Layered learning is a machine learning paradigm used to develop autonomous robotic-based agents by decomposing a complex task into simpler subtasks and learning each sequentially. Although the paradigm continues to have success in multiple domains, performance can be unexpectedly unsatisfactory. Using Boolean-logic problems and autonomous agent navigation, we show poor performance is due to the learner forgetting how to perform earlier learned subtasks too quickly (favoring plasticity) or having difficulty learning new things (favoring stability). We demonstrate that this imbalance can hinder learning so that task performance is no better than that of a sub-optimal learning technique, monolithic learning, which does not use decomposition. Through the resulting analyses, we have identified factors that can lead to imbalance and their negative effects, providing a deeper understanding of stability and plasticity in decomposition based approaches, such as layered learning.

To combat the negative effects of the imbalance, a complementary learning system is applied to layered learning. The new technique augments the original learning approach with dual storage region policies to preserve useful information from being removed from an agent’s policy prematurely. Through multi-agent experiments, a 20% task performance increase is obtained with the proposed augmentations over the original technique.

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The public is welcome to attend.