Phenome-scale directed network discovery with bi-directional mediated Mendelian randomization

Brielin C. Brown Data Science Institute Fellow, Columbia University Knowles and Lappalainen labs, New York Genome Center

A GWAS



Chromosome

Some of the polygenic background comes from effects of other traits



Y-axis clipped at 40 for comparison*





Asthma

Y-axis clipped at 40 for comparison*





Eosinophil %

Asthma

Mendelian Randomization is used to estimate the effect



Phenotypes live in directed networks



SNPs



Trait Class	Example
Blood biomarker	Cholesterol
Blood composition	White blood cell count
Blood trait	Mean sphered cell volume
Immune-related disease	Psoriasis
Heart-related	Illness of father: heart disease
Other disease	Basal cell carcinoma
Morphological	Hip circumference
Dietary	Alcohol intake frequency
Behavioral	Getting up in morning
Neurological	Anxious feelings
Eye-related	3mm weak meridian
Other	Average income before tax

bimmer = estimation of directed networks in biobanks

A simple model can capture network and genetic effects

$$Y_{j} = \sum_{i \neq j} Y_{i}G_{ij} + \sum_{m} X_{m}\beta_{mj} + \gamma$$
Phenotype
$$I = YG + X\beta + \gamma$$

$$Y_{j} = YG + X\beta + \gamma$$

The graph can be determined from the total effects



 $Y = YG + X\beta + \gamma$

$\rightarrow G = I - R^{-1} D[1/R^{-1}]$

R: Total effects matrix (important!) R_{ij} = Effect of trait i on j including all paths Estimated through MR

D[A]: Diagonal of A

Gaussian graphical models: $\Omega \cong \Sigma^{-1}$

This result implies a two-step strategy for estimating G



Problem #1: not all traits are observed



Welch-weighted Egger regression reduces false positives due to correlated pleiotropy in Mendelian randomization

Brielin C. Brown^{*1, 2} and David A. Knowles^{†2, 3, 4}

On bioRxiv now!



Method	$\mathrm{FPR} < ~5\%$	$\rm FPR<20\%$	Runtime (s)
WWER	77.4	92.7	0.634
Steiger	76.2	92.1	0.634
CAUSE	81.7	90.9	2958.892
MBE	84.8	89.6	38.140
MMR Mix	76.8	87.2	79.670
Egger	59.8	67.1	0.632
Median	52.4	63.4	8.594
MR PRESSO	45.7	54.3	313.527
raps	39.0	50.0	0.684
IVW	36.0	40.2	0.640
aps	35.4	39.6	0.635

WWER efficiently handles correlated pleiotropy



Beta B

-0.2 -0.1 0.0 0.1



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Problem #2: we only have an estimate of R

 $G = I - R^{-1}D[1/R^{-1}]$

versus

 $\hat{G} = I - \hat{R}^{-1} D[1/\hat{R}^{-1}]$

Recast matrix inversion as a constrained optimization problem

Find matrices U, V such that UV=I that minimize the loss:

$$\left| \left| W \circ \left(\hat{R} - U \right) \right| \right|_{F}^{2} + \lambda \sum_{i \neq j} |V_{ij}|$$

Fit with alternating direction method of multipliers (ADMM) Select λ with adaptation of *stability* criteria in GLASSO

Inverse Sparse Regression (inspre)

bimmer = bi-directed MR + sparse mediation analysis



bimmer performs well in simulation



bimmer

biobank

A wonderful resource for exploratory data analysis

>9000 phenotypes filtered to 411 based on h2 and rg

149 with >5 independent GWAS SNPs

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Directed graph on 149 UK Biobank phenotypes

WWER total effect estimates



2702 significant q < 0.05

Shrunk total effect estimate (U)



Directed graph estimate (G)



1658 entries > |0.01|Ubiquitous smaller effects 843 non-zeros

Directed graph on 149 UK Biobank phenotypes



The shortest path often explains only some of the effect



In and out-degree distributions are exponential





Causes and consequences of IMID

Exposure	Outcome	Path Length
SR: psoriasis	Alcohol intake frequency.	1
Impedance of leg (right)	SR: DVT	1
White blood cell (leukocyte) count	SR: psoriasis	1
Platelet crit	DD: Hayfever, etc	1
Platelet distribution width	SR: asthma	1
SR: psoriasis	Miserableness	1
Lymphocyte count	SR: psoriasis	2
SR: psoriasis	Mood swings	1
SR: psoriasis	SR: high cholesterol	1
SR: psoriasis	Fed-up feelings	1



Causes and consequences of diet



Average weekly beer intake

Causes and consequences of heart-related traits



Systolic blood pressure, automated

To conclude

- Biobanks hold tremendous promise for exploratory data analysis
 - Can be challenging to find creative analyses that leverage their multifactoral nature
- *bimmer* combines genetic instruments with sparse graph methods to generate *putatively causal* directed graphs from biobank-style data
 - I discourage making formal causal claims from large-scale analyses
- Our results suggest a large amount of the polygenic background for complex traits is explained by small, long-range effects of other phenotypes
 - This is related to the omnigenic concept, but says nothing about core genes
- Preprints and code are available!
 - bimmer: <u>https://bit.ly/3dY1RI3</u>, <u>https://github.com/brielin/bimmer/</u>
 - WWER: <u>https://bit.ly/2PYrIXi</u>, <u>https://github.com/brielin/WWER/</u>
 - <u>bb2991@columbia.edu</u>, Twitter: @brielinb

Thank you for listening!

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