Journal Club

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What I have done by now



➤ Paper Reading

- * Robust, automated sleep scoring by a compact neural network with distributional shift correction.
- ❖ SPINDLE: End-to-end learning from EEG/EMG to extrapolate animal sleep scoring across experimental settings, labs and species.

➤ Software & Hardware Coding

- ❖ Matlab codes for automated real-time sleep scoring
- ❖ Arduino codes for controlling the singlechips to manipulate stimulus signal

- ❖ Background
- Distributional shift correction
- Automated sleep scoring by neural network
- AccuSleep interface for sleep scoring

❖ Background

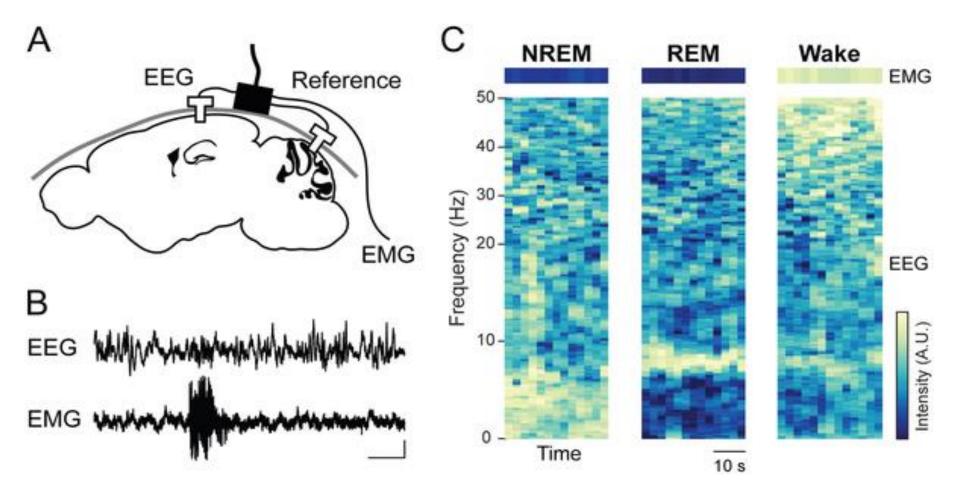


Fig 1. Overview of the signal collection process for sleep scoring in mice.

Distributional shift correction

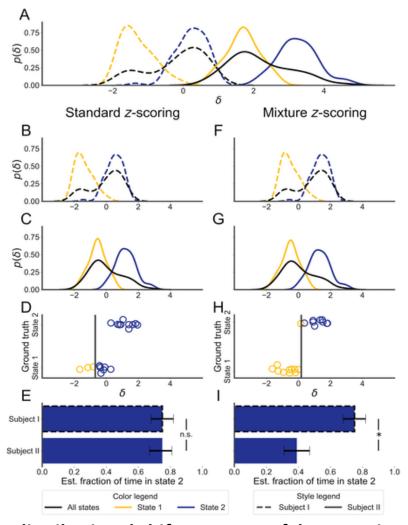


Fig 2. Correcting for distributional shift prevents a false negative in a simple model.

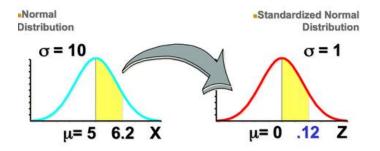
Distributional shift correction

z-scores

$$Z = \frac{\Phi - \mu}{\sigma}$$

Example

$$Z = \frac{X - \mu}{\sigma} = \frac{6.2 - 5}{10} = .12$$



Mixture z-scoring

$$Z_{M} = \frac{\Phi - w^{\mathsf{T}} \hat{\mu}}{\sqrt{w^{\mathsf{T}} (\hat{\sigma}^{2} + (\hat{\mu} - w^{\mathsf{T}} \hat{\mu})^{2})}}$$

$$\begin{split} \phi_Z &= \frac{\phi - \mu_G}{\sigma_G} = \frac{\phi - w^\top \mu}{\sqrt{w^\top (\sigma^2 + s)}} \qquad \mu_G \coloneqq \mathbb{E}[\phi] = w^\top \mu \\ w_i &\coloneqq P(Y = i) \qquad \sigma_G^2 \coloneqq \mathbb{V}[\phi] = w^\top (\sigma^2 + s) \\ \mathbb{E}[\phi|Y = i] \coloneqq \mu_i \qquad \mathbb{V}[\phi] = w^\top \sigma^2 + w^\top (\mu - w^\top \mu)^2 \end{split}$$

 $\sigma_i^2 := \mathbb{V}[\phi|Y=i]$ $s := (\mu - w^T \mu)^2$

 σ_G^2 comes from the law of total variance:

$$\mathbb{V}[\phi] = \mathbb{E}[\mathbb{V}[\phi|Y]] + \mathbb{V}[\mathbb{E}[\phi|Y]]$$

Distributional shift correction

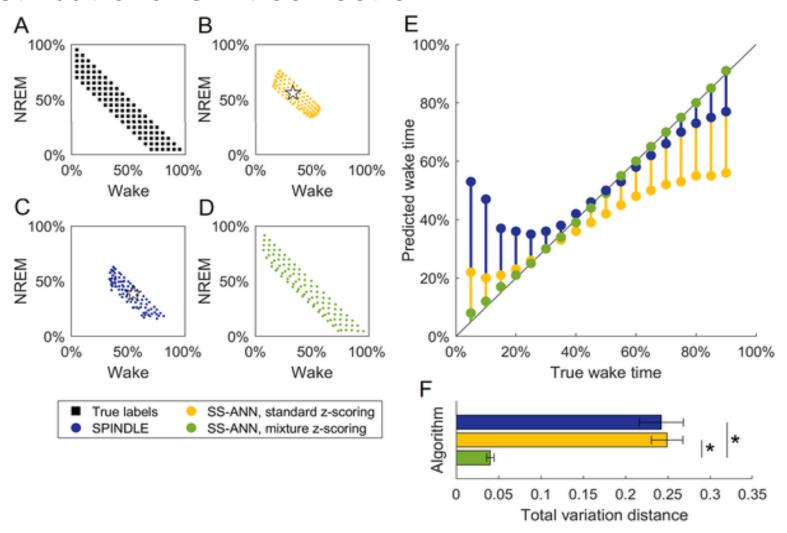


Fig 3. Comparison of sleep scoring algorithms on recordings with programmatically varied class balances.

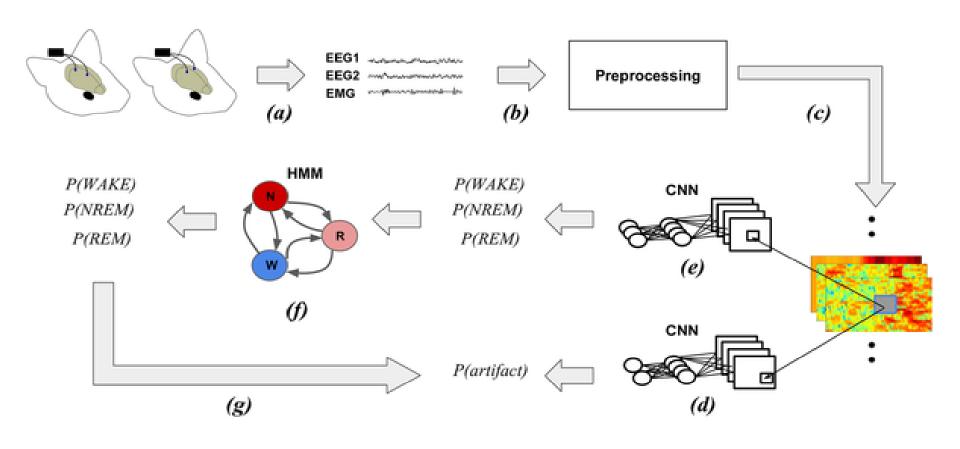


Fig 4. Conceptual overview of the SPINDLE framework.

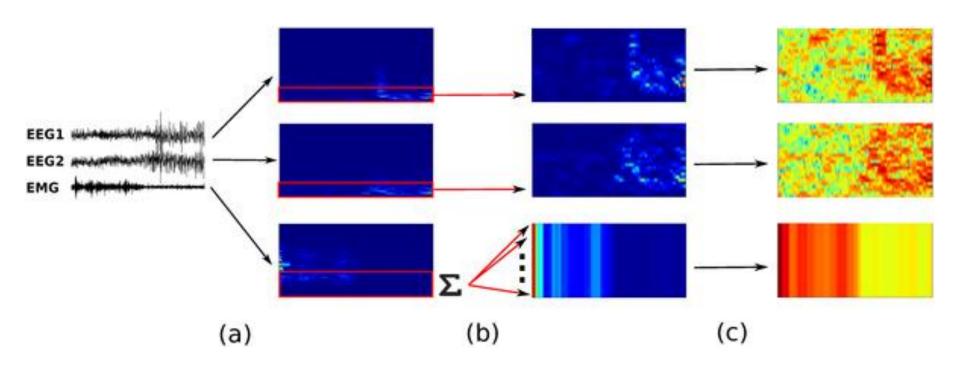


Fig 5. Data preprocessing and CNN input preparation.

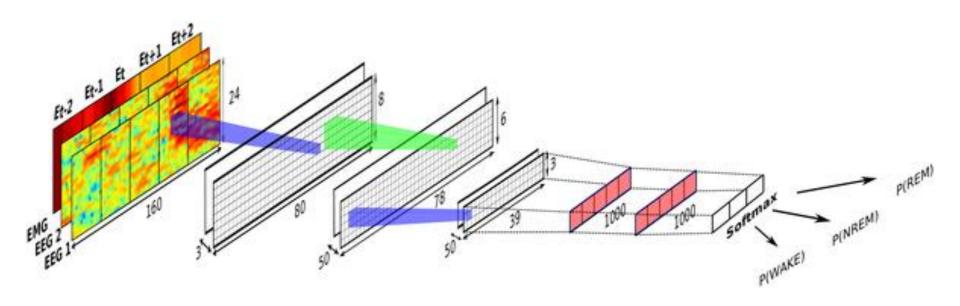


Fig 6. Sleep scoring CNN architecture.

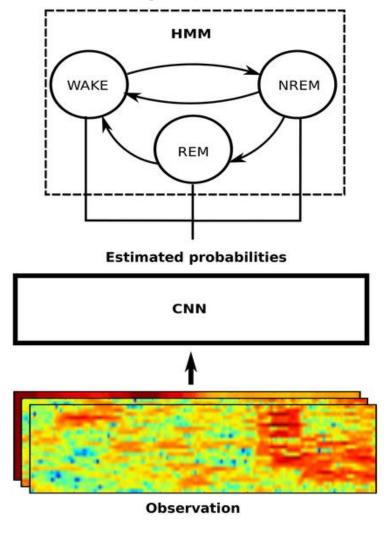


Fig 7. CNN-HMM for constraining state transitions.

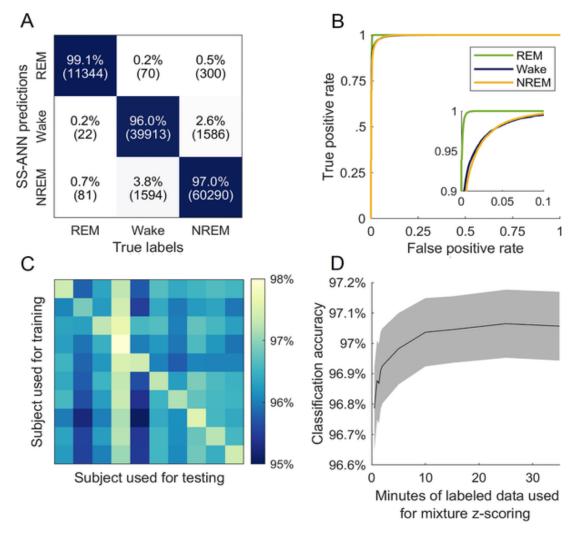


Fig 8. Validation of SS-ANN.

AccuSleep interface for sleep scoring



Fig 9. AccuSleep interface for automated sleep scoring.

AccuSleep interface for sleep scoring

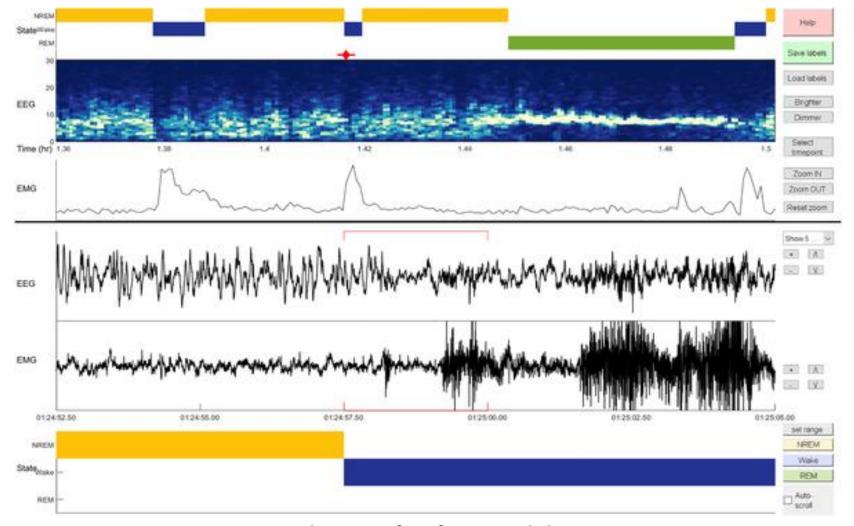
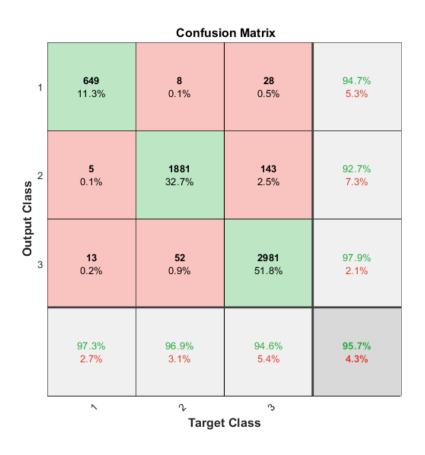


Fig 10. AccuSleep interface for manual sleep scoring.

❖ Our sesults



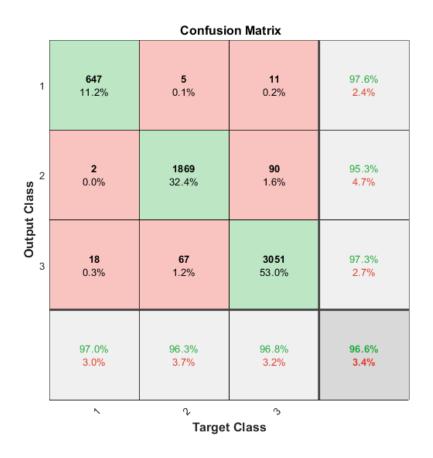
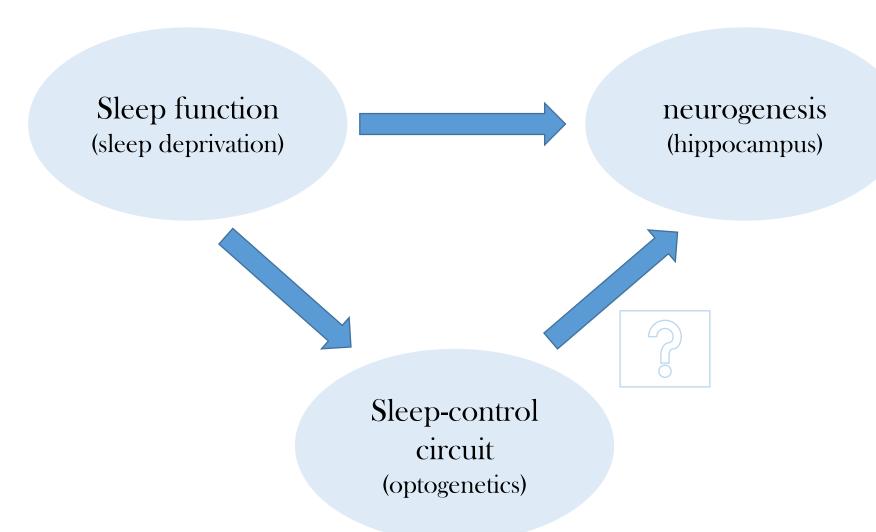


Fig 11. confusion matrix of auto-mated sleep scoring at different parameters.

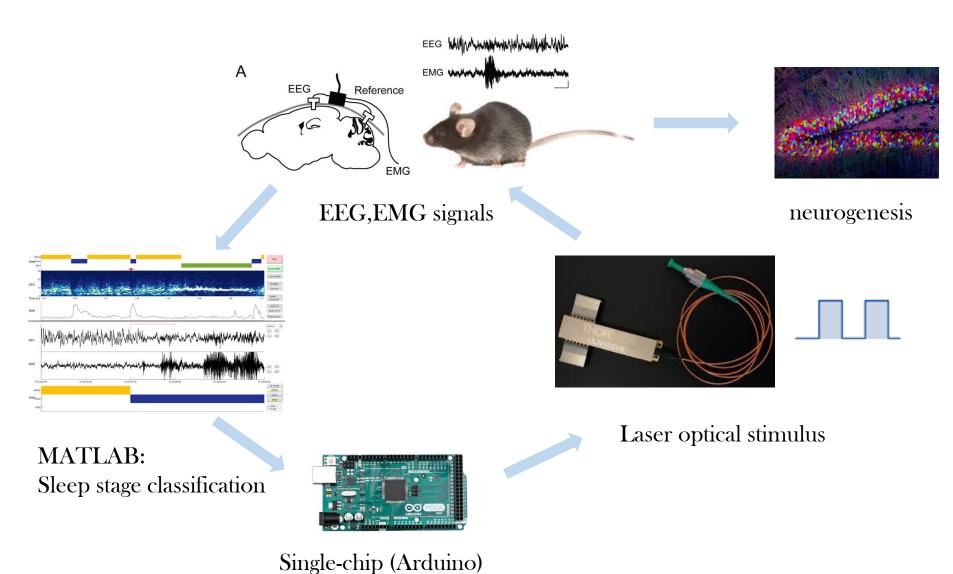
Project Plan

Project purpose



Project Plan

❖ Project design: close-loop



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References

Barger Z, Frye CG, Liu D, Dan Y, Bouchard KE (2019) **Robust, automated sleep scoring by a compact neural network with distributional shift correction.** PLOS ONE 14(12): e0224642. https://doi.org/10.1371/journal.pone.0224642 https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0224642

Miladinović Đ, Muheim C, Bauer S, Spinnler A, Noain D, et al. (2019) **SPINDLE: End-to-end learning from EEG/EMG to extrapolate animal sleep scoring across experimental settings, labs and species.** PLOS Computational Biology 15(4): e1006968.

https://doi.org/10.1371/journal.pcbi.1006968

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