ABSTRACT: Deep neural networks have shown a superior performance in many learning problems by learning hierarchical latent representations from a large amount of labeled data. However, the success of deep learning methods is under the closed-world assumption: no instances of new classes appear at test time. On the contrary, our world is open and dynamic, such that the closed-world assumption may not hold in many real applications. In other words, deep learning-based agents are not guaranteed to work in the open world, where instances of unknown and unseen classes are pervasive.

In this dissertation, we explore lifelong learning and representation learning to generalize deep learning methods to the open world. Lifelong learning is to identify novel classes and incrementally learn them without training from scratch, and representation learning is to be robust to data distribution shifts. Specifically, we propose 1) hierarchical novelty detection for detecting and identifying novel classes, 2) continual learning with unlabeled data to overcome catastrophic forgetting when learning the novel classes, 3) network randomization for learning representations robust across visual domain shifts, and 4) domain-agnostic contrastive representation learning to be robust to data distribution shifts.

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