Incorporating action information into computational models of the human visual system

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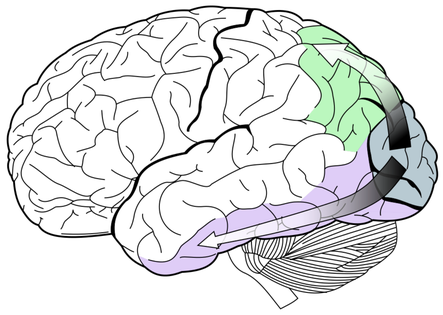
Background

Dorsal stream: visual stream responsible for discerning the location of objects and visually-guided behaviour.[1]



"Ventral-dorsal streams.svg" by Selket is licensed under CC BY-SA 3.0.

Figure 1. The dorsal stream runs from the occipital lobe to the parietal lobe (green path) whereas the ventral stream runs along the temporal lobe (purple path).

Neural network: a computing system inspired by neuroscience. Neurons are simplified into *units*, each of which take inputs and produce outputs. Units can be linked together to model increasingly complex input-output relationships.[2]

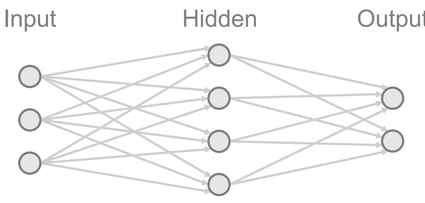


Figure 2. Illustration of a simple neural network with a single hidden layer.

Convolutional neural network: a type of neural network often used to analyze images. It uses a process called *convolution* to decrease sensitivity to changes in object position (shift invariance). Convolution involves repeatedly sampling patches of an image using filters.[2]

Deep neural network: a neural network with greater than one hidden layer.[2]

Introduction

The ventral visual stream can be modeled using Deep Convolutional Neural Networks (DCNNs).

- DCNNs approach human-level accuracy on image categorization tasks.[3,4,5]
- DCNNs predict neural representations of images.[6,7,8]

However, computational models of the dorsal visual stream remain relatively unexplored.[9] This is problematic, as:

- The ventral and dorsal streams are not entirely independent[10,11]
- The streams likely influence each other during development

Additionally, DCNN models of vision also suffer from flaws such as over-reliance on texture information.[12]

Research questions:

- Does incorporating action information improve computational models of the ventral visual system?
- How do the ventral and dorsal streams influence each other during development?

Methods

The study will involve creating three models:

1. **Two-task network:** a neural network trained with two cost functions, one approximating the function of the ventral visual stream and the other approximating the function of the dorsal stream.

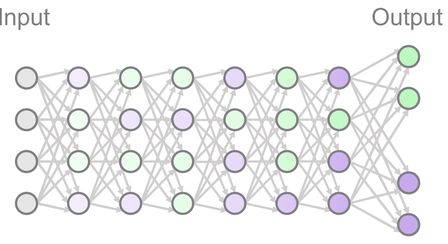


Figure 3. Simplified illustration of the two-task network. Function specificity towards the dorsal stream task is represented by green, and for the ventral stream task, by purple. Greater colour saturation represents greater function specificity.

2. **Single-task network:** a neural network trained with only a single cost function, approximating the function of the ventral stream.

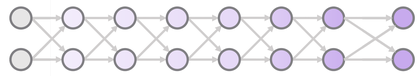


Figure 4. Simplified illustration of the single-task network.

3. **Lesioned network:** a copy of the trained two-task network, with the units that contributed the most to the dorsal stream task deactivated.

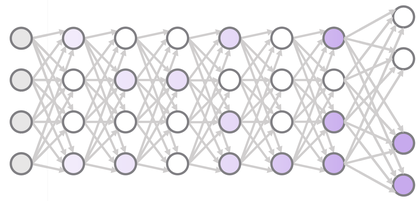


Figure 5. Simplified illustration of the lesioned network. Deactivated units are shown in white.

Each neural network will be evaluated using *performance metrics* and *representational metrics*. Performance metrics include:

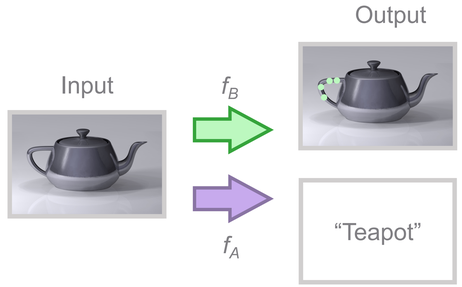
- Accuracy when evaluated with ImageNet
- Accuracy when evaluated with Stylized-ImageNet
- Transfer learning
- Robustness against distortions

Representational metrics include:

- Representation contribution analysis
- Representational similarity analysis

Training tasks:

To approximate ventral stream function, networks will be trained to perform object recognition. To approximate dorsal stream function, networks will be trained to generate realistic human grasp points.



"Utah teapot simple 2.png" by Dhatfield is licensed under CC BY-SA 3.0

Figure 6. An example of the two outputs generated by the two-task network from each input.

Hypotheses

1. The two-task network will do better on performance measures than the lesioned network and single-task network.
2. In the two-task network, more units will contribute towards the grasp point generation task than object recognition.
3. Representations in the two-task network will be more like human data than the single-task network.

Next Steps

Before creating the neural networks, a dataset must first be assembled for training and validation.

Dataset criteria:

- 12 object categories
- Minimum of 50 examples per category
- Multiple viewpoints of each object
- Must have object identity labels
- Must have human grasp point labels

Currently, efforts are being made to fulfill these criteria by collecting virtual 3D models from online and using a normative grasp model[13] to generate realistic grasp point labels.

Additionally, the dataset will be augmented using naturalistic data augmentation, such as by altering lighting or camera movement.

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