

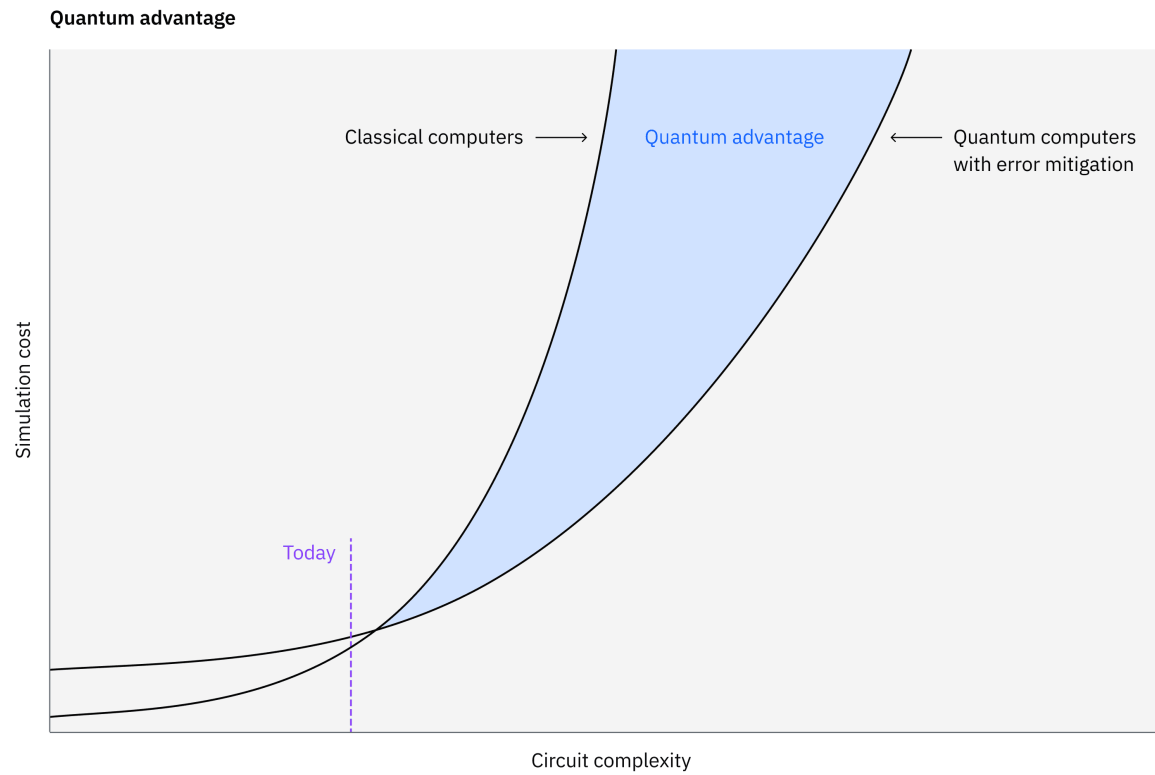
Subspaces in quantum computing and quantum machine learning

Alexander (Lex) Kemper

Department of Physics
North Carolina State University
<https://go.ncsu.edu/kemper-lab>



Quantum computers in 2026

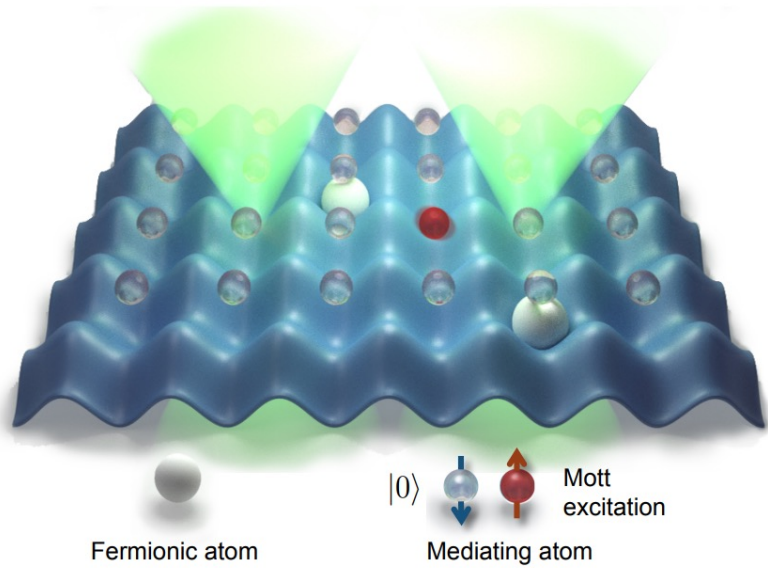


<https://www.ibm.com/quantum/blog/quantum-advantage-era>

Bespoke quantum simulator

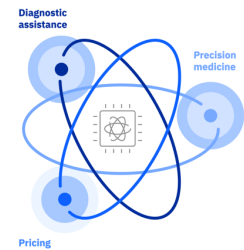


Digital algorithms

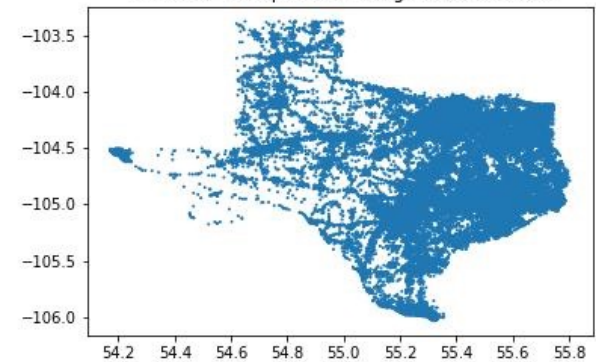


VectorStock® VectorStock.com/37124379

Figure 1
Quantum computers may enable three key healthcare use cases that reinforce each other in a virtuous cycle. For instance, accurate diagnoses enable precise treatments, as well as a better reflection of patient risks in pricing models.



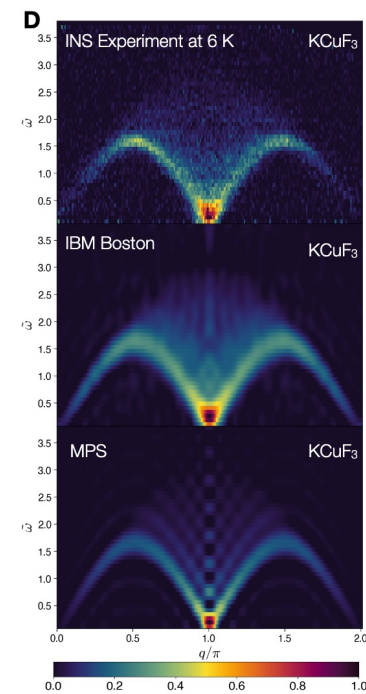
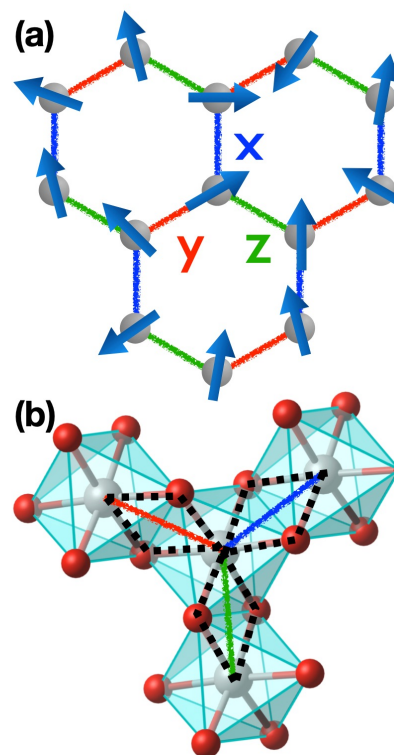
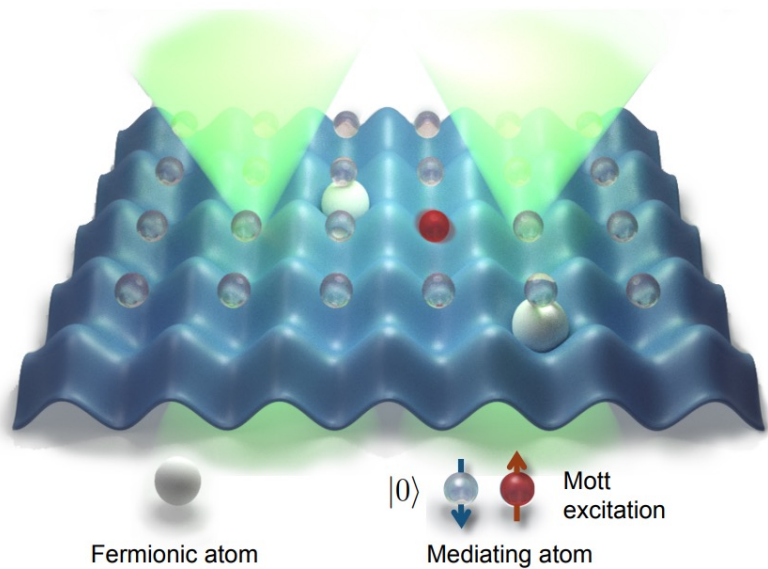
(Centers of) Required Coverage Areas in Texas



Bespoke quantum simulator



Digital algorithms



Lex' definition of quantum advantage: when I can use a quantum computer to answer a question relevant to condensed matter physicists.

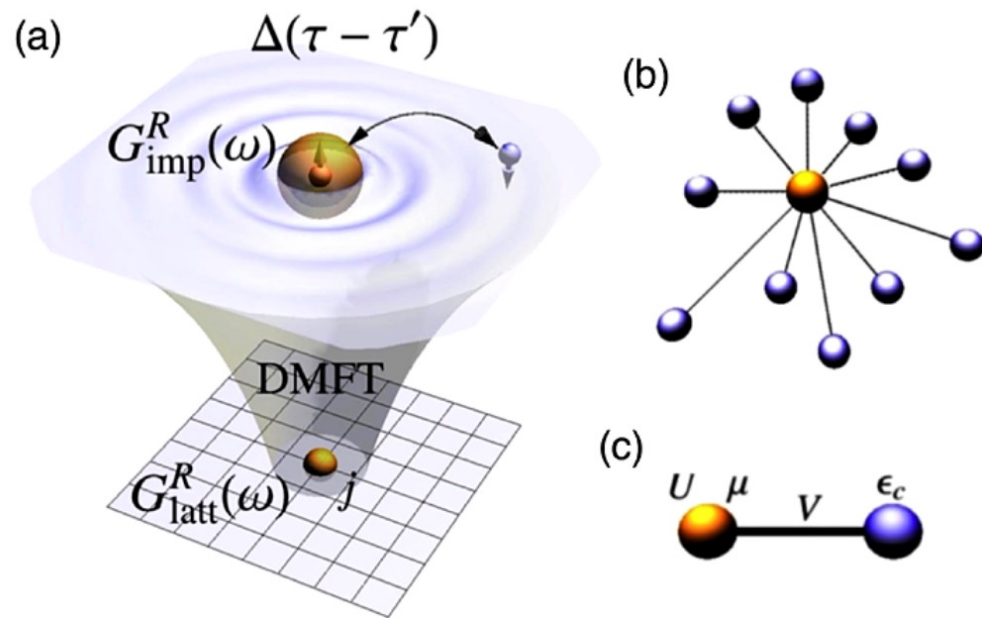
To get to a quantum advantage, we need a problem that is

- Relevant/interesting
- Can be used to interface with non-QC folks
- Runs on a few qubits (< 100)
- Doesn't require long qubit coherence times

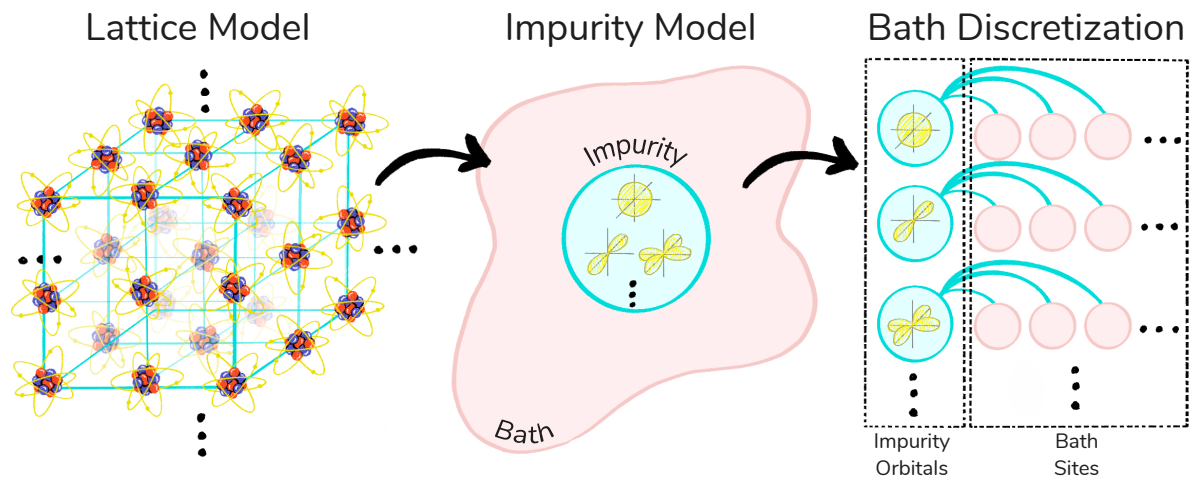
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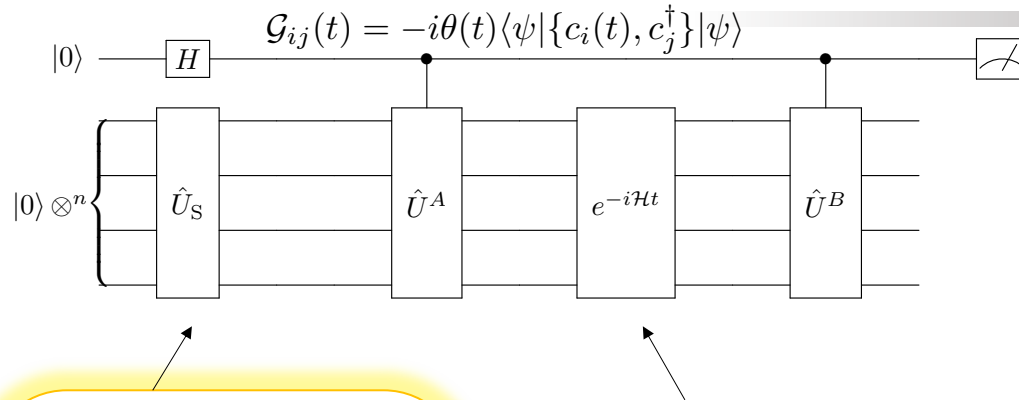


Kreula EPJ Quant. Tech. (2016)



$$G_{ij}(t) = -i\theta(t) \langle \psi | \{c_i(t), c_j^\dagger\} | \psi \rangle$$

A-Z quantum simulation



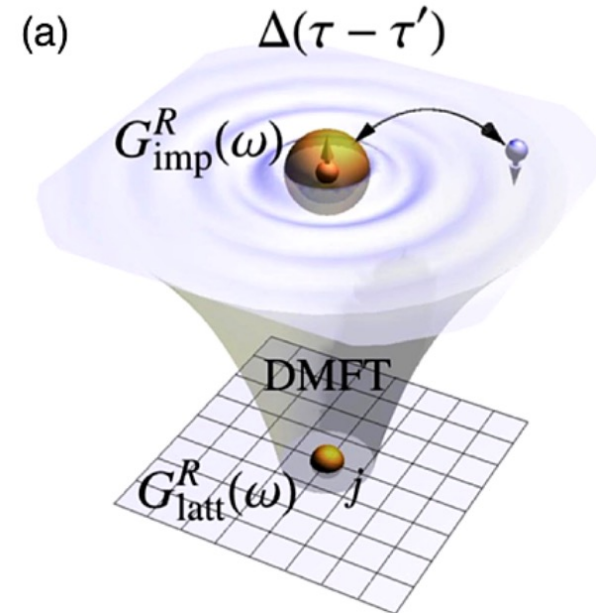
Prepare state of interest

- ☹️ Circuit to prepare interacting ground state is very deep
- ☹️ Variational approaches are very difficult in the presence of noise

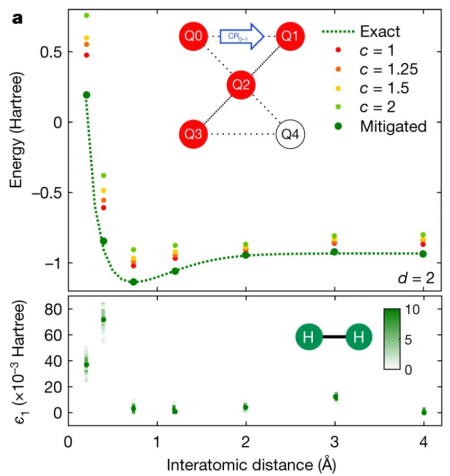
Time evolve

- ☹️ Standard Trotter decomposition leads to deep circuits with many gates
- ☹️ Alternative approaches (QSP) requires many ancillae

☹️ Your results will be very noisy anyway



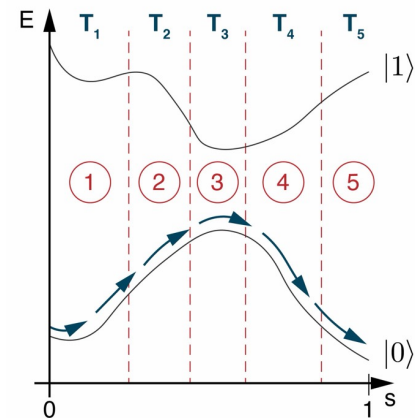
Variational Quantum Eigensolver



[Kandala, Abhinav, *et.al.*, *Nature* 549, no. 7671 (2017): 242-246.]

Barren Plateau

Adiabatic State Preparation



[Schiffer, Benjamin F., *et.al.*, *PRX Quantum* 3, no. 2 (2022): 020347]

Larger depth circuits

The problem: Hilbert space is unreasonably large... $|H| = 2^N$

... and diagonalization is thus difficult.

A solution:

1. Project the Hamiltonian into a smaller space spanned by some vectors $|\psi_j\rangle$
2. Solve the resulting (smaller) generalized eigenvalue problem

$$\mathcal{H}|\Psi\rangle = E\mathcal{S}|\Psi\rangle$$

3. Show (or hope) that your subspace spans the states of interest

Which states $|\psi_j\rangle$ to use as a subspace basis?

Krylov states (classical):

$$|\psi_j\rangle = \mathcal{H}^k |\phi_0\rangle$$

Real time evolution

$$|\psi_j\rangle = e^{-i\mathcal{H}t_j} |\phi_0\rangle$$

Apply Pauli operators, elements of H, or creation/annihilation operators

$$|\psi_j\rangle = \mathcal{O}_j |\phi_0\rangle$$

Cortes PRA 2022
Klymko PRXQ 2022
Stair JCTC 2022
Seki PRXQ 2021
Bespalova PRXQ 2021

Colless PRX 2018
McClellan PRA 2017
Bharti PRA 2021
Lim QST 2021

The problem: Hilbert space is unreasonably large... $|H| = 2^N$

... and diagonalization is thus difficult.

... although the physics we care about lives in a small corner of it.

- Ground states
- Excited states
- Thermal states

Eigenvector Continuation: Use ground/excited states of the Hamiltonian
at different parameters to span the space of interest

PHYSICAL REVIEW LETTERS **121**, 032501 (2018)

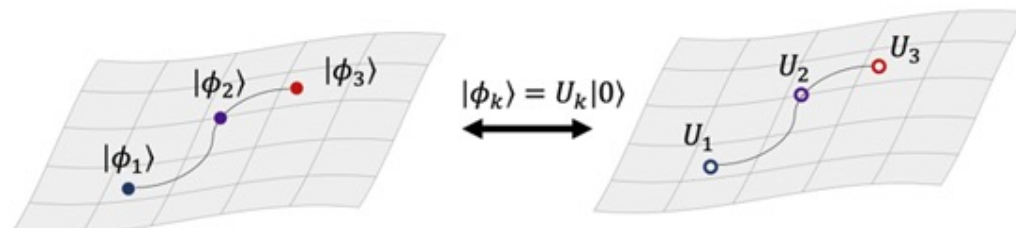
Featured in Physics

Eigenvector Continuation with Subspace Learning

Dillon Frame,^{1,2} Rongzheng He,^{1,2} Ilse Ipsen,³ Daniel Lee,⁴ Dean Lee,^{1,2} and Ermal Rrapaj⁵

- Ground state varies continuously in a parameter space and is spanned by a few low energy state vectors.

$$|\phi_3\rangle = \alpha_1 |\phi_1\rangle + \alpha_2 |\phi_2\rangle$$

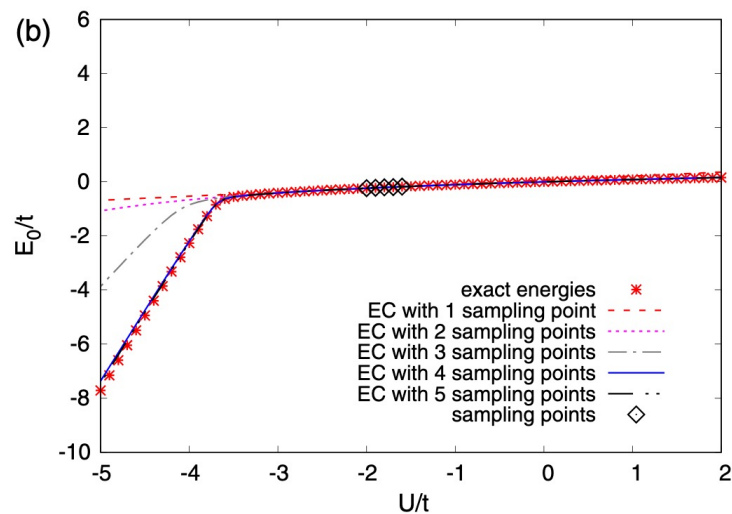
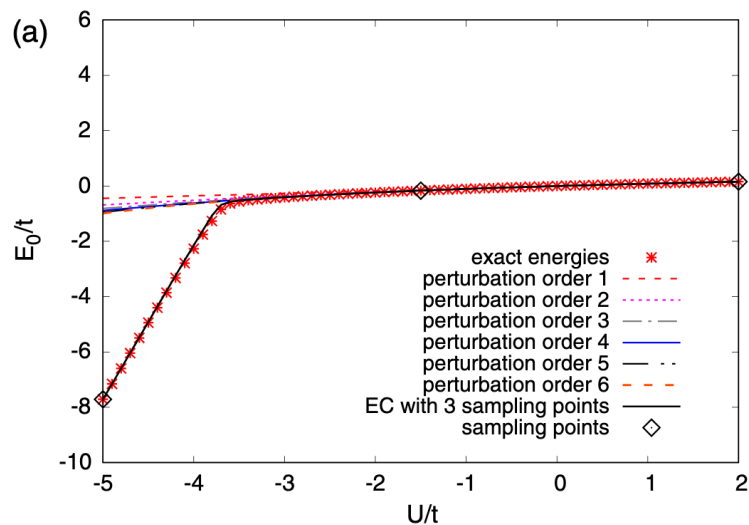


PHYSICAL REVIEW LETTERS **121**, 032501 (2018)

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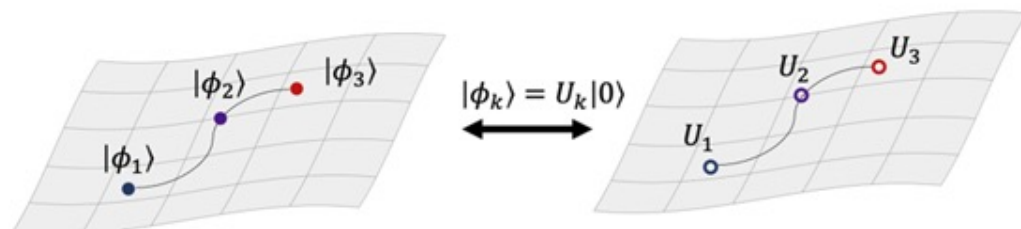
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- Make a subspace using low energy states at different points in parameter space
- The spanning states do not have to have any special relation to the problem of interest

$$\mathcal{H}_{target} = \{H(p_0), H(p_1), \dots, H(p_n)\}$$

Choose k Hamiltonians at k parameter points

$$\{H(p_0), H(p_1), \dots, H(p_k)\}$$

Solve for ground state vector

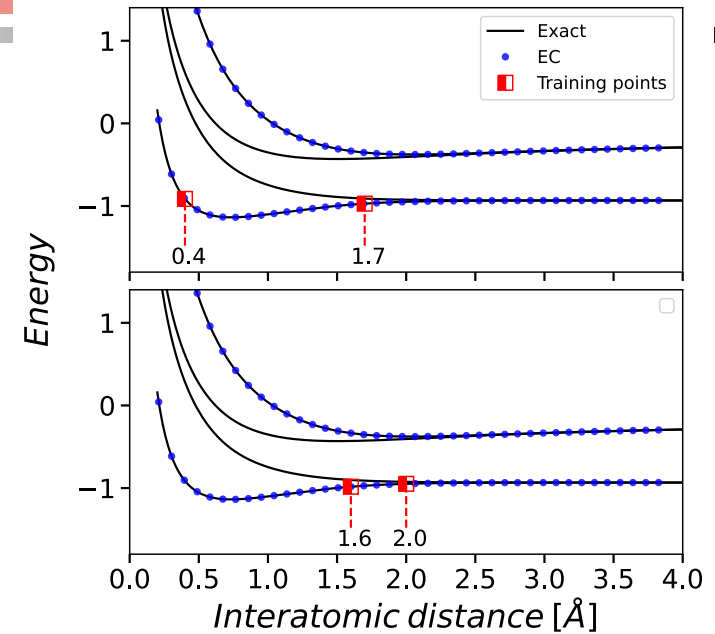
$$\{|\phi_0\rangle, |\phi_1\rangle, \dots, |\phi_k\rangle\}$$

k Low energy state vectors

Subspace
Diagonalization



Energy spectrum across the
parameter range



$$\mathcal{H}_{target} = \{H(p_0), H(p_1), \dots, H(p_n)\}$$

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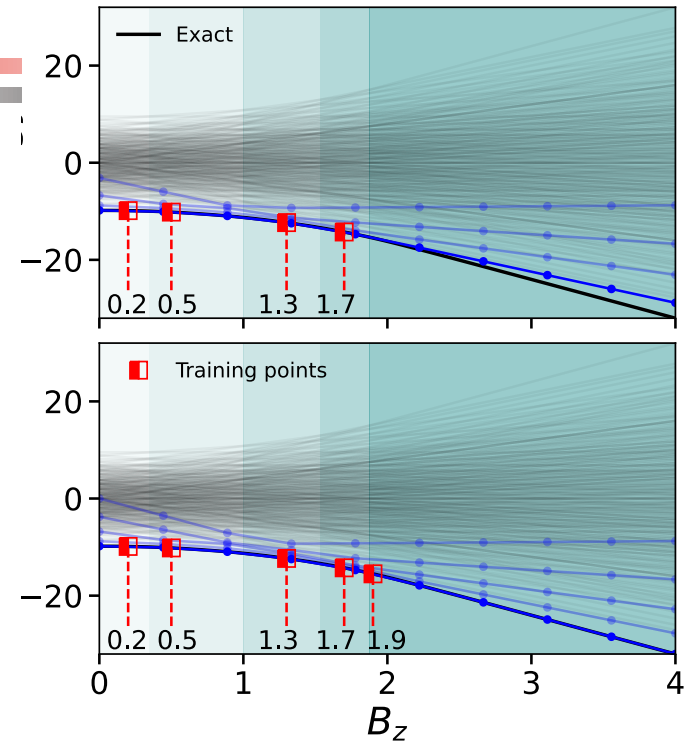
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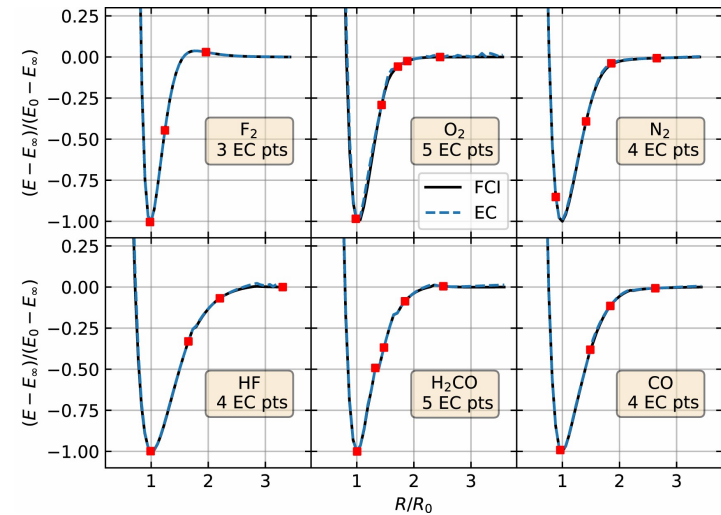
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Diagonalization



Energy spectrum across the
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Choose k Hamiltonians at k parameter points

$$\{H(p_0), H(p_1), \dots, H(p_k)\}$$

Solve for ground state vector

*We need low energy state vectors –
Exact ground states are not necessary!*

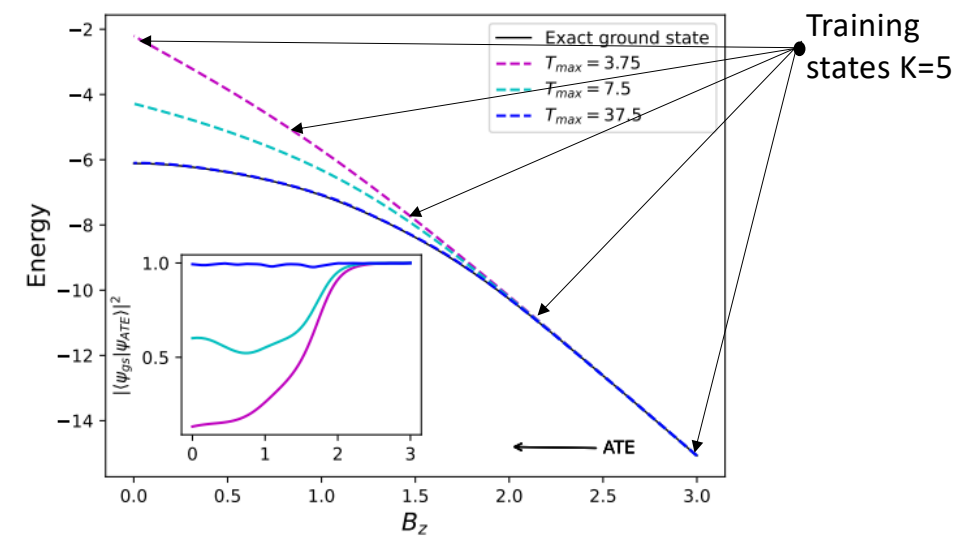
We can use any state preparation method

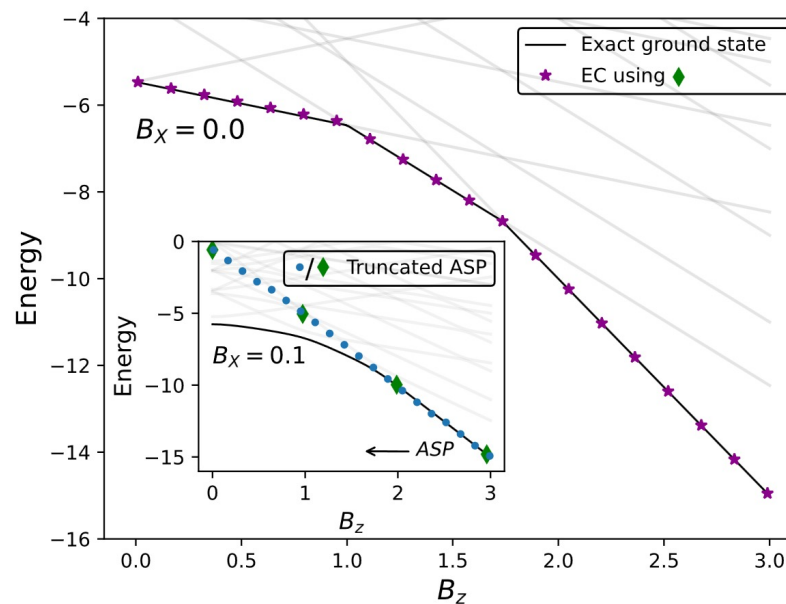
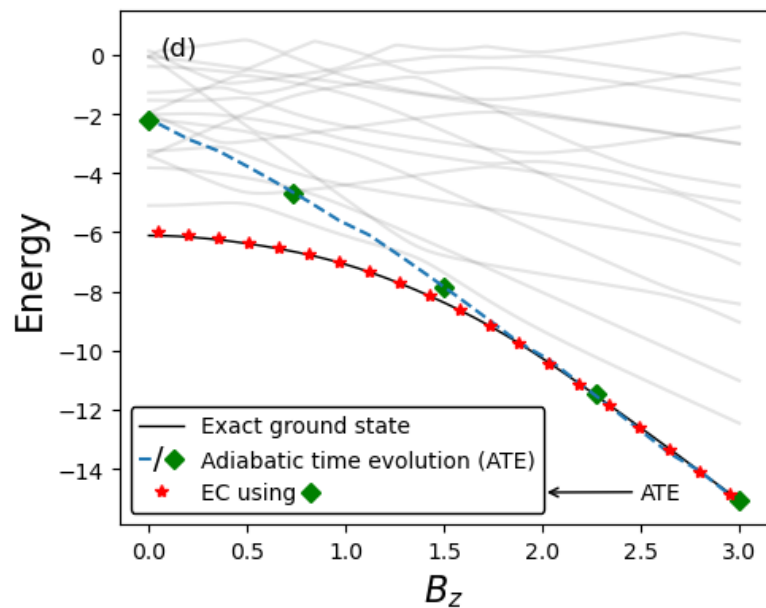
$$\{|\phi_0\rangle, |\phi_1\rangle, \dots, |\phi_k\rangle\}$$

k low energy state vectors

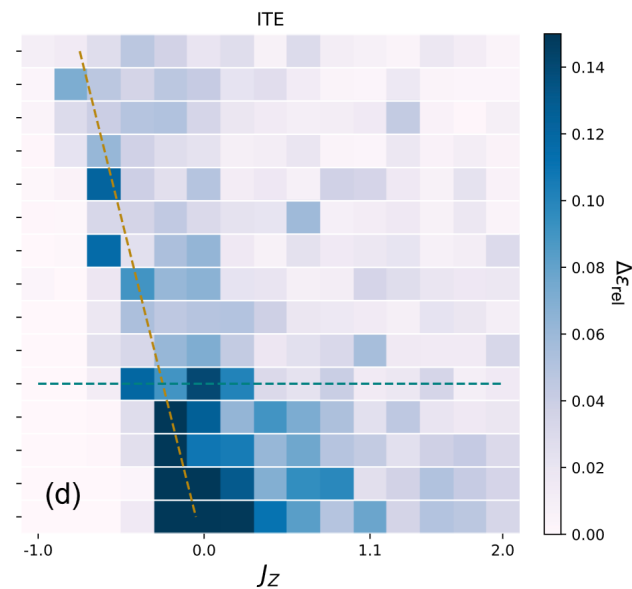
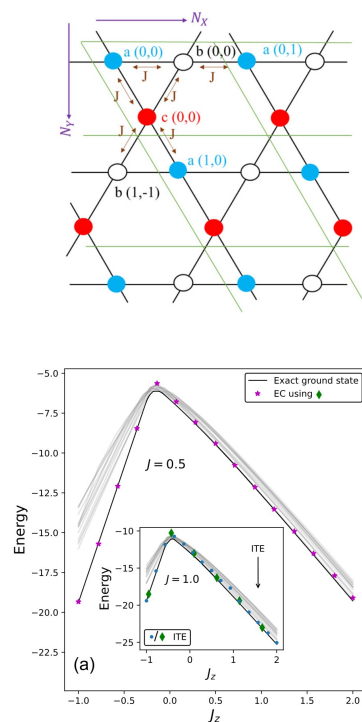
Subspace
Diagonalization

Energy spectrum across the
parameter range

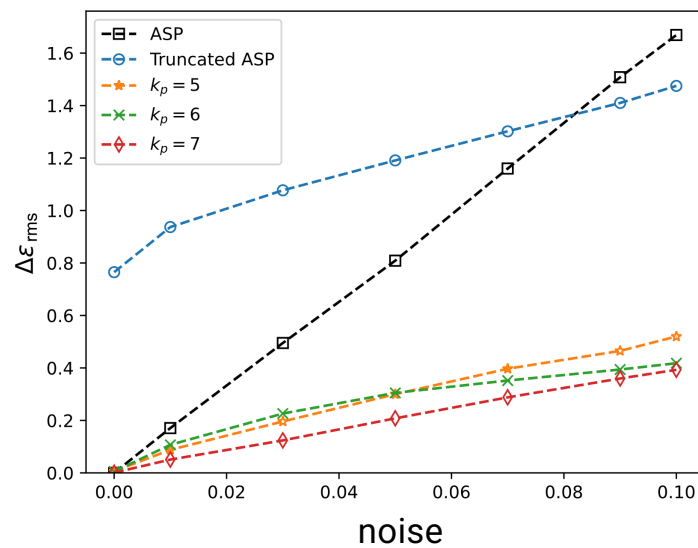
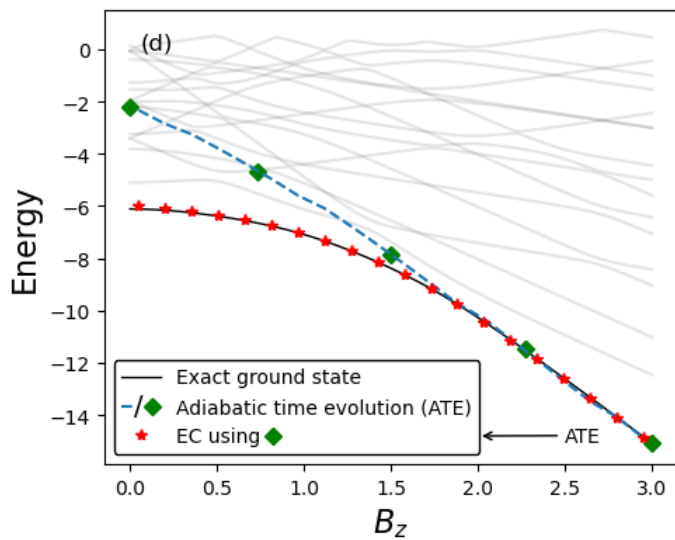




Straightforward subspace expansion \rightarrow improved results from adiabatic state preparation



Straightforward subspace expansion \rightarrow improved results from imaginary time evolution

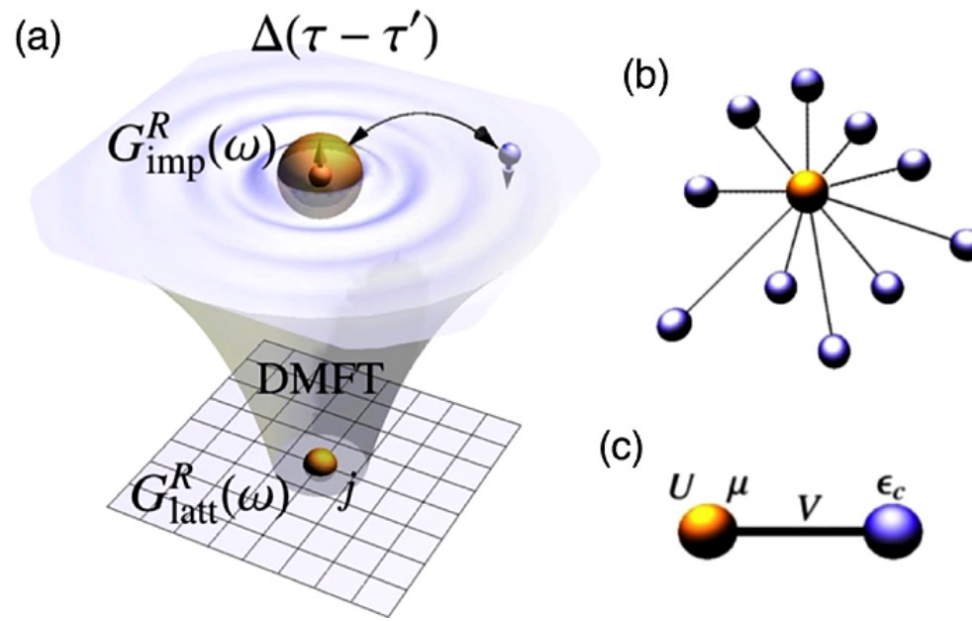


Straightforward subspace expansion -> noise resilience

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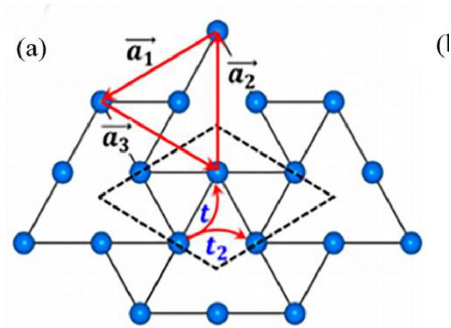
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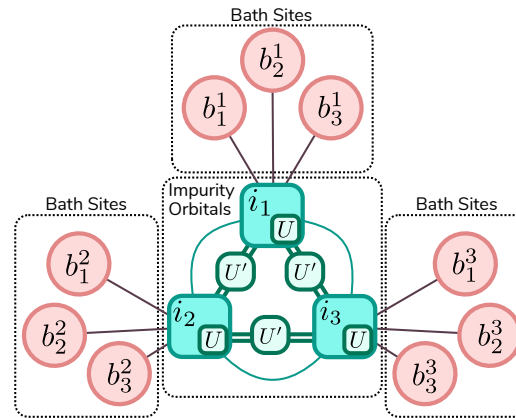


Kreula EPJ Quant. Tech. (2016)

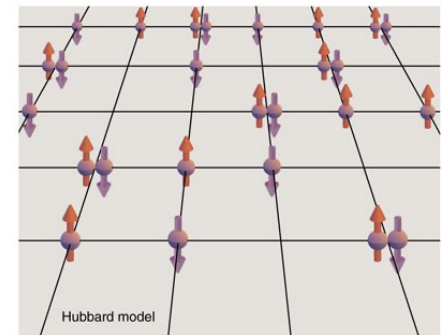
Fermionic Gaussian Subspace



Free fermions



Impurity model



Fully interacting

Complexity

Advantages of a basis based on fermionic gaussian states:

- Polynomially sized calculations to find the ground state
- Easy to prepare on QC
- One basis set spans the necessary space across entire DMFT phase diagram

Commun. Math. Phys. 356, 451–500 (2017)
Digital Object Identifier (DOI) 10.1007/s00220-017-2976-9

Communications in
**Mathematical
Physics**



Complexity of Quantum Impurity Problems


Sergey Bravyi, David Gosset

IBM T.J. Watson Research Center, Yorktown Heights, NY, USA. E-mail: sbravyi@us.ibm.com;
dngosset@us.ibm.com

Received: 28 November 2016 / Accepted: 6 June 2017
Published online: 31 August 2017 – © Springer-Verlag GmbH Germany 2017

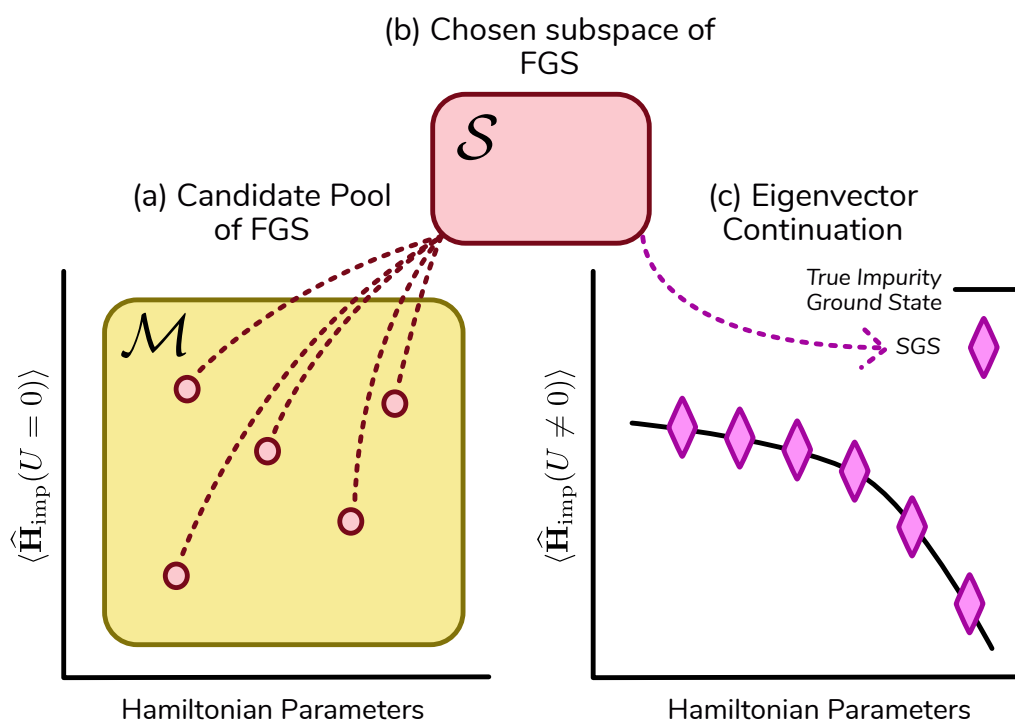
PHYSICAL REVIEW RESEARCH 3, 033188 (2021)

Quantum impurity models using superpositions of fermionic Gaussian states: Practical methods and applications

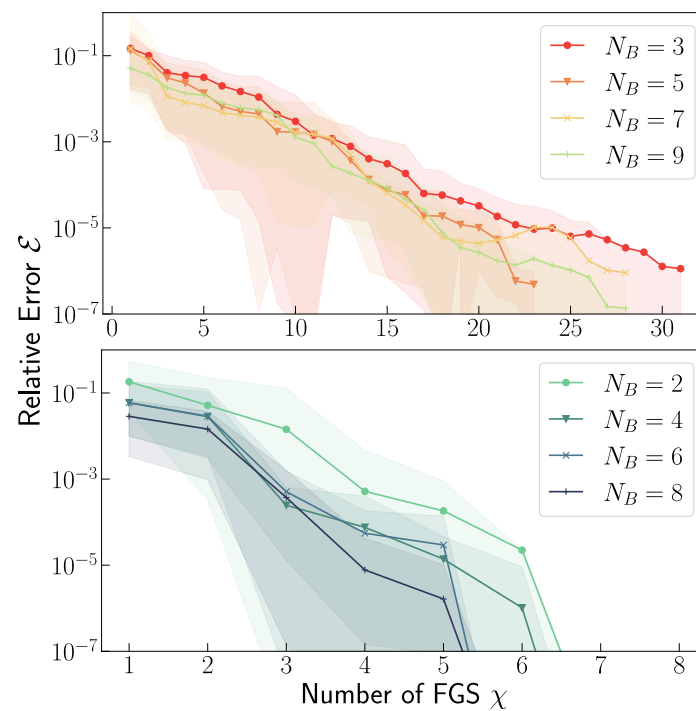
Samuel Boutin  and Bela Bauer
Station Q, Microsoft Corporation, Santa Barbara, California 93106 USA

“The low energy state is represented as a superposition of $\exp [O(b^3)]$ fermionic Gaussian states.”

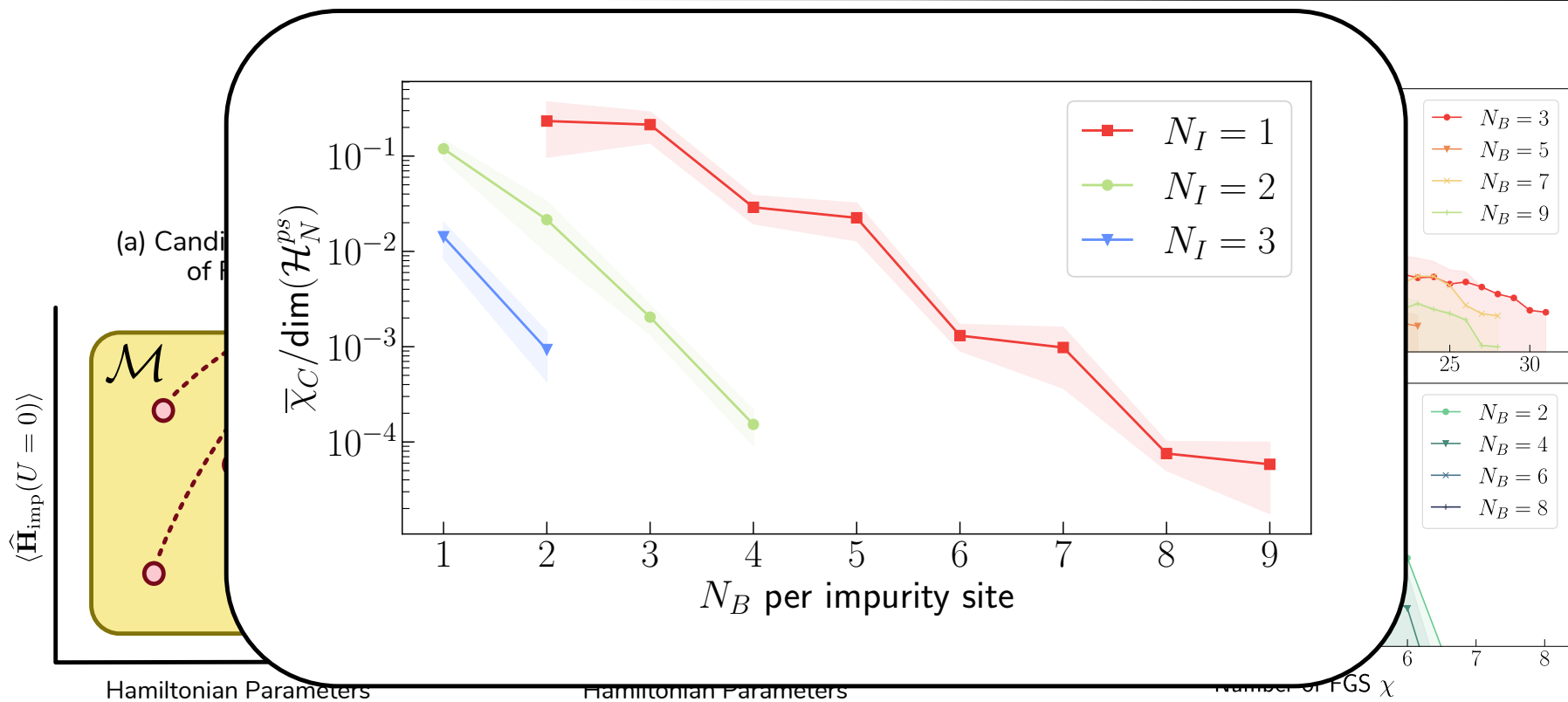
“Quantum impurity models provide a natural arena for studying the complexity of fermionic systems in an intermediate regime interpolating between the free and the fully interacting cases.”



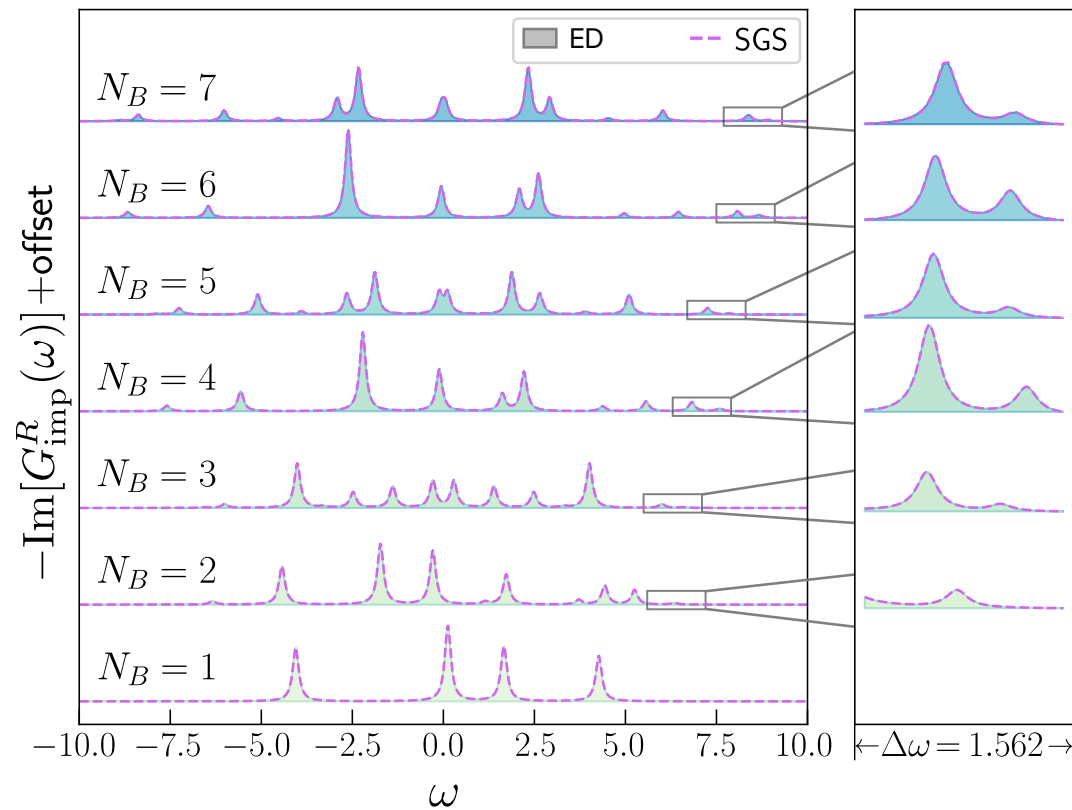
$$\tilde{H}\vec{\alpha} = \tilde{E}S\vec{\alpha}$$



Fermionic Gaussian Subspace



Fermionic Gaussian Subspace

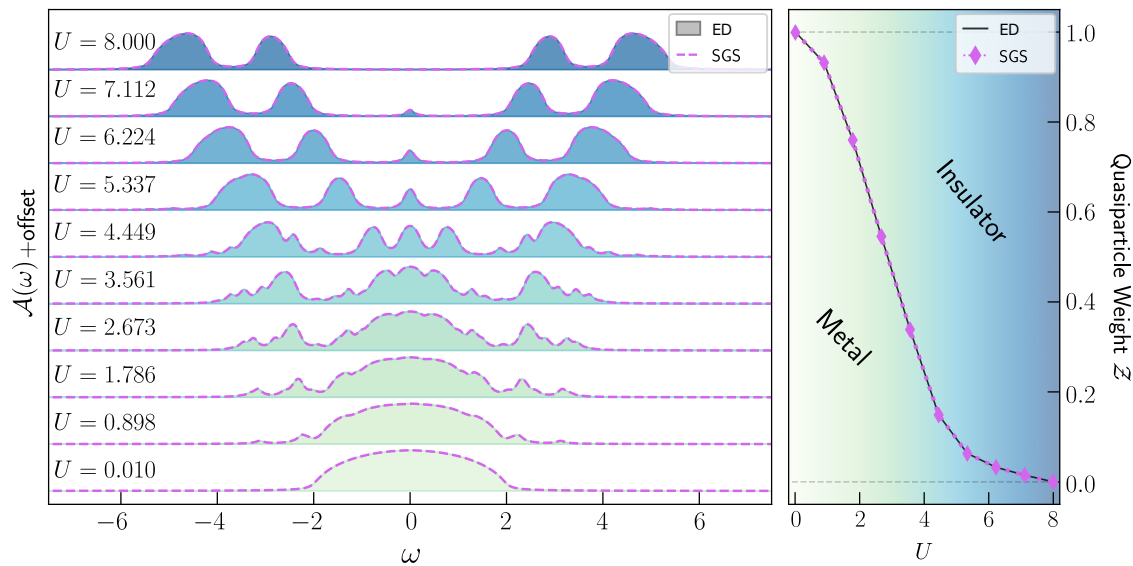


Now that we have the tools, let's see how it works:

- DMFT using sum of Gaussian states (SGS) (Hubbard Model w/ Bethe lattice)

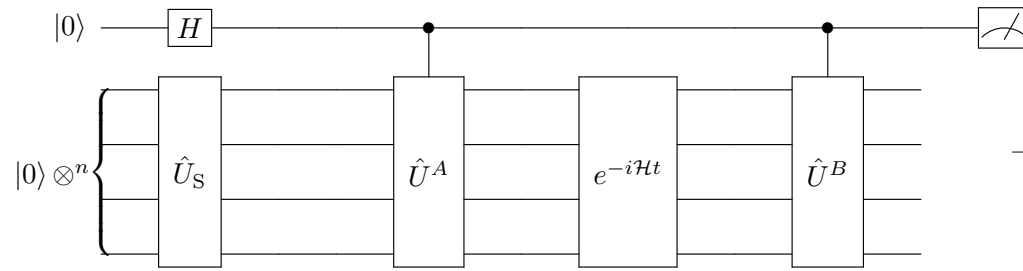
Shaded region = $|\psi\rangle$

dashed line = $\sum_{k=1}^{\chi} \alpha_k |\phi_k\rangle$



Increasing
interaction
strength on
impurity

A-Z quantum simulation



Prepare state of interest

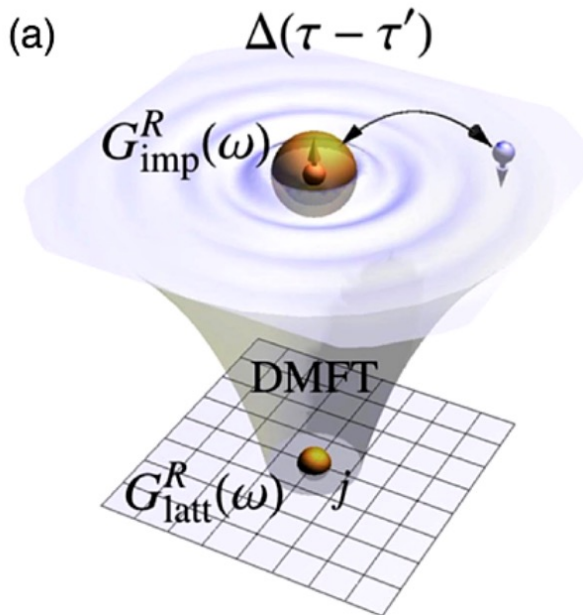
Time evolve

- *Physics-Informed Subspace Expansions*

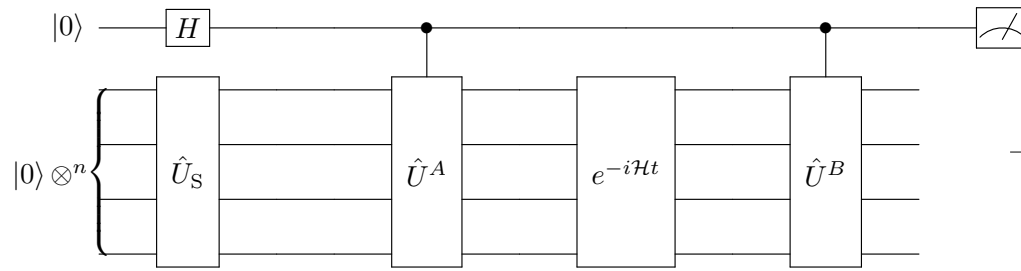
- *Lie-algebraic methods for time evolution*

Classical post-processing techniques

(a)



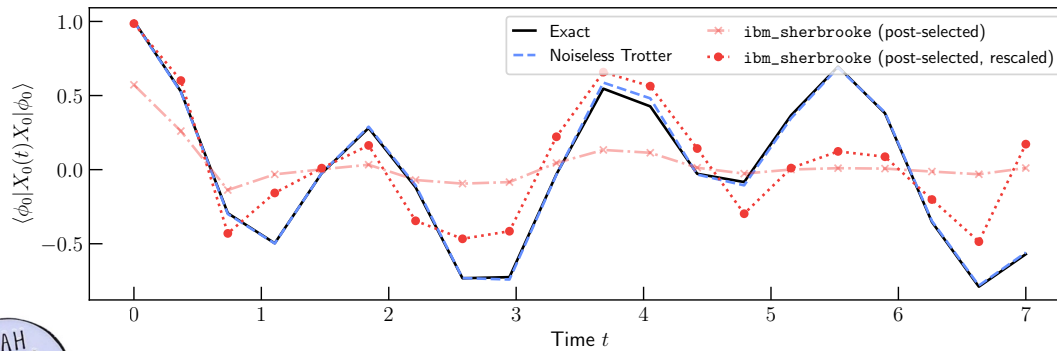
A-Z quantum simulation



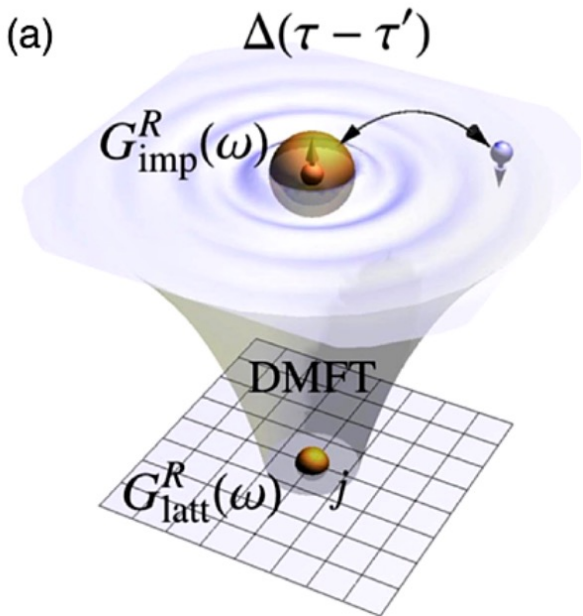
Classical post-processing techniques

Prepare state of interest

Time evolve



(a)



A-Z quantum simulation

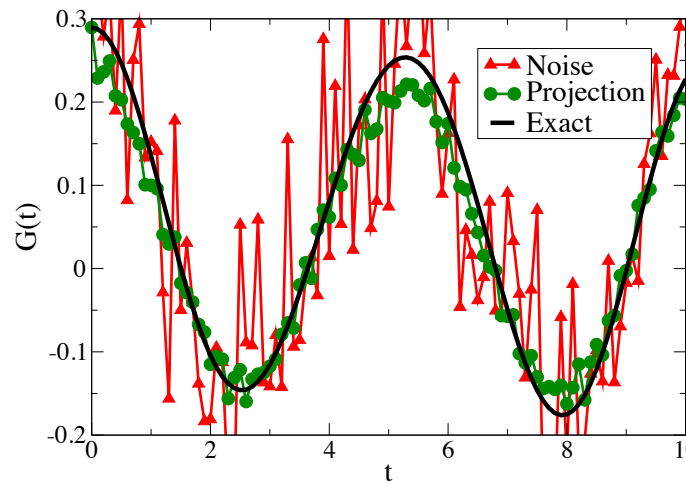
- It turns out that these are positive semi-definite (PSD) functions:

$$G_{AA}(t - t') = \text{Tr} [\rho A(t)^\dagger A(t')]$$

- Then this is a PSD matrix:

$$\underline{G} = \begin{pmatrix} f_0 & f_1 & f_2 & \cdots & f_n \\ f_1^* & f_0 & f_1 & \cdots & f_{n-1} \\ f_2^* & f_1^* & f_0 & \cdots & f_{n-2} \\ \vdots & & & \ddots & \vdots \\ f_n^* & f_{n-1}^* & f_{n-2}^* & \cdots & f_0 \end{pmatrix}$$

where $G_{AA}(t_i - t_j) \rightarrow f_{i-j}$



A-Z quantum simulation

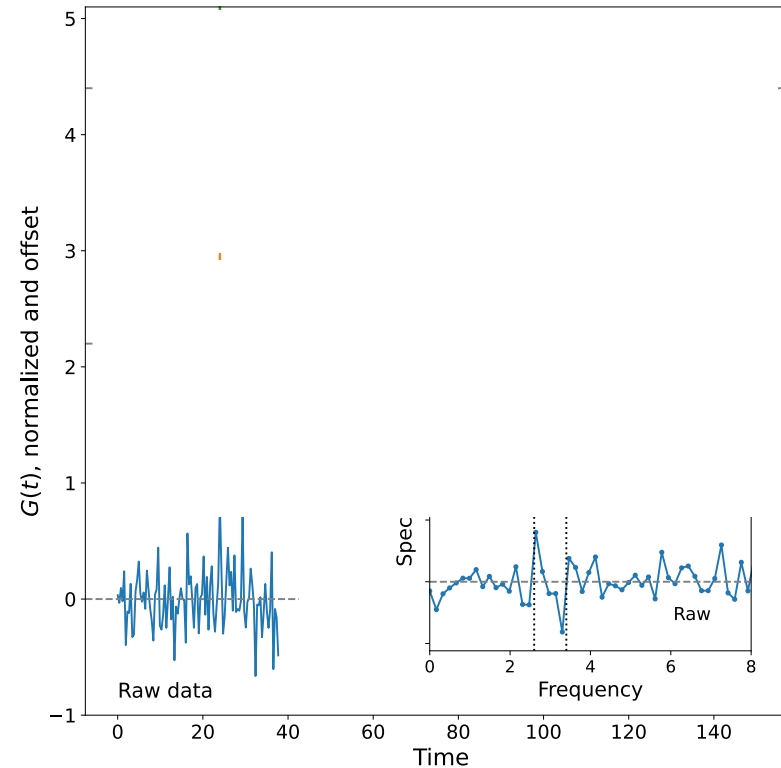
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A-Z quantum simulation

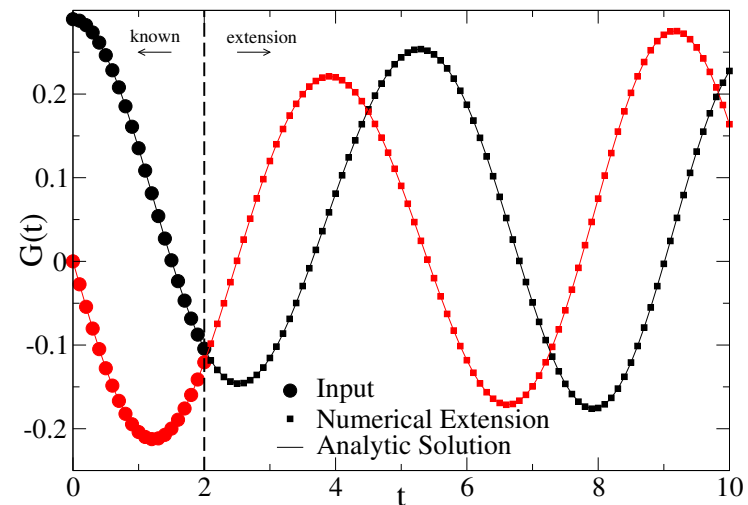
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A-Z quantum simulation

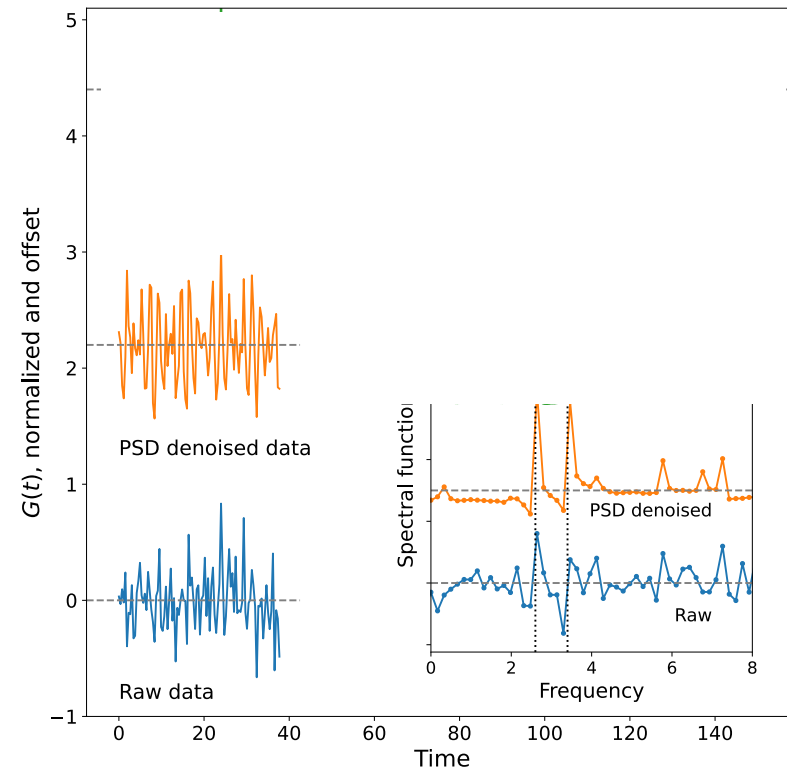
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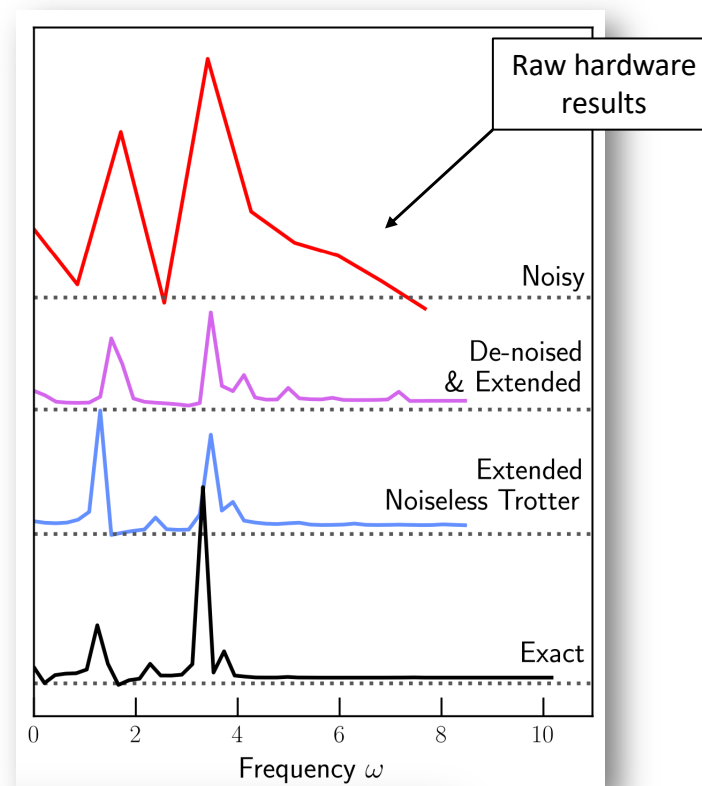
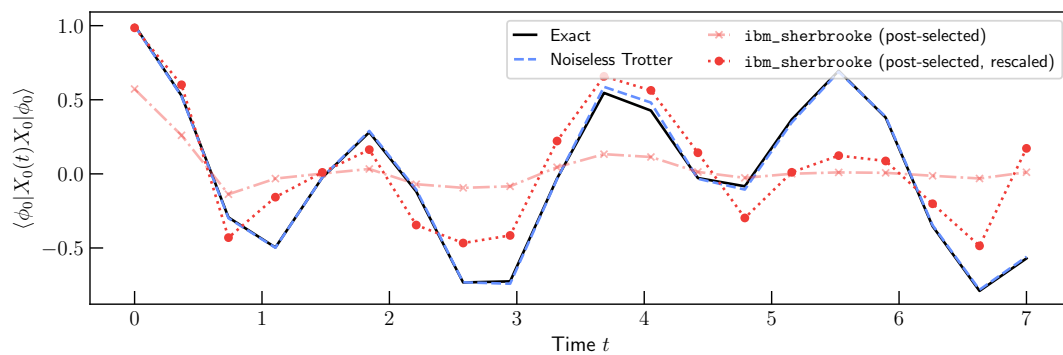
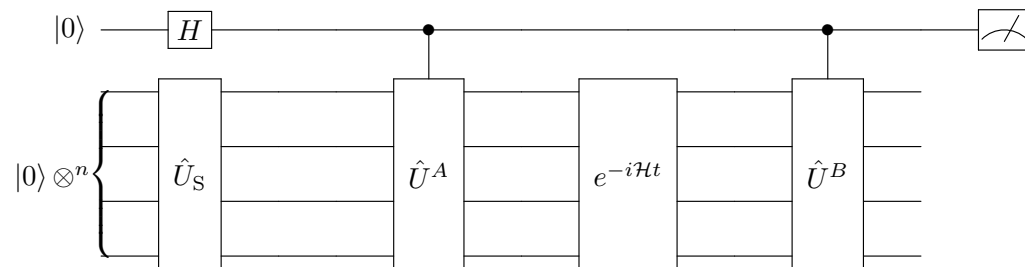
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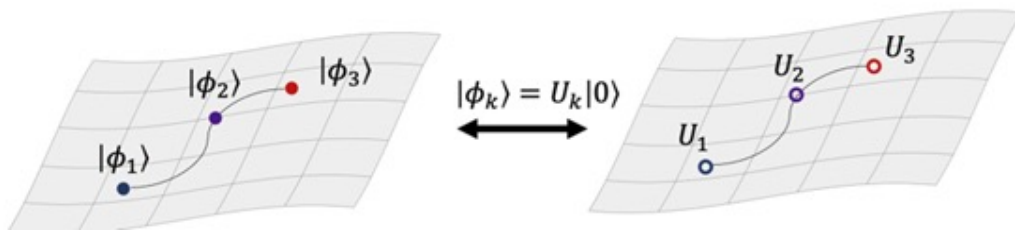
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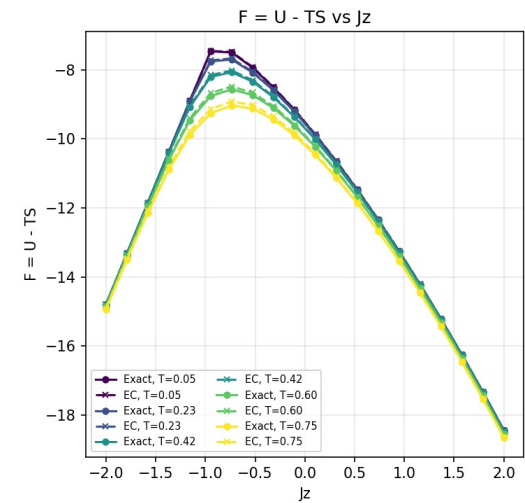
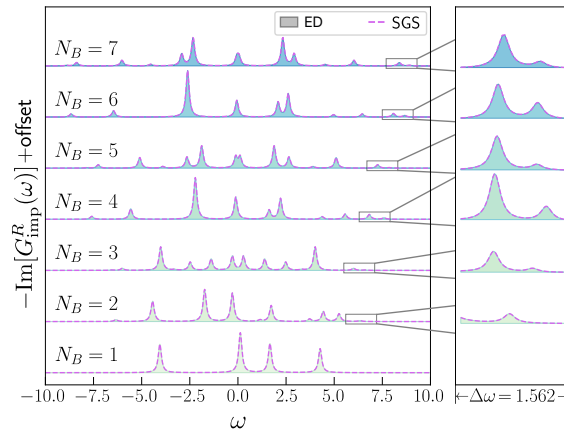
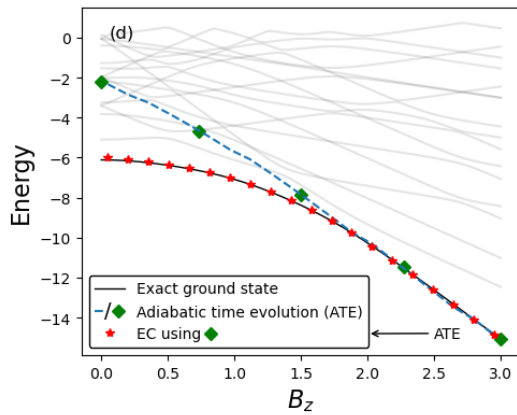




Subspaces with Eigenvector Continuation



Subspace methods can be readily added to many state preparation methods!



Why Low-Temperature Observables?

- Fundamental physics Insights (like, quantum phase transitions and critical points)
- Practical applications (like, quantum material discovery)

Existing Algorithm Gaps

- QITE/QMETTS: depth blows up at low T, no reuse
- VQG: barren plateaus, no parameter-reuse strategy
- Block-encoding: optimal at high T only
- No efficient cross-parameter thermal estimation

Algorithm Requirements

- Efficient at low temperature ($\beta \rightarrow$ large)
- Parameter-reuse across Hamiltonian families
- Observable estimation without full state prep
- Scalable to early FTQC devices

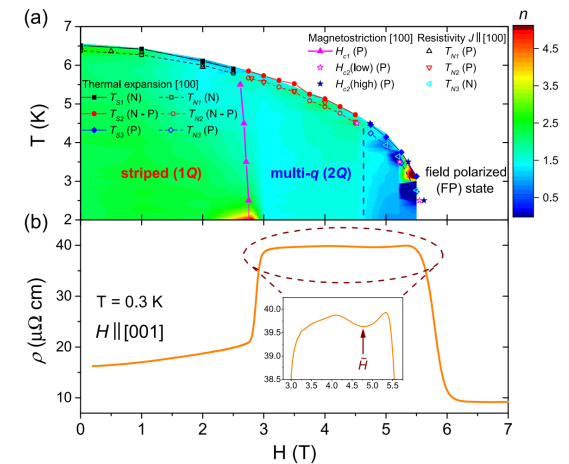


Fig. 1 Phase diagram of CeAuSb₂ its unusual magnetoresistance. a

Target:**1. Low-temperature thermal states**

At low-temperature, thermal state of a system Hamiltonian could be approximated with a few low-energy eigenstates, $k \ll |\mathcal{H}|$

$$\hat{\rho}_T = \frac{1}{Z_k} \sum_{n=0}^k e^{-\beta E_n} |E_n\rangle\langle E_n|, \quad Z_k = \sum_{n=0}^k e^{-\beta E_n}$$

2. Low-energy states

A low-energy state could be prepared by truncated state preparation methods

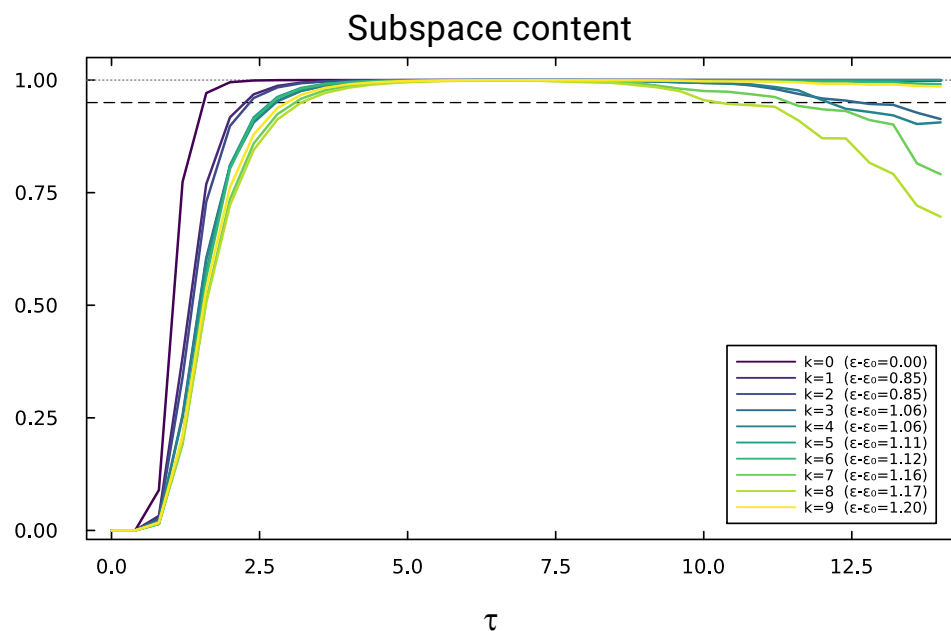
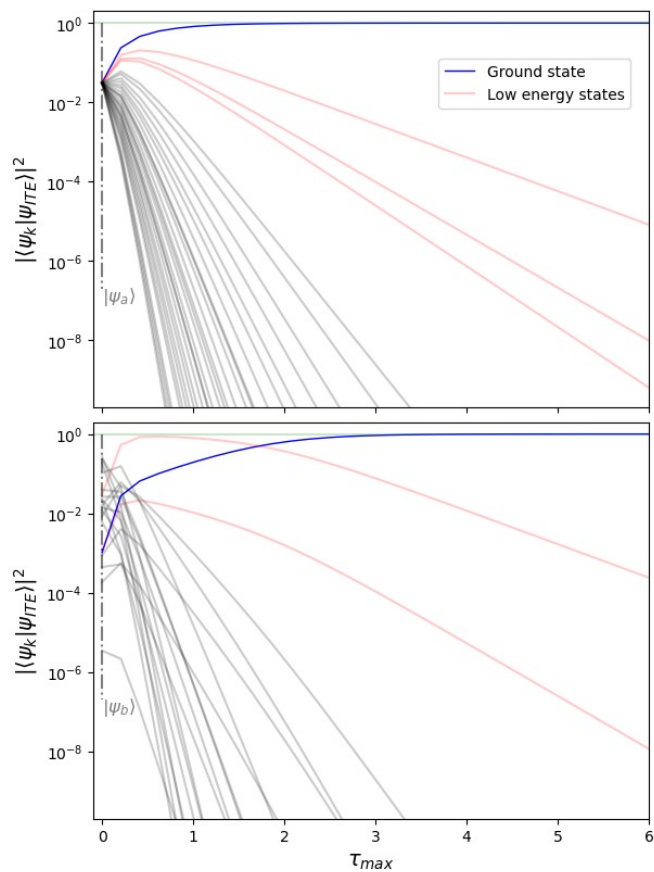
3. A sufficient subspace

To obtain a sufficient subspace up to convergence, we could repeat the previous step

4. Resource-efficient parameter sweep

A sufficient low-energy subspace could be used for a family of Hamiltonians using techniques like Eigenvector continuation (EC)

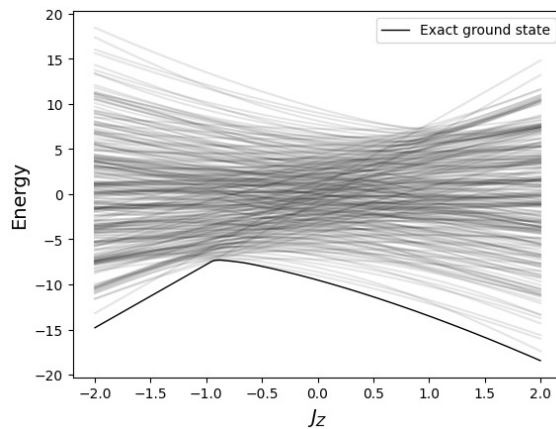
Quantum Imaginary Time Evolution



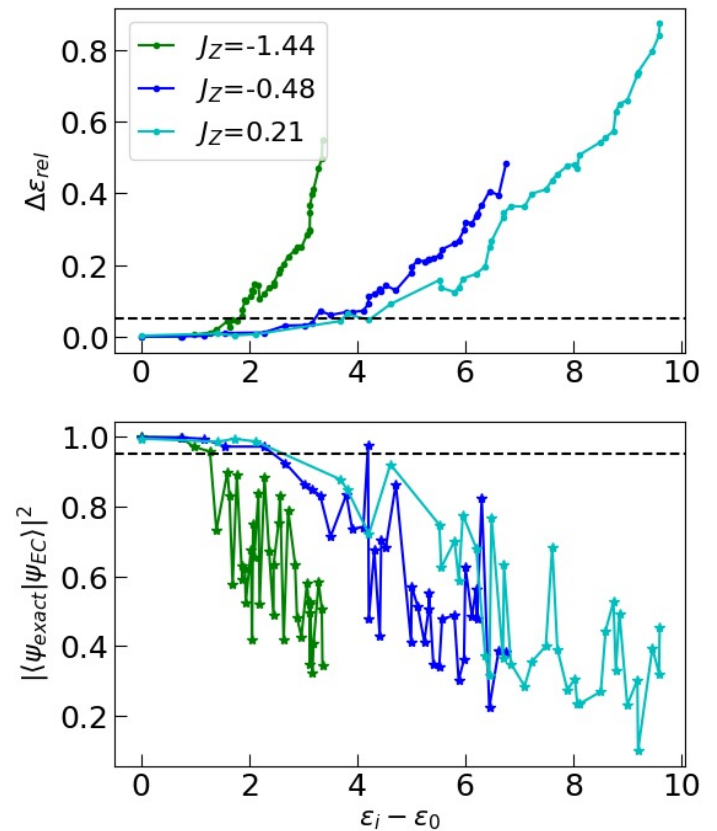
Energy gaps: “Low-temperature” is relative

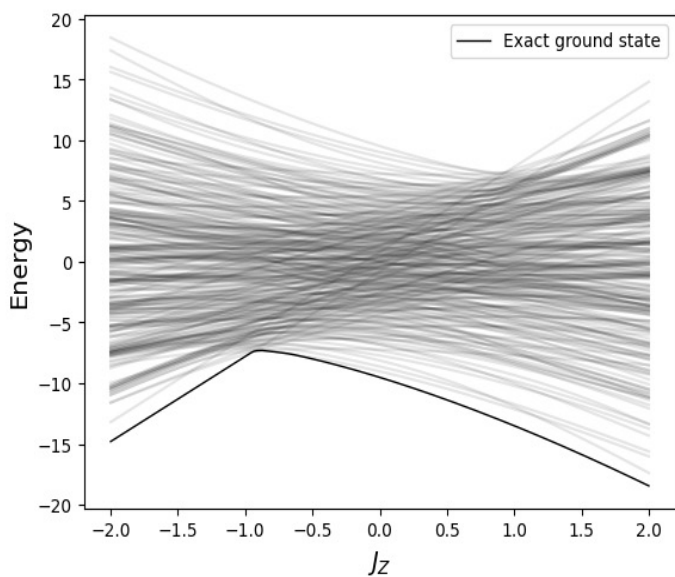
“*Low-temperature*” *Thermal States*: The number of lowest eigenstates required approximate a thermal state at temperature T depends on the number of states within the energy gaps proportional to the energy corresponding to the temperature T .

$$\mathcal{H}_{XXZ} = \sum_{i=1}^{N-1} J (X_i X_{i+1} + Y_i Y_{i+1}) + J_z Z_i Z_{i+1} + \sum_{k=1}^N B_z Z_k.$$

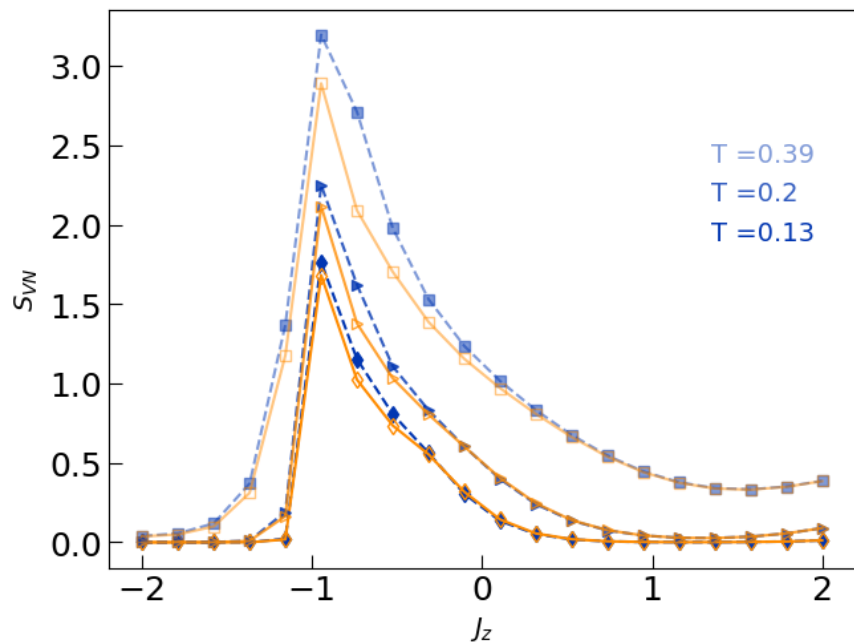


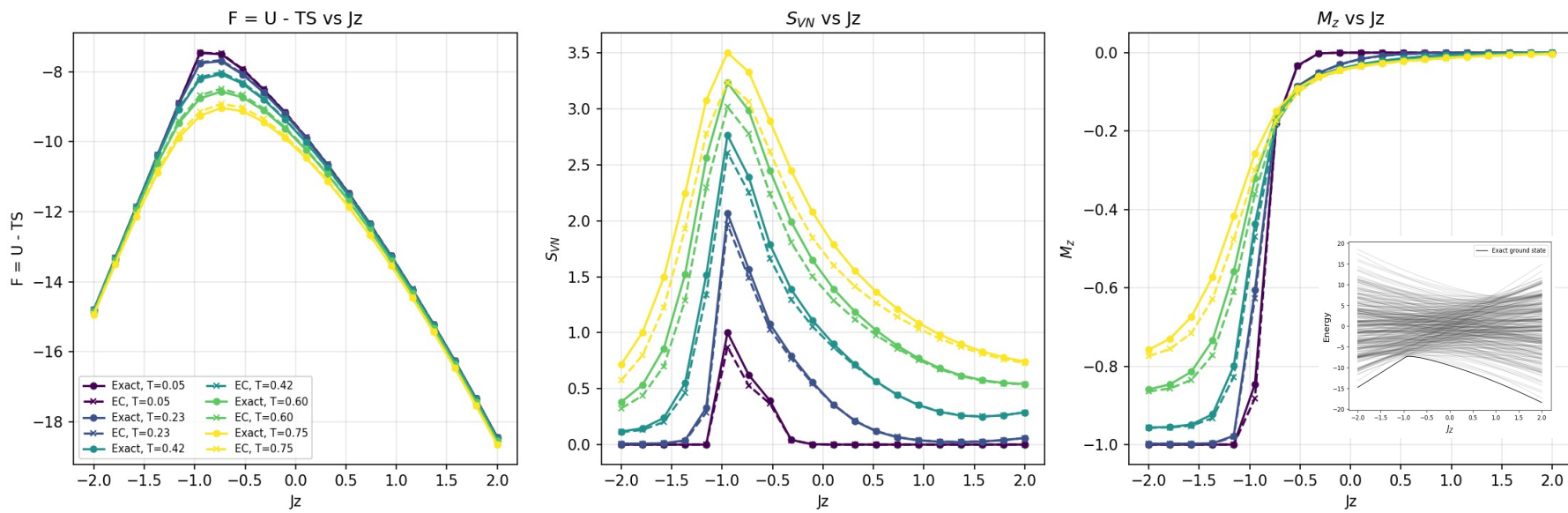
Spectrum of 1D- 8-site XXZ chain





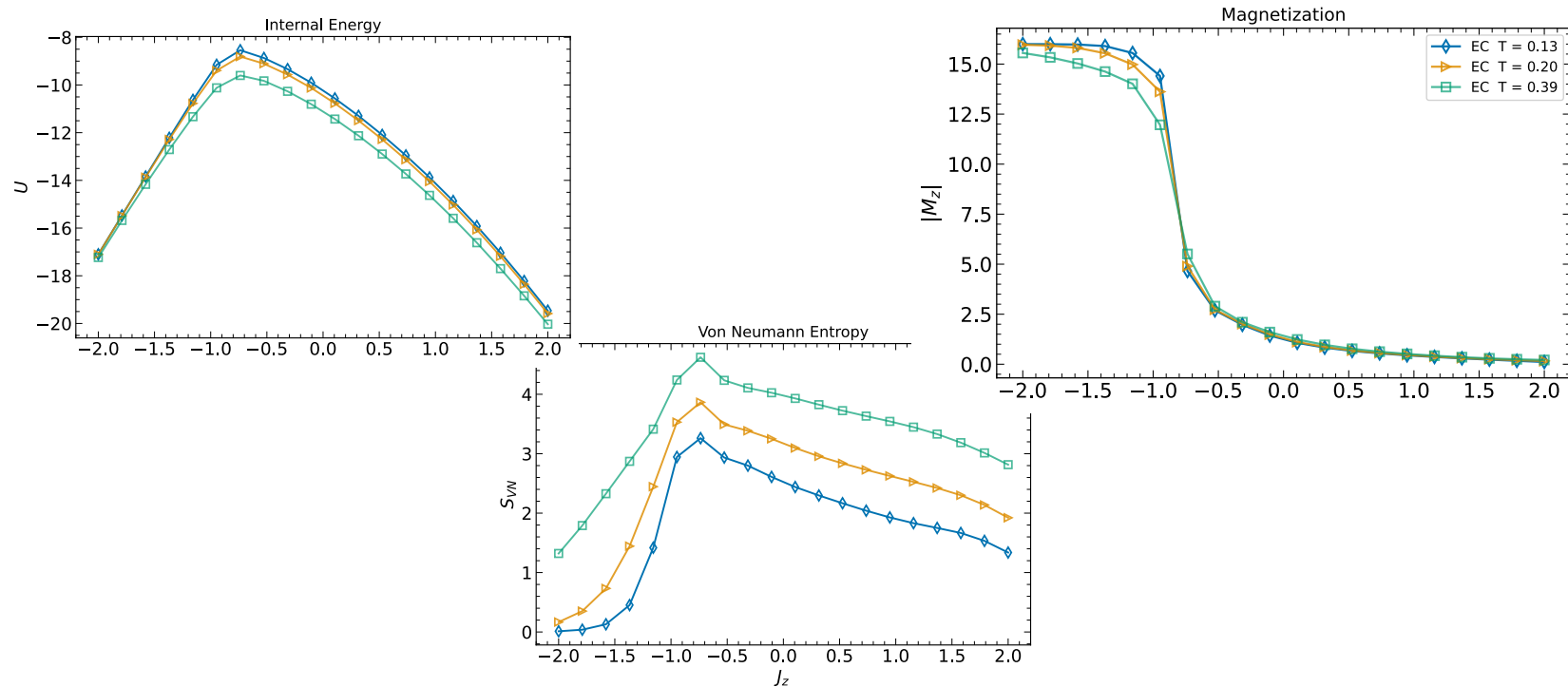
Spectrum of 1D- 8-site XXZ chain



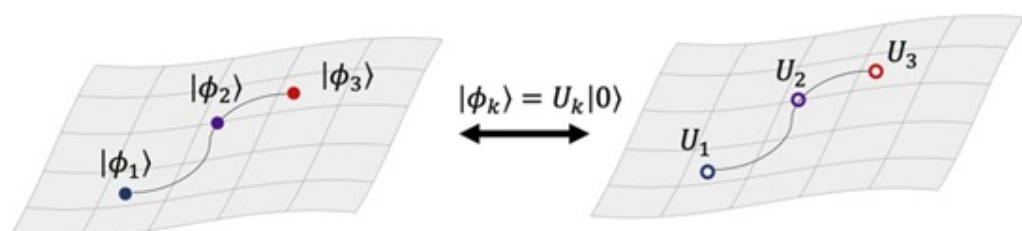


With relatively little computational effort, we can get thermal properties across the phase diagram

Results: Thermodynamics near phase transition for N=32



With relatively little computational effort, we can get thermal properties across the phase diagram even for large N



Subspace methods can be readily added to many state preparation methods!

