

## 0.1 Usage

**Overview:** The presented software consists of 3 components:

- A set of functions for parsing the mat-files to python, extracting the desired data from the structure, pre-processing
- A set of handcrafted neural network models, a common base class for them and the implementation of a Neural Architecture search for Regression
- A set of functions to visualize the results of the handcrafted networks and the architecture search.

For additional visualizations of hand-crafted models, navigate in a shell to the path where the weights are saved (should contain the folder 'tensorboard-logs') and execute the command " tensorboard --logdir="tensorboard-logs" --port=6006" and access the web interface with your browser at localhost:6006

**Configuration** The paths of the data folder and the one to store model weights and metrics to, the electrodes and the frequencies to use, training rates and duration can be configured in the file config.py.

**Adding a new model** requires the user to inherit from the AbstractNet class and then implement the build function and the \_\_init\_\_ function with the provided arguments:

```
def __init__(self, model_out_dir, frequency, electrodes):
    """
    Args:
        model_out_dir: directory to save model to
        frequency: the frequency to be used (shape[1])
        electrodes: the electrodes to be used (shape[0])
    """
    super(DeepDenseNet, self).__init__('WhatsTheNameOfYourModel?', model_out_dir, frequency, electrodes)
```

The following is a minimal example. For the complete documentation for creating a model see <https://keras.io/models/model/>

```
def build(self):
    """
    constructs a model using 1 Dense layer
    Returns:
        the constructed model
    """
    a = Input(self.input_shape)
    x = Flatten()(a)
    b = Dense(1, activation='relu', kernel_initializer='glorot-normal', bias_initializer='zeros', name='lfc2')(x)
    self.model = Model(a, b)
    super().build()
```

**Changing the data format** requires the user to extend preprocessing according to the .mat struct of the data. It should however be similar compared to the included preprocessor if data is in the frequency domain, e.g. fourier transformed.

## 0.2 Methodology

The basic workflow was derived from [Tzallas et al., 2007]

### 0.2.1 Pre-Processing

The provided data contains the coherence spectrum of the fourier transformed recorded EEG and audio stimulus. The provided labels are comprehension scores between [0, 1] in steps of 0.2, where each step means an understood word. Below is the covariance matrix of the coherence spectrum and the comprehension scores.

Mean Covariance between the Electrode–Audio Coherence spectrum at frequency 5 Hz and the Comprehension Scores

```
[[1.00992995  0.00153135]
 [0.00153135  0.13221692]]
```

Mean Covariance between the Electrode–Audio Coherence spectrum at frequency 10 Hz and the Comprehension Scores

```
[[1.00728738  0.00286027]
 [0.00286027  0.13221692]]
```

Thus no pre-processing in terms of signal processing was possible.

Data was extracted from the provided .mat-files, filtered to only use user-defined which were determined by cluster analysis of Dr. Strauß or all electrodes and only a certain frequency or all frequencies. The width of the frequency window was the provided value in Hz  $\pm 1$ , which left 5 channels, if a frequency was specified. The values in the coherence spectrum were then standardised (z-scores).

### 0.2.2 Classification: Neural Architecture Searching for Regression

Depending on the user input the shape of the input into the neural networks varied between  $(n, 64, 101)$ ,  $(n, 64, 5)$ ,  $(n, 6, 101)$ ,  $(n, 6, 5)$ , thus different network architectures are required to accept different inputs [Abadi et al., 2015]. This requires the programmer to train at least one model per input shape and in some cases to adjust the architecture when the results differ [Glorot and Bengio, 2010]. Architecture search can be a quite time consuming process when done by hand and involves the tuning not only of the architecture but also hyperparameters like the learning rate. Thus for each input shape every model would have to be trained a couple of times, which may consum up to several hours per model per input shape [Bengio, 2012].

A promising approach to automate architecture search and hyper-parameter tuning is the Neural Architecture Search [Jin et al., 2018]. It uses bayesian statistics over the metrics of the composed networks to infer an optimal model configuration.

### 0.2.3 Results

MSE	SmallDense	WideDense	DeepDense	MediumConv1D	NAS
5 Hz	0.1578	0.153	0.1401	0.1390	0.126088
10 Hz	0.16263	0.1542	0.14183	0.1400	0.14444911

## 0.3 Appendix: Logs and Plots

Due to an error of mine (passed 2 Metrics: MAE and MSE, the latter was also the loss function), the MAE is shown as MSE wrongly!

**5 Hz component**

Start of Log

Trained model SmallDenseNet-1.json

Sunday March 31, 2019 10:33PM

Dataset dir: C:\Users\Fabi\ownCloud\workspace\uni\7\neuroling\neuroling\_project\data\v1

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 64, 5)	0
flatten_1 (Flatten)	(None, 320)	0
1fc2 (Dense)	(None, 1)	321

Total params: 321

Trainable params: 321

Non-trainable params: 0

Parameters:

Batch size : 128

Epochs : 10000

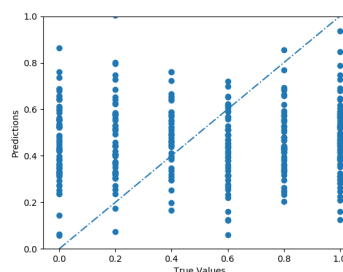
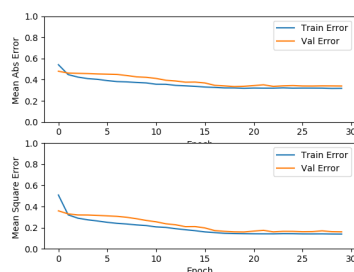
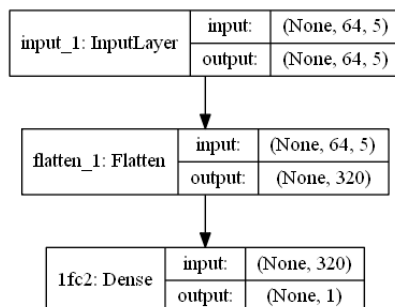
Learning rate : 0.02

Metrics

Loss : 0.15788422232073857

MSE : 0.3429352627324231

End of Log



Start of Log

Trained model DeepDenseNet-1.json

Sunday March 31, 2019 10:34PM

Dataset dir: C:\Users\Fabi\ownCloud\workspace\uni\7\neuroling\neuroling\_project\data\v1

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 64, 5)	0
flatten_1 (Flatten)	(None, 320)	0
3fc0 (Dense)	(None, 128)	41088
3fc1 (Dense)	(None, 64)	8256
3fc2 (Dense)	(None, 32)	2080
3fc3 (Dense)	(None, 16)	528
3fc4 (Dense)	(None, 8)	136
3fc5 (Dense)	(None, 4)	36
3fc6 (Dense)	(None, 2)	10
3fc7 (Dense)	(None, 1)	3

Total params: 52,137

Trainable params: 52,137

Non-trainable params: 0

Parameters:

Batch size : 128

Epochs : 10000

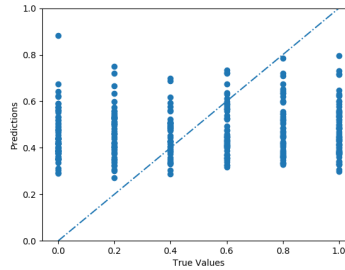
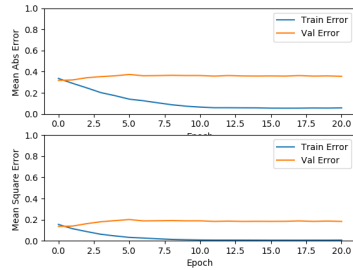
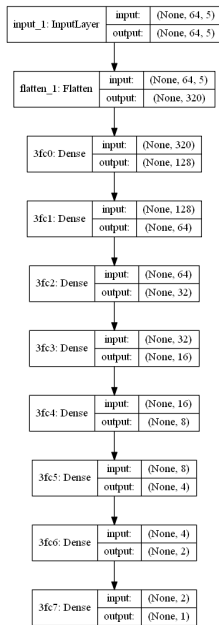
Learning rate : 0.02

Metrics

Loss : 0.14017007822935293

MSE : 0.32465702725972745

End of Log




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Start of Log

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Trained model WideDenseNet-1.json

Sunday March 31, 2019 10:34PM

Dataset dir: C:\Users\Fabi\ownCloud\workspace\uni\7\neuroling\neuroling-project\data\v1

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 64, 5)	0
flatten_1 (Flatten)	(None, 320)	0
0fc0 (Dense)	(None, 256)	82176
0fc1 (Dense)	(None, 64)	16448
0fc2 (Dense)	(None, 1)	65

Total params: 98,689

Trainable params: 98,689

Non-trainable params: 0

-----Parameters:-----

Batch size : 128

Epochs : 10000

Learning rate : 0.02

-----Metrics-----

Loss : 0.15357901974220498

MSE : 0.33593259657049457

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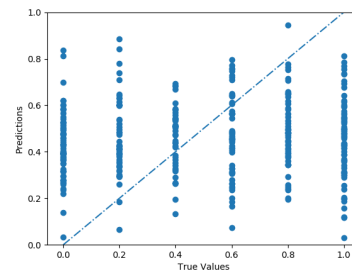
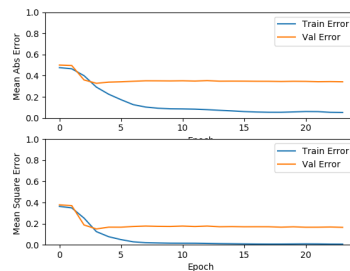
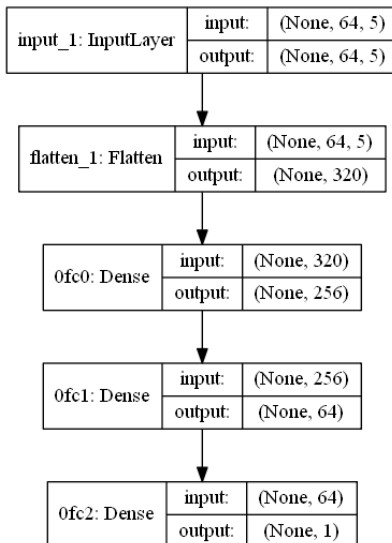
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End of Log

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Start of Log

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Trained model MediumConv1DNet-1.json

Sunday March 31, 2019 10:34PM

Dataset dir: C:\Users\Fabi\ownCloud\workspace\uni\7\neuroling\neuroling-project\data\v1

Layer (type)	Output Shape	Param #
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input_1 (InputLayer)	(None, 64, 5)	0
0c0 (Conv1D)	(None, 1, 5)	1605
flatten_1 (Flatten)	(None, 5)	0
0fc0 (Dense)	(None, 256)	1536
0fc1 (Dense)	(None, 64)	16448
0fc2 (Dense)	(None, 8)	520
0fc3 (Dense)	(None, 1)	9

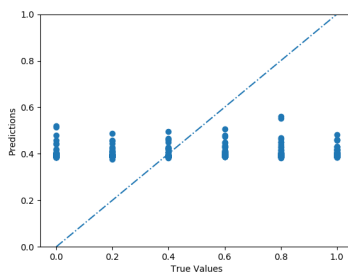
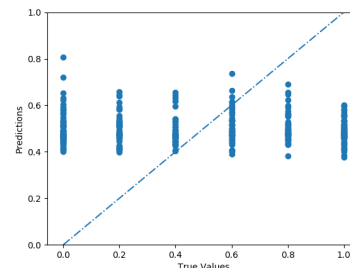
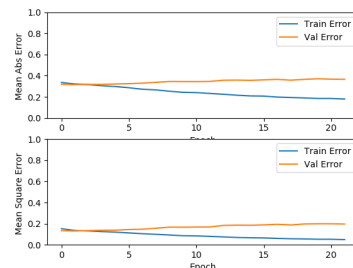
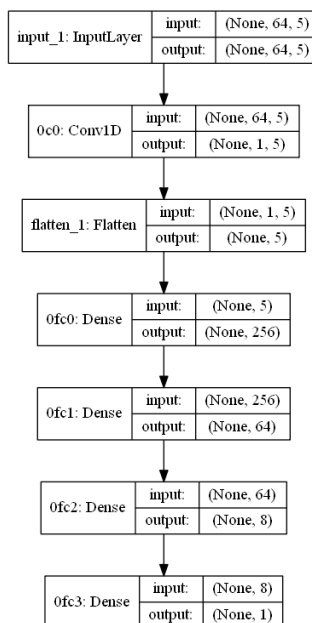
Total params: 20,118  
Trainable params: 20,118  
Non-trainable params: 0

-----Parameters:-----

Batch size : 128  
Epochs : 10000  
Learning rate : 0.02

-----Metrics-----  
Loss : 0.13900083992522577  
MSE : 0.3265306901380506

-----End of Log-----



10 Hz Component

-----Start of Log-----

Trained model SmallDenseNet-2.json  
Sunday March 31, 2019 10:29PM

Dataset dir: C:\Users\Fabi\ownCloud\workspace\uni\7\neuroling\neuroling-project\data\v1

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 64, 5)	0
flatten_1 (Flatten)	(None, 320)	0
1fc2 (Dense)	(None, 1)	321

Total params: 321

Trainable params: 321

Non-trainable params: 0

Parameters:

Batch size : 128

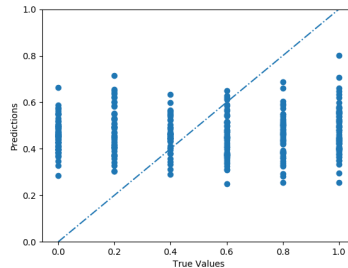
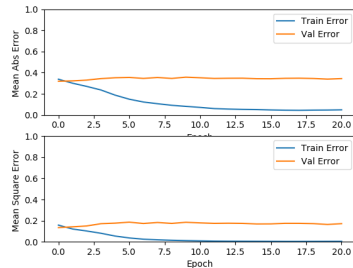
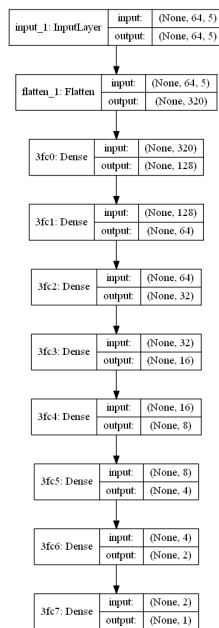
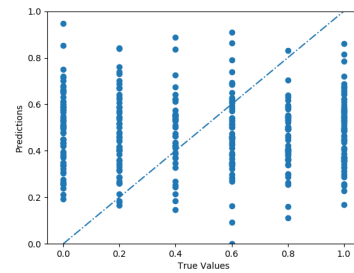
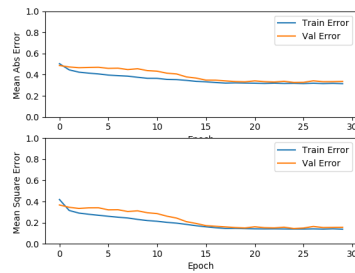
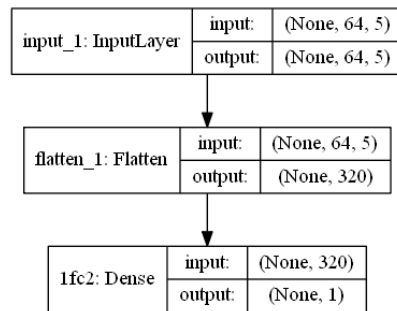
Epochs : 10000

Learning rate : 0.02

Loss : 0.1626390130016845

MSE : 0.34865260744370474

End of Log



Start of Log

Trained model WideDenseNet-2.json

Sunday March 31, 2019 10:30PM

Dataset dir: C:\Users\Fabi\ownCloud\workspace\uni\7\neuroling\neuroling-project\data\v1

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 64, 5)	0
flatten_1 (Flatten)	(None, 320)	0
0fc0 (Dense)	(None, 256)	82176
0fc1 (Dense)	(None, 64)	16448
0fc2 (Dense)	(None, 1)	65

Total params: 98,689

Trainable params: 98,689

Non-trainable params: 0

Parameters:

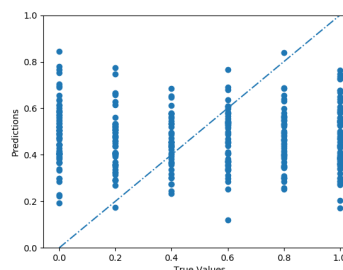
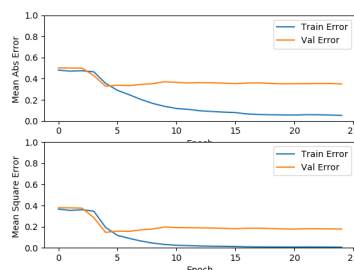
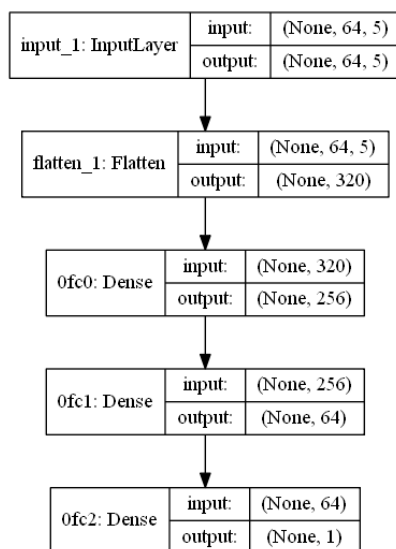
Batch size : 128

Epochs : 10000

Learning rate : 0.02

-----Metrics-----  
 Loss : 0.154226843073878  
 MSE : 0.3378447390705175

-----End of Log-----



-----Start of Log-----

Trained model MediumConv1DNet-2.json

Sunday March 31, 2019 10:30PM

Dataset dir: C:\Users\Fabi\ownCloud\workspace\uni\7\neuroling\neuroling-project\data\v1

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 64, 5)	0
0c0 (Conv1D)	(None, 1, 5)	1605
flatten_1 (Flatten)	(None, 5)	0
0fc0 (Dense)	(None, 256)	1536
0fc1 (Dense)	(None, 64)	16448
0fc2 (Dense)	(None, 8)	520
0fc3 (Dense)	(None, 1)	9

Total params: 20,118

Trainable params: 20,118

Non-trainable params: 0

-----Parameters:-----

Batch size : 128

Epochs : 10000

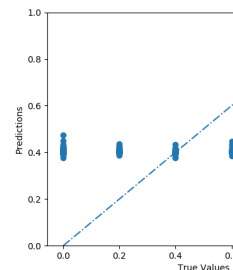
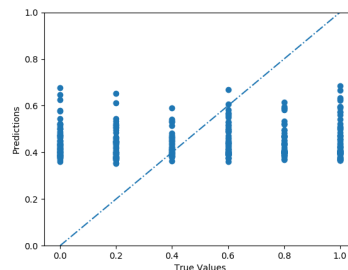
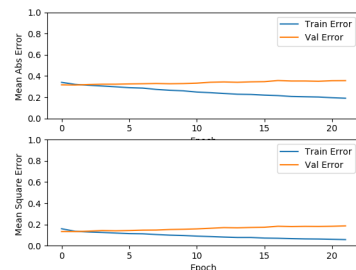
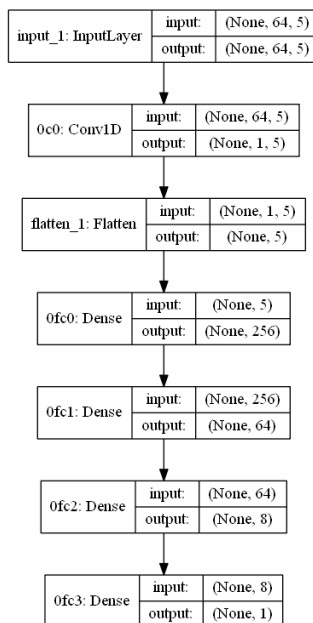
Learning rate : 0.02

-----Metrics-----

Loss : 0.14003431685053544

MSE : 0.32515802600480226

-----End of Log-----



# Bibliography

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