Informatics

Neural Network Arena:
Investigating Long-Term Dependencies in Deep Models

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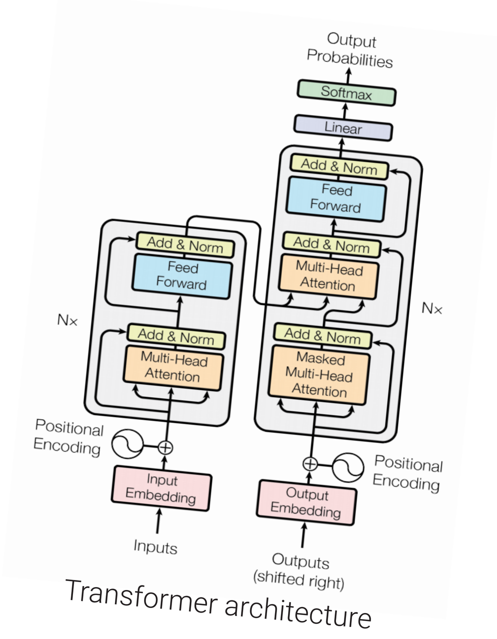
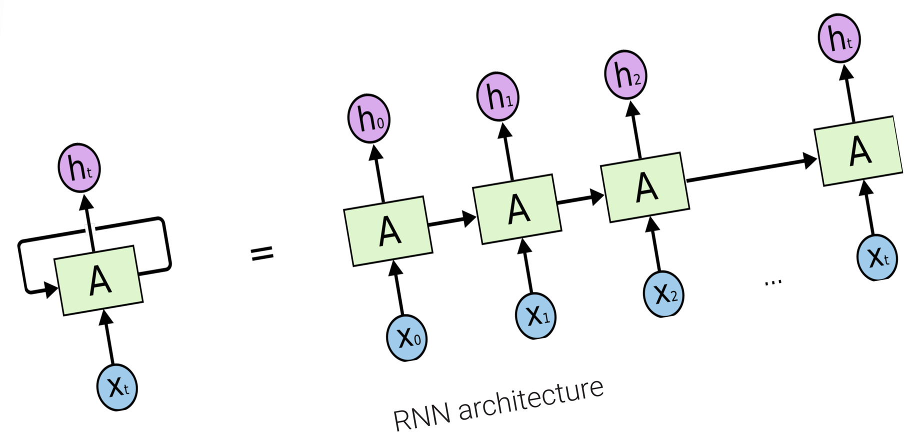
GitHub repository



Transformer architecture



RNN architecture

Implemented Models

- LSTM (Long Short-Term Memory)
- GRU (Gated Recurrent Unit)
- CT-RNN (Continuous-Time RNN)
- CT-GRU (Continuous-Time GRU)
- ODE-LSTM (Ordinary Differential Equation LSTM)
- NCP (Neural Circuit Policies)
- Unitary RNN
- Matrix Exponential Unitary RNN **new**
- Unitary NCP **new**
- Transformer
- Recurrent Network Augmented Transformer **new**
- Recurrent Network Attention Transformer **new**
- Memory Augmented Transformer **new**
- Differentiable Neural Computer
- Memory Cell **new**

Problem Statement

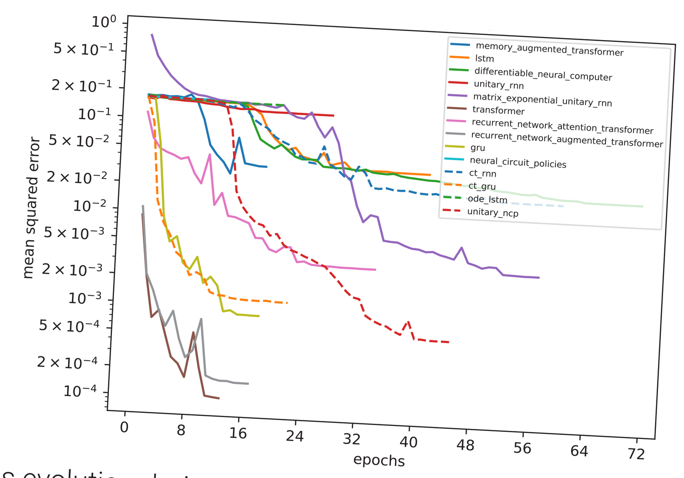
- implementation of a reusable benchmark suite to compare machine learning models used for sequence modeling
- benchmark suite should test the models for their capabilities to capture long-term dependencies and to model physical systems
- selection of state-of-the-art models should be implemented as well as possible outlined improvements
- thoroughly comparison of all implemented models using the benchmark suite
- all implemented models are Transformer or RNN (Recurrent Neural Network) architectures
- proof-of-concept design and implementation of a continuous-time memory cell architecture based on LTC Networks

Methodology

- extensive literature review in the domain of sequence modeling
- implementation of the benchmark suite and all the implemented models
- the benchmark suite was invoked three times on all models and the statistics of the invocation output were interpreted

Motivation

- provide an objective comparison and overview of all implemented models on various sequence modeling tasks
- especially RNN architectures have difficulties of capturing long-term dependencies when being learned by gradient descent
- investigate which mechanism works best in RNN architectures to counteract this difficulty



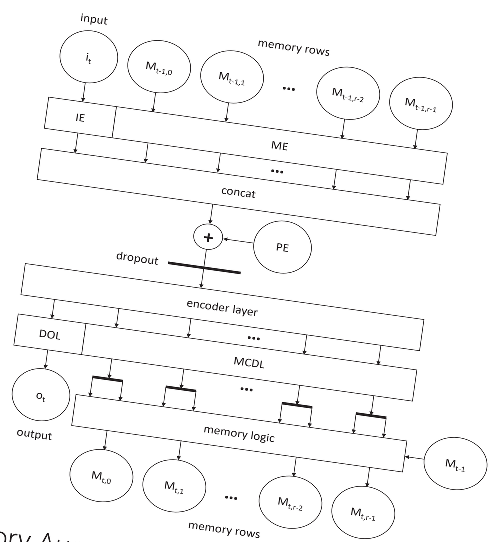
loss evolution during single training run for the Add Benchmark

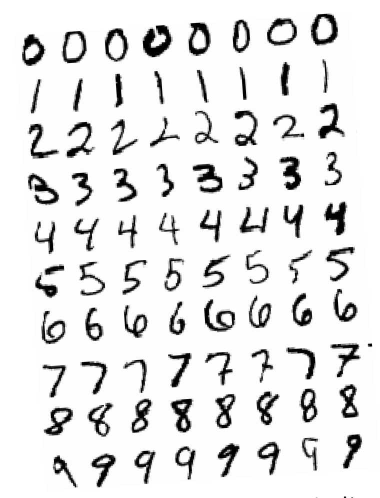
model	trainable parameters	training duration total [s]	training duration per epoch [s]	epochs	test mean squared error
transformer	21889	421.042 ± 62.125	33.175 ± 3.885	12.667 ± 0.577	0.000 ± 0.000
recurrent_network_augmented_transformer	3729	3369.947 ± 238.022	198.209 ± 6.384	17.000 ± 1.000	0.000 ± 0.000
gru	20241	423.332 ± 52.080	20.821 ± 0.322	20.333 ± 2.517	0.001 ± 0.000
ct_gru	19073	983.703 ± 123.086	48.464 ± 0.901	20.333 ± 2.887	0.001 ± 0.000
recurrent_network_attention_transformer	2349	10433.169 ± 3205.297	370.905 ± 13.507	28.000 ± 7.937	0.002 ± 0.002
differentiable_neural_computer	24774	6138.672 ± 4012.017	152.861 ± 2.424	40.333 ± 26.858	0.007 ± 0.011
ct_rnn	17025	9904.616 ± 1578.008	193.094 ± 1.600	51.333 ± 8.505	0.019 ± 0.003
matrix_exponential_unitary_rnn	17409	5956.370 ± 1220.646	115.400 ± 11.578	51.333 ± 6.028	0.022 ± 0.032
lstm	17217	589.247 ± 181.783	19.420 ± 0.162	30.333 ± 9.292	0.066 ± 0.085
unitary_rnn	2929	9694.727 ± 2483.450	278.442 ± 11.350	35.000 ± 9.849	0.094 ± 0.076
unitary_ncp	1885	3283.152 ± 1513.217	102.520 ± 0.625	32.000 ± 14.731	0.106 ± 0.092
memory_augmented_transformer	18066	3802.347 ± 1303.816	283.514 ± 8.116	13.333 ± 4.163	0.122 ± 0.083
neural_circuit_policies	1349	1007.356 ± 252.374	125.919 ± 0.414	8.000 ± 2.000	0.166 ± 0.001
ode_lstm	25537	748.046 ± 108.977	44.046 ± 0.415	17.000 ± 2.646	0.167 ± 0.002

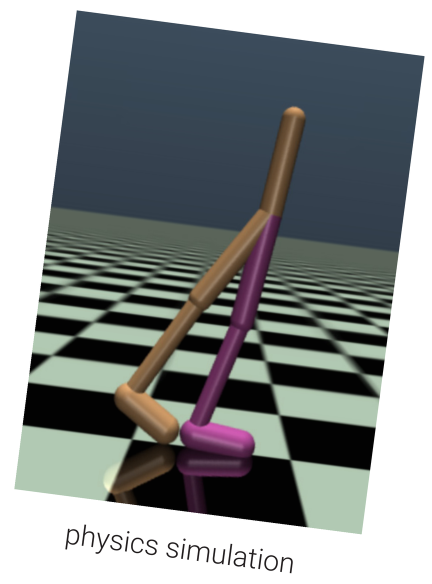
result statistics of Add Benchmark (μ ± σ, N = 3)

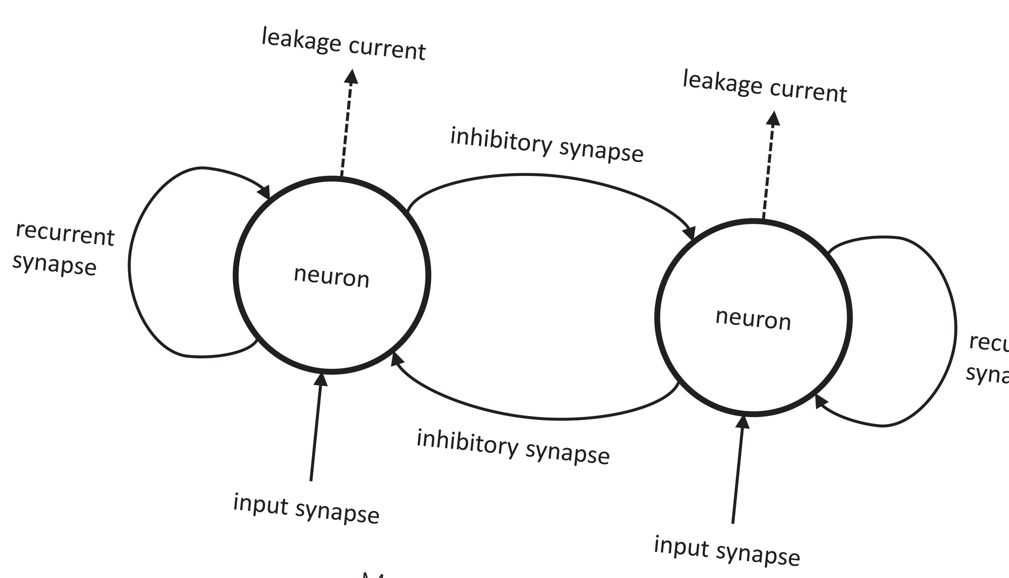
Results

- state-of-the-art in efficient unitary matrix parameterization was improved by using an approximated matrix exponential
- continuous-time memory cell architecture was successfully trained to store sparse activations
- positional encoding used in Transformer architectures shows deficiencies in tasks where exact positional information is required
- the newly introduced Memory Augmented Transformer architecture shows promising results in some tasks

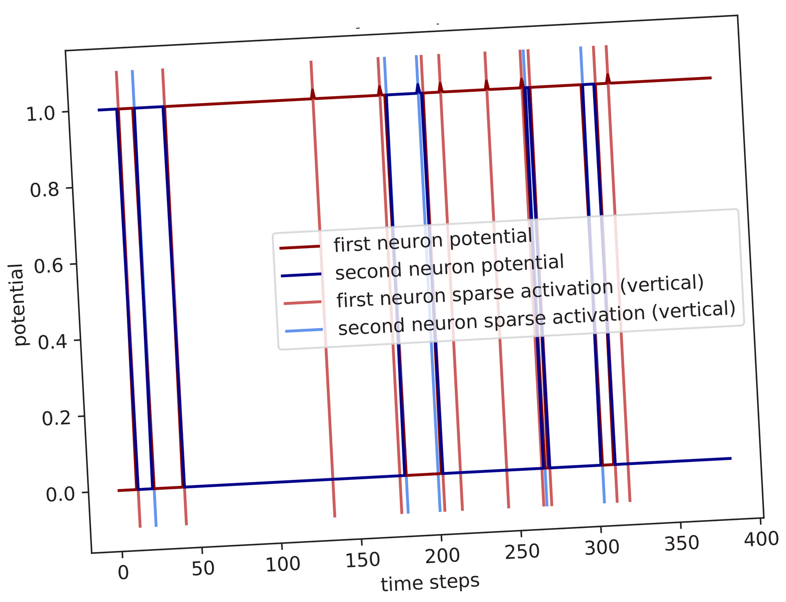

Memory Augmented Transformer architecture


MNIST handwritten digits


physics simulation



Memory Cell architecture



successful Memory Cell operation

Benchmark Suite Tasks

- Activity Benchmark - human activity classification of inertial sensor measurement data sequences
- Add Benchmark - adding up two marked numbers in a very long number sequence
- Walker Benchmark - predict the next state of a physics simulation given a sequence of previous simulation states
- Memory Benchmark - store a seen category exactly and recall it after seeing a sequence of irrelevant filler symbols
- MNIST Benchmark - digit classification using a sequence of MNIST handwritten digit image chunks
- Cell Benchmark - validates if sparse activations are correctly stored in the time-continuous memory cell architecture