

# Eric Anschuetz | Curriculum Vitae

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• US citizen

## Education

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○ <b>Massachusetts Institute of Technology</b>	<b>Cambridge, MA</b>
○ <i>Physics</i>	2017–2023
Ph.D., co-advised by Aram W. Harrow and Mikhail D. Lukin, 5.00/5.00 GPA ( <a href="#">Ph.D. thesis</a> )	
○ <b>Harvard University</b>	<b>Cambridge, MA</b>
○ <i>Physics</i>	2015–2017
A.M., 3.89/4.00 GPA, 3.95/4.00 major GPA, earned in Advance Standing program simultaneously with A.B.	
○ <b>Harvard University</b>	<b>Cambridge, MA</b>
○ <i>Physics and mathematics joint concentration, computer science secondary</i>	2013–2017
A.B., 3.92/4.00 GPA, <i>magna cum laude</i> with Highest Honors in physics	

## Experience

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### Research

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○ <b>California Institute of Technology</b>	<b>Pasadena, CA</b>
○ <i>Burke Fellow</i>	2023–
Investigated a variety of problems in quantum computation and statistical physics, including (but not limited to):	
- Hardness of approximation for quantum spin glasses	
• Proved disordered, sparse quantum spin models exhibit average-case algorithmic hardness-of-approximation in their ground state problem. ( <a href="#">to appear in Commun. Math. Phys., QIP 2026</a> )	
• Showed the SYK model exhibits no glassiness to very low temperatures; also showed low-energy states of the SYK model have very high circuit complexity. ( <a href="#">PRL 2025, QIP 2025</a> )	
• Demonstrated exact asymptotic value achieved by lowest-energy product states; also bounded the asymptotic value of the true ground state. ( <a href="#">Commun. Math. Phys. 2025</a> )	
- Statistical models of quantum neural networks	
• Proved quantum neural networks asymptotically are Wishart processes, thus unifying many previous models of trainability in such networks. ( <a href="#">ICLR 2025</a> )	
• Surveyed links between variational quantum algorithms not exhibiting barren plateaus in their loss landscapes and the ability for classical algorithms to efficiently simulate them; first demonstration of the classical simulability of quantum convolutional neural networks when they are efficiently trainable. ( <a href="#">Nat. Commun. 2025</a> )	
- Quantum foundations	
• Constructed new measure of quantum contextuality which provably lower-bounds memory complexity of classical simulation. ( <a href="#">QCE 2025</a> )	
• Used quantum contextuality to show arbitrarily large, unconditional expressivity separations between a class of quantum recurrent models and a broad class of classical neural sequence models; also showed the first lower bound on the classical complexity of simulation of certain subgroups of the Clifford hierarchy. ( <a href="#">arXiv 2024</a> )	

- Massachusetts Institute of Technology** Cambridge, MA
- *Ph.D. student, Aram Harrow and Mikhail D. Lukin groups* 2017–2023
  - Investigated a variety of problems in quantum information and statistical physics, including (but not limited to):
    - The trainability of quantum neural networks
      - Used techniques from random matrix theory, Morse theory, and statistical query learning to show shallow, local quantum neural networks are difficult to train. ([Nat. Comm. 2022](#))
      - Used techniques from Morse theory and large deviations theory to show shallow, nonlocal quantum neural networks are difficult to train. ([ICLR 2022](#))
    - The expressive power of quantum machine learning models using techniques from quantum foundations
      - Used quantum contextuality and the constant rank theorem to show an unconditional expressivity separation between a class of quantum recurrent models and a broad class of classical neural sequence models; also showed the first lower bound on the classical complexity of GKP state simulation. ([PRX Quantum 2022](#))
      - Used quantum contextuality to show an expressivity separation between a quantum generative model and certain classes of Bayesian networks. ([PRX 2022](#))
    - Quantum algorithms
      - Used coresets to improve throughput in variational quantum algorithms. ([Electronics 2021](#))
      - Constructed GAN-like architectures where a large classical model is aided by a small quantum computer. ([PRA 2019](#))
- Harvard University** Cambridge, MA
- *Undergraduate research assistant, Mikhail D. Lukin group* 2015–2017
  - Helped construct the “Atom Array” Rydberg atom experiment, investigating the use of controllable optical tweezers for deterministic trapping of ultracold atoms. Wrote and implemented the initial optical tweezer control algorithm in C++, interfacing with a software-defined radio. ([Science 2016](#))
- Teaching and Mentoring**
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- California Institute of Technology** Pasadena, CA
- *Undergraduate student mentor* 2025
  - Mentored (through [SURF](#)) an undergraduate student in research project studying the performance of quantum networks in learning properties of Hilbert space fragmented systems ([arXiv:2512.00751 \[quant-ph\]](#)).
- California Institute of Technology** Pasadena, CA
- *Undergraduate student mentor* 2024
  - Mentored (through [SURF](#)) an undergraduate student in research project studying quantum-classical hardness-of-approximation separations in the sparse SYK model ([arXiv:2506.09037 \[quant-ph\]](#)).
- QHack, Xanadu Quantum Technologies** Online
- *Volunteer* 2023
  - Presented lecture on quantum machine learning at QHack, a free quantum hackathon organized by Xanadu. Answered questions from students involving their projects throughout the hackathon.
- Massachusetts Institute of Technology** Cambridge, MA
- *Teaching assistant, 8.371[J] (Quantum Information Science II)* 2023
  - Aided in problem set creation and grading. Assisted students on assignments and in understanding the material in weekly office hours. Mentored students in performing independent research for their final projects.
- Massachusetts Institute of Technology** Cambridge, MA
- *High School Summer Program (HSSP) lecture* 2019
  - Presented lecture on quantum algorithms.

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| <p><b>Massachusetts Institute of Technology</b></p> <ul style="list-style-type: none"> <li>○ <i>Teaching assistant, 8.311 (Electromagnetic Theory)</i></li> </ul> <p>Led weekly recitations and prepared associated online lecture notes (available on my website). Assisted students on assignments and in understanding the material in weekly office hours.</p> <p><b>Massachusetts Institute of Technology</b></p> <ul style="list-style-type: none"> <li>○ <i>Master's student mentor</i></li> </ul> <p>Supervised master's thesis on developing methods for quantum compilation (<a href="#">master's thesis</a>, results published in <i>ACM Trans. Quantum Comput.</i> 2021).</p> | <p><b>Cambridge, MA</b></p> <p>2019</p> |
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## Awards and Honors

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- Sherman Fairchild Prize Postdoctoral Fellowship, California Institute of Technology (2023)
- Graduate Research Fellow, National Science Foundation (2017)
- Dean of Science Fellow, Massachusetts Institute of Technology (2017)
- Harvard College Scholar, Harvard University (2015)

## Publications

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M. Mints and E. R. Anschuetz, Fragmentation is efficiently learnable by quantum neural networks (2025), [arXiv:2512.00751 \[quant-ph\]](#).

A. Zlokapa, B. T. Kiani, and E. R. Anschuetz, Average-case quantum complexity from glassiness (2025), to be presented at *Quantum Information Processing*, [arXiv:2510.08497 \[quant-ph\]](#).

E. R. Anschuetz, D. Gamarnik, and J. Z. Lu, Decoded Quantum Interferometry requires structure (2025a), [arXiv:2509.14509 \[quant-ph\]](#).

M. H. Teo, W. Yang, J. Sud, T. Tomesh, F. T. Chong, and E. R. Anschuetz, k-contextuality as a heuristic for memory separations in learning, in *2025 IEEE International Conference on Quantum Computing and Engineering (QCE)* (2025).

M. Ding, R. King, B. T. Kiani, and E. R. Anschuetz, Optimizing sparse SYK (2025), [arXiv:2506.09037 \[quant-ph\]](#).

E. R. Anschuetz, Efficient learning implies quantum glassiness (2025a), to be presented at *Quantum Information Processing* and to be published in *Commun. Math. Phys.*, [arXiv:2505.00087 \[quant-ph\]](#).

E. R. Anschuetz, C.-F. Chen, B. T. Kiani, and R. King, Strongly interacting fermions are nontrivial yet nonglassy, *Phys. Rev. Lett.* **135**, 030602 (2025b), presented at *Quantum Information Processing*.

E. R. Anschuetz, A unified theory of quantum neural network loss landscapes, in *International Conference on Learning Representations*, edited by Y. Yue, A. Garg, N. Peng, F. Sha, and R. Yu (OpenReview, 2025).

E. R. Anschuetz, D. Gamarnik, and B. T. Kiani, Bounds on the ground state energy of quantum  $p$ -spin Hamiltonians, *Commun. Math. Phys.* **406**, 232 (2025c).

M. A. Perlin, R. Shaydulin, B. P. Hall, P. Minssen, C. Li, K. Dubey, R. Rines, E. R. Anschuetz, M. Pistoia, and P. Gokhale, Q-CHOP: Quantum constrained Hamiltonian optimization (2024), to be published in ACM Trans. Quantum Comput., [arXiv:2403.05653 \[quant-ph\]](#) .

E. R. Anschuetz and X. Gao, Arbitrary polynomial separations in trainable quantum machine learning (2024), [arXiv:2402.08606 \[quant-ph\]](#) .

M. Cerezo, M. Larocca, D. García-Martín, N. L. Diaz, P. Braccia, E. Fontana, M. S. Rudolph, P. Bermejo, A. Ijaz, S. Thanaisilp, E. R. Anschuetz, and Z. Holmes, Does provable absence of barren plateaus imply classical simulability?, [Nat. Commun. 16, 7907 \(2025\)](#).

E. R. Anschuetz, *The Trainability and Expressivity of Quantum Machine Learning Models*, Ph.D. thesis, Massachusetts Institute of Technology, Cambridge, MA, USA (2023).

E. R. Anschuetz, D. Gamarnik, and B. Kiani, Combinatorial NLTS From the Overlap Gap Property, [Quantum 8, 1527 \(2024\)](#).

P. Gokhale, E. R. Anschuetz, C. Campbell, F. T. Chong, E. D. Dahl, P. Frederick, E. B. Jones, B. Hall, S. Issa, P. Goiporia, S. Lee, P. Noell, V. Omole, D. Owusu-Antwi, M. A. Perlin, R. Rines, M. Saffman, K. N. Smith, and T. Tomesh, *SupercheQ: Quantum Advantage for Distributed Databases*, Tech. Rep. (Infleqtion, 2022).

E. R. Anschuetz, A. Bauer, B. T. Kiani, and S. Lloyd, Efficient classical algorithms for simulating symmetric quantum systems, [Quantum 7, 1189 \(2023a\)](#).

J. Viszlai, T. Tomesh, P. Gokhale, E. Anschuetz, and F. T. Chong, Training quantum Boltzmann machines with coresets, in [2022 IEEE International Conference on Quantum Computing and Engineering \(QCE\) \(2022\)](#) pp. 292–298.

E. R. Anschuetz, H.-Y. Hu, J.-L. Huang, and X. Gao, Interpretable quantum advantage in neural sequence learning, [PRX Quantum 4, 020338 \(2023b\)](#).

E. R. Anschuetz, L. Funcke, P. T. Komiske, S. Kryhin, and J. Thaler, Degeneracy engineering for classical and quantum annealing: A case study of sparse linear regression in collider physics, [Phys. Rev. D 106, 056008 \(2022\)](#).

E. R. Anschuetz and B. T. Kiani, Quantum variational algorithms are swamped with traps, [Nat. Commun. 13, 7760 \(2022\)](#).

M. S. Rudolph, S. Sim, A. Raza, M. Stechly, J. R. McClean, E. R. Anschuetz, L. Serrano, and A. Perdomo-Ortiz, *ORQVIZ: Visualizing High-Dimensional Landscapes in Variational Quantum Algorithms*, Tech. Rep. (Zapata Computing Inc., 2021).

E. R. Anschuetz, Critical points in quantum generative models, in [International Conference on Learning Representations](#), edited by K. Hofmann, A. Rush, Y. Liu, C. Finn, Y. Choi, and M. Deisenroth (OpenReview, 2022).

X. Gao, E. R. Anschuetz, S.-T. Wang, J. I. Cirac, and M. D. Lukin, Enhancing generative models via quantum correlations, [Phys. Rev. X 12, 021037 \(2022\)](#).

T. Tomesh, P. Gokhale, E. R. Anschuetz, and F. T. Chong, Coreset clustering on small quantum computers, [Electronics](#) **10**, 1690 (2021).

J. X. Lin, E. R. Anschuetz, and A. W. Harrow, Using spectral graph theory to map qubits onto connectivity-limited devices, [ACM Trans. Quantum Comput.](#) **2**, 1 (2021).

E. R. Anschuetz and C. Zanoci, Near-term quantum-classical associative adversarial networks, [Phys. Rev. A](#) **100**, 052327 (2019).

E. R. Anschuetz and Y. Cao, Realizing quantum Boltzmann machines through eigenstate thermalization (2019), [arXiv:1903.01359 \[quant-ph\]](#).

E. Anschuetz, J. Olson, A. Aspuru-Guzik, and Y. Cao, Variational Quantum Factoring, in [Quantum Technology and Optimization Problems](#), edited by S. Feld and C. Linnhoff-Popien (Springer International Publishing, Cham, 2019) pp. 74–85.

M. Endres, H. Bernien, A. Keesling, H. Levine, E. R. Anschuetz, A. Krajenbrink, C. Senko, V. Vuletic, M. Greiner, and M. D. Lukin, Atom-by-atom assembly of defect-free one-dimensional cold atom arrays, [Science](#) **354**, 1024 (2016)

## Talks

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- *Efficient Learning Implies Quantum Glassiness*, [Quantum Information Processing](#) (2026)
- *Average-case quantum complexity from glassiness*, invited talk, [International Workshop on Quantum Boltzmann Machines](#) (2025)
- *A Unified Theory of Quantum Neural Network Loss Landscapes*, [Quantum Techniques in Machine Learning \(QTML\)](#) (2025)
- *Efficient Learning Implies Quantum Glassiness*, invited talk, [AIMS Workshop and School on The Theory of Quantum Learning Algorithms](#) (2025)
- *Efficient Learning Implies Quantum Glassiness*, invited talk, [Foxconn Quantum Computing Seminar](#)
- *Decoded Quantum Interferometry Requires Structure*, invited talk, [Caltech Theory Tea](#)
- *Efficient Learning Implies Quantum Glassiness*, invited talk, [Quantum Many-Body Seminar, F.U. Berlin](#) (2025)
- *A Unified Theory of Quantum Neural Network Loss Landscapes*, [Theory of Quantum Computation, Communication and Cryptography \(TQC\)](#) (2025)
- *A Unified Theory of Quantum Neural Network Loss Landscapes*, invited talk, [Understanding Quantum Machine Learning workshop](#) (2025)
- *Efficient Learning Implies Quantum Glassiness*, invited talk, [University of Bologna Seminar](#) (2025)
- *Arbitrary Polynomial Separations in Trainable Quantum Machine Learning*, invited talk, [Quantum Techniques in Machine Learning \(QTML\)](#) (2024)
- *Arbitrary Polynomial Separations in Trainable Quantum Machine Learning*, invited talk, [aQa seminar](#) (2024)
- *A Unified Theory of Quantum Neural Network Loss Landscapes*, invited talk, [Quantum Machine Learning seminar, Google](#) (2024)
- *Rethinking Quantum Learning Algorithms*, invited keynote talk, [MMM11](#) (2024)

- *A Unified Theory of Quantum Neural Network Loss Landscapes*, invited talk, Quantum Learning Seminar, F.U. Berlin (2024)
- *Arbitrary Polynomial Separations in Trainable Quantum Machine Learning*, invited talk, QED-C Quantum Talent Showcase (2024)
- *Arbitrary Polynomial Separations in Trainable Quantum Machine Learning*, invited talk, SeeQA (2024)
- *Arbitrary Polynomial Separations in Trainable Quantum Machine Learning*, invited talk, Los Alamos National Laboratory (2024)
- *Quantum Theory and Algorithms*, invited talk, Planning Workshop on Quantum Computing, ASPLOS (2024)
- *Rethinking Quantum Neural Networks*, invited talk, CSUN (2024)
- *Interpretable Expressivity Separations in Trainable Quantum Machine Learning*, invited talk, IQIM Seminar, Caltech (2024)
- *Enhancing Generative Models via Quantum Correlations*, invited talk, Tensor Network Reading Group, Mila (2023)
- *A discussion on QML*, panel, CIFAR Quantum Information Science Program Meeting (2023)
- *Interpretable Quantum Advantage in Neural Sequence Learning*, invited talk, Centre for Quantum Technologies (2023)
- *Efficient classical algorithms for simulating symmetric quantum systems*, invited talk, Centre for Quantum Technologies (2023)
- *The Expressive Power of Restricted Quantum Machine Learning Architectures*, invited talk, QHack (2023)
- *Contextuality for Quantum Advantage*, invited tutorial, Harvard University (2022)
- *Interpretable Quantum Advantage in Neural Sequence Learning*, invited talk, Masaryk University (2022)
- *Critical Points in Hamiltonian Agnostic Variational Quantum Algorithms*, invited talk, Quantum Research Seminars Toronto (2021)
- *Critical Points in Hamiltonian Agnostic Variational Quantum Algorithms*, invited talk, Centre for Quantum Technologies (2021)
- *Critical Points in Hamiltonian Agnostic Variational Quantum Algorithms*, invited talk, Quantum Algorithms and Applications seminar, Microsoft (2021)
- *Quantum Advantage in Basis-Enhanced Neural Sequence Models*, Quantum Techniques in Machine Learning (QTML) (2021)
- *Near-Term Quantum-Classical Associative Adversarial Networks*, Quantum Techniques in Machine Learning (QTML) (2020)
- *Quantum Machine Learning on NISQ Devices*, invited talk, Tufts University (2020)
- *Improved Training of Quantum Boltzmann Machines*, American Physical Society March Meeting (2019)

## Reviewing

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Served as a reviewer for:

- *Annales Henri Poincaré*

- *Communications in Mathematical Physics*
- *Communications Physics*
- *FOCS*
- *ICLR*
- *ICML*
- *Nature Communications*
- *NeurIPS*
- *npj Quantum Information*
- *Machine Learning: Science and Technology*
- *Mitacs* (grant review)
- *New Journal of Physics*
- *Physical Review A*
- *Physical Review B*
- *Physical Review Letters*
- *Physical Review Research*
- *Physical Review X*
- *PRX Quantum*
- *QCTiP*
- *QIP* (program committee)
- *QSim* (program committee)
- *QTML* (program committee)
- *Quantum*
- *Quantum Algorithms: A Survey of Applications and End-to-end Complexities*
- *Quantum Machine Intelligence*
- *Quantum Science and Technology*
- *TQC*