Today's objectives:
1. Comfortable with discussing ideas in the group and sharing your opinion about what might be interesting to explore.
2. What kind of broad questions are you interested in?
3. This is also a space to collect resources and literature for your ideas.

Conceptual questions can be as simple as asking "if a neuron's spiking depends upon spiking of neurons in adjacent areas, and if this dependence is related to anatomical distance or morphological similarity between the neurons". Later you may also expand this question to probe broader themes.

Conceptual questions based on EEG: Example, "Question: We want to understand idiosyncrasies in how the brain activity maps to motor movements (e.g. hand movement). Hypothesis: we train an RNN to map EEG/ECoG activity to motor movements in each subject and analyze subject specific components of this transformation in our models. We predict…"

Key Concepts
Sequential Data: Neural recordings often consist of time series data where the activity of neurons is recorded over time. This temporal aspect is crucial for understanding how neural states evolve.
State Space Models: These models represent the neural activity in a low-dimensional state space, capturing the dynamics of neural populations over time.
Latent Variables: These are unobserved variables that can explain the observed high-dimensional neural activity. The goal is to infer these latent variables that evolve according to some dynamic rules.

BCI
Questions
How activity in motor areas relates to the motor imagery of four specific body movements and how that information is encoded in such activity?

Hypothesis: motor region's activity for basic body movements are similar between subjects, so we could train the RNN with the data of eight subjects and try to predict the labels of the last subject's data.

Ingredients:

- NN output:
    - left hand (class 1)
    - right hand (class 2)
    - both feet (class 3)
    - tongue (class 4)

- Inputs:
    - 22 EEG channels
    - 3 EOG channels

Datasets
https://www.bbci.de/competition/download/competition_iv/BCICIV_2a_gdf.zip
https://www.bbci.de/competition/iv/desc_2a.pdf

Slides:
Magnificent_Lupin(GroupB)

Kaggle Datasets
Search | Kaggle

Literature:

Task representations in neural networks trained to perform many cognitive tasks | Nature Neuroscience

Which kind of model is better at dealing with time series data?

Colab code:
RNN_BCI.ipynb
Magnificent Loupine Group B.ipynb

Discussion:
1. **Plotting raw data - all the variables (subset)**
2. "Event related potential": Seeing the average EEG time series but on a subset of trials, such as when there was hand, foot movement involved etc. What is the average activity when there is a hand movement?

Resources:

https://github.com/Jiaheng-Wang/IFNet
https://mne.tools/stable/auto_examples/preprocessing/eog_regression.html
https://www.youtube.com/watch?v=Y7s_-qdrAQo
https://braindecode.org/stable/auto_examples/model_building/plot_bcic_iv_2a_moabb_cropped.html

Recurrent Neural Network Tutorial (RNN) | DataCamp

July 16th

1. Preprocessing data (link)
2. Experimental paradigm (link)
3. Example (no_error)Magnificent_Lupin(EEG).ipynb

July 17

1. We use spectral/EEG features as training data for RNN
2. If it works, Yay! If it doesn't:
    a. Use denoised data
        i. If it doesn't have enough trials, we use some augmentation
    b. Denoising the data
3. Explain why you think RNN isn't working

The other dataset

1. https://moabb.neurotechx.com/docs/generated/moabb.datasets.Lee2019_MI.html

July 18

Magnificent Loupine Group B.ipynb - Colab (google.com)

We Solved the preprocessing issues finally:)

1. Optimize RNN

Broad questions:

1. Compare RNN vs. 1-D CNN: How do they differ, and what does having an RNN allow you to do? How is one better than the other? You have to run both codes and compare performances.
2. Neuroscience based question: Is your cortical activity during hand movements subjective or generalizable across subjects? If I were to train RNN on say, 8 subjects and test it on the 9th subject, does it still work?
    a. It works, only if subjects have some consistency in the way the data encodes motor movements
    b. It doesn't work (or doesnt work well): encoding is subjective
3. Comparisons across hemispheres:
    a. Train on one hemisphere, test on the other
4. Comparisons across electrodes or lobes
    a. Maybe training on electrodes on frontal lobe, testing on occipital lobe

July 19

1. making the code for 4 classes
2. Making the presentation(LINK)
3. Applying CNN
4. fixing the RNN (done mostly)
5. comparing the CNN and RNN
6. finding out about some neuroscience behind what we're doing

Jul 22

1. Implement dropouts and other regularization methods to prevent overfitting
2. Change optimizer from Adam to SGD

Jul 23

Guidelines:

A. What is the phenomena?
B. What is the key scientific question?
C. What was our hypothesis?
D. How did your modeling work?
E. What did you find? Did the modeling work?
F. What can you conclude?
G. What are the limitations and future directions?

Abstract (from NMA)
(A) The “train illusion” occurs when sitting in a stationary train and experiencing relative visual motion of an adjacent train outside the window; sometimes we feel like we’re moving even if we’re not (and vice versa). Previous literature has suggested that vestibular signals are used to disambiguate self-motion from motion of an adjacent object. (B) How noisy vestibular estimates of motion lead to illusory percepts of self motion is currently unknown. (C) We hypothesized that noisy vestibular signals are integrated leading the brain to decide whether self-motion is occurring or not, and that larger noise is linearly associated with more frequent errors in self-motion judgment. (D) To investigate this hypothesis, we constructed a drift diffusion model and simulated self-motion decisions under varying noise conditions, when true self motion was occurring or not. (E) We observed that higher noise did indeed lead to more frequent errors in self-motion perception but this relationship was not linear. (F) We conclude that accumulated noisy vestibular information can explain the occurrence of the train illusion, and the higher the noise (or the lower the signal-to-noise ratio), the more frequently such illusions will occur. (G) Future research should investigate whether trial-by-trial variations of noisy vestibular signals actually correlate with self-motion judgments.

Abstract not edited version:

1. Context: the interpretation of brain activity through different non-invasive techniques such as electroencephalography (EEG) is crucial for the development of brain-computer interfaces (BCI) which can potentially transform the lives of people with different types of paralysis or motor difficulties. Deep Learning techniques have been used to tackle the difficult task of interpreting raw EEG data in order to identify specific patterns of activity related to different motor tasks or the mental imagery of them.
2. Main Question:This research compares the performance of Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) on EEG data. The main question is which architecture, RNN or CNN, better classifies and interprets EEG signals. By evaluating accuracy on the test dataset, the study aims to highlight the strengths and limitations of each model.
3. Method: In this paper, we try to classify the signals by using preprocessing techniques such as band pass filters and training a Recurrent neural network (RNN) and Convolutional Neural Network (CNN). Later we fine tuned the hyper parameters for both networks to find the best model. Consequently, we used different regularization methods like weight decay (L2), Early stop, Drop out, and batch normalization to prevent overfitting.
4. Results: We ran each network on either one subject's data or several subjects grouped in one data pool. We found that running on individual subjects, RNN and CNN models achieved 0.64 and 0.46 accuracy on the test data respectively. Using ~~grouped~~ pooled data of several subjects performed not better than chance (0.52) on both networks.
5. Conclusion/discussion: our results indicate that Recurrent Neural Network (RNN) outperformed the Convolutional Neural Network (CNN) in terms of accuracy and reliability in decoding brain activity. The inherent capability of RNNs to capture temporal dependencies in sequential data proved to be advantageous for processing EEG signals which are inherently time-series in nature!

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Soan revised version Abstract:

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1. Context: Analysis of fine-scale dynamics in electroencephalography (EEG) is crucial in the field of brain-computer interfaces (BCI). It can help rehabilitation of various types of paralysis or motor difficulties. Deep Learning techniques have been used to tackle the difficulties in interpreting raw EEG data in order to identify specific patterns related to different motor tasks or their mental imagery.
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4. Results: We ran each network on one or multiple subjects. We found that training on one subject, the RNN and CNN models achieved accuracies of 0.64 s = 0.07, ± 0.02 and 0.46 s = 0.08, ± 0.01 respectively on the test data. Both models performed no better than the chance (0.52) on the grouped subjects' data due to the individual differences..
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Adding more neuroscience stuff:

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1- The first thing we can figure out is that signals between subjects are similar to each other or they are different.
2- At second we can figure out which two signals have more different from each other(accuracy high) and which two signal are look like each other the most(low accuracy)
3- What data looks like visualizing and analyzing the dataset a little more deeper.
4- Temporal Dynamics: The use of RNNs can highlight the temporal dynamics of brain activity, showing how neural signals evolve over time during motor imagery tasks. This can provide insights into the timing and sequence of neural activation related to specific motor imagery

5- Signal Preprocessing Techniques: Exploring different preprocessing methods like bandpass filtering and their effectiveness in removing artifacts while preserving neural signals can provide best practices for EEG data preparation

6- Classification Performance: By comparing the performance of various classifiers (e.g., SVM, neural networks) on the datasets, researchers can identify the most robust approaches for decoding motor imagery from EEG signals. This can inform the design of future BCIs

7- we can also try to visualize EOG signal, I don't it's useful or not and suitable for the project an the tasks we had done before

Update code:
Used Grid search to find the best hyperparam (link) # we need to get the mean and var of best model results as the output of the model.

Some Abstract
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Analysis of fine-scale dynamics in electroencephalography (EEG) is crucial in the field of brain-computer interfaces (BCI). It can help rehabilitation of various types of paralysis or motor difficulties. Deep Learning techniques have been used to tackle the difficulties in interpreting raw EEG data in order to identify specific patterns related to different motor tasks or their mental imagery. The current study compares the performance of two deep neural networks using Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) to classify EEG data during a task. The main question is which architecture, RNN or CNN, better classifies and interprets EEG signals according to their motor imagery. By evaluating the accuracy of the test dataset, the study aims to compare the strengths and limitations of each architecture. To prepare the EEG dataset, we used preprocessing techniques such as bandpass filters and trained a Recurrent neural network (RNN) and Convolutional Neural Network (CNN) to classify the data according to the types of motor imagery (e.g., moving the left or right hand). During training, we fine-tuned the hyperparameters through grid search to maximize the performance. Specifically, we used different regularization methods like weight decay (L2), early stopping, drop-out layers, and batch normalization to prevent overfitting. We ran each network on one or multiple subjects. We ran each network on one or multiple subjects. We found that training on one subject, the RNN and CNN models achieved accuracies of 0.64, s = 0.07, ± 0.02 and 0.46, s = 0.08, ± 0.01 respectively on the test

data. Both models performed no better than the chance with 0.52, s = 0.12 ± 0.04 on the grouped subjects' data due to the individual differences. These results suggest that RNNs are able to capture the idiosyncratic aspects of neural coding during motor imagery while the CNNs fail to identify temporal dependencies in sequential data essential to probe these effects.

Mohammad Mashreghi:
amiramirmashgh@gmail.com

Reyhane Zare
r_zare.elec@yahoo.com

July 24:
Slide samples(https://compneuro.neuromatch.io/projects/docs/projects_2020/neurons.html)