Towards large-scale brain imaging studies: How to deal with analytic variability?

Camille Maumet

VisAGeS

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UNIVERSITÉ DE RENNES 1
Inria inventeurs du monde numérique
Inserm Institut national de la santé et de la recherche médicale
cnrs
UMR IRISA

Outline

Introduction: VisAGeS and AI

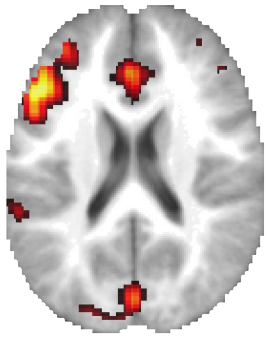
Large-scale brain imaging studies

Analytic variability

Introduction

VisAGeS and AI

VisAGeS research objectives



Understand the brain under **typical** and **pathological** conditions with **brain imaging**

Team leader: Christian Barillot

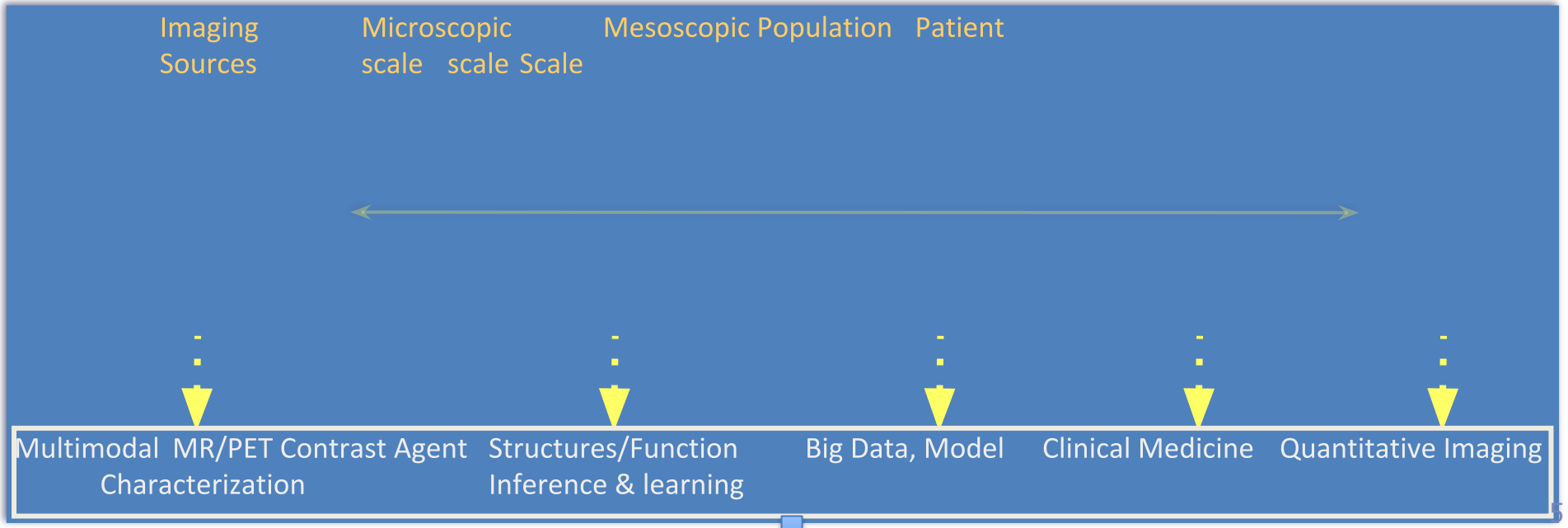
Goals

- Early Diagnosis
- Therapeutic choices
- New therapeutic protocols

Multiple sclerosis, Psychiatry, Parkinsonian disorders, Dementia, Stroke

(Slide content from Christian Barillot, adapted)

Multiscale «Brain Imaging Biomarkers»



Majors challenges

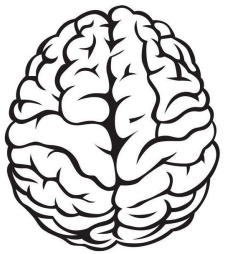
- Models and algorithms to reconstruct, analyze and transform
- Mass of data to store, distribute and "semantize"

Contributions & skills

- Model Inference
- Statistical Analysis & Modeling
- Sparse Representation (*compressed sensing, dictionary learning*)
- Machine Learning (*supervised/ unsupervised classification, discrete model learning*)
- Data fusion (*multimodal integration, registration, patch analysis, …*)
- High dimensional optimization
- Data integration
- Brain computer interface
- …

(Slide from Christian Barillot, adapted)

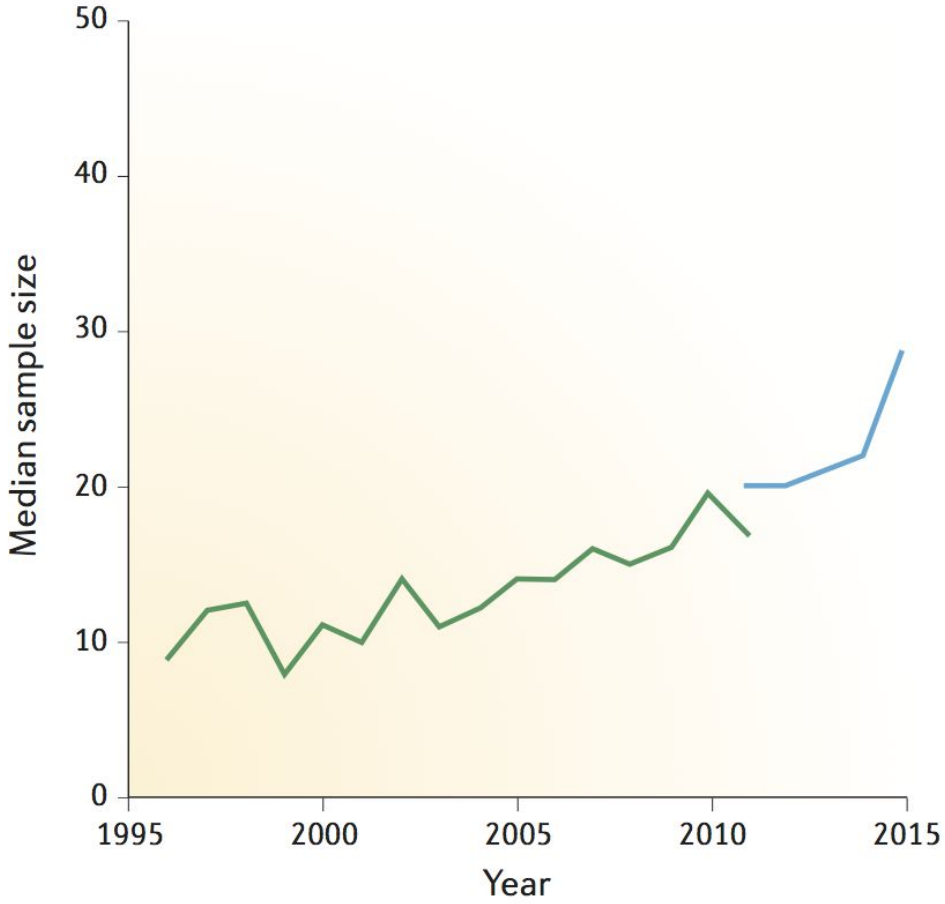
VisAGeS in AI



AI methods ⟷ Neuroimaging methods ⟷ Applied neuroimaging

Towards large-scale brain imaging studies

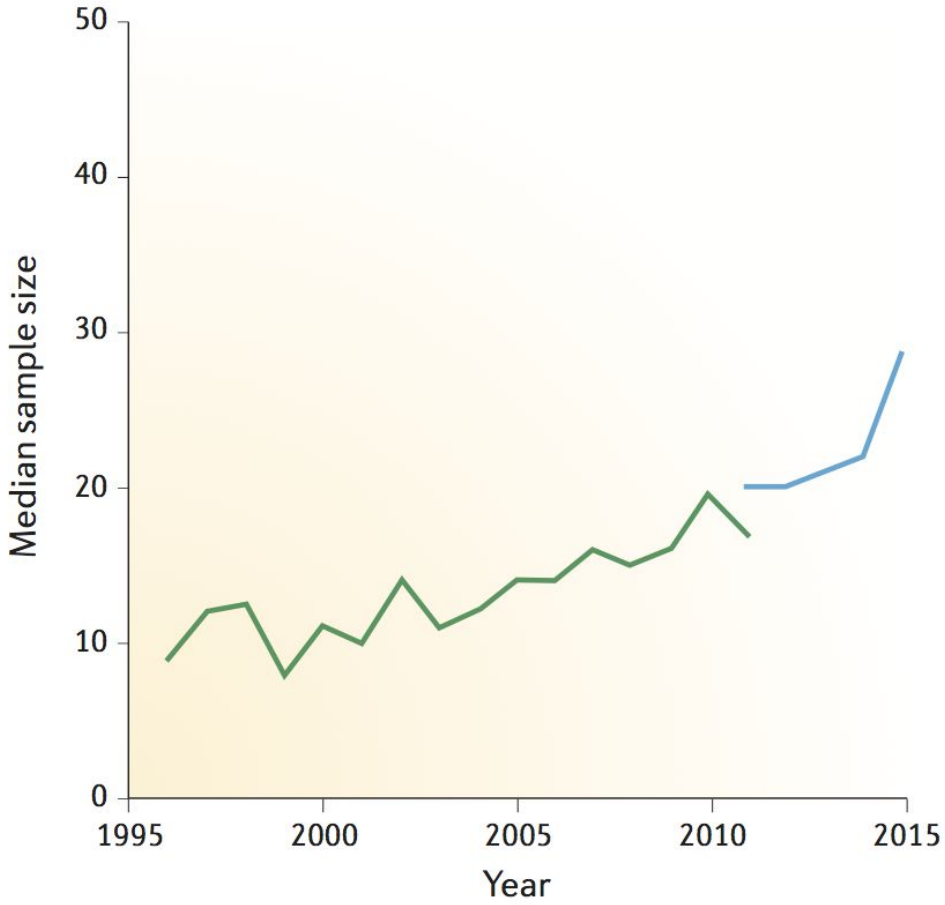
Sample sizes in brain imaging research



2015: 30 subjects / study

[Poldrack et. al, Nature Neuroscience 2017]

Sample sizes in brain imaging research



[Poldrack et. al, Nature Neuroscience 2017]

2015: 30 subjects / study

Low diversity &
Low statistical power

More and more open data are available!

Photo de Neil Conway

Single study
30 subjects

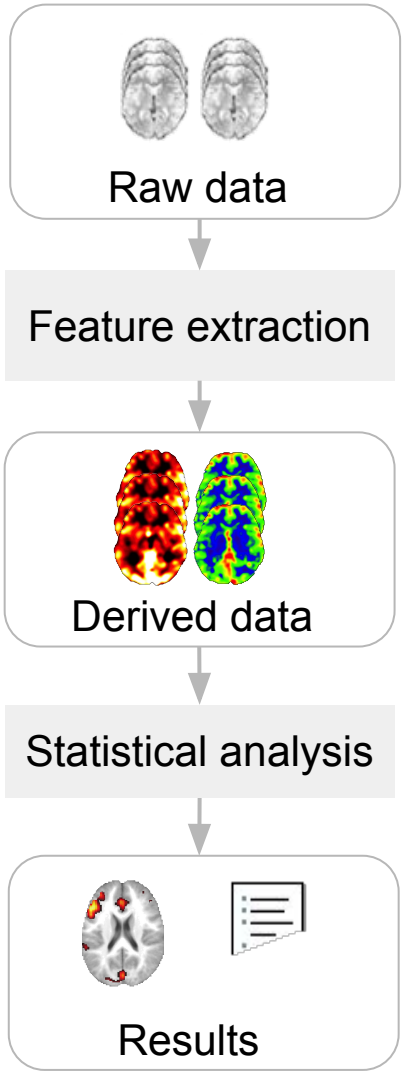
Consortium
1000 subjects

Cohort
1 000 - 100 000 subjets

+ Images
+ Homogeneous
- Fewer

How to deal with analytic variability?

Challenge: analytical variability



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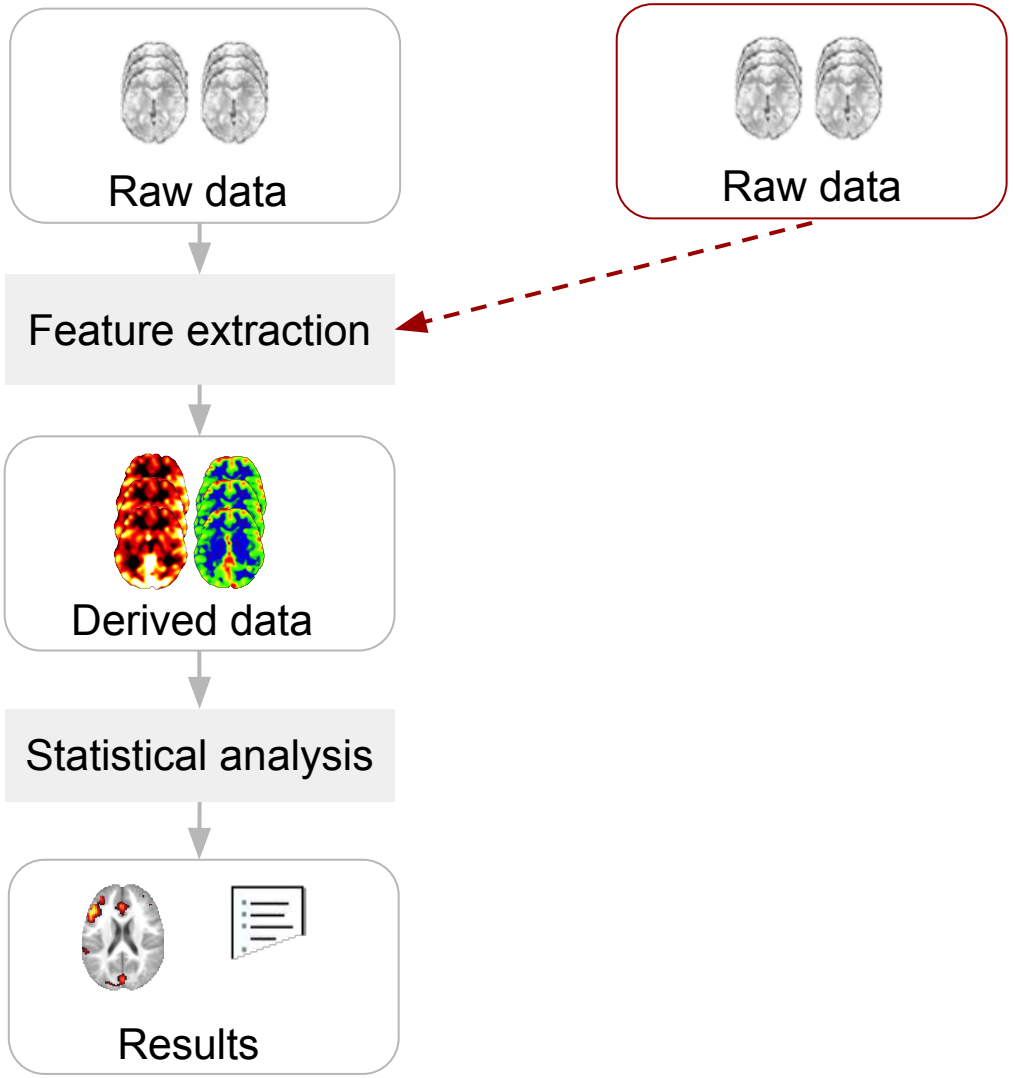

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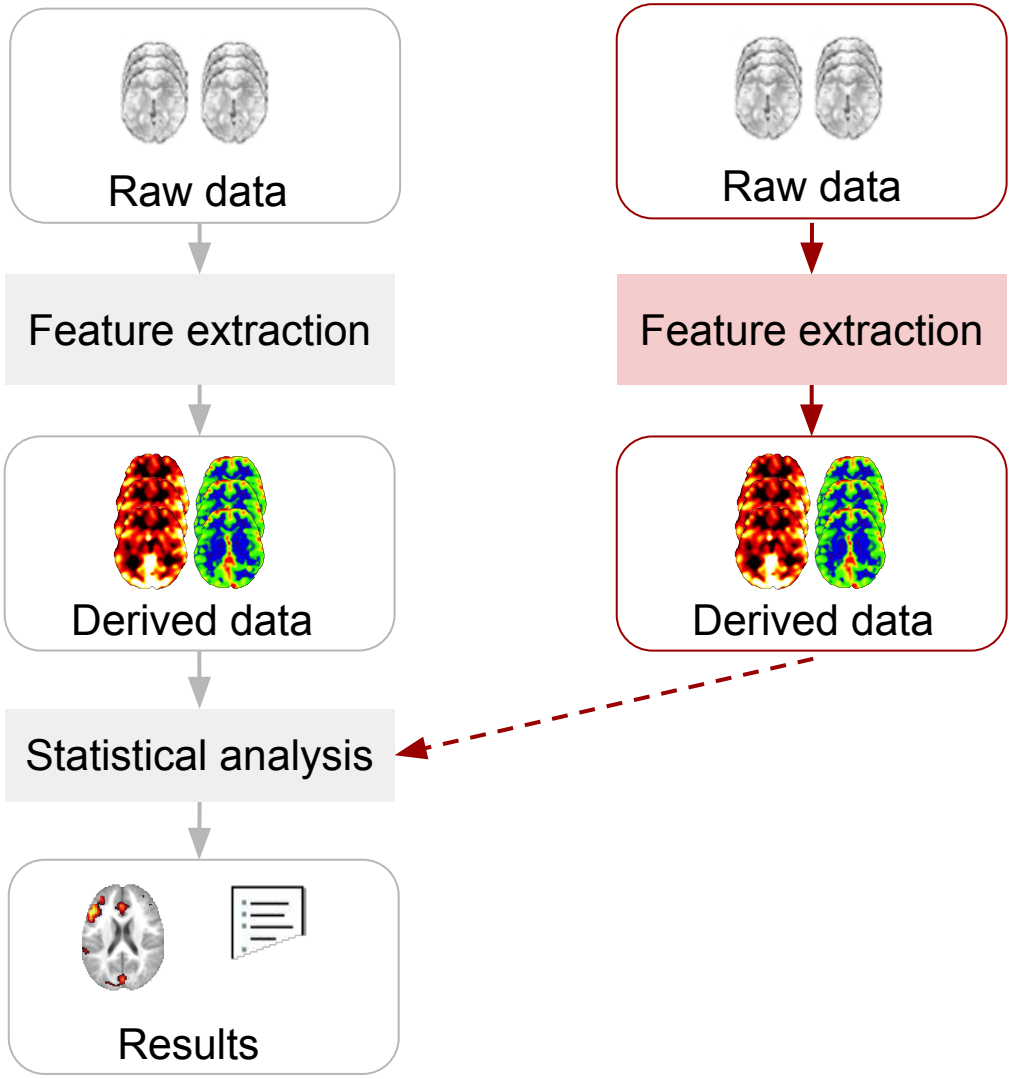

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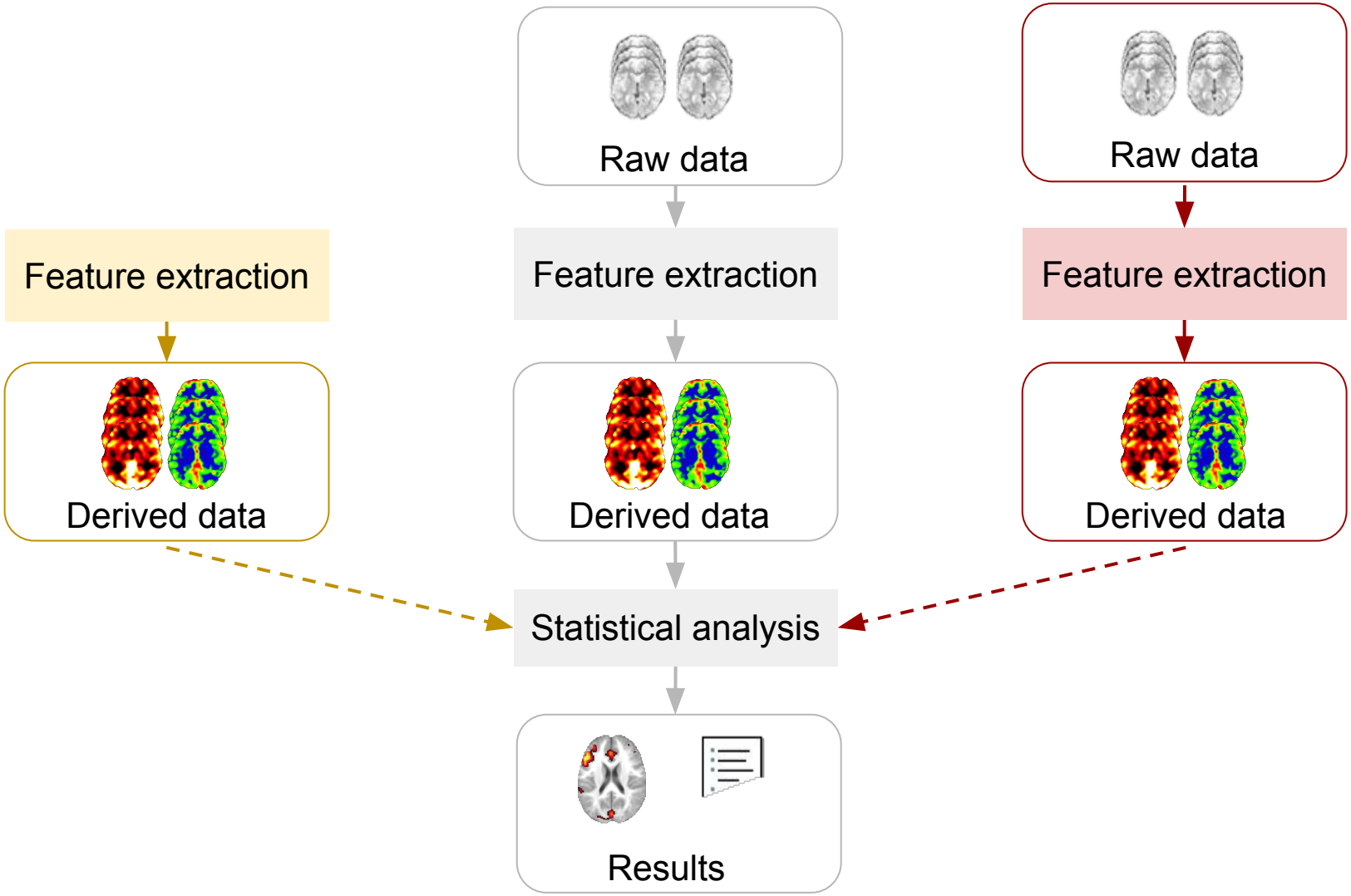

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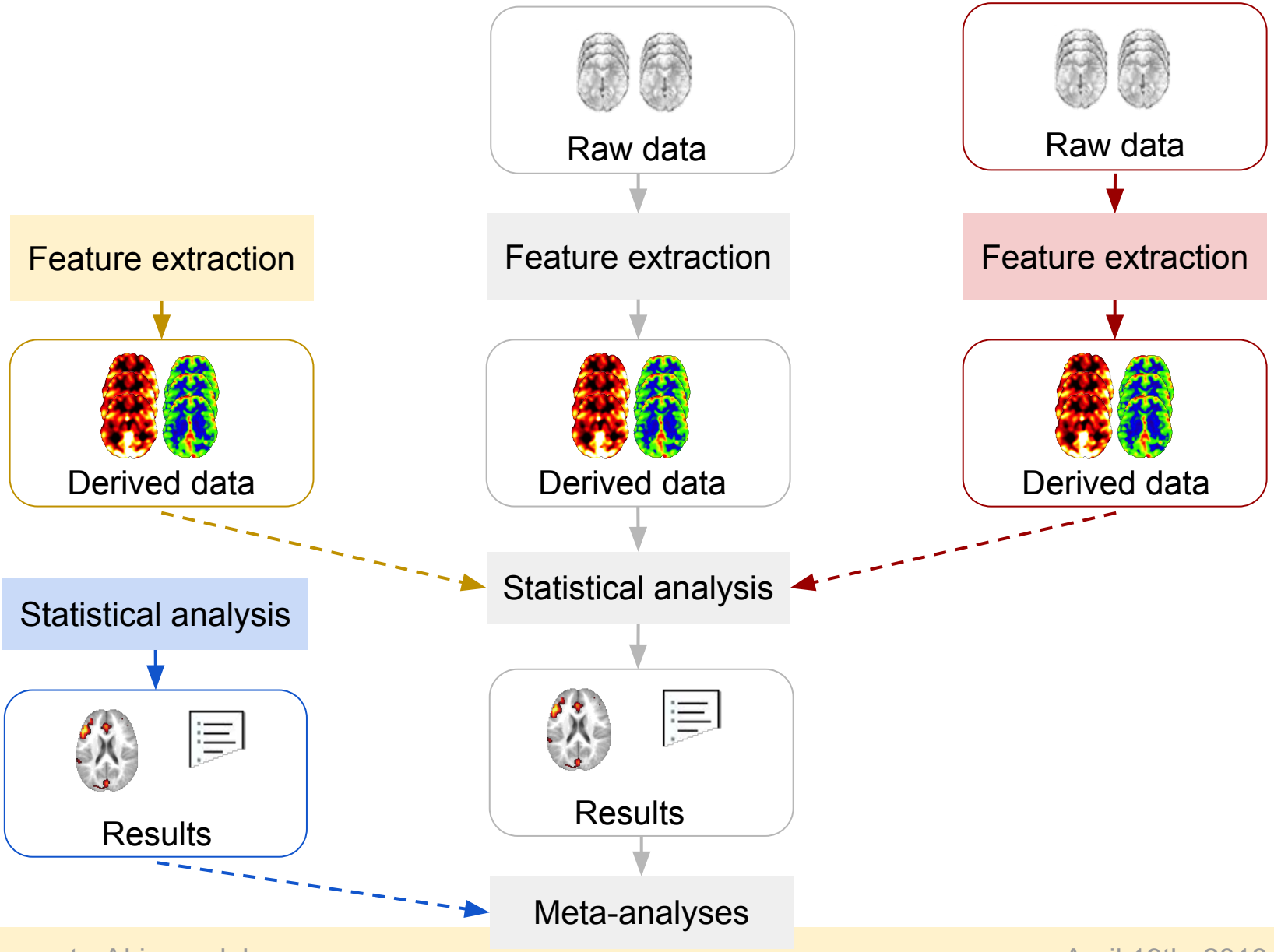

Quantify

Estimate variations
across pipelines

Compensate

Remove unwanted
"pipeline effect"

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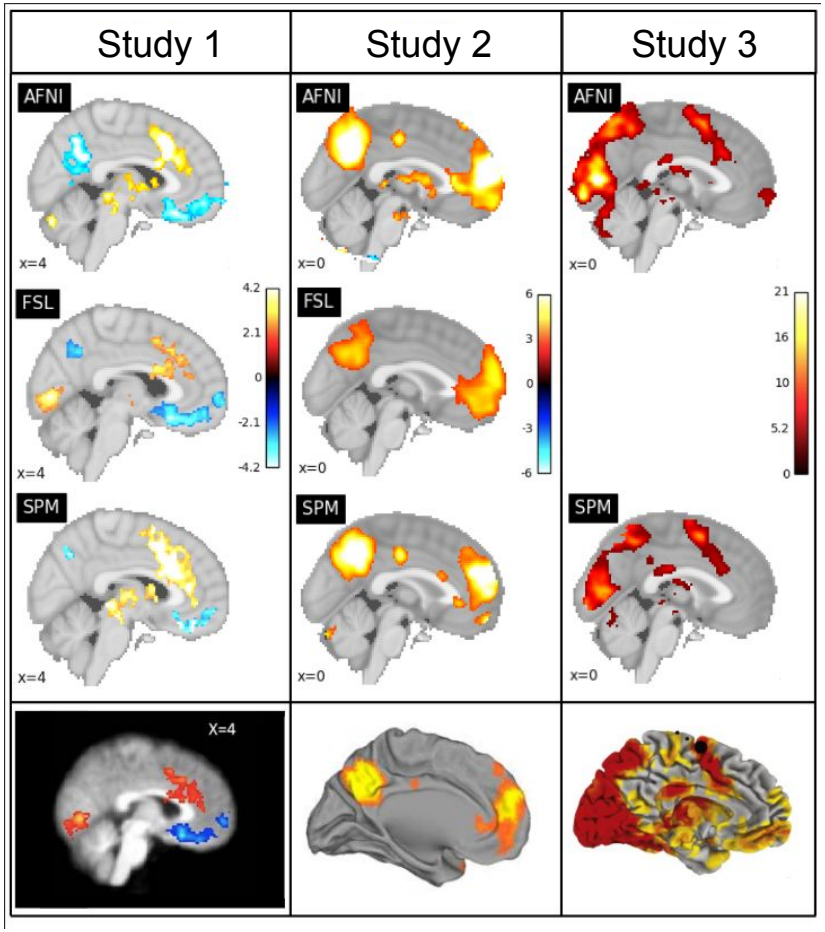
Impact of Analysis Software on Task fMRI Results

- 3 published studies
- Reanalysed with 3 fMRI tools
- Reusing the same data

Research question: how choice of software package impacts on analysis results?

Impact of Analysis Software on Task fMRI Results

Reproducing the main figure



Preprint: Bowring, Maumet* and Nichols*, 2018. www.hal.inserm.fr/inserm-01760535

Impact of Analysis Software on Task fMRI Results

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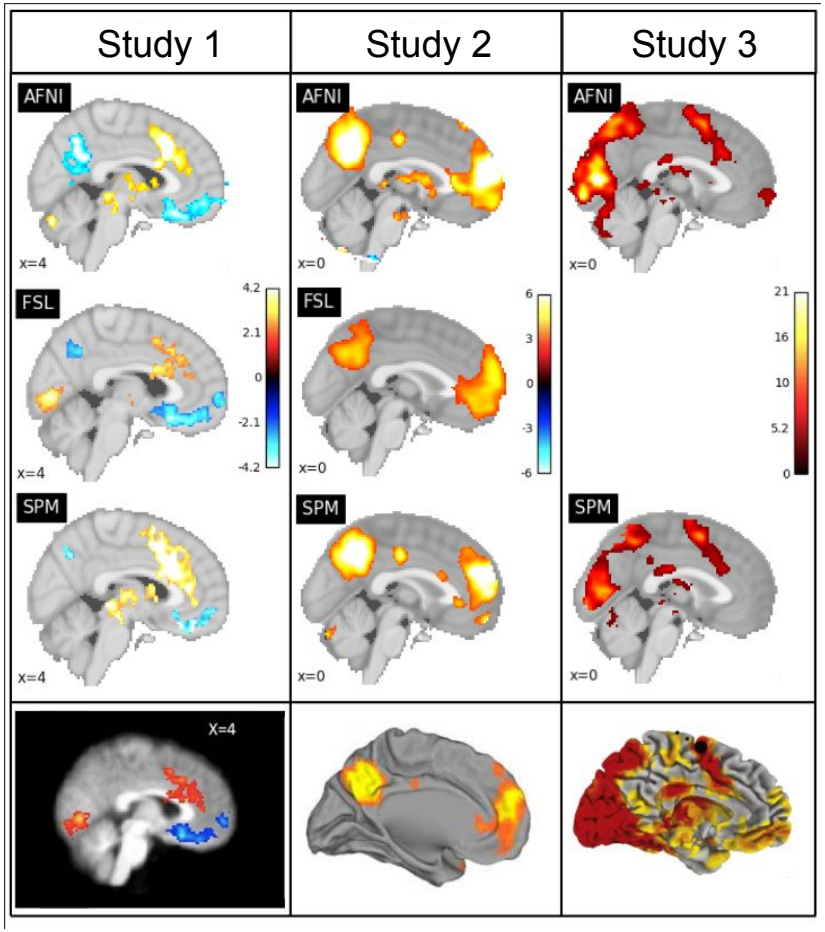
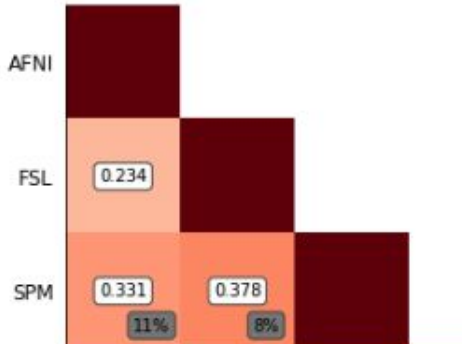


Dice coefficients: 0.23 - 0.38



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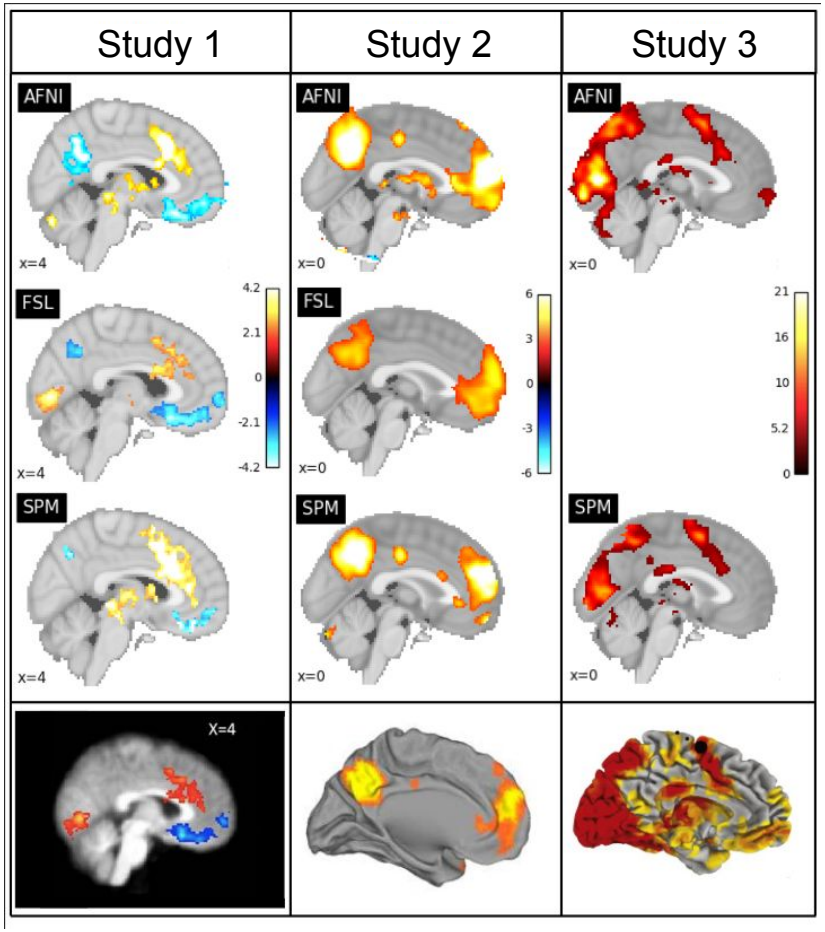

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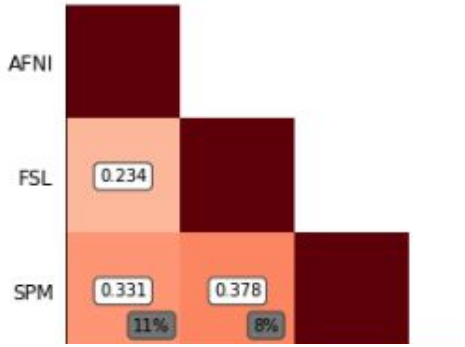
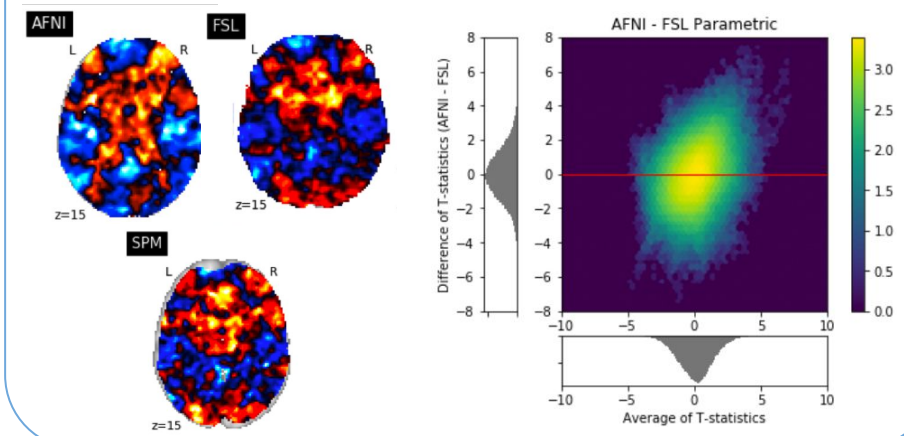


Unthresholded statistics



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Impact of Analysis Software on Task fMRI Results

- Challenges
  - Use the "same" pipeline across fMRI tools
    - Implementation details ↔ Methodological differences
  - How much difference is too much?
    - "Compatibility" across pipelines

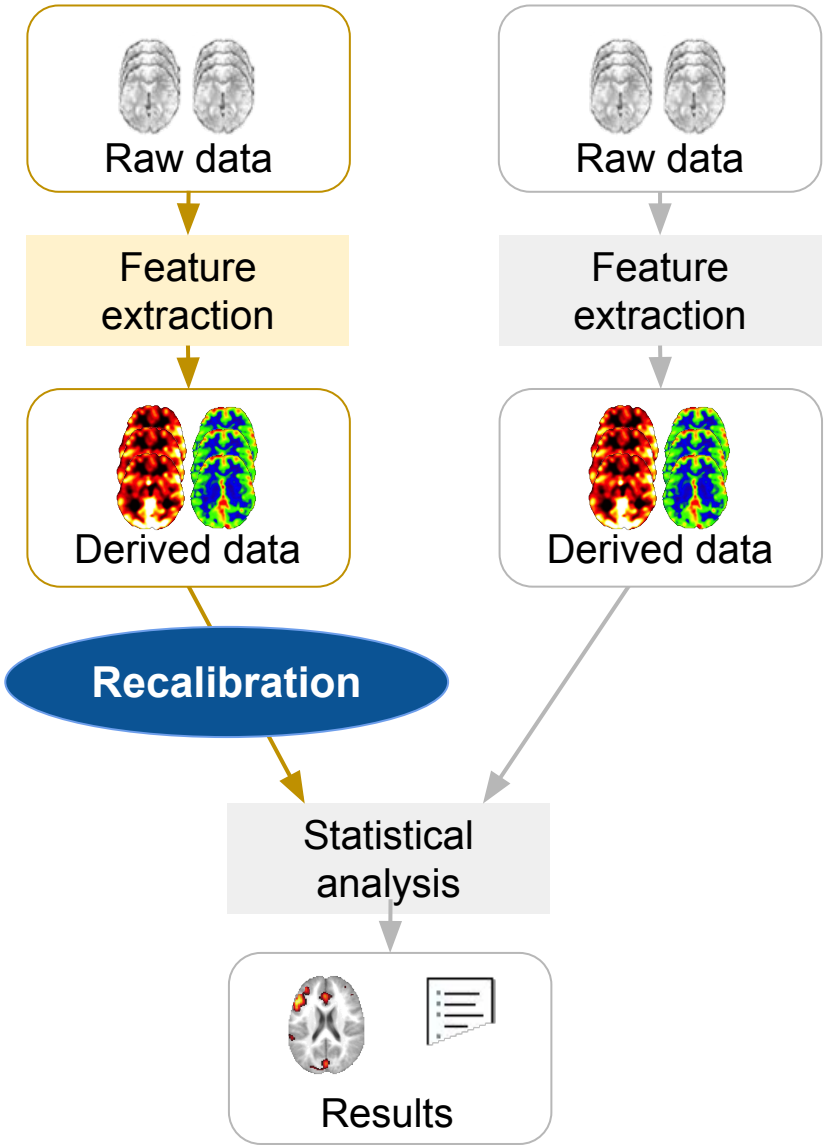
Quantify

Estimate variations across pipelines

Compensate

Remove unwanted "pipeline effect"

2. Remove unwanted "pipeline effect"



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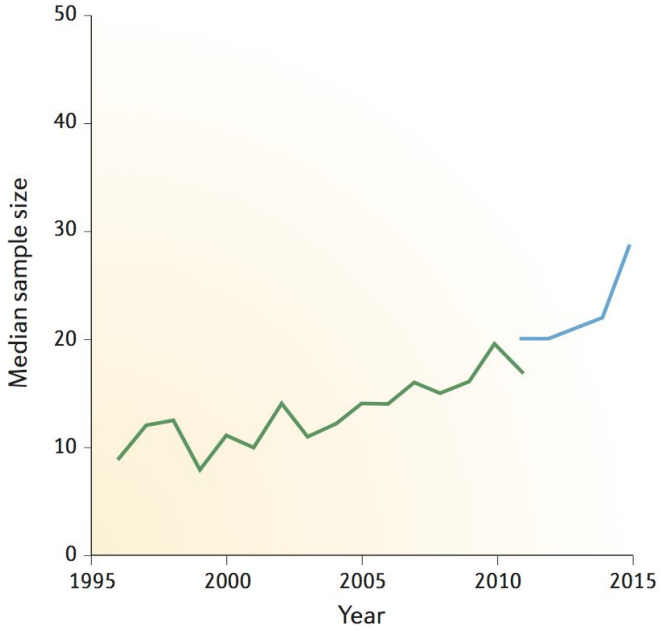

Photo de Neil Conway

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