EEG&EOG-based Sleep Staging

CS 182 Project

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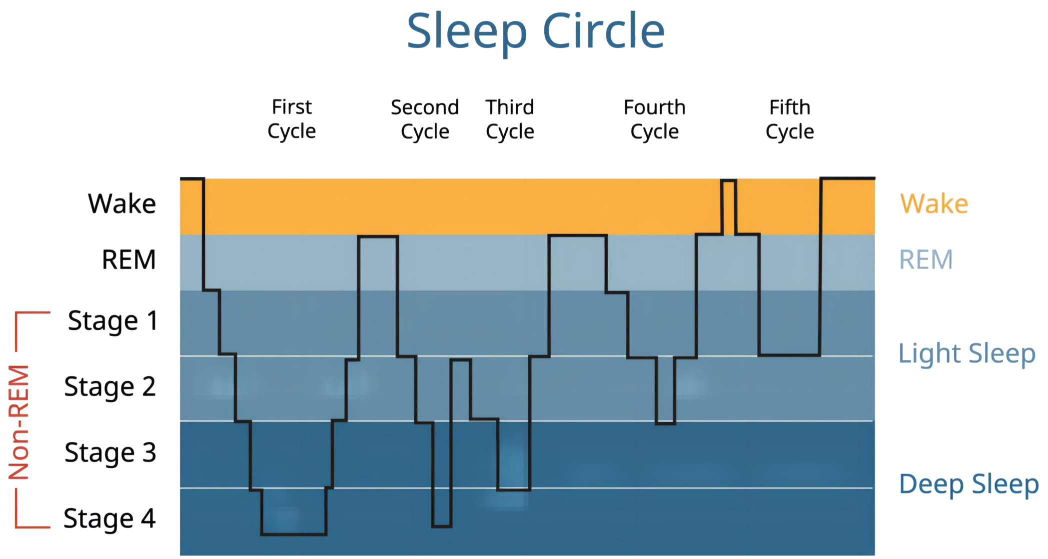
Content

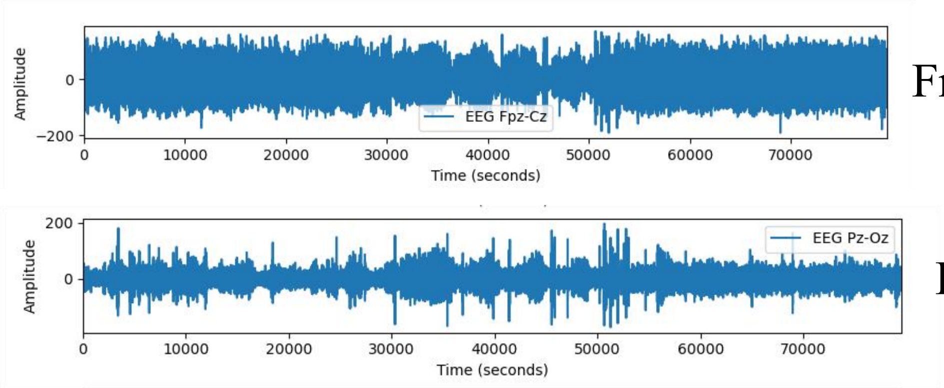
Research Background

- Crucial for understanding sleep patterns and overall health.
- 5 Sleep Stages: non-rapid eye movement (NREM:N1, N2, N3, N4) and rapid eye movement (REM) sleep



Research Background

- EEG (Electroencephalogram): measuring brain activities

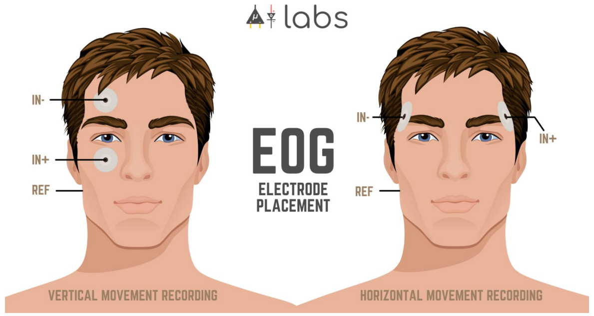


Frontopolar + Central zero

Parietal + Occipital

Fig. 1 A subject undergoing EEG monitoring

- EOG (Electrooculography): measuring eye movements



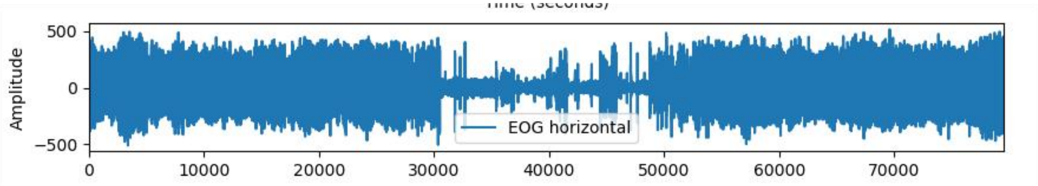


Fig. 2 Explanation to EOG

- Sleep stage can be classified based on EEG + EOG signals.

Status-of-art about Sleep-staging

Mainly focused on developing increasingly complex deep learning architectures[1]

lack of inter- -pretability and transparency

Year	System	Technique	ACC
2021	XSleepnet2[1]	CNN & RNN	0.864
2019	SleepEEGNet[2]	CNN & RNN	0.843
2020	DeepSleepNet+[3]	CNN	0.846
2022	SleepTransformer[4]	transformer	0.849

Do not have ideal accuracy

[1] Phan, H., Ch´en, O.Y., Tran, M.C., Koch, P., Mertins, A., De Vos, M.: Xsleepnet: Multi-view sequential model for automatic sleep staging. IEEE Transactions on Pattern Analysis and Machine Intelligence (2021)
[2] Mousavi, S., Afghah, F., Acharya, U.R.: Sleepeegnet: Automated sleep stage scoring with sequence to sequence deep learning approach. PloS one 14(5), e0216456(2019)
[3] Phan, H., Ch´en, O.Y., Koch, P., Lu, Z., McLoughlin, I., Mertins, A., De Vos, M.: Towards more accurate automatic sleep staging via deep transfer learning. IEEE Transactions on Biomedical Engineering 68(6), 1787–1798 (2020)
[4] Phan, H., Mikkelsen, K.B., Chen, O., Koch, P., Mertins, A., De Vos, M.: Sleep transformer: Automatic sleep staging with interpretability and uncertainty quantification. IEEE Transactions on Biomedical Engineering (2022)

Database

Public Data Set[5]: 152 patients, continuous sleep signals

- provide EEG and EOG signals during patients' sleeping
- provide sleep stages at each time

Fig. 1 EOG signal in dataset

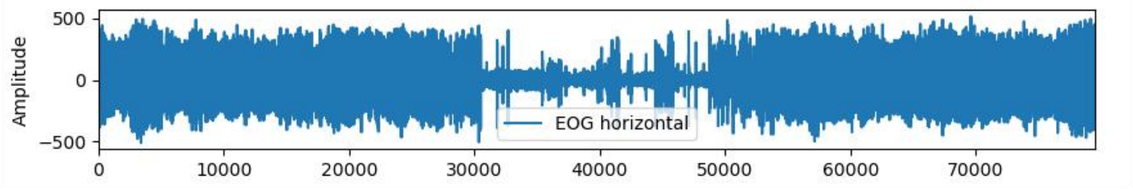
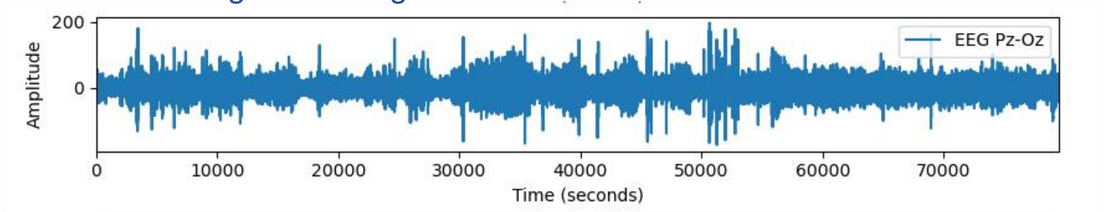
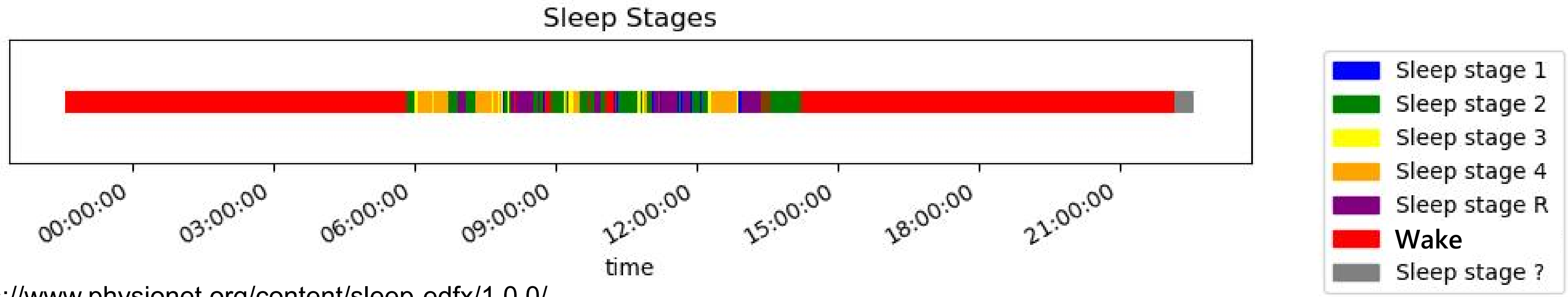


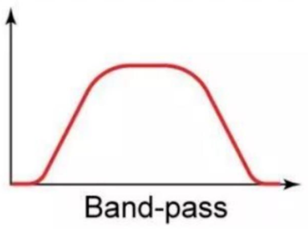
Fig. 2 EEG signal in dataset

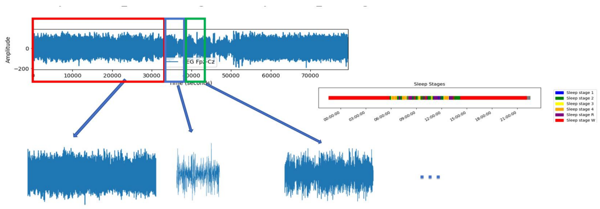




[5] https://www.physionet.org/content/sleep-edfx/1.0.0/

Research Pipeline





Dataset → Preprocessing → Signal-spliting →

Function	EEG	EOG
Time-domain		
std, iqr, skewness, kurtosis	✓	✓
number of zero-crossings	✓	✓
Hjorth mobility, Hjorth complexity	✓	✓
higuch fractal dimension, petrosian fractal dimension	✓	✓
permutation entropy, *binned entropy (4)*	✓	✓
Frequency-domain		
spectral Fourier statistics (4)	✓	✓
binned Fourier entropy (7)	✓	✓
Absolute spectral power in the 0.4-30 Hz band	✓	✓
Relative spectral power in the *applied frequency bands (6)*	✓	✓
EEG Charateristic		
fast delta + theta spectral power	✓	
alpha / theta spectral power	✓	
delta / beta spectral power	✓	
delta / sigma spectral power	✓	
delta / theta spectral power	✓	

Feature Extraction

Method
SVM
Logistic regr.
Catboost
BP Network
CNN

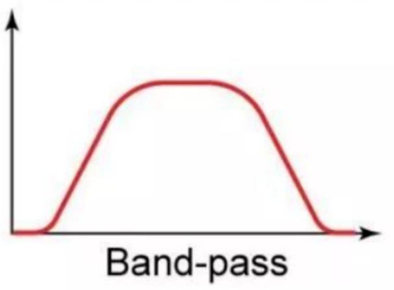
$$F1_{macro} = 2 \cdot \frac{\text{Precision}_{macro} \cdot Recall_{macro}}{\text{Precision}_{macro} + Recall_{macro}}.$$

$$kappa = \frac{p_o - p_e}{1 - p_e}$$

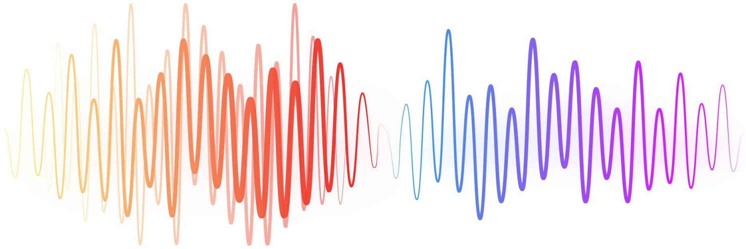
Model Evaluation ← Classification based on ML/DL ←

Preprocessing

0.4~30 Hz



removing artifacts or noise



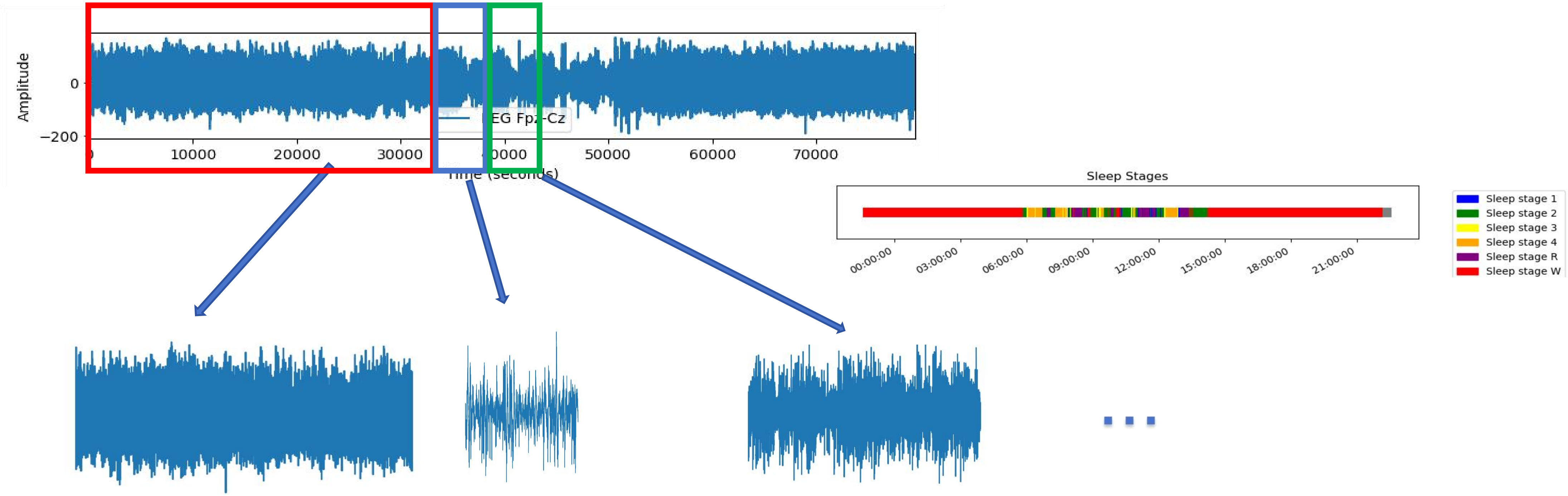
Signal without Noise

0.4~30 Hz: Clinically meaningful frequencies of sleep-wave patterns.[6]

[6] Malhotra, A., Younes, M., Kuna, S.T., Benca, R., Kushida, C.A., Walsh, J.Hanlon, A., Staley, B., Pack, A.I., Pien, G.W.: Performance of an automated polysomnography scoring system versus computer-assisted manual scoring. Sleep 36(4), 573–582 (2013)

Preprocessing

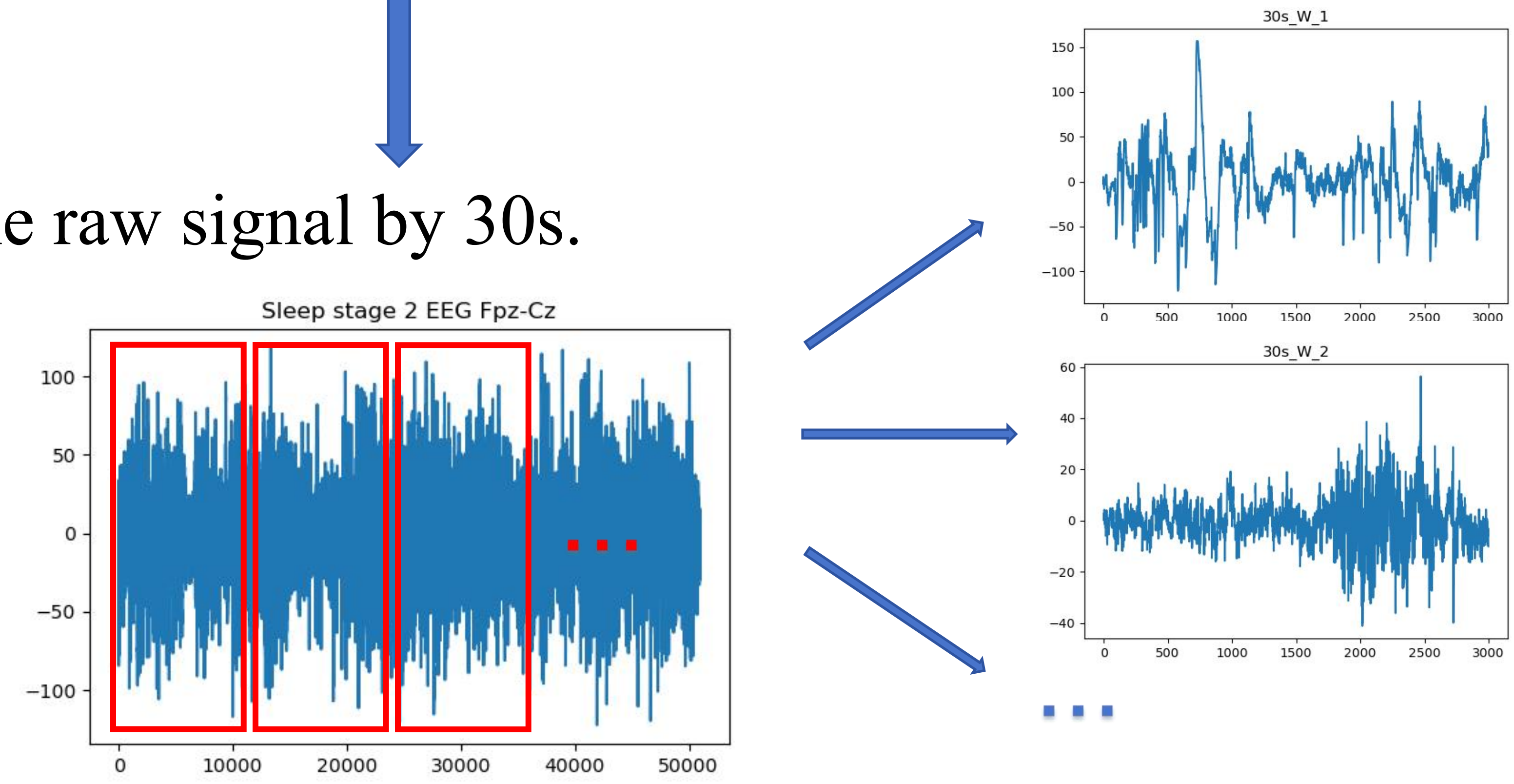
Firstly, we splited signals by sleep stages



signal spliting

We prefer to identify signals with same length

splited the raw signal by 30s.

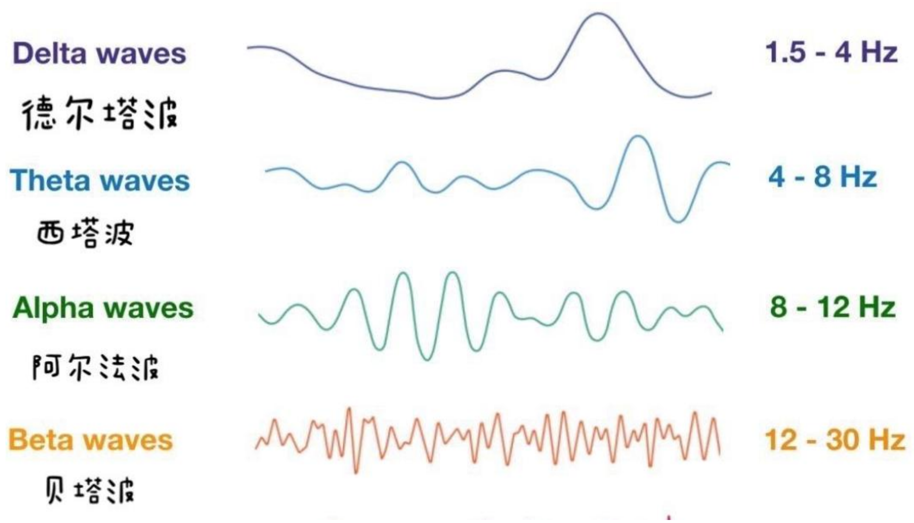


Fs=100 Hz

Feature Extraction

Multi-domain features:

- Time-domain features
- Frequency-domain features
- EEG Charateristic



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std, iqr, skewness, kurtosis	✓	✓
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alpha / theta spectral power	✓	
delta / beta spectral power	✓	
delta / sigma spectral power	✓	
delta / theta spectral power	✓	

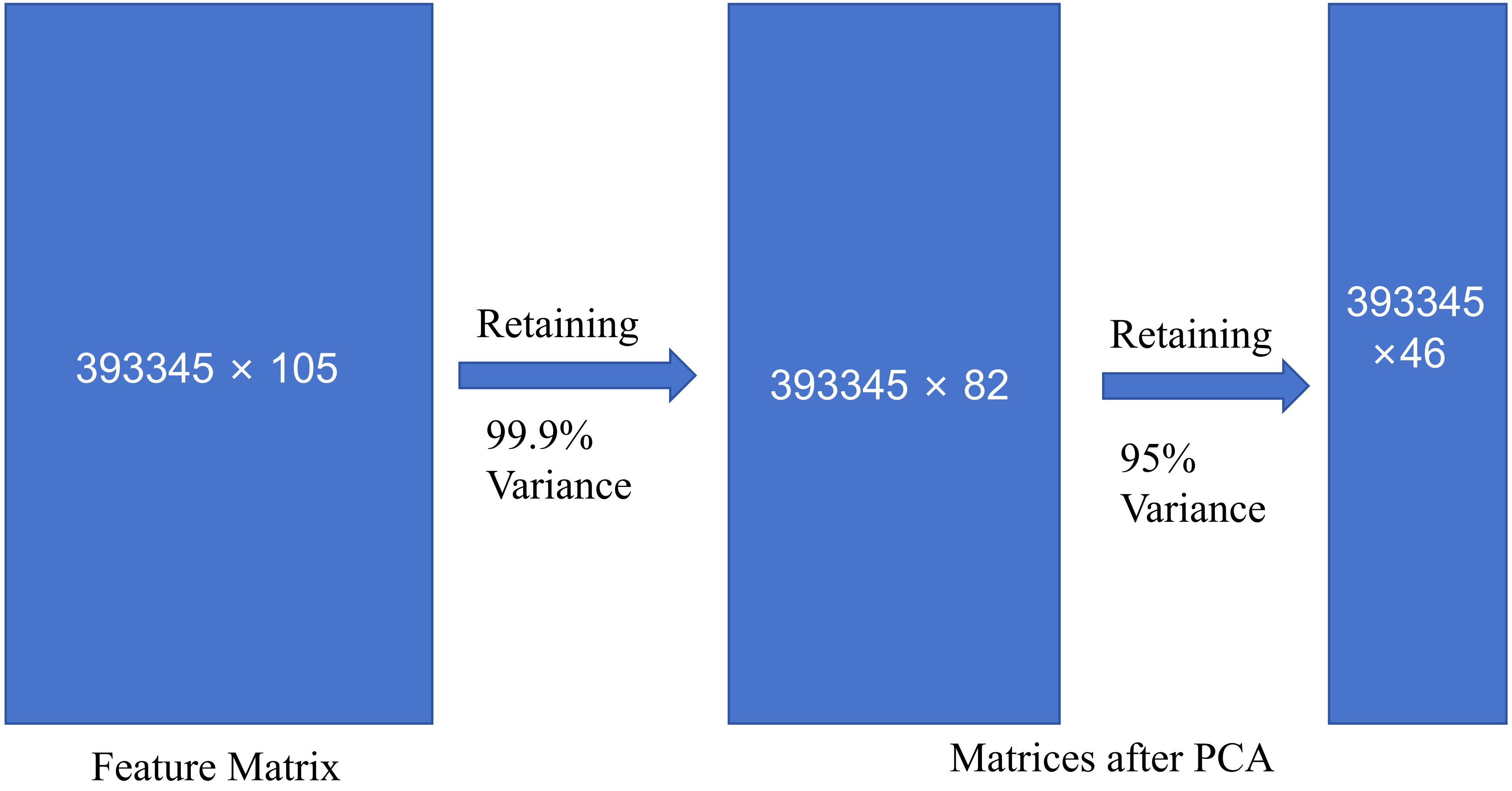
Hjorth Mobility: $\frac{signal's\ standard\ deviation}{first\ derivative's\ standard\ deviation}$

Hjorth Complexity: $\frac{signal's\ mobility}{first\ derivative's\ mobility}$

HFD: a technique for measuring the fractal dimension of a time series, quantifying its complexity and self-similarity by reconstructing it into multiple scales and analyzing the lengths of these scales.

Feature Extraction

We used **PCA** to reduce the dimension:



Classification Model

Based on Machine Learning and Deep Learning:

Method	Accuracy in Paper	Accuracy We Get
SVM	not mentioned	0.78
Logistic regr.	0.863	0.878
Catboost	0.864	Under Construction
BP Network	not mentioned	Under Construction
CNN	0.840	Under Construction

Model Evaluation

- Strategy: Cross-Validation (10-folder validation)
- Metric: ACC, Macro-F1, κ

$$\text{Precision}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FP}_i}.$$

$$\text{Precision}_{macro} = \frac{\sum_{i=1}^{n} \text{Precision}_i}{n}.$$

$$\text{Recall}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FN}_i}.$$

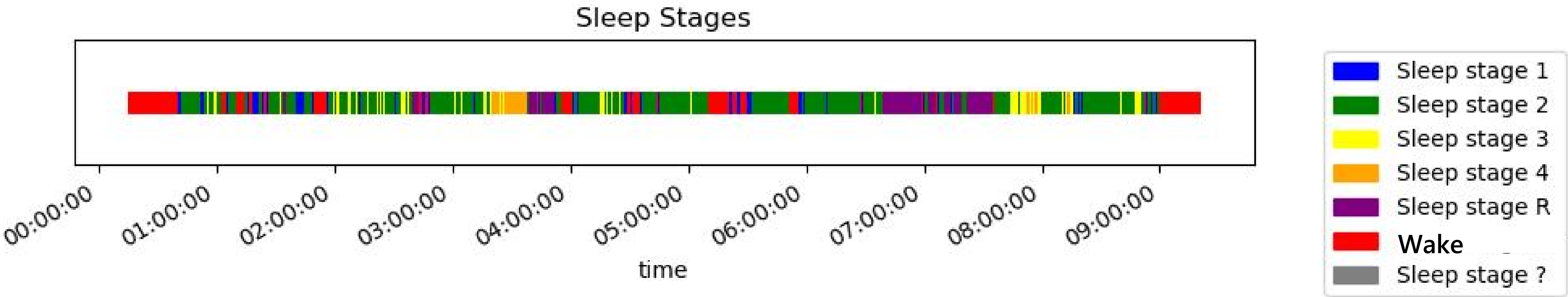
$$\text{Recall}_{macro} = \frac{\sum_{i=1}^{n} \text{Recall}_i}{n}.$$

$$F1_{macro} = 2 \cdot \frac{\text{Precision}_{macro} \cdot Recall_{macro}}{\text{Precision}_{macro} + Recall_{macro}}.$$

$$kappa = \frac{p_o - p_e}{1 - p_e}$$

Improvement and innovation

Consider the characteristic of sleep stages:



Notice that **"Sleep stage 3"** appears more esaily after **"Sleep stage 2"**, while **"Sleep stage 1"** appears more esaily after **"Wake"**...

Probabilistic graphical model or **Markov Model** can be used to help detect sleep stages in continuous sleeping signals.

RNN may be good to solve continuous sleeping signals.