Cortical Vision and Deep Learning

Neuro120, Section 6
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Oct.25th , 2021

Contents Today

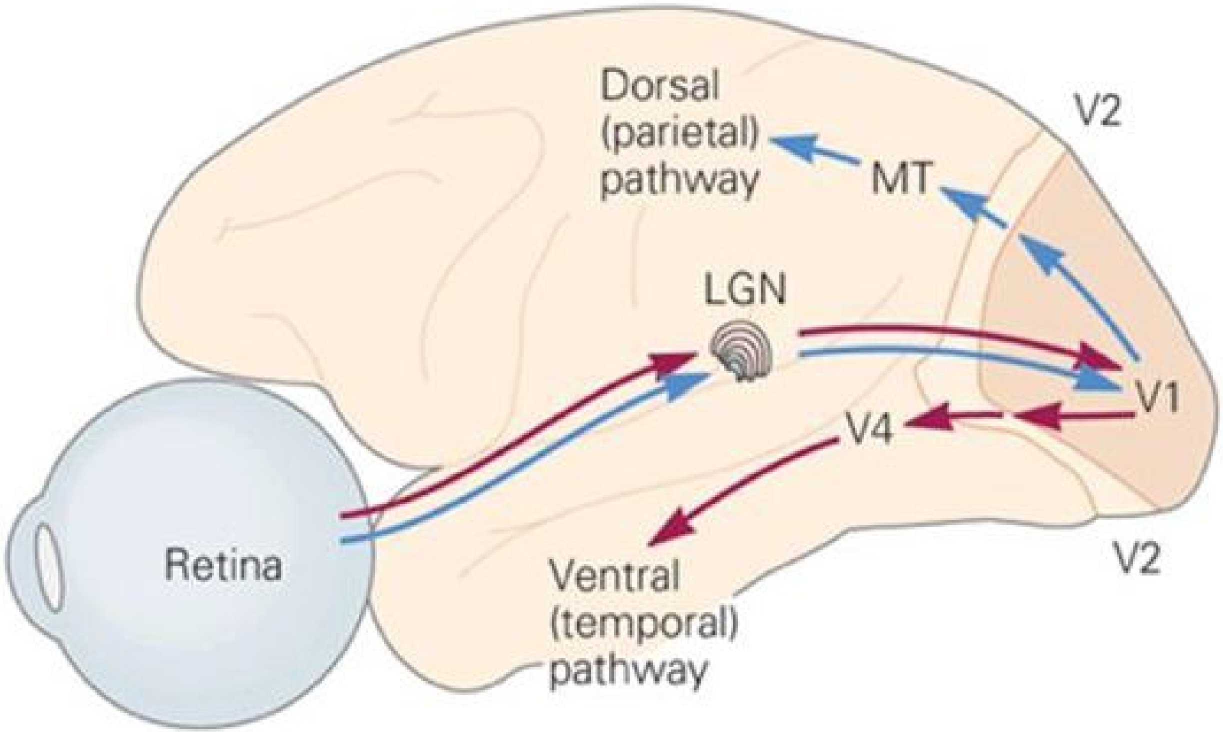
- Visual cortices
  - V1 , retinotopic map, feature maps
  - Ventral, dorsal stream
  - Inferotemporal cortex

- Deep Learning basics
  - Network architecture: MLP, CNN
  - Philosophy of Supervised Learning

- Neuroscience and DL

Grand scheme of visual pathway

- Retina -> LGN -> V1

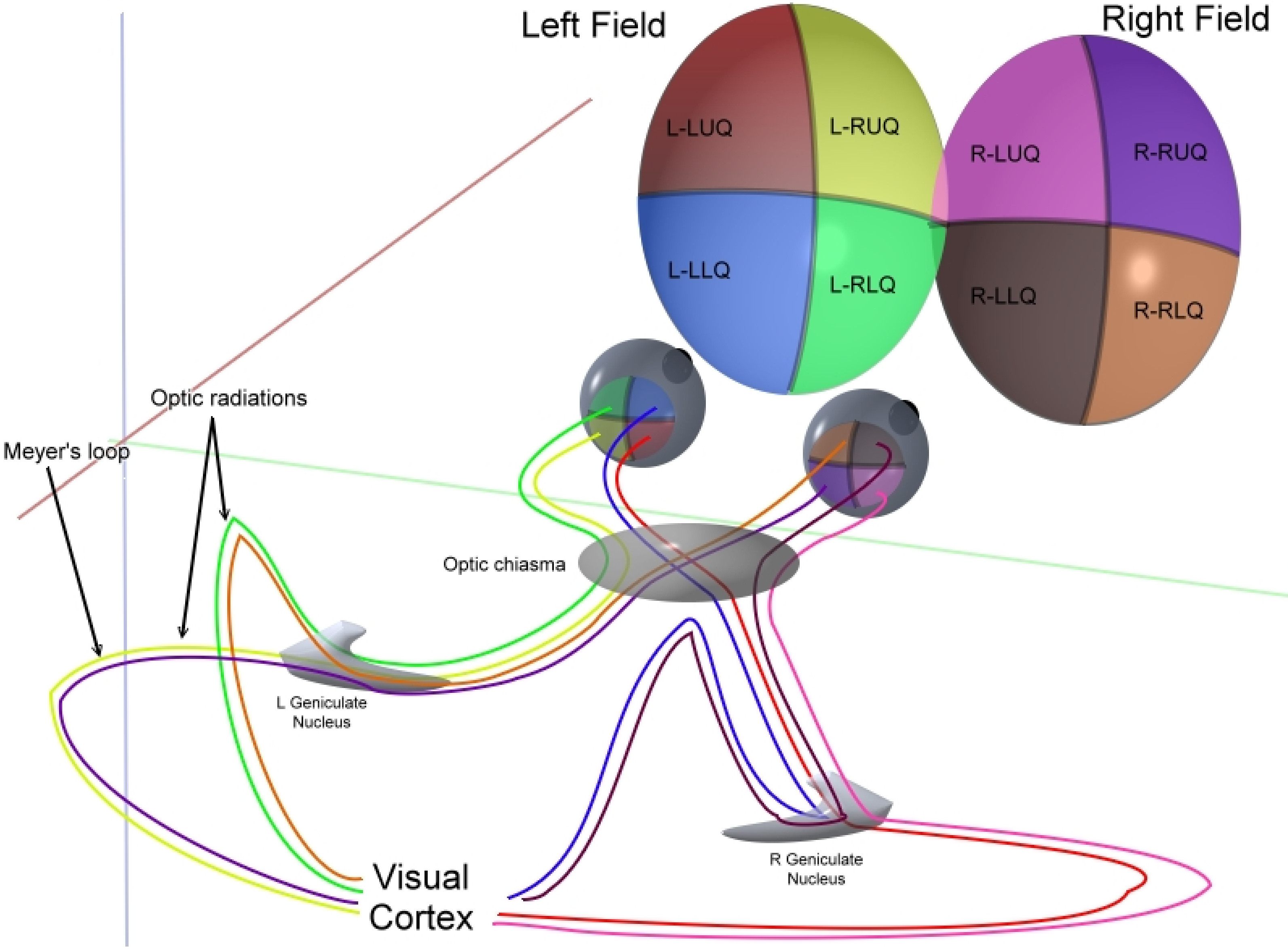


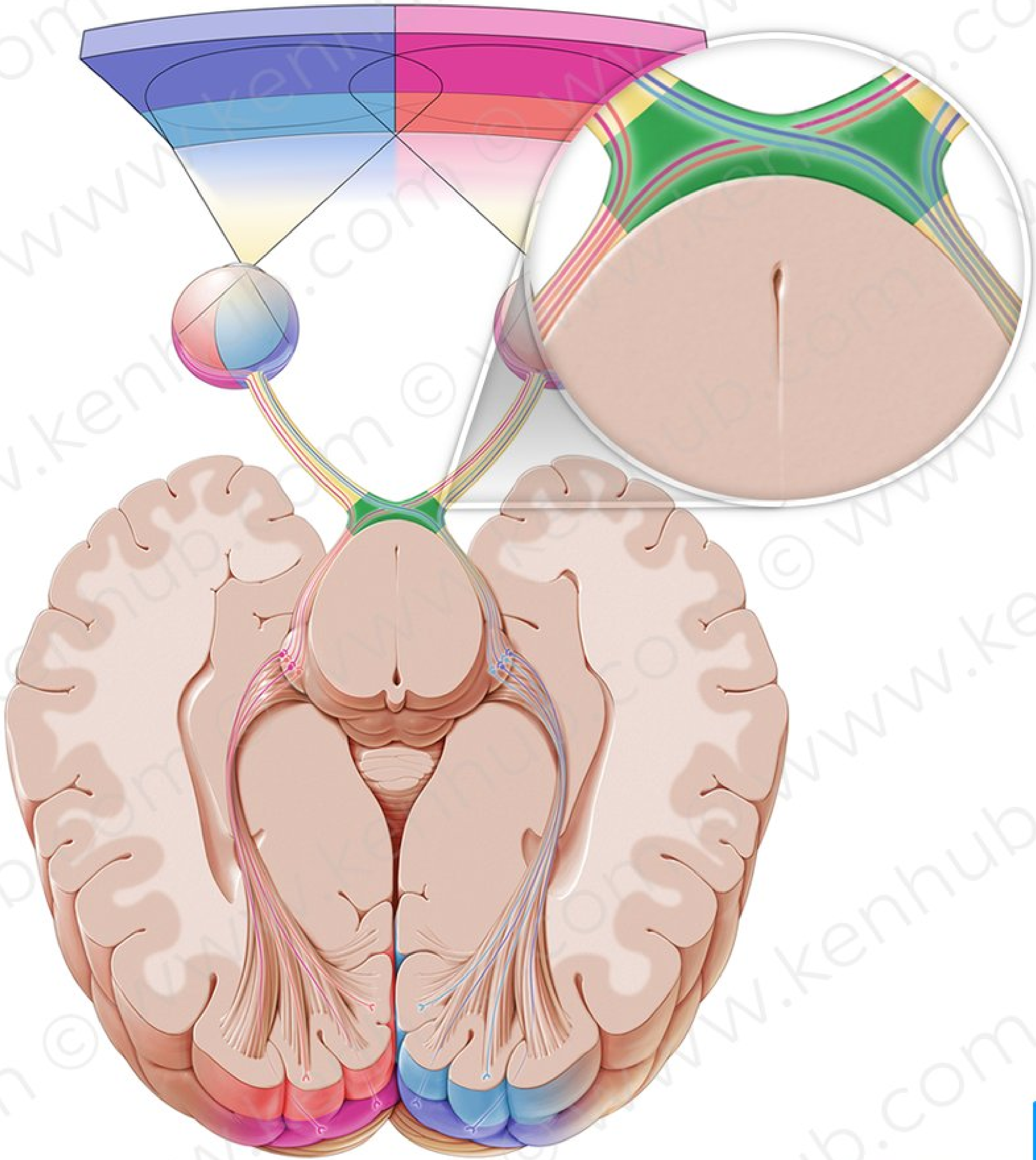
How retinal image maps onto V1?

- How to characterize this mapping?
  - Visual information …
    - From different location (retinal location)
    - Of different types (features)

Spatial Map: Optic Radiation

- Image inversion at Optic Lens.
  - *Left upper visual field -> Right lower on retina*
- Sorting at Optic chiasma, LGN
  - *Right visual field go to left hemisphere*
  - *Nerves from both retina for the same visual field go along at LGN.*
- Combination at V1
  - *Right visual field -> left hemisphere, up-down inverted*



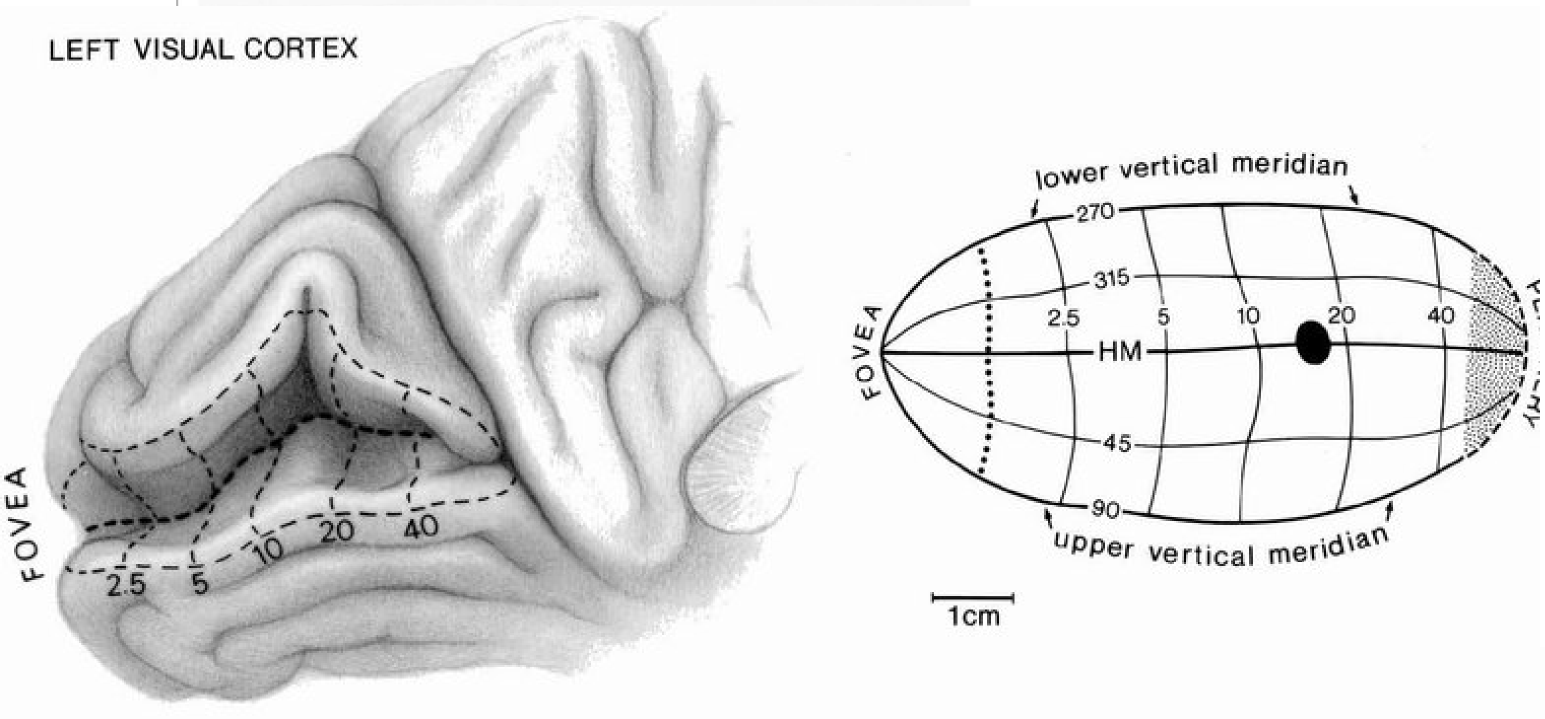


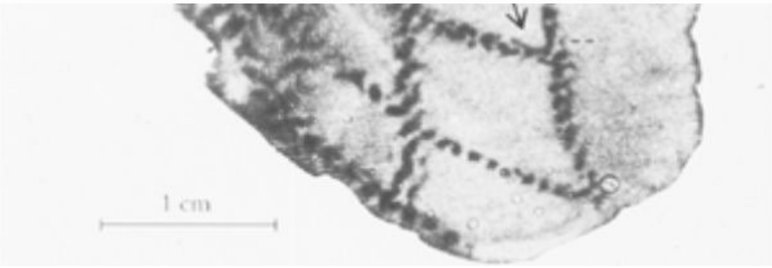
Exercise: how the visual information flow

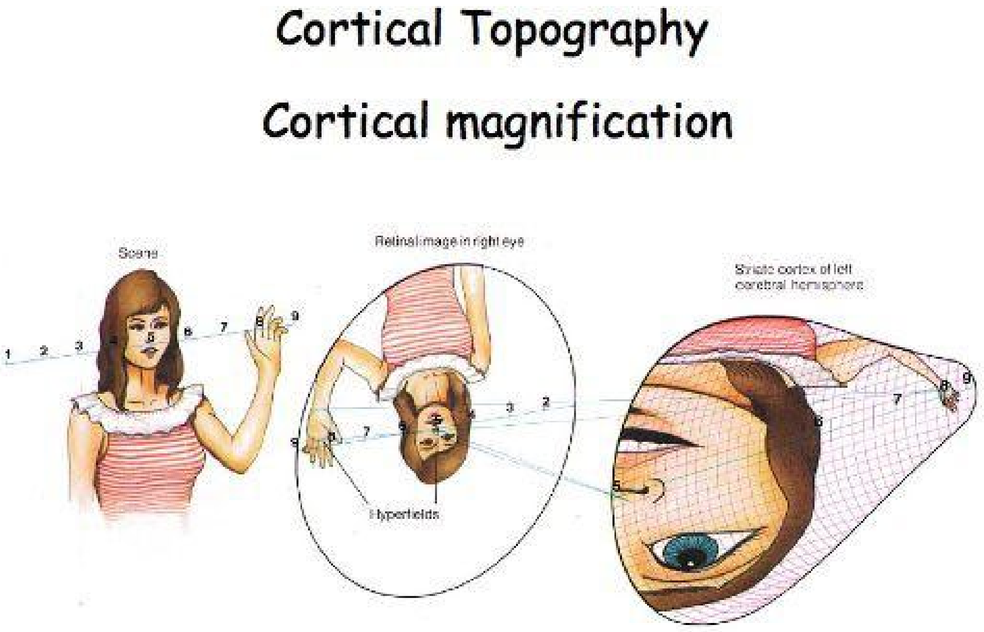
- Put your hand vertically in front of your nose, what does your V1 see?
  - Can you feel the different flow?

- Binocular rivalry
  - Multi-stability of dynamic perception.

Retinotopic mapping and cortical magnification







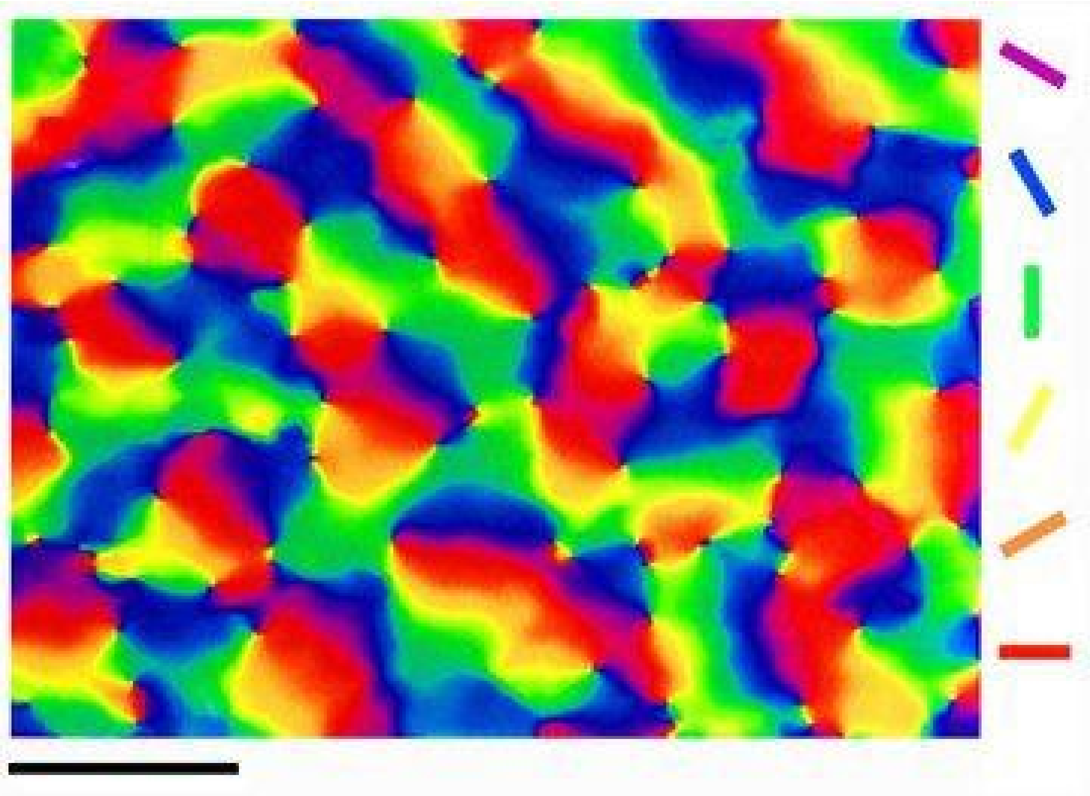
Input **Retina** **V1**

What happens during eye movement?

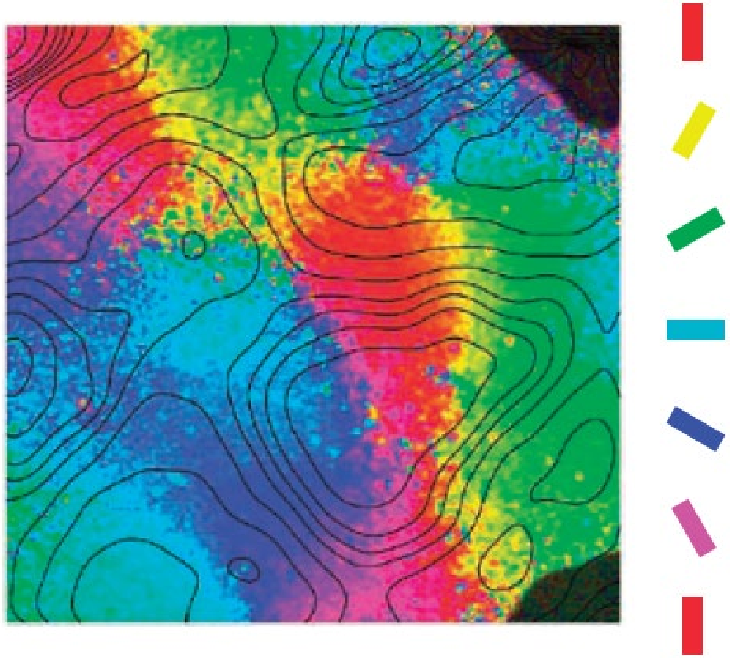
Harvey & Dumoulin, 2011, J Neuro

Feature Maps in V1

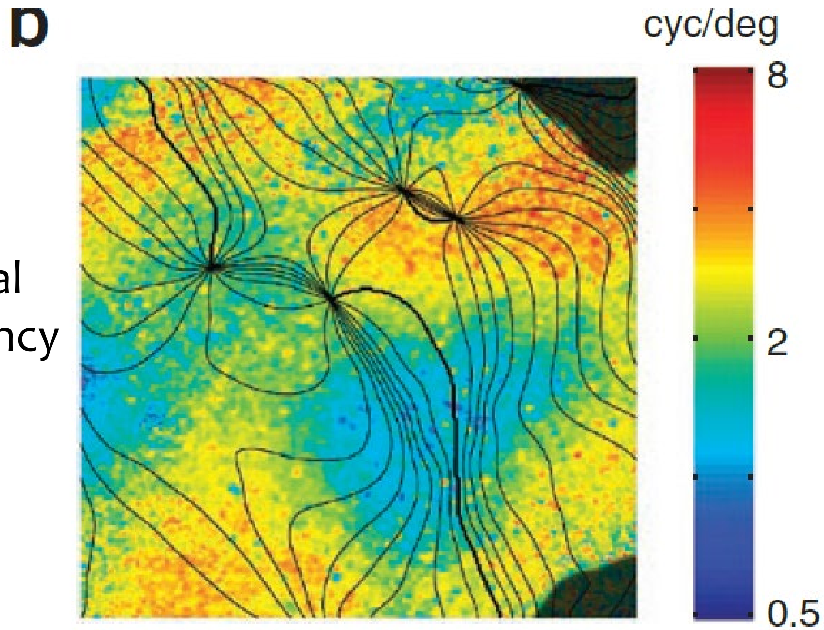
- Orientation map
- Spatial frequency map
- Etc.



Orientation Preference Map



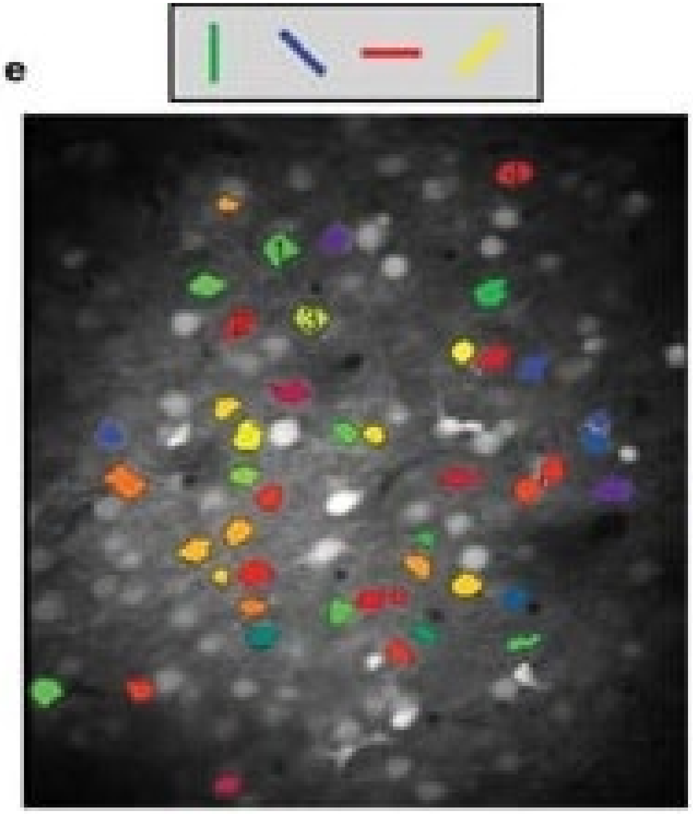
Spatial Frequency Map

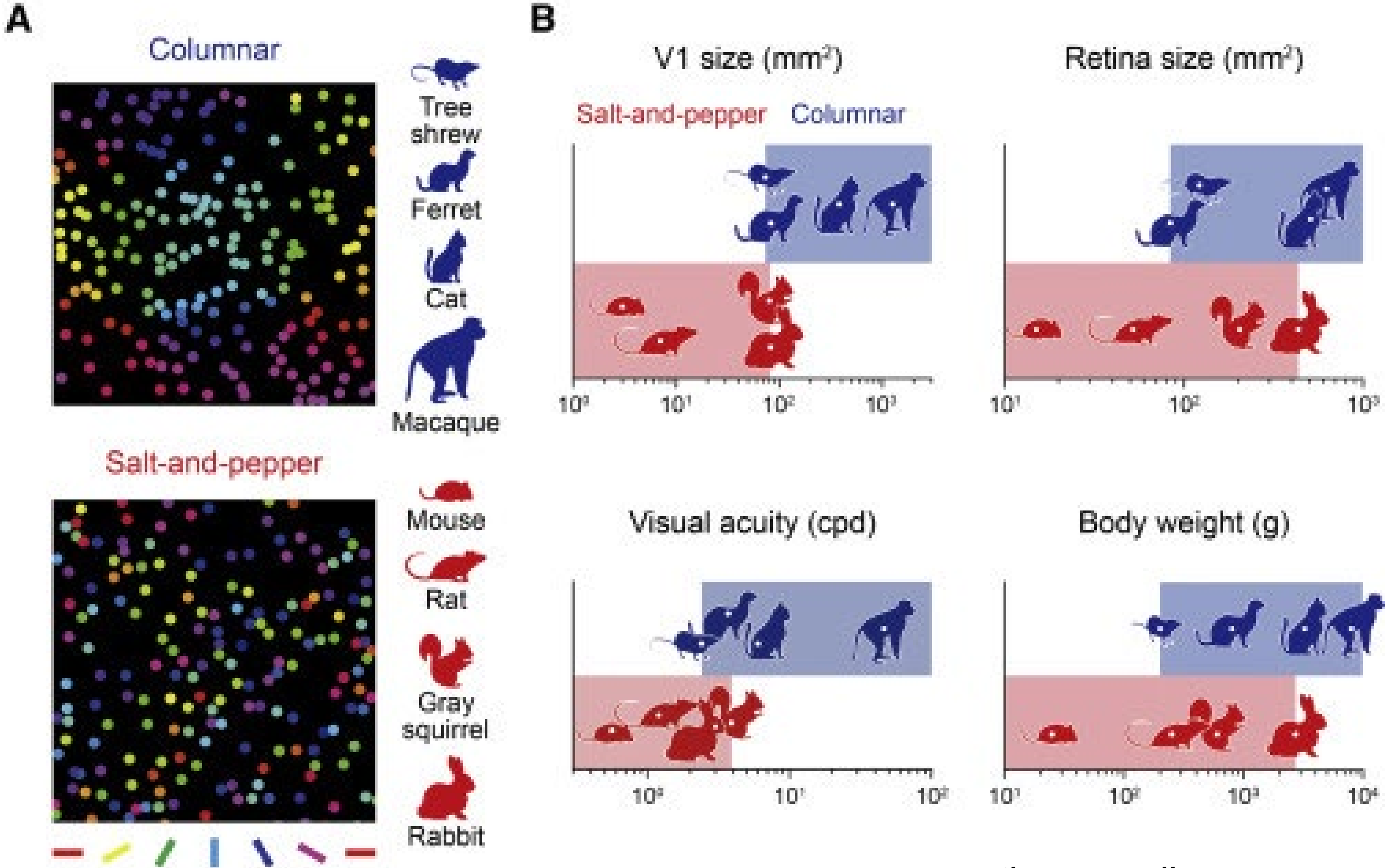


Orthogonal organization

Ian Nauhaus, Kristina J Nielsen, 2012, Nat Neuro

Alternative Organization in V1: "Salt and pepper"



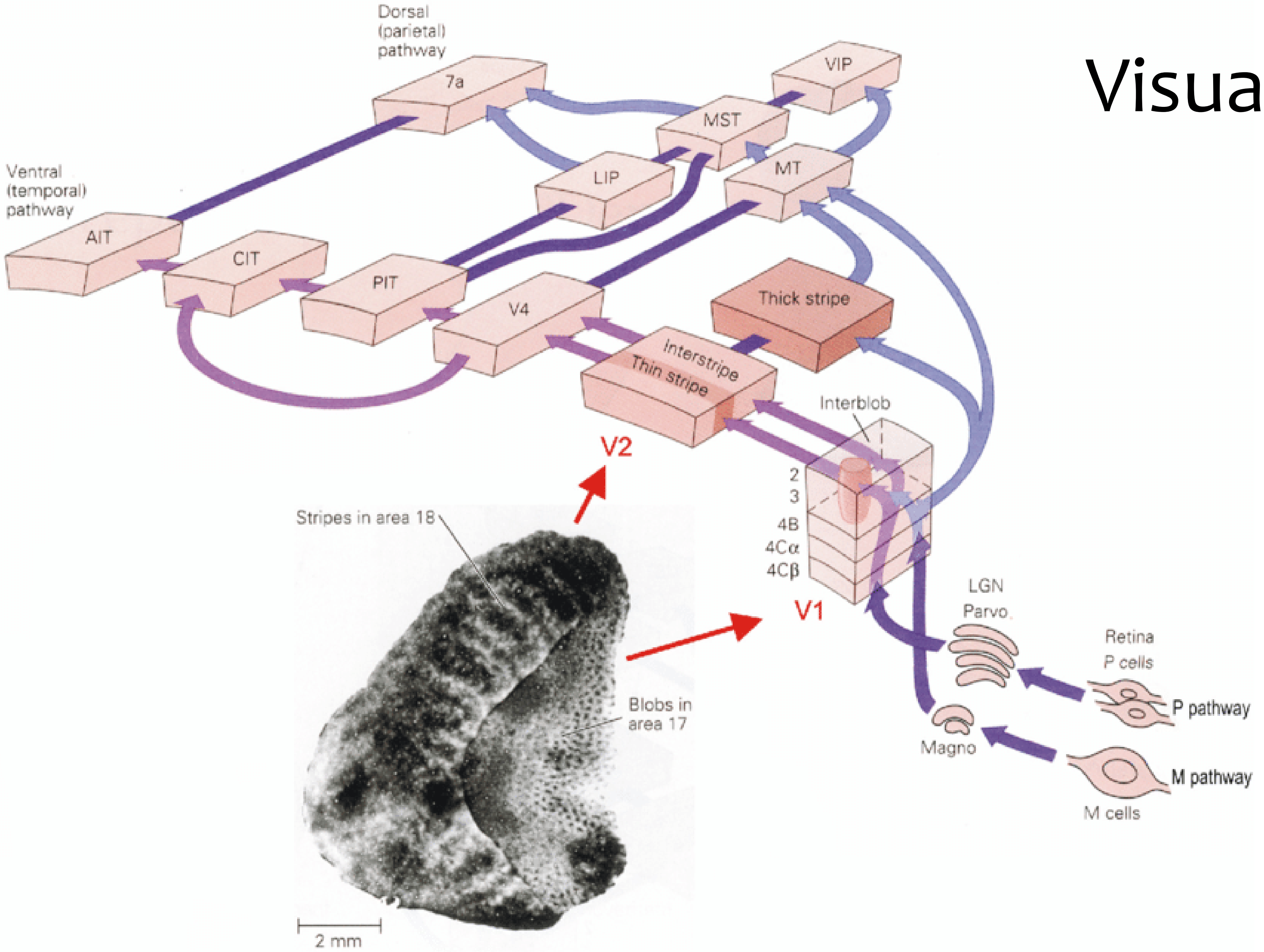


Jang, Song, Paik 2020 Cell Report

V1 organization

- Spatial arrangement
- Feature-wise arrangement

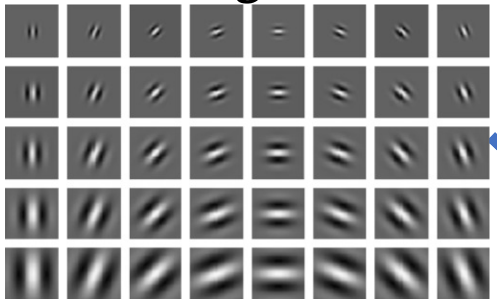
Visual Cortices

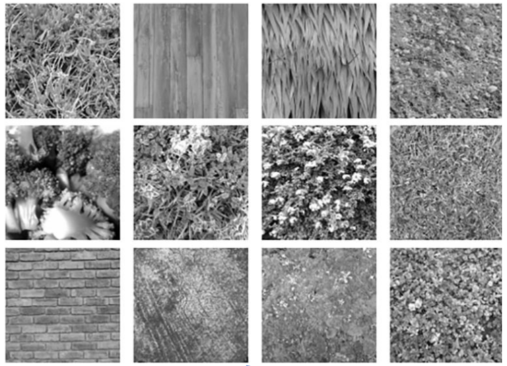


Classic Knowledge of visual areas.

Low- to Mid-Level Vision
Parametric image spaces

Classic Image Spaces
& Tuning Curves

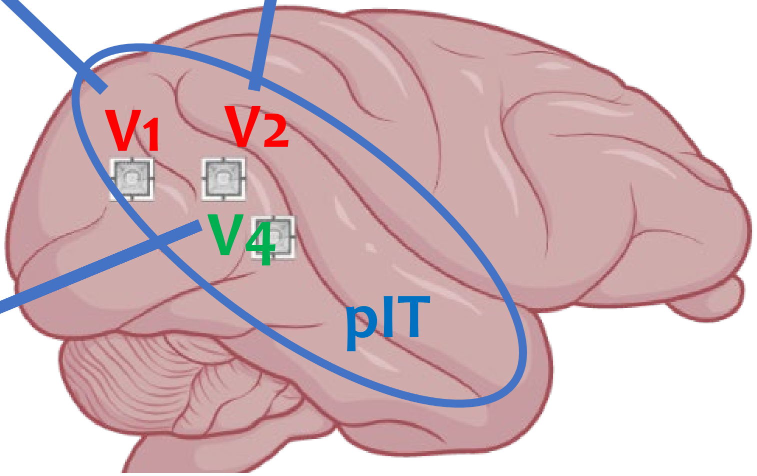




Ziemba, Freeman, Movshon, Simoncelli, (2016) PNAS

Angular separation = 90 & 135°

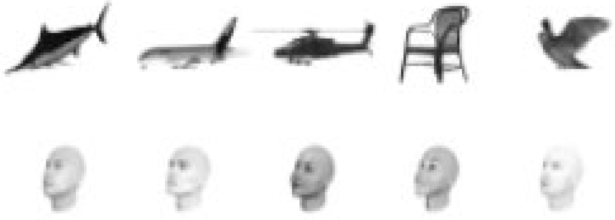
Pasupathy, Connor (2002)



High Level Vision
Object / Natural image

Most

Least

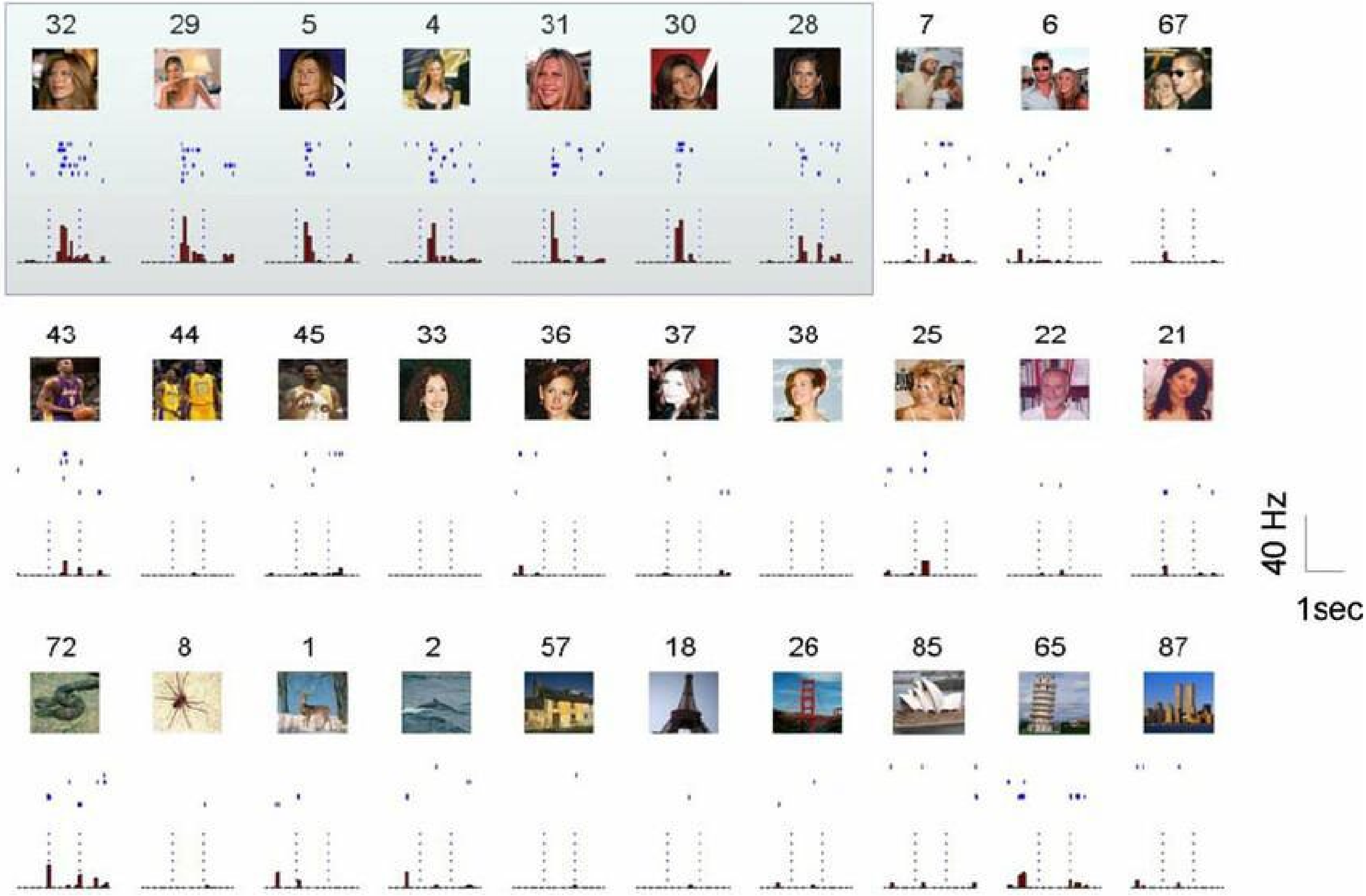


Bao, She, McGill, Tsao, (2020). *Nature*,

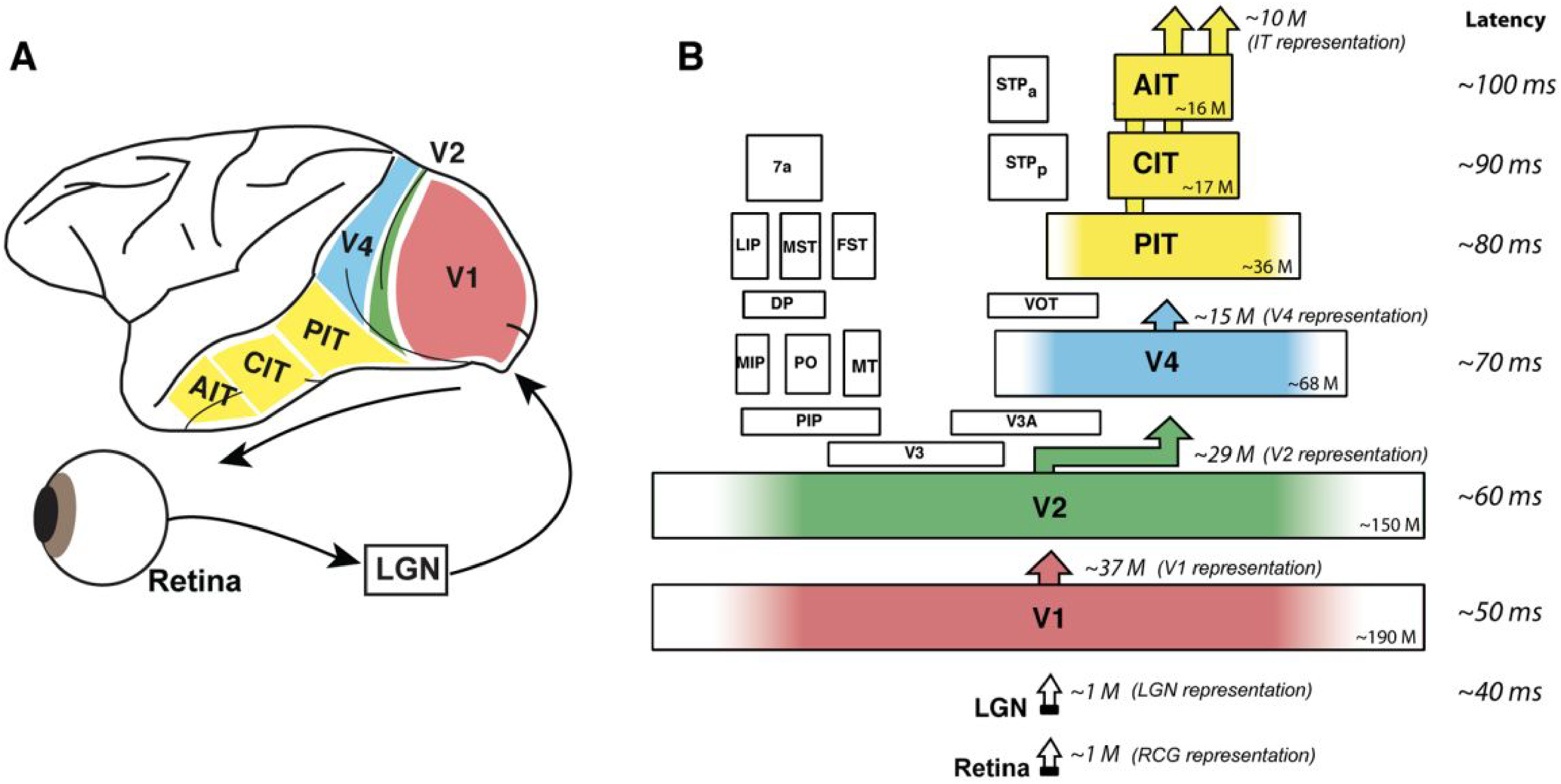
Natural images

IT: Population coding and Specific coding

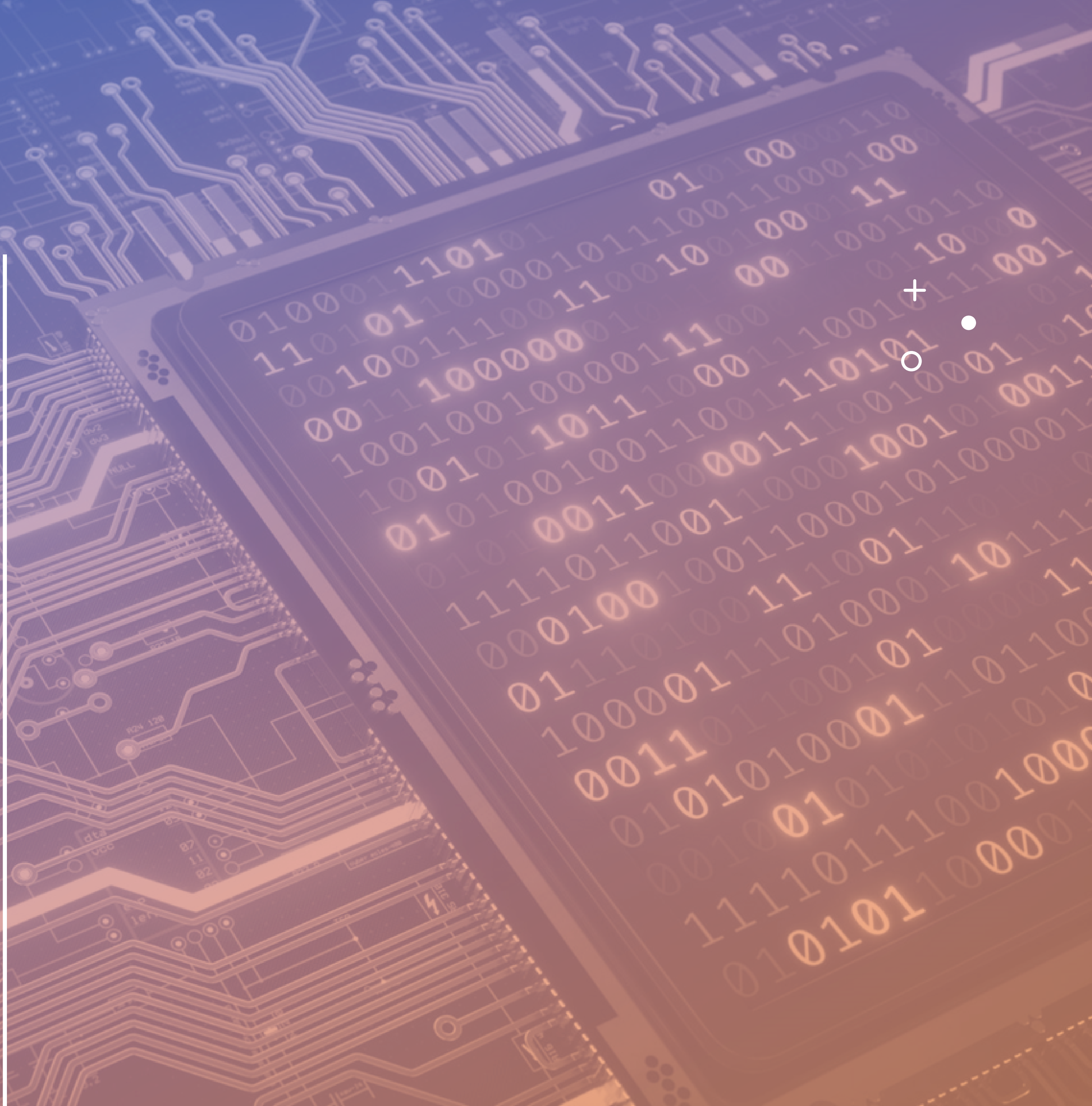
- Jennifer Aniston cell.
- Vs
- Population code



Understand Object Recognition as Feed Forward Network

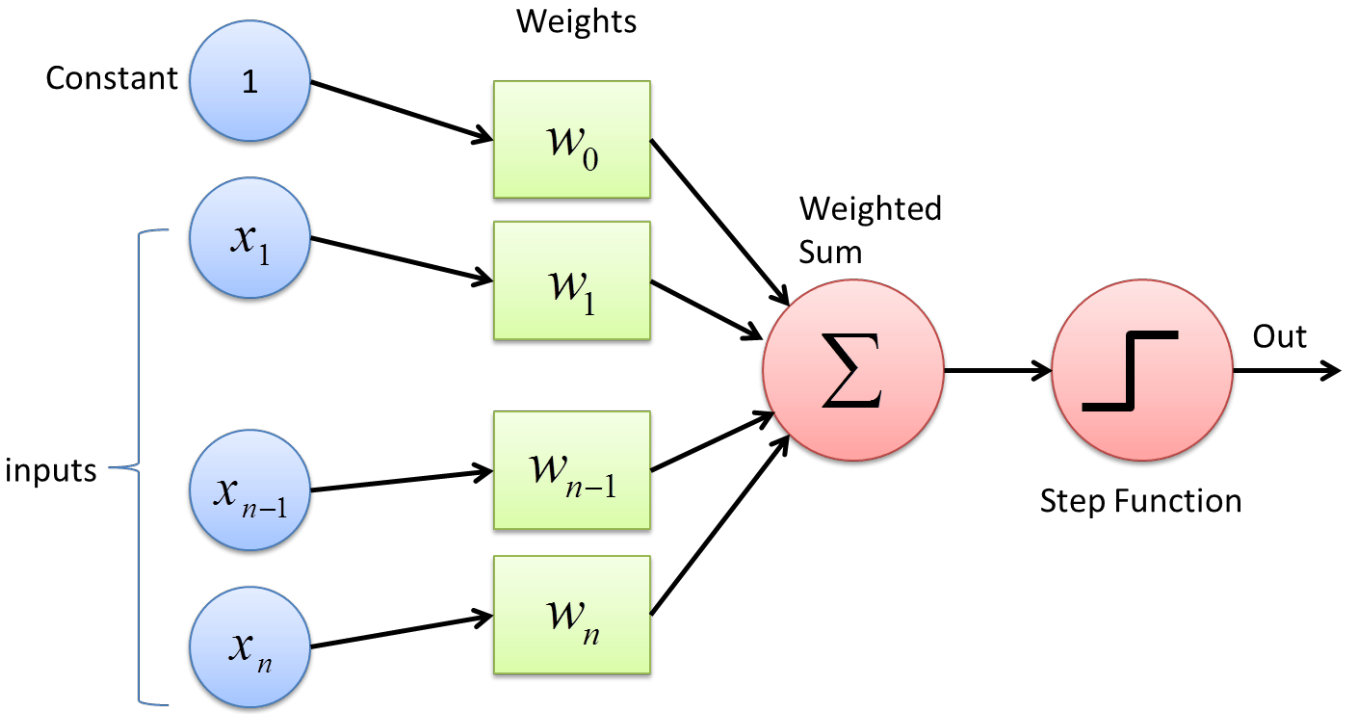


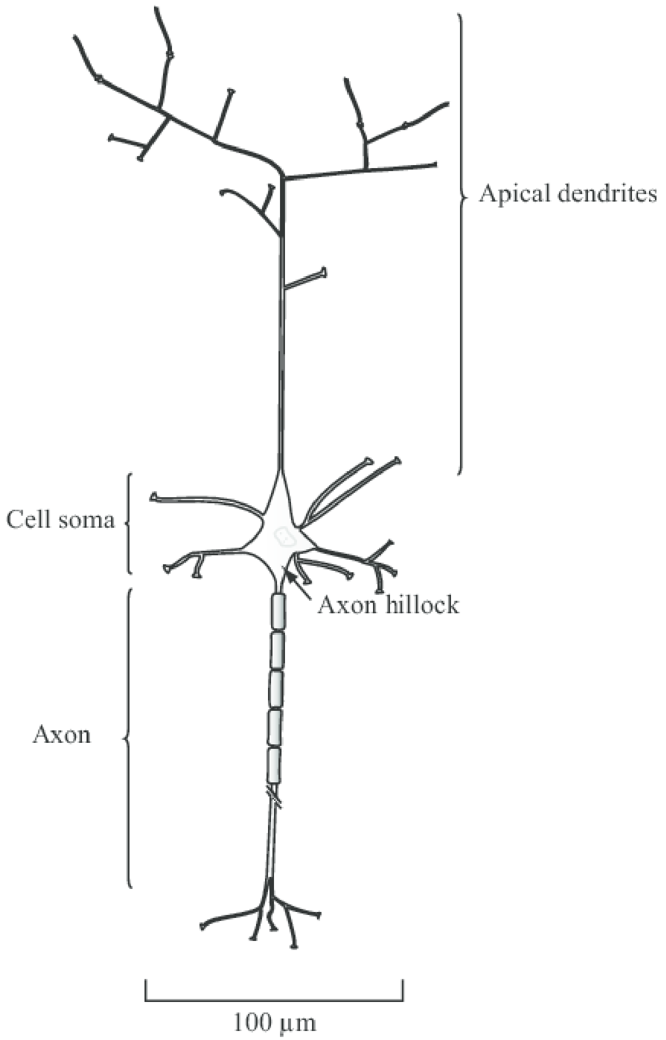
Deep Learning 101



Artificial Neurons (Perceptrons)

- Artificial neurons (Perceptrons)
  - Linear nonlinear functions $y = \phi(Wx)$



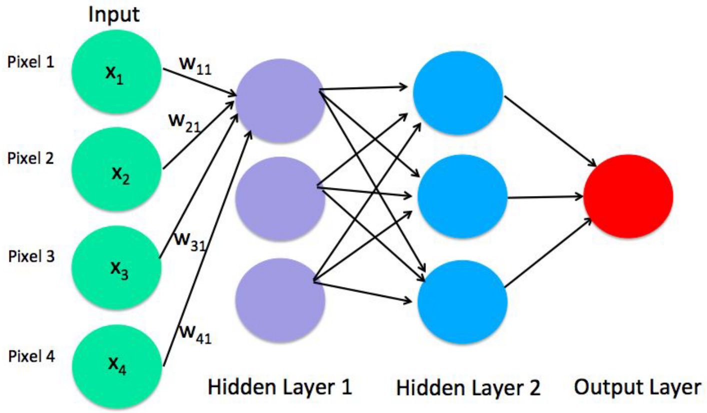


Deep Neural Networks

- Neuroscientist & Bio AI: Artificial neurons connected as a network.
  - Feed forward
  - Recurrent.

- Engineers & Mathematician: Series of differentiable math operations.

$$y = \tanh(W_2 \tanh(W_1 X))$$



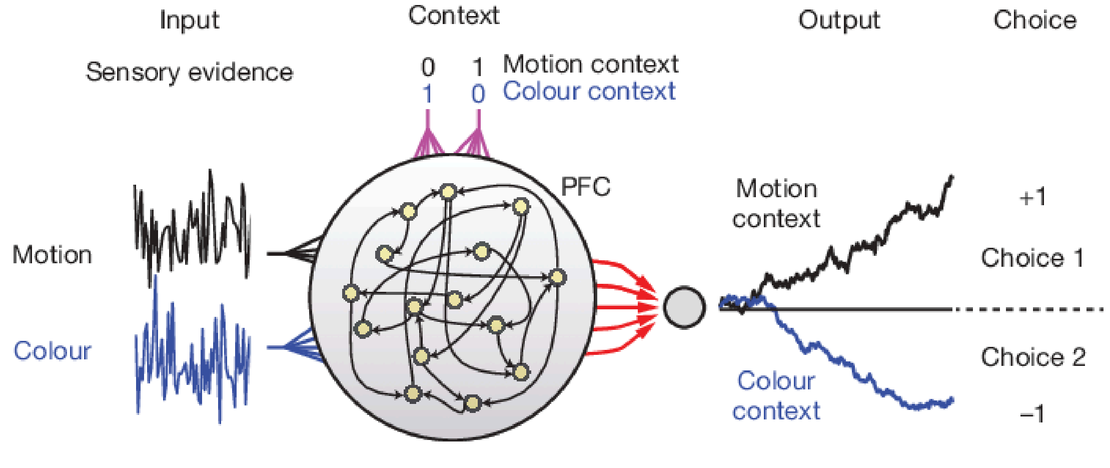
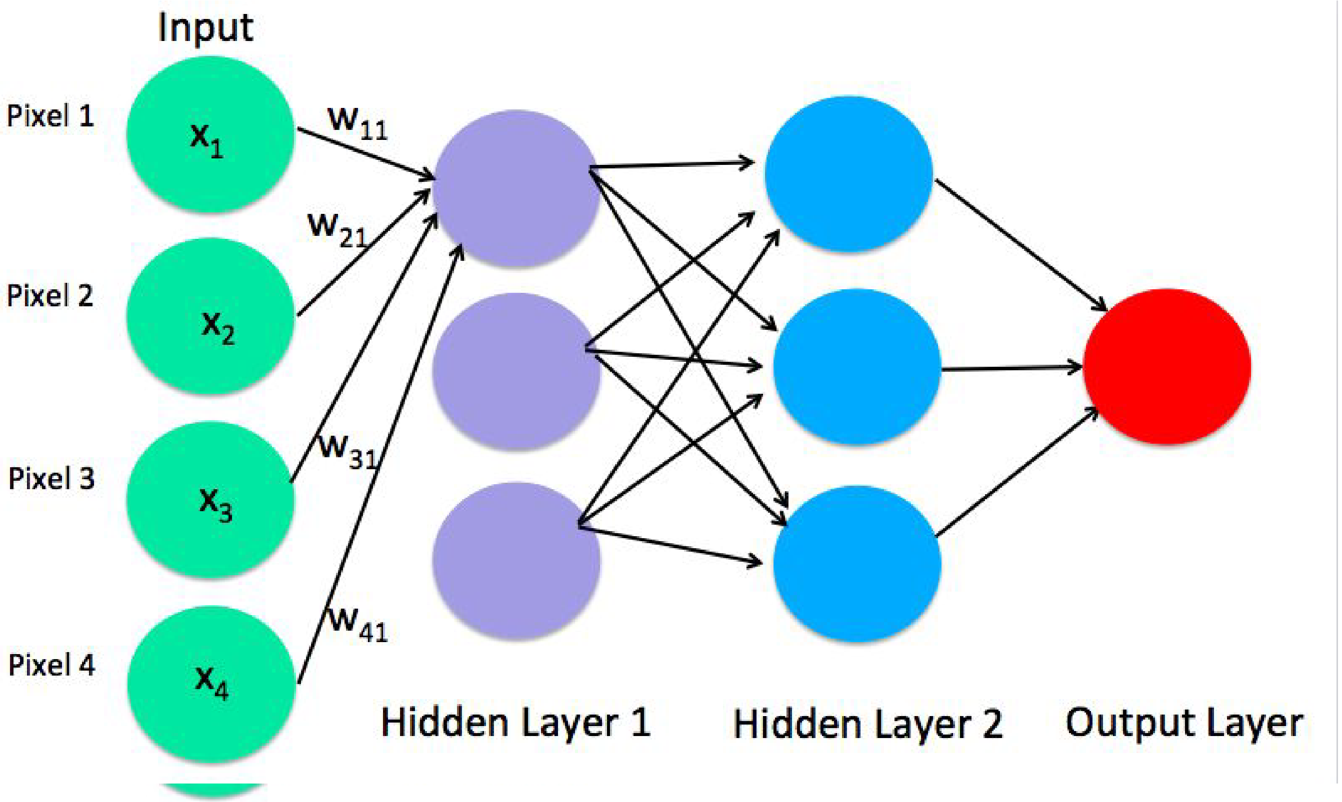


Figure 4 | A neural network model of input selection and integration. PFC

Feed Forward Network (Multi-Layer Perceptron, MLP)

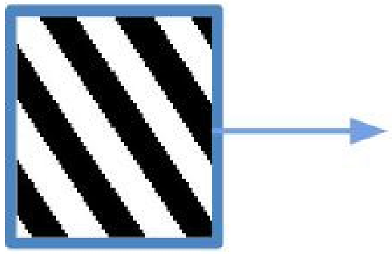
- Operations
  - Matrix multiplication
  - Element-wise nonlinearity.

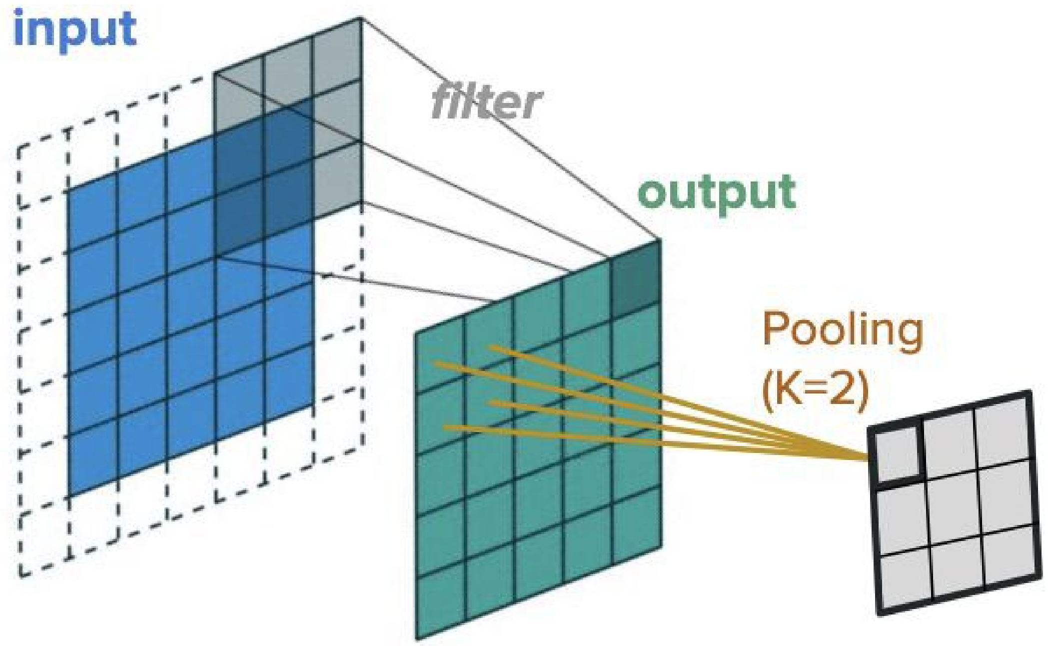
- Neural interpretation



Convolutional Neural Network

- Operations
  - Convolution
  - Pooling (downsampling)
  - Element-wise nonlinearity.
- Neural interpretation





Fun time!

- https://poloclub.github.io/cnn-explainer/
- https://www.cs.ryerson.ca/~aharley/vis/conv/
- [Neural Network 3D Simulation]()

Comparing CNN and MLP

MLP

- Any input
- Dense connection.
  - More parameter, more expressive

CNN

- Structured input
- Local connection
- Weight sharing (spatial invariance)
  - Fewer parameter.
- *Most CNN has MLP as the final part*

DL as Function Approximation

- On a high level, Supervised Learning is approximating a mapping $f: X \rightarrow y$. E.g.
  - Object recognition: Image → label
  - Speech recognition: Sound wave → word
  - Neural encoding: Stimuli / action → neural response
  - Neural Decoding: Neural response → Stimuli / Action
- Achieving this goal by learning from paired data $\{X_i, y_i\}$

What we need to do supervised learning?

- We parametrize the functions with parameter θ, f_θ (weights in neural network)

- We prepare a set of data $\{X_i, y_i\}$

- Learning objective/criterion: how well we are doing with f_θ?

- Learning rule: how to find the best performing parameter $\hat{\theta}$?

What we need to learn object recognition?

- We parametrize the functions with parameter θ, f_θ (weights in neural network)
  - Convolutional neural network
- We prepare a dataset of $\{X_i, y_i\}$
  - ImageNet: Millions of images with labels
- Learning objective/criterion: how well we are doing with f_θ?
  - Cross Entropy Loss
- Learning rule: how to find the best performing parameter $\hat{\theta}$?
  - Stochastic gradient descent (with batch)

Exercise: What we need to decode neural signal?

Firing of motor neurons → Actions

- Our network and parameter? θ, f_θ
  - MLP??

- We prepare a dataset of $\{X_i, y_i\}$
  - Training set of firing rate and hand direction
  - I/O coding design.

- Learning objective/criterion: how well we are doing with f_θ?
  - ???

- Learning rule:
  - Stochastic gradient descent (with batch)

Feel similar? You are right!

- This general framework encompass previous models
  - Linear regression $y = X\theta$
  - Linear nonlinear model $y = \exp(X\theta)$

  - *Easier to solve with analytical solutions.*

Comparing CNNs and Visual Cortices

Similarities

- Architecture:
  - Local connections
  - Retinotopy
  - Feature maps
  - Hierarchy
- Function:
  - Object recognition (?)
- (Arti)Physiology
  - Representation

Differences

- Architecture:
  - Fovea?
  - Cortical magnification?
  - Feedbacks?
  - Local circuit? Horizontal connections?
  - Spikes? Or does that matter
  - Neural morphology? Or does that matter
- Learning rule: gradient descent?
- Learning scheme: supervised?

How to use deep learning in neuroscience?

How Deep Learning can be connected to neuroscience?

1. Analysis tool:
   - Decoding, Encoding neural signal with NN

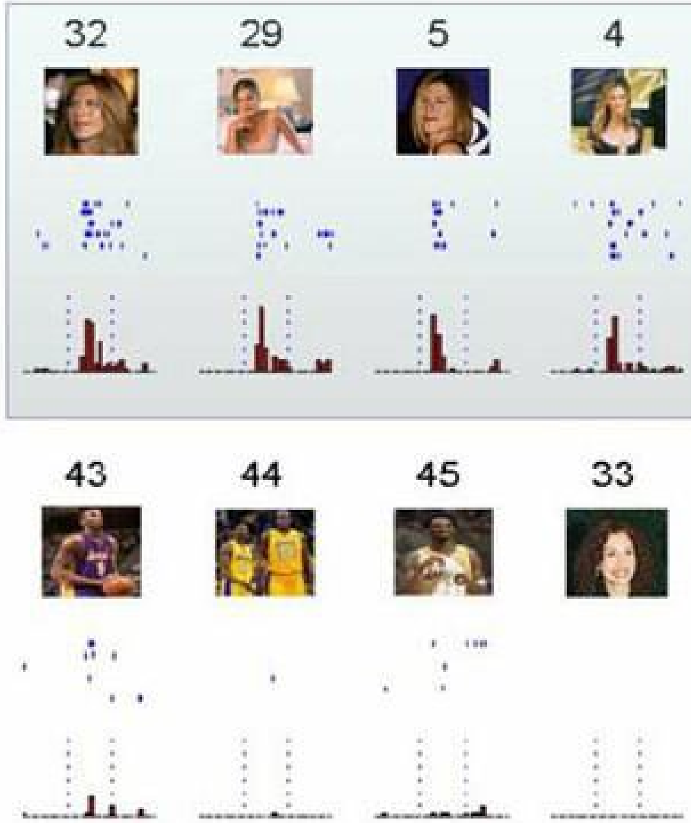
2. Deep neural network as the optimal scenario to study a neural system

   - *Test bed for our analysis pipeline and experimental system.*
   - Study CNN as a model system for object recognition (*part of my job*)
   - Study RNN / RL agent as model system for cognitive tasks.

3. A normative model of the brain.
   - NN evolved to a certain algorithm / computation, could the brain also use it?
   - what could be the computation in the brain?
   - Find similarity of representation in brain and NN.

Example: Activation Maximization *in vivo* and *in silico*

- What's the preferred stimuli for a neuron/unit?



Let's search for / synthesize it!

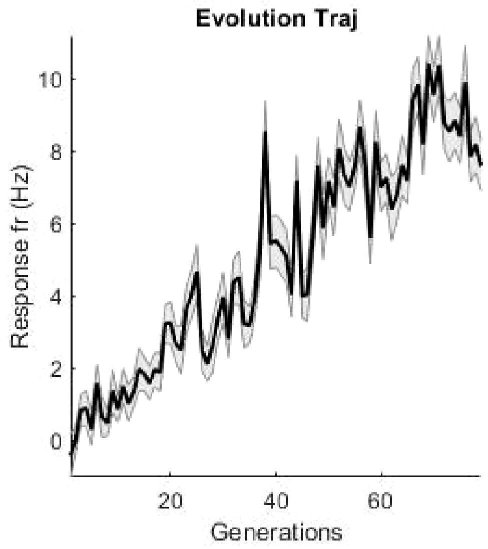
$$\hat{I} = \arg\max_{I} f(I)$$

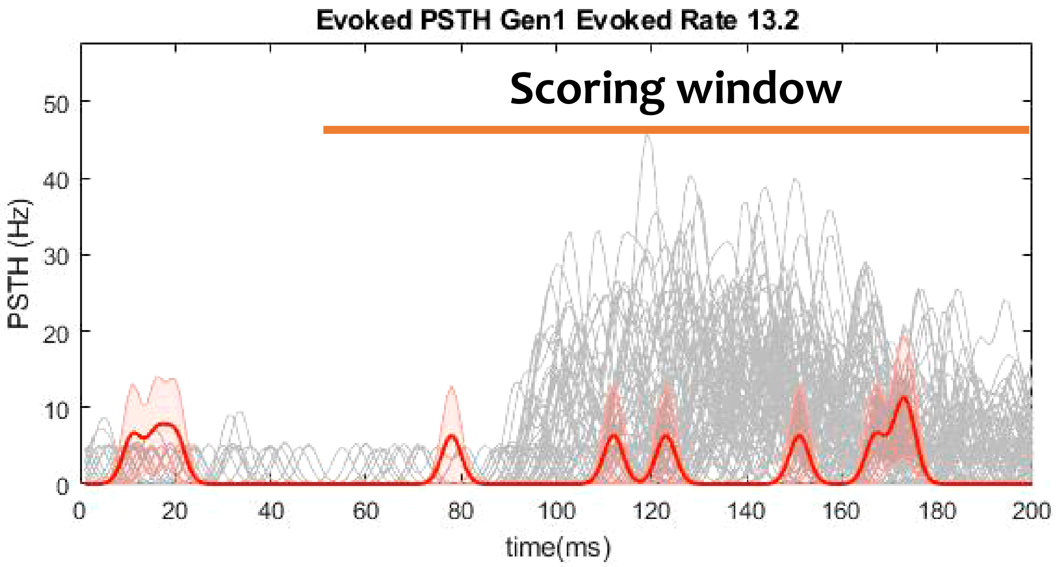
https://distill.pub/2017/feature-visualization/

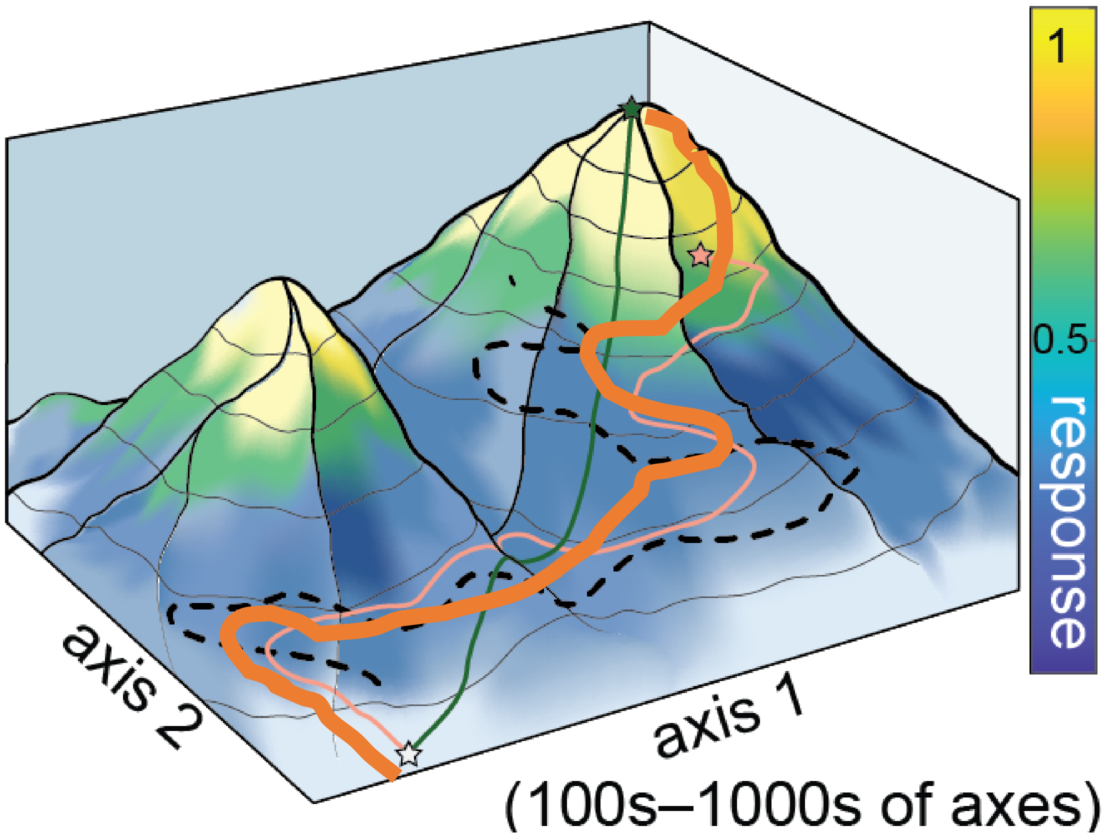
Evolution: search for activity maximizing image

Beto Evol (Manif) Exp 11 pref chan 26A

Gen1



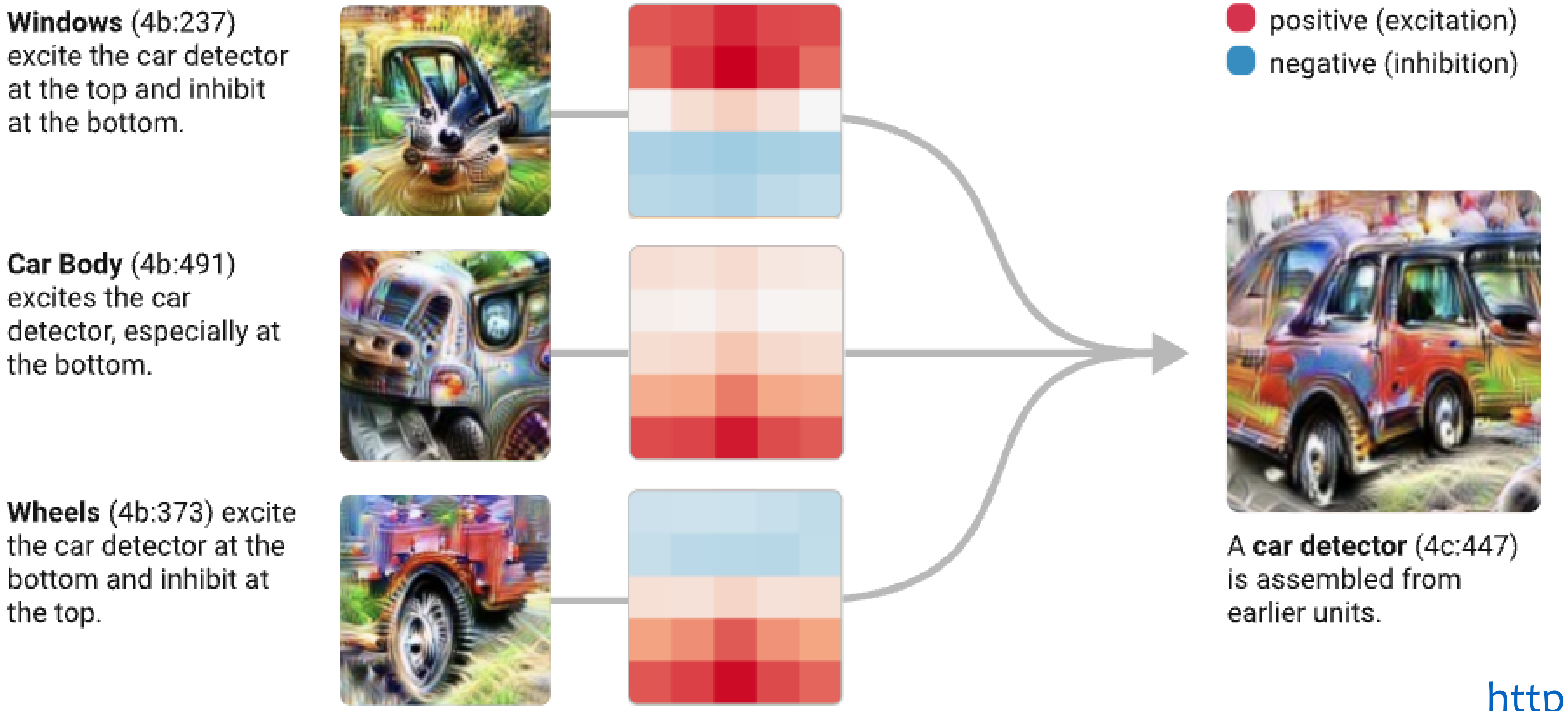




CMAES optimizer

Example: Neural Circuit in CNN (and brain?).

How preferred features build up through synaptic connections?



https://distill.pub/2020/circuits/