Unsupervised clustering for identification of novel sleep substages in mice

s154347 L. Rose[1] and s174197 A. Aspe[2]

[1]Molecular Sleep Lab, Department of Neuroscience, University of Copenhagen
[2]Mathematical Modelling and Computation, Technical University of Denmark

BACKGROUND

Sleep is for mice currently described by the three sleep stages: Wakefulness, Non-REM (NREM), and Rapid Eye Movement (REM). Previous studies have shown that it is possible to identify multiple substages of the current sleep stages. Thus, it remains an open question whether the current sleep stages cover all the heterogeneity of sleep or if identifying new substages would make sleep scoring more accurate.

In particular, we want to investigate how the latent variables from a **Mean-Covariance Restricted Boltzmann Machine (mcRBM)** and a **Variational Auto-Encoder (VAE)** can be utilized to identify the new substages.

Aims

1. Reproduce results from mcRBM model in [1]
2. Implement a VAE and optimize the model
3. Compare the latent spaces of mcRBM and VAE

METHODS

Variational Autoencoder (VAE)

Relationsship between probability of data and ELBO:

$$\log p(x) = \mathcal{D}_{KL}(q(z|x)|p(z|x)) + \mathcal{L}(x) \geq \mathcal{L}(x)$$

where

$$\mathcal{L}^{\beta}(x) = \mathbb{E}_{q(z|x)}[\log p(x|z)] - \beta \cdot \mathcal{D}_{KL}(q(z|x)|p(z))$$

The posterior is approximated by using the isotropic gaussian variational family:

$$p(z|x) \approx q(z|x)$$

We are using a gaussian prior $p(z)$ and a gaussian observation model $p(x|z)$

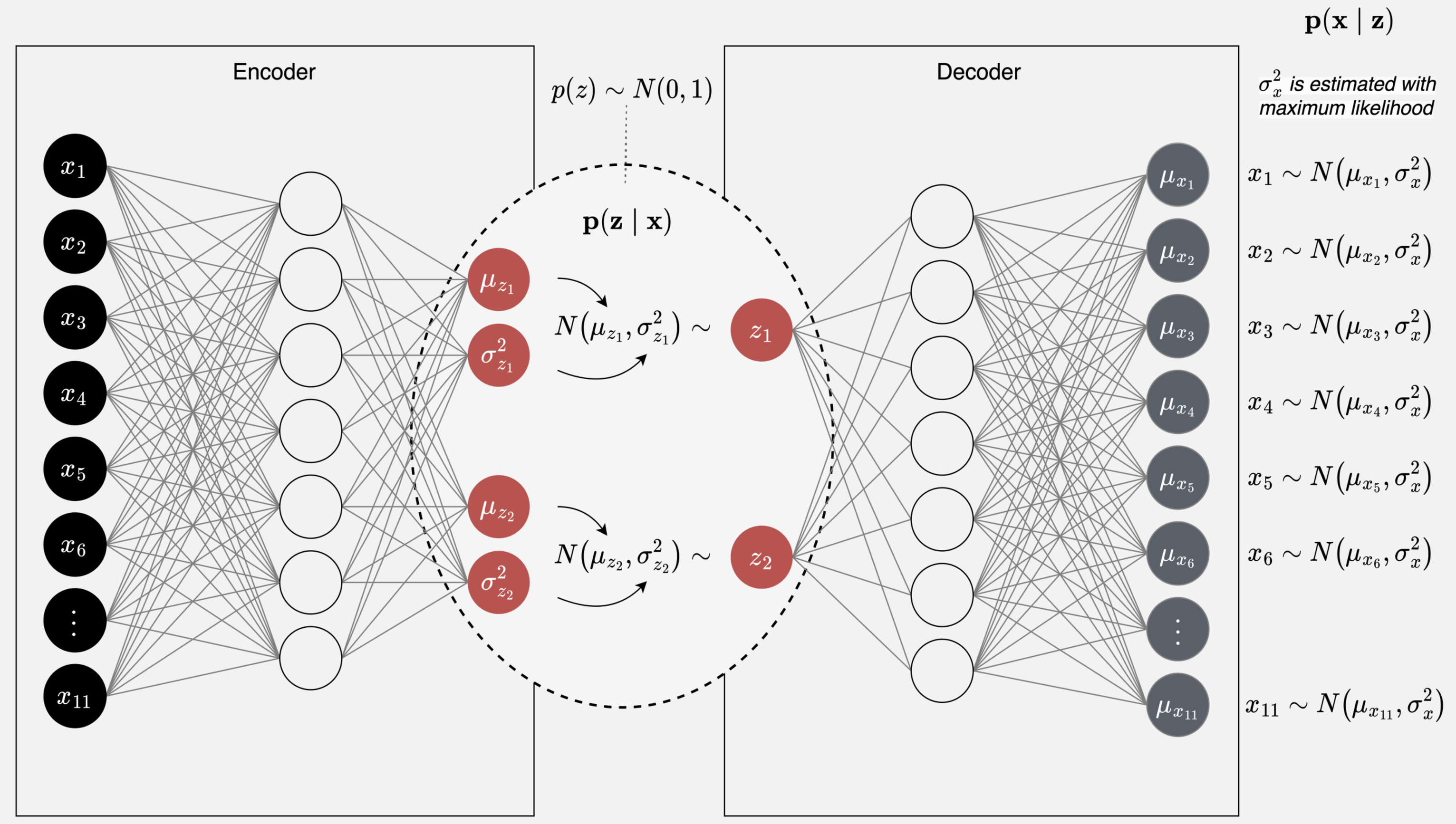

Figure 2: This figure shows an illustration of the VAE-model with 2 latent features.

Mean-Covariance Restricted Boltzmann Machine (mcRBM)

Gradient for mcRBM:

$$\frac{\partial \ln \mathcal{L}(\theta)}{\partial \theta} = -\sum_h p(h|v) \frac{\partial \mathrm{E}(v,h)}{\partial \theta} + \sum_{v,h} p(v,h) \frac{\partial \mathrm{E}(v,h)}{\partial \theta}$$

The above is complex to solve, instead we approximate it with CD:

$$CD_k(\theta, v^{(0)}) = -\sum_h p(h|v^{(0)}) \frac{\partial \mathrm{E}(v^{(0)},h)}{\partial \theta} + \sum_h p(h|v^{(k)}) \frac{\partial \mathrm{E}(v^{(k)},h)}{\partial \theta}$$

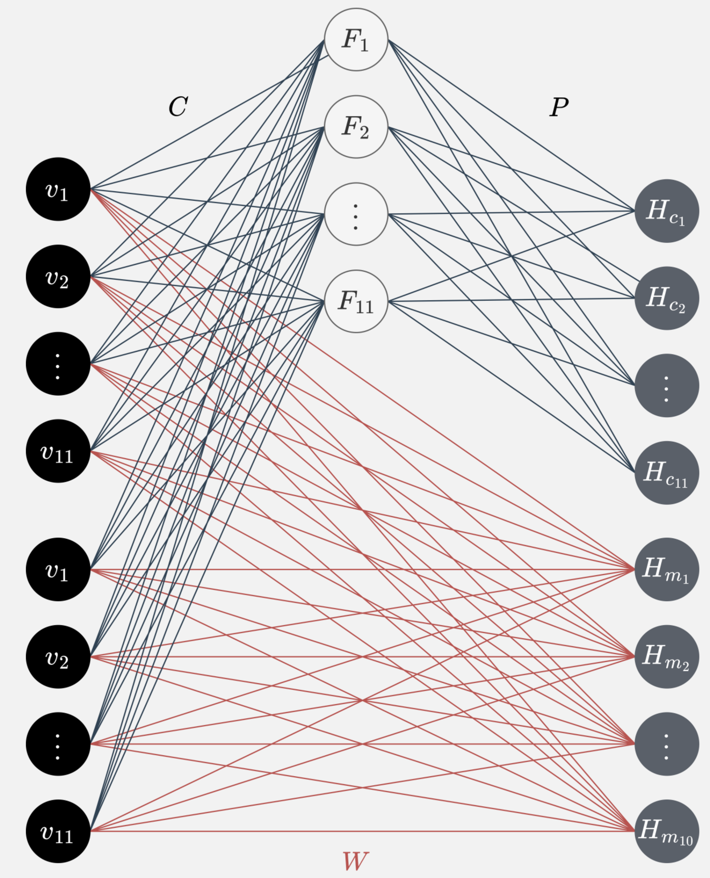

Figure 3: The figure illustrates the architecture of the mcRBM model.

LS	1			2	
SS	W	W	N	N	R
n = 1	1	1	1	0	0
n = 2	1	1	1	1	1
n = 3	0	0	0	0	0
n = 4	0	0	0	1	1
.					
n = 21	1	1	1	0	0

Table 1: The table shows how the latent states are created.

DATA

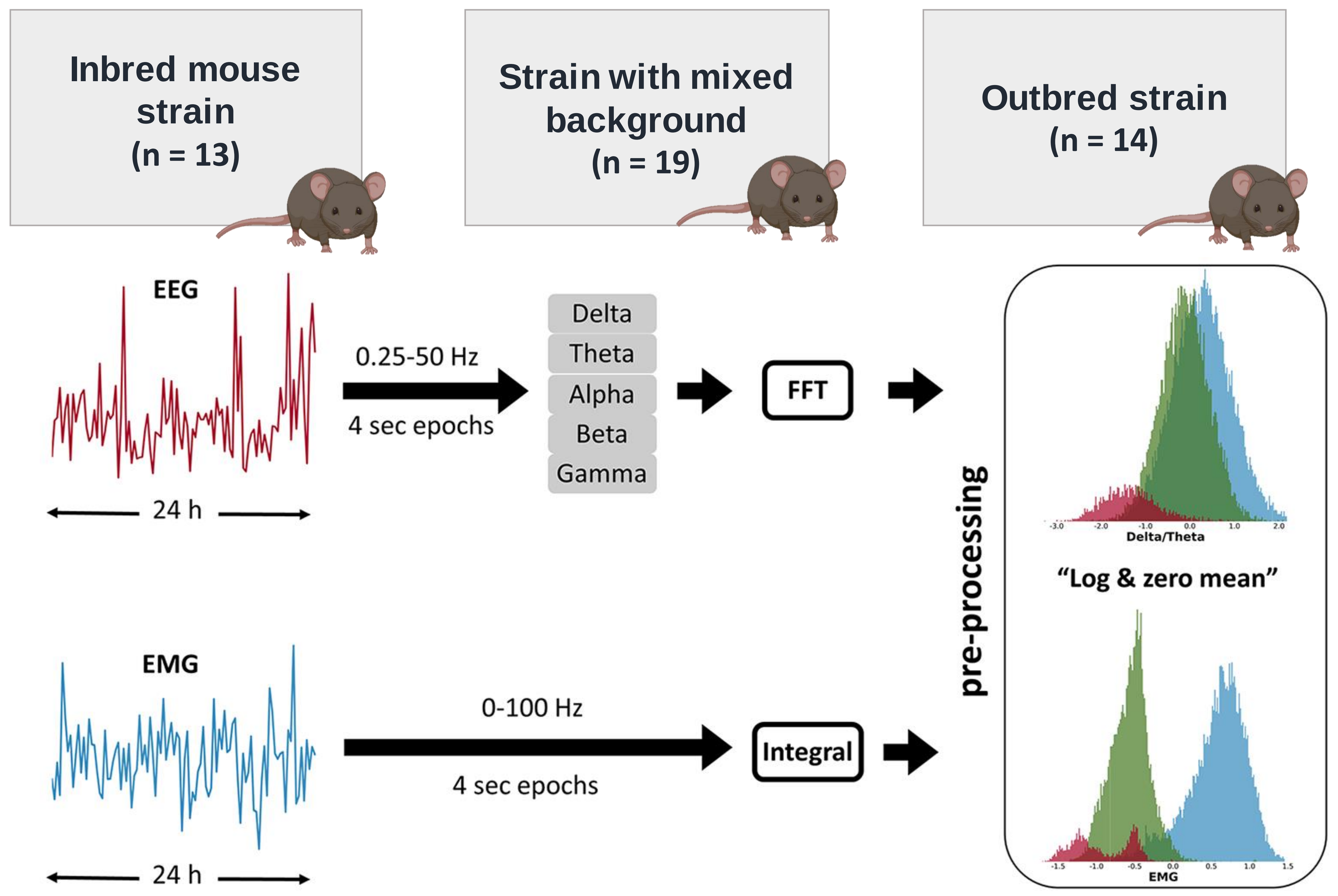

Figure 1: Figure is taken from [1] and illustrates the preprocessing pipeline for feature extraction. The features are used as input for both the VAE and mcRBM model.

RESULTS

Variational Autoencoder (VAE)

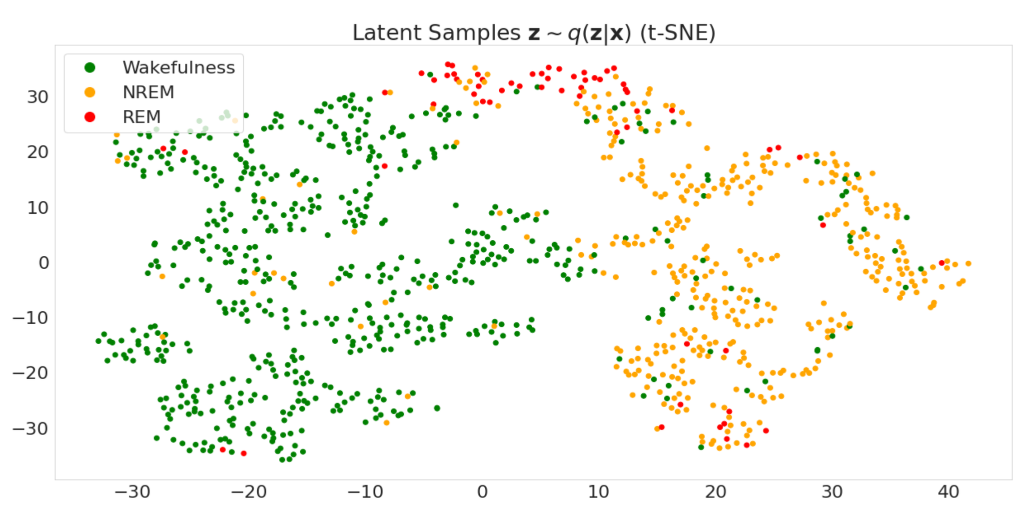

Figure 4: This plot shows a projection of the 3D feature space

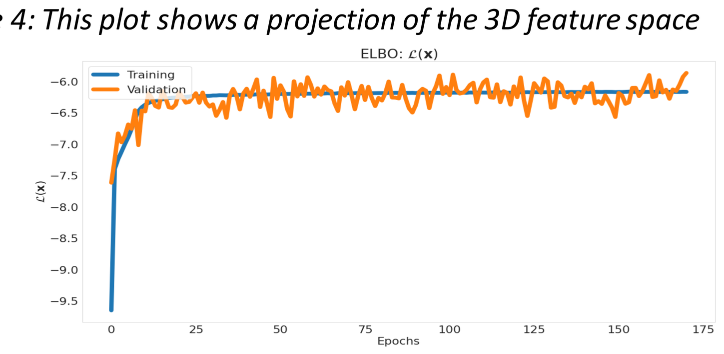

Figure 5: This plot shows the ELBO learning curve.

Key take aways

- Good separation of sleep stages
- Identification of subclusters
- No overfitting

Network specification

- Two hidden layers
- 3 latent features
- β = 1
- Adam optimizer
- Learning rate 1e-3

Mean–Covariance Restricted Boltzmann Machine (mcRBM)

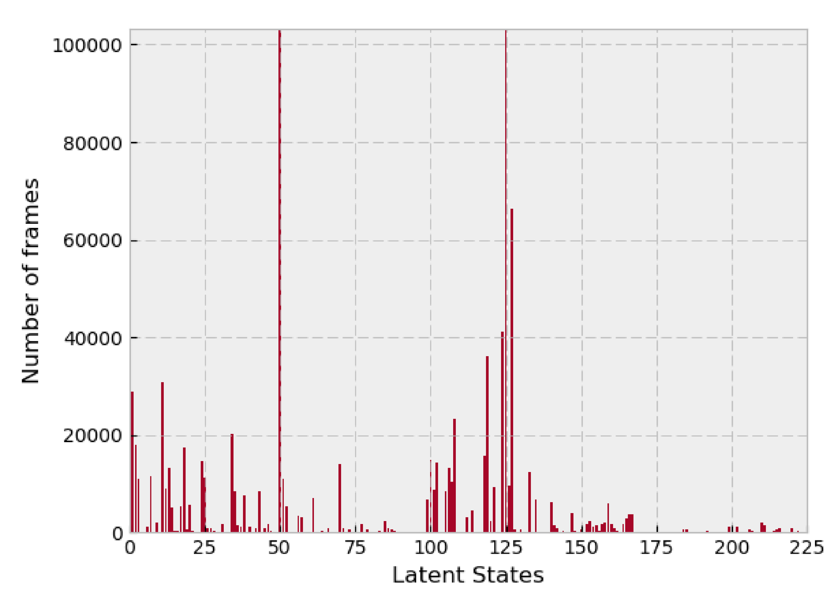

Figure 6: A histogram showing the number of epochs within each latent state

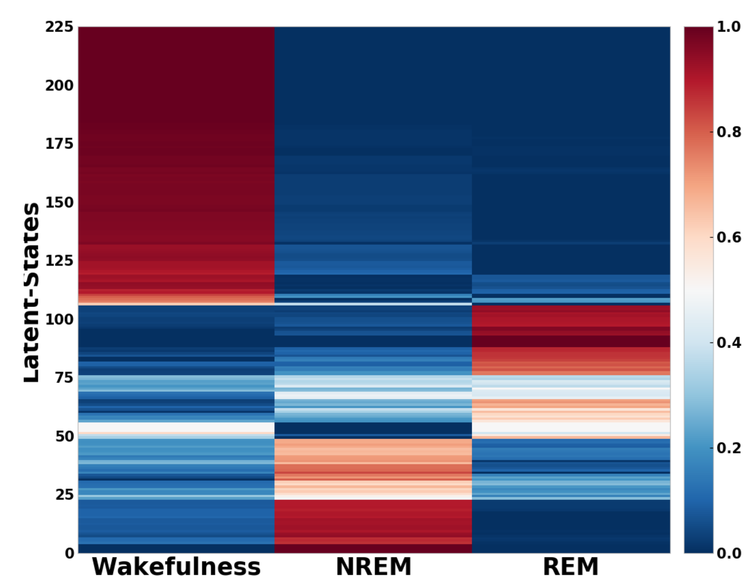

Figure 7: A heatmap showing the probability of belonging to either Wakefulness, NREM or REM for each Latent State

References

[1] Katsageorgiou et al. (2018) A novel unsupervised analysis of electrophysiological signals reveals new sleep substages in mice. PLOS Biology 16(5): e2003663. https://doi.org/10.1371/journal.pbio.2003663