





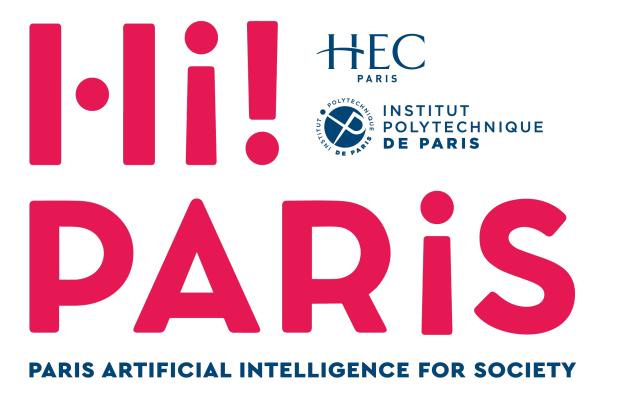






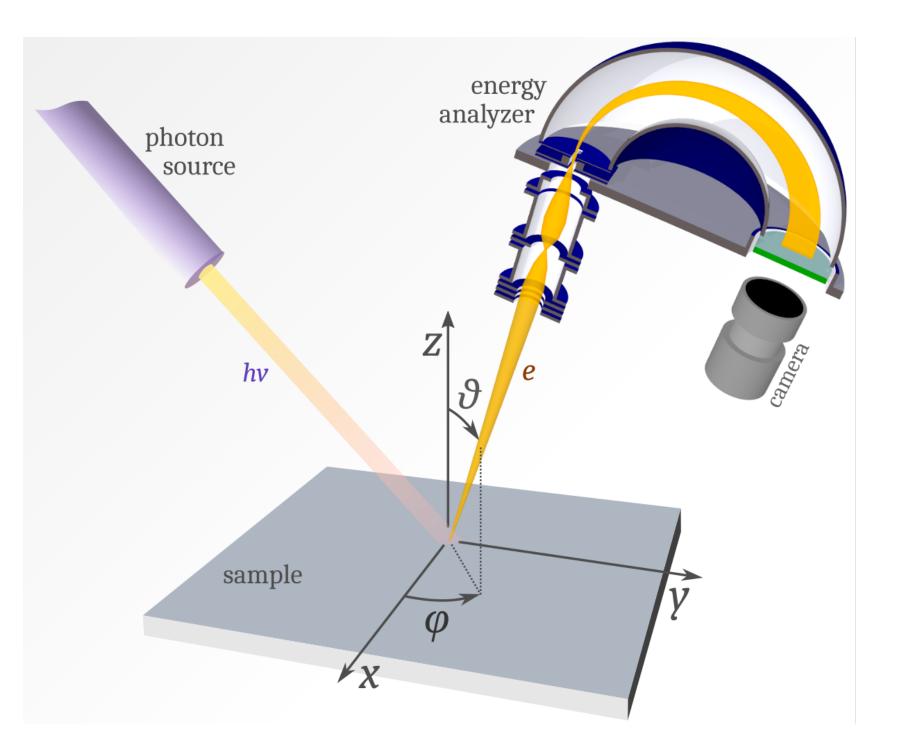


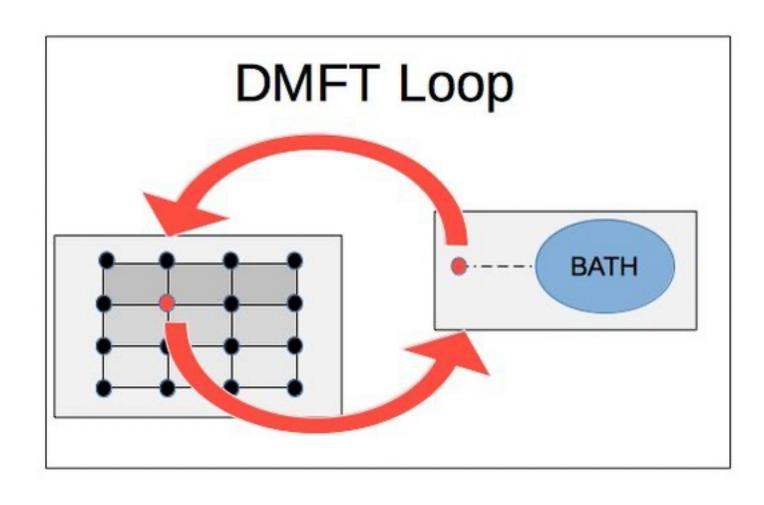
## Efficient Molecular Spectroscopy via Hybrid Subspace Methods

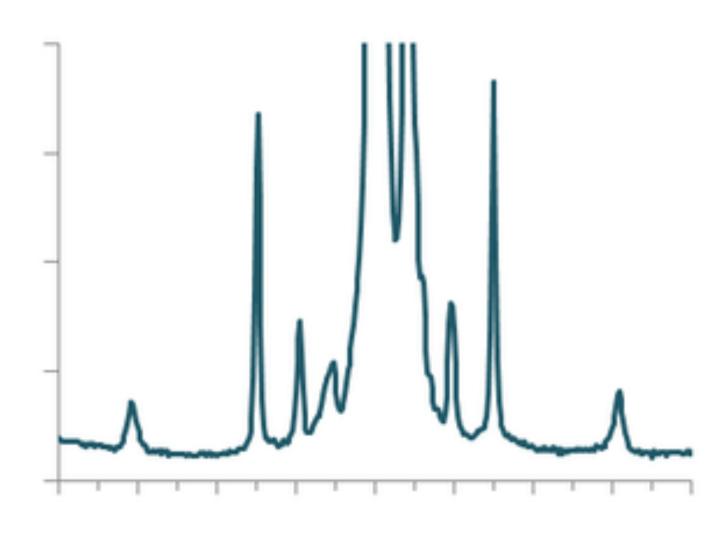


## Why do we care about spectral functions

- Spectral functions encode excitations energies and intensities
- They connect directly to experiments (ARPES, photoemission .. )
- Needed in materials, impurity models (DMFT)







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#### Compute real-time correlations for extract spectra

$$G_A(t',t) = \langle \psi_0 | A^{\dagger}(t')A(t) | \psi_0 \rangle$$

Link theory to experiments

#### Many-body Quantum Problem

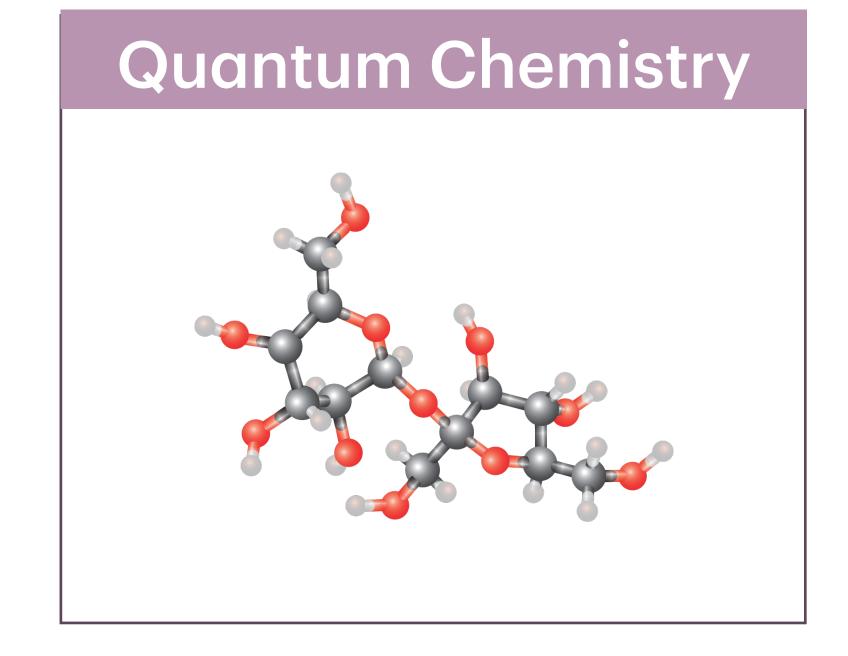
**Equilibrium properties** 

$$\hat{H}|\psi_0\rangle = E_0|\psi_0\rangle$$

**Dynamical Response** 

$$i\hbar \frac{\mathrm{d}}{\mathrm{d}t} |\psi(t)\rangle = \hat{H} |\psi(t)\rangle$$

# Lattice Models 1: up spin 1: down spin





#### Static Ground State Calculation

$$H|\psi_{\theta}\rangle = E|\psi_{\theta}\rangle$$

$$\theta_{\text{tg}} = \arg\min_{\theta} \left[ \langle \psi_{\theta} | H | \psi_{\theta} \rangle \right]$$

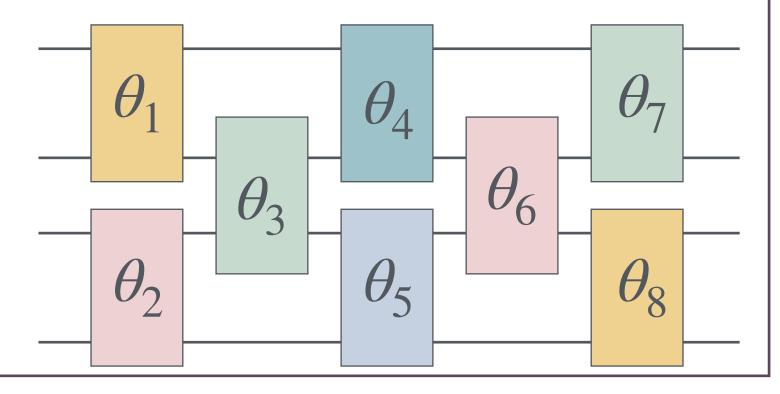
# Classical variational methods work well

- DMRG/Tensor networks
- Variational Quantum
   Montecarlo (VMC)

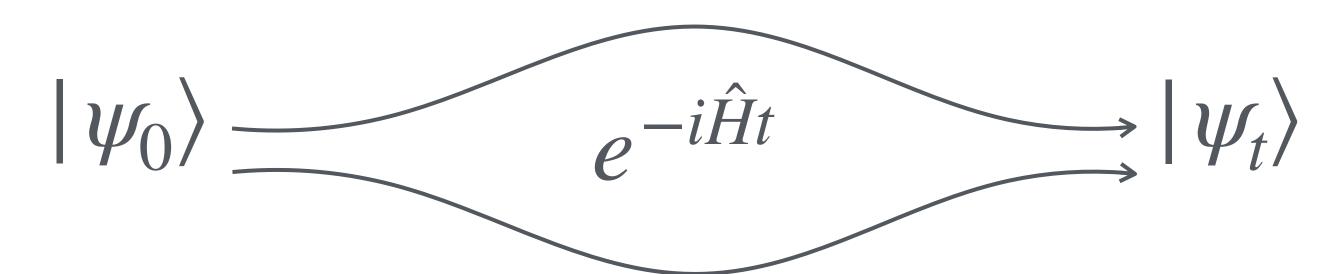
$$|\psi_{\theta}\rangle = \sum_{x} \psi_{\theta}(x) |x\rangle$$

# Quantum variational methods struggle

- Optimization cost (number of shots)
- Sampling noise
- Barren Plateaux



## Real time dynamics is the hard part

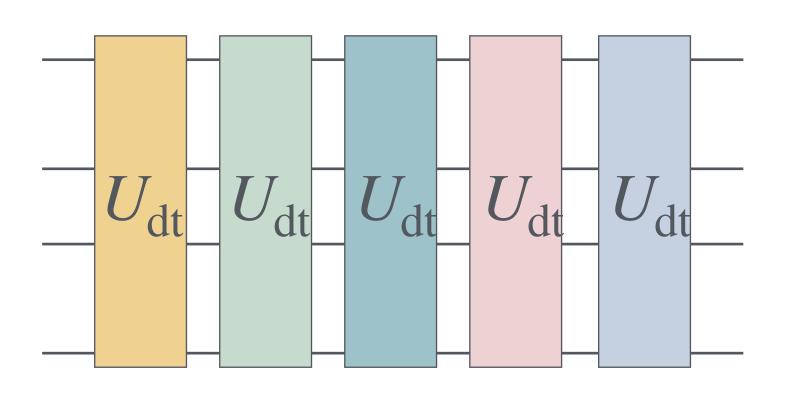


#### Classical variational methods

- Tensor network: bond dimension explodes with entanglement
- t-VMC: Sampling problems large time dynamics
- ED, Clifford simulation, Pauli propagation ....

#### Quantum Hardware

• Brute force not variational dynamics native on a quantum hardware



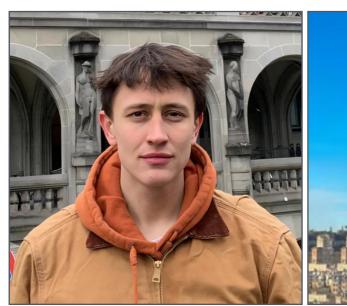
#### Plan of the talk

- I. Ground states with Classical simulations
  - I. Introduction to Variational Monte Carlo
  - II.Recent advances: Reaching chem. Precision with Importance sampling
- II. Hybrid subspace algorithm
- III. Extension to impurity models

#### Ground states with Classical simulations

Looking elsewhere: improving variational Monte Carlo gradients by importance sampling

A. Misery, L. Gravina, **AS**, F. Vicentini arXiv preprint arXiv:2507.05352









#### Variational Quantum Montecarlo

$$E = \frac{\langle \psi_{\theta} | H | \psi_{\theta} \rangle}{\langle \psi_{\theta} | \psi_{\theta} \rangle} = \sum_{x} \frac{\left| \langle x | \psi_{\theta} \rangle \right|^{2}}{\langle \psi_{\theta} | \psi_{\theta} \rangle} \frac{\langle \psi_{\theta} | H | x \rangle}{\langle \psi_{\theta} | x \rangle}$$
$$p_{\theta}(x) \qquad H_{loc}(x)$$

#### Computational complexity

$$H_{yx} = \sum_{y} \langle y | H | x \rangle$$

Sparsity of  $H_{yx}$ 

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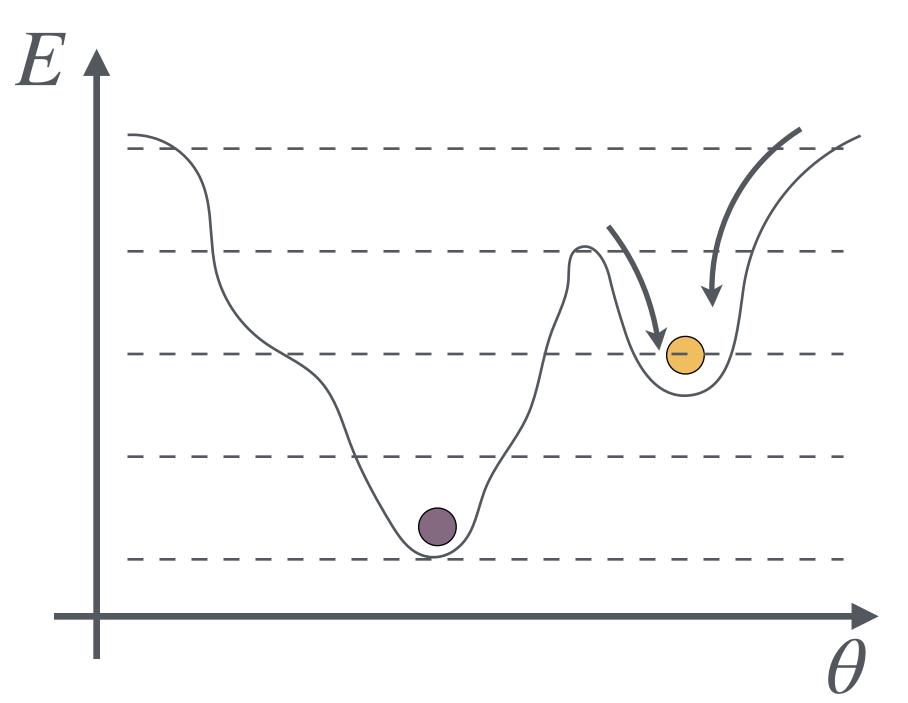
$$\partial_{\theta_k} E = \langle \partial_{\theta_k} \log \psi_{\theta} \Delta H_{loc(x)} \rangle$$

$$\theta_{k+1} = \theta_k - \eta \partial_{\theta_k} E$$

#### Computational complexity

$$H_{yx} = \sum_{y} \langle y | H | x \rangle$$

Sparsity of  $H_{yx}$ 



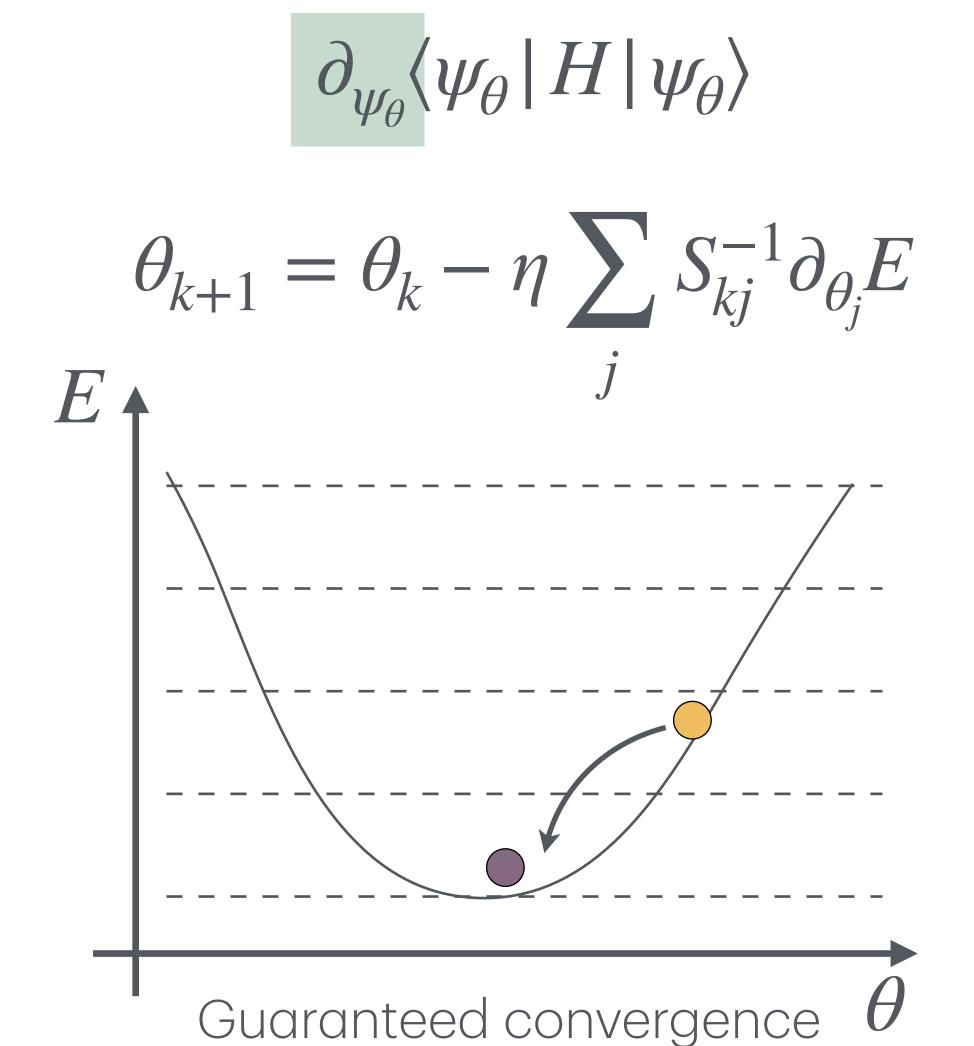
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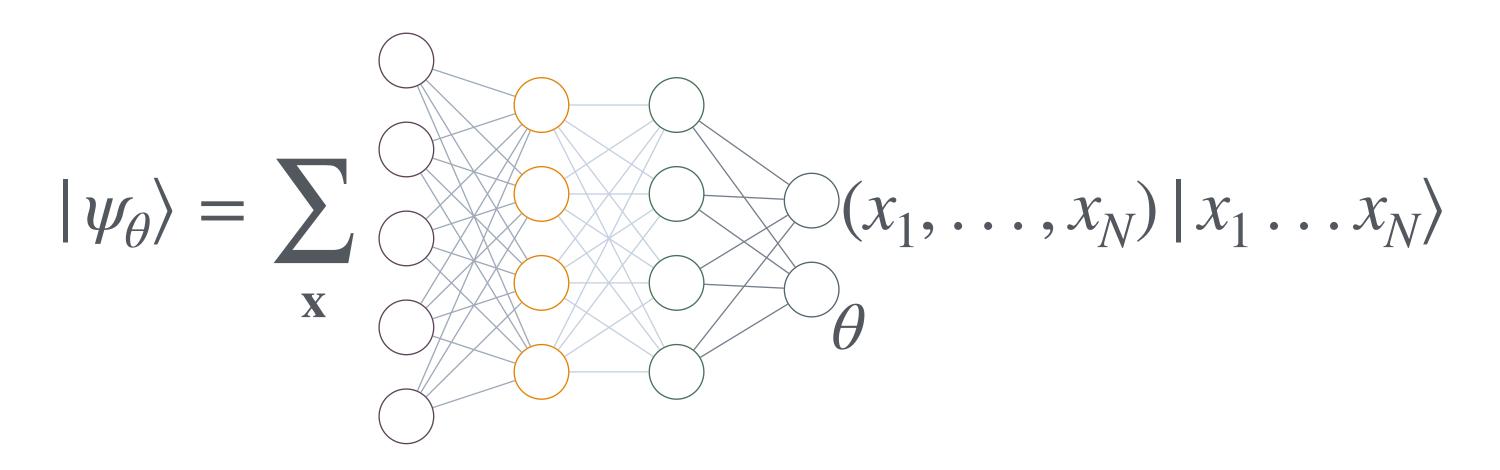
#### Computational complexity

$$H_{yx} = \sum_{y} \langle y | H | x \rangle$$

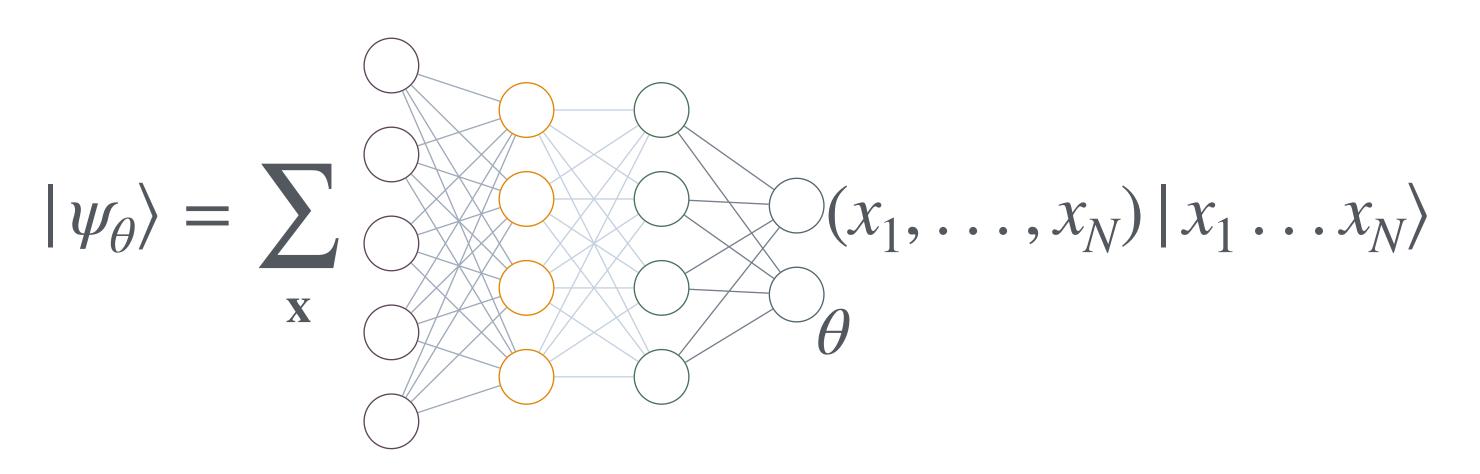
Sparsity of  $H_{vx}$ 

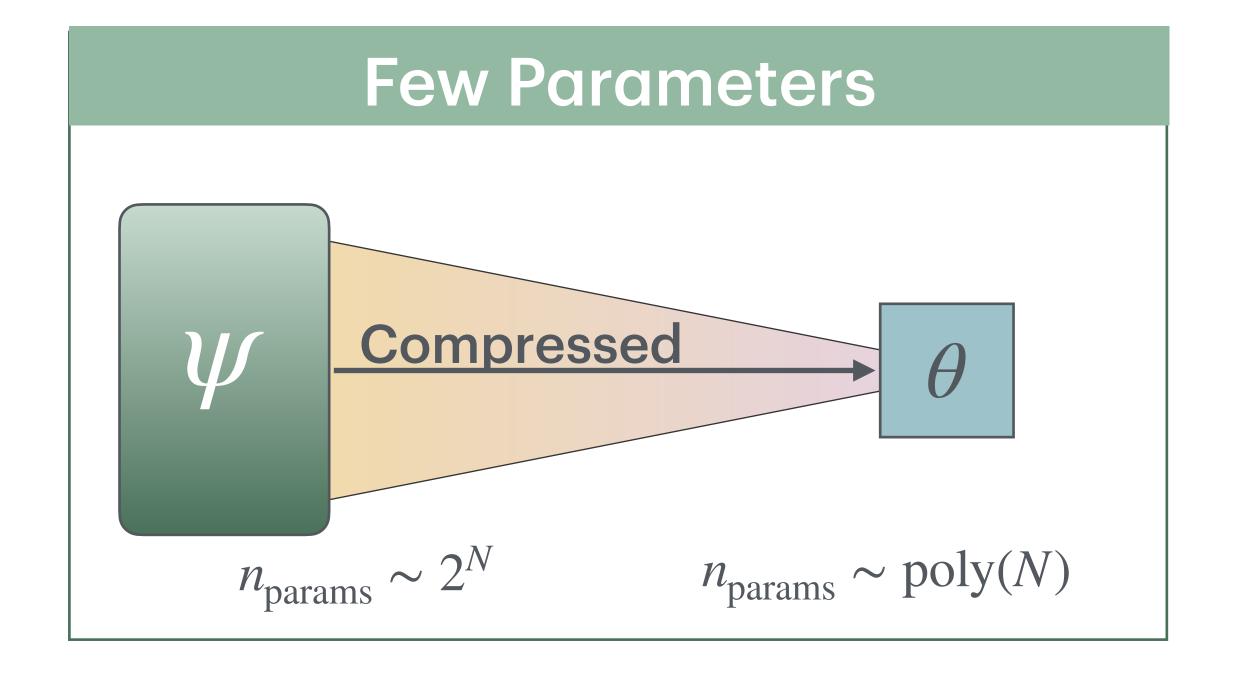


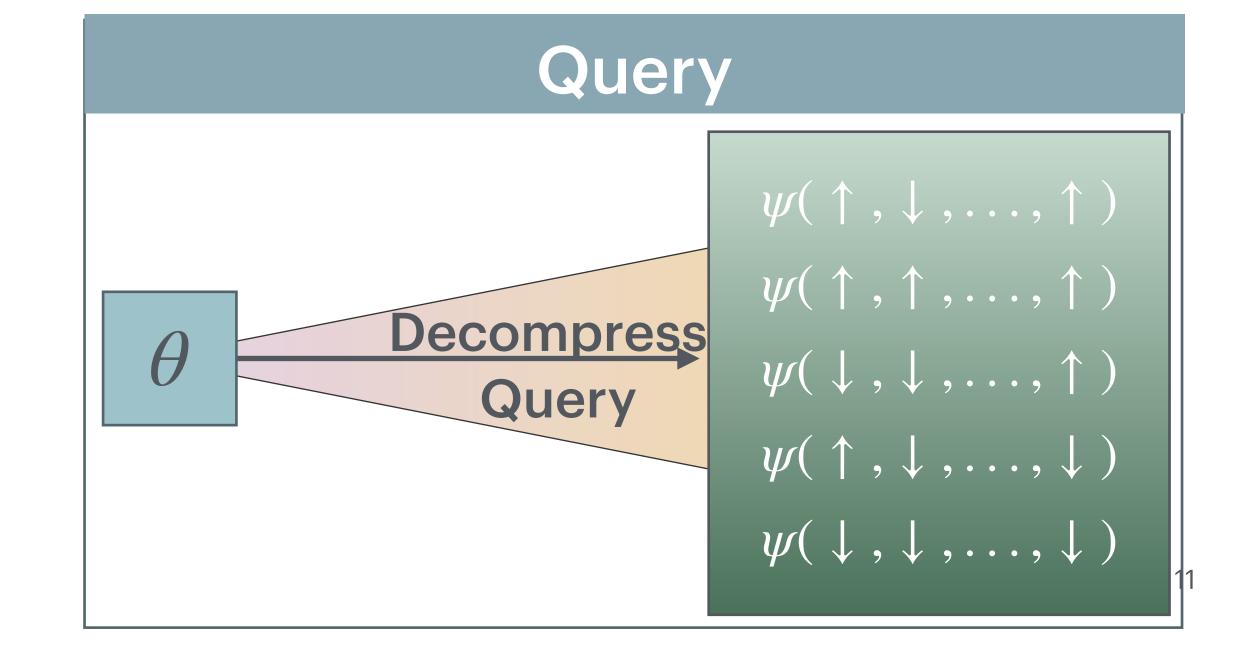
#### Neural Network Quantum States (NQS)



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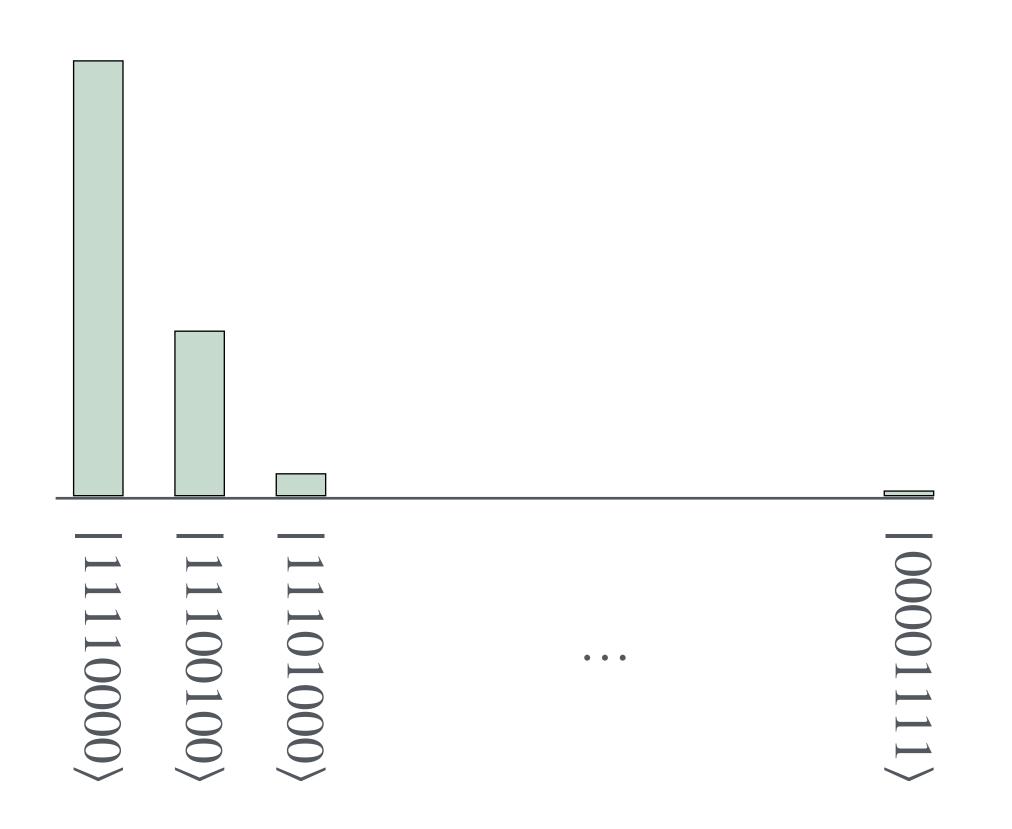




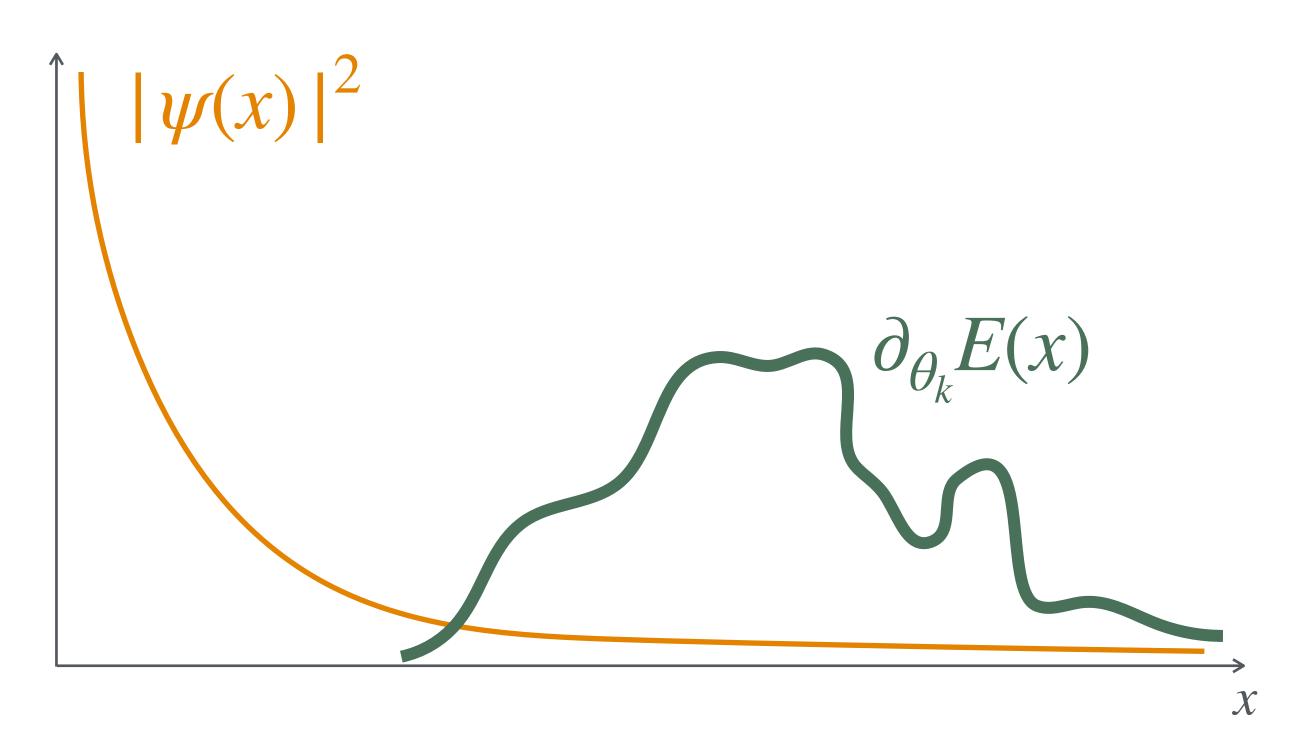


#### Why sampling from the Born probability fails

Molecular  $|\psi(x)|^2$  peaked on a few determinants



The gradient of the loss lives in low-probability regions

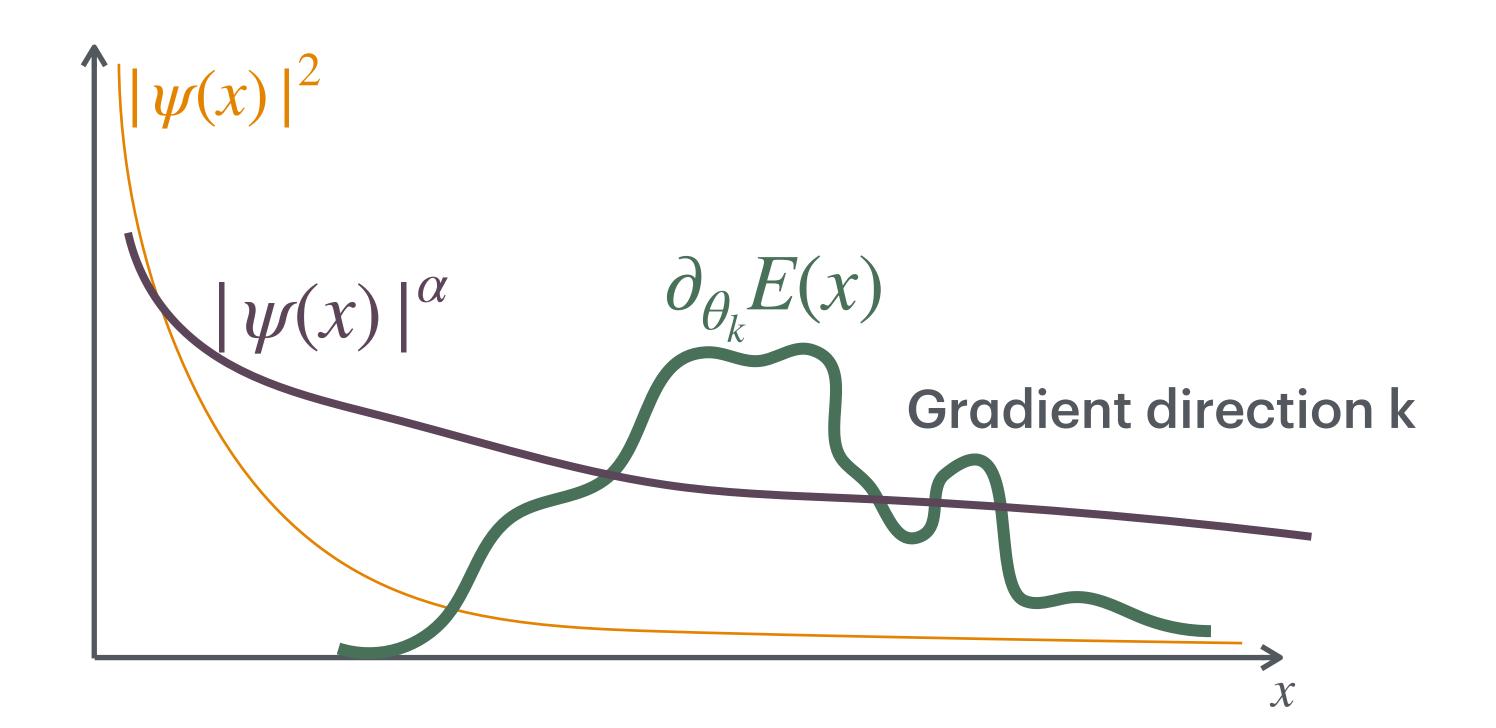


#### Importance Sampling

#### Goal Sample where gradient matters

$$q_{\alpha}(x) \propto |\psi(x)|$$

lpha < 2 broader distribution (Over dispersed sampling)



#### Optimal sampling distribution

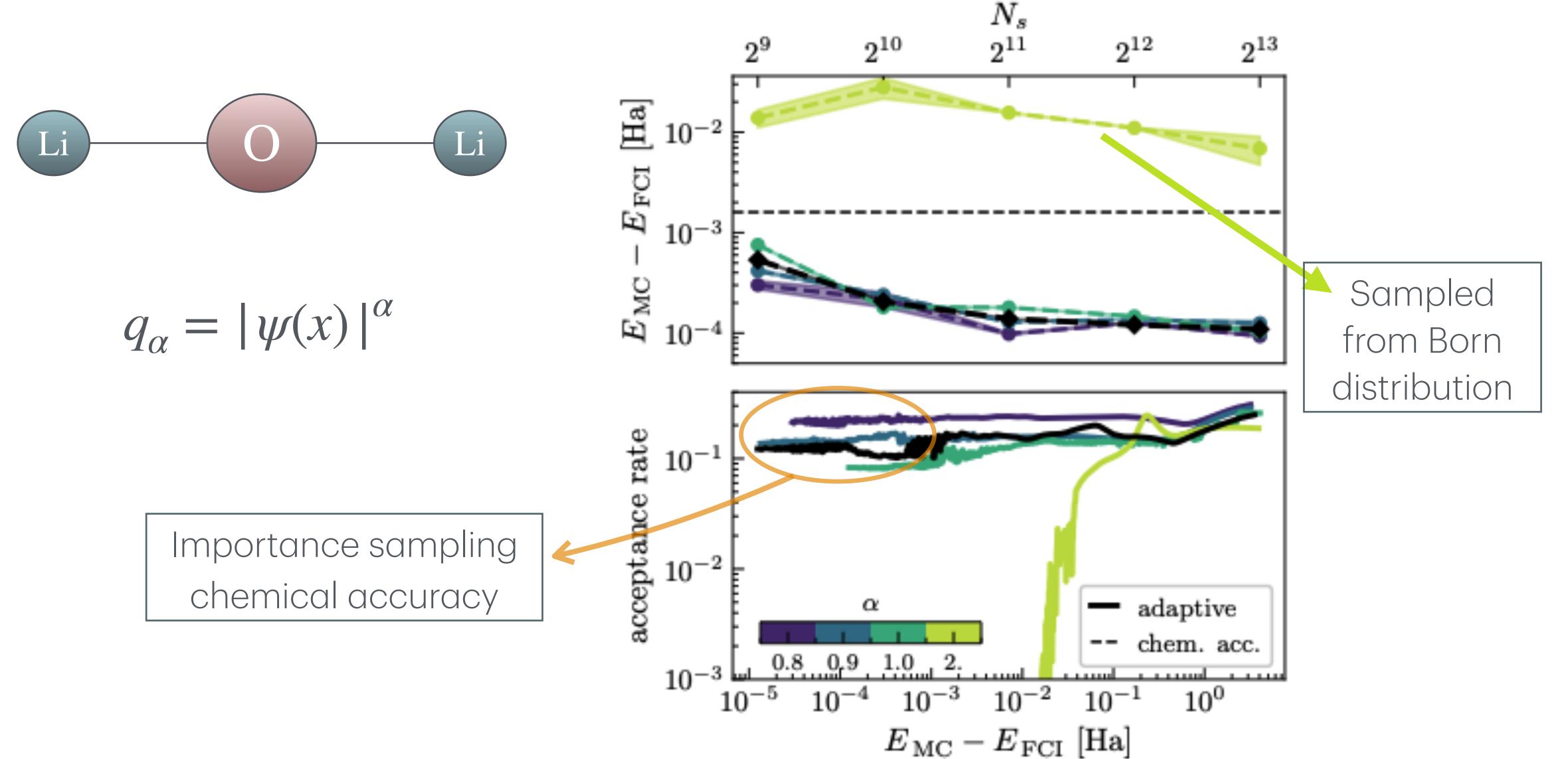
$$\mathcal{L}_{\mathrm{IS}} = \frac{1}{N_{\mathrm{p}}} \sum_{k=1}^{N_{\mathrm{p}}} \mathrm{SNR}_{q_{\alpha}} [\partial_{\theta_{k}} E]$$

$$\alpha' = \alpha + \eta \partial_{\alpha} \mathcal{L}_{\mathrm{IS}}$$

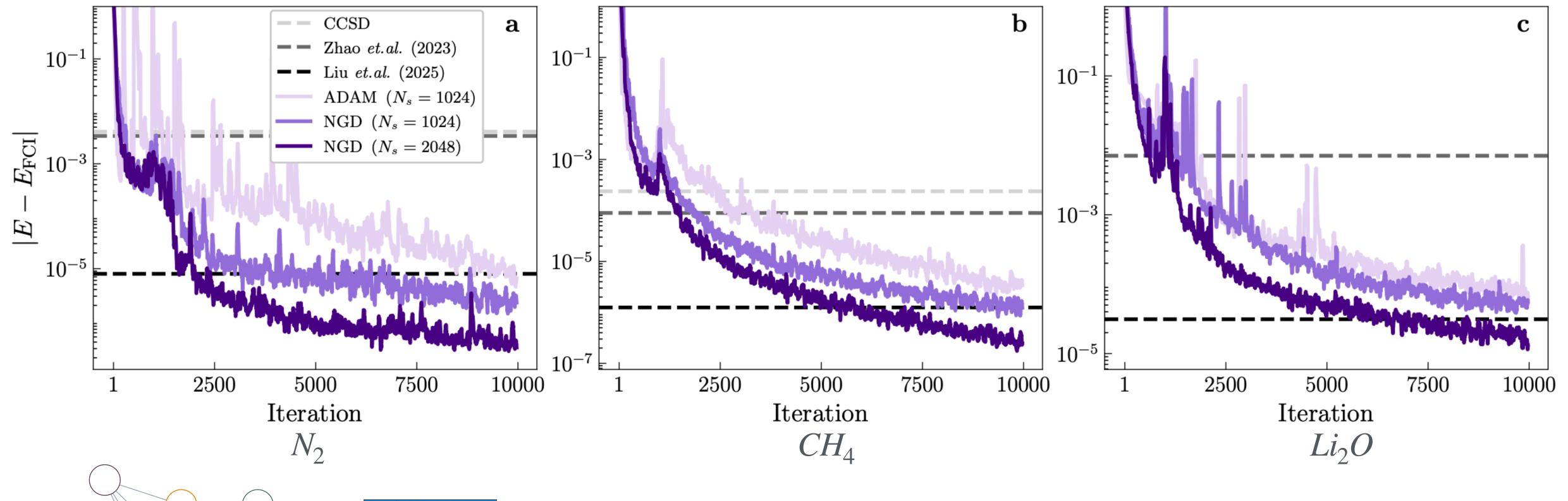
Optimize the Signal to Noise ratio of the gradient  $\longrightarrow$  improved variance less samples

$$q_{\vec{\alpha}} = f(x; \overrightarrow{\alpha})$$

## Over dispersed Sampling



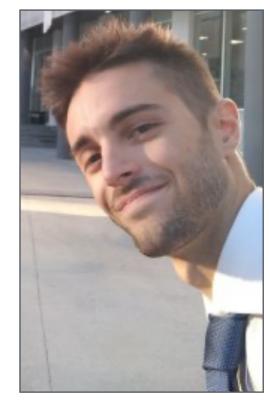
# Neural Network Sampling (preliminary)



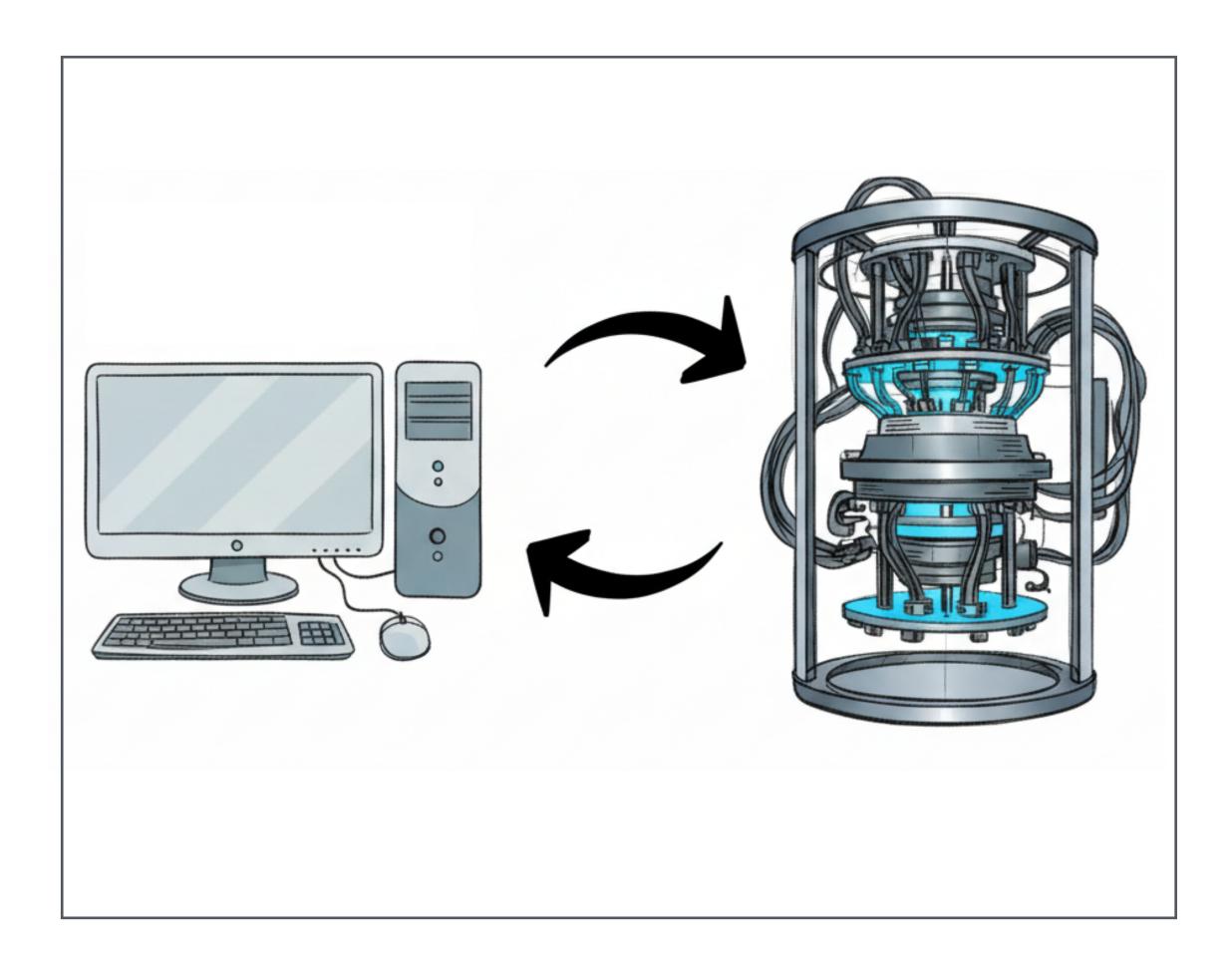
$$q_{\vec{\alpha}}(x) = \text{NN}(x; \overrightarrow{\alpha})$$

### Hybrid subspace algorithm

Classically Prepared, Quantumly Evolved:
Hybrid Algorithm for Molecular Spectra **AS**, S. Barison, F. Vicentini
arXiv preprint arXiv:2510.24911







# Hybrid subspace algorithm

	Classical techniques	Quantum Hardware
Variational Ground State		
Variational Dynamics		
Brute Force Dynamics		

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### Back to Spectroscopy

$$G_A(t) = \langle \psi_0 | \hat{A}^{\dagger}(t) \hat{A} | \psi_0 \rangle$$

Let us suppose to have a  $|\psi_A\rangle=A\,|\psi_0\rangle$  representation with VMC

... Dynamics is still a problem  $G_A(t)=e^{iE_0t}\langle A^\dagger A \rangle_0 \langle \psi_A \,|\, \hat{U}(t) \,|\, \psi_A \rangle$ 

### Back to Spectroscopy

$$G_{A}(t) = e^{iE_{0}t} \langle A^{\dagger}A \rangle_{0} \mathbb{E}_{y \sim |\psi_{A}(y)|^{2}} \left[ \sum_{x} \frac{\psi_{A}^{*}(x)}{\psi_{A}^{*}(y)} \langle x | \hat{U}(t) | y \rangle \right]$$

- 1. Sample  $|y\rangle$  from  $|\psi_A(y)|^2$
- 2. Evolve it on a quantum computer and measure it
- 3. Use the measured basis  $\mathcal{S}_y$  to project the propagator  $\hat{U}(t)$

$$\hat{U}(t) \longrightarrow P_{\mathcal{S}_{y}} \hat{U}(t) P_{\mathcal{S}_{y}} \approx \exp(-iP_{\mathcal{S}_{y}} \hat{H} P_{\mathcal{S}_{y}})$$

#### When the hybrid subspace algorithm work

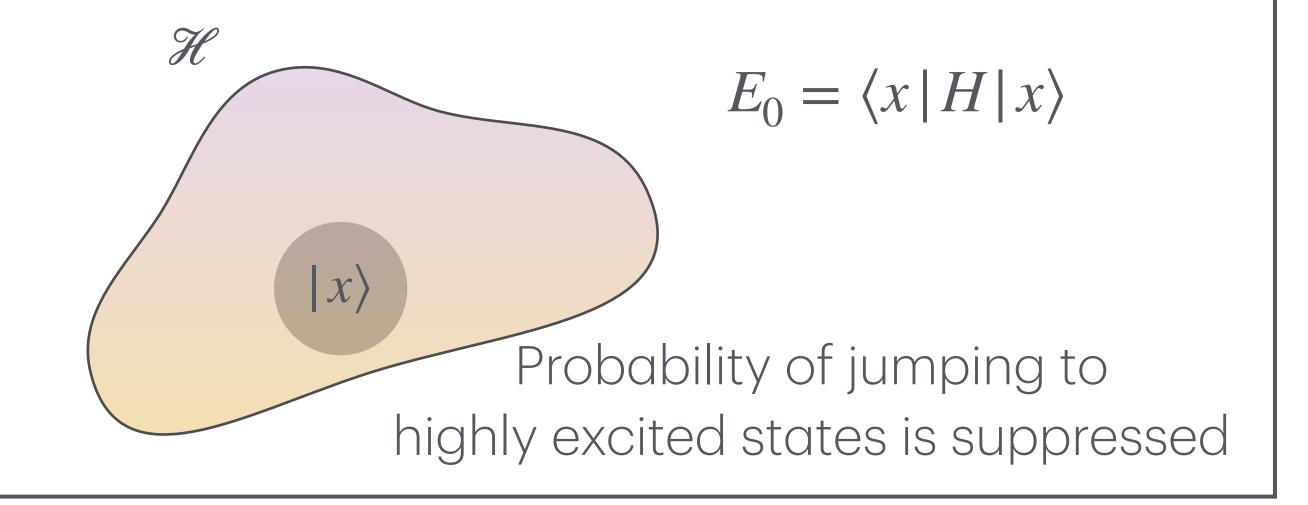
Ground state classically tractable

Quantum dynamics stays confined in  $U|x\rangle$ 

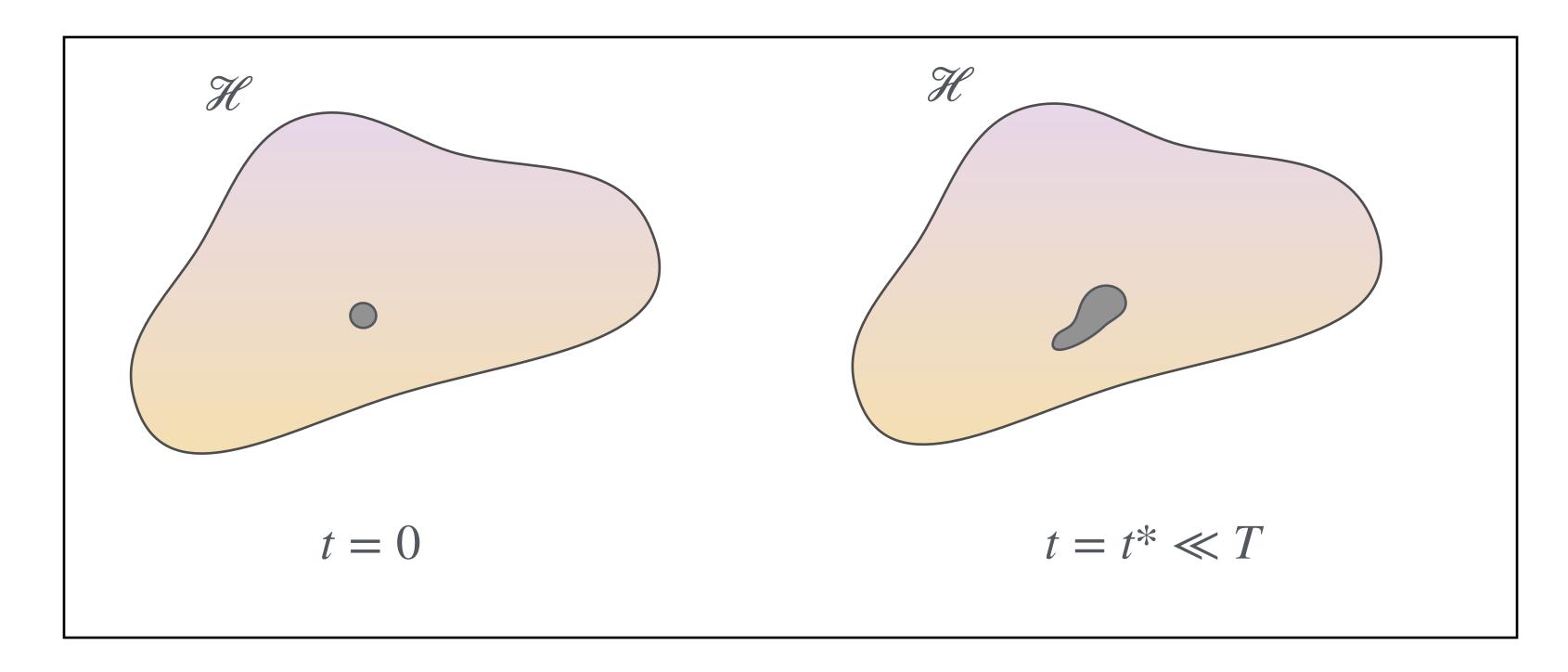
Subspace effective dimension tractable with ED

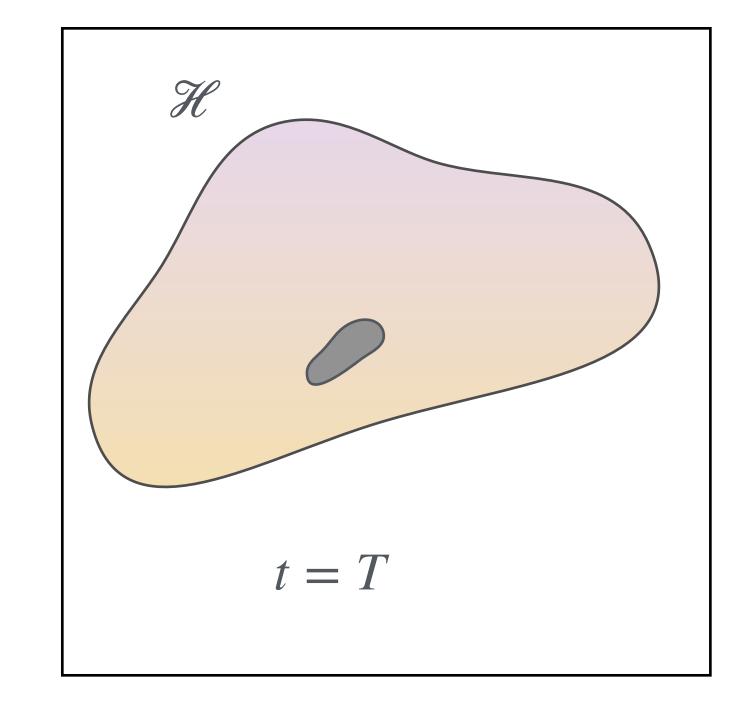
#### Hilbert space fragmentation

$$\# \langle x | \psi(t \ll T) \rangle \approx \# \langle x | \psi(T) \rangle$$



#### Effective thermalization in a subspace



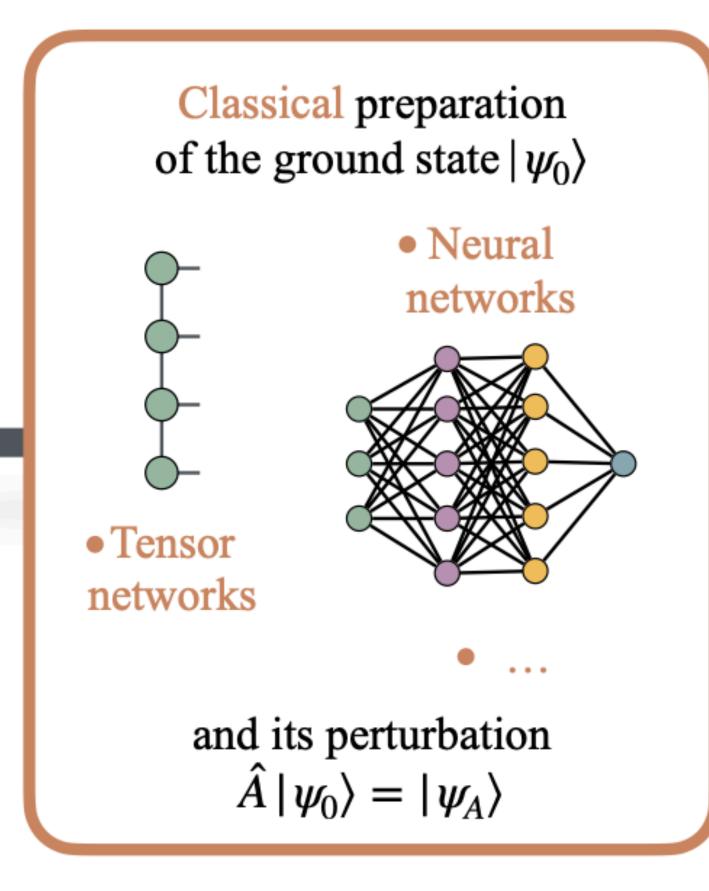


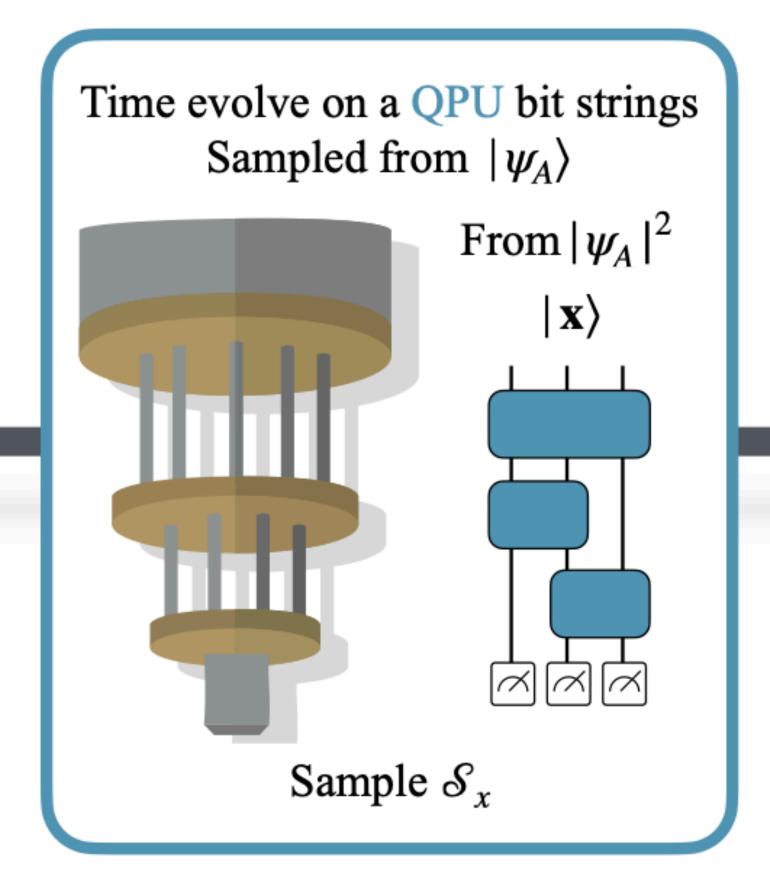
Small time quantum hardware

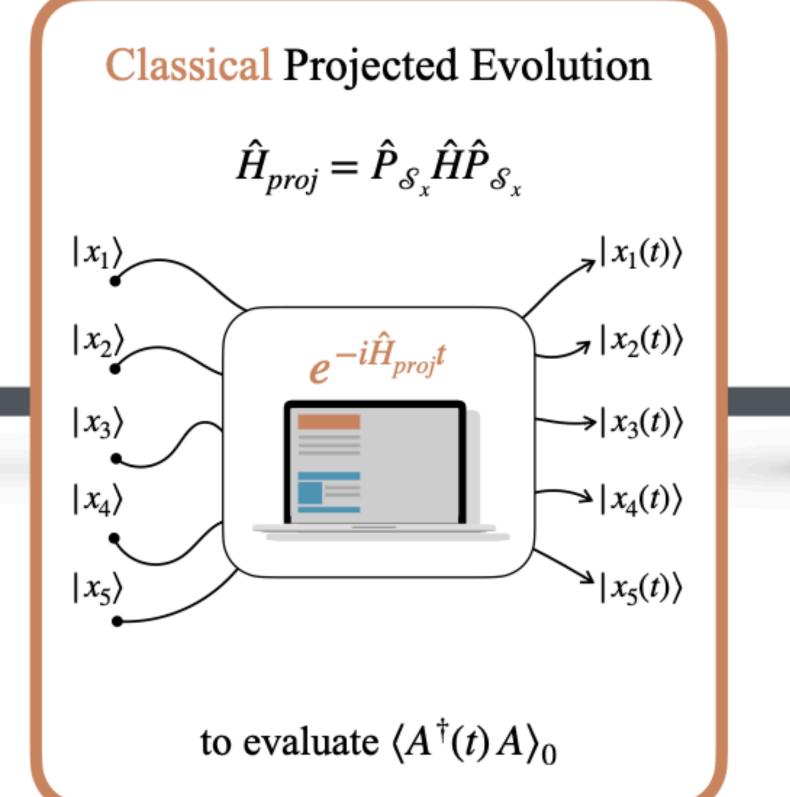
Subspace evolution extrapolates to large times

Large time to resolve small gaps

# Hybrid Quantum Classical Algorithm







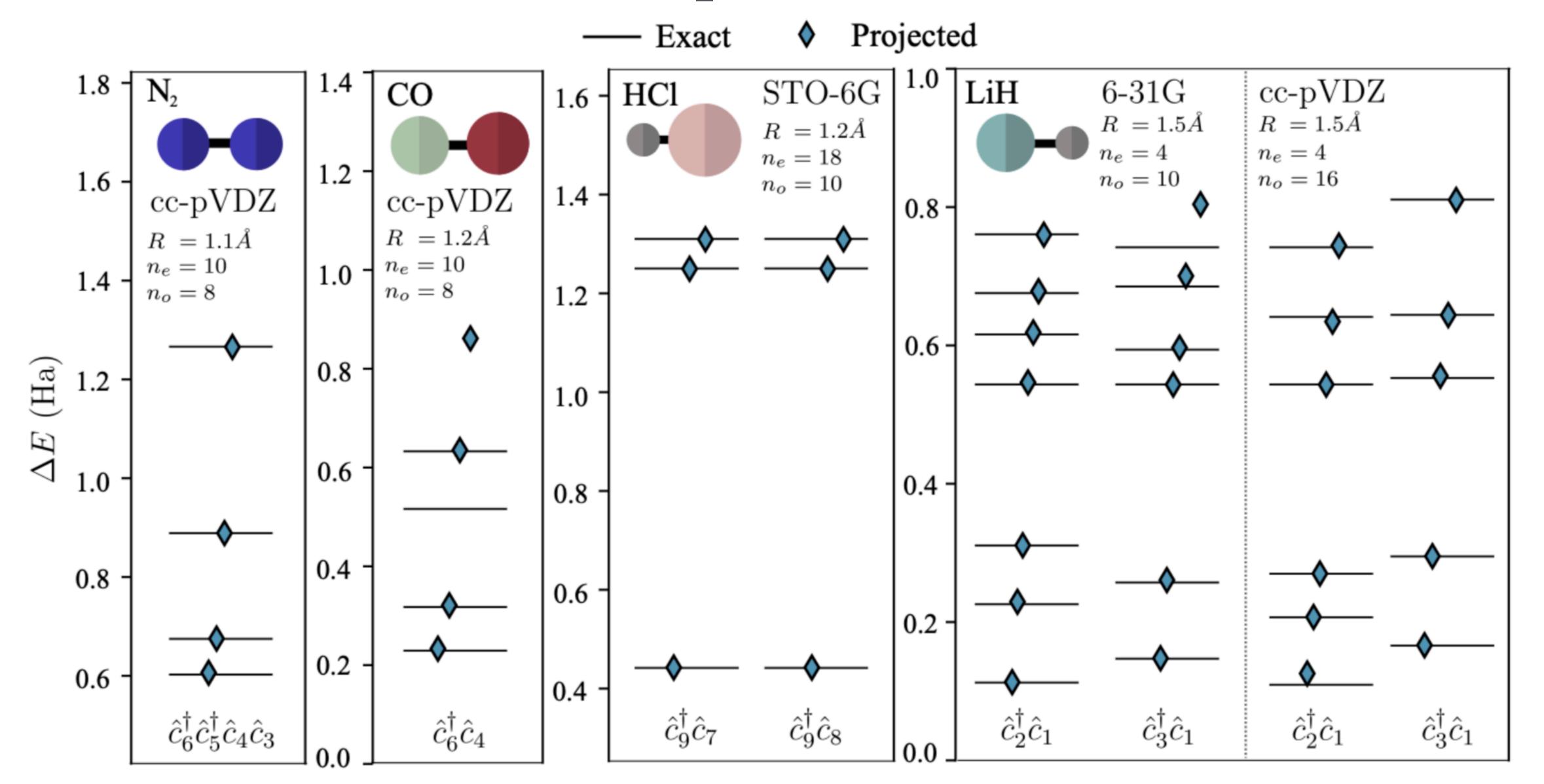
#### **QPU** friendly

- No ground state preparation
- Shallow quantum circuits

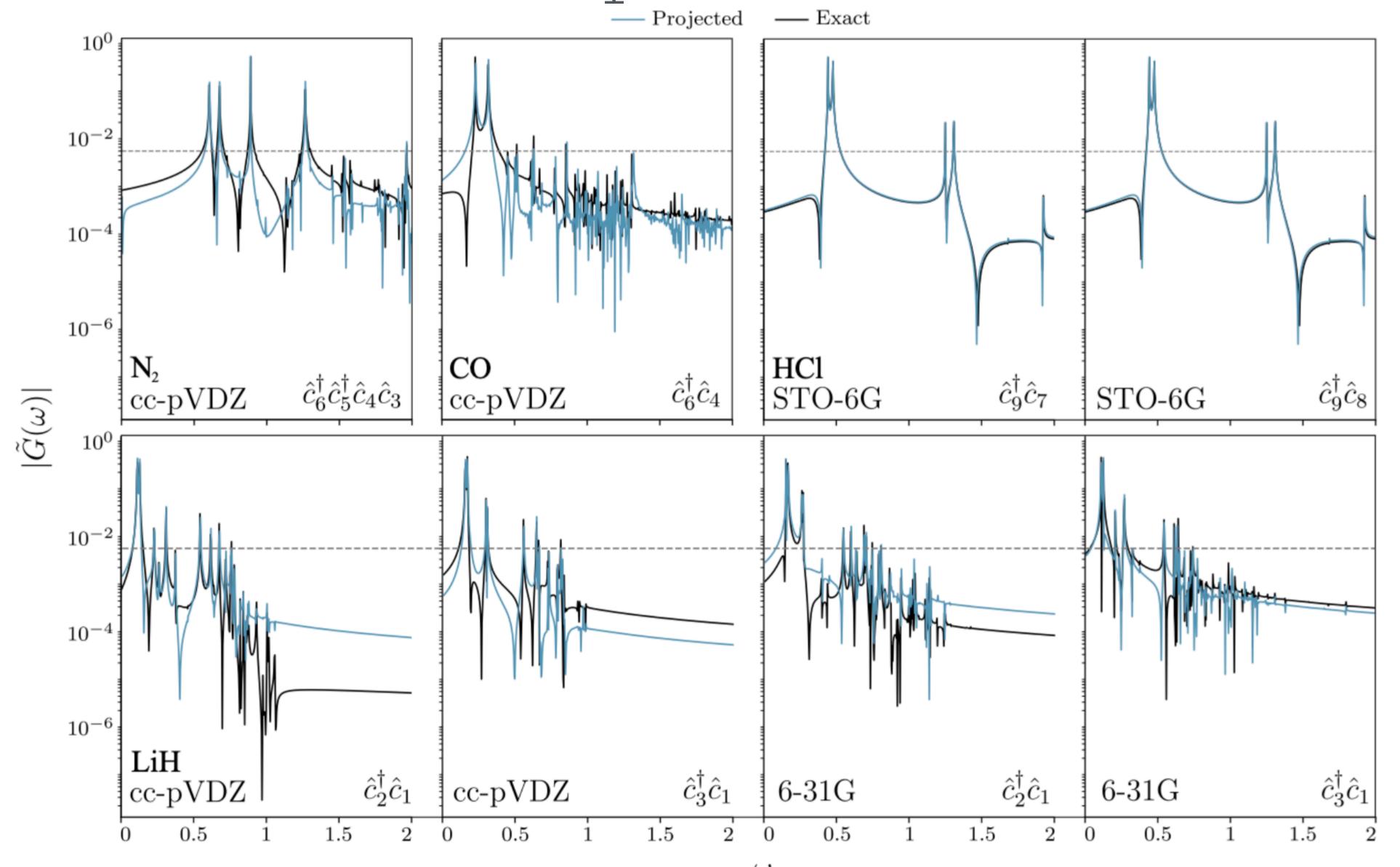
# Result: accurate spectra

Molecule	$n_o$	$n_e$	R	Basis	Perturbation	$\operatorname{Max}\dim\left[\mathcal{S}_{x} ight]$
$N_2$	8	10	1.1	cc-pvdz	$\hat{c}_6^{\dagger}\hat{c}_5^{\dagger}\hat{c}_4\hat{c}_3$	341
HCl	10	18	1.2	STO-6G	$\hat{c}_{\mathrm{o}}^{\dagger}\hat{c}_{7}$	8
HCl	10	18	1.2	STO-6G	$\hat{c}_9^\dagger \hat{c}_8 \ \hat{c}_6^\dagger \hat{c}_4 \ \hat{c}_2^\dagger \hat{c}_1$	8
$\mathbf{CO}$	8	10	1.2	$\operatorname{cc-pvdz}$	$\hat{c}_6^{\dagger}\hat{c}_4$	821
${ m LiH}$	10	4	1.5	6 - 31G	$\hat{c}_2^\dagger \hat{c}_1$	331
${ m LiH}$	16	4	1.5	$\operatorname{cc-pvdz}$	$\hat{c}_2^{\dagger}\hat{c}_1$	1421
${ m LiH}$	10	4	1.5	6 - 31G	$\hat{c}_3^{\dagger}\hat{c}_1$	298
${ m LiH}$	16	4	1.5	$\operatorname{cc-pvdz}$	$\hat{c}_3^\dagger \hat{c}_1$	1007

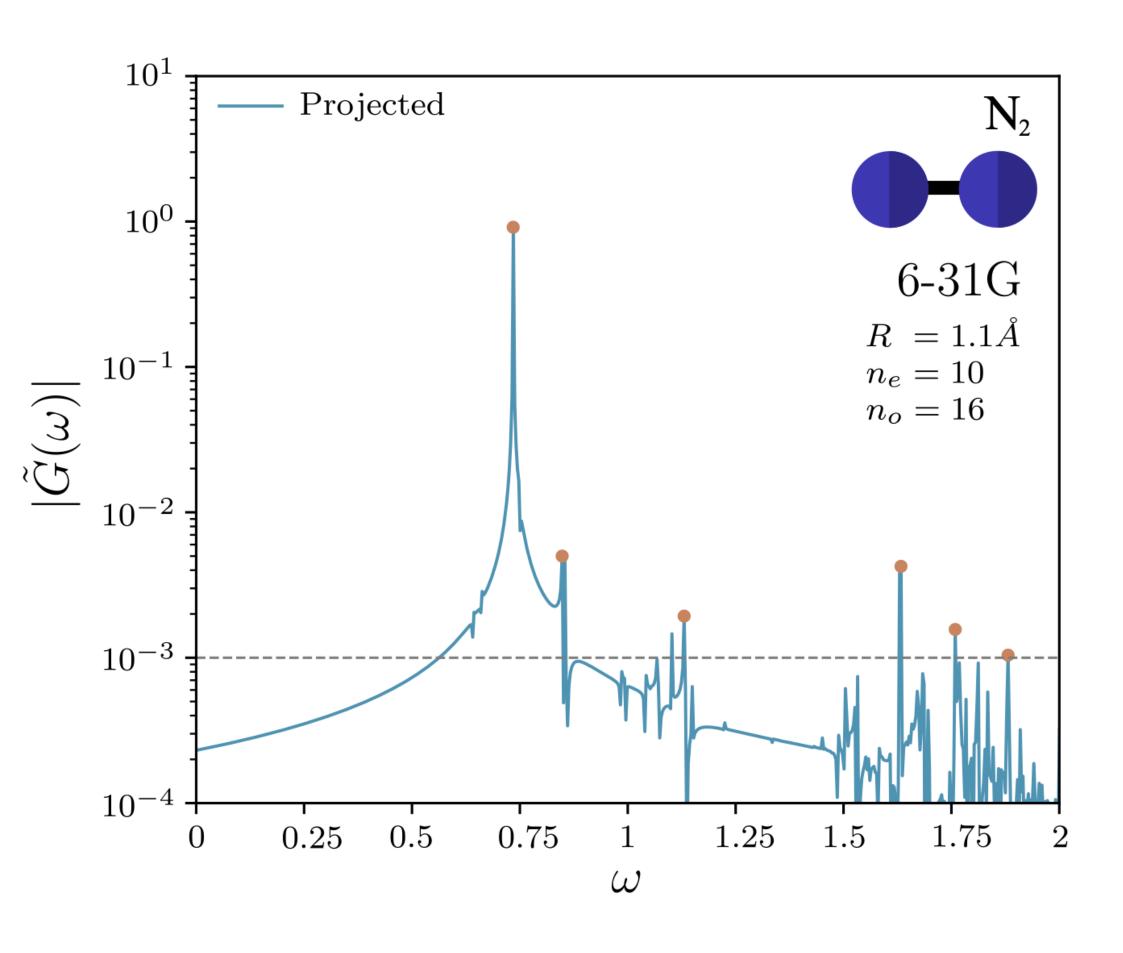
## Result: accurate spectra



# Result: accurate spectra



#### Tensor Network dynamics



 TN algorithm simulates the quantum computer behavior

Subspace reduction

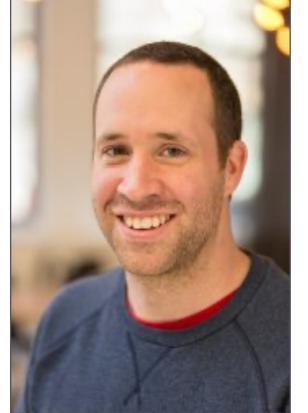
$$\bigcup_{x} \mathcal{S}_{x} \approx \frac{1}{256} \dim \mathcal{H}$$

## Extension to impurity models

N. Moumique, AS, M. Ferrero, F. Vicentini, T. Ayral







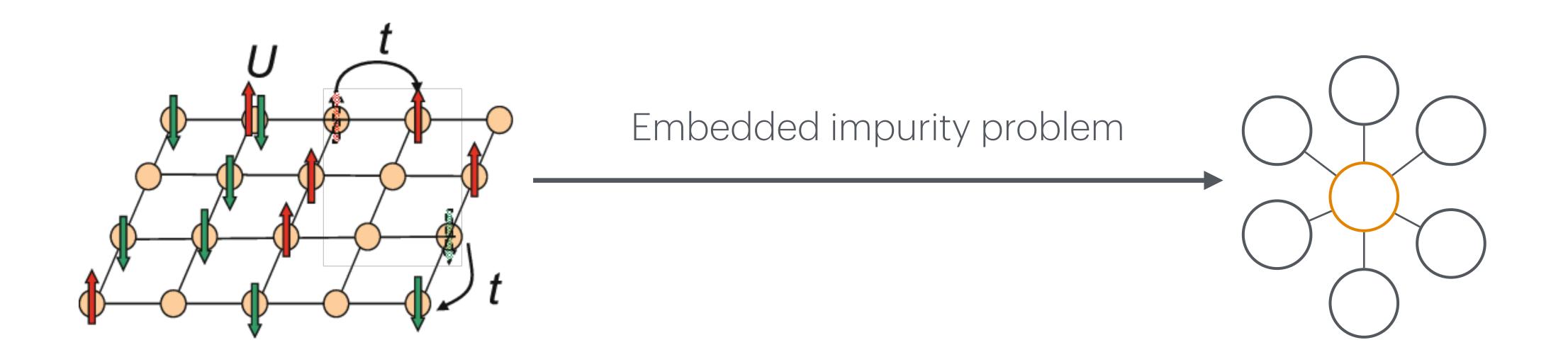






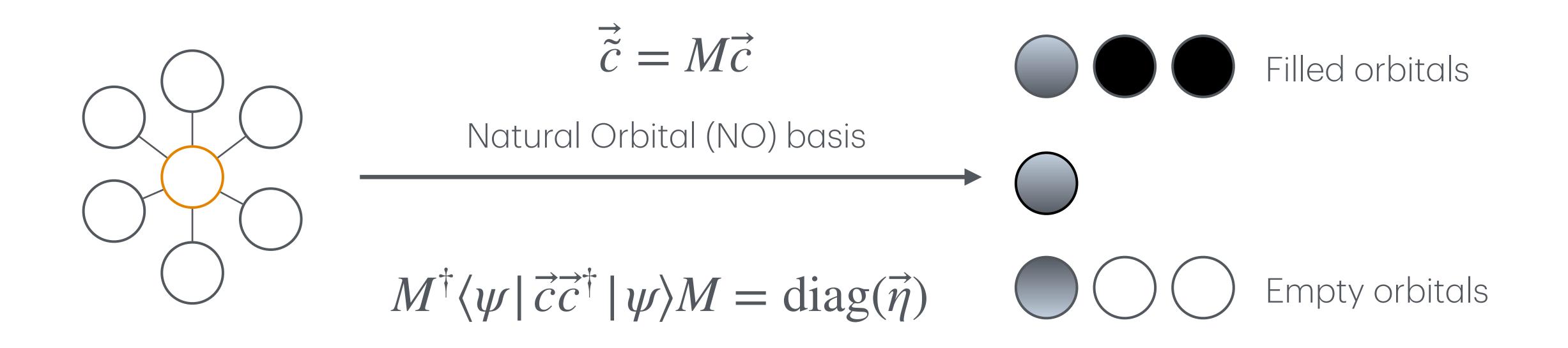
### Anderson Impurity Problem

#### Same idea <u>classical ground state</u> + <u>quantum dynamics</u> + <u>subspace evolution</u>



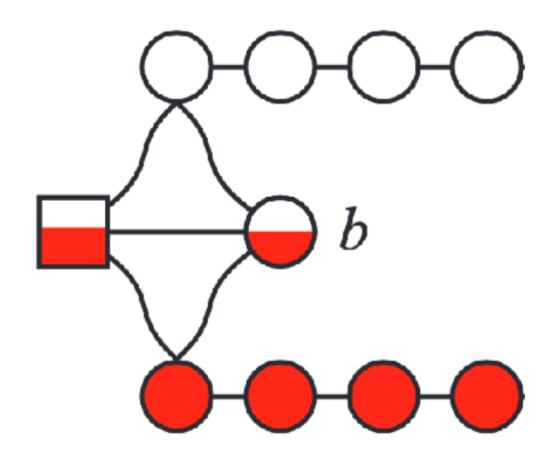
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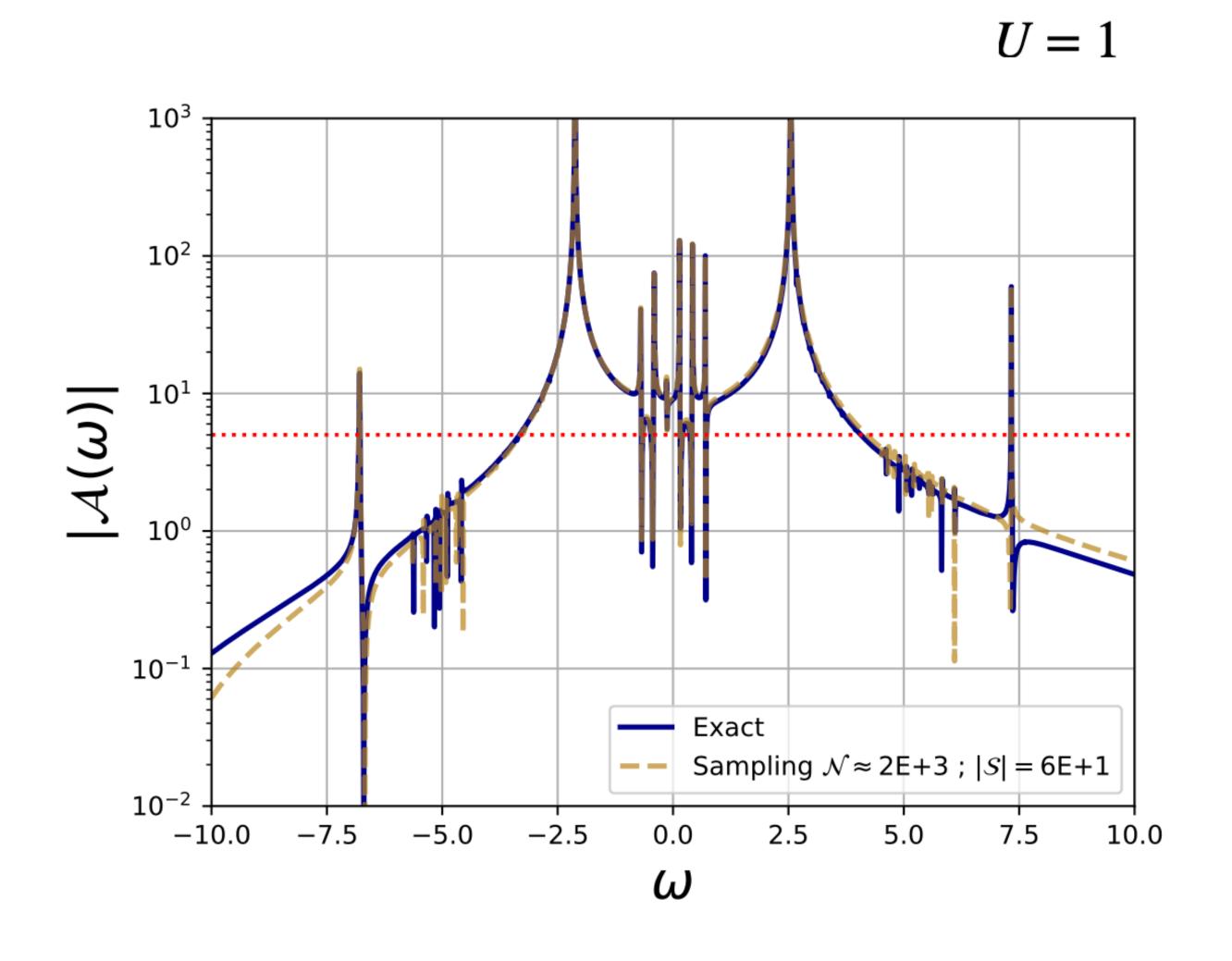
#### Same idea <u>classical ground state</u> + <u>quantum dynamics</u> + <u>subspace evolution</u>



### Anderson Impurity Problem

NO basis perturbed state  $c_{
m impurity}^\dagger |\psi_0
angle$ 





#### Summary

- Improved VMC with importance sampling from trained importance sampling distribution
- Introduced a Hybrid method to compute spectral functions on QC with subspace expansion
- We generalize the method, thanks to the NO technique, to impurity models
- Outlook: try the method on the quantum hardware

# Thanks for your attention



Looking elsewhere: improving variational Monte Carlo gradients by importance sampling

A. Misery, L. Gravina, **AS**, F. Vicentini arXiv preprint arXiv:2507.05352

Classically Prepared, Quantumly Evolved: Hybrid Algorithm for Molecular Spectra **AS**, S. Barison, F. Vicentini arXiv preprint *arXiv:2510.24911* 

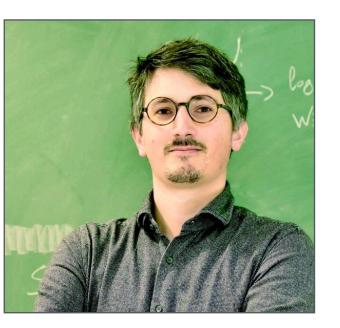






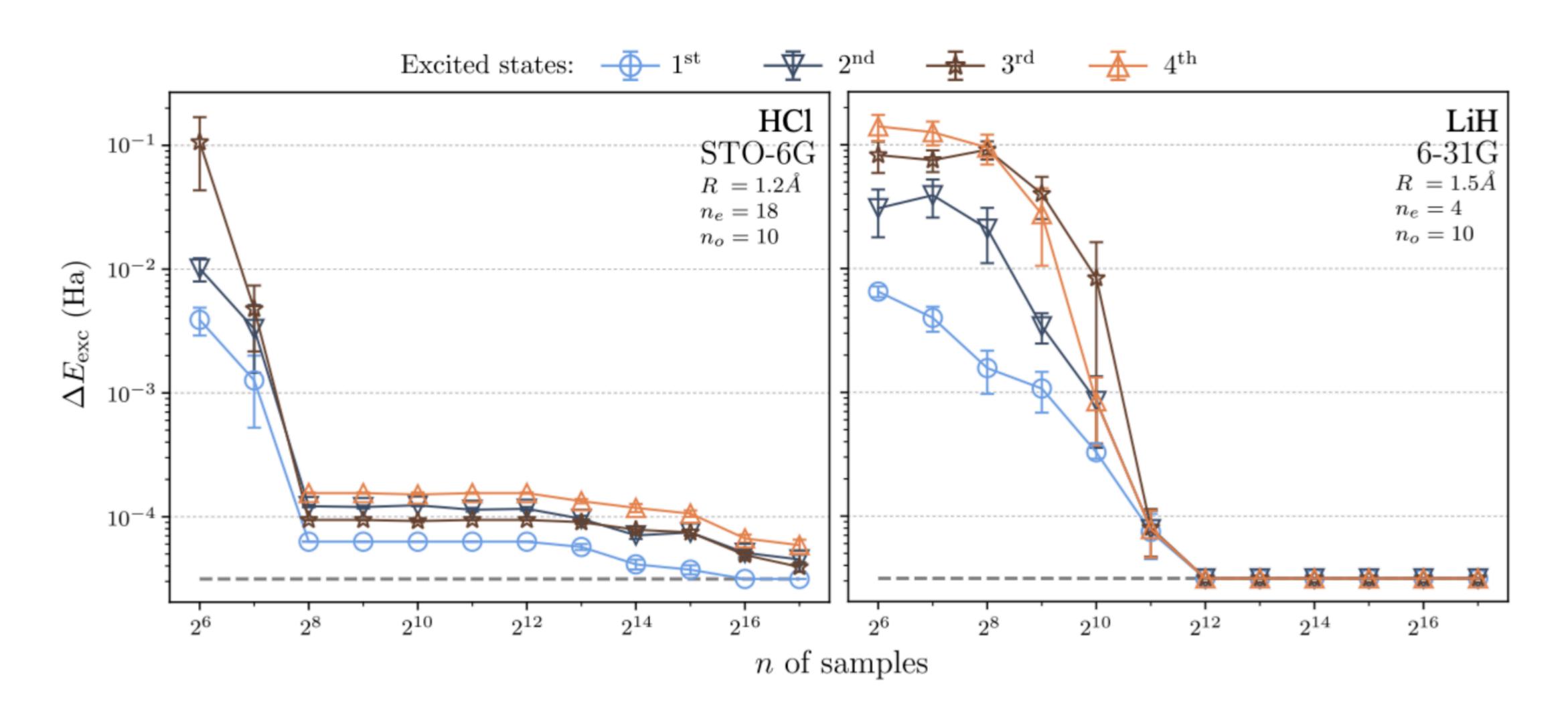








## Scaling with the number of samples



# Energies with NN sampling

Name	MF	n	$N_{\uparrow}+N_{\downarrow}$	K	HF Energy	CCSD	Ours	FCI
Hydrogen	H2	4	1+1=2	15	-1.06610864	-1.101150	-1.101150	-1.101150
Lithium Hydride	LiH	12	2+2=4	631	-7.76736213	-7.784455	-7.784460	-7.784460
Water	H2O	14	5+5=10	1390	-74.9644475	-75.015409	-75.015511	-75.015530
Methylene	CH2	14	5+3=8	2058	-37.4846329	-37.504411	-37.504419	-37.504435
Beryllium Hydride	BeH2	14	3+3=6	2074	-14.4432411	-14.472713	-14.472922	-14.472947
Ammonia	NH3	16	5+5=10	4929	-55.4547926	-55.520931	-55.521037	-55.521150
Methane	CH4	18	5+5=10	8480	-39.7265817	-39.806022	-39.806170	-39.806259
Diatomic Carbon	C2	20	6+6=12	2239	-74.2483215	-74.484727	-74.486037	-74.496388
Fluorine	F2	20	9+9=18	2951	-195.638041	-195.661086	-195.661067	-195.66108
Nitrogen	N2	20	7+7=14	2239	-107.498967	-107.656080	-107.656763	-107.660206
Oxygen	O2	20	9+7=16	2879	-147.631948	-147.747738	-147.749953	-147.750235
Lithium Fluoride	LiF	20	6+6=12	5849	-105.113709	-105.159235	-105.165270	-105.166172
Hydrochloric Acid	HC1	20	9+9=18	5851	-455.135968	-455.156189	-455.156189	-455.156189
Hydrogen Sulfide	H2S	22	9+9=18	9558	-394.311379	-394.354556	-394.354592	-394.354623
Formaldehyde	CH2O	24	8+8=16	20397	-112.354197	-112.498567	-112.500944	-112.501253
Phosphine	PH3	24	9+9=18	24369	-338.634114	-338.698165	-338.698186	-338.698400
Lithium Chloride	LiCL	28	10+10=20	24255	-460.827258	-460.847580	-460.848109	-460.849618
Methanol	CH4O	28	9+9=18	52887	-113.547027	-113.665485	-113.665485	-113.666485
Lithium Oxide	Li2O	30	7+7=14	20558	-87.7955672	-87.885514	-87.885637	_
Ethylene Oxide	C2H4O	38	12+12=24	137218	-150.927608	-151.120474	-151.120486	_
Propene	C3H6	42	12+12=24	161620	-115.657941	-115.885123	-115.886571	_
Acetic Acid	C2H4O2	48	16+16=32	461313	-224.805400	-225.050896	-225.0429767	_
Sulfuric Acid	H2O4S	62	25+25=50	1235816	-689.262656	-689.498410	-689.505237	_
Sodium Carbonate	CNa2O3	76	26+26=52	1625991	-575.016102	-575.299810	-575.299820	_