Classification of Sleep Phases with EEG and Accelerometer Data

Challenge Data – Dreem

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Overview

Section 1

Task Presentation

Dataset characteristics

- 31129 training points
- 30458 test points

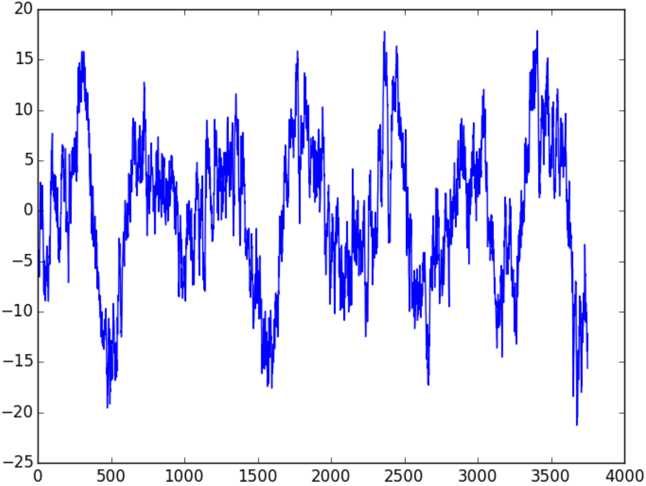
Features:

- 15 seconds of EEG data, 250 Hz, 1 channel $\rightarrow$ 3750 values
- 15 seconds of accelerometer data, 10 Hz, 3 channels $\rightarrow$ 350 values

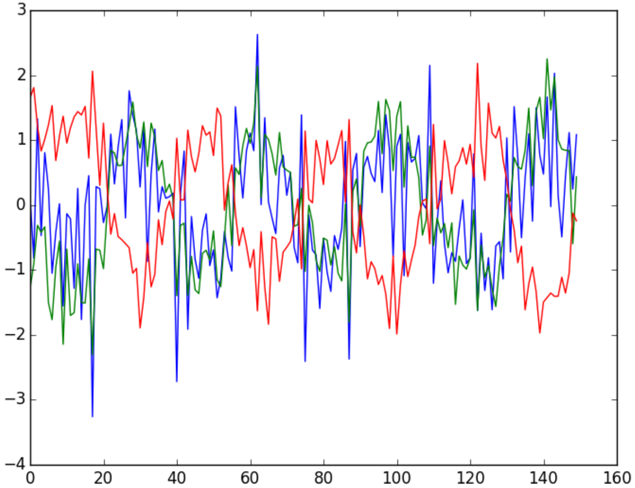
Signal categories

Class	Code	Description	Count
0		Wake	1342
1	N1	Light sleep ("somnolence")	428
2	N2	Intermediate sleep	15334
3	N3	Deep sleep	9640
4	REM	Paradoxical sleep	4385
		Total	31129

Typical EEG signal (REM sleep)



Typical ACC signal (N2 sleep)



Section 2

Feature Extraction

Wavelet transform

We first convolve the signal with a series of Ricker wavelets:

$$\psi_\sigma(t) = \frac{2}{\sqrt{3\sigma}\pi^{\frac{1}{4}}}\left(1 - \frac{t^2}{\sigma^2}\right) e^{\frac{-t^2}{2\sigma^2}}$$

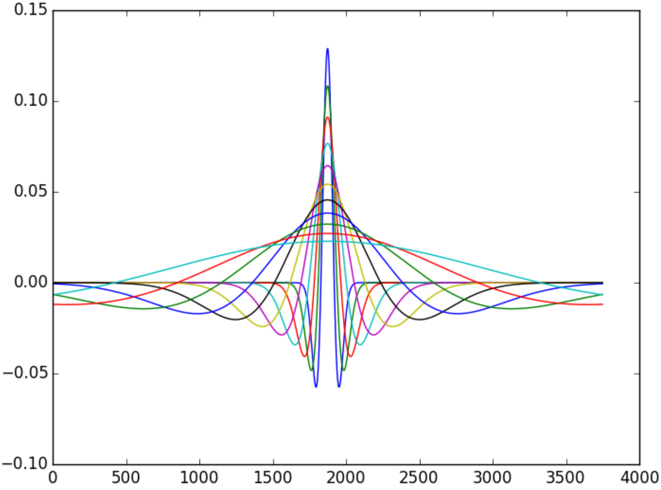
The values of σ are spaced regularly on a logarithmic scale:

$$\sigma_i = 2^i$$

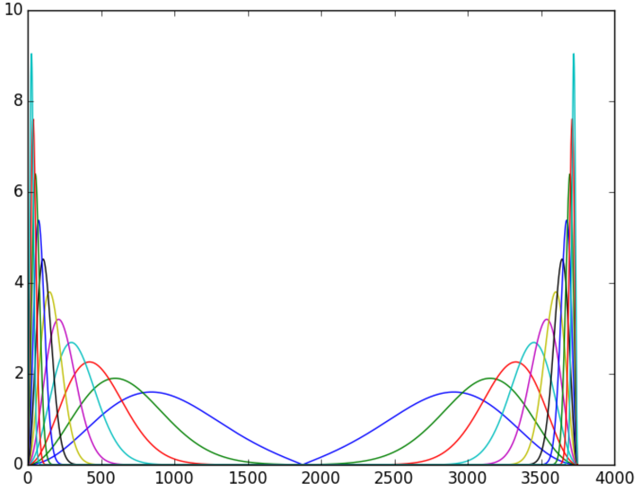
$$\sigma_0 = 1$$

$$\sigma_{10} = 1024$$

Wavelets


0.15
0.10
0.05
0.00
−0.05
−0.10
0
500
1000
1500
2000
2500
3000
3500
4000

Wavelets, in the Fourier domain

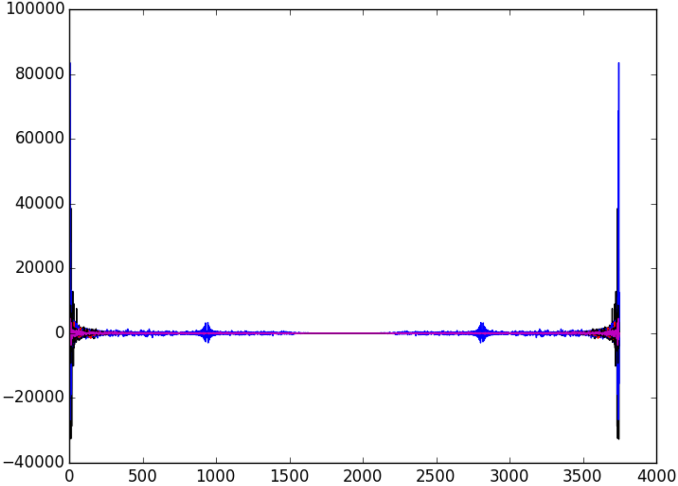


Remarks

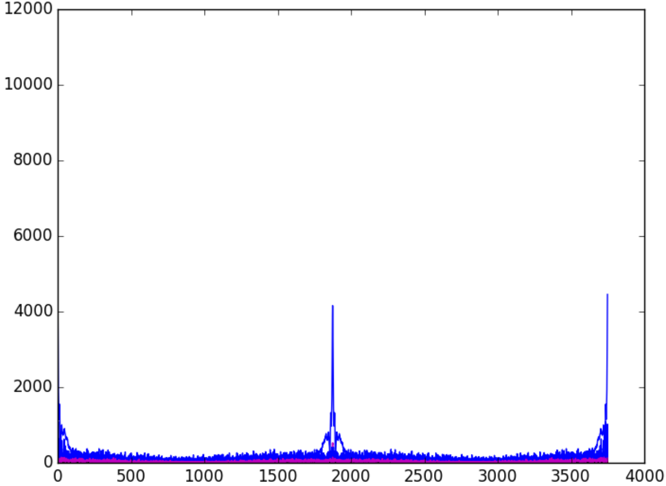
Convolution is equivalent to a multiplication in the Fourier domain, which has several implications:

- convolution can be done very quickly
- we can interpret the convolution by a wavelet as exacerbating certain frequency range while extinguishing others

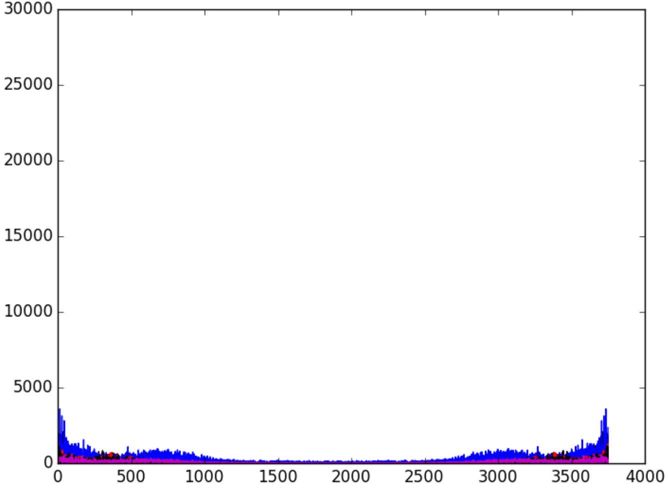
Our signal (EEG), in the Fourier domain



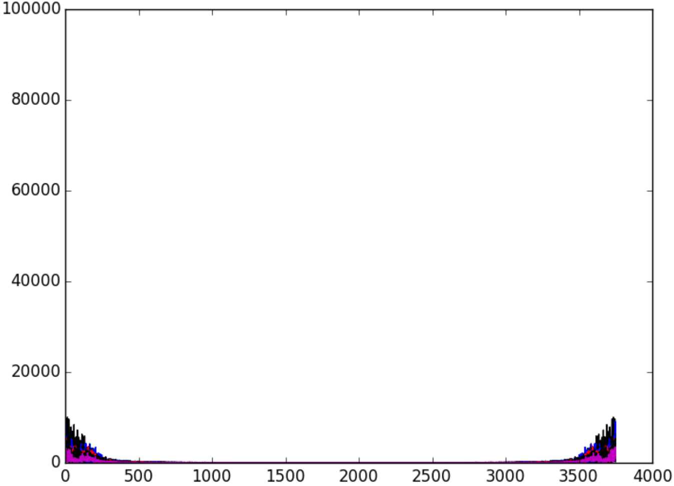
Now, convolved with a high-frequency wavelet ($\sigma = 1$)



With a lower frequency ($\sigma = 4$)



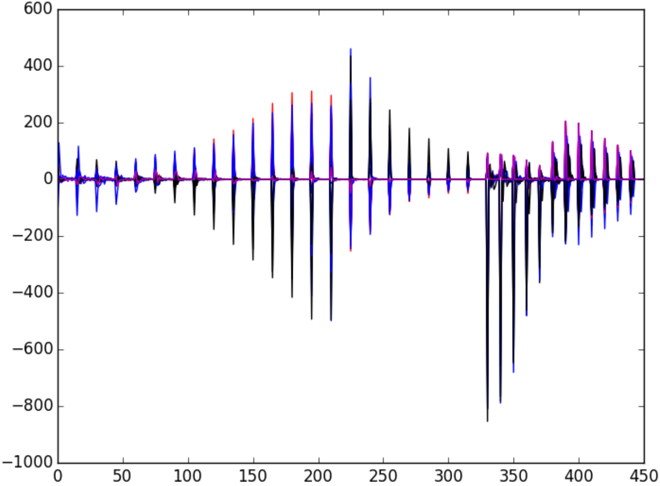
With an even lower frequency ($\sigma = 16$)



Dimensionality reduction

- It is impossible to run a classifier on 11×3750 features for 30000 examples.
- We use a PCA to transform the 3750-dimensional signal into a 15-dimensional signal.
- For the EEG, we end with $15 \times 11 = 165$ features
- Similar processing for the accelerometer data.

Feature vectors



Section 3

Classification Results

Random Forest Classification

- Classification is done with a random forest
- Parallel implementation provided by `scikit-learn`
- Tried using up to 128 trees to improve model performance (more trees improves the performance a little)

Random Forest vs. Linear Classifiers

Random forest classifiers worked much better than linear classifiers on this task:

- Linear classifiers are much slower to train
- The problem is not completely linearly separable in our feature space
- Error rate: 22% (linear classifier) vs. 15% (random forest)

Results

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Challenge data

Introduction | Actual ranking

> *This is the intermediary ranking which evolve during the entire season. We use the public score (the score made by participant on the public data set) to set the ranks.*

Submit a solution

Ranking	Date	User(s)	Algorithm	Public score	Tendance
1	30/01/2016 - 11:18:04	Antoine de Maleprade (Participant) & Alexandre Garcia (Participant)	-	0.896241	⇄
2	10/02/2016 - 12:23:08	Romain Lentgen (Participant) & Bryan D'aversa (Participant)	-	0.869064	⇄
3	23/02/2016 - 13:43:29	Alex Auvolat (Participant)	-	0.864354	⇄
4	05/02/2016 - 18:14:14	bn2nkm (Participant)	-	0.863496	⇄
5	31/01/2016 - 14:48:37	Sofia Calcagno (Participant) & Baptiste Rozière (Participant)	-	0.855556	↓
6	22/02/2016 - 02:40:01	Hugues THOMAS (Participant)	-	0.832282	↓
7	21/02/2016 -	Charles Darmon (Participant) & Marin De Beauchamp	-	0.819467	↓

Remarks

- Tried many variants, validating them on a subset of the training set, for local validation
- Results on the public leaderboard were usually far worse than on the validation set
  $\rightarrow$ overfitting...
- The best score I got on the leaderboard was actually with one of the first variants I tried