Midterm Project [ROBT613]

Fall Semester, 2020

This project aims to provide you a hands-on experience to apply machine learning algorithms to Event-Related Potential (EEG) data acquired from healthy subjects.

In a supervised learning framework, given $X := \{x_1, ..., x_m\}$ with corresponding labels $Y := \{y_1, ..., y_m\}$, where $y \in \pm 1$ for $i = 1, ..., m$. We seek to infer a function $g : X \to \{\pm 1\}$ to predict accurately whether a new observation belongs to class $+1$ or -1.

In general, the g - could be any learning machine (linear regression, logistic regression, support-vector machines, or neural networks) defined on any learning problem (supervised, semi-supervised, unsupervised.

This project, is a chance to you and your team to design a novel learning model to improve BCI/BMI system performance on ERP data (i.e. to come up with a new angle on an old problem). Successful implementation on benchmark datasets has a potential to become a fully-fledged research papers. As, everyone of you can go way above and beyond the state-of-the-art methods.

Important Dates:

- Announced date: October, 16, 2020
- Final Report Date: October, 30, 2020

Method of Delivery

Assignment deliverables should be submitted via Moodle to the course instructor before the due date.

Deliverables:

1. Report describing in detail the work of a team with the following sections (use the ieee-latex-conference-template; - length 4-6 pages long):

- Abstract
- Introduction
- Materials and Methods
- Results
- Conclusion
- References
- Contribution (what and how each member contributed to the project)

1. Source Codes in Jupyter Notebooks (well documented which include the descriptions of all code cells)

2. Video presentation explaining the work

Level of Collaboration Allowed

- Up to Two students can form a team in this project. Discussions on course materials and implementation of the project are encouraged.
- Each team should write the final solutions/reports separately and understand them fully. External resources can be consulted, but not copied from.
- You are expected to discuss and learn together (on your own) how to use a specific machine learning tool. There's bunch of tutorials both with videos, texts and other materials

Grading Criteria

- 35% - Implementation (a well documented Jupyter Notebook)
- 10% - The accuracy of the best model that has been selected after cross-validation for ERP classification
- 20% - Overall work and report quality
- 20% - Discussion (for example of success/failure; limitations, etc.)
- 15% - A video presentation of the entire workflow using a free screen capture software. The presentation should explain each code and summarize the work, in detail. Note your face does not have to appear in the presentation. You can only record your screen. The duration of your presentation should be 20 - 30 minutes.

Machine learning tools:

Since implementation of standard algorithms from scratch may take up significant amount of time, in this project, you are encouraged to use available machine learning tools/libraries and concentrate on model selection problem by applying an algorithm of your interest for a real-world problem. However,there is no restriction posed if you can manage your time and want to implement a novel algorithm from scratch.

Although there are so many machine learning libraries implemented in different languages, this task is based on the scikit-learn machine learning library to achieve your project goals.

Project Tasks:

Perform model selection (machine learning) to estimate the model with optimal hyperparameters. Different learning machines exist in the scikit-learn machine learning library such as linear models, neural networks, trees, or kernel methods etc. You are expected to adapt and apply an algorithm of your interest, and compare with other algorithms available in the scikit-learn. One of your goal is to try to outperform other standard algorithms/methods in terms of a generalization performance. Suppose you chose a neural network model, then your task would be to perform model selection and compare the algorithm with a support-vector machines, logistic regression and other algorithms/methods.

The following steps summarize the important steps in your project:

1. Consider an ERP data D
2. Apply an algorithm of your choice on D
3. Estimate its generalization error E_{test}
4. if generalization error is smaller than what exists in the literature for the same dataset:

- `End of the process: Outcome -> Grade A`

1. Else

- Go back to step 2 with another algorithm or change the learning strategy.

Specific Tasks

- Review the lecture Hyperparameters and Model Validation and write your own machine learning pipeline. Also, refer to the examples in the Hands-on data analysis session - Jupyter notebook tutorial and report best generalization performance.

- You should try to include some of the feature selection algorithms that are available in the scikit learn library (http://scikit-learn.org/stable/modules /featureselection.html). Read the following paper to learn more about the types of feature extraction methods that canbe used.

  - Lotte, Fabien, et al. "A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update." Journal of neural engineering 15.3 (2018): 031005.

Datasets

Most datasets for your project are available via MOABB toolbox (https://github .com/NeuroTechX/moabb). However, I have already downloaded and converted all ERP data into MNE format for easier processing and visualization.

You can download them and save in the local directory where the source codes will ba available.

https://drive.google.com/drive/folders/1d4wo-TjSjENMh-iH-BV9RmhpVr2 nP2Pu?usp=sharing

- NU data (data_allsubjects.pickle):
- ALS data (ALSdata.pickle):
- EPFL data (EPFLP300.pickle):
- BNCI data (BNCI2015003.pickle):

Loading the datasets

You can use the following function to load the data.

Make sure you install MNE version 0.18

```
pip install mne==0.18
```

```
def loaddata(filename):
    with open(filename, 'rb') as handle:
        data = pickle.load(handle)
    return data

---
import pickle

filename = 'NU data'
data = loaddata(filename)
```

Here, the loaded **data** will be MNE object that you are already familiar with, from which you can extract the numpy array, and convert it to sklearn acceptable 2D array.

Load the data

```python
import pickle
import mne

def loaddata(filename):
    with open(filename, 'rb') as handle:
        data = pickle.load(handle)
    return data
```

You can load these datasets from the shared google drive folder

- NU data (data_allsubjects.pickle):
- ALS data (ALSdata.pickle):
- BNCI data (BNCI2015003.pickle):
- EPFL data (EPFLP300.pickle)

```python
# load the file
filename = 'BNCI2015003.pickle'
data = loaddata(filename)

# the data is a list containing subject specific MNE data objects
print("Total number of subjects in the data:", len(data))
```

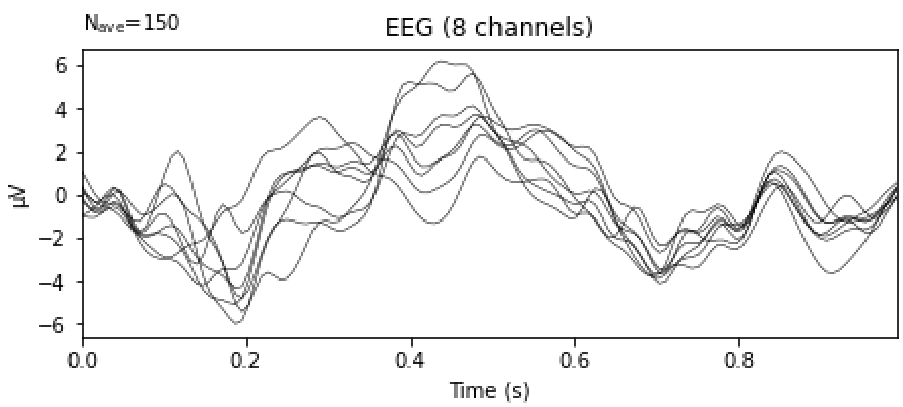
```
Total number of subjects in the data: 10
```

```python
subject = 0
data[subject]
```

```
# %%
s1 = data[0]
s1.info
```

```
<Info | 8 non-empty values
 bads: []
 ch_names: Fz, Cz, P3, Pz, P4, PO7, Oz, PO8
 chs: 8 EEG
 custom_ref_applied: False
 dig: 11 items (3 Cardinal, 8 EEG)
 highpass: 1.0 Hz
 lowpass: 24.0 Hz
 meas_date: unspecified
 nchan: 8
 projs: []
 sfreq: 128.0 Hz
>
```

```
s1['Target'].average().plot();
```



Classification using sklearn example

You can use the following example to get started

```
from sklearn.svm import LinearSVC
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
```

```
epochs = s1
```

```
epochs
```

```
<Epochs  |   1728 events (all good), 0 - 0.601562 sec, baseline off, ~16.5 MB, data loaded,
 'NonTarget': 1440
 'Target': 288>
```

```
epochs.pick_types(eeg=True)
X = epochs.get_data()  # features
y = epochs.events[:, -1] # labels
X.shape, y.shape
```

```
((1728, 16, 78), (1728,))
```

Vectorizer()

Transform n-dimensional array into 2D array of n_samples by n_features.

This class reshapes an n-dimensional array into an n_samples * n_features array, usable by the estimators and transformers of scikit-learn.

```
from mne.decoding import Vectorizer
clf = make_pipeline(Vectorizer(), StandardScaler(),
                    LogisticRegression(solver='lbfgs'))
```

```
clf.fit(X, y)
```

```
Pipeline(steps=[('vectorizer',
                 <mne.decoding.transformer.Vectorizer object at 0x000001B8B1A39280>),
                ('standardscaler', StandardScaler()),
                ('logisticregression', LogisticRegression())])
```

```
clf.predict(X[:9])
```

```
array([1, 1, 2, 1, 1, 1, 1, 1, 1], dtype=int64)
```

```
cross_val_score(clf, X, y, cv = 5)
```

```
array([0.88728324, 0.89017341, 0.91907514, 0.91304348, 0.87246377])
```

References:

1. Lectures 7, 8, 9, 10, 11
2. H. Cecotti and A. J. Ries, "Best practice for single-trial detection of event-related potentials: Application to brain-computer interfaces," Int. J. Psychophysiol., vol. 111, pp. 156–169, 2017
3. F. Lotte et al., "A review of classification algorithms for EEG-based brain–computer interfaces," J. Neural Eng., vol. 4, pp. R1–R13 Jun. 2007.
4. F. Lotte et al., "A review of classification algorithms for EEG-based brain–computer interfaces: A 10 year update," J. Neural Eng., vol. 15, no. 3, 2018, Art. no. 031005.

5. Abibullaev B, Zollanvari A. Learning discriminative spatiospectral features of ERPs for accurate brain–computer interfaces. IEEE journal of biomedical and health informatics. 2019 Jan 16;23(5):2009-20.