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INSTITUTE OF INFORMATION SYSTEMS AND MARKETING

Biosignals Decoder: Improve available classifiers through data augmentation using generative AI

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Seminar Presentation, Information & Market Engineering (IISM)

Agenda

- Motivation
- Related Work
- Gen AI: Variational Autoencoder
  - Theoretical Introduction
  - Architecture
- Results of the VAE
  - Learning Curves, Reconstructions and Latent Space
- Effect on the EEGNet
- Conclusion

Motivation
Setup

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- Collecting EEG Data is very time consuming and difficult
- EEG data has high variance, depending on person, day, sleeping, …
- **What if, if we can synthesize EEG Data to overcome those challenges?**

- In the following we will focus on EEG data collected during a Field Study:

Task: Math Hard

One Participant

10 Sessions

Mental Workload as Classes

Related Work

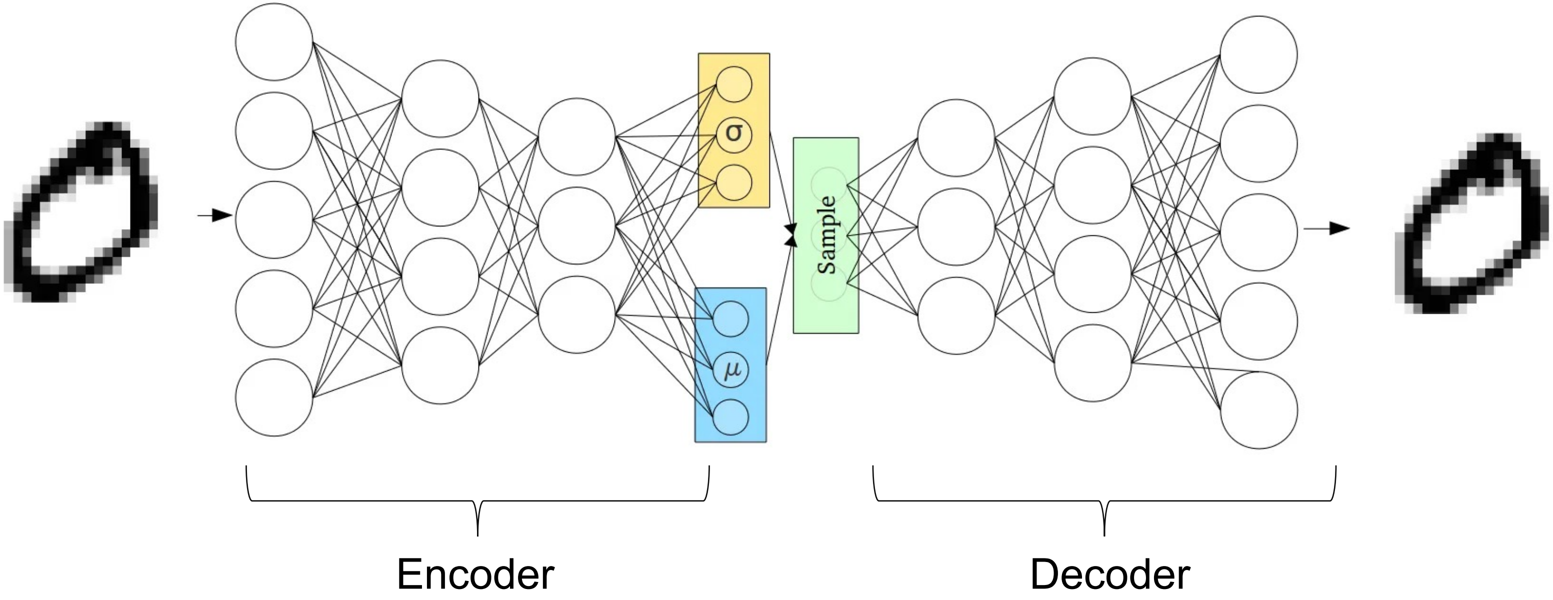
- Variational Autoencoder (Kingma et al. 2013 [1])
- β-VAE (Higgins et al. 2022 [2])
- TimeVAE (Desai et al. 2021 [3])
- EEGNet (Lawhern et al. 2016 [4])
- Conditional VAE (Sohn et al.2015 [5])

Variational Autoencoder
Theoretical Introduction

- Introduced by Kingma et. al 2013 [1]
- Consists of two neural networks: Encoder and Decoder
- Encoder maps input data to mean μ and std σ vector representing the parameter of a multivariate gaussian that we're sampling z from
- Decoder takes latent variable z for reconstruction

- $\mathcal{L}_{VAE} = \mathbb{E}_{q(z|x)}[||x - \hat{x}||^2] + \beta \cdot KL\big(q(z|x), N(0,1)\big)$ [2]
- i.e.
  - Total Loss = Reconstruction Loss + β · Kullback-Leibler-Divergence

Variational Autoencoder



Source: https://towardsdatascience.com/intuitively-understanding-variational-autoencoders-1bfe67eb5daf
Accessed 18.01.2024, Modified adding Encoder/Decoder label

Variational Autoencoder
Architecture

Encoder

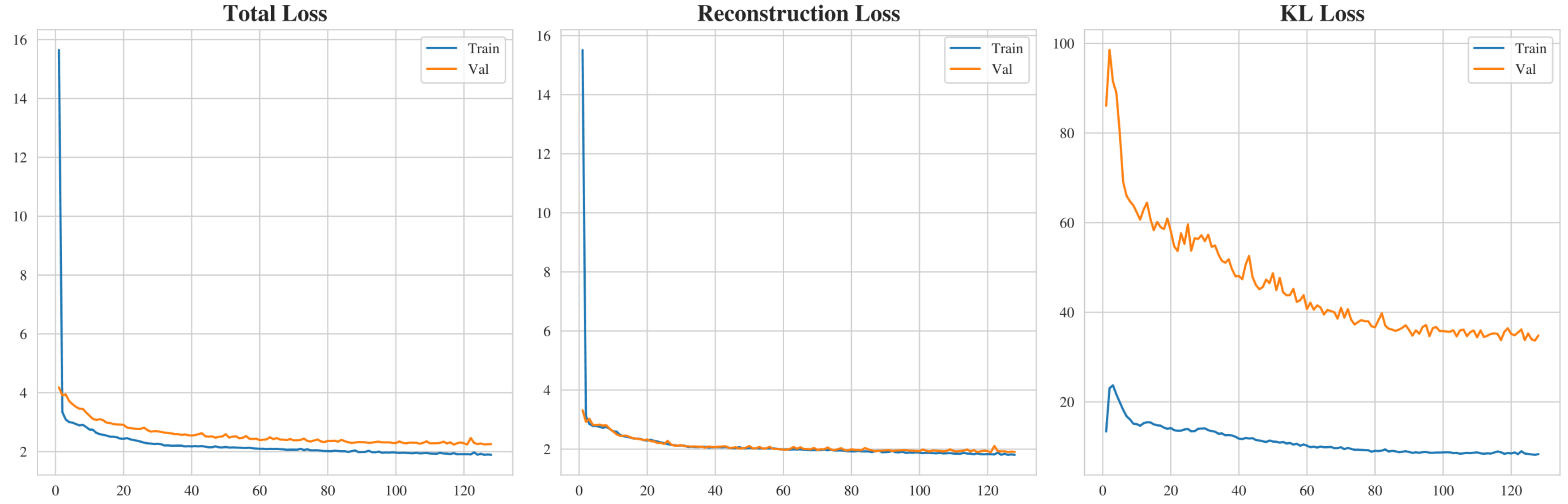
Layer (type)	Output Shape	Param #	Connected to
input_11 (InputLayer)	[(None, 250, 7)]	0	-
flatten_5 (Flatten)	(None, 1750)	0	input_11[0][0]
dense_30 (Dense)	(None, 32)	56032	flatten_5[0][0]
batch_normalization_25 (BatchNormalization)	(None, 32)	128	dense_30[0][0]
dense_31 (Dense)	(None, 16)	528	batch_normalization_25[0][0]
batch_normalization_26 (BatchNormalization)	(None, 16)	64	dense_31[0][0]
dense_32 (Dense)	(None, 16)	272	batch_normalization_26[0][0]
z_mean (Dense)	(None, 8)	136	dense_32[0][0]
z_log_var (Dense)	(None, 8)	136	dense_32[0][0]
sampling_5 (Sampling)	(None, 8)	0	z_mean[0][0], z_log_var[0][0]

Decoder

Layer (type)	Output Shape	Param #	Connected to
input_12 (InputLayer)	[(None, 8)]	0	-
dense_33 (Dense)	(None, 16)	144	input_12[0][0]
batch_normalization_27 (BatchNormalization)	(None, 16)	64	dense_33[0][0]
dense_34 (Dense)	(None, 16)	272	batch_normalization_27[0][0]
batch_normalization_28 (BatchNormalization)	(None, 16)	64	dense_34[0][0]
dense_35 (Dense)	(None, 32)	544	batch_normalization_28[0][0]
batch_normalization_29 (BatchNormalization)	(None, 32)	128	dense_35[0][0]
decoder_final_dense (Dense)	(None, 1750)	57750	batch_normalization_29[0][0]
reshape_5 (Reshape)	(None, 250, 7)	0	decoder_final_dense[0][0]

Results: Learning Curves

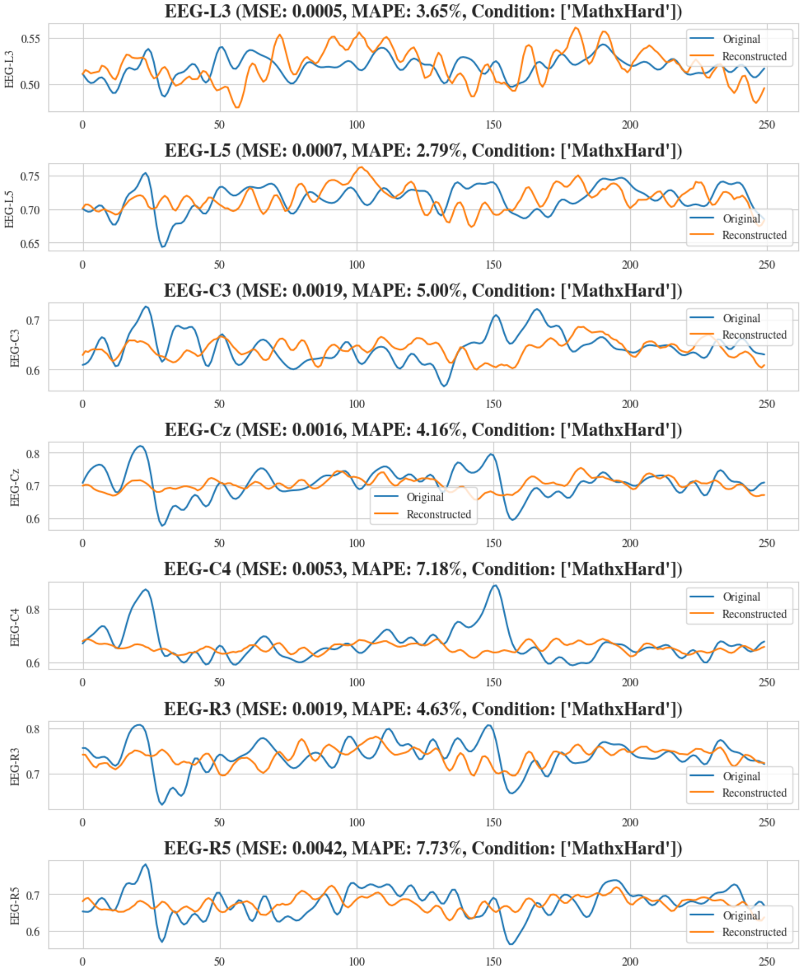
- Training on 128 Epochs, Batch Size: 4, Optimizer: Adam, Val Split: 0.2
- Latent Dimension: 8, Condition: Hard Math Tasks, $\beta = 0.01$



Results II: Reconstruction Examples

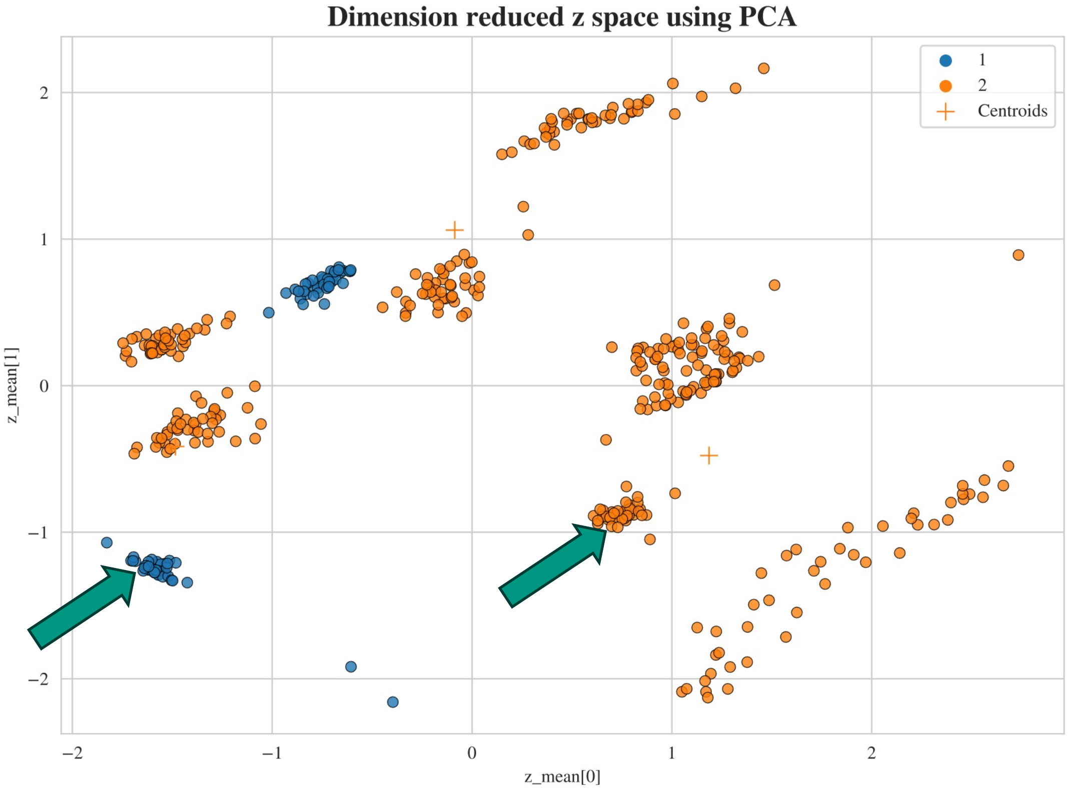
- Reconstruction ***Mean Absolute Percentage Error*** somewhat around 15%
- In example on the right side:
  - $MAPE(X_{21}, \hat{X}_{21}) \approx 5\%$
- Not fully able to reconstruct input data

- → Multivariate EEG Data reconstruction too complex for low amount of samples

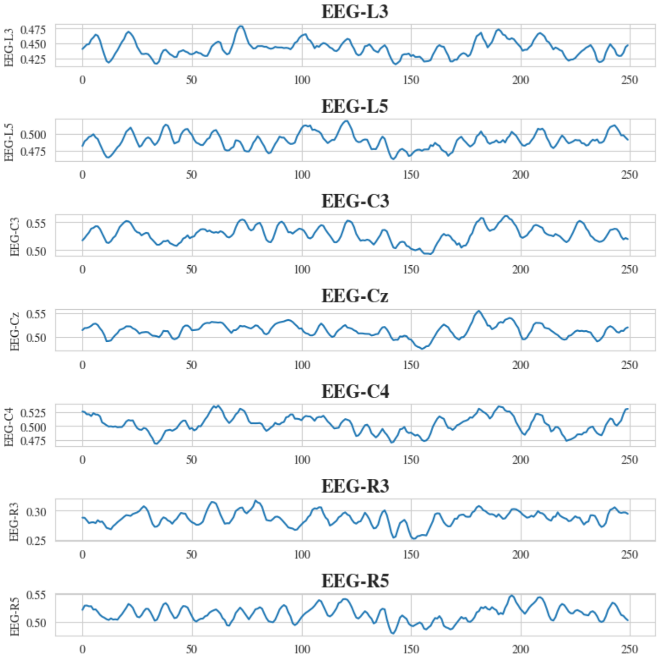


Results III: Visualization of the latent space

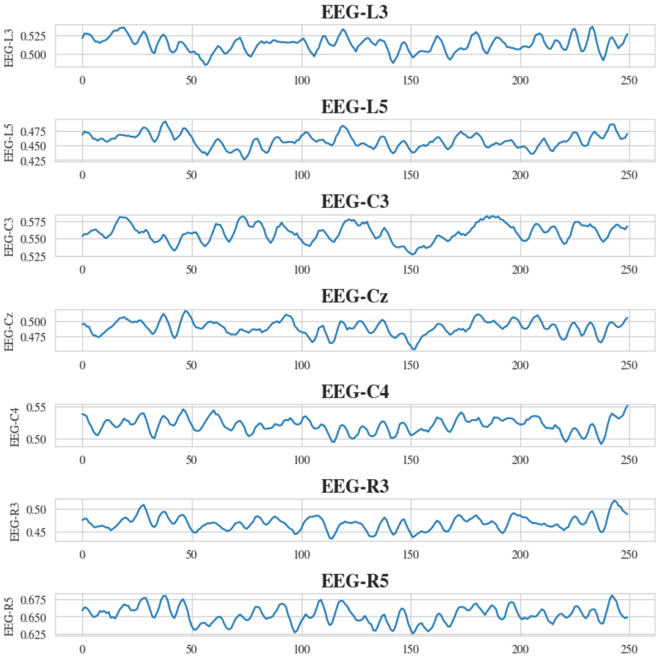
- Latent Dimension is 8
- Visualization in 2D using ***Principal Component Analysis*** (PCA)
- Mental Workload {1, 2} form a cluster in latent space
- We can sample from latent space to generate new data



Results IV: Sampling from the latent space



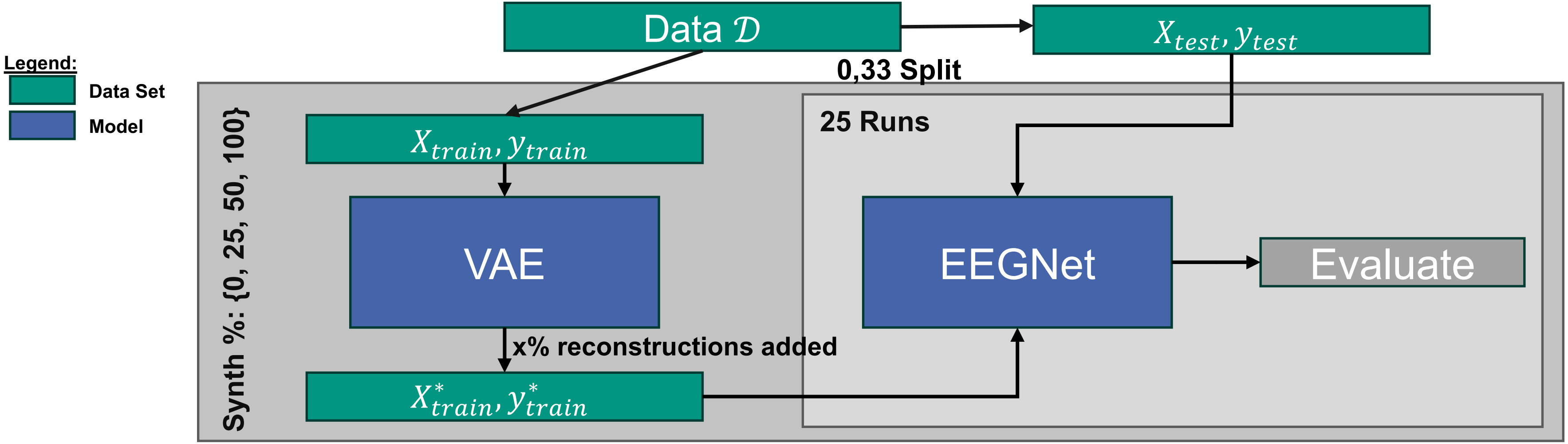
Seed (-1.5; -1.2), Class 1



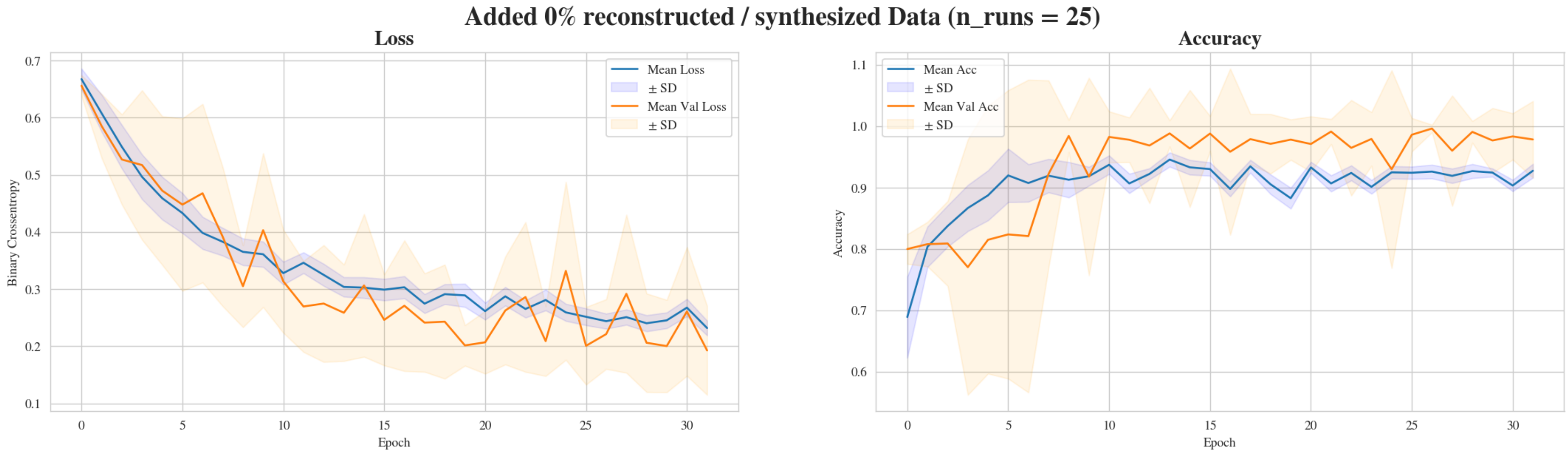
Seed (0.8; -0.9), Class 2

Results V: Training on EEGNet

- EEGNet Architecture used from Lawhern et al. 2016 [4]
  - Minor adjustments in the complexity, e.g. less kernels, ...
- Run fitting $n\_runs = 25$ with $\{0\%, 25\%, 50\%, 100\%\}$ added reconstructed data to X_train



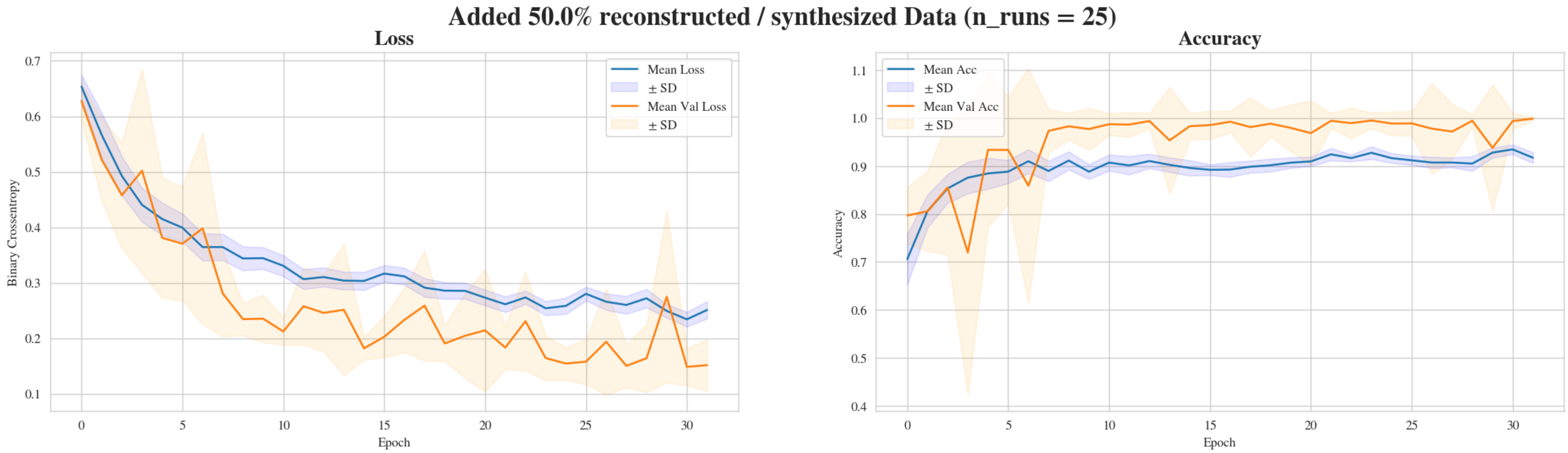
Results VI: Effect on EEGNet
0% Reconstructed / Synthesized Data



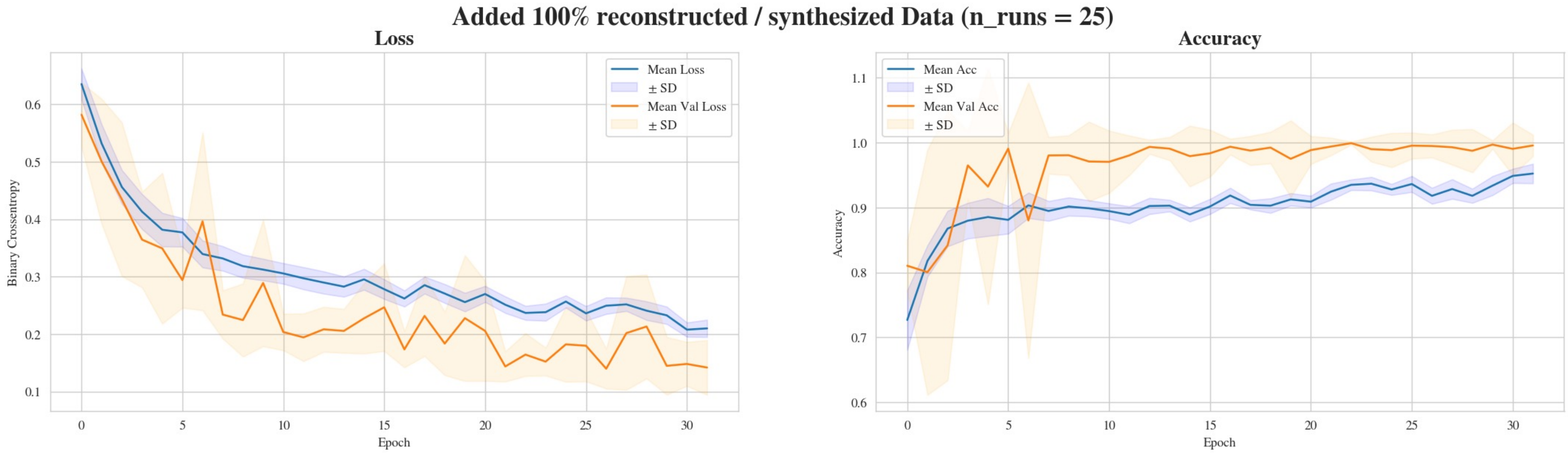
Results VI: Effect on EEGNet

25% Reconstructed / Synthesized Data

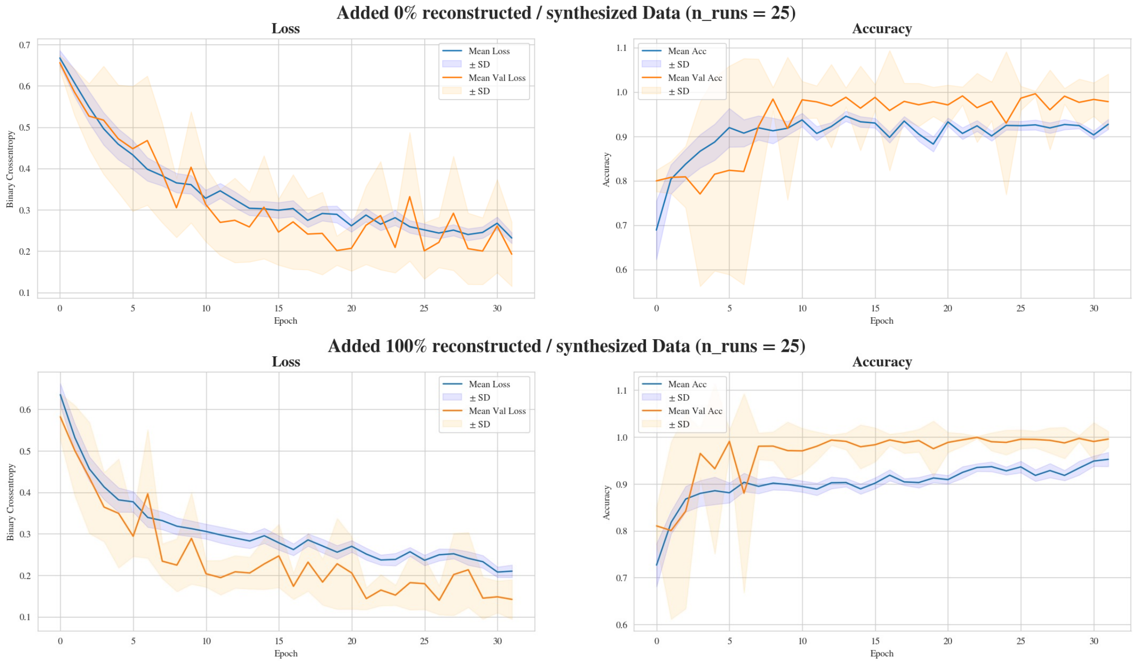
Results VI: Effect on EEGNet
50% Reconstructed / Synthesized Data



Results VI: Effect on EEGNet
100% Reconstructed / Synthesized Data



Results VI: Effect on EEGNet



→ Stability increased, Less Validation Loss ☺

Results VI: Effect on EEGNet

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- Aggregation Data of last Epoch (#32)

% Synth. Added	Mean Loss	SD Loss	Mean Val Loss	SD Val Loss	Mean ACC	SD ACC	Mean Val ACC	SD Val ACC
0%	0.2318	0.0129	**0.1926**	**0.0777**	0.9273	0.0113	**0.9784**	**0.0625**
25%	0.2934	0.0094	**0.1789**	**0.0479**	0.9130	0.0087	**0.9942**	**0.0162**
50%	0.2512	0.0158	**0.1518**	**0.0461**	0.9173	0.0111	**0.9986**	**0.0039**
100%	0.2101	0.0151	**0.1420**	**0.0475**	0.9524	0.0150	**0.9956**	**0.0164**

Conclusion

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- Due to **lack of training data** (roughly 440 samples per condition) very difficult to apply Deep Learning approaches
- **Huge hyperparameter space** – difficult to find optimal architecture and params
- Preprocessing / Data Wrangling took a lot of time also
- EEG Data has **very high variance**, depending on Person, day, …

- However, synthesizing EEG data is possible! ☺
  → Significant need for more training samples
- Adding synthetic data improves generalization ability of EEGNet
  - And also stabilizes training! ☺

References

- **[1] Kingma et. al 2013**, Auto-Encoding Variational Bayes
  https://arxiv.org/abs/1312.6114, Accessed 19.01.2024
- **[2] Higgins et. al 2022**, β-VAE: Learning basic visual concepts with a constrained variational framework
  https://openreview.net/pdf?id=Sy2fzU9gl, Accessed 19.01.2024
- **[3] Desai et. al 2021**, TimeVAE: A Variational Auto-Encoder for Multivariate Time Series Generation
  https://arxiv.org/abs/2111.08095, Accessed 19.01.2024
- **[4] Lawhern et al. 2016**, EEGNet: A Compact Convolutional Network for EEG-based Brain-Computer Interfaces
  https://arxiv.org/abs/1611.08024, Accessed 19.01.2024
- **[5] Sohn et al. 2015**, Learning Structured Output Representation using Deep Conditional Generative Models
  https://proceedings.neurips.cc/paper_files/paper/2015/file/8d55a249e6baa5c06772297520da2051-Paper.pdf, Accessed 19.01.2024

Thanks for listening.
Any questions?

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