Scalable Evaluation and Neural Models for Compositional Generalization

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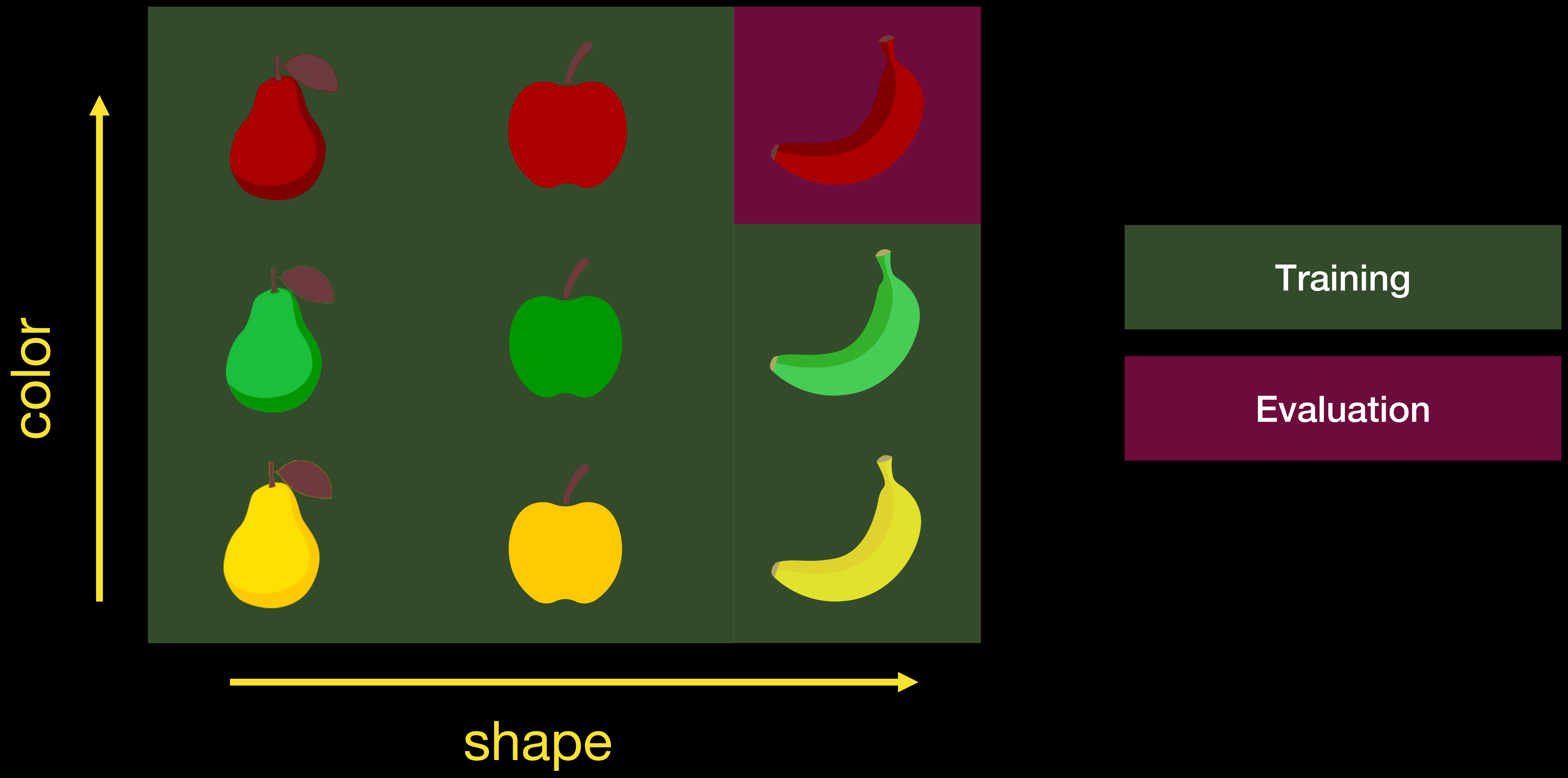
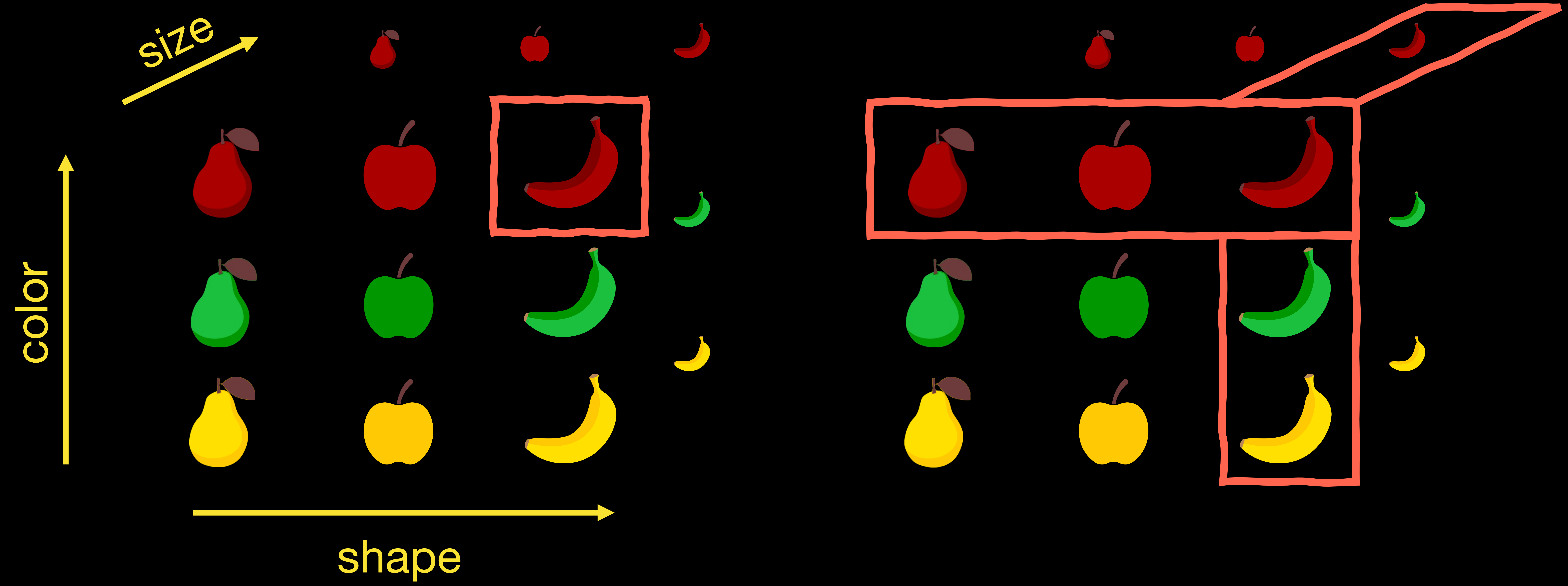
NEURAL INFORMATION PROCESSING SYSTEMS

We consider the problem of compositional evaluation.



Previous works evaluated compositional generalization under significantly heterogeneous assumptions, making comparability hard.



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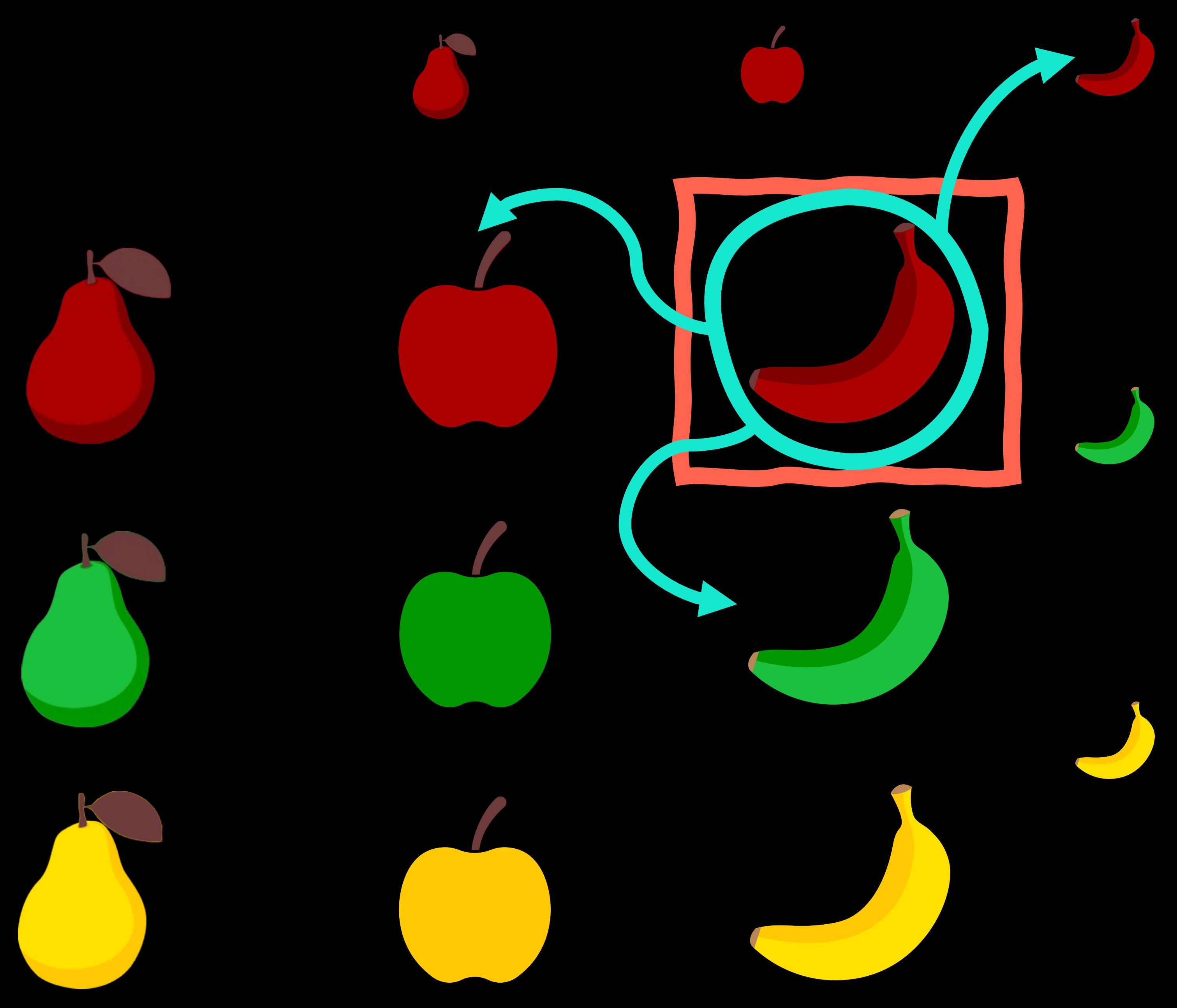
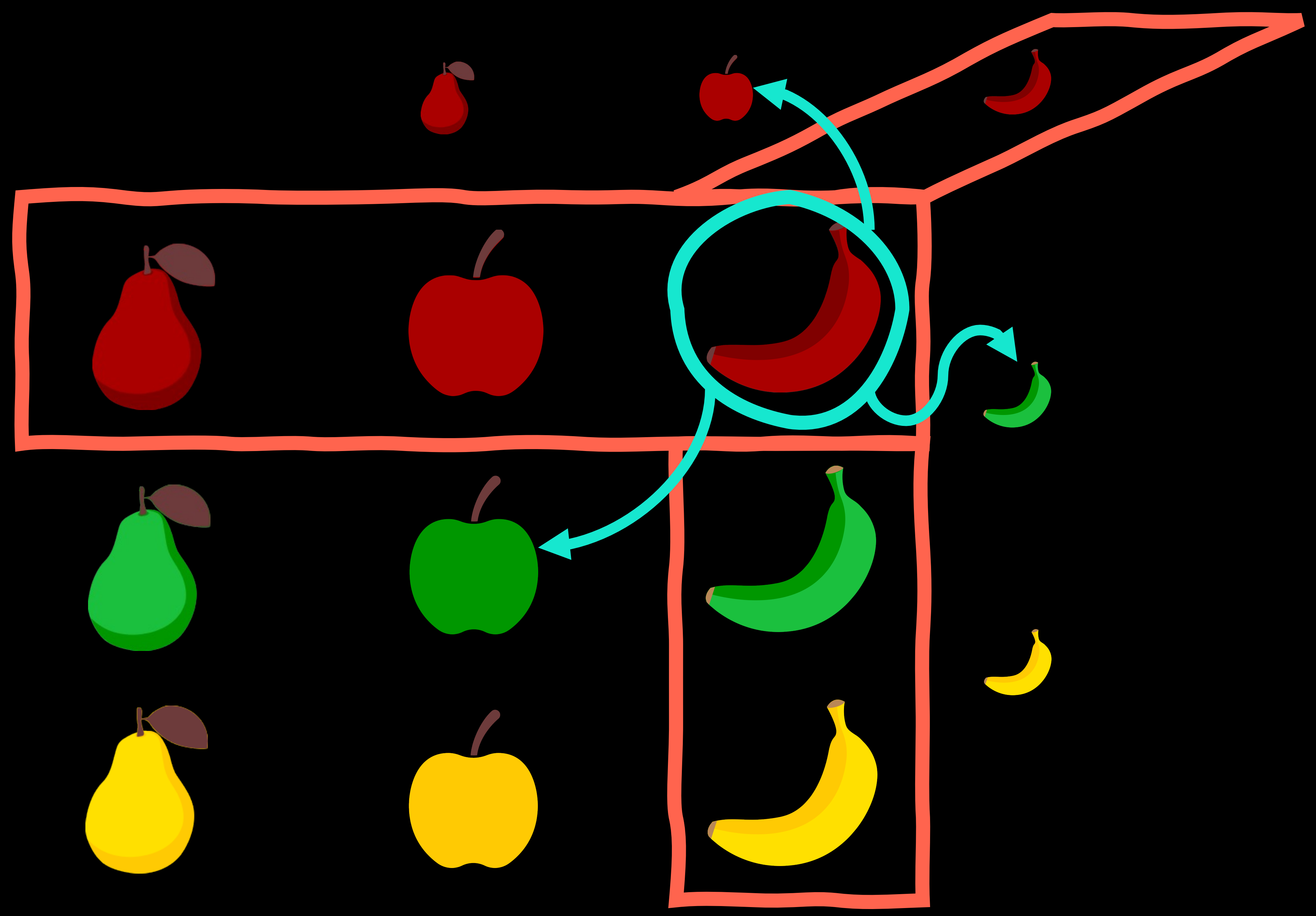
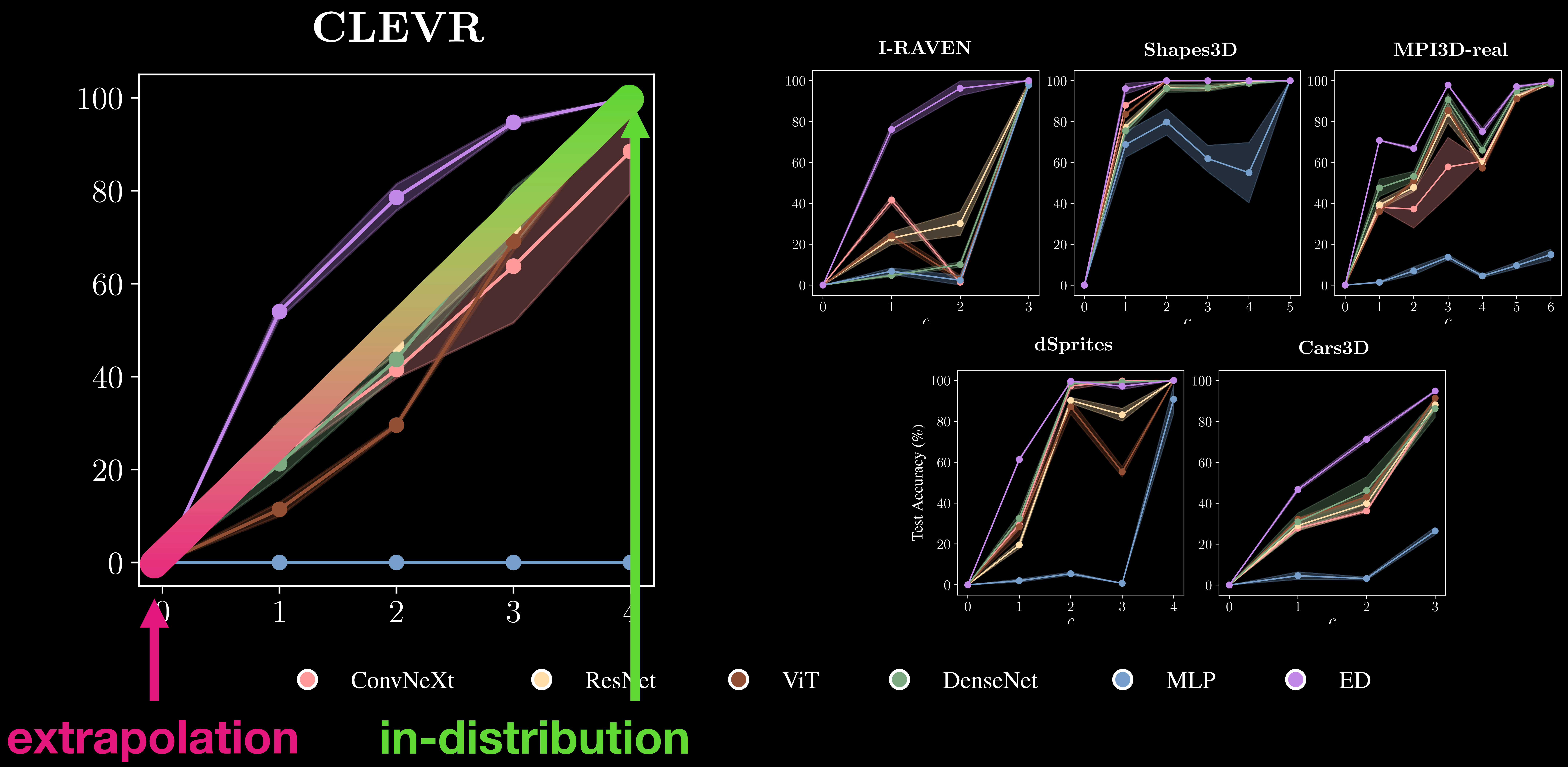


semantic similarity $(c) = 2$

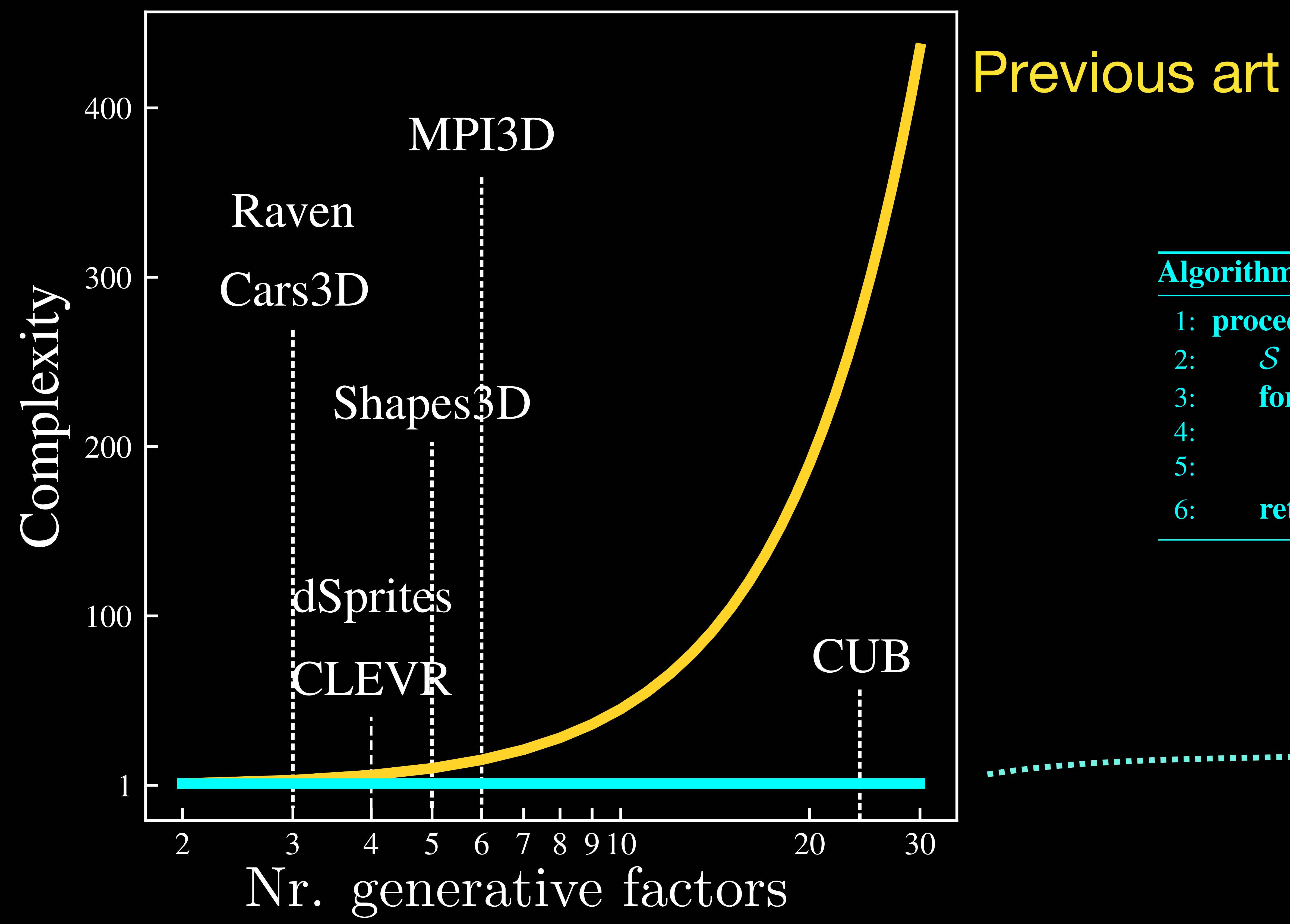


semantic similarity $(c) = 1$

Orthotopic evaluation framework allows rigorous compositional generalization testing.



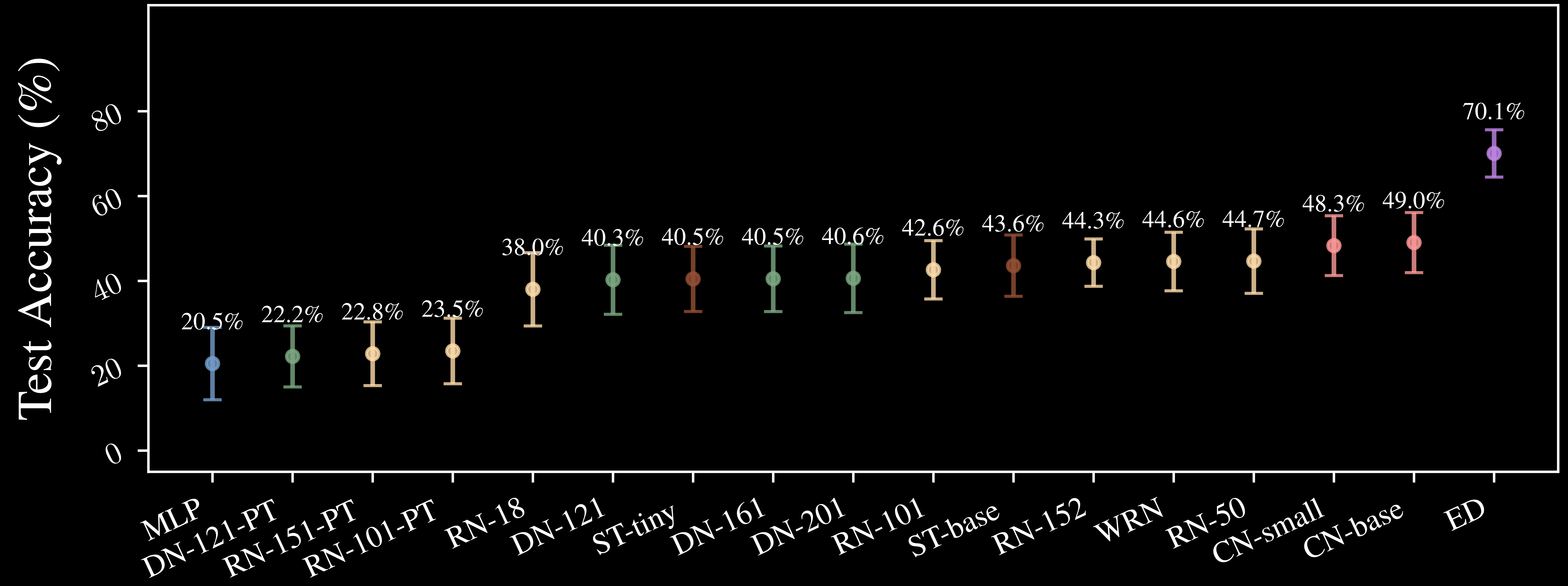
Orthotopic evaluation framework allows efficient compositional generalization testing.



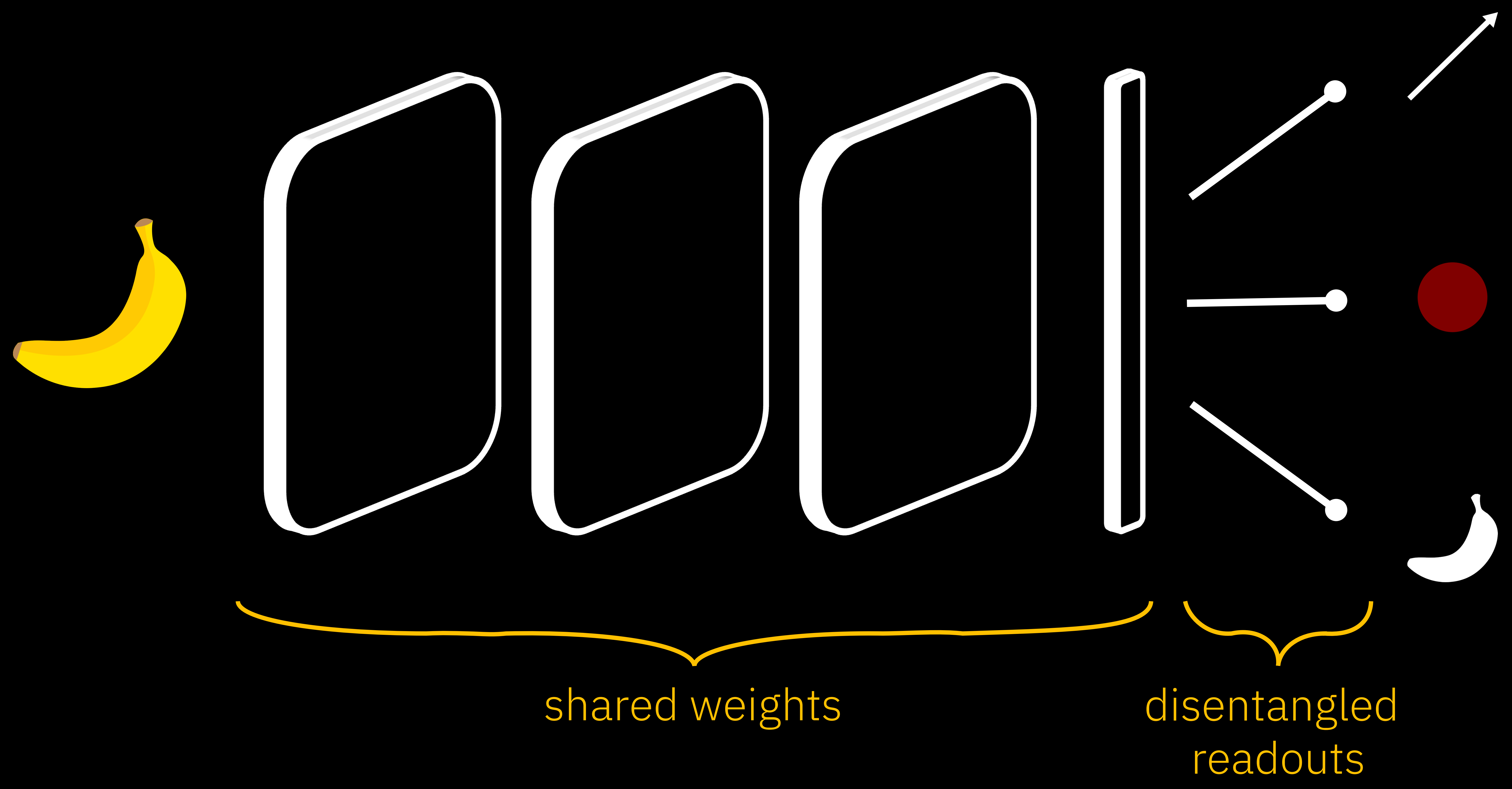
Algorithm 1 Orthotopic split generation.

procedure SPLITDATASET($\mathbf{X}$, $\mathbf{G}$, c)
    $\mathcal{S} = \binom{\mathbf{G}}{c+1} = \{\mathbf{S} \subseteq \mathbf{G} : |\mathbf{S}| = c+1\}$ ▷ Get all combinations of c factors in $\mathbf{G}$
    for each $s \in \mathcal{S}$ **do** ▷ Iterative orthotope pruning
        $\mathbf{X}_{proj} = \mathbf{proj}_s \mathbf{X}_{train}$ ▷ Project $\mathbf{X}$ onto the c-dimensional subspace s
        $\mathbf{X}_{train} = \mathbf{X}_{train} \setminus (\mathbf{X}_{proj} \cap \text{exclusion}(s))$ ▷ Pruning operation in the subspace s
    return $\mathbf{X}_{train}, \mathbf{X}^{\complement}_{train}$

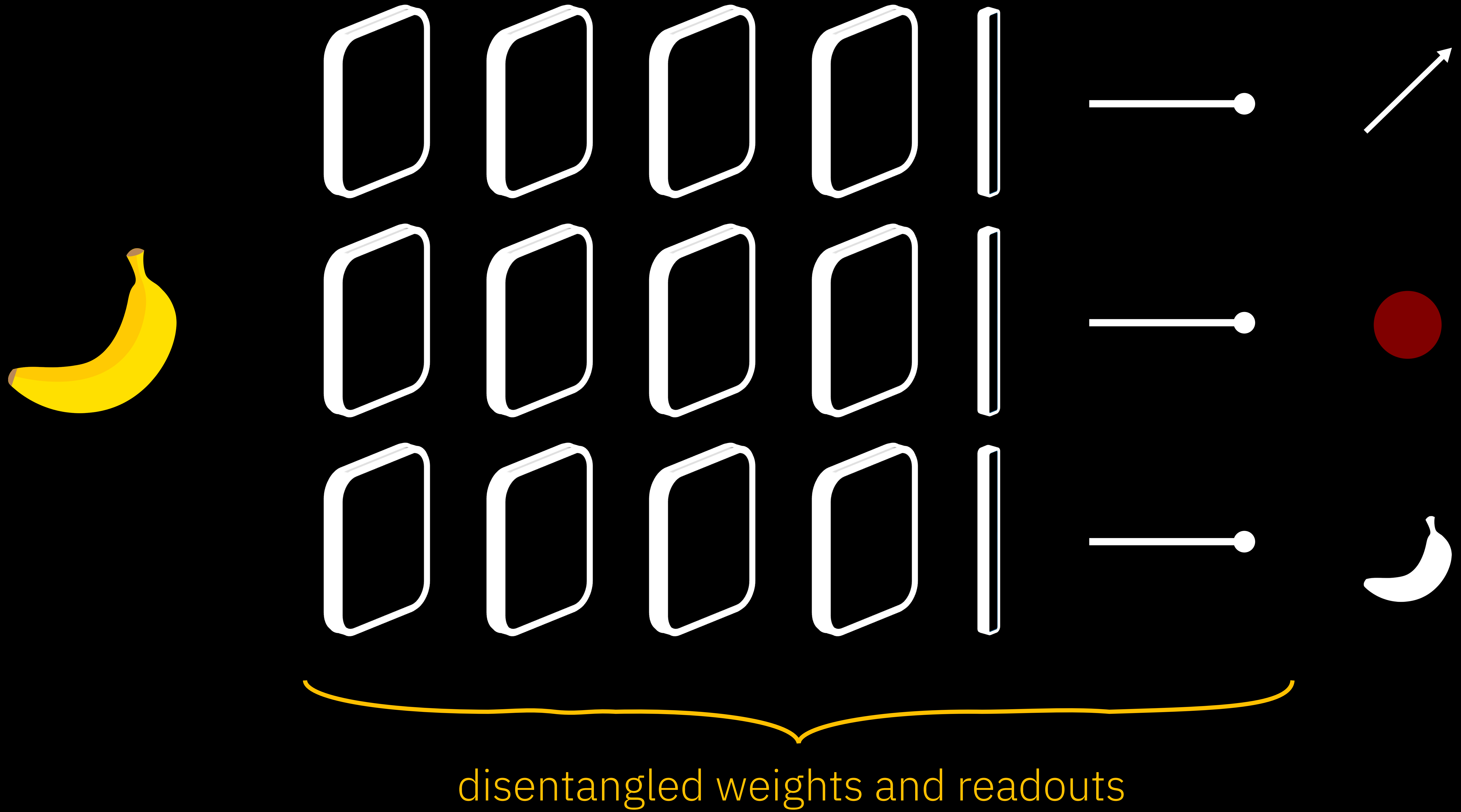
We provide an updated picture of compositional generalization in SOTA models, training more than 5000 models in total.



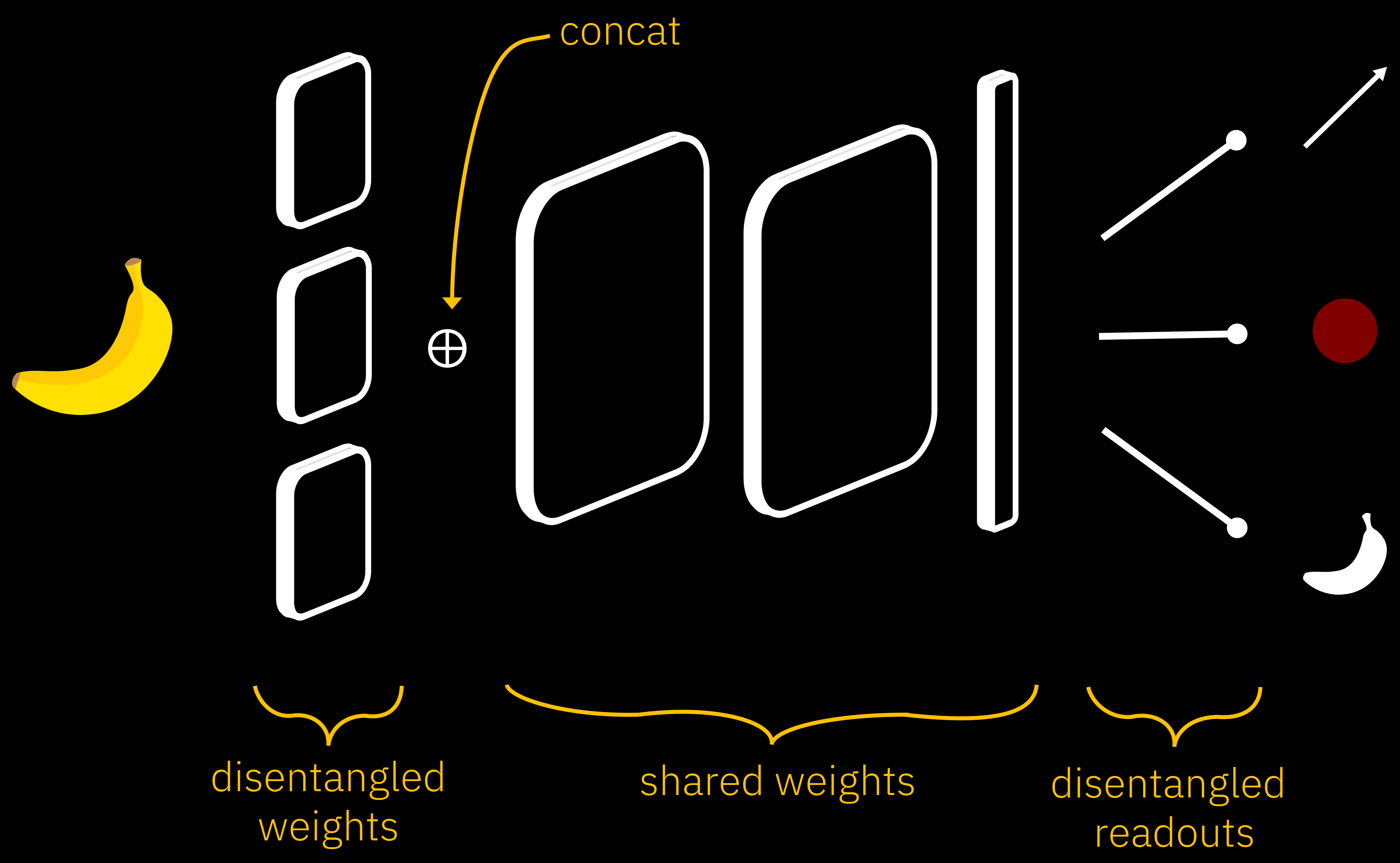
Monolithic networks are parameter-efficient but do not generalize well.



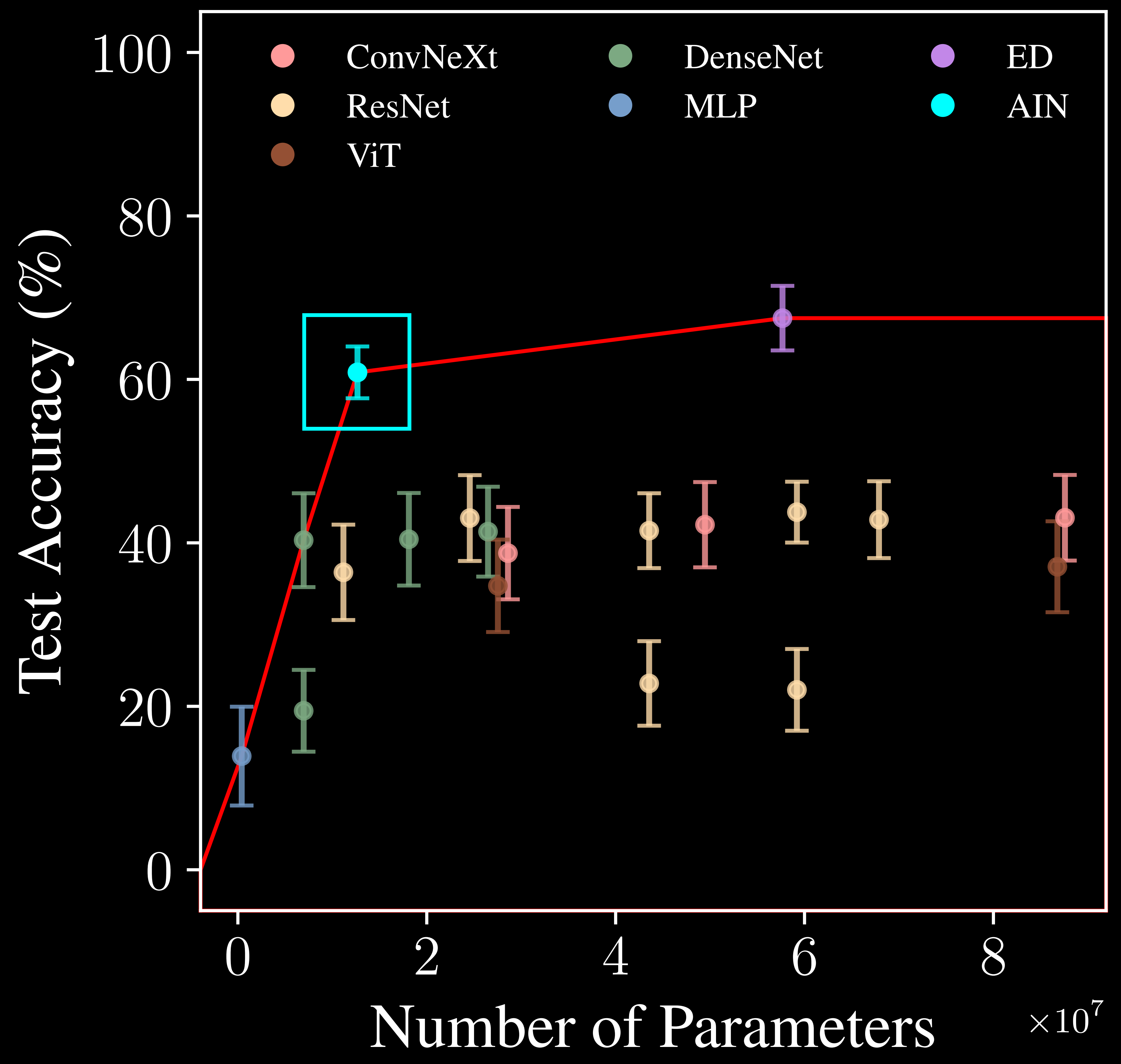
Disentangled networks generalize well but are very parameter-inefficient.



The solution? Attribute Invariant Networks generalize well and are parameter efficient!



AIN achieve Pareto optimality in compositional generalization.



TL;DR: Orthotopic evaluation makes measuring compositional generalization faster and more rigorous. Attribute Invariant Networks achieved the Pareto-optimality in this task.

github.com/IBM/scalable-compositional-generalization