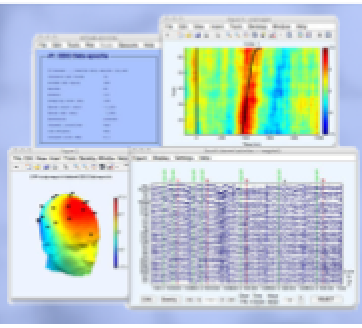


The EEGLAB News

Issue #21, March 2026

PracticalMEEG 2025 group picture from the workshop in Marseille, France, October 2025.

What's New

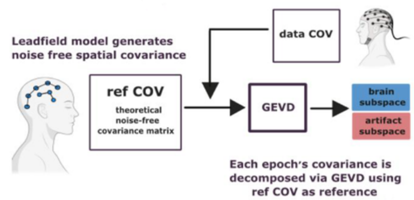
EEGLAB 2026.0 has been released. EEGLAB 2026.0 focuses on improved reproducibility across MATLAB and Python workflows, expanded STUDY level functionality, and robustness fixes across channel handling, visualization, and plug-in infrastructure. A new CLAUDE.md file was added to provide guidance for AI-assisted use of EEGLAB. See EEGLAB release notes for more details.

PracticalMEEG 2025 workshop successfully completed. The CuttingEEG association hosted PracticalMEEG 2025 at Aix-Marseille Université in Marseille, France, from October 27–31, 2025. This intensive training program featured hands-on tutorials for four open-source M/EEG analysis toolboxes: EEGLAB, FieldTrip, MNE-Python, and Brainstorm. The EEGLAB track provided comprehensive training for users with varying experience levels.

EEGLAB Course materials now available online. A comprehensive educational resource for teaching EEG/MEG data analysis using EEGLAB is now available on GitHub. Created by Arnaud Delorme and colleagues at UC San Diego, the course covers five major sessions: (1) Foundations, including BIDS and preprocessing, (2) ERP and time-frequency analysis, (3) Source localization and connectivity, (4) ICA component clustering, and (5) Statistical methods. The materials include PowerPoint presentations, MATLAB scripts, and sample datasets. Notably, 90% of the material is not EEGLAB-specific, making it broadly applicable to neurophysiological signal processing education.

Plug-Ins

Here, we highlight new EEGLAB plug-ins of possible wide interest to EEGLAB users. Please send descriptions of new plug-ins for consideration. These should have a brief lead introduction and further text and images to be published on a continuation page.



The GEDAI EEGLAB plug-in is an open-source MATLAB tool implementing the Generalized Eigenvalue De-Artifacting Instrument, a fully automated and unsupervised EEG denoising algorithm. GEDAI uses leadfield filtering and generalized eigenvalue decomposition (GEVD) to separate neural signals from artifacts without requiring clean reference data or manual component labeling. The plug-in constructs a theoretical reference covariance matrix from a biophysical EEG forward model and applies GEVD to each data epoch, identifying artifactual components as those that maximally deviate from the expected brain signal subspace. The optimal rejection threshold is automatically determined using the SENSAI subspace alignment criterion, enabling robust single-step correction of bad channels, physiological artifacts, and environmental noise, even in highly contaminated recordings, according to the authors. The preprint is available here, and a YouTube video here.

Open Science

Here we highlight news of open EEG and related data, tools, and other resources.

EEGManyArtifacts. We are seeking EEG researchers to contribute expert artifact annotations across diverse EEG datasets. Contributors will receive authorship on the resulting publication (and possibly win an iPad), and the aggregated annotations will be released openly as a high-quality benchmark for evaluating artifact detection and improving reproducibility. Get started at https://eegmanyartifacts.ucsd.edu/ (enroll before March 16).

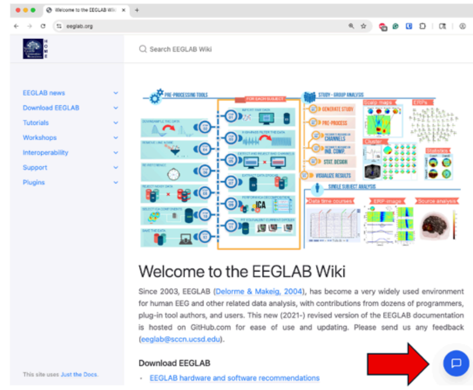
The 2025 EEG Foundation Challenge at NeurIPS concluded with success. The challenge, titled "From Cross-Task to Cross-Subject EEG Decoding," was part of the NeurIPS 2025 Competition Track and invited participants to develop machine learning methods that improve generalization in EEG decoding across tasks and subjects. Using the large-scale HBN-EEG dataset with recordings from over 3,000 participants, prepared in BIDS format using EEGLAB BIDS tools and served by the EEGDash deep learning interface to NEMAR and OpenNeuro, the competition achieved impressive engagement metrics:

- 762,000 open-source downloads (EEGDash + Braindecode)
- 1,197 registered competitors
- 8,622 model submissions
- 247 distinct institutions (210 academic, 37 industrial organizations)
- 742,000 active browser sessions on the challenge website during the competition period
- 120 days of continuous office hours with 3,934 direct support messages

The competition featured two supervised learning tasks: predicting behavioral performance in an active contrast change detection paradigm through cross-task transfer learning, and estimating psychopathology scores through subject-invariant representation learning. The challenge was organized by an international consortium of institutions spanning neuroscience, psychiatry, and machine learning, with sponsorship from Meta and other partners.

AI-Assisted EEG Analysis

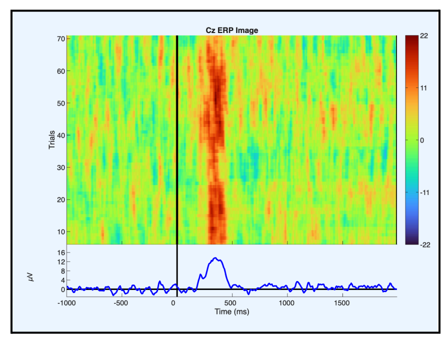
This new section highlights the use of AI-assisted tools for EEG analysis using EEGLAB.



EEGLAB AI Chatbot. A new AI chatbot is now available on the EEGLAB home page. Built on the Open Science Assistant (OSA) platform developed by Yahya Shirazi at SCCN, UCSD, the chatbot provides domain-specific guidance by drawing on EEGLAB documentation, tutorials, GitHub repositories, and mailing list archives. It can answer questions about EEGLAB functions, preprocessing pipelines, plug-in usage, data conversion, and more. SCCN, UCSD, is also sponsoring the use of similar dedicated assistants on the home pages of MNE, FieldTrip, BIDS, and HED events annotation standards, and the NEMAR.org tools and computing resource.

Vibe Coding EEGLAB. While chatbots like ChatGPT or the one above can now help write EEGLAB scripts, a new generation of AI coding tools goes further. Claude Code, an agentic command-line tool, can execute MATLAB code directly, iterating on errors until the pipeline it composes from user prompts runs to completion. EEGLAB now ships with a *CLAUDE.md* file that provides AI-specific instructions for any bot that reads it, guiding correct function usage, parameter choices, and best practices. As a demonstration, the following single prompt was given to Claude Code (model: Opus 4.6):

> *"Import the data eeglab_data.set using EEGLAB within MATLAB, high-pass filter the data at 0.5 Hz, run clean_rawdata, run ICA, remove bad components, extract data epochs and plot ERPimage for channel Cz. Look at the EEGLAB documentation at eeglab.org for inspiration."*



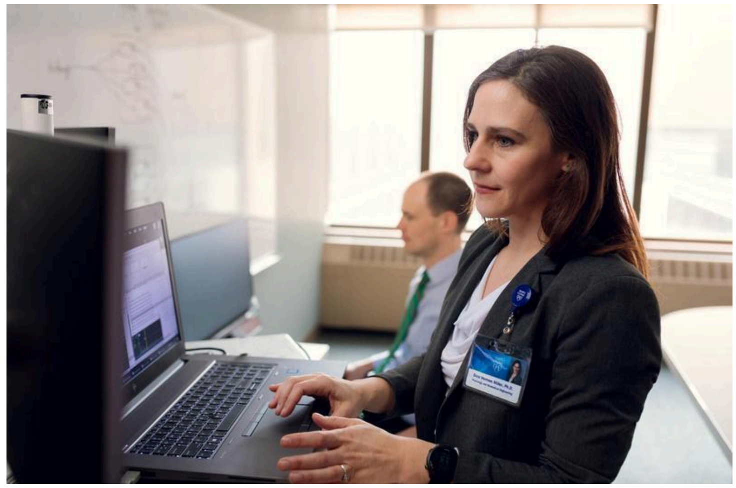
Without further guidance, the AI produced a complete 85-line MATLAB script that downloads EEGLAB if needed, detects the MATLAB installation, loads the data, filters at 0.5 Hz, runs *clean_rawdata* with standard parameters, performs ICA decomposition using Extended Infomax, classifies components using *ICLabel*, removes artifacts, extracts epochs on "square" visual presentation events, applies baseline correction, and plots and saves the resulting ERP-image for channel Cz (shown at right).

Strengths: The Claude-composed code is compact, well-documented, and functional. Without being prompted, the AI bot autonomously chose to use *ICLabel* for component classification. It correctly identified the "square" event type in the dataset's event structure (the time-locking event, instead of "response", which was the subject's response), and applied standard baseline removal. The resulting ERP image shows the expected clear 'P300' or 'Late Positive Complex' response feature.

Weaknesses: The ClaudeBot-generated script interpolates removed channels before running ICA decomposition without reducing the data rank. In general, this can produce rank-deficient decompositions - though *runica* (the ICA decomposition function used here) does typically handle this automatically. The *ICLabel* rejection threshold Claude selected (>=90% likelihood for all artifact categories) is reasonable, though conservative. These issues can be addressed by modifying the *CLAUDE.md* file now included in EEGLAB, which is automatically detected by AI assistants and provides them with specific preprocessing instructions. AI-generated analysis pipelines should still be carefully inspected and validated by the user.

Profiles

This section contains personal profiles of EEGLAB developers and/or users, with a description of how they use EEGLAB in their research.



Dr. Dora Hermes is an Associate Professor of Biomedical Engineering and Physiology at **Mayo Clinic** in Rochester, Minnesota. Her research examines how mesoscale electrophysiological signals, such as EEG and intracranial EEG, reflect neural network dynamics in health and neurological disease. She combines multimodal imaging, computational modeling, invasive recordings, and electrical stimulation to link fundamental neural activity to clinical applications, including brain-machine interfaces and neuroprosthetics.

Originally from the Netherlands, Hermes completed her undergraduate studies and PhD at **Utrecht University** in the lab of **Nick Ramsey**. Her academic path began in mathematics but shifted toward neuroscience after encountering the **Hodgkin–Huxley model**, which illustrated how mathematical models could illuminate biological processes.

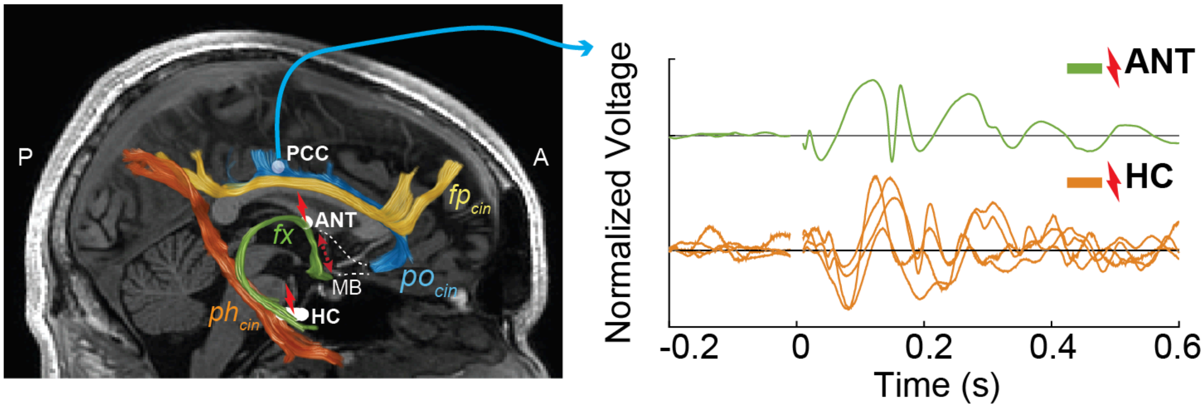
Her current work focuses on understanding how mesoscale signals arise from large neuronal populations embedded in complex brain networks. Because these signals compress many overlapping neural processes into a single observable measurement, her lab uses multimodal imaging and computational modeling to disentangle the network mechanisms that produce typical brain activity and those associated with neurological conditions such as epilepsy. Work with epilepsy patients motivates much of her research, particularly studies of how electrical stimulation influences neural populations and improves interventions such as **Deep Brain Stimulation**.

Hermes first used **EEGLAB** during her Master's studies while developing EEG-based brain computer interface experiments. She adopted standard EEG processing workflows, including filtering, rereferencing, and **Independent Component Analysis** based artifact removal. As her work moved toward intracranial EEG, her group developed script-based pipelines combining EEGLAB functions with custom MATLAB tools, enabling reproducible analysis and rapid testing of new methods.

In collaboration with **Arnaud Delorme** and **Scott Makeig**, her lab has developed tools for analyzing intracranial recordings collected during single-pulse electrical stimulation. These experiments measure **Brain Stimulation Evoked Potentials**, which allow researchers to probe effective connectivity in the human brain and quantify network changes following prolonged stimulation.

To encourage the growth of open data sharing for further analysis and discovery, recently Dora led the establishment of a recommended BIDS data structure for storing and sharing iEEG data, and now serves on the elected BIDS Steering Group. She also led the conversion of the international SCORE terminology for clinical EEG description to the open source Hierarchical Event Descriptors (HED) system for time series data event annotation, and often participates in HED Working Group discussions.

Her research relies on close collaboration with computational scientists, neurologists, and neurosurgeons studying epilepsy. Recent work with **Kai Miller** and **Gregg Worrell** showed how thalamic deep brain stimulation reshapes large-scale brain networks, highlighting how detailed signal analysis can produce insights with direct clinical impact.



Thalamic single-pulse electrical stimulation evokes network-specific brain stimulation evoked potentials. *Left: anatomical schematic showing stimulation of the anterior nucleus of the thalamus (ANT) and hippocampus (HC) with major connecting pathways. Right: normalized intracranial EEG responses illustrating distinct brain stimulation evoked potentials following ANT (green) and HC (orange) stimulation.*

Relevant publications:

Gregg, N. M., Ojeda Valencia, G., Pridalova, T., Huang, H., Kremen, V., Lundstrom, B. N., Van Gompel, J. J., Miller, K. J., Worrell, G. A., & Hermes, D. (2025). Thalamic stimulation induced changes in network connectivity and excitability in epilepsy. *Annals of Neurology, 97*(1), 1–13. https://doi.org/10.1002/ana.78087

Miller, K. J., Müller, K.-R., Ojeda Valencia, G., Huang, H., Gregg, N. M., Worrell, G. A., & Hermes, D. (2023). Canonical response parameterization: Quantifying the structure of responses to single-pulse intracranial electrical brain stimulation. *PLOS Computational Biology, 19*(5), e1011105. https://doi.org/10.1371/journal.pcbi.1011105

Upcoming Events

OHBM 2026. Come see us at the EEGLAB booth during the Organization for Human Brain Mapping Annual Meeting in Bordeaux, France, June 14-18, 2026.

Neuroergonomics 2026. A one-day tutorial workshop on July 13, 2026, is being planned for the Neuroergonomics Conference in Boston, focusing on source resolved analysis of multimodal brain and body imaging data within the Mobile Brain Body Imaging framework.

MOBI 2026. An EEGLAB mini-workshop will be presented during MOBI 2026, on the 24th of August in Berlin.

From the EEGLABLIST

This section contains messages from the EEGLABLIST that may be of general interest. Messages are edited for clarity.

On Source localization to the hippocampus (See the full thread summarized below)

Cedric Cannard opens by stating the common belief that hippocampal generators should be unrecoverable from typical 64-channel scalp EEG source reconstruction, and asks whether this remains true or whether this belief is well-founded – implicitly framing the discussion around identifiability versus wishful fitting of solution estimates to an ill-posed inverse problem.

John Richards argues that most subcortical nuclei lack the open field organization required to generate measurable scalp potentials. As a result, hippocampal sources identified by inverse methods likely reflect cortical activity, noise, or modeling error. Some deep cortical regions, such as the **Insular cortex**, may generate signals but are probably too attenuated to detect reliably.

Joseph Dien notes that inverse methods can place dipoles deep in the brain and therefore require convergent evidence. He rejects a strict cortex-only view, citing intracranial data suggesting some subcortical contributions to slow potentials, while arguing that the Hippocampus likely produces weak scalp signals because of its closed field geometry. He emphasizes that conclusions should rely on empirical evidence rather than model simplicity alone (Foti et al., 2011, Rektor et al., 2002, Oerlemans et al., 2025).

Eugen Masherov argues from clinical experience that deep sources, including the **Hippocampus**, can sometimes be localized from scalp EEG and confirmed surgically. He suggests non-dipolar field configurations may allow deeper sources to project to the scalp and cites intraoperative brainstem scalp correlations as evidence that long-range projections can occur.

Philip Zeman takes a pragmatic middle view. In his work, temporal lobe and hippocampal involvement appear in ICA-based localization, but he emphasizes the need for better methods to determine whether such results reflect true deep generators or mixtures of cortical sources.

Eric Rawls argues that the **Basal ganglia** are unlikely far-field generators because they lack an aligned pyramidal structure, whereas the hippocampus may plausibly contribute due to its organized pyramidal cells and supporting depth recordings. He notes that strong claims still require evidence beyond dipole fits.

Scott Makeig argues that the debate mainly reflects forward model uncertainty. Variability in skull conductivity can shift estimated dipole depth by centimeters, making deep sources inferred from template head models unreliable. He therefore recommends incorporating conductivity estimation rather than interpreting hippocampal dipole localizations based on fixed conductivity models (for full discussion and tools, see Akalin Acar et al., 2013, 2016, 2022).

Kevin Spencer urges skepticism toward claims of subcortical EEG or MEG sources without quantified forward model errors or cross-modal validation. He argues that ROI driven forward models do not validate inverse results and highlights SNR mapping studies that define where EEG and MEG can realistically detect sources (Goldenholz et al., 2009).

Diego Lozano-Soldevilla notes that intracranial recordings also suffer from volume conduction and reference effects. Correlations between hippocampal contacts and scalp signals, therefore, do not prove hippocampal generation and should be treated as constraints rather than ground truth (Herreras, 2016).

Makoto Miyakoshi points out that while conventional synaptic models make hippocampal scalp detection unlikely, alternative electrodiffusive or glial mechanisms could influence slow potentials. He stresses that dipole models can produce unrealistic amplitudes and calls for more biophysically realistic modeling (Nunez and Srinivasan, 2006, Sætra et al., 2021).

Yongxian Qian suggests that emerging MRI methods aimed at detecting neuronal electrical activity may eventually provide spatial ground truth for debates about hippocampal versus cortical generators.

On the selection of the EEG / ERP reference (read the full thread summarized below)

Dezhong Yao frames EEG referencing as a physics-constrained estimation problem in which both average reference and **REST reference** approximate an infinity reference. He argues REST is preferable because it uses a forward model to transform data from an arbitrary reference to an estimated zero reference. In his view, electrode density largely determines performance, and although imperfect head models reduce accuracy, they usually do not remove REST's advantag**e.** References: Dong et al., 2017, Yao et al., 2019, Nunez, 2010, Lepage et al., 2014.

Ramesh Srinivasan defends the **Average reference (EEG)** from first principles, arguing that the head behaves approximately as an electrically closed conductor. This supports the assumption that scalp potentials sum to zero, although undersampling beneath the head introduces error. He sees REST as a possible improvement but notes that it inherits forward model inaccuracies, so its benefit must be demonstrated empirically. References: [Bertrand et al., 1985].

John Richards questions whether REST's advantage depends on head model accuracy. Because it relies on a forward model, anatomical and conductivity errors should propagate into the rereferencing step. He therefore favors participant-specific head models when possible.

Joseph Dien remains skeptical that REST's added complexity is justified without clear empirical gains. He notes practical advantages of average reference, including reduced distortion from single channel references, improved signal to noise by averaging channels, and reproducibility due to its uniquely defined computation. References: [Dien, 1998], [Dien, 2017], [Junghöfer et al., 1999], [Kim et al., 2023].

Cedric Cannard argues from simulations and practice that REST often outperforms average reference and avoids misleading cancellations produced by mastoid references. Using **EEGLAB** with MRI-based lead fields can further improve REST, though template models remain usable. He also highlights the **Surface Laplacian** or **Current Source Density** transform as an alternative when individual MRIs are unavailable [Though surface Laplacian should tend to remove projections from tangentially oriented sources, e.g., those located in cortical sulci. - comment by **Scott Makeig**]. References: [Chella et al., 2016], [Hu et al., 2018].

In Print

Brandmeyer, T., Riggs, A., Reddi, V., Sullivan, H., Youn, C., Sivagnanam, S., Yoshimoto, K., Poldrack, R. A., Hardcastle, N., Markiewicz, C., Majumdar, A., Shirazi, Y., Truong, D., Makeig, S., & Delorme, A. (2026). Neuroelectromagnetic Data Archive and Repository: Open-source platform analysis. Aperture Neuro, 6(SI 1), 154162. https://doi.org/10.52294/001c.154162

Hermes, D., Pal Attia, T., Beniczky, S., Bosch-Bayard, J., Delorme, A., Lundstrom, B. N., Rogers, C., Rampp, S., Shirazi, S. Y., Truong, D., Valdes-Sosa, P., Worrell, G., Makeig, S., & Robbins, K. (2025). Hierarchical Event Descriptor library schema for EEG data annotation. Scientific data, 12(1), 1448. https://doi.org/10.1038/s41597-025-05791-2

Online

A web tutorial by Arnaud Delorme

What is the best ERP baseline?