SLEEP STAGE CLASSIFICATION FROM SINGLE CHANNEL EEG USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Quality Sleep is an important part of a healthy lifestyle as lack of it can cause a list of issues like a higher risk of cancer and chronic fatigue. This means that having the tools to automatically and easily monitor sleep can be powerful to help people sleep better. Doctors use a recording of a signal called EEG which measures the electrical activity of the brain using an electrode to understand sleep stages of a patient and make a diagnosis about the quality if their sleep.

In this report we will train a Convolutional neural network to do the sleep stage classification automatically from EEGs.

1 BACKGROUND

Recent approaches like Supratak et al. (2017) use a CNN sub-model that encodes each epoch into a 1D vector of fixed size and then a second LSTM sub-model that maps each epochs vector into a class from W, N1, N2, N3, REM. Others like [Tsinalis et al. (2016)] use Morlet wavelets for features extraction and Stacked sparse autoencoders to do this classification.

2 DATA

The Dataset used is from the publicly available EEG Sleep data Sleep-EDF Goldberger et al. (e 13) that was done on 20 subject, 19 of which have 2 full nights of sleep. We use the pre-processing scripts provided by Supratak et al. (2017) and split the train/test so that no study subject is in both at the same time.
In the input we have a sequence of 30s epochs of EEG where each epoch has a label W, N1, N2, N3, REM.

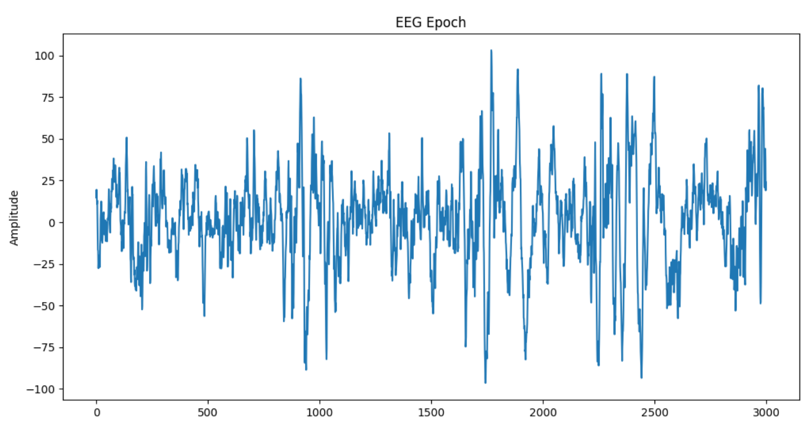

Figure 1: EEG Epoch

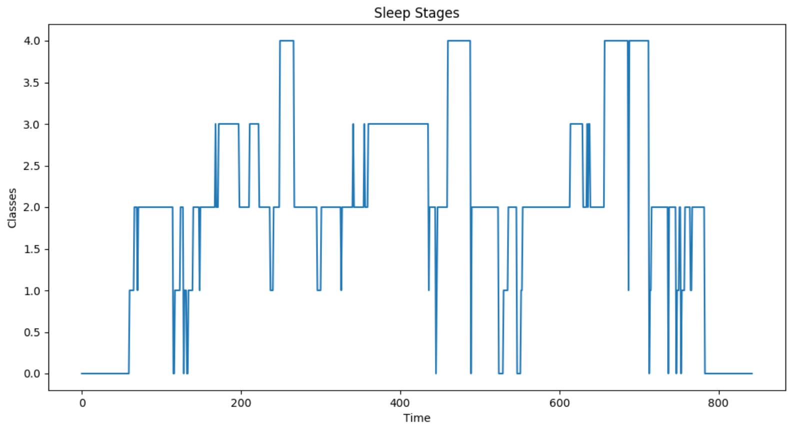

Figure 2: Sleep stages through the night

The general objective is to go from a 1D sequence like in fig 1 and predict the output hypnogram like in fig 2.

3 METHOD

Here we use a 1D CNN to encode each Epoch and then another 1D CNN or LSTM that labels the sequence of epochs to create the final hypnogram. This allows the prediction for an epoch to take into account the context.

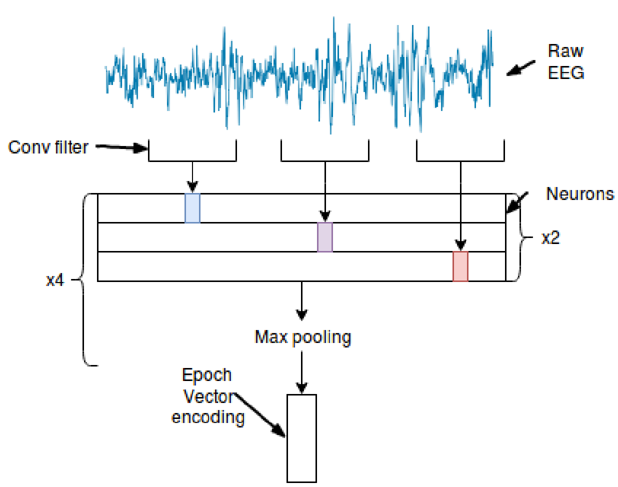

Figure 3: Epoch encoder

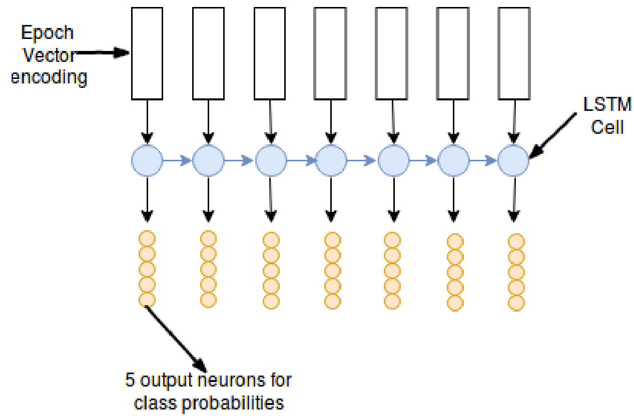

Figure 4: Sequential model for epoch classification

In what follows we compare these three approaches :

- CNN-CNN : This ones used a 1D CNN for the epoch encoding and then another 1D CNN for the sequence labeling.
- CNN-CNN-CRF : This model used a 1D CNN for the epoch encoding and then a 1D CNN-CRF for the sequence labeling.
- CNN-LSTM : This ones used a 1D CNN for the epoch encoding and then an LSTM for the sequence labeling.

4 Results

4.1 Sequential model comparison

Model	Accuracy	F1
CNN-CNN	0.87	0.81
CNN-CNN-CRF	**0.89**	**0.82**
CNN-LSTM	0.71	0.76

Table 1: Validation result

The LSTM based model is the least accurate because LSTMs usually require extensive parameter tuning to give decent performance (Learning rate, batch size, regularization...) which was not done here. CNN-CRF outperforms CNN only model which shows that the CRF helps by learning the transition probabilities between classes.

4.2 Comparison to the State of the art

Model	Test Epochs	Accuracy	F1
Supratak et al. (2017)	41950(20 fold CV)	0.82	0.76
Tsinalis et al. (2016)	37022	0.78	0.73
This work (CNN-CNN-CRF)	42308 (20 fold CV)	**0.84**	**0.78**

Table 2: Comparison to the state of the art

The CNN-CNN-CRF approach described here seems to work well even when compared to state of the art methods when evaluated in a similar setting : 20 folds cross-validation train and test folds are always independent in the sense that a subject cannot appear in both. Prediction are done in a Cross-validation setting and then the metrics are computed on the prediction for the full data.

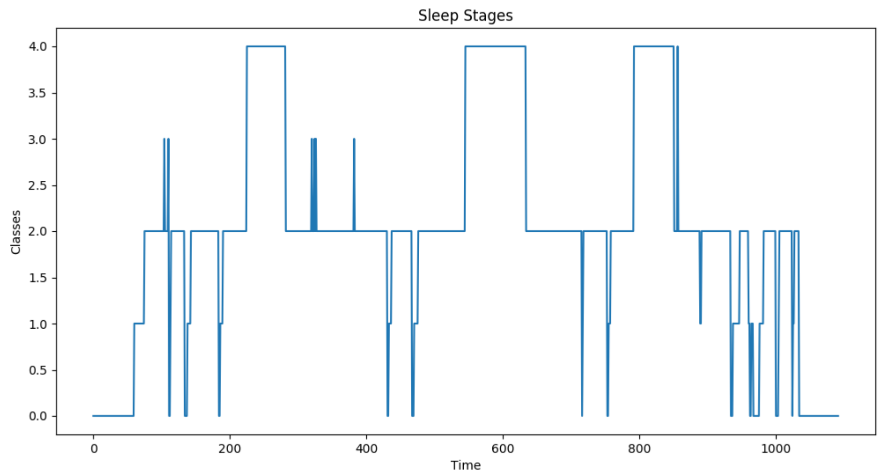

Figure 5: Ground truth Hypnogram example

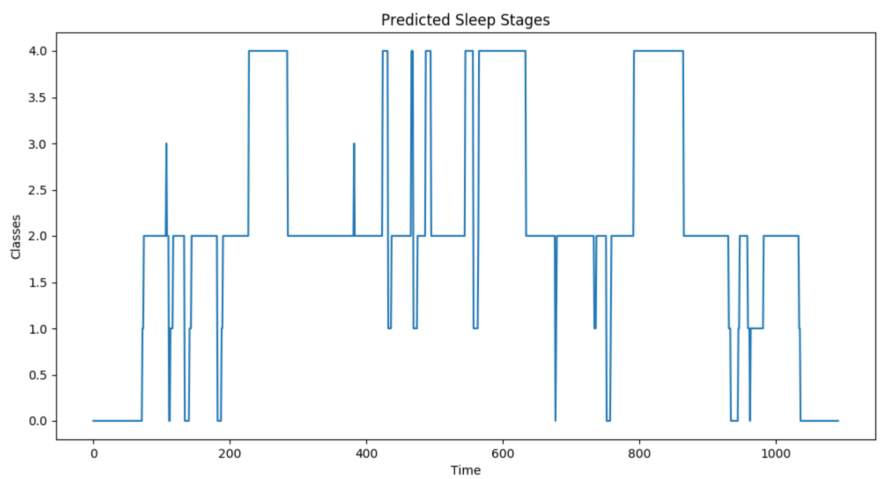

Figure 6: Predicted Hypnogram example

5 Conclusion

In this report we compare multiple approaches to sleep stages classification and show that CNN-CRF outperforms LSTMs and CNN-only models on Sleep-EDF.

We also make the code needed to reproduce the results available on github[1].

[1] https://github.com/CVxTz/EEG_classification

References

Goldberger, A. L., Amaral, L. A. N., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C.-K., and Stanley, H. E. (2000 (June 13)). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation*, 101(23):e215–e220. Circulation Electronic Pages: http://circ.ahajournals.org/content/101/23/e215.full PMID:1085218; doi: 10.1161/01.CIR.101.23.e215.

Supratak, A., Dong, H., Wu, C., and Guo, Y. (2017). Deepsleepnet: A model for automatic sleep stage scoring based on raw single-channel eeg. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(11):1998–2008.

Tsinalis, O., Matthews, P. M., and Guo, Y. (2016). Automatic sleep stage scoring using time-frequency analysis and stacked sparse autoencoders. *Annals of Biomedical Engineering*, 44(5):1587–1597.