

Using genetics and genomics to distinguish immune-mediated disease mechanisms and subtypes

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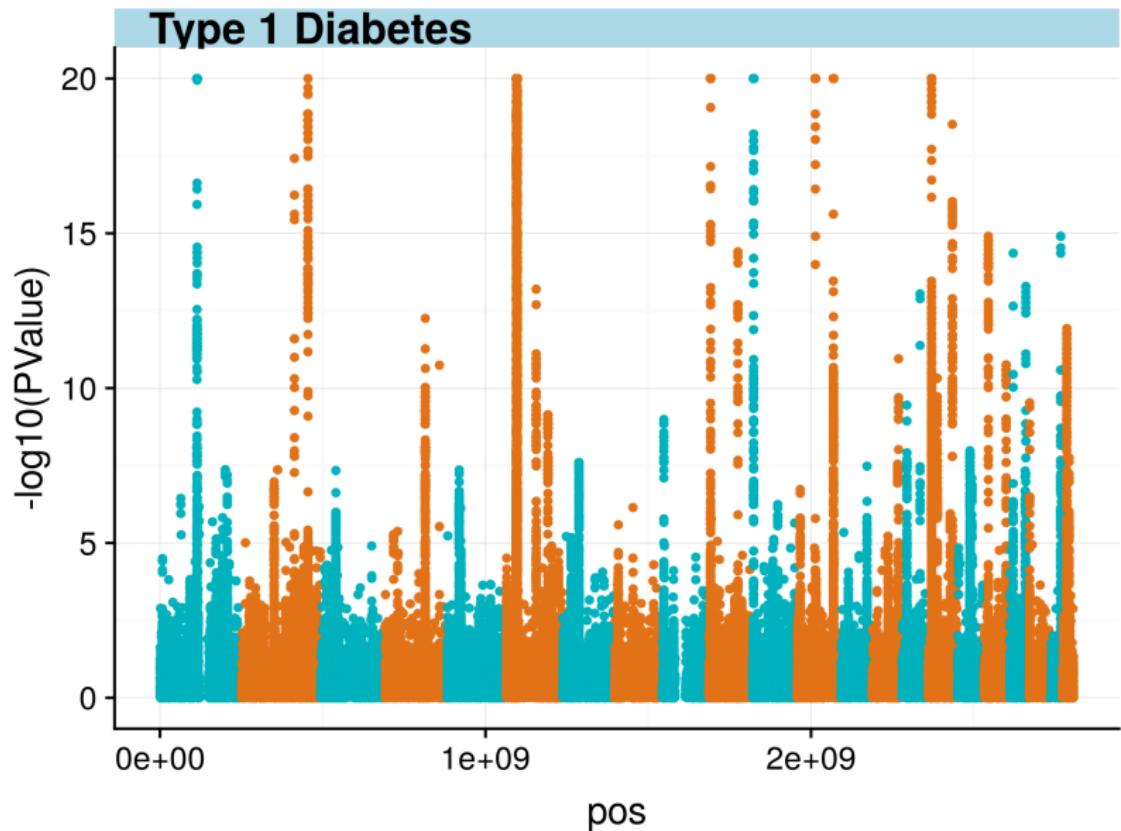


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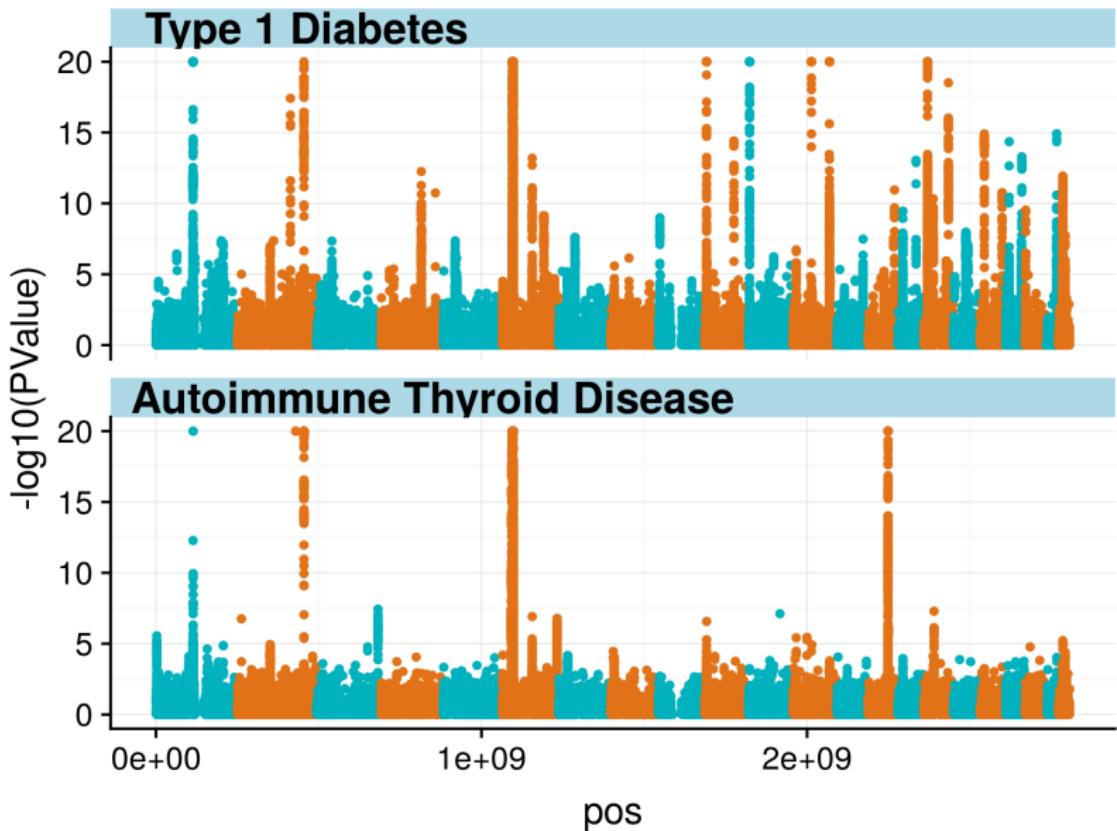
MRC

Biostatistics Unit

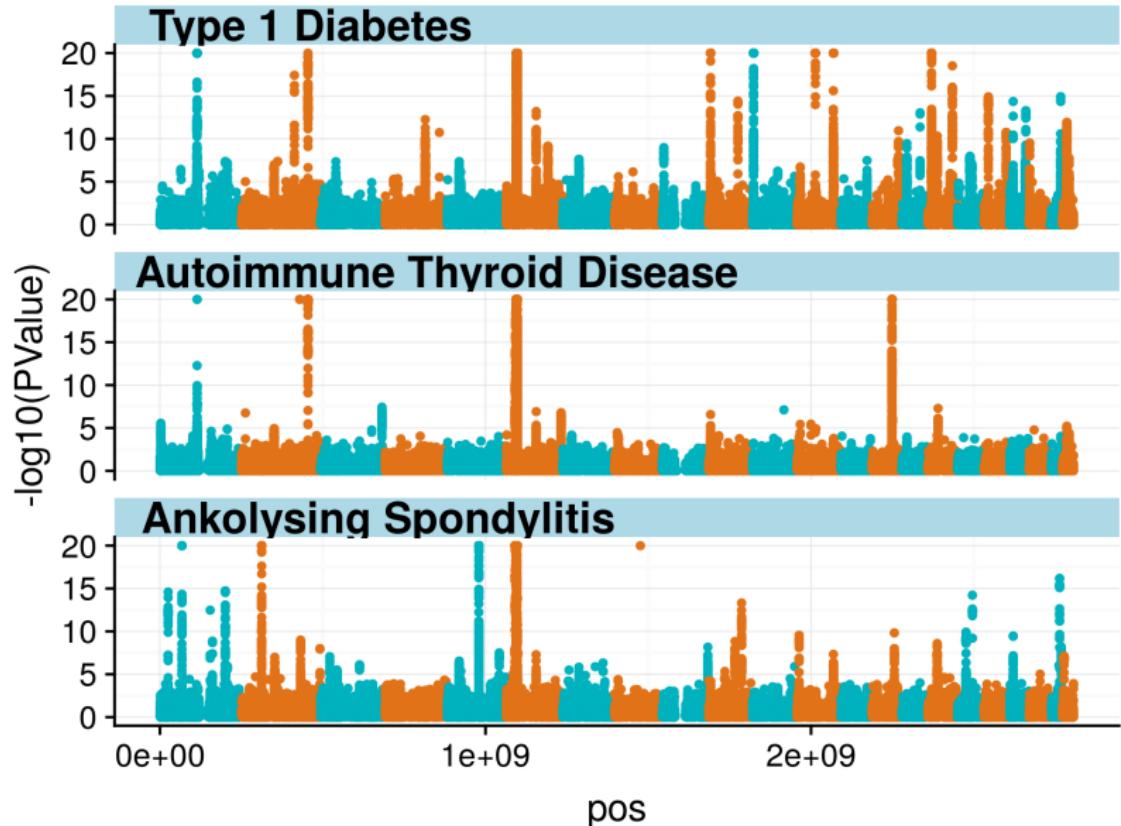
Immune mediated disease genetics



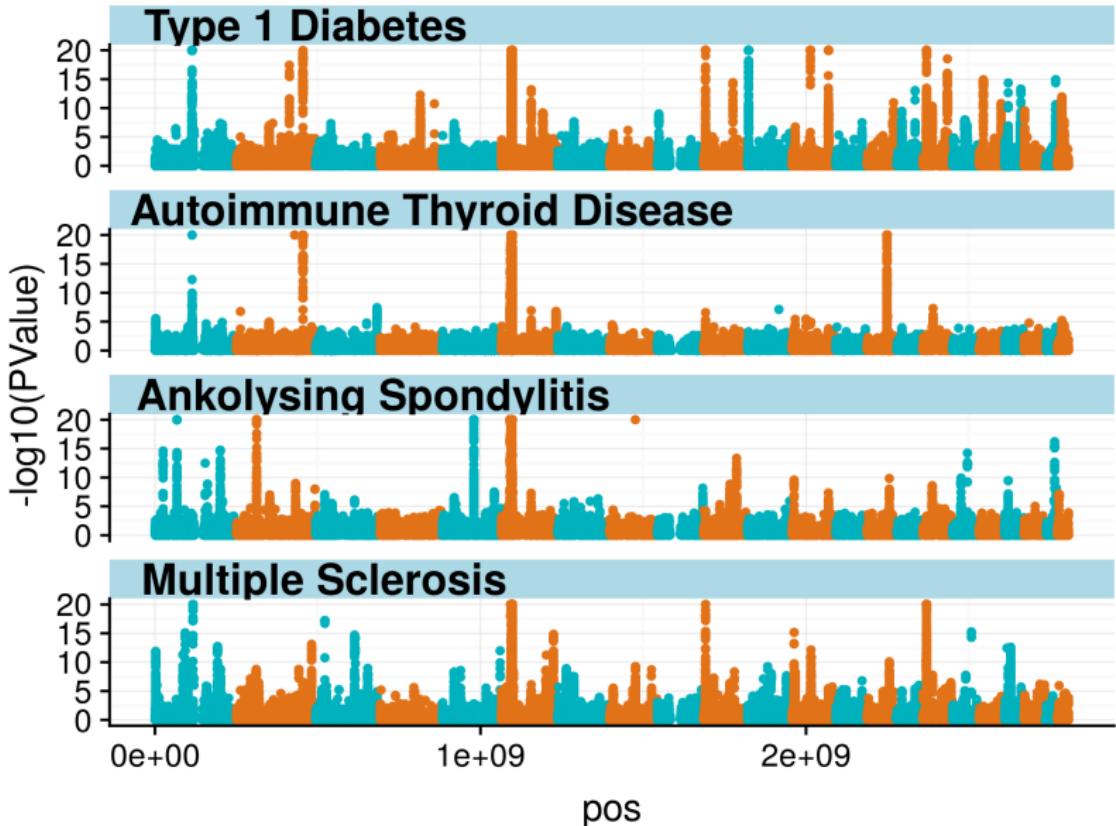
Immune mediated disease genetics



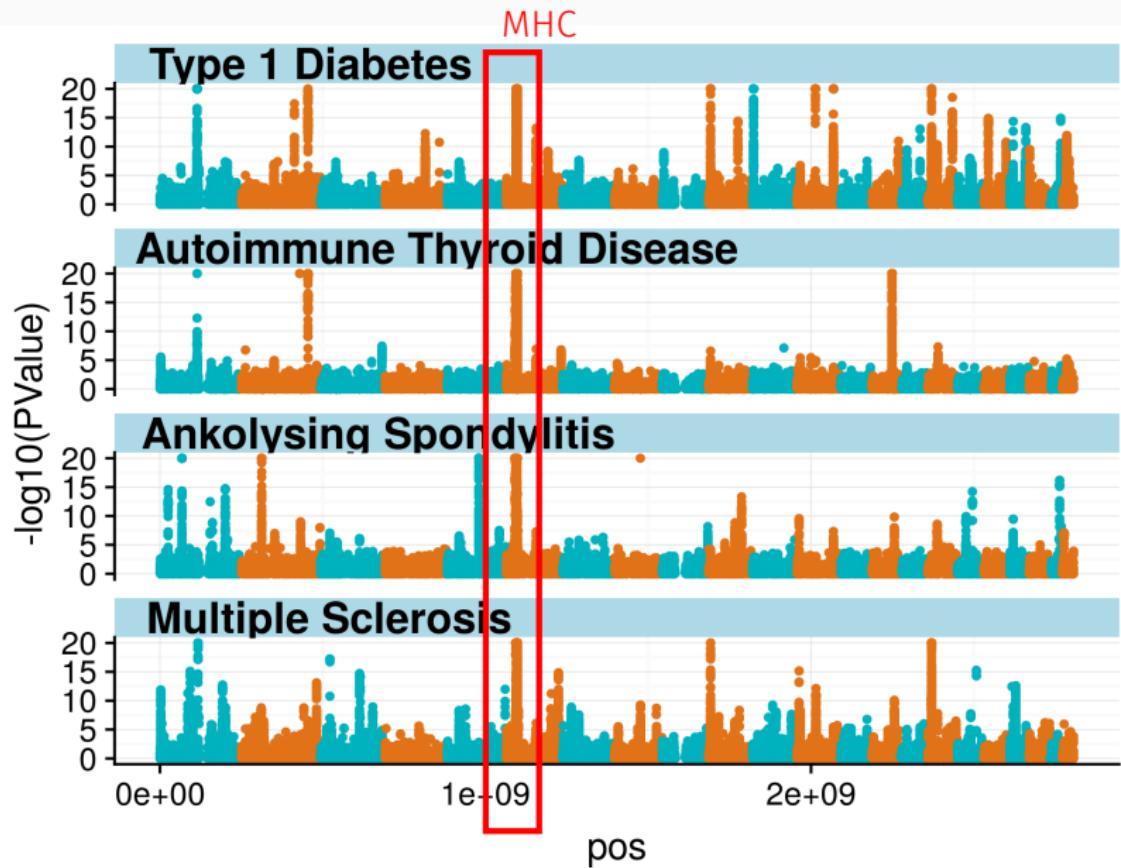
Immune mediated disease genetics



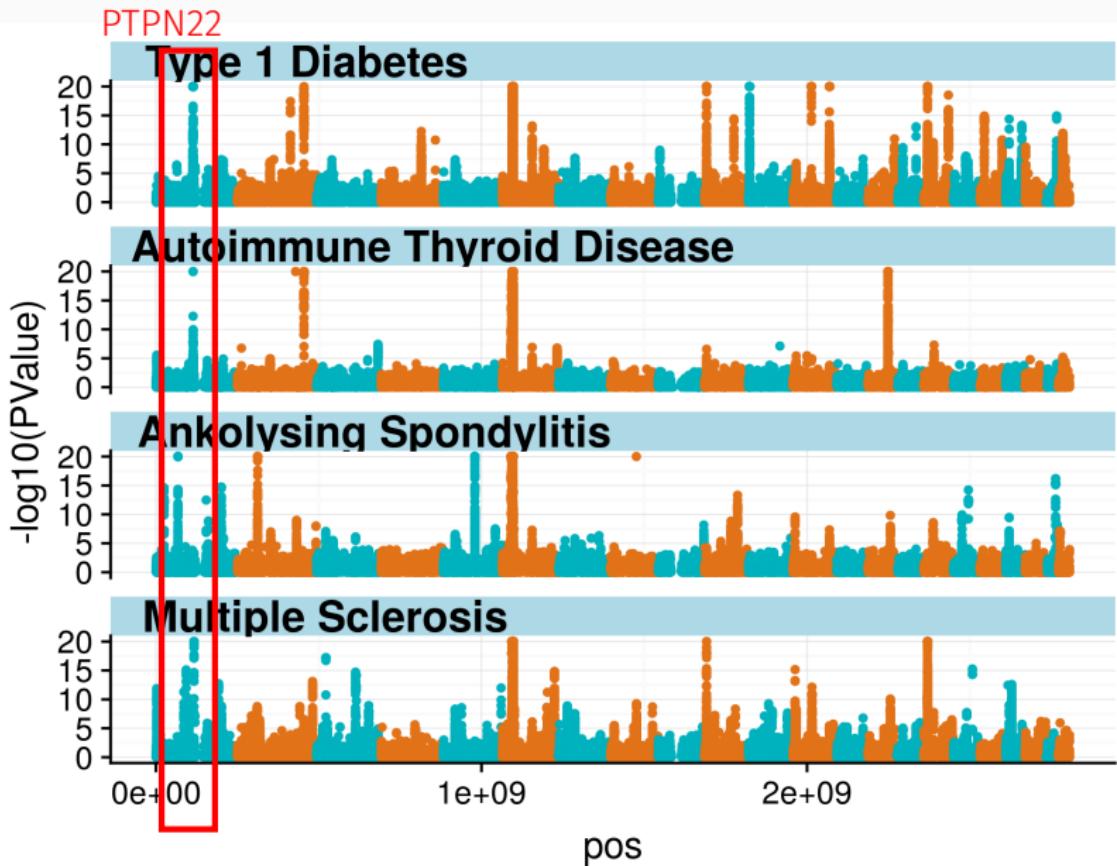
Immune mediated disease genetics



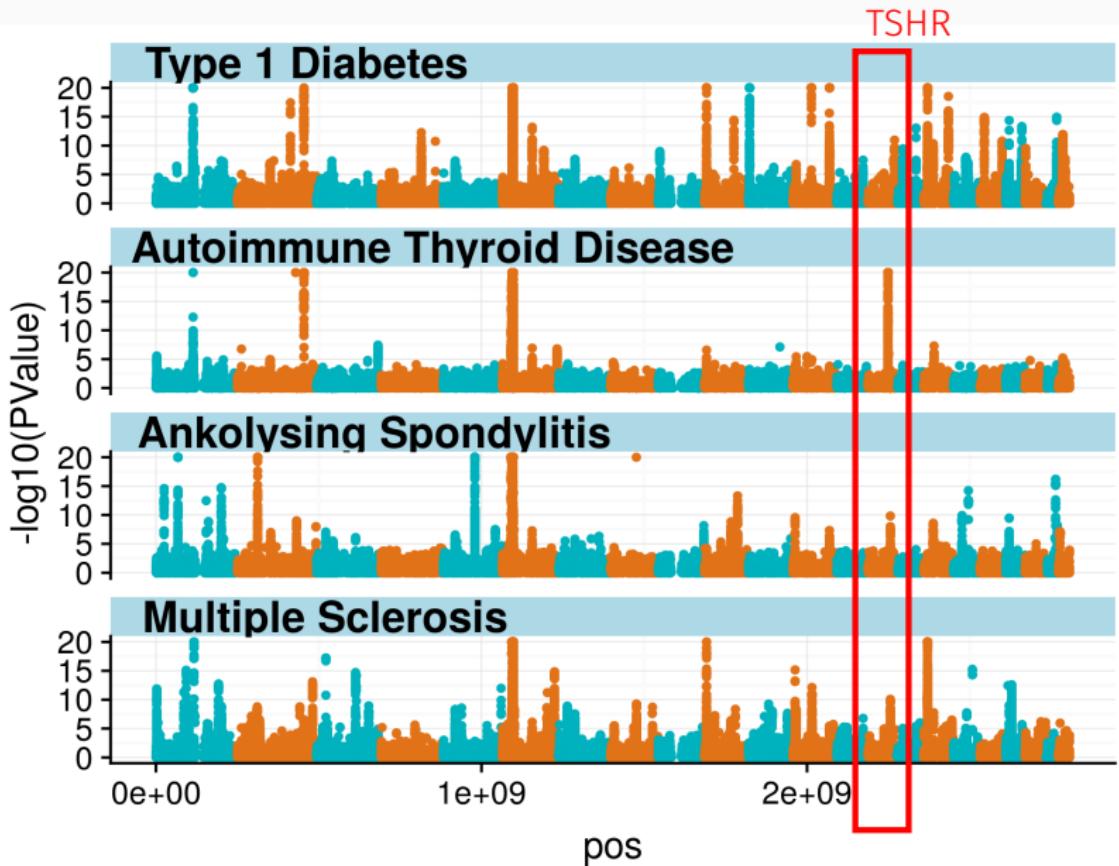
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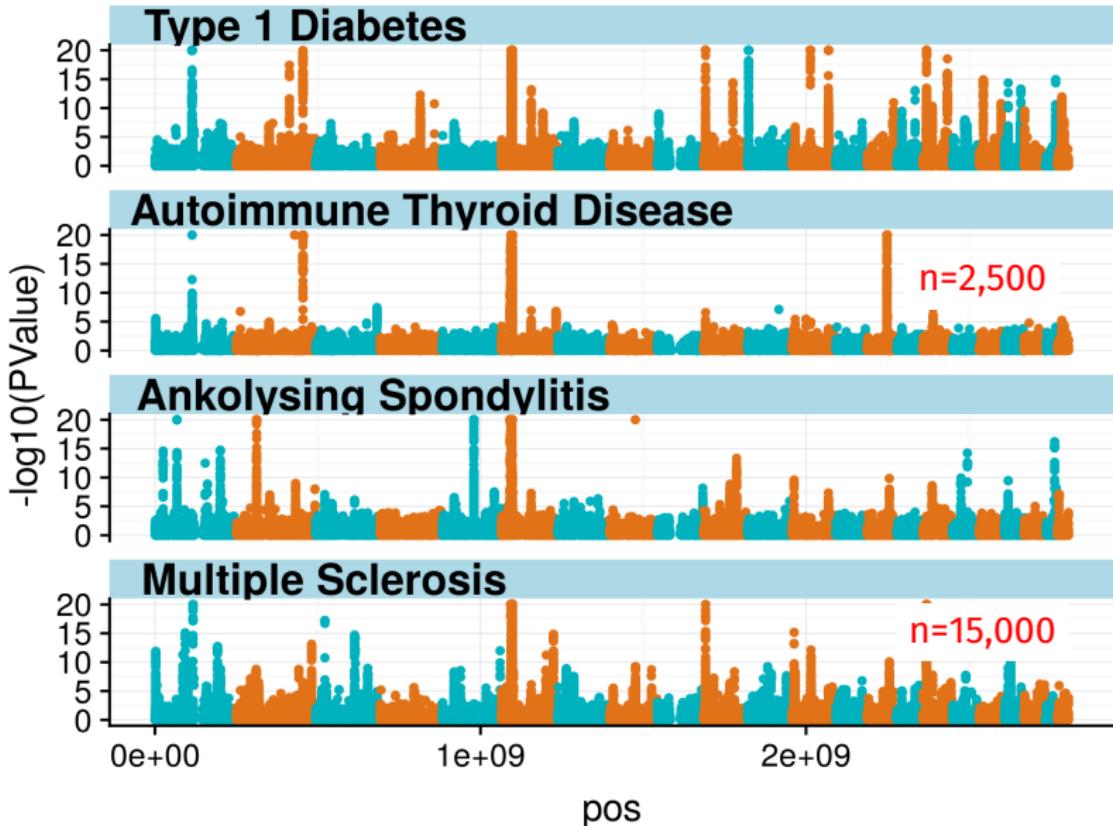
Immune mediated disease genetics



Immune mediated disease genetics



Immune mediated disease genetics



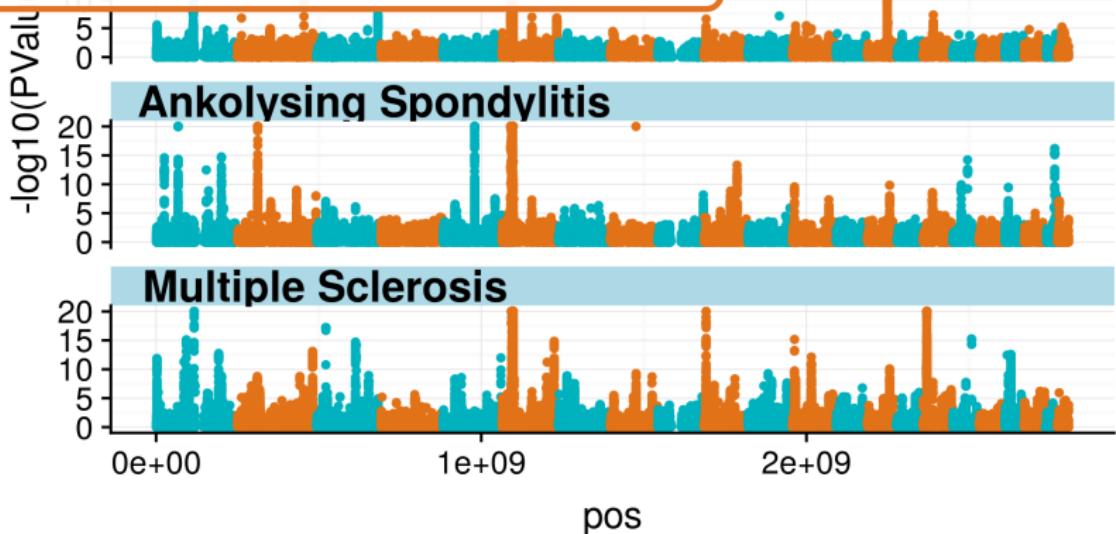
Immune mediated disease genetics

Challenges:

Power - varies by disease

Heterogeneity - between & within diseases

Dimension - prevents holistic overview



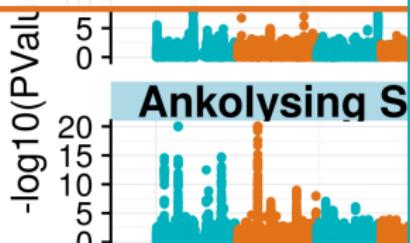
Immune mediated disease genetics

Challenges:

Power - varies by disease

Heterogeneity - between & within diseases

Dimension - prevents holistic overview



Solutions:

Borrow information across diseases

Compress signal across SNPs

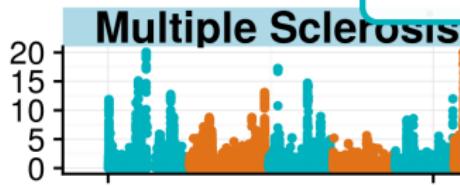
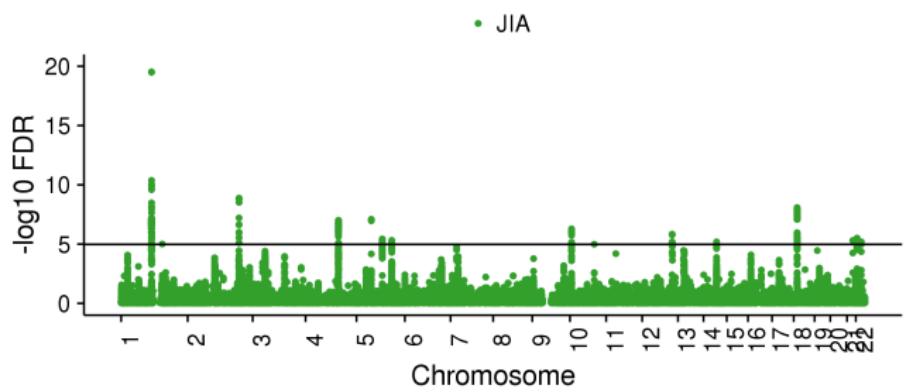
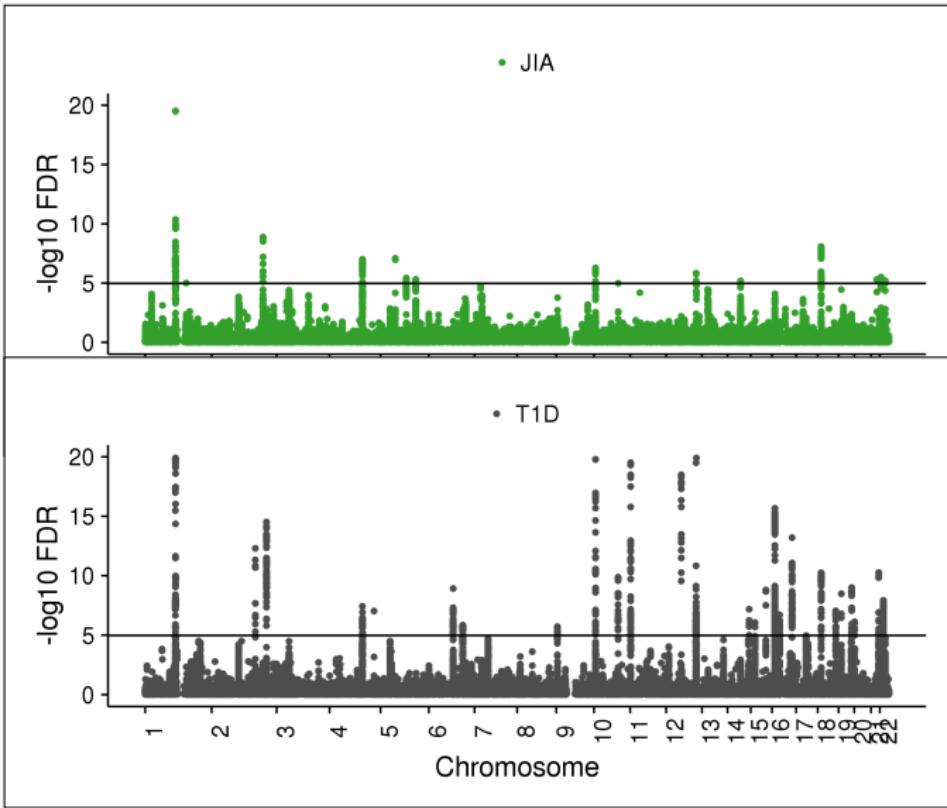


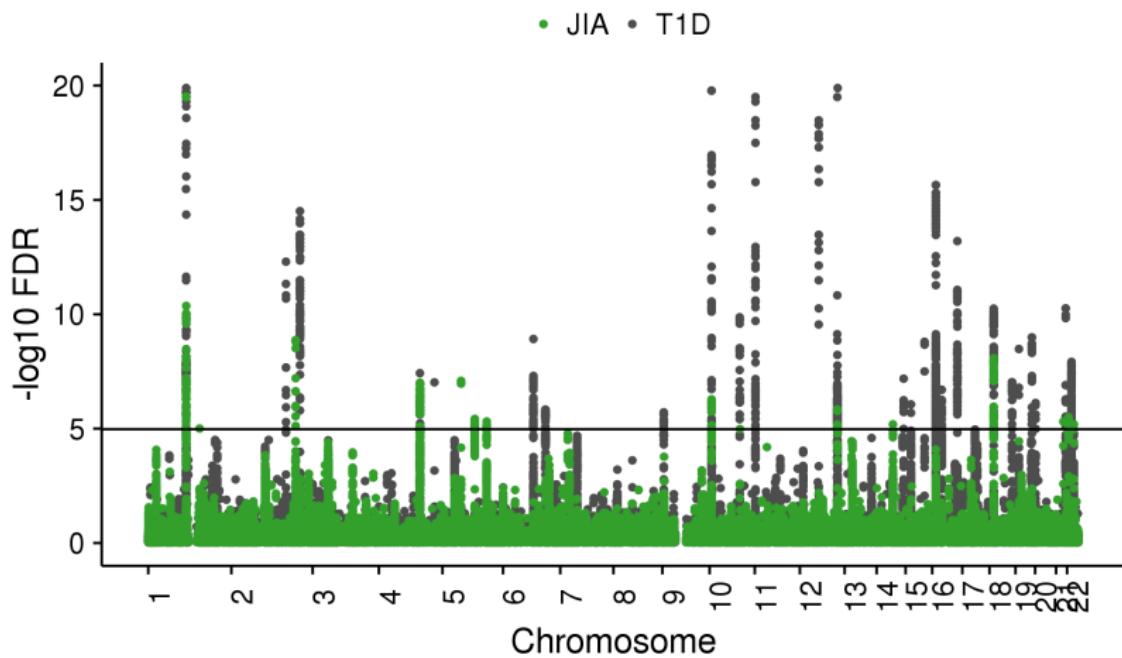
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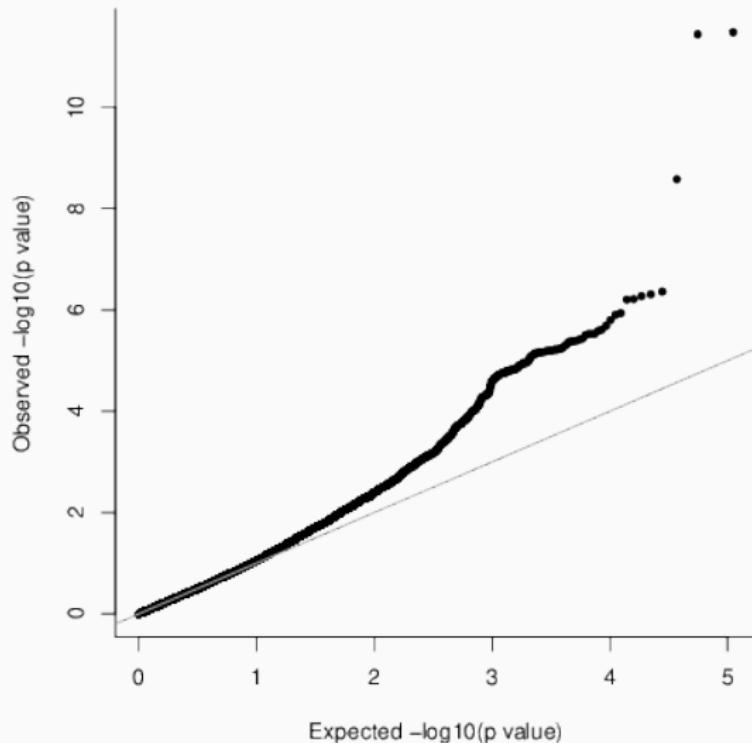
Sharing information between diseases to increase power



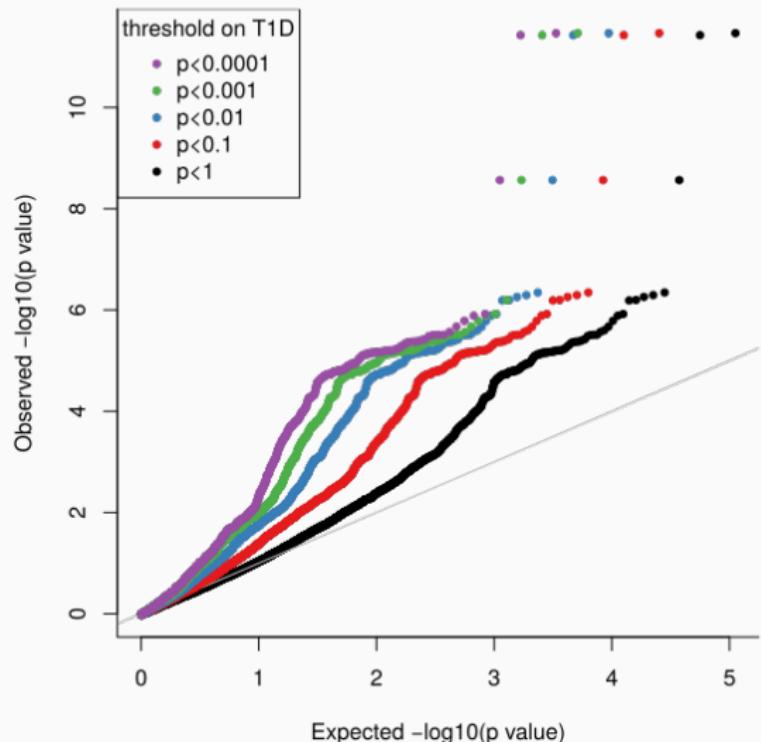




T1D association is informative for JIA



T1D association is informative for JIA



False discovery rates → conditional false discovery rates

False discovery rate, FDR

$$Pr(H_0 | P < \alpha) \propto \alpha \times Pr(H_0)$$

False discovery rates → conditional false discovery rates

False discovery rate, FDR

$$Pr(H_0|P < \alpha) \propto \alpha \times Pr(H_0)$$

Conditional false discovery rate, cFDR

$$Pr(H_0|P < \alpha, Q < \gamma) \propto \alpha \times Pr(H_0|Q < \gamma)$$

False discovery rates → conditional false discovery rates

False discovery rate, FDR

$$Pr(H_0|P < \alpha) \propto \alpha \times Pr(H_0)$$

Conditional false discovery rate, cFDR

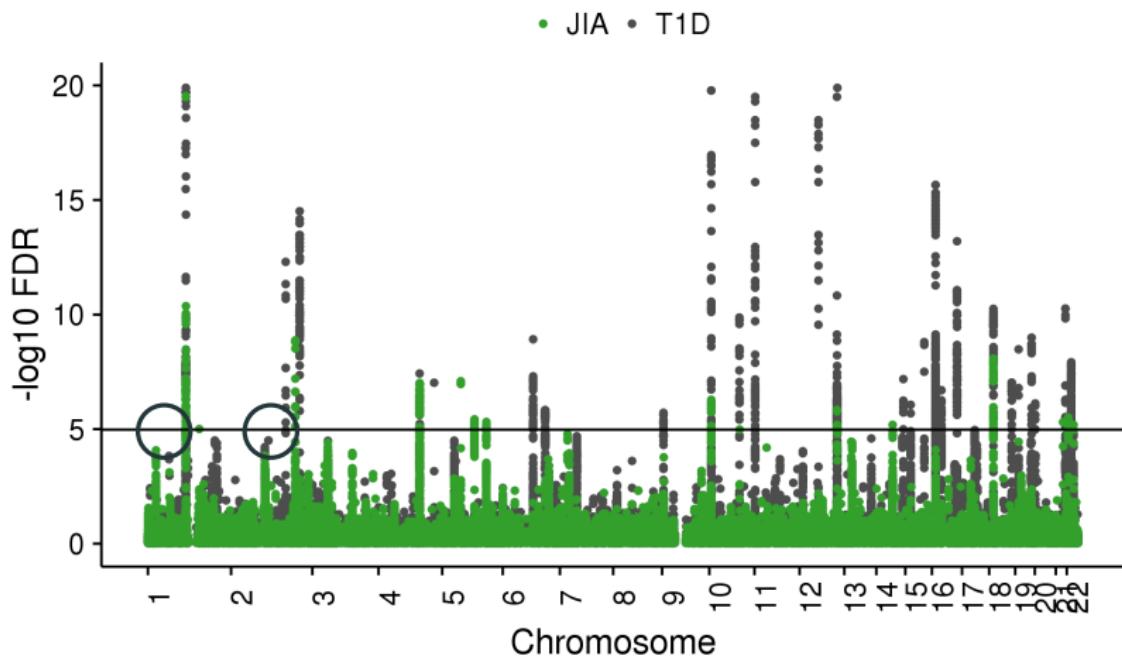
$$Pr(H_0|P < \alpha, Q < \gamma) \propto \alpha \times Pr(H_0|Q < \gamma)$$

If Q is independent of P then

$$cFDR = FDR$$

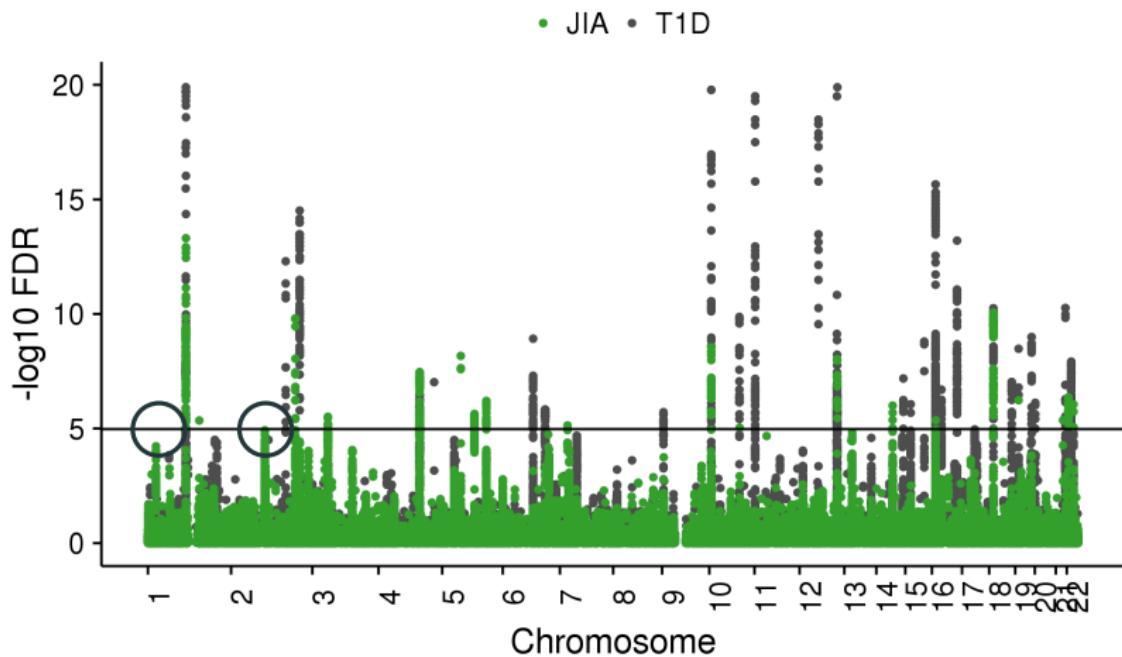
False discovery rates → conditional false discovery rates

FDR



False discovery rates → conditional false discovery rates

conditional FDR



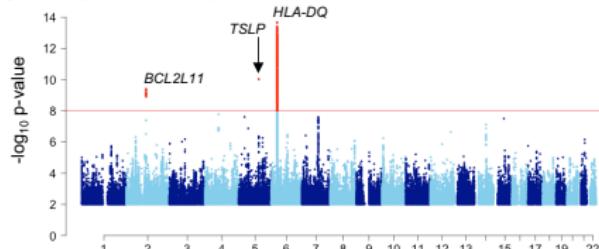
Example: Eosinophilic Granulomatosis with Polyangiitis (EGPA)

- ANCA-associated vasculitis + eosinophilia, asthma
- incidence of 0.5-3.7 per million
- considered a single disease
- not all patients are ANCA positive

ANCA positive (MPO)	161
ANCA negative	358
Controls	6717

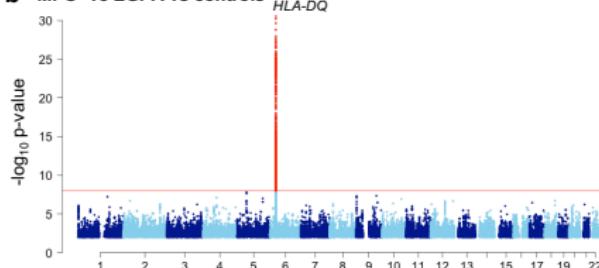
Eosinophilic Granulomatosis with Polyangiitis (EGPA)

a All EGPA vs controls



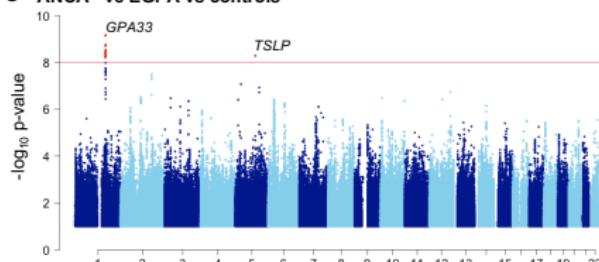
all EGPA

b MPO+ve EGPA vs controls



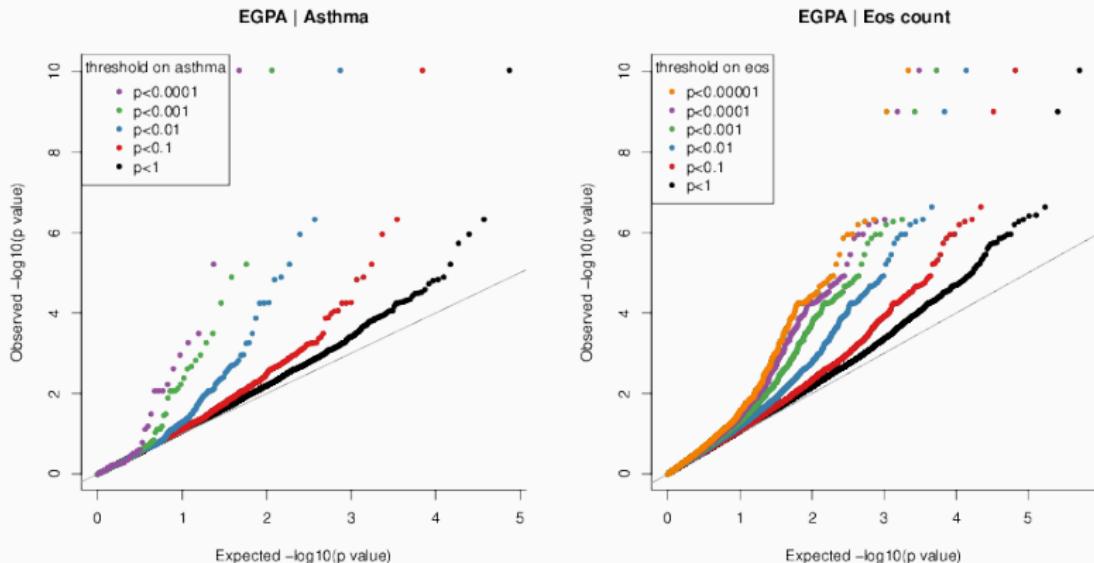
MPO+ EGPA

c ANCA –ve EGPA vs controls



ANCA- EGPA

Both asthma and eosinophilia are informative for EGPA

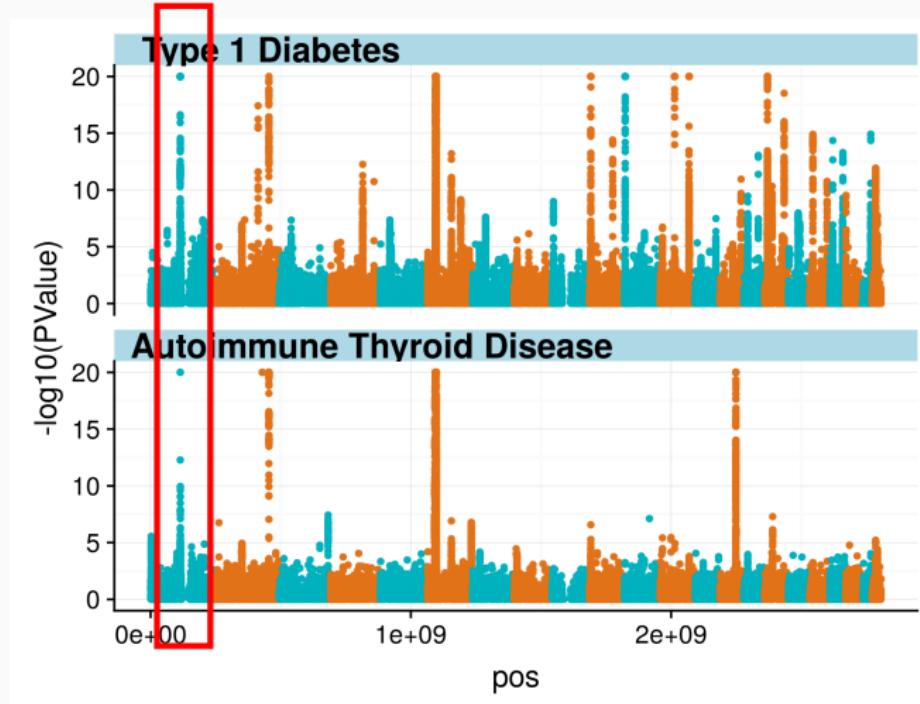


EGPA: Genetically distinct clinical subsets, shared associations with asthma and eosinophil count

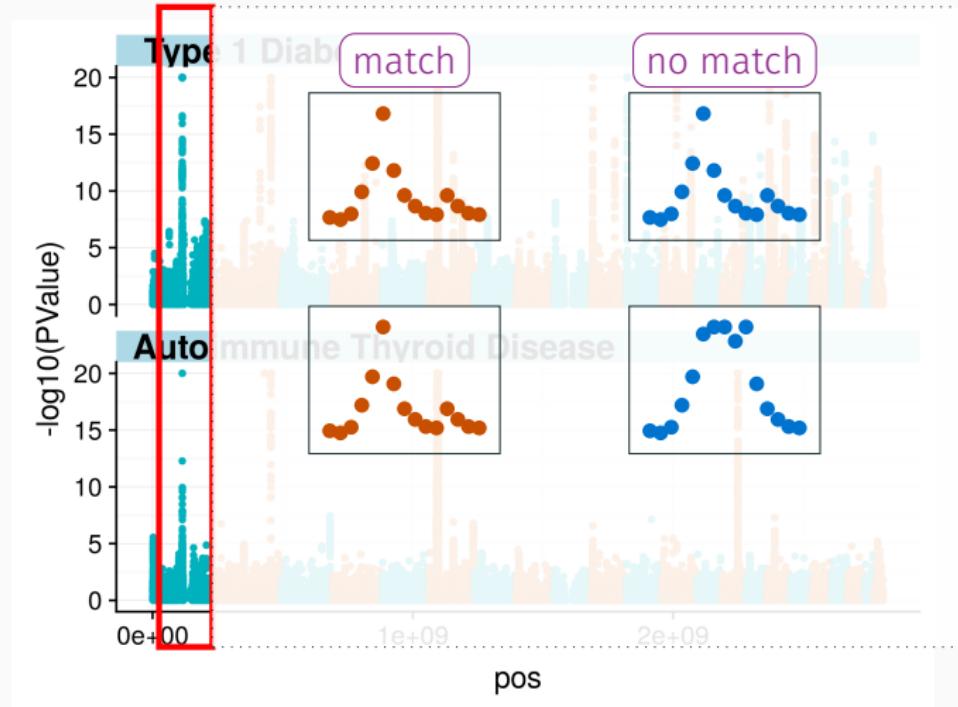
	MPO+ EGPA	ANCA- EGPA
<i>Distinct associations</i>	HLA-DQ	GPA33, (IL5)
<i>Shared associations</i>	BIM, TSLP	
<i>Conditional associations</i>		
Asthma	IL5, BACH2, 10p14 (GATA3?)	
Eosinophilia	CDK6, SOCS1, LPP, TBX3	
<i>Differential symptoms (%)</i>		
Glomerulonephritis	29	9
Neuropathy	79	57
<i>Treatment response (%)</i>		
Rituximab response	80	38

Compress information across
SNPs in same region

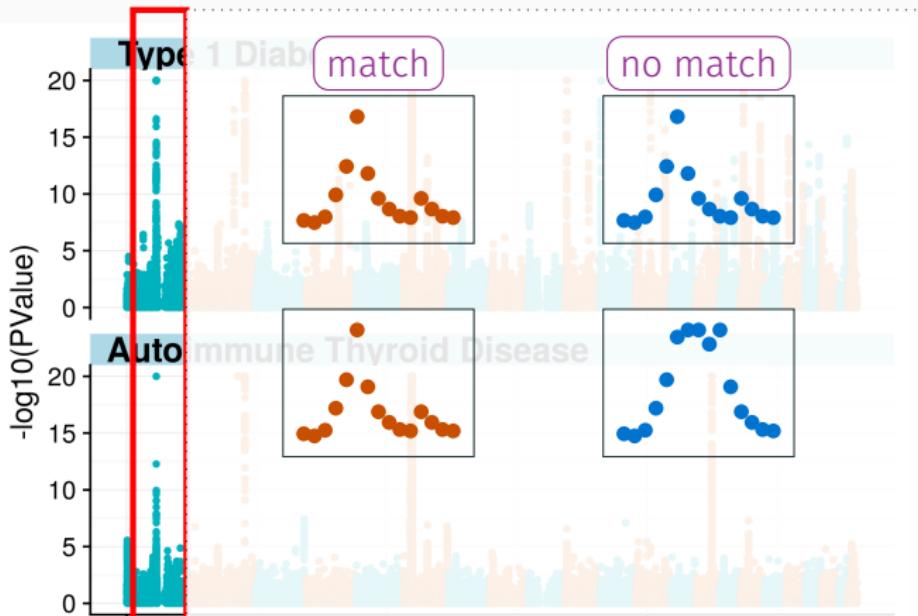
Colocalisation



Colocalisation



Colocalisation



Comparison of one disease pair within a region

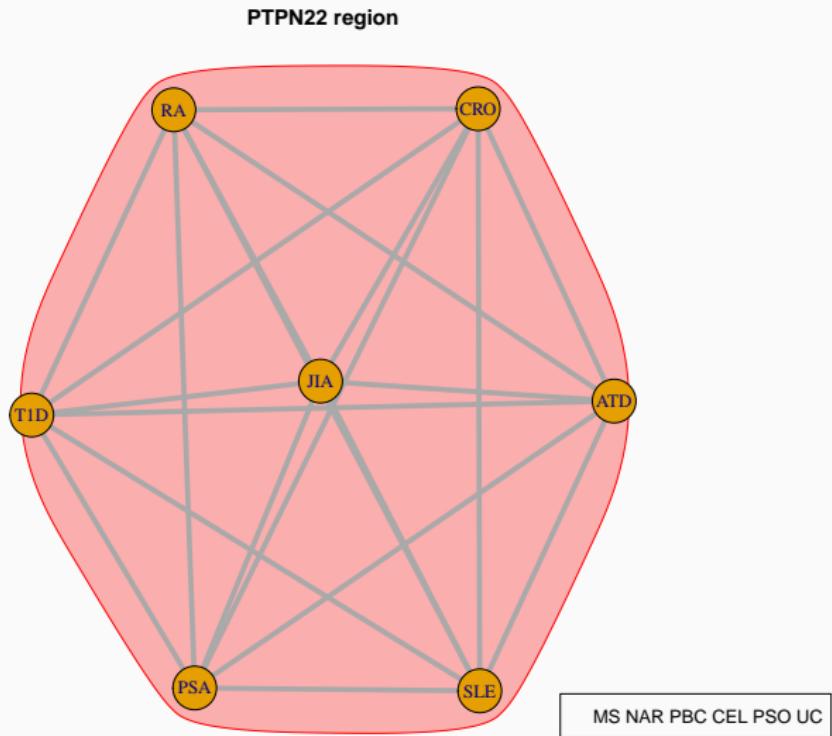
Assumes: single causal variant per disease, independent datasets

New: multiple uncorrelated causal variants, dependent controls

ImmunoChip: 13 diseases, 188 genetic regions with dense coverage

Disease	Study	Cases	Controls
Narcolepsy	Faraco	1,886	10,421
Psoriatic arthritis	Bowes	1,962	8,923
Autoimmune thyroid disease	Cooper	2,733	9,364
Juvenile arthritis	Hinks	2,816	13,056
Primary biliary cholangitis	Liu	2,861	8,514
Type 1 diabetes	Onengut	6,670	12,262
Coeliac disease	Trynka	10,413	8,274
Psoriasis	Tsoi	10,588	22,806
Anklyosing spondylitis	IGAS	10,619	15,145
Rheumatoid arthritis	Eyre	11,475	15,870
Systemic lupus erythematosus	Langefeld	11,590	15,984
Ulcerative colitis	Liu	13,449	31,766
Multiple sclerosis	IMSGC	14,498	24,091
Crohn's disease	Liu	16,619	31,766

Shared signal in PTPN22 region



Single ATD signal in *TSHR* region

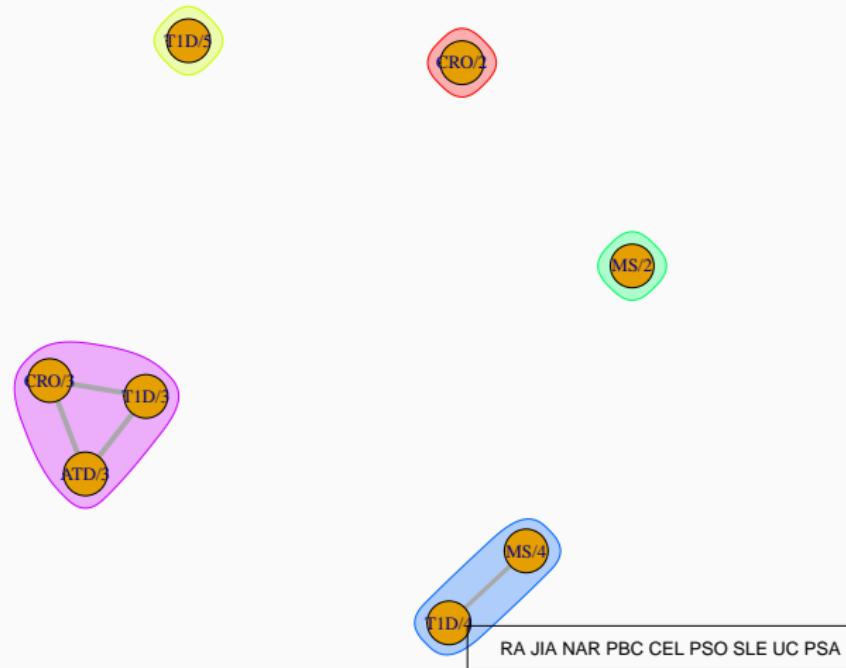
TSHR region



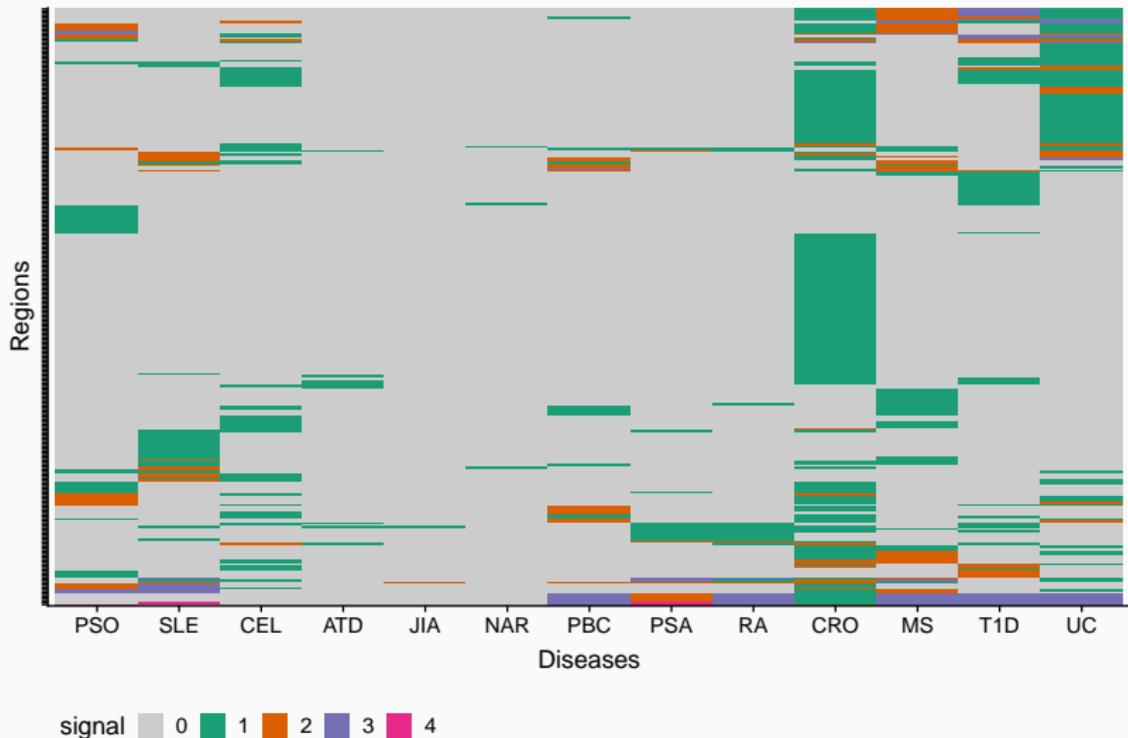
RA T1D JIA MS NAR PBC CEL PSO SLE CRO UC PSA

Multiple signals in *IL2RA* region

IL2RA region



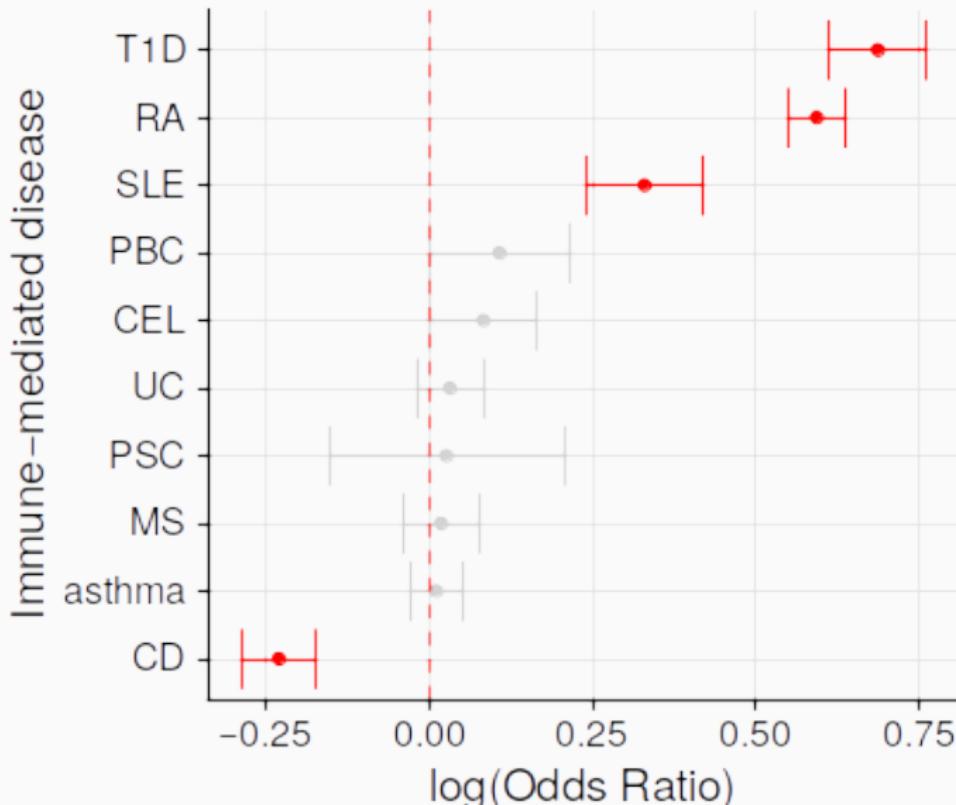
Overview



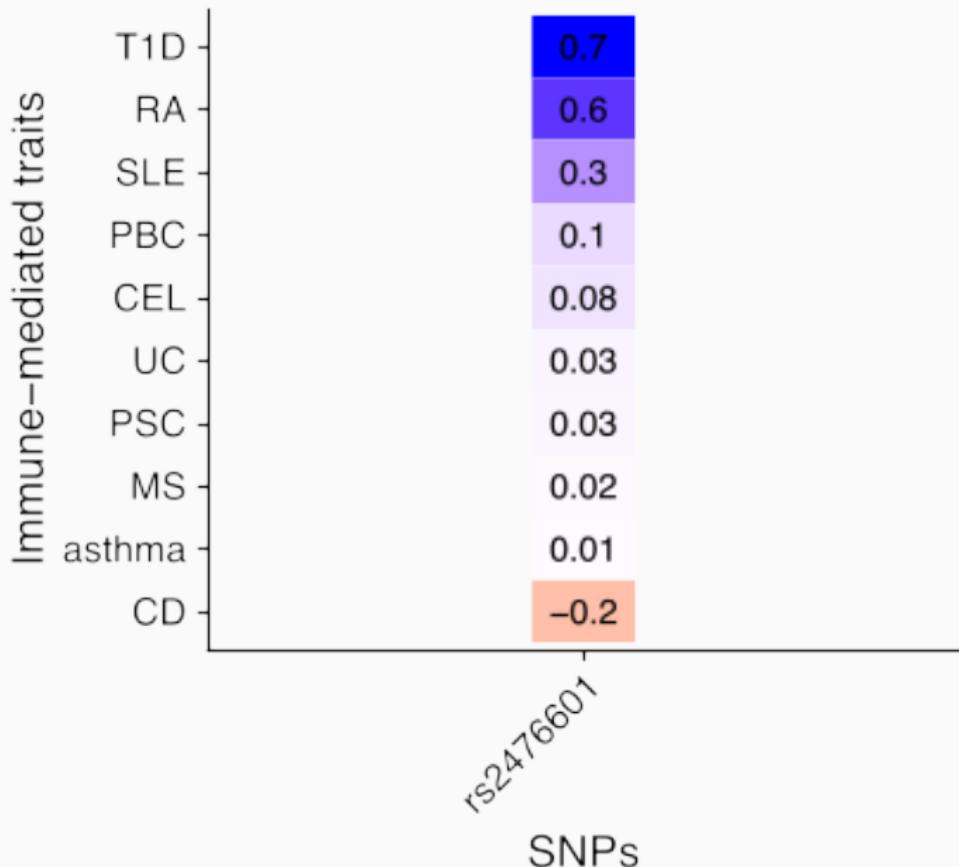
Informed dimension reduction

Heterogeneity across diseases

PTPN22 R620W (rs2476601)



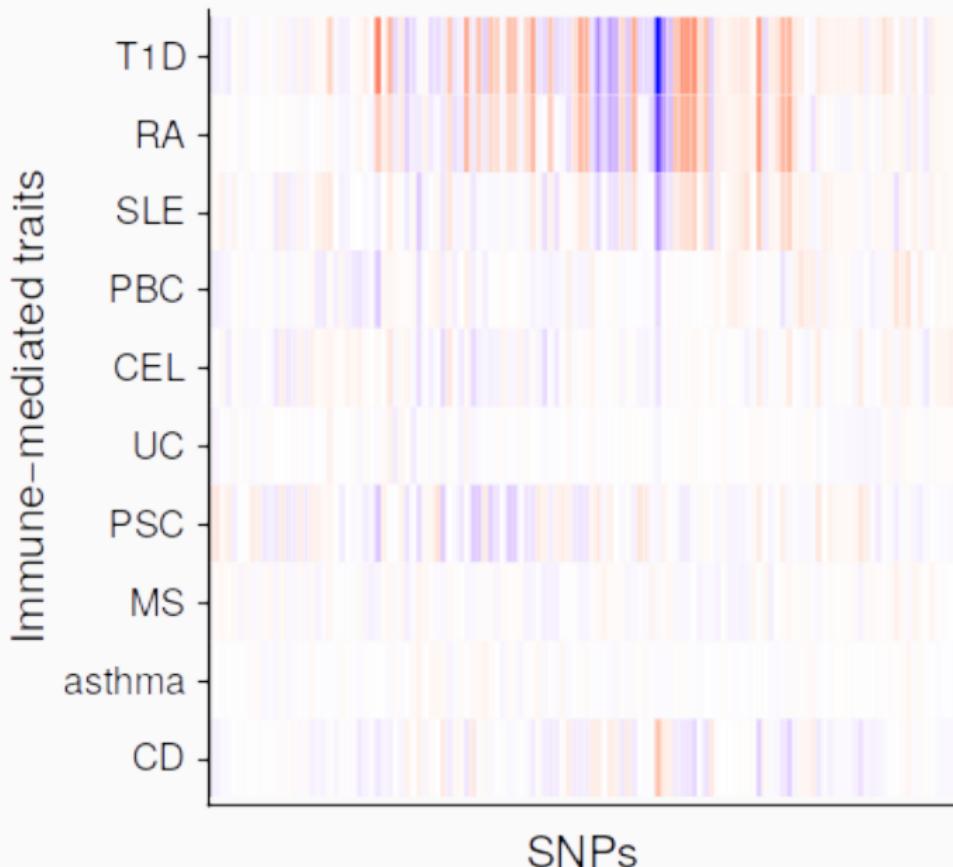
Heterogeneity across diseases



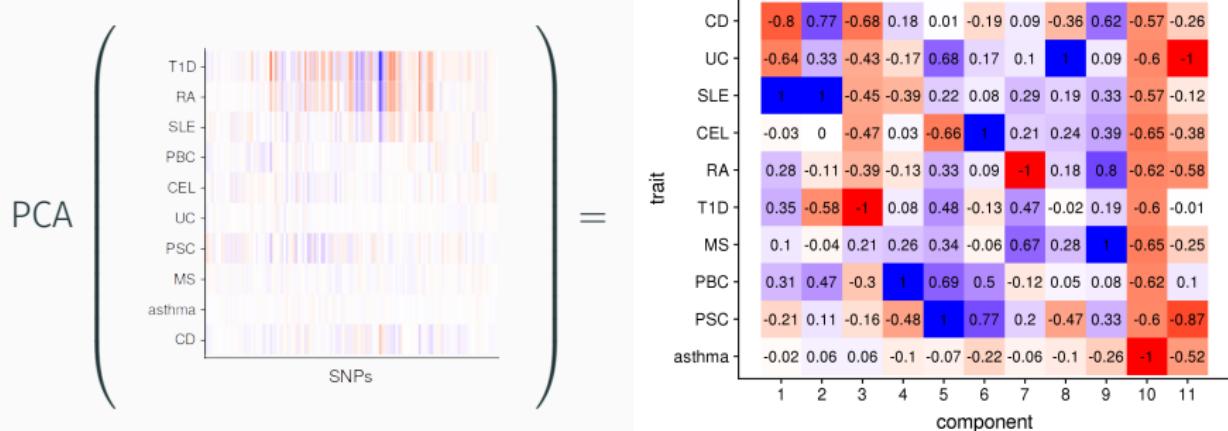
Heterogeneity across diseases

	SNP ⁻³	SNP ⁻²	SNP ⁻¹	rs2476601	SNP ⁺¹	SNP ⁺²	SNP ⁺³
T1D	0.1	0.1	0.1	0.7	0.3	0.2	-0.2
RA	0.02	0.02	0.1	0.6	0.3	0.2	-0.2
SLE	0.02	0.01	0	0.3	0.1	0.08	-0.07
PBC	0.006	0.02	0.001	0.1	-0.003	-0.02	0.008
CEL	0.03	0.04	0.01	0.08	0.008	-0.02	0.01
UC	-0.002	-0.004	0.009	0.03	0.005	0.004	-0.005
PSC	-0.09	-0.07	0.02	0.03	-0.04	0.006	0.01
MS	0.01	0.02	-0.04	0.02	-0.02	-0.03	0.02
asthma	-0.007	-0.01	0.003	0.01	0.01	0.02	-0.01
CD	0.005	0.009	0.003	-0.2	-0.07	-0.06	0.06

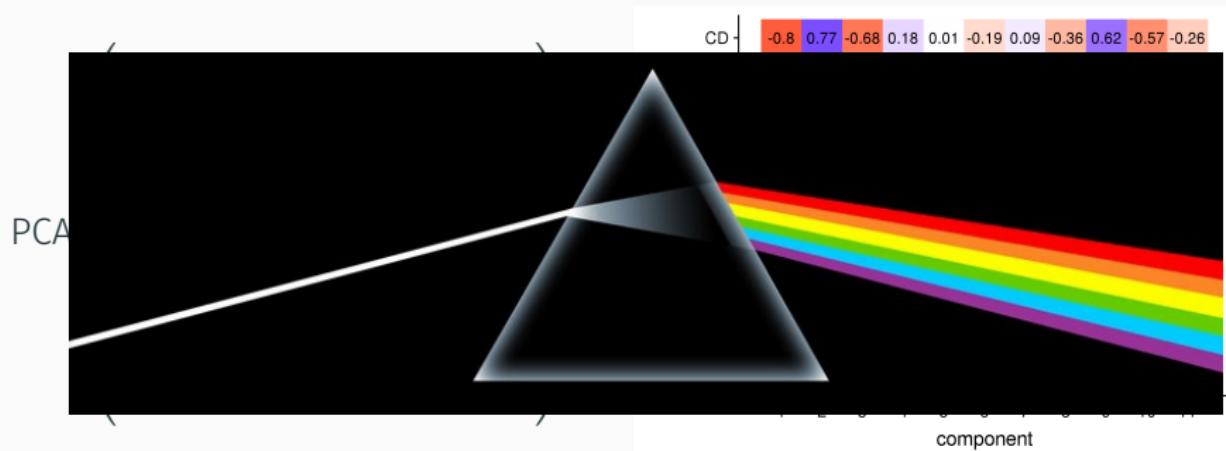
Heterogeneity across diseases



Principal components analysis to generate a new “basis”



Principal components analysis to generate a new “basis”

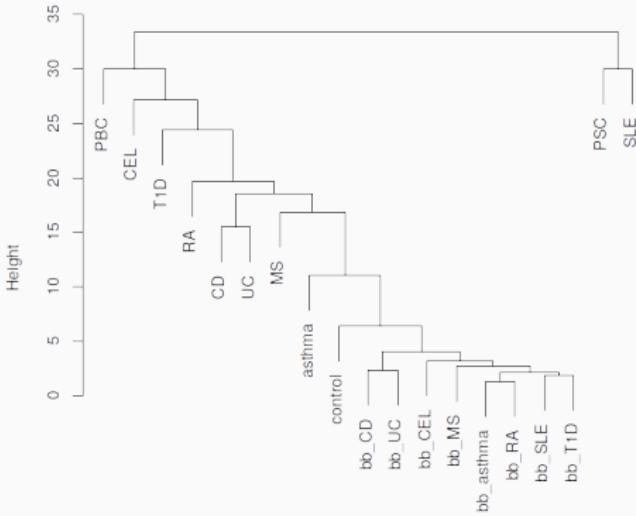


Basis diseases

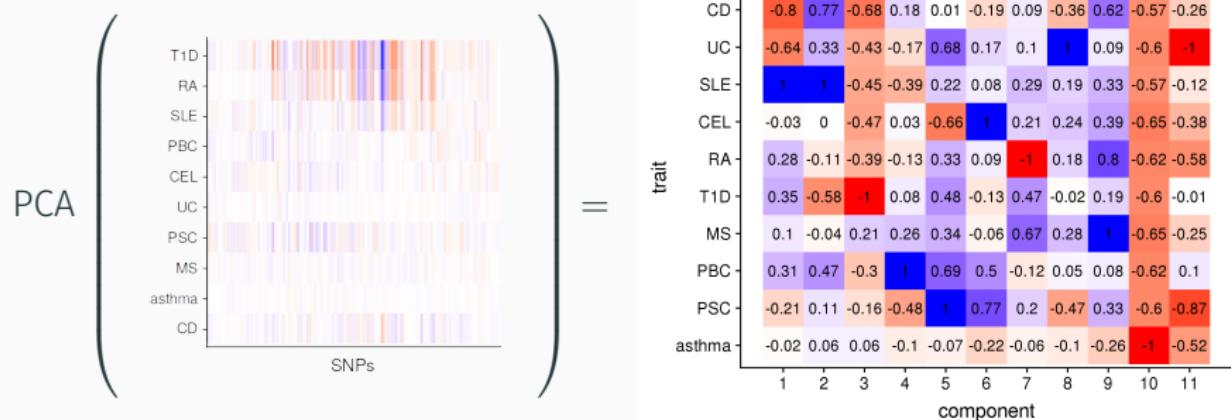
Disease	Study	Cases	Controls
asthma	Demenais	19954	107715
Rheumatoid arthritis	Okada	14361	43923
Ulcerative colitis	de Lange	12366	33609
Crohn's disease	de Laange	12194	28072
Multiple sclerosis	IMSGC	9772	17376
Type 1 diabetes	Cooper	5913	8829
Primary sclerosing cholangitis	Ji	4796	19955
Coeliac disease	Dubois	4533	10750
Systemic lupus erythematosus	Bentham	4036	6959
Primary biliary cholangitis	Cordell	2764	10475

Naive basis captures dataset, not disease

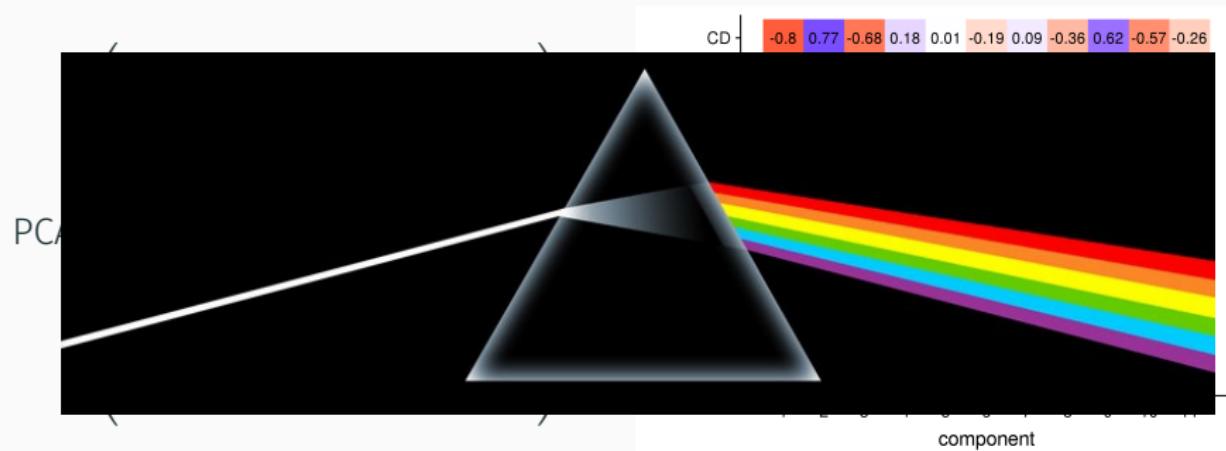
UK Biobank	Cases
Type 1 diabetes	286
Systemic lupus erythematosus	366
Multiple sclerosis	1,228
Coeliac disease	1,452
Ulcerative colitis	1,795
Crohn's disease	1,032
Rheumatoid arthritis	3,730
Asthma	39,049



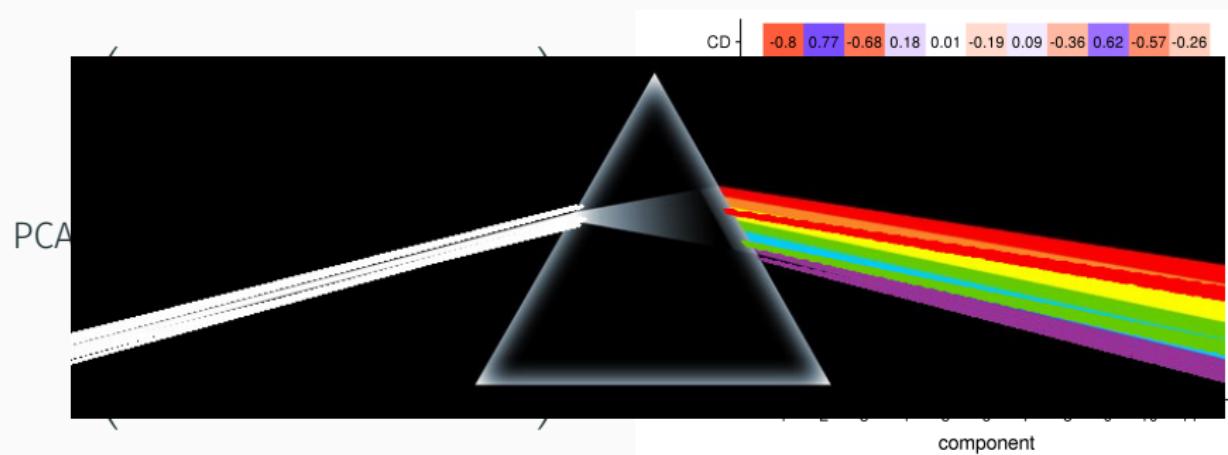
Solution: focus data before principal components analysis



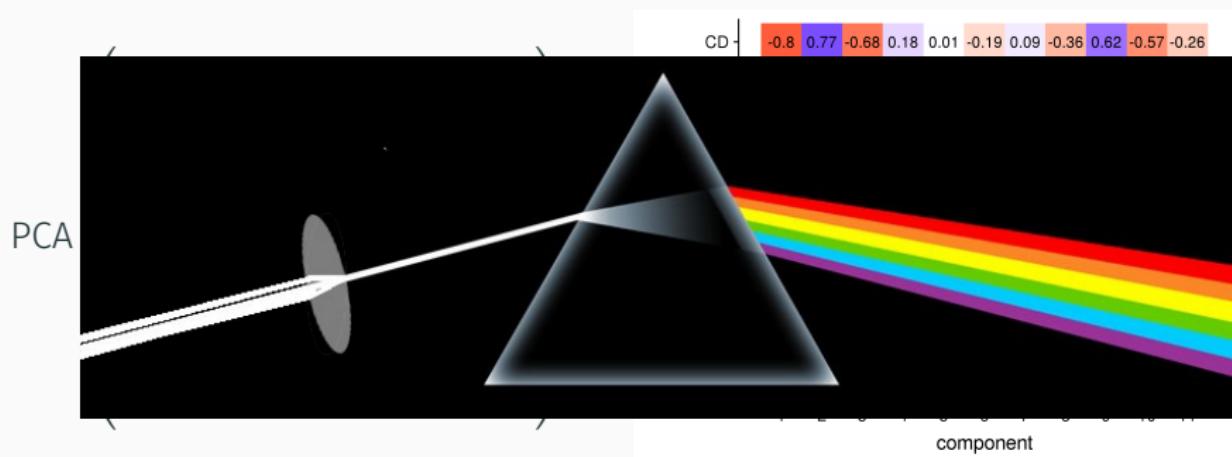
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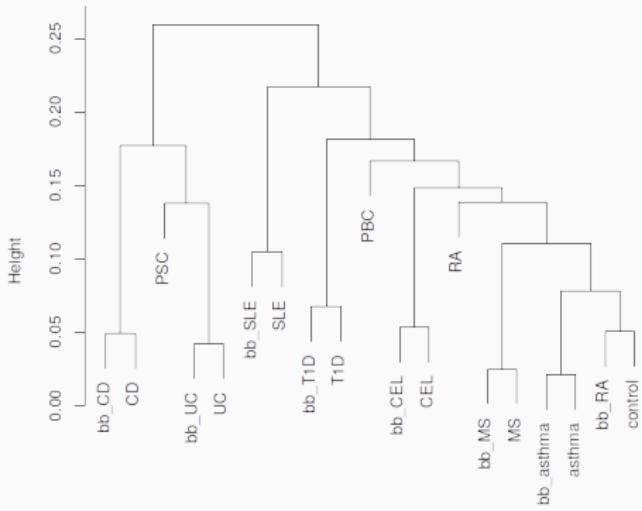


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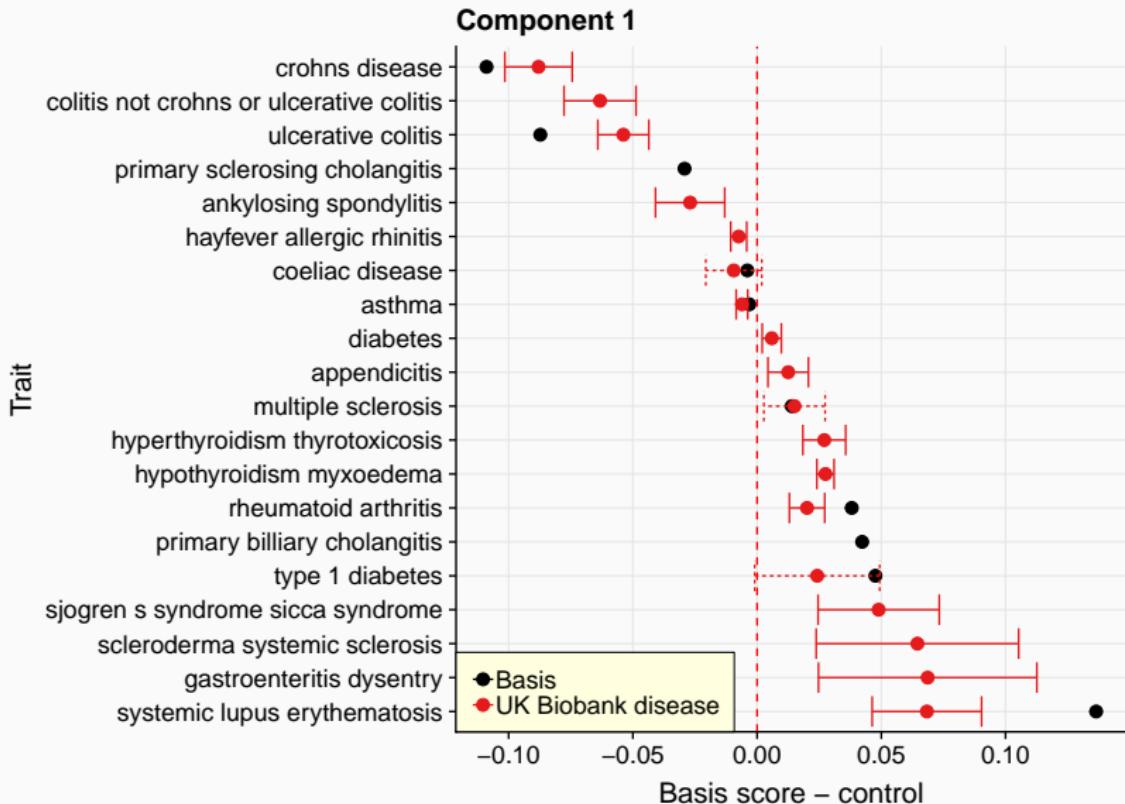


Focused basis captures disease information

UK Biobank	Cases
Type 1 diabetes	286
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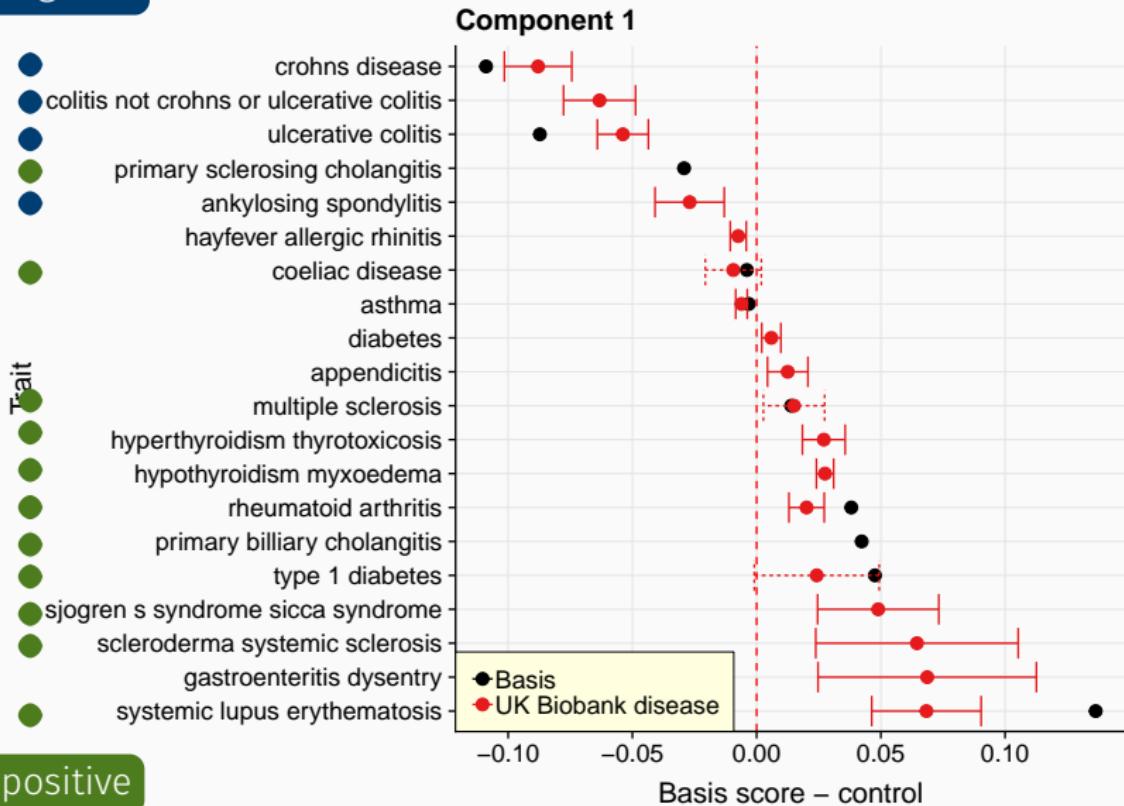


Component 1: sero+/- disease, innate/adaptive



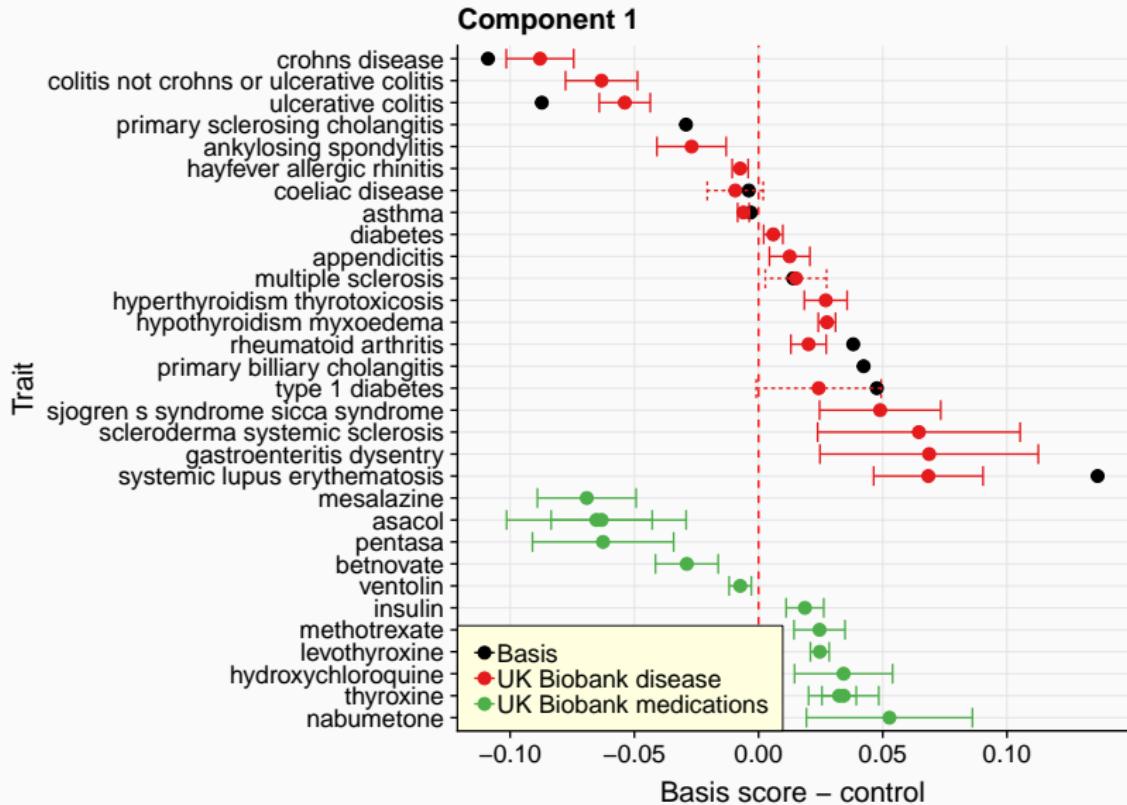
Component 1: sero+/- disease, innate/adaptive

seronegative

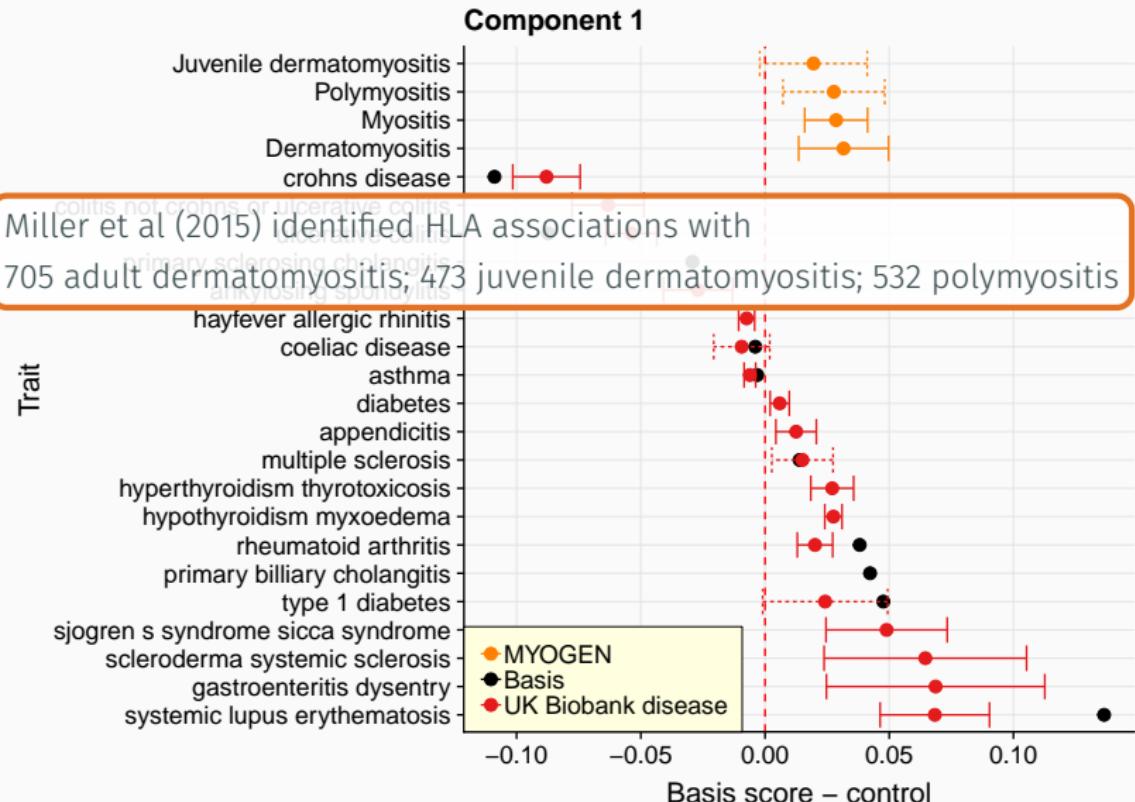


seropositive

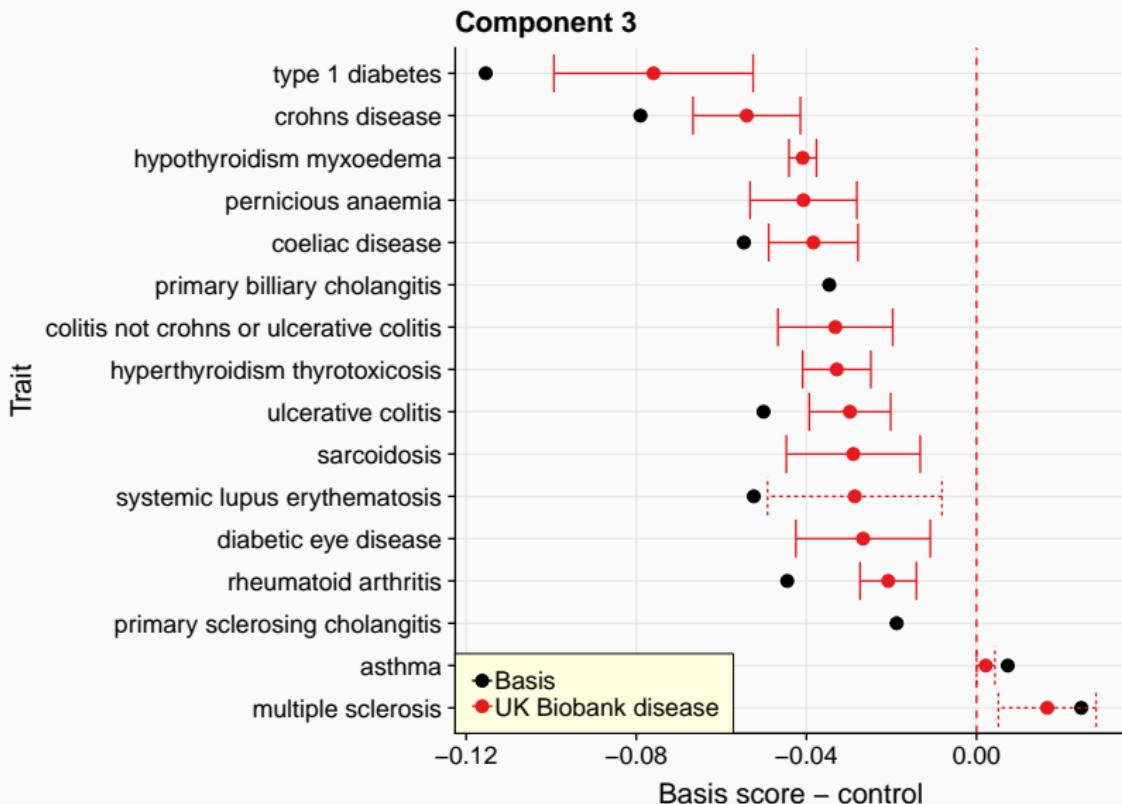
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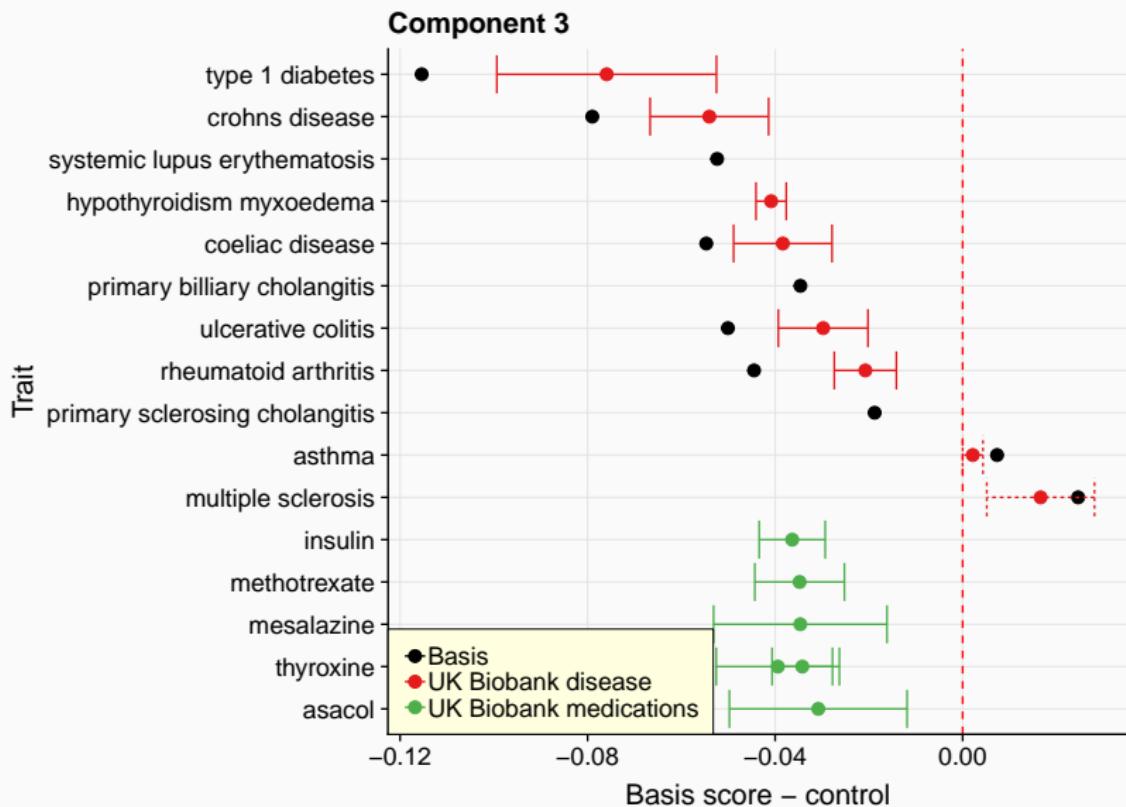
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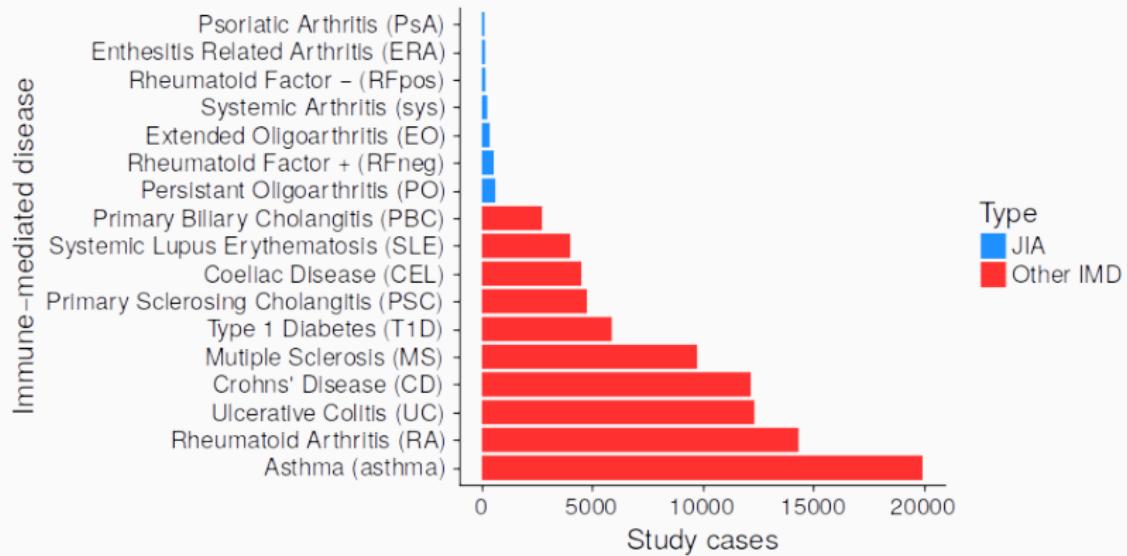
Component 3



Component 3

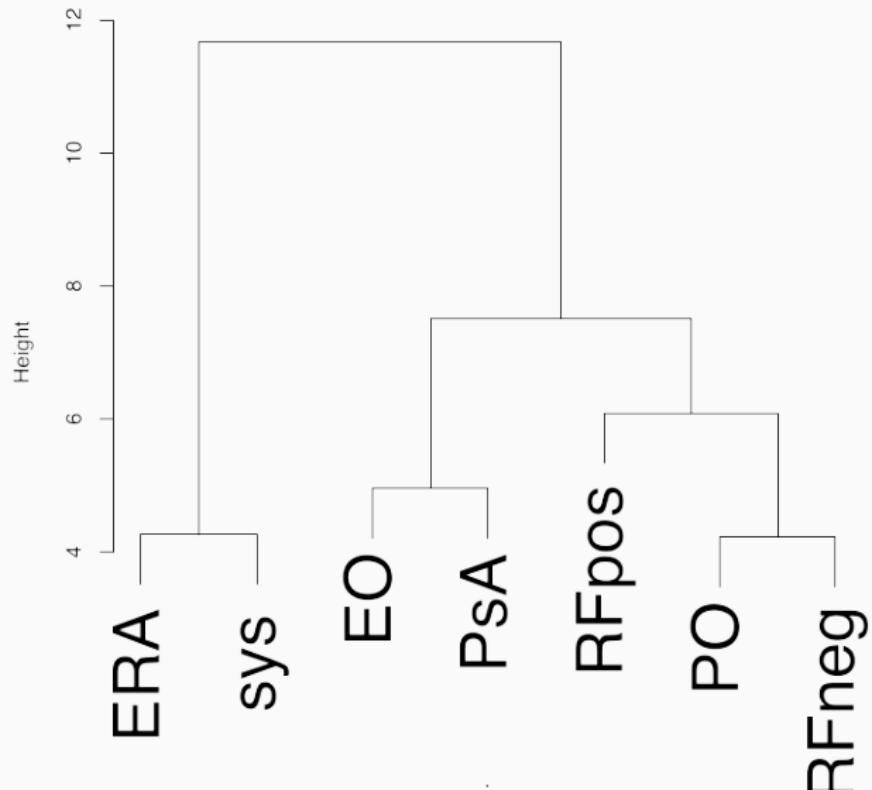


Component 3

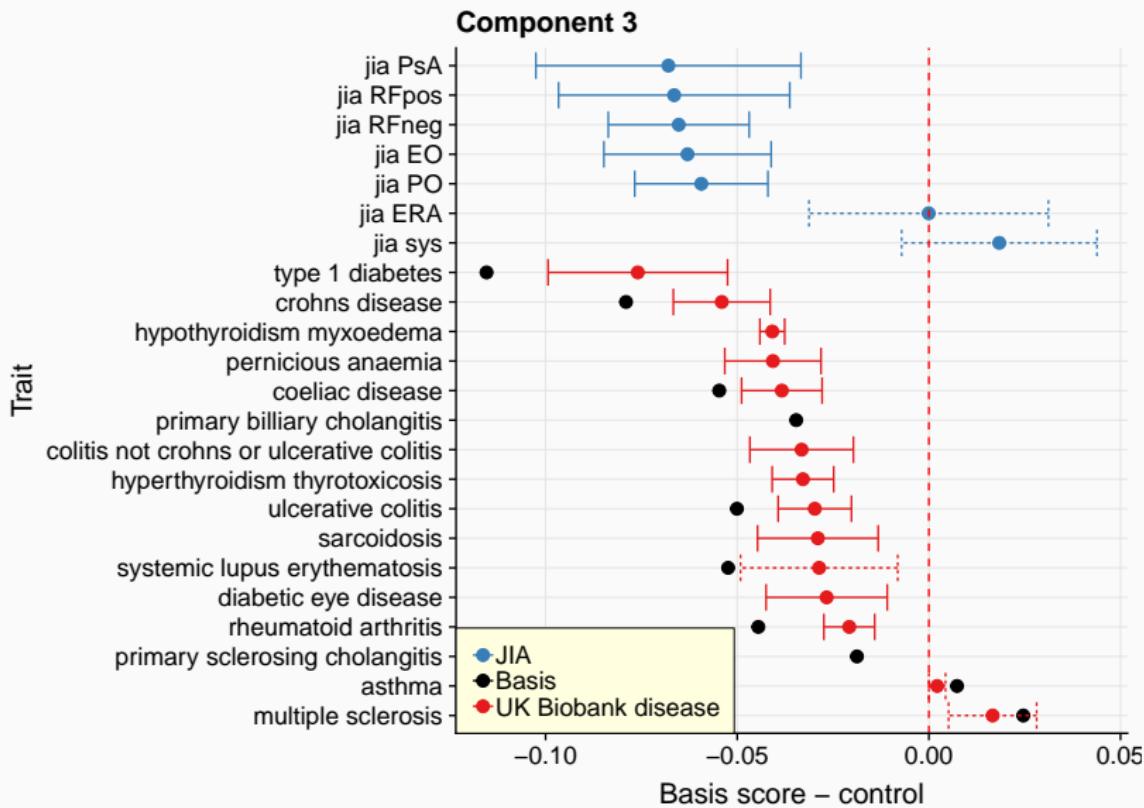


UK JIA genetics consortium

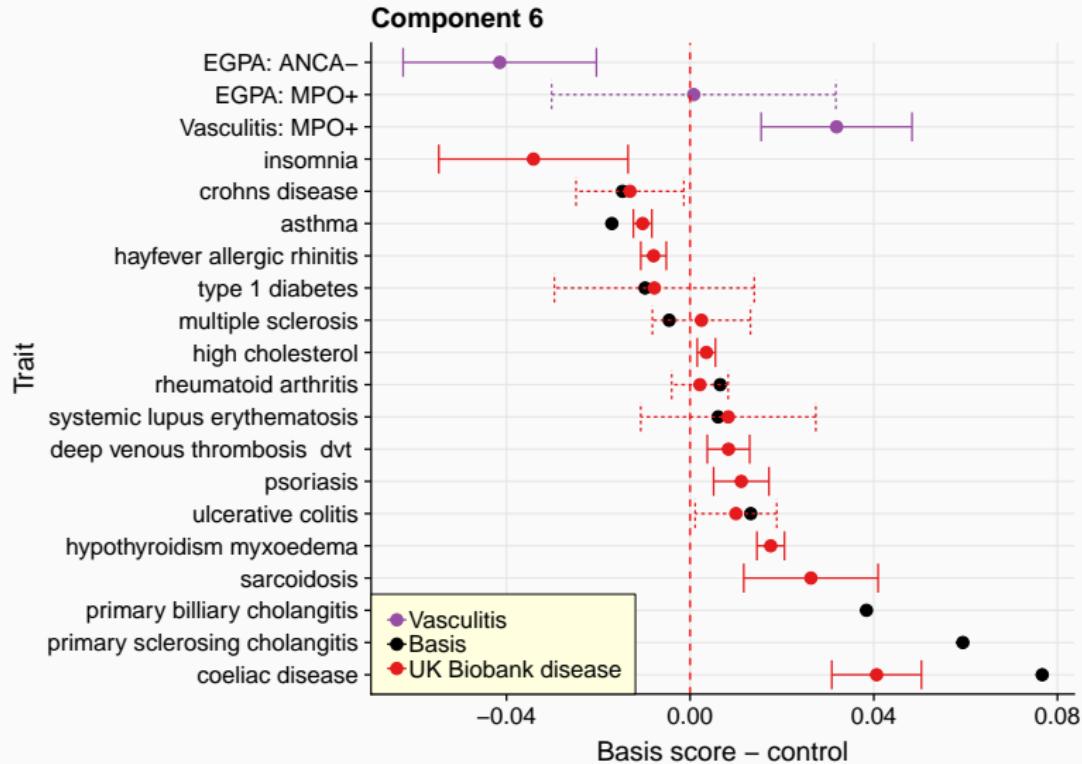
Component 3



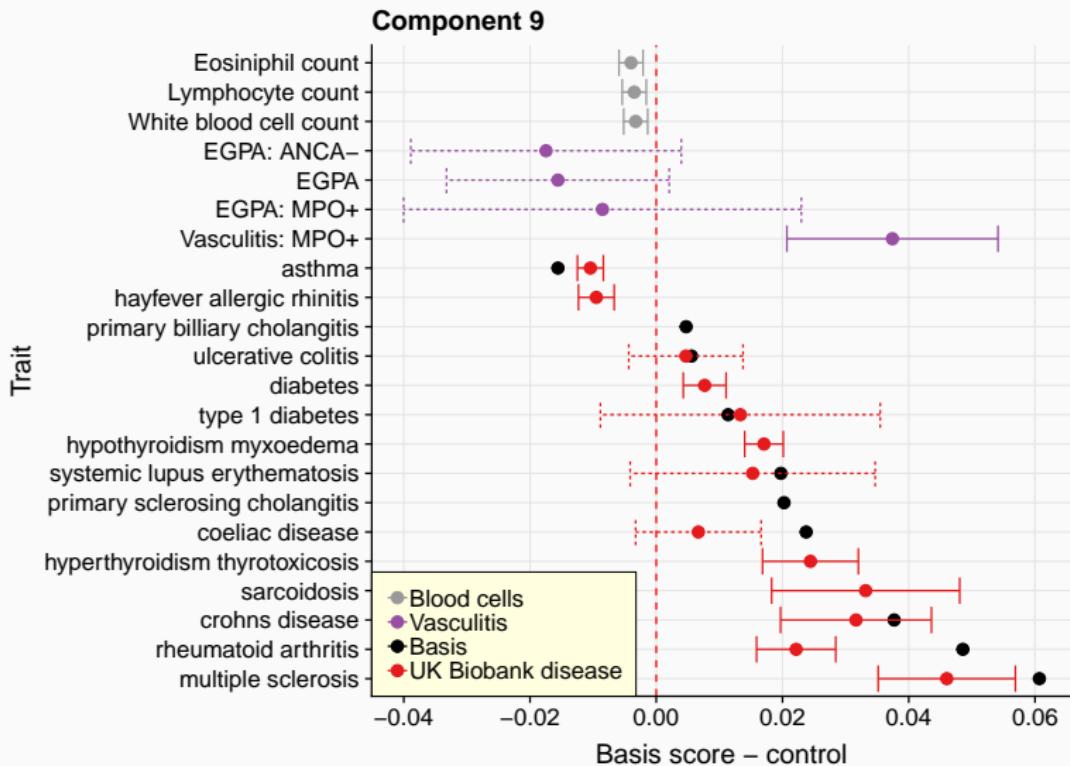
Component 3



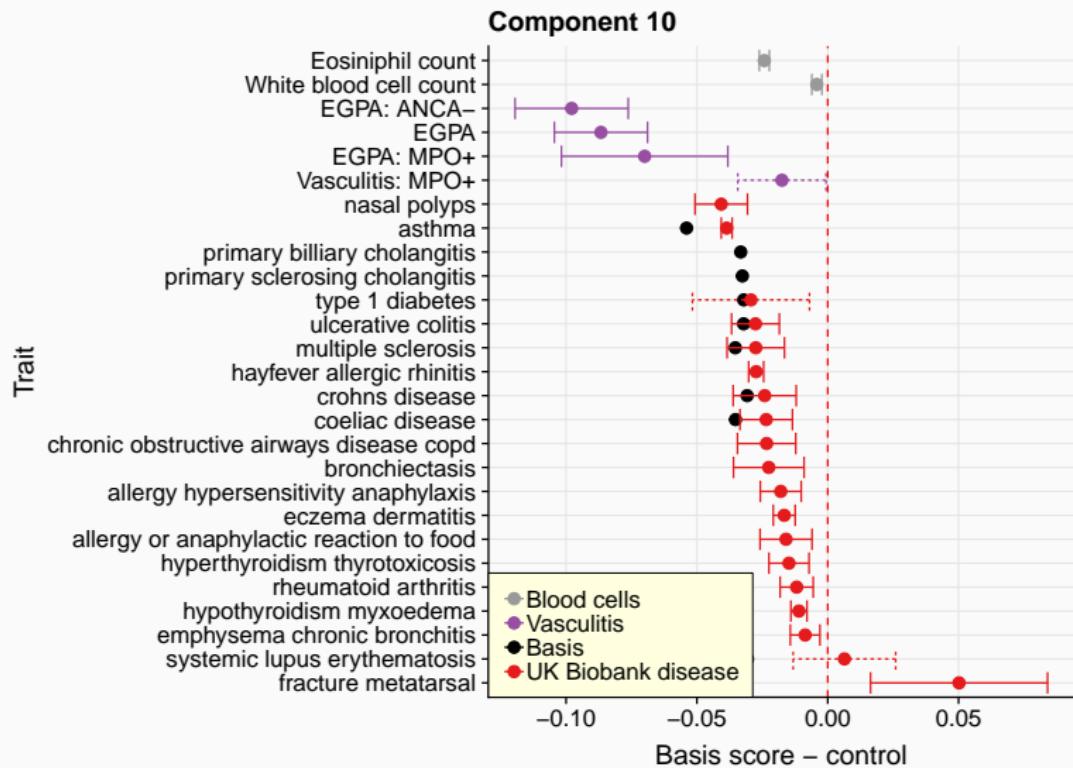
Vasculitis



Vasculitis



Vasculitis



Summary

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Summary

- Genetic sharing across immune mediated diseases is pervasive, but complex
- Sharing **should** be exploited to learn about less common diseases
- Region-wise overlap analysis useful to “zoom in”
- Dimension reduction obscures individual effects, offers manageable holistic view of multiple diseases
 - Focusing on OR rather than significance puts everything on same scale
 - Improves power: **many** fewer tests, stronger prior for association
 - Components are directions, from x to y, but interpretation difficult
 - Given difference on component, can identify driving SNPs - “zoom out”

Thanks to...



James Liley



Stasia Grinberg



Olly Burren

Patients, families, study PIs who shared data

Sample Cohorts

UK JIA Genetics Consortium

Childhood Arthritis Prospective Study (CAPS)

Childhood Arthritis Response to Medication Study
(CHARMS)

MYOGEN consortium

European Vasculitis Genetics Consortium

Cambridge

Ken Smith Paul Lyons

MYOGEN consortium

Fred Miller Chris Amos

Manchester

Wendy Thomson Anne Hinks

Joanna Cobb John Bowes

Annie Yarwood Sam Smith

Kimme Hyrich

University College London

Lucy Wedderburn Claire Deakin

