

Apprentissage automatique sur les bases de données biomédicales pour améliorer la compréhension des maladies neurodégénératives

C@fé-In
Sophia-Antipolis

Marco Lorenzi

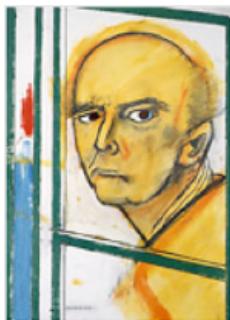
Université Côte d'Azur
Inria Sophia Antipolis, Asclepios Research Project

William Utermolhen (1933-2007)

Self-portraits



1967



1996



1997



1998



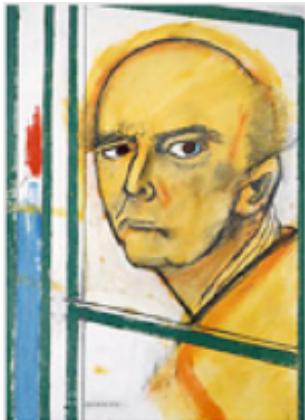
1999



2000

1995: Alzheimer's disease diagnosis

Alzheimer's disease: the most common form of dementia



Language problems

Memory loss

Functionality loss

Apraxia

Cognitive impairment

Mood alterations

Enormous human and societal cost

The disease with the largest economic impact (Europe et US)

Impact on families

~20,000 \$ every year in 1998

[Moore et al., *J Gerontol B Psychol Sci Soc Sci* 1998]

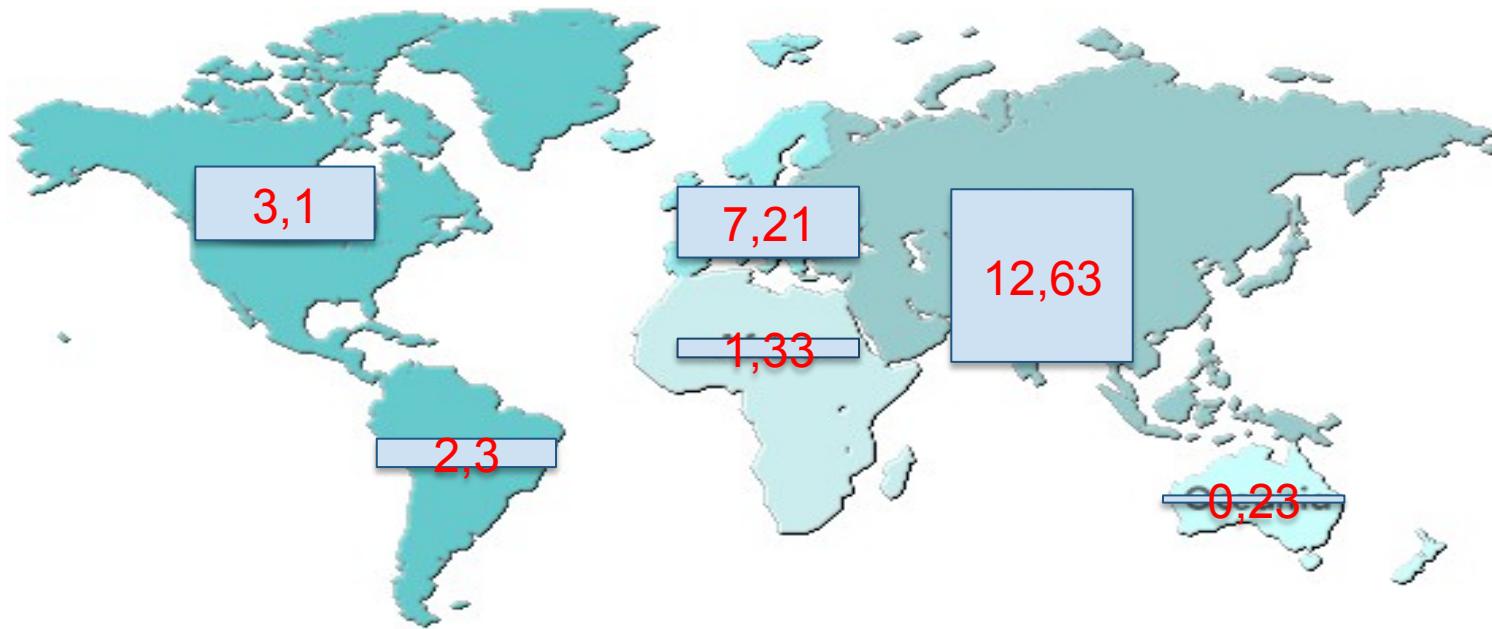
Health-care

160 billion \$ every year worldwide

[Wimo et al., *Dement Geriatr Cogn Disord* 1998]

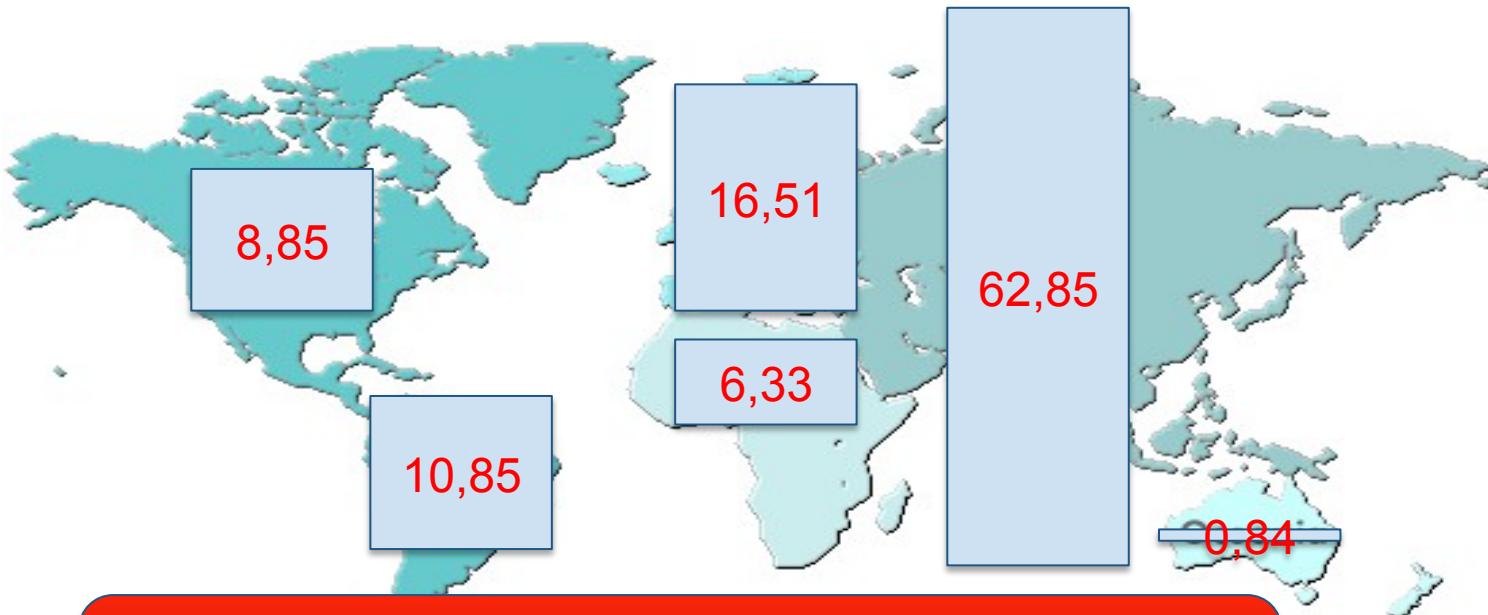
People affected in the world

26,6 millions in 2006



[Brookmeyer et al., Alzheimers and Dementia 2007]

People affected in the world 106 millions en 2050

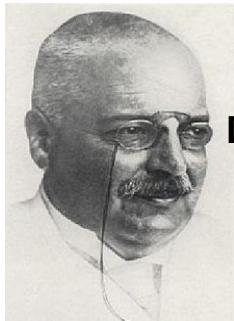


“Looming epidemic”
2017

No cures nor preventive measures

[Brookmeyer et al., *Alzheimers and Dementia* 2007]

Urgent need: understanding the disease

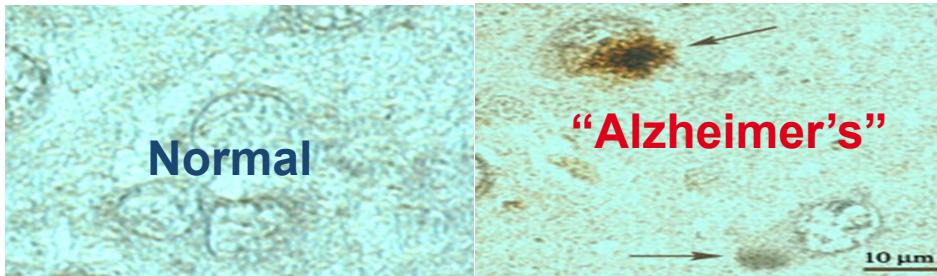


Dr. Aloysius “Alois”
Alzheimer
(1864-1915)

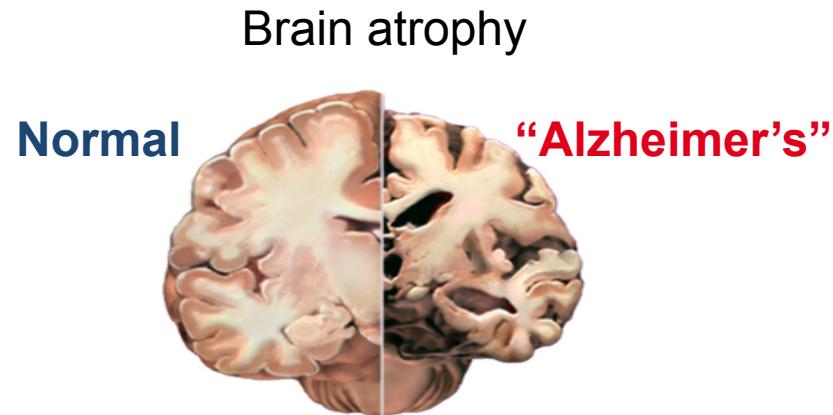


Auguste Deter
(1850-1906)

Amyloid plaques &
neurofibrillary tangles



[Kahn et al, PNAS 2007]



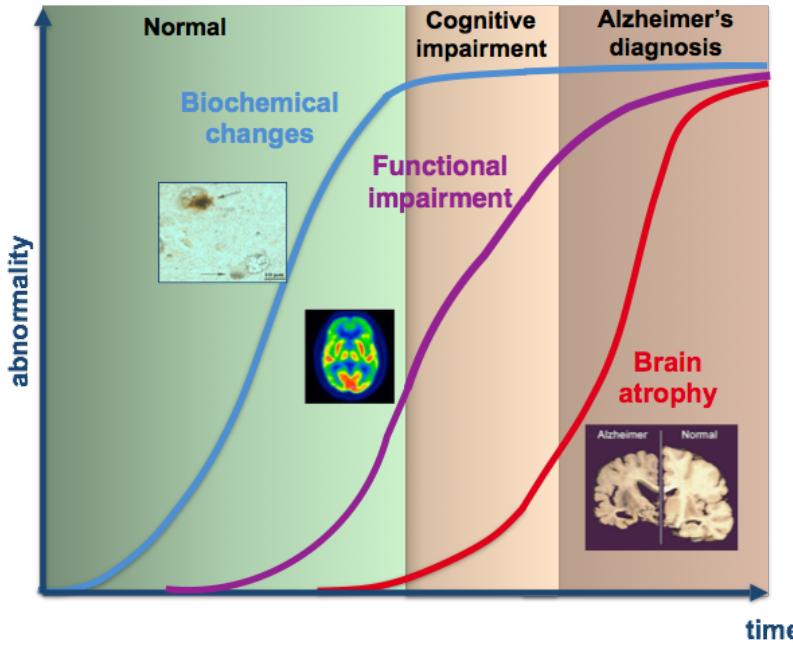
source <http://www.alz.org>



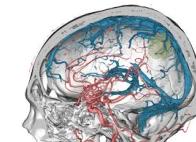
A story with several actors



Jack et al, Lancet Neurol 2010;
Frisoni et al, Nature Rev Neurol 2010



Sociodemographic



Vascularity



Genetics



Microbiome

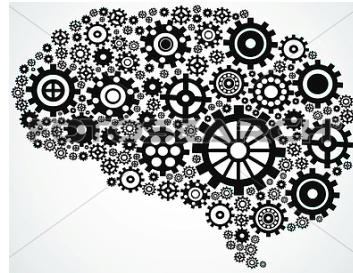
...



Multifactorial processes



**Disentangling
the pathological
mechanisms
drug discovery**



**Patient stratification
(diagnostic)**
effective clinical trials

Approaches

Forward
Models → Data

- Targeted
- Testing “mechanistic” hypothesis
- ☹ Difficult to account for several factors

Backward
Data → Models

- Exploring unknown interactions
- Based on inferential methods
- ☹ Generalization and validation



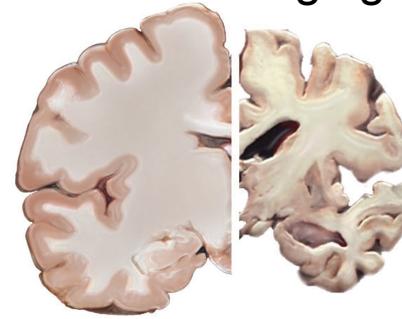
A research challenge



Data science
Statistical learning



Biomedical research
Neuroimaging



Combine heterogeneous data and observations for:

- Improve the understanding of the disease
- Better treatment
- Better diagnostic

Joint modeling of brain and genetic data in Alzheimer's disease

- Ingredients -

- **Data (disease markers)**
- **Algorithms**
- **Databases**

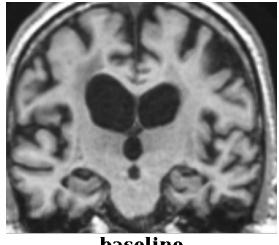
Joint modeling of brain and genetic data in Alzheimer's disease

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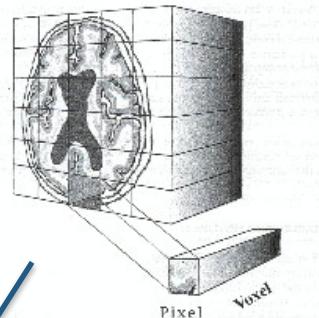
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Brain imaging

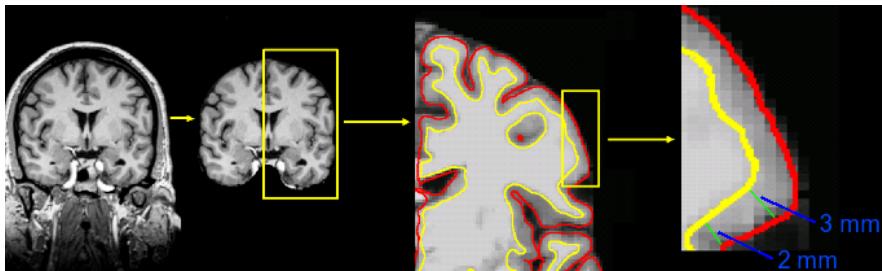
Quantify the brain structure



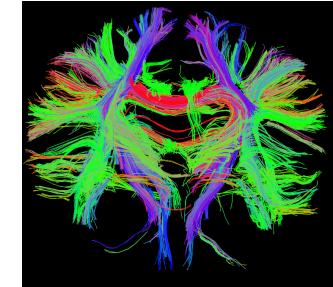
baseline



Grey matter



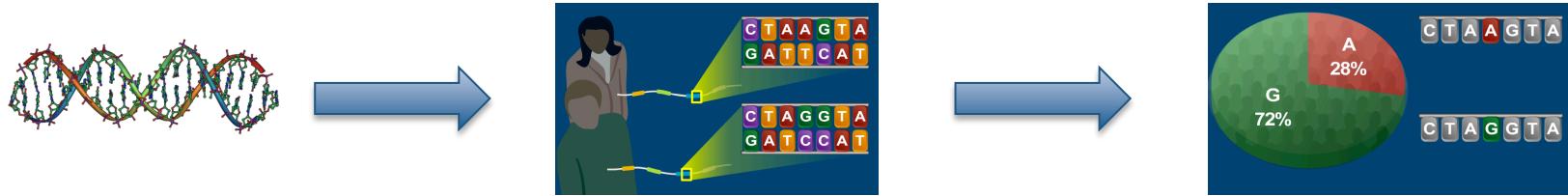
Brain cortical thickness



Connectivity

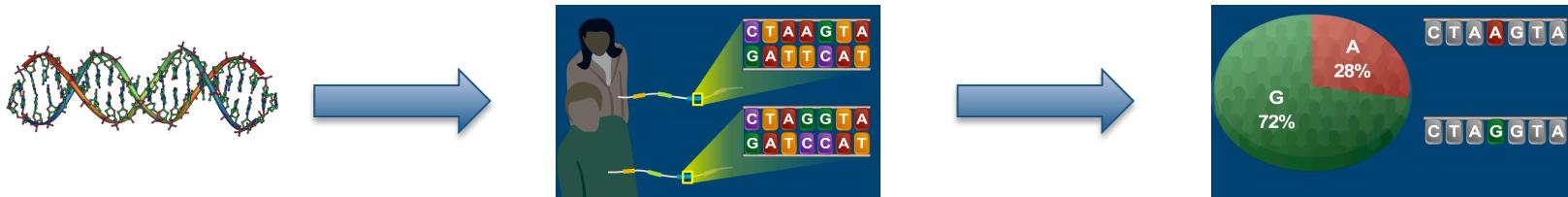
Genetics

Identifying meaningful genetic variants
(Single Nucleotide Polymorphism -SNP-) in a population



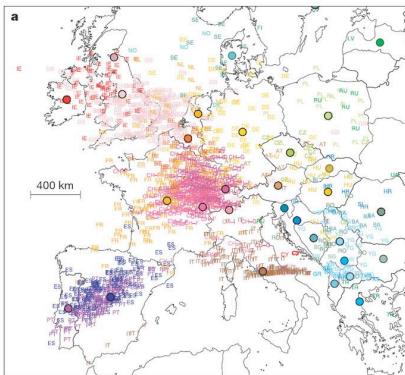
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Discovering the
encoded information

Novembre et al, *Nature*, 2008



Heritability

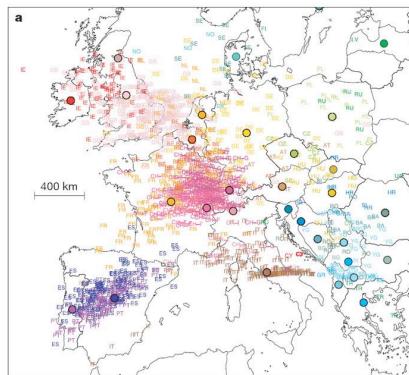
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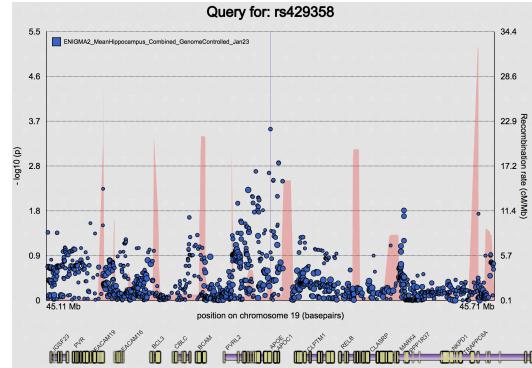
Discovering the encoded information

Novembre et al, *Nature*, 2008



Heritability

Association with a disease

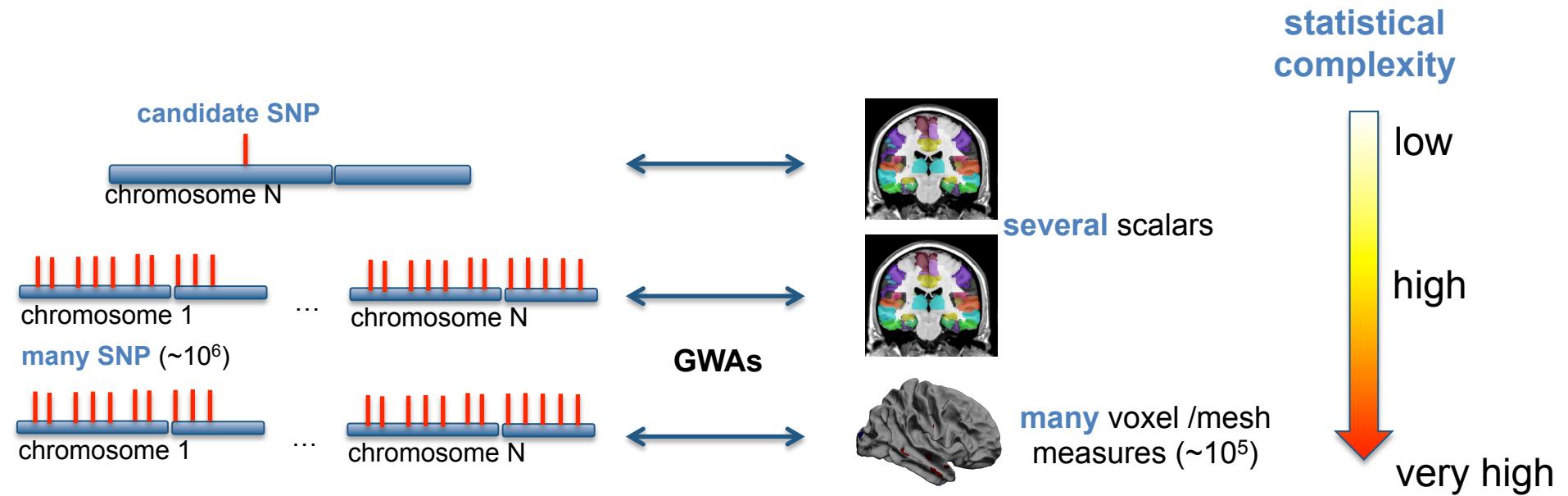


Joint modeling of brain and genetic data in Alzheimer's disease

- Ingredients -

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Association between SNP and brain features



Multivariate Association studies

Maximizing the joint relationship between genetic variants and brain features

$$\mathbf{X} = \begin{matrix} \text{~10}^6 \text{ SNPs} \\ \text{---} \\ \text{N individuals} \end{matrix}$$
$$\mathbf{Y} = \begin{matrix} \text{~10}^5 \text{ brain features} \\ \text{---} \\ \text{N individuals} \end{matrix}$$

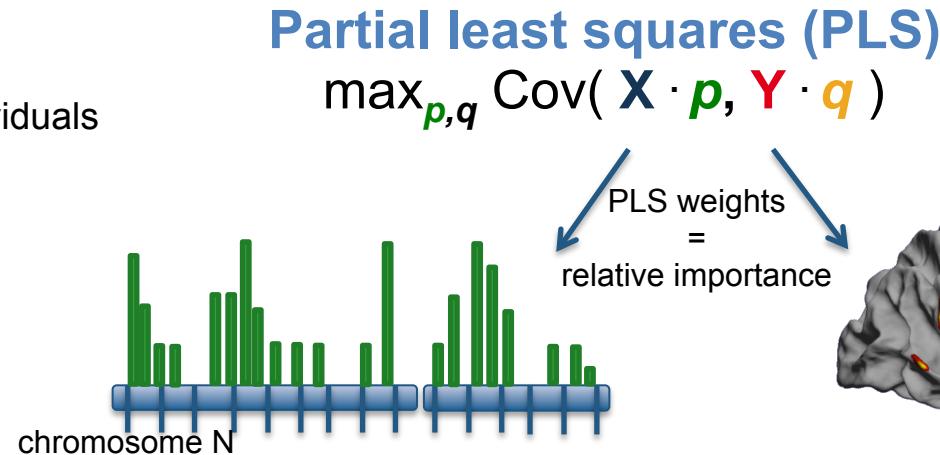
Partial least squares (PLS)
 $\max_{\mathbf{p}, \mathbf{q}} \text{Cov}(\mathbf{X} \cdot \mathbf{p}, \mathbf{Y} \cdot \mathbf{q})$

Multivariate Association studies

Maximizing the joint relationship between genetic variants and brain features

$$\begin{aligned} X &= \text{~10}^6 \text{ SNPs} \\ Y &= \text{~10}^5 \text{ brain features} \end{aligned}$$

N individuals



Multivariate Association studies

Maximizing the joint relationship between genetic variants and brain features

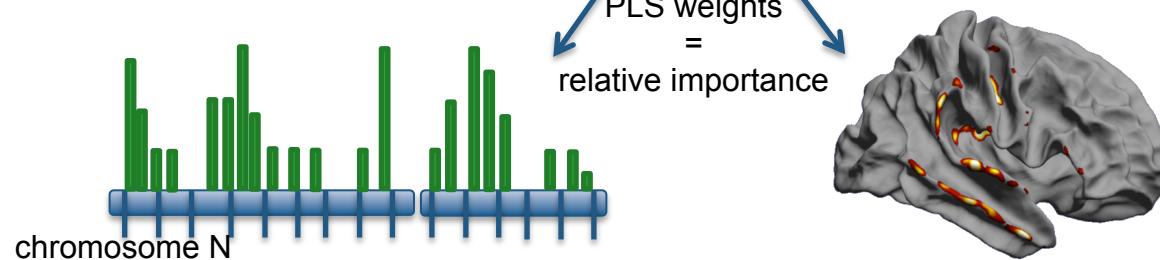
X = $\sim 10^6$ SNPs N individuals

Y = $\sim 10^5$ brain features N individuals

Partial least squares (PLS)

$$\max_{\textcolor{violet}{p},q} \text{Cov}(\textcolor{blue}{X} \cdot p, \textcolor{red}{Y} \cdot \textcolor{brown}{q})$$

PLS weights
=



Pros. Overcomes issues of mass univariate analysis

- Avoiding independent **multiple testing**
 - Exploring **SNP-SNP interaction** (epistatic effects)

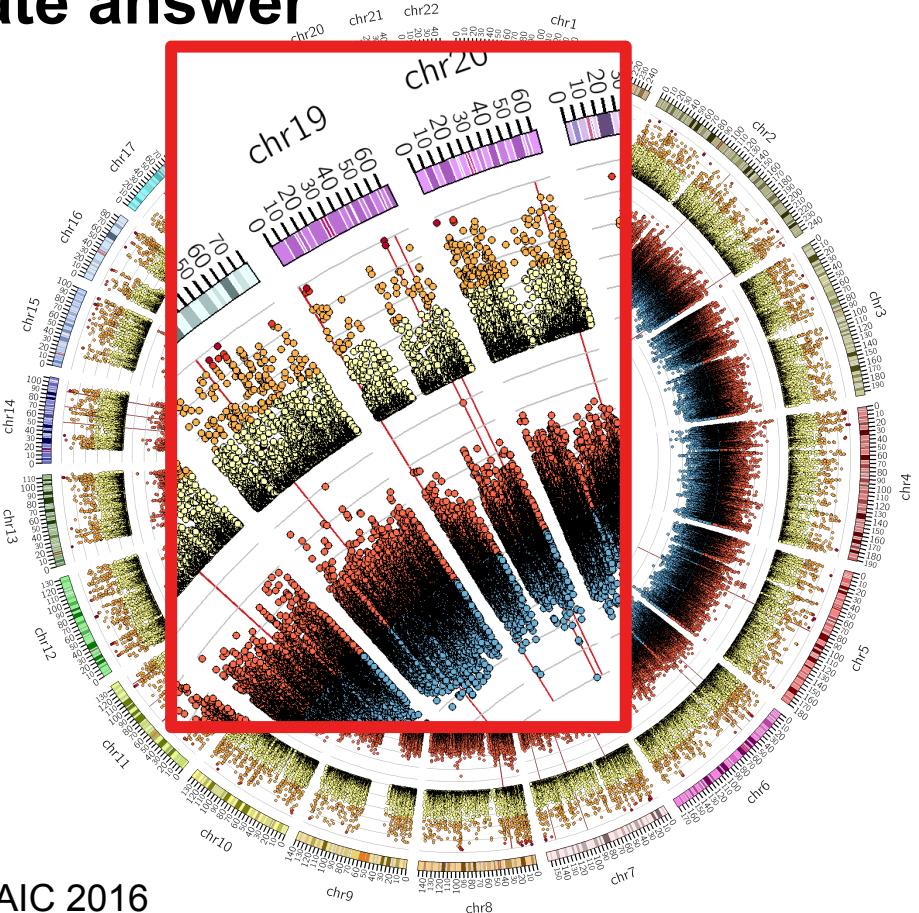
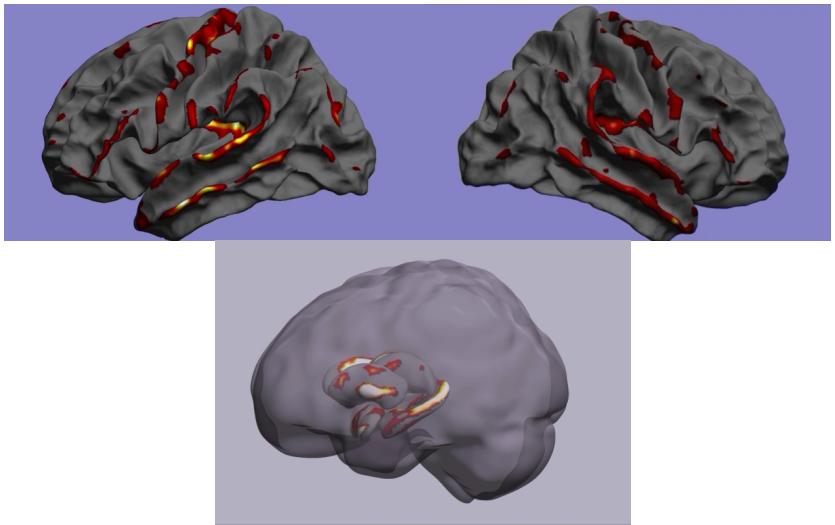
Cons.

- Overfitting and reproducibility
 - Computational complexity



A. Altmann

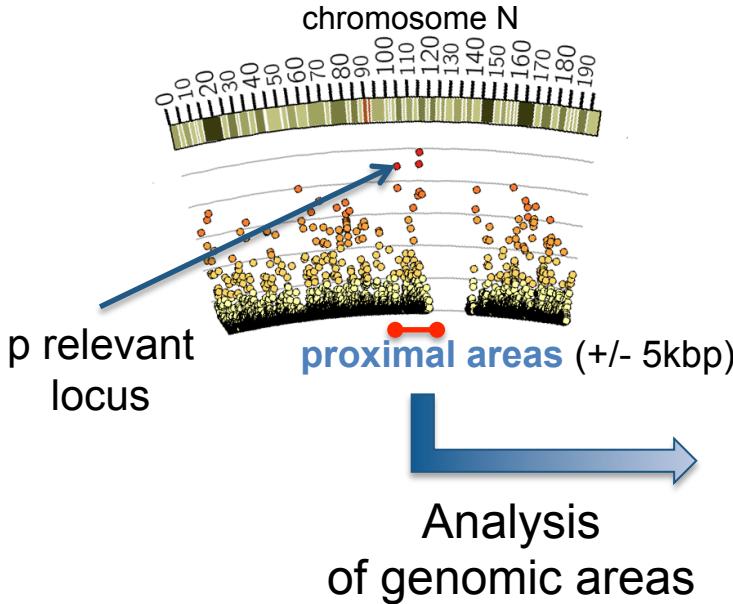
A multivariate answer



Lorenzi et al. AAIC 2016

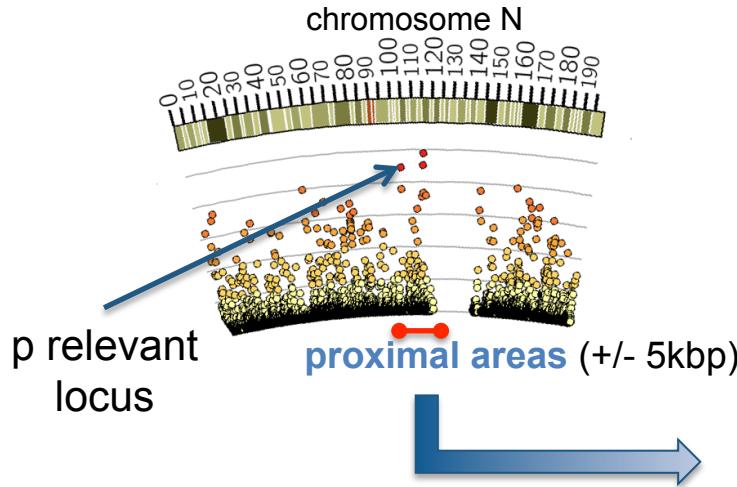
Investigating biological mechanisms through Meta-analysis

PLS statistical result



Investigating biological mechanisms through Meta-analysis

PLS statistical result



Querying gene annotation databases



Ve!P

McLaren et al. The Ensembl Variant Effect Predictor. Genome Biology, 2014

Investigating biological mechanisms through Meta-analysis



Ve!P



148 SNP-gene combinations

6 tested tissues

*hippocampus, whole blood,
Adipose subcutaneous, artery tibia, nerve tibial,
treated fibroblast*

14 Significantly expressed genes

TM2D1 (amyloid-beta binding protein),
IL10RA (increase in hippo in mouse model),
TRIB3
(neuronal cell death, modulates PSEN1 stability,
interacts with APP)

	Significance (p-value) training	Significance (p-value) testing
TM2D1	0.005	0.053
IL10RA	0.107	0.620
TRIB3	0.003	0.003
ZBTB7A	0.036	0.913
LYSMD4	0.000	0.206
CRYL1	0.621	0.118
FAM135B	0.000	0.559
IP6K3	0.000	0.465
ITGA1	0.099	0.731
KIN	0.001	0.206
LAMC1	0.002	0.062
LINC00941	0.000	0.690
RBPMS2	0.000	0.215
RP11-181K3.4	0.002	0.053

Joint modeling of brain and genetic data in Alzheimer's disease

- Ingredients -

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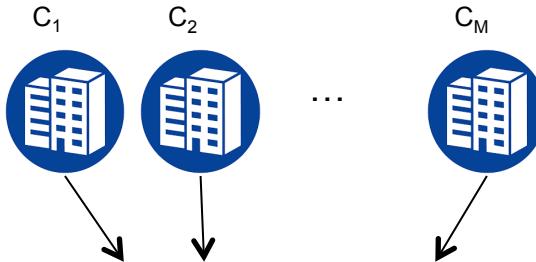
Large multicentric clinical studies



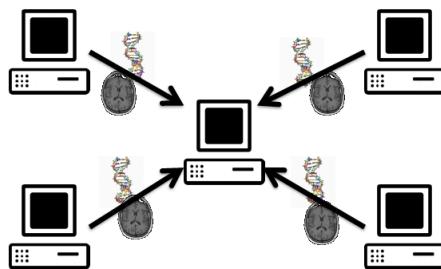
Data for ~100'000 individuals

Challenge: Meta-study

Meta-analysis in genetic studies



State-of-art:
analysis of **univariate** outcome
(p-value, effect size, standard error, ...)



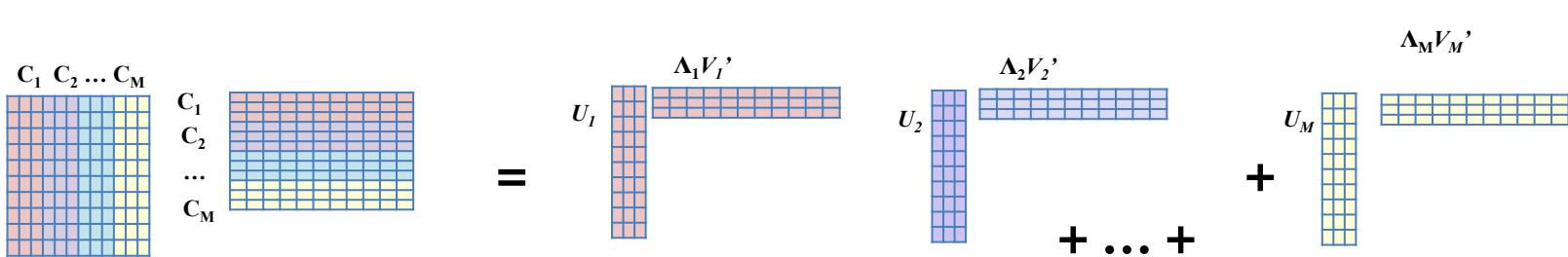
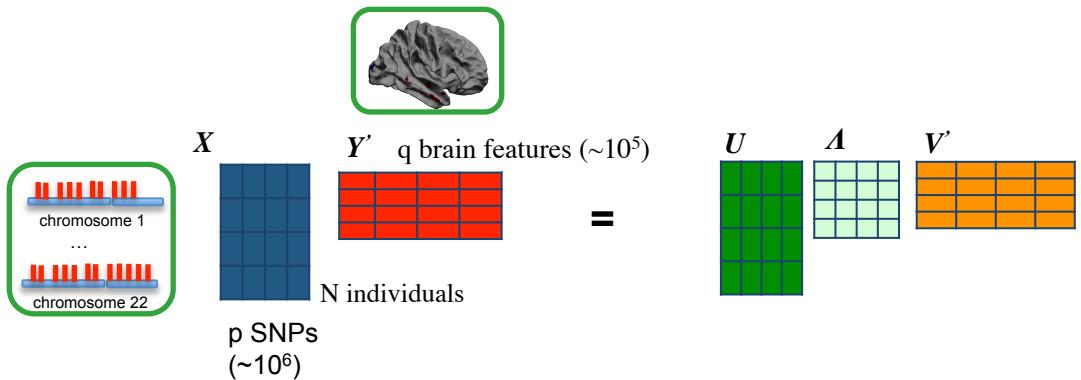
Cons.

- **Multiple testing** → low statistical power
- **No SNP-SNP interaction**
- Limited interpretability

Problem.

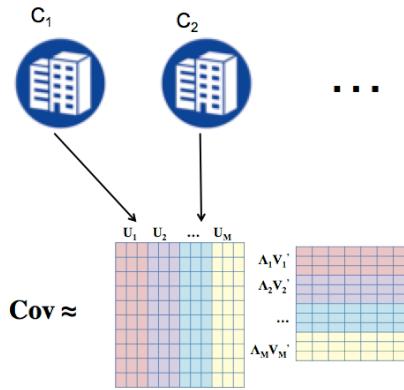
How to develop **multivariate imaging-genetics** modeling approaches within a **meta-analysis** context?

Extending meta-analysis for multivariate models

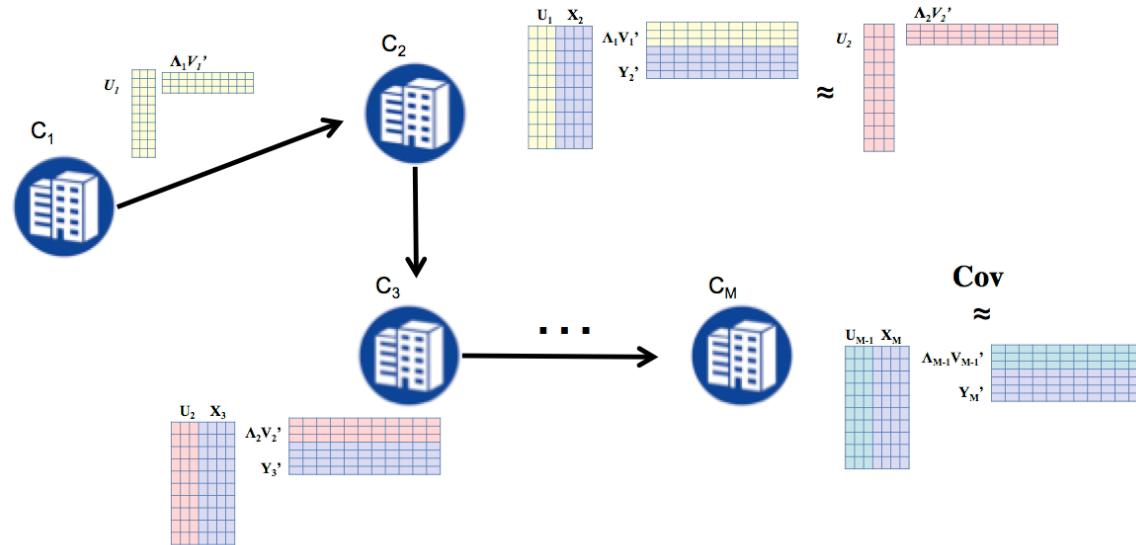


Extending meta-analysis for multivariate models

Meta PLS

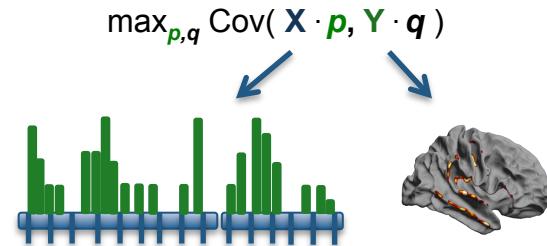


Sequential PLS



Conclusions

Linking **brain atrophy** to **biological functions** through
Multivariate analysis of **genotype-phenotype relationship**
+
thorough cross-validation for stability assessment



Warnings

- Often required to process large datasets with standard hardware
- Need of processing large datasets across different sites

Thank you!