Attempts to cVAE Architectures for EEG Psychiatric Disorders Dataset

MMI714 - Project

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Outline

- Problem Definition
- Understanding EEG Data
- Dataset
- Literature Review
- Problem Scope
- Model (attempts)
- Preliminary Results
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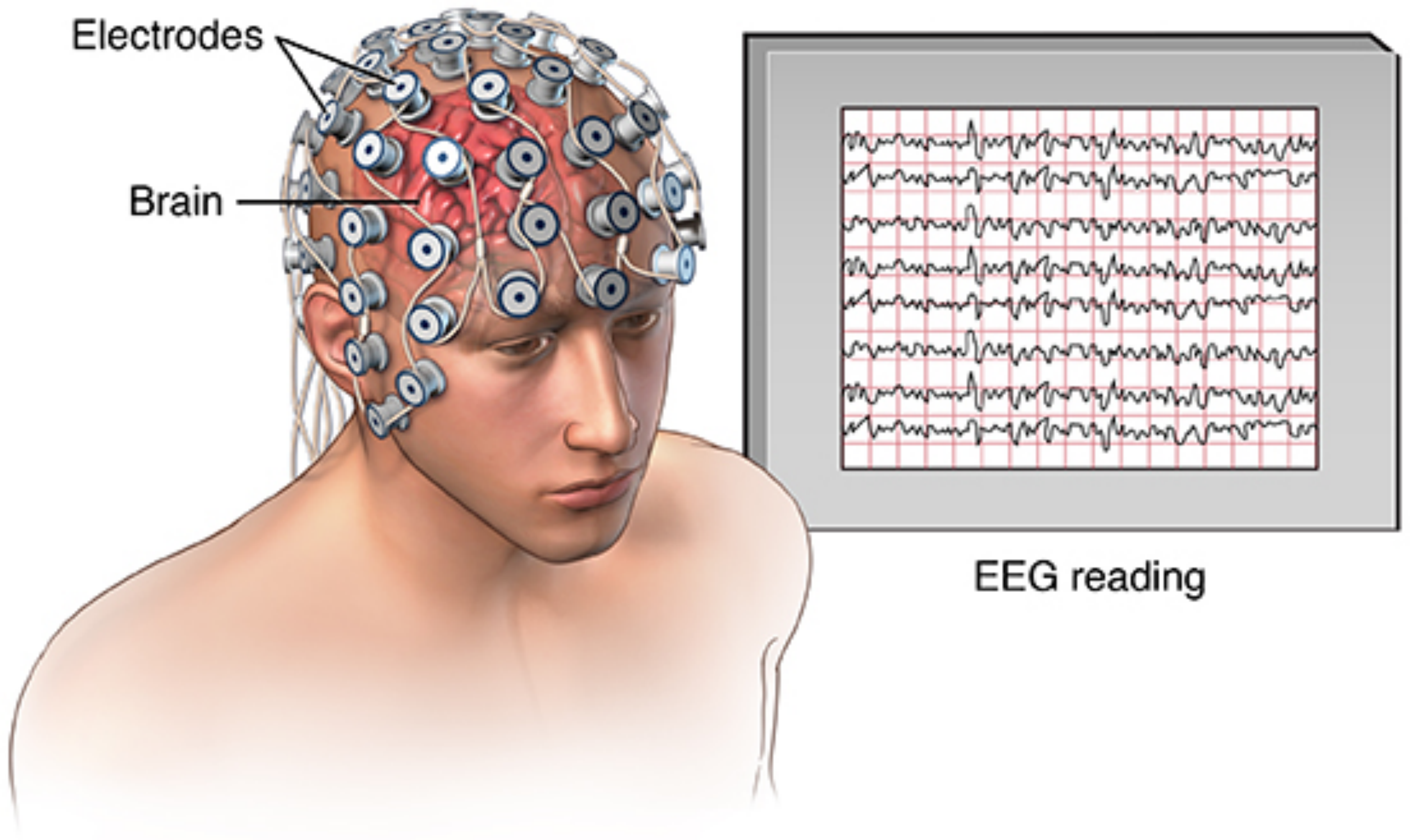
Problem Definition

- Develop a C-VAE to model and generate EEG-based features
  - distinguishing between psychiatric disorders and healthy controls
  - or among specific disorders.
- The C-VAE can enable:
  - improve feature representation for classification
  - synthesise of realistic EEG data conditioned on specific psychiatric labels
  - explore latent feature spaces for insights into disorder-specific patterns

Understanding EEG Data

- EEG records the brain's electrical activity
  - "listening" to the brain's signals, like tuning into a city's noise from afar.
- Brain cells (neurons) communicate using tiny electrical impulses.
  - EEG sensors detect these signals —> wave-like patterns



Understanding EEG Data

- **Brainwave Types:**
  - **Delta (slow)**: Deep sleep
  - **Theta**: Relaxation and daydreaming
  - **Alpha**: Calm and focus
  - **Beta (fast)**: Thinking and problem-solving
  - **Gamma**: Memory and learning
- Provides insights into brain states during rest or activity.

About Dataset - EEG Psychiatric Disorders Dataset*

- **Participants**:
- **Total:** 945 subjects 850 diagnosed, 95 healthy
- **6 large categories and 9 specific disorders:**
    - Schizophrenia
    - Mood Disorders: depressive and bipolar
    - Anxiety Disorders: panic and social anxiety
    - Obsessive-compulsive disorder
    - Addictive Disorders: alcohol use and behavioural addictions
    - Trauma & Stress-Related Disorders: PTSD, acute stress & adjustment disorder

***EEG Dataset with approx 1k attributes for identifying psychiatric disorders.**
Park, S. M. (2021, August 16). EEG machine learning. Retrieved from osf.io/8bsvr

About Dataset - EEG Psychiatric Disorders Dataset

Data Characteristics:

- Age range: 18–70 years.
- Exclusion: some disorders, brain injuries, IQ below 70

EEG Data:

- Resting-state EEG data -> 5 minutes with 19 or 64 channels
- Down-sampled to 128 Hz and included 19 channels
- Frequency-bands analysed

Features:

- **Power Spectral Density (PSD)**: Measures the power of signals across frequencies
- **Functional Connectivity (FC)**: Measures synchronisation between EEG signals across channels, calculated as coherence values

Literature Review

Semi-Supervised EEG Signals Classification System for Epileptic Seizure Detection (2019)

Learn features from raw EEG signals for classifying brain states

- Combines unsupervised feature learning using VAEs with supervised classification.
- **Architecture:**

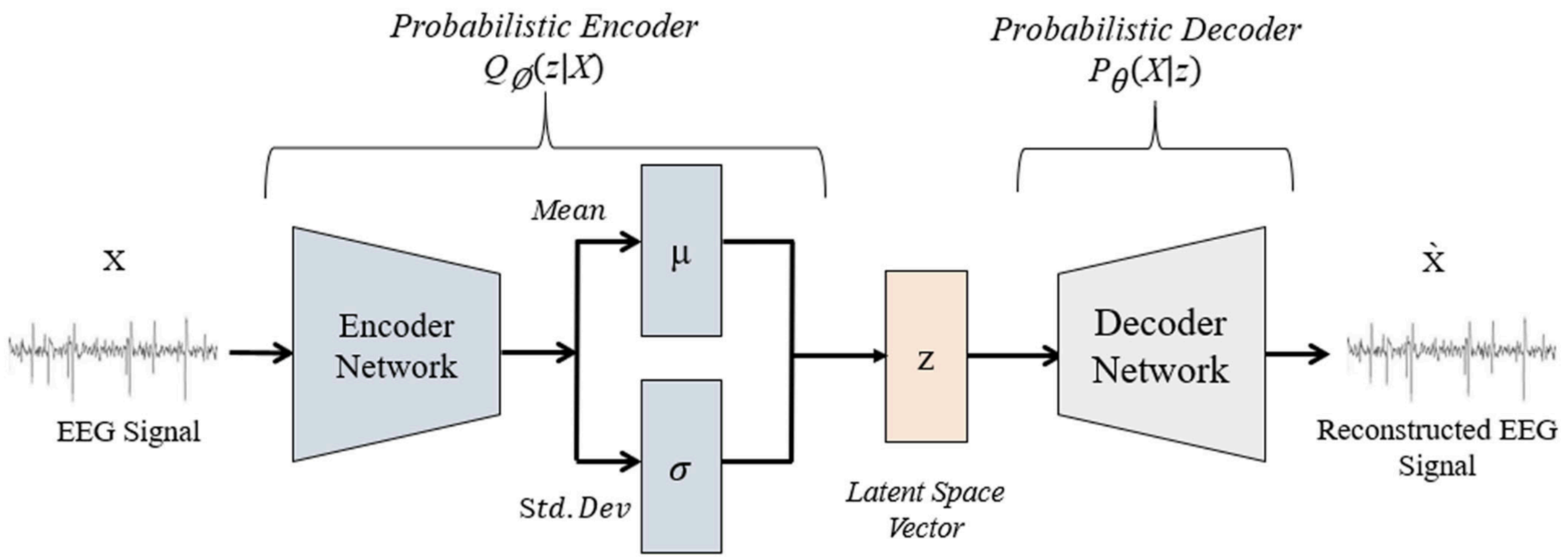


Fig. 1. Variational autoencoder.

- Classifier: Uses pre-trained VAE encoder weights to predict EEG states.

Literature Review

Effective Computational Techniques for Generating EEG Data (2020)

Address the challenge of insufficient EEG data for ML by generating synthetic samples with the same distribution as the original data

Data Generation:

- VAEs generate synthetic EEG signals
- Combines reconstruction loss with KL Divergence

Training:

- VAE trained on EEG signals recorded under some conditions

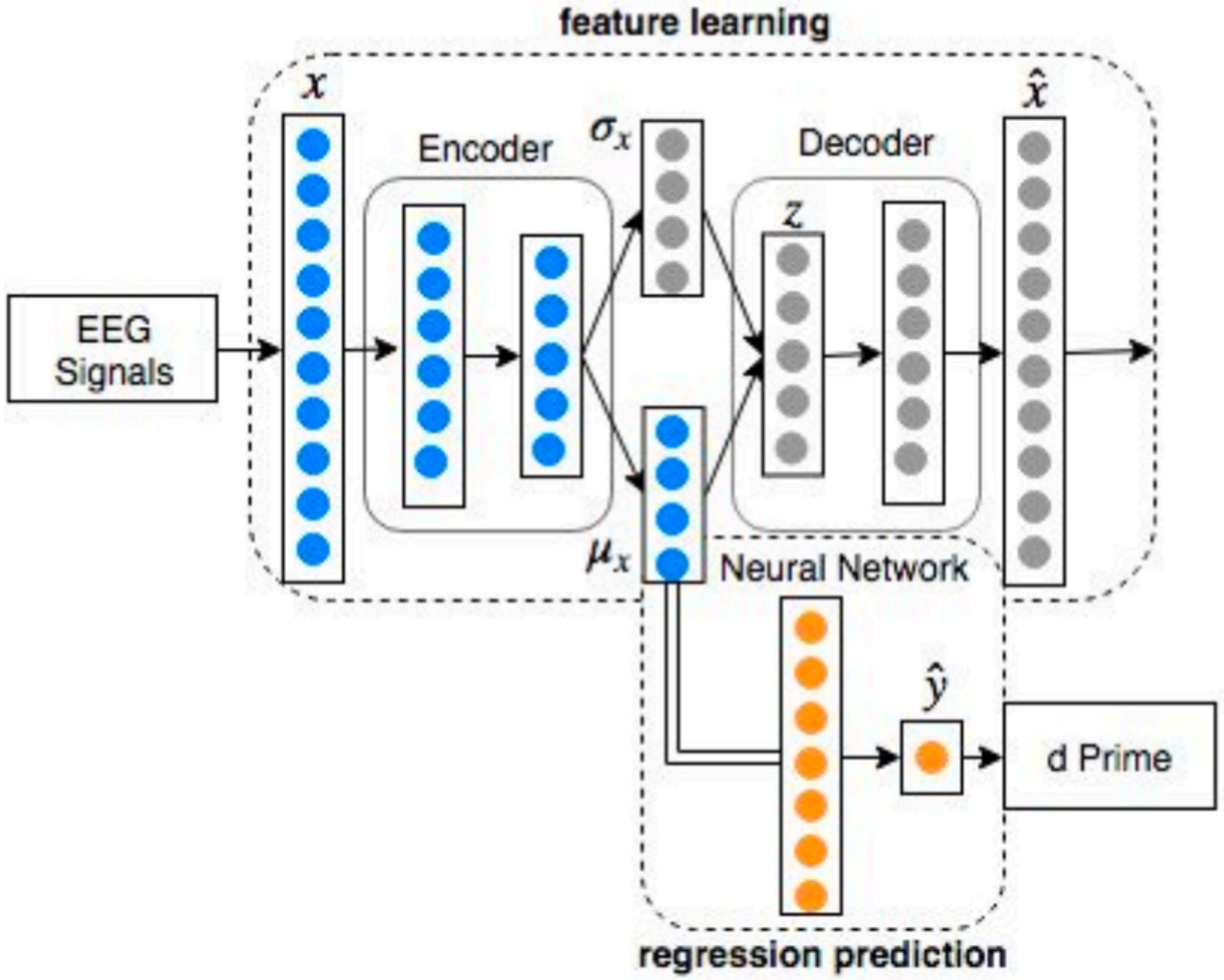
Evaluation:

- Generated data evaluated using a CNN classifier
- Classifier performance for quality of the generated EEG data

Literature Review

Predicting Cognitive Control in Older Adults using Deep Learning and EEG Data (2020)

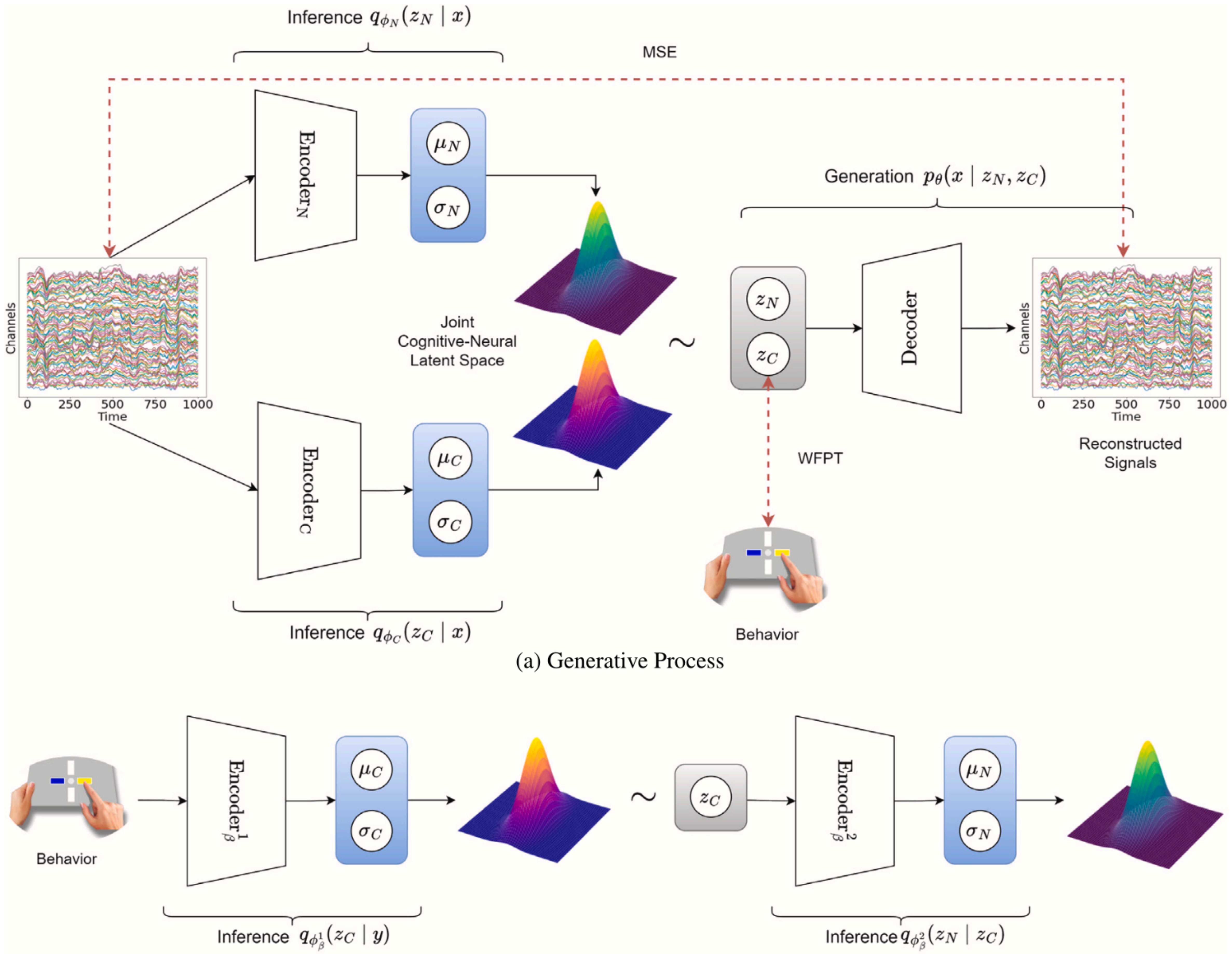
Explore correlations between EEG signals and cognitive control performance in older adults during a multitasking video game (NeuroRacer)



Literature Review

Deep latent variable joint cognitive modeling of neural signals and human behavior (2024)

NCVA to jointly model EEG signals and behavioral data



(a) Generative Process

(b) Regularized Discriminative Process

Literature Review

Image Generation using EEG data: A Contrastive Learning based Approach (2024)

Generate images from EEG signals by mapping latent spaces using a Multimodal Variational Autoencoder (MVAE)

Structural Similarity Index Measure (SSIM)quantifies generated image quality.

Asses structural accuracy based on human visual perception.

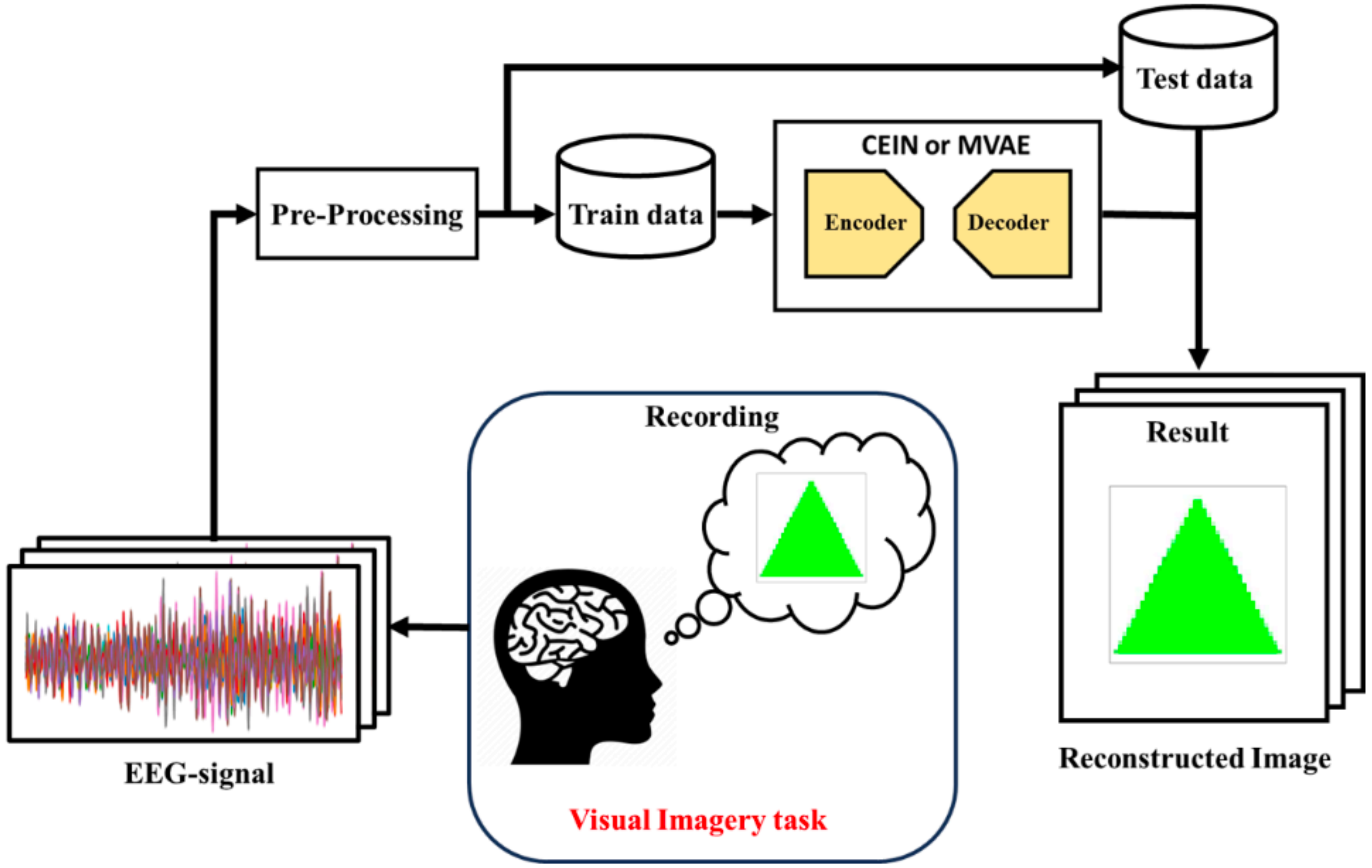
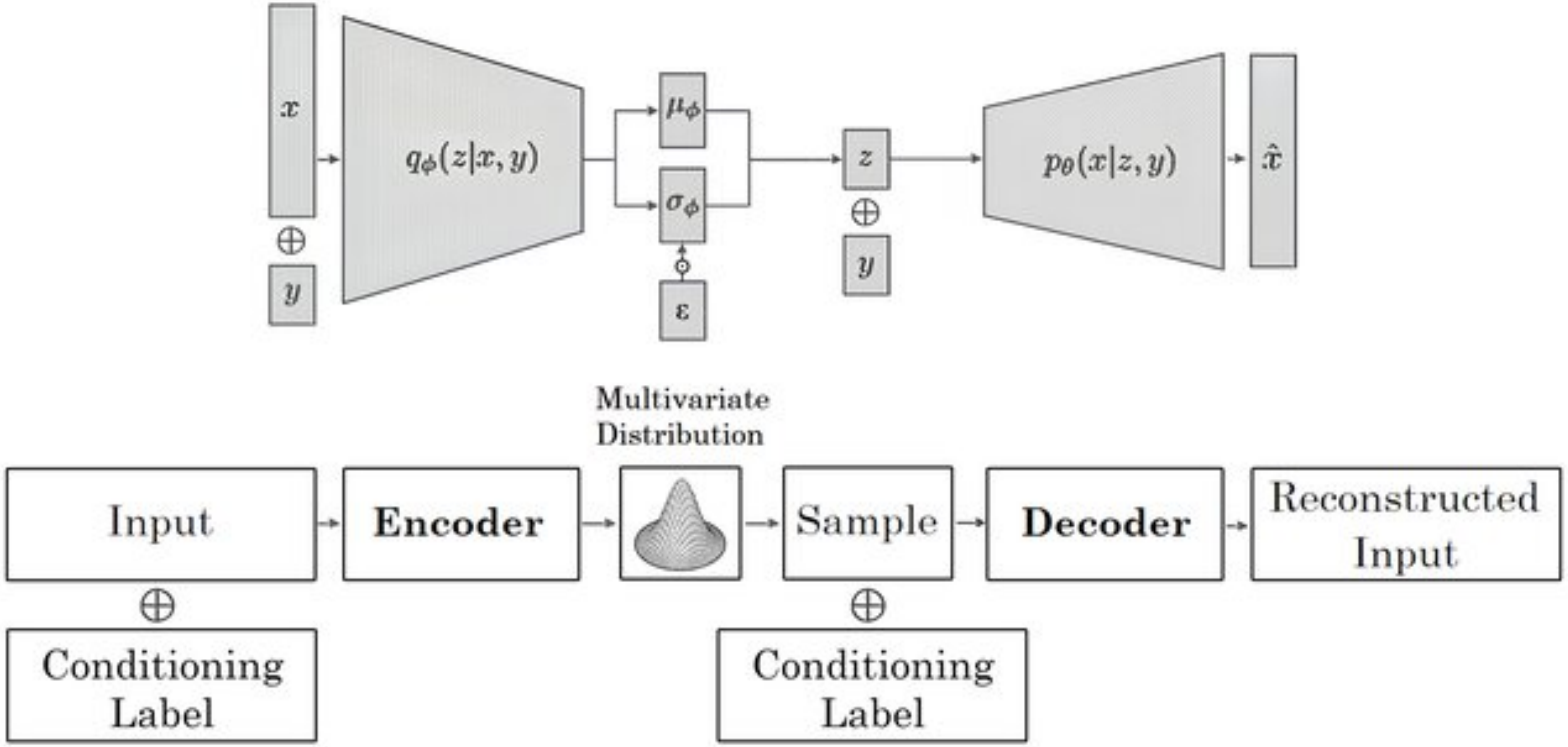


Fig. 1: Proposed method.

Problem Scope

- Input Data:
  - EEG features
  - Demographic features (?)
- Condition Labels:
  - Disorder categories
  - Control group (healthy individuals)
- Outputs:
  - Latent space representations: shared and unique patterns of disorders
  - Reconstructed EEG features conditioned on specified psychiatric labels

Model - cVAE

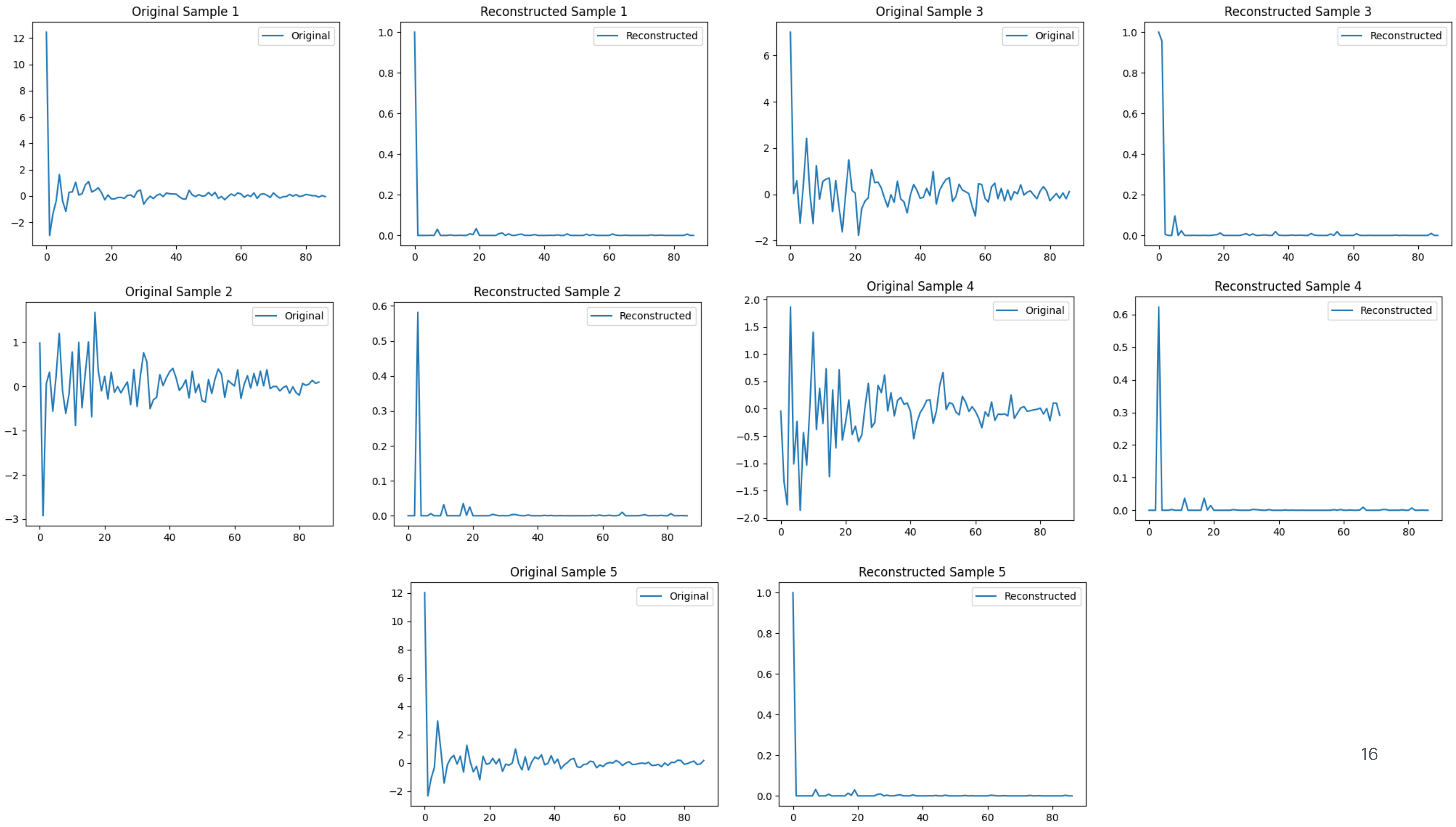


Loss = reconstruction loss + KL divergence

Model v1

- **Distinct Feature**: Unconditional – no external conditions or labels influence the latent space.
- Normalisation
- PCA
- Split data (80-10-10% ——> train-validation-test)
- Batch 64
- 50 epochs

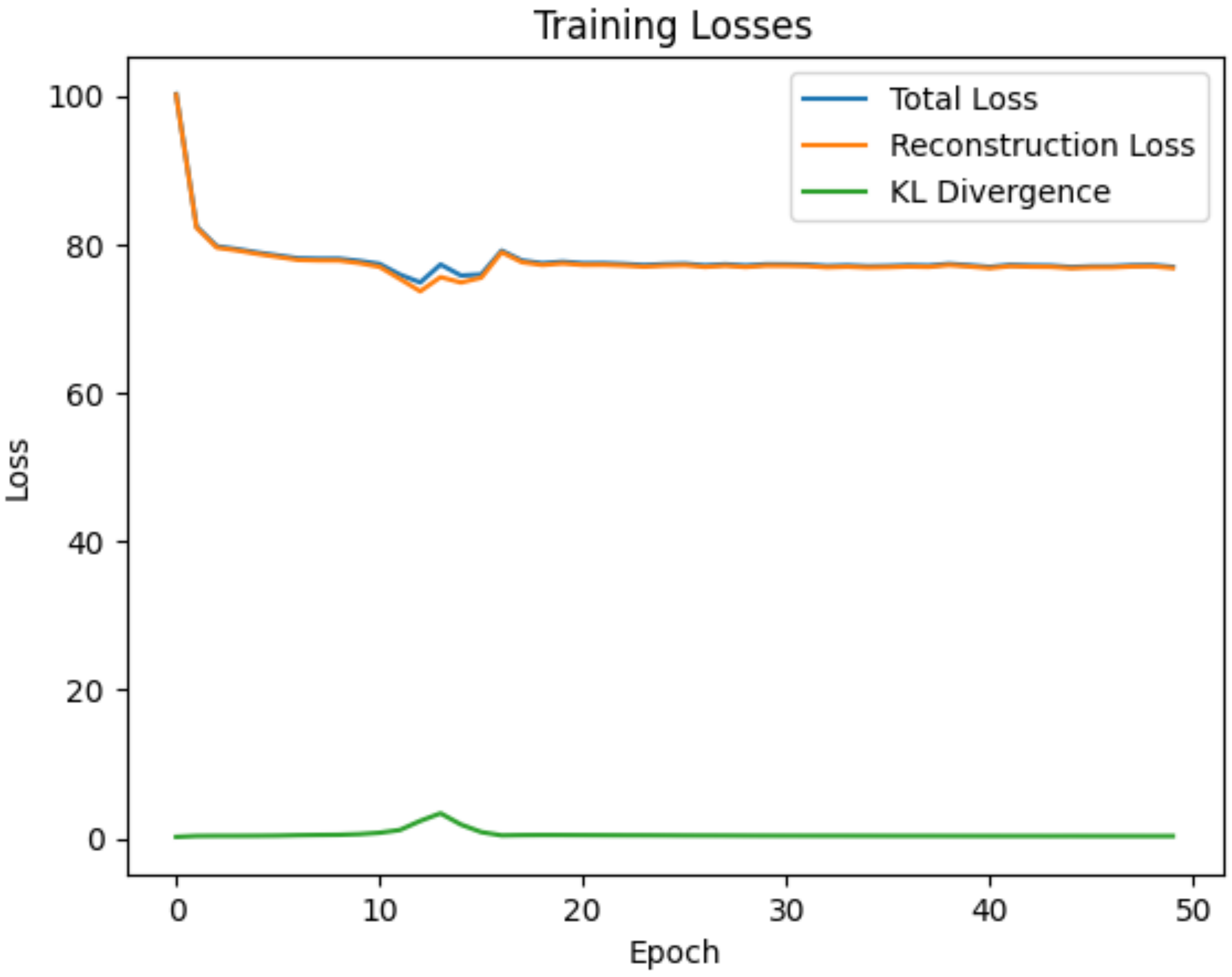
Model v1 cont.

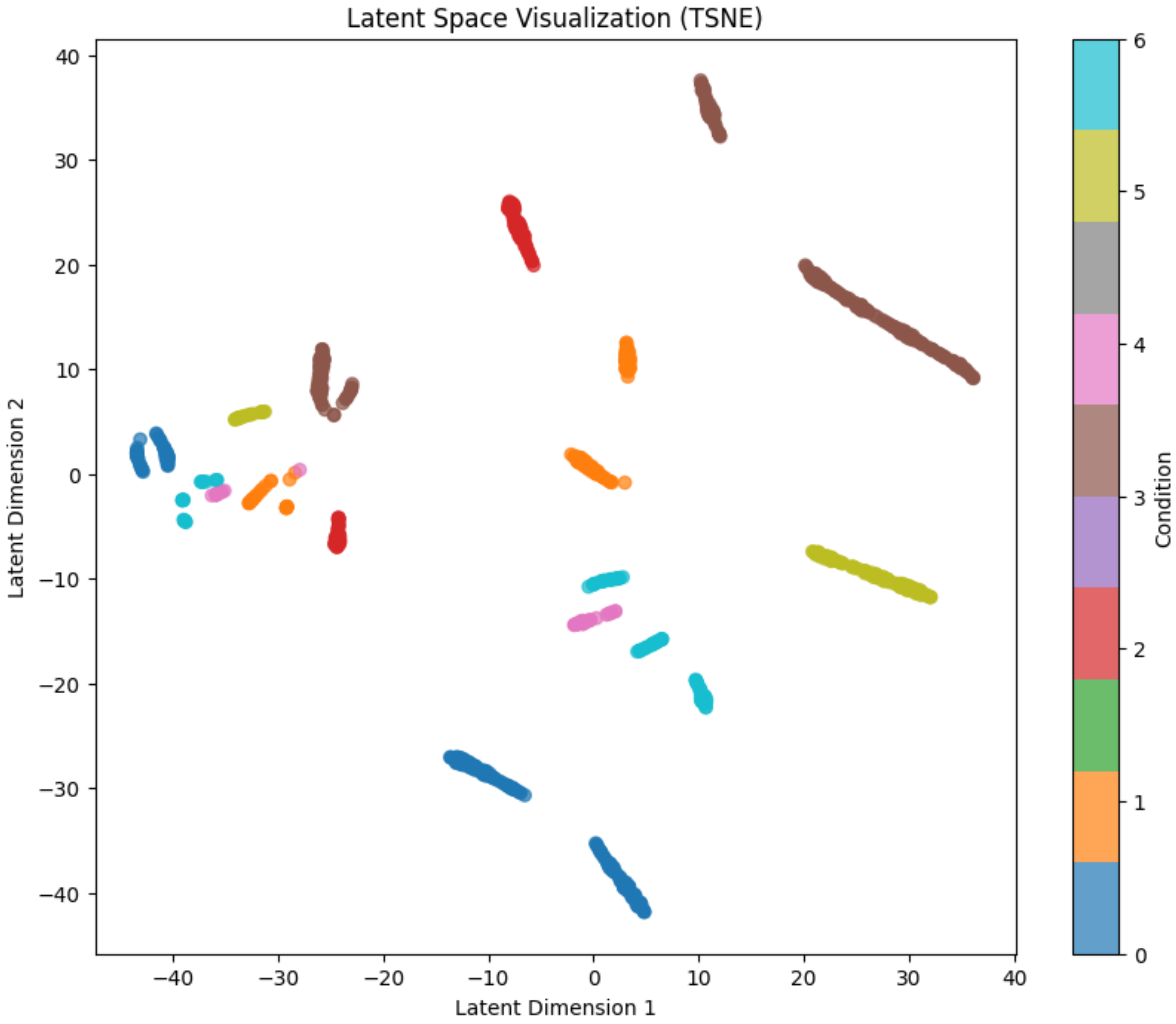


Model v2

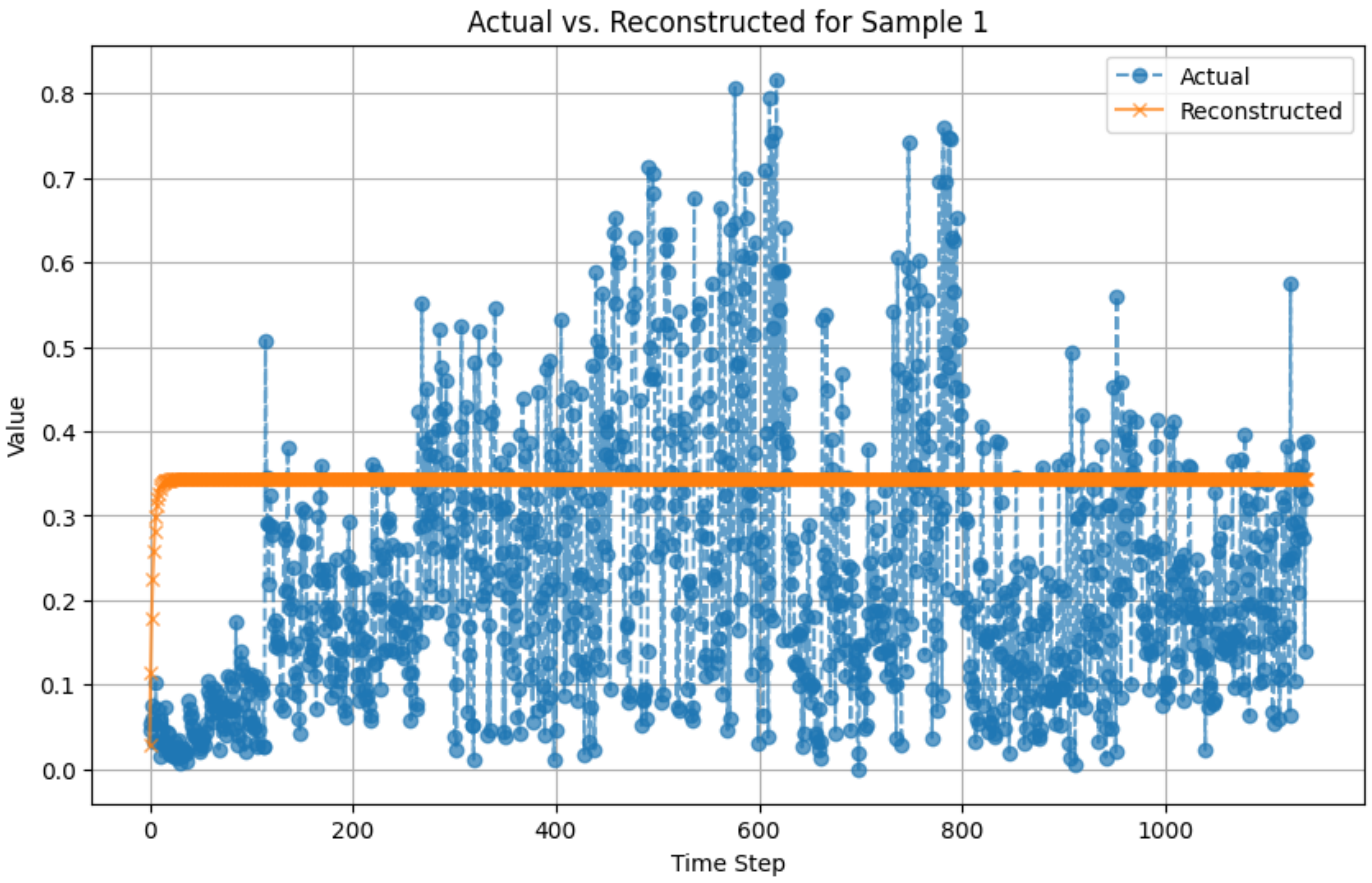
- **Distinct Feature**: Tailored for sequential time-series data with conditions, leveraging LSTM layers for temporal patterns.
- Normalisation
- PCA
- Split data (80-10-10% ——> train-validation-test)
- Batch 64
- 50 epochs

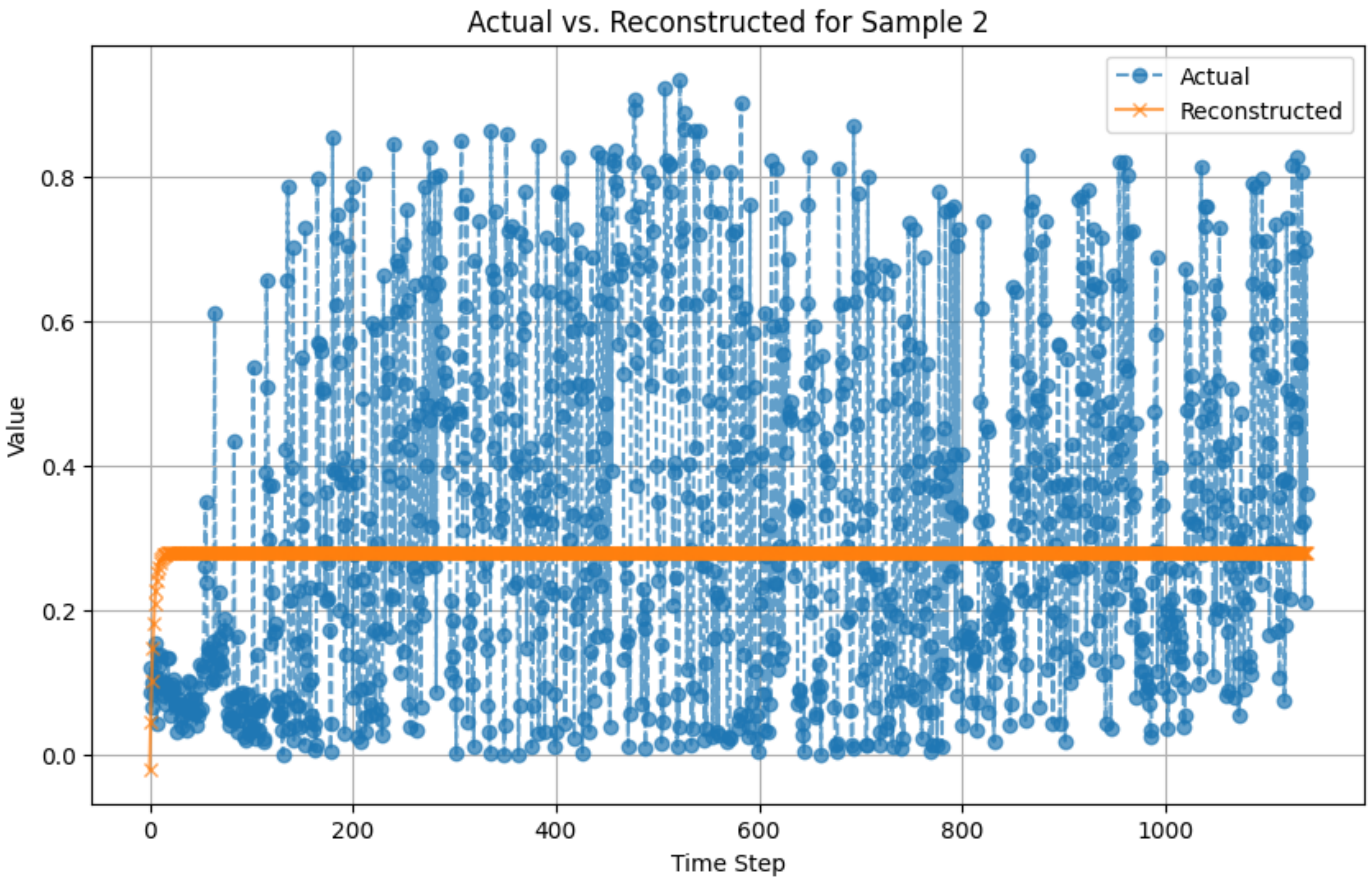
Model v2 cont.





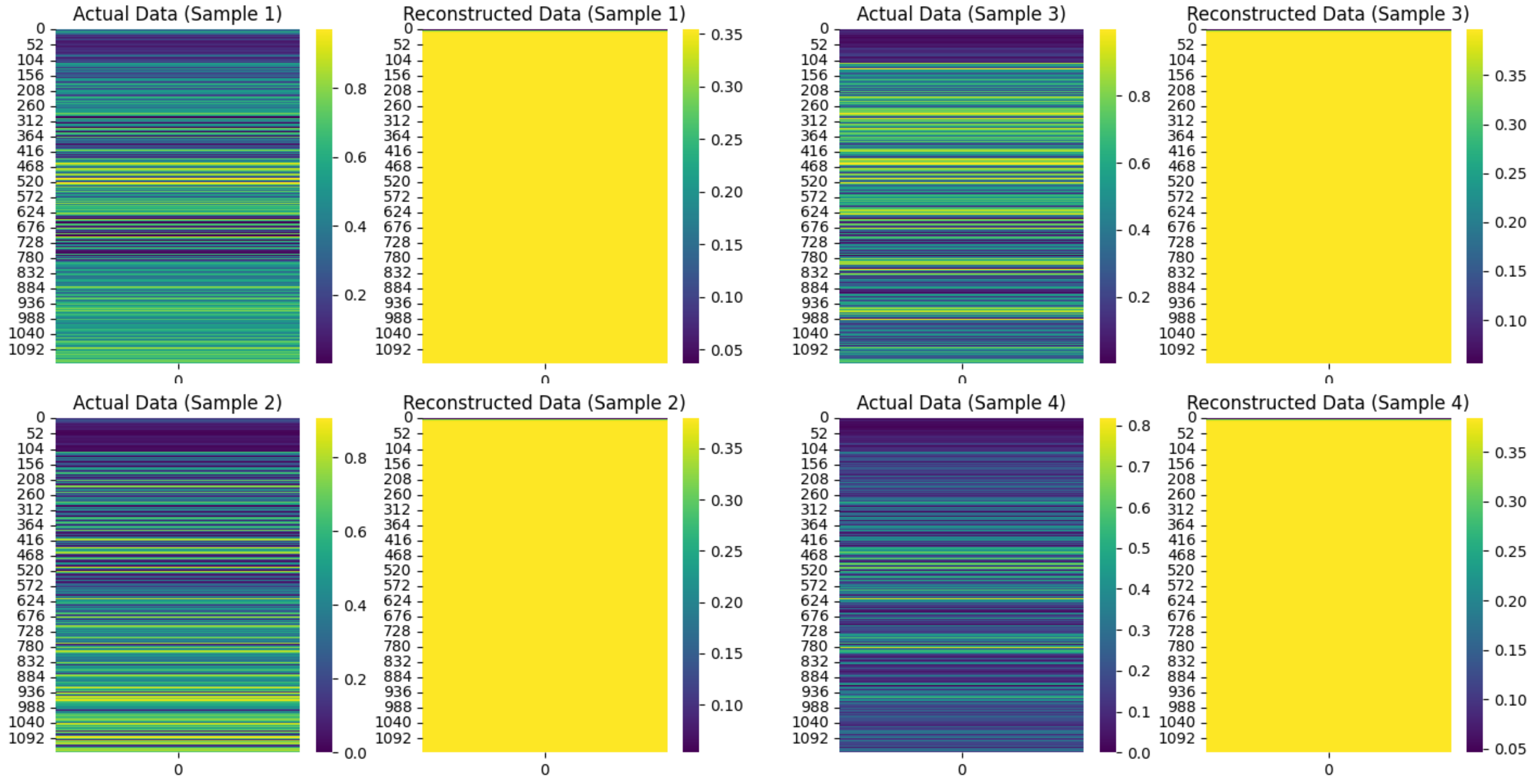
Model v2 cont.





actual and reconstructed time-series data for a specific condition

Model v2 cont.

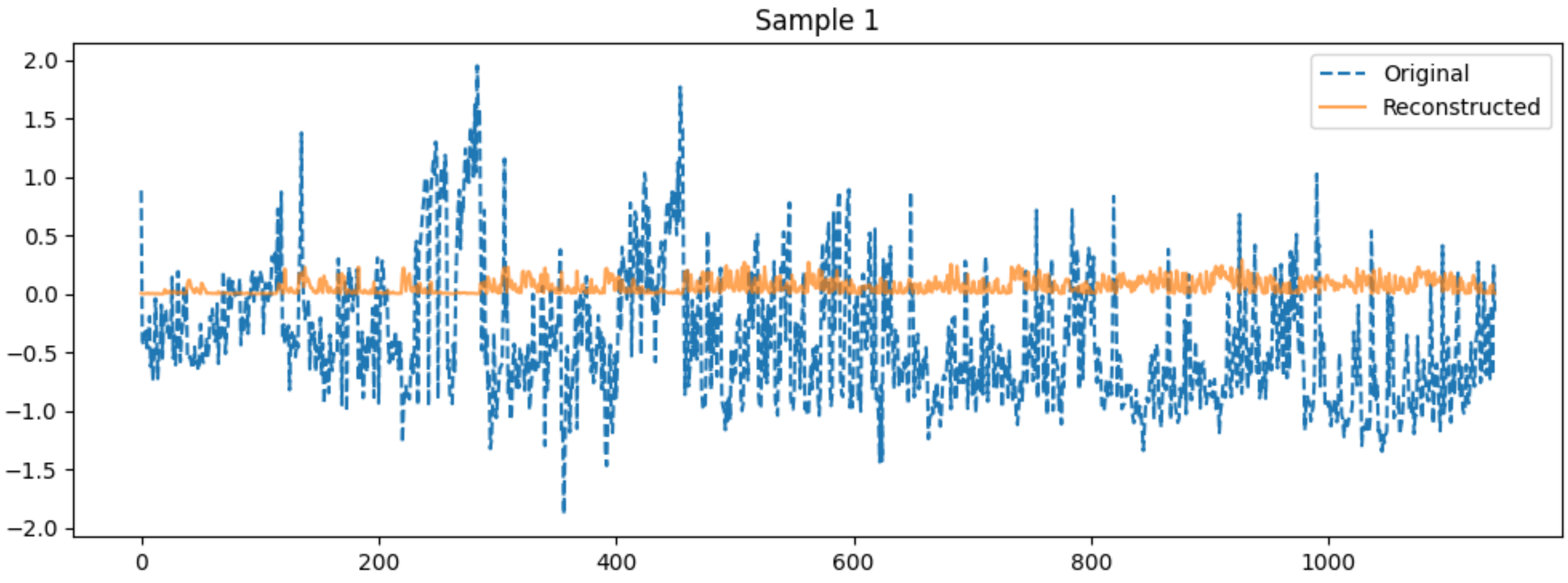


actual vs reconstructed data as heatmaps

Model v3

- Use all categorical data + EEG data
- **Distinct Feature**: TensorFlow-based implementation suitable for static data and deep-layered architectures.
- Normalise
- PCA
- Split data (80-10-10% ——> train-validation-test)
- Batch 64
- 50 epochs

Model v3 cont.

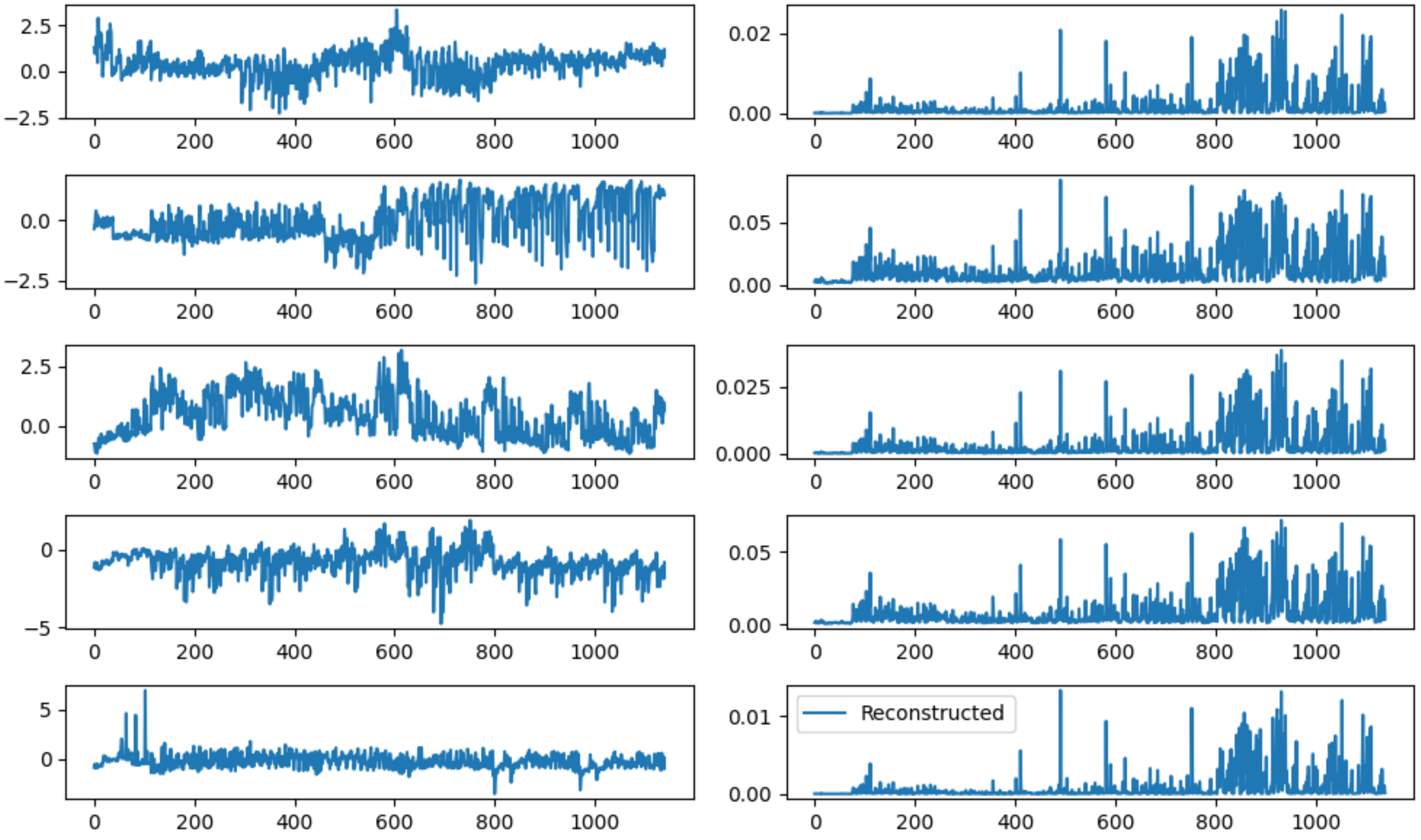


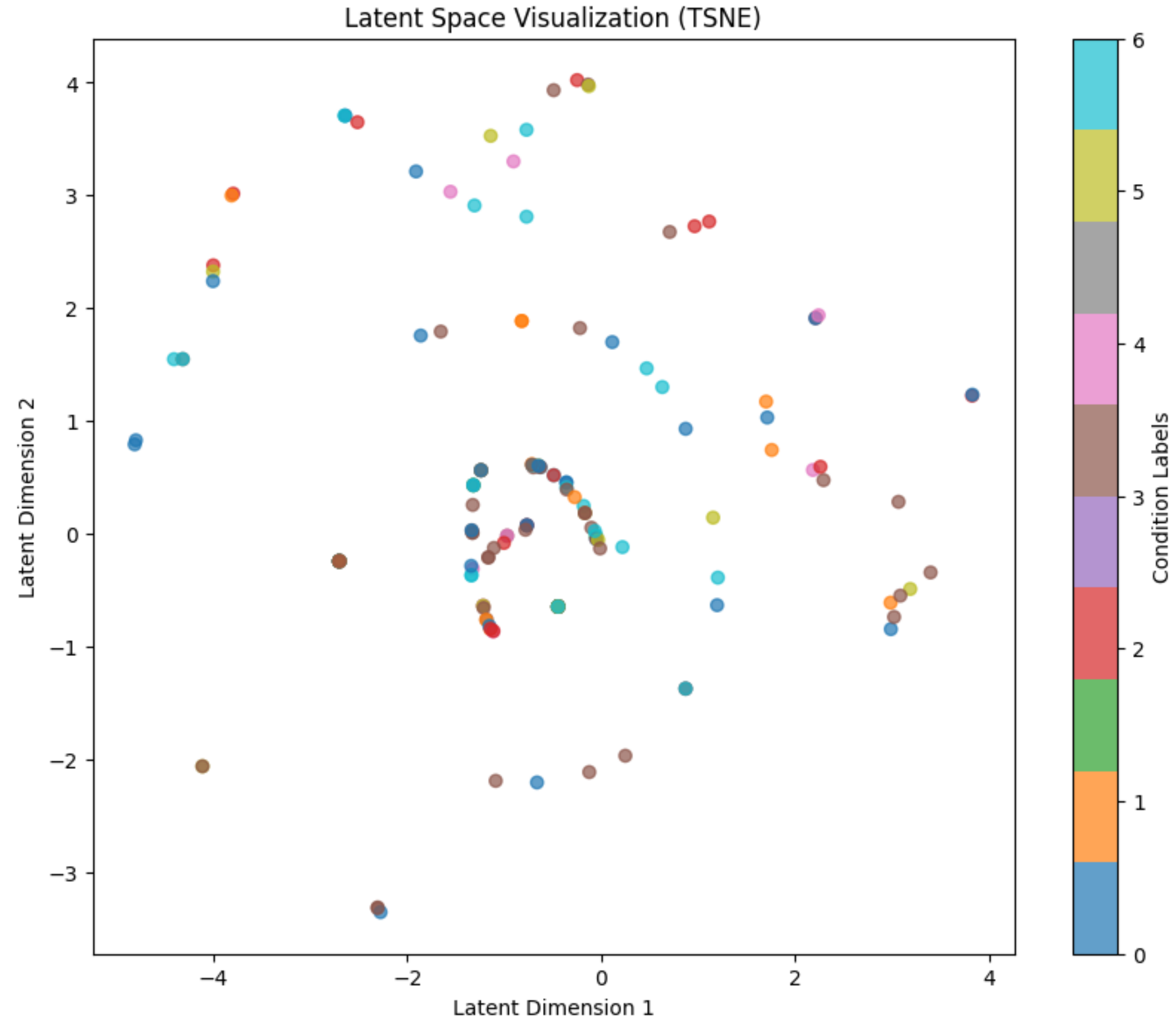
actual and reconstructed time-series data for a random condition

Model v4

- Use all categorical data + EEG data
- **Distinct Feature**: Highly modular design separates encoder, decoder, and latent space sampling, allowing easy extensions.
- Normalise
- PCA
- Split data (80-20% ——> train-test)
- Batch 30
- 50 epochs

Model v4


Reconstructed


Latent Space Visualization (TSNE)
Latent Dimension 1
Latent Dimension 2
Condition Labels

Preliminary Results

Aspect	Model v1 (VAE)	Model v2 (Time-Series CVAE)	Model v3 (CVAE)	Model v4 (Modular CVAE)
Type	Unconditional VAE	Conditional CVAE for time-series	Conditional CVAE for static data	Conditional CVAE for static data
Condition Input	None	Concatenated to hidden states and decoder input	Concatenated to input and decoder	Concatenated to input and decoder
Latent Dimensionality	User-defined	User-defined	User-defined	User-defined
Temporal Support	No	Yes (LSTM-based)	No	No
Framework	PyTorch	PyTorch	TensorFlow	TensorFlow
Depth	Simple	Moderate (LSTM layers)	Deep	Deep and modular
Intended Use	General latent modeling	Time-series modeling with conditions	Static data generation	Flexible static data generation

Preliminary Results

Model	Reconstruction Loss	KL Divergence	Total Loss	Mean Absolute Error
Model v1	77.691866	0.3292351	78.02109	0.22310533
Model v2	34.4010845	1.146553642	35.547639546	0.32755896
Model v3	1.0464692	1.372375131	2.41884434	0.78717851
Model v4	1.0626	0.0058	1.0684	0.7965

Conclusion & Future Work

- Some models are trained by try & error approach and got some results
- Still working on different architectures and different parameters
- Reading more papers to get ideas and compare

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- Try to improve current models or
  - Move on with one of the models and get a better result
- Compute the same metrics, visualisations and compare them
- DCI metrics

Thank you for listening!

Any Questions?