FOOOF-CUHK

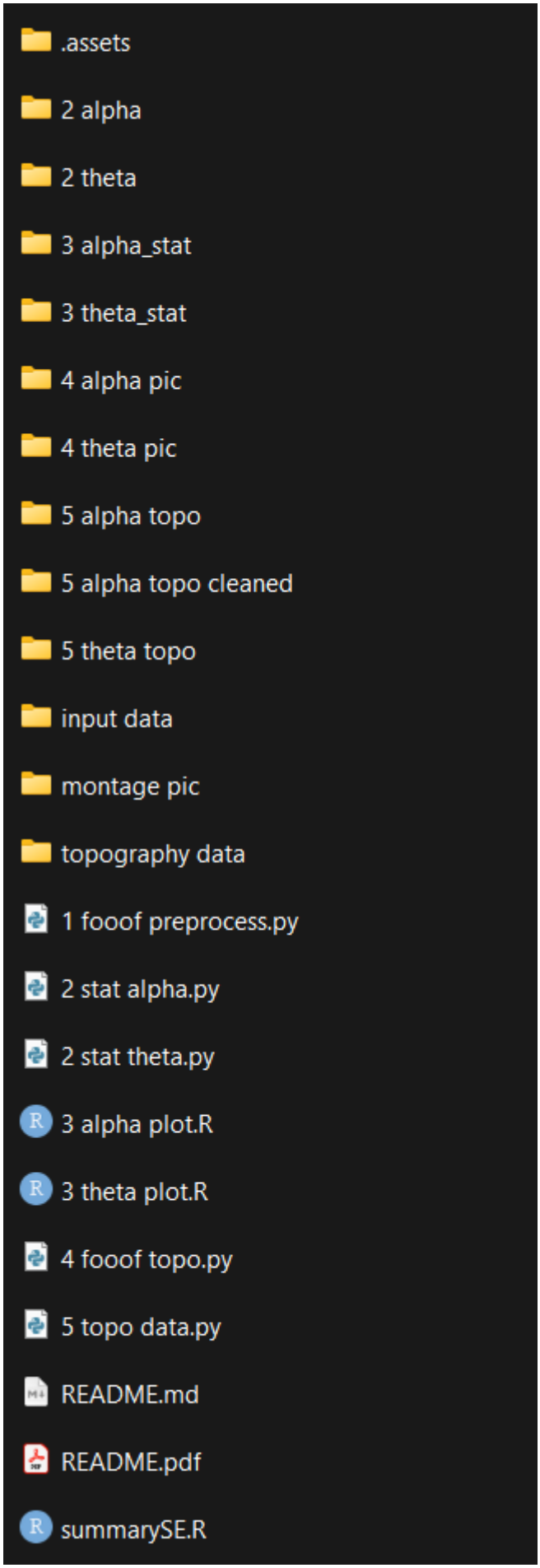
This project encompasses the development and application of the Fitting Oscillations & One Over F (FOOOF) code within Prof. Urs Maurer's Cognitive Neuroscience Lab at the Chinese University of Hong Kong (CUHK). The preparation of this document and tutorial is funded by the Hong Kong Polytechnic University (PolyU) start-up grant (P0043827) awarded to Dr. Shuting Huo. This code includes FOOOF processing, conducting statistical tests and plotting figures in Python and R. The work is published in Biological Psychology, https://doi.org/10.1016/j.biopsycho.2024.108824. The code was developed based on the package and tutorial from Thomas Donoghue's team: FOOOF - fitting oscillations & one over f — fooof 1.1.0 documentation (fooof-tools.github.io).

Abbreviation	Full Form
CUHK	The Chinese University of Hong Kong
PolyU	The Hong Kong Polytechnic University
FOOOF	Fitting Oscillations & One Over F
ap	aperiodic component
p	periodic component
CF	central frequency
PW	power
BW	bandwidth
sd	standard deviation
se	standard error

About this file

This file is the guildline for using the code to analyze the provided sample data. The code and documentation for this project were primarily authored by Junior Research Assistant Tak Kwan Lam, and were subsequently reviewed and refined by Research Assistant Professor Dr. Shuting Huo and Junior Research Assistant Yuxi Chen. Since the coder majored in Psychology rather than Computer Science, there is still room for improvement and optimization in this code. This project is only meant to demonstrate the pipeline of FOOOF analysis in Python. We strongly recommend you to read the original work by Thomas for more information and details about FOOOF. Due to the compression in PDF format, please refer to the provided .png files for the best visual experience. This tutorial is written in Typora markdown so it is recommended to use the .md file with Typora markdown reader for the best experience.

Project structure overview

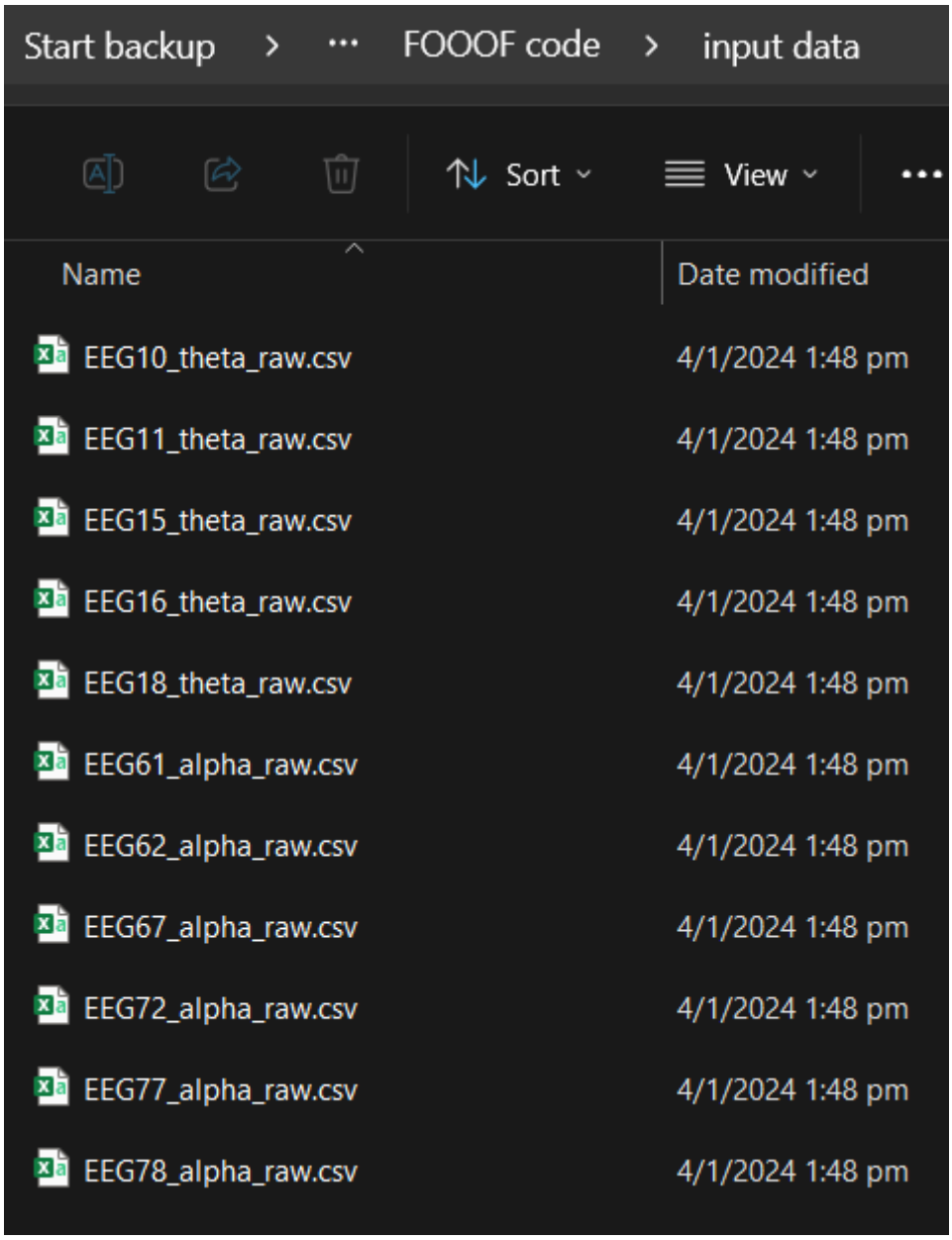


The current project includes fourteen folders, five Python scripts and three R scripts. We can firstly ignore those folders and starts by seeing the codes. The number in the file name indicates the sequence of running and output. Let's start by opening the `1 fooof preprocess.py`.

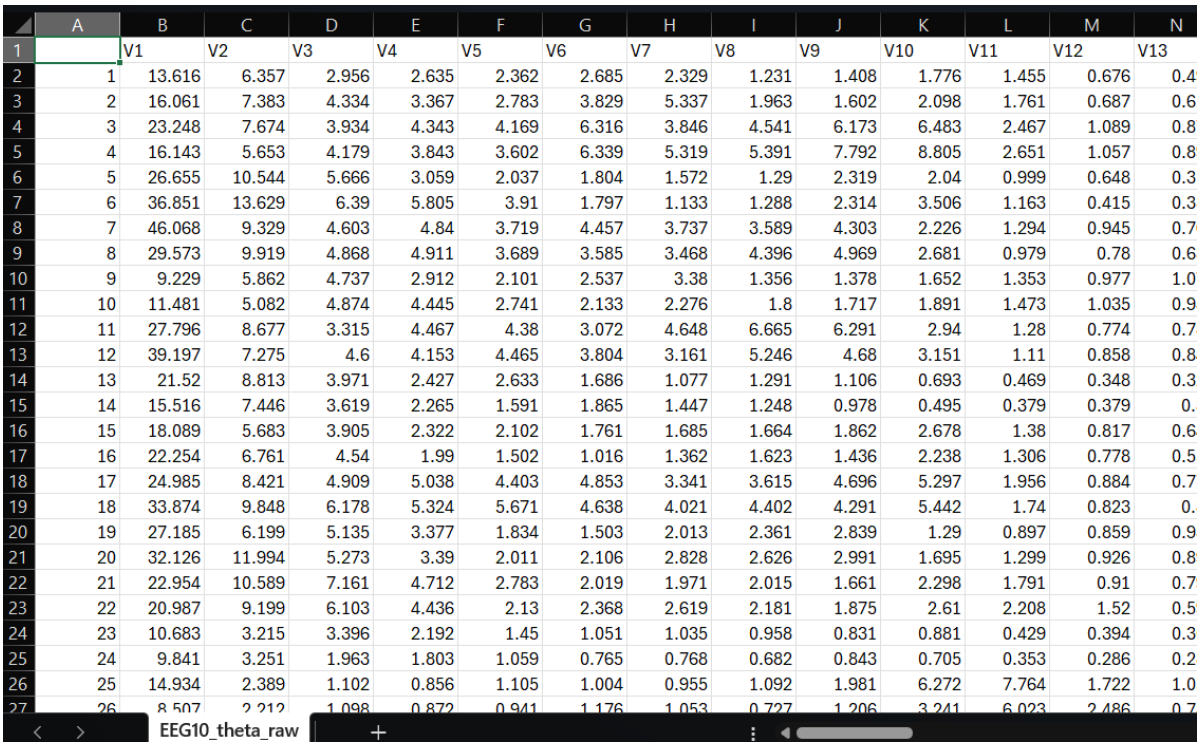
1 FOOOF preprocess

```python
# Import required code for visualizing example models
import os, shutil
# ensure working directory
cwd = os.path.dirname(os.path.realpath(__file__))
os.chdir(cwd)
import pandas as pd
import numpy as np
from fooof import FOOOF
from fooof.plts.annotate import plot_annotated_model
import matplotlib.pyplot as plt

# Specify the frequency range for alpha range
cut_off_component = 15 # the last 15 Hz is not used
max_Hz = 40 - cut_off_component
freqs = np.array(range(2, 41-cut_off_component))

# Specify the output directory
dir_path = f'2 alpha/'
# Specify the input directory
input_dir = 'input data'

# Check if dir_path is not empty and it exists
if dir_path and os.path.exists(dir_path):
    # Remove the directory and its contents
    if os.path.isdir(dir_path):
        shutil.rmtree(dir_path)
    else:
        os.remove(dir_path)
# Recreate the directory
os.makedirs(dir_path)

# create the linear result dataframe to save the results
linear_result = pd.DataFrame()
```

We start by specifying the variables and directories for the input and output folders. You may want to refer to other sources (e.g., generative AI) for more details in these codes. As shown above, the raw data was read from the `input data` folder and the output was stored in `2 alpha` and `2 theta` (shown below) folders.



The above image shows the content in the input data folder, which is the frequency data of each channel.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1		V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13
2	1	13.616	6.357	2.956	2.635	2.362	2.685	2.329	1.231	1.408	1.776	1.455	0.676	0.4
3	2	16.061	7.383	4.334	3.367	2.783	3.829	5.337	1.963	1.602	2.098	1.761	0.687	0.6
4	3	23.248	7.674	3.934	4.343	4.169	6.316	3.846	4.541	6.173	6.483	2.467	1.089	0.8
5	4	16.143	5.653	4.179	3.843	3.602	6.339	5.319	5.391	7.792	8.805	2.651	1.057	0.8
6	5	26.655	10.544	5.666	3.059	2.037	1.804	1.572	1.29	2.319	2.04	0.999	0.648	0.3
7	6	36.851	13.629	6.39	5.805	3.91	1.797	1.133	1.288	2.314	3.506	1.163	0.415	0.3
8	7	46.068	9.329	4.603	4.84	3.719	4.457	3.737	3.589	4.303	2.226	1.294	0.945	0.7
9	8	29.573	9.919	4.868	4.911	3.689	3.585	3.468	4.396	4.969	2.681	0.979	0.78	0.6
10	9	9.229	5.862	4.737	2.912	2.101	2.537	3.38	1.356	1.378	1.652	1.353	0.977	1.0
11	10	11.481	5.082	4.874	4.445	2.741	2.133	2.276	1.8	1.717	1.891	1.473	1.035	0.9
12	11	27.796	8.677	3.315	4.467	4.38	3.072	4.648	6.665	6.291	2.94	1.28	0.774	0.7
13	12	39.197	7.275	4.6	4.153	4.465	3.804	3.161	5.246	4.68	3.151	1.11	0.858	0.8
14	13	21.52	8.813	3.971	2.427	2.633	1.686	1.077	1.291	1.106	0.693	0.469	0.348	0.3
15	14	15.516	7.446	3.619	2.265	1.591	1.865	1.447	1.248	0.978	0.495	0.379	0.379	0.
16	15	18.089	5.683	3.905	2.322	2.102	1.761	1.685	1.664	1.862	2.678	1.38	0.817	0.6
17	16	22.254	6.761	4.54	1.99	1.502	1.016	1.362	1.623	1.436	2.238	1.306	0.778	0.5
18	17	24.985	8.421	4.909	5.038	4.403	4.853	3.341	3.615	4.696	5.297	1.956	0.884	0.7
19	18	33.874	9.848	6.178	5.324	5.671	4.638	4.021	4.402	4.291	5.442	1.74	0.823	0.
20	19	27.185	6.199	5.135	3.377	1.834	1.503	2.013	2.361	2.839	1.29	0.897	0.859	0.9
21	20	32.126	11.994	5.273	3.39	2.011	2.106	2.828	2.626	2.991	1.695	1.299	0.926	0.8
22	21	22.954	10.589	7.161	4.712	2.783	2.019	1.971	2.015	1.661	2.298	1.791	0.91	0.7
23	22	20.987	9.199	6.103	4.436	2.13	2.368	2.619	2.181	1.875	2.61	2.208	1.52	0.5
24	23	10.683	3.215	3.396	2.192	1.45	1.051	1.035	0.958	0.831	0.881	0.429	0.394	0.3
25	24	9.841	3.251	1.963	1.803	1.059	0.765	0.768	0.682	0.843	0.705	0.353	0.286	0.2
26	25	14.934	2.389	1.102	0.856	1.105	1.004	0.955	1.092	1.981	6.272	7.764	1.722	1.0
27	26	8.507	2.212	1.098	0.872	0.941	1.176	1.053	0.727	1.206	3.241	6.023	2.486	0.7

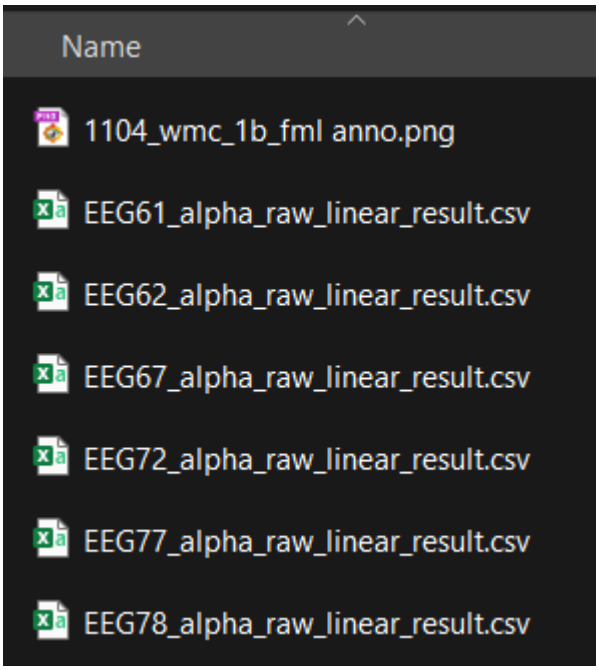
EEG10_theta_raw

Inside the .csv file are the voltage (mV) at 1 to 40 Hz frequency (V1 to V40) for every subject. The information for each participant can be found in the last four columns: subject ID (id), experiment conditions (exp, within subject factor), memory load (load, within subject factor), and group (age, adults vs. children, between subject factor).

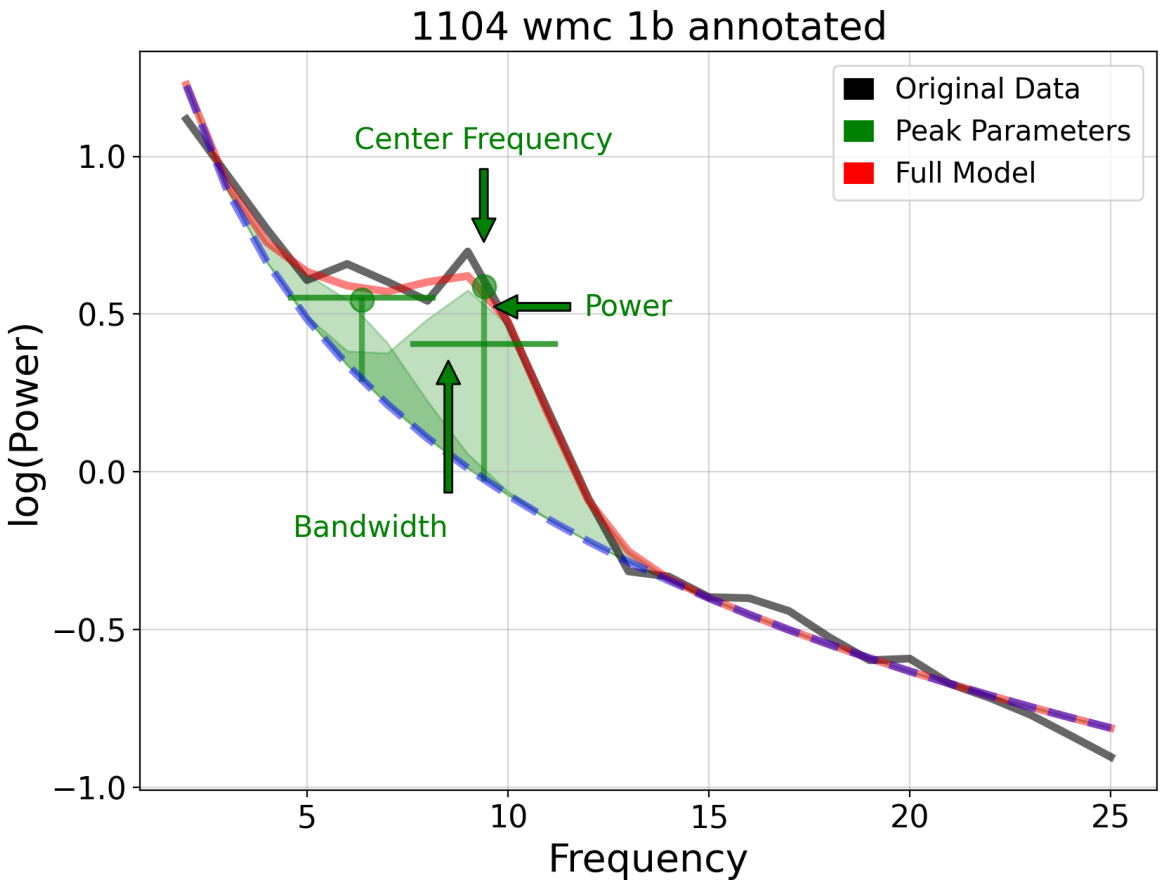
AN	AO	AP	AQ	AR	AS
V39	V40	id	exp	load	age
0.007	0.005	1108	wmc	1b	0
0.009	0.007	1108	wmc	2b	0
0.034	0.023	1606	wmc	1b	0
0.017	0.012	1606	wmc	2b	0
0.002	0.002	1608	wmc	1b	0
0.007	0.005	1608	wmc	2b	0
0.015	0.015	1612	wmc	1b	0
0.01	0.008	1612	wmc	2b	0
0.004	0.002	1632	wmc	1b	0
0.004	0.002	1632	wmc	2b	0
0.031	0.032	1634	wmc	1b	0
0.057	0.053	1634	wmc	2b	0
0.002	0.001	1635	wmc	1b	0
0.001	0.001	1635	wmc	2b	0
0.01	0.018	1640	wmc	1b	0
0.021	0.011	1640	wmc	2b	0
0.072	0.054	2003	wmc	1b	0
0.051	0.04	2003	wmc	2b	0
0.022	0.014	2004	wmc	1b	0
0.072	0.043	2004	wmc	2b	0
0.02	0.014	2006	wmc	1b	0
0.019	0.01	2006	wmc	2b	0
0.022	0.016	2901	wmc	1b	0
0.009	0.011	2901	wmc	2b	0
0.003	0.001	3001	wmc	1b	1
0.002	0.001	3001	wmc	2b	1

You can also use your own data following the above format and named them by the format `EEG[channel num]_[frequency band name]_raw.csv`

The `1 fooof preprocess` code generates the FOOOF-processed data for each channel and stored in folders corresponding to frequency bands.



The `.png` file (shown below) in the 2 alpha folder indicate the function of FOOOF and parameters.



The black curve is the original data read from input data. The blue dashed-curve is the aperiodic (ap) component modulated by FOOOF. The red curve is the full model combining the aperiodic (ap) and periodic (p) components, labeled as the 'Full Model' in the legend. The two gaussian green area is the periodic components. The peak parameters were provided for one of them: center frequency (the center frequency number of this peak), power (the relative power separated from ap component of the p component), and bandwidth (the frequency range width for this peak). The x-axis is the frequency ranged from 2~25 and y-axis is the logged power.

FOOOFed output

The .csv files in `2 alpha` and `2 theta` folders are the is the FOOOFed data for each participant in each condition, including CF = center frequency, PW = log(power), BW = bandwidth, offset is the intercept for the ap component and exponent is the slope for ap component. r_squared is the model r^2 (higher number means better fitting). And error is the mean squared error of the model. Noted that there might be multiple peaks for a participant in a condition. Hence, we need to distinguish and filter the data for statistical analysis.

PID	exp	load	age	CF	PW	BW	offset	exponent	r_squared	error	file_name
1104	wmc	1b	0	8.859119	0.621557	3.753233	1.742728	1.858473	0.979716	0.076209	EEG61_alpha_raw
1104	wmc	2b	0	8.628059	0.602743	5.129389	1.819115	1.988517	0.983761	0.074637	EEG61_alpha_raw
1104	wmv	1b	0	6.013343	0.361866	3	1.722888	1.61068	0.988747	0.045797	EEG61_alpha_raw
1104	wmv	1b	0	9.524016	0.406122	3			0.988747	0.045797	EEG61_alpha_raw
1104	wmv	2b	0	8.331516	0.543188	4.698531	1.70127	1.668674	0.97794	0.079324	EEG61_alpha_raw
1108	wmc	1b	0	9.791213	0.689724	3.806853	1.30979	1.539823	0.968018	0.071094	EEG61_alpha_raw
1108	wmc	1b	0	18.499	0.405637	3.945216			0.968018	0.071094	EEG61_alpha_raw
1108	wmc	2b	0	6.596591	0.344977	3	1.513601	1.63149	0.982341	0.055975	EEG61_alpha_raw
1108	wmc	2b	0	10.03163	0.591395	3			0.982341	0.055975	EEG61_alpha_raw
1108	wmc	2b	0	17.77524	0.405478	4.870596			0.982341	0.055975	EEG61_alpha_raw
1108	wmv	1b	0	9.484388	0.554473	4.016173	1.03113	1.331534	0.912957	0.115025	EEG61_alpha_raw
1108	wmv	2b	0	6.623312	0.368704	3	1.255469	1.488449	0.977937	0.062158	EEG61_alpha_raw
1108	wmv	2b	0	9.500049	0.624981	3			0.977937	0.062158	EEG61_alpha_raw
1108	wmv	2b	0	17.4714	0.40756	3.29857			0.977937	0.062158	EEG61_alpha_raw
1605	wmc	1b	0	10.55302	0.744104	4.741311	1.572485	1.503356	0.983843	0.04709	EEG61_alpha_raw
1605	wmc	1b	0	16.2315	0.296549	3.240465			0.983843	0.04709	EEG61_alpha_raw
1605	wmc	2b	0	11.63443	0.659644	5.359043	1.592812	1.597237	0.958709	0.086574	EEG61_alpha_raw
1605	wmv	1b	0	6.553768	0.434507	3	1.557456	1.546957	0.9784	0.067046	EEG61_alpha_raw
1605	wmv	1b	0	10.35763	0.803566	3.000017			0.9784	0.067046	EEG61_alpha_raw
1605	wmv	1b	0	13.26291	0.59977	5.599614			0.9784	0.067046	EEG61_alpha_raw
1605	wmv	2b	0	10.55745	0.701389	4.763212	1.412452	1.582583	0.978599	0.064555	EEG61_alpha_raw
1606	wmc	1b	0	9.055208	1.143976	4.722382	1.499644	1.694526	0.950017	0.13714	EEG61_alpha_raw
1606	wmc	2b	0	9.069774	1.118791	4.10536	1.539636	1.640109	0.960283	0.114135	EEG61_alpha_raw
1606	wmv	1b	0	9.686637	0.952734	4.996314	1.359548	1.581527	0.959097	0.115953	EEG61_alpha_raw
1606	wmv	2b	0	5.918894	0.370217	3	1.486897	1.676932	0.953319	0.121103	EEG61_alpha_raw
1606	wmv	2b	0	9.755661	0.944023	4.01594			0.953319	0.121103	EEG61_alpha_raw
1607	wmc	1b	0	10.03457	0.925415	3	1.566076	1.587583	0.9612	0.096975	EEG61_alpha_raw
1607	wmc	2b	0	9.925508	1.058999	3	1.437959	1.564488	0.940849	0.124519	EEG61_alpha_raw
1607	wmv	1b	0	10.05116	0.890196	3.125528	1.548487	1.612524	0.951814	0.106999	EEG61_alpha_raw
1607	wmv	2b	0	9.783069	0.924741	3	1.610538	1.641304	0.952594	0.107186	EEG61_alpha_raw

2 stat alpha

The beginning section of `2 stat alpha.py` also specified the variables and directories for input and output folder. `3 alpha_stat` folder stores the statistical results and the `4 alpha pic` folder stores the generated graphs. The current file also includes the code for plotting graphs, which might increase the difficulty in adapting this code to other data. It is recommended to separate the codes for statistical analysis and plotting.

```python
import os
# ensure working directory
cwd = os.path.dirname(os.path.realpath(__file__))
os.chdir(cwd)
import pandas as pd
import numpy as np
import shutil
from scipy import stats
import matplotlib.pyplot as plt
from PIL import Image
import itertools

# do the analysis on the specfic folder
dir_path = f'2 alpha/'
output_dir = f'3 alpha_stat/'
output_pic_dir = os.path.join(cwd, '4 alpha pic')

# Specify the frequency range for alpha range
cut_off_component = 15 # the last 15 Hz is not used
max_Hz = 40 - cut_off_component
freqs = np.array(range(2, 41-cut_off_component)) # 2 to 25 Hz


# Check if output_dir is not empty and it exists
if output_dir and os.path.exists(output_dir):
    # Remove the directory and its contents
    if os.path.isdir(output_dir):
        shutil.rmtree(output_dir)
    else:
        os.remove(output_dir)
# Recreate the directory
os.makedirs(output_dir)
os.makedirs(output_pic_dir, exist_ok=True)

# Get a list of all files in the directory
all_files = os.listdir(dir_path)
```

Redundant peaks that do not falls within the alpha frequency band (CF <= 8.2 Hz or CF >= 13.5 Hz) were filtered out and stored in `[Original file name]_peak_else_sub.csv`.

```python
    peak_else = linear_result[(linear_result['CF'] < 8.2) | (linear_result['CF'] > 13.5)]
    peak_else = pd.concat([peak_else, no_peak], axis=0)
    peak_else.to_csv(f'{output_dir}{file_name}_peak_else_sub.csv')
```

And we replaced the filtered data with CF = None, PW and BW = 0. Fittings with r^2 <= 0.7 were also filtered out.

```python
    # Replace 'CF' values with NaN and 'PW' with 0
    linear_result.loc[peak_else.index, 'CF'] = np.nan
    linear_result.loc[peak_else.index, 'PW'] = 0
    linear_result.loc[peak_else.index, 'BW'] = 0
    linear_result = linear_result.drop(no_peak.index)
    # filter out the participants with r_squared < 0.7
    linear_result = linear_result[linear_result['r_squared'] > 0.7]
```

For the circumstances in which one participant shows multiple peaks in one condition, the peak with largest PW was kept. The filtered data is stored as `[Original file name]_stat_data.csv`

```
    # keep the one with largest PW
    linear_result = linear_result.loc[linear_result.groupby(['PID', 'exp', 'load', 'age'])['PW'].idxmax()]
    linear_result.reset_index(drop=True, inplace=True)
    linear_result.to_csv(f'{output_dir}{file_name}_stat_data.csv')
    # Append the data to linear_result
    stat_data = pd.concat([stat_data, linear_result])
```

The `stat_data` is the dataframe containing the electrode data in the alpha band for all participants and conditions. The parameters were then averaged by subjects and conditions to avoid possible missing values in some channels. But if all channels are the missing values, the data here would still be CF = None, PW and BW = 0.

```
# Group the data by 'PID', 'exp', 'load', and 'age', and calculate the mean
mean_values = stat_data.groupby(['PID', 'exp', 'load', 'age'])[['CF', 'PW', 'BW', 'offset', 'exponent']].mean()
```

Additionally, we have written a script to verify whether the averaged dataframe includes data for each subject and condition. You may adjust the parameters in this script to align with your experimental design.

```
# Count the number of occurrences of each 'PID' value
pid_counts = mean_values['PID'].value_counts()
if any(pid_counts != 4):
    print("Alert: Some PID values do not appear exactly 4 times!")
else:
    print("All PID values appear exactly 4 times.")
```

And the averaged dataframe is stored as `mean_alpha_params.csv` in the output folder:

PID	exp	load	age	CF	PW	BW	offset	exponent
1104	wmc	1b	0	9.111439	0.79115	3.125708	1.884378	1.992298
1104	wmc	2b	0	8.9996	0.862575	3.457742	1.89228	1.997547
1104	wmv	1b	0	9.152957	0.779387	3.128941	1.832608	1.89081
1104	wmv	2b	0	8.956187	0.795952	3.452138	1.914524	1.92531
1108	wmc	1b	0	9.824598	0.757757	3.356074	1.391694	1.593638
1108	wmc	2b	0	9.976875	0.657001	3	1.497829	1.607481
1108	wmv	1b	0	9.949496	0.692775	3.214893	1.295852	1.555452
1108	wmv	2b	0	9.505782	0.737382	3.216818	1.414169	1.590604
1605	wmc	1b	0	10.43284	0.923922	4.523829	1.733701	1.65032
1605	wmc	2b	0	11.13728	0.879257	4.597858	1.534933	1.496475
1605	wmv	1b	0	10.63117	0.931301	5.116868	1.600791	1.594488
1605	wmv	2b	0	10.64825	0.859315	4.626529	1.577487	1.555034
1606	wmc	1b	0	9.243194	1.294268	4.492459	1.783159	1.793282
1606	wmc	2b	0	9.518963	1.271434	4.410441	1.806419	1.690295
1606	wmv	1b	0	9.694062	1.190672	4.282302	1.70836	1.642766
1606	wmv	2b	0	9.745809	1.089922	4.737176	1.777262	1.723217
1607	wmc	1b	0	9.910307	1.022835	3	1.634987	1.627483
1607	wmc	2b	0	9.925508	1.058999	3	1.437959	1.564488
1607	wmv	1b	0	9.95716	0.910821	3.020921	1.704068	1.740061
1607	wmv	2b	0	9.759823	0.939791	3	1.619358	1.638425
1608	wmc	1b	0	9.624807	0.874559	3.049059	1.648259	1.825907
1608	wmc	2b	0	9.597902	1.028012	3.062005	1.617983	1.722185
1608	wmv	1b	0	9.419834	0.931944	3.059113	1.692333	1.787471
1608	wmv	2b	0	9.364059	0.838634	3	1.60155	1.666319
1609	wmc	1b	0	10.1672	0.893192	5.229021	1.522548	1.88325
1609	wmc	2b	0	10.80185	0.720836	5.129145	1.541438	1.903625
1609	wmv	1b	0	10.10228	0.873563	5.054841	1.544866	1.942119
1609	wmv	2b	0	9.230868	0.993245	3.26251	1.610308	1.973586
1612	wmc	1b	0	9.550028	0.689377	4.217022	1.617928	1.733647
1612	wmc	2b	0	9.092246	0.898633	3.242637	1.507414	1.644059
1612	wmv	1b	0	9.276954	0.973843	3.391871	1.853235	1.963609
1612	wmv	2b	0	9.415717	0.685678	3	1.5478	1.70808
1615	wmc	1b	0	9.976919	0.639931	3.086872	1.520533	1.539616

Statistical testing

Our research interest is whether the n-back load modulated the periodic oscillations so we want to test if these parameters are significantly different between loads. To do this, we subtracted the five parameters from load 2b condition by 1b condition, then perform statistical analyses for each age group and each parameter. This data is stored as `mean_alpha_delta_nback_params.csv` and the t-test result stores in `one_sample_t_test.csv`.

```python
# one sample t test
group_1t = mean_values.groupby(['PID', 'age', 'exp', 'load'])
# Create a new DataFrame to store the results
result = pd.DataFrame(columns=['PID', 'age', 'exp', 'CF_diff',
                               'PW_diff', 'BW_diff', 'offset_diff', 'exponent_diff'])

# Loop over the groups
for name, group in group_1t:
    # If the load is '1b', store the values
    if name[3] == '1b':
        cf_1b = group['CF'].values
        pw_1b = group['PW'].values
        bw_1b = group['BW'].values
        offset_1b = group['offset'].values
        exponent_1b = group['exponent'].values
    # If the load is '2b', calculate the difference and store the result
    elif name[3] == '2b':
        cf_diff = group['CF'].values - cf_1b
        pw_diff = group['PW'].values - pw_1b
        bw_diff = group['BW'].values - bw_1b
        offset_diff = group['offset'].values - offset_1b
        exponent_diff = group['exponent'].values - exponent_1b
        # Create a temporary DataFrame from the dictionary
        temp_df = pd.DataFrame({'PID': name[0], 'age': name[1], 'exp': name[2],
                                'CF_diff': cf_diff, 'PW_diff': pw_diff, 'BW_diff': bw_diff,
                                'offset_diff': offset_diff, 'exponent_diff': exponent_diff})
       # Append the temporary DataFrame to the result DataFrame
        result = pd.concat([result, temp_df], ignore_index=True)

# print(result.head())
result.to_csv(f'{output_dir}mean_alpha_delta_nback_params.csv', index=False)
# We want to test if the population mean is 0.0
popmean = 0.0
# Group the data by 'age' and 'exp'
groups_1test = result.groupby(['age', 'exp'])
# Initialize an empty DataFrame to store the results
results_df = pd.DataFrame(columns=['age', 'exp', 'column', 'T statistic', 'P value'])
for (age, exp), group in groups_1test:
    # print(f"Age: {age}, Exp: {exp}")
    # Loop over the columns in the result DataFrame
    for column in result.columns:
        # Skip the 'PID', 'age', and 'exp' columns
        if column in ['PID', 'age', 'exp']:
            continue
        # Remove NaN values by row through each column
        group = group.dropna(subset=[column])

        # Perform the one-sample t-test
        t_statistic, p_value = stats.ttest_1samp(group[column], popmean)

        # Store the results in the DataFrame
        temp_df = pd.DataFrame({
            'age': age,
            'exp': exp,
            'column': column,
            'T statistic': round(t_statistic, 3),
            'P value': round(p_value, 3)
        }, index=[0])
        # Concatenate the new data to the results DataFrame
        results_df = pd.concat([results_df, temp_df], ignore_index=True)
print(results_df)
results_df.to_csv(f'{output_dir}one_sample_t_test.csv', index=False)

```

plotting results

To visualize the filtered data and statistical results, we utilize the functions from Thomas's FOOOF package. A function to lighten the color for each subject's curve was also included. More details for plotting are covered below.

Fig 4 alpha.png

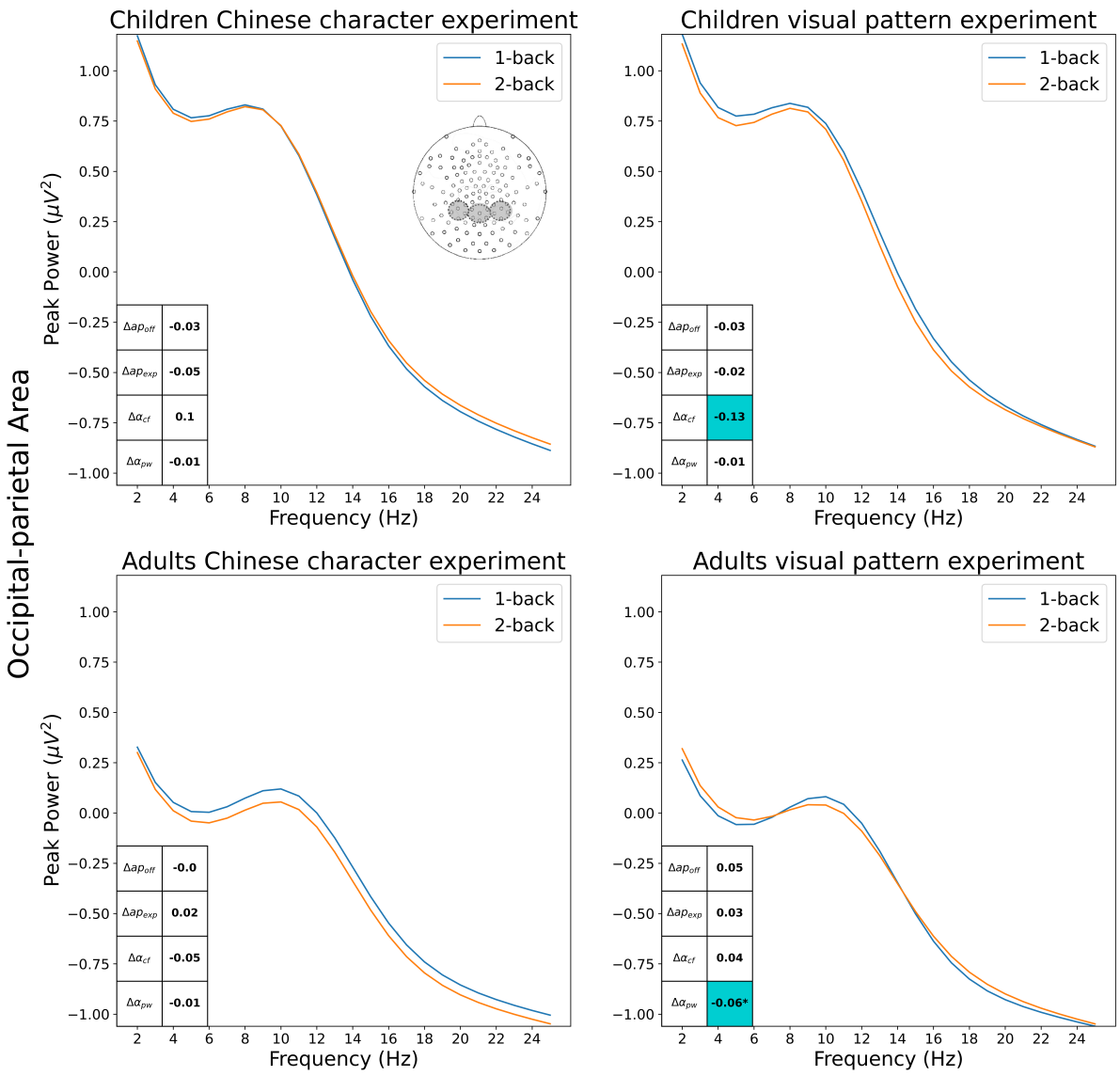

Occipital-parietal Area
Children Chinese character experiment
Children visual pattern experiment
Adults Chinese character experiment
Adults visual pattern experiment
1-back
2-back
Peak Power (μV^2)
Frequency (Hz)
Δap_{off} -0.03
Δap_{exp} -0.05
$\Delta \alpha_{cf}$ 0.1
$\Delta \alpha_{pw}$ -0.01
Δap_{off} -0.03
Δap_{exp} -0.02
$\Delta \alpha_{cf}$ -0.13
$\Delta \alpha_{pw}$ -0.01
Δap_{off} -0.0
Δap_{exp} 0.02
$\Delta \alpha_{cf}$ -0.05
$\Delta \alpha_{pw}$ -0.01
Δap_{off} 0.05
Δap_{exp} 0.03
$\Delta \alpha_{cf}$ 0.04
$\Delta \alpha_{pw}$ -0.06*

Fig 3 a.png

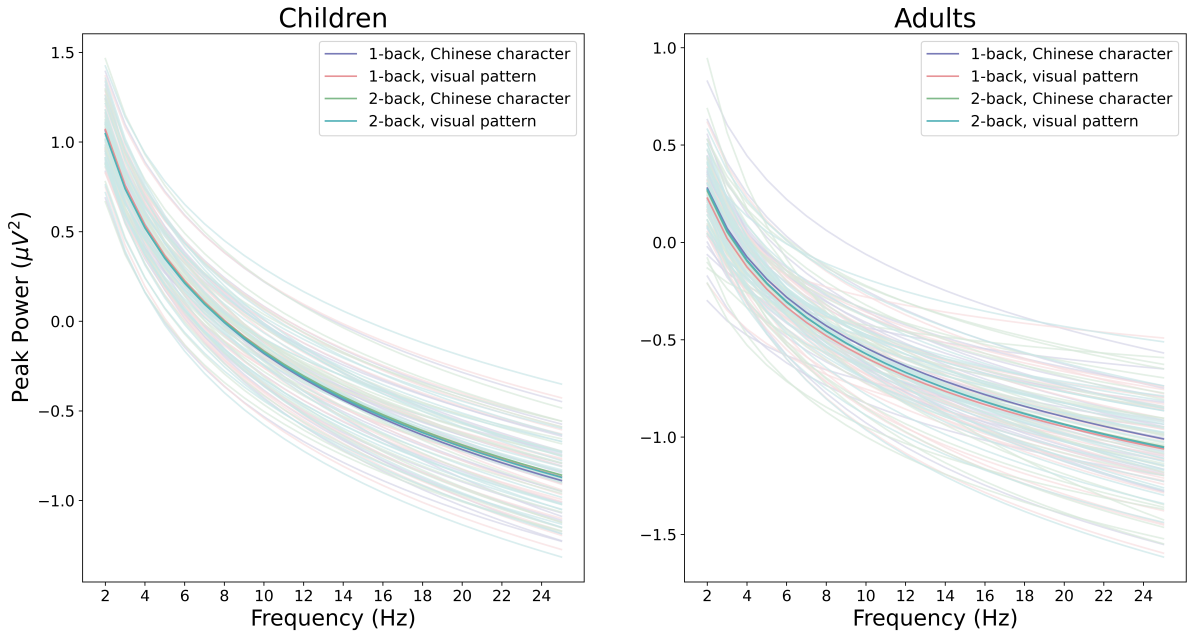
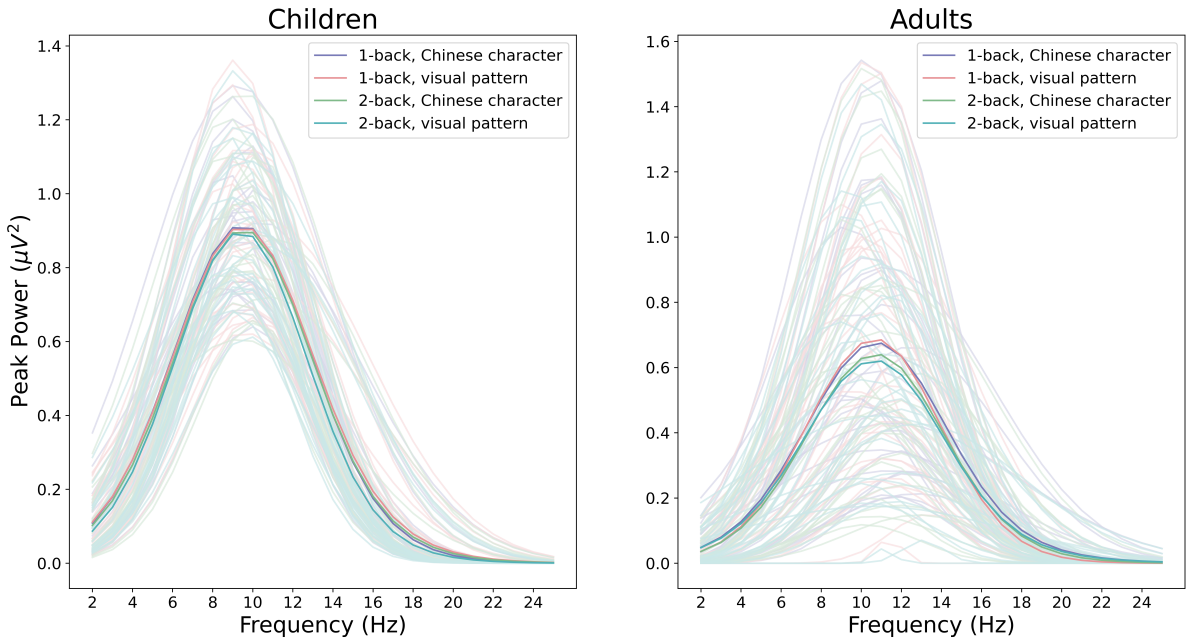

Children
Adults
1-back, Chinese character
1-back, visual pattern
2-back, Chinese character
2-back, visual pattern
Peak Power (μV^2)
Frequency (Hz)

Fig 3 g.png



The functions for plotting:

```python
# the fundtion to calculate the aperiodic power values
def calculate_y_ap(group):
    offset = np.repeat(group['offset'].values, len(freqs))
    exp = np.repeat(group['exponent'].values, len(freqs))
    y_ap = offset - np.log10(freqs ** exp)
    return y_ap

# the fundtion to calculate the periodic power values
def calculate_y_p(group):
    cf = np.repeat(group['CF'].values, len(freqs))
    pw = np.repeat(group['PW'].values, len(freqs))
    bw = np.repeat(group['BW'].values, len(freqs))

    ys = np.zeros_like(freqs)
    y_p = ys + pw * np.exp(-(freqs-cf)**2 / (2*bw**2))
    return y_p


def lighten_color(color, amount=0.5):
    """
    Lightens the given color by multiplying (1-luminosity) by the given amount.
    Input can be matplotlib color string, hex string, or RGB tuple.

    Examples:
    >> lighten_color('g', 0.3)
    >> lighten_color('#F034A3', 0.6)
    >> lighten_color((.3,.55,.1), 0.5)
    """
    import matplotlib.colors as mc
    import colorsys
    try:
        c = mc.cnames[color]
    except:
        c = color
    c = colorsys.rgb_to_hls(*mc.to_rgb(c))
    return colorsys.hls_to_rgb(c[0], 1 - amount * (1 - c[1]), c[2])
```

Fig4 alpha

The data for this plot is calculated by adding the power values of periodic (`y_p` function) and aperiodic (`y_ap` function) components together. The plot data outputs as `p+ap_alpha_load.csv`, which includes each participant's data.

```
groups = mean_values.groupby(['PID', 'age', 'load', 'exp'])
# Apply the function to each group
ap_power = groups.apply(calculate_y_ap).reset_index()
p_power = groups.apply(calculate_y_p).reset_index()

sub_info = ap_power[['PID', 'age', 'load', 'exp']]
# Create a new DataFrame with columns named from 'V2' to 'V{max_Hz}'
columns = ['V' + str(i) for i in range(2, max_Hz + 1)]
ap_power = pd.DataFrame(ap_power[0].to_list(), columns=columns)
p_power = pd.DataFrame(p_power[0].to_list(), columns=columns)
ap_power_all = pd.concat([sub_info, ap_power], axis=1)
p_power_all = pd.concat([sub_info, p_power], axis=1)
# print(ap_power_all.head())

########################################
# Alpha FOOOFed oscilation plot in Fig. 4 #
########################################

# Merge raw_data_eeg and ap_power_all on the group columns
merged_df = pd.merge(p_power_all, ap_power_all, on=['PID', 'age', 'load', 'exp'], suffixes=('_p', '_ap'))
# Subtract the ap_power_all columns from the raw_data_eeg columns
for i in range(2, max_Hz+1):
    merged_df[f'V{i}'] = merged_df[f'V{i}_p'] + merged_df[f'V{i}_ap'] #- merged_df[f'V{i}_ap']

# Drop the original columns
merged_df.drop(columns=[f'V{i}_p' for i in range(2, max_Hz+1)] + [f'V{i}_ap' for i in range(2, max_Hz+1)], inplace=True)
merged_df.to_csv(f'{output_dir}/p+ap_alpha_load.csv', index=False)
```

Then we averaged the power values by conditions so that we have one data for and condition each frequency for visualization.

```
    # Set the title
    ax.set_title(f'{age_group} {experiment}', fontsize=24)
    ax.set_xlabel('Frequency (Hz)', fontsize=20)
    if i not in [1, 3]:  # Dont plot y title for the right side of the subplot
        ax.set_ylabel(r'Peak Power ($\mu V^{2}$)', fontsize=20)
    new_ticks = np.arange(0, max_Hz-1, 2)
    # Generate new labels for these tick marks
    new_labels = new_ticks + 2 # starts from 2 Hz
    # Set the new x-axis tick marks
    ax.set_xticks(new_ticks)
    # Set the tick labels with larger font size
    ax.tick_params(axis='both', which='major', labelsize=14)
    # Set the x-axis labels
    ax.set_xticklabels(new_labels)
    ax.legend(fontsize=18, loc='upper right')
    # Set the same y-axis limits for all subplots
    ax.set_ylim(global_min, global_max)

    # Add an overall y-axis title
    fig.text(0.04, 0.5, 'Occipital-parietal Area', va='center', rotation='vertical', fontsize=28)

    # Get the t, p values for the plot
    off_t = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'offset_diff'), 'T statistic'].values[0]
    off_p = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'offset_diff'), 'P value'].values[0]
    exp_t = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'exponent_diff'), 'T statistic'].values[0]
    exp_p = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'exponent_diff'), 'P value'].values[0]
    cf_t = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'CF_diff'), 'T statistic'].values[0]
    cf_p = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'CF_diff'), 'P value'].values[0]
    pw_t = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'PW_diff'), 'T statistic'].values[0]
    pw_p = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'PW_diff'), 'P value'].values[0]
    bw_t = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'BW_diff'), 'T statistic'].values[0]
    bw_p = results_df.loc[(results_df['age'] == age) & (results_df['exp'] == exp) & (results_df['column'] == 'BW_diff'), 'P value'].values[0]

    # add significance mark(*) manually
    if i < 3:
        cell_text = [[r'$\Delta ap_{off}$', round(result.loc[(result['age'] == age) & (result['exp'] == exp), 'offset_diff'].mean(), 2)],
                [r'$\Delta ap_{exp}$', round(result.loc[(result['age'] == age) & (result['exp'] == exp), 'exponent_diff'].mean(), 2)],
                [r'$\Delta \alpha_{cf}$', round(result.loc[(result['age'] == age) & (result['exp'] == exp), 'CF_diff'].mean(), 2)],
                [r'$\Delta \alpha_{pw}$', round(result.loc[(result['age'] == age) & (result['exp'] == exp), 'PW_diff'].mean(), 2)]]
            #  [r'$\Delta \alpha_{bw}$', round(result.loc[(result['age'] == age) & (result['exp'] == exp), 'BW_diff'].values[0], 2)]]
    else:
        cell_text = [[r'$\Delta ap_{off}$', round(result.loc[(result['age'] == age) & (result['exp'] == exp), 'offset_diff'].mean(), 2)],
                [r'$\Delta ap_{exp}$', round(result.loc[(result['age'] == age) & (result['exp'] == exp), 'exponent_diff'].mean(), 2)],
                [r'$\Delta \alpha_{cf}$', round(result.loc[(result['age'] == age) & (result['exp'] == exp), 'CF_diff'].mean(), 2)],
                [r'$\Delta \alpha_{pw}$', str(round(result.loc[(result['age'] == age) & (result['exp'] == exp), 'PW_diff'].mean(), 2)) + '*']]
```

What's worth noticing is that we have a box at the left bottom of each subplot. It's the t values in the one sample t test. The text in the left column is formatted using LaTeX to visually represent mathematical expressions, such as $/Deltaap_{off}$. Note that the asterisks for significance were not added automatically.

Instead, cell colors were used to indicate significant results. Which can help you identify which cell to add the mark. Orange cell color indicates .05 level significance at t > 0, while blue indicates .05 level significance at t < 0. This code also add a montage picture in gray scale from the `montage pic/alpha.png` at the first subplot.

```
    table = ax.table(cellText=cell_text, loc='bottom left', bbox=[0, 0, 0.2, 0.4])
    # Set the font size of the table
    table.set_fontsize(20)

    cells = table.get_celld()
    for cell in cells.values():
        cell.set_text_props(horizontalalignment='center', weight='bold')

    # Center get bg color for the significance
    for key, cell in table.get_celld().items():
        t_list = [off_t, exp_t, cf_t, pw_t, bw_t]
        p_list = [off_p, exp_p, cf_p, pw_p, bw_p]
        for i, (t, p) in enumerate(zip(t_list, p_list)):
            if key[1] == 1 and key[0] == i:  # key[1] is the column index, key[0] is the row index
                if p <= 0.05 and t > 0:
                    cell.set_facecolor('darkorange')
                elif p <= 0.05 and t < 0:
                    cell.set_facecolor('darkturquoise')

    # Add the head map image to each subplot
    first_subplot = True
    for ax in axs.flat:
        if first_subplot:
            # Create a new axes for the image in the current subplot
            img_ax = ax.inset_axes([0.62, 0.48, 0.35, 0.35])
            img_ax.imshow(img)
            img_ax.axis('off')  # Hide the axis
            first_subplot = False

plt.savefig(os.path.join(output_pic_dir, f'Fig4 alpha.png'), dpi=500, bbox_inches='tight')
# plt.show()
```

The final figures are shown below:

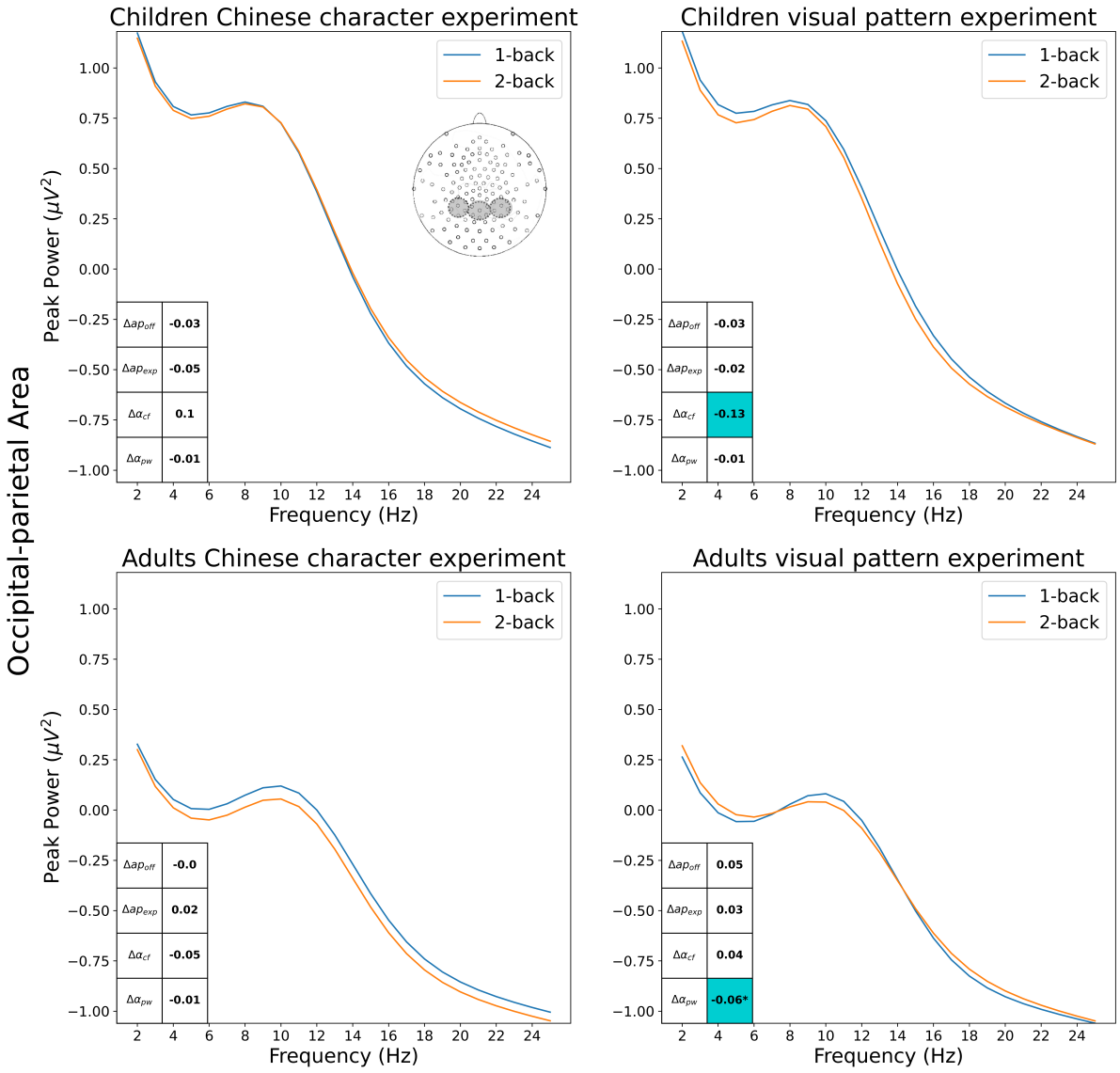


Fig 3 a & Fig 3 g

This plot is about plotting the aperiodic components in each condition each group., you can adjust the settings based on your need. The data input is the same as the previous plot, except the periodic component in the merged_df is subtracted (see row 367).

```
360  ################################################
361  # plot the aperiodic power load in Fig. 3 #
362  ################################################
363
364  merged_df = pd.merge(p_power_all, ap_power_all, on=['PID', 'age', 'load', 'exp'], suffixes=('_p', '_ap'))
365  # Subtract the ap_power_all columns from the raw_data_eeg columns
366  for i in range(2, max_Hz+1):
367      merged_df[f'V{i}'] = merged_df[f'V{i}_p'] + merged_df[f'V{i}_ap'] - merged_df[f'V{i}_p']
368
369  # Drop the original columns
370  merged_df.drop(columns=[f'V{i}_p' for i in range(2, max_Hz+1)] + [f'V{i}_ap' for i in range(2, max_Hz+1)], inplace=True)
371  # print(merged_df.head())
372  merged_df.to_csv(f'{output_dir}/ap_alpha_load.csv', index=False)
373  # calcualte the mean value for each column startswith V by groups_mean
374  groups_mean = merged_df.groupby(['age', 'load', 'exp'])
```

The selected color are `['#797BB7', '#E79397', '#80BA8A', '#51B1B7']`, two warm color and two cold color, which were lightened by 70% for each subject's line plot.

```python
# Loop over the conditions and plot each condition in a separate subplot
for i, (ax, (age)) in enumerate(zip(axs, conditions)):
    # Select the data for this age
    data = mean_df.xs(age, level='age')
    # Define the colors
    colors = ['#797BB7', '#E79397', '#80BA8A', '#51B1B7']
    # Create a cycle of colors
    color_cycle = itertools.cycle(colors)
    # Lighten the colors by 70%
    light_colors = [lighten_color(color, 0.3) for color in colors]
    # Create a cycle of light colors
    light_color_cycle = itertools.cycle(light_colors)

    # Each subject data
    PID_data = PID_df.xs(age, level='age')

    # Group by the first two levels of the index
    for (level0_value, level1_value), group in PID_data.groupby(level=[0, 1]):
        # 'group' is a subset of PID_data where the first level of the index equals 'level0_value'
        # and the second level of the index equals 'level1_value'
        # Get the next color in the cycle
        color = next(light_color_cycle)
        for pid in group.index:
            # Plot the data for this group
            ax.plot(group.loc[(pid, slice(None))], color=color, alpha=0.7)
```

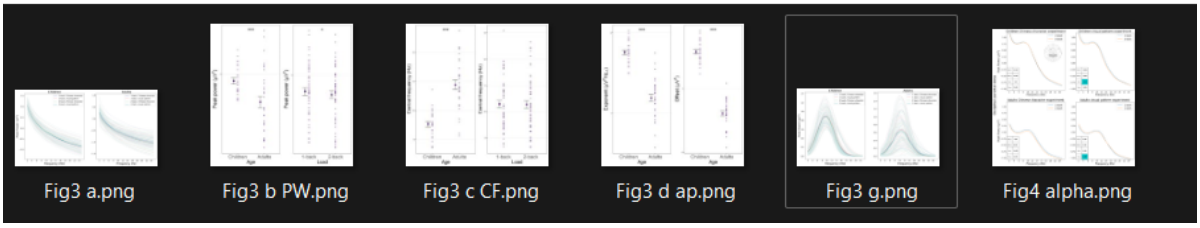
For periodic components, we subtracted the aperiodic components in the data:

```python
##################################################
# plot the periodic power load in Fig. 3 #
##################################################

merged_df = pd.merge(p_power_all, ap_power_all, on=['PID', 'age', 'load', 'exp'], suffixes=('_p', '_ap'))
# Subtract the ap_power_all columns from the raw_data_eeg columns
for i in range(2, max_Hz+1):
    merged_df[f'V{i}'] = merged_df[f'V{i}_p'] + merged_df[f'V{i}_ap'] - merged_df[f'V{i}_ap']
```

The above code was not sealed in a function for easy modification. Further details and examples can be found in the R script below.

3 alpha plot

The remaining 3 graphs in the `4 alpha pic` folder were plotted in R. ggplots2 package in R is highly recommended for statistical plots for the best visual experience.



In this code the coder used a self-wrote function again called `summarySE.R`. Ifor descriptive statistics. You can select other functions or packages according to your preference.

```r
library(lmerTest)
library(rstatix)
library(dplyr)
library(bruceR)
library(gridExtra)


set.wd()
source('summarySE.R')

stat_data<-read.csv("3 alpha_stat/mean_alpha_params.csv",header = TRUE)
stat_data <- stat_data %>% filter(!is.na(CF))
# View(stat_data)
stat_data$age<-as.factor(stat_data$age)

res.aov <- anova_test(
  data=stat_data, dv = PW, wid = PID,between = age,
  within = c(exp, load)
)
get_anova_table(res.aov)
"ANOVA Table (type III tests) PW

        Effect DFn DFd     F     p p<.05      ges
1          age   1  54 9.097 0.004     * 1.35e-01
2          exp   1  54 0.254 0.616       1.80e-04
3         load   1  54 4.288 0.043     * 1.00e-03
4      age:exp   1  54 0.005 0.944       3.49e-06
5     age:load   1  54 1.114 0.296       3.80e-04
6     exp:load   1  54 1.512 0.224       5.10e-04
7 age:exp:load   1  54 1.020 0.317       3.44e-04"
```

For data pre-processing, we just calculated the mean and se for the needed parameters in the para_data. The para_data_sub stores the variables with _sub which contains participant's data for the dot plot.

```r
###############
# exp & offset
###############
CF_sub_1 <- stat_data %>% summarySE(measurevar = "exponent", groupvars=c('PID', "age"))
CF_sub_1 <- CF_sub_1 %>%
  rename(y_mean = exponent_mean, y_median = exponent_median) %>%
  mutate(P_para = "exponent")
PW_sub_1 <- stat_data %>% summarySE(measurevar = "offset", groupvars=c('PID', "age"))
PW_sub_1 <- PW_sub_1 %>%
  rename(y_mean = offset_mean, y_median = offset_median) %>%
  mutate(P_para = "offset")
sub_p <- bind_rows(CF_sub_1, PW_sub_1)

CF_1 <- summarySE(CF_sub_1, measurevar = "y_mean", groupvars=c("age"))%>%
  mutate(P_para = "exponent")
PW_1 <- summarySE(PW_sub_1, measurevar = "y_mean", groupvars=c("age"))%>%
  mutate(P_para = "offset")
mean_p <- bind_rows(CF_1, PW_1)

# Exponent plot
para_data <- mean_p %>% filter(P_para == "exponent")
para_data_sub <- sub_p %>% filter(P_para == "exponent")

# Modify the data to include 'age' in 'P_para'
para_data <- para_data %>% mutate(P_para = paste(P_para, age, sep = "_"))
para_data_sub <- para_data_sub %>% mutate(P_para = paste(P_para, age, sep = "_"))
```

para_data:

	age	N	y_mean_mean	y_mean_median	sd	se	ci	P_para
1	0	25	1.757497	1.750471	0.1456513	0.02913026	0.06012190	exponent
2	1	31	1.191341	1.209402	0.2503659	0.04496704	0.09183495	exponent

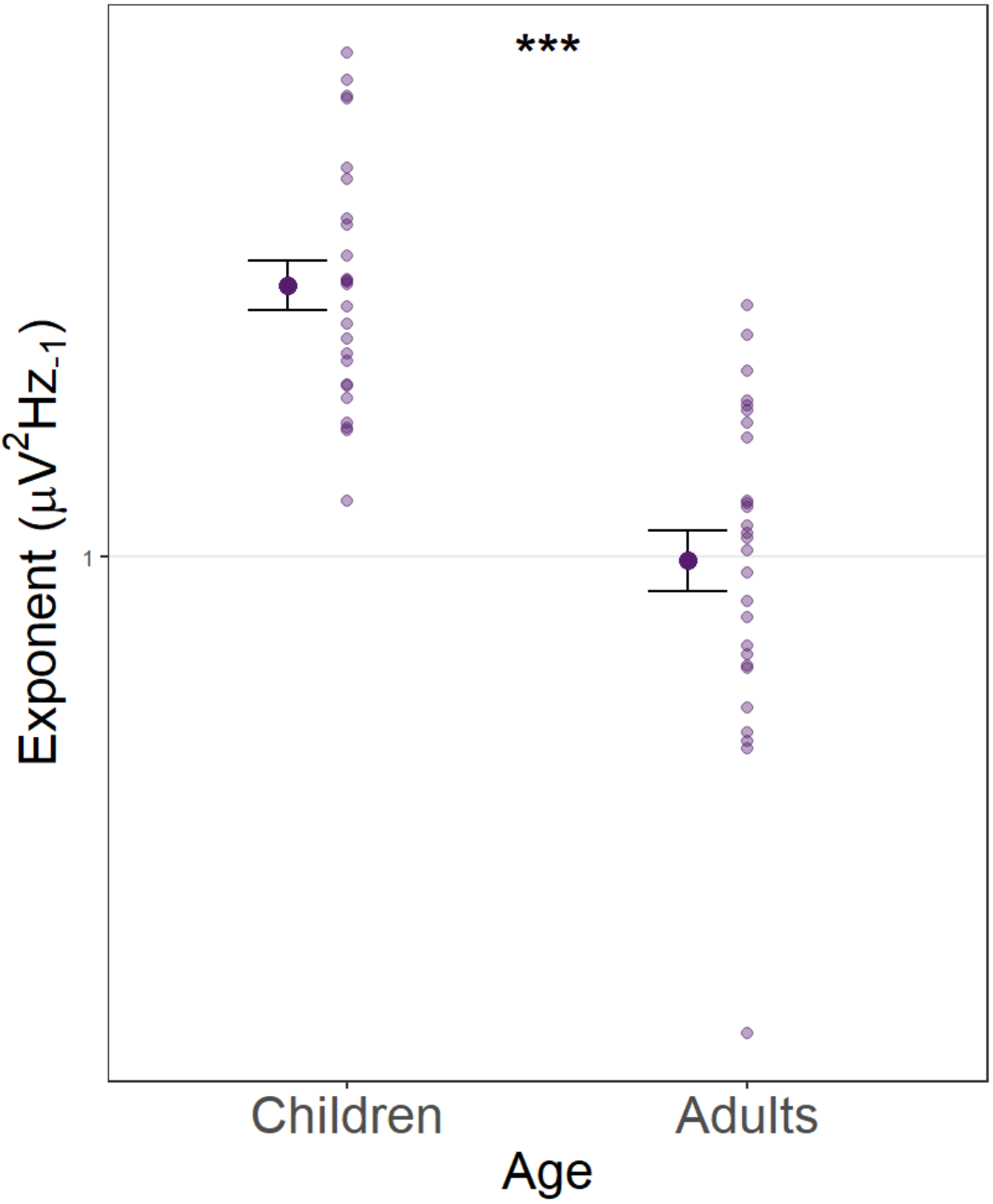
para_data_sub:

	PID	age	N	y_mean	y_median	sd	se	ci	P_para
1	1104	0	4	1.9514914	1.9588039	0.05213434	0.02606717	0.08295737	exponent
2	1108	0	4	1.5867939	1.5921209	0.02214808	0.01107404	0.03524254	exponent
3	1605	0	4	1.5740793	1.5747610	0.06484406	0.03242203	0.10318137	exponent
4	1606	0	4	1.7123900	1.7067560	0.06323628	0.03161814	0.10062304	exponent
5	1607	0	4	1.6426140	1.6329540	0.07267755	0.03633877	0.11564620	exponent
6	1608	0	4	1.7504706	1.7548282	0.07057193	0.03528596	0.11229568	exponent
7	1609	0	4	1.9256451	1.9228719	0.04021603	0.02010801	0.06399267	exponent
8	1612	0	4	1.7623486	1.7208633	0.13936402	0.06968201	0.22175926	exponent
9	1615	0	4	1.5082498	1.5443498	0.07667016	0.03833508	0.12199934	exponent
10	1619	0	4	1.8389415	1.8540837	0.14470486	0.07235243	0.23025773	exponent
11	1621	0	4	1.6775884	1.6581103	0.07058767	0.03529383	0.11232073	exponent
12	1623	0	4	1.4956443	1.4784689	0.07950366	0.03975183	0.12650807	exponent
13	1625	0	4	1.9033371	1.9161550	0.09548111	0.04774055	0.15193175	exponent
14	1627	0	4	1.8378967	1.8372548	0.07604051	0.03802026	0.12099742	exponent
15	1629	0	4	1.7857024	1.7833761	0.05157240	0.02578620	0.08206319	exponent
16	1632	0	4	1.7337446	1.7366784	0.02100797	0.01050398	0.03342837	exponent
17	1634	0	4	1.9202404	1.8854998	0.11539979	0.05769990	0.18362682	exponent
18	1635	0	4	2.0267927	2.0263313	0.05018810	0.02509405	0.07986047	exponent
19	1637	0	4	1.8009358	1.7826642	0.15020187	0.07510094	0.23900469	exponent
20	1640	0	4	1.7346181	1.7812216	0.12128318	0.06064159	0.19298860	exponent

The plot contains the following parts: The error bar was 0.15 offset to left to prevent overlap. The dot at the middle of the bar indicates the mean value for each group. The jitter dots for each participants for extreme values identification; and manually added the significance asterisks (***).

```
# Modify the data to include 'age' in 'P_para'
para_data <- para_data %>% mutate(P_para = paste(P_para, age, sep = "_"))
para_data_sub <- para_data_sub %>% mutate(P_para = paste(P_para, age, sep = "_"))

p7 <- ggplot(para_data, aes(x = P_para, y = y_mean_mean)) +
  geom_errorbar(aes(x = P_para, y = y_mean_mean,
                    ymin = y_mean_mean-se, ymax = y_mean_mean+se),
                width = .2, position = position_nudge(x = -0.15)) +
  geom_point(aes(x = P_para, y = y_mean_mean), position = position_nudge(x = -0.15),
             shape=21, size=3, color="#551C6E", fill="#551C6E") +
  geom_jitter(data = para_data_sub, aes(x = P_para, y = y_mean),
              position = position_jitter(width = 0), shape=21,
              size = 2, alpha=0.4, color="#551C6E", fill="#551C6E", show.legend=F) +
  # labs(title = 'exponent by age') +
  ylab(expression('Exponent '*'('*mu*'V'^'2'*'Hz'['-1']*')'))+
  scale_y_continuous(breaks = seq(0, max(para_data_sub$y_mean))) +
  xlab('Age')+
  # Note p significance manually
  geom_text(data = para_data, x = 1.5, y = max(para_data_sub$y_mean),
            label = "***", size = 8) + # p < .001
  scale_x_discrete(labels = c("exponent_0" = "Children", "exponent_1" = "Adults")) + # Add x-axis labels
  theme_bw() + # Change theme to black and white
  theme(
  panel.grid.major.x = element_blank(),
  panel.grid.minor = element_blank(),
  legend.title = element_blank(),
  legend.position = "none",
  strip.text = element_text(size = 20), # Increase size for strip text
  legend.text = element_text(size = 20), # Increase size for legend text
  axis.text.x = element_text(size = 20), # Increase size for axis text
  plot.title = element_text(size = 24, hjust = 0.5), # Increase size for plot title
  axis.title = element_text(size = 20) # Increase size for axis title
)
p7
```

Example plot for half of Fig3 d:



Two graphs were merged together during output for compactness:

```
png("4 alpha pic/Fig3 d ap.png", width = 8, height = 8, units = "in", res = 350)
grid.arrange(p7, p8, ncol = 2)
dev.off()
```

Fig3 d:

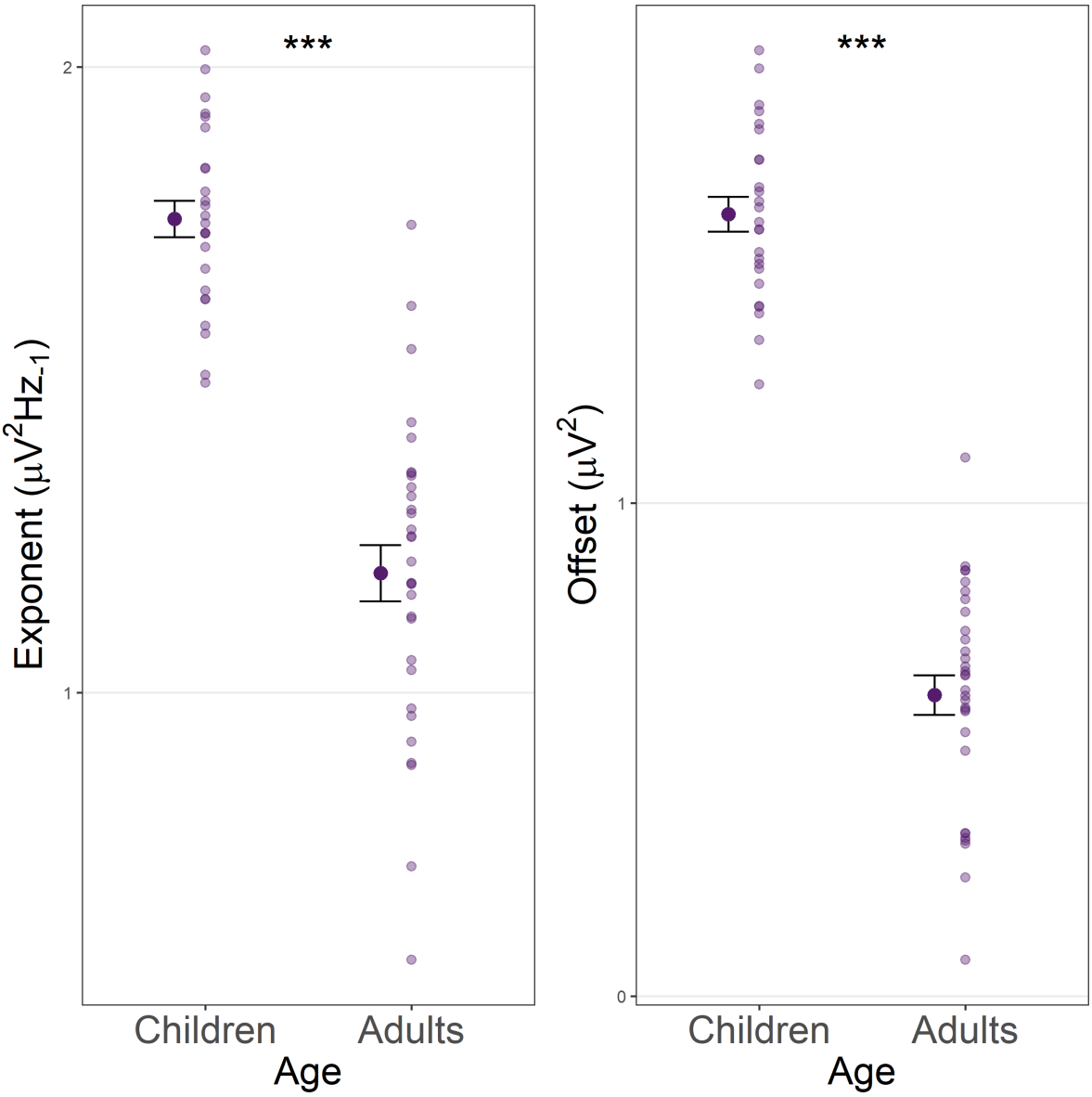
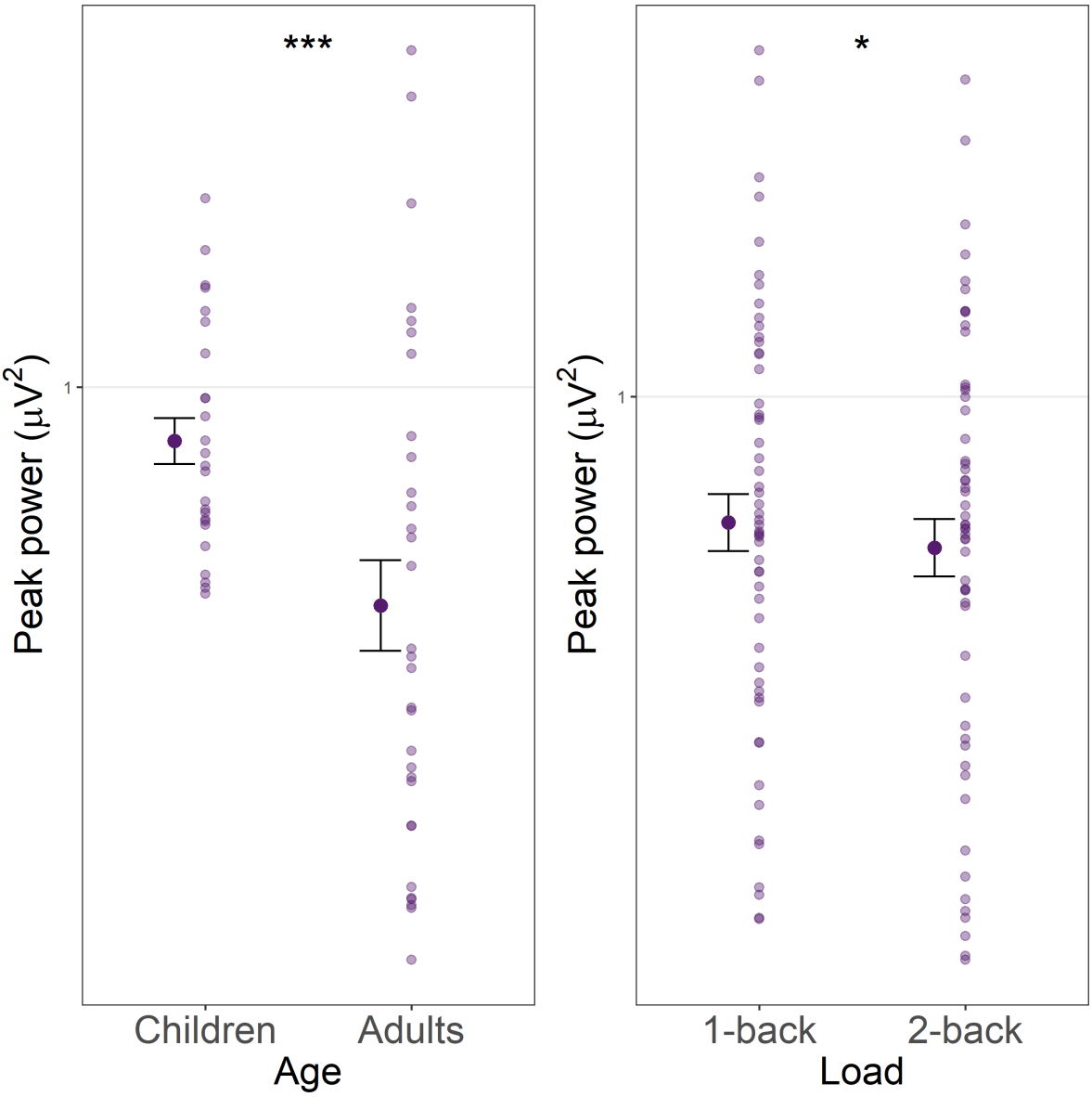
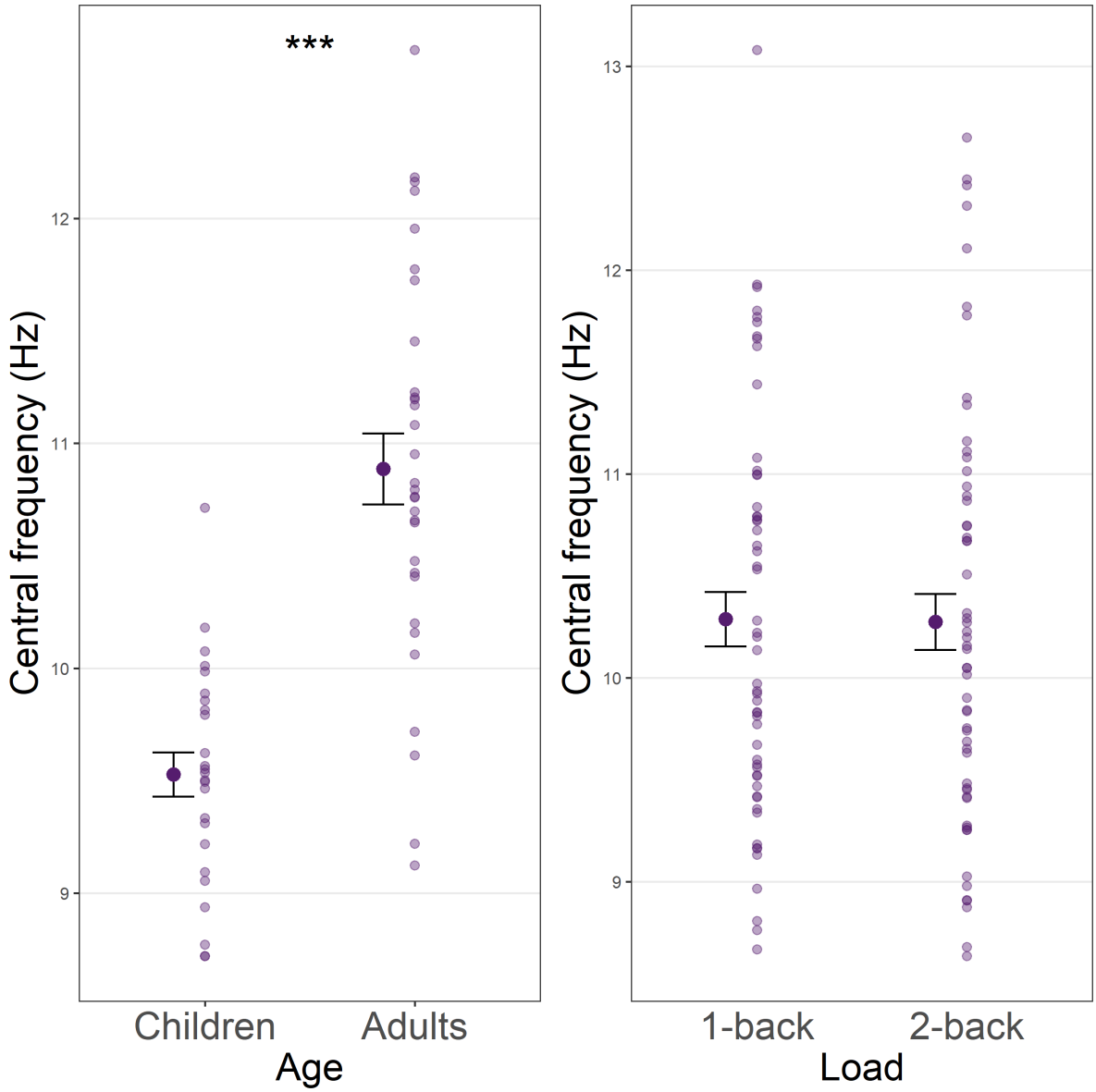


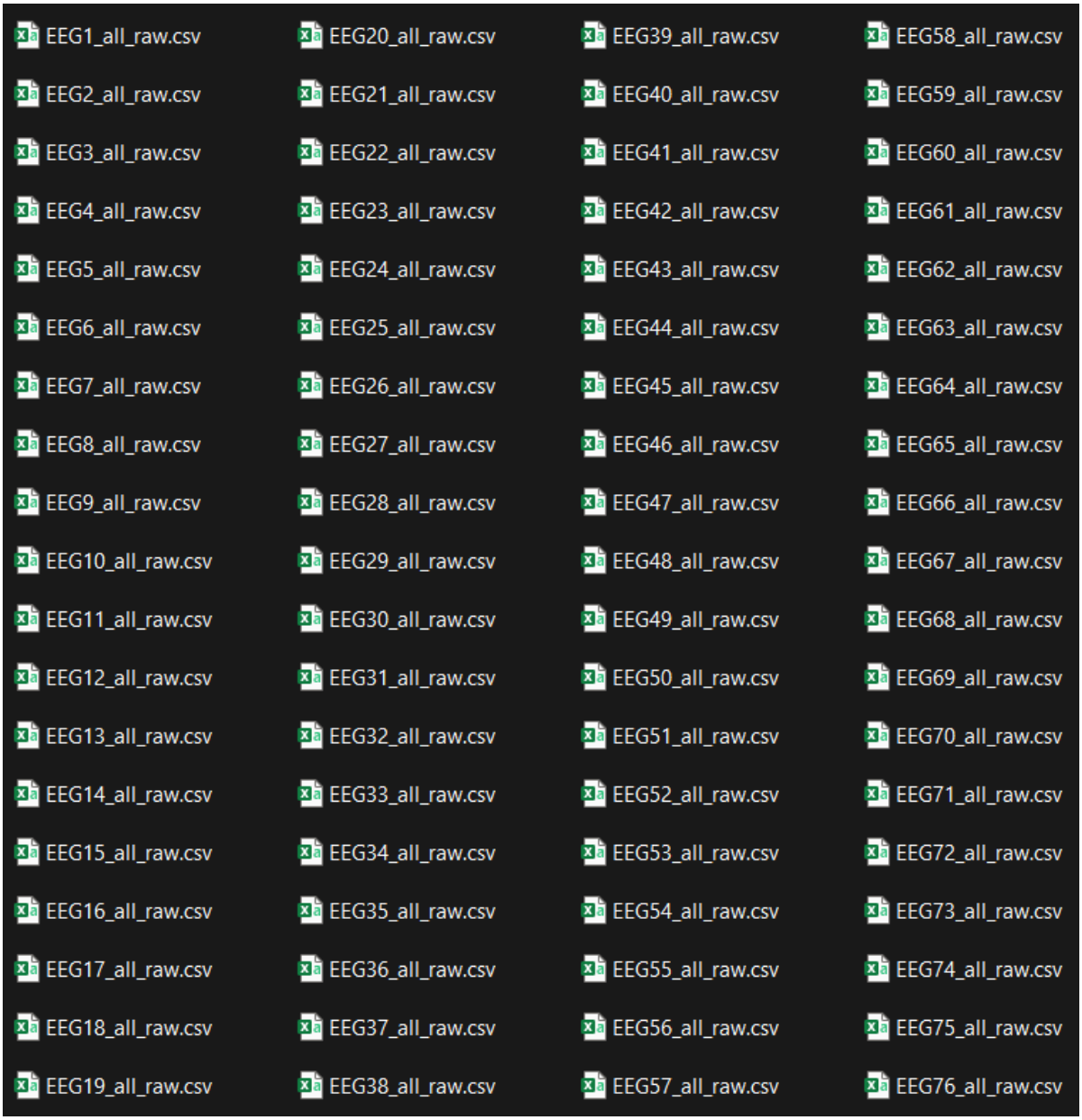
Fig3 b and Fig 3 c:


***
Peak power (μV²)
1
Children
Adults
Age
*
Peak power (μV²)
1
1-back
2-back
Load

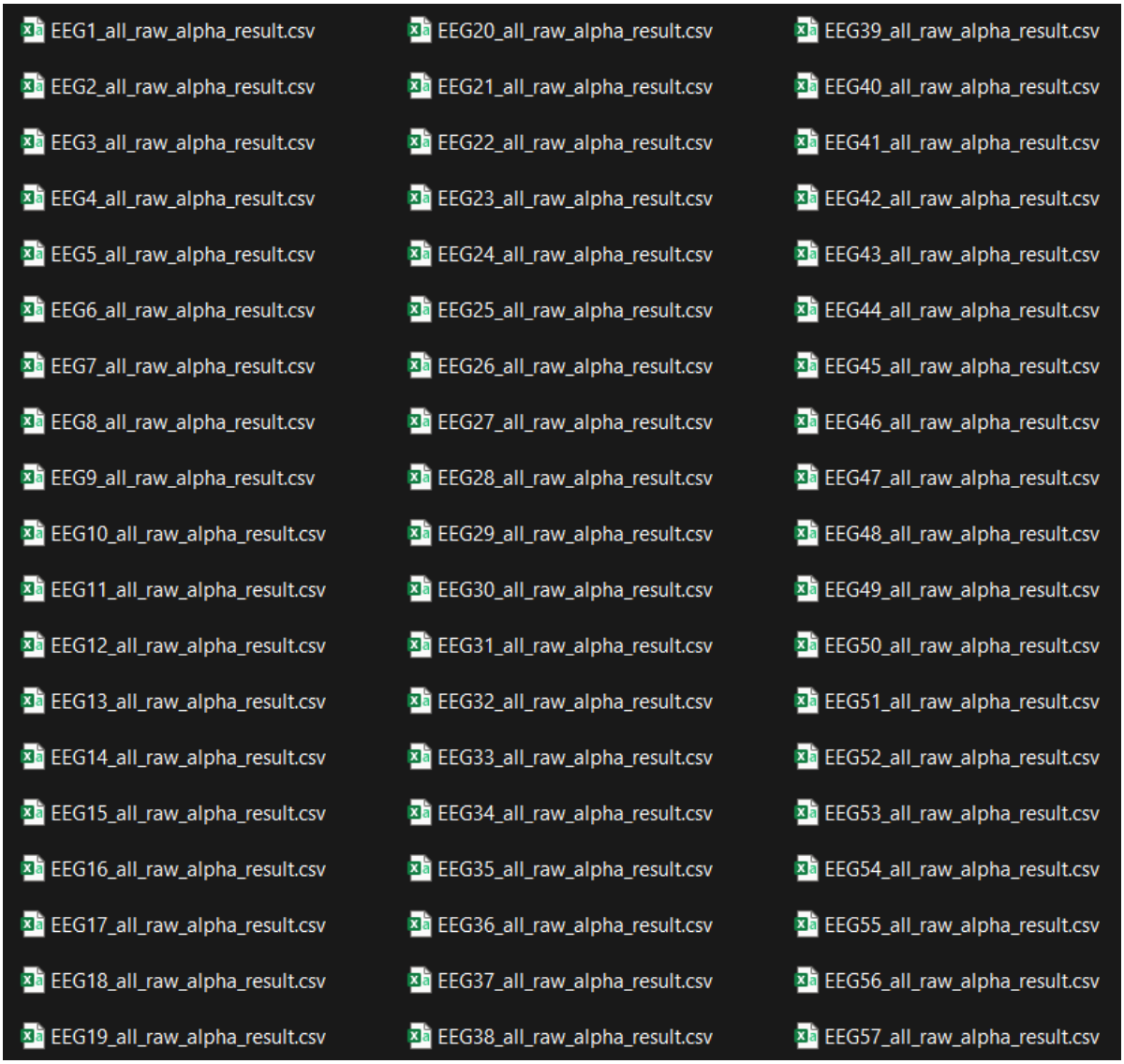


Topography data preprocess

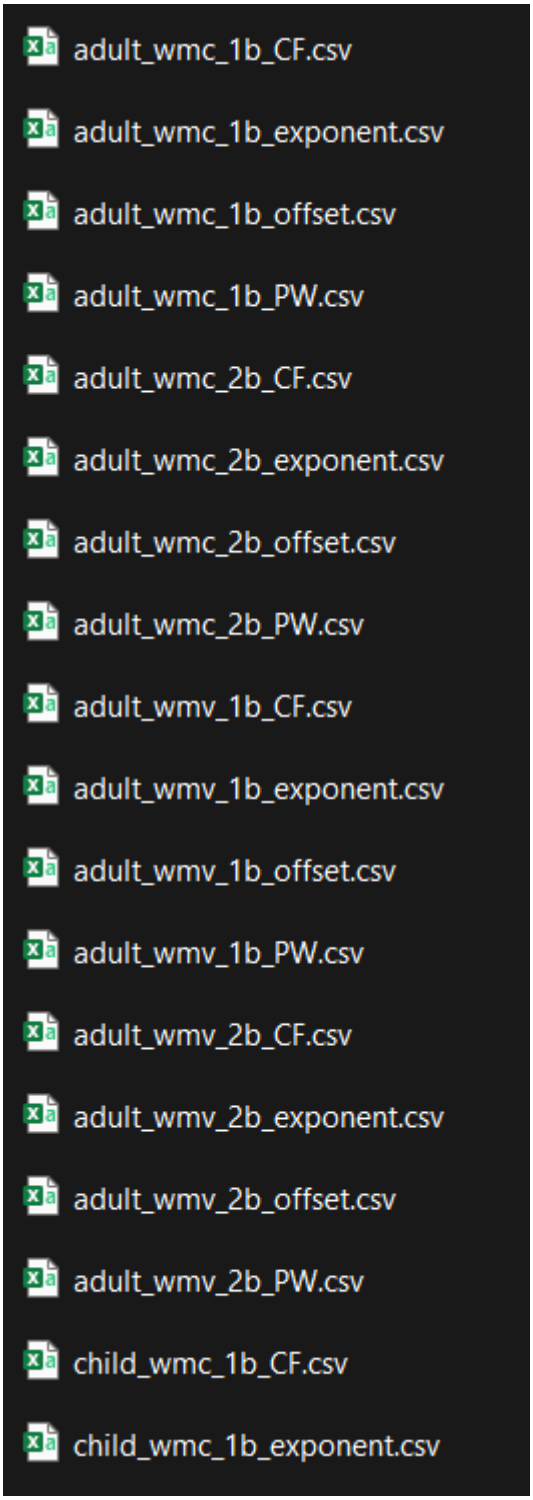
The `4 fooof topo.py` and `5 topo data`.py are the two files that use all channel data from `topography data` and output FOOOFed data in `5 alpha topo` and `5 theta topo`. The `5 topo cleaned` stores cleaned data for topography plots. The `topography data` folder has all channel data in it:



The `4 fooof topo.py` processed data from it and the output folder `5 alpha topo` has all channel's processed data:



Then the `5 topo data.py` used similar process in `2 stat alpha` to filter peaks. The output is also similar, but only `_PW` files are need for the topography plot.

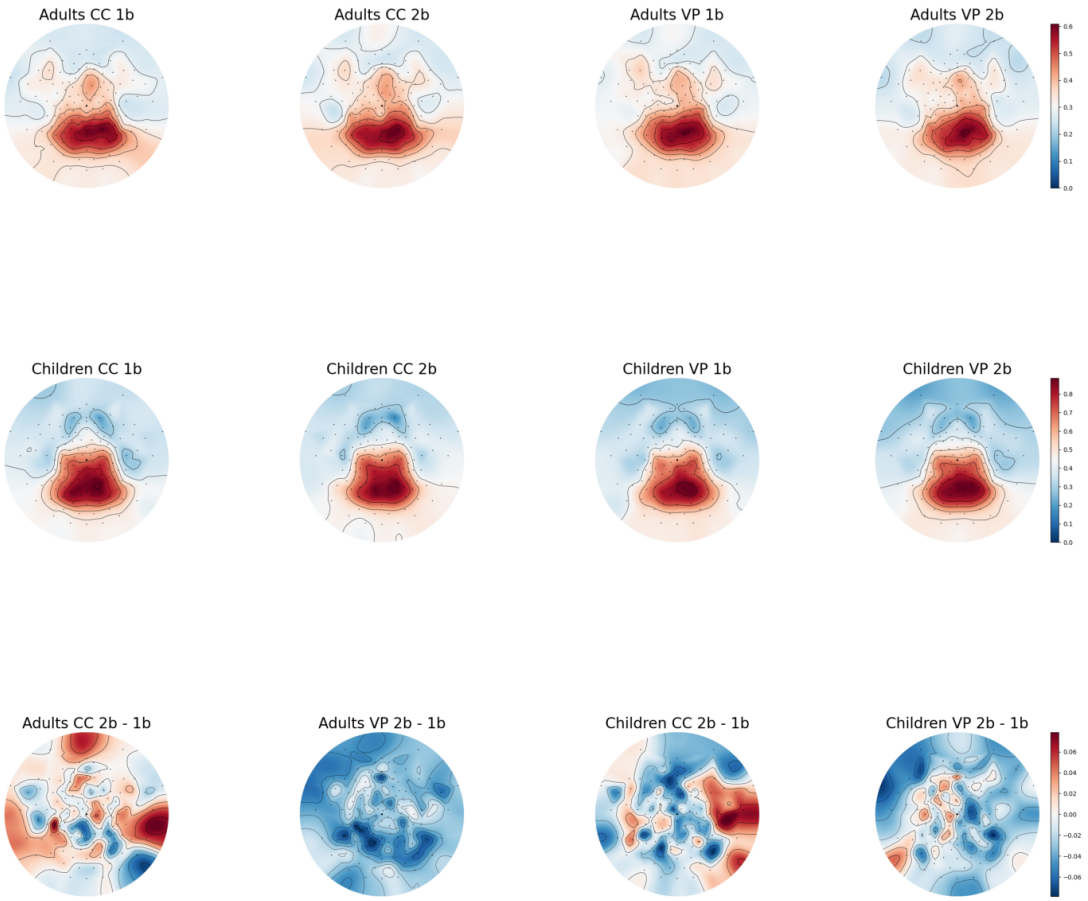


Then use the `6 topo plot`.py to plot topography. It used montage from the `montage files` and the cleaned folder data above. And it output pictures in `6 alpha topo` and `6 theta topo` folders. Each of them contains pictures for each conditions and a joint plot for all conditions. You can uncomment the codes in the `montage_fit` functions if you want to output the normalized topography.

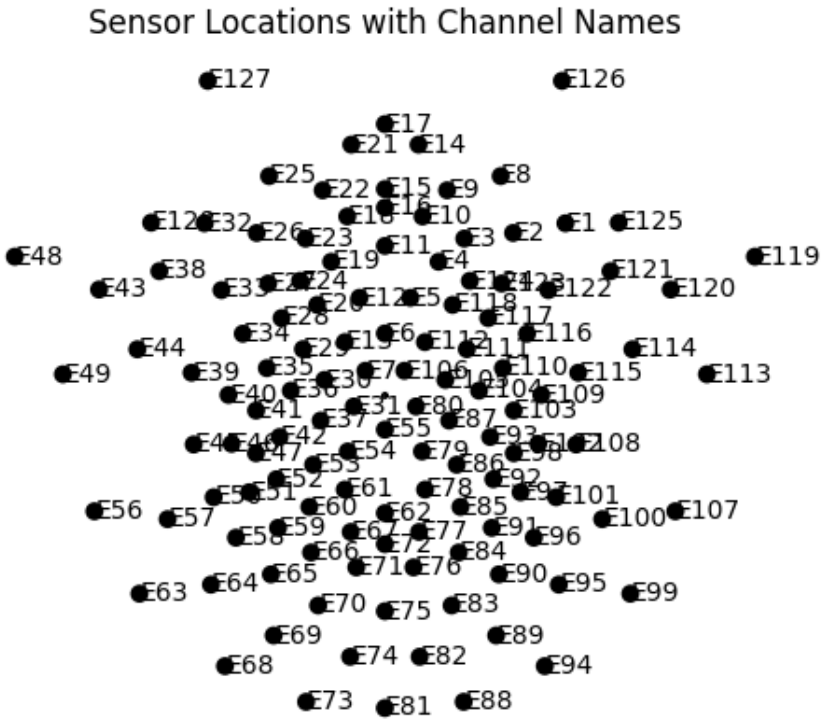
```python
# function to fit eeg data to montage
def montage_fit(data):
    # Convert the DataFrame to a 3D numpy array
    data = data.loc[:, 'EEG1': 'EEG128'].values[:, np.newaxis]

    # Initialize a new StandardScaler instance
    scaler = StandardScaler()

    # # Fit the scaler to the data and transform the data for normalizing data by rows
    # data = data.squeeze()  # remove singleton dimensions
    # data_zscore = scaler.fit_transform(data.T)

    # # Add an extra dimension to match the original data shape
    # data_zscore = data_zscore.T[:, np.newaxis]
```

The output folder contains a joint plot for all conditions. The four plots in the same row share one color bar at the right side of each row.

Topographies for alpha band in each condition each group



It also output the sensor location plot in the `montage files`, which helps to check is the sensor location is correctly imported.



End & contact info

This is the end of the tutorial. The code for theta band was not included as the structure is the same. Thank you for spending so much time reading this. If you have any questions related to coding, feel free to contact the coder by quentinlampsy@gmail.com.