Towards psychoinformatics with machine learning and brain imaging

Gaël Varoquaux

Inria

PARIETAL

Towards psychoinformatics with machine learning and brain imaging

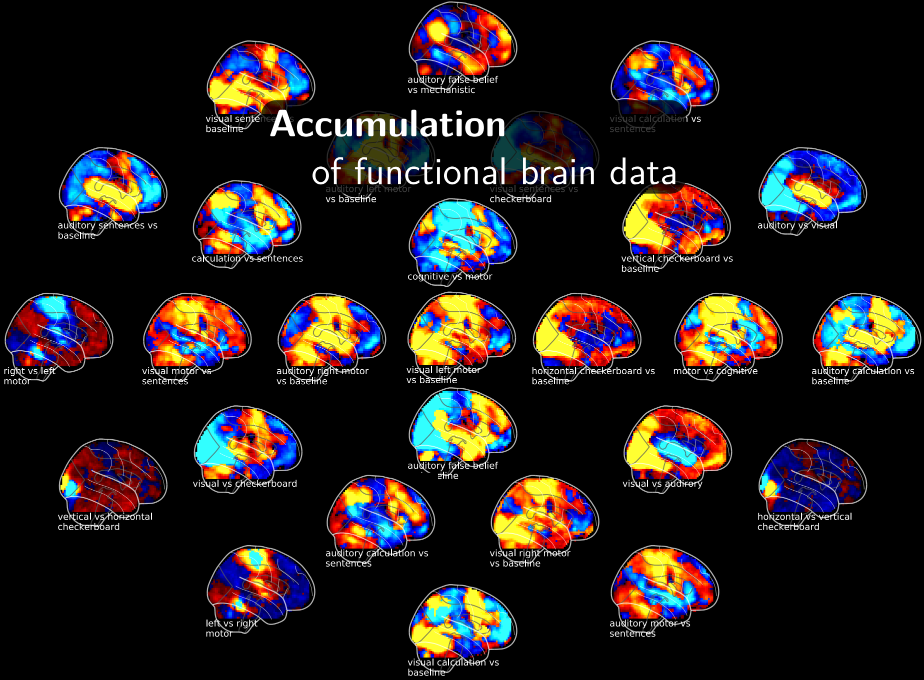
Gaël Varoquaux

Inria

PARIETAL

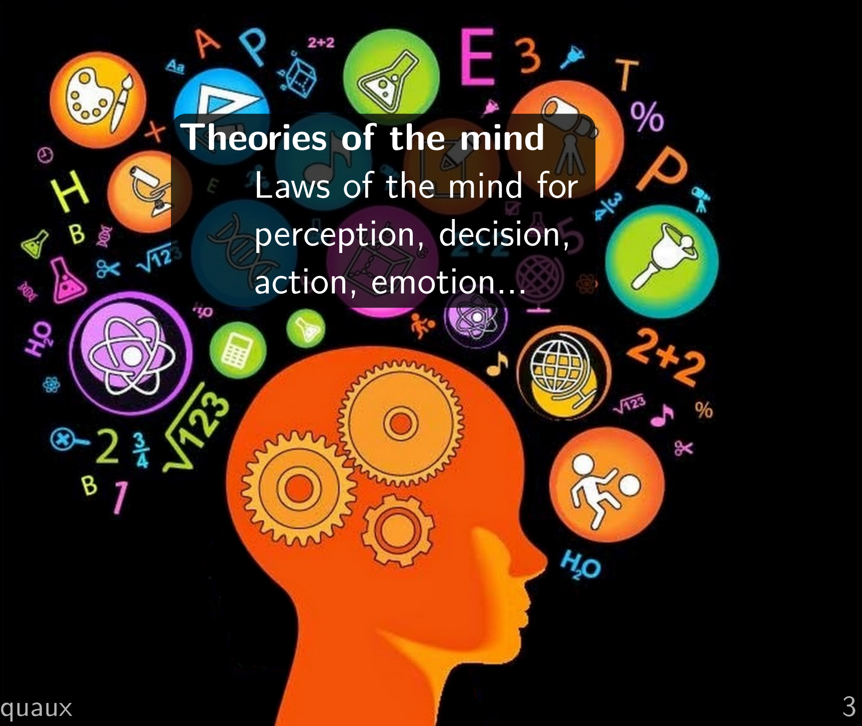
Propose and illustrate a research program

Accumulation
of functional brain data



Theories of the mind

Laws of the mind for perception, decision, action, emotion...



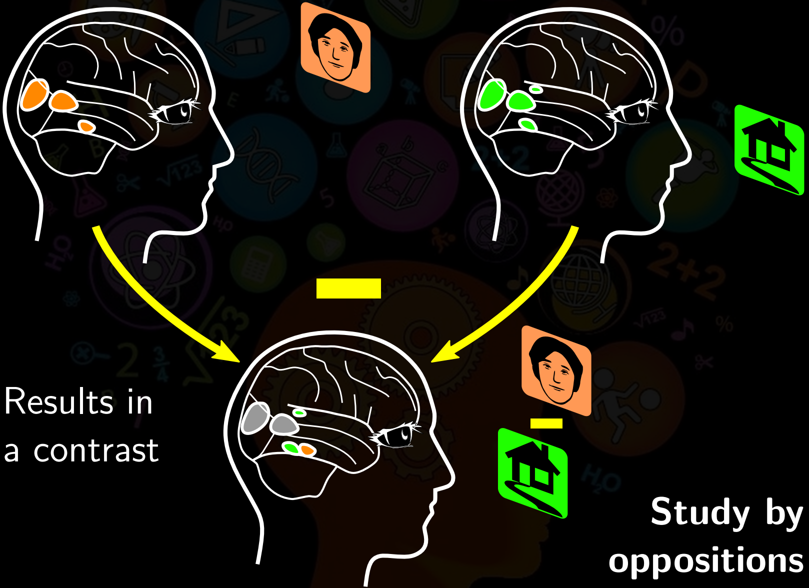
Studying mental processes

1 Craft an experimental condition that recruits it

Studying mental processes

1 Craft an experimental condition that recruits it
2 Do an *elementary psychological manipulation*

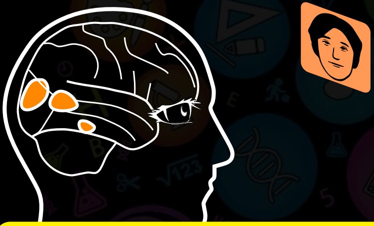
Studying mental processes



Results in a contrast

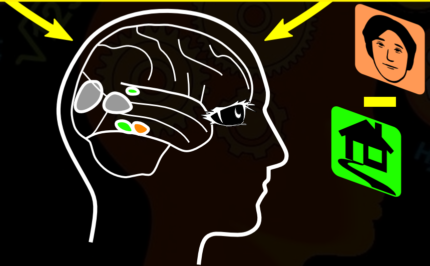
Study by oppositions

Studying mental processes



Results tied to a simple psychological manipulation

bound to a paradigm

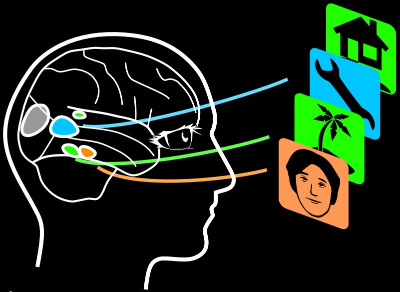


Proposing

Generalization

to build broader theories

Paradigm 1: Seen

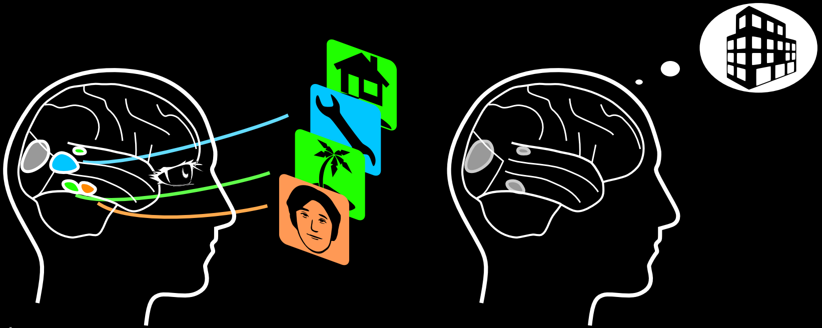


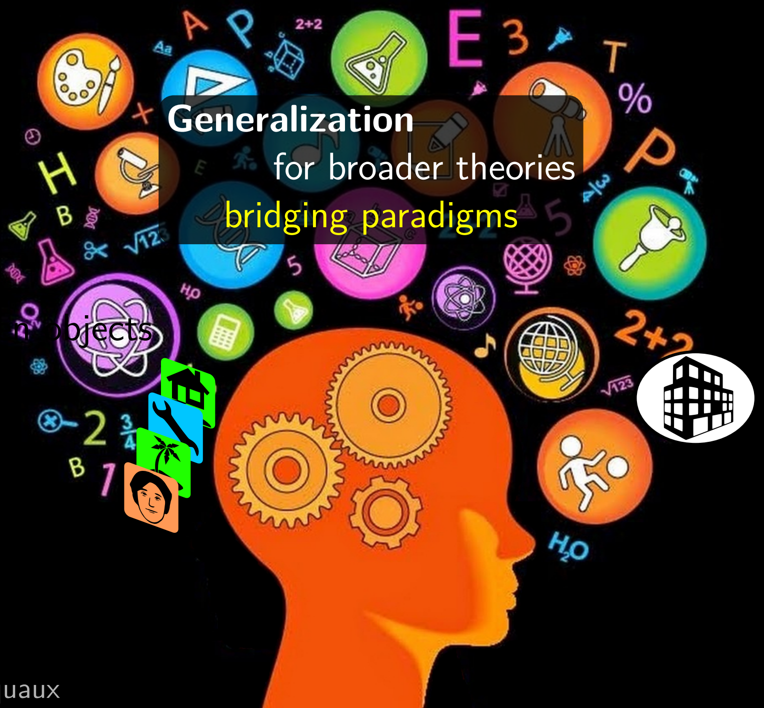
Proposing

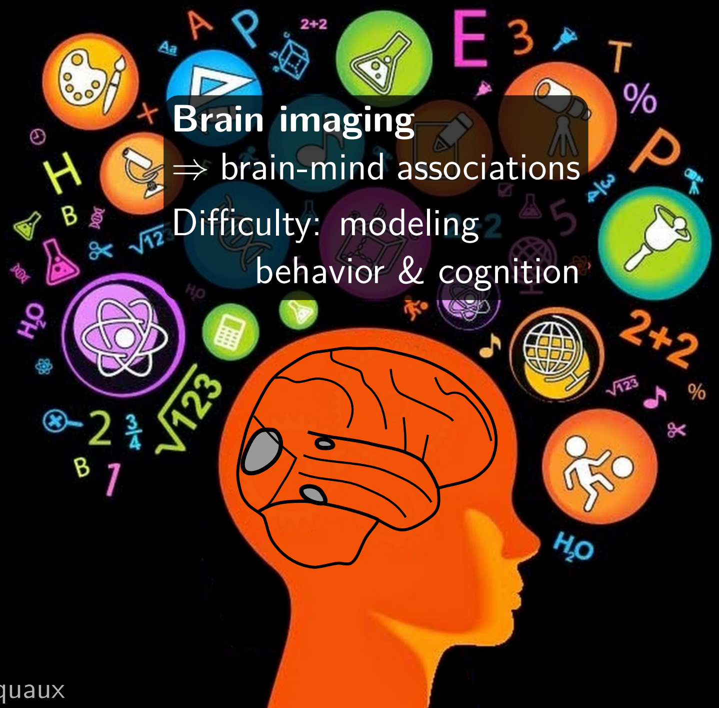
Generalization

to build broader theories

Paradigm 1: Seen   Paradigm 2: Imagined




Generalization
for broader theories
bridging paradigms
objects

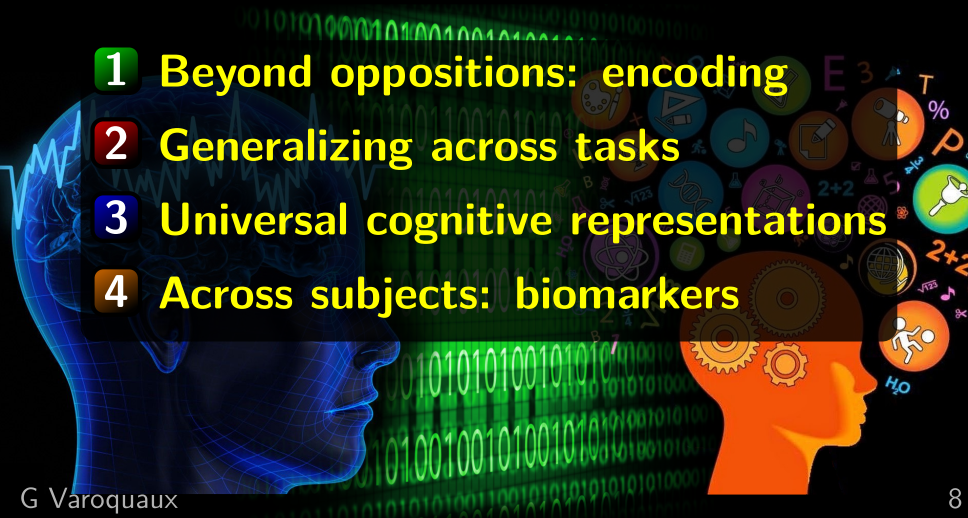


Brain imaging

⇒ brain-mind associations

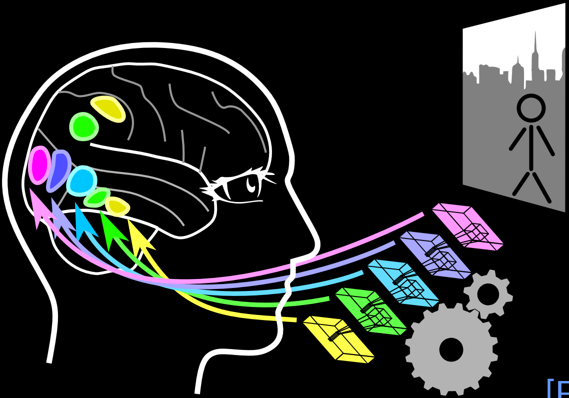
Difficulty: modeling behavior & cognition

Predictive models can broaden theories by generalizing brain-mind associations to arbitrary new tasks and stimuli [Varoquaux and Poldrack 2018]



1. **Beyond oppositions: encoding**
2. **Generalizing across tasks**
3. **Universal cognitive representations**
4. **Across subjects: biomarkers**

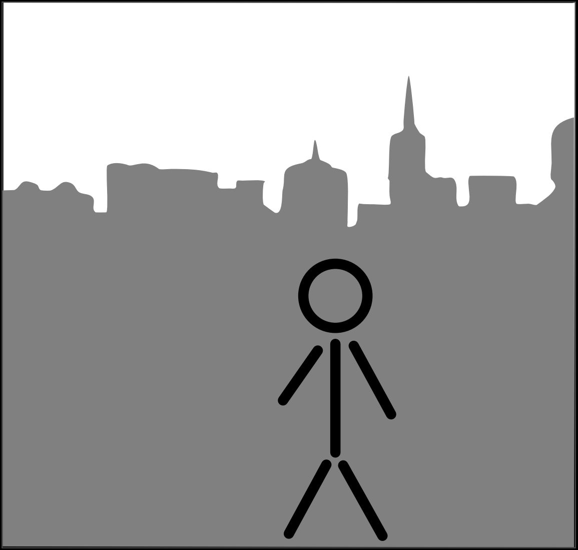
1 Beyond oppositions: encoding



[Eickenberg... 2017]

1 Decomposing psychological process

To study vision: Breaking down stimuli

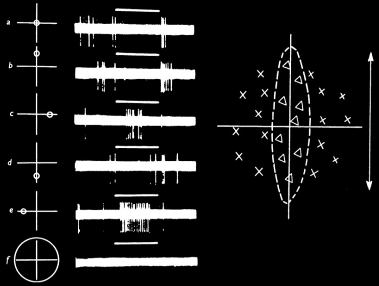


1 Decomposing psychological process

To study vision: Breaking down stimuli

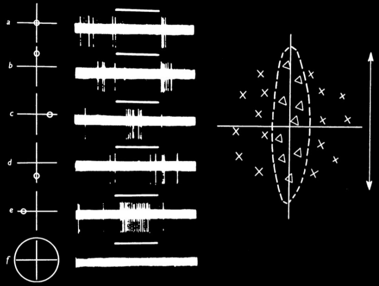
[Hubel and Wiesel 1962]

Neurons receptive to Gabors (edges)

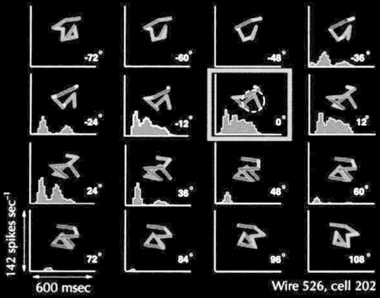


To study vision: Breaking down stimuli

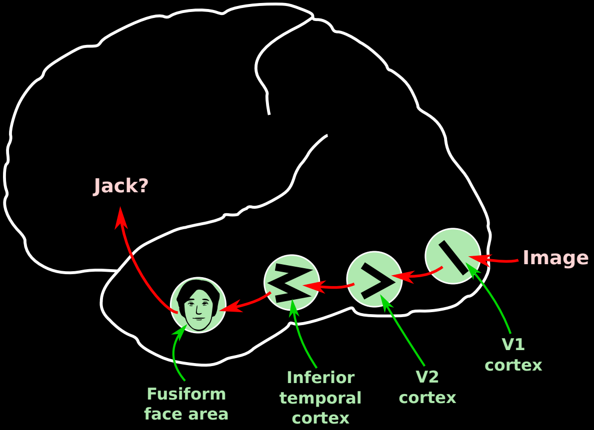
[Hubel and Wiesel 1962]
Neurons receptive to Gabors (edges)



[Logothetis... 1995]
Shapes in inferior temporal cortex



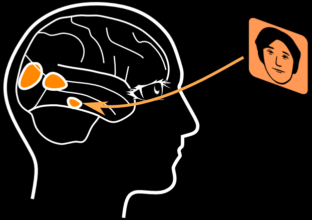
To study vision: Breaking down stimuli



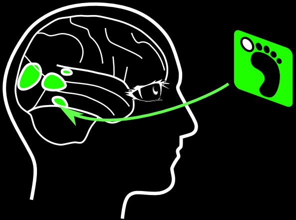
Is there a “face” region? A “foot” region? A “left big toe” region?

1 Crafting stimuli for cognitive oppositions

Is there a "face" region? A "foot" region? A "left big toe" region?

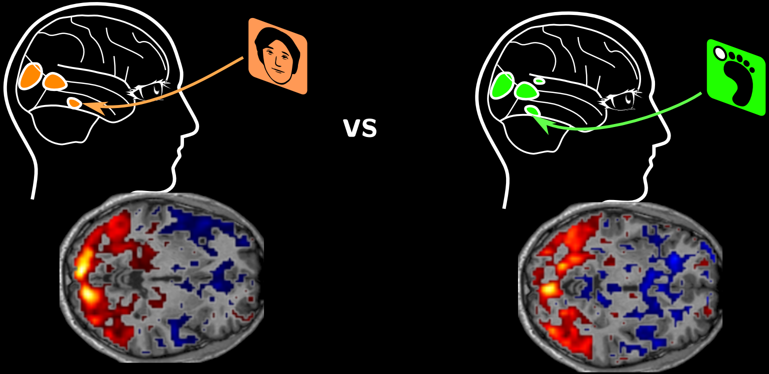


vs



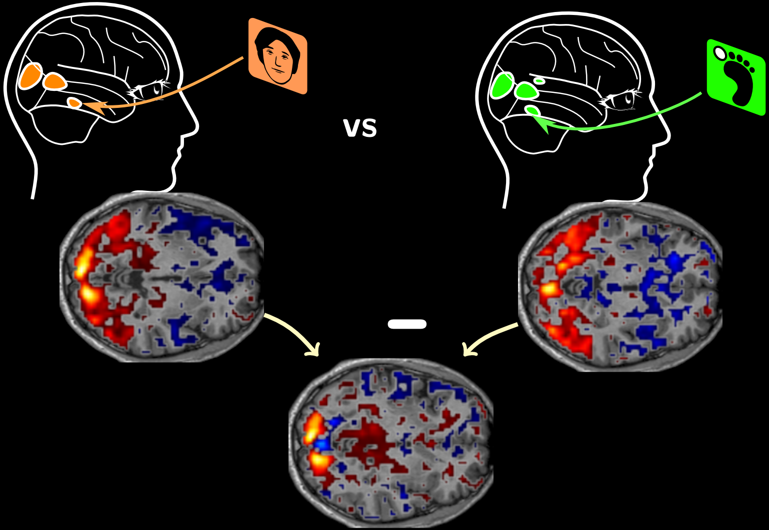
1 Crafting stimuli for cognitive oppositions

Is there a “face” region? A “foot” region? A “left big toe” region?



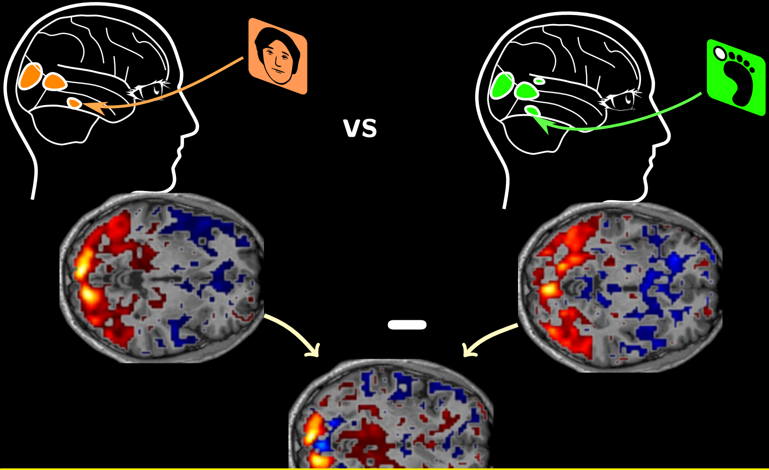
1 Crafting stimuli for cognitive oppositions

Is there a "face" region? A "foot" region? A "left big toe" region?



1 Crafting stimuli for cognitive oppositions

Is there a "face" region? A "foot" region? A "left big toe" region?

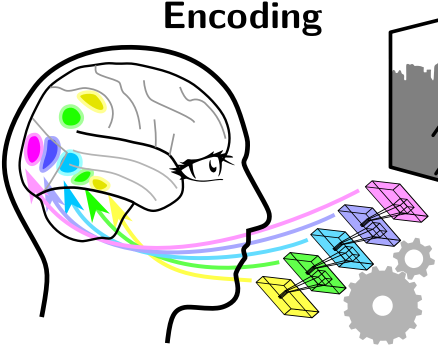


Representing only one aspect of the stimuli: too much reductionism

1 Not crafting stimuli for cognitive oppositions

Is there a "face" region? A "foot" region? A "left big toe" region?

Encoding

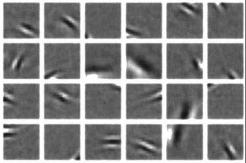


- Building *complex* representations of stimuli
- *Predicting* brain response from them

Representing only one aspect of the stimuli: too much reductionism

1 Decomposing visual stimuli

Low-level visual cortex is tuned to natural image statistics [Olshausen *et al.* 1996]

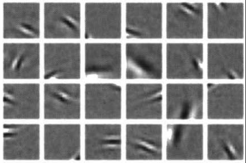


What drives high-level representations?

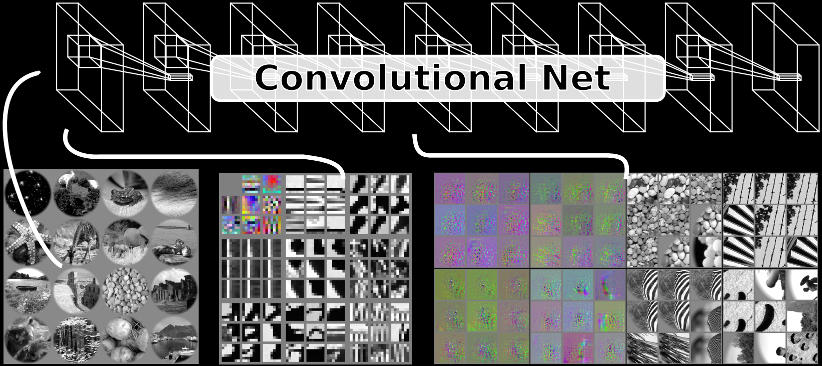
The concept of “left big toe”?

1 Decomposing visual stimuli

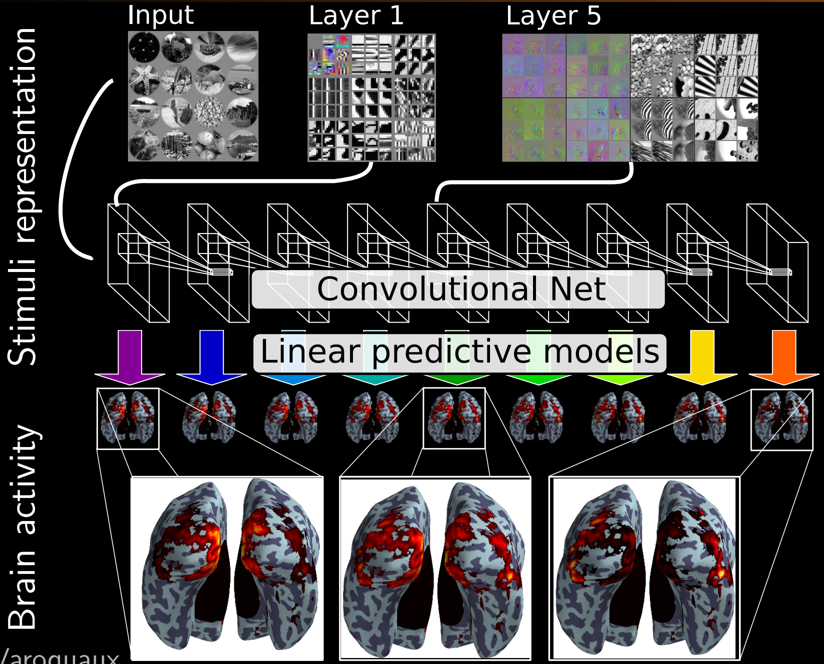
Low-level visual cortex is tuned to natural image statistics [Olshausen *et al.* 1996]



What drives high-level representations?

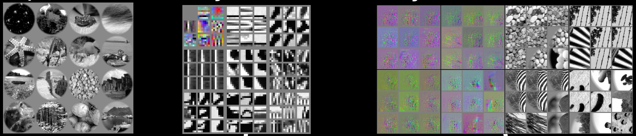


1 Brain mapping: encoding with conv nets



1 Brain mapping: encoding with conv nets

Stimuli representation



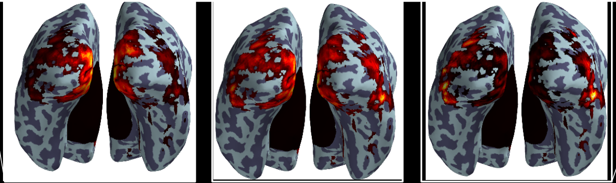
Explains the brain activity from the stimuli much better than hand-crafted features

On data from

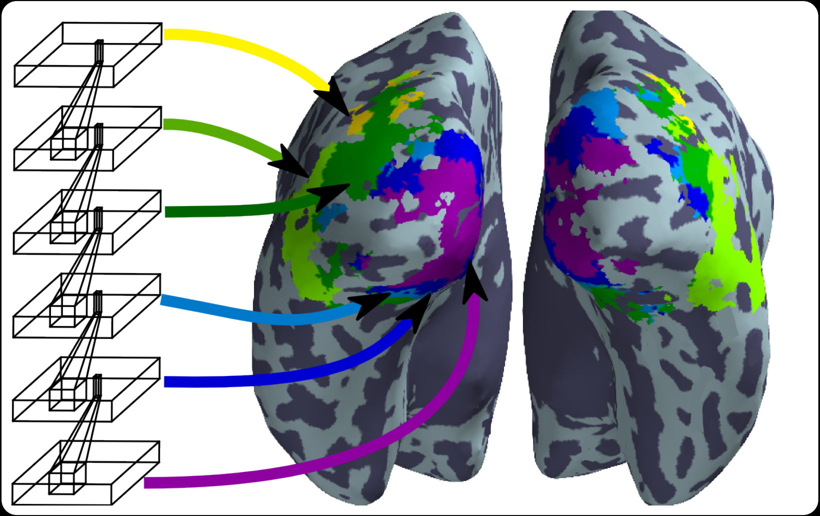
- [Kay... 2008] natural images
- [Huth... 2012] movies

[Eickenberg... 2017]

Brain activity



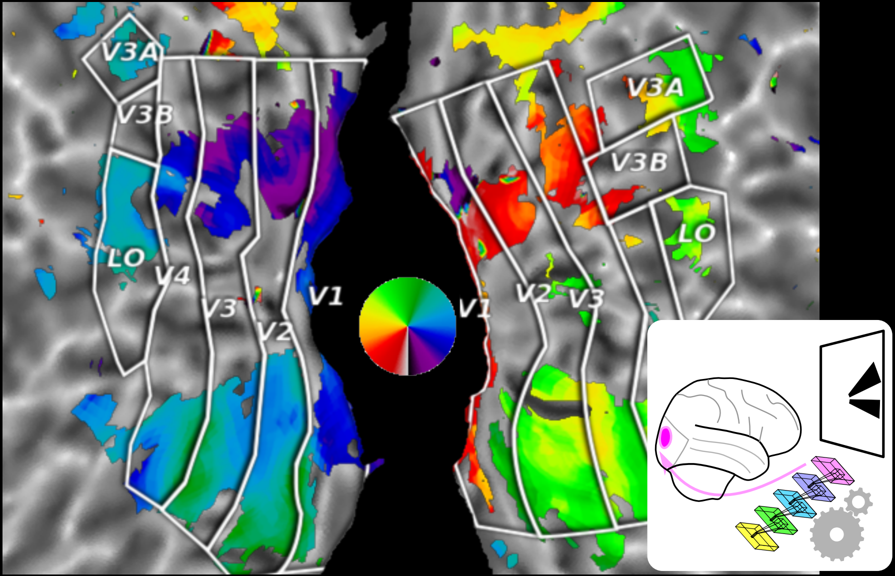
1 Brain mapping: encoding with conv nets



High-level conv-net layer map to high-level visual areas

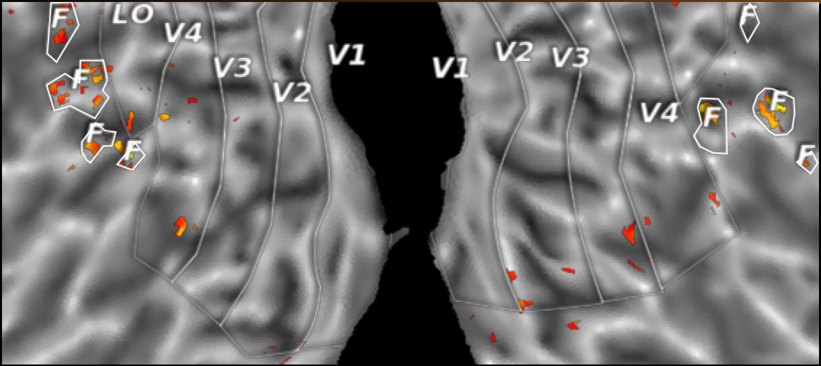
[Eickenberg... 2017]

1 Brain mapping with conv nets: retinotopy

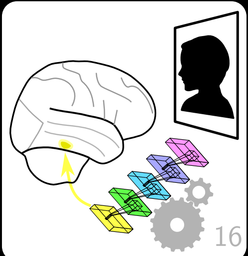


Mapping response to exentricity: artifical retinotopy

1 Brain mapping with conv nets: high-level concepts

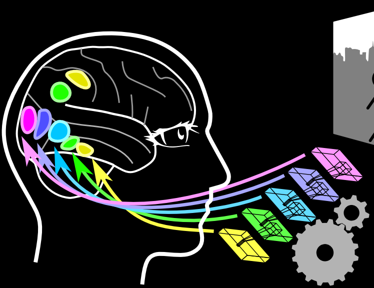


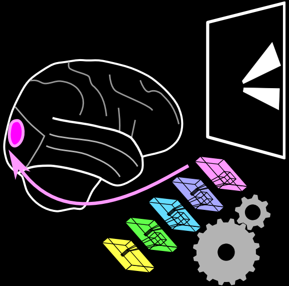
Opposing face versus place in the [Haxby... 2001] stimuli



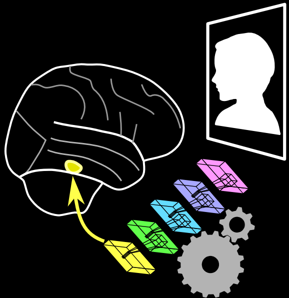
Beyond oppositions: encoding

Recovers the hierarchy of visual modules



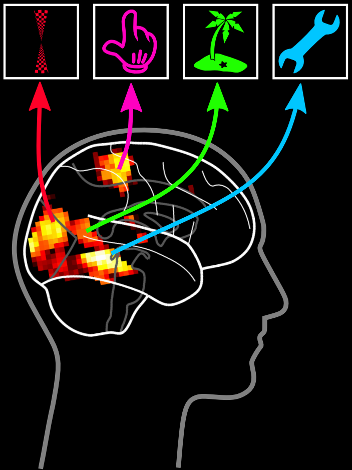


Generalizes from natural images to retinotopy or face vs place



[Eickenberg... 2017]

2 Generalizing across tasks

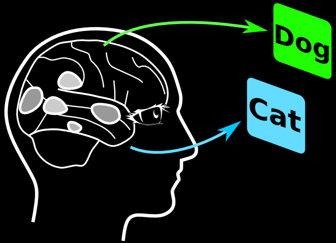


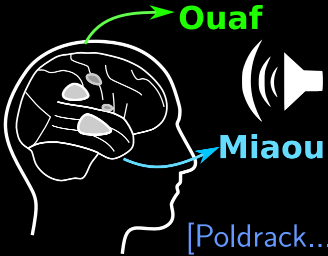
Characterizing the function of brain structures

How much is observed activity a consequence of specificities of the paradigm?

[Schwartz... 2013, Varoquaux... 2018]

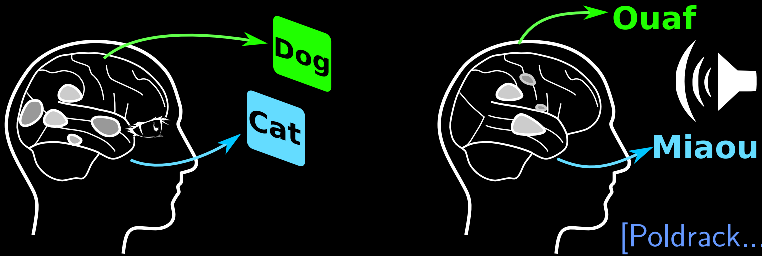
2 Large-scale decoding for reverse inference





[Poldrack... 2009]

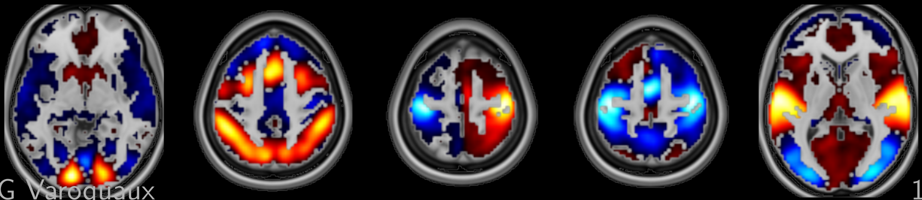
2 Large-scale decoding for reverse inference

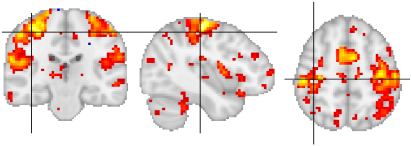


[Poldrack... 2009]

Variability: an opportunity and a challenge

- Technical heterogeneity (scanner, stimulus modality...)
- Paradigmatic isolation (cognition) [Newell 1973]





What is this brain doing?

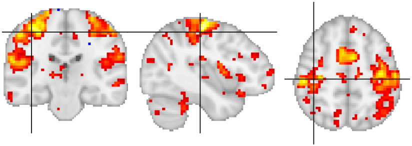
Describe tasks by their cognitive components

Multi-label prediction: presence or absence of each label

Visual	Checkboard	...
Auditory	Face	...
Foot	Place	...
Hand	Object	...
Calculation	Digit	...
Reading	Saccade	...

[Schwartz... 2013, Varoquaux... 2018]

2 Generalizing to arbitrary paradigms



What is this brain doing?

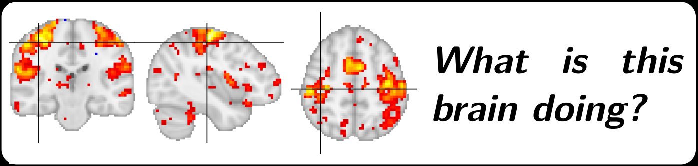
Describe tasks by their cognitive components

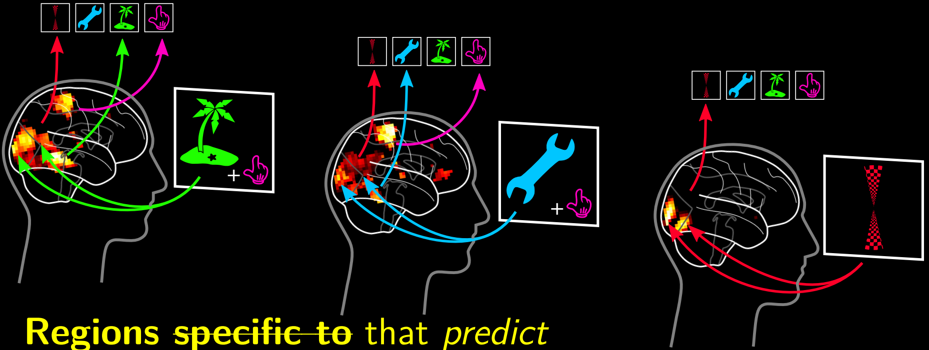
Multi-label prediction: presence or absence of each label

Visual | Checkboard | ...
Auditory | Face | ...
 | ... | ...

Prediction across studies

Describe a task never seen
from the brain activity it evokes





Regions ~~specific to~~ that *predict* **facets of cognition**

[Schwartz... 2013, Varoquaux... 2018]

30 studies **837** subjects **196** experimental conditions

6919 activation maps

Different labs

- Dehaene
- Poldrack
- Wager

...

Various cognitive domains

- Language
- Vision
- Decision making
- Mathematics

...

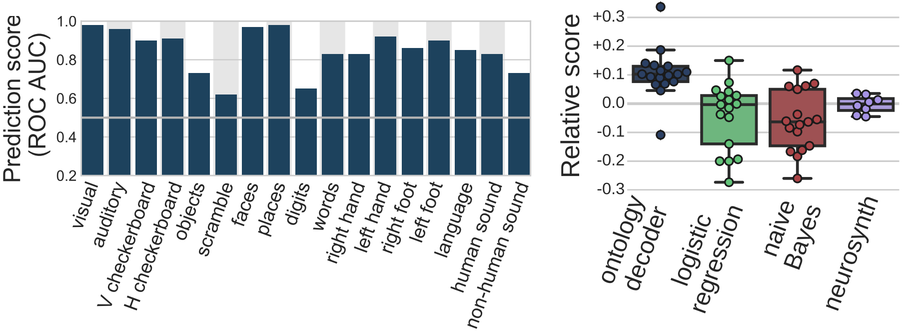
All manually preprocessed, labeled, and curated

[Schwartz... 2013, Varoquaux... 2018]

30 studies **837** subjects **196** experimental conditions

6919 activation maps

Decoding arbitrary new paradigms



 [Schwartz... 2013, Varoquaux... 2018]

2 Mapping: regions specific to facets of cognition

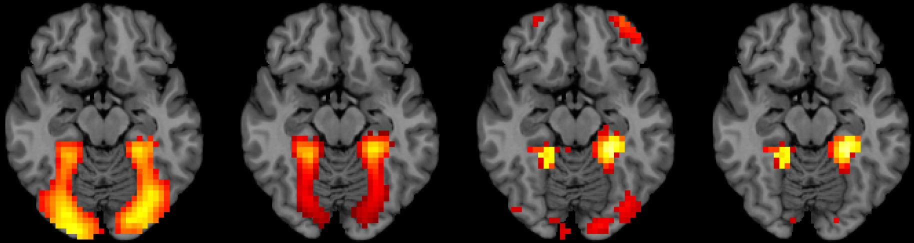
Contrasts: good rejection of confounds

Decoding: reverse inference

⇒ Consensus to define regions

The “place” concept

Forward term effect | **Forward ontology contrast** | **Reverse decoder map** | **Consensus forward & reverse**



Brain response to tasks with the “place” concept

Contrasting responses to “place” and related concepts

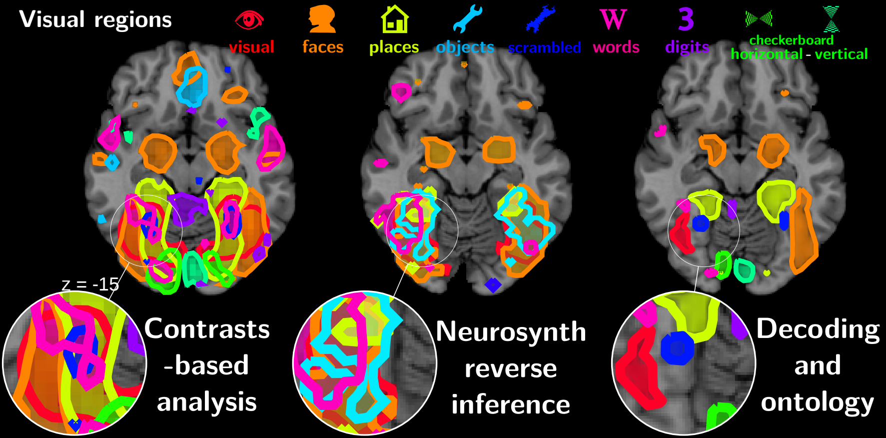
Regions that predict a place-recognition task

Regions selected by forward and reverse inference

Replaces the careful crafting of control conditions

[Schwartz... 2013, Varoquaux... 2018]

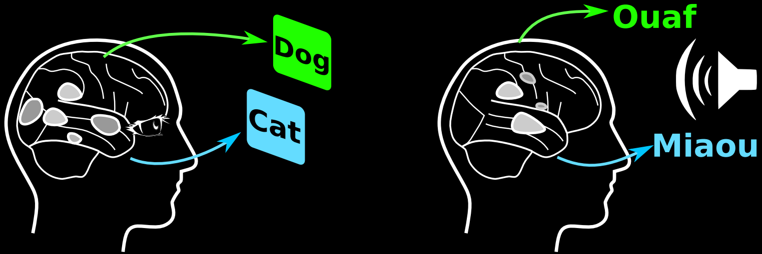
A functional atlas: central gyrus, motor networks



+ Language and auditory mapping in temporal cortex
+ Calculation and spatial attenation in IPS
+ Mapping the motor system

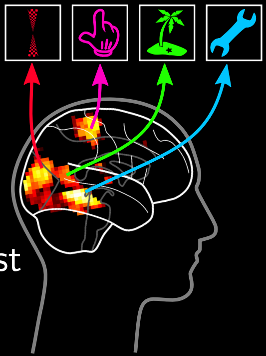
[Schwartz... 2013, Varoquaux... 2018]

Generalizing across tasks



Multi-label prediction

Prediction (discriminative models) more robust to heterogeneity

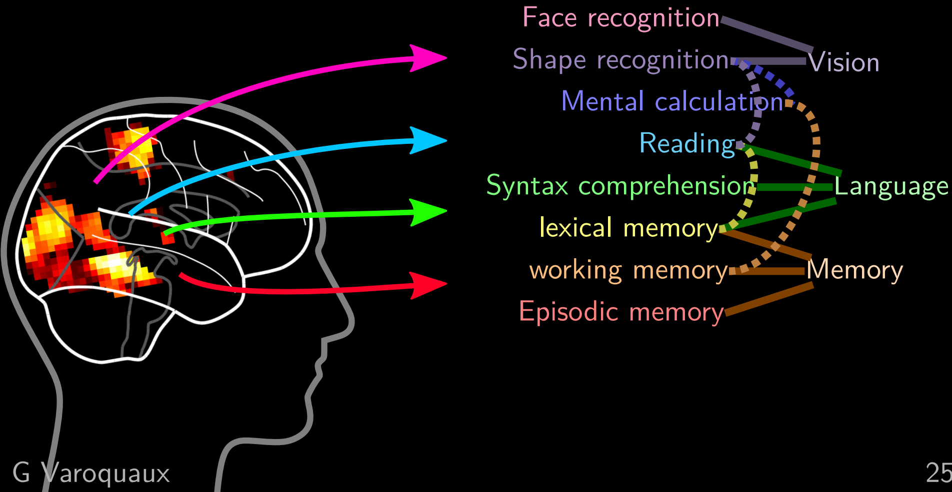


Decoding
⇒ evidence beyond a paradigm

Atlasing cognition

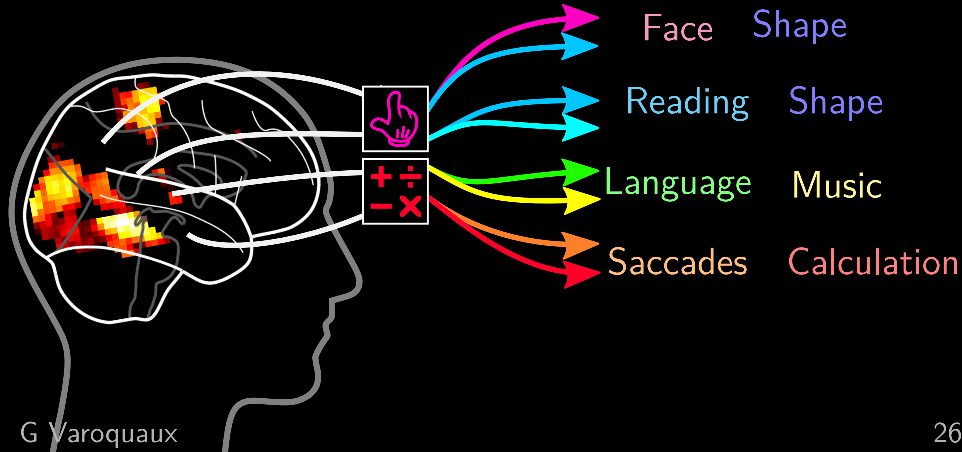
[Varoquaux... 2018]

Need an ontology of cognition



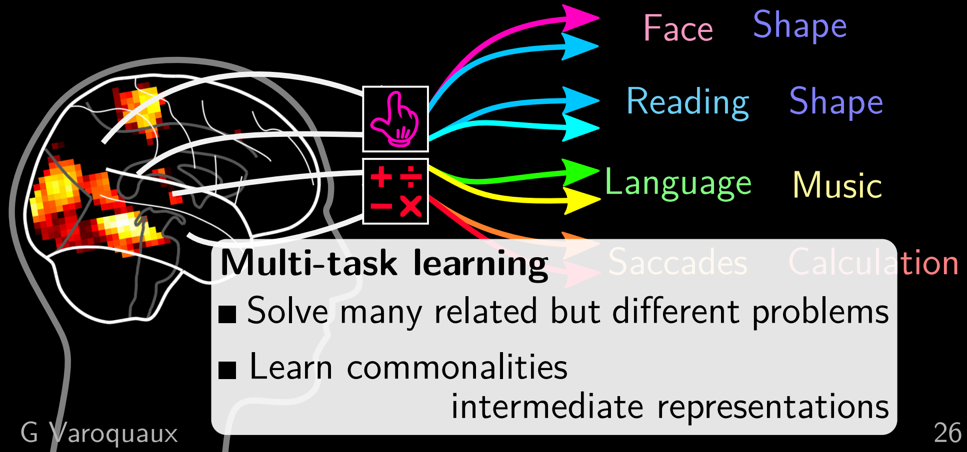
3 Universal cognitive representations

[Mensch... 2017]



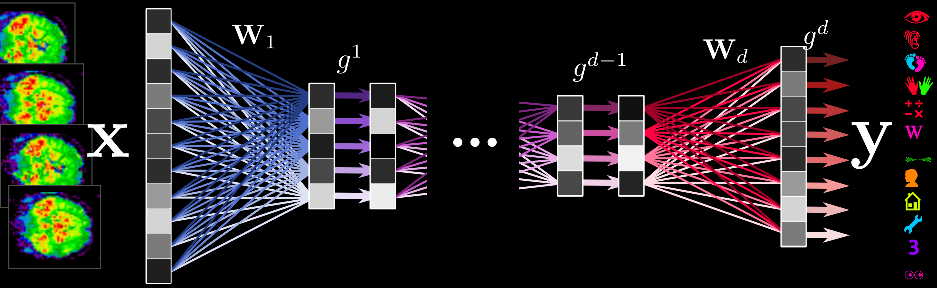
3 Universal cognitive representations

[Mensch... 2017]



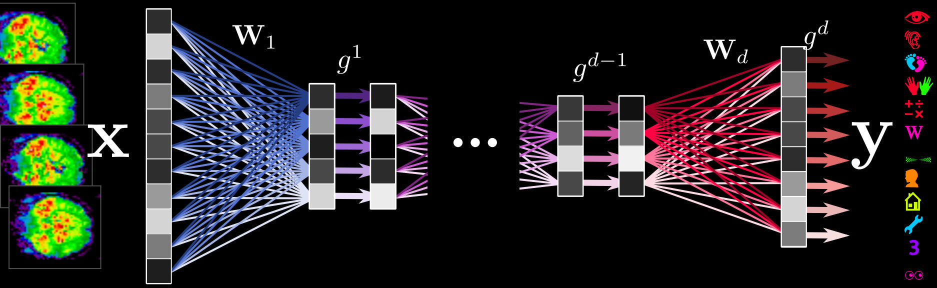
Multi-task learning

- Solve many related but different problems
- Learn commonalities
  intermediate representations



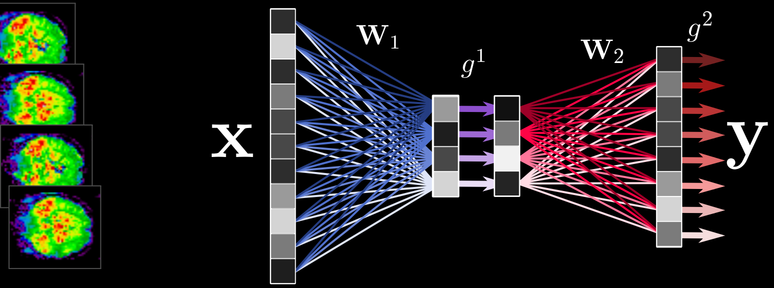
- Great for multiple output (tasks)

[Bengio 2009]



- Great for multiple output (tasks)
- Millions of parameters, thousands of data points

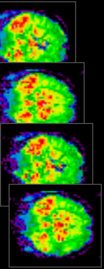
[Bengio 2009]

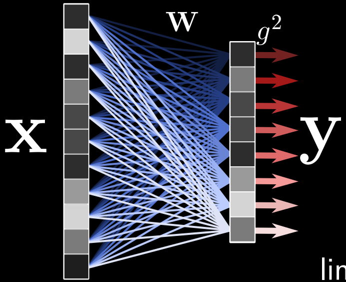


- Great for multiple output (tasks)
- Millions of parameters, thousands of data points

Simplify

3 Shallow architecture

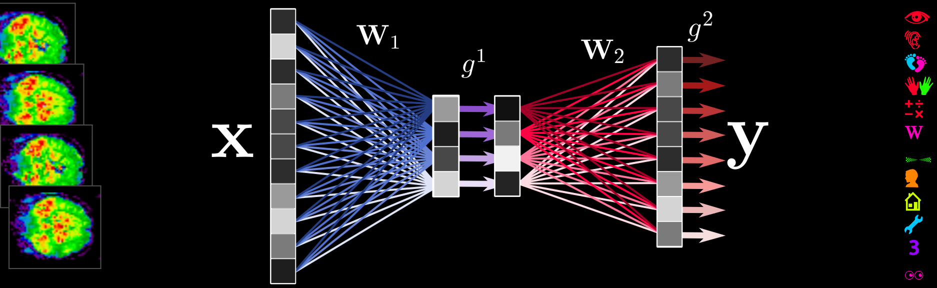




linear model

- Great for multiple output (tasks)
- Millions of parameters, thousands of data points

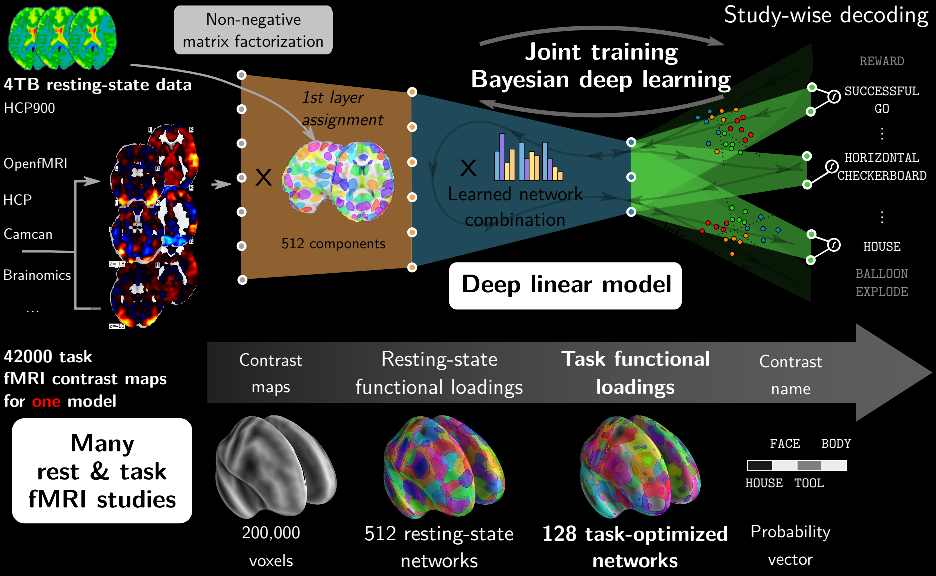
Simplify **simplify more**



- Great for multiple output (tasks)
- Millions of parameters, thousands of data points

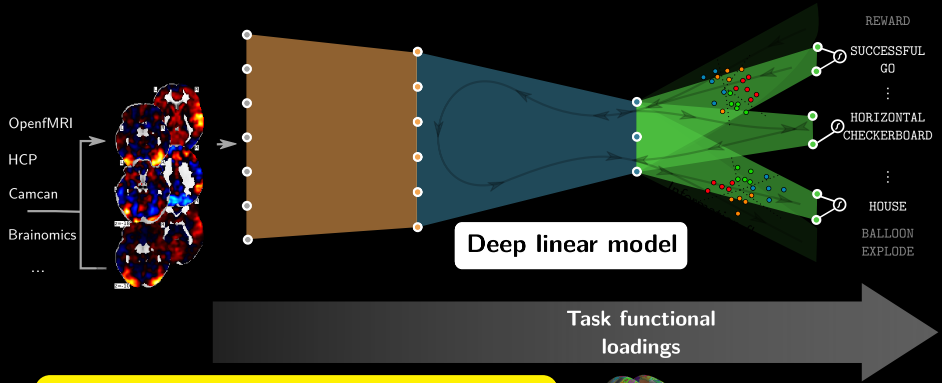
Simplify ~~**simplify more**~~

3 Deep linear model – multi-task – Bayesian

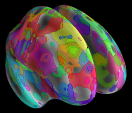


[Mensch... 2018]

3 Deep linear model – multi-task – Bayesian



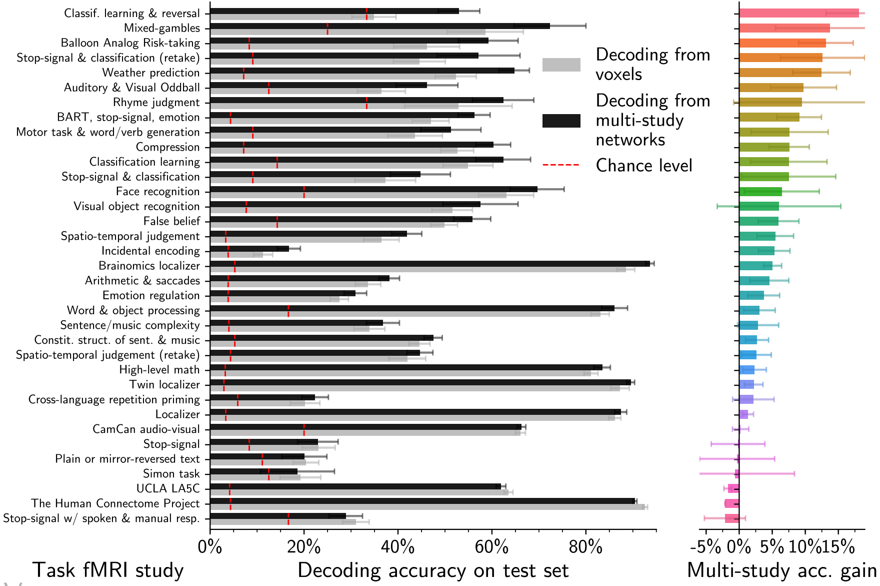
Intermediate representation: Task-optimized networks



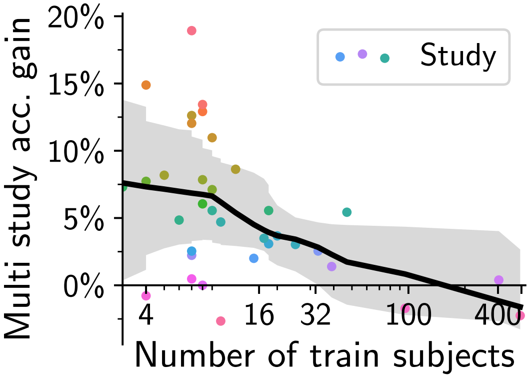
128 task-optimized networks

[Mensch... 2018]

Improves decoding in each study

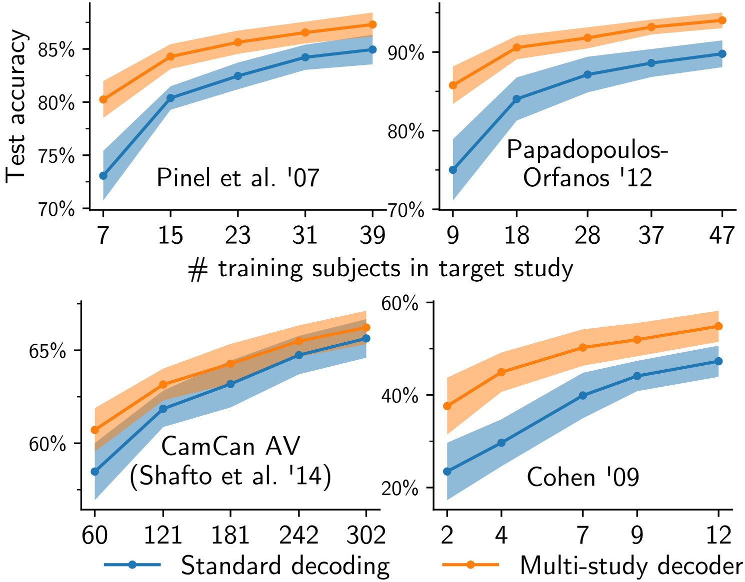


Improves decoding in each study

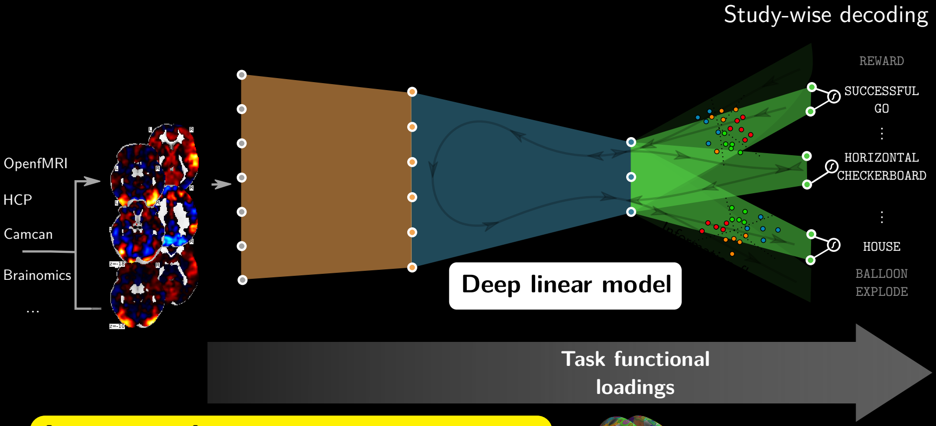


Small studies benefit from large ones

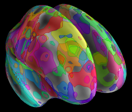
Enables smaller sample sizes



3 Deep linear model – multi-task – Bayesian



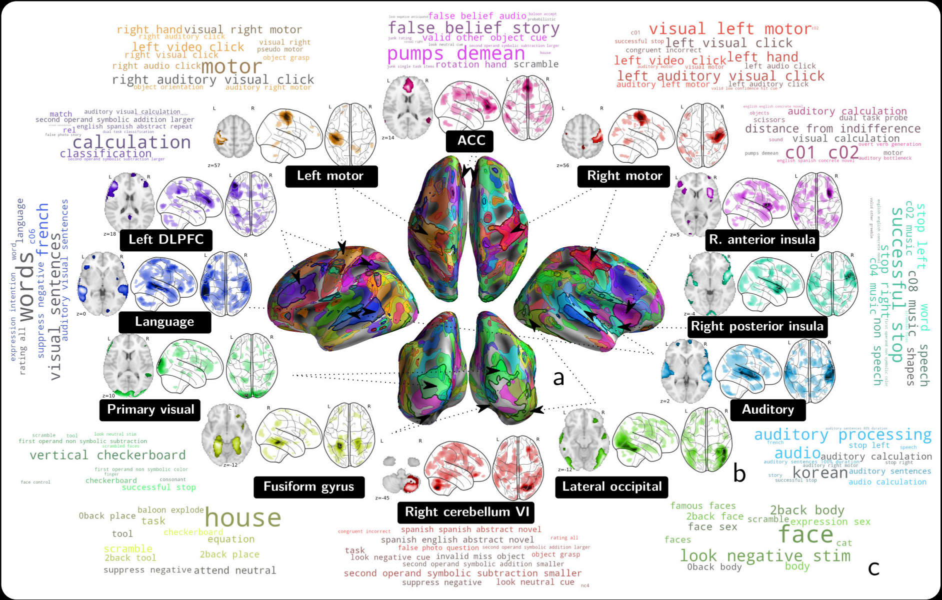
Intermediate representation: Task-optimized networks



128 task-optimized networks

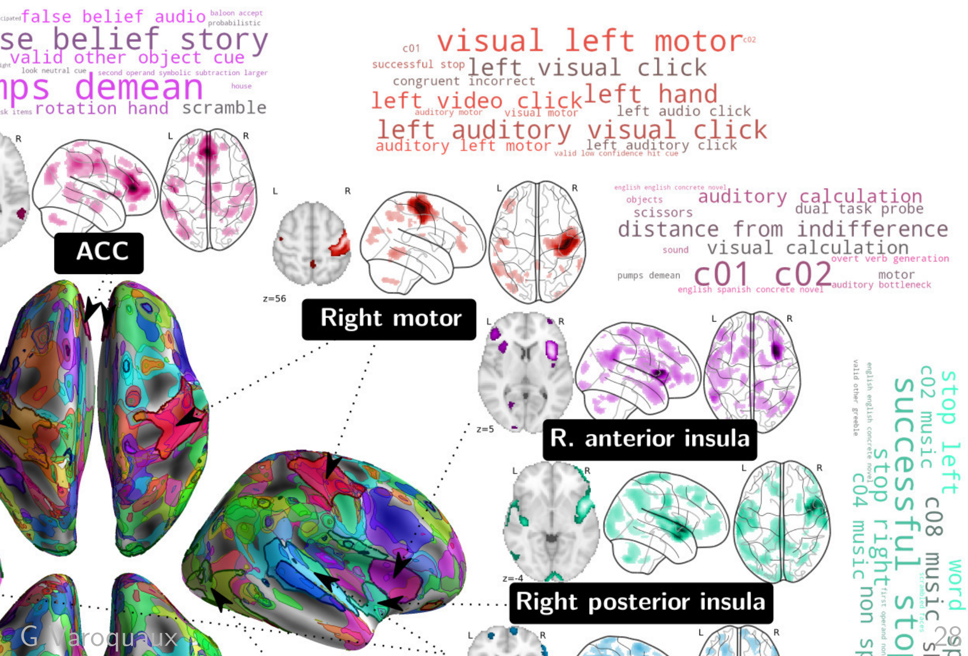
[Mensch... 2018]

3 Deep linear model – multi-task – Bayesian



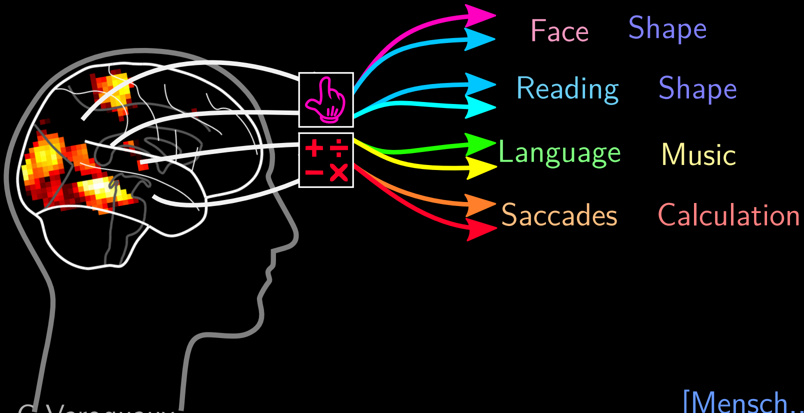
[Mensch... 2018]

3 Deep linear model – multi-task – Bayesian



Universal cognitive representations

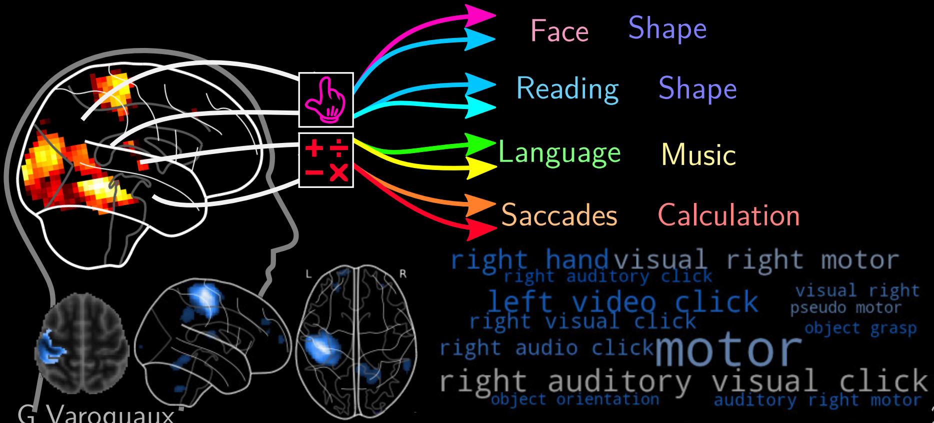
- Multi-task decoding:
  - decoding the original task labels
- Deep linear models:
  - intermediate representations across studies
  - statistical power from big to small studies



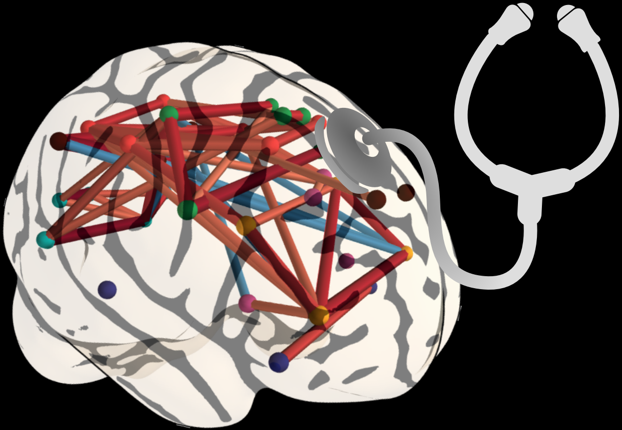
[Mensch... 2017]

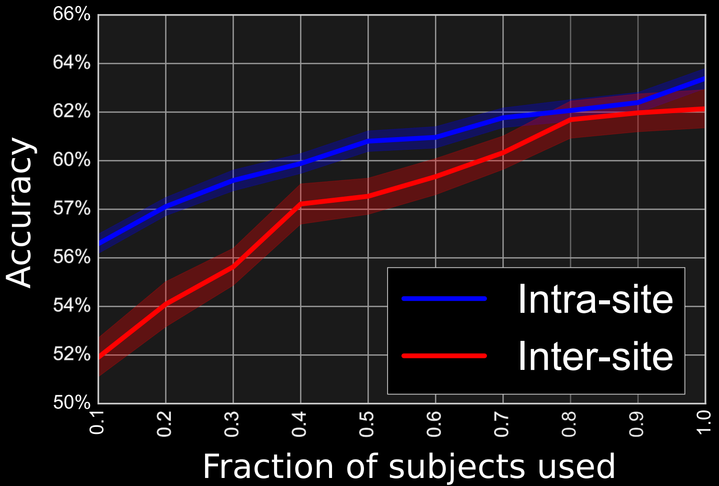
Universal cognitive representations

- Multi-task decoding:
  - decoding the original task labels
- Deep linear models:
  - intermediate representations across studies
  - statistical power from big to small studies



4 Across subjects: biomarkers





More data is better (up to 1000 subjects)

[Abraham... 2017]

4 Brain aging: a surrogate biomarker

Predicting brain aging $\neq$ chronological age

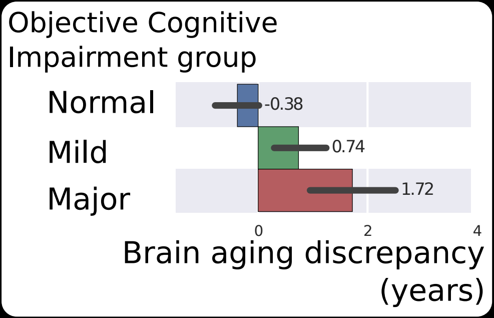
- **Multi-modal**: brain connectivity and morphology
- Age prediction: mean absolute error of **4.3 years**

[Liem... 2017]

Predicting brain aging $\neq$ chronological age

- **Multi-modal**: brain connectivity and morphology
- Age prediction: mean absolute error of **4.3 years**

- Discrepency with chronological age correlates with cognitive impairment

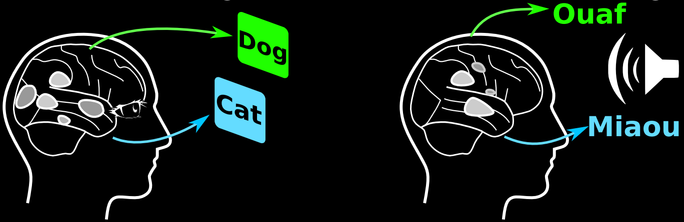


[Liem... 2017]

Prediction for broader theories

AI to model stimuli / the world

Explicit generalization across paradigms



Psychoinformatics with machine learning

Prediction for broader theories

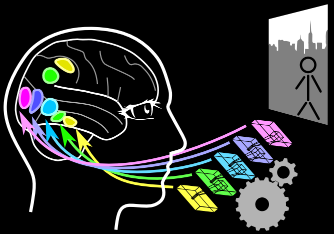
AI to model stimuli / the world

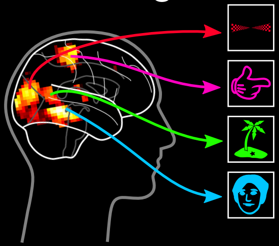
Explicit generalization across paradigms

Beyond oppositions

Encoding complete descriptions of tasks

Decoding multiple facets of cognitions





@GaelVaroquaux

Psychoinformatics with machine learning

Prediction for broader theories

AI to model stimuli / the world

Explicit generalization across paradigms

Beyond oppositions

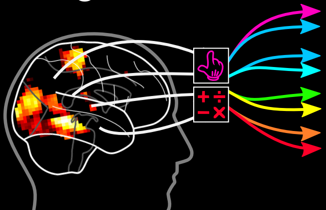
Encoding complete descriptions of tasks

Decoding multiple facets of cognitions

Useful with imperfect labels

Extracting common representations

Surrogate biomarkers



@GaelVaroquaux

Psychoinformatics with machine learning

Prediction for broader theories

AI to model stimuli / the world

Explicit generalization across paradigms

Beyond oppositions

Encoding complete descriptions of tasks

Decoding multiple facets of cognitions

Useful with imperfect labels

Extracting common representations

Surrogate biomarkers

Software: nilearn

http://nilearn.github.io

@GaelVaroquaux

References I

A. Abraham, M. P. Milham, A. Di Martino, R. C. Craddock, D. Samaras, B. Thirion, and G. Varoquaux. Deriving reproducible biomarkers from multi-site resting-state data: An autism-based example. *NeuroImage*, 147:736–745, 2017.

Y. Bengio. Learning deep architectures for ai. *Foundations and trends in Machine Learning*, 2:1–127, 2009.

M. Eickenberg, A. Gramfort, G. Varoquaux, and B. Thirion. Seeing it all: Convolutional network layers map the function of the human visual system. *NeuroImage*, 152:184–194, 2017.

J. V. Haxby, I. M. Gobbini, M. L. Furey, ... Distributed and overlapping representations of faces and objects in ventral temporal cortex. *Science*, 293:2425, 2001.

D. H. Hubel and T. N. Wiesel. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. *The Journal of physiology*, 160:106, 1962.

References II

A. G. Huth, S. Nishimoto, A. T. Vu, and J. L. Gallant. A continuous semantic space describes the representation of thousands of object and action categories across the human brain. *Neuron*, 76:1210, 2012.

K. N. Kay, T. Naselaris, R. J. Prenger, and J. L. Gallant. Identifying natural images from human brain activity. *Nature*, 452:352, 2008.

F. Liem, G. Varoquaux, J. Kynast, F. Beyer, S. K. Masouleh, J. M. Huntenburg, L. Lampe, M. Rahim, A. Abraham, R. C. Craddock, ... Predicting brain-age from multimodal imaging data captures cognitive impairment. *NeuroImage*, 2017.

N. K. Logothetis, J. Pauls, and T. Poggio. Shape representation in the inferior temporal cortex of monkeys. *Current Biology*, 5:552, 1995.

References III

A. Mensch, J. Mairal, B. Thirion, and G. Varoquaux. Learning neural representations of human cognition across many fMRI studies. In *NIPS*, 2017.

A. Mensch, J. Mairal, B. Thirion, and G. Varoquaux. Extracting universal representations of cognition across brain-imaging studies. *In prep*, 2018.

A. Newell. You can't play 20 questions with nature and win: Projective comments on the papers of this symposium. 1973.

B. Olshausen ... Emergence of simple-cell remainsceptive field properties by learning a sparse code for natural images. *Nature*, 381:607, 1996.

R. A. Poldrack, Y. O. Halchenko, and S. J. Hanson. Decoding the large-scale structure of brain function by classifying mental states across individuals. *Psychological Science*, 20:1364, 2009.

Y. Schwartz, B. Thirion, and G. Varoquaux. Mapping cognitive ontologies to and from the brain. In *NIPS*, 2013.

References IV

G. Varoquaux and R. A. Poldrack. Predictive models can overcome reductionism in cognitive neuroimaging. *In rev*, 2018.

G. Varoquaux and B. Thirion. How machine learning is shaping cognitive neuroimaging. *GigaScience*, 3:28, 2014.

G. Varoquaux, Y. Schwartz, R. A. Poldrack, B. Gauthier, D. Bzdok, J. Poline, and B. Thirion. Atlases of cognition with large-scale brain mapping. *In rev*, 2018.