Anthony Polloreno, Ph.D.

Member of Technical Staff @ Essential.ai
Post-Doctoral Researcher @ University of Colorado, Boulder
Researcher @ Sandia National Laboratories
Software Engineer @ Rigetti Computing
Researcher @ Lawrence Berkeley National Laboratory

Ph.D. Physics @ University of Colorado, Boulder
B.A. Computer Science, Math, Physics @ University of California, Berkeley

Researcher and software engineer with over a decade of experience scaling information processing systems.

Programming Languages and Frameworks

Languages: Python, Mathematica, Julia, Common Lisp, C++, Java, SQL **Frameworks & Tools**: MPI, Docker, Postgres, AWS, SQLAlchemy, Atlassian, Slurm, numpy, scipy, Jax, MaxText, PyTorch, pydantic, pants, Google Cloud, Kubernetes, instructor, EC2

Work and Research Experience

2024-Now | Scaling Lead at Essential.ai: *Large-Scale Model Pretraining and Hyperparameter Optimization*

- Led scaling efforts for large-scale model pretraining and post-training, optimizing training across 2048+ TPUs/GPUs.
- Designed and implemented a custom experimental database and tracking system integrated with Jax and MaxText, replacing external tools like WandB, increasing measurement throughput by 100×.
- Developed principled batch size scaling experiments to determine critical batch sizes across diverse datasets.
- Optimized parallelism strategies (DP, FSDP, TP, EP) for efficient model training.
- Applied the Maximal Update Parametrization for hyperparameter transfer across depth, width, sequence length, and training length, identifying critical points in the training loss landscape, reducing training costs by 90%.
- Extended Mixture of Experts scaling laws to memory-constrained setting, validating a batch size of 32M at 10B active parameters.
- Implemented novel spectral norm analysis using MUP to detect instabilities early in training, on 1B proxy models.
- Integrated second-order optimization methods (Shampoo, Muon) and first-order variants (AdamW with arctan).
- Conducted experiments selecting depth based on downstream evaluation performance, validating Kaplan et al.'s results that loss is weakly coupled to depth in small models.
- Investigated data decomposition to inform mixture compositions, regressing evaluation scores to training losses on individual datasets.
- Used policy iteration and LORA fine-tuning on LLaMA 8B models to build an in-house planner. Increased performance from 60% to 80% on financebench, achieving parity with GPT4.
- Developed full system integration tests to validate fine-tuned in-house models and monitor performance regressions, using Github actions, GCP and codalab for experiment management.

2023 - 2024 | Postdoctoral Associate at JILA: *Predictive Modeling and Analysis of Noise in Recurrent Networks*

- Derived scaling laws for the impact of computational errors on reservoir computing models (Echo State Networks) for time-series prediction. Demonstrated that increasing errors by 10× decreases the rate of learning by 10×.
- Extended the Information Processing Capacity (IPC) metric to analyze computational limits of stochastic reservoir computing.
- Demonstrated that IPC is at most polynomial in system size under noise constraints, contrasting previous assumptions of exponential scaling.
- Orchestrated large-scale computations in Jax on Amazon EC2 instances equipped with V100 tensor core GPUs, achieving efficient hardware utilization and significantly improved network training times by a factor of 10x.
- Published research on computational limits of reservoir computing in *Limits to Reservoir Learning*.

2022-2023 | Researcher at Sandia National Laboratories: *Scalable Error Propagation for Computational Systems*

- Developed and implemented analytical and numerical frameworks to model and analyze computational errors in circuits, creating scalable tools to assess how errors propagate, achieving a 100× increase in analysis speed and a 10× improvement in scalability over existing methods.
- Employed statistical techniques to identify and quantify error dynamics, advancing the understanding of error behavior in computational algorithms, with applications extending to quantum computational dynamics.
- Applied backpropagation and optimal control theory to significantly reduce errors on quantum gates by 10×.
- Formulated the problem as an instance of convex optimization, resulting in a 90% reduction in the number of required FPGA controls.
- Improved the simulability of the controls by 10× and demonstrated a 5× increase in gate performance over 87.5% of operating parameter values.

2019 - 2023 | Graduate Student at JILA and University of Colorado, Boulder: *Physical Information Processing*

- Used natural evolutionary strategies to achieve a 10,000× speed-up in the Quantum Approximate Optimization Algorithm (QAOA) by minimizing measurement overhead. Published in "The QAOA with Few Measurements".
- Conducted extensive numerical simulations using HPC clusters managed with Slurm, applying information theory to model and analyze the dynamics of physical systems and enabling quantum computation on 10× more qubits than existing platforms. Published in "Individual qubit addressing of rotating ion crystals in a Penning trap".
- Theoretically and numerically analyzed the fundamental scaling of signal processing, improving broadband detection speeds by 10×. Published in "Opportunities and limitations in broadband sensing".
- Developed a new efficient theory for benchmarking quantum computers, increasing the size of feasible characterization by 7×. Published in "A theory of direct randomized benchmarking".
- Published nine papers in four years, graduating two years earlier than average and leading collaborations with national laboratories and startups.
- Funded by a NASA Space Technology Graduate Research Opportunity (NSTGRO) Fellowship and a QISE-NET Award (Cohort 4).

2016 - 2019 | Software Engineer at Rigetti Computing: *Scaling Quantum Computers*

- Led development of control software, scaling measurement framework from 100s to millions of experiments while maintaining 100% code coverage.
- Designed a novel statistical experimental protocol for calibrating single qubit gates' DRAG parameter achieving 10× faster calibration.
- Led integration of public-facing algorithms and compiler repositories with in-house control software, creating a characterization server that sped up experiments by 100×.
- Led collaboration with Sandia National Laboratories, demonstrating 99% fidelity computational operations using automated, distributed statistical analysis of thousands of experiments with RabbitMQ/Celery/Redis. Results published in "Parametrically Activated Entangling Gate Protected from Flux Noise".
- Used machine learning for signal processing to filter RF signals to reduce data transfer overhead by 10×.
- Developed quantum machine learning algorithms using implicit kernels on quantum processors, achieving a 0.7% error rate improvement on MNIST classification.
- Enhanced automated system calibration routines with a Python DSL, leading a codebase refactor to increase engineering development speed by 2×.

Publications and Patents

Anthony M. Polloreno et al. "Limits to Reservoir Learning," *arXiv preprint*, 2023; **Anthony M. Polloreno et al.** "Impact of Markovian Errors on Random Circuits," *in progress*, 2023; **Anthony M. Polloreno et al.** "Theory of Direct Randomized Benchmarking," *arXiv preprint*, 2023; **Anthony M. Polloreno et al.** "Noisy Reservoir Computation," *arXiv preprint*, 2023; **Anthony M. Polloreno et al.** "Opportunities and Limitations in Broadband Sensing," *Physical Review Applied*, 2023; **Anthony M. Polloreno et al.** "QAOA with Few Measurements," *arXiv preprint*, 2022; **Ariel Shlosberg et al.** "Fault Tolerance in Small Circuits Using Bacon-Shor Codes," *arXiv preprint*, 2021; **Anthony M. Polloreno et al.** "Individual Qubit Addressing in Ion Crystals," *Physical Review Research*, 2022; **Anthony M. Polloreno et al.** "Decorrelation of Errors in Quantum Gates," *Quantum Science and Technology*, 2021; **Sabrina S. Hong et al.** "Parametrically Activated Entangling Gate Protected from Flux Noise," *Physical Review A*, 2020; **C. M. Wilson et al.** "Quantum Kitchen Sinks: Algorithm for Machine Learning on Quantum Computers," *arXiv preprint*, 2018; **S. A. Caldwell et al.** "Entangling Gates Using Transmon Qubits," *Physical Review Applied*, 2018; **Matthew Reagor et al.** "Universal Parametric Entangling Gates on Multi-Qubit Lattice," *Science Advances*, 2018, **Michael Justin Gerchick Scheer et al.** "Modular Quantum Processor Architectures," *US Patent App. 17/119,089*, 2021; **Alexander Papageorge et al.** "Operating a Quantum Processor with 3D Device Topology," *Google Patents*.