Material Conditionals in Probabilistic Learning Scenarios

Borut Trpin

We learn some information from indicative conditionals. However, standard probabilistic updating procedures seem unsatisfactory to model dynamics of these cases. The alternative option (AO) is to model probabilities of indicative conditionals as conditional probabilities, i.e. $P(a \rightarrow b) = P(b|a)$, and setting $P(b|a)=1$ or at least close to 1 in learning scenarios. This again raises a number of questions - e.g. why is learning from conditionals an exception and how to model learning from nested conditionals?

Somewhat surprisingly, material conditionals (MC) provide a viable option here because of the formal property that if and only if $P(b|a)=1$, then $P(a \supset b) = P(b|a)$, where $\supset$ denotes a material implication. This suggests that if AO is correct, then when one learns an indicative conditional, she learns a MC.

Modelling learning from conditionals as learning MC turns out to be successful with the following assumptions: (1) A conditional may convey implicit information, which needs to be made explicit during the analysis. The situation then (2) needs to be properly represented in a causal Bayes net. After taking (1 & 2) in consideration, standard Bayesian updating on a material conditional proceeds.

But this view also has some drawbacks as empirical data suggests that even in learning scenarios participants do not interpret conditionals as material conditionals. One of the questions I would like to address is, therefore, where the gap between the theoretical predictions and actual reasoning comes from.