Title	Summary	Cat.	Apps.
Neural persistence: A complexity measure for deep neural networks using algebraic topology (Rieck et al., 2019)	Topological complexity measure for neural networks based on their weights	(3)	(1)
Characterizing the shape of activation space in deep neural networks (Gebhart et al., 2019)	Topological characterization of the neuron activations given a sample	(3)	(3)
Exposition and interpretation of the topology of neural networks (Brüel Gabrielsson and Carlsson, 2019)	Topological analysis of the weights of convolutional neural networks and connection to generalization capacity of models	(3)	-
Path homologies of deep feedforward networks (Chowdhury et al., 2019)	Analysis of path and directed flag homology groups of MLPs' directed graph	(1)	-
Topology of deep neural networks (Naitzat et al., 2020)	Study of the topology of the data through layer transformations	(3)	-
Finding the homology of decision boundaries with active learning (Li et al., 2020)	Use of active learning to improve the methods of Topological data analysis of decision boundaries with application to model selection	(2)	(5)
Computing the testing error without a testing set (Corneanu et al., 2020)	Regression of test accuracy using topological vectorizations of persistence diagrams	(3)	(6)
Topological detection of trojaned neural networks (Zheng et al., 2021)	Study of trojaned networks in terms of the persistent homology of neuron activations and their correlations	(3)	(4)
Experimental stability analysis of neural networks in classification problems with confidence sets for persistence diagrams (Akai et al., 2021)	Study of persistence diagrams of last hidden layer activations and its connection with generalization	(3)	-
PHom-GeM: Persistent homology for generative models (Charlier et al., 2019)	Comparison between persistence diagrams of real and generated manifolds using generative models	(2)	(7)
TopoAct: Visually exploring the shape of activations in deep learning (Rathore et al., 2021)	Analysis of the Mapper graph of neuron activations for each layer	(3)	-
Deep neural network pruning using persistent homology (Watanabe and Yamana, 2020)	Pruning of neural networks using persistent homology	(3)	(2)

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Title	Summary	Cat.	Apps.
Intrinsic dimension, persistent homology and generalization in neural networks (Birdal et al., 2021)	Generalization error bounds using persistent homology dimension on the training weights	(3, 4)	(1)
Activation landscapes as a topological summary of neural network performance (Wheeler et al., 2021)	Study of the topology of the data through layer transformations and its connection with training accuracy	(3)	-
Topology of learning in feedforward neural networks (Gabella, 2021)	Analysis of the evolution of the weights of a neural network during training using Mapper	(3)	-
Topological uncertainty: Monitoring trained neural networks through persistence of activation graphs (Lacombe et al., 2021)	Uncertainty measurement of neural network predictions using the topology of neuron activations	(3)	(3, 5)
Topological measurement of deep neural networks using persistent homology (Watanabe and Yamana, 2022b)	Computation of persistence diagrams using neuron path relevance and connection with network expressivity and problem difficulty	(3)	-
Evaluating the disentanglement of deep generative models with manifold topology (Zhou et al., 2021)	Measurement of disentanglement of generative neural networks	(2)	-
Quantitative performance assessment of CNN units via topological entropy calculation (Zhao and Zhang, 2022)	Measurement of quality of convolutions in a neural network using persistent homology	(3)	-
Overfitting measurement of deep neural networks using no data (Watanabe and Yamana, 2022a)	Study of overfitting by analysing the points near the diagonal of a persistence diagram generated from the weights of a neural network	(3)	-
An adversarial robustness perspective on the topology of neural networks (Goibert et al., 2022)	Analysis of adversarial examples by means of the topology of the subgraph of under-optimized edges of neural networks	(3)	(3)
Representation topology divergence: A method for comparing neural network representations (Barannikov et al., 2022)	Definition of similarity between data representations using persistent homology	(3)	(7)
On the topological expressive power of neural networks (Petri and Leitão, 2020)	Measurement of expressivity of network architectures	(2)	-

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Title	Summary	Cat.	Apps.
Generalization bounds using data-dependent fractal dimensions (Dupuis et al., 2023)	Data-dependent generalization error bounds using persistent homology dimension on the training weights	(3, 4)	-
TopoBERT: Exploring the topology of fine-tuned word representations (Rathore et al., 2023)	Mapper graph of transformer-based models with applications in finetuning of language models	(3)	-
Experimental observations of the topology of convolutional neural network activations (Purvine et al., 2023)	Analysis of the Mapper graph of neuron activations and definition of a similarity function between layers using sliced Wasserstein distances between persistence diagrams generated from them	(3)	-
ReLU neural networks, polyhedral decompositions, and persistent homology (Liu et al., 2023b)	Detection of homological features in manifolds embedded in the input space of a neural network using the polyhedra decomposition induced by a ReLU feedforward neural network	(2)	-
Caveats of neural persistence in deep neural networks (Girrbach et al., 2023)	Connection between neural persistence and variance measures of neural network weights	(3)	-
On the use of persistent homology to control the generalization capacity of a neural network (Barbara et al., 2024)	Regression of generalization gap using the average persistence of zero dimensional persistence diagrams	(3)	(6)
Visualizing and analyzing the topology of neuron activations in deep adversarial training (Zhou et al., 2023)	Analysis of the Mapper graph of neuron activations of normally and adversarially trained neural networks	(3)	-
TopP&R: Robust Support Estimation Approach for Evaluating Fidelity and Diversity in Generative Models (Kim et al., 2023)	Approximation of the precision and recall scores for generative models using a persistent homology-based approach.	(2)	(7)
Topological structure of complex predictions (Liu et al., 2023a)	Analysis of the GTDA Reeb network of output spaces of neural networks	(2)	-
Topological dynamics of functional neural network graphs during reinforcement learning (Muller et al., 2024)	Study of reinforcement learning neural networks during training and inference using homology	(3)	-