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Benchmarking Spike-Based Visual Recognition:

a Dataset, Evaluation and Algorithms

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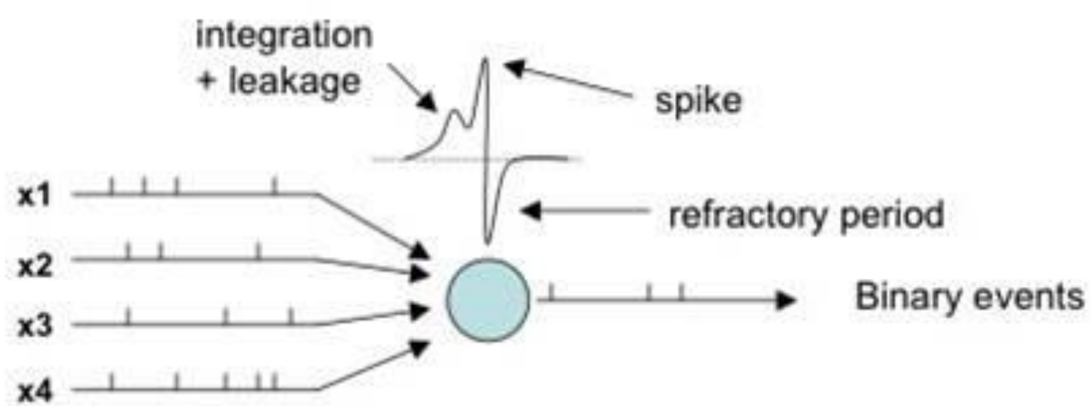
Background

- Spikes
- Spiking Neural Networks (SNNs)
- Special visual input for SNNs
  - e.g. DVS(Dynamic Vision Sensor)

DAVIS240: £3,346



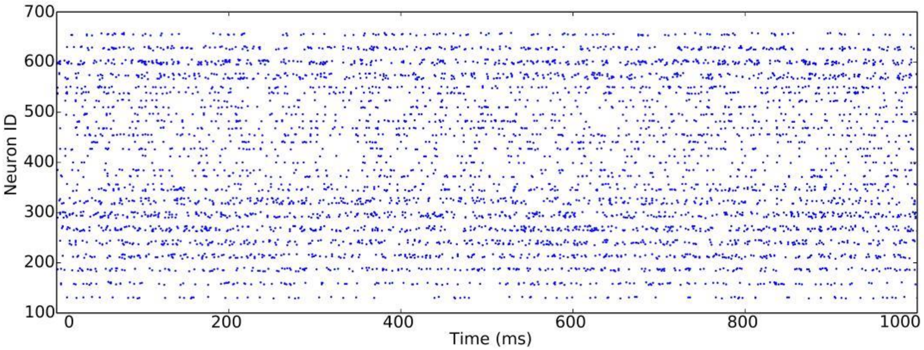
Aims and Motivations

- Unified spiking data
- Meaningful comparisons
- Promoting future research

Authors	Data	Accuracy
Matsugu et al. (2002)	Face plain images	98.3%
Fu et al. (2012)	JAFFE plain images	97.35%
O'Connor et al. (2013)	Poissonian Spiking MNIST	95.0%
Bichler et al. (2012)	DVS recorded Car trajectories	98%
Zhao et al. (2015)	DVS recorded Three postures	99.48%
…	…	…

A Dataset: NE15-MNIST

- Unified spiking data
  - Poissonian generator
  - Rank order coding generator
  - DVS recorded flashing image
  - DVS recorded moving image



A Dataset: NE15-MNIST

- Meaningful comparisons
  - On the same data
  - Among SNNs
  - vs. conventional algorithms

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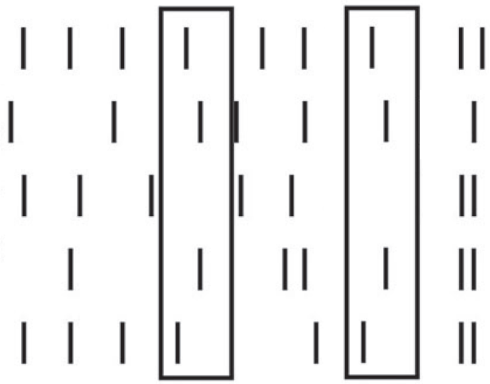
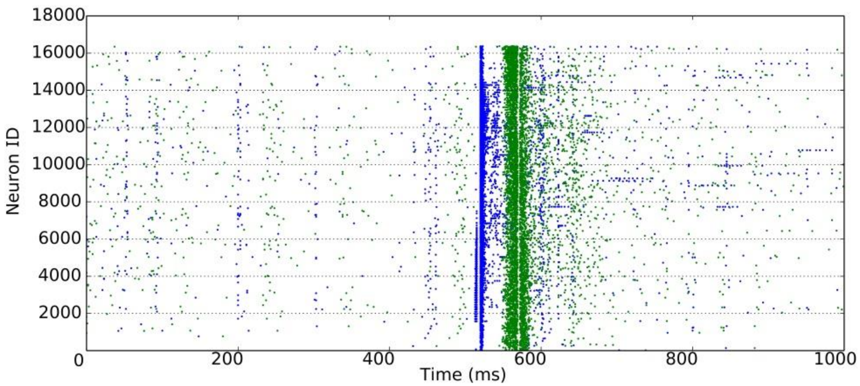
A Dataset: NE15-MNIST

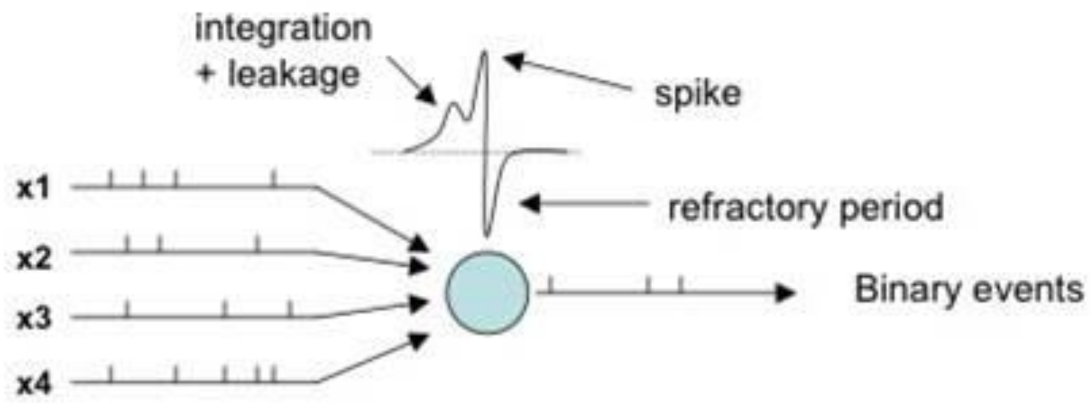
- Promoting future research
  - Poissonian: easier accessible
  - ROC: spatio-temporal pattern recognition
  - Flashing image: fast recognition
  - Moving image: invariant recognition





Evaluation on Spiking Vision Recognition

- Metrics on SNN models
  - Biological training time
  - Biological testing time
  - Response latency



	Preprocessing	Network	Training	Recognition
Brader et al. (2007)	None	Two layer, LIF neurons	Semi-supervised, STDP, calcium LTP/LTD	96.5%
Beyeler et al. (2013)	None	V1 (edge), V4 (orientation), and competitive decision, Izhikevich neurons	Semi-supervised, STDP, calcium LTP/LTD	91.6% 300 ms per test
Neftci et al. (2013)	Thresholding	Two layer RBM, LIF neurons	Event-driven contrastive divergence, supervised	91.9% 1 s per test
Diehl and Cook (2015)	None	Two layers, LIF neurons, inhibitory feedback	Unsupervised, exp. STDP, $3,000,000$ s of training $200,000$ s per iteration	95%
Diehl et al. (2015)	None	ConvNet or Fully connected, LIF neurons	Off-line trained with ReLU, weight normalization	99.1% (ConvNet), 98.6% (Fully connected); 0.5 s per test
Zhao et al. (2015)	Thresholding or DVS	Simple (Gabor), Complex (MAX) and Tempotron	Tempotron, supervised	Thresholding 91.3%, 11 s per test DVS 88.1%, 2 s per test

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Evaluation on Spiking Vision Recognition

- Metrics on H/W platforms
  - Feasibility due to H/W limits
  - Simulation time
  - Energy use

	System	Neuron Model	Synaptic Plasticity	Precision	Simulation Time	Energy/Power Usage
SpiNNaker (Stromatias et al., 2013)	Digital, Scalable	Programmable Neuron/Synapse, Axonal delay	Programmable learning rule	11- to 14-bit synapses	Real-time Flexible time resolution	8 nJ/SE 54.27 MSops/W
TrueNorth (Merolla et al., 2014)	Digital, Scalable	Fixed models, Config params, Axonal delay	No plasticity	122 bits params & states, 4-bit synapse [a]	Real-time	46 GSops/W
Neurogrid (Benjamin et al., 2014)	Mixed-mode, Scalable	Fixed models, Config params	Fixed rule	13-bit shared synapses	Real-time	941 pJ/SE
HI-CANN (Schemmel et al., 2010)	Mixed-mode, Scalable	Fixed models, Config params	Fixed rule	4-bit synapses	Faster than real-time [b]	198 pJ/SE 13.5 MSops/W (network only)
HiAER-IFAT (Yu et al., 2012)	Mixed-mode, Scalable	Fixed models, Config params	No plasticity	Analogue neuron/synapse	Real-time	22-pJ/SE (Park et al., 2014) 20GSops/W

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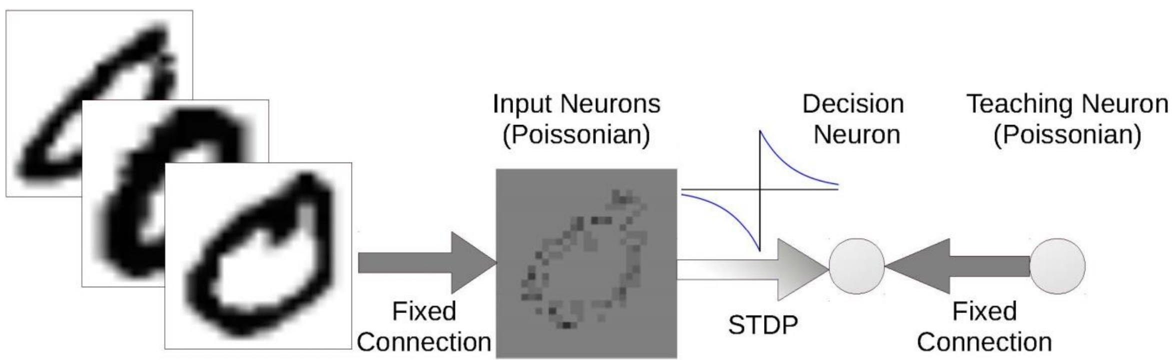
Benchmarking SNNs Algorithms

- state-of-the-art
  - 2-Layer STDP (Synaptic-timing dependent plasticity)
  - Spiking Deep Network (off-line training)
  - Spiking Convolutional Network(ConvNet) (off-line training)

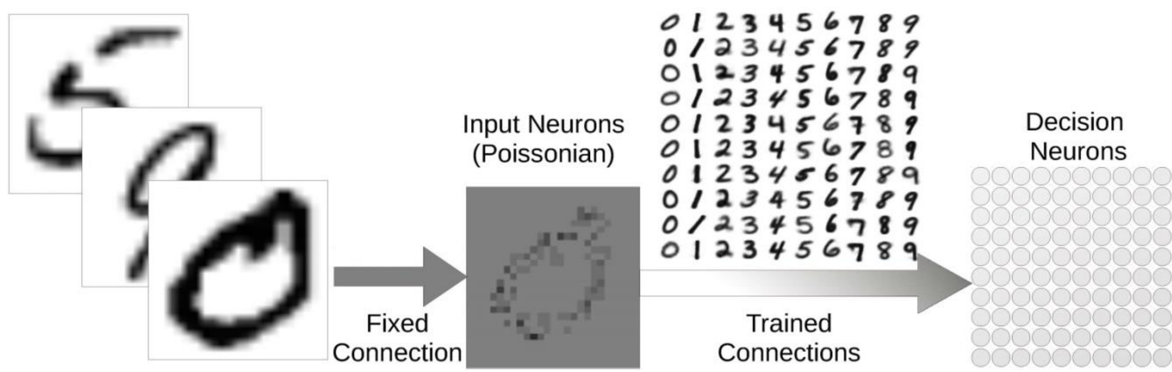
- Case studies on H/W (SpiNNaker)
  - STDP online training
  - Spiking Deep Belief Network (SDBN) (Evangelos Stromatias)
  - Spiking ConvNet (1st year, and future work)

Case Study I: 2-layer STDP

- Training

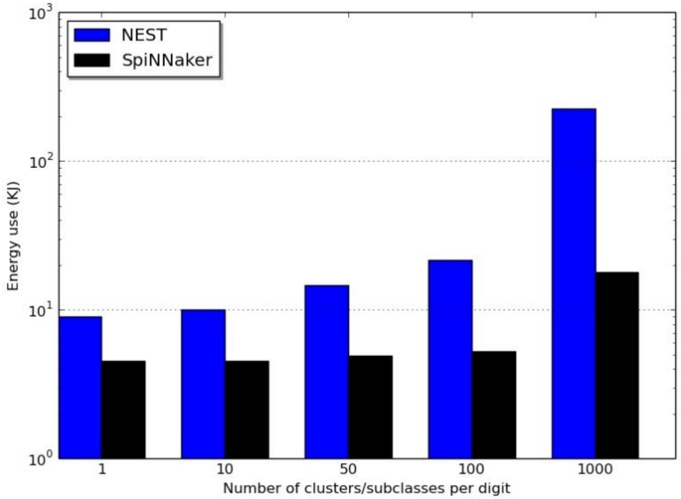


- Testing



Case Study I: 2-layer STDP

- Metrics on SNN models
  - biological training time: **18,000s, 0.3s / image**
  - biological testing time: **1s / image**
  - response latency: **10.7ms**
- Metrics on H/W platforms
  - feasibility due to H/W limits
  - simulation time
  - energy use



N: Nest
S: SpiNNaker

Subclasses per digit	Accuracy (%)		Simulation (s)		Power Use (W)	
	N	S	N	S	N	S
1	79.62	79.50	446.52		∼20	0.38
10	91.29	91.43	503.91		∼20	0.38
50	92.98	92.92	772.70	12,000	∼20	0.41
100	87.27	86.83	1,142.39		∼19	0.44
1000	89.65	89.74	12,585.28		∼17	1.50

This work has been submitted to Frontiers in Neuromphic Engineering and is under interactive review.

Future Work:
Towards the Robust Object Recognition

- state-of-the-art
  - 2-Layer STDP learned – 1 case study
  - Spiking DBN (off-line training) – online formalised training
  - Spiking ConvNet (off-line training) – future case study

- My exploration on Spiking DBN
  - Restricted Boltzmann Machine (RBM)
  - Deep Belief Net
  - Future work: spiking RBM & DBN

Current work has been written down in a study report.

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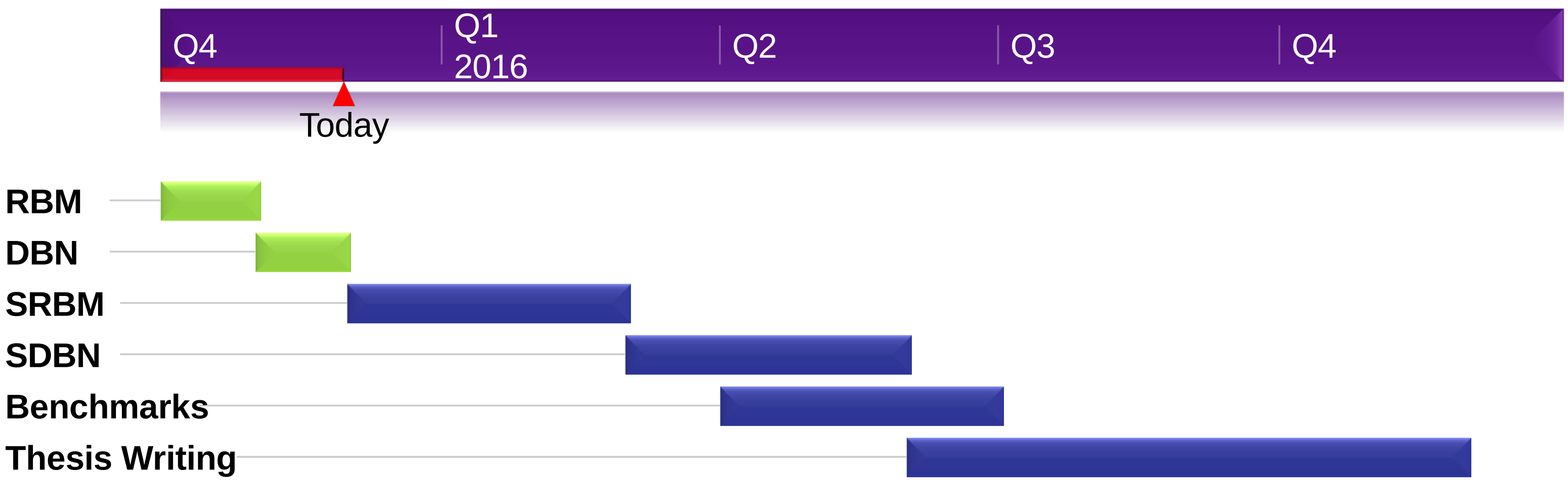
Potential Research Tasks

- Contrastive Divergence
  - RBM Validation
    - Maths of DBN
      - Practical Training Methods

Future Tasks

- Mean-Field Theory
  - SRBM Structure
    - STDP Learning for CD
      - Layered STDP Learning



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Questions?