Phil/LPS 31 Introduction to Inductive Logic Lecture 16

David Mwakima dmwakima@uci.edu Department of Logic and Philosophy of Science University of California, Irvine

June 2nd 2023

- ► Interpretations of Probability
 - ► Frequentist Interpretation of Probability

▶ At the beginning of the quarter we considered sentential logic as a formal system for representing the sentential structure of a natural language.

- At the beginning of the quarter we considered sentential logic as a formal system for representing the sentential structure of a natural language.
- ▶ In doing so we introduced formal symbols like p, q, r, s, t, \neg , \lor , (,).

- At the beginning of the quarter we considered sentential logic as a formal system for representing the sentential structure of a natural language.
- ▶ In doing so we introduced formal symbols like p, q, r, s, t, \neg , \lor , (,).
- We also said that logicians distinguish between the form and content of these symbols. And we said that the content of these formal symbols is their interpretation or intended meaning.

- At the beginning of the quarter we considered sentential logic as a formal system for representing the sentential structure of a natural language.
- ▶ In doing so we introduced formal symbols like p, q, r, s, t, \neg , \lor , (,).
- We also said that logicians distinguish between the form and content of these symbols. And we said that the content of these formal symbols is their interpretation or intended meaning.
- ➤ Similarly, when we introduced quantified relational logic we added formal symbols for variables, constants and quantifiers to capture more of the structure of sentences than sentential logic could capture. Here, the interpretation of the symbols was given using a model.

► In the last 4 weeks or so, we have studied probability and its application in decision theory as an inductive logic, in a formal way too!

- In the last 4 weeks or so, we have studied probability and its application in decision theory as an inductive logic, in a formal way too!
- ▶ Here we used the formal language of set theory to describe events and the formal system given by the Kolmogorov Axioms to characterize probability functions. We said a probability function is a function which obeys the Kolmogorov axioms or rules.

- In the last 4 weeks or so, we have studied probability and its application in decision theory as an inductive logic, in a formal way too!
- Here we used the formal language of set theory to describe events and the formal system given by the Kolmogorov Axioms to characterize probability functions. We said a probability function is a function which obeys the Kolmogorov axioms or rules.
- ► The Kolmogorov Axioms (or rules) for probability functions are formal in the same way that the truth-preserving rules of deductive logic are formal.

- In the last 4 weeks or so, we have studied probability and its application in decision theory as an inductive logic, in a formal way too!
- Here we used the formal language of set theory to describe events and the formal system given by the Kolmogorov Axioms to characterize probability functions. We said a probability function is a function which obeys the Kolmogorov axioms or rules.
- ► The Kolmogorov Axioms (or rules) for probability functions are formal in the same way that the truth-preserving rules of deductive logic are formal.
- By "in the same way", I mean that both are formulated in a general way that allows the possibility of many, and different, applications or interpretations.

▶ Here's what I mean. The formal system of sentential logic can be applied or interpreted in natural languages like Swahili, English, German, Chinese, Spanish and so on. It can also be applied or interpreted in artificial languages like Python, Java, C++ and so on.

- ▶ Here's what I mean. The formal system of sentential logic can be applied or interpreted in natural languages like Swahili, English, German, Chinese, Spanish and so on. It can also be applied or interpreted in artificial languages like Python, Java, C++ and so on.
- ► The situation is similar in the case of probability functions characterized by the Kolmogorov Axioms. There are lots of applications or interpretations because there are lots of things that satisfy, faithfully represent or model the Kolmogorov Axioms.

► Here are some examples:

- Here are some examples:
 - Any non-negative normalized additive set function defined on a finite or countable set is a probability function.

- Here are some examples:
 - Any non-negative normalized additive set function defined on a finite or countable set is a probability function.
 - ► The distribution function of a random variable is a probability function.

- Here are some examples:
 - Any non-negative normalized additive set function defined on a finite or countable set is a probability function.
 - The distribution function of a random variable is a probability function.
 - ▶ On the standard formulation of Quantum Mechanics, the norm squared of the wave function gives the probability of collapse to a given state when a measurement is made.

- Here are some examples:
 - Any non-negative normalized additive set function defined on a finite or countable set is a probability function.
 - The distribution function of a random variable is a probability function.
 - On the standard formulation of Quantum Mechanics, the norm squared of the wave function gives the probability of collapse to a given state when a measurement is made.
 - ► Weather forecasters give the probability that it will rain in Southern California as less than 3%.

- Here are some examples:
 - Any non-negative normalized additive set function defined on a finite or countable set is a probability function.
 - The distribution function of a random variable is a probability function.
 - On the standard formulation of Quantum Mechanics, the norm squared of the wave function gives the probability of collapse to a given state when a measurement is made.
 - ► Weather forecasters give the probability that it will rain in Southern California as less than 3%.
 - ▶ I think the probability that Manchester City will win this weekend's derby is 50% given how well Manchester United are currently playing.

- Here are some examples:
 - Any non-negative normalized additive set function defined on a finite or countable set is a probability function.
 - The distribution function of a random variable is a probability function.
 - On the standard formulation of Quantum Mechanics, the norm squared of the wave function gives the probability of collapse to a given state when a measurement is made.
 - ► Weather forecasters give the probability that it will rain in Southern California as less than 3%.
 - ▶ I think the probability that Manchester City will win this weekend's derby is 50% given how well Manchester United are currently playing.
- What these examples have in common is that they all appear to interpret or apply probability functions in different contexts and to address different problems.

Motivation: Interpreting Probability Functions

▶ In mathematics, we study probability functions, you might say, for their own sake. (How fun!) In statistics (which is what I study), we apply probability functions to model the distribution function of our data. The data either follows that distribution or it doesn't. This is an objective fact. But do statisticians know this fact or do they just subjectively believe this to be true?

Motivation: Interpreting Probability Functions

- ▶ In mathematics, we study probability functions, you might say, for their own sake. (How fun!) In statistics (which is what I study), we apply probability functions to model the distribution function of our data. The data either follows that distribution or it doesn't. This is an objective fact. But do statisticians know this fact or do they just subjectively believe this to be true?
- In physics, probability functions are applied in Quantum Mechanics. It is an objective fact that an electron in a superposition of spin states will collapse with a certain probability to one of the spin states when a measurement is made. Are quantum probabilities objective or subjective (once a measurement is made)?

Motivation: Interpreting Probability Functions

- In mathematics, we study probability functions, you might say, for their own sake. (How fun!) In statistics (which is what I study), we apply probability functions to model the distribution function of our data. The data either follows that distribution or it doesn't. This is an objective fact. But do statisticians know this fact or do they just subjectively believe this to be true?
- ▶ In physics, probability functions are applied in Quantum Mechanics. It is an objective fact that an electron in a superposition of spin states will collapse with a certain probability to one of the spin states when a measurement is made. Are quantum probabilities objective or subjective (once a measurement is made)?
- ▶ Weather forecasters (and the Instructor) seem to be talking about their beliefs. The beliefs here can be objective (based on precise measurements of wind patterns) or subjective (the Instructor doesn't know for sure).

➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability
 - Classical

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability
 - Classical
 - Frequentist

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability
 - Classical
 - Frequentist
 - Propensity

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability
 - Classical
 - Frequentist
 - Propensity
 - Logical

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability
 - Classical
 - Frequentist
 - Propensity
 - Logical
 - Subjective Interpretations of Probability

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability
 - Classical
 - Frequentist
 - Propensity
 - Logical
 - Subjective Interpretations of Probability
 - Subjective Bayesian

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability
 - Classical
 - Frequentist
 - Propensity
 - Logical
 - Subjective Interpretations of Probability
 - Subjective Bayesian
 - "Objective" Bayesian

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability
 - Classical
 - Frequentist
 - Propensity
 - Logical
 - Subjective Interpretations of Probability
 - Subjective Bayesian
 - ▶ "Objective" Bayesian
- In this course we're only going to talk about one interpretation from each of the major interpretations, namely, the Frequentist Interpretation of Probability and the Subjective Bayesian Interpretation of Probability.

- ➤ So we may distinguish between two main interpretations of probability and within each of the main interpretations we can, as philosophers typically do, make finer distinctions:
 - Objective Interpretations of Probability
 - Classical
 - Frequentist
 - Propensity
 - Logical
 - Subjective Interpretations of Probability
 - Subjective Bayesian
 - "Objective" Bayesian
- ▶ In this course we're only going to talk about one interpretation from each of the major interpretations, namely, the Frequentist Interpretation of Probability and the Subjective Bayesian Interpretation of Probability.
- ► For each of these interpretations, I want you to know: (1) the main ideas behind it; (2) the main advantages and drawbacks; (3) how evidence is evaluated.

Aristotle (4th century B.C.) said that the probable is that which happens often.

- ► Aristotle (4th century B.C.) said that the probable is that which happens often.
- ► First elaborated with precision and in detail by the English logician John Venn in the 19th century and later by von Mises.

- Aristotle (4th century B.C.) said that the probable is that which happens often.
- ► First elaborated with precision and in detail by the English logician John Venn in the 19th century and later by von Mises.
- ▶ To say that a random experiment has a stable objective probability P(E) associated with one of its possible outcomes E is to say that it has a characteristic tendency to do so.

- ► Aristotle (4th century B.C.) said that the probable is that which happens often.
- ► First elaborated with precision and in detail by the English logician John Venn in the 19th century and later by von Mises.
- To say that a random experiment has a stable objective probability P(E) associated with one of its possible outcomes E is to say that it has a characteristic tendency to do so.
- ► The magnitude of this tendency is measured by the limiting or long-run relative frequency with which the outcome in question is actually produced.

$$P(E) = \lim_{n \to \infty} \frac{\text{Number of times E occurs in } n \text{ trials}}{n}$$

Consider an ordinary coin that is being flipped in the standard way. As it is flipped repeatedly a sequence of outcomes is generated:

$$< H, T, H, T, T, T, H, H, T, T, H, T, T, T, T, T, H, T, H, T, T, T, H, H, H, H, H, \dots >$$

Consider an ordinary coin that is being flipped in the standard way. As it is flipped repeatedly a sequence of outcomes is generated:

$$< H, T, H, T, T, T, H, H, T, T, H, T, T, T, T, T, H, T, H, T, T, T, H, H, H, H, H, \dots >$$

We can associate with this sequence of results a sequence of relative frequencies as follows:

$$<1/1, 1/2, 2/3, 2/4, 2/5, 2/6, 3/7, 4/8, 4/9, 4/10, 5/11, 5/12, 5/13, 5/14, 5/15, 6/16, 7/18, 7/19, 7/20, 7/21, 8/22, 9/23, 10/24, 11/25, \cdots >$$

Consider an ordinary coin that is being flipped in the standard way. As it is flipped repeatedly a sequence of outcomes is generated:

$$< H, T, H, T, T, T, H, H, T, T, H, T, T, T, T, T, H, T, H, T, T, T, H, H, H, H, H, \dots >$$

We can associate with this sequence of results a sequence of relative frequencies as follows:

$$<1/1, 1/2, 2/3, 2/4, 2/5, 2/6, 3/7, 4/8, 4/9, 4/10, 5/11, 5/12, 5/13, 5/14, 5/15, 6/16, 7/18, 7/19, 7/20, 7/21, 8/22, 9/23, 10/24, 11/25, \cdots >$$

▶ The frequentist interpretation involves an idealization which says that in the limit, the relative frequencies in this sequence approach 1/2.

It is objective. The half life of C^{14} atoms is 5730 years. This means that the relative frequency of spontaneous disintegration of C^{14} within 5730 years is 1/2. We can use this as an objective measure of the probability that the next sample of C^{14} will decay and for carbon dating.

- It is objective. The half life of C^{14} atoms is 5730 years. This means that the relative frequency of spontaneous disintegration of C^{14} within 5730 years is 1/2. We can use this as an objective measure of the probability that the next sample of C^{14} will decay and for carbon dating.
- ▶ It is a faithful interpretation of the Kolmogorov Axioms for probability functions. This means that it can be shown that the identification of probability with the limit of relative frequencies is consistent with the Kolmogorov Axioms. *P(E)* is whatever this limit is (if it exists).

■ "The long run is a misleading guide to current affairs. In the long run we are all dead," wrote John Maynard Keynes in his 1923 work, A Tract on Monetary Reform. Although this is not what Keynes meant, a similar point has often been made against the frequentist interpretation. The point is that the use of the limit definition invites the objection that we can never in principle, not just in practice, observe an infinite sequence.

- "The long run is a misleading guide to current affairs. In the long run we are all dead," wrote John Maynard Keynes in his 1923 work, A Tract on Monetary Reform. Although this is not what Keynes meant, a similar point has often been made against the frequentist interpretation. The point is that the use of the limit definition invites the objection that we can never in principle, not just in practice, observe an infinite sequence.
- ▶ Although the notion of a limit involves an idealization, a more serious objection is that the limiting value of the sequence of the relative frequency of *E* might not exist. We only know that in the case where the experiment can be modeled using Bernoulli random variable (a random variable that can take on 1 of 2 possible values) the limit exists because of the Strong Law of Large Numbers.

- The long run is a misleading guide to current affairs. In the long run we are all dead," wrote John Maynard Keynes in his 1923 work, *A Tract on Monetary Reform*. Although this is not what Keynes meant, a similar point has often been made against the frequentist interpretation. The point is that the use of the limit definition invites the objection that we can never in principle, not just in practice, observe an infinite sequence.
- ▶ Although the notion of a limit involves an idealization, a more serious objection is that the limiting value of the sequence of the relative frequency of *E* might not exist. We only know that in the case where the experiment can be modeled using Bernoulli random variable (a random variable that can take on 1 of 2 possible values) the limit exists because of the Strong Law of Large Numbers.
- ► The observed relative frequency in any finite sample is irrelevant to the limiting frequency. This should remind us of Hume's problem of induction.

▶ Pollsters predict outcomes of election outcomes, which are single and non-repeatable events. Similarly, we talk about the probability that it will rain tomorrow, which is also a single and non-repeatable event.

- ▶ Pollsters predict outcomes of election outcomes, which are single and non-repeatable events. Similarly, we talk about the probability that it will rain tomorrow, which is also a single and non-repeatable event.
- ▶ If, however, probability is defined as a limiting frequency where the event is repeated potentially infinite many times, then it does not seem to make any sense to talk about probabilities of single occurrences (an election, tomorrow). This problem of the single case raises a problem about the applicability of the frequency interpretation of probability.