Fine-mapping, colocalization, & a bit more on pop gen and rare variation/sequencing

Ben Neale

March 10th

So you've done a GWAS and found some associations – what now?

- Some questions to contemplate:
- What are the causal variant/variants driving the signal?
- What are the proximal biological consequences of those base pair differences?
- What are genes, cells and biological processes that are perturbed by these differences?
- How do those perturbations influence physiology?
- Or as Lindon used to say "What does it all mean"

A typical locus zoom plot



A more complicated locus zoom plot



Statistical fine-mapping - some modeling considerations



We can also consider the binary case



Statistical fine-mapping – conceptual introduction



Position

Position

Statistical fine-mapping – conceptual introduction



Position

Position

Among the simplest models – Maller et al.

genetics

Bayesian refinement of association signals for 14 loci in 3 common diseases

The Wellcome Trust Case Control Consortium^{1,2}

The authors of this paper are:

ARTICLES

Julian B Maller^{1,2}, Gilean McVean^{1,2}, Jake Byrnes¹, Damjan Vukcevic¹, Kimmo Palin³, Zhan Su¹, Joanna M M Howson^{4,5}, Adam Auton¹, Simon Myers^{1,2}, Andrew Morris¹, Matti Pirinen¹, Matthew A Brown^{6,7}, Paul R Burton^{8,9}, Mark J Caulfield¹⁰, Alastair Compston¹¹, Martin Farrall¹², Alistair S Hall¹³, Andrew T Hattersley^{14,15}, Adrian V S Hill¹, Christopher G Mathew¹⁶, Marcus Pembrey¹⁷, Jack Satsangi¹⁸, Michael R Stratton^{3,19}, Jane Worthington²⁰, Nick Craddock²¹, Matthew Hurles³, Willem Ouwehand^{3,22,23}, Miles Parkes²⁴, Nazneen Rahman¹⁹, Audrey Duncanson²⁵, John A Todd⁵, Dominic P Kwiatkowski^{1,3}, Nilesh J Samani^{26,27}, Stephen C L Gough^{28,29}, Mark I McCarthy^{1,28,29}, Panagiotis Deloukas³ & Peter Donnelly^{1,2}

Formalized Marchini et al. 2007 and Servin & Stephens PLoS Genet 2007

Assumes a single causal variant

 $\mathrm{BF}_i = rac{\mathrm{Pr}(\boldsymbol{X}|M_i)}{\mathrm{Pr}(\boldsymbol{X}|M_0)}$ $\Pr(\boldsymbol{X}_i|M_i)\Pr(\boldsymbol{X}_{-i}|\boldsymbol{X}_i,M_i)$ $\Pr(\boldsymbol{X}|M_0)$ $\Pr(\boldsymbol{X}_i|M_i)\Pr(\boldsymbol{X}_{-i}|\boldsymbol{X}_i,M_0)$ $\Pr(\boldsymbol{X}|M_0)$ $\Pr(\boldsymbol{X}_i|M_i)\Pr(\boldsymbol{X}_{-i}|\boldsymbol{X}_i,M_0)\Pr(\boldsymbol{X}_i|M_0)$ $\Pr(\boldsymbol{X}|M_0)\Pr(\boldsymbol{X}_i|M_0)$ $\Pr(\boldsymbol{X}_i|M_i)\Pr(\boldsymbol{X}|M_0)$ $\overline{\Pr(oldsymbol{X}|M_0)}\Pr(oldsymbol{\overline{X}}_i|M_0)$ $= rac{\Pr(oldsymbol{X}_i|M_i)}{\Pr(oldsymbol{X}_i|M_0)}$ $\mathrm{BF}_{\mathrm{reg}} = rac{\mathrm{Pr}(\boldsymbol{X} \mid M)}{\mathrm{Pr}(\boldsymbol{X} \mid M_0)}$ $= \frac{\sum_{i=1}^{k} \Pr(\boldsymbol{X} \mid M_i) \Pr(M_i \mid M)}{\Pr(\boldsymbol{X} \mid M_0)}$

$$= \sum_{i=1}^{k} \operatorname{BF}_{i} \operatorname{Pr}(M_{i} \mid M).$$

Maybe there is more than one causal SNP?

Causal configuration γ

Fig. 1. The binary indicator vector γ determines which SNPs have non-zero causal effects (). The corresponding causal ...

0

0

0 2.1 0 0.1 0 0 0 3.1 0 0 Causal SNP effects λ

1.3 2.0 0.7 0.2 1.5 0.3 0.2 3.2 2.9 0.1 MLE $\hat{\lambda}$

0

User-specified prior variance for causal SNPs

JOURNAL ARTICLE

FINEMAP: efficient variable selection using summary data from genome-wide association studies 3

Christian Benner ख़, Chris C.A. Spencer, Aki S. Havulinna, Veikko Salomaa, Samuli Ripatti, Matti Pirinen ⊠ Author Notes

Variance of the trait

 $p(\boldsymbol{\lambda}|\boldsymbol{\gamma}) = \mathbf{N}(\boldsymbol{\lambda}|\mathbf{0}, s_{\boldsymbol{\lambda}}^{2}\boldsymbol{\sigma}^{2}\boldsymbol{\Delta}_{\boldsymbol{\gamma}}),$

Diagonal matrix with elements of gamma on the diagonal

Many methods for multiple causal variants

Caviar - 2014

Caviarbf - 2015

PAINTOR - 2015

FINEMAP - 2016

SuSIE - 2020

COJO and COJO-ABF - 2018

Identifying Causal Variants at Loci with Multiple Signals of Association

Farhad Hormozdiari,*¹ Emrah Kostem,*¹ Eun Yong Kang,* Bogdan Pasaniuc,^{1,2,2} and Eleazar Eskin*^{,2,3} *Department of Computer Science, [†]Department of Human Genetics, and [‡]Department of Pathology and Laboratory Medicine, University of California, Los Angeles, California 90095

Fine Mapping Causal Variants with an Approximate Bayesian Method Using Marginal Test Statistics

Wenan Chen,* Beth R. Larrabee,* Inna G. Ovsyannikova,[†] Richard B. Kennedy,[†] Iana H. Haralambieva,[†] Gregory A. Poland,[†] and Daniel J. Schaid*.¹ *Division of Biostatistics and [†]Mayo Clinic Vaccine Research Group, Mayo Clinic, Rochester, Minnesota 55905

Integrating Functional Data to Prioritize Causal Variants in Statistical Fine-Mapping Studies

Gleb Kichaev, Wen-Yun Yang, Sara Lindstrom, Farhad Hormozdiari, Eleazar Eskin, Alkes L. Price, Peter Kraft, Bogdan Pasaniuc 🗃

> JOURNAL ARTICLE FINEMAP: efficient variable selection using summary data from genome-wide association studies Christian Benner Z, Chris C.A. Spencer, Aki S. Havulinna, Veikko Salomaa, Samuli Ripatti, Matti Pirinen Z Author Notes

JOURNAL ARTICLE

A Simple New Approach to Variable Selection in Regression, with Application to Genetic Fine Mapping 👌

Gao W ARTICLE

DOI: 10.1038/s41467-017-02317-2 OPEN

Causal associations between risk factors and common diseases inferred from GWAS summary data

Zhihong Zhu¹, Zhili Zheng¹², Futao Zhang¹, Yang Wu¹, Maciej Trzaskowski¹, Robert Maier⁰, Matthew R. Robinson⁰, John J. McGrath⁰, ^{3,4,5}, Peter M. Visscher⁰, ¹³, Naomi R. Wray⁰, ¹³ & Jian Yang⁰, ¹³

Handy guide to assumptions differences in methods

	1	2
y	quantitative	binary
X	genotype	genotype and heterozygote
β	fixed	random

Paper	Assumptions
BIMBAM [Servin and Stephens, 2007]	y (1), X (2), β (2)
Maller et al. [Maller et al., 2012]	y (2), X (2), β (2)
fgwas [Pickrell, 2014]	y (1)(2), X (1), β (2)
CAVIAR [Hormozdiari et al., 2014]	$y(1)(2), X(1), \beta(1)(2)$
CAVIARBF [Chen et al., 2015]	y (1)(2), X (2), β (2)
PAINTOR [Kichaev et al., 2014]	y (1)(2), X (1), β (1)
FINEMAP [Benner et al., 2016]	y (1)(2), X (1), β (2)
SuSiE [Wang et al., 2018]	y (1), X (1), β (2)

Fine-mapping quantifies causal probability



Posterior inclusion probability (PIP)

• Probability under the model, given the data, that the variant is causal for the disease

95% credible set (CS)

 Smallest set of variants for a <u>single effect</u> that together have > 95% probability of being causal for the disease

Jacob Ulirsch

How robust are these methods? Replication Failure Rate



https://www.biorxiv.org/content/10.1101/2022.10.21.513123v1.full.pdf

position on chromosome

credible set 2

0.5

0.25

Replication Failure Rate





https://www.biorxiv.org/content/10.1101/2022.10.21.513123v1.full.pdf

What about modeling an 'infinitesimal' contribution?

Take this model

$$p(\boldsymbol{\lambda}|\boldsymbol{\gamma}) = \mathbf{N}(\boldsymbol{\lambda}|\mathbf{0}, s_{\boldsymbol{\lambda}}^2 \sigma^2 \boldsymbol{\Delta}_{\boldsymbol{\gamma}}),$$

And add this consideration:

$$\pi_0 N(0,s^2) + (1-\pi_0)\delta_0.$$



Adding functional information improves but does not guarantee replicability!



How does the associated variant impact function?



This is the GWAS!



How does the associated variant impact function?



This is the an eQTL study eQTL = expression quantitative trait locus

Exploring eQTL resources



Navigate to https://gtexportal.org/home

Click QTL browser

Click Locus Browser (Gene-centric)

🛃 GTEx Portal



Explore your favorite gene!

Example – <u>AKAP11</u>



Can we test whether these associations are the same? COLOC

PLOS GENETICS	BROWSE	PUBLISH	ABOUT	SEARCH	advanced search
GOPEN ACCESS 💆 PEER-REVIEWED				977 Save	1,459 Citation
Bayesian Test for Colocalisation betw Association Studies Using Summary S Claudia Giambartolomei 🖾, Damjan Vukcevic, Eric E. Schadt, Lude Franke, Arc	52,240 View	9 Share			

Published: May 15, 2014 • https://doi.org/10.1371/journal.pgen.1004383

Limited statistical evidence for shared genetic effects of eQTLs and autoimmune-disease-associated loci in three major immune-cell types

Sung Chun¹⁻³, Alexandra Casparino⁴, Nikolaos A Patsopoulos^{3,5,6}, Damien C Croteau-Chonka^{2,7}, Benjamin A Raby^{2,7}, Philip L De Jager^{2,3,5,6}, Shamil R Sunyaev^{1-3,8} & Chris Cotsapas^{3,4,9}

JLIM model – maximum likelihood treatment rather than Bayesian

- > \mathbb{H}_0 : No association with either trait
- > H1: Association with trait 1, not with trait 2
- > H₂: Association with trait 2, not with trait 1
- > H₃: Association with trait 1 and trait 2, two independent SNPs
- > H₄: Association with trait 1 and trait 2, one shared SNP

$$P(H_h|D) \propto \sum_{S \in S_h} P(D|S)P(S)$$

PP4

 $= P(H_4|D)$

$P(H_4 D)$
$= P(H_0 D) + P(H_1 D) + P(H_2 D) + P(H_3 D) + P(H_4 D)$
$\frac{P(H_4 D)}{P(H_4 D)}$
$=$ $\frac{P(H_0 D)}{D}$
$1 + \frac{P(H_1 D)}{P(H_0 D)} + \frac{P(H_2 D)}{P(H_0 D)} + \frac{P(H_3 D)}{P(H_0 D)} + \frac{P(H_4 D)}{P(H_0 D)}$

Managing multiple variants

Limited statistical evidence for shared genetic effects of eQTLs and autoimmune-disease-associated loci in three major immune-cell types

Sung Chun¹⁻³, Alexandra Casparino⁴, Nikolaos A Patsopoulos^{3,5,6}, Damien C Croteau-Chonka^{2,7}, Benjamin A Raby^{2,7}, Philip L De Jager^{2,3,5,6}, Shamil R Sunyaev^{1-3,8} & Chris Cotsapas^{3,4,9}

Naturally fits into the methodology

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G OPEN ACCESS 🖻 PEER-REVIEWED				140 Save	42 Citation	
A more accurate method for colocalis for multiple causal variants	ation ar	nalysis all	owing	6,668 View	38 Share	

Coloc multivariate extension

Version 2

Published: September 29, 2021 • https://doi.org/10.1371/journal.pgen.1009440

Alternate approaches – with potential specificity challenges

ARTICLES

genetics

TECHNICAL REPORTS

Integrative approaches for large-scale transcriptome-wide association studies

Alexander Gusev¹⁻³, Arthur Ko^{4,5}, Huwenbo Shi⁶, Gaurav Bhatia¹⁻³, Wonil Chung¹, Brenda W J H Penninx⁷, Rick Jansen⁷, Eco J C de Geus⁸, Dorret I Boomsma⁸, Fred A Wright⁹, Patrick F Sullivan¹⁰⁻¹², Elina Nikkola⁴, Marcus Alvarez⁴, Mete Civelek¹³, Aldons J Lusis^{4,13}, Terho Lehtimäki¹⁴, Emma Raitoharju¹⁴, Mika Kähönen¹⁵, Ilkka Seppälä¹⁴, Olli T Raitakari^{16,17}, Johanna Kuusisto¹⁸, Markku Laakso¹⁸, Alkes L Price¹⁻³, Päivi Pajukanta^{4,5} & Bogdan Pasaniuc^{4,6,19}

TWAS

A gene-based association method for mapping traits using reference transcriptome data

Eric R Gamazon^{1,2,9}, Heather E Wheeler^{3,9}, Kaanan P Shah^{1,9}, Sahar V Mozaffari⁴, Keston Aquino-Michaels¹, Robert J Carroll⁵, Anne E Eyler⁶, Joshua C Denny⁵, GTEx Consortium⁷, Dan L Nicolae^{1,4,8}, Nancy J Cox^{1,2,4} & Hae Kyung Im¹

PrediXcan

nature

genetics

TWAS and PrediXcan descriptions





TWAS

Why ought we be concerned?

PrediXcan

Wright-Fisher

EVOLUTION IN MENDELIAN POPULATIONS

SEWALL WRIGHT University of Chicago, Chicago, Illinois

Received January 20, 1930

THE GENETICAL THEORY OF NATURAL SELECTION

BY R. A. FISHER, Sc. D., F.R.S.

OXFORD AT THE CLARENDON PRESS 1930

Wright 1930



Site frequency spectra



Empirical SFS – very close to drift



Variance explained (alpha =0) – effect size is constant across frequency spectrum



Recall variance explained is 2pqa²

When we add the SFS + variance explained when alpha =0



Few preparatory remarks for the hall session

Microarray (genotyping)

QC removes loci with bad binding chemistry

Samples can be assigned highconfidence genotype calls at remaining loci

PLINK BED files include AA/AB/BB/NA call states, no probability information.



Microarray + imputation

Genotypes at directly measured SNPs are "hard calls"

Genotypes at imputed SNPs are **probability distributions** over possible genotype states, or a **genotype dosage**.

Oxford BGEN files contain probabilities for each genotype configuration.



Reference Haplotypes







Reference Haplotypes

С	G	Α	G	Α	т	С	т	С	С	т	т	С	т	т	С	т	G	т	G	С
С	G	Α	G	Α	Т	С	т	С	С	С	G	Α	С	С	т	С	Α	т	G	G
С	С	Α	Α	G	С	т	С	т	т	Т	т	С	т	т	С	т	G	т	G	С
С	G	А	Α	G	С	т	С	т	т	т	т	С	т	т	С	т	G	т	G	С
С	G	Α	G	А	С	т	С	т	С	С	G	А	С	С	т	т	Α	т	G	С
т	G	G	G	А	т	С	т	С	С	С	G	А	С	С	т	С	Α	т	G	G
С	G	А	G	Α	т	С	т	С	С	С	G	А	С	С	т	т	G	т	G	С
С	G	Α	G	Α	С	т	С	т	т	т	т	С	т	т	т	т	G	т	А	С
С	G	Α	G	Α	С	т	С	т	С	С	G	Α	С	С	т	С	G	т	G	С
С	G	Α	Α	G	С	Т	С	Т	Т	Т	Т	С	Т	Т	С	т	G	т	G	С



So where do sequencing data originate?

High-throughput sequencing

Also called:

- Shotgun sequencing
- Short read sequencing
- Next generation sequencing

Genome is broken down into small segments, and many segments are read in parallel

Segments are computationally assembled into a complete sequence using overlaps (*de novo assembly*) or aligned against an existing reference genome (alignment).



Illumina NovaSeqX 3 Terabases per flow cell run

From unmapped reads to true genetic variation in nextgeneration sequencing data Raw short reads NovaSeq A single run of a sequencer generates 2400-3000 GB ~150bp short reads

Quality calibration and annotation



The quality of each read is calibrated and additional information annotated for downstream analyses

Identifying genetic variation



SNPs and indels from the reference are found where the reads collectively provide evidence of a variant

Data processing and analysis methods



Sequenced variant calls

- GT best-guess genotype.
 - 0/0 for homozygous reference, 1/2 for heterozygous non-reference, ./. for missing
- GQ conditional genotype quality.
 - GQ 10, 20, 30 indicate 90%, 99%, 99.9% confidence in GT.
- DP total read depth
- AD read depth by allele.
 - AD = [10, 8] indicates 10 reads from the reference, 8 from first alternate.
- PL scaled likelihoods of each genotype configuration.

Sequencing data QC...

... is hard. For a few:

- depth is important: contamination and mapping errors can cause spurious heterozygous calls
- Low-complexity regions are filled with insertions and deletions that defy a fixed reference genome
- Handling multiallelic sites is complicated, and often necessary