

Continual Learning for Recurrent Neural Networks

Review + Empirical Evaluation

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Is sequential data processing important for CL?



Human activity recognition (sensors, videos)

Robot control (temporally-correlated raw data)

Finance (next stock value prediction)

Natural Language Processing (domain shift, translation)

...

Why do you focus on RNNs?



e.g CNNs? Transformers? → different questions

- Variable number of layers → unrolling
- Weight sharing over time steps
- Backpropagation through time (for deep RNNs)

Organized review of RNN in CL



Let's look at what is **already** here (*shallow* taxonomy)

- **Seminal works** simple studies on synthetic benchmarks
- **NLP** application-specific
- **Bio-inspired / alternative recurrent paradigms** Custom learning algorithms, ad-hoc architectures
- **Deep networks** LSTM, GRU...

The vast majority of works focus on **new** models / strategies



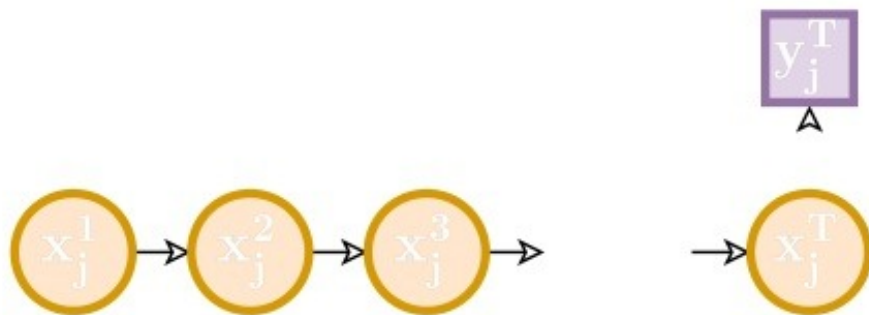
Dataset	Application	Scenario
Copy Task [103, 34]	synthetic	MT+NI
Delay/Memory Pro/Anti [32]	synthetic, neuroscience	MT+NI
Seq. Stroke MNIST [103, 34]	stroke classification	SIT+(NI/NC)
Quick, Draw! †	stroke classification	SIT+NC
MNIST-like [27] [26] †	object classification	SIT+(NI/NC)
CORe50 [92]	object recognition	SIT+(NI/NC)
MNLI [10]	domain adaptation	SIT+NI
MDSD [81]	sentiment analysis	SIT+NI
WMT17 [14]	NMT	MT+NC
OpenSubtitles18 [76]	NMT	MT+NC
WIPO COPPA-V2 [63] [107]	NMT	MT+NC
CALM [66]	language modeling	Online
WikiText-2 [118]	language modeling	SIT+NI/NC
AudioSet [27, 34]	sound classification	SIT+NC
LibriSpeech, Switchboard [119]	speech recognition	(SIT/MT)+NC
Synthetic Speech Commands †	sound classification	SIT+NC
Acrobot [65]	reinforcement learning	MT+NI

Benchmarks description



- Study the behavior of RNNs
 - with popular CL strategies
not designed for sequential data processing
 - on application-agnostic benchmarks

Our objective



Experimental evaluation



- Class-incremental (no task labels), single-head
- 6 strategies + Naive + Joint Training
 - EWC, MAS, LwF, GEM, A-GEM, Replay (random sampling)
- No architectural strategies
- Grid search protocol with held-out experiences

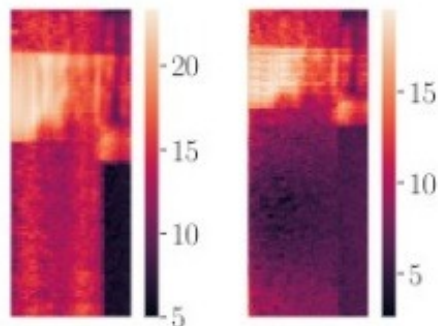
Benchmarks



- Split / Permuted MNIST (really?)

Application-agnostic, “closer” to real-world

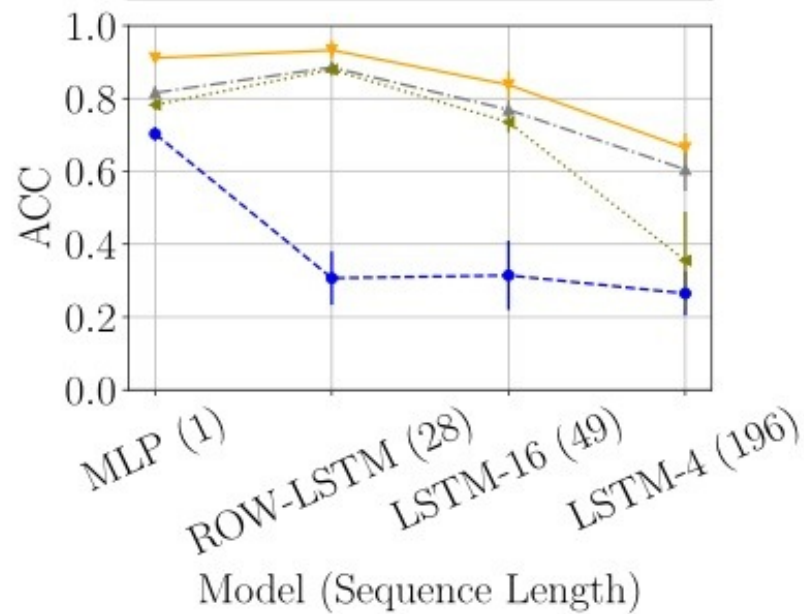
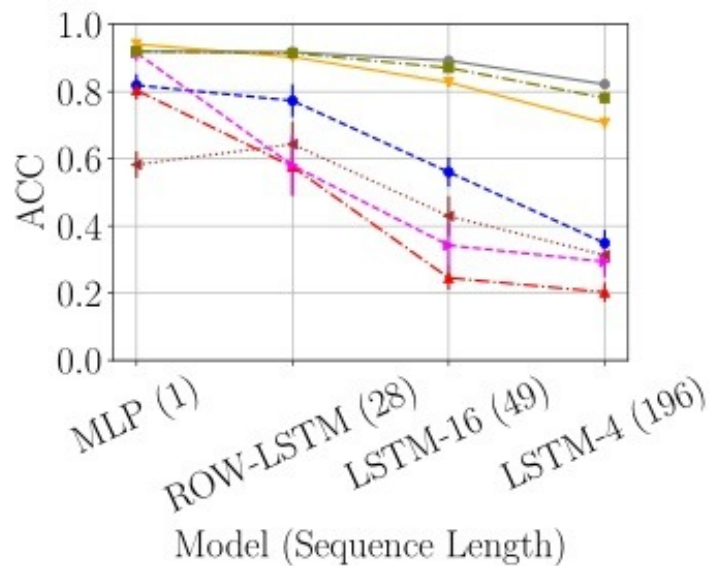
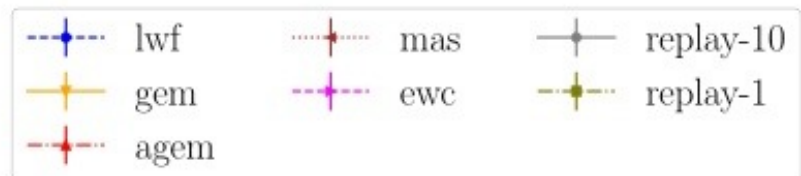
- Synthetic Speech Commands – audio with 101 time steps



- Quick, Draw! - variable sequence length



Sequence length affects forgetting





SSC	MLP	LSTM
EWC	0.10 \pm 0.00	0.10 \pm 0.00
LWF	0.05 \pm 0.00	0.12 \pm 0.01
MAS	0.10 \pm 0.00	0.10 \pm 0.00
GEM	0.55 \pm 0.00	0.53 \pm 0.01
A-GEM	0.05 \pm 0.00	0.09 \pm 0.01
REPLAY	0.81\pm0.03	0.73\pm0.04
NAIVE	0.10 \pm 0.00	0.10 \pm 0.00
Joint Training	0.93 \pm 0.00	0.89 \pm 0.02
QD	LSTM	
EWC	0.12 \pm 0.02	
LWF	0.12 \pm 0.01	
MAS	0.10 \pm 0.00	
GEM	0.47 \pm 0.03	
A-GEM	0.10 \pm 0.00	
REPLAY	0.49\pm0.02	
NAIVE	0.10 \pm 0.00	
Joint Training	0.96 \pm 0.00	

Impact on more
realistic
benchmarks

What for the future?



Just scratched the surface

- Adapt existing CL strategies
 - Orthogonal projections seem promising – find a better tradeoff
- Improve recurrent models and learning algorithms
 - BPTT alternatives – local algorithms
- Applications: place something somewhere... and leave it there!



Do you believe RNNs are worth studying in CL?

<https://arxiv.org/abs/2103.07492>