#### Lecture 12

Philosophy 109

Caley Howland

November 1, 2019

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• Last time, we ended up with proposal 3 to characterize inductive strength.

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- Last time, we ended up with proposal 3 to characterize inductive strength.
  - ▶ Proposal #3 "P∴C" is strong just in case (1) the probability of  $\sim C$  given that P is low, and (2) P is positively relevant to C—i.e., the probability of  $\sim C$  given that P is lower than the probability of  $\sim C$ .

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- The third proposal adds a positive relevance requirement.
- If we return to our card example, we can see how relevance works.
- The probability that c is a not a spade, given that c is black is 1/2. That is, the probability that  $\sim C$ , given that P is 1/2.
- This is not low (i.e., it is not less than 1/2). But, it is *lower* than the probability that c is not a spade (i.e., the probability of  $\sim C$ ), which is 3/4.

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- So, in this case, P is positively relevant to C
  - ► The probability of C given that  $P = \frac{1}{2}$ , which is greater than the probability of  $C = \frac{1}{4}$ .

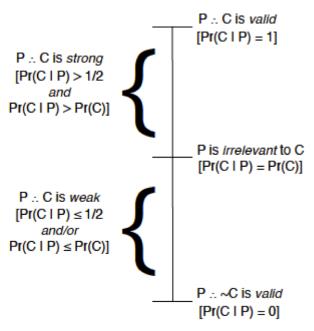
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- Thus, the argument "P ∴ C" does not come out strong on proposal #3 (because it fails the low conditional probability requirement). But this argument does satisfy the positive relevance requirement.

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- So, in this case, P is positively relevant to C
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- Thus, the argument "P ∴ C" does not come out strong on proposal #3 (because it fails the low conditional probability requirement). But this argument does satisfy the positive relevance requirement.
- With proposal #3 in hand, we can now explain how our "scale" of argument strength works.
  - ► It depends on Pr(C|P) and Pr(C|P) > Pr(C).

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# Monotonicity

- A crucial difference between validity vs strength is that deductive validity is monotonic, but inductive strength is non-monotonic.
- If an argument is valid, then it cannot be rendered invalid merely by adding additional premises to it. Let's think about why this is true.

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• On the other hand, an inductively strong argument can be rendered inductively weak merely by adding premises to it. Example, (A):

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     (C) If I walk out onto Lake Mendota, I will not get wet.

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- But consider A':
  - (P) It is January.
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- But consider A':
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    - ∴ (C) If I walk out onto Lake Mendota, I will not get wet.
- $\mathcal{A}'$  is weak. So adding a new premise—Premise (Q)—made it weak.

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  - (S) John rolls cigars for a living.

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  - (R) John has yellow stains on his fingers and smells like tobacco.
  - (S) John rolls cigars for a living.
- And so on. . . This non-monotonicity of inductive strength is a key feature. Diagramming can help explain why this can happen.

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## Numerical Probability

- So far, we have usually been relying on intuitions about the "inductive probabilities" in various examples.
  - Sometimes, we've discussed games of chance for which there are clear, numerical (inductive) probabilities.

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## Numerical Probability

- So far, we have usually been relying on intuitions about the "inductive probabilities" in various examples.
  - Sometimes, we've discussed games of chance for which there are clear, numerical (inductive) probabilities.
- But, we haven't seen a precise, general way to think about (or calculate) numerical probabilities of LSL sentences.
   This is our current topic.

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 It turns out that numerical probabilities can be understood (and calculated) using a simple numerical generalization
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- I will call these Probabilistic Truth Tables (or sometimes "Stochastic Truth Tables").
- A probabilistic truth-table is just a truth-table with an additional column. That column gives the inductive probabilities of each of the possible worlds (i.e., the inductive probabilities of each of the rows).

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- I will call these Probabilistic Truth Tables (or sometimes "Stochastic Truth Tables").
- A probabilistic truth-table is just a truth-table with an additional column. That column gives the inductive probabilities of each of the possible worlds (i.e., the inductive probabilities of each of the rows).
- It helps to start with a simple example (involving a game of chance).

- Let's start with our example of drawing a single card (c) at random from a standard deck of playing cards. There are various properties that our card might have. Here are two examples (as atomic LSL sentences).
  - H = c is a heart. R = c is a red card.

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#### Probabilistic Truth Table

• A **probabilistic truth-table** (involving *H* and *R*) will look like this.

World $(w_i)$	Н	R	$Pr(w_i)$	
$w_1$	Т	Т	1/4	[= Pr(H&R)]
$w_2$	Т	F	0	$[= Pr(H\& \sim R)]$
<i>w</i> <sub>3</sub>	F	Т	1/4	$[= Pr(\sim H\&R)]$
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- The column on the left names the interpretations, the worlds, but they are just determined by the guide columns like usual.
- The new right hand column assigns probabilities to these worlds.

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- Here, we are "assigning" probabilities to sentences in our language.
- Probability assignments are expressed by probability functions:  $Pr(\cdot) = n$

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- Real numbers include Naturals, Rationals, and Irrationals.
- Real numbers are uncountably infinite.
- We will generally round things so as not to deal with irrationals.

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  - Finite Additivity: for any mutually exclusive propositions p or q,  $Pr(p \lor q) = Pr(p) + Pr(q)$ .

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  - Outcomes of chance structures: dice.
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  - Objective Chances (e.g., from physics)
  - Degrees of belief: credences
- This last idea, that probability functions describe beliefs, is called "personalism", and is part of what's called Bayesianism

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  - In other words, we will stay pretty neutral.
- However, in the background think about probabilities as degrees of belief strength; we will come back to that.
- Plus, that is how to read Titelbaum: Titelbaum uses  $cr(\cdot)$  to make it explicit that is the kind of probability he is interested in.

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- An inductive probability assignment is just as assignment of world probabilities. (These are technically a kind of distribution.)
  - Numbers between 0 and 1 that sum to 1.
- Once we have world probabilities assigned (involving some atomic sentences), we can then calculate the probability of any LSL statement (involving those atomic sentences). In fact, the calculation is easy.
- The probability of an LSL sentence s is just the sum of the world probabilities of the possible worlds in which s is true.

## Probabilistic Truth Table

• Remember ou **probabilistic truth-table** (involving *H* and *R*).

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- Each possible world  $w_i$  has a definite, numerical probability.
- Once these world probabilities are given, all other probabilities can be calculated.

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- Well, which possible worlds are worlds in which  $H \rightarrow R$  is true?
- The only world in which  $H \to R$  is false is  $w_2$ . So, the probability of  $H \to R$  is just the sum of the world probabilities for  $w_1$ ,  $w_3$ , and  $w_4$ .

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- Therefore,  $Pr(H \to R) = \frac{1}{4} + \frac{1}{4} + \frac{1}{2} = 1$ .

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- Therefore,  $Pr(H \to R) = \frac{1}{4} + \frac{1}{4} + \frac{1}{2} = 1$ .
  - ► This makes sense, since all hearts are red cards. Thus, we can be certain that  $H \rightarrow R$  is true.

• What is  $Pr(R \rightarrow H)$ ?

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- The only world in which  $R \to H$  is false is  $w_3$ .
- So,  $Pr(R \to H) = \frac{1}{4} + 0 + \frac{1}{2} = \frac{3}{4}$ .

 Caley Howland
 Lecture 12
 11/1/19
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- So,  $Pr(R \to H) = \frac{1}{4} + 0 + \frac{1}{2} = \frac{3}{4}$ .
- According to Proposal 1 for inductive strength, the argument R : H is going to come out strong, since  $Pr(R \to H) = 3/4$ , which is high.

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