Autoencoder-based Hybrid Neural EEG/ERP Data Compression

Case-Study for 256-channel Binocular Rivalry Dataset

Contents

1. Introduction

- **Goal –** test the ENCODER-DECODER ANN architecture for EEG/ERP data compression
- **Lossless** or **almost lossless** compression
- **Compression from the point of ML** $\Longrightarrow$ as knowledge derived from data

Work still in progress!

1.1. Used Tools

PyTorch

NumPy

MNE
MEG + EEG ANALYSIS & VISUALIZATION

statsmodels

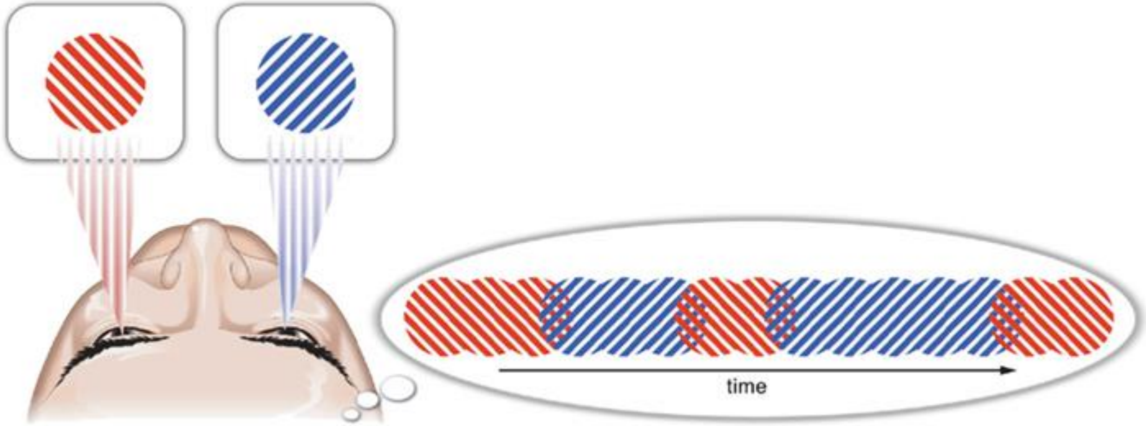
matplotlib

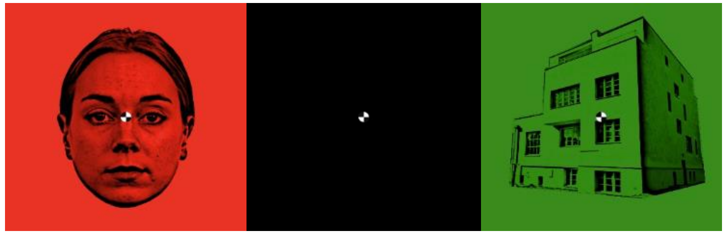
seaborn

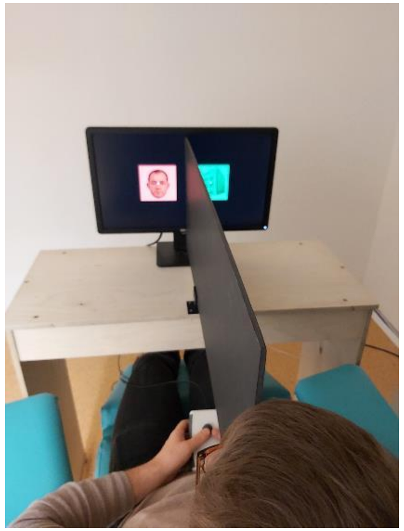
NVIDIA
CUDA

2. Dataset

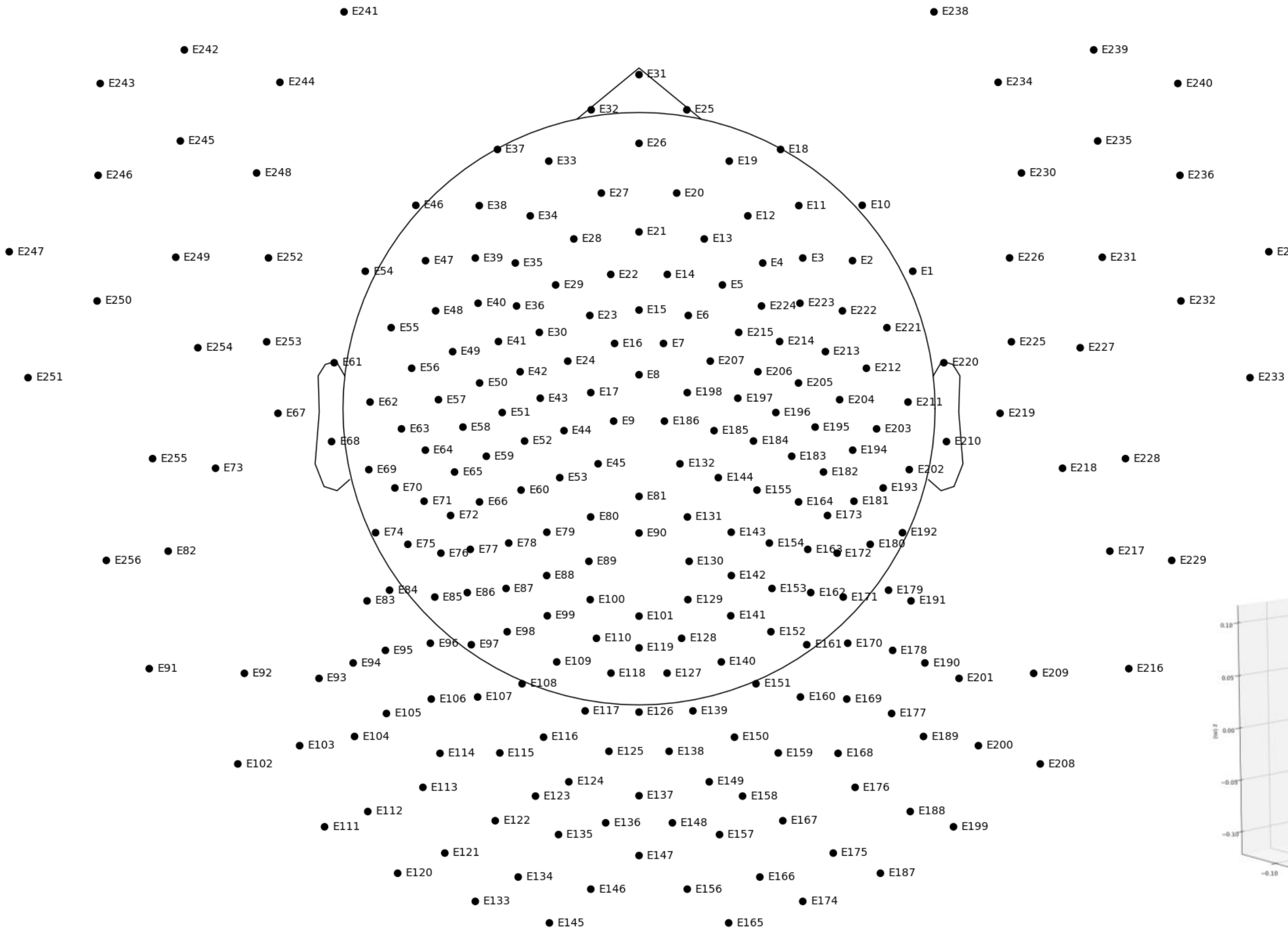
- **NIMH** (National Institute of Mental Health)
- **256**-electrode EEG
- **25 subjects**
- **Binocular rivalry** – two stimuli, one in each eye

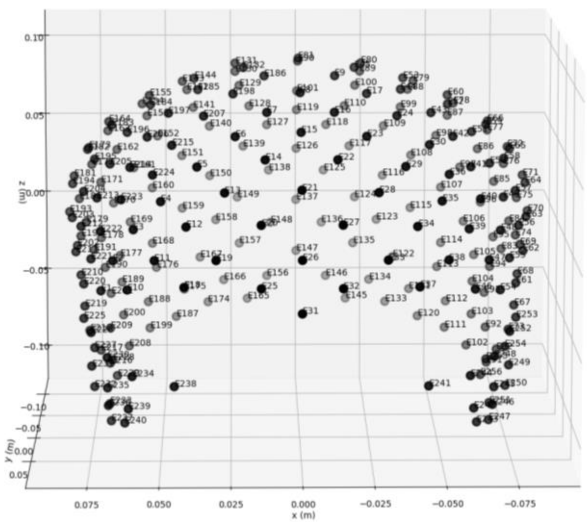


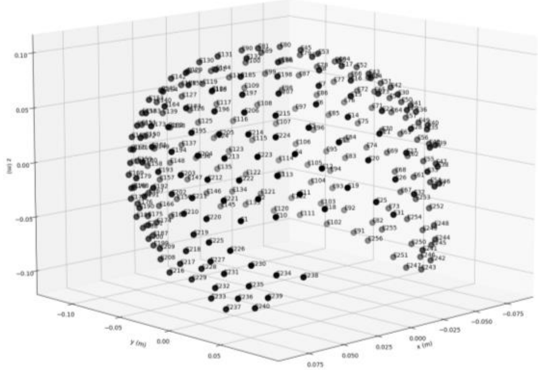


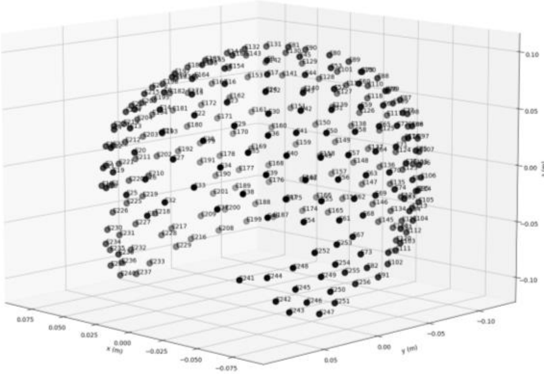


2.1. Electrode Placement









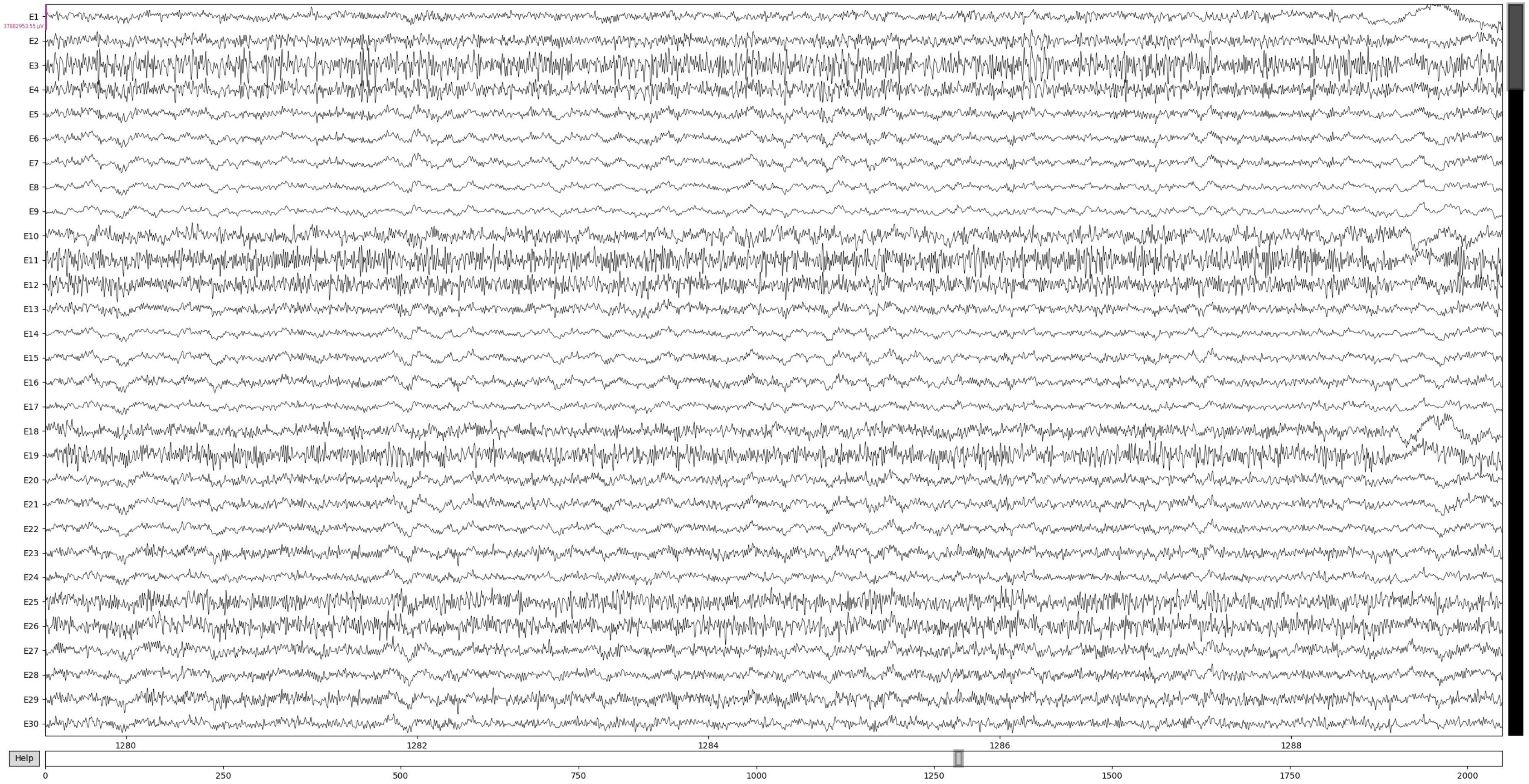
2.2. File Details

- **56.3 GB** of **.MAT** files $\Longrightarrow$ HDF5 already compressed with GZIP
- Contains extra 4 channels and 5 sec of zeroed segments at the start/end
- After **loading and extracting EEG signals**:

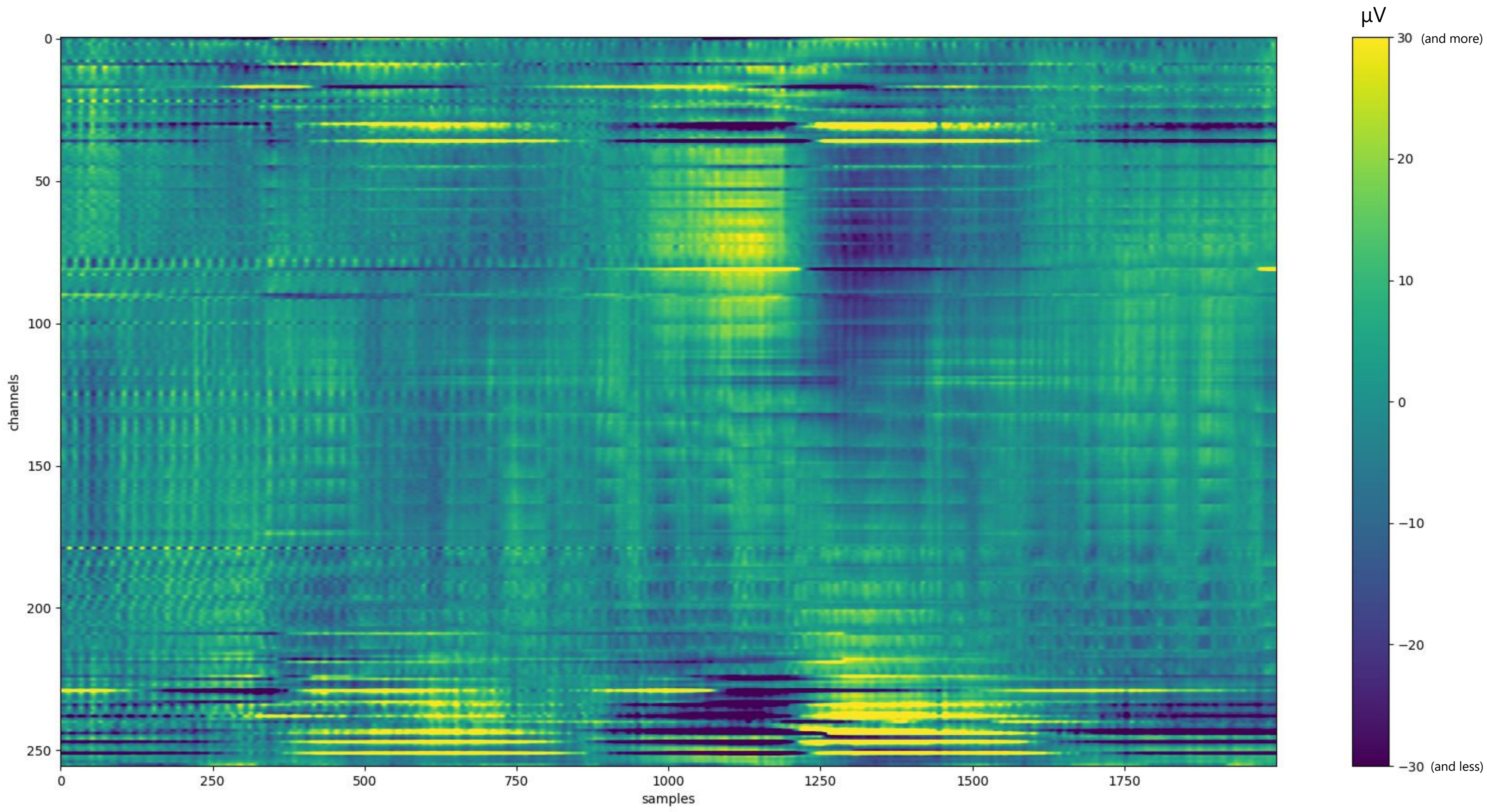
$$25 \cdot 3.98 \text{ GB} \approx \mathbf{99.5 \text{ GB of .NPY arrays (float64)}}$$

- Metadata is separated from the array
- e. g. array for the 1^{st} subject has a size of **260 × 2 057 837**

2.3. EEG Signal



2.3. EEG Signal (as an image)



3. Data Preprocessing

- Data has **specific behavior** that needs to be addressed
- In raw form, it is **too unwieldy**
- Preparing datasets for the future **ANN training**

CLEANUP

STATISTICS

SPLITS

TENSOR DATASETS

DATA TRANSFORM

3.1. Cleanup

1. **Removal of muscle artifacts etc.** (not by me)
2. **Removal of 4 extra channels** (not actually EEG)
3. **Clipping the zeroed segments** (not actually EEG)

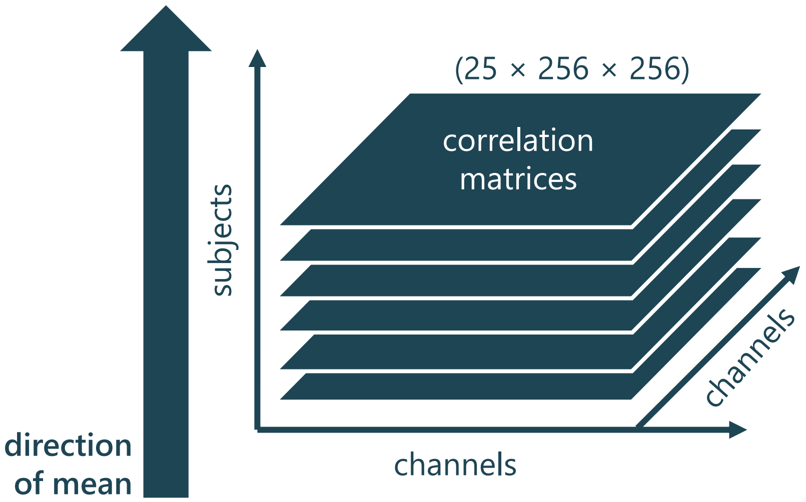
CLEANUP › STATISTICS › SPLITS › TENSOR DATASETS › DATA TRANSFORM

3.2. Statistics

1. **Correlation between channels** – is it reasonable to compress?
2. **Autocorrelation of the samples** – size of splits (explained later)

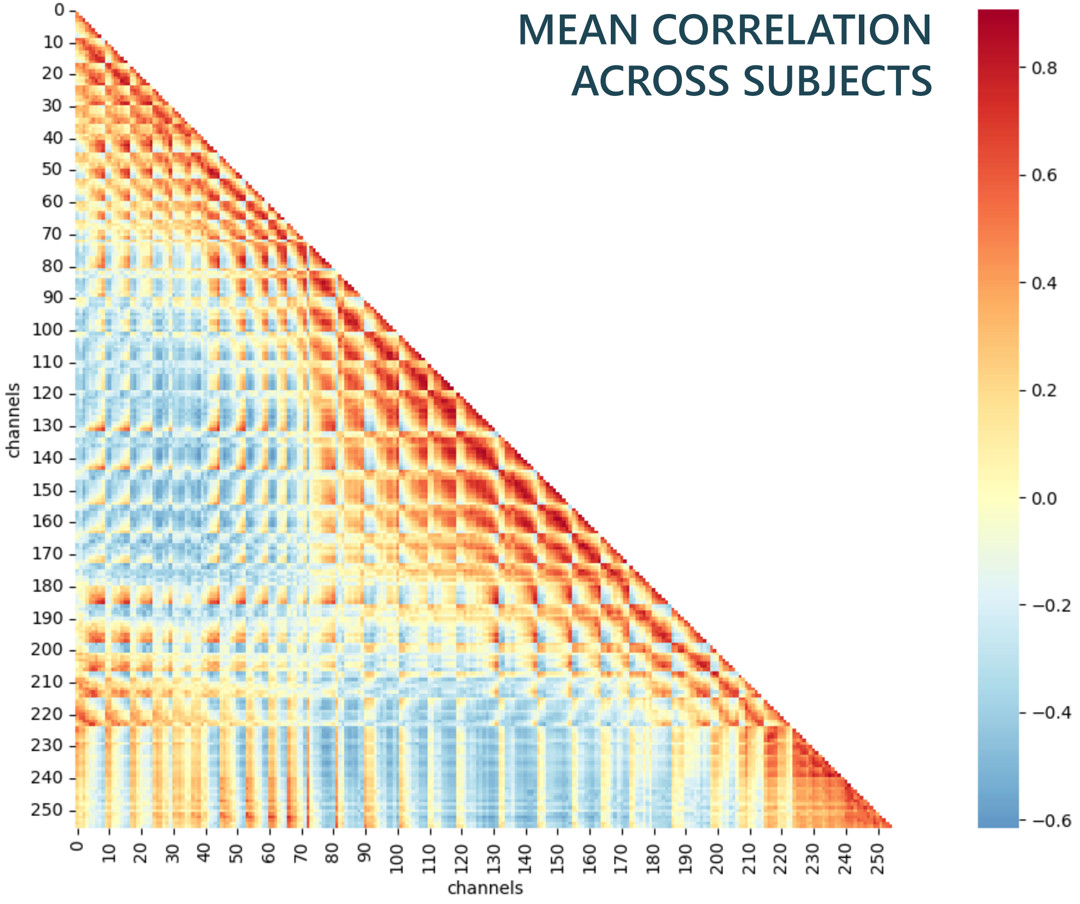
3.2.1. Correlation

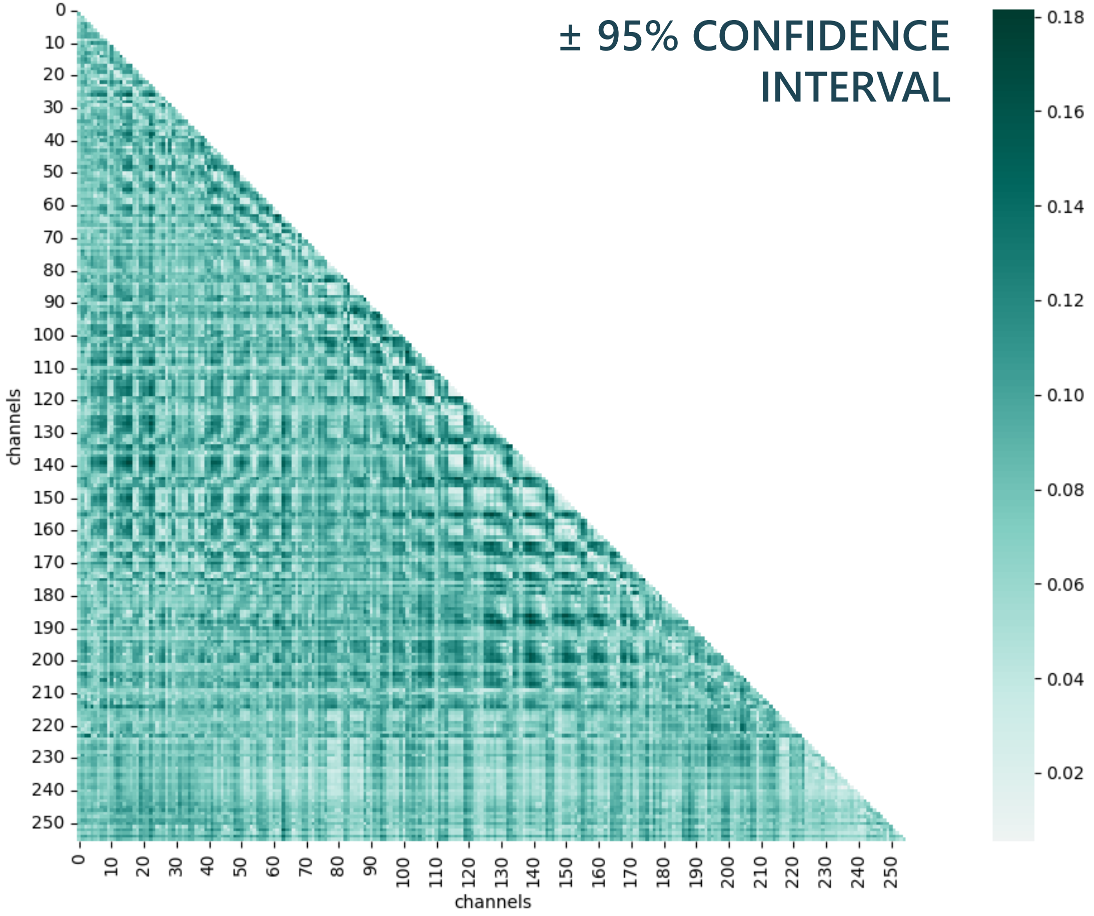
- **High/low correlation** ⟹ redundant information ⟹ better compression
- **Electrodes are close** ⟹ we expect them to correlate
- Similar across subjects?



CLEANUP | **STATISTICS** | SPLITS | TENSOR DATASETS | DATA TRANSFORM

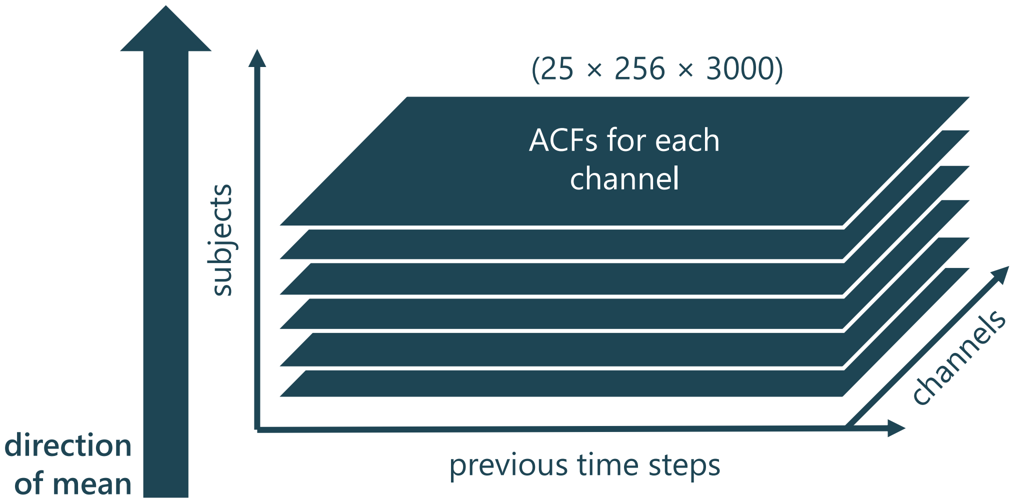
3.2.1. Correlation





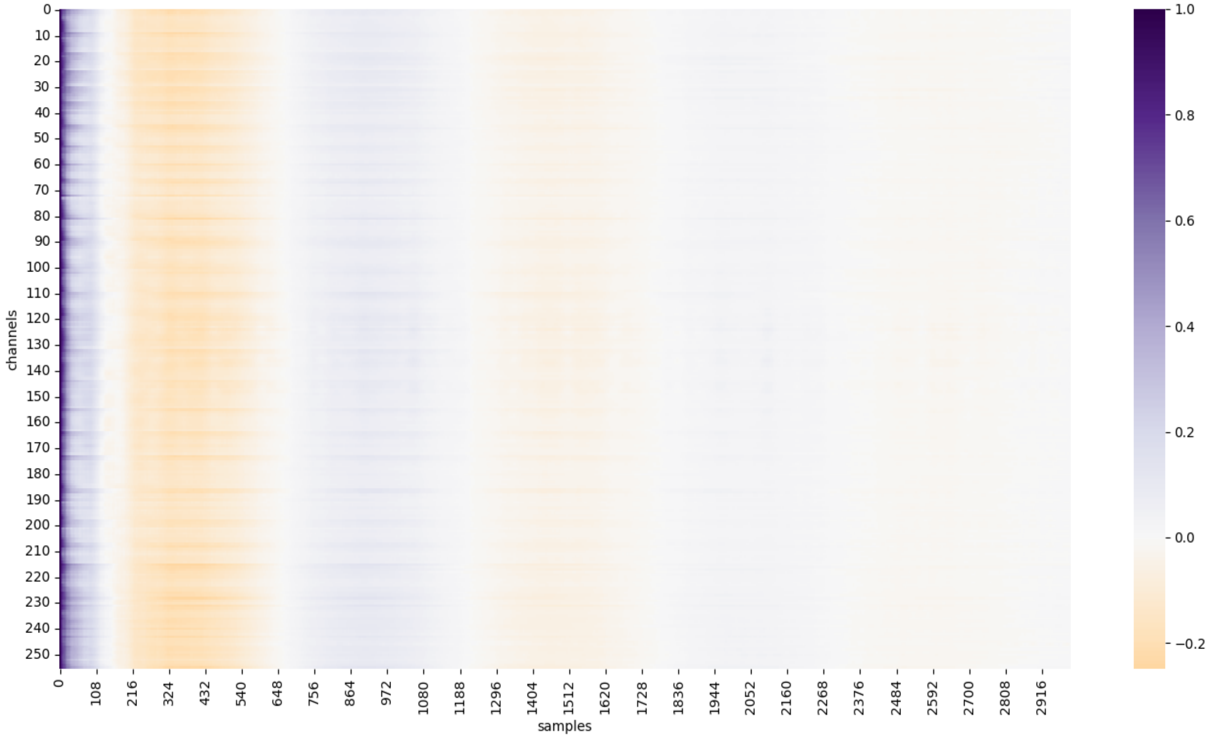
3.2.2. Autocorrelation

- **Impossible (and undesirable) to load the entire matrices at once**
- **Somehow determine the optimal split size** ⟹ ACF
- Similar across subjects?

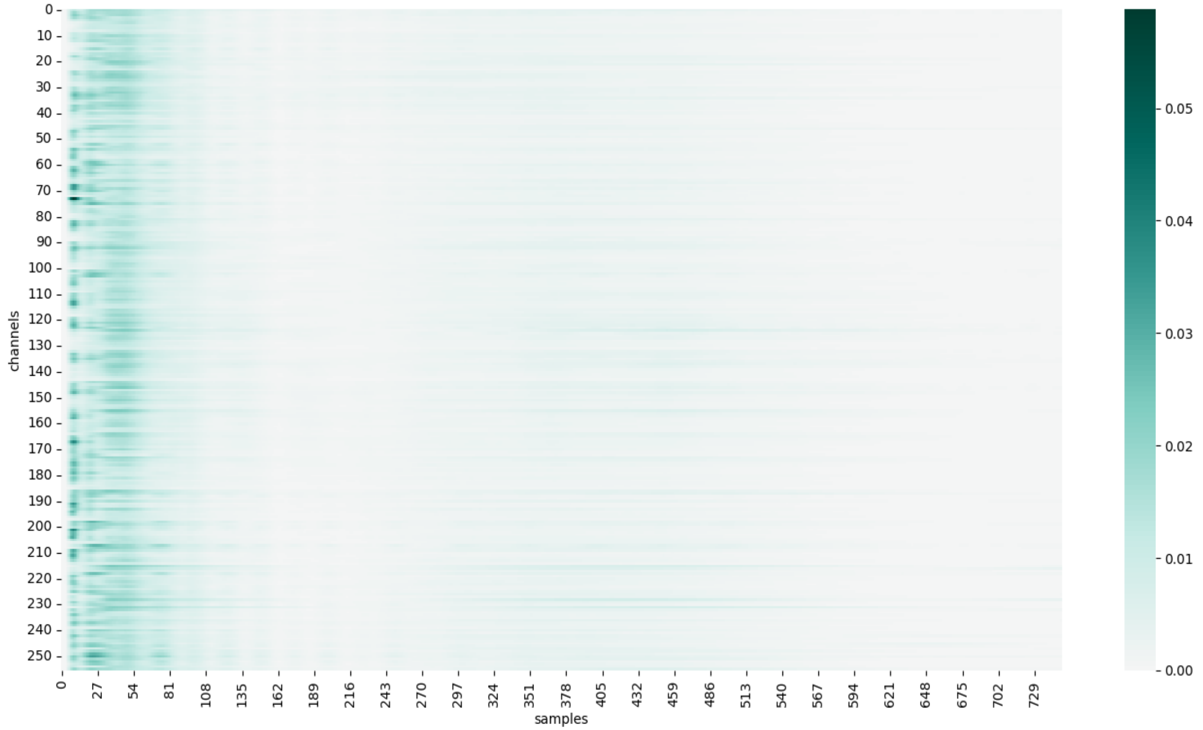


3.2.2. Autocorrelation

MEAN AUTOCORRELATION ACROSS SUBJECTS

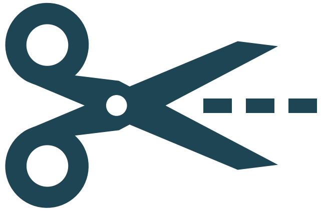


± 95% CONFIDENCE INTERVAL



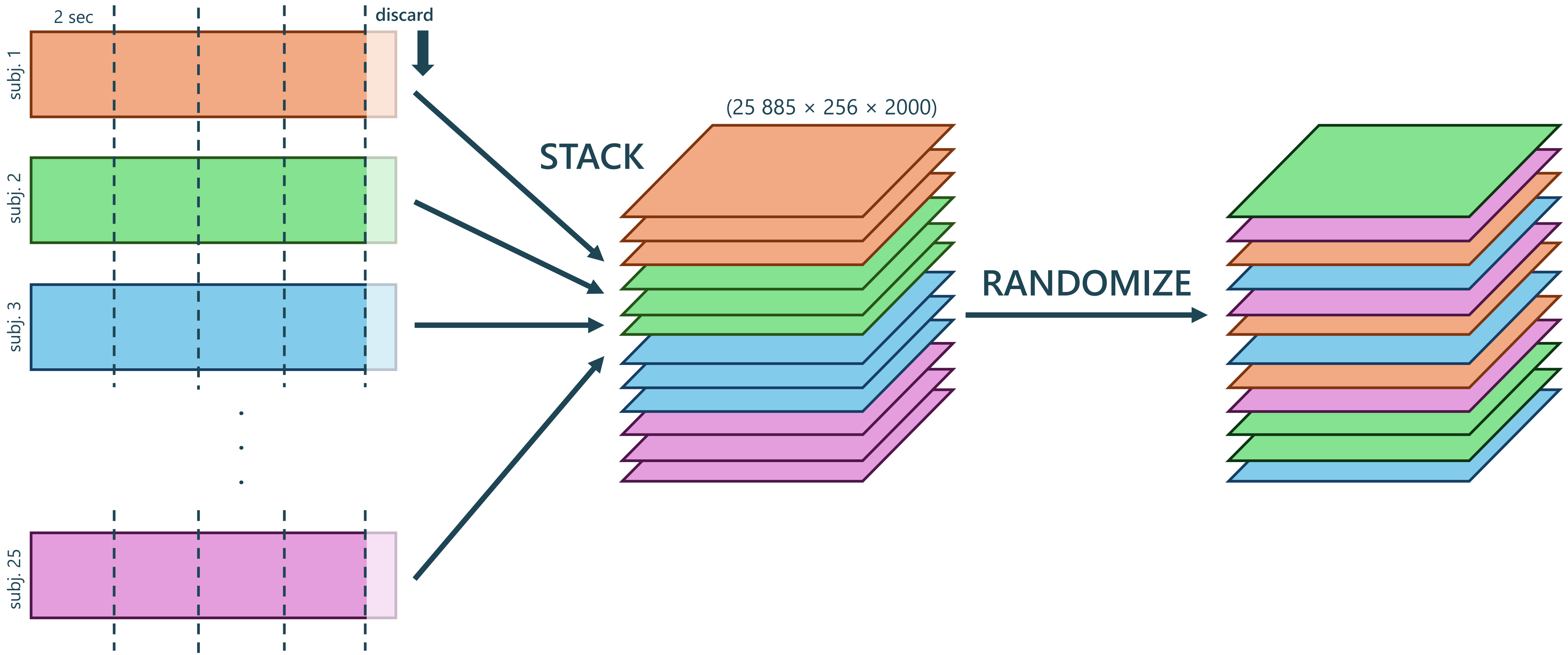
3.3. Splits

- Using the ACF, we determine split length as **2000 samples (2 sec)**
- **Must be uniform** $\Longrightarrow$ the “tail” gets discarded (OK here)
- Overall, we get **25 885 EEG chunks**



CLEANUP → STATISTICS → **SPLITS** → TENSOR DATASETS → DATA TRANSFORM

3.3. Splits



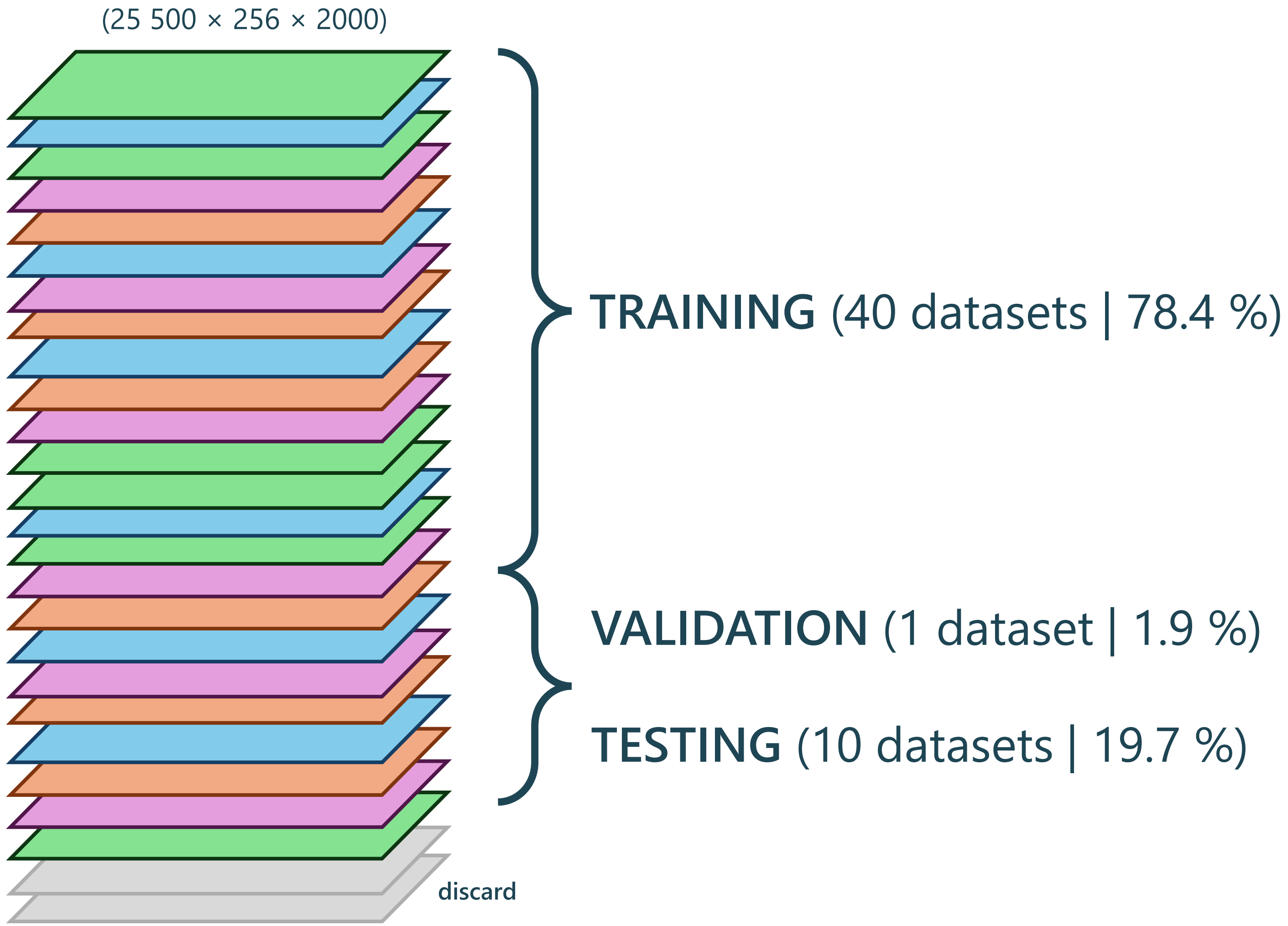
2 sec
discard
subj. 1
subj. 2
subj. 3
subj. 25
STACK
(25 885 × 256 × 2000)
RANDOMIZE

3.3. Tensor Datasets

- We need to make **training, validation, and testing datasets**
- Desired ratio is about **80 % for training, 20 % for validation/testing**
- Cannot fit massive datasets into memory $\Longrightarrow$ **multiple datasets**
- We want to evaluate learning across datasets $\Longrightarrow$ **same size**

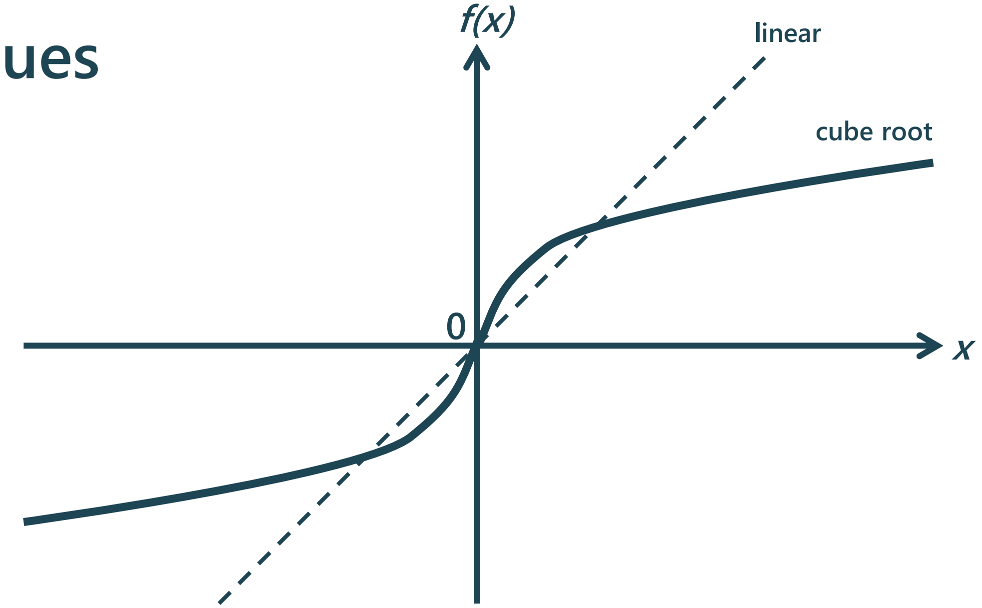
$(500 \times 256 \times 2\,000)$

3.3. Tensor Datasets



3.4. Data Transform

- **Extreme anomalies** ⟹ extreme errors when training (esp. with MSE)
- The majority of data has **relatively small values**
- Both **positive and negative values**
- **Solution** – cube root



4. Artificial Neural Network

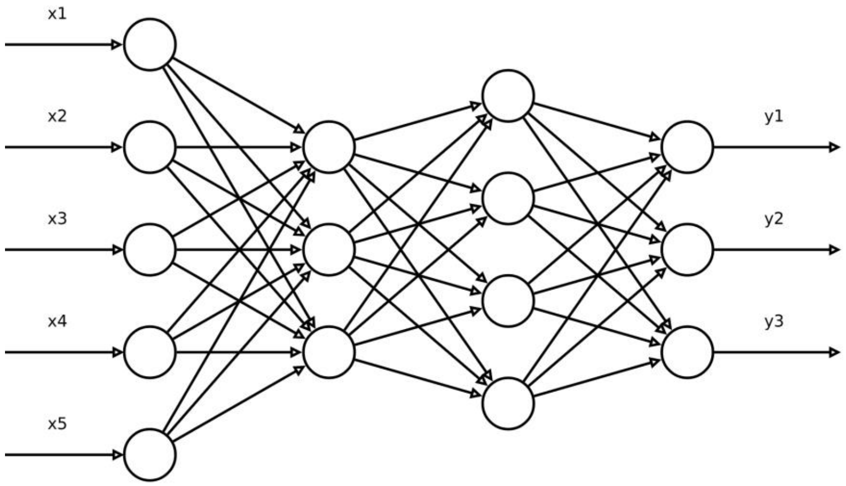
- Reduction of images ⟹ **Convolutional Autoencoder (CNN-AE)**
- **Unsupervised learning, regression**
- **Deterministic behavior** ⟹ sender knows how the data will be reconstructed by the receiver

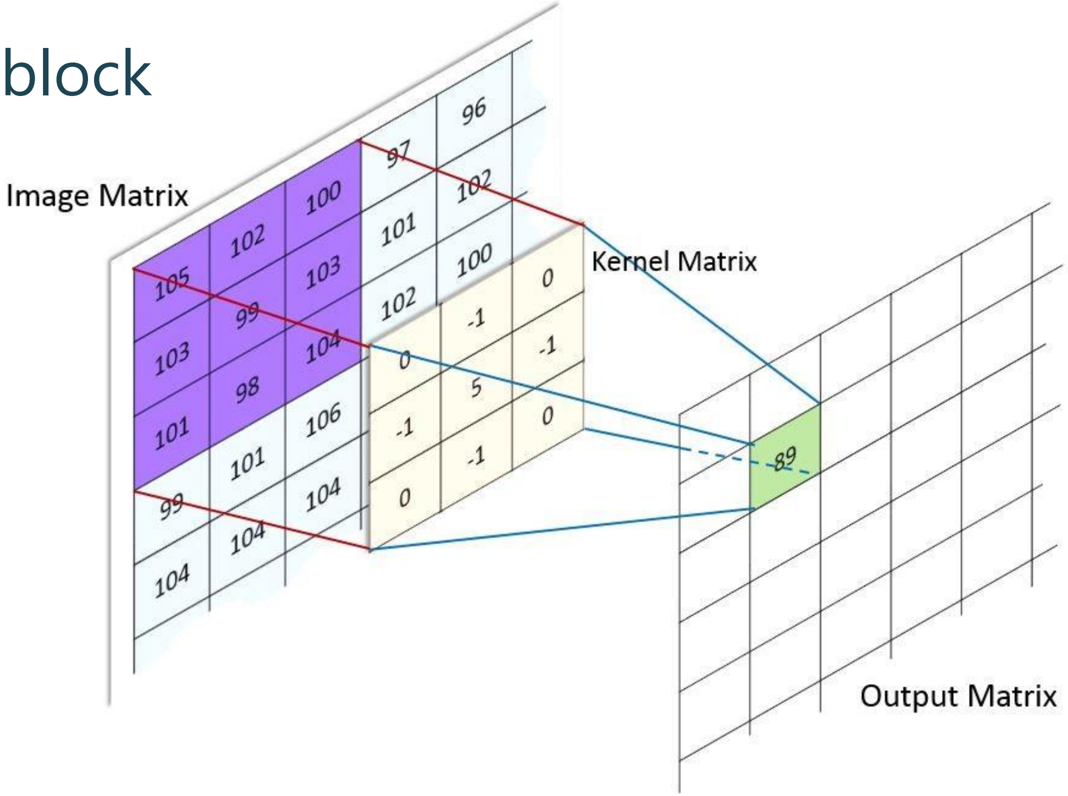
ARCHITECTURE → TRAINING → TRAINED MODEL

4.1. Architecture

1. **Convolutional layers** – main building block

2. **Linear layers** – in the bottleneck

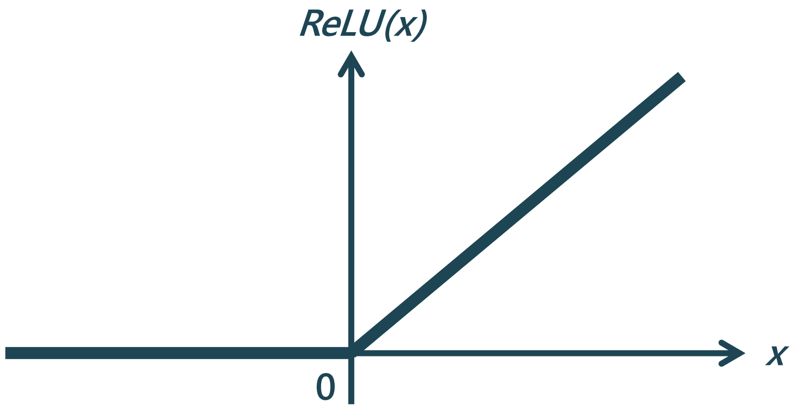


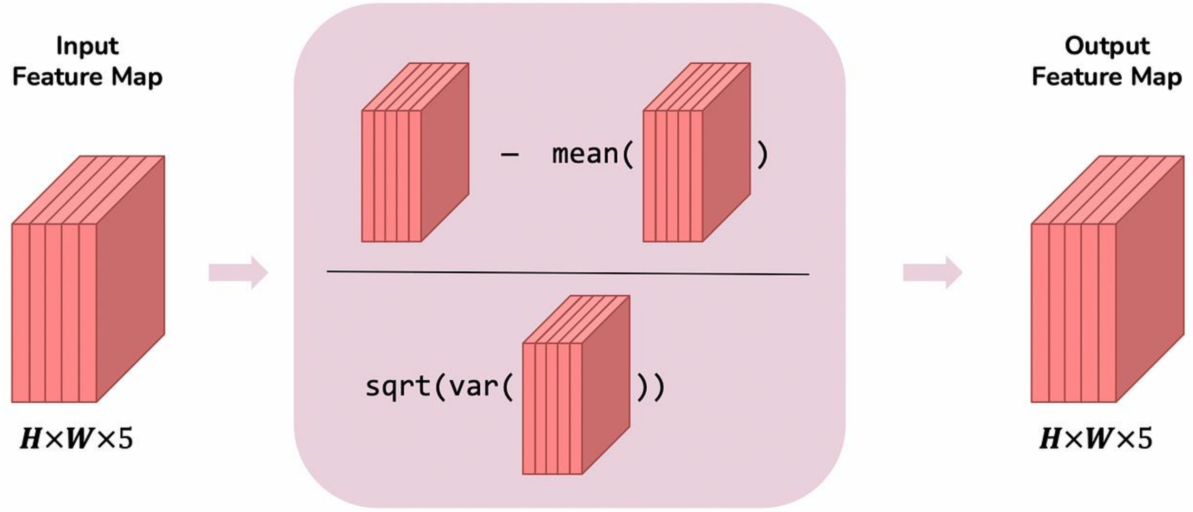


4.1. Architecture

3. **Batch Norm** – used to keep the learning stable

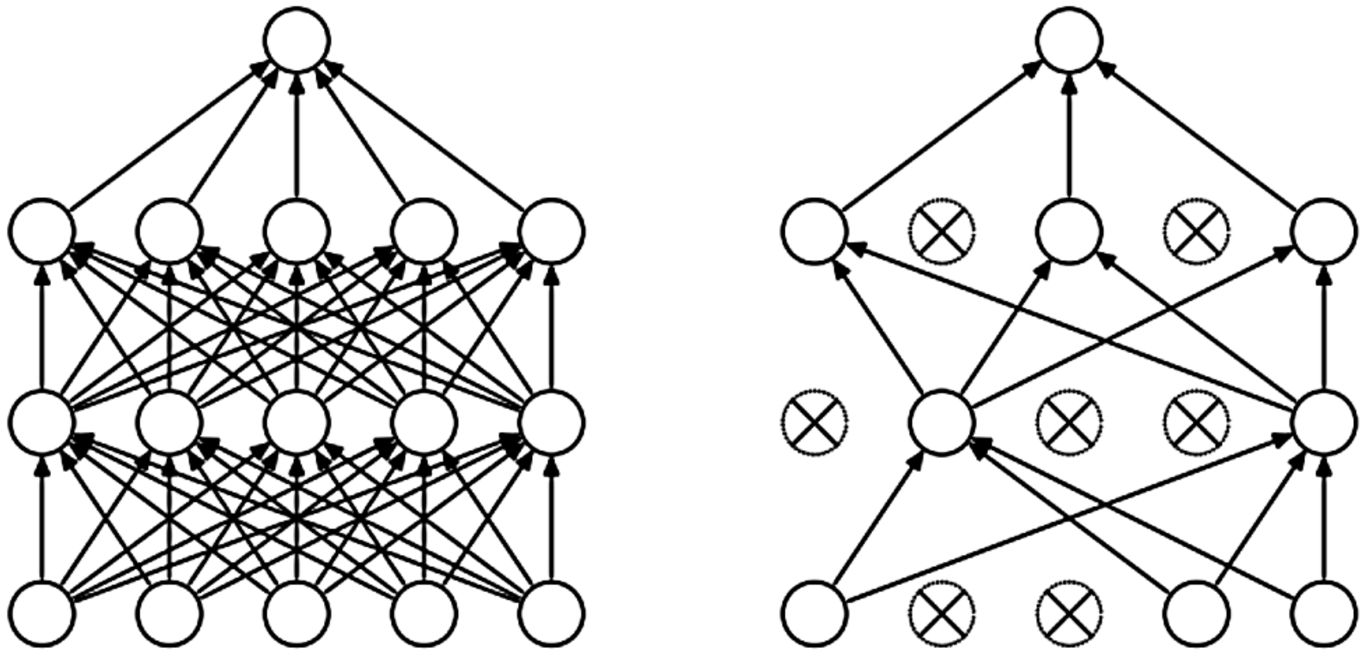
4. **ReLU** – activation function





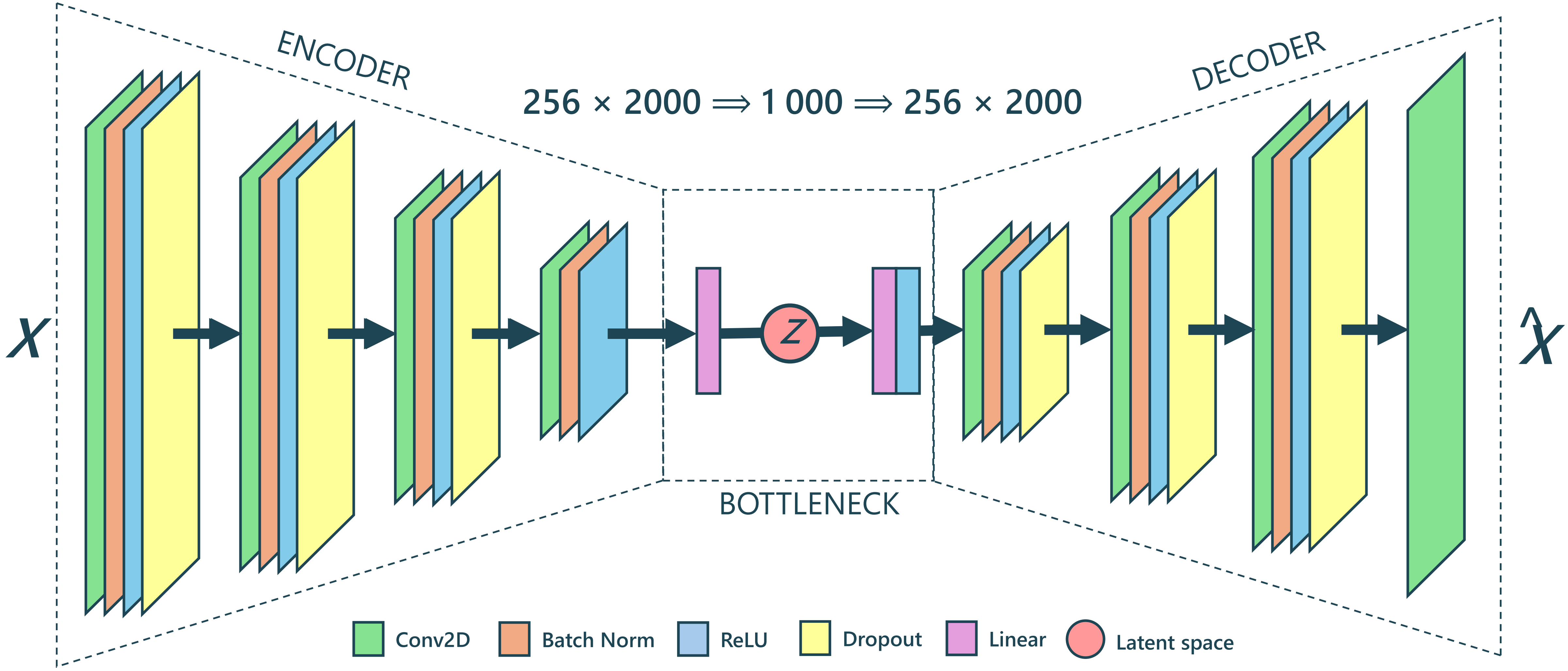
4.1. Architecture

5. **Dropout (25 %)** – to avoid overfitting



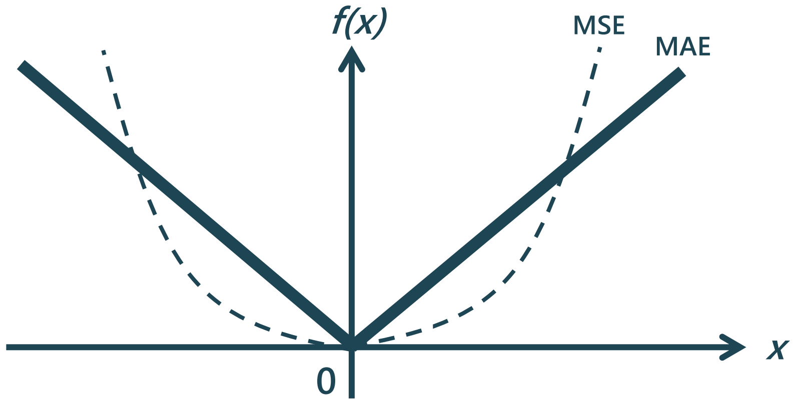
ARCHITECTURE | TRAINING | TRAINED MODEL

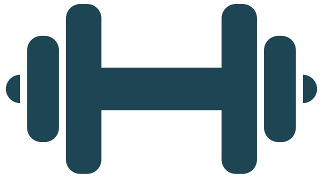
4.1. Architecture



4.2. Training

1. **Batch size** – 10 (50 batches per dataset)
2. **Epochs** – 20, each comprised of **2 000 parameter updates** (50 · 40)
3. **Loss function** – MAE, because of small numbers (cube root)

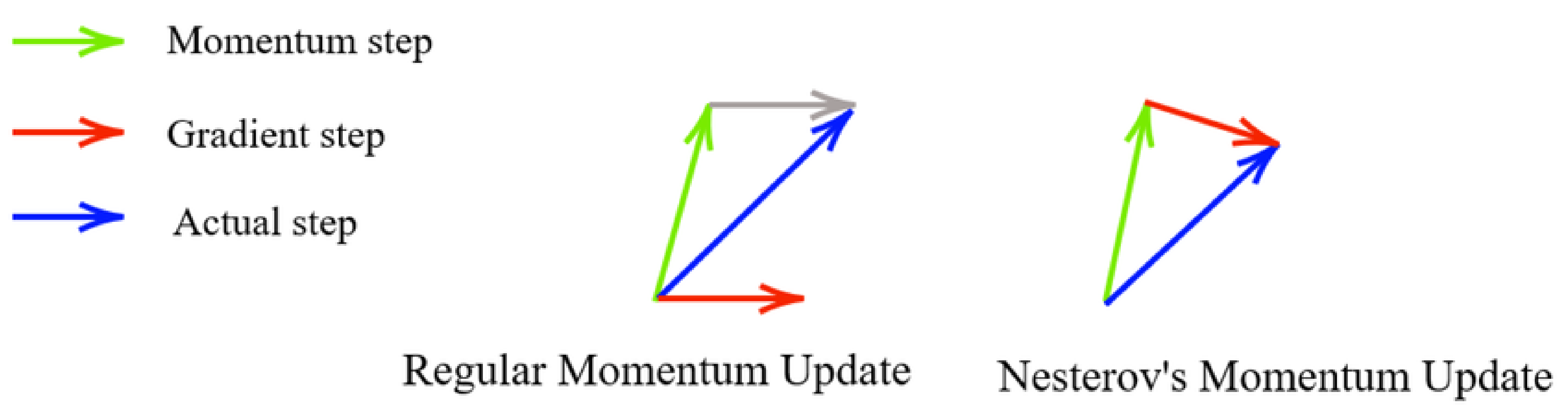




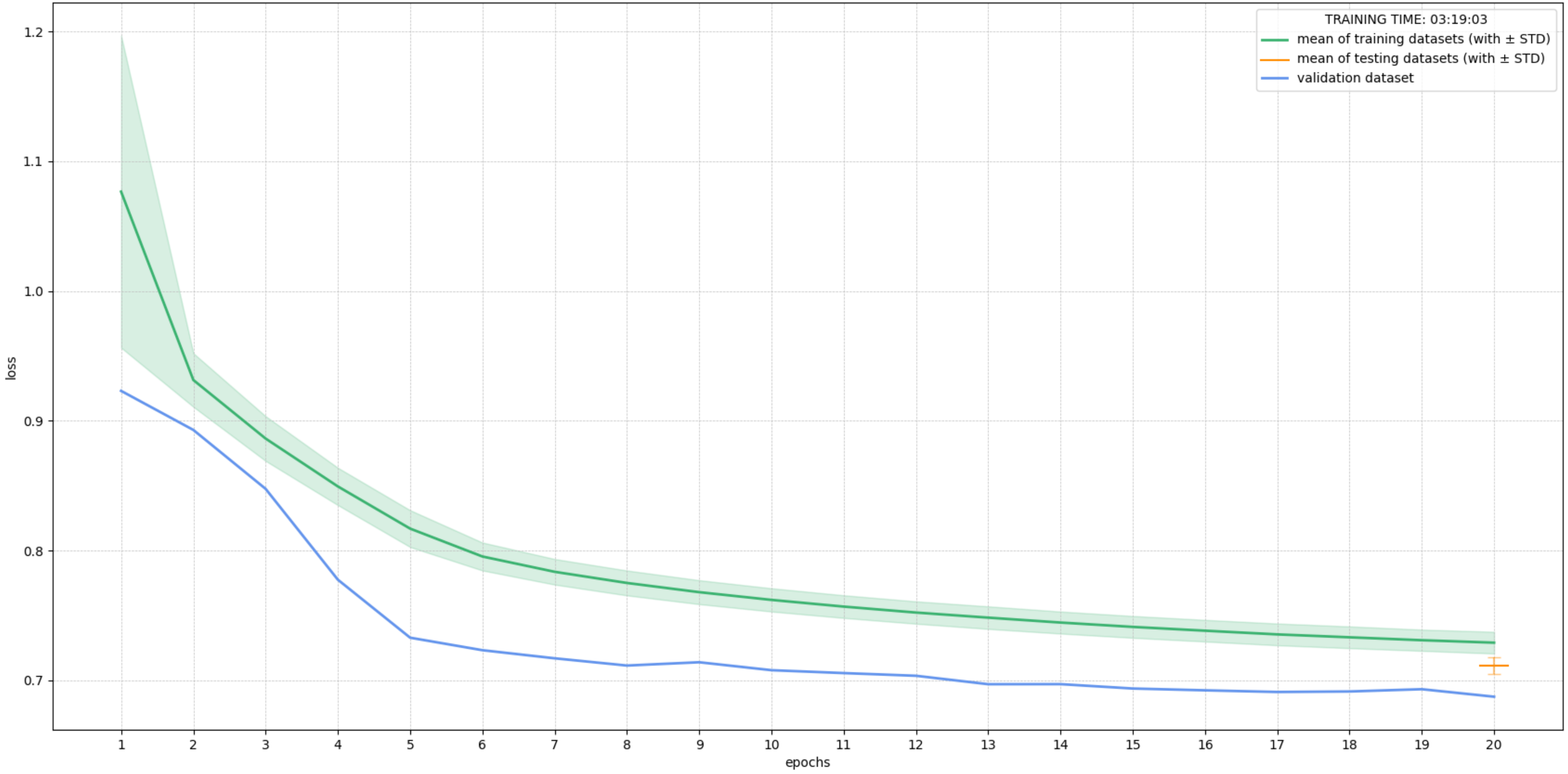
ARCHITECTURE → **TRAINING** → TRAINED MODEL

4.2. Training

4. **Optimizer** – NAdam (LR = 0.001)



4.2. Training


TRAINING TIME: 03:19:03
mean of training datasets (with ± STD)
mean of testing datasets (with ± STD)
validation dataset
loss
epochs
1.2
1.1
1.0
0.9
0.8
0.7
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20

4.3. Trained Model

- Total **training time 3:18:03**
- Parameters saved as a **488 MB .PT file**
- For the model to be used, it **requires both CNN-AE code and parameters**
- **Expects 256-channel EEG as input**
- **Usable on other EEG data or similar ERP experiments?** (lack of data)

ARCHITECTURE | TRAINING | TRAINED MODEL

5. Compression Mechanism

- Combination of lossy and lossless compression
- **Lossy** – reconstruction by the CNN-AE
- **Lossless** – original values for pixels with error higher than threshold

5.1. Sender

1. **Passes the data through CNN-AE** $\Longrightarrow$ gets both Z and $\hat{X}$
2. **A threshold is chosen** (5 µV in the following images)
3. Based on the reconstruction error $AE(X, \hat{X})$, **coordinates and differences get saved** (if they exceed the threshold)
4. Both Z **and value corrections get send to the receiver**

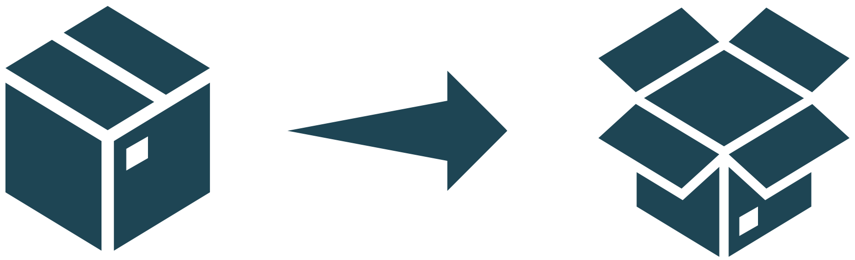
SENDER RECEIVER RESULTS

5.2. Receiver

1. **Passes Z through the decoder** $\Longrightarrow$ gets $\hat{X}$
2. **Updates values** based on the corrections

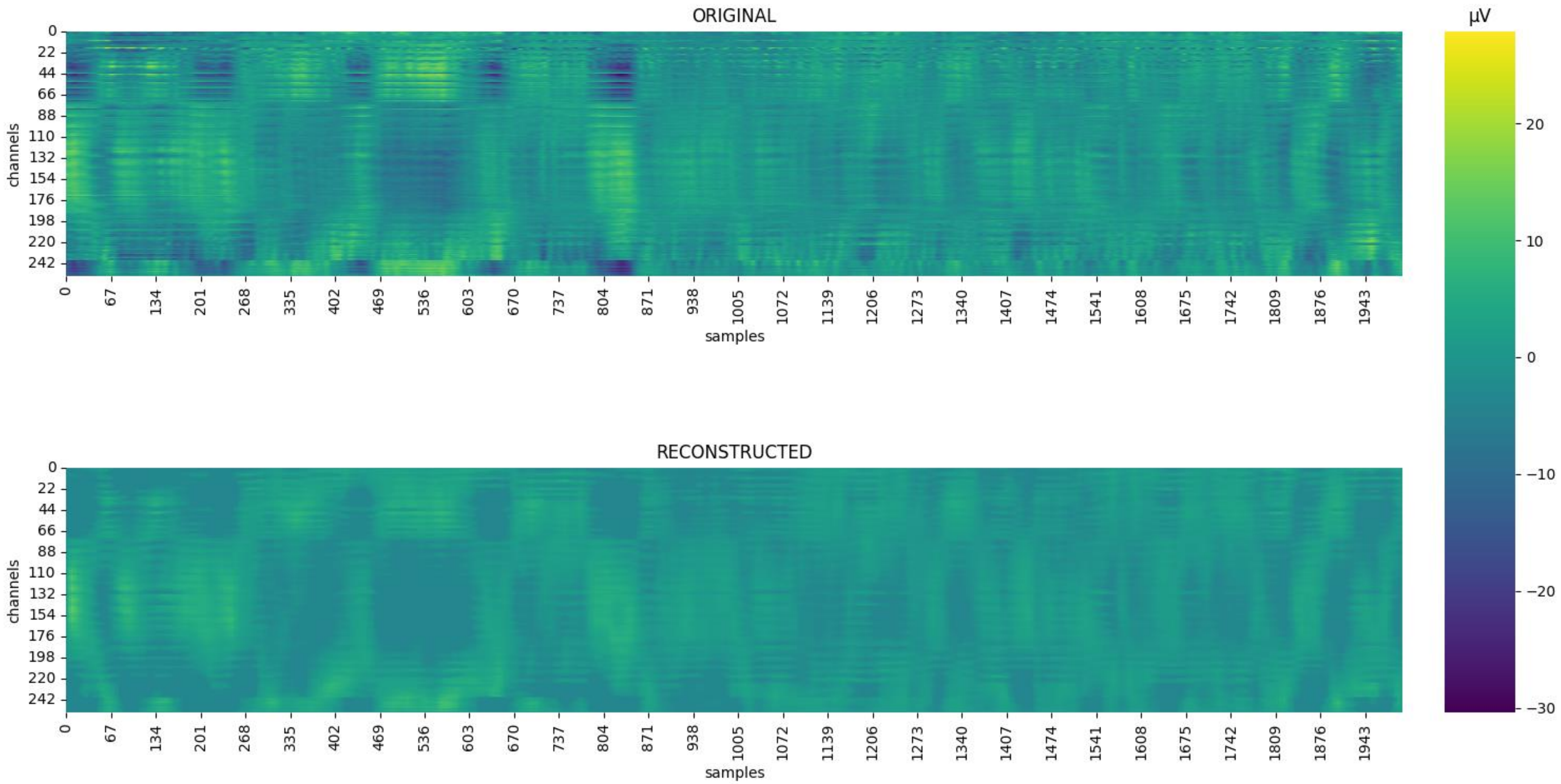
5.3. Results

- Tested on one testing dataset $\Longrightarrow$ **1.9 GB (float64)**
- Folder with compressed data $\Longrightarrow$ **481 MB (float32)** $\Longrightarrow$ **25.3 %**
- Adding GZIP on top of that $\Longrightarrow$ **106 MB** $\Longrightarrow$ **5.6 %**
- **Compression time 18.5 sec, decompression time 3.2 min**



SENDER
RECEIVER
RESULTS

5.3. Results (1)



ORIGINAL
RECONSTRUCTED
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198
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670
737
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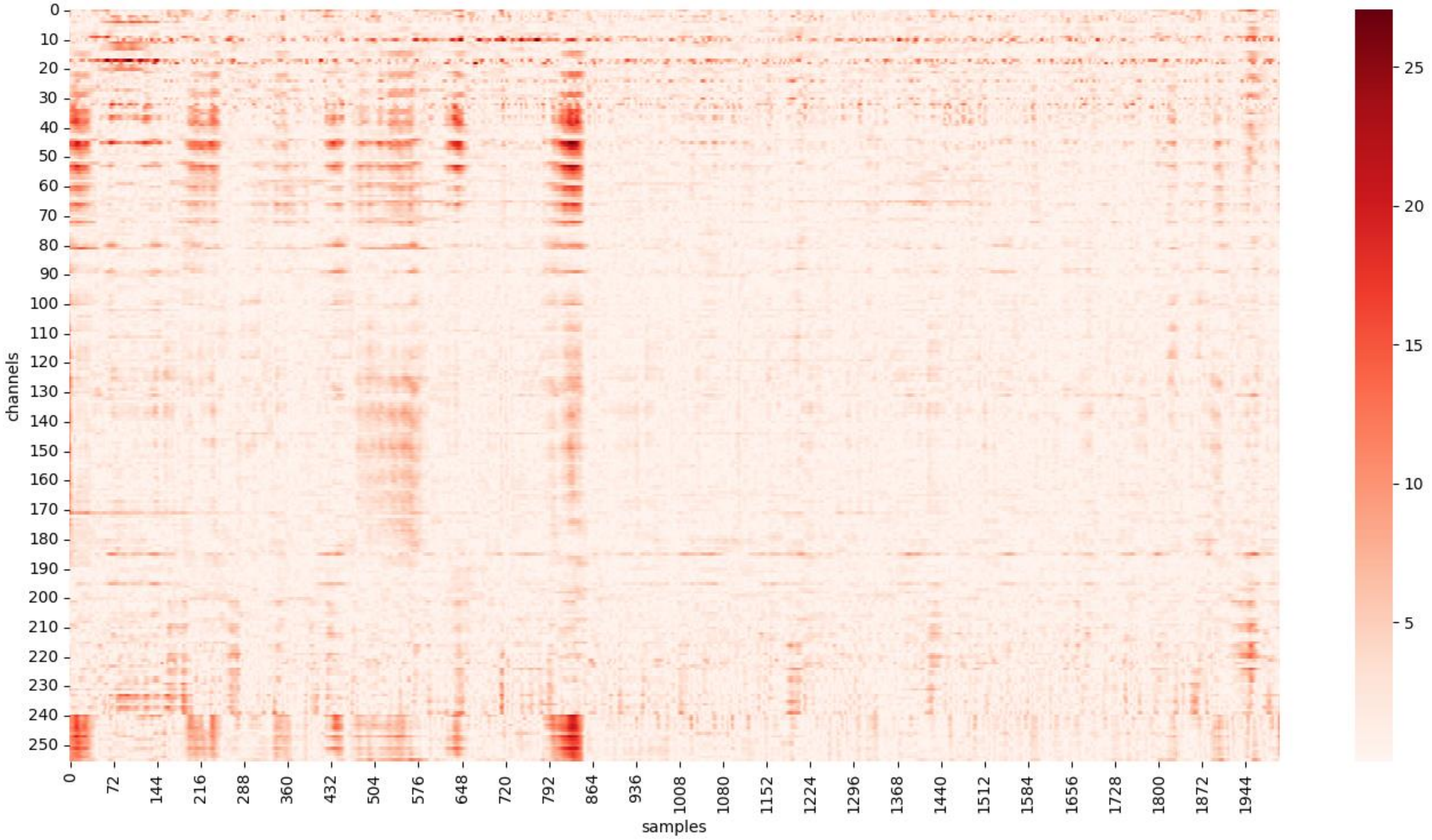
5.3. Results (1)



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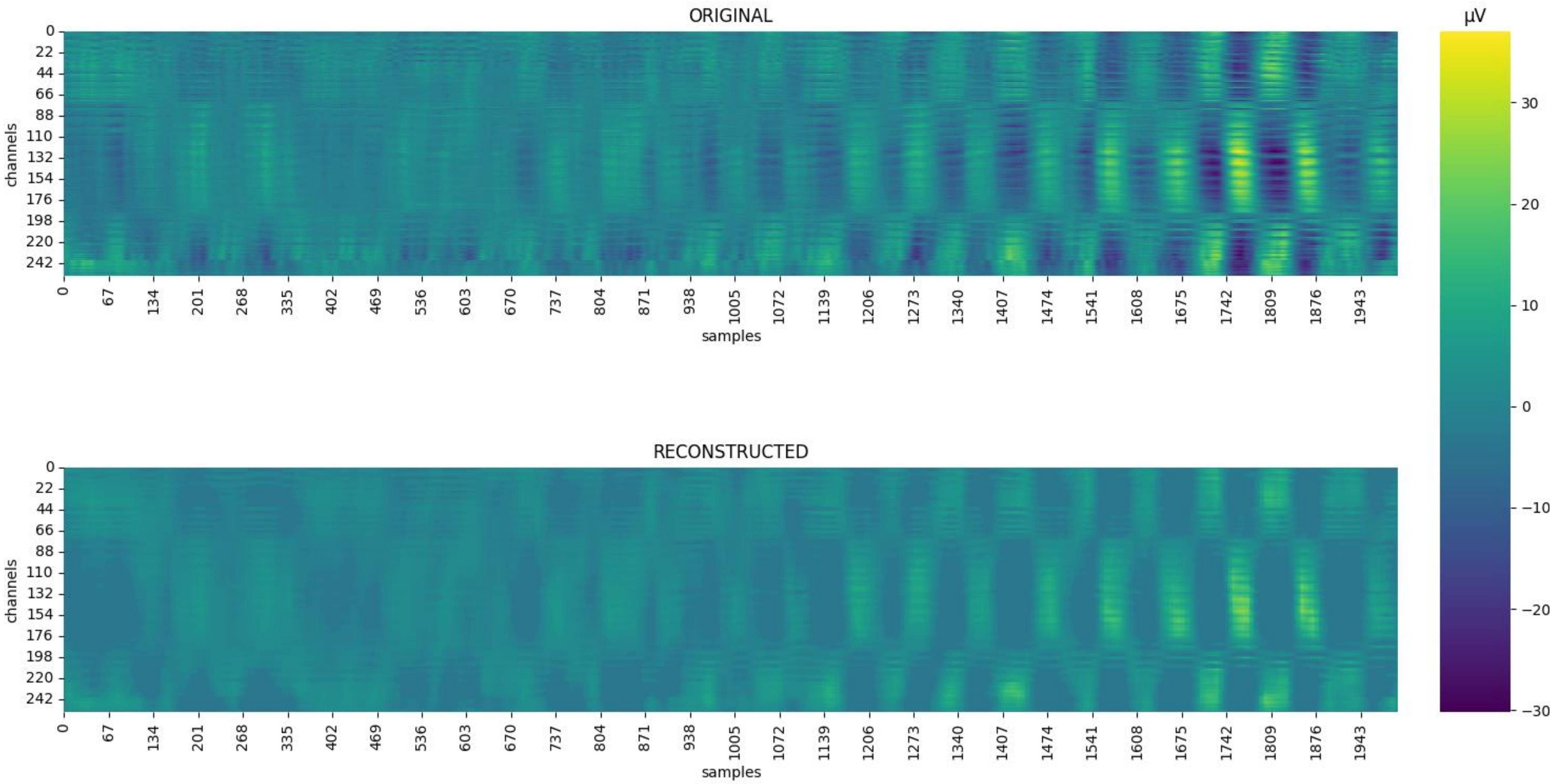
5.3. Results (2)



ORIGINAL
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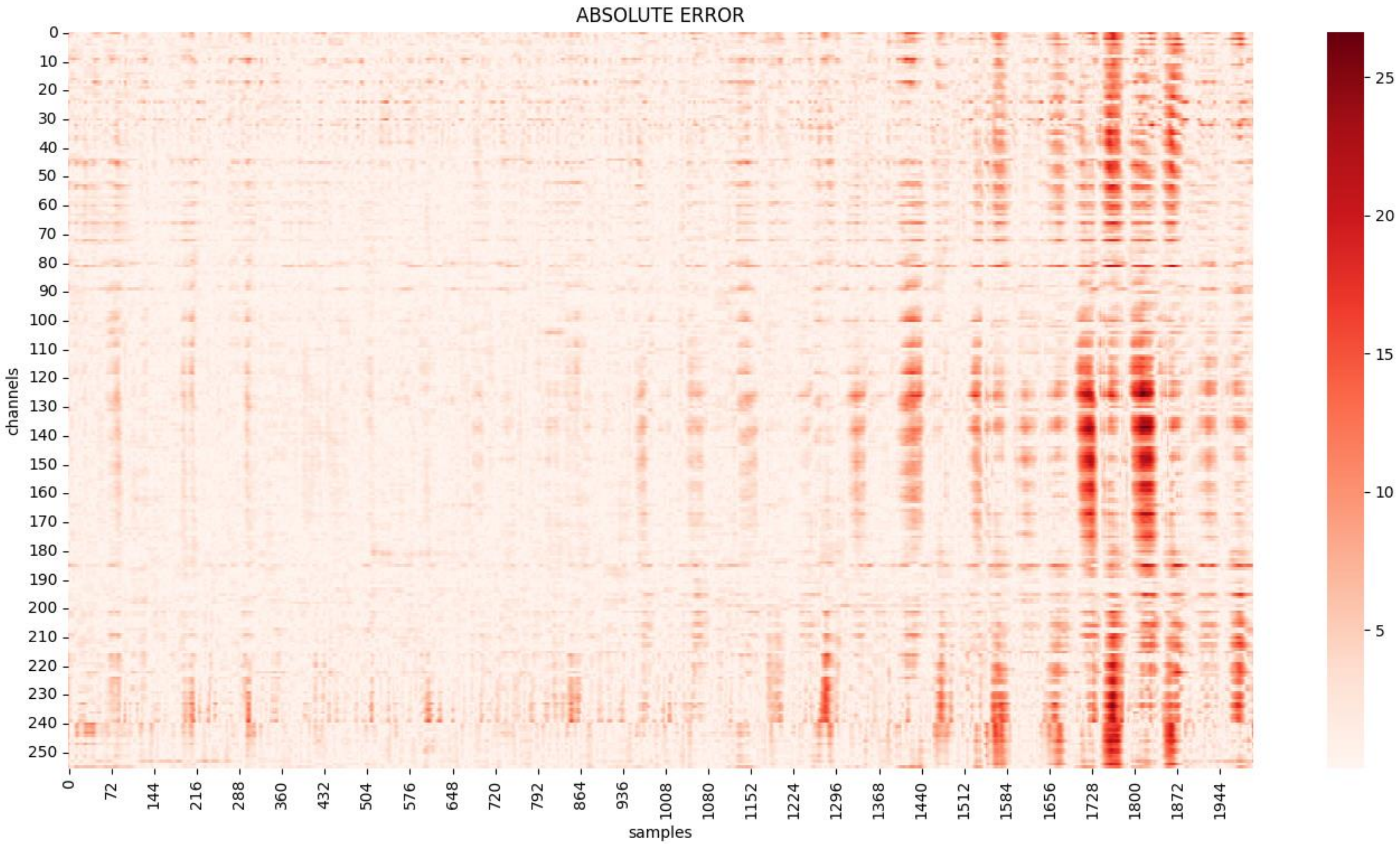
5.3. Results (2)


ABSOLUTE ERROR
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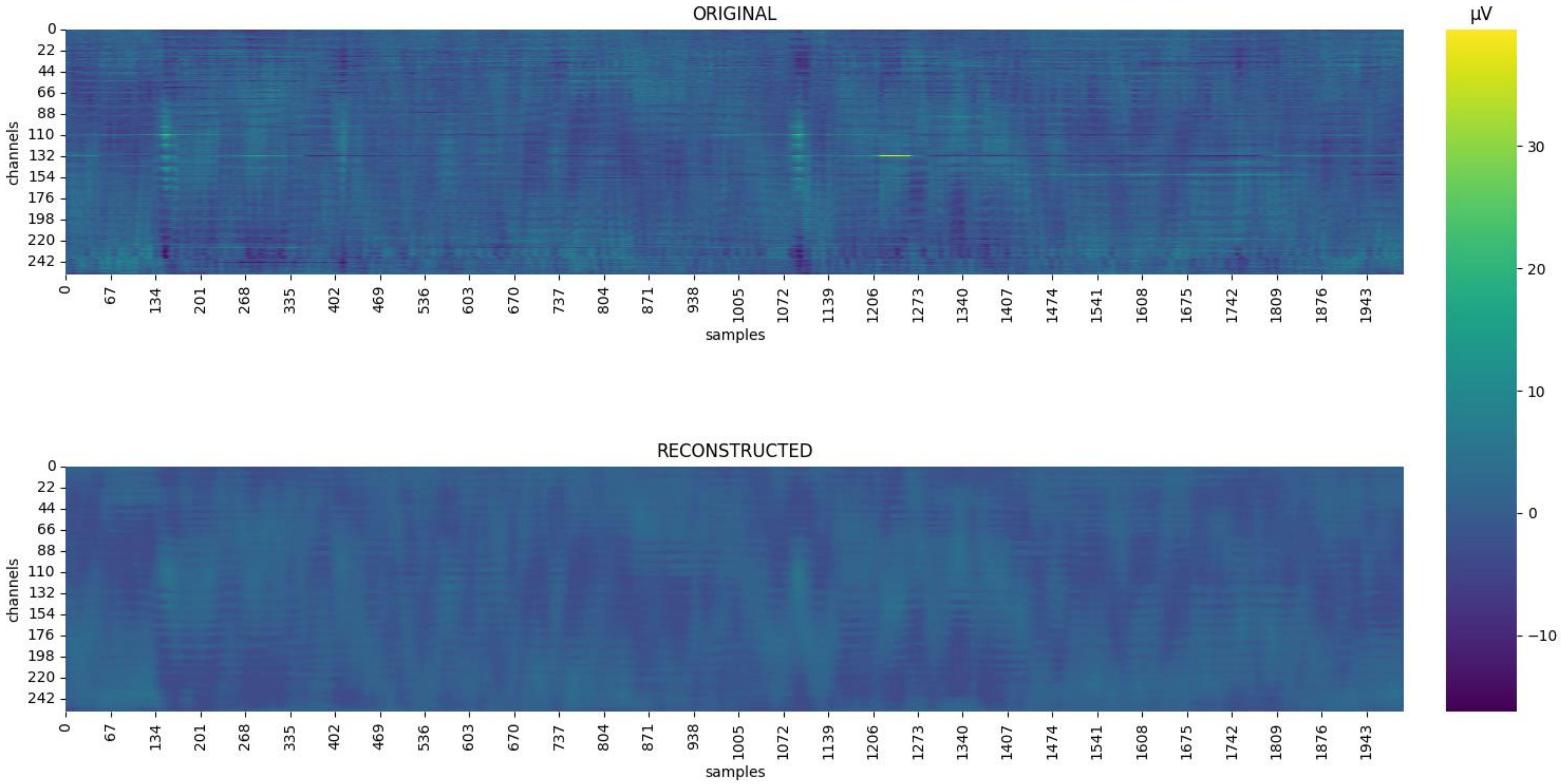
5.3. Results (3)



ORIGINAL
RECONSTRUCTED
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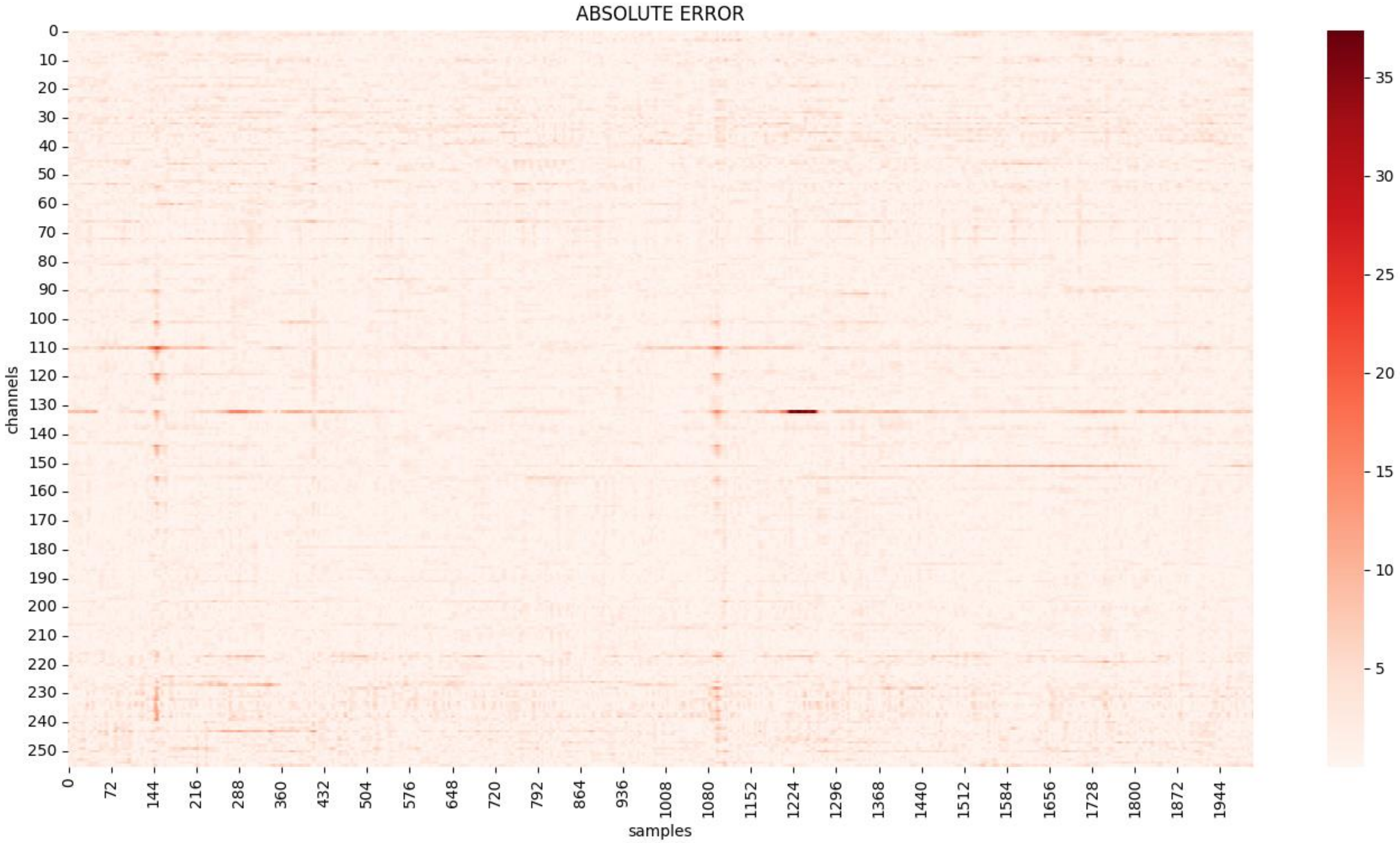
5.3. Results (3)



ABSOLUTE ERROR
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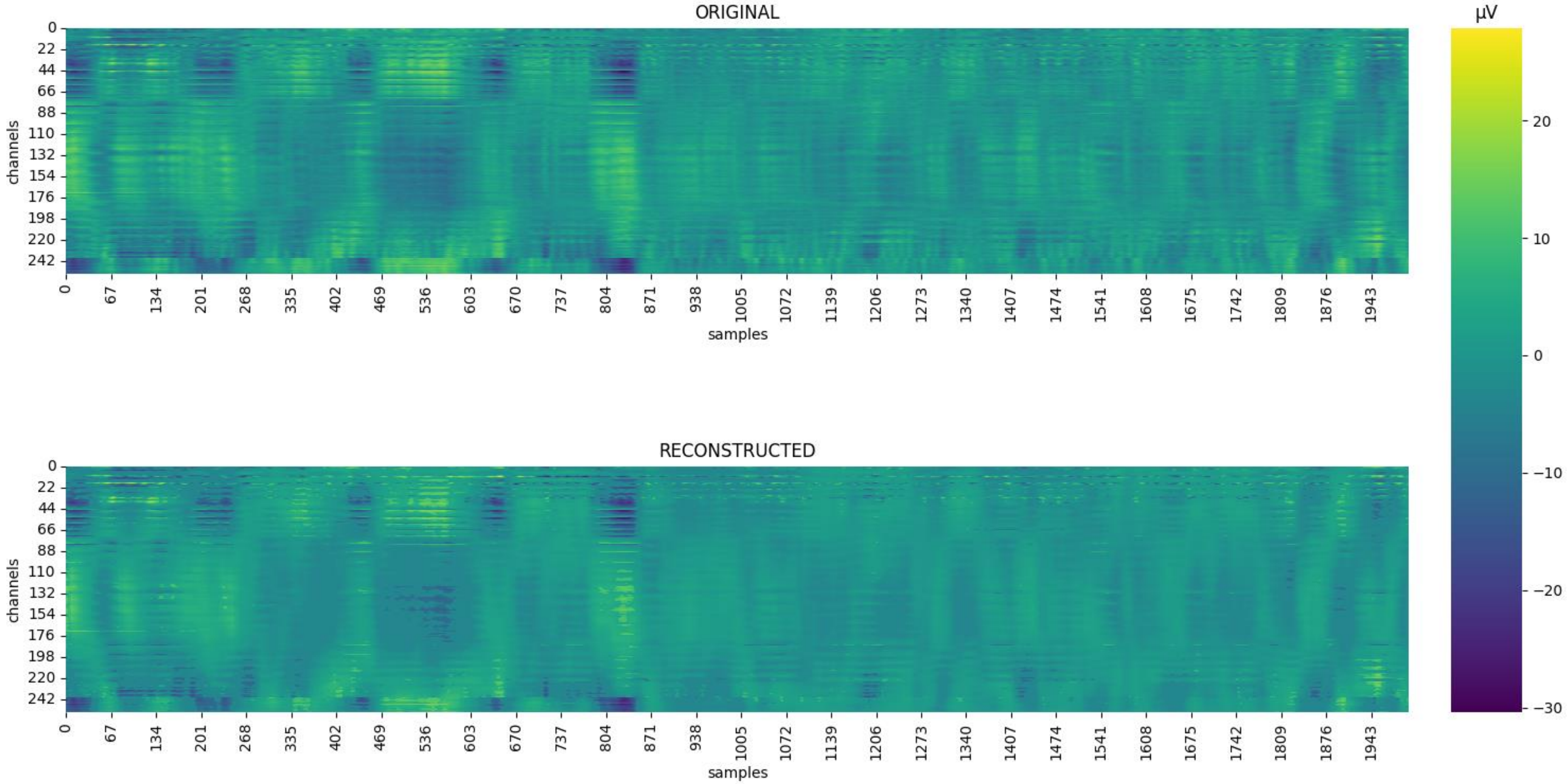
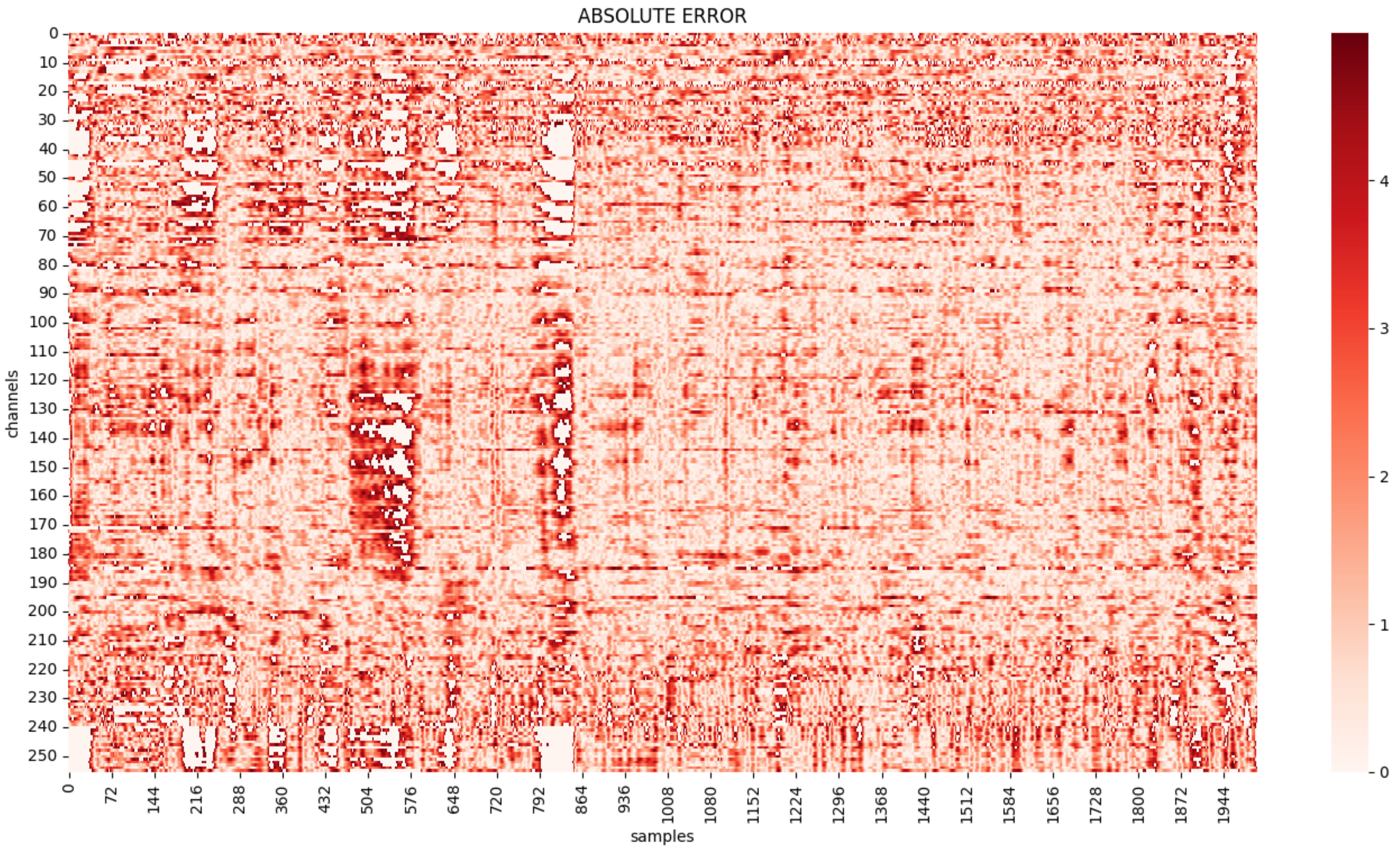
5.3. Results (decompression)



5.3. Results (decompression)



6. Future prospects

1. **Optimize used data types**
2. **Smarter representation of the corrections**
3. **Lossless compression?** (threshold set to 0)
4. **Test model performance on the data from different EEG/ERP experiments?**

7. Conclusion

- **Method** – the better the ANN (i.e. knowledge representation), the better the compression
- **Positives** – high compression rate, possible follow up research (e.g. latent space analysis), tailored to specific data, unsupervised learning
- **Negatives** – limited use, uncertain generalization, not fully lossless (currently), computational complexity, large datasets

Thank You For Your Attention!

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