

Jason Rute

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Greater Boston Area, USA

Research Interests

AI for symbolic problem-solving AI methods—such as reinforcement learning and language modeling—provide next-generation intelligence, whereas formal systems—such as theorem provers—provide the grounding needed for automatic evaluation and iterative improvement.

(Pre-2018) Computable probability theory and analysis The computable foundations of probability theory, including algorithmic randomness, computable analysis, constructive analysis, proof theory—applied to mathematical subjects such as probability theory, ergodic theory, and statistics.

Professional and Academic Experience

MIT-IBM Watson AI Lab, Cambridge MA Postdoctoral Research Scientist Nov 2021–Present

- Developed state-of-the-art neural theorem-proving model for the Coq proof assistant
- Improved large language models for generating code and tool use

CIBO Technologies, Cambridge MA Lead Data Scientist Apr 2018–Nov 2021

- Developed Scala code to improve an in-house Bayesian MCMC model calibration engine
- Managed a cross-functional team of software engineers, data scientists, and agronomists to create a software library of statistical agricultural data for production use
- Devised statistical methods to use this agricultural data to improve crop model performance

Pennsylvania State University, University Park PA Research Associate Sep 2013–Jun 2017

- Developed a theory of algorithmic randomness for capacities solving two open math questions
- Coordinated a large multi-section calculus course, overseeing other instructors
- Taught calculus and logic courses, with student evaluation scores well above department average

University of Hawaii, Manoa HI Junior Researcher Feb 2013–Jul 2013

- Researched algorithmically random Brownian motion and computable martingales

Carnegie Mellon University, Pittsburgh PA Graduate Teaching Assistant Aug 2008–Dec 2012

- Investigated theoretical limitations of simulating exchangeable random graph networks
- Studied the convergence of random points within time series with computable distributions

Selected Projects

AI for Theorem Proving

- Developed a novel graph neural network for Coq prover which learns to incorporate new definitions not seen during training. SoTA results. Accepted to ICML. (Paper: [arXiv:2401.02949](https://arxiv.org/abs/2401.02949))
- Extracted a large dataset (github.com/jasonrute/lean_proof_recording) of tactic proof steps from the mathlib library of Lean. Collaborated with OpenAI to train a language model on this data, resulting in a proof suggestion tactic (github.com/jesse-michael-han/lean-gptf) and automatic proof discovery. (Paper: [arXiv:2102.06203](https://arxiv.org/abs/2102.06203), Talk: [youtube:EXpmbAfBNnw](https://youtube.com/watch?v=EXpmbAfBNnw))

Formal Theorem Proving Formally verified mathematics in HOL-Light/OCaml as part of the Flyspeck project (github.com/flyspeck) to formally check Tom Hale's proof of the Kepler conjecture

Education

Carnegie Mellon University, Pittsburgh PA Sep 2008–Aug 2013

Ph.D. in Mathematical Sciences

- Thesis: Topics in algorithmic randomness and computable analysis
- Advisor: Jeremy Avigad

M.S. in Mathematical Sciences

University of Wisconsin, Madison WI

Sep 1999–Aug 2004

B.S. in Mechanical Engineering, Mathematics, and Philosophy

Papers

1. L. Blaauwbroek, M. Olsak, J. Rute, F. Schaposnik Massolo, J. Piepenbrock, V. Pestun. Graph2Tac: Online Representation Learning of Formal Math Concepts. Accepted to ICML 2024. [openreview:A7CtiozznN](https://openreview.net/forum?id=A7CtiozznN). [arXiv:2401.02949](https://arxiv.org/abs/2401.02949).
2. J. M. Han, J. Rute, Y. Wu, E. W. Ayers, S. Polu. Proof artifact co-training for theorem proving. ICLR 2022. [openreview:rpxJc9j04U](https://openreview.net/forum?id=rpxJc9j04U). [arXiv:2102.06203](https://arxiv.org/abs/2102.06203).
3. M. Hoyrup, J. Rute. Computable measure theory and algorithmic randomness. In V. Brattka, P. Hertling (eds) *Handbook of Computability and Complexity in Analysis* (Theory and Applications of Computability), 227–270, 2021. [doi:10.1007/978-3-030-59234-9_7](https://doi.org/10.1007/978-3-030-59234-9_7).
4. J. Rute. Algorithmic randomness and constructive/computable measure theory. In J. Franklin & C. Porter (Eds.), *Algorithmic Randomness: Progress and Prospects* (Lecture Notes in Logic), 58–114, 2020. [doi:10.1017/9781108781718.004](https://doi.org/10.1017/9781108781718.004). [arxiv:1812.03375](https://arxiv.org/abs/1812.03375).
5. N. L. Ackerman, J. Avigad, C. E. Freer, D. M. Roy, J. Rute. Algorithmic barriers to representing conditional independence. *Proceedings of Logic in Computer Science (LICS)*, 1–13, 2019. [doi:10.1109/LICS.2019.8785762](https://doi.org/10.1109/LICS.2019.8785762). [arXiv:1801.10387](https://arxiv.org/abs/1801.10387) (old).
6. J. N. Y. Franklin, T. H. McNicholl, J. Rute. Algorithmic randomness and Fourier analysis. *Theory Comput Systems*, 63:567–586, 2019. [doi:10.1007/s00224-018-9888-8](https://doi.org/10.1007/s00224-018-9888-8). [arXiv:1603.01778](https://arxiv.org/abs/1603.01778).
7. J. S. Miller, J. Rute. Energy randomness. *Israel Journal of Mathematics*, 227:1–26, 2018. [doi:10.1007/s11856-018-1731-z](https://doi.org/10.1007/s11856-018-1731-z). [arXiv:1509.00524](https://arxiv.org/abs/1509.00524).
8. T. Hales, M. Adams, G. Bauer, D. T. Dang, J. Harrison, C. Kaliszyk, V. Magron, S. McLaughlin, T. T. Nguyen, T. Q. Nguyen, T. Nipkow, S. Obua, J. Pleso, J. Rute, A. Solovyev, A. H. T. Ta, T. N. Tran, D. T. Trieu, H. L. Truong, J. Urban, K. K. Vu, R. Zumkeller. A formal proof of the Kepler conjecture. *Forum of Mathematics, Pi*, 5(E2), 2017. [doi:10.1017/fmp.2017.1](https://doi.org/10.1017/fmp.2017.1). [arXiv:1501.02155](https://arxiv.org/abs/1501.02155).
9. J. Rute. When does randomness come from randomness? *Theoretical Computer Science*, 635(C), 35–50, 2016. [doi:10.1016/j.tcs.2016.05.001](https://doi.org/10.1016/j.tcs.2016.05.001). [arxiv:1508.05082](https://arxiv.org/abs/1508.05082).
10. J. Rute. Computable randomness and betting for computable probability spaces. *Mathematical Logic Quarterly*, 62(4–5):335–366, 2016. [doi:10.1002/malq.201200089](https://doi.org/10.1002/malq.201200089). [arXiv:1203.5535](https://arxiv.org/abs/1203.5535).
11. J. Avigad, J. Rute. Oscillation and the mean ergodic theorem for uniformly convex Banach spaces. *Ergodic Theory and Dynamical Systems*, 35:4:1009–1027, 2015. [doi:10.1017/etds.2013.90](https://doi.org/10.1017/etds.2013.90). [arXiv:1203.4124](https://arxiv.org/abs/1203.4124).
12. B. Kjos-Hanssen, P. K. L. Nguyen, J. Rute. Algorithmic randomness for Doob’s martingale convergence theorem in continuous time. *Logical Methods in Computer Science*, 10(4:12):1-35, 2014. [doi:10.2168/LMCS-10\(4:12\)2014](https://doi.org/10.2168/LMCS-10(4:12)2014).
13. K. Miyabe, J. Rute. Van Lambalgen’s Theorem for uniformly relative Schnorr and computable randomness. *Proceedings of the 12th Asian Logic Conference*, 251–270, 2013. [doi:10.1142/9789814449274_0014](https://doi.org/10.1142/9789814449274_0014). [arXiv:1209.5478](https://arxiv.org/abs/1209.5478).
14. J. Avigad, E. Dean, J. Rute. A metastable dominated convergence theorem. *Journal of Logic and Analysis*, 4:3:1–19, 2012. [doi:10.4115/jla.2012.4.3](https://doi.org/10.4115/jla.2012.4.3).
15. J. Avigad, E. Dean, J. Rute. Algorithmic randomness, reverse mathematics, and the dominated convergence theorem. *Annals of Pure and Applied Logic*, 163(12):1854–1864, 2012. [doi:10.1016/j.apal.2012.05.010](https://doi.org/10.1016/j.apal.2012.05.010). [arXiv:1106.0775](https://arxiv.org/abs/1106.0775).

Select Talks

1. (Invited) [Title TBD]. "AI for the working mathematician" workshop. Joint Math Meetings. January 2025.
2. (Invited) Deep Learning for Interactive Theorem Proving. IPAM workshop on Machine Assisted Proofs. February 2023. [youtube:P5ew0BrRm_I](https://youtube.com/watch?v=P5ew0BrRm_I).
3. Neural theorem proving in Lean using proof artifact co-training and language models. New Technologies in Mathematics Seminar. Harvard CMSA (Online). March 2021. [youtube:EXpmbAfBNnw](https://youtube.com/watch?v=EXpmbAfBNnw).
4. LeanStep: a dataset and environment for (interactive) neural theorem proving. Lean Together 2021. Online. Jan 2021. [youtube:eSXICIL4COW](https://youtube.com/watch?v=eSXICIL4COW).

- Patents**
1. R Richt, J. Rute, J. P. Skelton. Correcting agronomic data from multiple passes through a farmable region. [US Patent 10,477,756 B1](#).
 2. J. Rute, M. Devyver. Automatic call classification using machine learning. [US Patent 10,498,888](#).

Skills **Programming** Python (NumPy, Pandas, Scikit Learn, Keras/TensorFlow), Scala, SQL, functional programming, Git, AWS, Lean theorem prover, Coq

Machine Learning Transformers, graph neural networks, Bayesian inference (MCMC, hierarchical models), deep reinforcement learning, natural language processing