Hidden Layers in Perceptual Learning

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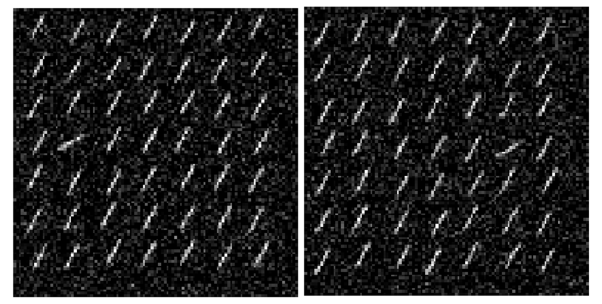
Background

- In this work, we examined open computational questions in visual perceptual learning, by modeling the learner using shallow CNNs.
- Studies in visual perceptual learning investigate the way human performance improves with practice, in the context of relatively simple, tractable visual tasks.
- The acquired skills are highly specific to simple visual features, such as location in the visual field, orientation; As such, they do not transfer - e.g., do not generalize to other orientations.
- We focused our investigation on two hallmark characteristics of perceptual learning – **Specificity** and **Enabling.**

Methods

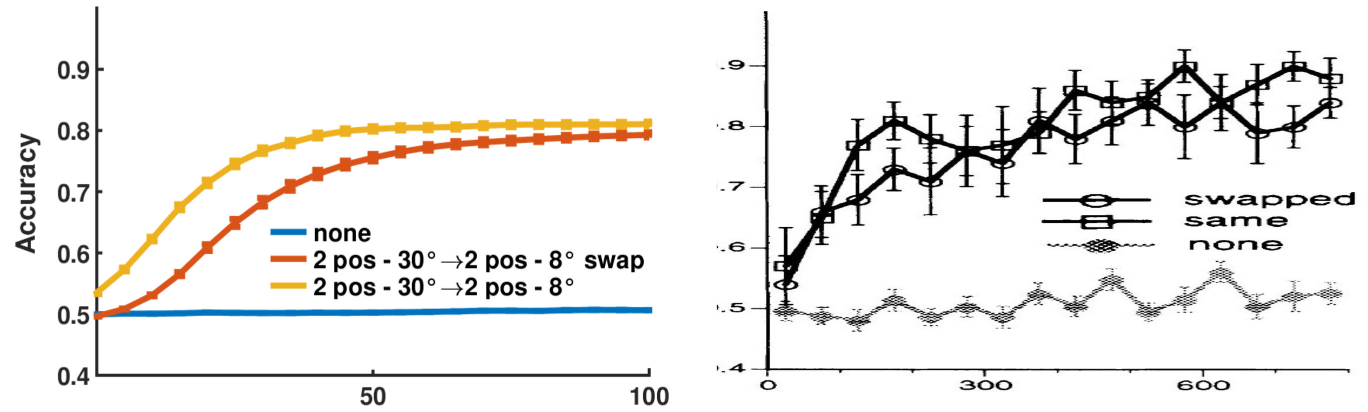
- We trained a two layer CNN using vanilla SGD, with a fixed learning rate and batch size. The network was initialized (32 repetitions) using a weight vector out of a fixed randomly generated set .
- In the first experimental setup (left), the task was to detect the presence of an odd line segment. The angular difference between the odd segment and the remaining segments controlled the level of difficulty (SNR) of the task
- In the second experimental setup (right), the task was to determine the rotation direction of a Gabor patch.



1

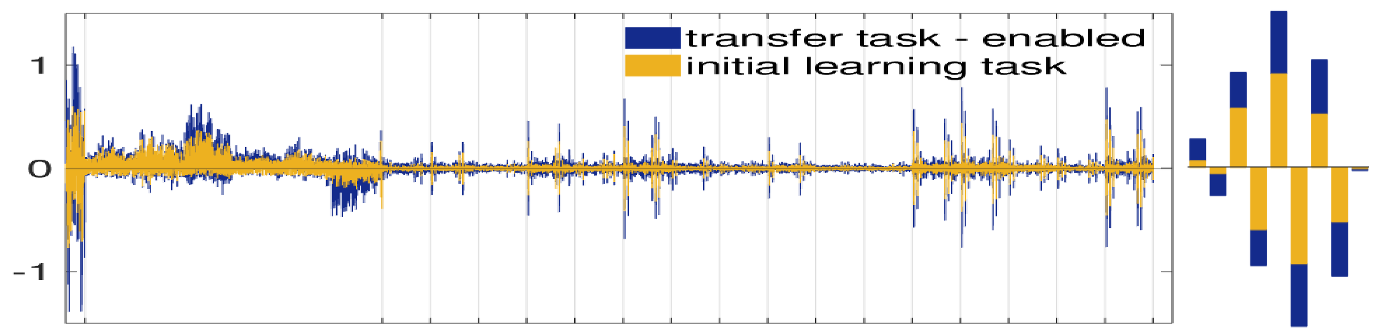
2

Experiment 1



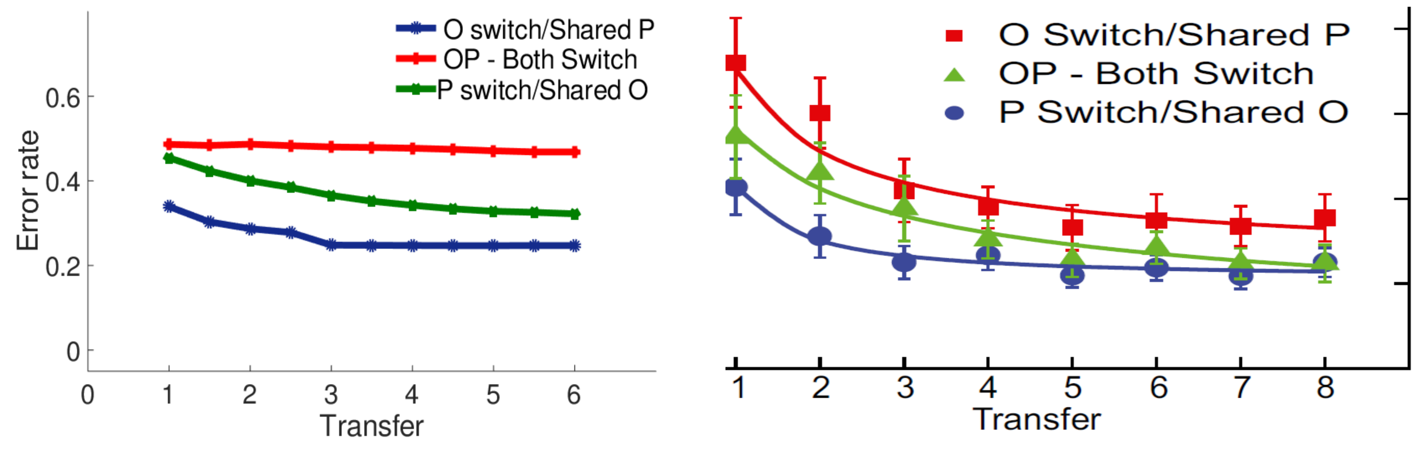
Left: training a CNN to detect an odd segment with 8º takes a very long time (bottom line). However, when the network has been first trained with a similar easy task using 30º, instantaneous improvement is seen, followed by speedy learning. The same happens even if the orientations of the background and odd elements was swapped between the odd element and the background. right) A qualitatively similar phenomenon as reported in human perceptual learning [1].

Dynamics of weight modifications



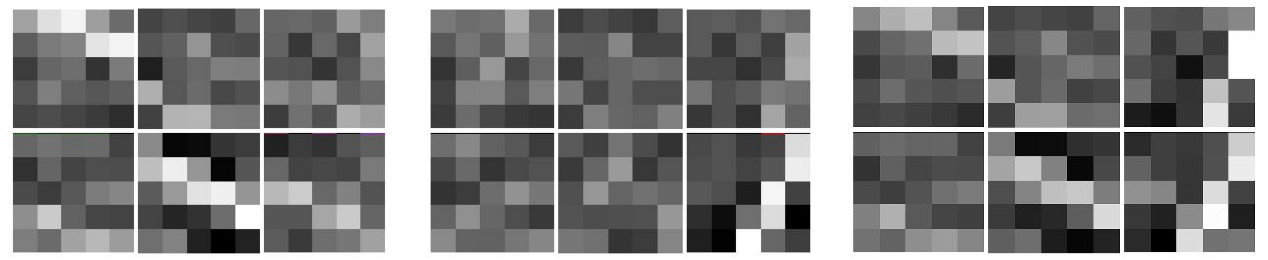
Blue bars show the weights at the end of the process, and super-imposed yellow bars show the intermediate weights after training with the initial easy (high SNR) task. Almost all weight changes correspond to amplification.

Experiment 2



Transfer to a new location and new stimulus orientation. Left: artificial CNN using 30º. Right: qualitatively similar phenomenon as reported in human perceptual learning [2].

Dynamics of weight modifications



The 6 convolution filters learned in the first conv-pool layer when: left) the network was trained to discriminate orientation o_1 only; middle) the network was trained to discriminate orientation o only$_2$; right) the network was trained to discriminate orientation o_2 after being trained with orientation o_1.

Training on a new transfer task modified primarily channels which had been less significant for the previous task.

Efficiency

Task	Accuracy	#bits
2 pos - 30°	99.79%	5.094
2 pos - 16°	99.40%	5.656
2 pos - 8°	96.90%	5.7188
8° enabled	98.43%	5.7188

The minimal number of bits required to store the network's weights without reducing performance by more than 1%. More bits (or higher precision) were required for harder discrimination tasks. The enabled network reached higher accuracy while requiring the same precision

Conclusions

- The shallow CNN networks qualitatively showed most of the characteristic behavior observed in perceptual learning, including the hallmark phenomena of specificity and its various manifestations in the forms of transfer or partial transfer, and learning enabling
- The pattern of weight modifications may identify the ways by which the domain of search in the parameter space during the network re-training can be significantly reduced, thereby accomplishing knowledge transfer

References

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2. Dosher, B. A.; Jeter, P.; Liu J.; Lu, Z. L. An Integrated Reweighting Theory of Perceptual Learning. Proceedings of the National Academy of Sciences, 110(33):13678–13683, 2013. 5
3. Liu, Z.; Weinshall, D. Mechanisms of Generalization in Perceptual Learning. Vision Res. 2000 40(1), 97–109.