

# Optimization-based computation with spiking neurons



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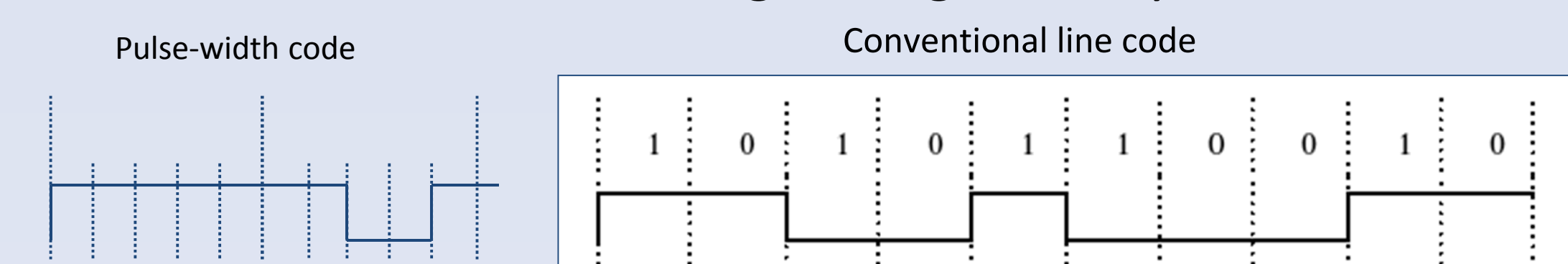
## Unary Coding of Numbers

- Reducing communication cost (energy/bit) is crucial
- Unary codes
  - Fixed-length ( $k$ ): for  $k=4 \rightarrow 0$  is 0000 and 4 is 1111
  - Saves energy
  - Costs either more space or more time

	Binary Serial	Binary Parallel	Unary Serial	Unary Parallel
Space	$O(1)$	$O(\log k)$	$O(1)$	$O(k)$
Time	$O(\log k)$	$O(1)$	$O(k)$	$O(1)$
Energy	$O\left(\frac{\log k}{2}\right)$	$O\left(\frac{\log k}{2}\right)$	$O(1)$	$O(1)$

## Temporal Coding

Small difference in time of signal edge conveys information

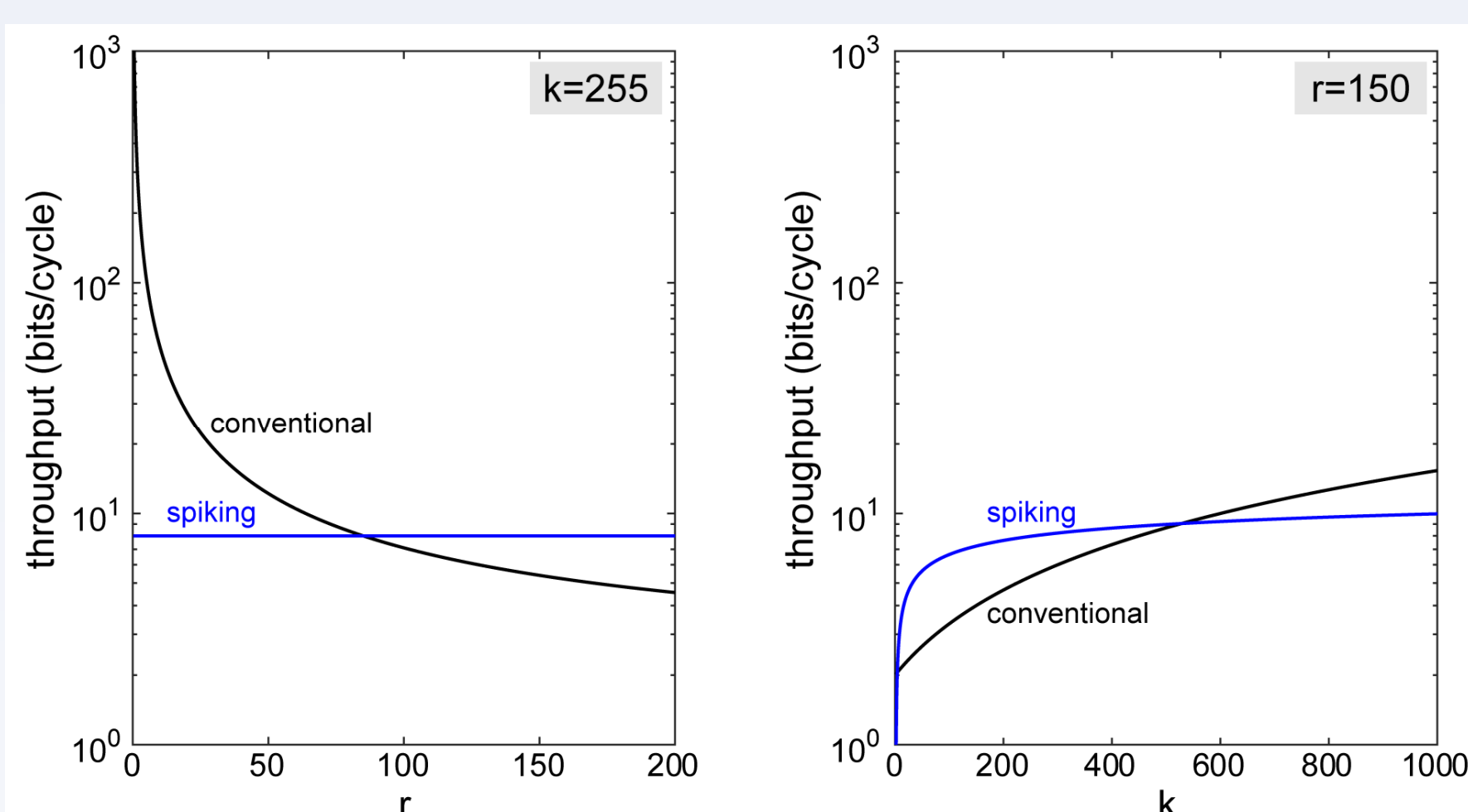


	Throughput (bits/second)	Energy (transitions/bit)
Pulse-width modulation or Phase shift (internal or global)	$O\left(\frac{P \log(k)}{w + \tau_{\text{spike}}}\right)$	$O\left(\frac{1}{\log(k)}\right)$
Winner-take-all	$O\left(\frac{\log(P)}{\tau_{\text{spike}}}\right)$	$O\left(\frac{P}{\log(P)}\right)$
Spike count	$O\left(\frac{\log(P+1)}{\tau_{\text{spike}}}\right)^\dagger$	$O\left(\frac{P}{\log(P+1)}\right)$
Weighted spike count – binary	$O\left(\frac{P}{\tau_{\text{spike}}}\right)^\dagger$	$O(1)$
Weighted spike count – latency	$O\left(\frac{P \log\left(\frac{\tau_{\text{spike}}}{\tau_{\text{step}}}\right)}{\tau_{\text{spike}}}\right)^\dagger$	$O\left(\frac{1}{\log\left(\frac{\tau_{\text{spike}}}{\tau_{\text{step}}}\right)}\right)$
Rank order coding	$O\left(\frac{\log(P!)}{\tau_{\text{spike}}}\right)^\dagger$	$O\left(\frac{P}{\log(P!)}\right)$
Synchrony group coding ( $g$ groups)	$O\left(\frac{\log(g^P)}{\tau_{\text{spike}}}\right)^\dagger$	$O\left(\frac{P}{\log(g^P)}\right)$
Conventional digital	$O\left(\frac{P}{\tau_{\text{spike}}}\right)$	$O(1)$

## Comparison: Temporal vs. Conventional

Compare bits per pulse-width cycle ( $w + \tau_{\text{spike}}$ )

Temporal =  $\log k$   
Conventional =  $2(k/r + 1)$



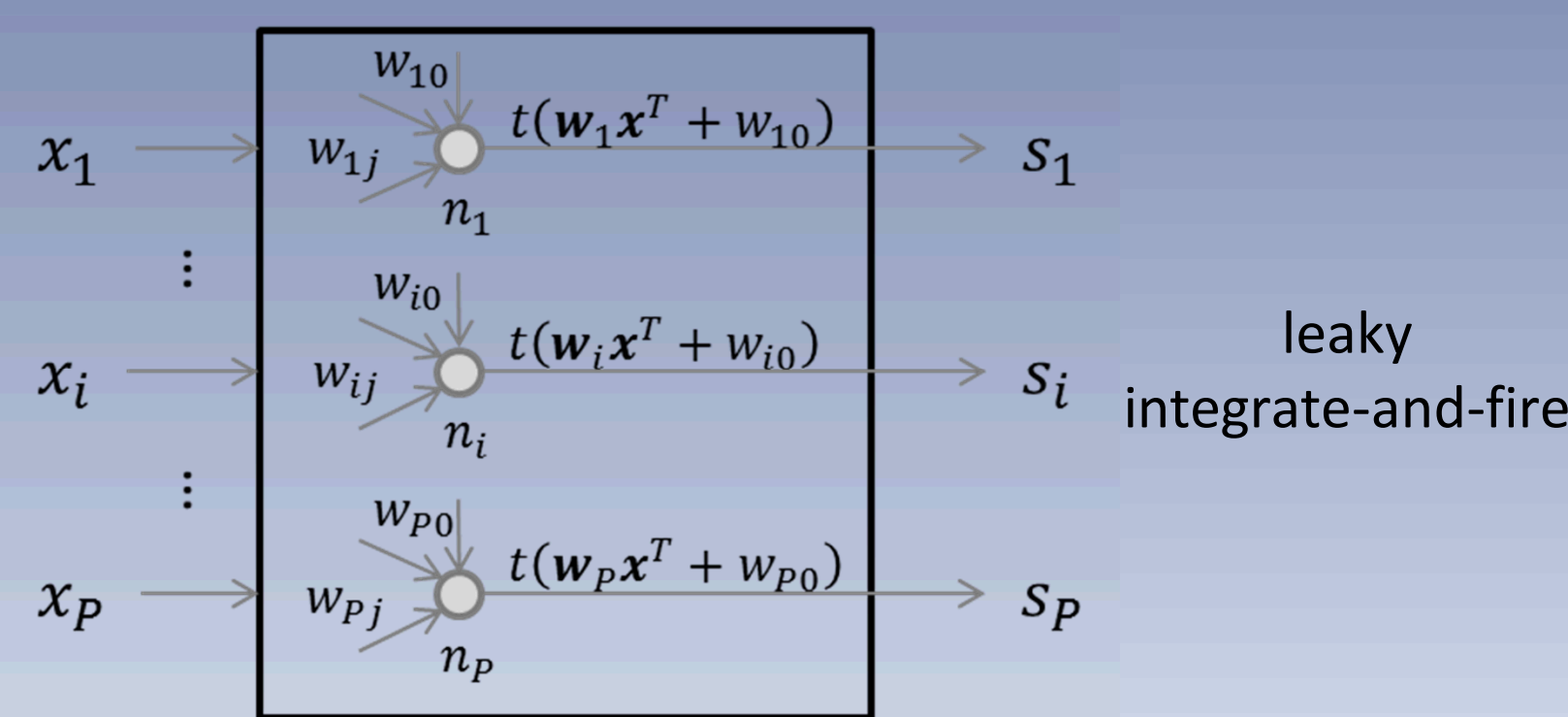
Benefit of finer edge detection (with  $k=255$ )

Benefit of smaller number range (with  $r = \tau_{\text{spike}} / \tau_{\text{step}} = 150$ )

## References

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## Neural Spiking Module



- Convert from input space to spiking
- Strength of input signal relates to timing of spike

## Parallel Random Access Machine (PRAM)

- Shared memory abstract computation architecture
- Metrics
  - Time ( $T_p$ ) – time required using  $P$  processors
    - $T_1$  – time required by serial processing of algorithm
  - Processors ( $P$ ) – number of processors needed
  - Work ( $W$ ) – total effort of algorithm ( $W = T_1$ )
  - cost – product of time & # processors (cost =  $T_p \times P$ )
  - Speedup ( $S_p$ ) – improvement achieved using  $P$  processors and parallel processing ( $S_p = T_1/T_p$ )

## SpikingSort PRAM Algorithm

**Input** : set of integers,  $\{x_1, x_2, \dots, x_N\}$

**Output** : sparse bit matrix of sorted sequence of spikes,  $S$

**for**  $\tau \leftarrow k$  **to** 0

**do for**  $i \leftarrow 1$  **to**  $N$ , in parallel

**if**  $x_i == \tau$  **then**

$S(\tau, i) = 1$

## Comparison of Sorting Algorithms

	$T_p$	$P$	cost
Parallel merge sort	$O(\log N)$	$O(N)$	$O(N \log N)$
Reif	$O(\log N)$	$O\left(\frac{N}{\log N}\right)$	$O(N)$
SpikingSort	$O(k)$	$O(N)$	$O(kN)$
SpikingSort, two-layer network	$O(2k)$	$O((k+1)N)$	$O(2k(k+1)N)$
SpikingSort, c-layer network	$O(ck)$	$O\left(\sum_{i=0}^{c-1} k^i N\right)$	$O\left(ck \sum_{i=0}^{c-1} k^i N\right)$
SpikingSort, constant $k$	$O(1)$	$O(N)$	$O(N)$

## SpikeMax PRAM Algorithm

**Input** : set of integers,  $\{x_1, x_2, \dots, x_N\}$

**Output** : the maximum,  $m = \max_i x_i$

**done** = **False**

**for**  $\tau \leftarrow k$  **to** 0

**if** **done** == **False** **then**

**do for**  $i \leftarrow 1$  **to**  $N$ , in parallel

**if**  $x_i == \tau$  **then**

$m = x_i$

**done** = **True**

## Comparison of Algorithms for Finding the Max

	$T_p$	$P$	cost
Shiloach and Vishkin	$O(1)$	$O(N^2)$	$O(N^2)$
Valiant	$O(\log N)$	$O\left(\frac{N}{\log N}\right)$	$O(N)$
SpikeMax	$O(k)$	$O(N)$	$O(kN)$
SpikeMax, when $k - d \leq \max_i x_i \leq k$	$O(d)$	$O(N)$	$O(dN)$
SpikeMax, when $N \gg k$ for constant $k$	$O(1)$	$O(N)$	$O(N)$

## SpikeOpt PRAM Algorithm

**Input** : set of integers,  $\{x_1, x_2, \dots, x_N\}$ , where  $N$  is odd

**Output** : median integer,  $m = \text{median}_i x_i$

**typedef enum** {INITIAL, SPIKING, DONE} is State

**state** = **SPIKING**

**do for**  $i \leftarrow 1$  **to**  $N$ , in parallel

$u_i = \sum_{j=1}^N \text{sign}(x_i - x_j)$

**while** **state**  $\neq$  **DONE**

**if**  $u_i == 0$  **then**

$m = x_i$

**state** == **DONE**

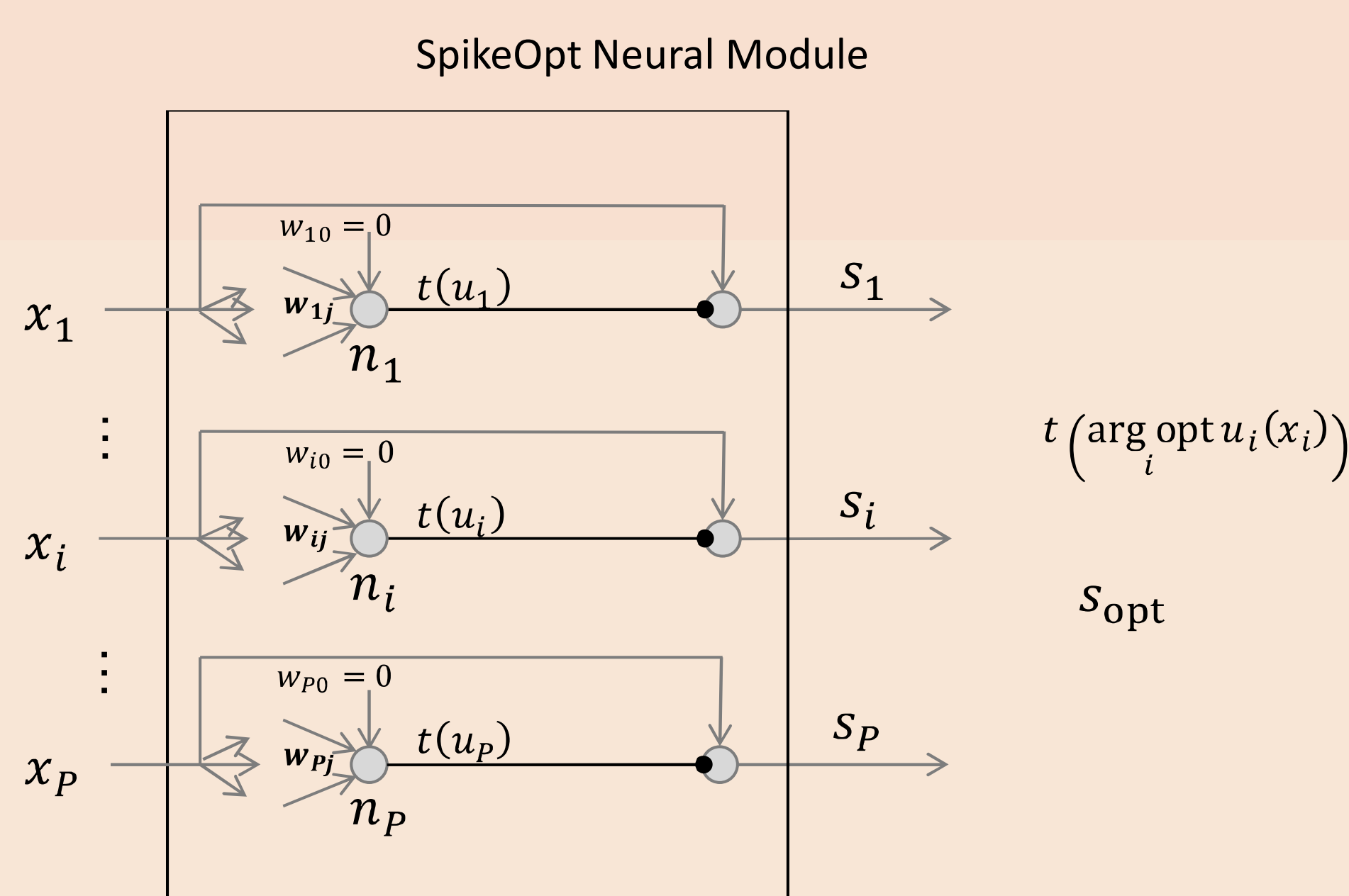
**else**

$u_i = u_i - \text{sign}(u_i)$

## Comparison of Algorithms for Finding the Median

	$T_p$	$P$	cost
Akl, for $0 < x < 1$	$O(N^{1-x})$	$O(N^x)$	$O(N)$
Cole and Yap	$O((\log \log N)^2)$	$O(N)$	$O(N(\log \log N)^2)$
Tishkin	$O(\log \log N)$	$O(N)$	$O(N \log \log N)$
Beliakov	$O(1)$	$O(N)$	$O(N)$
SpikingMedian	$O(k)$	$O(N)$	$O(kN)$
SpikeOpt (median), worst case	$O(N/2)$	$O(N)$	$O(N^2)$
SpikeOpt (median), symmetric distribution	$O(1)$	$O(N)$	$O(N)$
SpikeOpt (median), $ X  = d$ , constant $d$	$O(1)$	$O(N)$	$O(N)$

## Optimization-based Computation of Median Using SpikeOpt



## Median-filtering with SpikeOpt

