Conditionalisation Revisited

LoPSE seminars

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Consequences of Conditionalisation

Conditionalisation

Diachronic Conditionalisation: Let $\mathcal{B}$ be a set of propositions that includes possible evidence. Let c_t be your current credence on $\mathcal{B}$. Let $\mathcal{E} = \{E_1, \ldots, E_n\}$ be the partition of evidence that you can learn between t and some later moment $t+1$. Let c_{t+1} be your credence after learning $E_i \in \mathcal{E}$. The conditionalisation rule says that:

$$c_{t+1}(-) = c_t(-|E_i) = \frac{c_t(-\&E_i)}{c_t(E_i)}, \tag{1}$$

where $c_{t+1}(-)$ is of course defined only for $c_t(E_1) > 0$.

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1. When you learn new evidence, one consequence of conditionalisation is that you learn it with certainty.

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   2.3 Stake is determined by the bookie.

Conditionalisation Retains Certainties

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2. **Different perspective**: Once you rule out some possible worlds by learning, they remain ruled out forever as long as you conditionalise.

Forgetting Your Evidence

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2. information that is time or agent dependent
   2.1 I am sure that the proposition that today is Thursday is true. But in 24 hours, I will not be sure any more that the proposition that today is Thursday is true.

Memory Loss - Talbott's Spaghetti dinner

If we assume that I had spaghetti for dinner one year ago (on March 15, 1989), then where t_1 is 6:30pm on March 15, 1989; t_2 is 6:30pm on March 15, 1990; and S is the proposition that Talbott had spaghetti for dinner on March 15, 1989...if I am assumed to satisfy Temporal Conditionalization at every time from t_1 to t_2, it must be the case that I be as certain of S at t_2 as I was at t_1 ... But, in fact (and I knew this at t_1), if at t_2 I am asked how probable it is that I had spaghetti for dinner on March 15, 1989, the best I can do is to calculate a probability based on the relative frequency of spaghetti dinners in my diet one year ago.

Talbott, W.J. Two Principles of Bayesian Epistemology, *Philosophical Studies*, 62, 1991, p. 135–150.

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1. Talbott's point is that remaining certain of the truth of the proposition S (that he had spaghetti for dinner one year ago (on March 15, 1989)) is a requirement of rationality.
2. Defender's of conditionalisation may say that such norms are meant for ideally rational agents. Ideally rational agents do not forget (it is debatable).
3. But there is another example show that we need more than just an assumption that ideally rational agents do not forget.

Memory Loss - Two Paths to Shangri La

There are two paths to Shangri La, the Path by the Mountains, and the Path by the Sea. A fair coin will be tossed by the guardians to determine which path you will take: if heads you go by the Mountains, if tails you go by the Sea. If you go by the Mountains, nothing strange will happen: while traveling you will see the glorious Mountains, and even after you enter Shangri La, you will forever maintain your memories of that Magnificent Journey. If you go by the Sea, you will revel in the Beauty of the Misty Ocean. But, just as you enter Shangri La, your memory of this Beauteous Journey will be erased and be replaced by a memory of the Journey by the Mountains.

Arntzenius, F. Some Problems for Conditionalization and Reflection, *The Journal of Philosophy*, 100(7), 2003, p. 356–370.

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   1.4 You know you would possess those memories whichever path you travelled, so you take them as no evidence about the outcome of the coin and, presumably, assign credence $1/2$ to H

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   - 2.1 You violate conditionalisation only when you merely suspect you may have forgotten something.
   - 2.2 It might be irrational to forget something.
   - 2.3 But is it irrational to assign credence bigger than 0 to the contingent possibility that one forgot something at some point in the past?

Slippery Evidence

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7. Possible worlds, as we have discussed them so far, are too coarse-grained descriptions to give us answer.
8. We need to introduce more fine-grained entities than classical possible worlds.

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4. **Centred propositions** such as ‘it is 1pm now’ can be represented as sets of centred possible worlds.
5. We can call classical possible worlds **uncentred worlds** and propositions represented by sets of uncentred possible worlds as **uncentred porpositions**.

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5. Conditionalisation presupposes that an agent’s evidence may change, but the truth-values of the target propositions remain fixed.
6. Yet centred propositions present the agent with moving targets; as she gains (or loses) information, their truth-values may change as well.

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        1.3.1 Take a particular uncentered world (call it u). Consider all the centres associated with that world you entertained as live possibilities at t_i. Assign credence 0 to any centred world incompatible with E. Then take the credence assigned to u in Step 1 above, and distribute it among the remaining centred worlds associated with that uncentred world.

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2. **Notice:** The second step is underspecified. It does not say how we should distribute credences among the centred worlds.

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Example - Titlebaum p. 380

At t_1, you have no idea what time it is. You are wearing a watch that you are 60% confident is running reliably. The rest of your credence is divided equally between the possibility that the watch is entirely stopped, and the possibility that it is running but is off by an exactly an hour (perhaps due to daylight savings). You then glance at your watch, notice that it is running (the second hand is moving), and that it currently reads 1pm.

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Example Comtinued - Titlebaum p. 380

stopped	initial c	running and shows 1pm – step 1
stopped	0.2	0
reliable	0.6	0.75
1 hour off	0.2	0.25

How Do We Update on Centred Propositions?

Example Comtinued - Titlebaum p. 380

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   Take for example w_1: $(w_1, 12pm)$, $(w_1, 1pm)$, $(w_1, 2pm)$.

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   2.2 $c(w_2, 12pm) = 0$, $c(w_2, 1pm) = 0.75$, $c(w_1, 2pm) = 0$.
   2.3 $c(w_2, 12pm) = 0 - 0.25$, $c(w_2, 1pm) = 0$, $c(w_1, 2pm) = 0 - 0.25$

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> **Regularity Principle:** In a rational credence distribution, no logically contingent proposition receives unconditional credence 0.

1. Regularity Principle captures the common-sense idea that one's evidence is never so strong as to entirely rule out any logical possibility (a logically contingent proposition).

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3. **Notice:** Regularity is not entailed by the probability axioms.

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   3.1 Can we defend Conditionalisation somehow?
   3.2 We can, for example, use foundationalist epistemologies – e.g. sense data and phenomenal experiences are certain.

Jeffrey Conditionalisation

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3. But we seem to gain evidence between two times that is not certain (or should not be certain if you agree with the Regularity Principle).
4. What do we do then?

Jeffrey Conditionalisation

Jeffrey Conditionalisation Given any t_i and t_j with $i < j$, any X in $\mathcal{L}$, and a finite partition $B_1, B_2, \ldots, B_n$ in $\mathcal{L}$ whose elements each have non-zero cr_i,

$$cr_j(X) = cr_i(X|B_1) \times cr_j(B_1) + \cdots + cr_i(X|B_n) \times cr_j(B_n) \quad (2)$$

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Suppose that you learn B_1 with certainty from the finite partition $B_1, B_2, \ldots, B_n$.

$$\begin{aligned} cr_j(X) &= cr_i(X|B_1) \times 1 + \cdots + cr_i(X|B_n) \times 0 \\ &= cr_i(X|B_1) \end{aligned} \quad (3)$$

Classical Example

Example

The agent inspects a piece of cloth by candlelight, and gets the impression that it is green, although he concedes that it might be blue or even (but very improbably) violet. If G, B, and V are the propositions that the cloth is green, blue, and violet, respectively, then the outcome of the observation might be that, whereas originally his degrees of belief in G, B, and V were 0.3, 0.3, and 0.4, his degrees of belief in those same propositions after the observation are 0.7, 0.25, and 0.5.

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The worry is that even if we grant the existence of a sense datum for each potential learning experience, the quality of that sense datum might not be representable in a proposition to which the agent could assign certainty

Concrete Example – Titlebaum p. 160

Example Continued

Suppose that:

$c_1(G) = 0.3 \qquad c_1(B) = 0.3 \qquad c_1(V) = 0.4$

and

$c_1(mine|G) = 0.8 \qquad c_1(mine|B) = 0.5 \qquad c_1(mine|V) = 0$

and

$c_2(G) = 0.7 \qquad c_2(B) = 0.25 \qquad c_2(V) = 0.05$

so by Jeffrey conditionalisation

$$\begin{aligned} c_2(mine) &= c_1(mine|G)c_2(G) + c_1(mine|B)c_2(B) + c_1(mine|V)c_2(V) \\ &= 0.80 * 0.70 + 0.50 * 0.25 + 0 * 0.05 \\ &= 0.685 \end{aligned} \tag{4}$$

Concrete Example – Titlebaum p. 160

Example Continued

$$c_2(mine) = c_1(mine|G)c_2(G) + c_1(mine|B)c_2(B) + c_1(A|V)c_2(V) \quad (5)$$

Use the Law of Total probability on $cr_2(mine)$

$$c_2(mine) = c_2(mine|G)c_2(G) + c_2(mine|B)c_2(B) + cr_2(A|V)c_2(V) \quad (6)$$

It must be the case that

$$c_1(mine|G) = c_2(mine|G), c_1(mine|B) = c_2(mine|B) \dots \quad (7)$$

Rigidity

Rigidity: For any A in $\mathcal{L}$ and any B_m in $B_1, B_2, \ldots, B_n$

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Jeffrey Conditionalisation using a particular partition $B_1, B_2, \ldots, B_n$ is appropriate only when the agent's credences conditional on the B_m remain constant across two times.

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2. Jeffrey Conditionalisation is **not commutative**. It matters in which order we learn evidence (classical conditionalisation is commutative).

Caveat: Bayes' Theorem

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> **Bayes' Theorem:** $c(H|E) = \frac{c(E|H) * c(H)}{c(E)}$ for $c(E) \neq 0$.

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Non-Commutativity of Jeffrey Conditionalisation

Raven Example

Suppose I see a bird at twilight, and I clearly identify it to be a raven. Because of the difficulty in identifying the bird's color in the gloom, I do not observe that e – "The bird is black" – but the effect of my experience is to raise my confidence in e from 0.75 to 0.99. If h is "All ravens are black" and my background beliefs include that the bird is a raven.

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$c_{new}(h) = c_{old}(h|e) * c_{new}(e) + c_{old}(h|\neg e) * c_{new}(\neg e)$.

Non-Commutativity of Jeffrey Conditionalisation

1. Suppose that I take a second glance on a bird. I am more confident now, and so my credence in e is now 0.99. So my $c_{new}(e) = 0.99$, $c_{old}(e) = 0.8$, $c_{old}(\neg e) = 0.2$, and $c_{old}(h) \approx 0.747$.

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   1.3 Since $c_{old}(h) \approx 0.747$,
   $c_{old}(h|e) = \frac{c_{old}(e|h) * c_{old}(h)}{c_{old}(e)} = \frac{1 * 0.747}{0.8} \approx 0.933$.

   1.4 Also, $c_{old}(h|\neg e) = \frac{c_{old}(\neg e|h) * c_{old}(h)}{c_{old}(\neg e)} = \frac{0 * 0.747}{0.2} = 0$.

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1.5 $c_{new}(h) = 0.933 * 0.99 + 0 * 0.01 \approx 0.924$

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2. **Notice:** In this example, the result of successive applications of Jeffrey conditionalization firstly to $c(e) = 0.99$ and then $c(e) = 0.8$ is indeed the same as the result of applying Jeffrey conditionalization once first to $c(e) = 0.8$, as if the 0.99 experience had never occurred (this does not happen always).

Slippery Evidence – Problem for Jeffrey Conditionalisation

Raven Example – modified Titlebaum p. 378

0.1 I look out of a window. I see drops of water on my window. Experience directly influences my credences over the partition containing the centred propositions 1.) it's raining now and 2.) it's not raining now (maybe my neighbour is just watering his flowers.) I want to set my unconditional credence in the proposition S that it rains on (a specific) Sunday.

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0.2 Suppose that $e(\neg e)$ stands for 'it's (not) raining now'. By Jeffrey conditionalisation:

$$c_{new}(S) = c_{old}(S|e) * c_{new}(e) + c_{old}(S|\neg e) * c_{new}(\neg e) \quad (9)$$

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0.3 Whatever $c_{new}(e)$ and $c_{new}(\neg e)$ are, by the Bayes' Theorem:

$$c_{old}(S|e) = \frac{c_{old}(e|S) * c_{old}(S)}{c_{old}(e)} \tag{10}$$

The value of $c_{old}(S|e)$ has to remain the same (by rigidity).

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   1.1 Suppose 'now' means Sunday. Further, suppose that my initial credence in S (before the experience) is 0.5, the experience raised my credence in e from 0.6 to 0.8, and $1 > c_{old}(e|S) > 0$, then:

$$c_{old}(S|e) = \frac{c_{old}(e|S) * c_{old}(S)}{c_{old}(e)} = \frac{c_{old}(e|S) * 0.5}{0.6}, \qquad (11)$$

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   so $1 > c_{old}(S|e) > 0$.

   1.2 Suppose 'now' means Monday. On Monday you know whether it rained on that specific Sunday, so $c_{old}(S|e) = 1$ if it rained and $c_{old}(S|e) = 0$ if ir did not rain.

Thank you!