

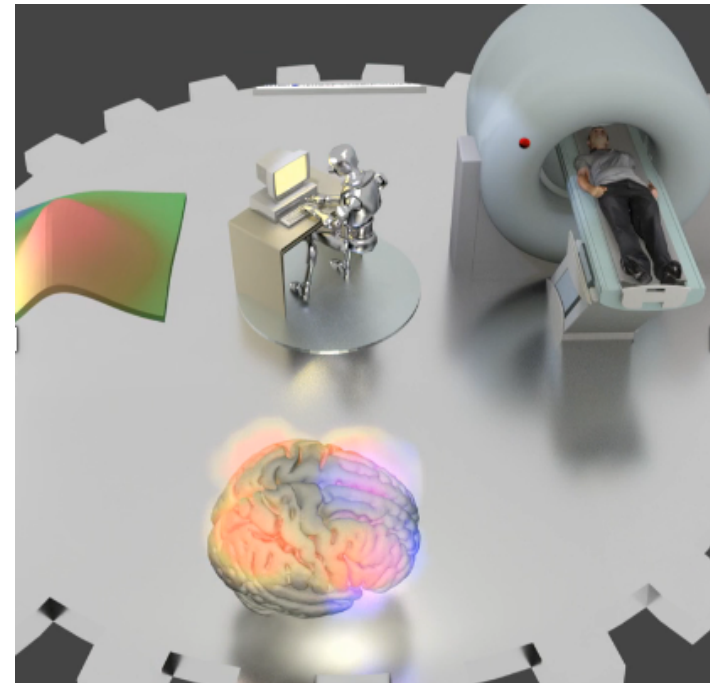
Neuroadaptive Bayesian Optimization

Implications for the Cognitive Sciences

Romy Lorenz

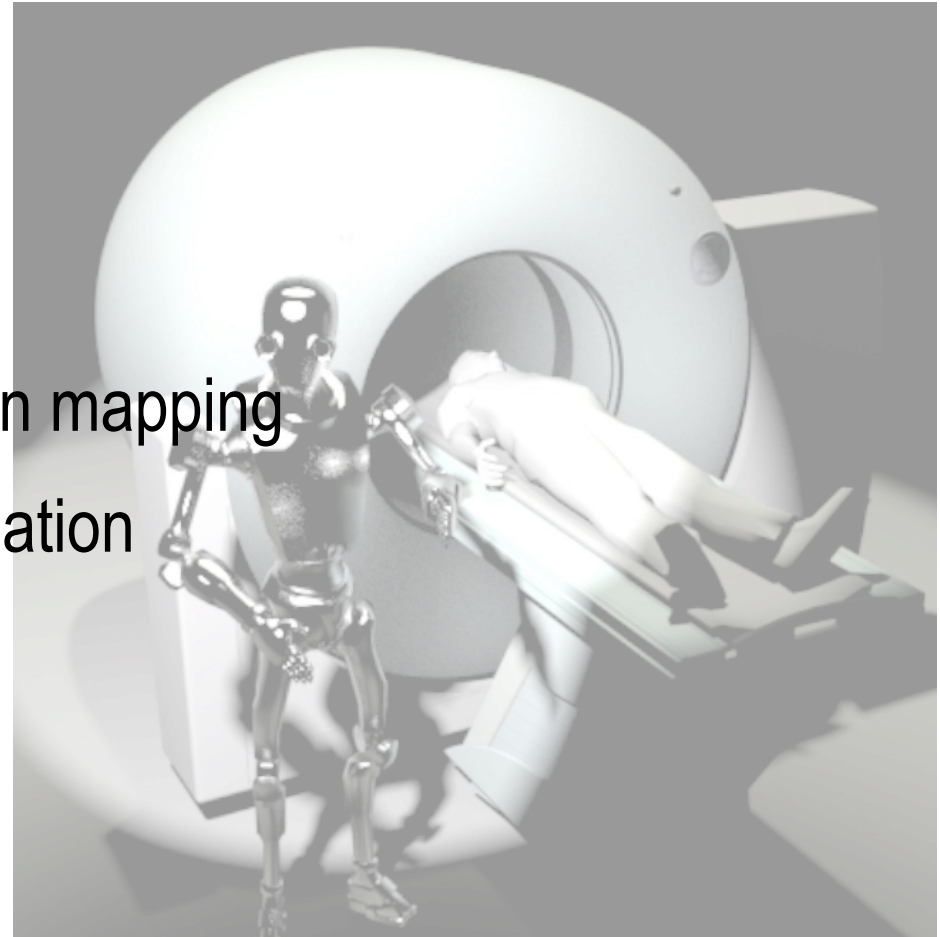
Postdoctoral Research Fellow

Cognitive, Clinical and Computational Neuroimaging Lab
Imperial College London



Overview

1. Motivation
2. The framework
3. Validation study
4. Application 1: Human brain mapping
5. Application 2: Brain stimulation
6. Ongoing work
7. Implications & Discussion



Overview

1. Motivation

2. The framework

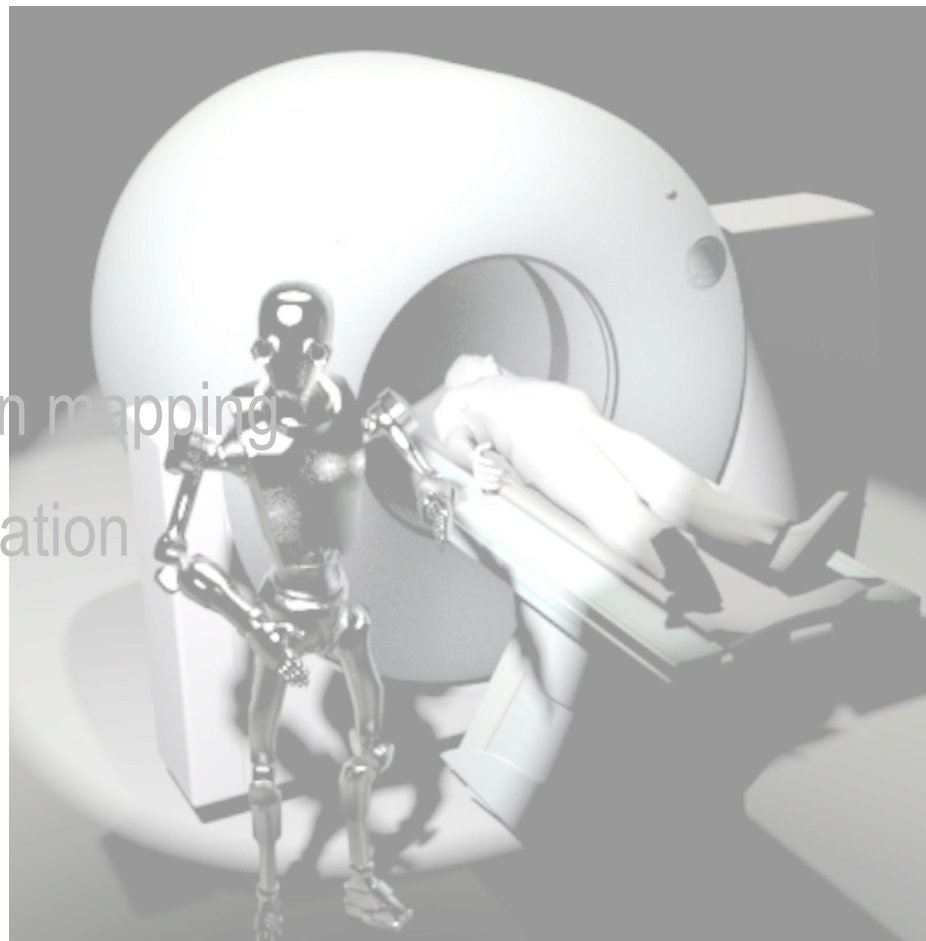
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4. Application 1: Human brain mapping

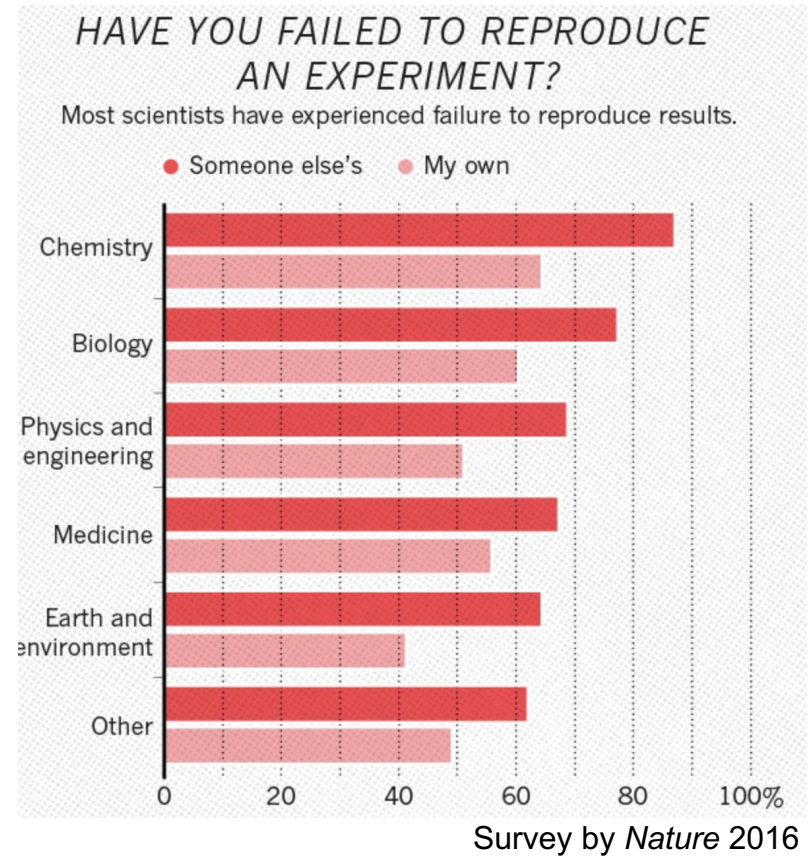
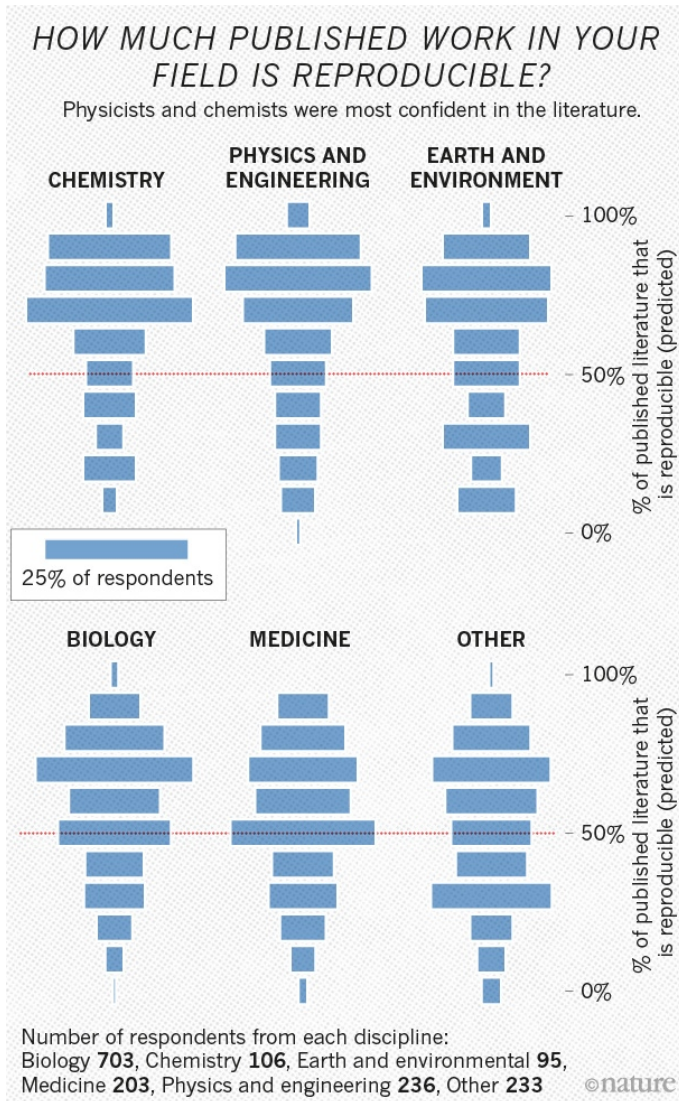
5. Application 2: Brain stimulation

6. Ongoing work

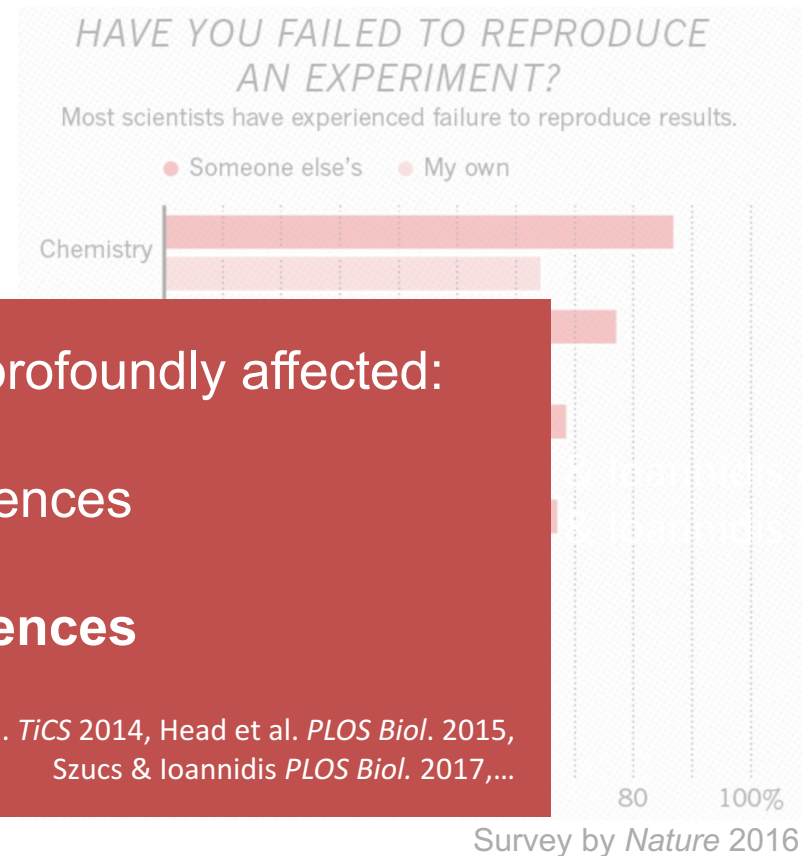
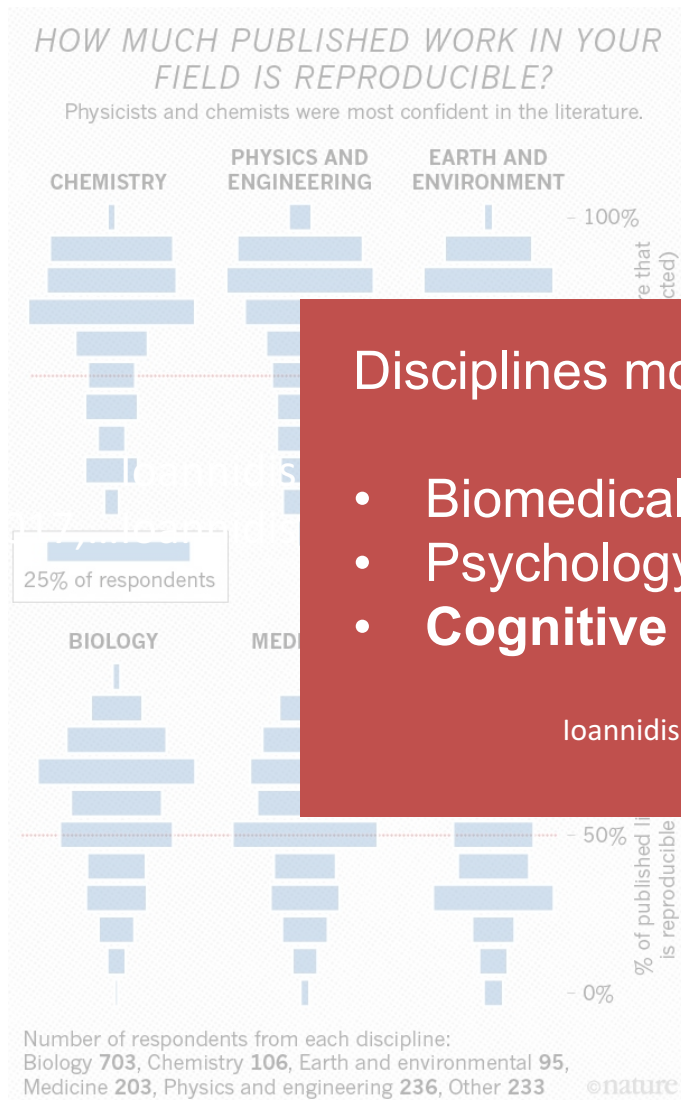
7. Implications & Discussion



Reproducibility crisis



Reproducibility crisis



Disciplines most profoundly affected:

- Biomedical sciences
- Psychology
- **Cognitive Sciences**

Ioannidis et al. *TiCS* 2014, Head et al. *PLOS Biol.* 2015,
Szucs & Ioannidis *PLOS Biol.* 2017,...

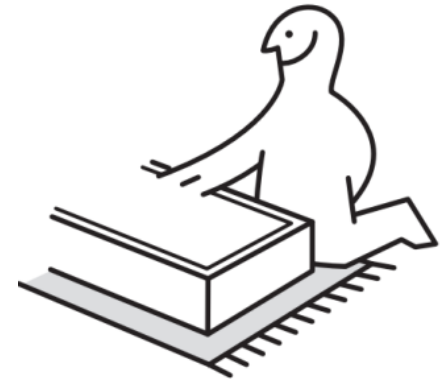
Reproducibility crisis in Cognitive Sciences

- Cognitive biases
 - IKEA-effect
 - Texas sharp-shooter effect
- Bad research practices
 - P-hacking
 - HARKing
 - File-drawer effect
- Limitations of methodology
 - Underpowered studies
 - “Narrow” experimental designs



Reproducibility crisis in Cognitive Sciences

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 - **“Narrow” experimental designs**



Aims of cognitive neuroscience

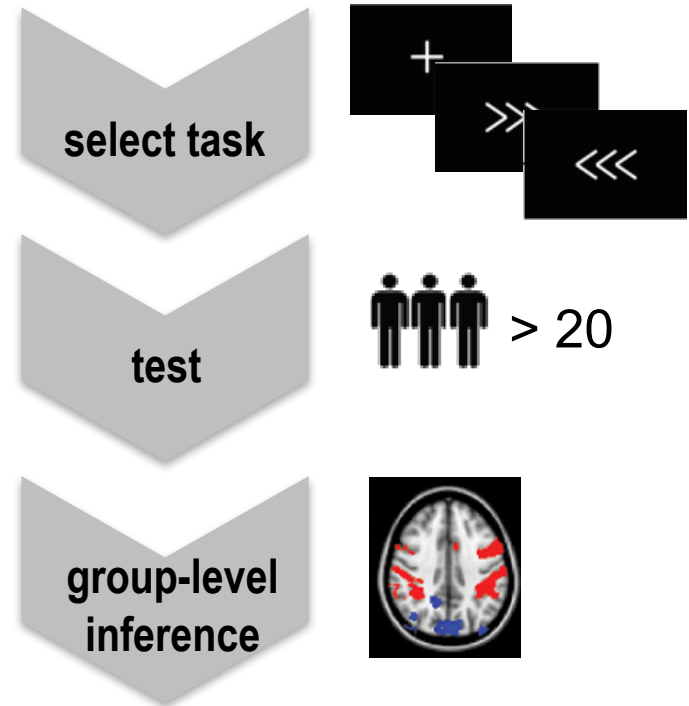
Research questions

What are the fundamental aspects of cognition?

What are the fundamental roles of distinct networks in the brain?

How can cognitive processes be modulated or enhanced?

Standard approach



Aims of cognitive neuroscience

Human-brain mapping

- Over-specified inferences about functional-anatomical mappings
- Inflated test statistics
(Westfall et al. *Wellcome Open Research* 2017)

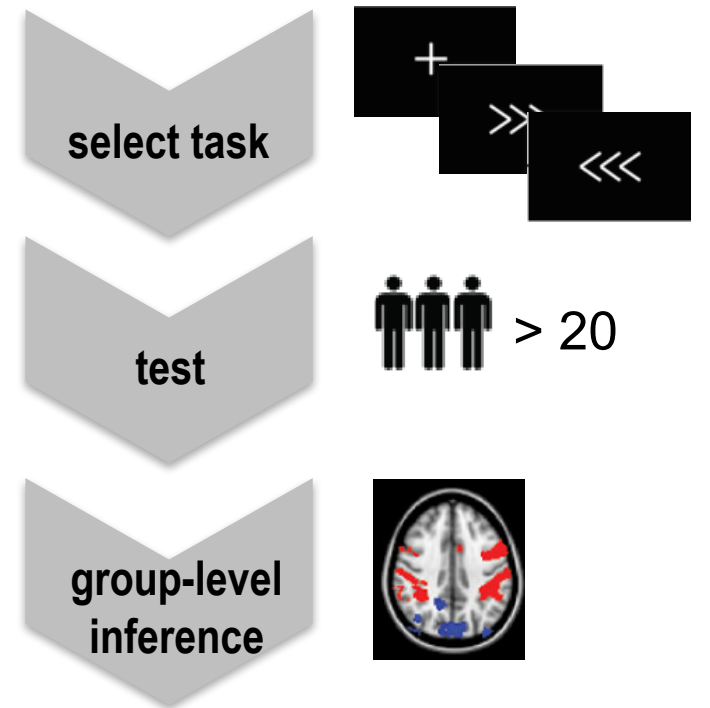
Biomarker discovery

- Which exact task conditions will be sensitive to certain patient group?
(Sprooten et al. *Human Brain Mapping* 2017)

Non-invasive brain stimulation

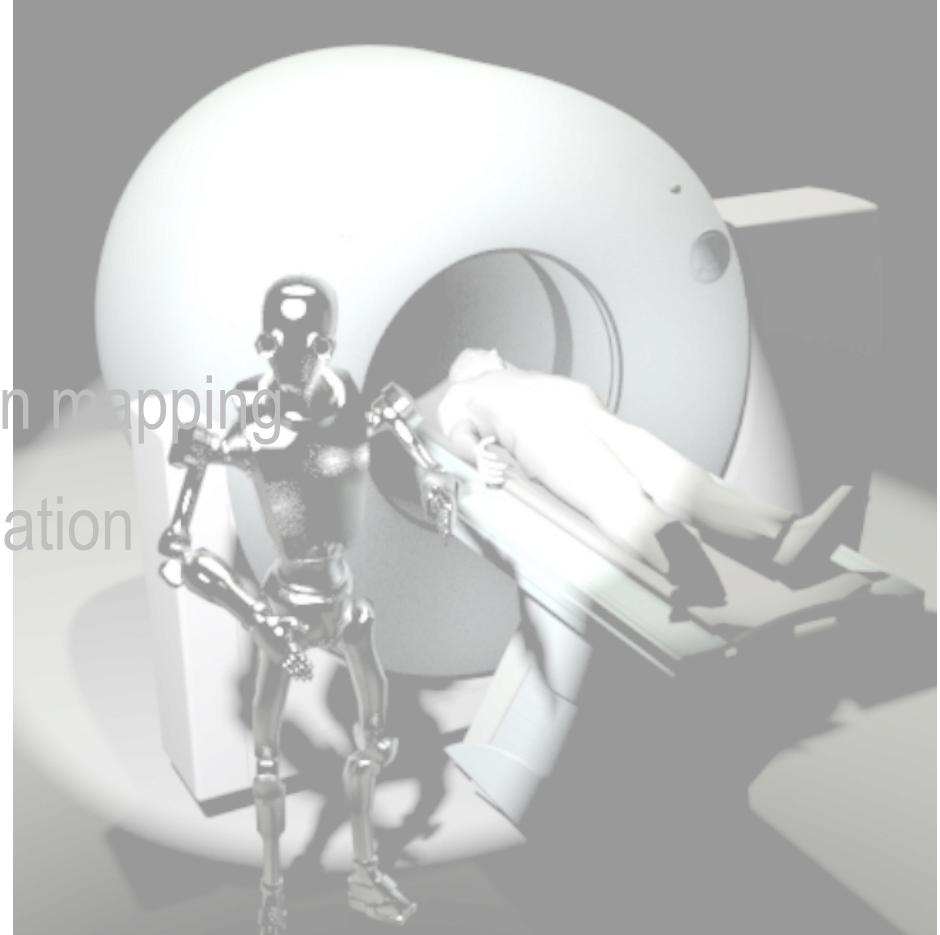
- Many *free* parameters, confusion surrounding efficacy

Standard approach



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The framework

neuroadaptive paradigms

open-loop

- stimuli manually adapted to subject
- subject modulates brain response
e.g. neurofeedback, communication with vegetative state patients

informed open-loop

- stimuli is triggered by brain state

closed-loop

machine learning

supervised

passive learning

- BCIs
- advanced neurofeedback
- neural selectivity

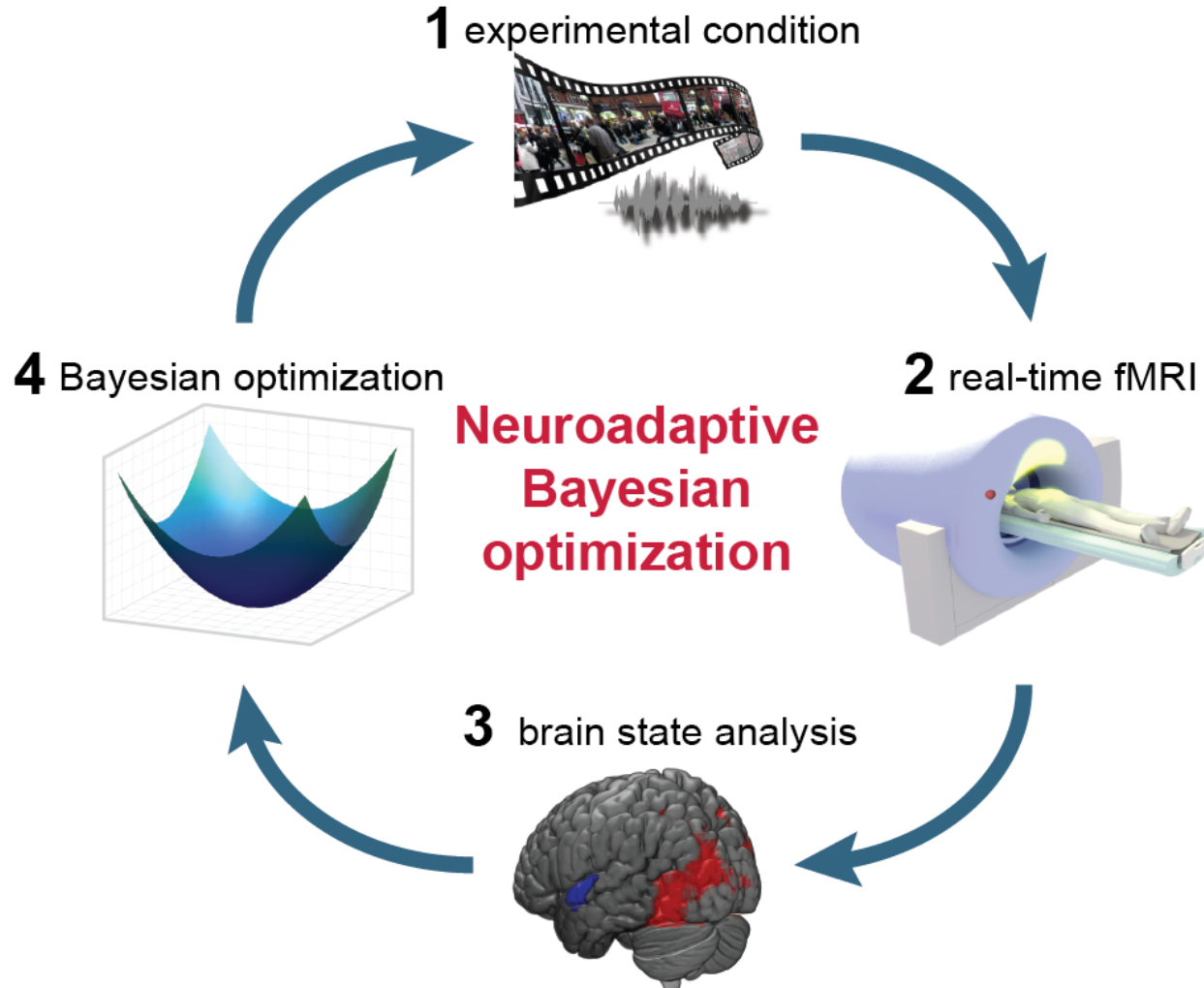
active learning

- tuning curve estimation

Bayesian optimization

Lorenz et al. *Trends in Cognitive Sciences* 2017

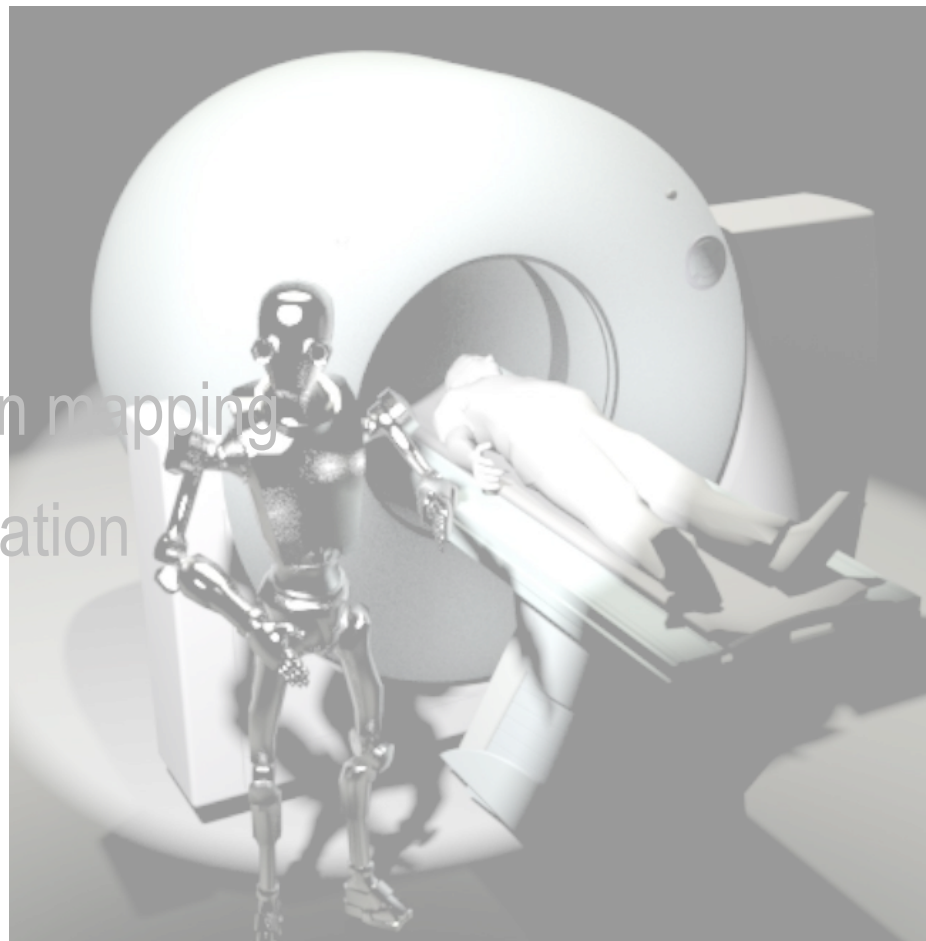
“The Automatic Neuroscientist”



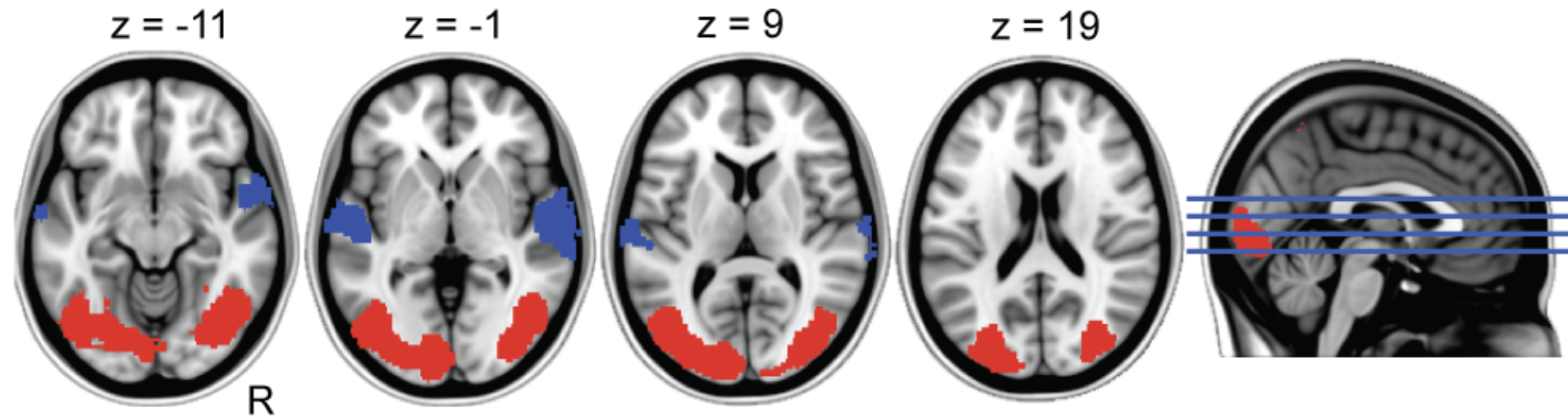
Lorenz et al. *NeuroImage* 2016

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Target brain state

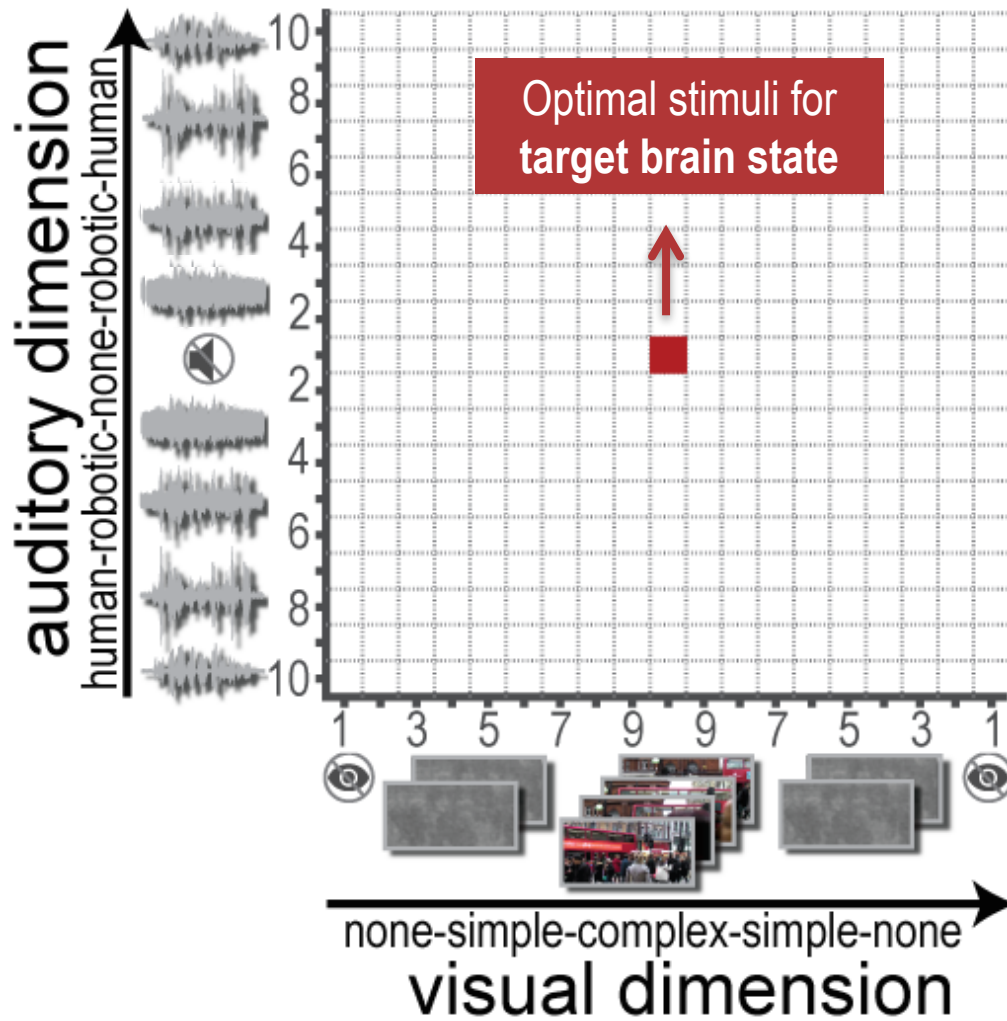


lateral occipital cortex activity \uparrow

superior temporal cortex activity \downarrow

masks derived from
Braga et al. *NeuroImage* 2013

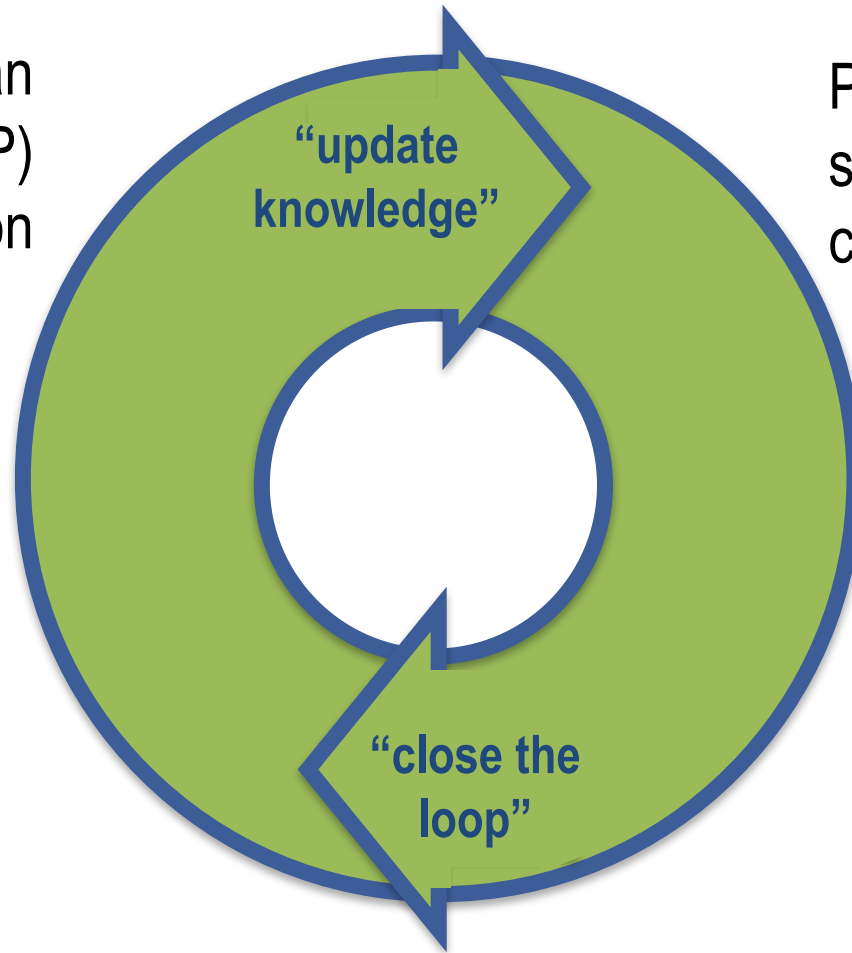
Experiment space



Bayesian optimization

Gaussian
process (GP)
regression

Propose new
stimuli
combination

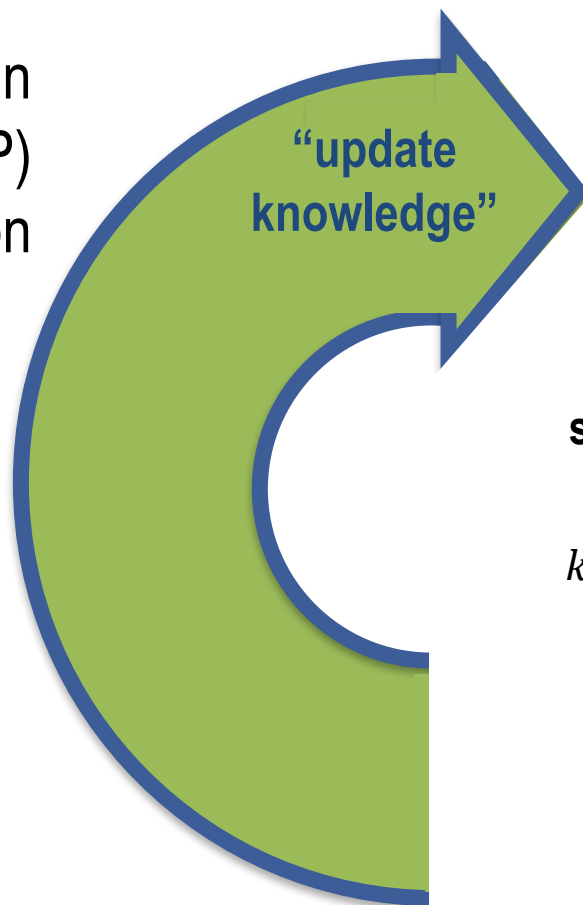


Rasmussen & Williams 2006
Brochu et al. *arXiv* 2010

Bayesian optimization

Gaussian
process (GP)
regression

choice of
covariance function



squared exponential kernel:

$$k(x, y) = \sigma^2 \exp \left\{ -\frac{(x - y)^2}{2 l^2} \right\}$$

$x, y \in \mathbb{R}^2$ audio-visual stimulus

$\sigma^2 \in \mathbb{R}$ variance of covariance kernel

$l \in \mathbb{R}$ length of covariance kernel

Rasmussen & Williams 2006
Brochu et al. *arXiv* 2010

Bayesian optimization

Expected improvement acquisition function:

$$EI(x) = (m(x) - f_{max})q(z) + var(x)p(z)$$

$m(x)$: predicted mean

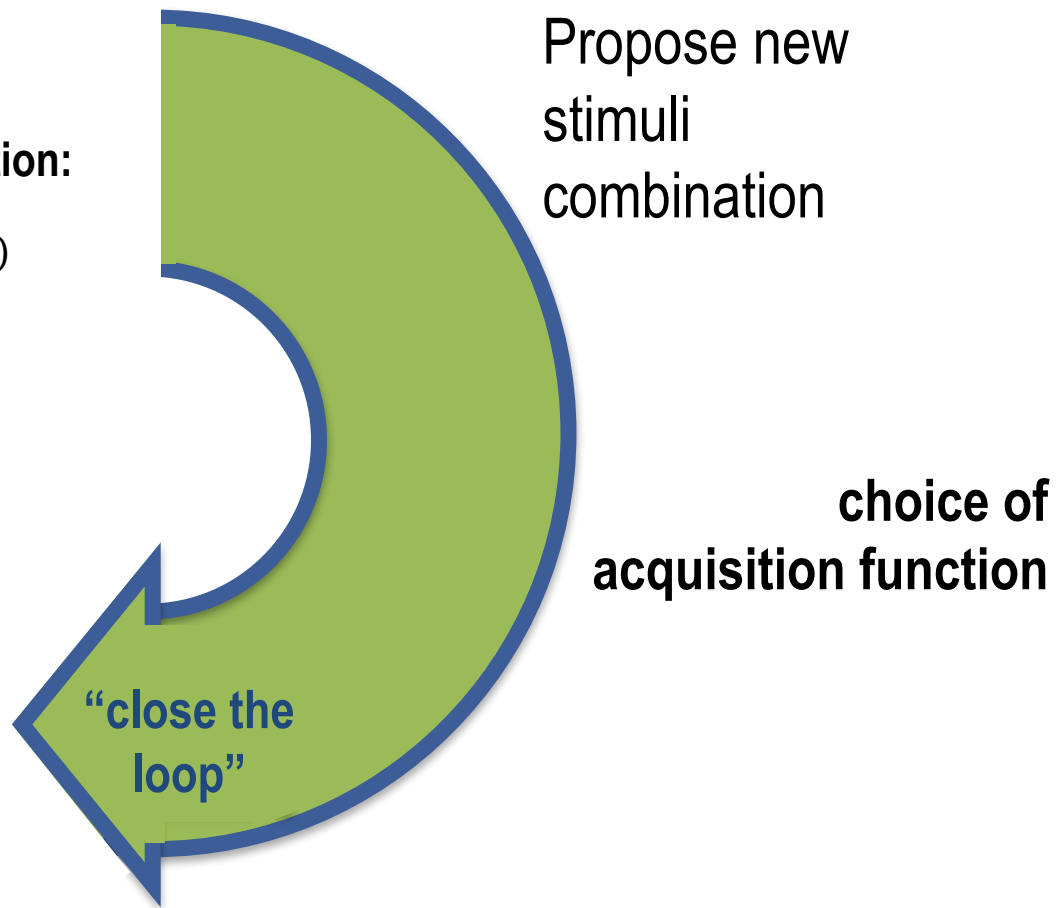
$var(x)$: predicted variance

f_{max} : maximum predicted value

$q()$: cumulative distribution function

$p()$: probability density function

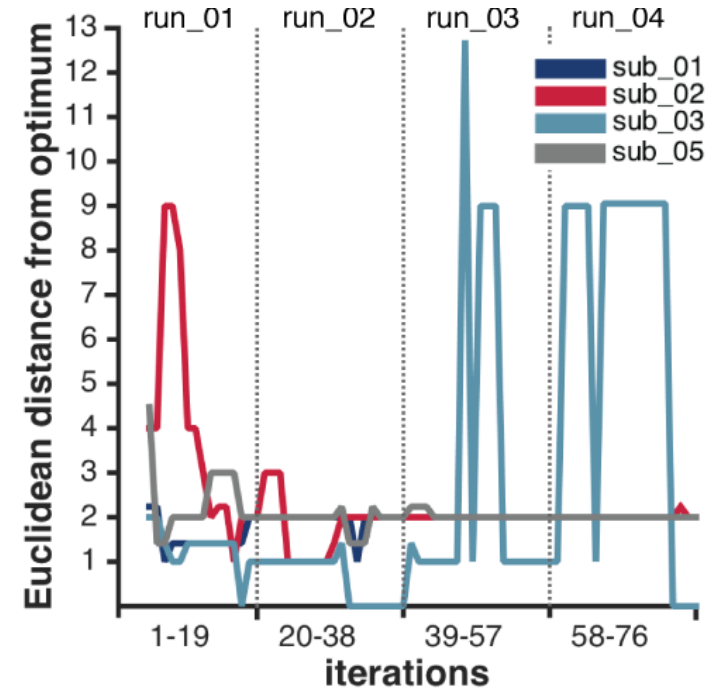
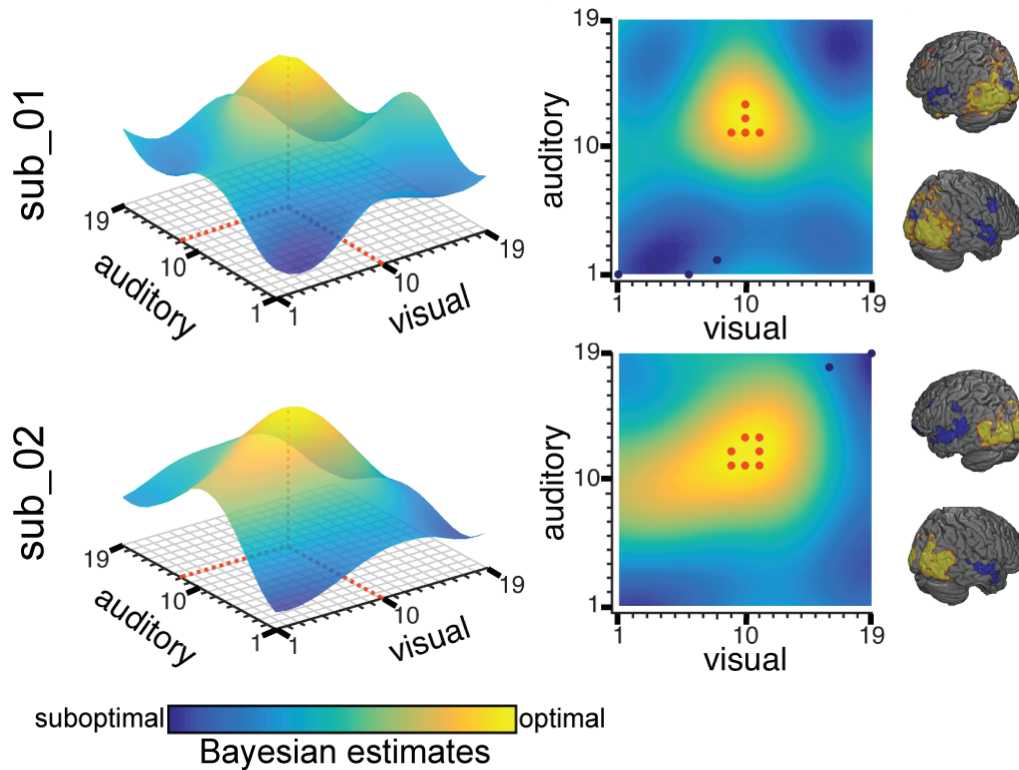
$$z = \frac{m(x) - f_{max}}{var(x)}$$



Rasmussen & Williams 2006
Brochu et al. *arXiv* 2010

Results

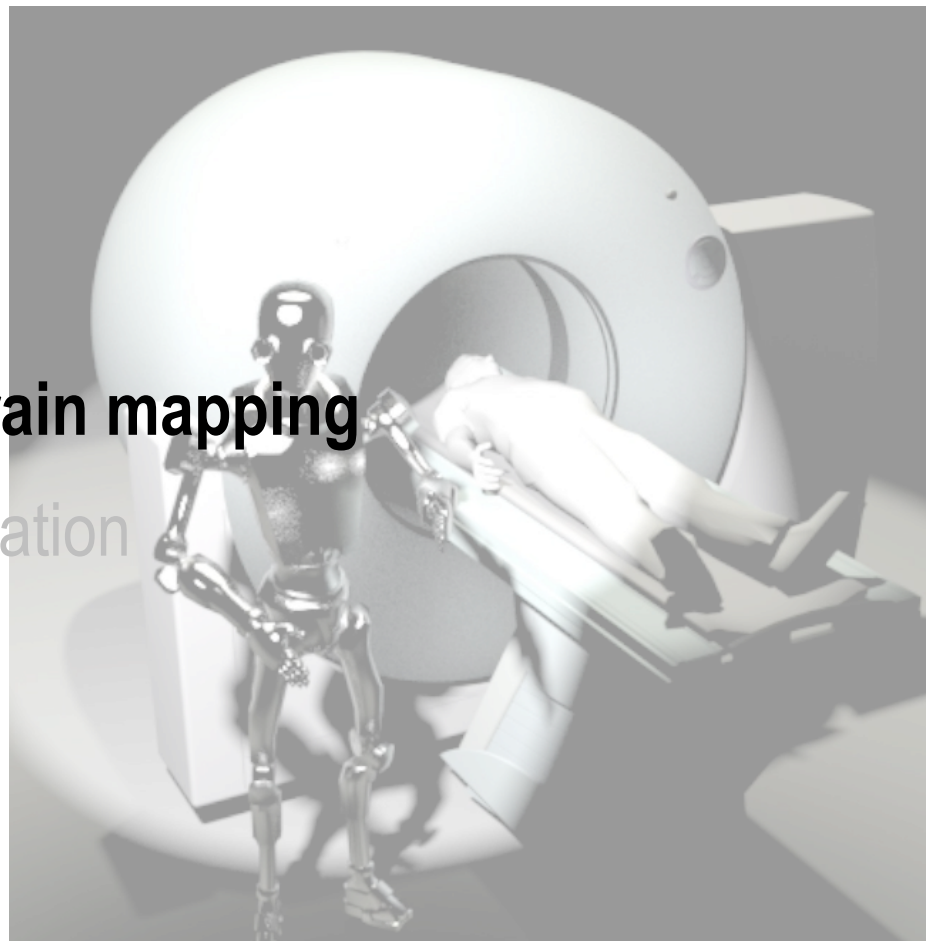
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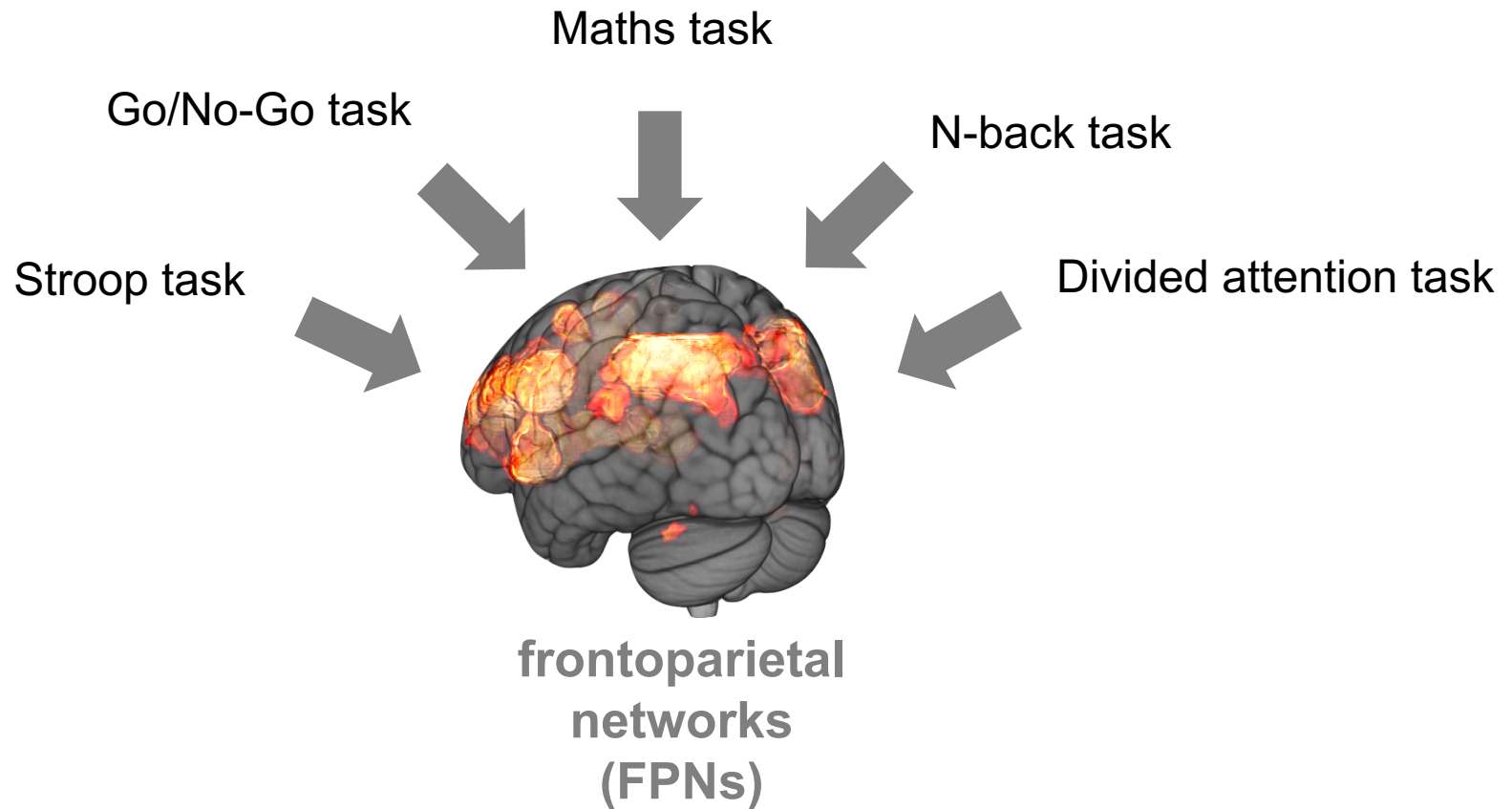
Lorenz et al. *NeuroImage* 2016

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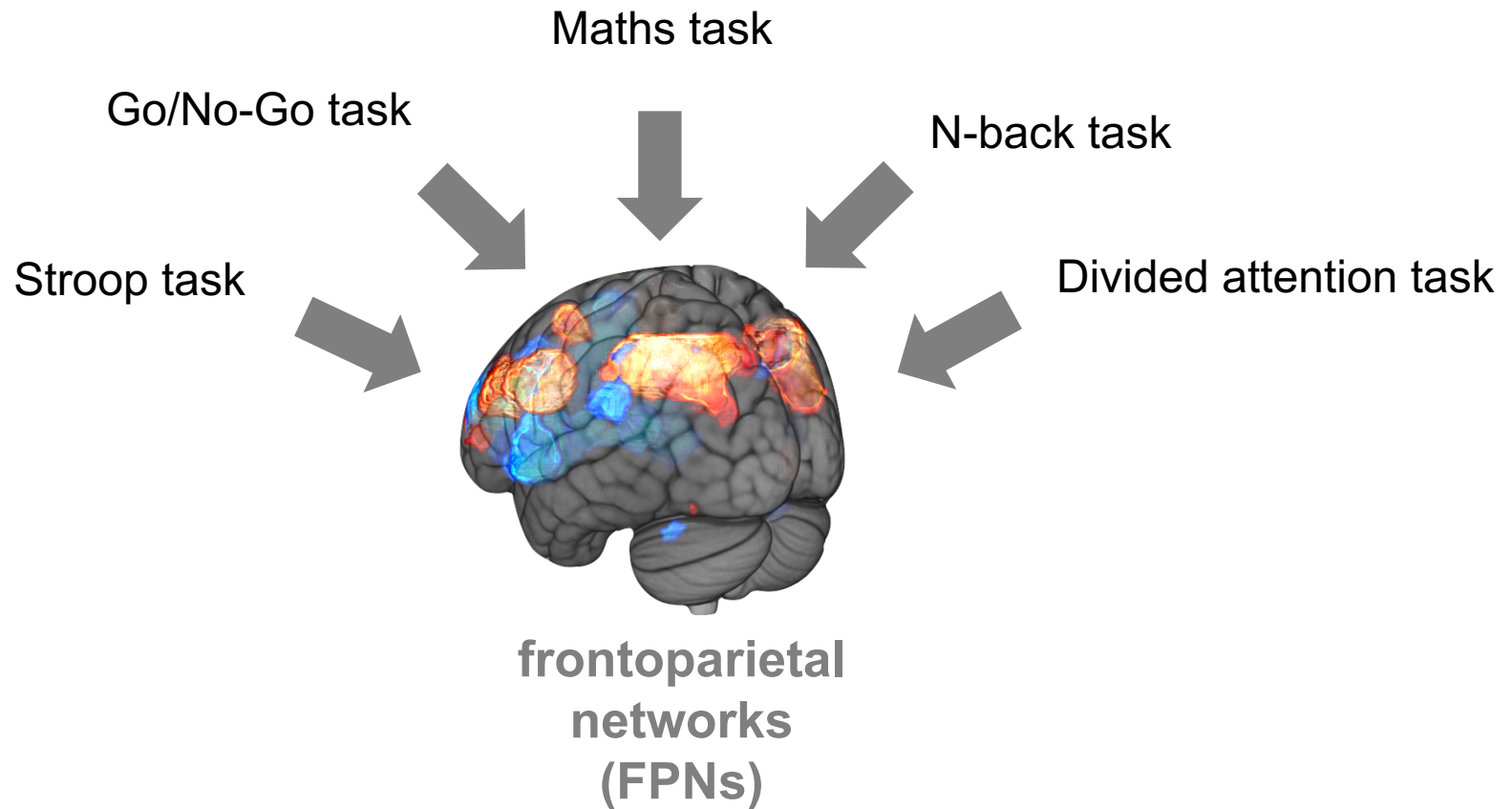


Motivation



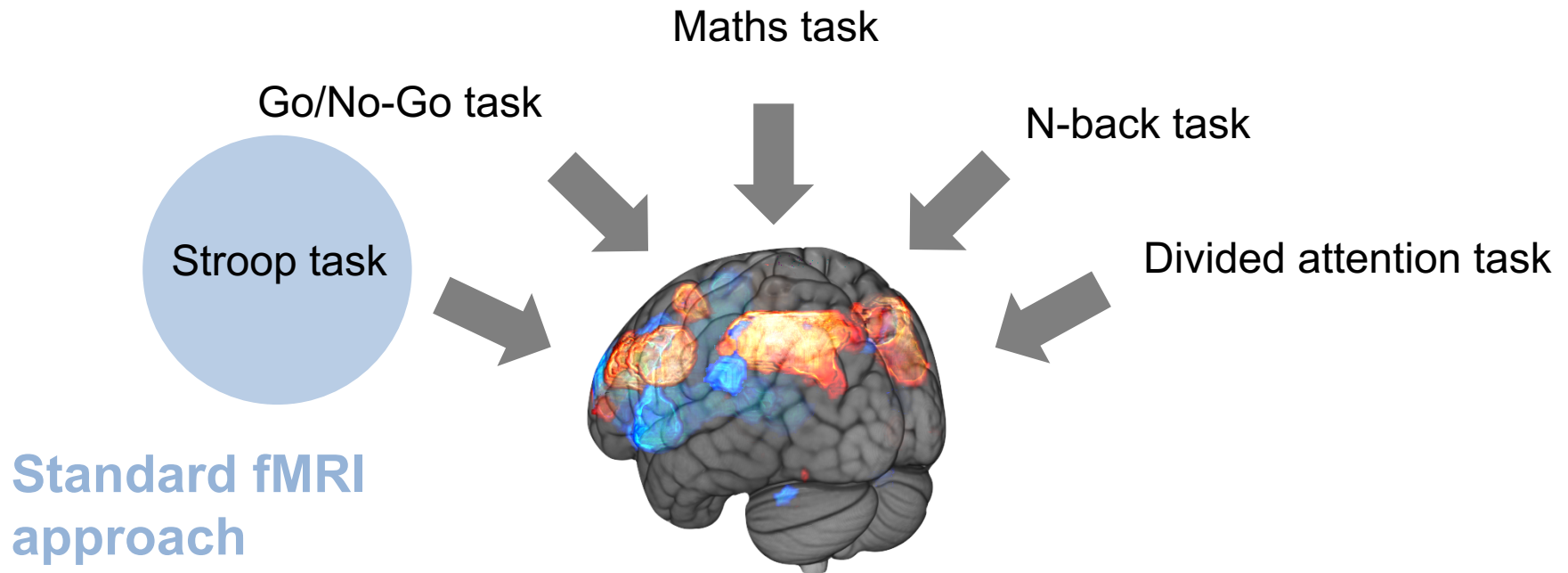
Duncan & Owen *TINS* 2000
Fedorenko et al. *PNAS* 2013

Motivation



Hampshire et al. *Neuron* 2012

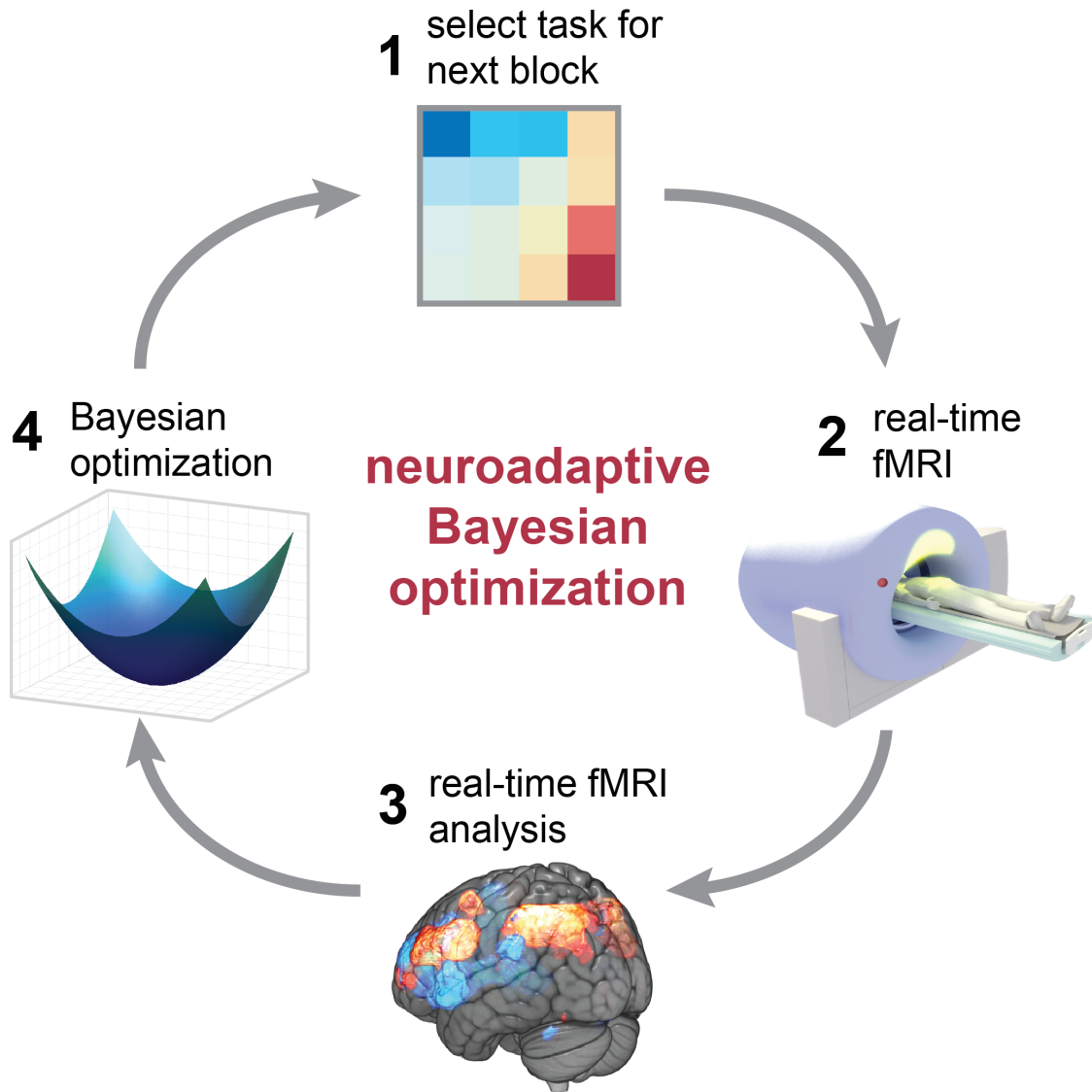
Motivation



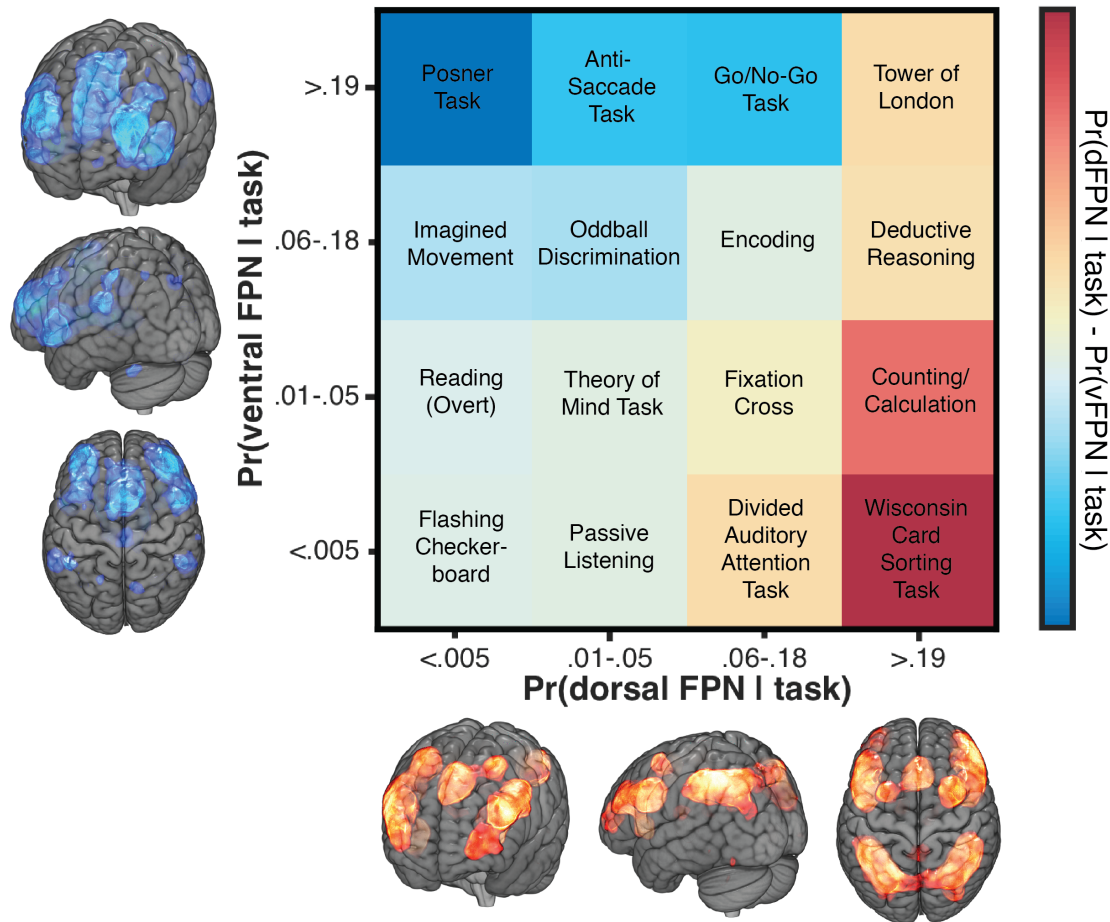
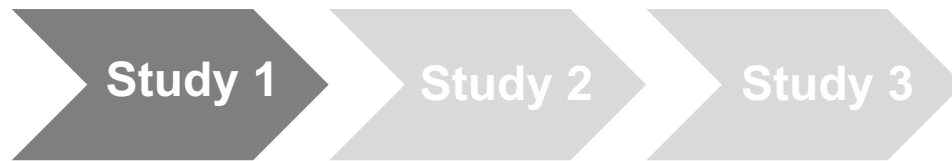
- **Limited generalizability**
- **Limited reproducibility**

Lorenz et al. *Trends in Cognitive Sciences* 2017
Westfall et al. *Wellcome Open Research* 2017

Searching across cognitive tasks

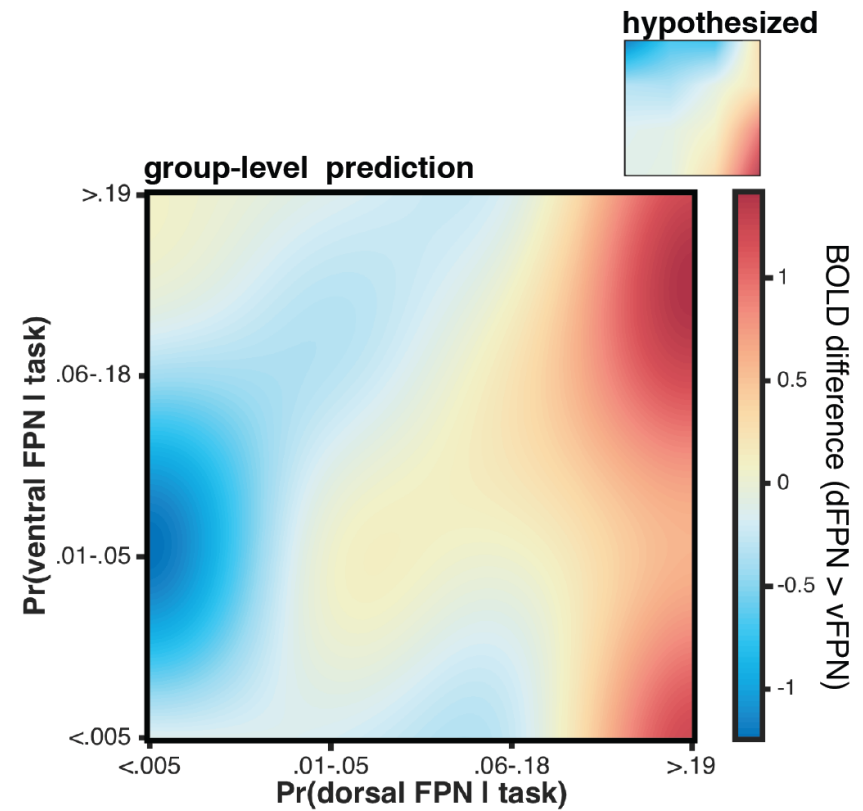
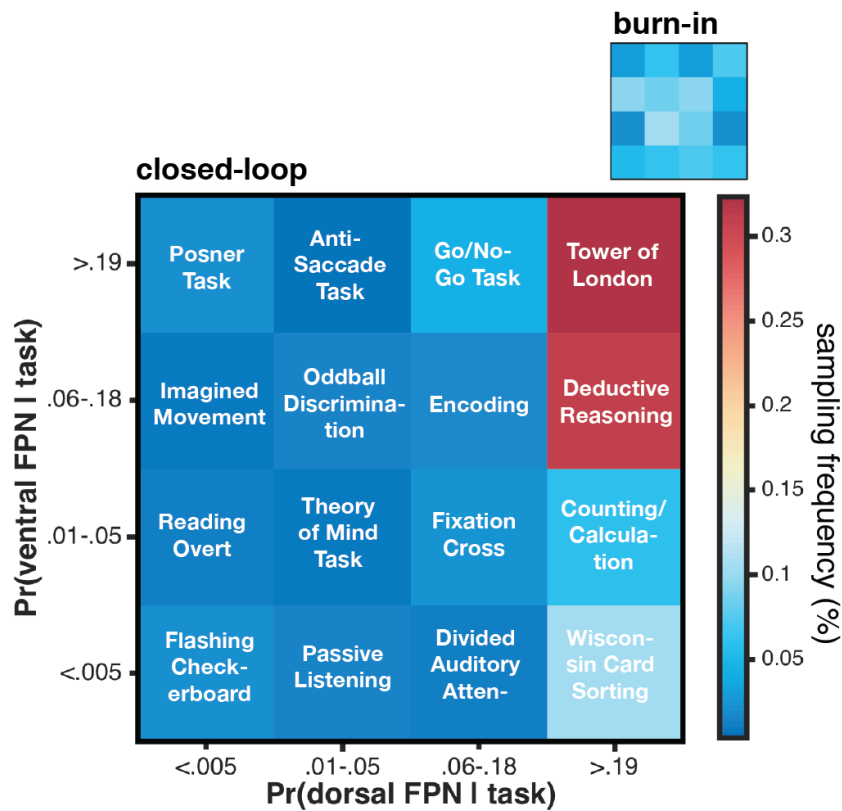


Task space based on meta-analysis



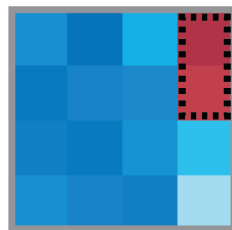
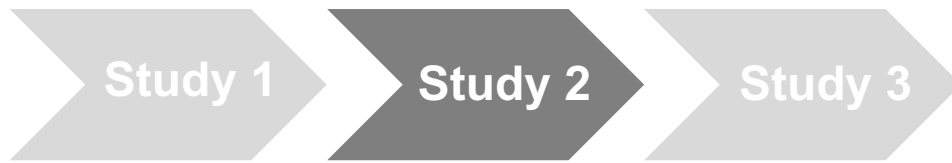
Yeo et al. *Cerebral Cortex* 2015

Find optimal tasks

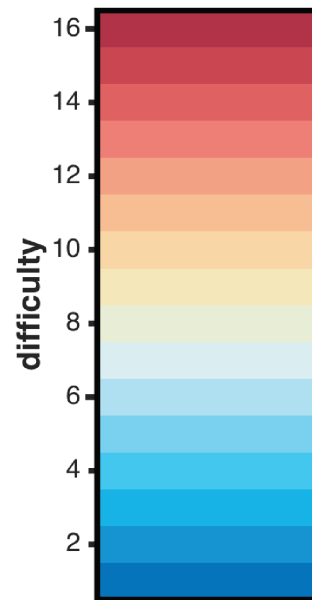


Tower of London & Deductive Reasoning tasks maximally dissociate FPNs

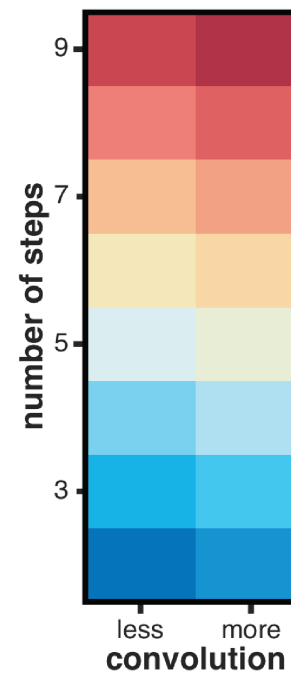
Zoom in task space and fine-tune tasks



Deductive Reasoning



Tower of London

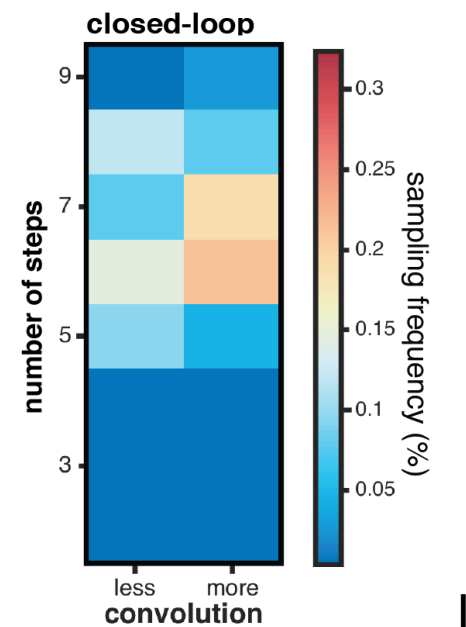
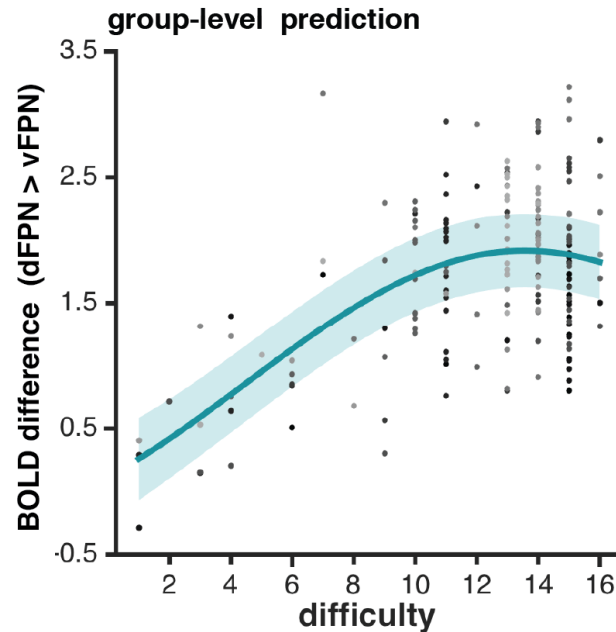
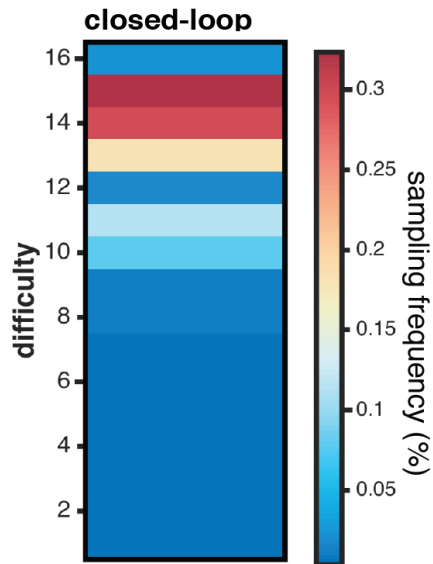


Find optimal task parameters

Study 1

Study 2

Study 3



Deductive Reasoning

Tower of London

Find *unique* functional profile

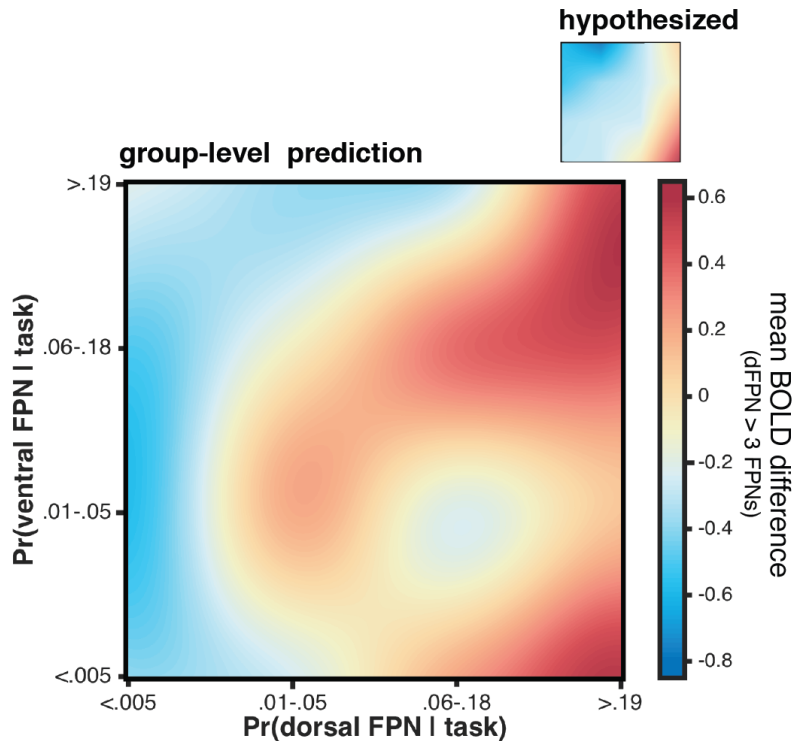
Study 1

Study 2

Study 3

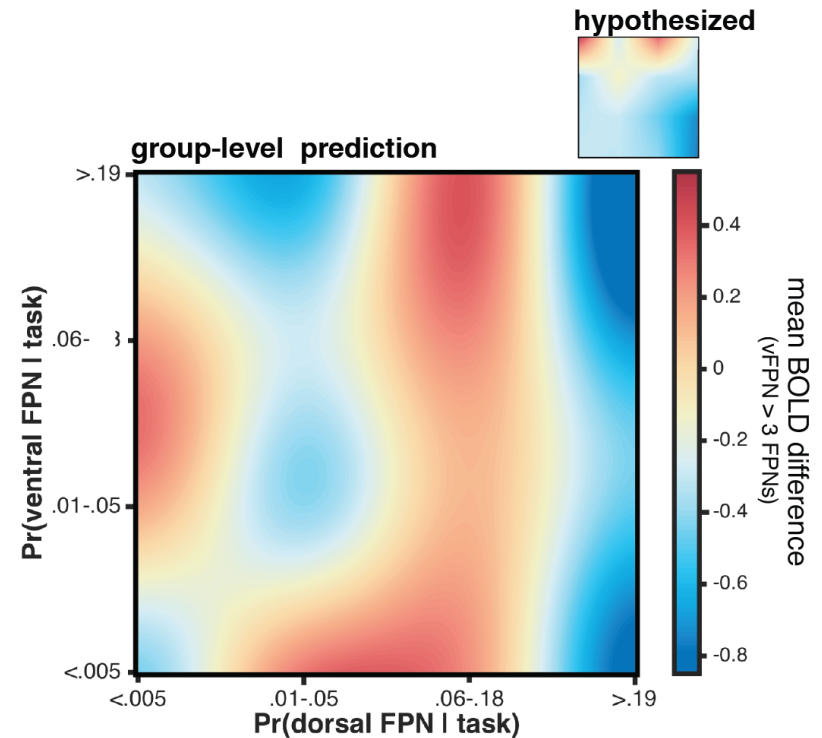


dorsal FPN > 3 other FPNs



**Tower of London, Deductive Reasoning, Encoding
& Wisconsin Card Sorting tasks**

ventral FPN > 3 other FPNs



**Go/No-Go, Divided Auditory Attention,
Passive Listening & Reading tasks**

Summary

- High inter-subject reliability
- Functional profile across many tasks is unique to each FPN
- Set of optimal tasks only partially corresponds to meta-analysis and previous functional labels
- Neurally-derived cognitive taxonomy needed
- **Powerful synergy between neuroadaptive Bayesian optimization and meta-analyses**

Lorenz et al. *under revision* (bioRxiv:128678)

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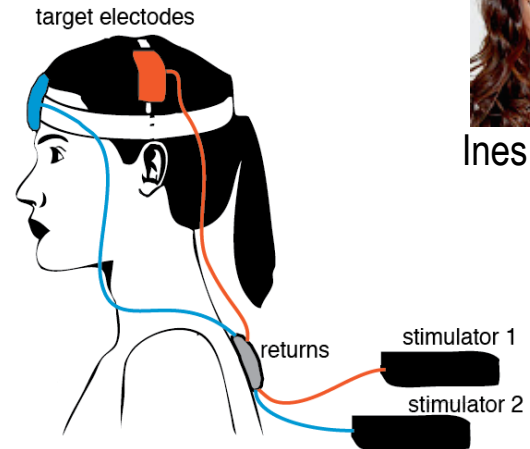
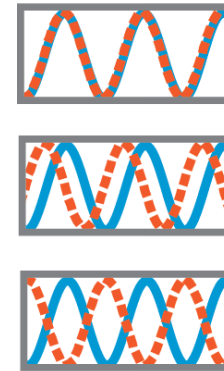
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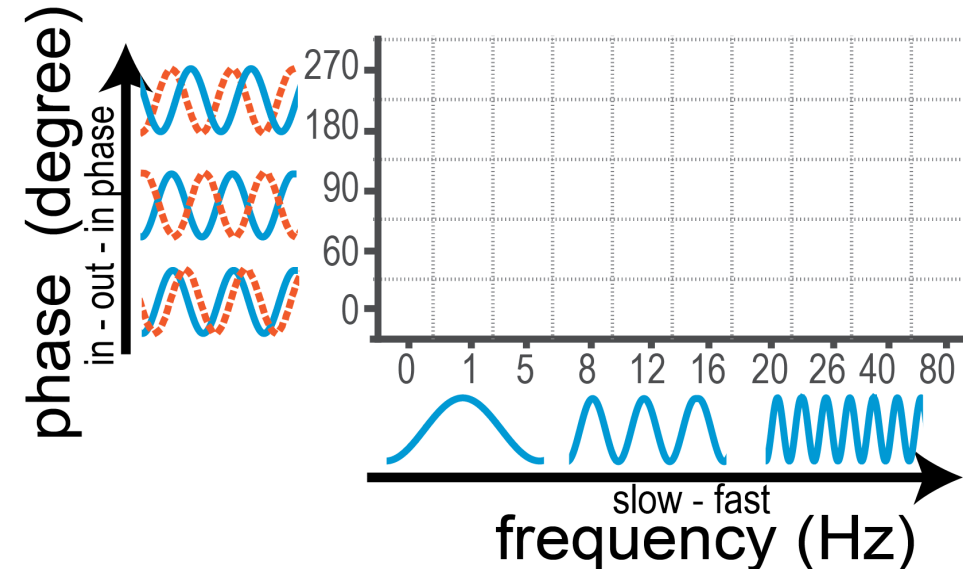
Transcranial alternating current stimulation (tACS)

■ Status Quo

- Ad hoc definition of frequency and phase
- Cohort testing



Ines Violante



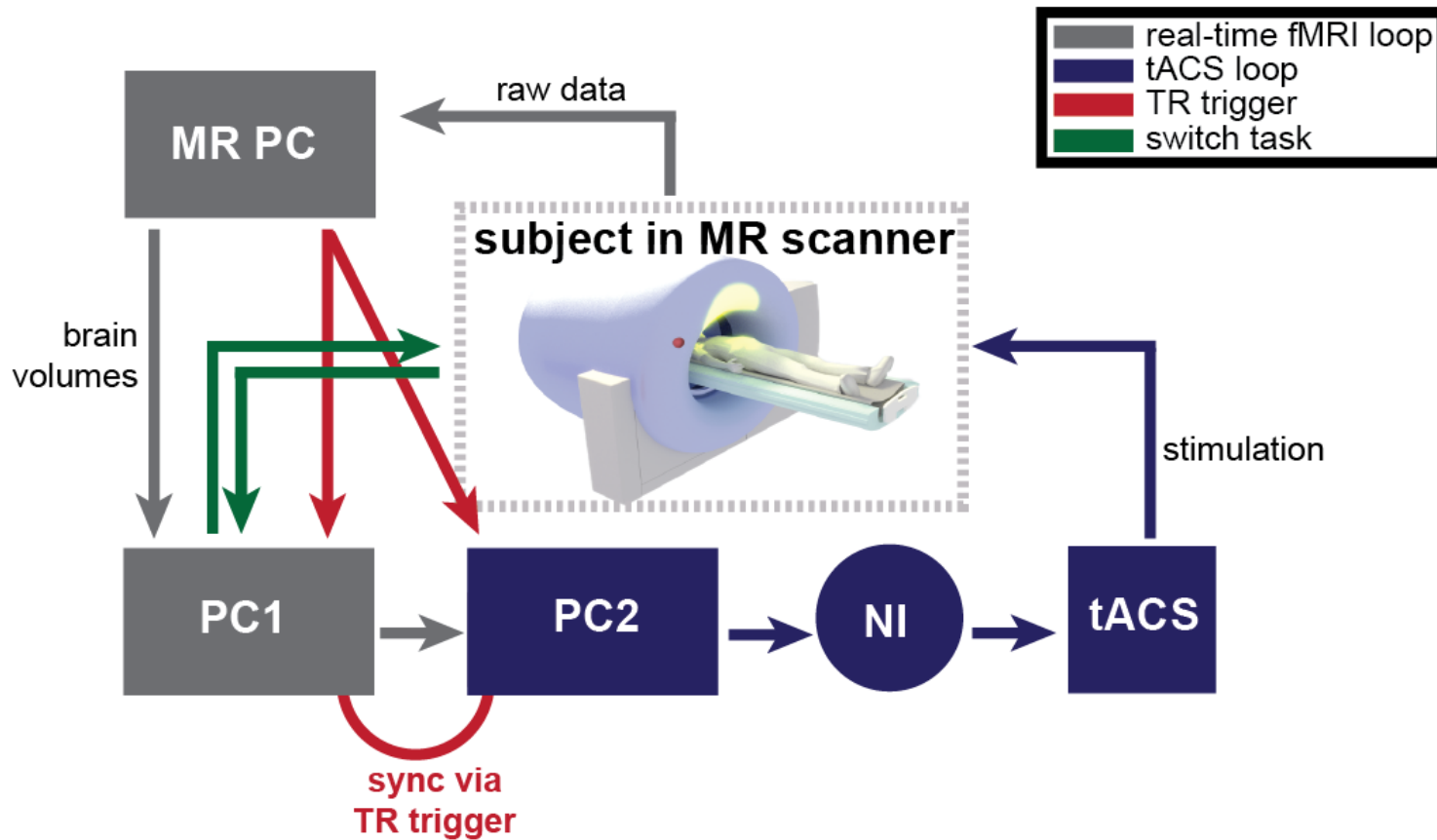
■ Limitation

1. How to choose frequency and phase?
2. Stimulation parameters may vary due to anatomy or pathology

Concurrent real-time fMRI/tACS



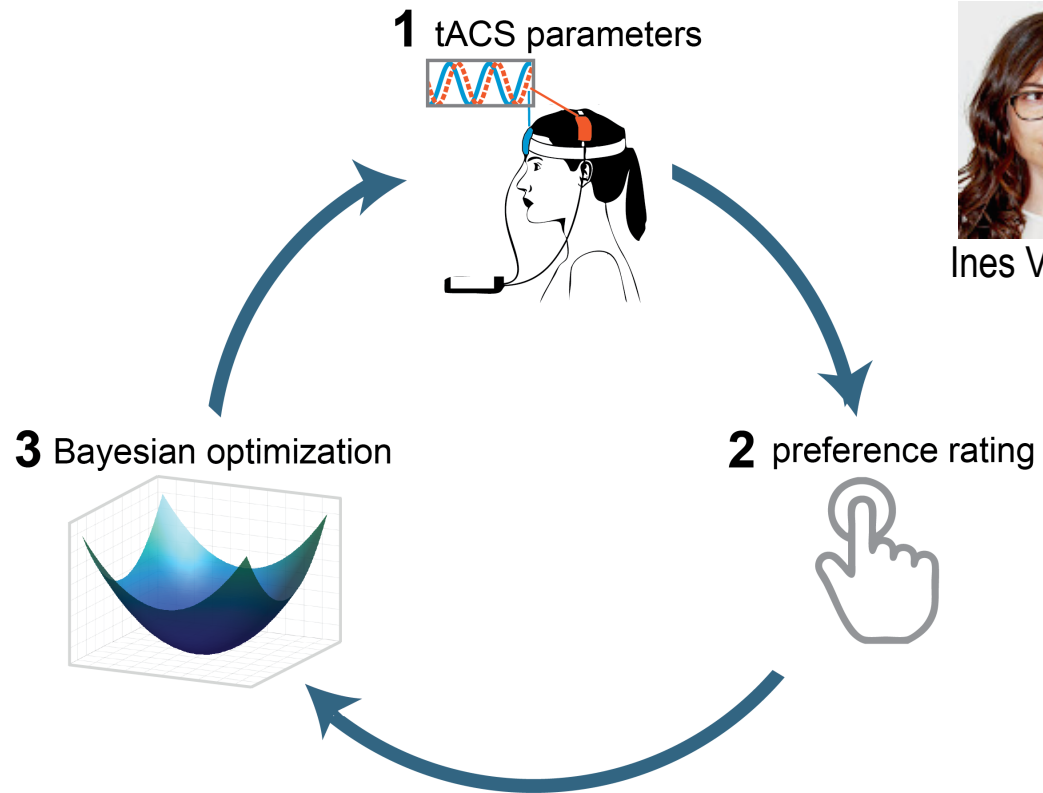
Ines Violante



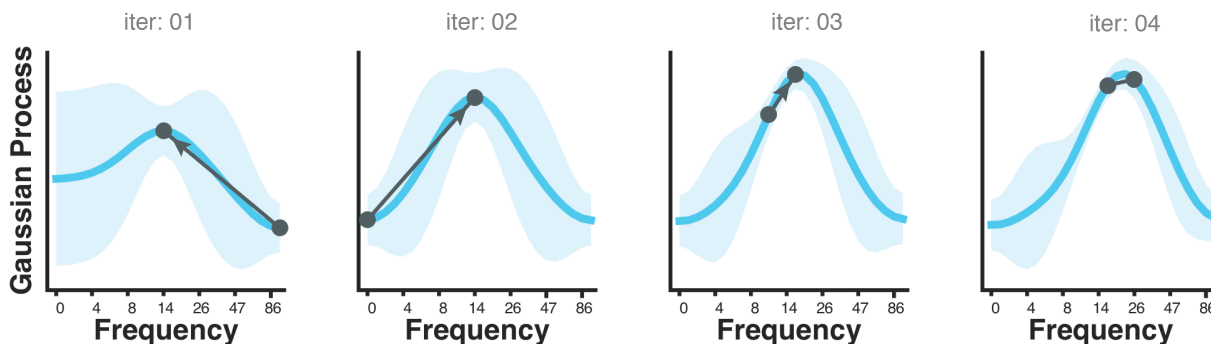
Lorenz et al. *PRNI* 2016
Lorenz et al. *in preparation*

Phosphenes perception

- *Phosphenes* = flash-like percepts during brain stimulation
- Major experimental challenge (neuromodulation, alertness)



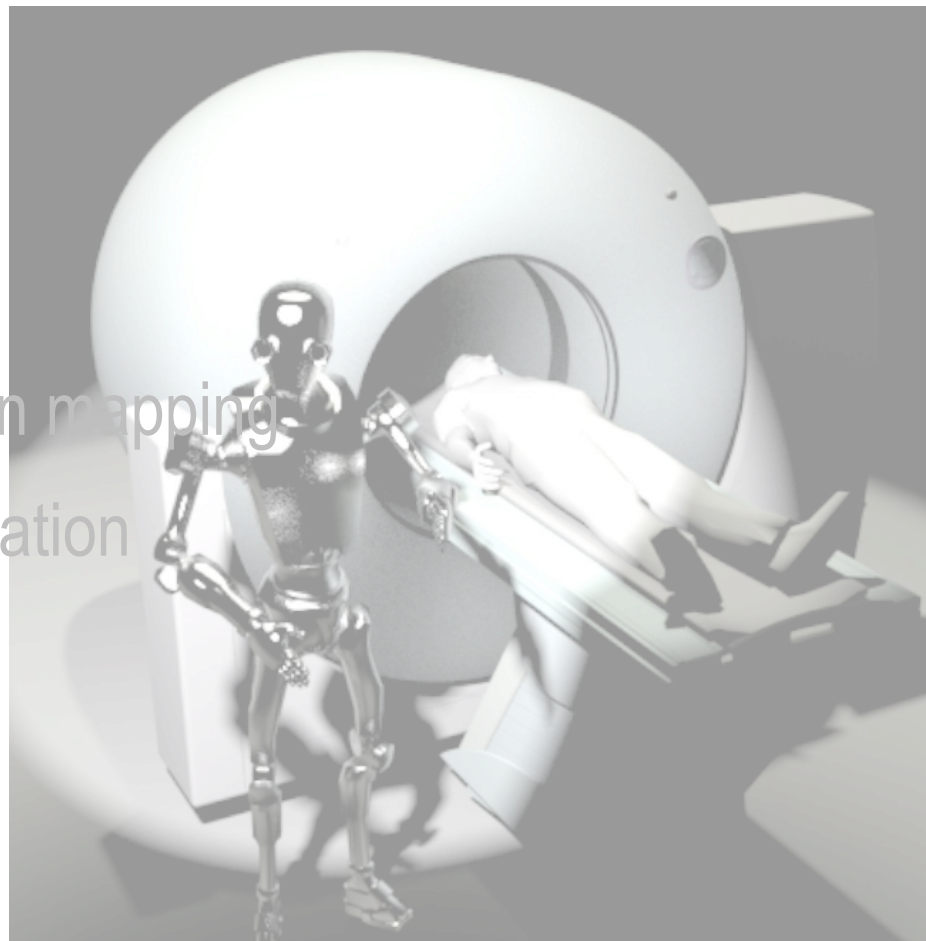
Ines Violante



Lorenz et al. *under revision*
(bioRxiv:150086)

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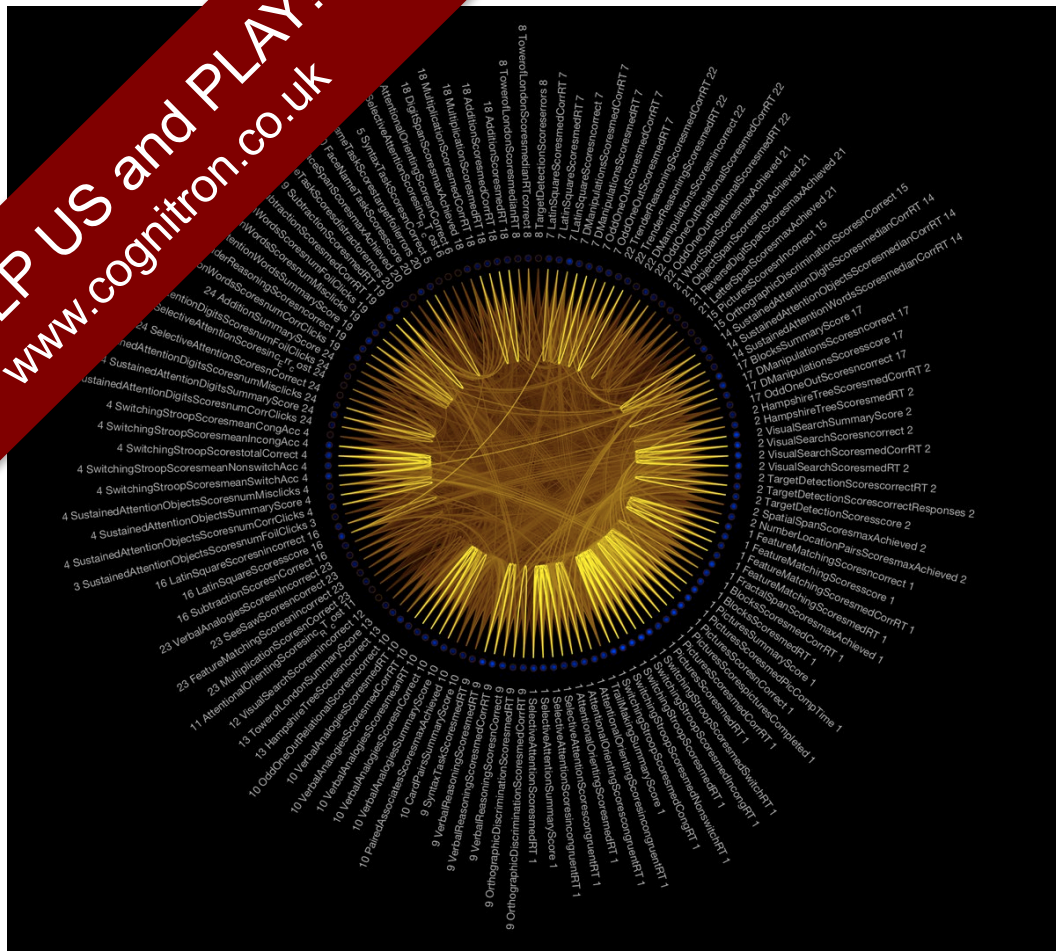
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Adam Hampshire

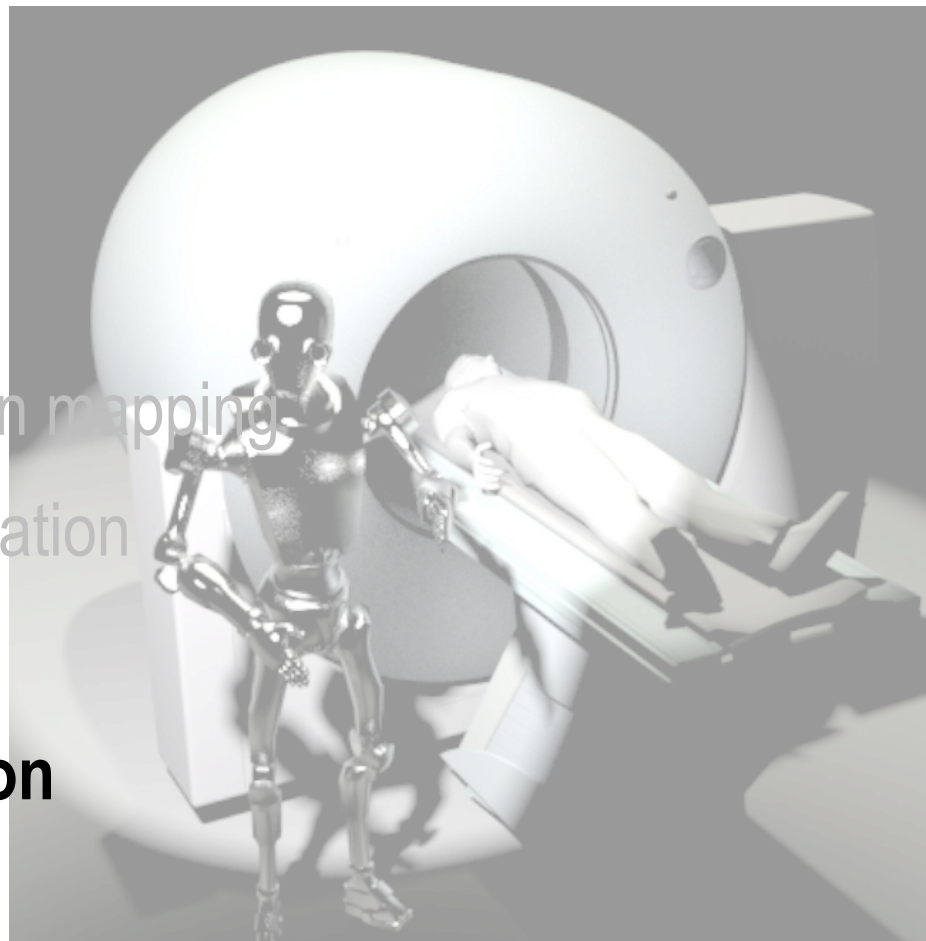
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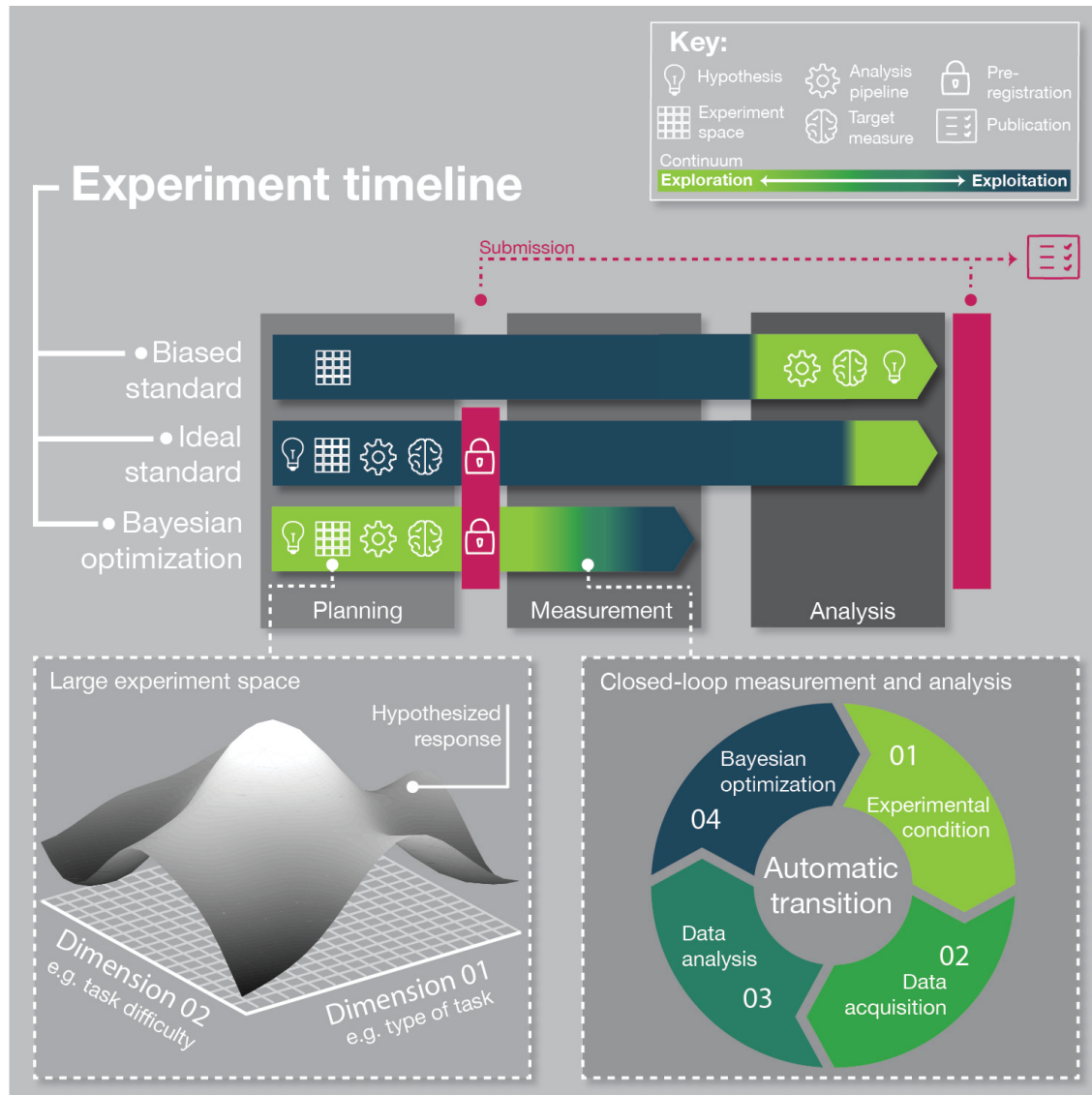
$N > 15,000$

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Implications for improving reproducibility



- More **flexible hypothesis** possible (exploration)
- Improved **specificity & generalizability** of research findings
- Can be combined with **pre-registration**

Lorenz et al. *TiCS* 2017

Future work – need for method development

- Addressing small effect sizes
 - Hierarchical optimization protocol
- Diagnosis: biomarker discovery
 - Novel acquisition functions
- Therapy: tuning to individual patient
 - Statistical inference on objective function/sampling trajectory
- General:
 - Stopping criteria
 - Non-stationarity in time (habituation)

Acknowledgement

Funding

EPSRC

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**Imperial College
London**

Cognitive, Clinical and Computational
Neuroimaging Laboratory **C³NL**

**Robert Leech
Adam Hampshire
Ines R. Violante**

 **UCL**

Gatsby Computational Neuroscience Unit

Ricardo P. Monti



Rob



Adam



Ines



Ricardo

• Code

- GP regression: <http://github.com/SheffieldML/GPy>
- Acquisition functions: <http://github.com/romylorenz/AcquisitionFunction>

• Publications

Lorenz R, Hampshire A, Leech R (2017). **Neuroadaptive Bayesian optimization and hypothesis testing**. *Trends in Cognitive Sciences*, 21(3): 155-167



Lorenz R, Monti RP, Violante IR, Anagnostopoulos C, Faisal AA, Montana G, Leech R (2016a). **The Automatic Neuroscientist: A framework for optimizing experimental design with closed-loop real-time fMRI**. *NeuroImage*, 129: 320-334



Lorenz R, Violante IR, Monti RP, Montana G, Hampshire A, Leech R. **Dissociating frontoparietal networks with neuroadaptive Bayesian optimization**. *Under revision* (preprint available on bioRxiv:128678)



Lorenz R*, Monti RP*, Hampshire A, Koush Y, Anagnostopoulos C, Faisal A, Sharp D, Montana G, Leech R, Violante IR (2016b. **Towards tailoring non-invasive brain stimulation using real-time fMRI and Bayesian optimization**), In *6th International Workshop on Pattern Recognition in Neuroimaging* (free version available on arXiv:1605.01270)



Lorenz R, Simmons L, Monti RP, Arthur J, Limal S, Leech R, Violante IR. **Assessing tACS-induced phosphene perception using adaptive Bayesian optimization**. *Under revision* (preprint available on bioRxiv: 150086)

Lorenz R, Monti RP, Koush Y, Sharp D, Montana G, Hampshire A, Leech R, Violante IR. **Towards tailoring non-invasive stimulation using neuroadaptive Bayesian optimization**. *In preparation*.