## MVMR LASSO analysis

## Eleanor Sanderson

```
colnames(df) <- paste("Column", original_cols, sep="-")
setwd(projectfolder)
linker <- read_csv("linker.csv")</pre>
## Rows: 488377 Columns: 2
## -- Column specification -----
## Delimiter: ","
## chr (1): ieu
## dbl (1): app
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
dat <- as_tibble(phenodat) %>%
  rename(app=eid) %>%
  inner_join(linker, by="app")
dat <- dat %>%
  rename(FID=ieu) %>%
       inner_join(snpdat, by="FID") %>%
      inner_join(PCs, by="FID")
setwd(datafolder)
#add in the scores created using the GWAS effect sizes
educationscore <- read_table2("education.sscore")</pre>
## Warning: 'read_table2()' was deprecated in readr 2.0.0.
## Please use 'read_table()' instead.
##
## -- Column specification ------
     '#FID' = col_character(),
##
##
     IID = col character(),
    NMISS_ALLELE_CT = col_double(),
##
    NAMED_ALLELE_DOSAGE_SUM = col_double(),
    SCORE1_AVG = col_double()
##
## )
```

```
cogscore <- read_table2("cognitive_ability.sscore")</pre>
## Warning: 'read_table2()' was deprecated in readr 2.0.0.
## Please use 'read_table()' instead.
##
## cols(
##
   '#FID' = col_character(),
## IID = col character(),
## NMISS_ALLELE_CT = col_double(),
   NAMED ALLELE DOSAGE SUM = col double(),
   SCORE1_AVG = col_double()
##
## )
educationscore update <- read table2("education new.sscore")</pre>
## Warning: 'read_table2()' was deprecated in readr 2.0.0.
## Please use 'read_table()' instead.
##
## cols(
   '#FID' = col_character(),
##
##
    IID = col_character(),
## NMISS ALLELE CT = col double(),
## NAMED_ALLELE_DOSAGE_SUM = col_double(),
   SCORE1_AVG = col_double()
## )
cogscore_update <- read_table2("cognitive_ability_new.sscore")</pre>
## Warning: 'read_table2()' was deprecated in readr 2.0.0.
## Please use 'read_table()' instead.
##
## -- Column specification ------
## cols(
    '#FID' = col_character(),
    IID = col_character(),
##
    NMISS_ALLELE_CT = col_double(),
##
##
    NAMED_ALLELE_DOSAGE_SUM = col_double(),
##
    SCORE1_AVG = col_double()
## )
educationscore <- educationscore %>%
                      rename(FID = '#FID') %>%
                      rename(edu_grs = SCORE1_AVG)
cogscore <- cogscore %>%
```

```
rename(FID = '#FID') %>%
                          rename(cog_grs = SCORE1_AVG)
educationscore_update <- educationscore_update %>%
                           rename(FID = '#FID') %>%
                          rename(edu_grs_update = SCORE1_AVG)
cogscore update <- cogscore update %>%
                           rename(FID = '#FID') %>%
                          rename(cog_grs_update = SCORE1_AVG)
scores <- educationscore %>%
  inner join(cogscore, by="FID") %>%
  inner_join(educationscore_update, by="FID") %>%
  inner_join(cogscore_update, by="FID") %>%
  select(FID, edu_grs, cog_grs, edu_grs_update, cog_grs_update)
dat <- dat %>%
  inner_join(scores, by="FID")
setwd(projectfolder)
snp_list_edu <- read.table("edu_snplist.txt")</pre>
snp_list_cog <- read.table("cog_snplist.txt")</pre>
source("fsw.R")
```

Data Analysis dataset: UKBiobank

Education SNPs taken from Okbay A, Beauchamp JP, Fontana MA, Lee JJ, Pers TH, Rietveld CA, et al. Genome-wide association study identifies 74 loci associated with educational attainment. Nature. 2016

Cognitive ability SNPs taken from Sniekers S, Stringer S, Watanabe K, Jansen PR, Coleman JR, Krapohl E, et al. Genome-wide association meta-analysis of 78,308 individuals identifies new loci and genes influencing human intelligence. Nat Genet. 2017.

Get the betas for the snps, identify any overlapping SNPs and generate the scores

4 SNPS are in LD across education and IQ lists The pairs are;

IQ: rs10191758, education: rs17824247 IQ: rs13010010, education: rs12987662 IQ: rs41352752, education: rs10061788 IQ: rs78164635, education: rs1008078

Cleaning the phenotype data - rename variables and create the age variable  $\,$ 

- create a list of SNPs for the instruments for the MR analysis
- remove the effect alleles from the column names in the SNP data
- replace edu age with 21 if highest qual is degree
- complete case data only
- remove age leaving education < 10
- standardise cognitive ability
- log bmi

Plot the distributions for each of the main variables used in the analysis

## 2. MVMR estimation

2SLS regression including each snp as a separate instrument

These regressions give similar results to those in Sanderson et al 2019. Differences have arrisen because: - here interim release data has not been excluded from the analysis - fewer covariates have been included in the estimation

Covariates included in each regression are; age, sex and 10 PC's.

Overall the results show that education has a bmi lowering effect and cognitive ability has limited evidence of any effect. When the SNPs are included individually the Sargan statistic is large - indicating substantial heterogenetiy in the results. However the instruments are relatively weak. When the genetic risk scores are used as instruments the instruments are strong and the effect estimates are further from the null for each exposure.

```
##
## Call:
## ivreg(formula = ivformula, data = dat, model = TRUE)
##
## Residuals:
##
        Min
                       Median
                                     30
                  1Q
                                             Max
  -0.72077 -0.11456 -0.01342 0.09806
                                        0.94307
##
##
## Coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept) 3.814e+00 9.259e-02 41.190 < 2e-16 ***
## edu_age
               -3.011e-02 4.795e-03
                                      -6.280 3.41e-10 ***
                           1.265e-02
                                                0.0119 *
## cog
                3.184e-02
                                        2.516
                2.294e-04
                           1.471e-04
                                        1.559
                                                0.1189
## age
## male
                4.129e-02
                           1.328e-03
                                      31.092
                                               < 2e-16 ***
## PC1
                1.623e-04
                           3.785e-04
                                        0.429
                                                0.6681
## PC2
               -6.167e-04
                           3.889e-04
                                      -1.586
                                                0.1128
## PC3
               -6.375e-04
                           3.796e-04
                                       -1.679
                                                0.0931 .
## PC4
                6.650e-05
                           2.925e-04
                                        0.227
                                                0.8201
## PC5
                1.036e-03
                           1.340e-04
                                        7.726 1.12e-14 ***
## PC6
                7.809e-05
                           3.588e-04
                                        0.218
                                                0.8277
                                                0.6729
## PC7
                1.357e-04
                           3.214e-04
                                        0.422
## PC8
               -2.957e-04
                           3.216e-04
                                       -0.919
                                                0.3579
## PC9
               -7.552e-04 1.540e-04
                                      -4.903 9.45e-07 ***
## PC10
                4.316e-04 2.827e-04
                                        1.527
                                                0.1268
##
```

```
## Diagnostic tests:
##
                               df1
                                     df2 statistic p-value
                                              7.76 < 2e-16 ***
## Weak instruments (edu age)
                                89 86048
                                              7.21 < 2e-16 ***
## Weak instruments (cog)
                                89 86048
## Wu-Hausman
                                 2 86133
                                             16.18 9.43e-08 ***
                                            249.57 < 2e-16 ***
## Sargan
                                      NΑ
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.168 on 86135 degrees of freedom
## Multiple R-Squared: -0.08027,
                                   Adjusted R-squared: -0.08044
## Wald test: 110.3 on 14 and 86135 DF, p-value: < 2.2e-16
fsw(indreg)
## Model sample size: 86150
## Sanderson-Windmeijer conditional F-statistics for first stage model:
          F value d.f. Residual d.f. Pr(>F)
## edu_age 1.82516
                     88
                                86048 0.1612
          1.79340
                     88
                                86048 0.1664
## cog
2SLS regression using the weighted scores
grsformula <- as.formula(paste("lnbmi ~ edu age + cog", covars,</pre>
                               "cog_grs", "edu_grs", sep = "+"))
scorereg <- ivreg(grsformula, data=dat, model=TRUE)</pre>
summary(scorereg, diagnostics=TRUE)
##
## ivreg(formula = grsformula, data = dat, model = TRUE)
## Residuals:
       Min
                 1Q
                      Median
                                   3Q
## -0.83436 -0.14848 -0.01108 0.13413 1.36285
## Coefficients:
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 4.441e+00 2.725e-01 16.299 < 2e-16 ***
              -6.306e-02 1.447e-02 -4.359 1.31e-05 ***
## edu_age
               1.116e-01 3.981e-02
                                      2.804 0.00504 **
## cog
## age
               2.146e-04 2.192e-04
                                     0.979 0.32776
## male
               4.067e-02 1.886e-03 21.565 < 2e-16 ***
## PC1
               5.391e-04 5.186e-04
                                     1.040 0.29854
## PC2
              -7.387e-04 5.032e-04 -1.468 0.14211
## PC3
              -9.667e-04 5.117e-04 -1.889 0.05889 .
## PC4
              -3.465e-04 3.989e-04 -0.869 0.38497
## PC5
              1.362e-03 2.208e-04 6.168 6.96e-10 ***
## PC6
               2.651e-05 4.635e-04 0.057 0.95440
```

```
## PC7
              -1.062e-04 4.225e-04 -0.251 0.80161
## PC8
              -3.330e-05 4.284e-04 -0.078 0.93804
## PC9
              -1.316e-03 2.953e-04 -4.457 8.31e-06 ***
## PC10
               1.426e-04 3.792e-04
                                      0.376 0.70678
##
## Diagnostic tests:
##
                               df1
                                     df2 statistic p-value
## Weak instruments (edu_age)
                                 2 86135
                                            275.62
                                                    < 2e-16 ***
## Weak instruments (cog)
                                 2 86135
                                            235.51
                                                   < 2e-16 ***
## Wu-Hausman
                                 2 86133
                                             25.09 1.27e-11 ***
## Sargan
                                 0
                                      NA
                                                NA
                                                         NA
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2164 on 86135 degrees of freedom
## Multiple R-Squared: -0.7919, Adjusted R-squared: -0.7922
## Wald test: 67.19 on 14 and 86135 DF, p-value: < 2.2e-16
```

## fsw(scorereg)

```
##
## Model sample size:
                       86150
##
## Sanderson-Windmeijer conditional F-statistics for first stage model:
            F value d.f. Residual d.f.
##
                                            Pr(>F)
## edu_age 24.83207
                        1
                                  86135 1.6545e-11 ***
## cog
           24.64298
                                  86135 1.9987e-11 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
```

\section(Adaptive LASSO results)

Using the unclumped list of SNPs - and all overlapping SNPs in the list for both exposures.

Some SNPs are excluded from the analysis due to not being present in the UK Biobank data rs10191758 - IQ/overlapping rs13010010 - IQ/overlapping rs4728302 - Education

Adaptive lasso based on 10 fold cross validation

```
\# MVadap.cv(Y,D,ivs,X,alpha = 0.05)
```

Adaptive lasso based on Sargan testing downward selection

```
# MVadap.dt(Y,D,ivs,X,alpha = 0.05, tuning = 0.1/log(length(Y)))
```

Adaptive lasso based on Sargan testing downward selection with a block structure applied to the SNPs

```
# MVadap.dtblock(Y,D,ivs,index1 = c(1:(lengthedu+lengthboth)), index2 = c((lengthedu+1):ncol(ivs)),X,al
```

2SLS regression with the score excluding the identified SNPs 9 SNPs were removed from the education score and 3 from the cognitive ability score

```
grsformula <- as.formula(paste("lnbmi ~ edu_age + cog", covars,</pre>
                               "cog_grs_update", "edu_grs_update", sep = "+"))
scorereg <- ivreg(grsformula, data=dat, model=TRUE)</pre>
summary(scorereg, diagnostics=TRUE)
##
## Call:
## ivreg(formula = grsformula, data = dat, model = TRUE)
## Residuals:
##
       Min
                 1Q
                      Median
                                   3Q
                                           Max
## -0.68613 -0.12599 -0.01267 0.11089 1.12316
##
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 4.091e+00 2.243e-01 18.240 < 2e-16 ***
## edu age
              -4.441e-02 1.204e-02 -3.687 0.000227 ***
## cog
               6.086e-02 3.626e-02 1.678 0.093281 .
## age
               1.186e-04 2.286e-04 0.519 0.603932
               4.157e-02 1.782e-03 23.323 < 2e-16 ***
## male
## PC1
               2.931e-04 4.461e-04 0.657 0.511224
## PC2
              -6.692e-04 4.271e-04 -1.567 0.117141
## PC3
              -7.560e-04 4.380e-04 -1.726 0.084387 .
## PC4
              -1.618e-04 3.329e-04 -0.486 0.626881
## PC5
               1.167e-03 1.894e-04
                                     6.161 7.26e-10 ***
## PC6
               7.248e-05 3.944e-04 0.184 0.854215
## PC7
               1.473e-05 3.570e-04 0.041 0.967093
## PC8
              -1.883e-04 3.641e-04 -0.517 0.605099
## PC9
              -1.004e-03 2.454e-04 -4.091 4.30e-05 ***
## PC10
               2.943e-04 3.197e-04 0.921 0.357307
##
## Diagnostic tests:
##
                               df1
                                     df2 statistic p-value
## Weak instruments (edu_age)
                                            235.81 < 2e-16 ***
                                 2 86135
## Weak instruments (cog)
                                 2 86135
                                            168.22 < 2e-16 ***
                                             19.43 3.66e-09 ***
## Wu-Hausman
                                 2 86133
                                                NA
                                                         NA
## Sargan
                                 0
                                      NA
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.1837 on 86135 degrees of freedom
## Multiple R-Squared: -0.2913, Adjusted R-squared: -0.2915
## Wald test: 92.42 on 14 and 86135 DF, p-value: < 2.2e-16
fsw(scorereg)
## Model sample size: 86150
## Sanderson-Windmeijer conditional F-statistics for first stage model:
           F value d.f. Residual d.f.
                                           Pr(>F)
##
```