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ParalESN: Enabling parallel information processing in Reservoir Computing

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Poster

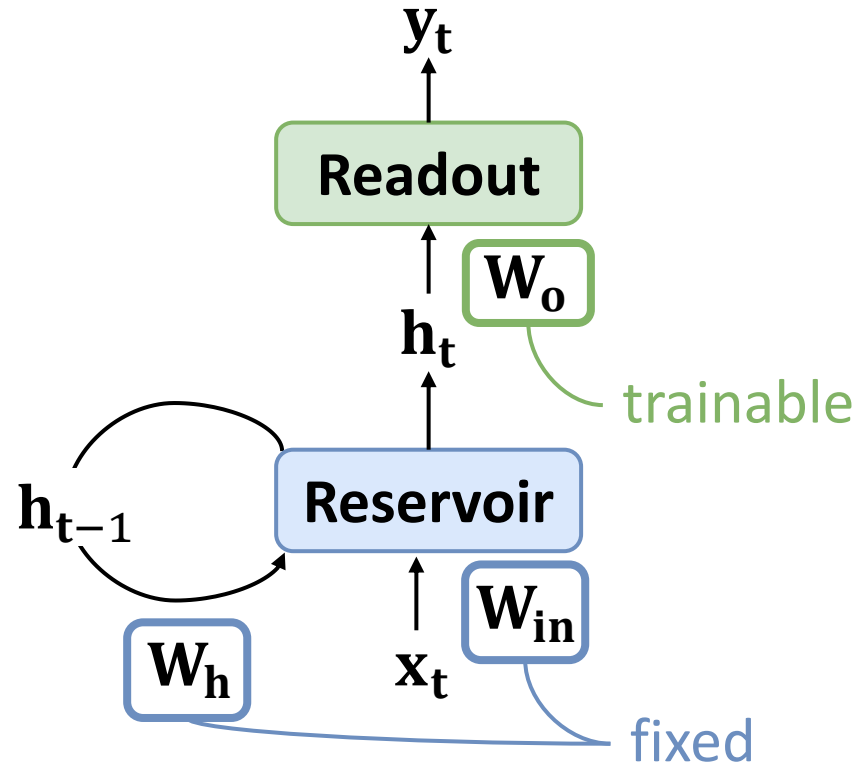
Tue, Jul 7, 2026 • 10:30 AM – 12:15 PM KST

“Randomization is computationally cheaper than optimization”

Reservoir Computing: efficient, untrained RNNs

Untrained dynamics of a (stable) dynamical system

No backpropagation-through-time (BPTT)



$$y_t = W_o h_t + b_o$$

$$h_t = \tanh(W_h h_{t-1} + W_{in} x_t + b_h)$$

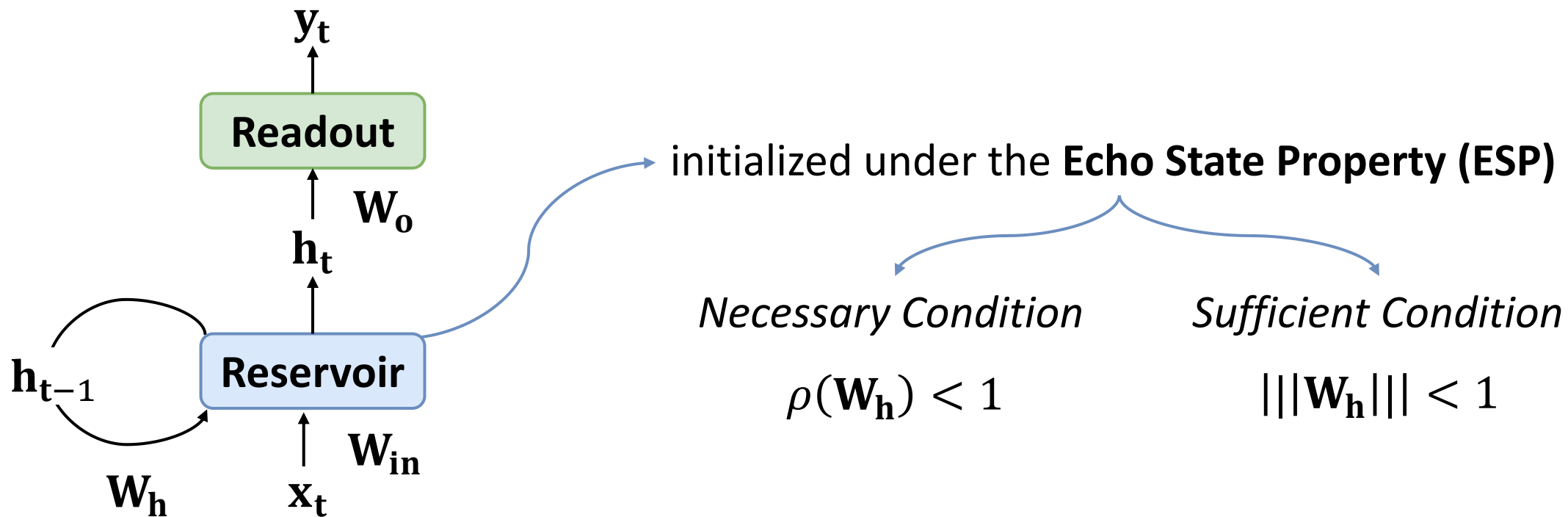
Verstraeten D. et al., *Neural networks* (2007)

Jaeger H. et al., *Neural networks* (2007)

Why does this work?

Untrained dynamics... but stable

High-dimensional random projection



Revisiting the Reservoir Computing paradigm to enable:

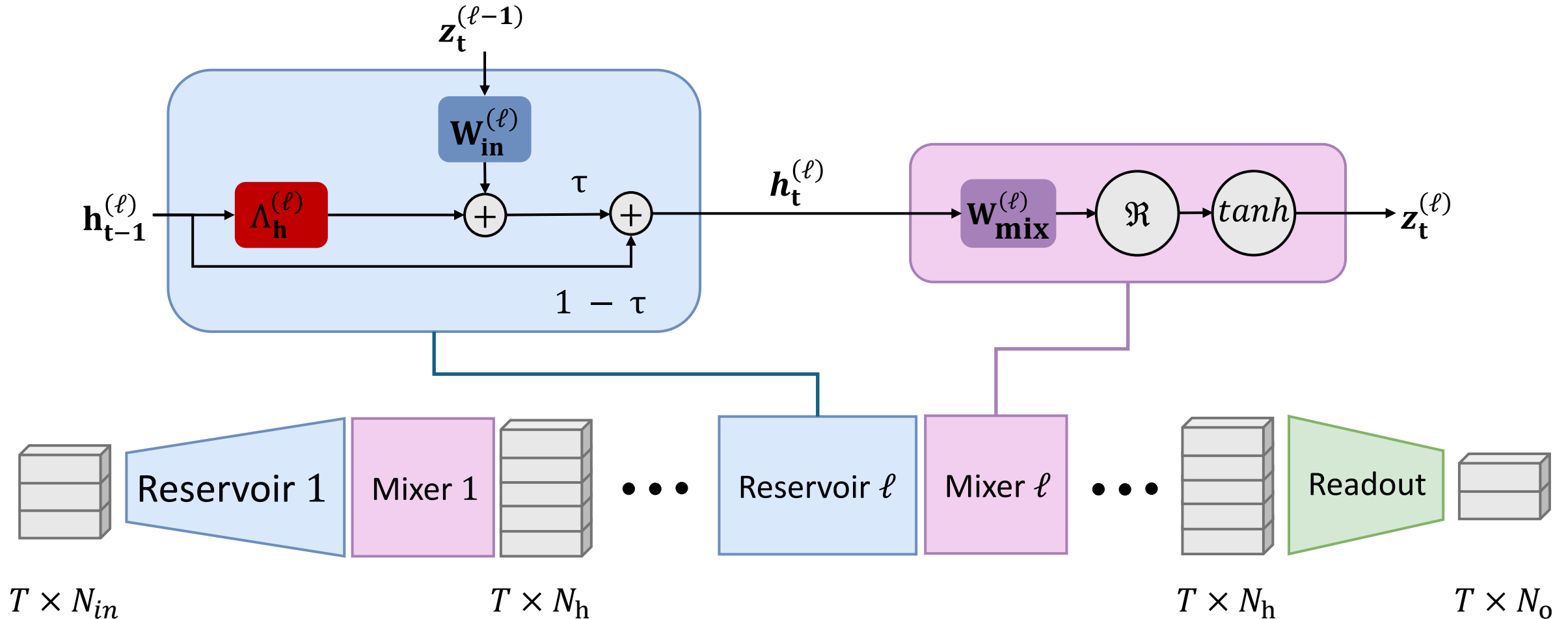
(i) Parallel recurrence

(ii) Higher-dimensional reservoir

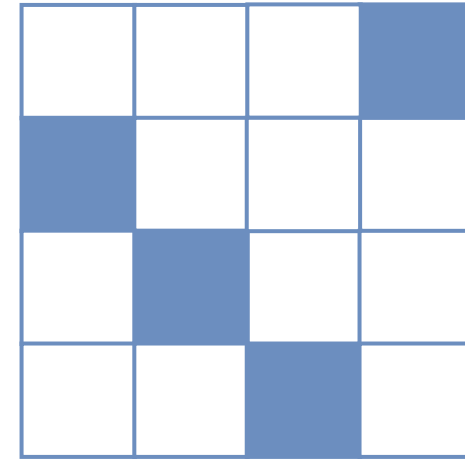
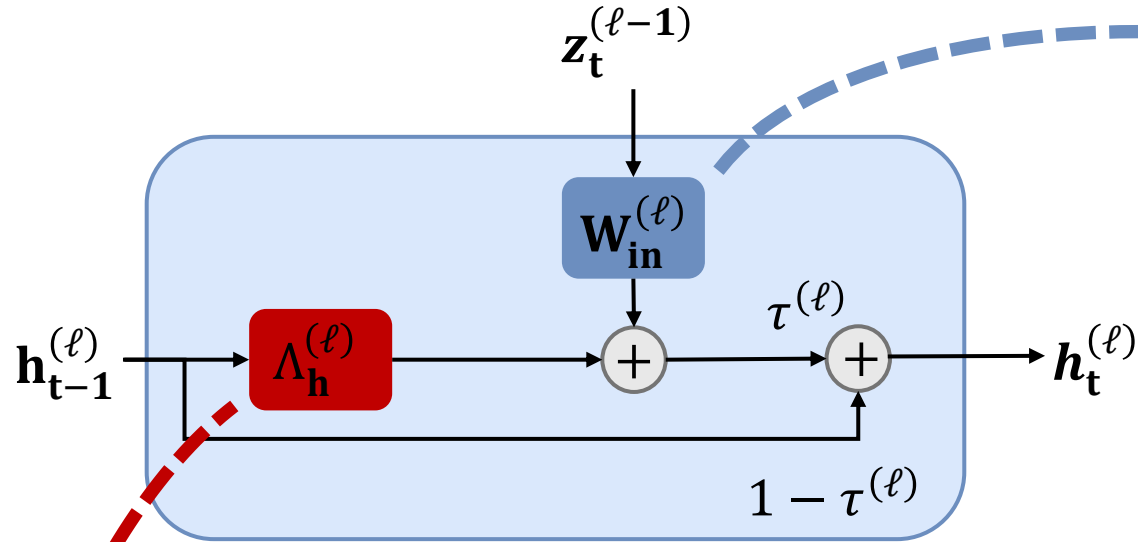
Parallel Echo State Networks (ParaESN)

(parallelizable) Linear reservoir

Complex-valued matrices

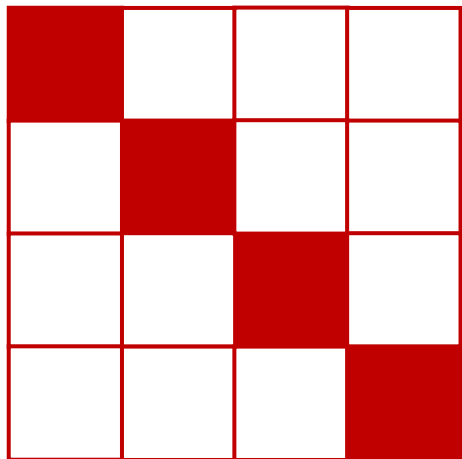


Revisiting reservoir structure through structured operators



ring

- memory-efficient
- simple shift + rescaling

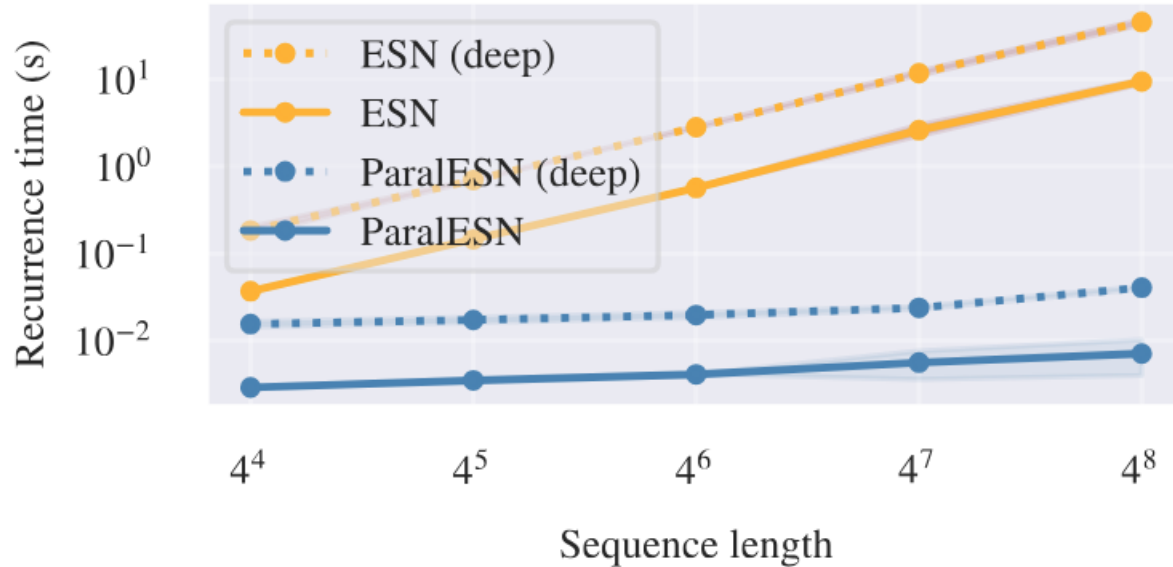


diagonal

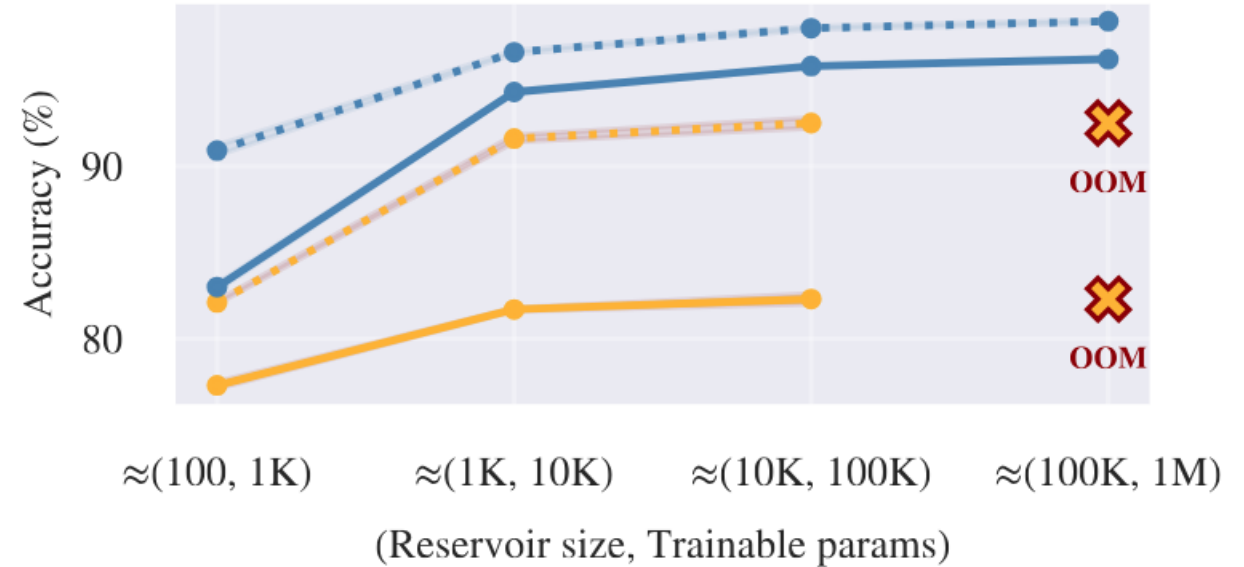
- memory-efficient
- efficient computations in the parallel scan

ParalESN is faster and more scalable than traditional reservoirs

Scaling logarithmically w.r.t. sequence length

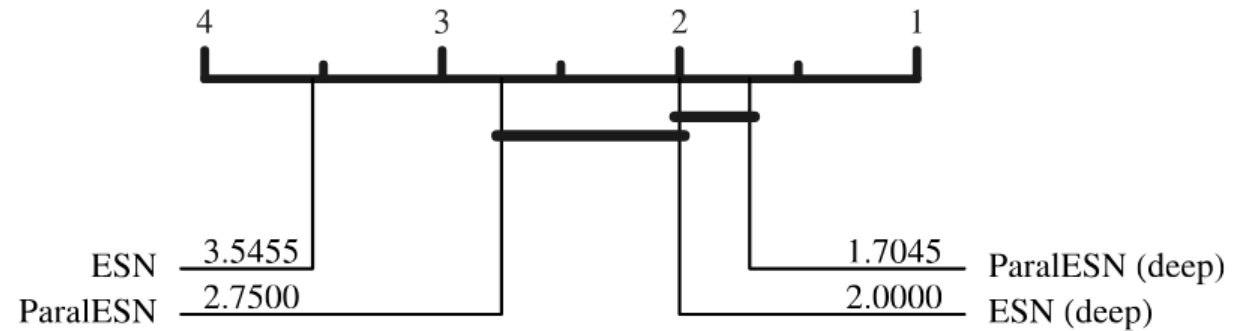
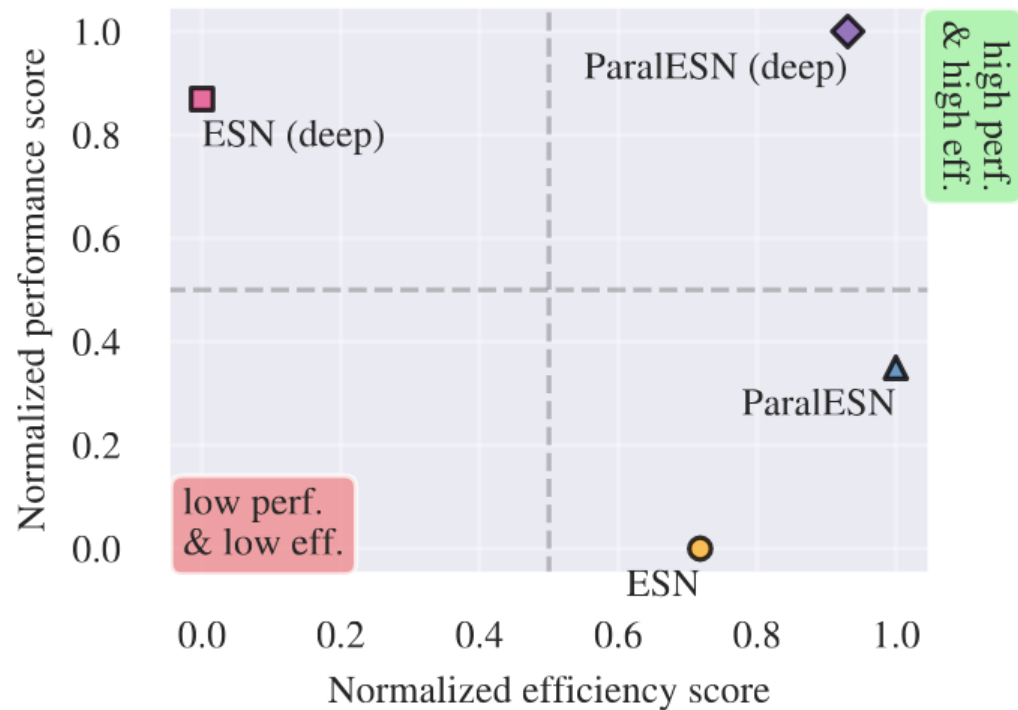


Scaling linearly w.r.t. hidden size



(sequential MNIST)

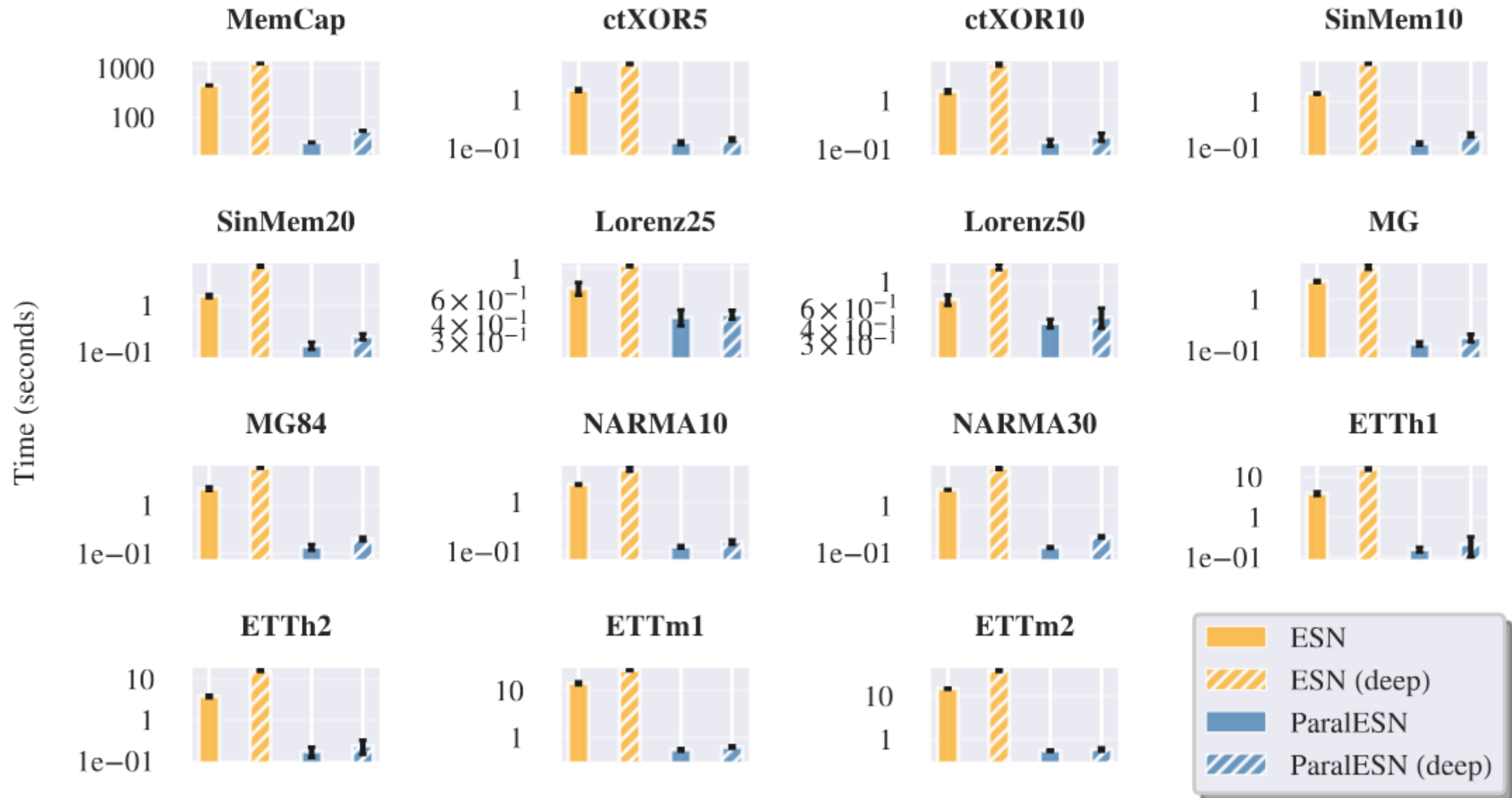
ParalESN consistently outperforms its traditional counterpart...



Results for benchmarks on time series

- **(left)** Trade-off between predictive performance and efficiency
- **(right)** Critical difference diagram

...while being more efficient by orders of magnitude



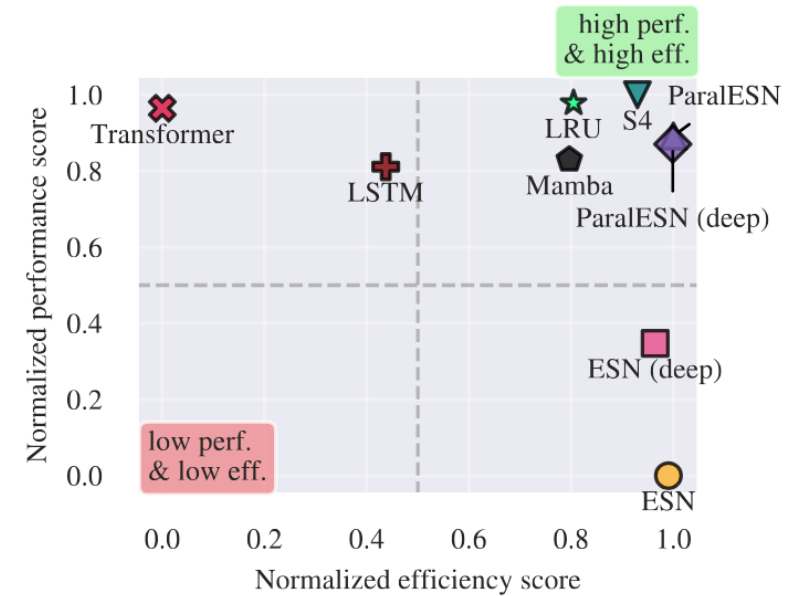
ParalESN is competitive with fully-trainable sequence models

sMNIST

MODEL	PARAMS.	↑ ACCURACY	↓ TIME (MIN.)	↓ EMISSIONS (KG)	↓ ENERGY (KWH)
LSTM	≈ 160k	97.5±1.4	80.8±6.8	0.34±0.14	1.02±0.42
TRANSFORMER	≈ 160k	98.4±0.1	141.0±14.1	0.60±0.28	1.81±0.86
S4*	≈ 160k	99.2±0.0	16.1±0.0	0.53±0.0	1.61±0.0
LRU	≈ 160k	98.5±0.2	29.1±1.85	0.18±0.02	0.57±0.05
MAMBA	≈ 200k	98.4±0.1	22.87±4.48	0.19±0.02	0.57±0.06
ESN	≈ 160k	82.5±7	4.3±0.1	0.02±0.00	0.07±0.00
ESN (DEEP)	≈ 160k	91.4±1.1	8.8±0.1	0.04±0.00	0.13±0.00
PARALESN	≈ 160k	96.2±1.3	2.7±0.7	0.01±0.00	0.04±0.10
PARALESN (DEEP)	≈ 160k	97.2±0.2	3.3±0.5	0.02±0.00	0.05±0.00

psMNIST

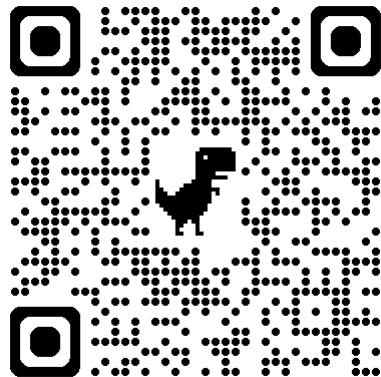
MODEL	PARAMS.	↑ ACCURACY	↓ TIME (MIN.)	↓ EMISSIONS (KG)	↓ ENERGY (KWH)
LSTM	≈ 160k	92.8±0.5	89.3±4.2	0.47±0.04	1.41±0.11
TRANSFORMER	≈ 160k	97.4±0.2	156.8±2.7	0.65±0.24	1.98±0.73
S4*	≈ 160k	97.9±0.0	9.87±0.0	0.35±0.0	1.07±0.0
LRU	≈ 160k	97.8±0.1	33.8±3.42	0.21±0.03	0.63±0.09
MAMBA	≈ 200k	92.6±0.1	43.25±5.02	0.24±0.03	0.73±0.08
ESN	≈ 160k	78.2±1.6	4.3±0.1	0.02±0.00	0.06±0.00
ESN (DEEP)	≈ 160k	82.1±3.7	7.3±0.1	0.04±0.00	0.11±0.00
PARALESN	≈ 160k	96.9±0.1	2.8±0.3	0.01±0.00	0.04±0.00
PARALESN (DEEP)	≈ 160k	95.2±0.1	3.1±0.2	0.02±0.00	0.05±0.00



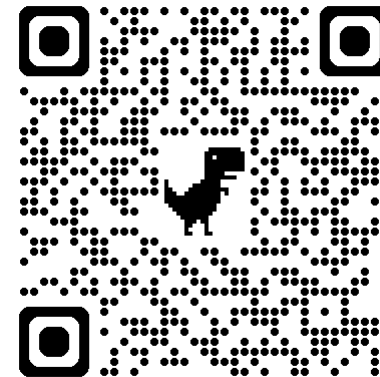
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paper



code