

# Package ‘GlmSimulatorR’

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**Type** Package

**Title** Creates Ideal Data for Generalized Linear Models

**Version** 1.0.0

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**Description** Creates ideal data for all distributions in the generalized linear model framework.

**License** GPL-3

**Encoding** UTF-8

**Imports** assertthat, stats, stringr, dplyr, statmod, magrittr, MASS, tweedie, ggplot2, cplm

**RoxygenNote** 7.2.3

**Suggests** testthat (>= 3.0.0), knitr, rmarkdown, covr

**VignetteBuilder** knitr

**Config/testthat/edition** 3

**NeedsCompilation** no

**Repository** CRAN

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simulate\_gaussian      *Create ideal data for a generalized linear model.*

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### Description

Create ideal data for a generalized linear model.

### Usage

```
simulate_gaussian(  
  N = 10000,  
  link = "identity",  
  weights = 1:3,  
  x_range = 1,  
  unrelated = 0,  
  ancillary = 1  
)  
  
simulate_binomial(  
  N = 10000,  
  link = "logit",  
  weights = c(0.1, 0.2),  
  x_range = 1,  
  unrelated = 0  
)  
  
simulate_gamma(  
  N = 10000,  
  link = "inverse",  
  weights = 1:3,  
  x_range = 1,  
  unrelated = 0,  
  ancillary = 0.05  
)  
  
simulate_poisson(  
  N = 10000,  
  link = "log",  
  weights = c(0.5, 1),  
  x_range = 1,  
  unrelated = 0  
)  
  
simulate_inverse_gaussian(  
  N = 10000,  
  link = "1/mu^2",  
  weights = 1:3,  
  unrelated = 0  
)
```

```

    x_range = 1,
    unrelated = 0,
    ancillary = 0.3333
)

simulate_negative_binomial(
  N = 10000,
  link = "log",
  weights = c(0.5, 1),
  x_range = 1,
  unrelated = 0,
  ancillary = 1
)

simulate_tweedie(
  N = 10000,
  link = "log",
  weights = 0.02,
  x_range = 1,
  unrelated = 0,
  ancillary = 1.15
)

```

### Arguments

N	Sample size. (Default: 10000)
link	Link function. See <a href="#">family</a> for details.
weights	Betas in glm model.
x_range	range of x variables.
unrelated	Number of unrelated features to return. (Default: 0)
ancillary	Ancillary parameter for continuous families and negative binomial. See details.

### Details

For many families, it is possible to pick weights that cause inverse link( $X * weights$ ) to be mathematically invalid. For example, the log link for binomial regression defines  $P(Y=1)$  as  $\exp(X * weights)$  which can be above one. If this happens, the function will error with a helpful message.

The intercept in the underlying link( $Y = X * weights + intercept$ ) is always  $\max(weights)$ . In `simulate_gaussian(link = "inverse", weights = 1:3)`, the model is  $(1/Y) = 1*X1 + 2*X2 + 3*X3 + 3$ .

links

- gaussian: identity, log, inverse
- binomial: logit, probit, cauchit, loglog, cloglog, log, logc, identity
- gamma: inverse, identity, log
- poisson: log, identity, sqrt
- inverse gaussian:  $1/\mu^2$ , inverse, identity, log

- negative binomial: log, identity, sqrt
- tweedie: log, identity, sqrt, inverse

The default link is the first link listed for each family.

ancillary parameter

- gaussian: standard deviation
- binomial: N/A
- gamma: scale parameter
- poisson: N/A
- inverse gaussian: dispersion parameter
- negative binomial: theta.
- tweedie: rho

### Value

A tibble with a response variable and predictors.

### Examples

```
library(GlmSimulator)
library(ggplot2)
library(MASS)

# Do glm and lm estimate the same weights? Yes
set.seed(1)
simdata <- simulate_gaussian()
linear_model <- lm(Y ~ X1 + X2 + X3, data = simdata)
glm_model <- glm(Y ~ X1 + X2 + X3,
  data = simdata,
  family = gaussian(link = "identity")
)
summary(linear_model)
summary(glm_model)
rm(linear_model, glm_model, simdata)

# If the link is not identity, will the response
# variable still be normal? Yes
set.seed(1)
simdata <- simulate_gaussian(N = 1000, link = "log", weights = c(.1, .2))

ggplot(simdata, aes(x = Y)) +
  geom_histogram(bins = 30)
rm(simdata)

# Is AIC lower for the correct link? For ten thousand data points, depends
# on seed!
set.seed(1)
simdata <- simulate_gaussian(N = 10000, link = "inverse", weights = 1)
glm_correct_link <- glm(Y ~ X1,
```

```
    data = simdata,
    family = gaussian(link = "inverse")
  )
  glm_wrong_link <- glm(Y ~ X1,
    data = simdata,
    family = gaussian(link = "identity")
  )
  summary(glm_correct_link)$aic
  summary(glm_wrong_link)$aic
  rm(simdata, glm_correct_link, glm_wrong_link)

# Does a stepwise search find the correct model for logistic regression? Yes
# 3 related variables. 3 unrelated variables.
set.seed(1)
simdata <- simulate_binomial(
  N = 10000, link = "logit",
  weights = c(.3, .4, .5), unrelated = 3
)

scope_arg <- list(
  lower = Y ~ 1,
  upper = Y ~ X1 + X2 + X3 + Unrelated1 + Unrelated2 + Unrelated3
)

starting_model <- glm(Y ~ 1,
  data = simdata,
  family = binomial(link = "logit")
)
glm_model <- stepAIC(starting_model, scope_arg)
summary(glm_model)
rm(simdata, scope_arg, starting_model, glm_model)

# When the response is a gamma distribution, what does a scatter plot between
# X and Y look like?
set.seed(1)
simdata <- simulate_gamma(weights = 1)
ggplot(simdata, aes(x = X1, y = Y)) +
  geom_point()
rm(simdata)
```

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