Catwalk: Unary Top-K for Efficient Ramp-No-Leak Neuron Design for Temporal Neural Networks

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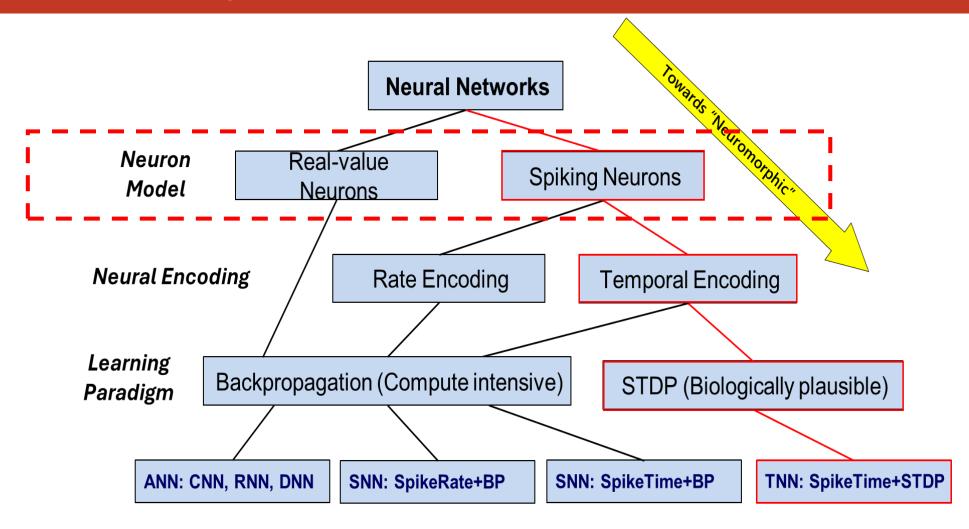
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Temporal Neural Networks (TNNs) 1,2

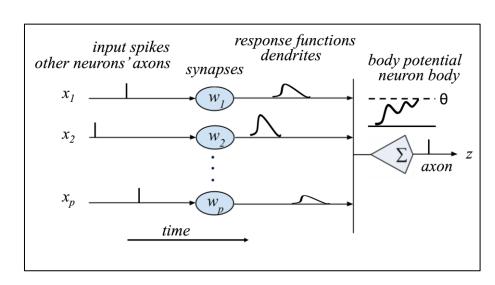


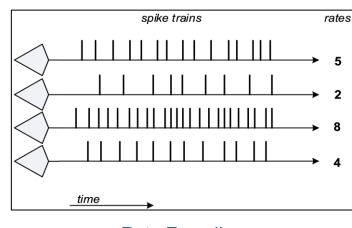
- ☐ TNNs are capable of continuous online learning and unsupervised clustering.
- This work focuses addresses the inefficiency of current spiking neuron implementations.

Why TNNs? – Neuromorphic Traits

- □ Spiking Neuron Spike Response Model
- ☐ Temporal Encoding³ One spike per neuron
- **□STDP** Form of Hebbian Learning

Condition	Action		
o/p spike occurs after i/p spike arrives	Increase synaptic weight		
o/p spike occurs before i/p spike arrives	Decrease synaptic weight		





precise timing relationships

3

4

values encoded as spike times relative to t=0

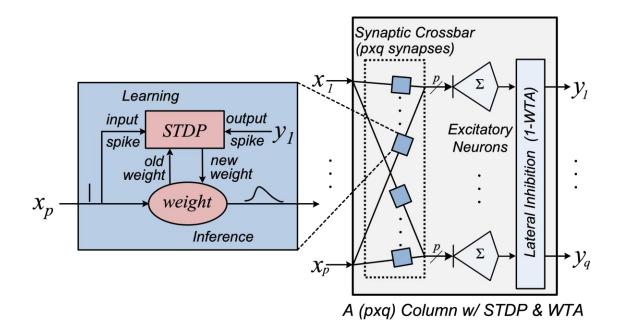
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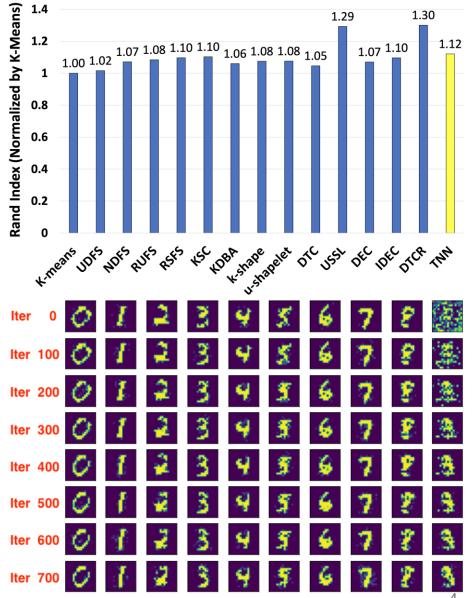
Rate Encoding

Temporal Encoding

TNNs – Online Learning and Clustering

- □ Excitatory neurons + Winner-Take-All inhibition
- ☐ A fully operational TNN building block!
 - Online Learning of MNIST digits⁴
 - Unsupervised time-series clustering⁵





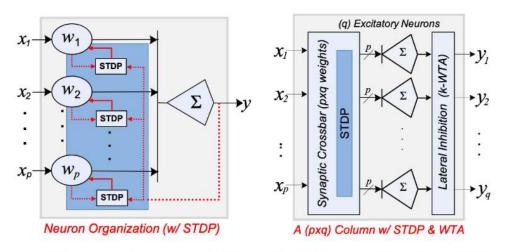
Previous TNN Implementations

stdp_case_gen

incdec

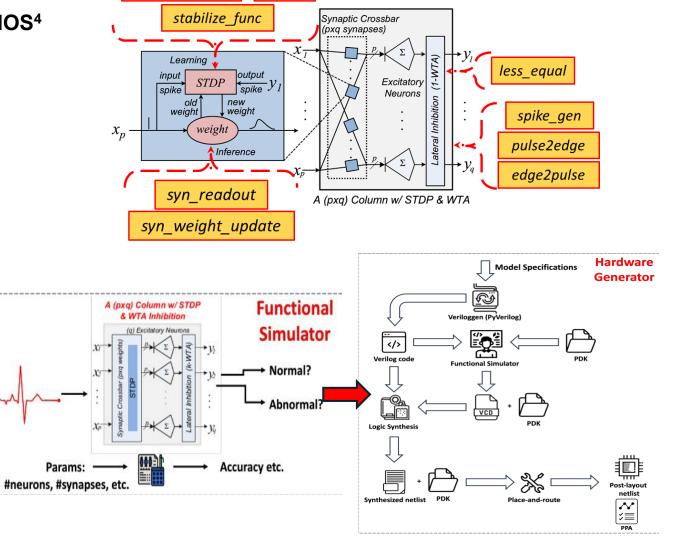
☐ TNN hardware developments

- Microarch implementation of TNNs in 45nm CMOS⁴
- TNN7: custom cell library for TNNs in 7nm⁶
- TNNGen: Automated SW-HW design flow⁷

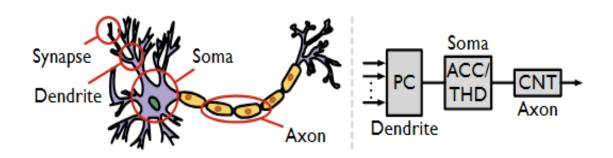


(a) Neuron: p Synapses, STDP

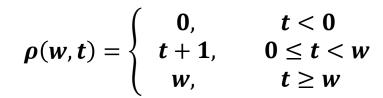
(b) Column: q Neurons & WTA



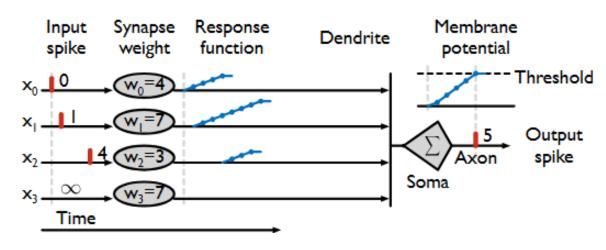
SRM0-RNL Neuron Model



Biological neuron and its RNL circuit representation for RNL response function.



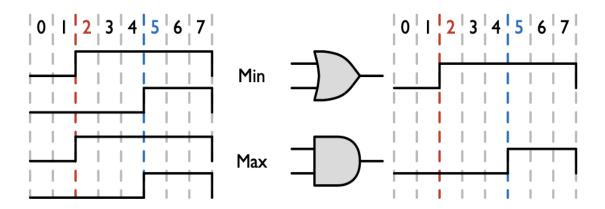
RNL response function equation.

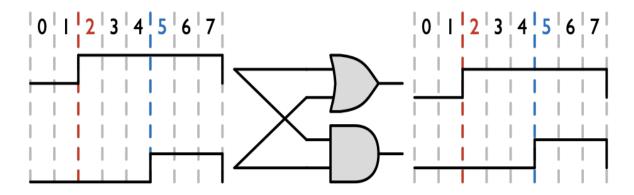


Existing SRM0-RNL neuron model with input spikes temporally-coded (red pulses).

- ☐ Existing SRM0-RNL neuron design assumes worst-case scenarios and are suboptimal.
 - For n-input neuron, PC must accumulate n inputs even when absence of temporal spikes.
 - However, neuron spikes are sparse (only 0.1% 10% of total neurons are spiking actively).

Unary Sorting





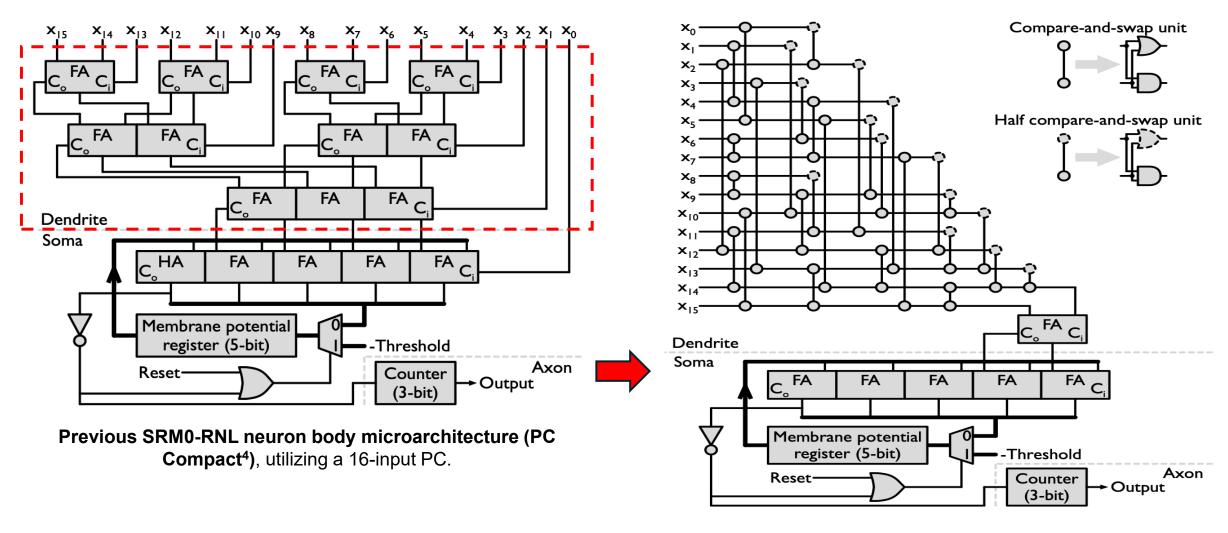
Min and max operations using temporal coding.

Compare-and-swap unit using min and max implementing a 2-input bitonic sorter.

- Bitonic sorting can be implemented via simple AND (min) and OR (max) gates.
 - Temporal spikes to SRM0-RNL neuron can be ranked, with larger values clustered at bottom.
 - Finding inputs with effective spikes allows implementation of more lightweight parallel counter (PC).

Propose Catwalk neuron model leveraging optimized spike aggregation with lightweight PC design!!

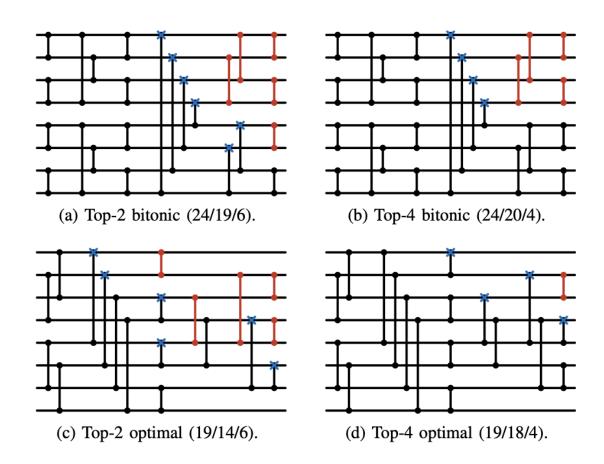
Catwalk Neuron: Microarchitecture



Catwalk SRM0-RNL neuron body microarchitecture, taking in 16-inputs and selecting top-2 outputs.

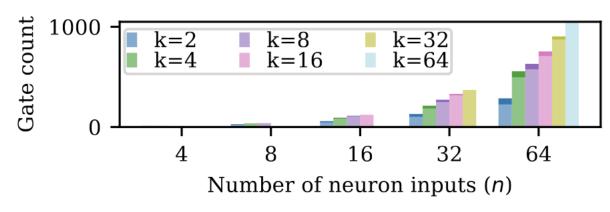
Catwalk Neuron: Top-k Selection Designs

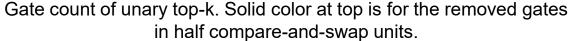
- Two types of unary sorters (i) bitonic and (ii) optimal⁷.
- Different unary sorters produce identical results with different cost reduction.
 - □ For top-2, bitonic and optimal sorters prunes identical compare-and-swap units.
 - **☐** For top-4, bitonic sorters prunes more.
- Final cost of unary top-k is independent of the cost reduction in compare-and-swap unit.
- \Box Higher the k, the higher the hardware cost.
- Catwalk neuron model incorporates the optimal sorters.

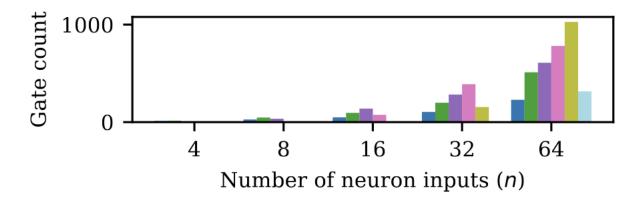


Comparison of unary top-k selector derived from different unary sorters with 8 inputs. (a) and (b) are pruning bitonic sorters, while (c) and (d) are pruning optimal,

Gate Count Analysis







Gate count of dendrite adopting unary top-k and compact PC.

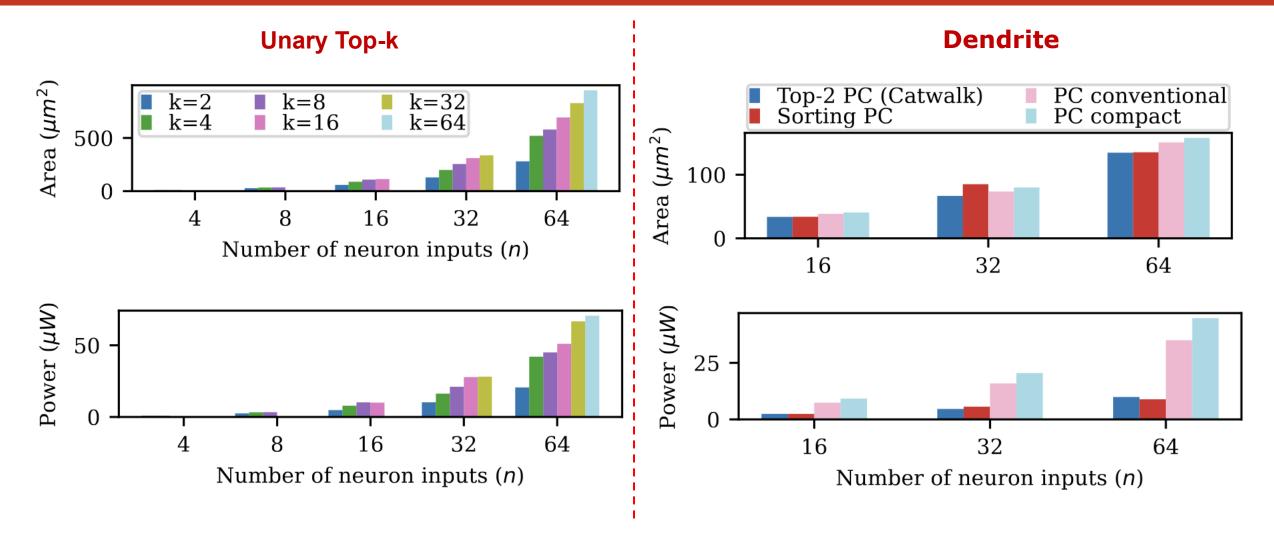
- Significant hardware savings from:
 - Pruned swap-and-compare units.
 - Removed gates from half compare-and-swap units.
- ☐ Increased cost savings with scaled inputs demonstrating potential of unary top-k.
- ☐ For dendrite designs, unary top-2 provides gains in gate count. Larger k values do not.

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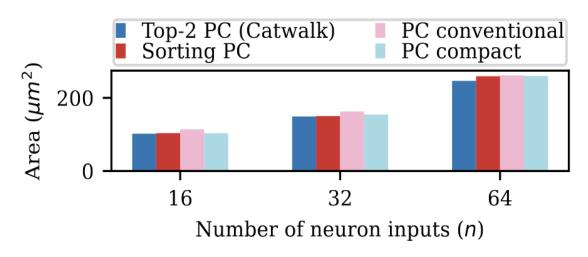
Evaluation Setup

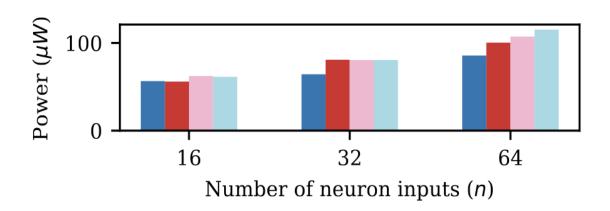
- Hardware evaluations performed using NanGate45 standard cell library for 45nm CMOS results.
- Design configurations:
 - A stand-alone sorting/top-k stage, including unary bitonic sorters and optimal unary top-k.
 - A sorting/top-k stage interfaced with a PC (a conventional design and a compact design).
 - Full SRM0-RNL neuron (bitonic sorting/optimal top-2 stage interfaced with a PC and augmented with a thresholding and firing unit).
- □ Synthesis and place-and-route performed using Synopsys Design Compiler and Cadence Innovus at 400MHz clock frequency.
 - Square floorplan with 70% utilization for each neuron input size (16, 32, and 64).
- □ Only *n*={4, 8, 16, 32, 64} are publicly available. Exploration of larger n is for future work.

Post-Synthesis Results: Top-K and Dendrite



Post-Synthesis Results: Neuron





Gate count of dendrite adopting unary top-k and compact PC.

- Neurons apply identical 5-bit accumulation and threshold implementation.
- Top-k uses optimal sorters, while sorting use bitonic sorters.
- Catwalk (Top-2 PC) improves area and power efficiencies by:
 - 1.05x and 1.35x over the neuron with compact PC.
 - 1.05x and 1.17x over the sorting-based neuron.

Post-PnR Results: Neuron

Neuron design	Power (µW)			Area
	Leakage	Dynamic	Total	$ (\mu m^2)$
	n = 16,	k=2		
PC conventional	5.11	94.65	99.76	245.25
PC compact [7]	4.84	96.95	101.80	239.13
Sorting PC	4.28	70.11	74.39	197.64
Top-k PC (Catwalk)	4.22	69.40	73.62	194.98
	n = 32,	k=2		
PC conventional	6.73	138.08	144.81	338.62
PC compact [7]	6.59	147.57	154.16	333.56
Sorting PC	5.73	<u>88.24</u>	93.97	256.42
Top-k PC (Catwalk)	5.66	86.79	92.45	252.97
	n = 64,	k = 2		
PC conventional	9.39	210.79	220.19	500.88
PC compact [7]	9.29	236.20	245.50	495.03
Sorting PC	8.12	129.59	137.71	364.15
Top-k PC (Catwalk)	7.85	124.21	132.06	355.38
	PC conventional PC compact [7] Sorting PC Top-k PC (Catwalk) PC conventional PC compact [7] Sorting PC Top-k PC (Catwalk) PC conventional PC conventional PC compact [7] Sorting PC	Neuron design Leakage $n = 16$, PC conventional 5.11 PC compact [7] 4.84 Sorting PC 4.28 Top-k PC (Catwalk) 4.22 $n = 32$, 6.73 PC conventional 6.73 PC compact [7] 5.73 Top-k PC (Catwalk) 5.66 $n = 64$, PC conventional 9.39 PC compact [7] 9.29 Sorting PC 8.12	Neuron design Leakage Dynamic $n = 16, k = 2$ PC conventional PC compact [7] 4.84 96.95 Sorting PC for PC (Catwalk) 4.28 70.11 Top-k PC (Catwalk) 4.22 69.40 $n = 32, k = 2$ PC conventional PC compact [7] 6.59 147.57 Sorting PC for PC for PC (Catwalk) 5.66 86.79 $n = 64, k = 2$ PC conventional PC compact [7] 9.39 210.79 PC compact [7] 9.29 236.20 Sorting PC 8.12 129.59	Neuron design Leakage Dynamic Total $n = 16, k = 2$ PC conventional PC compact [7] 5.11 94.65 99.76 PC compact [7] 4.84 96.95 101.80 Sorting PC Top-k PC (Catwalk) 4.28 70.11 74.39 73.62 73.62 PC conventional PC compact [7] 6.59 147.57 154.16 Sorting PC Sorting PC Top-k PC (Catwalk) 5.66 86.79 92.45 PC conventional PC compact [7] 9.39 210.79 220.19 PC conventional PC compact [7] 9.29 236.20 245.50 Sorting PC 8.12 129.59 137.71

- □ Catwalk efficiency compared to PC Compact:
 - Area efficiency: 1.23x, 1.32x and, 1.39x for n = 16, 32 and, 64, resp.
 - Power efficiency by 1.38x, 1.67x and 1.86x for n = 16, 32 and, 64, resp.
- Generally, area-power efficiency scales with inputs n.
- Demonstrates importance of opting for top-k over sorting, despite the identical functionality.

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Thank you!

Any Questions?

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