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# Visual pathways from the perspective of cost functions and multi-task deep neural networks

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## ABSTRACT

Vision research has been shaped by the seminal insight that we can understand the higher-tier visual cortex from the perspective of multiple functional pathways with different goals. In this paper, we try to give a computational account of the functional organization of this system by reasoning from the perspective of multi-task deep neural networks. Machine learning has shown that tasks become easier to solve when they are decomposed into subtasks with their own cost function. We hypothesize that the visual system optimizes multiple cost functions of unrelated tasks and this causes the emergence of a ventral pathway dedicated to vision for perception, and a dorsal pathway dedicated to vision for action.

To evaluate the functional organization in multi-task deep neural networks, we propose a method that measures the contribution of a unit towards each task, applying it to two networks that have been trained on either two related or two unrelated tasks, using an identical stimulus set. Results show that the network trained on the unrelated tasks shows a decreasing degree of feature representation sharing towards higher-tier layers while the network trained on related tasks uniformly shows high degree of sharing.

We conjecture that the method we propose can be used to analyze the anatomical and functional organization of the visual system and beyond. We predict that the degree to which tasks are related is a good descriptor of the degree to which they share downstream cortical-units.

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## 1. Introduction

The visual system is described as consisting of two parallel pathways. Research by Gross, Mishkin et al, integrating insights from lesion (Newcombe, 1969) and anatomical studies (Schneider, 1969), showed that these pathways emerge beyond the striate cortex with one involved in the identification of objects projecting ventrally, and the other involved in localization of objects, projecting to the parietal cortex (Gross & Mishkin, 1977; Mishkin, Ungerleider, & Macko, 1983). From the start of the dual-pathway theory, multiple pathways were believed to be computationally efficient (Gross & Mishkin, 1977). Support for this idea comes from research using artificial neural networks with one hidden layer, showing that location and identity are better learned when units in the hidden layers are uniquely assigned to one of these functions (Jacobs, Jordan, & Barto, 1991; Ruckl, Cave, & Kosslyn, 1989).

In the early nineties, Goodale & Milner argued that, on the basis of neuropsychological, electrophysiological and behavioral evidence, these pathways should be understood as have different goals. The ventral pathway (“vision for perception”) is involved in computing the transformations necessary for the identification and recognition of objects. The dorsal pathway (“vision for action”) is involved in sensorimotor transformations for visually guided actions directed at these objects (Goodale & Milner, 1992).

It was recently suggested that the brain uses a variety of cost functions for learning (Marblestone, Wayne, & Kording, 2016). These cost functions can be highly diverse. The brain must optimize a wide range of cost functions, such as keeping body temperature constant or optimizing future reward from social interactions. High-level cost functions, by necessity, also shape other cost functions that determine the organization of perception: a cost function that is being optimized to minimize hunger affects the visual recognition cost function as foods have to be recognized. Mechanistically, this could take place directly through, for instance, a reward modulation of object recognition learning, or indirectly through evolutionary pressure on the cost function associated with object recognition learning. In this paper, we try to understand how multiple pathways in the visual cortex might evolve from the perspective of Deep Neural Networks (DNNs, see Box 1) and cost functions (see Box 2), and what this implies for how object information is stored in these networks.

We start with a discussion of the relevance of DNNs (LeCun, Bengio, & Hinton, 2015; Schmidhuber, 2015) and, following Marblestone (Marblestone et al., 2016), of cost functions for understanding the brain in Section 2. We extend our discussion with the importance of optimizing different cost functions simultaneously, presenting a hypothesis on the relationship between relatedness of tasks and the degree of feature representation sharing.

We test this hypothesis in a computational experiment with DNNs in Section 3 to evaluate how much its feature representations contribute to each task. In Section 4, we discuss the degree to which we are able to translate our experimental findings to the division between the ventral and dorsal pathway, the multiple functions of the ventral cortex, and the

apparent co-occurrence of both distributed and modular representations related to object recognition.

We finish this paper with a discussion of how this framework can be used experimentally to understand the human brain while elaborating on the limitations of DNNs and cost functions. For brevity, we do not consider models of recurrent processing.

## 2. Multi-task DNNs as models of neural information processing in the brain

Artificial neural networks are inspired by computational principles of biological neuronal networks and are part of a large class of machine learning models that learn feature representations from data by optimizing a cost function. In this section, we discuss why we believe models based on optimizing cost functions, such as DNNs, are relevant for understanding brain function.

### 2.1. Similarities in architecture and behavior between DNNs and the brain

Alexnet (Krizhevsky, Sutskever, & Hinton, 2012), a model that is has been used extensively in research relating DNN's to the brain, consists of 7 layers (see Box 1). The first layer consists of filters with small kernels that are applied to each position of the input. In the subsequent four layers this procedure is repeated using the output of the preceding layer. This results in an increase in receptive field (RF) size and concurrently an increase in the specificity of tuning (Zeiler & Fergus, 2014). This increase of receptive field size and tuning specificity traversing the layers resemble the general architecture of feed-forward visual representations in the human brain (DiCarlo, Zoccolan, & Rust, 2012; Lamme & Roelfsema, 2000).

A number of BOLD-MRI studies have revealed that the neural activation's in early areas of visual cortex show the best correspondence with the early layers of DNNs and that higher-tier cortical areas show the best correspondence with higher-tier DNN layers (Eickenberg, Gramfort, Varoquaux, & Thirion, 2017; Güçlü & van Gerwen, 2015). MEG/EEG studies have furthermore shown that early layers of DNNs have a peak explained variance that is earlier than higher-tier DNN layers (Cichy, Khosla, Pantazis, Torralba, & Oliva, 2016; Ramakrishnan, Scholte, Smeulders, & Ghebreab, 2016). In addition, the DNN model has been shown to predict neural responses in IT, both from humans and macaque, much better than any other computational model (Khaligh-Razavi & Kriegeskorte, 2014; Yamins et al., 2014).

The correspondence between DNNs and the brain begs the question of the degree to which DNNs show ‘behavior’ similar to humans. Early results indicate that humans and DNNs have a similar pattern of performance in terms of the kinds of variation (size, rotation) that make object recognition harder or simpler (Kheradpisheh, Ghodrati, Ganjtabesh, & Masquelier, 2016). It has also been shown that higher-tier layers of DNNs follow human perceptual shape similarity while the lower-tier layers strictly abide by physical similarity (Kubilius, Bracci, & Op de Beeck, 2016). On the other hand, DNNs are, for instance, much more susceptible to the addition

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