Abstract

Machine Learning algorithms are designed to extract meaningful information from datasets and make accurate predictions. Among these, kernel methods have demonstrated strong performance in supervised learning tasks. Quantum Computing, on the other hand, has shown significant potential in solving computational problems that were previously intractable. The intersection of Quantum Computing and Machine Learning gave rise to whole new field of Quantum Machine Learning which has been studied extensively over years. Quantum Kernel Methods have been research largely and has shown potential when used with classical SVM for pattern recognition, classification tasks. A significant drawback of kernel methods is their inefficient quadratic scaling concerning the number of training samples.

To address this, we investigate and develop optimized kernel alignment method, specifically focusing on Clustered Centroid Kernel Alignment (CCKA). The method uses centroids of clusters within classes and centroids of the classes for calculating the kernel alignment. This method provides linear scalability in number of circuit executions while training and is independent of number of training samples depending fully on the number of clusters formed within the classes, ensuring consistent performance across varying dataset sizes without compromising classification accuracy. In training process, only the kernel entries for centroids of clusters within class and centroids of class as whole are calculated, which reduces the maximum kernel shape for n clusters within centroid and c classes (n, c). During the training process the along with the variational parameters the centroids and sub cluster centroids are optimized iteratively. We show that CCKA provides satisfactory results and can perform at a similar level as other methods of kernel alignment with linear and quadratic scaling during training for synthetic datasets as well as real world datasets.