

# Package ‘genphen’

October 17, 2017

**Type** Package

**Title** A tool for quantification of associations between genotypes and phenotypes with statistical learning techniques such as random forests and support vector machines as well as with Bayesian inference using hierarchical models

**Version** 1.4.0

**Date** 2016-09-28

**Author** Simo Kitanovski

**Maintainer** Simo Kitanovski <simo.kitanovski@uni-due.de>

**Description** Genetic association studies have become an essential tool for studying the relationship between genotypes and phenotypes. They are necessary for the discovery of disease-causing genetic variants. Here we provide a tool for conducting genetic association studies, which uses statistical learning techniques such as random forests and support vector machines, as well as using Bayesian inference with Bayesian hierarchical models. These techniques are superior to the commonly used (frequentist) statistical approaches, alleviating the multiple hypothesis problems and the need for P value corrections, which often lead to massive numbers of false negatives. Thus, with genphen we provide a framework to compare the results obtained using frequentist methods with those obtained using the more sophisticated methods provided by this tool. The tool also provides a few visualization functions which enable the user to inspect the results of such genetic association study and conveniently select the genotypes which have the highest strength of association with the phenotype.

**License** GPL (>= 2)

**Depends** R(>= 3.3), randomForest, e1071, ggplot2, effsize, Biostrings, rjags

**LazyLoad** yes

**biocViews** GenomeWideAssociation, Regression, Classification, SupportVectorMachine, Genetics, SequenceMatching, Bayesian, FeatureExtraction, Sequencing

**NeedsCompilation** no

## R topics documented:

genotype.saap . . . . . 2

genotype.saap.msa . . . . .	3
genotype.snp . . . . .	3
genotype.snp.msa . . . . .	4
phenotype.saap . . . . .	5
phenotype.snp . . . . .	5
plotGenphenBayes . . . . .	6
plotGenphenRfSvm . . . . .	7
plotManhattan . . . . .	8
plotSpecificGenotype . . . . .	9
runGenphenBayes . . . . .	10
runGenphenRf . . . . .	11
runGenphenSvm . . . . .	13
<b>Index</b>	<b>16</b>

---

genotype.saap	<i>SAAP genotype dataset</i>
---------------	------------------------------

---

## Description

The genotype.saap data is a character matrix with dimensions 120x154. It contains 154 amino acid protein sites across 120 organisms. The data is used in combination with the phenotype.aa data to quantify the association between each amino acid substitution pair and the phenotype vector.

## Usage

```
data(genotype.saap)
```

## Format

A matrix with 120 observations and 154 columns (some of which qualify as single amino acid polymorphisms).

## Value

Matrix with 120 rows and 154 columns, whereby each row is a protein sequence and the elements represent an amino acids.

## Source

<http://www.ncbi.nlm.nih.gov/genbank/>

## Examples

```
data(genotype.saap)
```

---

genotype.saap.msa	<i>SAAP genotype dataset (msa)</i>
-------------------	------------------------------------

---

**Description**

The genotype.saap.msa data is a multiple sequence alignment in Biostrings AAMultipleAlignment format. It contains 120 protein sequences, each with 154 sites (SAAPs). The data is used in combination with the phenotype.aa data to quantify the association between each amino acid substitution pair and the phenotype vector.

**Usage**

```
data("genotype.saap.msa")
```

**Format**

AAMultipleAlignment object with 120 sequences each made of 154 amino acid sites (SNPs), some of which qualify as single amino acid polymorphisms.

**Value**

AAMultipleAlignment object with 120 sequences each made of 154 amino acid sites (SNPs), some of which qualify as single amino acid polymorphisms.

**Source**

<http://www.ncbi.nlm.nih.gov/genbank/>

**Examples**

```
data("genotype.saap.msa")
```

---

genotype.snp	<i>SNP genotype dataset</i>
--------------	-----------------------------

---

**Description**

The genotype.snp data is a character matrix with dimensions 51x100. It contains 100 SNPs across 51 mouse strains, taken from the publicly available Mouse Hapmap data. We used it in combination with the phenotype.snp data to compute the association between each SNP and the phenotype data.

**Usage**

```
data(genotype.snp)
```

**Format**

A matrix with 51 observations (laboratory mouse strains) and 100 variables (SNPs).

**Value**

Matrix with 51 rows and 100 columns, whereby each column is a SNP, and the elements represent an alleles (nucleotides).

**Source**

<http://mouse.cs.ucla.edu/mousehapmap/emma.html>

**Examples**

```
data(genotype.snp)
```

---

genotype.snp.msa	<i>SNP genotype dataset (msa)</i>
------------------	-----------------------------------

---

**Description**

The genotype.snp.msa data is a multiple sequence alignment in Biostrings DNAMultipleAlignment format. It contains 51 DNA sequences, each with 100 sites (SNPs), taken from the publicly available Mouse Hapmap data. We used it in combination with the phenotype.snp data to compute the association between each SNP and the phenotype data.

**Usage**

```
data("genotype.snp.msa")
```

**Format**

DNAMultipleAlignment object with 51 sequences each made of 100 nucleotides (SNPs).

**Value**

DNAMultipleAlignment object with 51 sequences each made of 100 nucleotides (SNPs).

**Source**

<http://mouse.cs.ucla.edu/mousehapmap/emma.html>

**Examples**

```
data("genotype.snp.msa")
```

---

phenotype.saap	<i>Phenotype dataset</i>
----------------	--------------------------

---

**Description**

The phenotype data is a numerical vector of length 120. It represents 120 measured phenotypes for 120 organisms. We used it as a dependent variable in combination with the genotype.saap data, and quantified the association between each of the SAAP and the phenotype.

**Usage**

```
data(phenotype.saap)
```

**Format**

A numerical vector with 120 elements (organisms) which correspond to the rows of the genotype data.

**Value**

Vector of 120 metric elements, representing phenotypes measured for 120 organisms.

**Examples**

```
data(phenotype.saap)
```

---

phenotype.snp	<i>Phenotype dataset</i>
---------------	--------------------------

---

**Description**

The phenotype data is a numerical vector of length 51. It represents 51 measured phenotypes for 51 laboratory mouse strains. It is to be used as a dependent variable in combination with the SNP genotype data, in order to compute the association between each of the SNPs and the phenotype.

**Usage**

```
data(phenotype.snp)
```

**Format**

A numerical vector with 51 elements (laboratory mice) which correspond to the rows of the genotype data.

**Value**

Vector of 51 metric elements, representing phenotypes measured for 51 laboratory mice.

**Examples**

```
data(phenotype.snp)
```

---

`plotGenphenBayes`*Visualizing the genphen results of runGenphenBayes*

---

**Description**

This procedure visualizes the results obtained using the function `runGenphenBayes`.

**Usage**

```
plotGenphenBayes(genphen.results, hdi)
```

**Arguments**

<code>genphen.results</code>	data.frame resulting from <code>runGenphenBayes</code> .
<code>hdi</code>	single HDI level (e.g. 0.95) which has previously been estimated with <code>runGenphenBayes</code>

**Details**

This procedure plots the results of the function `runGenphenBayes`. Each association is shown as a point with respect to its Bayesian effect size (`mu.effect`), including the corresponding HDI.

**Value**

<code>plot</code>	ggplot plot object.
-------------------	---------------------

**Author(s)**

Simo Kitanovski <[simo.kitanovski@uni-due.de](mailto:simo.kitanovski@uni-due.de)>

**See Also**

`runGenphenRf`, `runGenphenSvm`, `runGenphenBayes`, `plotGenphenRfSvm`, `plotSpecificGenotype`

**Examples**

```
#Example:
data(genotype.saap)
# or data(genotype.saap.msa) in this case you cannot subset genotype.saap[, 1:5]
data(phenotype.saap)

# run analysis
genphen.bayes <- runGenphenBayes(genotype = genotype.saap[, 1:5],
                                phenotype = phenotype.saap,
                                mcmc.iter = 1000,
                                chain.nr = 2,
                                model = "tdist",
                                hdi.levels = c(0.95, 0.99))
plotGenphenBayes(genphen.results = genphen.bayes, hdi = 0.95)
```

---

`plotGenphenRfSvm`*Visualizing the genphen results of runGenphenRf or runGenphenSvm*

---

**Description**

This procedure visualizes the results obtained using the functions `runGenphenRf` or `runGenphenSvm`.

**Usage**

```
plotGenphenRfSvm(genphen.results)
```

**Arguments**

```
genphen.results  
data.frame resulting from runGenphenRf/runGenphenSvm.
```

**Details**

This procedure plots the results of the functions `runGenphenRf` or `runGenphenSvm`. Each association is shown as a point with respect to its effect size (Cohen's  $d$ ) and the classification accuracy (CA). The colors of the points correspond to the Cohen's  $k$ appas. The confidence intervals estimated for the CA point estimates are provided here as well.

**Value**

```
plot          ggplot plot object.
```

**Author(s)**

```
Simo Kitanovski <simokitanovski@uni-due.de>
```

**See Also**

```
runGenphenRf, runGenphenSvm, plotGenphenBayes, plotSpecificGenotype, plotManhattan
```

**Examples**

```
#Example 1 (RF results):  
data(genotype.snp)  
#or data(genotype.snp.msa) in this case you cannot subset genotype.snp[, 1:5]  
data(phenotype.snp)  
genphen.rf <- runGenphenRf(genotype = genotype.snp[, 1:5],  
                           phenotype = phenotype.snp,  
                           cv.fold = 0.66,  
                           cv.steps = 100,  
                           hdi.level = 0.99,  
                           ntree = 1000)  
plotGenphenRfSvm(genphen.results = genphen.rf)
```

---

`plotManhattan`*Visualizing genphen results with Manhattan plots*

---

**Description**

This procedure plots the complementary T-test results obtained using `runGenphenRf`, `runGenphenSvm` or `runGenphenBayes`.

**Usage**

```
plotManhattan(genphen.results)
```

**Arguments**

```
genphen.results
```

Data.frame resulting from `runGenphenRf`, `runGenphenSvm` or `runGenphenBayesian`.

**Details**

This procedure plots the results from a two-sample T-test analysis, conducted in each of the three functions: `runGenphenRf`, `runGenphenSvm` or `runGenphenBayesian`. The P-values resulting from the T-test are first corrected by the Benjamini -Hochberg correction procedure (FDR), followed by a  $-\log_{10}$  transformation. These values are then plotted as points, where each point corresponds to a single genotype-phenotype association as seen in a classical Manhattan plot.

**Value**

```
plot
```

 ggplot plot object.**Author(s)**

Simo Kitanovski <[simo.kitanovski@uni-due.de](mailto:simo.kitanovski@uni-due.de)>

**See Also**

`runGenphenRf`, `runGenphenSvm`, `plotGenphenBayes`, `plotGenphenRfSvm`, `plotSpecificGenotype`

**Examples**

```
#Example 1:
data(genotype.snp)
#or data(genotype.snp.msa) in this case you cannot subset genotype.snp[, 1:5]
data(phenotype.snp)
genphen.rf <- runGenphenRf(genotype = genotype.snp[, 1:5],
                          phenotype = phenotype.snp,
                          cv.fold = 0.66,
                          cv.steps = 100,
                          hdi.level = 0.99,
                          ntree = 1000)
plotManhattan(genphen.results = genphen.rf)
```



---

plotSpecificGenotype *Visualizing specific genotypes*

---

### Description

This procedure visualizes the phenotypic distribution linked to each of the genetic states of a specific genotype.

### Usage

```
plotSpecificGenotype(genotype, phenotype, index)
```

### Arguments

genotype	Character matrix or data frame, containing SNPs/SAAPs as columns or alternatively as a DNAMultipleAlignment/AAMultipleAlignment Biostrings object.
phenotype	Numerical vector whose elements correspond to the genotype.
index	Index (number) of the specific genotype column within the genotype data which is to be plotted.

### Details

This procedure allows the user to inspect a specific genotype with respect to the the phenotype. It uses a boxplot notation to plot the phenotypes as a function of the states of that genotype. The resulting boxplot will visualize whether the different states of the specific genotype are linked to different and disjoint phenotypic distributions, which is a signature of a strong association between the genotype and the phenotype.

### Value

plot `ggplot` object

### Author(s)

Simo Kitanovski <simo.kitanovski@uni-due.de>

### See Also

runGenphenRf, runGenphenSvm, runGenphenBayesian, plotGenphenResults, plotManhattan

### Examples

```
#Example 1:
data(genotype.snp) #or data(genotype.snp.msa)
data(phenotype.snp)
specific.genotype.plot <- plotSpecificGenotype(genotype = genotype.snp,
phenotype = phenotype.snp, index = 1)

#Example 2:
data(genotype.saap) #or data(genotype.saap.msa)
data(phenotype.saap)
specific.genotype.plot <- plotSpecificGenotype(genotype = genotype.saap,
phenotype = phenotype.saap, index = 3)
```

---

runGenphenBayes	<i>Conducting genetic association analysis with Bayesian inference, using hierarchical models.</i>
-----------------	--

---

### Description

This procedure performs a Bayesian two-sample t-test, to quantify the association between genotypes (SNPs or SAAPs) and phenotypes.

### Usage

```
runGenphenBayes(genotype, phenotype, chain.nr, mcmc.iter, model, hdi.levels)
```

### Arguments

genotype	Character matrix or data frame, containing SNPs/SAAPs as columns or alternatively as DNAMultipleAlignment or AAMultipleAlignment Biostrings object.
phenotype	Numerical vector, where each element is a measured phenotype corresponding to the observations of the genotype data.
chain.nr	Number of MCMC chains to simulate (recommended > 1).
mcmc.iter	Number of MCMC iterations used in the Bayesian inference (recommended >= 1000).
model	The hierarchical model used for the Bayesian inference (currently only two models are available). In case of a normally distributed phenotype, the model 'ndist' should be used, and 'tdist' if it is t-distributed (more robust to outliers).
hdi.levels	Highest density intervals (HDI) (default = c(0.95, 0.99)).

### Details

This procedure takes two types of data as input: first a genotype data (SNPs or SAAPs), each represented as a categorical vector; second a phenotype represented by a vector of continuous numbers, whose elements correspond to the elements of the genotype data. It then performs a Bayesian two-sample t-test analysis, computing the contrast between the phenotype means in the two groups ( $\mu_1 - \mu_2$ ). The high density intervals (HDIs) of the posteriors are also provided to quantify the reliability of the contrast.

In the classical two-sample t-test two assumptions are made: first, the phenotypes in each group should be normally distributed, and second they should have equal variances. Here, we have designed hierarchical models such that these assumptions are relaxed. Thus, we allow for the phenotype in either group to either be normally (model = 'ndist') or t-distributed (model = 'tdist'), while allowing heterogeneous variances.

### Value

Five classes of results are computed for each genotype-phenotype association, stored as a row in a data frame:

```
site, g.1, g.1, count.1, count.1
      General information about the genotype.
```

mu.1, mu.2, sd.1, sd.2  
 Mean posterior estimates for the mean phenotype associated with each genotype (mu.1 and mu.2), as well as the mean standard deviation posteriors sd.1 and sd.2.

mu.effect, mu.effect.95.L, mu.effect.95.H  
 The bayesian effect size mu.effect = mu.1 - mu.2, including the high density interval (HDI).

ess.mu.1, ess.mu.2  
 Effective sampling size estimated for mu.1 and mu.2

t.test.pvalue P-value score from a classical two-sample T-test.

**Author(s)**

Simo Kitanovski <simo.kitanovski@uni-due.de>

**References**

- Kruschke, John. Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan. Academic Press, 2014.

**See Also**

runGenpenRf, runGenpenSvm, plotGenphenBayes, plotSpecificGenotype, plotManhattan

**Examples**

```
data(genotype.saap)
# or data(genotype.saap.msa) in this case you cannot subset genotype.saap[, 1:5]
data(phenotype.saap)

# run analysis
genphen.bayes <- runGenphenBayes(genotype = genotype.saap[, 1:5],
                                phenotype = phenotype.saap,
                                mcmc.iter = 1000,
                                chain.nr = 2,
                                model = "tdist",
                                hdi.levels = c(0.95, 0.99))
```

---

runGenphenRf

*Conducting genetic association analysis with random forest*

---

**Description**

This procedure quantifies the accuracy with which one can predict a given genotypes (SNPs or SAAPs) from the corresponding phenotypes using random forest.

**Usage**

```
runGenphenRf(genotype, phenotype, cv.fold, cv.steps, hdi.level, ntree)
```

**Arguments**

genotype	Character matrix or data frame, containing SNPs/SAAPs as columns or alternatively as DNAMultipleAlignment or AAMultipleAlignment Biostrings object.
phenotype	Numerical vector, where each element is a measured phenotype corresponding to the observations of the genotype data.
cv.fold	The cross-validation fraction (0, 1) of the data which is used to train the classifier (default = 0.66). The remaining fraction (1-cv.fold) of the data is used to test the classifier.
cv.steps	Number of steps in the cross-validation to be performed to estimate the classification accuracy and the corresponding highest density intervals (recommended $\geq 100$ ).
hdi.level	Highest density level (default = 0.99).
ntree	Number of trees to grow in the random forest model.

**Details**

This procedure takes two types of data as input: first a genotype data (SNPs or SAAPs), each represented as a categorical vector; second a phenotype represented by a vector of continuous numbers, whose elements correspond to the elements of the genotype data. It then performs a random forest classification analysis, computing the classification accuracy (CA) with which one can predict the categories of a given genotype from the numerical values of the phenotype (predictor). If there is a significant association between a given genotype and phenotype, then one should be able to accurately predict the states of the genotype from that phenotype (CA = 1 for a perfect classification). To obtain a robust CA, this procedure applies cross-validation, training the models on a subset of the genotype-phenotype data, and then testing the models on the remaining data. Thus, in addition to the CA point estimate, one also estimates the corresponding confidence intervals.

In some instances the two states of the genotype are not evenly represented, i.e. one allele of a SNP might be represented in 90% of the individuals, while the other allele might only be represented in 10% of the individuals. Such data compositions can lead to skewed CA estimates. Therefore, to verify the CA, the procedure also computes the Cohen's kappa statistic (Cohen 1960), which compares the observed classification accuracy (CA) with the classification accuracy expected by chance (CA<sub>exp</sub>). If CA > CA<sub>exp</sub>, the procedure will yield high kappas (kappa = 1 in an ideal case), otherwise low kappas are to be expected (kappa ~ 0).

The function runGenphenRf also computes statistics such as Cohen's d (effect size) and the P-value resulting from a two-sample T-test, allowing the user to compare the random forest based results with those computed with simpler techniques which are frequently used for genetic association studies.

**Value**

Five classes of results are computed for each genotype-phenotype association, stored as a row in a data frame:

site, g.1, g.1, count.1, count.1	General information about the genotype.
ca, ca.hdi.low, ca.hdi.high, ca.hdi.length	Mean classification accuracy and its HDI.
kappa, kappa.hdi.low, kappa.hdi.high, kappa.hdi.length	Cohen's kappa statistics and its HDI.
effect.size, effect.CI.low, effect.CI.high	Cohen's effect size and CI.

t.test.pvalue P-value score from a classical two-sample T-test.

### Author(s)

Simo Kitanovski <simo.kitanovski@uni-due.de>

### References

- Breiman, Leo. Random forests. Machine learning 45.1 (2001): 5-32.
- Cohen, Jacob. Statistical power analysis for the behavior science. Lawrence Erlbaum Association (1988).
- Cohen, Jacob. A coefficient of agreement for nominal scales (1960).

### See Also

runGenphenSvm, runGenphenBayesian, plotGenphenResults, plotSpecificGenotype, plotManhattan

### Examples

```
data(genotype.saap)
#or data(genotype.saap.msa) in this case you cannot subset genotype.saap[, 1:5]
data(phenotype.saap)
genphen.rf <- runGenphenRf(genotype = genotype.saap[, 1:5],
                           phenotype = phenotype.saap,
                           cv.fold = 0.66,
                           cv.steps = 100,
                           hdi.level = 0.99,
                           ntree = 1000)
```

---

runGenphenSvm	<i>Conducting genetic association analysis with linear support vector machines (LSVM)</i>
---------------	---

---

### Description

This procedure quantifies the accuracy with which one can predict a given genotypes (SNPs or SAAPs) from the corresponding phenotypes using linear support vector machines (LSVM).

### Usage

```
runGenphenSvm(genotype, phenotype, cv.fold, cv.steps, hdi.level)
```

### Arguments

genotype	Character matrix or data frame, containing SNPs/SAAPs as columns or alternatively as DNAMultipleAlignment or AAMultipleAlignment Biostrings object.
phenotype	Numerical vector, where each element is a measured phenotype corresponding to the observations of the genotype data.
cv.fold	The cross-validation fraction (0, 1) of the data which is used to train the classifier (recommended = 0.66). The remaining fraction (1-cv.fold) of the data is used to test the classifier.

<code>cv.steps</code>	Number of steps in the cross-validation to be performed to estimate the classification accuracy and the corresponding highest density intervals (recommended $\geq 100$ ).
<code>hdi.level</code>	Highest density interval (default = 0.99).

### Details

This procedure takes two types of data as input: first a genotype data composed of a set of single nucleotide polymorphisms (SNPs) or alternatively single amino acid polymorphisms (SAAPs), each of which is represented by a column of character amino acids; second a numerical phenotype vector, where the elements sorted to correspond to the rows of the genotype data. This method quantifies the association between the polymorphic site (SNP or SAAP) and the phenotype via a classification analysis using linear support vector machines. The analysis results in a classification accuracy score between 0 and 1, where 1 indicates a perfect association between the genotype and the phenotype. To validate the classification accuracy, the tool also computes the Cohen's kappa statistics (Cohen 1960) which compares the observed classification accuracy with the expected classification accuracy. If the expected and observed classification accuracies are in concordance, the computed association can be taken seriously, otherwise it can be discarded as noise.

The function `runGenphenSvm` also computes statistics such as Cohen's *d* (effect size) and the *P*-value resulting from a two-sample *T*-test, allowing the user to compare the linear support vector based results with those computed with simpler techniques which are frequently used for genetic association studies.

### Value

Five classes of results are computed for each SAAP with respect to the phenotype, resulting in a 18 element vector which is stored as a row in the final data frame:

<code>effect.size</code> , <code>effect.CI.low</code> , <code>effect.CI.high</code>	Cohen's effect size and CI.
<code>ca</code> , <code>ca.hdi.low</code> , <code>ca.hdi.high</code> , <code>ca.hdi.length</code>	Mean classification accuracy and its HDI.
<code>kappa</code> , <code>kappa.hdi.low</code> , <code>kappa.hdi.high</code> , <code>kappa.hdi.length</code>	Cohen's kappa statistics and its HDI.
<code>site</code> , <code>g.1</code> , <code>g.2</code> , <code>count.1</code> , <code>count.2</code>	General information about the genotype.
<code>t.test.pvalue</code>	<i>P</i> -value score from an two-sample <i>T</i> -test.

### Author(s)

Simo Kitanovski <[simo.kitanovski@uni-due.de](mailto:simo.kitanovski@uni-due.de)>

### References

- Cortes, Corinna, and Vladimir Vapnik. Support-vector networks. *Machine learning* 20.3 (1995): 273-297.
- Cohen, Jacob. *Statistical power analysis for the behavior science*. Lawrence Erlbaum Association (1988).
- Cohen, Jacob. A coefficient of agreement for nominal scales (1960).

**See Also**

`runGenpenRf`, `runGenpenBayes`, `plotGenphenRfSvm`, `plotGenphenBayes`, `plotSpecificGenotype`,  
`plotManhattan`

**Examples**

```
data(genotype.saap)
#or data(genotype.saap.msa) in this case you cannot subset genotype.saap[, 1:5]
data(phenotype.saap)
genphen.svm <- runGenphenSvm(genotype = genotype.saap[, 1:5],
                             phenotype = phenotype.saap,
                             cv.fold = 0.66,
                             cv.steps = 100,
                             hdi.level = 0.99)
```

# Index

## \*Topic **dataset**

phenotype.saap, [5](#)

phenotype.snp, [5](#)

genotype.saap, [2](#)

genotype.saap.msa, [3](#)

genotype.snp, [3](#)

genotype.snp.msa, [4](#)

phenotype.saap, [5](#)

phenotype.snp, [5](#)

plotGenphenBayes, [6](#)

plotGenphenRfSvm, [7](#)

plotManhattan, [8](#)

plotSpecificGenotype, [9](#)

runGenphenBayes, [10](#)

runGenphenRf, [11](#)

runGenphenSvm, [13](#)