BIOGRAPHICAL SKETCH

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NAME: Manning, Jeremy R.

eRA COMMONS USER NAME (agency login): MANNINGJ

POSITION TITLE: Assistant Professor of Psychology

EDUCATION/TRAINING *(Begin with baccalaureate or other initial professional education, such as nursing, include postdoctoral training and residency training if applicable.)*

INSTITUTION AND LOCATION	DEGREE (if applicable)	Completion Date MM/YYYY	FIELD OF STUDY
Brandeis University, Waltham, MA	BS	05/2006	Neuroscience, Computer Science
University of Pennsylvania, Philadelphia, PA	PHD	05/2011	Neuroscience
Princeton University, Princeton, NJ	Postdoctoral Fellow	07/2015	Neuroscience, Computer Science

A. Personal Statement

My role on this project will be to help design and run experiments, and to collect, analyze, and interpret the behavioral and electrophysiological data we collect. I will also assist in publishing and presenting the results of the proposed research. My training and experience has afforded me the broad background in electrophysiology, cognitive modeling, and machine learning that is necessary to carry out the proposed research. In my doctoral work (mentor: Michael Kahana, Department of Psychology, University of Pennsylvania) I used model-based analyses of EEG, ECoG, and single-neuron recordings from human neurosurgical patients to track and identify neural patterns during memory and navigation experiments. In my postdoctoral work (mentors: Kenneth Norman, Department of Psychology and Princeton Neuroscience Institute, Princeton University; David Blei, Department of Computer Science, Princeton University) I used (and developed) cutting-edge probabilistic models to track these patterns in healthy individuals using fMRI. My current research program is aimed at developing the next generation of techniques for inferring cognitive states and tracking them over time, based on constraints from neural data, behavioral data, and cognitive models. My focus is on using these techniques to refine our understanding of how memories are organized during encoding, and how we search through these memories at retrieval. The current application supports my current research program by furthering our understanding of memory dysfunction in epilepsy patients, and how healthy memory function might be restored in these individuals.

1. Manning JR, Jacobs J, Fried I, Kahana MJ. Broadband shifts in local field potential power spectra are correlated with single-neuron spiking in humans. J Neurosci. 2009 Oct 28;29(43):13613-20. PubMed PMID: 19864573; PubMed Central PMCID: PMC3001247.
2. Manning JR, Polyn SM, Baltuch GH, Litt B, Kahana MJ. Oscillatory patterns in temporal lobe reveal context reinstatement during memory search. Proc Natl Acad Sci U S A. 2011 Aug 2;108(31):12893-7. PubMed PMID: 21737744; PubMed Central PMCID: PMC3150951.
3. Manning JR, Sperling MR, Sharan A, Rosenberg EA, Kahana MJ. Spontaneously reactivated patterns in frontal and temporal lobe predict semantic clustering during memory search. J Neurosci. 2012 Jun 27;32(26):8871-8. PubMed PMID: 22745488; PubMed Central PMCID: PMC3412364.
4. Manning JR, Lew TF, Li N, Sekuler R, Kahana MJ. MAGELLAN: a cognitive map-based model

of human wayfinding. J Exp Psychol Gen. 2014 Jun;143(3):1314-30. PubMed PMID: 24490847; PubMed Central PMCID: PMC4038664.

B. Positions and Honors

Positions and Employment

2011 - 2015 Postdoctoral Research Associate, Princeton University, Princeton Neuroscience Institute and Department of Computer Science, Princeton, NJ

2015 - Assistant Professor of Psychology, Dartmouth College, Hanover, NH

Other Experience and Professional Memberships

Honors

2006 Systems and Integrative Biology Training Grant, NIH

2008 Computational Neuroscience Training Grant, NIH

2010 Ruth L. Kirshstein National Research Service Award for an Individual Predoctoral Fellowship, NIMH

C. Contribution to Science

1. One major scientific contribution of my work has been to further our understanding of the relation between single-neuron action potentials and population (local field) activity in humans. The dominant view in the human electrocorticography literature has been that single-neuron action potentials are best characterized by high frequency (gamma band) spectral changes in the local field potential. I undertook a systematic study of rare simultaneous single-neuron and population recordings taken from human neurosurgical patients. I found that, somewhat surprisingly, broadband (non-oscillatory) changes in the local field potential were a much stronger correlate of single-neuron firing than were oscillatory changes (including in the gamma band). My Journal of Neuroscience paper reporting these results has since been cited around 180 times in the 5 years since its publication, and many of these citations are in papers that have carried out direct follow-up studies of this work.

    a. Manning JR, Jacobs J, Fried I, Kahana MJ. Broadband shifts in local field potential power spectra are correlated with single-neuron spiking in humans. J Neurosci. 2009 Oct 28;29(43):13613-20. PubMed PMID: 19864573; PubMed Central PMCID: PMC3001247.

2. Another major contribution of my work has been to expand our understanding of how episodic (autobiographical) memories are encoded and retrieved by our brain's memory systems. A fundamental historical intuition held by philosophers and psychologists such as Aristotle, Hume, James, and others has been that our experiences are "tagged" using the ever-changing stream of contextual cues that defines our subjective experience. For example, hearing a particular song on your way to work might remind you of another time you heard the same song years ago, which might in turn dredge up other related information (where you were, who you were with, etc.). Despite an extensive behavioral and computational literature hypothesizing a central role for contextual information in how we encode and retrieve autobiographical memories, prior to my work there had been no direct neural evidence for such representations. I carried out a series of studies using data from human neurosurgical patients who volunteered to study and recall lists of randomly chosen words. I used computational models to isolate neural patterns that behaved like contextual representations, and studied these representations as the patients encoded and retrieved memories. This framework allowed me to directly observe the neural basis of these contextual representations, and the role they play in memory encoding and retrieval.

    a. Manning JR, Polyn SM, Baltuch GH, Litt B, Kahana MJ. Oscillatory patterns in temporal lobe

reveal context reinstatement during memory search. Proc Natl Acad Sci U S A. 2011 Aug 2;108(31):12893-7. PubMed PMID: 21737744; PubMed Central PMCID: PMC3150951.

b. Manning JR, Sperling MR, Sharan A, Rosenberg EA, Kahana MJ. Spontaneously reactivated patterns in frontal and temporal lobe predict semantic clustering during memory search. J Neurosci. 2012 Jun 27;32(26):8871-8. PubMed PMID: 22745488; PubMed Central PMCID: PMC3412364.

c. Manning JR, Kahana MJ. Interpreting semantic clustering effects in free recall. Memory. 2012 Jul;20(5):511-7. PubMed PMID: 22646657; PubMed Central PMCID: PMC3393836.

3. A third contribution of my work relates to how patterns of interactions (connectivity) across brain regions reflects ongoing cognitive processes. Standard approaches to examining how patterns of brain connectivity reflect cognition entail computing functional connections between every pair of observed measurements. For example, standard functional connectivity approaches to fMRI data entail computing the correlation between every pair of voxel time series. The number of computations required to relate these full brain functional connectivity patterns to cognitive states can become prohibitive. Further, computing full brain voxel-by-voxel connectivity matrices effectively treats each voxel as independent, even though it is well known that brain data exhibit strong spatial correlations. I have developed a probabilistic modeling approach for looking at brain connectivity patterns in a much more mathematically compact way. The general approach involves re-representing patterns of brain activity using a relatively small number of network "hubs" distributed throughout the brain. This turns connectivity analysis into an optimization problem: given a brain dataset, we must compute the most probable number of network hubs, where the hubs go in the brain, how big the hubs are, and how the hubs are connected to each other at each moment in time during an experiment. Because most neuroimaging datasets may be adequately described by on the order of a few hundred network hubs, this reduces the computational complexity of analyses of connectivity patterns by several orders of magnitude.

   a. Manning JR, Ranganath R, Keung W, Turk-Browne N, Cohen J, Norman KA, Blei DM. Hierarchical topographic factor analysis. International Workshop on Pattern Recognition in NeuroImaging. International Workshop on Pattern Recognition in Neuroimaging; IEEE. 2014; c2014.

   b. Manning JR, Ranganath R, Norman KA, Blei DM. Topographic factor analysis: a Bayesian model for inferring brain networks from neural data. PLoS One. 2014;9(5):e94914. PubMed PMID: 24804795; PubMed Central PMCID: PMC4012983.

4. A fourth contribution of my work relates to our understanding of how our memory systems encode, organize, and retrieve spatial information. For example, how do we build up useful representations of novel environments? Or how do we use our existing knowledge to explore efficiently? Electrophysiological studies in animals and humans over the past half-century have led to the discovery of networks of navigationally relevant neuronal populations, such as place cells and grid cells (which respond preferentially when an animal is located in a particular place), head direction cells (which respond preferentially when an animal is headed in a particular direction), and others. These findings have inspired a number of low-level biologically detailed models of how the known neural machinery might support higher level cognitive representations. However, these low-level models are not intended to explain high-level navigation behaviors such as exploration strategies. Meanwhile, an extensive behavioral literature on navigating humans and non-human animals has inspired high-level descriptive models based on egocentric and allocentric spatial encoding strategies. These high-level models attempt to explain complex behaviors like exploration strategies, but do not attempt to connect these strategies to the underlying neural machinery. I undertook a major modeling effort to bridge these two spatial modeling literatures. The result was the MAGELLAN model of spatial navigation, which operates at the same high level as strategy-based models, but makes quantitative predictions about the way in which people build up mental representations

of unfamiliar environments and use those representations to navigate efficiently.

   a. Manning JR, Lew TF, Li N, Sekuler R, Kahana MJ. MAGELLAN: a cognitive map-based model of human wayfinding. J Exp Psychol Gen. 2014 Jun;143(3):1314-30. PubMed PMID: 24490847; PubMed Central PMCID: PMC4038664.

5. A fifth contribution of my work is in the domain of color vision. I have developed a Bayesian framework for exploring how our visual systems form predictions about the visual world from observed photoreceptor responses. For example, at each location on our retinas, we may have a single rod or cone photoreceptor. Each photoreceptor class is maximally sensitive to a particular wavelength of light. (This is similar to the notion that a digital camera may have at most a single red, green, or blue sensor at each location on its sensory array.) Nonetheless, our subjective experience is that each point in space has an identifiable color that matches the objects in the environment rather than the placements of receptors on our retinas. This means that our visual systems must constantly infer what the visual world most probably is to account for the observed receptor responses. To explore the deeper theoretical properties of these processes, I build models of the visual world, retinal responses, and inference algorithms for reasoning and making predictions about the world given receptor responses. I then ask questions like: given some statistical facts about the visual world, how should we arrange our receptors to achieve the best expected prediction accuracies? Or, if we knew nothing about the statistical properties of natural images, or the identities (i.e., peak wavelength sensitivities) of the receptors on our retinae, under what physical conditions could our visual systems learn to see in color? In other words, how much knowledge must be "pre-programmed" into our visual systems, and how much can be learned through experience?

   a. Manning JR, Brainard DH. Optimal design of photoreceptor mosaics: why we do not see color at night. Vis Neurosci. 2009 Jan-Feb;26(1):5-19. PubMed PMID: 19193250; PubMed Central PMCID: PMC2671005.
   b. Benson NC, Manning JR, Brainard DH. Unsupervised learning of cone spectral classes from natural images. PLoS Comput Biol. 2014 Jun;10(6):e1003652. PubMed PMID: 24967877; PubMed Central PMCID: PMC4072515.

Complete List of Published Work in My Bibliography:
http://www.ncbi.nlm.nih.gov/myncbi/1nWkordOylkke/bibliography/48047420/public/?sort=date&direction=ascending

D. Research Support

Completed Research Support

5F31MH088118-02, National Institute of Mental Health 2010/02/01-2011/05/31
Jeremy Manning (PI)
The neural representation of context and its role in free recall
Role: PI