“What are my chances of success?”

This is me

Eating fried frog legs

Start where you can

Learning what the next step to take, is just as important as taking it

Ask for help

It might surprise you just how many people are willing to help if you ask nicely

Come prepared

Plan ahead which questions you want to ask, and a mental list of topics you would like to be asked about

Remember success is a slide

It takes a lot of hard work to achieve your goal, keep the prize in mind when it gets tough to continue

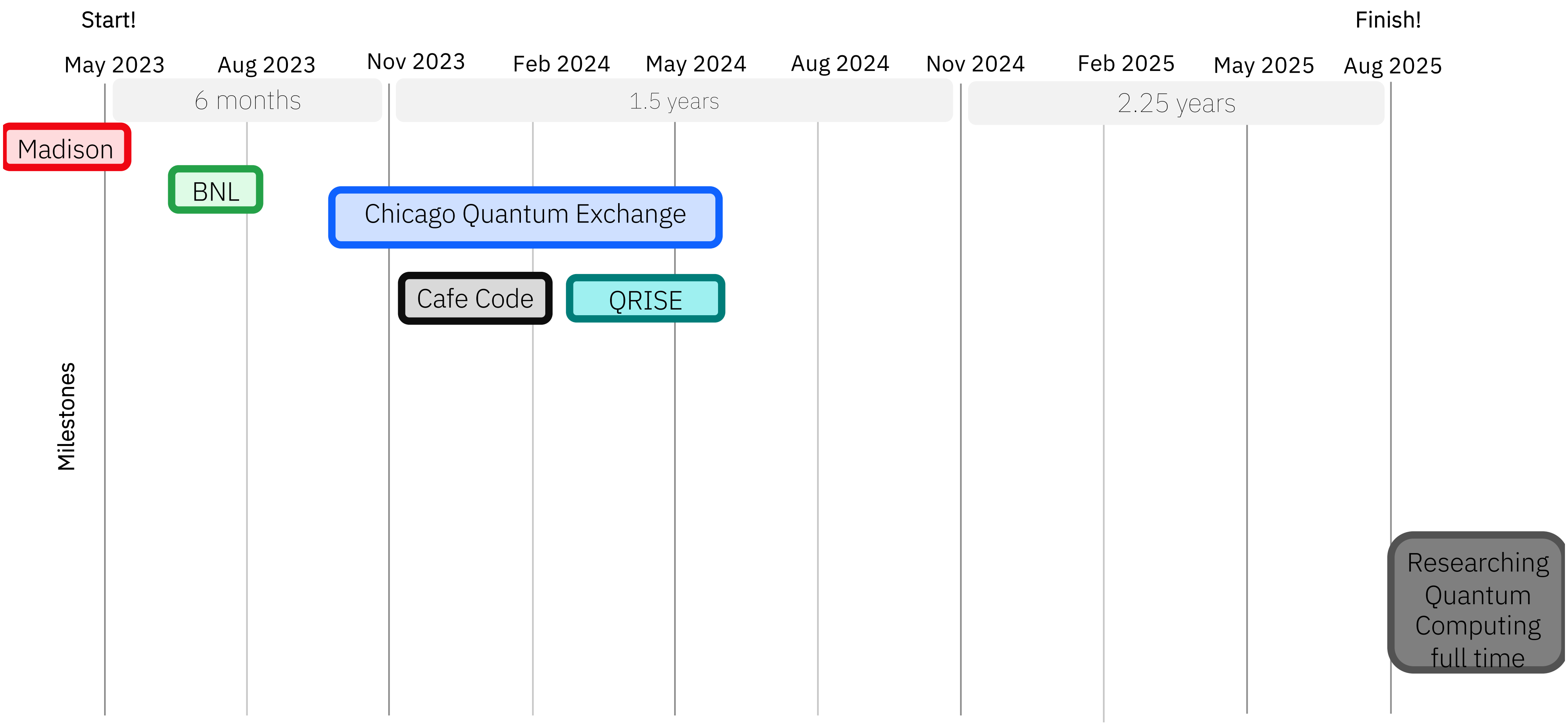
Start where you can

Choose projects that progress the goal

Search for accessible opportunities

Look to be challenged, not overwhelmed

Example:
QRISE Hackathon


Start!
Finish!
May 2023
Aug 2023
Nov 2023
Feb 2024
May 2024
Aug 2024
Nov 2024
Feb 2025
May 2025
Aug 2025
6 months
1.5 years
2.25 years
Madison
BNL
Chicago Quantum Exchange
Cafe Code
QRISE
Milestones
Researching Quantum Computing full time

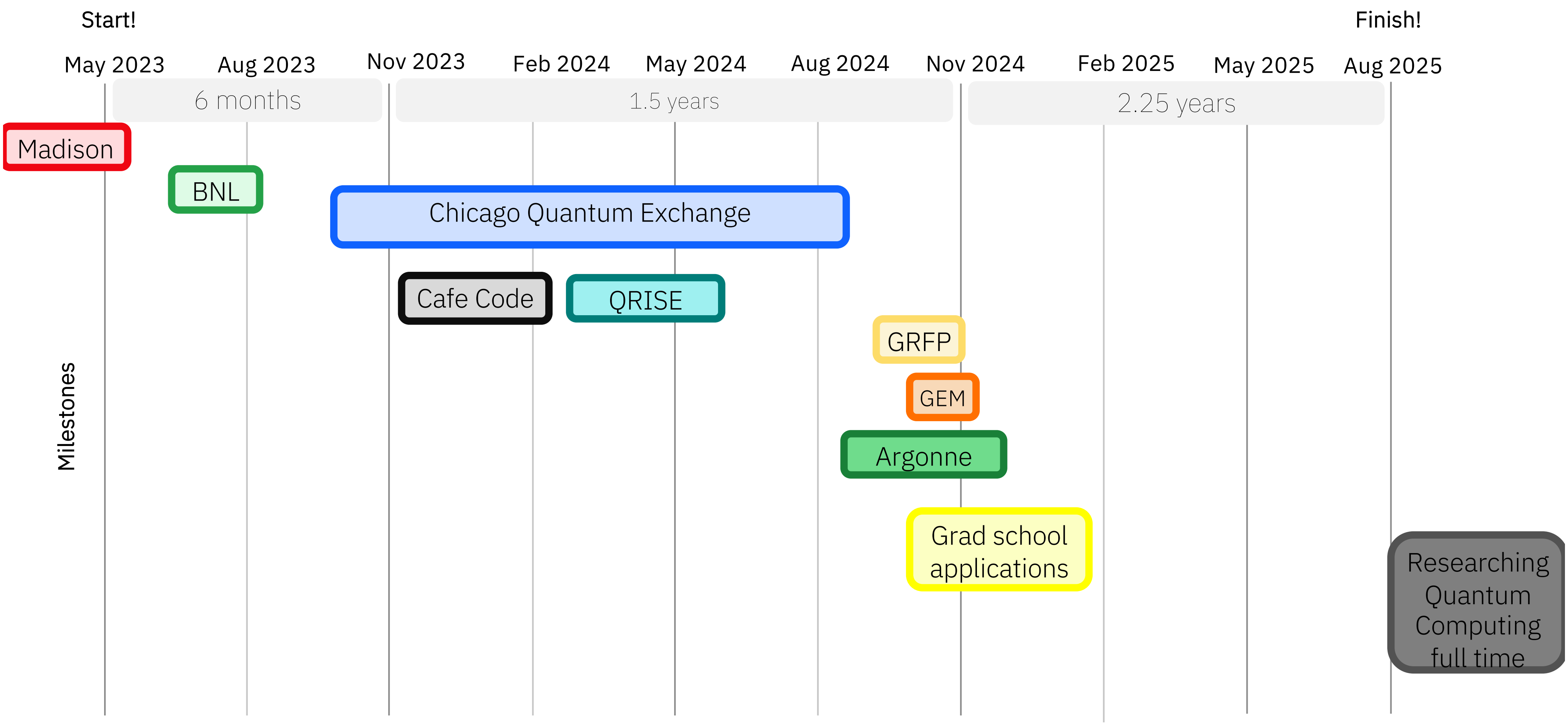
Ask for help

Be proactive; find people who will help you

Own up if you don't understand; people who act smart get less help

Example:
GRFP application

Becky Durst
Mohammad Ramadan
Jeffrey Larson
Ji Liu
Siby Jose
Evan Toler
Wandi Ding
Sam Smiley
Emily Easton
Baha Balentekin
Matthew Tremba
Corrina Callahan
Bruce Lindvall
Josh Myers-dean
Amy Trethaway
Sridhar Tayur
Abhishek Aggarwal

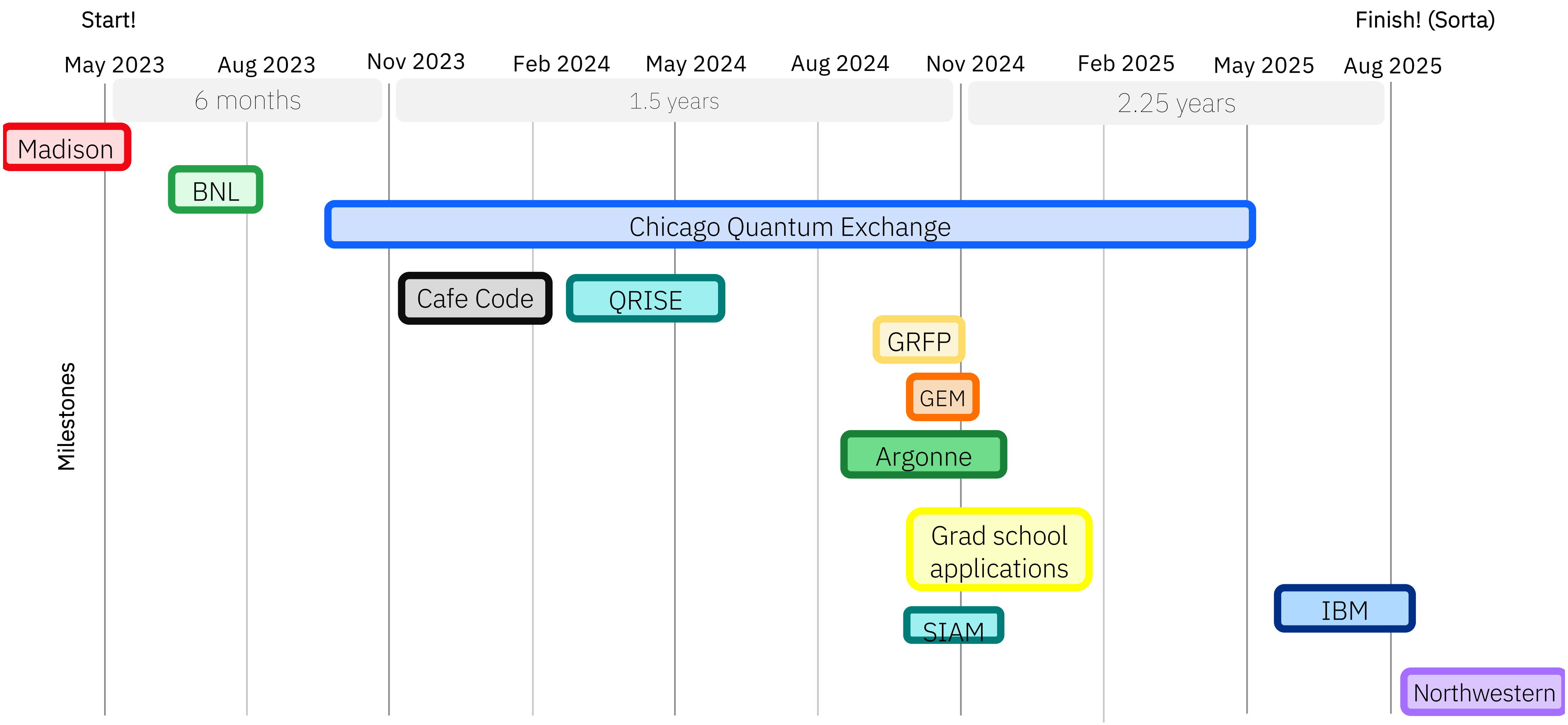


Start!
Finish!
May 2023
Aug 2023
Nov 2023
Feb 2024
May 2024
Aug 2024
Nov 2024
Feb 2025
May 2025
Aug 2025
6 months
1.5 years
2.25 years
Milestones
Madison
BNL
Chicago Quantum Exchange
Cafe Code
QRISE
GRFP
GEM
Argonne
Grad school applications
Researching Quantum Computing full time

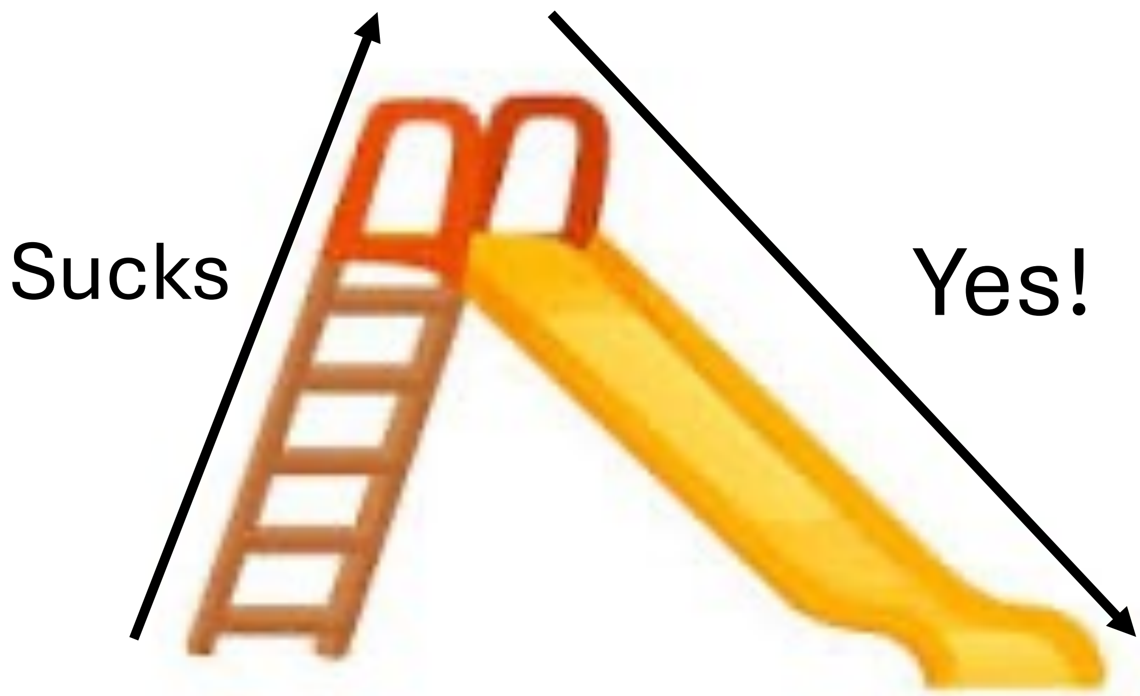
Come prepared

- Come with questions about their research
- Memorize your elevator pitch
- Scout and research people you want to talk with
- Follow up

Example:
SIAM conference

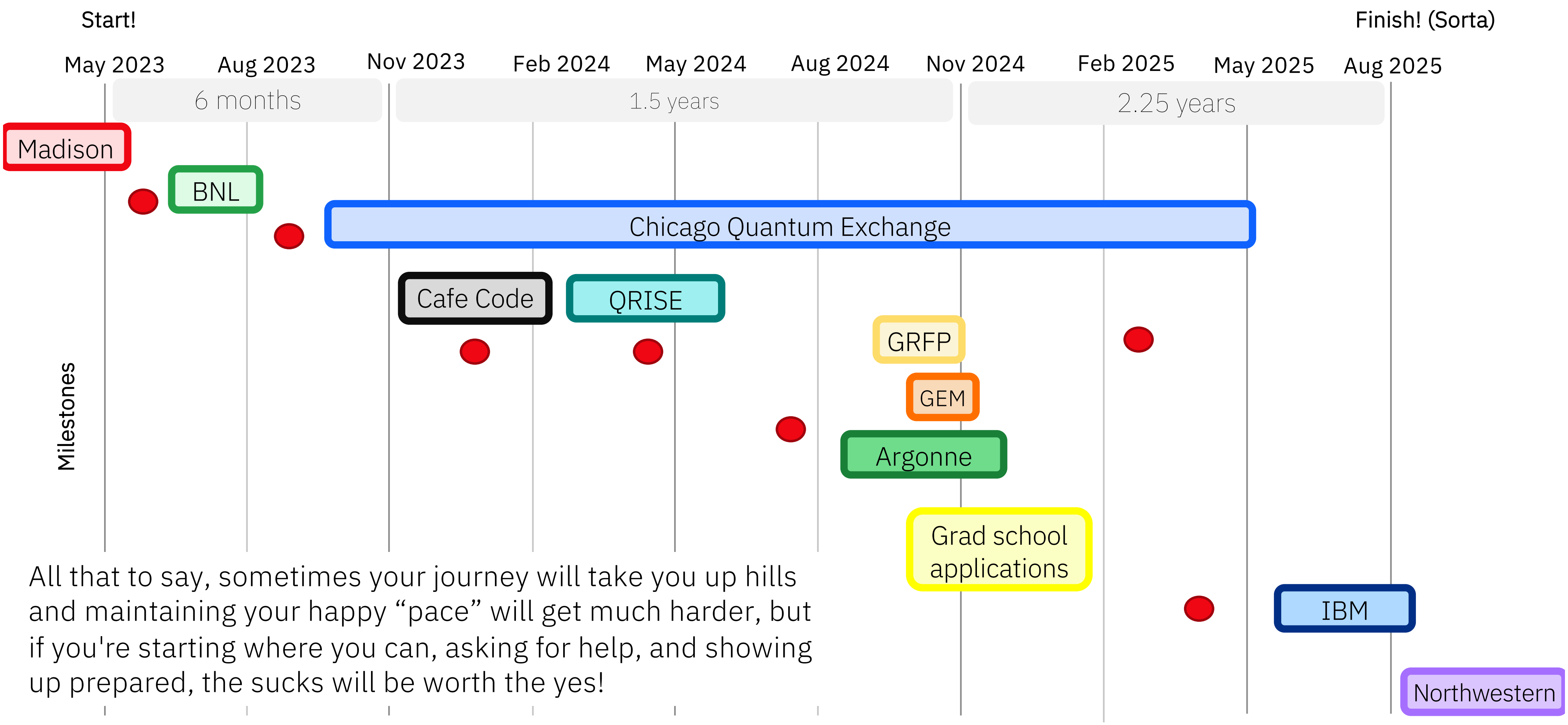

Start!
Finish! (Sorta)
May 2023
Aug 2023
Nov 2023
Feb 2024
May 2024
Aug 2024
Nov 2024
Feb 2025
May 2025
Aug 2025
6 months
1.5 years
2.25 years
Milestones
Madison
BNL
Chicago Quantum Exchange
Cafe Code
QRISE
GRFP
GEM
Argonne
Grad school applications
IBM
SIAM
Northwestern

Remember success is a slide



The many moments of doubt

- 1. Got rejected from all grad programs I applied to
- 2. Believed I would never again be allowed to work in a STEM research role
- 3. Wanted to do research but didn't think I was smart enough
- 4. Seriously wondered if any of the work I did was getting me closer to my goal
- 5. Quit my full-time job for an internship, on the belief it would help me get into grad school
- 6. Application to GRFP rejected
- 7. Lost the GEM fellowship because of Northwestern's political landscape



All that to say, sometimes your journey will take you up hills and maintaining your happy "pace" will get much harder, but if you're starting where you can, asking for help, and showing up prepared, the sucks will be worth the yes!

Email me at:

Kaytlin.harrison@gmail.com

Thank You

Happy to connect on LinkedIn

Some example topics to ask about

- What is research in a National Lab is like
- How to get into university research
- Where to find **Scholarships and Grant funds**
- Research in Quantum Optimization (specifically QAOA)
- Transferring from a Community College
- Which Quantum Stocks to buy (just kidding!)
- Applying for the GRFP
- Applying STEM skills in a STEM **adjacent role**

Research at Argonne

Integration of Dynamic ADAPT-QAOA and QuCLEAR to reduce quantum gates in QAOA Circuits

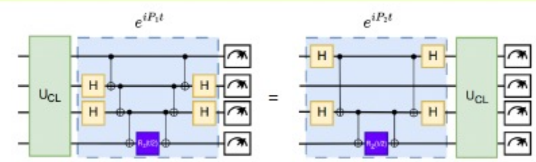
Kaytlin Harrison, Ji Liu, Jeffrey Larson
Mathematics and Computer Science Division, Argonne National Laboratory

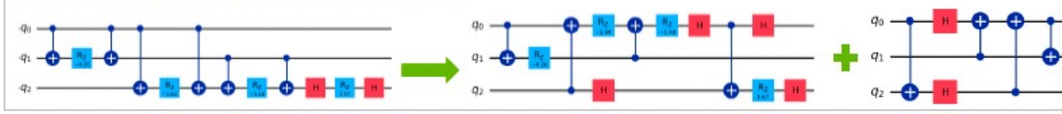
BACKGROUND

- **The Quantum Approximation Optimization Algorithm (QAOA)** solves QUBO problems like MaxCut by alternating between the Cost Hamiltonian Hc, which encodes the problem, and the Mixer Hamiltonian Hm which perturbates the system and lets us explore the solution space. These Hamiltonians use parameterized quantum gates which are optimized classically to minimize Hc
- A **key limitation** of QAOA is the high number of quantum gates required to encode the Hamiltonians[1]
- QuCLEAR and Dynamic ADAPT-QAOA (AQ) are unique optimization techniques that reduce the number of quantum gates needed for Standard QAOA

QuCLEAR: QUANTUM CLIFFORD EXTRACTION AND ABSORPTION

QuCLEAR optimizes quantum circuits by extracting select clifford gates and processing them classical, reducing the number of quantum operations required[3]





Dynamic ADAPT-QAOA

Dynamic AQ selects the mixer that will maximize the gradient, and determines is the Hc for a given layer is needed, optimizing the circuit by reducing the number of quantum gates required for convergence[2]

The energy variation due to the added parameters

$$\delta E_n\left(\beta_n, \gamma_n; A\right) = \langle \Psi_n\left(\beta_n, \gamma_n; A\right) | H | \Psi_n\left(\beta_n, \gamma_n; A\right) \rangle$$

Enables the definition of the energy gradient

$$\mathcal{G}_p\left(\gamma_n; A\right) \equiv \frac{\partial}{\partial \beta_n} \delta E_n\left(\beta_n, \gamma_n; A\right)\Big|_{\beta_n=0}$$

Evaluating the gradient identifies the optimal mixer

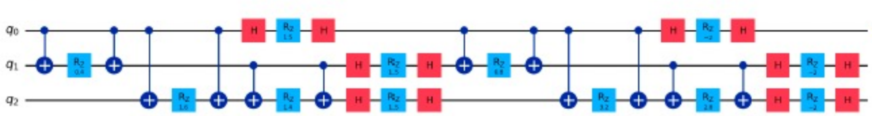
$$M_n = \underset{A \in n}{\operatorname{argmax}} \left[\left| \mathcal{G}_n\left(\gamma_n; A\right) \right| \right]$$

MOTIVATION

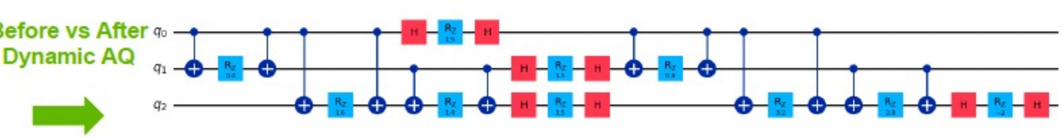
- Will combining optimizations reduces quantum gates and error?
- Can Dynamic AQ and QuCLEAR work in tandem?
- Does the order of optimization matter?
- Is this a scalable solution?

METHODS

- Proof that order of optimization is inconsequential
- Empirical analysis of clifford gate counts for QAOA, Dynamic AQ, QuCLEAR, and their combination
- A look at scalability of both approaches combined



Before vs After Dynamic AQ



ORDER OF OPTIMIZATION

Initial setup: Layers of alternating Hc and Hm

$$\text{Layer } 0 = |0\rangle$$
$$\text{Layer } 0+1 = M_1 C_1 |0\rangle$$
$$\textstyle\sum_0^{n-1} \text{Layers} = M_{n-1} C_{n-1} \dots M_1 C_1 |0\rangle$$

First: Use Dynamic AQ to determine the mixer M_n for layer n

$$M_n = \text{argmax}\left[\left|\frac{\partial}{\partial\beta}\langle\psi_{n-1} e^{-i\beta_n A} e^{-i\gamma_n H}\middle|H\middle|e^{-i\beta_n A} e^{-i\gamma_n H}\psi_{n-1}\rangle\right|\right]$$
$$\textstyle\sum_0^{n} \text{Layers} = M_n C_n M_{n-1} C_{n-1} \dots M_1 C_1 |0\rangle$$

Second: Use QuCLEAR to determine the optimized circuit and clifford circuit

$$\textstyle\sum_0^{n} \text{Layers} = M_n C_n U_{CL} U_{\text{opt}} |0\rangle = U_{CL} M_n' C_n' U_{\text{opt}} |0\rangle$$
$$\text{where } M_n' = U_{CL}^\dagger M_n U_{CL} \quad C_n' = U_{CL}^\dagger C_n U_{CL}$$

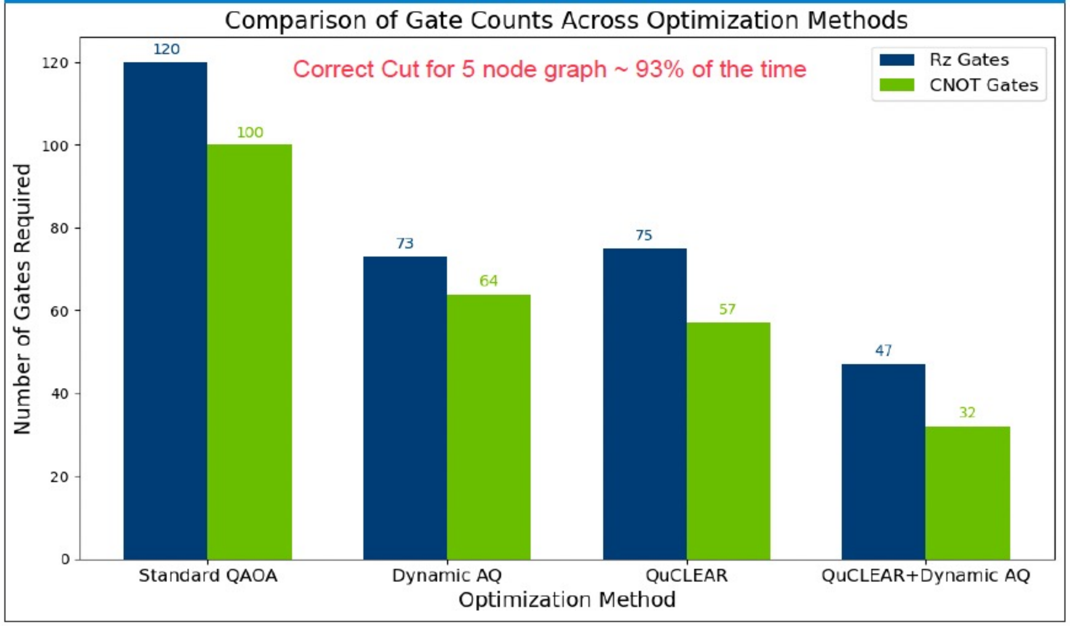
Now: Reverse order and use QuCLEAR first to optimize layers 0 to $n-1$

$$\textstyle\sum_0^{n-1} \text{Layers} = U_{CL} U_{\text{opt}} |0\rangle$$

Next: Use the QuCLEAR optimized layers and apply Dynamic AQ to get M_n

$$M_n = \text{argmax}\left[\left|\frac{\partial}{\partial\beta}\left\langle 0\middle|U_{\text{opt}}^\dagger U_{CL}^\dagger e^{-i\beta_n A} e^{-i\gamma_n H}\middle|H\middle|e^{-i\beta_n A} e^{-i\gamma_n H} U_{CL} U_{\text{opt}}\middle|0\right\rangle\right|\right]$$
$$M_n' = \text{argmax}\left[\left|\frac{\partial}{\partial\beta}\left\langle 0\middle|U_{\text{opt}}^\dagger e^{-i\beta_n A'} e^{-i\gamma_n H'} U_{CL}^\dagger\middle|H\middle|U_{CL} e^{-i\beta_n A'} e^{-i\gamma_n H'} U_{\text{opt}}\middle|0\right\rangle\right|\right]$$
$$\sum_0^n \text{Layers} = U_{CL} M_n' C_n' U_{\text{opt}} |0\rangle$$

EMPIRICAL RESULTS

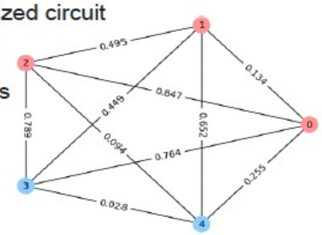


SCALABILITY

- In a 5-node example, QuCLEAR cut CNOT gates by 43% and RZ gates by 37.5%, while Dynamic AQ reduced them by 36% and 39%, respectively. Combined, they achieved reductions of 68% in CNOT gates and 60% in RZ gates
- But Dynamic AQ's gradient calculation introduces a computational bottleneck due to expensive matrix multiplications
- Inspired by Adapt-VQE, this is solved by calculating gradients in O(n) time using FT-QC. Until such devices exist, we rely on costly classical methods for validation[4]

SUMMARY

- Combining Dynamic AQ and QuCLEAR reduces quantum gates and sources of error
- The application order of techniques does not affect the final optimized circuit
- Dynamic AQ scales well with quantum gradient computations



FUTURE RESEARCH

Dynamic AQ's costliest step is gradient calculation. Future work could shrink the mixer pool or use machine learning to predict the best mixer, avoiding gradient evaluations

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[1]Mazumder, A., & Tayur, S. (2024). Five starter problems: Solving quadratic unconstrained binary optimization models on quantum computers. *arXiv:2401.08989*. [2]Yanakiev, N., et al. (2023). Dynamic-ADAPT-QAOA: An algorithm with shallow and noise-resilient circuits. *arXiv:2309.00047*. [3]Liu, J., et al. (2024). QuCLEAR: Clifford extraction and absorption for significant reduction in quantum circuit size. *arXiv:2408.13316*. [4] Zhu, L. An adaptive quantum approximate optimization algorithm for solving combinatorial problems on a quantum computer. arXiv:2005.10258 (2022)