Are Neural Nets Modular?

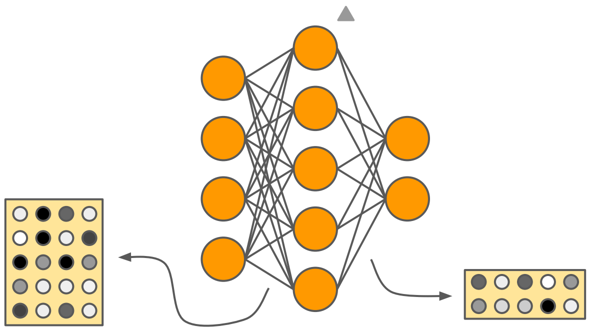
Inspecting Functional Modularity Through Differentiable Weight Masks

Róbert Csordás, Sjoerd van Steenkiste, Jürgen Schmidhuber

ICLR 2021

Inspection via Differentiable Weight Masking

Start with pre-trained weights on the full task



▲ Illustration. We use multi-layer networks and do weight-level analysis.

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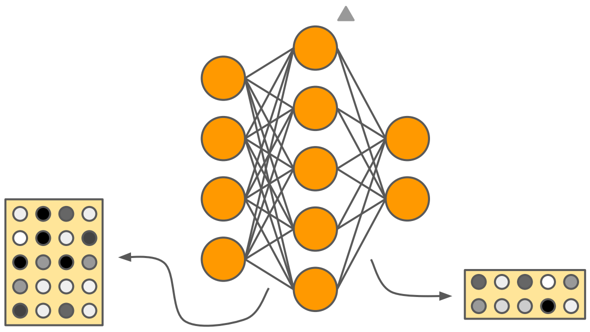

12+45 = 57
42*2 = 84
75+85 = 60
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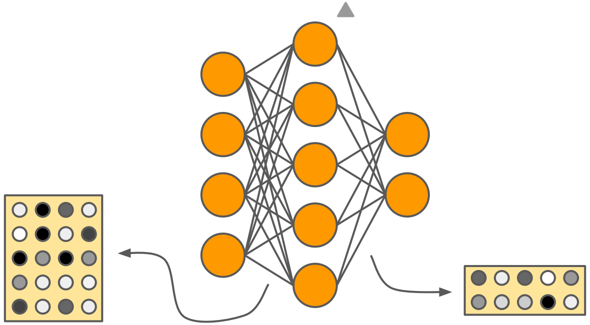

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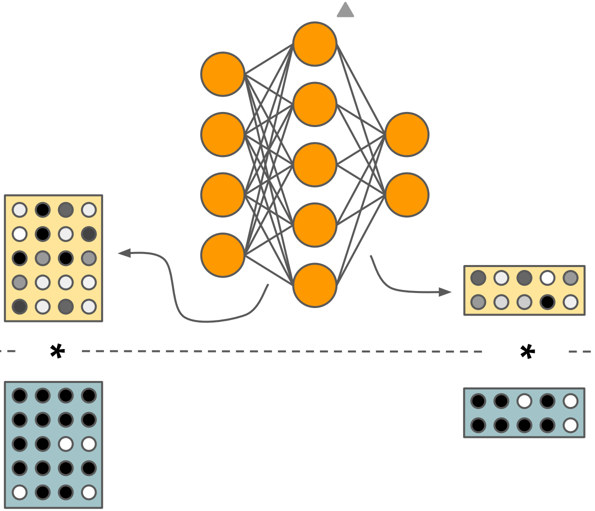

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Train binary weight masks on a subtask

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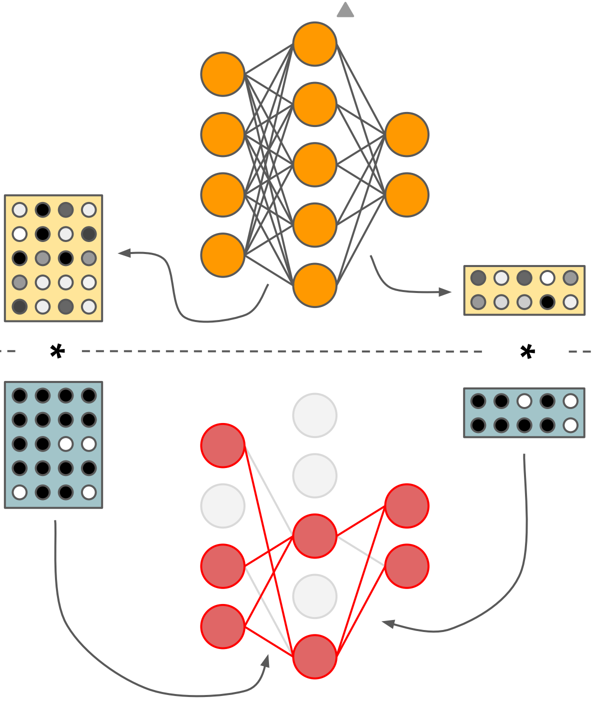

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Train binary weight masks on a subtask

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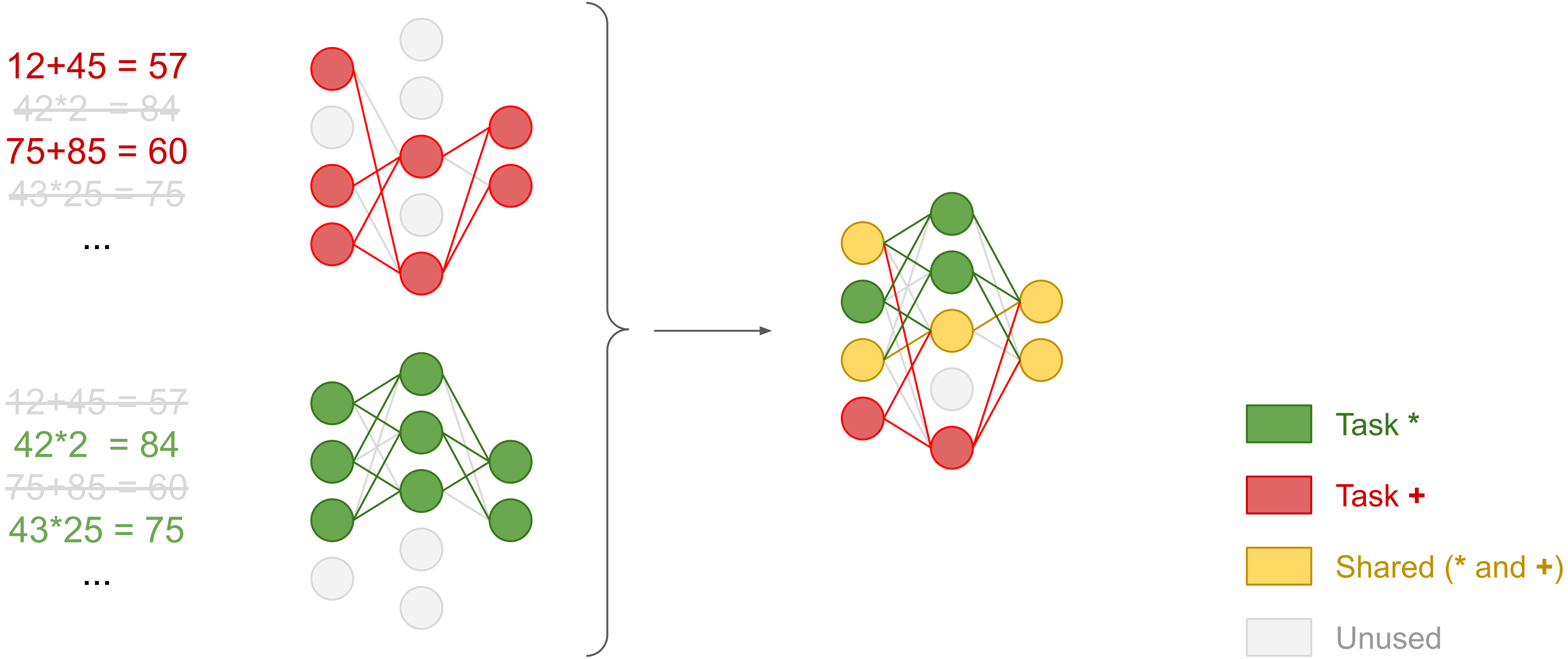
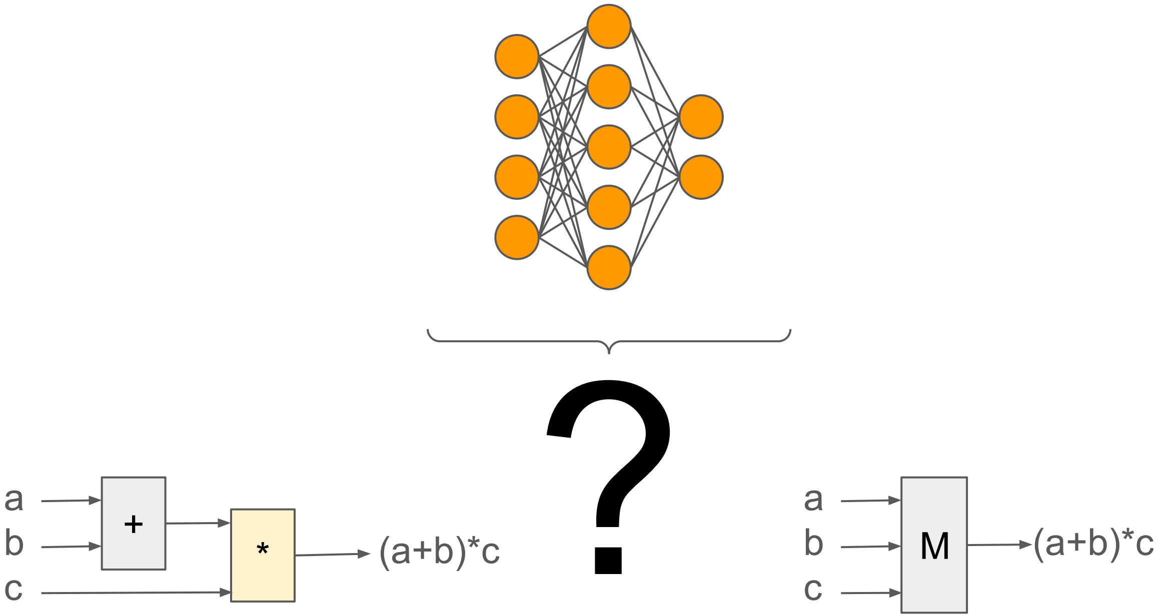
Inspection via Differentiable Weight Masking

Same is done for all subtasks of interest

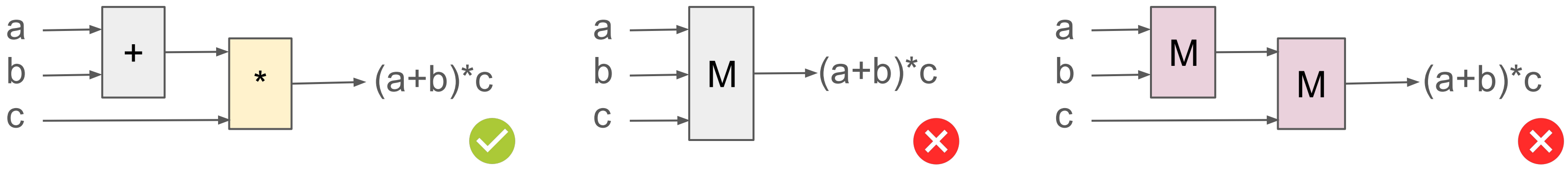


Are neural networks modular?



Compositionality and modularity

- $P_{specialize}$: Different modules for separate functions



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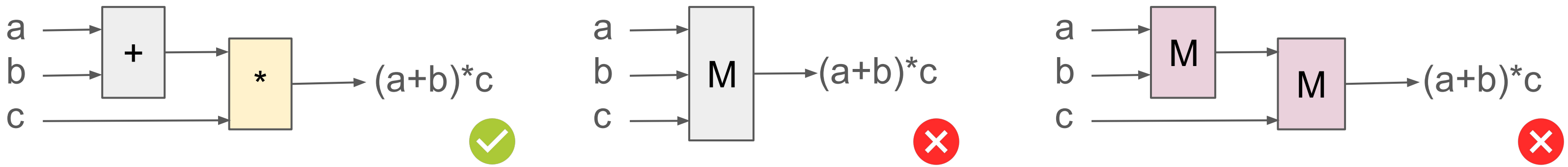


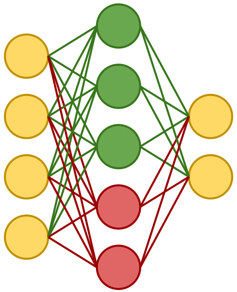
- P_{reuse}: Use the same module for identical functions

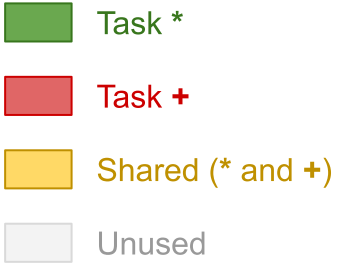
Analysis

$P_{specialize}$: Different modules for separate functions

Input vector:	n_1 n_2 op=*	n_1 n_2 op=+
Output vector:	$n_1 * n_2$	$n_1 + n_2$

Expectation





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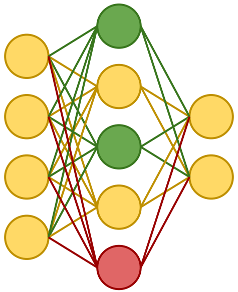
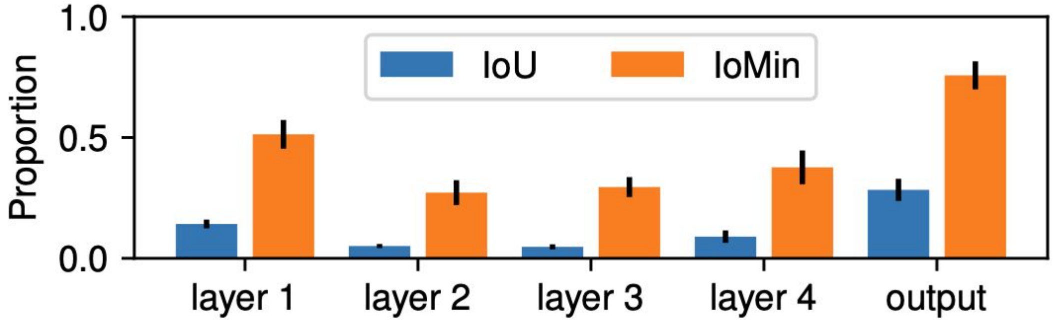
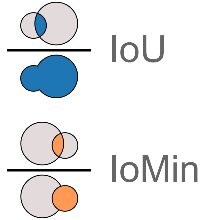
What we found:





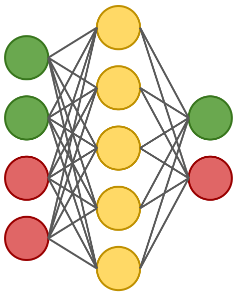


Analysis

P_{reuse}: Use the same module for identical functions

Input vector:	n_1	n_2	0	0	0	0	n_3	n_4
Output vector:	$n_1 + n_2$		--		--		$n_3 + n_4$	

Expectation



Task 1 (n_1+n_2)

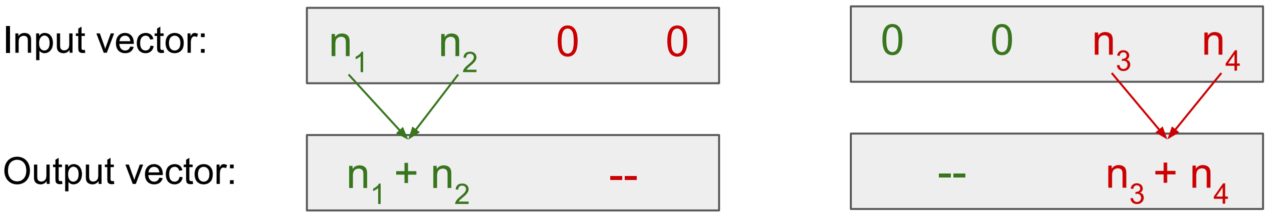
Task 2 (n_3+n_4)

Shared

Unused

Analysis

P_{reuse}: Use the same module for identical functions



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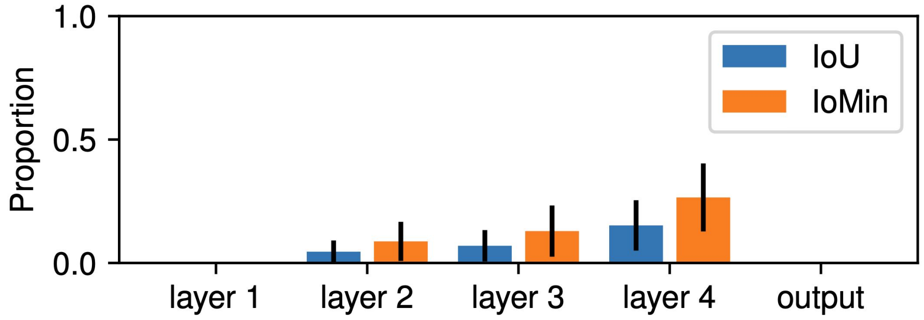
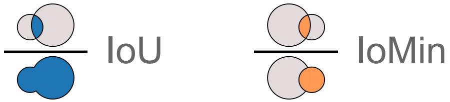
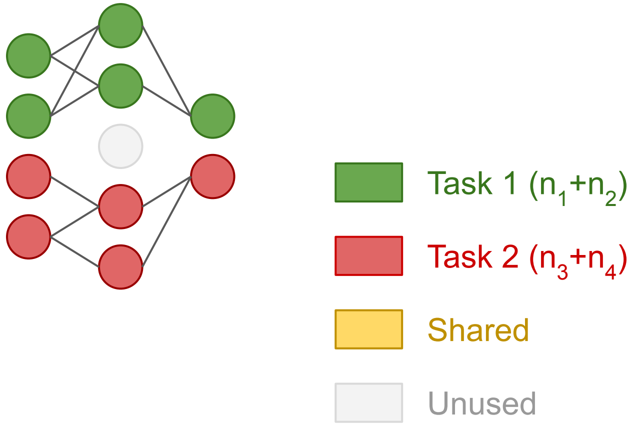


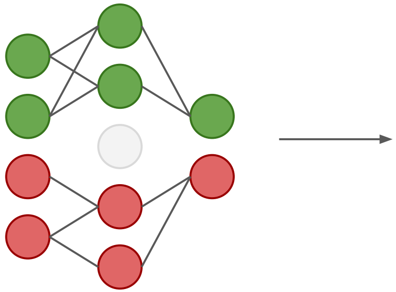




Analysis

P_{reuse}: Use the same module for identical functions

Confirmation: invert masks



Task 1 (n_1+n_2)

Task 2 (n_3+n_4)

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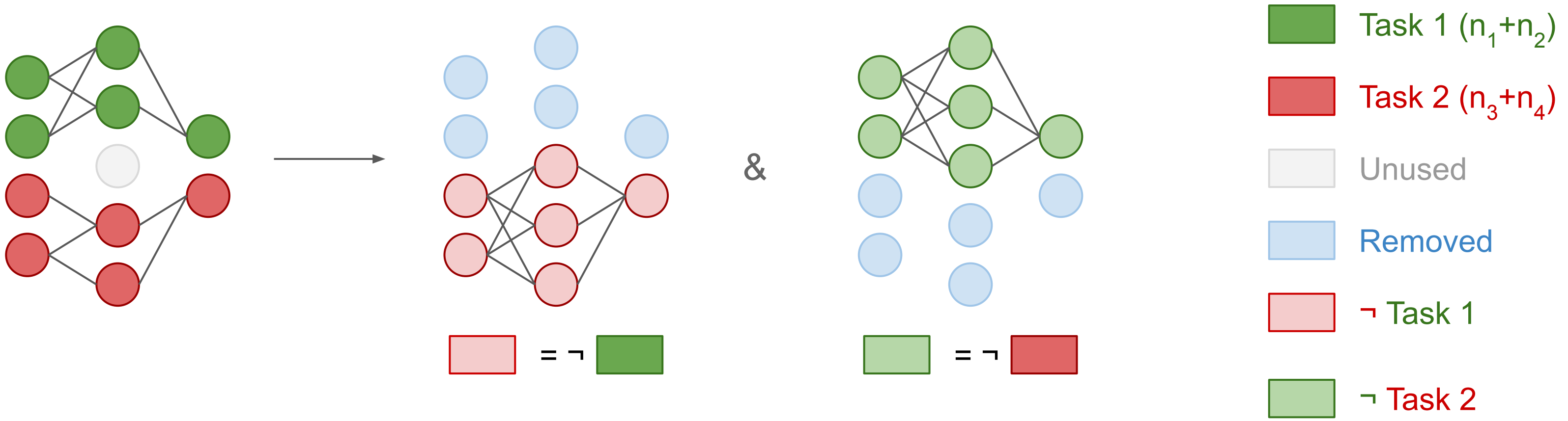

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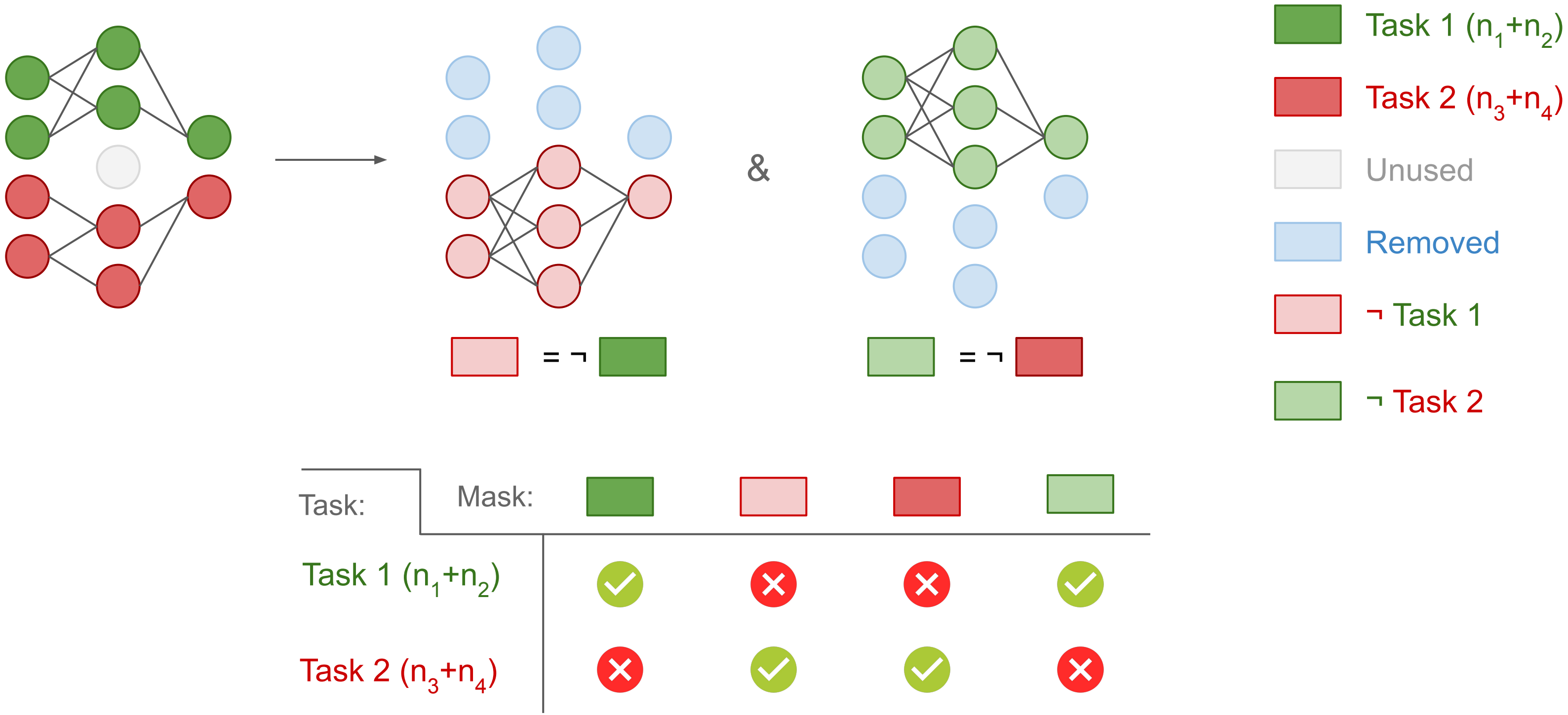
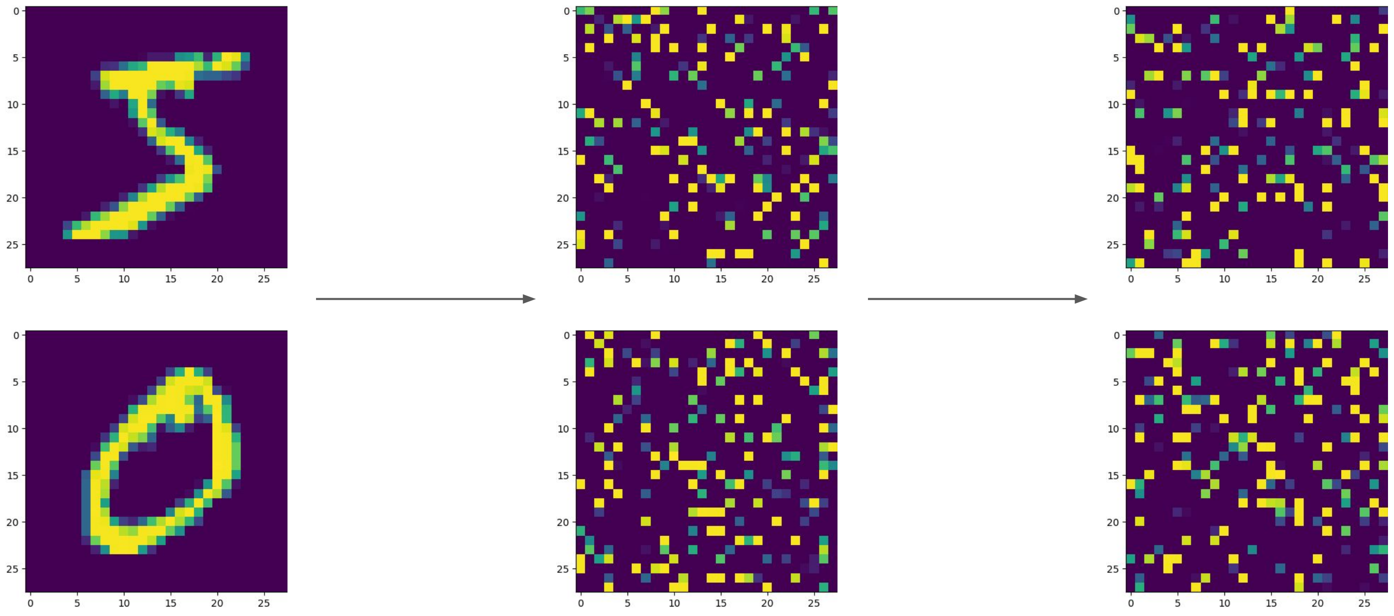


Analysis

P_{reuse}: Use the same module for identical functions

- We also test the effect on sequentially training to classify new permutations of MNIST.

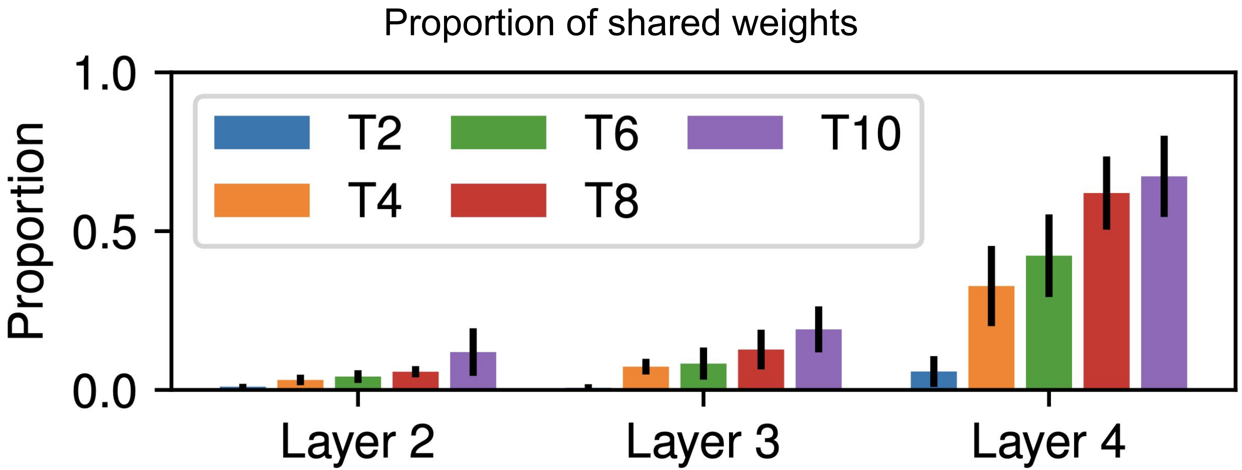


T0 T1 T2

Analysis

P_{reuse}: Use the same module for identical functions

- We also test the effect on sequentially training to classify new permutations of MNIST.
- Layers are not reused, even though re-learning the first layer is enough.



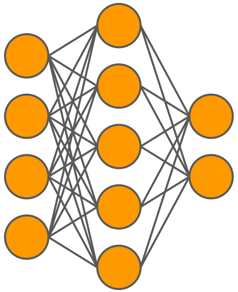
Analysis - summary

$P_{specialize}$: Different modules for separate functions ✓

P_{reuse}: Use the same module for identical functions ✗

Analyzing generalization: SCAN

All networks have the **same**, frozen weights



Trained: i.i.d

- Train set
- Jump test
- Length test

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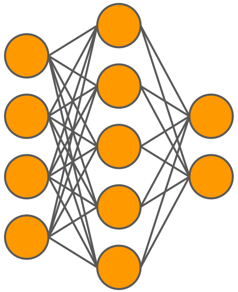

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- Jump test ✓
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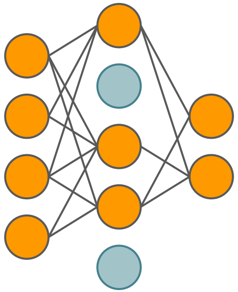
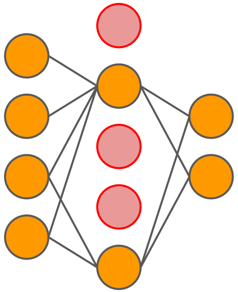


Trained: jump train
- Train set ✓
- Jump test ✗



Trained: length train
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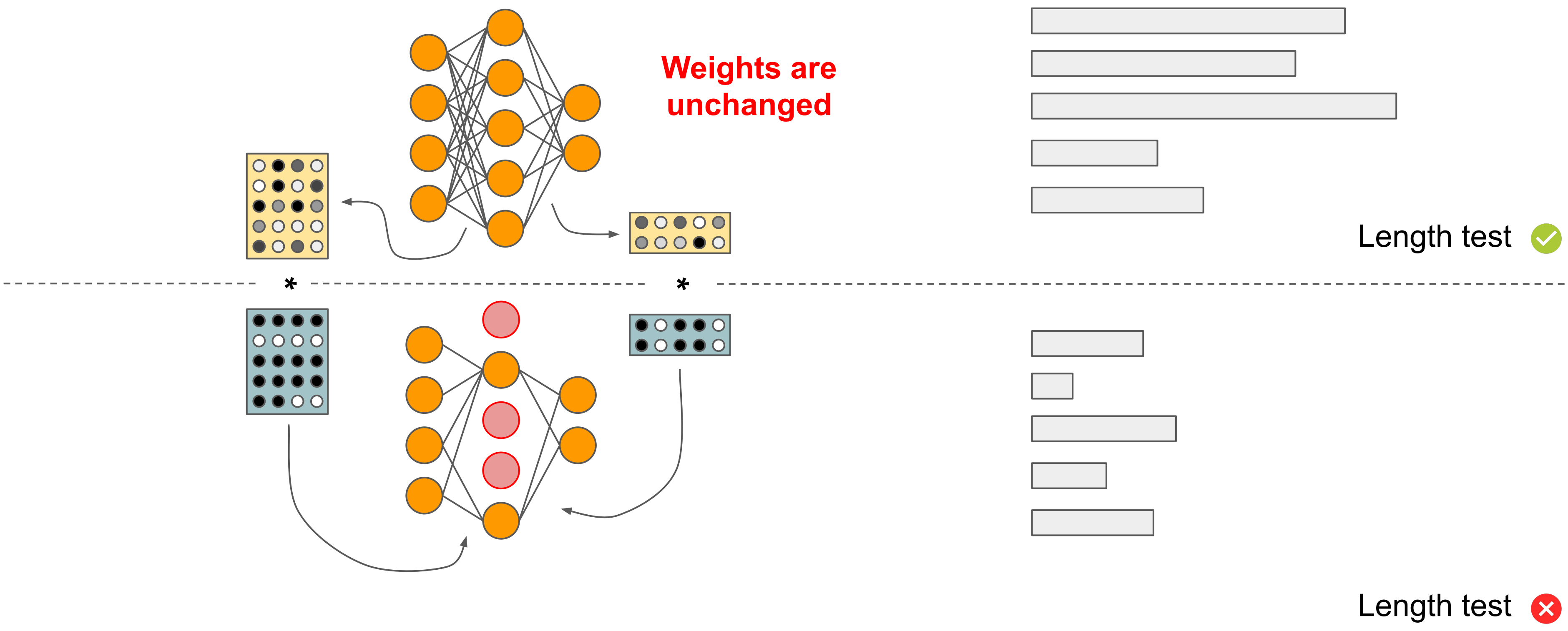
- Length test ✗

Responsible for complex JUMP

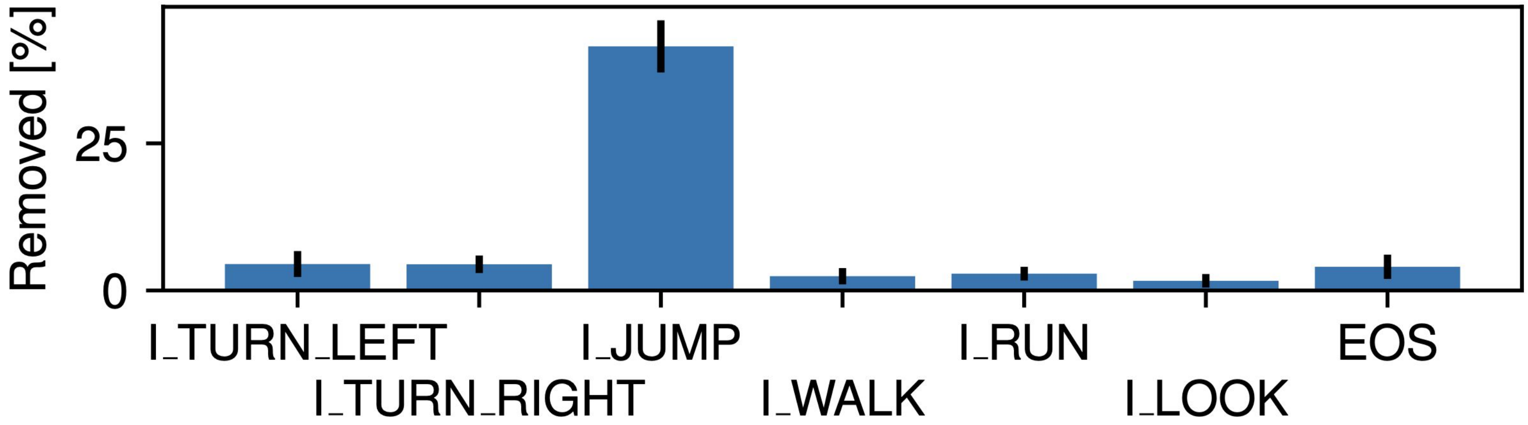
Responsible for longer samples

Analyzing generalization: SCAN



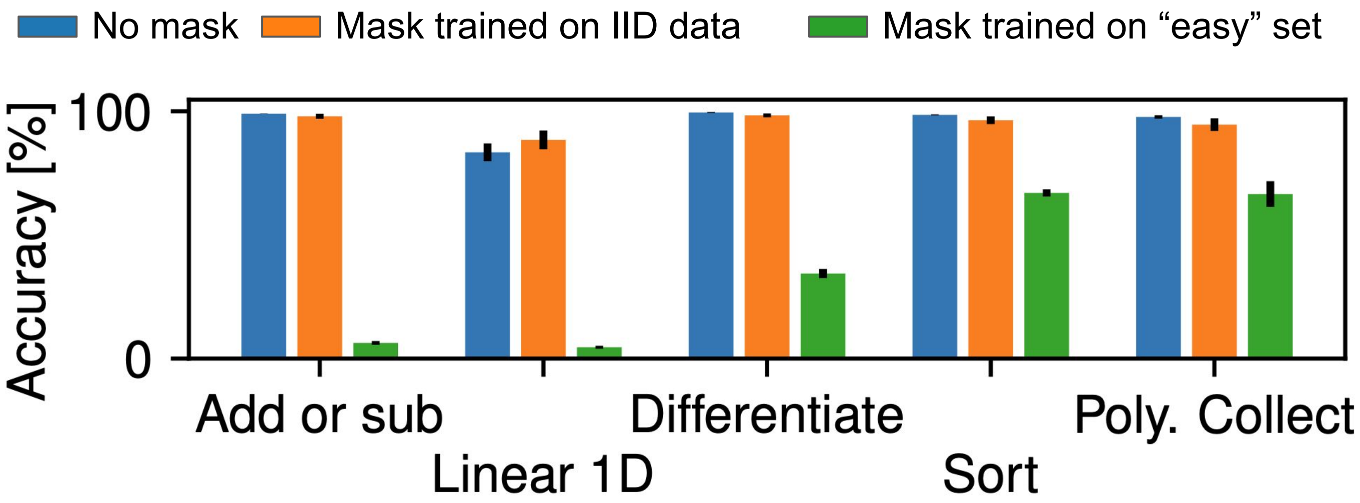
Analyzing generalization: SCAN

Percentage of weights per output token removed from last layer when trained on Add Jump split



Task-specific weights are responsible for solving different splits,
even after successfully trained on the i.i.d data

Mathematics Dataset: Similar results



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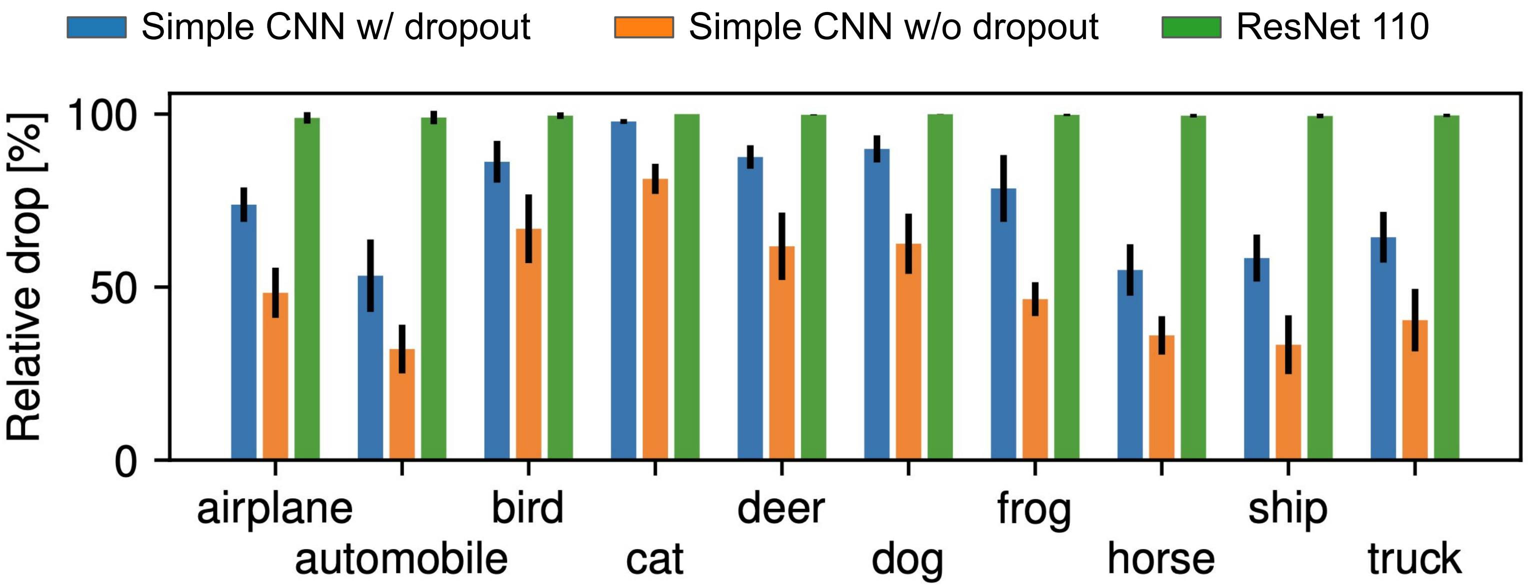
Sharing in CNNs (CIFAR 10)

Classification depends heavily on unshared features, which, when removed, cause a huge drop in performace.



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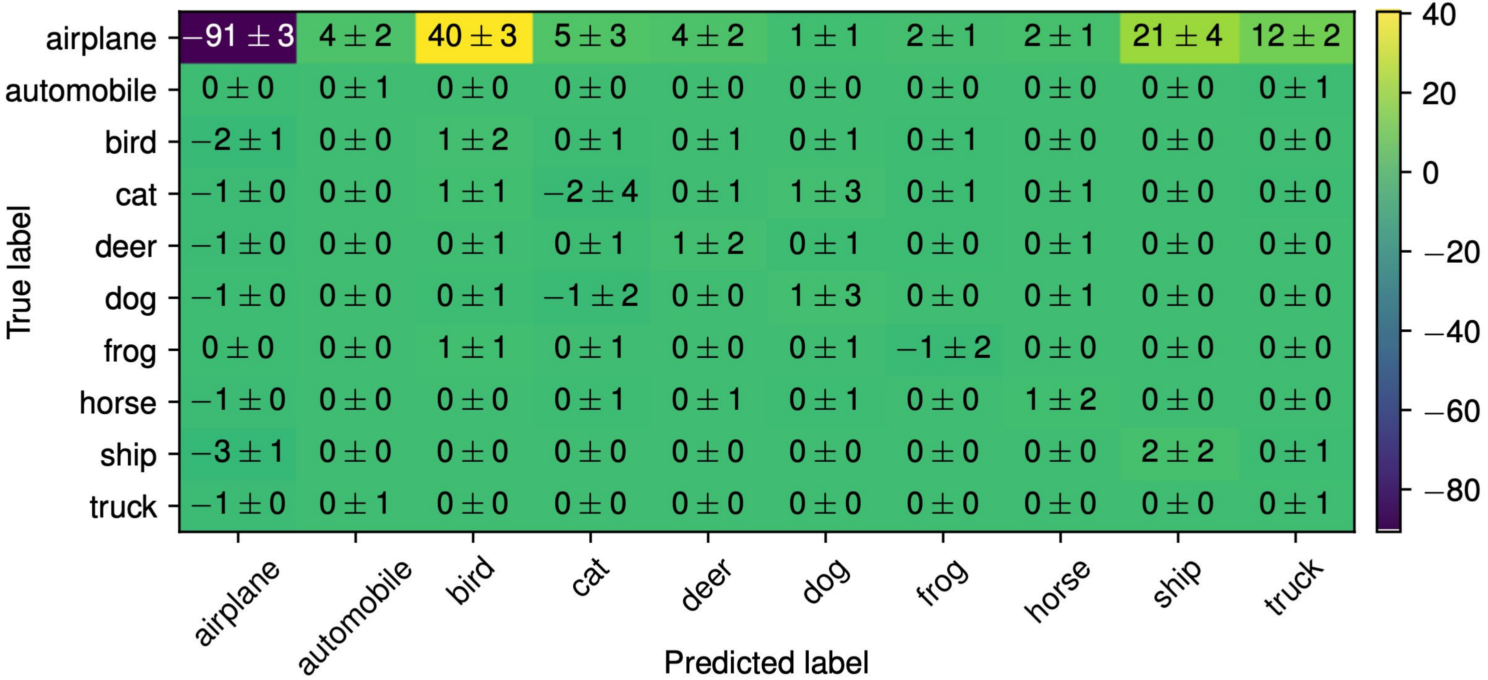
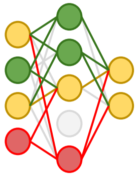
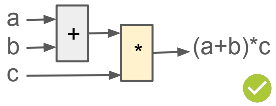


Concluding remarks

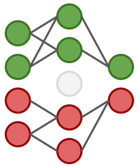
- We proposed a masking based method for discovering subnetworks responsible for specific functions



- Analyze properties of discovered modules



- We found that modules tend to resist sharing



- Generalization issues on SCAN and Mathematics Dataset is a result of learning a non-universal, pattern recognition-like solution.