Visual neuroscience

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Integrating neuroscience across species and scales

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Neuroscientists have an ever-expanding array of tools for measuring brain activity at multiple scales, motivating efforts to integrate diverse datasets and capitalize on their complementary strengths. The new Triple-N dataset introduced by Li et al. tackles this challenge by conducting large-scale macaque electrophysiology in an experimental paradigm matched to the human 7T fMRI Natural Scenes Dataset.

The ongoing collection of large datasets in neuroscience promises a more complete understanding of the brain. Yet, each of these datasets is associated with tradeoffs intrinsic to measurement modalities. While fMRI achieves broad spatial coverage, it averages activity over thousands of neurons and is limited by the sluggish pace of blood flow. Electrophysiology tracks single neurons at millisecond precision but samples regions sparsely and unevenly. Moreover, neuroscience experiments are typically highly specialized and divergent across experimental approaches and laboratories. In this context, advances in neuroscience will come not simply from collecting more data, but from thoughtful integration across experiments and datasets.

An exciting trend in the field of visual neuroscience is the creation of rich, reusable, large-scale community data resources. Such resources facilitate cross-community engagement as groups test hypotheses and compare models. A defining example is the Natural Scenes Dataset (NSD)[1], which provides high-resolution human 7T fMRI responses to tens of thousands of natural images. In the years since its initial release, the NSD has supported diverse investigations of visual coding[2,3], functional organization[4,5], computational models of the visual system[6,7] and more. In this issue of *Nature Neuroscience*, Li et al.[8] present the Triple-N dataset, a large-scale macaque electrophysiology resource designed with an explicit eye toward integration with the NSD fMRI data. Together, these datasets offer a powerful and more integrated view of the brain.

Triple-N pairs large-scale image presentation in five macaques with recordings from Neuropixels probes in visual cortex[9]. A set of 1,000 images previously shown to NSD participants were presented to each monkey (Fig. 1), establishing a shared basis to compare individuals, species and measurement modalities. The data include 71 sessions with 30 recording sites across inferotemporal (IT) cortex, capturing activity from more than 30,000 units. Additional recordings from early visual areas, including V1, V2 and V4, situate high-level responses from IT within a broader visual hierarchy. The use of fMRI to guide electrode positioning[10] provided a principled way to focus recordings on category-selective regions. Notably, the dataset also includes sampling of locations beyond commonly studied face-, body-, color- and scene-selective patches, venturing into less well-characterized territory considered to be 'no-man's land'[11].

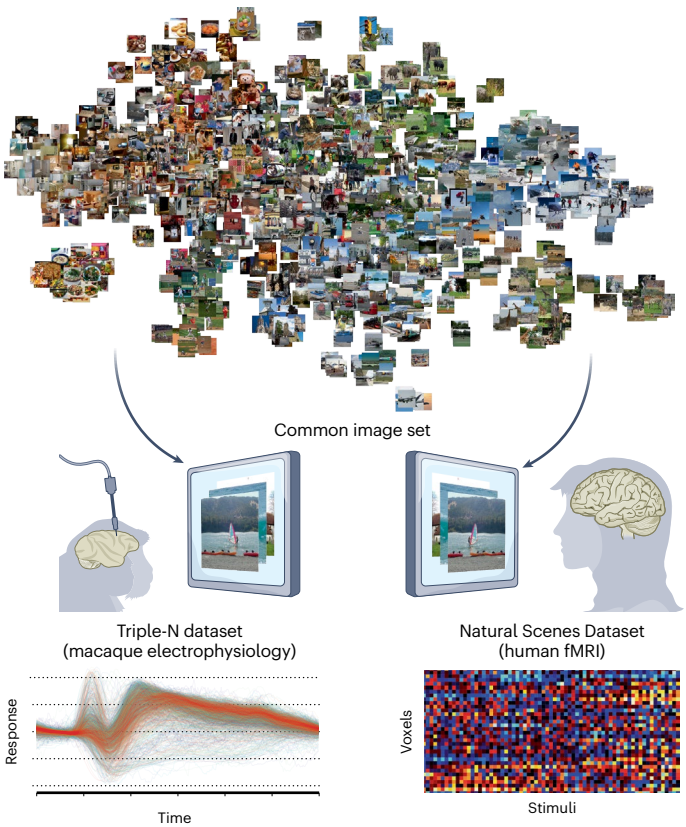

Fig. 1 | Integrating macaque electrophysiology and human neuroimaging using a common set of visual stimuli. In Triple-N, macaques viewed a set of 1,000 natural images also used in the Natural Scenes Dataset. Macaque electrophysiology provides temporally precise neuronal responses, shown here as time courses of mean firing rate. Human fMRI provides broad spatial coverage of the brain, shown here as a matrix of voxel response magnitudes.

The Triple-N dataset enables many new opportunities for cognitive and computational neuroscience. For example, sampling patches with both known and unknown selectivity profiles provides an exciting opportunity to assess whether category-selective visual regions are best understood as isolated modules or as landmarks within a smoother topographic map of image space[5,11]. As another example, Triple-N enables a principled way to study what is shared across primate vision and what is distinctly human. Convergence in how macaque neurons

and human voxels represent the same images might suggest universal principles of perception[12]. Alternatively, representations might diverge, especially regarding stimuli with rich linguistic or semantic content. As a final example, perhaps the most compelling contribution of Triple-N is the ability to examine the neural activity dynamics that underlie visual processing. Li et al. present an initial preview of such dynamics — recorded units displayed fast transient responses, delayed and sustained responses, and responses marked by early suppression — hinting at the rich diversity hidden behind typical time-averaged analyses. Recent studies have found intriguing dynamic shifts in the neural code of face cells[13]; whether these stimulus-dependent dynamics generalize more broadly across the visual system can now be assessed with the temporal resolution and spatial coverage of Triple-N.

Triple-N is poised to reshape how the field evaluates computational models of vision. Current primate neural benchmarks, such as those aggregated in BrainScore[14], are mainly assembled from small, heterogeneous datasets that vary in stimulus coverage, cortical region and recording method. Model performance on these benchmarks has begun to saturate[7], often with static feedforward models. Triple-N offers an opportunity to extend current benchmarks by requiring that models explain nuanced temporal dynamics, including distinctions in dynamics between cell types. Such a benchmark could both mitigate overly optimistic evaluations of model performance and reinvigorate interest in recurrent and dynamic architectures.

Like any experimental dataset, Triple-N has limitations. The Triple-N image set is far from an exhaustive sample of visual experience, limiting the scope of claims and generalization. The same is true of task design: the passive viewing in Triple-N prioritizes stimulus-driven responses but does not reflect real-world perception or the tasks that organisms perform[15]. Future datasets that combine the shared-image logic of Triple-N with richer behavioral demands could help to reveal how attention, memory, goals and decisions reshape the visual code. Finally, Triple-N provides localized sampling of the brain. Although Neuropixels probes provide dense access to neurons within recording sites, each session captures only a narrow sample of cortex. Many important questions in vision concern communication between areas characterized by feedforward sweeps, feedback signals, recurrent loops and distant cross-area interactions. Future resources with simultaneous recordings across multiple distant regions would help to illuminate large-scale circuit interactions.

Triple-N is not merely a dataset, but a piece of scientific infrastructure — a shared foundation with which many laboratories can test models, develop methods and answer questions that have been difficult to address. Together, Triple-N, NSD and other large-scale community data resources may help to precipitate a highly needed integration of diverse neuroscience data.

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Competing interests

The authors declare no competing interests.