Curriculum Vitae (.pdf)
Liam Paninski
June 28, 2017

Current position

Professor, Department of Statistics, Center for Theoretical Neuroscience, Doctoral Program in Neurobiology and Behavior, and Kavli Institute for Brain Science, Columbia University.

Co-director, Grossman Center for the Statistics of Mind.

Co-director, Columbia NeuroTechnology Center.

Education

New York University; Ph.D., Neural Science (2003).

Brown University; B.S., Neuroscience (1999).

Previous experience

Assistant (2005-8) and Associate (2008-13) Professor, Department of Statistics, Columbia University.

Senior research fellow, Gatsby Computational Neuroscience Unit, University College London (2004-5).

Postdoctoral fellow, Center for Neural Science, HHMI, NYU (2003).

Papers

[119] Jimenez, J. et al (2017). Anxiety cells in a hippocampal-hypothalamic circuit. Submitted.

[118] Naka, A. et al (2017). Complementary connectivity defines distinct networks of neocortical somatostatin interneurons. Submitted.

[117] Giovanucci, A. et al (2017). OnACID: Online Analysis of Calcium Imaging Data in Real Time. Submitted.

[116] Klaus et al (2017). The spatiotemporal organization of the striatum encodes action space. Submitted.

[115] Parthasarathy, N., Batty, E. et al (2017). Deep Networks for Decoding Natural Images from Retinal Signals. Biorxiv 153759.

[114] Lee, J. et al (2017). YASS: Yet another spike sorter. Biorxiv 151928.

[113] Yu et al (2017). The central amygdala controls learning in the lateral amygdala. Biorxiv 126649.

[112] Giovanucci et al (2017). Cerebellar granule cells acquire a widespread feedback control signal during motor learning. Nature Neuroscience 20: 727-734.

[111] Buesing et al (2017). A Statistical Model of Shared Variability in the Songbird Auditory System. bioRxiv 113670.

[110] Friedrich, J. et al (2016+). Multi-scale approaches for high-speed imaging and analysis of large neural populations. bioRxiv 091132.

[109] Mena, G. et al (2016+). Removing Stimulation Artifacts From Neural Recordings Using Structured Gaussian Processes. bioRxiv 089912.

[108] Batty, E. et al (2017). Multilayer Network Models of Primate Retinal Ganglion Cells. ICLR.

[107] Sun, R., Archer, E. & Paninski, L. (2016+). Variational inference for super resolution microscopy. AISTATS17 / bioRxiv 081703.

[106] Linderman, S., Miller, A., Adams, R., Blei, D., Paninski, L., Johnson, M. (2016+). Recurrent Switching Linear Dynamical Systems. AISTATS17 / ArXiv 1610.08466.

[105] Pakman, A., Gilboa, D., Carlson, D. & Paninski, L. (2016+). Stochastic Bouncy Particle Sampler. ICML17 / Arxiv 1609.00770.

[104] Zhou, P. et al (2016+). Efficient and accurate extraction of in vivo calcium signals from microendoscopic video data. Arxiv 1605.07266.

[103] Rahnama Rad, K., Machado, T. & Paninski, L. (2016+). Robust and scalable Bayesian analysis of spatial neural tuning function data. In press, Ann. Applied Stat., Arxiv 1606.07845

[102] Sumbul, U., Roossien, D., Chen, F., Barry, N., Boyden, E., Cai, D., Cunningham, J. & Paninski, L. (2016). Automated scalable segmentation of neurons from multispectral images. NIPS; Arxiv 1611.00388.

[101] Archer, E., Gao, Y., Paninski, L. & Cunningham, J. (2016). Latent linear-dynamical neural population models through nonlinear embedding. NIPS; Arxiv 1605.08454.

[100] Friedrich, J., Zhou, P. & Paninski, L. (2016). Fast Active Set Method for Online Spike Inference from Calcium Imaging. NIPS; PLoS Comput. Bio. 13: e1005423.

[99] Merel, J., Shababo, B., Naka, A., Adesnik, H. & Paninski, L. (2016). Bayesian methods for event analysis of intracellular currents. Journal of Neuroscience Methods 269: 21-32.

[98] Merel, J., Carlson, D., Paninski, L. & Cunningham, J. (2016). Neuroprosthetic decoder training as imitation learning. PLoS Comp. Bio 12: e1004948.

[97] Carlson, D., Stinson, P., Pakman, A. & Paninski, L. (2016). Partition Functions from Rao-Blackwellized Tempered Sampling. ICML.

[96] Picardo, M., Merel, J., Katlowitz, K., Vallentin, D., Okobi, D, Benezra, S., Clary, R., Pnevmatikakis, E., Paninski, L., and Long, M. (2016). Population-level representation of a temporal sequence underlying skilled behavior. Neuron 90: 866?876.

[95] Gabitto M., Pakman A., Bikoff J., Abbott L., Jessell T. & Paninski, L. (2016). Bayesian sparse regression analysis reveals the extent of spinal V1 interneuron diversity. Cell, 165: 220-33.

[94] Pnevmatikakis, E., Soudry, D., Gao, Y., Machado, T., Merel, J., Pfau, D., Reardon, T., Mu, Y., Lacefield, C., Yang, W., Ahrens, M., Bruno, R., Jessell, T., Yuste, R., Peterka, D. & Paninski, L. (2016). Simultaneous denoising, deconvolution, and demixing of calcium imaging data. Neuron 89: 285?299.

[93] Yang, W., Miller, J., Carillo-Reid, L. Pnevmatikakis, E., Paninski, L., Yuste, R., & Peterka, D. (2016). Simultaneous multi-plane imaging of neural circuits. Neuron 89: 269-84.

[92] Archer, E., Park, M., Buesing, L., Cunningham, J. & Paninski, L. (2015). Black-box variational inference for state-space models. arXiv:1511.07367

[91] Freeman, J., Field, G., Li, P., Greschner, M., Gunning, D., Mathieson, K., Sher, A., Litke, A., Paninski, L., Simoncelli, E. & Chichilnisky, E.J. (2015). Mapping nonlinear receptive field structure in primate retina at single cone resolution. eLife 4:e05241.

[90] Soudry, D., Keshri, S., Stinson, P., Oh, M.-W., Iyengar, G. & Paninski, L. (2015). Efficient "shotgun" inference of neural connectivity from highly sub-sampled activity data. PLoS Comp. Bio. 11: e1004464.

[89] Machado, T., Miri, A., Pnevmatikakis, E., Paninski, L. & Jessell, T. (2015). Primacy of flexor locomotor pattern revealed by ancestral reversion of motor neuron identity. Cell 162: 338-350.

[88] Merel, J., Pianto, D., Cunningham, J. & Paninski, L. (2015). Encoder-decoder optimization for brain-computer interfaces. PLoS Comp. Bio 11: e1004288.

[87] Buesing, L., Machado, T., Cunningham, J. & Paninski, L. (2014). Clustered factor analysis of multineuronal spike data. NIPS.

[86] Ramirez, A., Pnevmatikakis, E., Merel, J., Miller, K., Paninski, L. & Bruno, R. (2014). Spatiotemporal receptive fields of barrel cortex neurons revealed by reverse correlation of synaptic input. Nat. Neurosci. 17: 866-75.

[85] Mena, G. & Paninski, L. (2014). On quadrature methods for refractory point process likelihoods. Neural Computation 26: 2790-7.

[84] Pnevmatikakis, E., Merel, J., Pakman, A. & Paninski, L. (2014). Bayesian spike inference from calcium imaging data. Asilomar Conf. on Signals, Systems, and Computers.

[83] Pakman, A., Huggins, J., Smith, C. & Paninski, L. (2014). Fast penalized state-space methods for inferring dendritic synaptic connectivity. J. Comput. Neurosci. 36: 415-43

[82] Ramirez, A. & Paninski, L. (2014). Fast generalized linear model estimation via expected log-likelihoods. J. Comput. Neurosci. 36: 215-34.

[81] Shababo, B., Paige, B., Pakman, A. & Paninski, L. (2013). Bayesian inference and online experimental design for mapping neural microcircuits. NIPS.

[80] Pnevmatikakis, E. and Paninski, L. (2013). Sparse nonnegative deconvolution for compressive calcium imaging: algorithms and phase transitions. NIPS.

[79] Pfau, D., Pnevmatikakis, E. & Paninski, L. (2013). Robust learning of low-dimensional dynamics from large neural ensembles. NIPS.

[78] Pakman, A. and Paninski, L. (2013). Auxiliary-variable exact Hamiltonian Monte Carlo samplers for binary distributions. NIPS.

[77] Merel, J., Fox, R., Jebara, T. & Paninski, L. (2013). A multi-agent control framework for co-adaptation in brain-computer interfaces. NIPS.

[76] Smith, C. & Paninski, L. (2013). Computing loss of efficiency in optimal Bayesian decoders given noisy or incomplete spike trains. Network: Computation in Neural Systems 24: 75-98.

[75] Pakman, A. & Paninski, L. (2013). Efficient multivariate truncated normal sampling via exact Hamiltonian Monte Carlo. J. Comput. Graph. Stat. 23.

[74] Pnevmatikakis, E., Rahnama Rad, K., Huggins, J., & Paninski, L. (2013). Fast Kalman filtering and forward-backward smoothing via a low-rank perturbative approach. J. Comput. Graph. Stat. 23.

[73] Sadeghi et al. (2013). Monte Carlo methods for localization of cones given multielectrode retinal ganglion cell recordings. Network: Computation in Neural Systems 24: 27-51.

[72] Doi et al. (2012). Efficient coding of spatial information in the primate retina. Journal of Neuroscience 32: 16256-16264.

[71] Pnevmatikakis, E., Kelleher, K., Chen, R., Josic, K., Saggau, P. & Paninski, L. (2012). Fast nonnegative spatiotemporal calcium smoothing in dendritic trees. PLoS Comp. Bio. 8: e1002569.

[70] Paninski, L., Rahnama Rad, K. & Vidne, M. (2012). Robust particle filters via sequential pairwise reparameterized Gibbs sampling. CISS '12.

[69] Mishchenko, Y. & Paninski, L. (2012) Bayesian compressed sensing approach to reconstructing neural connectivity from subsampled anatomical data. J. Comput. Neuro. 33: 371-88.

[68] Pnevmatikakis & Paninski, L. (2012). Fast interior-point inference in high-dimensional sparse, penalized state-space models. AISTATS '12.

[67] Smith, C., Wood, F. & Paninski, L. (2012). Low rank continuous-space graphical models. AISTATS '12.

[66] Vidne et al. (2012). The impact of common noise on the activity of a large network of retinal ganglion cells. J. Comput. Neuro. 33: 97-121.

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[62] Rahnama Rad, K. & Paninski, L. (2011). Information rates and optimal decoding in large neural populations. NIPS.

[61] Mishchenko, Y. & Paninski, L. (2011). Efficient methods for sampling spike trains in networks of coupled neurons. Annals of Applied Statistics 5: 1893-1919.

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[59] Butts, D., Weng, C., Jin, J. Alonso, J.-M. & Paninski, L. (2011). Temporal precision in the visual pathway through the interplay of excitation and stimulus-driven suppression J. Neurosci. 31: 11313-11327.

[58] Mishchenko, Y., Vogelstein, J. & Paninski, L. (2011). A Bayesian approach for inferring neuronal connectivity from calcium fluorescent imaging data. Annals of Applied Statistics 5: 1229-1261.

[57] Ramirez, A., Ahmadian, Y., Schumacher, J., Schneider, D., Woolley, S. & Paninski, L. (2011). Incorporating naturalistic correlation structure improves spectrogram reconstruction from neuronal activity in the songbird auditory midbrain. J. Neurosci. 31: 3828-42.

[56] Escola, S., Fontanini, A., Katz, D. & Paninski, L. (2011). Hidden Markov models for the inference of neural states and improved estimation of linear receptive fields. Neural Computation 23: 1071-1132.

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[51] Pillow, J., Ahmadian, Y. & Paninski, L. (2011). Model-based decoding, information estimation, and change-point detection in multi-neuron spike trains. Neural Computation 23: 1-45.

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[48] Rahnama Rad, K. & Paninski, L. (2010). Efficient estimation of two-dimensional firing rate surfaces via Gaussian process methods. Network: Computation in Neural Systems 21: 142-68.

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Neuroscience (special issue on statistical analysis of neural data) 29: 107-126.

[46] Koyama, S. & Paninski, L. (2010). Efficient computation of the most likely path in integrate-and-fire and more general state-space models. Journal of Computational Neuroscience 29: 89-105.

[45] Lawhern, V., Wu, W., Hatsopoulos, N. & Paninski, L. (2010). Population neuronal decoding using a generalized linear model with hidden states. J. Neurosci. Methods 189: 267-280.

[44] Babadi, B., Casti, A., Xiao, Y. & Paninski, L. (2010). A generalized linear model of the impact of direct and indirect inputs to the lateral geniculate nucleus. Journal of Vision 10: 22.

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[39] Wu, W., Kulkarni, J., Hatsopoulos, N. & Paninski, L. (2009). Neural decoding of goal-directed movements using a linear state-space model with hidden states. IEEE Transactions on Neural Systems and Rehabilitation Engineering 17: 370-378.

[38] Escola, S., Eisele, M., Miller, K. & Paninski, L. (2009). Maximally reliable Markov chains under energy constraints. Neural Computation 21: 1863-912.

[37] Toyoizumi, T., Rahnama Rad, K. & Paninski, L. (2009). Mean-field approximations for coupled populations of generalized linear model spiking neurons. Neural Computation 21, 1203-1243.

[36] Huys, Q. & Paninski, L. (2009). Smoothing of, and parameter estimation from, noisy biophysical recordings. PLOS Computational Biology 5: e1000379.

[35] Lewi, J., Butera, R. & Paninski, L. (2009). Sequential optimal design of neurophysiology experiments. Neural Computation 21: 619-687.

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[33] Lewi, J., Butera, R., Schneider, D., Woolley, S. & Paninski, L. (2008). Designing neurophysiology experiments to optimally constrain receptive field models along parametric submanifolds. NIPS.

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[31] Pillow, J., Shlens, J., Paninski, L., Sher, A., Litke, A., Chichilnisky, E. & Simoncelli, E. (2008). Spatiotemporal correlations and visual signaling in a complete neuronal population. Nature 454: 995-999.

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[29] Kulkarni, J. & Paninski, L. (2008). Efficient analytic computational methods for state-space decoding of goal-directed movements. IEEE Signal Processing Magazine 25 (special issue on brain-computer interfaces): 78-86.

[28] Ahrens, M., Paninski, L. & Sahani, M. (2008). Inferring input nonlinearities in neural encoding models. Network: Computation in Neural Systems 19: 35-67.

[27] Paninski, L., Haith, A. & Szirtes, G. (2008). Differentiable integral equation methods for computing likelihoods in the stochastic integrate-and-fire model. J. Comput. Neuroscience 24: 69-79.

[26] Kulkarni, J. & Paninski, L. (2007). Common-input models for multiple neural spike train data. Network: Computation in Neural Systems 18: 375-407.

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[14] Paninski, L. (2004). Maximum likelihood estimation of cascade point-process neural encoding models. Network: Computation in Neural Systems 15: 243-262.

[13] Paninski, L., Pillow, J. & Simoncelli, E. (2004). Comparing integrate-and-fire-like models estimated using intra- and extra-cellular data. Neurocomputing 65: 379-385.

[12] Paninski, L., Pillow, J. & Simoncelli, E. (2004). Maximum likelihood estimation of a stochastic integrate-and-fire neural encoding model. Neural Computation 16: 2533-2561.

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Books

Paninski, L., Eden, U., Brown, E. & Kass, R. Statistical analysis of neurophysiological data. Under contract, Springer.

Gerstner, W., Kistler, W., Naud, R. & Paninski, L. (2014). Neuronal dynamics. Cambridge U. Press.

Invited reviews / book chapters

Paninski, L. & Cunningham, J. (2017). Statistical methods for analyzing neural data. Current Opinion in Neurobiology (to appear).

Yuste, R., Watson, B., Paninski, L., Vogelstein, J. (2009). Imaging action potentials with calcium indicators. Imaging Neurons: A Laboratory Manual, 2ed., eds. Yuste, R. & Konnerth, A., CSHL Press.

Paninski, L., Kass, R., Brown, E. & Iyengar, I. (2008). Statistical analysis of neuronal data via integrate-and-fire models. Stochastic Methods in Neuroscience, eds. Laing, C. & Lord, G., Oxford.

Paninski, L., Pillow, J. & Lewi, J. (2007). Statistical models for neural encoding, decoding, and optimal stimulus design. Computational Neuroscience: Progress in Brain Research, eds. Cisek, P., Drew, T. & Kalaska, J.

Simoncelli, E., Paninski, L., Pillow, J. & Schwartz, O. (2004). Characterization of neural responses with stochastic stimuli. Chapter 23 of The New Cognitive Neurosciences, 3ed, ed. Gazzaniga, M..

Grants

Collaborative Research in Computational Neuroscience, NEI R01 EY018003, co-PI w/ E. Simoncelli and E.J. Chichilnisky, 2006-12.

Gatsby Initiative in Brain Circuitry Pilot Grant, co-PI w/ S. Woolley, 2006-8.

Alfred P. Sloan Research Fellowship, 2007.

NSF Faculty Early Career Development (CAREER) IOS-0641912, 2007-12

McKnight Scholar award, 2008-12.

Collaborative Research in Comput. Neuroscience, NSF IIS-0904353, co-PI w/ R. Yuste, 2009-12.

DARPA award, Reliable Neural-interface Technology program, co-PI w/ B. Pesaran, 2011-3.

MURI award, "Imaging how a neuron computes," co-PI w/ R. Yuste et al., 2012-.

ONR award, Generalized Factor Analysis, Exact Hamiltonian Monte Carlo Methods, and Spike-and-Slab Models for Non-Gaussian Multivariate Analysis, 2014-.

Collaborative Research in Comput. Neuroscience, NSF IIS-1430239 (Simoncelli and Chichilnisky, co-PIs), 2014-.

Simons Global Brain Research Awards (4) with M. Long, M. Ahrens, J. Freeman, L. Abbott, J. Cunningham, M. Churchland, S. Fusi, W. Freiwald, 2014-.

DARPA SIMPLEX program (Blei, Yuste, Jebara co-PIs), 2015-7.

IARPA MICrONS program (multiple co-PIs), 2015-.

NSF BIGDATA: Collaborative Research: IA: Hardware and software for spike detection and sorting in massively parallel electrophysiological recording systems for the brain (multiple co-PIs), 2015-.

Google Faculty Award, 2015.

NIH BRAIN Initiative R01 EB22913: Next-Generation Calcium Imaging Analysis Methods, 2016-.

NIH BRAIN Initiative R21 EY027592: Optimal calcium imaging with shaped excitation, co-PI D. Peterka, 2016-.

DARPA NESD program (multiple co-PIs), 2016-.

NIH BRAIN Initiative 1U01NS103489-01: High-speed volumetric imaging of neural activity throughout the living brain, co-PI N. Ji et al, 2017-.

International Brain Lab (multiple co-PIs), 2017-.

NSF Neuronex (multiple co-PIs), 2017-.

Advising

Postdoctoral research advisor: J. Kulkarni, Q. Huys, Y. Ahmadian, Y. Mishchenko, L. Badel, E. Pnevmatikakis, K. Sadeghi, A. Pakman, D. Pianto, L. Buesing, D. Soudry, U. Sumbul, E. Archer, A. Dubbs, J. Friedrich, L. Grosenick, D. Carlson, X. Deng, X. Wei, S. Chen, D. Hernandez, P. Zhou

Ph.D. research advisor: S. Escola, J. Vogelstein, J. Lewi, M. Nikitchenko, K. Rahnama Rad, M. Vidne, A. Ramirez, D. Ferreira, A. Calabrese, C. Smith, T. Machado, D. Pfau, J. Merel, G. Mena, E. Batty, R. Sun, P. Stinson, J. Lee, H. Razaghi.

M.A. research advisor: M. Yajima, C. Gohil, J. Bahk, W. Yao

Undergraduate research advisor: G. Fudenberg, J. Huggins, A. Qian, T. Rutten, W. Falcon.

Other duties

Mindscope advisory council, Allen Institute for Brain Science

Scientific advisor board, Cognescent