Statistical Methods for High Dimensional Biology STAT/BIOF/GSAT 540

Lecture I – course introduction
Paul Pavlidis
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Today's topics

- What the course is about
- Course mechanics
- Introduction to high-dimensional biology

Your instructors

- Dr. Jenny Bryan Associate Professor of Statistics/MSL
 - jenny@stat.ubc.ca
- Dr. Gaby Cohen-Freue Assistant Professor of Statistics
 - gcohen@stat.ubc.ca
- Dr. Paul Pavlidis Associate Professor of Psychiatry/CHiBi
 - paul@chibi.ubc.ca
- TAs: Luolan (Gloria) Li (<u>Ili@bcgsc.ca</u>) and Shaun Jackman (<u>sjackman@gmail.com</u>)
- Office hours: please contact us by email to set up a meeting

Course audience

- Researchers who want to know how to analyze large data sets from biological studies
- Genomics-focused, but information is broadly applicable
- Statistics students might find the math parts easy
- Biology students might find the biology easy
- We are counting on you to help make it work: help your peers!

Prerequisites

Officially, none. But:

- **Statistics** You should have already taken university level "Statistics 101". You'll get a refresher, but you should be prepared to get comfortable thinking about things like "probabilities" and "specificity".
- **Biology No requirements**, but you are expected to learn things like the difference between a DNA and RNA and a gene and a genome. We assume you are here because you are interested in biology and will pick it up.
- No R experience required but you must be prepared to do a lot of self-guided learning.
- You'll use your own computer to run R. If you can't install R on your computer, ask us for options.

What you can expect to learn

- Conceptual and practical knowledge you need to handle large biological data sets
 - Less about specific types of data, more about generally applicable approaches and principles
- You will be able to critically evaluate analyses in the literature
- Implementation of analyses using the R/Bioconductor computing environment

Not about:

- Formal mathematical theory underpinning the approaches
- Gory details of how to analyze any particular type of data at a low level

Topics covered

Probability foundations

Exploratory data analysis

Data QC and preprocessing

Basic statistical inference ("one gene at a time")

Large-scale inference ("genome-wide")

Count-based data (e.g. RNA-seq) analysis

DNA methylation analysis (new this year)

Principal Component Analysis

Clustering

Classification

Resampling and bootstrap

Model selection and regularization

Gene sets and gene networks

Course mechanics

Course web site

http://www.ugrad.stat.ubc.ca/~stat540/

- Lecture notes
- Lab notes
- Assignments

Discussion group: Google groups

http://groups.google.com/group/stat540_2014

- TAs will add you
- Privacy issues: to be addressed Wednesday

Lectures

- ESB 4192
- Lectures shared among three professors
- Notes provided on web before class

Sections/Labs

- Wednesdays in room ESB 1042
- Officially from 12-1, but we will start at 11
 - 11-12: R help
 - 12-1: TA Office hour (this week: Mol. Bio. Primer)
- Self-guided exercises to help you learn to use R for analysis.
- Using your own computer (other options possible)
- Exercise material will be made available ahead of time
- Towards end of course, more time devoted to working on group projects.

Readings

- No textbook, but we can give suggestions
- Lectures often come with suggested background papers (reviews or primary literature)
- Make sure you can access journals online (e.g. via the UBC VPN)
 - http://it.ubc.ca/services/email-voice-internet/myvpn/setup-documents
 - Some resources are via SpringerLink, which requires use of the UBC network for access.

Evaluation

Homeworks

- Two assignments worth 25 points each

Group project

- Planning + project + poster session 40 points
- 10 Points for "other"
 - e.g. Preparedness, participation.

Homework assignment

- One for February, one for March.
- Involve detailed analysis of real data
- Deliverables include a short report and R code
- Two weeks from assignment to due date
- Lateness penalties

New for 2014: we may suggest/require that incremental progress be submitted along the way

Group projects

- Starts today start thinking about it
- A few minutes for group project pitches on Jan 20 and Jan 22.
- Form groups by Fri Jan 24 (3-4 people)
- Friday Jan 31: initial project proposals
- Feb 28: final project proposal
- Final session of the course is the poster session

Group projects: where do they come from?

- Historically, almost all projects have been based on a data set provided by a student (i.e., collected in their lab).
- Occasionally, instead based on an idea from a student, where the data comes from published sources.
- If you need help thinking up an idea for a project let us know. But this has never been needed before (beyond refinement). If you are unsure of where you are going to get a project from, wait until you hear the project pitches.

Examples of past group projects

- Genomic copy number alterations for prognosis of prostate cancer
- Learning about proteins from other proteins: Protein Database Prediction
- Conditional epistasis profiling in yeast
- Epigenetic biomarkers for cancer diagnosis
- Comparative metagenomics: metabolic potential
- Epigenome and transcriptome in rice strains
- Analysis of HPV E2 protein on host gene expression
- Effects of Mutations in Histone Modifying Enzymes on Gene Expression Profiles
- Methodological considerations in analysis of Illumina Infinium methylation data
- Gene expression in invasive ragweeds
- Modeling time-course expression of SET domain-containing genes in mouse embryos
- Gene expression in blood of humans with asthma challenged with allergen

High-dimensional biology

- I. What is it
- 2. What kinds of methods are used to analyze it
- 3. Some examples

Collecting data the lowdimensional way

- Pick one variable (e.g. "activity of a protein") and study it under various conditions.
- Repeat this for another variable
- Usually "hypothesis-driven"
- Powerful, but knowledge accumulates slowly and synthesis is difficult

Biology is complicated

- Thousands of "parts"
- Limitations of the "one thing at a time approach" – how do the parts work together?
- Technology enabling increasingly detailed analyses – measure many things in parallel

• Drawback: Fishing expeditions?

Defining "high dimensional"

- Large number of features measured in each sample/subject/individual ("high content")
 - Genes, proteins, DNA sites, brain regions, etc.
- Not usually talking about huge numbers of samples (e.g. individuals studied) –
 - often 10s, but can be 1000s (some genetics studies)
- Studies can sometimes be "non-hypothesis driven"

Example of a question answered with a high-dimensional approach

- Tumor type A is deadly and type B is more easily treatable (but still bad)
- Telling A from B is difficult
 - Cells look the same, etc. we only find out by seeing what happens to the patients.
- We know that cancer is a "gene" disease

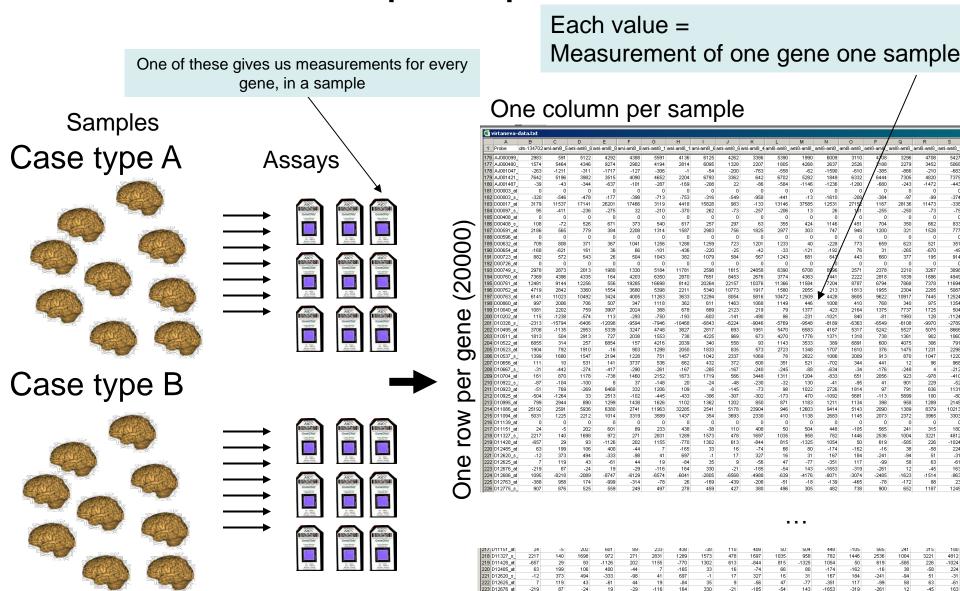
Questions:

- Where is the difference?
- Can we find new targets for drugs or for diagnosis?
 - (Drug targets are usually proteins, encoded by genes)

Looking for insight from genomics

- Since cancer is a disease of genes, let's look at the genes not just one, but all of them
- We are hypothesizing that there is some difference in genes between the two types, if only we could find it
- But we're not starting with a specific hypothesis. We're going to test thousands of hypotheses
- In this example, we're going to look at "gene expression levels" – a measure of "how active" is each gene.

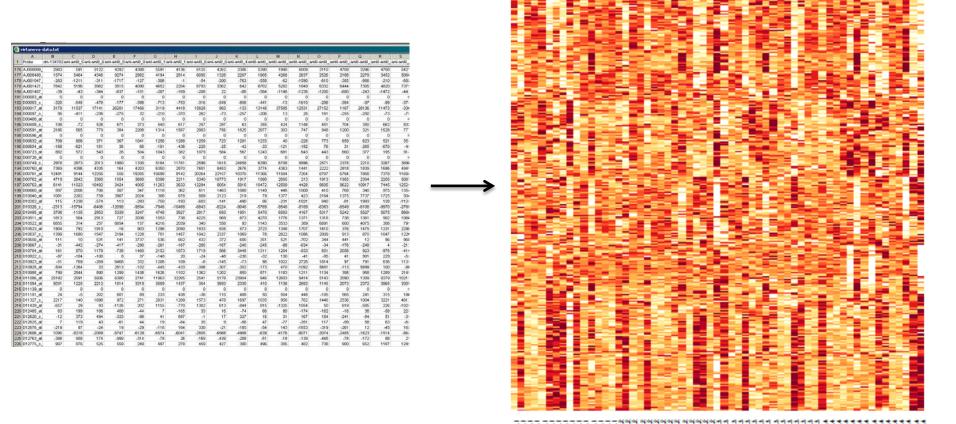
Example experiment



A partial list of things to assay

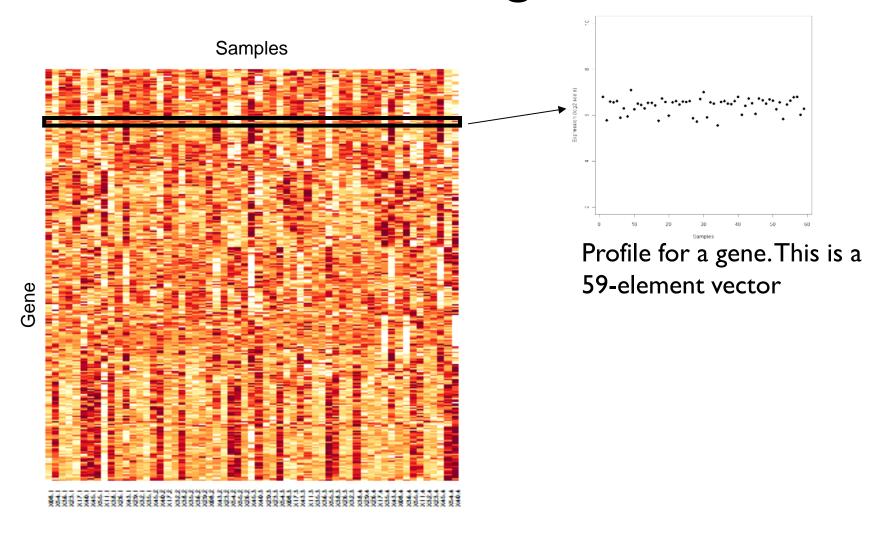
- DNA/Chromatin
 - Genotypes, copy numbers ("mutations" and variants)
 - DNA methylation
 - Chromatin state (histone marks, transcription factors ...)
- RNA
 - Quantification of transcripts (protein coding, non-coding)
 - Transcript variants (splicing, editing)
- Proteins
 - Detection, Quantification
 - Binding and complexes
- Metabolites and other small molecules
- Phenotypic screens
 - RNAi (etc.)
 - Genetic interactions
- Cellular composition of a sample (cell types)

Alternative representation

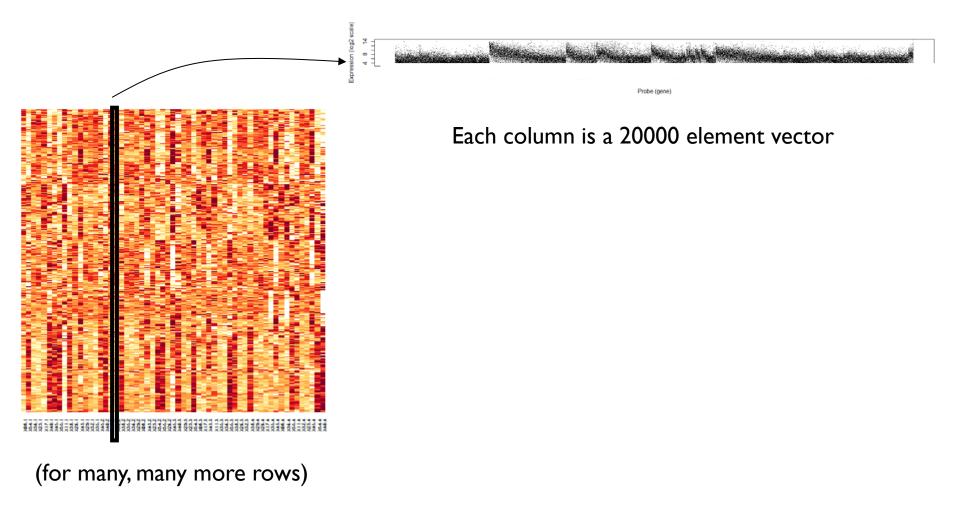


Lighter colours mean higher levels of gene expression ("activity") Only show part of the data!

Profile for a gene



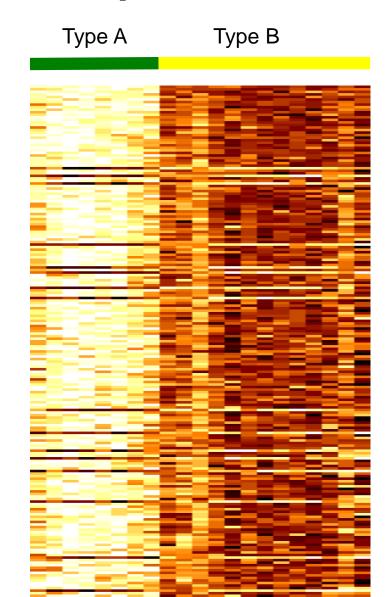
Profile for a sample



One type of analysis

- I've ranked the genes by how different they are between types A and B (tstatistic)
- Only the first few genes are shown
- Though it can be a lot more complicated, most "high-dimensional" studies boil down to something like this, at least in part

What's the big deal?



Pitfalls and challenges

- Signals can be small and buried in lots of nonsignals; False positives are a danger.
- Need to detect outliers, batch effects and other confounds
- Can we make better use of the fact that we're testing 20,000 genes than just doing a t-test on each one?
- Data sets (and questions) are often much more complex
- Getting just a list of "hits" isn't enough can we understand something more about the "system"

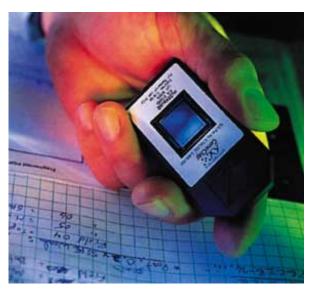
High-dimensional technologies

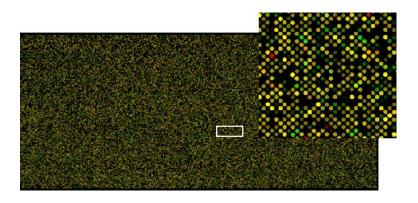
- DNA & RNA sequencing
 - Transcriptomes, exomes, full genomes
- Complex gene library construction
 - Expression vectors, protein tags, knockdowns
- Microarrays and other robotic/parallel tech.
 - Screens, high-content assays ...
- Mass spectroscopy
- Flow cytometry
- Imaging

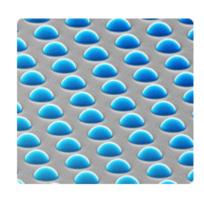
Microarrays

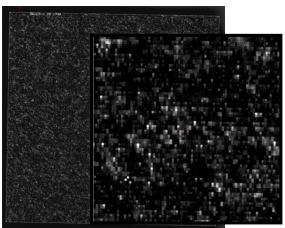












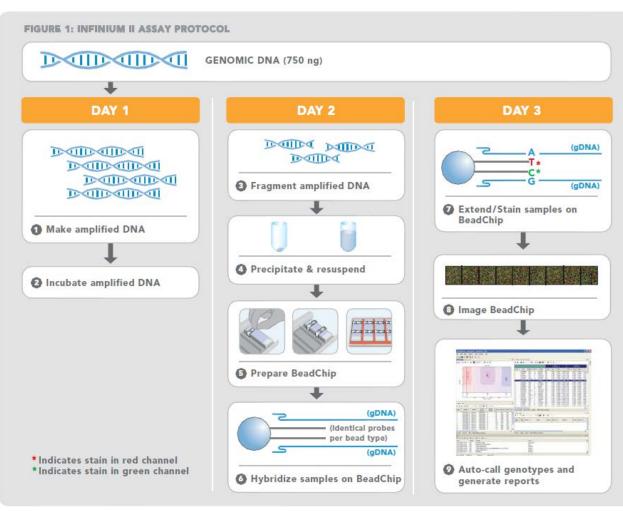
Agilent SurePrint

Illumina Beadarray

Affymetrix Genechip

SNP arrays

- Similar idea to the RNA arrays, but hybridize genomic DNA, and probe is designed to be sensitive to the allele
- Intensities are converted into a "call", with a quality score.
- Low-quality calls are usually simply treated as missing data.
- DNA methylation arrays involves specialized versions of these (+bisulphile convestion)

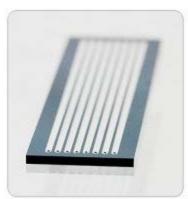


Illumina

Sequencing-based assays

- Instead of using hybridization to a designed probe, determine the DNA sequence of the sample
- Several competing platforms
- Genotyping: Compare to a reference
- RNA: quantify how many times you see a sequence





Up to eight samples can be loaded onto the flow cell for simultaneous analysis on the Illumina Genome Analyzer.

Analysis modes

- What is the general toolkit available for the analysis of data?
- How are these specialized for highdimensional data?

Exploratory analysis

- The first thing you do with your data
- Graphs and other visualizations, often combined with data reduction
- Use to spot problems, formulate hypotheses
- Often rely on power of human brain
- Data reduction essential to make exploration tractable for large data sets, even then it can be a challenge
- Follow up with more formal analysis

Model fitting and hypothesis testing

- Formally test a specific question about the data
- Is what I see "statistically significant"?
- False positives are a major risk in large data sets
- Can exploit repeating structure of the data to improve ability to find true positives

Unsupervised learning

- "Learn" undiscovered groupings in the data
- Clustering -- how do my samples or features group together?
- Useful as an exploratory technique as well as "data mining" when backed with quantitative analyses
- Example: Finding previously unknown groups of subjects based on a gene profile

Supervised learning

- Can I predict an unmeasured feature of a sample from a measured one?
- Less common than unsupervised learning, most commonly used in clinically-oriented settings – development of biomarkers
- Example: predicting tumour drug response based on gene profiles

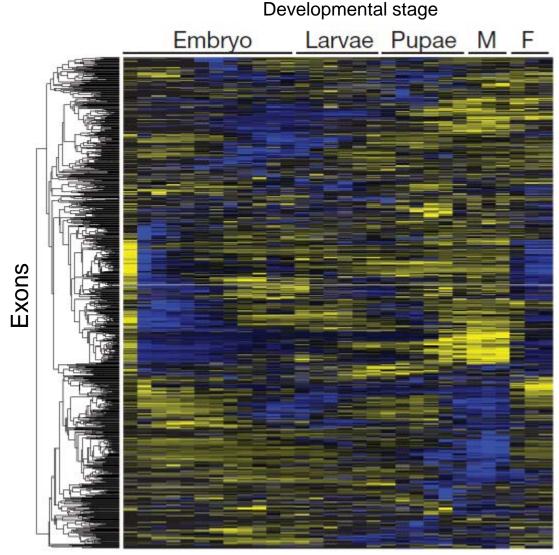
Other methods

- Many analyses just give a list of genes
- "Downstream" analysis needed to make sense of it - "biological interpretation"
 - Overlay/combine/compare with other data
 - Transform one data set into another type of data at a different granularity
 - Genes \rightarrow pathways
- Usually these end up returning to exploratory etc. modes

More examples

- Illustrate some real-life cases of highdimensional data
- We hope to teach you enough in the course to do at least primitive versions of these analyses
- ... or at least be able to read the papers
- ... even if it's a type of experiment we don't teach in detail.

Example I: Analysis of RNA in fly lifespan with RNA-seq



Colour indicates use pattern of the exon

- 30 developmental stages
- Analysis at the exon level
- Heat maps
- Clustering
- GO enrichment
- Generates many new hypotheses

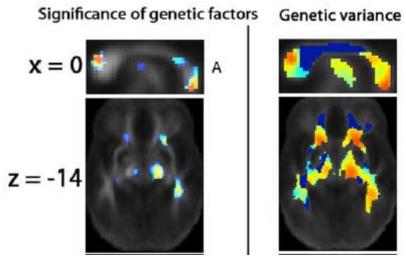
The developmental transcriptome of Drosophila melanogaster

Brenton R. Graveley³*, Angela N. Brooks²*, Joseph W. Carlson³*, Michael O. Duff⁴*, Jane M. Landolin³*, Li Yang²*, Carlo G. Artier t⁴, Marijke J. van Baren¹, Nathan Boley⁵, Benjamin W. Booth³, James B. Brown⁵, Lucy Cherbas², Carrie A. Davis⁵, Alex Doblin⁵, Renhua Li⁷, Wei Lin⁸, John H. Malone⁴, Nicolas R. Mattiuzzo⁵, David Mingli⁸, Fania B. Luch⁵, Chris Zaleski⁸, Dayu Zhang⁷, Marco Blanchette^{D,23}, Sandrine Dudolt⁴, Brian Eads⁸, Richard E. Green⁵, Ann Hammonds⁵, Lichun Jiang⁸, Phi Kapranov⁸, Lauru Langton⁸, Nortest Perminon⁸, Jeremp E. Sandler⁵, Kenneth H. Wan⁷, Aarron Willingh⁷, Vi Zhang⁶, Vi Zou⁸, Justen Andrews⁸, Peter J. Bickel⁸, Sleven E. Brenne^{2,27}, Michael R. Brenn⁵, Peter Cherbas^{7,8}, Thomas R. Gingeras ^{8,18}, Roger A. Hoskin⁸, Thomas C. Kaufman⁸, Brian Oliver⁸ & Sussa E. Celniket⁸.



Example 2: How much of brain structure* differences are accounted for by:

- Relatedness (twins)
- IQ



* Fractional anisotropy / White matter integrity

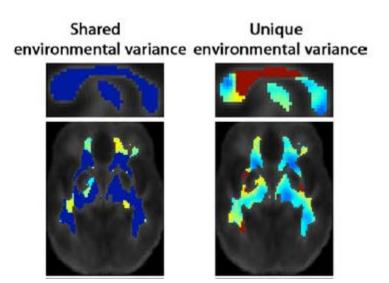
2212 - The Journal of Neuroscience, February 18, 2009 - 29(7):2212-2224

Behavioral/Systems/Cognitive

Genetics of Brain Fiber Architecture and Intellectual Performance

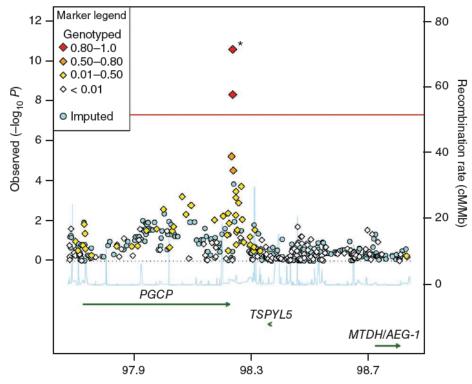
Ming-Chang Chiang,¹ Marina Barysheva,¹ David W. Shattuck,¹ Agatha D. Lee,¹ Sarah K. Madsen,¹ Christina Avedissian,¹ Andrea D. Klunder,¹ Arthur W. Toga,¹ Katie L. McMahon,² Greig I. de Zubicaray,² Margaret J. Wright,³ Anuj Srivastava,⁴ Nikolay Balov,⁴ and Paul M. Thompson¹

http://www.ncbi.nlm.nih.gov/pubmed/19228974



- 92 identical or fraternal twins
- 1.5 million voxels per subject
- Linear models, factor analysis
- Multiple test correction
- Heat maps
- Genetics explains 80% of the variance
- Brain structures correlated with IQ ~0.3

Example 3: Genetics of migraine



Chromosome 8 coordinate

- 13,500 individuals
- 429,912 DNA sites tested
- Analysis* with multiple test correction to identify markers associated with migraine
- One site is "A" in 0.267 of the migraineaffecteds but only 0.216 of the controls
- 40% higher risk of migraine if you have "A"

Genome-wide association study of migraine implicates a common susceptibility variant on 8q22.1

Verneri Anttila^{1,2,*}, Hreinn Stefansson³, Mikko Kallela⁴, Unda Todt^{5,6}, Gisela M Terwindt⁷, M Stella Calafato^{1,8}, Dale R Nyholt⁹, Antigone S Dimas^{1,10,11}, Tobias Freilinger^{12,13}, Bertram Müller-Myhsok¹⁴, Ville Artto⁴, Michael Inouye^{1,15}, Kirsi Alakurtti^{1,2}, Mari A Kaunisto^{2,16}, Eija Hämäläinen^{1,2}, Boukje de Vries¹⁵, Anine H Stam⁷, Claudia M Weller¹⁵, Axel Heinze¹⁷, Katja Heinze-Kuhn¹⁷, Ingrid Goebel^{5,6}, Guntram Borck^{5,6}, Hartmut Göbel¹⁷, Stacy Steinberg³, Christiane Wolf¹⁴, Asgeir Björnsson³, Gretar Gudmundsson¹⁸, Malene Kirchmann¹⁹, Anne Hauge¹⁹, Thomas Werge²⁰, Jean Schoenen²¹, Johan G Eriksson^{16,22–24}, Knut Hagen²⁵, Lars Stowner²⁵, H-Erich Wichmann^{26–28}, Thomas Meitinger^{29,30}, Michael Alexander^{31,32}, Susanne Moebus³³, Stefan Schreiber^{34,35}, Yurii S Aulchenko³⁶, Monique M B Breteler³⁶, Andre G Uitterlinden³⁷, Albert Hofman³⁶, Cornelia M van Duijn³⁶, Päivi Tikka-Kleemola³⁸, Salli Vepsäläinen⁴, Susanne Lucae¹⁴, Federica Tozzi³⁹, Pierandrea Muglia^{39,40}, Jeffrey Barrett¹, Jaakko Kaprio^{2,24,41}, Markus Färkkilä⁴, Leena Peltonen^{1,2,42,48}, Kari Stefansson³, John-Anker Zwart^{25,43}, Michel D Ferrari⁷, Jes Olesen¹⁹, Mark Daly⁴², Maija Wessman^{2,16}, Arn M J M van den Maagdenberg^{7,15}, Martin Dichgans^{12,13}, Christian Kubisch^{5,6,44,45}, Emmanouil T Dermitzakis¹¹, Rune R Frants¹⁵ & Aarno Palotie^{1,2,42,46,47} for the International Headache Genetics Consortium

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