Machine Learning for Personalized Genomics

Jean-Philippe Vert







C3BI Kick-off meeting, Institut Pasteur, Paris, March 16, 2015

Institut Curie / Inserm U900 / MINES ParisTech partnership







Inserm

- A joint lab about ``Cancer computational genomics, bioinformatics, biostatistics and epidemiology"
- Located in Institut Curie, a major hospital and cancer research centre in Europe, and MINES ParisTech

4 teams + 1 platform

Systems Biology (Barillot):

- Modelling, simulating biological systems
- Building an in silico atlas of cancer pathways

Clinical Biostatistics (Asselain / Paoletti):

- Clinical trials for targeted therapies
- Predictive biomarkers

Cancer Genetic Epidemiology (Andrieu):

Genetic and environmental factors in breast cancer

Machine learning (Vert):

Learning from « big omics data » for personalized medicine



Human genome project (1990-2003)

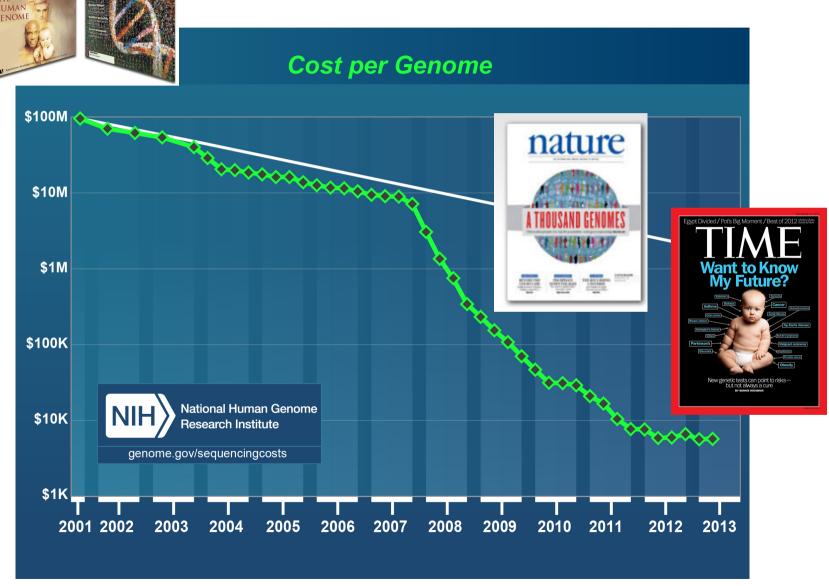
- Goal: sequence the 3,000,000,000 base pairs of the human genome
- Consortium of 20 laboratories, 6 countries
- 13 years, \$3,000,000,000







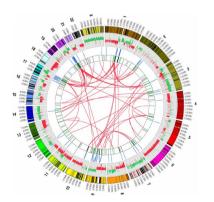
The **second** revolution



A flood of omics data



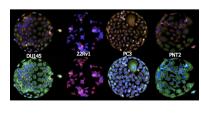
Interactome



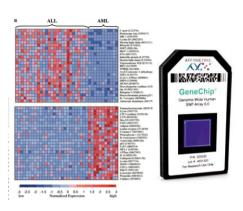
Mutations
Structural variations



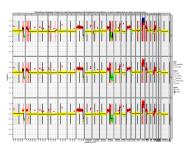
Genome



Phenome

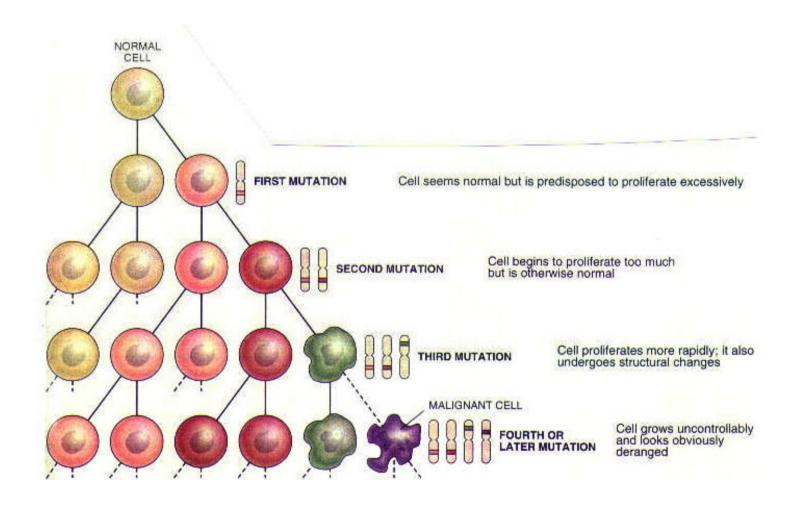


Transcriptome

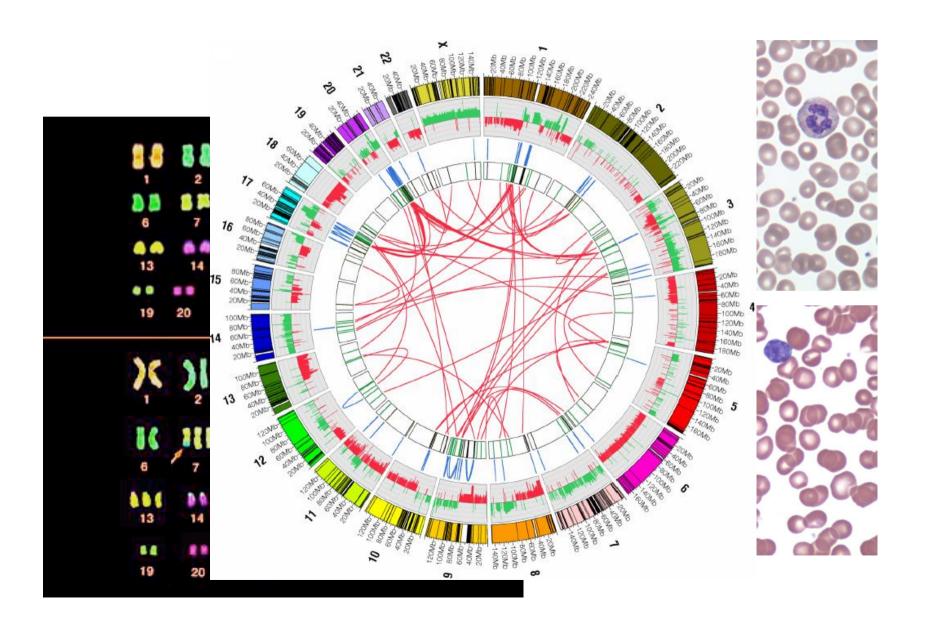


Epigenome

All cancers are different

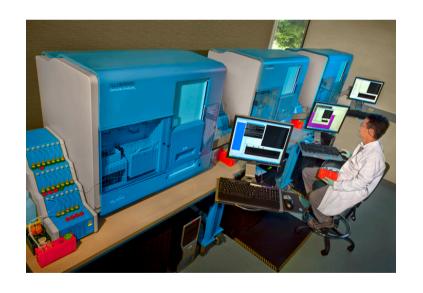


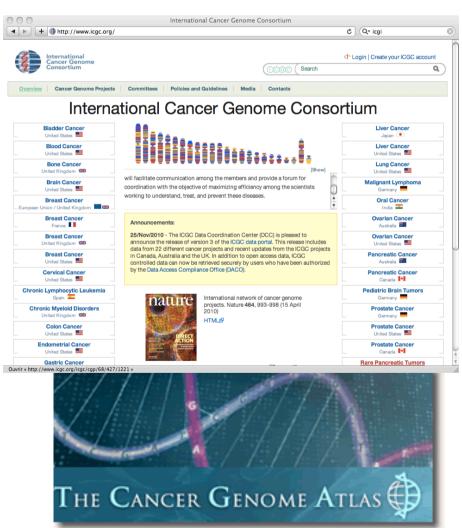
Cancer: different views



Big data!

http://aws.amazon.com/1000genomes/











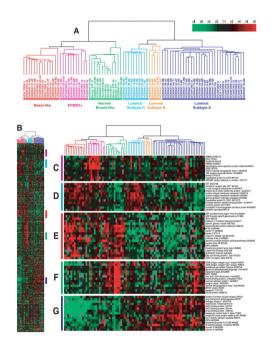




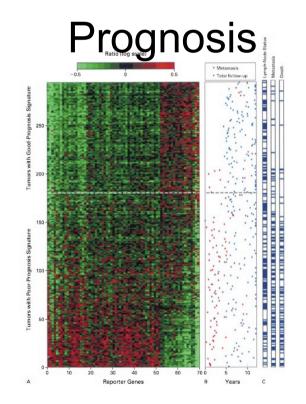


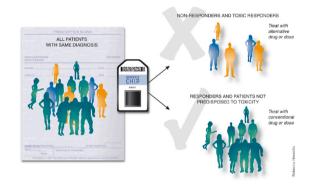


Opportunities



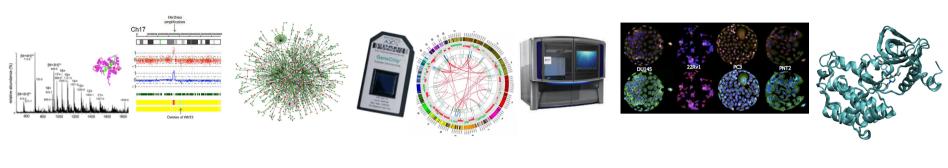
Diagnosis

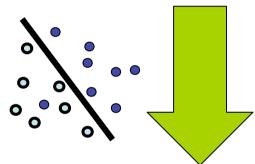




Response to drugs

Rationale of my team

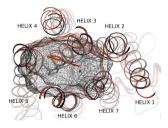




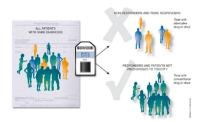
Machine learning



Mecanisms, drug targets

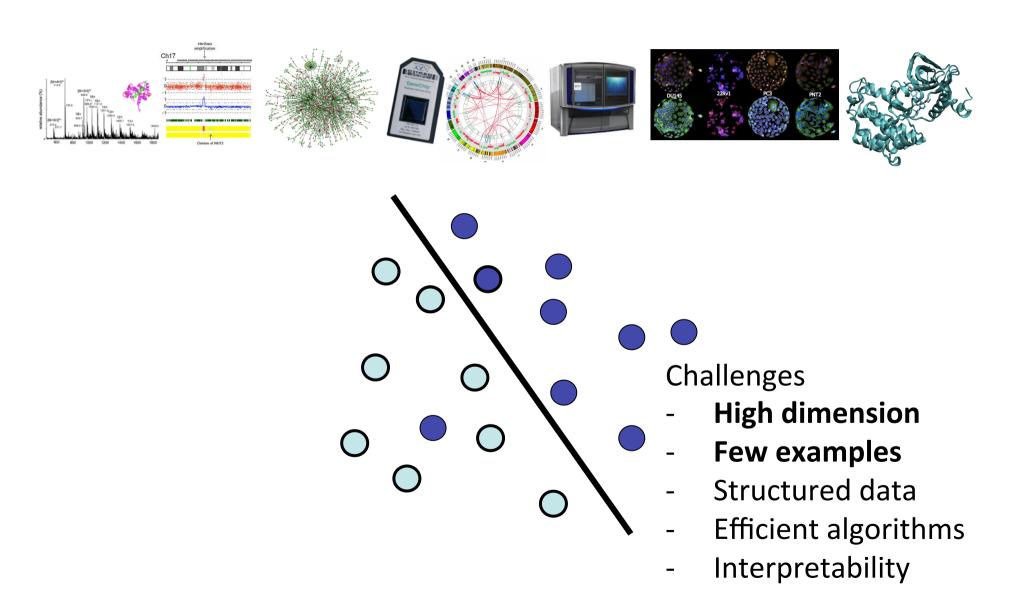


Drug design

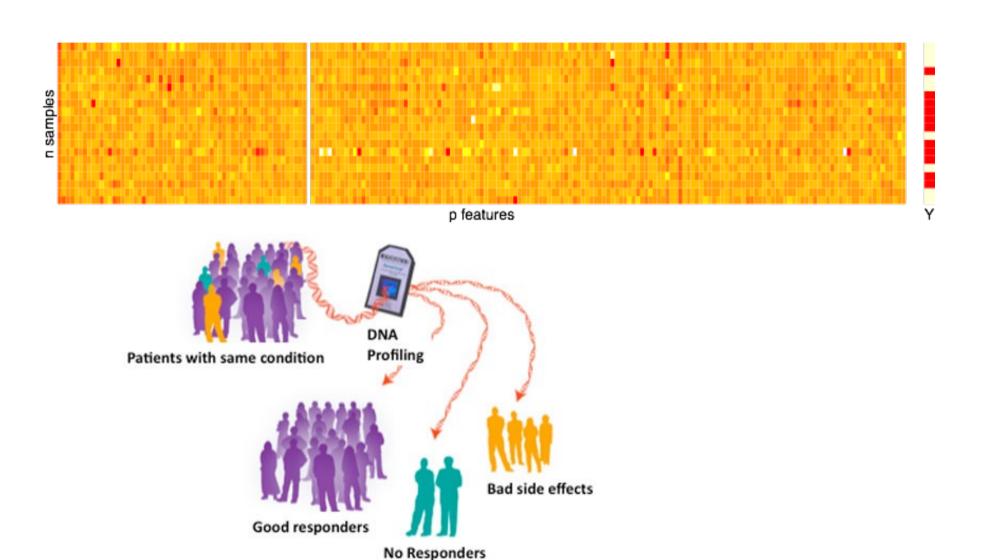


Personalized medicine

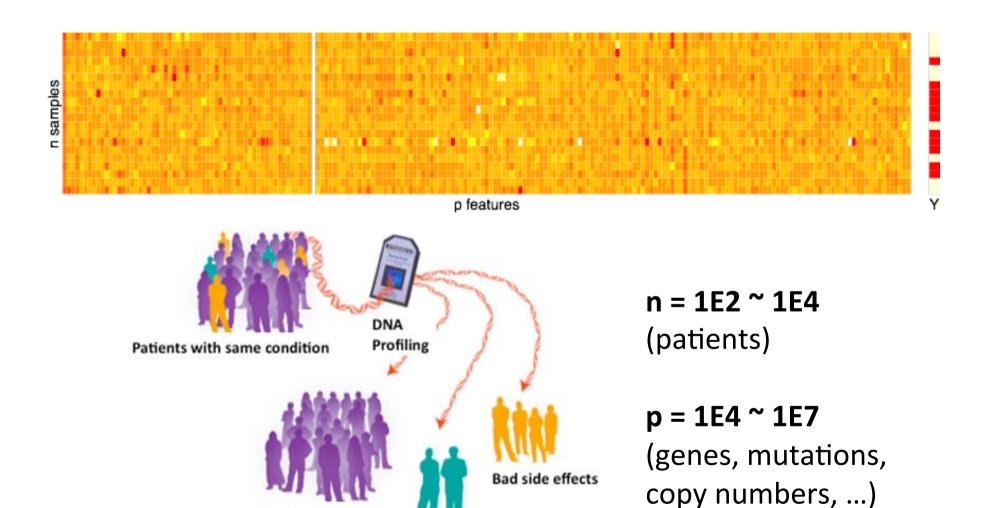
Machine Learning?



Example: Patient stratification



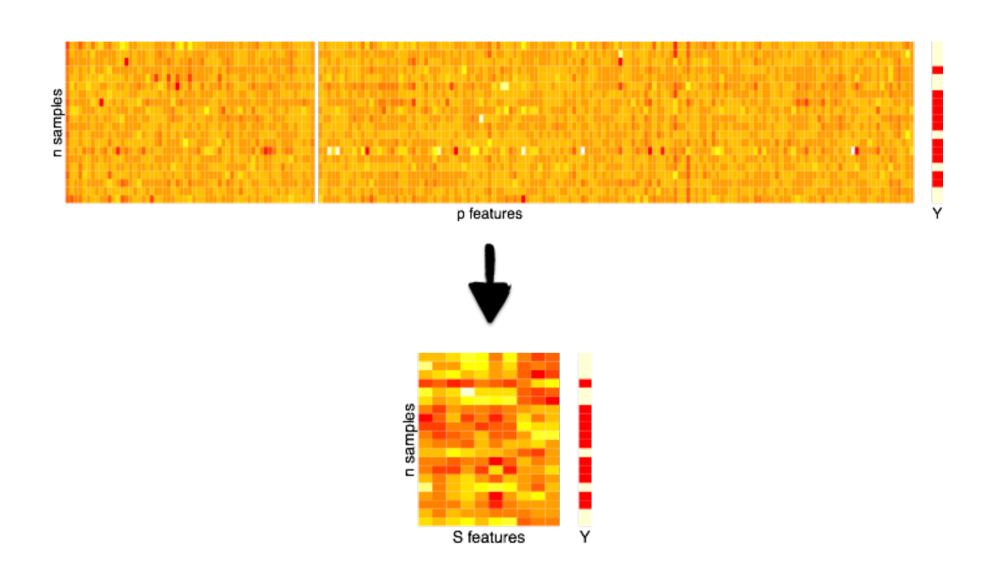
Problem: n << p



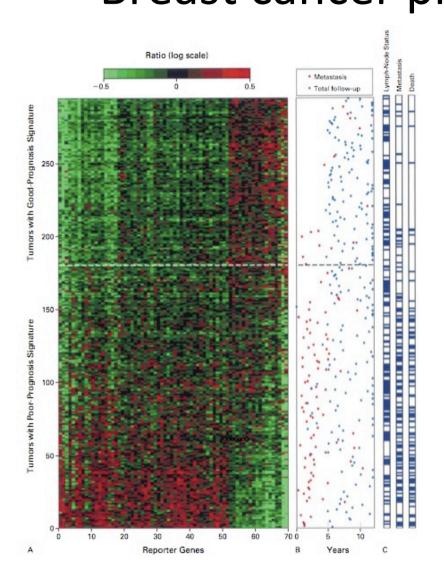
No Responders

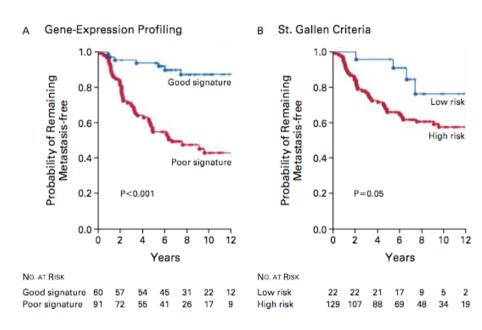
Good responders

Feature Selection

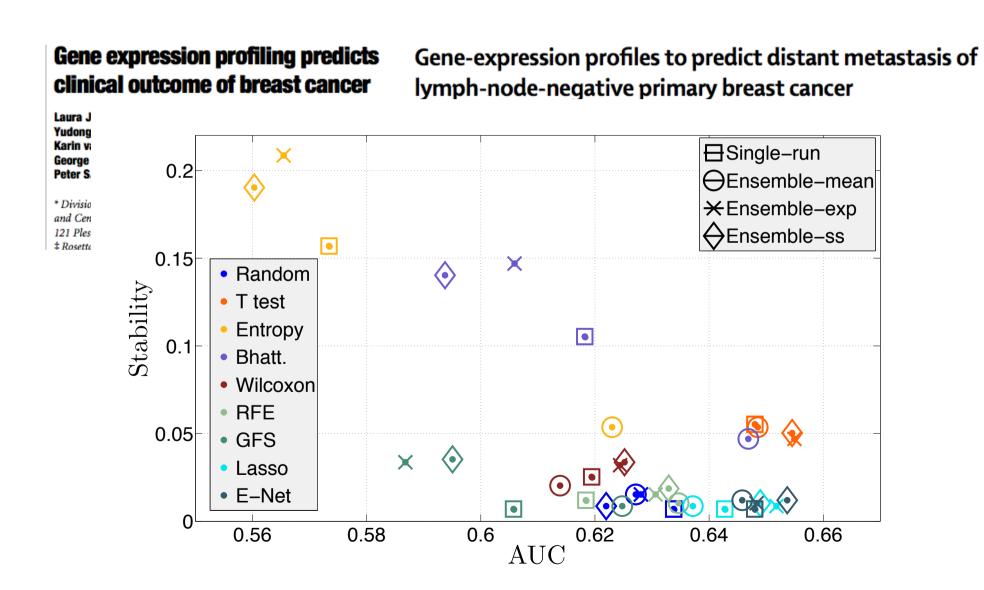


Example: Breast cancer prognostic signature

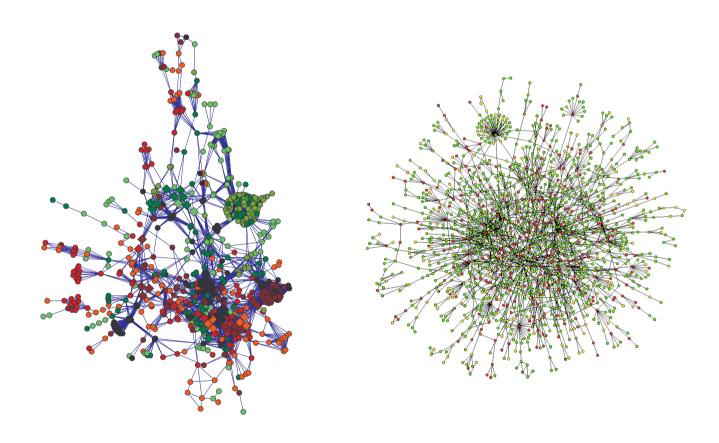




But...



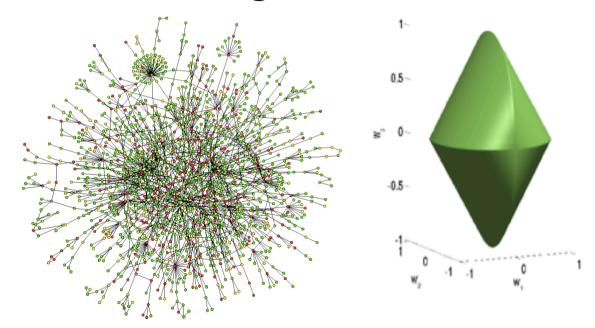
Prior knowledge: gene network



Can we « force » the signature to be « coherent » with a known network?

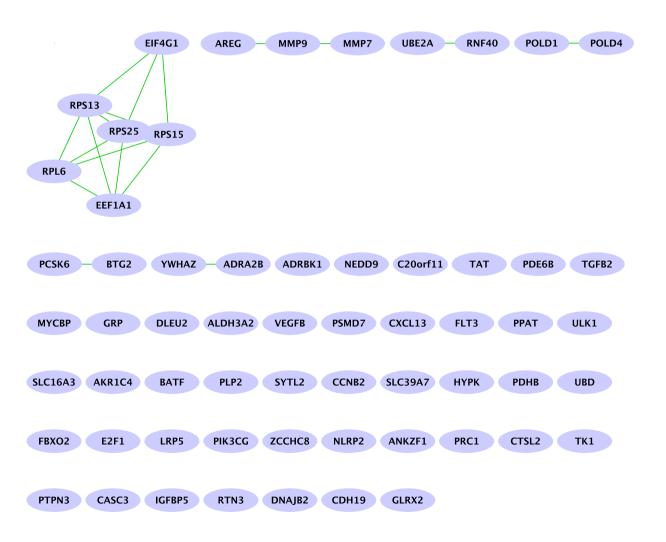
Example: the graph lasso

 Step 1: Using the network, define a subset of « candidate » signatures

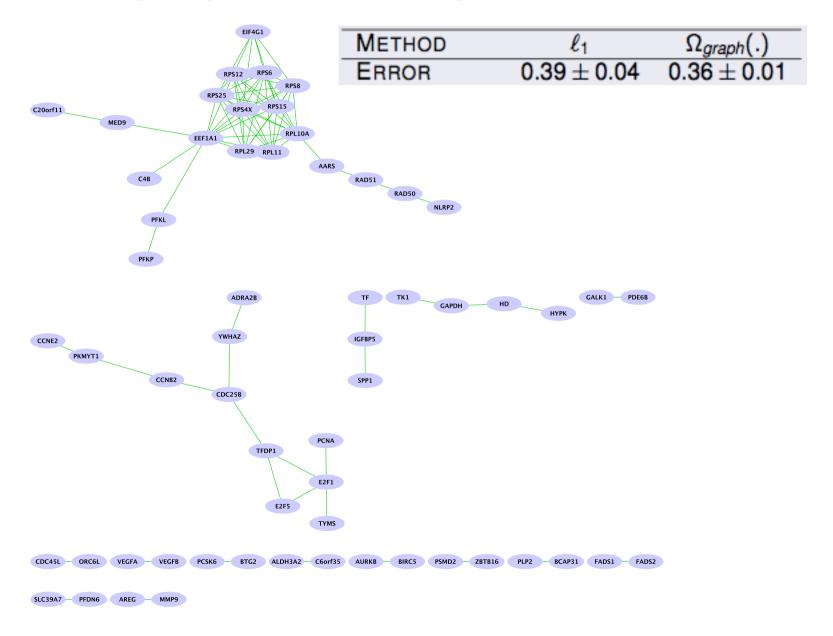


• Step 2: Among the candidates, find the best signature to explain the data

Classical signature



The graph lasso signature



Example: Toxicogenetics / Pharmacogenomics

Toxicogenetics Challenge Data

Chemical descriptors

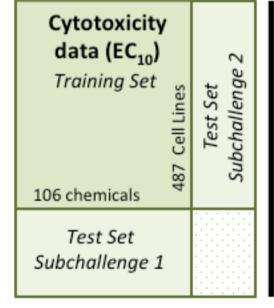
Genotypes RNASeq

STOTILE

46K transcripts

Not
available

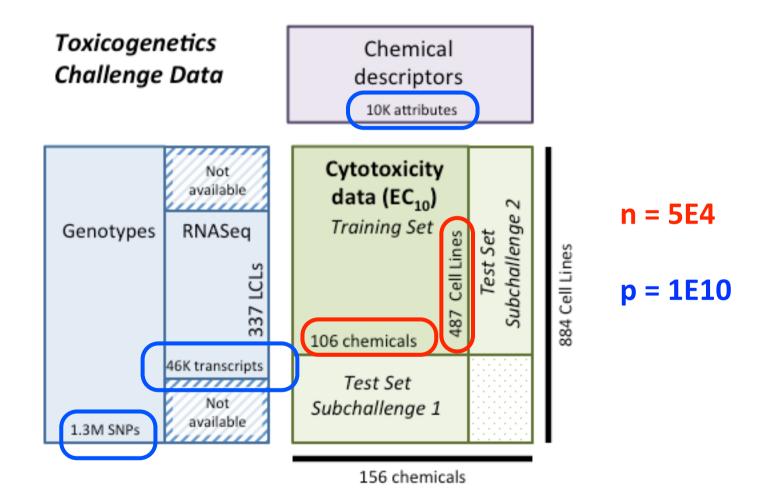
Not
available



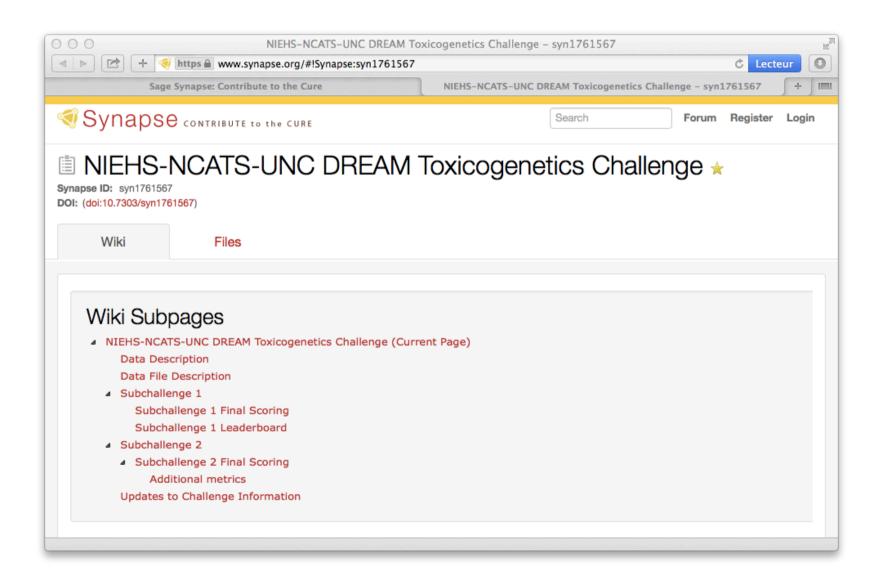
884 Cell Lines

156 chemicals

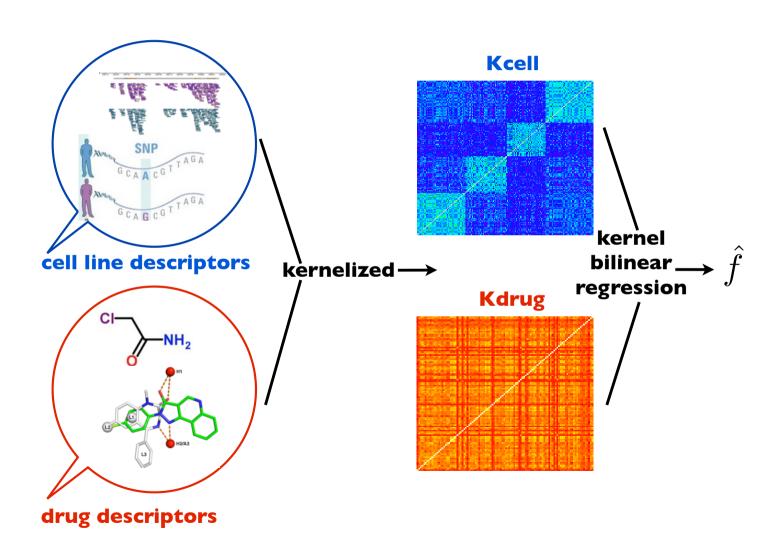
Problem: n << p



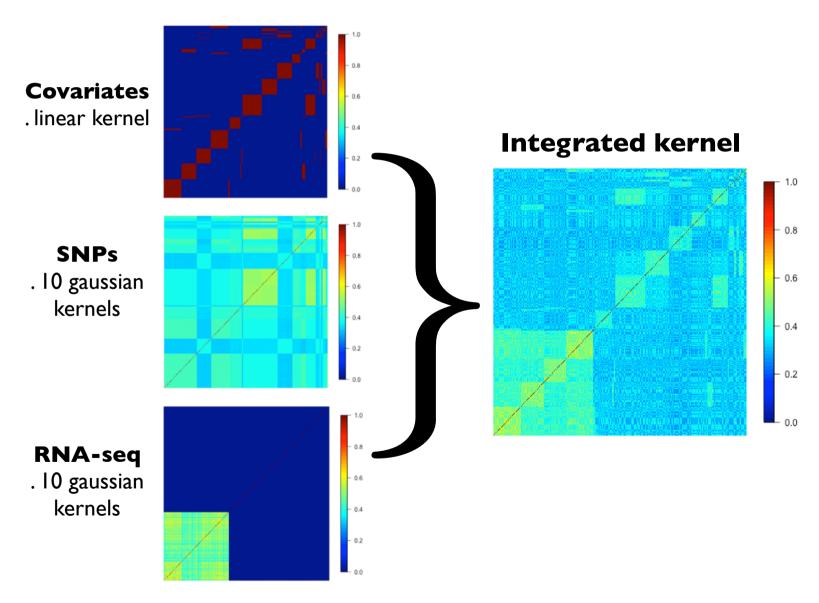
Crowd-sourcing initiatives



Our approach

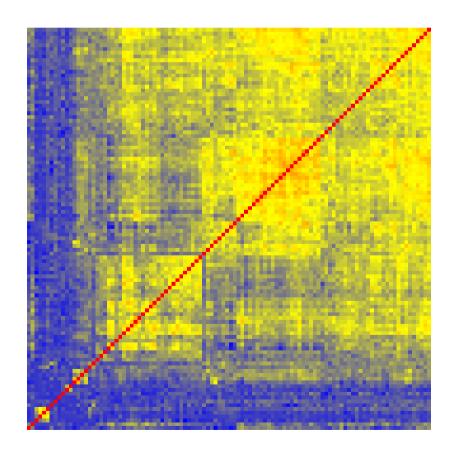


Cell line descriptors (30 kernels)

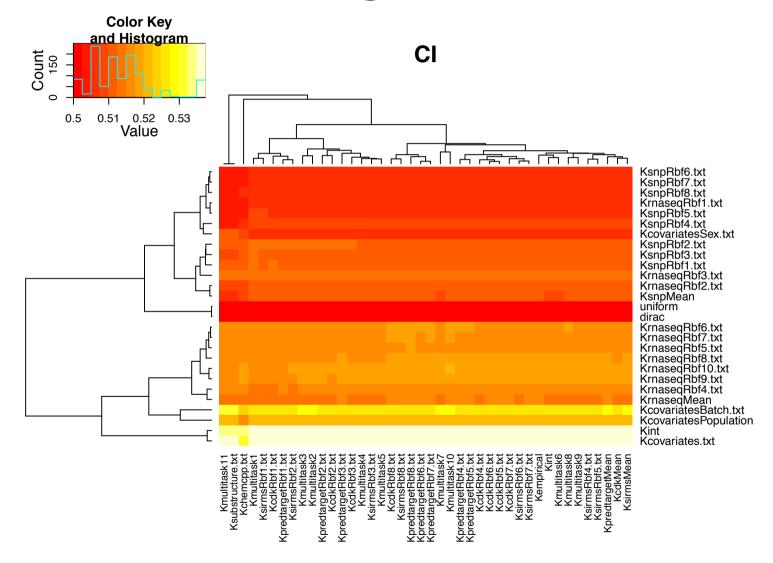


Chemical descriptors (49 kernels)

- Descriptors of chemical structures
- Multitask kernels
- Empirical correlation
- Integrated kernel

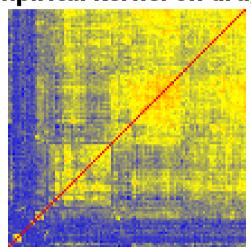


Learning occurs...

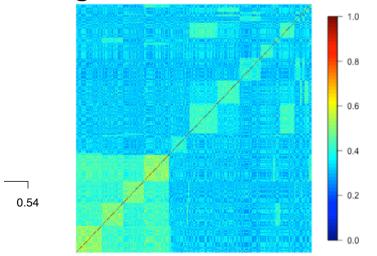


Final submission (ranked 2nd)

Empirical kernel on drugs



Integrated kernel on cell lines







Conclusion

- Lots of data due to technological progress
- Opportunities: precision medicine, quantitative biology
- Challenges:
 « small N », weak
 signal, complex
 systems



Thanks!



BIOMÉ RIEUX









