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Neuromatch Academy: a 3-week, online summer school in computational neuroscience

Bernard Marius 't Hart[1], Titipat Achakulvisut[2], Ayoade Adeyemi[3], Athena Akrami[4], Bradly Alicea[5], Alicia Alonso-Andres[6], Diego Alzate-Correa[7], Arash Ash[8], Jesus J. Ballesteros[9], Aishwarya Balwani[10], Eleanor Batty[11], Ulrik Beierholm[12], Ari S. Benjamin[2], Upinder Bhalla[13], Gunnar Blohm[14], Joachim C H Blohm[14], Kathryn Bonnen[15], Marco Brigham[16,17], Bingni W Brunton[18], John S Butler[19], Brandon Caie[14], N Alex Cayco Gajic[20], Sharbatanu Chatterjee[21], Spyridon Chavlis[22], Ruidong Chen[23], You Cheng[24], H.M. Chow[25], Raymond Chua[26], Yunwei Dai[27], Isaac David[28], Eric EJ DeWitt[29], Julien Denis[30], Alish Dipani[31], Arianna Dorschel[32], Jan Drugowitsch[33], Kshitij Dwivedi[34], Sean Escola[35], Haoxue Fan[36], Roozbeh Farhoodi[2], Yicheng Fei[37], Pierre-Étienne Fiquet[38], Lorenzo Fontolan[39], Jeremy Forest[40], Yuki Fujishima[41], Byron V Galbraith[42], Mario Galdamez[43], Richard Gao[44], Julijana Gjorgjieva[45], Alexander Gonzalez[46], Qinglong Gu[47], Yueqi Guo[48], Ziyi Guo[49], Pankaj K. Gupta[25], Busra Tugce Gurbuz[50], Caroline Haimerl[38], Jordan B. Harrod[51], Alexandre Hyafil[52], Martin Irani[53], Daniel Jacobson[54], Michelle Johnson[2], Ilenna Simone Jones[2], Gili Karni[55], Robert E. Kass[56], Hyosub Edward Kim[57], Andreas M Kist[58], Randal Koene[59], Konrad Kording[2], Matthew R. Krause[60], Arvind Kumar[61], Norma K. Kühn[62], RAY LC[63], Matthew L. Laporte[14], Junseok Lee[64], Songting Li[65], Sikun Lin[66], Yang Lin[67], Shuze Liu[2], Tony Liu[2], Jesse A. Livezey[68], Linlin Lu[69], Jakob H Macke[70], Kelly Mahaffy[71], A Lucas Martins[72], Nicolás Martorell[73], Manolo Martínez[74], Marcelo G Mattar[75], Jorge Aurelio Menendez[76], Kenneth D Miller[77], Patrick J Mineault[78], Nosratullah Mohammadi[79], Yalda Mohsenzadeh[80], Elenor Morgenroth[81], Taha Morshedzadeh[82], Alice Claudia Mosberger[77], Madhuvanthi Muliya[83], Marieke Mur[80], John D. Murray[47], Yashas ND[84], Richard Naud[85], Prakriti Nayak[86], Anushka Oak[87], Itzel Olivos Castillo[37], Seyedmehdi Orouji[24], Jorge Otero-Millan[88], Marius Pachitariu[89], Biraj Pandey[18], Renato Paredes[90], Jesse Parent[91], Il Memming Park[92], Megan A. K. Peters[24], Xaq Pitkow[43,37], Panayiota Poirazi[22], Haroon Popal[93], Sandhya Prabhakaran[94], Tian Qiu[95], Srinidhi Ragunathan[96], Raul Rodriguez-Cruces[97], David Rolnick[26], Ashish Kumar Sahoo[98], Saeed Salehinajafabadi[99], Cristina Savin[38], Shreya Saxena[100], Paul Schrater[101], Karen Schroeder[77], Alice C Schwarze[18], Madineh Sedigh-Sarvestani[102], K Yuvaraj Sekhar[103], Reza Shadmehr[104], Maryam M. Shanechi[105], Siddhant Sharma[106], Eric Shea-Brown[18], Krishna V. Shenoy[107], Carolina L. Shimabukuro[108], Sergey Shuvaev[109], Man Ching Alison Sin[110], Maurice Smith[111], Nicholas A. Steinmetz[18], Karolina Stosio[112], Elizabeth Straley[43], Gabrielle Strandquist[18], Carsen

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Stringer[89]**, Rimjhim Tomar**[113]**, Ngoc Tran**[109]**, Sofia Triantafillou**[114]**, Lawrence Udeigwe**[115]**, Davide Valeriani**[33]**, Vincent Valton**[116]**, Maryam Vaziri-Pashkam**[117]**, Peter Vincent**[118]**, Gal Vishne**[119]**, Pascal Wallisch**[38]**, Peiyuan Wang**[120]**, Claire Ward**[121]**, Michael Waskom**[38]**, Kunlin Wei**[122]**, Anqi Wu**[123]**, Zhengwei Wu**[43]**, Brad Wyble**[124]**, Lei Zhang**[125]**, Daniel Zysman**[126]**, Federico d'Oleire Uquillas**[127]**, and Tara van Viegen**[127]

1 CVR, York University, Toronto **2** University of Pennsylvania, Philadelphia **3** Square wave Limited **4** Sainsbury Wellcome Centre, University College London **5** Orthogonal Research and Education Laboratory **6** Neuroscience Institute of Alicante **7** The Ohio State University, Columbus. **8** Smartalpha.AI, Ankara **9** Massachusetts General Hospital, Boston, MA. **10** Georgia Institute of Technology **11** Harvard University **12** Durham University, England **13** National Centre for Biological Sciences, Tata Institute of Fundamental Research, Bangalore, India **14** Center for Neuroscience Studies, Queen's University, Kingston, Ontario **15** New York University, New York City **16** Narrativa Comum Lda **17** Computational and Cognitive Neuroscience Summer School, https://www.ccnss.org/ **18** University of Washington, Seattle **19** TU Dublin, School of Mathematical Sciences, City Campus, Dublin Ireland **20** Ecole Normale Supérieure, PSL University, Paris **21** University College London (presently Laboratoire Jean Perrin, Sorbonne Université) **22** Institute of Molecular Biology and Biotechnology (IMBB), Foundation for Research and Technology-Hellas (FORTH), Greece **23** Massachusetts Institute of Technology **24** University of California, Irvine **25** The University of British Columbia, Vancouver, Canada **26** McGill University & Mila, Montreal **27** East China Normal University, Shanghai **28** National Autonomous University of Mexico **29** Champalimaud Research, Lisbon **30** INMED, Marseille **31** Upload AI LLC **32** ETH Zürich **33** Harvard Medical School, Boston MA **34** Goethe University Frankfurt **35** Columbia University **36** Harvard University, Cambridge, MA, USA **37** Rice University **38** New York University **39** Howard Hughes Medical Institute **40** New York University, New York **41** Kyushu University **42** Talla, Inc **43** Baylor College of Medicine **44** University of California San Diego **45** Max Planck Institute for Brain Research, Frankfurt, Germany **46** Stanford University **47** Yale University **48** Johns Hopkins University, Baltimore MD **49** Brandeis University **50** Bilkent University, Turkey **51** Harvard-MIT Health Sciences and Technology, Cambridge MA **52** Centre de Recerca Matemàtica, Spain **53** Neurodynamics of Cognition Laboratory, School of Medicine, Pontificia Universidad Catolica de Chile **54** Lockheed Martin **55** Minerva schools at KGI **56** Carnegie Mellon University **57** University of Delaware **58** Division of Phoniatrics and Pediatric Audiology, Department of Otorhinolaryngology, Head & Neck Surgery, University Hospital Erlangen, Friedrich-Alexander-University Erlangen-Nürnberg, Waldstr. 1, 91054 Erlangen, Germany **59** Carboncopies Brain Research Foundation, San Francisco **60** Montreal Neurological Institute, McGill University **61** KTH Royal Institute of Technology, Stockholm, Sweden **62** Neuro-Electronics Research Flanders empowered by imec, VIB and KU Leuven **63** City University of Hong Kong **64** Ecole Normale Supérieure, Paris, France **65** School of Mathematical Sciences, MOE-LSC, and Institute of Natural Sciences, Shanghai Jiao Tong University, Shanghai, China **66** University of California, Santa Barbara **67** Tsinghua University **68** Lawrence Berkeley National Laboratory **69** Peking University, Suoxinda **70** University of Tübingen and Max Planck Institute for Intelligent Systems **71** University of Connecticut **72** Champalimaud Center for the Unknown **73** University of Buenos Aires **74** Universitat de Barcelona **75** University of California, San Diego **76** Gatsby Computational Neuroscience Unit, University College London **77** Columbia University, New York **78** Independent Researcher **79** Institute for Advanced Studies in Basic Sciences (IASBS) **80** Western University, London, ON **81** Ecole Polytechnique Federale Lausanne **82** University of Toronto, Toronto **83** SASTRA Deemed University, Thanjavur, India **84** PES University, Bengaluru **85** University of Ottawa, Ottawa **86** King's College London **87** University of Houston **88** University of California, Berkeley **89** HHMI Janelia Research Campus **90** The University of Edinburgh **91** Orthogonal Research and Education Lab, Champaign-Urbana, IL USA **92** Stony Brook University **93** Temple University, Philadelphia **94** Moffitt Cancer Center, Florida **95** Institute of Neuroscience, Chinese Academy of Science, Shanghai **96** Cactus Communication, India **97** McGill University **98** National Institute of Science Education and Research, India **99** Bernstein Center for Computational Neuroscience. Berlin **100** University of Florida, Gainesville, FL **101** University of Minnesota, Minneapolis MN **102** Max Planck Florida Institute for Neuroscience **103** Freelance Machine Learning Consultant **104** Johns Hopkins University **105** University of Southern California **106** Blue Marble Space Institute of Science, Seattle, Washington, USA **107** Departments of Electrical Engineering, Bioengineering and

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Neurobiology, Stanford University, Stanford CA 94305 and Howard Hughes Medical Institute at Stanford University, Stanford, CA 94305 **108** University of Buenos Aires, Argentina **109** Cold Spring Harbor Laboratory **110** Cornell University **111** Harvard University, School of Engineering and Applied Sciences, Cambridge MA **112** Volkswagen Group Machine Learning Research Lab, Munich **113** Czech Academy of Sciences, Prague **114** University of Pittsburgh **115** Manhattan College **116** University College London **117** National Institute of Mental Health **118** Sainsbury Wellcome Centre **119** The Hebrew University, Jerusalem, Israel **120** Arizona State University, Tempe, AZ **121** Albert Einstein College of Medicine **122** Peking University **123** Columbia University, USA **124** Penn State University, State College, PA **125** Department of Cognition, Emotion, and Methods in Psychology, Faculty of Psychology, University of Vienna, Vienna, Austria **126** DeepLearning.AI **127** Princeton Neuroscience Institute, Princeton University, NJ, USA

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Software

- Review
- Repository
- Archive

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Neuromatch Academy: a 3-week, online summer school in computational neuroscience

Summary

Neuromatch Academy (*https://academy.neuromatch.io*; (van Viegen et al., 2021)) was designed as an online summer school to cover the basics of computational neuroscience in three weeks. The materials cover dominant and emerging computational neuroscience tools, how they complement one another, and specifically focus on how they can help us to better understand how the brain functions. An original component of the materials is its focus on modeling choices, i.e. how do we choose the right approach, how do we build models, and how can we evaluate models to determine if they provide real (meaningful) insight. This meta-modeling component of the instructional materials asks what questions can be answered by different techniques, and how to apply them meaningfully to get insight about brain function.

Week 1	Week 2	Week 3
W1D1 *Model Types*	W2D1 *Deep Learning*	W3D1 *Bayesian Decision*
W1D2 *Project Day 1*	W2D2 *Linear Systems*	W3D2 *Hidden Dynamics*
W1D3 *Model Fitting*	W2D3 *Biological Neuron Models*	W3D3 *Optimal Control*
W1D4 *Generalized Linear Models*	W2D4 *Dynamic Networks*	W3D4 *Reinforcement Learning*
W1D5 *Dimensionality Reduction*	W2D5 *Project Day 2*	W3D5 *Network Causality*

Table 1. 2021 Neuromatch Academy Topics. *Organized chronologically by week (W) and day of week (D), e.g. week 2 day 4 = W2D4. In addition, there are two days of preparatory instruction in coding Python, the materials for which can be found in W0D1 for 2020. The schedule shown here is from 2021, which was updated by dropping Modeling Practice day (old W1D2) and a second Deep Learning day (old W3D5) in favour of two dedicated project days and changing the order to group topics better conceptually. The content for these two days can still be found in the release tagged 'NMA2020'.*

Materials consist of highly curated recorded lectures and tutorials, organized in 'days,' as well as a growing number of data sets with starter notebooks for group projects (5 in 2020; 12 added in 2021). Each day constitutes one teaching module and covers one topic in computational neuroscience (see table 1). While the content is organized as a 3-week crash-course of consecutive teaching modules that build on one another, it can be rolled out at any pace, in its entirety or as stand-alone parts, provided prerequisites for each part are met. Most days can be used as separate, independent modules and can, for example, be combined with other instructional content. To facilitate this, we not only provide general prerequisites for the entire course but also daily topic-specific prerequisites (see wiki on OSF). The material is meant to either be taught to small groups of ~10 attendees guided by a teaching assistant, for instruction in a classroom, or for usage in other (potentially for-profit) events and could also be used for self-study.

Each instruction module (day) consists of 1) an introductory lecture (~30 minutes) that broaches the topic to students and explains the general approach, followed by 2) hands-on tutorials in the form of several ipython notebooks (~3 hours) with code-completion assignments and answers, and further instruction through embedded micro-lectures, and finally 3) an outro lecture (~30 minutes) to recapitulate the covered material and provide an outlook on its applicability to neuroscience research. Each day is meant to instruct the basics of a given topic and further readings are supplied.

All tutorials are available online in a permanent archive of the 2021 edition of NMA, which has a copy of the GitHub repository, a Jupyter Book and a set of tips we gave NMA teaching assistants, as well as links to many of the data sets for the group projects. This main archive describes where all materials can be found, and provides a table of pre-requisites for each day in the course, that should help self-study and integration of the material in other courses. There is a backup of all videos in a separate archive and the most up-to-date material is planned to stay available as an online Jupyter Book. The material is largely self sufficient and could be used for self-study or as parts of another course. For both purposes, the solutions to problems are provided in the OSF archive and the GitHub repository. Projects are best done in a group of students, and materials to get students started are self-contained. Each data set for group projects is introduced, usually accompanied by a video explaining what is in the data set. We also provide Python code to either download the NMA-curated data set, or set up a connection with an external data base.

Attendees do group projects to apply and consolidate what they learn in the lectures and tutorials, and in 2020 we provided five curated data sets (see table 2) to use for these projects, including videos describing the data and ipython notebooks to get started. In 2021 we increased the number of curated data sets, and grouped them conceptually.

Category	**Data set**	**Year**	**Contains**
Neurons	Steinmetz data (Steinmetz et al., 2019)	2020	neuropixels recording (waveforms, task events, spikes) in mice doing a visual discrimination task
	Stringer data (Stringer et al., 2019, 2021)	2020	activity from ~10,000 V1 neurons, recorded with calcium imaging from a mouse in total darkness
	Allen Institute data (no citation)	2021	recordings from VIP, SST, etc from mice doing a visual adaptation task, with novel or familiar images
fMRI	HCP data (Barch et al., 2013; Van Essen et al., 2013)	2020	fMRI time series in 7 tasks and resting state for 340 human participants, and parcellation in ROIs
	FSL course task (no citation)	2021	complements HCP data with 2 language tasks, data at voxel level
	HCP retinotopy (Benson et al., 2018)	2021	allows visualizing receptive fields across brain regions
	Kay natural images (Kay et al., 2008; Naselaris et al., 2009)	2020	voxels from V1/V2/V3/V4, and annotated objects

Category	Data set	Year	Contains
	Bonner navigation data (Bonner & Epstein, 2017)	2021	activity from 12 participants watching scenes or navigation sequences
	Algonauts video clip data (Kriegeskorte et al., 2008)	2021	activity in 10 participants watching 1000+ video clips algonauts
	Cichy objects/animals data (Cichy et al., 2014)	2021	activity in 16 participants watching 92 images
ECoG/EEG	Miller face/house data (Kai J. Miller et al., 2016, 2015, 2017)	2021	ECoG recordings from participants watching faces and houses
	Miller finger flex data (K. J. Miller et al., 2009; Kai J. Miller et al., 2012)	2021	ECoG recordings from participants moving their fingers
	Schalk joystick track data (Schalk et al., 2008, 2007)	2021	ECoG recordings from participants moving a joystick on 2D trajectories
	Memory N-back data (no citation)	2021	ECoG recordings in participants responding to repeated house images 0, 1 or 2 stimuli back
	Miller motor imagery data (Kai J. Miller et al., 2010)	2021	ECoG recordings from participants moving and imagining to move their fingers
Behavior	Caltech data set (no citation)	2021	pose-tracking from socially interacting mice
	IBL data (The International Brain Laboratory et al., 2021)	2020	behavior of mice doing a visual detection task with a bias

Table 2. Data sets for group projects. *Many of the data sets are available through a set of OSF repositories: fMRI(2020), fMRI(2021), Neurons and ECoG/EEG.*

Statement of Need

Need for training

Neuroscience makes use of a broad range of computational techniques, but very few institutions have enough local expertise to provide meaningful instruction in all of them. As a result, most computational neuroscience researchers around the world lack appropriate training and we aim to provide that here. Additionally, by focussing on meta-modeling, i.e. which method to apply in which situation, we assure that computational methods will be used in such a way as to lead to meaningful new insights into brain function.

Need for accessible materials

Neuroscience, like any academic discipline, struggles to be more diverse and inclusive, in the social sense. We aim to remove some of the barriers to good educational materials for computational neuroscience. By making the material freely available online, we make them available to anyone worldwide; we thus remove the need to be part of geographically restricted, rich, prestigious institutions to gain access to high-level training (e.g. the notebooks have been mirrored on gitee and videos on bilibili to make the material more accessible in China). Freely accessible materials should also alleviate negative effects of systemic biases and gatekeeping leading to discrimination in access to resources. A further step towards increased diversity is made by having diverse lecturers who may serve as role models. Finally, we have added captions in English and translated them in Mandarin and

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Spanish for both people with hearing difficulties and those who are not fluent in English (YouTube metrics indicate ~35% of views use captions). While our efforts do not achieve full inclusivity and diversity in neuroscience, we believe it is a step in the right direction.

Experience

In early 2020, the organizers of the in-person summer school "CoSMo" (*Co*mputational *S*ensory and *Mo*tor Science) were confronted with the COVID pandemic and decided to create an online version. They quickly realized that the school could be scaled up and be more accessible to students all over the world with more diverse backgrounds, and somehow made this happen (Blohm, 2021). They adopted the matching algorithm (Achakulvisut et al., 2020) used at the Neuromatch Conferences (NMC) for creating student groups ("pods") for the summer school and to find mentors for project groups. The summer school team joined forces with the NMC team, called itself Neuromatch Academy and quickly got a lot of attention (Sadnicka et al., 2021). This created the current Neuromatch community (Kording, 2021), that aims to use technology and online tools to make the future of neuroscience more accessible, inclusive and positive.

A first step in building an accessible content base was to recruit a pool of lecturers and content creators with an eye towards maximizing diversity in dimensions such as gender, race and career status. This helps to reduce intrinsic forms of bias within the lectures and exercises, and also helps to broadcast the accessibility of the discipline to a wider audience.

The materials (intro, outro and micro-lectures as well as tutorials) went through several instances of quality control, before we used it in our own summer school. First, a group of content reviewers provided feedback on the material which was integrated by the primary content creators. Second, a group of skilled programmers served as tutorial editors who went through the tutorials to review and edit code and make sure it all adhered to our standards. For example, they made sure code was as simple as possible and that all plots used the same look. Third, two separate groups of content testers independently went through all the material as if they were students, providing feedback to tutorial writers who integrated this feedback. They reported errors and omissions and provided pedagogical advice on confusing or misleading parts to the rest of the team. They also made sure the micro-lectures connected with the material in the tutorials. For example, we made sure the hands-on tutorials are do-able within the time frame, while providing bonus materials for faster attendees. After this step, videos of lectures were finalized. Fourth, the tutorial and code editors once again made sure all tutorials worked, used the same style and connected with the rest of the material. Contributors to the content creation process are listed in Appendix 1. For future rounds of our summer school, we also had content testers provide structured feedback on the material during the actual summer school, and about ~90% of attendees and TA's filled in end-of-day surveys during the actual summer school in 2020. We have and will use this feedback to further improve the materials and organization of the summer school. The most recent version of the materials can be found on GitHub https://github.com/NeuromatchAcademy/ and in the Jupyter Book. Issues can be filed on the GitHub repository, for further improvements.

Our quality-control processes ensured that the course content was well received. During the summer of 2020, we taught the Neuromatch Academy Computational Neuroscience material to 1757 interactive students in 64 countries with 191 teaching assistants, and in the summer of 2021 we taught 1873 students from 87 countries with 198 teaching assistants guiding a pod, augmented with 28 teaching assistants who specialized in project supervision. In 2020 there were also ~6000 registered observer students, and >9000 in 2021. In both years, the summer school ran 24/7 across all timezones with no major glitches. The percentage of interactive students that completed at least 50% of classes was 86% in 2020 and 58% in 2021. In 2020, of all respondents to the end-of-day survey, 94% would recommend NMA to a friend, and in 2021 we asked "Overall, how was your experience with NMA?" to which 88% of responses was either Very Good or Excellent.

Acknowledgements

The Neuromatch Academy summer school also crucially relied on many teaching assistants, mentors and people organizing the community. Many of these people provided valuable feedback which will be used to improve the material and experience in coming summer schools. We wish to thank everyone involved in making NMA a success!

Appendix 1: Author Contributions

Team	Members
Curriculum Design & Management	Akrami A; Blohm G; Bonnen K; DeWitt EEJ; Escola S; Hyafil A; Kording K; Kumar A; Macke JH; Mineault PJ; Murray JD; Peters MAK; Pitkow X; Schrater P; Stringer C; Valton V; Wallisch P; Wyble B; d'Oleire Uquillas F; van Viegen T
Group Projects	Akrami A; Alicea B; Butler JS; DeWitt EEJ; Gupta PK; LC RAY; Lee J; Mohammadi N; Murray JD; Pachitariu M; Parent J; Pitkow X; Rodriguez-Cruces R; Saxena S; Schrater P; Sharma S; Steinmetz NA; Straley E; Strandquist G; Valton V; Waskom M; Zhang L
Day Coordinators	W1D2: Blohm G W1D3: Hyafil A W1D4: Macke JH W1D5: Murray JD W2D1: Kording K W2D2: Brunton BW W2D3: Wallisch P W2D4: Pitkow X W2D5: DeWitt EEJ W3D1: Kumar A W3D2: Kumar A W3D3: Kording K W3D4: Stringer C W3D5: DeWitt EEJ
Intro & Outro Lecturers	W1D1: Blohm G; Peters MAK W1D2: Blohm G; Peters MAK W1D3: Drugowitsch J; Wei K W1D4: Park IM; Savin C W2D1: Kording K; Schrater P; Pitkow X W2D2: Shea-Brown E; Shenoy KV W2D3: Escola S; Shanechi MM W2D4: Shadmehr R; Smith M W3D1: Bhalla U; Poirazi P W3D2: Miller KD W3D3: Kording K; Kass RE; Triantafillou S W3D4: Johnson M; Mur M W3D5: Rolnick D
Micro-Lecturers	W1D1: Kording K W1D2: Blohm G; Schrater P W1D3: Wu A W1D4: Wu A W1D5: Cayco Gajic NA W2D1: Kording K; Valton V W2D2: Brunton BW W2D3: Fei Y W2D4: Pitkow X W2D5: DeWitt EEJ; Mattar MG W3D1: Naud R W3D2: Gjorgjieva J W3D3: Kording K; Liu T W3D4: Stringer C; Mohsenzadeh Y W3D5: Brigham M

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Team	Members
Tutorial writers	W1D1: Kording K; Galbraith BV; Laporte ML W1D2: Blohm G; Schrater P; 't Hart BM W1D3: Fiquet PÉ; Galbraith BV W1D4: Benjamin AS; Fiquet PÉ W1D5: Murray JD; Cayco Gajic NA W2D1: Kording K; Valton V; Krause MR W2D2: Brunton BW; Pandey B; Schwarze AC; Strandquist G; Pitkow X W2D3: Fei Y; Galbraith BV; Haimerl C; Livezey JA; Pitkow X W2D4: Schrater P; Saxena S; Wu Z; Pitkow X W2D5: DeWitt EEJ; Galbraith BV; Krause MR; Mattar MG W3D1: Kumar A; Murray JD; Gu Q; Li S W3D2: Kumar A; Murray JD; Gjorgjieva J; Gu Q; Li S W3D3: Kording K; Benjamin AS; Liu T W3D4: Stringer C; Menendez JA W3D5: DeWitt EEJ; Brigham M
Code Editing & Management	Bonnen K; Batty E; Chavlis S; Dwivedi K; Farhoodi R; Fontolan L; Galbraith BV; Gao R; Krause MR; Kording K; Kühn NK; Livezey JA; Laporte ML; Mineault PJ; Parent J; Pandey B; Pitkow X; Sedigh-Sarvestani M; Sharma S; Salehinajafabadi S; Strandquist G; Valton V; Waskom M; Wu Z
Quality Control & Testing	Alicea B; Bonnen K; Balwani A; Beierholm U; Butler JS; Cheng Y; Chua R; Caie B; David I; DeWitt EEJ; Dipani A; Farhoodi R; Gupta PK; Gonzalez A; Jones IS; Jacobson D; Kording K; Koene R; Kist AM; Kim HE; LC RAY; Laporte ML; Lu L; Morshedzadeh T; Martorell N; Orouji S; Oak A; Olivos Castillo I; Popal H; Paredes R; Prabhakaran S; Pitkow X; Parent J; Rodriguez-Cruces R; Schroeder K; Sharma S; Stosio K; Salehinajafabadi S; Sedigh-Sarvestani M; Strandquist G; Tomar R; Udeigwe L; Vaziri-Pashkam M; Valeriani D; Zysman D; Zhang L
Copyright Checks & Corrections	Blohm G; Jacobson D; Karni G; Kording K; LC RAY; Martorell N; Morgenroth E; Parent J; Park IM; Sedigh-Sarvestani M; Stringer C; Shuvaev S; Tran N; Udeigwe L; Ward C
Video Editing	Adeyemi A; Ash A; Alicea B; Blohm JCH; d'Oleire Uquillas F; Fujishima Y; Forest J; Gurbuz BT; Harrod JB; Irani M; Lin S; Mohammadi N; Mineault PJ; Nayak P; Oak A; Qiu T; Valeriani D; van Viegen T; Vaziri-Pashkam M
Captioning	Blohm JCH; Chow HM; Chatterjee S; Dorschel A; Denis J; Fan H; Martins AL; Mosberger AC; Muliya M; Mahaffy K; ND Y; Olivos Castillo I; Ragunathan S; Sekhar KY; Sin MCA; Sahoo AK; Vishne G
Spanish Translations	Alzate-Correa D; Alonso-Andres A; Ballesteros JJ; Galdamez M; Martínez M; Otero-Millan J; Shimabukuro CL; Vincent P
Mandarin Translations	Chen R; Chow HM; Dai Y; Fan H; Guo Y; Guo Z; Lin Y; Liu S; Wang P

Table A1: Contributions of Neuromatch Academy content creators.

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