# The Reasoner

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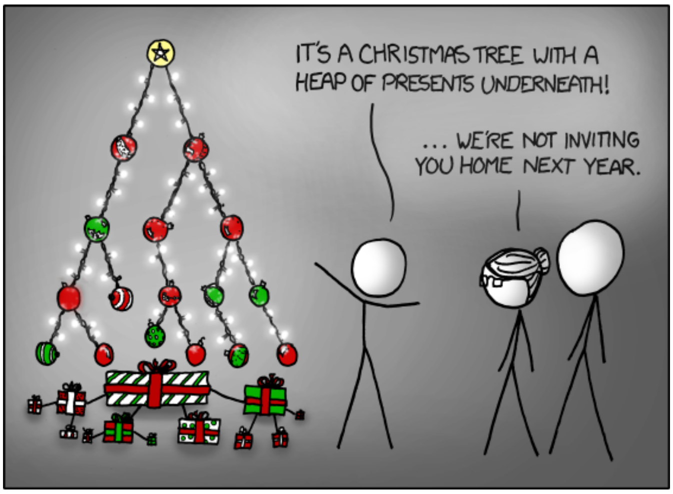
## Contents



## Editorial

Dear Readers, we're close to a well deserved break, but of course reasoning never sleeps! It is my great pleasure to introduce you to my interview with Juergen Landes. A mathematician who doesn't mind at all spanning philosophical foundations and practical applications of inductive logic, Juergen touches on a number of topics of interest to the reasoning community, and to the wider community of researchers. Many thanks to

Juergen for sharing his thoughts and Seasonal Greetings to all Reasoners!




Hykel Hosni
University of Milan

## Features

### Interview with Juergen Landes

**Hykel Hosni :** Can you tell us about your background and how you eventually got interested in Reasoning?

**Juergen Landes:** As a kid, my dream was to become a researcher making discoveries. And since the corporate world isn't much interested in discoveries for the sake of discovery, it was clear to me that I had to attend a university. I read popular science books on the universe and Grand Unification Theory (which aims to provide a theory which unifies all physical forces), Scientific American and Physik in unserer Zeit. Eventually, I enrolled in my home town (Frankfurt) with two majors in the subjects which interested me most in school: maths and physics.

I soon dropped physics for two reasons: i) I liked theoretical physics much more than experimental physics but hated the idea that a great theory I might invent could be refuted by Nature. No such thing happens to mathematical theories. ii) Continuing to study physics would have entailed conducting classical experiments in the afternoons on instruments designed for students to conduct exactly these experiments, making error calculations and writing reports. This was wasting my time, I felt. So, I decided to become a mathematician instead.

My main interests were in the most fundamental questions there are in maths, so I specialised in logic. I thus moved to Freiburg, where I wrote my Diploma Thesis (which roughly means a combined bachelor and master thesis in today's terms) in Parametrized Complexity Theory. This theory aims to provide answers to the question: How long does it take an algorithm to solve instances of a class of problems? For example: given a finite list of integers, what is the maximum run time of an algorithm $A$ to correctly order the numbers by size?

After completing my studies, I wanted to do a PhD in logic. Without a possibility to continue in Freiburg, I entered a crowded job market. After a frustratingly long time, I finally received an offer from Jeff Paris in Manchester to work on uncertain reasoning which I gladly accepted. That is how I, finally, became interested in reasoning proper. I guess, we are just not born with innate interest in reasoning. What a shame!

**HH:** What was your PhD thesis on?

**JL:** I worked on the Principle of Spectrum Exchangeability in polyadic Pure Inductive Logic.

Let me explain. Pure Inductive Logic "is the study of rational probability treated as a branch of mathematical logic" (2015, Pure Inductive Logic, Paris, Jeff B. & Vencovská, Alena, CUP). Inductive Logic proper originates with Rudolf Carnap and his famous Continuum of Inductive Methods. It starts out as an exercise in explicating common sense uncertain reasoning: it is a formal approach to capture how rational agents reason in the face of uncertainty. Technically, the goal is to assign probabilities to sentences of a logical language. The probabilities are interpreted as the agent's degree of belief in the sentences being true.

The main methodology for assigning probabilities is to investigate principles (axioms) which aim to capture (parts of) human rationality. These axioms put down constraints on the probabilities one may assign. With axioms and a formal language in place the formal mathematical analysis, motivated by philosophical and practical considerations, can be brought to bear.

Typically, one aims to show that all probability functions satisfying a set of axioms can be represented as integrals over particularly simple probability functions. Such results are known as de Finetti-style representation theorems, first proved for exchangeable sequences (1974, Theory of Probability, Bruno de Finetti, Wiley). Such a representation theorem not only gives one a better view of all probability functions consistent with a set of axioms, it also often allows for much simpler proofs: first, one shows that every simple probability function in the representation theorem has property $P$, then one shows that any convex combination of simple functions with property $P$ also possesses property $P$; hence, the axioms entail $P$ .*QED*

Before I started to work on Pure Inductive Logic, most work was on first order languages with unary relation symbols without equality and function symbols. At first, I investigated an axiom of exchangeability (Spectrum Exchangeability) on first order languages with relation symbols of arbitrary arity and without equality and function symbols. I later added the equality symbol to the language which brought to light interesting connections to the principle of Language Invariance (2011, A survey of some recent results on Spectrum Exchangeability in Polyadic Inductive Logic Landes, Jürgen and Paris, Jeff B. and Vencovská, Alena, Synthese, 19-47). This highly intuitive principle requires that inferences about a particular matter at hand ought not to change, if the underlying language is enriched by further (relation) symbols about which we have zero information.

The Manchester group has continued to work on polyadic languages (e.g., PhD Theses by Elizabeth Howarth and Tahel Ronel and (Paris & Vencovská, 2015, Pure Inductive Logic, CUP)).

**HH:** And then?

**JL:** Since leaving Manchester in 2009, I've been a postdoc on four different projects working on uncertain reasoning in varying contexts.

My first day in regular employment happened to be my 30th birthday. My role was to support the Life Cycle Analysis (LCA) of micro algae producing methane by modelling multi-criterial decision making under uncertainty. LCA aims to list and assess the environmental impacts that goods and services produce. Unfortunately, the PI of the project was diagnosed with cancer half-way through this one-year project – he's made a full recovery. This left me as the only formal person in a lab of actual scientists getting their hands dirty with methanisation processes. By now, these methanisation processes have made their way into the real world, you may find them in biogas installations at farms near you.

For the second postdoc I moved to Munich, where I worked on designing automated contract negotiations in temporary employment agencies via multi-agent systems.

My third postdoc was with Jon Williamson in Kent (you might know him as founder of The Reasoner), who happens to be a former student of Jeff Paris. While this job was back on familiar formal grounds, it was my first job in philosophy. We worked on uncertain reasoning in the objective Bayesian approach. Roughly, this approach works as follows: one first determines the set of probability functions ($\mathbb{E}$) consistent with the evidence. On first pass, one may think it's reasonable to adopt any function in $\mathbb{E}$. However, this approach requires one to pick the function in $\mathbb{E}$ which has greatest entropy (, if there is a unique such function). We showed how to justify this approach axiomatically (2013, Objective Bayesianism and the maximum entropy principle, Jürgen Landes and Jon Williamson, Entropy, 3528-3591) [my most cited paper] and (2015, Justifying objective Bayesianism on predicate languages, 17(4), 2459-2543).

**HH:** Do you think then that MaxEnt is the best justified principle of uncertain reasoning?

**JL:** While this maximum entropy approach is language invariant, if relation symbols are added one has zero information about. It *fails* to be language invariant, if we add formal expressions for chances to the language. It fails, what we call, Chance Invariance. Under this construal of invariant inferences: it is the Centre of Mass approach, which simply picks out the centre of mass of the acceptable probability functions, which satisfies Chance Invariance. Against all hope, I think this peculiar finding should get more press (2017, Invariant Equivocation, Jürgen Landes and George Masterton, Erkenntnis, 141-167).

I've just completed my fourth postdoc. On this project, we aimed to assign a probability to the causal claim that a drug causes a particular adverse drug reaction. While there are many approaches marrying probabilities and causation, we used the Bayesian network machinery to "merely" assign a probability to one causal hypothesis (2018, Epistemology of Causal Inference in Pharmacology, Jürgen Landes, Barbara Osimani Roland Poellinger, European Journal for Philosophy of Science, 3-49). I've been much interested in the confirmatory value of varied evidence to the causal hypothesis in this framework (2019, Variety of Evidence, Jürgen Landes, Erkenntnis, forthcoming, DOI: 10.1007/s10670-018-0024-6; more manuscripts under review).

**HH:** What's next then?

**JL:** Early this month, I've returned from paternity leave after the birth of our third child in August 2018. I now work on my own research project on Evidence and Objective Bayesian Epistemology. In this three-year project, I will investigate justifications and applications of amalgamating all the available evidence within the objective Bayesian approach: Why and how does one (best) aggregate the available evidence?

**HH:** That's a fascinating and timely question – we look forward to reading about your take on the problem. To more personal questions, now. You certainly crossed borders between countries, disciplines and sectors over the past decade. Today the rise of rightwing populists and anti-EU nationalists are pushing forward a view which will make it increasingly harder for the new generation of scientists to do that. Any thoughts?

**JL:** Yes, way too many thoughts.

First, we all don't walk a mile in someone else's shoes any more before we judge. In fact, we don't even seem to consider a different opinion, upbringing or socio-economic background other than our own to be proper. As a result, societies are becoming more and more partitioned into ever more divided sections in which opinions from the outside no further penetrate. This facilitates populism around the world.

Take us academics for example, more and more of us (are forced to) work in different countries where we work at universities in large cities and communicate with colleagues and increasingly also staff in English; all day every day. Everyone has a decently waged; also not necessarily stable; work contract. We engage in academic cerebral exercises which are worlds apart from a typical day of early school leavers without any prospects for a decent job. We all are living in our own bubbles; although, we are ever more connected over the Internet.

I'm deeply troubled by any nationalist movement, independent of country and time. We should always remember that there may be a time in the much too near future in which the bombs might be falling (the economy collapse, natural disaster strike, etc.) right where we stand now. Wouldn't it then be great to have some friends who could shelter our kids? To me, that's a no-brainer.

The best; and clinching; argument for the EU must be the long long years of peace it has brought to Europe. Just remember, not so long ago France and England fought a war that lasted for 100 years. Preventing wars for decades must be worth the tiny bit of autonomy politicians (not countries!) give up as well as all membership fees.

As for crossing disciplines, I can only advise to limit the number of cross-overs to a small number. Every time you cross, you start from close to zero: you lack a grasp of the interesting debates, an understanding of the type of argument required to publish in top journals, a personal network, a well-stacked library and so on. Eventually, you may well end up with a publication record that does not impress in university departments since too many publications are outside their sphere of interest (2013, Embedding philosophers in the practices of science: bringing humanities to the sciences, Nancy Tuana, Synthese, 1955-1973). We welcome back the above-mentioned bubbles.

**HH:** Can you see drawbacks in crossing borders?

**JL:** Crossing countries is a somewhat different matter. That is something I found deeply rewarding. Furthermore, it made very clear to me that every country is populated by human beings which are not so different from each other. There's absolutely no reason for countries to get angry at another. It's long overdue that we all grew up.

However, there are serious downsides to being an academic nomad. I'm not talking about the inevitable minor issues like contributions to different pension systems, hassle with different bureaucracies and trips to embassies. I'm talking about the problem of making friends and maintaining friendships over a long period of time. Just imagine, every time you meet an interesting person you immediately think: in a few year's time, we will live in different cities and, probably, different countries. That's not ideal.

The problem is worse for those of us who have children: Raising the young is extremely time consuming and tiring. Not having a social support network in place (parents/good friends living around the corner) because of a recent move does not make things any easier. Been there, done it, sent a postcard (3 times).

**HH:** Speaking of populisms, we desperately need to get more people interested in sound reasoning and argumentation. You said before it's a shame it is not an innate interest of ours, so can you think of actions we could take, as a community, to play a leading role in urging the general public to pay attention to reasoning?

**JL:** Most of our work is far far removed from the every-day lives of ordinary people. I don't think that we stand a serious chance in engaging them in our academic brain activities.

Grabbing the attention of inquisitive and excitable children, who may well recognise the value of good reasoning, appears more effective in the long run to me. I've recently attended a talk by Andy Oxman. He and his colleagues teach kids about recognising and evaluating claims. Scaling up this and other such initiatives is a way forward I believe in.

While I think that getting the general public interested in reasoning as too big a task, involving people facing complicated problems routinely at work makes more sense to me. The work by Vincenzo Crupi and others (e.g., 2017, Understanding and improving decisions in clinical medicine (I): Reasoning, heuristics, and error, Internal and Emergency Medicine, Vincenzo Crupi and Fabrizio Elia, 689-691) is the type of project I would like to see more of.

Finally, engaging the *interested* public, at a Ted Conference say, is a good idea.

# News

## Calls for Papers

Knowing the Unknown: Philosophical Perspectives on Ignorance: special issue of *Synthese*, deadline 20 February.
Hybrid Data and Knowledge Driven Decision Making under Uncertainty: special issue of *Information Sciencesl*, deadline 30 February.
Thought Experiments in the History of Philosophy of Science: special issue of *HOPOS*, deadline 31 March.
Folk Psychology: Pluralistic Approaches: special issue of *Synthese*, deadline 15 May.
Imprecise Probabilities, Logic and Rationality: special issue of *International Journal of Approximate Reasoning*, deadline 1 June.

# What's Hot in . . .

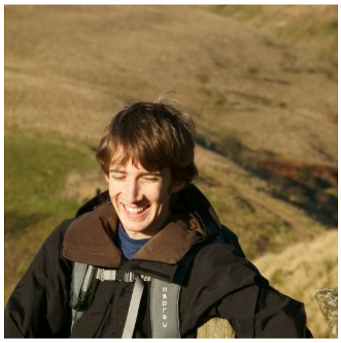
## Medieval Reasoning

Many times, students and colleagues alike have asked me what would be a good introduction to medieval logic and I always struggle to find a good answer. Usually, I begin by telling them where *not* to start from: William and Martha Kneale, *The Development of Logic* (Oxford 1962). (And not because Kneale & Kneale is not a classic, groundbreaking text – it is both. Nor because it hasn't aged gracefully – although it hasn't aged particularly well, at all. But because one would get the impression that medieval logicians – despite reaching stunning levels of apparent sophistication – got some very simple stuff very, very wrong. I don't think that this is a fair evaluation, nor is it a historically correct assessment. Overall it's better to leave Kneale & Kneale on the side at the beginning, perhaps to be revisited later on.) However, pointing beginners in the direction of a good introductory textbook is a trickier business. Most overviews of medieval logic are either too partial or are fairly obsolete – quite often, both – and in many cases, not really fit for readers lacking a background in Ancient and Medieval philosophy. Alexander Broadie's *Introduction to Medieval Logic* (2nd ed. Oxford 1993), while being a fairly accessible and basic text, is a bit outdated and, despite its title, focuses heavily on the first half of the 14th century. Just as elementary (albeit just as partial and outdated as well), Paul Vincent Spade's *Thoughts, Words and Things: An Introduction to Late Medieval Logic and Semantic Theory* (version 1.1 2002, https://pvspade.com/Logic/docs/thoughts1_1a.pdf) has both the faults and virtues of an informal handbook put together from lecture notes and circulated but never polished for publication. Jan Pinborg's *Medieval Semantics: Selected Studies on Medieval Logic and Grammar* (English translation, London 1984), while not as basic, has more thematic and chronologic breadth, but unfortunately its age shows. Normann Kretzmann's, Anthony Kenny's and Jan Pinborg's (eds.) *The Cambridge History of Later Medieval Philosophy* (Cambridge 1982) is largely devoted to medieval logic and semantics, to the point that it's still one of the most complete overviews around. Some more recent overviews that collect a good number of rich and detailed articles are Dov Gabbay's and John Woods' (eds.) *Handbook of the History of Logic II: Mediaeval and Renaissance Logic* (Amsterdam 2008), and Catarina Dutilh Novaes' and Stephen Read's (eds.) *Cambridge Companion to Medieval Logic* (Cambridge 2016). Some other studies and anthologies come to mind – among those that are at least partially in English: Klaus Jacobi's (ed.) *Argumentationstheorie* (1993), Mikko Yrjönsuuri's (ed). *Medieval Formal Logic* (2001), Dutilh Novaes' *Formalizing Medieval Logical Theories* (2007), and Terry Parson's *Articulating Medieval Logic* (2014).

The above are all very interesting reads, but – for the most part – they don't seem to make for viable introductions. It looks like a *Medieval Logic for Dummies (from 400 to 1450 ca.)* has yet to be written – and until somebody does, I won't be able to give a short, simple answer to those who ask. In the meantime there's plenty of exciting stuff to skim through if you want to dive into the subject headfirst.

Graziana Ciola
UCLA

## Uncertain Reasoning



Twenty years ago this December James M. Joyce published "A Nonpragmatic Vindication of Probabilism" (Philosophy of Science, 1998). This paper inspired a whole new way to think about epistemic norms. The basic idea of "scoring rules" or "inaccuracy measures" was not new to Joyce, indeed, the basics have been around since at least the fifties. If you're predicting whether or not it will rain and your predictions are given in the form of "yes" / "no" answers, it's clear what counts as a good forecast: if it rains, you did well if you said that it would, and you did poorly if you said that it wouldn't. If, instead, you give your predictions in the form of a probability of rain, it's less clear how to measure success. If it rains and you said that the probability of rain was 90%, that is quite good – better than saying 80%, worse than saying 95% – but how exactly should one measure the quality of forecasts? This is important since we use probabilistic forecasts in our decision making, and so it is important to know how to assess the quality of a forecast. In essence, what one wants is some form of "distance from the truth" which one could use to measure how "close" your probabilistic predictions were. But there are a great many different ways to measure the distance from the truth, how can we choose between them?

What Joyce pointed out was that, while it might be unclear which measure of forecast quality is the one we ought to use, there are some features that they arguably ought to share, and that those common features are enough to build an argument that our degrees of belief ought to obey the axioms of probability theory (among other things). The details of Joyce's original argument needn't concern us here; there have been many different versions of the general approach since 1998. The argumentative strategy – argue that certain principles of scoring rules constrain whatever epistemic utility function governs our epistemic behaviour, use these principles to prove what epistemic norms we ought to obey – is one that has been taken up by many people, and put to many uses. Not just probabilism, but conditionalisation and the principal principle have been justified in broadly this way. This way of proceeding, argues Joyce, is one that avoids the pitfalls and problems that appear to plague the other standard way of justifying norms of credence, namely "sure loss" betting arguments. (What are typically called "Dutch book arguments" but for reasons I mentioned last month, I'm avoiding that term.) For an up to date overview of the literature inspired by Joyce's paper, see Richard Pettigrew's recent book "Accuracy and the Laws of Credence" (OUP 2016).

This continues to be an interesting and fruitful area of research, and I'll return to the topic in a future column.

Seamus Bradley
Philosophy, University of Tilburg

## Mathematical Philosophy

The current spectacular developments in machine learning go hand in hand with a growing popular interest in the discipline. But interest of formal philosophers in machine learning predates the discipline's recent rise from an obscure branch of artificial intelligence to its epitome activity. The reason is that machine learning and formal epistemology share a concern with the same fundamental question: *how to learn from data?* How to infer conclusions from given data, conclusions that go beyond the data itself? How could this be formalized, or even—the characteristic business of machine learning—automatized?

Thus several approaches within machine learning have been directed by epistemologists at philosophical problems. In some instances, like *causal reasoning* (Pearl, *Causality*, Cambridge, 2009), there has long been much interaction between philosophers and computer scientists. As another example, *formal learning theory*, initiated by, among others, Putnam (*J. Symb. Log.* 30(1), 49–57, 1965), evolved into a technical field in computer science (Osherson et al., *Systems That Learn*, MIT, 1985), and has more recently been developed further as a project within philosophy of science (Kelly, *The Logic of Reliable Inquiry*, Oxford, 1996). Other instances are more unidirectional. Schurz (*Philos. Sci.* 75, 278–305, 2008) has proposed a Reichenbachian justification of induction based on results in *competitive online learning* (Cesa-Bianchi and Lugosi, *Prediction, Learning, and Games*, Cambridge, 2006). Harman and Kulkarni (*Reliable Reasoning*, MIT, 2006) have highlighted the philosophical relevance of *statistical learning theory*, the framework that underlies supervised learning (Vapnik, *Statistical Learning Theory*, Wiley, 1998).

On a more grand level, a number of philosophers have argued that machine learning prompts novel ways of doing philosophy of science. This is in itself not new; Thagard (MIT, 1988), for instance, defended a *computational philosophy of science* inspired by artificial intelligence. Nor is this the norm; Harman and Kulkarni employ the statistical learning theory framework in a largely traditional analysis of the questions of induction and its justification, like the Goodman riddle and the role of simplicity. But work within formal learning theory is explicitly committed to a more pragmatic *means-ends epistemology* (Schulte, *Brit. J. Philos. Sci.* 50(1): 1–31, 1999), that, instead of the traditional focus on justifying inductive reasoning in general, starts with the *complexity* of a given inductive problem, thus determining the epistemic goals that are still feasible for it. Wheeler (*The Routledge Companion to Philosophy of Social Science*, 321–329, 2017) goes much further still and declares "traditional, Enlightenment epistemology" bankrupt, to be replaced by the "primacy of practice" of a pragmatist *machine epistemology*.

Certainly the concurrent advent of *big data* has contributed to the perception that machine learning is largely a practical enterprise, a matter of unleashing rough-and-ready algorithms on vast amounts of data. In the most extreme version of this picture, theoretical analysis is not just hopelessly lagging behind, it is superfluous; and some have even speculated, notoriously, about the consequences for scientific theorizing. This presumed opposition between theory and practice, however, is also a theme *within* machine learning. Vapnik, in the introductory chapter to *The Nature of Statistical Learning Theory* (2nd edition, Springer, 2000), paints a picture of the history of machine learning where the practitioner is set against the theorist. Vapnik chides the "artificial intelligence hardliners" ("they who declared that 'Complex theories do not work; simple algorithms do'") for repeatedly making excessive promises, and concludes confidently that "a new methodological situation in the learning problem has developed where practical methods are the result of a deep theoretical analysis of the statistical bounds rather than the result of inventing new smart heuristics". Written still before the modern rehabilitation of neural networks in the form of *deep learning*, this now sounds overly confident. The theme has indeed recently flared up again in the community, following Rahimi and Recht's speech at NIPS 2017 in which they liken current machine learning research to alchemy.

The predictable outrage notwithstanding, Rahimi and Recht nowhere commit to theory for the sake of theory; they do not take issue with the primacy of the pragmatic goal of finding algorithms that work well in practice. Their argument is that a theoretical understanding is important for this goal: it is the step back that facilitates, so to speak, a more efficient search through the space of possible algorithms. Continuous with this theoretical work, a further step back, would be the *foundational* work that is the province of philosophers. This concerns, for instance, what it should mean when Rahimi and Recht speak about "rigorous, reliable, verifiable knowledge," and how this could be grounded in the relevant mathematics. This also concerns the outer limits on learning algorithms' capabilities, the subject of my own work on *universal prediction* (University of Groningen, 2018).

The gap between theory and practice is particularly conspicuous in what has been called a paradox of deep learning: neural networks perform astonishingly well in practice, much better than they *should*, in theory. This is illustrated by Zhang et al. ("Understanding deep learning requires rethinking generalization," *ICLR 2017*) with a simple experiment: essentially, the authors took some standard architectures and data sets, and then changed the data by reshuffling the labels in a random manner. This guaranteed that there was no relation between instances and labels: yet the networks still managed to attain extremely low training error, entailing a wide divergence between training error and generalization error (the latter *must* still be very high: the labeling is fully random so there is nothing to learn!). But explanations based on statistical learning theory rely on a connection between training error (or more generally the architecture of the network) and generalization error, wherefore the demonstrated possibility of varying the latter while keeping the former constant implies that these explanations simply do not apply. Depending on one's perspective, one could take this as another illustration of the impotence of theory, or of the dire need for a greater theoretical effort. In either case, the proper way to understand deep learning is an important ongoing debate in the machine learning community, that merits attention from philosophers, too.

Tom Sterkenburg
Munich Centre for Mathematical Philosophy

## Evidence-Based Medicine

Precision medicine is not new, but it is currently a hot topic in EBM. Often used interchangeably with personalised medicine, this new approach to healthcare aims to individualise treatments by recognizing the ways in which patients can differ person to person in the nature of disease and in patient response to treatments. It is well known that patients will respond differently to treatments that are effective for other people with the same disease. It is being increasingly recognised that this is due to biological differences in the patients and the diseases themselves, often at the genetic level. Two very recent papers articulate what precision medicine aims to do: identify the genetic differences among patients with a certain disease, and use new technologies to enable us to make sense of the level of complexity associated with using genetics to make predictions.

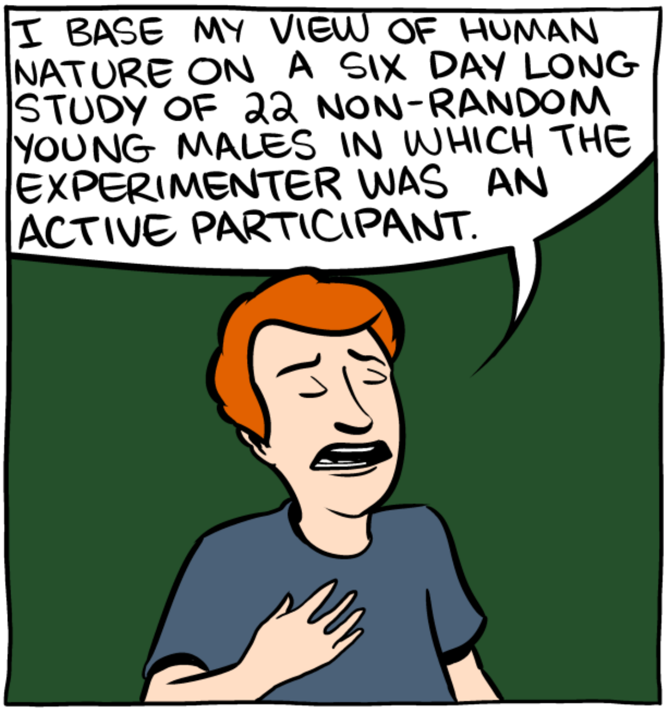
One study classified subtypes of acute myeloid leukemia (AML) by their gene expression and DNA-methylation patterns. AML is a single disease as it has a specific characterization: "blocked myeloid lineage differentiation and accumulation of leukemic blast cells". But it is a "highly heterogeneous disease" as it can be caused by many different types of genetic alterations. These different genetic alterations define separate sub-types of AML, and patients with different sub-types will require different specific treatments. This study identified patterns in the expression of genes in tumor cells from AML patients, which revealed gene regulatory networks that are specific to the different sub-types of AML. There were a number of recurrent alterations important for lukemic growth identified that present possibilities for targeted treatment. Without this knowledge patients may receive treatment that will not be effective as it is not targeted against their specific AML subtype.

The results of this study are claimed to be able to base targeted treatments for specific AML sub-types. It is important to note here that while precision medicine aims to take results such as these and use them to target individual patients, it is actually sub-populations of patients with specific AML subtypes that can be targeted, rather than individual patients per se. Drugs will not be tailored to any one individual, but novel drugs can be designed with specific sub-populations in mind, and extant drugs can be better targeted at specific sub-populations. This is why precision medicine may be a better term than personalised medicine, as these techniques allow us to be more precise in targeting treatments to any one individual. This may seem like a small semantic difference, but being clear about this tempers the ability to make grandiose claims about treating individuals - it still might be the case that precision treatments are not effective for individuals due to chance or other factors, both biological and environmental.

Difficulties face the implementation of this research both broadly and specifically. A difficulty facing precision medicine is practical in nature: the level of complexity associated with using results from disciplines such as genetics. One way in which precision medicine hopes to overcome this challenge is through the use of technology, in particular AI. A practical difficulty specific to oncology is that "tumors change over time, progressing from benign to malignant, becoming metastatic, and developing resistance to certain therapies". Essentially, the tumor cells evolve, resulting in 'intratumour heterogeneity'. This means that due to tumour evolution, using genetic markers of cancer subtypes may quickly not be useful for targeting therapies. An enterprise hoping to provide solutions to both difficulties is the REVOLVER system, that has recently published results on predicting changes in tumour evolution using an AI system. This system uses a machine-learning approach known as transfer learning (TL)19 to predict the next steps in specific tumor cell evolution. Tumor evolution seems to be predictable due to the prognostic value of histopathological staging and molecular markers. Problems facing using this data to predict tumor evolution are the complexity of patterns in the available data and stochastic forces in the mechanisms of tumor cell evolution. The REVOLVER system can deal better with complexity and stochasticity than a human reasoner. This enables more precise information for specific cancer patients as to what might happen during the course of their disease.

I have written about AI in this column before, and with that case (triaging in opthamology) the system was again used to work with large quantities of data to improve the efficiency of health care delivery. Precision medicine offers much in the way of improving how we treat severe diseases, but as the data sets get larger and more complex we will increasingly have to turn to AI. It is promising that there is development in this field that can meet this challenge. Interestingly, at present the data sets are not actually large enough for the AI systems to provide the high degree of precision we require. But with precision medicine research considered a major growth area in medicine we will likely not have to wait too long to overcome this problem.

D.J. Auker-Howlett
Philosophy, Kent




This is what I hear when people cite the Zimbardo prison experiment.

## Events

### December

KEiMS: Conference on Knowledge Exchange in the Mathematical Sciences, Aston University, 3–4 December.
CvC: Causation vs Constitution: Loosening the Friction, Bergen, 3–4 December.
AxiMet: Axiomatizing Metatheory—Truth, Provability, and Beyond, Salzburg, Austria, 6–7 December.
ML4H: Workshop on Machine Learning for Health, Montréal, Canada, 8 December.
DiI: Workshop on Disagreement in Inquiry, University of Tartu, 8 December.
RLPO: Reinforcement Learning Under Partial Observability, Montréal, Canada, 8 December.
RPiB: Real Patterns, University of Barcelona, 14 December.
W'sBaD: What's so Bad About Dialetheism?, Kyoto University, Japan, 15–17 December.

### January

PoMaL: Graduate Conference on the Philosophy of Mathematics and Logic, University of Cambridge, 19–20 January.
FiSS: Foundations in Social Science—Mechanisms, Actions, Functions, University of Duisburg-Essen, Germany, 24–25 January.
VoUiS: Varieties of Understanding in Science, Utrecht, The Netherlands, 24–25 January.

### February

DMaMG: Dark Matter and Modified Gravity Conference, Aachen, Germany, 6–8 February.

## Courses and Programmes

### Courses

SSA: Summer School on Argumentation: Computational and Linguistic Perspectives on Argumentation, Warsaw, Poland, 6–10 September.

### Programmes

APhil: MA/PhD in Analytic Philosophy, University of Barcelona.
Master Programme: MA in Pure and Applied Logic, University of Barcelona.
Doctoral Programme in Philosophy: Language, Mind and Practice, Department of Philosophy, University of Zurich, Switzerland.
Doctoral Programme in Philosophy: Department of Philosophy, University of Milan, Italy.
LogiCS: Joint doctoral program on Logical Methods in Computer Science, TU Wien, TU Graz, and JKU Linz, Austria.
HPSM: MA in the History and Philosophy of Science and Medicine, Durham University.
Master Programme: in Statistics, University College Dublin.
LoPhiSC: Master in Logic, Philosophy of Science and Epistemology, Pantheon-Sorbonne University (Paris 1) and Paris-Sorbonne University (Paris 4).
Master Programme: in Artificial Intelligence, Radboud University Nijmegen, the Netherlands.
Master Programme: Philosophy and Economics, Institute of Philosophy, University of Bayreuth.
MA in Cognitive Science: School of Politics, International Studies and Philosophy, Queen's University Belfast.
MA in Logic and the Philosophy of Mathematics: Department of Philosophy, University of Bristol.
MA Programmes: in Philosophy of Science, University of Leeds.
MA in Logic and Philosophy of Science: Faculty of Philosophy, Philosophy of Science and Study of Religion, LMU Munich.
MA in Logic and Theory of Science: Department of Logic of the Eotvos Lorand University, Budapest, Hungary.
MA in Metaphysics, Language, and Mind: Department of Philosophy, University of Liverpool.
MA in Mind, Brain and Learning: Westminster Institute of Education, Oxford Brookes University.
MA in Philosophy: by research, Tilburg University.
MA in Philosophy, Science and Society: TiLPS, Tilburg University.
MA in Philosophy of Biological and Cognitive Sciences: Department of Philosophy, University of Bristol.
MA in Rhetoric: School of Journalism, Media and Communication, University of Central Lancashire.
MA programmes: in Philosophy of Language and Linguistics, and Philosophy of Mind and Psychology, University of Birmingham.
MRes in Methods and Practices of Philosophical Research: Northern Institute of Philosophy, University of Aberdeen.
MSc in Applied Statistics: Department of Economics, Mathematics and Statistics, Birkbeck, University of London.
MSc in Applied Statistics and Datamining: School of Mathematics and Statistics, University of St Andrews.

MSc in Artificial Intelligence: Faculty of Engineering, University of Leeds.
MSc in Cognitive & Decision Sciences: Psychology, University College London.
MSc in Cognitive Systems: Language, Learning, and Reasoning, University of Potsdam.
MSc in Cognitive Science: University of Osnabrück, Germany.
MSc in Cognitive Psychology/Neuropsychology: School of Psychology, University of Kent.
MSc in Logic: Institute for Logic, Language and Computation, University of Amsterdam.
MSc in Mind, Language & Embodied Cognition: School of Philosophy, Psychology and Language Sciences, University of Edinburgh.
MSc in Philosophy of Science, Technology and Society: University of Twente, The Netherlands.
MRes in Cognitive Science and Humanities: Language, Communication and Organization: Institute for Logic, Cognition, Language, and Information, University of the Basque Country (Donostia San Sebastián).
Open Mind: International School of Advanced Studies in Cognitive Sciences, University of Bucharest.
Research Master in Philosophy and Economics: Erasmus University Rotterdam, The Netherlands.

# Jobs and Studentships

## Jobs

Assistant Professor: in Epistemology, California State University at Sacramento, deadline: until filled.
Assistant Professor: in Logic & Epistemology, University of North Carolina at Greensboro, deadline: until filled.
Assistant Professor: in Philosophy of Medicine, University of North Carolina at Greensboro, deadline: until filled.
Assistant Professor: in Philosophy of Science, University of Florida, deadline: until filled.
Lecturer: in Actuarial Science, University of California Santa Barbara, deadline: until filled.
Professor: in Philosophy of Science, City University of New York, deadline 3 December.
Research Associate: in Bayesian modelling, University of Sheffield, deadline 12 December.
Research Fellow: in Data Science, University of Bristol, deadline 3 January.
Lecturer: in Statistical Science, University College London, deadline 9 February.