# A first introduction to on ADRminer

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This tutorial aims at illustrate the functionalities of the ADRminer package. It is based on spontaneous reports from the FAERS. The data that will be used throughout the document are from the second and third semester of 2013 and can be downloaded [here][id] (the ASCII version). We assume that the data are uncompressed and gathered in a common directory

```
list.files()

## [1] "aers_ascii_2012q2" "AERS_ASCII_2013q3" "faers_ascii_2012q4"

## [4] "faers_ascii_2013q1" "faers_ascii_2013q2" "Tutorial.knit.md"
```

# Data import

The first step is to import the data and to convert them into objects that can be handled by the ADRminer package. ADRminer provides with a function which facilitate the importation of the data from the AERS This function requires at least three arguments:

- 1. a path to the drug file
- 2. a path to the adverse reaction file

## primaryid age gndr\_cod reporter\_country occp\_cod

3. a path to the demo file, the latter being used to collect individuals characteristics such as the age and gender of the patients

```
drugFile <- c("./faers_ascii_2013q2/asii/DRUG13Q2.txt")
reacFile <- c("./faers_ascii_2013q2/asii/REAC13Q2.txt")
demoFile <- c("./faers_ascii_2013q2/asii/DEM013Q2.txt")
library(ADRminer)

## Loading required package: Matrix
## Loading required package: glmnet
## Loaded glmnet 1.9-8

##
## Loading required package: data.table
## Loaded ADRminer 0.80

faers13q2 <- readFAERS(drugFile, reacFile, demoFile)
faers13q2

##
## $4 class: pvInd
## @drug: Sparse matrix: 53356 x 8549
## @drug: Sparse matrix 53356 x 6286
## @cov: Covariate data.frame: 53356 x 5</pre>
```

Using the default value of readFAERS, we see that the  ${\tt faers13q2}$  is an object of class S4  ${\tt pvInd}$ , which is made of

- 1. a sparse matrix containing 53356 spontaneous reports and involving x 8549 different drugs
- 2. a sparse matrix containing 53356 spontaneous reports and involving x 8549 different adverse events
- 3. a data.frame containing indivdual covariates extracted from the DEMO\*\*.txt file

it is really unlikely that a signal generation procedure will be restricted on one semester. Accordingly we extended the rbind function to the class pvInd in order to merge several pvInd object

```
## data import from the third semester 2013
drugFile <- c("./AERS_ASCII_2013q3/ASCII/DRUG13Q3.txt")</pre>
reacFile <- c("./AERS_ASCII_2013q3/ASCII/REAC13Q3.txt")</pre>
demoFile <- c("./AERS_ASCII_2013q3/ASCII/DEM013Q3.txt")</pre>
faers13q3 <- readFAERS(drugFile, reacFile, demoFile)</pre>
faers13q3
##
## S4 class: pvInd
## @drug: Sparse matrix: 52157 x 8955
## @ae: Sparse matrix 52157 x 6322
## @cov: Covariate data.frame: 52157 x 5
## primaryid age gndr_cod reporter_country occp_cod
faers13q23 <- rbind(faers13q2, faers13q3)</pre>
##
## S4 class: pvInd
## @drug: Sparse matrix: 53356 x 8549
## @ae: Sparse matrix 53356 x 6286
## @cov: Covariate data.frame: 53356 x 5
## primaryid age gndr_cod reporter_country occp_cod
##
## S4 class: pvInd
## @drug: Sparse matrix: 52157 x 8955
## @ae: Sparse matrix 52157 x 6322
## @cov: Covariate data.frame: 52157 x 5
## primaryid age gndr_cod reporter_country occp_cod
faers13q23
##
## S4 class: pvInd
## @drug: Sparse matrix: 105512 x 13036
```

We see that spontaneous reports are concatenated. Note that the number of drugs and adverse events increase as both file do not involve the same drugs and adverse events.

## @ae: Sparse matrix 105512 x 7930
## @cov: Covariate data.frame: 105512 x 5

## primaryid age gndr\_cod reporter\_country occp\_cod

Some basic functions have been developed to access and manipulate the object faers13q23. In particular, we can use the pvIndResize function to eliminate drugs and adverse events associated with a too small (say less than 50) number of spontaneous reports which will drastically decrease the number of drugs and adverse events.

```
faers13q23resize <- pvIndResize(faers13q23, aeMarginMin = 50, drugMarginMin = 50)
faers13q23resize</pre>
```

```
##
## S4 class: pvInd
## @drug: Sparse matrix: 105512 x 543
## @ae: Sparse matrix 105512 x 860
## @cov: Covariate data.frame: 105512 x 5
## primaryid age gndr_cod reporter_country occp_cod
```

## Signal detection analysis

#### Gamma Poisson Shrinker

The first method illustrated in this tutorial is the Gamma Poisson Shrinker (GPS) initially proposed by DuMouchel (American Statistician 1999) as well as its extension to the multiple comparison framework (Ahmed et al. Stat Med 2009). The corresponding function is gps which can take a number of arguments. The default parametrisation corresponds to the extension proposed in Ahmed et al. (2009): the drug adverse event pairs are ranked according to the posterior probability of a null hypothesis (H0: the relatvie risk rr0 <= 1 and a signal is generated based on an estimated False Discovery Rate (FDR, Benjamini an Hochberg JRSSB 1995) less than 0.05. Alternatively, it is also possible to use the detection strategy proposed in Szarfman et al. (Drug Safety 2002) which consists in highlighting drug-ae pairs associated with EB05 > 2.

```
resGPSpH0 <- gps(faers13q23resize)
## equivalent to resGPSpH0 <- gps(faers13q23resize, assocMeasure = "posH0",
## detectCriter = "FDR", criterThres = 0.05))</pre>
```

The number of generated signals is:

```
resGPSpHO$nSig
```

```
## [1] 12581
```

A summary of the characteristics of the generated signals is stored in \$sig

#### head(resGPSpHO\$sig)

```
##
                                                      n expected postHO
                   drug
                                              event
                                                                            rrr
## 1
            ALPRAZOLAM
                                                           1.0405
                                                                       0 176.84
                               Accidental overdose 184
## 2
               Avandia Cardiac failure congestive 355
                                                           7.6285
                                                                       0 46.54
## 3
               Avandia
                             Myocardial infarction 525
                                                         15.0176
                                                                       0 34.96
## 4 CLOZAPINE TABLETS
                                                           1.0649
                                                                       0 272.32
                                  Granulocytopenia 290
## 5
              Diazepam
                               Exposure via father 185
                                                           0.4113
                                                                       0 449.84
              Diazepam
                              Small for dates baby 178
                                                                       0 436.92
## 6
                                                           0.4074
     drugMargin aeMargin FDR postHO
##
```

```
## 1
              555
                         435
                                0
                                         0
## 2
             2525
                         701
                                0
                                         0
## 3
             2525
                        1380
                                         0
                                         0
## 4
              765
                         323
                                0
## 5
              448
                         213
                                0
                                         0
## 6
              448
                                0
                                         0
                         211
```

Here are the results obtained with the detection strategy proposed by Szarfman et al.

It is also possible to perform stratified GPS analysis according to covariates stored in the pvInd object "faers13q23resize\$cov". However, this may require to recode some covariates into factors with a reasonable number of categories especially if one is willing to stratify according to several covariates such as age and gender.

Here we illustrate how to recode the age covariate into a new factor variable

```
hist(faers13q23resize$cov$age, breaks = 100)
```

# Histogram of faers13q23resize\$cov\$age



ageFac <- cut(faers13q23resize\$cov\$age, c(0,1,10,25,50, 120), include.lowest = T)
table(ageFac)</pre>

```
## ageFac
## [0,1] (1,10] (10,25] (25,50] (50,120]
## 804 1838 5528 19502 43826
```

```
ageFac <- addNA(ageFac) ## this is to consider NA values as a category
table(ageFac)</pre>
```

```
## ageFac
## [0,1] (1,10] (10,25] (25,50] (50,120] <NA>
## 804 1838 5528 19502 43826 34014
```

### faers13q23resize\$cov\$ageFac <- ageFac</pre>

The syntax to run stratified GPS according to ageFac is then

```
resGPSstrat <- gps(faers13q23resize, strat="ageFac")</pre>
```

```
## varStrat
## (1,10] (10,25] (25,50] (50,120] [0,1] NA
## 1838 5528 19502 43826 804 34014
```

### resGPSstrat\$nSig

### ## [1] 12512

## head(resGPSstrat\$sig)

##			drug				event	n	expected	postH0
##	1		Avandia	Car	rdiad	c failure c	ongestive	355	9.334	0
##	2		Avandia		Му	ocardial i	nfarction	525	17.074	0
##	3	CLOZAPI	NE TABLETS			Granulo	cytopenia	290	1.505	0
##	4		Enbrel		Inje	ection site	erythema	1186	180.990	0
##	5		Enbrel			Injection	site pain	1402	215.582	0
##	6		Methadose I	Orug with	drawa	al syndrome	neonatal	251	3.210	0
##		rrr	${\tt drugMargin}$	aeMargin	FDR	postH0				
##	1	38.034	2525	701	0	0				
##	2	30.748	2525	1380	0	0				
##	3	192.684	765	323	0	0				
##	4	6.553	22085	1447	0	0				
##	5	6.503	22085	1762	0	0				
##	6	78.205	524	435	0	0				