Decoding Brain Signals

Microsoft machine learning competition

Ruslan Aydarkhanov, 4th place

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Background

Faculty of bioengineering and bioinformatics

MSc in neurosciences

Minor in computational neurosciences

Doctoral program in neuroscience

Brain-Computer Interfaces

Basic machine learning courses during Masters + self-education

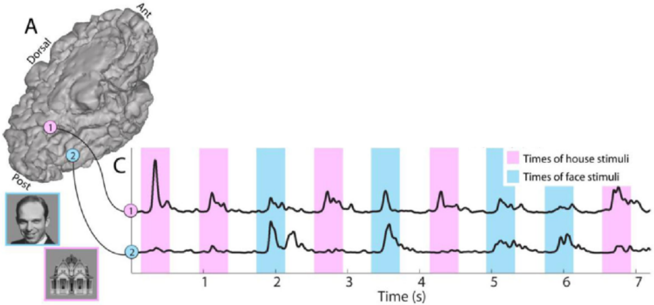
Azure ML platform

No access to testing dataset
Solutions are submitted as Azure ML services and tested remotely
No teams

1. Pure Azure ML
   - Fast development of simple models
   - GUI, drag and drop
   - Not flexible and limited in tools
2. Building models locally
   - Python + all its package zoo
   - Same structure for all projects on Azure ML
   - Outdated scikit-learn v0.15.1 on Azure ML (newest is v0.17.1) -> virtualenv
   - Learning and validation on a laptop

Competition

Decoding Brain Signals



Miller et al, 2014

- Electrocorticogram (ECoG)
- up to 64 channels
- window $\pm$ 400 ms around stimulus presentation onset
- 4 patients
- 200 training samples per patient
  40 samples in public dataset
  60 samples in private dataset
- Performance metric: classification accuracy

Data processing

Basics of EEG/ECoG processing

- Spatial filtering and decomposition
  - ✓ common average reference (CAR)
  - laplacian
  - PCA, ICA, CSP …
- ✓ Band-pass filtering in time
- Frequency band power
  - Power spectral density
  - Signal envelope (hilbert transform)
  - ✓ Wavelet transform

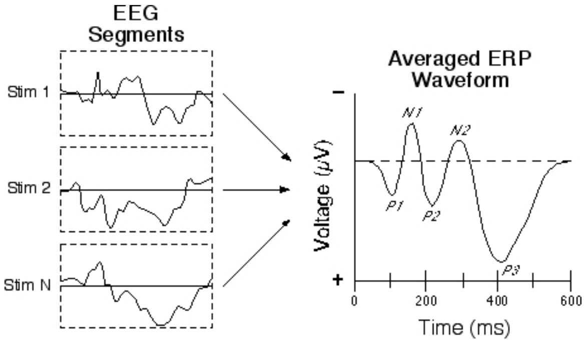
Features

- ✓ Event-related potential (ERP)
- ✓ Wavelet transform
- ✓ Event-related broadband (ERBB)
- ✓ Covariance matrix projected on a Riemannian tangent space

Feature selection

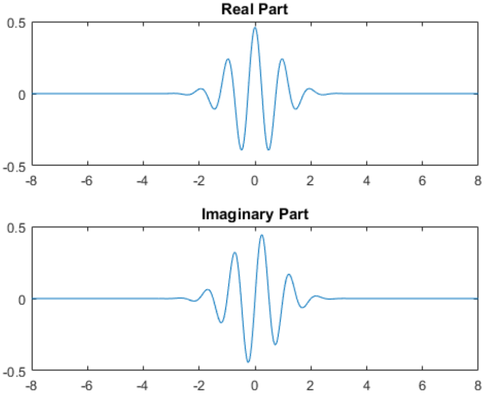
- ✓ ANOVA
- Genetic algorithm

Event-related potential (ERP)



- Bandpass filtering 1-10 Hz
- Window from -50 to 350 ms
- Down-sample by factor of 30

Wavelet transform



Continuous wavelet transform

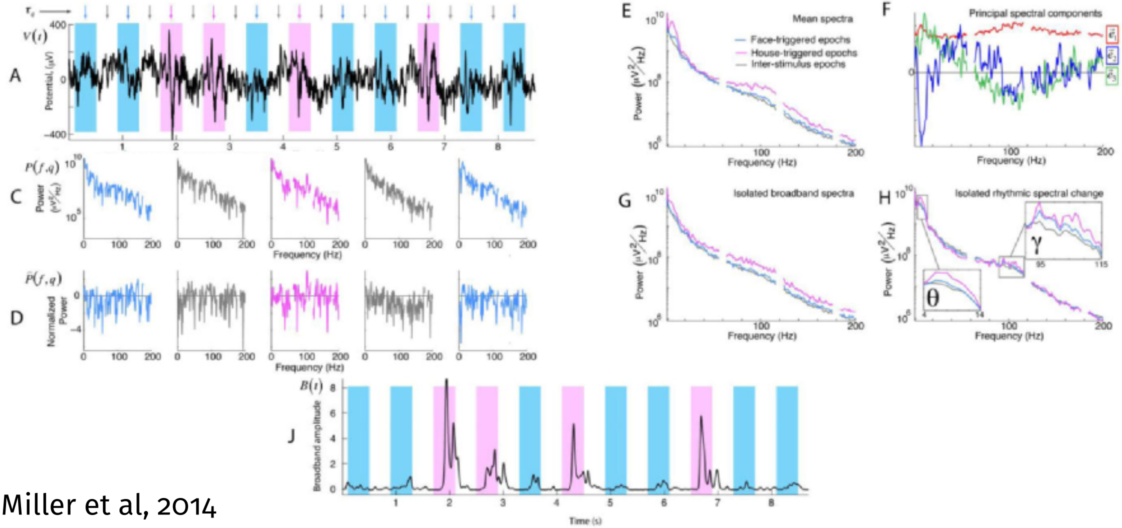
- Complex morlet wavelets for 4-10 Hz

  $$e^{j*w*x} * e^{-x^2/2}$$

- Convolution + absolute value -> Instant frequency power estimation
- Window from -50 to 350 ms
- Down-sample by factor of 30

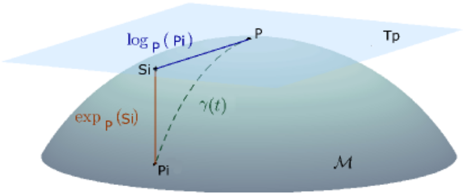
Python library for EEG: MNE

Event-related broadband (ERBB)



Miller et al, 2014

Riemannian projection



- Compute covariance matrices with shrinkage from raw data
- Pick up the projection reference point
- Project on a tangent space

Python library: pyRiemann

Developed by the winner Alexandre Barachant

Originally for neural data, but can be applied to any set of semi-positive definite (SPD) matrices, e.g. covariance matrices

Classifiers

Simple classifiers:

- Arbitrary combination of features
- Individual classifiers for patients
- Logistic regression with patient-specific L1 penalty (grid search)
- Stratified 5-fold cross-validation

Ensemble:

- Weighted average of 8 best first-layer classifiers
- Stacked classifier
  - Input is 5-fold out-of-sample predictions
  - SVM with CV Grid Search of parameters
  - No validation

Intermediate progress

- Local cross-validation correlated well with leaderboard
- Leader position for 1 month with one ERP model (score 81)
- Adding more features, learning multiple models
- Averaging and stacking
- Small testing set (4 x 40) -> struggle for each sample in the end
- Both private and public scores are very noisy

Results

Name	Highest Public Score	Highest Private Score	Final Ranking
Alexandre Barachant	**90.625**	93.75	1
KyuHwa Lee	**88.75**	92.5	2
Jean-Remi King	86.25	88.3333	3
Ruslan Aydarkhanov	**89.375**	88.3333	4
Marouane FELJA	82.5	84.1667	5
Igor Inozemtsev	81.875	84.1667	6
lmzintgraf	**89.375**	82.9167	7
Pablo Seibelt	81.25	82.5	8
Carlos Aranda Torres	81.875	82.5	9
Bruce Cragin	77.5	82.0833	10

My solution: https://github.com/Aydarkhan/decoding_brain_signals_MS

Leaders' solutions

- Alexandre Barachant, 1st place
  - Average of 5 models of L2-penalized logistic regression
  - ERP, Riemannian projection
  - **Covariance matrices in frequency domain** projected on tanget space, averaging models across frequency bins
  - **Cross-covariance matrices** (covariance of Hankel matrices)
- Kyuhwa Lee, 2nd place
  - Average of 2 models of **Gradient Boosting Machine**
  - PSD with multitaper on 2 windows 0-300ms and 100-400ms
  - Instant band power with Hilbert transform in low band < 10 Hz and high band 10-70 Hz
- Jean-Remi King, 3rd place
  - **Bagging** of 5 models of logistic regression
  - ERP, Riemannian projection
  - PSD and time-frequency features

Lessons and take home messages

- Competitive spirit boosts your efficiency
- Tried many things in short time

- Write good code from the beginning
- Feature engineering is crucial -> check the literature (especially with small and high-dimensional datasets)
- For brain data take into account
  - time - channel
  - spectral characteristics
  - interaction between channels
- Ensemble methods are powerful

Thank you for your attention!

Questions