QML Report 1

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1 Introduction

- Objective : Develop a hybrid quantum ML model to mimic the path quality of Dijkstra's but with only local information of map on a dynamic graph.
- Emergency escape plan for cars during natural disasters that requires minimal computation time and can run optimally in time during a disaster.

2 Escape Routing Problem

- Assumptions : Predefined exit locations, one epicentre, Earthquake effects propagate, and cars have real time updates on traffic information (locally).
- Map : Using Python OSMnx package, convert any selected map region to graph representation. Paper tests on an undirected graph with (V = 357, E = 549).$W(V_1, V_2)$ represents travel time on the edge. UB to speed on roads in set nominally.
- Modelling : Initiation by activating earthquake with static effect on edge weights of edges withing epicentre. Then a dynamic effect takes place. Similarly , travel time increase in weights propagates from the exit points dynamically as time increases. T =T+1 as a car transverses an edge.
- Damage radius is dynamic wrt t s.t $r_{epi} = 0.5 + \sqrt{0.0002 * t}$. Update of weights initally is given by

$$w \leftarrow \begin{cases} w * 5 & d_{epi} \leq 0.3 r_{epi} \\ w * 2 & 0.3 r_{epi} \leq d_{epi} \leq 0.75 r_{epi} \\ w * 1.3 & 0.75 r_{epi} \leq d_{epi} \leq r_{epi} \\ w & else \end{cases}$$

Dynamic time update of weights due to epicentre is given by :

$$w \leftarrow \begin{cases} min\{w * \sqrt{0.003 * t + 1}, 5\} & d_{epi} \leq 0.3r_{epi} \\ min\{w * \sqrt{0.002 * t + 1}, 4\} & 0.3r_{epi} \leq d_{epi} \leq 0.75r_{epi} \\ min\{w * \sqrt{0.001 * t + 1}, 3\} & 0.75r_{epi} \leq d_{epi} \leq r_{epi} \\ w & else \end{cases}$$

Exit effect is modelled as

$$w \leftarrow \begin{cases} min\{w * \sqrt{0.03 * t + 1}, 5\} & d_{exit} \leq 0.5r_{exit} \\ min\{w * \sqrt{0.02 * t + 1}, 4\} & 0.5r_{exit} \leq d_{exit} \leq 0.75r_{exit} \\ min\{w * \sqrt{0.01 * t + 1}, 3\} & 0.75r_{exit} \leq d_{exit} \leq r_{exit} \\ w & else \end{cases}$$

Data engineering :

- Heuristics to represent 2 critical global parameters : Distance from destination - Euclidian Distance between node and exit and Direction from exit by cosine distance between transversing edge and node to exit.
- Input has : epicentre, start, exit, edge coordinates, required time, edge betweenness centrality, euclidean distance, cosine distance.
- Evaluation metrics : arrival rate, defined by the probability of finding the correct path between two nodes, and accuracy, defined as total travel time along a path relative to the node wise Dijkstra result.

3 Hybrid Supervised Learning Architecture

- Feature-wise linear modulation(FiLM) NN is used to create a smooth trainable conditional network. FiLM layet takes in earthquake coordinates.
- Remaining features are taken by the traditonal NN.
- FiLM layer is a modulating agent for element wise shifting and scaling operations and its influence enables more adaptive and accurate routing prediction.
- Architecture :
- FiLM layer of the architecture takes in 2 qubits from data reuploading about the earthquake coordinates . the encoding gates are repeated 5 times and interlaced with varioational unitaries

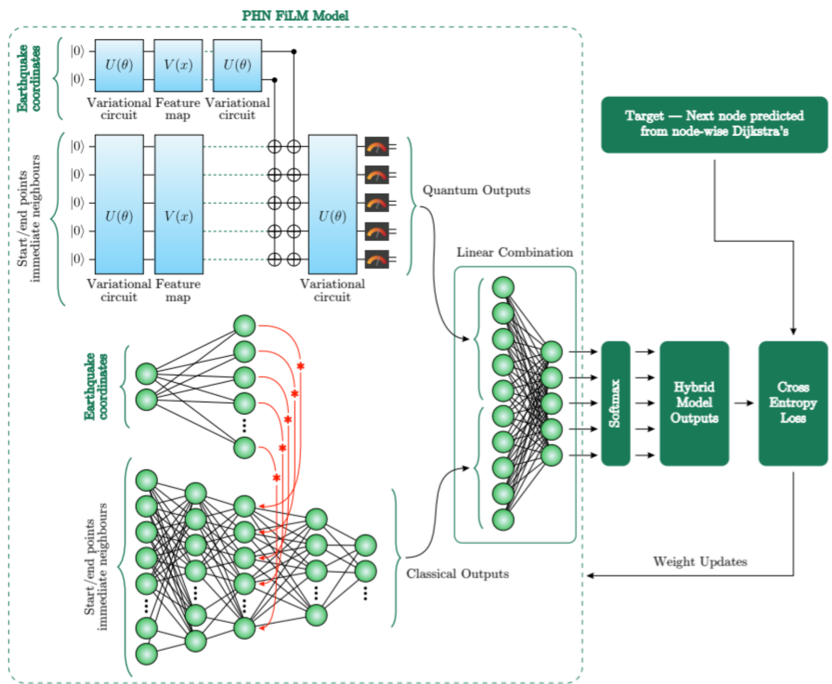

Figure 1: Model Architecture

- Variational uniteries are known as Basic entagular layer (BEL) built using 4 sublayer X rotations and CNOT gates. Denoted by

$$U_{BEL}(\theta) = \prod_{t=1}^{n_{sublay}} \prod_{1=1}^{n_{qubits}} CX_{q,q+1} e^{-\frac{i}{2}\theta\sigma}$$

- The inner product is called the encoding layer.
- The final quantum state of the system is given by :

$$|\psi\rangle = U_{BEL}^{main}(\theta)[\prod_{c=1}^{2} \prod_{t=3}^{7} CX_{c,t}] \, |\psi\rangle_{FiLM} \otimes |\psi\rangle_{main}$$

- Output of QN are concatenated with that of classical network . Ten values are then passed through fully connected layet ot be reduced to 5 values. Output of the architecture are 5 numbers that act as logit layer. Neighbouring node corresponding to highest number is chosen as next node.

4 Conclusion

- According to the analysis done by the authors the model seems to be promising. However the authors have tested it on only a small graph and graphs of larger sizes need testing to check for accuracy and time constraints. Authors also suggest reinforcement model instead of supervised setting as an avenue for further exploration. The analysis concluded that the model could learn to match dijkstra's optimality with only local information making it computationally workable in evolving situation. Hybrid model seems to have 7% more accuracy than just the classical approach.