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# Towards reproducible neuroimaging - across different analysis pipelines

Camille Maumet

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Submitted on 27 Feb 2024

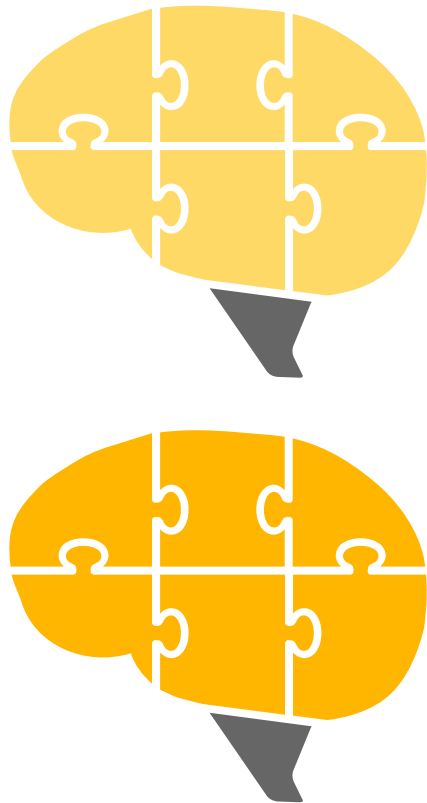
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Feb 20, 2024



# Towards reproducible neuroimaging

across different analysis pipelines

McGill Seminar Series in Quantitative Life  
Sciences and Medicine

Camille Maumet

Inria, Univ Rennes, Inserm, CNRS, IRISA



# A crisis in experimental research

The **reproducibility crisis** has led to **reduced confidence in research findings**

## **Low reproduction rates in many fields**

Cancer research: <11%

Psychology: 36%

Medicine: 44%

(Begley & Ellis 2012) (Open Science Collab 2016) (Ioannidis 2005)

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(Begley & Ellis 2012) (Open Science Collab 2016) (Ioannidis 2005)

**Wasted money  
& effort** for  
research



**Delayed  
translation** into  
clinical practice



**Reduced trust**  
in science

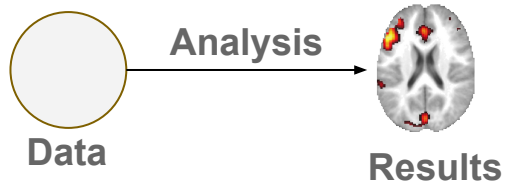


# Reproducible research



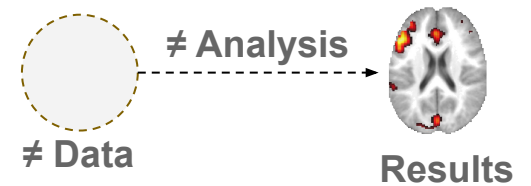
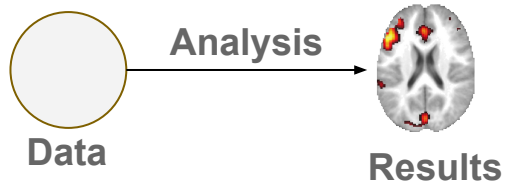
# Reproducible research

Original study



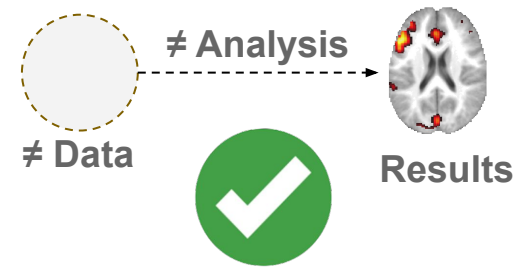
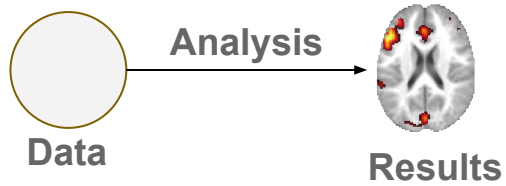
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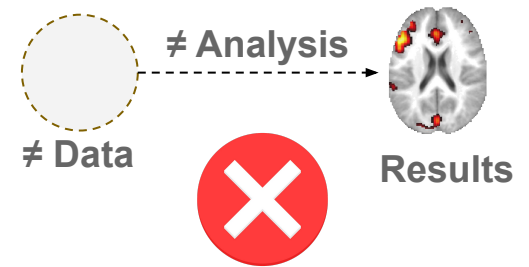
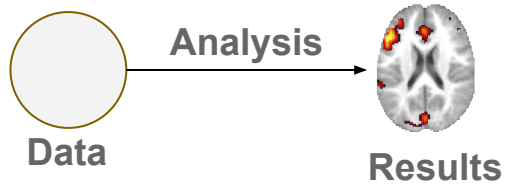
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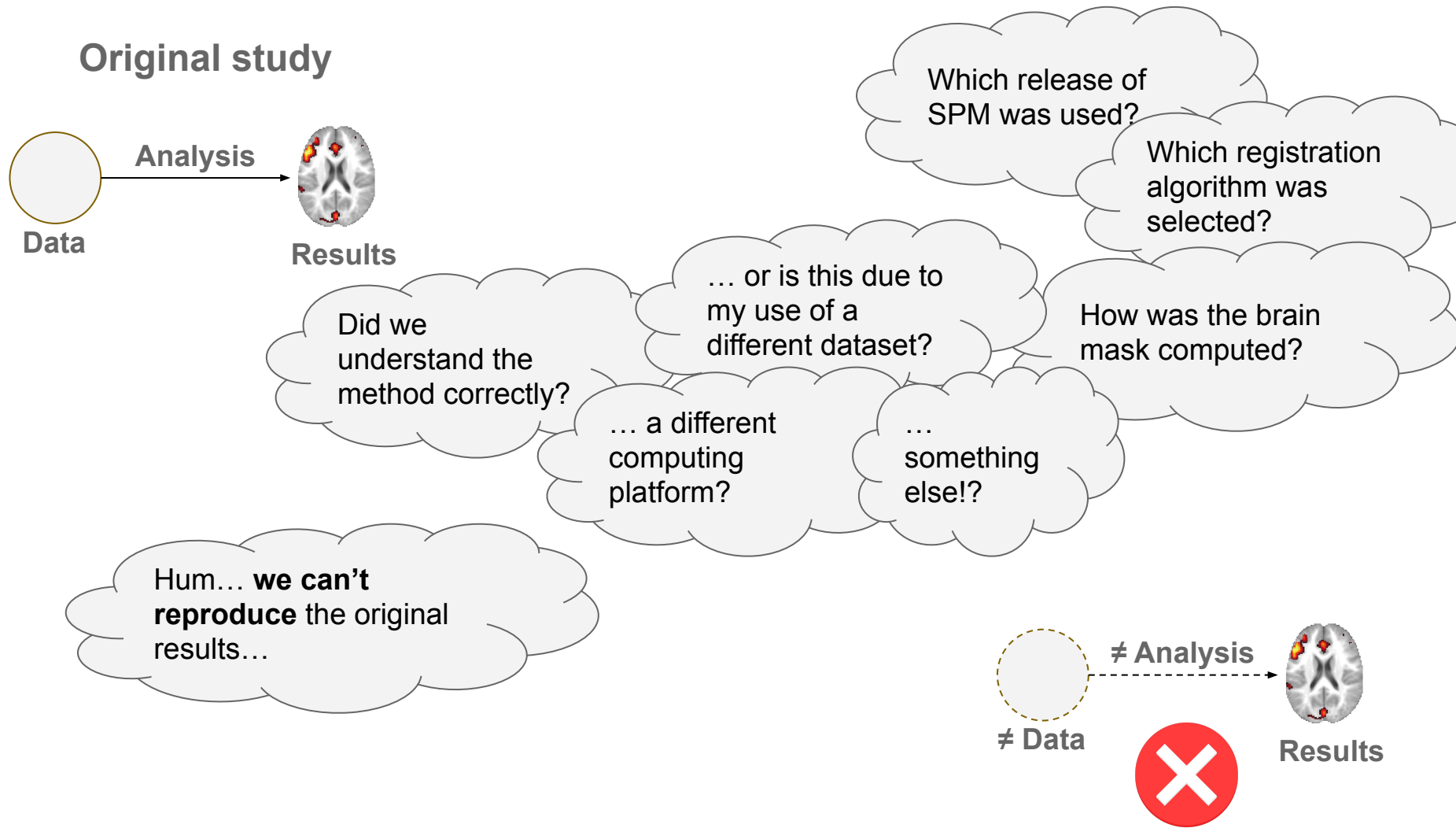


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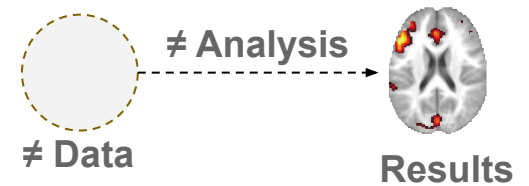
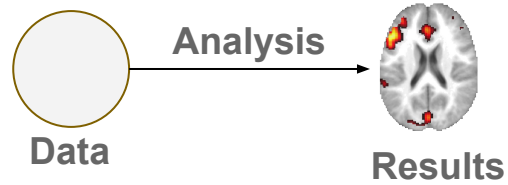
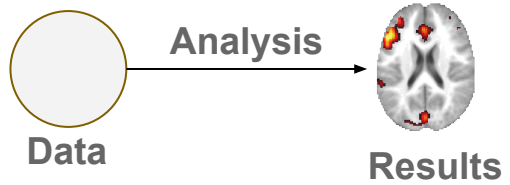


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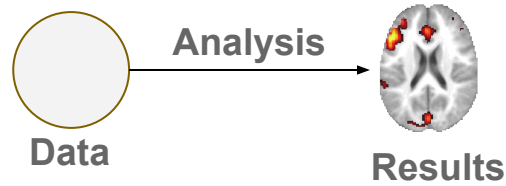
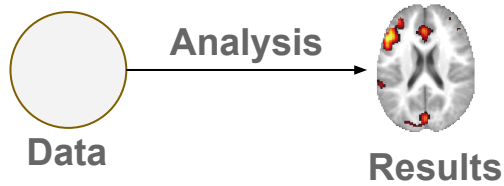
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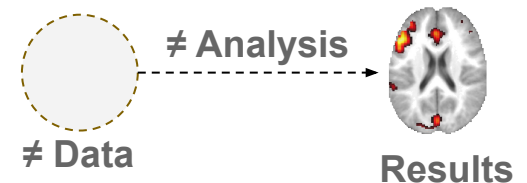


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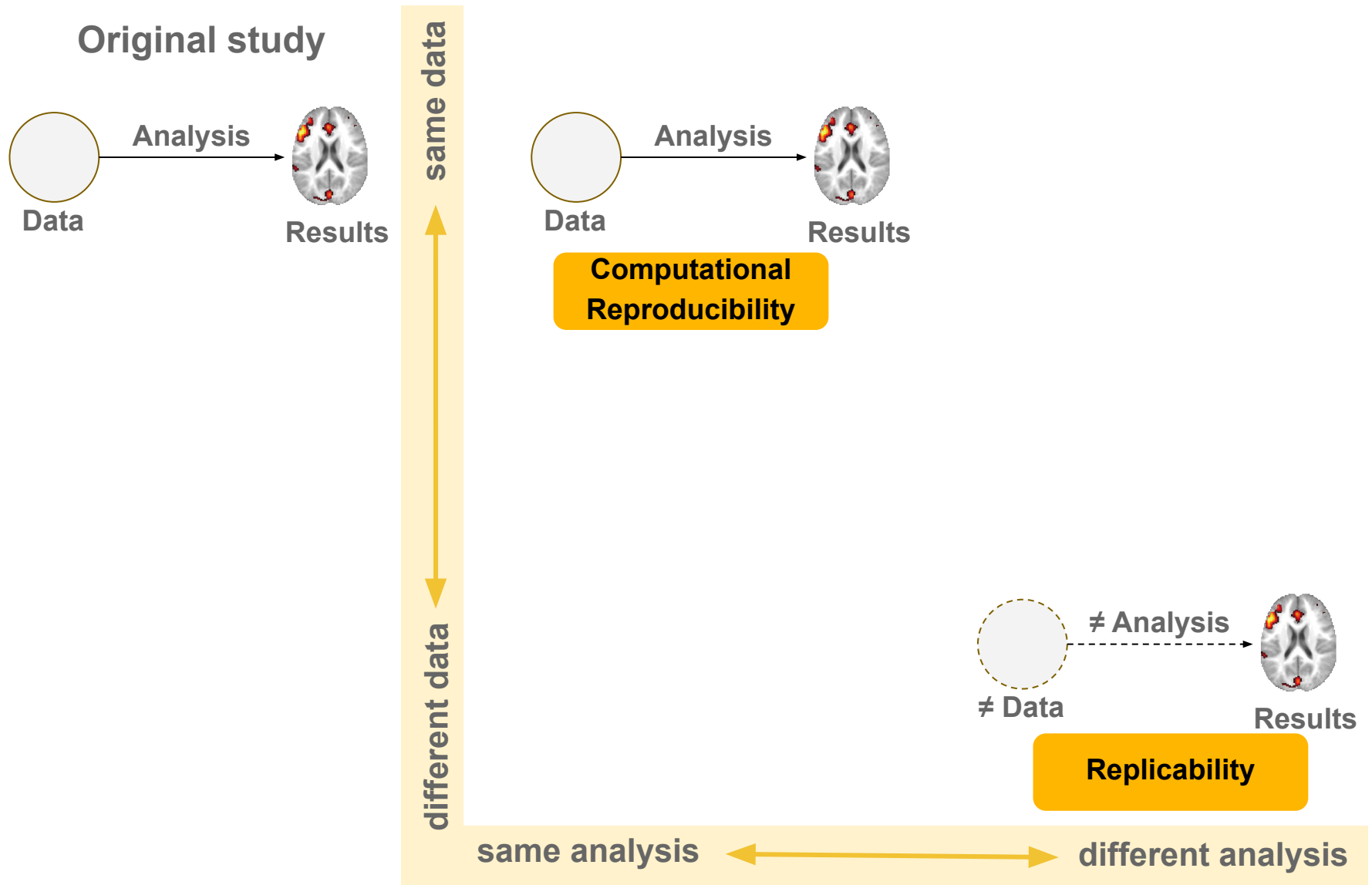


**Computational  
Reproducibility**

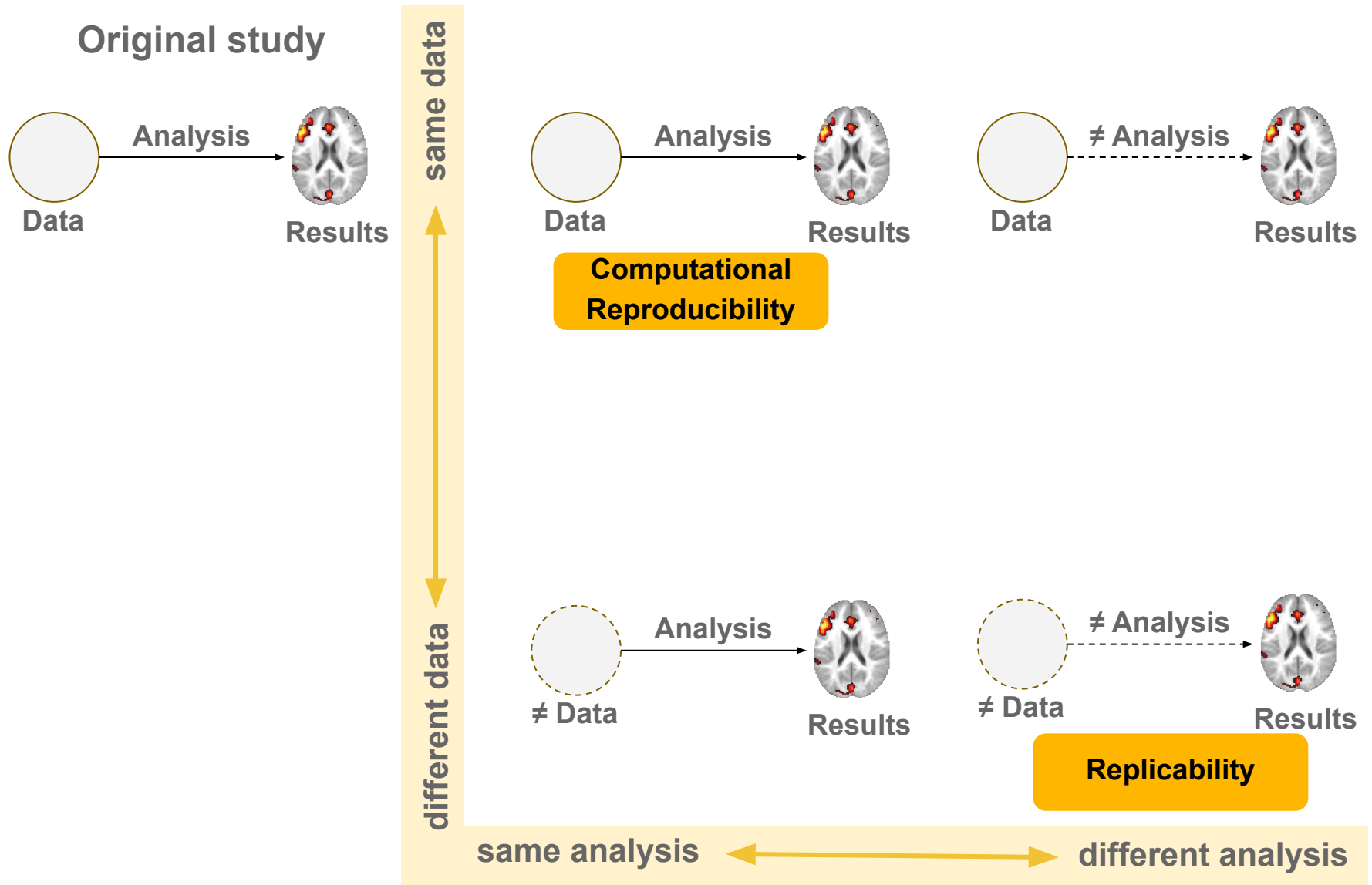


**Replicability**

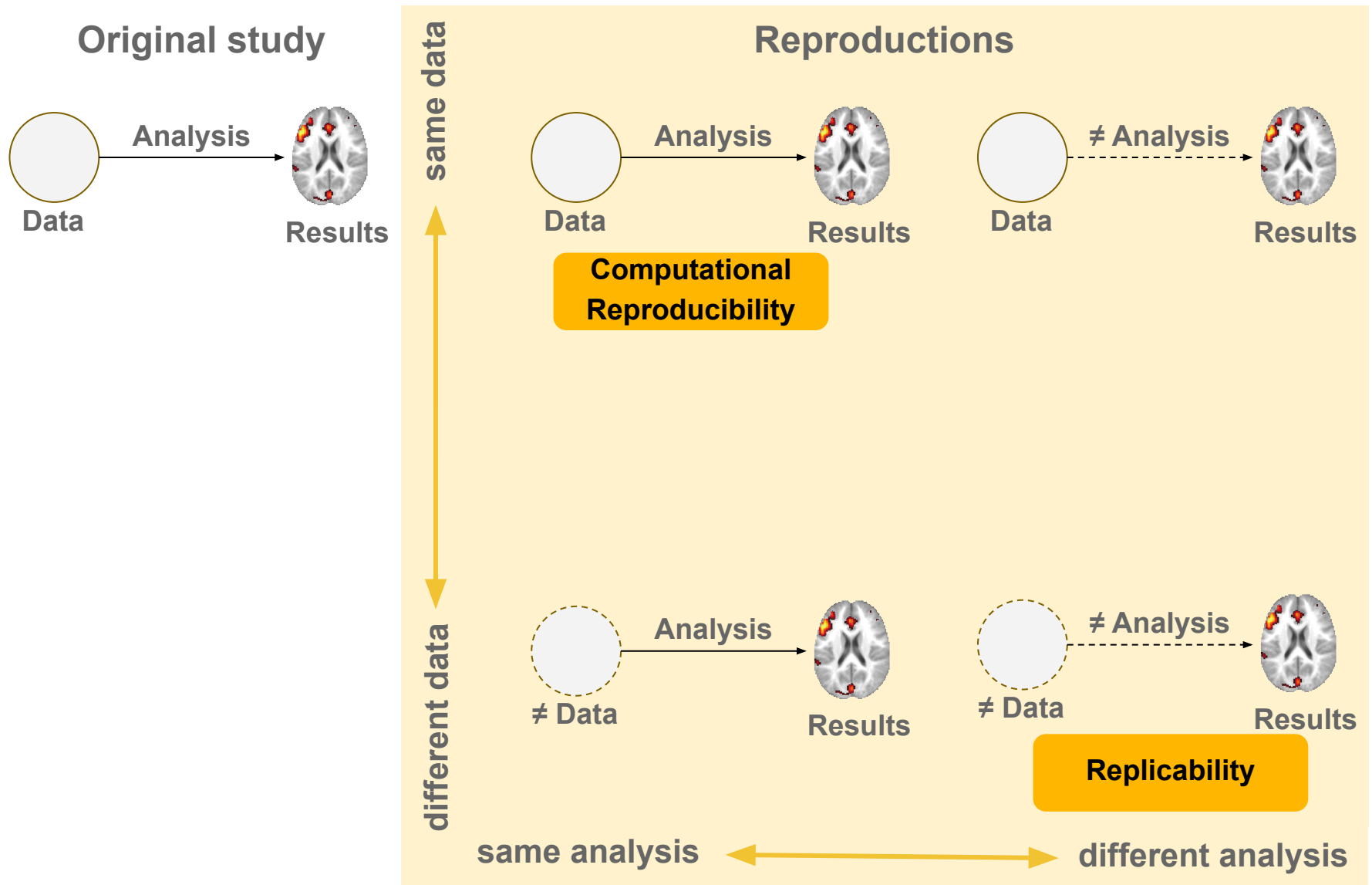
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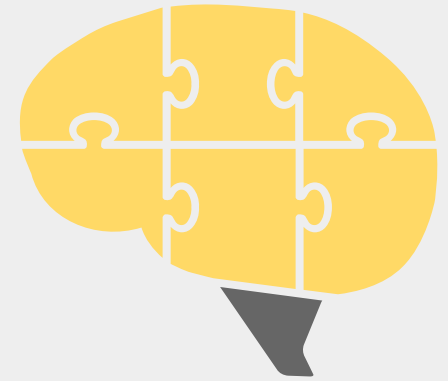
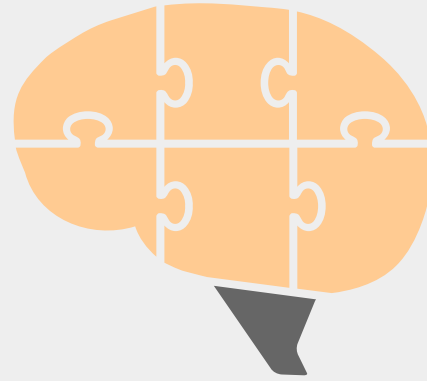


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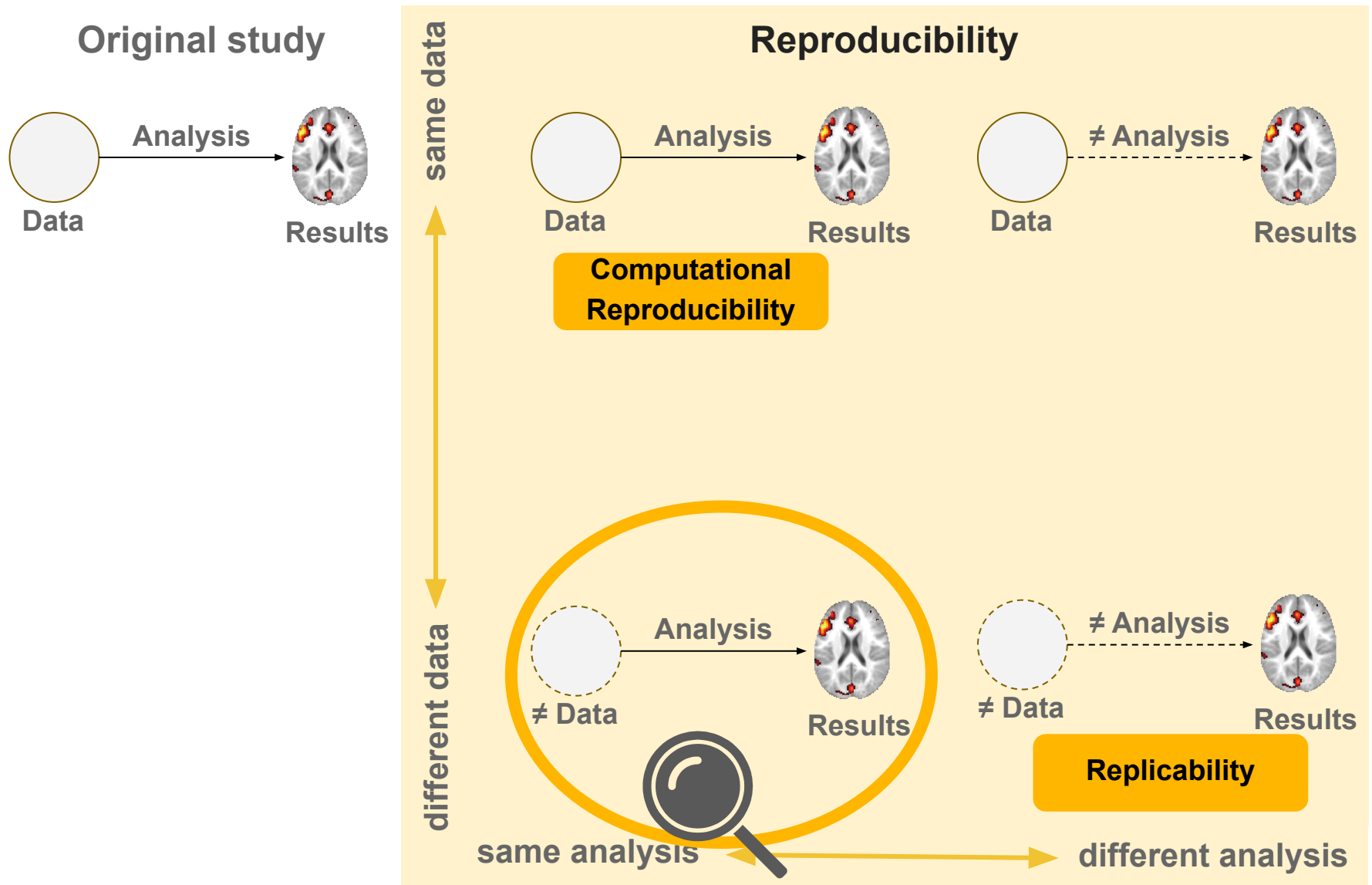




On our way to fix  
**irreproducibility...**



# Reproducible research

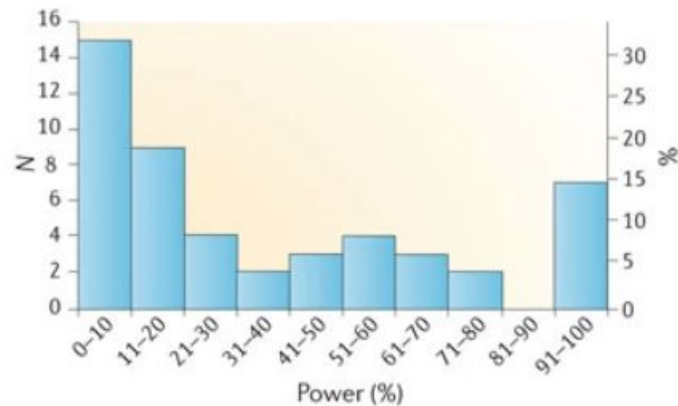


# Fixing irreproducibility with different data

## Small samples

## Low statistical power

Power of neuroscience studies



(Button et. al, 2013)

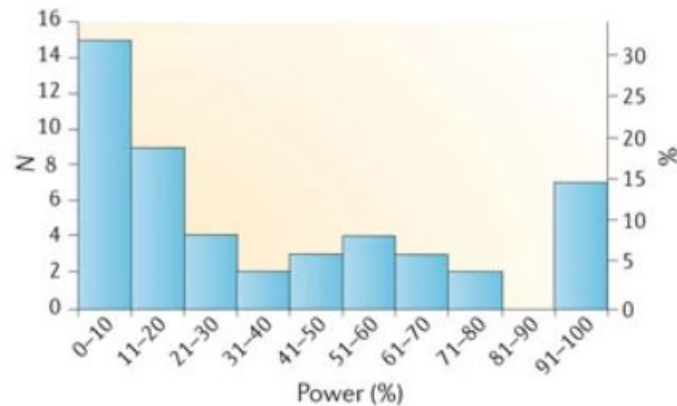
High rate of **false positives**  
in the literature

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## Lack of representativity and diversity of the samples

### X-ray: Lung opacity detection

Model trained on male images, tested on female images



(Larrazabal et. al, 2020)

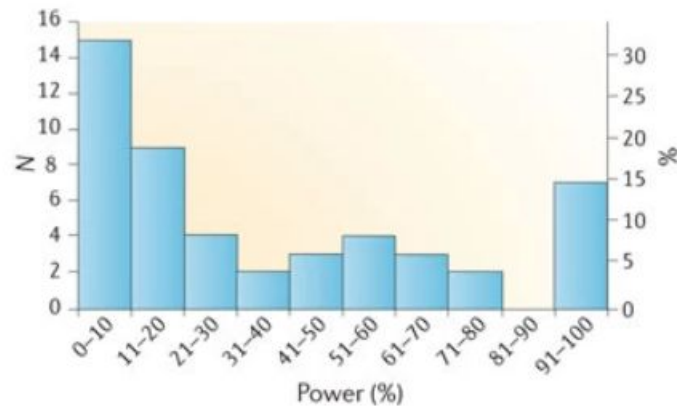
Lack of **generalisability**  
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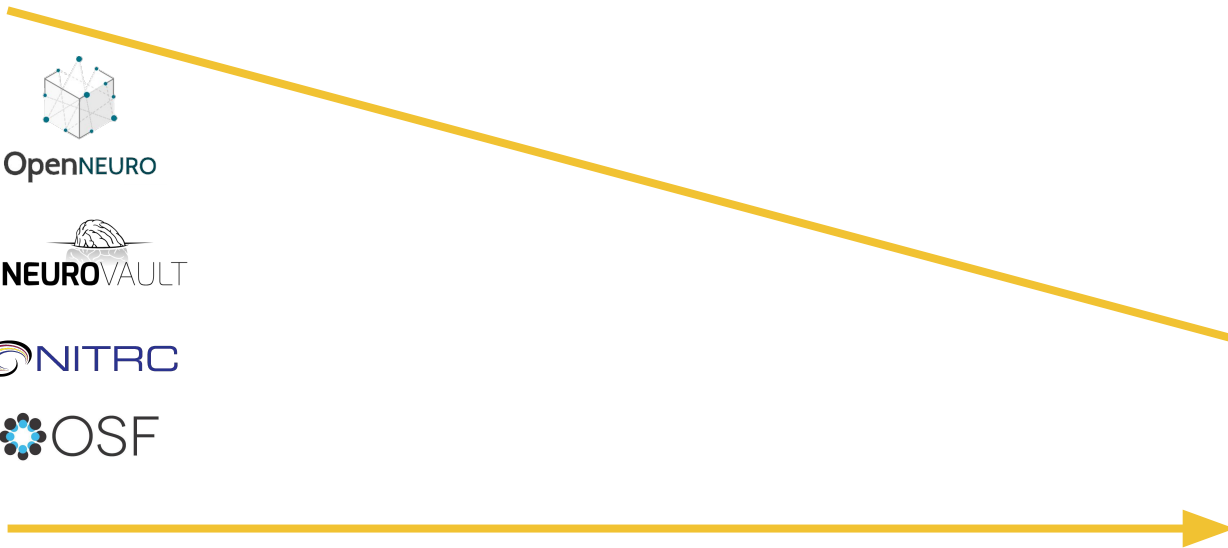
Lack of **generalisability**  
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**Solution: Data  
Sharing**

# Neuroimaging data sharing

**Single study**

30 sub.



OpenNEURO



NEUROVAULT



OSF

# Neuroimaging data sharing

## Single study

30 sub.



OpenNEURO



NEUROVAULT

NITRC

OSF

## Consortium

1000 sub.



ABIDE  
Autism Brain Imaging  
Data Exchange



CORR  
CONSORTIUM FOR  
RELIABILITY AND  
REPRODUCIBILITY



1000 Functional  
Connectomes Project

# Neuroimaging data sharing

**Single study**

30 sub.



OpenNEURO



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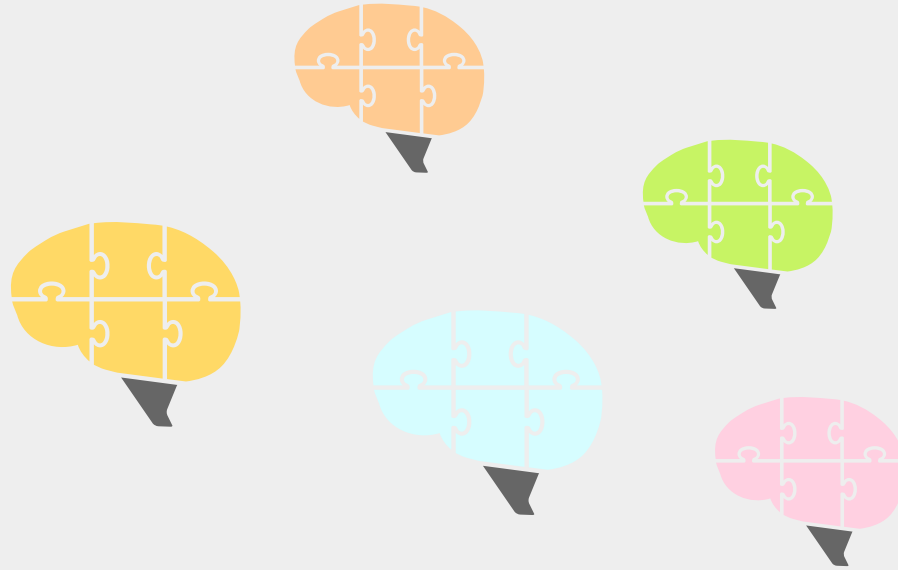


HUMAN  
Connectome  
PROJECT

**Cohort**

100 000 sub.

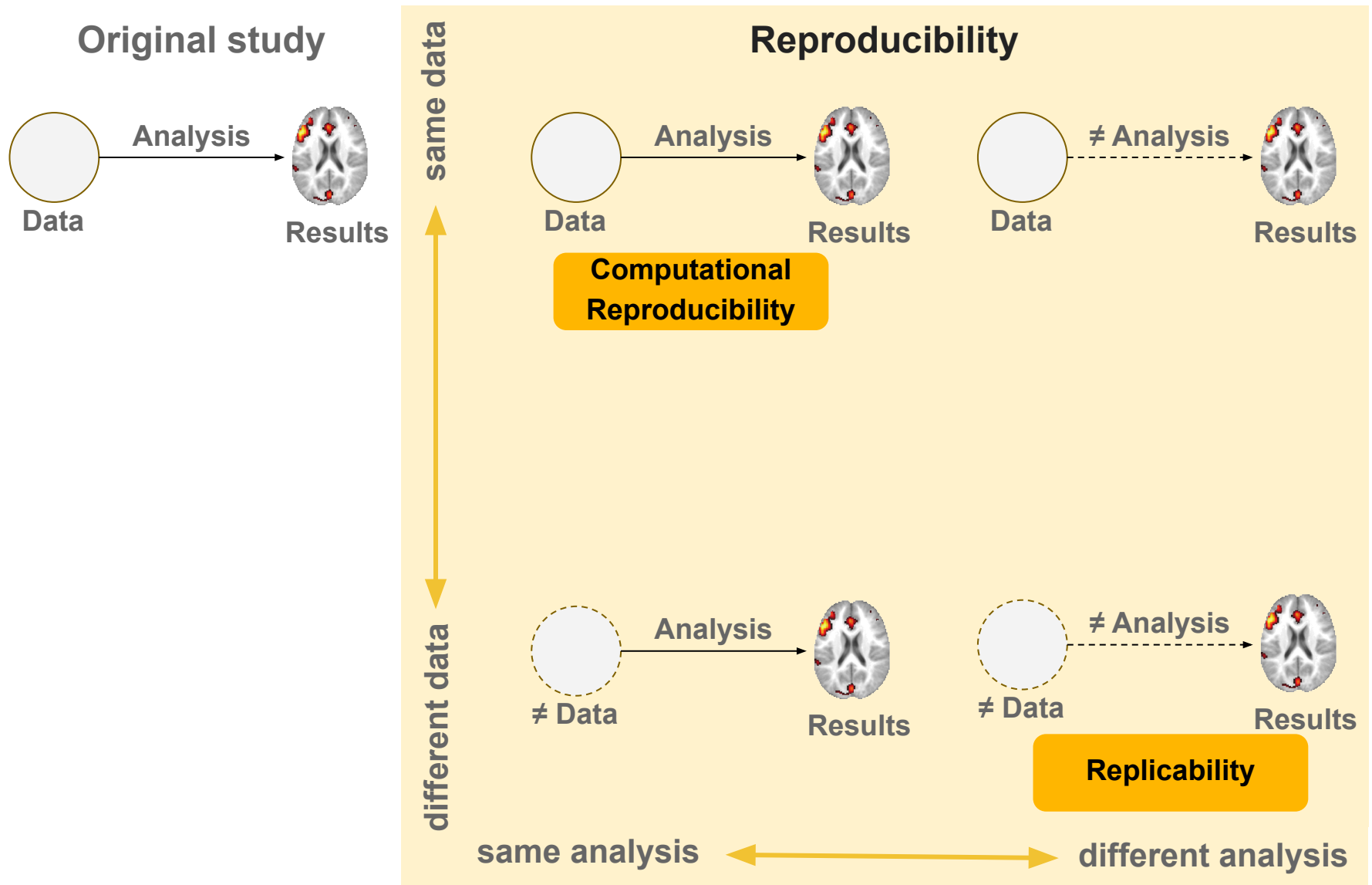
biobank\*  
improving the health of future generations



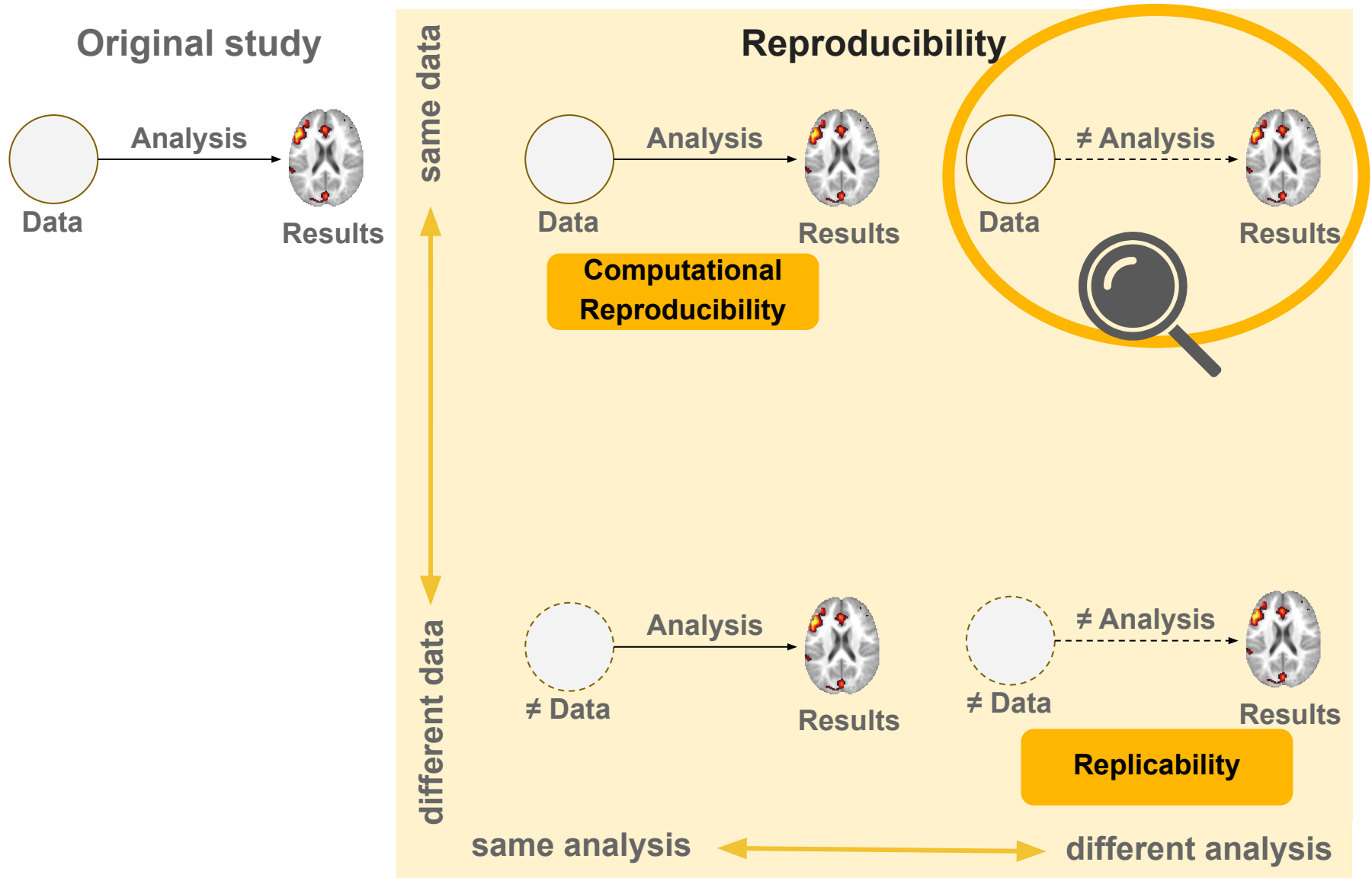
**Different pipelines...**  
different results?



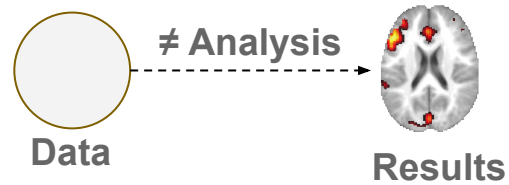
# Reproducible research



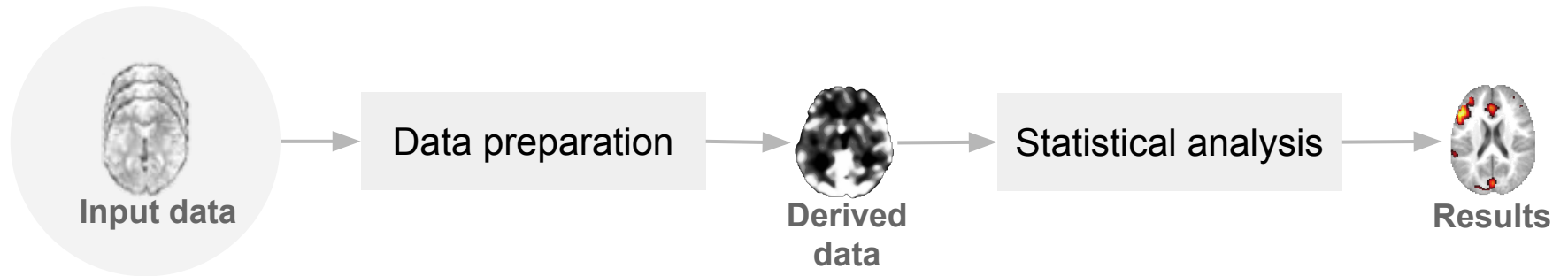
# Reproducible research



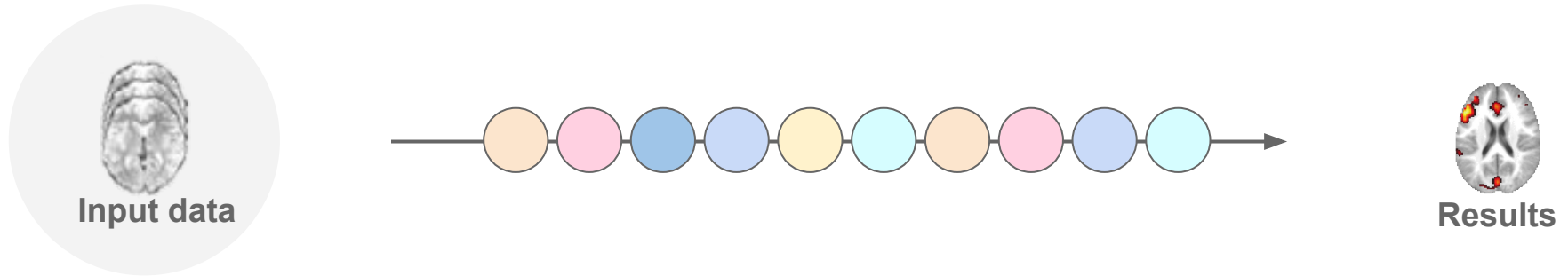
# A multiplicity of analysis pipelines



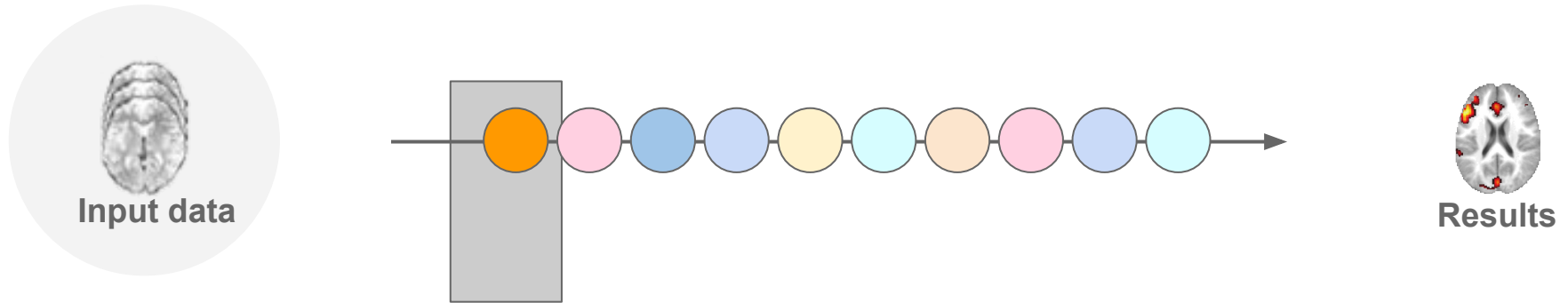
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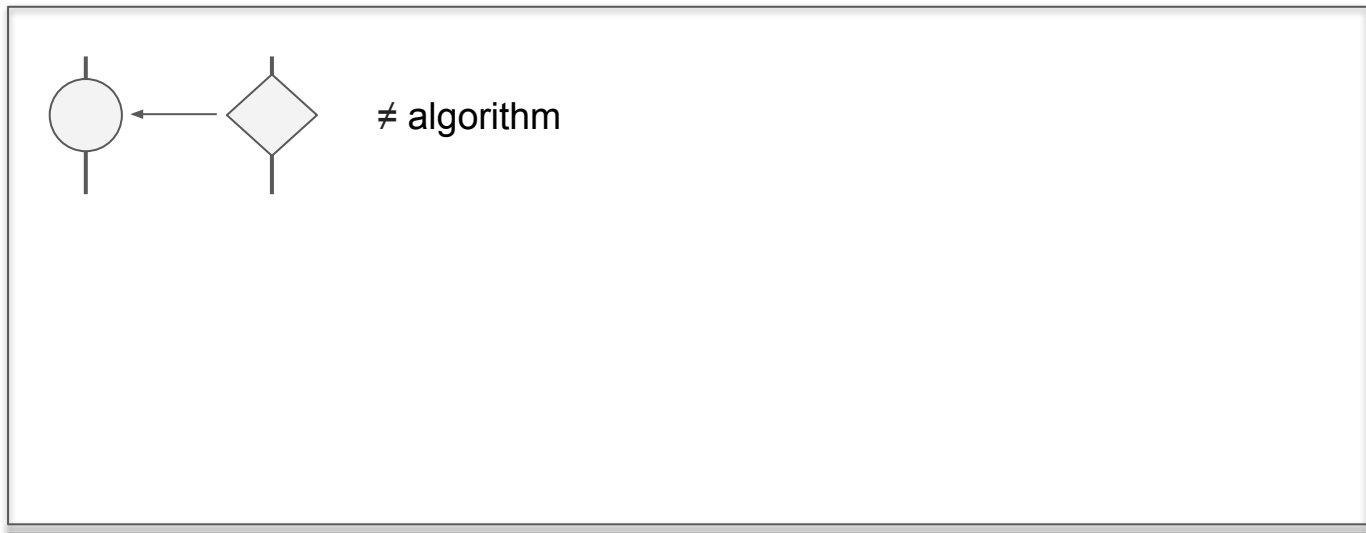
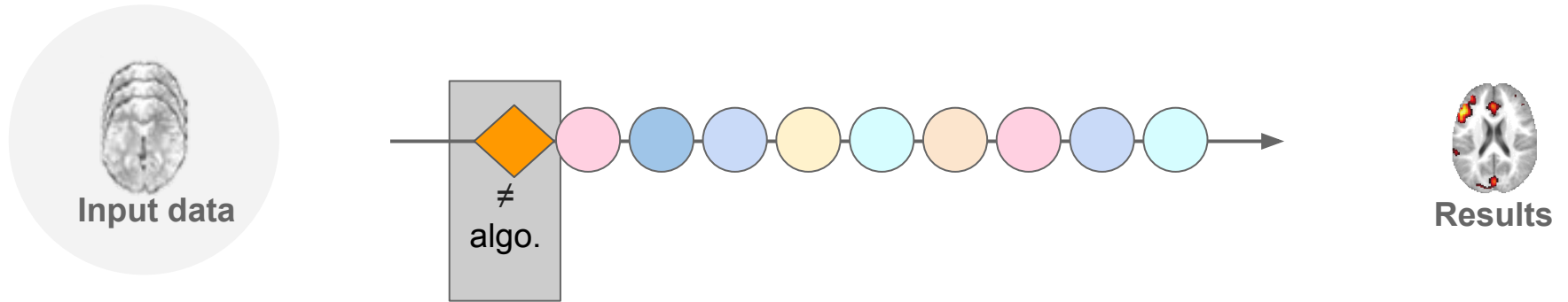
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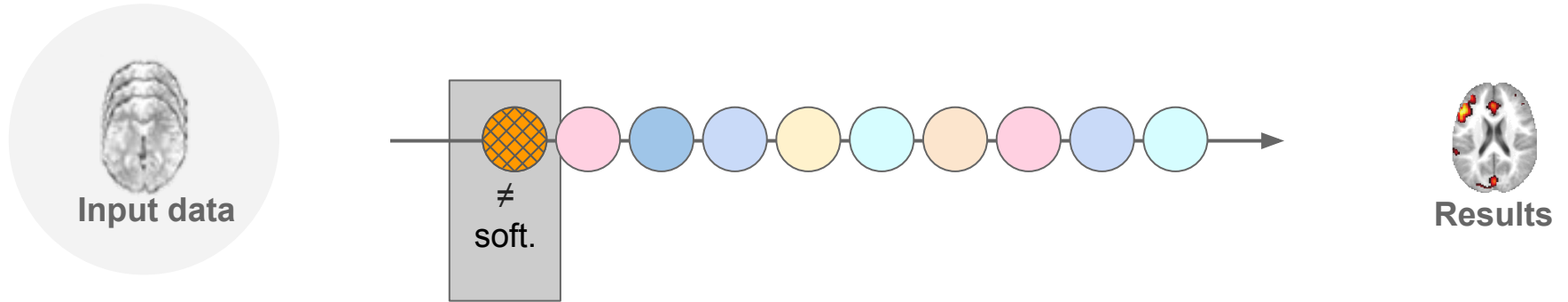
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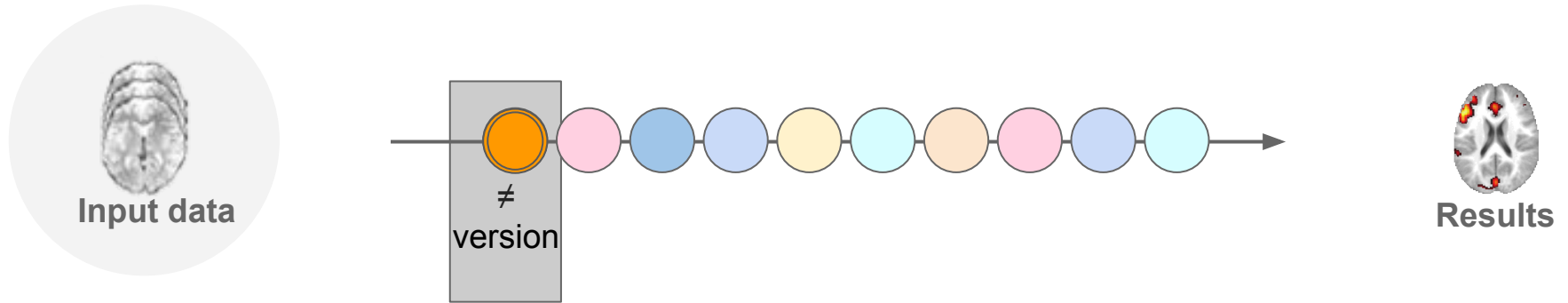


# A multiplicity of analysis pipelines

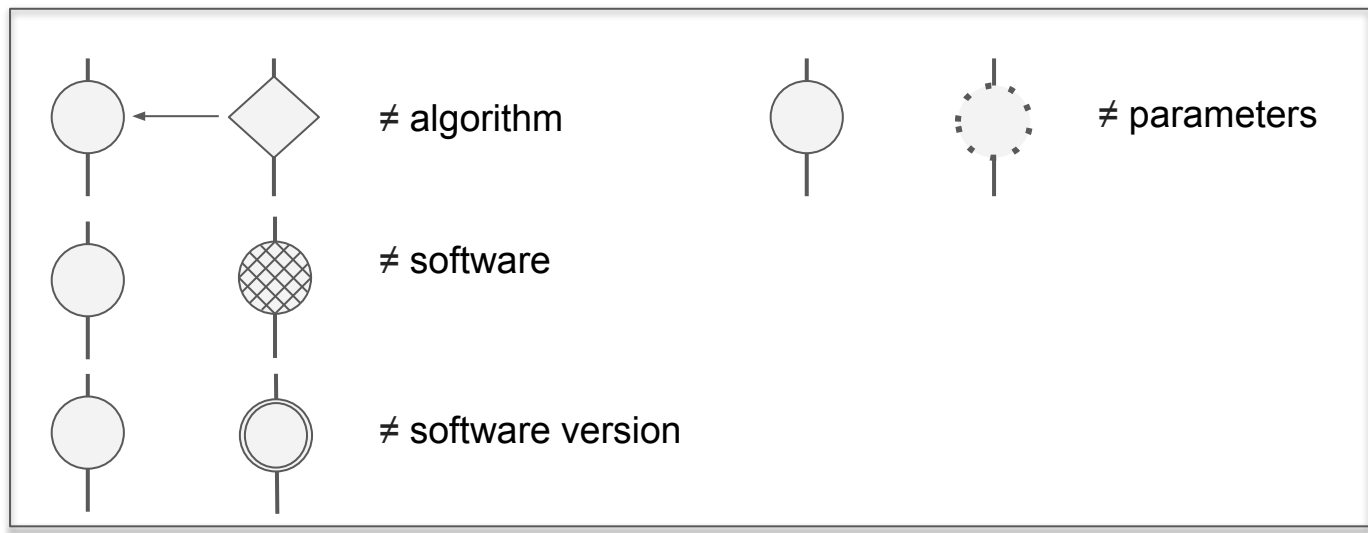
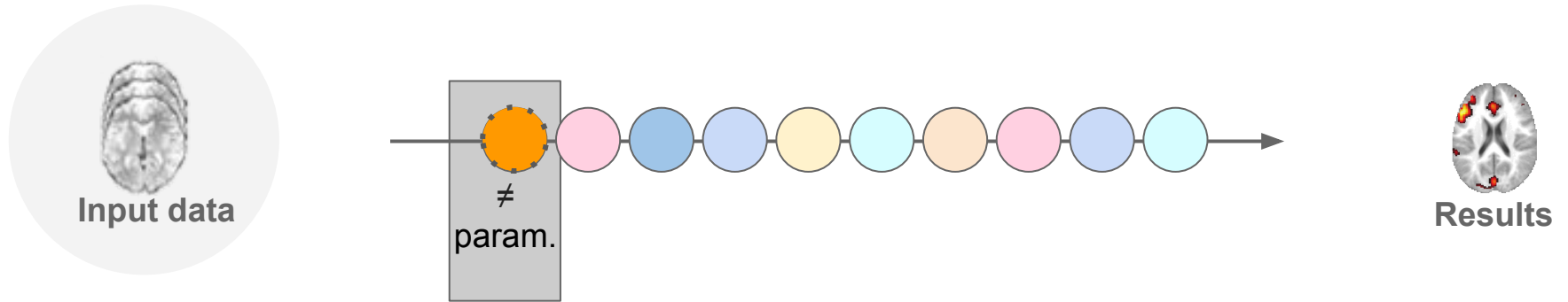




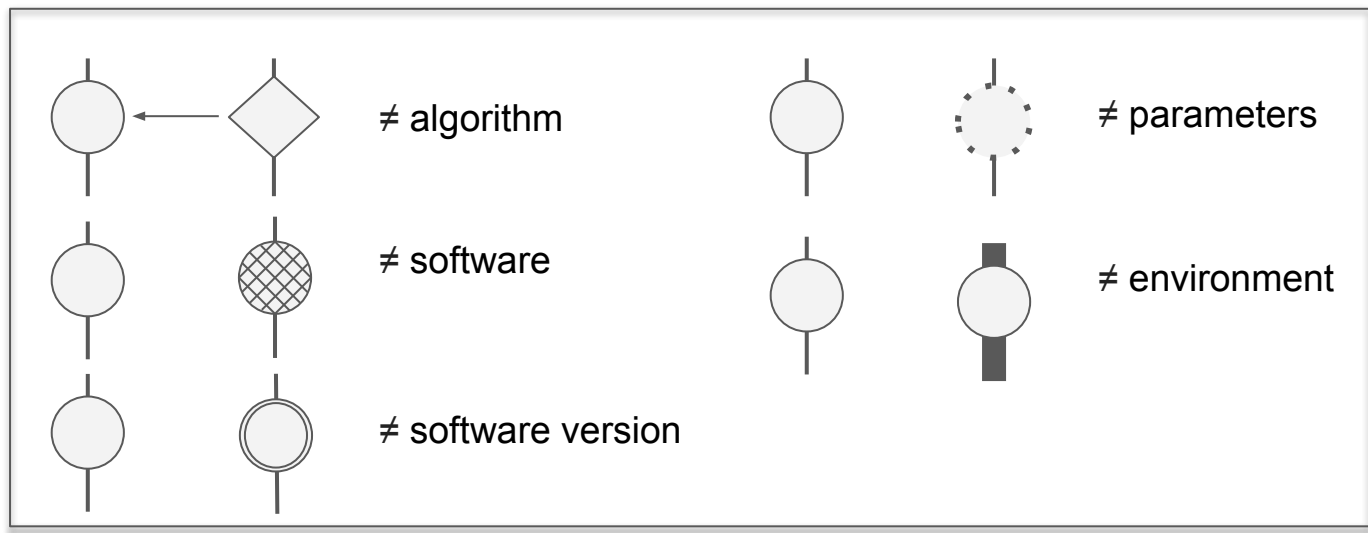
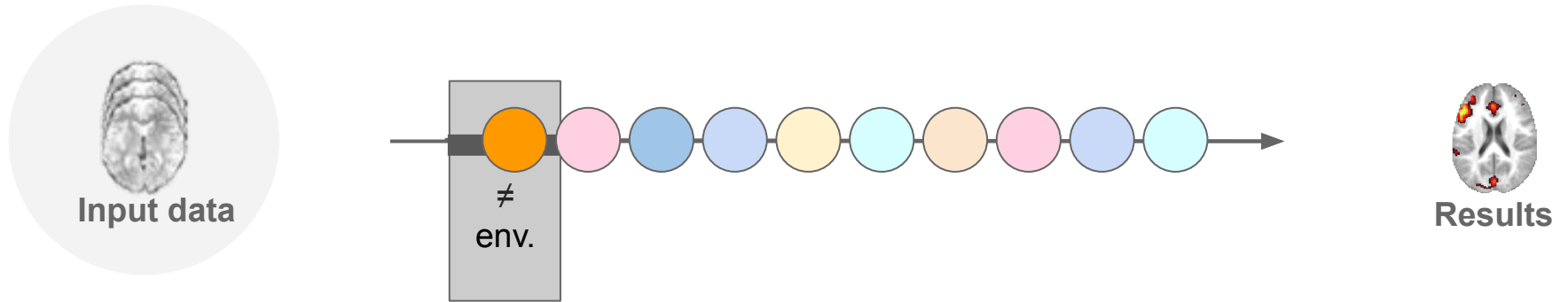
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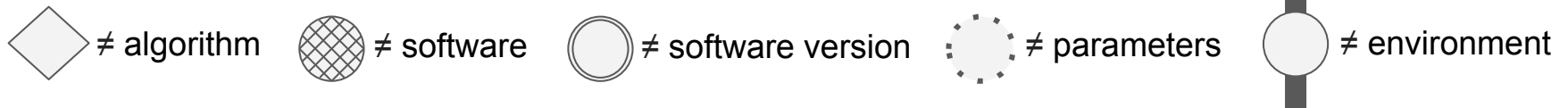
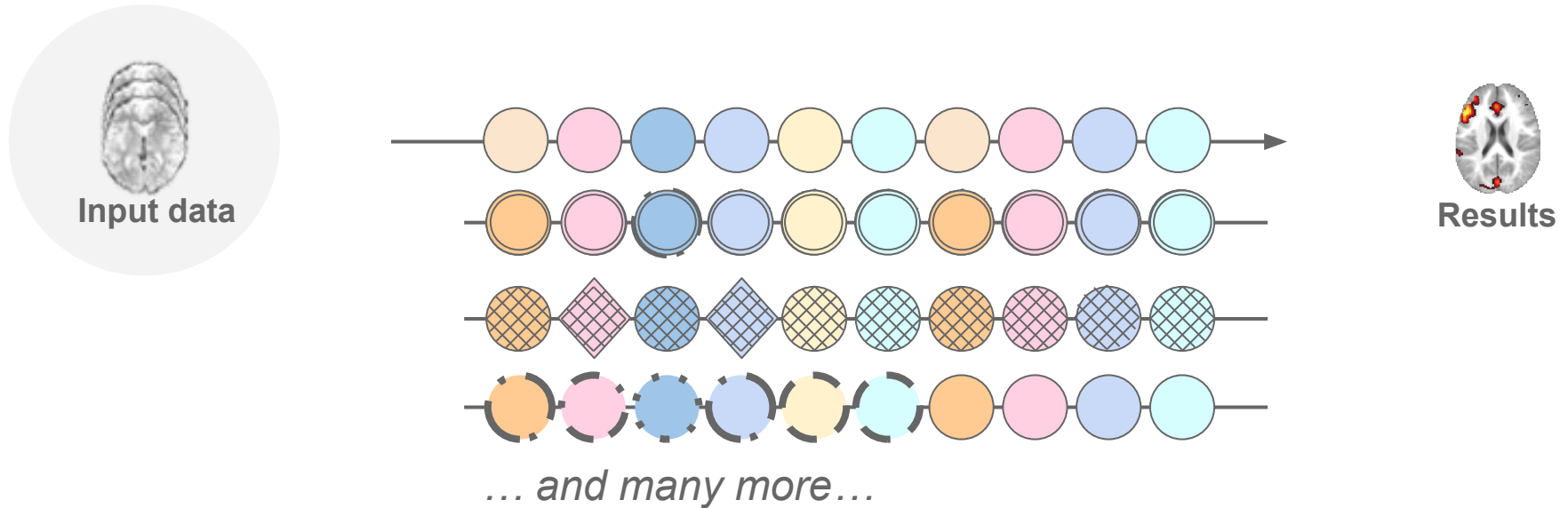
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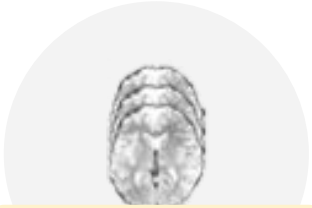
# A multiplicity of analysis pipelines



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# Many-analyst project : NARPS

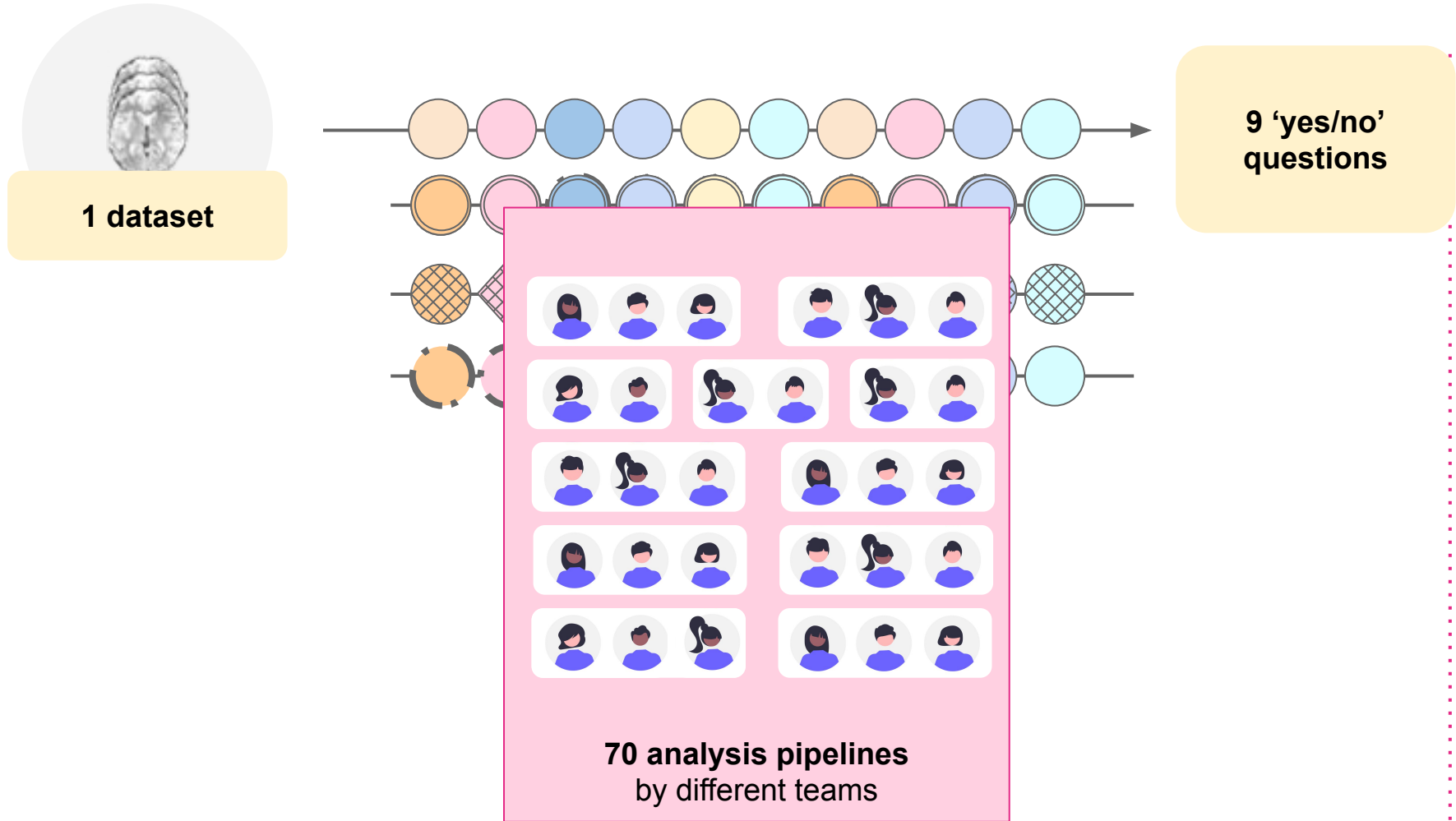


**1 dataset**

**9 'yes/no'  
questions**

[Botvinik-Nezer et. al, Nature 2020]

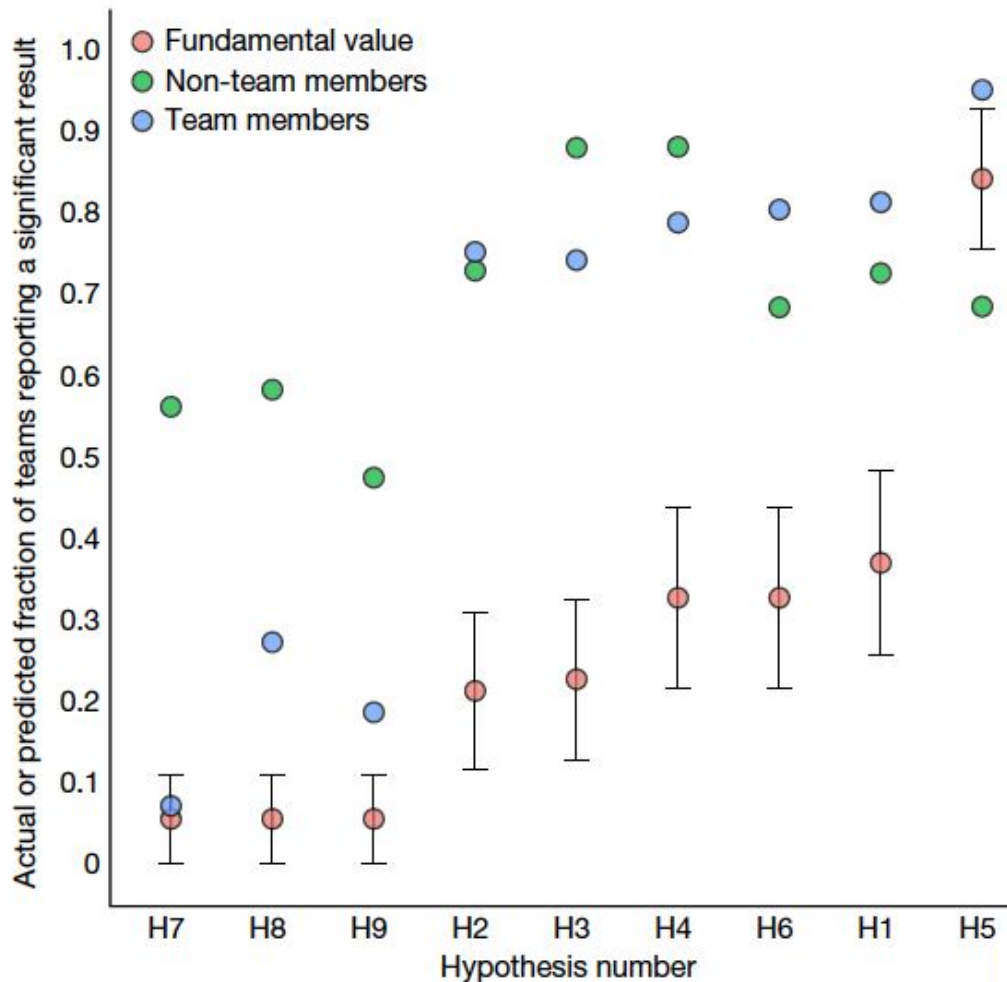
# Many-analyst project : NARPS



[Botvinik-Nezer et. al, Nature 2020]

# Many-analyst project : NARPS

Results over the **70 post-processing pipelines**:

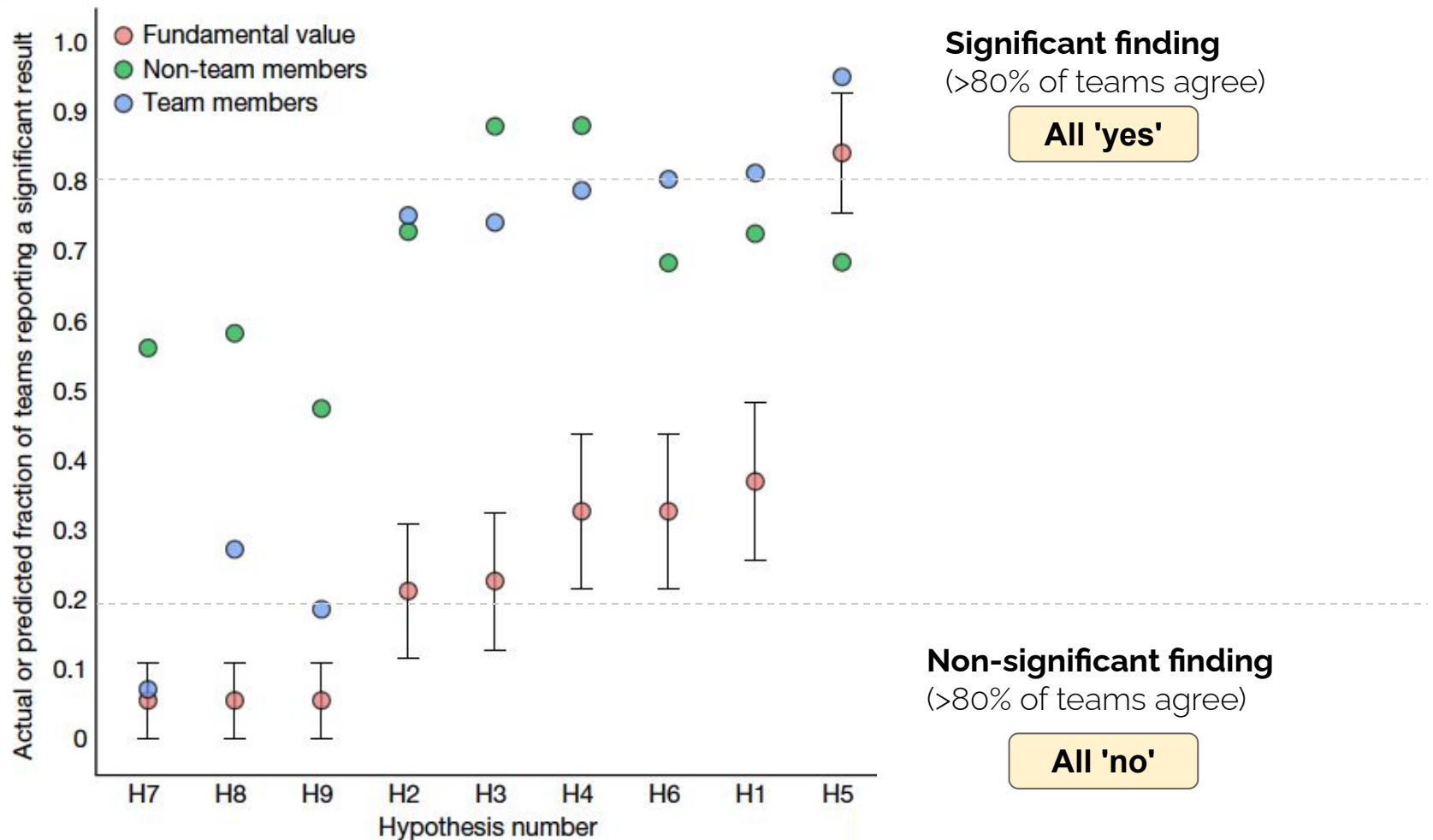


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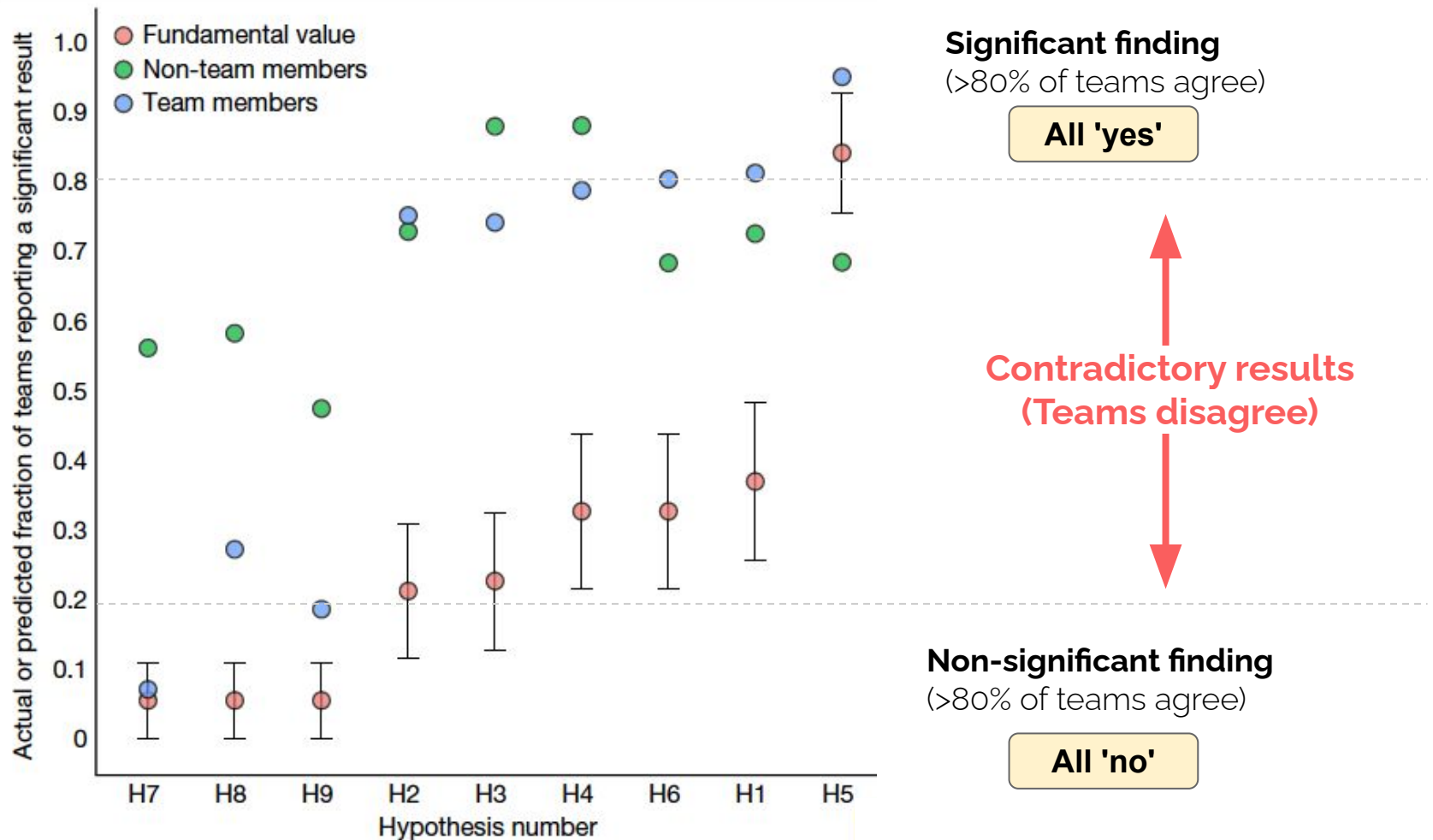
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# Many-analyst project : NARPS

Results over the **70 post-processing pipelines**:



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[Botvinik-Nezer et. al, Nature 2020]

# Variability across neuroimaging software

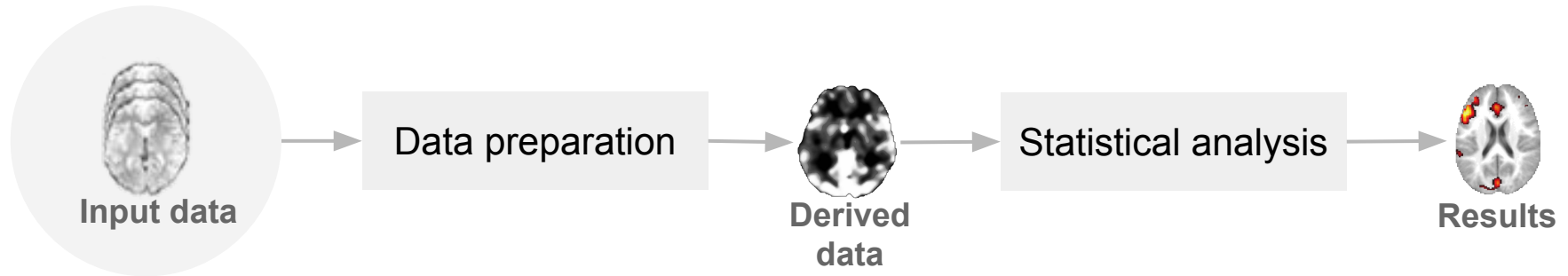


Alex Bowring



Tom Nichols  
Oxford Uni. (UK)

## Principles of functional MRI



# Variability across neuroimaging software

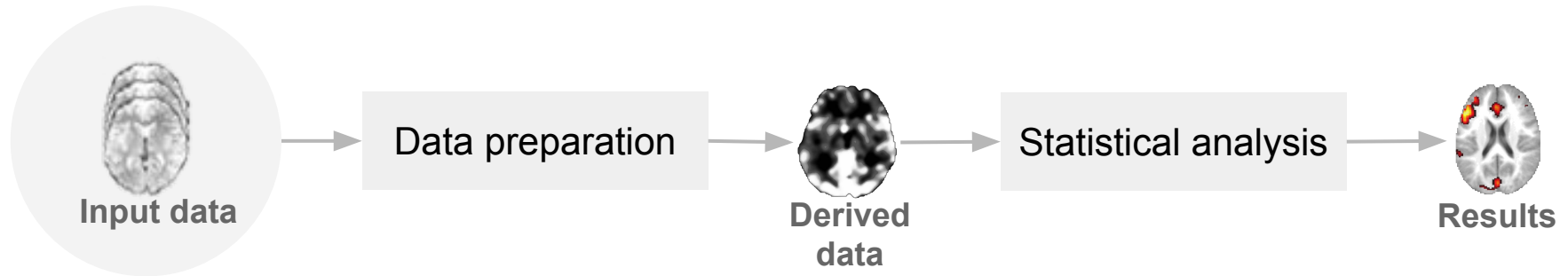


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## Principles of functional MRI



# Variability across neuroimaging software



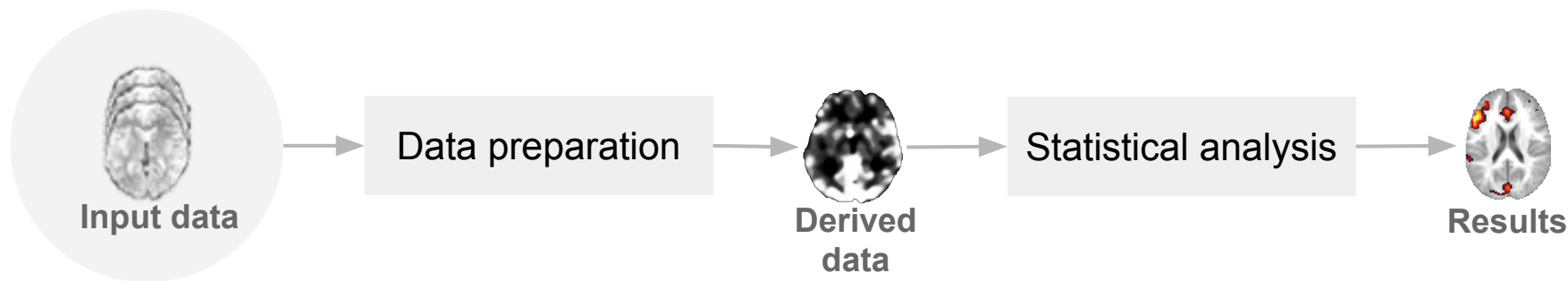
Alex Bowring



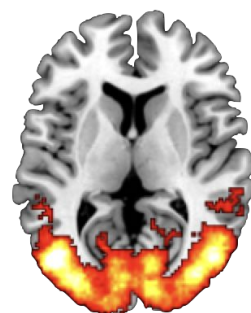
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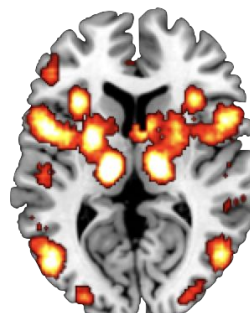
## Principles of functional MRI



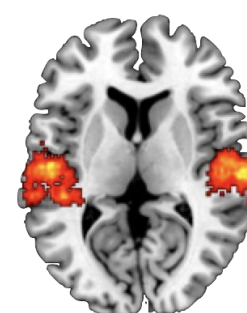
## fMRI results: Activations maps



 Visual



 Hand motion



 Music

# Variability across neuroimaging software

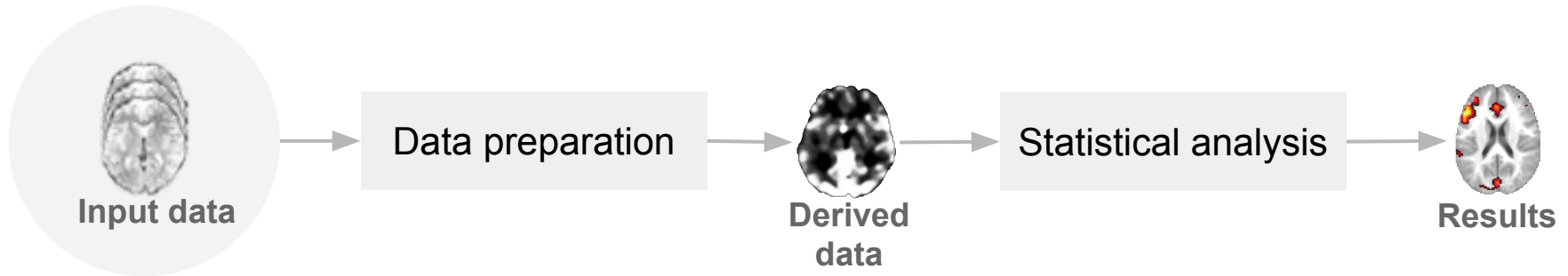


Alex Bowring



Tom Nichols  
Oxford Uni. (UK)

## Principles of functional MRI



**Goal 1**: Investigate the **variability** observed in **fMRI results** when using **different software packages**

# Variability across neuroimaging software



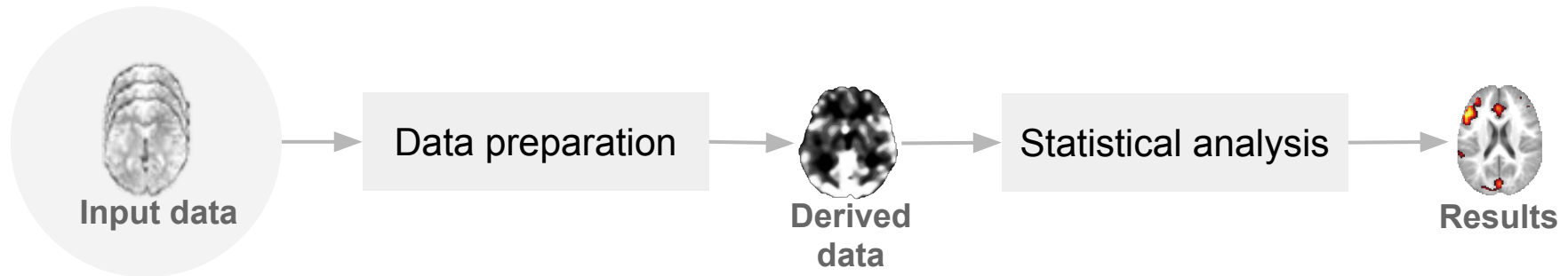
Alex Bowring



Tom Nichols

Oxford Uni. (UK)

## Principles of functional MRI



**Goal 1**: Investigate the **variability** observed in **fMRI results** when using **different software packages**

- **Reproduced 3 studies** from the literature
- Using **3 fMRI software: AFNI, FSL, SPM**  
(used in 80% literature ([Carp, 2012](#)))
- **Pipelines aligned** using available configurations.

# Variability across neuroimaging software

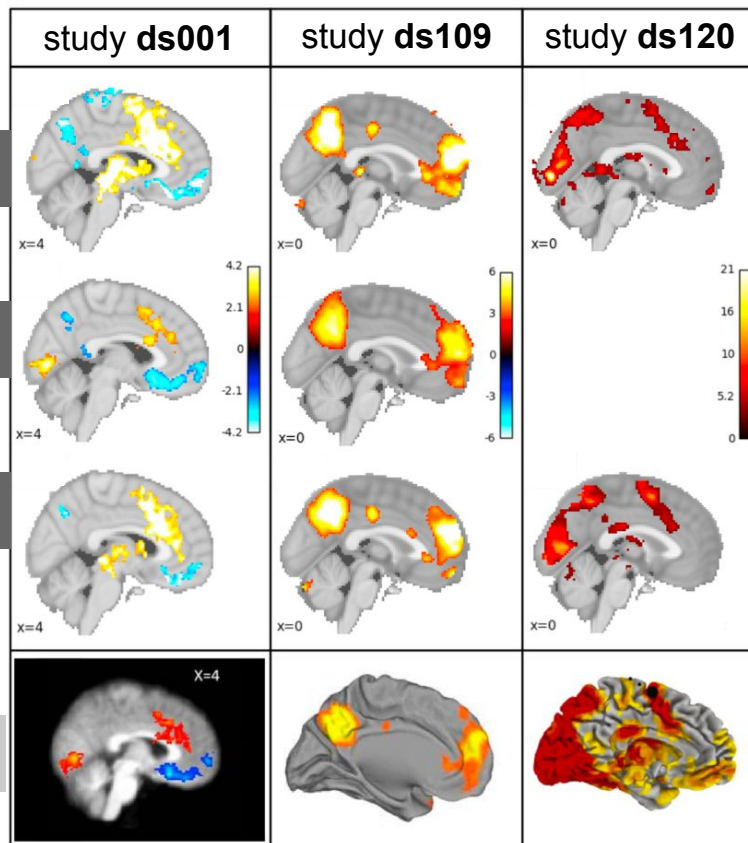


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Oxford Uni. (UK)

- Variability in the activation maps



[Bowring Maumet\* Nichols\*, HBM 2019]

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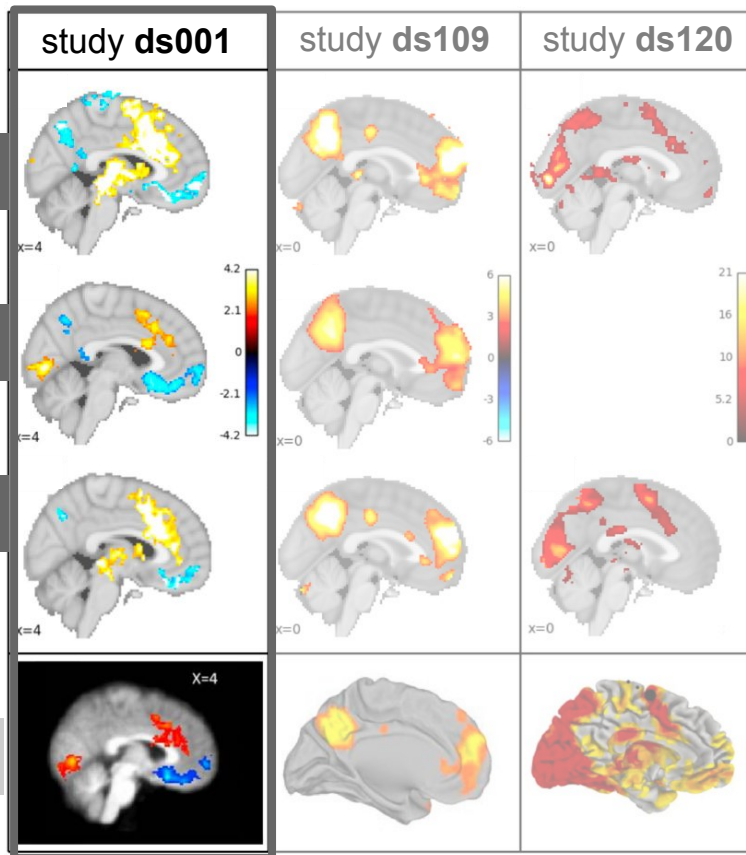


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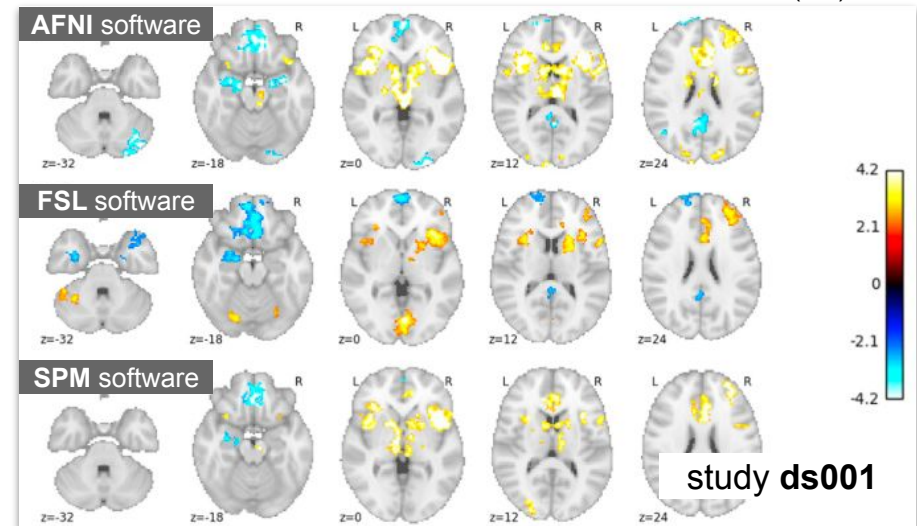
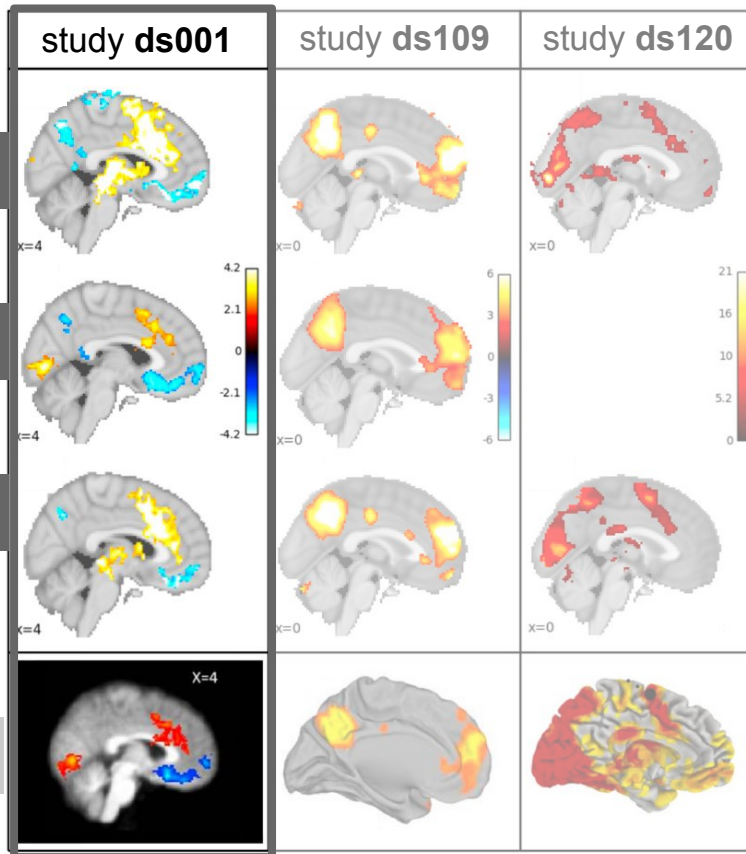


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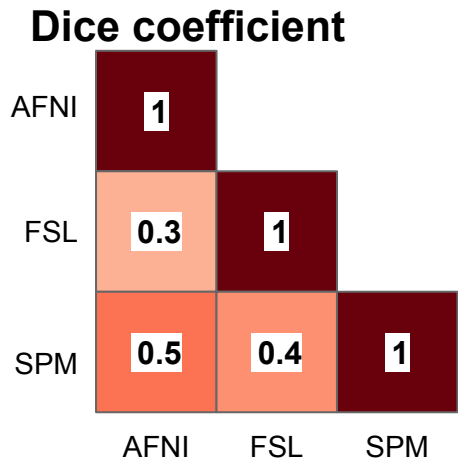
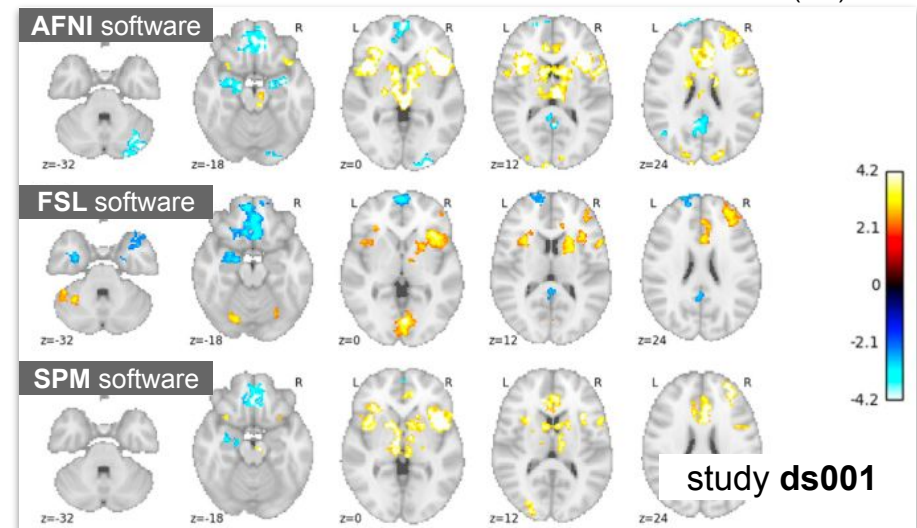
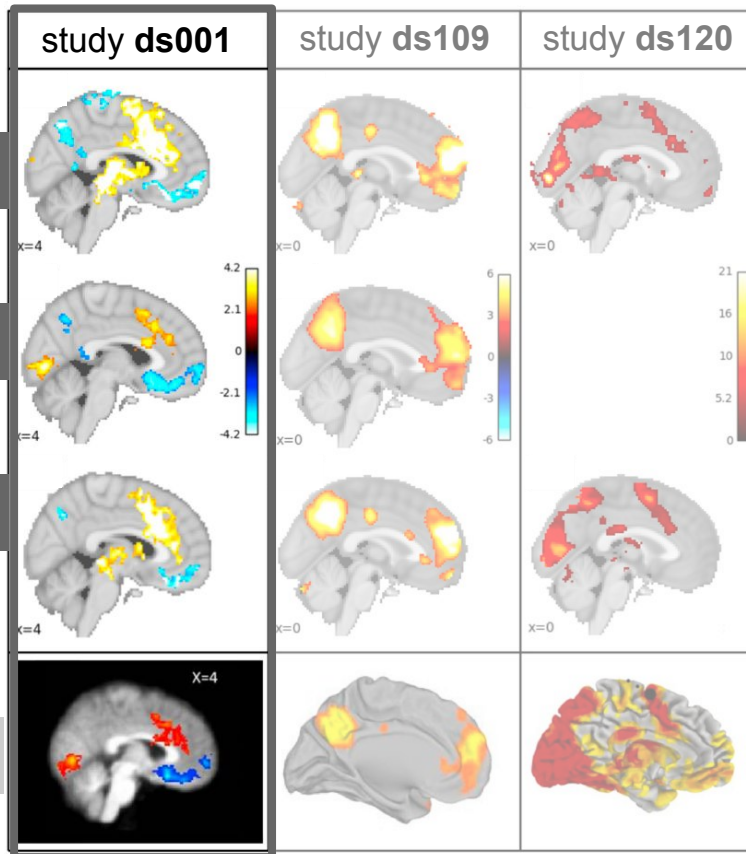
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Oxford Uni. (UK)

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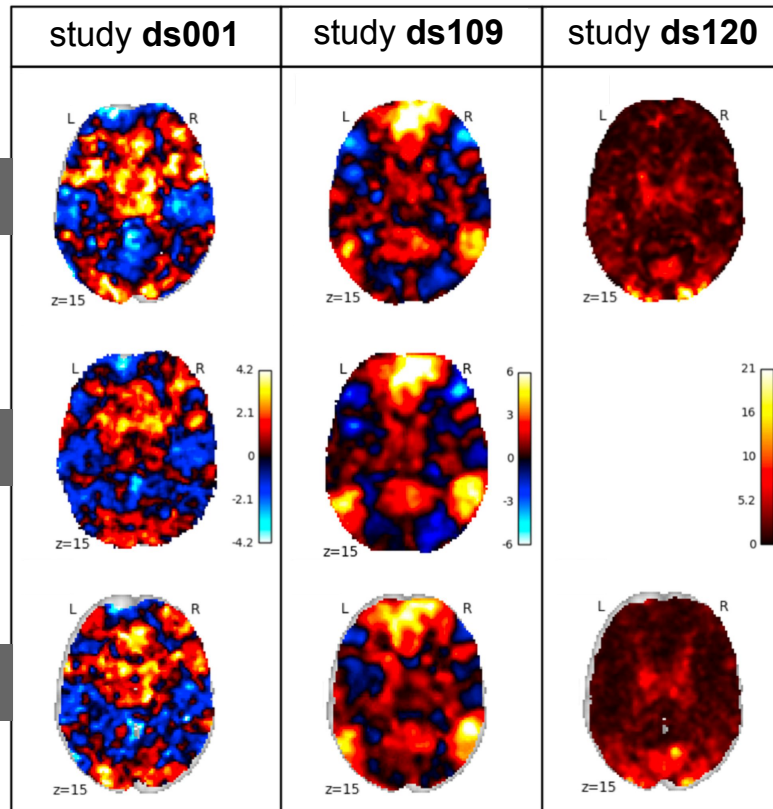
[Bowring Maumet\* Nichols\*, HBM 2019]

# Variability across neuroimaging software



Alex Bowring Tom Nichols  
Oxford Uni. (UK)

- Variability in the unthresholded statistic maps



## Correlations

AFNI vs. FSL	0.62
AFNI vs. SPM	0.61
FSL vs. SPM	0.68

**Conclusion:** The choice of software impacted both the final activation and statistic maps.

[Bowring Maumet\* Nichols\*, HBM 2019]

# Variability across neuroimaging software



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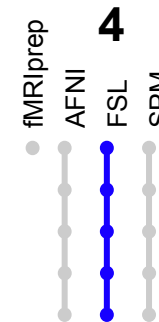
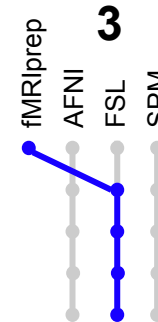
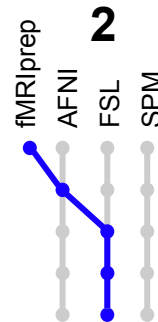
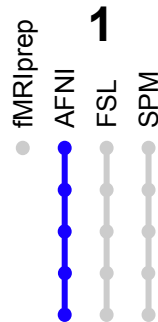


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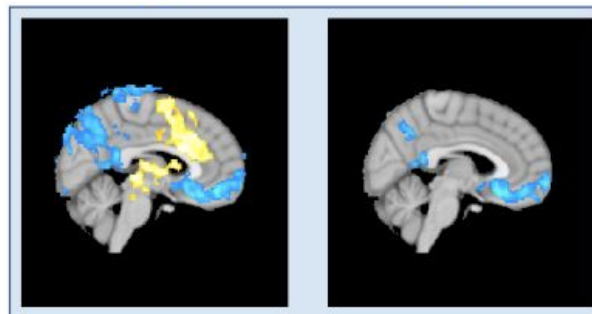
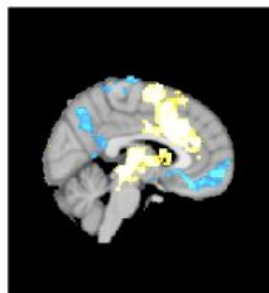
**Goal 2:** Investigate how remaining differences in software implementations can explain the observed differences

## study ds001

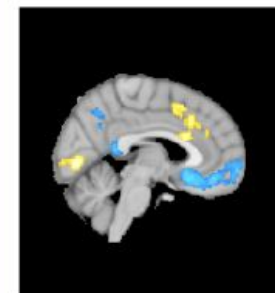
1. Preprocessing
2. Subject-level Signal
3. Subject-level Drift
4. Subject-level Noise
5. Group-level Stat



AFNI  
software



FSL  
software



[Bowring Nichols\* Maumet\*, HBM 2021]

# Variability across neuroimaging software



Alex Bowring

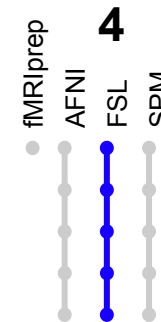
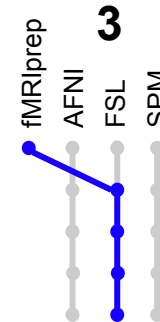
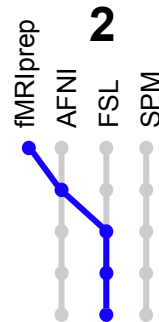
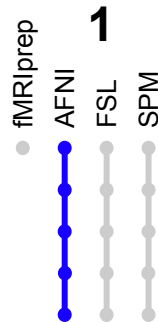


Tom Nichols  
Oxford Uni. (UK)

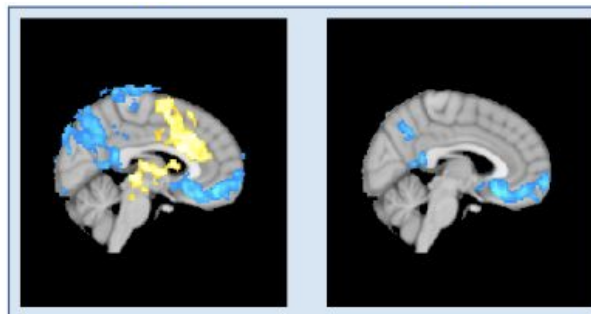
**Goal 2:** Investigate how remaining differences in software implementations can explain the observed differences

## study ds001

1. Preprocessing
2. Subject-level Signal
3. Subject-level Drift
4. Subject-level Noise
5. Group-level Stat



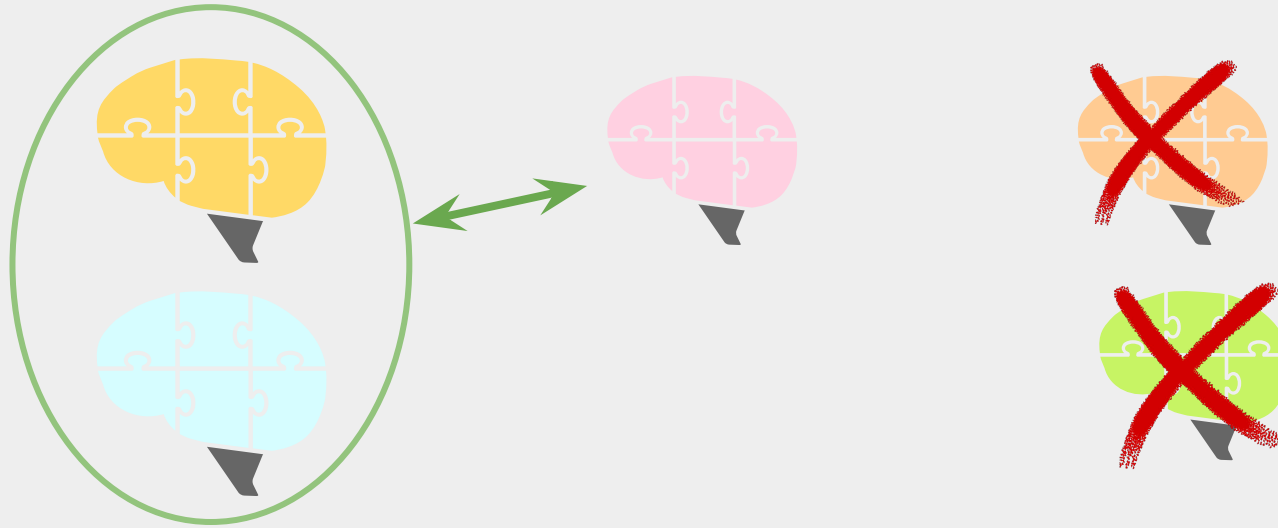
AFNI  
software



FSL  
software

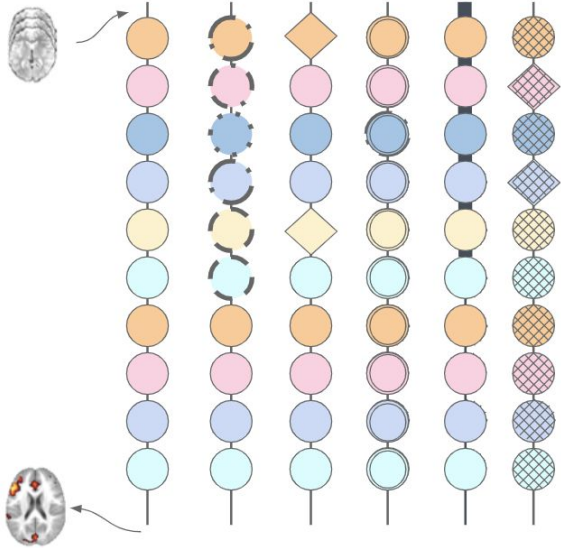
**Conclusion:** 1 main contributing factor was found but different for each study

[Bowring Nichols\* Maumet\*, HBM 2021]

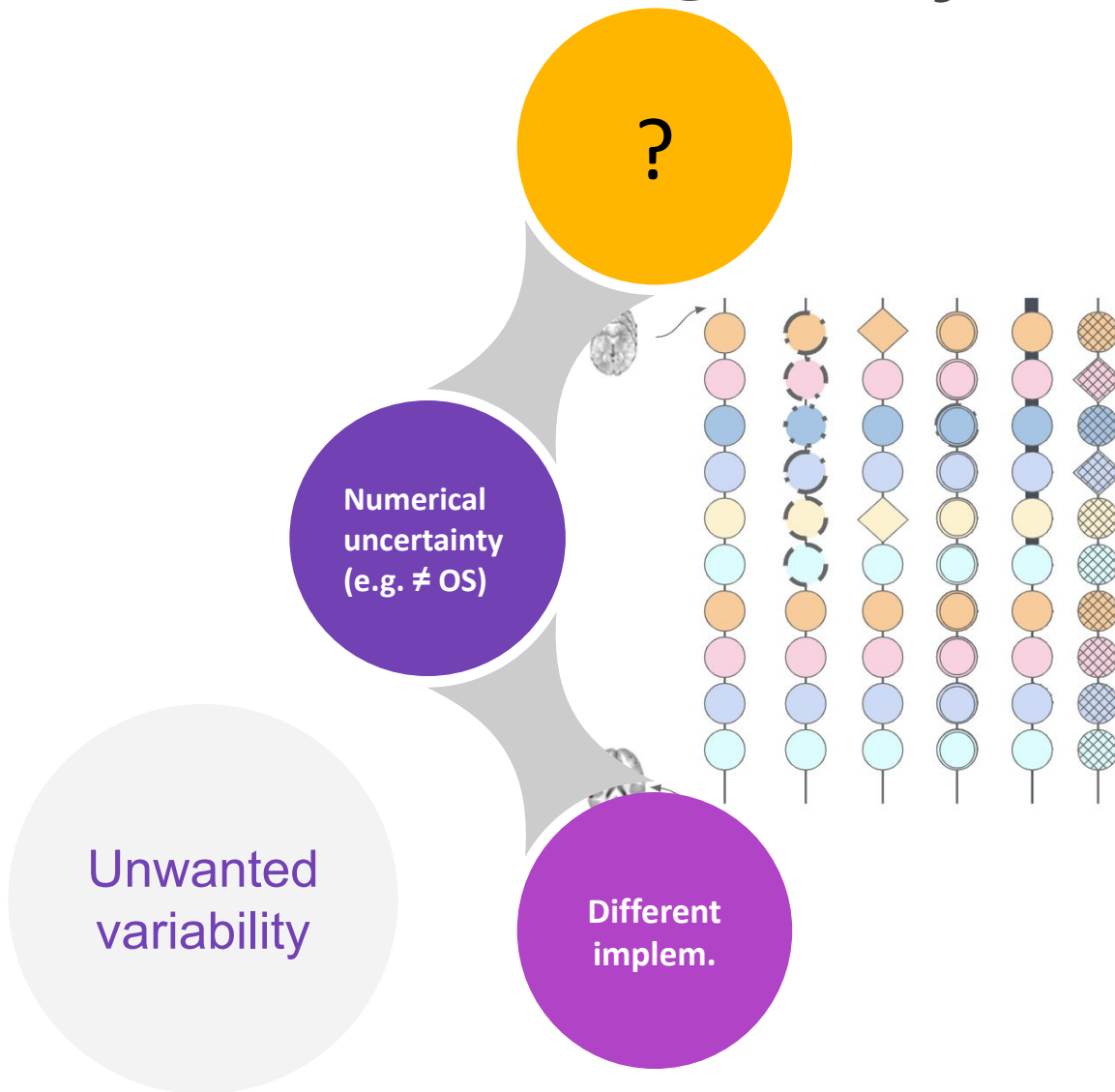


**Understanding**  
analytical variability

# Understanding analytical variability...

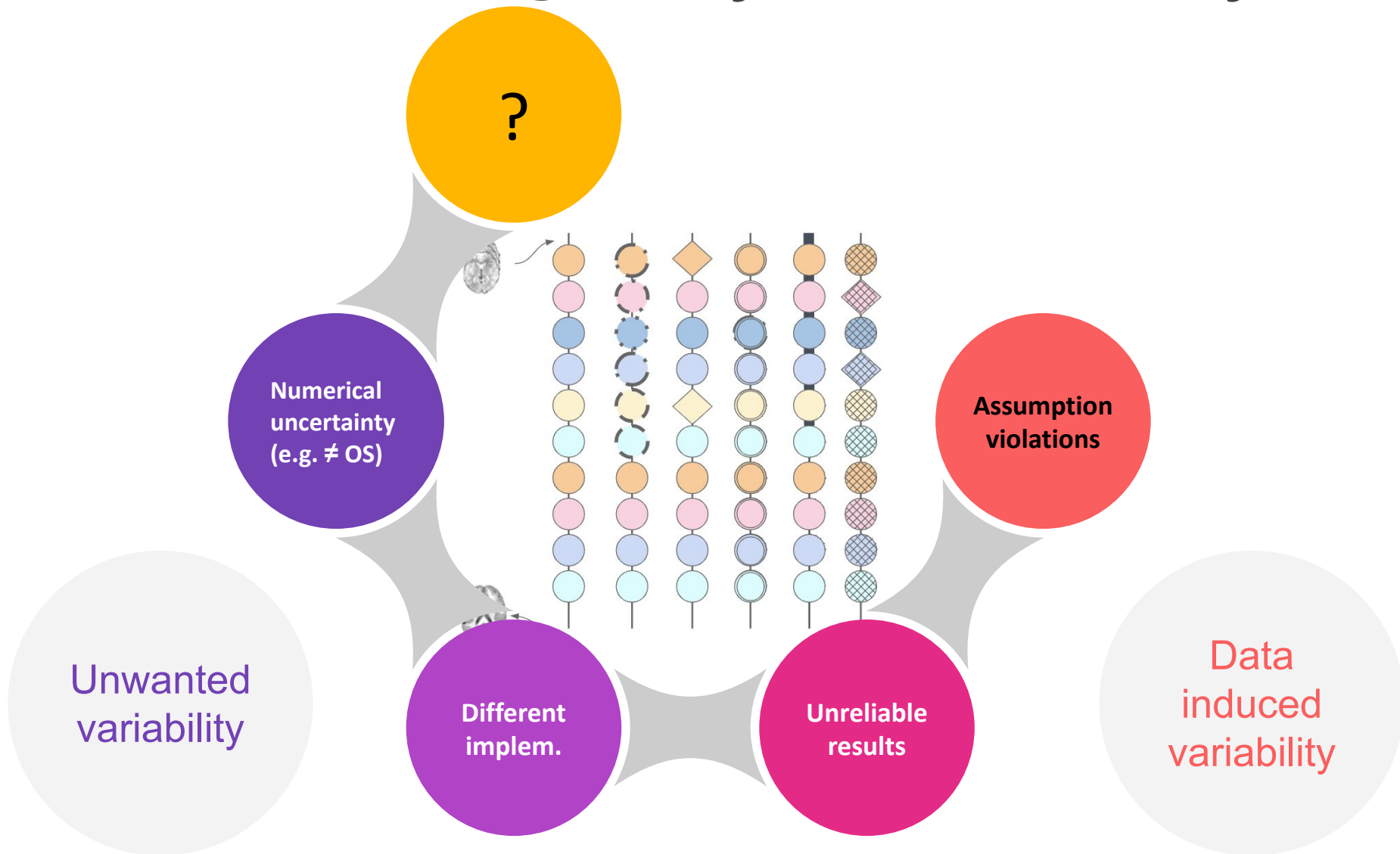


# Understanding analytical variability...

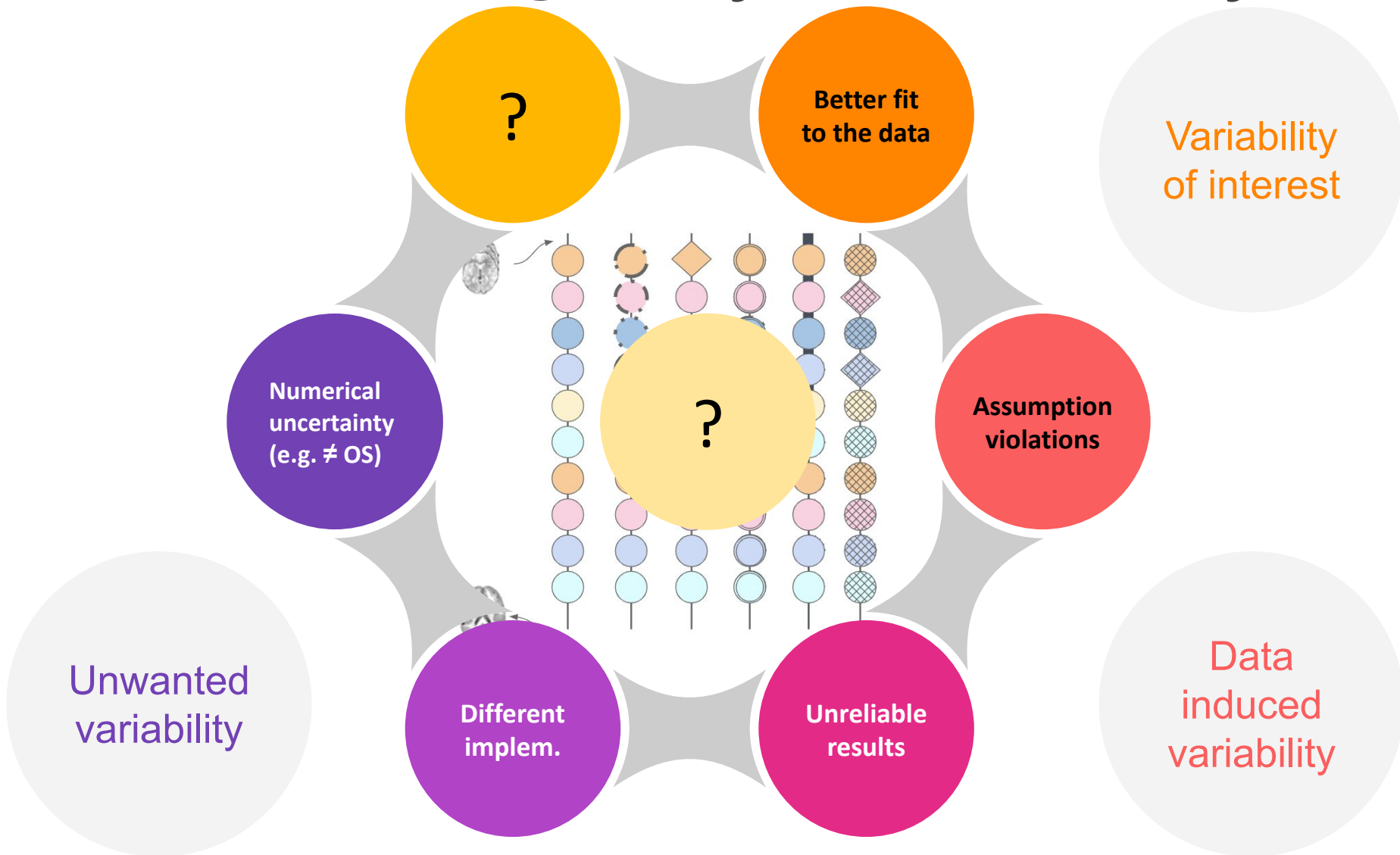


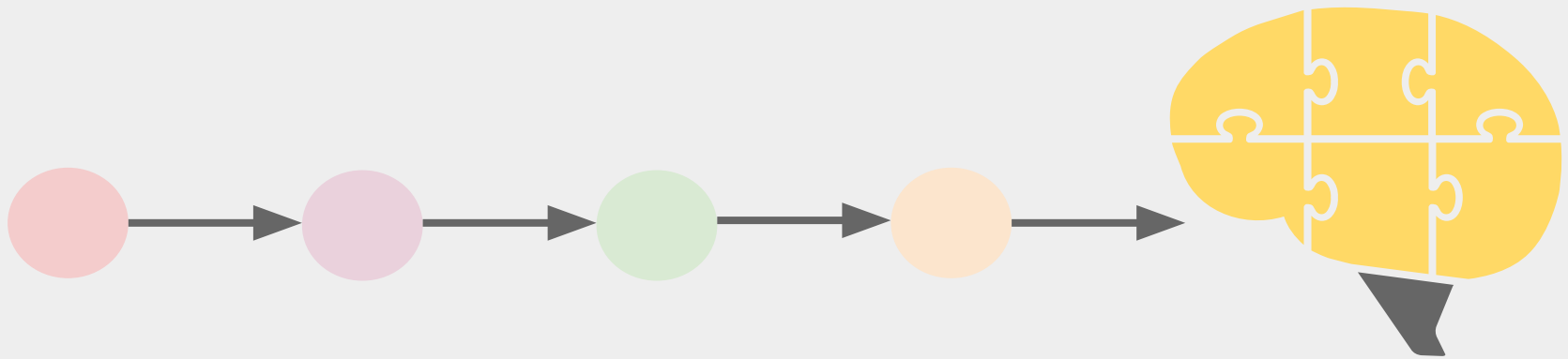


# Understanding analytical variability...



# Understanding analytical variability...





**Describing** the  
neuroimaging  
**pipeline space**

# NARPS open pipelines



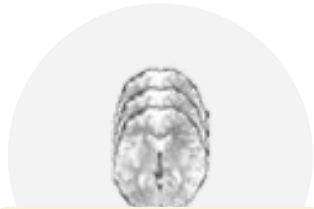
**Boris Clenet**



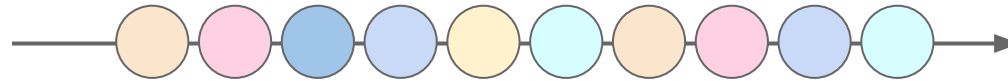
**Elodie Germani**



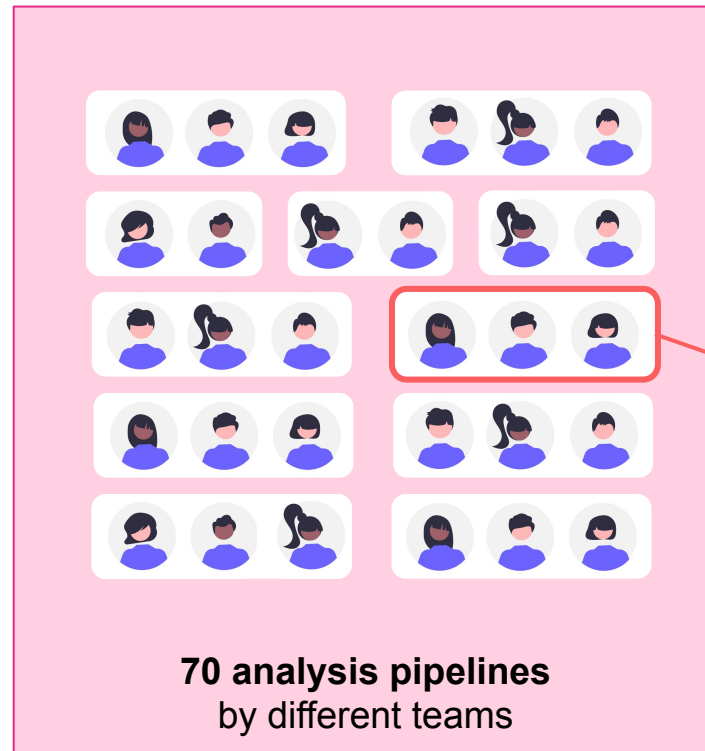
**Jérémy Lefort-Besnard**



**1 dataset**



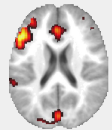
**9 'yes/no' questions**



**70 analysis pipelines**  
by different teams

1- H1: "yes"

2- Activation +  
Statistic brain  
maps



3- Textual  
description of the  
methods

# NARPS open pipelines



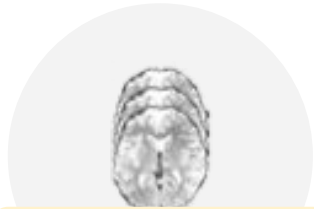
**Boris Clenet**



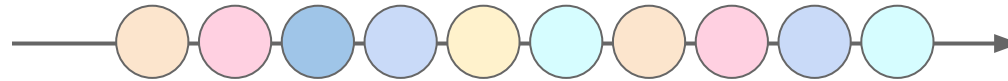
**Elodie Germani**



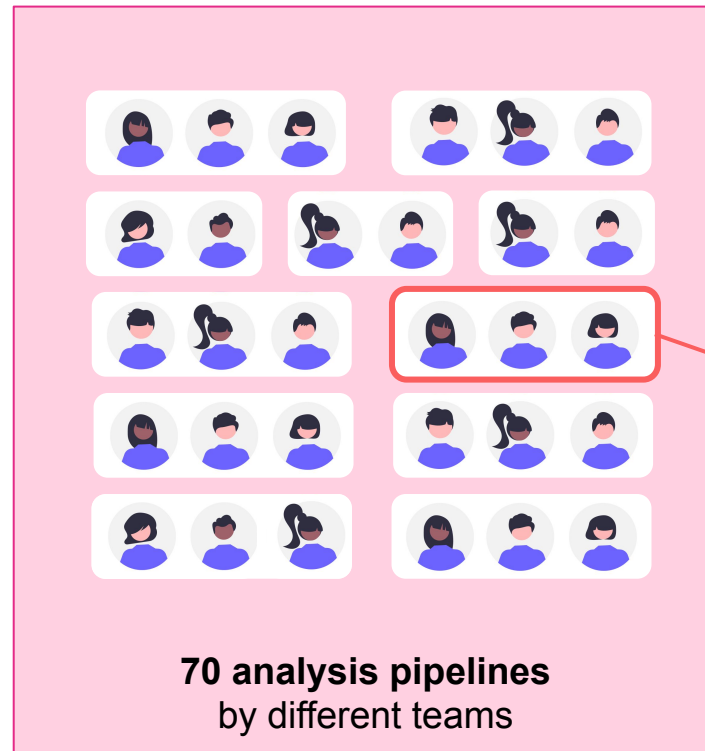
**Jérémy Lefort-Besnard**



**1 dataset**



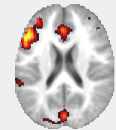
**9 'yes/no' questions**



**70 analysis pipelines**  
by different teams

1- H1: "yes"

2- Activation +  
Statistic brain  
maps



3- Textual  
description of the  
methods

**+ Code**



[https://github.com/Inria-Empenn/narps\\_open\\_pipelines/](https://github.com/Inria-Empenn/narps_open_pipelines/)

# NARPS open pipelines



**Boris  
Clenet**



**Elodie  
Germani**



**Jérémy  
Lefort-Besnard**

brainhack.org

**Credits** - This project was presented and received contributions during the following events:

- Empenn hackathon (February 2024)
- [Brainhack Marseille 2023](#) (December 2023)
- [ORIGAMI lab](#) hackathon (September 2023)
- [OHBM Brainhack 2023](#) (July 2023): Arshitha Basavaraj, Boris Clenet, Rémi Gau, Élodie Germani, Yaroslav Halchenko, Camille Maumet, Paul Taylor.
- [e-ReproNim FENS NENS Cluster Brainhack](#) (June 2023) : Liz Bushby, Boris Clenet, Michael Dayan, Aimee Westbrook.
- [OHBM Brainhack 2022](#) (June 2022): Elodie Germani, Arshitha Basavaraj, Trang Cao, Rémi Gau, Anna Menacher, Camille Maumet.



[https://github.com/Inria-Empenn/narps\\_open\\_pipelines/](https://github.com/Inria-Empenn/narps_open_pipelines/)

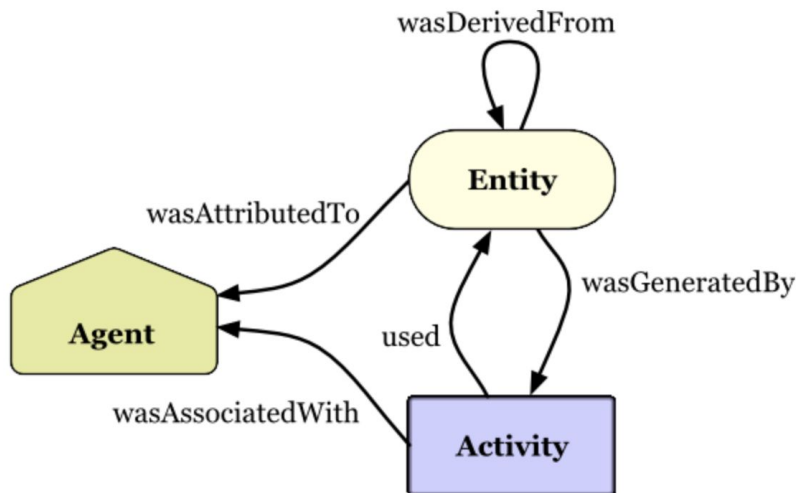
# Tracing provenance in neuroimaging



Satra Ghosh

“Provenance describe how an artifact or set of artifacts was produced” [Wikipedia](#)

- Based on W3C PROV



- As part of neuroimaging standardization efforts



<https://www.w3.org/TR/2013/NOTE-prov-primer-20130430/>

# Provenance Use Case 1 **An unambiguous description of the methods**





# Provenance Use Case 1 **An unambiguous description of the methods**



Which release of SPM was used?

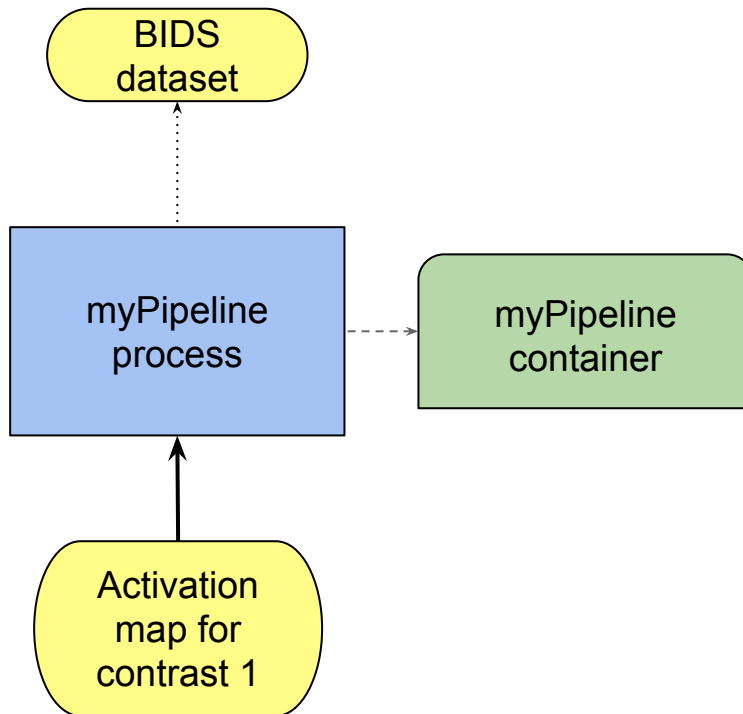
Which registration algorithm was selected?

How was the brain mask computed?

# Provenance Use Case 1 **An unambiguous description of the methods**

Can we  
**reproduce**  
**exactly the same**  
**results**  
(same data, same  
methods)?

# Provenance Use Case 1 **An unambiguous description of the methods**



Can we  
**reproduce  
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# Provenance Use Case 2 **Dealing with unwanted variability**

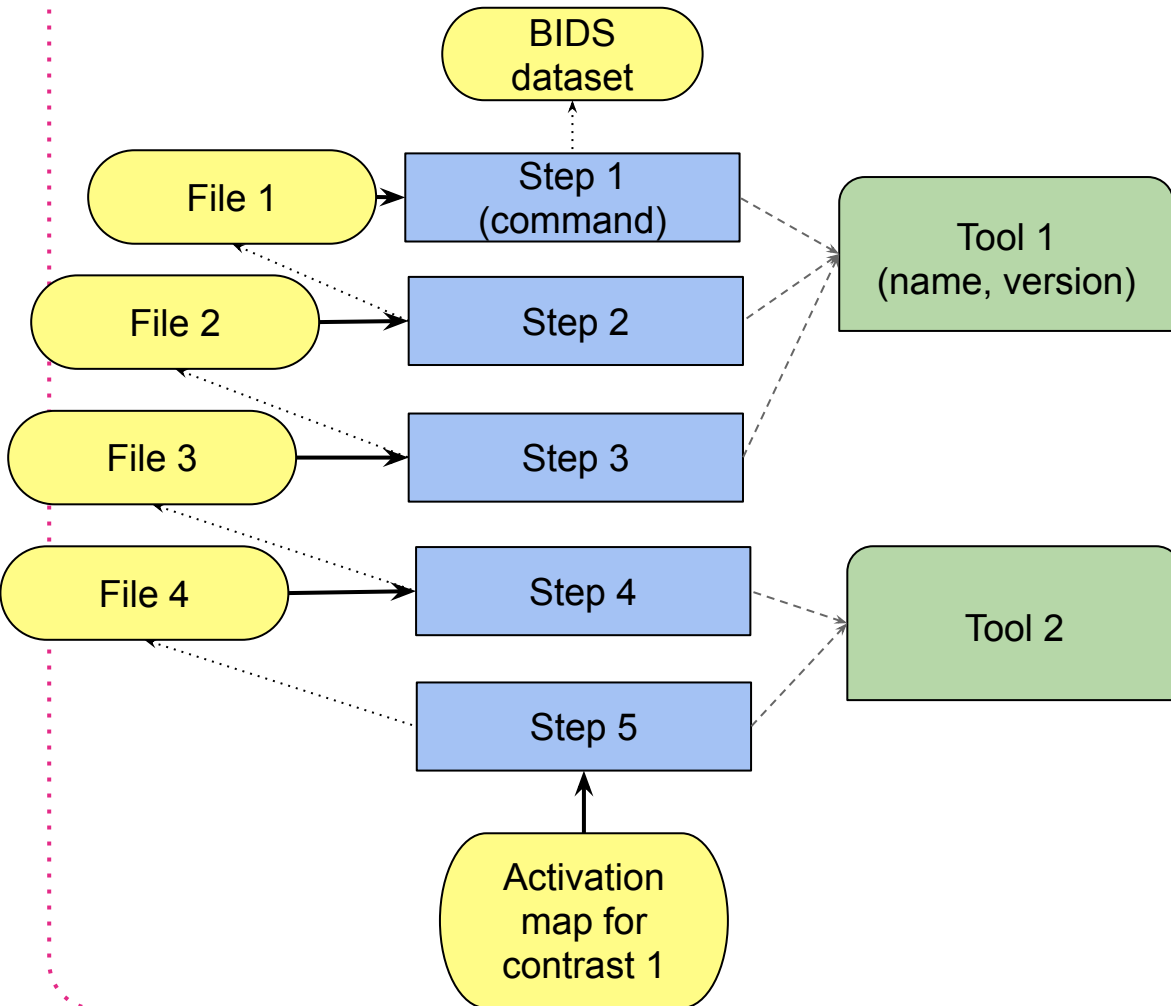
A previously widely-used **parameter is no longer considered as best practice**

# Provenance Use Case 2 **Dealing with unwanted variability**

A previously widely-used **parameter is no longer considered as best practice**

**A bug was found in a given tool version, can we retrieve all corresponding results?**

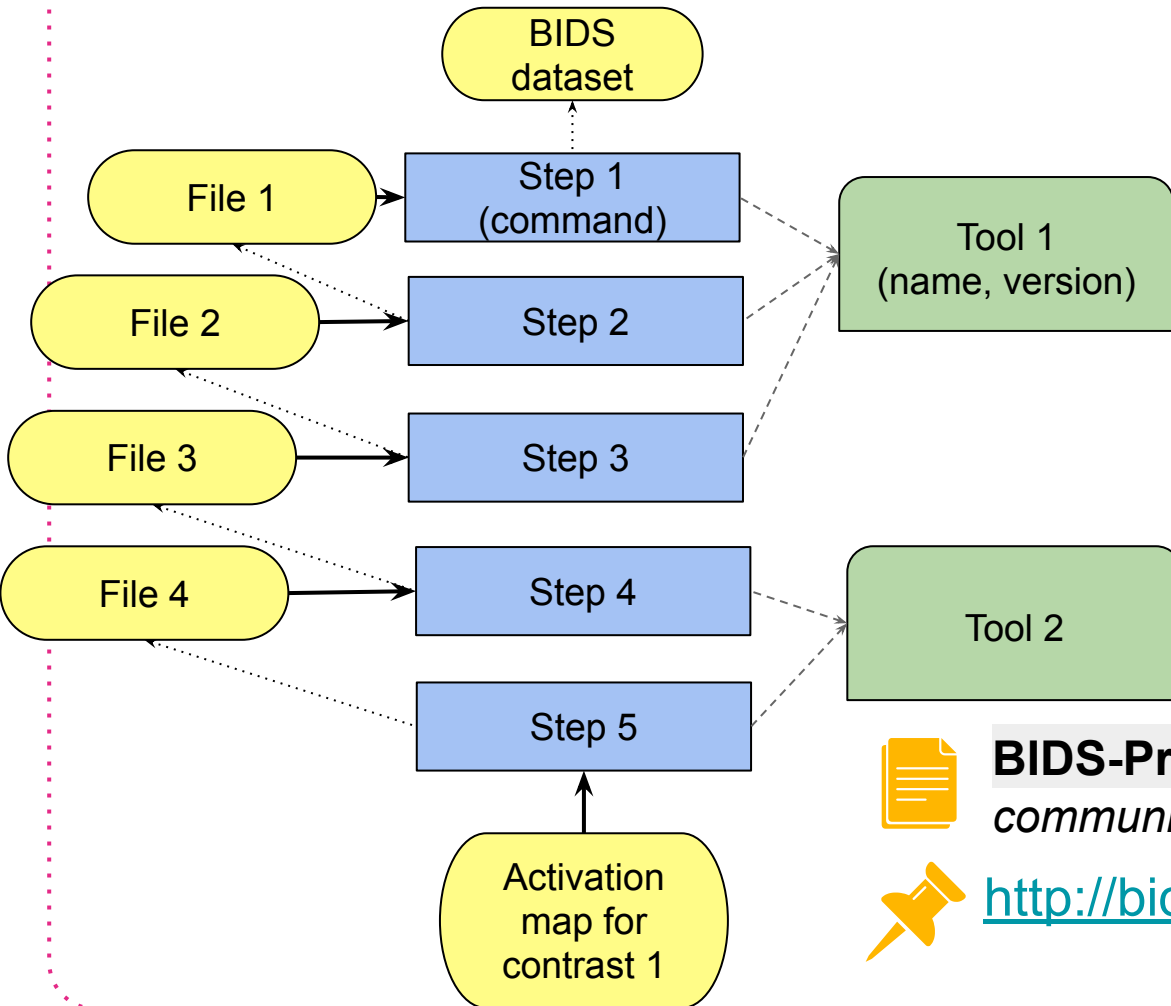
# Provenance Use Case 2 **Dealing with unwanted variability**



A previously widely-used **parameter is no longer considered as best practice**

A bug was found in a given tool **version**, can we retrieve all corresponding results?

# Provenance Use Case 3 Exploring factors impacting analytical variability



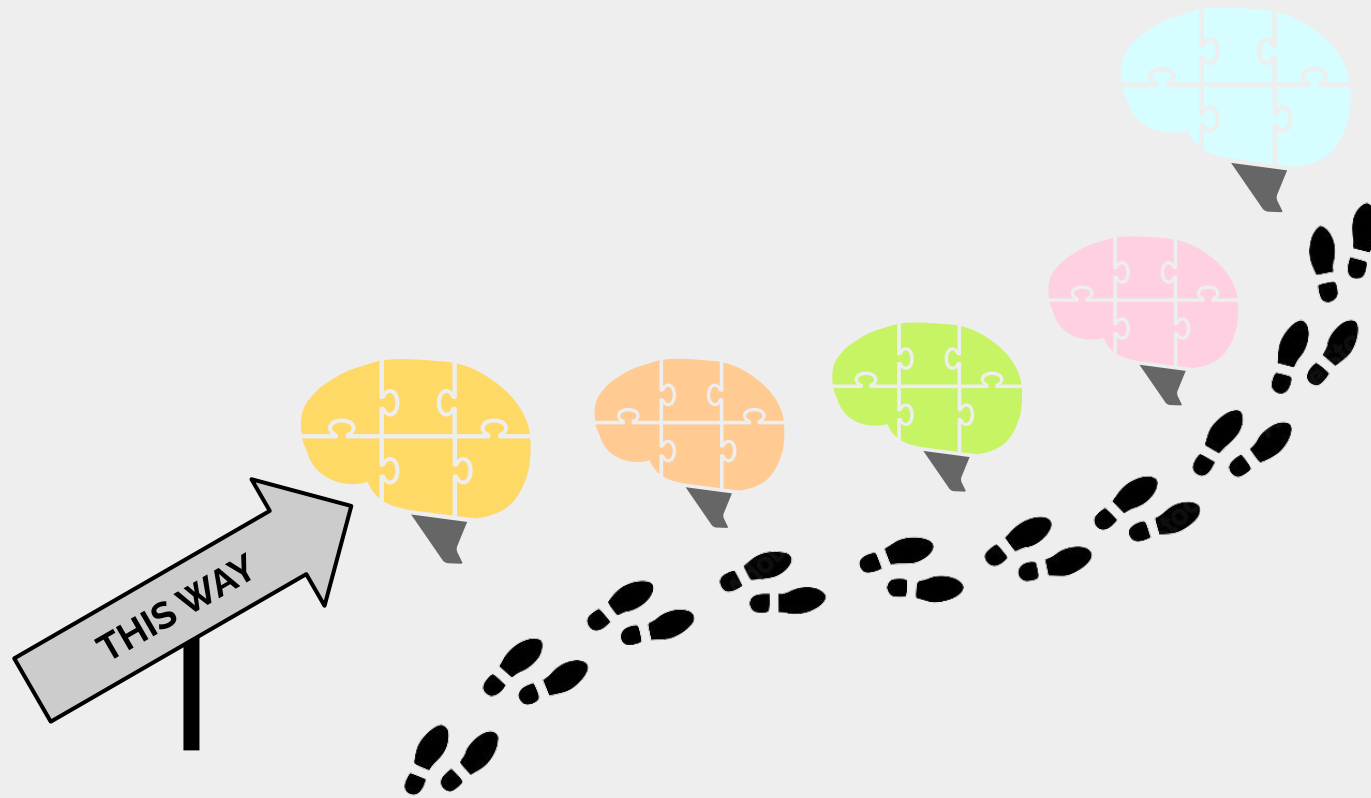
Are my conclusions dependant on the **size of the smoothing kernel** used at Step 5?



**BIDS-Prov** will soon be open for community feedback!



<http://bids.neuroimaging.io/bep028>



# Which solutions **for** **practitioners?**



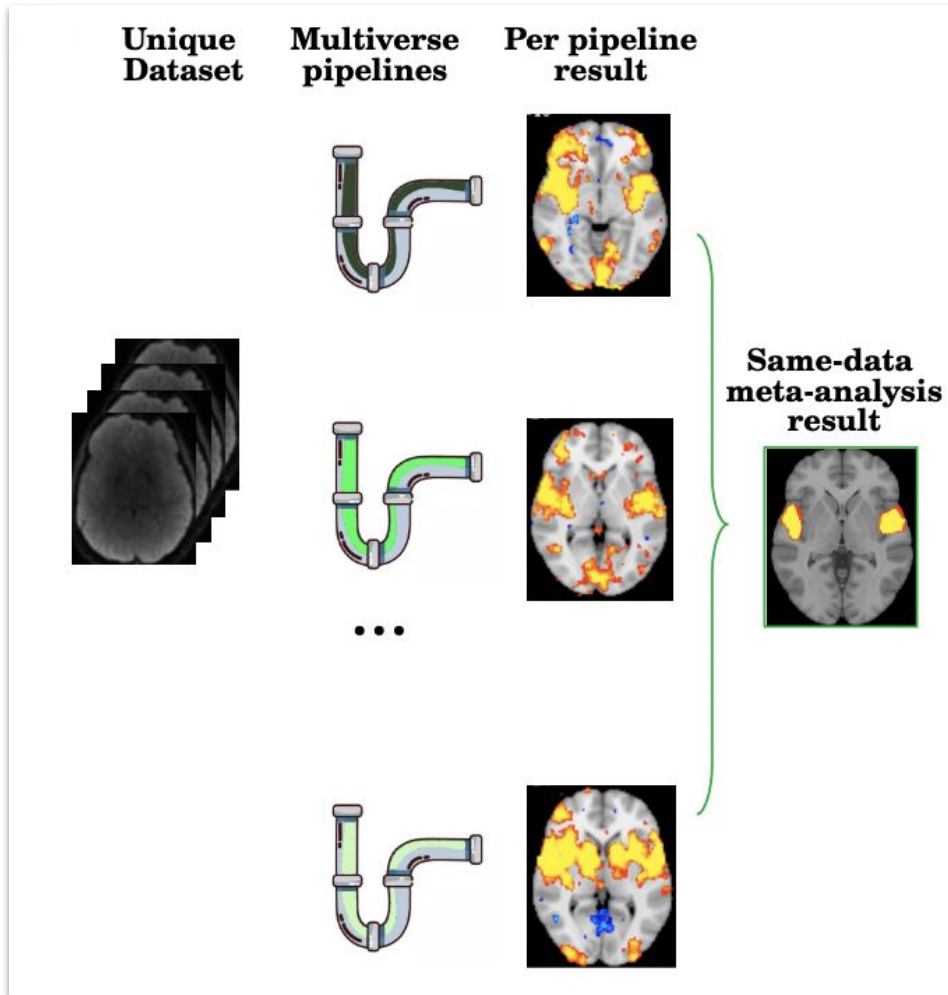
# Same data meta-analysis



Jérémy  
Lefort-Besnard



Tom Nichols  
Oxford Uni. (UK)



**Goal:** Investigate the validity of same-data meta-analysis methods

[Lefort-Besnard Nichols\*  
Maumet\*, OHBM 2024]

# Validity of mega-analyses in neuroimaging

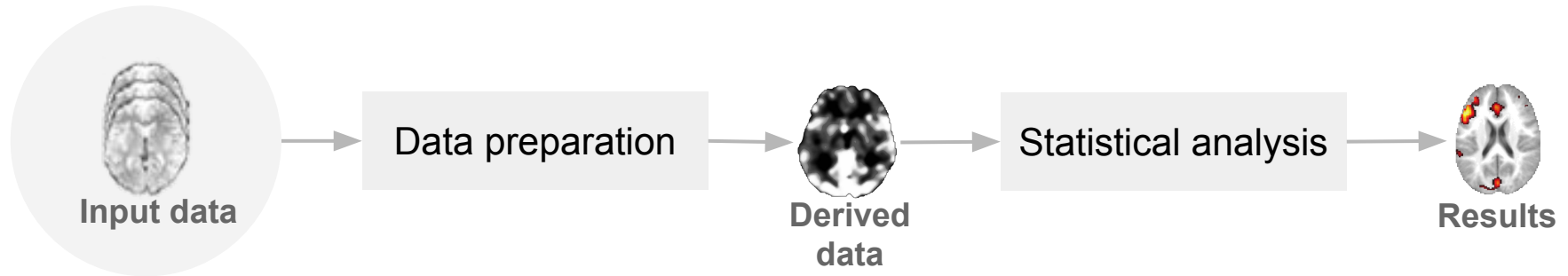


Xavier  
Rolland



Pierre  
Maurel

## Multi-stage functional MRI analysis



# Validity of mega-analyses in neuroimaging

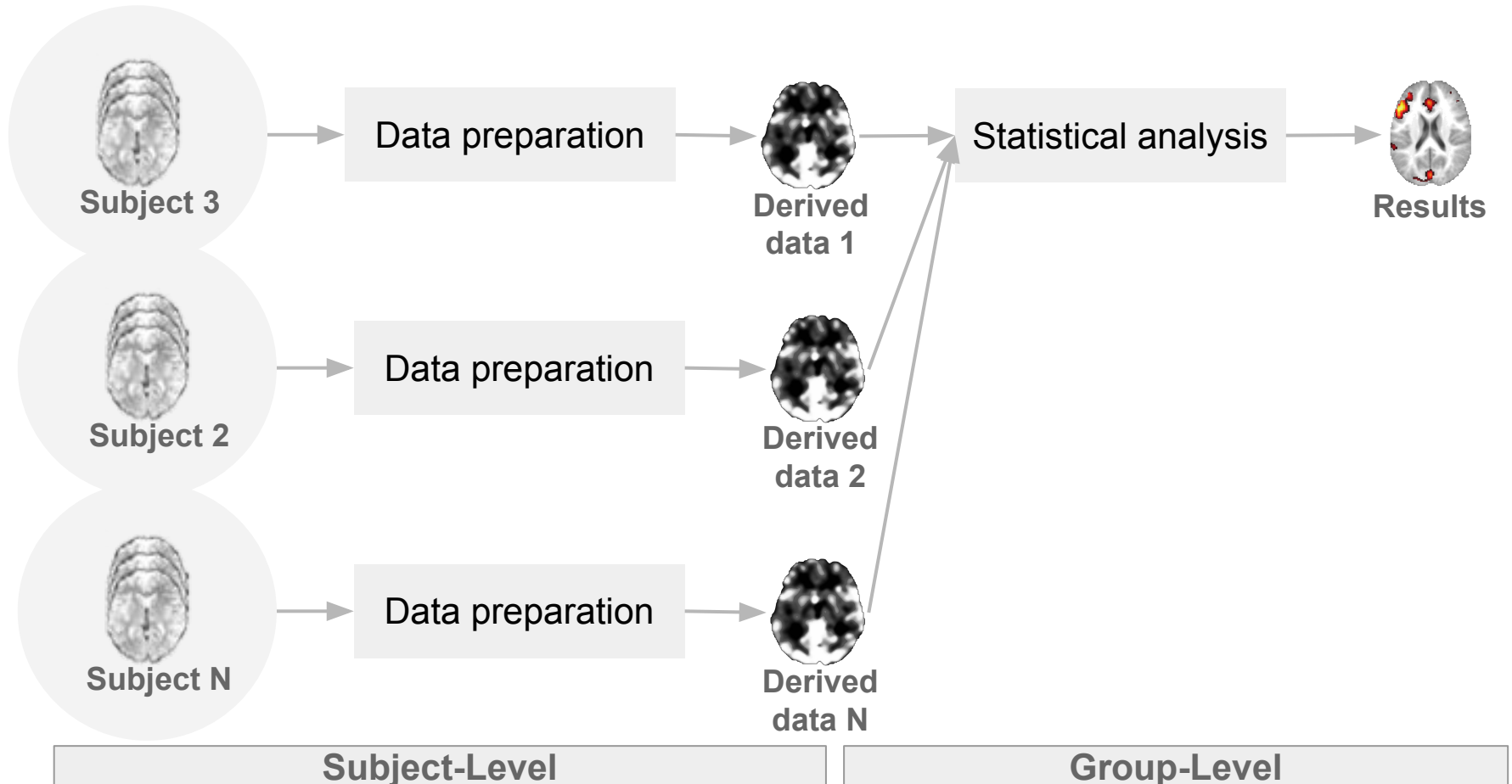


Xavier Rolland



Pierre Maurel

## Multi-stage functional MRI analysis



# Validity of mega-analyses in neuroimaging

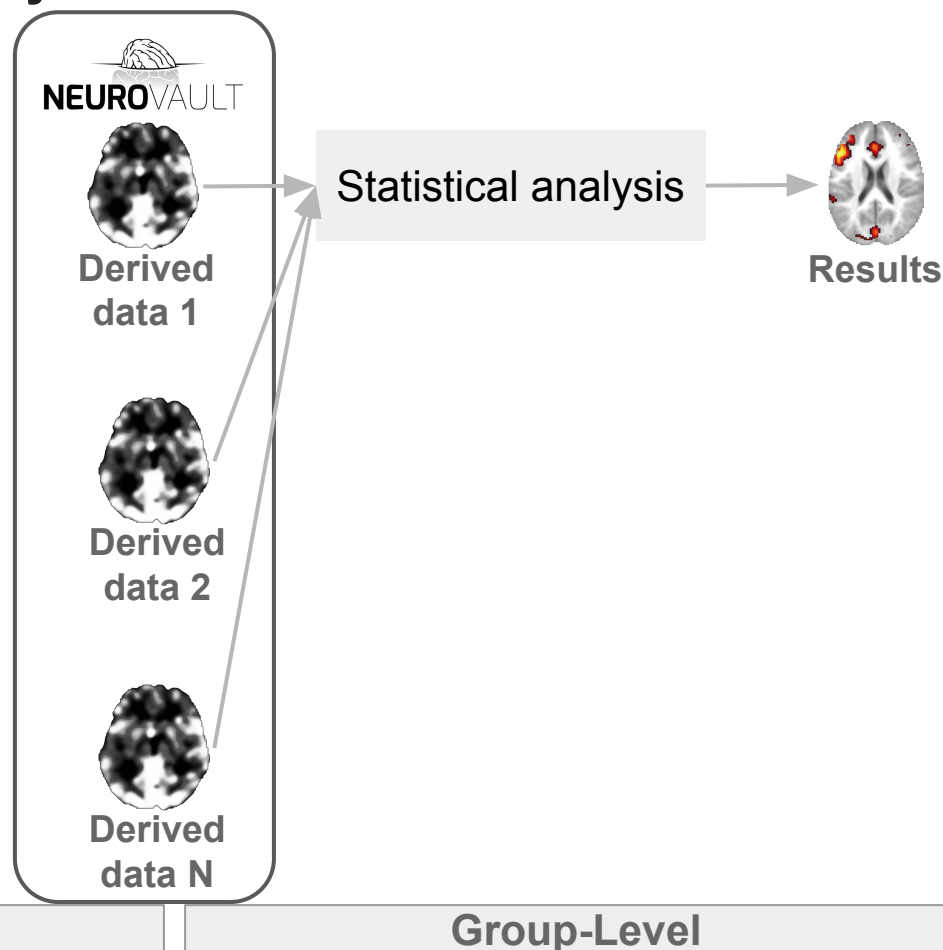


Xavier Rolland



Pierre Maurel

## Multi-stage functional MRI analysis



# Validity of mega-analyses in neuroimaging

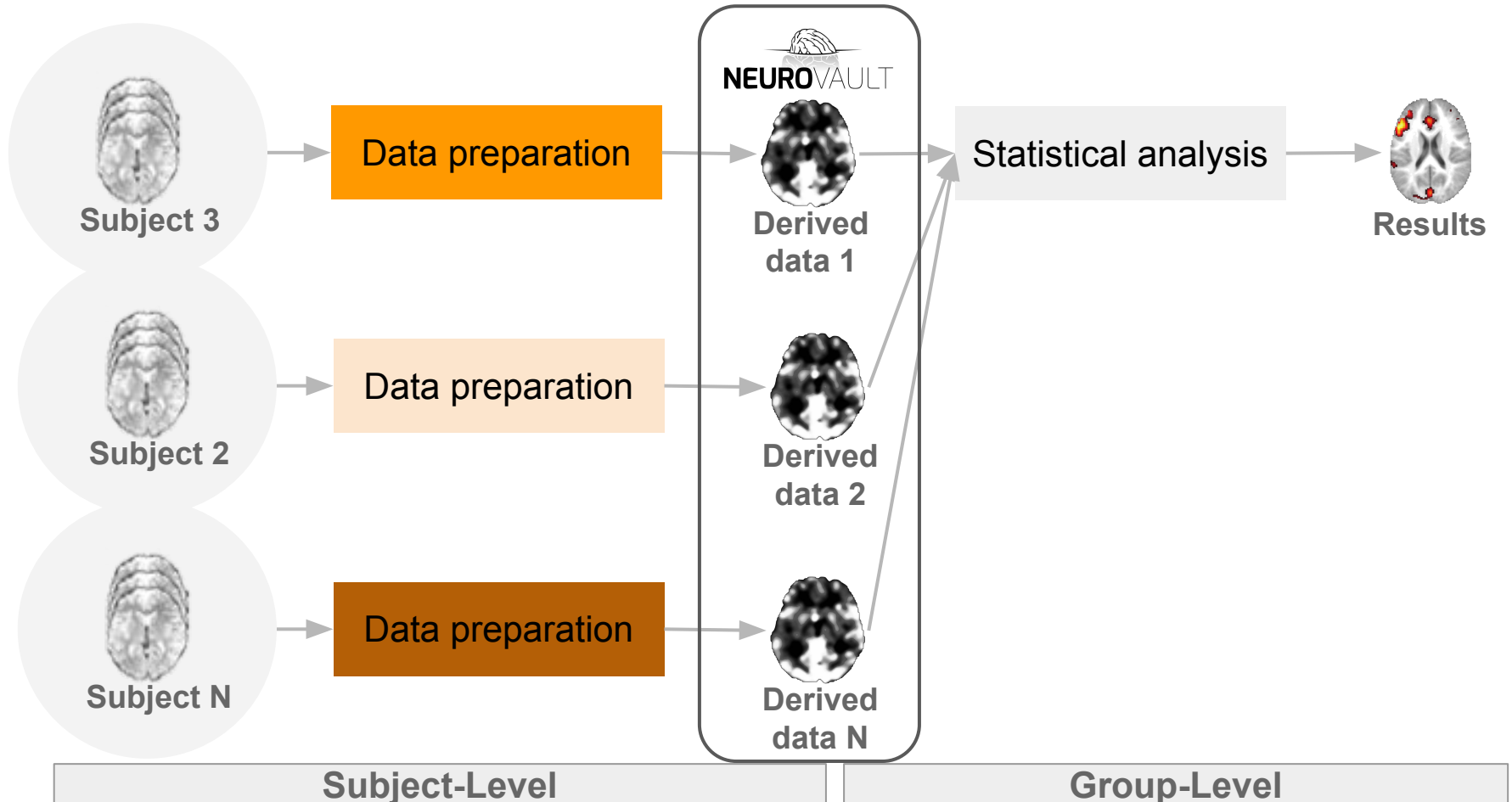


Xavier Rolland



Pierre Maurel

## Multi-stage functional MRI analysis



# Validity of mega-analyses in neuroimaging

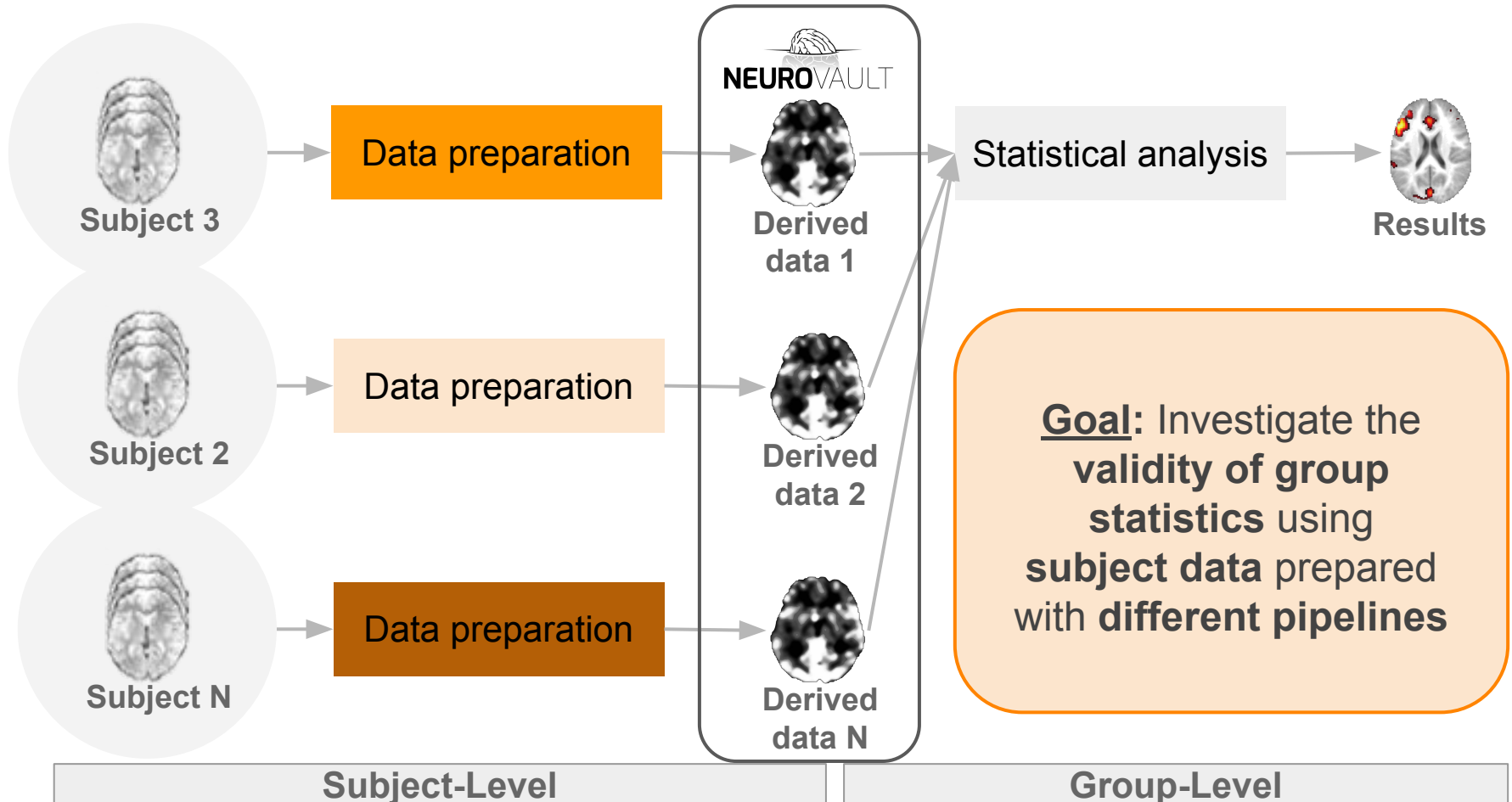


Xavier Rolland



Pierre Maurel

## Multi-stage functional MRI analysis



# Validity of mega-analyses in neuroimaging



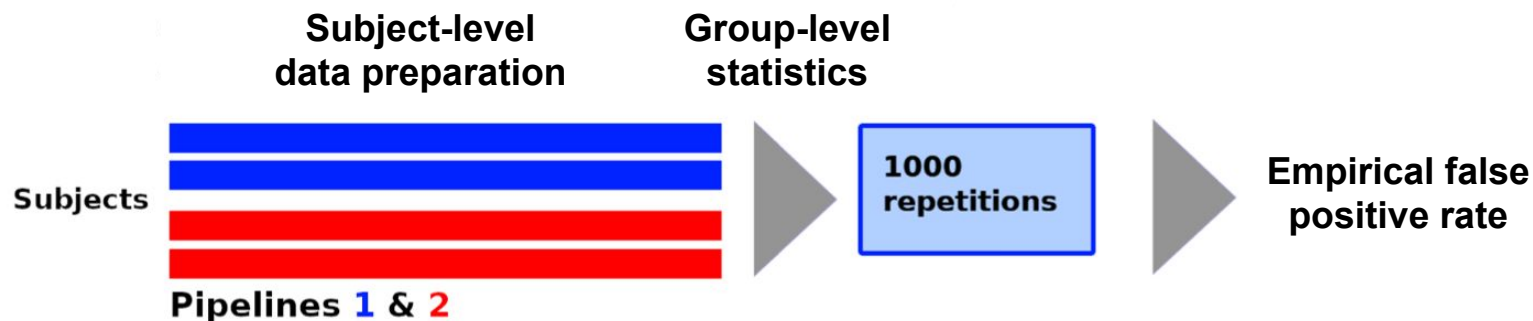
Xavier  
Rolland



Pierre  
Maurel

**Goal:** Investigate the **validity of group statistics** using **subject data** prepared with **different pipelines**

- HCP Young-Adult (1000 subjects)
- **3 pipeline variations**
  - Spatial smoothing: 5 or 8 mm
  - Modelling of the brain response: with/out derivative
  - Correction for subject motion: 0,6, 24 covariates



# Validity of mega-analyses in neuroimaging



Xavier  
Rolland

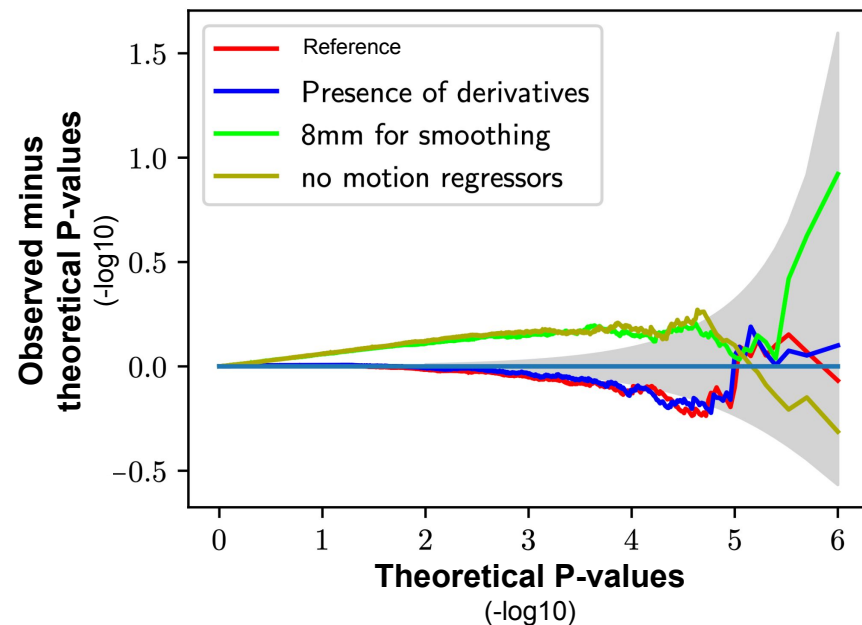


Pierre  
Maurel

"Reference" pipeline :

- canonical HRF
- smoothing 5mm
- 24 motion regressors

- P-p plots (Bland-Atlman)



**Conclusion: Invalidity of the mega-analyses for multiple variations studied (e.g. different smoothing, 1+ variation)**

[Rolland Maurel Maumet, ISBI 2022]



# Leveraging large and open datasets



Elodie  
Germani



Elisa  
Fromont

## Shared data with limited metadata



500 000+ images

A variety of fMRI tasks, preprocessing and analysis  
Minimal metadata required.

# Leveraging large and open datasets



Elodie  
Germani



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Fromont

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500 000+ images

A variety of fMRI tasks, preprocessing and analysis  
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**Goal: Can we take advantage of a large pool of unlabelled data to help answer new research questions?**

# Leveraging large and open datasets



Elodie  
Germani



Elisa  
Fromont

## Shared data with limited metadata

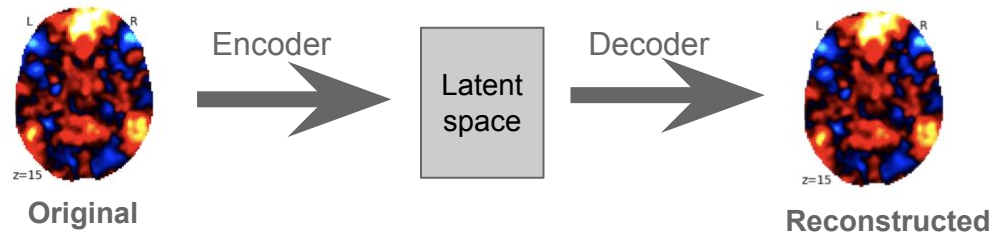


500 000+ images

A variety of fMRI tasks, preprocessing and analysis  
Minimal metadata required.

**Goal:** Can we take advantage of a large pool of unlabelled data to help answer new research questions?

- Step 1: Build a model-agnostic representation of fMRI statistic maps



- Step 2: Fine-tune a classifier (predicting cognitive process:   )

# Leveraging large and open datasets



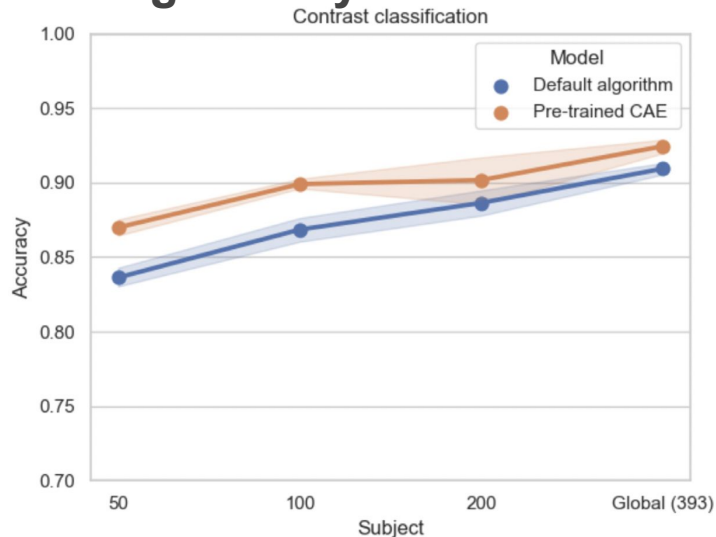
Elodie  
Germani



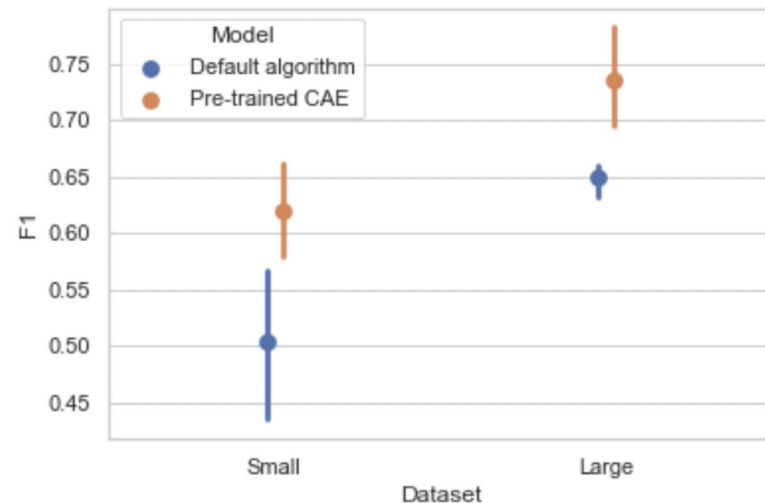
Elisa  
Fromont

- Tested on two datasets:
  - **Single large study** (HCP Young adult) 23 tasks x 787 subjects
  - **Collection of studies** (Brainpedia) 29 studies, 36 tasks, 826 subjects

## Single study



## Collection of studies



**Conclusion:** The pre-trained classifier always performed better especially when the problem was complex (small samples, heterogeneity).

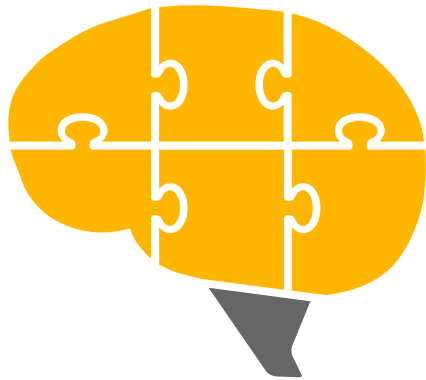
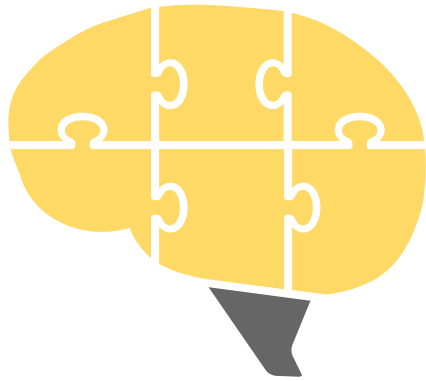
[[Germani](#) Fromont\* [Maumet](#)\*, Gigascience 2023]

Feb 20, 2024



McGill

QLS SQV  
QUANTITATIVE LIFE SCIENCES SCIENCES QUANTITATIVES DU VIVANT



# Towards reproducible neuroimaging across different analysis pipelines

**Camille Maumet**

# Thank you!

**Credit:** Presentation template and icons by [SlidesCarnival](https://www.slidescarnival.com/), adapted



**@cmaumet.bsky.social**



**@cmaumet@fediscience.org**