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Visual cortex: Big data analysis uncovers food specificity

Michael M. Bannert[1,2,3] and Andreas Bartels[1,2,3,*]
[1]Vision and Cognition Lab, Centre for Integrative Neuroscience, Department of Psychology, University of Tübingen, Tübingen, Germany
[2]Max Planck Institute for Biological Cybernetics, Tübingen, Germany
[3]Bernstein Center for Computational Neuroscience, Tübingen, Germany
*Correspondence: andreas.bartels@tuebingen.mpg.de
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In visual cortex, anatomically distinct patches respond to distinct categories, such as faces or text. New research confirms this parcellation using unsupervised analysis of functional magnetic resonance imaging data obtained from humans viewing tens of thousands of images, discovering one more preference: for food.

Our brain's mechanisms for object recognition transform complex visual experiences into simple concepts, allowing us to interact with, reason about, or simply name seen objects. The brain achieves this task faithfully, although one and the same object can give rise to vastly diverse visual inputs due to differences in viewing conditions such as perspective, occlusion, or illumination. Our brain's capacity for object recognition is even more impressive if one considers that modern deep learning models fall short of the robustness observed in biological vision[1]. Research over the past three decades has suggested that the human ventral visual pathway is functionally specialised for processing ecologically relevant stimulus categories, with distinct areas being selective for the perception of faces, scenes, bodies, text. In a typical neuroimaging study probing stimulus selectivity, observers view a few handfuls of selected stimuli from the category in question and a limited number of control stimuli. Higher brain responses to the probed category than to the controls indicate evidence for category selectivity (Figure 1A). Such interpretation, however, depends on certain assumptions, including whether the stimuli are representative of the studied categories, or whether control conditions are appropriately matched to rule out alternative accounts related to differences in low-level visual features, or in high-level properties such as salience, and so on. A new study reported in this issue of *Current Biology* by Khosla *et al.*[2] found that functional specialisation can be observed in brain data without reliance on manually selected stimuli dedicated to test a particular human-conceived hypothesis.

Khosla *et al.*[2] analysed a recently published large fMRI dataset[3] consisting of brain responses recorded in eight observers viewing 10,000 natural images from everyday life. Decomposing the high-dimensional voxel activity patterns to few underlying components, the authors obtained five components whose response was highly consistent across participants. Four of them responded most strongly to images showing either faces, bodies, scenes, or text. This replicates prior work relying on traditional approaches demonstrating functional selectivity for these categories in ventral visual pathway. These results confirmed both the power of the new approach as well as the ecological validity of prior experiments. Surprisingly, the remaining component responded most strongly to a completely different class of stimuli, namely food.

This new study is remarkable in two ways. First, it represents a new approach to neuroscience that will define the field for years to come: the use of big data, the combination of data- and hypothesis-driven analyses, and the exploitation of deep learning models. Second, the actual neuroscientific contribution: the identification of a food-selective component in ventral visual pathway. This was unexpected because previous attempts to find food responses were unsuccessful[4]; but more importantly, unlike other dominant categories represented in ventral visual pathway, food is not visually definable. Food has no typical visual low-level features, subcomponents, or high-level Gestalt properties, but instead comes in all shapes, forms, and colours. Its category membership is a cognitively learned association. This has numerous implications, including for the definition

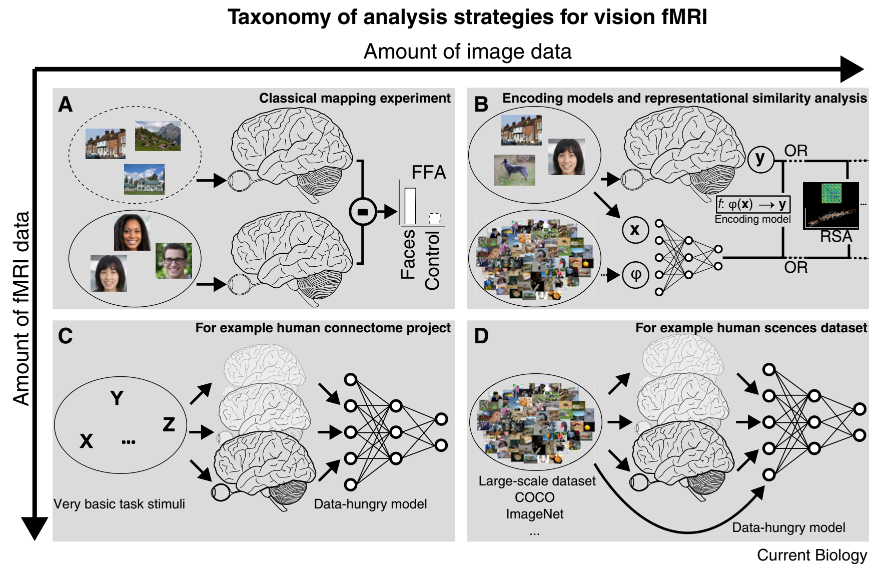

Figure 1. Taxonomy of fMRI experiments according to two axes — amount of fMRI data and amount of stimulus material.
(A) In typical fMRI mapping experiments observers view a few images from the probed category (for example, faces) in one condition and control images from a different condition (for example, scenes), while limited data are collected. Specialised areas show higher responses to the probed than to the control condition. (B) Deep neural networks trained on large amounts of image data are used to model brain responses on natural images collected in a small number of scan sessions. Popular models are encoding models or representational similarity analysis. Note that image models are typically viewed as models of image processing in the brain, not as models of the data. (C) The Human-Connectome-Project collected data from 1,200 participants but used only very limited task stimuli. (D) The Natural Scenes Dataset recorded large amounts of fMRI data in eight participants in response to a large amount of images. In an integrative 'hypothesis-neutral' effort, the new Khosla *et al.*[2] study combines big brain data with analyses involving big image data as well.

of visual processing, and the role of multi-modal learning in ventral visual pathway. No doubt this finding will inspire numerous future studies. Apparently, the time was ripe for this question: two other laboratories report similar findings based on the same public dataset[5,6].

The new studies contrast with previous work in that they replace targeted stimulus design and *de novo* data collection with data exploration of existing large-scale fMRI datasets of responses to images depicting everyday life. In other words: instead of searching the metaphorical haystack for the needle that would functionally isolate the hypothesised visual activity in the brain, the authors present the haystack itself and examine brain responses to a huge sample from all possible visual inputs. After all, conventional selectivity studies notoriously suffered from several fundamental problems. The space of conceivable control stimuli for any category is infinitely large. This inspired alternative interpretations: for example, a visual low-level account suggested that face *versus* scene regions are systematically biased by round versus rectilinear shapes, respectively[7]. A high-level account suggested that expertise, not face-ness, drives responses in face regions[8]. Others argued that the myriad of categories in our visual world cannot possibly each occupy their own territory in limited brain space. Consistent with this, each known category is also represented as distributed voxel activity pattern throughout ventral visual pathway[9]. Finally, visual neuroscientists, in trying to map visual concepts to neural ones, may fail in match-making and select cognitive concepts that may not correspond to any particularly relevant neural concept (the haystack-problem). Object-level concepts like faces and houses may thus simply appear relevant as they appeal to everyday intuitions. A solution is to not impose our own concepts upon the brain and to let the data speak for themselves. A large set of natural stimuli can accomplish this while conveniently ensuring the ecological validity of the findings as well as robustness to variability in the stimulus space.

Natural stimuli[10,11] and blind data decomposition of resulting brain responses[12] have been used before, but not on the refined level or scale of the present study[2]. In fact, neuroscience has from its beginnings involved data-driven and hypothesis-neutral parcellations of brain function and structure: the first evidence for functional specialization originated from explorative neuropsychological assessment of the highly specific cognitive or perceptual deficits (‘Seelenblindheit’) following rarely occurring local brain lesions. Now, modern electrophysiological research explores the at times stunningly distinct perceptual or cognitive experiences when small currents stimulate tiny patches of cortex in patients through electrodes[13]. Likewise, neuroanatomy led to the idea that function is derived from structure, and hence differences in structure imply differences in function. This concept has been so powerful that Brodmann’s cytoarchitectonic maps obtained 120 years ago still serve as landmarks, and are currently complemented using new, molecular tools. In visual neuroscience, visual maps beyond the primary one were first delineated using fibre degradation along vertical meridians[14], later using retinotopic mapping. Similarly, the century old guiding principle of connectivity-driven brain parcellation still serves as a model for modern parcellation using functional connectivity or diffusion MRI.

Modern imaging neuroscience can be classified along two dimensions: the amount of fMRI data; and the amount of stimulus data (Figure 1). Large image and video datasets can serve as priors for modelling fMRI data, and have led to the impressive achievement of reconstructing visual experience from fMRI activity[15] (Figure 1B). Beyond this, large image datasets allow training of deep neural networks that recognise objects with unprecedented accuracy. Deep neural networks acquire features that resemble receptive fields in the brain and that predict fMRI activity[16]. Hence, deep neural networks can be regarded as models of the brain and need not be fitted to fMRI data but to images instead (Figure 1B). This difference cannot be overstated if one contrasts the millions of images available for deep learning with the few hundred (noisy) trials produced by typical fMRI sessions. Image data are cheap and abundant, fMRI data are expensive and scarce. Also large fMRI datasets have their value, for example for quantitative and flexible meta-analytic inference[17]. The Human Connectome Project) amassed fMRI data to explore relationships between brain regions, genes, and behaviour, at a scale also satiating data-hungry deep learning analysis[18] (Figure 1C). The presently used Natural Scenes Dataset, however, excels in that it combines big datasets in the domain of both fMRI and natural, ecologically relevant images (Figure 1D).

Despite its indisputable strengths, the Natural Scenes Dataset confronts fMRI analysts with challenges, too. While it covers a large variety of everyday scenes, the subject sample of eight participants is small. How well do the results generalise across brains? Khosla *et al.*[2] answered this question by using half of the participants for data exploration, then pre-registering their analysis, and confirming their findings in the remaining subjects. Another difficulty is that the relationship between neuroimaging and stimulus data in the Natural Scenes Dataset is correlational only. Does the food component generalise to other images as well? Can the food response be accounted for by other factors, for example by low-level image properties such as colour, shape, or high-level properties such as saliency or arousal? Khosla *et al.*[2] addressed each of these potential alternative accounts in control analyses. These first exploited the vast stimulus-response material offered within the dataset itself. For example, the authors compared visually highly matched pairs of food versus non-food items, or food in atypical food colours versus non-food in typical food colours, among other comparisons.

A second set of control analyses used a deep neural network trained to predict the scores of the food component. This deep neural network then allowed to confirm that also across a million novel images food remained the driving force of the response, also for greyscale versions of images, and for hand-picked food versus non-food pairs that looked otherwise highly similar. This aggregate of control analyses is on one hand expected for results of a correlational nature. On the other hand, it matches if not supersedes the controls encountered in many traditional experiments — a feat made possible by the big data available here. Indeed, the current study shows how powerful big data approaches are in comparison to hypothesis-driven ones, in that big data studies allow for both, unsupervised (or hypothesis-neutral) data exploration and hypothesis- and model-driven control analyses. The latter — if based on the same data — are strictly speaking still correlational and not causal in nature, but provide good opportunity to debunk spurious correlations based on targeted hypotheses. Finally, the richness of a large natural stimulus dataset provides inherent controls and provides robustness of the observed results across the huge variability observed in the wild.

Nevertheless, it remains unclear what the causal determinants of food responses in the brain are; equally, whether the ‘food’ responses can possibly be subdivided into different classes, levels of hierarchy, or how and whether the different anatomical locations involved differ functionally. Possibly some answers are still hidden within the existing dataset, and others may require hypothesis-driven targeted experiments, particular tasks, or multi-modal stimuli involving gustatory and auditory dimensions, or target personal preferences and reward associations. Another key question raised by the results of Khosla *et al.*[2] is why the authors found selectivity only in component space, not voxel space. This differs fundamentally to the face selectivity for which functional specificity is astounding[19] and anatomical location is deemed crucial[20]. Does this reflect a truly distributed representation of food or are there, perhaps at a finer, neural dimension, modules with stricter specialisation, which, when damaged, might even cause deficits in visual food perception? Does the distributed response result from the visual heterogeneity of the in principle non-visual concept of food?

Although selective food agnosia has not (yet) been reported, independent analyses[5,6] of the NSD did map food selectivity in the brain by contrasting hand-labelled food images against non-food images. The failure of previous mapping experiments[4] suggests that the availability of large datasets might have been the limiting factor. At any rate, Khosla *et al.*[2] provide an encouraging first example of the potential of 'big image data' and 'big fMRI data' to tackle these questions.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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Pollinator cognition: Framing bee memories in an ecological context

Martin Giurfa[1,2]
[1]Centre de Recherches sur la Cognition Animale, Centre de Biologie Intégrative (CBI), University of Toulouse, CNRS, UPS, 31062 Toulouse cedex 9, France
[2]Institut Universitaire de France (IUF), Paris, France
Correspondence: martin.giurfa@univ-tlse3.fr
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Bee memory has been well characterized in laboratory experiments, but its relevance for foraging in an ecological context is less well studied. A new study shows that short-term memory in bumble bees correlates with springtime foraging efficiency, when floral resources are abundant, but not with summer foraging efficiency, when resources are scarce.

Memories constitute the essence of our individual life, as they establish a bridge between our past and future. They build our identity and personal history, and provide the basis for predictions about events to come in environments in which survival would be impossible in the absence of stored, available knowledge. Accepted definitions posit that while learning is the process that allows acquisition of new information *via* individual experience, memory refers to the persistence of learning in a state that can be revealed at a later time, when it is necessary to respond adaptively to novel events[1,2]. In this framework, memory can be seen as the sum of processes (and underlying neural