

# Robust Control for Quantum Systems

learning optimal control under noise

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- ▶ simplest quantum system: **qubit**  
classical bit is either 0 or 1, **qubit** can be both.

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examples:

$$\psi_1 = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \quad \psi_2 = \begin{pmatrix} 0.6 \\ 0.8 \end{pmatrix} \quad \psi_3 = \begin{pmatrix} \cos \theta \\ i \sin \theta \end{pmatrix}$$



## Introduction to quantum system

evolution of quantum state vector  $\psi(t) \in \mathbb{C}^d$ :

$$\text{Schrödinger's equation} \quad \dot{\psi}(t) = -iH(t; f(t))\psi(t).$$

- ▶ **Hamiltonian**  $H$ :  $\mathbb{C}^{d \times d}$ , Hermitian,  $(t; f(t))$ -dependent.
- ▶  $f(t)$ : reflects our control.

our Hamiltonian model:

$$H(t) = \omega \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} + f(t) \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

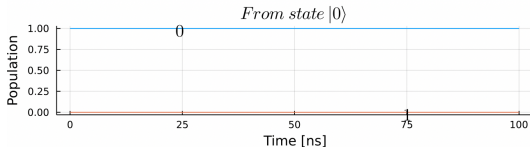
## Demonstration of "control":

assume  $H(t) := f(t) \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$ , start from  $\psi(0) = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ .

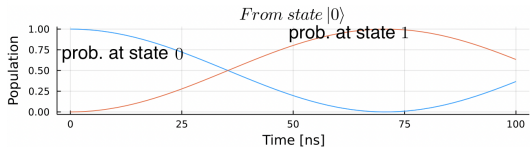
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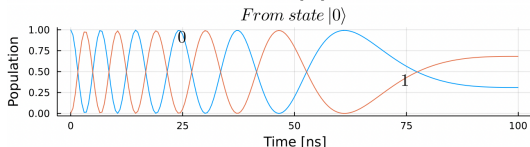
$$f(t) \equiv 0$$



$$f(t) \equiv \text{const}$$



$$f(t) = c \cdot (100 - t)^2$$





## Control problem

given:

$$\begin{cases} \dot{\psi} = -iH(t; f(t))\psi, \\ \psi(0) = \psi_0 := \begin{pmatrix} 1 \\ 0 \end{pmatrix}. \end{cases}$$

we want:

$$\psi(T) = \psi_{tg} := \begin{pmatrix} 0 \\ 1 \end{pmatrix}.$$

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$$L(f(t)) = 1 - |\langle \psi(T), \psi_{tg} \rangle|^2$$

Q: when does  $L(f) = 0$ ?

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# Noise attack

the optimization problem

$$\begin{aligned} & \min_{f:[0,T] \rightarrow \mathbb{R}} L(f) \\ \text{s.t.} \quad & \begin{cases} \dot{\psi} = -iH(t; f(t))\psi, \\ \psi(0) = \psi_0. \end{cases} \end{aligned}$$

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noise-aware loss function:

$$L_{NA} = \mathbb{E}^\epsilon [e^{L(f;\epsilon)}] = \frac{1}{2\delta} \int_{\epsilon} e^{L(f;\epsilon)} d\epsilon.$$

## Why is this challenging?

updated optimization problem

$$\begin{aligned} \min_{f:[0,T] \rightarrow \mathbb{R}} \quad & \mathbb{E}^\epsilon [e^{\mu L(f;\epsilon)}] \\ \text{s.t.} \quad & \begin{cases} \dot{\psi} = -iH(t; f(t); \epsilon)\psi, \\ \psi(0) = \psi_0. \end{cases} \end{aligned}$$

- ▶  $f$  in infinite-dim space
- ▶ need  $\partial_f L$  to update  $f$
- ▶ ODE constraint
- ▶ integral  $\int_\epsilon$  in loss

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We use Juqbox, a Julia package!

- ▶  $f$  in infinite-dim space
- ▶ need  $\partial_f L$  to update  $f$
- ▶ ODE constraint
- ▶ integral  $\int_\epsilon$  in loss
- ▶ approximate  $f$  by finite basis
- ▶ get gradient by adjoint method
- ▶ quadrature/Monte-Carlo sampling



## Test problem: 1-dim uniform noise

## Hamiltonian

$$H(\epsilon) = \omega A + f(t)B + \epsilon C$$

where

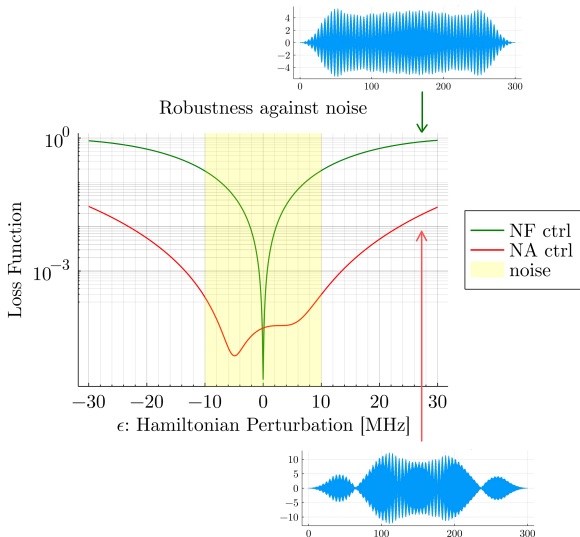
- ▶  $\omega A$ : natural evolution,
- ▶  $f(t)B$ : human control,
- ▶  $\epsilon C$ : uniform noise,
- ▶  $A, B, C$  are fixed, Hermitian matrices  $\in \mathbb{C}^{3 \times 3}$ .

our goal

$$\text{start from } \psi(0) = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \text{arrive at } \psi(T) = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}.$$

## Comparison between NF and NA methods

- ▶ noise-free method is only accurate for  $\epsilon \approx 0$ ;
- ▶ noise-aware method behaves robustly under large noise;
- ▶ good generalization ability.



## Test problem: high-dim noise

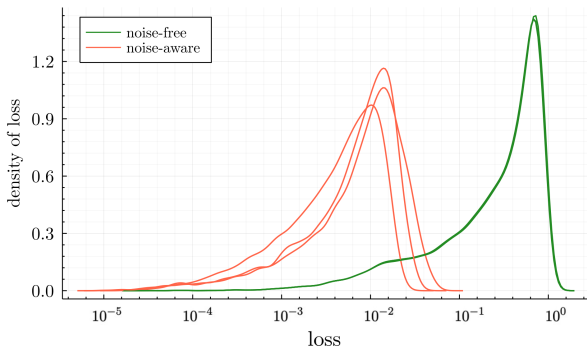
► noise model:

$$\begin{pmatrix} \epsilon_1 & \epsilon_4 \\ \epsilon_4 & \epsilon_2 & \epsilon_5 \\ & \epsilon_5 & \epsilon_3 \end{pmatrix}$$

$$\epsilon_i \sim \text{Unif}(-\delta_i, \delta_i).$$

► curse of dimensionality:  
–MC method.

Error distribution for different methods



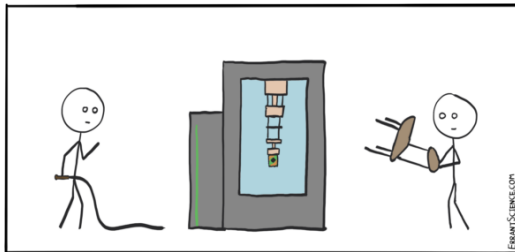
## Contribution and future work

### contribution:

- ▶ implement risk-aware loss functions
- ▶ test on 1-dim noise
- ▶ test on higher-dim noise

### future work:

- ▶ N-qubit system
- ▶ non-uniform noise
- ▶ new loss function
- ▶ ...



Two physicists trying to control a qubit in the lab

## References



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