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

April 19th, 2018

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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»

- Imaging Sources
- Microscopic Scale
- Mesoscopic Population
- Patient

- Multimodal «Brain Imaging Biomarkers»
- From Bench to the Bed
- From ms to Century (3*10^12 ratio)
- From nm to m (10^9 ratio)

**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

[Graph showing the increase in median sample size from 1995 to 2015.]

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!

Single study
30 subjects

Consortium
1000 subjects

+ Images
+ Homogeneous
- Fewer

Cohort
1 000 - 100 000 subjects
How to deal with analytic variability?
Challenge: analytical variability

1. Raw data
2. Feature extraction
3. Derived data
4. Statistical analysis
5. Results
Challenge: analytical variability
Challenge: analytical variability

1. Raw data
2. Feature extraction
3. Derived data
4. Statistical analysis
5. Results

1. Raw data
2. Feature extraction
3. Derived data
Challenge: analytical variability

Feature extraction

Derived data

Raw data

Feature extraction

Derived data

Statistical analysis

Results

Feature extraction

Derived data

Raw data

Feature extraction

Derived data
Challenge: analytical variability

Feature extraction → Derived data

Feature extraction → Derived data

Feature extraction → Derived data

Statistical analysis → Results

Statistical analysis → Results

Statistical analysis → Results

Meta-analyses
 Quantify
Estimate variations across pipelines

Compensate
Remove unwanted "pipeline effect"
Quantify
Estimate variations across pipelines

Compensate
Remove unwanted "pipeline effect"
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

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<th>Study 1</th>
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Preprint: Bowring, Maumet* and Nichols*, 2018. [www.hal.inserm.fr/inserm-01760535](http://www.hal.inserm.fr/inserm-01760535)
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Dice coefficients: 0.23 - 0.38

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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"

- Raw data
  - Feature extraction
  - Derived data
  - Recalibration
  - Statistical analysis
  - Results
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