



umcg

Department of genetics

Lude Franke > **Gene expression analysis using
microarrays and RNA-seq**

From caterpillar to butterfly

The dramatic consequences of gene regulation in biology:

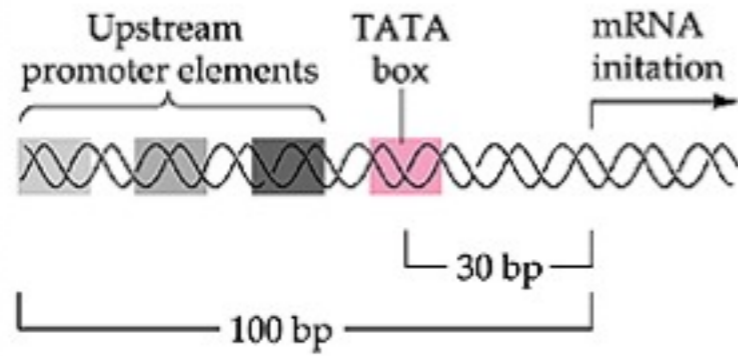


Same genome, but:
Different tissues
Different physiology
Different expression pattern

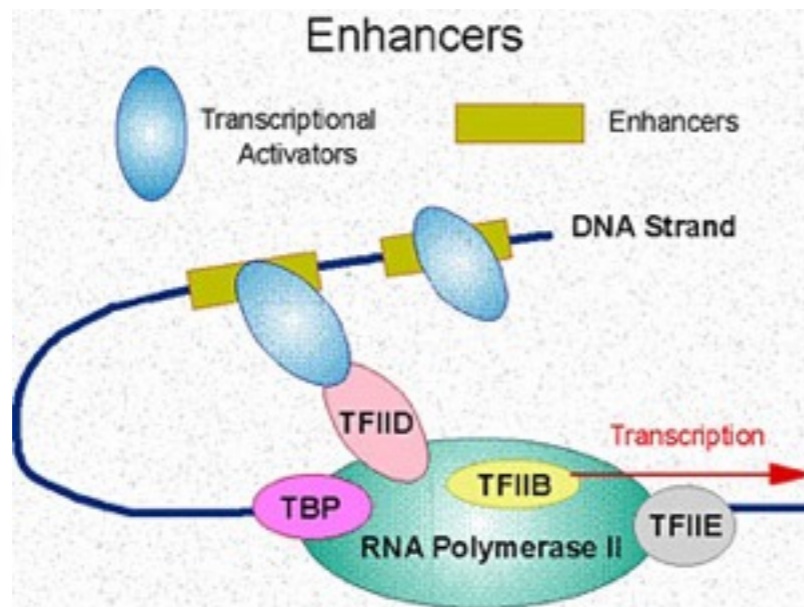
Koninginnenpage (*Papilio machaon*)

Eukaryotic gene expression regulation

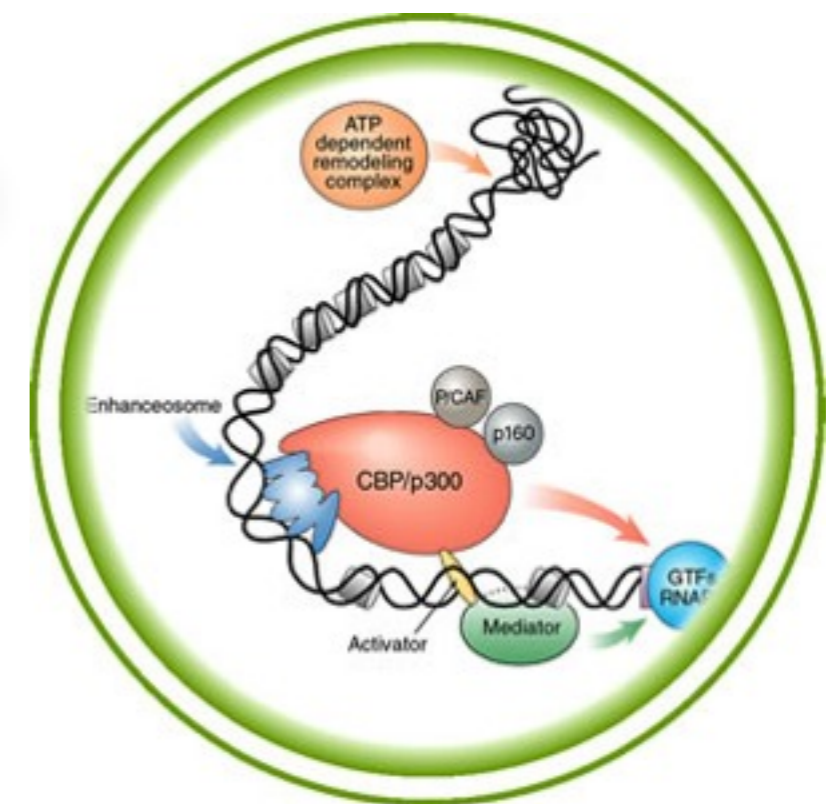
1



2



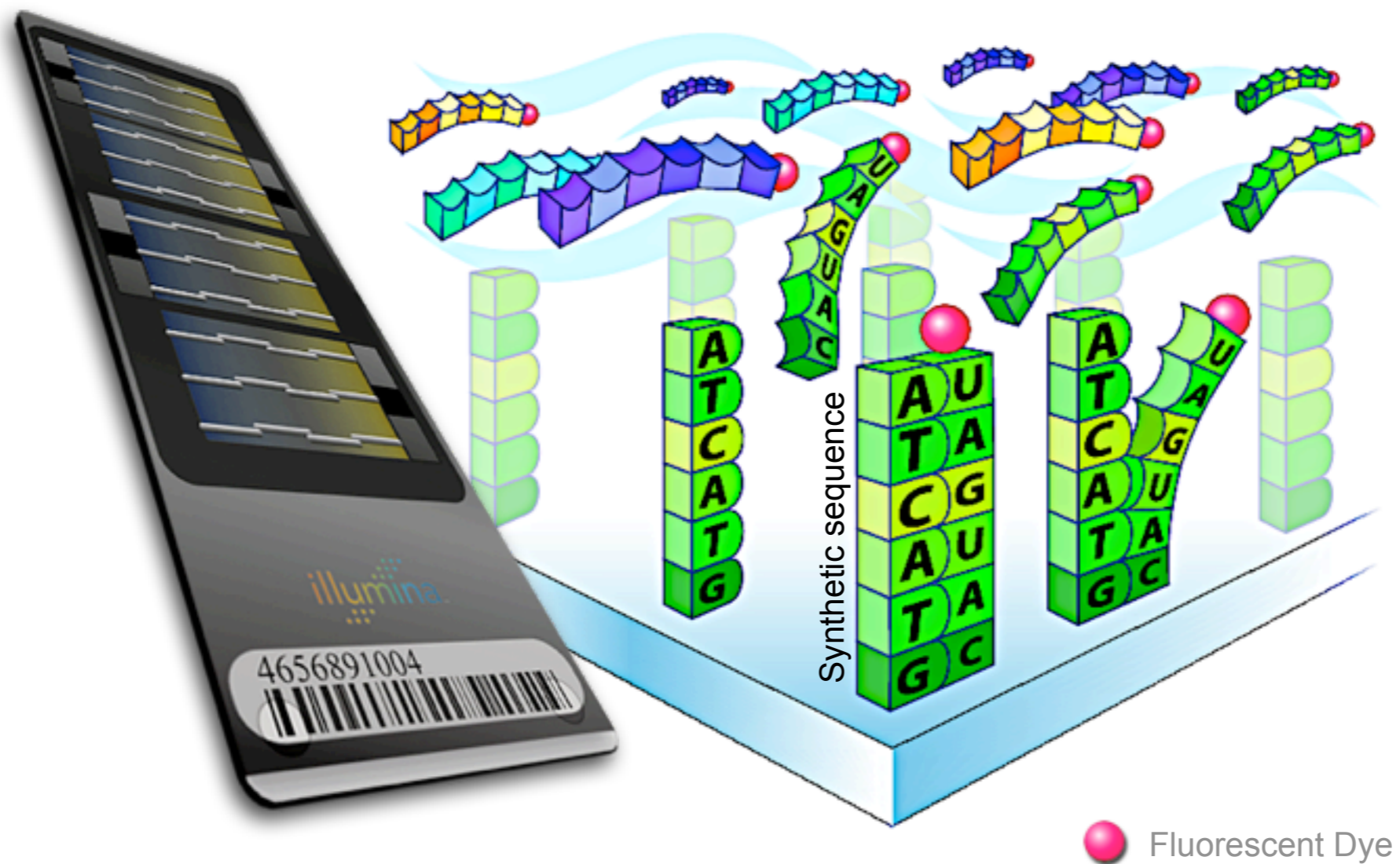
3



Gene expression determines

- Physiological status (nutrition, environment)
- Sex and age
- Various tissues and cell types
- Response to stimuli (drugs, signals, toxins)
- Health and disease
 - underlying pathogenic diversity
 - progression and response to treatment
 - patient classes of varying prospects

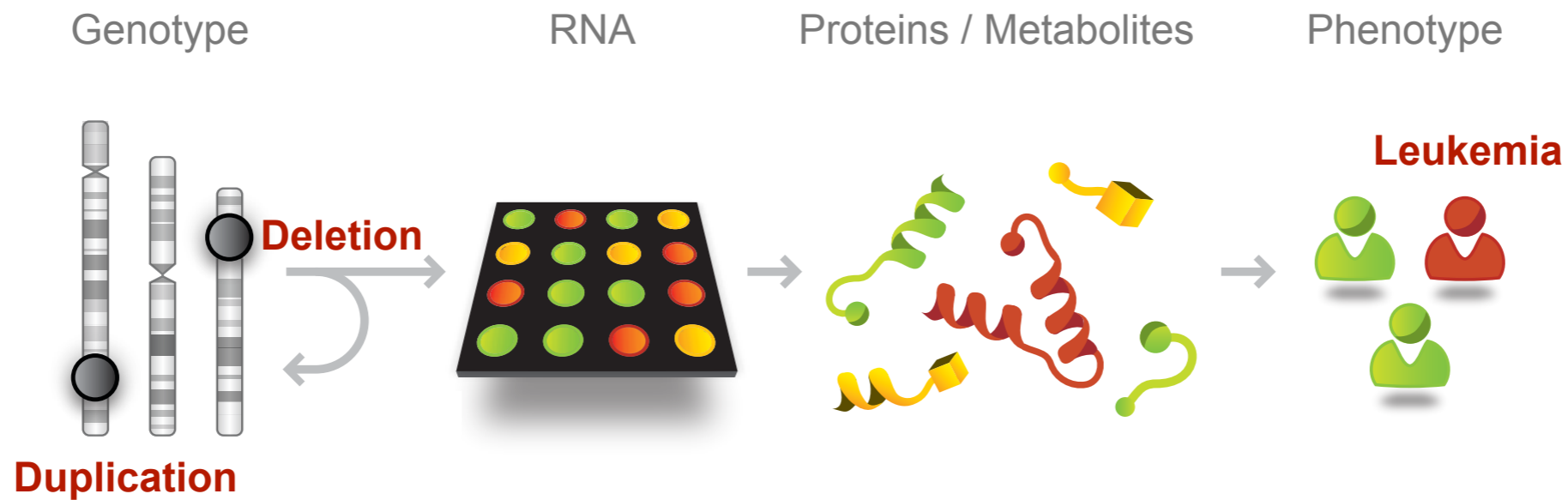
Oligonucleotide array (Microarray or GeneChip)



Leukemia

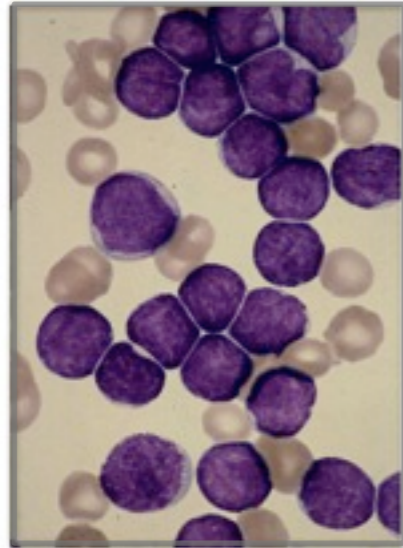
Cancer of the blood or bone marrow

Characterized by an abnormal proliferation (production by multiplication) of blood cells, usually white blood cells (leukocytes).

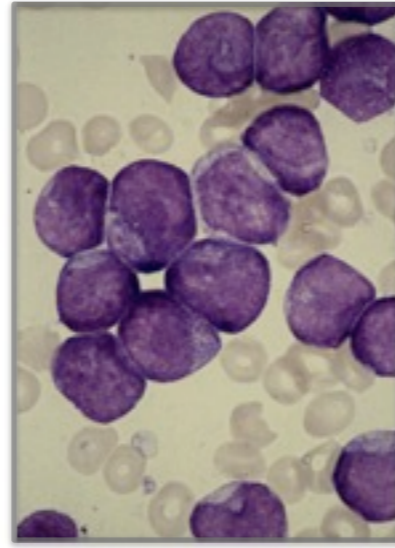


Leukemia

Acute lymphoblastic leukemia (ALL)

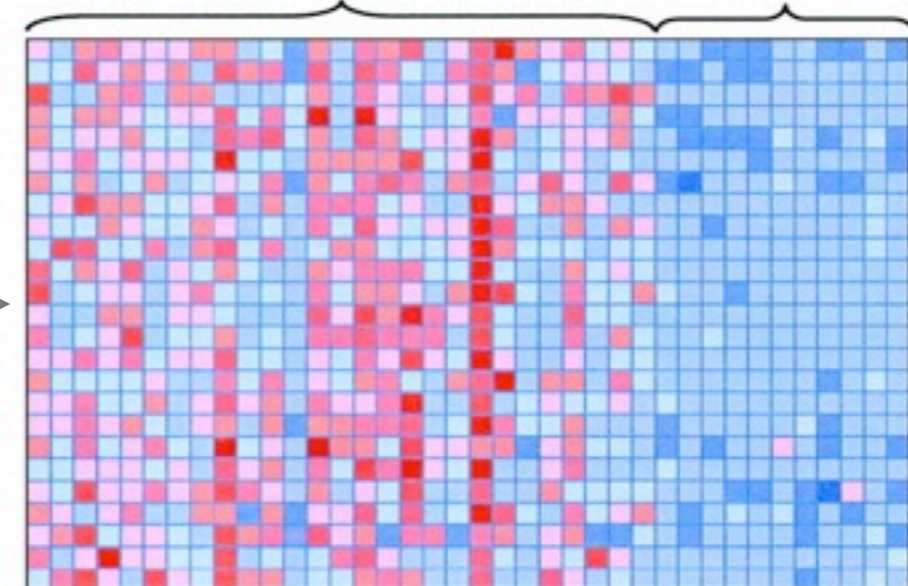


Acute myeloid leukemia (AML)



versus

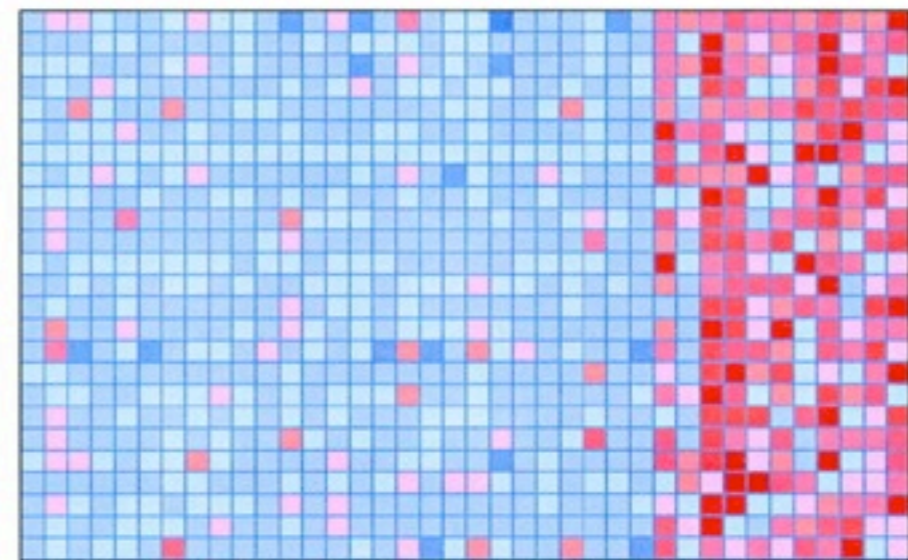
Patients → ALL AML



Subset of genes →

Why important:

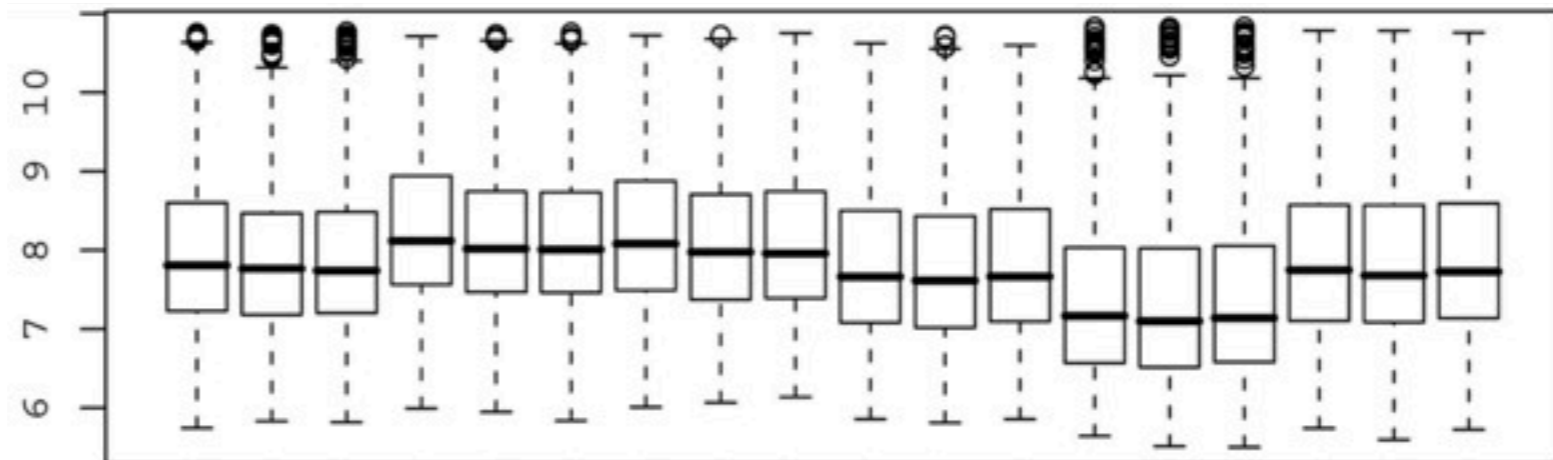
- Crucial to distinguish between ALL & AML: Require different treatments
- Identification of diagnostic genes
- Insight in affected genes & pathways



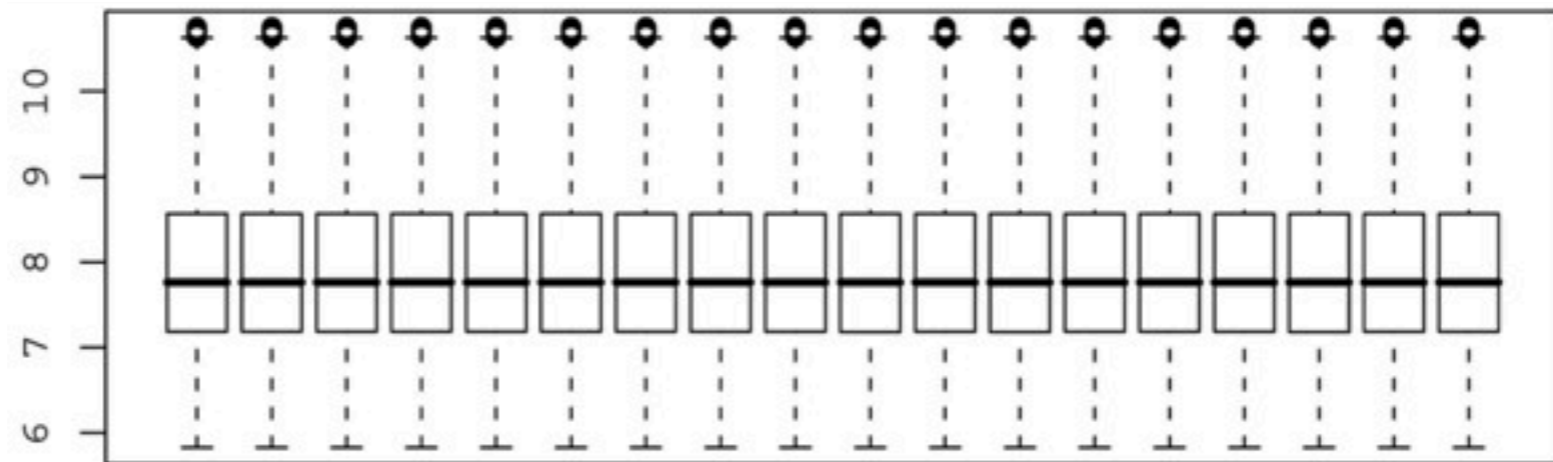
Quantile Normalization

Different samples

Before normalization



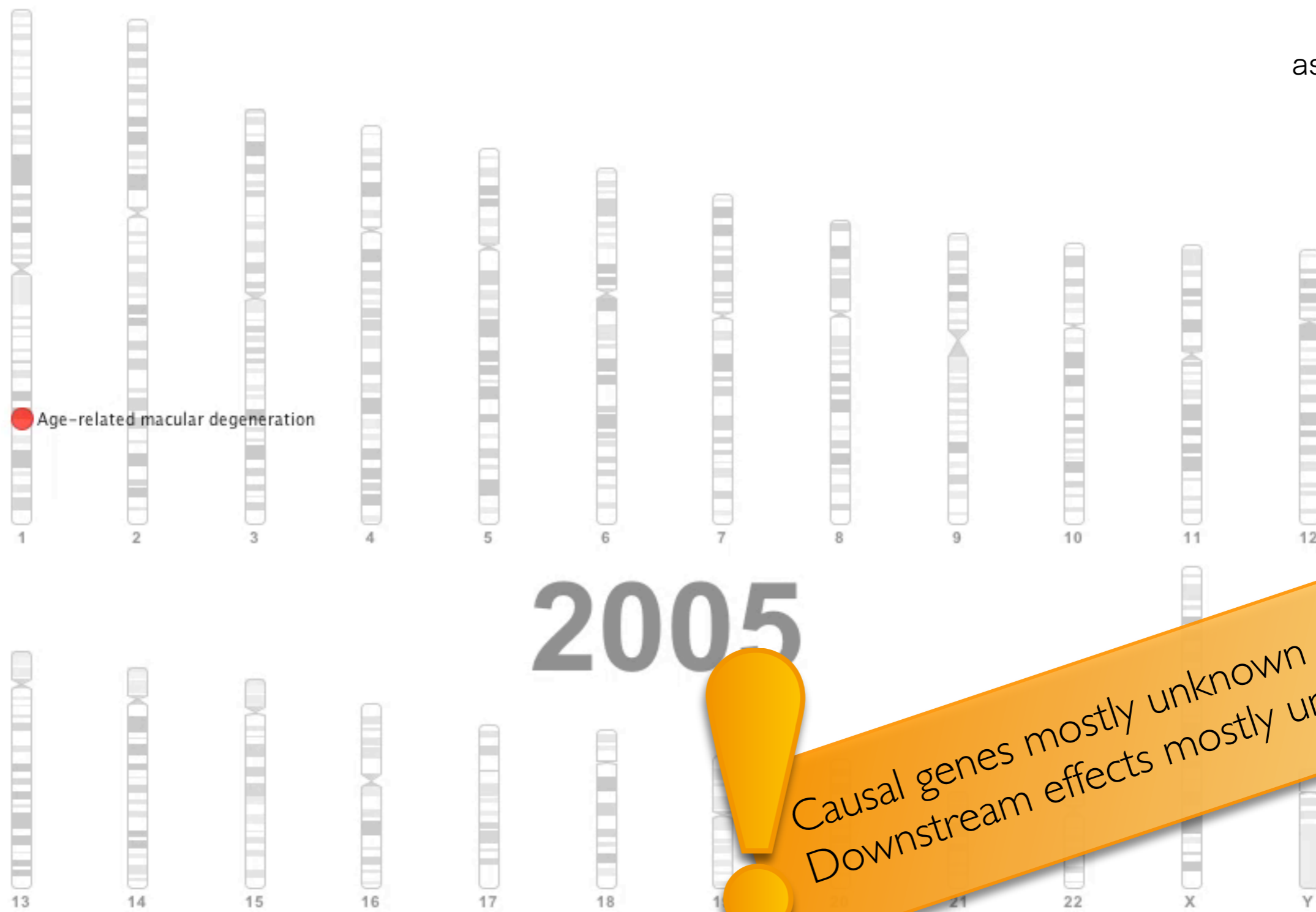
After normalization



Seven years of GWAS studies

Gene atlas

6,054
disease
associations



Causal genes mostly unknown
Downstream effects mostly unclear

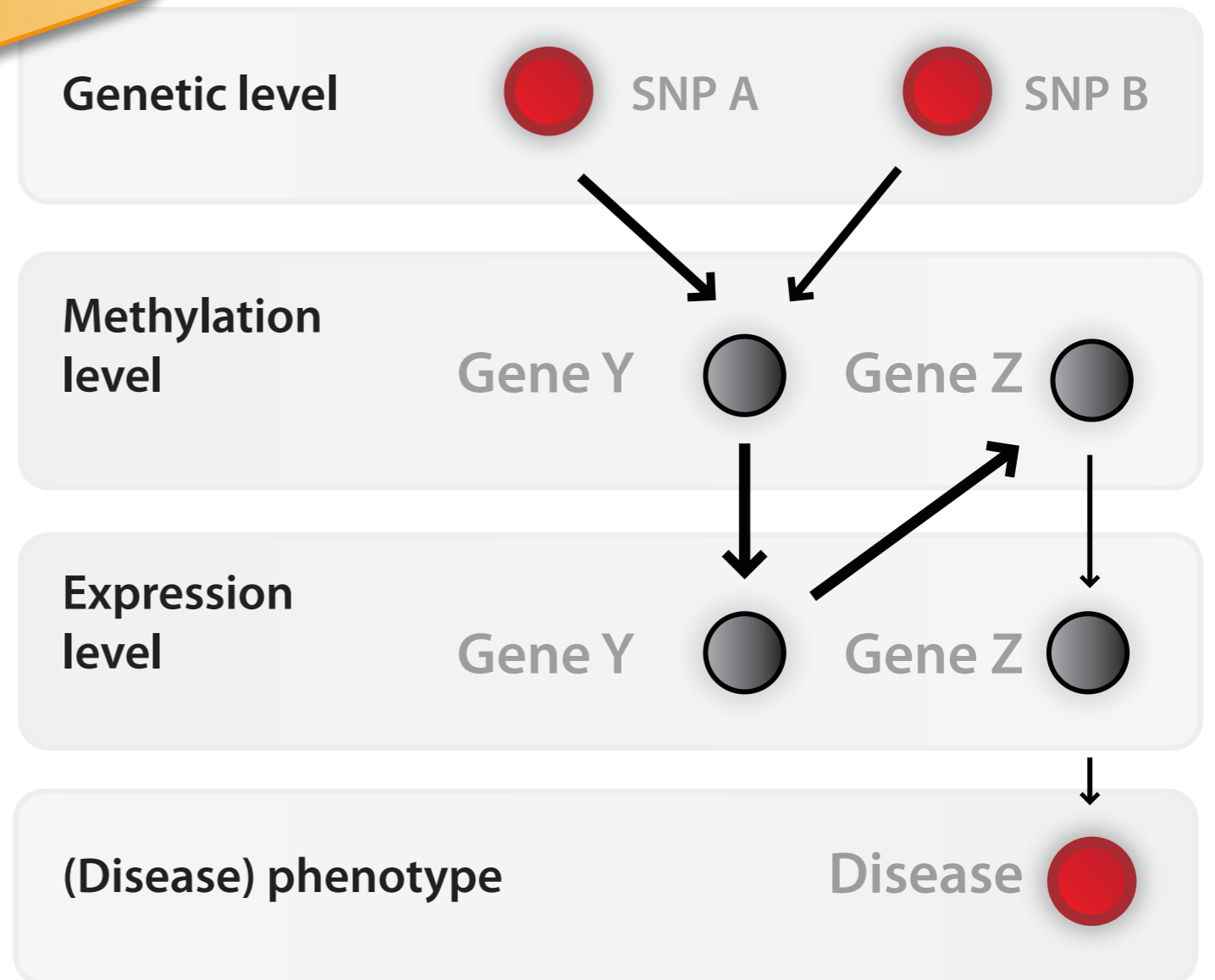




A4

Functional Follow up

Goal: Elucidate the downstream pathways that are affected



Common strategy:

Knock-down, knock-out,
overexpression assay in:

- Cell line
- Model organism



Advantages:

- One single perturbation
- Different perturbations possible
- Many potential read-outs
- Cost-effective

Disadvantages:

- Effects *in vitro* the same as *in vivo*?
- Effect of knock-out the same of SNP variant?
- Effects in model organism comparable to humans?
- Possible to observe measurable effect for SNPs with a very small effect size (e.g. 1.1)?

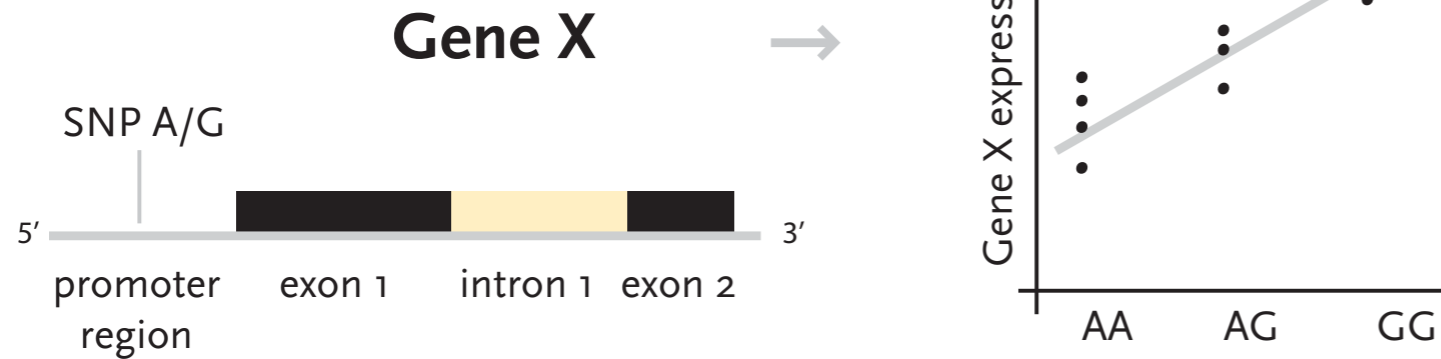
Don't we need many samples?

Genetical genomics: High-throughput systematic approach to gain insight in the effects of genetic variants on gene, protein and metabolite expression.

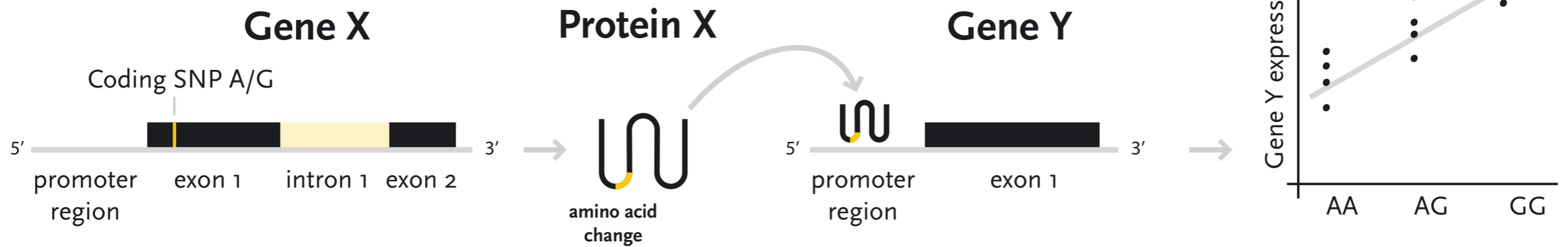


Genetical genomics: What is an eQTL?

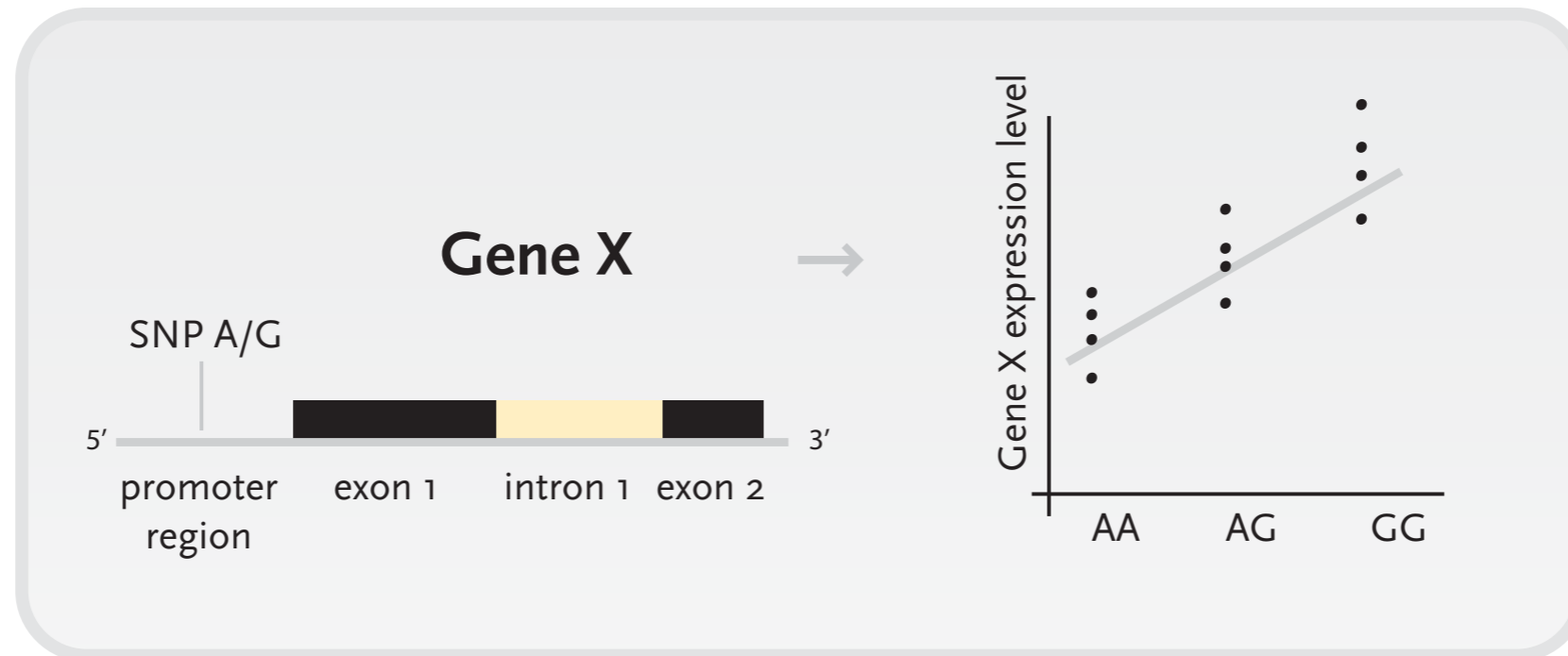
Cis-eQTL



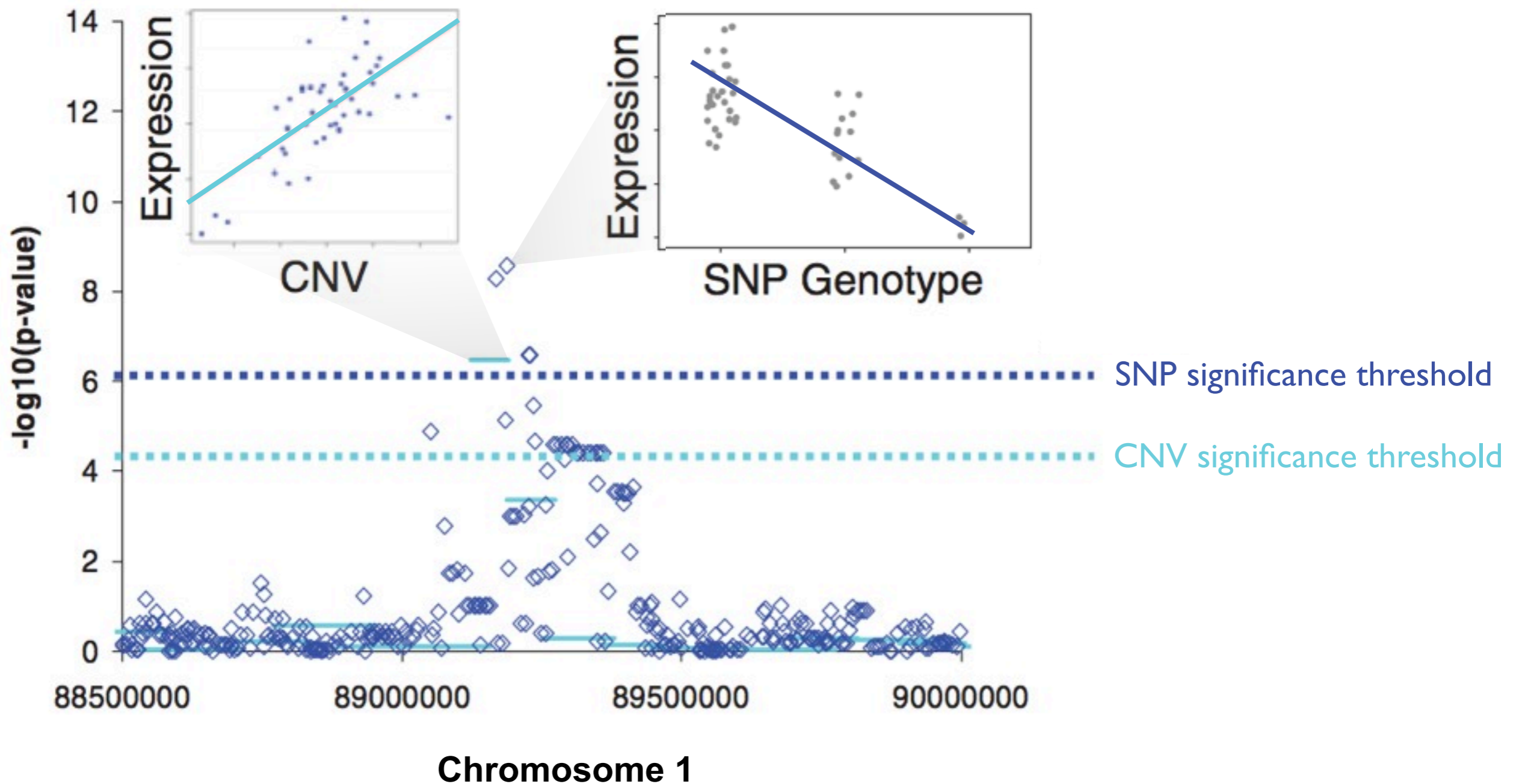
Trans-eQTL



A few *cis*-eQTL examples:

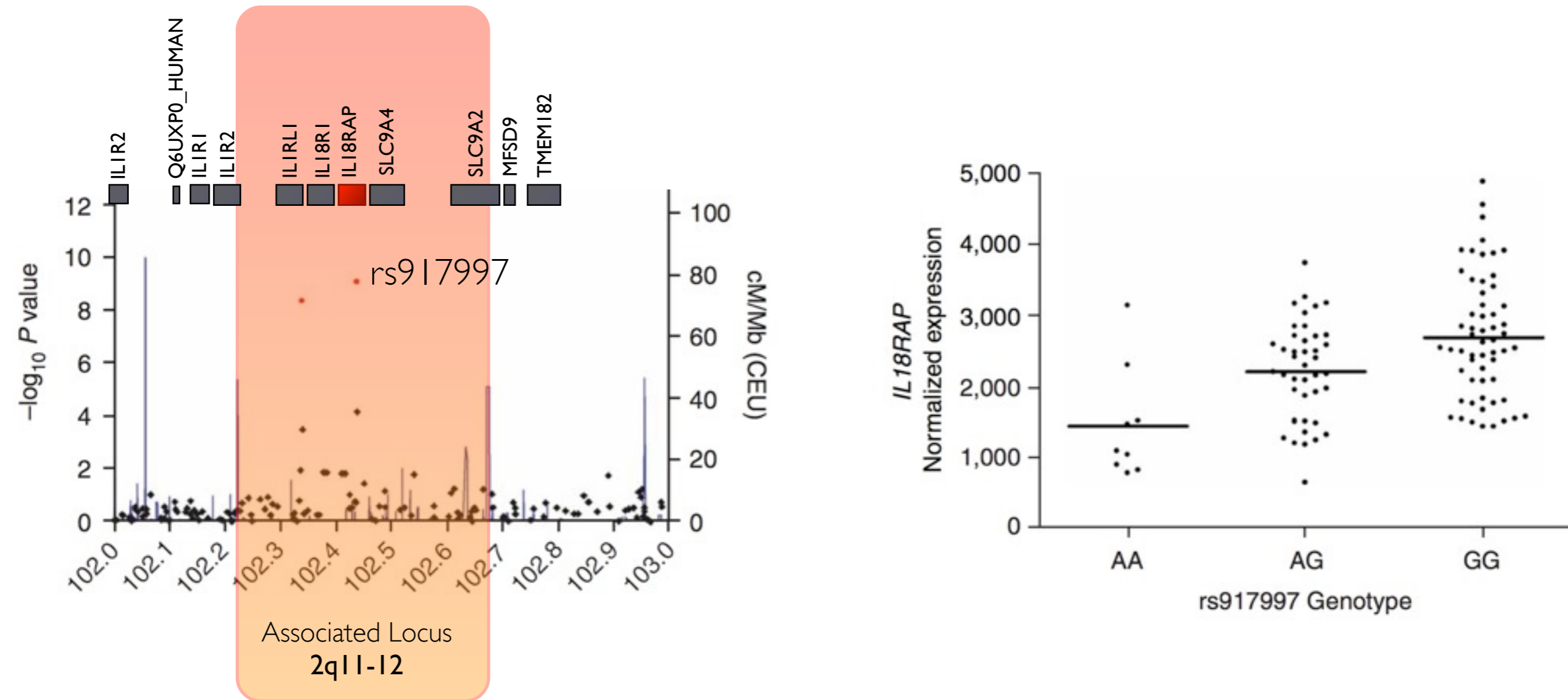


Effects of CNVs on *cis*-gene expression (GBP3, 45 JPT samples)



cis-eQTLs: celiac disease

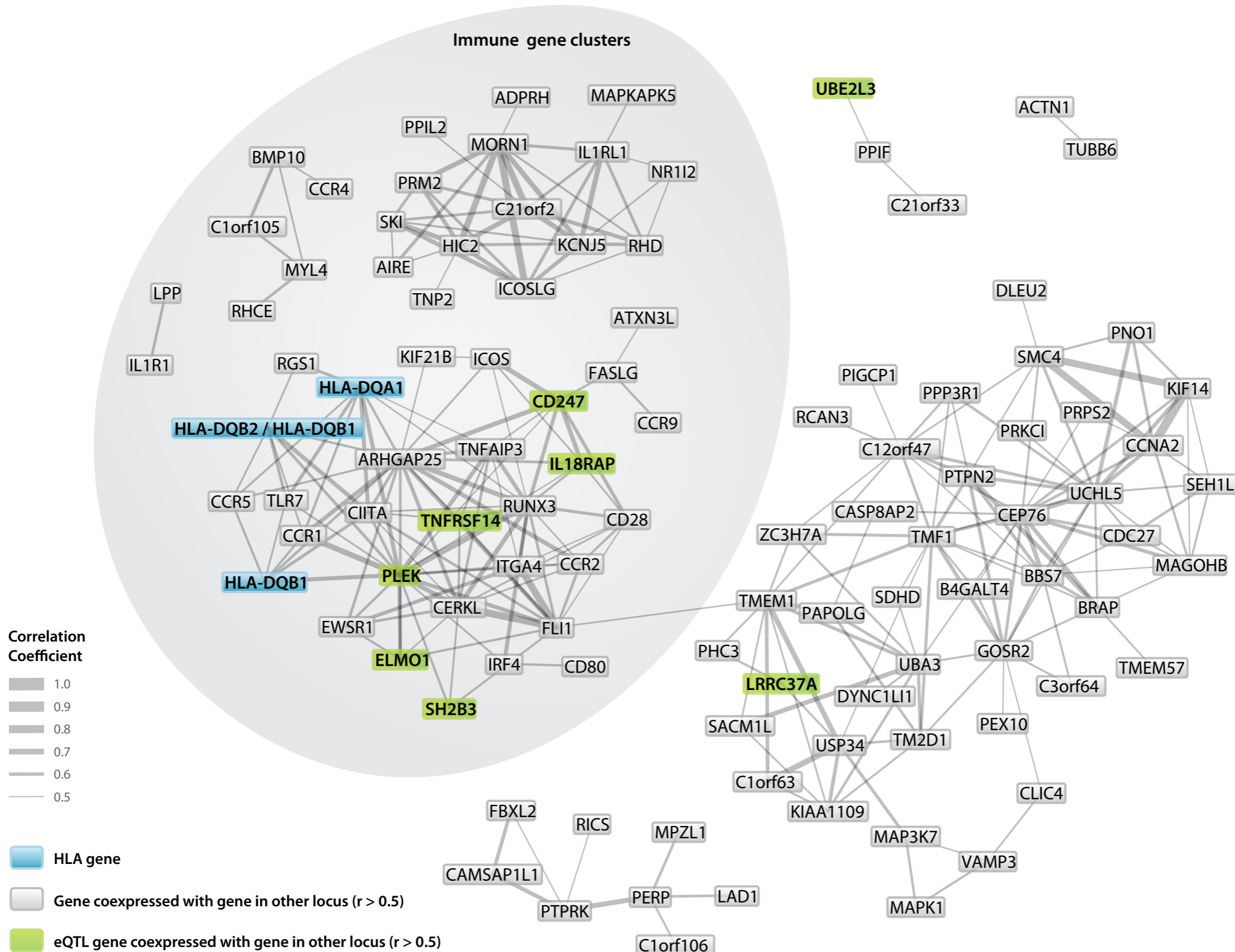
Hunt *et al*, 2008, *Nature Genetics*: 9 associated loci (*cis*-eQTL analysis in 119 samples)



Dubois *et al*, 2010, *Nature Genetics*: 40 associated loci

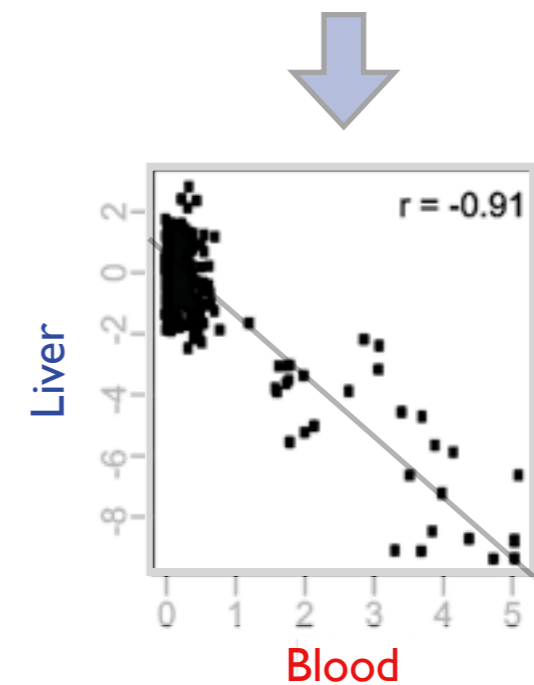
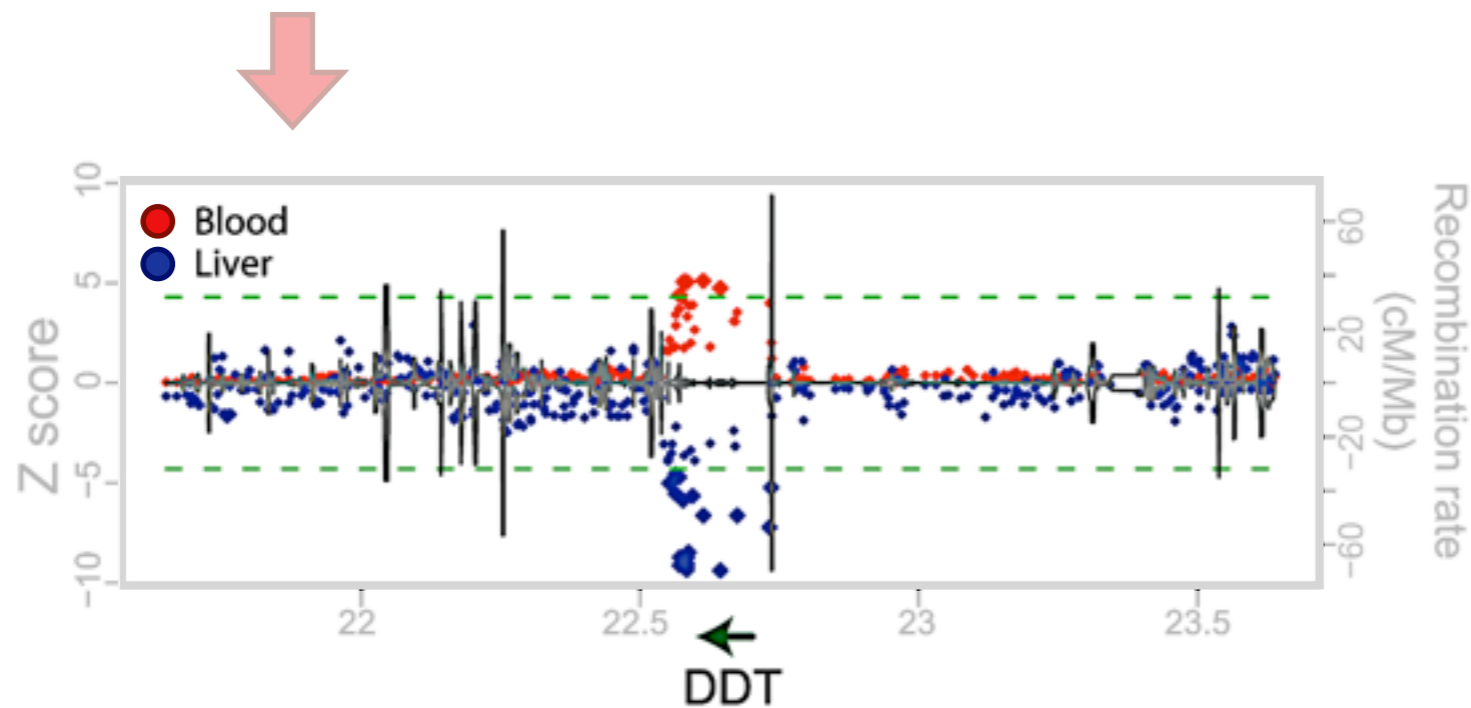
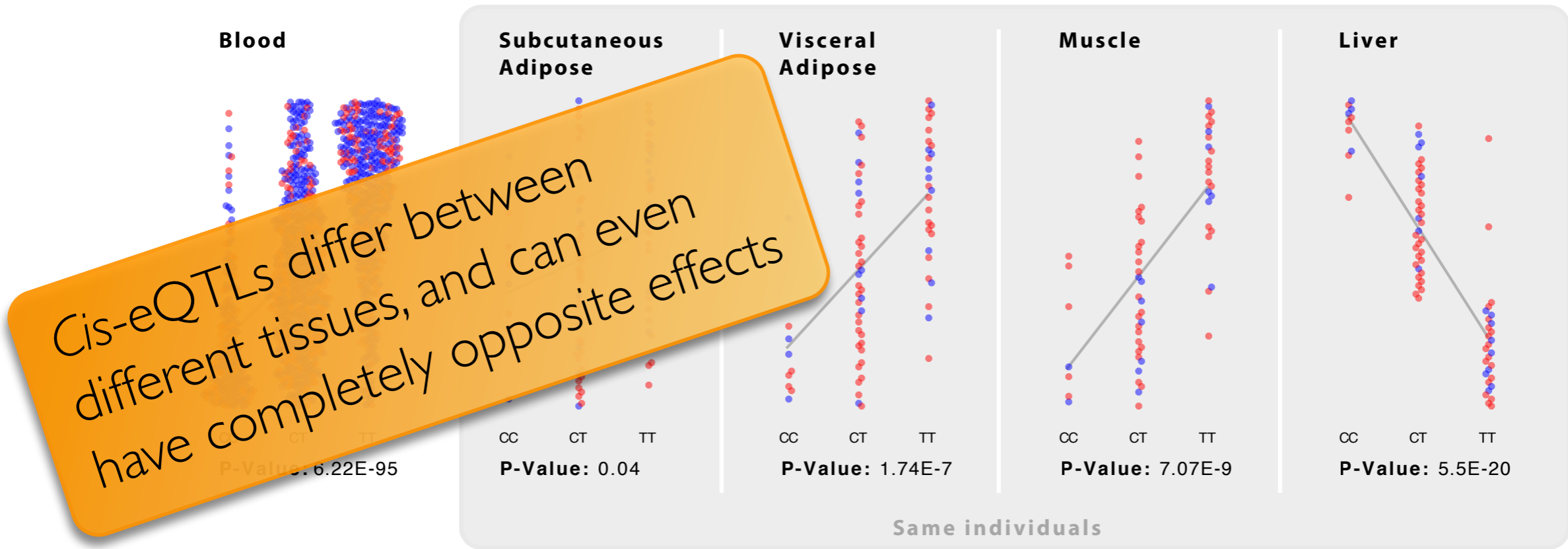
cis-eQTL study conducted in peripheral blood (1,469 unrelated individuals):

50% of loci affect gene expression in *cis*.



cis-eQTLs: Effects can differ between tissues

SNP rs2186366 (chr. 22, 22584113 bp) affects DDT

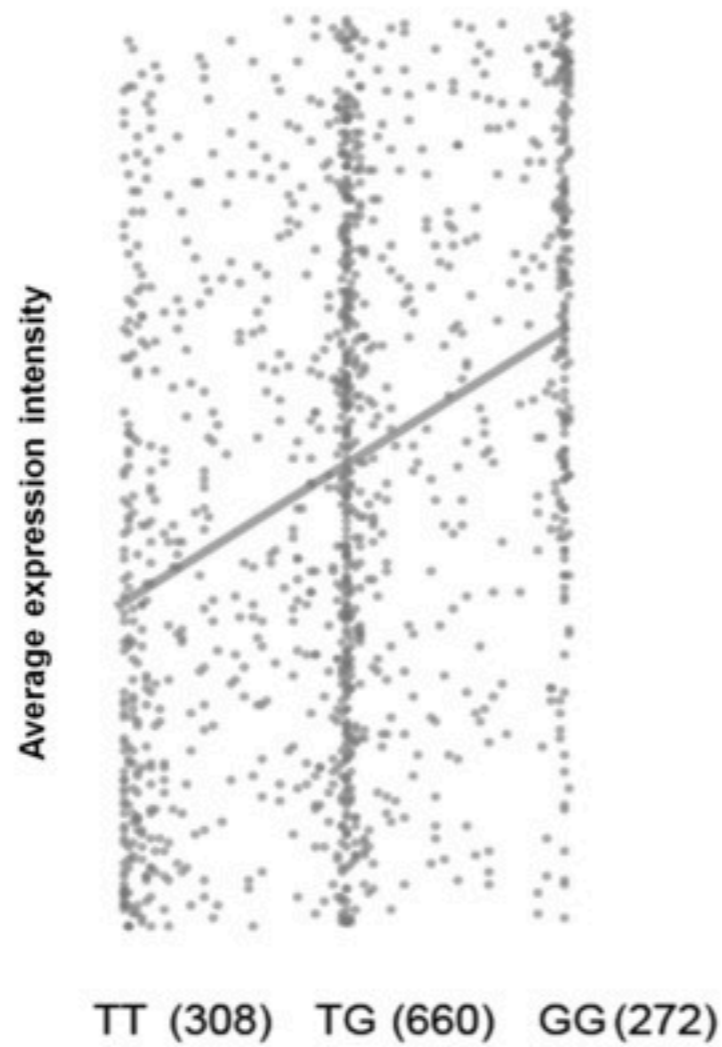


Genetic variants can affect non-coding genes (lincRNAs)

Effect of age related macula degeneration SNP rs13278062

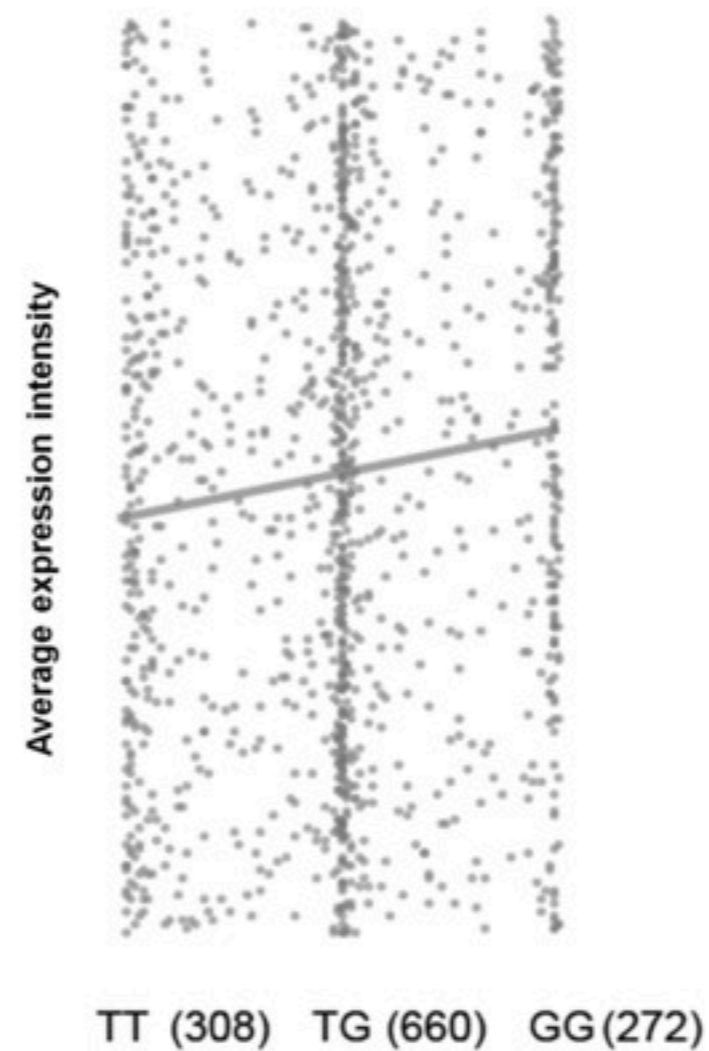
LincRNA LOC389641

$P = 4.31 \times 10^{-32}$

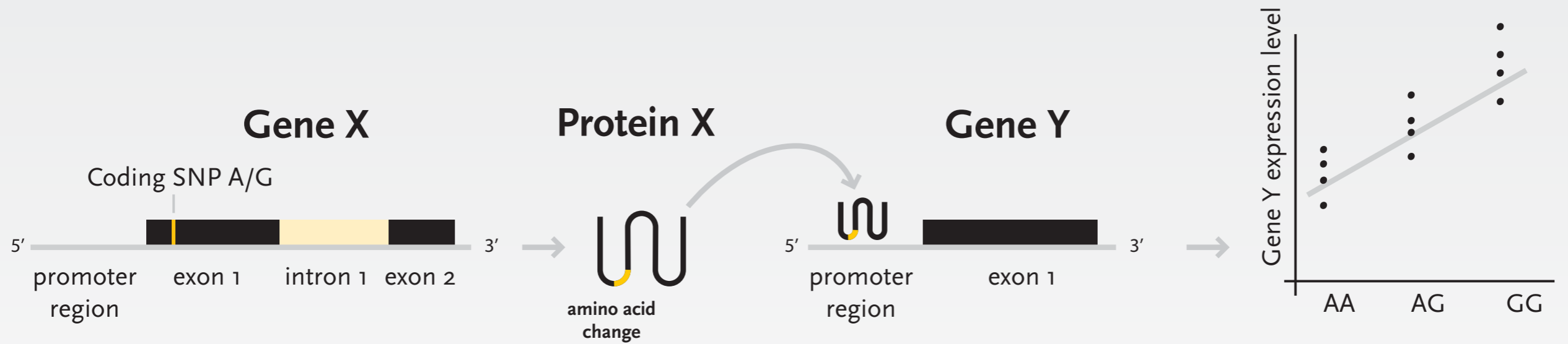


Protein coding TNFRSF10A

$P = 4.21 \times 10^{-4}$



A few trans-eQTL examples



nature

September 2010

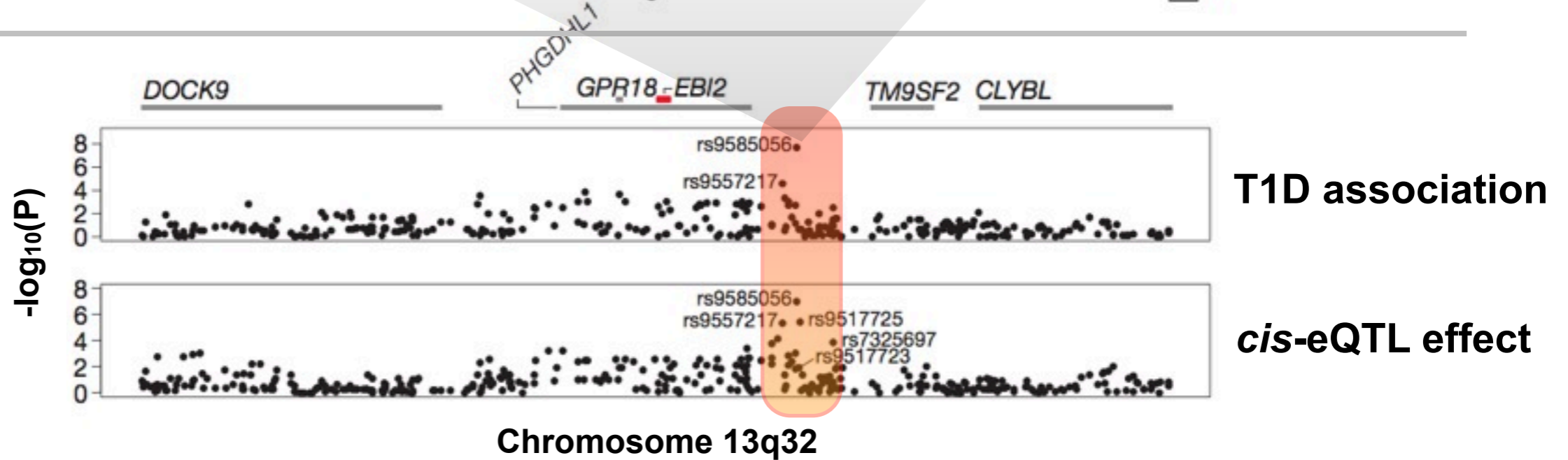
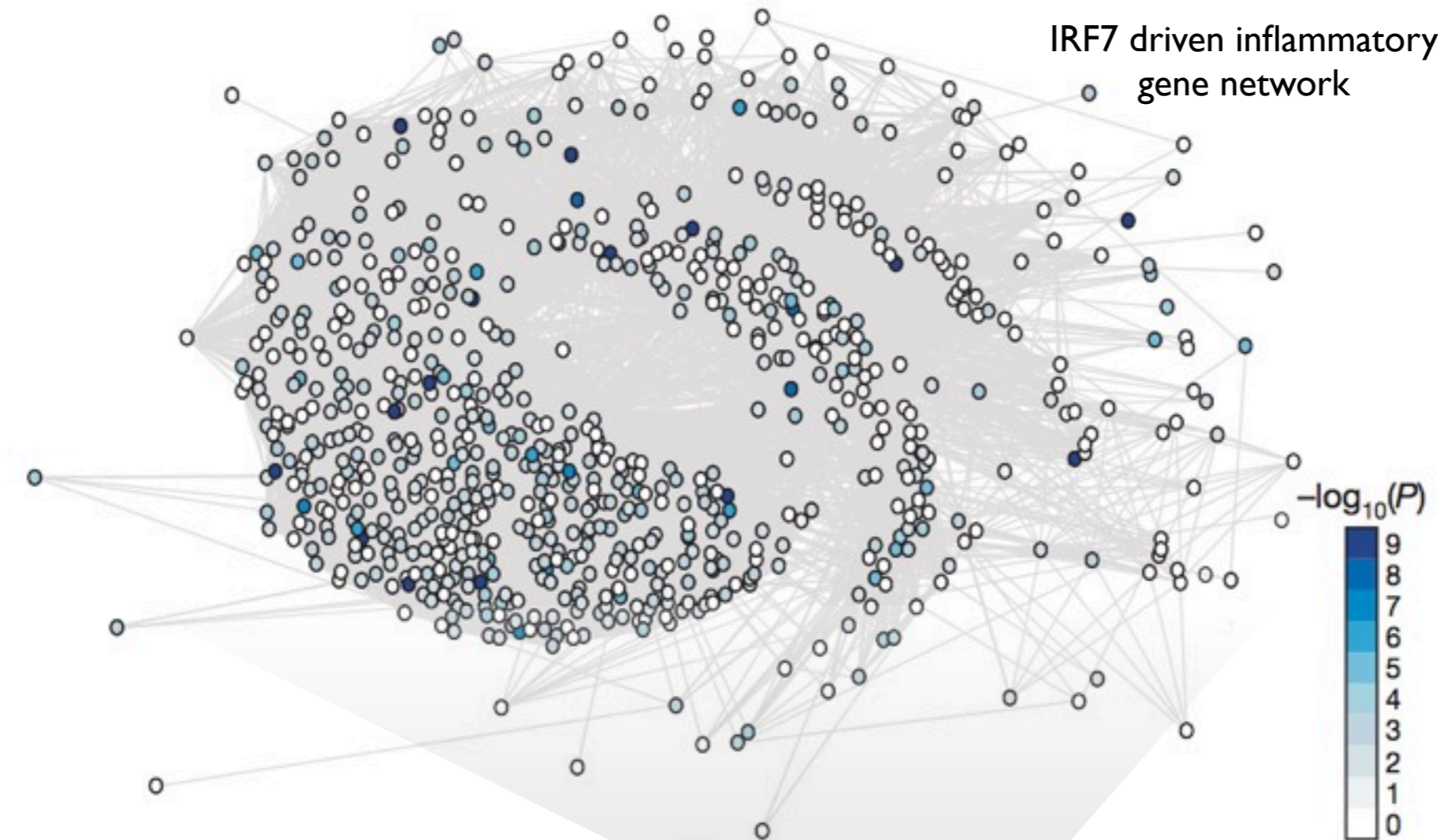
A trans-acting locus regulates an anti-viral expression network and type 1 diabetes risk

Matthias Heinig^{1,2*}, Enrico Petretto^{3,4*}, Chris Wallace⁵, Leonardo Bottolo^{3,4}, Maxime Rotival⁶, Han Lu³, Yoyo Li³, Rizwan Sarwar³, Sarah R. Langley³, Anja Bauerfeind¹, Oliver Hummel¹, Young-Ae Lee^{1,7}, Svetlana Paskas¹, Carola Rintisch¹, Kathrin Saar¹, Jason Cooper⁵, Rachel Buchan³, Elizabeth E. Gray⁸, Jason G. Cyster⁸, Cardiogenics Consortium†, Jeanette Erdmann⁹, Christian Hengstenberg¹⁰, Seraya Maouche⁶, Willem H. Ouwehand^{11,12}, Catherine M. Rice¹², Nilesh J. Samani¹³, Heribert Schunkert⁹, Alison H. Goodall¹³, Herbert Schulz¹, Helge G. Roeder², Martin Vingron², Stefan Blankenberg¹⁴, Thomas Münzel¹⁴, Tanja Zeller¹⁴, Silke Szymczak¹⁵, Andreas Ziegler¹⁵, Laurence Tiret⁶, Deborah J. Smyth⁵, Michal Pravenec¹⁶, Timothy J. Aitman³, Francois Cambien⁶, David Clayton⁵, John A. Todd⁵, Norbert Hubner^{1,17} & Stuart A. Cook^{3,18}

rs9585056 near Epstein–Barr virus induced gene 2 (*EBI2*):

- Affects interferon regulatory factor 7 (IRF) driven inflammatory network
- Associated with type 1 diabetes ($P = 7 \times 10^{-10}$)

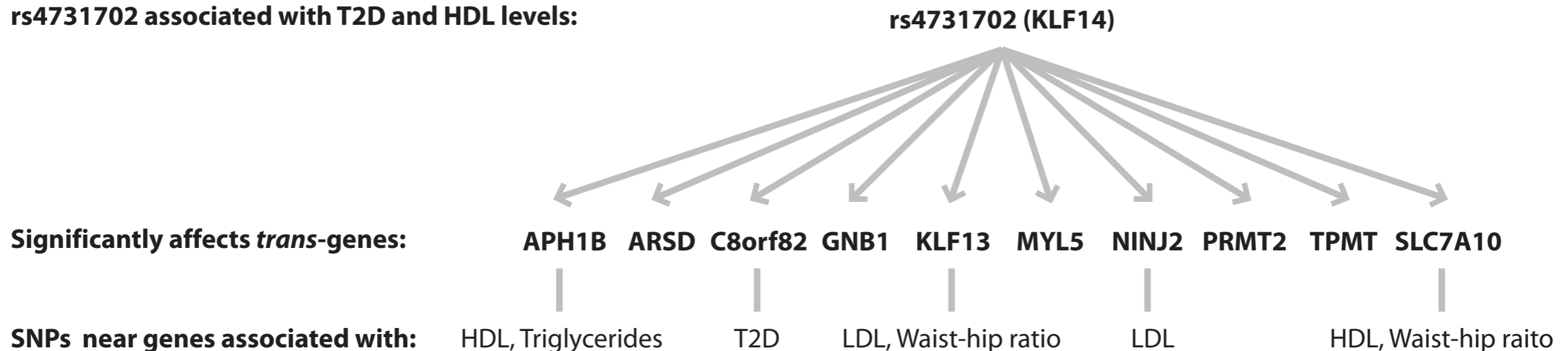
trans-eQTLs: T1D SNP affects anti-viral gene network



Identification of an imprinted master *trans* regulator at the *KLF14* locus related to multiple metabolic phenotypes

Kerrin S Small^{1,2,10}, Åsa K Hedman^{3,10}, Elin Grundberg^{1,2,10}, Alexandra C Nica⁴, Gudmar Thorleifsson⁵, Augustine Kong⁵, Unnur Thorsteindottir^{5,6}, So-Youn Shin², Hannah B Richards⁷, the GIANT Consortium⁸, the MAGIC Investigators⁸, the DIAGRAM Consortium⁸, Nicole Soranzo^{1,2}, Kourosh R Ahmadi¹, Cecilia M Lindgren³, Kari Stefansson^{5,6,10}, Emmanouil T Dermitzakis^{4,10}, Panos Deloukas^{2,10}, Timothy D Spector^{1,10} & Mark I McCarthy^{3,7,9,10} for the MuTHER Consortium⁸

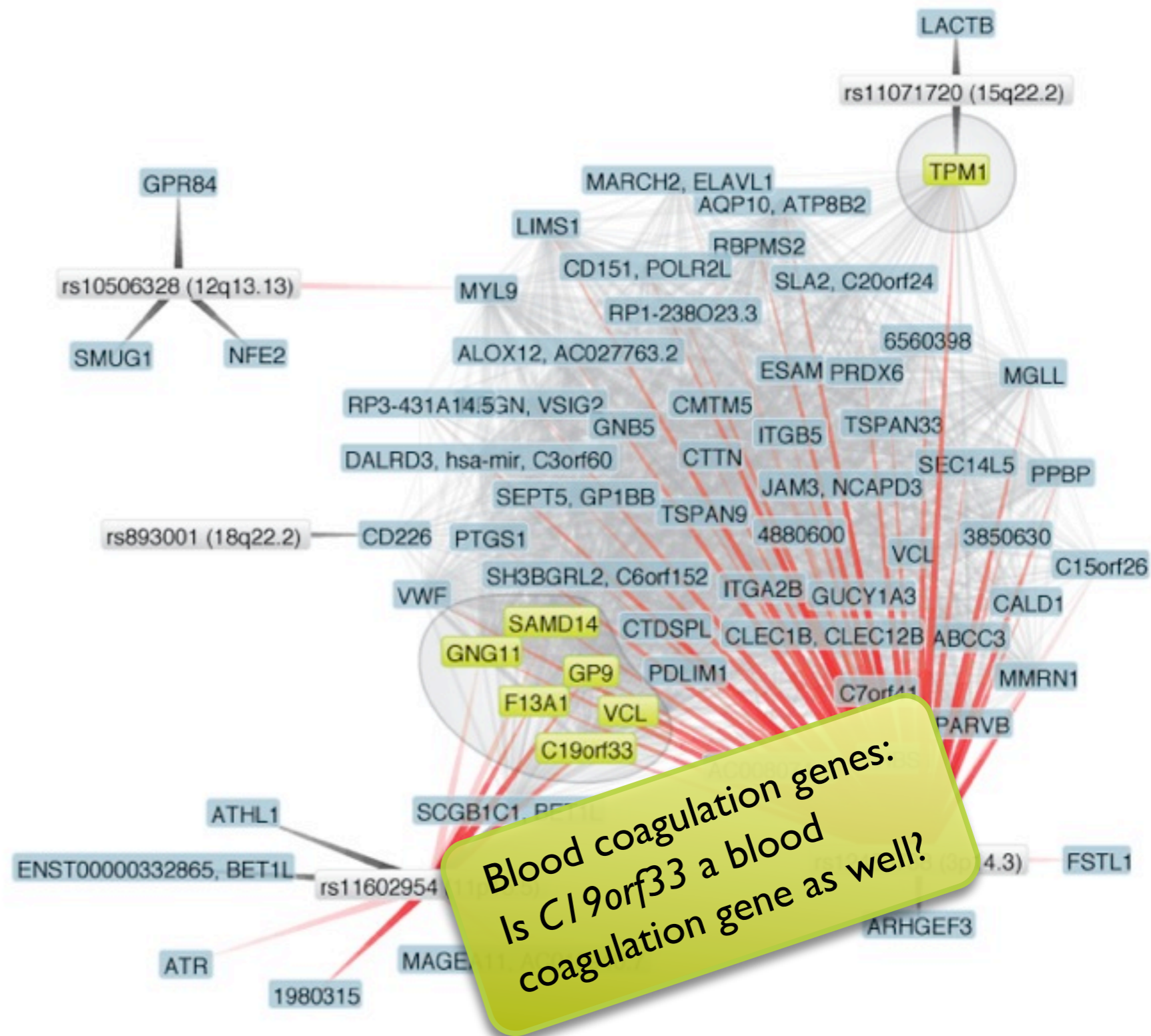
rs4731702 associated with T2D and HDL levels:



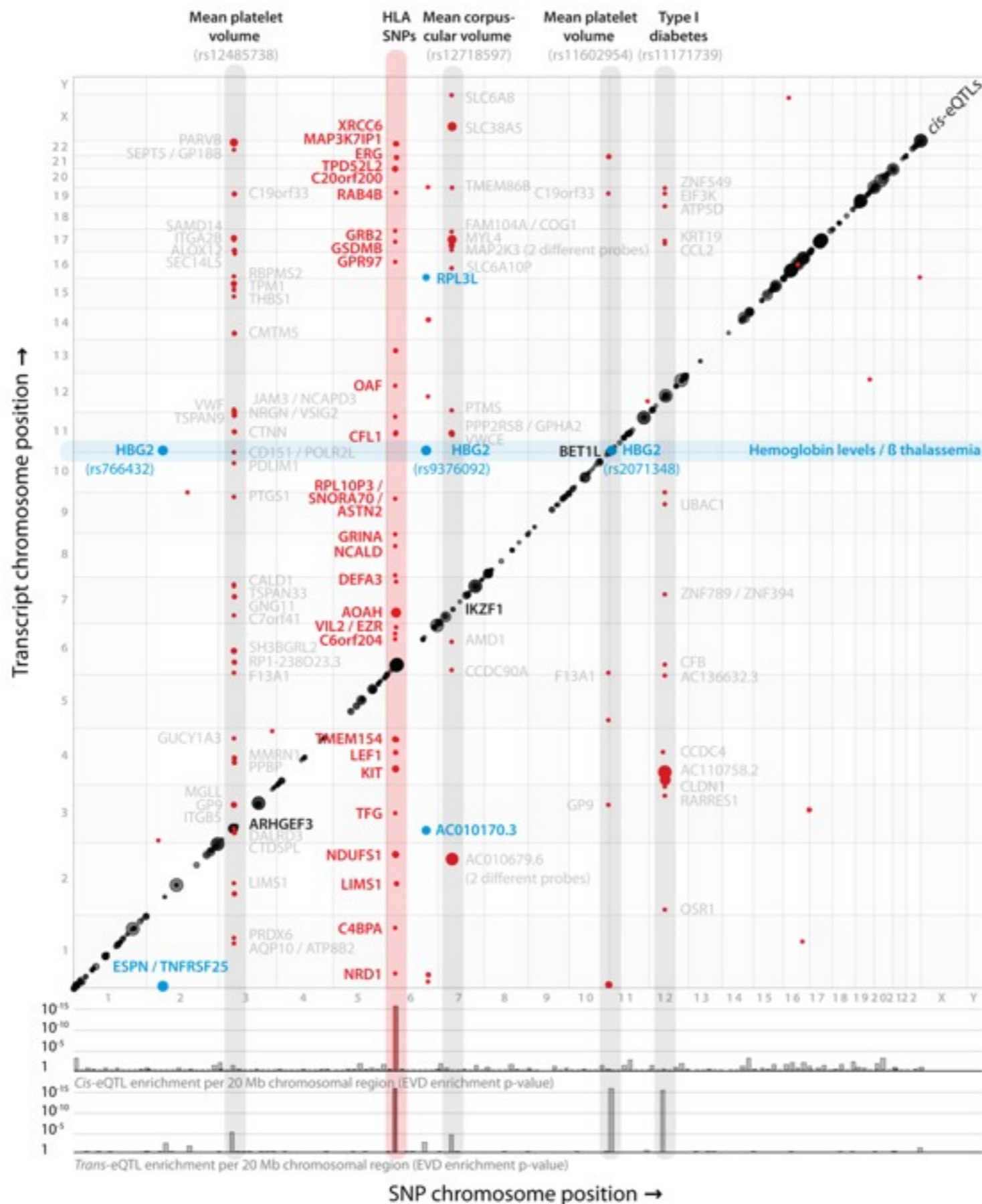
trans-eQTLs: Mean platelet volume & blood coagulation

Trans effects of mean platelet volume SNPs

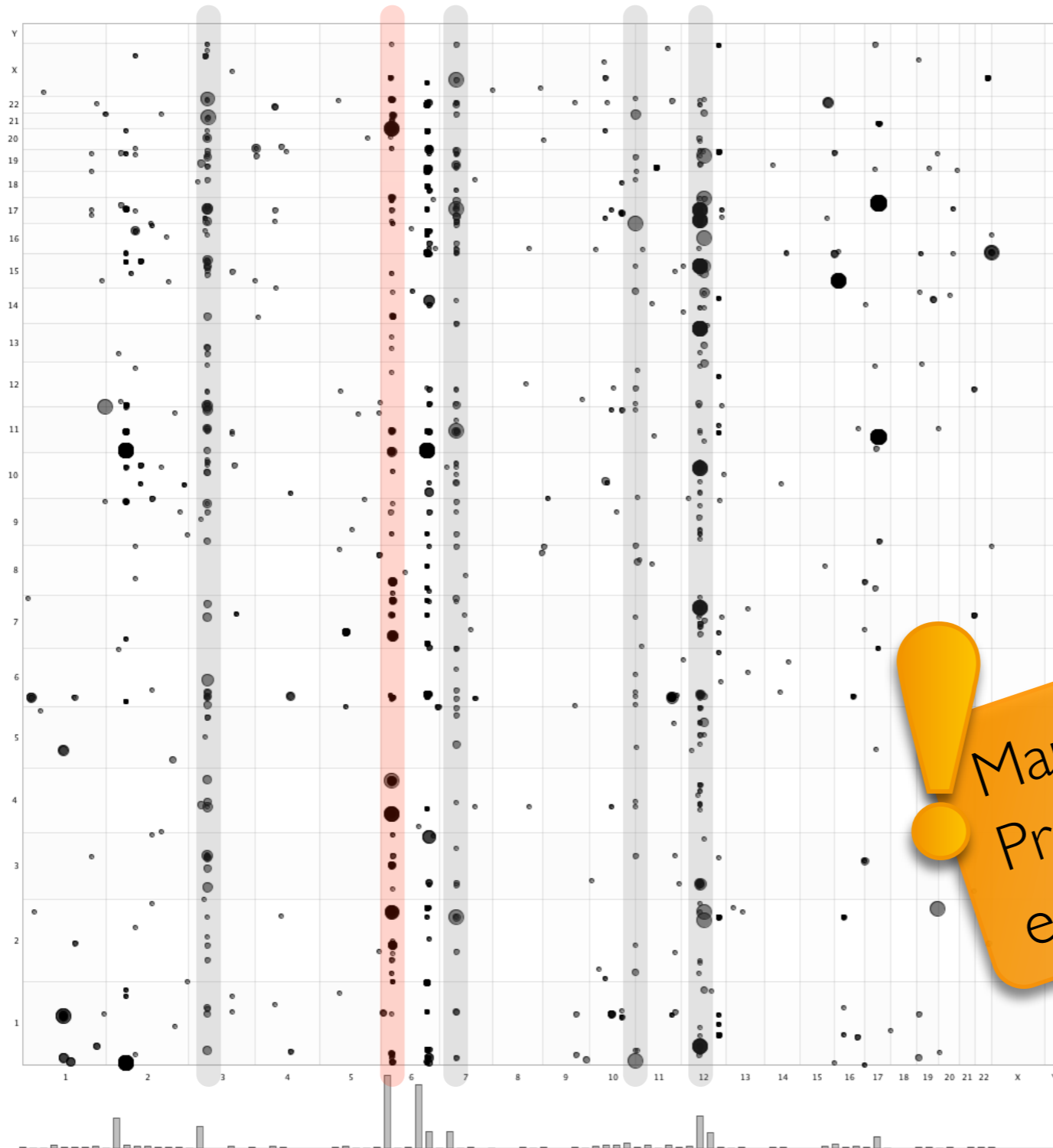
(1,469 peripheral blood samples)



Many trans-eQTLs found in 1,469 samples



Scaling up to 5,300 samples: Work in progress



Many more trans-eQTLs.
Previously identified trans-eQTLs can be replicated

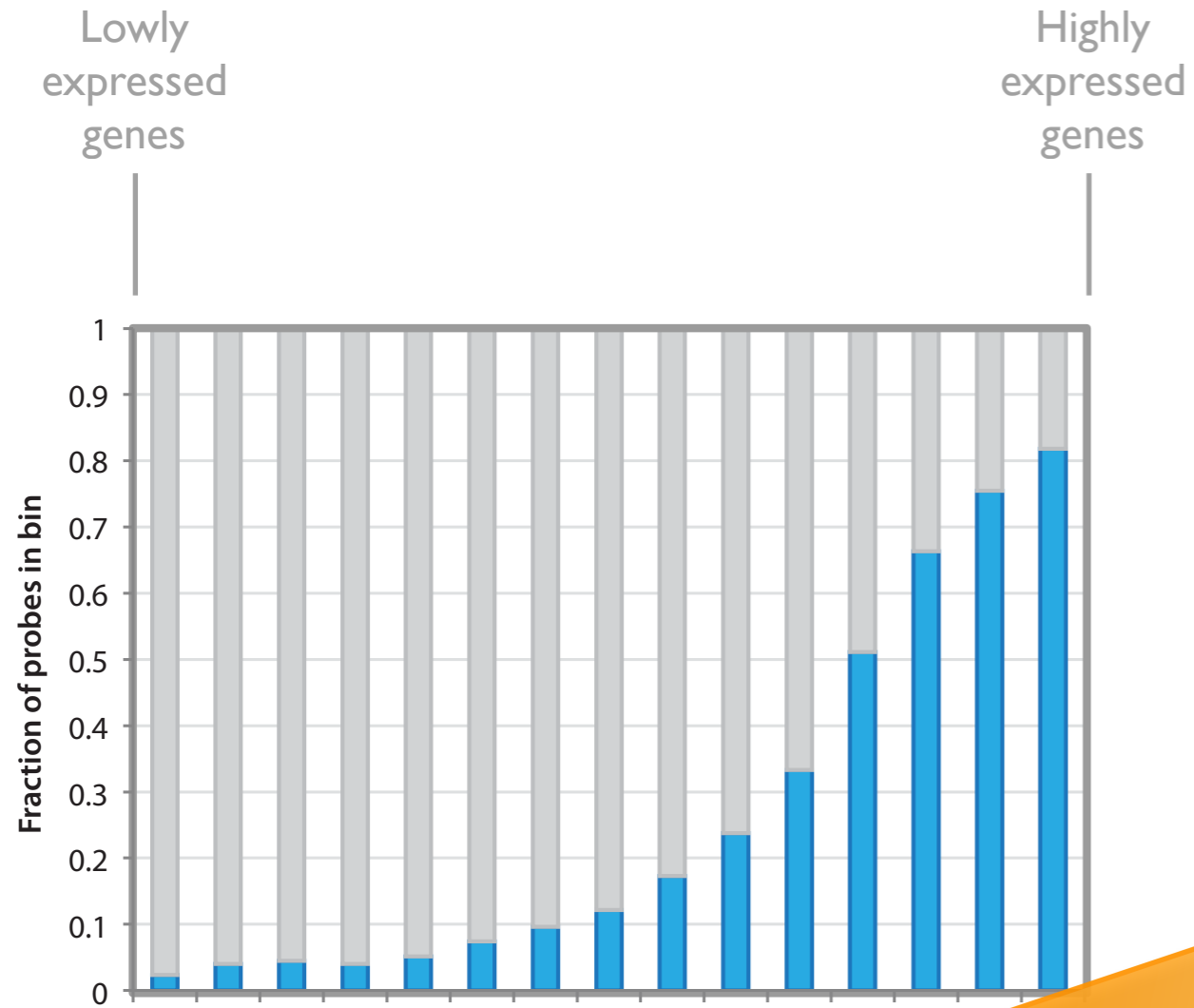
Scaling up: eQTL mapping in 7,508 primary blood samples

Discovery:	Dataset	Country	Sample Size
	Groningen	The Netherlands	1,469
	Rotterdam Study	The Netherlands	762
	Estonian Biobank	Estonia	891
	SHIP-Trend	Germany	963
	DILGOM	Finland	509
	InChianti	United Kingdom / Italy	611
	Heart and Vascular Health Study	USA	106
		Meta-analysis	5,311

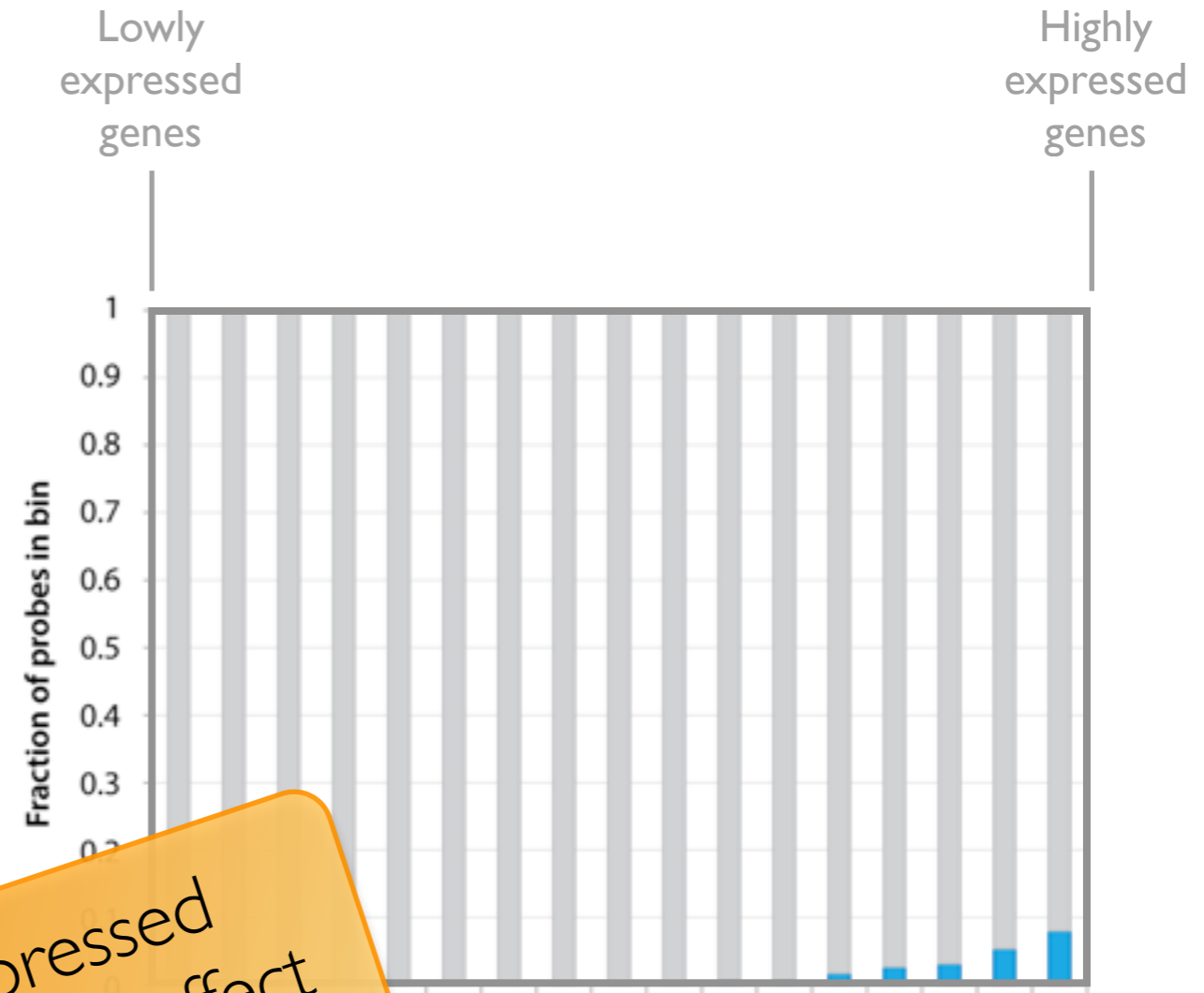
Replication:	Dataset	Country	Sample Size
	KORA F4	Germany	740
	BSGS	Australia	892
	Monocytes (Julian Knight)	United Kingdom	283
	B-Cells (Julian Knight)	United Kingdom	282
		Total	2,197

eQTL properties

Detectability of *cis*-eQTLs depends on expression level

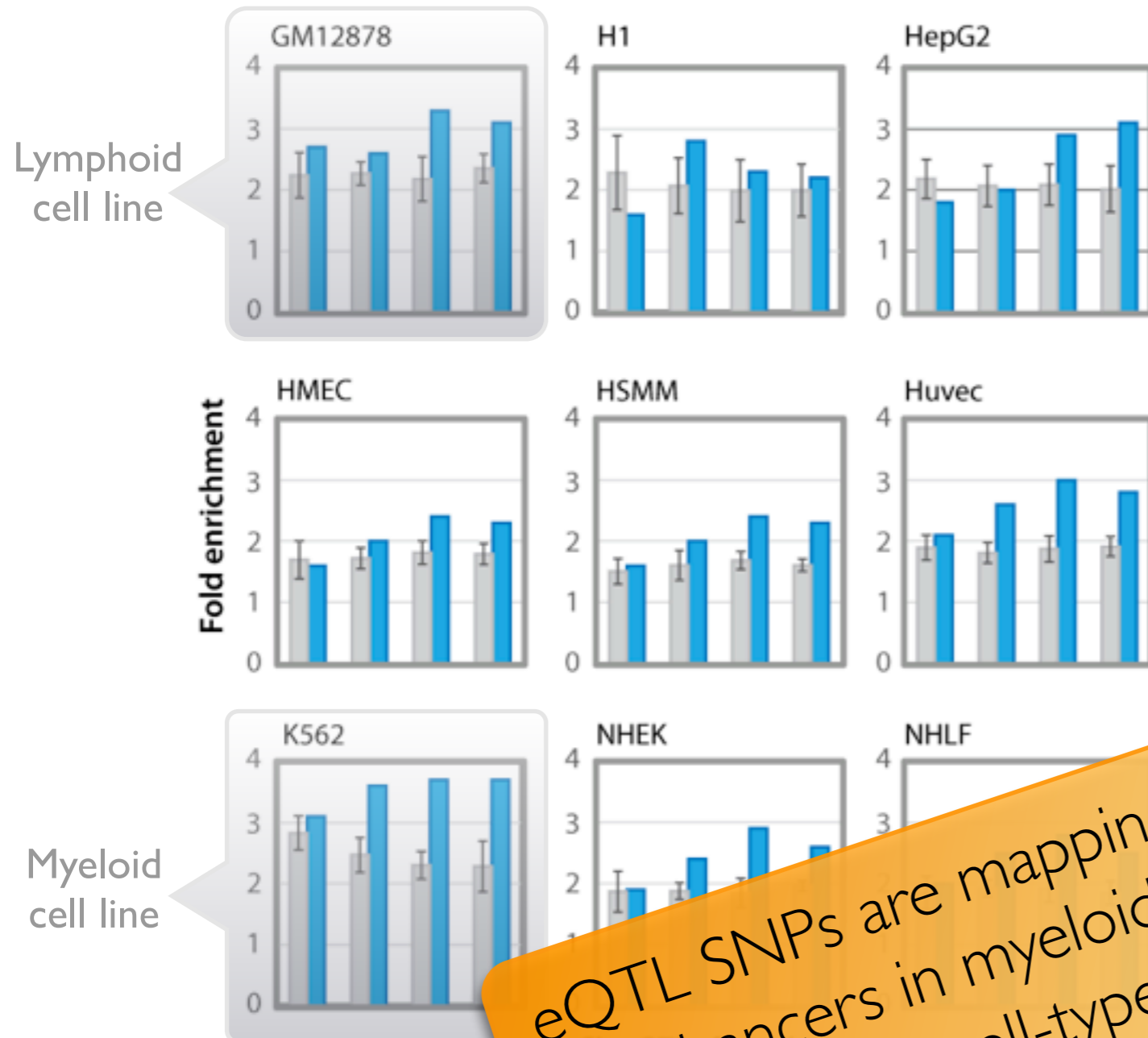


Detectability of *trans*-eQTLs depends on expression level



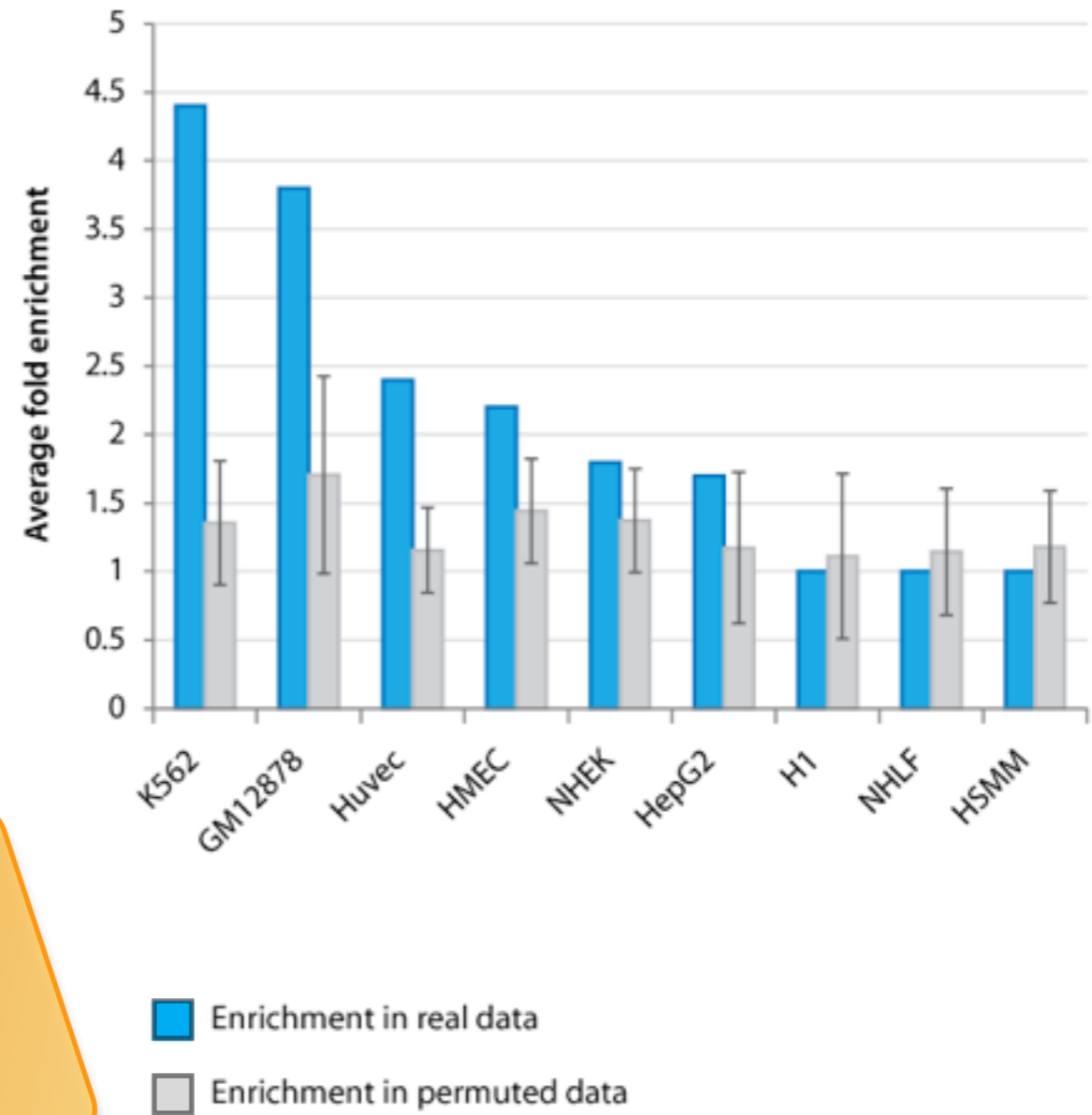
Most highly expressed genes show eQTL effect

cis-eQTL enhancer enrichment (Haploreg)



eQTL SNPs are mapping in enhancers in myeloid and lymphoid cell-types

trans-eQTL enhancer enrichment



One *trans*-eQTL highlighted: SLE

Systemic Lupus Erythematosis (~0.1% prevalence)



2003:

Interferon-inducible gene expression signature in peripheral blood cells of patients with severe lupus

PNAS

Emily C. Baechler¹, Franak M. Batliwalla¹, George Karypis¹, Patrick M. Gaffney¹, Ward A. Ortmann¹, Karl J. Espe¹, Katherine B. Shark¹, William J. Grande¹, Karis M. Hughes¹, Vivek Kapur¹, Peter K. Gregersen¹, and Timothy W. Behrens¹

Interferon and Granulopoiesis Signatures in Systemic Lupus Erythematosus Blood

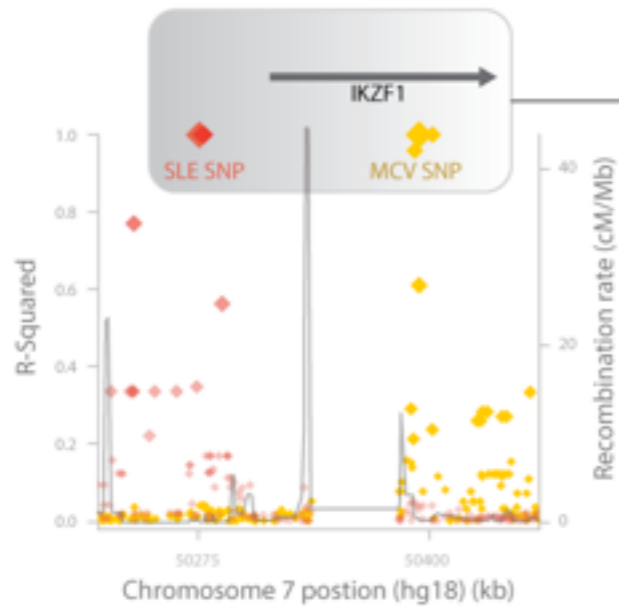
JEM

Lynda Bennett,^{1,2} A. Karolina Palucka,¹ Edsel Arce,^{1,2} Victoria Cantrell,^{1,2} Josef Borvak,¹ Jacques Banchereau,¹ and Virginia Pascual^{1,2}

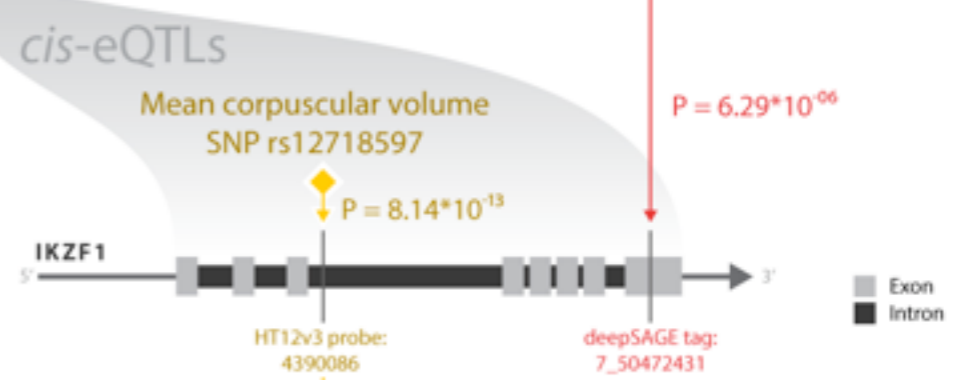


Strongly differentially expressed genes: *MX1*, *IFITM1*, *IFI44L*, *CTQB* & More

Cause or consequence of SLE?



Systemic lupus erythematosus allele rs4917014 (T) affects IKZF1 in cis and many genes in trans:

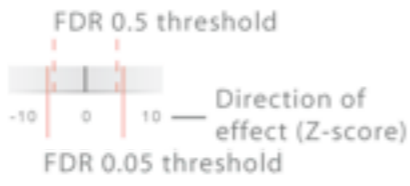


MCV trans-eQTL effects

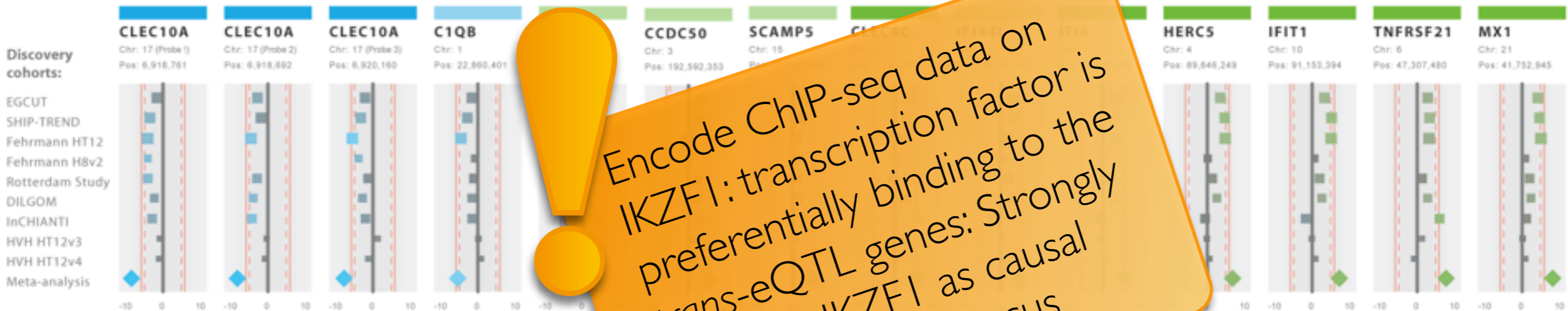
- Genes involved in hemoglobin and erythrocyte metabolic processes:
- AC010679.1, ALDH5A1, AP2S1, B4GALT3, C19orf62, C1orf128, C22orf13, C5orf4, CCBP2, CSDA, E2F2, EIF2AK1, EIF359, FAM104A, FBXO7, GCAT, GPR146, HAGH, HEMGN, HK1, HPS1, KCNH2, KLC3, KRT1, LGALS3, MAP2K3, MARCH8, MCOLN1, MSI2, OSBP2, PDLIM7, PFDN5, PLEK2, PPP2R5B, PTMS, RAP1GAP, RIOK3, RP11-529I10.4, RPIA, SESN3, SIAH2, SLC38A5, SLC6A8, SLC7A5, STOML2, TFDP1, TGM2, TMEM86B, TSTA3, VWCE

Trans-eQTL Legend:

- Increases expression (FDR < 0.05)
- Increases expression (FDR < 0.5)
- Decreases expression (FDR < 0.5)
- Decreases expression (FDR < 0.05)



SLE trans-eQTL effects



Encode ChIP-seq data on IKZF1: transcription factor is preferentially binding to the trans-eQTL genes: Strongly suggests IKZF1 as causal gene in this SLE locus

Replication cohorts:

Cohort	CLEC10A (Chr: 17)	C1QB (Chr: 1)	CCDC50 (Chr: 3)	SCAMP5 (Chr: 15)	HERC5 (Chr: 4)	IFIT1 (Chr: 10)	TNFRSF21 (Chr: 6)	MX1 (Chr: 21)
B-Cells		✓						✓
Monocytes	✓	✓	✓					✓
Peripheral blood (KORA F4)	✓	✓	✓					✓
Peripheral blood (BSGS)			✓	✓	✓	✓	✓	✓

Genes involved in complement

Type I Interferon response genes
Enrichment of IKZF1 binding (Wilcoxon P = 0.05)

Do it yourself:

How to conduct
an eQTL study

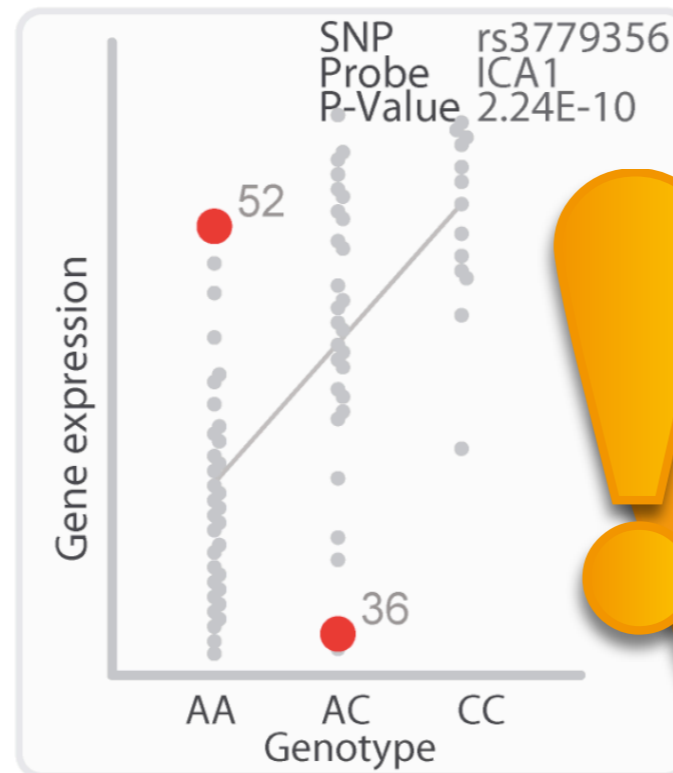
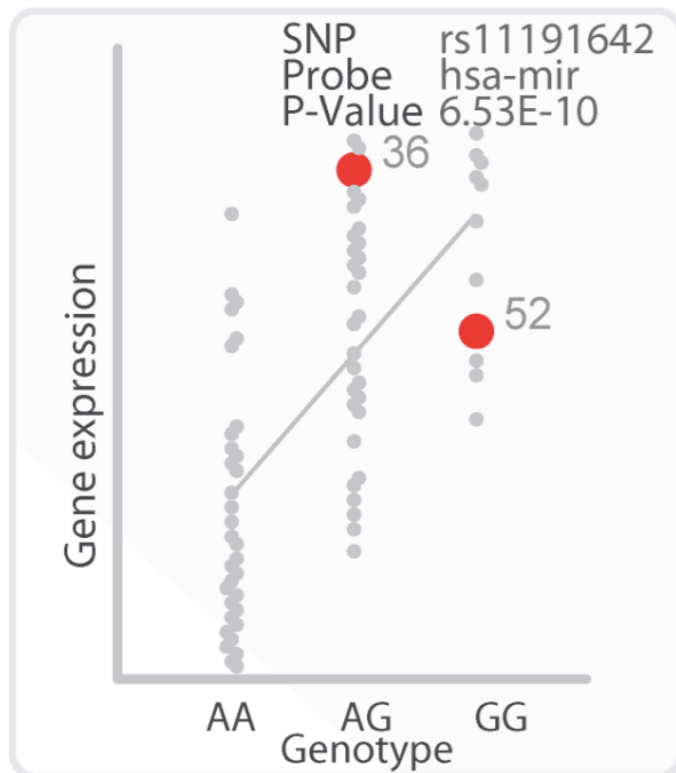
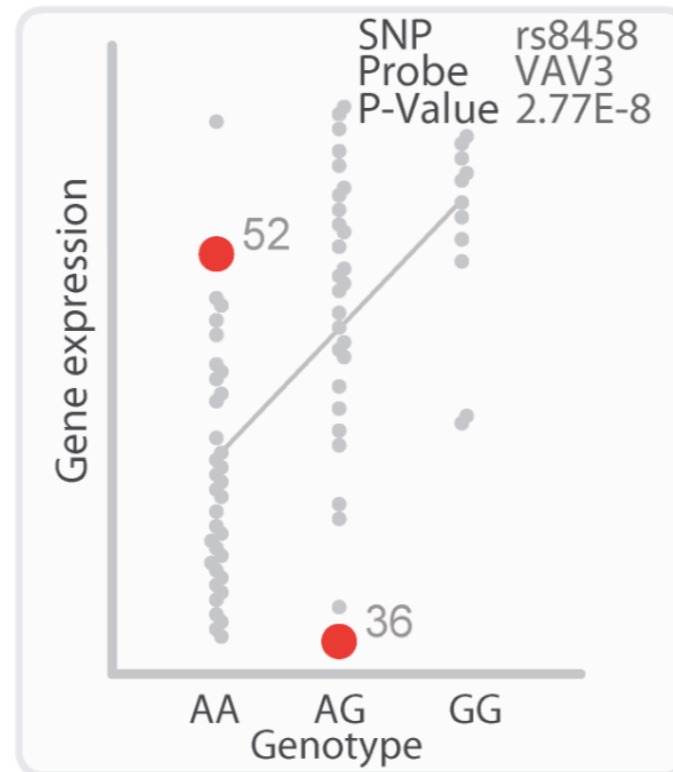
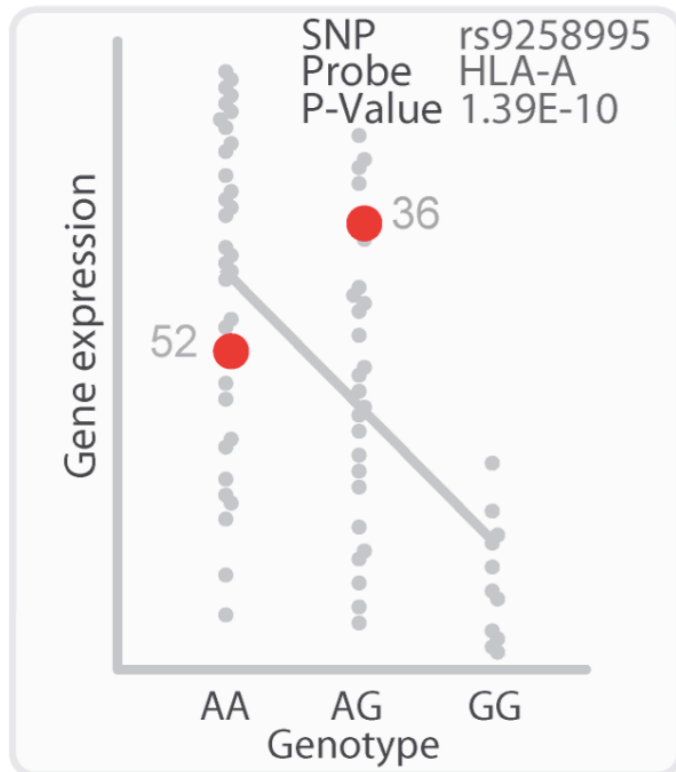
Conducting an eQTL study is not very difficult:

- Collect genotype data
- Collect gene expression data
- Correlate SNP genotypes with expression levels.

Two considerations:

- Sample mix-ups might have actually have happened
- A considerable amount of expression variation is not genetically determined, but due to differences in physiological or metabolic state

Sample mix-ups: how to identify them



What is going on with sample 36 and 52?
Sample mix-up?

What happened to our data

Assumed plate layout

	1	2	3	4	5	6
A	65	101	70	106	68	103
B	54	108	63	112	58	110
C	42	115	52	41	47	37
D	113	45	40	53	36	48
E	107	55	111	64	109	62
F	100	66	104	71	102	69

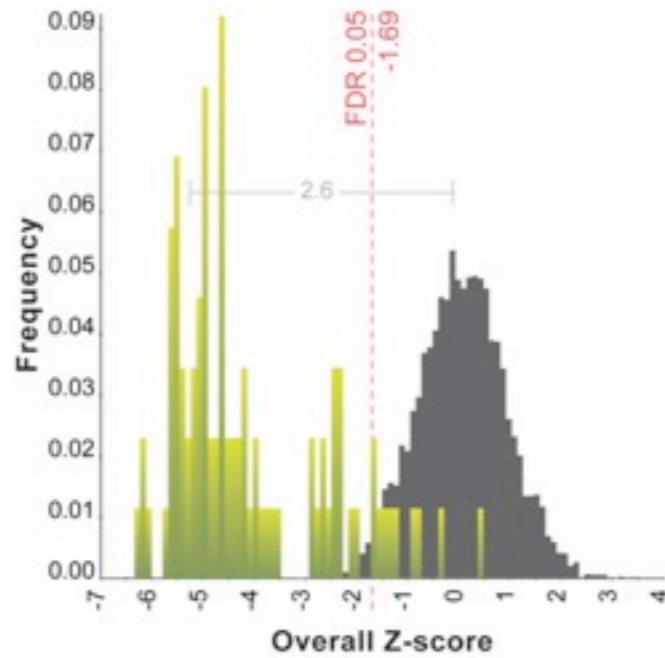
Actual plate layout

	1	2	3	4	5	6
A	100	101	102	103	104	106
B	107	108	109	110	111	112
C	113	115	36	37	40	41
D	42	45	47	48	52	53
E	54	55	58	62	63	64
F	65	66	68	69	70	71

columns swapped

Sample mix-ups: how to identify them

Frequency distribution before sample mix-up correction:

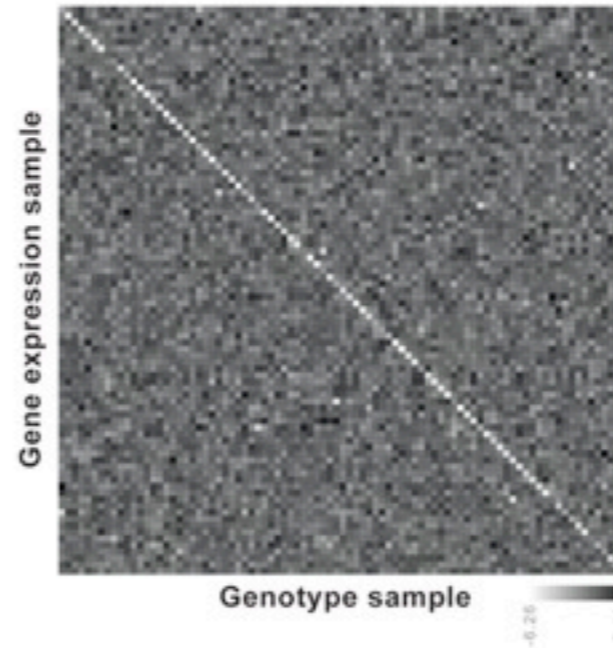


Legend

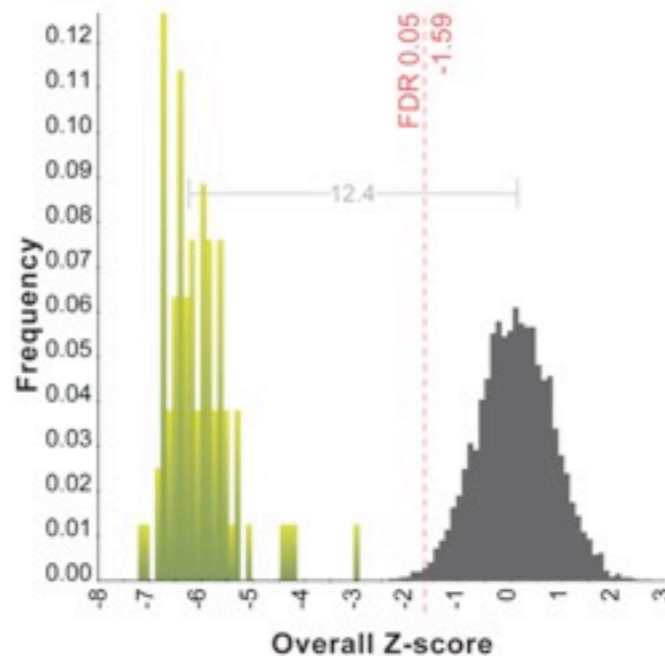
- Self - self
- Self - other (null distribution)

Signal-to-noise ratio

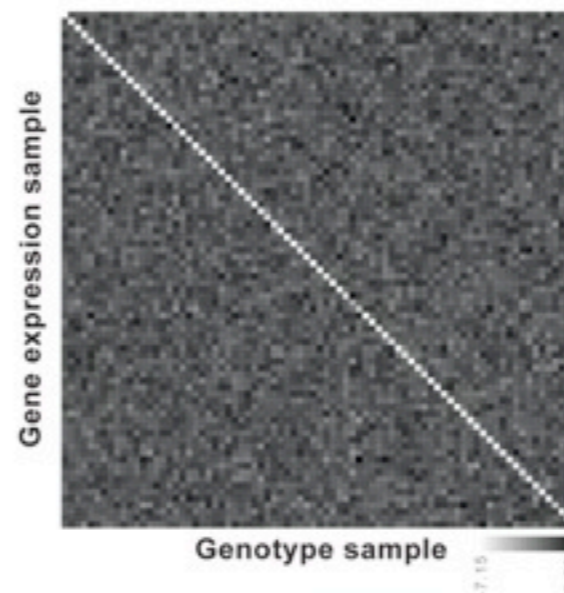
Overall Z-score heatmap before sample mix-up correction:



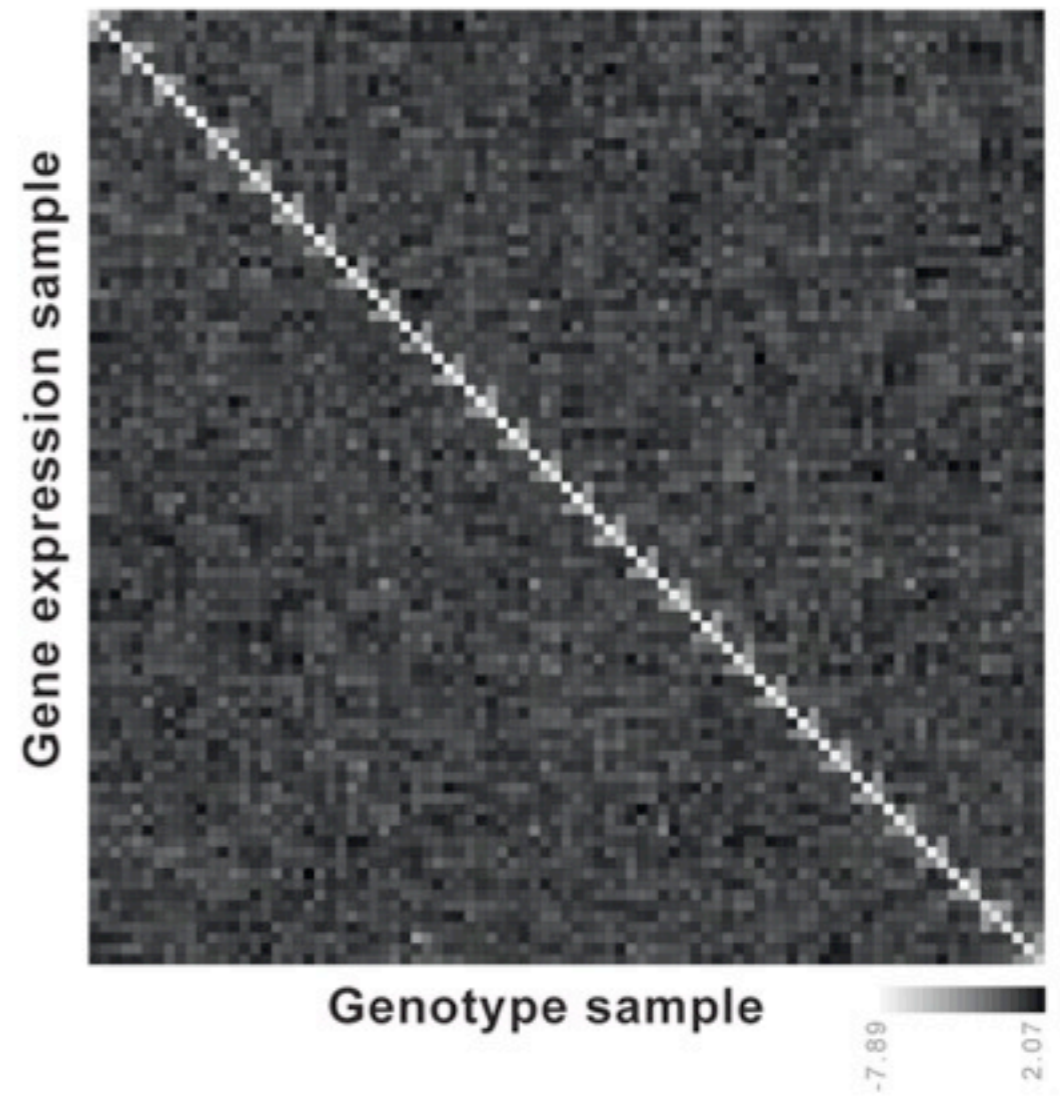
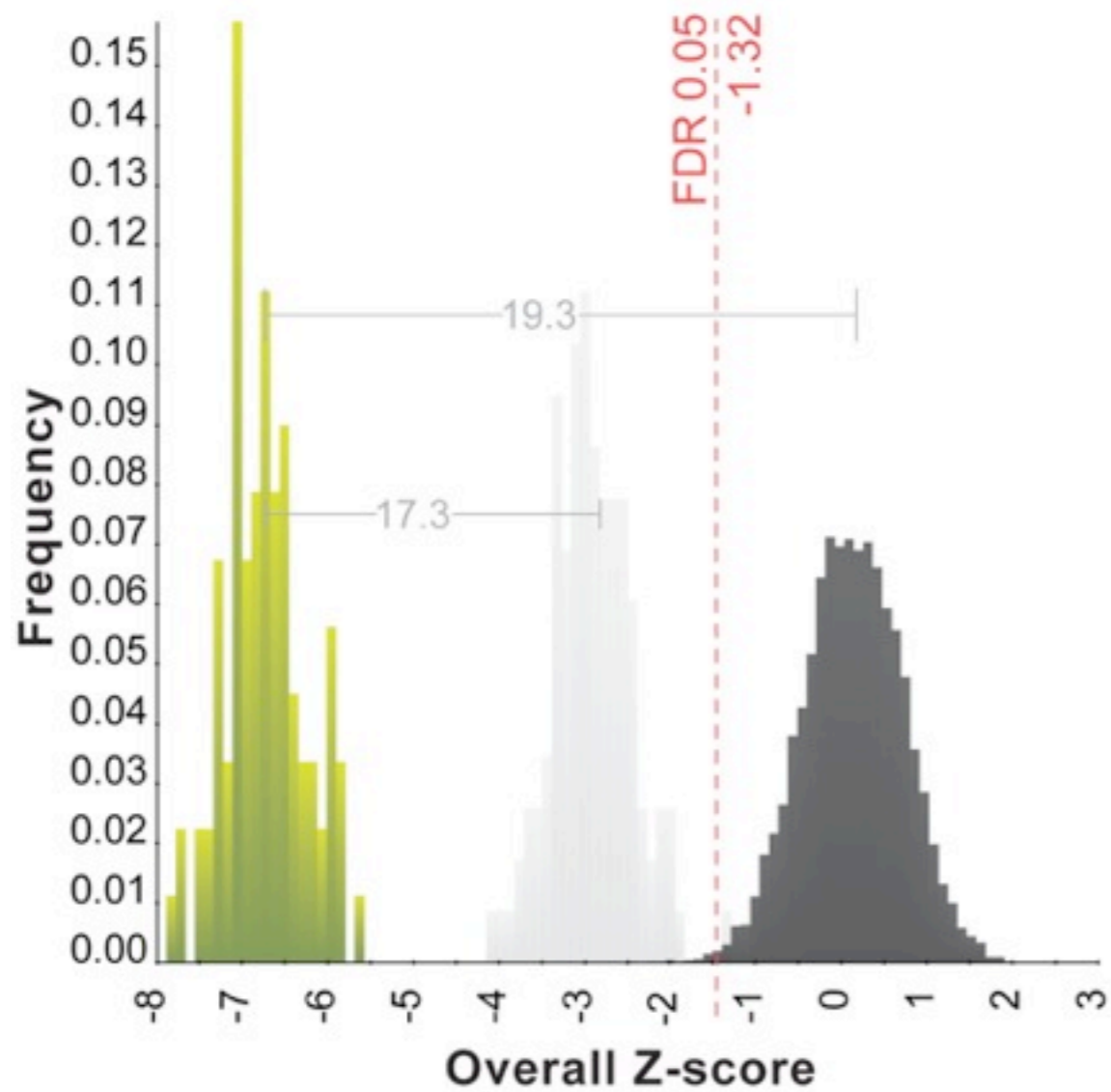
Frequency distribution after sample mix-up correction:



Overall Z-score heatmap after sample mix-up correction:

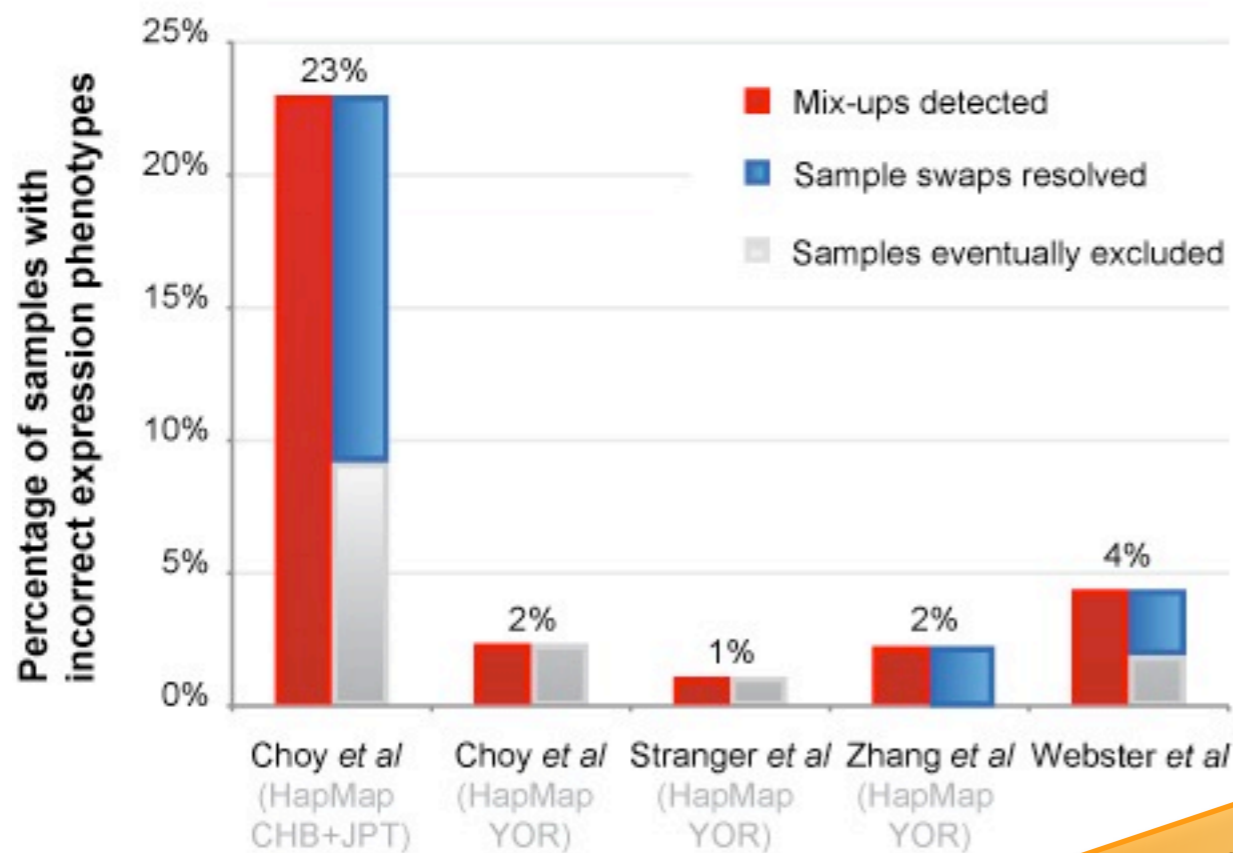


Sample mix-ups: related samples



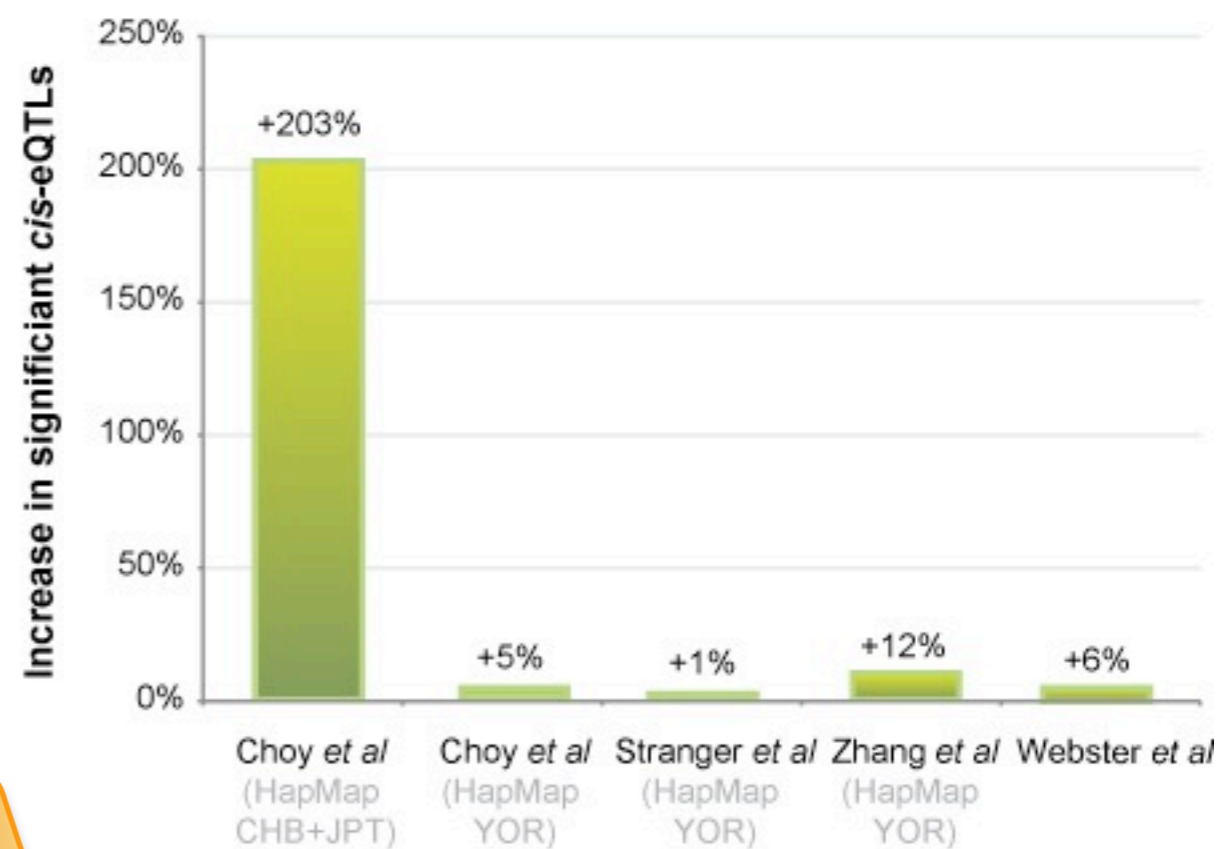
Sample mix-ups: do they happen?

eQTL datasets with mix-ups



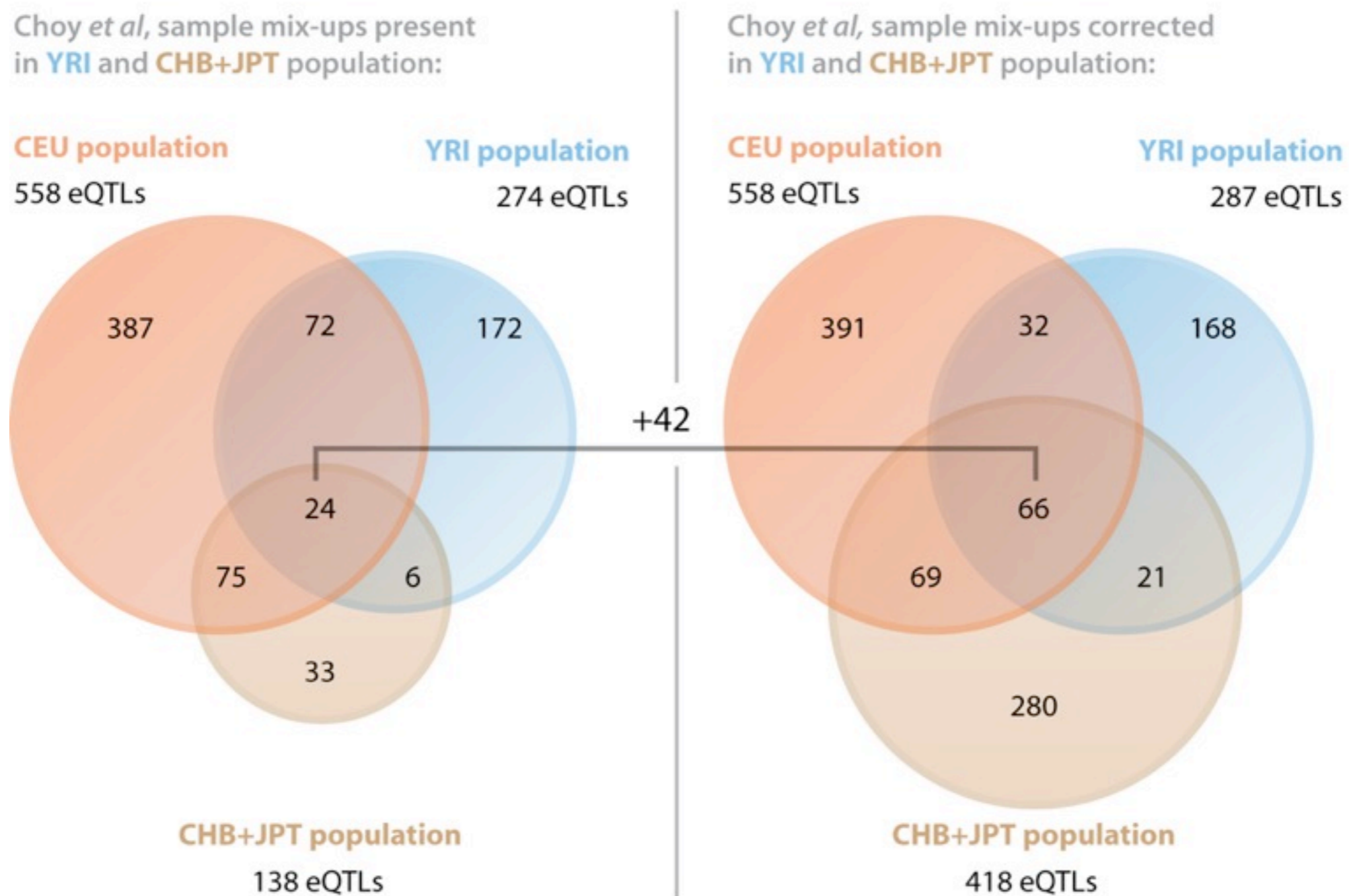
On average 3% of eQTL samples are mixed-up

Effect of correcting for these mix-ups



Sample mix-ups: effect of sample mix-up correction

Choy *et al* dataset, all 270 HapMap samples



Comparing same samples using different platforms

Comparison between different eQTL studies on the same HapMap CHB+JPT population.

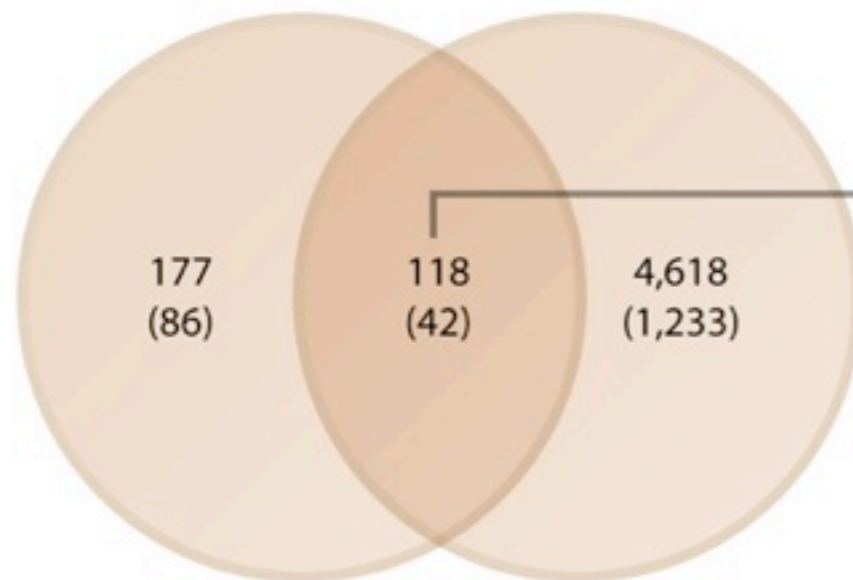
Sample mix-ups present in Choy CHB + JPT population

Choy CHB+JPT pop.

295 unique SNP-gene combinations
(122 unique eQTL genes)

Stranger CHB`+JPT pop.

4,736 unique SNP-gene combinations
(1,244 unique eQTL genes)



Comparison between different eQTL studies on the same HapMap CHB+JPT population.

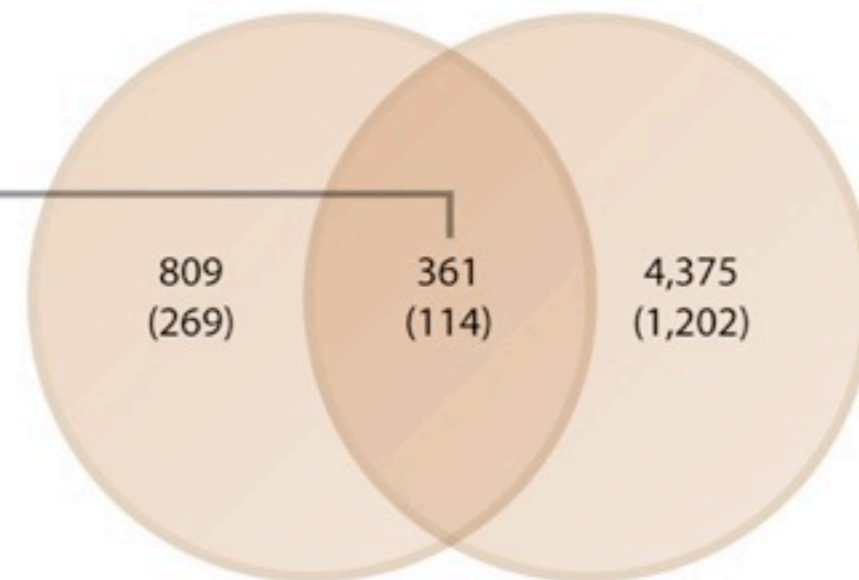
Sample mix-ups corrected in Choy CHB+JPT population

Choy CHB+JPT pop.

1,170 unique SNP-gene combinations
(361 unique eQTL genes)

Stranger CHB`+JPT pop.

4,736 unique SNP-gene combinations
(1,244 unique eQTL genes)



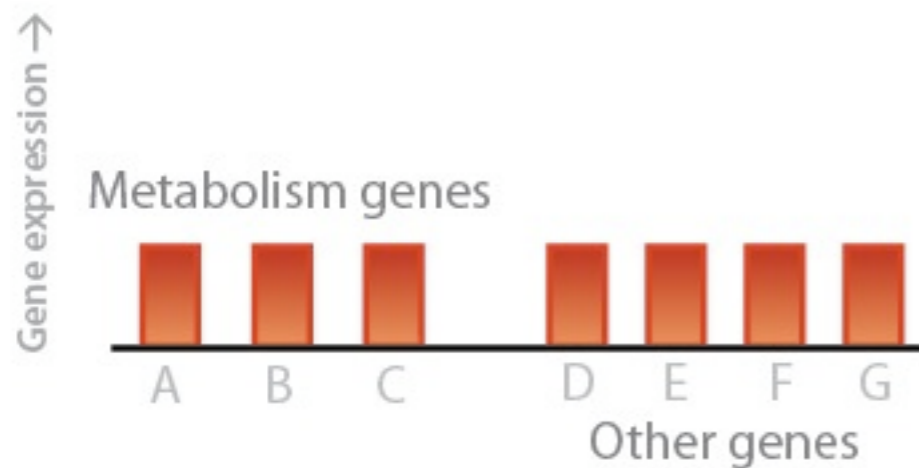
+243

Remove non-genetic expression variation

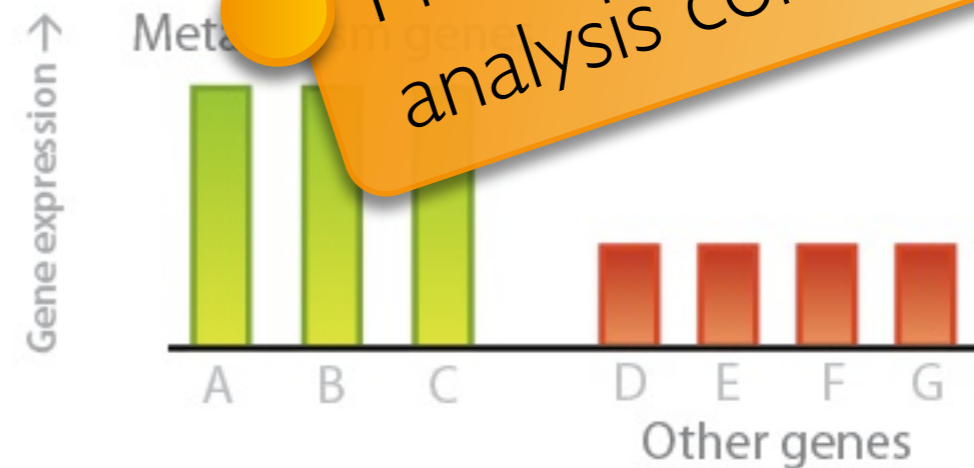
Large proportion of expression variation is determined by genetic variation but due to e.g.:

- Physiological state of samples
- Environmental state of samples (e.g. fasting vs. non-fasting)

RNA blood expression
when you wake up



RNA blood
expression
after dinner



Get rid of this 'noise'?
Principal component
analysis correction

Correct for sample-mixups and non-genetic components

HapMap Population	Original data	After sample mix-up identification and correction	After mix-up correction and removal of physiological and metabolic components
CEU	558	558	717
YRI	274	287	383
CHB+JPT	138	418	661
Meta-analysis	1277	1508	1995

! 56% increase in detectable eQTLs

nature

April 2010

Transcriptome genetics using second generation sequencing in a Caucasian population

Stephen B. Montgomery^{1,2}, Micha Sammeth³, Maria Gutierrez-Arcelus¹, Radoslaw P. Lach², Catherine Ingle², James Nisbett², Roderic Guigo³ & Emmanouil T. Dermitzakis^{1,2}

Understanding mechanisms underlying human gene expression variation with RNA sequencing

Joseph K. Pickrell¹, John C. Marioni¹, Athma A. Pai¹, Jacob F. Degner¹, Barbara E. Engelhardt², Everlyne Nkadori^{1,3}, Jean-Baptiste Veyrieras¹, Matthew Stephens^{1,4}, Yoav Gilad¹ & Jonathan K. Pritchard^{1,3}

Observations:

- RNA-sequencing can interrogate entire transcriptome
- Possible to investigate allele-specific expression
- With limited read-depth accurate gene expression levels can be established

eQTLs in single-end, paired-end and deepSAGE data

