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From a Locally Competitive Algorithm to Sensory Relevance Models

Walter Woods
Portland State University

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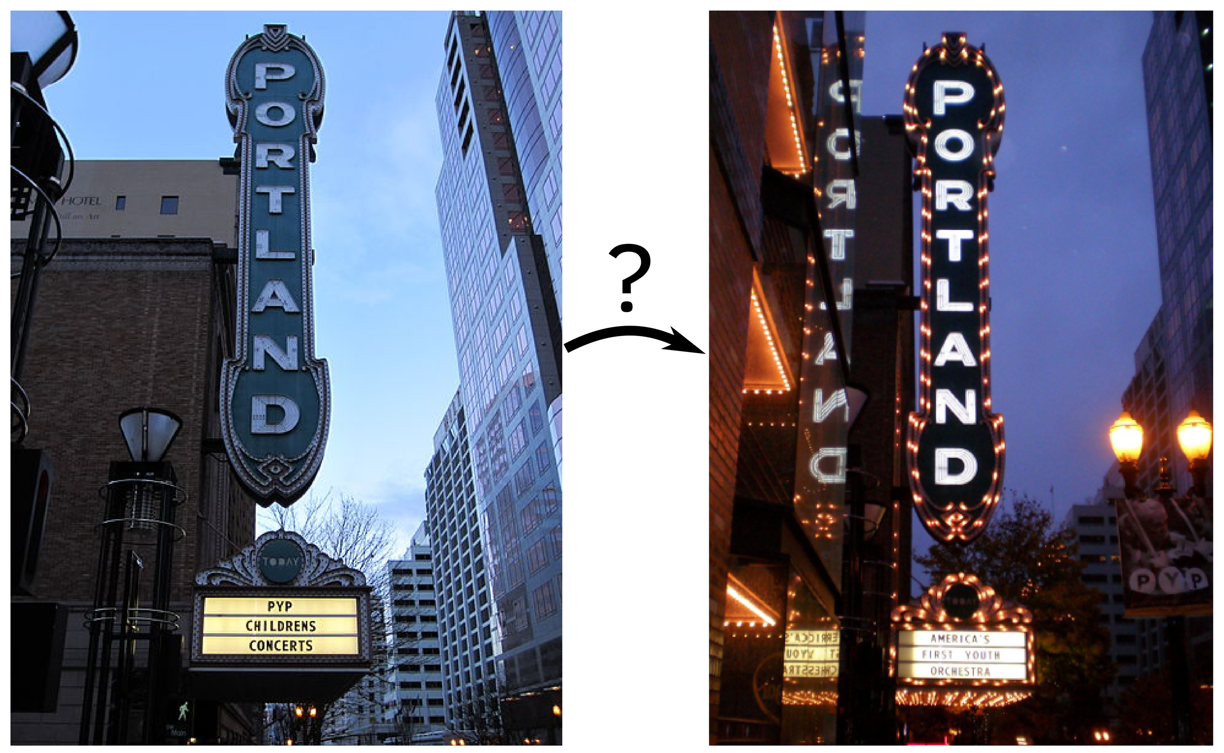
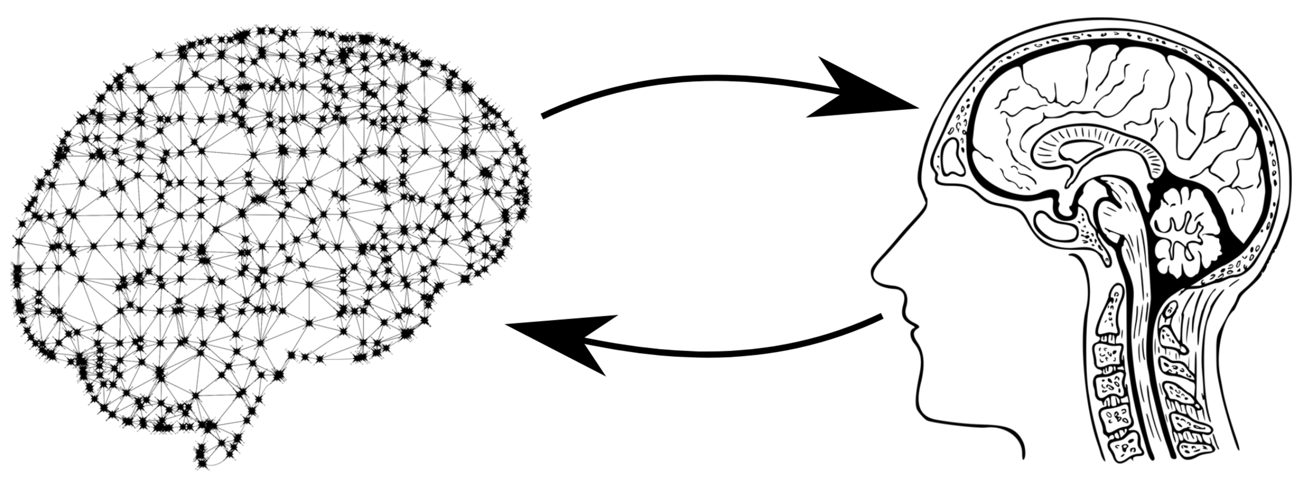
Walt Woods and Christof Teuscher; teuscher.:Lab, Department of Electrical and Computer Engineering, Portland State University, Portland, OR, USA; {wwoods, teuscher}@pdx.edu

Background

Machine Learning (ML): developing computers that learn without explicit programming.



Human-in-the-Loop (HIL): ML methods that rely on feedback from a human operator.



Sparse Coding

The tree diagram at the top of this poster (Fig. 2) illustrates the primary principle behind sparse coding: whole objects can be broken down into distinct components. This concept also works backwards: an input stimulus can be represented as the sum of many distinct components, called dictionary elements, which can in turn be used to identify whole objects. This happens through a process known as unsupervised learning; in this work, the Locally Competitive Algorithm (LCA) by Rozell et al. (2007) was adapted for next-generation hardware.

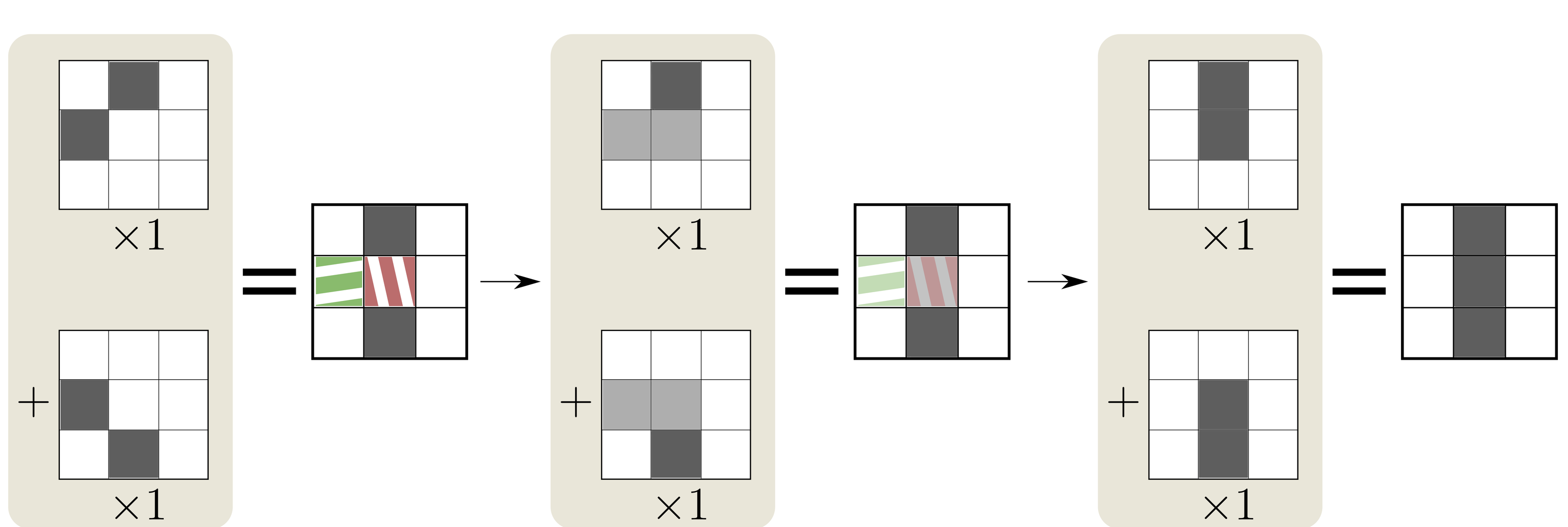


Fig. 1 - Demonstration of Oja's rule, used to learn the optimal dictionary elements for a set of input patterns. Over time, the dictionary used to encode inputs can more accurately represent different input patterns.

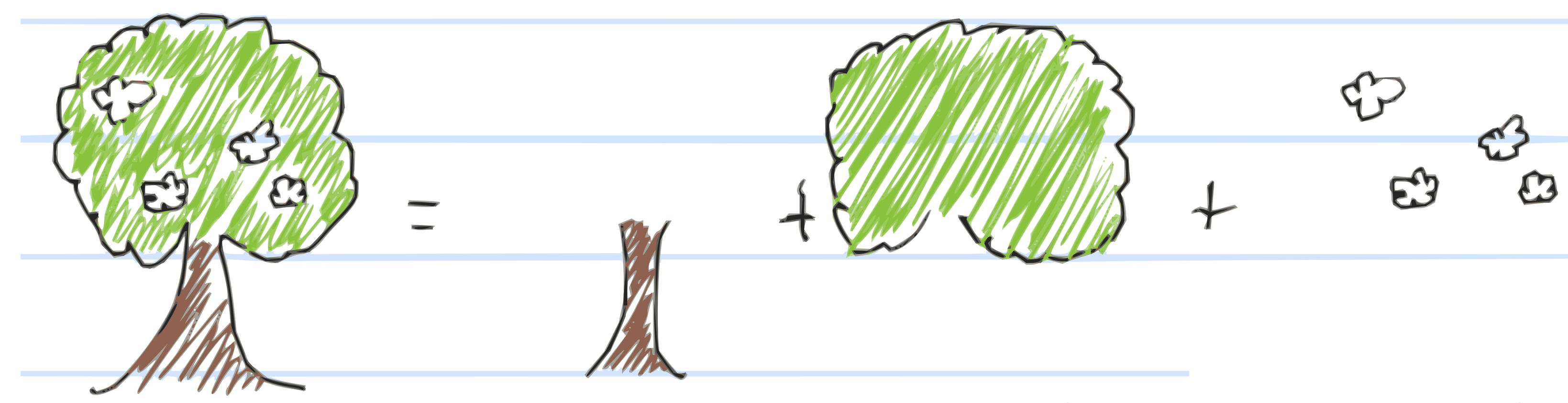


Fig. 2 - Sparse coding is representing an input stimulus as a sum of distinct parts; the pattern of distinct parts used can then be used to identify larger patterns in the stimulus, such as the type of object creating the stimulus.

Memristors

Memristors combine storage and logic into a single, nanoscale device. The result is extraordinary savings in power consumption, processing speed, and circuit area, at the cost of additional design requirements due to their analog nature. These devices made the SSLCA possible.

Memristor	Type	$max(V_{read})$ (V)	R_{max} (kΩ)	R_{min} (kΩ)
Batas [2]	*	4.0	87	5.5
Berdan *[4]*	TiO_2	4.0	94	5.0
Biolek [5]	*	3.9	9.4	0.59
Merrikh-Bayat *[19]*	TiO_2	1.2	280	17
Eshraghian [7]	†	0.031	1 400 000	79 000
Lehtonen [16]	*	0.82	410 000	28 000
Pershin [25]	*	0.000 007 0	9.6	1.5
TEAM [14]	*	0.48	0.13	0.061
Yang *[39]*	$Ag, Cu; TiO_2$	1.4	180	54
Jo *[11]*	Ag/Si	4.0	370 000	24 000
Miao *[20]*	TaO_x	4.0	17	1.1
Miller *[21]*	TiO_2	4.0	1.4	0.085
Oblea *[22]*	$Ge2Se3; Ag$	0.32	11	0.70
Jo & Lu *[12]*	Ag/Si	2.9	12	0.72

Fig. 3 - There are many research groups developing memristor technology; shown here is a selection of devices and their qualities published as Woods *et al.*, *NANOARCH*, 2015.

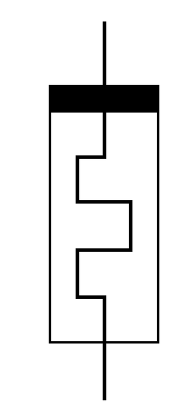


Fig. 4 - The circuit symbol for a memristor

Our SSLCA Architecture

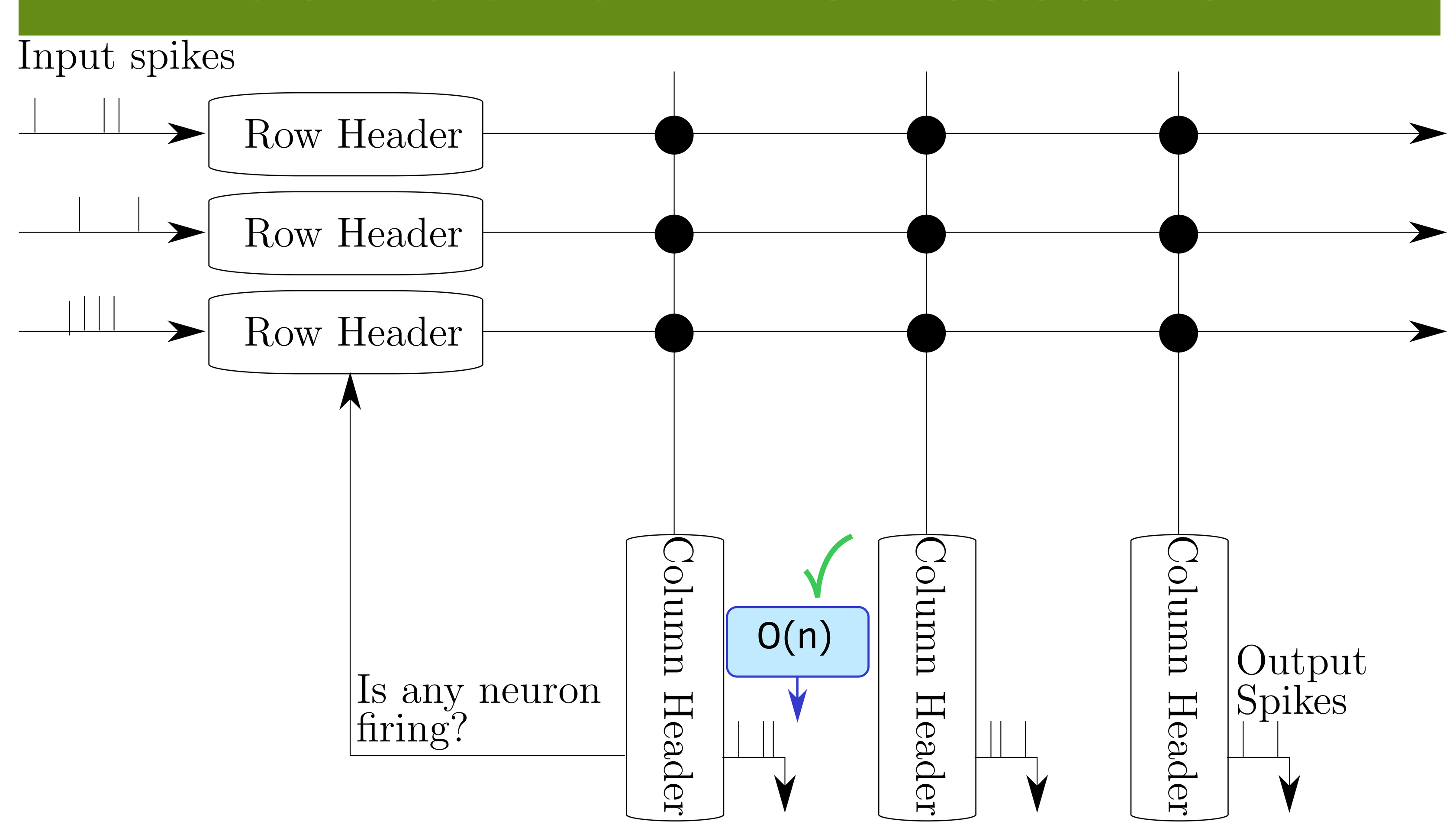


Fig. 4 - The layout of the *Simple, Spiking Architecture* (SSLCA); memristors are at the junctions of the horizontal and vertical nanowires. Read the paper on ArXiv for more information: "Fast and Accurate Sparse Coding of Visual Stimuli with a Simple, Ultra-Low-Energy Spiking Architecture."

What We Can Do Now

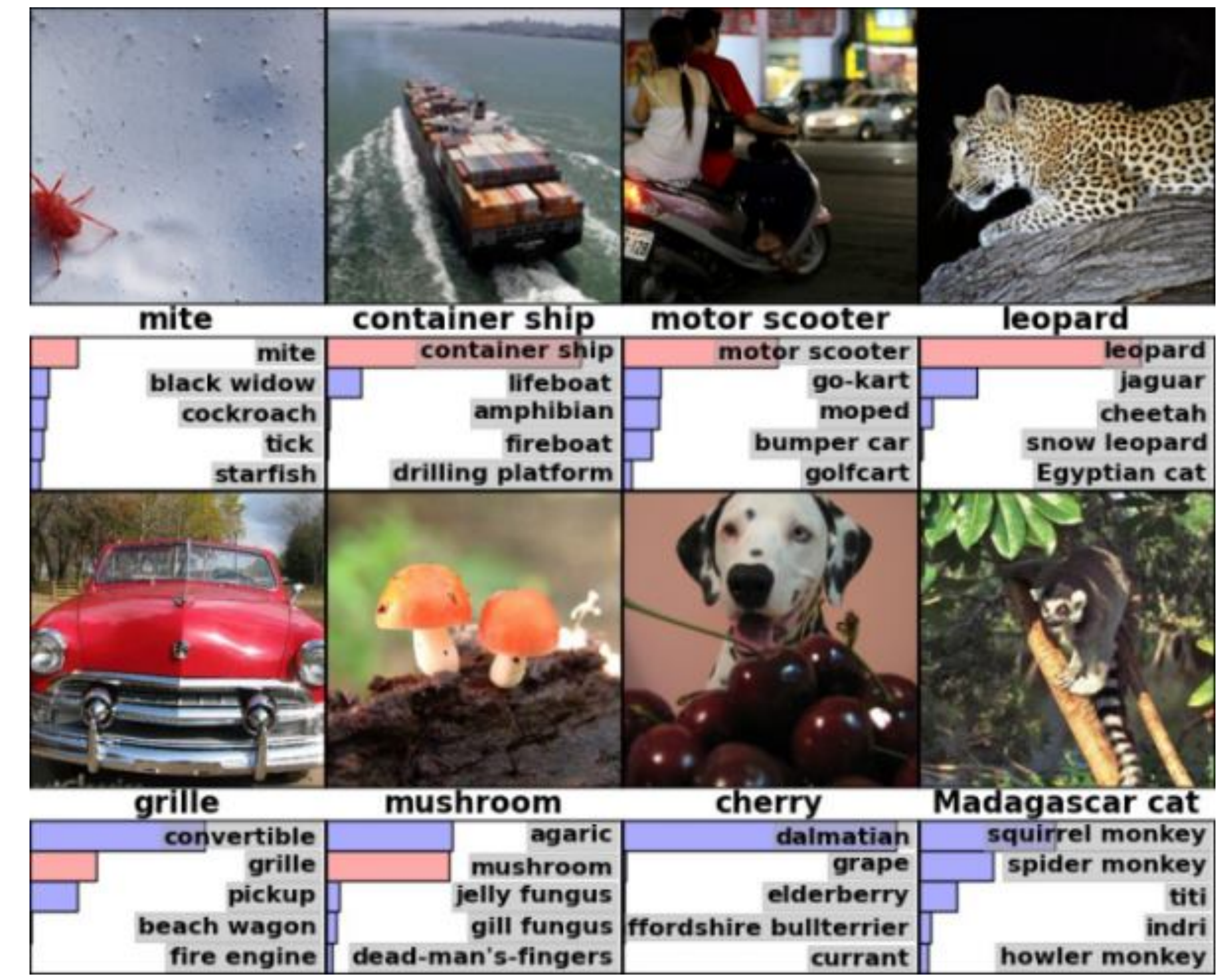


Fig. 5 - Current ML focuses around learning an approximation for input -> output mappings, or otherwise optimizing an objective function. This approach yields very little ability to investigate the internal operation of the ML method.

What We Should Be Able To Do

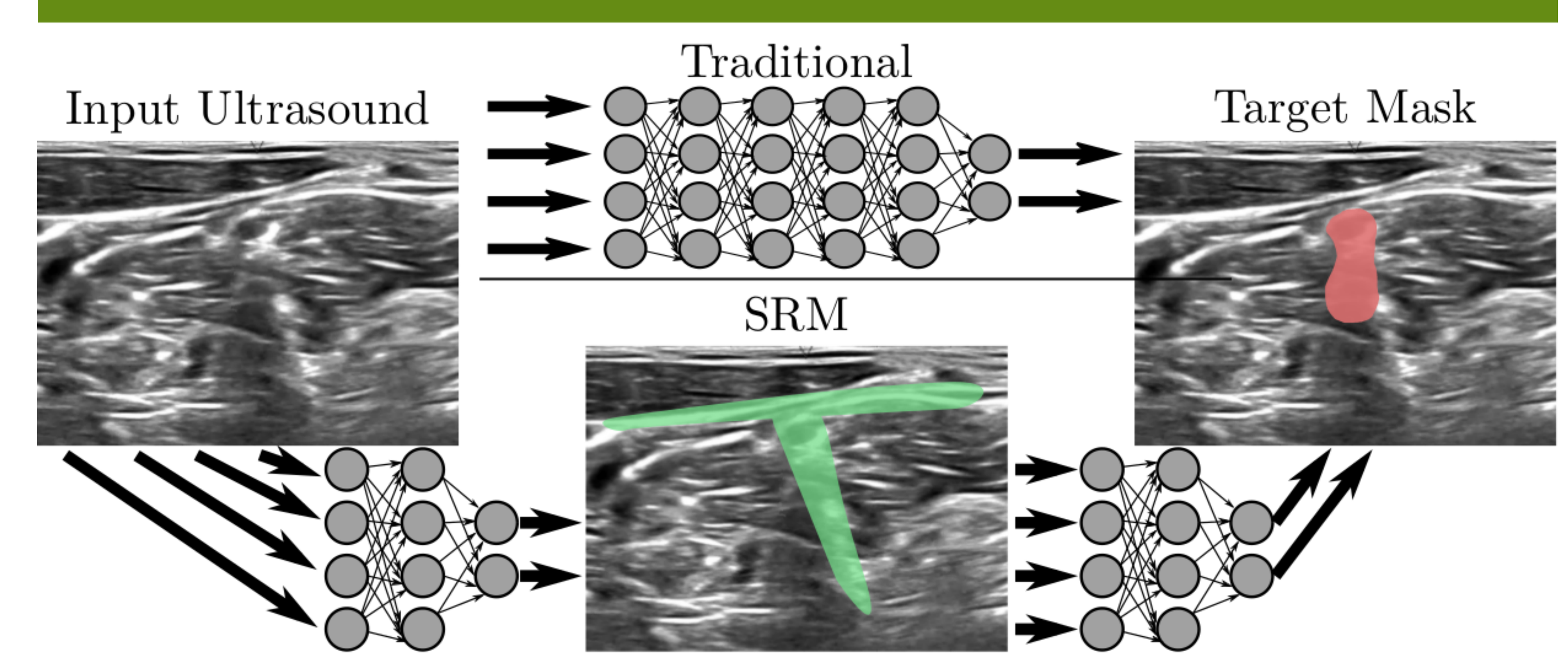


Fig. 6 - By bringing in ideas from HIL research, we hope to make ML more investigable by injecting an intuitive means of communicating the operations happening in the middle of the network. Adding an intermediate step allows us to not only see what is happening in the middle, but also to manipulate it.

teuscher.:Lab
teuscher-lab.com

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