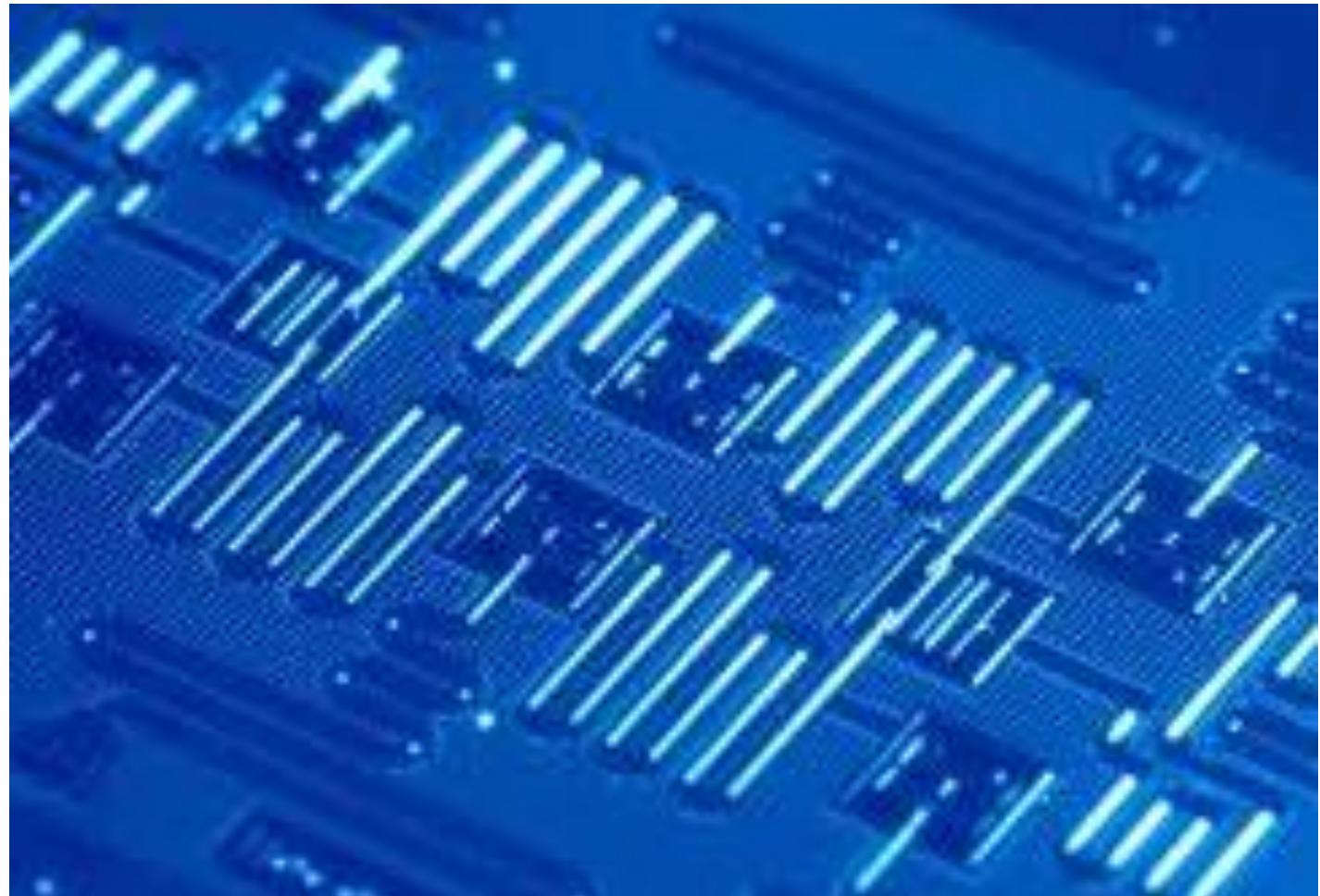


Numerical analysis of protected qubits

TR CONTROL:

Gabriel Vandersippe,
Eliot Delachaux



Source : IBM (via The Quantum Insider)

Outline

1. Brief introduction to superconducting circuits
2. Project Motivations
3. Results with Krylov techniques (Eliot)
4. Results with Tensor Networks (Gabriel)

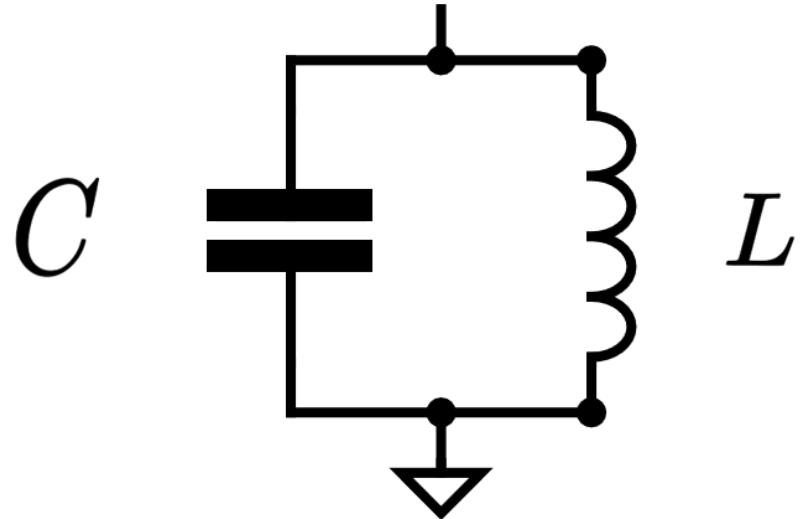
Using Python packages :

NumPy, QuTiP, SCQubits, Matplotlib, SciPy, JAX, Pandas

Using Julia packages :

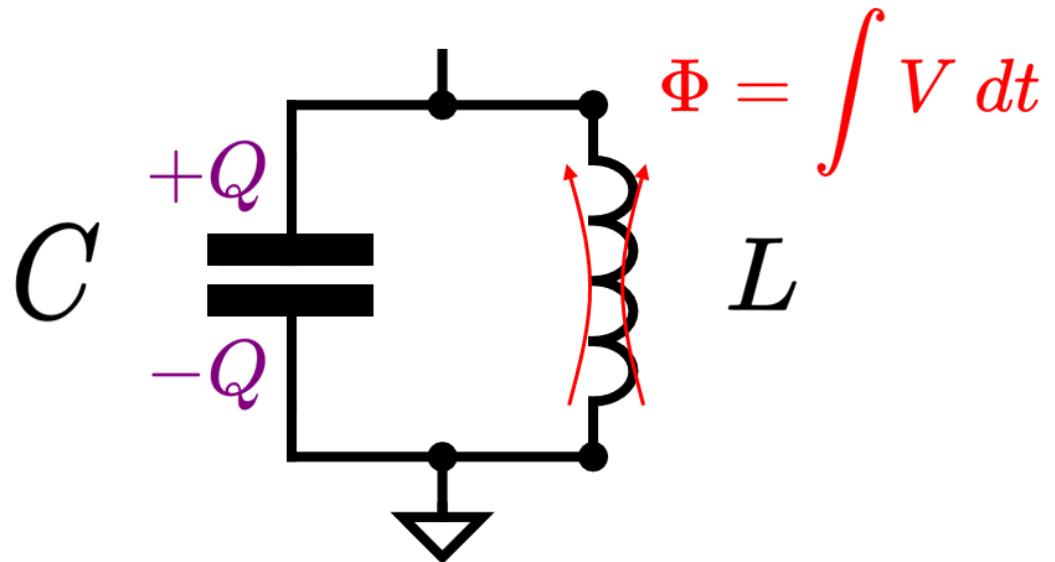
ITensors, ITensorMPS, KrylovKit, CairoMakie, LinearAlgebra, HypergeometricFunctions, CSV, DataFrames

Introduction : Harmonic Oscillator



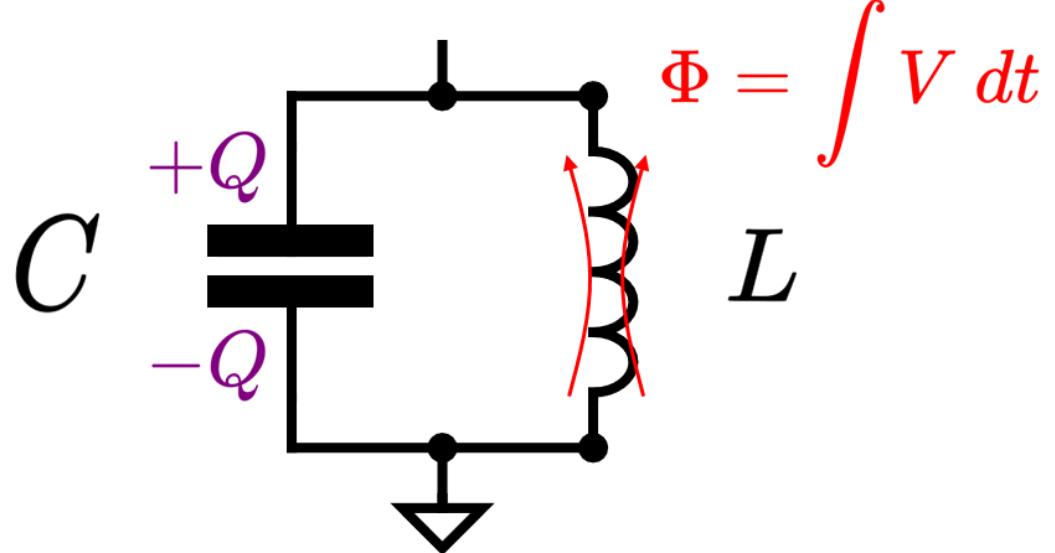
$$H = \underbrace{\frac{Q^2}{2C}}_{\text{Kinetic}} + \underbrace{\frac{\Phi^2}{2L}}_{\text{Potential}}$$

Introduction : Harmonic Oscillator

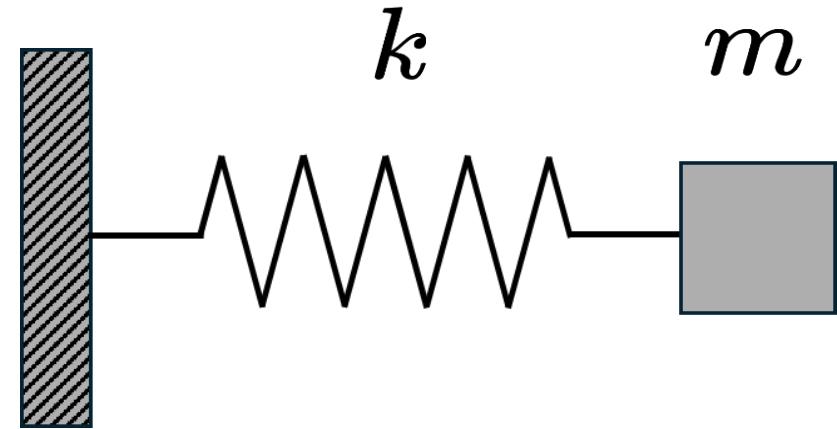


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Introduction : Harmonic Oscillator



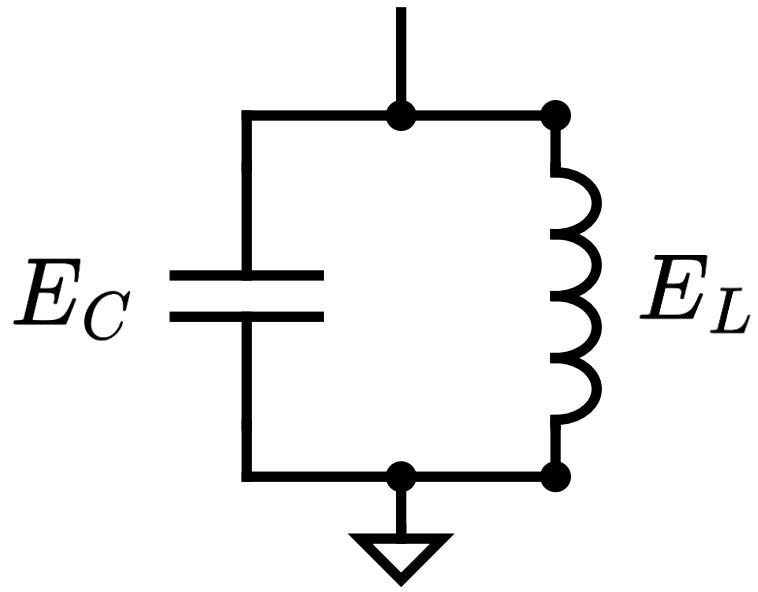
$$\Phi = \int V dt$$



$$H = \underbrace{\frac{Q^2}{2C}}_{\text{Kinetic}} + \underbrace{\frac{\Phi^2}{2L}}_{\text{Potential}}$$

$$H = \underbrace{\frac{1}{2m} \mathbf{p}^2}_{\text{Kinetic}} + \underbrace{\frac{k}{2} \mathbf{x}^2}_{\text{Potential}}$$

Quantizing the Harmonic Oscillator



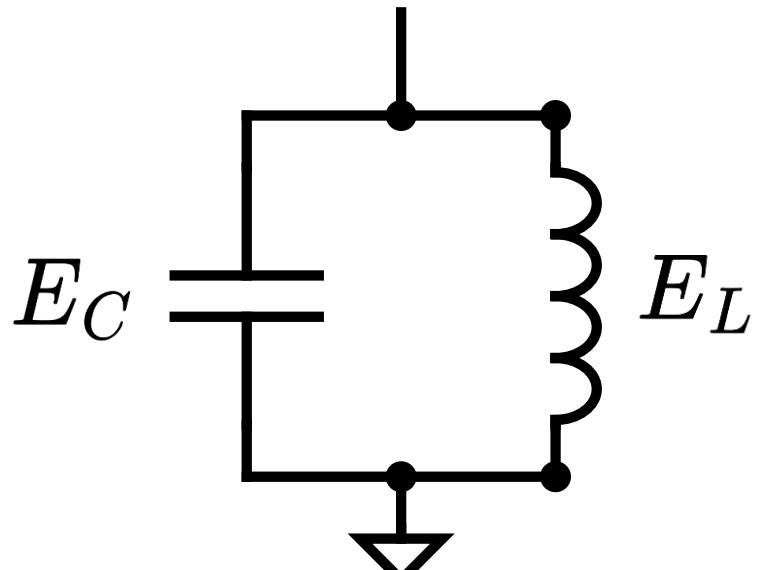
Hamiltonian :

$$H = \underbrace{\frac{Q^2}{2C}}_{\text{Kinetic}} + \underbrace{\frac{\Phi^2}{2L}}_{\text{Potential}}$$

Correspondence principle : $H \rightarrow \hat{H}$ Operator

$$\Rightarrow \hat{H} = 4E_C \hat{n}^2 + \frac{E_L}{2} \hat{\varphi}^2$$

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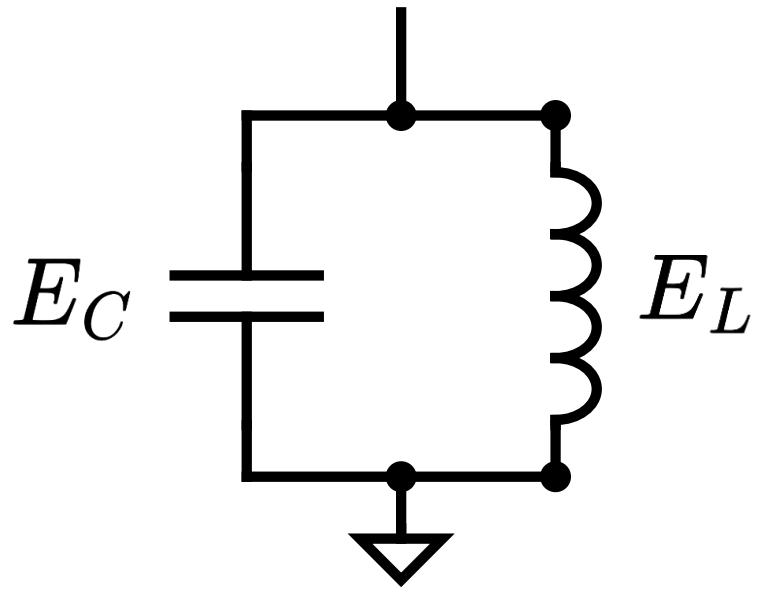
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$$\Rightarrow \hat{H} = 4E_C \hat{n}^2 + \frac{E_L}{2} \hat{\varphi}^2$$

$$= \hbar\omega \begin{pmatrix} 0 & 0 & 0 & \dots \\ 0 & 1 & 0 & \dots \\ 0 & 0 & 2 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

Infinite basis : $\{|0\rangle, |1\rangle, \dots |n\rangle, |n+1\rangle, \dots\}$

Quantizing the Harmonic Oscillator



Hamiltonian :

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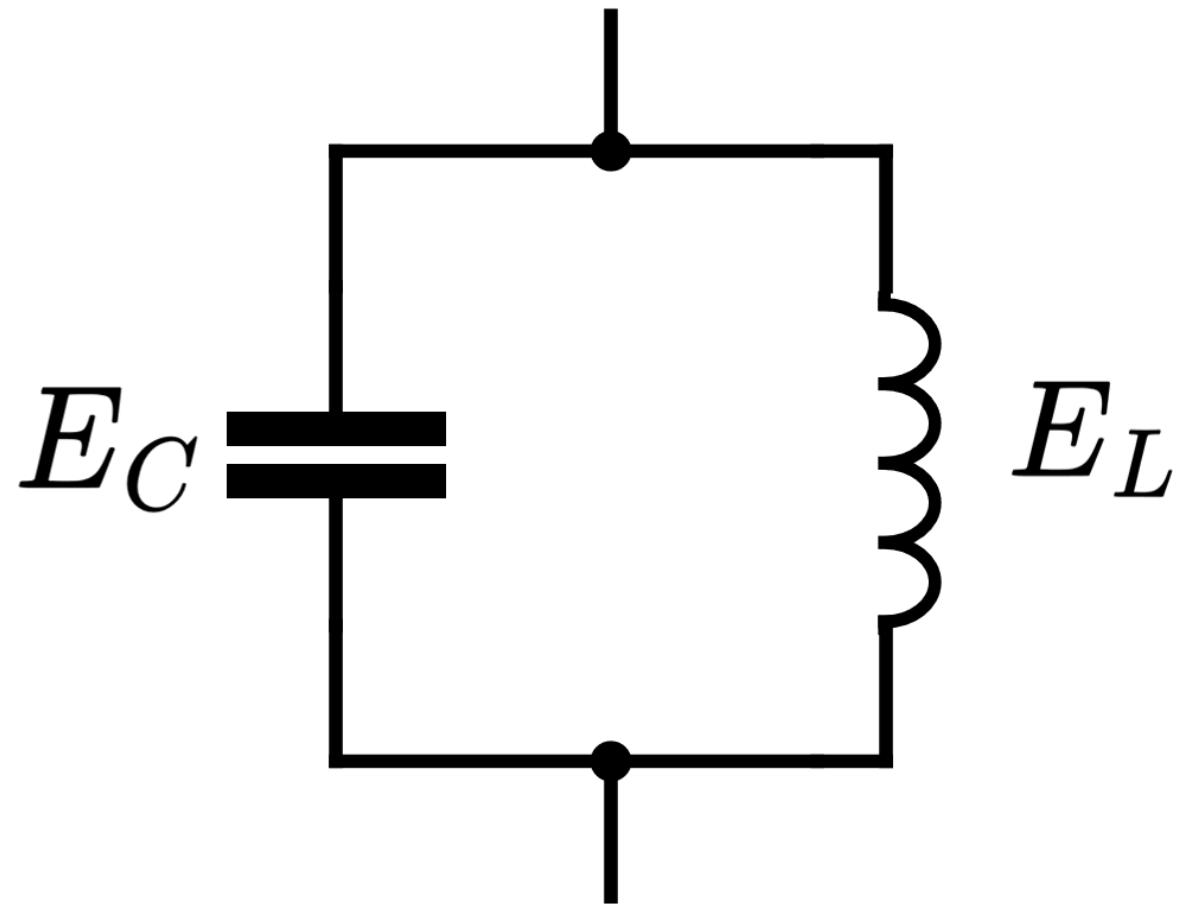
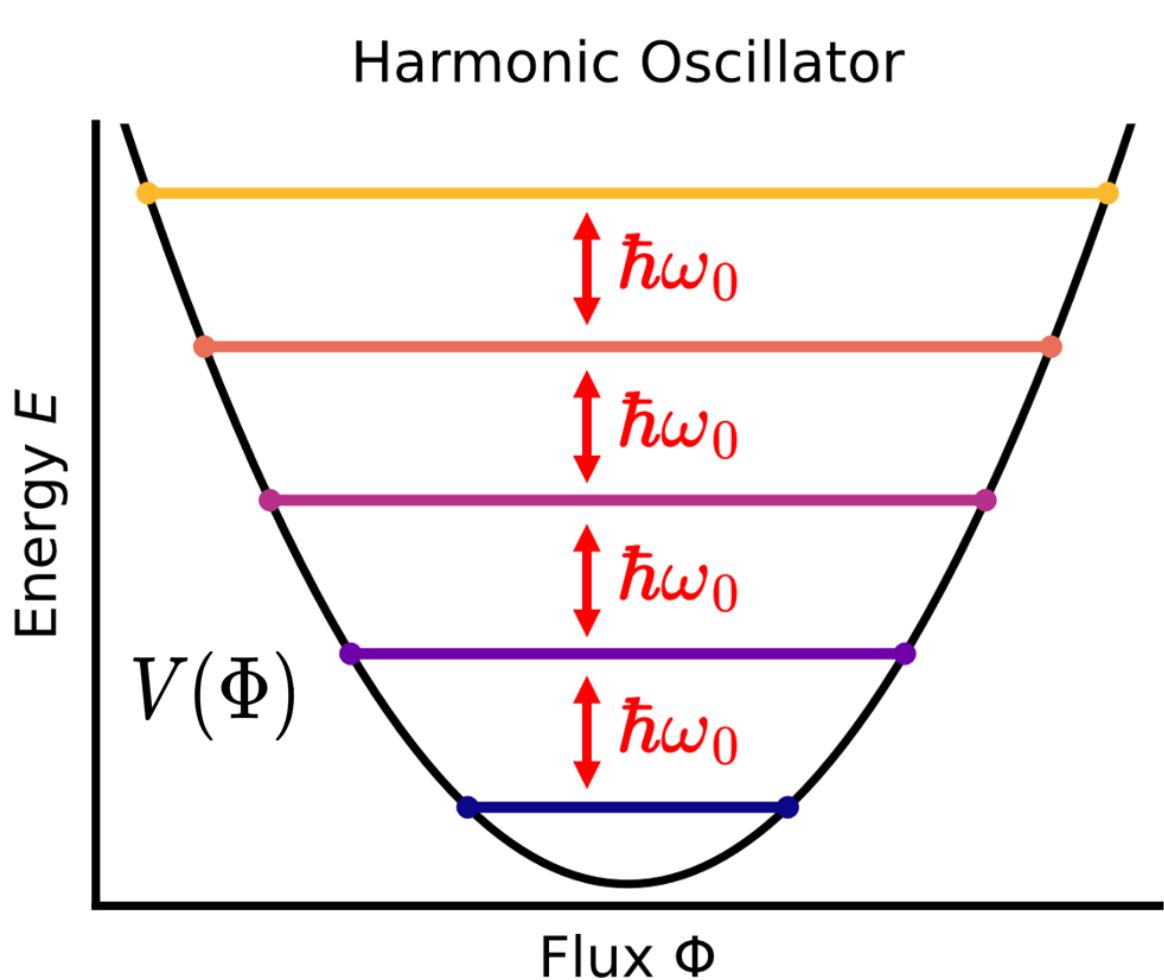
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Infinite basis : $\{|0\rangle, |1\rangle, \dots |n\rangle, |n+1\rangle, \dots\}$

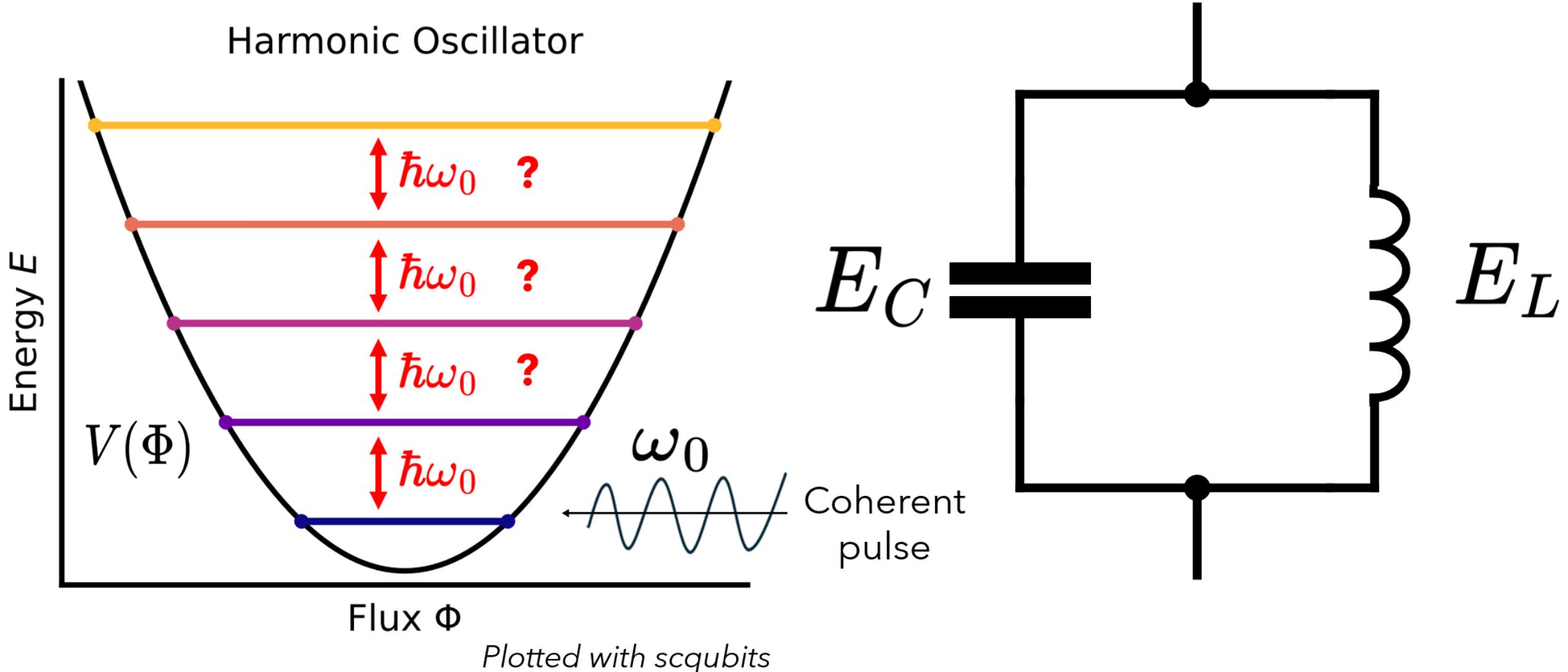
cutoff

Harmonic oscillator to Qubit

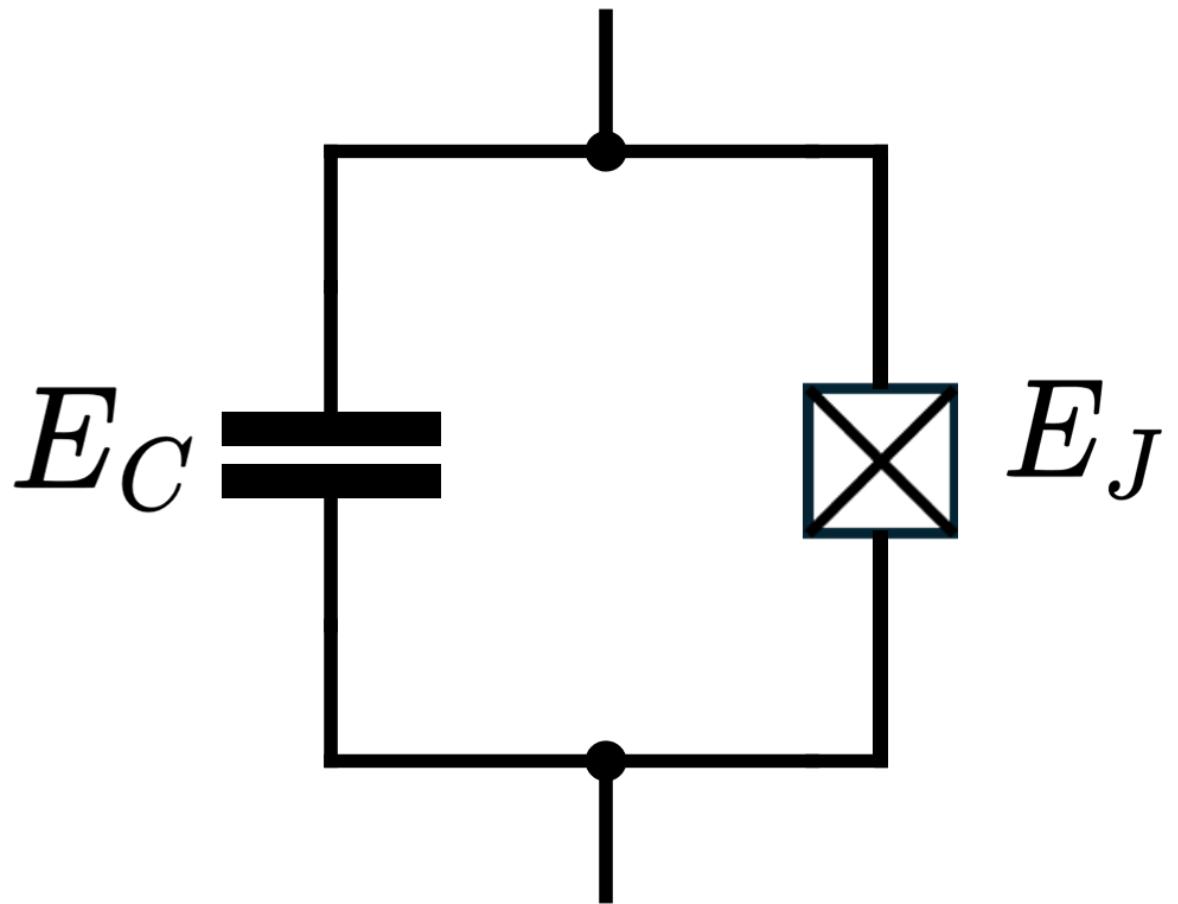
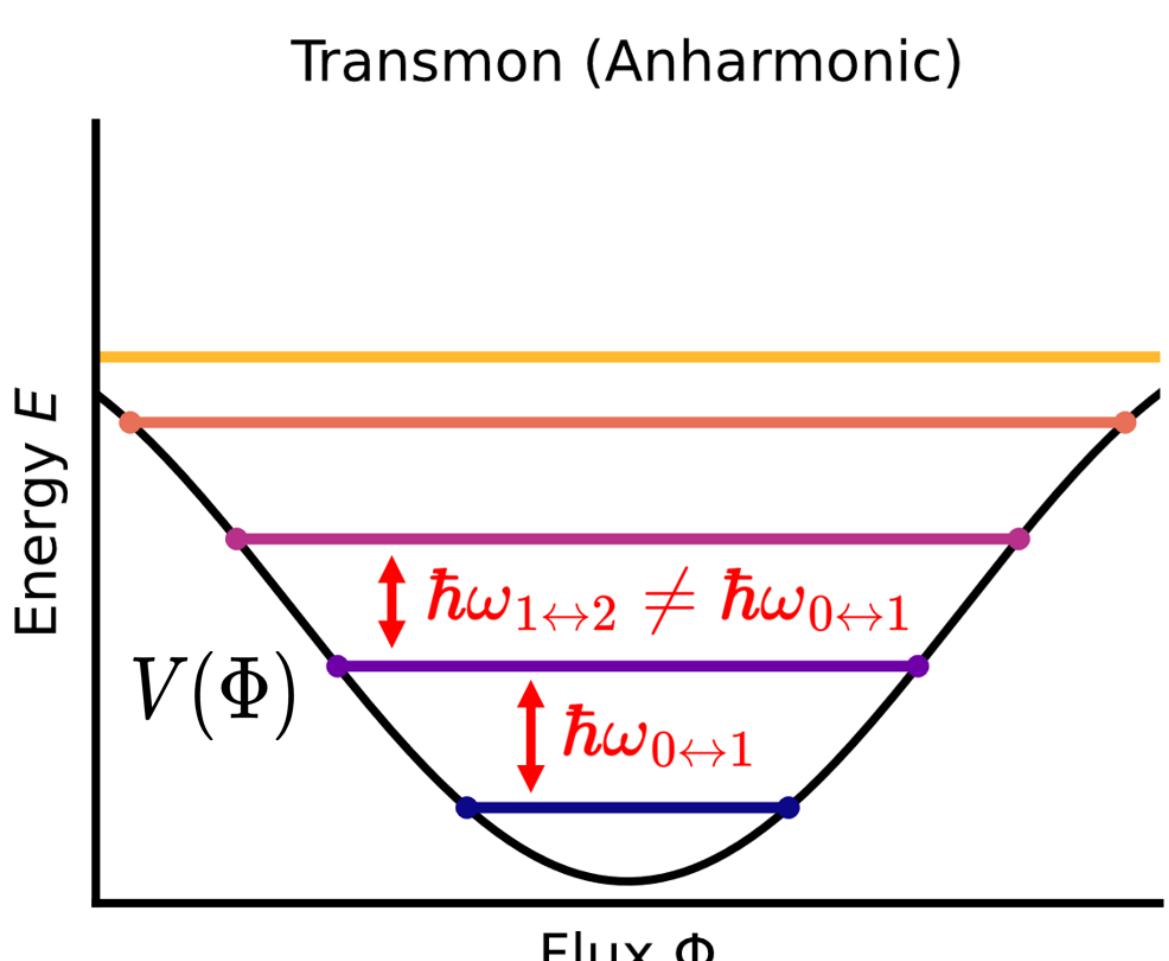


Plotted with scqubits

Harmonic oscillator to Qubit

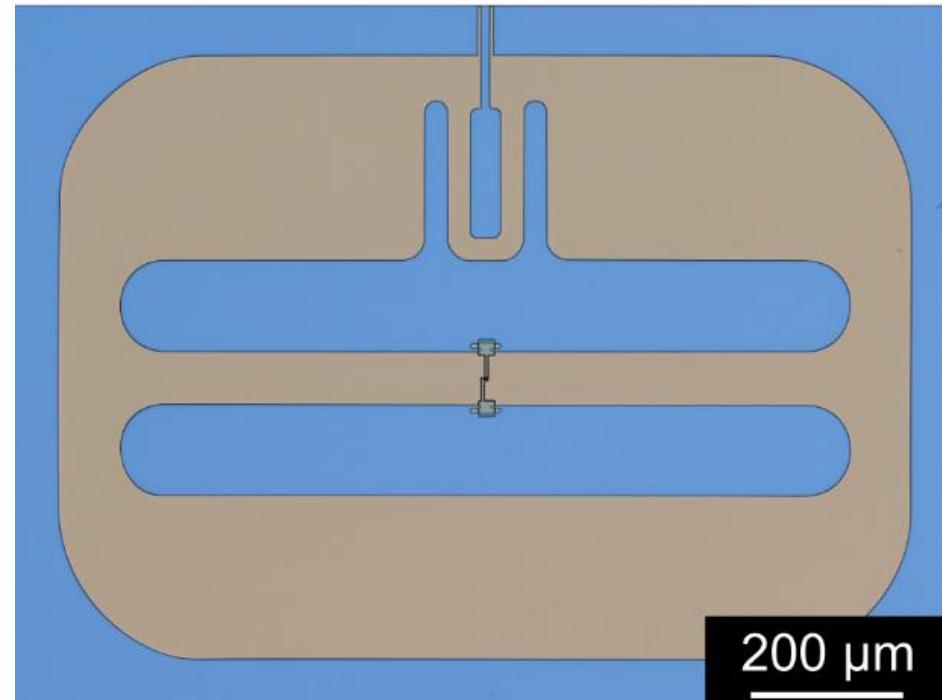
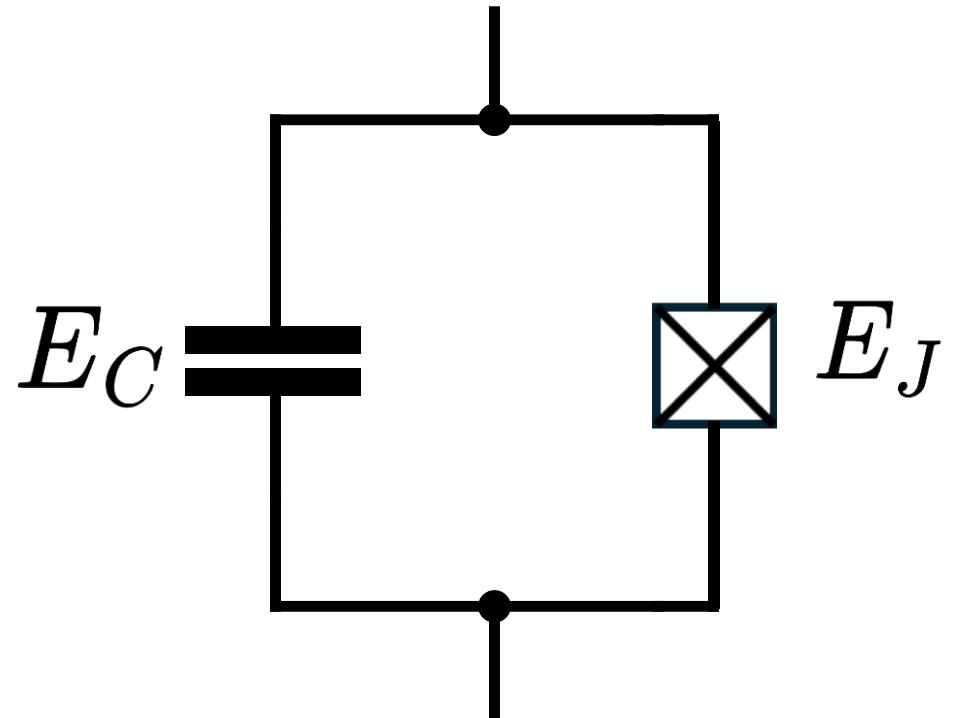


Harmonic oscillator to Qubit



Plotted with scqubits

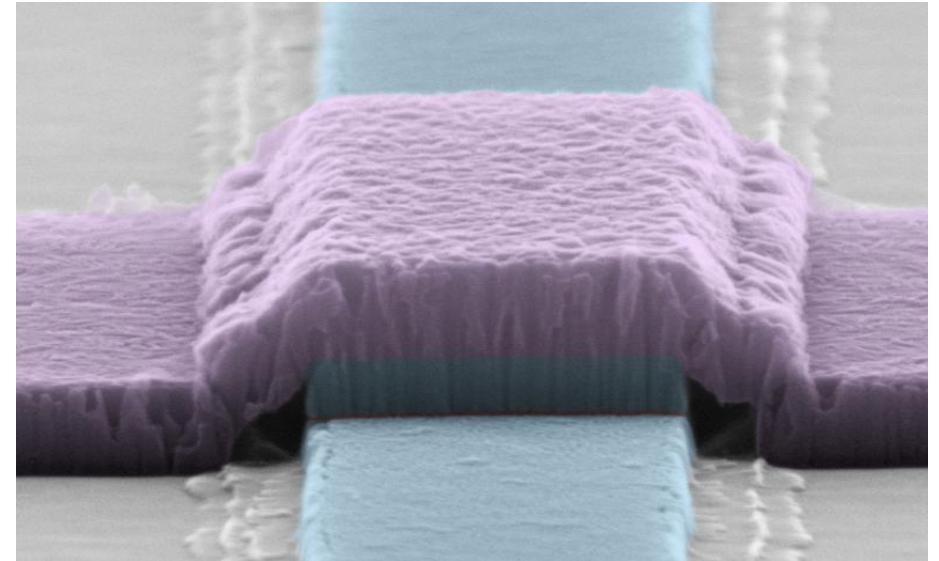
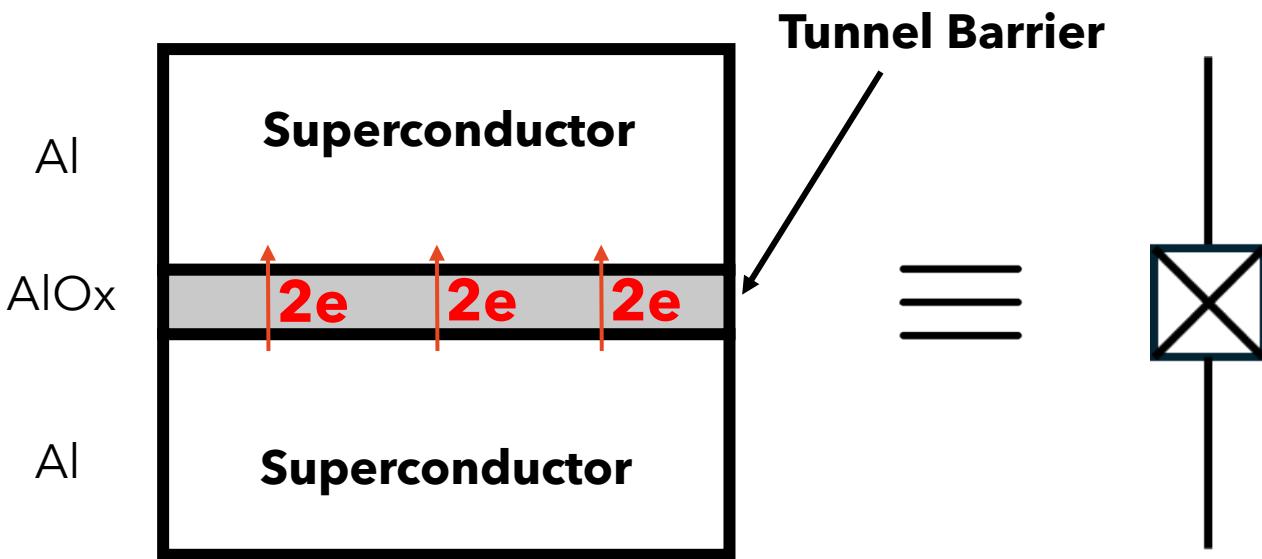
Transmon



Houck lab

arXiv : 2003.00024

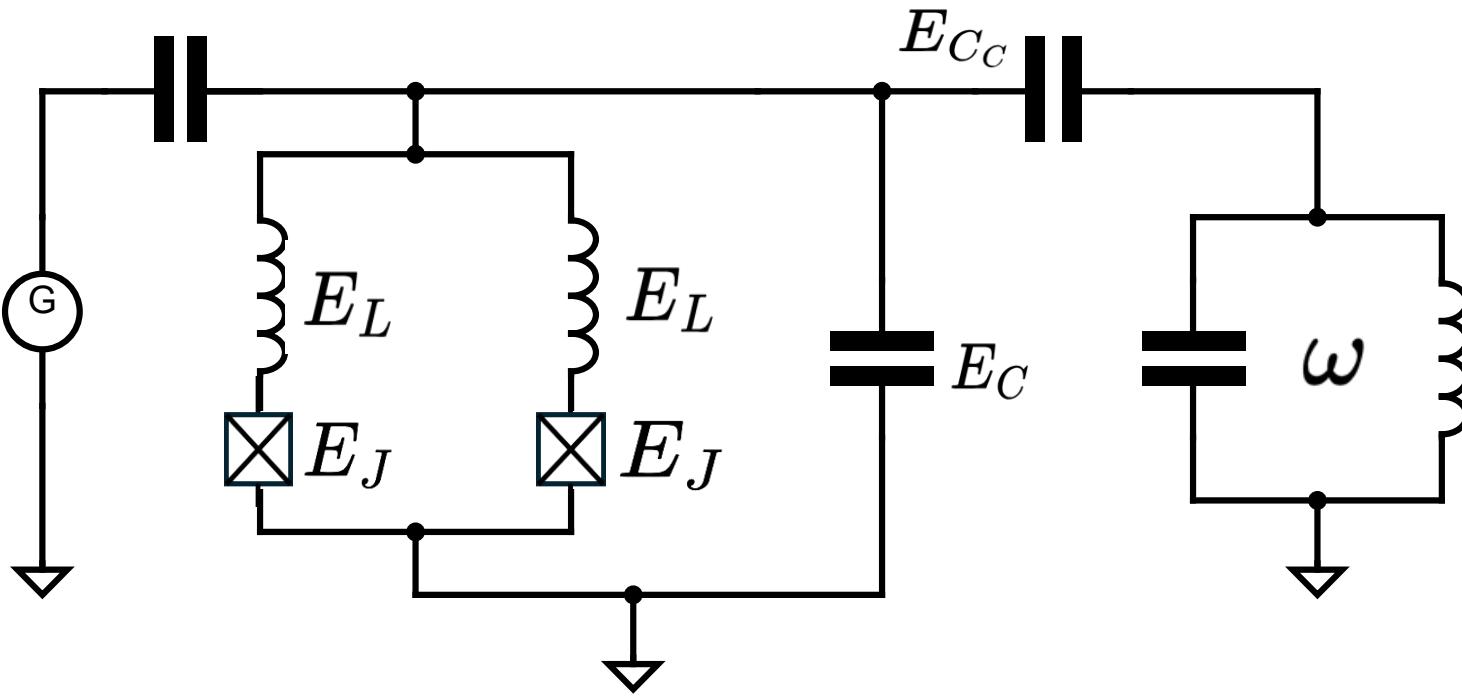
Josephson Junction



Source : NQISRC

$$H = 4E_C n^2 - E_J \cos(\varphi)$$

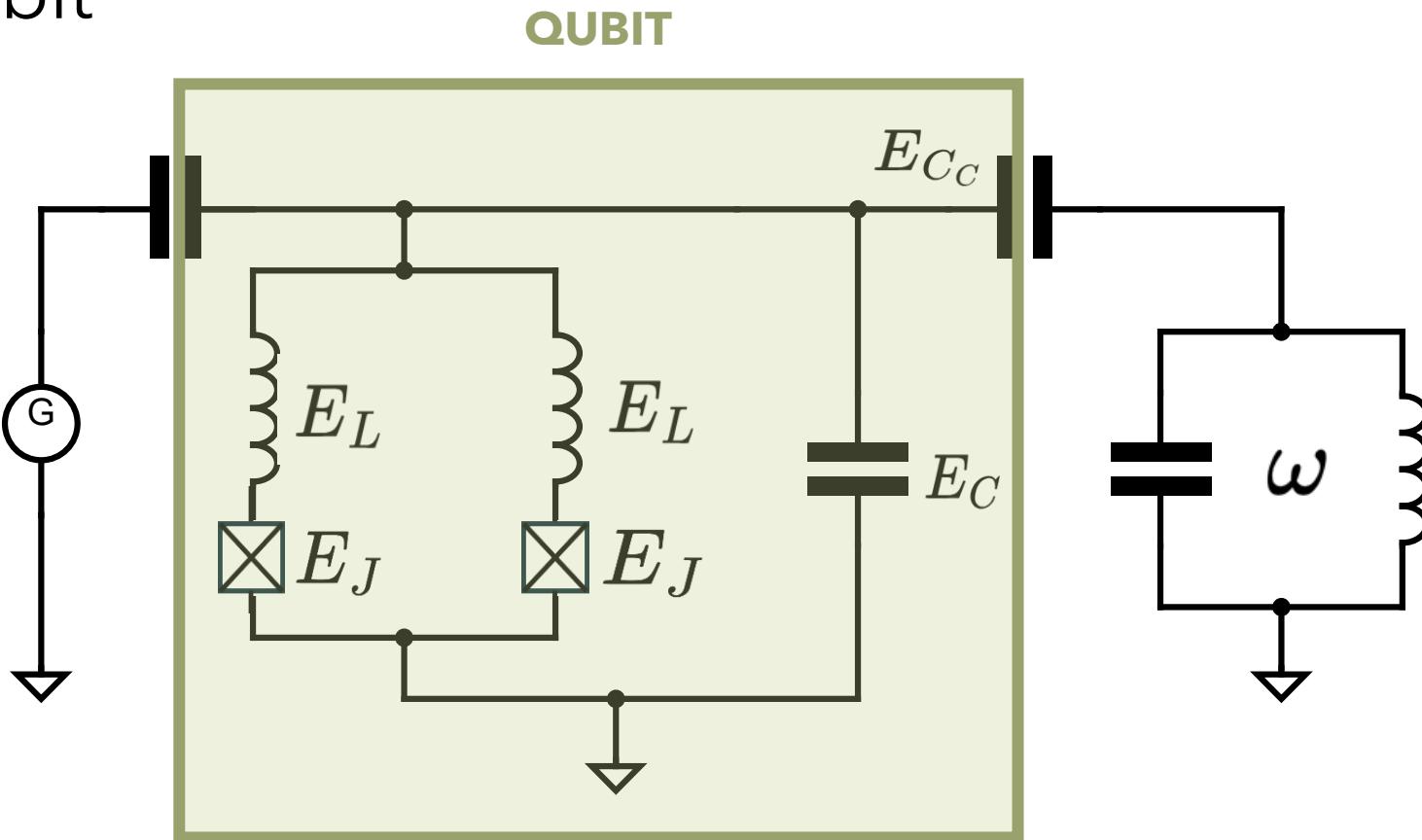
Kite Qubit



$$\hat{H} =$$

$$d =$$

Kite Qubit

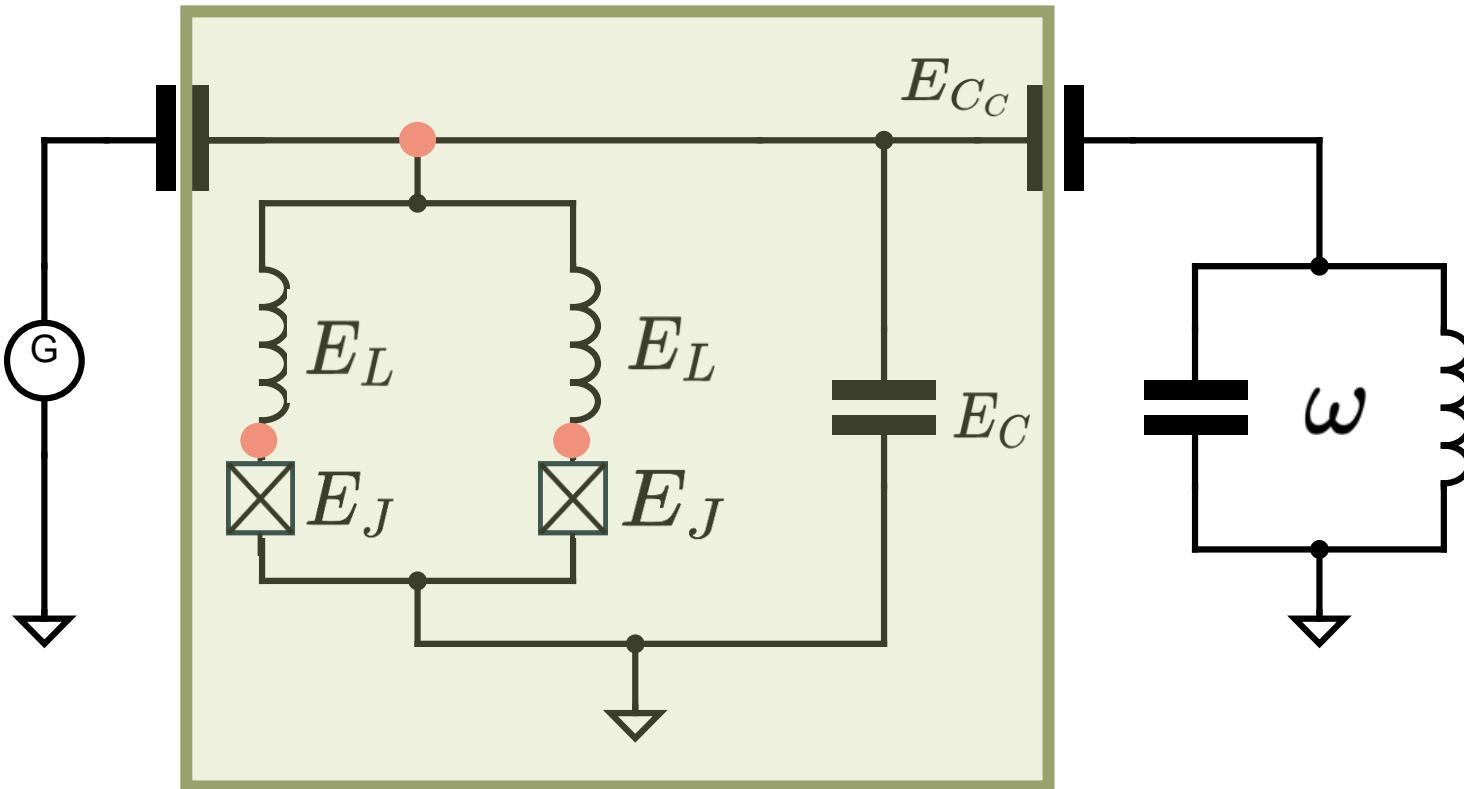


$$\hat{H} = \hat{H}_q$$

$$d = (n_1 * n_2 * n_3)$$

Kite Qubit

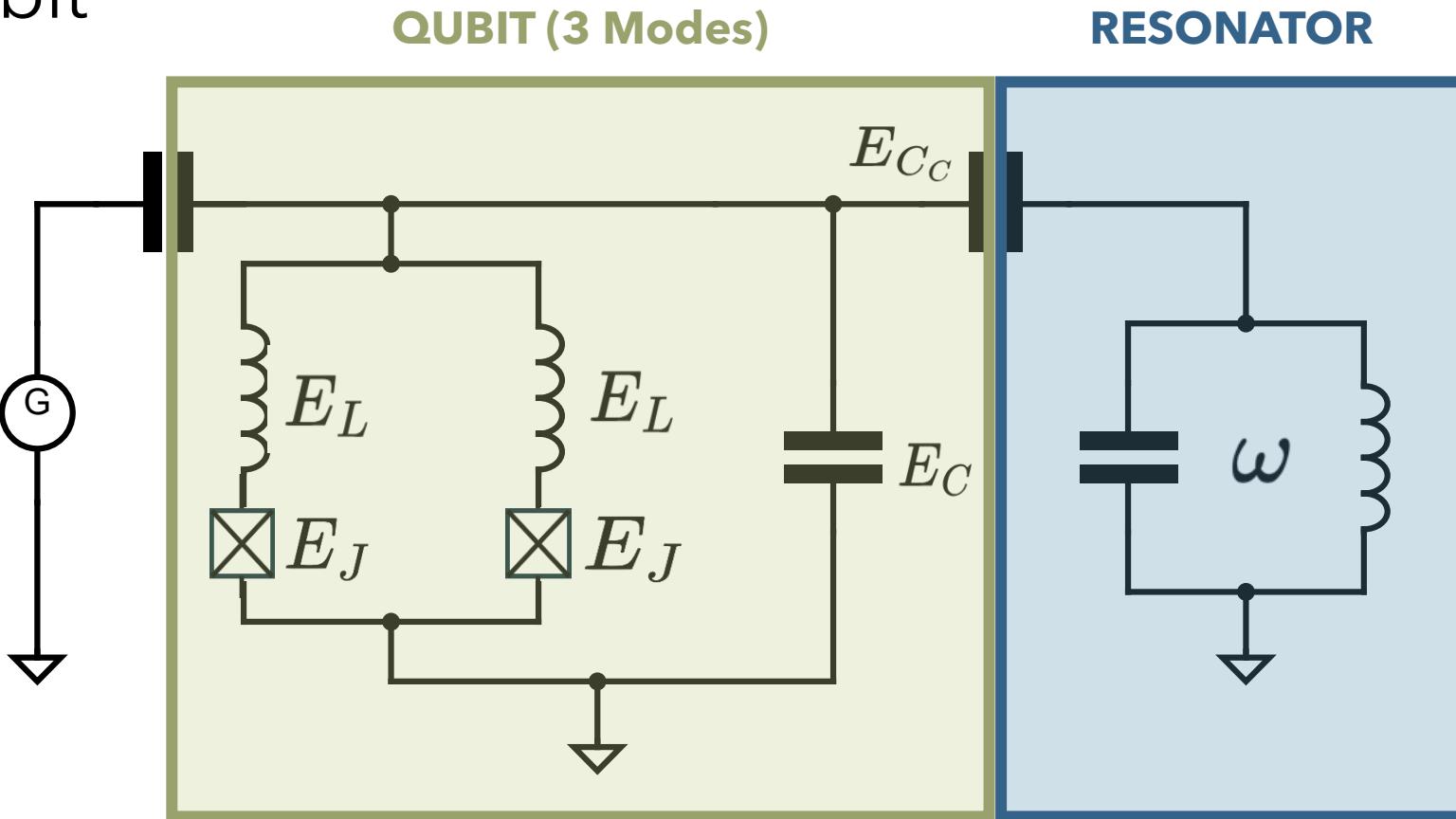
QUBIT (3 Modes)



$$\hat{H} = \hat{H}_q$$

$$d = (n_1 * n_2 * n_3)$$

Kite Qubit



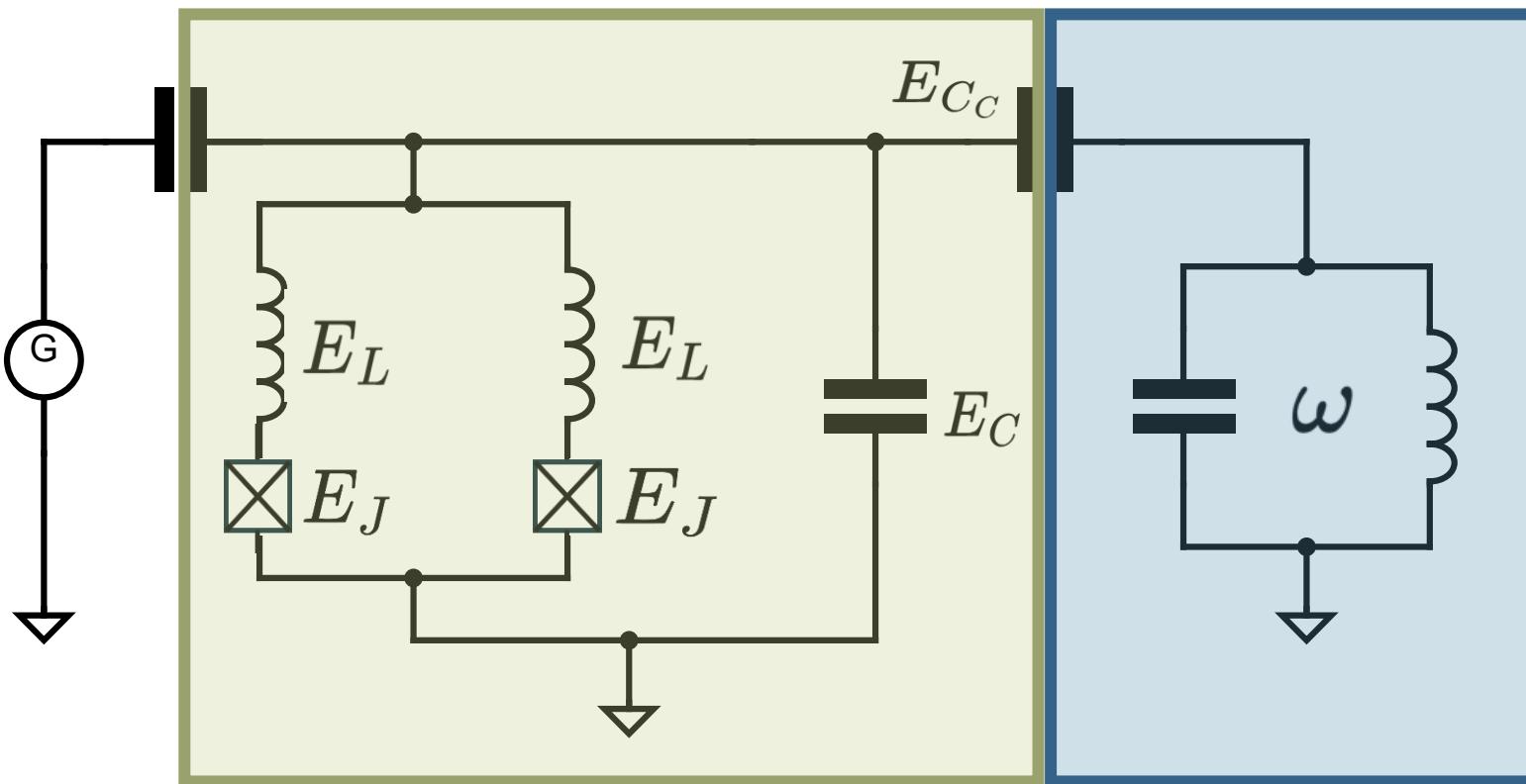
$$\hat{H} = \hat{H}_q + \hat{H}_r$$

$$d = (n_1 * n_2 * n_3) * n_4$$

Kite Qubit

QUBIT (3 Modes)

RESONATOR



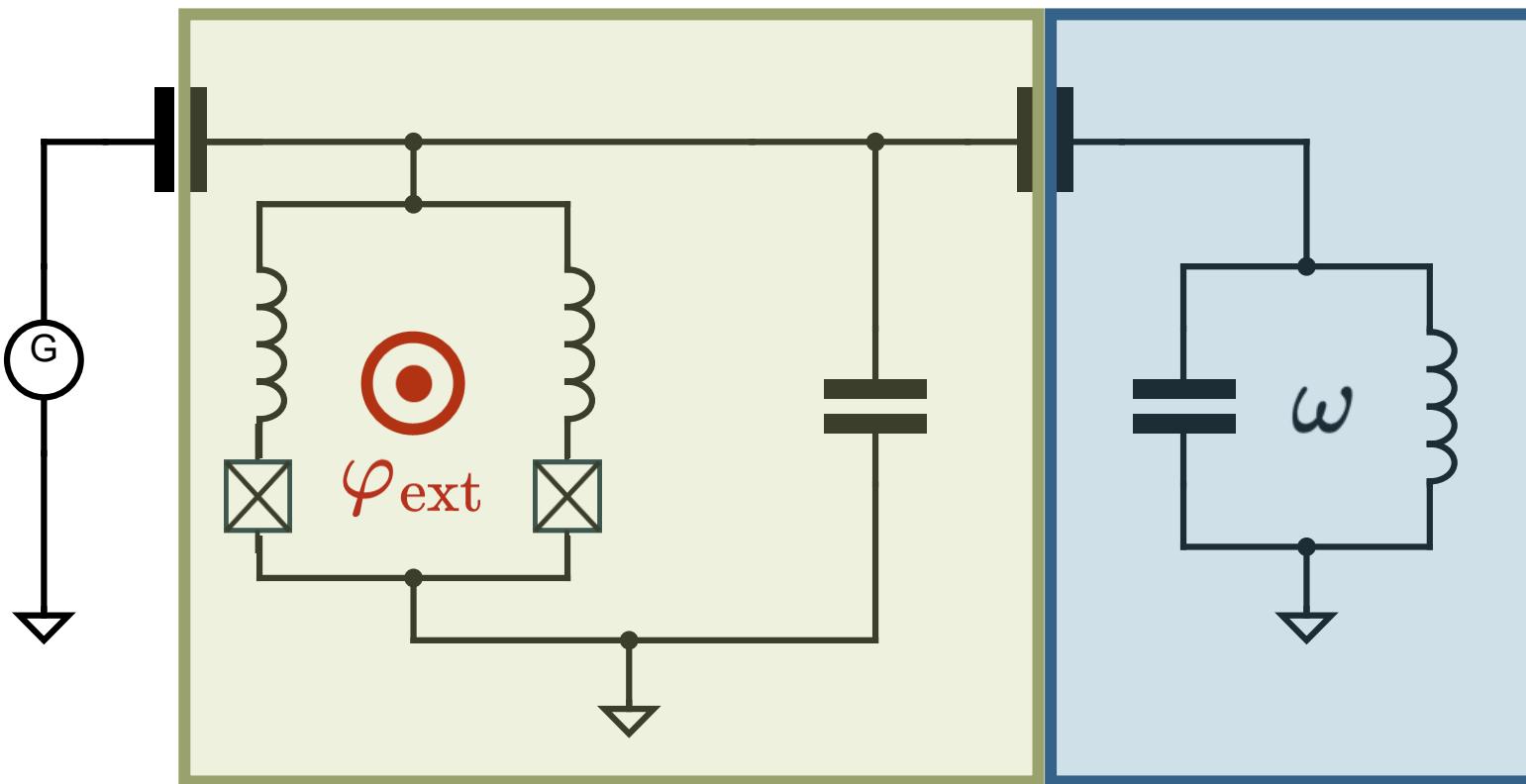
$$\hat{H} = \hat{H}_q + \hat{H}_r - g \hat{O}_1 \hat{O}_2$$

$$d = (n_1 * n_2 * n_3) * n_4$$

Kite Qubit

QUBIT (3 Modes)

RESONATOR



$$\hat{H} = \hat{H}_q + \hat{H}_r - g \hat{O}_1 \hat{O}_2$$

$$d = (n_1 * n_2 * n_3) * n_4$$

Motivations

$$\hat{H} = \begin{pmatrix} & & & n \\ & \cdots & & \\ \vdots & & & \vdots \\ & \cdots & & \end{pmatrix}$$

A diagram showing a 4x4 matrix with red annotations. A horizontal double-headed arrow at the top spans the first three columns and is labeled n . A vertical double-headed arrow on the right side spans all four rows and is also labeled n . The matrix itself has three diagonal ellipses (\cdots) indicating it is a square matrix.

Motivations

$$\hat{H} = \begin{pmatrix} & & n \\ & \cdots & \\ \vdots & & \vdots \\ & \cdots & \end{pmatrix}$$

Exact Diagonalization
(ED) :

$$\mathcal{O}(n^3)$$

Motivations

$$\hat{H} = \begin{pmatrix} & & n \\ & \cdots & \\ \vdots & & \vdots \\ & \cdots & \end{pmatrix}$$

Exact Diagonalization
(ED) :

$$\mathcal{O}(n^3)$$

Recall that

$$n = n_1 * n_2 * n_3 * n_4$$

Motivations

$$\hat{H} = \begin{pmatrix} & & & n \\ & \cdots & & \\ \vdots & & & \vdots \\ & \cdots & & \end{pmatrix}$$

Exact Diagonalization
(ED) :

$$\mathcal{O}(n^3)$$

Recall that

$$n = n_1 * n_2 * n_3 * n_4$$

For example,

$$\begin{aligned} n &= 19 * 32 * 32 * 5 \\ &= 97\ 280 \end{aligned}$$



Krylov Techniques

The power algorithm : Dominant Eigenspace

For a given matrix \mathbf{A} , eigenbasis $\{(\lambda_1, |\psi_1\rangle), \dots, (\lambda_n, |\psi_n\rangle)\}$
with $|\lambda_n| > |\lambda_{n-1}| > \dots > |\lambda_1|$

For a random vector $|\Psi_0\rangle$

$$\lim_{k \rightarrow \infty} \frac{\mathbf{A}^k |\Psi_0\rangle}{\|\mathbf{A}^k |\Psi_0\rangle\|} = |\psi_n\rangle$$

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But : More interested by lower energies

Krylov solver

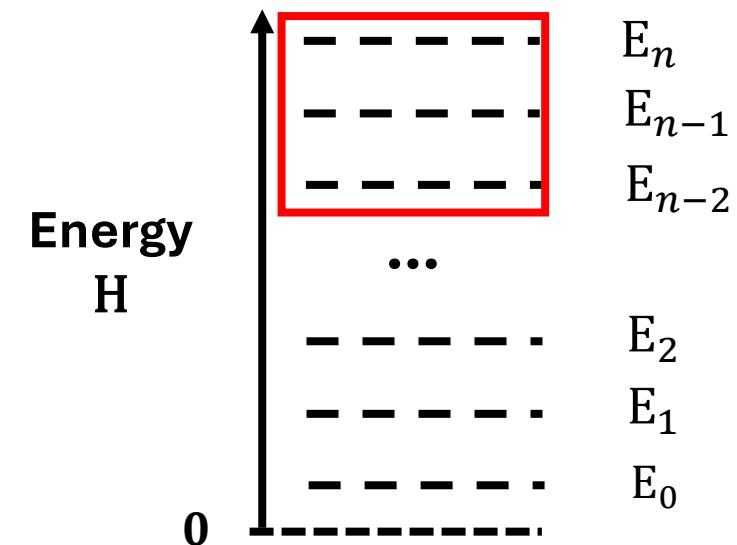
$$\mathcal{K}_m(H, v) = \underbrace{\text{span}\{v, Hv, H^2v, \dots, H^{m-1}v\}}_T$$

Constructed with Matrix*Vector

Krylov solver

$$\mathcal{K}_m(H, v) = \underbrace{\text{span}\{v, Hv, H^2v, \dots, H^{m-1}v\}}_{\text{Constructed with Matrix*Vector}}$$

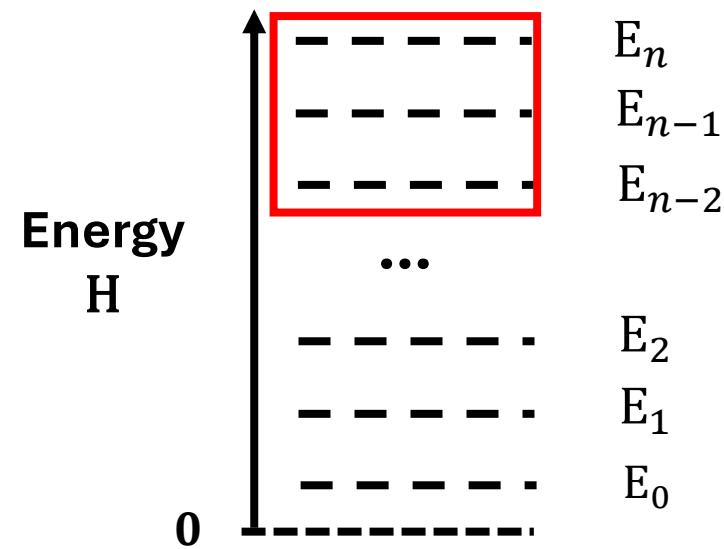
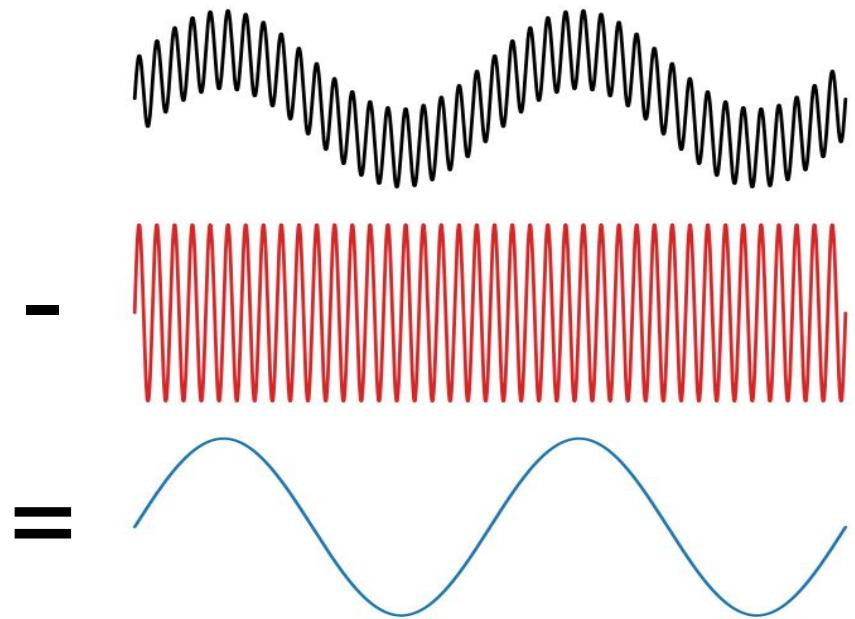
Dominant Eigenvector
↓



Krylov solver

$$\mathcal{K}_m(H, v) = \underbrace{\text{span}\{v, Hv, H^2v, \dots, H^{m-1}v\}}_{\text{Constructed with Matrix*Vector}}$$

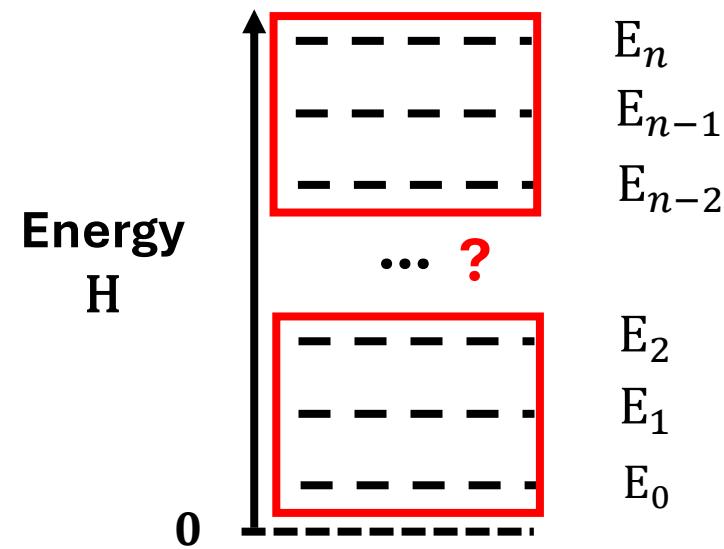
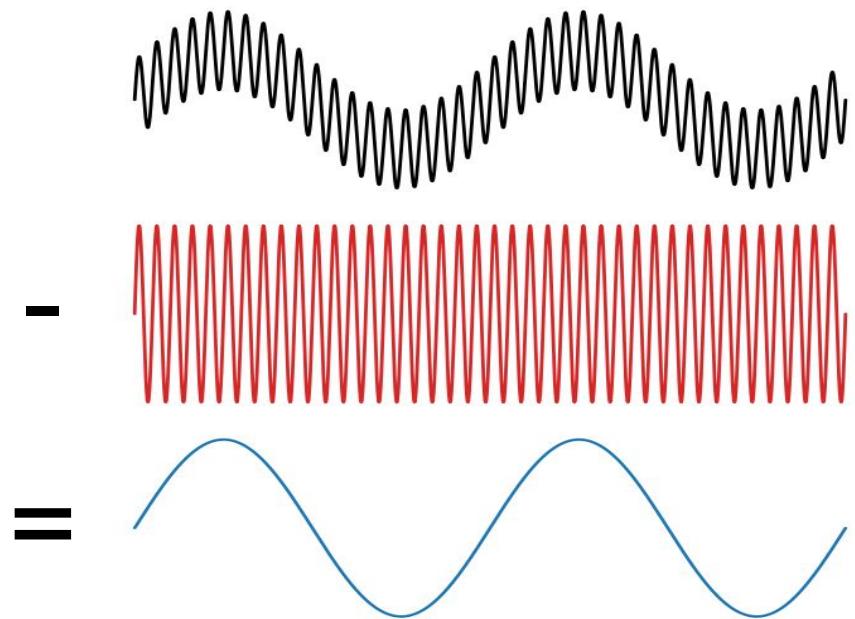
Dominant Eigenvector
↓



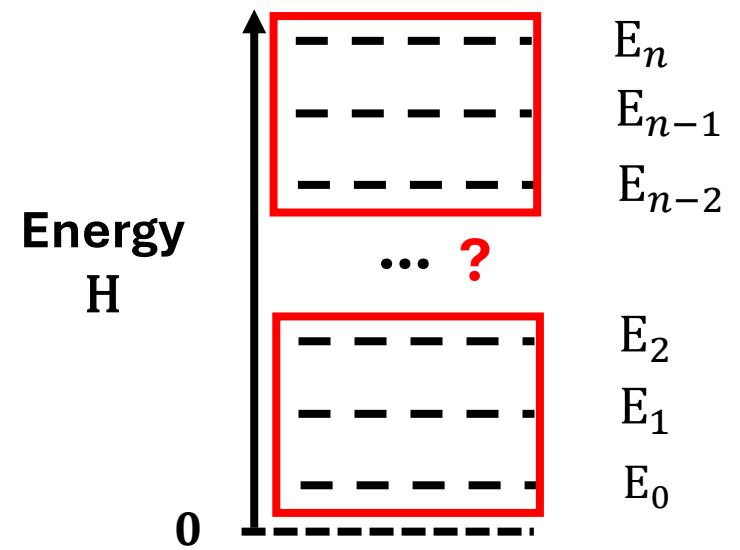
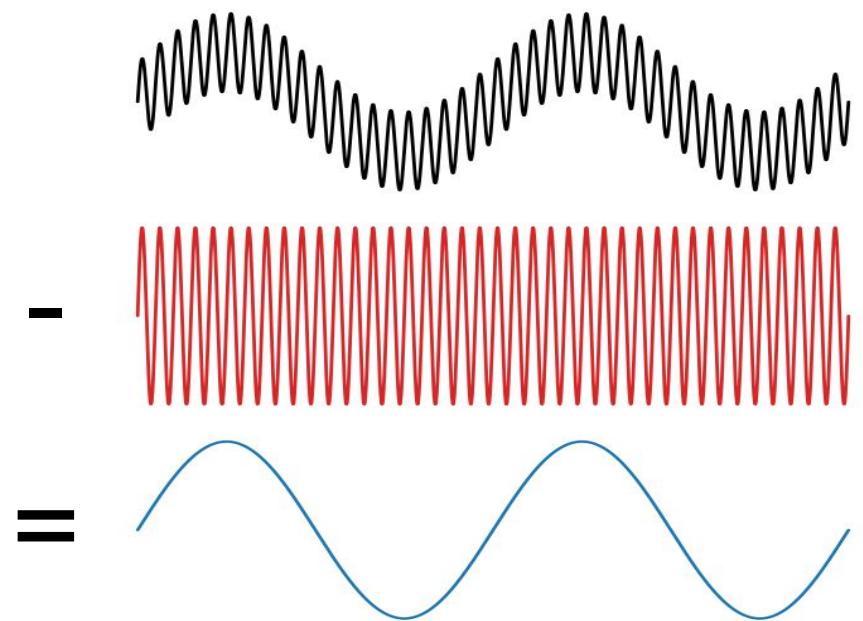
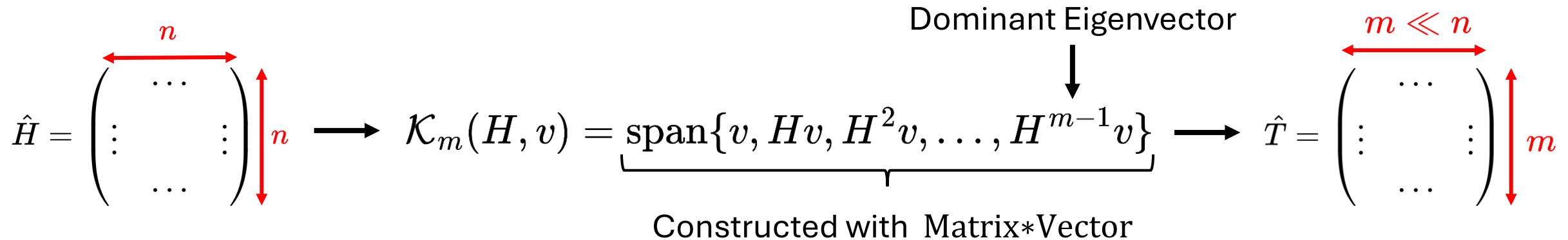
Krylov solver

$$\mathcal{K}_m(H, v) = \underbrace{\text{span}\{v, Hv, H^2v, \dots, H^{m-1}v\}}_{\text{Constructed with Matrix*Vector}}$$

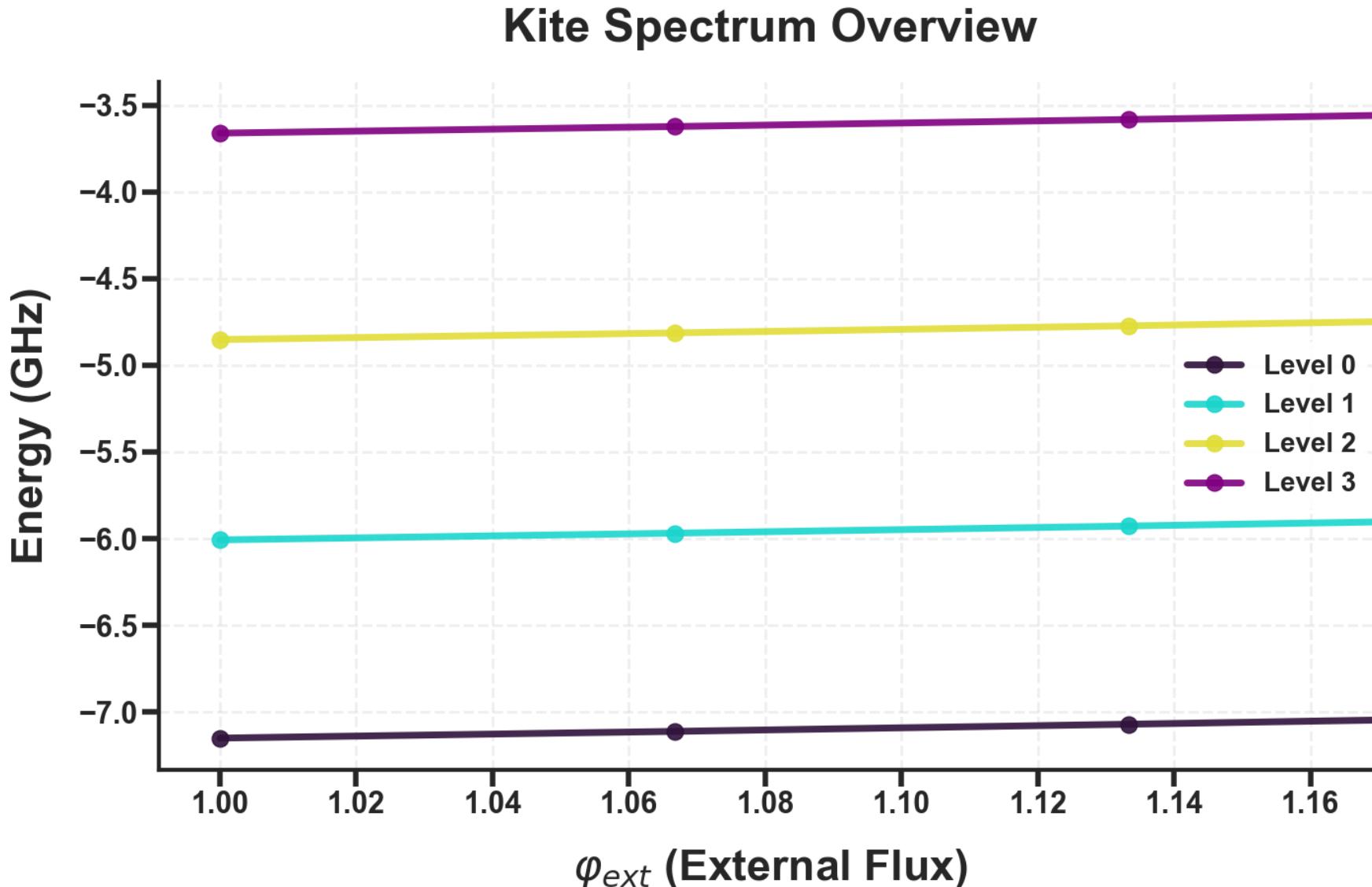
Dominant Eigenvector
↓



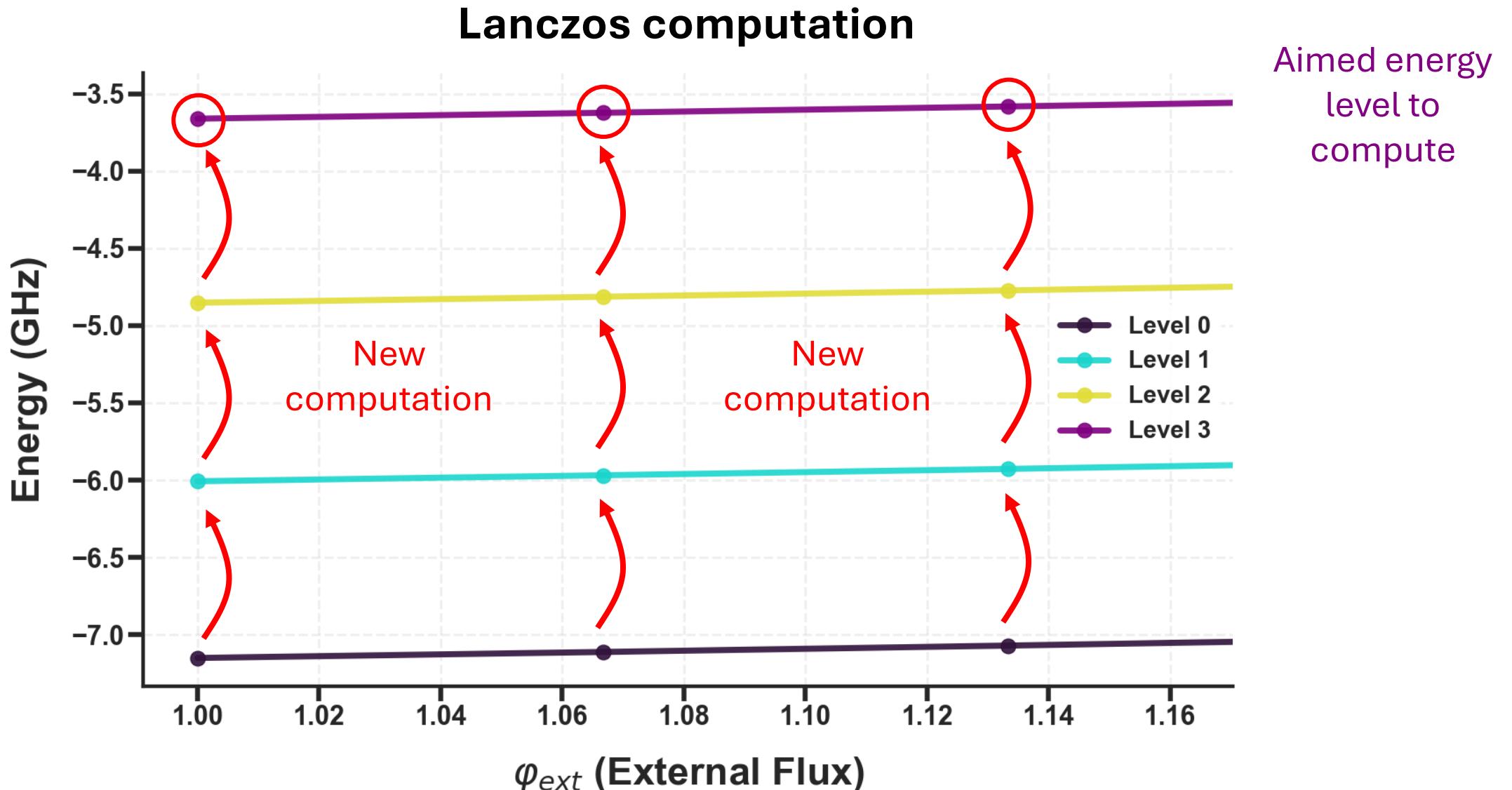
Krylov solver



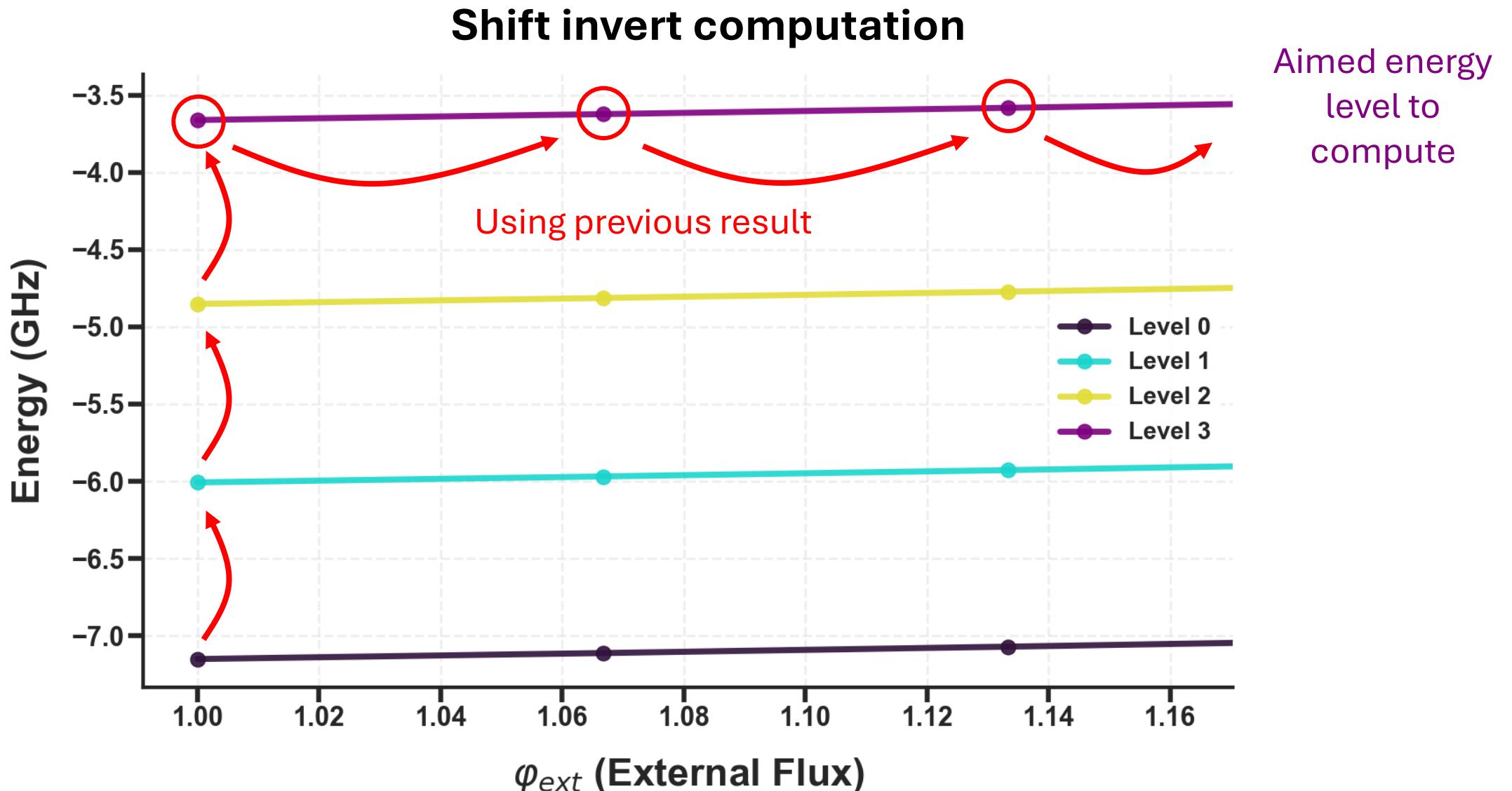
The idea



The idea



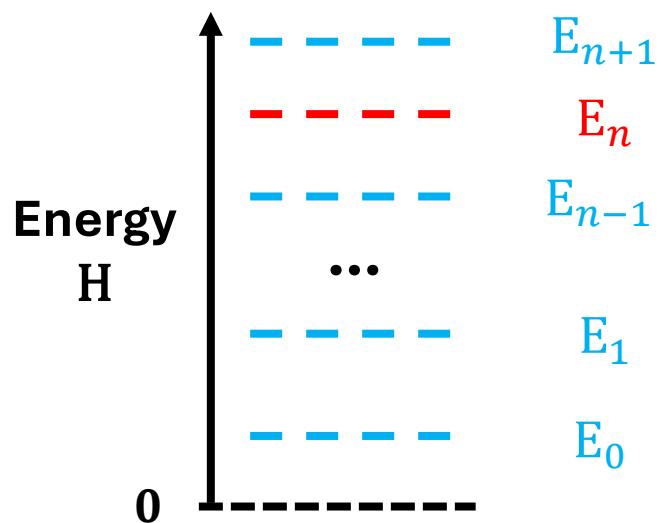
The idea



Shift Invert : conceptually

$E_n \approx E$: Mixed with other energies → propel it to the top of the spectrum

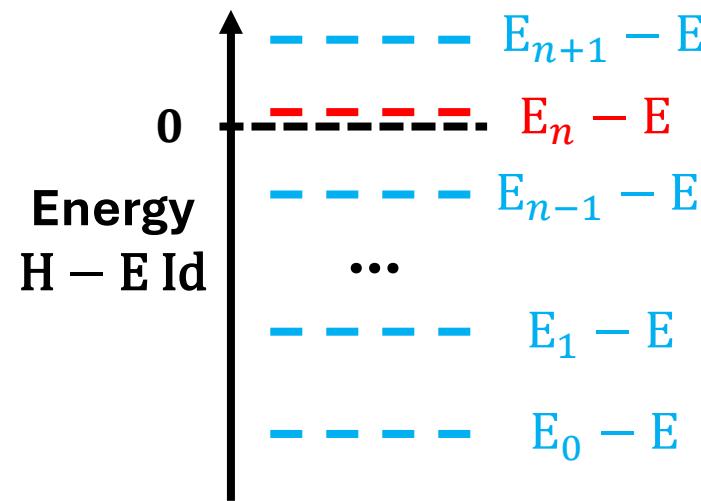
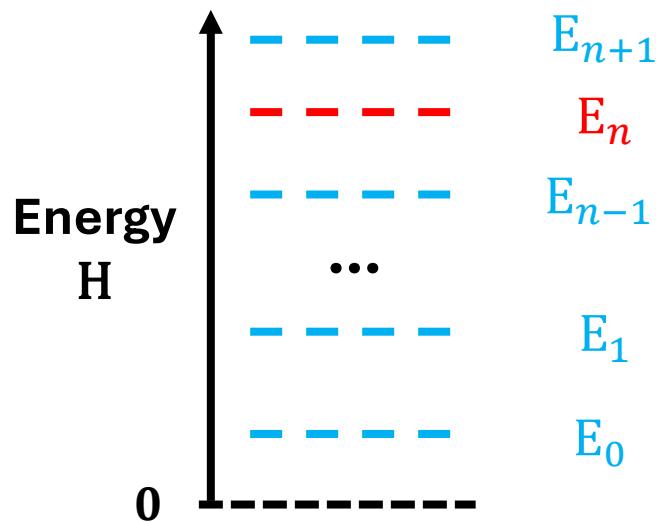
guess



Shift Invert : conceptually

$E_n \approx E$: Mixed with other energies → propel it to the top of the spectrum

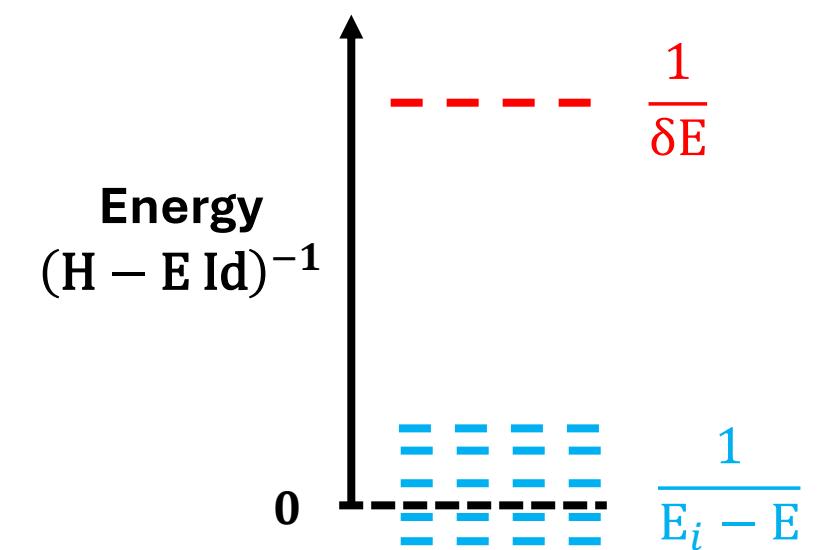
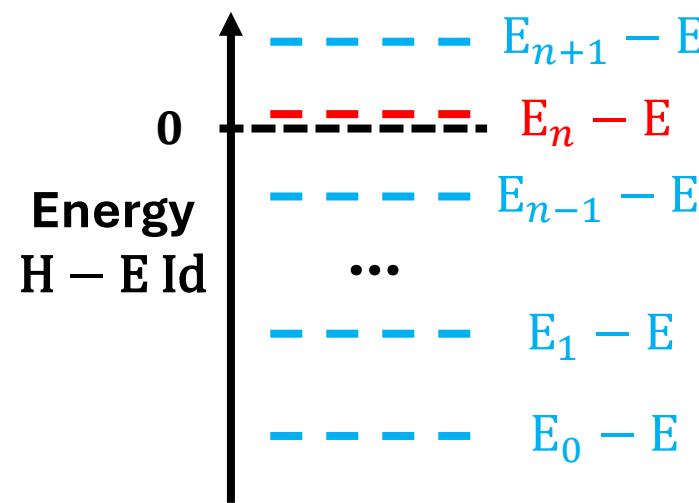
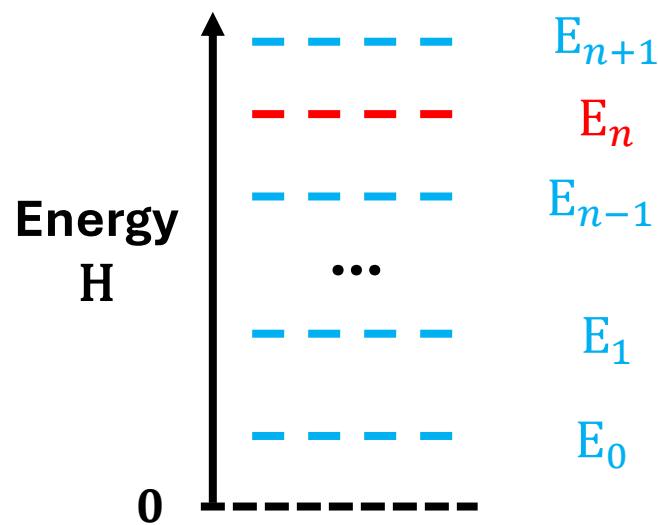
guess



Shift Invert : conceptually

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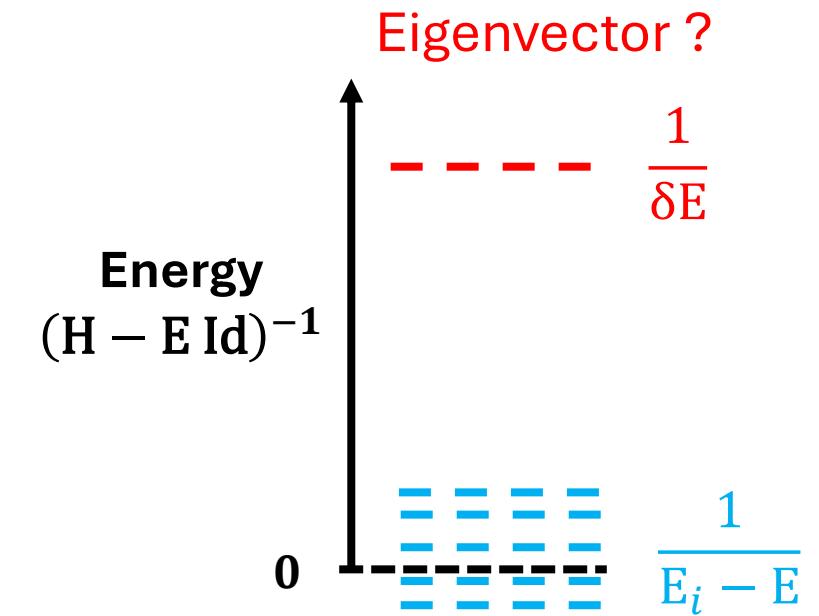
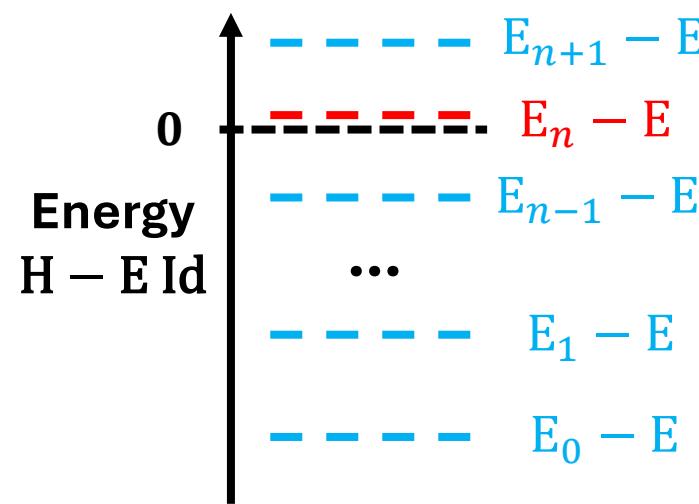
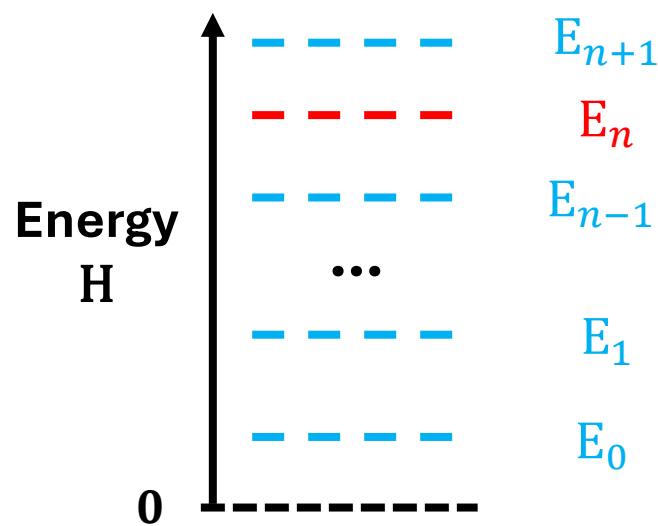
guess



Shift Invert : conceptually

$E_n \approx E$: Mixed with other energies \rightarrow propel it to the top of the spectrum

guess



$(H - E \text{Id})^{-1}$ computationally hard

Minres algorithm

$$(H - E \text{ Id})^{-1} |\Psi^{(n)}\rangle = |\Psi^{(n+1)}\rangle \iff (H - E \text{ Id}) |\Psi^{(n+1)}\rangle = |\Psi^{(n)}\rangle$$

Minres algorithm

$$(H - E \text{ Id})^{-1} |\Psi^{(n)}\rangle = |\Psi^{(n+1)}\rangle \iff (H - E \text{ Id}) |\Psi^{(n+1)}\rangle = |\Psi^{(n)}\rangle$$

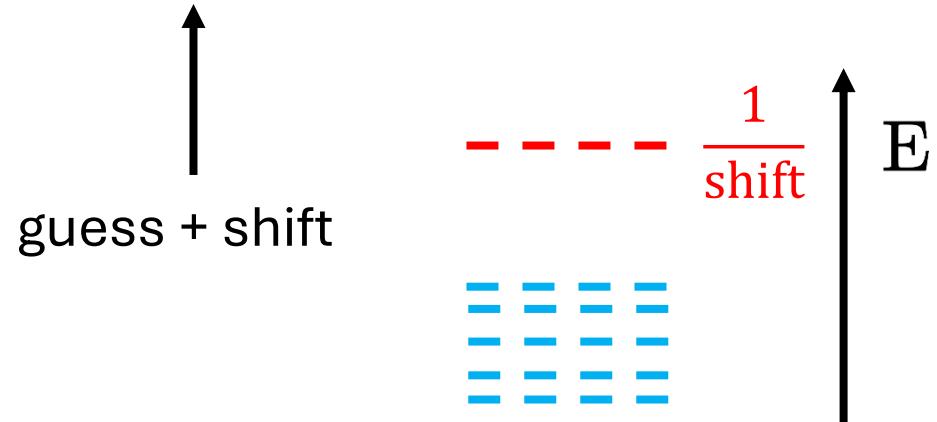
}

Solvable with Minres

- Krylov Solver $AX = Y$
- A invertible

Minres algorithm

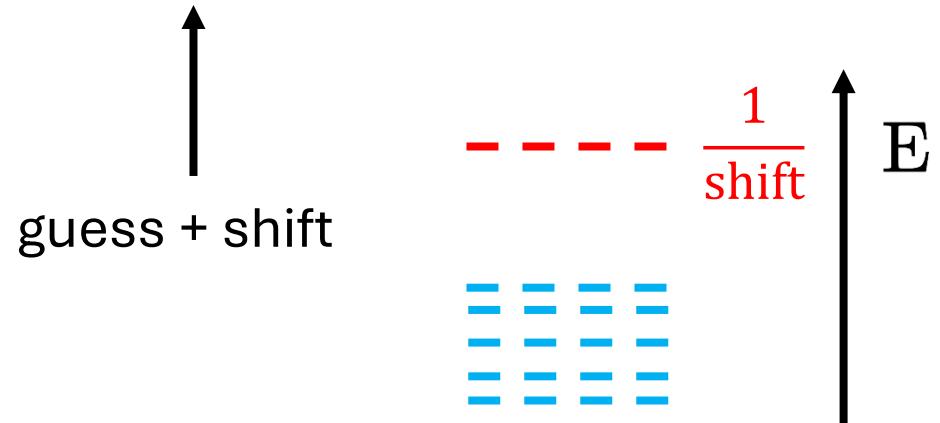
$$(H - E \text{ Id})^{-1} |\Psi^{(n)}\rangle = |\Psi^{(n+1)}\rangle \iff (H - E \text{ Id}) |\Psi^{(n+1)}\rangle = |\Psi^{(n)}\rangle$$



Solvable with Minres
→ Krylov Solver $AX = Y$
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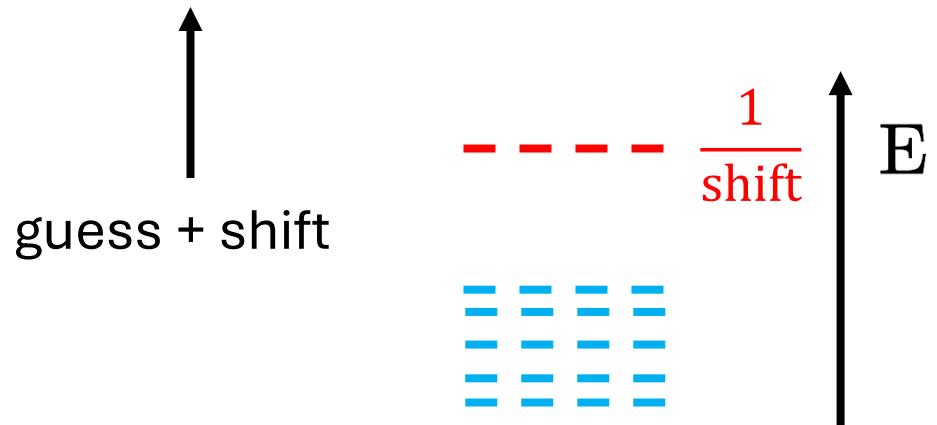
Solvable with Minres
→ Krylov Solver $AX = Y$
→ A invertible

$$\begin{aligned} & H_n & H_{n+1} \\ & (|\psi_n\rangle, \lambda_n) & (|\psi_{n+1}\rangle, \lambda_{n+1}) ? \\ & \bullet \quad \bullet & \\ & \varphi_{ext} & \varphi_{ext} + \delta\varphi \end{aligned}$$

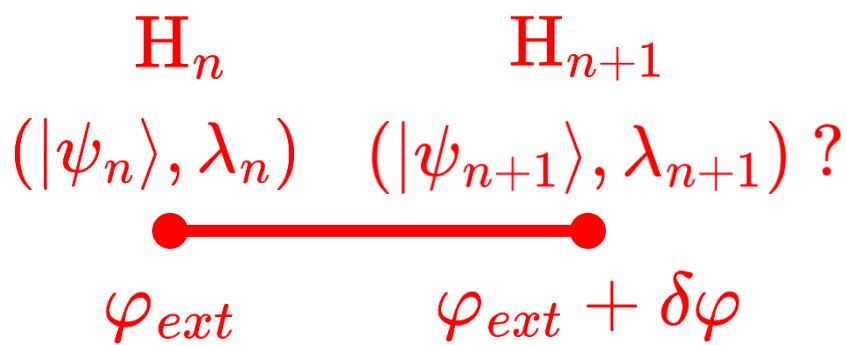
$$(H_{n+1} - [\langle \psi_n | H_{n+1} | \psi_n \rangle + \text{shift}] \text{ Id}) X^{(0)} = |\psi_n\rangle$$

Minres algorithm

$$(H - E \text{ Id})^{-1} |\Psi^{(n)}\rangle = |\Psi^{(n+1)}\rangle \iff (H - E \text{ Id}) |\Psi^{(n+1)}\rangle = |\Psi^{(n)}\rangle$$



Solvable with Minres
 \rightarrow Krylov Solver $AX = Y$
 $\rightarrow A$ invertible

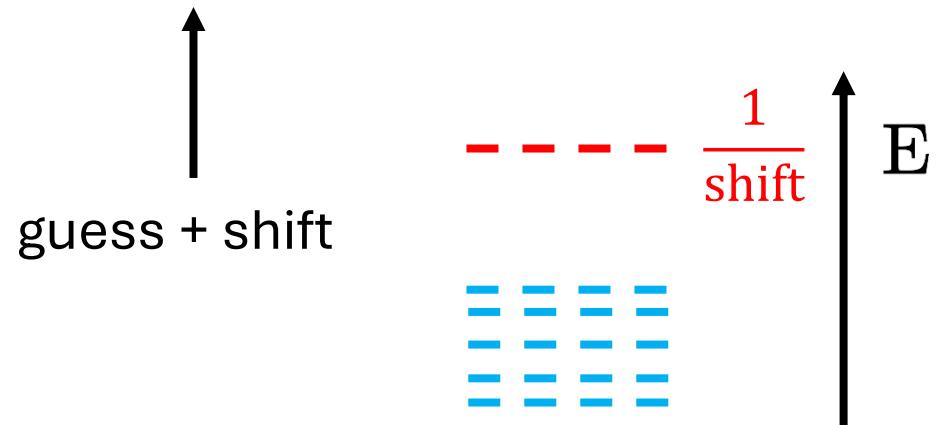


$$(H_{n+1} - [\underbrace{\langle \psi_n | H_{n+1} | \psi_n \rangle}_{\simeq \lambda_n + \langle \psi_n | \delta H | \psi_n \rangle} + \text{shift}] \text{ Id}) X^{(0)} = |\psi_n\rangle$$

First order approximation

Minres algorithm

$$(H - E \text{ Id})^{-1} |\Psi^{(n)}\rangle = |\Psi^{(n+1)}\rangle \iff (H - E \text{ Id}) |\Psi^{(n+1)}\rangle = |\Psi^{(n)}\rangle$$



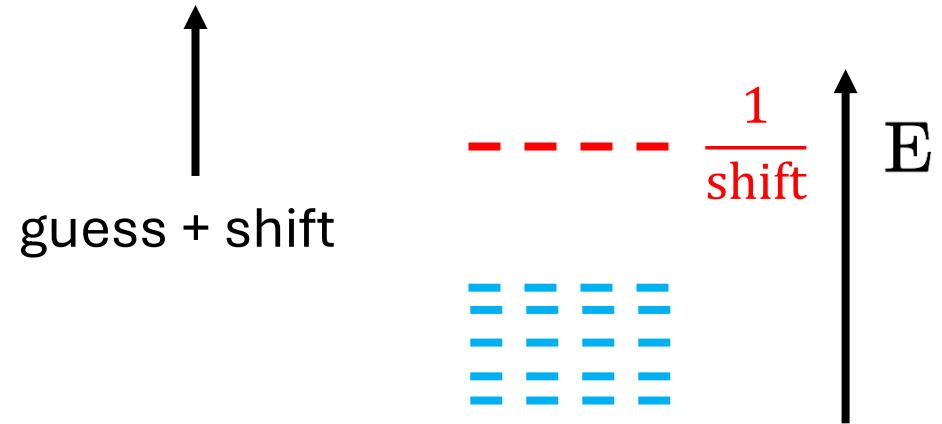
Solvable with Minres
→ Krylov Solver $AX = Y$
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$$\begin{array}{cc} H_n & H_{n+1} \\ (|\psi_n\rangle, \lambda_n) & (|\psi_{n+1}\rangle, \lambda_{n+1}) ? \\ \varphi_{ext} & \varphi_{ext} + \delta\varphi \end{array}$$

$$(H_{n+1} - [\langle \psi_n | H_{n+1} | \psi_n \rangle + \text{shift}] \text{ Id}) X^{(1)} = X^{(0)}$$

Minres algorithm

$$(H - E \text{ Id})^{-1} |\Psi^{(n)}\rangle = |\Psi^{(n+1)}\rangle \iff (H - E \text{ Id}) |\Psi^{(n+1)}\rangle = |\Psi^{(n)}\rangle$$



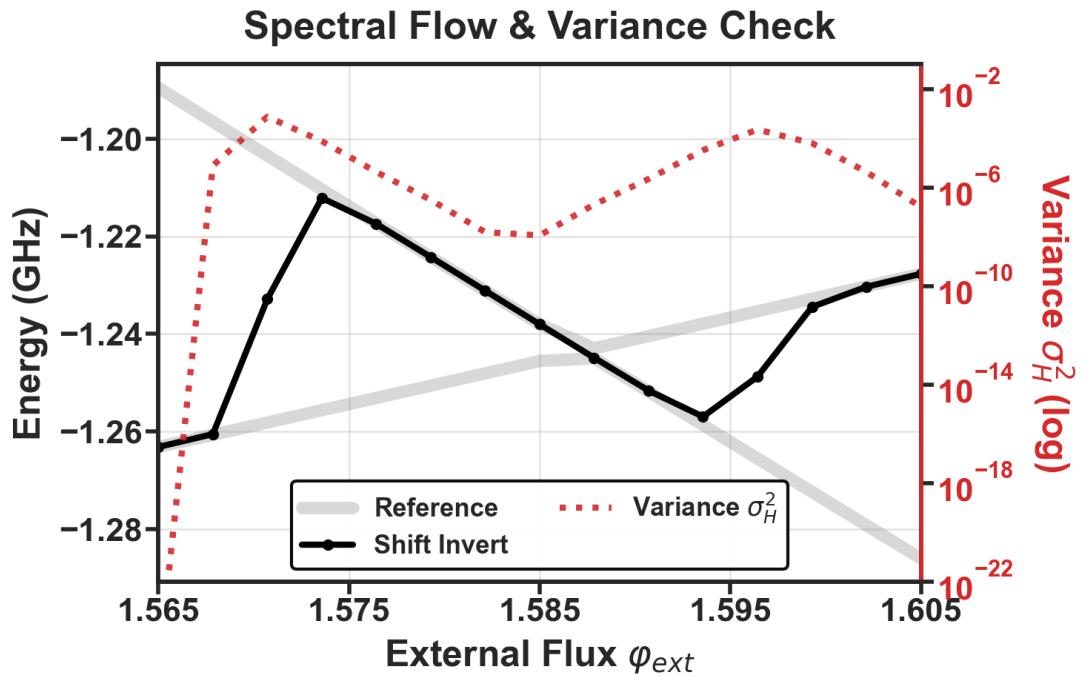
Solvable with Minres
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$$\begin{array}{cc} H_n & H_{n+1} \\ (|\psi_n\rangle, \lambda_n) & (|\psi_{n+1}\rangle, \lambda_{n+1}) ? \\ \bullet \quad \quad \quad \bullet \\ \varphi_{ext} & \varphi_{ext} + \delta\varphi \end{array}$$

$$(H_{n+1} - [\langle \psi_n | H_{n+1} | \psi_n \rangle + \text{shift}] \text{ Id}) X^{(k+1)} = X^{(k)}$$

■ Self consistency accuracy check

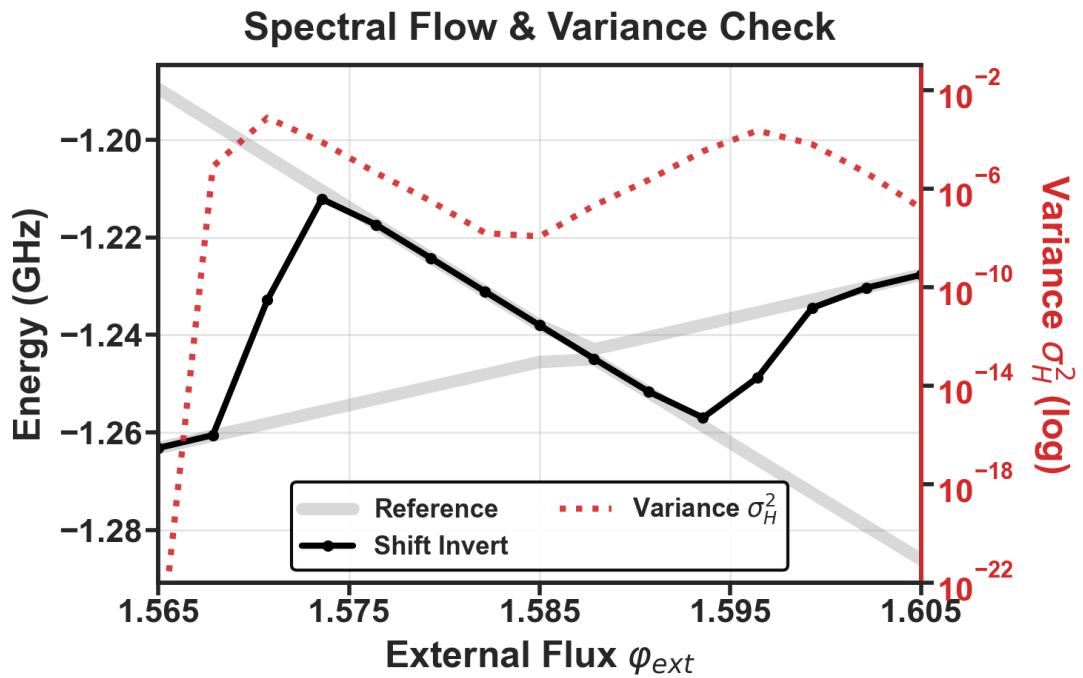
$$\sigma_H^2 = \langle \psi | H^2 | \psi \rangle - \langle \psi | H | \psi \rangle^2 \simeq 0$$



■ Self consistency accuracy check

$$\sigma_H^2 = \langle \psi | H^2 | \psi \rangle - \langle \psi | H | \psi \rangle^2 \simeq 0$$

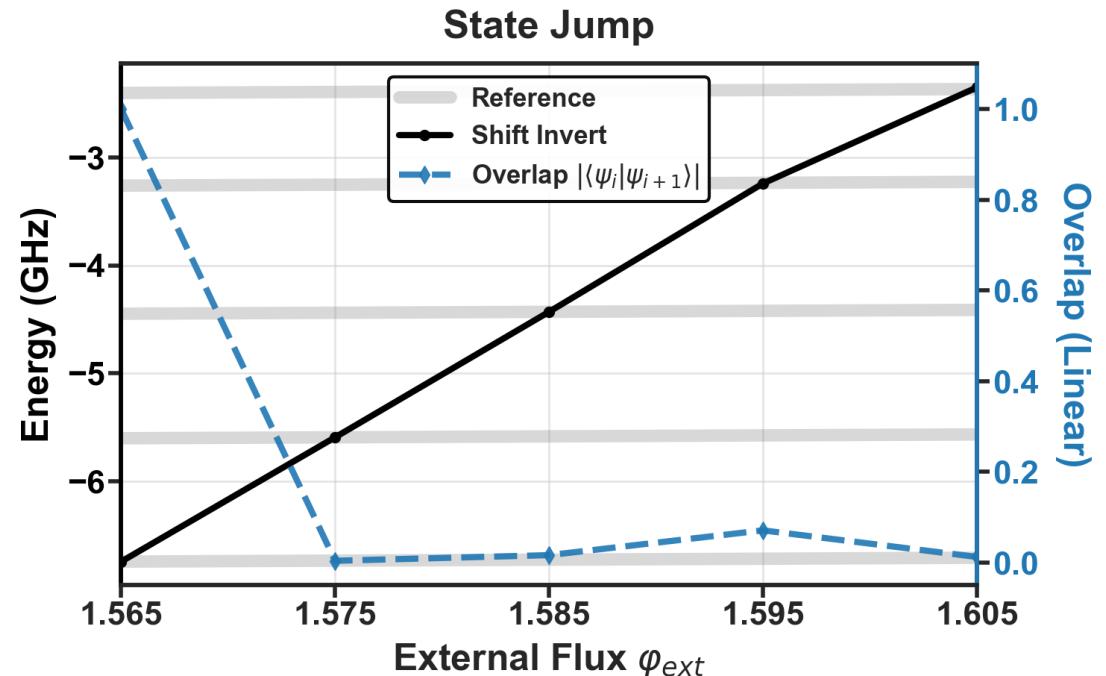
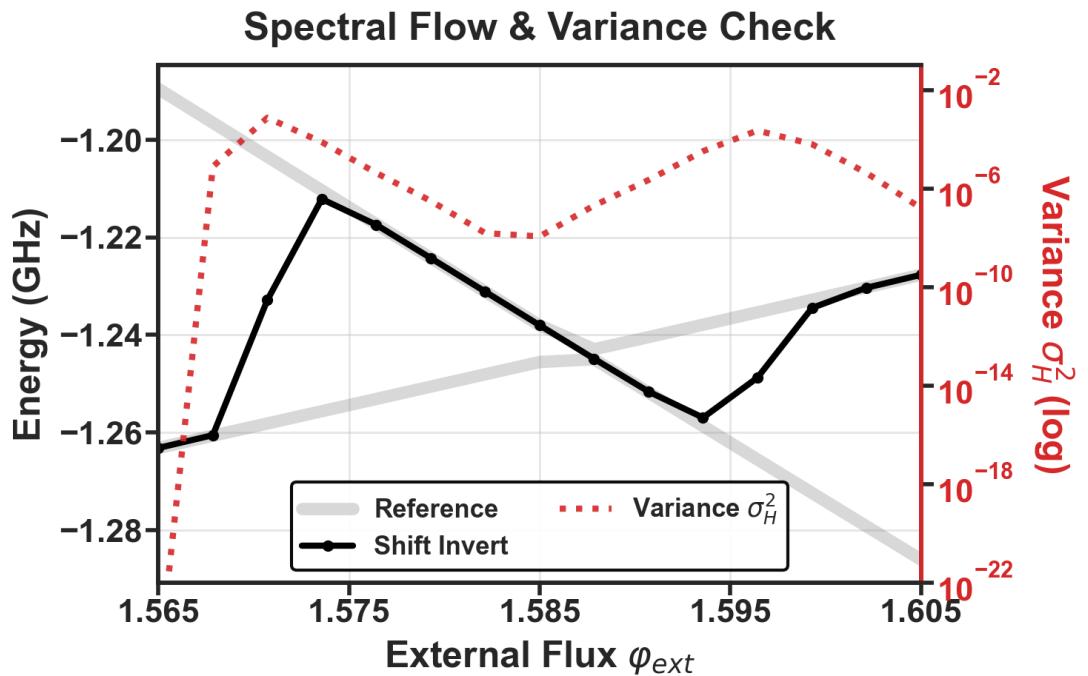
$$|\langle \psi_i | \psi_{i+1} \rangle| \simeq 1$$



Self consistency accuracy check

$$\sigma_H^2 = \langle \psi | H^2 | \psi \rangle - \langle \psi | H | \psi \rangle^2 \simeq 0$$

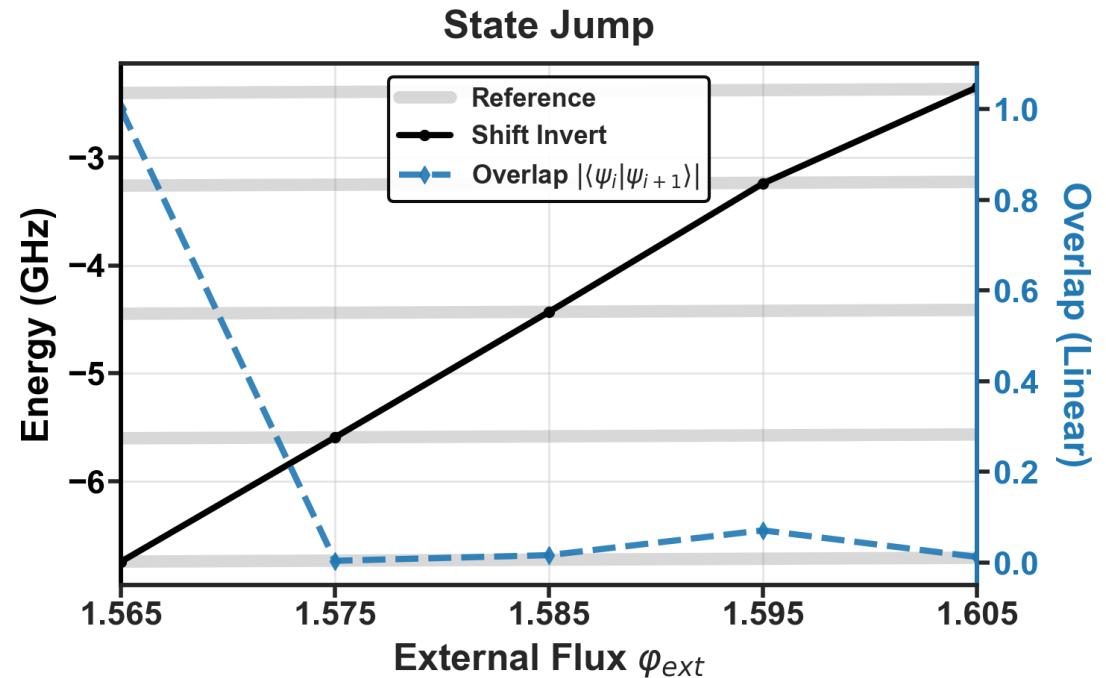
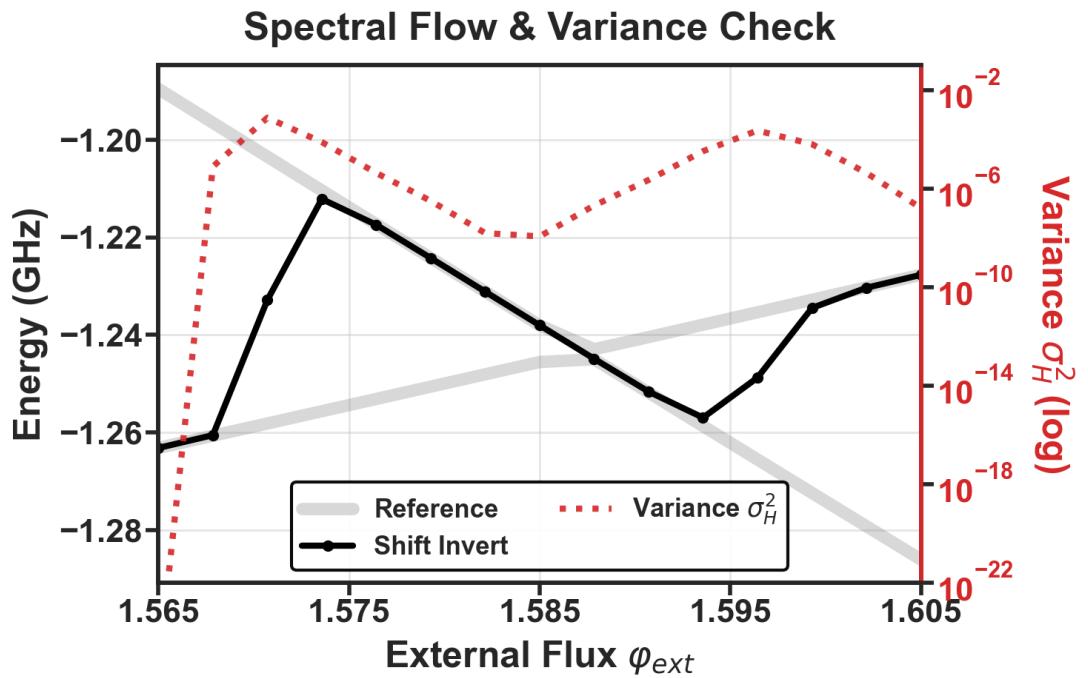
$$|\langle \psi_i | \psi_{i+1} \rangle| \simeq 1$$



Self consistency accuracy check

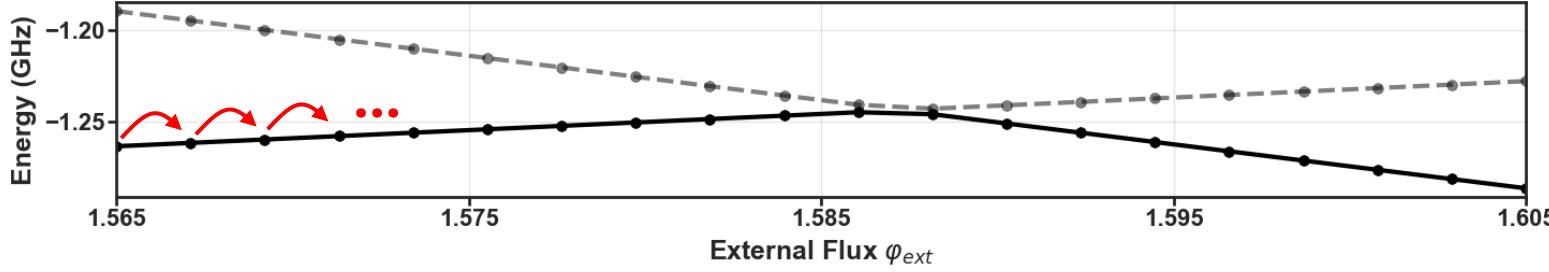
$$\sigma_H^2 = \langle \psi | H^2 | \psi \rangle - \langle \psi | H | \psi \rangle^2 \simeq 0$$

$$|\langle \psi_i | \psi_{i+1} \rangle| \simeq 1$$



Choose carefully shift value

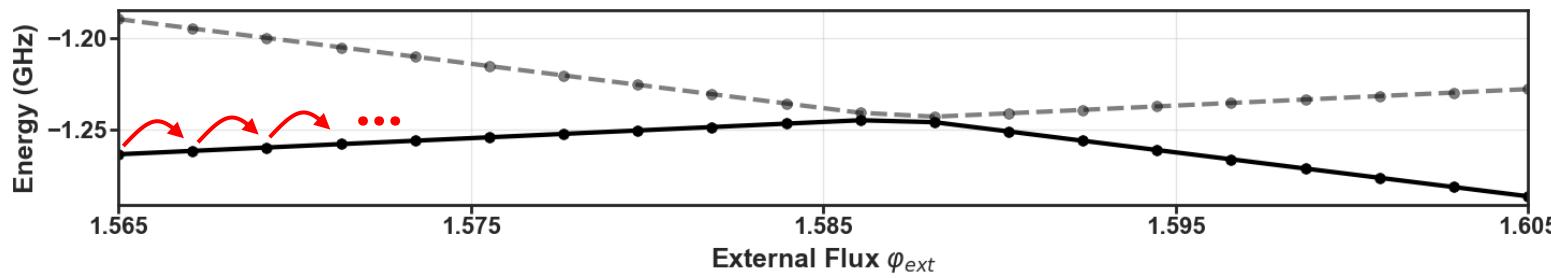
Shift Benchmark



Follow the lower branch
for different shift values

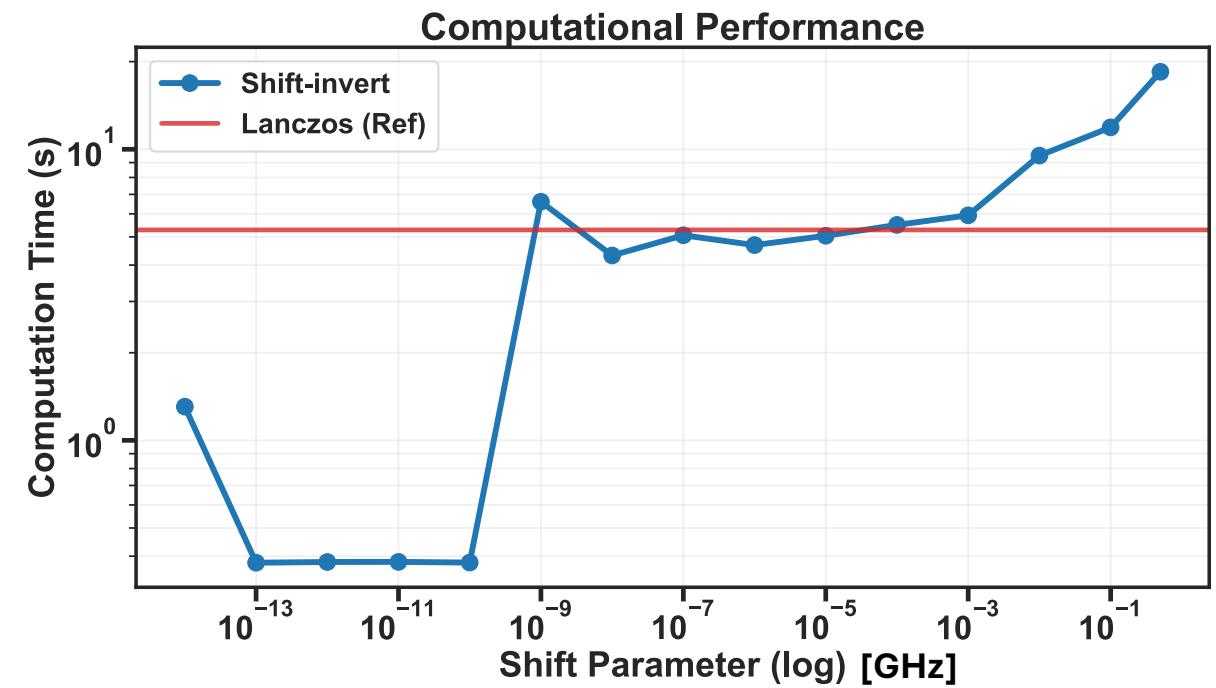
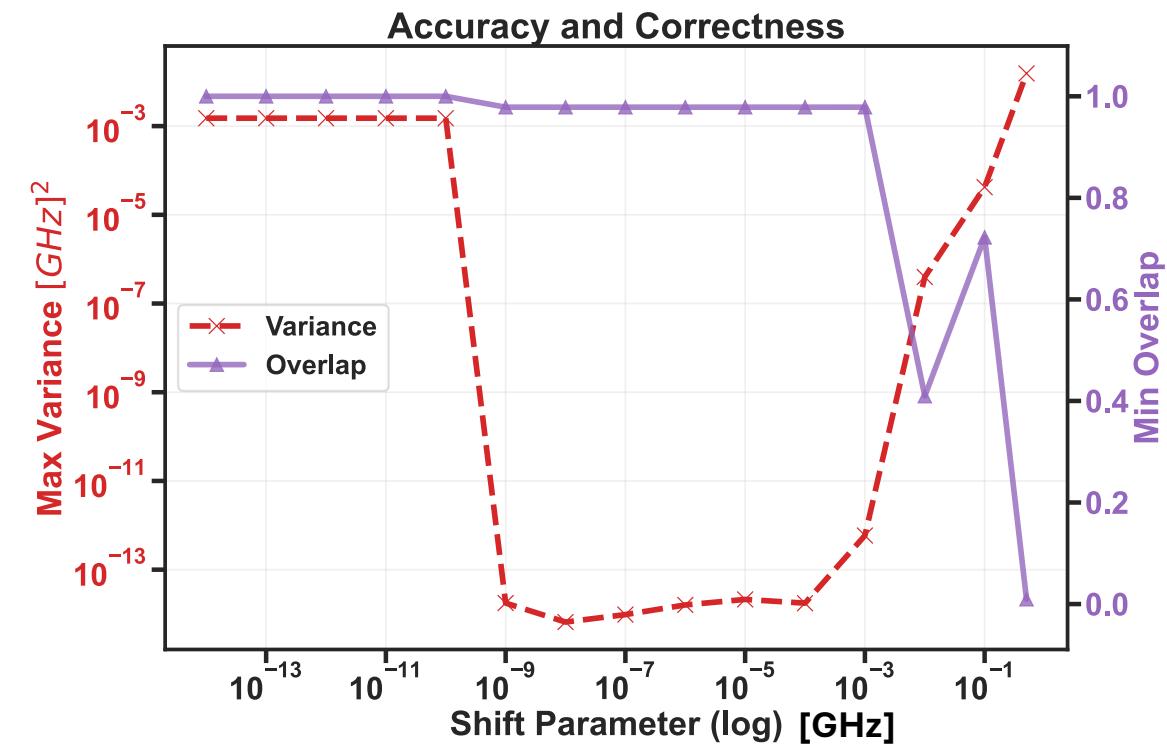
- Variance
- Overlap
- Computational time

Shift Benchmark

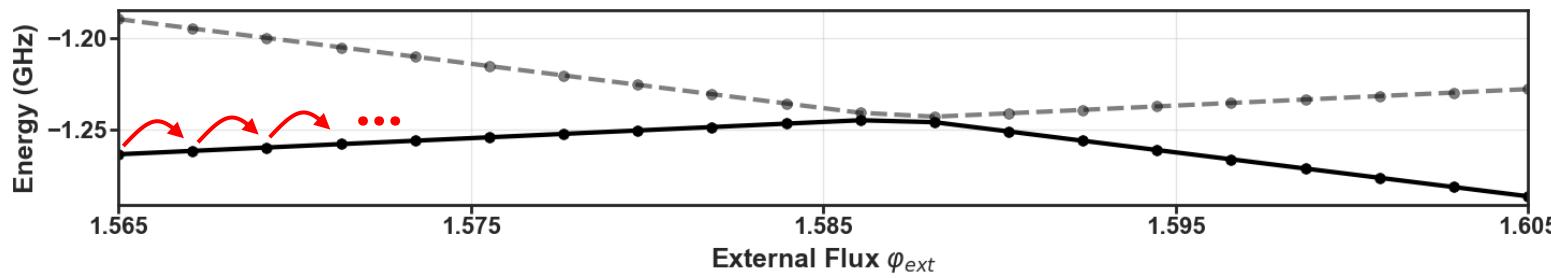


Follow the lower branch
for different shift values

- Variance
- Overlap
- Computational time

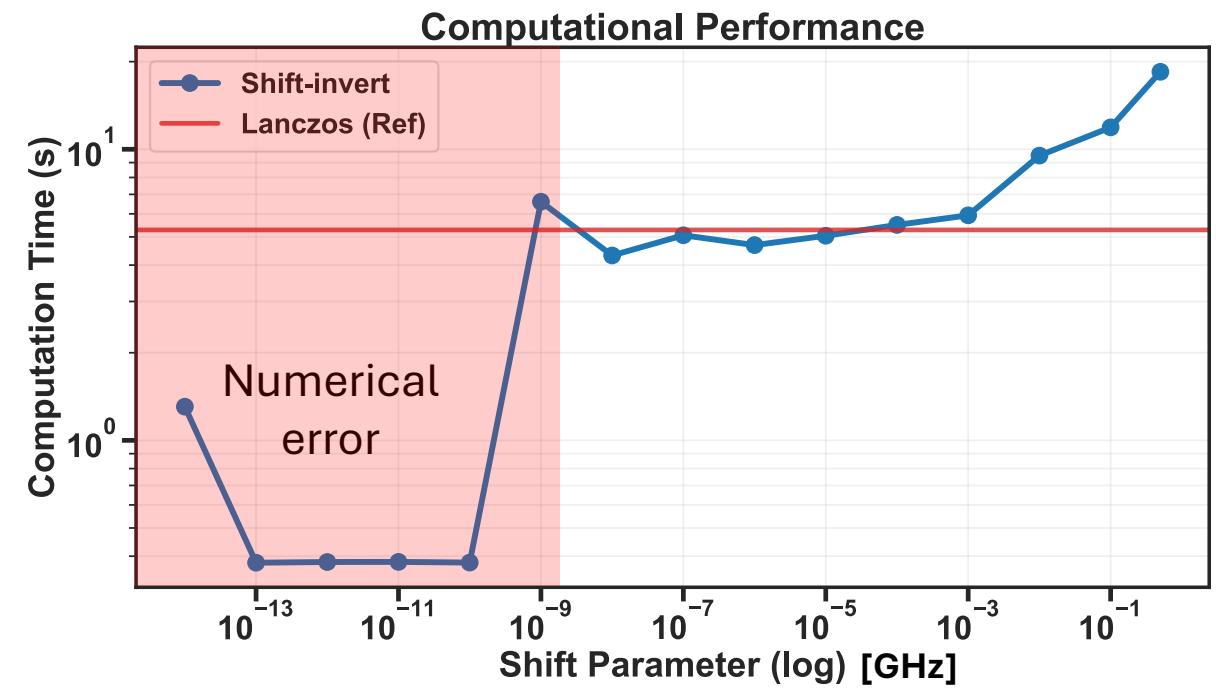
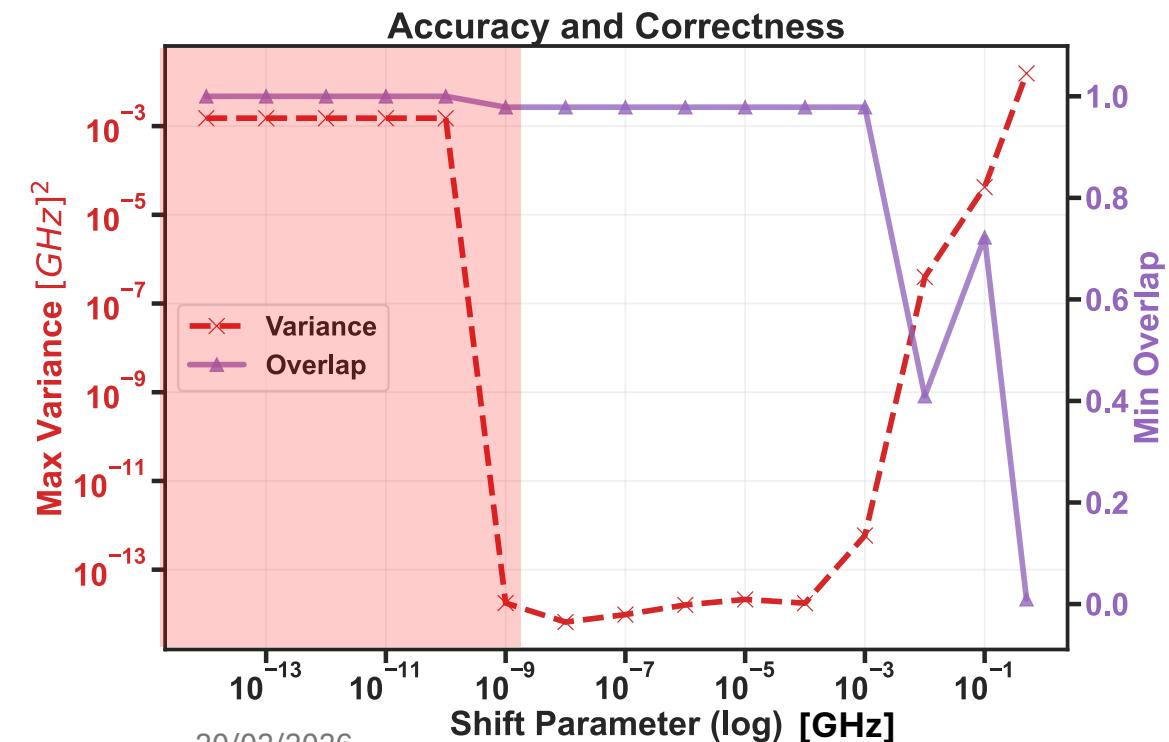


Shift Benchmark

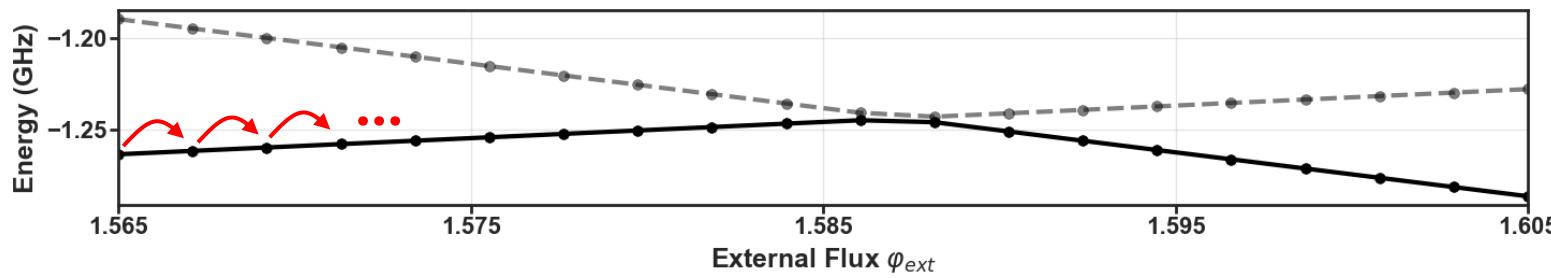


Follow the lower branch
for different shift values

- Variance
- Overlap
- Computational time

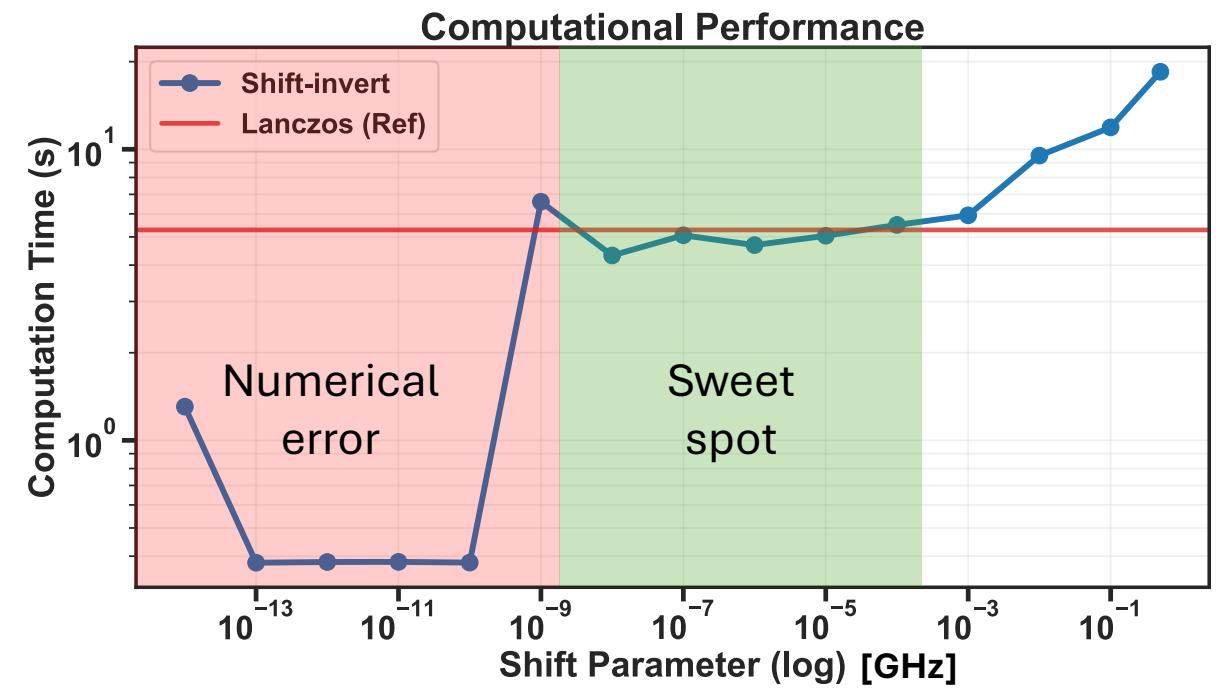
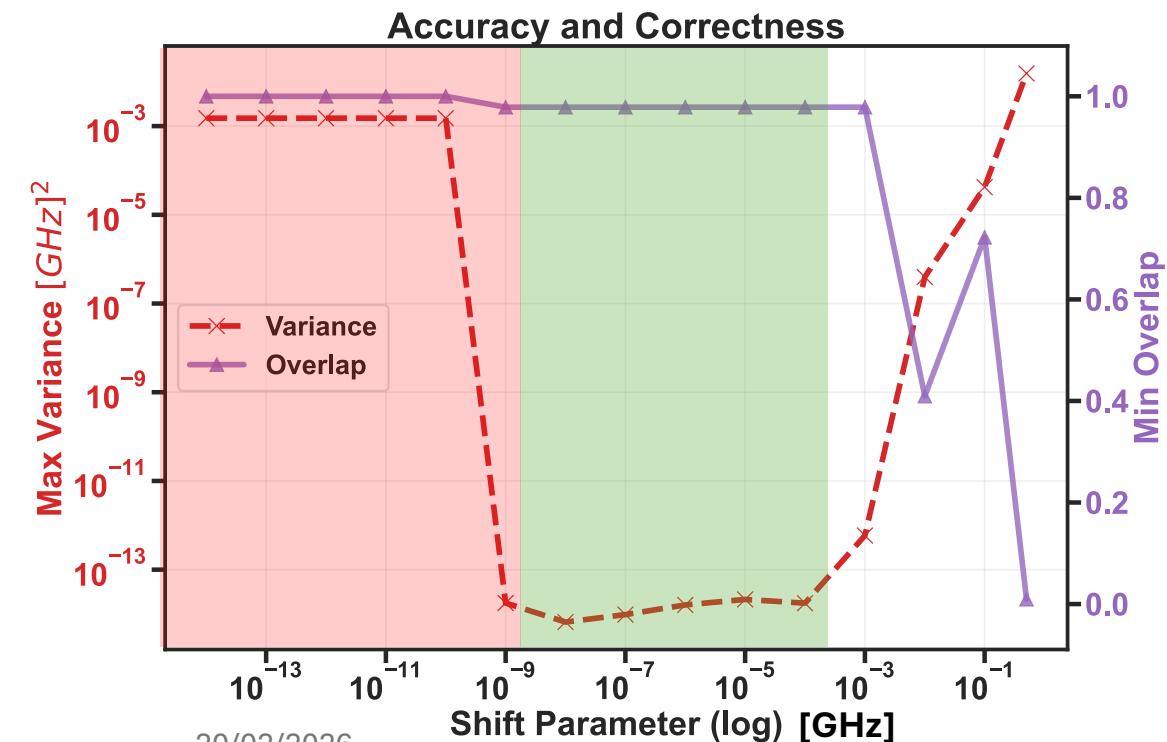


Shift Benchmark

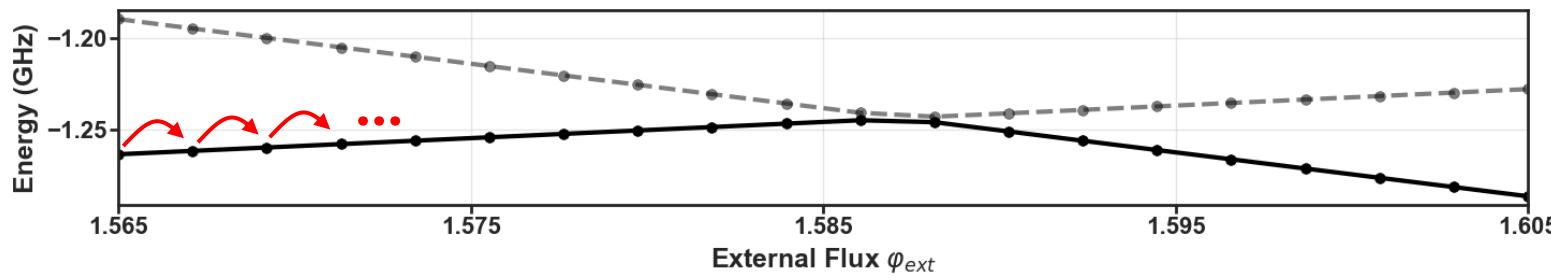


Follow the lower branch
for different shift values

- Variance
- Overlap
- Computational time

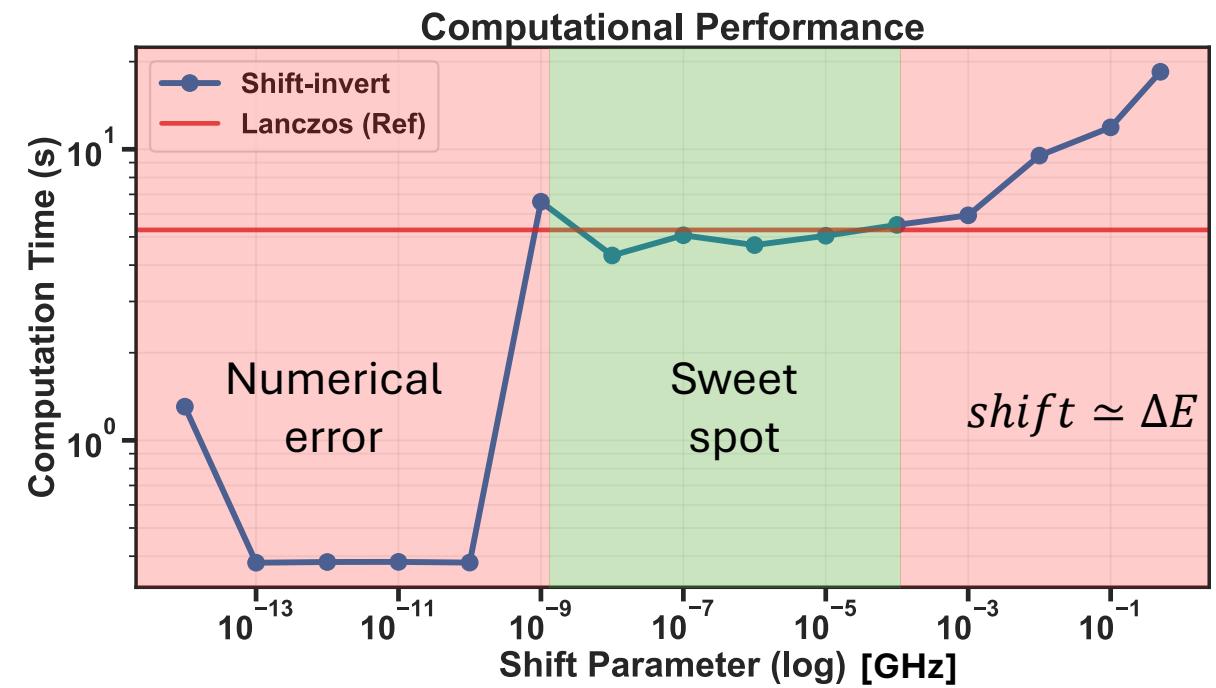
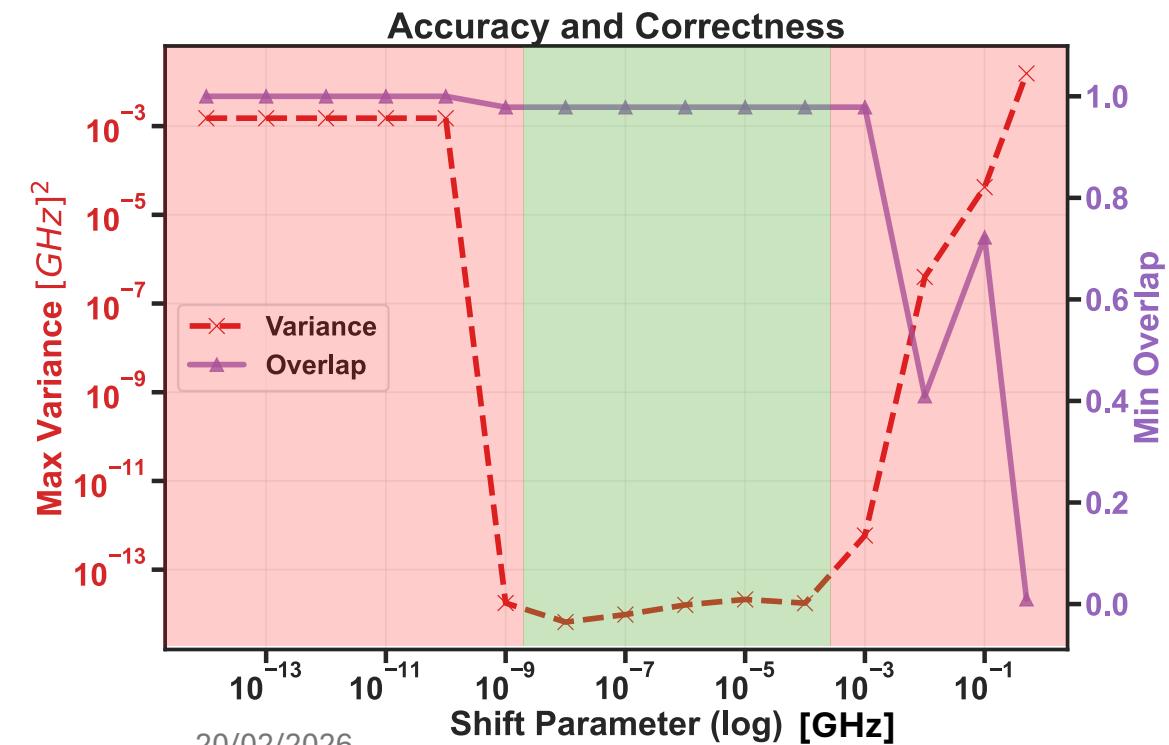


Shift Benchmark

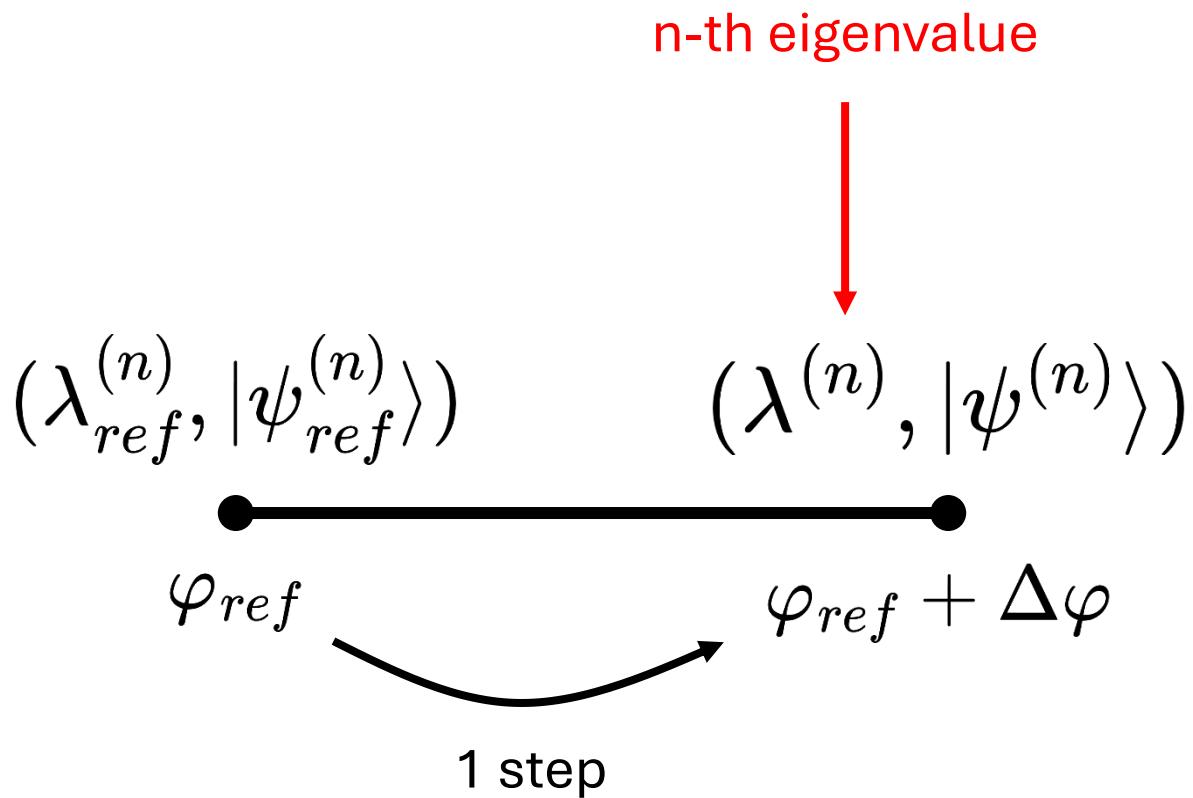


Follow the lower branch
for different shift values

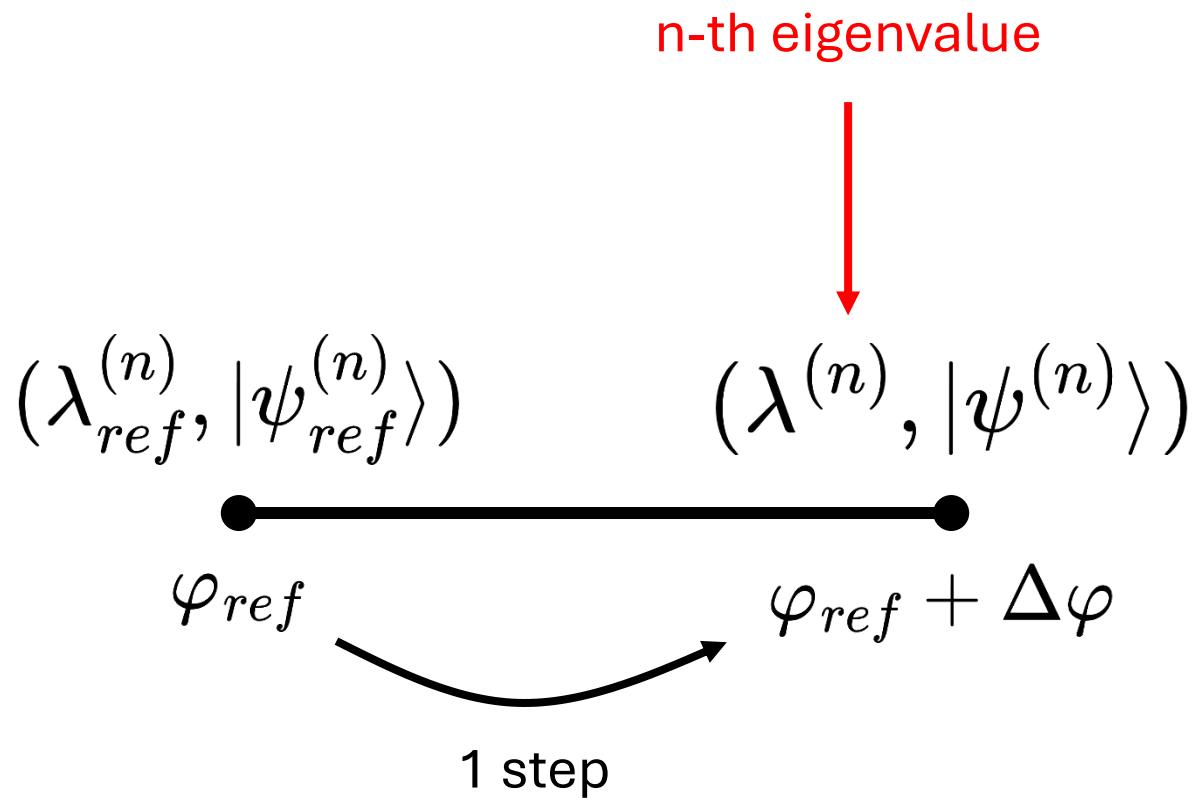
- Variance
- Overlap
- Computational time



Final benchmark



Final benchmark



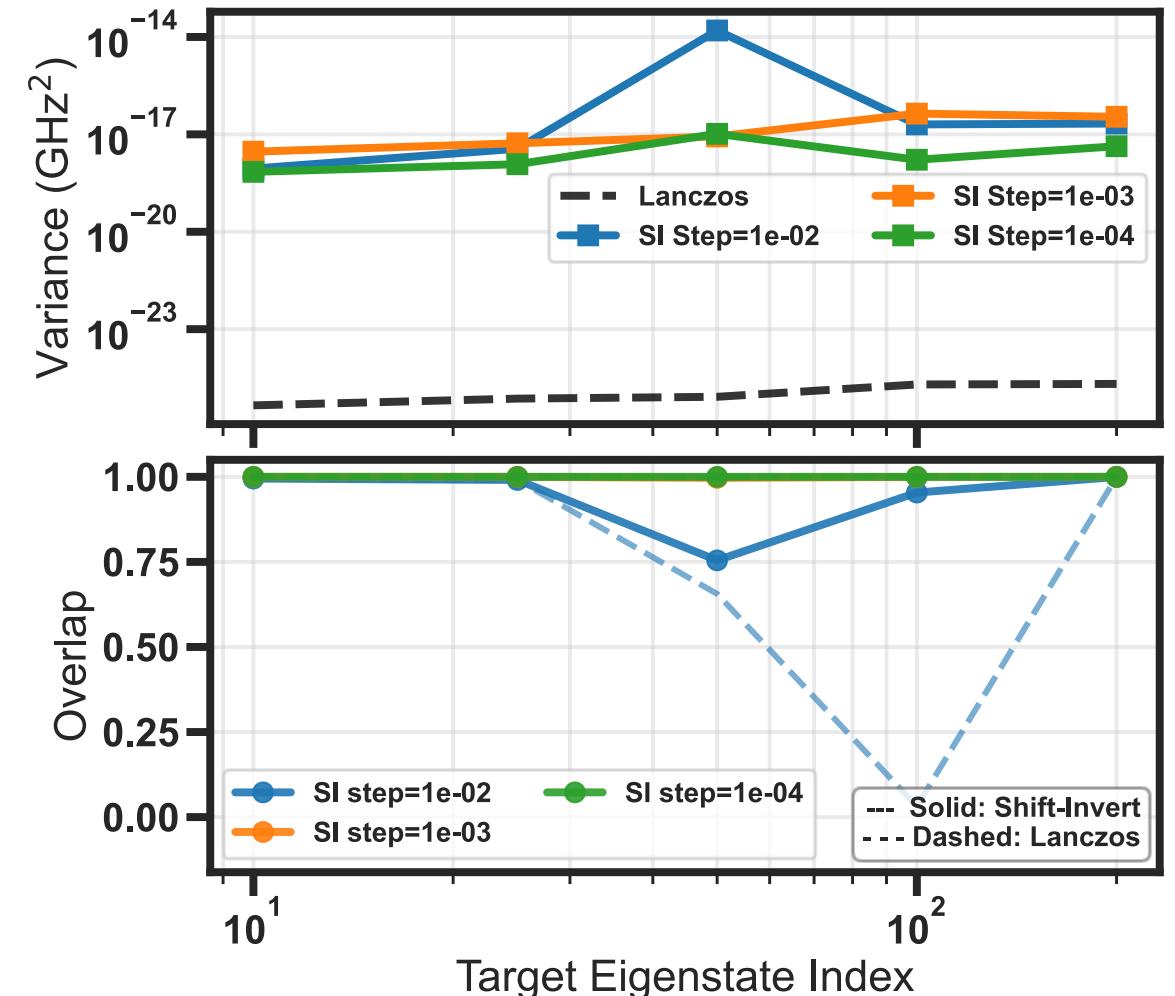
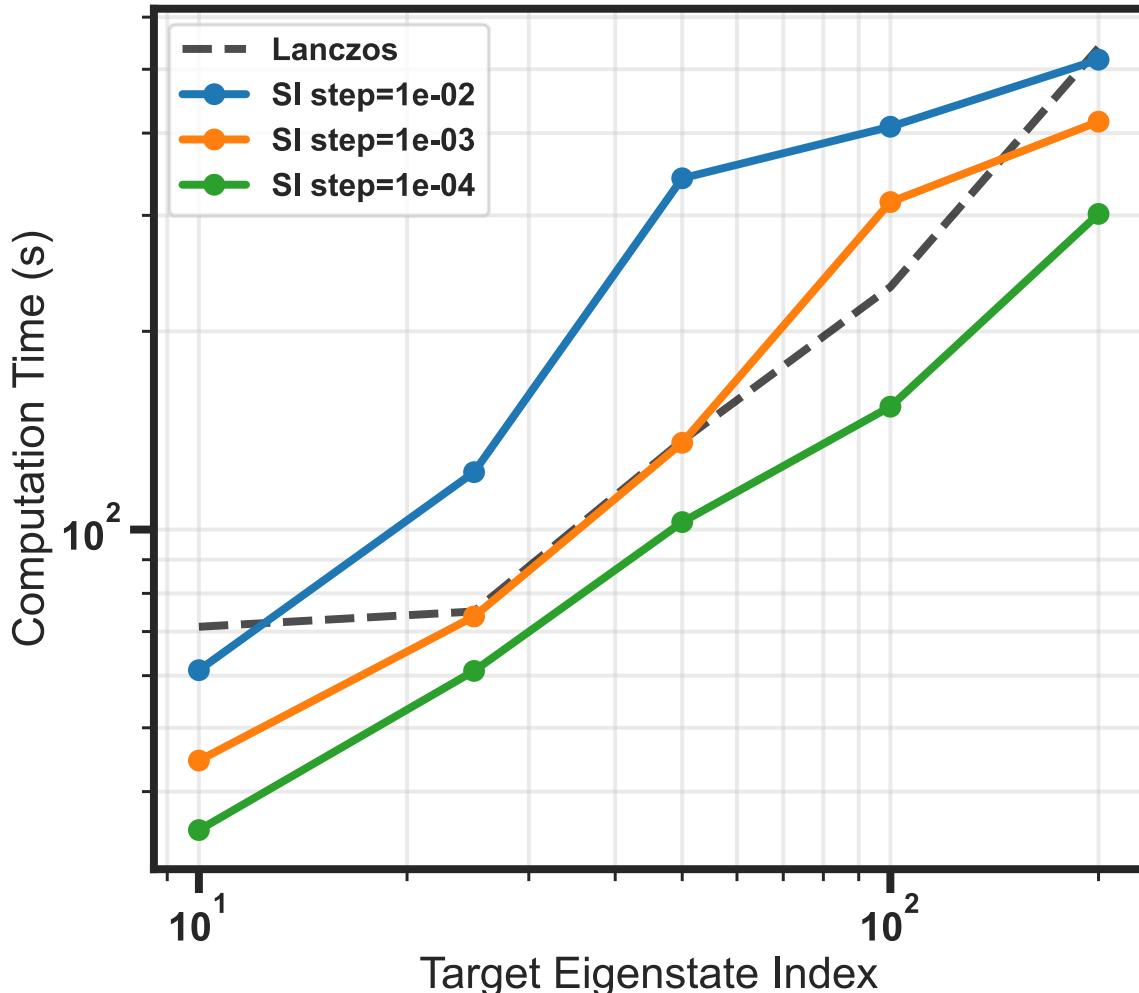
Varying parameters :

- n
- $\Delta\varphi$

Benchmark metrics :

- Computation time
- Variance
- Overlap

Shift invert versus Lanczos



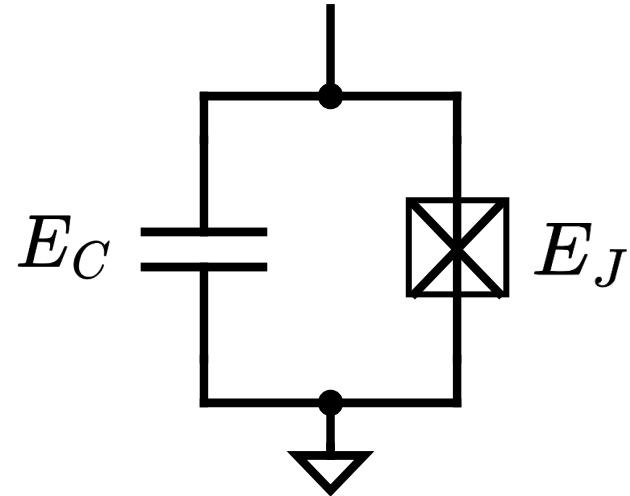
Conclusion

- Usefull in very specific case
- Could be optimized (Minres for complex Hamiltonian)
- Cannot beat Lanczos when we want several eigenvalues

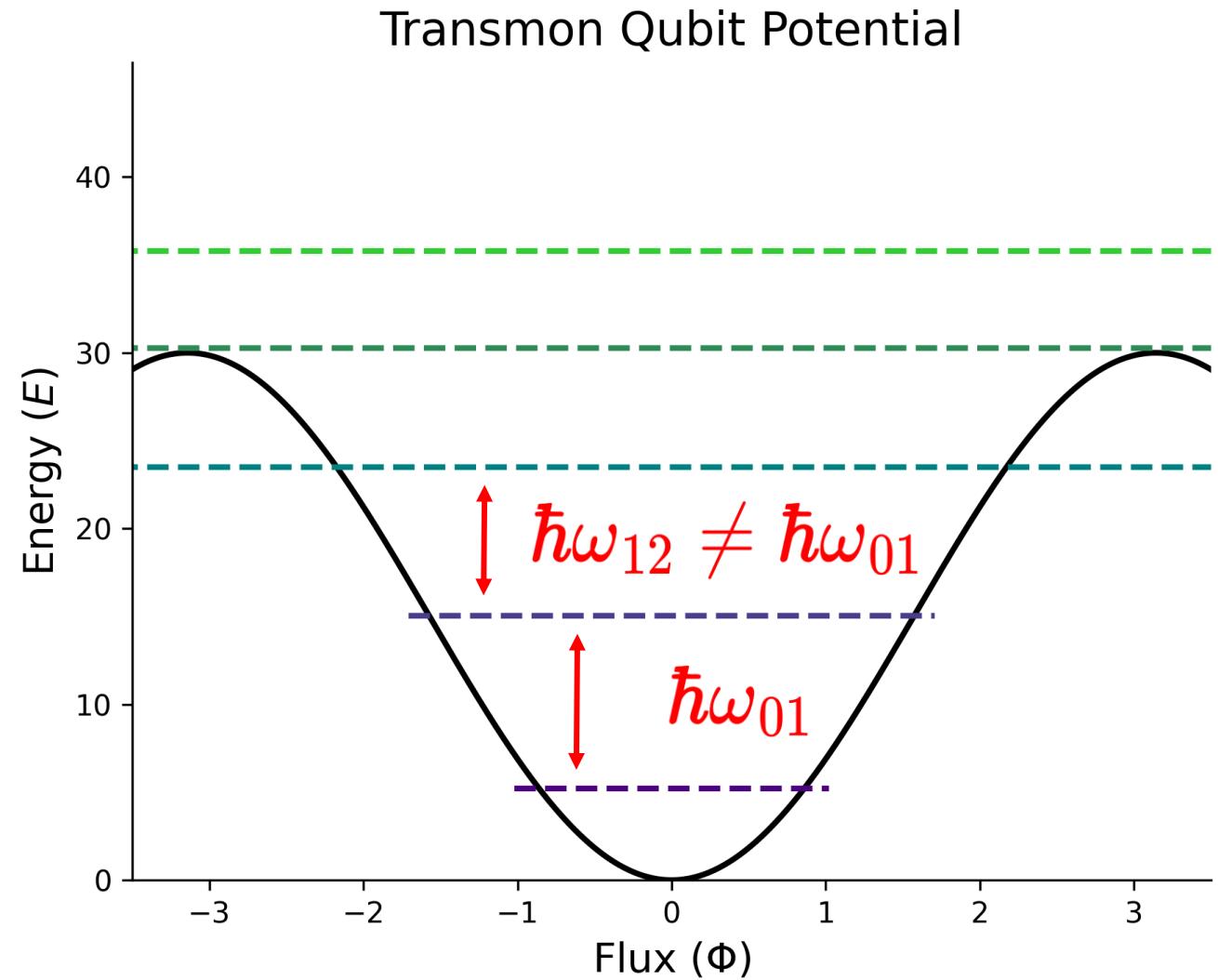
Annex Common Part



Transmon



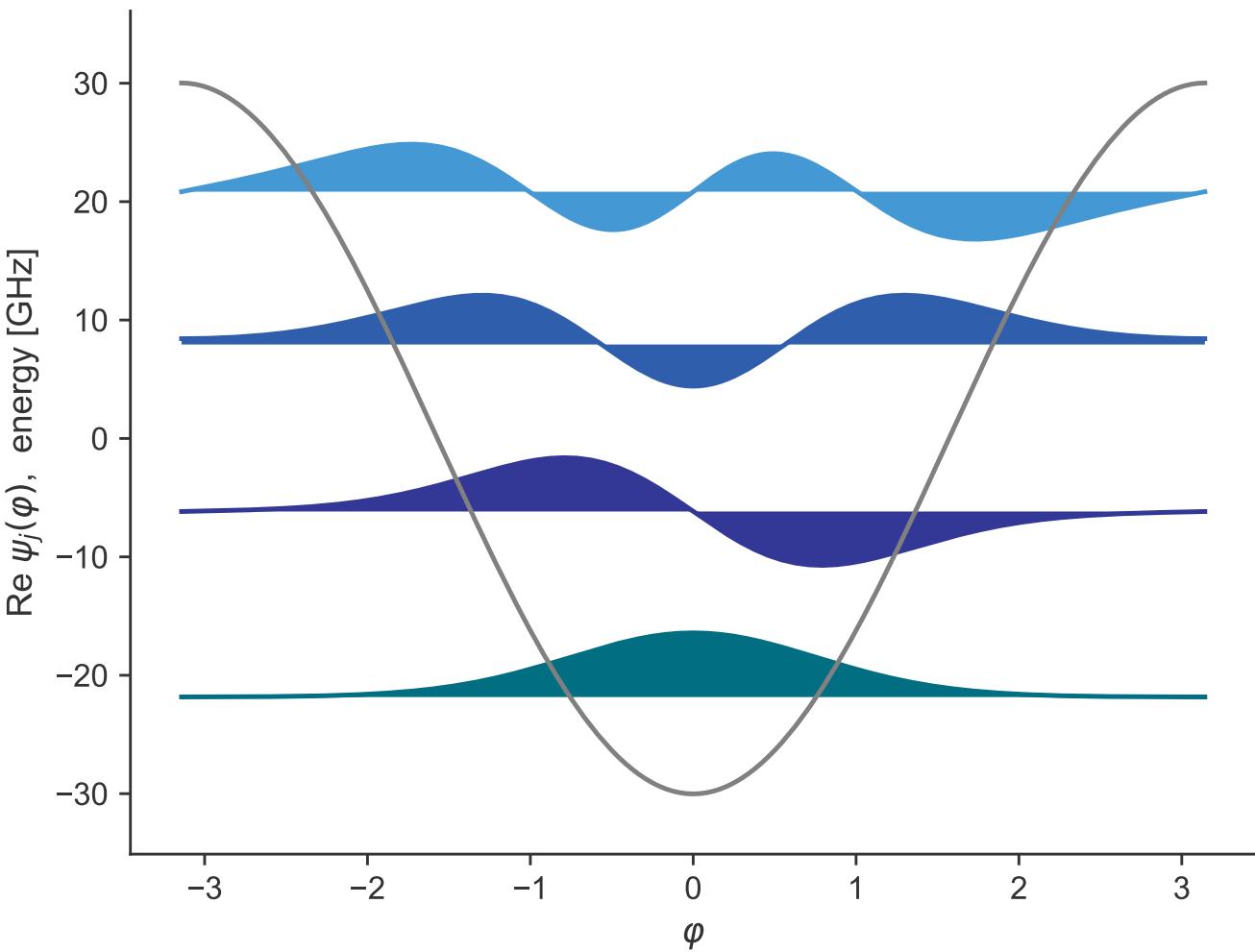
$$\hat{H} = 4E_{CJ}(\hat{n} - n_g)^2 - E_J \cos(\hat{\varphi})$$



Transmon : wavefunctions

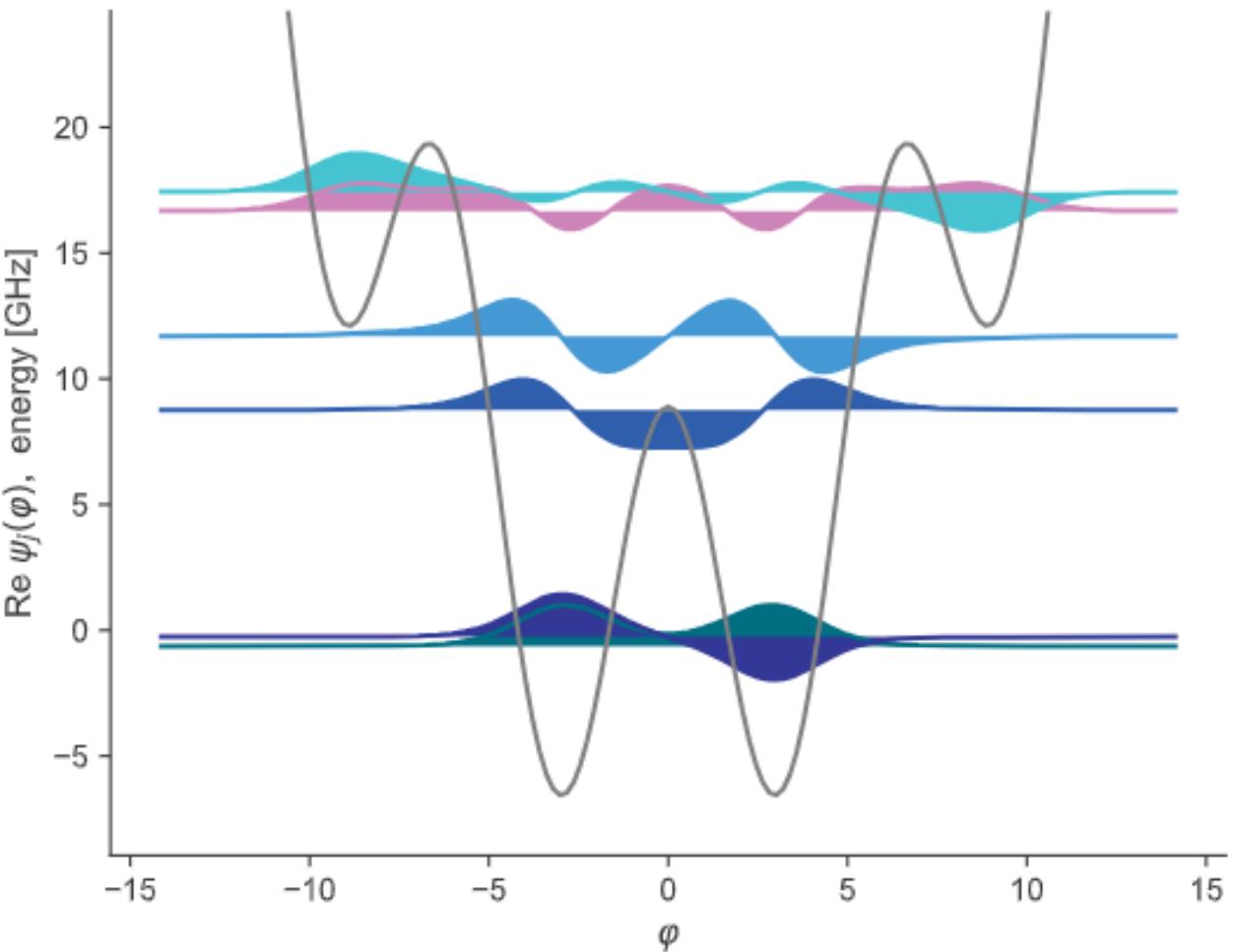
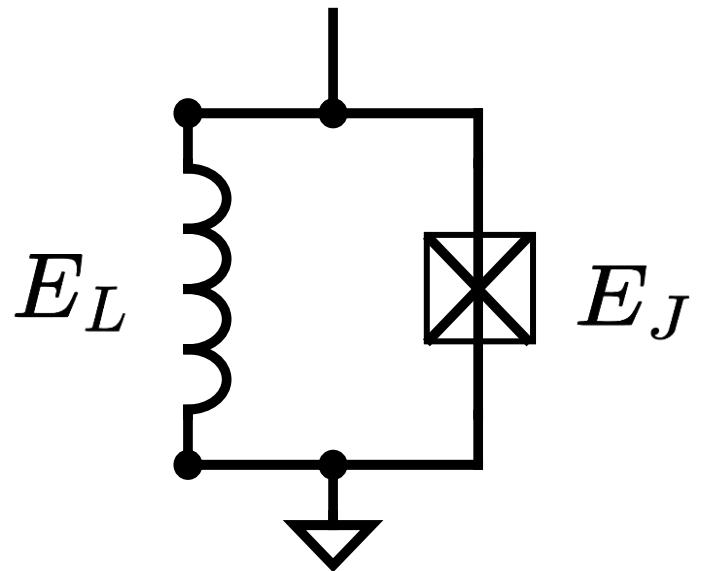
Simulated with
different packages

- Scqbits
- Qutip
- Numpy



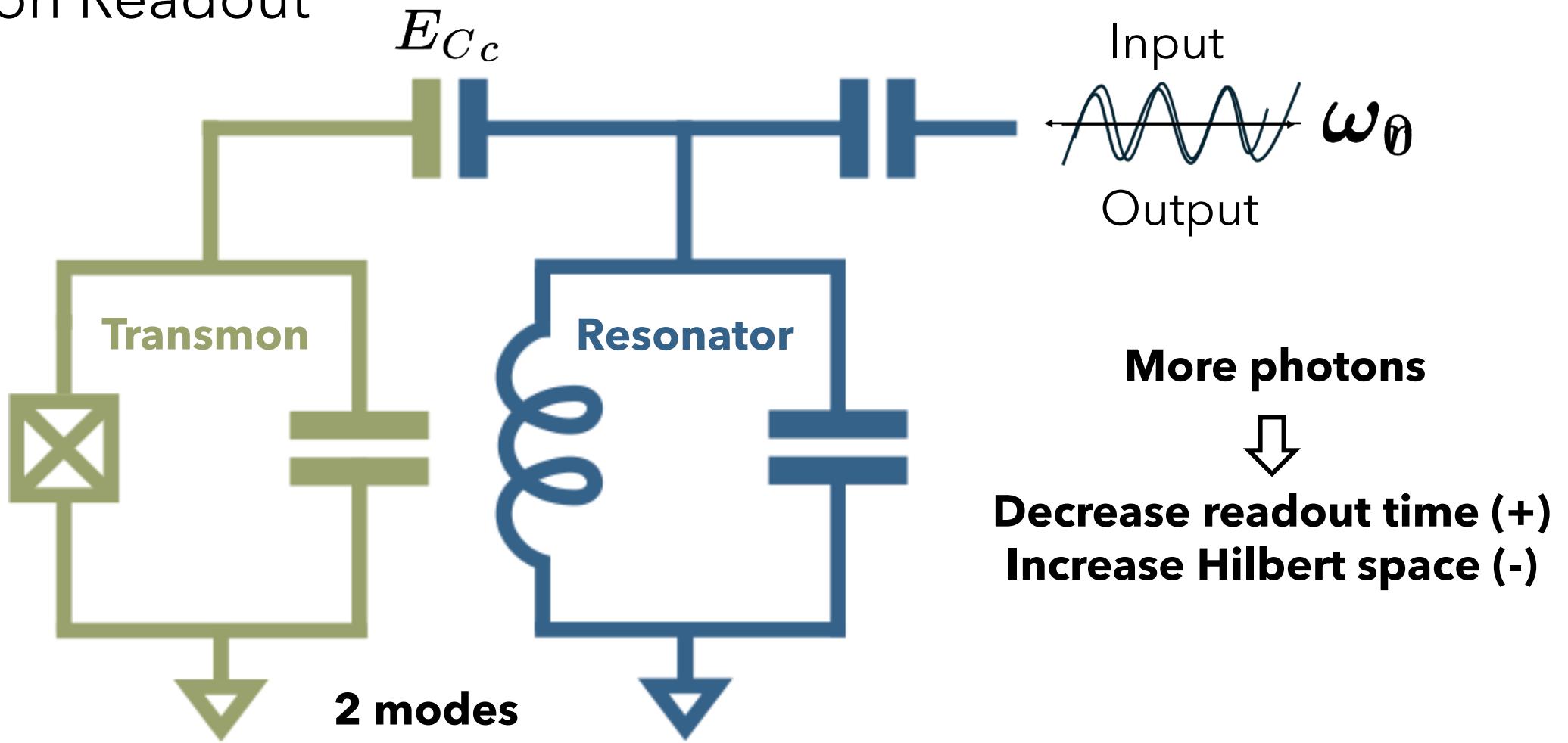
$$\hat{H} = 4E_{CJ}(\hat{n} - n_g)^2 - E_J \cos(\hat{\varphi})$$

Fluxonium



$$\hat{H} = 4E_C\hat{n}^2 + \frac{E_L}{2}(\hat{\phi} - \phi_{ext})^2 - E_J \cos(\hat{\phi})$$

Transmon Readout



$$\hat{H} = \hat{H}_T + \hat{H}_R - 4E_{Cc}in_{ZPF}\hat{n}_T(\hat{a}^\dagger - \hat{a})$$

Cross-Kerr : Measurement

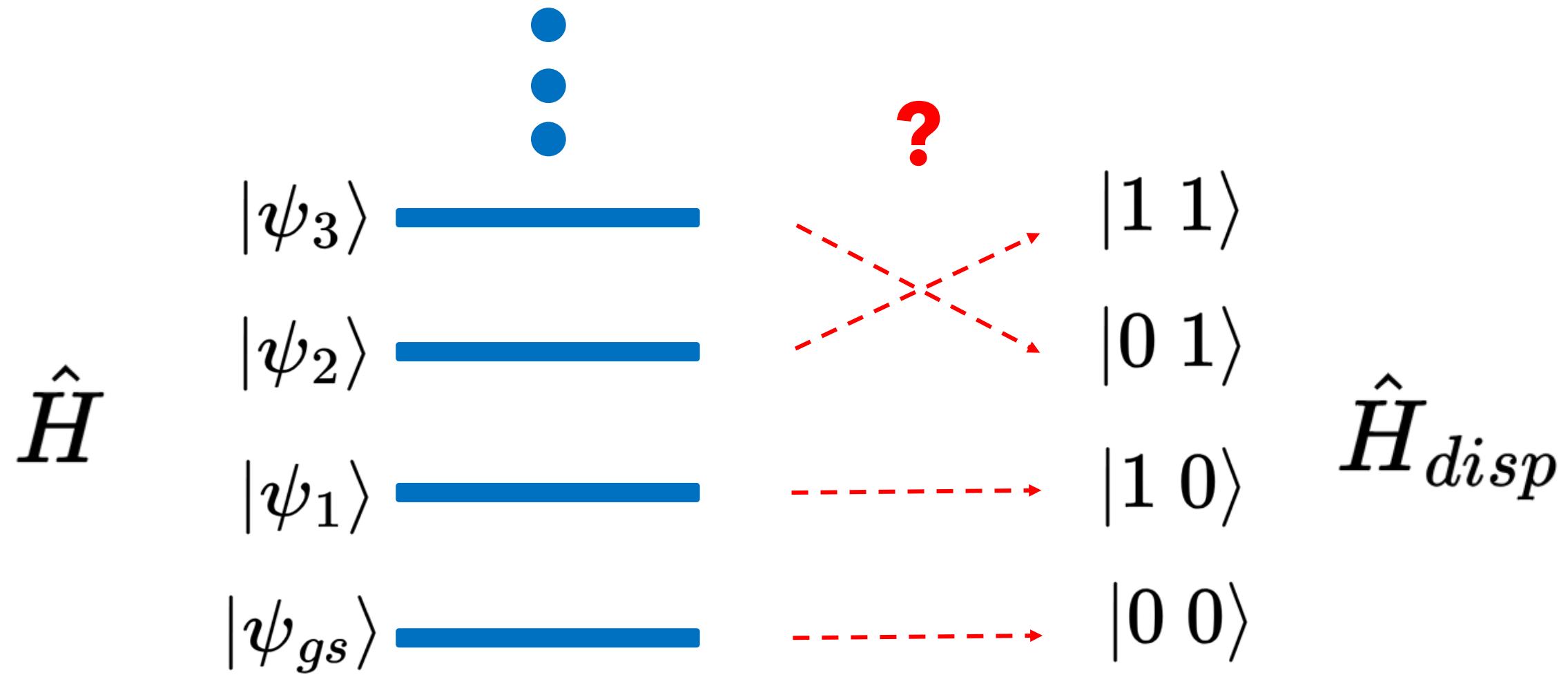
Hamiltonian in the dispersive regime, i.e. $|g/\Delta| \ll 1$, truncated to the first two levels (Blais *et al.*, 2004) :

$$\hat{H}_{disp} \simeq \hbar\omega'_r \hat{a}^\dagger \hat{a} + \frac{\hbar\omega'_q}{2} \hat{\sigma}_z + \hbar\chi \hat{a}^\dagger \hat{a} \hat{\sigma}_z$$

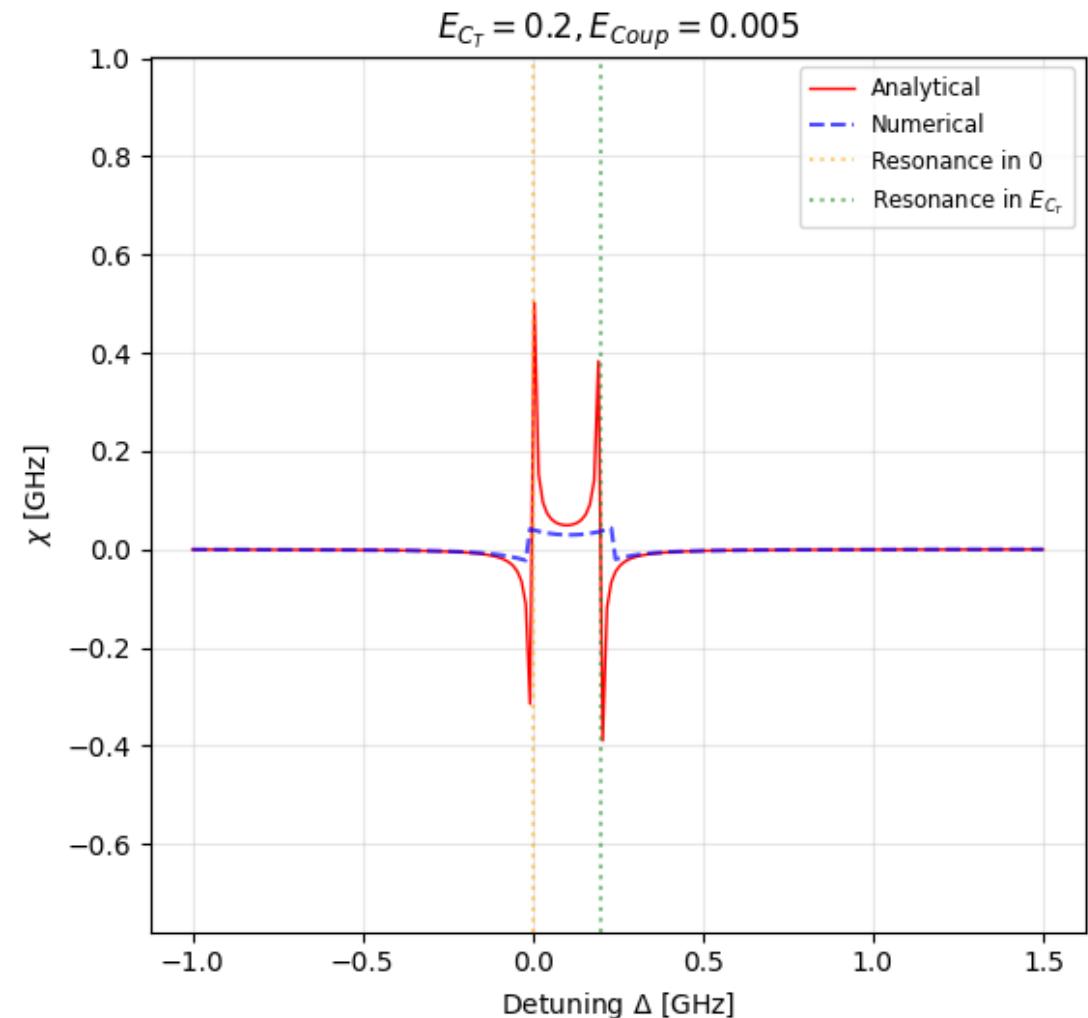
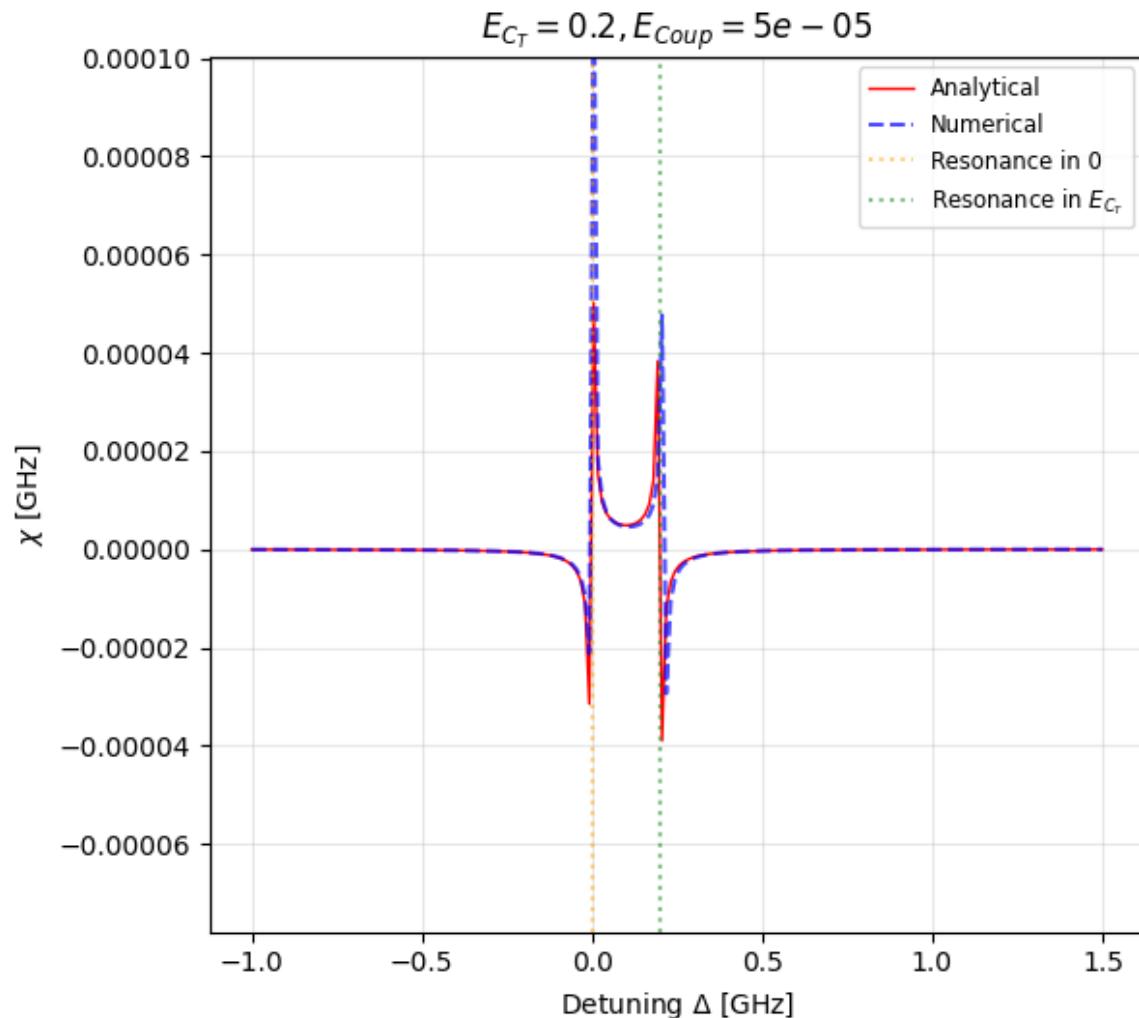
Dispersive shift

$$\left\{ \begin{array}{l} \text{Eigenstates : } |0\ 0\rangle, |1\ 0\rangle, |0\ 1\rangle, |1\ 1\rangle, \dots \\ \text{Eigenvalues : } \pm \frac{\omega'_q}{2}, \omega'_r \pm \left(\frac{\omega'_q}{2} + \chi \right), \dots \end{array} \right.$$

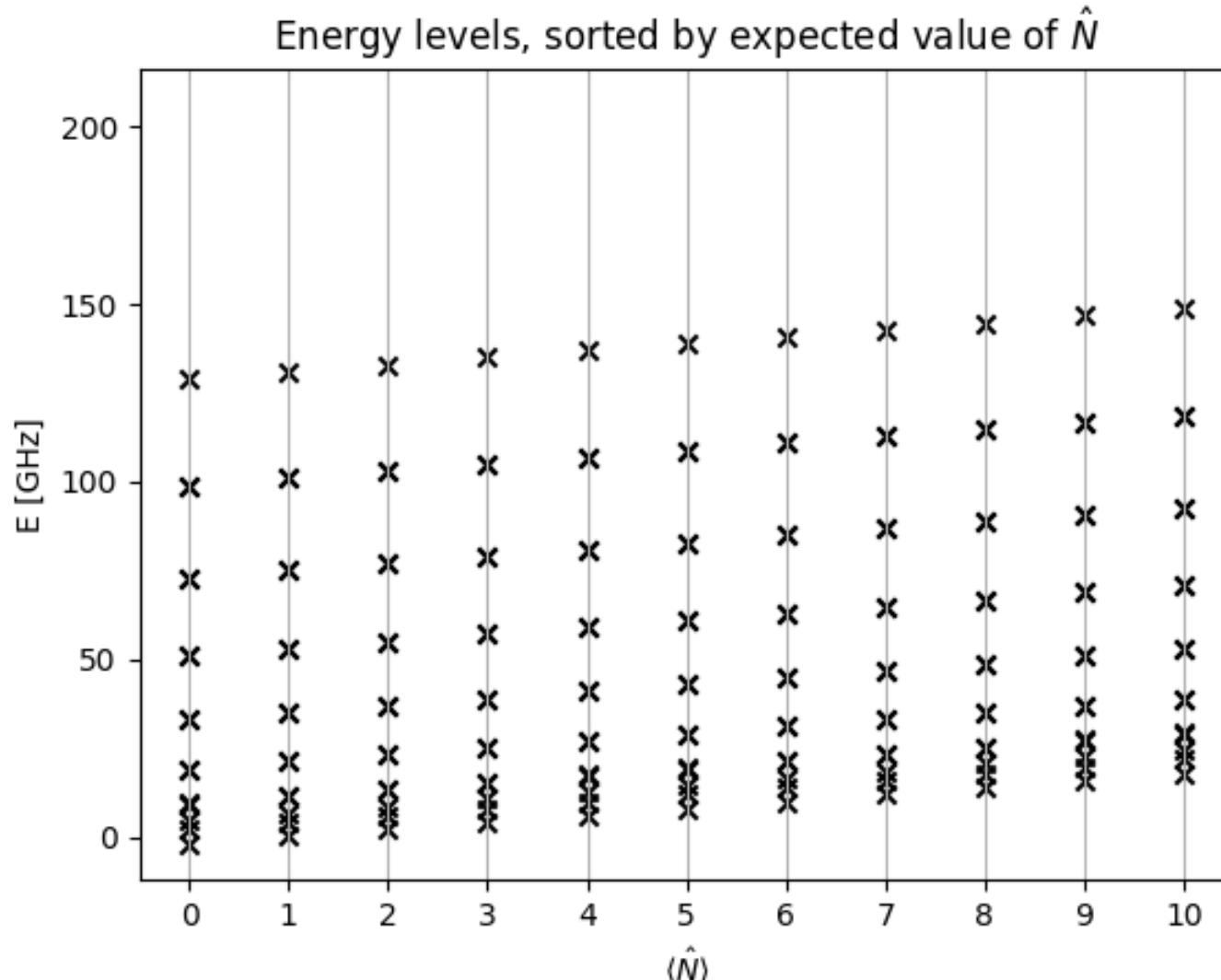
Maximizing overlap



Dispersive shift χ as function of detuning Δ



Another Method



Kite Qubit Hamiltonian (no assymetry)

$$\begin{aligned} H = & 4E_C(n + n_\Sigma + n_g)^2 + 2E_{C_J}(n_\Sigma^2 + n_\Delta^2) \\ & + E_L(\varphi_\Sigma^2 + \varphi_\Delta^2) \\ & - 2E_J \cos(\varphi - \varphi_\Sigma) \cos\left(\varphi_\Delta + \frac{\varphi_{\text{ext}}}{2}\right) \\ & + \hbar\omega\left(N_R + \frac{1}{2}\right) \\ & + E_{C_C}(n + n_\Sigma + n_g)n_R \end{aligned}$$

Annex Eliot

The power algorithm : Find the dominant eigenspace

1. Spectral Decomposition (Operator View)

$$A = \sum_i \lambda_i |\psi_i\rangle\langle\psi_i| \quad \text{with} \quad |\lambda_0| \leq \dots < |\lambda_{\max}|$$

2. Initial State Expansion

$$|\Psi^{(0)}\rangle = c_{\max} |\psi_{\max}\rangle + \sum_{i \neq \max} c_i |\psi_i\rangle$$

3. Applying A^n (Power Iteration)

$$A^n |\Psi^{(0)}\rangle = c_{\max} \lambda_{\max}^n |\psi_{\max}\rangle + \sum_{i \neq \max} c_i \lambda_i^n |\psi_i\rangle$$

⇒ Even faster when $|\Psi^{(0)}\rangle \simeq |\psi_{\max}\rangle$

4. Factorization \& Convergence

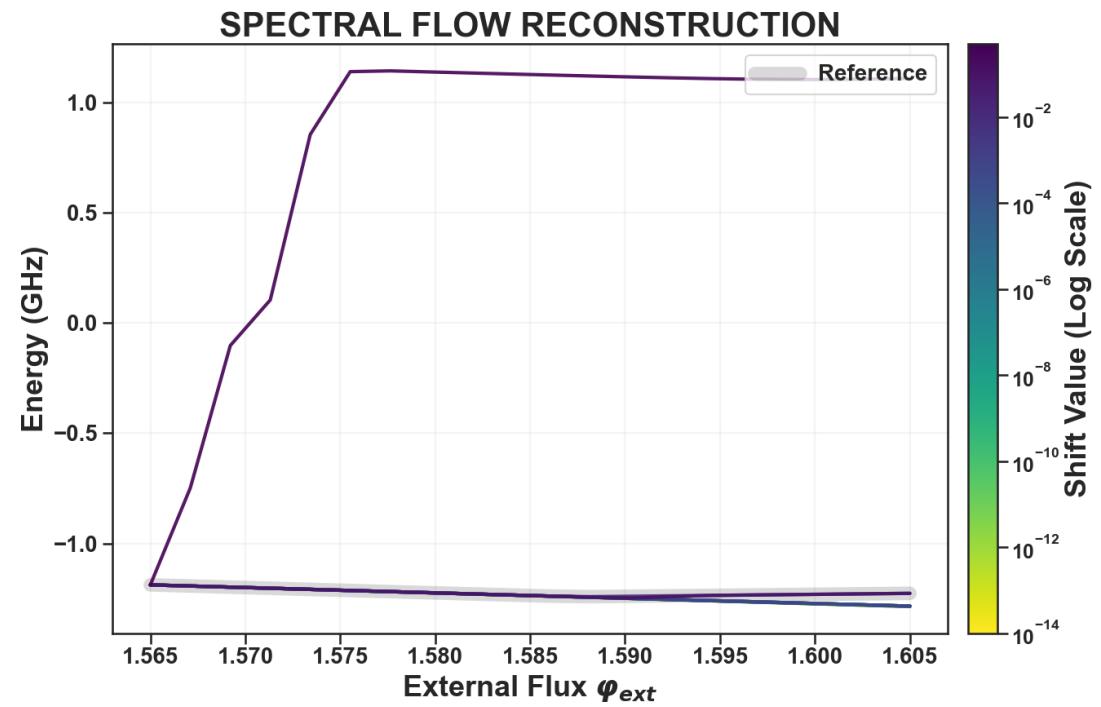
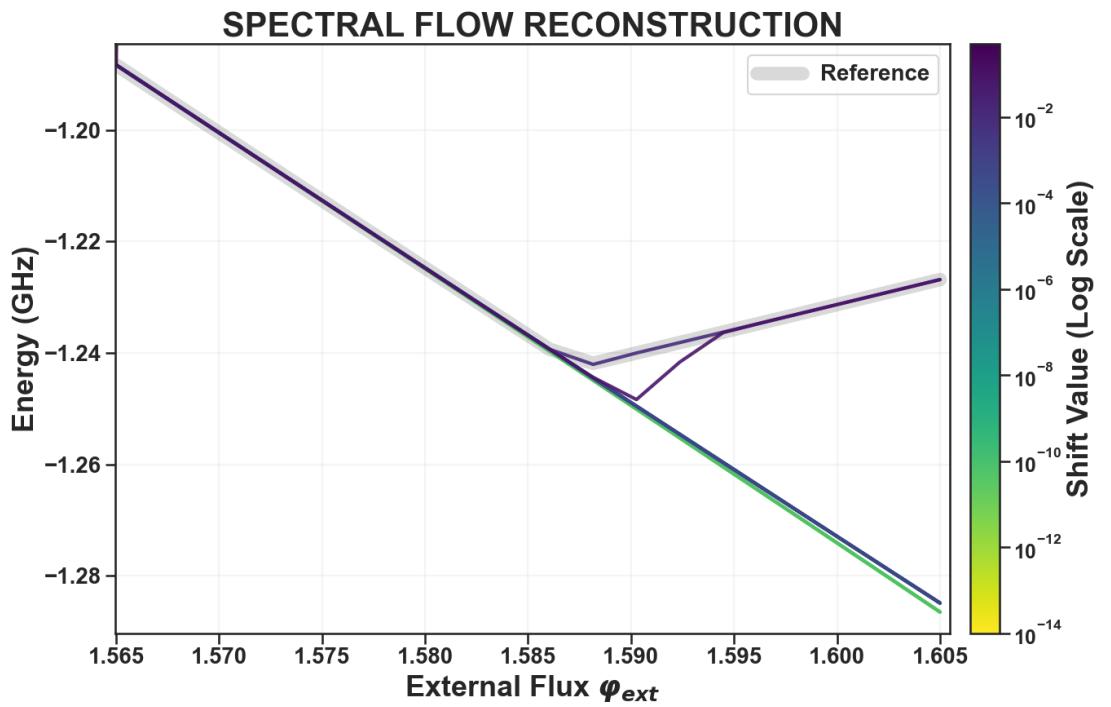
$$= \lambda_{\max}^n \left[c_{\max} |\psi_{\max}\rangle + \sum_{i \neq \max} c_i \underbrace{\left(\frac{\lambda_i}{\lambda_{\max}} \right)^n}_{\rightarrow 0 \text{ as } n \rightarrow \infty} |\psi_i\rangle \right]$$

$$\Rightarrow \lim_{n \rightarrow \infty} \mathbf{A}^n |\Psi^{(0)}\rangle \propto |\psi_{\max}\rangle$$

Shift Invert

- Starting point $\begin{cases} \lambda \\ \psi \end{cases} \text{ s.t. } H(\varphi_{ext})|\psi\rangle = \lambda|\psi\rangle$ and we want $\begin{cases} \tilde{\lambda} \\ \tilde{\psi} \end{cases} \text{ s.t. } H(\varphi_{ext} + \delta\varphi)|\tilde{\psi}\rangle = \tilde{\lambda}|\tilde{\psi}\rangle$
- As we are doing small variations, $\begin{cases} |\tilde{\psi}\rangle = |\psi\rangle + \delta\psi \\ \tilde{\lambda} = \lambda + \delta\lambda \end{cases}$
- so $(H(\varphi_{ext} + \delta\varphi) - \lambda \text{ Id})$ has $\delta\lambda$ as eigenvalue $\implies (H(\varphi_{ext} + \delta\varphi) - \lambda \text{ Id})^{-1}$ has $\frac{1}{\delta\lambda} \gg 1$ as eigenvalue
- Power method on $(H(\varphi_{ext} + \delta\varphi) - \lambda \text{Id})^{-1} \implies (H(\varphi_{ext} + \delta\varphi) - \lambda \text{Id})^{-1}|\tilde{\psi}\rangle = \frac{1}{\delta\lambda}|\tilde{\psi}\rangle$
 $\implies H(\varphi_{ext} + \delta\varphi)|\tilde{\psi}\rangle = \underbrace{(\lambda + \delta\lambda)}_{\tilde{\lambda}}|\tilde{\psi}\rangle$
- $A^{-1}|\Psi^{(n)}\rangle = |\Psi^{(n+1)}\rangle \Leftrightarrow A|\Psi^{(n+1)}\rangle = |\Psi^{(n)}\rangle$ We will use minres from scipy to solve it

Follow trajectory, shift benchmark



N_{power} and ϵ benchmark

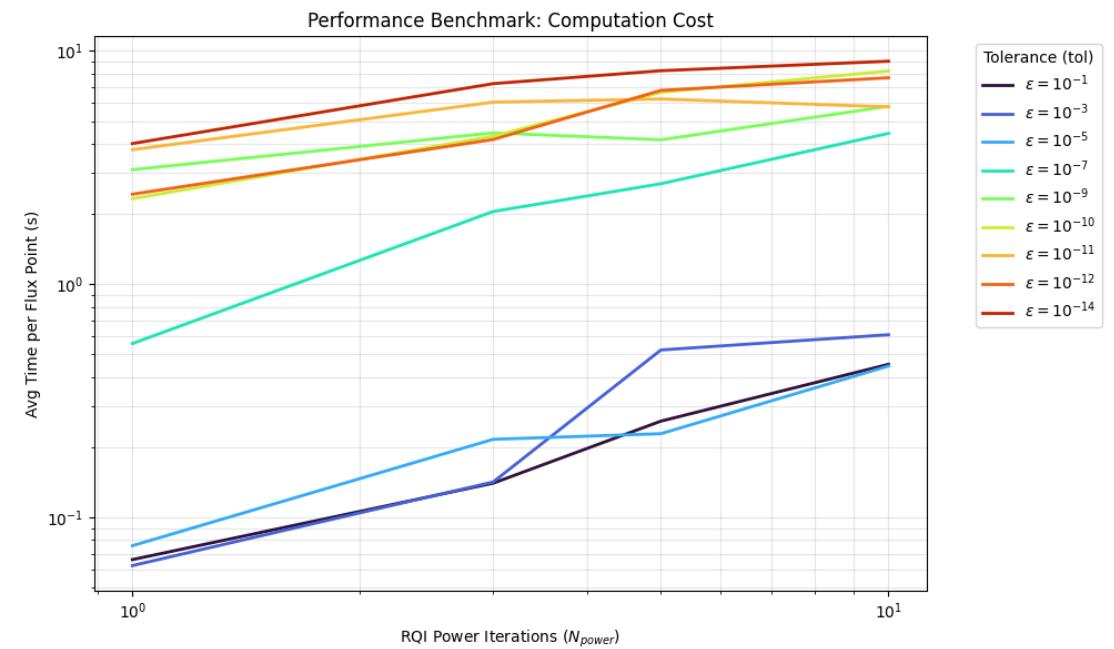
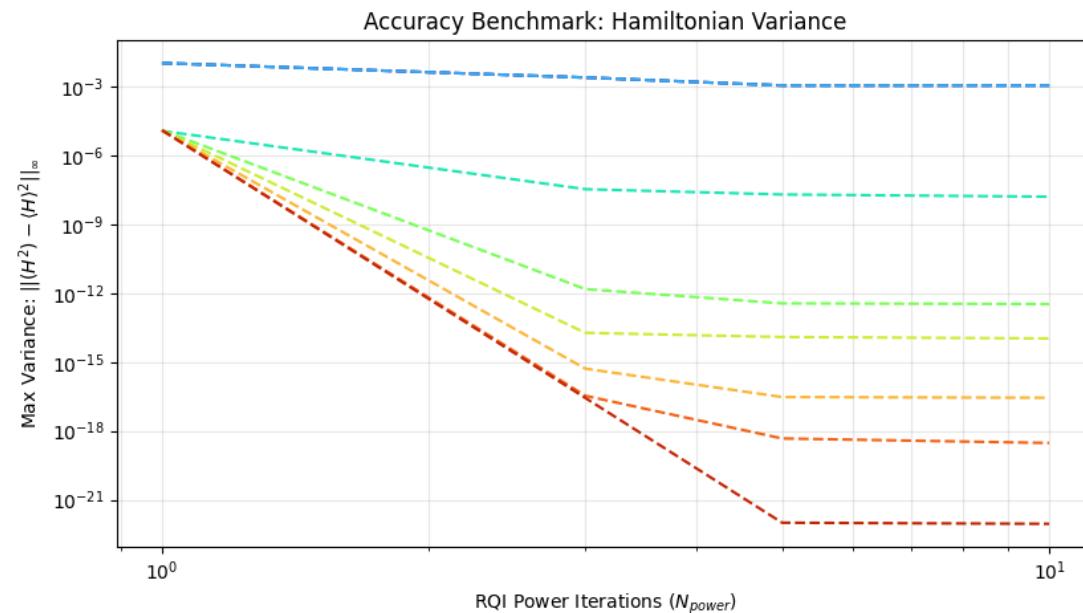
$$(H(\varphi_{ext} + \delta\varphi) - (\lambda + shift) \text{ Id})|\Psi^{(1)}\rangle = |\Psi^{(0)}\rangle$$

1

$$(H(\varphi_{ext} + \delta\varphi) - (\lambda + shift) \text{ Id})|\Psi^{(N_{power})}\rangle = |\Psi^{(N_{power}-1)}\rangle$$

Solved N_{power}

times with precision ϵ



Shift invert versus Lanczos different dim

