A new age of computing: Predicting energy demand with a hybrid quantum-classical computing framework

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1 INTRODUCTION

In 2024 Google announced a new quantum computing chip named Willow, showing the world that significant progress is being made in the world of quantum computing. Quantum systems produce atypical patterns that classical systems are thought not to produce efficiently [1]. This suggest that quantum computer would be a good fit for increasing performance of machine learning problems however access is limited as of now. Because of the limited access researchers have tried emulating quantum computing on classical machines creating hybrid quantum-classical computing setups. These setups have shown that performance increases can already be achieved in the accuracy department, this is evident in other research such as [Ganguly] where it was applied on a high spectral image recognition deep learning method. For this research, we want to see if similar performance increases can be achieved on a prophet Long Short Term Memory (LSTM) model using a hybrid quantum-classical setup to predict energy demand based on economic and climate predictors.

1.1 Research question

This thesis wants to answer the following research question: "To what extent can the TensorFlow quantum computing framework approximate the same accuracy as its classical computing counterpart when trying to predict energy demand using climate and economic predictors using a Prophet Long Short-Term Memory neural network and can those predictions be used on all seasons"

1.2 Sub-question: Accuracy

Does the Tensorflow quantum framework yield similar results to its classical computing counterpart.

1.3 Sub-question: Is computational speed and requirement similar

Simulating quantum computing using a framework leads to extra operations. Does this severely limit the usability on current machines or are we still able to train, test and engineer on current hardware?

2 RELATED WORK

2.1 Energy demand forecasting

Previous research done by [van de Sande et al.] found that a ensemble model prophet-lstm is best suited for enhancing predictability of wintertime energy demand. This research will be extending [van de Sande et al.] by seeing if this method also enhances predictability of energy demand for the other seasons and if we can increase this performance by utilizing a hybrid quantum-classical computing setup.

2.2 Quantum Computing

Currently we are in the Noisy Intermediate-Scale Quantum (NISQ) era [5]. To navigate this era more research has been done in recent years which has led to Quantum Software Frameworks. These frameworks allow researchers to emulate a quantum computer on classical hardware, one of these frameworks is TensorFlow Quantum (TFQ) [6]. Frameworks like TFQ have led to research on hybrid quantum-setups to see if using these frameworks can increase performance. One of these use cases that have been found is quantum machine learning (QML), which has already been applied in practice for deep-learning and also LSTM's. For example [Hsu et al.] did research on "Quantum Kernel-Based Long Short-term Memory for Climate Time-Series Forecasting.", and [Khan et al.] did research on "Quantum long short-term memory (QLSTM) vs. classical LSTM in time series forecasting: a comparative study in solar power forecasting." The latter demonstrates confidence that the proposed research question could benefit from a Quantum Long Short-Term Memory (QLSTM) setup since the findings of [Khan et al.] highlight that performance of QLSTM increased due to the intricate spatiotemporal patterns inherent in renewable energy data. Making QLSTM a promising approach for achieving significant improvements.

3 METHODOLOGY

The basis of the methodology will be similar to the setup [Khan et al.] has used since it closely resembles the end goal of this thesis, however it is expected that during the process we will run into other problems since we are trying to predict energy usage using both economical and cilmat predictors. But the high-overview of the process is as follows:

(1) Encode classical data to be used in quantum framework, similar to the method of [Khan et al.].
(2) Recreate LSTM model from [van de Sande et al.] in TensorFlow quantum computing framework.
(3) Use both classical and quantum version of the model to predict energy prices in the winter.
(4) Compare accuracy, precision, recall, F1-score, area under the ROC curve (AUC-ROC), mean squared error (MSE) for both models
(5) Use both models to see how they perform on other seasons using the same metric is as the step above.

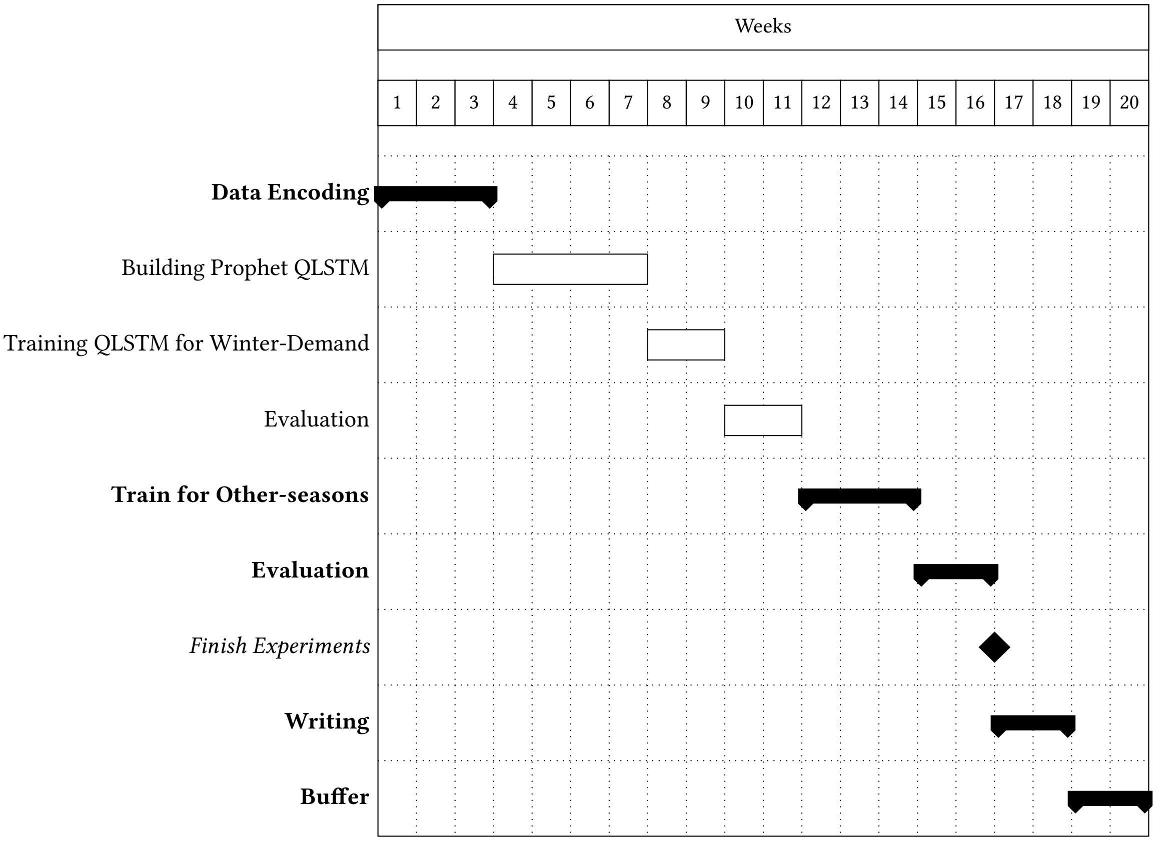
(6) Compare rates of convergence, Stability of Learning, Generalization performance ,and Evaluation of time.

4 RISK ASSESSMENT

The majority of the risk in this project lies in the fact that Quantum computing is a relatively new concept and this leads to two main concern. The first one is that according to the literature Hybrid quantum-classical setups are very resource intensive. So chances are that local training might not be possible due to technical constraints. if this is the case I will have to make use of a cloud alternative like a google colab environment. The other one is that the quantum frameworks that are available are not as extensive as there classical computing counter parts. If certain utilities are not available it might force me to build the solution from scratch. Another option is that the parts that are not possible in quantum frameworks are handled by classical computing frameworks sort of like a ensemble method.

5 PROJECT PLAN

Due to the fact that I work alongside the thesis project I will be starting in January, in this month I will gather more literature.On average I will be spending around 16-20 hours a week on the project. Since I am building on top of a previous students thesis most of the classical data engineering and exploratory data analysis has already been achieved. This leaves me with the opportunity to do the quantum encoding of the data and the creation of the prophet lstm model in TensorCircuit instead. I will start of trying to create a minimum viable version of the quantum version of the model so that I can start training during March. During this time I will have to finish one more class. From April on-wards I have finished the final class and will have be finalizing the training of the model. In may the results should be in and I can compare the classical prophet lstm to the quantum prophet lstm. leaving me the first half on june with a buffer. I will be utilizing a Scrum-board to track what I am working on each week.



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