Deep learning has solved various computer vision problems in the last decade. We use computational topology, namely persistent homology groups, to analyze the spaces of internal feature representations of convolutional neural networks (CNNs). We observed the correspondence between the summaries of the homological persistence groups of the decision boundary and ResNet-18 CNN training error during the phenomenon of deep double descent. Furthermore, a considered specific persistence summary suggests an analogy to epoch-wise double descent so that we may better understand the internal representations during the critically parametrized regime.

Mainly, we develop and compare multiple approaches to CNN models processing using the persistence homology. Our best method, the Differentiable Persistence Accuracy Estimator (DPAE), achieves very high accuracy in predicting CNN's performance (R2 score close to 0.99). Our DPAE is a topologically optimized end-to-end architecture involving differentiable persistence computation. Moreover, DPAE overperforms the original classical machine learning-based method on its native Small CNN Zoo dataset. We publicly release the complete source code of DPAE and other presented experiments.