexample did work only in tandem with an episode of learning something new. If that were so, defenders of Reverse Bayesianism or Awareness Rigidity could still claim that their theory applies to a large class of cases. It applies to cases of awareness refinement without learning and also to cases of awareness expansion. For recall that the first putative counterexample featuring awareness expansion—FRIENDS—did not challenge Reverse Bayesianism insofar as the latter is formulated in terms of its close cousin, Awareness Rigidity. So the force of Steele and Stefánsson's counterexamples would be rather limited.

Or perhaps there is a more straightforward counterexample that only depicts mere refinement without an episode of learning and that still challenges Reverse Bayesianism and Awareness Rigidity. As we shall soon see, this is indeed the case.

3 A better counterexample

Steele and Stefánsson's counterexample to Reverse Bayesianism in the case of refinement is rather complex, perhaps unnecessarily so. We now present something simpler:

LIGHTING: You have evidence that favors a certain hypothesis, say a witness saw the defendant around the crime scene. You give some weight to this evidence. In your assessment, that the defendant was seen around the crime scene raises the probability that the defendant was actually there. But now you wonder, what if it was dark when the witness saw the defendant? You become a bit more careful

and settle on this: if the lighting conditions were good, you should still trust the evidence, but if they were bad, you should not. Unfortunately, you cannot learn about the actual lighting conditions, but the mere realization that it *could* have been dark makes you lower the probability that the defendant was actually there, based on the same evidence.

This scenario is simpler because it consists of mere refinement. You wonder about the lighting conditions but you do not learn what they were. Still, mere refinement in this scenario challenges Reverse Bayesianism and Awareness Rigidity. That this should be so is not easy to see. Fortunately, the theory of Bayesian networks helps to see why.

A Bayesian network is a formal model that consists of a graph accompanied by a probability distribution. The nodes in the graph represent random variables that can take different values. We will use ‘nodes’ and ‘variables’ interchangeably. The nodes are connected by arrows, but no loops are allowed, hence the name direct acyclic graph (DAG). Bayesian networks are relied upon in many fields, but have been little used to model awareness growth. We think instead they are a good framework for this purpose. Awareness growth can be modeled as a change in the graphical network—nodes and arrows are added or erased—as well as a change in the probability distribution from the old to the new network.

To model the scenario LIGHTING with Bayesian networks, we start with this graph:

$$H \rightarrow E,$$

where H is the hypothesis node and E the evidence node. If an arrow goes from H to E , the probability distribution associated with the Bayesian network should be defined by conditional probabilities of the form $P(E = e|H = h)$, where uppercase letters represent the variables (nodes) and lower case letters represent the values of these variables.¹

Since you trust the evidence, you think that it is more likely under the hypothesis that the defendant was present at the crime scene than under the alternative hypothesis:

$$P(E=seen|H=present) > P(E=seen|H=absent)$$

The inequality is a qualitative ordering of how plausible the evidence is in light of competing hypotheses. No matter the numbers, by the probability calculus, it follows that the evidence raises the probability of the hypothesis $H=present$.

Now, as you wonder about the lighting conditions, the graph should be amended:

$$H \rightarrow E \leftarrow L,$$

where the node L can have two values, $L=good$ and $L=bad$. A plausible way to update your assessment of the evidence is as follows:

$$P^+(E=seen|H=present \wedge L=good) > P^+(E=seen|H=absent \wedge L=good)$$

$$P^+(E=seen|H=present \wedge L=bad) = P^+(E=seen|H=absent \wedge L=bad)$$

Note the change in the probability function from $P()$ to $P^+()$. Here is what you are thinking: if the lighting conditions were good, you should still trust the evidence like you did before. But if the lighting conditions were bad, you should regard the evidence as no better than chance.

Should you now assess the evidence at your disposal—that the witness saw the defendant at the crime scene—any differently than you did before? The evidence would have the same

¹ A major point of contention in the interpretation of Bayesian networks is is the meaning of the directed arrows. They could be interpreted causally—as though the direction of causality proceeds from the events described by the hypothesis to event described by the evidence—but they need not be. REFERENCES?

value if the likelihood ratios associated with it relative to the competing hypotheses were the same before and after awareness growth:

$$\frac{P(E=e|H=h)}{P(E=e|H=h')} = \frac{P^+(E=e|H=h)}{P^+(E=e|H=h')}. \quad (C)$$

But it would be quite a coincidence if (C) were true. For concreteness, let's use some numbers:

$$P(E=seen|H=present) = P^+(E=seen|H=present \wedge L=good) = .8$$

$$P(E=seen|H=absent) = P^+(E=seen|H=absent \wedge L=good) = .4$$

$$P^+(E=seen|H=present \wedge L=bad) = P^+(E=seen|H=absent \wedge L=bad) = .5.$$

So the ratio $\frac{P(E=seen|H=present)}{P(E=seen|H=absent)}$ equals 2. Before the growth in awareness, you thought the evidence favored the hypothesis $H=present$ moderately strongly. That seemed reasonable. But, after the growth in awareness, the ratio $\frac{P^+(E=seen|H=present)}{P^+(E=seen|H=absent)}$ drops to $\frac{.65}{.45} \approx 1.44$.² This argument can be repeated with several other numerical assignments. So, quite often, mere refinement can weaken the evidence, even without learning anything new.³

Need a more general argument here. Simulation?

Why does all this matter? We have seen that, after awareness growth, you should regard the evidence at your disposal as one that favors $H=present$ less strongly. Since the prior probability of the hypothesis should be the same before and after awareness growth, it follows that

$$P^+(H=present|E=seen) \neq P(H=present|E=seen).$$

This outcome violates Awareness Rigidity. For recall that in cases of refinement, Awareness Rigidity requires that the probability of basic propositions stay fixed.

Reverse Bayesianism is also violated. For example, the ratio of the probabilities of $H=present$ to $E=seen$, before and after awareness growth, has changed:

$$\frac{P^{E=seen}(H=present)}{P^{E=seen}(H=seen)} \neq \frac{P^{+,E=seen}(H=present)}{P^{+,E=seen}(H=seen)},$$

where $P^{E=seen}()$ and $P^{+,E=seen}()$ represent the agent's degrees of belief, before and after awareness growth, updated by the evidence $E=seen$.

²The calculations here rely on the dependency structure encoded in the Bayesian network (see starred step below).

$$\begin{aligned} P^+(E=seen|H=present) &= P^+(E=seen \wedge L=good|H=present) + P^+(E=seen \wedge L=bad|H=present) \\ &= P^+(E=seen|H=present \wedge L=good) \times P^+(L=good|H=present) \\ &\quad + P^+(E=seen|H=present \wedge L=bad) \times P^+(L=bad|H=present) \\ &= * P^+(E=seen|H=present \wedge L=good) \times P^+(L=good) \\ &\quad + P^+(E=seen|H=present \wedge L=bad) \times P^+(L=bad) \\ &= .8 \times .5 + .5 \times .5 = .65 \end{aligned}$$

$$\begin{aligned} P^+(E=seen|H=absent) &= P^+(E=seen \wedge L=good|H=absent) + P^+(E=seen \wedge L=bad|H=absent) \\ &= P^+(E=seen|H=absent \wedge L=good) \times P^+(L=good|H=absent) \\ &\quad + P^+(E=seen|H=absent \wedge L=bad) \times P^+(L=bad|H=absent) \\ &= * P^+(E=seen|H=absent \wedge L=good) \times P^+(L=good) \\ &\quad + P^+(E=seen|H=absent \wedge L=bad) \times P^+(L=bad) \\ &= .4 \times .5 + .5 \times .5 = .45 \end{aligned}$$

³If you did learn that the lighting conditions were bad, the evidence would become even weaker, effectively worthless:

$$\frac{P^{+,L=bad}(E=seen|H=present)}{P^{+,L=bad}(E=seen|H=absent)} = 1,$$

where $P^{+,L=bad}()$ is the new probability function after learning that $L=bad$.

4 Downstream and upstream refinement

Unlike MOVIES, the counterexample LIGHTING works even though it only depicts a case of awareness growth that consists in refinement without learning. Defenders of Reverse Bayesianism and Awareness Rigidity can no longer claim that their theories work when awareness growth is not intertwined with learning. So, Steele and Stefánsson's critique of these theories sits now on firmer ground. And yet, the scope of this critique should not be exaggerated. As we shall now see, there are cases of refinement in which Reverse Bayesianism and Awareness Rigidity are perfectly fine in their place.

Consider this variation of the LIGHTING scenario:

VERACITY: A witness saw that the defendant was around the crime scene and you initially took this to be evidence that the witness was actually there. But then you worry that the witness might be lying or misremembering what happened. Perhaps, the witness was never there, made things up or mixed things up. But despite that, you do not change anything of your initial assessment of the evidence.

The rational thing to do here is to stick to your guns and not change your earlier assessment of the evidence. Why should that be so? And what is the difference with LIGHTING? Once again, Bayesian networks prove to be a good analytic tool here.

The graphical network should initially look like this:

$$H \rightarrow E$$

But, as your awareness grows, the graphical network should be updated:

$$H \rightarrow E \rightarrow R$$

The hypothesis node H bears on the whereabouts of the defendant. Note the difference between E and R . The evidence node bears on what the witness saw. The reporting node bears on what the witness reports to have seen. The chain of transmission from 'seeing' to 'reporting' may fail for various reasons, such as lying or confusion.

Even if VERACITY is a case of refinement, the old and new probability functions agree with one another completely. The conditional probabilities, $P(E = e|H = h)$ should be the same as $P^+(E = e|H = h)$ for any values e and h of the variables H and E that are shared before and after awareness growth. Given the dependency structure of the two Bayesian networks—first, $H \rightarrow E$ and then $H \rightarrow E \rightarrow R$ —the equality is easy to establish formally.⁴ Thus, Reverse Bayesianism and Awareness Rigidity are perfectly fine in scenarios like VERACITY.

A confusion should be eliminated at this point. We do not intend to suggest that the assessment of the probability of the hypothesis $H=present$ should undergo no change at all. If you worry that the witness could have lied, shouldn't this affect your belief in what they said about the defendant's whereabouts? Surely so. But note that in VERACITY an episode of awareness refinement takes place together with a form of retraction. Initially, what is taken to be known, after the learning episode, is that the witness *saw* the defendant around the crime scene. But after the growth in awareness, you realize your learning is in fact limited to what the witness *reported* to have seen. So the previous learning episode is retracted and replaced by a more careful statement of what you learned. This retraction will affect the probability you assign to the hypothesis $H=seen$, but this does not conflict with Reverse Bayesianism or Awareness Rigidity. In LIGHTING, instead, no retraction of the evidence takes place. The evidence that is known remains the fact that the witness saw the defendant around the crime scene, even though that experience could have been misleading due to bad lighting conditions.

⁴GIVE PROOF

Where does this leave us? The following are now well-established: (a) Reverse Bayesianism (or its close cousin Awareness Rigidity) handles successfully cases of awareness expansion; (b) it also handles successfully cases of refinement like VERACITY; but (c) it does fail in cases of refinement like LIGHTING. So, ultimately, Steele and Stefánsson’s critique only targets a subclass of refinement cases. The scope of this critique is therefore somewhat limited. And yet, we do not think the prospects for Reverse Bayesianism are good. In this respect, we tend to agree with Steele and Stefánsson. But we conjecture that there is a deeper difficulty for Reverse Bayesianism, besides possible counterexamples that may be leveled against it. The deeper difficulty is that it seeks to provide a formal, almost algorithmic solution to the problem of awareness growth, and this formal aspiration is likely to lead us down the wrong path.

To see why, consider again the distinction between the two cases of refinement. Reverse Bayesianism is perfectly fine in scenarios like VERACITY, but fails in scenarios like LIGHTING. What is that so? In one scenario, what the witness saw could have occurred under good or bad lighting conditions; in the other, what the witness saw could have been reported truthfully or untruthfully. The two scenarios are structurally different, and this difference can be appreciated by looking at the Bayesian networks used to model them. In VERACITY, the new node is added downstream. Since the conditional probabilities associated with the upstream nodes are unaffected, Reverse Bayesianism is vindicated. By contrast, in LIGHTING, the new node is added upstream. Since the conditional probabilities that are associated with the downstream nodes will often have to change, Reverse Bayesianism fails here.

This discussion suggests a conjecture: structural—possibly causal—features about how we conceptualize a specific scenario seems to be the guiding principles about how we update the probability function through awareness growth, not a formal principle like Reverse Bayesianism. We further elaborate on this conjecture in the final section.

5 Material, not formal constraints

Those who sympathize with a formal, algorithmic solution to the problem of awareness growth might offer the following reply: Granted, Reverse Bayesianism (or its close cousin, Awareness Rigidity) is not a general enough formal constraint since it fails sometimes. But, arguably, a weaker formal constraint may be immune from counterexamples. We are skeptical toward this line of argument. We now explore what a weaker formal constraint might be like for upstream refinement cases like LIGHTING, and show that this strategy is unlikely to succeed.

Recall that, in LIGHTING, the probability functions $P()$ and $P^+()$ do not assign the same weight to the evidence relative to the competing hypotheses, except in somewhat exceptional circumstances. But despite that, the two probability functions agree in one important respect:

$$P(E = e|H = h) \geq P(E = e|H = h') \text{ iff } P^+(E = e|H = h) \geq P^+(E = e|H = h'), \quad (C^*)$$

where (i) E and H are nodes that are part of the graphical network before and after awareness growth, and (ii) there is a direct path from H to E before and after awareness growth. In other words, the plausibility ordering between hypotheses and evidence is preserved.

How good is condition (C^*) as a formal constraint that governs the relationship between $P()$ and $P^+()$ in cases of upstream refinement? At first, it looks promising. Assume the Bayesian network has a node E with an incoming arrow from node H , before and after awareness growth. After awareness growth, another variable Y is added upstream. The new graph looks like this:

$$H \rightarrow E \leftarrow Y.$$

To establish (C^*) , all we need is the following assumption:

$$P(E = e|H = h) \geq P(E = e|H = h')$$

$$\begin{aligned}
& \text{iff} \\
& P^+(E = e | H = h \wedge Y = y) \geq P^+(E = e | H = h' \wedge Y = y) \quad (\text{EQUAL}) \\
& \text{iff}
\end{aligned}$$

$$P^+(E = e | H = h \wedge Y = y') \geq P^+(E = e | H = h' \wedge Y = y')$$

This assumption says that the plausibility ordering remains the same before and after awareness growth *all else being the same*. It holds in LIGHTING and should also hold in Steele and Stefánsson's scenario MOVIES, another case of upstream refinement.⁵ It is a minimal assumption, but enough to establish (C*).⁶

So the algorithmic solution to the problem of awareness growth might go like this: for expansion and downstream refinement, uses Awareness Rigidity, and for downstream refinement, use the weaker formal constraint (C*) which holds if (EQUAL) holds.

But this solution cannot work in the end. There will be cases in which the plausibility ordering is not preserved because (EQUAL) does not hold. For suppose you have evidence that—in your judgment—reliably tracks a hypothesis, say you think that appearance as of

⁵We briefly explain why. At first, the graphical network looks like this:

$$\text{Genre} \rightarrow \text{Enjoyment} \leftarrow \text{Language},$$

where each node can take two values: *Genre=comedy* and *Genre=thriller*; *Language=french* and *Language=german*; and *Enjoyment=yes* and *Enjoyment=no*. Assume you are ranking the options in terms of how they are going to contribute to your enjoyment (*Enjoyment=yes*). This ranking can be encoded by conditional probability statements of the form

$$P(\text{Enjoyment}=x | \text{Language}=y \wedge \text{Genre}=z) \geq P(\text{Enjoyment}=x | \text{Language}=y' \wedge \text{Genre}=z').$$

The first episode of awareness growth in MOVIES consists in realizing that the linguistic difficulty of the movie could also be a factor. So the expanded graphical network now becomes:

$$\begin{aligned}
& \text{Difficulty} \\
& \downarrow \\
& \text{Genre} \rightarrow \text{Enjoyment} \leftarrow \text{Language}
\end{aligned}$$

Your ranking of what is likely to give you enjoyment should now be updated and made more specific, but much of the earlier ordering can be retained, that is:

$$P(\text{Enjoyment}=x | \text{Language}=y \wedge \text{Genre}=z) \geq P(\text{Enjoyment}=x | \text{Language}=y' \wedge \text{Genre}=z')$$

$$\begin{aligned}
& \text{iff} \\
& P^+(\text{Enjoyment}=x | \text{Language}=y \wedge \text{Genre}=z) \geq P^+(\text{Enjoyment}=x | \text{Language}=y' \wedge \text{Genre}=z').
\end{aligned}$$

The difference with condition (C*) is that here two propositions, not just one, are conditioned on. So (C*) should be generalized, accordingly, but the general idea remains the same.

⁶For simplicity, we assume that variables are binaries. From (EQUAL) and via this chain of equivalences:

$$[a \geq a' \& b \geq b'] \text{ iff } [ak \geq a'k \& b(1-k) \geq b'(1-k) \text{ (with } k > 0)] \text{ iff } [ak + b(1-k) \geq a'k + b'(1-k)],$$

it follows that

$$\begin{aligned}
& P(E = e | H = h) \geq P(E = e | H = h') \\
& \text{iff} \\
& P^+(E = e | H = h \wedge Y = y) \times P^+(Y = y) + P^+(E = e | H = h \wedge Y = y') \times P^+(Y = y') \\
& \geq \\
& P^+(E = e | H = h' \wedge Y = y) \times P^+(Y = y) + P^+(E = e | H = h' \wedge Y = y') \times P^+(Y = y')
\end{aligned}$$

We are done since, by the law of total probability and the probabilistic dependencies in the graph, (C*) is equivalent to the above statement.

hands reliably tracks the presence of hands:

$$P(E = \textit{as-of-hands} | H = \textit{hands}) > P(E = \textit{as-of-hands} | H = \textit{no-hands})$$

You now entertain a ‘switching hypothesis’: when you see a hand, there is no hand, and when you do not see a hand, there is a hand. In this case, (EQUAL) would be violated since

$$P^+(E = \textit{as-of-hands} | H = \textit{hands} \wedge Y = \textit{switching}) < P^+(E = \textit{as-of-hands} | H = \textit{no-hands} \wedge Y = \textit{switching})$$

No matter how weak a formal constraint might be, there is likely a counterexample.

To be sure, formal constraints such as (EQUAL) and (C^*) are still appropriate in a large class of cases. They are appropriate in ordinary scenarios of upstream refinement that do not involve switching hypotheses, LIGHTING and MOVIES being two examples. Arguably, they are appropriate in most skeptical scenarios. For what skeptical scenarios often do is to suggest that the evidence might have null value, not so much switching its value. But, ultimately, it is the structural and subject-matter features of a specific scenario that justify one formal requirement or another, like Reverse Bayesianism, Awareness Rigidity or constraints such as (EQUAL) and (C^*). Thus, the primary theoretical task for a theory of awareness growth is to identify these structural features, not churning out formal constraints.

6 Conclusion

We argued that Steele and Stefánsson’s case against Reverse Bayesianism is weaker than it might seem at first. The scenario MOVIES—which is their key counterexample—is unconvincing since it mixes learning and refinement. To avoid this, we constructed a more clear-cut case of refinement, LIGHTING, in which both Awareness Rigidity and Reverse Bayesianism fail unequivocally. At the same time, we showed that there are cases of downstream refinement like VERACITY in which Reverse Bayesianism and Awareness Rigidity are perfectly fine in their place. In cases of upstream refinement, like LIGHTING, one can be tempted to formulate a weaker formal constraint that would still vindicate the formalistic aspiration of Reverse Bayesianism. But no matter the constraint, there are likely to be counterexamples to it.

We conclude with a general moral. We think that the awareness of agents grows while holding fixed certain material structural assumptions, based on commonsense, semantic stipulations or causal dependency. To model awareness growth, we need a formalism that can express these material structural assumptions. This can be done using Bayesian networks, and we offered some illustrations of this strategy, for example, by distinguishing two forms of refinement on the basis of different structural assumptions. These material assumptions also guide us in formulating the adequate conservative constraints, and these will inevitably vary on a case-by-case basis. Our approach stands in stark contrast with much of the literature on awareness growth from a Bayesian perspective. This literature is primarily concerned with a formal, almost algorithmic solution to the problem. We suspect that seeking such formal solution is doomed to fail. Insofar as Reverse Bayesianism is an expression of this formalistic aspiration, we agree with Steele and Stefánsson that we are better off looking elsewhere.