EEG-to-fMRI Neuroimaging Cross Modal Synthesis in Python

David Calhas

Abstract—Electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) are two ways of recording brain activity; the former provides good time resolution but poor spatial resolution, while the converse is true for the latter. Recently, deep neural network models have been developed that can synthesize fMRI activity from EEG signals, and vice versa. Because these generative models simulate data, they make it easier for neuroscientists to test ideas about how EEG and fMRI signals relate to each other, and what both signals tell us about how the brain controls behavior. To make it easier for researchers to access these models, and to standardize how they are used, we developed a Python package, EEG-to-fMRI, which provides cross modal neuroimaging synthesis functionalities. This is the first open source software enabling neuroimaging synthesis. Our main focus is for this package to help neuroscience, machine learning, and health care communities. This study gives an in-depth description of this package, along with the theoretical foundations and respective results.

Index Terms—Electroencephalography, Functional Magnetic Resonance Imaging, Synthesis, Deep Learning, Learning, Machine Learning, Computer Vision

Introduction
Neuronal activity, usually measured through electroencephalography (EEG), is related to haemodynamical activity, measured through functional magnetic resonance imaging (fMRI). The first captures the dynamics of the electrical field, whose source is located from the firing neurons’ action potentials. In its turn, the second measures the blood supply dynamics. These two while being studied simultaneously [1], [2], [3], [4], [5], [6], [7], [8] differ in many aspects such as: temporal and spatial resolution, brain functions captured, recording and hardware cost. Recently we have seen several studies that use deep neural network models [9] to learn a mapping from EEG data to and from fMRI data [10], [11]. These are a type of generative models [12], that sample/synthesize instances from a different data source (instead of a distribution). Such a model could allow health care cost reductions and discoveries of new neuroscience insights on the relationship between these two modalities. Indeed, pathologies that require MRI scans diagnostics benefit from a lower cost EEG assessment, since availability of MRI hardware is very scarce [13]. As Python [14] becomes a hub for scientific development [15], [16], [17] we find the need to provide open source software that provides solutions for EEG to fMRI synthesis, urgent, in order for third party scientific contributions coming from other laboratories to coexist and health care software integration to develop for diagnostic settings. To that end, we provide a description of the open source software EEG-to-fMRI, which originated from an academic scientific project funded by Fundação para a Ciência e Tecnologia, and make publicly available a github repository.

Methods
The mapping function provided in this software is the one proposed by [11]. It consists on transforming the EEG from a channel by time representation to a channel by time-frequency one; achieved using the short time Fourier transform (scipy.fft.fft) available in the SciPy package. The latter corresponds to the second step of the diagram illustrated in Figure 1. In the second step, this representation is then forward through a deep neural network (implemented as a tf.keras.Model), with contributions ranging from Resnet blocks [19], an automated machine learning framework [20] and Fourier features [21]. Ultimately, this enables the prediction of an fMRI volume associated with a 26 second segment of an EEG recording.

Description
The dependencies of each component are described in an UML diagram. Overall to install the package, the user is required to install the following dependencies: tensorflow 2.9.0, matplotlib 3.5.3, mne 0.23.4, nilearn 0.7.0, tensorflow_probability 0.12.2, tensorflow_determinism 0.3.0, and tensorflow_addons 0.19.0. As seen there is a high dependency in tensorflow related packages. This is due to the whole system provided being built in tensorflow, a library that enables automatic differentiation and is widely used for deep learning model development.

Package modules
This package, as it is provided, has eight main modules:

- models: here you will find the code that implements the models for synthesis and classification. The synthesis models are located in the synthesizers.py, where the class EEG_to_fMRI is implemented. This class defines a tf.keras.Model, composed of two encoders, one for the EEG and another for the fMRI. Additionally, there is
The pipeline of the EEG to fMRI synthesis project consists of processing EEG recordings, that are sourced from a human subject that goes through an EEG recording session, then processing the channel by time signal and taking the short time Fourier transform. The latter, gives us the time frequency representation of the EEG signal. The novelty of this software is that it provides a model that given as input the EEG signal it predicts the corresponding fMRI volume associated with that segment. A video demonstration of the whole pipeline is available on Youtube.
New data integration
In order to use the software provided for new data, we recommend that the dataset is structured as shown in Figure 3. If the data is provided as illustrated then the user only has to name the directory of the data as 01. This should suffice for the correct loading of the data. Any type of issue that is encountered for this package should be published as an issue in the official github repository.

Building an EEG to fMRI model
For the user to build an EEG to fMRI model, they have to first import the correct library module and tensorflow.

```python
from tensorflow as tf
from eeg_to_fmri.models.synthesizers import parameters
from eeg_to_fmri.models.synthesizers import na_specification_eeg
from eeg_to_fmri.models.fmri_ae import na_specification_fmri

Let us define the size of the EEG representation $\vec{x} \in \mathbb{R}^{64 \times 134 \times 10 \times 1}$, the fMRI representation $\vec{y} \in \mathbb{R}^{64 \times 64 \times 30 \times 1}$, and the latent representation, for both the EEG and fMRI, that is $\vec{z}_x, \vec{z}_y \in \mathbb{R}^{7 \times 7 \times 7}$.

```python
fmri_dim=(64,64,30,1)
l_latent_dim=(7,7,7)
```  
Then, we have to define the parameters for the model, these are provided as a variable in the synthesizers.py.

```python
learning_rate, weight_decay, kernel_size, stride_size, batch_size, latent_dimension, n_channels, max_pool, batch_norm,
skip_connections, dropout,
n_stacks, outfilter, local=True, parameters,
```

Some of these parameters will also be used to define the fMRI encoder. Since the fMRI encoder is a different class, we need to define the initialization parameters.

```python
fmri_parameters=(parameters, latent_dim, fmri_dim, kernel_size, stride_size, n_channels, max_pool, batch_norm,
weight_decay, skip_connections, dropout,
n_stacks, outfilter, local=True, parameters,
```

Next, we have all of the parameters necessary to build a simple deterministic version of the EEG to fMRI model.

```python
with tf.device('/CPU:0'):
    model = EEG_to_fmri(latent_dim, eeg_dim,
                        na_specification_eeg, n_channels,
                        weight_decay=weight_decay,
                        skip_connections=True, batch_norm=True,
                        fourier_features=True, random_fourier=True,
                        topographical_attention=True,
                        conditional_attention_style=True,
                        conditional_attention_style_prior=False,
                        local=True, seed=None,
                        fmri_args=fmri_parameters)
```
The model is built once it is specified the input dimension, this is done through the `tf.keras.Layer#build`. This will initialize all of the weights of the network.

```
model.build((None,) + eeg_dim, (None,) + fmri_dim)
```

**Cost function and optimization**

Regarding the cost function, which is provided in the `losses.py` file, we can specify different metrics that are provided. Take, for instance, the example of using an approximation of the mean absolute error at the output for the fMRI volume prediction \( \hat{y} \), and approximation of the latent representations of the fMRI as proposed by [11]. This is reduced to the mathematical formula

\[
\mathcal{L}(\hat{x}, y, \hat{z}, z_r) = \|\hat{y} - y\|_1 + 1 - \frac{\hat{z}_r \cdot \hat{z}_r}{||\hat{z}_r||_2^2 ||z_r||_2^2},
\]

(1)

In terms of code, this is already implemented and can be loaded directly.

```
from eeg_to_fmri.learning import losses
loss_fn=losses.mae_cosine
```

The optimizer is already provided in the `tensorflow` library and its corresponding learning rate is given in the parameters variable.

```
optimizer=
tf.keras.optimizers.Adam(learning_rate)
```

Training the model requires an input, the EEG \( \hat{x} \), and an output, the fMRI \( \hat{y} \). The architecture processes both the EEG and fMRI, producing the latent representation for both. Proceeding the latent EEG representation, \( \hat{z}_r \), is fed to the decoder which estimates the fMRI \( \hat{y} \).

```
def apply_gradient(model, optimizer, loss_fn, x, y, return_logits=False, call_fn=None):
    with tf.GradientTape(persistent=True) as tape:
        logits=model(x, y, training=True)
        if len(model.losses):
            regularization=tape.gradient(tf.math.add_n(model.losses),
                model.trainable_variables)
            optimizer.apply_gradients(zip(gradients,
                model.trainable_variables))
        loss=loss_fn(y, logits)+regularization
    if return_logits:
        return tf.reduce_mean(loss)
    return self.decoder(x)
```

The training routine functions are found in the `learning` module. The function `apply_gradient` computes the forward and backward pass of the neural network. Note that the input of the `EEG_to_fMRI` model is composed of two tensors, the EEG and fMRI, which is the reason why one gives the model both \( x \) and \( y \).

The loss computes both the estimation of the fMRI according to the ground truth. The first element of the list is the estimated fMRI volume and the second and third items are the latent EEG and fMRI representations, respectively.

```
def mae_cosine(y_true, y_pred):
    return tf.reduce_mean(tf.math.abs(y_true - y_pred))
```

At test time, the `EEG_to_fMRI` model can discard the fMRI input. To that end, only the decoder attribute is called, which is composed of the EEG encoder and the decoder.

```
def call(self, x1, x2):
    if self.training:
        return [self.decoder(x1),
                self.eeg_encoder(x1),
                self.fmri_encoder(x2)]
```

Note that, the `pretrained_EEG_to_fMRI` class processes a pre-trained model of the type `EEG_to_fMRI` and builds a new model that only processes EEG and outputs an fMRI prediction given the representation learned. This class is built to be then appended with a classifier, that can be either a `ViewLatentContrastiveClassifier` or a `ViewLatentLikelihoodClassifier`.

**Examples**

In this section, we walk through the examples given in jupyter notebooks.

**Synthesis**

We provide a compressed version of the dataset of [25]. Users can directly execute the code and have both the python package, as well as the dataset, setup in a google colab environment. The flow of execution has been already described. In the end a synthesized fMRI is shown, as illustrated in Figure 2. This image is built using the `viz_utils.py`. The user can find metrics for synthesis evaluation in `eeg_to_fmri.metrics.quantitative_metrics`. We report results from [11] study on the NODDI dataset [25]. An example with a reduced dataset is available in this `synthesis` notebook. The best model, which used the configuration of the `eeg_to_fmri.models.synthesizers.EEG_to_fMRI` achieved 0.3972 RMSE and 0.4613 SSIM. This constitutes the state-of-the-art for this task and provides a view that can be applied in EEG only datasets for classification task.

**Classification**

We also provide a compressed version of the dataset of [26]. This example, available in this `classification` notebook, is based on a publicly available dataset that contains individuals diagnosed with schizophrenia and healthy controls. The whole goal of the project is to be applied in an health care setting and to this end we employ an end to end software solution. The whole software package is able to synthesize fMRI and adapt to a classification setting, that given EEG recordings outputs a set of probabilities for each group of people considered in the dataset.

**Collaboration**

Ultimately, the goal of this package is to collect, in one package, methods for EEG to fMRI synthesis. We welcome contributions from authors of related work such as [10]. In the future, we plan to add a module or example folder with implementations of these approaches, so that other research groups can easily access them and reproduce key results.

On a higher level, this software is encouraged for testing its applicability in health care settings. The impact, that such mappings from EEG to fMRI, would have on society is enormous, given that
the diagnostic is faithful. Take for instance the example of the MRI machine density across the African continent. In the worst case scenario, Nigeria has a density of 0.33 MRI machines per million people, according to [13]. To let that sink in, imagine having to wait in a line of 3 million people to get a diagnostic exam. This type of waiting bottleneck impacts greatly the development of diseases for the worse. Countries in such conditions would greatly benefit from contributions that further advance this scientific field. Even fortunate countries, whose economy thrives, that are able to provide their populations with a good ratio of MRI machines, they still have small portions of the population who live in remote areas. These people find it hard to get quality health care, without having to travel significant distances.

Conclusion

This is the first package, to the best of our knowledge, that provides a machine learning oriented synthesis between functional neuroimaging modalities (EEG and fMRI). It is targeted to help the neuroscience community, in tasks such as modality augmentation, resolution enhancement, neuroimaging explainability techniques, among others. We hope to motivate researchers, scientists, and software developers to contribute to this package which we have been so passionate about throughout the last years.

Acknowledgments

This work was supported by national funds through Fundação para a Ciência e Tecnologia under the PhD Grant SFRH/BD/5762/2020 to David Calhas.

REFERENCES


