# samplesizelogisticcasecontrol Package

September 24, 2021

> library(samplesizelogisticcasecontrol)

## Random data generation functions

Let  $X_1$  and  $X_2$  be two variables with a bivariate normal ditribution with mean (0, 0) and covariance [1, 0.5; 0.5, 2].  $X_2$  corresponds to the exposure of interest. Let  $X_3 = X_1X_2$  and define functions for generating random data from the distribution of  $(X_1, X_2)$  and  $(X_1, X_2, X_3)$ .

```
> mymvn <- function(n) {</pre>
          <-c(0, 0)
   mu
    sigma \leftarrow matrix(c(1, 0.5, 0.5, 2), byrow=TRUE, nrow=2, ncol=2)
          <- rmvnorm(n, mean=mu, sigma=sigma)
    dat
+ }
> myF <- function(n) {
    dat <- mymvn(n)</pre>
    dat <- cbind(dat, dat[, 1]*dat[, 2])</pre>
+ }
  Generate some data
> data <- myF(200)</pre>
> colnames(data) <- paste("X", 1:3, sep="")</pre>
> data[1:5, ]
             X 1
                           X2
[1,] -0.1141327 1.85152786 -0.21131996
[2,] 1.2357848 1.29814042 1.60422227
[3,] -1.0944167 0.06226012 -0.06813852
[4,] -0.9736883 -2.26825489 2.20857336
[5,] 0.5367609 -1.64848892 -0.88484438
```

### Examples of univariate calculations

We have the logistic model  $logit = \mu + \beta X$  and are testing  $\beta = 0$ . Suppose the disease prevalence is 0.01, the log-odds ratio for the exposure X is 0.26 and that the exposure follows a Bernoulli(p) distribution with p = 0.15.

```
> prev <- 0.01
> logOR <- 0.26
> p <- 0.15
   Compute the sample sizes
> sampleSize_binary(prev, logOR, probXeq1=p)
$ss.wald.1
[1] 4472
$ss.wald.2
[1] 4498
$ss.score.1
[1] 4467
$ss.score.2
[1] 4441
   The same result can be obtained assuming X is ordinal and passing in the
2 probabilities P(X = 0) and P(X = 1).
> sampleSize_ordinal(prev, logOR, probX=c(1-p, p))
$ss.wald.1
[1] 4472
$ss.wald.2
[1] 4498
$ss.score.1
[1] 4467
$ss.score.2
[1] 4440
   Let X be ordinal with 3 levels. The vector being passed into the probX
argument below is (P(X=0), P(X=1), P(X=2)).
> sampleSize_ordinal(prev, logOR, probX=c(0.4, 0.35, 0.25))
$ss.wald.1
[1] 975
$ss.wald.2
[1] 985
$ss.score.1
[1] 973
$ss.score.2
[1] 963
```

```
Now let the exposure X be N(0,1).

> sampleSize_continuous(prev, logOR)

$ss.wald.1
[1] 625

$ss.wald.2
[1] 644

$ss.score.1
[1] 621

$ss.score.2
[1] 602
```

For the univariate case with continuous exposure, we can specify the probability density function of X in different ways. Consider X to have a chi-squared distribution with 1 degree of freedom. Note that the domain of a chi-squared pdf is from 0 to infinity, and that the var(X) = 2.

```
> sampleSize_continuous(prev, logOR, distF="dchisq(x, 1)",
                        distF.support=c(0,Inf), distF.var=2)
$ss.wald.1
[1] 170
$ss.wald.2
[1] 242
$ss.score.1
[1] 168
$ss.score.2
[1] 113
> f <- function(x) {dchisq(x, 1)}</pre>
> sampleSize_continuous(prev, logOR, distF=f, distF.support=c(0, Inf),
                         distF.var=2)
$ss.wald.1
[1] 170
$ss.wald.2
[1] 242
$ss.score.1
[1] 168
$ss.score.2
[1] 113
```

If we do not set distF.var, then the variance of X will be approximated by numerical integration and could yield slightly different results.

```
> sampleSize_continuous(prev, logOR, distF="dchisq(x, 1)", distF.support=c(0,Inf))
$ss.wald.1
[1] 170
$ss.wald.2
[1] 242
$ss.score.1
[1] 168
$ss.score.2
[1] 113
  Let X have the distribution defined by column X_1 in data.
> sampleSize_data(prev, logOR, data[, "X1", drop=FALSE])
$ss.wald.1
[1] 614
$ss.wald.2
[1] 632
$ss.score.1
[1] 611
$ss.score.2
[1] 594
```

## Examples with confounders

We have the logit model  $logit = \mu + \beta_1 X_1 + \beta_2 X_2$  and are interested in testing  $\beta_2 = 0$ . Here we must have log-odds ratios for  $X_1$  and  $X_2$ , and we will use the distribution function mymvn defined above to generate 200 random samples. Note that logOR[1] corresponds to  $X_1$  and logOR[2] corresponds to  $X_2$ .

```
> logOR <- c(0.1, 0.13)
> sampleSize_data(prev, logOR, mymvn(200))
$ss.wald.1
[1] 1350
$ss.wald.2
[1] 1370
$ss.score.1
[1] 1347
```

```
$ss.score.2
[1] 1328
```

Now we would like to perform a test of interaction,  $\beta_3 = 0$ , where  $logit = \mu + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$  and  $X_3 = X_1 X_2$ . The vector of log-odds ratios must be of length 3 and in the same order as  $(X_1, X_2, X_3)$ .

```
> logOR <- c(0.1, 0.15, 0.11)
> sampleSize_data(prev, logOR, myF(1000))
$ss.wald.1
[1] 1405
$ss.wald.2
[1] 1447
$ss.score.1
[1] 1391
$ss.score.2
[1] 1350
```

### Pilot data from a file

Suppose we want to compute sample sizes for a case-control study where we have pilot data from a previous study. The pilot data is stored in the file:

```
> file <- system.file("sampleData", "data.txt", package="samplesizelogisticcasecontrol")
> file
```

[1] "/tmp/RtmpEcqBJ2/Rinst526d2f7f8840/samplesizelogisticcasecontrol/sampleData/data.txt"

Here the exposure variable is "Treatment", and "Gender\_Male" is a dummy variable for the confounder gender. We will use the data from only the controls and define a new variable of interest which is the interaction of gender and treatment. In our model, both gender and treatment will be confounders. First, read in the data.

```
> data <- read.table(file, header=1, sep="\t")</pre>
```

Create the interaction variable

```
> data[, "Interaction"] <- data[, "Gender_Male"]*data[, "Treatment"]
> data[1:5, ]
```

	Casecontrol	Gender_Male	Treatment	Interaction
1	0	0	0	0
2	1	1	0	0
3	0	0	0	0
4	1	1	1	1
5	1	1	0	0

Now subset the data to use only the controls

```
> temp <- data[, "Casecontrol"] %in% 0
> data2 <- data[temp, ]</pre>
```

The data that gets passed in should only contain the columns that will be used in the analysis with the variable of interest being the last column.

```
> vars <- c("Gender_Male", "Treatment", "Interaction")
> data2 <- data2[, vars]</pre>
```

Define the log-odds ratios for gender, treatment, and the interaction of gender and treatment. The order of these log-odds ratios must match the order of the columns in the data.

```
> logOR <- c(0.1, 0.13, 0.27)
    Compute the sample sizes
> sampleSize_data(prev, logOR, data2)
$ss.wald.1
[1] 9402
$ss.wald.2
[1] 9404
$ss.score.1
[1] 9403
$ss.score.2
[1] 9400
```

Note that the same results can be obtained by not reading in the data and creating a new interaction variable, but by setting the input argument of data to be of type *file.list*.

#### Power calculation using pilot data

```
Using the pilot data, estimate the log-odds ratios from a logistic regression:
```

```
> fit <- glm(Casecontrol ~ Gender_Male + Treatment + Interaction, data=data, family=binomi
> summary(fit)
Call:
glm(formula = Casecontrol ~ Gender_Male + Treatment + Interaction,
   family = binomial(), data = data)
Deviance Residuals:
   Min
             1Q
                 Median
                              3Q
                                     Max
-0.8870 -0.8398 -0.8108
                        1.4989
                                   1.5996
Coefficients:
           Estimate Std. Error z value Pr(>|z|)
Gender_Male 0.08297
                      0.19627
                                0.423
                                        0.672
Treatment
            0.21373
                      0.19447
                                1.099
                                        0.272
Interaction -0.30629
                      0.27771 -1.103
                                        0.270
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' '1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 1213.1 on 999 degrees of freedom
Residual deviance: 1211.5 on 996 degrees of freedom
AIC: 1219.5
Number of Fisher Scoring iterations: 4
  Extract the estimates needed
> coef
          <- fit$coefficients
          <- coef[-1]
> logOR
> logOR
Gender_Male
             Treatment Interaction
Estimate the power assuming a study size of 15000 subjects with 10 percent
of them cases.
> power_data(prev, logOR, data[, vars], sampleSize=15000, cc.ratio=0.1)
$pow.wald.1
[1] 0.8020756
$pow.wald.2
[1] 0.8010627
```

\$pow.score.1
[1] 0.8035882

\$pow.score.2
[1] 0.8045952

#### **Session Information**

> sessionInfo()

R version 4.1.0 (2021-05-18)

Platform: x86\_64-pc-linux-gnu (64-bit) Running under: CentOS Linux 7 (Core)

Matrix products: default

BLAS/LAPACK: /usr/local/intel/compilers\_and\_libraries\_2020.2.254/linux/mkl/lib/intel64\_lin

#### locale:

[1] LC\_CTYPE=en\_US.UTF-8 LC\_NUMERIC=C
[3] LC\_TIME=en\_US.UTF-8 LC\_COLLATE=C

[5] LC\_MONETARY=en\_US.UTF-8 LC\_MESSAGES=en\_US.UTF-8

[7] LC\_PAPER=en\_US.UTF-8 LC\_NAME=C

[9] LC\_ADDRESS=C LC\_TELEPHONE=C

[11] LC\_MEASUREMENT=en\_US.UTF-8 LC\_IDENTIFICATION=C

#### attached base packages:

[1] stats graphics grDevices utils datasets methods base

#### other attached packages:

[1] samplesizelogisticcasecontrol\_2.0.0 mvtnorm\_1.1-2

loaded via a namespace (and not attached):

[1] compiler\_4.1.0 tools\_4.1.0