

Machine Learning Neurosciences

Michel Dojat

► **To cite this version:**

Michel Dojat. Machine Learning

Neurosciences. Workshop ECCOREV "Intelligence artificielle et Big Data", Nov 2018, Aix-en-Provence, France. hal-02165616

HAL Id: hal-02165616

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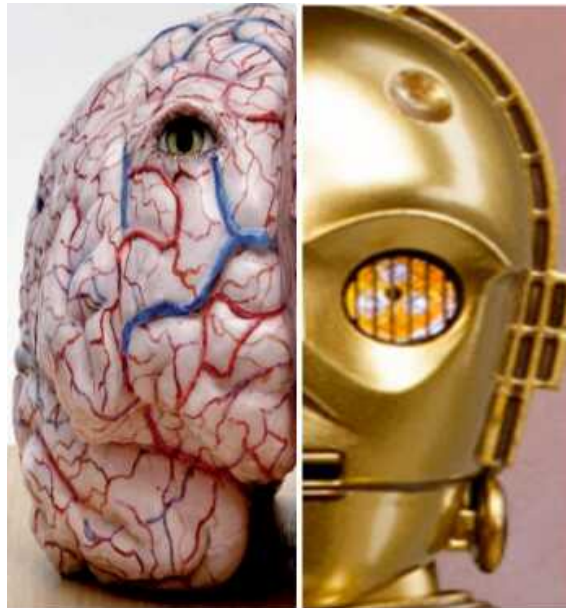
Submitted on 26 Jun 2019

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Machine Learning & Neurosciences

Michel Dojat



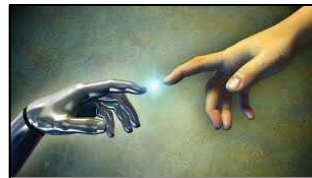
Artificial Intelligence

Intelligent Agent: an entity that takes the best possible action in a situation



- How to build an artificial intelligent agent?
- Test our models of natural intelligent agents?

*Computer
science*

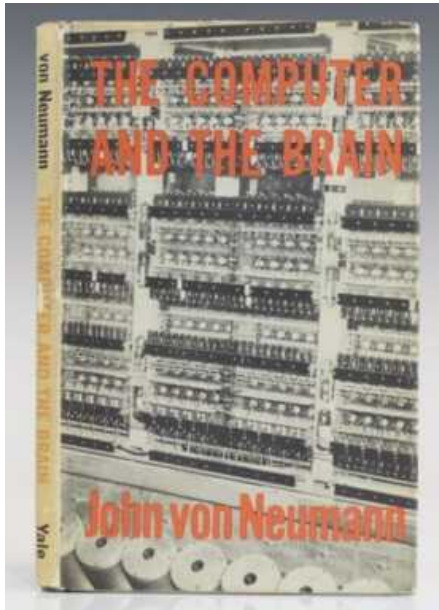


Neuroscience

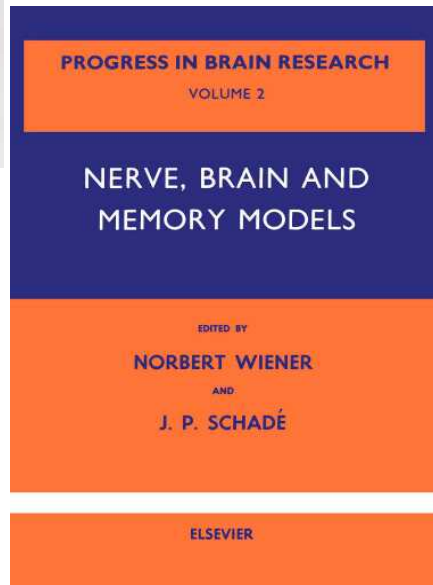


*Integration of heterogeneous datasets
Management of large repositories of data &
knowledge
Knowledge discovery*

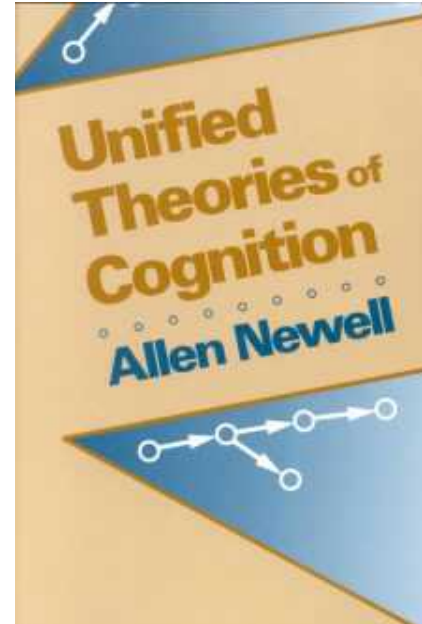
Computer & Brain



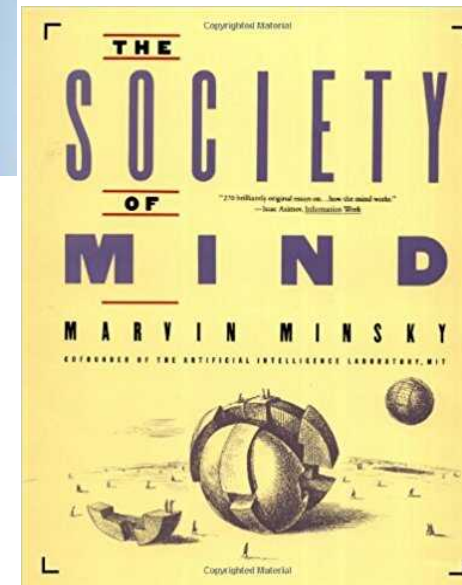
1958
Yale University Press, New Haven



1963



1982



1988

Two main approaches

- Machine Learning

- Bio-inspired

- Artificial life

- Neural Networks

- WMcCulloch & W Pitts (1943)
Artificial neurons

- D Hebb (1949)
Learning by modification of connections

- F Rosenblatt (1963)
Convergence theorem

- M Minsky & S Paper
Perceptrons (1969)

- Classification (SVM,...)

Operations on large vectors

- Symbolic Processing

- Problem-solving

- Planning

- Logic

- Knowledge representation

- Common knowledge

- Meta-knowledge

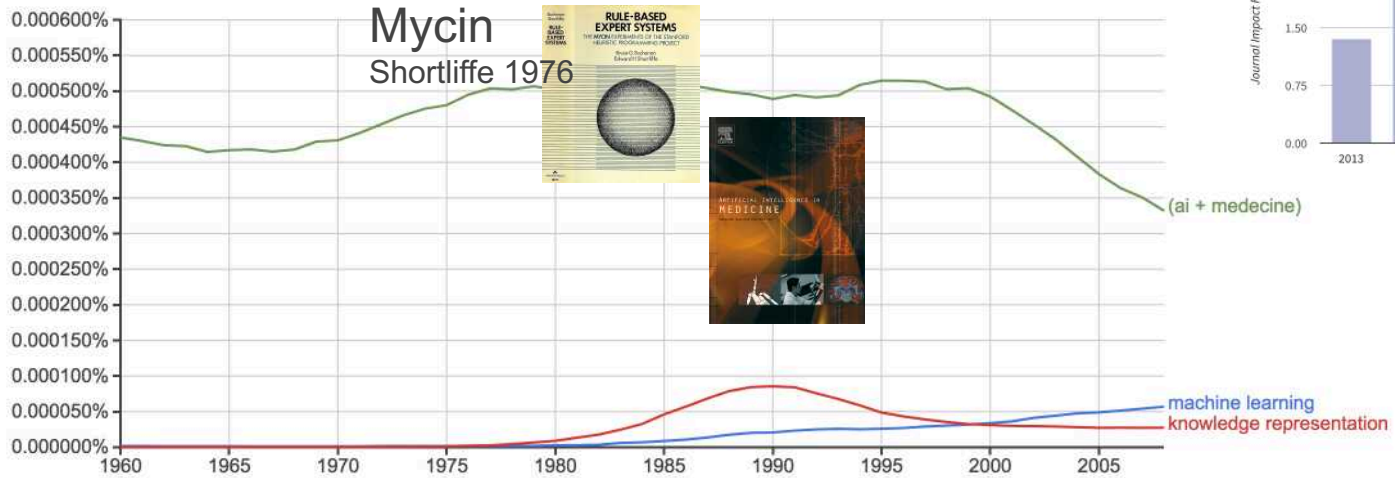
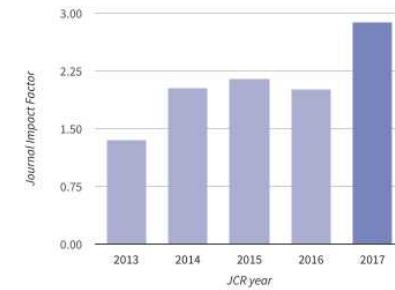
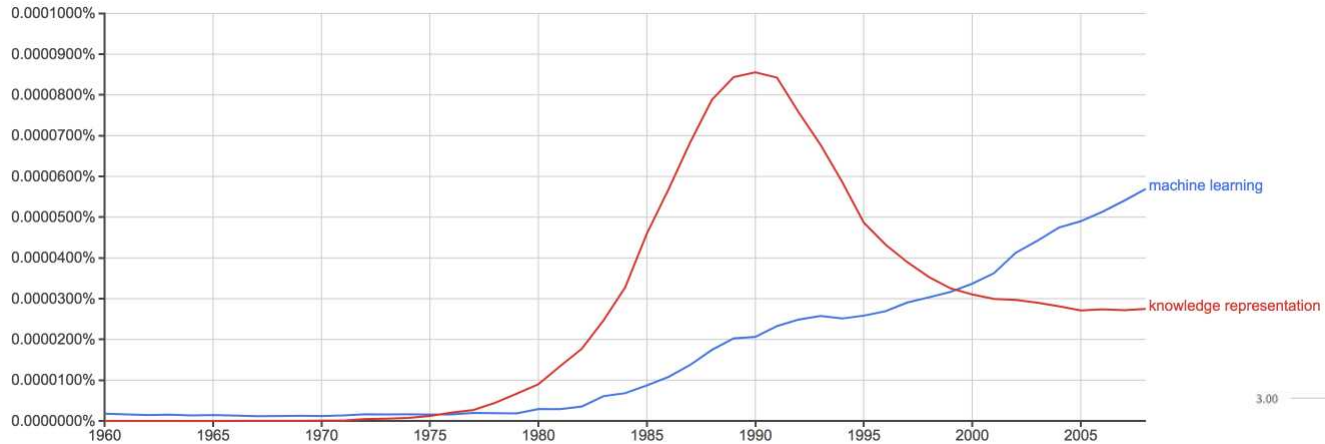
- Ontology

- Multi-agents

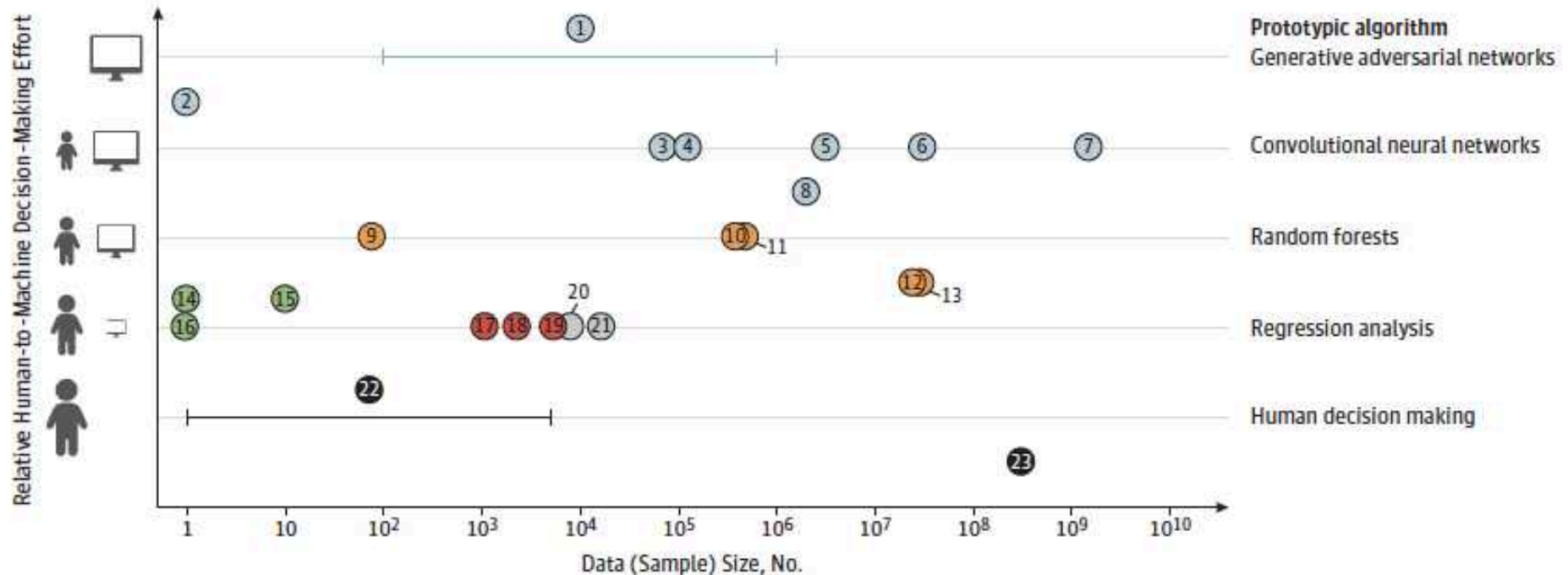
- Co-construction

Rule-based manipulation of symbols

But ...



ML: Natural extension of traditional statistical approaches



Deep learning

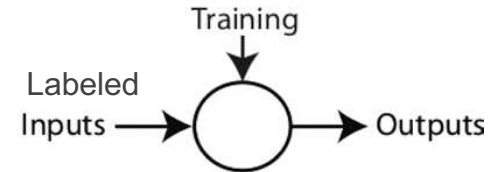
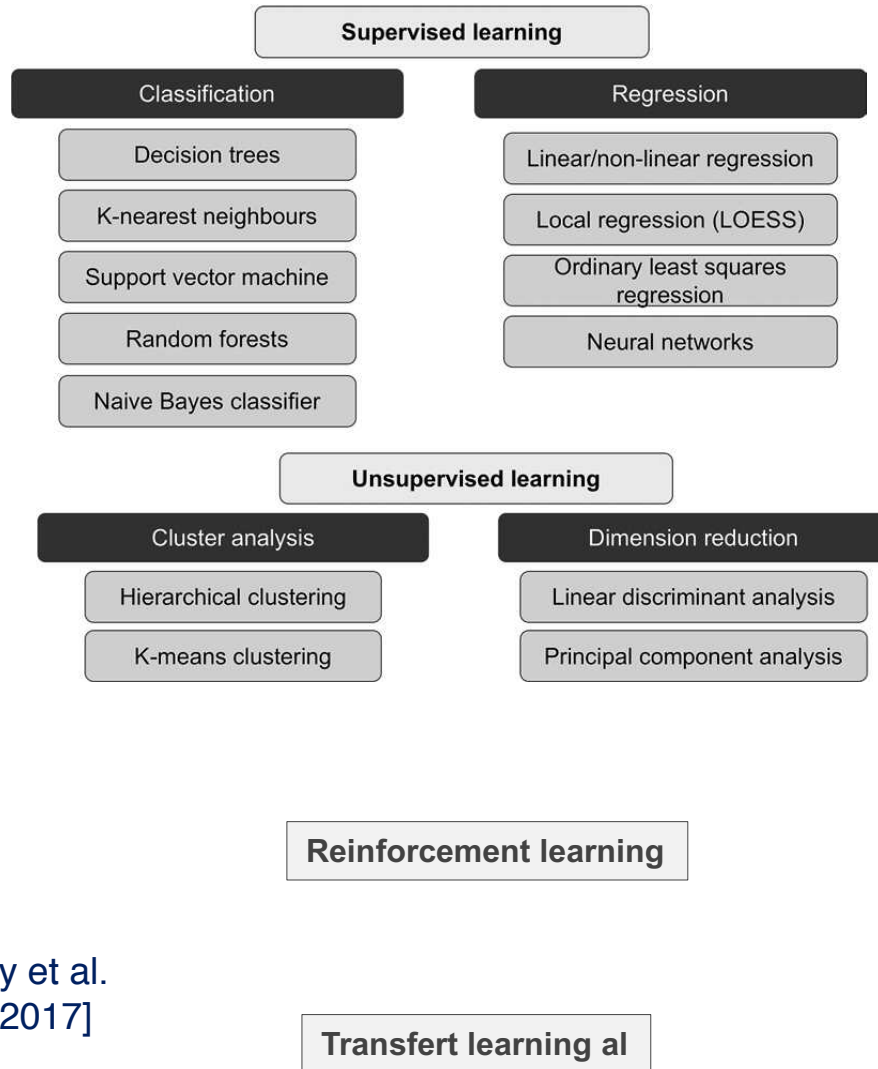
Risk calculators

Other

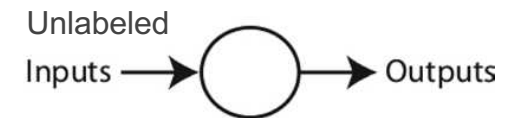
Classic machine learning Knowledge-Based systems

Beam & Kohane Nature 2018

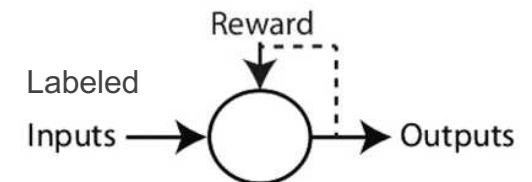
ML Approaches



Learns known patterns
Predicts outcome



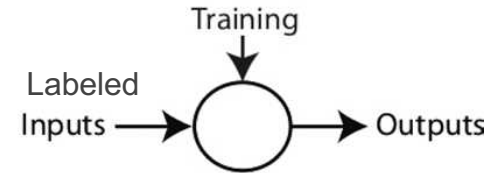
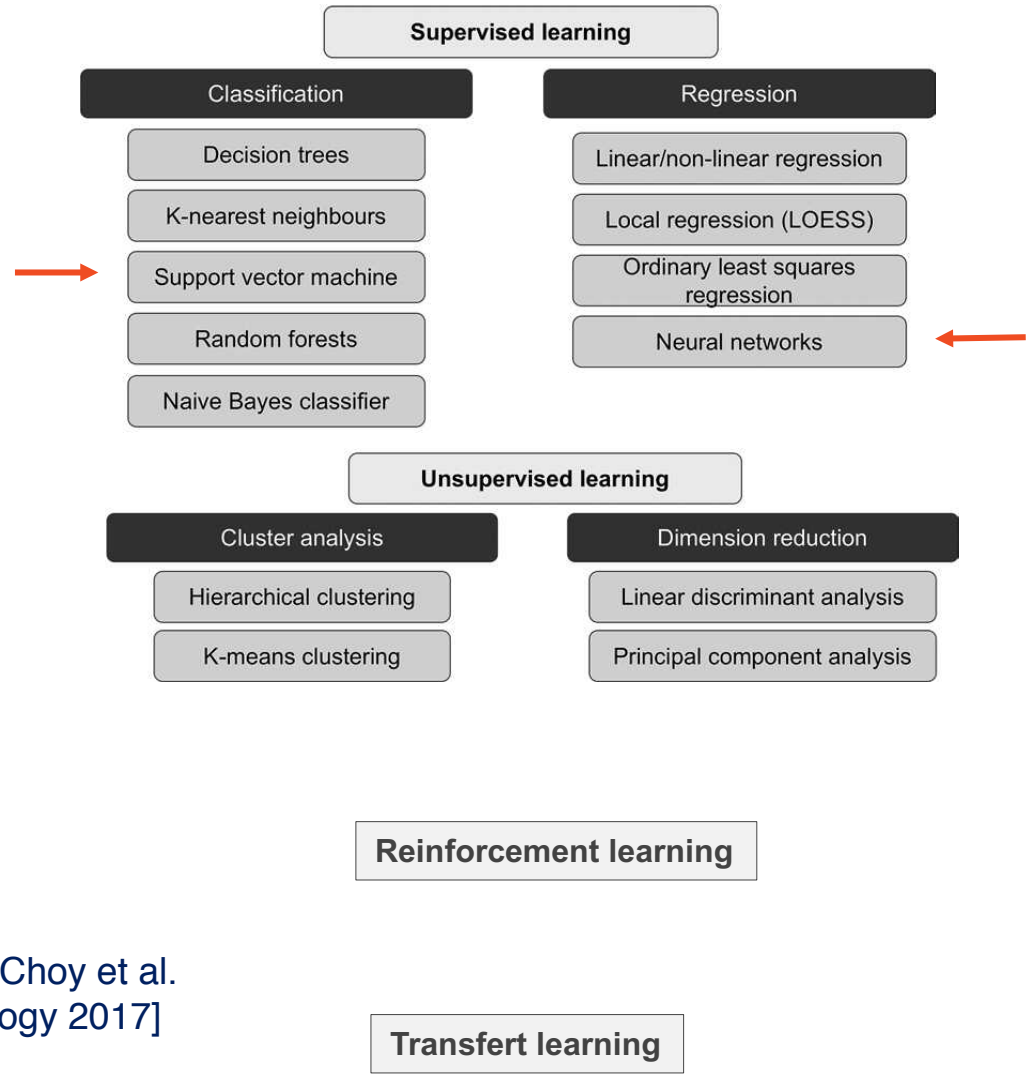
Learns unknown patterns
Find hidden patterns



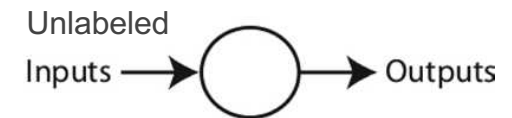
Generates data
Interacts with environment
Applies learned patterns to
a different but related task

[From Choy et al.
Radiology 2017]

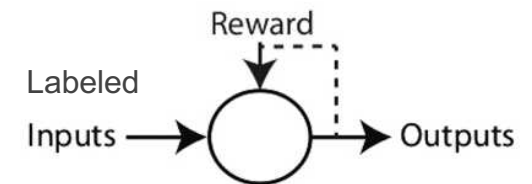
ML Approaches



Learns known patterns
Predicts outcome



Learns unknown patterns
Find hidden patterns



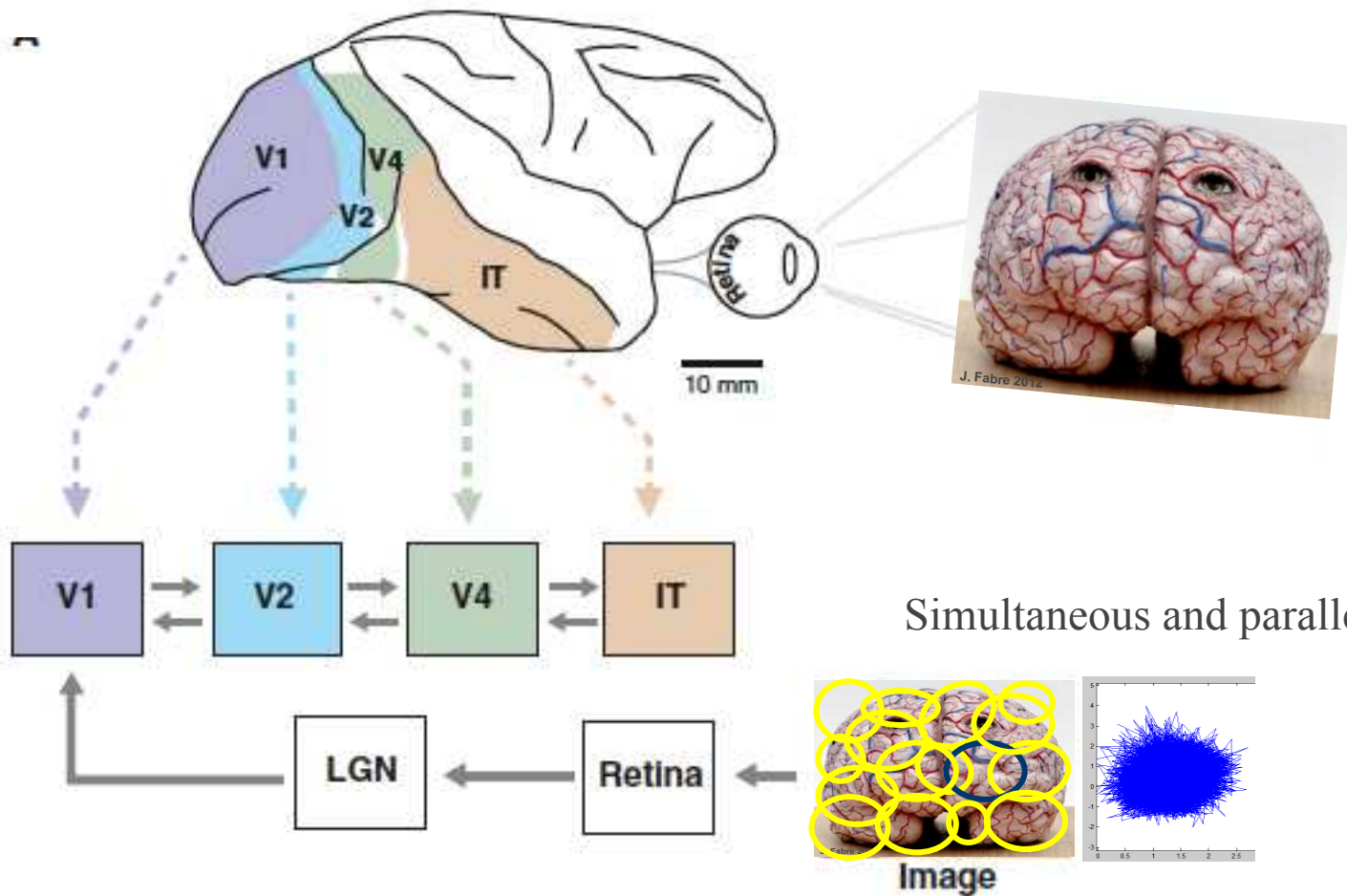
Generates data
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[From Choy et al.
Radiology 2017]

Neurosciences - ML Cross fertilization

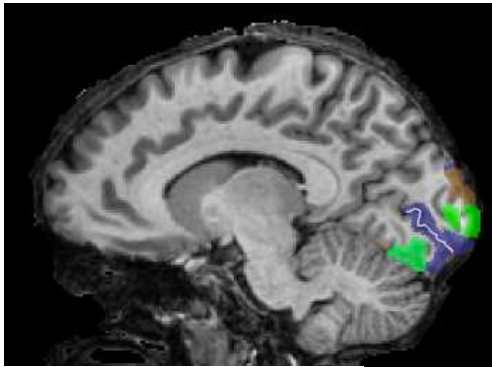
- The Human Visual System
 - Encoding / Decoding
- Deep Learning in NN
 - CNN as Models of the Visual System
- Discussion - Perspectives

Mammalian visual system

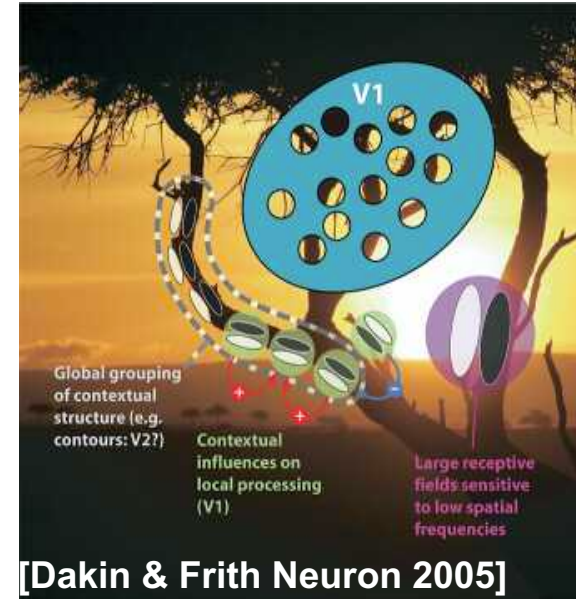
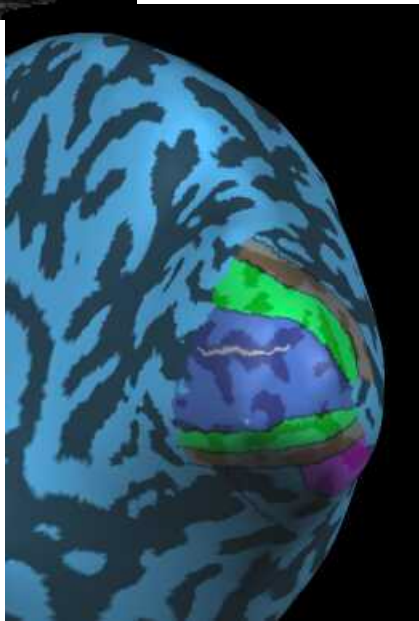


[adapted from Cox & Dean curr bio 2014]

Human visual system



CORTEX

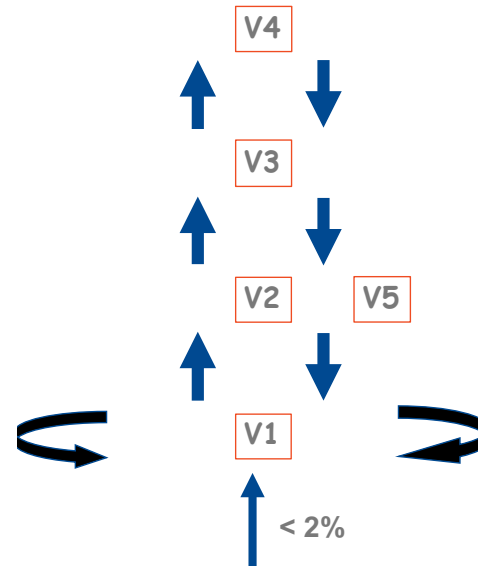
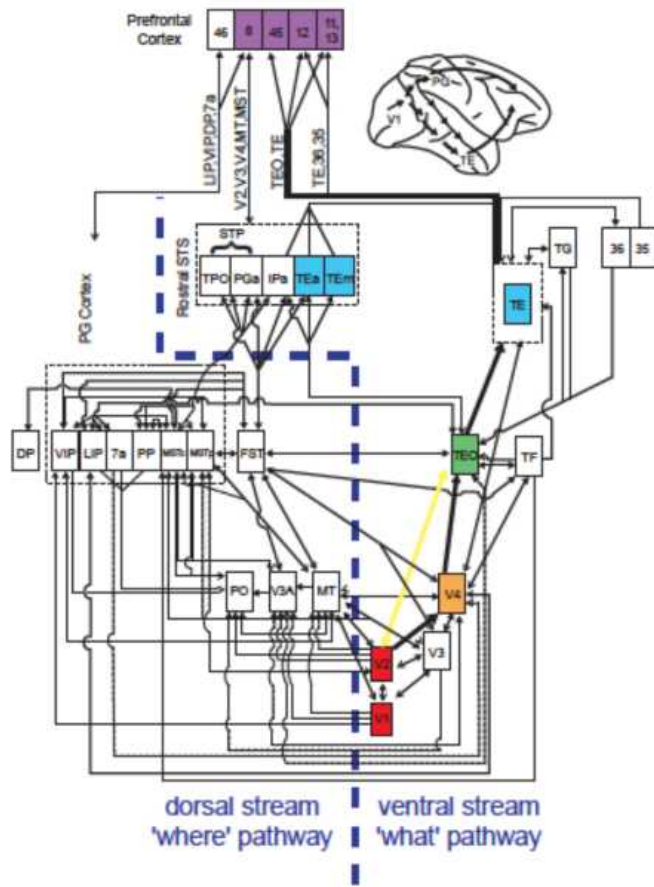


[Dakin & Frith Neuron 2005]

[Escher, Balcony 1945]

Brain connectivity

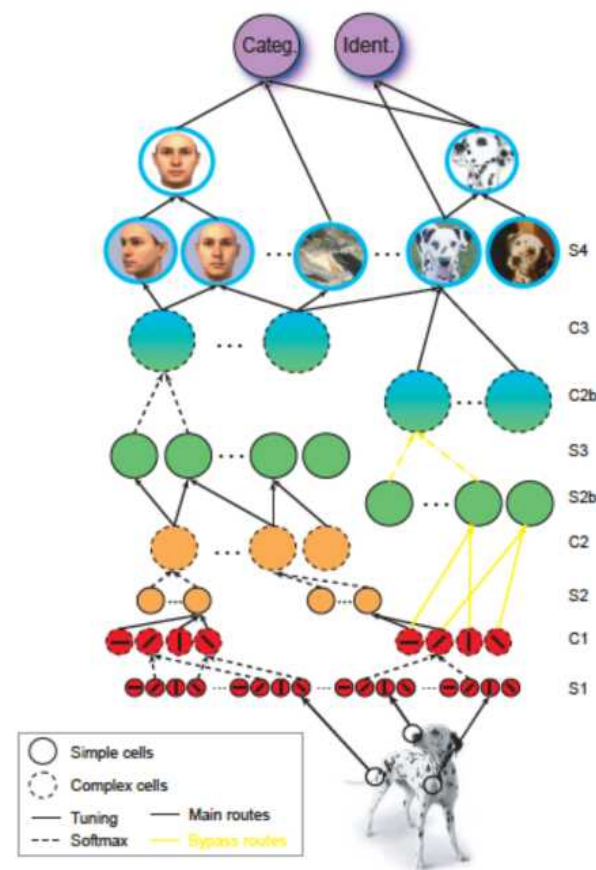
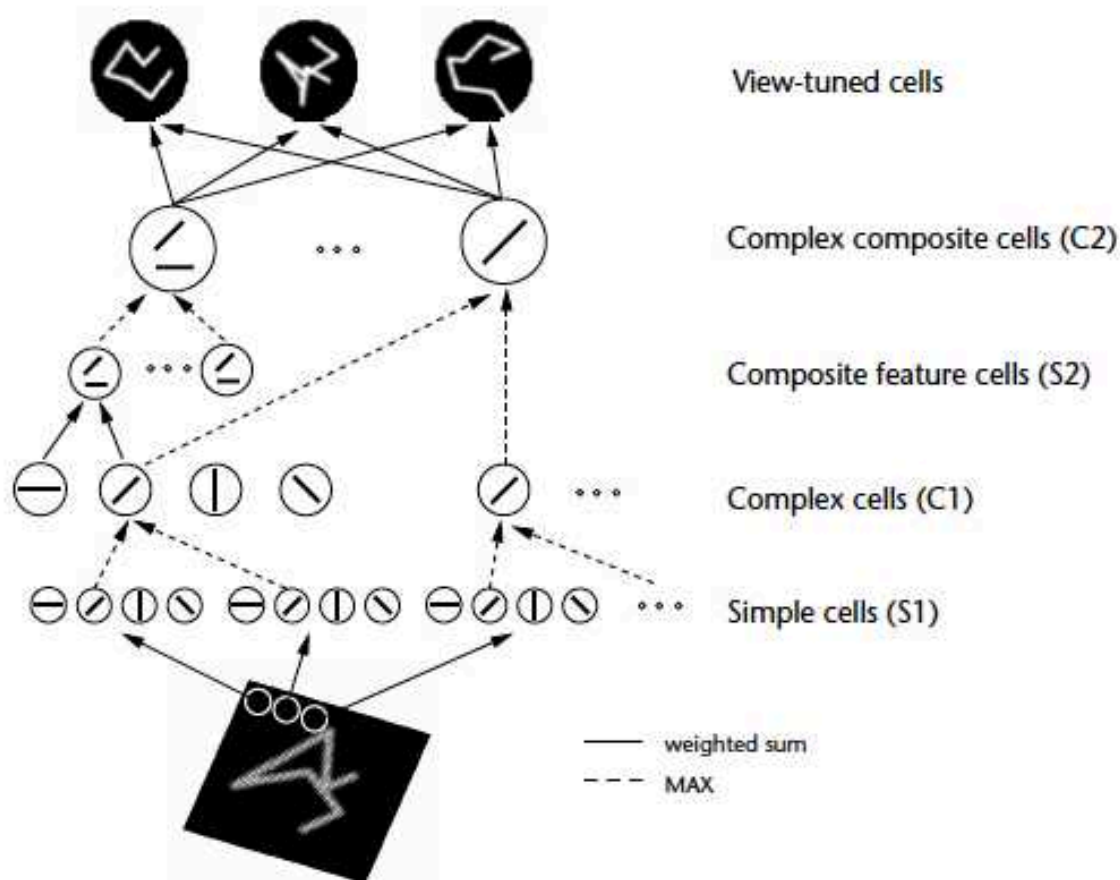
- Hierarchical model
- Several areas interconnected (layers)
- Receptive field sizes increasing
 - Local features
 - Global grouping



[Serre et al 2005 Tech Report]

MAX pooling

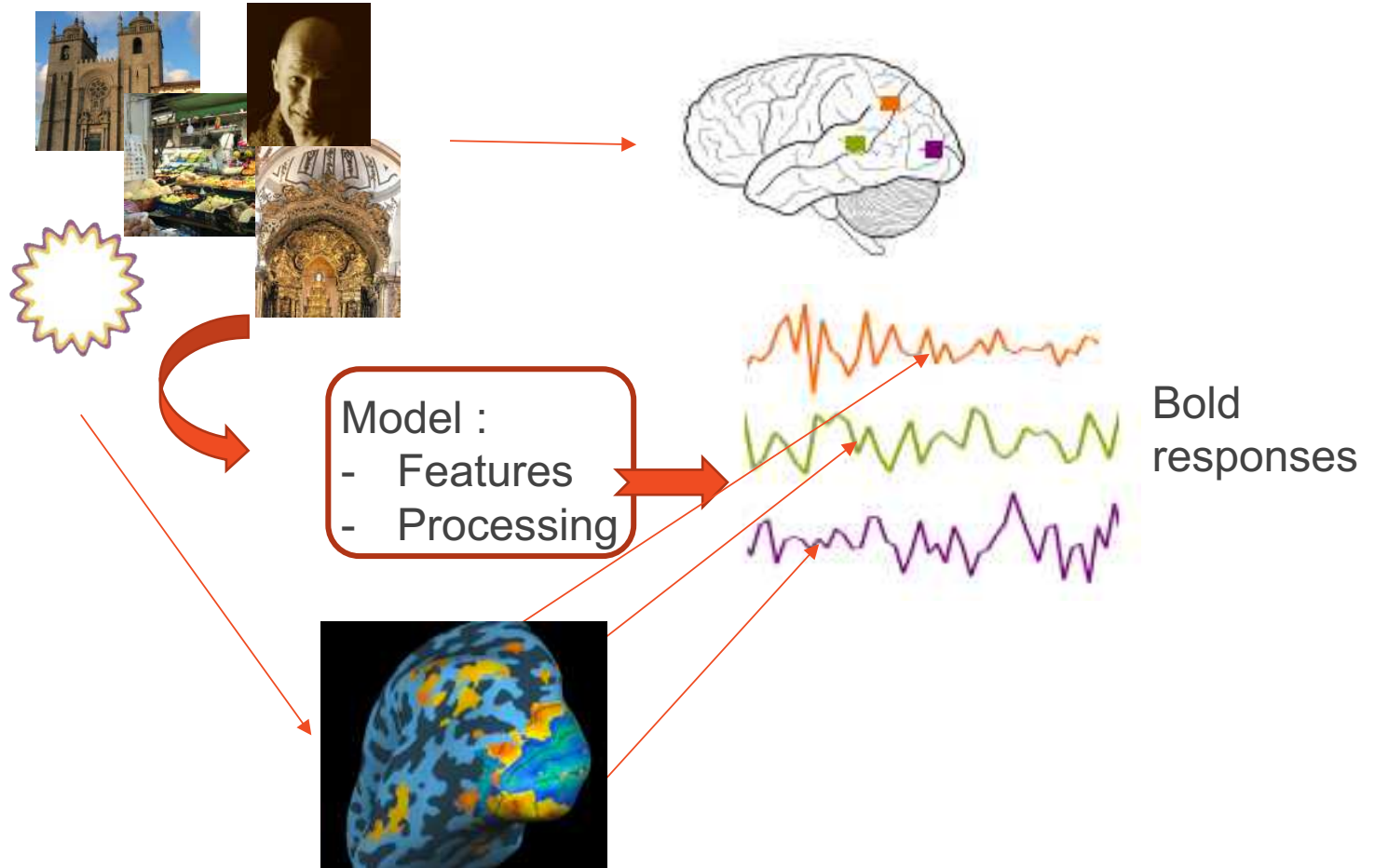
MAX pooling: invariance to scale and translation; key mechanism for object recognition



[Riesenhuber & Poggio Nature 1999]

[Serre et al 2005 Tech Report]

Visual representation in the Human Brain

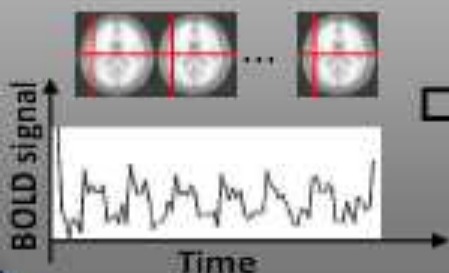


Functional imaging: Encoding models

Univariate Voxel Analysis

Standard Statistical Analysis (encoding)

Input



$$Y = X\hat{\beta} + \epsilon$$

Voxel-wise
GLM model
estimation

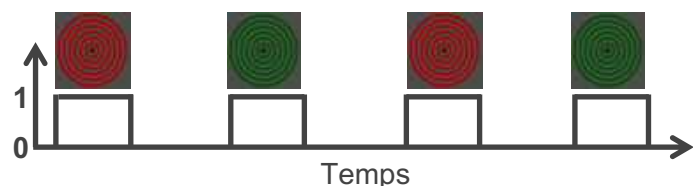
Independent
statistical
test at each
voxel

Correction
for
multiple
comparisons

Output

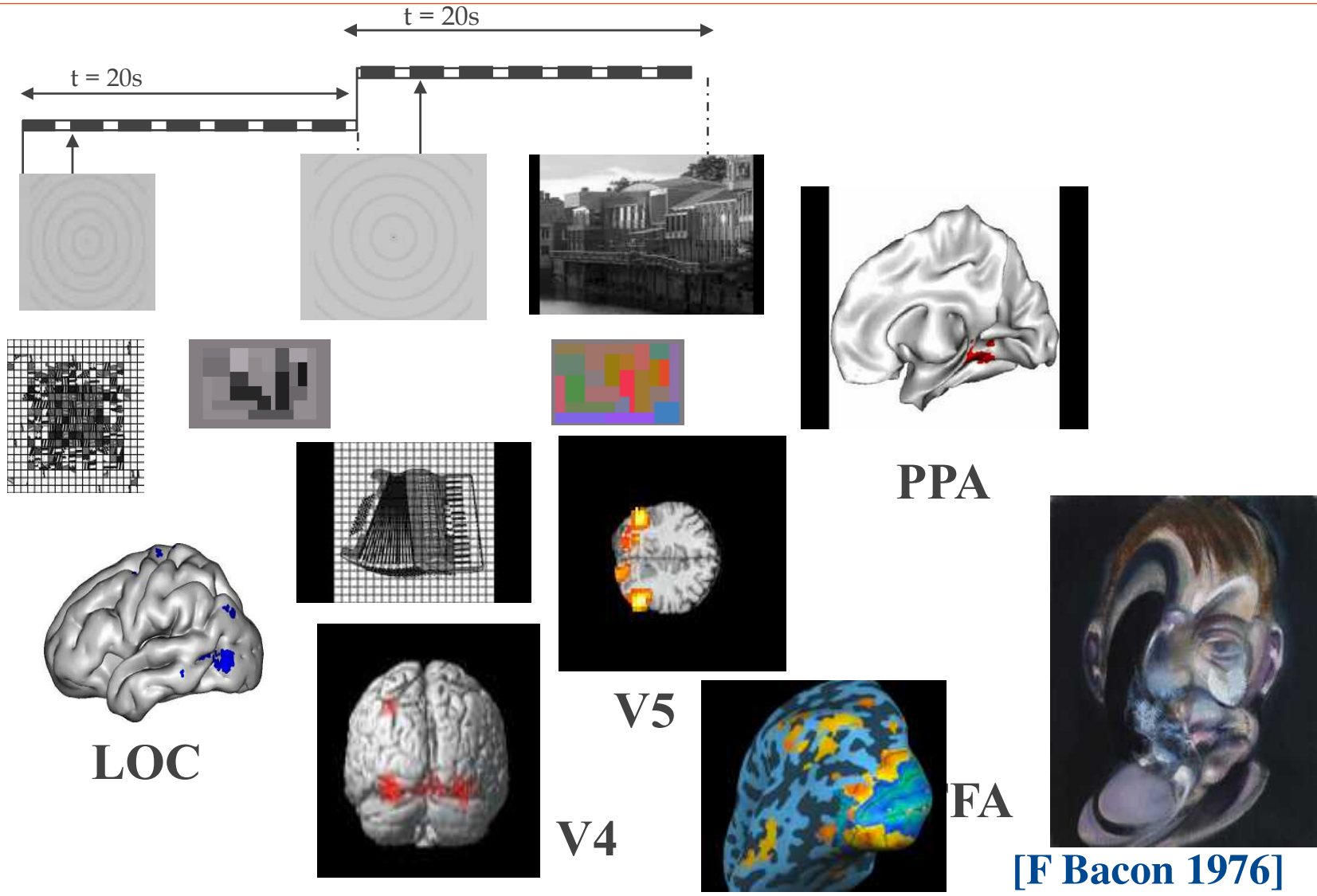


$p < 0.05 \rightarrow 2500$ false positive !

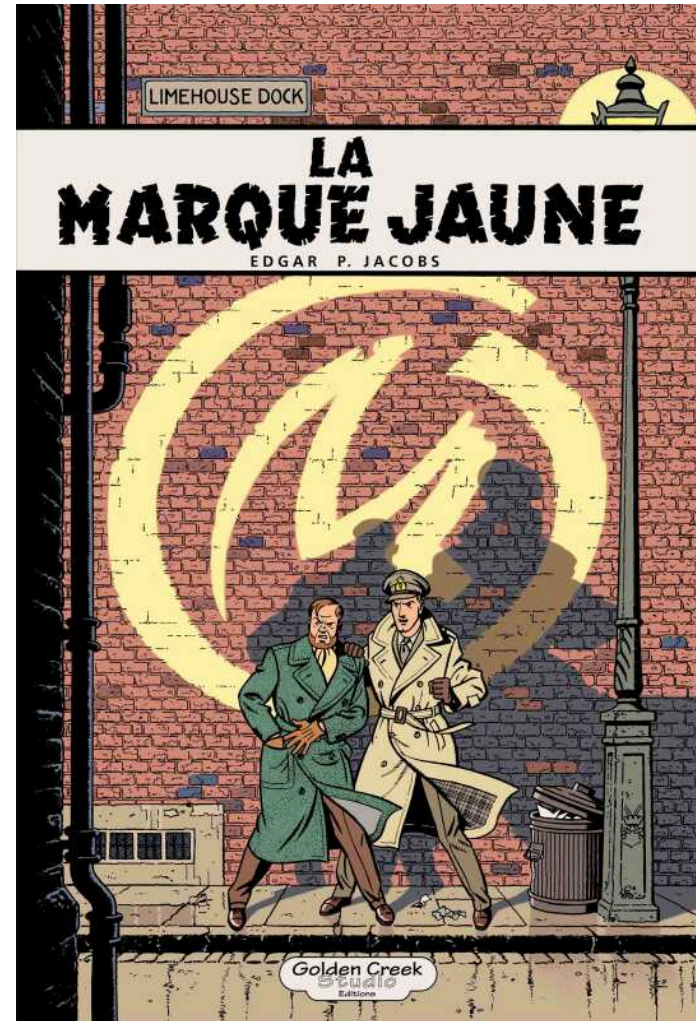


Some examples

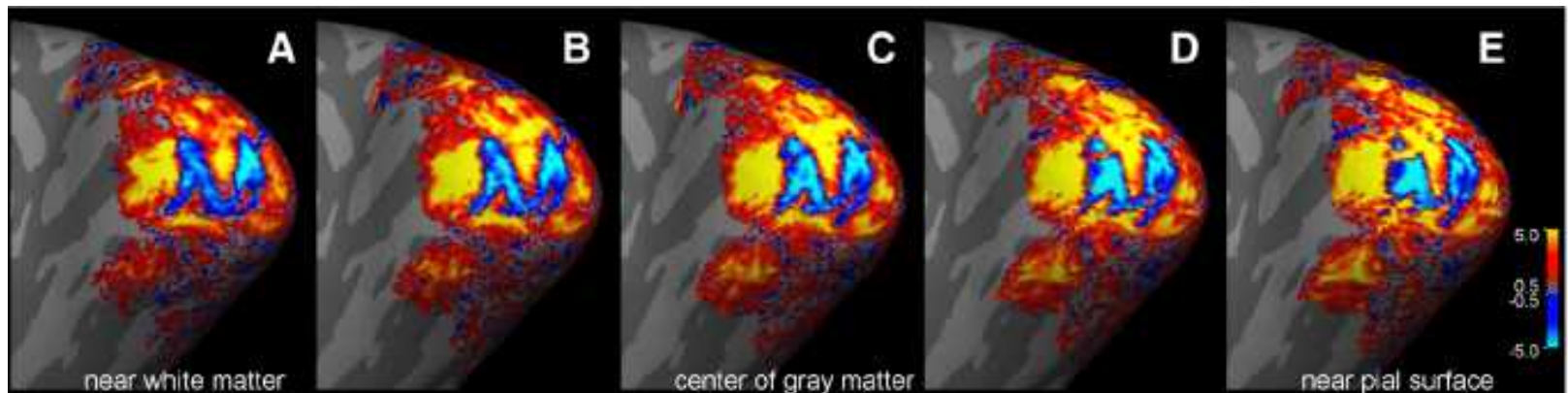
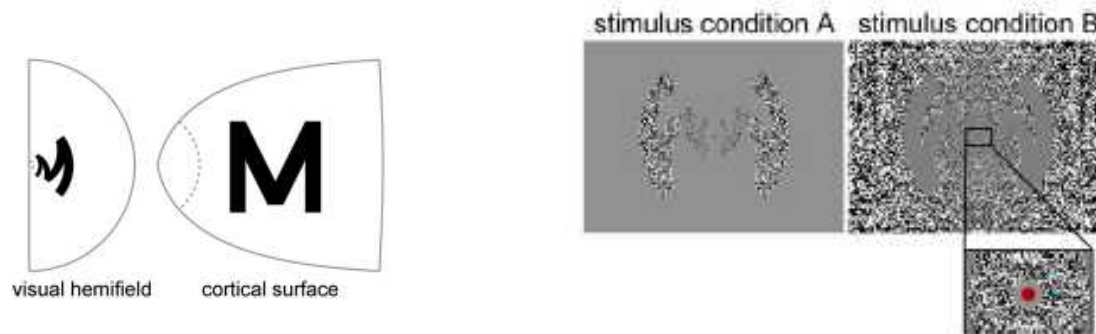
Localizers



Cortical activation – Space localisation

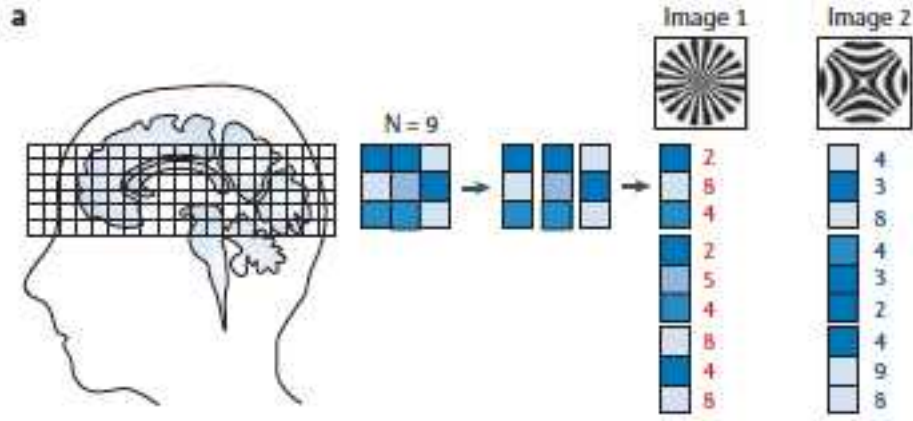


Cortical activation – Space localisation

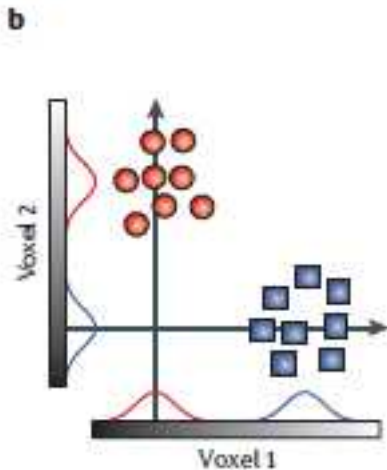


[Polimeni et al. NeuroIm 2010]

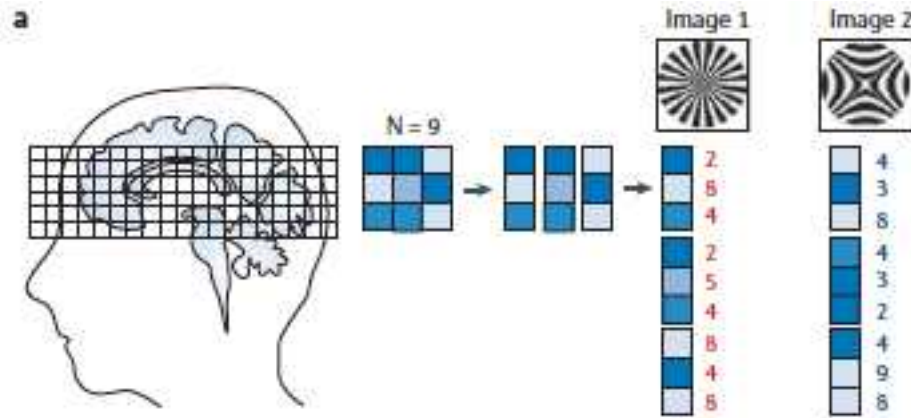
Pattern recognition



[Haynes and Rees Nat Neuro 2006]



Pattern recognition

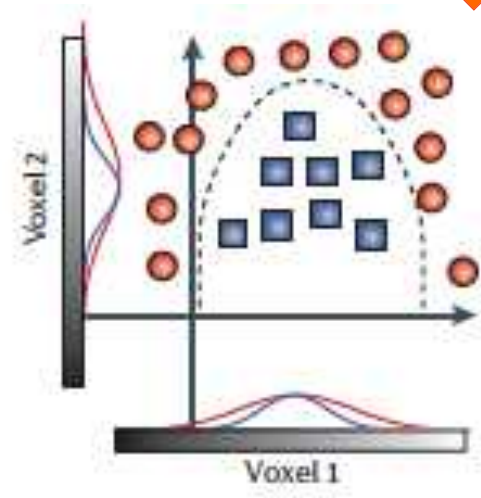
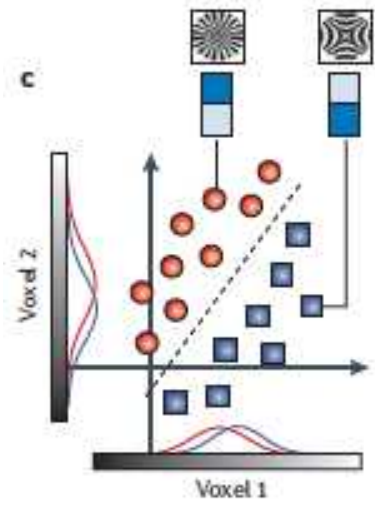
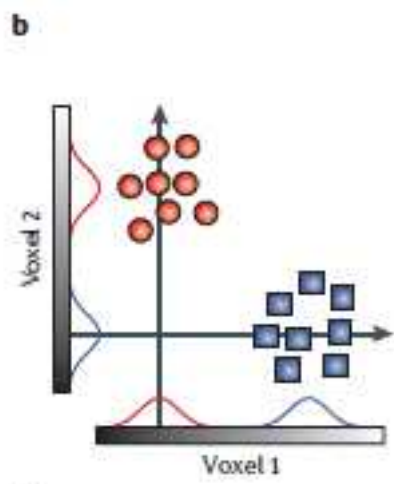


$$f(x) = w + b$$

$$f(x^*) = wx^* + B$$

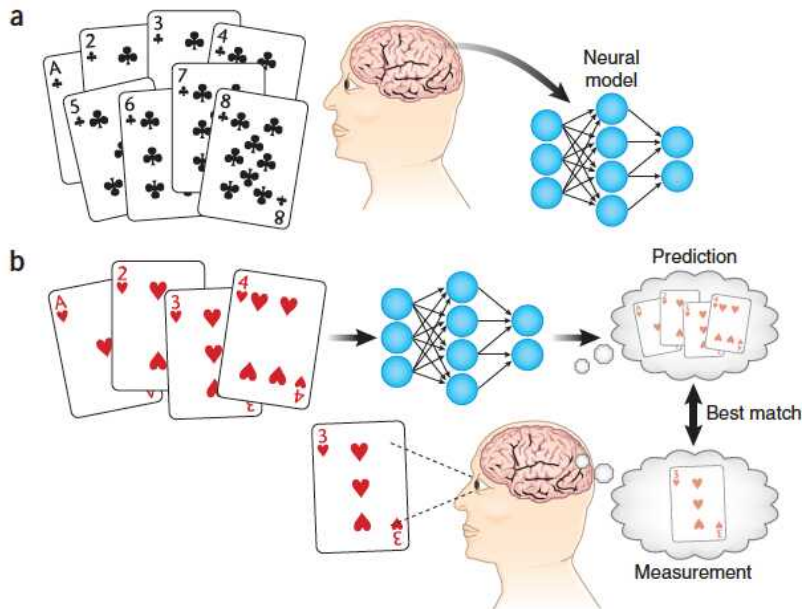
$$w = \sum_{i=1}^N \alpha_i x_i$$

Risque d'overfitting



[Haynes and Rees Nat Neuro 2006]

Mind Reading



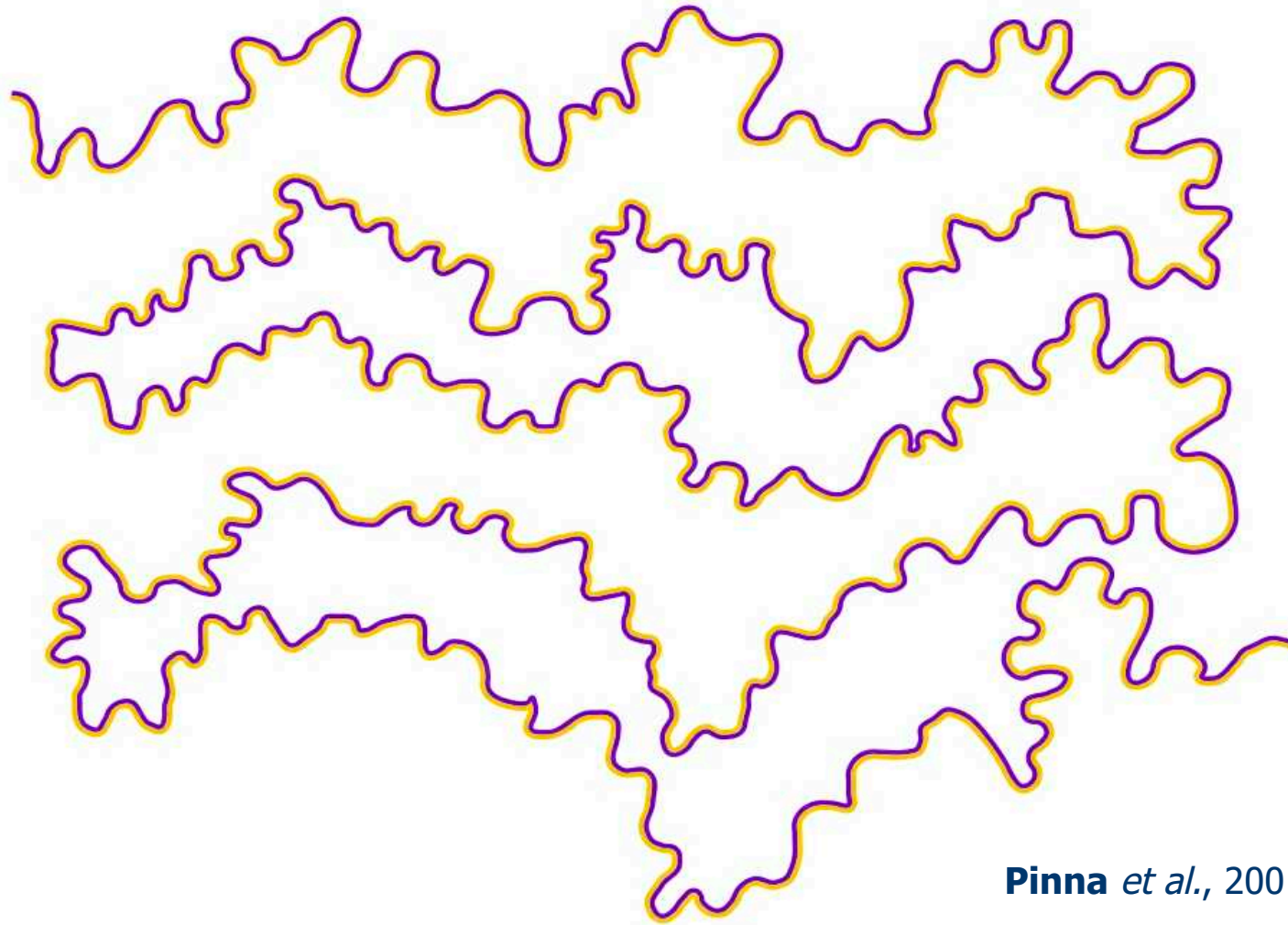
Identifying natural images from
human brain activity
Kendrick N. Kay, Thomas Naselaris,
Ryan J. Prenger & Jack L. Gallant

Nature Vol 452|20 March 2008

[Wandell Nature 2008]

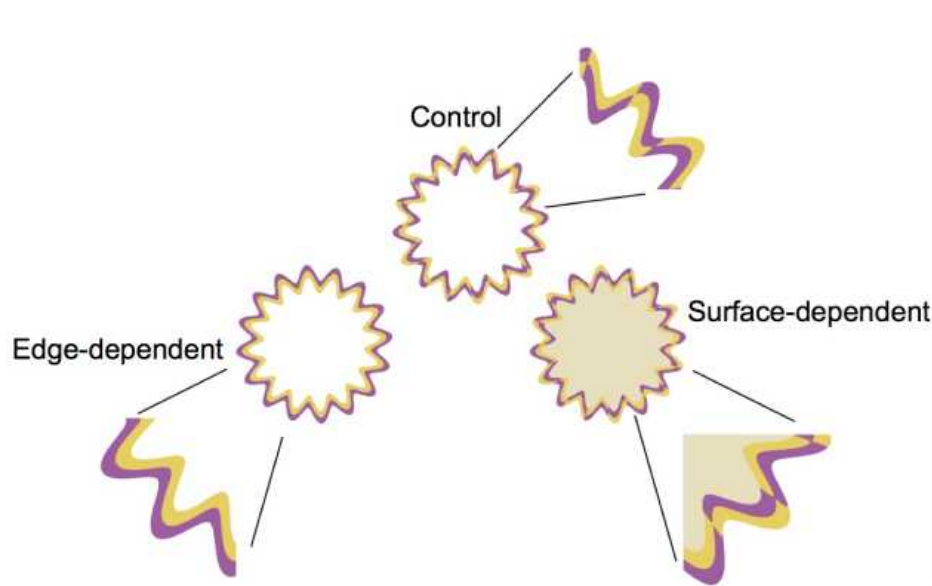
A general brain reading device to access the visual contents of
purely mental phenomena such as dreams and imagery

Water color effect



Pinna *et al.*, 2001.

Water color effect

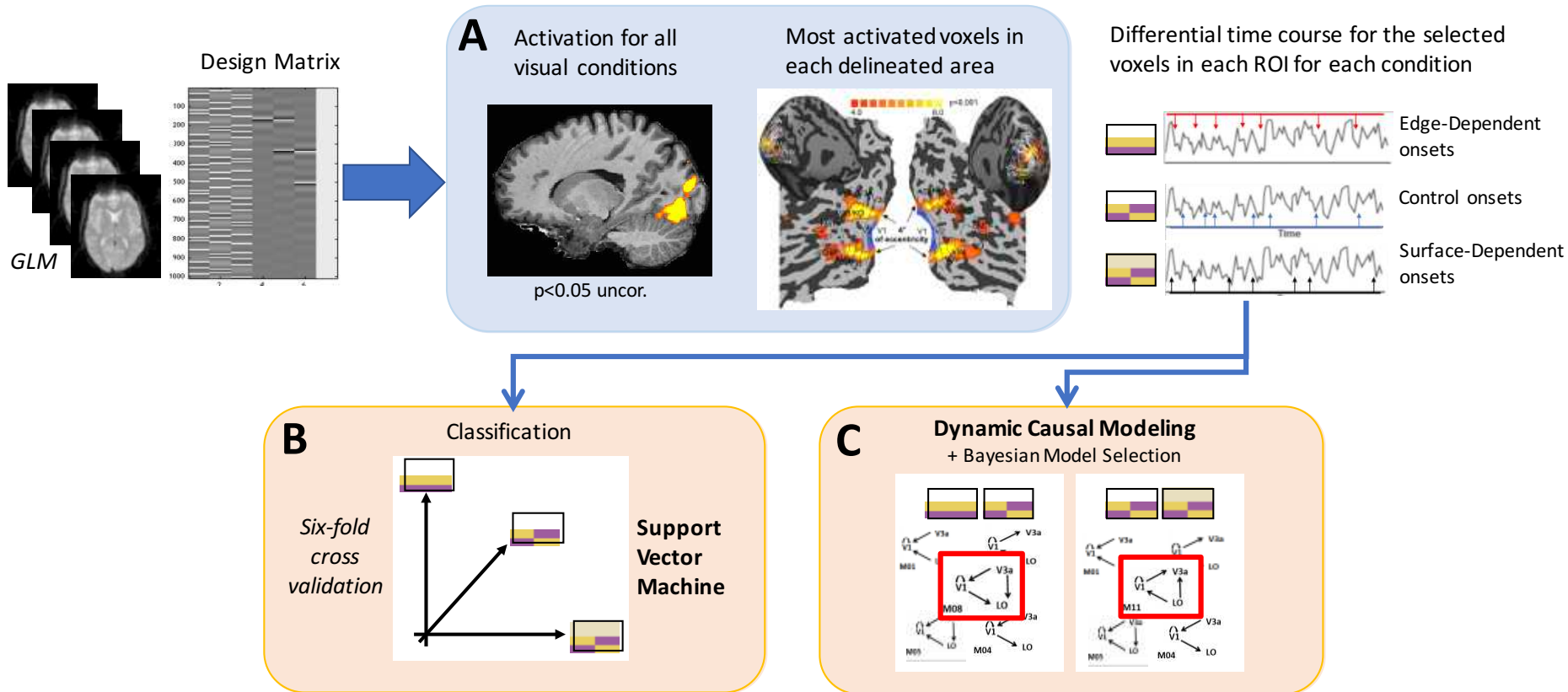


Stimulus and response differences tested by classifiers.

	Edge continuity	Interior chromaticity	Interior perceived color
Edge-dependent vs Control	X		X
Surface vs Control		X	X
Surface vs Edge-dependent	X	X	

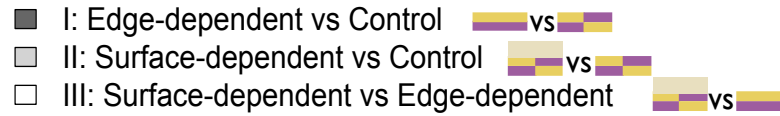
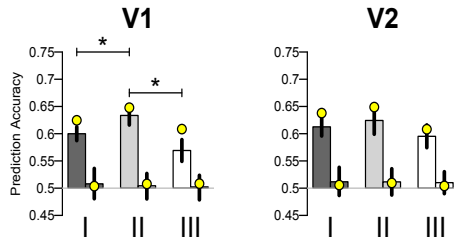
Gérardin *et al.*, Neuroimage 2018

Method

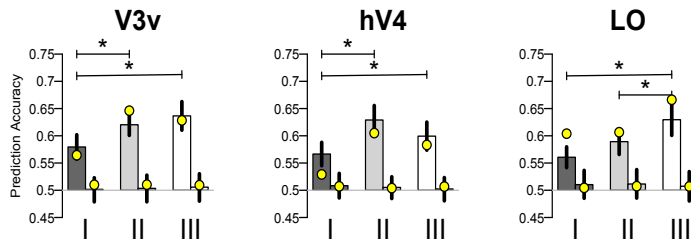


Results

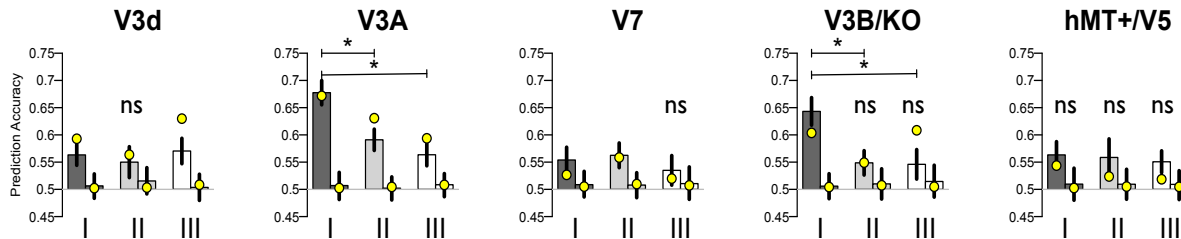
Retinotopic areas



Ventral visual areas



Dorsal visual areas



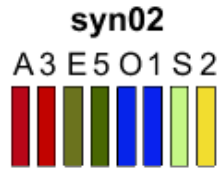
Multi-Voxel Pattern Analysis (MVPA) from fMRI data.

Conclusion



- Filling-in is best classified and best correlate with appearance by dorsal areas V3A & V3B/KO
- Uniform chromaticity by ventral areas hV4 & LO
- Feedback modulation from V3A to V1 and LO for filling-in
- Feedback from LO modulating V1 and V3A for uniform chromaticity

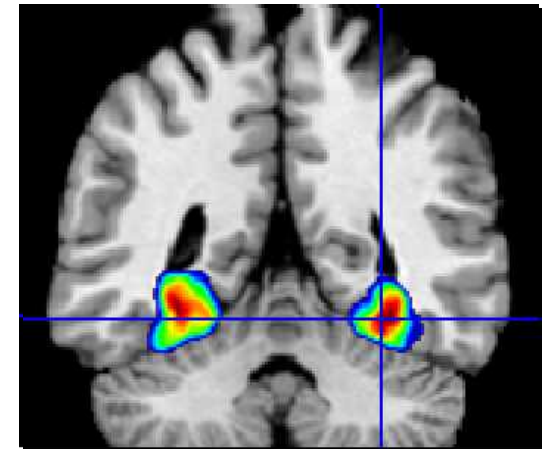
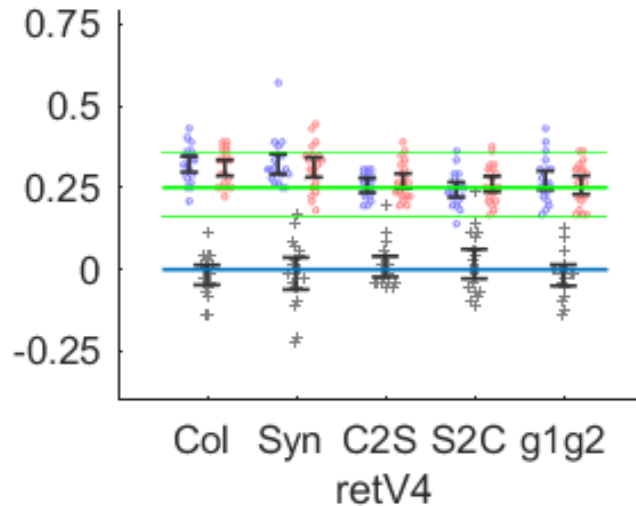
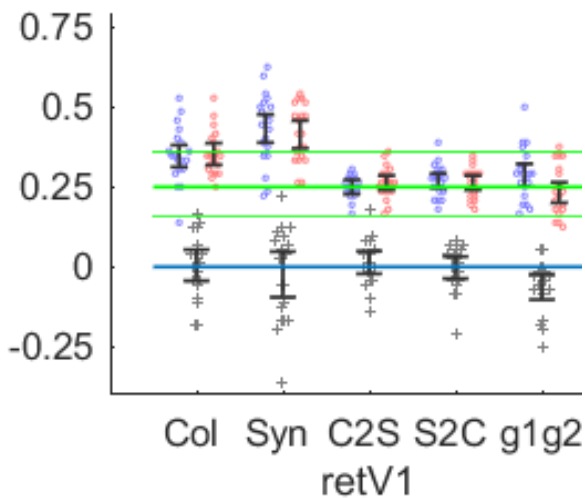
Color decoding



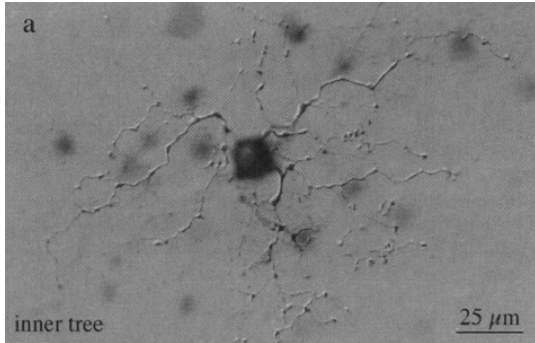
Multivariate pattern analysis of fMRI data for imaginary and real colours in grapheme-colour synaesthesia

Mathieu J. Ruiz, Michel Dojat, Jean-Michel Hupe

bioRxiv 214809; doi: <https://doi.org/10.1101/214809>

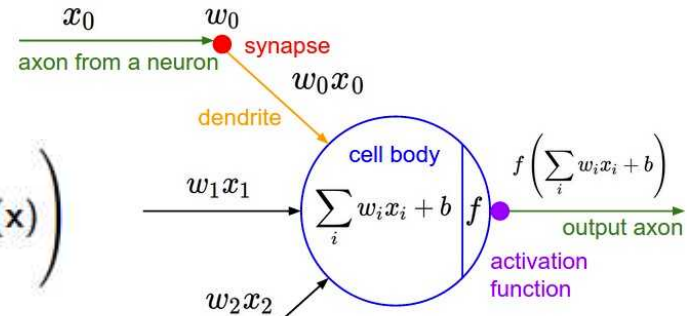


Neural Networks



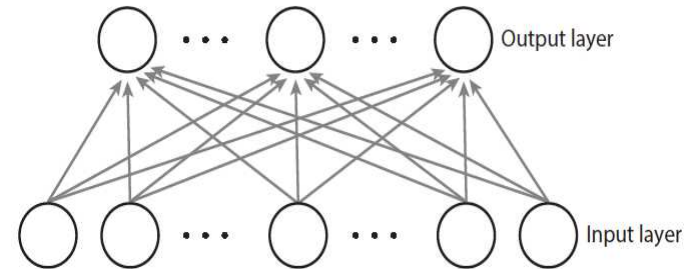
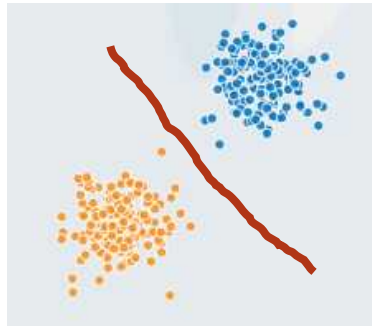
Artificial neurons (bio-inspirés)

$$y(\mathbf{x}, \mathbf{w}) = f \left(\sum_{j=0}^M w_j \phi_j(\mathbf{x}) \right)$$

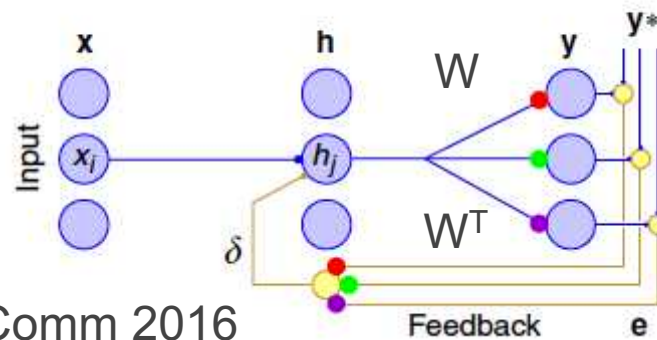
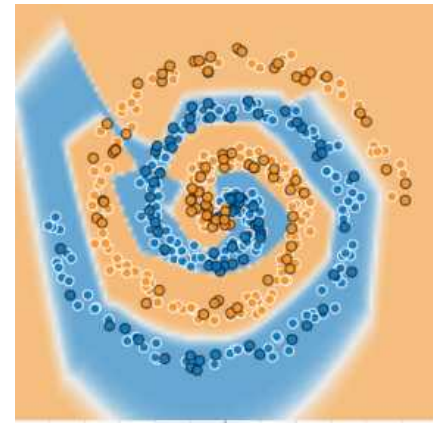
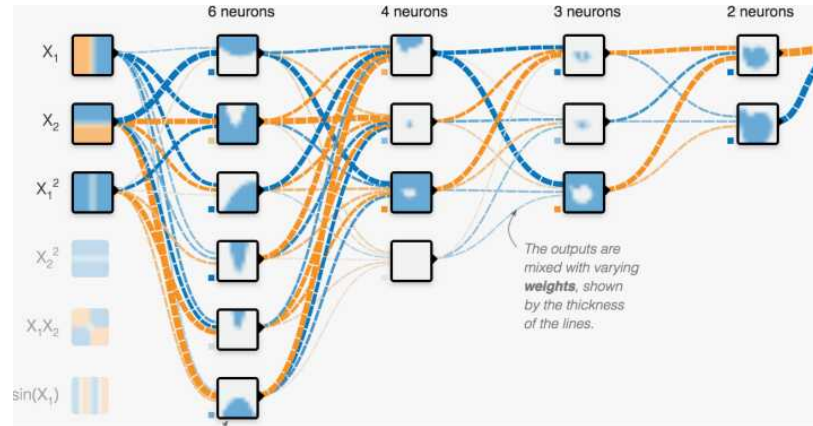
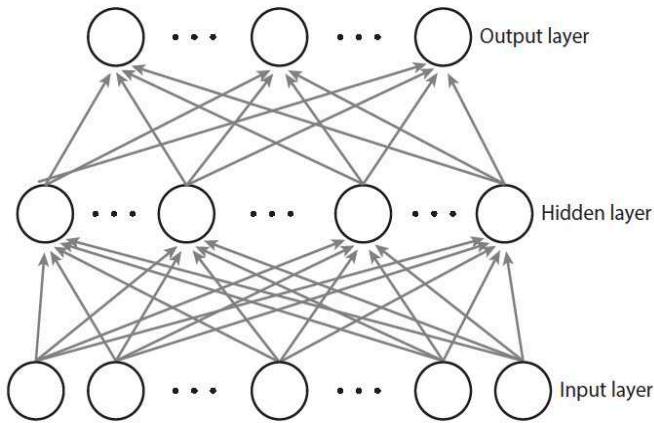


x : observations, w : weights, y : output
 ϕ : models basis or activation functions

$$t(\mathbf{x}) = y(\mathbf{x}, \mathbf{w}) + \epsilon(\mathbf{x})$$



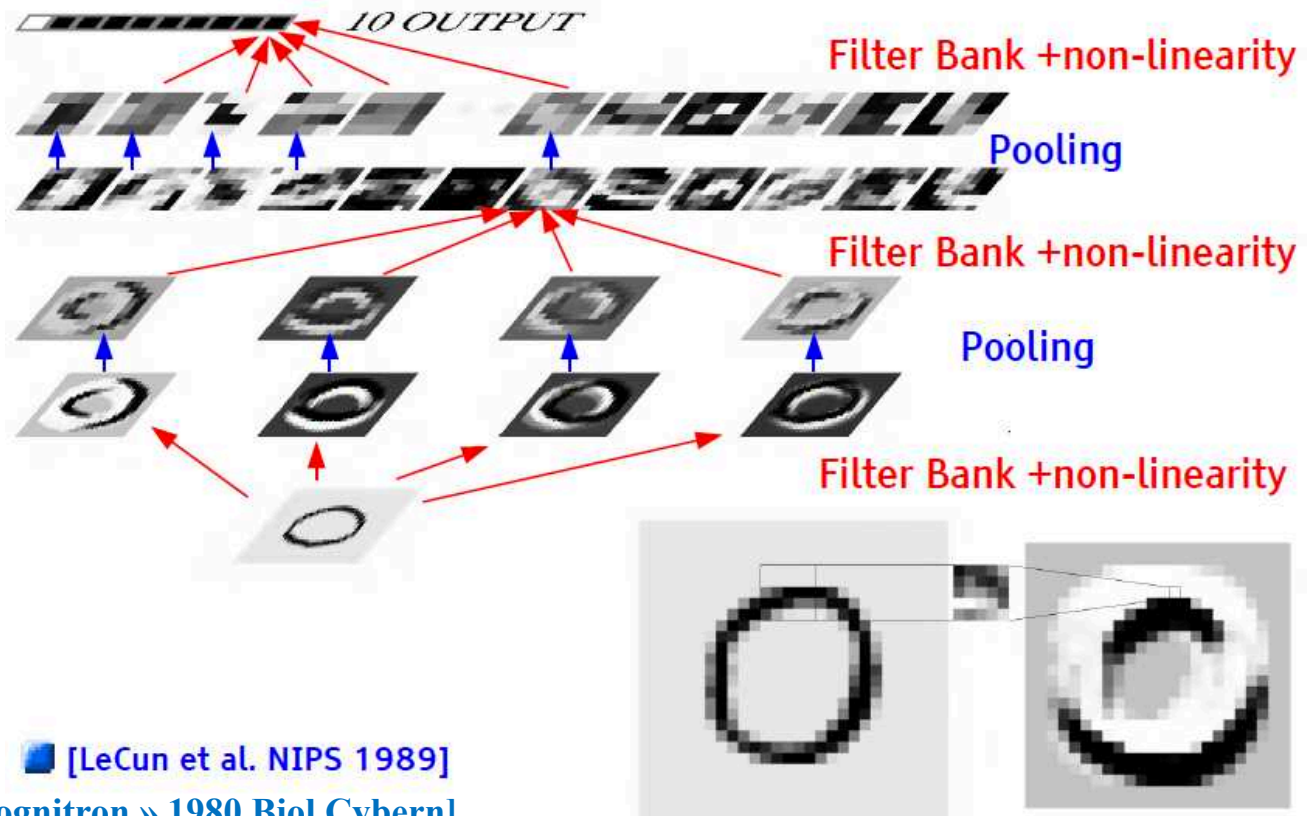
Multi-layer network



Lillicrap Nat Comm 2016

Convolutional Neural Network

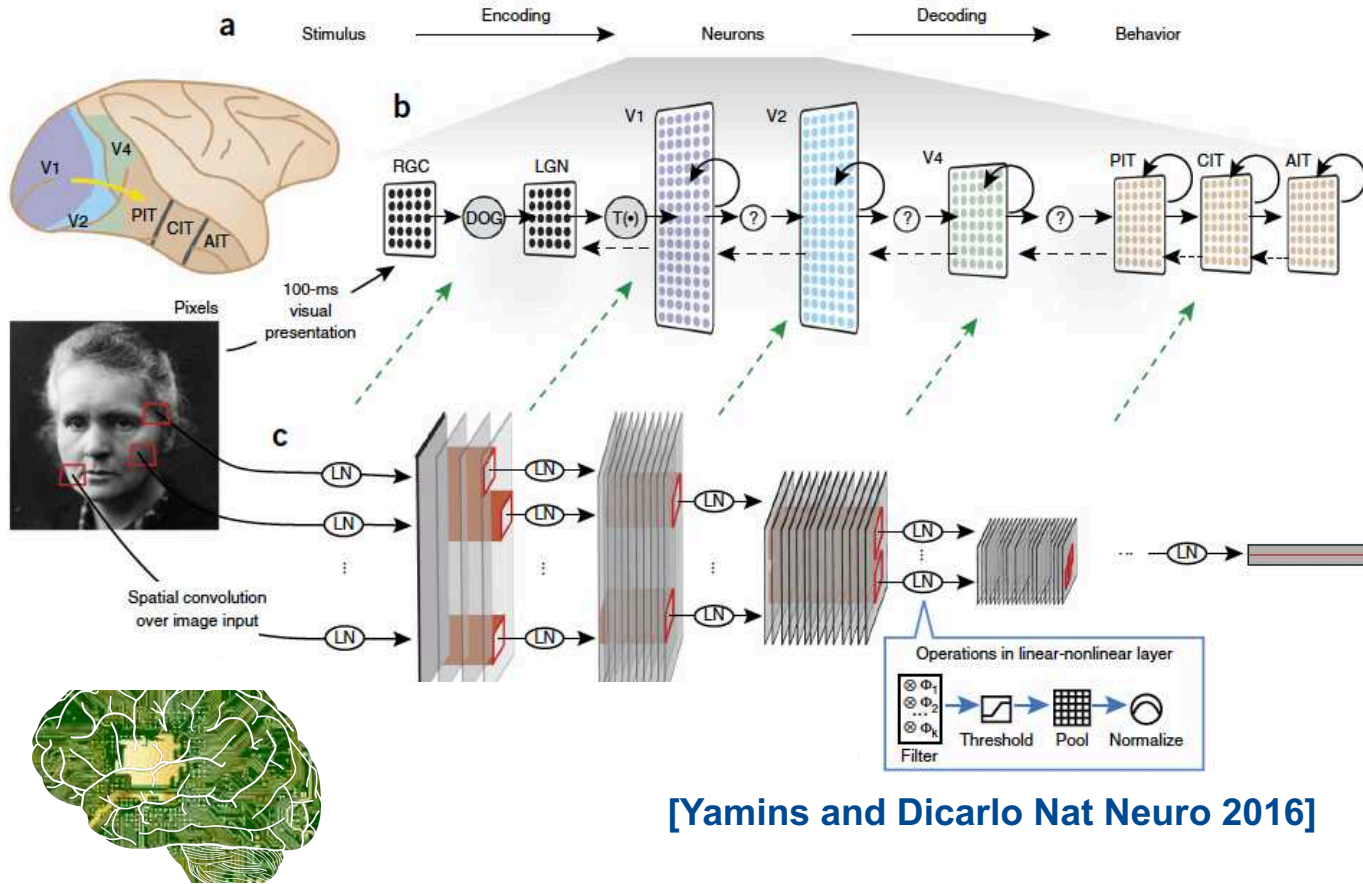
Multi-scale representation
Hierarchical extraction of information
Features of filters learnt



[LeCun et al. NIPS 1989]

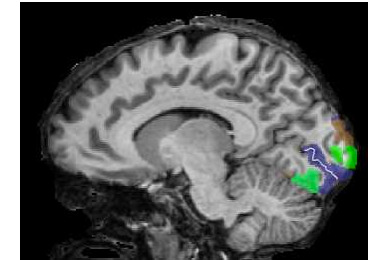
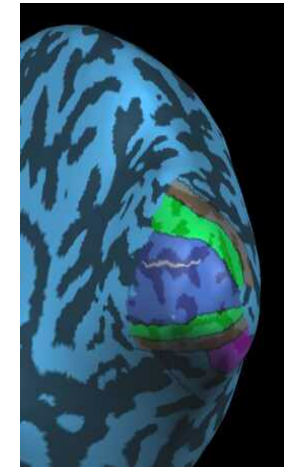
[Fukushima « Neocognitron » 1980 Biol Cybern]

CNN as a model of the visual system ...



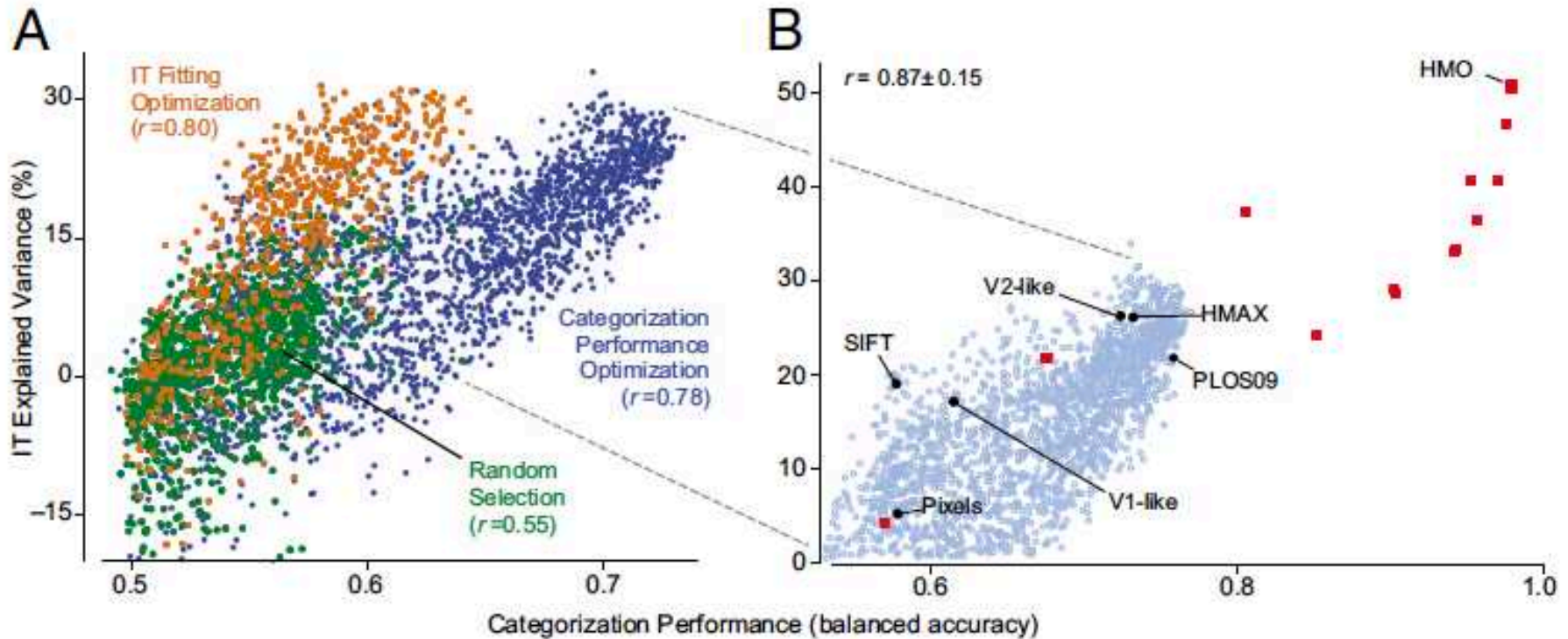
[Yamins and Dicarlo Nat Neuro 2016]

- ✓ Receptive field
- ✓ Hierarchical model
- ✓ Max pooling



[Dojat Lavoisier ed. 2017]

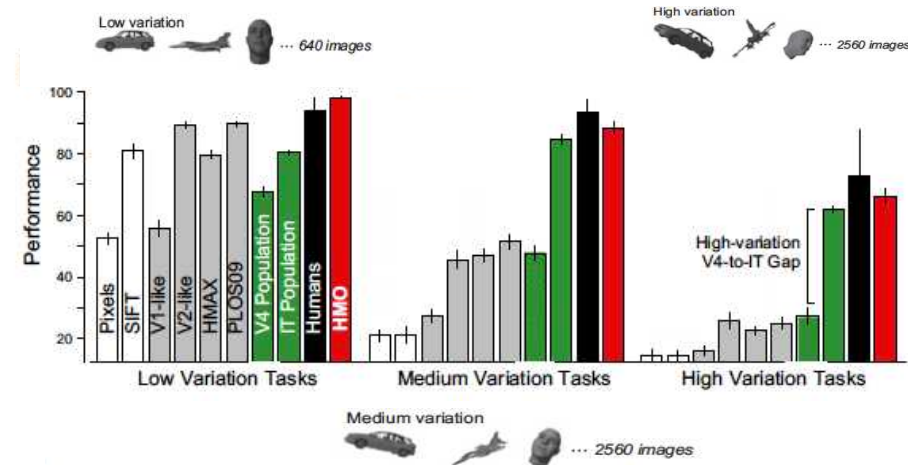
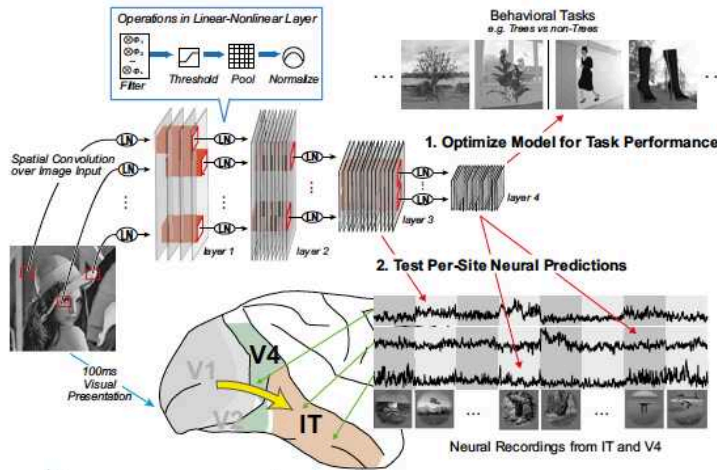
Hierarchical models for neural responses prediction



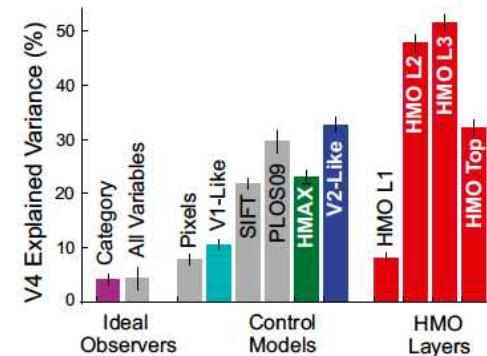
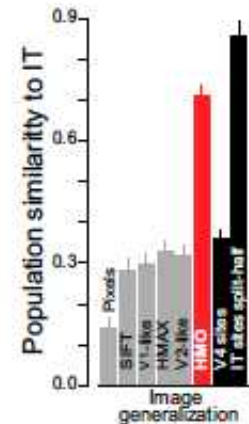
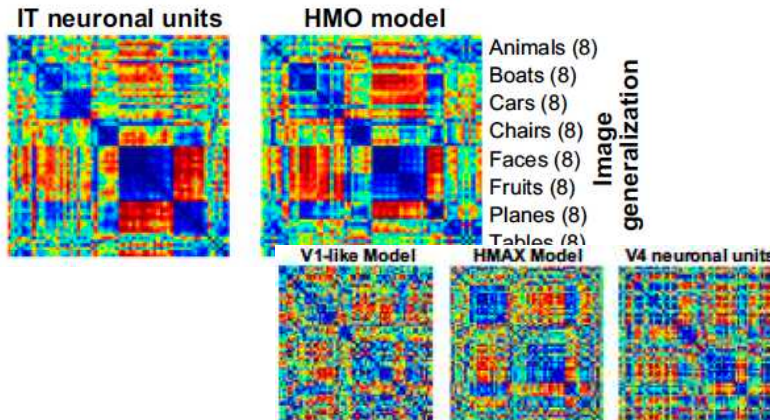
[Yamins et al 2014 PNAS]

Hierarchical models for neural responses prediction

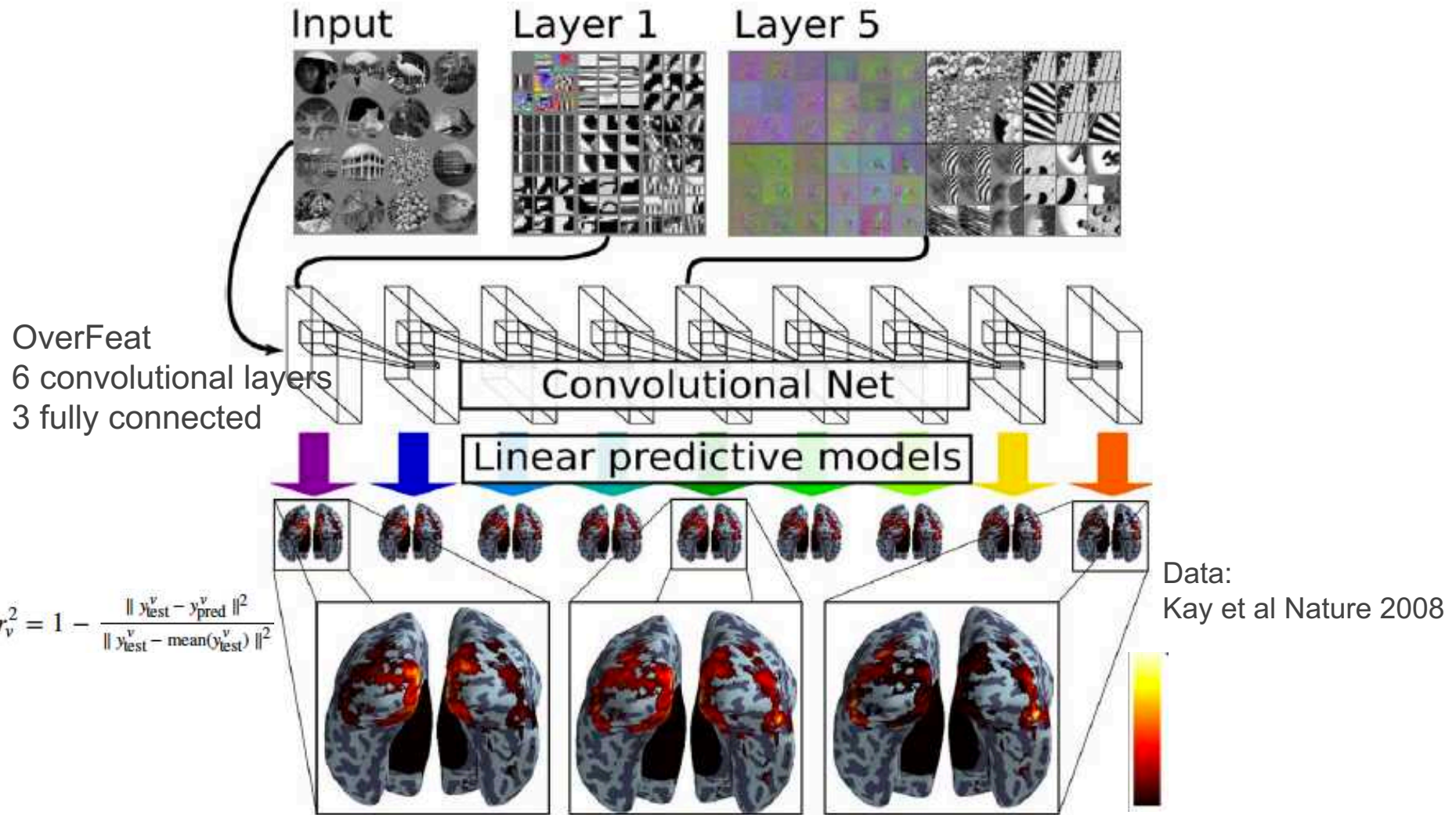
[Yamins et al 2014 PNAS]



Representation dissimilarity matrices



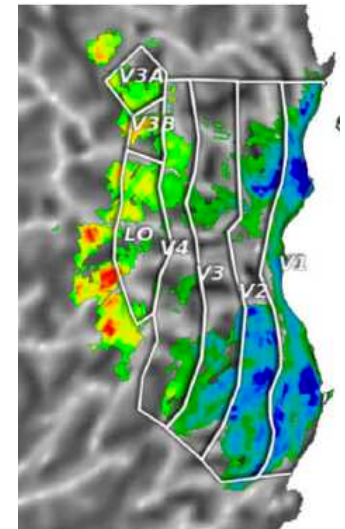
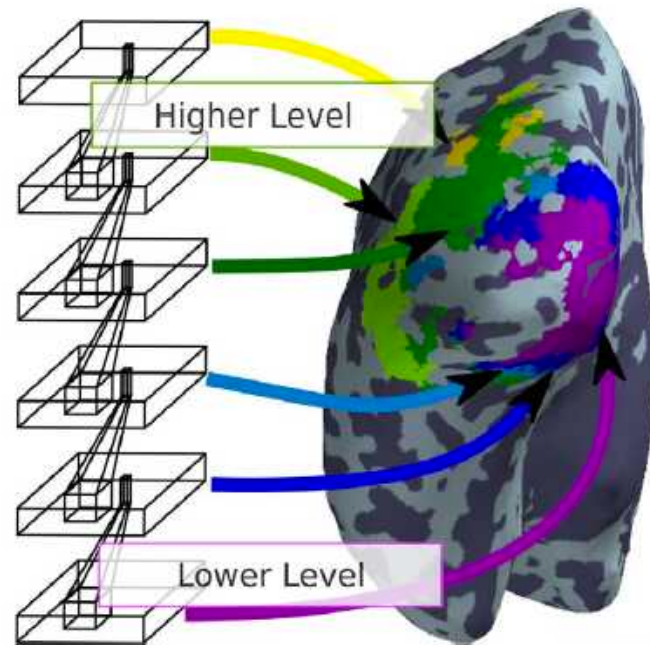
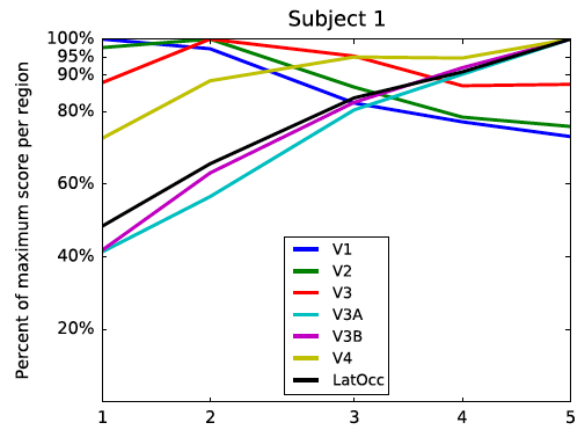
Hierarchical models for functional responses prediction



[Eickenberg Neuroimage 2017]]

Hierarchical models for functional responses prediction

[Eickenberg Neuroimage 2017]



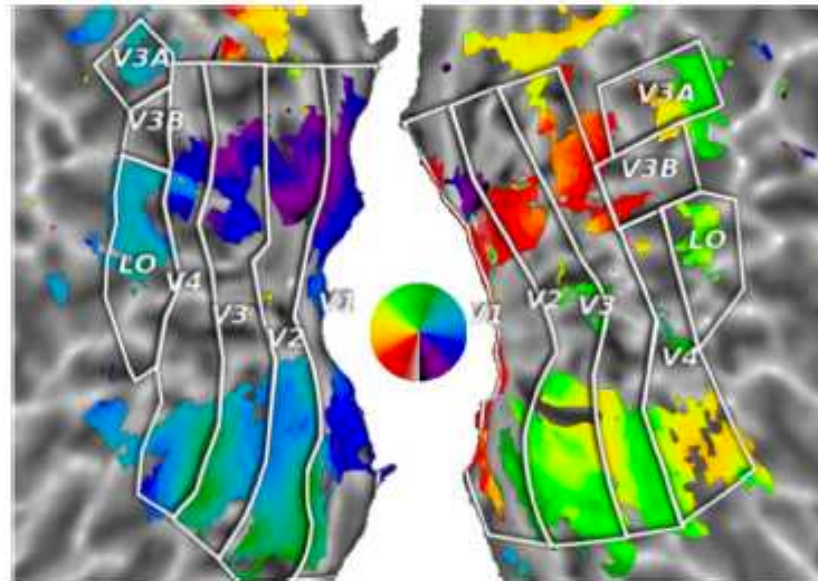
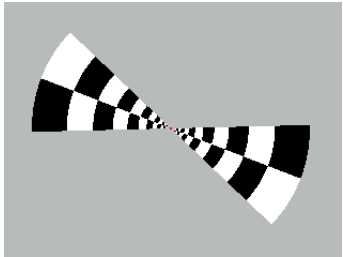
Lower level Higher level

Data:
Naselaris et al Neuron
2009

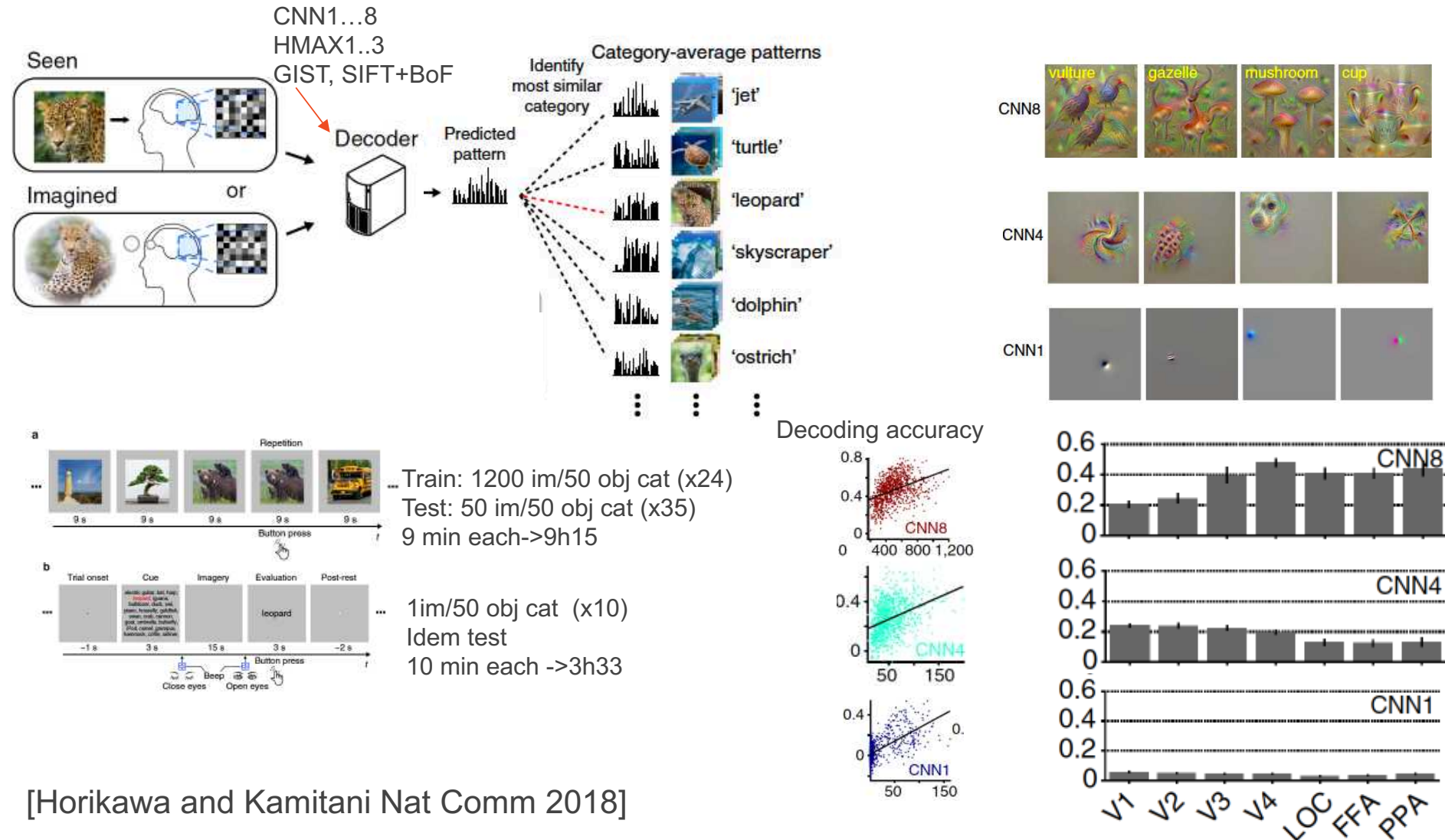
[Güclü and van Gerven J Neuro 2015; Cadena et al 2017 bioRxiv;
Cichy et al 2017 Scient Rep; Greene et al PLOS 2018;
Seeliger et al . NeuroIm 2018; Wen et al Scient Rep 2018]

Hierarchical models for functional responses prediction

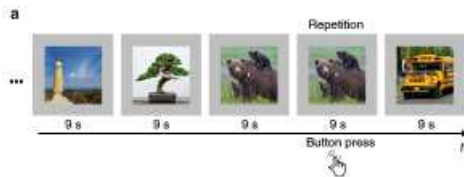
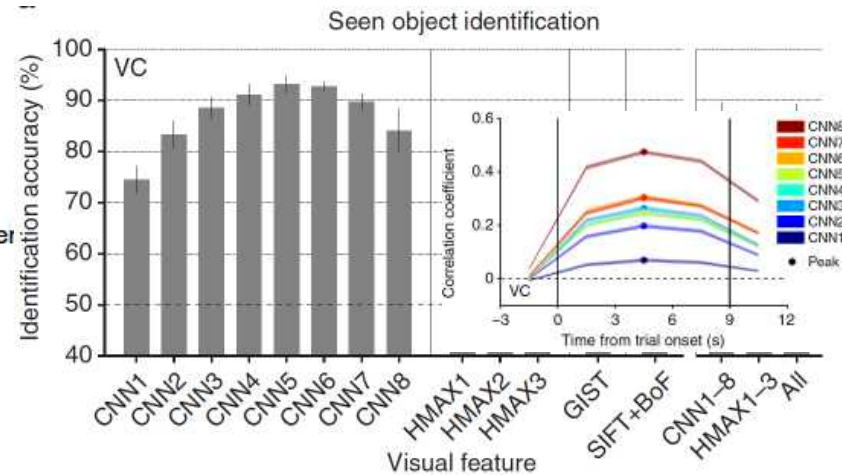
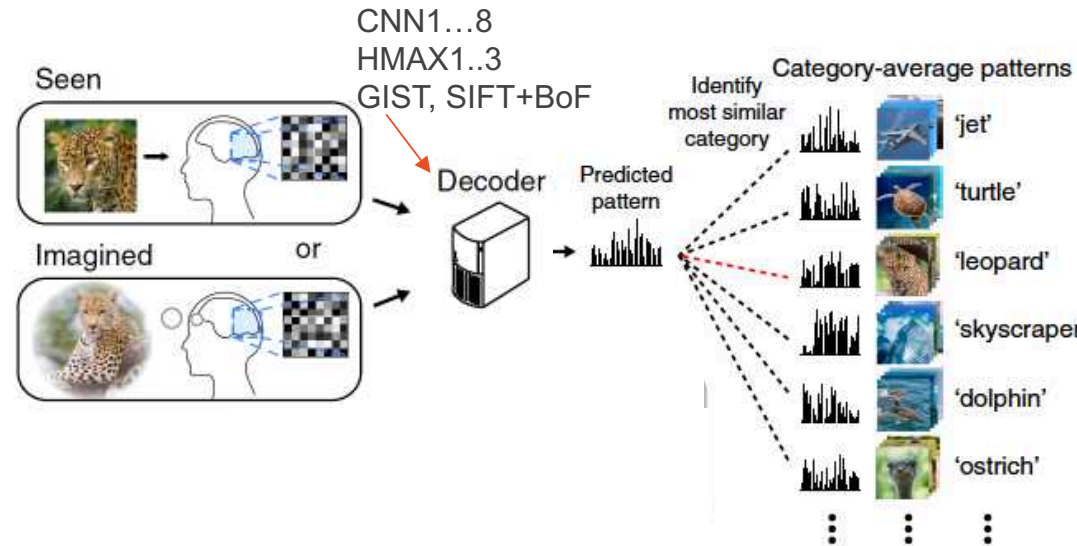
[Eickenberg Neuroimage 2017]



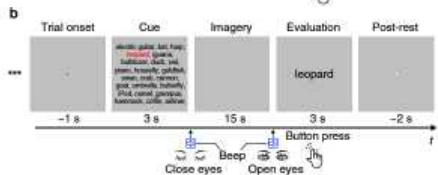
Seen/imagined object arbitrary categories



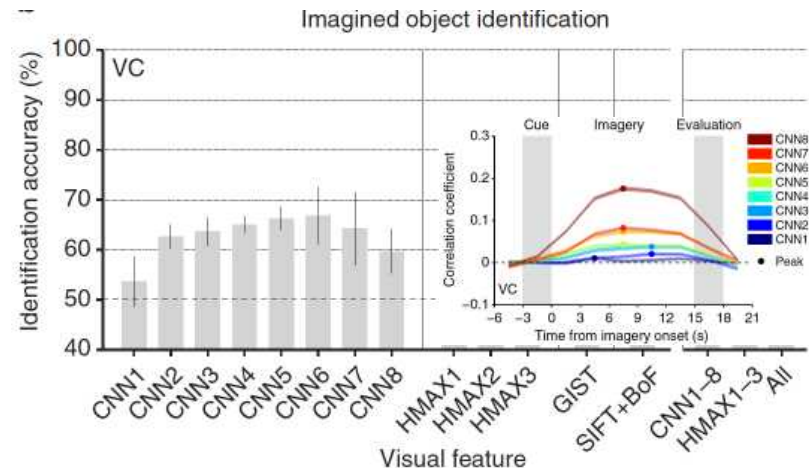
Seen/imagined object arbitrary categories



... Train: 1200 im/50 obj cat (x24)
Test: 50 im/50 obj cat (x35)
9 min each -> 9h15



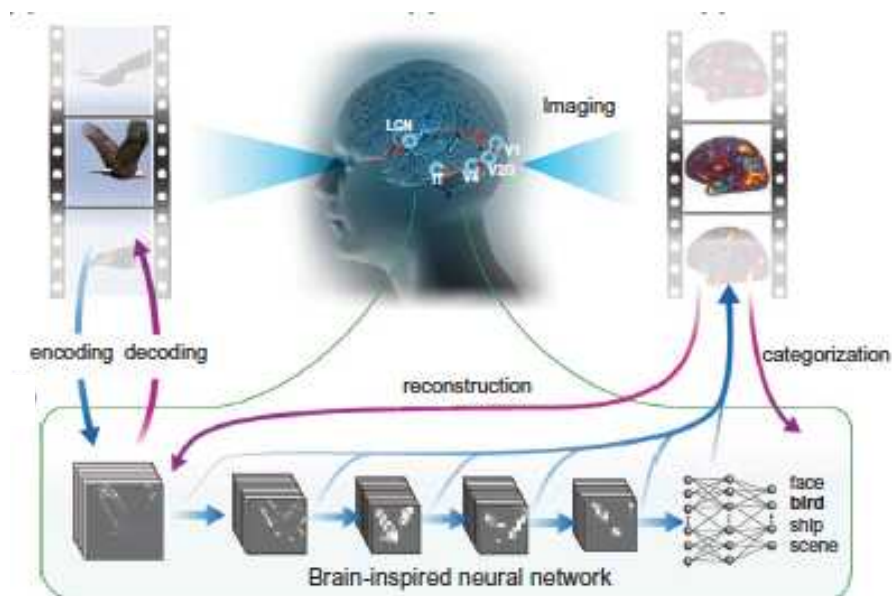
... 1im/50 obj cat (x10)
Idem test
10 min each -> 3h33



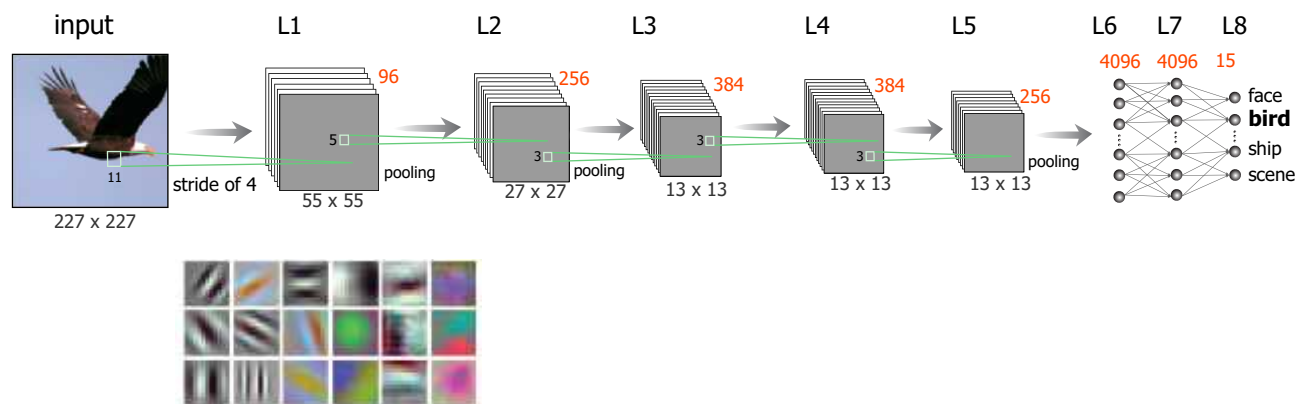
[Horikawa and Kamitani Nat Comm 2018]

Dynamic natural vision

[Wen et al CC 2017]



2.4h Training movie x 2
 40 min Testing movie x 10
 3 subjects, 3T scanner
 3.5mm³, 220x220mm²
 AlexNet 8 layers

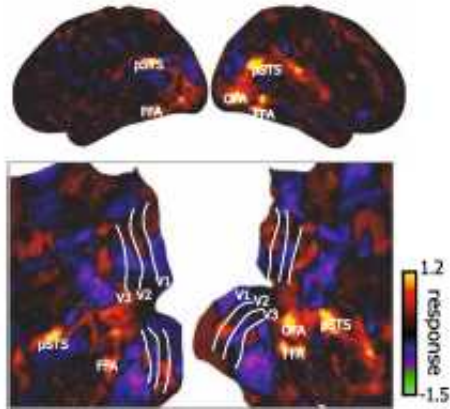


Exploring visual representation

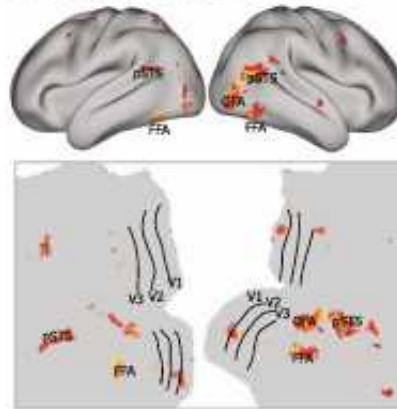
2000 human faces

64 000 images
80 classes
800 categories

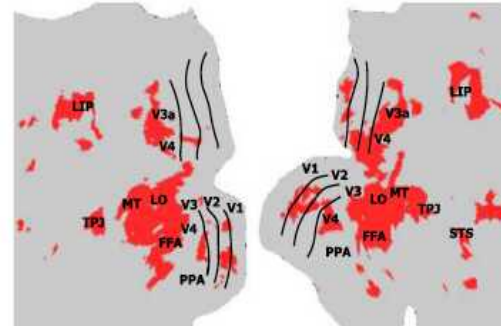
a. Model simulation



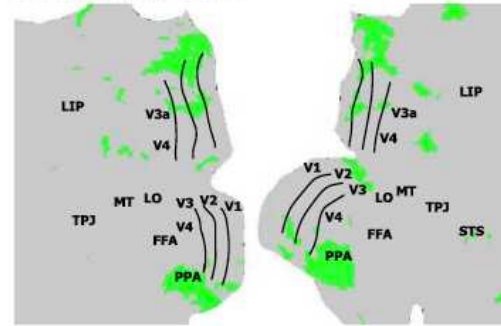
b. Functional localizer



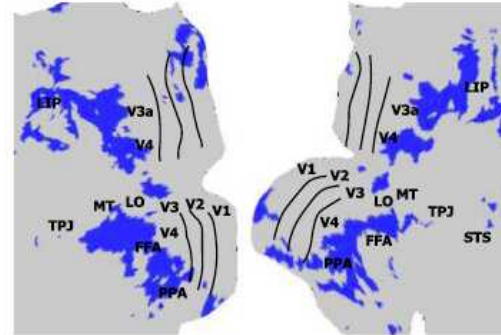
biological objects



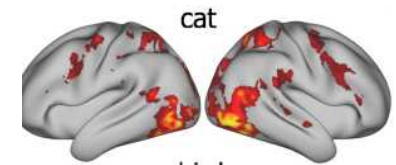
background scenes



nonbiological objects

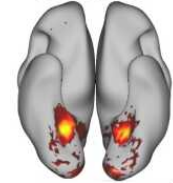


bear bird cat chicken
dog elephant goose horse
lion monkey sheep tiger



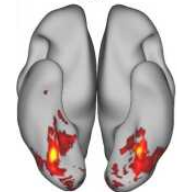
bedroom boat bridge building
classroom corridor door factory
house kitchen livingroom market

restaurant



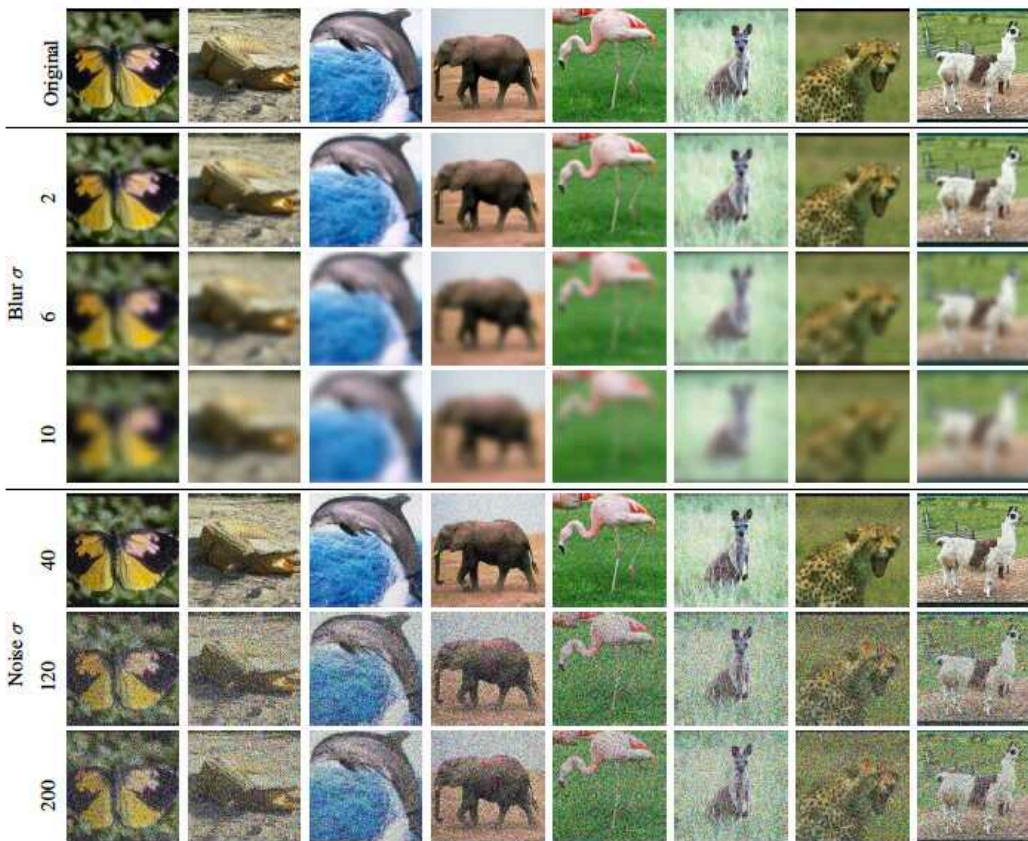
airplane bag ball bike bottle
bowl car cellphone watch
drink flag hat instrument

car

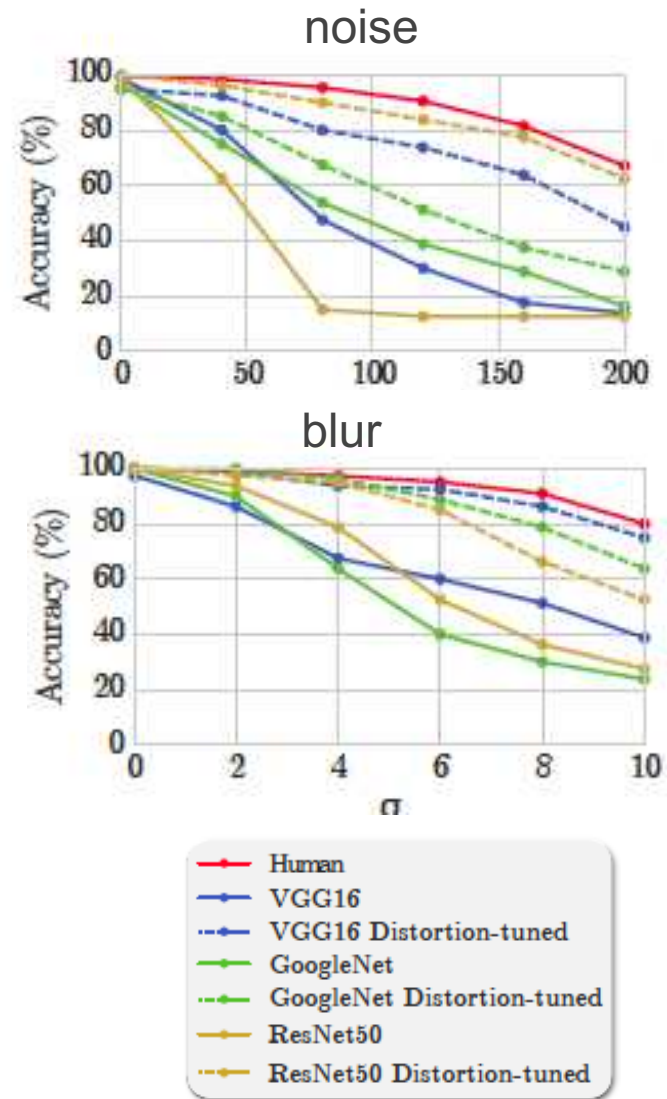


[Wen et al. Scient Rep 2018]

Nobody is perfect ...



[Dodge and Karam ICCV 2017]

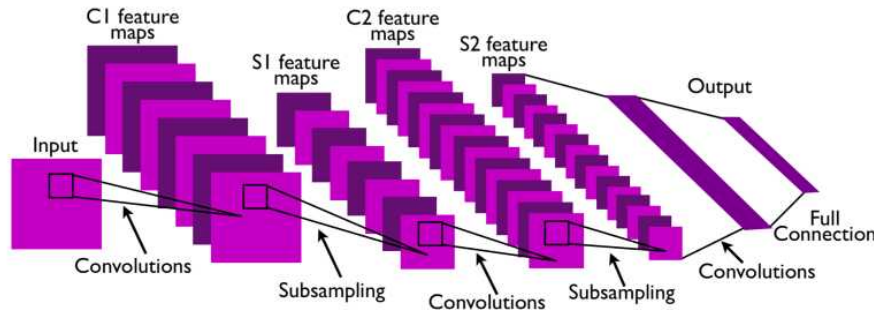


CNN as a model of the visual system ...

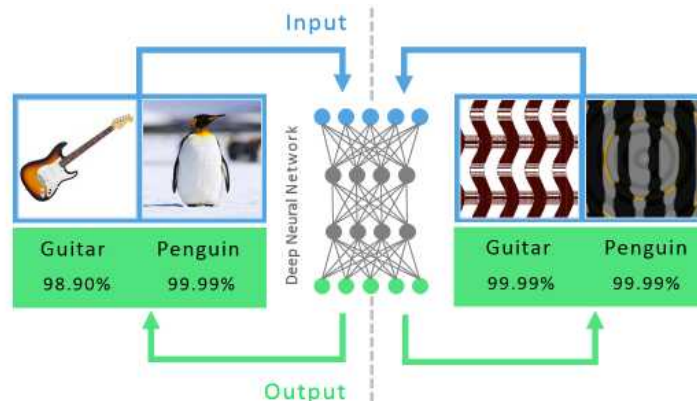
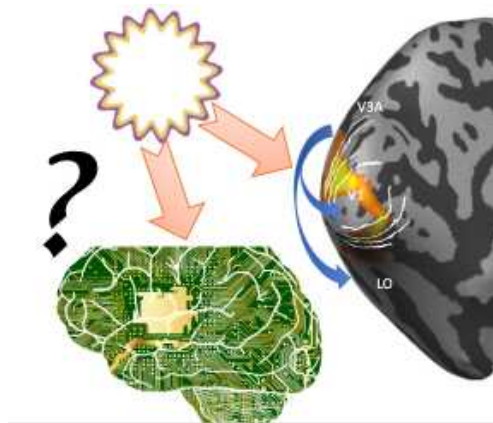
- CNN driven for image recognition
 - Explains significant variance of neuroimaging data in ventral stream
 - Models a hierarchical representation of feedforward visual information processing (i.e. ventral stream)
 - Supports the generation of expected cortical activation
 - Supports decoding & then semantic categorisation
 - Validates the existing models

BUT still incomplete ...

CNN as a model of the visual system ...



[Lecun et al 2010]

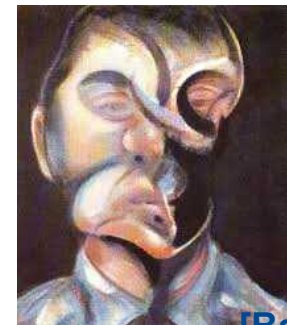


[Nguyen et al CVPR 2015]

- ✓ Receptive field
- ✓ Hierarchical model
- ✓ Max pooling
- ✓ Layer2layer conn.
- ✓ Magnitude factor
- ✓ Color
- ✓ Metamer
- ✓ Attention
- ✓ Local vs Global
- ✓ Perspective effects
- ✓ Learning
- ✓ Illusion
- ✓ Eye mvt



[Dali 1941]



[Bacon 1972]

Illusions - Hallucinations

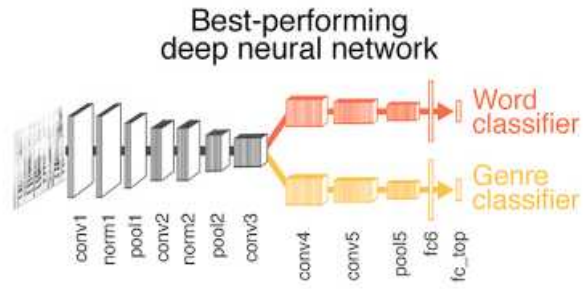
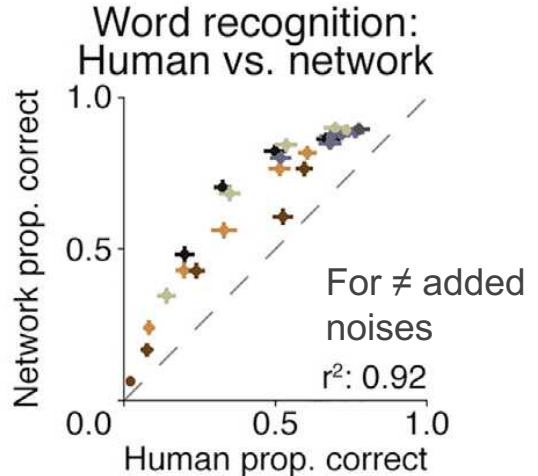
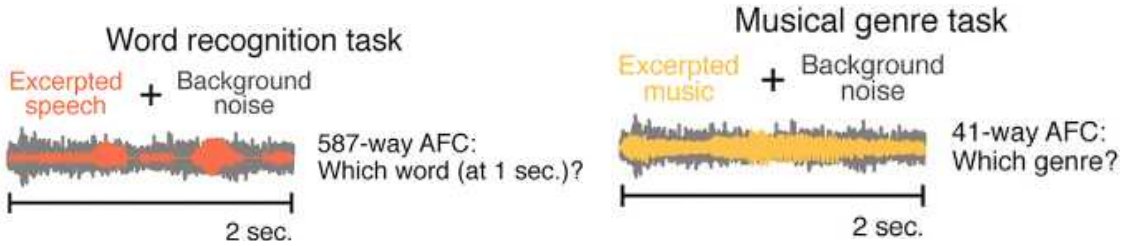


[Ffytche 2007 Dial Clin Neurosc]

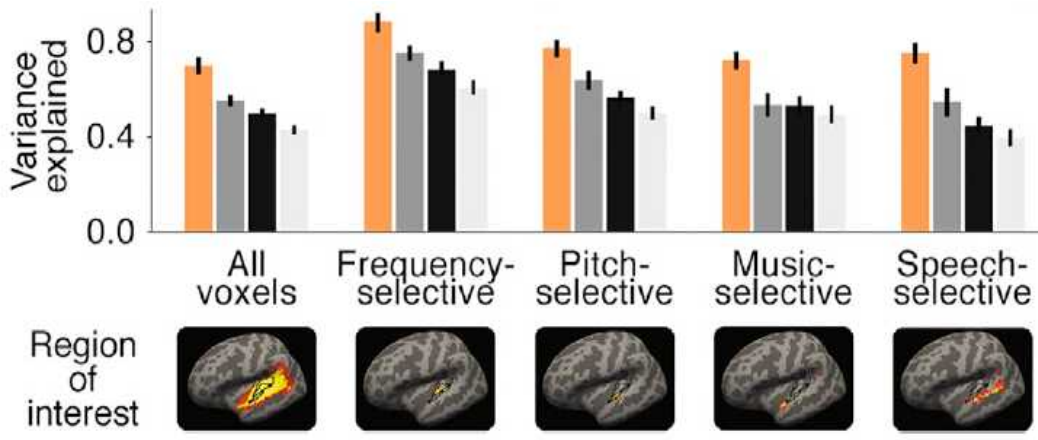
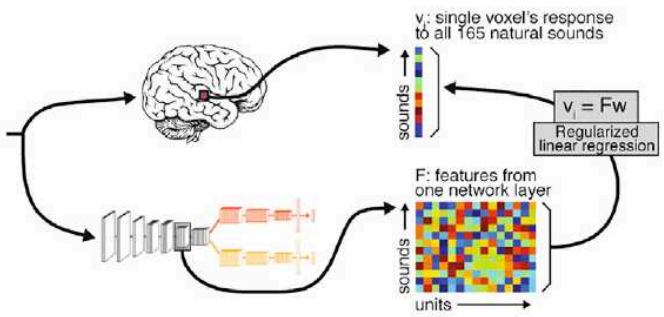


DeepDream.com

CNN a model for ... auditory cortical responses



- 165 everyday sounds:
- person screaming
 - velcro
 - whistling
 - frying pan sizzling
 - alarm clock
 - cat purring
 - guitar riff
 - ... etc. ...

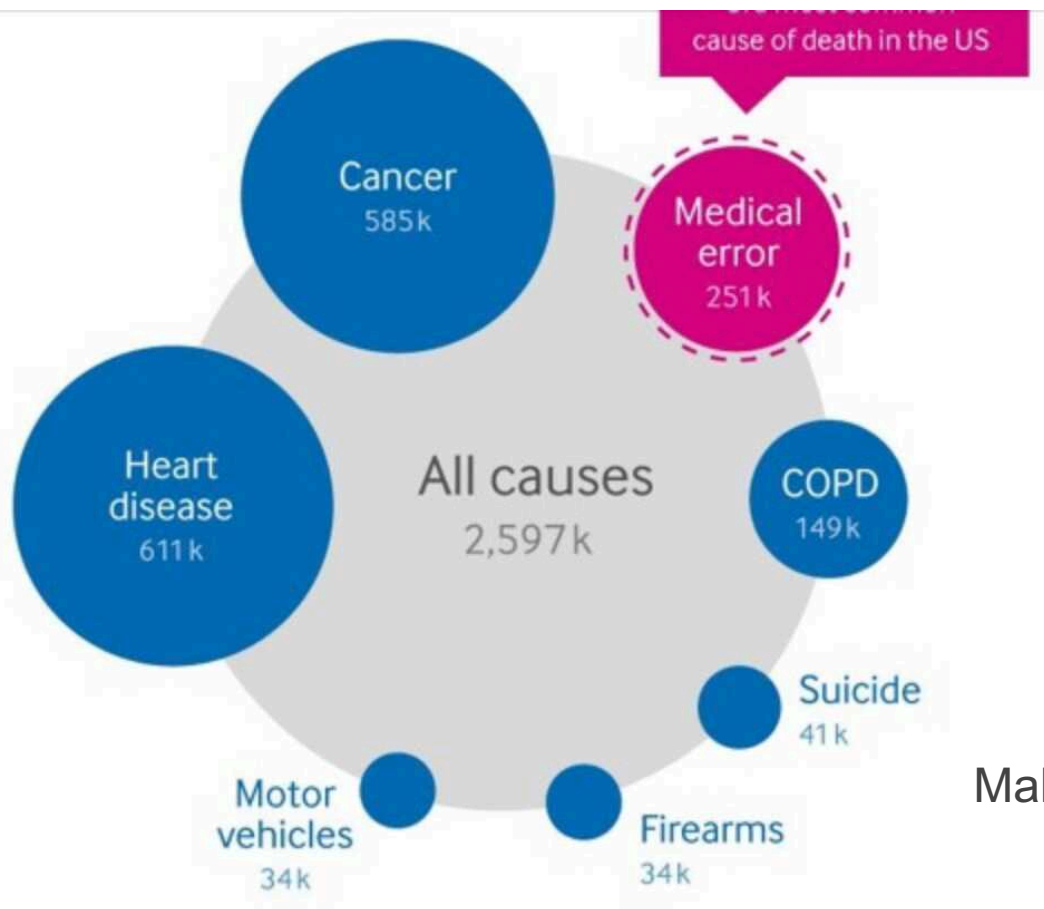


- Trained network (selected architecture, trained filters)
- Spectrotemporal model
- Random-filter network (selected architecture, untrained filters)
- Random-filter network (unselected architectures, untrained filters)

[Kell et al Neuron 2018]

AI for catching human errors

Medical error-the third leading cause of death in the US



Makari et al BMJ 2016

New tools ...

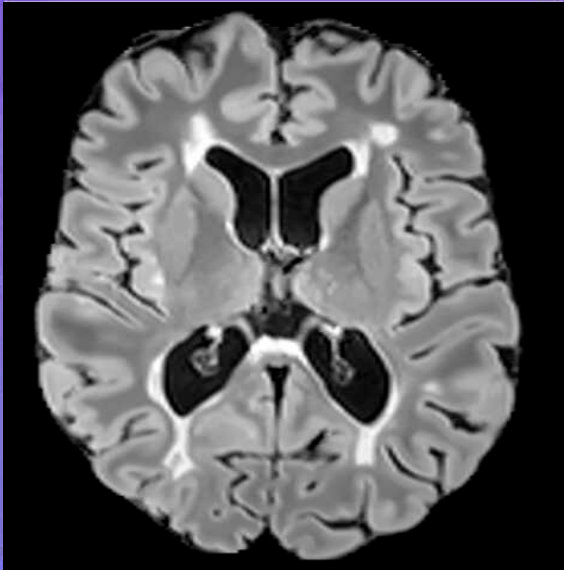
<http://clickme.ai/>

Help the AI recognize this image before time runs out!

There is no contest at the moment.

Click and then brush with your mouse to reveal image parts best describing a:

MS lesion



100 pts ————— 0 pts

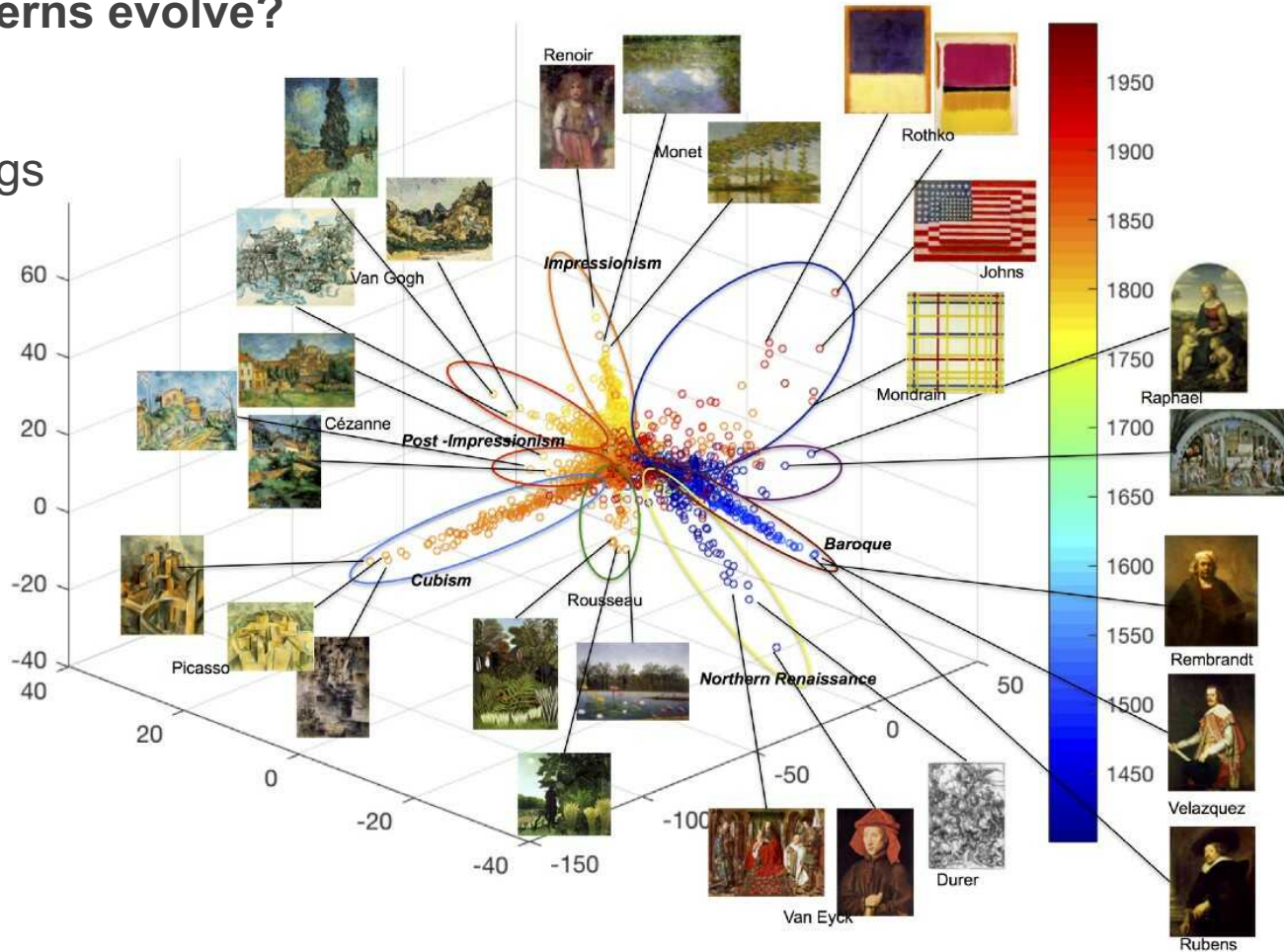
Skip this image: it has a strange label or poor quality.

Your score: 149.60 | High score: 170.49

Art History

How characteristics of style are identified?
How the patterns evolve?

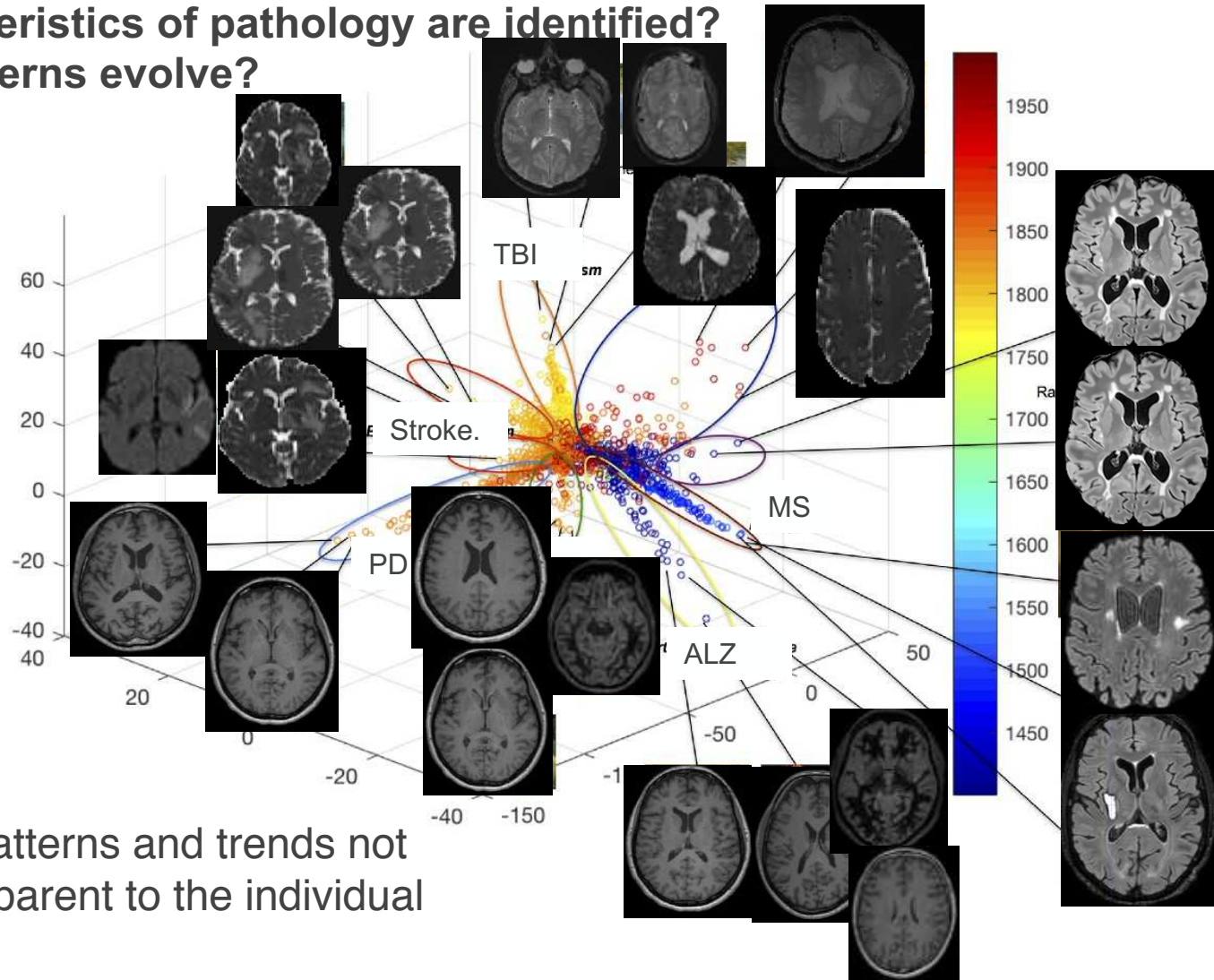
76921 paintings
Train(85%)
Val (9.5%)
Test (5.5%)



Elgammal et al. 2018 arxiv 1801.07729

e-Nosology

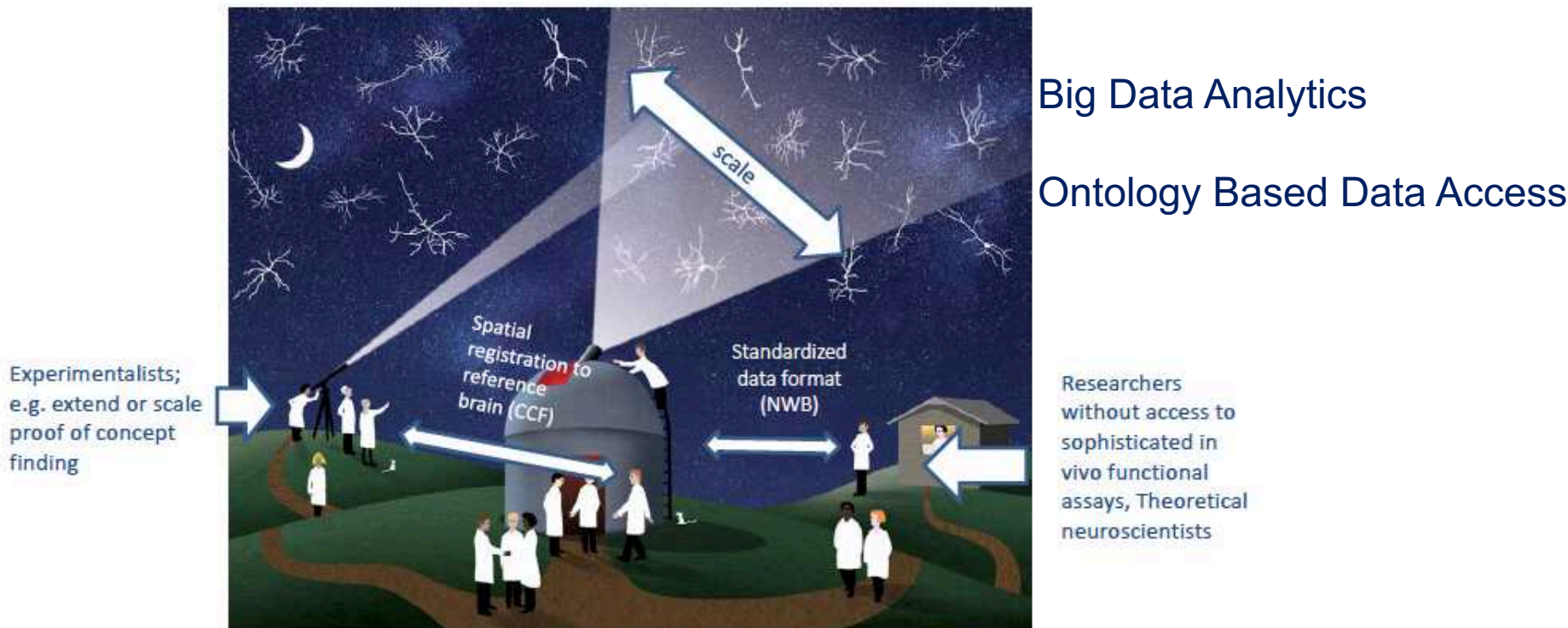
How characteristics of pathology are identified?
How the patterns evolve?



« to discover
fundamental patterns and trends not
necessarily apparent to the individual
human eye »

New models for neuroscience

How from the activity of millions of neurons distributed in several brain areas emerge simple percepts and how they are linked to emotion, motivation or action?



from Mike Hawrylycz

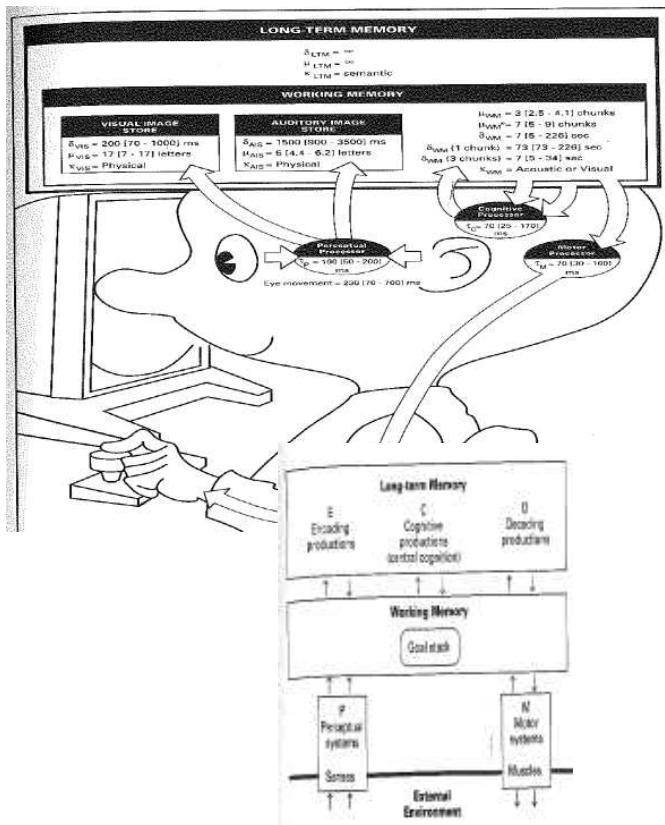
Future

Mixing Hype AI (Supervised L+ **Reinforcement L**) + Old fashion AI (Tree search)
[Silver et al Nature 2016]



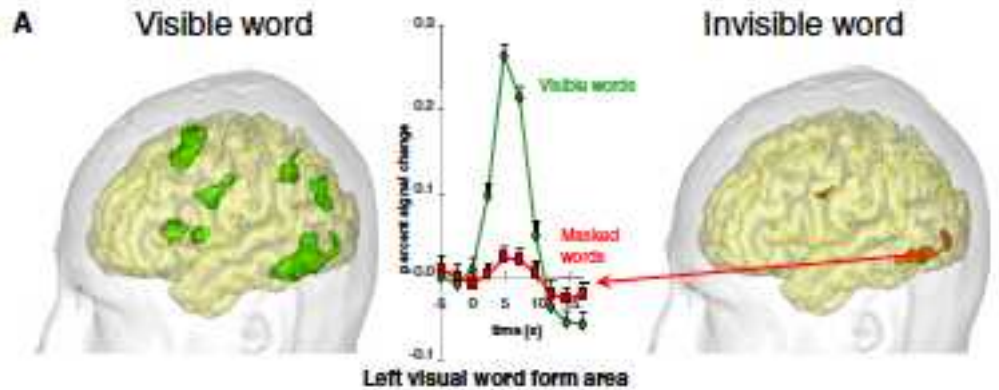
Consciousness model

Soar:
[Newell 1983, 92]



Global workspace theory
[Baars 1988, 97, 2002]

Global ignition
[Dehaene 2003]



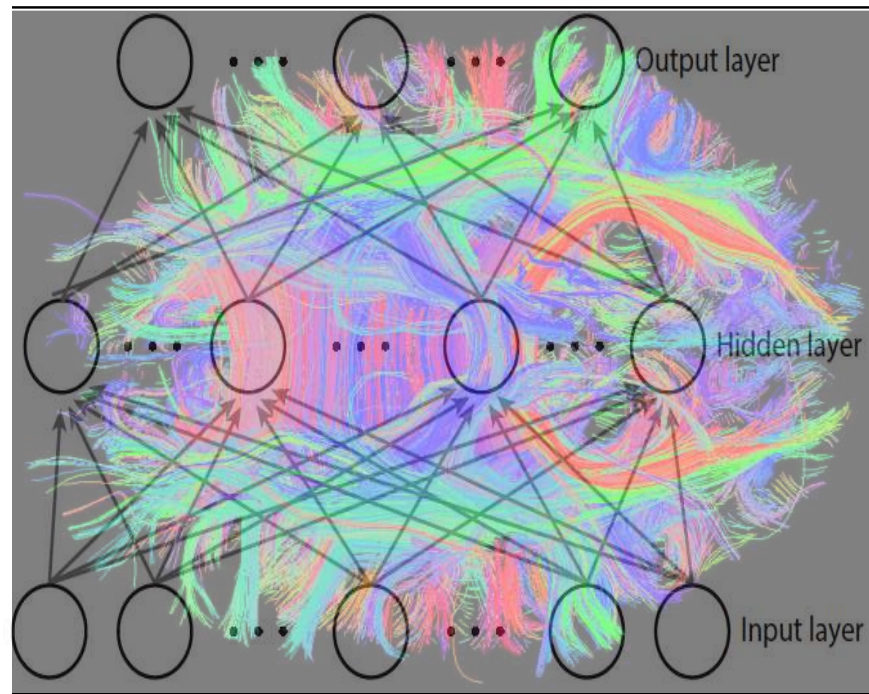
[Dehaene and Changeux Neuron 2011]

The Unreasonable Effectiveness of Data

- Classifiers based on millions of specific features perform better than elaborate models that try to discover general rules.

[Halevy et al IEEE Intell Syst 2009]

But ...



But ...

