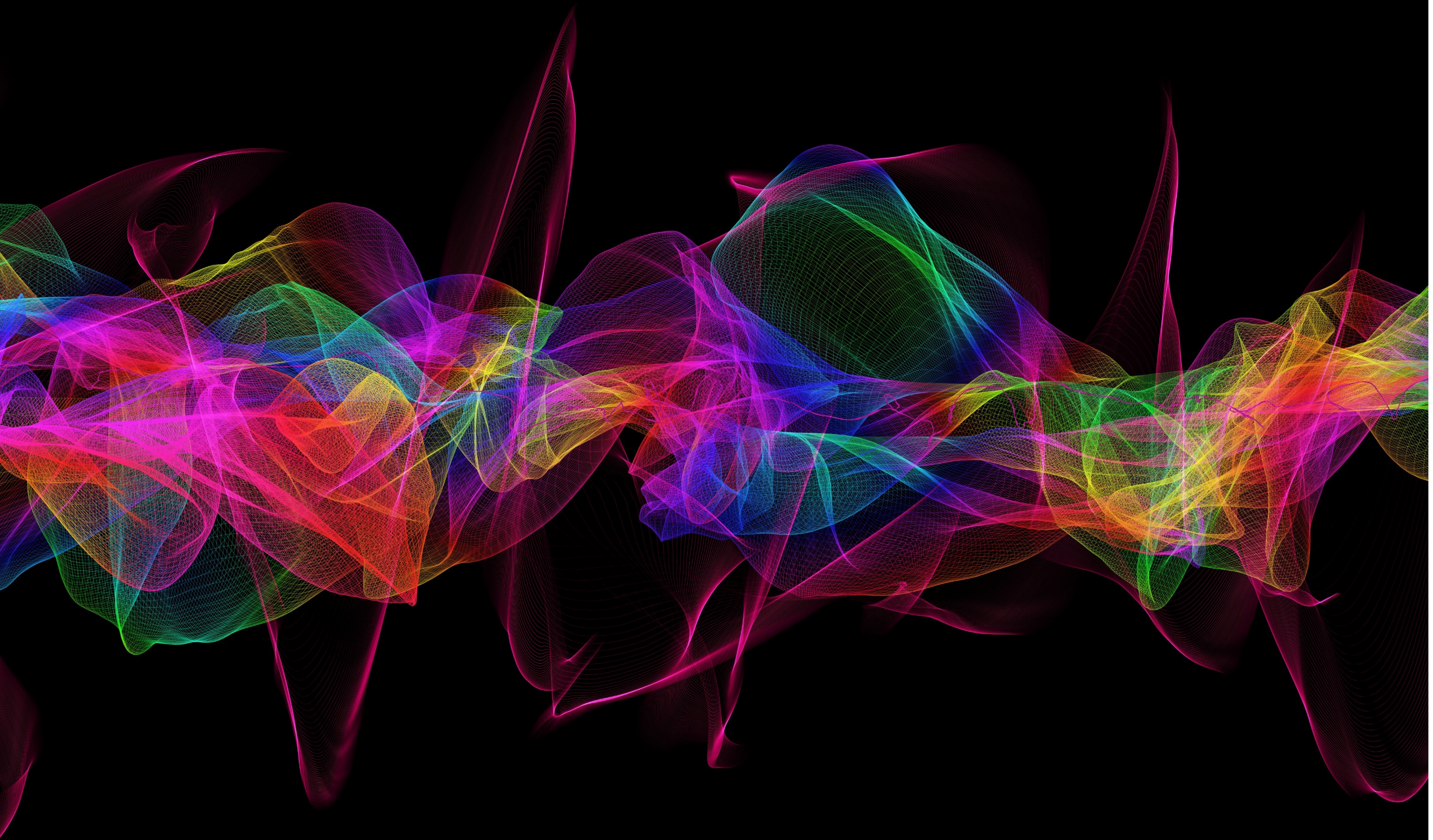
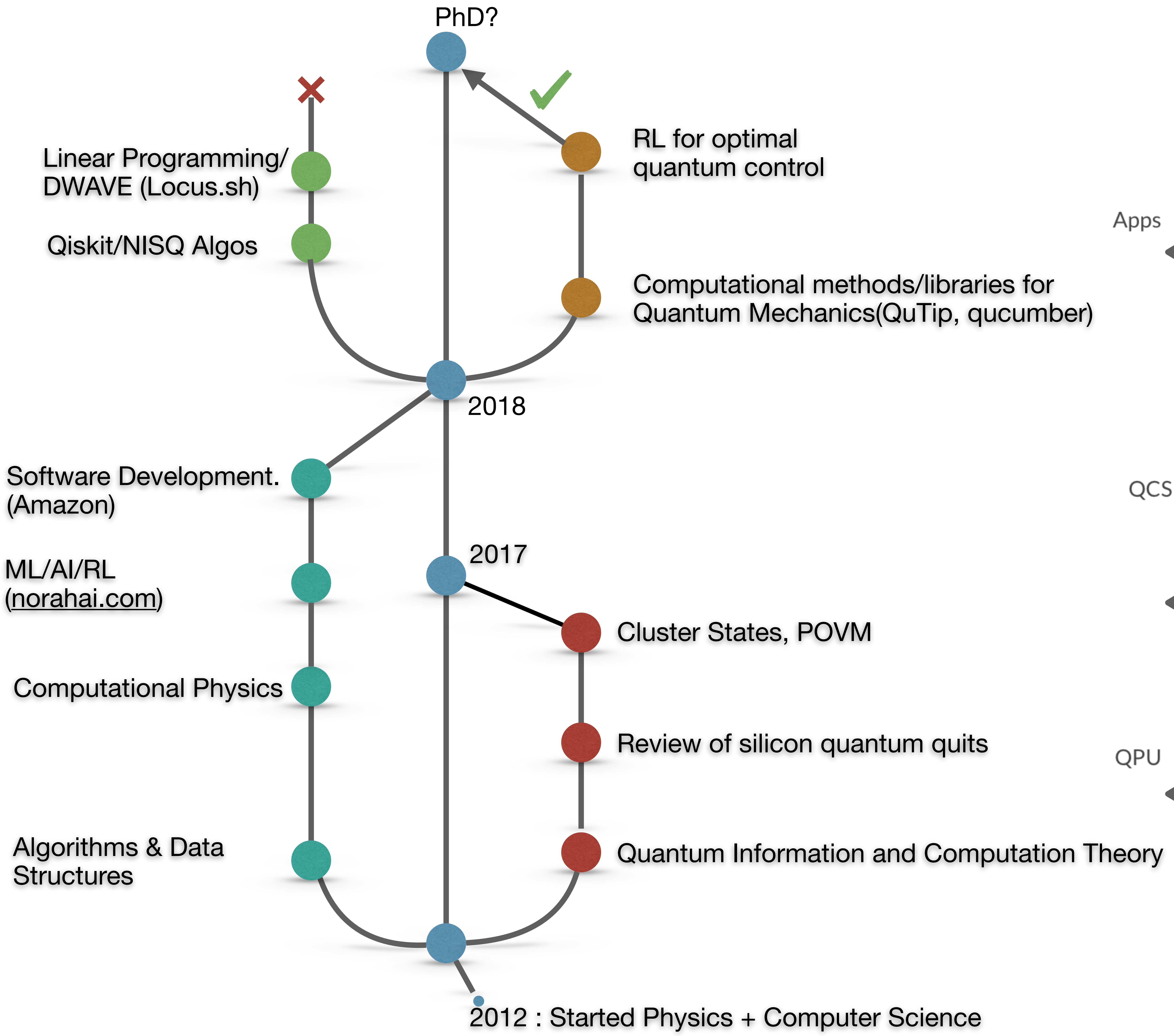
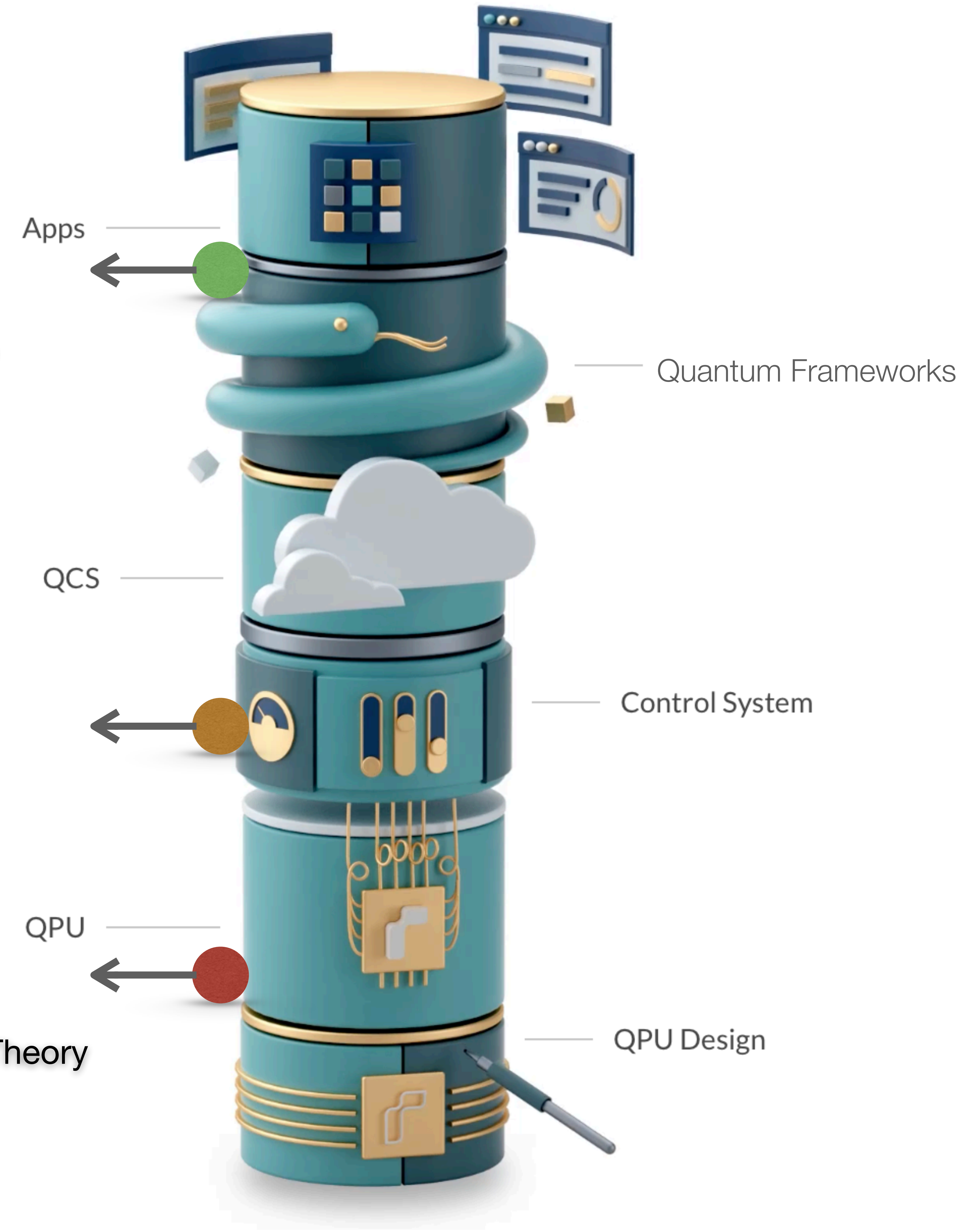


OPTIMAL QUANTUM CONTROL

Kevin Abraham





Stacks of a Quantum Computer
Image : Rigetti Quantum Computing

Hardware Components of a Quantum Computer

Error source ?		
Quantum Data Plane		
Qubit Implemementation Error (relaxation, dephasing)		

Hardware Components of a Quantum Computer

Error source ?		
Quantum Data Plane	Control and Measurement Plane	
Qubit Implememtation Error (relaxation, dephasing)	Signal Cross Talk Error	

Hardware Components of a Quantum Computer

Error source ?		
Quantum Data Plane	Control and Measurement Plane	
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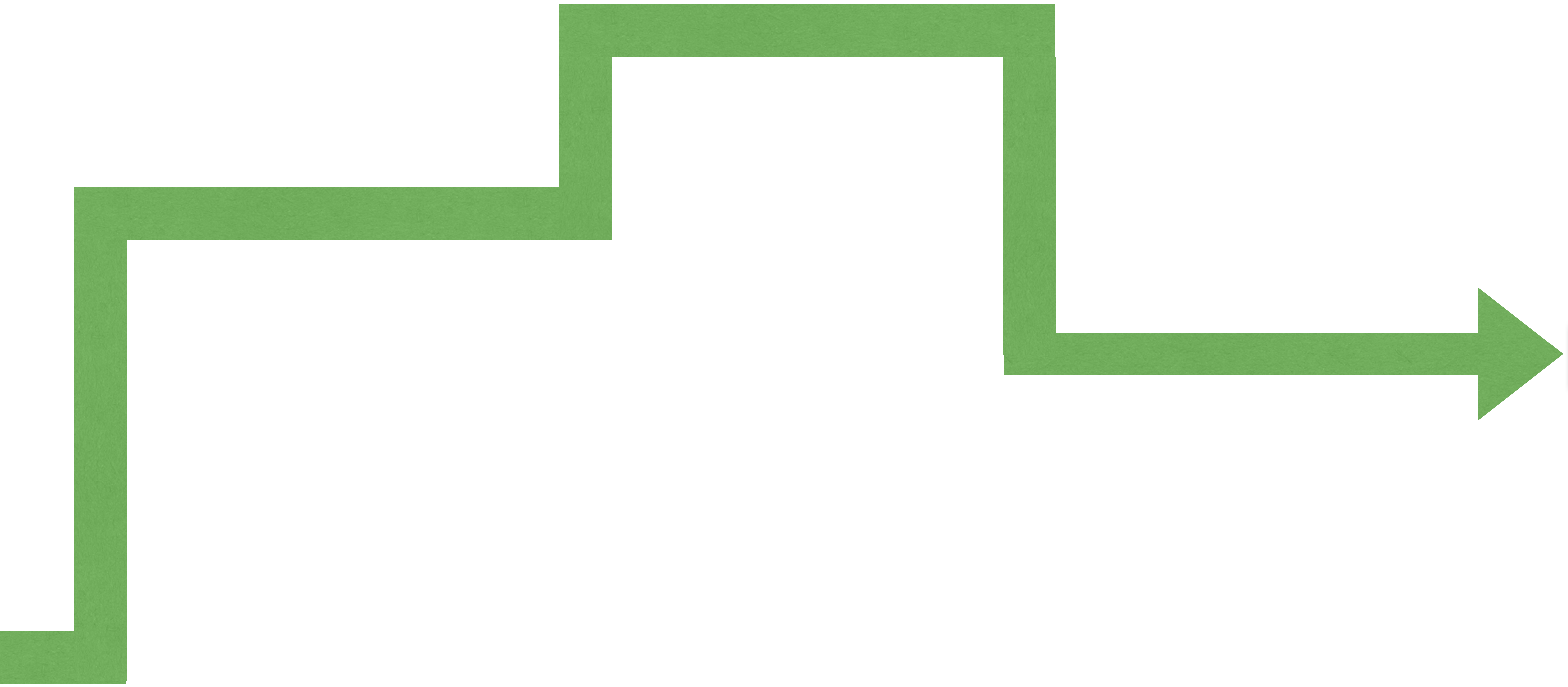
Requires extreme quantum engineering and fabrication for improving these		

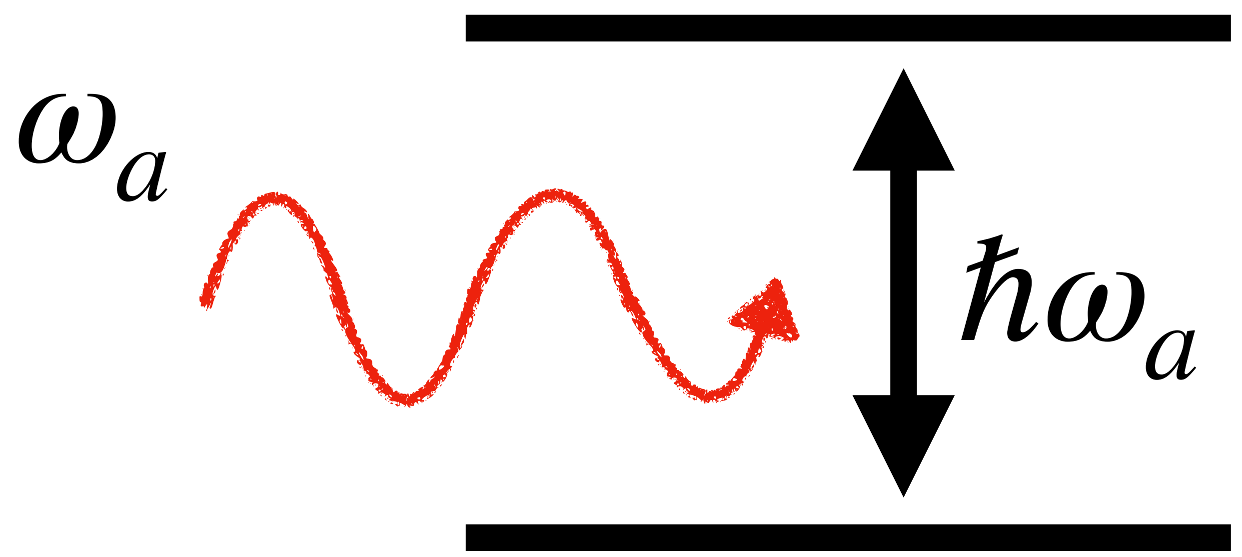
Hardware Components of a Quantum Computer

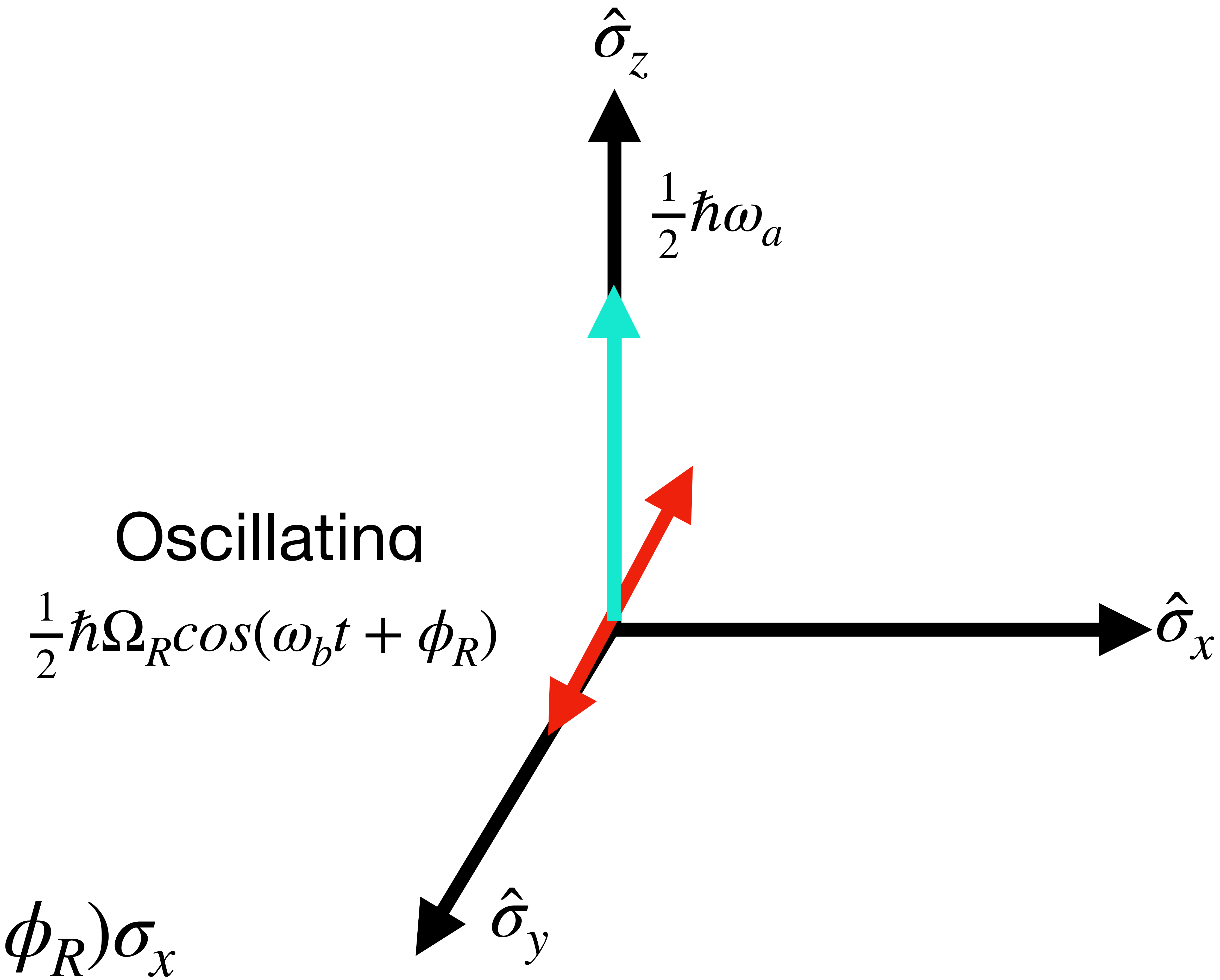
Error source ?		Reducing the hardware error ?
Quantum Data Plane	Control and Measurement Plane	Control Processor Plane
Qubit Implememtation Error (relaxation, dephasing)	Signal Cross Talk Error	What can the control process do to minimise the impact of noise ?
Requires extreme quantum engineering and fabrication for improving these		



Pulse Shaping

Preface : Rabi Oscillations



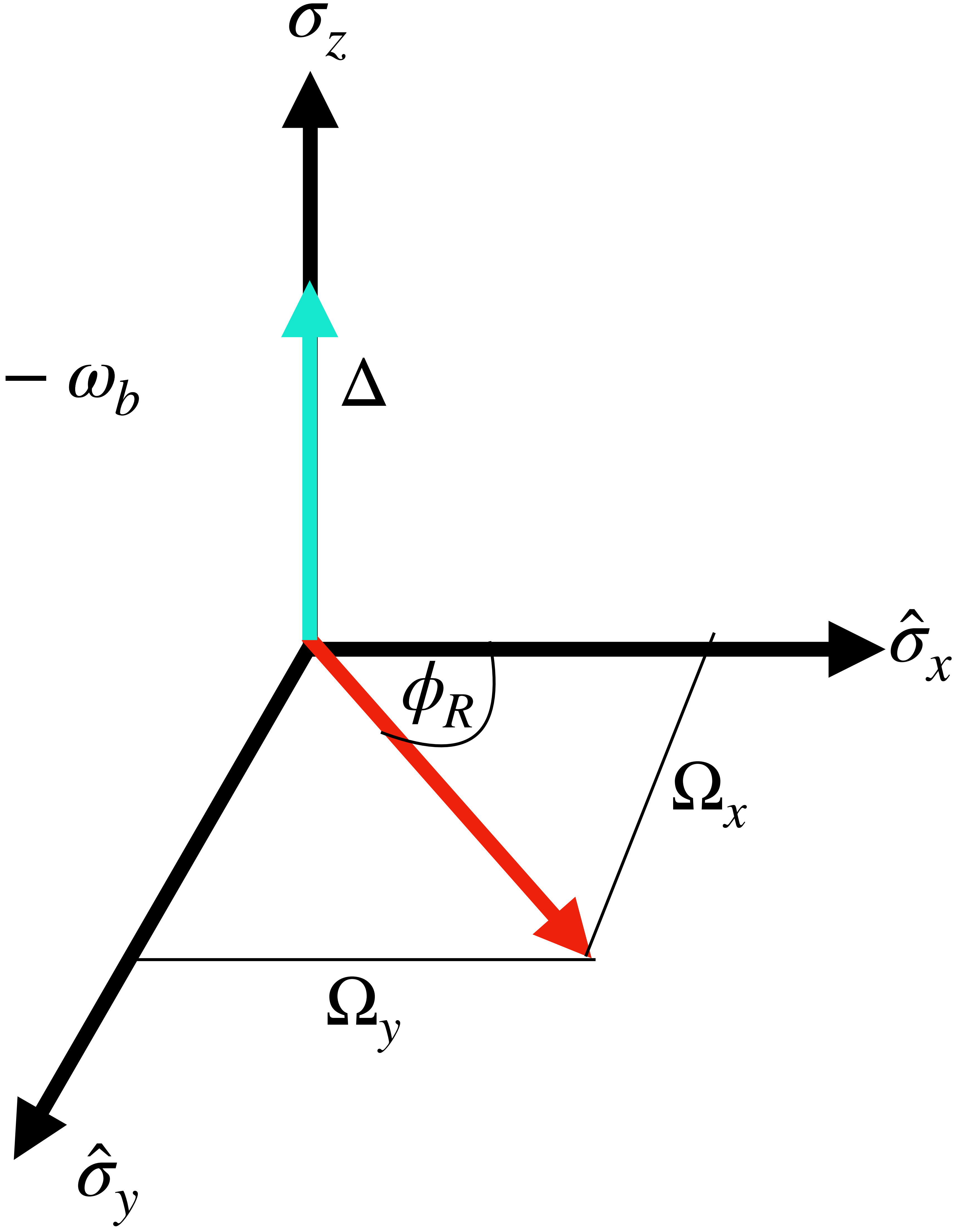


$$H = \frac{1}{2}\hbar\omega_a\sigma_z + \frac{1}{2}\hbar\Omega_R cos(\omega_b t + \phi_R)\sigma_x$$

Rotating Frame

$$H' = \frac{1}{2}\hbar(\Omega_x\sigma_x + \Omega_y\sigma_y + \Delta\sigma_z)$$

$$\Delta = \omega_a - \omega_b$$



Rabi Pulse

$$H' = \frac{1}{2}\hbar\Omega(X(t)\sigma_x + Y(t)\sigma_y) + \Delta\sigma_z$$

The rotation can be controlled

Rotation Speed $\longleftrightarrow$ Amplitude

Rotation Axis $\longleftrightarrow$ Phase : tan(X/Y)

Rotation Angle = Speed*Duration

= Area under the pulse envelope

RL FOR OPTIMAL QUANTUM CONTROL

What Reinforcement Learning?

Why Reinforcement Learning?

How Reinforcement Learning?

Problem Parameters

Ω Rabi Frequency

T Process Time

$\dfrac{\Delta}{\Omega}$ Relative Detuning

T_π $\dfrac{1}{2\Omega}$

γ_1 Spin Relaxation Factor

γ_2 Decoherence Factor

Problem Statement

Given no information about the system besides simulator of the system find the optimal pulse sequence to perform a unitary operation in the exact T given.

Target: The learned policy should be adaptable to:

- Variations in the problem parameter
- Different unitary operations

Training

Observables	$<\sigma_x> \quad <\sigma_y> \quad <\sigma_z>$ $\gamma_1 \quad \gamma_2 \quad F$
Reward	$F_{new} - F_{old}$ For end state F_{new} if $F_{new} > 0.99$

$$F \implies F(\Psi_\rho, \Psi_p) = || < \Psi_\rho | \Psi_p > ||^2$$

Environment

Qubit dynamics Simulation in Qutip,

with continuous actions

Tensorflow environment

(TFPyEnvironment) compactible

Agent

https://medium.com/@thechrisyoon/deriving-policy-gradients-and-implementing-reinforce-f887949

https://lilianweng.github.io/lil-log/2018/04/08/policy-gradient-algorithms.html

Neural Network (Actor network)

https://math.stackexchange.com/questions/3179912/policy-gradient-reinforcement-learnin
action-space

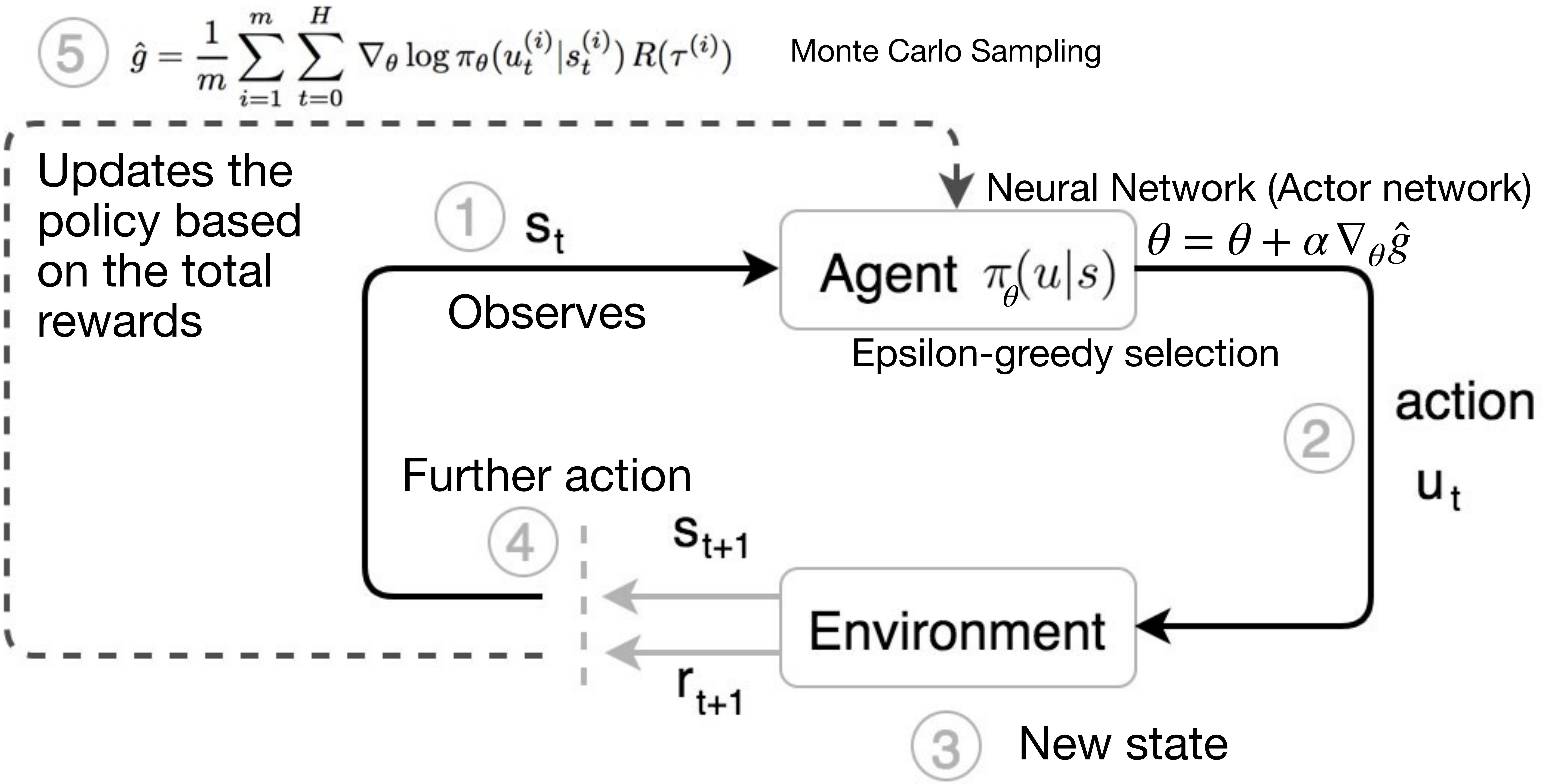
Policy Gradient Approach with replay buffer

(and discounted reward)

https://ml4a.github.io/ml4a/how_neural_networks_are_trained/

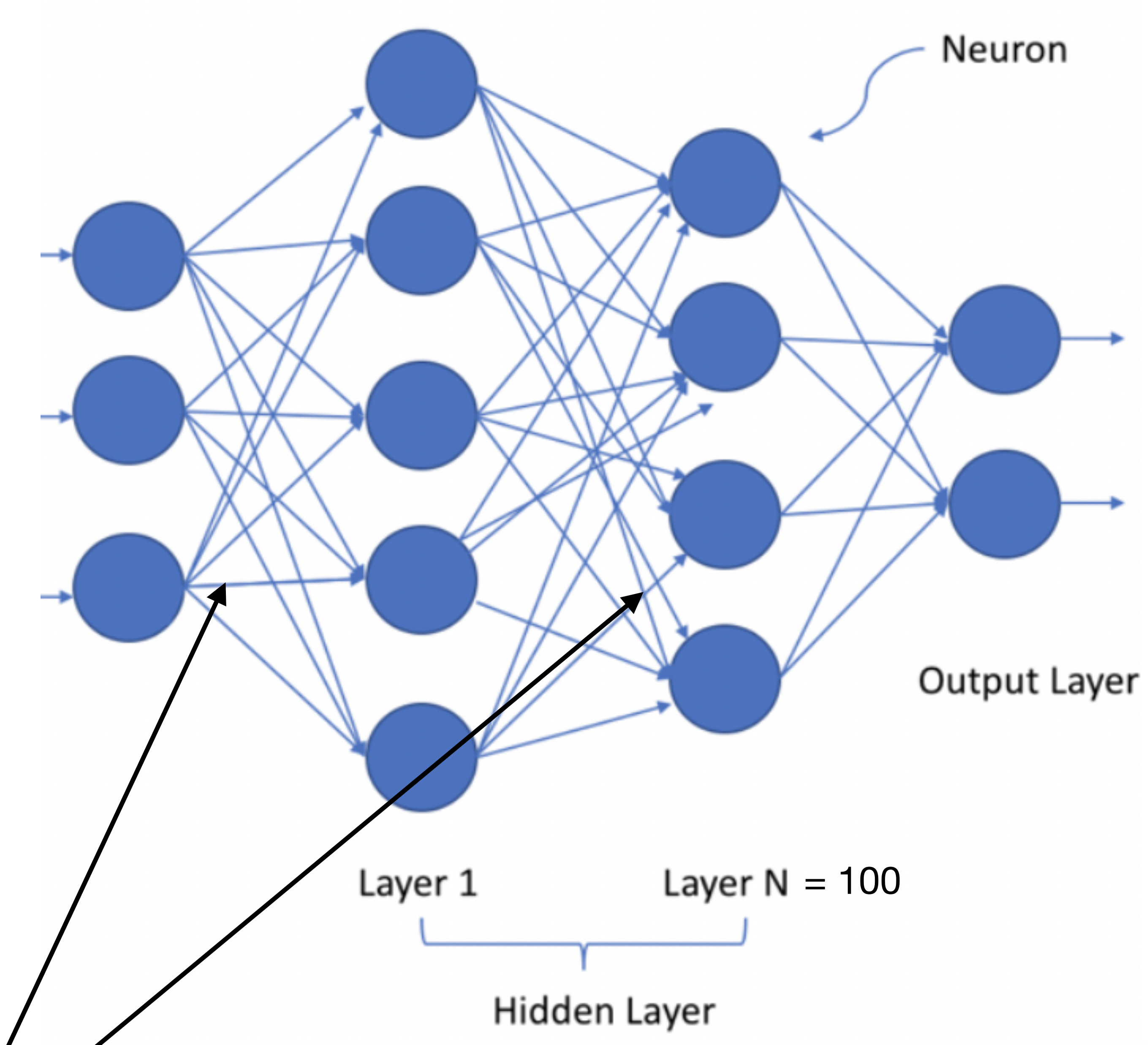
https://medium.com/@jonathan_hui/rl-policy-gradients-explained-9b13b688b146

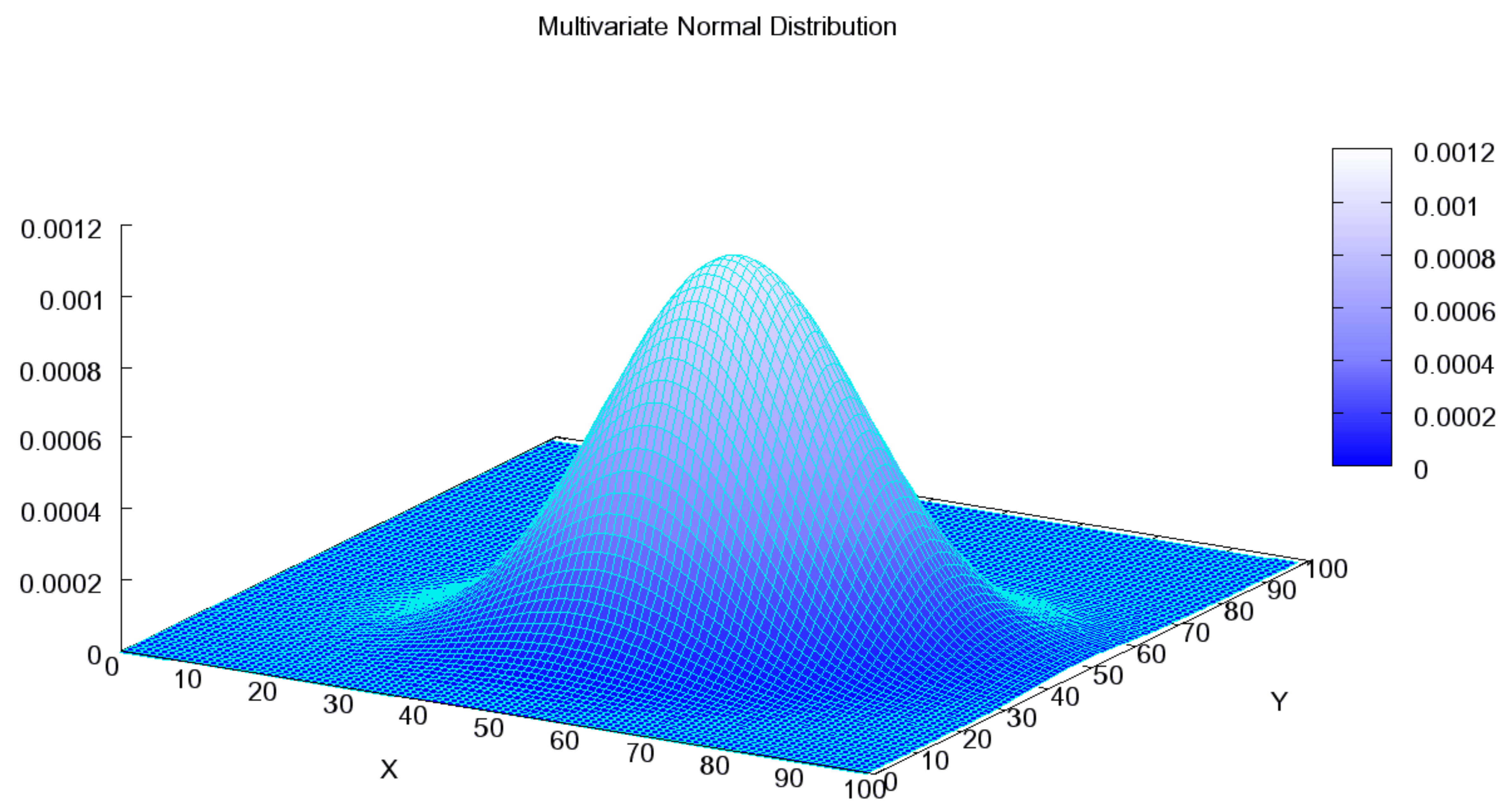
Policy Gradient



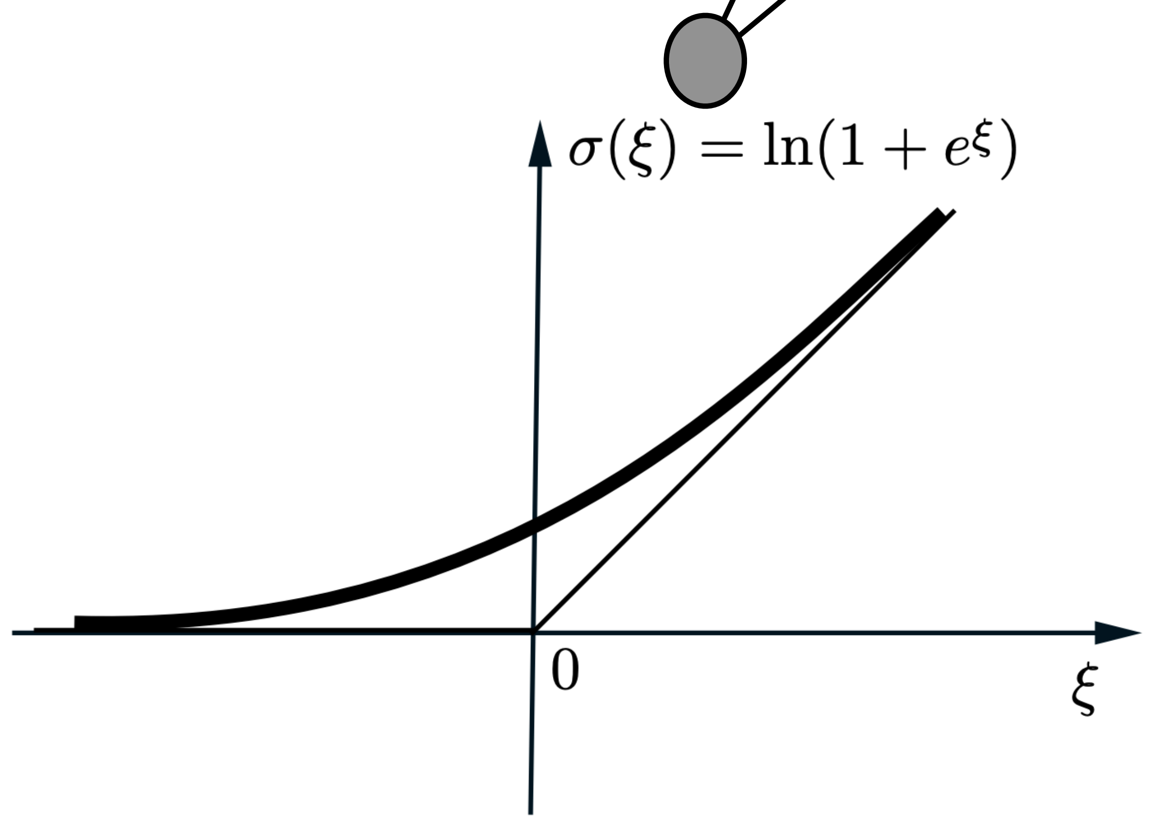
Agent

Observations Converted to Batches



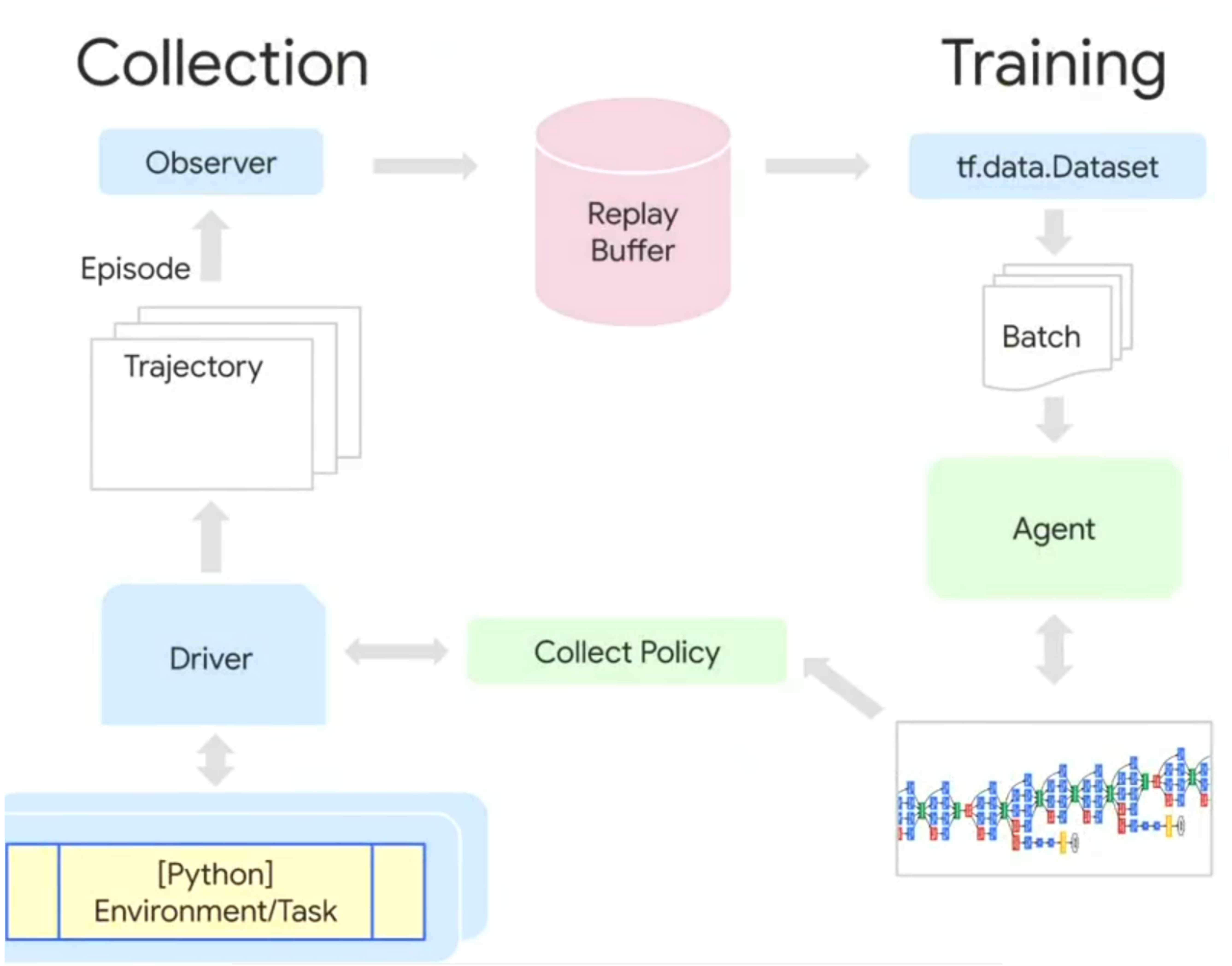


The softmax function on the a hidden layer gives the probability distribution. The Output layers are the possible set of actions.

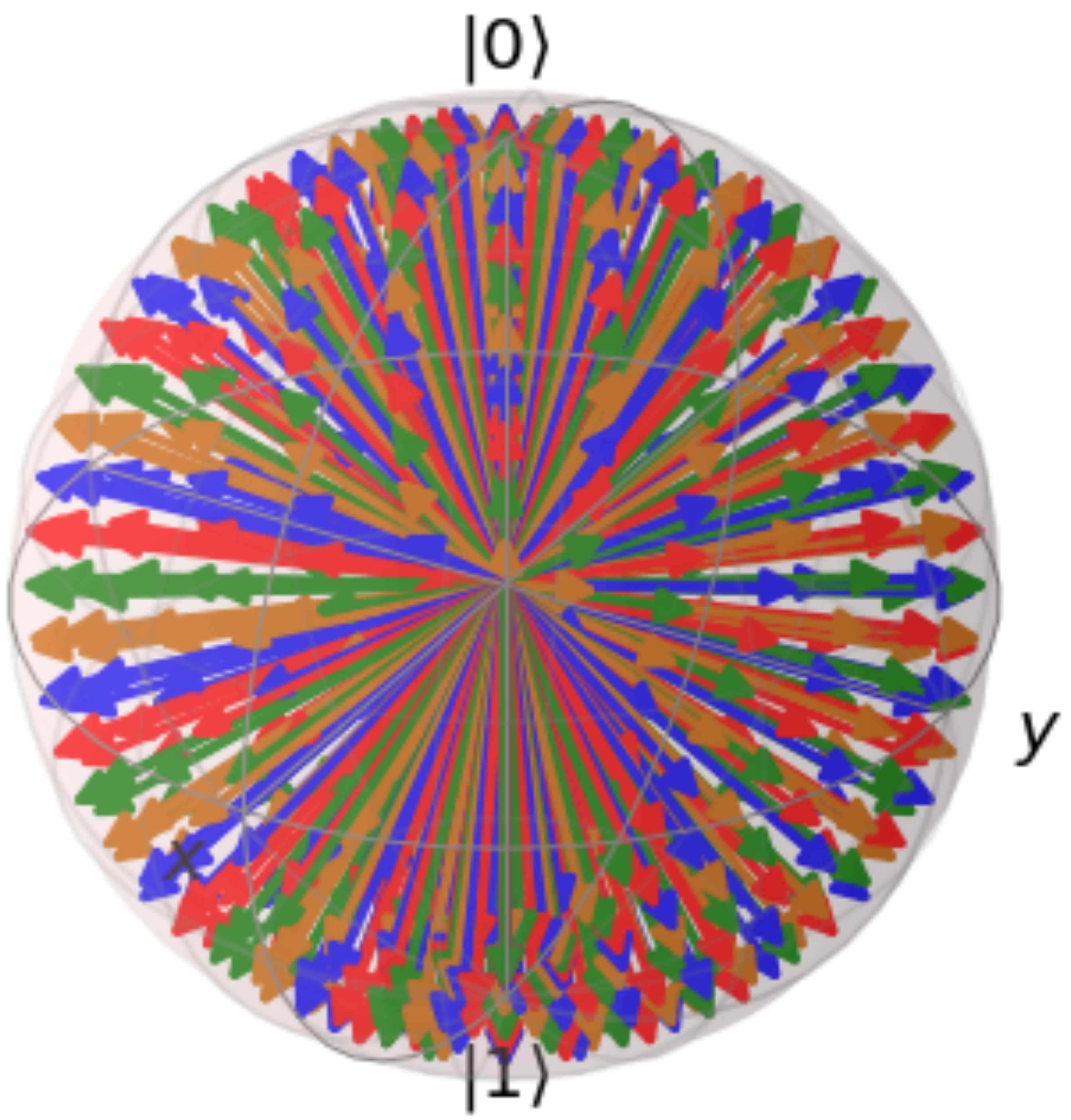


Relu smoothens the fn for differentiability

Uses Adam Optimiser for back-propogating errors



TF-AGENT : Image from TensorFlow Dev Summit 2019

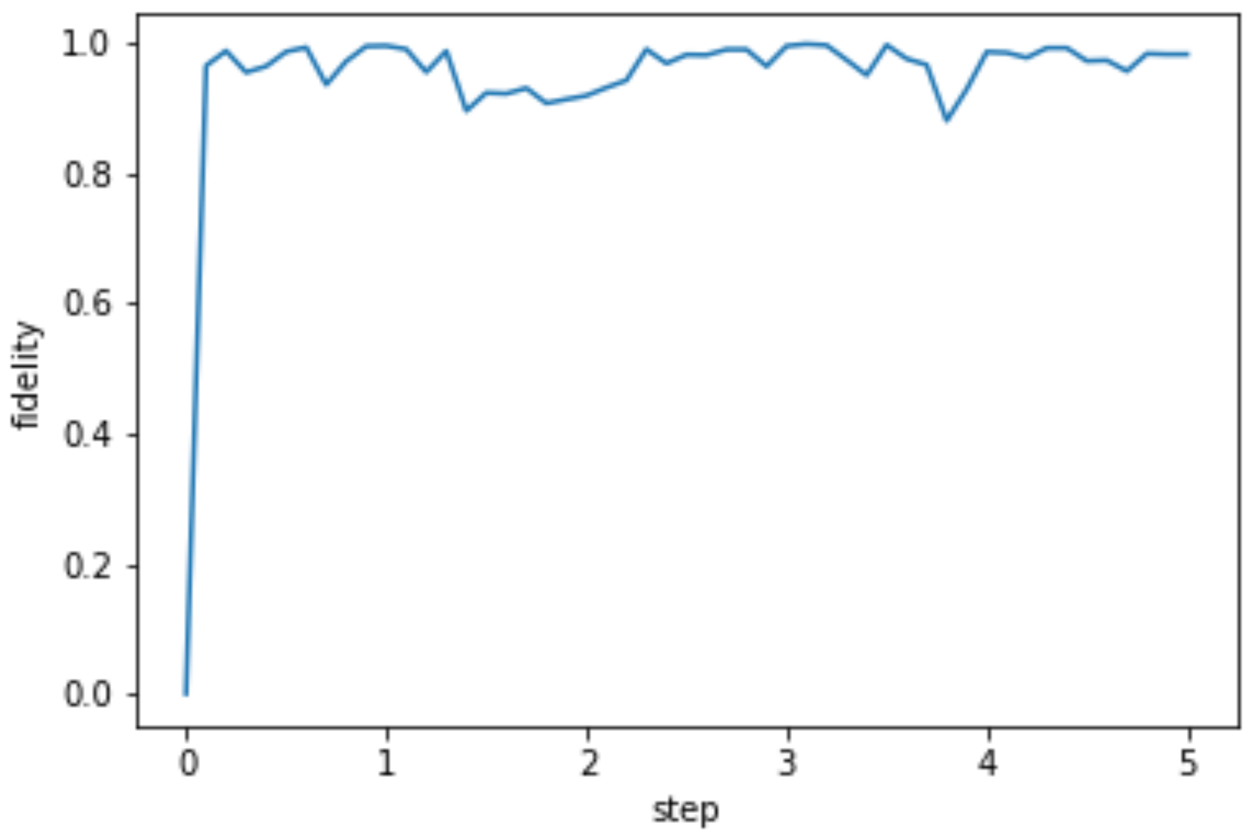


Initial Sates

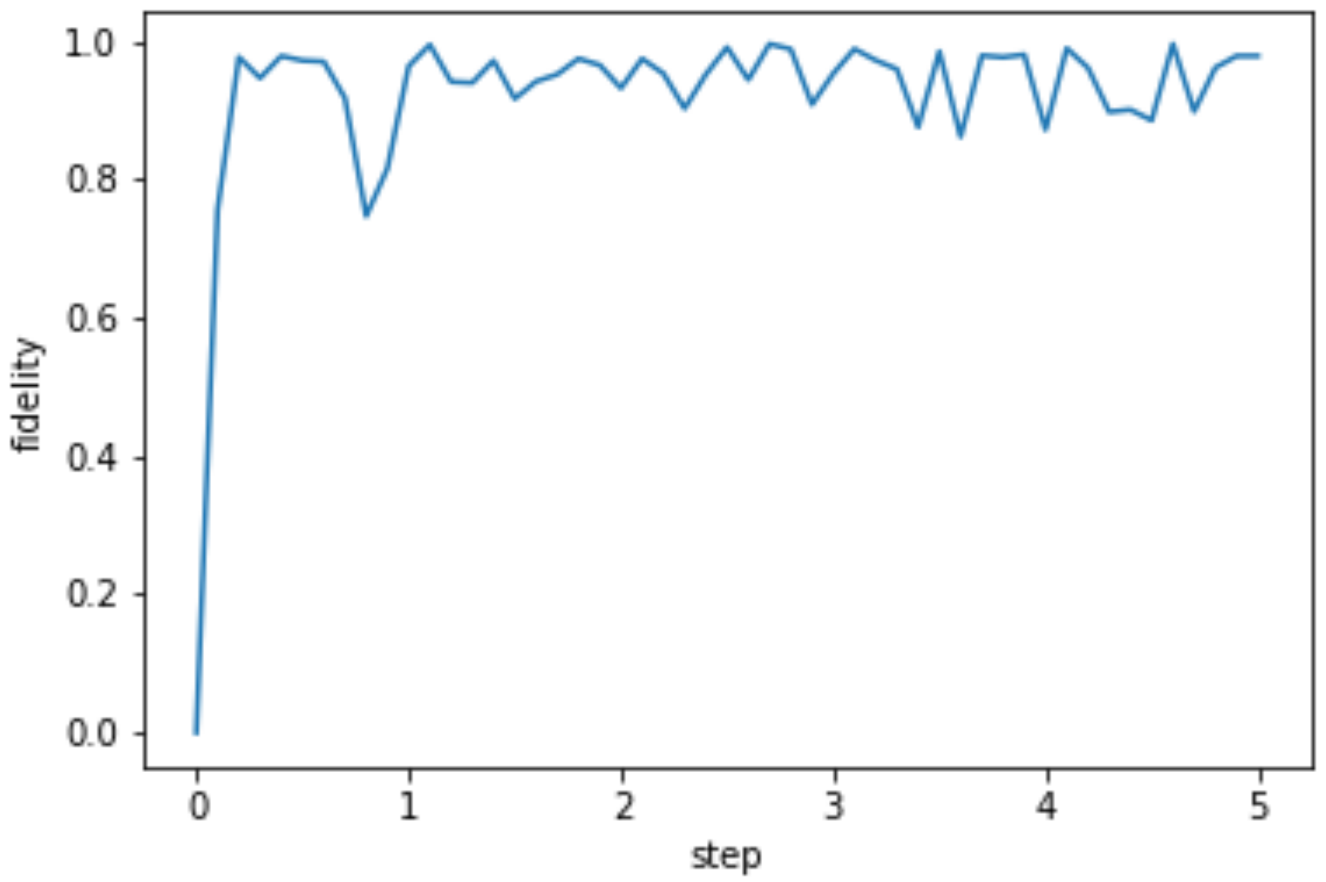
Results

$$\Omega = 1 \quad \frac{\Delta}{\Omega} = 0 \qquad T = 5\,T_\pi$$

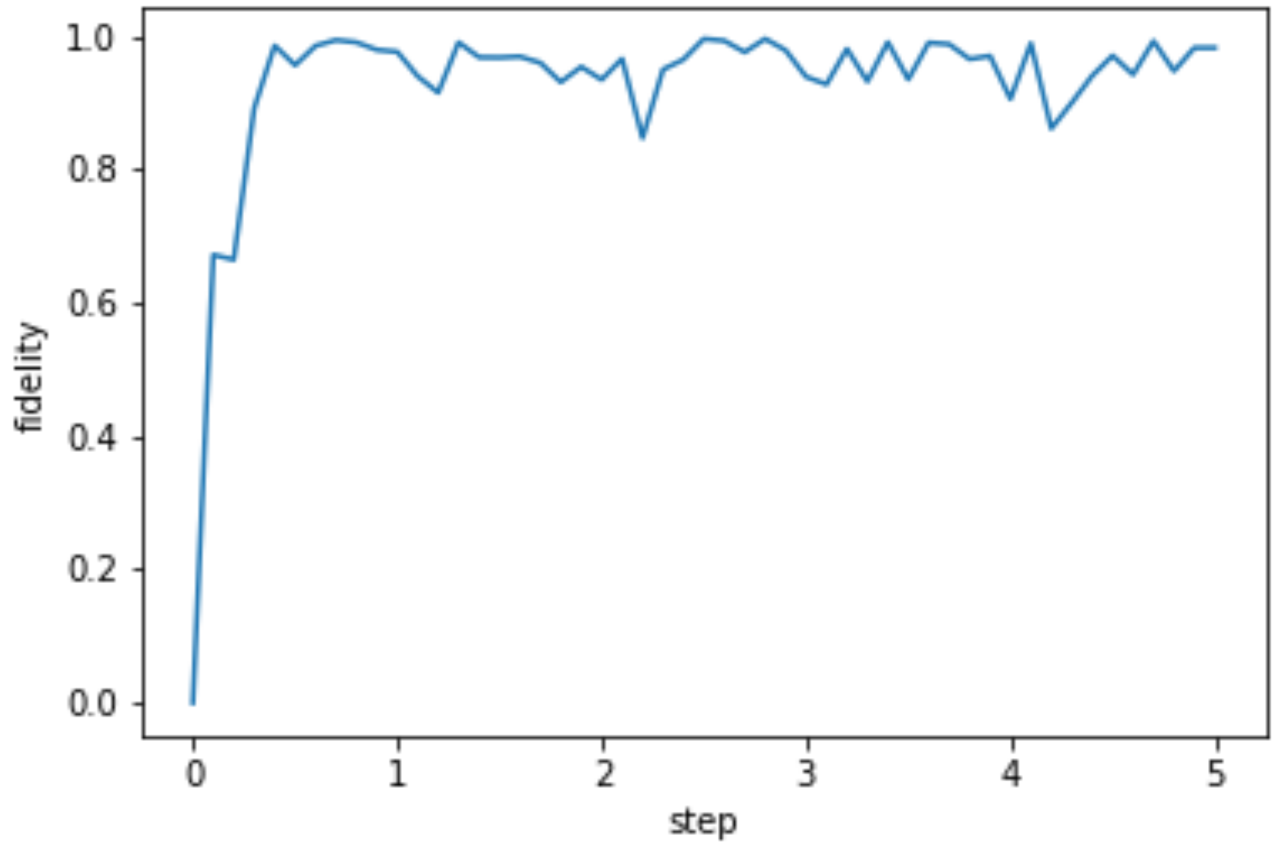
$$\Omega = 1 \quad \frac{\Delta}{\Omega} = 0.3 \quad T = 5\,T_\pi$$



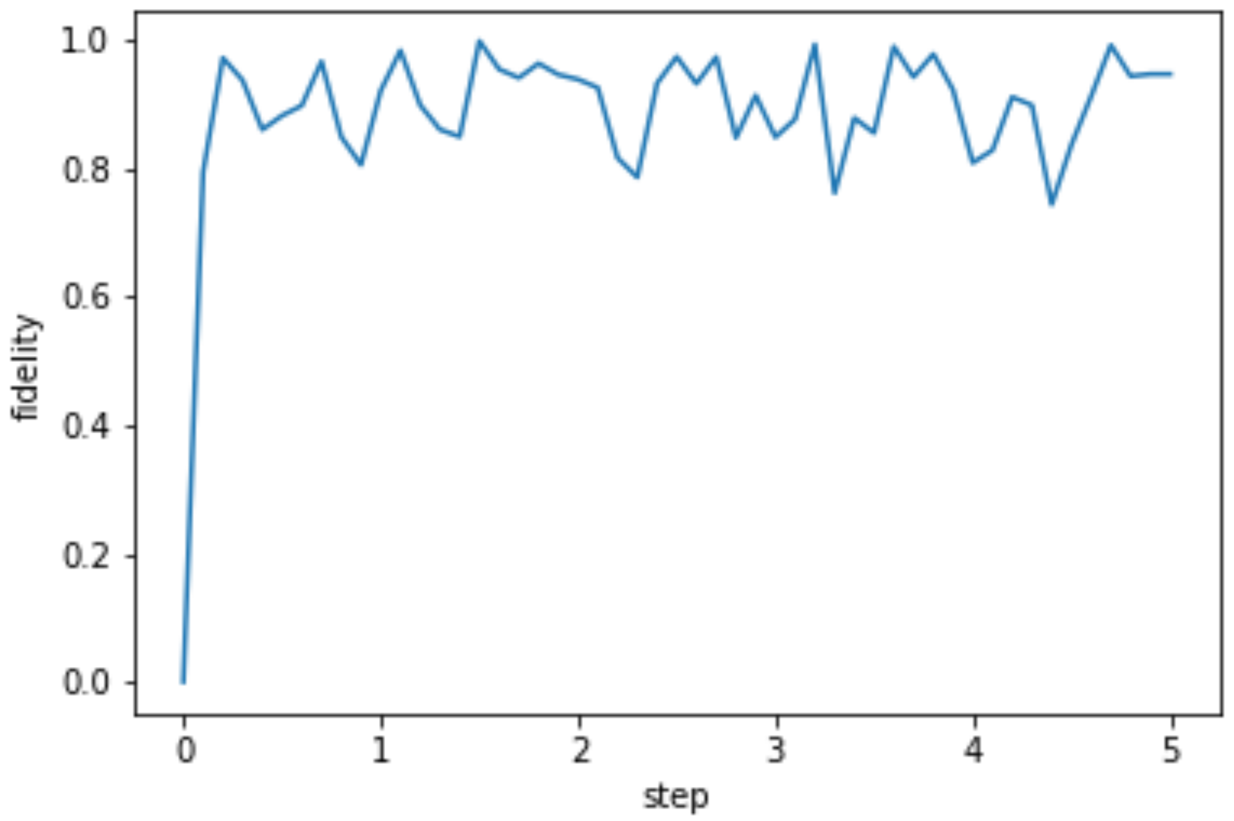
$\gamma_1 = 0 \qquad \gamma_2 = 0$



$\gamma_1 = 0 \qquad \gamma_2 = 0$

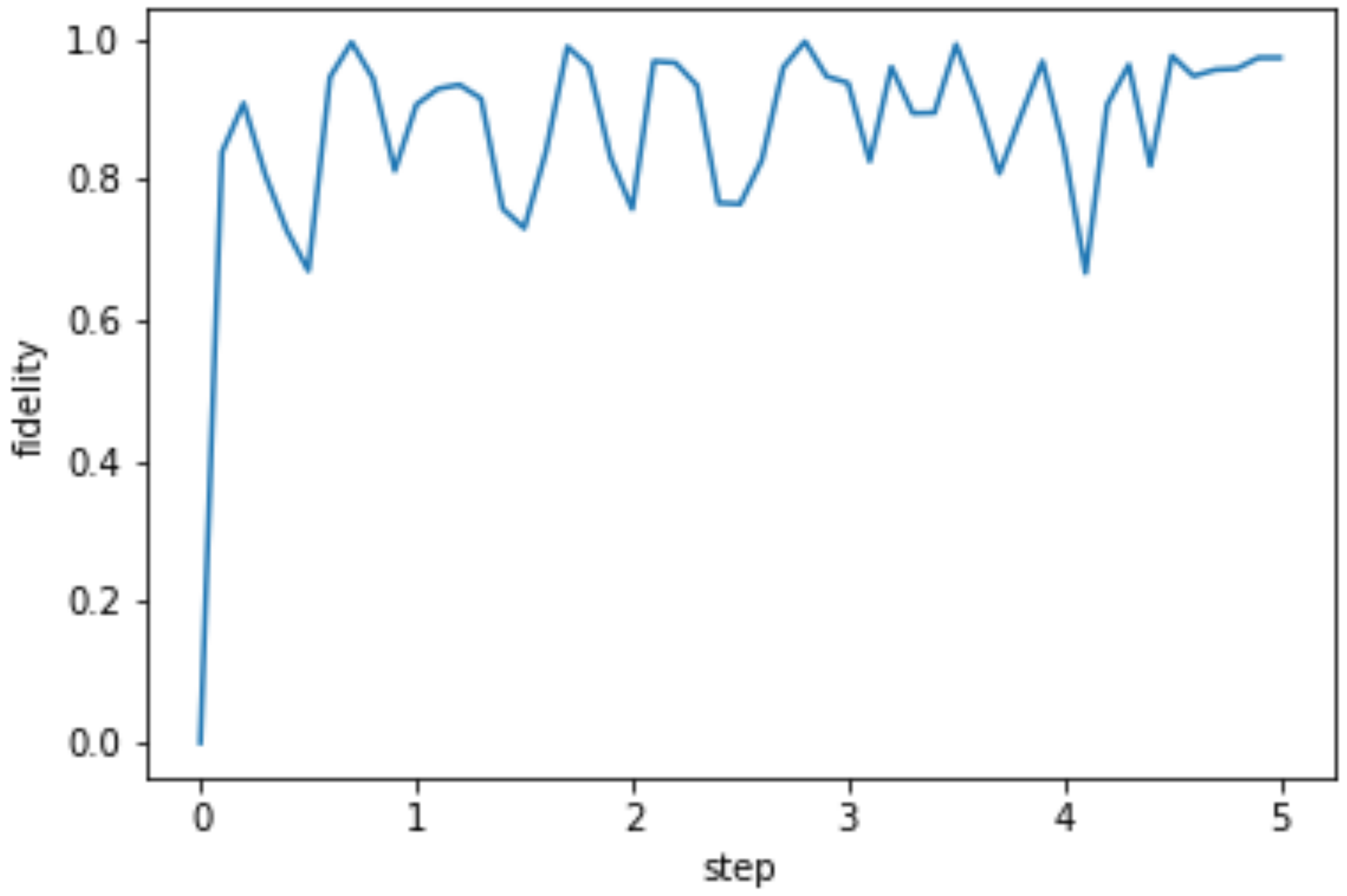


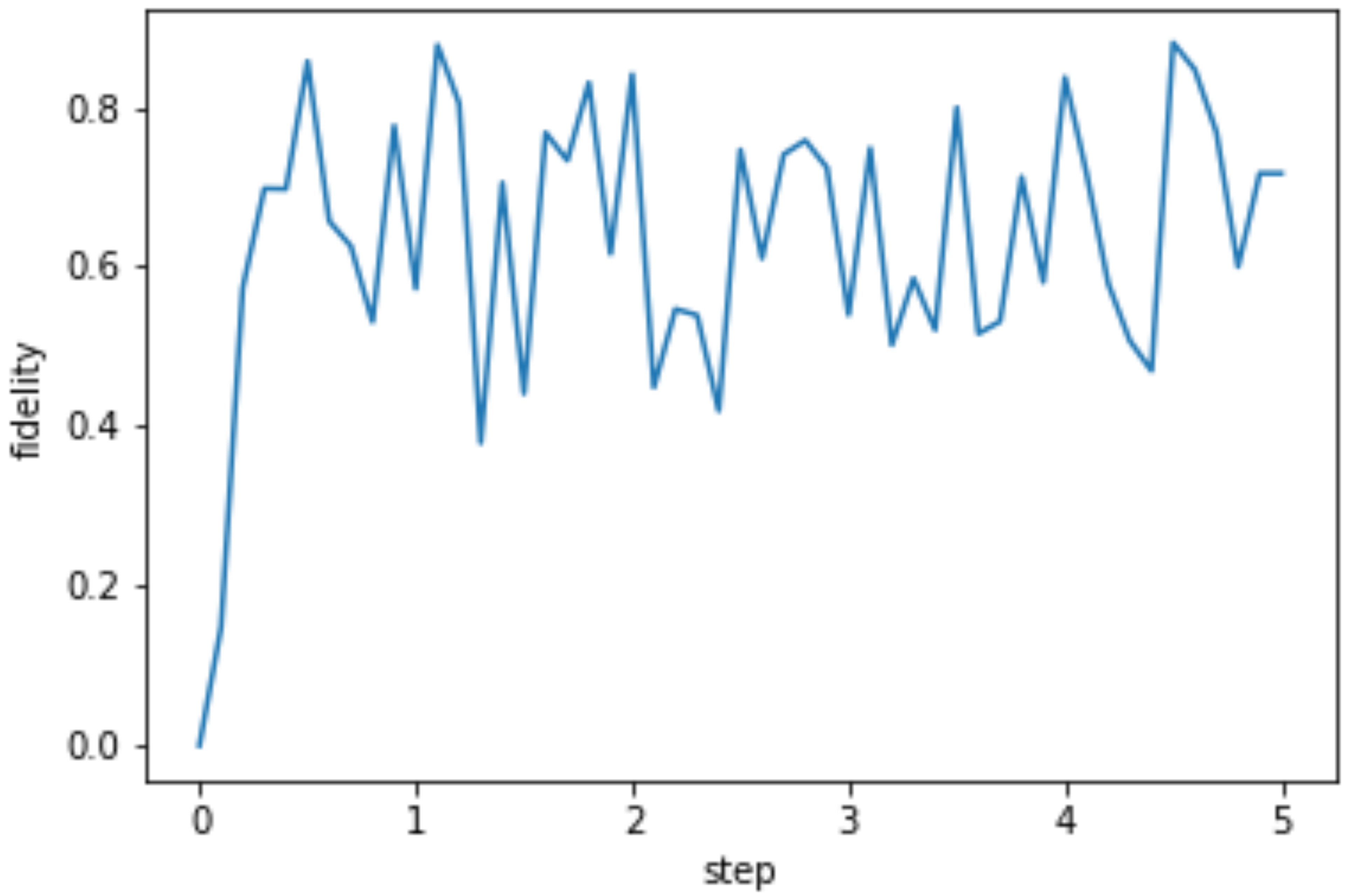
$\gamma_1 = 0.5 \quad \gamma_2 = 0.5$



$\gamma_1 = 0.5 \quad \gamma_2 = 0.5$

$$\Omega = 1 \quad \frac{\Delta}{\Omega} = 0.7 \quad T = 5\, T_{\pi}$$





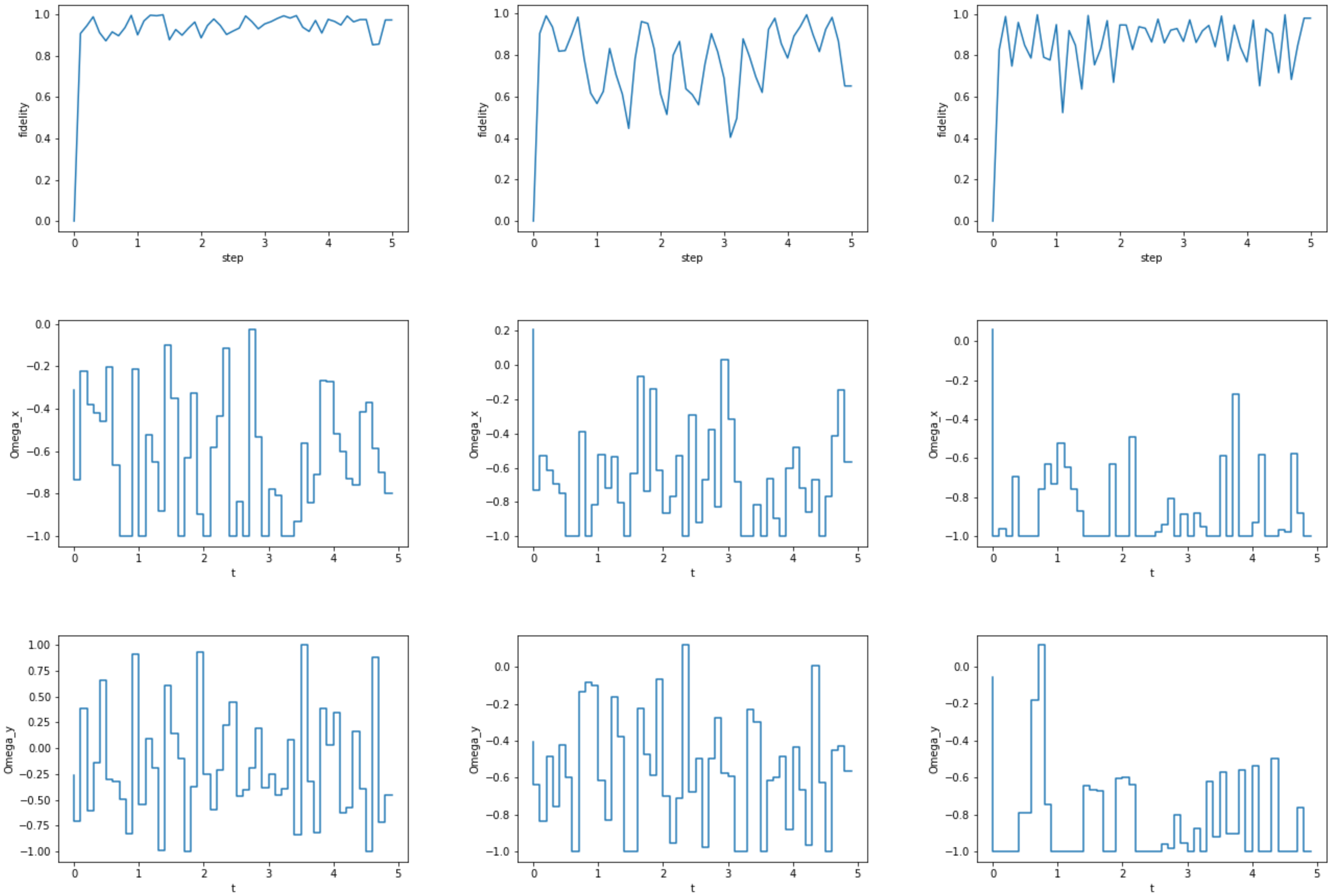
$\gamma_1 = 0 \qquad \gamma_2 = 0.1$

$\gamma_1 = 0 \qquad \gamma_2 = 0.1$

$\Omega = 1$

$\dfrac{\Delta}{\Omega} = 0.1$

$T = 5\,T_\pi$

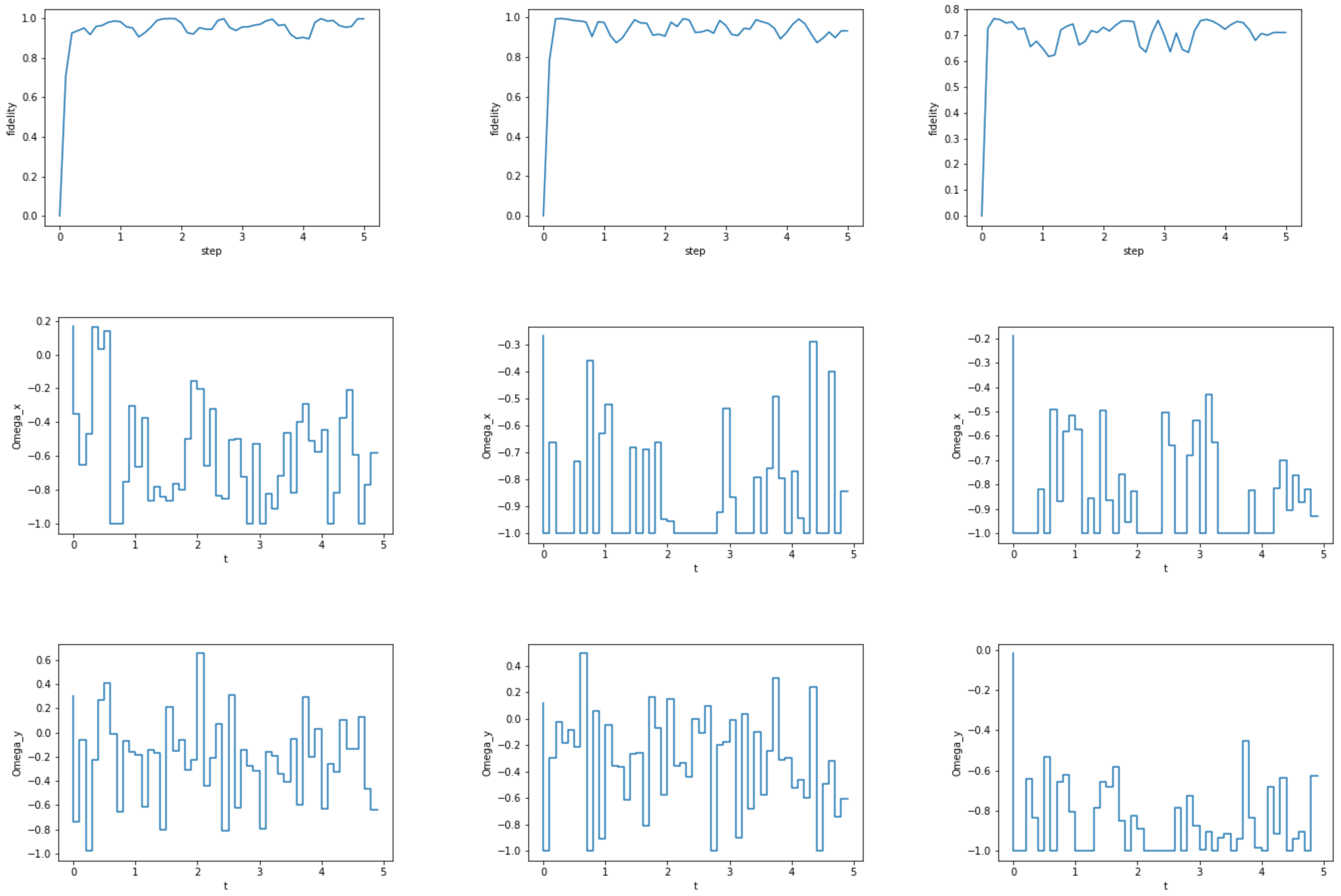


$\gamma_1 = 0$ $\gamma_1 = 10$ $\gamma_1 = 100$

$$\Omega = 1$$

$$\frac{\Delta}{\Omega} = 0.1$$

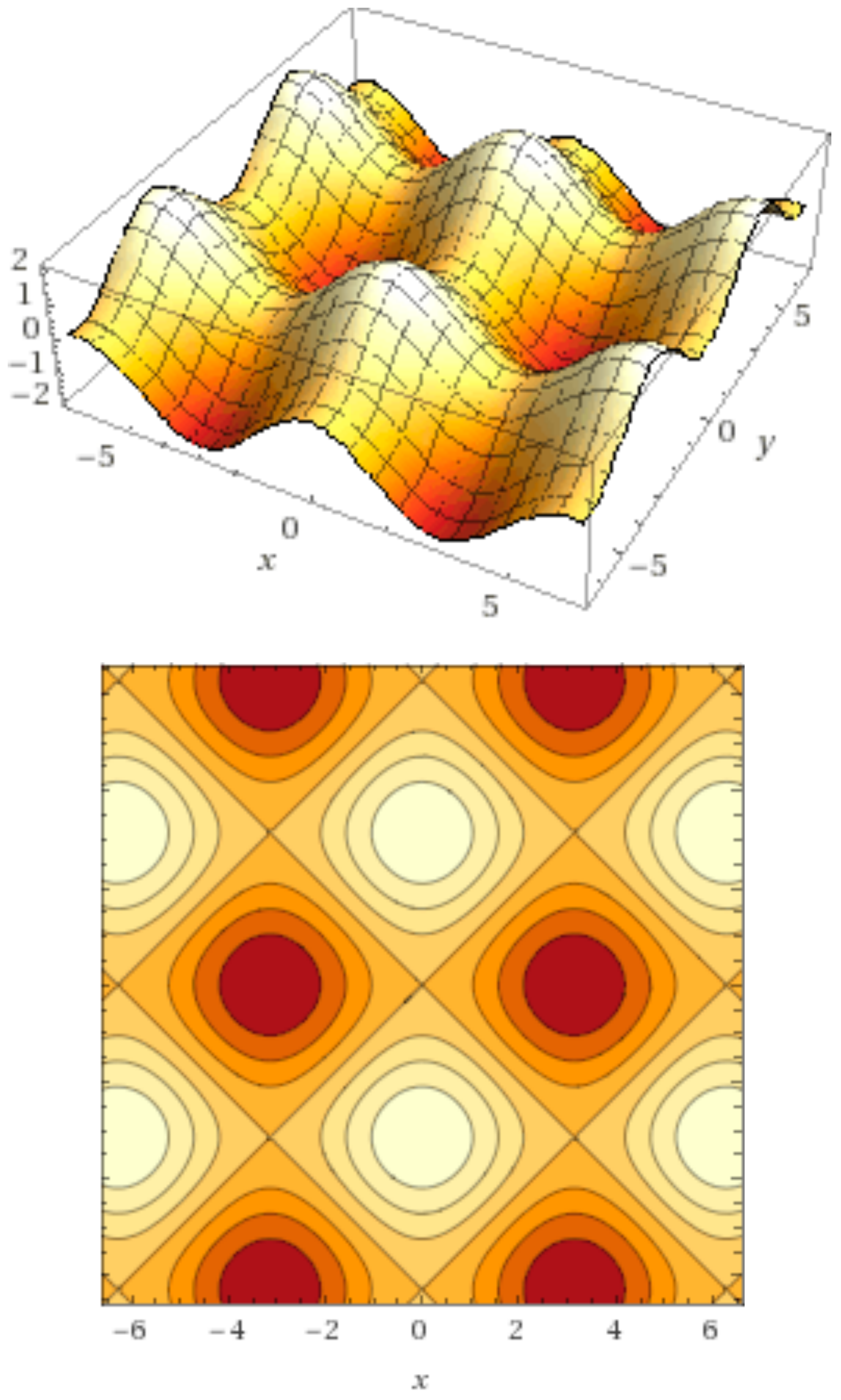
$$T = 5\, T_\pi$$

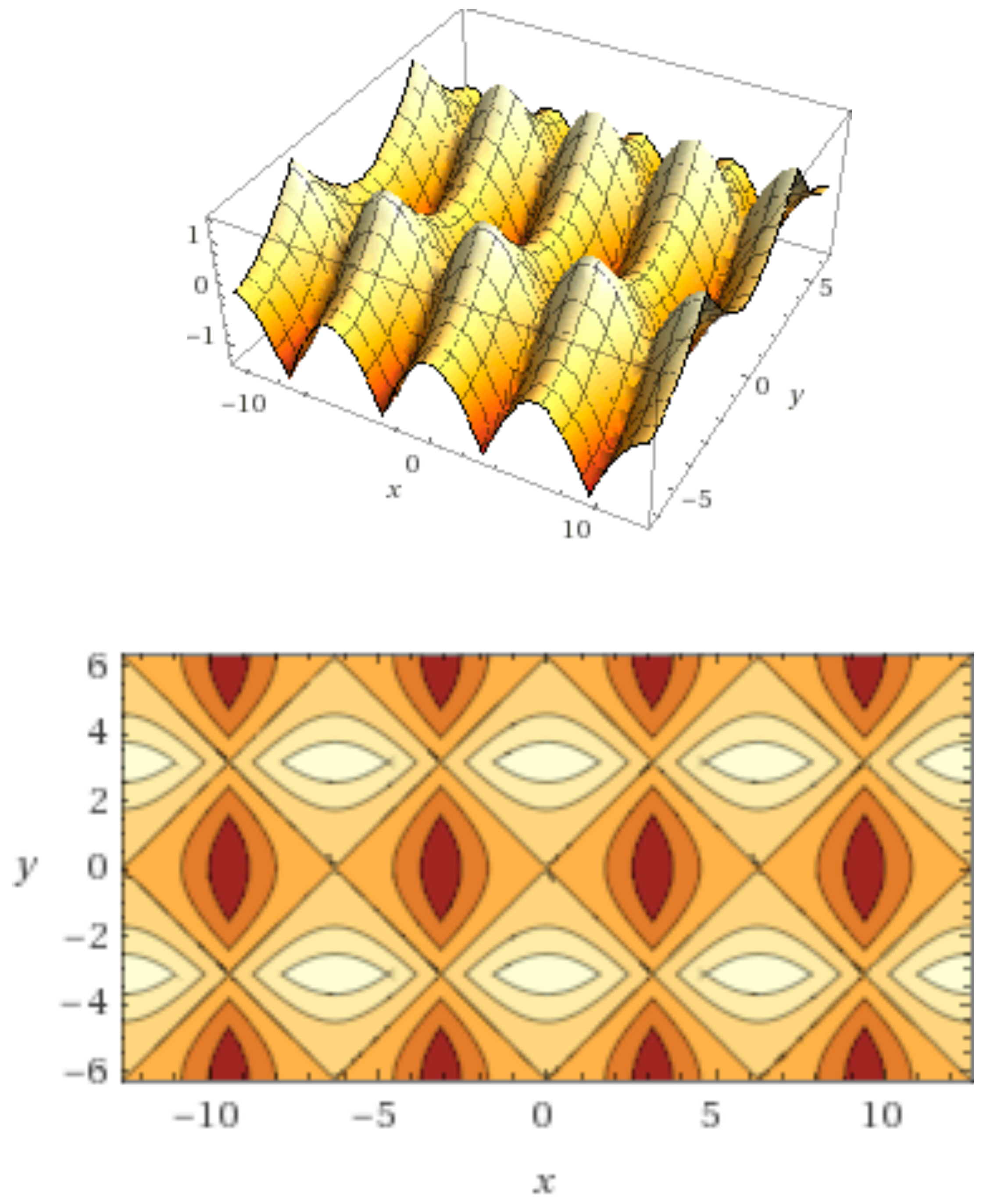


$\gamma_2 = 1$ $\gamma_2 = 10$ $\gamma_2 = 100$

An Open Question and Probable Interpretation

$$Fidelity \quad \text{VS} \quad \sqrt{Fidelity}$$





$$cos(x) - cos(y)$$

$$\sqrt{1 + cos(x)} - \sqrt{1 + cos(y)}$$

Scope of Improvements

Teaching the impact of error for generalisation with

<expected_state | resultant_state>

Expected state : state expected by the action in the absence of noise

Resultant_state : Actual state resulted by the action

Florian Frank,1 Thomas Unden,1 Jonathann Zoller,2 Ressa S. Said,2 Tommaso

Calarco,2 Simone Montangero,2, 3 Boris Naydenov,1 and Fedor Jelezko1

Silicon Quantum ElectronicsSusan N. Coppersmith, Mark A. Eriksson

Griffiths introduction to quantum mechanics

Resonantly driven CNOT gate for electron spins

D. M. Zajac,1 A. J. Sigillito,1 M. Russ,2 F. Borjans,1 J. M. Taylor,3,4

Reinforcement Learning and Optimal Contro

Dimitri P. Bertsekas Massachusetts Institute of Technology

A Survey of Optimization Methods from