Towards improved sample complexity using a quantum model based SAC

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Reminder: Utility of quantum control

- Control: System = Controllable part + Not controllable part
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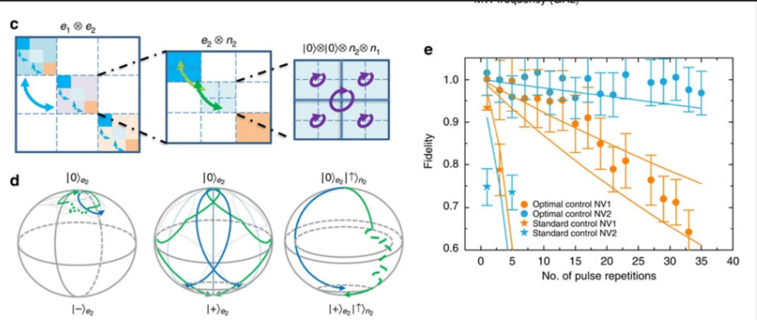
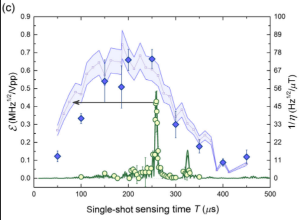
  - metrology applications

Diamond spins ↑↑↓





[1]

[2]

[1]F. Dolde et. al. (Nature 2014)
[2]F. Poggiali et. al. (PRX 2018)

Definitions

- Constraint 1: Transmon H (control structure H_u fixed) (Magesan et. al. 2020)

$$
\begin{aligned}
H(t)/\hbar &= H_0 + \sum_{u \in \mathcal{C}} u(t) H_u && (1)\\
&= \sum_{j=1}^{2} \omega_j \hat{b}_j^\dagger \hat{b}_j + \frac{\delta_j}{2} \hat{b}_j^\dagger \hat{b}_j (\hat{b}_j^\dagger \hat{b}_j - 1) && (2)\\
& J \sum_{j=1}^{2} (\hat{b}_j^\dagger \hat{b}_{j+1} + \hat{b}_j \hat{b}_{j+1}^\dagger) + \sum_{j=1}^{2} \Delta_j(t)(\hat{b}_j + \hat{b}_j^\dagger)
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- Formal Goal:

$$\boldsymbol{\Delta}^* = \operatorname*{arg\,max}_{\boldsymbol{\Delta}=[\Delta_1,\ldots,\Delta_m], m \le N} \mathcal{F}(E_{\boldsymbol{\Delta}}, V) \tag{3}$$

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- So, far only two things interacting: policy $\pi(\mathbf{a}_k \mid \mathbf{s}_k)$ and $\mathcal{E}(\mathbf{a}_k, \mathbf{s}_k)$

Model addition

- Suppose the agent is now able to store and interact with an internal representation of $\mathcal{E}$. Let's denote that with $\hat{\mathbf{P}}_\theta(\mathbf{s}_{k+1} \,|\, \mathbf{s}_k, \mathbf{a}_k) = \hat{\mathcal{E}}_\theta$.

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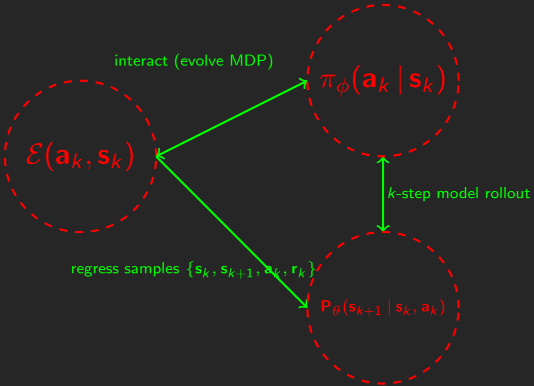

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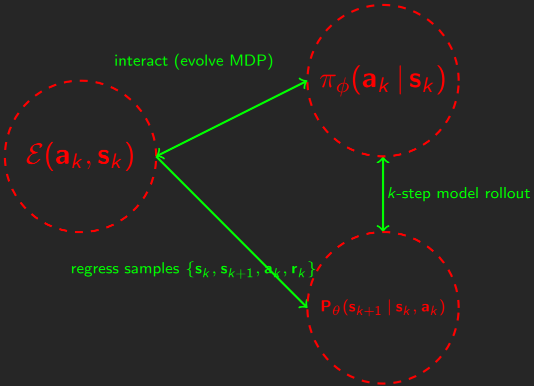

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- Have a choice to go function approximation route for model or ODE solver

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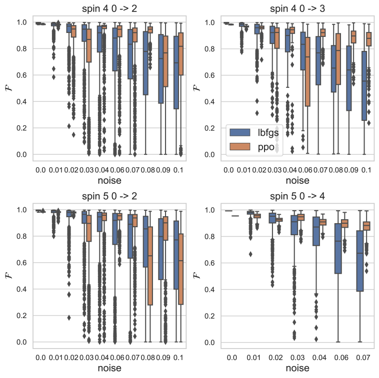

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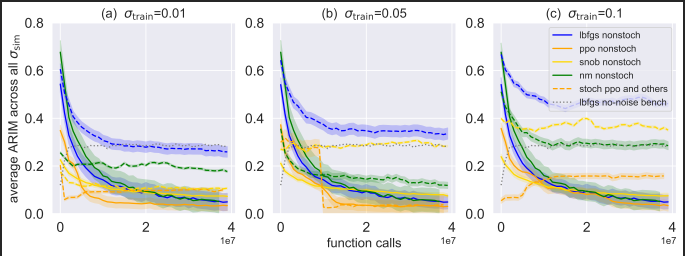
- as $\mathbb{E}[\mathcal{F}]$ is optimized (Khalid et. al. 2022 arxiv:2207.07801)

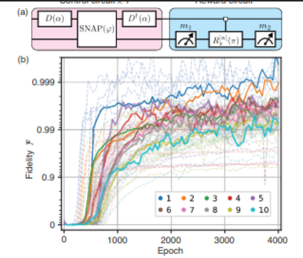


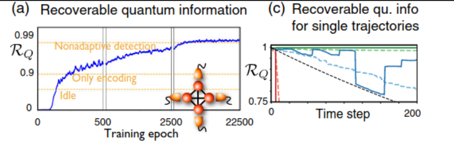
Why RL?

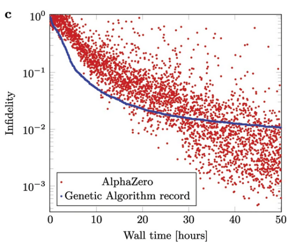
- Black box optimization (we don't need a model)
  - Note not adaptive!
  - Controller solution is a point in the solution space and not a function.
  - It does not *react* to perturbations

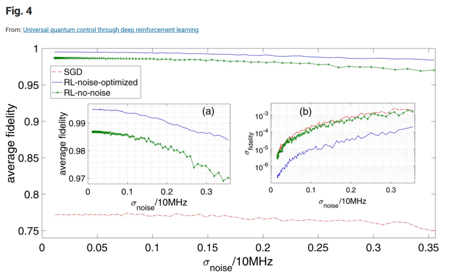
Why RL?

- Several other results in the past 3-4 years









cite[3]

[3] TL: Sivak… (PRX 2022) TR: Fösel… (PRX 2018) BL: Dalgaard… (Nature 2020) BR: Niu… (Nature 2018)

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- at the moment constraint is a δ-perfect Hamiltonian where δ has to be small

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  2. optimal convergence to π^* after repeated Bellman iterations for the tabular case ensures asymptotic performance reaches that of other Model-free methods like DDPG, PPO

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- Generalization bound on the model $\mathbf{P}_\theta(\mathbf{s}_{k+1} \,|\, \mathbf{s}_k, \mathbf{a}_k)$ error ϵ_m yields the lower bound on k-branched rollouts (Thm 4.2.)

$$J(\pi) \geq J(\pi)_{\mathrm{branch}} - 2r_{\max}\left[\frac{\gamma^{k+1}\epsilon_\pi}{(1-\gamma^2)+\frac{\gamma^k+2}{(1-\gamma)}}\epsilon_\pi + \frac{k}{1-\gamma}(\epsilon_m + 2\epsilon_\pi)\right] \tag{7}$$

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$$\mathbf{s}_{t:t+T} = \arg\max_{\mathbf{a}_{t:t+T}} \mathbb{E}_{f_\theta}\left[\sum_{i=t}^{t+T} \mathbf{r}(\mathbf{s}_i, \mathbf{a}_i)\right] \tag{8}$$

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- CEM is an importance sampling approximator. In it the cross entropy is maximized by the MLE for most natural exponential families which $\mathcal{N}$ and a randomization over various guesses converges to the optimizer of (8)

- We guess a set of Hamiltonians $\{H\}_B$ close to the true Hamiltonian H^* generating the unitary dynamics and use an ODE solver (standard or neural). This becomes our model $\mathbf{P}_\theta(\mathbf{s}_{k+1} \,|\, \mathbf{s}_k, \mathbf{a}_k)$ where $\theta = \{H\}_B$.

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- We use the SU(N) parameterization: $H_i = \sum_{p=1}^{\dim(\mathrm{span}(SU(N)))} \alpha_p \sigma_p$ where σ_p are the generalized pauli matrices $\mathbb{1} \otimes \cdots \otimes \sigma_x$ and so on...

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- We use the SU(N) parameterization: $H_i = \sum_{p=1}^{\dim(\mathrm{span}(SU(N)))} \alpha_p \sigma_p$ where σ_p are the generalized pauli matrices $\mathbb{1} \otimes \cdots \otimes \sigma_x$ and so on...
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- We train the set using PETS by regressing onto the states or rewards.
- We found that state regression has a better transmon-dependent loss landscape than predicted fidelity regression

Results: Step 1: With $\mathbf{P}_\theta(\mathbf{s}_{k+1} \mid \mathbf{s}_k, \mathbf{a}_k)$ being perfect, how many real samples does it take?

Target gate is the CNOT

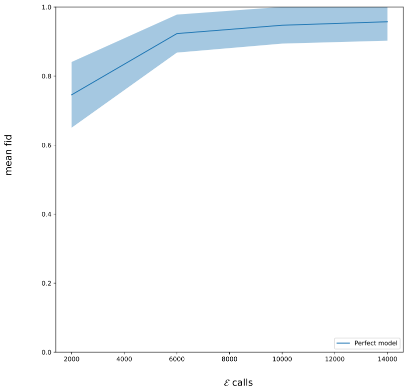

Figure: Sanity test and optimal lower bound (baseline) for the MBSAC

Understanding the exploitation-exploration tradeoff for the quantum control setting in the perfect model setting

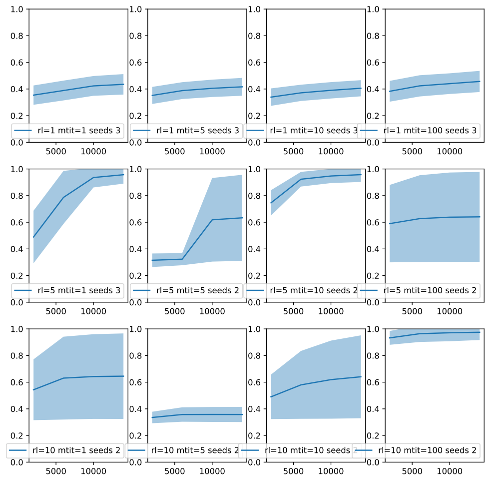

Figure: branch rollout length (rl) k (model explore) tradeoffs w.r.t. training per k model train iterations (mtit)

Step 2: How good is the δ-perfect model? What is the effect of δ on sample complexity?

- Maybe not the smartest way to pick δ but we choose it to be partially adversarial

$$\Lambda = \|F(H^*(\Delta_i)) - F(H_2(\Delta_i))\| \approx \delta \ \forall i \tag{9}$$

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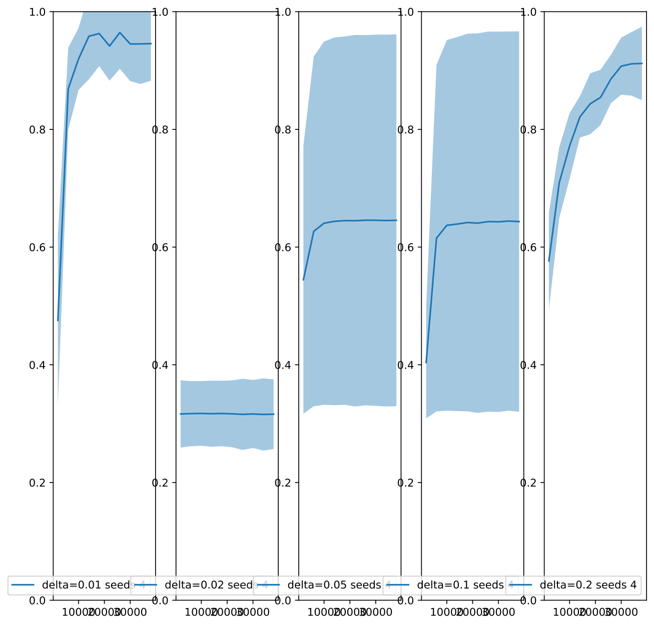

1.0
0.8
0.6
0.4
0.2
0.0
10000
20000
30000
delta=0.01 seeds 4
delta=0.02 seeds 4
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Step 3: Now train and contrast

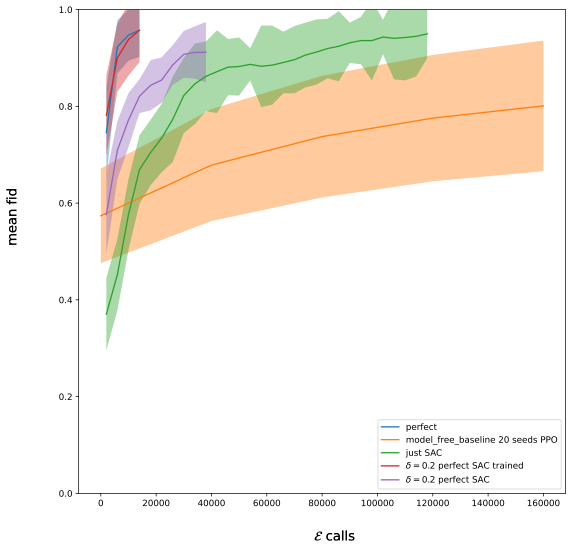

Figure: Various

Improving the definition of δ-perfection

Use Burgath et. al. (2022) upper bound

$$\|U^* - U_2\| \leq \left\| \int_0^T dsH^*(s) - H_2(s) \right\| \left(1 + \left\| \int_0^T dsH^*(s) \right\| + \left\| \int_0^T dsH_2(s) \right\| \right) \tag{10}$$

set $\|U^* - U_2\|$ as fidelity difference δ? and solve the above relaxed optimization problem?

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- Some of above with Noisy Lindblad dynamics and shot coarse-graining