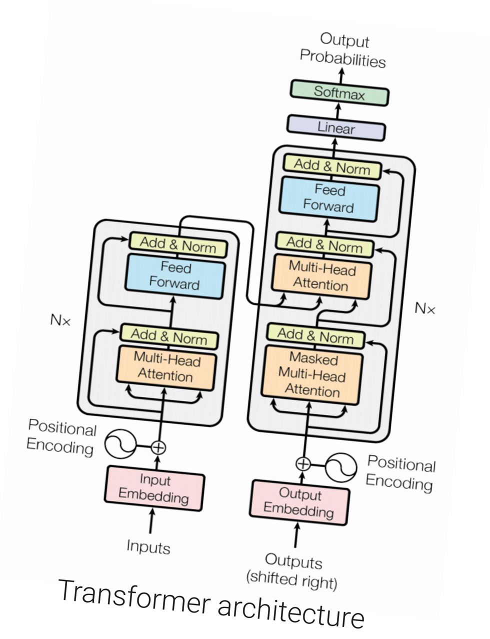
# Informatics

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

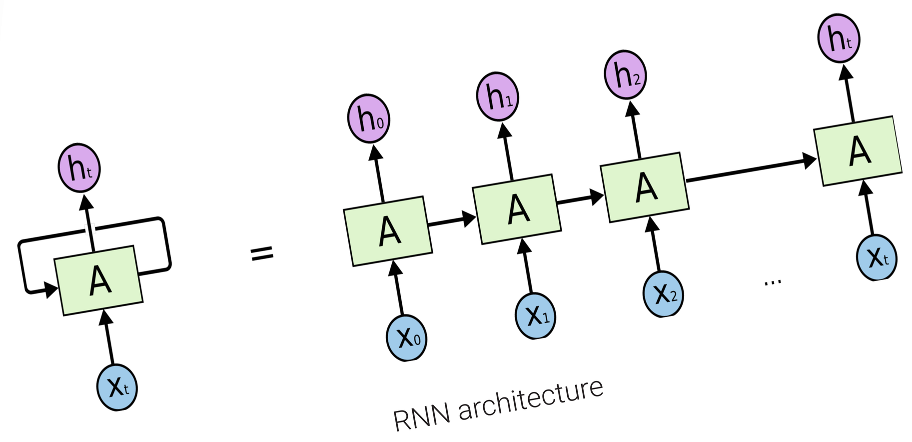

Hannes Brantner
Computer Engineering

**TU Wien Informatics**
Institute of Computer Engineering
Cyber-Physical Systems Group
Supervisor: Univ.Prof. Dipl.-Ing. Dr.rer.nat. Radu Grosu
Contact: e01614466@student.tuwien.ac.at


## GitHub repository

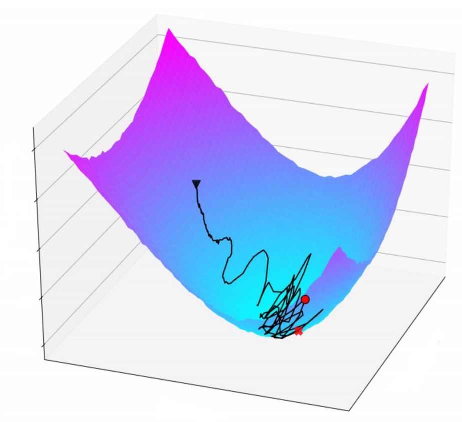


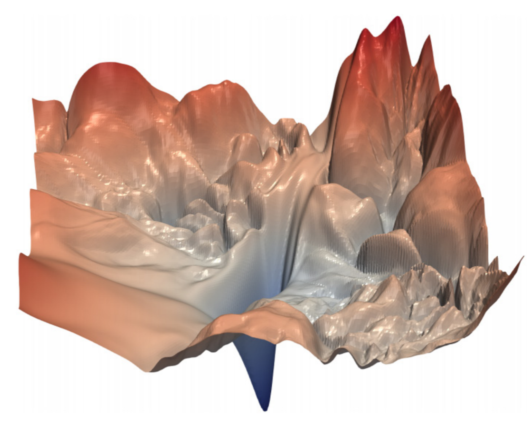
Transformer architecture


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**

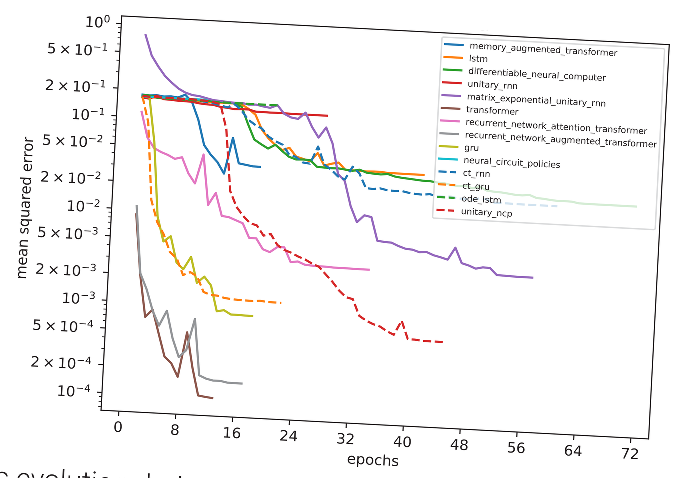
## Problem Statement
- implementation of a reusable benchmark suite to compare machine learning models used for sequence modeling
- benchmark suite should test the models for their capabilities to capture long-term dependencies and to model physical systems
- selection of state-of-the-art models should be implemented as well as possible outlined improvements
- thoroughful 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


loss surface and applied gradient descent procedure


rugged loss surface

## 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

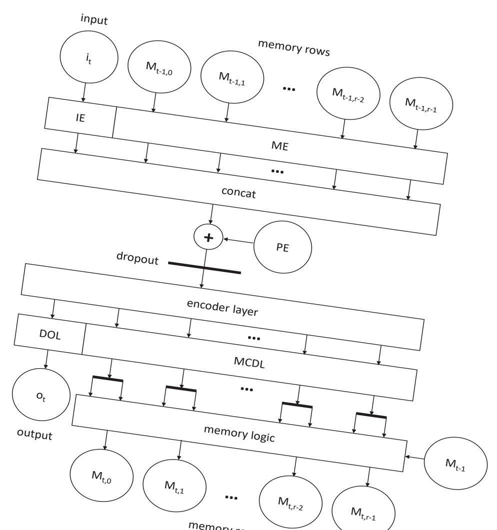
## Motivation
- provide an objective comparison and overview of all implemented models on various sequence modeling tasks
- especially RNN architectures have difficulties of capturing long-term dependencies when being learned by gradient descent
- investigate which mechanism works best in RNN architectures to counteract this difficulty
- each model is just a parameterized function whose parameters are optimized by derivating a loss function that compares model output with expected output
- parameters are updated according to the gradient which should not vanish or explode („walk down the hill“)

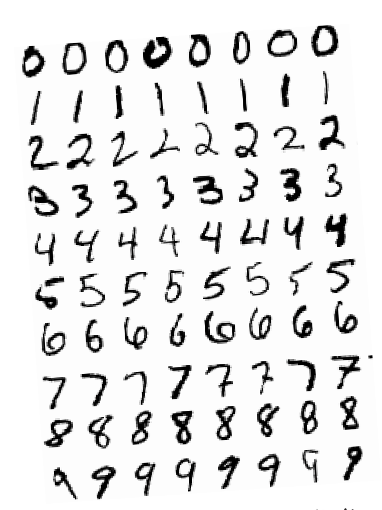


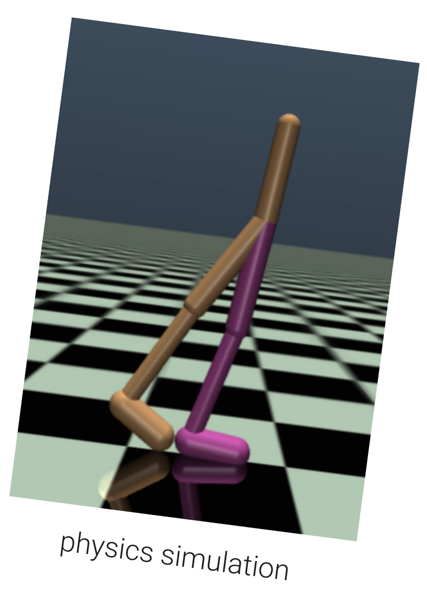
loss evolution during single training run for the Add Benchmark

| 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 |

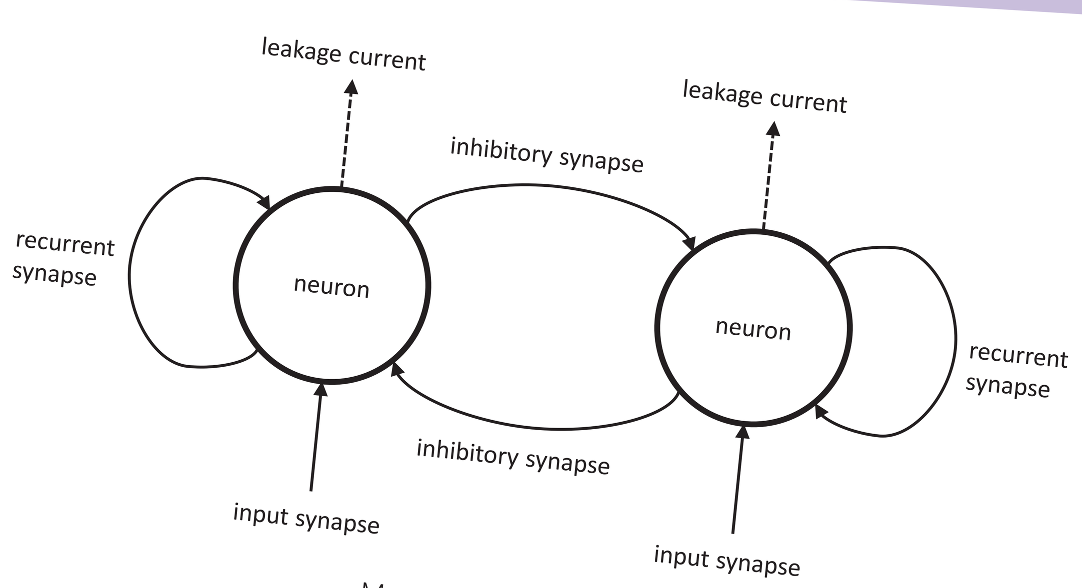
result statistics of Add Benchmark ($\mu \pm \sigma$, N = 3)


Memory Augmented Transformer architecture

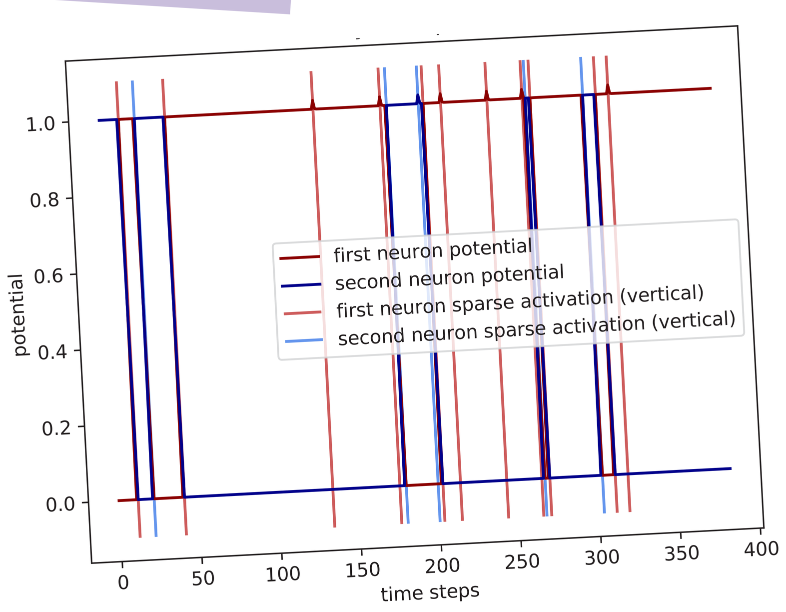

MNIST handwritten digits


physics simulation

## Results
- state-of-the-art in efficient unitary matrix parameterization was improved by using an approximated matrix exponential
- continous-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 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