UNIVERSITY of WASHINGTON

## Session 12:

Mendelian Randomization

## Drawback of observational studies

## CONFOUNDING


sChool of public health

## We can leverage genetic variation to (partly) overcome these issues



## Mendelian Randomization

> Basic principle: "genetic variants which mirror the biological effects of a modifiable environmental exposure and alters disease risk should be associated with disease risk to the extent predicted by their influence on exposure to the risk factor."
> The random allocation of genetic variants from parents to offspring means these variants will generally be unrelated to other factors which affect the outcome.
> Furthermore, associations between the genotype and the outcome will not be affected by reverse causation
 because disease does not affect genotype

## Possible effects of C-reactive protein (CRP) concentrations on cardiovascular (CV) events

Expected outcome from hypothetical randomized clinical trial of selective CRP-lowering intervention, and from Mendelian randomization analysis, if CRP were causal in developing CV.


## The three key assumptions in MR analyses

1. Relevance assumption: G (SNP or a combination of SNPs) is robustly associated with X (exposure)
2. Independence assumption: G is unrelated to any confounders $C$, that can bias the relationship between $G$ and $Y$ (outcome). In other words, there are no common causes of $G$ and $Y$ (e.g., population stratification)

3. Exclusivity assumption: G is related to Y only through its association with $X$-i.e., $G$ is not associated with $Y$ either directly or indirectly through other traits (i.e., no pleiotropy)

## Assumption 1: Relevance assumption

> A "weak" instrument variable (IV) has been defined as having F<10, where

$$
F=\frac{R^{2}(n-1-k)}{\left(1-R^{2}\right) k} \quad \begin{aligned}
& \mathrm{R}^{2} \text { is variance in } \mathrm{X} \text { explained by the } \mathrm{IV}(\mathrm{~s}), \\
& \mathrm{n} \text { is sample size and } \mathrm{k} \text { is number of } \mathrm{V} \mathrm{~s}
\end{aligned}
$$

> Weak IVs can lead to biased effect estimates (in the direction of the observed $X-Y$ association) in the presence of confounding of the $X-Y$ relationship.


## Assumption 2: Independence assumption

> G is independent of factors (measured and unmeasured) that confound the X-Y relationship
> Since G is randomized at birth and thus, independent of non-genetic confounders and not modified by the course of disease, the main concern is population stratification; i.e., if ancestry is related to G and Y .
> If you have individual-level data, you can adjust for this (e.g., PCs)


## Assumption 3: Exclusivity assumption

$>$ This assumption is the trickiest
$>$ Assumes that $G$ is only associated with $Y$ via $X$ and thus the association between $G$ and $Y$ is fully mediated by $X$ and not through any unmeasured factor(s).


## Scenarios invalidating assumption 3



## BREAKOUT ACTIVITY

> In which examples (a-f) below do the MR assumptions not hold for assessing the association between exposure $(\mathrm{X})$ and outcome (Y)? Why? Why not?
a. genetic

b. genetic $\qquad$ mediator $\longrightarrow$ exposure $\longrightarrow$ outcome
c. genetic $\longrightarrow$ exposure $\longrightarrow$ outcome variants $v$
related variable
d. genetic $\longrightarrow$ related variable $\longrightarrow$ outcome variants $v$ exposure
e. genetic $\longrightarrow$ outcome $\longrightarrow$ exposure variants

## BREAKOUT ACTIVITY

> In which examples (a-f) below do the MR assumptions not hold for assessing the association between exposure $(\mathrm{X})$ and outcome (Y)? Why? Why not?
a. genetic variants
b.
c. $\underset{\text { variants }}{\text { genetic }} \longrightarrow \underset{v}{\operatorname{exposure}} \longrightarrow$ outcome
variants related variable
Pathway from $G$ to $Y$ does not pass via the
d. $\underset{\text { variants }}{\text { genetic }} \longrightarrow \underset{\downarrow}{\text { related variable }} \longrightarrow$ outcome exposure exposure; assumptions not met. However, assumptions are met for the related variable, which could instead be tested as the exposure.
e. $\underset{\substack{\text { variants } \\ \text { genetic }} \text { outcome } \longrightarrow \text { exposure }] ~}{l}$ Reverse causation; G incorrectly identified as primarily affecting the exposure

# Best (but oft-forgotten) practices: the design, analysis, and interpretation of Mendelian randomization studies ${ }^{1}$ 

Philip C Haycock, ${ }^{2} *$ Stephen Burgess, ${ }^{3}$ Kaitlin H Wade, ${ }^{2}$ Jack Bowden, ${ }^{2,4}$ Caroline Relton, ${ }^{2}$ and George Davey Smith ${ }^{2}$

TABLE 2
Different design strategies for MR

| Study design |  | Test |
| :--- | :--- | :--- |
| G-X + G-Y | Implies $\mathrm{X} \rightarrow \mathrm{Y}$ | Comments |
| One-sample MR | Various hypotheses | No estimation of magnitude of causal effect |
|  |  | Requires individual-level data; lower power; MR estimates <br> are biased toward the confounded observational |
| association by weak instruments |  |  |

[^0]
## One-sample MR

> Access to SNPs, risk factor, and outcome for all participants
> The causal effect of $X$ on $Y$ can be estimated using 2-stage least-squares (2SLS) regression:

1. $X=a+\gamma G$
2. $\mathrm{Y}=\mathrm{c}+\beta X^{*}$, where $X^{*}$ are the genetically predicted exposure levels as measured in (1)
> The causal estimate is given by $\beta$
> Can be implemented in R using the "ivpack" package
$>$ Weak IVs cause bias towards the confounded X-Y association

## Two-sample MR

> GWAS summary statistics for G-X and the G-Y associations are estimated in two non-overlapping samples.
> Assumes the two populations are similar (ancestry, age, etc.)
> Weak IVs cause bias towards the null
> Note: The G-X and G-Y associations need to be coded using the same effect allele

## Two-sample MR

## Example IV criteria (can vary) based on G-X

- Genome-wide significant variants ( $\mathrm{P}<5 \times 10^{-8}$ )
- Independent (e.g., r²<0.10)
- Common (MAF>1\%, if sufficiently large N )
- Exclude palindromic variants (e.g., A/T, G/C) if MAF~50\%
- Exclude incompatible alleles between G-X and G-Y (e.g., if a variant has A/G alleles for exposure but A/C for outcome

Extract these variants from G-X and G-Y GWAS summary statistics to conduct MR

## Two-sample MR: Inverse-variance weighted (IVW) method to estimate the causal effect of $X$ on $Y$

$$
\begin{aligned}
& \hat{\beta}=\frac{\sum_{k} \beta_{1 k} \beta_{2 k} \sigma_{\beta_{2 k}}^{-2}}{\sum_{k} \beta_{1 k} \sigma_{\beta_{2 k}}^{-2}} \\
& \operatorname{se}(\hat{\beta})=\sqrt{\frac{1}{\sum_{k} \beta_{1 k}^{2} \sigma_{\beta_{2 k}}^{-2}}}
\end{aligned}
$$

$\beta_{1 k}$ is the mean change in $X$ per allele for SNP $k, \beta_{2 k}$ is the mean change in $Y$ per allele for SNP $k, \sigma_{\beta 2 k}^{-2}$ is the inverse variance for the G-Y association.

## MR-base: An easy tool for Mendelian Randomization Analysis

> http://app.mrbase.org/
> A web-based platform (MR-Base) and an R-package "TwoSampleMR".
> Has catalogued thousands of genotype-phenotype associations and also allows manual file upload.

To begin analysis in the web application please review the data access agreement and accept by logging in with your google account.

## $\infty$ MRBASE

## A platform for Mendelian randomisation using summary data from genome-wide association

studies

## Current status

Beta phase release
App version:
1.2.2 3a435d (31 January 2019)

R version
3.5.1

Host:
e4ec2116cb55
R/TwoSampleMR version:
0.4.18

Database version:
0.2.0 (17 December 2017 )

To use MR-Base using the TwoSampleMR R package directly; https://github.com/MRCIEU/TwoSampleMR
See our sister website LD Hub for automated LD score regression:
http://dsc.broadinstitute.org/
@)MRBASE

## ©MRBASE

IV Acknowledgements Data access agreement

## TwoSampleMR R package

## Hongjie Che

 hongjie.chen41@gmail.com
## A platform for Mendelian randomisation using summary data from genome-wide association

studies

Select the exposure (Instrumental variable),
outcome and analysis scheme here.

To begin analysis in the web application please review the data access agreement and accept by logging in with your google account.


## Current status

Beta phase release
App version:
1.2.2 3a435d (31 January 2019)

R version:
3.5.1

Host:
e4ec2116cb55
R/TwoSampleMR version:
0.4.18

Database version:
0.2 .0 ( 17 December 2017)

To use MR-Base using the TwoSampleMR R package directly:
https://github.com/MRCIEU/TwoSampleMR
See our sister website LD Hub for automated LD score regression:
http://ldsc.broadinstitute.org/

Logged in as
Hoogsie Chen
hongiechenA1@mailicom
\& Peform MR analysis
\#choose exposures
$\equiv$ choose outcomes
$\equiv \mathrm{Run} \mathrm{MR}$
Q Quick SNP lookup


## 

Choose instrumen
Select exposure source
O Manual file upload
O NHGR1-EEI GWAS catalog

- mR Base GWAS catalog
- Gene expression QTLS
- Protein level QTLs
0 Metabolite level QTLS
O Metabolite level OTLL
O Methylation level QTLs
$p$-value threshold

| 5e-08 | 0.001 |
| :--- | :--- |
| - Perform clumping | Clumping distance (kb) |
|  | 10000 |

Display columns
$\square$
0
Trait
Trait
Note
Show $10 \checkmark$ entries
10 it

MR Base GWAS catalog
The MR Base database holds a collection of the summary statistics from a large number of GWASs. It is possibie to use this resource to manually identify instruments, and to therefore use these traits as exposures by find ing the independent GWAS significant hits from these summary
associations.
To use a trait a as an exposure, highlight the relevant row in the table below (multiple traits can be selected). All sNPs with p values below the specified threshold will be extracted, and clumping will be used to remove SNPs in Lo with sentinal SNPs. These SNPs will be used as instruments
To use a trait as as ene
in the MR analysis.


| LD Rsq |  |  |  |
| :---: | :---: | :---: | :---: |
| 0.001 |  |  |  |
| Clumping distance (kb) |  |  |  |
| 10000 |  |  |  |
| - First author | $\square$ Sample size | $\square$ Access | $\square$ sd |
| - Consortium | 0 Number of variants | $\square$ Category | $\square$ Sex |
| - Number of cases | $\square$ year | - Population | - Subcategory |
| 0 Number of co | $\square$ Pubm | $\square$ | $\square$ |

[^1]
## @OMRBASE

## © Welcome to MR Base

i About
© Acknowledgements

* Data access agreement

TwoSampleMR R package

## Logged in as Hongie Ch

 hongile Chenhongie.chen41@gmail.com
© Perform MR analysis \# Choose exposures $\equiv$ Choose outcomes三 Run MR

Q Quick SNP lookup

Select outcomes for analysis
The MR Base database houses a large collection of summary statistic data from hundreds of GWAS studies. In order to perform two sample MR, the SNPS that were selected for the exposures will be extracted from the outcomes that you select here. Please select the outcomes that you want to test for being causally influenced by the exposures.

## Studies available in MR base

| Display columns | $\square$ Firstauthor | $\square$ Sample size | $\square$ Access | $\square \mathrm{Sd}$ |
| :---: | :---: | :---: | :---: | :---: |
| $\square \mathrm{ID}$ | $\square$ Consortium | - Number of variants | - Category | $\square$ Sex |
| $\checkmark$ Trait | - Number of cases | $\square$ Year | $\square$ Population | - Subcategory |
| $\checkmark$ Note | - Number of controls | $\square$ Pubmedid | $\square$ Priority | $\square$ Unit |

$\square$ Number of variant
$\square$ PubmedID

Select the outcome GWAS data to be used

Search:
of $\mid \uparrow \quad$ Number of $\mid \uparrow \quad$ i $\dagger$
10597

GWAS meta analysis)
1127 ER + Breast cancer (Combined Oncoarray;
iCOGS; GWAS meta analysis)
iCOGS; GWAS meta analysis)
1128 ER-Breast cancer (Combined Oncoarray;
iCOGS; GWAS meta analysis)
1129 Breast cancer (Oncoarray)
1130 Breast cancer (iCOGS)
1131 Breast cancer (GWAS)
1132 ER + Breast cancer (Oncoarray)
1133 ER + Breast cancer (iCOGS)
1134 ER + Breast cancer (GWAS)
1135 ER- Breast cancer (Oncoarray)
Breast Cancer
Breast Cancer
Showing 1 to 10 of 28 entries filtered from 21,266 total entres Search for the outcome of interest

## @oMRBASE

## © Welcome to MR Base <br> i About <br> II Acknowledgements <br> > Data access agreement <br> TwoSampleMR R package <br> <br> $\equiv$ Run MR <br> <br> Q Quick SNP lookup

 <br> <br> ongife Che <br> <br> ongife Che hongjie.chen41@gmail.com hongjie.chen41@gmail.com <br> <br> \& Perform MR analysis <br> <br> \& Perform MR analysis <br> <br> \# Choose exposures <br> <br> \# Choose exposures <br> <br> $\equiv$ Choose outcomes <br> <br> $\equiv$ Choose outcomes <br> Use clumping to prune SNPs for LD <br> LD proxies <br> a particular exposure SNP is not present in an outcome dataset, should proxy SNPs be used instead through LD tagging? <br> $\square$ Use proxies? <br> Minimum LD Rsq value <br> 0.6 0.8 <br>  <br> Allow palindromic SNPs? <br> MAF threshold for aligning palindromes <br> }
## LD clumping

Most two sample MR methods require that the instruments do not have LD between them.

## Linkage disequilibrium

O Do not check for LD between SNPs

## Allele harmonisation

An important step in two sample MR is making sure that the effects of the SNPs on the exposure correspond to the same allele as their effects on the outcome. This is potentially difficult with palindromic SNPs.

## Handling reference alleles

O All effect alleles are definitely on the positive strand
O Attempt to align strands for palindromic SNPs
O Exclude palindromic SNPs

## Select methods for analysis

Many methods exist for performing two sample MR. Different methods have sensitivities to different potential issues, accommodate different scenarios, and vary in their statistical efficiency.

## choose which methods to use:

## $\checkmark$ Wald ratio

$\square$ Maximum likelihood

- MR Egger
$\square$ MR Egger (bootstrap)
$\square$ Simple median
- Weighted median
$\square$ Penalised weighted median
$\nabla$ Inverse variance weighted
$\square$ IVW radial
$\square$ Inverse variance weighted (multiplicative random effects)
$\square$ Inverse variance weighted (fixed effects)
$\square$ Simple mode
$\square$ Weighted mode
$\square$ Weighted mode (NOME)
$\square$ Simple mode (NOME)
Robust adjusted profile score (RAPS)
$\square$ Sign concordance test
$\square$ Unweighted regression


## Submit

 perform the analysis.
## 4 Perform MR analysis

After setting up the analysis scheme, click here to submit the request to perform the MR analysis

## MR results

Select analysis
Exposure

- Age at menopause || id:1004

Outcome

- Breast cancer (Combined Oncoarray; iCOGS; GWAS meta analysis) || id:1126
© Welcome to MR Base
i About
Ib Acknowledgements
> Data access agreement

TwoSampleMR R package

## Logged in as

Hongjie Chen
hongjie.chen41@gmail.com
© Perform MR analysis
$\equiv$ Choose exposures
$\equiv$ Choose outcomes
\#Run MR
MR Results
Q Quick SNP/ookup

上 Generate HTML report

Exposure details
Name: Age at menopause
D: 1004
Number of instruments used: 42
Units: years
Number of cases: NaN
Number of controls: NaN
Sample size: 69360
PubmedID: 26414677
First author: Day
Consortium: ReproGen
Year: 2015

Outcome details
Name: Breast cancer (Combined Oncoarray; COGS; GWAS meta analysis)
D: 1126
SNPs in GWAS: 10680257

Number of instruments identified: 35
... of which are LD proxies: 0 \# of instruments were found in the outcome GWAS, Units: log odds
Number of cases: 122977
Number of controls: 105974
Sample size: 228951
PubmedID: 29059683
First author: Michailidou K
Consortium: BCAC
ear: 201

## Downloads for all analyse

д Download harmonised summary statistics
』 Download MR results
$\downarrow$ Download leave-one-out sensitivity analysis

[^2]This table shows the MR estimates from each method of the causal effect of the exposure on the outcome. The effects are reported in the units that were used to estimate the SNP effects.

Test statistics corresponding to MR analysis approaches selected.

Method comparison plot
Single SNP analysis
The causal effect of exposure on outcome is estima
using each SNP singly using the Wald ratio, and using each SNP singly using the Wald ratio, and
represented in a forest plot. The MR estimate using all represented in a forest plot. The MR estimate using a
SNPs using the MR Egger and IVW methods are also SNPs using the MR Egger and IVW methods are also
shown. Formal estimates of heterogeneity are shown in shown. Formal es
the tables below.
$\star$ Download PDF of this graph which were used in the MR analysis.

Leave-one-out analysis Funnel plot
Graphs

Causal effect of exposure on outcome, by SNP

Evidence of heterogeneity of associations (confirmed in "Heterogeneity statistics" tab) suggests some SNPs exhibit horizontal pleiotropy.
...but MR-Egger is unbiased even if heterogeneity assumption is violated, and MR-Egger is significant here.

## BREAKOUT ACTIVITY

> (Explore MR-Base (http://www.mrbase.org) to conduct your own MR study. Run an MR study of smoking pack years and lung cancer risk following the example in class. )

## Bidirectional MR analysis

> Approach to overcome reverse causation $(\mathrm{X} \leftarrow \rightarrow \mathrm{Y}$ )
$>$ IVs for both X and Y are used to assess the causal association in both directions

1. Is $G_{X}$ associated with $Y$ ?
2. Is $G_{Y}$ associated with $X$ ?
(Also confirm that $G_{X}$ is associated with $X$ and that $G_{Y}$ is associated with $Y$


## BMI and CRP - what causes what?

## > There is a consistent observed association between high BMI and high CRP levels

Gray: 95\% CI for FTO loci as IV for residual BMI.


Gray: 95\% CI for CRP locus rs3091244 as IV for CRP.


Blue dots represent a scatter plot of the correlation between circulating CRP and residual BMI. Gray areas represent 95\% confidence regions around IV estimates. Black area represents 95\% confidence regions around simple linear regression estimates.

> The observed association between circulating CRP and measured BMI is suggested to be driven by BMI, with adiposity causally influencing circulating CRP levels and not vice-versa

Table 5. Observational and instrumental variable derived relationships between BMI and circulating CRP.

| 4 Previous table | - Figures and tables index |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Effect estimates |  |  |  |  |
| Outcome /explanatory variable | Observational | Instrumental variable | $\mathrm{P}_{\text {IV }}$ | $\mathbf{P}_{\text {diff }}$ | $F_{\text {first }}$ |
| CRP/BMI | 1.46 (1.44, 1.48) | 1.41 (1.10, 1.80) | 0.006 | 0.8 | 31.1 |
| BMI/CRP | 1.03 (1.00, 1.07) | -0.24 (-0.58, 0.11) | 0.2 | <0.0001 | 57.3 |

## Considerations for MR analyses

> Large sample sizes are needed

- As genetic effects on risk factors are typically small, MR estimates of association have much wider confidence intervals than conventional epidemiological estimates.
> Consider the three core assumptions and how they apply in your study
- In practice, this is very difficult, especially for the third assumption of no pleiotropy.
> Look for consistency across MR approaches
- Tells you how robust your results are given the different assumptions
> In the end, it is a helpful tool to complement observational findings
- You can never assume causality because you can never be 100\% sure that all assumptions are met

Table 1. Summary of some methods proposed for Mendelian randomization: inverse-variance weighted method and robust methods.
$\left.\begin{array}{|l|l|l|l|l|l|}\hline \text { Method } & \begin{array}{l}\text { Consistency } \\ \text { assumption }\end{array} & \text { Strengths and weaknesses } & \text { Reference } & \text { Software } \\ \hline \begin{array}{l}\text { Inverse-variance } \\ \text { weighted }\end{array} & \begin{array}{l}\text { All variants valid or } \\ \text { balanced pleiotropy }\end{array} & \begin{array}{l}\text { Most efficient (greatest statistical power), biased if average } \\ \text { pleiotropic effect differs from zero }\end{array} & 18 & & \text { * } \\ \hline \text { MR-Egger } & \text { InSIDE } & \begin{array}{l}\text { Sensitive to outliers, sensitive to violations of InSIDE assumption, } \\ \text { InSIDE assumption often not plausible, often less efficient }\end{array} & 19 & \text { * }\end{array}\right\}$

Each of the methods in the table can be implemented using summarized data. False positive rates refer to the simulation study by Slob and Burgess ${ }^{27}$. InSIDE is the Instrument Strength Independent of Direct Effect assumption.

## Mendelian Randomization in R

> Encodes several methods for performing Mendelian randomization analyses with summarized data. Summarized data on genetic associations with the exposure and with the outcome can be obtained from large consortia. These data can be used for obtaining causal estimates using instrumental variable methods.
> https://cran.r-project.org/web/packages/MendelianRandomization/index.html
> https://www.youtube.com/channel/UCHjMrVSqOu1rcrYQPAD bNA

| Uploads > PLAY ALL |  |  |
| :---: | :---: | :---: |
|  |  |  |
| Multivariable MR using the MVMR R Package | Summary MR using the RadialMR R Package | Summary MR, MRBase and the TwoSampleMR R Package |
| 뚜리주 19:36 | 사이.] 20:32 | 40:03 |
| Multivariable MR using the MVMR R Package | Summary MR using the RadialMR R Package | Introduction to MRBase and TwoSampleMR |
| 1 K views $\cdot 1$ year ago | 555 views - 1 year ago | 2.9 K views $\cdot 1$ year ago |


[^0]:    ${ }^{1} \mathrm{G} \times \mathrm{E}$, gene-environment interaction; G-X, SNP-exposure association; G-Y, SNP-outcome association, M, mediator; MR, Mendelian randomization; SNP, single nucleotide polymorphism; X, hypothesized exposure; Y, outcome variable of interest.

[^1]:    Showing 1 to 10 of 21,266 entries

[^2]:    Download single SNP MR results

