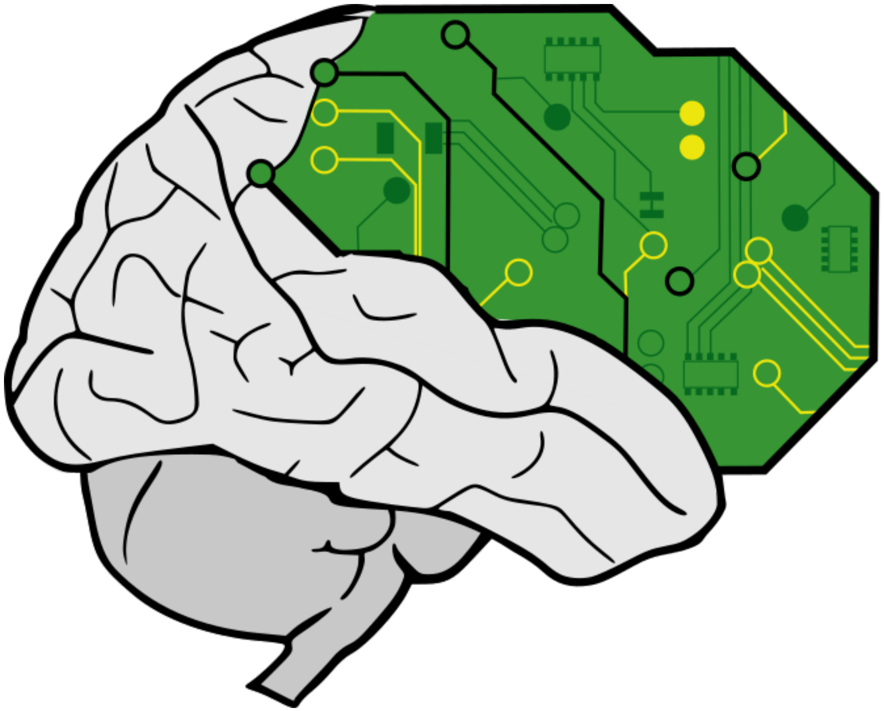
# Elementary Computational Architectures in Brains & Machines

Jean-Rémi KING, *New York University*



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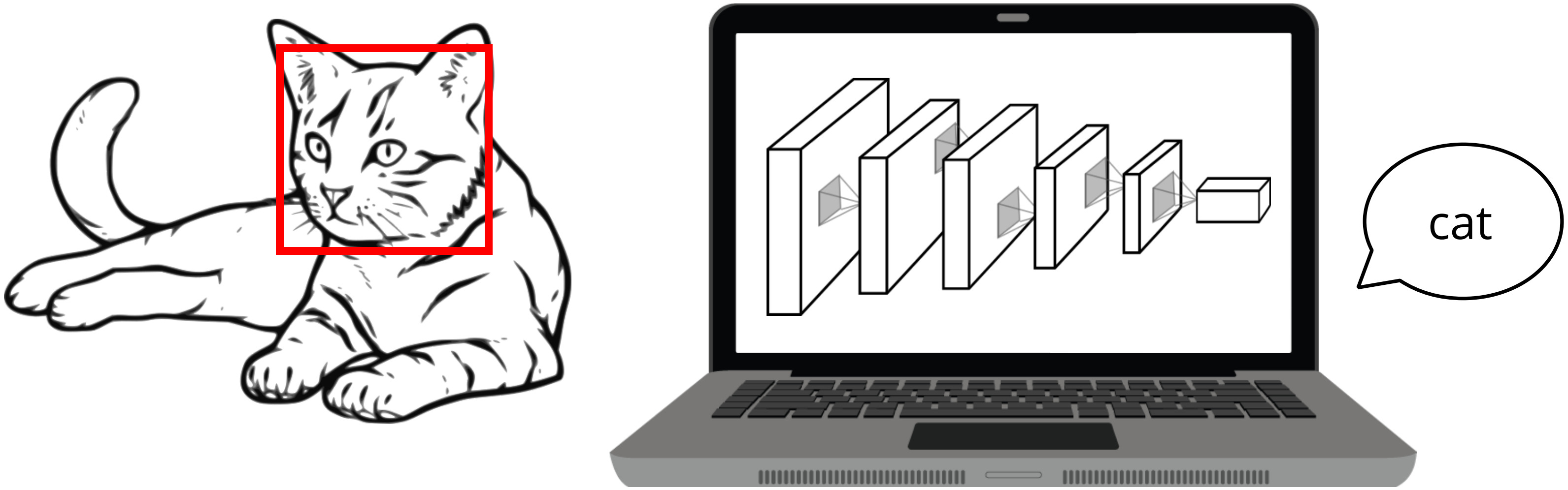

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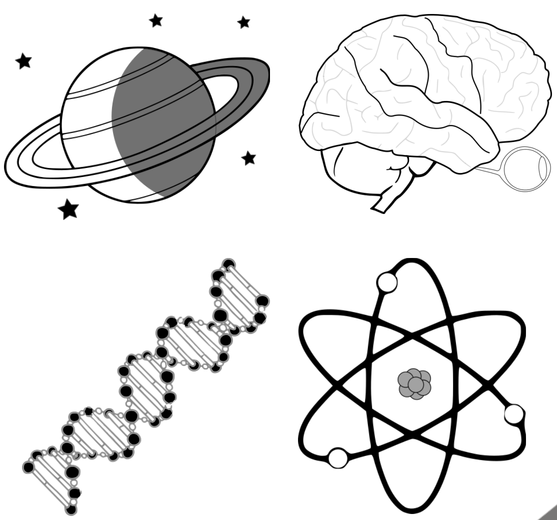

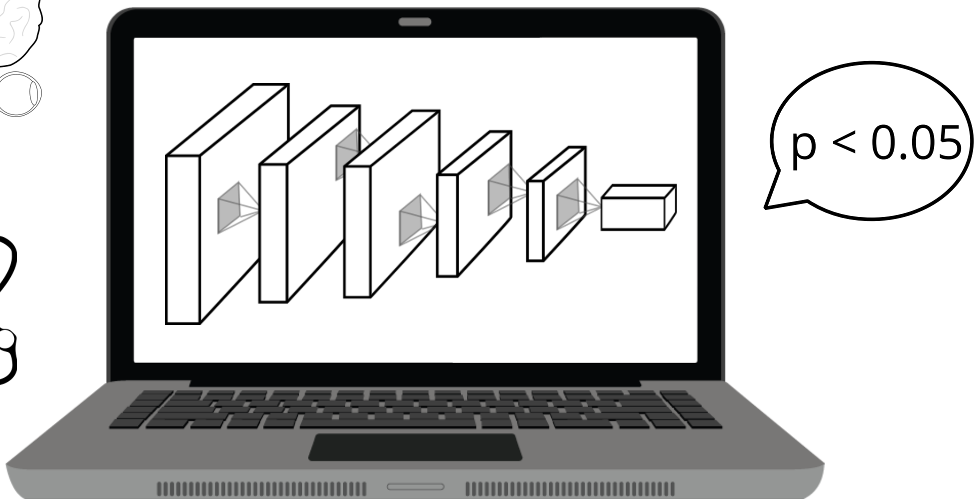

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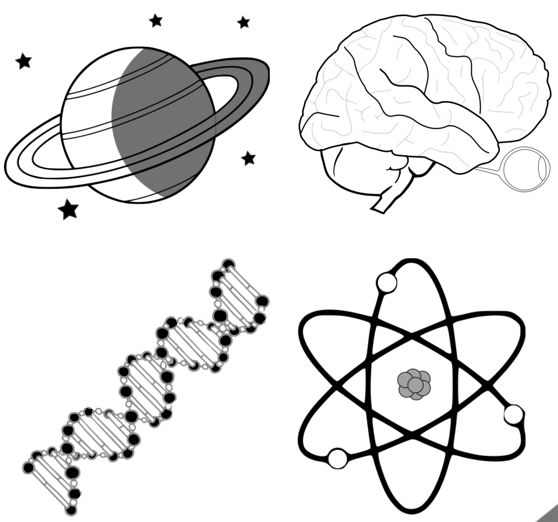

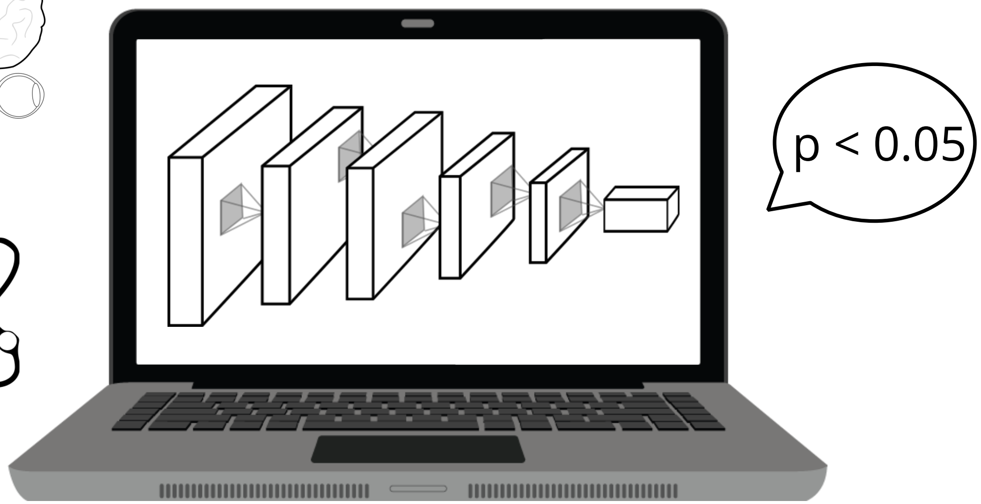

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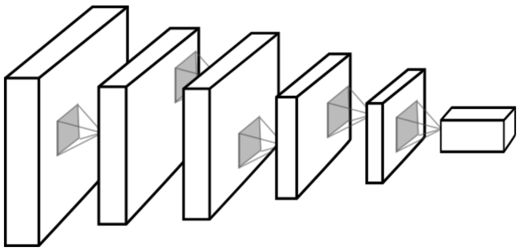
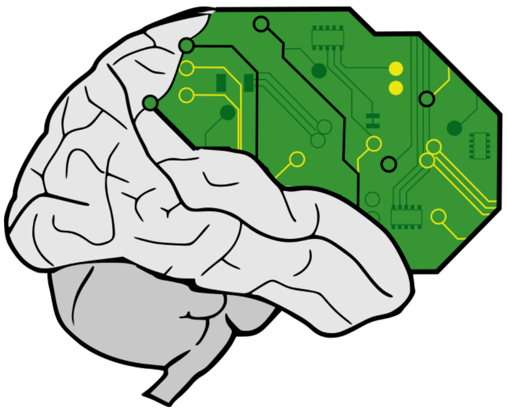
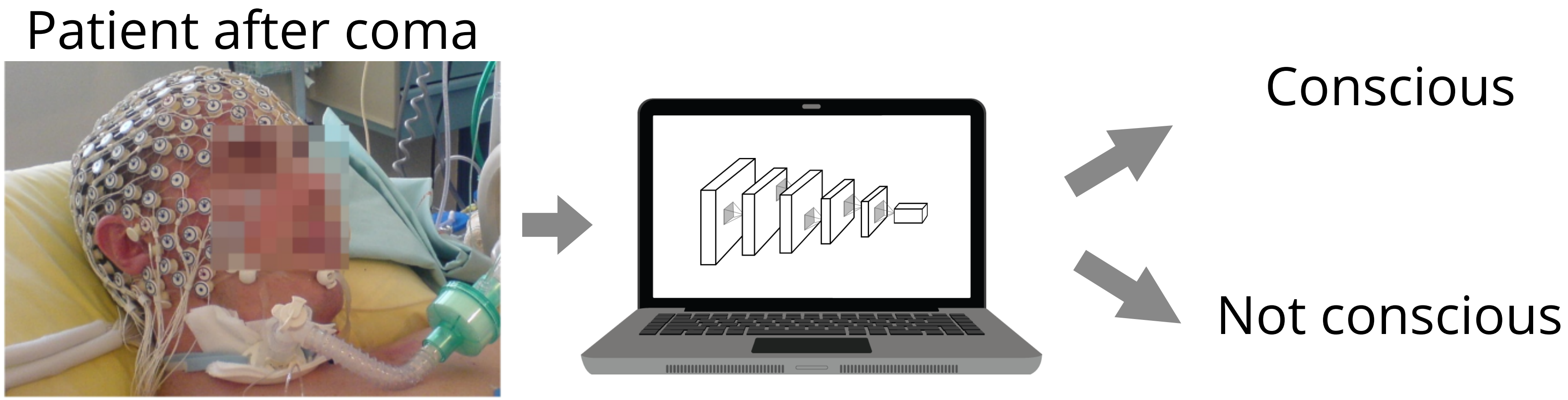
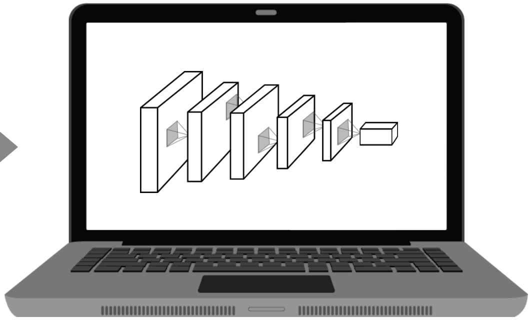


2. Theory




Patient after coma
Conscious
Not conscious

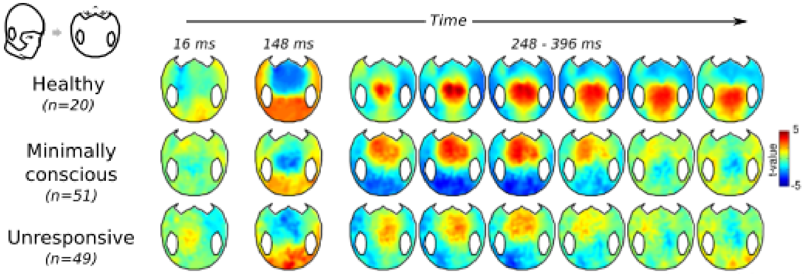
Patient after coma



Conscious

Not conscious

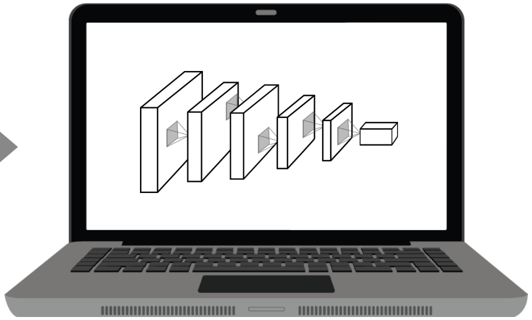
1: Sustained brain responses




**King** et al, *Science* 2011
**King** et al, *Neuroimage* 2013

Brain
activity
patterns

Patient after coma



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Brain activity patterns

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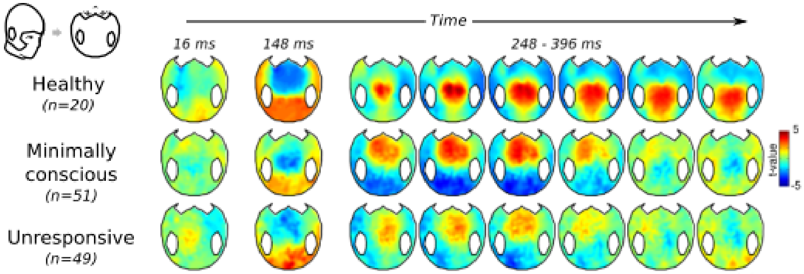
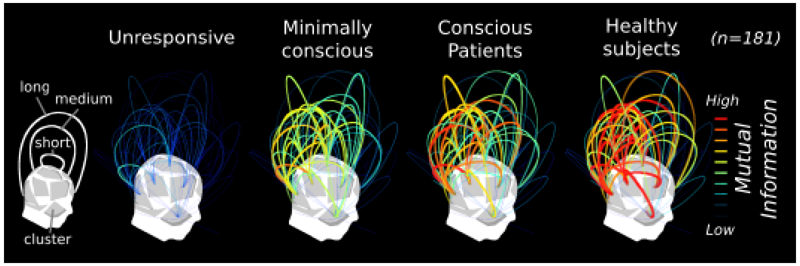



**King** et al, *Science* 2011
**King** et al, *Neuroimage* 2013

2: Inter-region communication




**King***, Sitt* et al, *Current Biology* 2014

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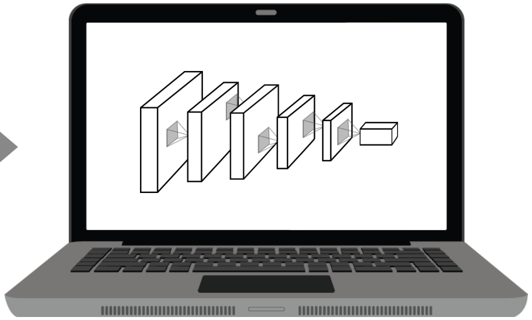

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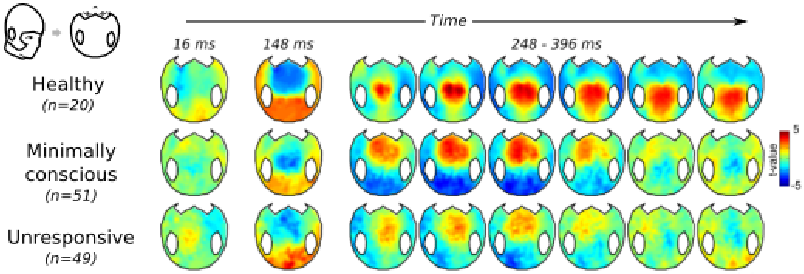


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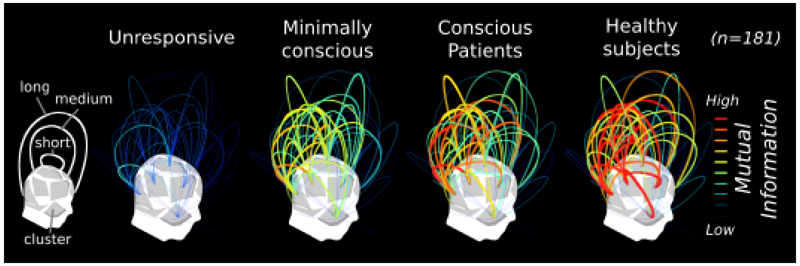


**King***, Sitt* et al, *Current Biology* 2014

3: Oscillations

4: Travelling waves

5: Signal complexity

...

Sitt*, **King*** et al, *Brain* 2014
**King** et al, *PLoS one* 2014
**King** & Dehaene, *TICS* 2014
**King** & Dehaene, *Phil.T Royal Soc.B* 2014
Dehaene & **King**, 2016
Sitt*, **King***, et al *US Patent* 2016
Engemann*, Raimondo*, **King**, et al,
*under review*

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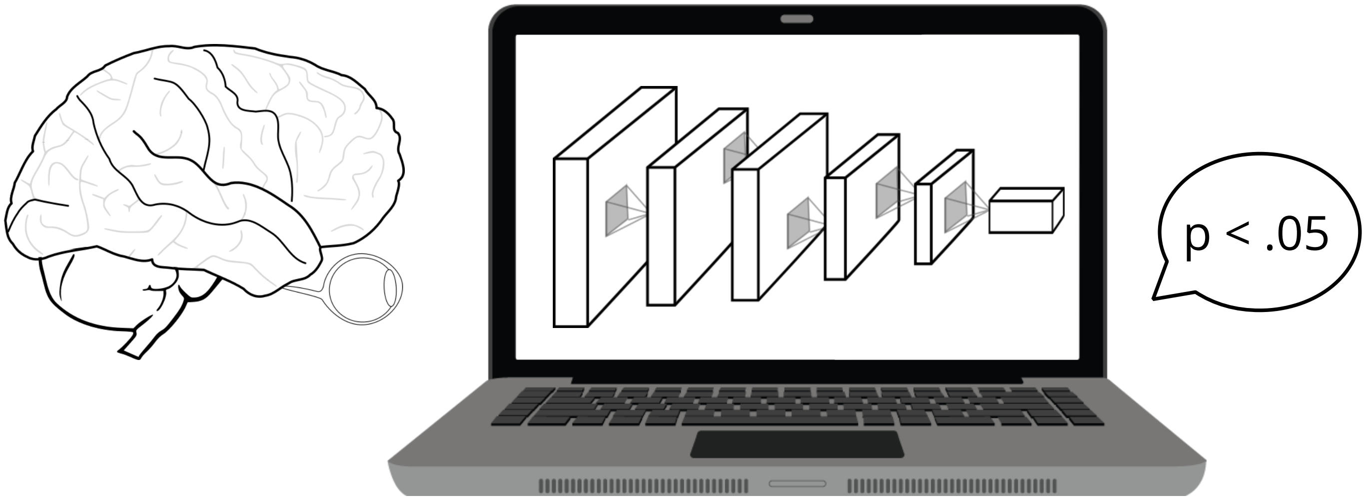

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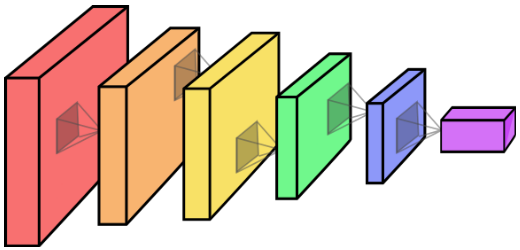

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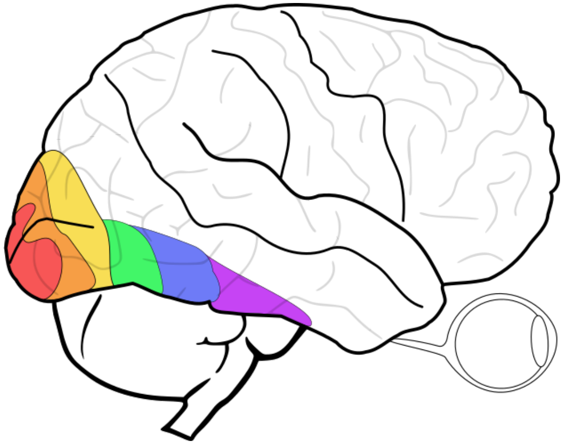
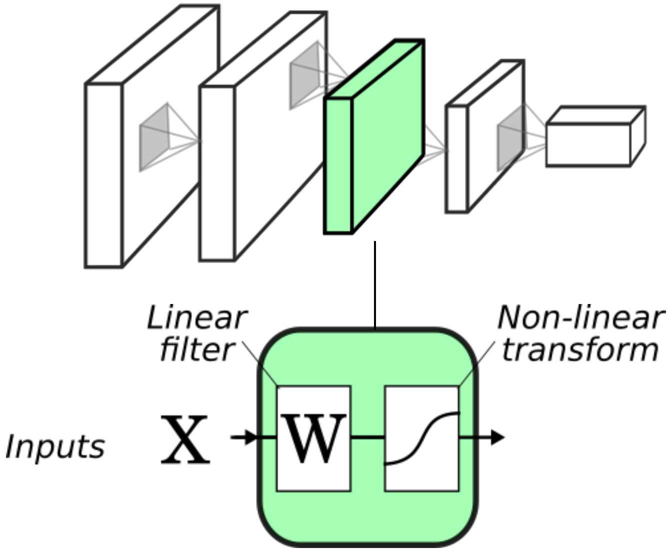
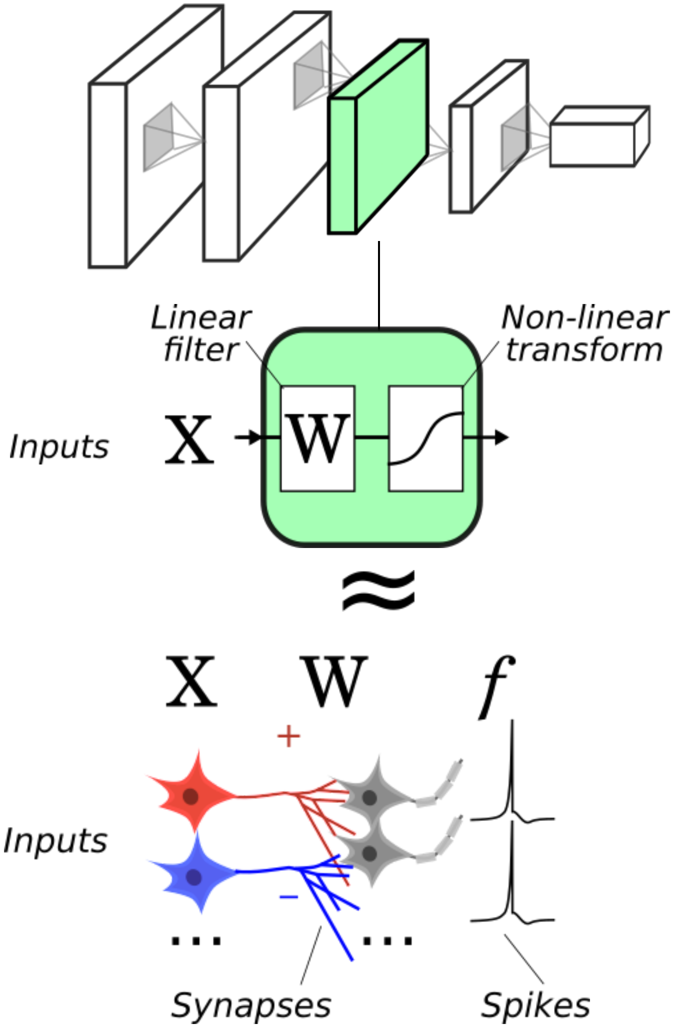


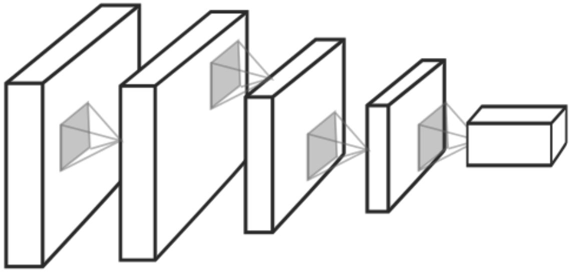
Deep
Net



Deep Net

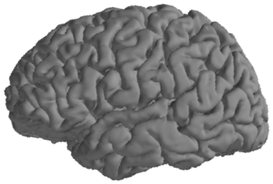

Linear filter
Non-linear transform
Inputs
X
W
≈
X
W
f
+
Inputs
−
...
...
Synapses
Spikes

Deep
Net

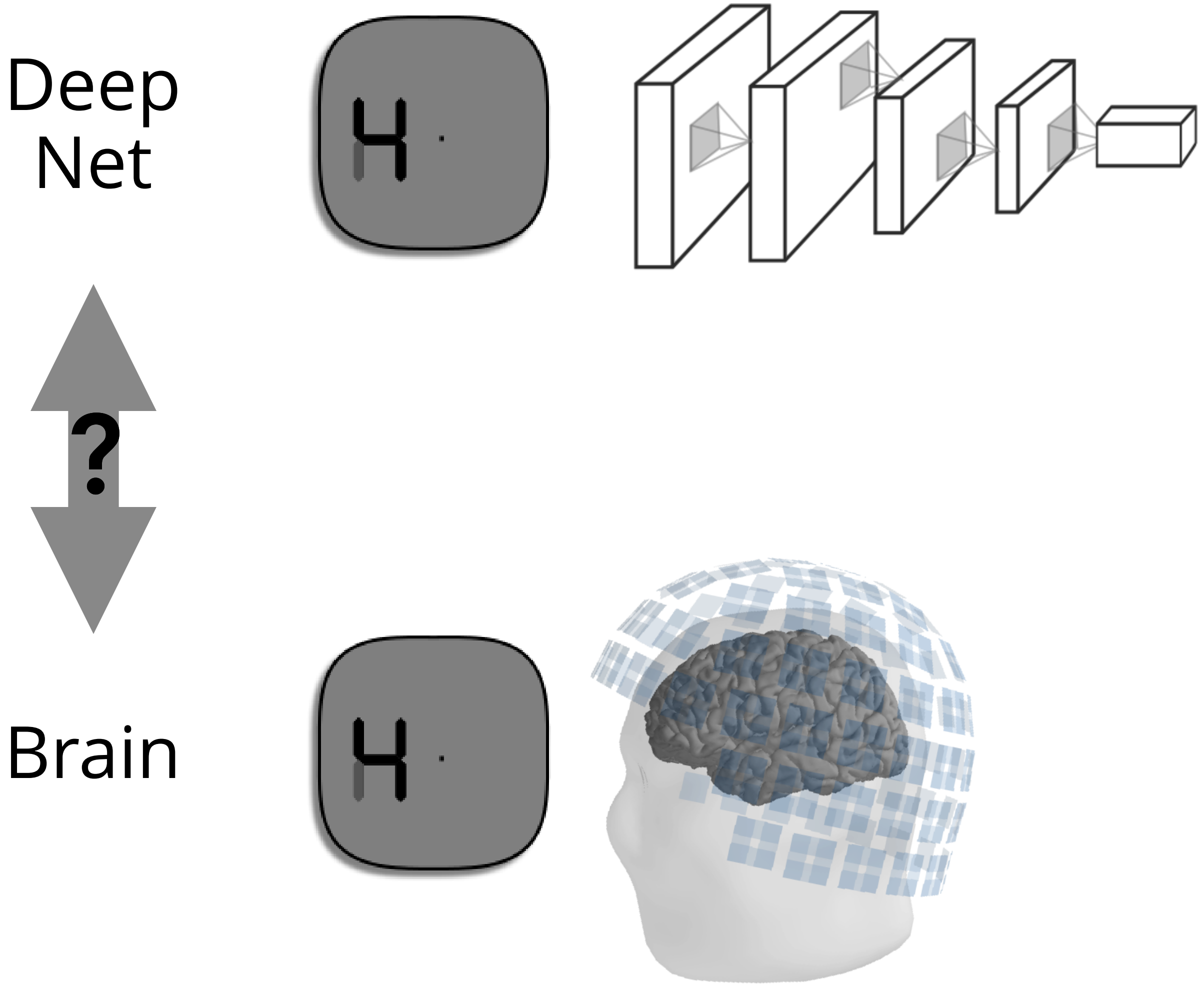


?

Brain



Gwilliams & **King**, 2017 *NIPS workshop*
Gwilliams & **King**, *submitted*



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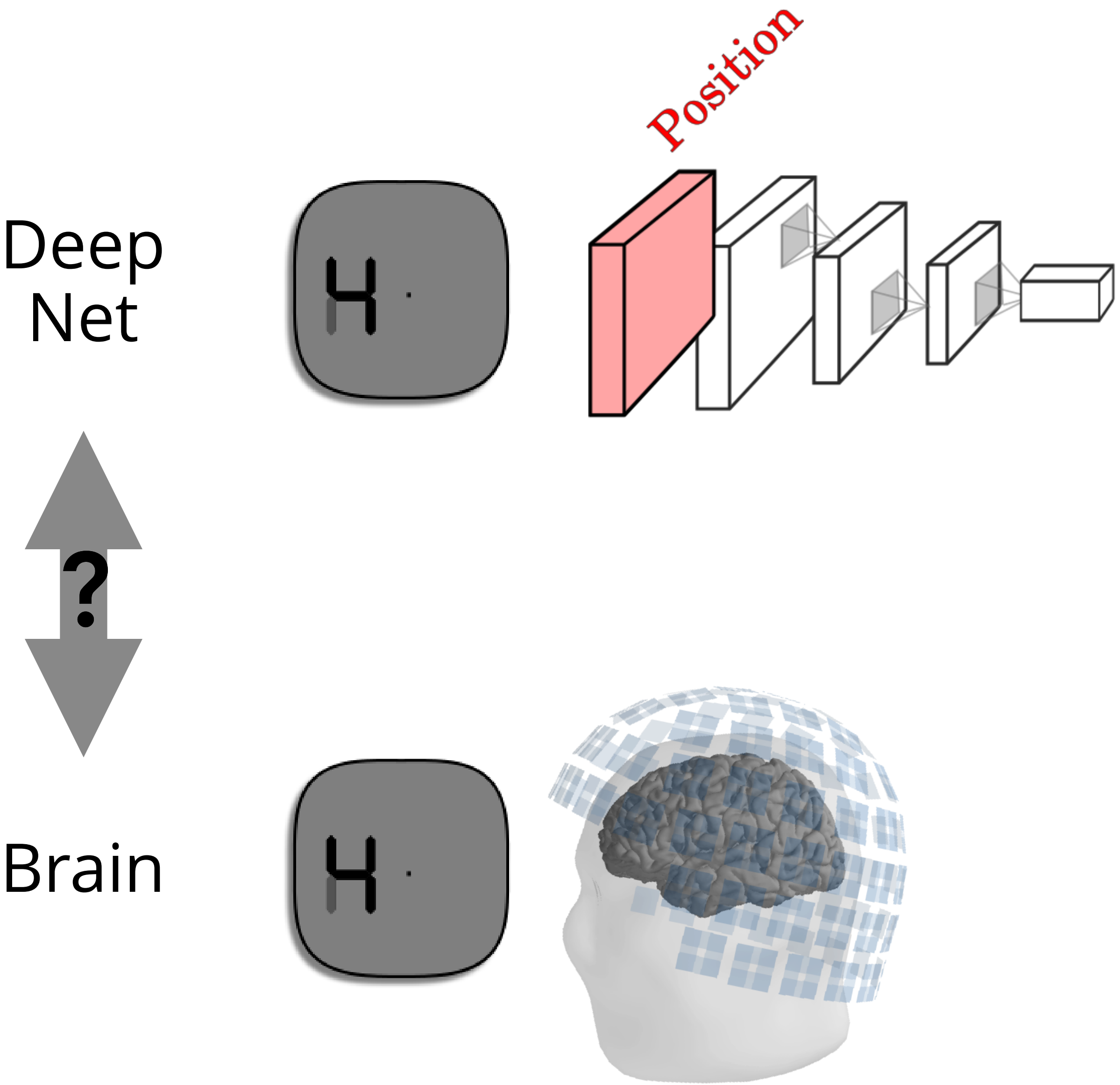

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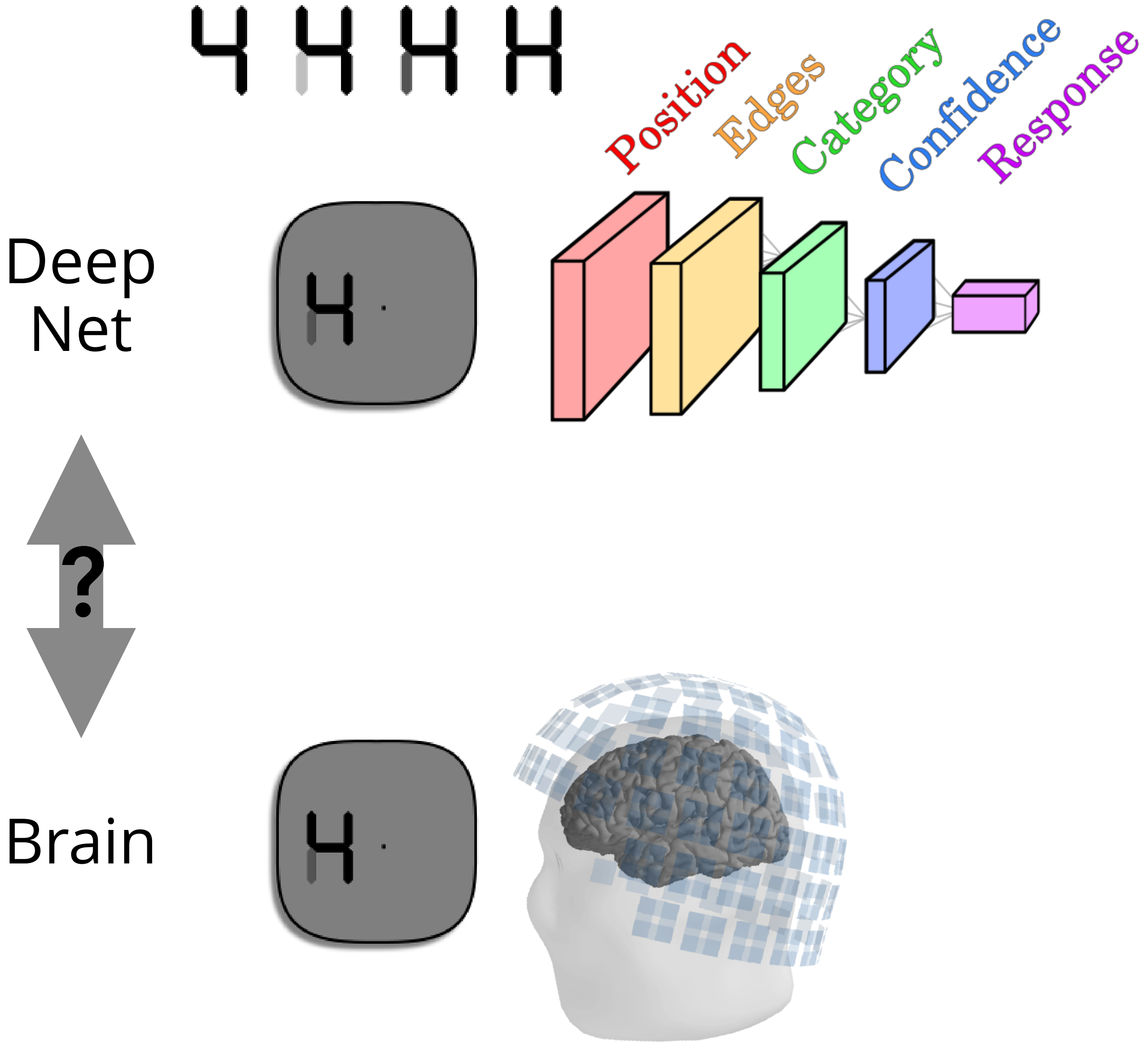

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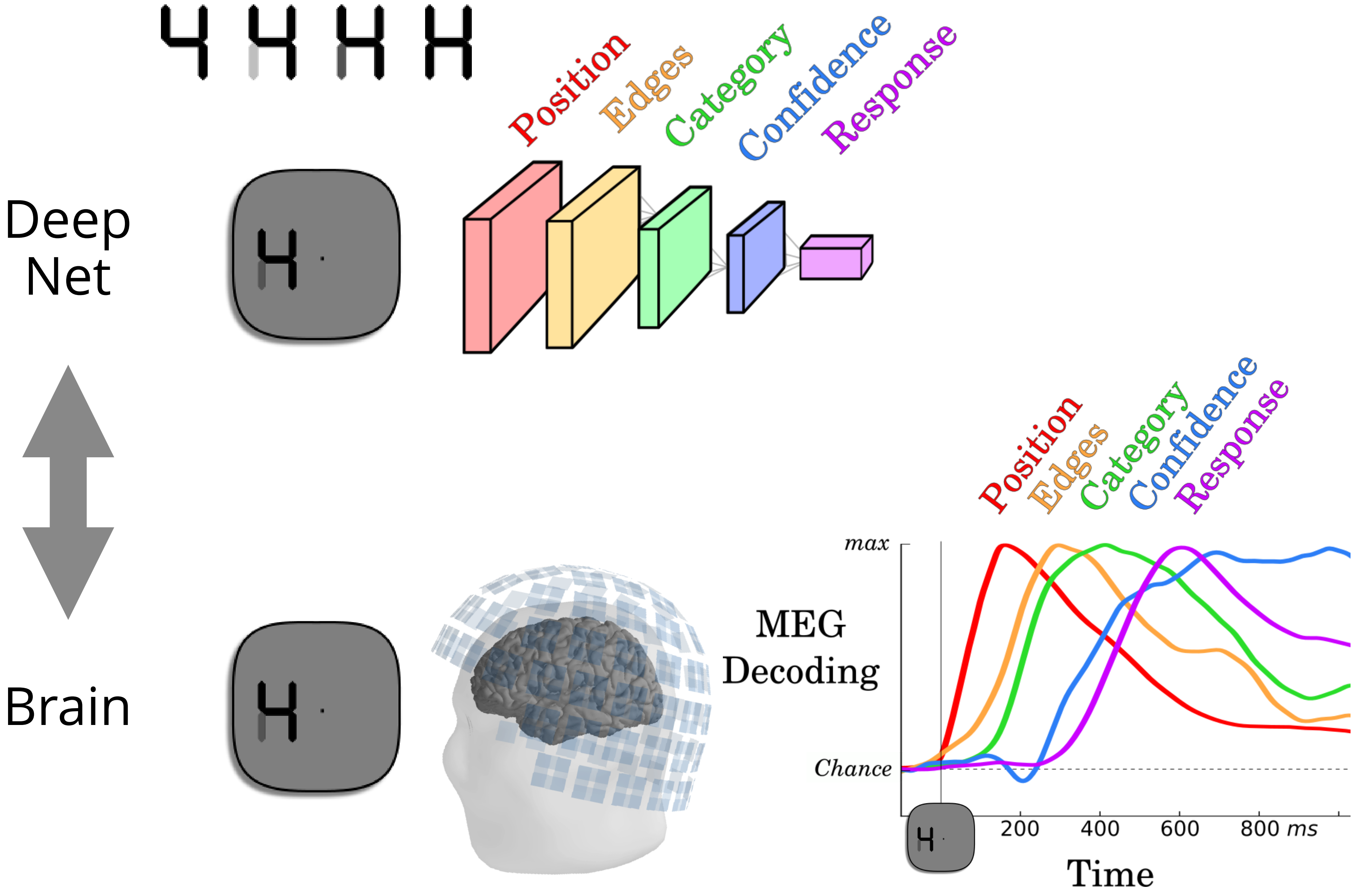
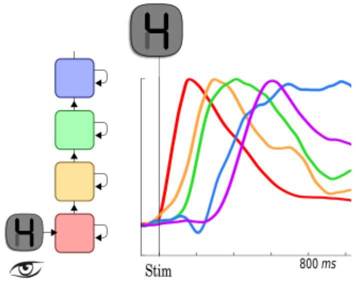
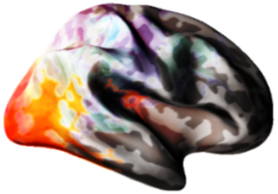


## Hierarchical Transforms



Gwilliams & **King**, 2017 *NIPS* + *submitted*

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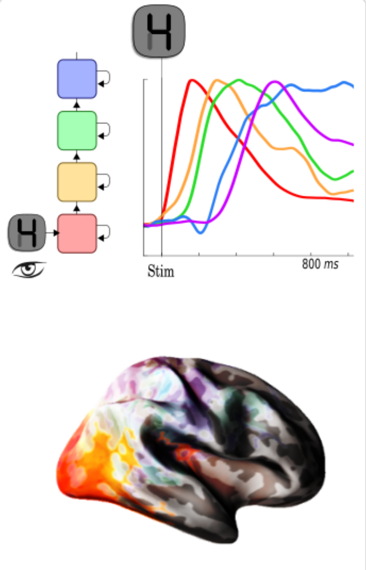
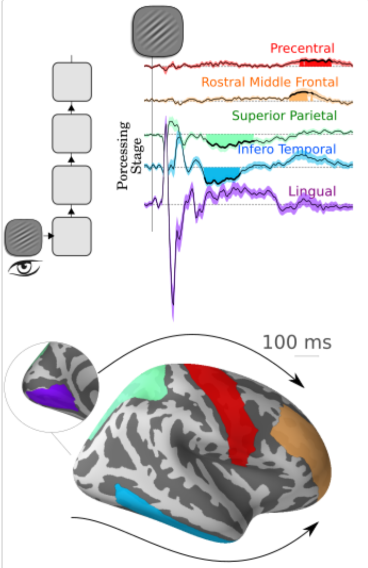


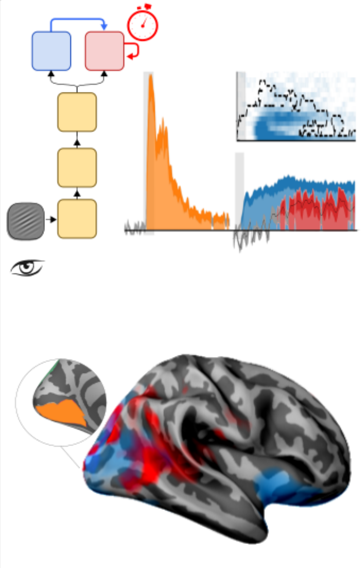

Gwilliams & **King**,
2017 *NIPS* + *submitted*

## Cascading Feature



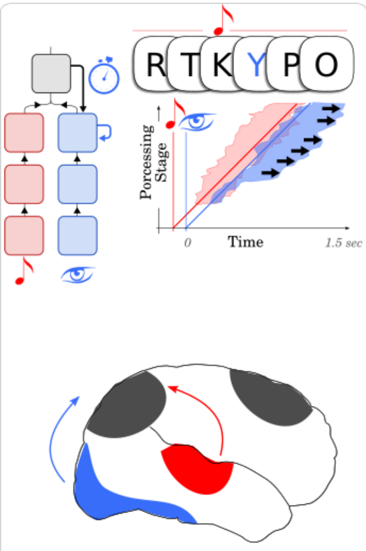

**King** et al,
*Neuron* 2016

## Update Gating



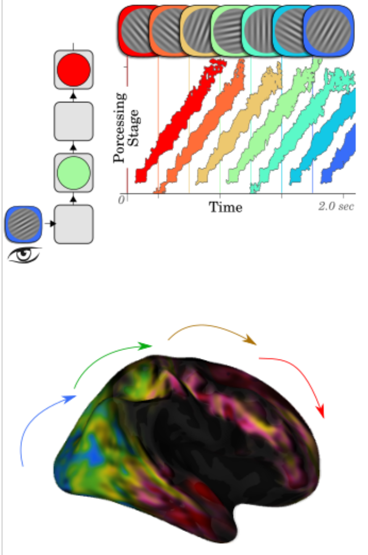
Quentin, **King** et al,
*under review at*
*Nature Neuro*

## Serial Buffering




Marti, **King** & Dehaene
*Neuron* 2015

## Parallel Cascade



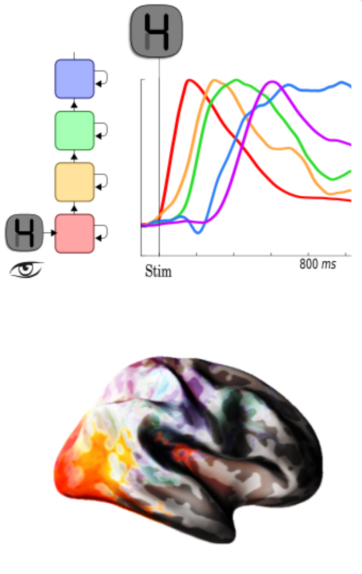

**King** & Wyart,
*CCN* 2017 + *submitted*

# Project

## 1. Identify the elementary architectures of computations

*in the brain and in artificial neural networks*

### Hierarchical Transforms

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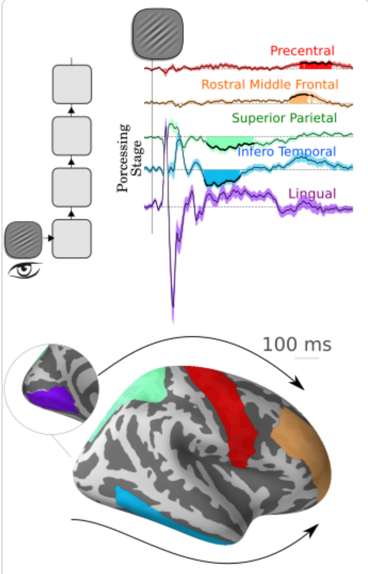


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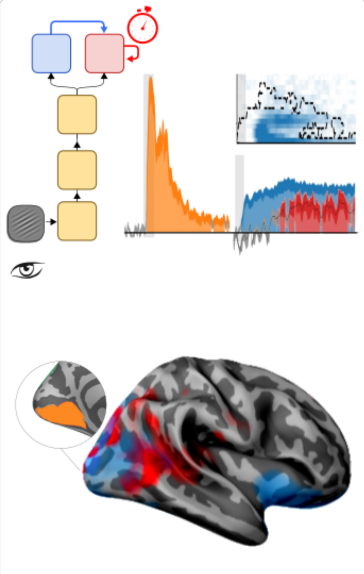

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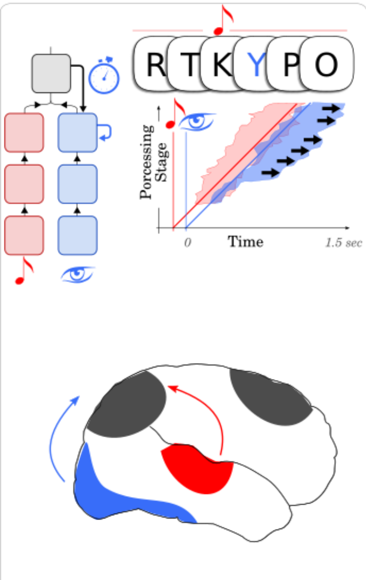


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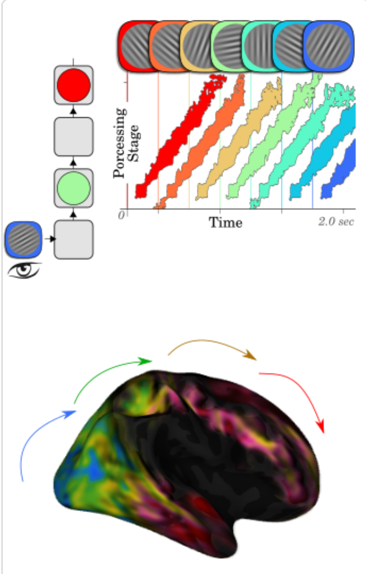


**King** & Wyart,
*CCN 2017* + *submitted*

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1. Identify the elementary architectures of computations

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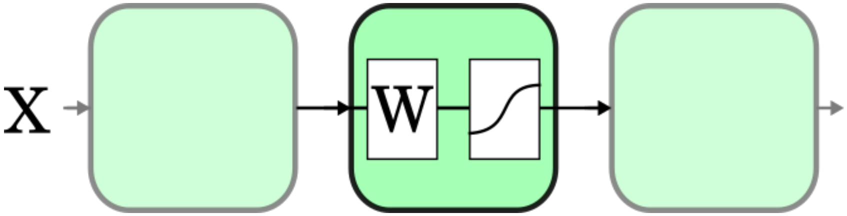
Deep Net



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1. Identify the elementary architectures of computations

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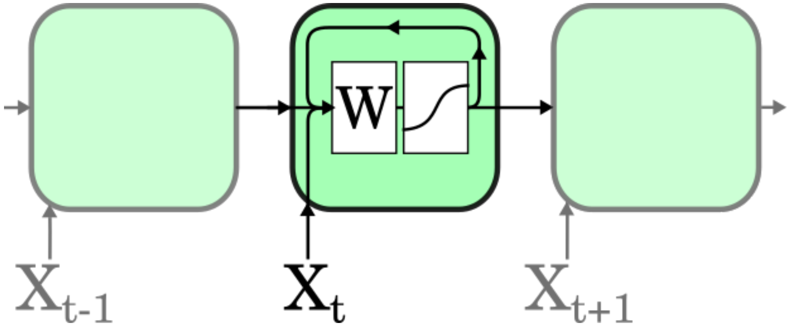
Recurrent Net



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## 1. Identify the elementary architectures of computations

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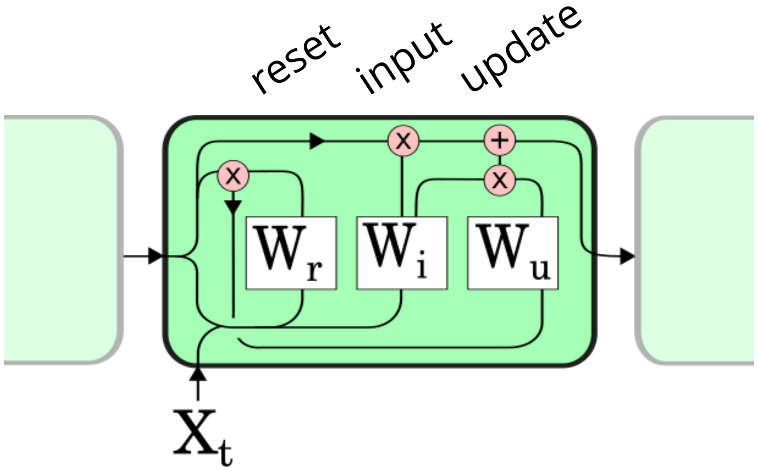
2500 citations

Gated Recurrent Unit

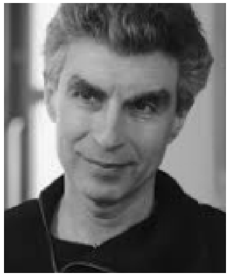
*Cho et al, 2014*




*K. Cho*

facebook AI Research NYU

*Y. Bengio*



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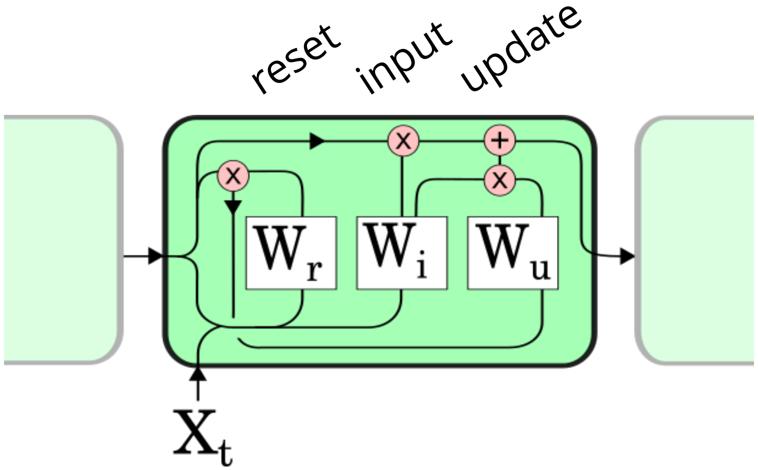


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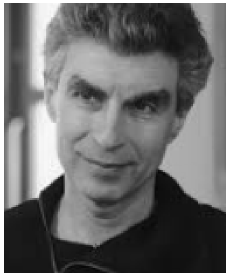

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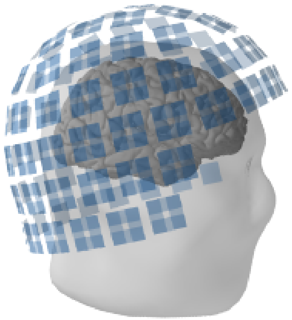

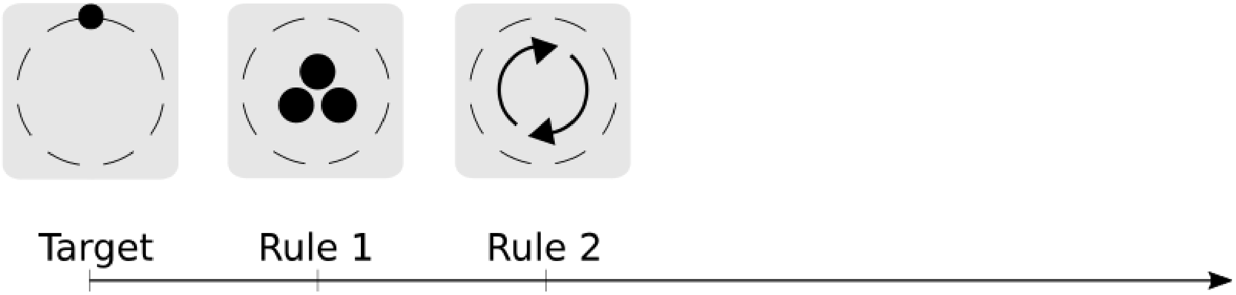

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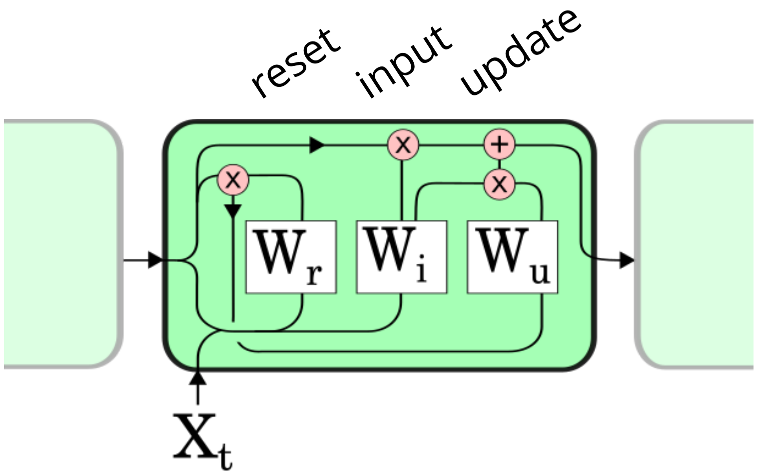


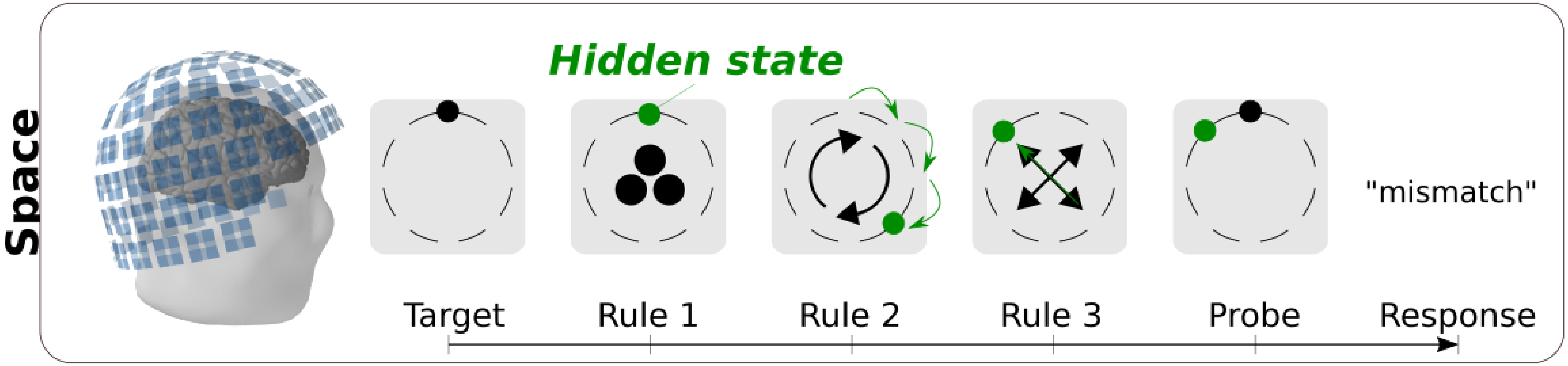

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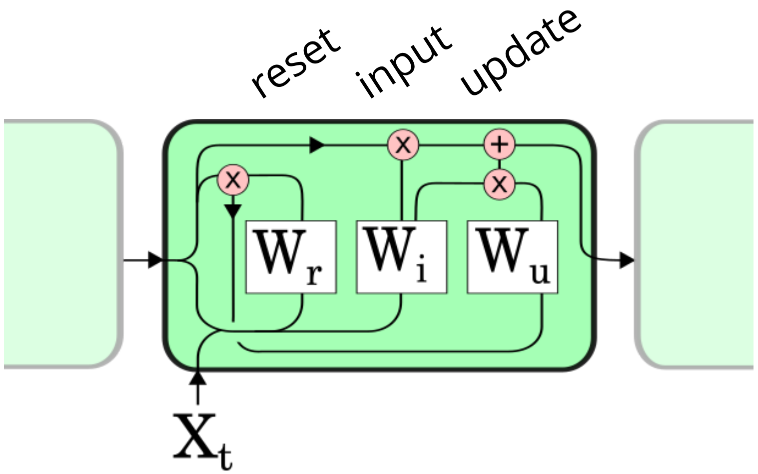


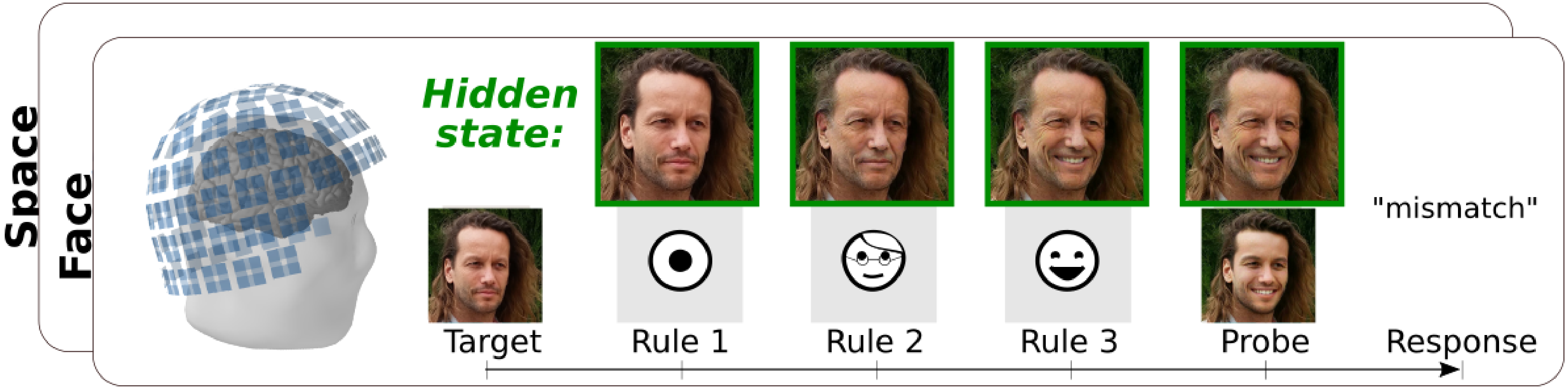

# Project

## 1. Identify the elementary architectures of computations
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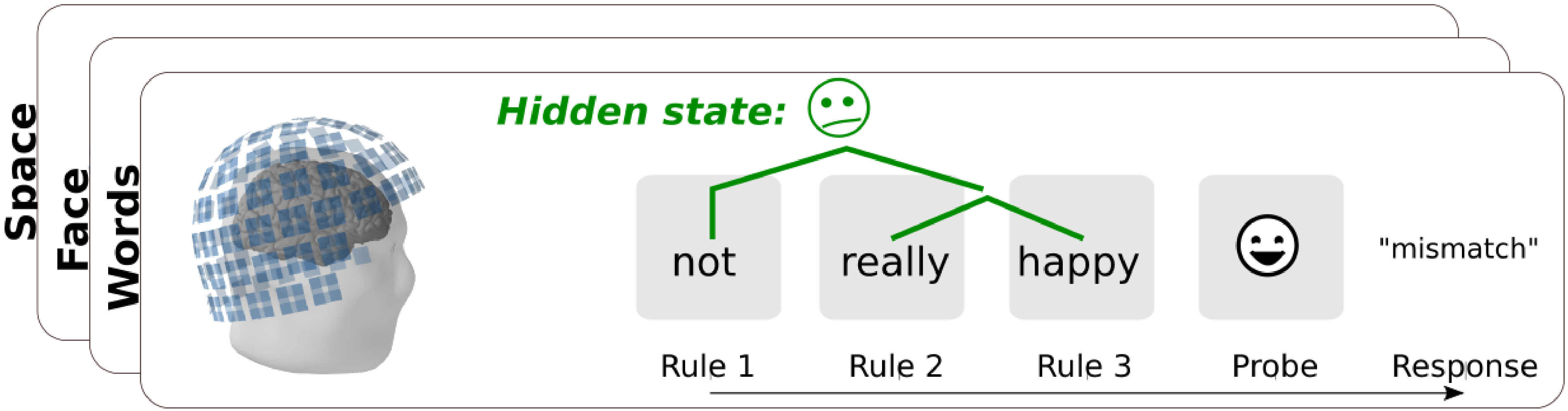
**Short term objectives:**

1.1 Can we identify the neural signatures of elementary recurrent architectures?

1.2 Are they dissociated in time, space, frequency?

1.3 Are they generic across tasks?



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1. Identify the elementary architectures of computations

2. Identify the architecture underlying the efficiency of the human brain
*at processing, acquiring, and sharing information.*

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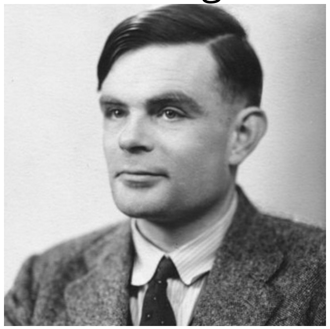
Turing



Chomsky

Recursive architecture

Hypothesis

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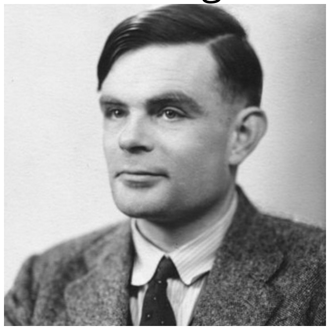

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I told Marie that I thought she'd call me

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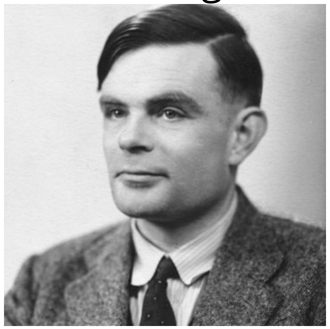
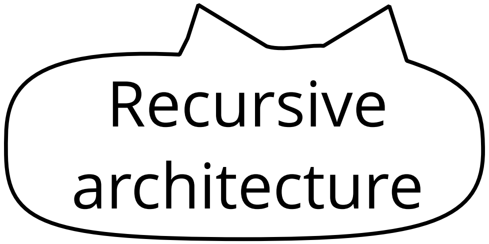


Chomsky

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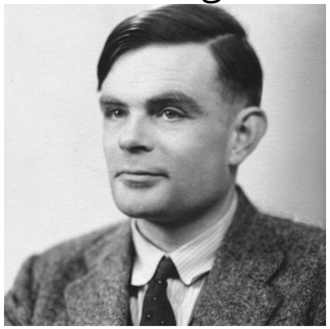

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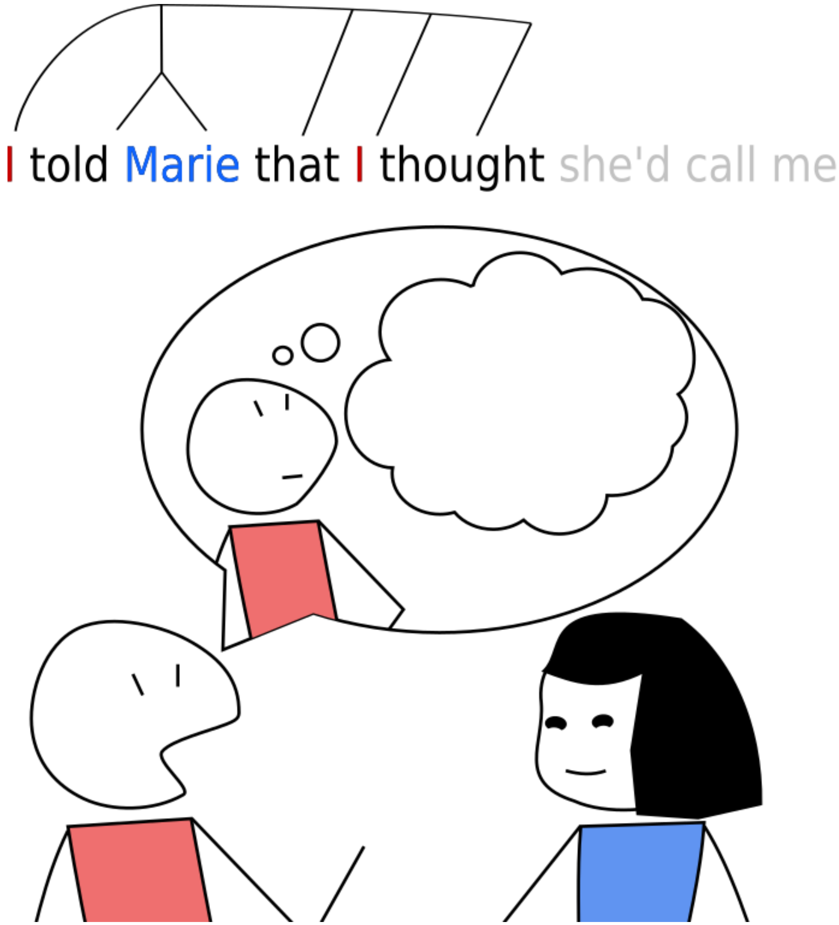

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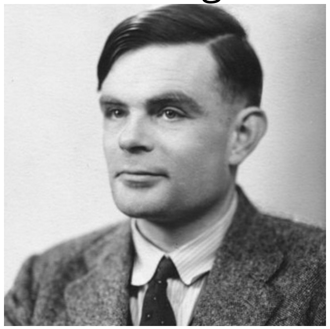

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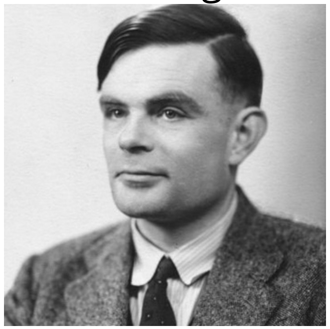
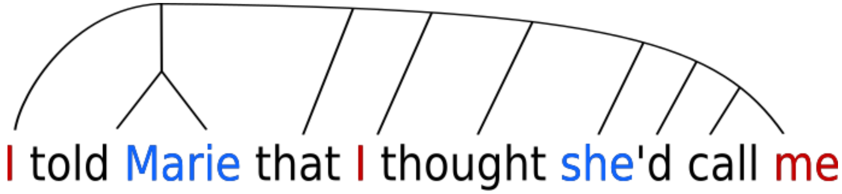
Turing

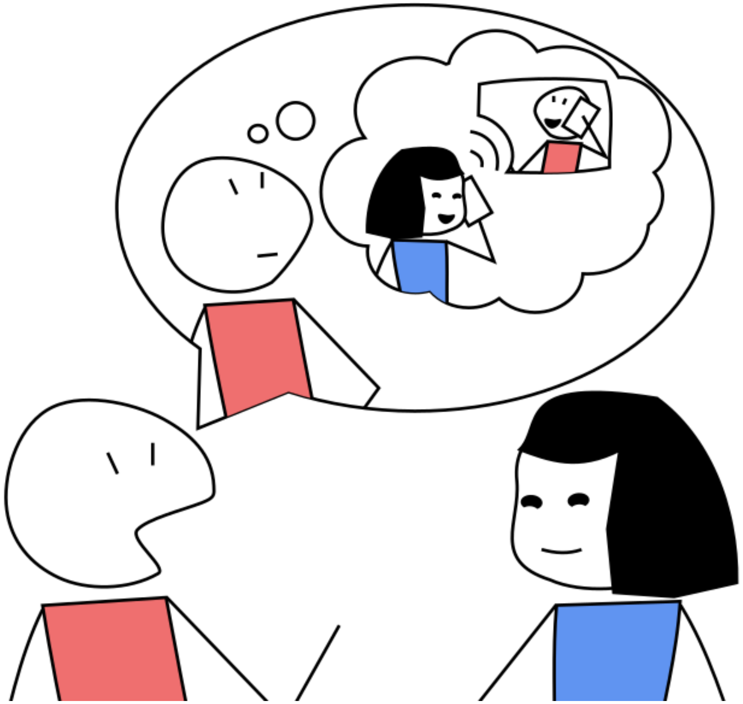


Chomsky

Recursive architecture

Hypothesis



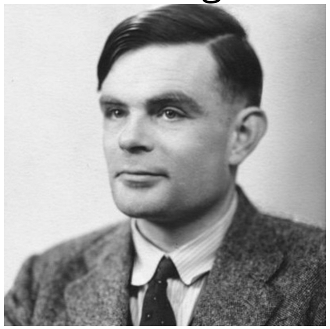



# Project

1. Identify the elementary architectures of computations

2. Identify the architecture underlying the efficiency of the human brain
*at processing, acquiring, and sharing information.*

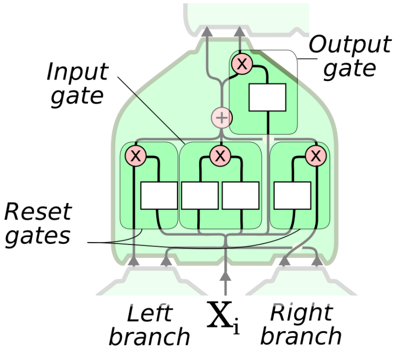
Turing



Chomsky

Recursive architecture

## Hypothesis




Recursive Network

NYU

Bowman

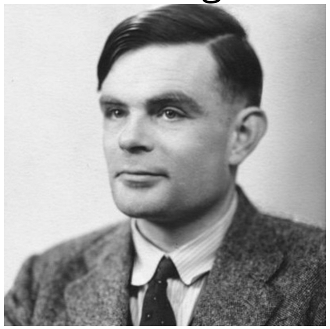
## Computational Framework

# Project

1. Identify the elementary architectures of computations

2. Identify the architecture underlying the efficiency of the human brain
*at processing, acquiring, and sharing information.*

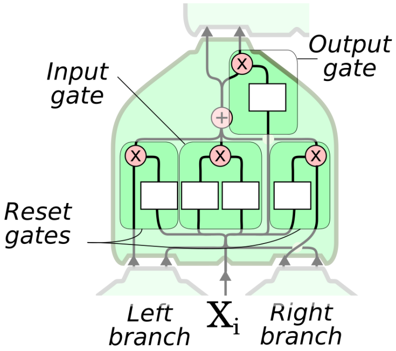
Turing



Chomsky

Recursive architecture

## Hypothesis

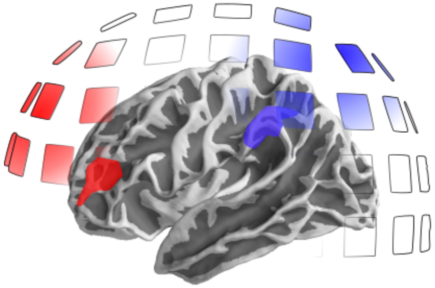



Recursive Network

NYU

Bowman

## Computational Framework



## Experimental Test!

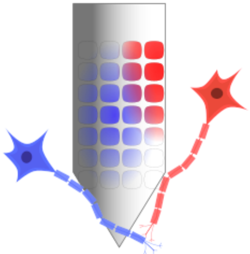
C. Bénar

D. Schön

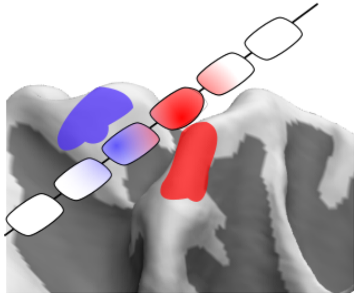
V. Jirsa

## Multi-scale neuroimaging

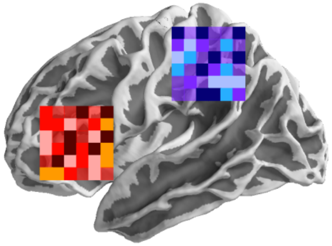
Single Cell



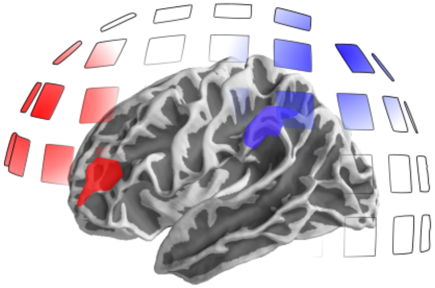
Depth EEG



fMRI



M/EEG



# Exceptional lab

# Inter-disciplinary language research

BLRI
Brain & Language Research Institute
LabEx, Projet Convergence

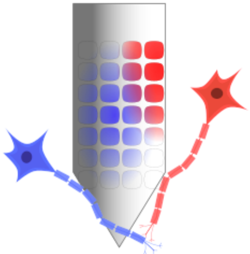
C. Bénar

D. Schön

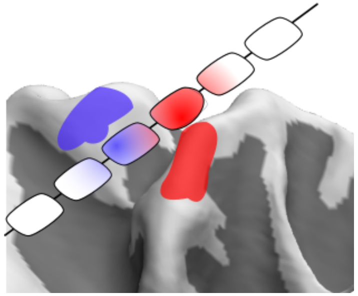
V. Jirsa

# Multi-scale neuroimaging

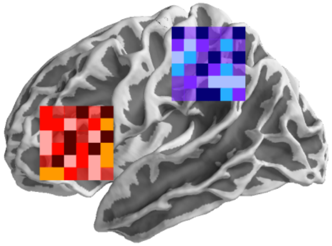
Single Cell



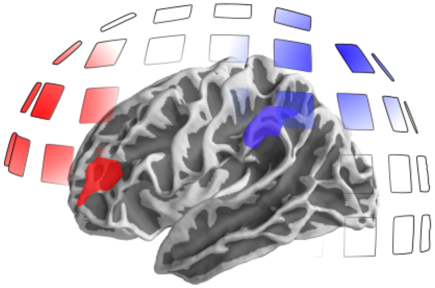
Depth EEG



fMRI



M/EEG

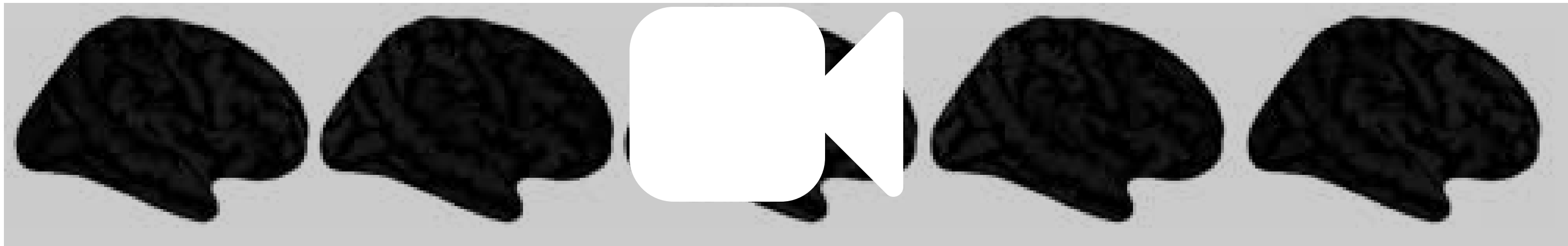


# Exceptional lab

# Elementary Computational Architectures in Brains & Machines

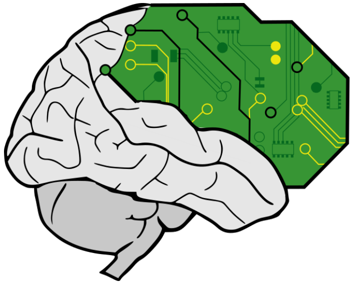
## 1. Method

*Machine Learning to decode brain activity*



## 2. Theory

*Machine Learning as a framework for cortical computations*



# Supervision

Larzabal

Kasdan

Debruin

Phang

Phang & King *submitted*

Pescetelli

King et al, *Neuron* 16

Meade

Meade et al & King, *in prep*

Gwilliams

Gwilliams & King *NIPS* 17

# Metrics

- Papers: 32
- First/last author: 13
- Patent: 1
- Citations: 979
- H-index: 15
- Invited plenary talks: 3

# Main collaborators

Wyart

Inserm

Melloni

Dehaene

Inserm

Poeppel

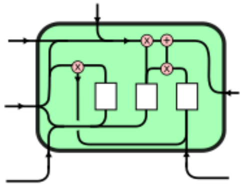
NYU

Jirsa

Gramfort

Dynamical Systems

Neuroscience



Cognitive Science

Machine Learning

Natural Language Processing

Schön

Berwick

NYU facebook

Cho

NYU

Bowman

Inserm

Bénar

Max Planck FIAS NYU Inserm BLRI Aix*Marseille université

# Funding

DGA — Ph.D. Scholarship

Marie Skłodowska-Curie Actions — Marie Curie Global Fellowship

IN·DEI·NOMINE·FELICITER — Excellence Initiative Fellowship

? ATIP Avenir 2018 **Final round...**

# Awards

ASSC William James Prize 2017

Biomag Young Investigator Award

CNS Postdoct. Award

Bettencourt-Schueller Young Researcher Award

# Community

Reviewer: PNAS, nature COMMUNICATIONS, Science AAAS, erc

Mentor: Google Summer of Code 2018 2017 2016 2015

Open Source Developer: ipyvolume, scikit learn, pyRiemann, MNE

Challenger: Microsoft

**Objective:** $max\ P(y|X) \propto P(X|y)\ P(X)$

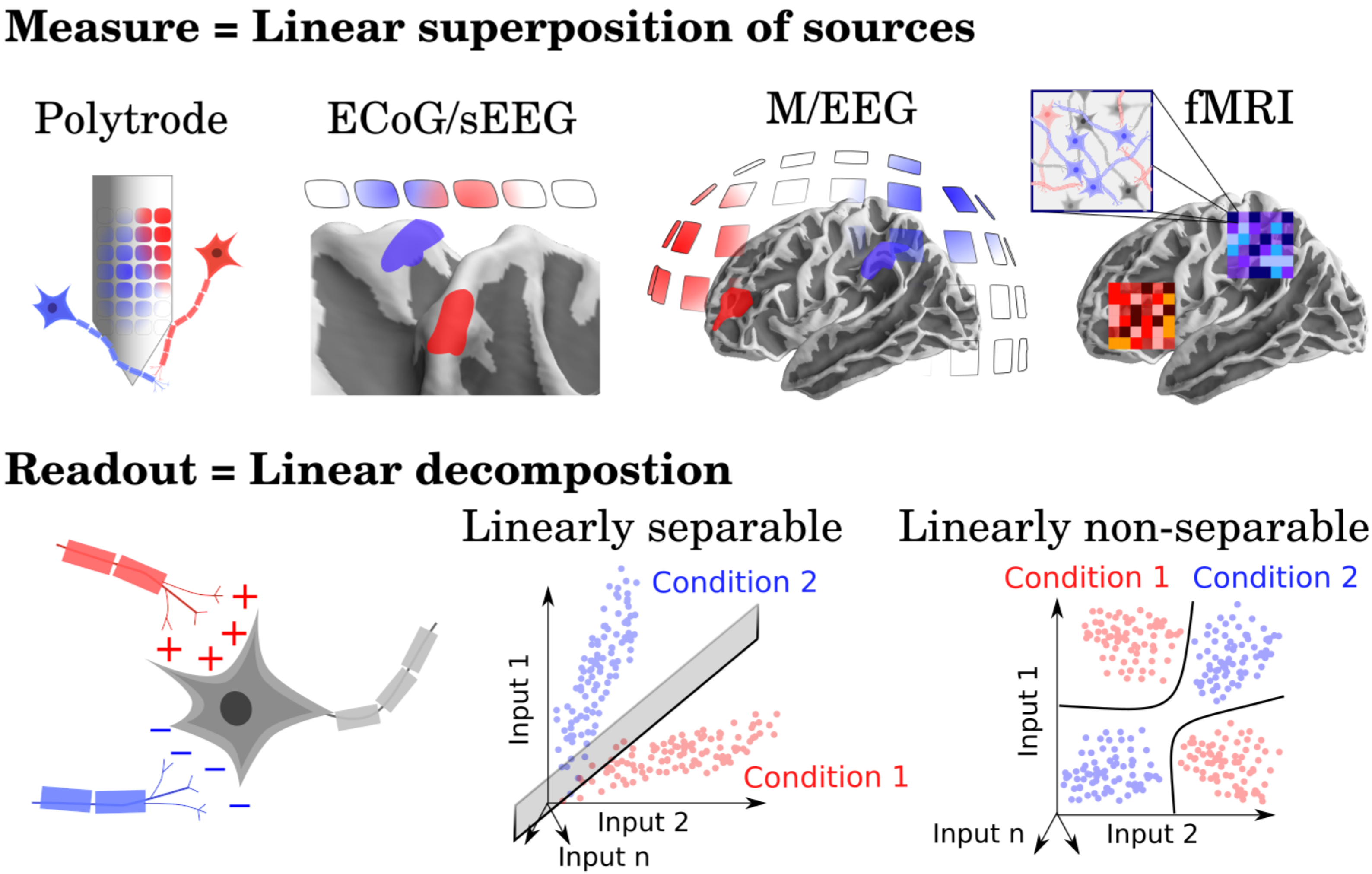
**Method:**

$argmin\ Loss(y, \hat{y}=f(X)) + Regularization(f)$

| | | |
|---|---|---|
| $l_2$: $\|y\text{-}\hat{y}\|^2$ | Linear: $\hat{y}=wX$ | $l_0$: $0$ |
| log: $log(1+e^{-y\hat{y}})$ | Shallow: $\hat{y}=k(wX)$ | $l_1$: $\|w\|$ |
| hinge: $max(0, 1\text{-}y\hat{y})$ | Deep: $\hat{y}=k_n(\ldots(k_1(wX))$ | $l_2$: $\|w\|^2$ |

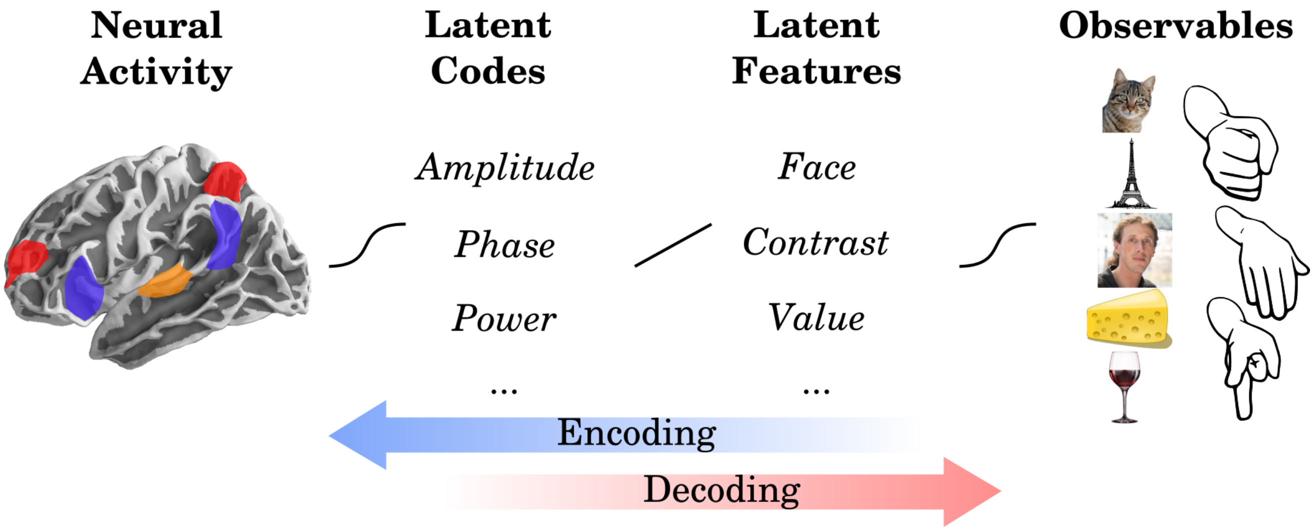
**Examples of linear models:**

| | | | |
|---|---|---|---|
| GNB: | l2 | $w=Xy$ | None |
| LDA: | l2 | $w=(X'X)^{-1}\ Xy$ | None |
| Ridge: | l2 | $w=(X'X+\lambda I)^{-1}\ Xy$ | l2 |
| Logistic: | log | $argmin(log(1+exp(-ywX))$ | l1 and/or l2 |
| SVM: | hinge | $armgin(max(0, 1\text{-}y(wx))$ | l1 and/or l2 |

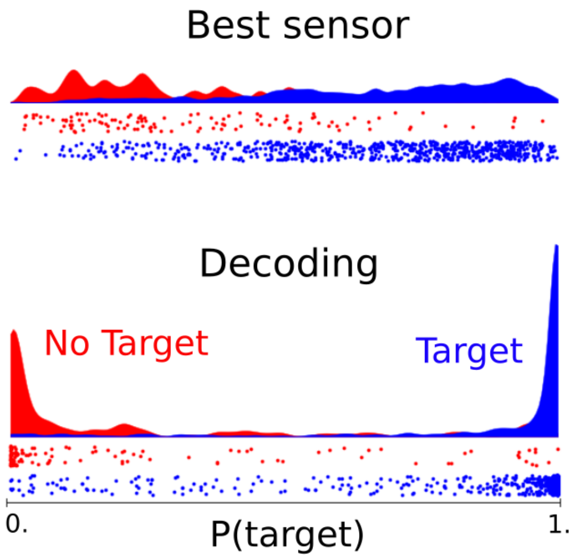


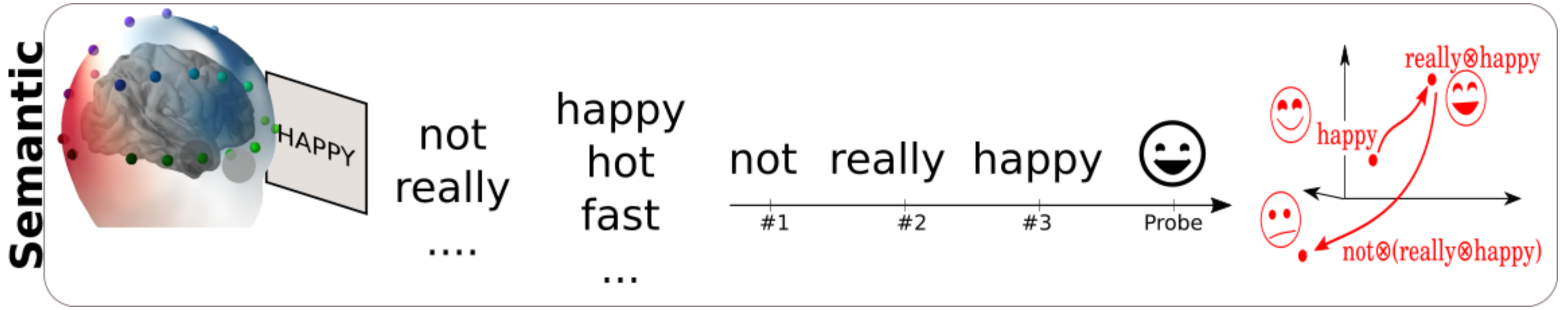
Measure = Linear superposition of sources
Polytrode
ECoG/sEEG
M/EEG
fMRI
Readout = Linear decompostion
Linearly separable
Linearly non-separable
Condition 2
Input 1
Condition 1
Input 2
Input n
Condition 1
Condition 2
Input 1
Input n
Input 2

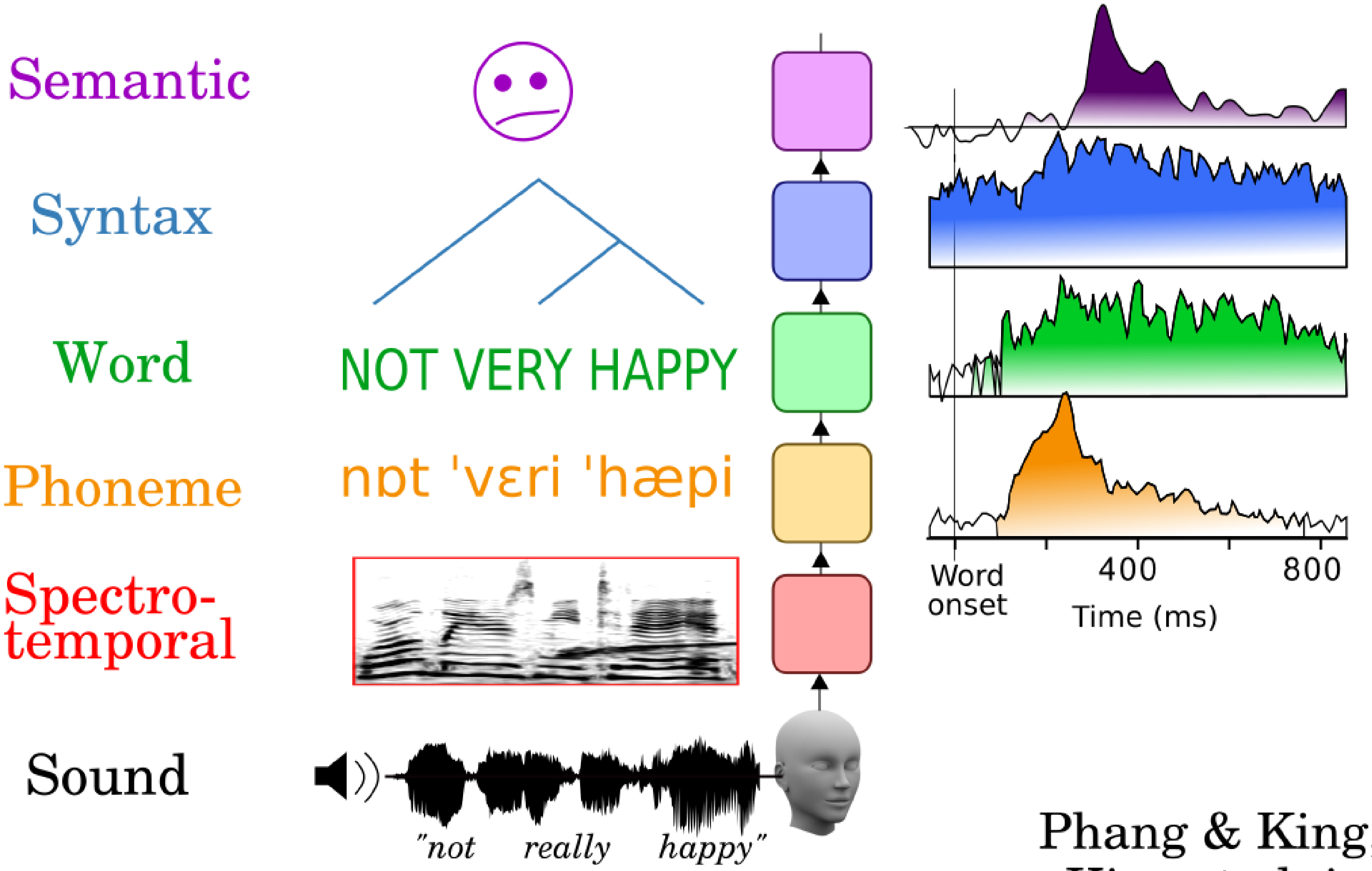
King et al, *The Mental Algorithmics Program*, accepted




King et al, *Neuron* 2016



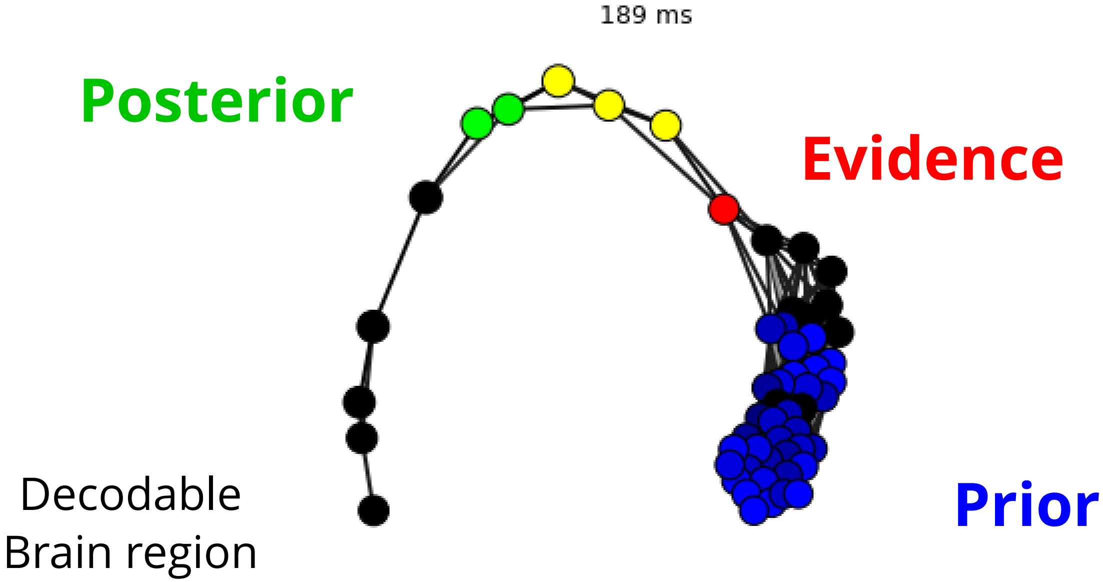



Phang & King, *submitted*
King et al, *in progress*

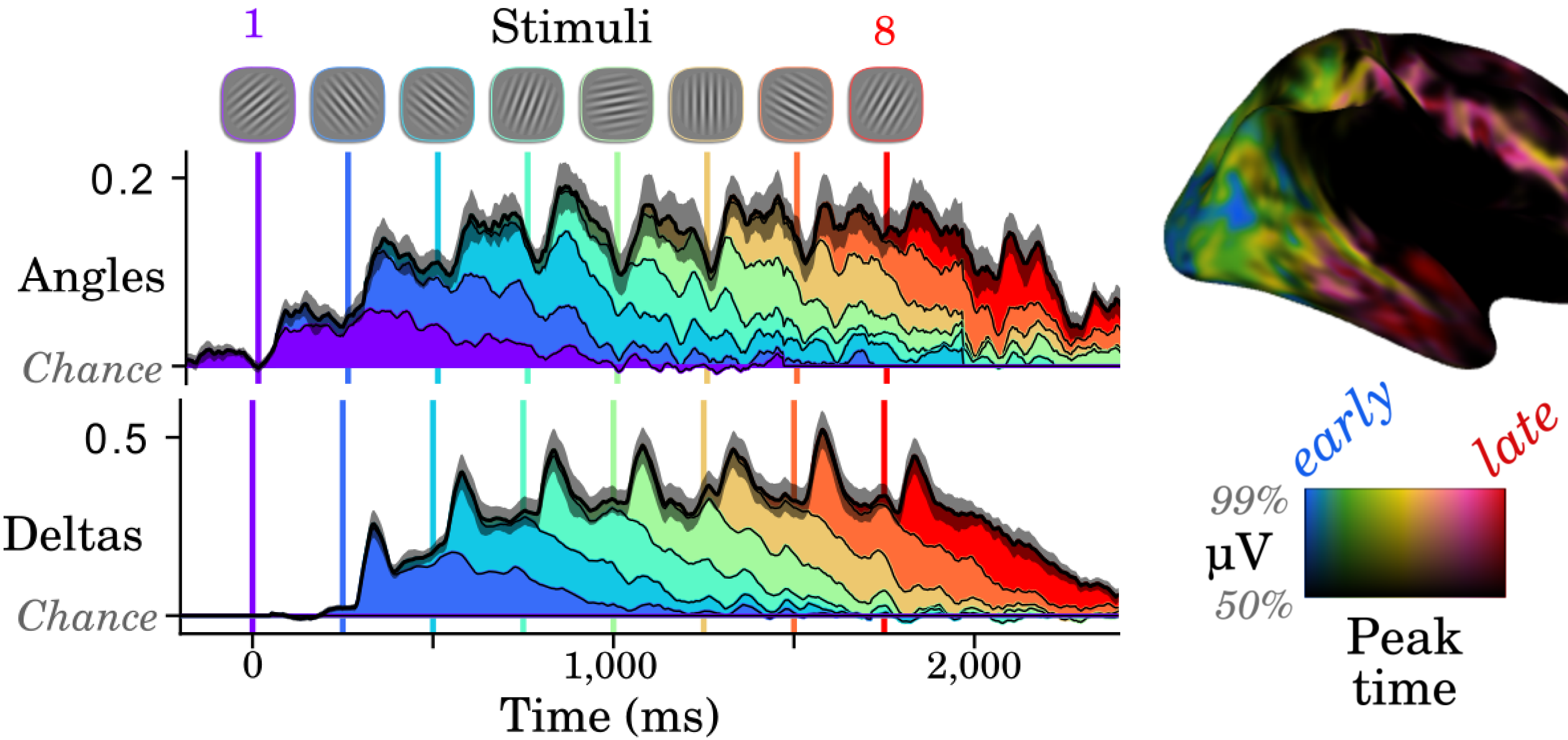
**Visibility** $\propto$ **Stimulus** x **Expectations**

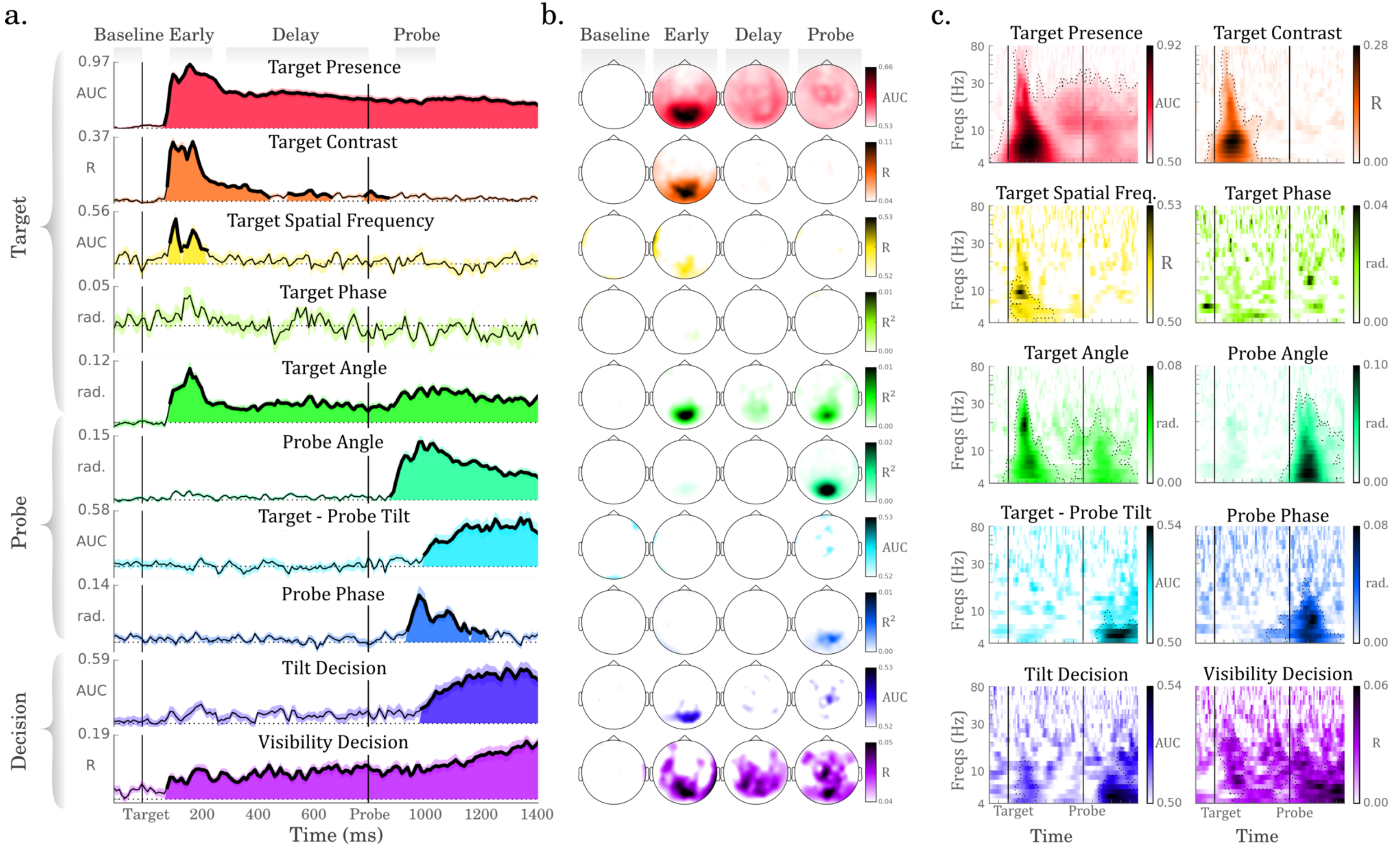
$$P(H|E) \propto P(E|H) \times P(H)$$




Meade et al & King, *in prep*

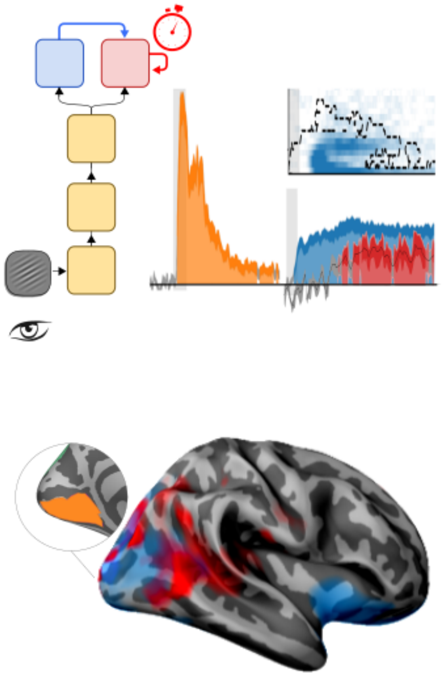
King & Wyart, *submitted*



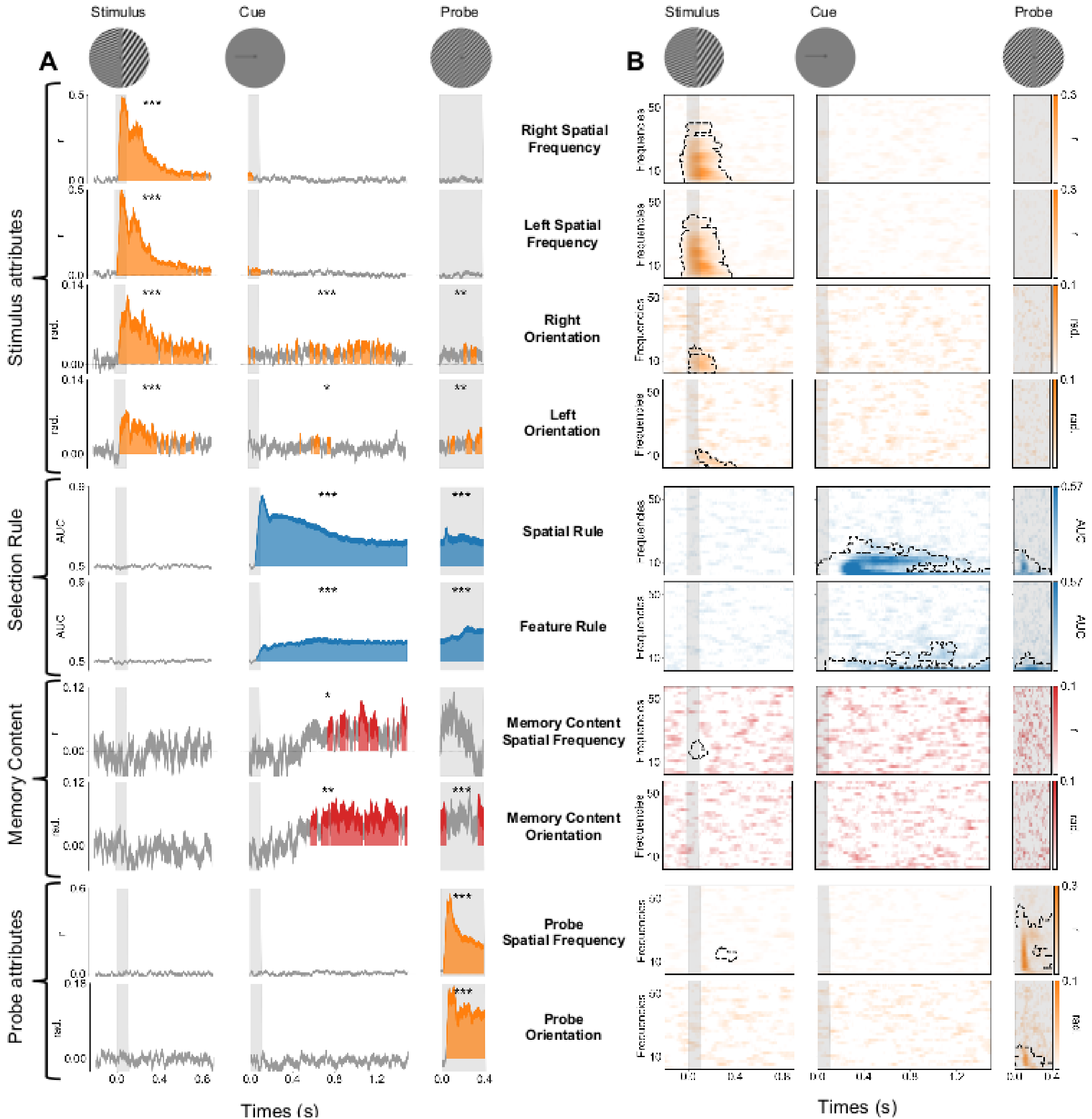


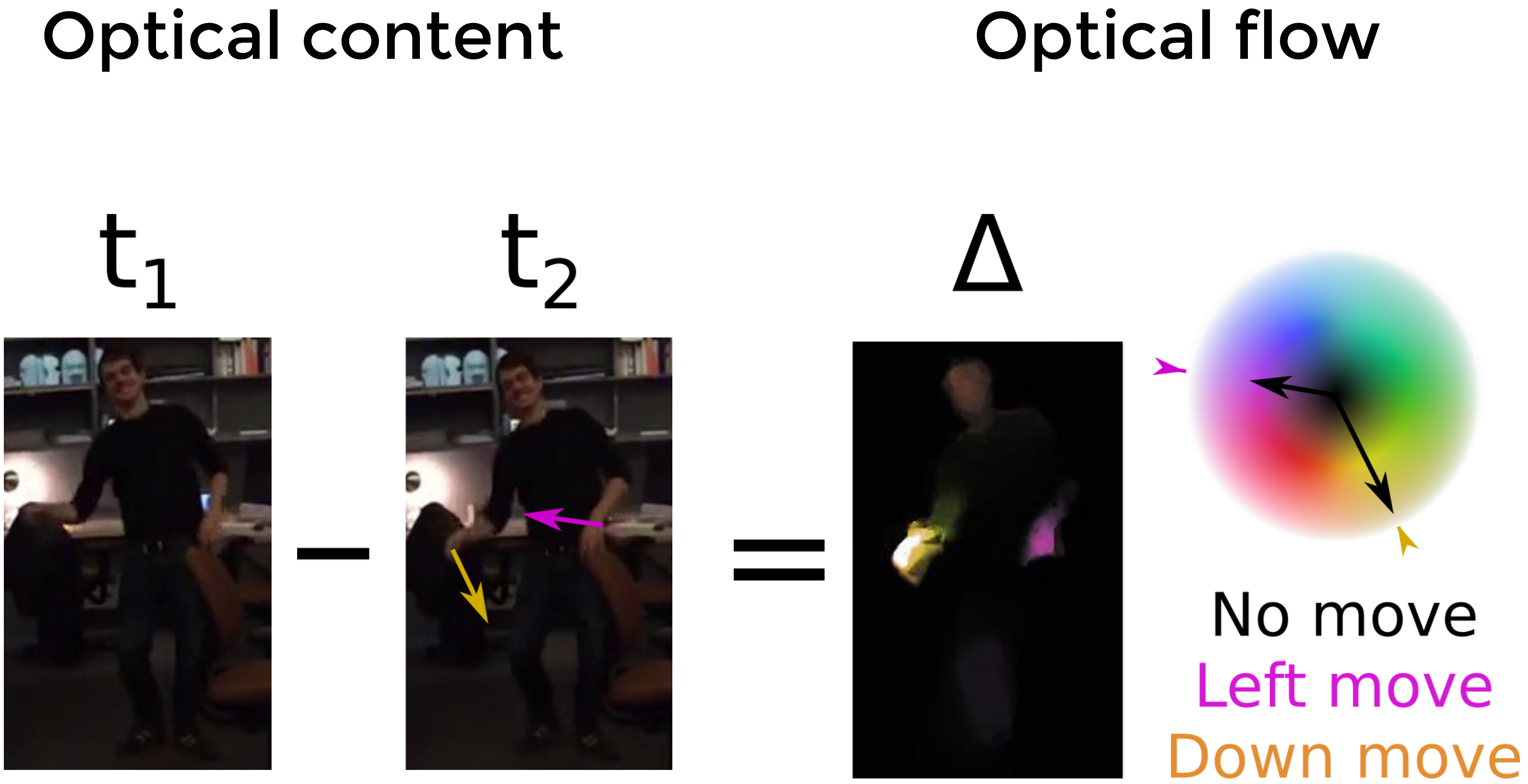

King et al, *Neuron* 2016

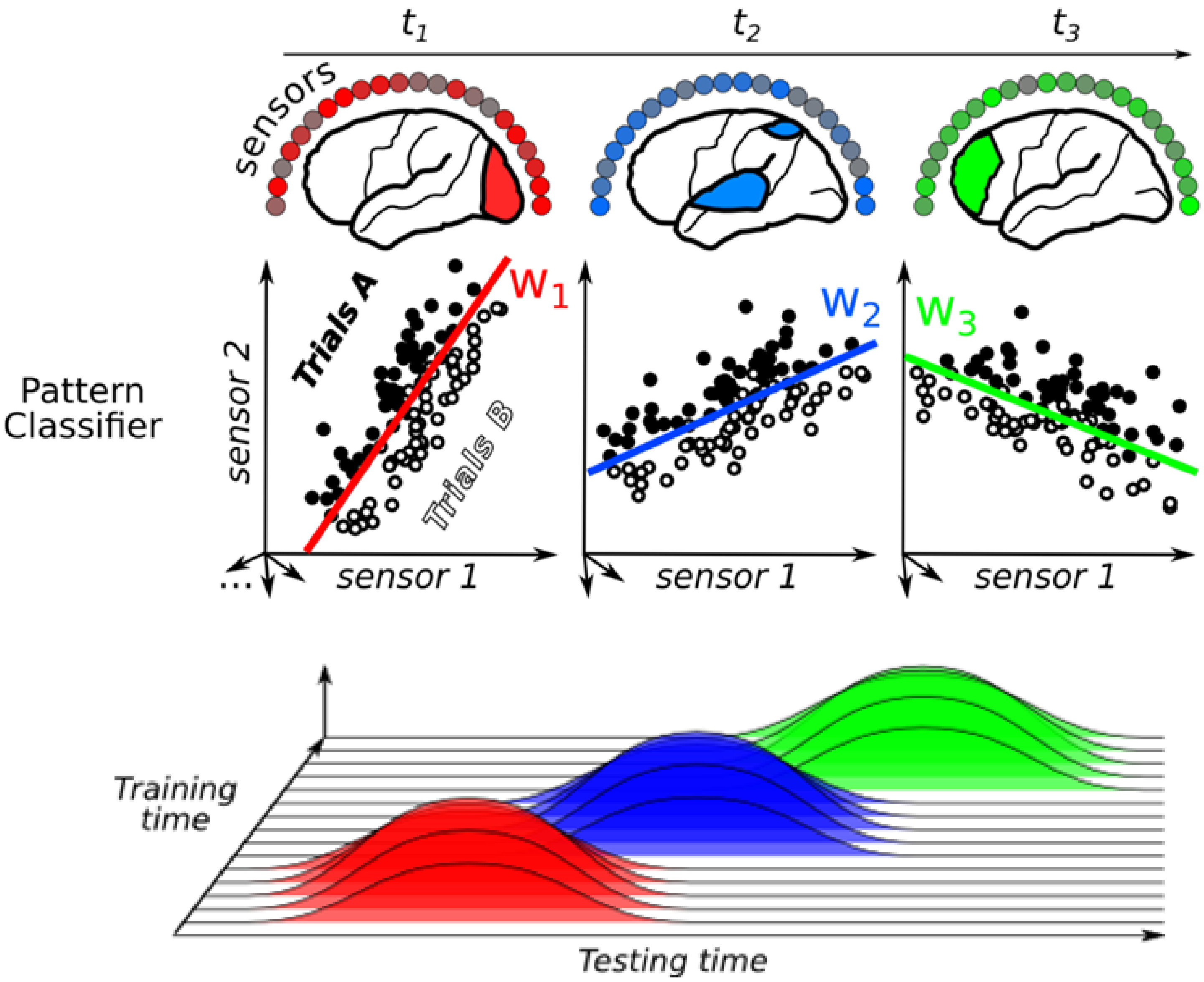
Update Gating



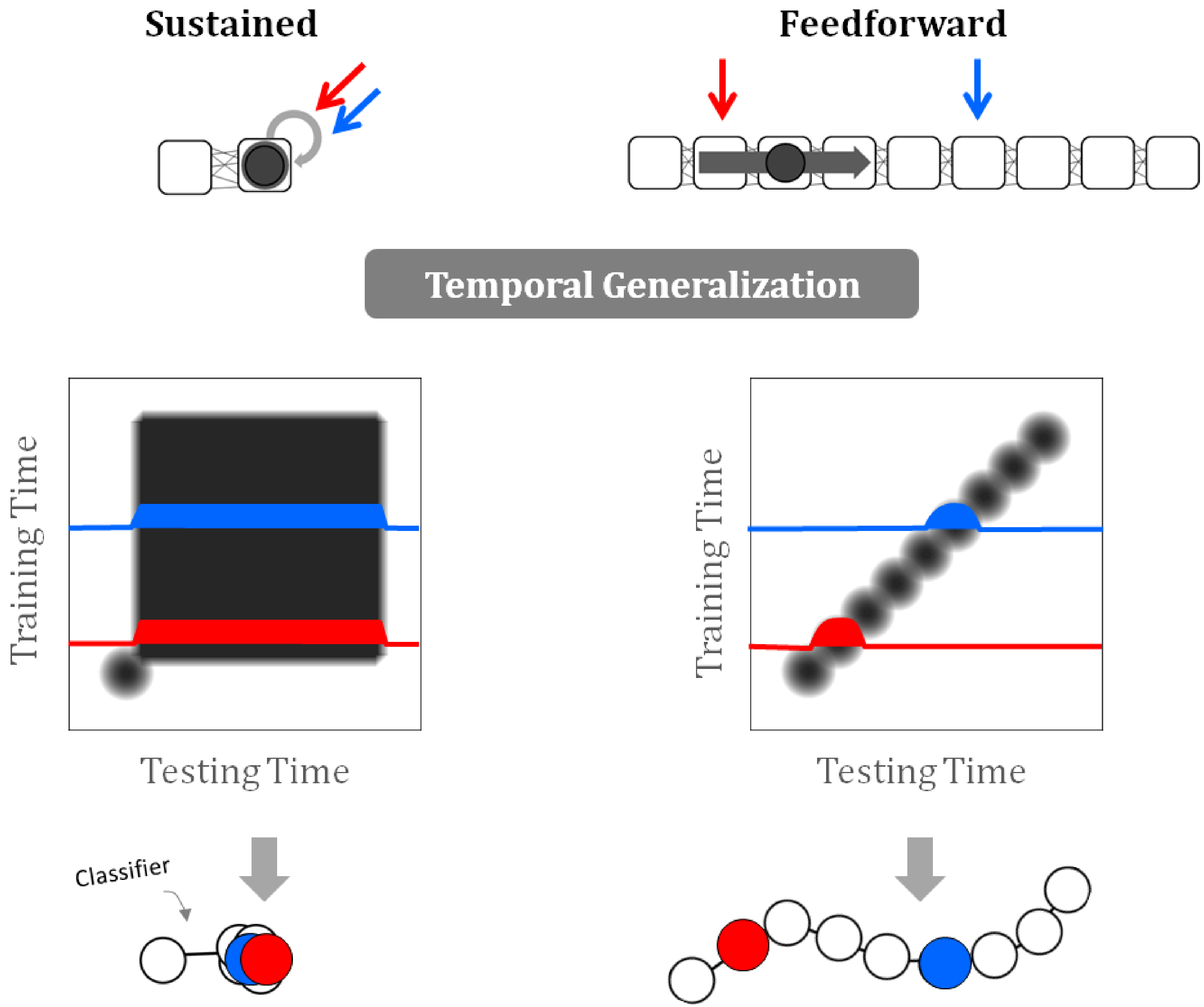
Quentin, **King** et al, *under review at Nature Neuro*




Optical content
Optical flow
$t_1$
$t_2$
$\Delta$
No move
Left move
Down move




King & Dehaene, *TICS* 2014


Sustained
Feedforward
Temporal Generalization
Training Time
Testing Time
Training Time
Testing Time
Classifier