

# Package ‘EmpiricalCalibration’

July 13, 2015

**Type** Package

**Title** Routines for performing empirical calibration of observational study estimates

**Version** 1.0.1

**Date** 2015-07-13

**Author** Martijn Schuemie, Marc Suchard

**Maintainer** Martijn Schuemie <schuemie@ohdsi.org>

**Description** Routines for performing empirical calibration of observational study estimates. By using a set of negative control hypotheses we can estimate the empirical null distribution of a particular observational study setup. This empirical null distribution can be used to compute a calibrated p-value, which reflects the probability of observing an estimated effect size when the null hypothesis is true taking both random and systematic error into account.

**VignetteBuilder** knitr

**Imports** ggplot2,  
MASS

**Suggests** knitr,  
rmarkdown,  
OhdsiRTools

**License** Apache License 2.0

## R topics documented:

calibrateConfidenceInterval . . . . .	2
calibrateP . . . . .	3
calibratePWithCiUsingMcmc . . . . .	4
caseControl . . . . .	5
cohortMethod . . . . .	6
computeTraditionalP . . . . .	7
fitNull . . . . .	7
fitSystematicErrorModel . . . . .	8
plotCalibration . . . . .	9
plotCalibrationEffect . . . . .	9
plotCoverage . . . . .	10
plotForest . . . . .	11

plotTrueAndObserved . . . . .	12
sccs . . . . .	12
simulateControls . . . . .	13
<b>Index</b>	<b>15</b>

---

calibrateConfidenceInterval
<i>Calibrate confidence intervals</i>

---

**Description**

Calibrate confidence intervals

**Usage**

calibrateConfidenceInterval(logRr, seLogRr, model)

**Arguments**

- |         |  |
|---------|--|
| logRr   | A numeric vector of effect estimates on the log scale.   |
| seLogRr | The standard error of the log of the effect estimates. Hint: often the standard error = (log(<lower bound 95 percent confidence interval>) - log(<effect estimate>))/qnorm(0.025). |
| model   | An object of type systematicErrorModel as created by the <a href="#">fitSystematicErrorModel</a> function.   |

**Details**

Compute calibrated confidence intervals based on a model of the systematic error.

**Value**

A data frame with calibrated confidence intervals and point estimates.

**Examples**

```
data <- simulateControls(n = 50 * 3, mean = 0.25, sd = 0.25, trueLogRr = log(c(1, 2, 4)))
model <- fitSystematicErrorModel(data$logRr, data$seLogRr, data$trueLogRr)
newData <- simulateControls(n = 15, mean = 0.25, sd = 0.25, trueLogRr = log(c(1, 2, 4)))
result <- calibrateConfidenceInterval(newData$logRr, newData$seLogRr, model)
```

---

calibrateP	<i>Calibrate the p-value</i>
------------	------------------------------

---

## Description

calibrateP computes calibrated p-values using the fitted null distribution

## Usage

```
calibrateP(logRr, seLogRr, null, pValueConfidenceInterval = FALSE)
```

## Arguments

logRr	A numeric vector of one or more effect estimates on the log scale
seLogRr	The standard error of the log of the effect estimates. Hint: often the standard error = (log(<lower bound 95 percent confidence interval>) - log(<effect estimate>))/qnorm(0.025)
null	An object of class null created using the fitNull function
pValueConfidenceInterval	If true, computes the 95 percent confidence interval of the calibrated p-value

## Details

This function computes a calibrated two-sided p-value as described in Schuemie et al (2014).

## Value

A two-sided calibrated p-value.

## References

Schuemie MJ, Ryan PB, Dumouchel W, Suchard MA, Madigan D. Interpreting observational studies: why empirical calibration is needed to correct p-values. *Statistics in Medicine* 33(2):209-18,2014

## Examples

```
data(sccs)
negatives <- sccs[sccs$groundTruth == 0, ]
null <- fitNull(negatives$logRr, negatives$seLogRr)
positive <- sccs[sccs$groundTruth == 1, ]
calibrateP(positive$logRr, positive$seLogRr, null)
```

---

calibratePWithCiUsingMcmc

*Compute p-value confidence intervals using MCMC*


---

## Description

Compute p-value confidence intervals using MCMC

## Usage

```
calibratePWithCiUsingMcmc(logRrNegatives, seLogRrNegatives, logRrPositives,
  seLogRrPositives, scale = c(0.1, 200), iter = 10000)
```

## Arguments

logRrNegatives	A numeric vector of effect estimates of the negative controls on the log scale.
seLogRrNegatives	The standard error of the log of the effect estimates of the negative controls.
logRrPositives	A numeric vector of effect estimates of the positive controls on the log scale.
seLogRrPositives	The standard error of the log of the effect estimates of the positive controls.
scale	A vector of two numbers representing the scale of the likelihood space around the mean and standard deviation of the error distribution, respectively.
iter	Number of iterations of the MCMC.

## Details

This is an experimental function for computing the 95 percent confidence interval of a calibrated p-value using Markov-Chain Monte Carlo (MCMC). This should give better estimates than the default function when the standard deviation of the error distribution is close to zero.

## Examples

```
controls <- simulateControls()
p <- calibratePWithCiUsingMcmc(controls$logRr,
  controls$seLogRr,
  controls$logRr[1],
  controls$seLogRr[1],
  scale = c(0.05, 25),
  iter = 10000)

mcmc <- attr(p, "mcmc")
mean(mcmc$acc) # Acceptance rate
plot(ts(mcmc$chain[, 1])) # Trace for the mean
plot(ts(mcmc$chain[, 2])) # Trace for the precision
mean(mcmc$chain[, 1])
mean(mcmc$chain[, 2])
```

---

caseControl*Odds ratios from a case-control design*

---

**Description**

Odds ratios from a case-control design

**Usage**

```
data(caseControl)
```

**Format**

A data frame with 47 rows and 4 variables:

**drugName** Name of the drug

**groundTruth** Whether the drug is a positive (1) or negative (0) control

**logRr** The log of the incidence rate ratio

**seLogRr** The standard error of the log of the incidence rate ratio

**Details**

A dataset containing the odds ratios (and standard errors) produced using a case-control design. The outcome is upper GI bleeding, the drug of interest (`groundTruth = 1`) is sertraline. Also included are 46 negative control drugs, for which we believe there to be no causal relation with upper GI bleeding. We used a database of medical records from general practices in the USA, the General Electric (GE) Centricity database, which contains data on 11.2 million subjects. We restricted on study period (start of 1990 through November 2003), age requirements (18 years or older), available time prior to event (180 days), number of controls per case (6), and risk definition window (30 days following the prescription). Controls were matched on age and sex. Cases of upper GI bleeding were identified on the basis of the occurrence of ICD-9 diagnosis codes in the problem list. These codes pertain to esophageal, gastric, duodenal, peptic, and gastrojejunal ulceration, perforation, and hemorrhage, as well as gastritis and non-specific gastrointestinal hemorrhage. For more information on this set see Schuemie et al (2014).

**References**

Schuemie MJ, Ryan PB, Dumouchel W, Suchard MA, Madigan D. Interpreting observational studies: why empirical calibration is needed to correct p-values. *Statistics in Medicine* 33(2):209-18,2014

cohortMethod

*Relative risks from a new-user cohort design***Description**

Relative risks from a new-user cohort design

**Usage**`data(cohortMethod)`**Format**

A data frame with 31 rows and 4 variables:

**drugName** Name of the drug**groundTruth** Whether the drug is a positive (1) or negative (0) control**logRr** The log of the incidence rate ratio**seLogRr** The standard error of the log of the incidence rate ratio**Details**

A dataset containing the relative risks (and standard errors) produced using a new-user cohort design. The outcome is acute liver injury, the drug of interest (`groundTruth = 1`) is Isoniazid. Also included are 30 negative control drugs, for which we believe there to be no causal relation with acute liver injury. We used the Thomson MarketScan Medicare Supplemental Beneficiaries database, which contains data on 4.6 million subjects. We selected two groups (cohorts): (1) all subjects exposed to isoniazid and (2) all subjects having the ailment for which isoniazid is indicated, in this case tuberculosis, and having received at least one drug that is not known to cause acute liver injury. We removed all subjects who belonged to both groups and subjects for which less than 180 days of observation time was available prior to their first exposure to the drug in question. Acute liver injury was identified on the basis of the occurrence of ICD-9-based diagnosis codes from inpatient and outpatient medical claims and was defined broadly on the basis of codes associated with hepatic dysfunction, as have been used in prior observational database studies. The time at risk was defined as the length of exposure + 30 days, and we determined whether subjects experienced an acute liver injury during their time at risk. Using propensity score stratification, the cohorts were divided over 20 strata, and an odds ratio over all strata was computed using a Mantel-Haenszel test. The propensity score was estimated using Bayesian logistic regression using all available drug, condition, and procedure covariates occurring in the 180 days prior to first exposure, in addition to age, sex, calendar year of first exposure, Charlson index, number of drugs, number of visit days, and number of procedures. For more information on this set see Schuemie et al (2014).

**References**

Schuemie MJ, Ryan PB, Dumouchel W, Suchard MA, Madigan D. Interpreting observational studies: why empirical calibration is needed to correct p-values. *Statistics in Medicine* 33(2):209-18, 2014

---

computeTraditionalP	<i>Compute the (traditional) p-value</i>
---------------------	--

---

**Description**

computeTraditionalP computes the traditional two-sided p-value based on the log of the relative risk and the standard error of the log of the relative risk.

**Usage**

```
computeTraditionalP(logRr, seLogRr)
```

**Arguments**

logRr	A numeric vector of one or more effect estimates on the log scale
seLogRr	The standard error of the log of the effect estimates. Hint: often the standard error = $(\log(\text{lower bound 95 percent confidence interval}) - \log(\text{effect estimate})) / \text{qnorm}(0.025)$

**Value**

A two-sided (traditional) p-value.

**Examples**

```
data(sccs)
positive <- sccs[sccs$groundTruth == 1, ]
computeTraditionalP(positive$logRr, positive$seLogRr)
```

---

fitNull	<i>Fit the null distribution</i>
---------	----------------------------------

---

**Description**

fitNull fits the null distribution to a set of negative controls

**Usage**

```
fitNull(logRr, seLogRr)
```

**Arguments**

logRr	A numeric vector of effect estimates on the log scale
seLogRr	The standard error of the log of the effect estimates. Hint: often the standard error = $(\log(\text{lower bound 95 percent confidence interval}) - \log(\text{effect estimate})) / \text{qnorm}(0.025)$

**Details**

This function fits a Gaussian function to the negative control estimates as described in Schuemie et al (2014).

**Value**

An object of type null containing the mean and standard deviation (both on the log scale) of the null distribution.

**References**

Schuemie MJ, Ryan PB, Dumouchel W, Suchard MA, Madigan D. Interpreting observational studies: why empirical calibration is needed to correct p-values. *Statistics in Medicine* 33(2):209-18,2014

**Examples**

```
data(sccs)
negatives <- sccs[sccs$groundTruth == 0, ]
null <- fitNull(negatives$logRr, negatives$seLogRr)
```

---

```
fitSystematicErrorModel
```

*Fit a systematic error model*

---

**Description**

Fit a systematic error model

**Usage**

```
fitSystematicErrorModel(logRr, seLogRr, trueLogRr)
```

**Arguments**

logRr	A numeric vector of effect estimates on the log scale.
seLogRr	The standard error of the log of the effect estimates. Hint: often the standard error = (log(<lower bound 95 percent confidence interval>) - log(<effect estimate>))/qnorm(0.025).
trueLogRr	A vector of the true effect sizes.

**Details**

Fit a model of the systematic error as a function of true effect size. This model is an extension of the method for fitting the null distribution. The mean and standard deviations of the error distributions are assumed to be linear with respect to the true effect size, and each component is therefore represented by an intercept and a slope.

**Value**

An object of type systematicErrorModel.

**Examples**

```
controls <- simulateControls(n = 50 * 3, mean = 0.25, sd = 0.25, trueLogRr = log(c(1, 2, 4)))
model <- fitSystematicErrorModel(controls$logRr, controls$seLogRr, controls$trueLogRr)
model
```



---

plotCalibration	<i>Create a calibration plot</i>
-----------------	----------------------------------

---

**Description**

plotCalibration creates a plot showing the calibration of our calibration procedure

**Usage**

```
plotCalibration(logRr, seLogRr)
```

**Arguments**

logRr	A numeric vector of effect estimates on the log scale
seLogRr	The standard error of the log of the effect estimates. Hint: often the standard error = (log(<lower bound 95 percent confidence interval>) - log(<effect estimate>))/qnorm(0.025)

**Details**

Creates a calibration plot showing the number of effects with  $p < \alpha$  for every level of  $\alpha$ . The empirical calibration is performed using a leave-one-out design: The p-value of an effect is computed by fitting a null using all other negative controls. Ideally, the calibration line should approximate the diagonal. The plot shows both theoretical (traditional) and empirically calibrated p-values.

**Value**

A Ggplot object. Use the ggsave function to save to file.

**Examples**

```
data(sccs)
negatives <- sccs[sccs$groundTruth == 0, ]
plotCalibration(negatives$logRr, negatives$seLogRr)
```

---

plotCalibrationEffect	<i>Plot the effect of the calibration</i>
-----------------------	---

---

**Description**

plotCalibrationEffect creates a plot showing the effect of the calibration.

**Usage**

```
plotCalibrationEffect(logRrNegatives, seLogRrNegatives, logRrPositives,
  seLogRrPositives, null = NULL, xLabel = "Relative risk")
```

**Arguments**

logRrNegatives	A numeric vector of effect estimates of the negative controls on the log scale.
seLogRrNegatives	The standard error of the log of the effect estimates of the negative controls.
logRrPositives	A numeric vector of effect estimates of the positive controls on the log scale.
seLogRrPositives	The standard error of the log of the effect estimates of the positive controls.
null	An object representing the fitted null distribution as created by the fitNull function.
xLabel	The label on the x-axis: the name of the effect estimate.

**Details**

Creates a plot with the effect estimate on the x-axis and the standard error on the y-axis. Negative controls are shown as blue dots, positive controls as yellow diamonds. The area below the dashed line indicated estimates with  $p < 0.05$ . The orange area indicates estimates with calibrated  $p < 0.05$ .

**Value**

A Ggplot object. Use the ggsave function to save to file.

**Examples**

```
data(sccs)
negatives <- sccs[sccs$groundTruth == 0, ]
positive <- sccs[sccs$groundTruth == 1, ]
plotCalibrationEffect(negatives$logRr, negatives$seLogRr, positive$logRr, positive$seLogRr)
```

---

plotCoverage	<i>Plot the coverage</i>
--------------	--------------------------

---

**Description**

Plot the coverage

**Usage**

```
plotCoverage(logRr, seLogRr, trueLogRr, region = 0.95)
```

**Arguments**

logRr	A numeric vector of effect estimates on the log scale
seLogRr	The standard error of the log of the effect estimates. Hint: often the standard error = $(\log(\text{lower bound 95 percent confidence interval}) - \log(\text{effect estimate})) / \text{qnorm}(0.025)$
trueLogRr	A vector of the true effect sizes
region	Size of the confidence interval. Default is .95 (95 percent).

**Details**

Plot the fractions of estimates where the true effect size is below, above or within the confidence interval, for one or more true effect sizes.

**Examples**

```
data <- simulateControls(n = 50 * 3, mean = 0, sd = 0.15, trueLogRr = log(c(1, 2, 4)))
plotCoverage(data$logRr, data$seLogRr, data$trueLogRr)
```

---

plotForest	<i>Create a forest plot</i>
------------	-----------------------------

---

**Description**

plotForest creates a forest plot of effect size estimates.

**Usage**

```
plotForest(logRr, seLogRr, names, xLabel = "Relative risk")
```

**Arguments**

logRr	A numeric vector of effect estimates on the log scale
seLogRr	The standard error of the log of the effect estimates. Hint: often the standard error = (log(<lower bound 95 percent confidence interval>) - log(<effect estimate>))/qnorm(0.025)
names	A vector containing the names of the drugs or outcomes
xLabel	The label on the x-axis: the name of the effect estimate

**Details**

Creates a forest plot of effect size estimates (ratios). Estimates that are significantly different from 1 (alpha = 0.05) are marked in orange, others are marked in blue.

**Value**

A Ggplot object. Use the ggsave function to save to file.

**Examples**

```
data(sccs)
negatives <- sccs[sccs$groundTruth == 0, ]
plotForest(negatives$logRr, negatives$seLogRr, negatives$drugName)
```

---

`plotTrueAndObserved`      *Plot true and observed values*

---

### Description

Plot true and observed values, for example from a simulation study.

### Usage

```
plotTrueAndObserved(logRr, seLogRr, trueLogRr, xLabel = "Relative risk")
```

### Arguments

<code>logRr</code>	A numeric vector of effect estimates on the log scale.
<code>seLogRr</code>	The standard error of the log of the effect estimates. Hint: often the standard error = $(\log(\text{lower bound 95 percent confidence interval}) - \log(\text{effect estimate})) / qnorm(0.025)$ .
<code>trueLogRr</code>	A vector of the true effect sizes.
<code>xLabel</code>	The label on the x-axis: the name of the effect estimate.

### Details

Creates a forest plot of effect size estimates (ratios). Estimates that are significantly different from the true value ( $\alpha = 0.05$ ) are marked in orange, others are marked in blue.

### Value

A Ggplot object. Use the `ggsave` function to save to file.

### Examples

```
data <- simulateControls(n = 50 * 3, mean = 0.25, sd = 0.25, trueLogRr = log(c(1, 2, 4)))
plotTrueAndObserved(data$logRr, data$seLogRr, data$trueLogRr)
```

---

`sccs`      *Incidence rate ratios from Self-Controlled Case Series*

---

### Description

Incidence rate ratios from Self-Controlled Case Series

### Usage

```
data(sccs)
```

**Format**

A data frame with 46 rows and 4 variables:

**drugName** Name of the drug  
**groundTruth** Whether the drug is a positive (1) or negative (0) control  
**logRr** The log of the incidence rate ratio  
**seLogRr** The standard error of the log of the incidence rate ratio

**Details**

A dataset containing the incidence rate ratios (and standard errors) produced using a Self-Controlled Case Series (SCCS) design. The outcome is upper GI bleeding, the drug of interest (groundTruth = 1) is sertraline. Also included are 45 negative control drugs, for which we believe there to be no causal relation with upper GI bleeding. We used a database of medical records from general practices in the USA, the General Electric (GE) Centricity database, which contains data on 11.2 million subjects. We restricted on study period (start of 1990 through November 2003), age requirements (18 years or older), available time prior to event (180 days), and risk definition window (30 days following the prescription). Time 30 days prior to the first prescription was removed to account for possible contra-indications. Cases of upper GI bleeding were identified on the basis of the occurrence of ICD-9 diagnosis codes in the problem list. These codes pertain to esophageal, gastric, duodenal, peptic, and gastrojejunal ulceration, perforation, and hemorrhage, as well as gastritis and non-specific gastrointestinal hemorrhage. For more information on this set see Schuemie et al (2014).

**References**

Schuemie MJ, Ryan PB, Dumouchel W, Suchard MA, Madigan D. Interpreting observational studies: why empirical calibration is needed to correct p-values. *Statistics in Medicine* 33(2):209-18,2014

---

simulateControls	<i>Simulate (negative) controls</i>
------------------	-------------------------------------

---

**Description**

Simulate (negative) controls

**Usage**

```
simulateControls(n = 50, mean = 0, sd = 0.1, seLogRr = runif(n, min =
  0.01, max = 0.2), trueLogRr = 0)
```

**Arguments**

n	Number of controls to simulate.
mean	The mean of the error distribution (on the log RR scale).
sd	The standard deviation of the error distribution (on the log RR scale).
seLogRr	The standard error of the log of the relative risk. This is recycled for the controls. The default is to sample these from a uniform distribution.
trueLogRr	The true relative risk (on the log scale) used to generate these controls. This is recycled for the controls.

**Details**

Generate point estimates given known true effect sizes and standard errors

**Examples**

```
data <- simulateControls(n = 50 * 3, mean = 0.25, sd = 0.25, trueLogRr = log(c(1, 2, 4)))  
plotTrueAndObserved(data$logRr, data$seLogRr, data$trueLogRr)
```

# Index

## \*Topic **datasets**

- caseControl, [5](#)
- cohortMethod, [6](#)
- sccs, [12](#)

- calibrateConfidenceInterval, [2](#)
- calibrateP, [3](#)
- calibratePWithCiUsingMcmc, [4](#)
- caseControl, [5](#)
- cohortMethod, [6](#)
- computeTraditionalP, [7](#)

- fitNull, [7](#)
- fitSystematicErrorModel, [2](#), [8](#)

- plotCalibration, [9](#)
- plotCalibrationEffect, [9](#)
- plotCoverage, [10](#)
- plotForest, [11](#)
- plotTrueAndObserved, [12](#)

- sccs, [12](#)
- simulateControls, [13](#)