Unsupervised Dictionary Learning For Neuromorphic Processors

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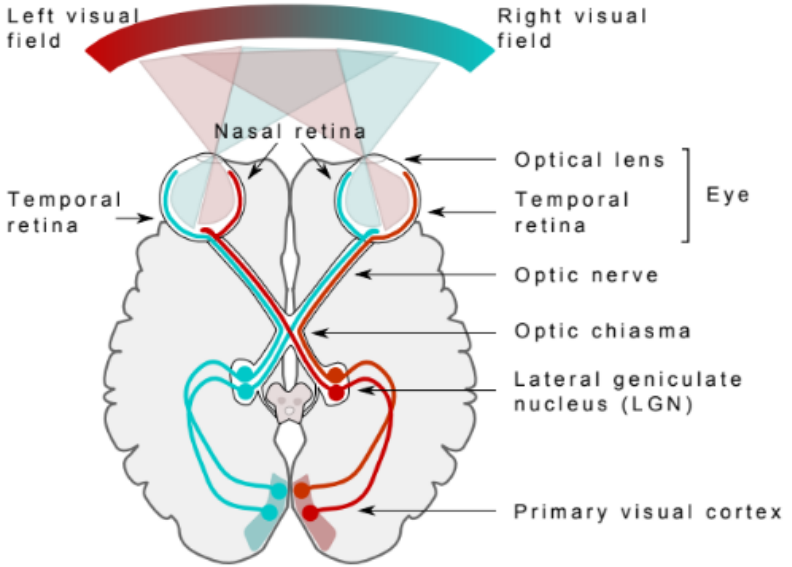
What is Sparse Coding?

First introduced by Olshausen & Field (Nature, 1996)

Unsupervised feature learning algorithm

Use an overcomplete set of feature vectors to find sparse coefficients.



Human visual system

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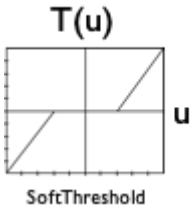
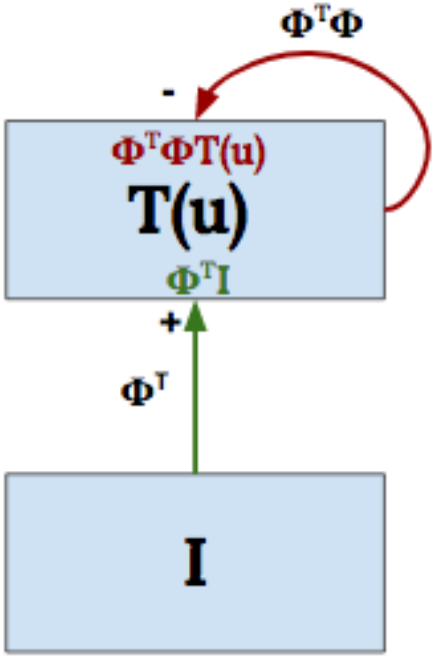
$$E = \frac{1}{2}\overbrace{|| \overrightarrow{I} - \{\overleftrightarrow{\Phi} T(\overrightarrow{u})\}||_2^2}^{\text{Reconstruction Term}} + \overbrace{\lambda||T(\overrightarrow{u})||_1}^{\text{Sparsity Term}}$$



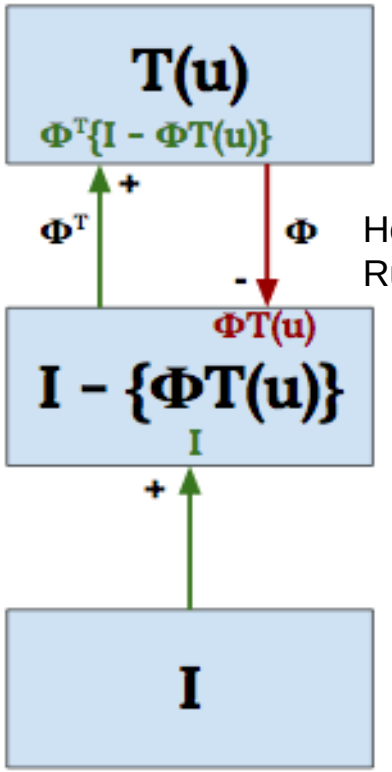
Non-Spiking LCA Dictionary Learning

$$\frac{d\vec{u}}{dt} = \overbrace{-\vec{u}}^{\text{Leak}} + \overbrace{\overleftrightarrow{\Phi}^T \{\vec{I} - \overleftrightarrow{\Phi}\vec{T}(\vec{u})\}}^{\text{Residual}} + \overbrace{\vec{T}(\vec{u})}^{\text{Self Interaction}}$$



$$E = \tfrac{1}{2}\,\|I - \Phi T(u)\|_2^2 + \lambda\|T(u)\|_1$$

$$\Delta\Phi \propto -dE/d\,\Phi = T(u) \otimes \{I - \Phi T(u)\}$$
$$= T(u) \otimes R$$



Doesn't support dictionary learning

Rozell, et al. Neural Computation 2008

Supports dictionary learning

P. Schultz, et al. arXiv. 2014

Non-Spiking LCA Applications

Live Event-based Video Interpolation

On Input

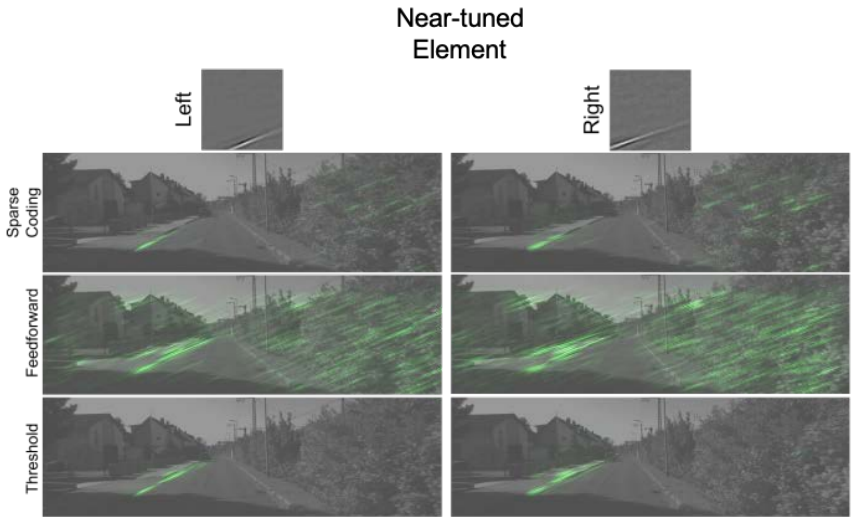
Off Input

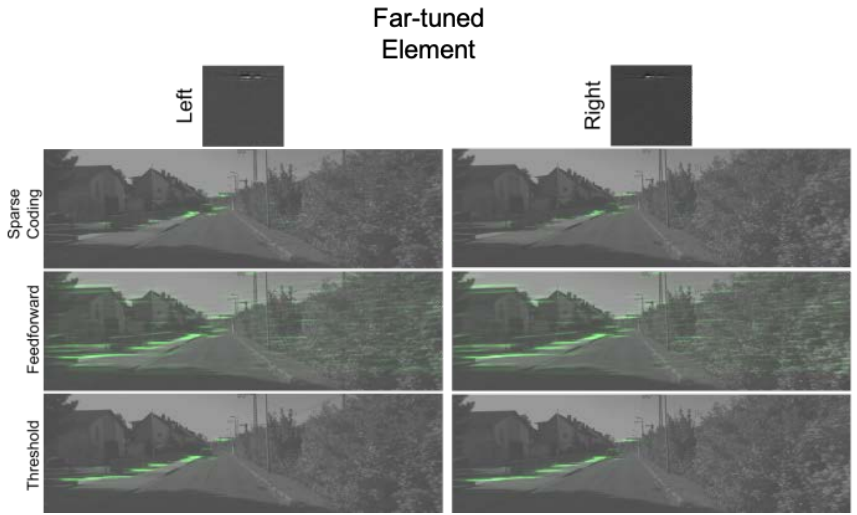
Reconstruction

Y. Watkins, D. Mascarenas and G. Kenyon, “Sparse Coding Enables the Reconstruction of High-Fidelity Images and Video from Retinal Spike Trains”, in Proceedings of 2018 Neuromorphic Computing, Knoxville, Tennessee, July 23-26, 2018.

Non-Spiking LCA Applications

Online Depth Sensing

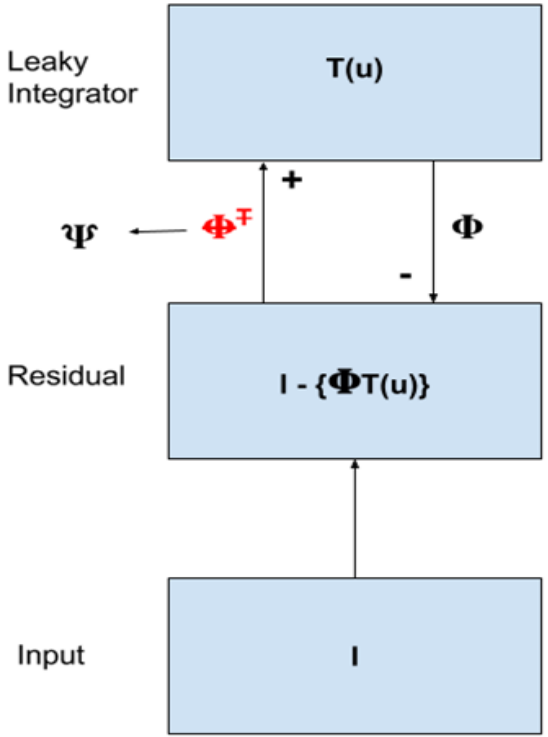




Lundquist, S. Y., Mitchell, M., Kenyon, G.T., Sparse Coding on Stereo Video for Object Detection, *arXiv:1705.07144*, 2017; *workshop on Learning with Limited Labeled Data: Weak Supervision and Beyond, NIPS 2017*.

Towards Spiking LCA Dictionary Learning on Loihi: Constraints and Solutions

$$\Delta\Phi \propto T(u) \otimes \{I - \Phi T(u)\} - f(\Phi)$$
$$f(\Phi)_{ij} = |\Phi_{ij}|\Phi_{ij}$$



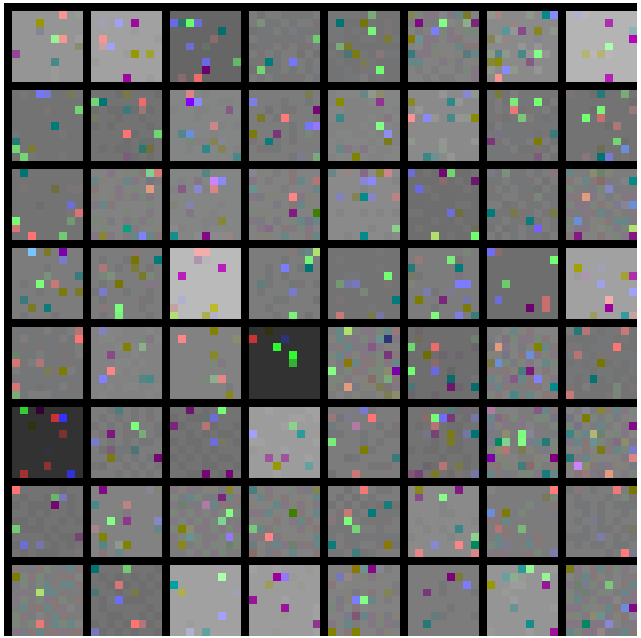
Constraint 1: Can't perform transpose operation
Solution: Learn both the weight matrix (Φ) and the transpose (Φ^T) as separate plastic connections but initialized as transposes of each other $\Psi_0 = \Phi_0^T$

Constraint 2: Can't normalize weights $||\Phi||_2$=1 during training
Solution: Decrease LCA threshold when a neuron spikes, and slowly increase towards original threshold in between spikes. Weights decay at a rate proportional to the square of weights.

Constraint 3: Both positive and negative values must be represented by spikes
Solution: Modulate firing relative to a baseline rate for representing positive and negative values

Constraint 4: Low precision (8-bit) weights Φ
Solution: Attractor dynamics

Spiking Unsupervised Dictionary Learning Results



Learning a dictionary over one epoch.

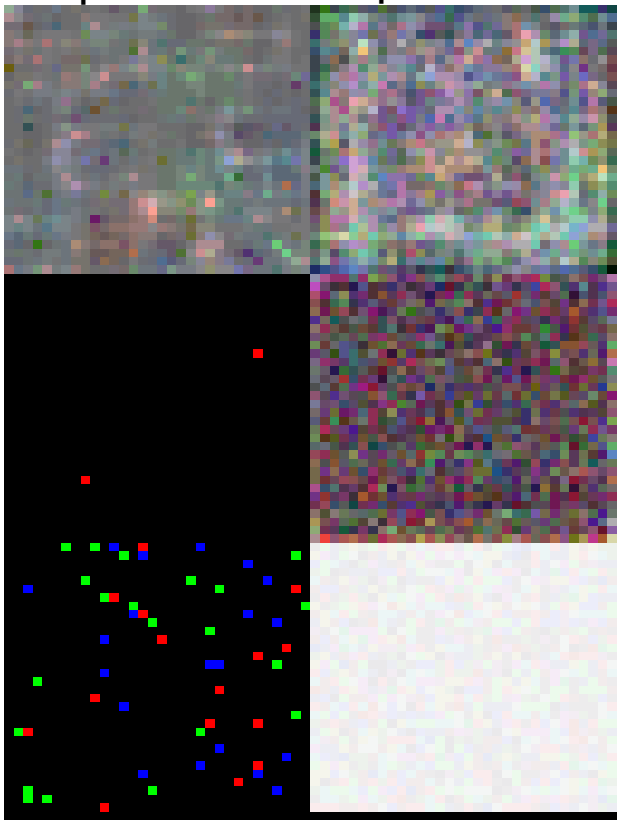
$$\text{Trace} = \Sigma \exp[-(t - t_i)/\tau]$$

Spike train | Spike trace

Recon

Residual

Input



Conclusion

Implemented LCA model that supports on-line unsupervised dictionary learning

Dictionary learning applications: Video interpolation, depth sensing

Constraints and solutions

Dictionary learning and sparse solving results

Thank you