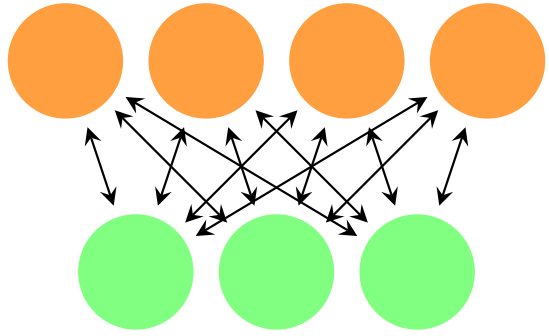
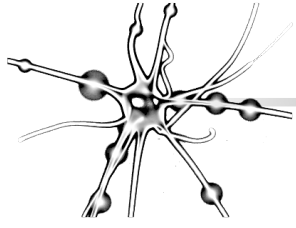
A REVIEW OF

REAL-TIME CLASSIFICATION AND SENSOR FUSION WITH A SPIKING DEEP BELIEF NETWORK

by P. O'CONNOR ET AL. (2013)



Pedro Mediano



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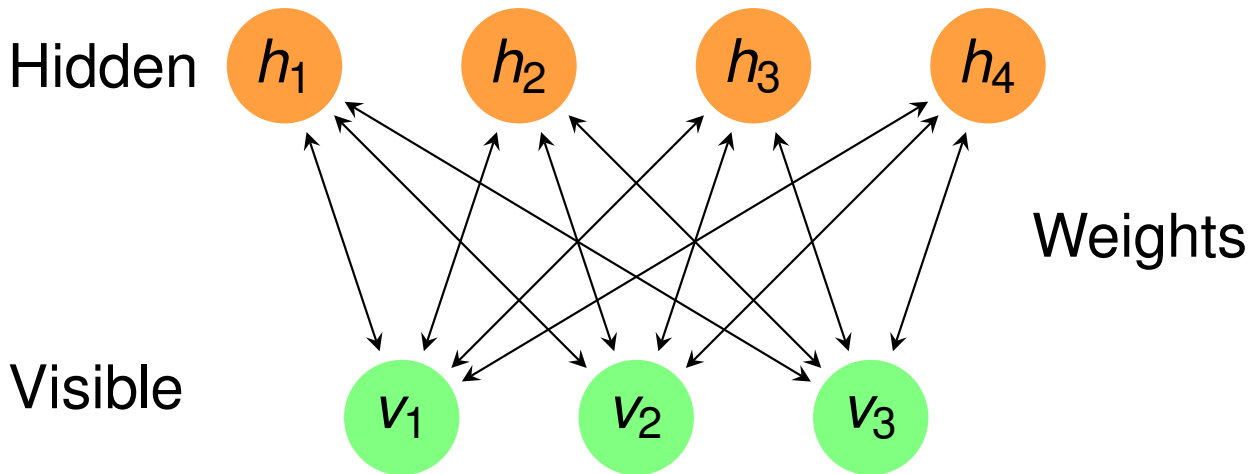
Background

DEEP BELIEF NETWORKS



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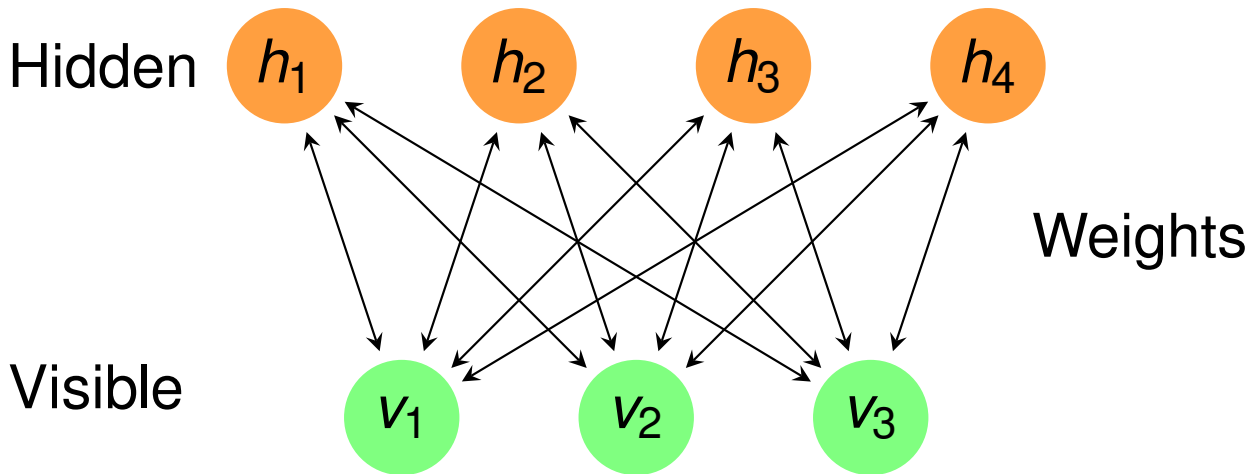

- Each neuron is a binary variable.
- Neural activations are sigmoidal:

$$p(v_i = 1|\mathbf{h}, \theta) = \sigma\left(\sum_j w_{ij} h_j + b_i\right)$$

TRAINING A DBN

A DBN represents a probability distribution through an **energy function**,

$$p(\mathbf{v}, \mathbf{h}|\theta) \propto \exp\left(-E(\mathbf{v}, \mathbf{h}|\theta)\right)$$

$$E(\mathbf{v}, \mathbf{h}|\theta) = -\sum_{ij} w_{ij} v_i h_j - \sum_i b_i^{(v)} v_i - \sum_j b_j^{(h)} h_j$$

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Maximize marginal $p(\mathbf{v}|\theta)$ with gradients

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1. Clamp data to visible units.

(Hinton 2006)

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We compute gradients using **contrastive divergence**:

1. Clamp data to visible units.
2. Sample hidden units.
3. Perform *k* visible-hidden sampling iterations.
4. Estimate weight gradient.
5. Use your favourite gradient-based optimizer.

(Hinton 2006)

SPIKING NEURONS

- They use Leaky Integrate-and-Fire (LIF) neurons,

$$\frac{dv}{dt} = \tau^{-1}(v_{rest} - v) + I$$

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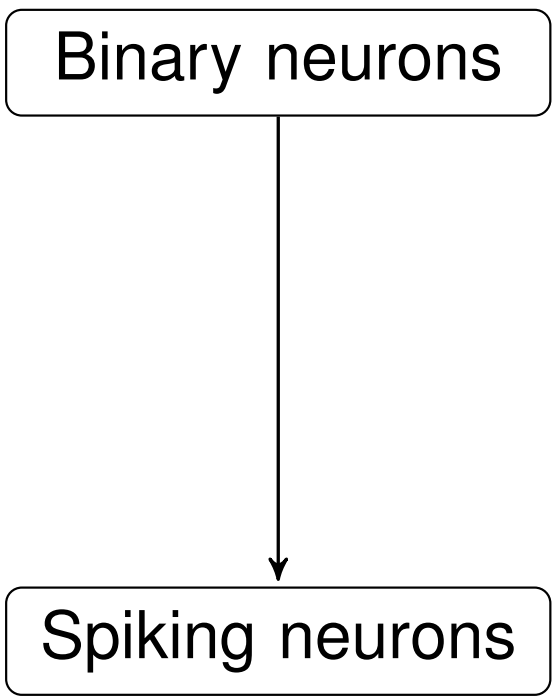
  - Non-differentiable.

CONTRIBUTIONS

GOING SPIKY

OR HOW TO TRANSFORM YOUR DBN INTO A SNN



GOING SPIKY

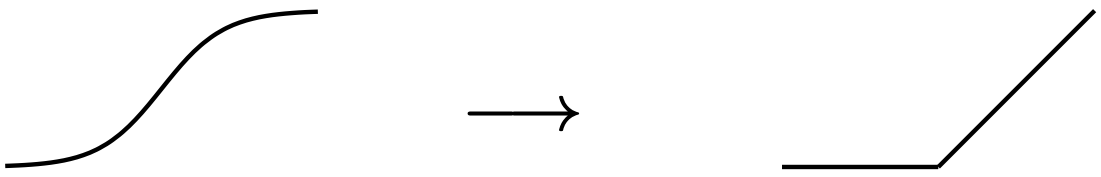
OR HOW TO TRANSFORM YOUR DBN INTO A SNN

Binary neurons

↓

NReLU

Change the activation function of your neurons.



Spiking neurons

(Nair and Hinton 2010)

GOING SPIKY

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Binary neurons

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NReLU

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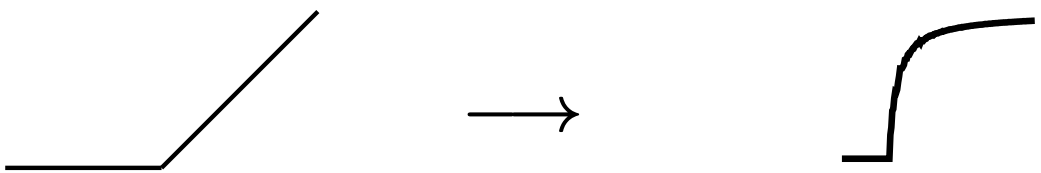
Siegert neurons

Spiking neurons

Change again to a more realistic activation function.

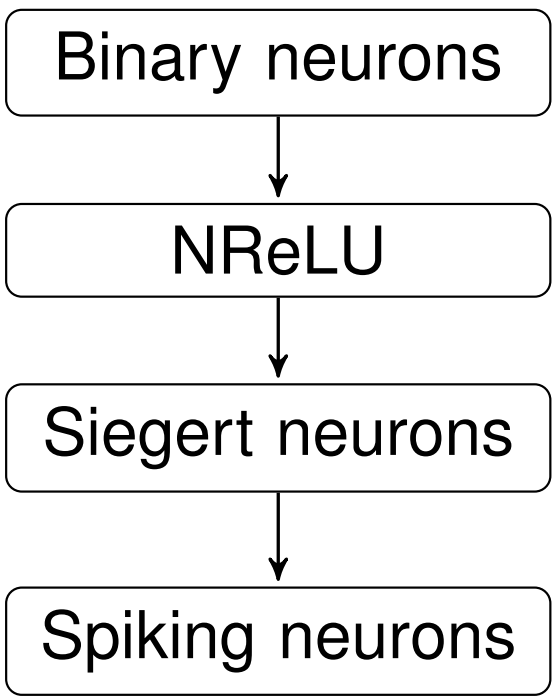


Note that we can still use CD.

(Siegert 1951)

Going spiky

Or how to transform your DBN into a SNN



Siegert neurons map directly to LIF.

Note that Siegerts are **long-time** approximation of a **single** LIF neuron.

FULL ALGORITHM

1. Set up Siegert DBN.
2. Train it with CD.
3. Replace neurons with LIF.
4. Replace pixels with Poisson sources.

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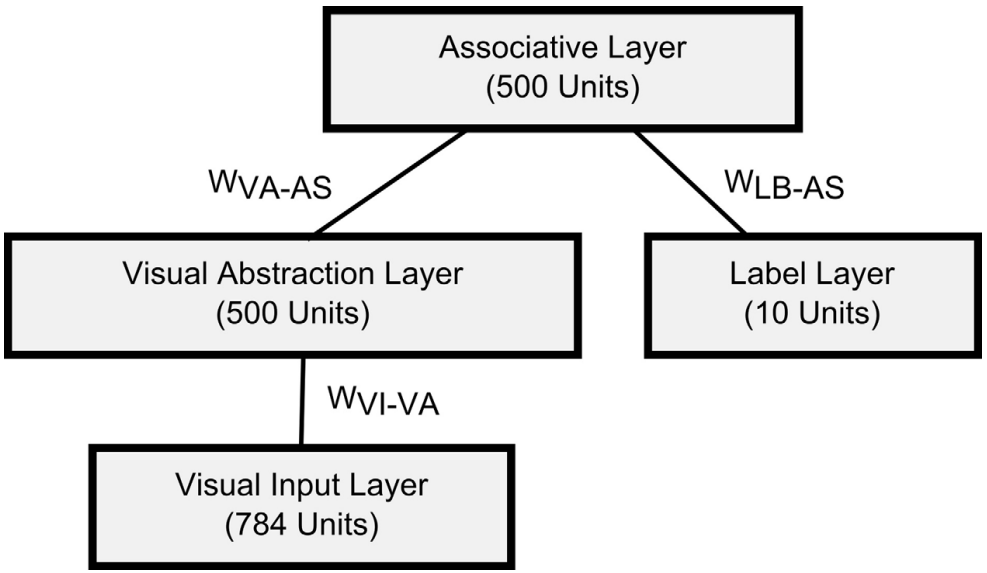
- Note:
  They actually use a small modification called Persistent CD, plus fast weights, momentum and sparsification.

NETWORK ARCHITECTURE



- 2k neurons smaller than first MNIST DBN.
- 5k neurons smaller than MNIST state-of-the-art.

(Hinton 2006, Ciresan 2011)

RESULTS

MNIST, of course.

Network type	**Accuracy**
Binary-sigmoid	97.48
Siegert	95.20
LIF	94.09

Experimental results in video (using event camera):

`https://sites.google.com/site/thebrainbells/`

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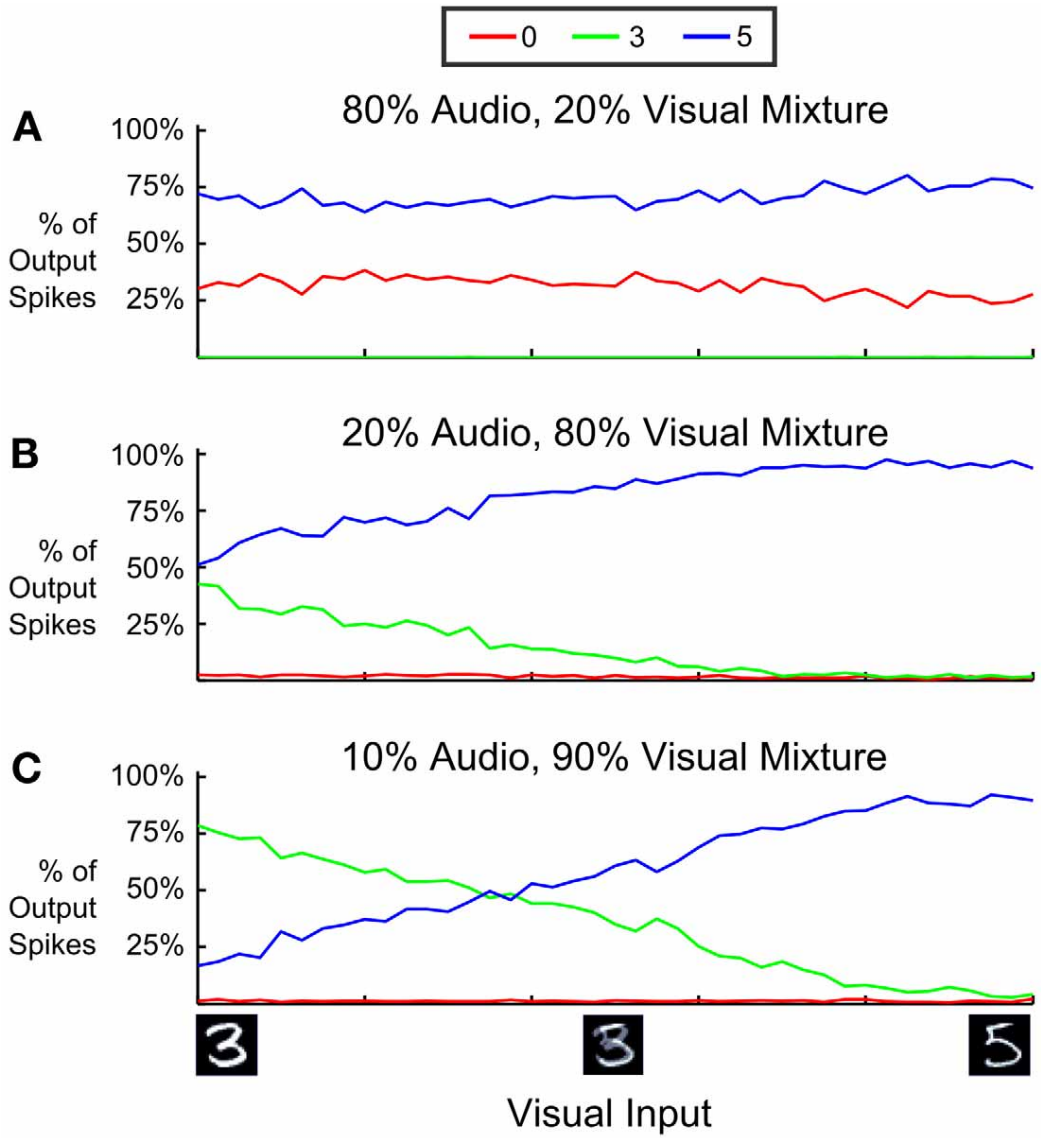

Discussion

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- Effective proof of concept – SNNs *can* work.
- Opens door to more accesible hardware implementations.
- Insights in neuroscience?

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- Spiky hacks (e.g. spike normalization).
- Misleading information (NReLU, sensor fusion, STD).
- They claim only 1% accuracy loss.
  $\rightarrow$ It's actually closer to 3.5%.

Follow-up work

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- ✗ Succeeded at learning with spiking neurons.

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- 33 citations since 2013.
- First example in Wikipedia “Spiking neural network”.

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If interested, check out new paper on CNNs:

Diehl et al. *Fast-Classifying, High-Accuracy Spiking Deep Networks Through Weight and Threshold Balancing*. IJCNN 2015 (to appear).