Annotating GWAS results

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shared drive Danielle/FUMA_new2023.ppt



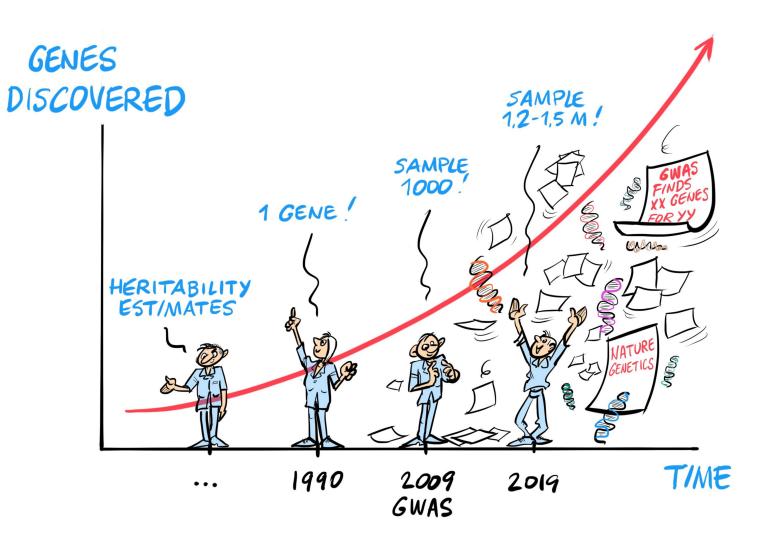








The revolution in genetics



Current genome-wide discovery studies

- They are HUGE: sample sizes typically 100,000's, but even over 1 million is not uncommon!
- Standard quality control and analyses pipelines are thoroughly benchmarked and widely shared
- Good quality GWAS study ALWAYS includes out of sample replication(s) (most journals would not accept without attempted replication)
- There may still be some 'bad quality' GWAS studies (small, replication not included), but generally:

The primary outcome of most GWAS studies is replicable, and highly reliable. Although slight changes in the order of significance may occur with increasing sample size and increasing accuracy, top hits are unlikely to be refuted Article

A saturated map of common genetic variants associated with human height

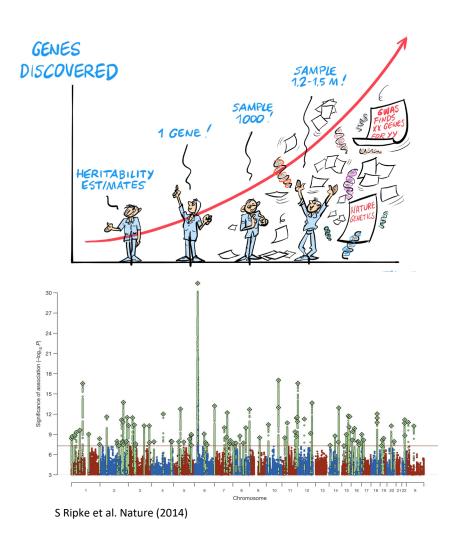
Article

Stroke genetics informs drug discovery and risk prediction across ancestries

https://doi.org/10.1038/s41586-022-05165-3	
Received: 15 December 2021	
Accepted: 29 July 2022	
Published online: 30 September 2022	
Open access	
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Previous genome-wide association studies (GWASs) of stroke – the second leading cause of death worldwide – were conducted predominantly in populations of European ancestry^{1,2}. Here, in cross-ancestry GWAS meta-analyses of 110,182 patients who have had a stroke (five ancestries, 33% non-European) and 1,503,898 control individuals, we identify association signals for stroke and its subtypes at 89 (61 new) independent loci: 60 in primary inverse-variance-weighted analyses and 29 in secondary meta-regression and multitrait analyses. On the basis of internal cross-ancestry validation and an independent follow-up in 89.084 additional cases

The revolution in genetics...



Lots of genes associated with many traits, but..

...unfortunately, this success has not yet translated at the same pace into mechanistic insight.

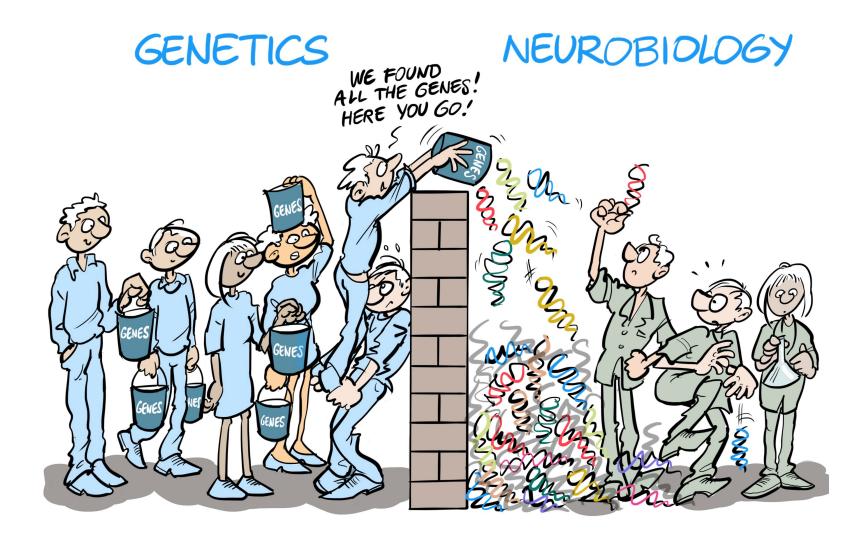
GWAS alone does not provide mechanistic insight: GWAS can provide testable hypotheses on biological mechanisms – functional follow up studies are needed to prove causality/involved mechanisms etc

Why do we need mechanistic insight?

- To <u>understand</u>: if we want to explain why some people fall ill and others don't, we want to know what happens at molecular, cellular and organismal levels
- To <u>treat</u>: mechanistic insight may aid in developing novel treatments by providing starting points

For prediction we do not necessarily need mechanistic insight though. But - prediction makes most sense if it can be tailored to treatment

Why is translation of GWAS into mechanistic insight so hard?



1. Correlation between variants (LD)

Significant association P-values are distributed over **blocks of correlated** genetic variants: actual causal variant is unclear 1. Correlation between variants (LD) Significant association P-values are distributed over **blocks of correlated** genetic variants: actual causal variant is unclear

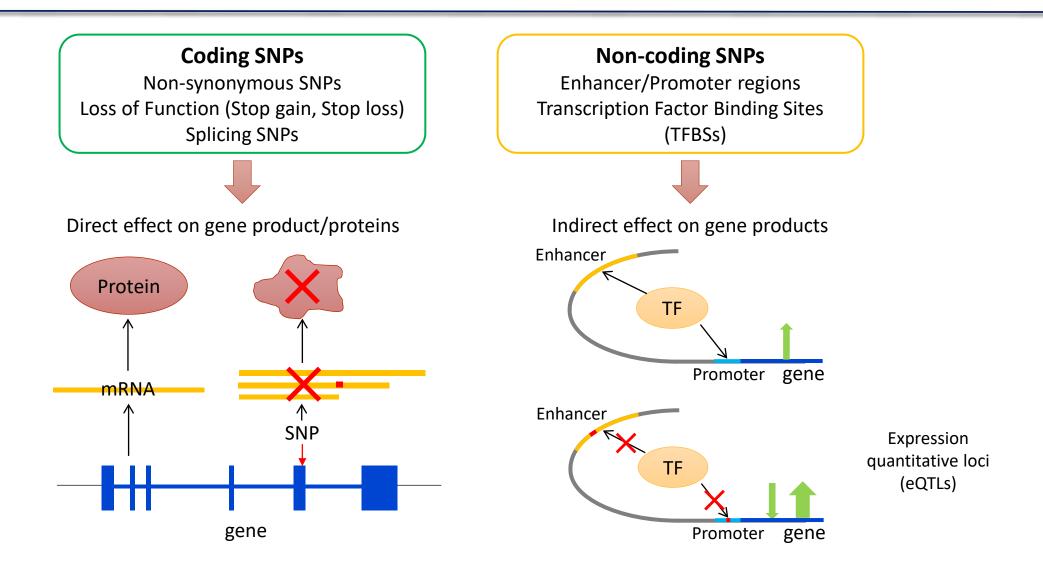
Solution: - functional annotation (functional variants more likely to be causal than non-functional ones, e.g. tools FUMA, VEP, ANNOVAR)

- **statistical fine-mapping** (the known correlation structure can be modeled against the observed pattern of association values to pinpoint the most likely causal SNPs, this can be integrated with functional information (e.g. tools FINEMAP, PAINTOR)

2. Many GWAS hits are in **non-coding regions**

The majority of GWAS hits are not in exonic regions but are intronic or non-genic. That means they do not directly lead to a different protein structure and their impact on protein function may be less straightforward to assess.

Coding and Non-coding SNPs



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Solution: link GWAS variants to genes via **functional annotation** using regulatory information from external resources, such as GTEX (e-QTL), chromatin interactions, i.e. add information on the association of a variant with DNA transcription and RNA or protein levels

3. *Many traits are polygenic*

When a trait is polygenic, multiple genetic variants of small effect contribute. A single genetic variant, even if it is known to be causal, is usually not informative for biology

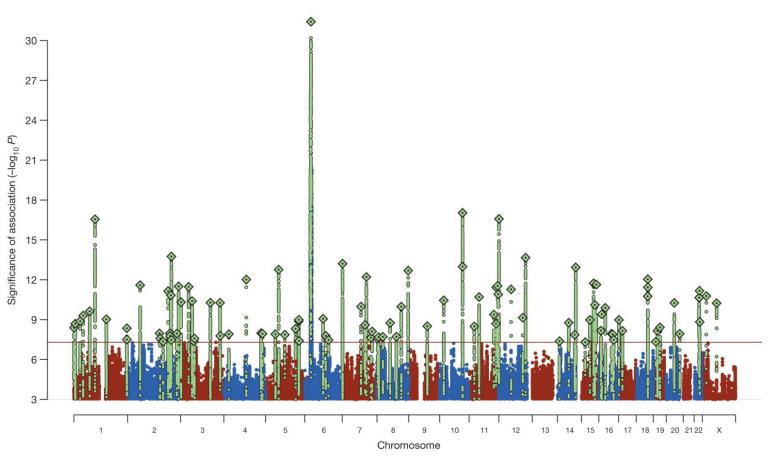
3. *Many traits are polygenic*

When a trait is polygenic, multiple genetic variants of small effect contribute. A single genetic variant, even if it is known to be causal, is usually not informative for biology

Solution: map associated SNPs to genes and look for **convergence** in biological pathways, shared cellular or synaptic function, colocalization, co-expression in tissue or cell types (e.g. tools MAGMA, Ldscore regression, DEPICT)

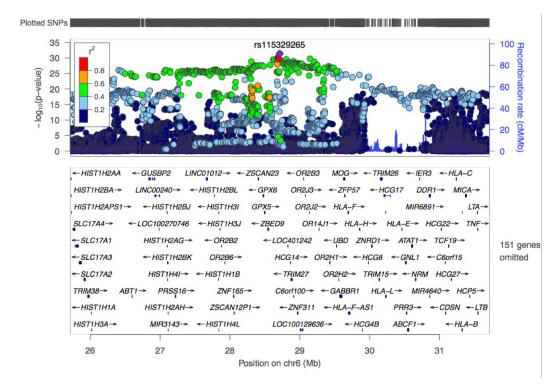
This will be covered in next session on gene-set analysis

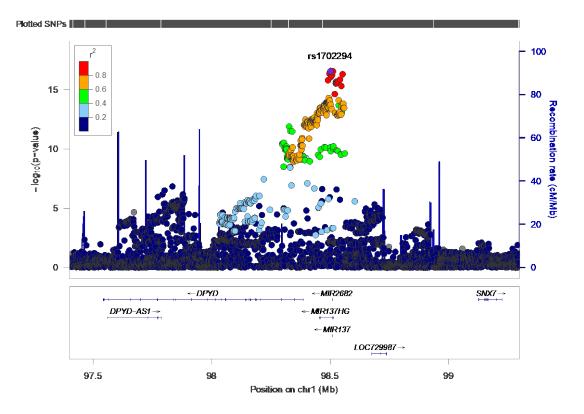
Awesome GWAS results



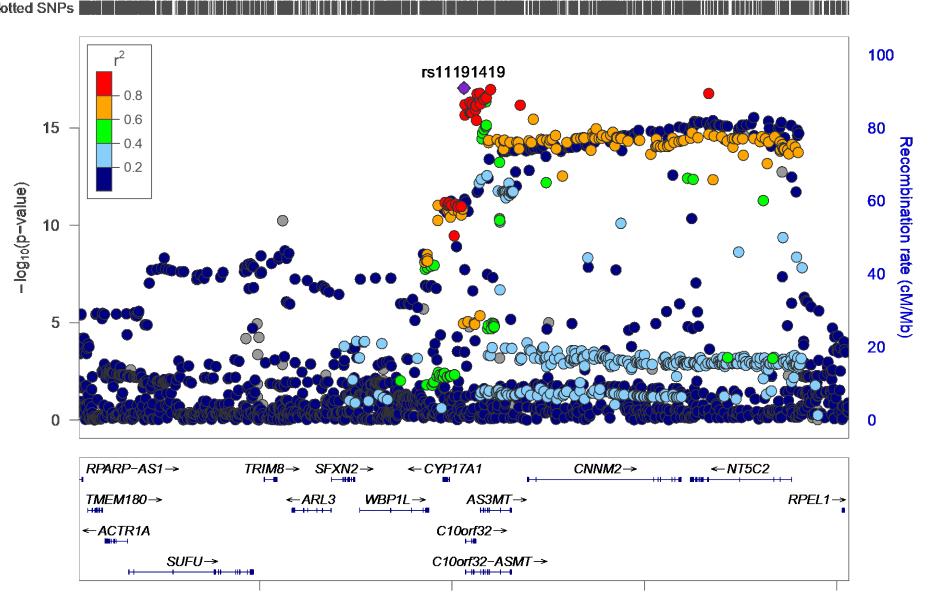
S Ripke et al. Nature (2014)

Awesome GWAS results - but how to interpret?







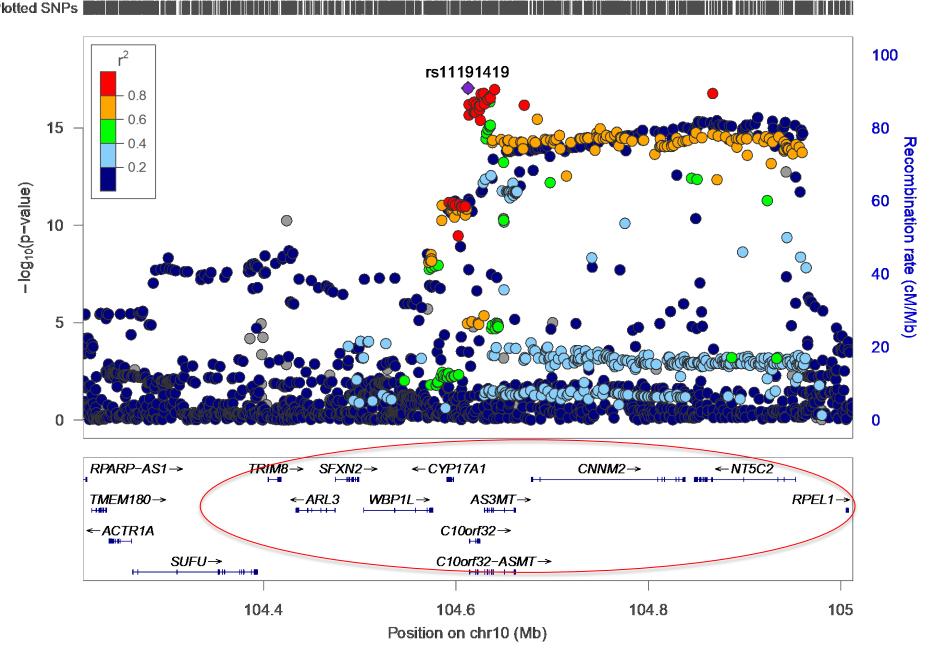


104.6 Position on chr10 (Mb) 104.8

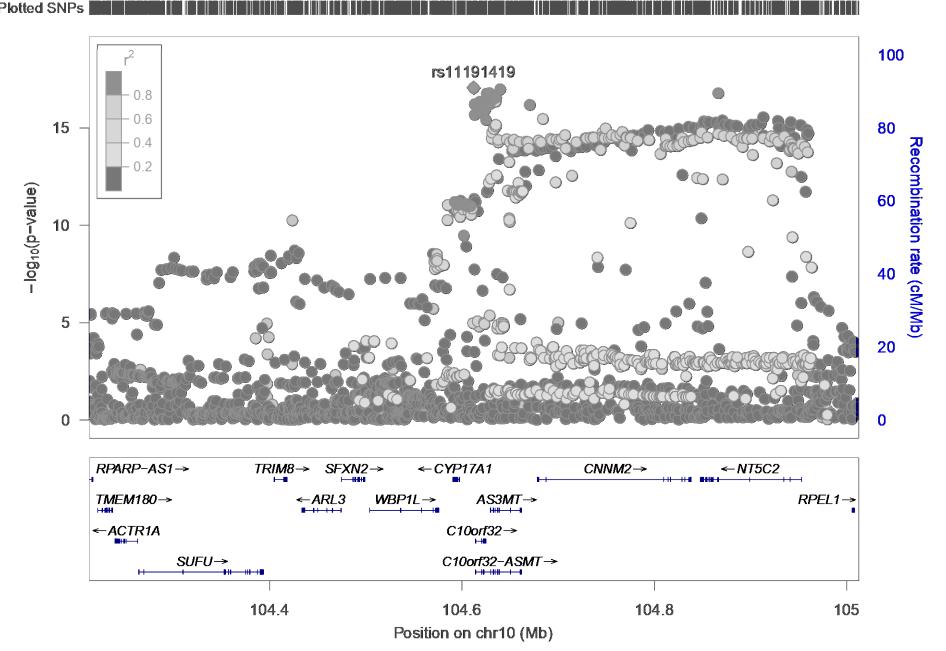
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104.4

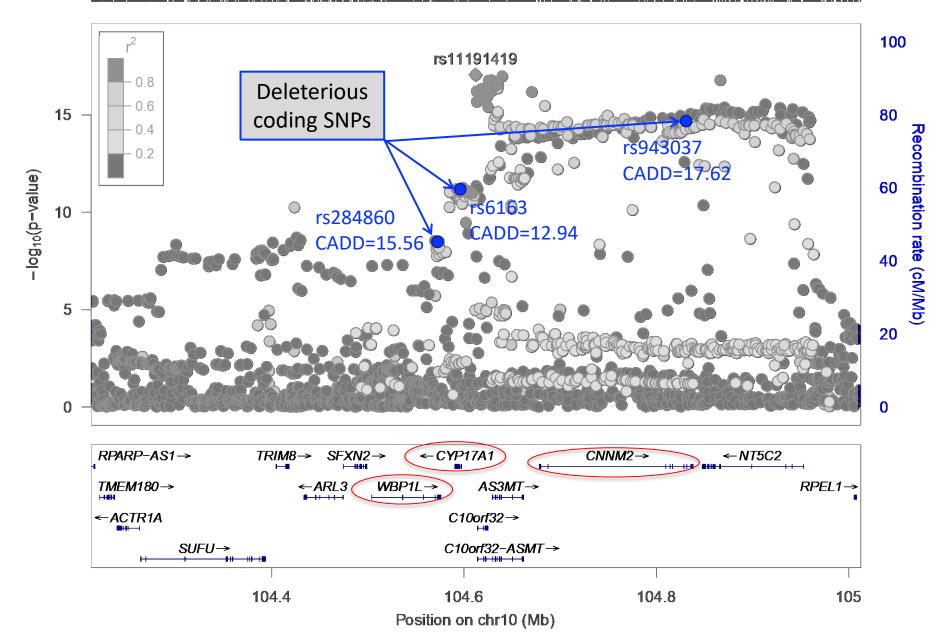




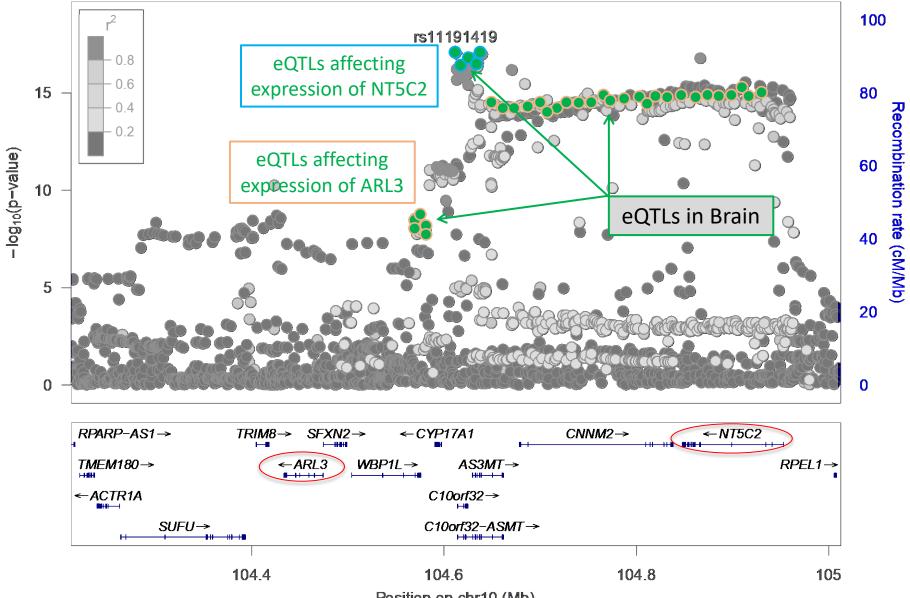






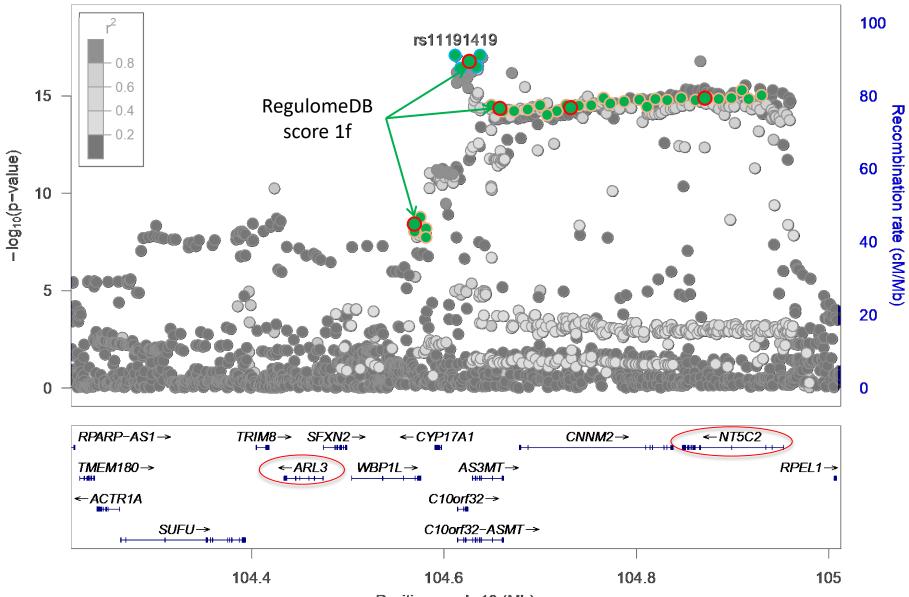






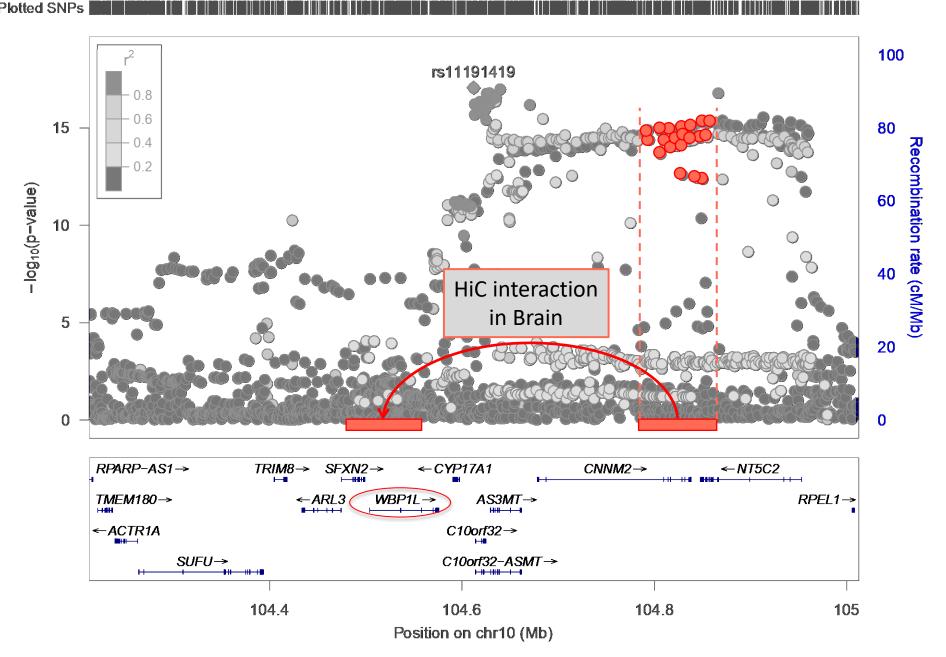
Position on chr10 (Mb)



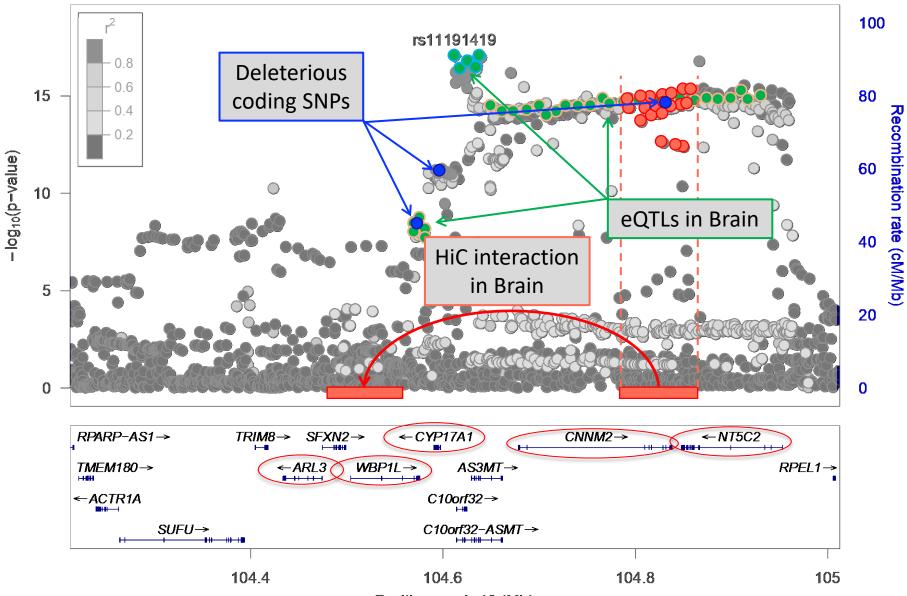


Position on chr10 (Mb)









Position on chr10 (Mb)

1. Linkage disequilibrium (LD)

Identify all SNPs in LD with significant hits.



PLINK

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2. Variant annotation

Functional consequence on genes (e.g. exonic, intronic or splicing site)

ANNOVAR



PLINK

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ANNOVAR

3. Functional annotation

Deleteriousness, regulatory elements and epigenetic data

CADD







BBBMRI.n Biobanking and BioMolecular resources Research Infrastructure The Netherlands

HiC



000 Genomes

Deep Catalog of Human Genetic Variation



1. Linkage disequilibrium (LD)

Identify all SNPs in LD with significant hits.

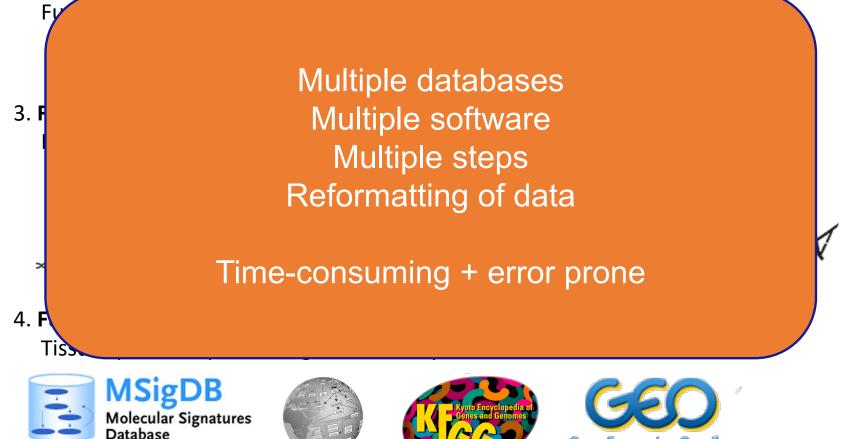
000 Genomes Deep Catalog of Human Genetic Variatio

Gene Expression Omnibus



PLINK

2. Variant annotation



WIKIPATHWAYS



FUMA: Functional Mapping and Annotation of genetic associations

Available at http://fuma.ctglab.nl

FUMAGWAS	Home	Tutorial	Browse Examples	SNP2GENE	GENE2FUNC	Links	Updates	Login	Register

FUMA GWAS

Functional Mapping and Annotation of Genome-Wide Association Studies

FUMA is a platform that can be used to annotate, prioritize, visualize and interpret GWAS results. The SNP2GENE function takes GWAS summary statistics as an input, and provides extensive functional annotation for all SNPs in genomic areas identified by lead SNPs. The GENE2FUNC function takes a list of gene IDs (as identified by SNP2GENE or as provided manually) and annotates genes in biological context To submit your own GWAS, login is required for security reason. If you have't registered yet, you can do from here. You can browse example results of FUMA for a few GWAS from Browse Examples without registration or login.

Please post any questions, suggestions and bug reports on Google Forum: FUMA GWAS users.

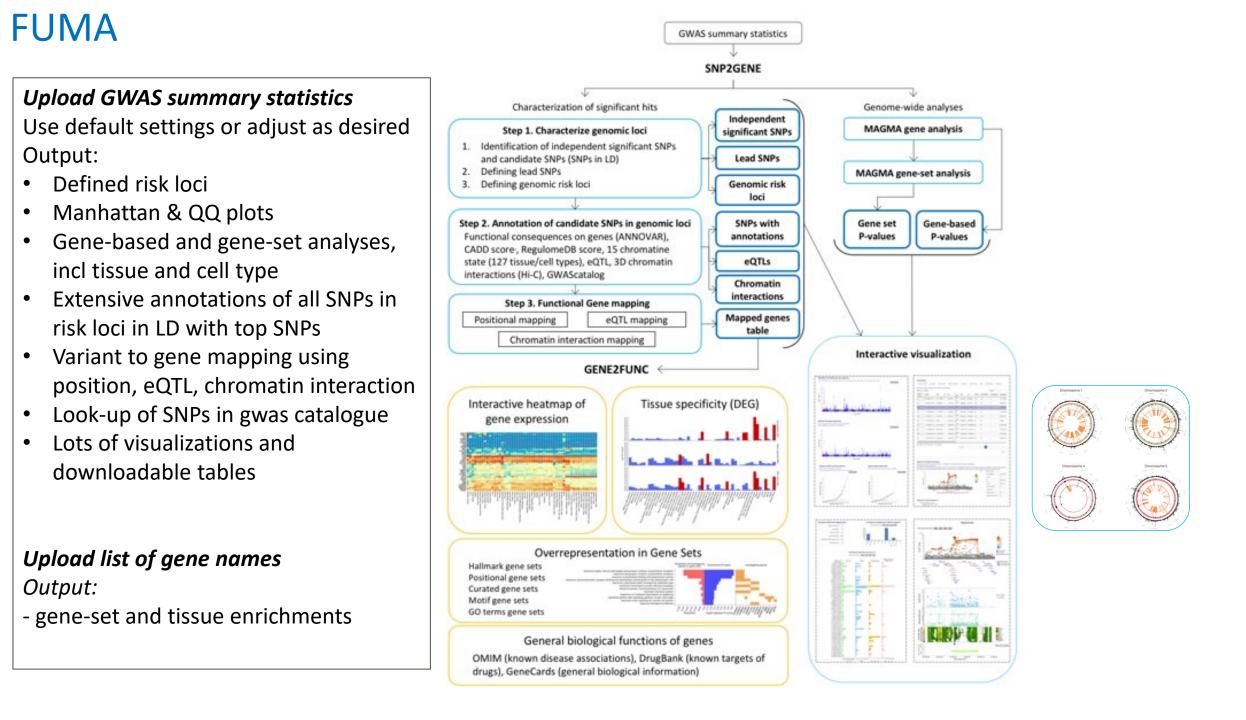
Citation:

When using FUMA, please cite the following. K. Watanabe, E. Taskesen, A. van Bochoven and D. Posthuma. Functional mapping and annotation of genetic associations with FUMA. *Nat. Commun.* **8**:1826. (2017). https://www.nature.com/articles/s41467-017-01261-5

Depending on which results you are going to report, please also cite the original study of data sources/tools used in FUMA (references are available at Links).

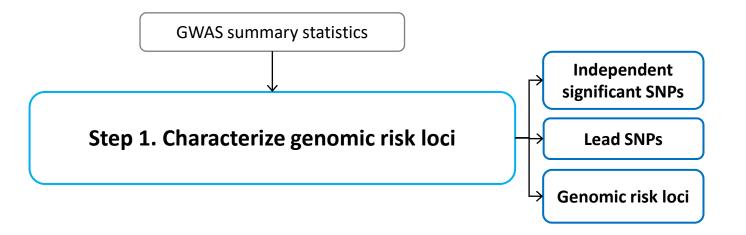
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Developed by Kyoko Watanabe

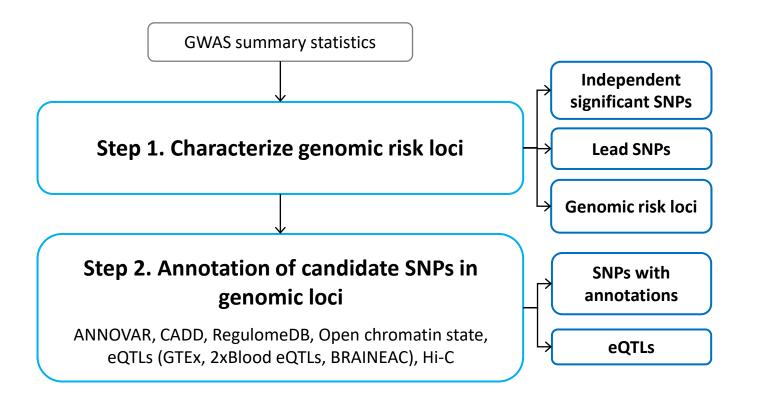


FUMA GWAS summary statistics SNP2GENE **Upload GWAS summary statistics** Characterization of significant hits Genome-wide analyses Independent Use default settings or adjust as desired Step 1. Char 1. Identification of ir **SNP2GENE** Output: and candidate SN 2. Defining lead SNP Defined risk loci Defining genomic 3. loci Manhattan & QQ plots Step 2. Annotation of candidate SNPs in genomic loci SNPs with Gene set Gene-based P-values Gene-based and gene-set analyses, Functional consequences on genes (ANNOVAR), annotations P-values CADD score, RegulomeDB score, 15 chromatine eQTLs state (127 tissue/cell types), eQTL, 3D chromatin incl tissue and cell type interactions (Hi-C), GWAScatalog Chromatin Extensive annotations of all SNPs in interactions Step 3. Functional Gene mapping Mapped genes Positional mapping eQTL mapping risk loci in LD with top SNPs table Chromatin interaction mapping Variant to gene mapping using Interactive visualization GENE2FUNC position, eQTL, chromatin interaction Tissue specificity (DEG) Interactive heatmap of Look-up of SNPs in gwas catalogue gene expression Lots of visualizations and **GENE2FUNC** downloadable tables Overrepresentation in Gene Sets Upload list of gene names Hallmark gene sets Positional gene set *Output:* Curated gene sets Motif gene sets - gene-set and tissue enrichments GO terms gene sets General biological functions of genes OMIM (known disease associations), DrugBank (known targets of drugs), GeneCards (general biological information)

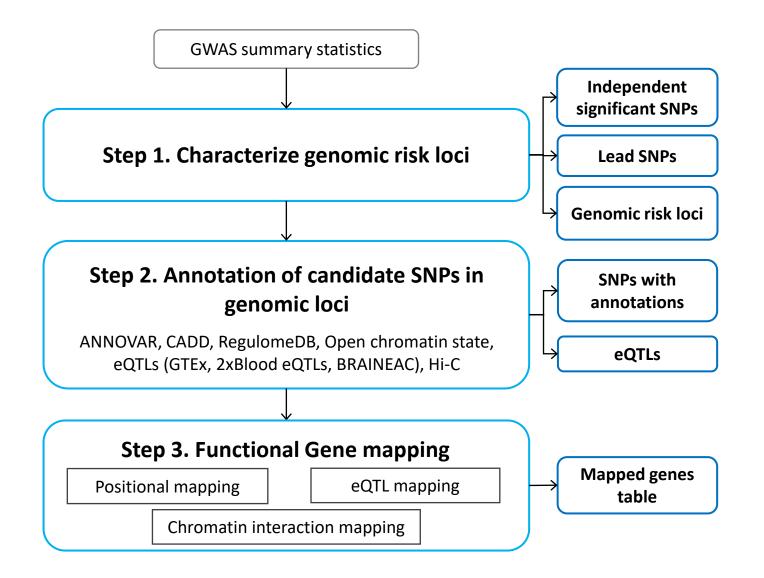
SNP2GENE

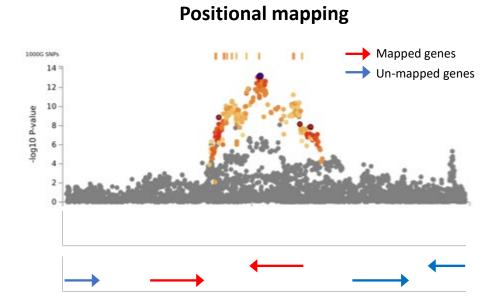


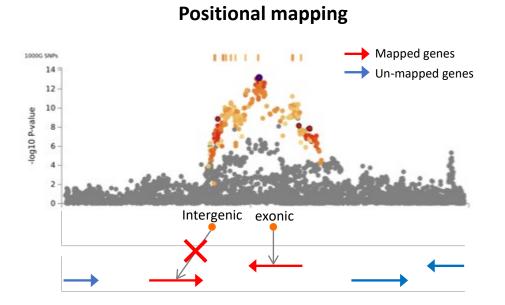
SNP2GENE

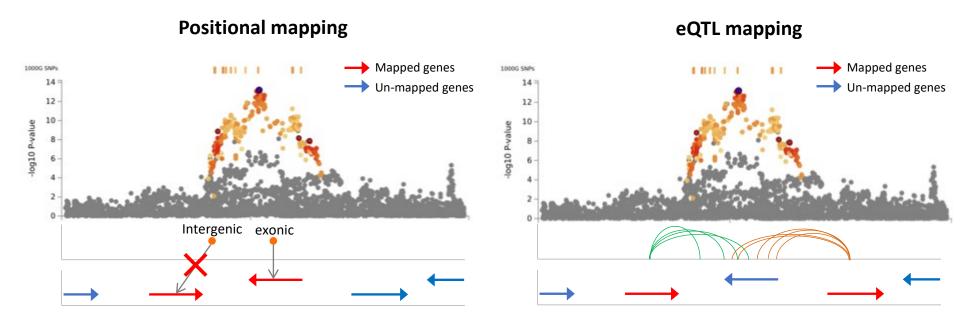


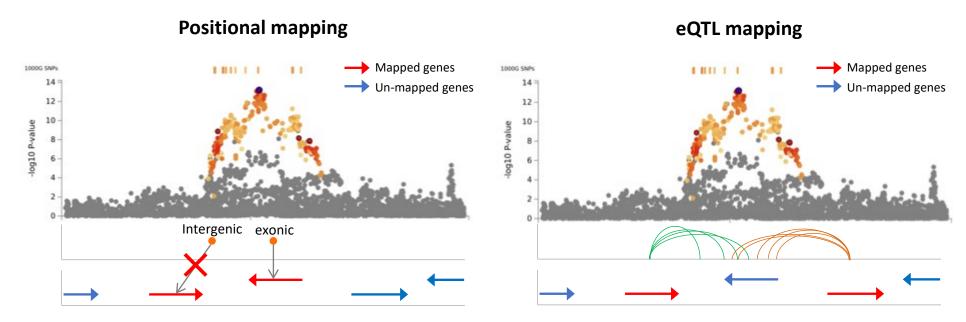
SNP2GENE











Optional filtering of SNPs based on functional annotations prior to gene mapping

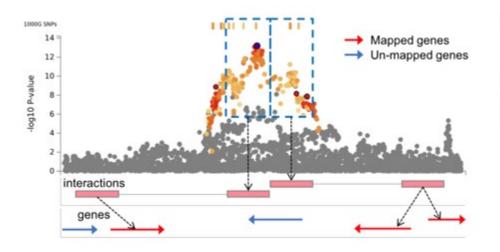
CADD score (>12.37 is considered as highly deleterious)

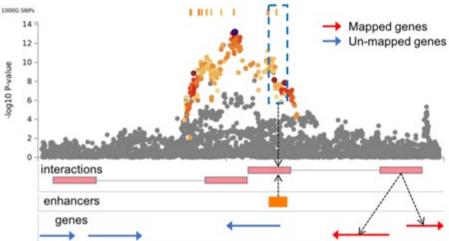
RegulomeDB score (categorical score from 1a to 7)

15-core chromatin status (1-7 states are considered as open, tissue specific)

*Parameters can be set for each mapping separately

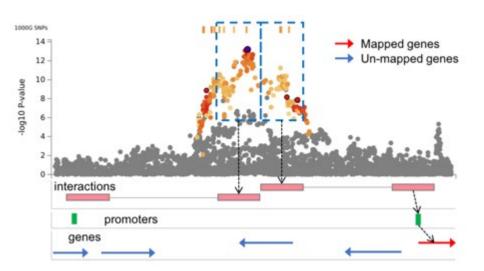
Chromatin interaction mapping



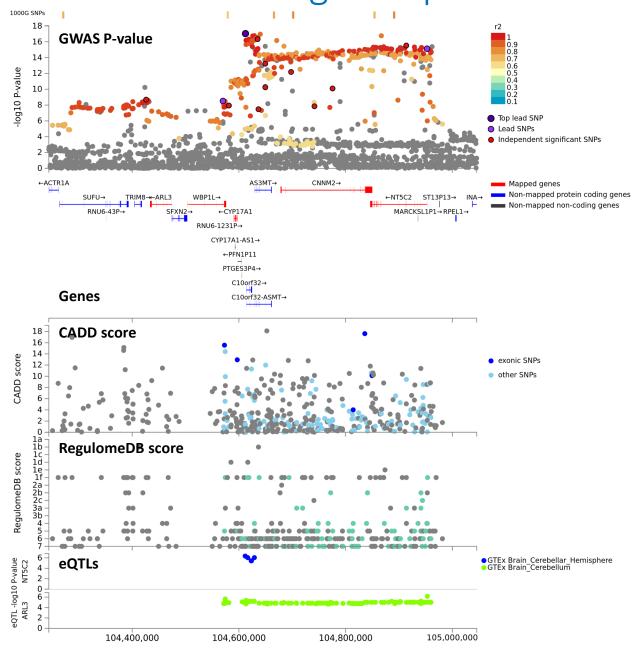


Map SNPs in a genomic region interacting with promoter region of genes (250bp up- and 500bp downstream of TSS) in selected tissue types.

SNPs can be further filtered on overlap with predicted enhancers or promotor regions from Roadmap.

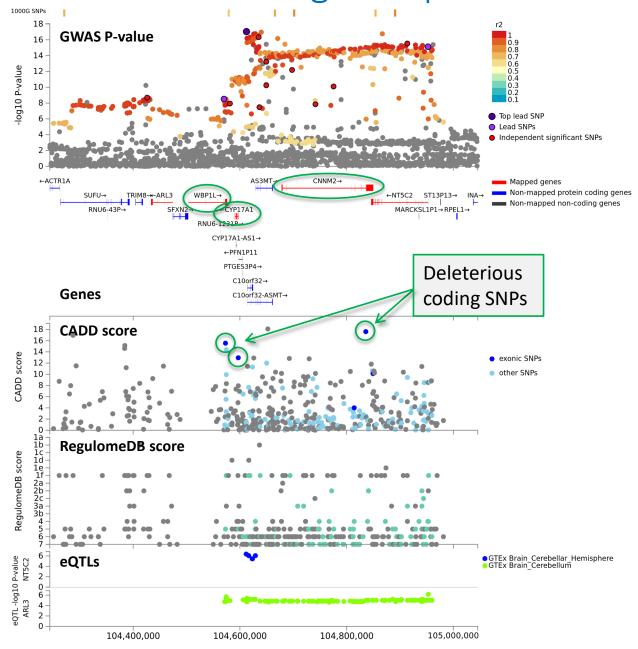


FUMA: regional plot



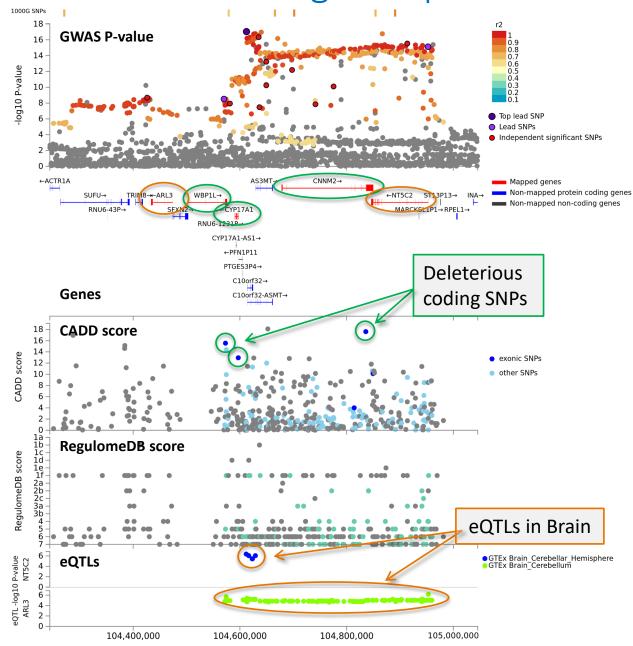
Chromosome 10

FUMA: regional plot



Chromosome 10

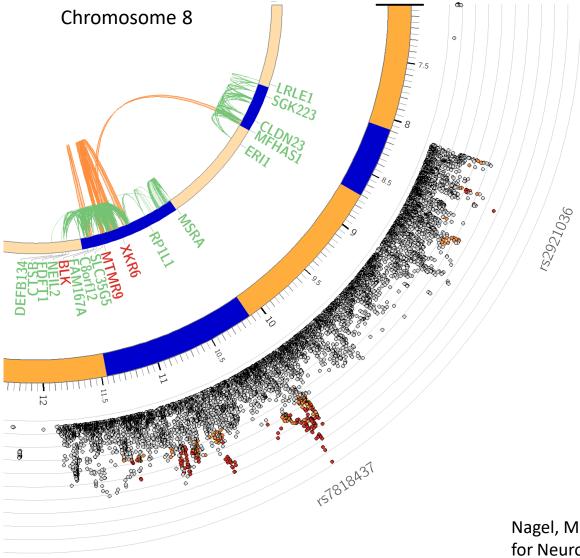
FUMA: regional plot



Chromosome 10

FUMA: circos plot

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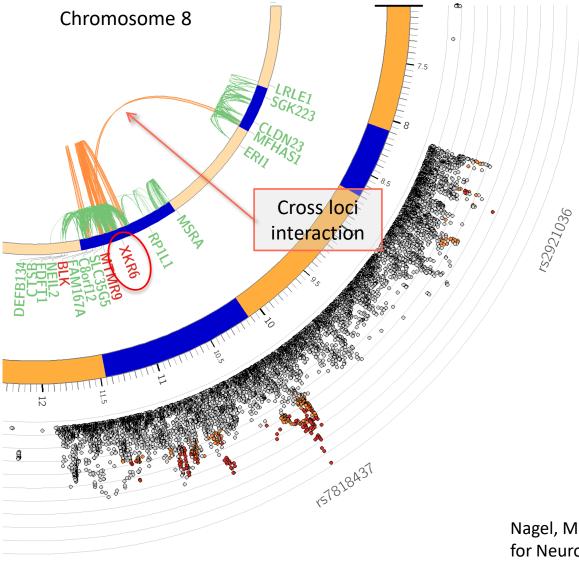


Chromatin interactions can map SNPs to distal genes.

Nagel, M. et al. Meta-Analysis of Genome-wide Association Studies for Neuroticism in 449,484 Individuals Identifies Novel Genetic Loci and Pathways. (2018) *Nat. Genet*.

FUMA: circos plot

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Chromatin interactions can map SNPs to distal genes.

XKR6 is mapped by within and cross loci interactions and also mapped by eQTLs.

Nagel, M. et al. Meta-Analysis of Genome-wide Association Studies for Neuroticism in 449,484 Individuals Identifies Novel Genetic Loci and Pathways. (2018) *Nat. Genet*.

FUMA Practical

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