

Keep it real: rethinking the primacy of experimental control in cognitive neuroscience

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Highlights

- Laboratory experiments are often designed to isolate a handful of intuitive variables
- The brain, however, has evolved to navigate a complex, multidimensional world
- This creates a tension between experimental control and ecological generalizability
- Naturalistic paradigms should provide the basis for model construction and evaluation

Abstract

Naturalistic experimental paradigms in neuroimaging arose from a pressure to test the validity of models we derive from highly-controlled experiments in real-world contexts. In many cases, however, such efforts led to the realization that models developed under particular experimental manipulations failed to capture much variance outside the context of that manipulation. The critique of non-naturalistic experiments is not a recent development; it echoes a persistent and subversive thread in the history of modern psychology. The brain has evolved to guide behavior in a multidimensional world with many interacting variables. The assumption that artificially decoupling and manipulating these variables will lead to a satisfactory understanding of the brain may be untenable. We develop an argument for the primacy of naturalistic paradigms, and point to recent developments in machine learning as an example of the transformative power of relinquishing control. Naturalistic paradigms should not be deployed as an afterthought if we hope to build models of brain and behavior that extend beyond the laboratory into the real world.

Keywords: ecological validity, experimental design, generalizability, naturalistic stimuli, representative design

Cognitive neuroscientists employ clever experimental manipulations in hopes of discovering interpretable relationships between brain, behavior, and the environment. There is a commitment—often implicit—in both our scientific thinking and writing that the models we derive from tightly-controlled experimental manipulations will provide some traction in real-world contexts. This commitment relies on the assumption that the human brain implements a set of nomothetic principles or rules that capture the underlying principles or rules by which the world works. We assume that these rules, like in classical physics, are relatively simple and interpretable, and, once discovered, will extrapolate to the richness of human behavior (Jolly and Chang, 2019). We proceed by filtering out as many seemingly irrelevant variables (considered “confounds” or “noise”) as possible in hopes of isolating the handful of latent variables (considered “signal”) dictating brain–behavior relationships. To what extent do our models actually generalize outside the laboratory? What proportion of neural or behavioral variability do our models predict in real-life contexts? These kinds of questions have prompted the neuroimaging community to begin adopting more naturalistic experimental paradigms (Hasson and Honey, 2012; Maguire, 2012; Hamilton and Huth, 2018).

Naturalistic paradigms have generally been considered a testbed for models developed under highly-controlled experimental paradigms. In neuroimaging, naturalistic stimuli were introduced optimistically

in hopes of validating existing models (Bartels and Zeki, 2004; Hasson et al., 2004). This optimism has declined over the intervening years. In the following, we provide a historical context for naturalistic neuroimaging and appeal to representative design as a principled inductive basis for ecological generalizability (Brunswik, 1947). We assume that no cognitive neuroscientist would be satisfied with a science strictly confined to peculiar experimental manipulations with little relevance outside the laboratory. However, the world outside the laboratory is not amenable to many of the assumptions of classical experimental design; real-world ecological variables are often multidimensional and nonlinearly interacting. To make matters worse, evolution has built a brain that capitalizes on these interactions to guide adaptive behavior.

To be clear, we are not arguing indiscriminately against controlled experiments. Experimental manipulations provide a powerful and necessary tool for testing hypotheses and models. Our argument pertains to the source and character of these hypotheses. As experimentalists, we often bootstrap hypotheses from experimental manipulations, thus superimposing the assumptions of experimental design on the process of hypothesis formation and data generation. When data from the experimental manipulation adjudicate in favor of the hypothesis, we generally assume that we have discovered something meaningful about brain and behavior. However, when stringent design considerations constrict both hypotheses and data, we risk maneuvering ourselves into theoretical corners that are difficult to reconcile with ecological brain function. We argue that this necessitates a shift toward the primacy of naturalistic paradigms in developing and evaluating models of brain and behavior.

What problems does the brain confront outside the laboratory?

Evolution has shaped our brains to guide behavior in a multidimensional, uncertain world. The importance of this fact has been periodically reasserted in the schools of functional and ecological psychology (e.g., Brunswik, 1943; Gibson, 1979), but the implications remain underappreciated. We contend that many properties of the brain, as an evolutionary solution for guiding adaptive behavior, undermine many of the theoretical assumptions of cognitive neuroscience outlined above (see Hasson et al., 2019, for an extended discussion). Evolution does not have the privilege of operating under controlled laboratory conditions, does not generally produce “optimal” solutions, and does not appeal to human-interpretable design principles (Dennett, 1995). In the case of the brain, evolution has converged on a high-dimensional modeling organ for estimating whatever structure in the world is relevant for guiding context-specific behavior. In this respect, the brain does not operate like a scientist, as the kind of estimation needed to guide behavior does not necessitate the kind of understanding scientists seek. In other words, the brain is not necessarily designed to rely on simple, human-interpretable variables; it does not always cleanly segregate variables into signal and noise; and it does not necessarily respect the theoretical boundaries imposed by our experimental designs.

Ecological variables in the environment are poorly understood. Any ecologically relevant “signal” in the environment is multidimensional and there are nonlinearities and interactions among dimensions (Campbell, 1973; Cronbach, 1975). Furthermore, ecologically relevant dimensions of the environment are always mixed with non-relevant dimensions. The brain cannot simply ignore non-relevant dimensions; it must learn to actively adjust particular dimensions in order to guide behavior. In most ecological situations, the relevant dimensions for a particular action (e.g., recognizing a face, or interpreting the meaning of words in a particular context) are always mixed with non-relevant dimensions (e.g., luminance, motion, or occlusion of the face; the sentence structure used or the accent of a speaker). To perform these tasks, the brain must dynamically weight and re-weight all the incoming dimensions as a function of task and context. In other words, there are no two systems such that one processes the “signal” and the other processes “confounds” or “noise.” Classical controlled experiments, where the vast majority of these variables are artificially clamped or factored out, ignore exactly the problem the brain must face, and may hinder our understanding of the solutions the

brain has found to overcome it. It is surprisingly difficult to generalize from a contrived experiment artificially isolating five experimental variables to other contexts with five, ten, or perhaps hundreds of dimensions (e.g., Cronbach et al., 1963; Yarkoni, 2019).

Take for example the seminal findings of Hubel and Wiesel (1962): probing the visual system of the anaesthetized cat with differently oriented edges reveals an orderly model of orientation tuning in primary visual cortex (V1). It was thought that extending this systematic program to other stimulus features would eventually allow us to piece together a complete model of early visual function. However, despite revealing some important insights, the limits of this program have become increasingly evident. For example, work by David and colleagues (2004) has demonstrated that the spatiotemporal tuning of V1 neurons differs substantially between naturalistic and non-naturalistic contexts, likely due to nonlinear relationships among neural variables and environmental variables. Models of neural tuning derived from synthetic stimuli in the vein of Hubel and Wiesel may not generalize well to the real-world conditions in which our brains evolved (Simoncelli and Olshausen, 2001; Felsen and Dan, 2005). Olshausen and Field (2005) famously cautioned that “we can rightfully claim to understand only 10% to 20% of how V1 actually operates under normal conditions,” attributing this in part to biased stimulus sampling and a tendency toward easily-interpretable hypotheses.

Systematic and representative design

Advocates for naturalistic paradigms often appeal to their “ecological validity,” a term that originates with Egon Brunswik (1949, 1947).¹ Brunswik championed a heterodox school of psychological theory summarized as “probabilistic functionalism,” emphasizing the messy, probabilistic nature of organism–environment relations and the importance of Darwin’s adaptive fitness in guiding behavior (Tolman and Brunswik, 1935; Brunswik, 1943). Brunswik (1949) contended that psychology maintains a “double standard” in the application of sampling theory (Neyman, 1934; Kruskal and Mosteller, 1980) to subjects and stimuli: whereas subjects are sampled with the goal of generalizing to the population, stimuli and tasks generally are not.

Brunswik challenged the paradigm of “systematic design”—the practice of artificially reducing the world to a small number of hand-picked variables for experimental manipulation—on grounds that it fails to actually isolate variables of interest and imposes non-naturalistic relationships among variables (Brunswik, 1955). In contrast, Brunswik advocated for “representative design,” arguing that we should sample stimuli or conditions in a way that respects both the distribution and intercorrelations of ecological variables if we hope to achieve generalizability beyond the boundaries of the experimental manipulation. Ecological generalizability demands a “representative sampling of situations” where “situational instances in an ecology are analogous to individuals in a population” (Brunswik, 1955, p. 198). Ecologically relevant configurations of variables carve out a manifold in a multidimensional space of organism–environment relations. Systematic experimental manipulations that clamp or orthogonalize certain variables risk unintentionally relocating an experiment off the manifold into a peculiar region of this space, thus forfeiting ecological generalizability.

Though considered heretical during Brunswik’s lifetime, the critical thrust of his program has nonetheless permeated a variety of fields (Hammond, 1955; Jenkins, 1974; Bronfenbrenner, 1977; Neisser and Hyman, 2000; Fiedler, 2011). For example, Barker’s (1965) “ecological psychology” advocates for the psychologist as a “transducer” of psychological phenomena *in situ*, rather than the traditional “operator/transducer” who manipulates the environment and organism to “send messages to [them]self.” This critique also resonates with the ongoing “stimulus-as-fixed-effect” controversy in psycholinguistics (Coleman, 1964; Clark, 1973;

¹ Brunswik in fact used the term “ecological validity” in a narrow sense to indicate the utility of a perceptual cue with respect to an ecologically-relevant state of the environment—modern usage more closely resembles Brunswik’s notion of “representative design” (Araújo et al., 2007; Hammond and Stewart, 2001).

Baayen et al., 2008), social psychology (Wells and Windschitl, 1999; Judd et al., 2012), and neuroimaging (Bedny et al., 2007; Westfall et al., 2016). Most famously, this line of thought reached a zenith with Gibson's (1979) theory of "direct perception," which forcefully elevated the environment itself to a principal object of study, emphasizing in particular the organism- and context-specific elements of the environment that afford adaptive behavior (i.e., "affordances"). At the behavioral level, an organism cannot be decoupled from the environment in which it evolved (Gomez-Marin and Ghazanfar, 2019).

Much of cognitive neuroscience still operates in the regime of Hubel and Wiesel, using contrived, non-naturalistic stimuli and tasks in hopes of revealing fundamental features of functional neuroanatomy. We have used disjoint tasks to devise complex taxonomies of memory (e.g., Squire, 2004) and attention (e.g., Carrasco, 2011), subdividing the brain into a mosaic of regions reflecting intuitive, hand-picked contrasts (e.g., Kanwisher et al., 1997; Kanwisher, 2010); but rarely do we reassemble these manipulations into functional, ecological behavior. How do these disparate systems conspire to perform complex, real-world behavior (e.g., summarizing a complex idea and verbally conveying it to a colleague, a task many readers perform every day)? The assumption that we can someday cobble together these piecemeal processes and representations into a satisfying model of brain and behavior is tenuous at best (Newell, 1973; Meehl, 1990).

To further illustrate this point, consider working memory processes in a daily context, such as reading a story, as opposed to a laboratory context, such as a delayed match-to-sample task. In the delayed match-to-sample task, the process of protecting information in a working memory buffer is isolated from other perceptual, decision-making, and motor-related processes by the structure of the task itself. However, in real-life, each word we accumulate while reading a story interacts with and is synthesized with all previous written or spoken words. The naturalistic reading task reveals that neural systems, across all levels of the processing hierarchy, need to accumulate, maintain, and synthesize information at their preferred processing timescale, making the classical distinction between processing systems and memory systems intangible (see Hasson et al., 2015).

Lessons from machine learning

Recent advances in artificial neural networks (ANNs) provide an instructive foil for experimental neuroscience. The machine learning community has made tremendous strides in building neurally-inspired models that match or exceed human performance in cognitive tasks spanning visual processing, language processing, and complex gameplay (LeCun et al., 2015). Why have neural network models developed in the machine learning community so dramatically outstripped models developed in psychology and neuroscience laboratories?

One of the key developments was to relinquish some amount of control and embrace the complexity of real life. The machine learning community does not fixate on "experimental design" in the way that neuroscientists do. They do not manufacture a small set of well-behaved inputs in estimating their models; instead, they use vast, largely-unconstrained training data sampled from the real world. They do not impose the strong constraint that their models must learn human-interpretable representations or rules. Instead, machine learning has—for pragmatic reasons—prioritized predictive power over interpretable, explanatory models (Breiman, 2001; Yarkoni and Westfall, 2017). The implicit goal in most cases is not to model the brain or a given experimentally-defined cognitive process, but to model the phenomenon of interest in the world. Take for example a deep convolutional neural network for face recognition that matches (and exceeds) human performance in recognizing face identities (Schroff et al., 2015). This model is trained on face images spanning numerous identities sampled "in the wild" to include all manner of naturalistic "confounds"—differences in expression, lighting, head angle, and so on. The same model trained on a

tightly-controlled subset of facial images would fail dramatically due to biased, non-representative sampling (Srivastava and Grill-Spector, 2018).

The way these models learn to map noisy, real-world inputs along objective functions to perform complex tasks resonates with Gibson's (1979) notions of direct perception. Much like the brain, the structure of the fitted model is inseparable from the task the model is trained to perform in the world. In the same way that evolutionary theory shifted our understanding of biology to a few relatively simple processes and principles, the effectiveness of artificial neural networks in learning cognitive tasks may force us to rethink the neural code (see Hasson et al., 2019, and Richards et al., 2019). The recent success of neural networks in solving many of the tasks we study in cognitive neuroscience serves as a cautionary tale for those probing the brain for easily-interpretable representations.

Studying ecological brain function without losing control

Most psychologists and neuroscientists are trained to respect the primacy of experimental control. We celebrate the ingenuity of tasks that manage to isolate a handful of interpretable variables from confounds. When a particular task or manipulation fails to elicit the desired effect, we often adjust the task or fine-tune the manipulation in hopes of homing in on the effect. This research program hinges on the assumption that the brain extrapolates from a number of human-interpretable representations and processes to navigate the world; and that using clever designs to experimentally isolate the neural implementation of these rules will allow us to extrapolate to ecological behavior. With these assumptions in hand, we consider tightly-controlled experimental manipulations as the principal (perhaps only) source of insight into the underlying neural code (Gillis and Schneider, 1966), whereas naturalistic paradigms are treated as a necessary (albeit inconvenient) testbed for validating these theories. But what if these assumptions are unsound? What if nonlinearities and interactions among environmental variables hamstring generalization from contrived experiments? What if neural systems rely more on exhaustive sampling and brute-force estimation and interpolation rather than rule-based extrapolation? How is the cognitive neuroscientist to proceed?

Naturalistic paradigms are not a panacea and are not trivial to implement or analyze. We do believe there is value in using controlled experiments to test hypotheses, but contend that these hypotheses should stem from ecological considerations and address head-on the actual problems brains confront in the world. Controlled experiments can reveal important boundary conditions of ecological brain function, and no single paradigm can be exhaustively representative or generalizable. However, we believe that non-naturalistic experimental manipulations have occupied an overly privileged position in cognitive neuroscience.

We caution against allowing classical experimental manipulations to play an outsized role in hypothesis formation. For example, if the goal is to differentiate neural systems processing articulatory and semantic features of words, rather than using tightly-controlled lists of words and nonwords, we recommend using natural speech stimuli and comparing models of articulation and semantic content (e.g., de Heer et al., 2016). When designing an experiment, we recommend, whenever possible, to use naturalistic tasks and to sample stimuli and conditions (including controls) from ecological contexts; for example, sampling social stimuli from each subject's personal social network (Parkinson et al., 2017), probing memory using naturalistic recall (Chen et al., 2017; Zadbood et al., 2017; Heusser et al., 2018), comparing natural language across modalities and contexts (Stephens et al., 2010; Regev et al., 2013; Yeshurun et al., 2017; Deniz et al., 2019), and using data-driven modeling to capture the complexity of naturalistic neural responses (Haxby et al., 2011; Baldassano et al., 2017; Chang et al., 2018). Appealing to representative sampling in experimental design will tend to introduce (ecological) intercorrelations among variables, and may reduce statistical power for low-frequency phenomena (Hamilton and Huth, 2018). Our thesis, however, is that anyone adopting the

alternative approach—clamping or and artificially orthogonalizing these variables—must contend with the challenge of ecological generalizability.

In the context of representative design, Brunswik contends that the “challenge of further [isolating variables] must be met by after-the-fact, mathematical means” (Brunswik, 1955, pp. 202–203). This resonates with the more recent notion of “late commitment” in cognitive neuroscience (Kriegeskorte et al., 2008, p. 19), wherein theoretical assumptions are relaxed at the stage of experimental design and data collection, and later imposed at the analysis stage. Representative design is also conducive to a “system identification” approach for mapping from models of the environment to neural responses (Wu et al., 2006; Gallant et al., 2012; Nunez-Elizalde et al., 2019). In this framework, explicit models capturing, e.g., visual or semantic content (Nishimoto et al., 2011; Huth et al., 2012, 2016) are constructed to predict brain activity for naturalistic stimuli or tasks. In both of these frameworks, hypotheses are formalized as explicit models of the stimulus or task, and the relative quality of a given model is quantified in terms of its accuracy in predicting neural responses to novel input.

We can summarize these examples into several concrete recommendations, many of which are reflected in the exceptional body of work presented in this special issue: (1) formulate hypotheses with ecological considerations in mind; (2) rather than constraining data collection, sample brain activity under representative contexts for the ecological behaviors you wish to study; (3) find manipulations for characterizing the boundary conditions that naturally emerge in real-life contexts; (4) when possible, formalize hypotheses as explicit models capable of making quantitative predictions of neural activity under the most naturalistic conditions possible; (5) interrogate your models with the goal of understanding not only the neural data, but also the structure of the task, stimulus, or environment; (6) use your insights to generate new predictions to be tested in real-life contexts or under more controlled conditions as necessary.

Building a more ecological research program demands increasingly rich data and quantitative tools for describing brain, behavior, and environment. Publicly shared naturalistic datasets (e.g., Hanke et al., 2014) have exceptional re-use value and can serve as benchmarks for model comparison. These datasets will eventually become exhausted as competing models improve and reach ceiling performance; data generators will never be out of work and there will always be a market for innovations in data acquisition. Developing technologies, such as continuous intracranial electroencephalography (iEEG; e.g., Wang et al., 2018), functional near-infrared spectroscopy (fNIRS; e.g., Liu et al., 2017), high-density diffuse optical tomography (HD-DOT; e.g., Fishell et al., 2019), and wearable magnetoencephalography (MEG; Boto et al., 2018) promise higher-fidelity and more ergonomic neuroimaging. Even the workhorse fMRI is beginning to see increased adoption of immersive virtual reality paradigms (Spiers and Maguire, 2007; Maguire, 2012). Finally, we live in an age of ubiquitous real-life behavioral data collection (for better or worse); experience sampling technologies such as mobile sensing (Miller, 2012; Harari et al., 2016) provide new windows into naturalistic behavior, and can be used to procure subject-specific representative stimuli (Nielson et al., 2015; Rissman et al., 2016).

Conclusion

We hope our argument has punctuated the fundamental tension between experimental control and ecological generalizability. We cannot naively decompose organism–environment relations into contrived experimental manipulations in hopes of recomposing them into a satisfying understanding of ecological brain function. By dogmatically adhering to systematic design, we risk creating a cognitive neuroscience of contrived experimental manipulations that have little meaning outside the laboratory—confining ourselves to what Brunswik (1947, p. 110) referred to as “a self-created ivory-tower ecology.” Naturalistic paradigms should not be relegated to post hoc model validation—they should provide a foundation from which theories are

developed (Hasson et al., 2019). We are optimistic that the increasing adoption of naturalistic paradigms will not only complement our existing models, but revolutionize them.

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References

- Araújo, D., Davids, K., Passos, P., 2007. Ecological validity, representative design, and correspondence between experimental task constraints and behavioral setting: comment on Rogers, Kadar, and Costall (2005). *Ecol. Psychol.* 19, 69–78. <https://doi.org/10.1080/10407410709336951>
- Baayen, R.H., Davidson, D.J., Bates, D.M., 2008. Mixed-effects modeling with crossed random effects for subjects and items. *J. Mem. Lang.* 59, 390–412. <https://doi.org/10.1016/j.jml.2007.12.005>
- Baldassano, C., Chen, J., Zadbood, A., Pillow, J.W., Hasson, U., Norman, K.A., 2017. Discovering event structure in continuous narrative perception and memory. *Neuron* 95, 709–721. <https://doi.org/10.1016/j.neuron.2017.06.041>
- Barker, R.G., 1965. Explorations in ecological psychology. *Am. Psychol.* 20, 1–14. <https://doi.org/10.1037/h0021697>
- Bartels, A., Zeki, S., 2004. Functional brain mapping during free viewing of natural scenes. *Hum. Brain Mapp.* 21, 75–85. <https://doi.org/10.1002/hbm.10153>
- Bedny, M., Aguirre, G.K., Thompson-Schill, S.L., 2007. Item analysis in functional magnetic resonance imaging. *NeuroImage* 35, 1093–1102. <https://doi.org/10.1016/j.neuroimage.2007.01.039>
- Boto, E., Holmes, N., Leggett, J., Roberts, G., Shah, V., Meyer, S.S., Duque Muñoz, L., Mullinger, K.J., Tierney, T.M., Bestmann, S., Barnes, G.R., Bowtell, R., Brookes, M.J., 2018. Moving magnetoencephalography towards real-world applications with a wearable system. *Nature* 555, 657–661. <https://doi.org/10.1038/nature26147>
- Breiman, L., 2001. Statistical modeling: the two cultures (with comments and a rejoinder by the author). *Stat. Sci.* 16, 199–231. <https://doi.org/10.1214/ss/1009213726>
- Bronfenbrenner, U., 1977. Toward an experimental ecology of human development. *Am. Psychol.* 32, 513–531. <https://doi.org/10.1037/0003-066X.32.7.513>
- Brunswik, E., 1943. Organismic achievement and environmental probability. *Psychol. Rev.* 50, 255–272. <https://doi.org/10.1037/h0060889>
- Brunswik, E., 1947. *Perception and the Representative Design of Psychological Experiments*, University of California Press, Berkeley, CA. <http://www.worldcat.org/oclc/9551141>
- Brunswik, E., 1949. Systematic and representative design of psychological experiments with results in physical and social perception, in: Neyman, J. (Ed.), *Proceedings of the Berkeley Symposium on Mathematical Statistics and Probability*. University of California Press, Berkeley, CA, pp. 143–202.

<https://projecteuclid.org/euclid.bsmmsp/1166219204>

- Brunswik, E., 1955. Representative design and probabilistic theory in a functional psychology. *Psychol. Rev.* 62, 193–217. <https://doi.org/10.1037/h0047470>
- Campbell, D.T., 1973. The social scientist as methodological servant of the experimenting society. *Policy Stud. J.*, 72–75. <https://doi.org/10.1111/j.1541-0072.1973.tb00128.x>
- Carrasco, M., 2011. Visual attention: the past 25 years. *Vision Res.* 51, 1484–1525. <https://doi.org/10.1016/j.visres.2011.04.012>
- Chang, L.J., Jolly, E., Cheong, J.H., Rapuano, K., Greenstein, N., Chen, P.H.A., Manning, J.R., 2018. Endogenous variation in ventromedial prefrontal cortex state dynamics during naturalistic viewing reflects affective experience. *bioRxiv*, 487892. <https://doi.org/10.1101/487892>
- Chen, J., Leong, Y.C., Honey, C.J., Yong, C.H., Norman, K.A., Hasson, U., 2017. Shared memories reveal shared structure in neural activity across individuals. *Nat. Neurosci.* 20, 115–125. <https://doi.org/10.1038/nn.4450>
- Clark, H.H., 1973. The language-as-fixed-effect fallacy: a critique of language statistics in psychological research. *J. Verbal Learning Verbal Behav.* 12, 335–359. [https://doi.org/10.1016/S0022-5371\(73\)80014-3](https://doi.org/10.1016/S0022-5371(73)80014-3)
- Coleman, E.B., 1964. Generalizing to a language population. *Psychol. Rep.* 14, 219–226. <https://doi.org/10.2466/pr0.1964.14.1.219>
- Cronbach, L.J., 1975. Beyond the two disciplines of scientific psychology. *Am. Psychol.* 30, 116–127. <https://doi.org/10.1037/h0076829>
- Cronbach, L.J., Rajaratnam, N., Gleser, G.C., 1963. Theory of generalizability: a liberalization of reliability theory. *Br. J. Math. Stat. Psychol.* 16, 137–163. <https://doi.org/10.1111/j.2044-8317.1963.tb00206.x>
- David, S.V., Vinje, W.E., Gallant, J.L., 2004. Natural stimulus statistics alter the receptive field structure of V1 neurons. *J. Neurosci.* 24, 6991–7006. <https://doi.org/10.1523/jneurosci.1422-04.2004>
- de Heer, W.A., Huth, A.G., Griffiths, T.L., Gallant, J.L., Theunissen, F.E., 2017. The hierarchical cortical organization of human speech processing. *J. Neurosci.* 37, 6539–6557. <https://doi.org/10.1523/jneurosci.3267-16.2017>
- Deniz, F., Nunez-Elizalde, A.O., Huth, A.G., Gallant, J.L., 2019. The representation of semantic information across human cerebral cortex during listening versus reading is invariant to stimulus modality. *J. Neurosci.* 39, 7722–7736. <https://doi.org/10.1016/j.neuron.2011.08.026>
- Dennett, D.C., 1995. *Darwin's Dangerous Idea: Evolution and the Meanings of Life*, Simon and Schuster, New York, NY. <http://www.worldcat.org/oclc/892927037>
- Felsen, G., Dan, Y., 2005. A natural approach to studying vision. *Nat. Neurosci.* 8, 1643–1646. <https://doi.org/10.1038/nn1608>
- Fiedler, K., 2011. Voodoo correlations are everywhere—not only in neuroscience. *Perspect. Psychol. Sci.* 6, 163–171. <https://doi.org/10.1177/1745691611400237>
- Fishell, A.K., Burns-Yocum, T.M., Bergonzi, K.M., Eggebrecht, A.T., Culver, J.P., 2019. Mapping brain

- function during naturalistic viewing using high-density diffuse optical tomography. *Sci. Rep.* 9, 11115. <https://doi.org/10.1038/s41598-019-45555-8>
- Gallant, J.L., Nishimoto, S., Naselaris, T., Wu, M.C.K., 2012. System identification, encoding models, and decoding models: a powerful new approach to fMRI research. *Visual Population Codes*, MIT Press, Cambridge, MA, 163–188. <http://www.worldcat.org/oclc/712930865>
- Gibson, J.J., 1979. *The Ecological Approach to Visual Perception*. Psychology Press, New York, NY. <http://www.worldcat.org/oclc/962481298>
- Gillis, J., Schneider, C., 1966. The historical preconditions of representative design, in: Hammond, K.R. (Ed.), *The Psychology of Egon Brunswik*, Holt, Rinehart & Winston, New York, NY, pp. 204–236. <http://www.worldcat.org/oclc/500480614>
- Gomez-Marin, A., Ghazanfar, A.A., 2019. The life of behavior. *Neuron* 104, 25–36. <https://doi.org/10.1016/j.neuron.2019.09.017>
- Hamilton, L.S., Huth, A.G., 2018. The revolution will not be controlled: natural stimuli in speech neuroscience. *Lang. Cogn. Neurosci.* 1–10. <https://doi.org/10.1080/23273798.2018.1499946>
- Hammond, K.R., 1955. Probabilistic functioning and the clinical method. *Psychol. Rev.* 62, 255–262. <https://doi.org/10.1037/h0046845>
- Hammond, K.R., Stewart, T.R., 2001. *The Essential Brunswik: Beginnings, Explications, Applications*. Oxford University Press, Oxford, England. <http://www.worldcat.org/oclc/59150825>
- Hanke, M., Baumgartner, F.J., Ibe, P., Kaule, F.R., 2014. A high-resolution 7-Tesla fMRI dataset from complex natural stimulation with an audio movie. *Sci. Data* 1, 140003. <https://doi.org/10.1038/sdata.2014.3>
- Harari, G.M., Lane, N.D., Wang, R., Crosier, B.S., Campbell, A.T., Gosling, S.D., 2016. Using smartphones to collect behavioral data in psychological science: opportunities, practical considerations, and challenges. *Perspect. Psychol. Sci.* 11, 838–854. <https://doi.org/10.1177/1745691616650285>
- Hasson, U., Chen, J., Honey, C.J., 2015. Hierarchical process memory: memory as an integral component of information processing. *Trends Cogn. Sci.* 19, 304–313. <https://doi.org/10.1016/j.tics.2015.04.006>
- Hasson, U., Honey, C.J., 2012. Future trends in neuroimaging: neural processes as expressed within real-life contexts. *Neuroimage* 62, 1272–1278. <https://doi.org/10.1016/j.neuroimage.2012.02.004>
- Hasson, U., Nastase, S.A., Goldstein, A., 2019. Direct-fit to nature: an evolutionary perspective on biological (and artificial) neural networks. *bioRxiv*, 764258. <https://doi.org/10.1101/764258>
- Hasson, U., Nir, Y., Levy, I., Fuhrmann, G., Malach, R., 2004. Intersubject synchronization of cortical activity during natural vision. *Science* 303, 1634–1640. <https://doi.org/10.1126/science.1089506>
- Haxby, J.V., Guntupalli, J.S., Connolly, A.C., Halchenko, Y.O., Conroy, B.R., Gobbini, M.I., Hanke, M., Ramadge, P. J., 2011. A common, high-dimensional model of the representational space in human ventral temporal cortex. *Neuron* 72, 404–416. <https://doi.org/10.1016/j.neuron.2011.08.026>
- Heusser, A.C., Fitzpatrick, P.C., Manning, J.R., 2018. How is experience transformed into memory? *bioRxiv*, 409987. <https://doi.org/10.1101/409987>

- Hubel, D.H., Wiesel, T.N., 1962. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. *J. Physiol.* 160, 106–154. <https://doi.org/10.1113/jphysiol.1962.sp006837>
- Huth, A.G., de Heer, W.A., Griffiths, T.L., Theunissen, F.E., Gallant, J.L., 2016. Natural speech reveals the semantic maps that tile human cerebral cortex. *Nature* 532, 453–458. <https://doi.org/10.1038/nature17637>
- Huth, A.G., Nishimoto, S., Vu, A.T., Gallant, J.L., 2012. A continuous semantic space describes the representation of thousands of object and action categories across the human brain. *Neuron* 76, 1210–1224. <https://doi.org/10.1016/j.neuron.2012.10.014>
- Jenkins, J.J., 1974. Remember that old theory of memory? Well, forget it. *Am. Psychol.* 29, 785–795. <https://doi.org/10.1037/h0037399>
- Jolly, E., Chang, L.J., 2019. The Flatland fallacy: moving beyond low-dimensional thinking. *Top. Cogn. Sci.* 11, 433–454. <https://doi.org/10.1111/tops.12404>
- Judd, C.M., Westfall, J., Kenny, D.A., 2012. Treating stimuli as a random factor in social psychology: a new and comprehensive solution to a pervasive but largely ignored problem. *J. Pers. Soc. Psychol.* 103, 54–69. <https://doi.org/10.1037/a0028347>
- Kanwisher, N., 2010. Functional specificity in the human brain: a window into the functional architecture of the mind. *Proc. Natl. Acad. Sci. U.S.A.* 107, 11163–11170. <https://doi.org/10.1073/pnas.1005062107>
- Kanwisher, N., McDermott, J., Chun, M.M., 1997. The fusiform face area: a module in human extrastriate cortex specialized for face perception. *J. Neurosci.* 17, 4302–4311. <https://doi.org/10.1523/jneurosci.17-11-04302.1997>
- Kriegeskorte, N., Mur, M., Bandettini, P.A., 2008. Representational similarity analysis—connecting the branches of systems neuroscience. *Front. Syst. Neurosci.* 2, 4. <https://doi.org/10.3389/neuro.06.004.2008>
- Kruskal, W., Mosteller, F., 1980. Representative sampling, IV: the history of the concept in statistics, 1895–1939. *Int. Stat. Rev.* 48, 169–195. <https://doi.org/10.2307/1403151>
- LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. *Nature* 521, 436–444. <https://doi.org/10.1038/nature14539>
- Liu, Y., Piazza, E.A., Simony, E., Shewokis, P.A., Onaral, B., Hasson, U., Ayaz, H., 2017. Measuring speaker–listener neural coupling with functional near infrared spectroscopy. *Sci. Rep.* 7, 43293. <https://doi.org/10.1038/srep43293>
- Maguire, E.A., 2012. Studying the freely-behaving brain with fMRI. *Neuroimage* 62, 1170–1176. <https://doi.org/10.1016/j.neuroimage.2012.01.009>
- Meehl, P.E., 1990. Why Summaries of Research on Psychological Theories are Often Uninterpretable. *Psychol. Rep.* 66, 195–244. <https://doi.org/10.2466/pr0.1990.66.1.195>
- Miller, G., 2012. The smartphone psychology manifesto. *Perspect. Psychol. Sci.* 7, 221–237. <https://doi.org/10.1177/1745691612441215>
- Neisser, U., Hyman, I.E., 2000. *Memory Observed: Remembering in Natural Contexts*, Worth, New York, NY. <http://www.worldcat.org/oclc/1040762184>

- Newell, A., 1973. You can't play 20 Questions with nature and win, in: Chase, W. G. (Ed.), *Visual Information Processing*, Academic Press, New York, NY, pp. 283–308. <http://www.worldcat.org/oclc/876592699>
- Neyman, J., 1934. On the two different aspects of the representative method: the method of stratified sampling and the method of purposive selection. *J. R. Stat. Soc.* 97, 558–625. <https://doi.org/10.1111/j.2397-2335.1934.tb04184.x>
- Nielson, D.M., Smith, T.A., Sreekumar, V., Dennis, S., Sederberg, P.B., 2015. Human hippocampus represents space and time during retrieval of real-world memories. *Proc. Natl. Acad. Sci. U.S.A.* 112, 11078–11083. <https://doi.org/10.1073/pnas.1507104112>
- Nishimoto, S., Vu, A.T., Naselaris, T., Benjamini, Y., Yu, B., Gallant, J.L., 2011. Reconstructing visual experiences from brain activity evoked by natural movies. *Curr. Biol.* 21, 1641–1646. <https://doi.org/10.1016/j.cub.2011.08.031>
- Nunez-Elizalde, A.O., Huth, A.G., Gallant, J.L., 2019. Voxelwise encoding models with non-spherical multivariate normal priors. *Neuroimage* 197, 482–492. <https://doi.org/10.1016/j.neuroimage.2019.04.012>
- Olshausen, B.A., Field, D.J., 2005. How close are we to understanding V1? *Neural Comput.* 17, 1665–1699. <https://doi.org/10.1162/0899766054026639>
- Parkinson, C., Kleinbaum, A.M., Wheatley, T., 2017. Spontaneous neural encoding of social network position. *Nat. Hum. Behav.* 1, 0072. <https://doi.org/10.1038/s41562-017-0072>
- Regev, M., Honey, C.J., Simony, E., Hasson, U., 2013. Selective and invariant neural responses to spoken and written narratives. *J. Neurosci.* 33, 15978–15988. <https://doi.org/10.1523/jneurosci.1580-13.2013>
- Rissman, J., Chow, T.E., Reggente, N., Wagner, A.D., 2016. Decoding fMRI signatures of real-world autobiographical memory retrieval. *J. Cogn. Neurosci.* 28, 604–620. https://doi.org/10.1162/jocn_a_00920
- Schroff, F., Kalenichenko, D., Philbin, J., 2015. FaceNet: a unified embedding for face recognition and clustering, in: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 815–823. <https://doi.org/10.1109/CVPR.2015.7298682>
- Simoncelli, E.P., Olshausen, B.A., 2001. Natural image statistics and neural representation. *Annu. Rev. Neurosci.* 24, 1193–1216. <https://doi.org/10.1146/annurev.neuro.24.1.1193>
- Spiers, H.J., Maguire, E.A., 2007. Decoding human brain activity during real-world experiences. *Trends Cogn. Sci.* 11, 356–365. <https://doi.org/10.1016/j.tics.2007.06.002>
- Squire, L.R., 2004. Memory systems of the brain: a brief history and current perspective. *Neurobiol. Learn. Mem.* 82, 171–177. <https://doi.org/10.1016/j.nlm.2004.06.005>
- Srivastava, M., Grill-Spector, K., 2018. The effect of learning strategy versus inherent architecture properties on the ability of convolutional neural networks to develop transformation invariance. *arXiv*, arXiv:1810.13128. <https://arxiv.org/abs/1810.13128>
- Stephens, G. J., Silbert, L.J., Hasson, U., 2010. Speaker–listener neural coupling underlies successful communication. *Proc. Natl. Acad. Sci. U.S.A.* 107, 14425–14430. <https://doi.org/10.1073/pnas.1008662107>
- Tolman, E.C., Brunswik, E., 1935. The organism and the causal texture of the environment. *Psychol. Rev.* 42,

43–77. <https://doi.org/10.1037/h0062156>

- Wang, N.X., Olson, J.D., Ojemann, J.G., Rao, R.P., Brunton, B.W., 2016. Unsupervised decoding of long-term, naturalistic human neural recordings with automated video and audio annotations. *Front. Hum. Neurosci.* 10, 165. <https://doi.org/10.3389/fnhum.2016.00165>
- Wells, G.L., Windschitl, P.D., 1999. Stimulus sampling and social psychological experimentation. *Pers. Soc. Psychol. Bull.* 25, 1115–1125. <https://doi.org/10.1177/01461672992512005>
- Westfall, J., Nichols, T.E., Yarkoni, T., 2016. Fixing the stimulus-as-fixed-effect fallacy in task fMRI. *Wellcome Open Res.* 1, 23. <https://doi.org/10.12688/wellcomeopenres.10298.2>
- Wu, M.C.-K., David, S.V., Gallant, J.L., 2006. Complete functional characterization of sensory neurons by system identification. *Annu. Rev. Neurosci.* 29, 477–505. <https://doi.org/10.1146/annurev.neuro.29.051605.113024>
- Yarkoni, T., 2019. The generalizability crisis. *PsyArXiv*. <https://doi.org/10.31234/osf.io/jqw35>
- Yarkoni, T., Westfall, J., 2017. Choosing prediction over explanation in psychology: lessons from machine learning. *Perspect. Psychol. Sci.* 12, 1100–1122. <https://doi.org/10.1177/1745691617693393>
- Yeshurun, Y., Swanson, S., Simony, E., Chen, J., Lazaridi, C., Honey, C.J., Hasson, U., 2017. Same story, different story: the neural representation of interpretive frameworks. *Psychol. Sci.* 28, 307–319. <https://doi.org/10.1177%2F0956797616682029>
- Zadbood, A., Chen, J., Leong, Y.C., Norman, K.A., Hasson, U., 2017. How we transmit memories to other brains: constructing shared neural representations via communication. *Cereb. Cortex* 27, 4988–5000. <https://doi.org/10.1093/cercor/bhx202>