



Analyzing single trial EEG data using the hu-neuro-pipeline package

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The Frömer et al. (2018) pipeline

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ORIGINAL RESEARCH
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Group-Level EEG-Processing Pipeline for Flexible Single Trial-Based Analyses Including Linear Mixed Models

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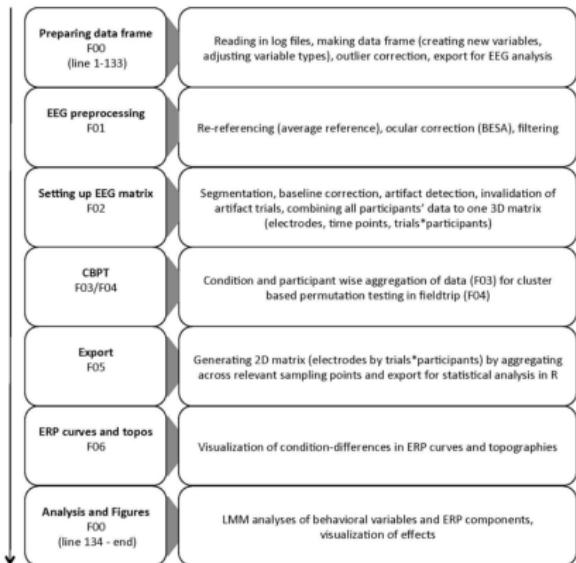
Keywords: EEG, ERICLab, Linear mixed models, cluster-based permutation tests, processing pipeline

INTRODUCTION

EEG do something 100 times, still every time to the same ITI (is it really a 100 or 1000 ms? I don't know). But what does this tell us about the effect? How does one express in clustering option and print shape no brain response to this task? How does variability in neural responses relate to variability in behavior?

Additional file 1: *EEG-Processing Pipeline*. The pipeline consists of statistical and signal processing methods, parallel to the emergence of open source toolboxes (implementing these

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5
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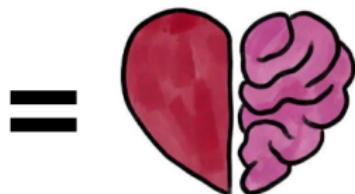
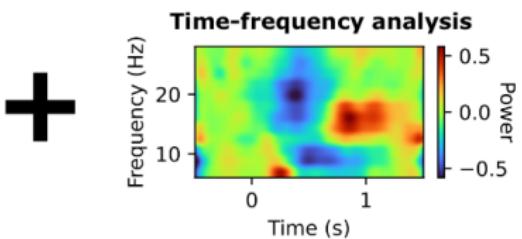
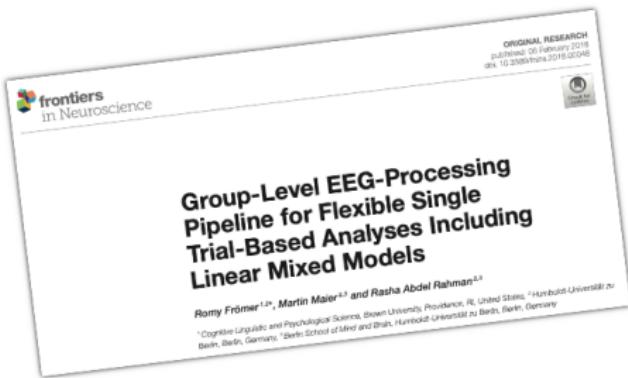
#2

The Frömer et al. (2018) pipeline

- Allows single trial analysis of ERP amplitudes
 - Random effects for items (Bürki et al., 2018)
 - Trial and item level covariates (Volpert-Esmond et al., 2021)
 - Continuous predictor variables
 - Unbalanced designs
 - Brain–behavior associations



Python implementation



#4



Python, I choose you!



Blog post: https://dominiquemakowski.github.io/post/2020-05-22-r_or_python

Online course: <https://swcarpentry.github.io/python-novice-inflammation>



MNE-Python

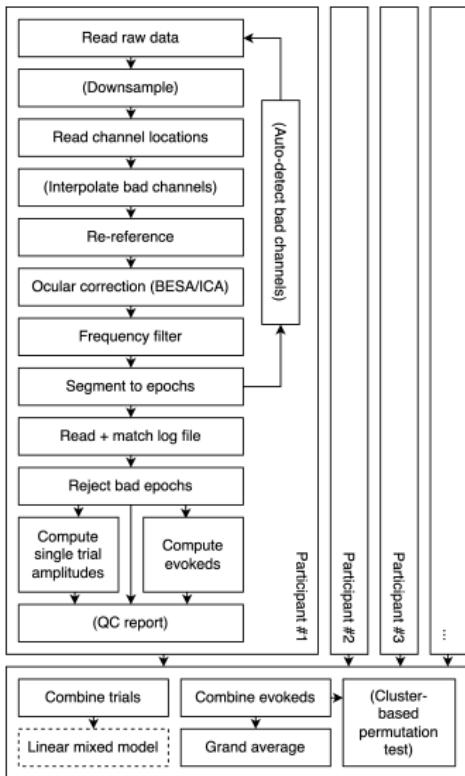
- Versatile
 - EEG, MEG, ECoG, fNIRS
 - Preprocessing, statistics, time-frequency analysis, visualization, machine learning, connectivity, source localization, ...
- Open source
 - > 350 contributors on GitHub (December 2023)
 - Funded by NIH, NSF, ERC, Google, Amazon, ...
 - Code review, automated tests, user forum, office hours, ...



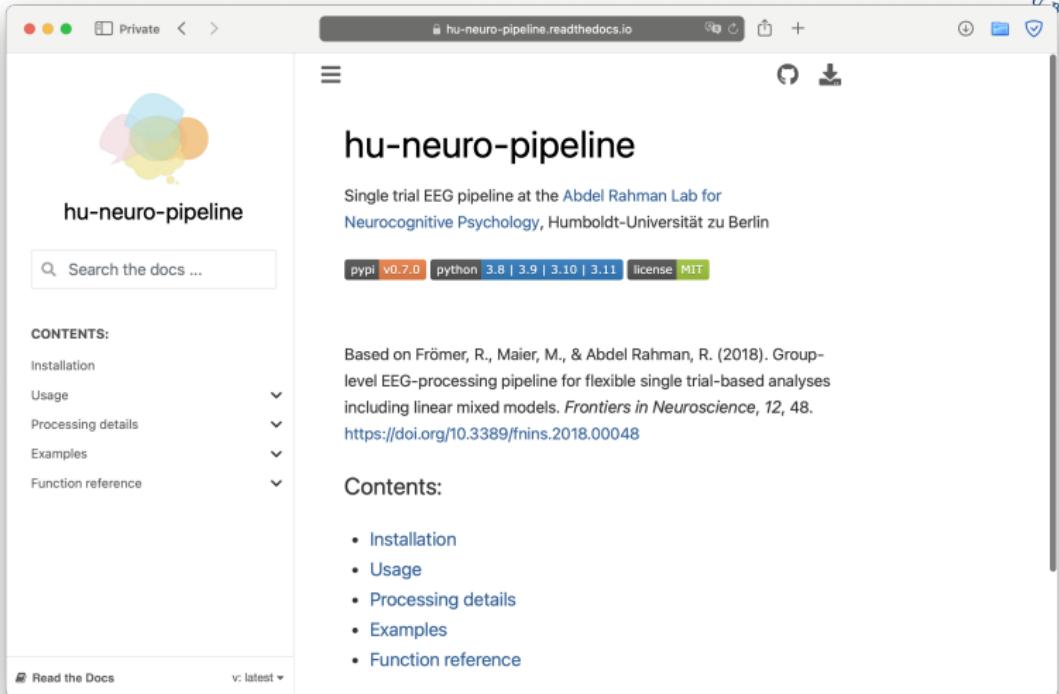
Python implementation

- No MATLAB required
- No Python skills required – can be called from R
- New features:
 - Time-frequency analysis
 - Fully automatic ocular correction (ICA)
 - Automatic bad channel detection
 - Automatic missing trial detection
 - Example datasets
- Code standards, documentation, version control
(<https://github.com/alexenge/hu-neuro-pipeline/>)

Python implementation



Python implementation



The screenshot shows a web browser window displaying the hu-neuro-pipeline.readthedocs.io documentation. The page features a header with the project logo (three overlapping colored circles) and title, a search bar, and a navigation menu. The main content area includes a brief introduction, installation instructions, and a table of contents.

hu-neuro-pipeline

Single trial EEG pipeline at the [Abdel Rahman Lab for Neurocognitive Psychology](#), Humboldt-Universität zu Berlin

pypi v0.7.0 python 3.8 | 3.9 | 3.10 | 3.11 license MIT

CONTENTS:

- Installation
- Usage
- Processing details
- Examples
- Function reference

Based on Frömer, R., Maier, M., & Abdel Rahman, R. (2018). Group-level EEG-processing pipeline for flexible single trial-based analyses including linear mixed models. *Frontiers in Neuroscience*, 12, 48.
<https://doi.org/10.3389/fnins.2018.00048>

Contents:

- Installation
- Usage
- Processing details
- Examples
- Function reference

Installation

For Python users:

```
# Install via the command line from the Python Packaging Index (PyPI)
pip install hu-neuro-pipeline
```

For R users:

```
# Install reticulate for interfacing with Python from R
install.packages("reticulate")

# Install Python (Miniconda distribution)
reticulate::install_miniconda()

# Install the actual package from PyPI
reticulate::py_install("hu-neuro-pipeline", pip = TRUE, python_version = "3.8")
```

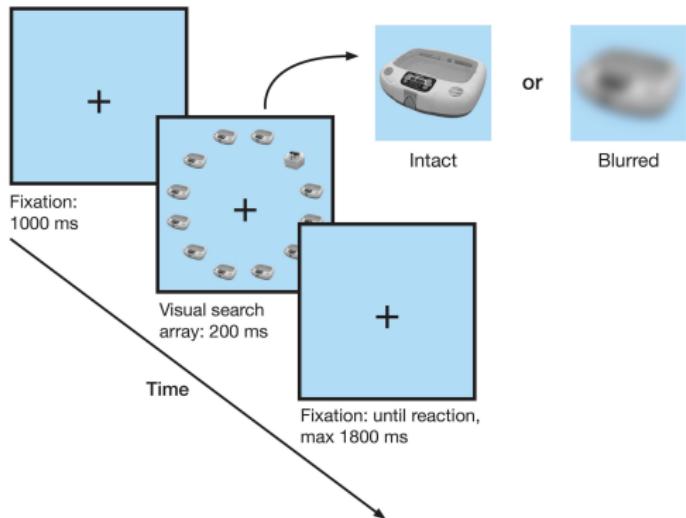
General usage

```
# Import the Python package
pipeline <- reticulate::import("pipeline")

# Run the pipeline
res <- pipeline$group_pipeline(...)
```

Minimal example

```
ucap_paths <- pipeline$datasets$get_ucap(participants = 2, path = "data")
```



For details, see Frömer et al. (2018)

#12

Minimal example

```

# Run the pipeline
res <- pipeline$group_pipeline(
  # Input/output paths
  raw_files = "data/ucap/raw",
  log_files = "data/ucap/log",
  output_dir = "output",
  # Preprocessing options
  besa_files = "data/ucap/cali",
  # Epoching options
  triggers = c(201:208, 211:218),
  components = list(
    "name" = list("N2", "P3b"),
    "tmin" = list(0.25, 0.4),
    "tmax" = list(0.35, 0.55),
    "roi" = list(
      c("FC1", "FC2", "C1", "C2", "Cz"),
      c("CP3", "CP1", "CPz", "CP2", "CP4", "P3", "Pz", "P4", "P03", "P0z", "P04")
    )
  ),
  # Averaging options
  average_by = list(
    blurr_left = "n_b == 'blurr' and DeviantPosRL == 'li' and RT > 200",
    blurr_right = "n_b == 'blurr' and DeviantPosRL == 're' and RT > 200",
    normal_right = "n_b == 'normal' and DeviantPosRL == 're' and RT > 200",
    normal_left = "n_b == 'normal' and DeviantPosRL == 're' and RT > 200"
  )
)

```

Pipeline inputs

```
# Input/output paths
raw_files = "data/raw",
log_files = "data/log",
output_dir = "output",
```

- Directory or list of raw EEG files (.vhdr)
- Directory or list of behavioral log files (.txt/.tsv/.csv)
- Output directory

Pipeline inputs

```
# Preprocessing options  
besa_files = "data/cali",
```

- Directory path or list of BESA files (.matrix)
- Default bandpass filter (0.1–40 Hz)
- Default re-referencing (common average)

Pipeline inputs

```
# Epoching options
triggers = c(201:208, 211:218),
components = list(
  "name" = list("N2", "P3b"),
  "tmin" = list(0.25, 0.4),
  "tmax" = list(0.35, 0.55),
  "roi" = list(
    c("FC1", "FC2", "C1", "C2", "Cz"),
    c("CP3", "CP1", "CPz", "CP2", "CP4", "P3", "Pz", "P4", "P03", "POz", "P04")
  )
),
```

- List of numerical EEG triggers
- List of ERP component definitions:
 - name: Custom label for each component
 - tmin + tmax: Onset and offset times (in s)
 - roi: List of channel names for each component

Pipeline inputs

```
# Epoching options
triggers = c(201:208, 211:218),
components = list(
  "name" = list("N2", "P3b"),
  "tmin" = list(0.25, 0.4),
  "tmax" = list(0.35, 0.55),
  "roi" = list(
    c("FC1", "FC2", "C1", "C2", "Cz"),
    c("CP3", "CP1", "CPz", "CP2", "CP4", "P3", "Pz", "P4", "P03", "POz", "P04")
  )
),
```

- Default baseline correction (-0.2 – 0.0 s)
- Default rejection of bad epochs (peak-to-peak ampl. > 200 μ V)

Pipeline inputs

```
# Averaging options
average_by = list(
    blurr_left = "n_b == 'blurr' and DeviantPosRL == 'li' and RT > 200",
    blurr_right = "n_b == 'blurr' and DeviantPosRL == 're' and RT > 200",
    normal_right = "n_b == 'normal' and DeviantPosRL == 're' and RT > 200",
    normal_left = "n_b == 'normal' and DeviantPosRL == 're' and RT > 200"
)
```

- List with all (combinations of) conditions to create by-participant averages for:
 - List names are custom labels for each average
 - List values are query strings to select log file rows (trials/epochs)

More pipeline inputs

- Downsampling (`downsample_sfreq`)
- Interpolate bad channels (`bad_channels`)
- Frequency filter (`highpass_freq`, `lowpass_freq`)
- Epoch duration (`epochs_tmin`, `epochs_tmax`)
- Baseline duration (`baseline`)
- Skip log file rows (`skip_log_rows`, `skip_log_conditions`)
- Threshold for artifact rejection (`reject_peak_to_peak`)
- ...

See https://hu-neuro-pipeline.readthedocs.io/en/latest/usage_inputs.html

Pipeline outputs

Extract directly from the pipeline run:

```
trials <- res[[1]]    # Single trial data frame
evokeds <- res[[2]]   # Evokeds data frame
config <- res[[3]]    # List of pipeline options
```

Or read from the output directory:

```
library(tidyverse)
trials <- read_csv("output/trials.csv")
evokeds <- read_csv("output/ave.csv")
config <- jsonlite::read_json("output/config.json")
```

See https://hu-neuro-pipeline.readthedocs.io/en/latest/usage_outputs.html

Pipeline outputs

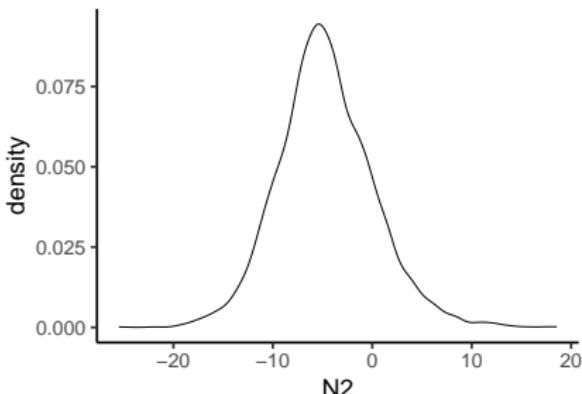
```
# Single trial data frame
print(trials)

## # A tibble: 3,840 x 32
##   participant_id VPNNummer version    wdh lfdNr n_b    Standard Deviant Objektpaar
##   <chr>           <dbl> <dbl> <dbl> <chr> <chr>    <chr>      <dbl>
## 1 05              5     1     1     1 norm~ objekt7~ objekt~       8
## 2 05              5     1     1     2 blurr objekt3~ objekt~      10
## 3 05              5     1     1     3 blurr objekt3~ objekt~      10
## 4 05              5     1     1     4 norm~ objekt2~ objekt~       3
## 5 05              5     1     1     5 norm~ objekt8~ objekt~      15
## 6 05              5     1     1     6 norm~ objekt6~ objekt~       7
## 7 05              5     1     1     7 blurr objekt1~ objekt~       2
## 8 05              5     1     1     8 norm~ objekt8~ objekt~      16
## 9 05              5     1     1     9 norm~ objekt2~ objekt~       9
## 10 05             5     1     1    10 norm~ objekt4~ objekt~      11
## # i 3,830 more rows
## # i 23 more variables: BedCode_alt <chr>, BedCode_neu <chr>, bot <dbl>,
## #   DeviantPosRL <chr>, DeviantPosNR <dbl>, BedCodeRL <chr>, key <dbl>,
## #   ErrorCode <dbl>, RT <dbl>, Pos1 <chr>, Pos2 <chr>, Pos3 <chr>, Pos4 <chr>,
## #   Pos5 <chr>, Pos6 <chr>, Pos7 <chr>, Pos8 <chr>, Pos9 <chr>, Pos10 <chr>,
## #   Pos11 <chr>, Pos12 <chr>, N2 <dbl>, P3b <dbl>
```

Pipeline outputs

```
# Single trial N2 mean amplitudes
ggplot(trials, aes(x = N2)) +
  geom_density() +
  theme_classic(base_size = 30)
```

```
## Warning: Removed 7 rows containing non-finite values (`stat_density()`).
```



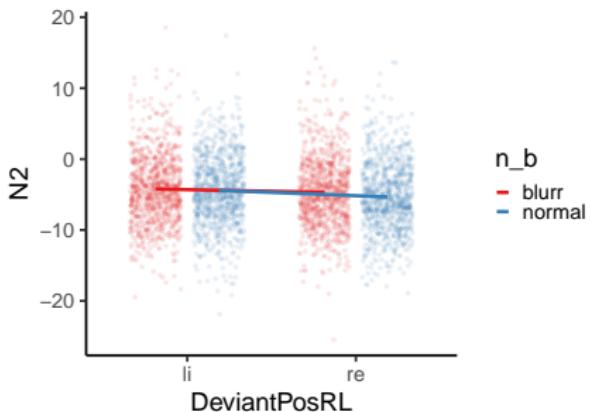
Pipeline outputs

```
# Linear mixed-effects model
form <- N2 ~ n_b * DeviantPosRL + (1 | participant_id)
mod <- lme4::lmer(form, trials)
summary(mod)

## Linear mixed model fit by REML ['lmerMod']
## Formula: N2 ~ n_b * DeviantPosRL + (1 | participant_id)
##   Data: trials
##
## REML criterion at convergence: 22696.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.6856 -0.6130 -0.0002  0.6148  5.1121
##
## Random effects:
##   Groups      Name        Variance Std.Dev.
##   participant_id (Intercept) 2.287    1.512
##   Residual           21.780    4.667
## Number of obs: 3833, groups: participant_id, 2
##
## Fixed effects:
##                   Estimate Std. Error t value
## (Intercept)      -4.2285    1.0800 -3.915
## n_bnrmal       -0.1796    0.2132 -0.842
## DeviantPosRLre  -0.4587    0.2132 -2.151
## n_bnrmal:DeviantPosRLre -0.4732    0.3015 -1.569
##
## Correlation of Fixed Effects:
```

Pipeline outputs

```
# Single trial N2 mean amplitudes by condition
ggplot(trials, aes(x = DeviantPosRL, y = N2, color = n_b, group = n_b)) +
  geom_point(position = position_jitterdodge(0.3), alpha = 0.1) +
  stat_summary(
    geom = "line",
    linewidth = 2.0,
    position = position_dodge(0.75)
  ) +
  theme_classic(base_size = 30)
```



Pipeline outputs

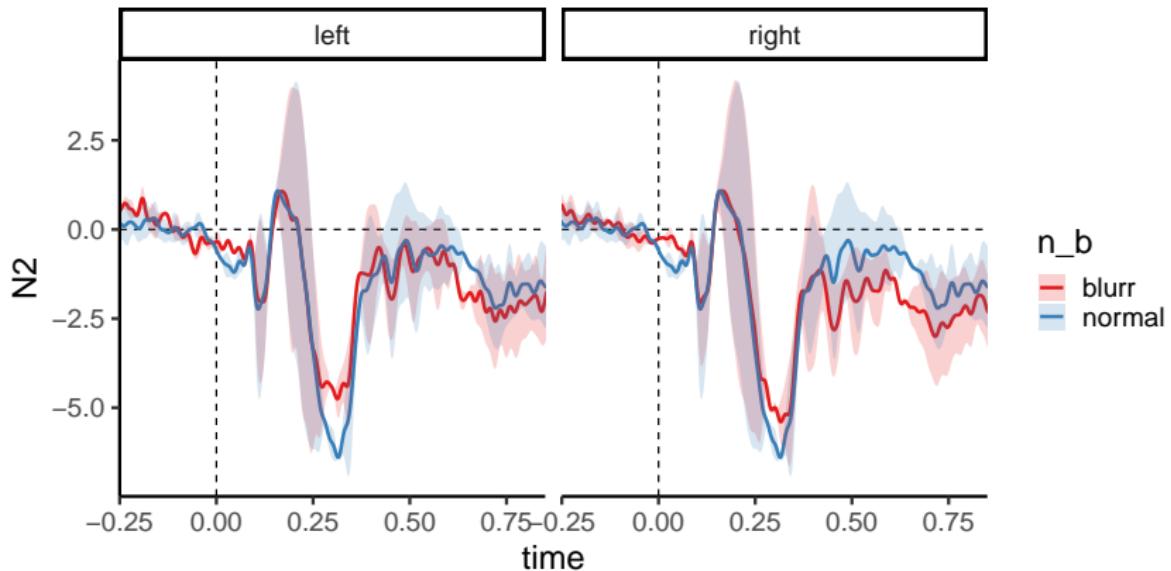
```
# Evokeds by participant and condition
print(evokeds)

## # A tibble: 8,000 x 69
##   participant_id label      query    time     Fp1     Fpz     Fp2     AF7     AF3     AFz
##   <chr>          <chr>    <chr>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1 05            blurr_left n_b ~ -0.5    -0.559   -1.41   -1.45   -0.617   -1.12   -1.49
## 2 05            blurr_left n_b ~ -0.498   -0.550   -1.37   -1.35   -0.640   -0.930   -1.45
## 3 05            blurr_left n_b ~ -0.496   -0.528   -1.34   -1.28   -0.666   -0.788   -1.43
## 4 05            blurr_left n_b ~ -0.494   -0.486   -1.31   -1.23   -0.689   -0.722   -1.42
## 5 05            blurr_left n_b ~ -0.492   -0.427   -1.29   -1.21   -0.701   -0.743   -1.40
## 6 05            blurr_left n_b ~ -0.49    -0.355   -1.27   -1.22   -0.698   -0.838   -1.39
## 7 05            blurr_left n_b ~ -0.488   -0.283   -1.26   -1.24   -0.675   -0.977   -1.38
## 8 05            blurr_left n_b ~ -0.486   -0.222   -1.26   -1.27   -0.633   -1.12    -1.37
## 9 05            blurr_left n_b ~ -0.484   -0.187   -1.26   -1.30   -0.577   -1.24   -1.36
## 10 05           blurr_left n_b ~ -0.482   -0.185   -1.26   -1.34   -0.515   -1.31   -1.35
## # i 7,990 more rows
## # i 59 more variables: AF4 <dbl>, AF8 <dbl>, F9 <dbl>, F7 <dbl>, F5 <dbl>,
## #   F3 <dbl>, Fz <dbl>, F4 <dbl>, F6 <dbl>, F8 <dbl>, F10 <dbl>, FT7 <dbl>,
## #   FC5 <dbl>, FC3 <dbl>, FC1 <dbl>, FC2 <dbl>, FC4 <dbl>, FC6 <dbl>,
## #   FT8 <dbl>, T7 <dbl>, C5 <dbl>, C3 <dbl>, C1 <dbl>, Cz <dbl>, C2 <dbl>,
## #   C4 <dbl>, C6 <dbl>, T8 <dbl>, TP9 <dbl>, TP7 <dbl>, CP5 <dbl>, CP3 <dbl>,
## #   CP1 <dbl>, CPz <dbl>, CP2 <dbl>, CP4 <dbl>, CP6 <dbl>, TP8 <dbl>, ...
```

Pipeline outputs

```
# Time course plot with within-participant standard errors
evokeds |>
  separate_wider_delim(label, delim = "_", names = c("n_b", "DeviantPosRL")) |>
  Rmisc::summarySEwithin(
    measurevar = "N2",
    withinvars = c("time", "n_b", "DeviantPosRL"),
    idvar = "participant_id"
  ) |>
  mutate(time = as.numeric(levels(time))[time]) |>
  ggplot(aes(
    x = time,
    y = N2,
    ymin = N2 - se,
    ymax = N2 + se,
    color = n_b,
    fill = n_b
  )) +
  facet_wrap(~DeviantPosRL) +
  geom_hline(yintercept = 0, linetype = "dashed") +
  geom_vline(xintercept = 0, linetype = "dashed") +
  geom_line(linewidth = 1) +
  geom_ribbon(color = NA, alpha = 0.2) +
  coord_cartesian(xlim = c(-0.2, 0.8)) +
  theme_classic(base_size = 20)
```

Pipeline outputs



Pipeline outputs

```
# List of pipeline options
names(config)
```

```
## [1] "raw_files"           "log_files"           "output_dir"
## [4] "clean_dir"           "epochs_dir"          "report_dir"
## [7] "to_df"                "downsample_sfreq"    "veog_channels"
## [10] "heog_channels"        "montage"             "bad_channels"
## [13] "ref_channels"         "besa_files"          "ica_method"
## [16] "ica_n_components"     "highpass_freq"       "lowpass_freq"
## [19] "triggers"              "triggers_column"     "epochs_tmin"
## [22] "epochs_tmax"           "baseline"            "skip_log_rows"
## [25] "skip_log_conditions"   "reject_peak_to_peak" "components"
## [28] "average_by"             "perform_tfr"          "tfr_subtract_evoked"
## [31] "tfr_freqs"              "tfr_cycles"          "tfr_mode"
## [34] "tfr_baseline"           "tfr_components"      "perm_contrasts"
## [37] "perm_tmin"               "perm_tmax"            "perm_channels"
## [40] "perm_fmin"               "perm_fmax"            "n_jobs"
## [43] "vhdr_files"              "auto_rejected_epochs" "package_versions"
```

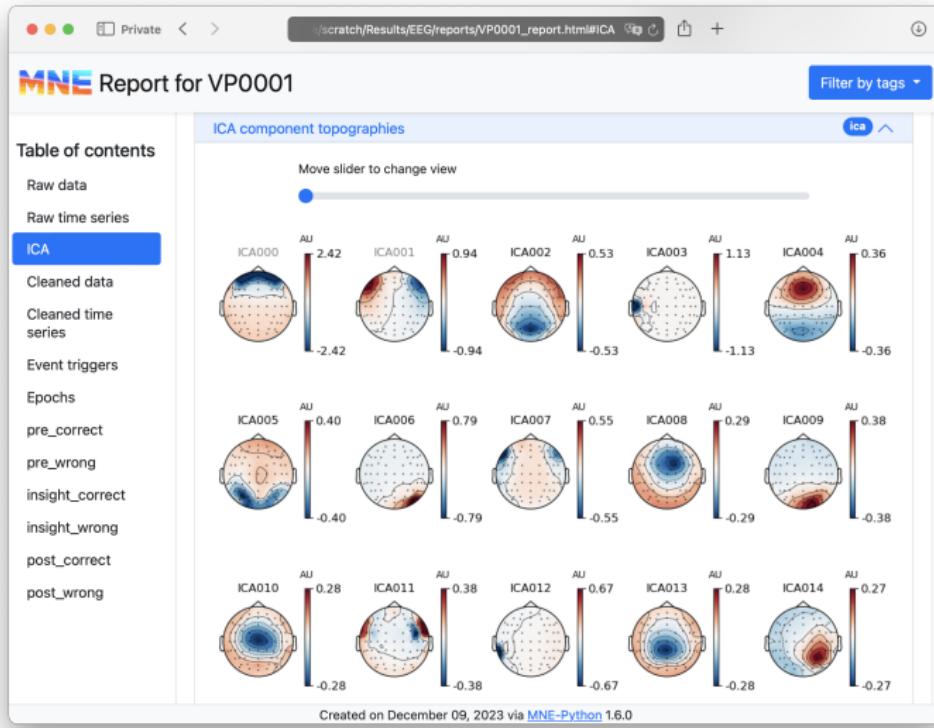
```
# Number of rejected epochs per participant
lengths(config$auto_rejected_epochs)
```

```
## 05 07
## 7 0
```

More pipeline outputs

- Cleaned continuous data (`clean_dir`)
- Epoched data (`epochs_dir`)
- Automated QC reports (`reports_dir`)

QC reports



Cluster-based permutation tests

```
# Permutation test input
perm_contrasts = list(
  c("blurr_left", "normal_left"),
  c("blurr_right", "normal_right")
)

# Permutation test output
clusters <- read_csv("output/clusters.csv") # or clusters <- res[[4]]
print(na.omit(clusters))

## # A tibble: 3,954 x 6
##   contrast           time channel t_obs cluster p_val
##   <chr>             <dbl> <chr>    <dbl> <chr>    <dbl>
## 1 blurr_left - normal_left 0     T7      735. pos_204    1
## 2 blurr_left - normal_left 0     TP9      13.1 pos_204    1
## 3 blurr_left - normal_left 0.002 AF8     -17.3 neg_52    1
## 4 blurr_left - normal_left 0.002 FC3     381. pos_26    1
## 5 blurr_left - normal_left 0.002 C3      115. pos_26    1
## 6 blurr_left - normal_left 0.002 TP9     91.4 pos_204    1
## 7 blurr_left - normal_left 0.002 TP7     15.6 pos_204    1
## 8 blurr_left - normal_left 0.004 AF8     -20.3 neg_52    1
## 9 blurr_left - normal_left 0.004 F3      23.1 pos_27    1
## 10 blurr_left - normal_left 0.004 TP9     53.8 pos_204   1
## # i 3,944 more rows
```

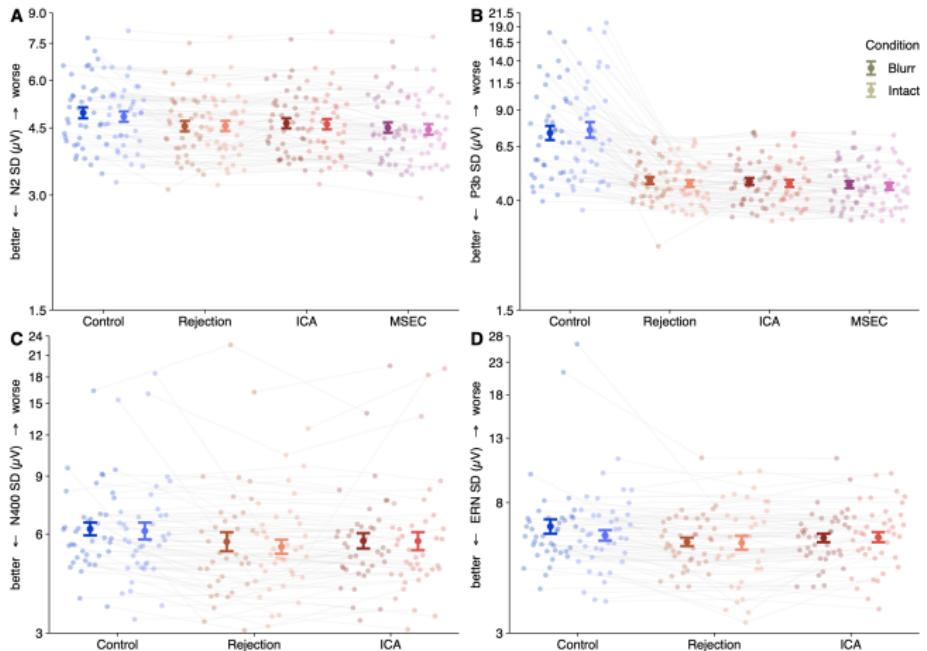
Artifact correction

- **Multiple source eye correction (MSEC)**
 - Requires .matrix files from BESA

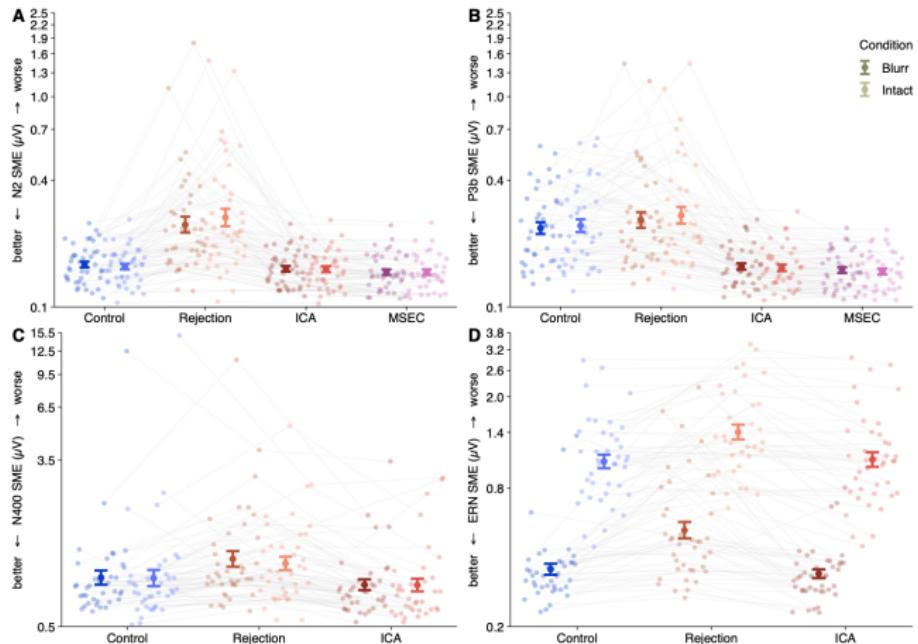
Artifact correction

- **Independent component analysis (ICA)**
 - Different algorithms available
(e.g., `ica_method = "fastica"`)
 - Can specify initial number of principal components with
`ica_n_components`
 - Automatic detection + exclusion of eye movement components
based on correlation with HEOG and VEOG (see https://mne.tools/stable/generated/mne.preprocessing.ICA.html#mne.preprocessing.ICA.find_bads_eog)
 - Verify in QC reports
 - Other selection methods (manual selection, ICLabel) not yet implemented

Artifact correction

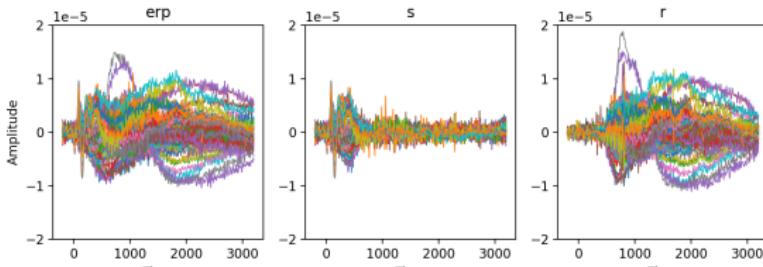


Artifact correction



Artifact correction

- Coming soon: **Residue iteration decomposition (RIDE)**
 - For correcting speech artifacts
 - Based on iterative separation of stimulus- and response-related ERP components (Ouyang et al., 2011, 2015, 2016)
 - Subtract response-related component from single trials using their voice onset times



Artifact rejection

- Per-channel peak-to-peak amplitude threshold via `reject_peak_to_peak` (default: 200.0)
- In addition to or instead of BESA or ICA

Repairing bad channels

- Pass participant-specific vectors of bad channel labels
 - E.g., `bad_channels = list("05" = c("C3", "P7"), ...)`
- Uses spherical spline interpolation
- Experimental: Automatic bad channel detection (`bad_channels = "auto"`)
 - Based on channel *SDs* across epochs

AUTOMATE

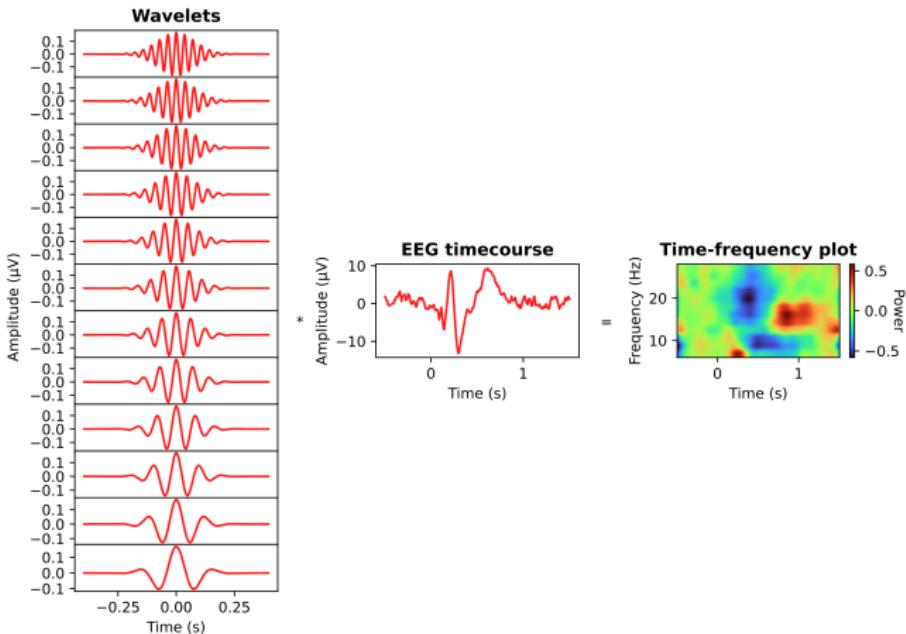


Detecting missing epochs

- Requires log file column (`triggers_column`) with the EEG trigger for every trial
- Pipeline magically detects and deletes log file trials with missing EEG



Time-frequency analysis



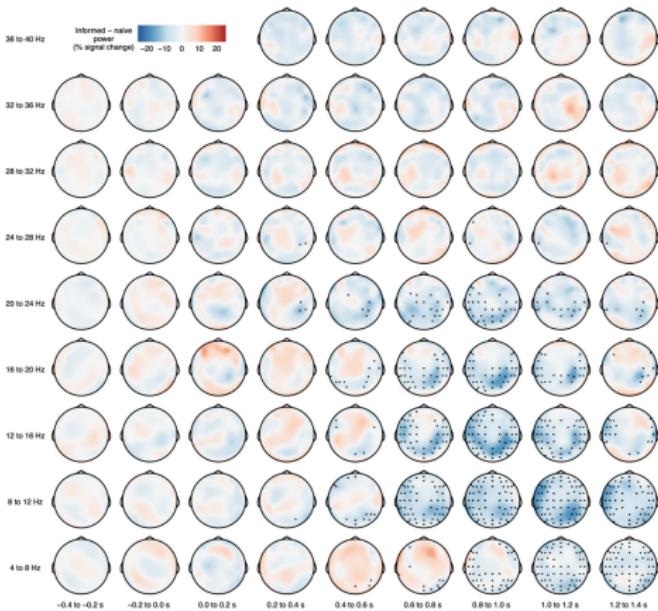
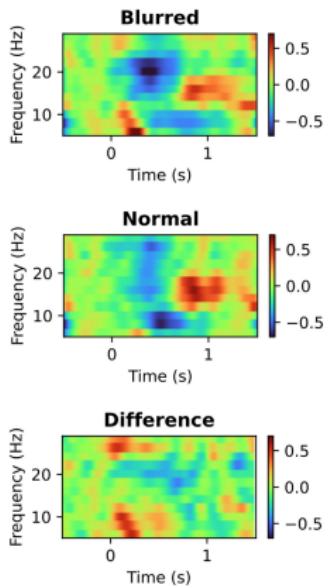
See <https://github.com/alexenge/tfr-workshop>

Time-frequency analysis

```
# Time-frequency analysis options
perform_tfr = TRUE,
tfr_components = list(
  "name" = list("alpha"),
  "tmin" = list(0.0), "tmax" = list(0.2),
  "fmin" = list(8.0), "fmax" = list(14.0),
  "roi" = list(c("P09", "P07", "P03", "POz", "P04", "P08", "P010", "O1", "Oz", "O2"))
)
```

- `tfr_components` extracts single trial power values
- Additional options:
 - Morlet frequencies (`tfr_freqs`, default 4, 5, 6, ..., 40 Hz)
 - Morlet no. of cycles (`tfr_cycles`, default 2, 2.5, 3, ..., 20)
 - Baseline window (`tfr_baseline`, default -450 ms to -50 ms)
 - Baseline method (`tfr_method`, default percent signal change)

Time-frequency analysis



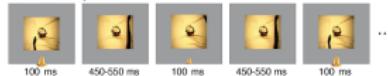
See Enge et al. (2023)

Example datasets

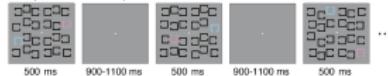
A. Face Perception N170



B. Passive Auditory Oddball MMN



C. Simple Visual Search N2pc



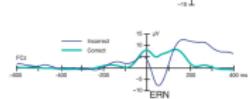
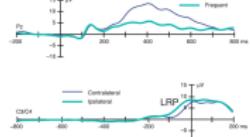
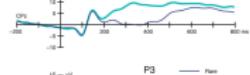
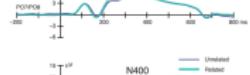
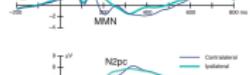
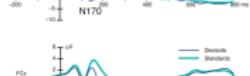
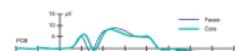
D. Word Pair Judgment N400



E. Active Visual Oddball P3



F. Flankers ERN and LRP



```
# Download example data from UCAP pipeline$datasets$get_ucap()
```

```
participants = 10,
path = "data"
)
```

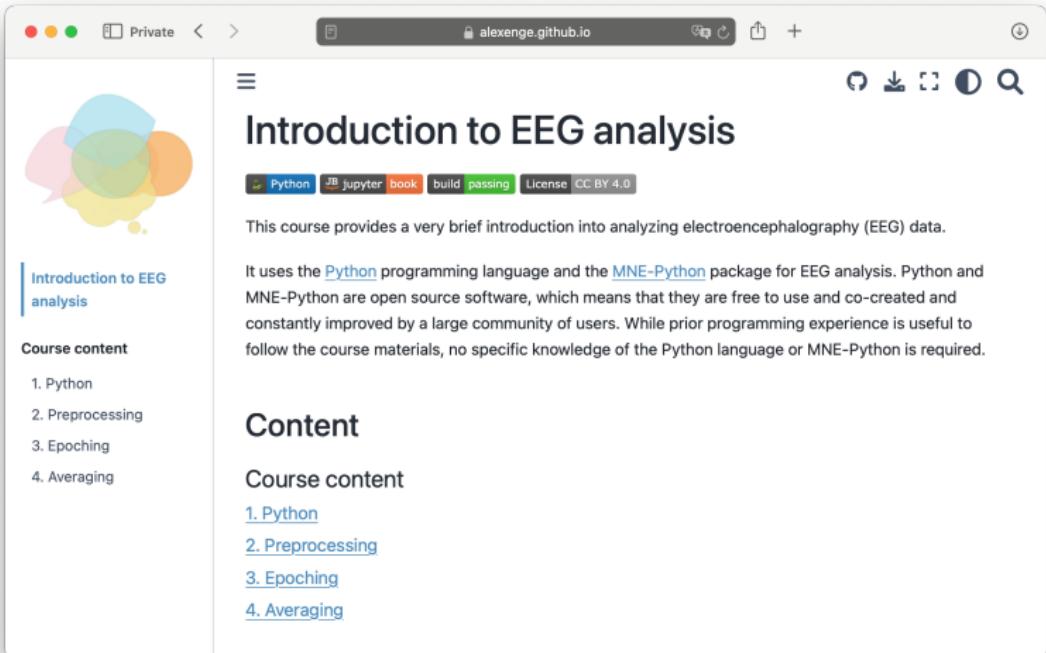
```
# Download example data from ERP CORE pipeline$datasets$get_erpcore("N170")
pipeline$datasets$get_erpcore("MMN")
pipeline$datasets$get_erpcore("N2pc")
pipeline$datasets$get_erpcore("N400")
pipeline$datasets$get_erpcore("P3")
pipeline$datasets$get_erpcore("ERN")
```

Plans

- Enhance documentation (examples, boilerplate, preprint)
- Unit tests
- Mixed models with `pymer4` or `bambi`
- Better permutation tests (Frossard & Renaud, 2021, 2022)
- BIDS interface
- Your ideas + contributions?

See <https://github.com/alexenge/hu-neuro-pipeline/issues>

Learning/teaching EEG analysis



The screenshot shows a web browser window with the URL alexenge.github.io/intro-to-eeg. The page title is "Introduction to EEG analysis". On the left sidebar, there is a colorful graphic of overlapping brain regions (blue, green, yellow, orange) and a list of course content: "Introduction to EEG analysis", "Course content", "1. Python", "2. Preprocessing", "3. Epoching", and "4. Averaging". The main content area contains the following text:

This course provides a very brief introduction into analyzing electroencephalography (EEG) data. It uses the [Python](#) programming language and the [MNE-Python](#) package for EEG analysis. Python and MNE-Python are open source software, which means that they are free to use and co-created and constantly improved by a large community of users. While prior programming experience is useful to follow the course materials, no specific knowledge of the Python language or MNE-Python is required.

Content

Course content

- [1. Python](#)
- [2. Preprocessing](#)
- [3. Epoching](#)
- [4. Averaging](#)

See <https://alexenge.github.io/intro-to-eeg>

Thanks



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