Life-long learning in Quantum machine learning

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Abstract: Life-long computation involves incrementally acquired, time-changing data. We propose updating VQC-based classifiers over time and detecting changes with quantum distances. Sequential models are used to assist VQCs and accelerate the estimation process of parameter values.

Quantum machine learning has emerged as a transformative approach, promising to tackle Machine learning (ML) problems that demand large-scale computation, especially on massive data. A data-intensive category of problems is represented by life-long computation, where data is not available all at once but is instead acquired incrementally over time. Incremental learning (IL), or more generally life-long learning, represents algorithms capable of continuously learning, adapting to changes in the learning environmentm, maintaining model capabilities over time and deliver timely predictions. To address these challenges, we propose **QUARTA**, a hybrid computational solution leveraging two quantum components. One for a supervised learning task aiming at training and updating a classification model, the other one for an unsupervised learning task used to compute quantum distances on potential changing data that trigger model adaptation. Both components operate on different data encodings each representing distinct descriptive feature sets.

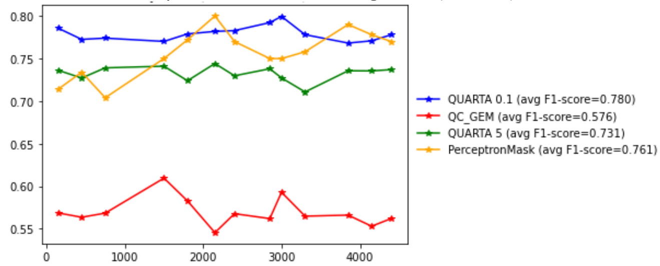
To accommodate changes in data and adapt the models accordingly, we employ variational quantum circuits (VQCs). These circuits consist of fixed gate structures with trainable parameters optimized during a learning process. When changes occur in the data, the model adapts by updating these parameters.

However, VQCs are computationally costly due to their iterative nature and are prone to the barren plateau problem, where gradients vanish exponentially, resulting in a flat optimization landscape. These challenges are particularly problematic in life-long computation scenarios, where VQCs would be executed continuously.

To address these issues, we propose a paradigm shift that leverages ML techniques for parameter estimation. Predictive ML can efficiently search for optimal parameters and significantly enhance the execution of VQCs. Our approach employs sequence modeling to assist conventional optimizers in parameter estimation over time—specifically on data acquired sequentially. This enables faster convergence and the identification of optimal values with fewer iterations compared to standalone optimization, ultimately unlocking the potential of VQCs for life-long learning applications.

The sequential ML models considered in our approach, both quantum and classical (referred to as **QLSTM** and LSTM), can forecast the parameter values of parameterized gates by capturing patterns and correlations over time.

Fig. 1 Accuracy values of QUARTA in comparison to classical computing competitors (top). Accuracy values of VQCs supported by QLSTM and LSTM in comparison to VQCs working alone (bottom).



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	9	**10**	**11**	**12**
VQC	74,91 (11,54)	**74,91** (11,54)	74,91 (11,54)	74,91 (11,54)
LSTM $For + It$ I**=8**	71,78 (8,85)	67,65 (19,19)	60,85 (17,77)	58,48 (22,16)
LSTM $It + For + It$ I**=8**	72,22 (10,6)	67,05 (22)	59,51 (14,06)	59,51 (14,06)
QLSTM $For + It$ I**=8**	**75,89** (9,19)	73,37 (8,8)	**75,95** (8,73)	**75,29** (10,02)
QLSTM $It + For + It$ I**=8**	75,49 (8,74)	74,5 (10,57)	59,51 (14,06)	59,51 (14,06)