DONDERS INSTITUTE

Probing neural representations with task-optimized deep neural networks

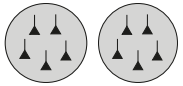
Umut Güçlü

Radboud University Radboudumc

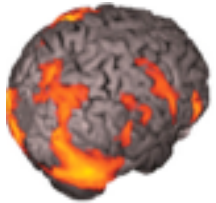
Modeling how the brain responds to the environment

stimulus **x**

neural response **z**



measurement **y**



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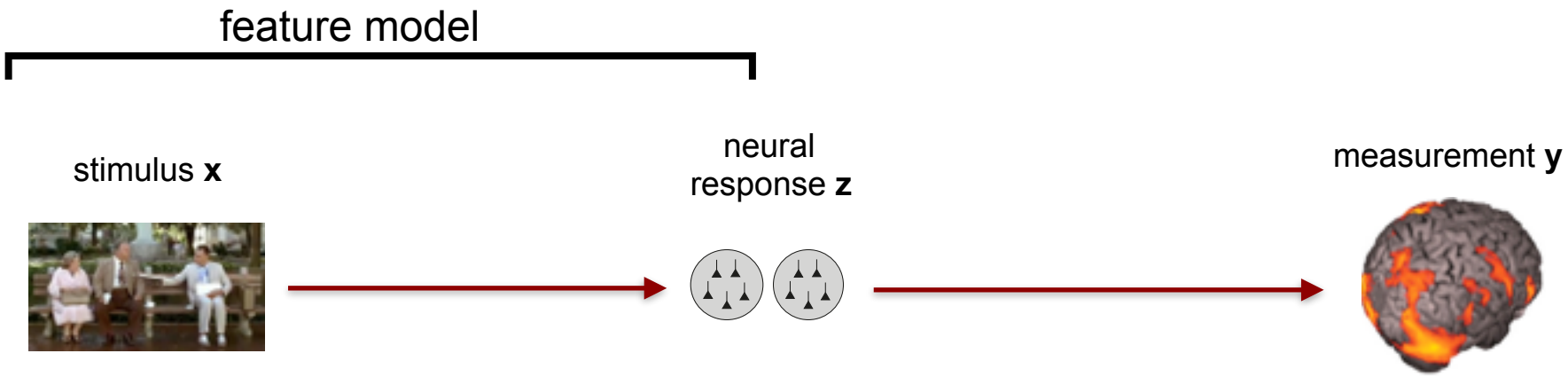

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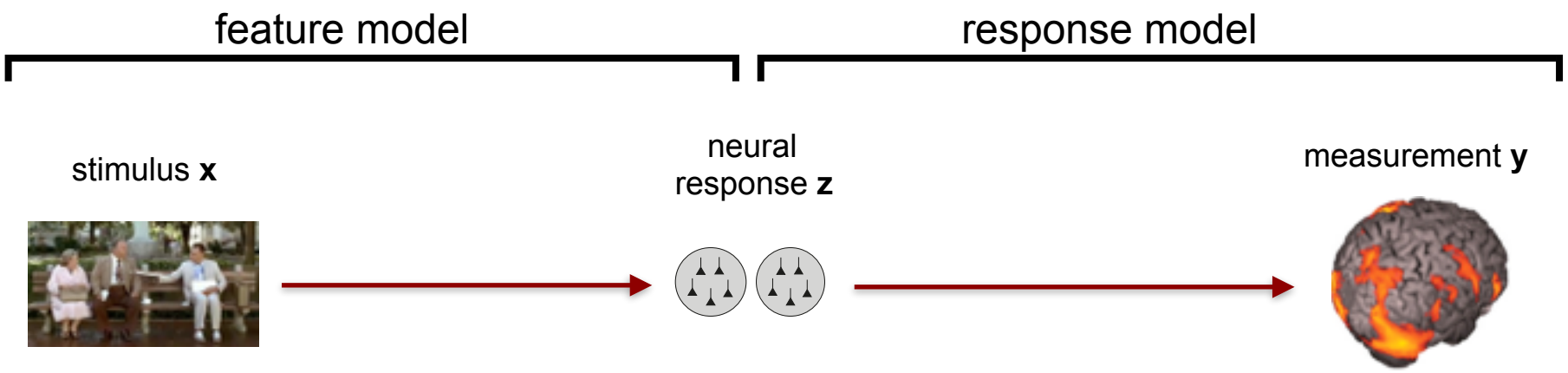

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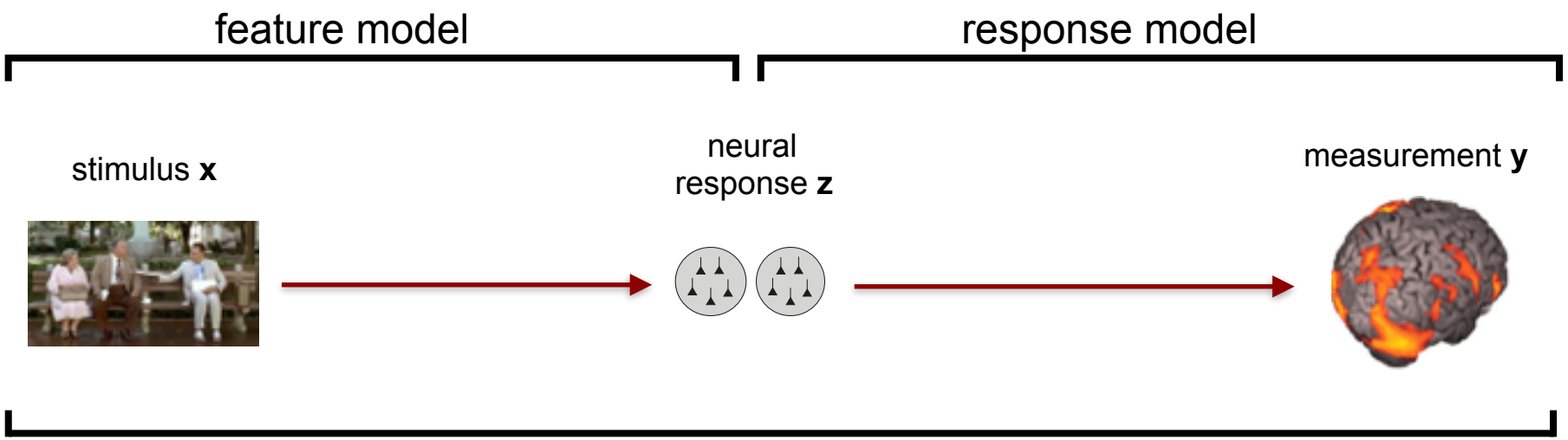

Encoding model

$$p(\mathbf{y} \mid \mathbf{x})$$

Probing neural representations

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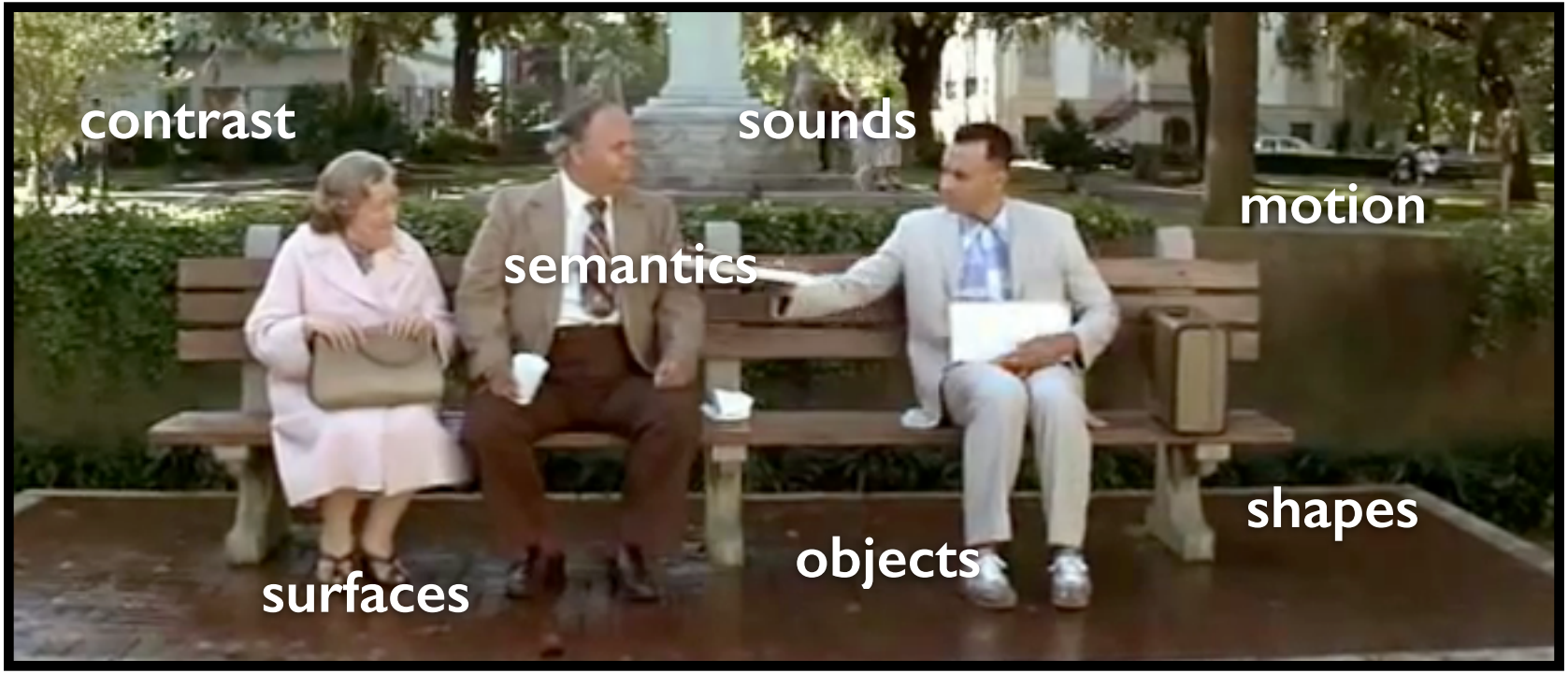

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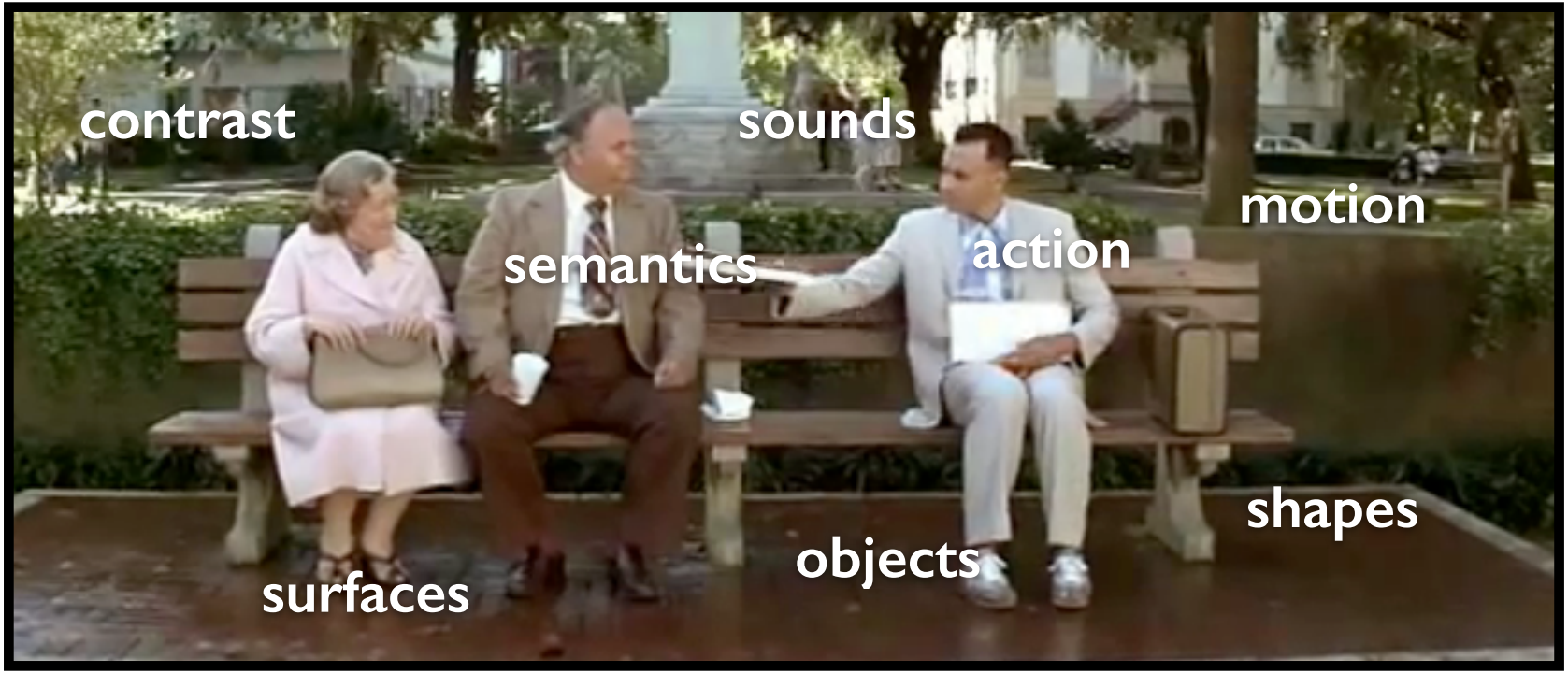

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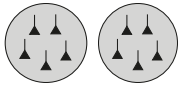

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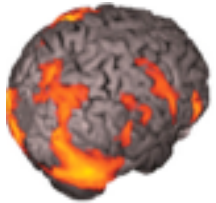

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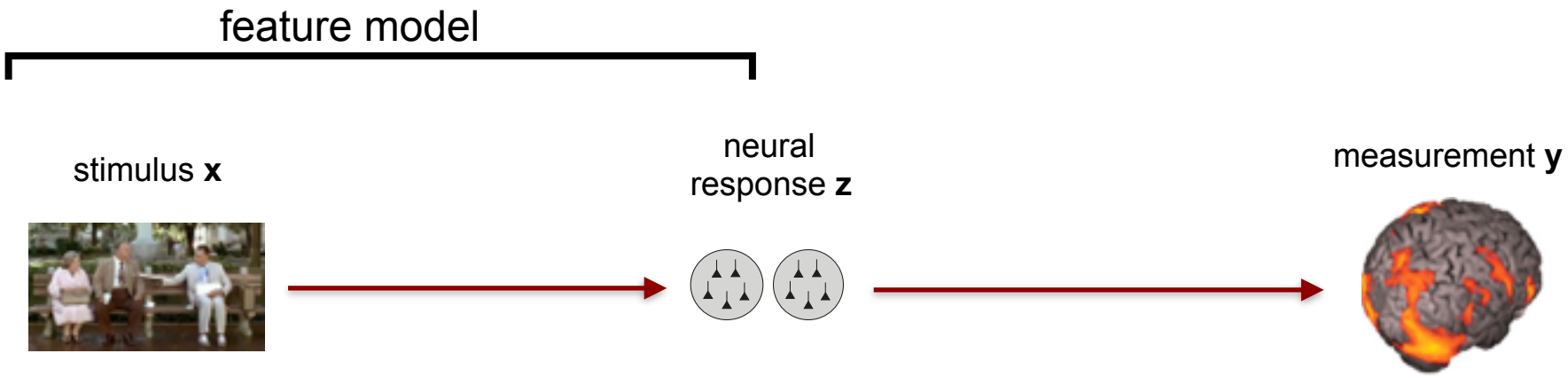

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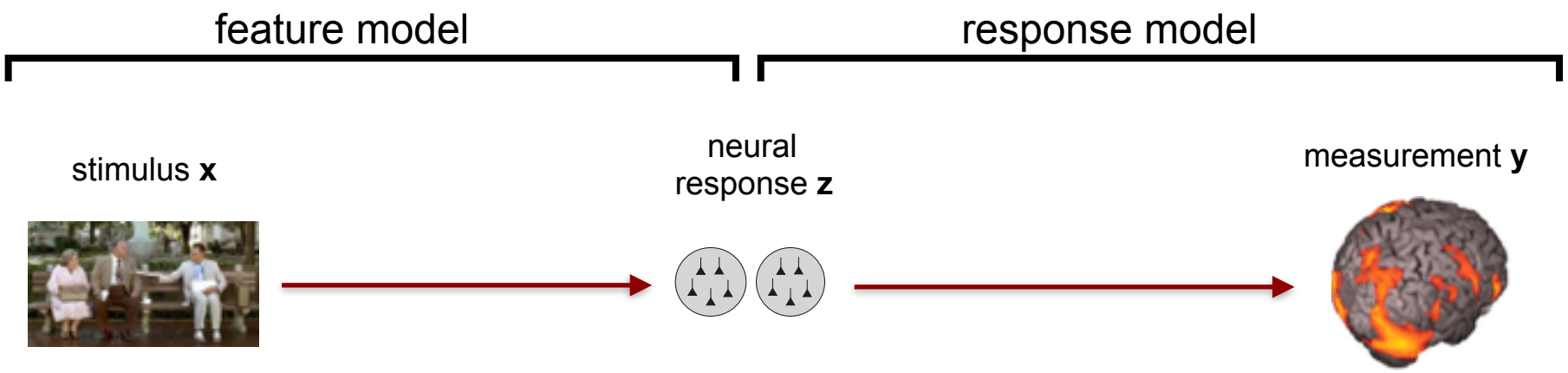

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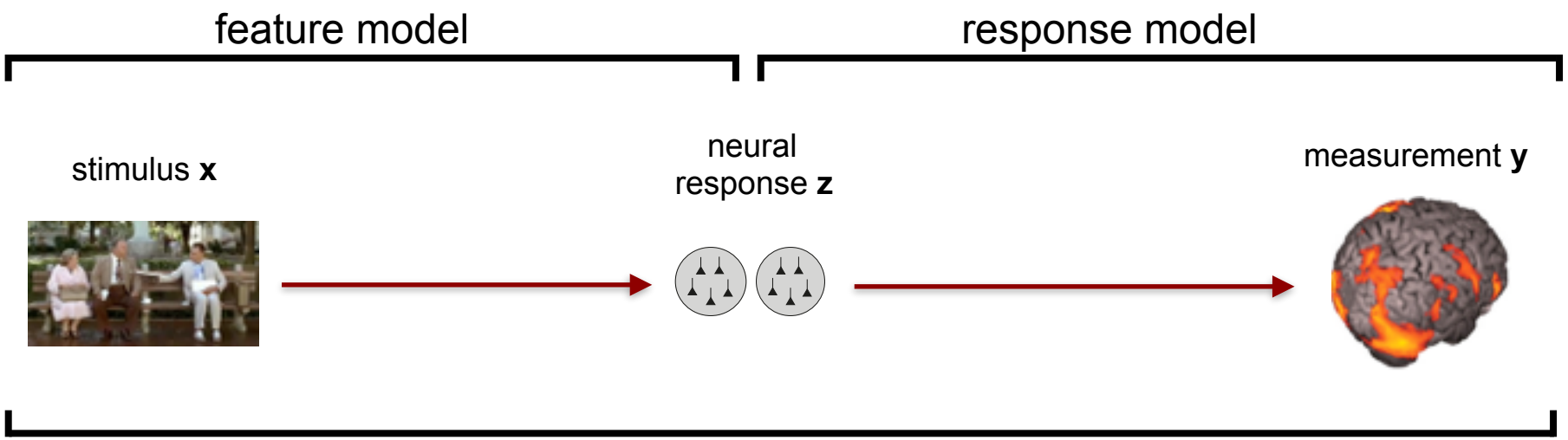

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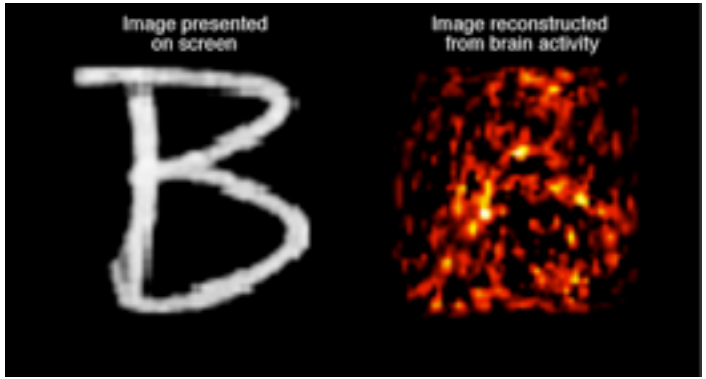
Previous work

Linear mapping $\mathbf{y} \sim \mathcal{N}(\mathbf{B}^T\mathbf{x}, \mathbf{\Sigma})$



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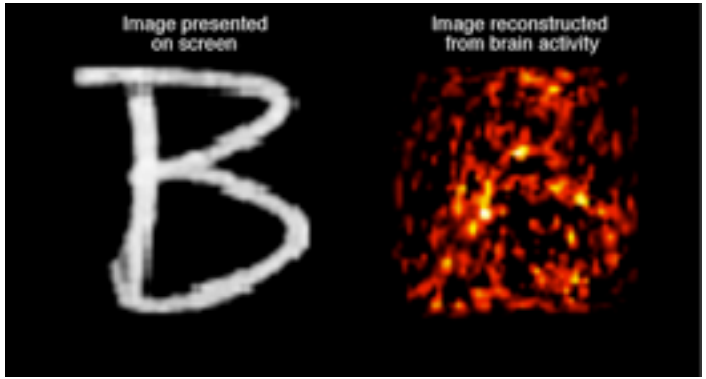

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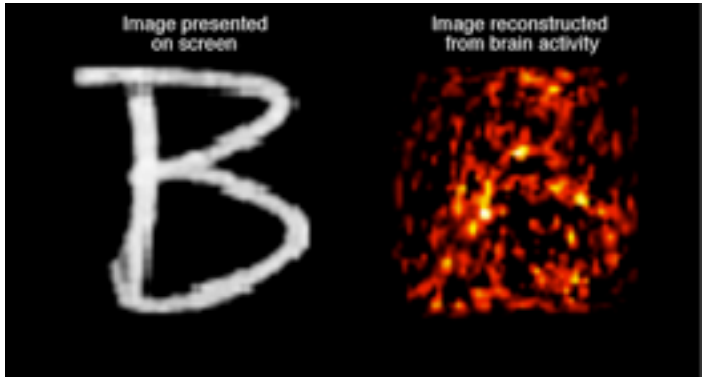
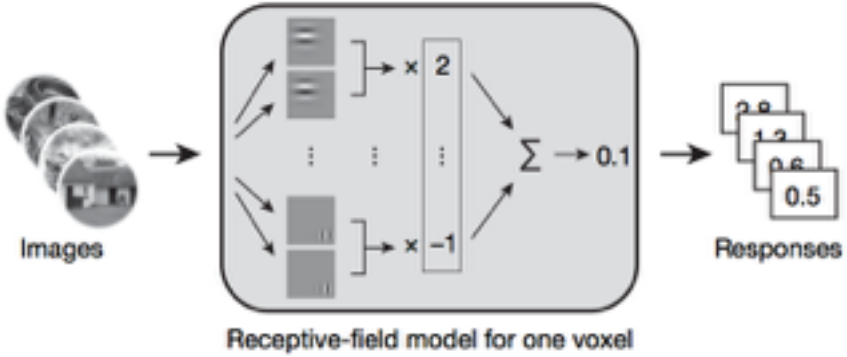


Gabor wavelet model



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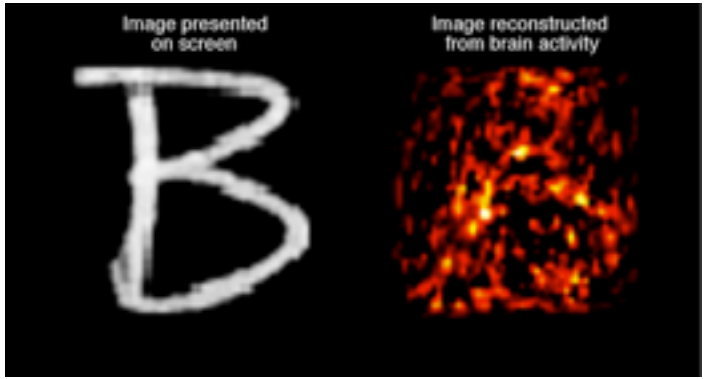

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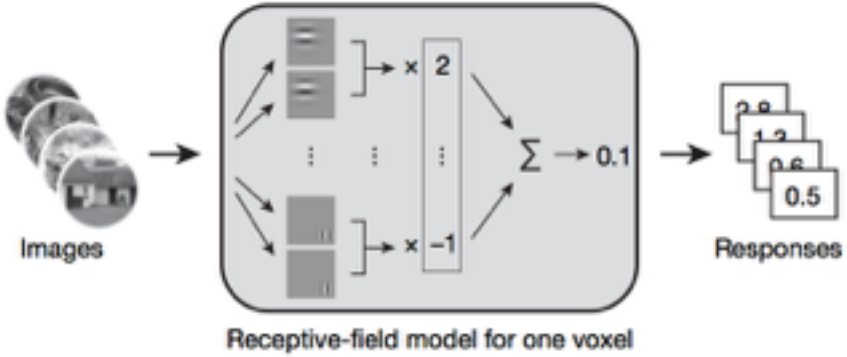
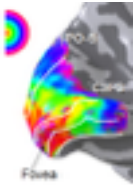


- Models of responses in early visual cortex



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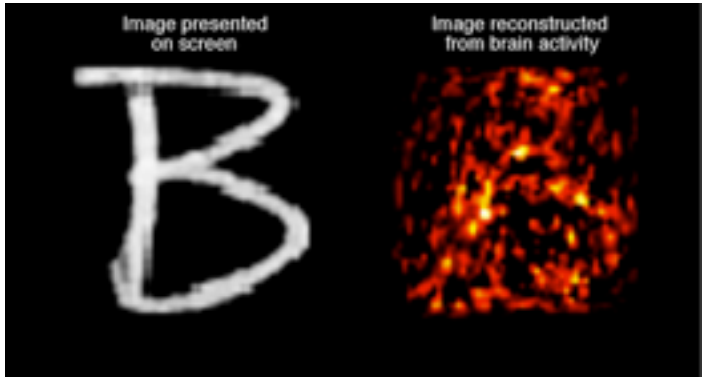

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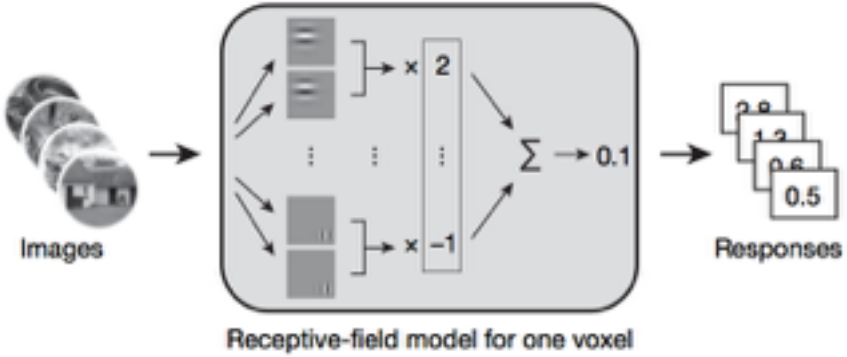

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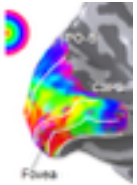
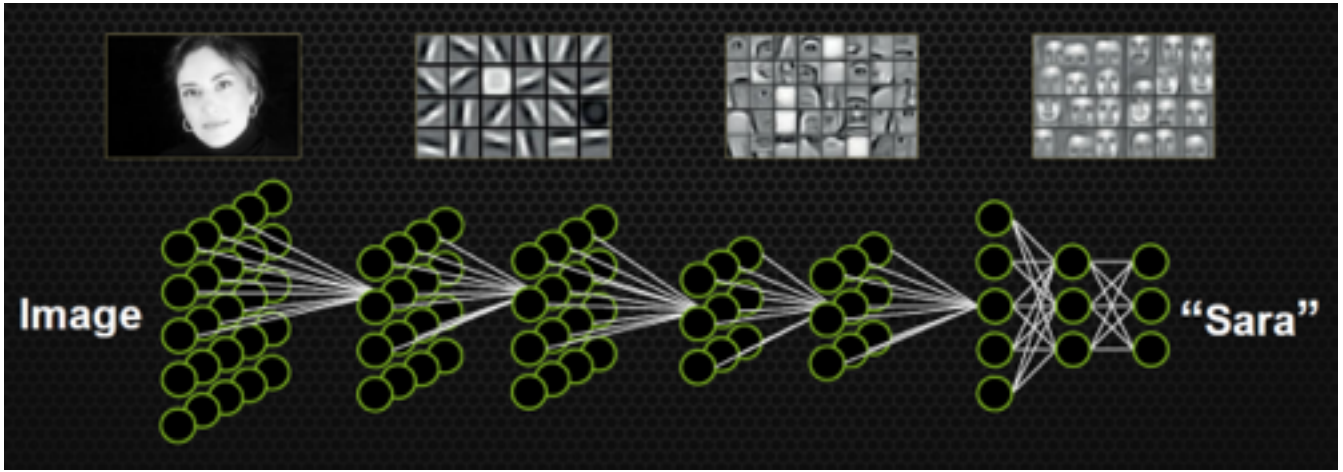


- How to model more complex representations in downstream areas?

Schoenmakers et al. (2013). NeuroImage; Kay et al. (2008). Nature.

Deep neural networks



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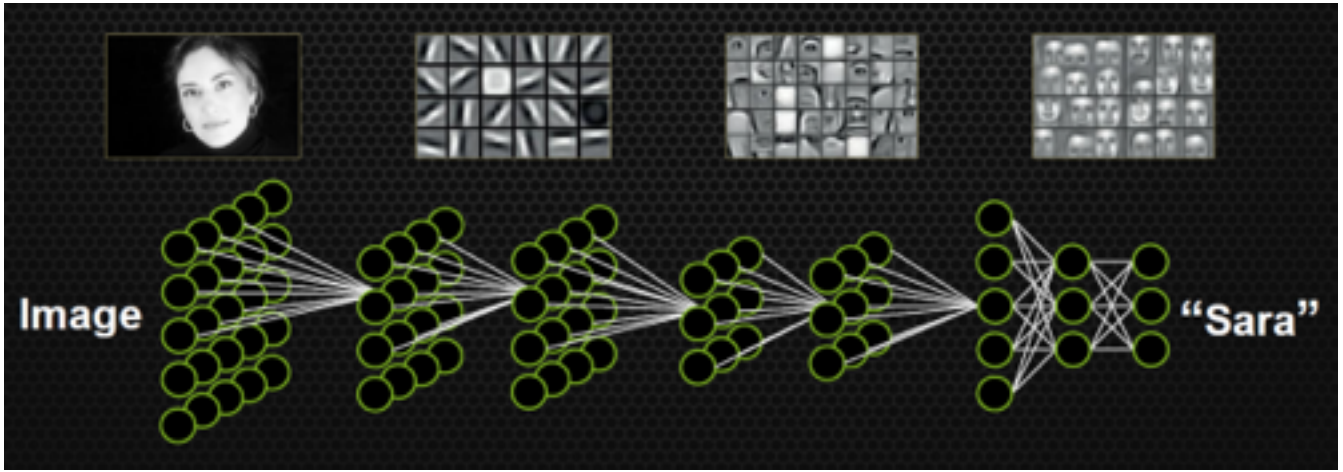
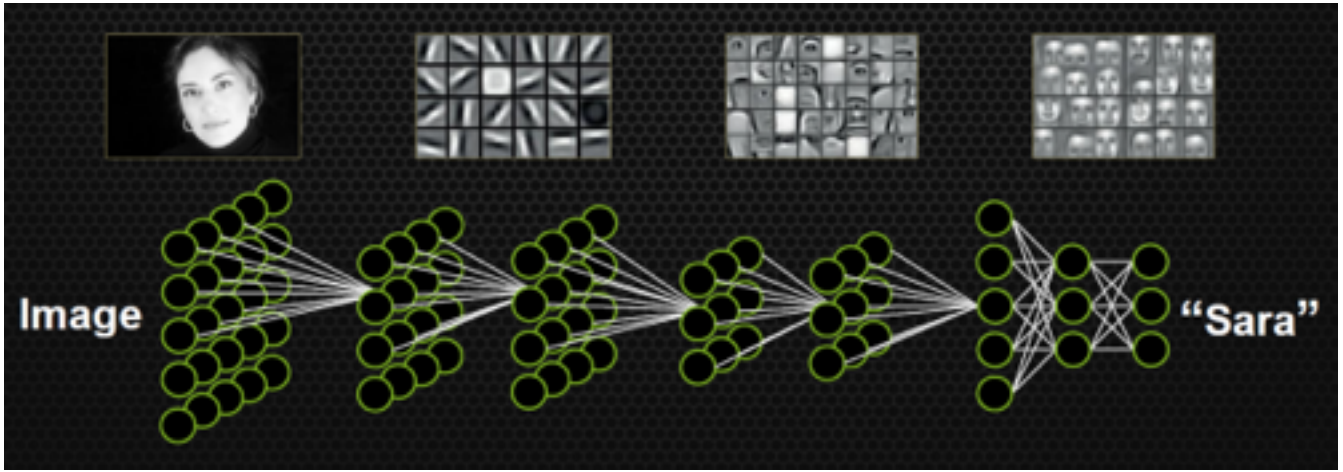


- Computational model consisting of artificial neurons that are organized in terms of layers

Deep neural networks



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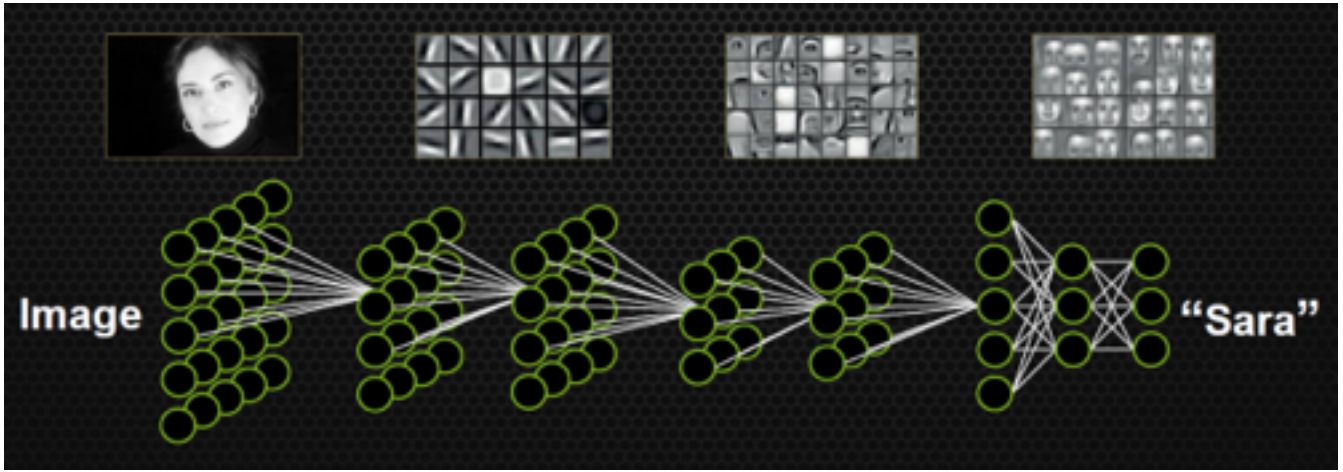

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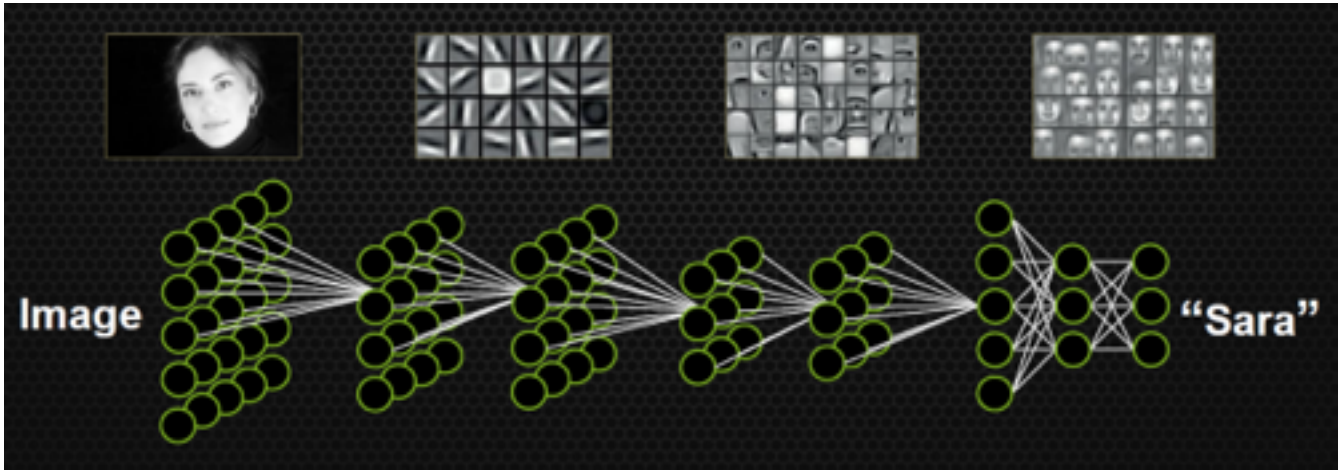

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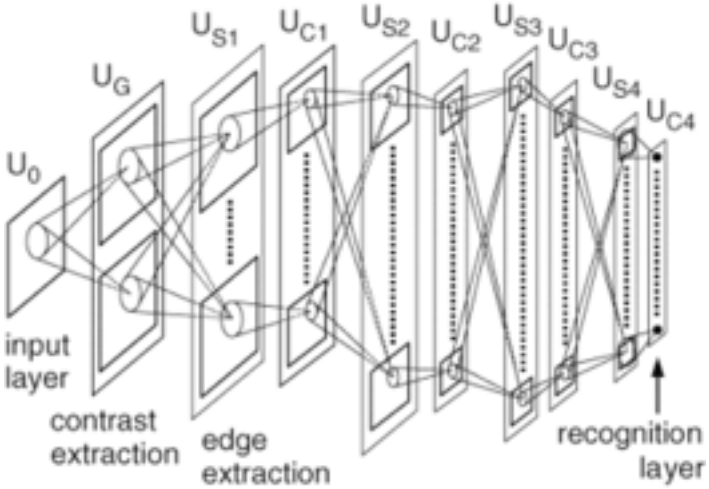
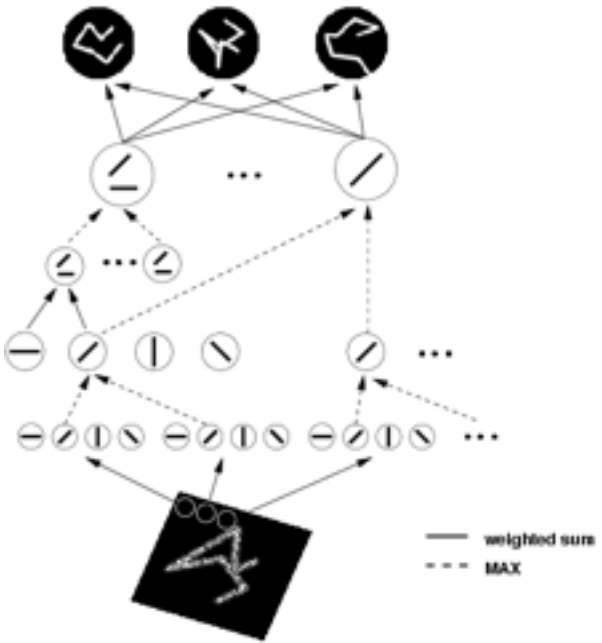
- Each layer incorporates particular filtering steps
- Learns a mapping between an input (e.g. image) and an output (e.g. image categories) by adjusting 'synaptic' weights between artificial neurons
- Representations in hidden layers capture increasingly complex characteristics of their input

Neuroscientific inspiration

- Inspired by classical models of stimulus transformations in sensory cortex



Fukushima, 1980, Biol. Cybern.



Riesenhuber & Poggio, 1999, Nat. Neurosci.

Resurgence

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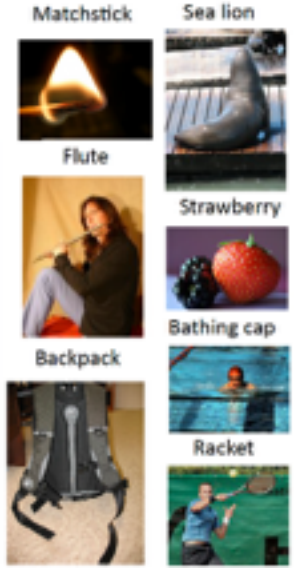
- Relies on combination of various tricks (convolution, pooling, dropout, etc.) as well as availability of massive labeled datasets and ample computational resources (GPUs)

The ImageNet dataset [Fei-Fei et al. 2012]
- 1.2 million training samples
- 1000 categories

Fast Graphical Processing Units (GPU)
- Capable of over 1 trillion operations/second



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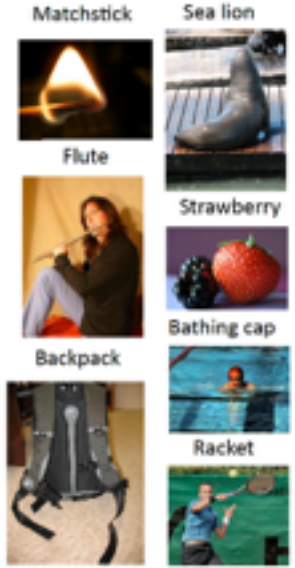
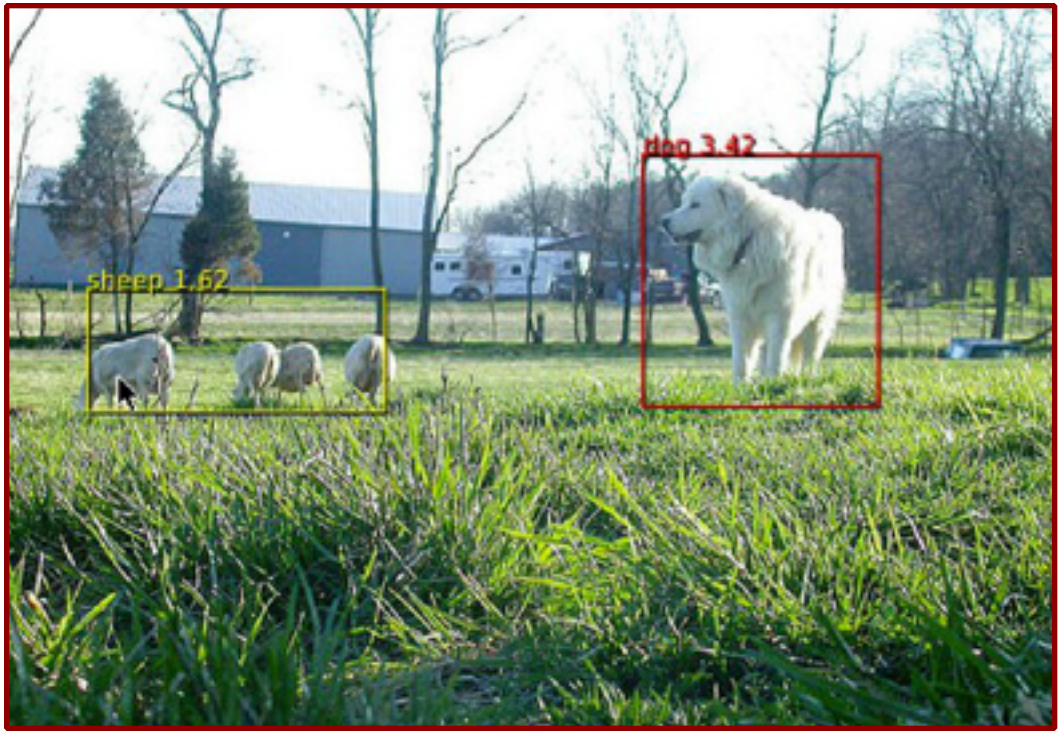


- Revolutionized computer vision, natural language processing, robotics, artificial intelligence

Example: Object detection



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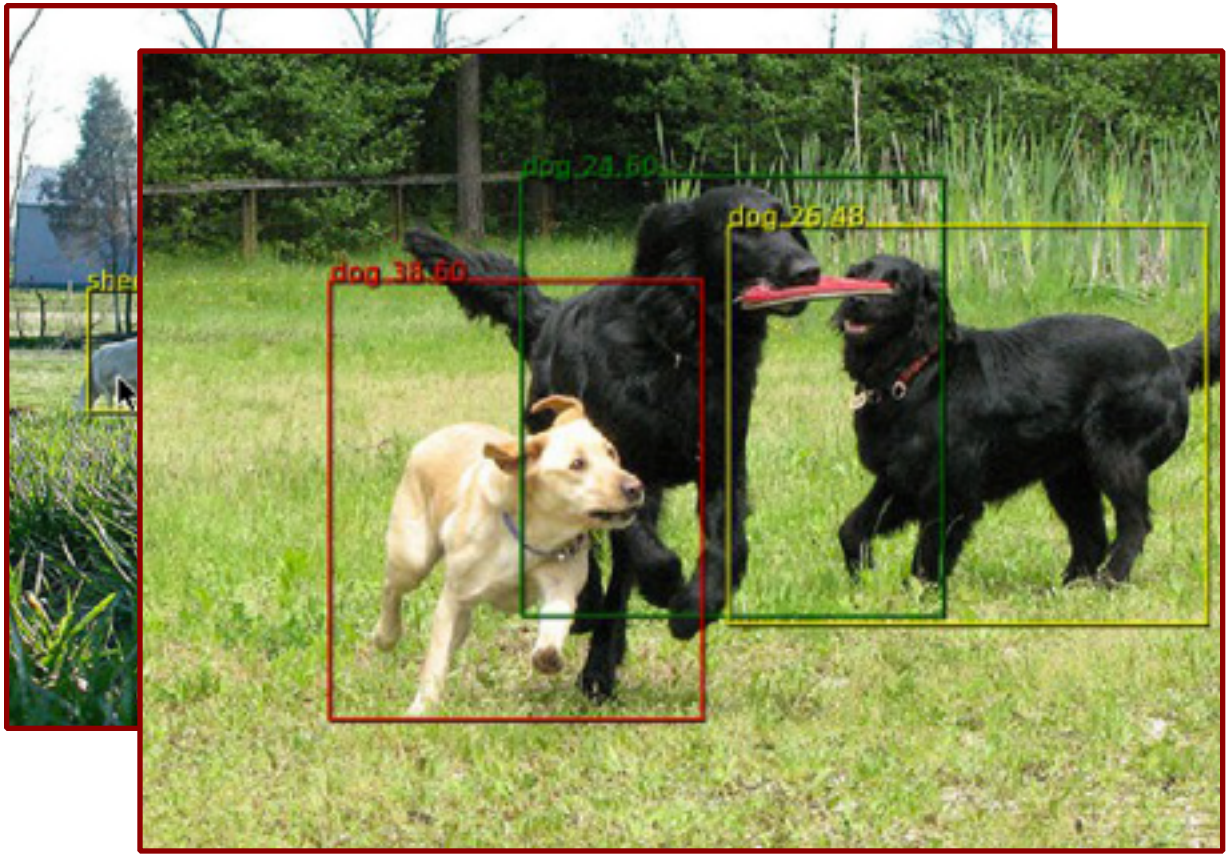

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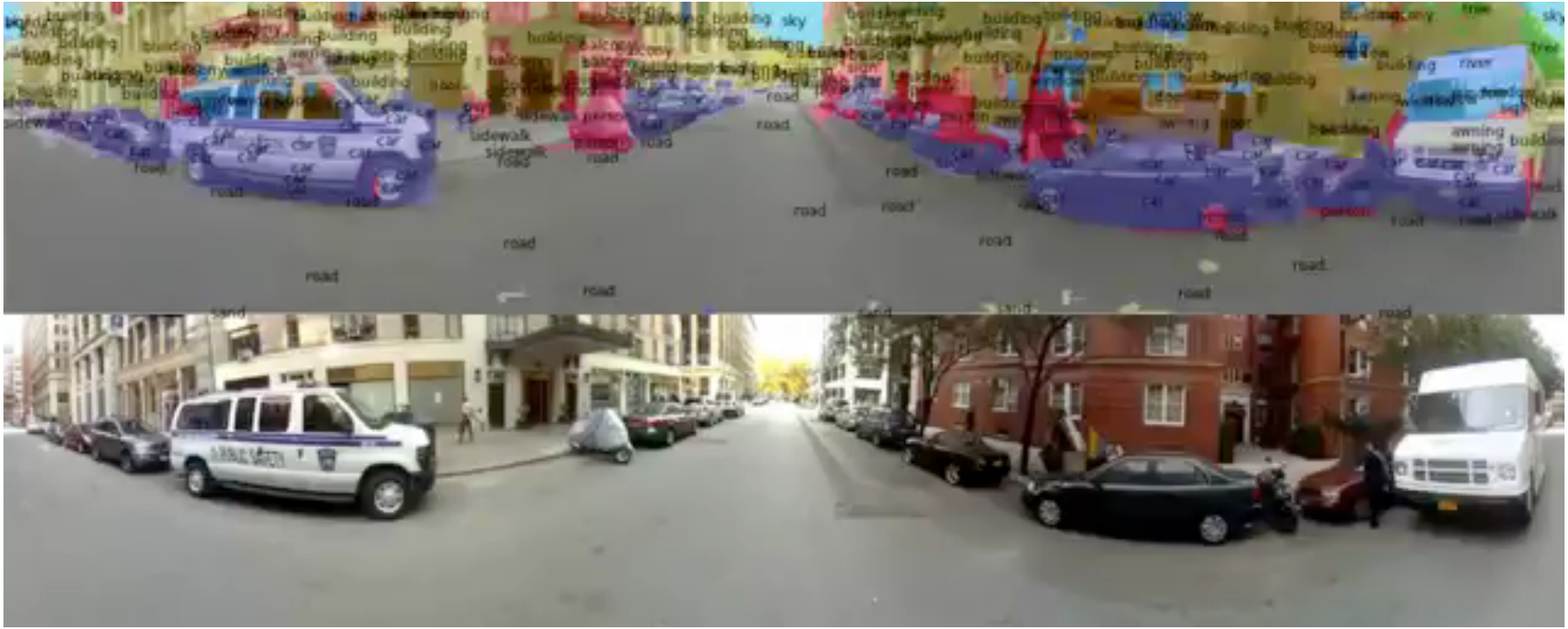
Example: Semantic segmentation



Farabet et al. (2012). ICML.

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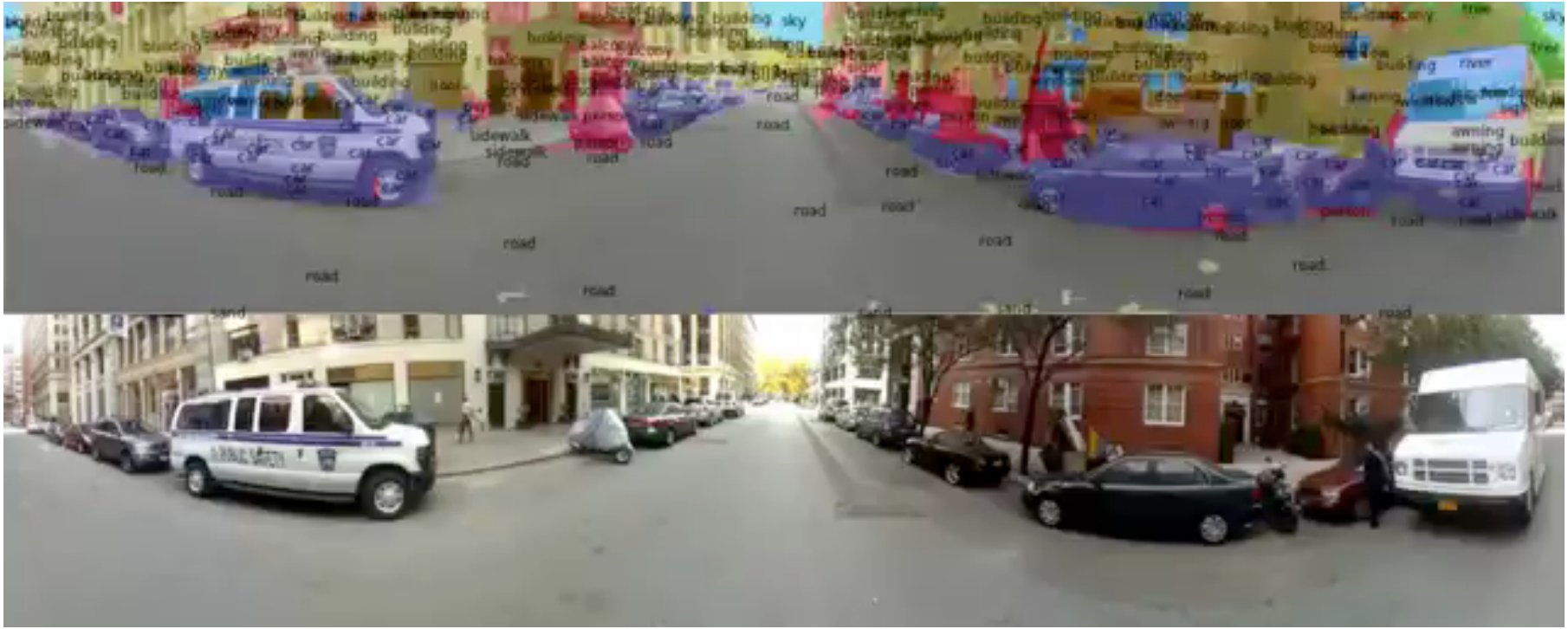

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Gatys et al. (2015). arxiv.

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Example: Deep dreaming

http://deepdreamgenerator.com

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Example: DQN playing Breakout

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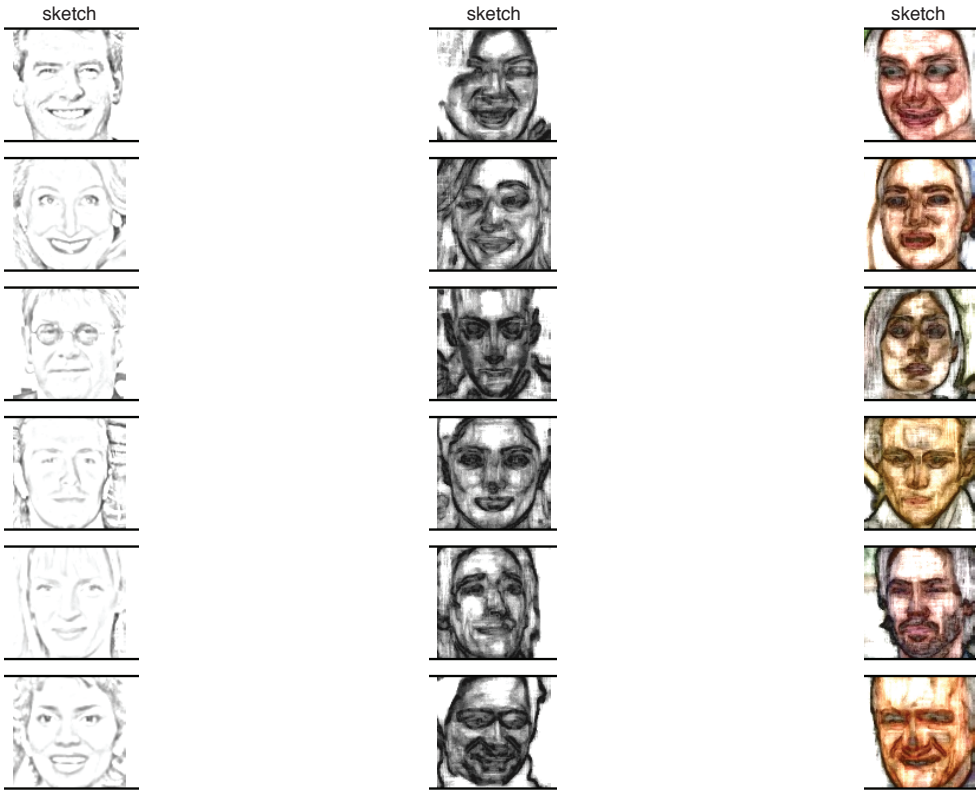
Example: Colorization and filling-in



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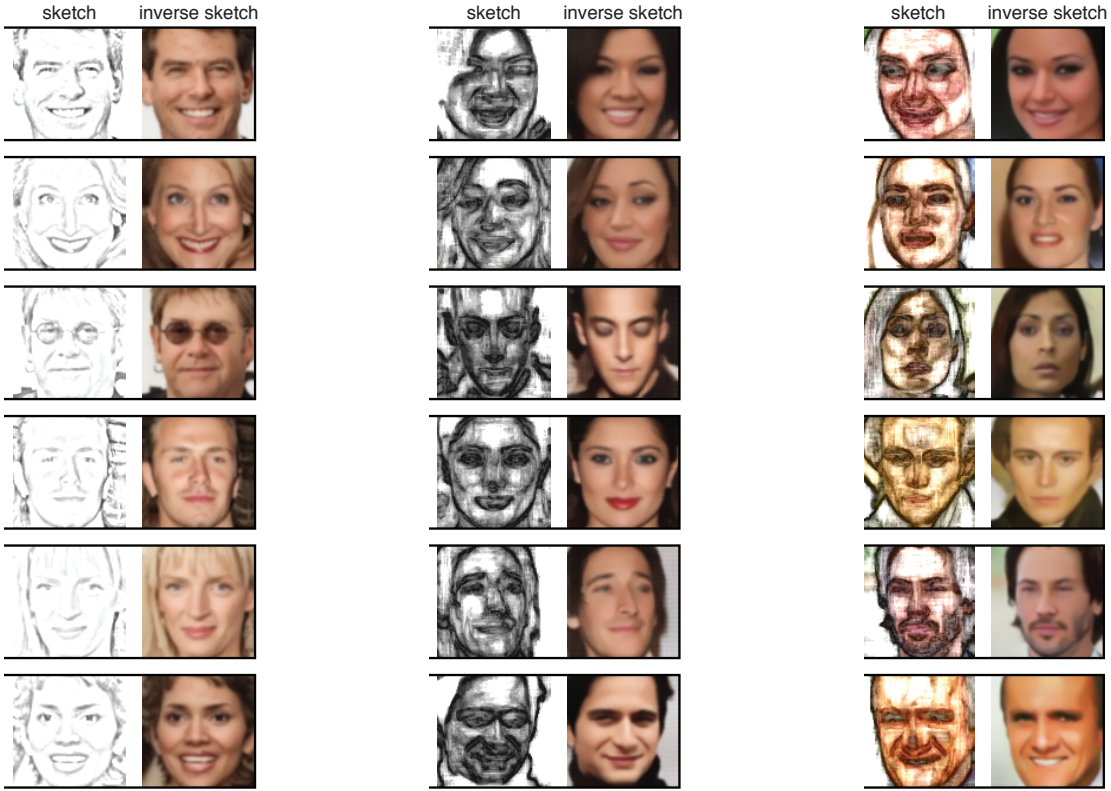

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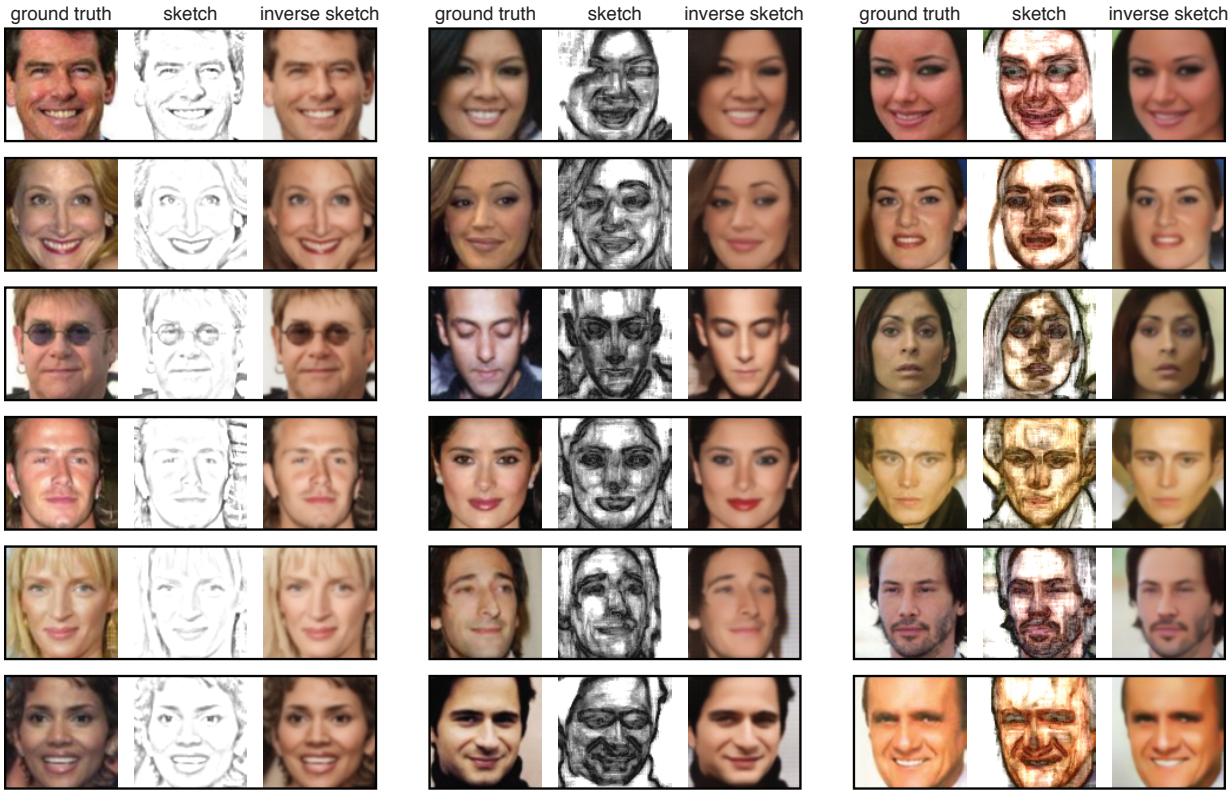

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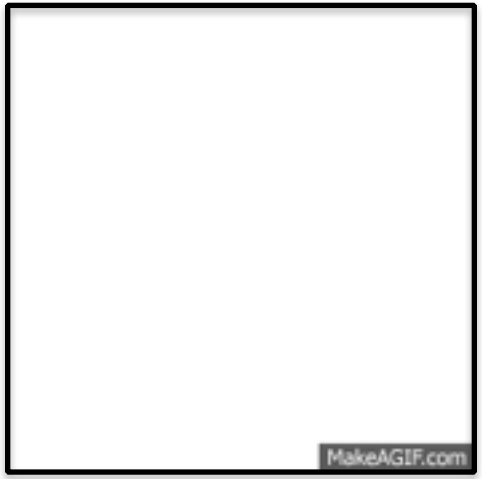

colour reconstruction

grayscale reconstruction

Examples: Colorization and filling-in

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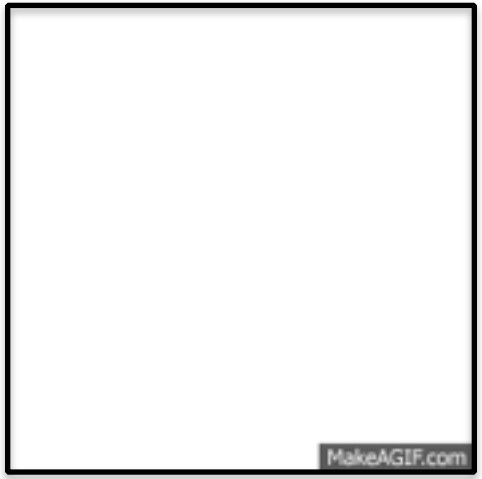

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Example: Generating music

Güçlütürk, Güçlü, van Lier, van Gerven. (2016). arxiv.

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- fMRI measures local changes in blood-oxygen-level dependent hemodynamic responses to sensory stimulation.
- Any subset of the DNN representations that emerge from this hierarchy of nonlinear transformations can be used to probe neural representations by comparing DNN and fMRI responses to the same sensory stimuli.
- Considering that the sensory systems are biological neural networks that routinely perform the same tasks as their artificial counterparts, it is not inconceivable that DNN representations are suitable for probing neural representations.

Probing neural representations with DNNs

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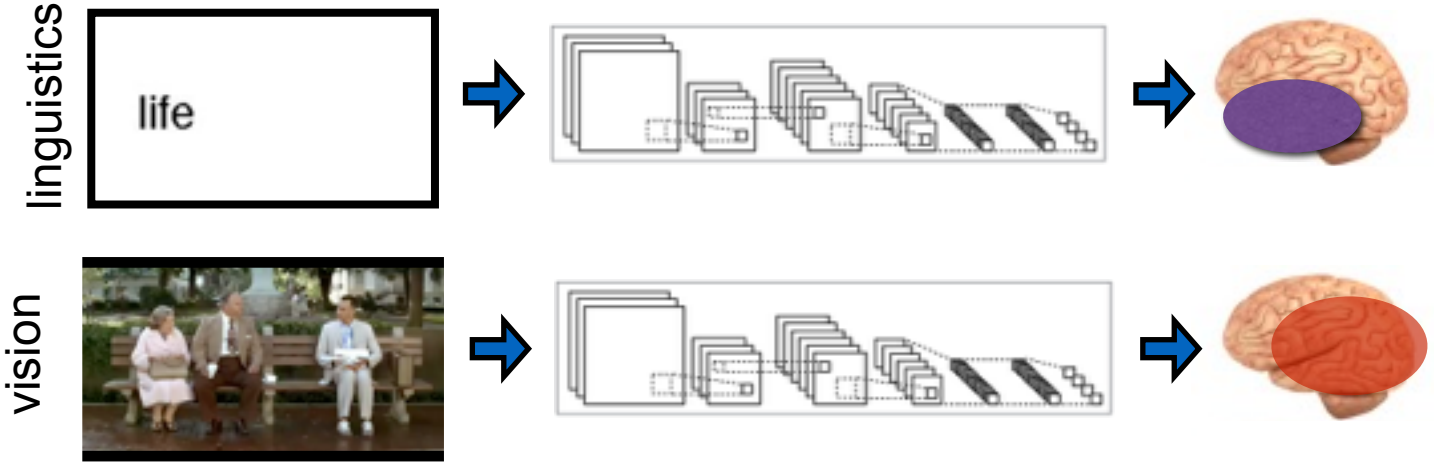

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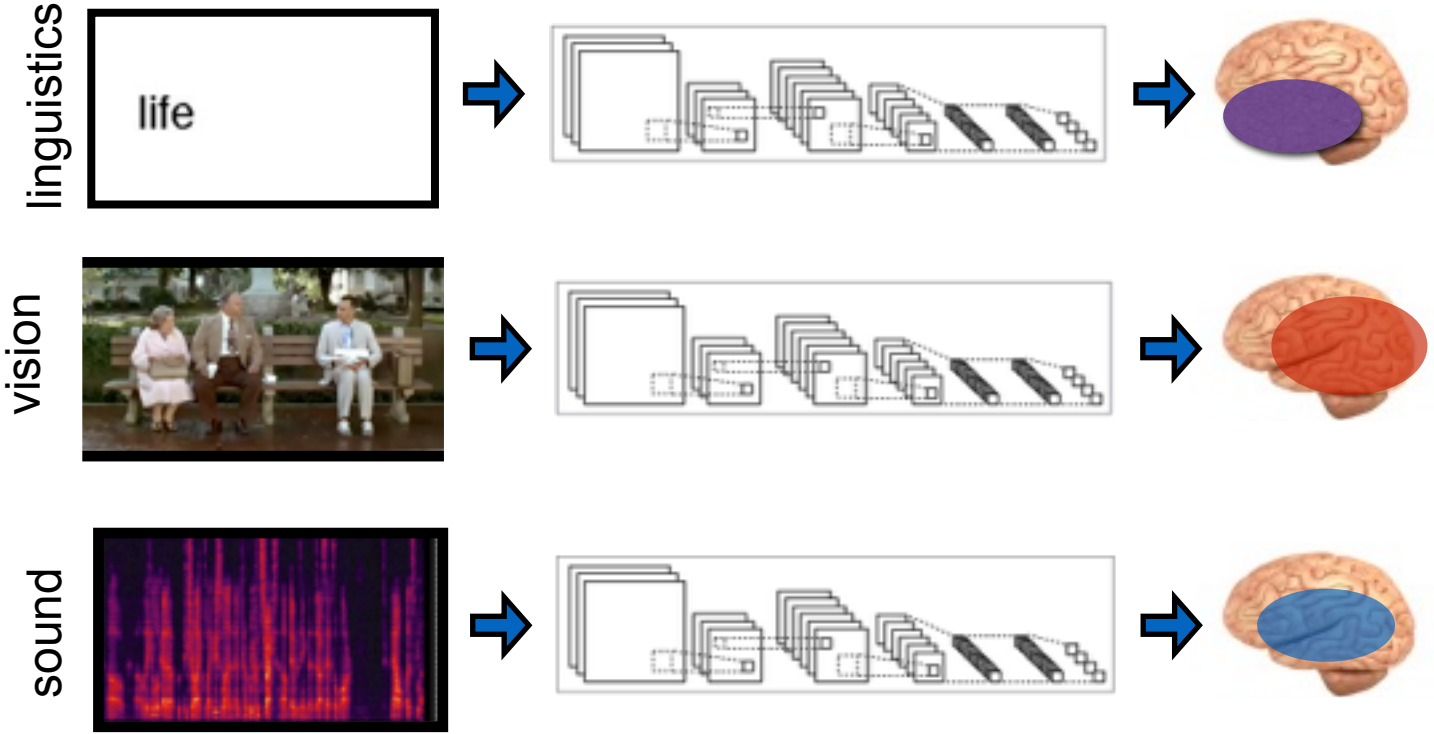
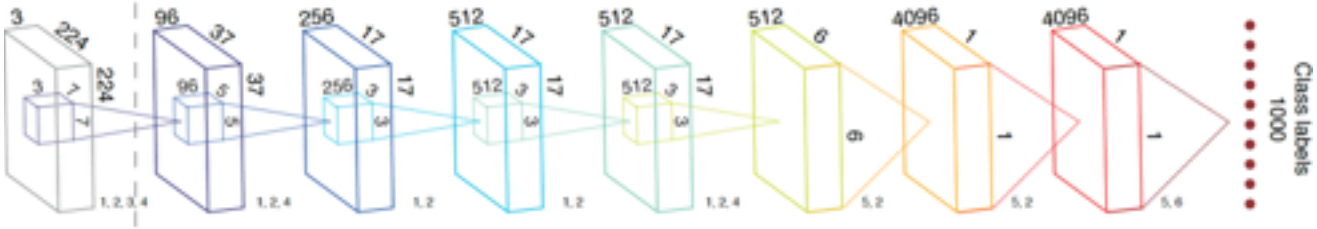


Güçlü, U., van Gerven, M., 2015. Neuroimage. In Press; Güçlü, U., van Gerven, M.A.J., 2015. Arxiv.

DNN-based encoding model



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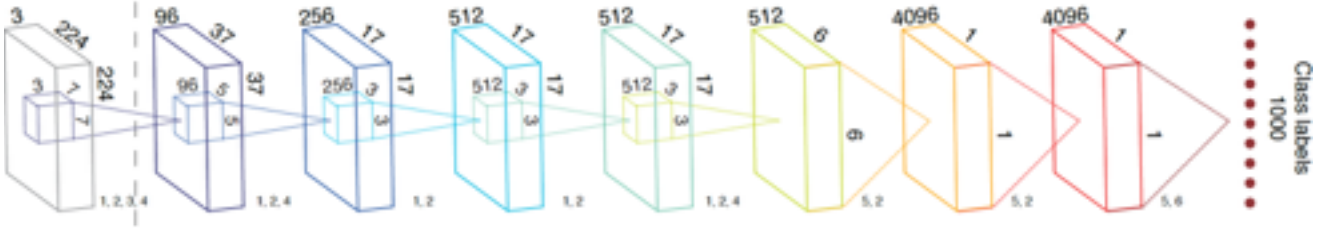

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- Model of the ventral stream

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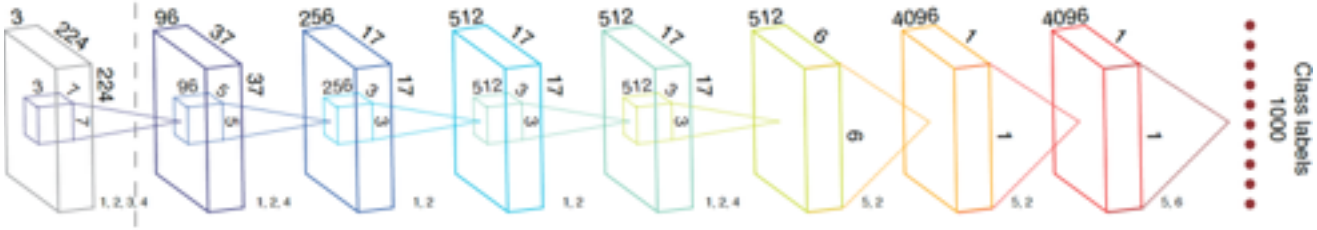

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- Eight layers of filters tiled in such a way that they respond to overlapping regions in the visual field

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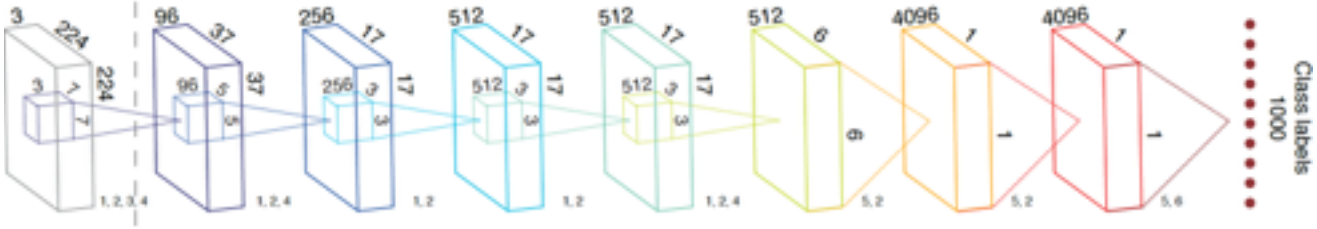

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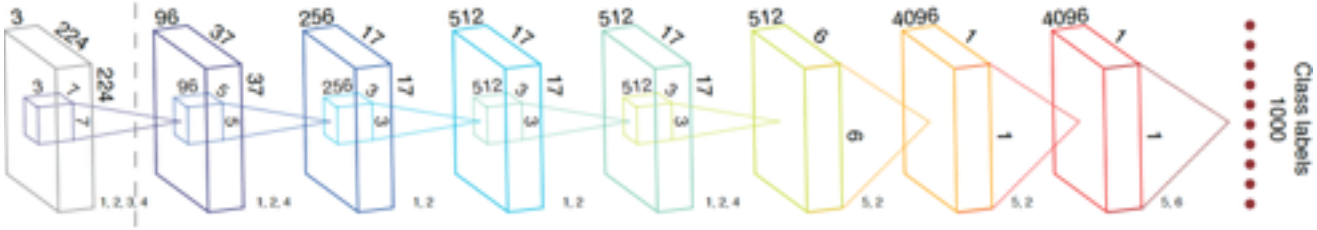

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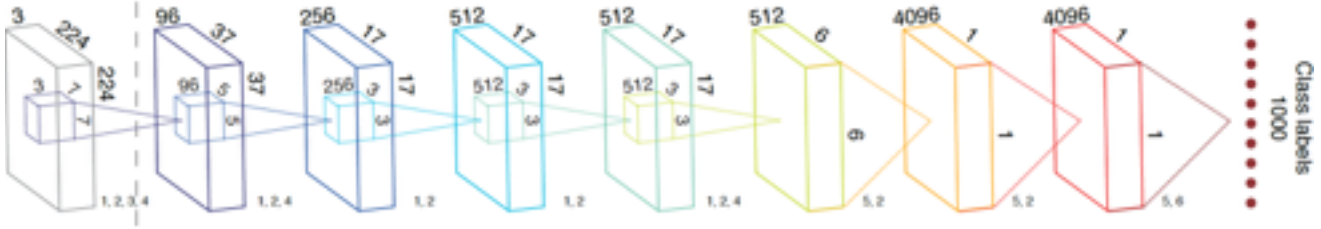

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- DNN features mapped to neural responses using kernel ridge regression

Deep neural network representations

- What stimulus properties are represented by artificial neurons?

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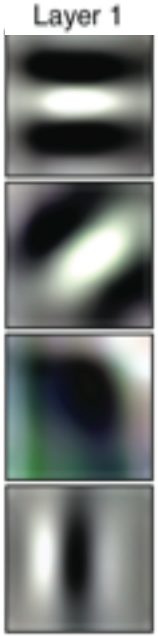

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Deep neural network representations

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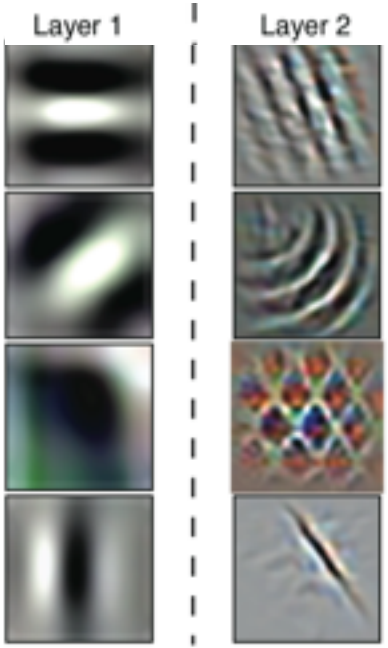

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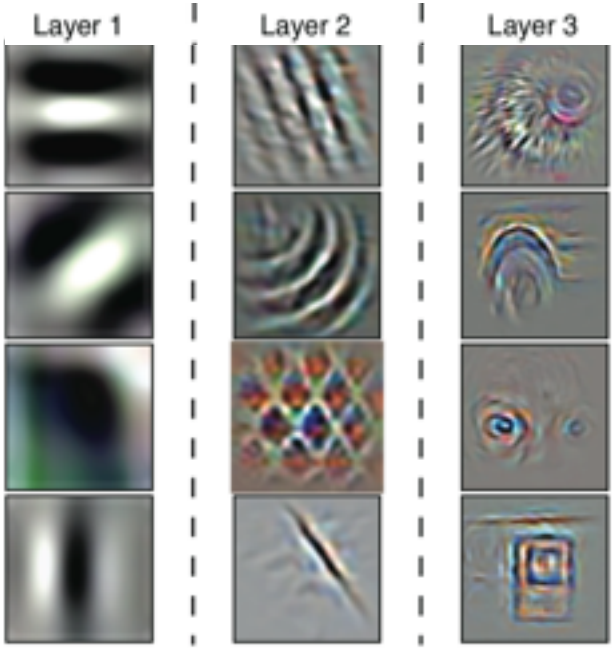

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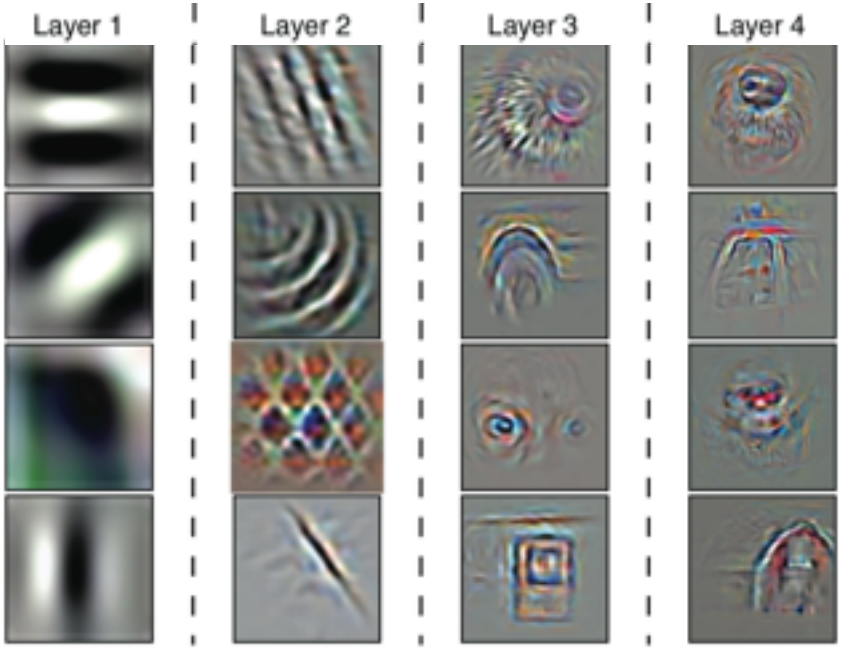

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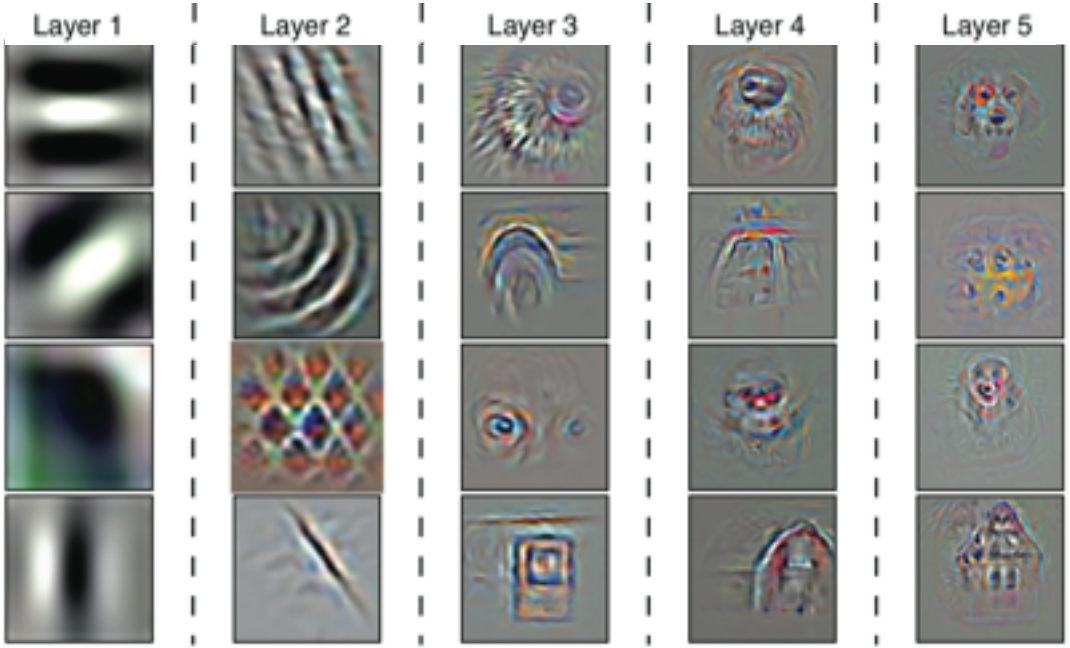

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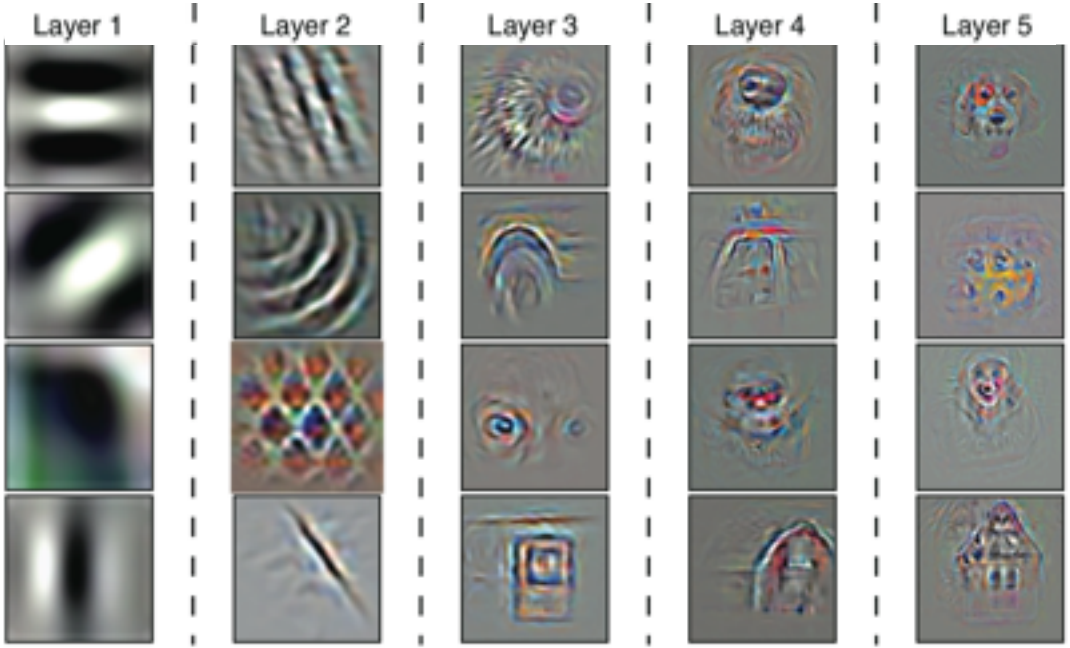
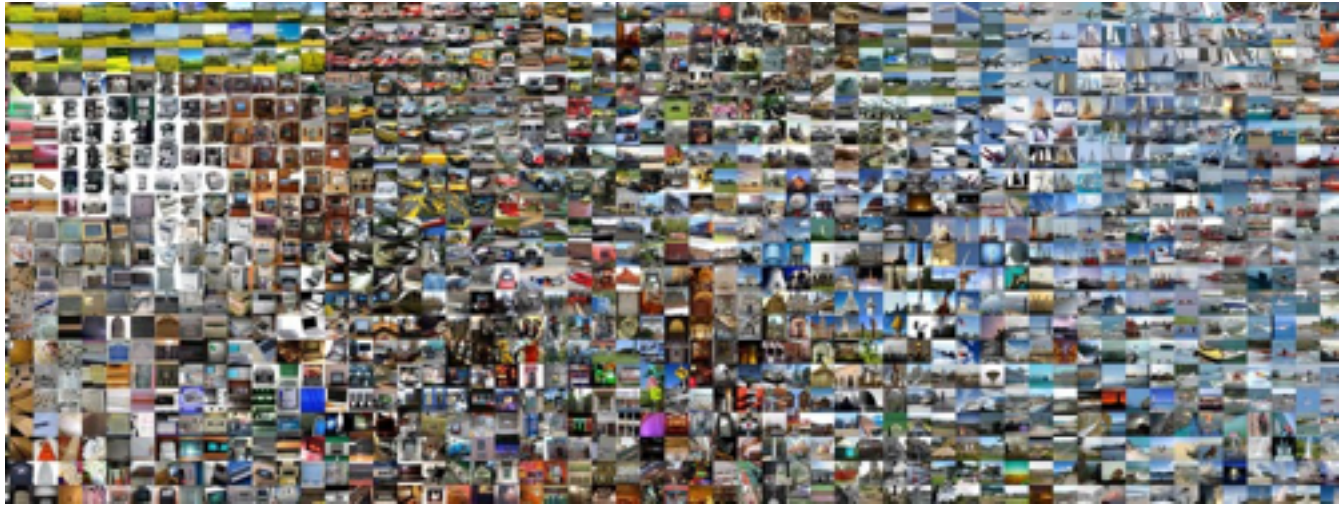


- Deep layers code for increasingly complex stimulus properties

Güçlü, U., & van Gerven, M. A. J. (2015). J. Neuroscience.

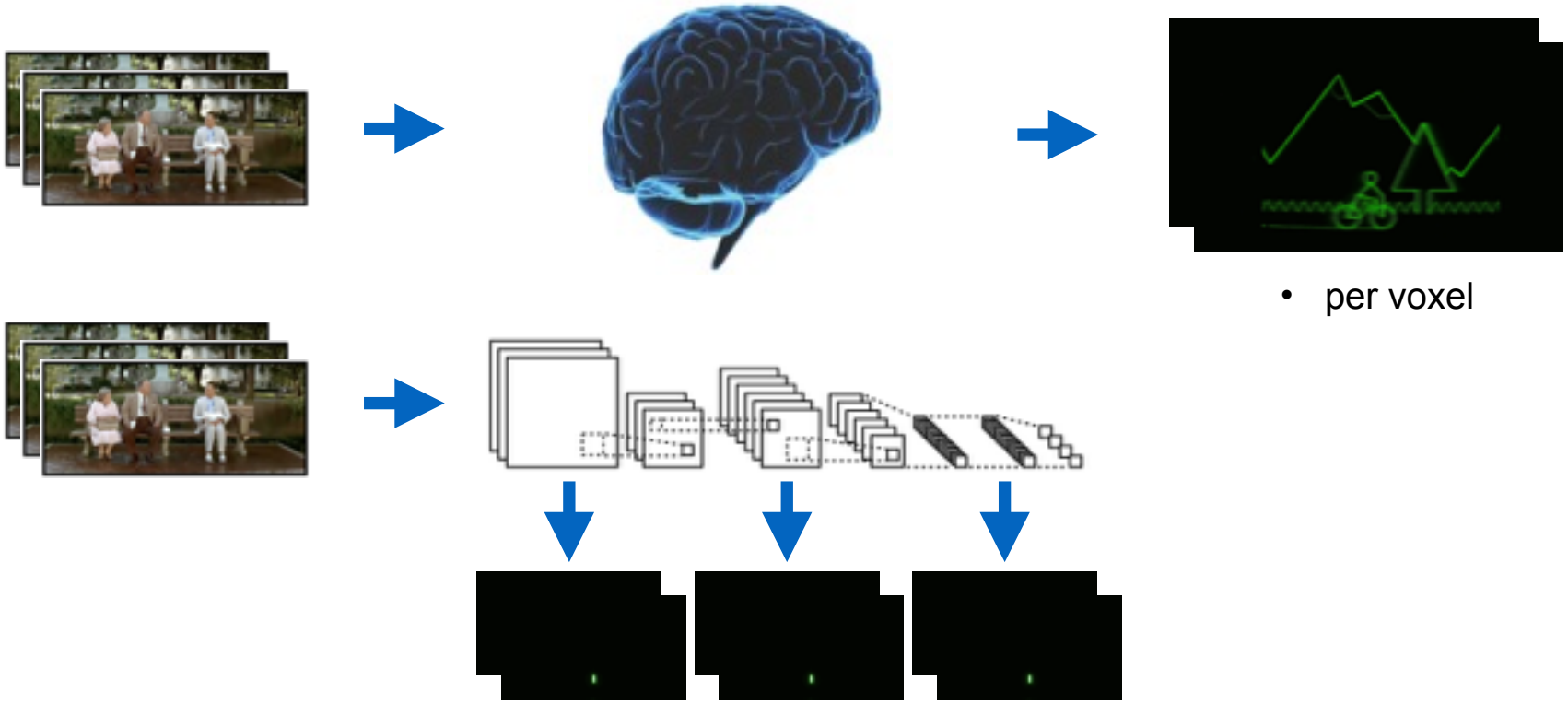
Recipe

- 1870 natural images



Güçlü, U., & van Gerven, M. A. J. (2015). J. Neuroscience.

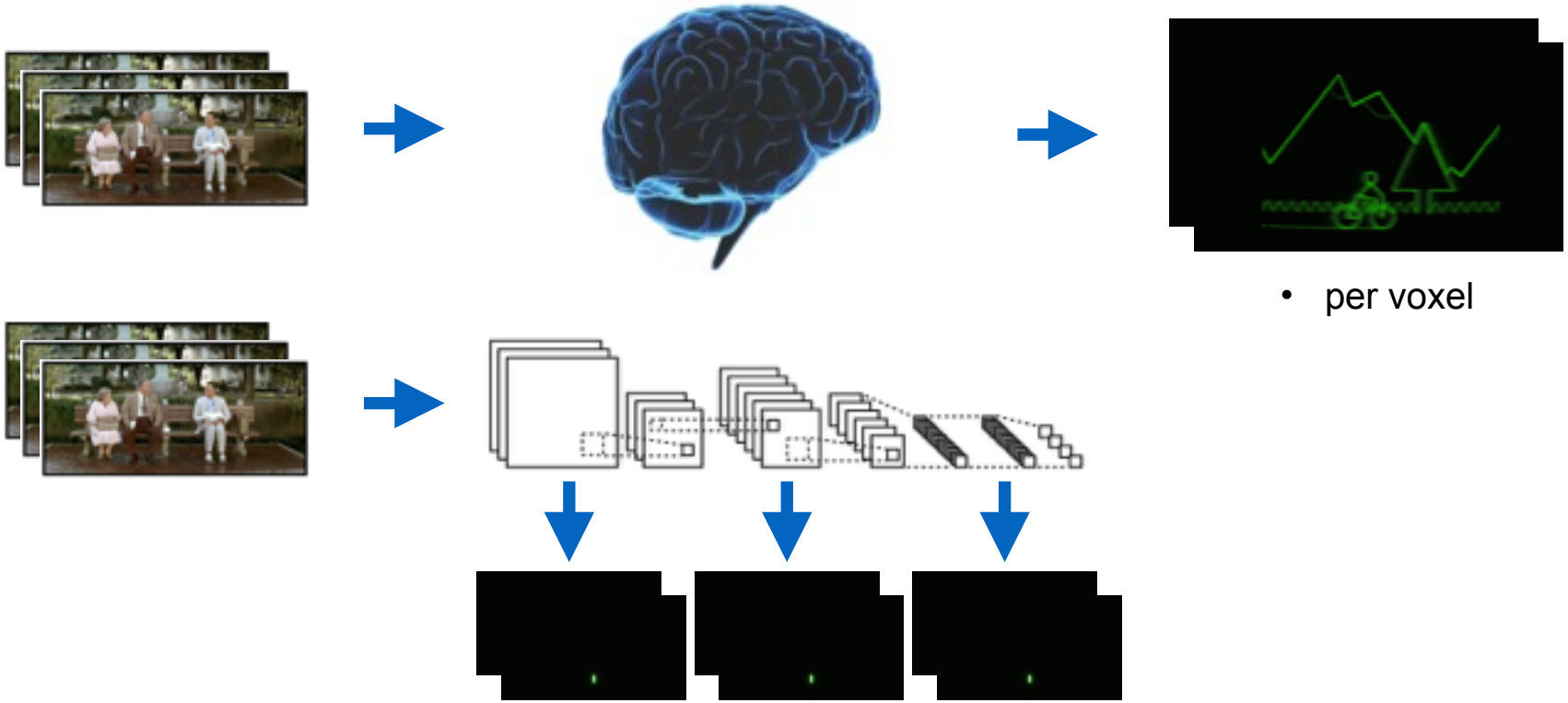
Recipe



- per voxel

- per layer

Recipe



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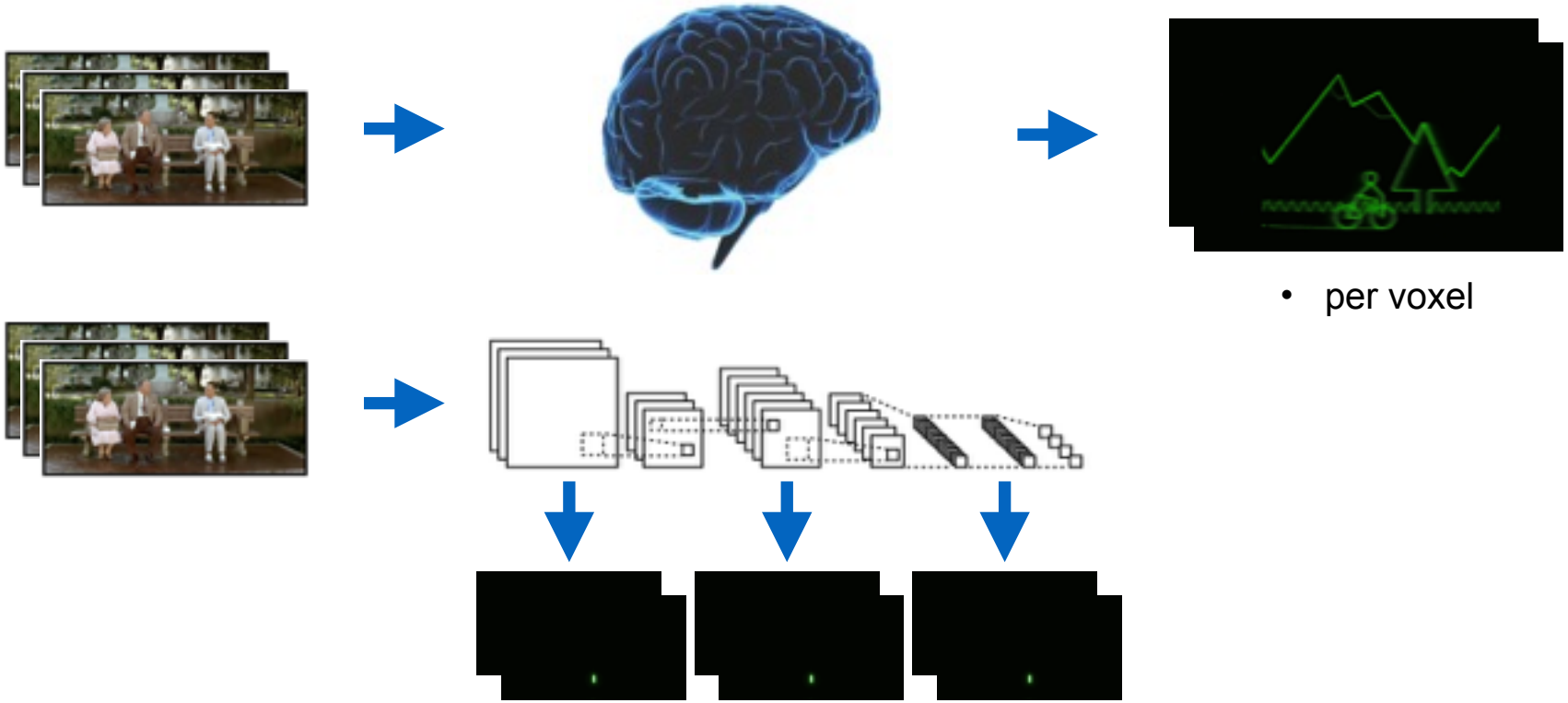

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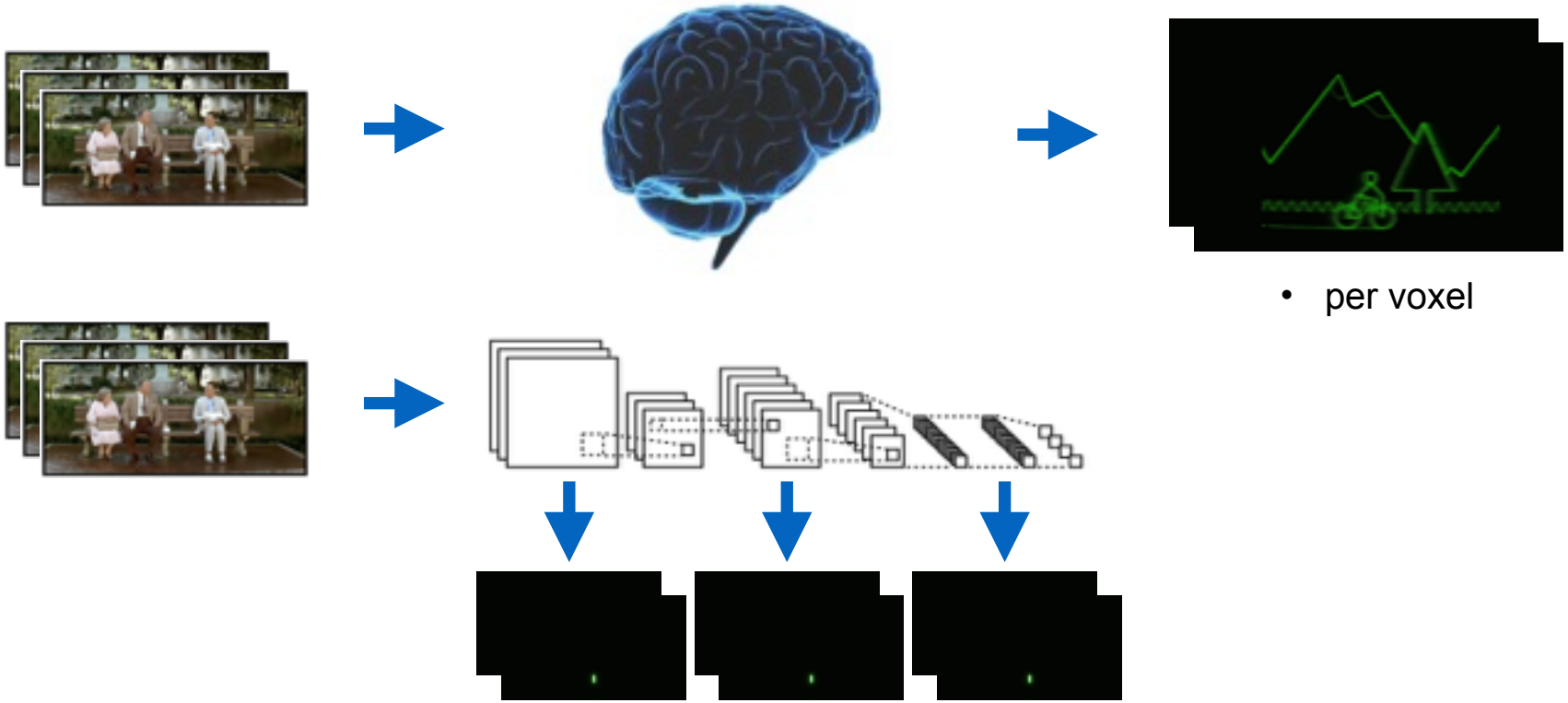

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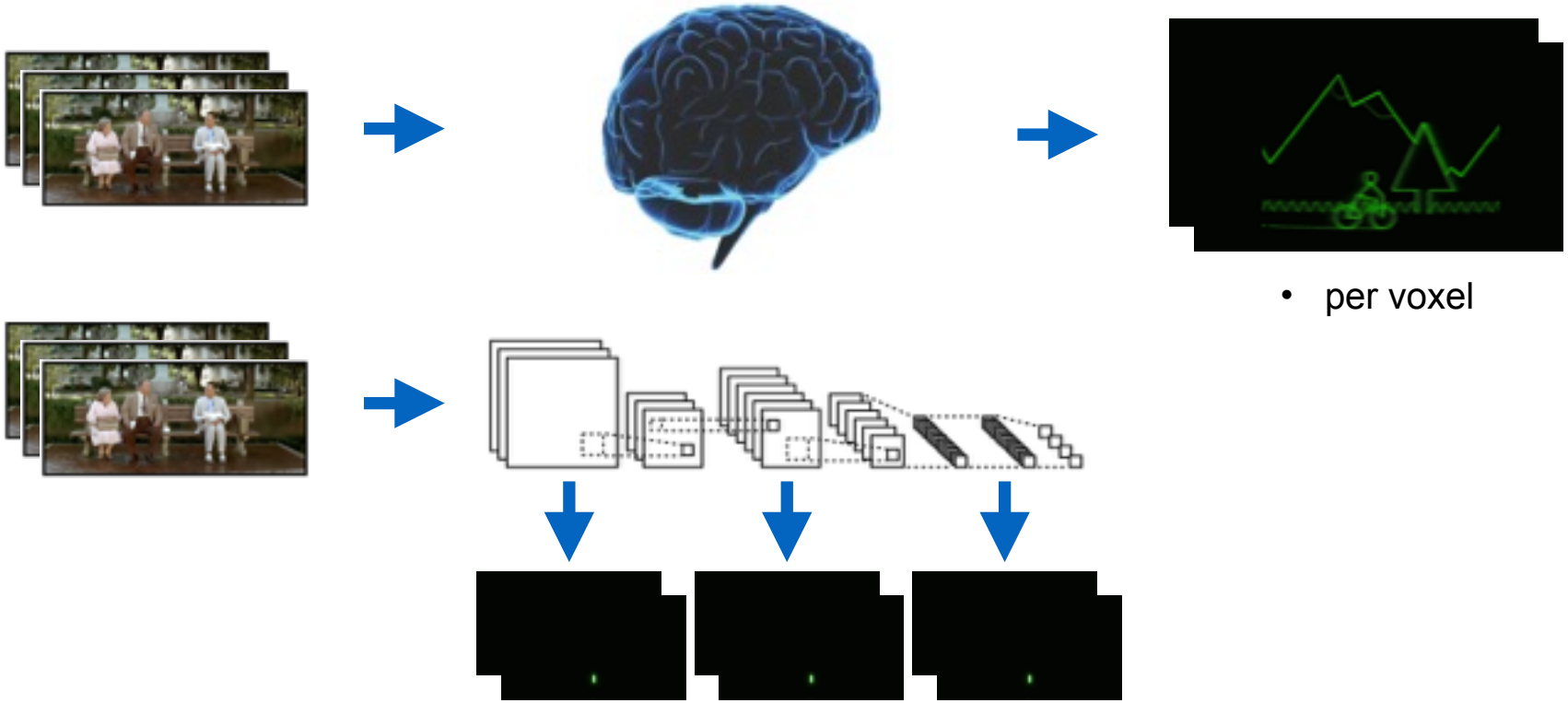

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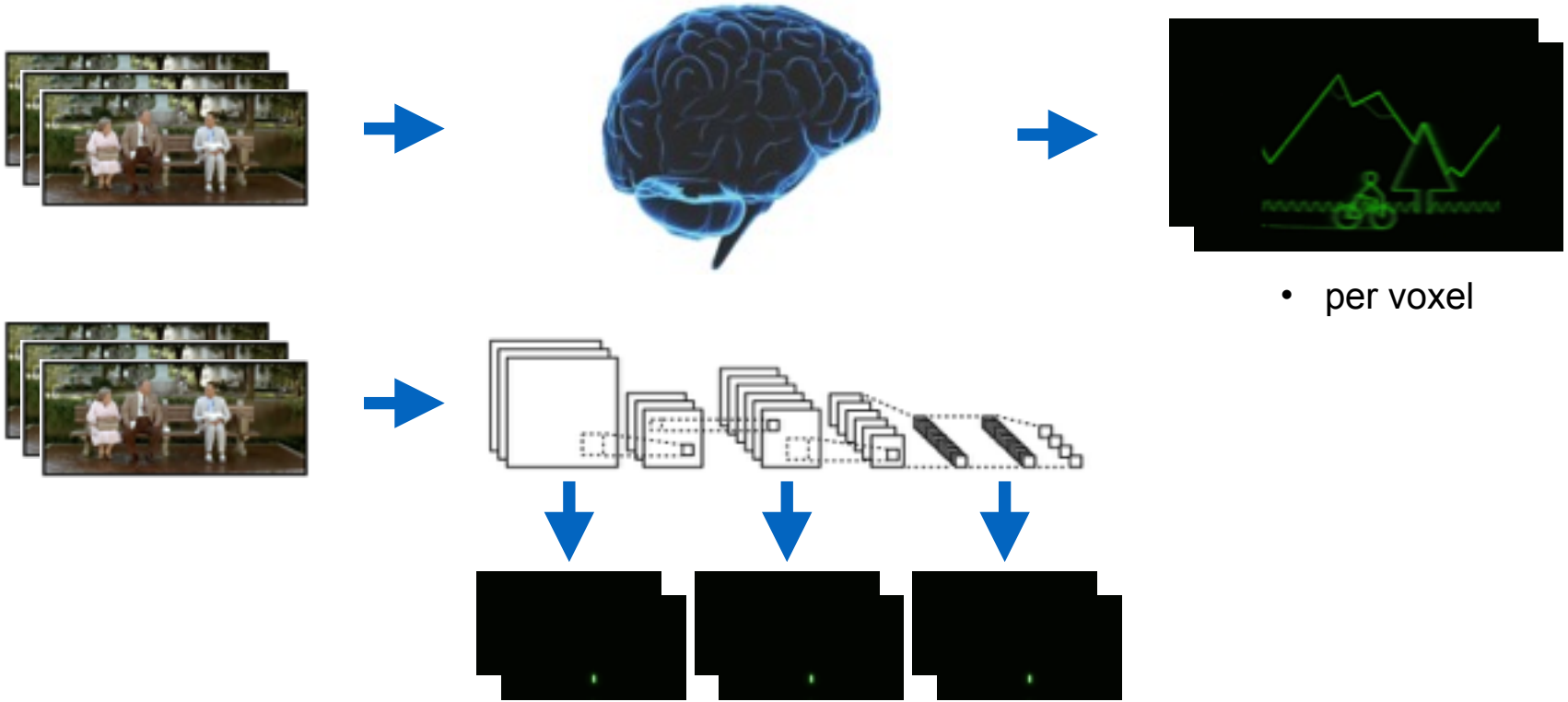
Recipe

- Present each image to the subjects & record activity of voxels



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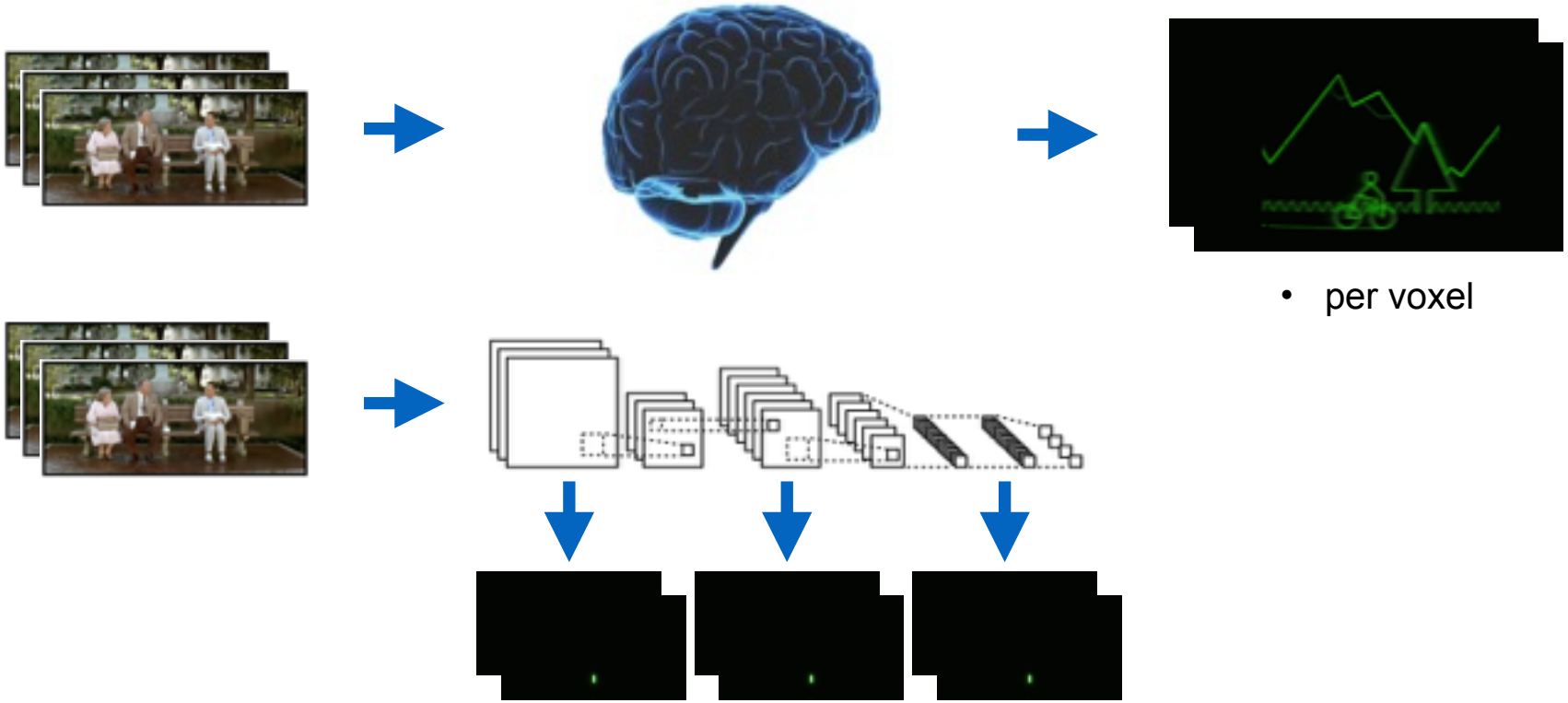

- per voxel

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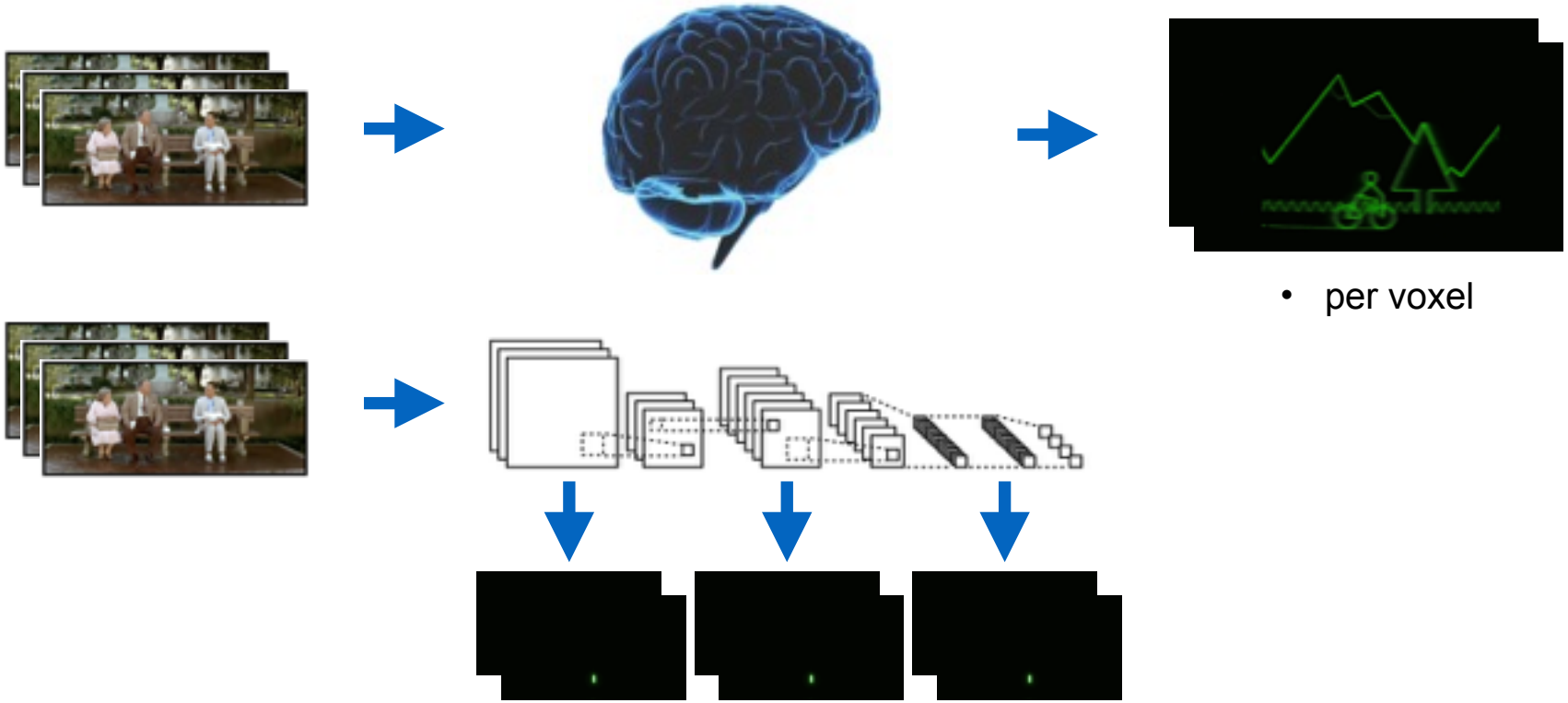
Recipe

- Present each image to the model & record activity of artificial neurons



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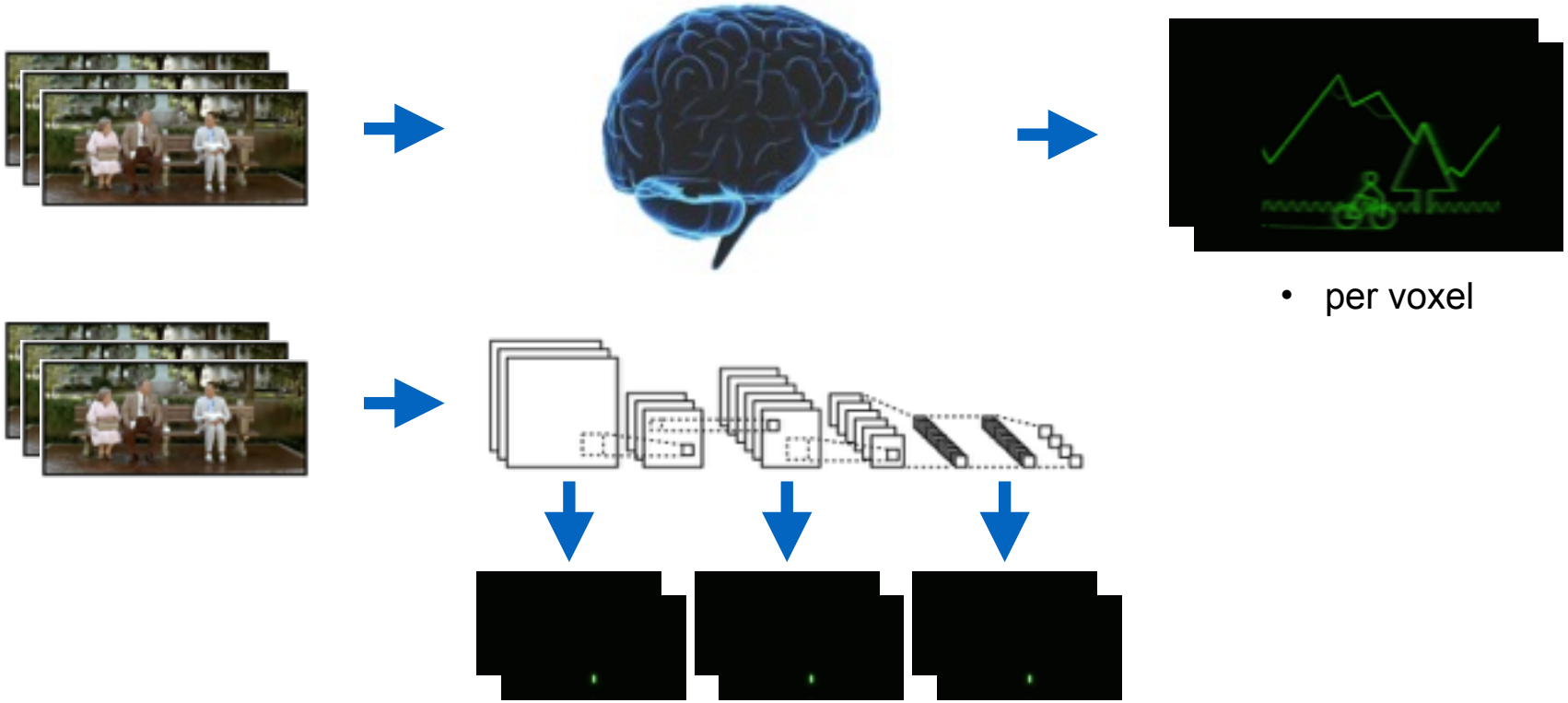

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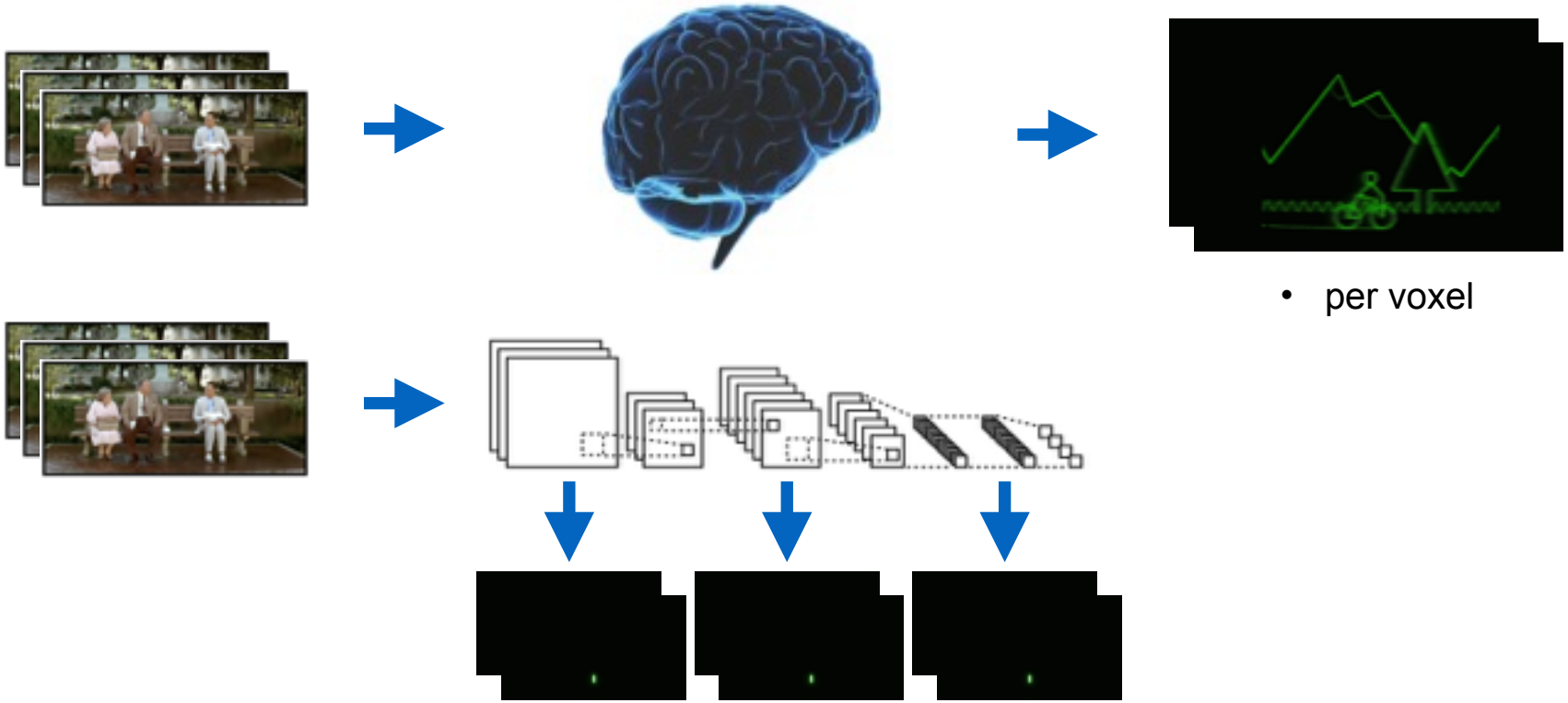
Recipe

- Regress activity of artificial neurons in each layer onto activity of voxels



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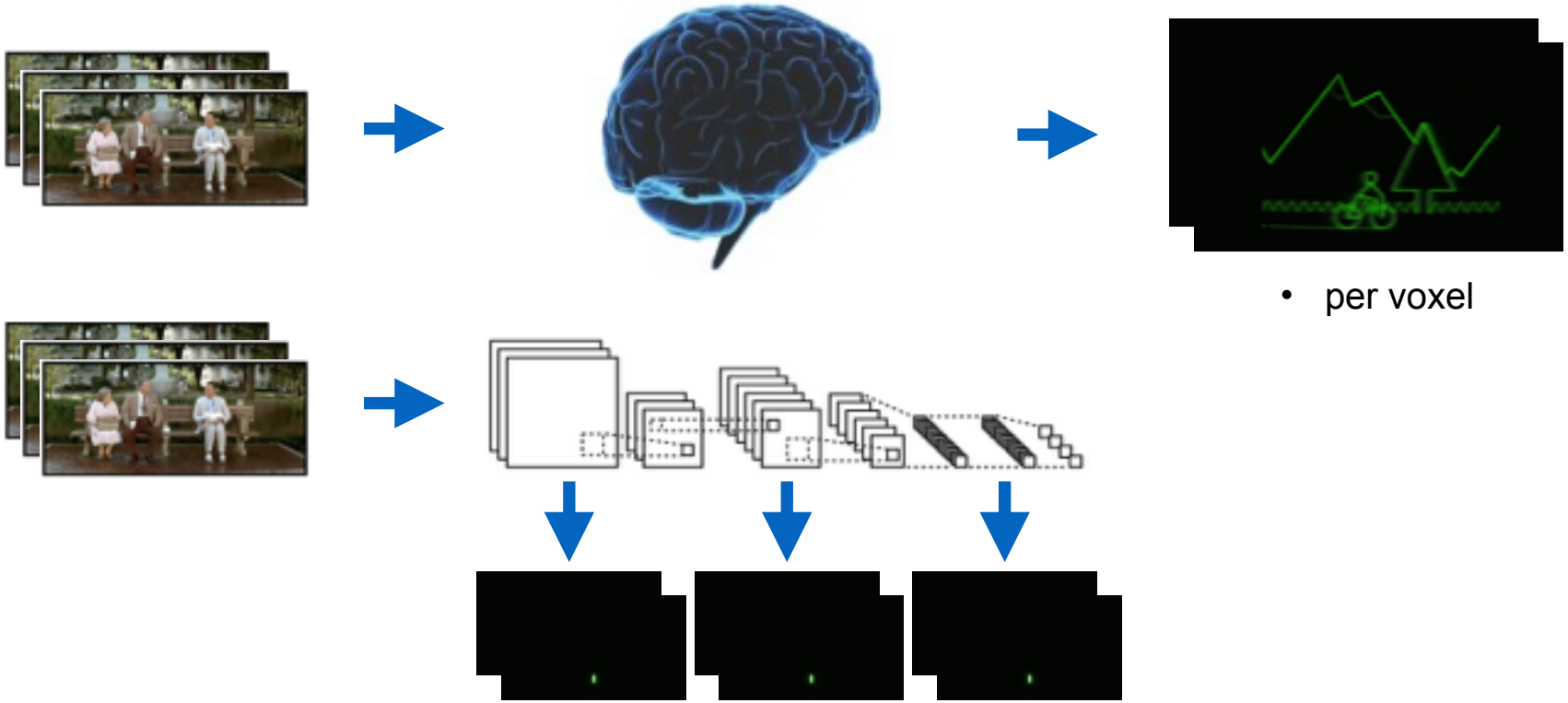

- per voxel

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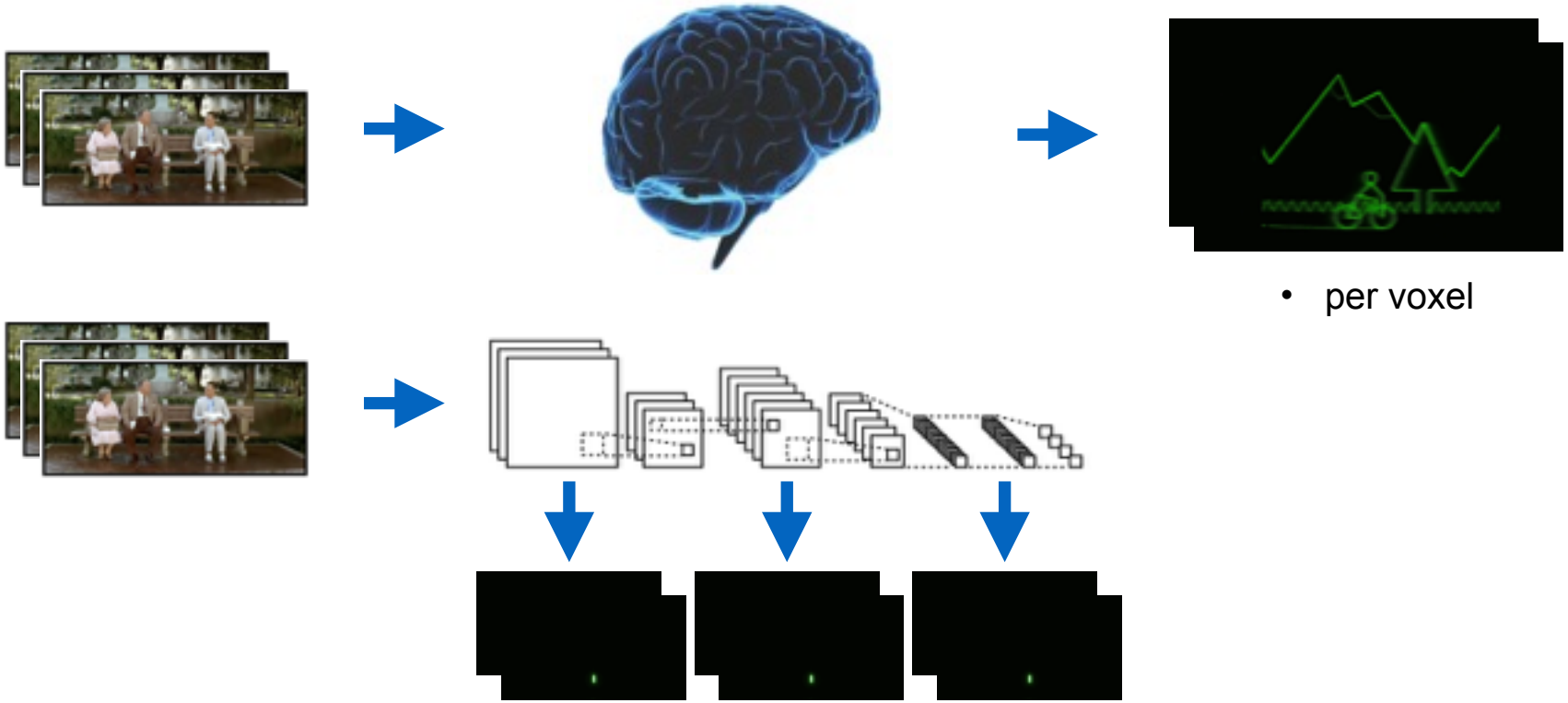
Recipe

- Assign each voxel to the layer that results in the best prediction accuracy



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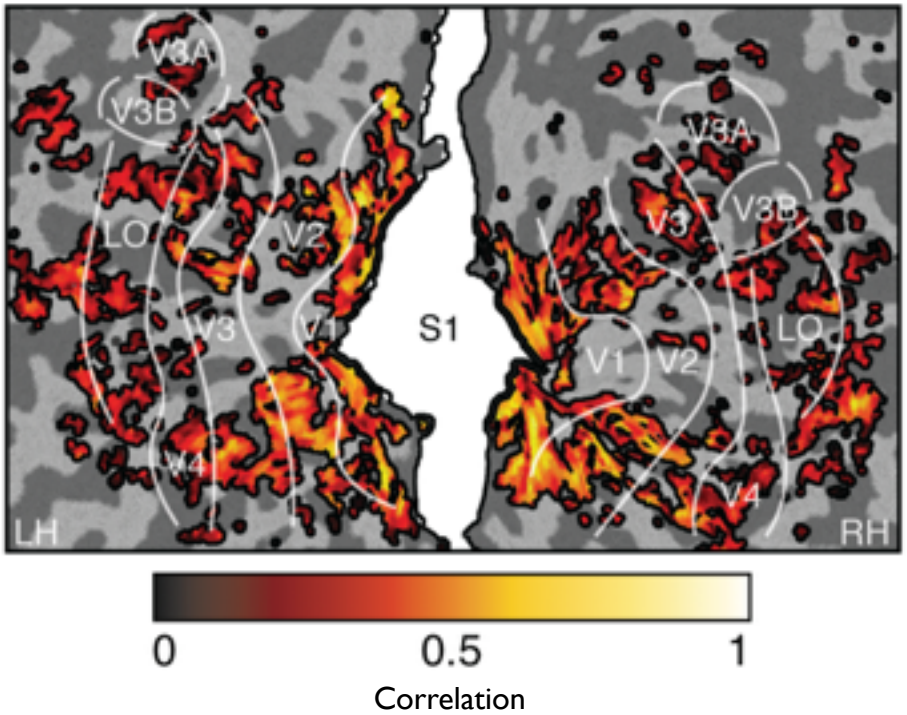
Encoding of voxel responses



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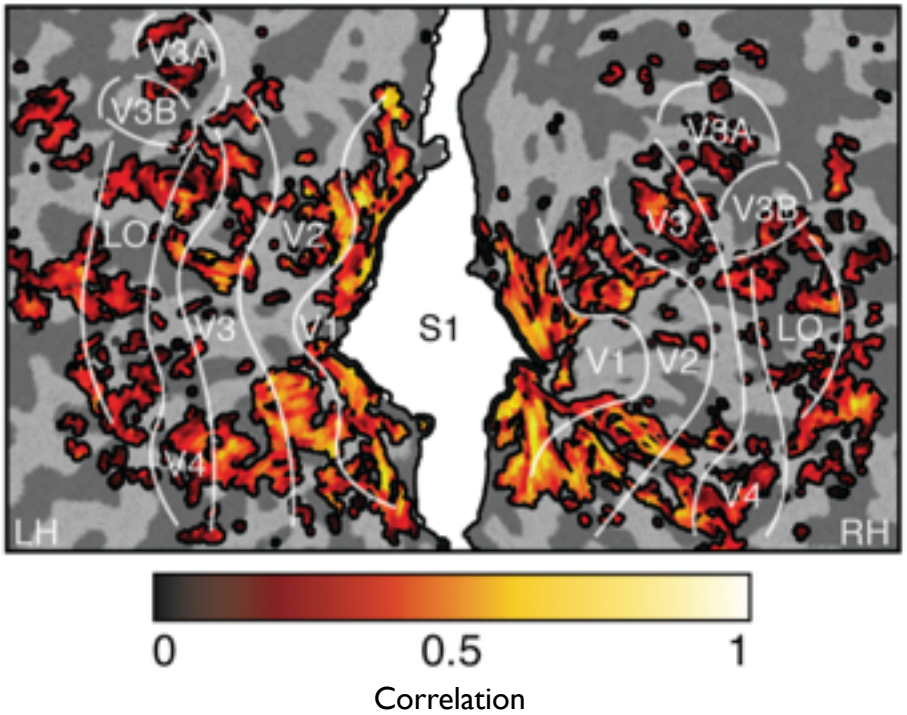
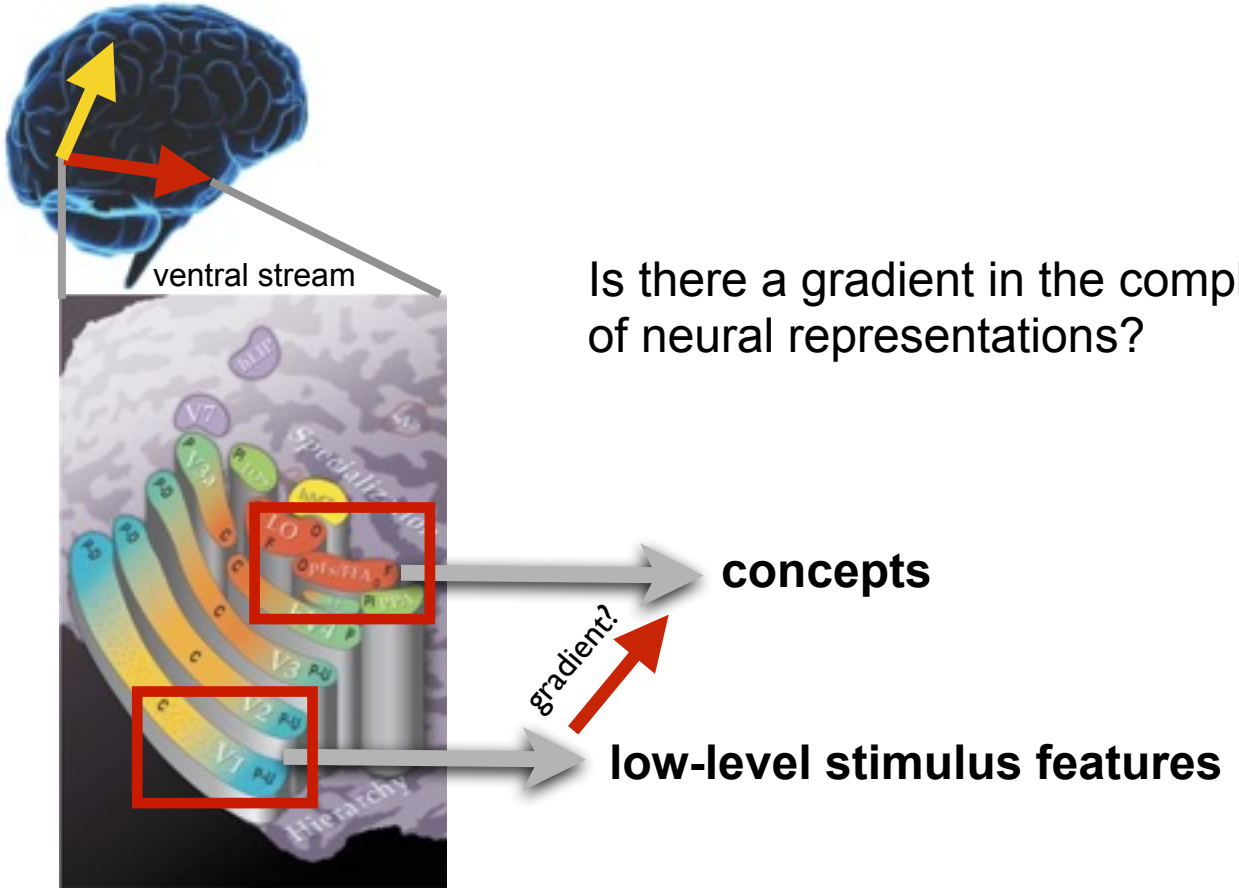


- High correlations between measured and predicted responses throughout the ventral stream

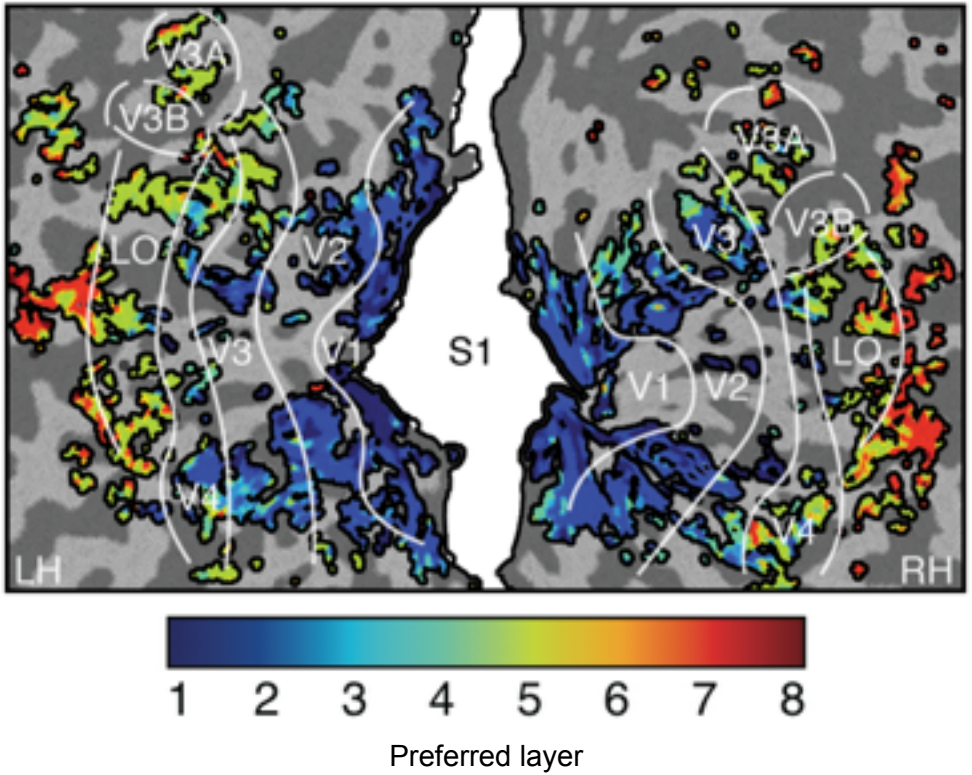
Güçlü, U., & van Gerven, M. A. J. (2015). J. Neuroscience.

From low-level stimulus properties to abstract concepts



Is there a gradient in the complexity of neural representations?

A representational gradient across the ventral stream



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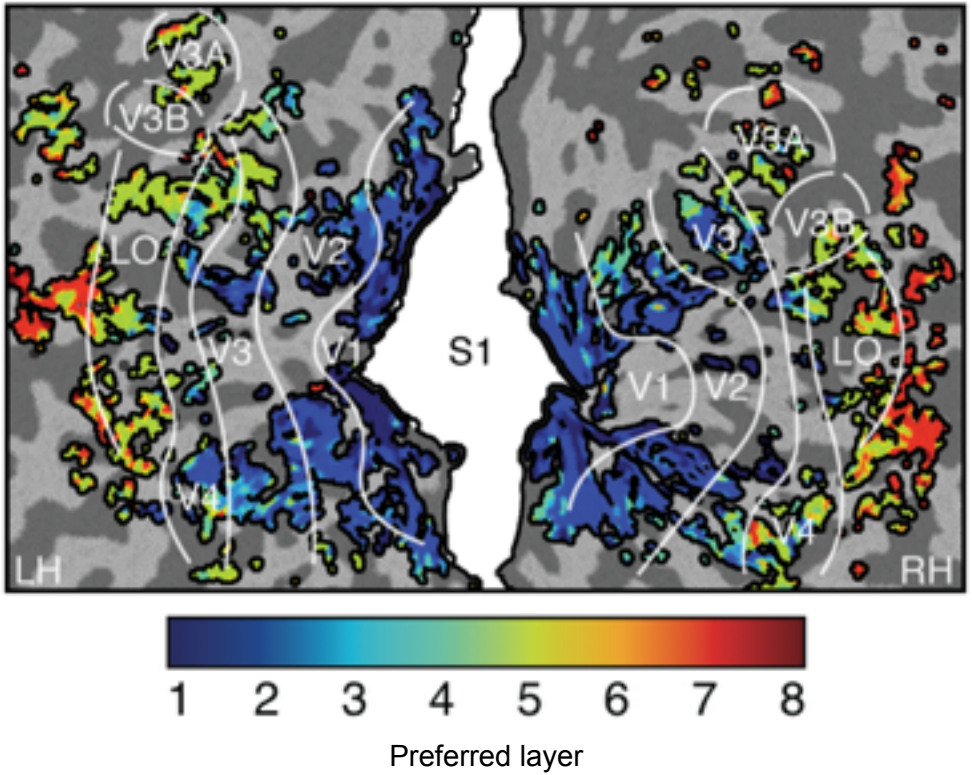

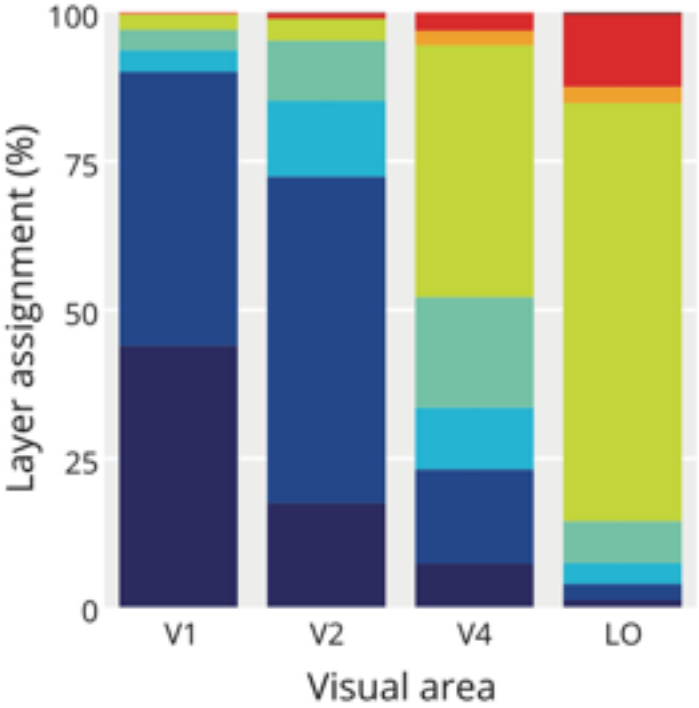

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Characterizing non-classical receptive fields

- For each feature we can compute properties such as complexity, invariance, and RF size

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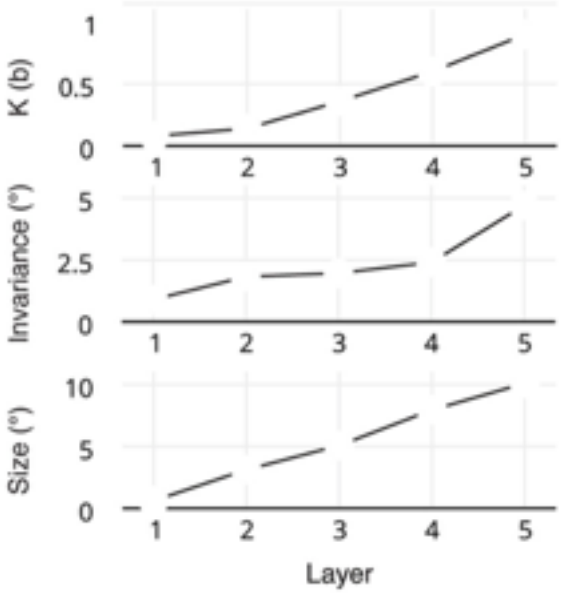
Layer-wise characterization



Characterization in terms of feature classes

- Features were manually assigned to low-level (blob, contrast, edge), mid-level (contour, shape, texture) and high-level (irregular pattern, object part, entire object) feature classes

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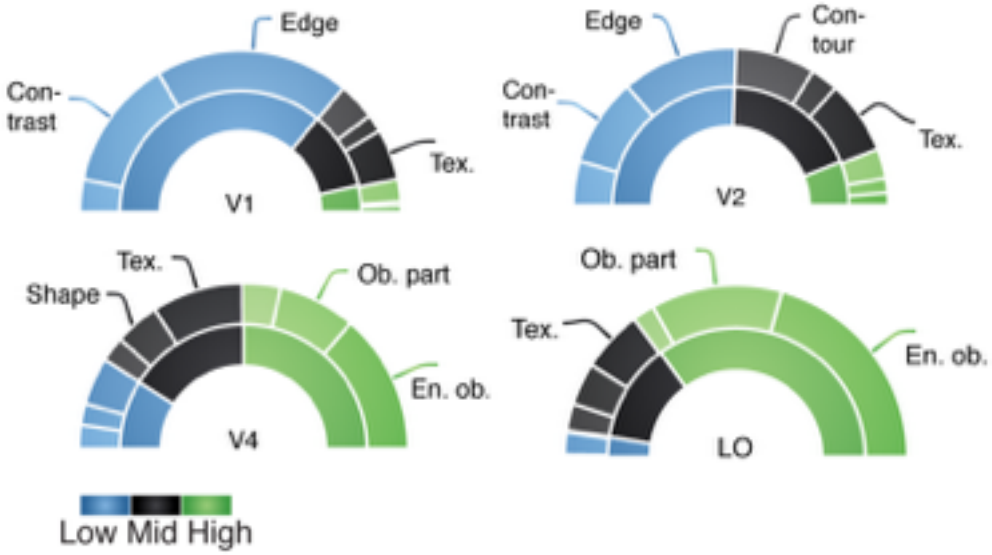

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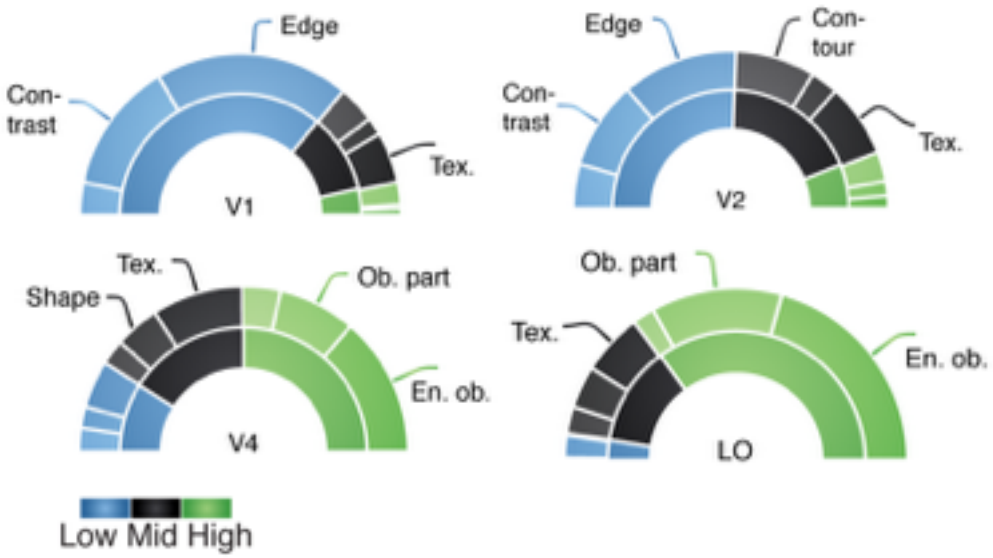
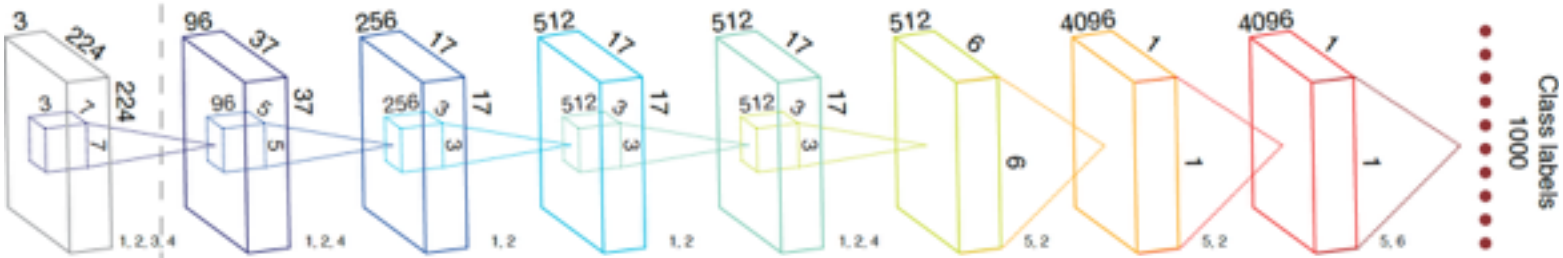
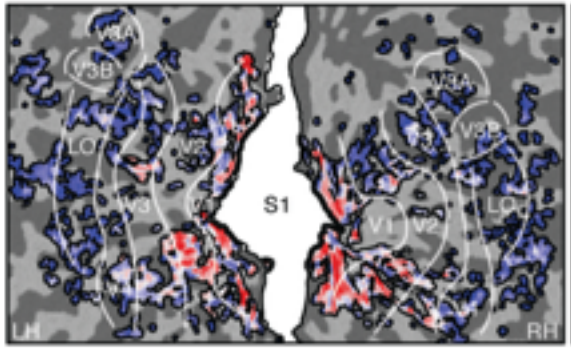


- Confirmation that more complex feature classes better predict downstream responses

Mapping low-, mid- and high-level features to the cortical sheet





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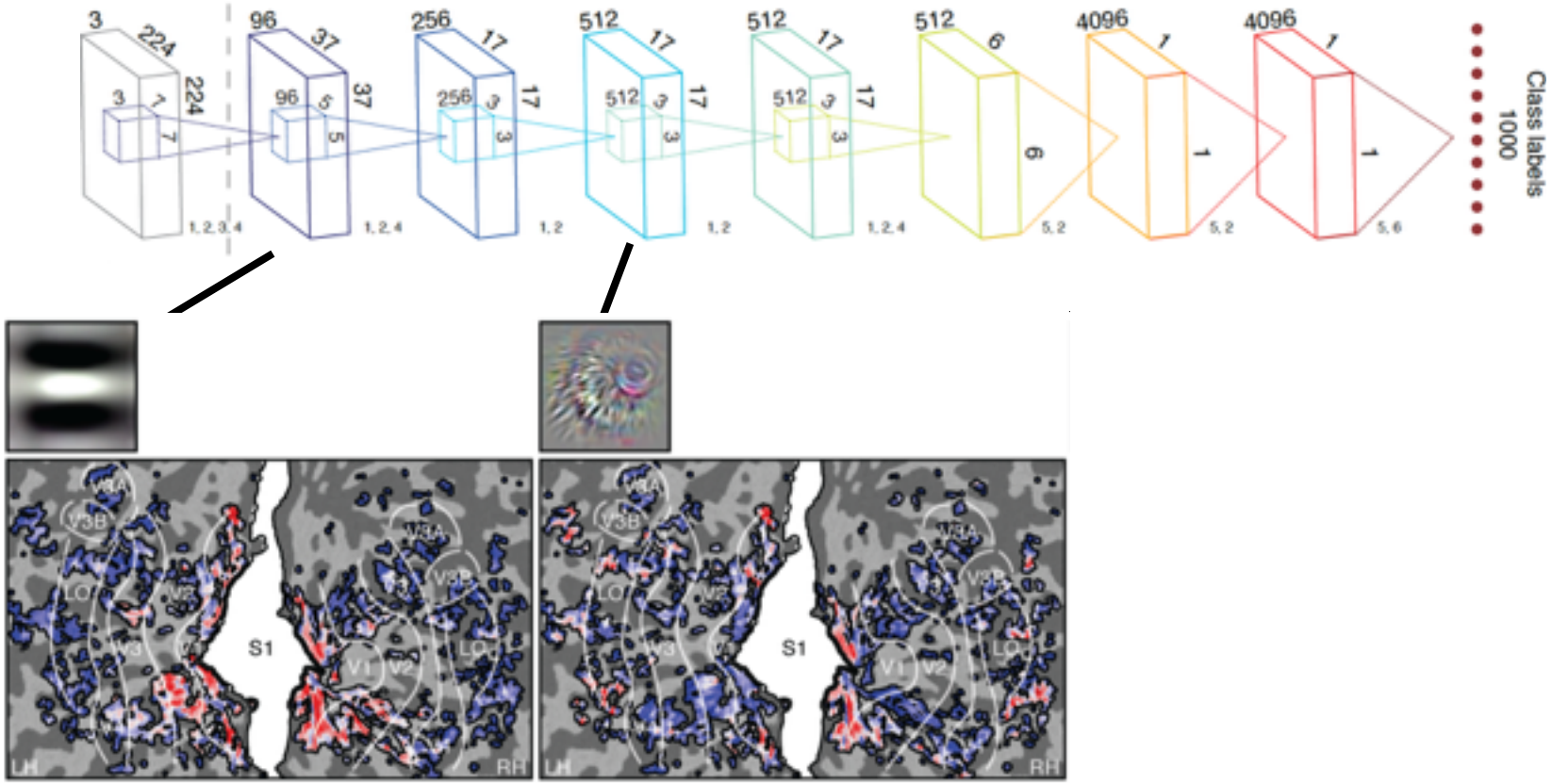

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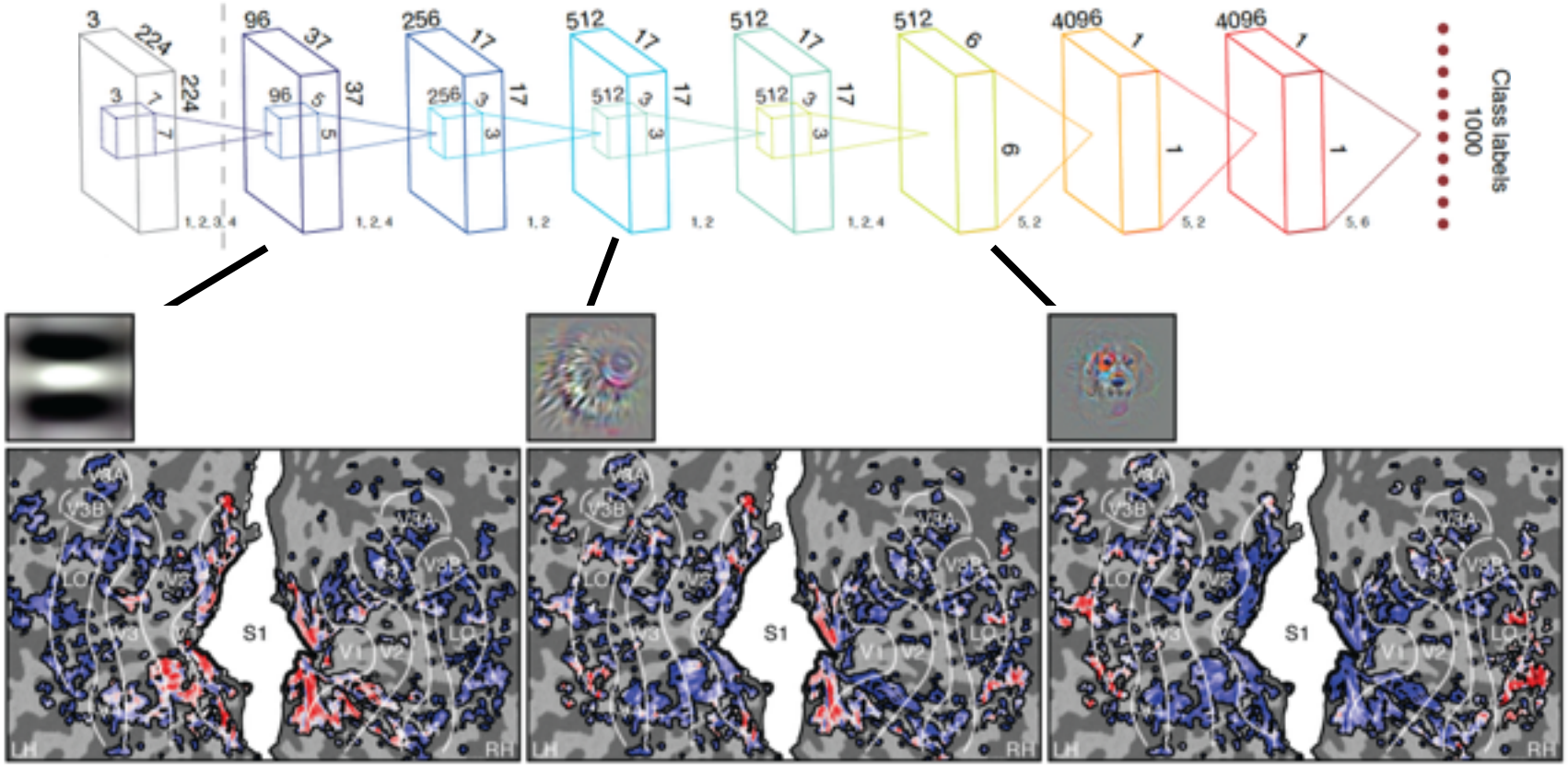

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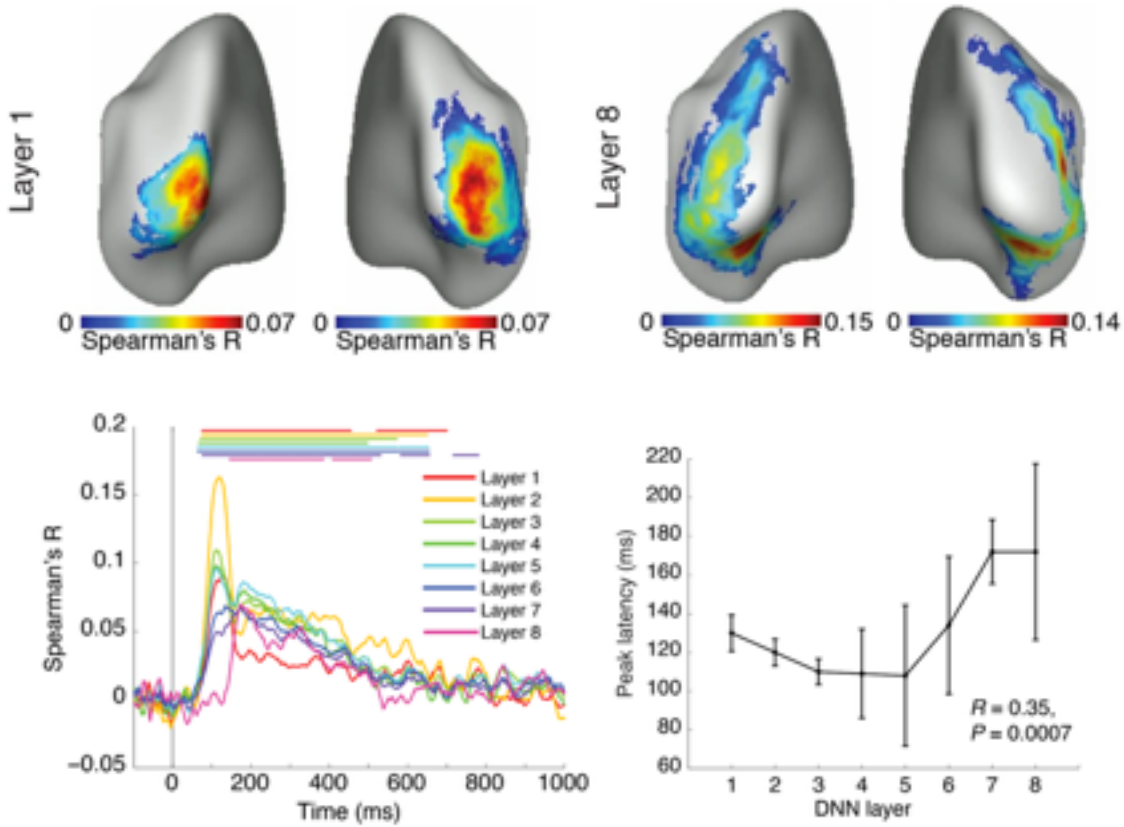
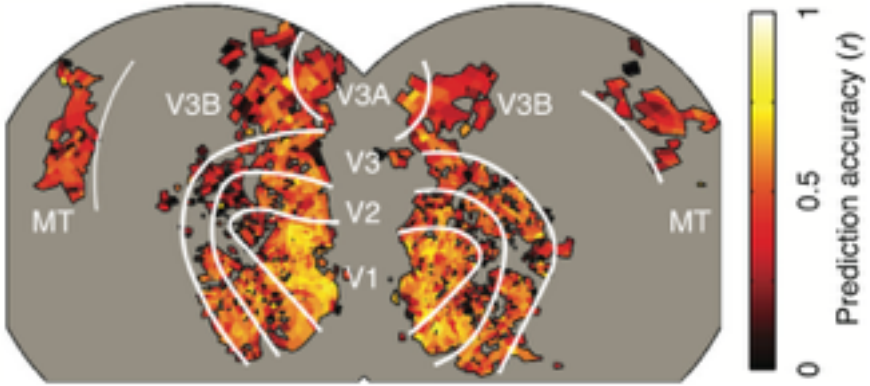
Related work: A representational gradient in space and time

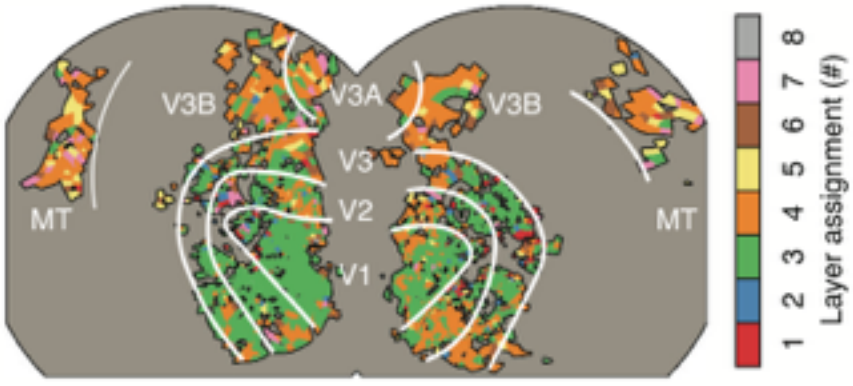


Cichy, R.M. et al. 2016. Deep neural networks predict hierarchical spatio-temporal cortical dynamics of human visual object recognition. arXiv Prepr.

A representational gradient across the dorsal stream

- DNN trained for action recognition
- Learns spatio-temporal receptive fields
- Recovers representational gradient in dorsal stream

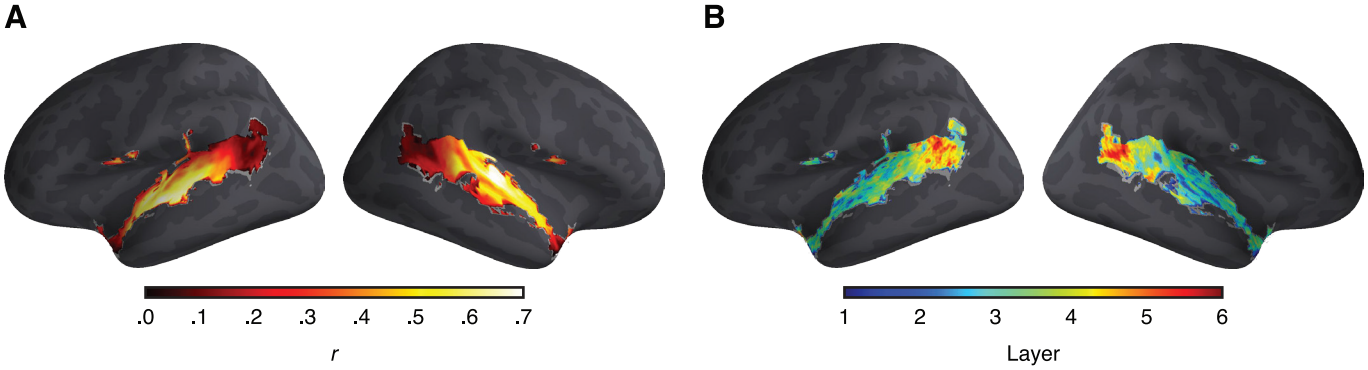




Güçlü, U., & van Gerven, M. A. J. (2015). Neuroimage.

A representational gradient across superior temporal gyrus

- DNN trained on automatic music tagging (genre, instrument, mood, etc.)
- Learns temporal receptive fields
- Recovers representational gradient in superior temporal gyrus

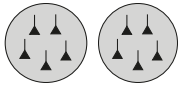


Güçlü, U., & van Gerven, M. A. J. (2016). arxiv.

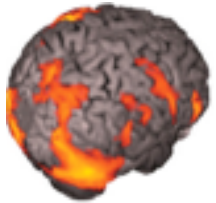
Modeling how the brain responds to the environment

stimulus **x**

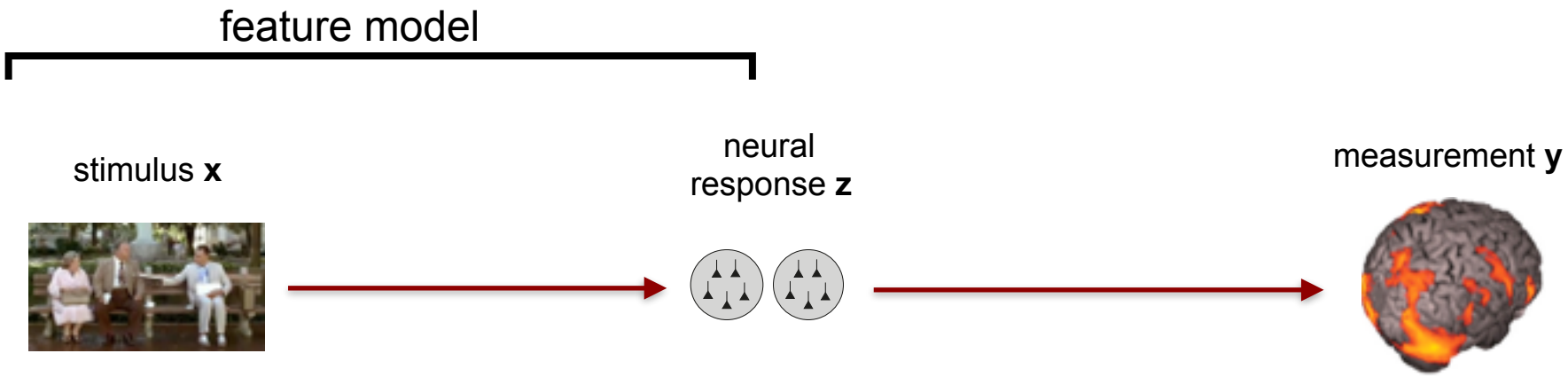
neural response **z**



measurement **y**



Modeling how the brain responds to the environment



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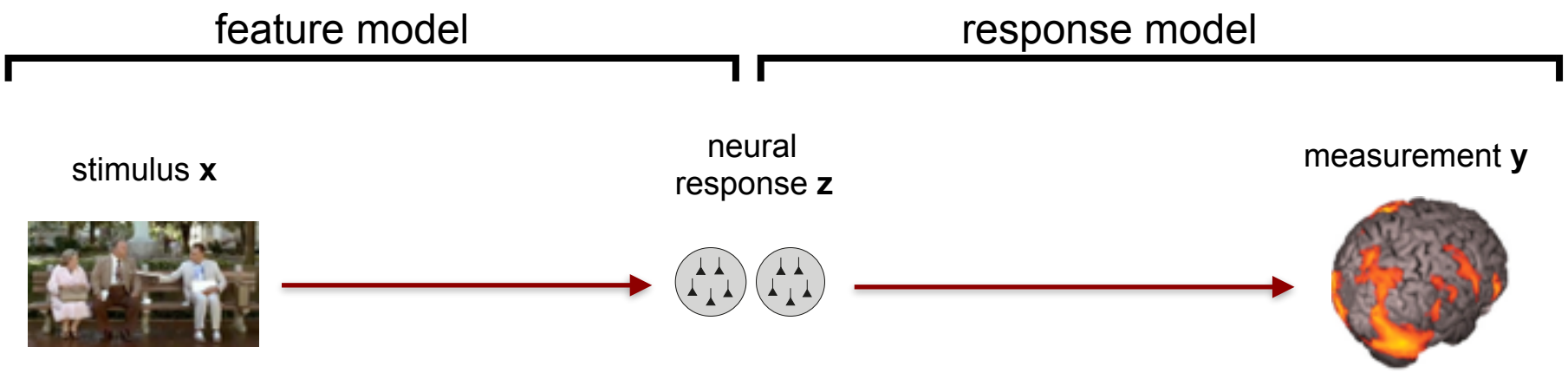

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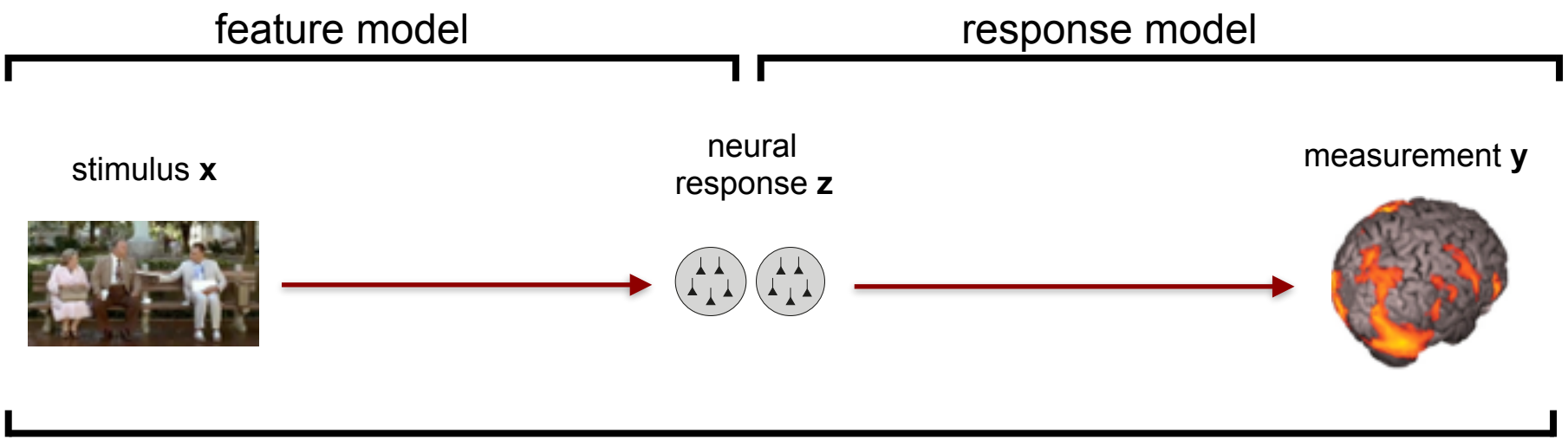

Encoding model

$$p(\mathbf{y} \mid \mathbf{x})$$

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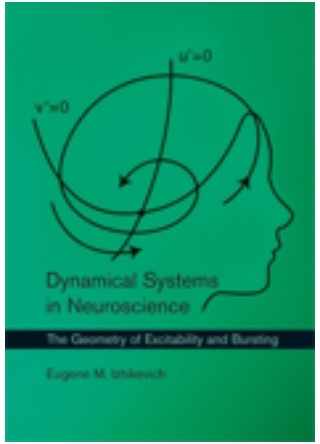

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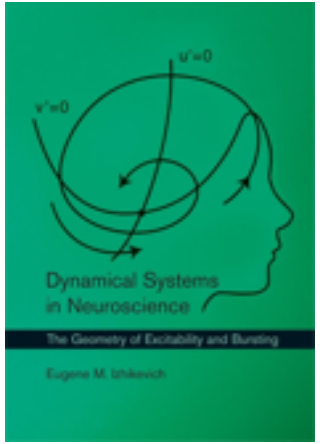

- How to model these dynamics?

Modeling dynamics: Recurrent neural networks

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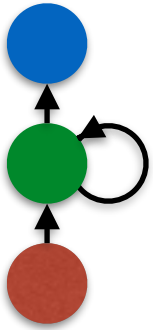

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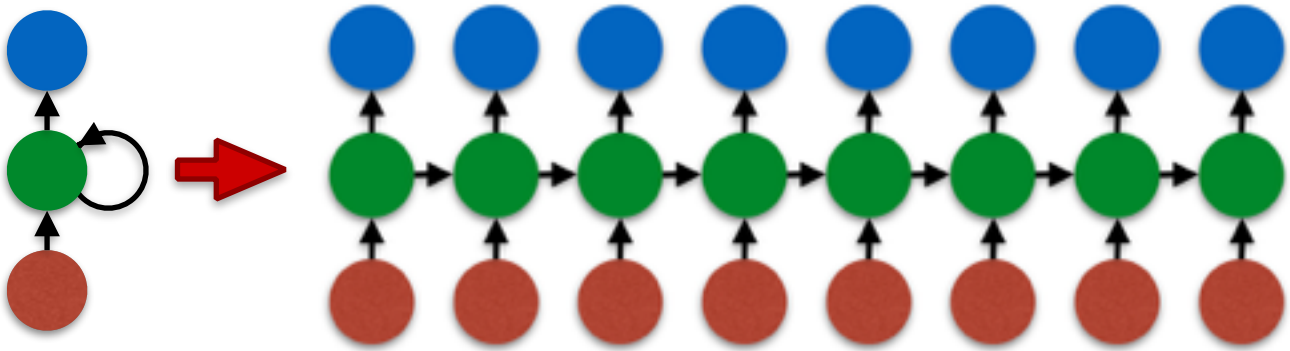

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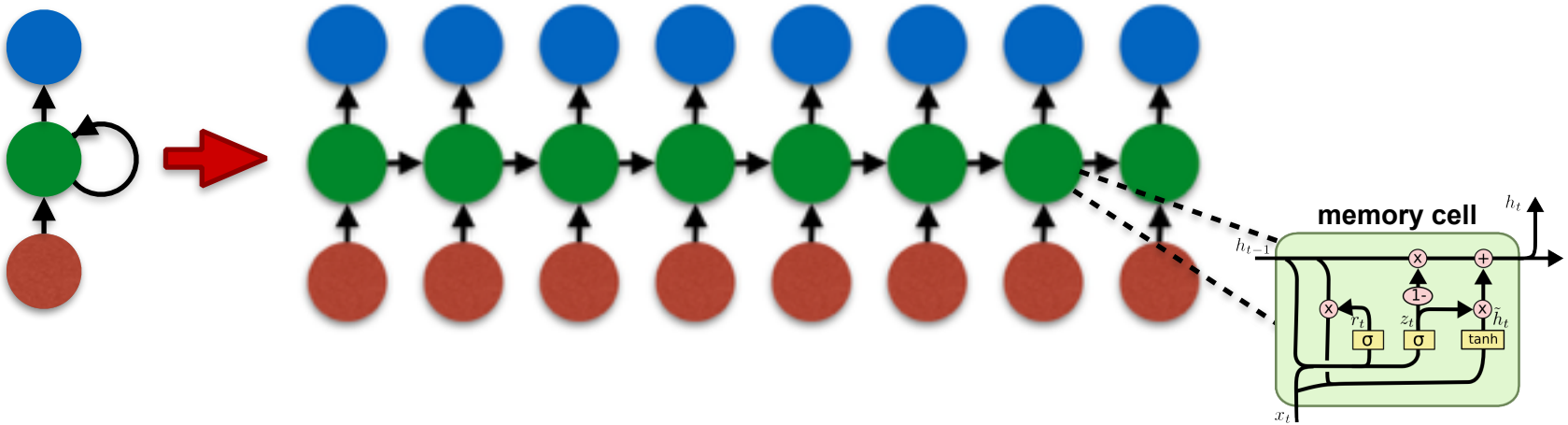
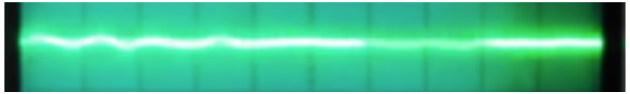
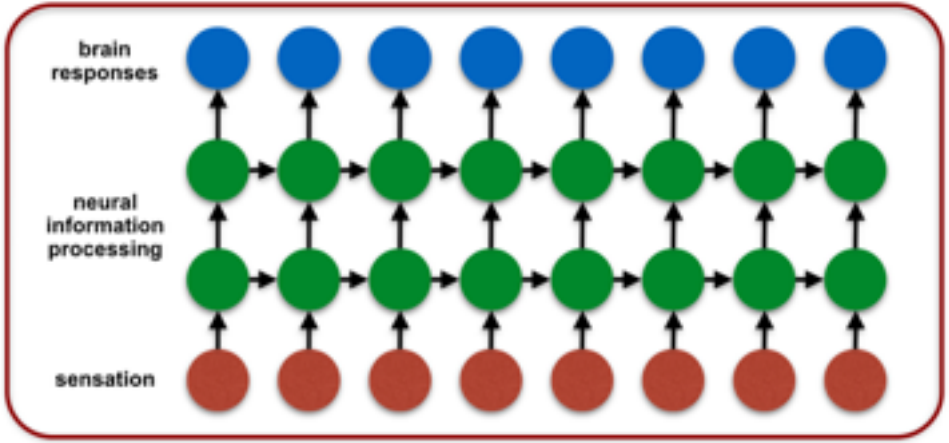


- Inference realized by unrolling the network and applying backpropagation through time
- Make use of memory cells to keep explicit track of long-term dependencies

Using RNNs to model stimulus-response relationships





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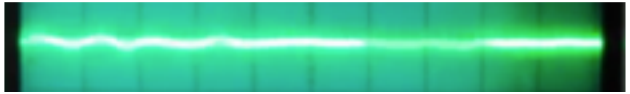

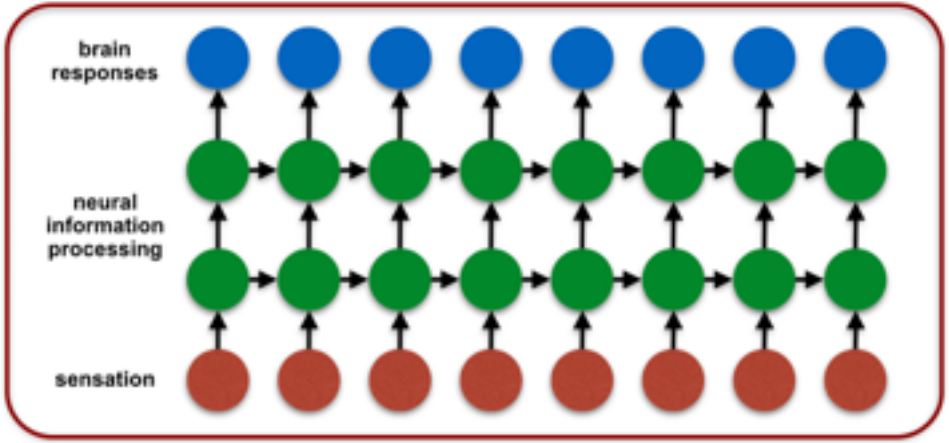

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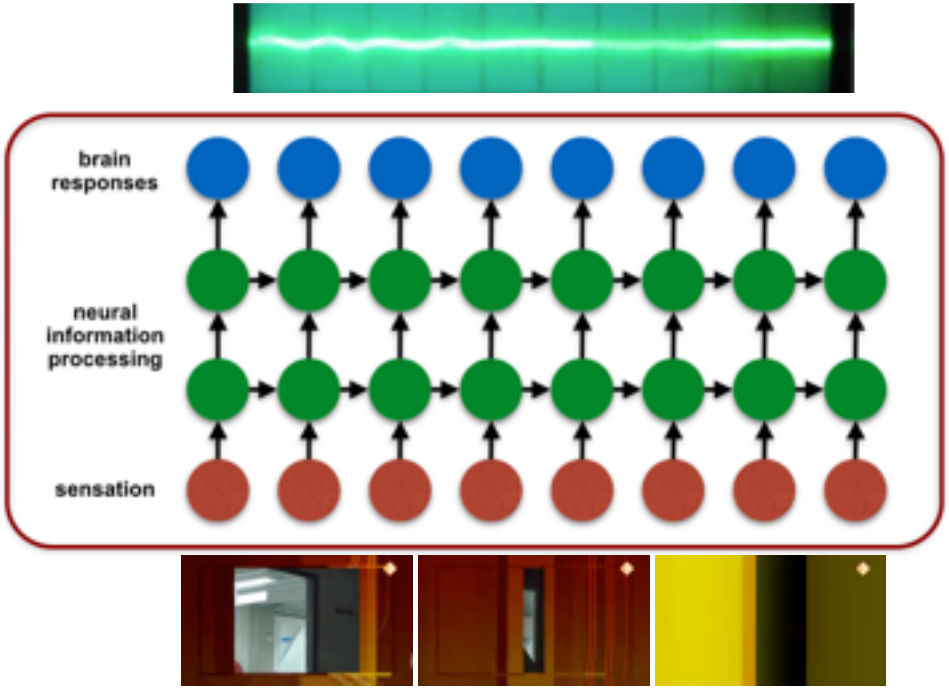

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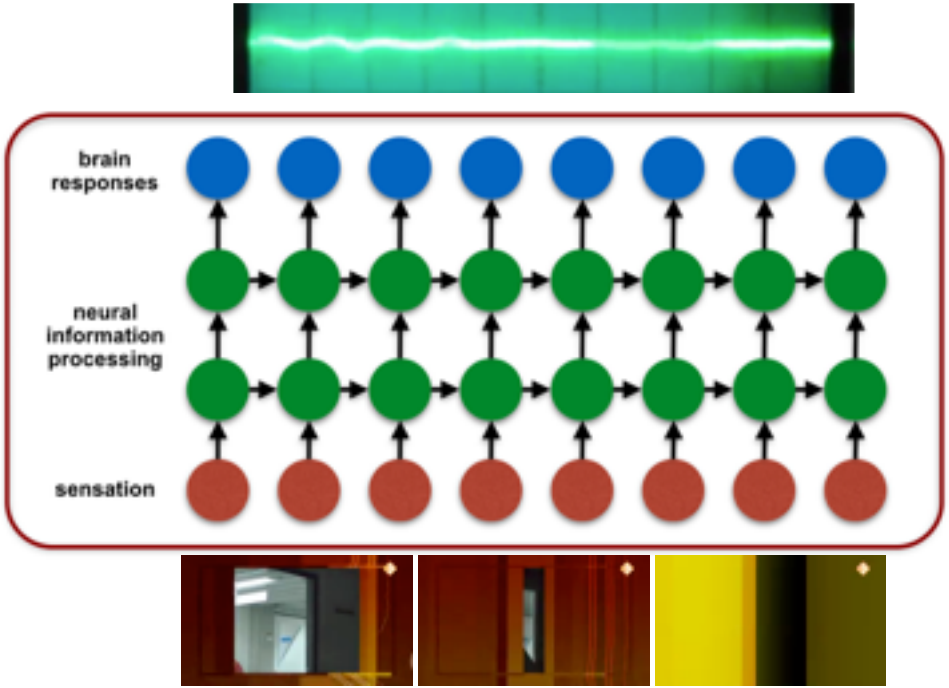

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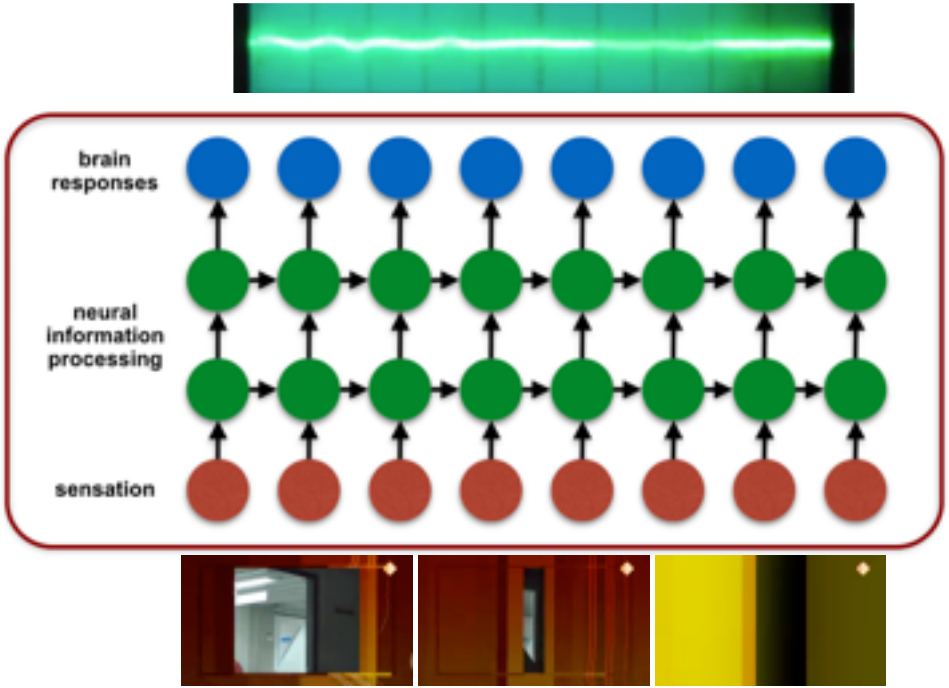

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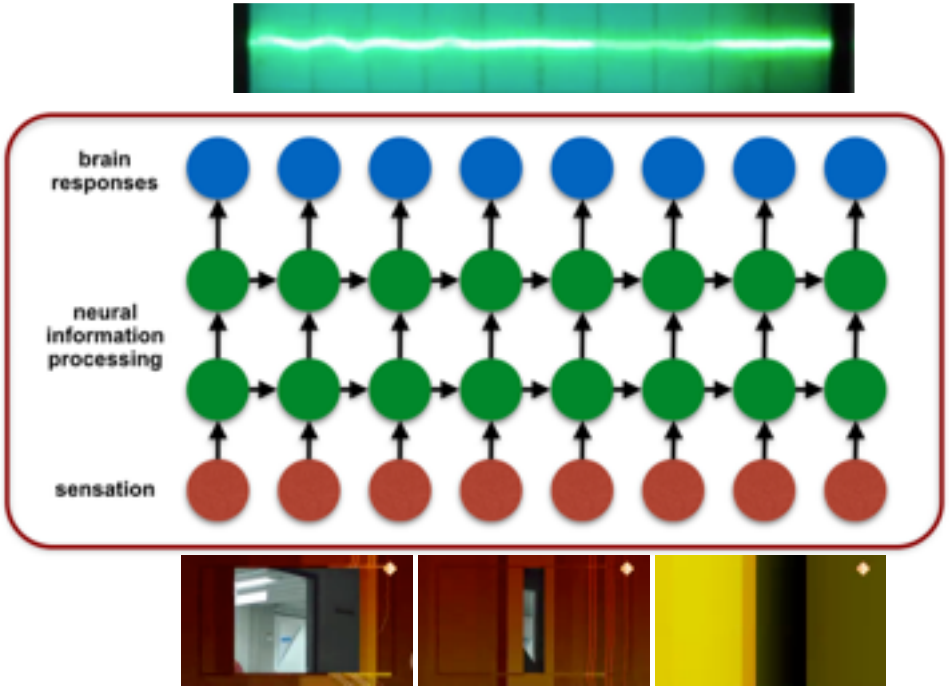

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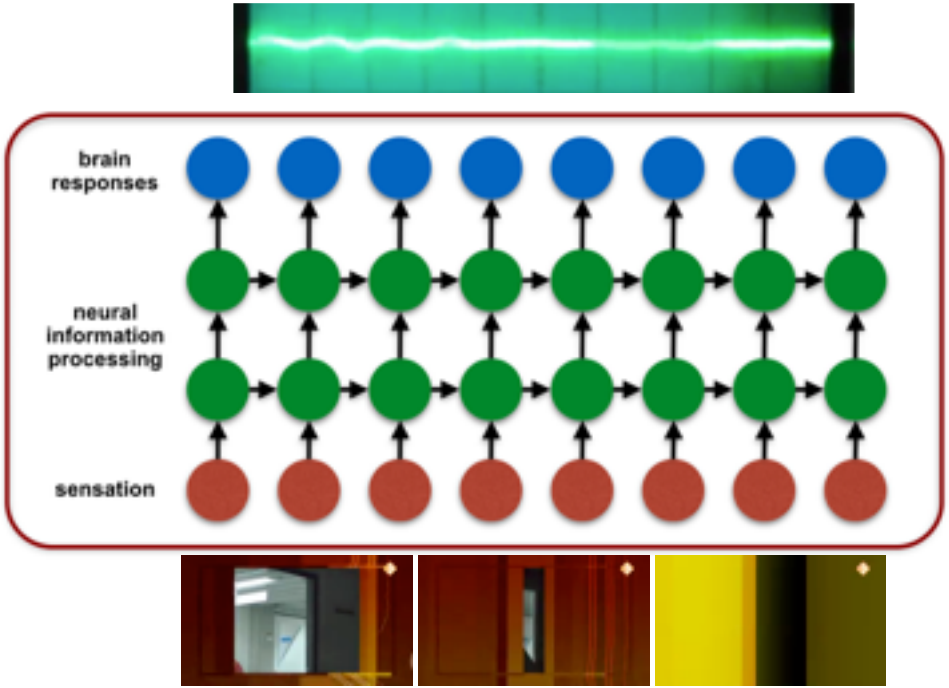

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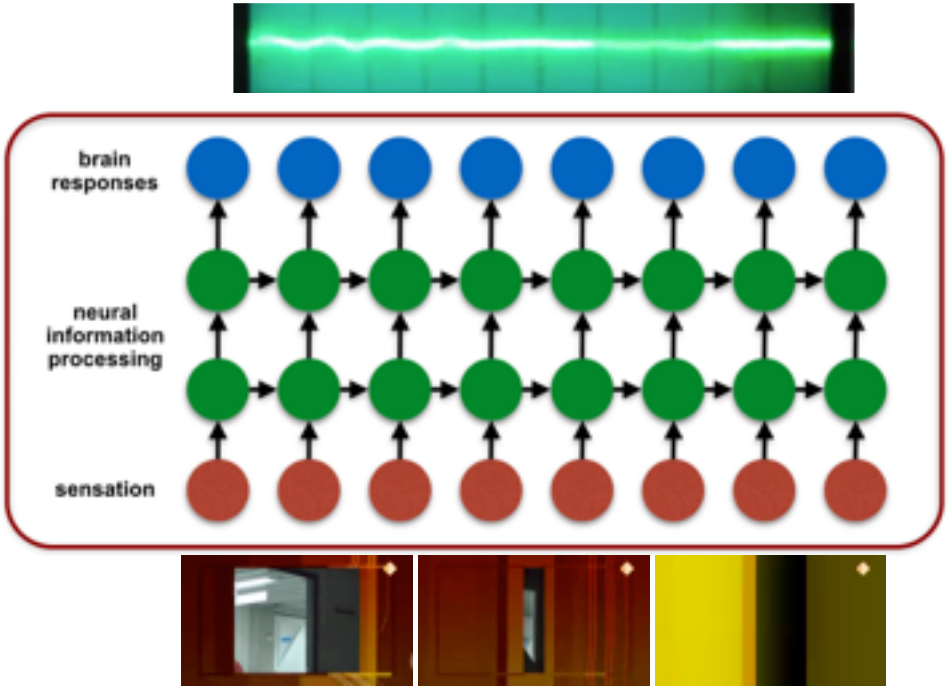

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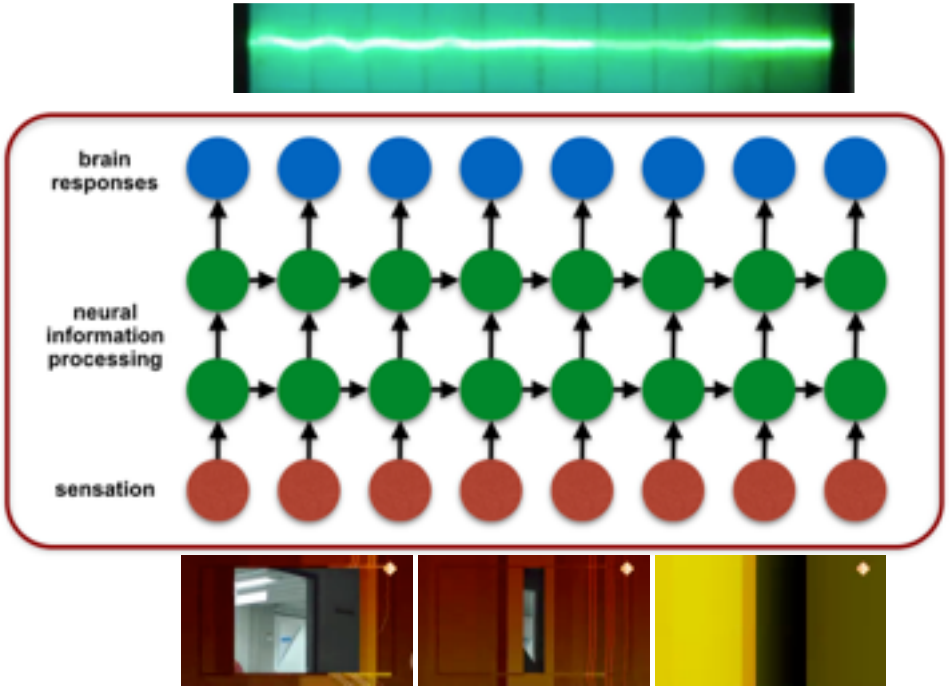

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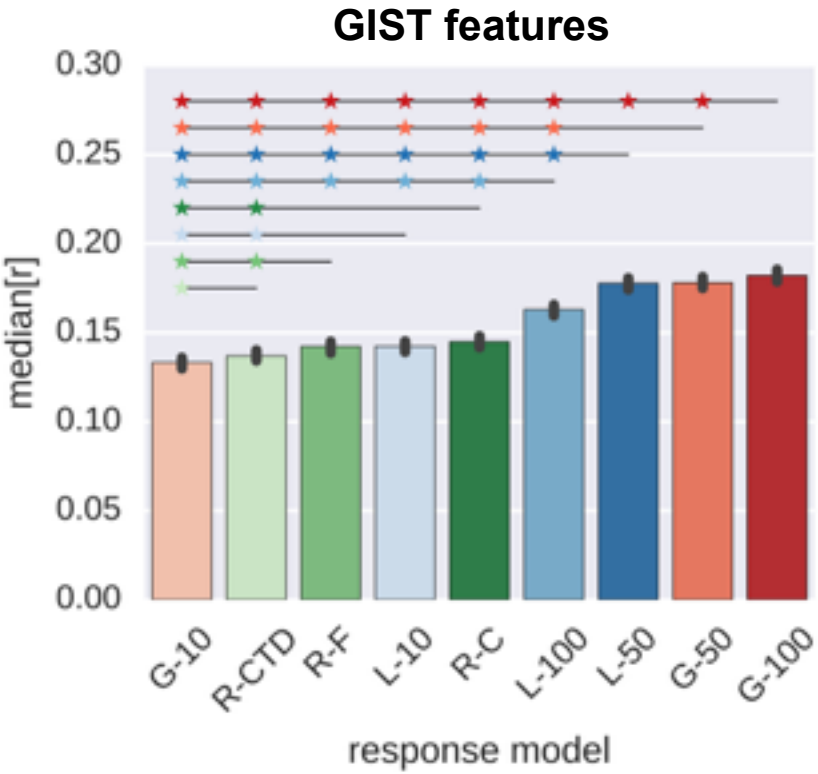
- Indirect coupling modelled via memory cells (LSTM vs. GRU)

Comparing RNNs with standard approaches



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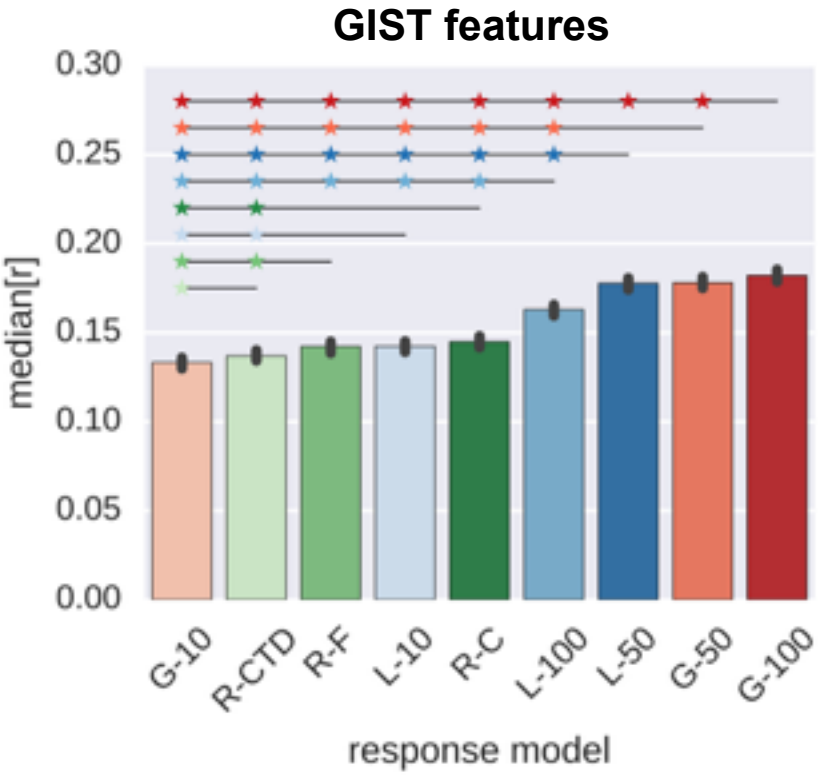

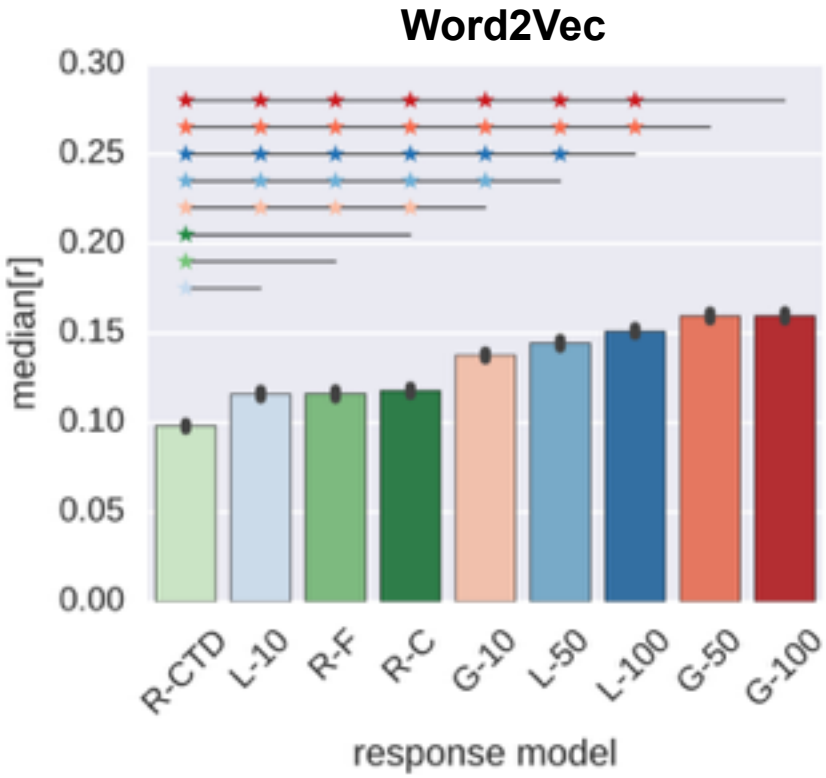

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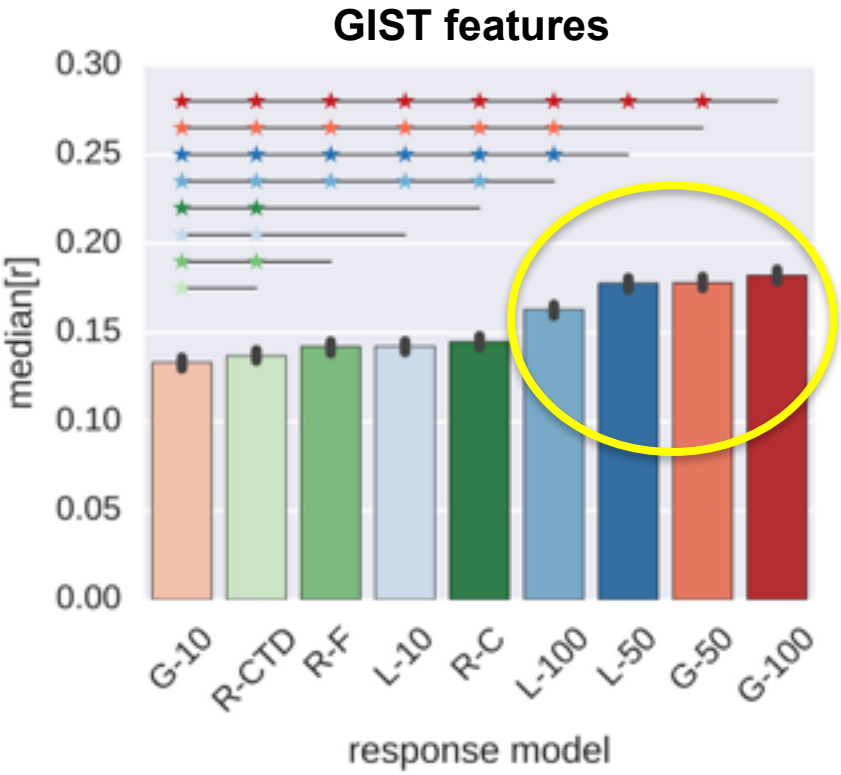

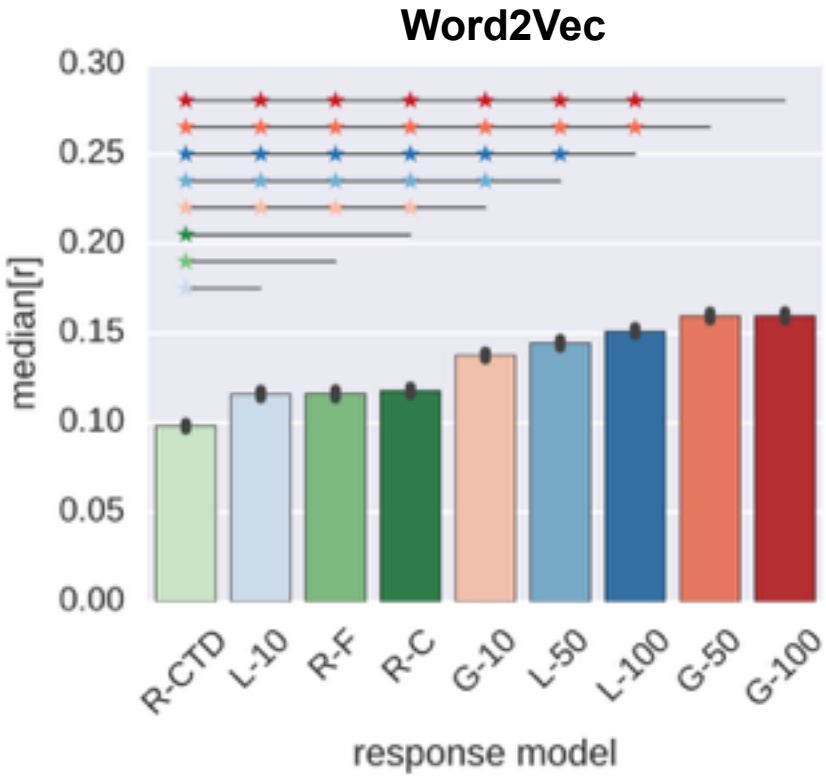

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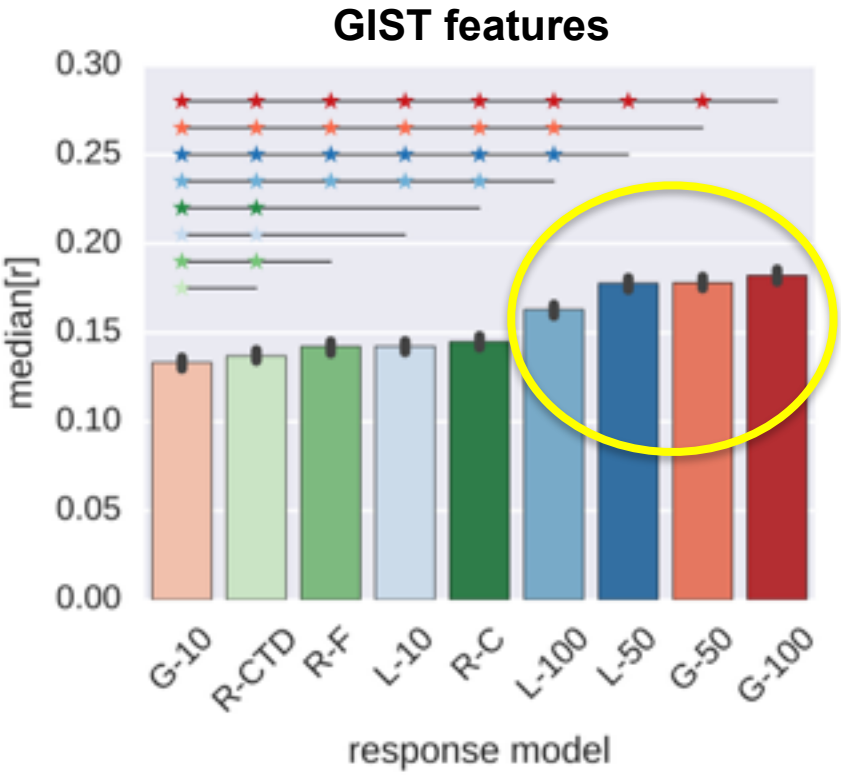
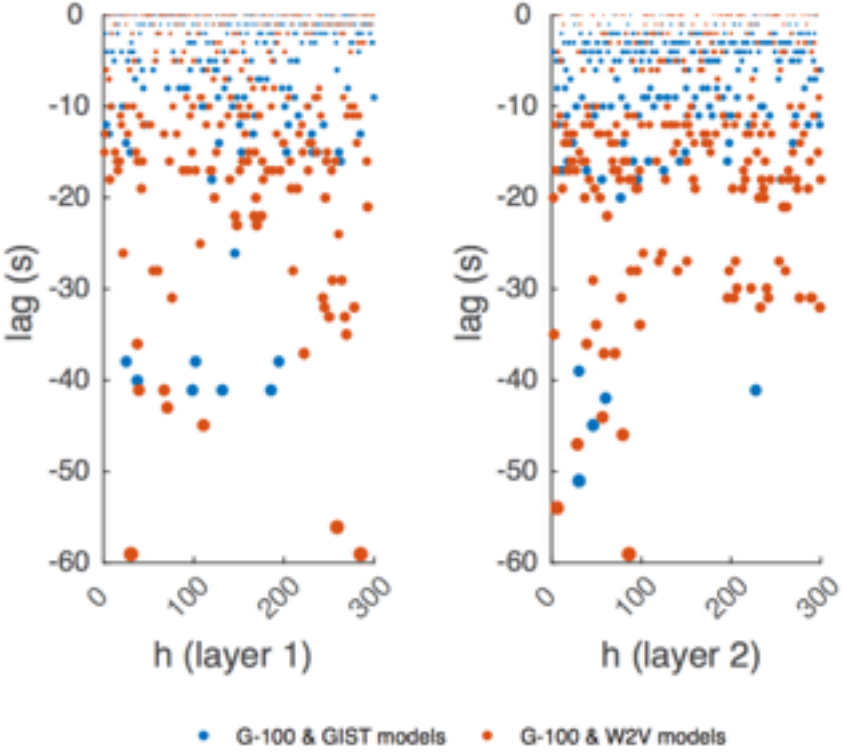


Interrogating RNNs

- Compute cross-correlations between input features and RNN hidden states



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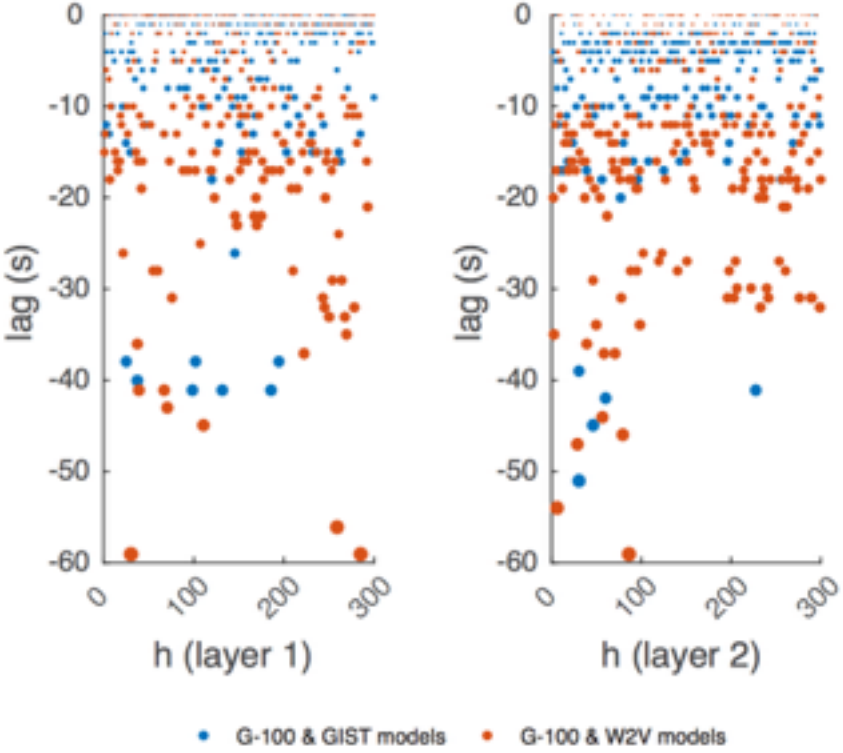

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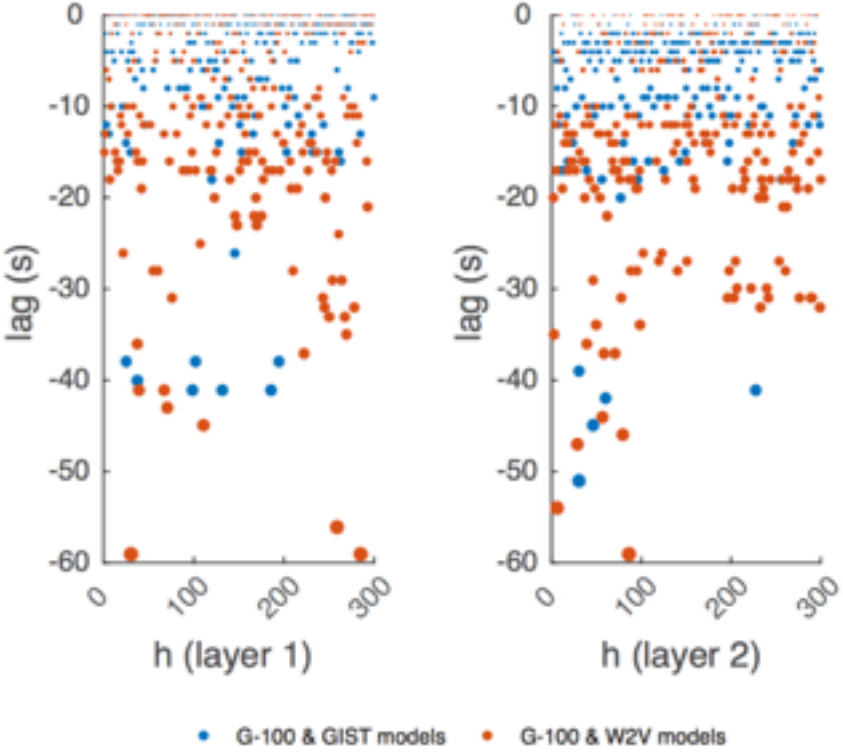

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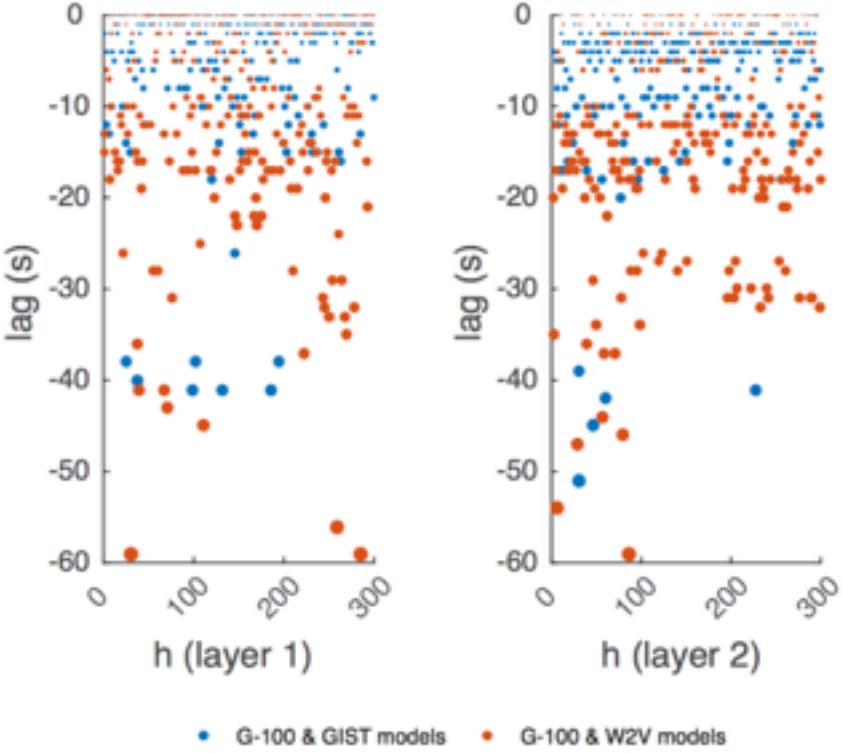

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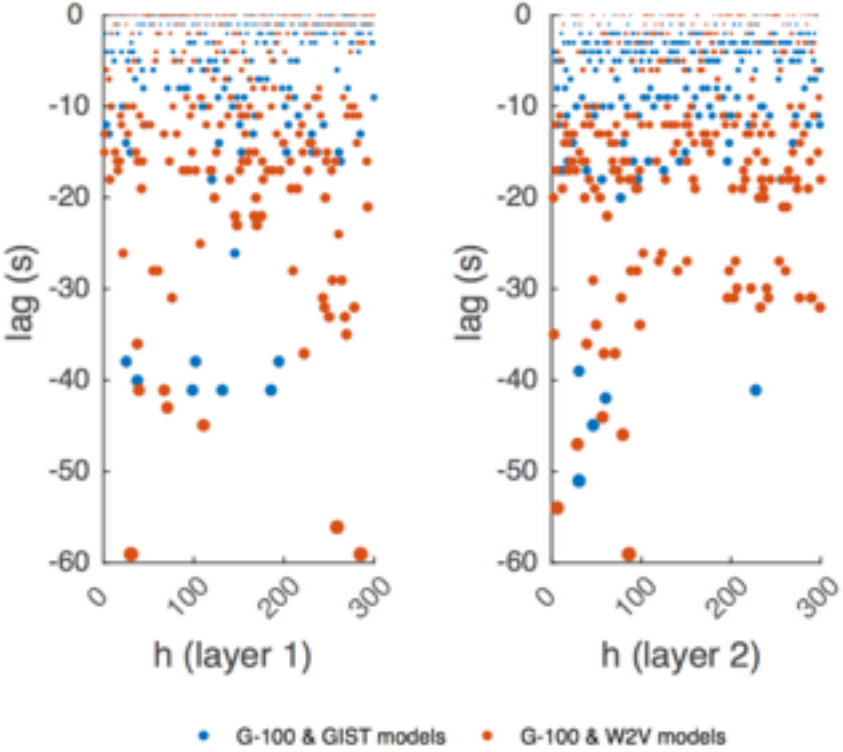

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- May reflect the fact that semantic states are more persistent than low-level visual features across the stimulus sequence

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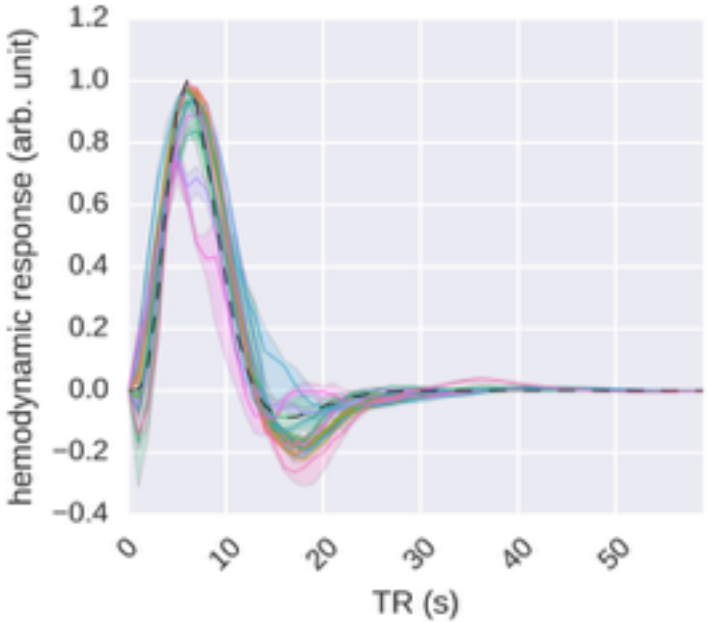

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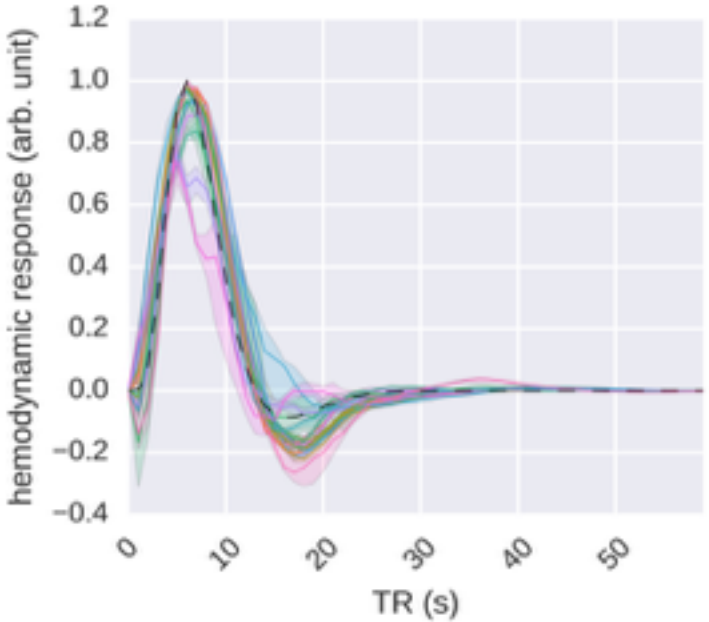

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- Only model we know of which estimates HRFs from continuous designs

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  - No-flattening theorems
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- General approach to model-based cognitive neuroscience

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  - ANNs trained to recognize music reveal functional differentiation across STG
  - ANNS that are trained to play games may reveal neural correlates of reward estimation and decision making

Further reading

Güçlü, U., van Gerven, M.A.J., 2015. Deep neural networks reveal a gradient in the complexity of neural representations across the ventral stream. J. Neurosci. 35, 10005–10014.

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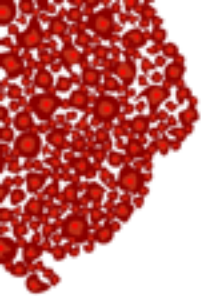

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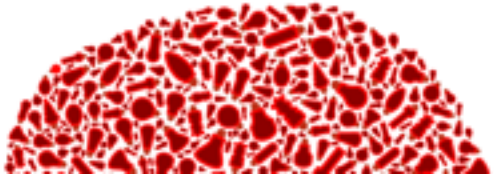

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