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RESEARCH VISION

My career has followed a single driving question: how does the brain process information as it actually unfolds in the world? Early on, I recognized that the tightly controlled experiments dominating neuroscience were stripping away the very complexity the brain evolved to handle. My response was to bring the real world into the scanner — having people watch movies, listen to stories, hold conversations — and develop inter-subject correlation (ISC), a family of methods that measure how brains align across individuals during shared experience, now used in over 19,000 publications worldwide.

This model-free approach revealed a cortical timescale hierarchy in which memory is not a separate system but an intrinsic property of perception, and showed that successful communication is literally written in synchronized neural activity between speaker and listener. When deep learning arrived, it offered something ISC could not: explicit computational models that could engage with natural, continuous input. My lab found striking alignment between large language models and the brain's language systems — but also a fundamental gap: industry AI learns from data volumes no human could encounter and lacks the developmental trajectory, embodiment, and social grounding that shape a human mind.

That gap is now the frontier. My "understanding by building" program constructs AI agents that learn from real human experience as humans do, anchored by the First 1,000 Days Project, which recorded over a million hours of infant life across diverse households. Agents trained on these recordings already reproduce individual children's language trajectories with striking precision — and the act of building them has itself yielded new insight: a system learning continuously from a changing world cannot update and act simultaneously without destabilizing, forcing a separation between online processing and deferred consolidation that mirrors, at the level of pure computation, why the brain concentrates learning during sleep.

ACADEMIC EMPLOYMENT

2017 – Professor, Department of Psychology and the Neuroscience Institute, Princeton University

2014 – 2017 Associate Professor, Princeton University

2008 – 2014 Assistant Professor, Princeton University

2004 – 2008 Postdoctoral Fellow, NYU (Advisors: David Heeger and Nava Rubin)

EDUCATION

1999 – 2004 Ph.D., Neurobiology, Weizmann Institute of Science (Advisor: Rafael Malach)

1995 – 1998 M.Sc., Cognitive Science, Hebrew University of Jerusalem

1991 – 1994 B.Sc., Philosophy and Cognitive Science, Hebrew University of Jerusalem

HONORS AND AWARDS

2019 – Fellow, Association for Psychological Science

2018 –Google Research Fellow

2016 – 2024NIH Director's Pioneer Award

2004 – 2007Human Frontier Science Program (HFSP) Long-Term Fellowship

2004 / 2005Rothschild Fellowship

2000 – 2004Feinberg Fellowship for Doctoral Degree in Neurobiology

CONTRIBUTIONS TO SCIENCE

I. Neuroscience in the Real World

I was a pioneering force in advancing the study of neural processes in naturalistic contexts — an approach that has fundamentally transformed the scope and trajectory of contemporary neuroscience. Early in my career, I recognized that models developed under tightly controlled lab conditions often fail to generalize to everyday cognition. In 2004, I co-authored one of the first studies to apply naturalistic stimuli in neuroimaging, introducing inter-subject-based analyses that helped launch the now-thriving field of naturalistic neuroscience. The 2004 Science paper has been cited over 2,100 times; the broader ISC methodology appears in over 31,900 publications.

- Hasson, U., Nir, Y., Levy, I., Fuhrmann, G., & Malach, R. (2004). Intersubject synchronization of cortical activity during natural vision. *Science*, 303(5664), 1634–1640.
- Hasson, U., Malach, R., & Heeger, D. J. (2010). Reliability of cortical activity during natural stimulation. *Trends in Cognitive Sciences*, 14(1), 40–48.
- Nastase, S. A., Goldstein, A., & Hasson, U. (2020). Keep it real: Rethinking the primacy of experimental control in cognitive neuroscience. *NeuroImage*, 222, 117254.
- Yeshurun, Y., Nguyen, M., & Hasson, U. (2021). The default mode network: where the idiosyncratic self meets the shared social world. *Nature Reviews Neuroscience*, 22(3), 181–192.

II. Methods for Studying Cognition in the Real World

A central challenge in cognitive neuroscience is inferring mental states from brain activity during complex, real-life experiences. To address this, I introduced a suite of inter-subject analyses that measure shared neural responses across individuals. Inter-subject correlation (ISC) quantifies the similarity of temporal dynamics across brains, revealing regions engaged in shared processing. I later extended this to Inter-Subject Functional Correlation (ISFC) to map shared large-scale network dynamics, and Inter-Subject Spatial Pattern Correlation (ISPC) to identify common representational structures. These methods have been used in over 19,300 publications across the field and have proven effective across imaging modalities (single unit, ECoG, fMRI, EEG, MEG), sensory domains, species (human, primate, rodent, bat), and clinical populations (autism, schizophrenia, depression, aphasia, addiction).

- Simony, E., Honey, C. J., Chen, J., et al., & Hasson, U. (2016). Dynamic reconfiguration of the default mode network during narrative comprehension. *Nature Communications*, 7(1), 12141.
- Chen, J., Leong, Y. C., Honey, C. J., et al., Norman, K. A., & Hasson, U. (2017). Shared memories reveal shared structure in neural activity across individuals. *Nature Neuroscience*, 20(1), 115–125.
- Nastase, S. A., Gazzola, V., Hasson, U., & Keysers, C. (2019). Measuring shared responses across subjects using intersubject correlation. *Social Cognitive and Affective Neuroscience*, 14(6), 667–685.
- Regev, M., Simony, E., Lee, K., et al., Chen, J., & Hasson, U. (2019). Propagation of information along the cortical hierarchy as a function of attention. *Cerebral Cortex*, 29(10), 4017–4034.

III. Neural Coupling and Social Communication

I introduced the concept of brain-to-brain coupling, extending ISC beyond passive synchrony to model dynamic, directional coupling between interacting brains. By incorporating time-lagged ISC and hyperscanning, this approach maps how shared understanding emerges during conversation and illuminates the neural basis of both successful and

disrupted social interactions. My most recent work identifies a shared model-based linguistic space through which thoughts are transmitted between brains in natural conversation.

- Stephens, G. J., Silbert, L. J., & Hasson, U. (2010). Speaker–listener neural coupling underlies successful communication. *PNAS*, 107(32), 14425–14430.
- Hasson, U., Ghazanfar, A. A., Galantucci, B., Garrod, S., & Keysers, C. (2012). Brain-to-brain coupling: a mechanism for creating and sharing a social world. *Trends in Cognitive Sciences*, 16(2), 114–121.
- Silbert, L. J., Honey, C. J., Simony, E., Poeppel, D., & Hasson, U. (2014). Coupled neural systems underlie the production and comprehension of naturalistic narrative speech. *PNAS*, 111(43), E4687–E4696.
- Hasson, U., & Frith, C. D. (2016). Mirroring and beyond: coupled dynamics as a generalized framework for modelling social interactions. *Phil. Trans. Royal Society B*, 371(1693), 20150366.
- Zada, Z., Goldstein, A., Michelmann, S., et al., & Hasson, U. (2024). A shared model-based linguistic space for transmitting our thoughts from brain to brain. *Neuron*, 112(18), 3211–3222.

IV. The Processing Timescale Hierarchy and Process-Memory Framework

Working with naturalistic stimuli revealed something no controlled experiment could: the brain integrates information across radically different timescales, from milliseconds in early sensory cortex to minutes in higher-order regions. This topographic hierarchy reconceptualizes memory not as a separate system but as an intrinsic property of each cortical area's processing window. The framework provides a foundation for understanding narrative comprehension, language, and psychiatric conditions where temporal integration is disrupted — and maps directly onto the layer hierarchy of large language models. Key papers carry 700–1,000 citations each.

- Hasson, U., Yang, E., Vallines, I., Heeger, D. J., & Rubin, N. (2008). A hierarchy of temporal receptive windows in human cortex. *Journal of Neuroscience*, 28(10), 2539–2550.
- Lerner, Y., Honey, C. J., Silbert, L. J., & Hasson, U. (2011). Topographic mapping of a hierarchy of temporal receptive windows using a narrated story. *Journal of Neuroscience*, 31(8), 2906–2915.
- Honey, C. J., Thesen, T., Donner, T. H., et al., & Hasson, U. (2012). Slow cortical dynamics and the accumulation of information over long timescales. *Neuron*, 76(2), 423–434.
- Hasson, U., Chen, J., & Honey, C. J. (2015). Hierarchical process memory: Memory as an integral component of information processing. *Trends in Cognitive Sciences*, 19(6), 304–313.
- Baldassano, C., Chen, J., Zadbood, A., et al., Hasson, U., & Norman, K. A. (2017). Discovering event structure in continuous narrative perception and memory. *Neuron*, 95(3), 709–721.
- Hasson, U. (2025). Uncovering a timescale hierarchy by studying the brain in a natural context. *Journal of Neuroscience*, 45(12): e2368242025.

V. Deep Learning as a Cognitive Model of the Brain in Natural Contexts

Moving from model-free ISC to explicit computational accounts, my lab uses deep learning to decode the neural code during natural language, brain-to-brain interaction, and child development. We found striking alignment between large language models and brain activity in the language cortex — shared computational principles, matched geometric structure in neural embeddings, and a layer hierarchy that mirrors the brain's own timescale hierarchy. These findings establish that biological and artificial neural networks share deep computational principles when both engage with natural input. Our 2022 *Nature Neuroscience* paper has been cited over 450 times; the 2020 *Neuron* framework over 390 times.

- Hasson, U., Nastase, S. A., & Goldstein, A. (2020). Direct fit to nature: an evolutionary perspective on biological and artificial neural networks. *Neuron*, 105(3), 416–434.
- Goldstein, A., Zada, Z., Buchnik, E., et al., & Hasson, U. (2022). Shared computational principles for language processing in humans and deep language models. *Nature Neuroscience*, 25(3), 369–380.

- Goldstein, A., Grinstein-Dabush, A., Schain, M., et al., & Hasson, U. (2024). Alignment of brain embeddings and artificial contextual embeddings in natural language points to common geometric patterns. *Nature Communications*, 15(1), 2768.
- Zada, Z., Goldstein, A., Michelmann, S., et al., & Hasson, U. (2024). A shared model-based linguistic space for transmitting our thoughts from brain to brain. *Neuron*, 112(18), 3211–3222.
- Goldstein, A., Wang, H., Niekerken, L., et al., & Hasson, U. (2025). A unified acoustic-to-speech-to-language embedding space captures the neural basis of natural language processing. *Nature Human Behavior*, 1–15.

VI. Understanding by Building: Agents That Learn Like the Human Mind

Deep learning models revealed both the promise and the limits of industry AI as a model of cognition: the alignment is real, but AI learns from data volumes no human encounters and lacks a developmental trajectory, embodiment, or social grounding. This gap motivates my current program — "understanding by building" — which proposes studying the mind by constructing agents that learn from real human experience under cognitively feasible constraints, and testing whether they come to compute as the brain does. The program is organized around three mutually reinforcing objectives: (1) dense real-life recording of human development, (2) building AI agents that learn as humans do, and (3) aligning artificial and biological neural computation. When the agents diverge from the brain, they reveal missing computational principles; when they align, they become working mechanistic explanations.

A central result: agents trained day by day on a single child's speech learned to reproduce that child's vocabulary trajectory with a mean error of 22 days across developmental milestones—and the act of building them revealed, at the level of pure computation, why the brain must defer learning to sleep. A system that updates its weights continuously while processing a non-repeating stream destabilizes; it must accumulate error online and consolidate offline, mirroring the brain's sleep-dependent consolidation cascade.

- Hasson, U., Goldstein, A., & Raviv, H. (in press). Understanding by building agents that learn like the human mind and brain. *Trends in Cognitive Sciences*.
- Raviv, H., et al., & Hasson, U. (2026). The First 1,000 Days (1kD) Project: collecting and analyzing an ultra-dense naturalistic dataset of human baby development. *bioRxiv*. <https://doi.org/10.64898/2026.03.19.712982>.
- Raviv, H., et al., & Hasson, U. (2026). The richness of experience: agent-based learning reveals the mechanisms of early language acquisition. *bioRxiv*. <https://doi.org/10.64898/2026.03.28.715023>.

VII. Open Naturalistic Datasets

Advancing open science has been a core commitment throughout my career. My lab has built and publicly released large-scale neuroimaging and behavioral datasets that have become community resources for naturalistic neuroscience.

- The Conversations ECoG Dataset — the most extensive collection of high-resolution brain recordings during real-life conversation, using ECoG in patients undergoing epilepsy monitoring at NYU Langone. hassonlab.princeton.edu
- The First 1,000 Days (1kD) Project — an ultra-dense longitudinal dataset of 17 infants across 15 diverse U.S. households, recorded 12–14 hours per day from birth, totaling over 1.5 million hours of audio and video. hassonlab.princeton.edu
- The Narratives fMRI Dataset — fMRI recordings from 345 participants listening to 27 spoken stories (~4.6 hours of unique audio), serving as a benchmark for models of naturalistic language comprehension. Nastase et al. (2021), *Scientific Data*, 8(1), 250.
- The Podcast ECoG Dataset — ECoG recordings from 9 participants (1,330 electrodes) listening to a 30-minute podcast. Zada et al. (2025), *bioRxiv*.