An Optimization-Based Approach to Understanding Sensory Systems

Daniel Yamins[*]

Nothing in biology makes sense except in light of evolution.

— Theodosius Dobzhansky

Nothing in neurobiology makes sense except in light of behavior.

— Gordon Shepherd

Abstract *Recent results have shown that deep neural networks (DNN) may have significant potential to serve as quantitatively precise models of sensory cortex neural populations. However, the implications these results have for our conceptual understanding of neural mechanisms are subtle. This is because many modern DNN brain models are best understood as the products of task-constrained optimization processes, unlike the intuitively simpler hand-crafted models from earlier approaches. In this chapter, we illustrate these issues by first discussing the nature of information processing in the primate ventral visual pathway, and review results comparing the response properties of units in goal-optimized DNN models to neural responses found throughout the ventral pathway. We then show how DNN visual system models are just one instance of a more general optimization framework whose logic may be applicable to understanding the underlying constraints that shape neural mechanisms throughout the brain.*

An important part of a scientist's job is to answer "why" questions. For cognitive neuroscientists, a core objective is to uncover the underlying reasons why the structures of the human brain are as they are. Since brains are biological systems, answering such questions is ultimately a matter of identifying the evolutionary and developmental constraints that shape brain structure and function. Such constraints are in part architectural: what large-scale brain structures are put in place genetically to help a brain help its host organism better meet evolutionary challenges? In light of the centrality of behavior in understanding the brain, an ethological investigation is also indicated: what behavioral goals most strongly constrain a given neural system? And since many complex behaviors in higher organisms are not entirely genetically determined and must instead be partly derived through experience of the world, a core question of learning is also involved: how do learning rules that absorb experiential data constrain what brains look like?

The interactions between architectural structure, behavioral goals, and learning rules suggest a *quantitative optimization framework* as one route toward answering these "why" questions. Put simply, this means: postulating one or several goal behavior(s) as driving the evolution and/or development of a neural system of interest; finding architecturally plausible computational models that (attempt to) optimize for the behavior; and then quantitatively comparing the internal structures arrived at in the optimized models to measurements from large-scale neuroscience experiments. To the extent that there is a match between optimized models and the real data that is very substantially better than that found for various controls (e.g. models designed by hand or optimized for other tasks), this is evidence that something important has been understood about the underlying constraints that shape the brain system under investigation. Though it might sound challenging to put this approach into practice, recent successes suggest we might add to our list of maxims the observation that *nothing in computational cognitive neuroscience makes sense except in light of optimization*.

Case Study: The Primate Ventral Visual Stream

The most thoroughly developed example of these optimization-based ideas is the visual system — and in particular, the ventral visual stream in humans and non-human primates. While a complete review of the work that lead to the present understanding of the primate ventral stream is beyond the scope of this chapter (see DiCarlo *et al.*[1] for a summary), discussing key computational aspects of the ventral stream in some detail will lay the groundwork for the optimization approach more generally.

[*] Departments of Psychology and Computer Science, and the Stanford Neurosciences Institute, Stanford University; yamins@stanford.edu

The computational crux of the vision problem. The human brain effortlessly reformats the "blooming, buzzing confusion" of unstructured visual datastreams into powerful abstractions that serve high-level behavioral goals such as scene understanding, navigation, and action planning[2]. But parsing retinal input into rich object-centric scene descriptions is a major computational challenge. The crux of the problem is that the axes of the low-level input space (i.e. light intensities at each retinal "pixel") don't correspond to the natural axes along which high-level constructs vary. For example, translation, rotation in depth, deformation, or re-lighting of a single object (e.g. one person's face) can lead to large and complex non-linear transformations of the original image. Conversely, images of two ecologically quite distinct objects, e.g. different individuals' faces, may be very close in pixel space. Behaviorally-relevant dimensions are thus highly "tangled" in the original input space[3], and to recognize objects and understand scenes the brain must accomplish a complex and often ill-posed non-linear untangling process rapidly and accurately[1].

Hierarchy and Retinotopy in the Ventral Pathway Sparked by the seminal ideas of Hubel and Wiesel, six decades of work in systems neuroscience have shown that the homologous visual system in humans and non-human primates generates robust object recognition behavior via a series of anatomically-distinguishable cortical areas known as the ventral visual stream (Fig. 1a-b)[1,4–7]. Two basic principles of architectural organization emerging from this work are that the ventral stream is:

1. *hierarchical*, with visual information passing along a cascade of processing stages embodied by the distinct cortical areas, and
2. *retinotopic*, composed of structurally similar operations with spatially local receptive fields tiling the overall visual field, with decreasing spatial resolution in each subsequent stage of the hierarchy.

Visual areas early in the hierarchy, such as V1 cortex, capture low-level features including edges and center-surround patterns[8,9]. Neural population responses in the highest ventral visual area, anterior inferior temporal (AIT) cortex, can be used to decode object category, robust to significant variations present in natural images[10–12]. Mid-level visual areas such as V2, V3, V4 and posterior IT (PIT) are less well-characterized by such "word models" than higher or lower visual areas closer to the sensorimotor periphery. Nonetheless, these intermediate areas appear to contain computations at an intermediate level of complexity between simple edges and complex objects, along a pipeline of increasing receptive field size[1,13–20]

Linear-Nonlinear Cascades. A core hypothesis is that ventral stream employs sensory cascades because: (i) the overall stimulus-to-neuron transforms required to support complex behaviors are extremely complicated — after all, since the original input tangling is highly non-linear, the inverse untangling process is also highly non-linear; but (ii) the capacities of any single stage of neural processing are limited to comparatively simple operations such as weighted sums of inputs, thresholding nonlinearities, and local normalization[8]. To build up a sufficiently complex end-to-end transform with a reasonable number of neurons, a cascade of stages is needed. Complex non-linear transformations arise from multiple such stages applied in series[21]. Such cascades are present not just in the visual system but are common in a wide variety of sensory areas[22–25].

A very simplified version of the feedforward component of the multi-stage sensory cascade may thus be represented symbolically by:

$$\text{stimulus} \xmapsto{T_1} \mathbf{n}_1 \xmapsto{T_2} \mathbf{n}_2 \ldots \xmapsto{T_{\text{top}}} \mathbf{n}_{\text{top}} \tag{1}$$

where the $\mathbf{n}_i$ represent neural responses in brain area i, and T_i is the transform computed by the neurons in area i based on input from area $i-1$. In the macaque ventral stream this will (at least) include several subcortical stages prior to the ventral stream (e.g. the retinal ganglion and LGN), followed by cortical areas V1, V2, V4, PIT, and AIT. The homologous structure in humans is similar but likely to be substantially more complex[26].

Robust empirical observations[8] suggest that the transforms T_i can be reasonably well-modeled as *Linear-Nonlinear* (LN) blocks of the form:

$$T_i = N_i \circ L_i.$$

Biologically, the linear transforms L_i are inspired by the observation that neurons are admirably suited for taking dot-products, i.e. summing up their inputs on each incoming dendrite, weighted by synaptic strengths. The transforms L_i formalize the synaptic strengths as numerical matrices. Mathematically, the L_i map the input feature space output by one area to an intermediate feature space in the next. In the case of L_1 (the transform

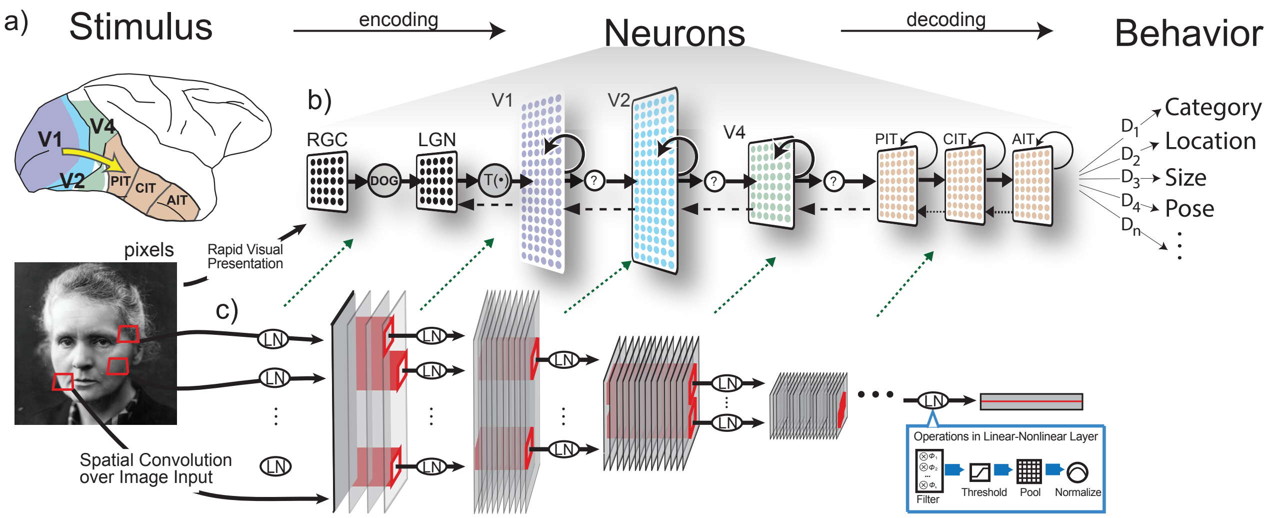


Figure 1: Hierarchical Convolutional Neural Networks As Models of Sensory Cortex. (a.) The basic framework in which sensory cortex is studied is one of *encoding*, the process by which stimuli are transformed into patterns of neural activity, and *decoding*, the process by which neural activity generates behavior. **(b.)** The ventral visual pathway of humans and non-human primates is one of the most comprehensively studied sensory systems in neuroscience. It consists of a series of connected cortical brain areas that are thought to operate in a sensory cascade, from early visual areas such as V1, to later visual areas such as inferior temporal (IT) cortex. Neural responses in the ventral pathway are believed to encode an abstract representation of objects in visual images. **(c.)** Hierarchical Convolutional Neural Networks (HCNNs) are multilayer neural networks that have been proposed as models of the ventral pathway. Each layers of an HCNN is made up of a Linear-Nonlinear (LN) combination of simple operations such as filtering, thresholding, pooling, and normalization. The filterbank in each layer consists of a set of weights analogous to synaptic strengths. Each filter in the filter bank corresponds to a distinct template, analogous to gabor wavelets with different frequencies and orientations (the image shows a model with four filters in layer 1, 8 in layer two, and so on). The operations within a layer are applied locally to spatial patches within the input, corresponding to simple, limited-size receptive fields (the red boxes in the figure). The composition of multiple layers leads to a complex nonlinear transform of the original input stimulus. At each layer, retinopy decreases and effective receptive field size increases.

between the input image and the first visual area, taken to be either subcortical or in V1), the input space is the three-channel RGB-like representation of pixels, while the output space is substantially higher-dimensional, corresponding to number of different neural projections computed at each retinotopic location. An extensive line of research characterizing V1 responses[8,27,28] yielded the realization that the linear transforms early on the in cascade can be reasonable well-characterized as spatial convolution with a filterbank of Gabor wavelets in a range of frequencies and orientations[29].

The nonlinear component N_i has been shown to involve combinations of very basic transforms, including rectification, pooling, and normalization operations[8,19]. While the T_i's are simple, it is critical that they are at least somewhat nonlinear: the composition of linear operations is linear, so additional complexity can't be built up by a sequence of linear operations, and there would be no evolutionary point to allocating multiple brain areas for them in the first place.

It is tempting to ascribe specific functional roles for each of the constituent operations within an LN block, described in terms of features of the original input stimulus. While this may be possible early in the sensory cascade, the compounding of multiple nonlinearities makes it unlikely that this type of description is adequate for intermediate or higher sensory areas. Instead, it is probably more effective to think of the LN block as combining a dimension-expanding component (the linear filtering step), a dimension-reducing aggregation component (the pooling operation), and a range-centering component to ensure that the cascade can be effectively extended hierarchically (the normalization operations). These features allow LN cascades to cover a wide range of complex nonlinear functions in an efficient manner[30,31], consistent with the idea that good LN cascade architectures can be discovered by evolutionary and developmental processes.

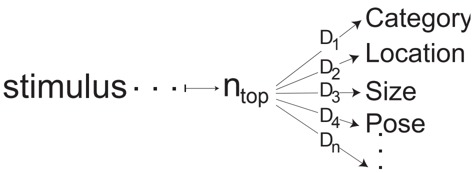
A Common Visual Feature Basis. The features computed by the sensory cascade are often thought of as constituting a *visual representation*. One way to interpret this idea is that the output from area n_{top} —

which is considerably *upstream* of highly-task-modulated decision making or motor areas — is able to support observed organism output behaviors via simple decoders. Symbolically, this is the observation that the pipeline in diagram (1) can be extended to:

$$\text{stimulus} \ldots \longmapsto \mathbf{n}_{\text{top}} \xmapsto{D} \text{behavior} \tag{2}$$

where D is a population decoder. The requirement that D be "simple" just means that it can also be cast in the form of a single LN block rather than itself requiring many stages of nonlinearity. In the case of the macaque visual system, the role of n_{top} seems to be played by anterior IT cortex, where it has been robustly shown that simple decoders such as linear classifiers or linear regressors operating on neural responses in IT cortex can support patterns of visual behavior at a high degree of behavioral resolution[3,6,10,12,32]. The linear classifiers embody a computational description of hypothetical decoding circuits downstream of the ventral visual representation[33,34].

The representation concept is enhanced by the observation that IT cortex can provide useful support for *many different* visual behaviors. In addition to object category, attributes such as fine-grained within-category identification, object position, size, and pose, and complex lighting and material properties, can be decoded from IT neural activity[35,36]. Symbolically, this might be represented by the diagram:



in which $D_1, D_2, \ldots$ are different readout decoders for the various possible visually-driven behaviors.

A key observation is that for naturalistic scenes with realistically high levels of image variability, these same visual properties cannot be robustly read out from the visually-evoked neural responses in earlier areas such as the retina, V1 or V2 using simple decoders, and only partially in intermediate areas such as V4[10,35]. Of course, the information *must* in some way be present in these areas since the properties can be determined by looking at the image. However, as alluded to earlier, these properties are "tangled up" in the representations in early areas, and so cannot be easily decoded. The nonlinear operations of the ventral stream cascade culminating in the IT representation have reformatted the information in the input image stimuli into a *common basis* from which it is possible to generate many different behaviorally-relevant readouts.

Not Just an Information Channel. These considerations suggest that the ventral stream is *not* best thought of as a "channel" in the sense of Shannon information theory. As a result of (converse of) the Shannon's famous channel coding theorem, with every step of the cascade, the system can only lose information in an information-theoretic sense[37]. The more stages in the case, the less good it will be as a pure information channel. The existence of a many-stage LN cascade in the ventral pathway suggests that the evolutionary constraint on the system is *not* the veridical preservation of information about the stimulus. Rather, the constraining evolutionary goal of the sensory cascade is more likely to be making behaviorally-relevant information — such as the identity of a face present in the image — much more *explicitly* available for easy access by downstream brain areas, while discarding other information about the stimuli — such as pixel-level details — that are less behaviorally relevant.

Neural Network Models of the Ventral Stream

In this section, we'll discuss how the neurophysiological observations described above can be formalized mathematically. But before diving into models of the ventral stream, it is worth briefly considering why we might want to make quantitative neural network models of the ventral stream in the first place. After all, neuroscientists did not need such models to discover the important insights described in the previous section.

Two convergent problems, however, strongly motivate the building of large-scale formal models. First, the simpler word-model approach that had been useful for characterizing the shape of visual feature tuning curves in earlier cortical areas such as the retina or V1 were found to be difficult to generalize to intermediate and higher-level visual areas[38]. Though some progress has been made using intuition to find visual features to which intermediate and higher-area neurons would respond[7,20,39], a more systematic approach is needed to organize and generalize these disparate observations. Second, it turned out that the most naive implementations of multi-layer hierarchical retinotopic models performed very poorly on tests of performance generalization in real-world settings[40]. Although hierarchy and retinotopy appeared to be important high-level principles, they were insufficiently detailed to actually produce operational algorithms with anything like the visual abilities of a macaque or a human. Echoing Feynman's famous dictum that "What I cannot create, I do not understand," the inability to create from scratch a truly working visual recognition system meant that some key feature of understanding was missing.

Hierarchical Convolutional Neural Networks Hierarchical Convolutional Neural Networks (HCNNs) are a broad generalization of Hubel and Wiesel's ideas that has been developed over the past 40 years by researchers in biologically-inspired computer vision[41–43]. HCNNs consist of cascades of layers containing simple neural circuit motifs repeated retinotopically across the sensory input (Fig. 1c). Each layer is simple, but a deep network composed of such layers computes a complex transformation of the input data — roughly analogous to the organization the ventral stream. The specific operations comprising a single HCNN layer were inspired directly by the LN neural motif[8], including: convolutional filtering, a linear operation that takes the dot-product of local patches in the input stimulus with a set of templates, typically followed by rectified activation, mean or maximum pooling[44], and some form of normalization[45]. All the basic operations exist within a single HCNN layer, which is designed to be analogous to single cortical area within the visual pathway.

A key feature of HCNNs is that all operations are applied locally, over a fixed-size input zone that is smaller than the full spatial extent of the input. HCNNs employ *convolutional weight sharing*, meaning that the same filter templates are applied at all spatial locations. Since identical operations are applied everywhere, spatial variation in the output arises entirely from spatial variation in the input stimulus. It is unlikely the brain literally implements weight sharing, since the physiology of the ventral stream appears to rule out the existence of a single "master" location in which shared templates could be stored. However, the natural visual statistics of the world are themselves largely shift invariant in space (or time), so experience-based learning processes in the brain should tend to cause weights at different spatial locations to converge. Shared weights are therefore likely to be a reasonable approximation, at least within the central visual field.

Although the local fields seen by units in a single HCNN layer have a fixed small size, the effective receptive field size relative to the original input increases with succeeding layers in the hierarchy. Like the brain's ventral pathway, multi-layer HCNNs typically become less retinotopic with each succeeding layer, consistent with empirical observations[4]. However, the number of filter templates used in each layer typically increases. Thus, the dimensionality changes through the layers from being dominated by spatial extent, to being dominated by more abstract feature dimensions. After many layers, the spatial component of the output may be so reduced that convolution is no longer meaningful, whereupon networks may be extended using one or more fully connected layers that further process information without explicit retinotopic structure. The last layer is usually used for *readout*, e.g. for each of several visual categories, the likelihood of the input image containing an object of the given category might be represented by one output unit.

Learning Modern Deep HCNNs The earliest HCNNs were not particularly effective either at solving vision tasks or quantitatively describing neurons. Arbitrary hierarchical retinotopic nonlinear functions don't appear to compute useful representations[46], and hand-designed filterbanks in multi-layer networks were also not performant[38,46]. It was realized early on, however, that the parameters of the HCNNs could be *learned* — that is, optimized so that the network output maximized performance. Parameters subject to optimization include both discrete choices about the particular architecture to be used (how many layer? how many features per layer? what local receptive field should be used at a given layer?), as well as the continuous parameters of the linear transforms L_i at each layer.

Initial attempts to learn HCNNs lead to intriguing and suggestive results[42], but were not entirely satisfactory either in terms of neural similarity or task performance. However, recent work in computer vision and artificial intelligence has sought to use advances in hardware-accelerated computing to optimize parameters of deep neural networks to maximize their performance on more challenging large-scale visual tasks[47]. Leveraging computer vision and machine learning techniques, together with large amounts of real-world labelled images used as

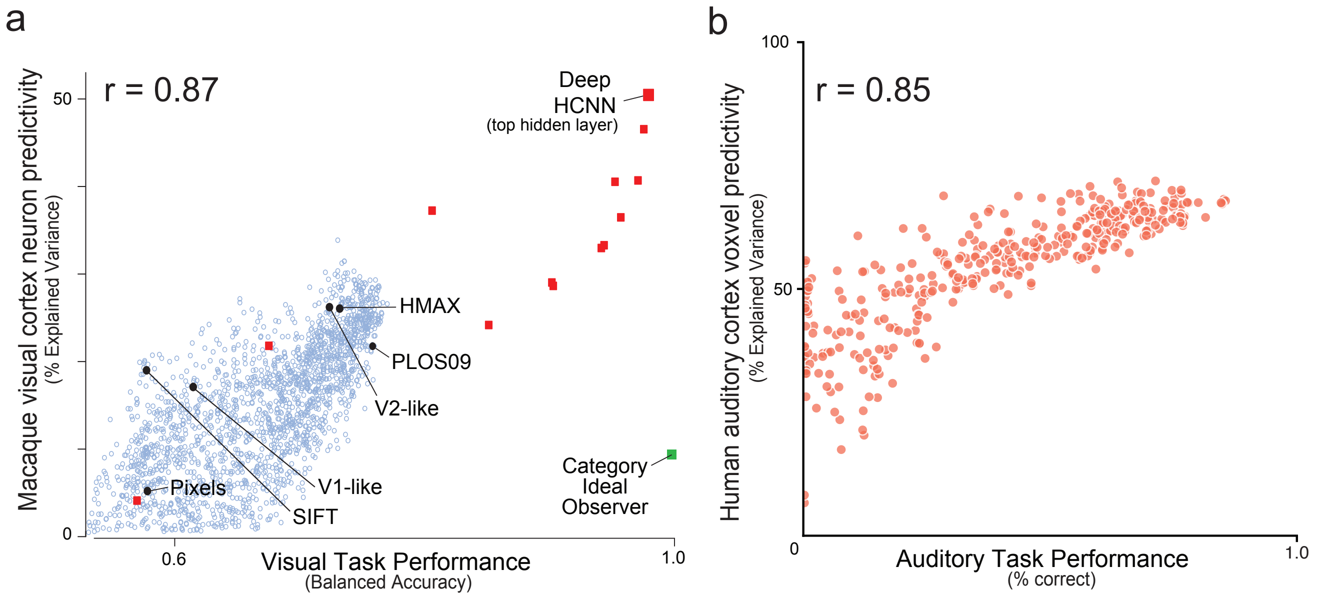


Figure 2: (a.) Visual object categorization task performance (x-axis) is highly correlated with ability to predict IT cortex neural responses (y-axis) (adapted from Yamins *et al.*[54]). Blue dots are various 3-layer (shallow) HCNN models, either with random weights or optimized either for categorization performance or to predict IT responses. Black squares represent a variety of previous models. Red dots represent increasing performance and predictivity over time as a deep HCNN is trained. r value is for red and black points. Green square is a category observer with perfect semantic category knowledge, to control for how much neural variance is explained just by categorical features alone. **(b.)** Analogous result for neural networks optimized for auditory tasks (adapted from Kell *et al.*[55]).

supervised training data[48,49], HCNNs have arguably achieved human-level performance on several challenging object categorization tasks[50,51].

In fact, the power of HCNNs trained on large datasets goes beyond merely doing well on training sets. Unlike small datasets that are prone to severe overfitting, large highly variable datasets such as ImageNet have yielded networks that can serve as useful bases for solving a variety of other visual tasks[52,53]. State-of-the-art solutions to ImageNet categorization often exhibit especially good transfer capabilities[50]. In other words, training HCNNs in a supervised manner has at least some power to produce robust visual representations.

Quantitative Matches Between HCNNs and Ventral Pathway Areas A core result linking the deep HCNNs used in modern computer vision to ideas from visual systems neuroscience is that an HCNN's ability to predict neural responses in visual cortex is strongly correlated with its performance on challenging object categorization tasks[54,56]. Such correlations have been investigated by high-throughput studies comparing tens of thousands of distinct HCNN model instantiations to neural data from both large-scale array electrophysiology experiments in macaques[54] as well human fMRI[57]. While the correlation is present for HCNNs with randomly chosen architectures, it is especially high when architectures are optimized for task performance (Fig. 2a).

Inferior Temporal Cortex: Tighter relationships between HCNNs and neural data are observed on a per-area basis. Model responses from hidden layers near the top of HCNNs optimized for ImageNet categorization performance are highly predictive of neural responses in IT cortex, both in electrophysiological (Fig. 3a)[54,58], and fMRI data[57,59]. These deep, goal-optimized neural networks (red squares in Fig. 3a) have thus yielded the first quantitatively accurate, predictive model of population responses in a higher cortical brain area. These quantitative models are also substantially better at predicting neural response variance in IT than semantic models based on word-level descriptions of object category or other attributes (green square in Fig. 3a)[54]. Recent high-performing ImageNet-trained architectures also appear to provide the best matches to the visual behavioral patterns of primates[60].

Intermediate Visual Areas: Intermediate layers of the same HCNNs that match IT neurons also yield state-of-the-art predictions of neural responses in V4 cortex (Fig. 3b)[54,59], the dominant cortical input to IT. Similarly, recent models with especially good performance have distinct layers clearly segregating late-intermediate visual area PIT neurons from downstream central IT (CIT) and AIT neurons[61]. These results are important because they show that high-level ecologically-relevant constraints on network function — ie. the categorization task imposed at the network's output layer — are strong enough to inform upstream visual features in a non-trivial way. In other words, HCNN models suggest that the computations performed by the circuits in V4 are structured so that downstream computations in AIT can support high-variation robust categorization tasks. Thus, even though there may be no simple word-model describing *what* the features in an intermediate cortical area such as V4 are, HCNNs can provide a principled description of *why* the area's neural responses might be as they are.

Early Visual Cortex: Results in early visual cortex are equally striking. The filters emergent in HCNNs' early layers from the learning process naturally resemble Gabor wavelets without having to build this structure in[48]. Extending the correspondence between HCNN layers and ventral stream layers down further, it has been shown that lower HCNN layers match neural responses in early visual cortex areas such as V1 (Fig. 3c)[57,59,62]. In fact, recent high-resolution results show that early-intermediate layers of performance-optimized HCNNs are substantially better models of macaque V1 neural responses to natural images than previous state-of-the-art models that were hand-designed to replicate qualitative neuroscience observations[63].

Taken together, these results indicate that combining two general biological constraints — the behavioral constraint of object recognition performance, and the architectural constraint imposed by the HCNN model class — leads to improved models of multiple areas through the visual pathway hierarchy.

A Contrast to Curve Fitting A key feature of these results is that the parameters of the HCNN models are optimized to solve a visual performance goal that is ethologically plausible for the organism, rather than being directly fit to neural data. Yet, the resulting neural network effectively models the biology as well or better than direct curve fits[54,63]. This is the idea of *goal-driven* modeling[43]. Goal-driven modeling is attractive as a method for building quantitative cortical models for several reasons. Practically speaking, it does not require the collection of the unrealistically massive amounts of neurophysiological data that would be needed to fit deep networks to such data. Second, because model validity is assessed on a completely different metric (and different dataset) than the one used to choose model parameters, the results are comparatively free from overfitting and/or multiple-comparison problems. Finally, the approach posits an evolutionally plausible functional *reason* for choices of model parameters throughout the hierarchy.

A Tripartite Optimization Framework

While the results described in the previous section are in some ways specific to the primate ventral pathway, they are based on a more general underlying logic that can apply to neural network modeling problems throughout computational neuroscience. Specifically, three fundamental components underlie all functionally-optimized neural network models:

- An **architecture class** $\mathcal{A}$ containing potential neural network structures from which the real system is drawn. $\mathcal{A}$ captures the structural constraints on the network drawn from knowledge about a brain system's anatomical and functional connectivity.
- A **computational goal** that the system seeks to accomplish, mathematically expressed as a loss target function
$$\mathcal{L} : \mathcal{A} \longrightarrow \mathbb{R}$$
to be minimized by parameter choices within the set $\mathcal{A}$. For any potential network $\mathbf{a} \in \mathcal{A}$, the value $\mathcal{L}(\mathbf{a})$ represents the error that network incurs in attempting to solve the computational goal. $\mathcal{L}$ captures the functional constraints on the network drawn from hypotheses about the organism's behavioral repertoire.
- A **learning rule** by which optimization for $\mathcal{L}$ occurs within the architecture class $\mathcal{A}$. This is a function
$$\mathcal{R}_{\mathcal{L}} : \mathcal{A} \longrightarrow \mathcal{A}$$
such that, at least statistically, for any non-optimal network $\mathbf{A} \in \mathcal{A}$,
$$\mathcal{L}(\mathcal{R}_{\mathcal{L}}(\mathbf{A})) < \mathcal{L}(\mathbf{A}). \tag{3}$$

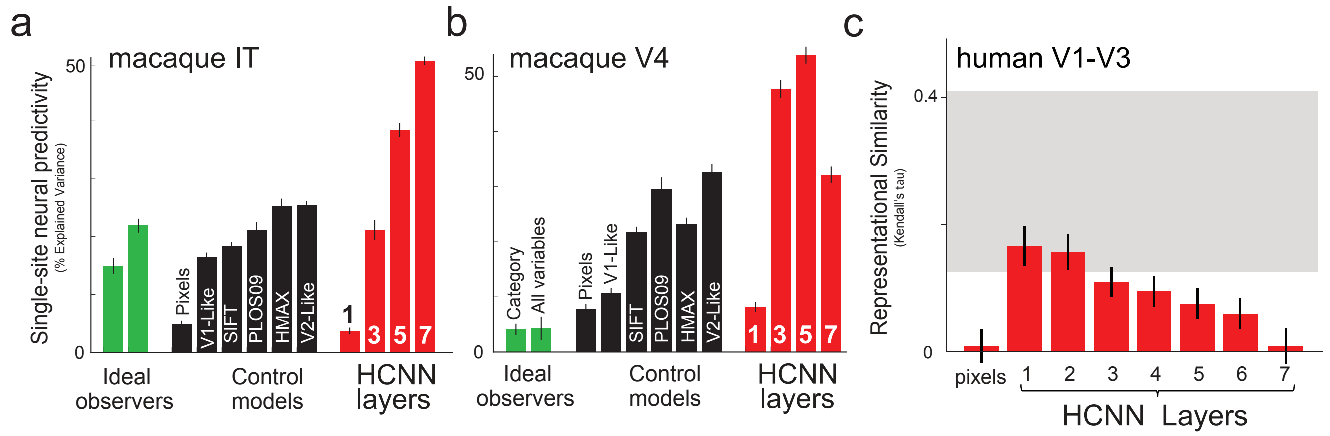


Figure 3: (a.) Based on Yamins *et al.*[54], comparison of ability of various computational models to predict neural responses of populations of macaque IT neurons (right). The HCNN model (red bars) is a significant improvement in neural response prediction compared to previous models (black bars) and task ideal observers (green bars). The top HCNN layer 7 best predicts IT responses. **(b.)** Similar to **a.**, but for macaque V4 neurons. Note that intermediate layer 5 best predicts V4 responses.**(c.)** Representational similarity between visual representations in HCNN model layers and human V1-V3, based on fMRI data (adapted from Khaligh-Razavi & Kriegeskorte[57]). Horizontal gray bar represents the inherent noise ceiling of the data. Note that earlier HCNN model layers most resemble early visual areas.

> Biologically, the learning rule captures the way that the error signal from mismatches between the system's current output and the correct outputs (as as defined by the computational goal) is used to identify better parameter choices, over evolutionary and developmental timeframes.

This framework predicts that, statistically, the actual biologically-observed system is approximated by the optimal solution within $\mathcal{A}$ to the goal posed by $\mathcal{L}$, i.e.

$$\mathbf{A}^* = \arg\min_{\mathbf{A}\in\mathcal{A}} \mathcal{L}(\mathbf{A}), \tag{4}$$

to the extent that the optima is actually reachable from chosen initial conditions via the learning rule. Of course, biological systems produced by evolution and development are not guaranteed to be optimal for their evolutionary niche, so this prediction is really more an informed heuristic for hypothesis generation rather than a candidate natural law. In fact, any practically implementable learning rule will not perfectly meet the criterion in eq. 3, being subject to the same problem that evolution/development faces: failures to achieve optimum due to incomplete optimization or capture by local minima. Insofar as the model of the learning rule and initial condition distribution is itself biologically accurate, the same patterns of performance failures should be observed in both the model and the real behavioral data[60].

Returning to the example of the primate ventral stream, the model architecture class $\mathcal{A}$ has been taken to include feedforward HCNNs, broadly capturing aspects of the known neuroanatomical structure of ventral visual pathway. The parameters describing this class of models include (1) discrete choices about (e.g.) the number of layers in the cascade, the specific nonlinear operations to employ at each layer, and the sizes of local receptive fields (see Yamins & DiCarlo[43] for more details on these parameters), and (2) the continuous-valued filter templates embodied by the linear transforms L_i at each layer. The loss target $\mathcal{L}$ has typically been chosen as categorization error on the 1000-way object recognition task in the ImageNet dataset[47], capturing the fact that primates have especially strong invariant object recognition capacities.

The learning rule used for optimizing HCNNs to solve categorization problems is composed of two pieces, corresponding to the two types of model parameters: (1) an "outer loop" of metaparameter optimization used for selecting the discrete parameters, typically either just random choice[40] or a simple evolutionary algorithm[54], and (2) an "inner loop" of smooth optimization of the synaptic strength parameters L_i, typically involving *gradient descent*:

$$\frac{dL_i}{dt} = -\lambda(t) \cdot \nabla_{L_i}[\mathcal{L}]. \tag{5}$$

This expression formalizes the idea that learning modifies the synaptic strengths L_i of the visual system over time — the derivative dL_i/dt — by greedily seeking to minimize the value of the loss target, scaled in magnitude by the *learning rate* $\lambda(t)$.

There are many variants of gradient descent that have been explored in the machine learning literature, some of which scale better or achieve faster or better optimization[64–66]. Though Hebbian learning rules have been proposed many times in neuroscience[67,68] and have attractive theoretical properties[69], explicit error-based rules such as gradient descent have proven substantially more computationally effective. There is much debate about the biological realism of gradient descent[70], and an ongoing area of research seeks to discover more biologically plausible versions of explicit error-driven learning rules[71,72].

While a vast oversimplification, the relationship between optimizing discrete architecture parameters and synaptic strength parameters is somewhat analogous to the relationship between evolutionary and developmental learning. Changes to synaptic strengths are continuous and can occur without modifying the overall system architecture, and thus could support experience-driven optimization during the lifetime of the organism. Changes in the discrete parameters, in contrast, restructure the computational primitives, the number of sensory areas (model layers) and the number of neurons in each area, and thus are more likely to be selected over evolutionary time.

Mapping Models to Data A goal-optimized model generates computationally precise hypotheses for how data collected from the real system will look. Testing these hypotheses involves assessing metrics of similarity between the model and the brain system, both for the output behaviors of the system, as well as for internal responses of the system's neural components. Several commonly-used metrics for assessing the mapping of models to empirical data include (from coarsest to finest resolution):

- *Behavioral consistency.* Even before any neural data is collected, high-throughput systematic measurements of psychophysical data can be used obtain a "fingerprint" of human behavioral responses across a wide variety task conditions[60]. This fingerprint can then be compared to output behavior on these tasks as generated by neural network models. For example, Rajalingham *et al.*[60] show that achieving consistency with high-resolution human error patterns in visual categorization tasks is a very strong test of correctness for models of the primate visual system.
- *Population-level neural comparison.* The Representation Dissimilarity Matrix (RDM) is a convenient tool for comparing two neural representations at a population level[73]. Each entry in the RDM corresponds to one stimulus pair, with high/low values indicating that the population as a whole treats the pair stimuli as very different/similar. Taken over the whole stimulus set, the RDM characterizes the layout of the images in the high-dimensional neural population space. A measure of how similar the representations are between real neural populations and those produced by a neural network can be obtained by assessing the correlations between the RDMs from each layer of a neural network models and the RDMs from real neural populations. This technique, which is called Representational Similarity Analysis (RSA), has been effectively used for comparing visual representations in human fMRI data to HCNN models[57].
- *Single-neuron regression.* Linear regression is a convenient method for mapping units from neural network models to individual neural recording sites[54]. For each neural site, this technique seeks to identify a linear weighting of neural network model output units (typically from one network layer) that is most predictive of that neural site's actual output on a fixed set of sample images. The "synthetic neuron" then produces response predictions on novel stimuli not used in the regression training, which are then compared to the actual neural site's output. Accuracy in regression prediction has shown to be a useful tool for achieving finer-grained model-brain mappings when higher resolution (e.g. electrophysiological) data is available[54,61].

See Yamins & DiCarlo[43] for a more detailed description and evaluation of these and other mapping procedures.

Properly Assessing Model Complexity When comparing any two models of data, it is important to ensure that model complexity is taken into account: a complex model with many parameters may not be an improvement over a simple model with fewer parameters, even if the former has a somewhat better fit to the data. However, even though goal-optimized deep neural networks have many parameters *before* task optimization, those parameters are *determined* by the optimization process in attempting to solve the computational goal itself. Thus, when the optimized networks are subsequently mapped to brain data, these parameters are no longer available for free modification to fit the neurons. Hence, although it may at first be somewhat counterintuitive, these pre-determined parameters cannot be counted when assessing model complexity, e.g. when computing scores such as the Akaike or Bayesian Information Criteria[74]. Instead, once the optimized network has been produced, the only free parameters used when comparing to neural data are just those required by the mapping procedure itself. For example, when using Representational Similarity Analysis, *no* free parameters are needed at all, since building the RDM matrix requires is a parameter-free procedure. Thus, if a larger goal-optimized neural network achieves between match between its RDMs and those in neural populations, it has done so fairly — that is, *not* by using those parameters to better (over)fit the neural data, but instead because the bigger network has (presumably) achieved better performance on the computational goal, and the computational goal is itself highly relevant to the real biological constraints on the neural mechanism. Similarly, when performing single-neuron regression, the number of free parameters is equal to the number of model neurons used as linear regressor dimensions. In this case, it is necessary (but easy) to ensure fair comparisons between models with different numbers of features by simply subsampling a fixed number of model units as regressors (as done in e.g. Yamins *et al.*[54]) or using some unsupervised dimension reduction procedure (such as PCA) prior to regression.

Relationship to Previous Work in Visual Modeling Other approaches to modeling the visual system can be placed in context of the optimization framework. Efficient coding hypotheses seek to generate efficient, low-dimensional representations of natural input statistics. This corresponds to a choice of architecture class $\mathcal{A}$ containing "hourglass-shaped" networks[75] composed of a compressive intermediate encoding followed by a decoding that produces image-like output. The loss target is then (roughly) of the form:

$$\mathcal{L}(x) = ||x - \mathbf{D}(\mathbf{E}(x))|| + \textbf{Regularization}(\mathbf{E}(x))$$

where $\mathbf{E}(x)$ is the network encoding of image x, and $\mathbf{D}$ is the corresponding decoding. The first term of $\mathcal{L}$ is the reconstruction error, measuring the ability of the decoded representation to reproduce the original input, while the second term prevents overfitting by imposing a "simpleness prior" on the encoder. Efficient coding is an attractive idea because it combines functional requirements and biophysical constrains (e.g. metabolic efficiency). Early versions of this idea such as sparse autoencoders[76] have shown promise in training shallow (one-layer) convolutional networks that naturally discover the Gabor-like filter patterns seen in V1 cortex. More recent methods such as variational autoencoders, generative adversarial networks (GANs) and BiGANs[77–79], essentially correspond to improvements in the choice of regularization functions, and have shown promise in training deeper networks. While such ideas have been effective in limited visual domains, improving their applicability to unrestricted visual image space is an open question, and an important area for innovation[80].

Another line of work has attempted to fit neural networks directly to data from V1[81], V2[82], and V4[83] cortex. These results are consistent with the optimization framework insofar as they involve finding parameters that optimize a loss function — in this case, the mismatch between network output and the measured neural data. Such investigations can be very informative, as they contribute to the discovery of which classes of neural architectures best capture the data. However, unlike the goal-driven modeling approach, or the efficient coding ideas, these direct curve-fits do not generate a normative explanation underlying *why* the neural responses are as they are.

An interesting approach combines neural fits and normative explanations. In McIntosh *et al.*[84], comparatively shallow HCNNs were fit to responses in retinal ganglion cells (RGCs). A key finding in this work was that characteristic properties of bipolar cells, which are upstream of the RGCs, naturally emerge in the networks' first layers, just by forcing the network's last layer to correctly emulate RGC response patterns. While this work does not explain why the RGCs are as they are, it does suggest a kind of conditional normative explanation for why the bipolar cell patterns are as they are, given the RGC as output. Understanding whether this holds for other parts of the retinal circuit (e.g the intermediate cells in the amacrine layer), and whether the RGC patterns themselves arise from a higher-level downstream computational goal, are exciting open questions.

Beyond the Visual System The goal-driven optimization approach has also had success building quantitatively accurate models of the human auditory system[55,85]. Using HCNNs as the architecture class, but substituting a computational goal defined by speech and music genre recognition, this work finds a strong correlation between auditory task performance and auditory cortex neural response predictivity (Fig. 2b). A representational hierarchy is also found in auditory cortex, suggesting interesting similarities to the visual system, in that the robustness to variability (e.g. position, size, and pose tolerance) that makes convolutional networks useful for visual object recognition may have rough equivalents in the auditory domain that make convolution useful for parsing auditory "objects". However, the work of Kell *et al.*[55] goes beyond models of a single processing stream, exhibiting multi-stream networks that solve several auditory tasks simultaneously with an initial common architecture that subsequently splits into multiple task-specific pathways. The different pathways of the network differentially explain neural variance in different parts of auditory cortex, illustrating how task-optimized neural networks can help further understanding of large-scale functional organization in the brain. Recent work has begun to tackle somatosensory systems along similar lines[86].

A functionally-driven optimization approach has also been effective at driving progress in modeling the motor system[87,88]. This work shows how imposing the computational goal of creating behaviorally-useful motor output constrains internal neural network components to match otherwise non-obvious features of neurons in motor cortex, and provides a modern computational basis for earlier work on movement efficiency[89]. Unlike work on sensory systems, the goals in motor networks are not representational, but instead focus on the generation of dynamic patterns of motor prepration and movement[90]. For this reason, the models involved in these efforts are typically recurrent neural networks (RNNs) rather than feedforward HCNNs. These results show that the goal-driven optimization idea has power across a wide range of network architectures and behavioral goal types.

Analyzing Constraints Rather Than Optima A classic approach to analyzing a population of (in most cases, sensory) neurons is to classify the shape of their tuning curves in response to systematically changing input stimuli along certain characteristic axes that are key drivers of the populations' variability. This approach has been successful in a variety of brain areas, most notably in early visual cortex[27], where tuning curves illustrating the orientation and frequency selectivity of V1 neurons laid the groundwork for Gabor-wavelet based models.

Relative to the optimization framework described above, the analysis of tuning curves is essentially an attempt to characterize optimal networks $\mathbf{A}^*$ in non-optimization-based terms. When a small number of mathematically-simple stimulus-domain axes can be found in which the tuning curves of $\mathbf{A}^*$ have a mathematically-simple shape, $\mathbf{A}^*$ can largely be constructed by a simple closed-form procedure without any reference to learning through iterative optimization. This is to some extent feasible for V1 neurons, and perhaps in early cortical areas in other domains such as primary auditory cortex[91]. It is possible that this type of simplification is most helpful for understanding neural responses that arise largely from highly constrained stereotyped genetic developmental programs rather than those that depend heavily on experience-driven learning[92], or where biophysical constraints — such as metabolic cost or noise reduction — might also impose "simplicity priors" on the neural architecture[76,87].

In general, however, it is not guaranteed that closed-form expressions describing the response properties of task-optimized models can be found. Evolution and development are under no general constraint to make their products conform to simple mathematical simple shapes, especially for intermediate and higher cortical areas at a remove from the sensory or motor periphery. However, even if such analytical simplifications do not exist, the optimization framework nonetheless provides a method for generating meta-understanding via characterizing the constraints on the system, rather than analyzing the specific outcome network itself. By varying the architectural class, the computational goal, or the learning rule, and identifying which choices lead to networks that best match the observed neural data, it is possible to learn much about the brain system of interest even if its tuning curves are inscrutable.

Understanding Multiple Optima What happens when multiple optimal network solutions exist? For many architecture classes there may be infinitely many qualitatively very similar networks with the same or substantially similar outputs — e.g. those created by applying orthonormal rotations to linear transforms present in the network. Sometimes, however, qualitatively very distinct networks might achieve similar performance levels on a task. For example, very deep Residual Network architectures[51] and comparatively shallower (but much more locally complex) architectures arising from Neural Architecture Search[50] achieve roughly similar performance on ImageNet categorization despite key structural differences.

The optimization framework does not require there be a unique best solution to the computational goal to make useful predictions. If several subclasses of high-performing solutions to a given task are identified, this is equivalent to formulating multiple very qualitatively distinct hypotheses for the neural circuits underlying function in a given brain area. Recent work in modeling rodent whisker-trigeminal cortex, in which similar task performance on whisker-driven shape recognition can be achieved by several distinct neural architecture classes, illustrates this idea[86]. Comparison of the distinct model types to experimental results either from detailed behavioral or neural experiments is then likely to point toward one of these hypotheses as explaining the data better than others. Techniques similar to those used to create the models in the first place can be deployed to generate *optimal stimuli* for separating the predictions of the multiple models as widely possible, which would in turn directly inform experimental design. In these cases, the optimization framework serves as an efficient generator of strong hypotheses.

In contrast, if most high-performing solutions to a computational goal fall into a comparatively narrower band of variability, the set of model solutions may correspond to actual variability in the the real subject population. For some brain regions, especially those in intermediate or higher cortical areas, the particular collection of neural circuits present in any one subject's brain may vary considerably between conspecifics[93]. The optimization framework naturally supports at least two potential sources of such variation, including:

- Variation of **initial conditions**, described as a probability distribution over starting point models $\mathbf{A}_0$ to which the learning rule is applied. For example, different random draws of initial values for linear filters L_i will lead to distinct final optimized HCNNs. While many high-level representational properties are shared between these networks, meaningful differences can exist[94], and may explain aspects of the variation between real visual systems.
- Variation of **computational goal**, described as a distribution over stimuli in the dataset defining the goal task. This idea captures the concept that different individuals will experience somewhat different stimulus diets during development and learning.

Understanding the computational sources of intra-specific variation is itself an important modeling question for future work[95].

A Contravariance Principle Though it may at first seem counterintuitive, the *harder* the computational goal, the *easier* the model-to-brain matching problem is likely to be. This because the set of architectural solutions to an easy goal is large, while the set of solutions to a challenging goal is comparatively smaller. In mathematical terms, the size of the set of optima is *contravariant* in the difficulty of the optimization problem.

A simple thought experiment makes this clear: imagine if, instead of trying to solve 1000-way object classification in the real-world ImageNet dataset, one simply asked a network to solve binary discrimination between two simple geometric shapes shown on uniform gray backgrounds. The set of networks that can solve the latter task is much less narrowly constrained than that which solve the former. And given that primates actually do exhibit robust object classification, the more strongly constrained networks that pass the same harder performance tests are more likely to be homologous to the real primate visual system. A detailed example of how optimizing a network to achieve high performance on a low-variation training set can lead to poor performance generalization and neurally inconsistent features is illustrated in *Hong *et al.*[35].

The contravariance principle makes a strong prescription for using the optimization framework to design effective computationally-driven experiments. Unlike the typical practice in experimental neuroscience, but echoing recent theoretical discussions of task dimensionality Gao *et al.*[96], it does *not* make sense from the optimization perspective to choose the most reduced version of a given task domain and then seek to thoroughly understand the mechanisms that solve the reduced task before attempting to address more realistic versions of the task. In fact, this sort of highly reductive approach is likely to lead to confusing results, precisely because the reduced task may admit many spurious solutions. Instead, it is more effective to impose the challenging real-world task from the beginning, both in designing training sets for optimizing the neural network models, and in designing experimental stimulus sets for making model-data comparisons. Even if the absolute performance numbers of networks on the harder computational goal are lower, the resulting networks are likely to be better models of the real neural system.

There is a natural balance between network size and capacity. In general, the optimization-based approach is likely to be most efficient when the network sizes are just large enough to solve the computational task. Thus, another way to constrain networks while still using a comparatively simple computational goal is to reduce the network size. This idea is consistent with results from experiments measuring neural dynamics in the fruit fly, where a small but apparently near-optimal circuit has been shown to be responsible for the fly's simple but robust navigational control behaviors[97]. It remains unknown whether the specific architectural principles discovered in such simplified settings will prove useful for understanding the larger networks needed for achieving more sophisticated computational goals in higher organisms.

Major Future Directions

The optimization framework suggests a wide variety of important future directions to be explored.

Better Sensory Models. Within the domain of the visual system, there are many substantial differences remaining between state-of-the-art models and the real neural system. For neurons throughout the macaque ventral visual stream, the best neural network models are able to explain only approximately 65 percent of the reliable time-averaged neural responses to static natural stimuli. This neural result is echoed by the fact that while the models are behaviorally consistent with primate and human visual error patterns at the category or object level[32], they fail to entirely account for error patterns at a the finest image-by-image grain[60], especially in the context of adversarially-created stimuli[98]. Closing the explanatory gap will require a next generation of improved models.

Another major open direction involves understanding recurrence and feedback in visual (and other sensory) processing, and the corresponding modeling of neurons' temporal dynamics. While some recent progress has been made on functionally-driven neural models of temporal dynamics that integrate RNN motifs into HCNNs[61,99], it it is unlikely that a full understanding of the functional role of feedback has been achieved. While most modeling efforts have so far focused on the ventral visual pathway, understanding the functional demands that lead to the emergence of multiple visual pathways, or combining constraints at multiple levels (e.g. behavioral and biophysical), is another key direction for future work. Likewise, little attention has been paid to understanding the physical layout of brain areas. While some of the most robust results in human cognitive neuroscience involve the identification of subregions of visual cortex that selectively respond to certain classes stimuli, e.g. the well-known face, body and place areas[100–102], the computational-level constraints leading to these topographical features are poorly understood.

Learning. Though the optimization framework has shown exciting progress at the intersection of machine learning and computational neuroscience, there is a fundamental problem confronting the approach. Typical neural network training uses heavily supervised methods involving huge numbers of high-level semantic labels, e.g. category labels for thousands examples in each of thousands of categories[47,103]. Viewed as technical tools for tuning algorithm parameters, such procedures can be acceptable, although they limit the purview of the method to situations with large existing labelled datasets. As real models of learning in the brain, they are highly unrealistic, because, among other reasons, human infants and non-human primates simply do not receive millions of category labels during development. There has been a substantial amount of research on unsupervised, semi-supervised, and self-supervised visual learning methods[76–78,104–106]. Despite these advances, the gap between supervised and unsupervised approaches still remains significant. The discovery of procedures that are computationally powerful but use substantially less labelled data is a key challenge for understanding learning real biological learning.

Modeling Integrated Agents Rather Than Isolated Systems. Cognition is not just about the passive parsing of sensory streams or disembodied generation of motor commands. Humans are agents, interacting with and modifying their environment via a tight visuomotor loop. Effective courses of action based both on sensory input and the agent's goals afford the agent the opportunity to restructure its surroundings to better pursue those goals. By the same token, however, constructing and evaluating a complex action policy imposes a substantial additional computational challenge for the agent that goes considerably beyond "mere" sensory processing. Applying the optimization framework to modeling full agents is an exciting possibility, and some recent speculative work in deep reinforcement learning has made progress in direction[107,108]. However, fully fleshing out neural network models of memory, decision making, higher cognition that have the resolution and completeness to be quantitatively compared to experimental data will require substantial improvements at the algorithmic level.

The problem of learning becomes especially acute in the context of interactive systems. Human infants employ an active learning process that builds representations underlying sensory judgments and motor planning[109–111]. Children exhibit a wide range of interesting, apparently spontaneous, visuo-motor behaviors — including navigating their environment, seeking out and attending to novel objects, and engaging physically with these objects in novel and surprising ways[110–116]. Modeling these key behaviors, and the brain systems that underly them, is a formidable challenge for computational cognitive neuroscience[117].

References

1. DiCarlo, J. J., Zoccolan, D. & Rust, N. C. How does the brain solve visual object recognition? *Neuron* **73**, 415–34 (2012).

2. James, W. The principles of psychology (Vol. 1). *New York: Holt* **474** (1890).

3. DiCarlo, J. J. & Cox, D. D. Untangling invariant object recognition. *TICS* (2007).

4. Malach, R., Levy, I. & Hasson, U. The topography of high-order human object areas. *Trends in cognitive sciences* **6**, 176–184 (2002).

5. Felleman, D. & Van Essen, D. Distributed hierarchical processing in the primate cerebral cortex. *Cerebral Cortex* **1**, 1–47 (1991).

6. Rust, N. C. & DiCarlo, J. J. Selectivity and tolerance ("invariance") both increase as visual information propagates from cortical area V4 to IT. *J Neurosci* **30**, 12978–95 (2010).

7. Connor, C. E., Brincat, S. L. & Pasupathy, A. Transformation of shape information in the ventral pathway. *Curr Opin Neurobiol* **17**, 140–7 (2007).

8. Carandini, M., Demb, J. B., Mante, V., Tolhurst, D. J., Dan, Y., Olshausen, B. A., Gallant, J. L. & Rust, N. C. Do we know what the early visual system does? *J Neurosci* **25**, 10577–97 (2005).

9. Movshon, J. A., Thompson, I. D. & Tolhurst, D. J. Spatial summation in the receptive fields of simple cells in the cat's striate cortex. *The Journal of physiology* **283**, 53–77 (1978).

10. Majaj, N. J., Hong, H., Solomon, E. A. & DiCarlo, J. J. Simple Learned Weighted Sums of Inferior Temporal Neuronal Firing Rates Accurately Predict Human Core Object Recognition Performance. *The Journal of Neuroscience* **35**, 13402–13418 (2015).

11. Yamane, Y., Carlson, E. T., Bowman, K. C., Wang, Z. & Connor, C. E. A neural code for three-dimensional object shape in macaque inferotemporal cortex. *Nat Neurosci* **11**, 1352–1360 (2008).

12. Hung, C. P., Kreiman, G., Poggio, T. & Dicarlo, J. J. Fast readout of object identity from macaque inferior temporal cortex. *Science* **310**, 863–866 (2005).

13. Freeman, J. & Simoncelli, E. Metamers of the ventral stream. *Nature Neuroscience* **14**, 1195–1201 (2011).

14. DiCarlo, J. J. & Cox, D. D. Untangling invariant object recognition. *Trends Cogn Sci* **11**, 333–41 (2007).

15. Schmolesky, M. T., Wang, Y., Hanes, D. P., Thompson, K. G., Leutgeb, S., Schall, J. D. & Leventhal, A. G. Signal timing across the macaque visual system. *J Neurophysiol* **79**, 3272–8 (1998).

16. Lennie, P. & Movshon, J. A. Coding of color and form in the geniculostriate visual pathway (invited review). *J Opt Soc Am A Opt Image Sci Vis* **22**, 2013–33 (2005).

17. Schiller, P. Effect of lesion in visual cortical area V4 on the recognition of transformed objects. *Nature* **376**, 342–344 (1995).

18. Gallant, J., Connor, C., Rakshit, S., Lewis, J. & Van Essen, D. Neural responses to polar, hyperbolic, and Cartesian gratings in area V4 of the macaque monkey. *Journal of Neurophysiology* **76**, 2718–2739 (1996).

19. Brincat, S. L. & Connor, C. E. Underlying principles of visual shape selectivity in posterior inferotemporal cortex. *Nat Neurosci* **7**, 880–6 (2004).

20. Yau, J. M., Pasupathy, A., Brincat, S. L. & Connor, C. E. Curvature processing dynamics in macaque area V4. *Cerebral Cortex* **23**, 198–209 (2012).

21. Sharpee, T. O., Kouh, M. & Reyholds, J. H. Trade-off between curvature tuning and position invariance in visual area V4. *PNAS* **110**, 11618–11623 (2012).

22. Pickles, J. O. An Introduction to the Physiology of Hearing (2008).

23. Romanski, L. M. & LeDoux, J. E. Information cascade from primary auditory cortex to the amygdala: corticocortical and corticoamygdaloid projections of temporal cortex in the rat. *Cerebral Cortex* **3**, 515–532 (1993).

24. Hegner, Y. L., Lindner, A. & Braun, C. A somatosensory-to-motor cascade of cortical areas engaged in perceptual decision making during tactile pattern discrimination. *Human brain mapping* **38**, 1172–1181 (2017).

25. Petersen, C. C. The Functional Organization of the Barrel Cortex. *Neuron* **56**, 339–355 (2007).

26. Wang, L., Mruczek, R. E., Arcaro, M. J. & Kastner, S. Probabilistic maps of visual topography in human cortex. *Cerebral cortex* **25**, 3911–3931 (2014).

27. Hubel, D. H. & Wiesel, T. N. Receptive fields of single neurones in the cat's striate cortex. *The Journal of physiology* **148**, 574–591 (1959).

28. Ringach, D. L., Shapley, R. M. & Hawken, M. J. Orientation selectivity in macaque V1: diversity and laminar dependence. *Journal of Neuroscience* **22**, 5639–5651 (2002).

29. Willmore, B., Prenger, R. J., Wu, M. C.-K. & Gallant, J. L. The berkeley wavelet transform: a biologically inspired orthogonal wavelet transform. *Neural computation* **20**, 1537–1564 (2008).

30. Poole, B., Lahiri, S., Raghu, M., Sohl-Dickstein, J. & Ganguli, S. Exponential expressivity in deep neural networks through transient chaos. In *Advances in neural information processing systems*, 3360–3368 (2016).

31. Bengio, Y. Deep learning of representations for unsupervised and transfer learning. In *Proceedings of ICML Workshop on Unsupervised and Transfer Learning*, 17–36 (2012).

32. Rajalingham, R., Schmidt, K. & DiCarlo, J. J. Comparison of object recognition behavior in human and monkey. *J. Neurosci.* **35**, 12127–36 (2015).

33. Freedman, D. J., Riesenhuber, M., Poggio, T. & Miller, E. K. Categorical representation of visual stimuli in the primate prefrontal cortex. *Science* **291**, 312–316 (2001).

34. Pagan, M., Urban, L. S., Wohl, M. P. & Rust, N. C. Signals in inferotemporal and perirhinal cortex suggest an untangling of visual target information. *Nature neuroscience* **16**, 1132–1139 (2013).

35. *Hong, H., *Yamins, D. L., Majaj, N. J. & DiCarlo, J. J. Explicit information for category-orthogonal object properties increases along the ventral stream. *Nature neuroscience* **19**, 613–622 (2016).

36. Nishio, A., Shimokawa, T., Goda, N. & Komatsu, H. Perceptual Gloss Parameters Are Encoded by Population Responses in the Monkey Inferior Temporal Cortex. *The Journal of Neuroscience* **34**, 11143–11151 (2014).

37. Cover, T. M. & Thomas, J. A. *Elements of information theory* (John Wiley & Sons, 2012).

38. Pinto, N., Cox, D. D. & Dicarlo, J. J. Why is real-world visual object recognition hard? *PLoS Computational Biology* (2008).

39. Tanaka, K. Columns for complex visual object features in the inferotemporal cortex: clustering of cells with similar but slightly different stimulus selectivities. *Cerebral Cortex* **13**, 90–99 (2003).

40. Pinto, N., Doukhan, D., DiCarlo, J. J. & Cox, D. D. A High-Throughput Screening Approach to Discovering Good Forms of Biologically Inspired Visual Representation. *PLoS Comput Biol* (2009).

41. Fukushima, K. Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. *Biological cybernetics* **36**, 193–202 (1980).

42. LeCun, Y. & Bengio, Y. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks* 255–258 (1995).

43. Yamins, D. L. & DiCarlo, J. J. Using goal-driven deep learning models to understand sensory cortex. *Nature neuroscience* **19**, 356–365 (2016).

44. Serre, T., Oliva, A. & Poggio, T. A feedforward architecture accounts for rapid categorization. *Proc Natl Acad Sci U S A* **104**, 6424–9 (2007). 0027-8424 (Print) Journal Article.

45. Carandini, M. & Heeger, D. J. Normalization as a canonical neural computation. *Nature Reviews Neuroscience* **13**, 51–62 (2012).

46. Pinto, N., Doukhan, D., Dicarlo, J. J. & Cox, D. D. A high-throughput screening approach to discovering good forms of biologically inspired visual representation. *PLoS Computational Biology* **5** (2009).

47. Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K. & Fei-Fei, L. ImageNet: A Large-Scale Hierarchical Image Database. In *CVPR09*, 248–255 (2009).

48. Krizhevsky, A., Sutskever, I. & Hinton, G. E. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, 1097–1105 (2012).

49. Bergstra, J., Yamins, D. & Cox, D. Making a science of model search: Hyperparameter optimization in hundreds of dimensions for vision architectures. In *Proceedings of The 30th International Conference on Machine Learning*, 115–123 (2013).

50. Zoph, B., Vasudevan, V., Shlens, J. & Le, Q. V. Learning transferable architectures for scalable image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 8697–8710 (2018).

51. He, K., Zhang, X., Ren, S. & Sun, J. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 770–778 (2016).

52. Simonyan, K. & Zisserman, A. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556* (2014).

53. Girshick, R. Fast r-cnn. In *Proceedings of the IEEE international conference on computer vision*, 1440–1448 (2015).

54. Yamins, D. L., Hong, H., Cadieu, C. F., Solomon, E. A., Seibert, D. & DiCarlo, J. J. Performance-optimized hierarchical models predict neural responses in higher visual cortex. *Proceedings of the National Academy of Sciences* **111**, 8619–8624 (2014).

55. Kell, A. J., Yamins, D. L., Shook, E. N., Norman-Haignere, S. V. & McDermott, J. H. A Task-Optimized Neural Network Replicates Human Auditory Behavior, Predicts Brain Responses, and Reveals a Cortical Processing Hierarchy. *Neuron* **98**, 630–644 (2018).

56. Yamins, D. L., Hong, H., Cadieu, C. & DiCarlo, J. J. Hierarchical modular optimization of convolutional networks achieves representations similar to macaque IT and human ventral stream. In *Advances in neural information processing systems*, 3093–3101 (2013).

57. Khaligh-Razavi, S.-M. & Kriegeskorte, N. Deep supervised, but not unsupervised, models may explain IT cortical representation. *PLoS computational biology* **10**, e1003915 (2014).

58. Cadieu, C. F., Hong, H., Yamins, D. L., Pinto, N., Ardila, D., Solomon, E. A., Majaj, N. J. & DiCarlo, J. J. Deep neural networks rival the representation of primate IT cortex for core visual object recognition. *PLoS computational biology* **10**, e1003963 (2014).

59. Güçlü, U. & van Gerven, M. A. Deep neural networks reveal a gradient in the complexity of neural representations across the ventral stream. *The Journal of Neuroscience* **35**, 10005–10014 (2015).

60. Rajalingham, R., Issa, E. B., Bashivan, P., Kar, K., Schmidt, K. & DiCarlo, J. J. Large-scale, high-resolution comparison of the core visual object recognition behavior of humans, monkeys, and state-of-the-art deep artificial neural networks. *Journal of Neuroscience* **38**, 7255–7269 (2018).

61. Nayebi, A., Bear, D., Kubilius, J., Kar, K., Ganguli, S., Sussillo, D., DiCarlo, J. J. & Yamins, D. L. Task-Driven convolutional recurrent models of the visual system. In *Advances in Neural Information Processing Systems*, 5290–5301 (2018).

62. Seibert, D., Yamins, D. L., Ardila, D., Hong, H., DiCarlo, J. J. & Gardner, J. L. A performance-optimized model of neural responses across the ventral visual stream. *bioRxiv* (2016). URL `http://biorxiv.org/content/early/2016/01/12/036475`.

63. Cadena, S. A., Denfield, G. H., Walker, E. Y., Gatys, L. A., Tolias, A. S., Bethge, M. & Ecker, A. S. Deep convolutional models improve predictions of macaque V1 responses to natural images. *PLoS computational biology* **15**, e1006897 (2019).

64. Bottou, L. Large-scale machine learning with stochastic gradient descent. In *Proceedings of COMPSTAT'2010*, 177–186 (Springer, 2010).

65. Zeiler, M. D. ADADELTA: an adaptive learning rate method. *arXiv preprint arXiv:1212.5701* (2012).

66. Kingma, D. P. & Ba, J. Adam: A Method for Stochastic Optimization (2014).

67. Song, S., Miller, K. D. & Abbott, L. F. Competitive Hebbian learning through spike-timing-dependent synaptic plasticity. *Nature neuroscience* **3**, 919 (2000).

68. Montague, P. R., Dayan, P. & Sejnowski, T. J. A framework for mesencephalic dopamine systems based on predictive Hebbian learning. *Journal of neuroscience* **16**, 1936–1947 (1996).

69. Gerstner, W. & Kistler, W. M. Mathematical formulations of Hebbian learning. *Biological cybernetics* **87**, 404–415 (2002).

70. Stork, D. G. Is backpropagation biologically plausible. In *International Joint Conference on Neural Networks*, vol. 2, 241–246 (IEEE Washington, DC, 1989).

71. Bengio, Y., Lee, D.-H., Bornschein, J., Mesnard, T. & Lin, Z. Towards biologically plausible deep learning. *arXiv preprint arXiv:1502.04156* (2015).

72. Lillicrap, T. P., Cownden, D., Tweed, D. B. & Akerman, C. J. Random feedback weights support learning in deep neural networks. *arXiv preprint arXiv:1411.0247* (2014).

73. Kriegeskorte, N., Mur, M., Ruff, D. A., Kiani, R., Bodurka, J., Esteky, H., Tanaka, K. & Bandettini, P. A. Matching categorical object representations in inferior temporal cortex of man and monkey. *Neuron* **60**, 1126–41 (2008).

74. Schwarz, G. *et al.* Estimating the dimension of a model. *The annals of statistics* **6**, 461–464 (1978).

75. Hinton, G. E. & Salakhutdinov, R. R. Reducing the dimensionality of data with neural networks. *science* **313**, 504–507 (2006).

76. Olshausen, B. A. & Field, D. J. Emergence of simple-cell receptive field properties by learning a sparse code for natural images. *Nature* **381**, 607–609 (1996).

77. Kingma, D. P. & Welling, M. Auto-Encoding Variational Bayes (2013).

78. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. & Bengio, Y. Generative adversarial nets. In *Advances in neural information processing systems*, 2672–2680 (2014).

79. Donahue, J., Krähenbühl, P. & Darrell, T. Adversarial feature learning. *arXiv preprint arXiv:1605.09782* (2016).

80. Karras, T., Aila, T., Laine, S. & Lehtinen, J. Progressive growing of gans for improved quality, stability, and variation. *arXiv preprint arXiv:1710.10196* (2017).

81. Klindt, D., Ecker, A. S., Euler, T. & Bethge, M. Neural system identification for large populations separating "what" and "where". In *Advances in Neural Information Processing Systems*, 3506–3516 (2017).

82. Vintch, B., Zaharia, A., Movshon, J. & Simoncelli, E. P. Efficient and direct estimation of a neural subunit model for sensory coding. In *Advances in neural information processing systems*, 3104–3112 (2012).

83. Cadieu, C., Kouh, M., Pasupathy, A., Connor, C. E., Riesenhuber, M. & Poggio, T. A model of V4 shape selectivity and invariance. *J Neurophysiol* **98**, 1733–50 (2007).

84. McIntosh, L., Maheswaranathan, N., Nayebi, A., Ganguli, S. & Baccus, S. Deep learning models of the retinal response to natural scenes. In *Advances in neural information processing systems*, 1369–1377 (2016).

85. Güçlü, U., Thielen, J., Hanke, M. & Van Gerven, M. Brains on beats. In *Advances in Neural Information Processing Systems*, 2101–2109 (2016).

86. Zhuang, C., Kubilius, J., Hartmann, M. J. & Yamins, D. L. Toward Goal-Driven Neural Network Models for the Rodent Whisker-Trigeminal System. In *Advances in Neural Information Processing Systems*, 2555–2565 (2017).

87. Sussillo, D., Churchland, M. M., Kaufman, M. T. & Shenoy, K. V. A neural network that finds a naturalistic solution for the production of muscle activity. *Nature neuroscience* **18**, 1025–1033 (2015).

88. Lillicrap, T. P. & Scott, S. H. Preference distributions of primary motor cortex neurons reflect control solutions optimized for limb biomechanics. *Neuron* **77**, 168–179 (2013).

89. Flash, T. & Hogan, N. The coordination of arm movements: an experimentally confirmed mathematical model. *Journal of neuroscience* **5**, 1688–1703 (1985).

90. Churchland, M. M., Cunningham, J. P., Kaufman, M. T., Foster, J. D., Nuyujukian, P., Ryu, S. I. & Shenoy, K. V. Neural population dynamics during reaching. *Nature* **487**, 51 (2012).

91. Chi, T., Ru, P. & Shamma, S. A. Multiresolution spectrotemporal analysis of complex sounds. *The Journal of the Acoustical Society of America* **118**, 887–906 (2005).

92. Espinosa, J. S. & Stryker, M. P. Development and plasticity of the primary visual cortex. *Neuron* **75**, 230–249 (2012).

93. Baldassarre, A., Lewis, C. M., Committeri, G., Snyder, A. Z., Romani, G. L. & Corbetta, M. Individual variability in functional connectivity predicts performance of a perceptual task. *Proceedings of the National Academy of Sciences* **109**, 3516–3521 (2012).

94. Li, Y., Yosinski, J., Clune, J., Lipson, H. & Hopcroft, J. Convergent Learning: Do different neural networks learn the same representations? In *NIPS Workshop on Feature Extraction: Modern Questions and Challenges*, 196–212 (2015).

95. Van Horn, J. D., Grafton, S. T. & Miller, M. B. Individual variability in brain activity: a nuisance or an opportunity? *Brain imaging and behavior* **2**, 327–334 (2008).

96. Gao, P., Trautmann, E., Byron, M. Y., Santhanam, G., Ryu, S., Shenoy, K. & Ganguli, S. A theory of multineuronal dimensionality, dynamics and measurement. *bioRxiv* 214262 (2017).

97. Turner-Evans, D., Wegener, S., Rouault, H., Franconville, R., Wolff, T., Seelig, J. D., Druckmann, S. & Jayaraman, V. Angular velocity integration in a fly heading circuit. *Elife* **6**, e23496 (2017).

98. Kurakin, A., Goodfellow, I. & Bengio, S. Adversarial examples in the physical world. *arXiv preprint arXiv:1607.02533* (2016).

99. Spoerer, C. J., McClure, P. & Kriegeskorte, N. Recurrent convolutional neural networks: a better model of biological object recognition. *Frontiers in psychology* **8**, 1551 (2017).

100. Kanwisher, N., McDermott, J. & Chun, M. M. The fusiform face area: a module in human extrastriate cortex specialized for face perception. *J Neurosci* **17**, 4302–11 (1997).

101. Downing, P., Jiang, Y., Shuman, M. & Kanwisher, N. A Cortical Area Selective for Visual Processing of the Human Body. *Science* **293**, 2470–2473 (2001).

102. Epstein, R. & Kanwisher, N. A cortical representation of the local visual environment. *Nature* **392**, 598–601 (1998).

103. Mahajan, D., Girshick, R., Ramanathan, V., He, K., Paluri, M., Li, Y., Bharambe, A. & van der Maaten, L. Exploring the limits of weakly supervised pretraining. In *Proceedings of the European Conference on Computer Vision (ECCV)*, 181–196 (2018).

104. Tarvainen, A. & Valpola, H. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In *Advances in neural information processing systems*, 1195–1204 (2017).

105. Settles, B. *Active Learning*, vol. 18 (Morgan & Claypool Publishers, 2011).

106. Sener, O. & Savarese, S. A Geometric Approach to Active Learning for Convolutional Neural Networks. *CoRR* **abs/1708.00489** (2017).

107. Wayne, G., Hung, C.-C., Amos, D., Mirza, M., Ahuja, A., Grabska-Barwinska, A., Rae, J., Mirowski, P., Leibo, J. Z., Santoro, A. *et al.* Unsupervised Predictive Memory in a Goal-Directed Agent. *arXiv preprint arXiv:1803.10760* (2018).

108. Yang, G. R., Ganichev, I., Wang, X.-J., Shlens, J. & Sussillo, D. A dataset and architecture for visual reasoning with a working memory. *arXiv preprint arXiv:1803.06092* (2018).

109. Kidd, C., Piantadosi, S. T. & Aslin, R. N. The Goldilocks Effect: Human Infants Allocate Attention to Visual Sequences That Are Neither Too Simple Nor Too Complex. *PLOS ONE* **7**, 1–8 (2012).

110. Goupil, L., Romand-Monnier, M. & Kouider, S. Infants ask for help when they know they don't know. *Proceedings of the National Academy of Sciences* **113**, 3492–3496 (2016).

111. Begus, K., Gliga, T. & Southgate, V. Infants Learn What They Want to Learn: Responding to Infant Pointing Leads to Superior Learning. *PLOS ONE* **9**, 1–4 (2014).

112. Fantz, R. L. Visual experience in infants: Decreased attention to familiar patterns relative to novel ones. *Science* **146**, 668–670 (1964).

113. Twomey, K. E. & Westermann, G. Curiosity-based learning in infants: a neurocomputational approach. *Developmental Science* **21** (2018).

114. Hurley, K. B., Kovack-Lesh, K. A. & Oakes, L. M. The influence of pets on infants' processing of cat and dog images. *Infant Behav Dev* **33**, 619–628 (2010).

115. Hurley, K. B. & Oakes, L. M. Experience and distribution of attention: Pet exposure and infants' scanning of animal images. *J Cogn Dev* **16**, 11–30 (2015).

116. Gopnik, A., Meltzoff, A. & Kuhl, P. *The Scientist In The Crib: Minds, Brains, And How Children Learn* (HarperCollins, 2009).

117. Haber, N., Mrowca, D., Fei-Fei, L. & Yamins, D. L. Learning to Play with Intrinsically-Motivated Self-Aware Agents (2018).