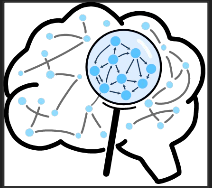
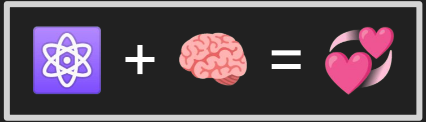
Quantum Hybrid Neural Decoding

QHack 2023

Introduction

Inspired by advances in neuroscience and related recording technology, the Neural Latents Benchmark Challenge (NLB) released datasets of brain activity and a Machine Learning Challenge for the neuroscience community in 2021.

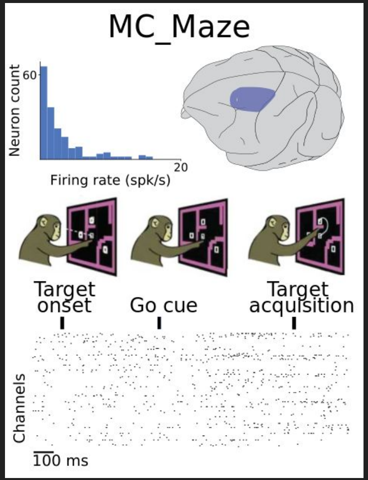




In this project, I continue work on the NLB dataset by exploring the intersection between Hybrid Quantum ML and Neural Decoding.

Data Overview

The NLB MC_Maze dataset is a set of neural activity recordings from Macaque Monkeys. A monkey with a brain implant views a screen, and is instructed to move a digital cursor through a simple maze. Each electrode on the monkey's implant records neural activity, measured by proximate spikes in voltage. These spikes in activity can be used to predict the actual movement that the monkey performed.

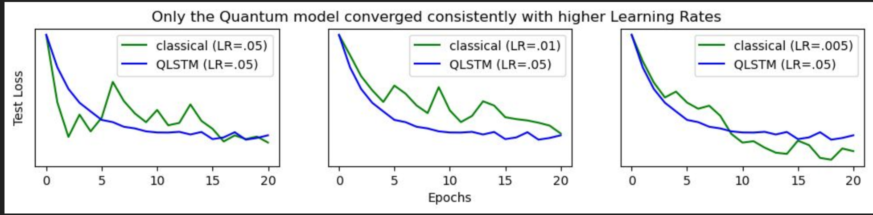


Credit -- The dataset was provided by Krishna Shenoy, Mark Churchland, and Matt Kaufman from Stanford University, and you can learn more about the task design, data collection, and their analyses of the data in a number of papers, including Churchland et al. 2010.

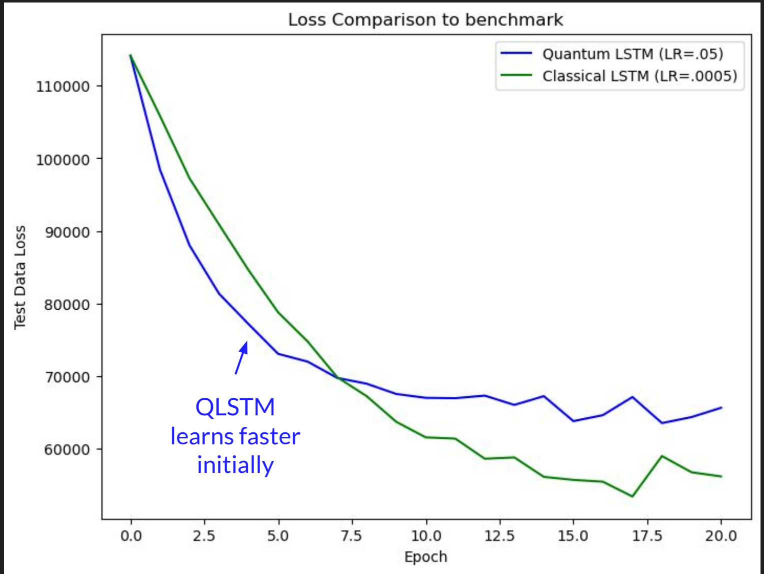
Process & Key Results

- Both Classical and Quantum-Hybrid Time Series models were trained to decode the monkey's neural signals and predict the X-dimension hand velocity.

- Notably, the QLSTM model is able to afford a higher learning rate, and therefore can learn faster over the initial epochs
  - SEE 'Future work' for more - this may be valuable for Brain-Computer Interfaces Research
  - The faster learning can be attributed to a higher learning rate. When the Classical Model was trained with a comparably high learning rate, the loss was erratic and the model did not consistently converge - examples below:



- The classical benchmark achieved overall better results vs. the small & shallow Quantum-Hybrid LSTM (QLSTM) architecture
  - QLSTM used only 4 qubits for each VQC. As Quantum Computing Scales, this performance gap may be overcome with wider quantum layers.



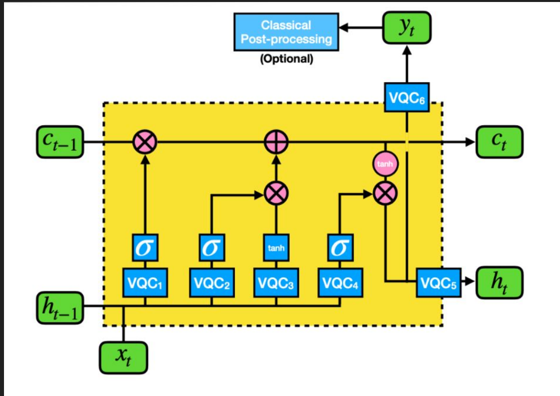
Predicting X-dim velocity	Classic LSTM	QLSTM
R^2	.53	.41

Discussion and Future Work

- 🧠 Brain-Computer-Interfaces (BCIs) have shown great promise allowing users with tetraplegia to control a mouse cursor, write sentences with imagined handwriting, produce artificial speech from imagined speech, feed themselves with a robotic neural prosthetic, play video games, and more.

- 🧠 However, BCIs have been limited to a clinical setting where researchers and participants collaborate in real-time to collect trial data and fit a neural decoder. The neural signal that is recorded in non-stationary for various reasons (e.g. array movement, neural drift, etc) and so **decoders need to be retrained often**. Typically a decoder is trained at least every day, on the newest collected data, meaning the **model is training while the participant waits** until the trial can continue. Often neural decoding in this clinical setting is limited to simple linear methods, in part because they fit quickly.

- 🧠 We have shown, that an QLSTM fits faster with a higher learning rate than possible with classical LSTM. Future developments of quantum machine learning could potentially lead to extremely fast fitting of non-linear models allowing BCI researchers to experiment and collaborate in real-time with more powerful decoding algorithms.



Quantum LSTM Cell
Image credit to Samuel Yen-Chi Chen, Shinjae Yoo, Yao-Lung L. Fang ([2009.01783] Quantum Long Short-Term Memory)

Potential Future Research at AE Studio:

- *Solidify this result using Learning Rate Schedulers for both models*
- *Applying VQCs in architectures besides LSTMs for Neural Decoding*
- *Wider Quantum layers on real hardware instead of simulators*

Neural Latents Benchmark '21: Evaluating latent variable models of neural population activity, Felix Pei and Joel Ye and David M. Zoltowski and Anqi Wu and Raeed H. Chowdhury and Hansem Sohn and Joseph E. O'Doherty and Krishna V. Shenoy and Matthew T. Kaufman and Mark Churchland and Mehrdad Jazayeri and Lee E. Miller and Jonathan Pillow and Il Memming Park and Eva L. Dyer and Chethan Pandarinath; ARXIV: https://arxiv.org/abs/2109.04463