

Integrating multiple sources and shapes of genomic data to prioritise autoimmune disease-candidate genes

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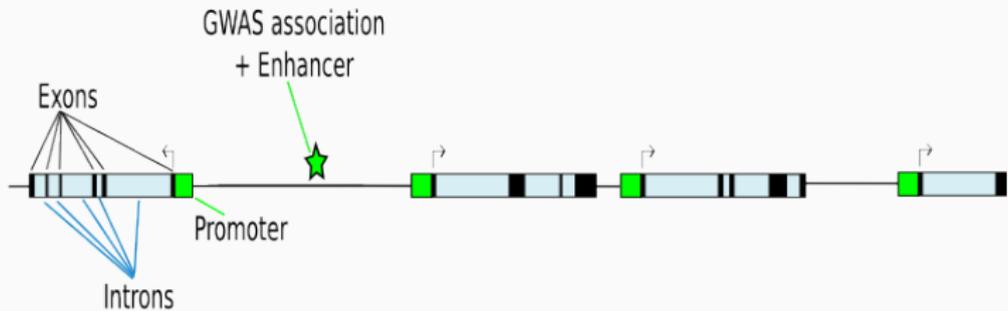
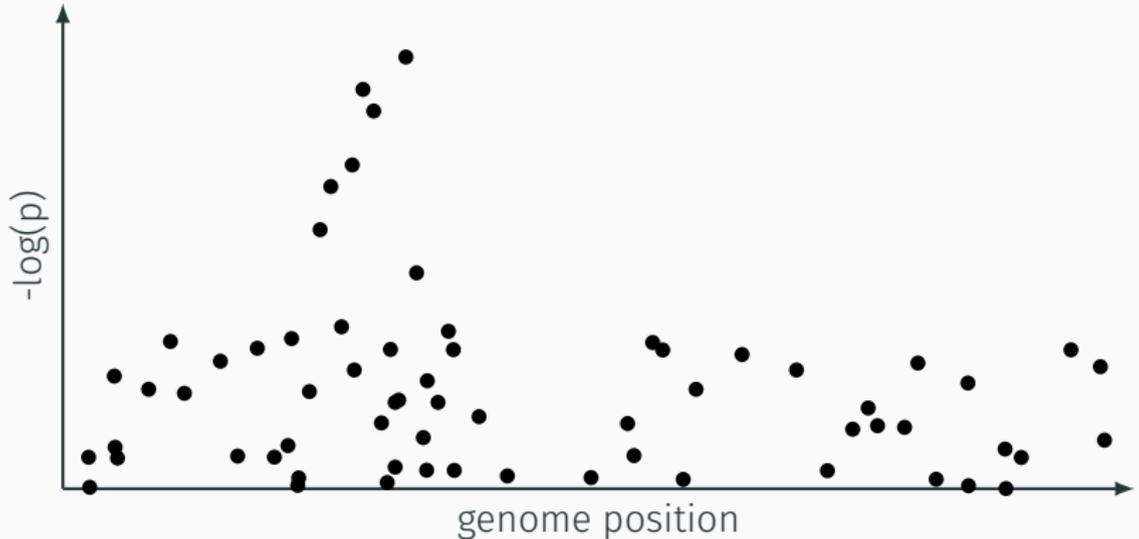


Olly Burren



Dan Rainbow

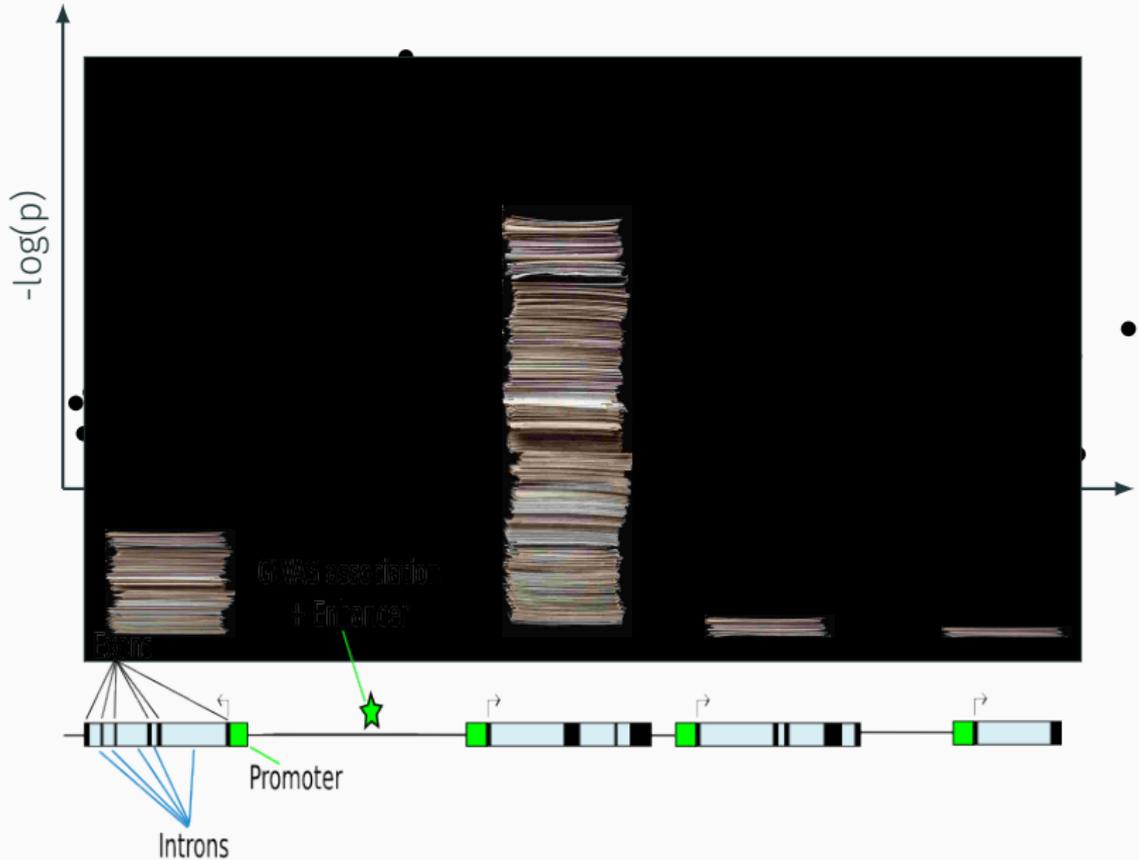
Which gene alters disease risk?



Which *gene* alters disease risk?



Which gene alters disease risk?



Which *gene* alters disease risk?



1. Colocalisation of disease and gene expression variants

Integrate GWAS and eQTL datasets via colocalisation

0.5-8M variants

genotypes

> 10k genes

expression

100s individuals

summaries

> 10k genes

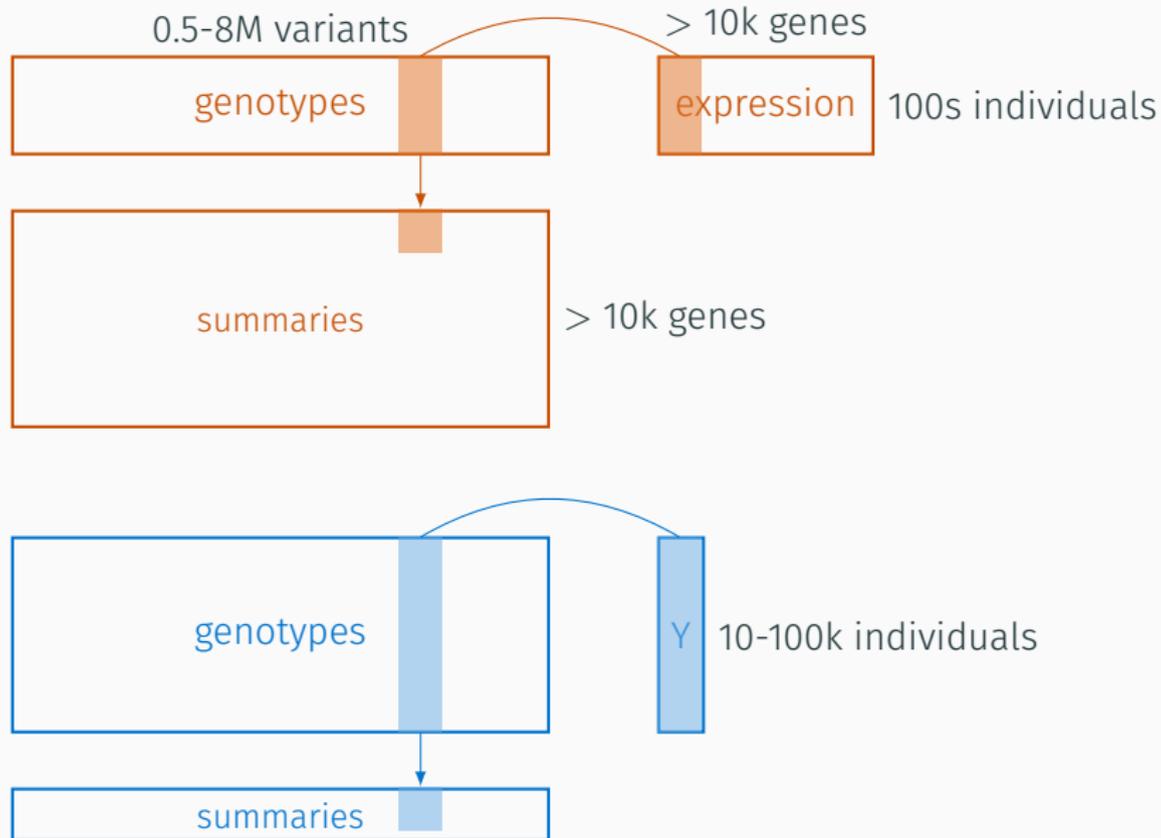
genotypes

Y

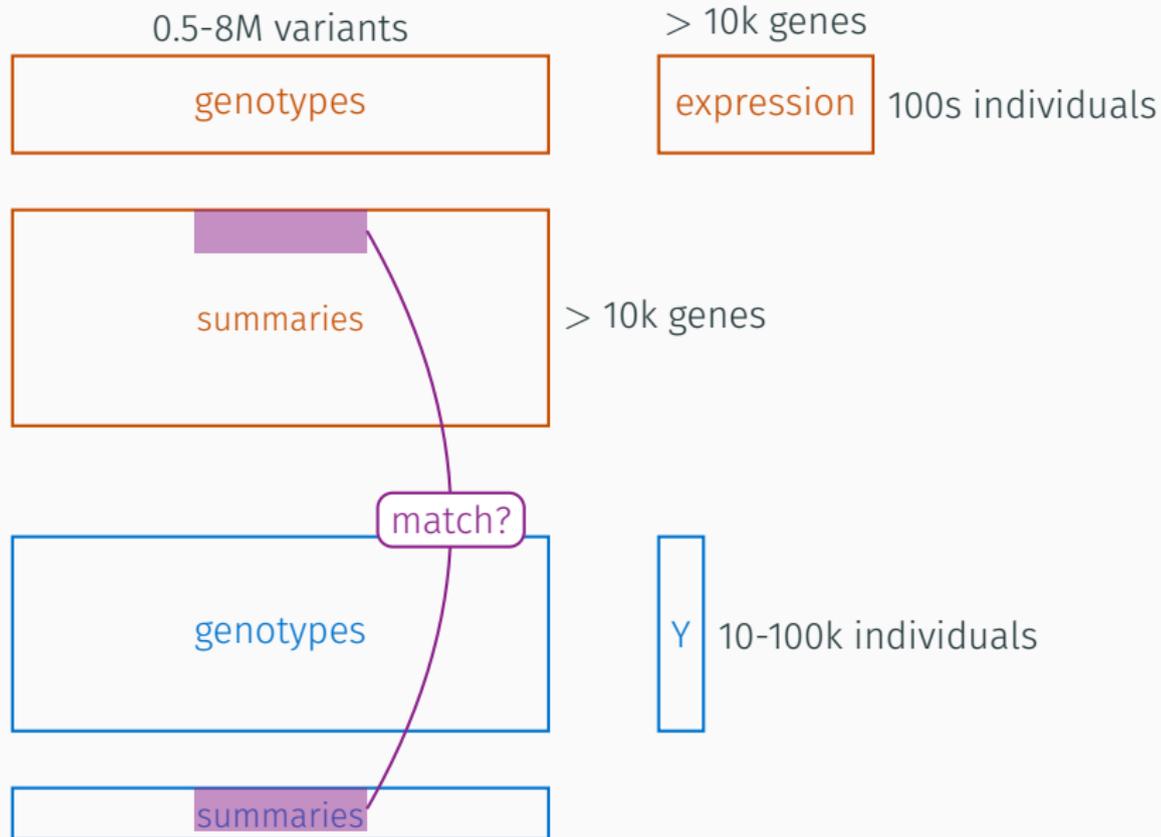
10-100k individuals

summaries

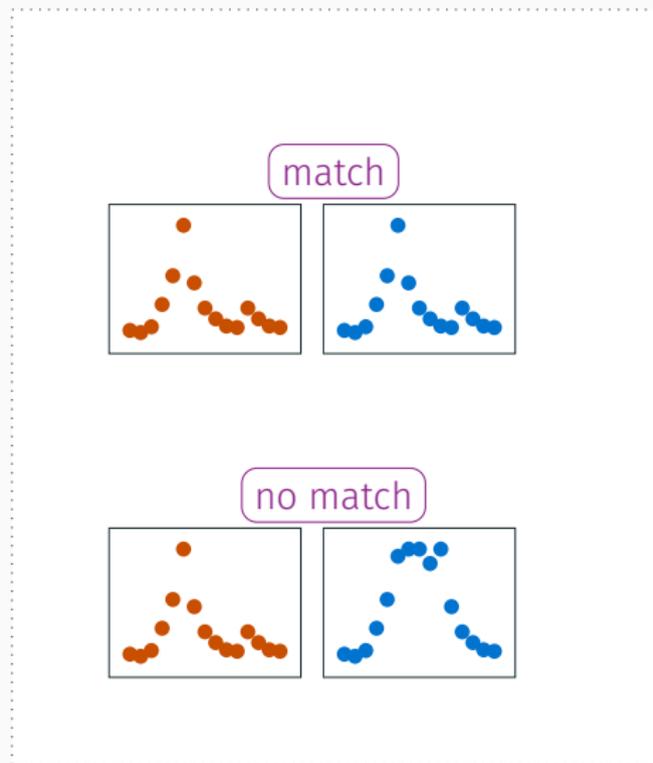
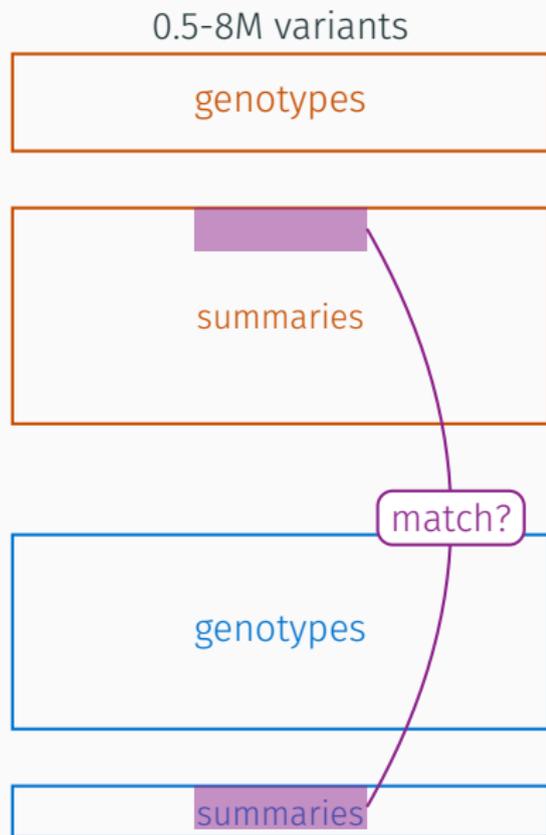
Integrate GWAS and eQTL datasets via colocalisation



Integrate GWAS and eQTL datasets via colocalisation

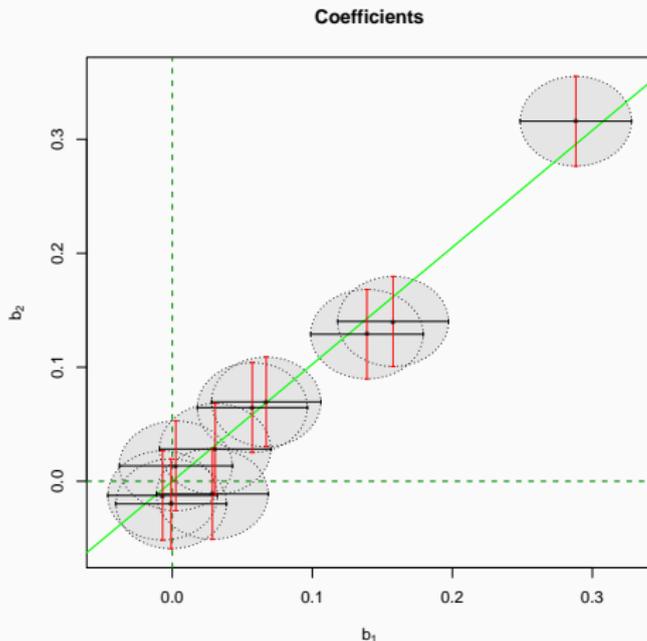


Integrate GWAS and eQTL datasets via colocalisation



Colocalisation methods (1) testing proportionality of effects

If two traits share one or more causal variants, then regression coefficients for the traits against any set of variants *in the neighbourhood of those causal variants* should be proportional.



Colocalisation methods (2) enumeration of possibilities

- Assume at most one causal variant in a region
- Partition possible configurations of association into hypotheses

$$H_0 \quad \bigcirc - \bigcirc - \bigcirc - \bigcirc - \bigcirc \quad \times 1$$

$$H_1 \left\{ \begin{array}{l} \text{●} - \bigcirc - \bigcirc - \bigcirc - \bigcirc \\ \bigcirc - \text{●} - \bigcirc - \bigcirc - \bigcirc \\ \dots \end{array} \right\} \times n$$

$$H_3 \left\{ \begin{array}{l} \text{●} - \text{●} - \bigcirc - \bigcirc - \bigcirc \\ \text{●} - \bigcirc - \text{●} - \bigcirc - \bigcirc \\ \dots \end{array} \right\} \times \frac{n(n-1)}{2}$$

$$H_2 \left\{ \begin{array}{l} \text{●} - \bigcirc - \bigcirc - \bigcirc - \bigcirc \\ \bigcirc - \text{●} - \bigcirc - \bigcirc - \bigcirc \\ \dots \end{array} \right\} \times n$$

$$H_4 \left\{ \begin{array}{l} \text{●} - \bigcirc - \bigcirc - \bigcirc - \bigcirc \\ \bigcirc - \text{●} - \bigcirc - \bigcirc - \bigcirc \\ \dots \end{array} \right\} \times n$$

Comparison of two approaches

	Proportionality	Enumeration
N. causal variants	any	one
Density required	any	dense
Data required	full	summary
Variant selection	complicated	-

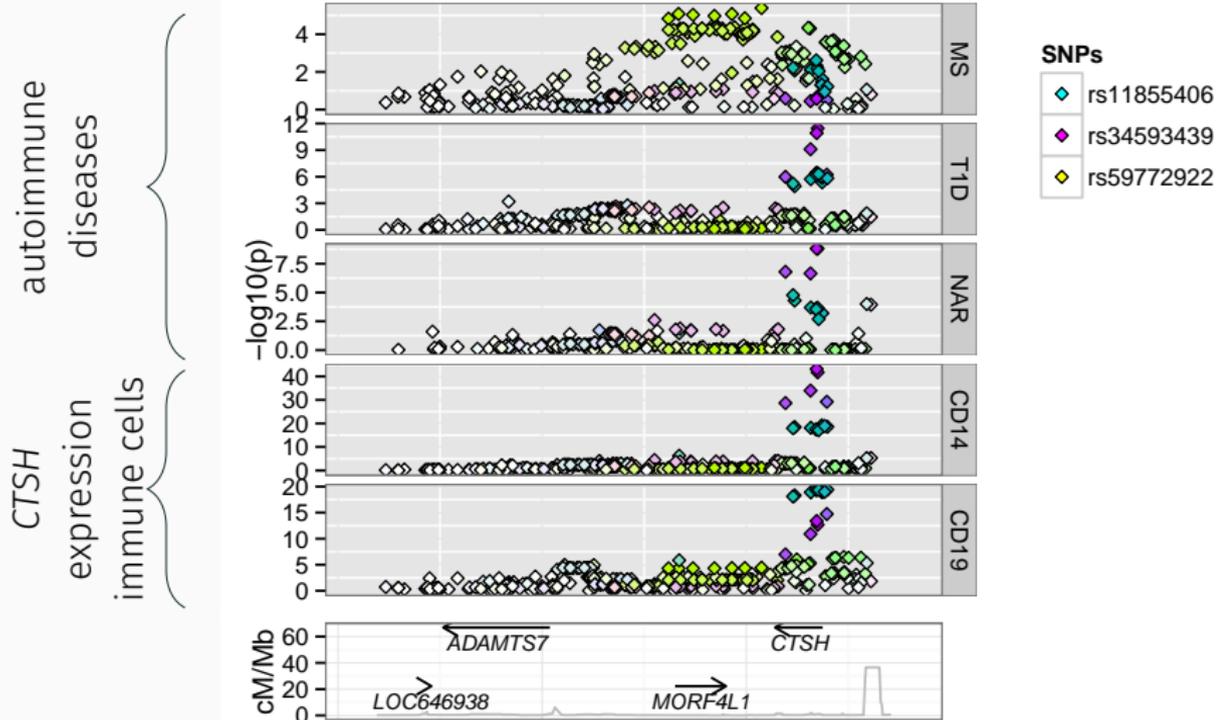
Selection of variants for proportionality testing

Too many → too many degrees of freedom (loss of power)

Most significant → biased coefficients (type 1 errors)

Solutions: dimension reduction on genotype matrix, model averaging

Colocalisation points to *CTSH* in CD14⁺ monocytes



Colocalisation analysis of ten autoimmune diseases with B cell, monocyte, stimulated monocyte eQTLs



+

B cells, monocytes (~ 300 samples)

Genetics of gene expression in primary immune cells identifies cell type-specific master regulators and roles of HLA alleles

Benjamin P Fairfax¹, Seiko Makino¹, Jayachandran Radhakrishnan¹, Katharine Platt¹, Stephen Leslie², Alexander Dilthey³, Peter Ellis⁴, Cordelia Langford⁵, Fredrik O Vannberg^{1,6} & Julian C Knight¹

Brain-acting genetic variant expression. Using paired gene expression quantification in B cells, respectively, Addison disease locus, with PLEK suggesting roles for cell pathogenesis. We also in ADAM and ARHGAP24 in cell populations identify disease susceptibility.

Defining the genetic disease variants underlying other disease association studies functional activity of many the context of relevant cell state¹⁻⁵. This context-de

Innate Immune Activity Conditions the Effect of Regulatory Variants upon Monocyte Gene Expression

Benjamin P. Fairfax¹, Peter Humberg, Seiko Makino, Vivek Narasimhan, David Wang, Fengyan Liu, Luke Justice, Katharine Platt, Robert Andrews, Chris Miccio, Julian C. Knight¹

Introduction: Many genetic variants associated with common disease susceptibility occur close to immune-related genes in noncoding DNA, suggestive of a regulatory function. The definition of functional variants and the specific genes that they regulate remains challenging and in many cases is unresolved. We hypothesized that a significant proportion of variants, including those implicated in disease, may show activity in a context-specific manner and therefore only be identifiable upon triggering of immune responses.

Methods: We mapped inter-individual variation in gene expression as a quantitative trait, defining expression quantitative trait loci (eQTLs). To investigate the effect of innate immune stimuli on eQTLs, we exposed primary CD14⁺ human monocytes from 432 European volunteers to the inflammatory protein interferon- γ (IFN- γ) or differing durations (2 or 24 hours) of lipopolysaccharide (LPS). eQTL mapping was performed on a genome-wide basis with an additive linear model. A subset of 228 individuals with expression data available for all experimental conditions enabled cross-treatment comparisons.

Results: Stimulation with LPS or IFN- γ resulted in profound effects across monocyte eQTLs, with hundreds of genes and associated pathways demonstrating context-specific eQTLs dependent on the type and duration of stimulus. Context-specific eQTLs frequently interconnected canonical pathways of monocyte signaling and included by total genes and effector molecules. These eQTLs are typically more distal to the transcriptional start site and, in some cases, showed reversal of

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<https://doi.org/10.1038/nature12464>

See this article as B. Fairfax et al., Science 349, 1246-1250 (2015). DOI: 10.1126/science.12464

FIGURES IN THE FULL ARTICLE

Fig. 1. Genotypes modulates the gene expression response to innate immune stimuli in monocytes.

Fig. 2. Trans-eQTL demonstrate context specificity and identify master regulatory loci after treatment.

Fig. 3. Stimulus-specific effects for a stimulus-specific trans-eQTL.

Fig. 4. Cis regulation of IRF2 at rs12499 has profound transcriptional consequences in monocytes.

Fig. 5. Stimulus-specific eQTL and GWAS.

Fig. 6. Examples of context-specific eQTLs informative for disease risk.

SUPPLEMENTARY MATERIALS

Materials and Methods
Figs. S1 to S12

?

candidate causal autoimmune genes

Activated monocytes (~ 300 samples)

In context, parallelizing the expression of class II genes, induced eQTLs were searched for disease-
risk loci with context-specific associations to many putative causal genes including at ATM, IRF2,

also with
of signaling
IRF2 expression
a single-nucleotide polymorphism (rs12499)
observed after 2 hours of LPS stimulation of a

Colocalisation identified six candidate causal autoimmune disease genes

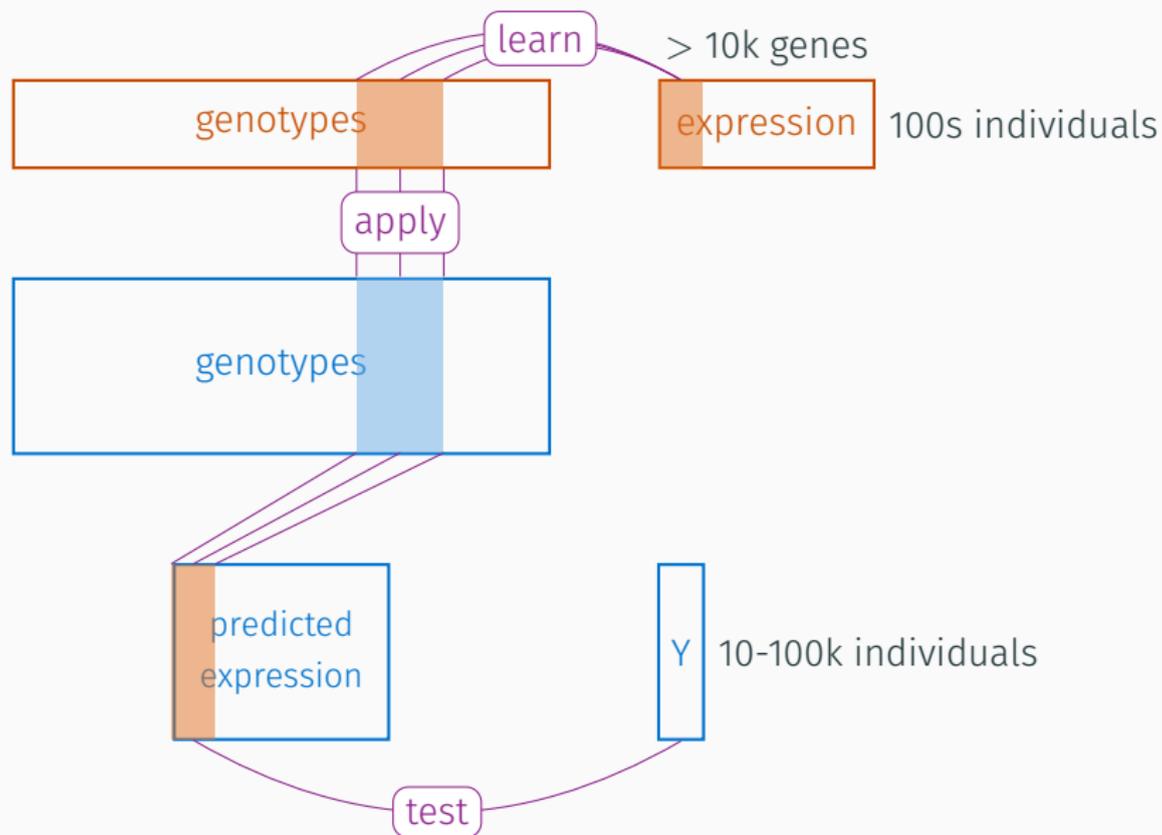
Gene	Disease(s)	Direction
<i>Resting B cells + monocytes</i>		
<i>RGS1</i>	Celiac, MS	-
<i>SYNGR1</i>	Primary Biliary cirrhosis	+
<i>Resting + activated monocytes</i>		
<i>ADAM15</i>	Crohn's	?
<i>CARD19</i>	Crohn's, ulcerative colitis	+
<i>LTBR</i>	Primary Biliary cirrhosis	+
<i>CTSH</i>	T1D, narcolepsy	-

2. Transcriptome-wide association study

Integrate GWAS and eQTL datasets via TWAS



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TWAS of T1D with B cell, monocyte, stimulated monocyte eQTLs



+

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Genetics of gene expression in primary immune cells identifies cell type-specific master regulators and roles of HLA alleles

Benjamin P Fairfax¹, Seiko Makino¹, Jayachandran Radhakrishnan¹, Katharine Plant¹, Stephen Leslie², Alexander Dhillon³, Peter Ellis⁴, Cordelia Langford⁵, Fredrik O Vannberg^{6,7}, & Julian C Knight¹

Trans-acting genetic vari- ant expression. Using paired mono- expression quantita- B cells, respectively. Addi- disease locus, with IPW, suggesting roles for cell- pathogenesis. We also de- ACMT and ATRXAP2 in a cell populations identify disease susceptibility.

Defining the genetic deter- understanding the biologi- cations. This is particularly variants underlying other wide association studies (functional activity of many the context of relevant cell state^{1,2}. This context-dep-

Innate Immune Activity Conditions the Effect of Regulatory Variants upon Monocyte Gene Expression

Benjamin P. Fairfax¹, Peter Humberg, Seiko Makino, Vivek Karasikhat, Daniel Wong, Evelyn Lee, Luke Justice, Katharine Plant, Robert Andrews, Chris McGee, Julian C. Knight¹

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Results: Stimulation with LPS or IFN- γ resulted in profound effects across monocyte eQTLs, with hundreds of genes and associated pathways demonstrating context-specific eQTLs dependent on the type and duration of stimulus. Context-specific eQTLs frequently interconnected established canonical pathways of monocyte signaling and included key nodal genes and effector molecules. These eQTLs are typically more distal to the transcriptional start site and, in some cases, showed reversal of

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NEW COLLECTION OF
GENETIC VARIANTS

FIGURES IN THE FULL ARTICLE

Fig. 1. Genotype modulates the gene expression response to innate immune stimuli in monocytes.

Fig. 2. Trans-eQTL demonstrate context specificity and identify master regulator loci after treatment.

Fig. 3. Temporal effects for a stimulus-specific trans-eQTL.

Fig. 4. CX3 regulation of IRF2 at rs133499 has profound transcriptional consequences in tonsils.

Fig. 5. Stimulus-specific eQTL and GWAS.

Fig. 6. Examples of context-specific eQTL informative for disease risk.

SUPPLEMENTARY MATERIALS
Materials and Methods
Figs S2 to S22

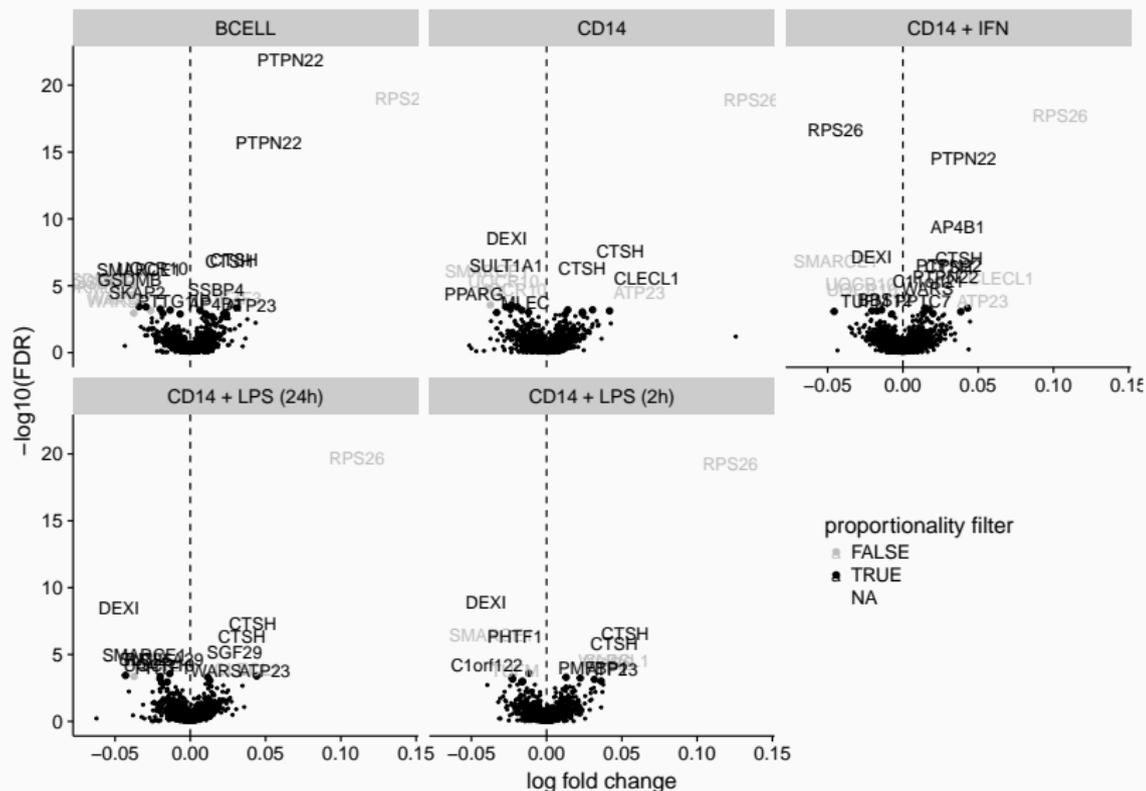
Activated monocytes (~ 300 samples)

on context, paralleling the expression of class II genes. Induced eQTLs were enriched for disease-risk loci with context-specific associations to many putative causal genes including at ATRX, IRF2,

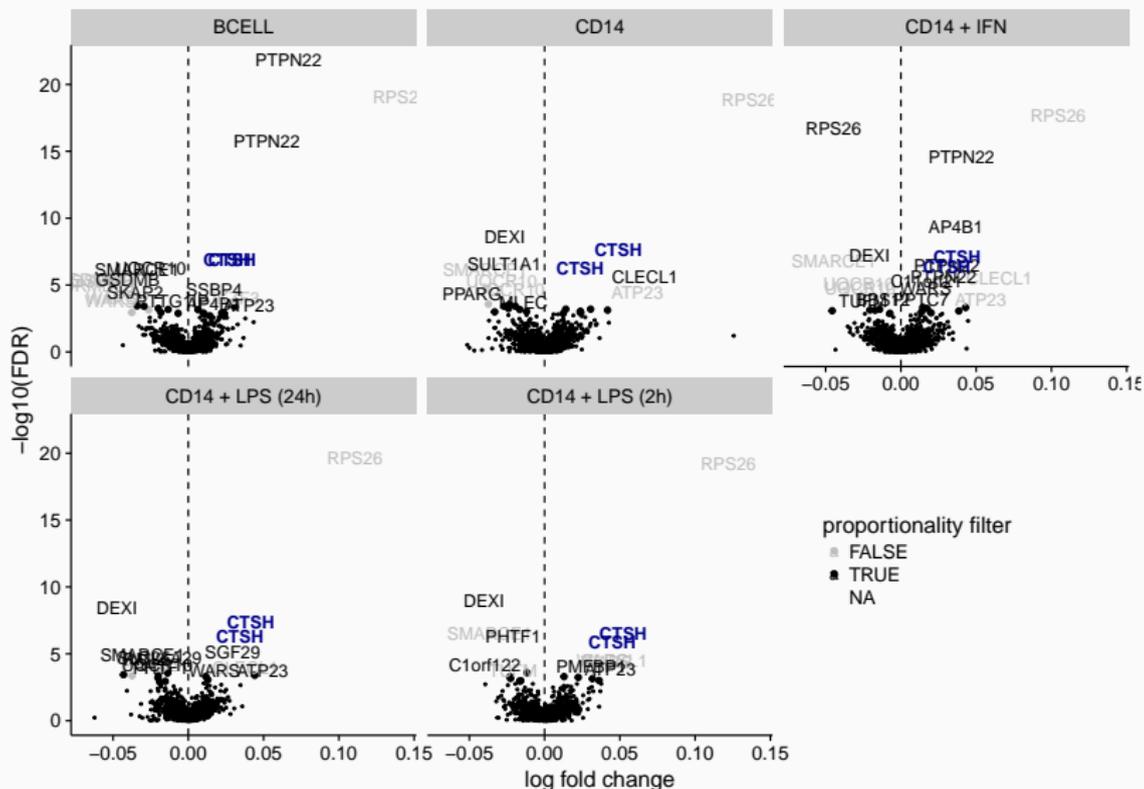
Site with eQTLs
induced
a single-nucleotide polymorphism (rs2272)
monocytes after 2 hours of LPS stimulation of a

?
candidate causal
autoimmune genes

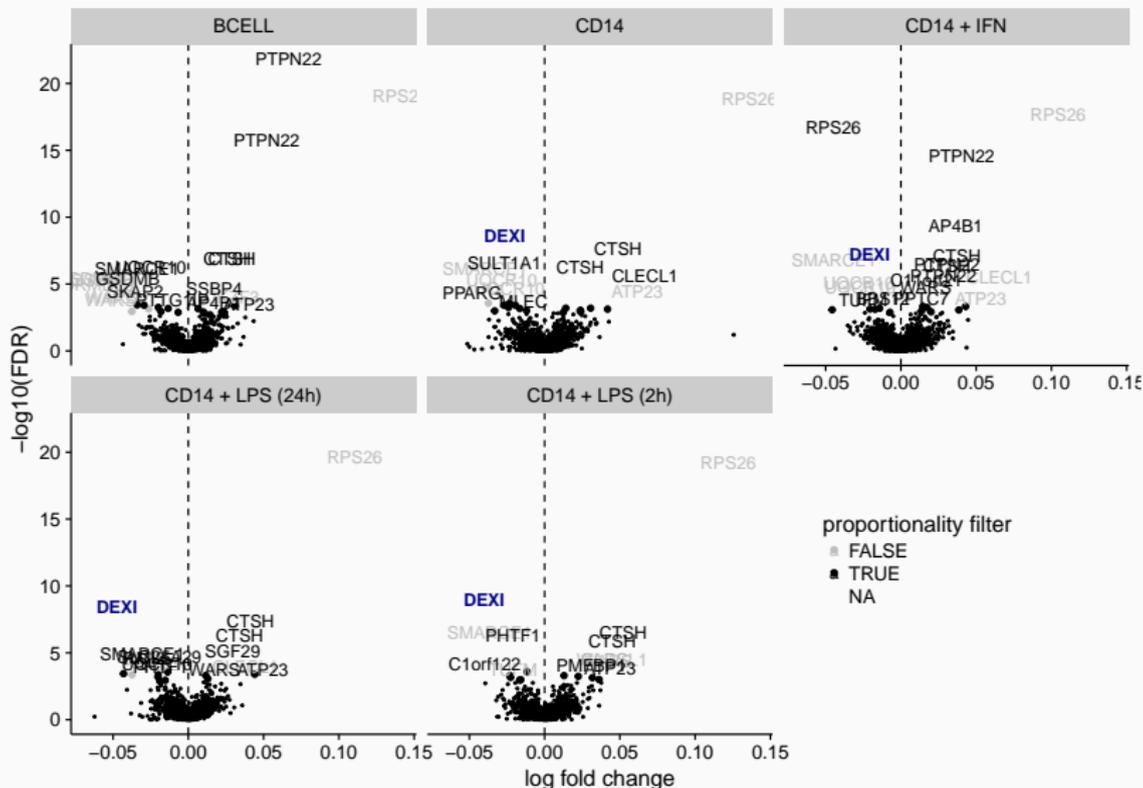
TWAS identified 88 T1D candidate genes, 61 after filtering



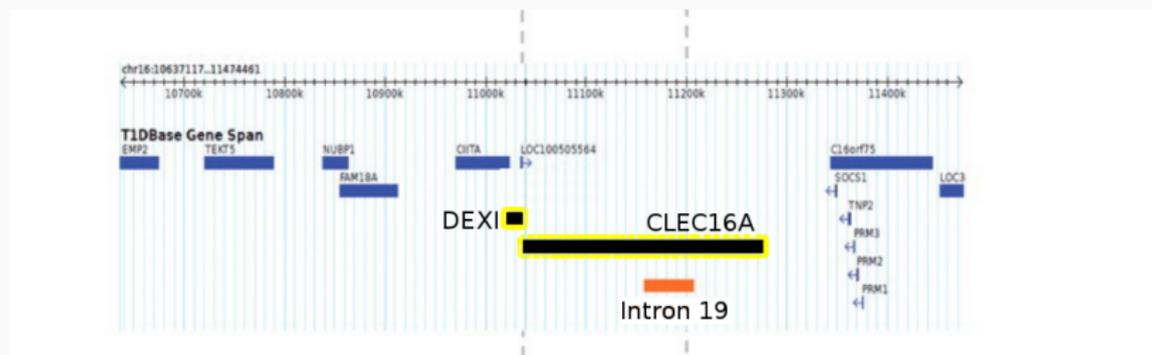
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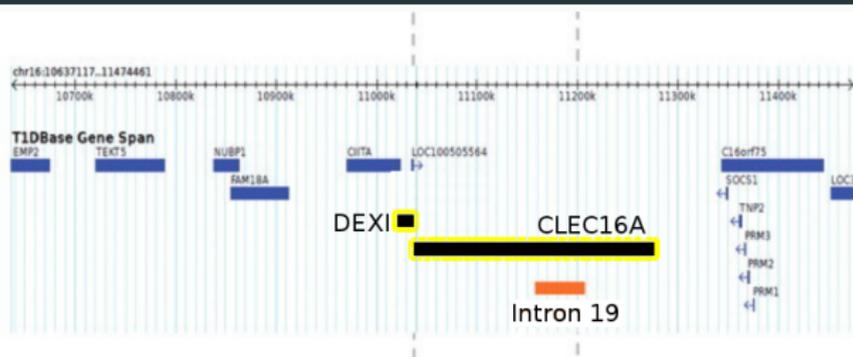
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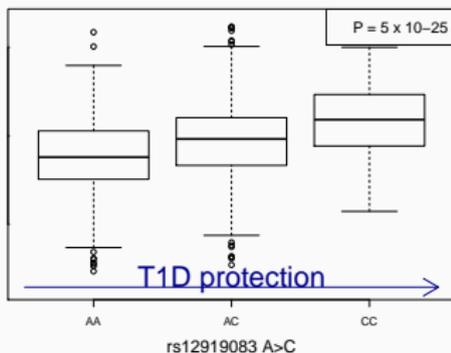
TWAS candidate *DEXI* supported by 3C experiments



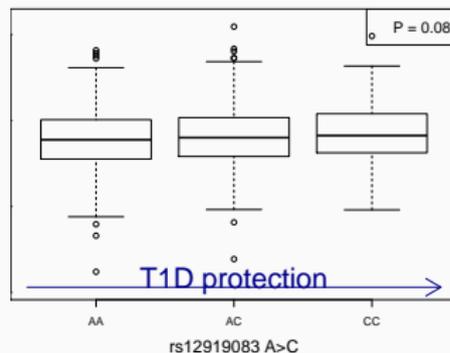
TWAS candidate *DEXI* supported by 3C experiments



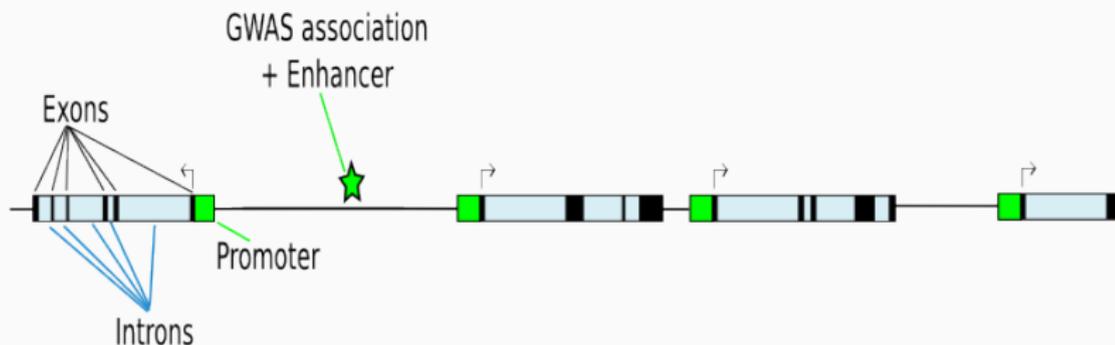
DEXI expression



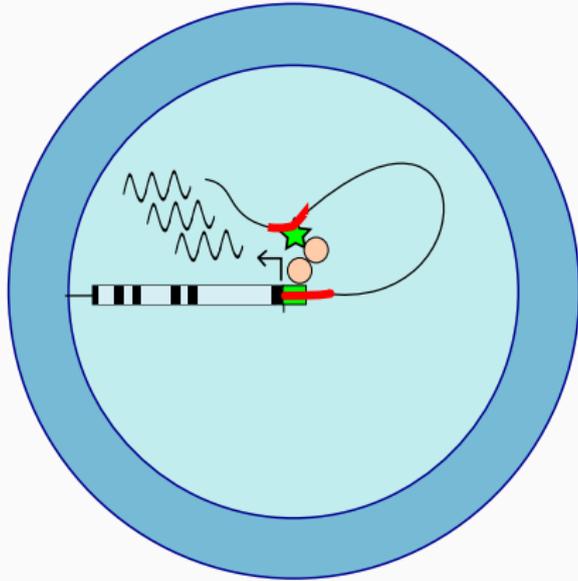
CLEC16A expression



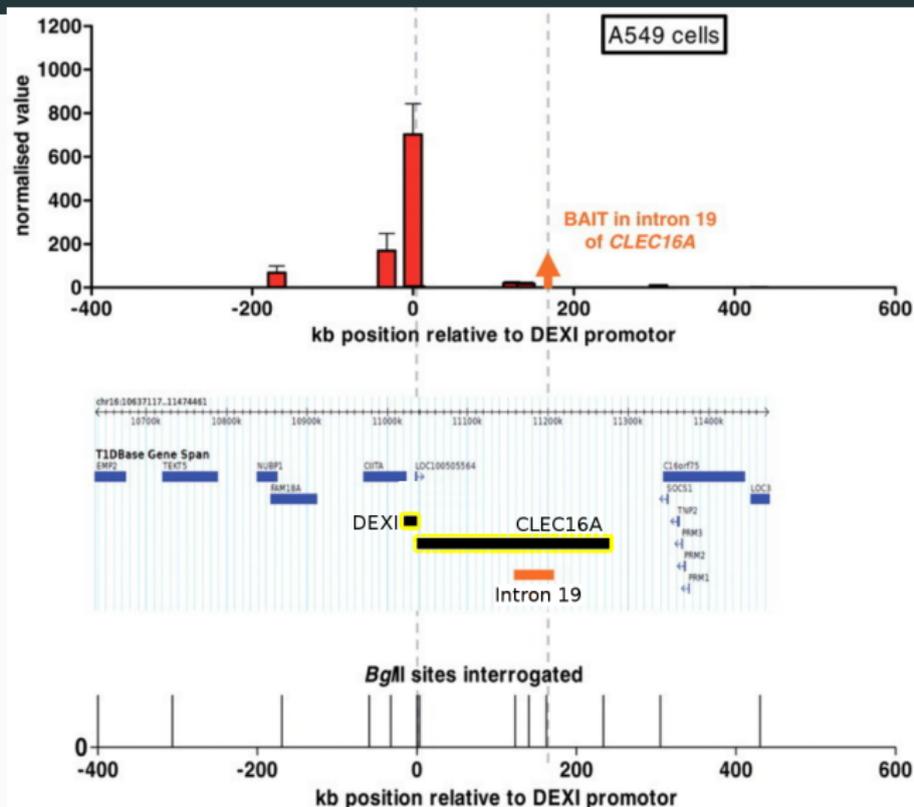
3D folding of DNA in nucleus connects enhancers to promoters



3D folding of DNA in nucleus connects enhancers to promoters

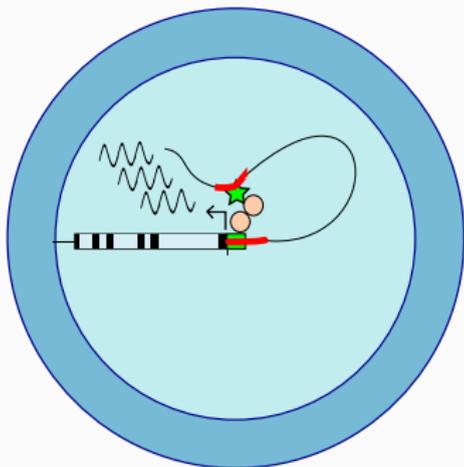


TWAS candidate *DEXI* supported by 3C experiments



3. Link promoters and regulatory elements through 3D DNA structure

Promoter capture Hi-C in 17 primary human blood cell types



Endothelial precursors

Erythroblasts

Neutrophils + precursors

Megakaryocytes

Macrophages (M0,M1,M2)

CD4⁺ T cells, naïve and total

CD8⁺ T cells, naïve and total

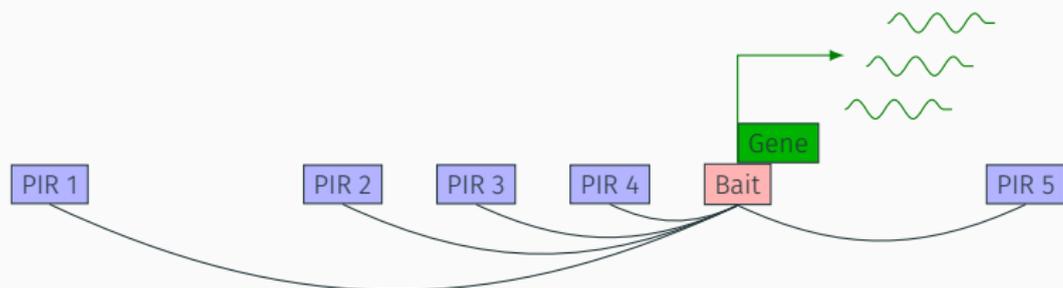
Monocytes

Fetal thymus

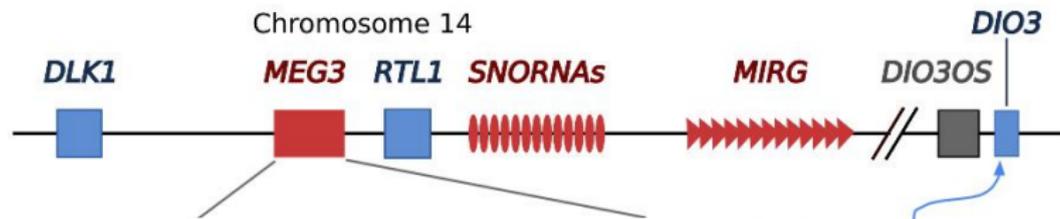
B cells, naïve and total

Total CD4⁺, non-activated and activated at 4 hours

Promoter capture Hi-C in 17 primary human blood cell types



Integrate GWAS + PCHI-C to prioritise candidate disease genes



Imprinted association: paternally inherited risk variant for T1D



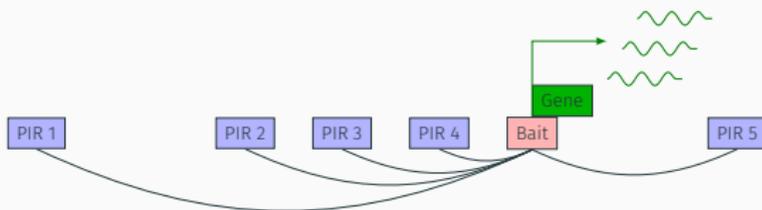
Aggregate by *Hind*III fragment or set of *Hind*III fragments

PChi-C prioritisation in six autoimmune diseases



six diseases

+



CD4⁺ T cells, activated and non-activated

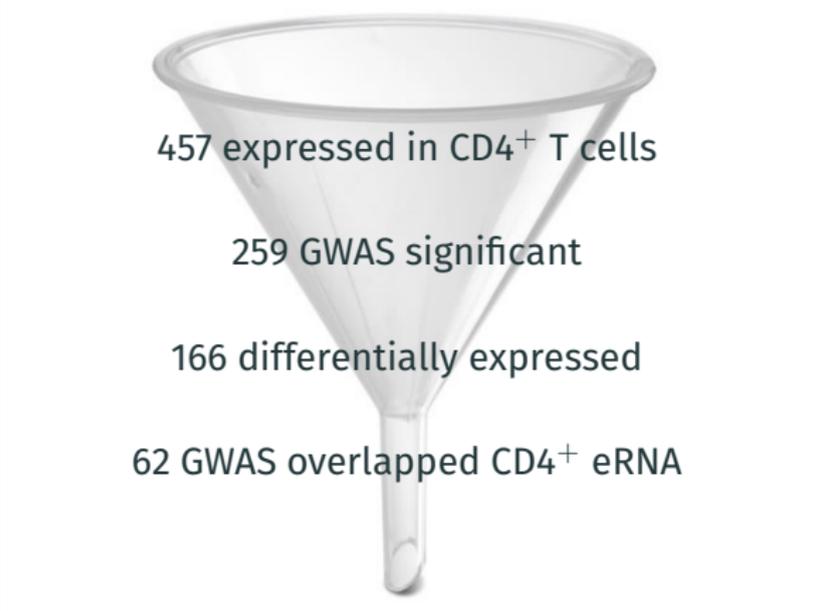
=

?

candidate causal
autoimmune genes

602 autoimmune disease prioritised genes in CD4⁺ T cells

602 prioritised genes



457 expressed in CD4⁺ T cells

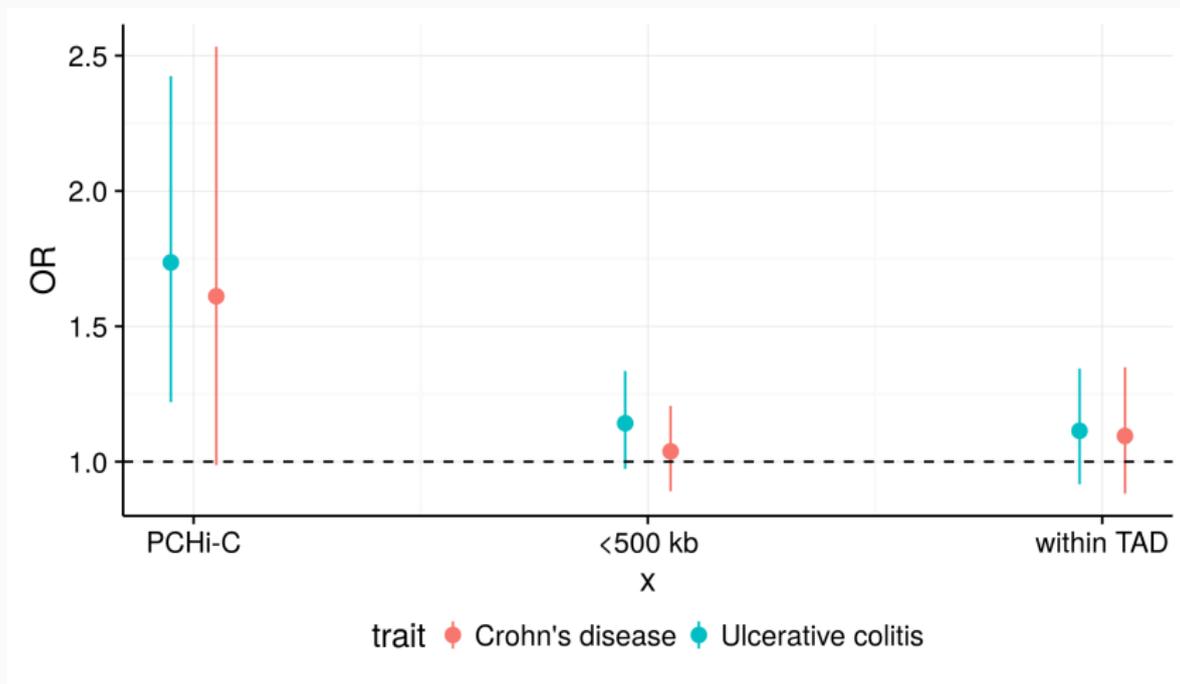
259 GWAS significant

166 differentially expressed

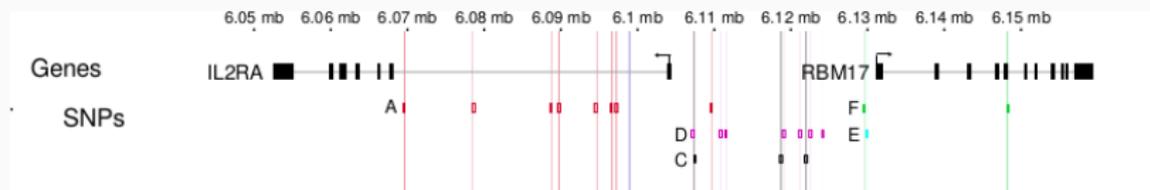
62 GWAS overlapped CD4⁺ eRNA

Require functional validation experiments

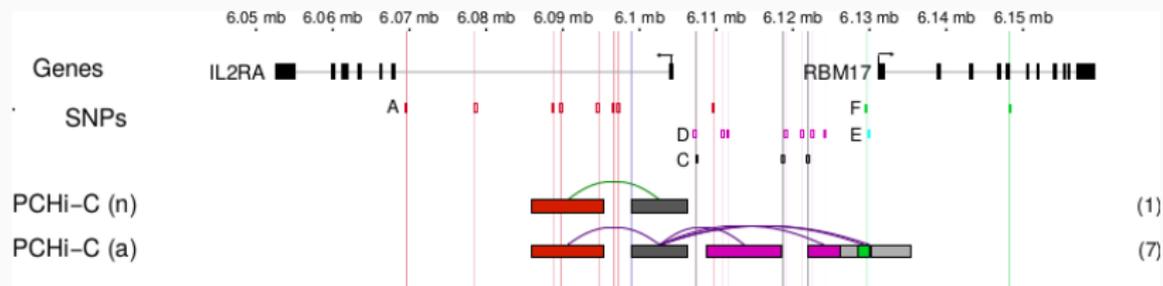
Prioritised IBD genes are enriched for differential expression in IBD patients



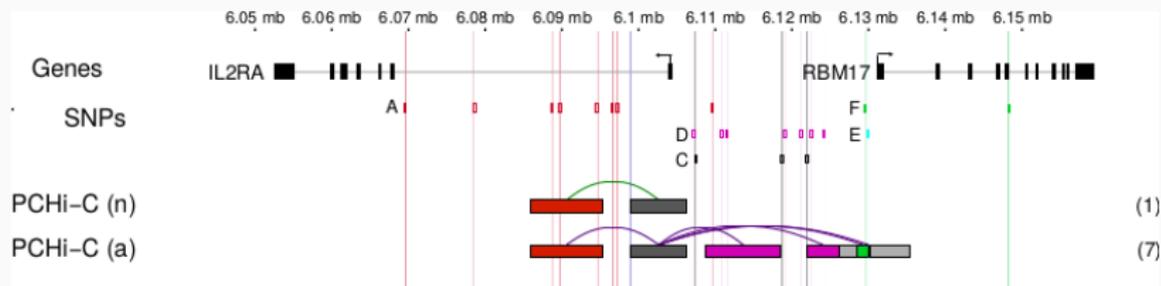
IL2RA prioritised in both activated and non-activated cells



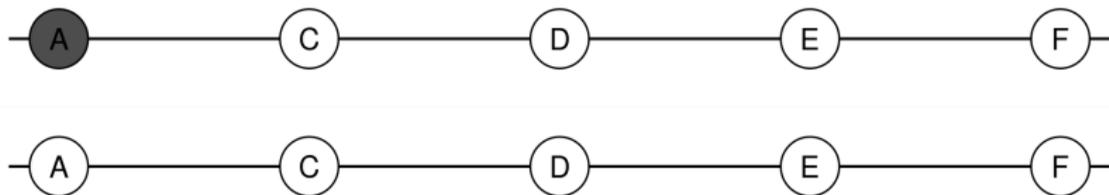
IL2RA prioritised in both activated and non-activated cells



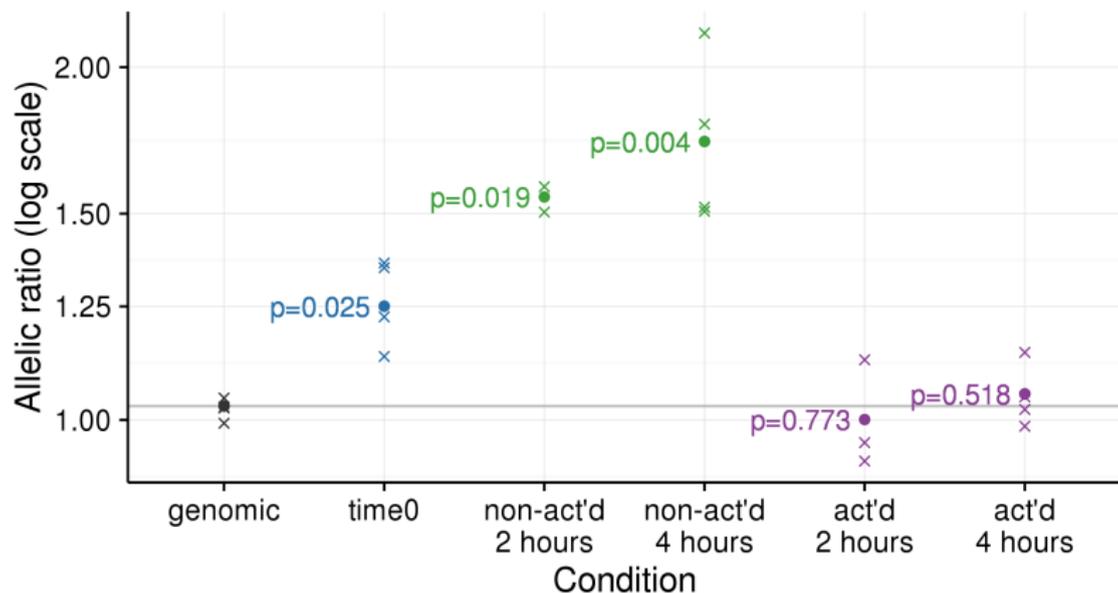
IL2RA prioritised in both activated and non-activated cells



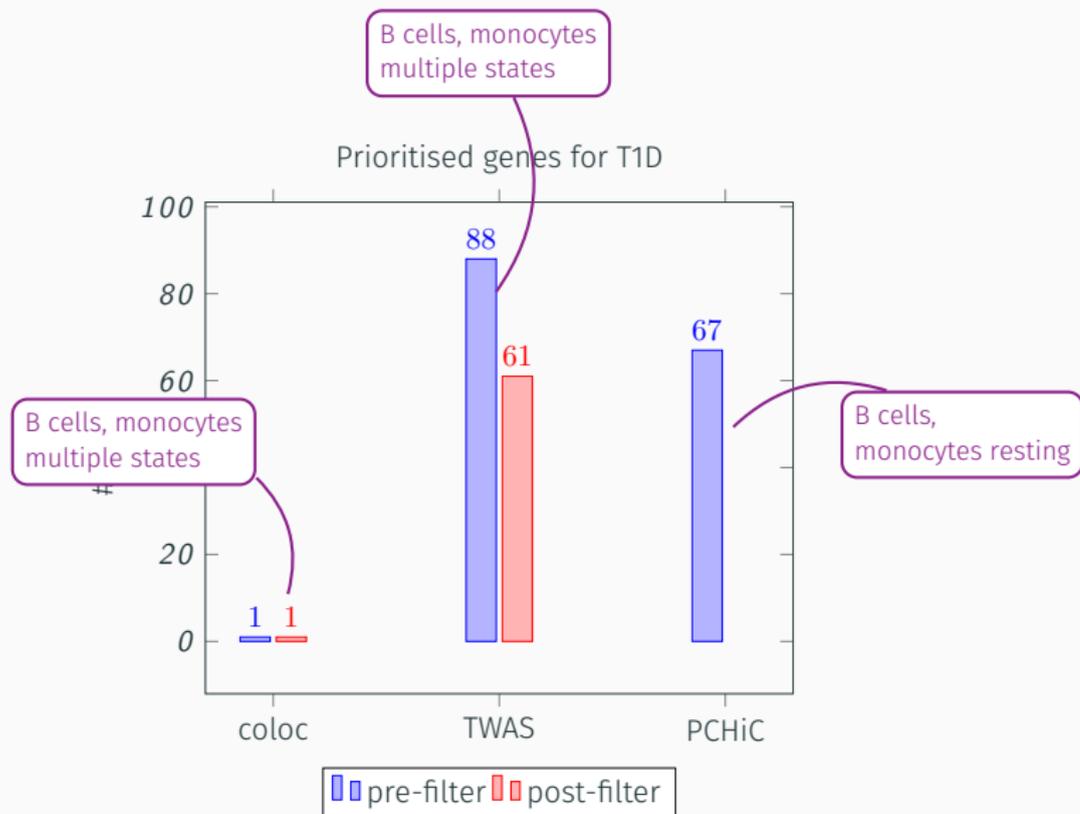
Allele specific expression: quantify relative expression of two chromosomes using targeted PCR and sequencing



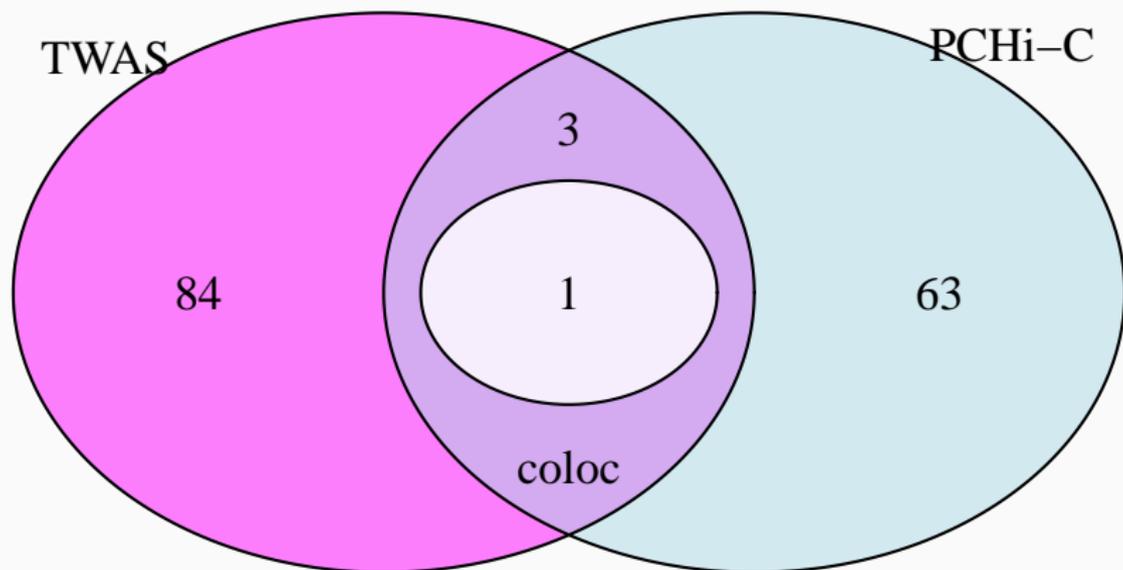
Allele specific expression confirms effect of group A variants



Summary numbers: one disease, similar cell types



Summary numbers: one disease, similar cell types



Summary of methods

Colocalisation

are GWAS and eQTL signals “the same”?

Close to sufficient for causality

very stringent hypothesis, possibility of false negatives

TWAS

what genes are (predicted to be) differentially expressed in patients?
appear to be lots!

Possibly necessary, **NOT** sufficient evidence of causality

PCHi-C methods

does a GWAS variant lie in a region which contacts a gene promoter?

useful circumstantial evidence; **NOT** causality

Remaining challenges and opportunities

Cell diversity

- Amazing diversity in gene expression, chromatin binding and chromatin conformation - we only study common, accessible cells!
- eQTL datasets need to be larger, more diverse
- PChI-C *already* covers greater diversity than eQTL

Evidence synthesis

- Different methods, different assumptions → different genes

Wider adoption of methods

- Datasets need to be more available
- Methods need to be easier to apply

Thanks to



Hui Guo



Stasia Grinberg



Olly Burren



Dan Rainbow

Diabetes and Inflammation Laboratory

Xaquín Castro Dopico, Ellen Schofield, John Todd, Linda Wicker, Tony Cutler

PChI-C Collaboration

Biola Javierre, Jonathan Cairns, Mattia Frontini, Willem Ouwehand, Peter Fraser, Mikhail Spivakov

Cambridge NIHR BioResource

Capture Hi-C Plotter: <http://www.chicp.org> 



