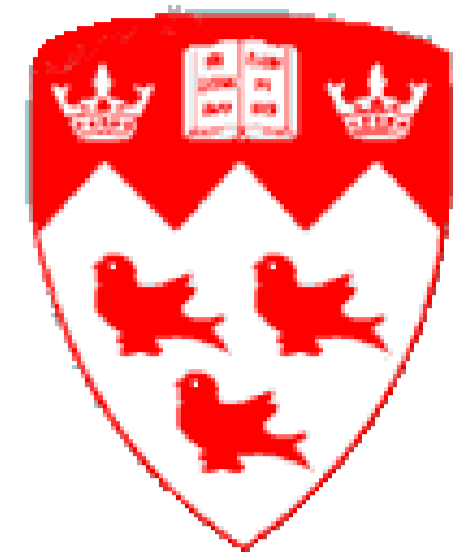


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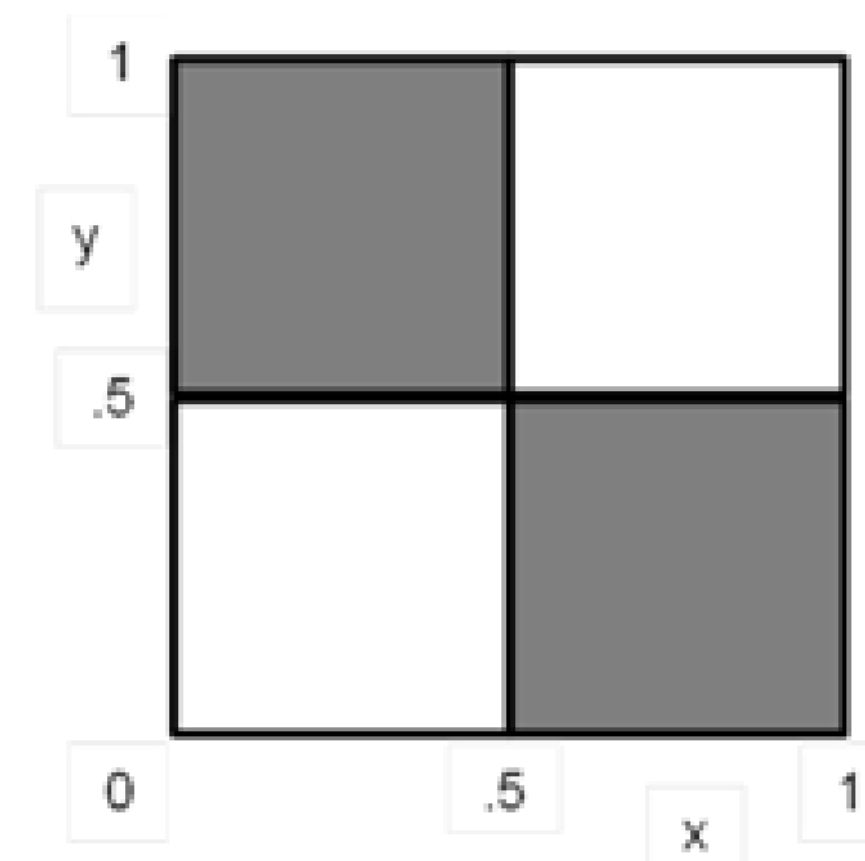
Abstract

Autonomous learning is the ability to learn effectively without external assistance, a desirable characteristic in both engineering and computational-modeling. We extend a constructive neural-learning algorithm, sibling-descendant cascade-correlation (SDCC), to monitor lack of progress in learning in order to autonomously abandon unproductive learning. The extended algorithm simulates results of experiments with infants who abandon learning on difficult tasks. It also avoids network overtraining effects in a more realistic manner than conventional use of validation test sets.

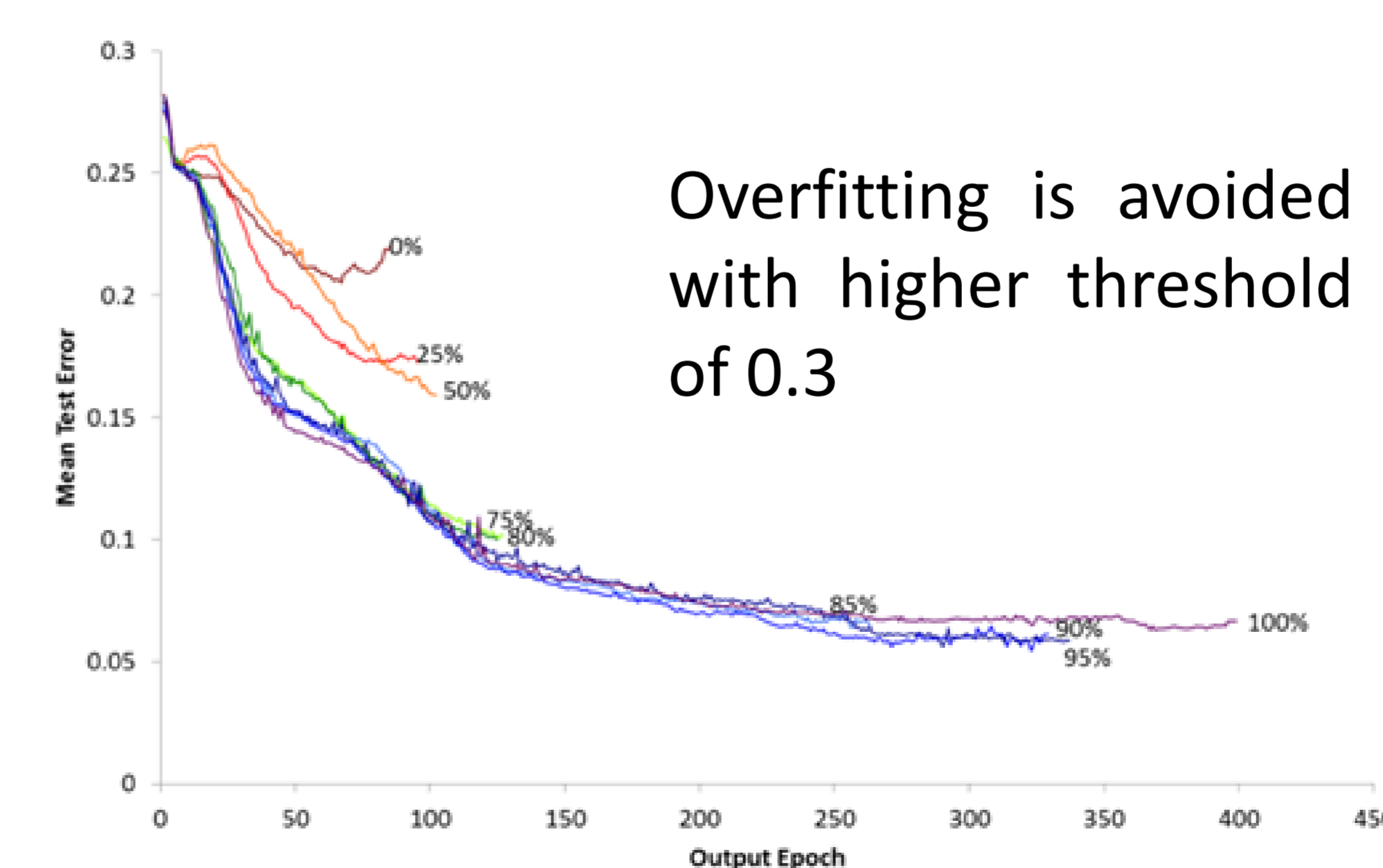
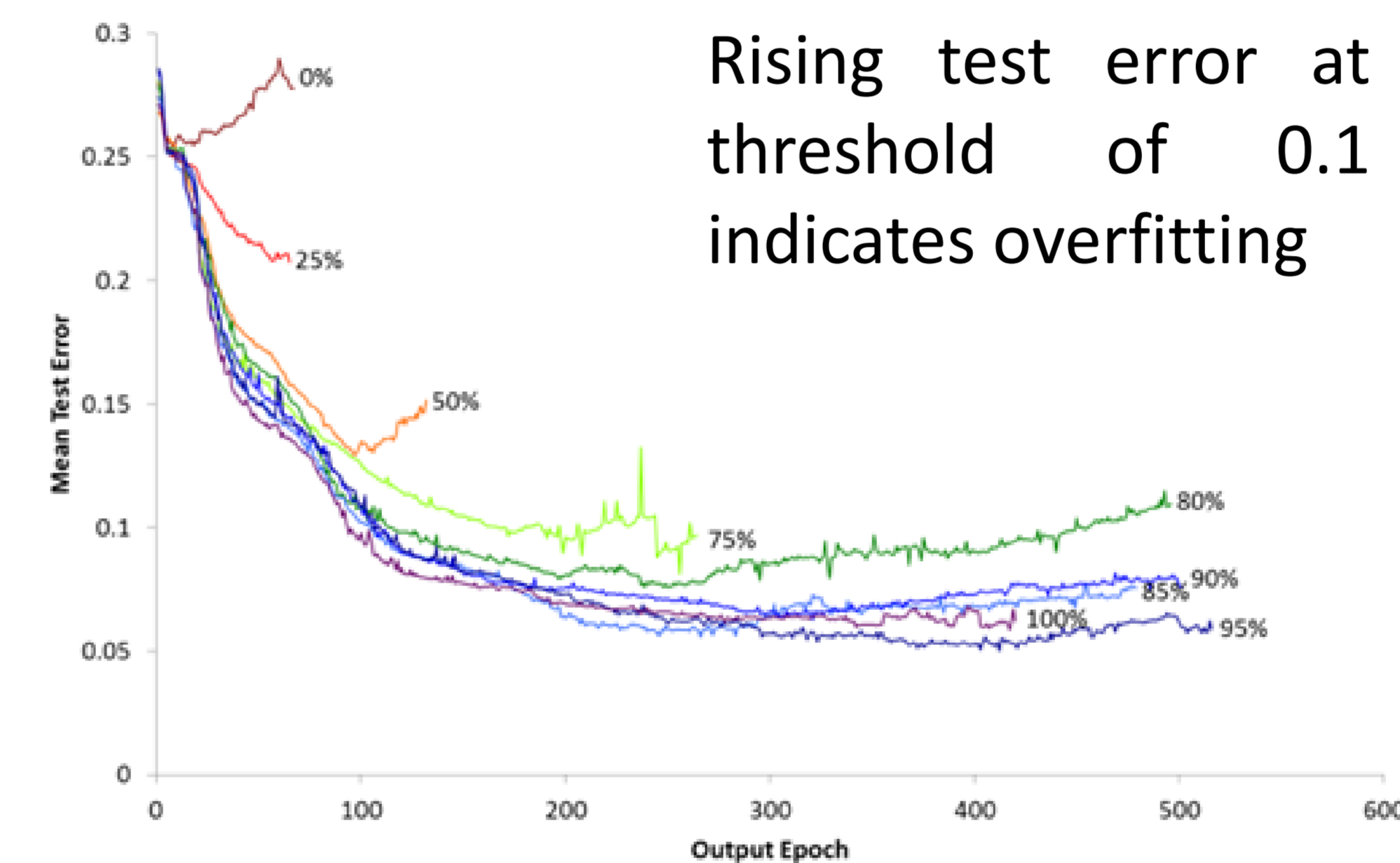
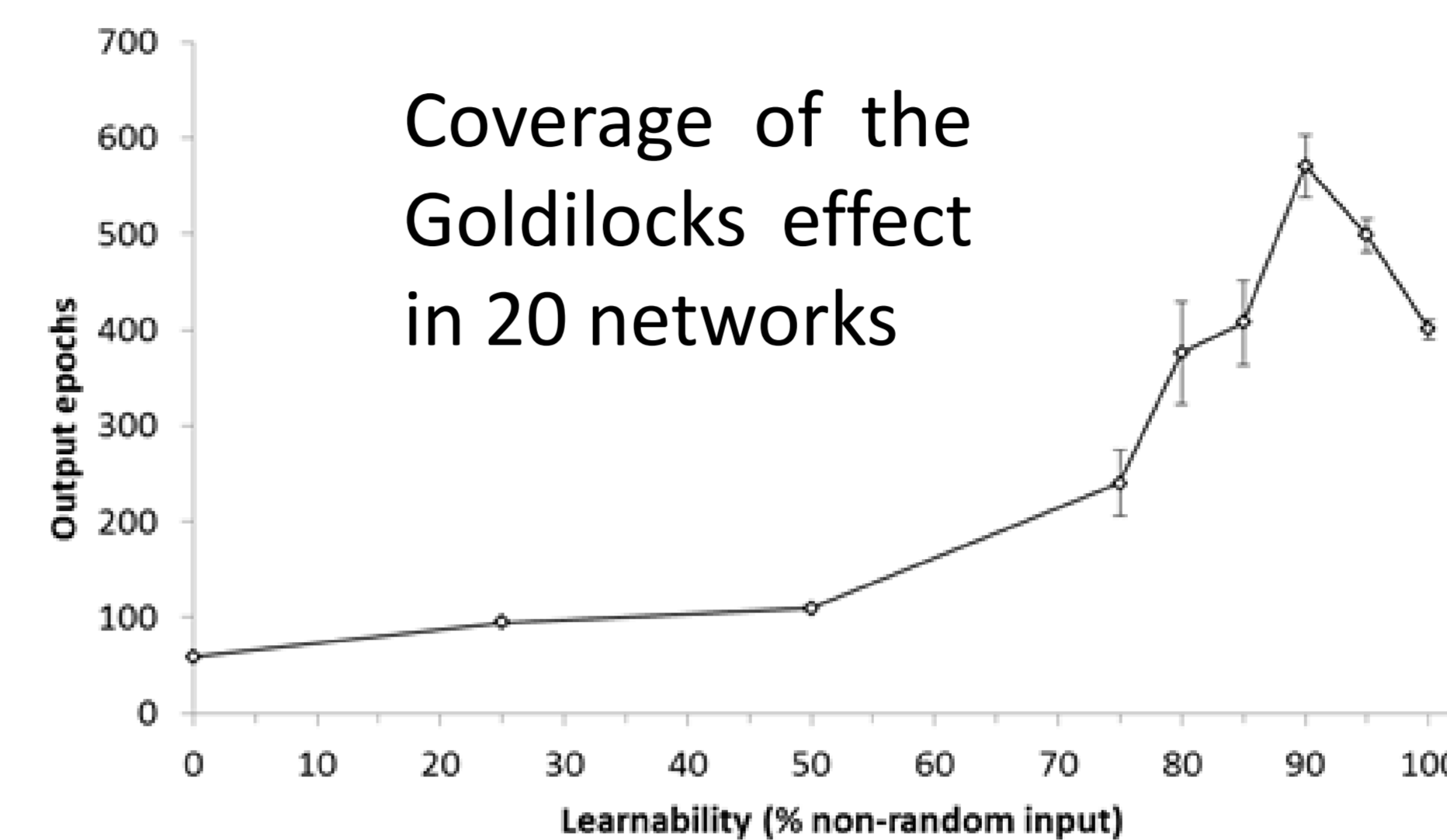
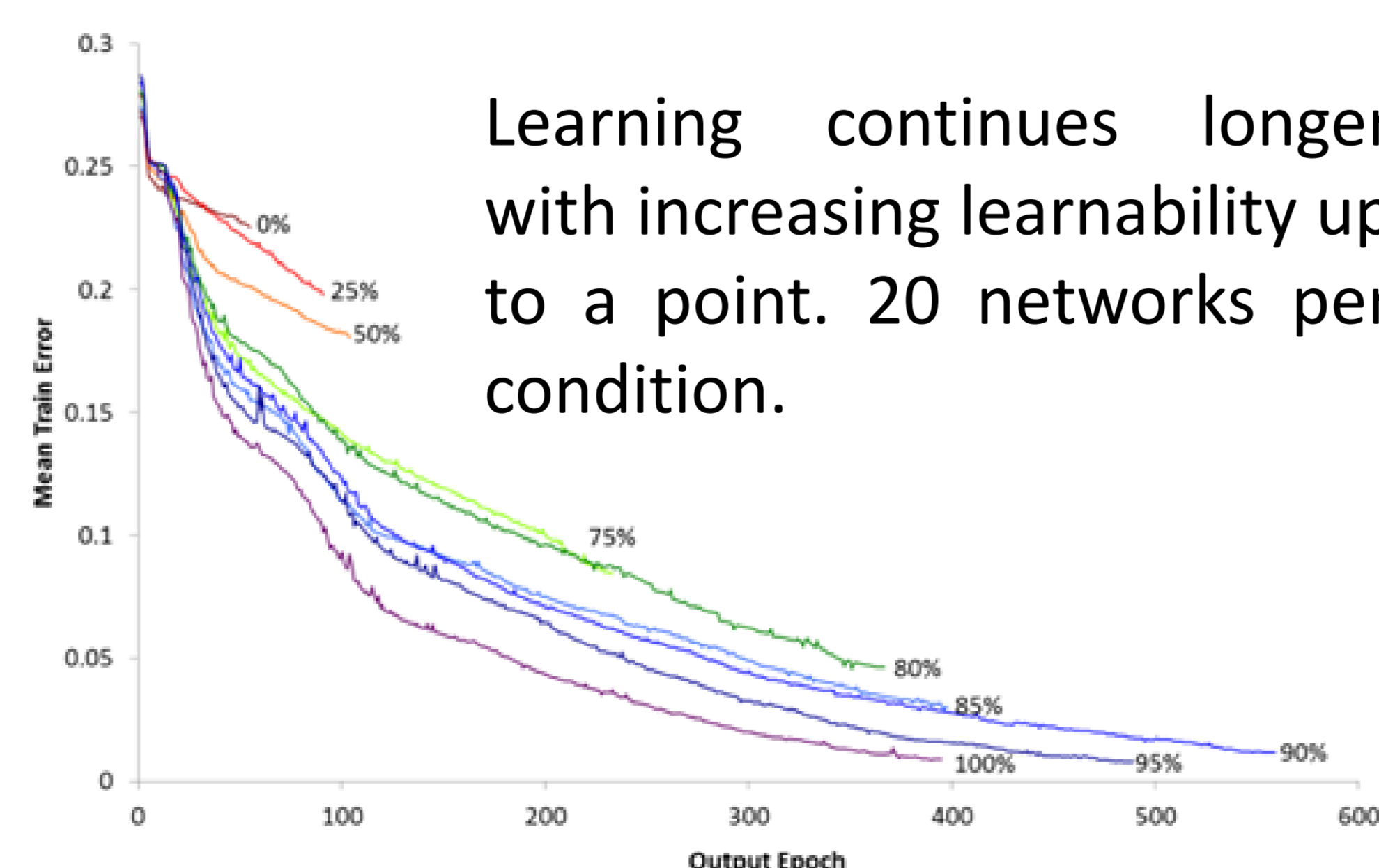
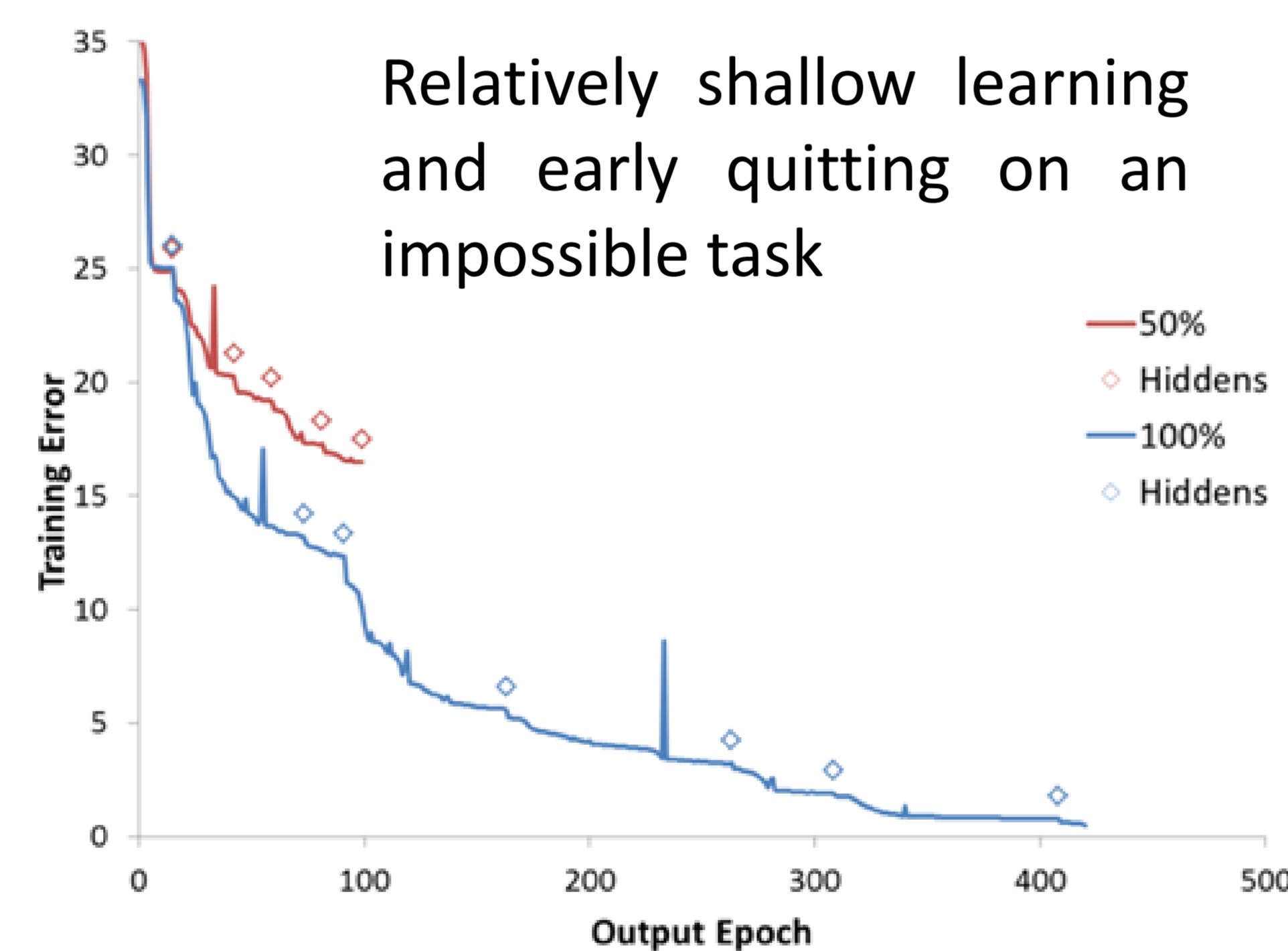
Background

An important characteristic of autonomous learners is that they can shape their own learning and development, in large part by choosing what problems to work on. Such choices include selecting a problem to learn and deciding whether to continue learning on the selected task or abandon it in favor of something else. Knowing when to stop learning has two obvious components – quitting when the problem has been mastered and when it is unlikely to be mastered. The total cost of learning can be conceptualized as energy expenditure plus opportunity cost: $Cost_{Total} = Energy_{Learn} + Cost_{Opportunity}$. The net payoff of learning is the benefit of successful learning minus the total cost of learning: $Payoff_{Net} = Benefit_{Learn} - Cost_{Total}$. In continuing to work on an unlearnable problem, there would be a large negative payoff. Here learning continues until absolute error change is less than a threshold for patience epochs.

Continuous XOR



Results



Discussion

- Extension of SDCC to abandon unproductive learning covers early quitting of impossible tasks and the Goldilocks effect in infants.
- Learning is prolonged with decreasing threshold and increasing patience.
- Increasing threshold is a more realistic way to suppress overfitting than using validation test sets.

Future work

- ❑ Further exploration of the effects of threshold and patience parameters.
- ❑ Extension to other tasks including learnable tasks that vary in difficulty.
- ❑ Prediction and coverage of quitting phenomena in current and future psychology experiments.

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