Learning, Randomness, and Complexity

Center for Formal Epistemology, Carnegie Mellon University
October 8-9, 2022

Program

Saturday, October 8, 2022

8:30am-9:00am	Light breakfast
9:00am-9:10am	Opening Remarks by **Kevin Kelly**, Center for Formal Epistemology Director
9:10am-10:25am	**Chris Porter** (Drake University) **Learning, Randomness, and Depth**
10:25am-10:45am	Coffee break
10:45am-12:00pm	**Johanna Franklin** (Hofstra University) **Algorithmic randomness and mind changes**
12:00pm-2:00pm	Lunch break
2:00pm-3:15pm	**Gordon Belot** (University of Michigan) **That Does Not Compute: David Lewis on Credence and Chance**
3:15pm-3:30pm	Coffee break
3:30pm-4:45pm	**Francesca Zaffora Blando** (Carnegie Mellon University) **Learning and Chances for Computable Bayesian Agents**

Sunday, October 9, 2022

8:30am-9:00am	Light breakfast
9:00am-10:15am	**Simon Huttegger** (University of California, Irvine) **Superconditioning**
10:15am-10:45am	Coffee break
10:45am-12:00pm	**Kevin Kelly** (Carnegie Mellon University) **Random Sampling, Topological Complexity, and Learnability**

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Abstracts

Chris Porter (Drake University)

Title: Learning, Randomness, and Depth

Abstract: In "General Random Sequences and Learnable Sequences," published in the Journal of Symbolic Logic in 1977, C.P. Schnorr and P. Fuchs provide several characterizations of a certain type of sequential learning in terms of notions of algorithmic randomness. Unlike more recent randomness-theoretic notions of learning, i.e., those found in the work of Osherson and Weinstein and Zaffora Blando, which characterize learnability as a type of non-randomness, on the account by Schnorr and Fuchs, learnability is coextensive with a general notion of randomness, namely randomness with respect to some computable probability measure.

In light of these two orthogonal approaches to learnability, as well as the seemingly counterintuitive identification of learnability with a general notion of randomness, one may be drawn to the conclusion that Schnorr and Fuchs mistakenly characterize their work in terms of learnability. My aim for the talk is to argue that the results of Schnorr and Fuchs do, in fact, track an interesting learning-theoretic notion, that of a sequence being fathomable (in a sense I will lay out). Moreover, drawing on recent joint work with Laurent Bienvenu, I will highlight the relationship between the work of Schnorr and Fuchs and work on logical depth, a notion developed by Charles Bennett as a measure of useful information. Combining the Schnorr-Fuchs perspective on learnability with results on logical depth provides a characterization of logical deep sequences as unfathomable.

Johanna Franklin (Hofstra University)

Title: Algorithmic randomness and mind changes

Abstract: The most frequently encountered definitions of algorithmic randomness are based on tests, martingales, or variants of Kolmogorov complexity that are inherently computably enumerable and are thus defined using only positive information. I will discuss difference randomness, which is defined using tests in which elements may enter a test component and then be removed, and which thus allow the use of both positive information and a certain amount of negative information. I will further present some ways in which difference randomness is intrinsically connected to several notions of computational strength.

Gordon Belot (University of Michigan)

Title: That Does Not Compute: David Lewis on Credence and Chance

Abstract: Following Lewis, many philosophers hold reductionist accounts of chance (on which claims about chance are to be understood as claims that certain patterns of events are instantiated) and maintain that rationality requires that credence should defer to chance (in the sense that one's credence in an event, conditional on the chance of that event being x, should be x). It is a shortcoming of an account of chance if it implies that this norm of rationality is unsatisfiable by computable agents. Here it is shown, using considerations from the theories of inductive learning and of algorithmic randomness, that this shortcoming is more common than one might have hoped.

Francesca Zaffora Blando (Carnegie Mellon University)

Title: Learning and Chances for Computable Bayesian Agents

Abstract: I will discuss two themes that are central to Bayesian epistemology—learning and chances—from the perspective of computable Bayesian agents. First, I will show that the randomness notions studied within the field of algorithmic randomness can be used to elucidate two fundamental aspects of Bayesian learning: convergence to the truth and merging of opinions. I will provide an overview of a number of results (most of which are joint with Simon Huttegger and Sean Walsh) which reveal that algorithmic randomness is conducive to learning for computable Bayesian agents. I will conclude with a few remarks on Bayesian conceptions of chance for computable agents.

Simon Huttegger (University of California, Irvine)

Title: Superconditioning

Abstract: When can a shift from a prior to a posterior be represented by conditionalization? A well-known result, known as "superconditioning" and going back to work by Diaconis and Zabell (Updating Subjective Probability, 1982), provides a sharp answer. I will extend this result in a number of directions and discuss its significance for a number of topics of philosophical interest. In particular, I'm going to consider shifts from a prior to a set of posteriors, shifts from a prior to multiple sets of posteriors, and shifts that involve some kind of conceptual change in the underlying probability space.

Kevin Kelly (Carnegie Mellon University)

Title: Random Sampling, Topological Complexity, and Learnability (joint work with Konstantin Genin, University of Tübingen)

Abstract: One of the most important and elegant insights of formal learning theory is that empirical information determines an information topology on possibilities and that the topological complexity of the answers to a question determine the best sense in which its answer can be learned: e.g., the verifiable hypotheses are exactly the open propositions in the information topology, the refutable propositions are the closed propositions, the hypotheses that can be verified in the limit are countable unions of locally closed hypotheses, etc. But that basic insight holds in a purely propositional setting in which one receives propositional information about the world. In statistical inference, one receives information only about a randomly drawn sample. Genin (2017, 2018) lifted the insight to statistical inference by showing, in a very general measure-theoretic setting, that a range of potential concepts of statistical verifiability all generate the same topology on statistical possibilities, which may (robustly) be called the information topology of statistical inference. However, his result is restricted (loosely speaking) to contexts in which all probability measures are continuous or all probability measures are discrete. That raises a question about the true statistical generality of the learning theoretic insight. In this talk, I explain how to drop Genin's restriction entirely, to obtain a fully general topological characterization of statistical verifiability in arbitrary IID sampling contexts. The generalization is based upon a minor sharpening of Genin's fundamental observations concerning inductive errors that can arise when one attempts to implement a quantitatively precise statistical inference method by means of sample information of finite precision.