

Methodology for Predictive calculator

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1 Brief Summary of the Project

This Matura project investigates and evaluates the arithmetic capabilities of different neural networks.

The project began with a literature review to generate a hypothesis regarding the weaknesses of neural networks in performing simple arithmetic. This literature review was submitted as the Zwischenprodukt, alongside a proof-of-concept notebook featuring a comparison of Feed-forward Neural Networks (FNNs) of different sizes.

The next step was to build a Recurrent Neural Network (RNN) and similar attention-based RNNs to investigate their arithmetic capabilities and compare them to those of the FNN using a benchmark.

The benchmark's baseline was defined to be the performance of a basic FNN's performance on different, but roughly still similar arithmetic tasks.

Afterwards, the same was done for the transformer type of neural network model. Here, their exact functionality was thoroughly investigated, because of their unique architectures.

Lastly a similar workflow was repeated for some bigger, pre-trained models. And finally all the findings were collected and evaluated as a whole.

2 Introduction to this document

The goal of this document is assisting reproducibility and showing how the findings discussed in the other document have been obtained.

All of the code written for this project is available in the github repository:
<https://github.com/AntonStantan/matura>

In this project all of the code was written in Jupyter Lab.

Most of the models were trained locally on a Nvidia GPU device: *Nvidia Jetson Orin Nano Super Developer Kit*

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2.1 Drop-Out

When introducing a Drop-Out with an industry standard value of 0.3; contrary to the expectation of reducing over-fitting, which in some way is present, as the models aren't able to generalize beyond the training range, this has a negative effect on the model. The MSEs of models with Drop-out are higher then, the ones of the previous models without drop-out.

3 Recurrent Neural Network (RNN)

3.1 Introduction

Recurrent Neural Networks (RNNs) work similar to FNNs with one key difference: There is a vector called the hidden-state. This vector contains information about previous inputs. The hidden-state of the previous time-step, in addition to the input of the current time-step, is fed into a model which computes the hidden-state of the present time-step. The output of each time-step is calculated by feeding the respective hiddenstate to a model.

Numerical Visualization:

Let:

- x_t : Input at time step t
- h_t : Hidden state at time step t
- y_t : Output at time step t
- W_{xh} : Weight matrix connecting input to hidden state
- W_{hh} : Weight matrix connecting previous hidden state to current hidden state (recurrent weights)
- W_{hy} : Weight matrix connecting hidden state to output
- b_h : Bias vector for the hidden layer
- b_y : Bias vector for the output layer
- σ : Activation function (commonly \tanh or ReLU for the hidden state)
- σ_{out} : Activation function for the output (e.g. softmax for classification, or linear in our case of regression)

$$h_t = \sigma(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$$

$$y_t = \sigma_{out}(W_{hy}h_t + b_y)$$

Useful sources for the creation of the first RNN prototype:

4 attention



Figure 1: You can see the aforementioned Nvidia Jetson device booting up.