# Package 'workingfunctions'

# February 23, 2025

Title Statistical reporting and visualization for common methods		
Version 0.1		
<b>Description</b> Statistical reporting and visualization for common methodology used in psychology. Functions to minimize code and automate procedures using common R packages.		
<b>Depends</b> R ( $>= 3.5$ ), ggplot2, tcR		
Imports MASS, future, future.apply, gtable, gtools, irr, openxlsx, pROC, plyr, psych, reshape2, stringr, xgboost, DescTools, Rmisc, ggfortify, ggrepel, car, dplyr, lmerTest, sjstats, doSNOW, foreach, ggpubr, gridExtra, scales, pwr, mirt, nlme, MplusAutomation, NLP, openNLP, tm, spelling, catR, lavaan, ggExtra, QuantPsyc, semPlot, R.utils, purrr, emmeans, ez, Ckmeans.1d.dp		
License GPL		
Encoding UTF-8		
LazyData true		
Author Dimitrios Zacharatos [aut, cre]		
Maintainer Dimitrios Zacharatos <dzacharatos@yahoo.com></dzacharatos@yahoo.com>		

# **Contents**

RoxygenNote 7.3.2

alpha_diagnostics
call_to_string
cdf
cfa_icc_index
change_data_type
clear_stopwords
clear_text
comparison_combinations
compute_ability
compute_adjustment
compute_aggregate
compute_aov_es
compute_confidence_inteval

2 Contents

compute_crosstable
compute_descriptives
compute_dissatenuation
compute_dummy_comparisons
compute_frequencies
compute_icc_thurstonian
compute_info_1pl
compute_info_2pl
compute_info_3pl
compute_kruskal_wallis_test
compute_kurtosis
compute_map
compute_moving_average
compute_one_way_test
compute_posthoc
compute_power_r
compute_power_r_matrix
compute_residual_stats
compute_scores
compute_se_theta
compute_skewness
compute_standard
compute_standard_error       27         compute_unidimensional_ability       28
1
1 = 5
confusion
confusion_matrix_percent
convert_excel_unix_timestamp
c_bind
data_frame_index
decompose_datetime
deg2rad
detach_package
df_admission
df_automotive_data
df_blood_pressure
df_crop_yield
df_difficile
df_insurance
df_responses_state
df_sexual_comp
display_upper_lower_triangle
dotnames
drop_levels
dummy_arrange
environment_options
excel confusion matrix

Contents 3

excel_critical_value	44
excel_generic_format	45
excel_matrix	47
extract_components	
flatten_list	
generate_comparisons_matrix	
generate_correlation_matrix	
generate_data	
generate_factor	
generate_matrix_A	
generate_matrix_lambda_hat	
generate_missing	
generate_multiple_responce_vector	
generate_string	
generate_unique_comparisons_index	
getfwp	
get_mplus_thu_3t	
icc_cfa	
increase_index	
install_all_packages	
install_load	
key_to_cfa_model	
k_fold	
k_sample	
matrix_triangle	60
mean_sd_alpha	
mgsub	61
min_max_index	62
model_loadings	62
off_diagonal_index	63
outlier_summary	64
output_compare_model_logistic	64
output_separator	65
padNA	
plot_acf	
plot_boxplot	
plot_cfa	
plot confusion	68
plot_corrplot	69
plot_crosstable	69
plot histogram	70
plot_icc_thurstonian	71
plot_interaction	72
<u> </u>	73
plot_irt_onefactor	
plot_loadings	74
plot_logistic_model	75
plot_mosaic	76
nlot mtmm	76

4 Contents

plot_multiplot	. 77
plot_normality_diagnostics	. 78
plot_oneway	. 79
plot_oneway_diagnostics	. 80
plot_outlier	. 81
plot_qq	
plot_response_frequencies	. 82
plot_roc	
plot_scatterplot	
plot_scree	
plot_separability	
plot_trees_xgboost	
plot_ts	. 87
proper	. 88
proportion_accurate	
questions_by_keys	
questions_dimensions_dataframe	
rad2deg	
rank3_to_triplets	
rank_df_to_binary	
rank_to_binary	
raw_alpha	
rbind_all	
recode_scale_dummy	
remove nc	
remove_outliers	
remove_user_packages	
replace_na_with_previous	
report_alpha	
report_cfa	
report_choric_serial	
report_correlation	
report_dataframe	
report_efa	
report_factorial_anova	
report_hlr	
report irt	
report_lda	
report_logistic	
report_manova	
•	
report_normality_tests	
report_pdf	
report_regression	
report_ttests	
report_wtests	
report_xgboost	
response dimension	118

alpha\_diagnostics 5

	response_frequency	118
	result_confusion_performance	119
	round_dataframe	120
	shrout	121
	simulate_cfa_fit	122
	simulate_correlation_from_sample	123
	split_str	123
	split_str_df	124
	stat_word_char	125
	string_aes	125
	sub_str	
	swap	
	symmetric_matrix	
	tag_pos	
	text_similarity	
	trim_df	
	ts_smoothing	
	wrapper	
	write_txt	132
Index		133
muex		133
a⊥pha	a_diagnostics Item total correlation and r drop	

# Description

Item total correlation and r drop

# Usage

```
alpha_diagnostics(df)
```

# Arguments

df

dataframe with one dimension

```
set.seed(12345)
df<-data.frame(matrix(.5,ncol=6,nrow=6))
correlation_martix<-as.matrix(df)
diag(correlation_martix)<-1
df<-round(generate_correlation_matrix(correlation_martix,nrows=1000),0)+5
psych::alpha(df)
alpha_diagnostics(df=df)</pre>
```

6 cdf

call\_to\_string

Model call to string

# Description

Takes a call object and convert it to string

# Usage

```
call_to_string(model)
```

# Arguments

model

Model object

# **Examples**

```
df<-generate_correlation_matrix()
model<-lm(df$X1~df$X2)
call_to_string(model)</pre>
```

cdf

Check dataframe

# **Description**

dataframe summary

# Usage

```
cdf(
   df,
   name_length = (getOption("width")/3),
   digits = 2,
   nuniques = 0,
   parralel = FALSE,
   file = NULL
)
```

# **Arguments**

df dataframe
name\_length number of characters to be displayed for names
digits number of rounding digits
nuniques number of unique items to display
parralel if TRUE it will run using multiple cores
file output filename

cfa\_icc\_index 7

### **Examples**

cfa\_icc\_index

index of items to convert from lavaan to thurstonian order for analysis

# **Description**

index of items to convert from lavaan to thurstonian order for analysis

# Usage

```
cfa_icc_index(nitems, nfactors = 3)
```

# **Arguments**

nitems number of items in the questionnaire

nfactors number of factors

# **Examples**

```
cfa_icc_index(nitems=18,nfactors=3)
```

change\_data\_type

dataframe data type transformations

# Description

dataframe data type transformations

# Usage

```
change_data_type(df, type)
```

8 clear\_stopwords

### Arguments

df dataframe

type "character" "numeric" "factor" "factor\_character" "character\_factor"

For "factor\_character" if factors are found, are converted to characters For "character\_factor" if characters are found, are converted to factors

#### **Examples**

```
cdf(df=change_data_type(df=mtcars, "character"))
cdf(df=change_data_type(df=mtcars, "numeric"))
cdf(df=change_data_type(df=mtcars, "factor"))
df<-change_data_type(df=mtcars, "factor")
cdf(df=change_data_type(df=df, "factor_character"))</pre>
```

clear\_stopwords

Remove stopwods

#### **Description**

Remove stopwods

Remove stopwods

### Usage

```
clear_stopwords(text, stopwords = stopwords::stopwords("english"))
clear_stopwords(text, stopwords = stopwords::stopwords("english"))
```

### **Arguments**

text character vector

stopwords character words to remove

```
text1<-"word_one word_two word_three"
text2<-"word_three word_four word_six"
text3<-"All the Lorem Ipsum generators on the Internet tend to repeat predefined
chunks as necessary, making this the first true generator on the Internet."
text4<-"It uses a dictionary of over 200 Latin words, combined with a handful of
model sentence structures, to generate Lorem Ipsum which looks reasonable."
text5<-"The generated Lorem Ipsum is therefore always free from repetition,
injected humour, or non-characteristic words etc."
stopwords<-stopwords::stopwords("english")
text<-c(text1,text2,text3,text4,text5)
clear_stopwords(text,stopwords=stopwords)
text1<-"word_one word_two word_three"
text2<-"word_three word_four word_six"</pre>
```

clear\_text 9

text3<-"All the Lorem Ipsum generators on the Internet tend to repeat predefined chunks as necessary, making this the first true generator on the Internet." text4<-"It uses a dictionary of over 200 Latin words, combined with a handful of model sentence structures, to generate Lorem Ipsum which looks reasonable." text5<-"The generated Lorem Ipsum is therefore always free from repetition, injected humour, or non-characteristic words etc." stopwords<-stopwords::stopwords("english") text<-c(text1,text2,text3,text4,text5) clear\_stopwords(text,stopwords=stopwords)

clear\_text

Clear text

### **Description**

Clear text

Clear text

#### Usage

clear\_text(text)
clear\_text(text)

#### Arguments

text

character vector

#### **Examples**

text1<-"word\_one word\_two word\_three"
text2<-"word\_three word\_four word\_six"</pre>

text3<-"All the Lorem Ipsum generators on the Internet tend to repeat predefined chunks as necessary, making this the first true generator on the Internet." text4<-"It uses a dictionary of over 200 Latin words, combined with a handful of model sentence structures, to generate Lorem Ipsum which looks reasonable." text5<-"The generated Lorem Ipsum is therefore always free from repetition, injected humour, or non-characteristic words etc." text<-c(text1,text2,text3,text4,text5) clear\_text(text)

text1<-"word\_one word\_two word\_three"
text2<-"word\_three word\_four word\_six"</pre>

text3<-"All the Lorem Ipsum generators on the Internet tend to repeat predefined chunks as necessary, making this the first true generator on the Internet." text4<-"It uses a dictionary of over 200 Latin words, combined with a handful of model sentence structures, to generate Lorem Ipsum which looks reasonable." text5<-"The generated Lorem Ipsum is therefore always free from repetition, injected humour, or non-characteristic words etc."

text<-c(text1,text2,text3,text4,text5)</pre>

clear\_text(text)

10 compute\_ability

comparison\_combinations

Produce combinations for comparisons from dataframe names

# Description

Produce combinations for comparisons from dataframe names

# Usage

```
comparison_combinations(df, all_orders = TRUE)
```

# **Arguments**

df dataframe

all\_orders if TRUE the order of combination is considered i.e. the combination X1 X2 also

appears as X2 X1 if FALSE it is assumed that X1 X2 and X2 X1 are the same

and only one of them appears

# **Examples**

```
comparison_combinations(generate_correlation_matrix(n=10)[,1:4])
```

compute\_ability

Compute subject ability for thurstonian models

# Description

Computes person ability for binary thurstonian coded items for a single dimension

# Usage

```
compute_ability(
  response,
  eta,
  gamma,
  lambda,
  psi,
  plot = FALSE,
  map = compute_map(eta = eta, mean = 0, sd = 1)
)
```

compute\_adjustment 11

# **Arguments**

response item responses eta eta or ability

gamma gamma or threshold lambda lambda or loading

psi or error

plot if TRUE plots icc curves using the plot\_icc\_thurstonian function

map vector from compute map

# **Examples**

```
gamma<-c(0.556,-1.253,-1.729,0.618,0.937,0.295,-0.672,-1.127,-0.446,0.632,1.147,0.498)
psi<-c(2.172,1.883,2.055,1.869,2.231,2.100,1.762,1.803,1.565,1.892,1.794,1.686)
lambda<-c(1.082,1.082,-1.297,-1.297,0.802,0.802,1.083,1.083)
gamma<-gamma[response_dimension(c(1:12),3,c(1,2))]
psi<-psi[response_dimension(c(1:12),3,c(1,2))]
eta<-seq(-6,6,by=0.1)
response1<-c(0,0,0,0,0,0,0,0,0)
response2<-c(1,1,1,1,1,1,1,1)
response3<-c(1,0,1,0,1,0,1,0)
response4<-c(0,1,0,1,0,1,0,1)
map<-compute_map(eta=eta,mean=0,sd=1)
compute_ability(response1,eta,gamma,lambda,psi,map=map,plot=FALSE)
compute_ability(response3,eta,gamma,lambda,psi,map=map,plot=FALSE)
compute_ability(response4,eta,gamma,lambda,psi,map=map,plot=FALSE)
compute_ability(response4,eta,gamma,lambda,psi,map=map,plot=FALSE)</pre>
```

compute\_adjustment

Compute adjustments

#### **Description**

Compute adjustments

### Usage

```
compute_adjustment(a, ntests)
```

### **Arguments**

a alpha criterionntests number of tests

```
compute_adjustment(0.05,100)
```

12 compute\_aov\_es

compute\_aggregate

Descriptive statistics

# Description

uses plyr

# Usage

```
compute_aggregate(df, iv, file = NULL)
```

# Arguments

df dataframe

iv index of independent variables

file output filename

### **Details**

returns xlsx

### **Examples**

```
compute_aggregate(df=mtcars,iv=9)
compute_aggregate(df=mtcars,iv=9:10)
compute_aggregate(df=mtcars,iv=9:11)
compute_aggregate(df=mtcars,iv=9:11,file="descriptives")
```

 ${\tt compute\_aov\_es}$ 

Compute eta and omega

# Description

Computes omega using aov object. Based on http://stats.stackexchange.com/a/126520

# Usage

```
compute_aov_es(model, ss = "I")
```

# **Arguments**

model object aov

ss Character type of sums of squares "I" "III" "III"

### **Examples**

```
form<-formula(uptake~Treatment)
one_way_between<-aov(form,CO2)
factorial_between<-aov(uptake~Treatment*Type,CO2)
compute_aov_es(model=one_way_between,ss="I")
sjstats::anova_stats(one_way_between,digits=10)
compute_aov_es(model=one_way_between,digits=10)
compute_aov_es(model=one_way_between,digits=10)
compute_aov_es(model=one_way_between,ss="III")
sjstats::anova_stats(one_way_between,digits=10)
compute_aov_es(model=factorial_between,ss="I")
sjstats::anova_stats(factorial_between,digits=10)
compute_aov_es(model=factorial_between,ss="II")
sjstats::anova_stats(factorial_between,digits=10)
compute_aov_es(model=factorial_between,digits=10)
compute_aov_es(model=factorial_between,ss="III")
sjstats::anova_stats(factorial_between,ss="III")
sjstats::anova_stats(car::Anova(factorial_between,Type=3),digits=10)</pre>
```

compute\_confidence\_inteval

Compute confidence interval

# Description

Compute confidence interval

# Usage

```
compute_confidence_inteval(vector)
```

# **Arguments**

vector

vector

```
set.seed(1)
vector<-rnorm(1000)
compute_confidence_inteval(vector)</pre>
```

compute\_descriptives

compute\_crosstable

Compute crosstables

### **Description**

Compute crosstables

# Usage

```
compute_crosstable(df, factor_index = NULL, combinations = NULL)
```

# Arguments

df dataframe
factor\_index index of factors
combinations index of comparisons

### **Examples**

```
combinations<-data.frame(index1=c("vs","am","gear"),index2=c("cyl","cyl","cyl"))
compute_crosstable(df=mtcars,combinations=combinations)
combinations<-data.frame(index1=c("vs","am"),index2=c("cyl","cyl"))
compute_crosstable(df=mtcars,combinations=combinations)
compute_crosstable(df=mtcars,factor_index=8:10)</pre>
```

compute\_descriptives Descriptive statistics

# Description

uses psych

# Usage

```
compute_descriptives(df, dv, iv = NULL, file = NULL)
```

# Arguments

df dataframe

dv index of dependent variablesiv index of independent variables

file output filename

### **Details**

returns xlsx

compute\_dissatenuation 15

### **Examples**

```
compute_descriptives(df=mtcars,dv=1:5)
compute_descriptives(df=mtcars,dv=1:2,iv=9:10)
compute_descriptives(df=mtcars,dv=1:2,file="descriptives_no_factor")
compute_descriptives(df=mtcars,dv=1:2,iv=9:10,file="descriptives_factor")
```

compute\_dissatenuation

Compute dissatenuation

# **Description**

Compute dissatenuation

### Usage

```
compute_dissatenuation(variable1, error1, variable2, error2)
```

# **Arguments**

variable1 vector

error1 vector error measurement for variable1

variable2 vector

error2 vector error measurement for variable2

# **Examples**

```
set.seed(1)
compute_dissatenuation(rnorm(10),rnorm(10),rnorm(10),rnorm(10))
```

compute\_dummy\_comparisons

Compute number of dummy comparisons

# **Description**

Compute number of dummy comparisons

# Usage

```
compute_dummy_comparisons(items)
```

### **Arguments**

items number of items per block

# **Examples**

```
compute_dummy_comparisons(1)
compute_dummy_comparisons(2)
compute_dummy_comparisons(3)
compute_dummy_comparisons(4)
compute_dummy_comparisons(5)
compute_dummy_comparisons(6)
```

compute\_frequencies

Frequencies by levels

# Description

returns frequency proportion percent

# Usage

```
compute_frequencies(df, ordered = TRUE, file = NULL)
```

# **Arguments**

df dataframe

ordered if TRUE it will output frequencies in descending order

file output filename

# **Details**

returns xlsx

```
compute_frequencies(df=generate_missing(generate_factor(nrows=10,ncols=10),missing=5))
compute_frequencies(df=generate_factor())
compute_frequencies(df=generate_factor(),file="descriptives")
```

compute\_icc\_thurstonian

Compute item characteristic curves for thurstonian models

# **Description**

Computes icc curves for binary thurstonian coded items for a single dimension

### Usage

```
compute_icc_thurstonian(eta, gamma, lambda, psi, plot = FALSE)
```

### **Arguments**

eta eta or ability

gamma gamma or threshold lambda lambda or loading

psi psi or error

plot if TRUE plots icc curves using the plot\_icc\_thurstonian function

### **Examples**

```
 \begin{array}{l} \operatorname{gamma} < -\operatorname{c}(0.556, -1.253, -1.729, 0.618, 0.937, 0.295, -0.672, -1.127, -0.446, 0.632, 1.147, 0.498) \\ \operatorname{psi} < -\operatorname{c}(2.172, 1.883, 2.055, 1.869, 2.231, 2.100, 1.762, 1.803, 1.565, 1.892, 1.794, 1.686) \\ \operatorname{lambda} < -\operatorname{c}(1.082, 1.082, -1.297, -1.297, 0.802, 0.802, 1.083, 1.083) \\ \operatorname{gamma} < -\operatorname{gamma} [\operatorname{response\_dimension}(\operatorname{c}(1:12), 3, \operatorname{c}(1, 2))] \\ \operatorname{psi} < -\operatorname{psi} [\operatorname{response\_dimension}(\operatorname{c}(1:12), 3, \operatorname{c}(1, 2))] \\ \operatorname{eta} < -\operatorname{seq}(-6, 6, \operatorname{by} = 0.01) \\ \operatorname{compute\_icc\_thurstonian}(\operatorname{eta} = \operatorname{eta}, \operatorname{gamma} = \operatorname{gamma}, \operatorname{lambda} = \operatorname{lambda}, \operatorname{psi} = \operatorname{psi}, \operatorname{plot} = \operatorname{FALSE}) \\ \end{array}
```

compute\_info\_1pl

Compute item information for 1PL model

# Description

Compute item information for 1PL model

### Usage

```
compute_info_1pl(b, theta)
```

# Arguments

b numeric difficulty parameter

theta numeric theta

18 compute\_info\_2pl

### **Examples**

```
compute_info_1pl(b=1,theta=-3)
compute_info_1pl(b=1,theta=-2)
compute_info_1pl(b=1,theta=-1)
compute_info_1pl(b=1,theta=0)
compute_info_1pl(b=1,theta=1)
compute_info_1pl(b=1,theta=2)
compute_info_1pl(b=1,theta=3)
ti<-compute_info_1pl(b=1,theta=seq(-6,6,by=.01)) # test information
plot(ti,x=seq(-6,6,by=.01))</pre>
```

compute\_info\_2pl

Compute item information for 2PL model

### **Description**

Compute item information for 2PL model

### Usage

```
compute_info_2pl(a, b, theta)
```

# **Arguments**

a numeric discrimination parameter
b numeric difficulty parameter
theta numeric theta

```
compute_info_2pl(a=1.5,b=1,theta=-3)
compute_info_2pl(a=1.5,b=1,theta=-2)
compute_info_2pl(a=1.5,b=1,theta=-1)
compute_info_2pl(a=1.5,b=1,theta=0)
compute_info_2pl(a=1.5,b=1,theta=1)
compute_info_2pl(a=1.5,b=1,theta=2)
compute_info_2pl(a=1.5,b=1,theta=3)
ti<-compute_info_2pl(a=1.5,b=1,theta=3)
ti<-compute_info_2pl(a=1,b=-2,theta=seq(-6,6,by=.01)) # test information
plot(ti,x=seq(-6,6,by=.01))
ti<-compute_info_2pl(a=2,b=0,theta=seq(-6,6,by=.01)) # test information
plot(ti,x=seq(-6,6,by=.01))
ti<-compute_info_2pl(a=3,b=2,theta=seq(-6,6,by=.01)) # test information
plot(ti,x=seq(-6,6,by=.01))</pre>
```

compute\_info\_3pl

compute\_info\_3pl

Compute item information for 3PL model

# **Description**

Compute item information for 3PL model

# Usage

```
compute_info_3pl(a, b, g, theta)
```

# Arguments

a numeric discrimination parameter
b numeric difficulty parameter
g numeric guessing parameter
theta numeric theta

# **Examples**

```
compute_info_3pl(a=1.5,b=1,g=.2,theta=-3)
compute_info_3pl(a=1.5,b=1,g=.2,theta=-2)
compute_info_3pl(a=1.5,b=1,g=.2,theta=-1)
compute_info_3pl(a=1.5,b=1,g=.2,theta=0)
compute_info_3pl(a=1.5,b=1,g=.2,theta=1)
compute_info_3pl(a=1.5,b=1,g=.2,theta=2)
compute_info_3pl(a=1.5,b=1,g=.2,theta=3)
ti<-compute_info_3pl(a=1.5,b=1,g=.2,theta=seq(-6,6,by=.01)) # test information
plot(ti,x=seq(-6,6,by=.01))</pre>
```

```
{\tt compute\_kruskal\_wallis\_test}
```

Kruskal Wallis test

# **Description**

Kruskal Wallis test

### Usage

```
compute_kruskal_wallis_test(formula, df)
```

20 compute\_kurtosis

# Arguments

formula one way formula in form of y~x. It will ignore more complex formulas

df dataframe eta squared ranges between 0 and 1

epsilon squared ranges between 0 and 1

eta squared multiplied by 100 indicates the percentage of variance in the depen-

dent variable explained by the independent variable

# **Examples**

compute\_kurtosis

Compute kurtosis

# **Description**

Compute kurtosis

### Usage

```
compute_kurtosis(vector)
```

# **Arguments**

vector

vector

# Note

```
b_2 = m_4 / s^4 - 3 = (g_2 + 3) (1 - 1/n)^2 - 3. Used in MINITAB and BMDP.
```

```
set.seed(1)
vector<-rnorm(1000)
compute_kurtosis(vector)
e1071::kurtosis(vector)</pre>
```

compute\_map 21

compute\_map

Simulate prior distribution

# Description

Simulate prior distribution

# Usage

```
compute_map(eta, mean = 0, sd = 1)
```

# Arguments

eta vector mean numeric sd numeric

# Examples

```
eta<-seq(-6,6,by=0.1)
compute_map(eta=eta,mean=0,sd=1)</pre>
```

compute\_moving\_average

Moving Average

# Description

compute moving average

# Usage

```
compute_moving_average(df, w)
```

# Arguments

df dataframe w window

```
compute_moving_average(df=mtcars,w=5)
```

22 compute\_posthoc

```
compute_one_way_test one way test
```

#### **Description**

one way test

### Usage

```
compute_one_way_test(formula, df, var.equal = TRUE)
```

# **Arguments**

formula one way formula in form of y~x. It will ignore more complex formulas

df dataframe eta squared ranges between 0 and 1

epsilon squared ranges between 0 and 1

eta squared multiplied by 100 indicates the percentage of variance in the depen-

dent variable explained by the independent variable

var.equal if TRUE it assumes equal variances

#### Note

eta and omega for Welch statistics are not adequately tested and they should not be consulted

# **Examples**

```
form<-formula(qsec~cyl)
compute_one_way_test(formula=form,df=mtcars,var.equal=TRUE)
compute_one_way_test(formula=form,df=mtcars,var.equal=FALSE)
oneway.test(formula=form,data=mtcars,var.equal=TRUE)
oneway.test(formula=form,data=mtcars,var.equal=FALSE)
car::Anova(aov(form,data=mtcars),type=2)
model<-lm(form,data=mtcars)
lsr::etaSquared(aov(form,data=mtcars),type=3,anova=TRUE)
sjstats::anova_stats(model,digits=22)</pre>
```

compute\_posthoc

Games Howell Tukey post hoc tests

# **Description**

Based on http://www.psych.yorku.ca/cribbie/6130/games\_howell.R

### Usage

```
compute_posthoc(y, x, method = c("games-howell", "tukey"))
```

compute\_power\_r 23

# **Arguments**

y Vector continous variable

x Vector factor

method Character "games-howell" "tukey" or c("games-howell", "tukey")

# **Examples**

```
result<-compute_posthoc(mtcars[,6],mtcars[,10])</pre>
```

compute\_power\_r

Compute r power curve

# Description

Compute r power curve

# Usage

```
compute_power_r(
  n = 100,
  r = NULL,
  sig.level = 0.05,
  alternative = c("two.sided", "less", "greater"),
  title = "",
  base_size = 10
)
```

base font size

# Arguments

```
n number of observations

r correlation coefficient

sig.level alpha (type I error probability)

alternative a character string specifying the alternative hypothesis, must be one of "two.sided" (default), "greater" or "less"

title plot title
```

# **Examples**

base\_size

```
compute_power_r(n=100,r=.5,sig.level=.05,alternative=c("two.sided"))
```

```
compute_power_r_matrix
```

Compute correlation matrix

# **Description**

Compute correlation matrix

### Usage

```
compute_power_r_matrix(m, ...)
```

### **Arguments**

```
m correlation matrix
```

... arguments passed to compute\_power\_r

### **Examples**

```
compute_power_r_matrix(m=stats::cor(mtcars,use="pairwise.complete.obs"),n=100)
```

```
compute_residual_stats
```

Residuals for matrices

# Description

Root Mean Squared Residual Number of absolute residuals > 0.05 Proportion of absolute residuals > 0.05. It can either accept a psych EFA model or it can compare two correlation or covariance matrices

#### Usage

```
compute_residual_stats(model, data = NULL)
```

### **Arguments**

model psych EFA model. It has to be a correlation or covariance matrix if data is not

**NULL** 

data correlation or covariance matrix

```
\label{lem:model} $$ model < -psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="pa",oblique.scores=TRUE) $$ compute\_residual\_stats(model) $$
```

compute\_scores 25

compute\_scores

Compute subject ability for thurstonian models

### **Description**

Computes person ability for binary thurstonian coded items for a single dimension

# Usage

```
compute_scores(mydata, ...)
```

# **Arguments**

mydata item responses

... arguments passed to compute\_ability

# **Examples**

```
 \begin{array}{l} \operatorname{gamma} < -\operatorname{c}(0.556, -1.253, -1.729, 0.618, 0.937, 0.295, -0.672, -1.127, -0.446, 0.632, 1.147, 0.498) \\ \operatorname{psi} < -\operatorname{c}(2.172, 1.883, 2.055, 1.869, 2.231, 2.100, 1.762, 1.803, 1.565, 1.892, 1.794, 1.686) \\ \operatorname{lambda} < -\operatorname{c}(1.082, 1.082, -1.297, -1.297, 0.802, 0.802, 1.083, 1.083) \\ \operatorname{gamma} < -\operatorname{gamma} [\operatorname{response\_dimension}(\operatorname{c}(1:12), 3, \operatorname{c}(1, 2))] \\ \operatorname{psi} < -\operatorname{psi} [\operatorname{response\_dimension}(\operatorname{c}(1:12), 3, \operatorname{c}(1, 2))] \\ \operatorname{eta} < -\operatorname{seq}(-6, 6, \operatorname{by} = 0.1) \\ \operatorname{map} < -\operatorname{compute\_map}(\operatorname{eta} = \operatorname{eta}, \operatorname{mean} = 0, \operatorname{sd} = 1) \\ \operatorname{response\_df} < -\operatorname{data}. \operatorname{frame}(\operatorname{matrix}(\operatorname{nrow} = 0, \operatorname{ncol} = 8)) \\ \operatorname{response\_df} [1, ] < -\operatorname{c}(0, 0, 0, 0, 0, 0, 0, 0) \\ \operatorname{response\_df} [2, ] < -\operatorname{c}(1, 1, 1, 1, 1, 1, 1, 1, 1) \\ \operatorname{response\_df} [3, ] < -\operatorname{c}(1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
```

compute\_se\_theta

Compute the SE of theta

# **Description**

Compute the SE of theta

### Usage

```
compute_se_theta(info)
```

### **Arguments**

info

numeric information

26 compute\_standard

# **Examples**

```
\label{lem:compute_se_theta} $$ compute_se_theta(1) $$ ti<-compute_info_2pl(a=10,b=0,theta=seq(-3,3,by=.01)) $$ $$ test information $$ plot(compute_se_theta(ti),x=seq(-3,3,by=.01)) $$
```

compute\_skewness

Compute skewness

# Description

Compute skewness

# Usage

```
compute_skewness(vector)
```

### **Arguments**

vector

vector

# Note

```
b_1 = m_3 / s^3 = g_1 ((n-1)/n)^(3/2). Used in MINITAB and BMDP.
```

# **Examples**

```
set.seed(1)
vector<-rnorm(1000)
compute_skewness(vector)
e1071::skewness(vector)</pre>
```

 ${\tt compute\_standard}$ 

compute standard scores

# **Description**

compute standard scores

# Usage

```
compute_standard(vector, mean = 0, sd = 1, type = "z", input = "non_standard")
```

### **Arguments**

vector vector

mean numeric applicable to "uz" sd numeric applicable to "uz"

type "z" "uz" "sten" "t" "stanine" "center" "center\_reversed" "percent" "percentile"

"scale\_zero\_one" "normal\_density" "cumulative\_density" "all"

input "standard" "non\_standard" standard inputs are z scores and non standard are raw

scores

# **Examples**

```
vector<-c(rnorm(10),NA,rnorm(10))</pre>
compute_standard(vector, type="z")
compute_standard(vector,mean=0,sd=1,type="uz")
compute_standard(vector,type="sten")
compute_standard(vector,type="t")
compute_standard(vector,type="stanine")
compute_standard(vector, type="center")
compute_standard(vector,type="center_reversed")
compute_standard(vector,type="percent")
compute_standard(vector,type="scale_zero_one")
ndf <-compute\_standard(seq(-6,6,.01), mean=0, sd=1, type="normal\_density")
plot(ndf)
cdf<-compute_standard(ndf,mean=0,sd=1,type="cumulative_density")</pre>
plot(cdf)
compute_standard(vector, type="all")
compute_standard(seq(-6,6,.1),type="all",input="standard")
```

compute\_standard\_error

Compute standard error

### **Description**

Compute standard error

### Usage

```
compute_standard_error(vector)
```

### **Arguments**

vector vector

```
set.seed(1)
vector<-rnorm(1000)
compute_standard_error(vector)</pre>
```

```
compute_unidimensional_ability
```

Compute theta for unidimensional models

# Description

Compute theta for unidimensional models

### Usage

```
compute_unidimensional_ability(
   a,
   b,
   g = NULL,
   d = 1.702,
   u,
   lim_theta = c(-6, 6)
)
```

### **Arguments**

```
a numeric vector discrimination parameters
b numeric vector difficulty parameters
g numeric vector guessing parameters
d numeric scaling constant usually it is a value that approximating 1.749
u numeric vector responses
lim_theta vector minimum and maximum value of theta
```

```
 \begin{array}{l} \mathsf{a} < -\mathsf{c}(0.39, 0.45, 0.52, 0.3, 0.35, 0.43, 0.42, 0.44, 0.34, 0.42) \\ \mathsf{b} < -\mathsf{c}(-1.96, -1.9, -1.38, -0.58, 0.48, -0.81, -0.35, 1.59, 1.33, 2.93) \\ \mathsf{u} < -\mathsf{c}(1, 1, 1, 1, 0, 0, 1, 0, 1, 0) \\ \# \ \mathsf{SHOULD} \ \mathsf{RETURN} \ 0.48402574251176 \\ \mathsf{compute} \_ \mathsf{unidimensional}\_ \mathsf{ability}(\mathsf{a} = \mathsf{a}, \mathsf{b} = \mathsf{b}, \mathsf{u} = \mathsf{u}, \mathsf{d} = 1.7, \mathsf{g} = \mathsf{NULL}) \\ \mathsf{a} < -\mathsf{c}(1.27, 0.9, 0.94, 0.95, 0.55, 0.6, 0.44, 0.4) \\ \mathsf{b} < -\mathsf{c}(-0.54, 0.18, 0.21, 1.26, 1.73, -0.87, 1.72, 2.67) \\ \mathsf{u} < -\mathsf{c}(1, 1, 1, 1, 0, 0, 0, 0) \\ \# \ \mathsf{SHOULD} \ \mathsf{RETURN} \ 1.04621621510192 \\ \mathsf{compute} \_ \mathsf{unidimensional}\_ \mathsf{ability}(\mathsf{a} = \mathsf{a}, \mathsf{b} = \mathsf{b}, \mathsf{u} = \mathsf{u}, \mathsf{d} = 1.7, \mathsf{g} = \mathsf{NULL}) \\ \mathsf{a} < -\mathsf{c}(0.41, 0.32, 0.33, 1.2, 0.63, 0.62, 0.7, 0.61, 0.38, 0.53, 0.6, 1.16) \\ \mathsf{b} < -\mathsf{c}(-1.4, -1.3, -1.17, 0.2, 0.71, 0.86, -0.12, 0.12, 2.06, 1.38, 1.18, -0.33) \\ \mathsf{u} < -\mathsf{c}(1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0) \\ \# \ \mathsf{SHOULD} \ \mathsf{RETURN} \ 0.0860506282671103 \\ \mathsf{compute} \_ \mathsf{unidimensional}\_ \mathsf{ability}(\mathsf{a} = \mathsf{a}, \mathsf{b} = \mathsf{b}, \mathsf{u} = \mathsf{u}, \mathsf{d} = 1.7, \mathsf{g} = \mathsf{NULL}) \\ \end{aligned}
```

```
compute_unidimensional_theta
```

Compute theta for unidimensional models

# Description

Compute theta for unidimensional models

#### **Usage**

```
compute_unidimensional_theta(a, b = 0, g = 0, i = 1, d = 1.702, theta = 0)
```

# Arguments

a	numeric discrimination parameter
b	numeric difficulty parameter
g	numeric guessing parameter
i	numeric innatentiveness parameter
d	numeric scaling constant usually a value 1.749 or 1.702
theta	numeric or vector theta

### Note

```
when scaling constant=1 it has no effect in equation when innatentiveness=1 and guessing=0 function computes a 2PL score when innatentiveness=1 and guessing!=0 function computes a 3PL score when innatentiveness!=1 and guessing!=0 function computes a 4PL score
```

```
compute_unidimensional_theta(a=10,b=0)
x<-seq(-3,3,by=.01)
plot(compute_unidimensional_theta(a=5,b=0,theta=x),x=x)
plot(compute_unidimensional_theta(a=5,b=-1,theta=x),x=x)
plot(compute_unidimensional_theta(a=5,b=1,theta=x),x=x)
plot(compute_unidimensional_theta(a=.1,b=0,theta=x),x=x)
plot(compute_unidimensional_theta(a=1,b=0,theta=x),x=x)
plot(compute_unidimensional_theta(a=10,b=0,theta=x),x=x)
plot(compute_unidimensional_theta(a=10,b=0,g=0,theta=x),x=x)
plot(compute_unidimensional_theta(a=10,b=0,g=.1,theta=x),x=x)
plot(compute_unidimensional_theta(a=10,b=0,g=.5,theta=x),x=x)
plot(compute_unidimensional_theta(a=10,b=0,g=0,i=1,theta=x),x=x)
plot(compute_unidimensional_theta(a=10,b=0,g=0,i=.9,theta=x),x=x)
plot(compute_unidimensional_theta(a=10,b=0,g=0,i=.9,theta=x),x=x)
plot(compute_unidimensional_theta(a=10,b=0,g=0,i=.6,theta=x),x=x)</pre>
```

30 confusion

compute\_y\_logistic

Compute y for logistic function

# **Description**

This function requires x range to produce a vector with y values

### Usage

```
compute_y_logistic(intercept, coefficient, x)
```

# Arguments

intercept Numeric
coefficient Numeric
x Numeric

# **Examples**

```
x<--10:10
compute_y_logistic(0,1,x)
compute_y_logistic(0,1,1)
plot(x,compute_y_logistic(0,1,x),type="l");grid();abline(b=0,a=.5)</pre>
```

confusion

Create a confusion matrix from observed and predicted vectors

# **Description**

Generates a confusion matrix from observed and predicted values.

# Usage

```
confusion(observed, predicted)
```

# Arguments

observed Vector of observed variables. These are the true class labels.

predicted Vector of predicted variables. These are the predicted class labels.

#### **Details**

This function creates a confusion matrix by comparing the observed (true) class labels with the predicted class labels. The confusion matrix is a table that is often used to describe the performance of a classification model.

The function performs the following steps: 1. Identifies the unique class labels from both the observed and predicted vectors. 2. Sorts the class labels in a mixed order (if they are character variables) using 'gtools::mixedsort'. 3. Constructs a table to represent the confusion matrix with the sorted class labels as levels.

The output is a confusion matrix, where rows represent the predicted class labels and columns represent the observed class labels.

### **Examples**

```
# Example with numeric observed and predicted values
confusion(observed=c(1,2,3,4,5,10),predicted=c(1,2,3,4,5,11))
# Example with repeated observed and predicted values
confusion(observed=c(1,2,2,2,2),predicted=c(1,1,2,2,2))
```

confusion\_matrix\_percent

Confusion matrix with row and column percent

### Description

Generates a confusion matrix from observed and predicted values, including row and column percentages.

### Usage

```
confusion_matrix_percent(observed, predicted)
```

# **Arguments**

observed Vector of observed variables. These are the true class labels.

Predicted Vector of predicted variables. These are the predicted class labels.

### **Details**

This function creates a confusion matrix by comparing the observed (true) class labels with the predicted class labels. Additionally, it calculates row and column percentages to provide a more detailed performance analysis.

The function performs the following steps: 1. Computes the confusion matrix from the observed and predicted values. 2. Calculates the overall accuracy by dividing the sum of diagonal elements by the total number of observations. 3. Appends row and column sums to the confusion matrix. 4. Computes precision and recall for each class and appends these metrics to the matrix. 5. Returns a formatted data frame with the confusion matrix,row and column percentages,and overall accuracy.

### Note

Total measures - Accuracy: (TP+TN)/total
Total measures - Prevalence: (TP+FN)/total
Total measures - Proportion Incorrectly Classified: (FN+FP)/total
Horizontal measures - True Positive Rate - Sensitivity: TP/(TP+FN)
Horizontal measures - True Negative Rate - Specificity: TN/(FP+TN)
Horizontal measures - False Negative Rate - Miss Rate: FN/(TP+FN)
Horizontal measures - False Positive Rate - Fall-out: FP/(FP+TN)
Vertical measures - Positive Predictive value - Precision: TP/(TP+FP)
Vertical measures - Negative Predictive value: TN/(FN+TN)
Vertical measures - False Omission Rate: FN/(FN+TN)
Vertical measures - False Discovery Rate: FP/(TP+FP)

# **Examples**

```
# Example with numeric observed and predicted values
confusion_matrix_percent(observed=c(1,2,3,4,5,10),predicted=c(1,2,3,4,5,11))
# Example with repeated observed and predicted values
confusion_matrix_percent(observed=c(1,2,2,2,2),predicted=c(1,1,2,2,2))
# Example with random observed and predicted values
observed<-factor(round(rnorm(10000,m=10,sd=1)))
predicted<-factor(round(rnorm(10000,m=10,sd=1)))
confusion_matrix_percent(observed,predicted)</pre>
```

# Description

Convert UNIX EXCEL timestamp

#### **Usage**

```
convert_excel_unix_timestamp(timestamp)
```

# **Arguments**

timestamp unix or excel timestamp

```
convert_excel_unix_timestamp(1)
```

c\_bind 33

 $c\_bind$ 

cbind dataframes with unequal lengths or row lengths

# Description

cbind dataframes with unequal lengths or row lengths

# Usage

```
c_bind(..., first = TRUE)
```

# **Arguments**

... dataframes or vectors to bind

first Logical

# Author(s)

Ananda Mahto

# **Examples**

```
c_bind(rnorm(10),rnorm(11),rnorm(12),rnorm(13))
```

data\_frame\_index

dataframe index

# Description

dataframe index

# Usage

```
data_frame_index(nrow, ncol)
```

# Arguments

nrow number of rows
ncol number of collumns

```
data_frame_index(5,5)
```

34 decompose\_datetime

decompose\_datetime

Decompose datetime objects to dataframe collumns

### **Description**

Decompose datetime objects to dataframe collumns

# Usage

```
decompose_datetime(
    x,
    format = "",
    origin = "1970-01-01",
    tz = "GMT",
    extended = FALSE,
    breaks = c(-1, 5, 13, 16, 20, 23),
    ...
)
```

#### **Arguments**

x datetime object

format date time format

origin Starting date. The default is the unix time origin "1970-01-01"

tz Timezone

extended if TRUE it will display additional day time categories WEEKDAY MONTH JULIAN QUARTER DAY\_PERIOD

breaks Numeric vector Breaks define hour of day for classifiying into "Night", "Morning", "Noon", "Afternoon", "Evening".

... arguments passed to as.POSIXct This argument is used if extended=TRUE

```
timestamp1<-as.numeric(as.POSIXct(Sys.Date()))
timestamp2<-as.numeric(as.POSIXct(Sys.time()))
d1<-Sys.Date()
d2<-Sys.time()
decompose_datetime(x=d1)
decompose_datetime(x=d2)
decompose_datetime(x=d1,extended=TRUE)
decompose_datetime(x=d2,extended=TRUE)
decompose_datetime(x="01/15/1900",format="%m/%e/%Y")
decompose_datetime(x="01/15/1900",format="%m/%e/%Y",extended=TRUE)
decompose_datetime(x=as.Date(as.POSIXct(10000,origin="1970-01-01")))
decompose_datetime(x=as.Date(as.POSIXct(timestamp1,origin="1970-01-01")))</pre>
```

deg2rad 35

```
format="\%m/\%e/\%Y") \\ decompose\_datetime(x=as.Date(as.POSIXct(timestamp2,origin="1970-01-01")), \\ format="\%m/\%e/\%Y")
```

deg2rad

Convert degrees to radians

# Description

Convert degrees to radians

# Usage

deg2rad(degrees)

# Arguments

degrees

degrees

# **Examples**

deg2rad(180)

detach\_package

Unload library

# Description

Unload library

# Usage

detach\_package(package)

# Arguments

package

Package name

36 df\_automotive\_data

df\_admission

Admission Data

# Description

This data set contains information about graduate admission, including GRE scores, GPA, and the ranking of the undergraduate institution.

### Usage

```
df_admission
```

#### **Format**

A data frame with 8 rows and 4 variables:

```
admit Binary variable indicating admission (0 = No, 1 = Yes)
gre GRE (Graduate Record Examination) score
gpa Grade Point Average
rank Ranking of the undergraduate institution (1 = highest, 4 = lowest)
```

#### **Source**

researchpy repo

df\_automotive\_data

Automotive Data

# Description

This data set contains various automotive information including engine location, dimensions, weight, engine type, number of cylinders, and other specifications.

# Usage

```
df_automotive_data
```

#### **Format**

A data frame with 38 rows and 26 variables:

```
engine.location Location of the engine (e.g., front, rear)wheel.base Wheelbase of the vehicle in incheslength Length of the vehicle in incheswidth Width of the vehicle in inches
```

df\_blood\_pressure 37

height Height of the vehicle in inches
curb.weight Curb weight of the vehicle in pounds
engine.type Type of engine (e.g., dohc, ohcv, ohc, 1)
num.of.cylinders Number of cylinders in the engine
engine.size Size of the engine in cubic inches
fuel.system Fuel system used (e.g., mpfi, 2bbl, mfi, 1bbl)
bore Diameter of the cylinders in the engine
stroke Stroke length of the engine
compression.ratio Compression ratio of the engine
horsepower Horsepower generated by the engine
peak.rpm Peak RPM of the engine
city.mpg Miles per gallon in the city
highway.mpg Miles per gallon on the highway
price Price of the vehicle

#### Source

Downloaded from Kaggle.com by the user Ramakrishnan Srinivasan. see https://www.kaggle.com/toramky/automobile-dataset

df\_blood\_pressure

Blood Pressure Data

#### **Description**

This data set contains blood pressure readings for patients before and after a certain treatment or intervention.

### Usage

df\_blood\_pressure

#### Format

A data frame with 30 rows and 5 variables:

patient Unique identifier for each patient
sex Sex of the patient (e.g., Male, Female)
agegrp Age group of the patient (e.g., 30-45, 46-59)
bp\_before Blood pressure reading before the intervention
bp\_after Blood pressure reading after the intervention

#### Source

researchpy repo

38 df\_difficile

df\_crop\_yield

Crop Yield Data

#### **Description**

This data set contains information about crop yields based on different fertilizer types and water conditions.

# Usage

```
df_crop_yield
```

#### **Format**

A data frame with 20 rows and 3 variables:

Fert Type of fertilizer used (A or B)

Water Watering condition (High or Low)

Yield Crop yield (in unspecified units)

#### **Source**

researchpy repo (simulated data, not real)

df\_difficile

Difficile Data

### **Description**

This data set contains information about the impact of different doses on libido.

## Usage

```
df_difficile
```

#### **Format**

A data frame with 15 rows and 3 variables:

person Unique identifier for each person

dose Dose received (e.g., 1, 2, 3)

libido Libido level of the person

#### **Source**

researchpy repo

df\_insurance 39

df\_insurance

Insurance Data

#### **Description**

This data set contains information about insurance charges based on various factors such as age, sex, BMI, number of children, smoking status, and region.

#### Usage

df\_insurance

#### **Format**

A data frame with 19 rows and 7 variables:

age Age of the individual

sex Sex of the individual (e.g., male, female)

bmi Body Mass Index of the individual

children Number of children covered by the insurance

smoker Smoking status (yes or no)

**region** Region where the individual resides (e.g., southwest, southeast, northwest, northeast)

charges Insurance charges

# Source

researchpy repo

df\_responses\_state

Responses State Data

### Description

This data set contains simulated state information paired with participant numbers from the responses data set.

#### Usage

df\_responses\_state

#### Format

A data frame with 28 rows and 2 variables:

Participant. Number Unique identifier for each participant

State State code where the participant resides (e.g., MI, OH, CO, CA, MA, WA)

df\_sexual\_comp

#### **Source**

researchpy repo (simulated data, not real)

df\_sexual\_comp

Sexual Compatibility Data

# Description

This data set contains responses to questions about sexual compatibility, including scores, gender, and age.

# Usage

```
df_sexual_comp
```

### **Format**

A data frame with 22 rows and 13 variables:

- Q1 Response to question 1
- **Q2** Response to question 2
- **Q3** Response to question 3
- **Q4** Response to question 4
- **Q5** Response to question 5
- **Q6** Response to question 6
- **Q7** Response to question 7
- **Q8** Response to question 8
- Q9 Response to question 9
- Q10 Response to question 10

score Total score

**gender** Gender of the respondent (1 = Male, 2 = Female)

age Age of the respondent

#### **Source**

researchpy repo

```
display_upper_lower_triangle
```

Return upper diagonal from one matrix and lower diagonal from another matrix

#### **Description**

Return upper diagonal from one matrix and lower diagonal from another matrix

#### Usage

```
display_upper_lower_triangle(m_upper, m_lower, diagonal = NA)
```

### **Arguments**

m\_upper matrix m\_lower matrix

diagonal if "upper" it returns upper diagonal if "lower" it returns lower diagonal if NA

returns NA in diagonal otherwise it returns any value spesified

#### **Examples**

```
m1<-matrix(1:9,nrow=3,ncol=3)
m2<-matrix(11:19,nrow=3,ncol=3)
display_upper_lower_triangle(m_upper=m1,m_lower=m2,diagonal="upper")
display_upper_lower_triangle(m_upper=m1,m_lower=m2,diagonal="lower")
display_upper_lower_triangle(m_upper=m1,m_lower=m2,diagonal=NA)
display_upper_lower_triangle(m_upper=m1,m_lower=m2,diagonal=1)
display_upper_lower_triangle(m_upper=m1,m_lower=m2,diagonal=c("X1","X2","X3"))
display_upper_lower_triangle(m_upper=m1,m_lower=m2,diagonal=c(1,2,3))
display_upper_lower_triangle(m_upper=m1,m2)</pre>
```

dotnames

Get the names of objects in the arguments

# Description

Get the names of objects in the arguments

# Usage

```
dotnames(...)
```

#### **Arguments**

... objects

42 dummy\_arrange

#### Author(s)

Ananda Mahto

drop\_levels

Drops unused factor levels

### **Description**

Drops unused factor levels

### Usage

```
drop_levels(df, factor_index = NULL, minimum_frequency = 5)
```

#### **Arguments**

df dataframe

 ${\tt factor\_index} \qquad {\tt numeric\ index\ of\ factors.}\ If\ NULL\ the\ function\ uses\ is.factor()\ to\ discriminate$ 

factors

minimum\_frequency

the minimum frequency each factor will have, levels with frequency bellow or

equal to the defined frequency will be renamed "Other"

# Examples

```
factor1<-factor(c(rep("A",10),rep("B",10)),levels=c("A","B","C","D"))
factor2<-factor(c(rep("A",10),rep("B",10)),levels=c("A","B","C","D"))
numeric1<-c(1:20)
df<-data.frame(numeric1,factor1,factor2)
df$factor1
drop_levels(df=df,minimum_frequency=9)
drop_levels(df=df,minimum_frequency=10)</pre>
```

dummy\_arrange

Takes a vector with multiple responses and dummy arranges it in a dataframe

# Description

Takes a vector with multiple responses and dummy arranges it in a dataframe

## Usage

```
dummy_arrange(vector)
```

environment\_options 43

## Arguments

vector Vector

#### **Examples**

environment\_options

Load environment options

### **Description**

Load environment options

### Usage

```
environment_options()
```

# **Examples**

```
environment_options()
```

excel\_confusion\_matrix

Write matrix or dataframe to excel sheet

### **Description**

Usefull for correlation matrices since it uses conditional formatting for matrices

# Usage

```
excel_confusion_matrix(
   df,
   workbook,
   title = "Rows: Expected Collumns: Observed"
)
```

44 excel\_critical\_value

#### **Arguments**

df dataframe or matrix

workbook workbook title comment

#### **Examples**

```
filename<-"excel_confusion_matrix.xlsx"
if (file.exists(filename)) file.remove(filename)
observed<-factor(round(rnorm(10000,m=10,sd=1)))
predicted<-factor(round(rnorm(10000,m=10,sd=1)))
confusion(observed,predicted)
cm<-confusion_matrix_percent(observed,predicted)
wb<-openxlsx::createWorkbook()
excel_confusion_matrix(cm,wb)
openxlsx::saveWorkbook(wb,invisible(paste(filename)),TRUE)</pre>
```

excel\_critical\_value

Write matrix or dataframe to excel sheet

#### **Description**

Usefull for generic data where conditional formating of a spesific collumn is required

#### Usage

```
excel_critical_value(
   df,
   workbook,
   sheet = "output",
   title = NULL,
   comment = NULL,
   numFmt = "#0.00",
   critical = NULL
)
```

#### **Arguments**

df dataframe or matrix

workbook workbook sheet sheet title title comment comment

numFmt number formatting

critical list in the form of (collumn1=critical\_value1,collumn2=critical\_value2...)

excel\_generic\_format 45

#### **Examples**

```
comment<-list(mpg="Miles/(US) gallon",</pre>
              cyl="Number of cylinders",
              disp="Displacement (cu.in.)",
              hp="Gross horsepower",
              drat="Rear axle ratio",
              wt="Weight (1000 lbs)",
              qsec="1/4 mile time",
              vs="Engine (0=V-shaped,1=straight)",
              am="Transmission (0=automatic,1=manual)",
              gear="Number of forward gears",
              carb="Number of carburetors",
              extra_comment1="test1",
              extra_comment2="test2")
filename<-"excel_critical_value.xlsx"
if (file.exists(filename)) file.remove(filename)
wb<-openxlsx::createWorkbook()
df<-generate_missing(generate_correlation_matrix())</pre>
critical<-list(X1="<0.05",X5="<0")</pre>
excel_critical_value(df=df,workbook=wb,sheet="critical",comment=list(X1="test"),
                     numFmt="#0.00",critical=critical)
openxlsx::saveWorkbook(wb,invisible(paste(filename)),TRUE)
filename<-"excel_critical_value_comment.xlsx"
if (file.exists(filename)) file.remove(filename)
wb<-openxlsx::createWorkbook()
df<-generate_missing(mtcars)</pre>
critical<-list(mpg=">20",am="=0")
excel_critical_value(df=df,workbook=wb,sheet="critical",comment=comment,
                     numFmt="#0.00",critical=critical)
openxlsx::saveWorkbook(wb,invisible(paste(filename)),TRUE)
filename<-"excel_critical_value_comment_min_max.xlsx"
if (file.exists(filename)) file.remove(filename)
wb<-openxlsx::createWorkbook()
df<-generate_missing(mtcars)</pre>
critical<-list(mpg=c(">20","<11"),am="=0")</pre>
excel_critical_value(df=df,workbook=wb,sheet="critical",comment=comment,
                     numFmt="#0.00",critical=critical)
openxlsx::saveWorkbook(wb,invisible(paste(filename)),TRUE)
```

excel\_generic\_format Generic function for creating workbooks and worksheets

# Description

This function is used by excel\_matrix and excel\_critical\_value functions

## Usage

```
excel_generic_format(
```

```
df,
workbook,
sheet = "output",
title = NULL,
comment = NULL,
numFmt = "#0.00"
)
```

#### **Arguments**

df dataframe or matrix
workbook workbook
sheet sheet
title title
comment comment
numFmt number formatting

```
comment<-list(mpg="Miles/(US) gallon",</pre>
              cyl="Number of cylinders",
              disp="Displacement (cu.in.)",
              hp="Gross horsepower",
              drat="Rear axle ratio".
              wt="Weight (1000 lbs)",
              qsec="1/4 mile time",
              vs="Engine (0=V-shaped,1=straight)",
              am="Transmission (0=automatic,1=manual)",
              gear="Number of forward gears",
              carb="Number of carburetors",
              extra_comment1="test1",
              extra_comment2="test2")
mtcor<-data.frame(cor(mtcars))</pre>
filename<-"excel_generic.xlsx"
if (file.exists(filename)) file.remove(filename)
wb<-openxlsx::createWorkbook()</pre>
openxlsx::addWorksheet(wb, "sheet")
openxlsx::addWorksheet(wb, "correlation")
openxlsx:: \verb|writeData| (wb, \verb|sheet=||| sheet|||, x=mtcars|, colNames=TRUE|, rowNames=TRUE|)
openxlsx::writeData(wb,sheet="correlation",x=mtcor,colNames=TRUE,rowNames=TRUE)
excel_generic_format(df=mtcars,workbook=wb,sheet="sheet",title="test",
                      comment=comment,numFmt="#0.00")
excel_generic_format(df=mtcor,workbook=wb,sheet="correlation",title="correlation",
                      comment=comment,numFmt="#0.00")
openxlsx::saveWorkbook(wb,invisible(paste(filename)),TRUE)
```

excel\_matrix 47

excel\_matrix

Write matrix or dataframe to excel sheet

### **Description**

Usefull for corellation matrices. It uses conditional formatting for matrices, which outlines high and low values using background color

# Usage

```
excel_matrix(
   df,
   workbook,
   sheet = "output",
   title = NULL,
   comment = NULL,
   numFmt = "#0.00",
   conditional_formatting = FALSE,
   diagonal_length = nrow(df)
)
```

# Arguments

```
df
                  dataframe or matrix
                  workbook
workbook
sheet
                  sheet
title
                  title
comment
                 comment
numFmt
                 number formatting
conditional_formatting
                 if TRUE it will use conditional formatting
                 if TRUE it will add background fill to diagonal
diagonal
diagonal_length
                 length of diagonal for background fill
```

48 extract\_components

```
vs="Engine (0=V-shaped,1=straight)",
              am="Transmission (0=automatic,1=manual)",
              gear="Number of forward gears",
              carb="Number of carburetors",
              extra_comment1="test1",
              extra_comment2="test2")
mtcor<-data.frame(cor(mtcars))</pre>
filename<-"excel_matrix.xlsx"
if (file.exists(filename)) file.remove(filename)
wb<-openxlsx::createWorkbook()</pre>
excel_matrix(mtcars,wb,sheet="matrix",comment=comment,
             conditional_formatting=TRUE,diagonal=FALSE)
excel_matrix(mtcars,wb,sheet="diagonal_non_square",comment=comment,
             conditional_formatting=FALSE,diagonal=TRUE)
excel_matrix(mtcars[1:10,1:10],wb,sheet="diagonal_square",comment=comment[1:10],
             conditional_formatting=FALSE,diagonal=TRUE)
excel_matrix(mtcars,wb,sheet="matrix_diagonal_non_square",comment=comment,
             conditional_formatting=TRUE,diagonal=TRUE)
excel_matrix(mtcars[1:10,1:10],wb,sheet="matrix_diagonal_square",comment=comment[1:10],
             conditional_formatting=TRUE,diagonal=TRUE)
excel_matrix(mtcor,wb,sheet="r",comment=comment,
             conditional_formatting=FALSE,diagonal=FALSE)
excel_matrix(mtcor,wb,sheet="conditional_formatting_r",comment=comment,
             conditional_formatting=TRUE,diagonal=TRUE)
openxlsx::saveWorkbook(wb,invisible(paste(filename)),TRUE)
```

extract\_components

Extract variance components from model

#### Description

Extract variance components from model

#### Usage

```
extract_components(model, title = "")
```

#### **Arguments**

model model containing variance components title plot title

```
design<-expand.grid(time=1:3,item=1:3,person=1:10)
design<-change_data_type(design,type="factor")
design$response<-rowSums(change_data_type(design[,1:2],type="numeric"))+rnorm(90,0,0.1)
model<-mixlm::lm(response~r(time)*r(person)+r(item)*r(person),data=design)
extract_components(model)</pre>
```

flatten\_list 49

flatten\_list

Flatten two dimensional list

# Description

Flatten two dimensional list

# Usage

```
flatten_list(mydata)
```

# Arguments

mydata

list with two dimensions

```
generate_comparisons_matrix
```

Generate comparisons matrix

# Description

Generate comparisons matrix

## Usage

```
generate_comparisons_matrix(items)
```

# Arguments

items

number of items

```
generate_comparisons_matrix(2)
generate_comparisons_matrix(3)
generate_comparisons_matrix(4)
generate_comparisons_matrix(5)
generate_comparisons_matrix(6)
```

50 generate\_data

```
generate_correlation_matrix
```

Generate dataframe which outputs a predetermined correlation matrix

# **Description**

Generate dataframe which outputs a predetermined correlation matrix

### Usage

```
generate_correlation_matrix(correlation_martix, nrows = 10)
```

# Arguments

# **Examples**

```
df<-data.frame(matrix(.999,ncol=2,nrow=2))
correlation_martix<-as.matrix(df)
diag(correlation_martix)<-1
df<-generate_correlation_matrix(correlation_martix,nrows=100)
stats::cor(df)</pre>
```

generate\_data

Generate dataframe with random numbers

# Description

Generate dataframe with random numbers

### Usage

```
generate_data(
  nrows = 10,
  ncols = 5,
  mean = 0,
  sd = 1,
  min = 1,
  max = 5,
  type = "normal"
)
```

generate\_factor 51

### **Arguments**

nrows	number of rows to generate
ncols	number of collumns to generate
mean	mean of generated vectors
sd	standard deviation of generated vectors
min	minimum value in generated vector
max	maximum value in generated vector
type	character "normal" "uniform"

# **Examples**

```
generate_data(nrows=10,ncols=5,mean=0,sd=1,type="normal")
generate_data(nrows=10,ncols=5,min=1,max=5,type="uniform")
```

generate\_factor

Generate dataframe of factors

### **Description**

Generate dataframe of factors

# Usage

```
generate_factor(vector = LETTERS[1:5], nrows = 2, ncols = 10, type = "random")
```

# Arguments

vector	factor pool
nrows	number of rows to generate
ncols	number of collumns to generate
type	"balanced" or "random" "balanced" generates balanced factor vectrors, "random" generates random factor vectors

```
generate_factor(vector=LETTERS[1:5],ncols=5,nrows=10,type="random")
generate_factor(vector=LETTERS[1:5],ncols=5,nrows=10,type="balanced")
generate_factor(vector=LETTERS[1:5],ncols=1,nrows=10,type="balanced")
generate_factor(vector=LETTERS[1:5],ncols=1,nrows=10,type="random")
```

generate\_matrix\_A

Generate Matrix A

# Description

Generate Matrix A

## Usage

```
generate_matrix_A(blocks = 3, items = 3)
```

# Arguments

blocks number of blocks

items number of items per block

# **Examples**

```
generate_matrix_A(blocks=3,items=3)
```

```
generate_matrix_lambda_hat
```

Generate matrix lambda for spesified number of comparisons

# Description

Generate matrix lambda for spesified number of comparisons

# Usage

```
generate_matrix_lambda_hat(blocks = 3, items = 3)
```

# Arguments

blocks number of blocks

items number of items per block

```
generate_matrix_lambda_hat(blocks=3,items=4)
```

generate\_missing 53

generate\_missing

Generate missing data

### **Description**

Generate missing data

### Usage

```
generate_missing(df, missing = 5)
```

### **Arguments**

df vector or dataframe

missing number of missing data per vector

### **Examples**

```
generate_missing(rnorm(10),missing=5)
generate_missing(generate_data(nrow=10,ncol=2),missing=5)
```

```
generate_multiple_responce_vector
```

Generate multiple responce vector

# Description

Generate multiple responce vector

### Usage

```
generate_multiple_responce_vector(
  responces = 1:4,
  responded = 1:4,
  length = 10
)
```

### **Arguments**

responces unique categories allowed

responded number of categories observed in iteration

length length of returned vector

```
generate_multiple_responce_vector(responces=1:4,responded=1:4,length=10)
```

generate\_string

Generate random strings

### **Description**

Generate random strings

## Usage

```
generate_string(
  vector = c(LETTERS, letters, 0:9),
  vector_length = 1,
  nchar = 5
)
```

## **Arguments**

vector character pool

vector\_length number of strings to generate nchar Length of generated strings

# **Examples**

```
generate_string(nchar=10)
generate_string(nchar=10,vector_length=10)
```

```
generate_unique_comparisons_index
```

Generate index for unique comparisons

### **Description**

Generate index for unique comparisons

# Usage

```
generate_unique_comparisons_index(items)
```

## **Arguments**

items

number of items

getfwp 55

# **Examples**

```
generate_unique_comparisons_index(1)
generate_unique_comparisons_index(2)
generate_unique_comparisons_index(3)
generate_unique_comparisons_index(4)
generate_unique_comparisons_index(5)
generate_unique_comparisons_index(6)
```

getfwp

Get working file path

# Description

Get working file path

# Usage

getfwp()

# **Examples**

#getfwp()

get\_mplus\_thu\_3t

Simulate prior distribution

# Description

Simulate prior distribution

# Usage

```
get_mplus_thu_3t(model)
```

# Arguments

model

mplus thurstonian cfa model with 3 traits

56 increase\_index

icc\_cfa

Select responses for each dimension

# Description

Select responses for each dimension

# Usage

```
icc_cfa(eta, gamma, lambda, psi)
```

### **Arguments**

eta eta or ability

gamma or threshold lambda or loading

psi or error

# **Examples**

```
icc_cfa(seq(-6,6,.1),1,1,1)
```

increase\_index

index dataframe picks

# Description

index dataframe picks

# Usage

```
increase_index(blocks, items)
```

# Arguments

blocks number of blocks

items number of items per block

```
increase_index(3,3)
```

install\_all\_packages 57

# Description

Install all packages available in CRAN

# Usage

```
install_all_packages()
```

### **Details**

Install all packages available in CRAN. Already installed packages are not downloaded or installed

install\_load

Install and load multiple packages

# Description

Install and load multiple packages. If packages exist, they are loaded, if packages don't exist, they are downloaded installed and loaded

### Usage

```
install_load(package)
```

# Arguments

package

Vector Package names

# Author(s)

Steven Worthington

```
install_load("car")
install_load(c("car","ggplot2"))
```

58  $k_{\pm}$ fold

key\_to\_cfa\_model

Converts key to cfa model spesification

#### **Description**

This function uses the key spesification used in report\_alpha function and converts the key to a cfa model spesification

### Usage

```
key_to_cfa_model(key)
```

#### **Arguments**

key

index of trait names and items constituring a trait

#### **Examples**

```
\label{eq:population_model} \begin{split} &\text{population_model}<-\text{'t1}=\text{'x1}+.5*\text{x2}+.5*\text{x3}} \\ & & \text{t2}=\text{'x4}+.5*\text{x5}+.5*\text{x6} \\ & & \text{t3}=\text{'x7}+.5*\text{x8}+.5*\text{x9'} \end{split} \\ &\text{model\_data}<-\text{lavaan}::&\text{simulateData(population\_model,sample.nobs}=1000)} \\ &\text{key}<-\text{list(f1}=\text{paste0("x",1:3),f2}=\text{paste0("x",4:6),f3}=\text{paste0("x",7:9))} \\ &\text{model}<-\text{key\_to\_cfa\_model(key)} \\ &\text{fit}<-\text{lavaan}::&\text{cfa(model,model\_data)} \end{split}
```

k\_fold

K-Fold train test sampling

### **Description**

Splits a dataframe into train and test dataframes for model evaluation. Prepared data include data objects for xgboost.

### Usage

```
k_fold(df, model_formula, k = 10)
```

### **Arguments**

df Dataframe containing the dataset to be split.

model\_formula Model formula specifying the predictors and outcome variable.

k Integer value representing the number of folds. Defaults to 10.

k\_sample 59

#### **Details**

This function performs k-fold cross-validation by splitting the input dataframe into k folds. Each fold serves as a test set once, while the remaining k-1 folds form the training set.

The function prepares data objects for xgboost model training and evaluation, including train/test datasets and xgboost DMatrix objects.

The output is a list containing the following elements: - 'f': List of train and test datasets for each fold. - 'index': Vector of fold indices. - 'model\_formula': Model formula used for generating the datasets. - 'variables': Names of the variables in the model formula. - 'predictors': Names of the predictor variables. - 'outcome': Name of the outcome variable. - 'xgb': List of xgboost DMatrix objects for training and testing.

#### **Examples**

```
# Example with the 'infert' dataset
infert_formula<-formula(case~education+spontaneous+induced)
result<-k_fold(infert,k=10,model_formula=infert_formula)

# Example with the 'mtcars' dataset
model_formula<-as.formula(mpg ~ cyl + disp + hp + drat + wt + qsec + vs + am + gear + carb)
result<-k_fold(mtcars,k=2,model_formula=model_formula)</pre>
```

k\_sample

Train test sampling

## Description

Splits a dataframe into train and test dataframes for model evaluation. Prepared data include data objects for xgboost.

#### Usage

```
k_sample(df, model_formula, k = 1)
```

#### **Arguments**

df Dataframe containing the dataset to be split.

model\_formula Model formula specifying the predictors and outcome variable.

k Integer value representing the number of folds. Defaults to 1 (train-test split).

#### **Details**

This function performs k-fold cross-validation or a simple train-test split (if k=1) by splitting the input dataframe into k folds. Each fold serves as a test set once, while the remaining k-1 folds form the training set.

60 matrix\_triangle

The function prepares data objects for xgboost model training and evaluation, including train, test, and validation datasets and xgboost DMatrix objects.

The output is a list containing the following elements: - 'f': List of train,test,and validation datasets for each fold. - 'index': Vector of fold indices. - 'model\_formula': Model formula used for generating the datasets. - 'variables': Names of the variables in the model formula. - 'predictors': Names of the predictor variables. - 'outcome': Name of the outcome variable. - 'xgb': List of xgboost DMatrix objects for training,testing,and validation.

### **Examples**

```
# Example with the 'infert' dataset
infert_formula<-formula(case~education+spontaneous+induced)
result<-k_sample(df=infert,k=10,model_formula=infert_formula)

# Example with the 'mtcars' dataset
model_formula<-as.formula(mpg ~ cyl + disp + hp + drat + wt + qsec + vs + am + gear + carb)
result<-k_sample(df=mtcars,k=10,model_formula=model_formula)</pre>
```

matrix\_triangle

Return upper or lower matrix triangle

#### Description

Return upper or lower matrix triangle

### Usage

```
matrix_triangle(m, off_diagonal = NA, diagonal = NULL, type = "lower")
```

## **Arguments**

m matrix

off\_diagonal off diagonal value

diagonal diagonal value. If NULL it returns the diagonal of the input matrix type "upper" displays upper triangle, "lower" displays lower triangle

```
m<-matrix(1:9,nrow=3,ncol=3)
matrix_triangle(m=m)
matrix_triangle(m=m,diagonal=NA,type="lower")
matrix_triangle(m=m,diagonal=NULL,type="lower")
matrix_triangle(m=m,diagonal=NA,type="upper")
matrix_triangle(m=m,diagonal=NULL,type="upper")</pre>
```

mean\_sd\_alpha 61

mean\_sd\_alpha

Mean and SD

### **Description**

Mean and SD

### Usage

```
mean_sd_alpha(df, divisor = NULL)
```

### **Arguments**

df dataframe with one dimension

divisor number to use for dividing the rowsums

### **Examples**

```
set.seed(12345)
df<-data.frame(matrix(.5,ncol=6,nrow=6))
correlation_martix<-as.matrix(df)
diag(correlation_martix)<-1
df<-round(generate_correlation_matrix(correlation_martix,nrows=1000),0)+5
mean_sd_alpha(df)
mean_sd_alpha(df,divisor=100)</pre>
```

mgsub

Sub for multiple patterns

### **Description**

Sub for multiple patterns

### Usage

```
mgsub(mydata, pattern, replacement, ...)
```

### **Arguments**

mydata Character

pattern Character to search for replacement Replacement character ... arguments passed to gsub

```
mgsub(mydata="#$%^&*_+",pattern=c("%","*"),"REPLACE",fixed=TRUE)
```

62 model\_loadings

min\_max\_index

Return the minimum and maximum index of a vector

# Description

Return the minimum and maximum index of a vector

### Usage

```
min_max_index(vector)
```

#### **Arguments**

vector

Vector

# **Examples**

```
vector1<-c(1,2,3,4,5,4,3,2,1)
vector2<-c(1,2,3,4,5,5,3,2,1)
vector3<-c(1,2,3,5,5,4,3,2,1)
vector4<-c(1,2,3,4,6,4,3,2,1)
vector5<-c(1,6,3,4,6,4,3,2,1)
vector<-vector1
which(vector==max(vector),arr.ind=TRUE)
which(vector==min(vector),arr.ind=TRUE)
min_max_index(vector1)
min_max_index(vector2)
min_max_index(vector3)
min_max_index(vector4)
min_max_index(vector5)</pre>
```

 $model\_loadings$ 

Pattern and structure matrix

### **Description**

Pattern and structure matrix

### Usage

```
model_loadings(model, cut = NULL, matrix_type = "pattern", sort = TRUE, ...)
```

off\_diagonal\_index 63

## **Arguments**

```
model psych EFA model

cut cut point for loadings

matrix_type "pattern" "structure" "all"

sort if TRUE it will sort loadings

... arguments passed to psych::fa.sort
```

#### Note

Check to see if you have multicolinearity values above .8 in the matrix are problematic Structure matrix represents Loadings after rotation

Pattern matrix represents Loadings before rotation

#### **Examples**

```
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="pa",oblique.scores=TRUE)
model_loadings(model=model,cut=NULL,matrix_type="pattern")
model_loadings(model=model,cut=0.4,matrix_type="structure")
model_loadings(model=model,cut=0.4,matrix_type="all",sort=FALSE)</pre>
```

 $off\_diagonal\_index$   $index\ of\ off\ diagonal$ 

### **Description**

index of off diagonal

### Usage

```
off_diagonal_index(length)
```

### **Arguments**

length length of diagonal

```
off_diagonal_index(length=6)
```

outlier\_summary

Percent of outliers in vector

## Description

Percent of outliers in vector

#### Usage

```
outlier_summary(vector)
```

# Arguments

vector

numeric vector

#### **Details**

returns dataframe

# **Examples**

```
vector<-generate_missing(rnorm(1000))
df<-generate_missing(mtcars[,1:2])
outlier_summary(vector)
data.frame(sapply(mtcars,outlier_summary))</pre>
```

```
\verb"output_compare_model_logistic"
```

Compare logistic regression models models

# Description

Compare logistic regression models models

### Usage

```
output_compare_model_logistic(model1, model2)
```

### **Arguments**

```
model1 object glm model
model2 object glm model
```

output\_separator 65

#### **Examples**

output\_separator

Output separator

#### **Description**

Heading, main output, and instructions for output for the console environment

#### Usage

```
output_separator(
   string,
   output = NULL,
   instruction = NULL,
   length = getOption("width")/2
)
```

#### **Arguments**

string Title of output output object to print

instruction Character provided instructions regarding the output

length Numeric Length of separator measured in number of characters

```
output_separator(string="TEST",output="TEST",instruction="TEST",length=100)
output_separator(string="TEST",instruction="TEST",length=100)
output_separator(string="TEST",output="TEST",length=100)
output_separator(string="TEST")
```

plot\_acf

padNA

pad NA's to collumns in dataframe

# Description

pad NA's to collumns in dataframe

# Usage

```
padNA(df, rowsneeded, first = TRUE)
```

## Arguments

df dataframe

rowsneeded Numeric number of rows needed

first Boolean

# Author(s)

Ananda Mahto

plot\_acf

Plot autocorrelation function of correlation covariance and partial correlation

# Description

uses ggplot

## Usage

```
plot_acf(df, lag.max = length(df), base_size = 10, title = "")
```

# Arguments

df ts object

lag.max maximum lags to include

base\_size base font size title plot title

#### **Details**

returns plot

plot\_boxplot 67

## **Examples**

```
ts_data<-ts(UKDriverDeaths,start=1969,end=1984,frequency=12)
plot_acf(df=ts_data,base_size=20)</pre>
```

plot\_boxplot

**Boxplot** 

# Description

**Boxplot** 

### Usage

```
plot_boxplot(df, title = "", base_size = 10)
```

# Arguments

df dataframe or vector with continous or ordinal data

title Plot title

base\_size numeric base font size

### **Details**

uses ggplot

# **Examples**

```
vector<-generate_missing(rnorm(1000))
df<-generate_missing(mtcars[,1:2])
plot_boxplot(df=vector)
plot_boxplot(df=generate_missing(vector))
plot_boxplot(df=df)</pre>
```

plot\_cfa

Plot cfa model

# Description

Plot cfa model

## Usage

```
plot_cfa(model, ...)
```

68 plot\_confusion

#### **Arguments**

model lavaan object

arguments passed to semPlot::semPaths

#### **Examples**

```
model='LATENT1=~X1+X2+X3
       LATENT2=~X4+X5+X6'
df<-lavaan::simulateData(model=model,model.type="cfa",</pre>
                               return.type="data.frame", sample.nobs=100)
df<-generate_missing(df)</pre>
fit<-lavaan::cfa(model,data=df,missing="ML")</pre>
plot_cfa(fit)
model='LATENT1=\sim X1+X2+X3+X4+X5+X6
       LATENT2=~X1+X2+X3+X4+X5+X6
```

plot\_confusion

Plot confusion matrix

#### **Description**

This function creates a confusion matrix plot with observed and predicted outcomes, including row and column percentages, and various accuracy metrics.

#### Usage

```
plot_confusion(observed, predicted, base_size = 10, title = "")
```

# **Arguments**

observed Vector of observed outcomes. This can be numeric or factor values representing the true class labels.

predicted Vector of predicted outcomes. This should have the same length as the observed

vector and represent the predicted class labels.

base\_size Integer value representing the base font size for the plot. Defaults to 10. title String representing the title of the plot. Defaults to an empty string.

#### **Details**

This function generates a confusion matrix plot using ggplot2. It provides a visual representation of the confusion matrix with observed outcomes on the x-axis and predicted outcomes on the y-axis. The cells of the matrix are filled with the count of observations and annotated with the corresponding

The plot also includes various accuracy metrics in the caption, such as: - Overall Accuracy: Proportion of correctly classified observations (diagonal elements). - Off-diagonal Accuracy: Proportion of misclassified observations (off-diagonal elements). - Cohen's Kappa (Unweighted, Linear, and Squared): Measures the agreement between observed and predicted outcomes.

plot\_corrplot 69

## **Examples**

```
# Example with numeric class labels
plot_confusion(observed=c(1,2,3,1,2,3),predicted=c(1,2,3,1,2,3))
# Example with factor class labels
observed<-c(rep("male",10),rep("female",10),"male","male")
predicted<-c(rep("male",10),rep("female",10),"female","female")
plot_confusion(observed=observed,predicted=predicted)</pre>
```

plot\_corrplot

Correlation matrix plots

# **Description**

Correlation matrix plots

# Usage

```
plot_corrplot(mydata, title = "", base_size = 10, fill_limits = c(-1, 0, 1))
```

# Arguments

mydata correlation matrix

title plot title base\_size base font size

fill\_limits lower and upper limit for fill

### **Examples**

```
plot_corrplot(stats::cor(mtcars),title="Correlation")
plot_corrplot(stats::cor(mtcars),base_size=20)
```

plot\_crosstable

Plot crosstables

### **Description**

Plot crosstables

70 plot\_histogram

### Usage

```
plot_crosstable(
   df,
   factor_index,
   combinations = NULL,
   shape = 16,
   angle = 0,
   base_size = 10,
   title = ""
)
```

### **Arguments**

```
df dataframe
factor_index index of factors
combinations index of comparisons
shape shape of points
angle angle of xaxis labels
base_size base font size
title plot title
```

### **Examples**

```
combinations<-data.frame(index1=c("vs","am","gear"),index2=c("cyl","cyl","cyl"))
plot_crosstable(df=mtcars,factor_index=8:9)
plot_crosstable(df=mtcars,combinations=combinations)</pre>
```

plot\_histogram

Histograms with density function

# Description

Histograms with density function

### Usage

```
plot_histogram(
   df,
   bins = 30,
   title = "",
   base_size = 10,
   xlims = NULL,
   fill = "gray25",
   color = "gray50",
   ylab = "Count"
)
```

plot\_icc\_thurstonian 71

## Arguments

df dataframe or vector with continous or ordinal data

bins number of bars to display

title plot title

base\_size numeric base font size

xlims x axis limits fill color of bar

color color of bar outline

ylab y label

#### **Details**

uses ggplot

# **Examples**

```
vector<-generate_missing(rnorm(1000))
df<-generate_missing(mtcars[,1:2])
plot_histogram(df=vector)
plot_histogram(df=df,xlims=c(0,50))
plot_histogram(df=df)
plot_multiplot(plotlist=plot_histogram(df=mtcars),cols=4)</pre>
```

# Description

Plot icc curves for binary thurstonian coded items for a single dimension using the compute\_icc\_thurstonian function

### Usage

```
plot_icc_thurstonian(mydata, title = "Item Characteristic Curve")
```

# Arguments

mydata dataframe from compute\_icc\_thurstonian function

title plot title

72 plot\_interaction

#### **Examples**

```
 \begin{array}{l} {\rm gamma} < -c(\emptyset.556,-1.253,-1.729,0.618,0.937,0.295,-0.672,-1.127,-0.446,0.632,1.147,0.498) \\ {\rm psi} < -c(2.172,1.883,2.055,1.869,2.231,2.100,1.762,1.803,1.565,1.892,1.794,1.686) \\ {\rm lambda} < -c(1.082,1.082,-1.297,-1.297,0.802,0.802,1.083,1.083) \\ {\rm gamma} < -{\rm gamma} [{\rm response\_dimension}(c(1:12),3,c(1,2))] \\ {\rm psi} < -{\rm psi} [{\rm response\_dimension}(c(1:12),3,c(1,2))] \\ {\rm eta} < -{\rm seq}(-6,6,by=1) \\ {\rm result} < -{\rm compute\_icc\_thurstonian}({\rm eta} = {\rm eta},{\rm gamma} = {\rm gamma},{\rm lambda} = {\rm lambda},{\rm psi} = {\rm psi},{\rm plot} = {\rm TRUE}) \\ {\rm plot\_icc\_thurstonian}({\rm result\$icc}) \\ \end{array}
```

plot\_interaction

Plot two way interaction graphs

### **Description**

Plot two way interaction graphs

# Usage

```
plot_interaction(
   df,
   dv,
   iv,
   base_size = 20,
   type = "se",
   order_factor = TRUE,
   title = "",
   note = ""
)
```

# Arguments

df	dataframe
dv	index of continous variables
iv	index of factors
base_size	base font size
type	error bar type to display (1) "se" for standard error (2) "ci" for confidence interval (3) "sd" for standard deviation (4) "" for no error bar
order_factor	if TRUE it will sort the categorical axis by the continous variable value
title	plot title
note	footnote

plot\_irt\_onefactor 73

#### **Examples**

plot\_irt\_onefactor

Return data for irt plots

#### **Description**

Return data for irt plots

#### **Usage**

```
plot_irt_onefactor(model, theta = seq(-6, 6, 0.1), title = "", base_size = 10)
```

#### **Arguments**

model object mirt
theta theta
title plot title
base\_size base size

```
cormatrix<-psych::sim.rasch(nvar=5,n=50000,low=-4,high=4,d=NULL,a=1,mu=0,sd=1)$items
model<-mirt::mirt(cormatrix,1,empiricalhist=TRUE,calcNull=TRUE)</pre>
plot_irt_onefactor(model=model,base_size=10,title="Normal Test")
cormatrix<-psych::sim.rasch(nvar=5,n=50000,low=-6,high=-4,d=NULL,a=1,mu=0,sd=1)$items
model<-mirt::mirt(cormatrix,1,empiricalhist=TRUE,calcNull=TRUE)</pre>
plot_irt_onefactor(model=model,base_size=10,title="Easy Items")
cormatrix<-psych::sim.rasch(nvar=5,n=50000,low=4,high=6,d=NULL,a=1,mu=0,sd=1)$items
model<-mirt::mirt(cormatrix,1,empiricalhist=TRUE,calcNull=TRUE)</pre>
plot_irt_onefactor(model=model,base_size=10,title="Difficult Items")
cormatrix<-psych::sim.rasch(nvar=5,n=50000,low=-4,high=-4,d=NULL,a=0.01,mu=0,sd=1)$items
model<-mirt::mirt(cormatrix,1,empiricalhist=TRUE,calcNull=TRUE)</pre>
plot_irt_onefactor(model=model,base_size=10,title="Low Discrimination")
cormatrix<-psych::sim.poly(nvar=5,n=50000,low=-4,high=4,a=1,c=0,z=1,d=NULL,
                           mu=0, sd=1, cat=5, mod="logistic", theta=NULL)$items
model<-mirt::mirt(cormatrix,1,itemtype="graded")</pre>
plot_irt_onefactor(model=model,base_size=10,title="graded response")
```

74 plot\_loadings

plot\_loadings

Plot loadings

## **Description**

Plot loadings

#### Usage

```
plot_loadings(
  model,
  matrix_type = NULL,
  title = "",
  base_size = 10,
  color = c("#5E912C", "white", "#5F2C91"),
  sort = TRUE
)
```

# **Arguments**

```
model psych EFA model
matrix_type "pattern" "structure"
title plot title
base_size base font size
color color ranges for heatmap
sort TRUE or FALSE sort loadings
```

```
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="pa",oblique.scores=TRUE)
plot_loadings(model=model,matrix_type="structure")
plot_loadings(model=model,matrix_type="pattern")
cm<-matrix(c(1,.8,.8,.1,.1,.1,</pre>
              .8,1,.8,.1,.1,.1,
              .8, .8, 1, .1, .1, .1,
              .1, .1, .1, 1, .8, .8,
              .1, .1, .1, .8, 1, .8,
              .1, .1, .1, .8, .8, 1),
              ncol=6,nrow=6)
df1<-generate_correlation_matrix(cm,nrows=10000)</pre>
model1<-psych::fa(df1,nfactors=2,rotate="oblimin",fm="pa",oblique.scores=TRUE)</pre>
plot_loadings(model=model1,matrix_type="pattern",base_size=30)
cm<-matrix(c(1,.1,.1,.1,.1,.1,</pre>
              .1,1,.1,.1,.1,.1,
              .1, .1, 1, .1, .1, .1,
              .1, .1, .1, 1, .8, .8,
              .1, .1, .1, .8, 1, .8,
```

plot\_logistic\_model 75

# Description

Logistic model plot

#### Usage

```
plot_logistic_model(df, outcome = "outcome", title = "", base_size = 10)
```

#### Arguments

df dataframe with predictor and outcome outcome should be last

outcome name of outcome variable

title Character plot title base\_size base font size

76 plot\_mtmm

nlot	mosaic

Plot mosaic plots

# Description

Plot mosaic plots

#### Usage

```
plot_mosaic(df, factor_index, base_size = 10, title = "")
```

## **Arguments**

df dataframe
factor\_index index of factors
base\_size base font size
title plot title

## **Examples**

```
plot_mosaic(df=mtcars,factor_index=8:9)
plot_mosaic(df=mtcars,factor_index=9:10)
```

plot\_mtmm

Plot multitrait multimethod matrix

## Description

Plot multitrait multimethod matrix

## Usage

```
plot_mtmm(df, key, method, subject, title = "")
```

## **Arguments**

df	
	dataframe

key List index of trait names and items constituring a trait

method name of dataframe collumn spesifying the method used for the row observed

subject name of dataframe collumn spesifying subject id

title plot title

plot\_multiplot 77

#### **Examples**

```
\label{eq:population_model} \begin{split} &\text{t} 1=^{\times} 1+.9*x2+.9*x3\\ &\quad &\text{t} 2=^{\times} 4+.9*x5+.9*x6\\ &\quad &\text{t} 3=^{\times} x7+.9*x8+.9*x9 \end{split} \text{model\_data} - \text{lavaan} : \text{simulateData} (\text{population\_model\_sample.nobs} = 1000)\\ &\text{model\_data} - \text{model\_data} [\text{sample} (1:1000,1000,\text{TRUE}),]\\ &\text{model\_data} - \text{rbind} (\text{model\_data\_model\_data\_model\_data})\\ &\text{model\_data} \\ &\text{model\_data} \\ &\text{sid} \\ &\text{-rep} (1:1000,3)\\ &\text{key} \\ &\text{-list} (\text{t1=paste0} ("x",1:3),\text{t2=paste0} ("x",4:6),\text{t3=paste0} ("x",7:9))\\ &\text{plot\_mtmm} (\text{df=model\_data\_key=key\_method="method",subject="id")} \end{split}
```

plot\_multiplot

Multiple ggplot plots in one graph

#### **Description**

Multiple ggplot plots in one graph

#### Usage

```
plot_multiplot(..., plotlist = NULL, cols = 2, layout = NULL)
```

## **Arguments**

plot objects
plotlist a list of plots

cols number of columns in layout

layout a matrix specifying the layout. If present, 'cols' is ignored

```
p1<-ggplot(ChickWeight,aes(x=Time,y=weight,colour=Diet,group=Chick))+
           geom_line()+
           ggtitle("Growth curve for individual chicks")+
           theme_bw()
p2<-ggplot(ChickWeight,aes(x=Time,y=weight,colour=Diet))+
           geom_point(alpha=.3)+
           geom_smooth(alpha=.2,size=1,method="loess",formula="y~x")+
           ggtitle("Fitted growth curve per diet")+
           theme_bw()
p3<-ggplot(subset(ChickWeight,Time==21),aes(x=weight,colour=Diet))+
           geom_density()+
           ggtitle("Final weight, by diet")+theme_bw()
p4<-ggplot(subset(ChickWeight,Time==21),aes(x=weight,fill=Diet))+
           geom_histogram(colour="black",binwidth=50)+facet_grid(Diet~.)+
           ggtitle("Final weight, by diet")+theme_bw()
cars_plot<-plot_histogram(mtcars)</pre>
```

```
plot_multiplot(p1,p2,p3,p4,cols=2)
plot_multiplot(plotlist=plot_histogram(mtcars[,1:4]),cols=2)
plot_multiplot(plotlist=plot_histogram(mtcars),layout=matrix(1:4,ncol=2,byrow=TRUE))
plot_multiplot(plotlist=plot_scatterplot(mtcars[,1:4]),cols=2)
plot_multiplot(plotlist=cars_plot,layout=matrix(1:4,ncol=2,byrow=TRUE))
plot_multiplot(plotlist=cars_plot,cols=3)
```

plot\_normality\_diagnostics

Normality plots

#### **Description**

plot histogram density boxplot qq plot

#### Usage

```
plot_normality_diagnostics(
   df,
   breaks = NULL,
   title = "",
   file = NULL,
   w = 10,
   h = 10
)
```

# Arguments

df dataframe or vector with continous or ordinal data breaks number of bars to display title plot title plot title output filename w width of pdf file h height of pdf file

## **Details**

uses plot base

```
vector<-generate_missing(rnorm(1000))
df<-generate_missing(mtcars[,1:2])
plot_normality_diagnostics(df=vector,title="",file="rnorm",breaks=30)
plot_normality_diagnostics(df=vector,title="")
plot_normality_diagnostics(df=df,title="mtcars")
plot_normality_diagnostics(df=df,title="mtcars",file="rnorm")</pre>
```

plot\_oneway 79

plot\_oneway

Plot means with standard error for every level in a dataframe

## **Description**

Plot means with standard error for every level in a dataframe

## Usage

```
plot_oneway(
    df,
    dv,
    iv,
    base_size = 20,
    type = "se",
    order_factor = TRUE,
    title = "",
    note = "",
    width = 60
)
```

## Arguments

df	dataframe
dv	index of continous variables
iv	index of factors
base_size	base font size
type	error bar type to display (1) "se" for standard error (2) "ci" for confidence interval (3) "sd" for standard deviation (4) "" for no error bar
order_factor	if TRUE it will sort the categorical axis by the continous variable value
title	plot title
note	footnote
width	wrap width for x title

```
plot_oneway(df=mtcars,dv=2:3,iv=9:10,type="ci")
plot_oneway(df=mtcars,dv=2:3,iv=9:10,type="sd")
plot_oneway(df=mtcars,dv=2:3,iv=9:10,type="",order_factor=FALSE)
plot_oneway(df=mtcars,dv=2:3,iv=9:10,type="",order_factor=TRUE)
```

```
plot_oneway_diagnostics
```

Plot one way diagnostics

## **Description**

Plot one way diagnostics

#### Usage

```
plot_oneway_diagnostics(df, dv, iv, base_size = 10)
```

## **Arguments**

df	dataframe

dv index of continous variables

iv index of factorsbase\_size base font size

#### Note

Residuals vs Fitted should be equally spread horizontally otherwize the assumption of equality of variances is violated

Normal QQ should show values in the diagonal otherwise the assumption of normality is violated

plot\_outlier 81

plot\_outlier

Outlier graph using mean median and boxplot algorythms

#### **Description**

Outlier graph using mean median and boxplot algorythms

#### Usage

```
plot_outlier(df, method = "mean", title = "", base_size = 10)
```

#### **Arguments**

df dataframe or vector with continous or ordinal data

method "mean" "median" "boxplot"

title plot title base\_size base font size

#### Author(s)

unknown

#### **Examples**

```
vector<-generate_missing(rnorm(1000))
df<-generate_missing(mtcars[,1:2])
plot_outlier(df=vector,method="mean",title="random vector")
plot_outlier(df=vector,method="median")
plot_outlier(df=vector,method="boxplot")
plot_outlier(df=df,method="mean",title="random vector")
plot_outlier(df=df,method="median")
plot_outlier(df=df,method="boxplot")
plot_multiplot(plotlist=plot_outlier(df=mtcars[,2:5],method="mean"),cols=2)</pre>
```

plot\_qq

qq plots

# Description

qq plots

```
plot_qq(df, title = "", base_size = 10)
```

#### **Arguments**

df dataframe or vector with continous or ordinal data

title plot title

base\_size numeric base font size

#### **Details**

uses ggplot

## **Examples**

```
vector<-generate_missing(rnorm(1000))
df<-generate_missing(mtcars[,1:2])
plot_qq(df=vector)
plot_qq(df=df)
plot_multiplot(plotlist=plot_qq(df=mtcars),cols=4)</pre>
```

```
plot_response_frequencies
```

Plot response frequencies

## **Description**

Plot response frequencies

#### Usage

```
plot_response_frequencies(
   df,
   factor_index,
   base_size = 10,
   title = "",
   width = 100
)
```

## Arguments

```
df dataframe
factor_index index of factors
base_size base font size
title plot title
```

width wrap width for x title

```
plot_response_frequencies(df=mtcars,factor_index=1:10)
```

plot\_roc 83

plot_roc	Plot Receiver Operating Characteristic (ROC) curve	
plot_roc	Plot Receiver Operating Characteristic (ROC) curve	

#### Description

Generates a ROC curve from observed outcomes and predicted probabilities.

## Usage

```
plot_roc(observed, predicted, base_size = 10, title = "")
```

## **Arguments**

observed	Vector of observed outcomes. These are the true class labels.
predicted	Vector of predicted outcome probabilities. These are the predicted probabilities for the positive class.
base_size	Integer value representing the base font size for the plot. Defaults to 10.
title	String representing the title of the plot. Defaults to an empty string.

#### **Details**

This function generates a ROC curve to evaluate the performance of a binary classification model. The ROC curve is a plot of the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings.

The function performs the following steps: 1. Computes the ROC curve and its confidence interval using 'pROC::roc'. 2. Generates ROC plots for both reversed and non-reversed order of class levels.

3. Creates a list of ROC plots, each with an AUC value, control level, and direction.

The output is a list of ggplot objects representing the ROC curves for different class level orders.

```
# Example with random observed and predicted values
observed<-round(abs(rnorm(100,m=0,sd=0.5)))
predicted<-abs(rnorm(100,m=0,sd=0.5))
plot_roc(observed=observed, predicted=predicted)

# Example with generated correlation matrix
df1<-data.frame(matrix(0.999,ncol=2,nrow=2))
correlation_matrix<-as.matrix(df1)
diag(correlation_matrix)<-1
df1<-generate_correlation_matrix(correlation_matrix,nrows=1000)
df1$X1<-ifelse(abs(df1$X1) < 1,0,1)
df1$X2<-abs(df1$X2)
df1$X2<-(df1$X2 - min(df1$X2)) / (max(df1$X2) - min(df1$X2))
plot_roc(observed=round(abs(df1$X1),0),predicted=abs(df1$X2))</pre>
```

84 plot\_scatterplot

plot\_scatterplot

Plot plot\_scatterplot

#### **Description**

Plot plot\_scatterplot

## Usage

```
plot_scatterplot(
    df,
    method = lm,
    formula = y ~ x,
    base_size = 10,
    coord_equal = FALSE,
    all_orders = FALSE,
    title = "",
    combinations = NULL,
    string_aes = TRUE
)
```

#### Arguments

df dataframe if dataframe consists of 2 collumns the second collumn is the outcome

and the first collumn is the predictor

method smoothing method, "auto", "lm", "glm", "gam", "loess" or a function, e.g. MASS::rlm

or mgcv::gam, stats::lm, or stats::loess

formula used in smoothing function for geom\_smooth

base\_size base font size

coord\_equal if TRUE axes maintain equal scale

all\_orders if TRUE the order of combination is considered

title Plot title

combinations dataframe if not NULL user can provide a dataframe for variable combinations

for x and y axis. First column represents x and second column represents y

string\_aes if TRUE string\_aes function is used for names

plot\_scree 85

plot\_scree

Scree plot displaying the Kaiser and Jolife criteria for factor extrac-

## Description

Scree plot displaying the Kaiser and Jolife criteria for factor extraction

#### Usage

```
plot_scree(df, base_size = 15, title = "", color = c("#5F2C91", "#5E912C"))
```

#### **Arguments**

df dataframe
base\_size base font size
title plot title

color color of line and point outline

#### **Examples**

```
plot_scree(df=mtcars,title="",base_size=15)
```

plot\_separability Plo

Plot separability

#### **Description**

This function creates a separability plot showing the density distribution of predicted probabilities for different observed categories.

```
plot_separability(observed, predicted, base_size = 10, title = "")
```

86 plot\_trees\_xgboost

#### **Arguments**

Vector of observed outcomes. This can be numeric or factor values representing the true class labels.

predicted

Vector of predicted outcome probabilities. This should have the same length as the observed vector and represent the predicted probabilities.

base\_size

Integer value representing the base font size for the plot. Defaults to 10.

title

String representing the title of the plot. Defaults to an empty string.

#### **Details**

This function generates a separability plot using ggplot2. It shows the density distribution of predicted probabilities for different observed categories. The plot helps to visualize how well the predicted probabilities separate the different observed categories.

The plot includes the following components: - Density curves for each observed category,representing the distribution of predicted probabilities. - A legend indicating the observed categories. - The total number of observations is included in the plot caption.

#### **Examples**

```
# Example with numeric class labels
df1<-data.frame(matrix(.999,ncol=2,nrow=2))
correlation_matrix<-as.matrix(df1)
diag(correlation_matrix)<-1
df1<-generate_correlation_matrix(correlation_matrix,nrows=1000)
df1$X1<-ifelse(abs(df1$X1) < 1,0,1)
df1$X2<-abs(df1$X2)
df1$X2<-(df1$X2 - min(df1$X2)) / (max(df1$X2) - min(df1$X2))
plot_separability(observed=round(abs(df1$X1),0),predicted=abs(df1$X2))</pre>
```

#### prosess coerugate

# Description

Plot trees for xgboost::xgb.train

#### Usage

```
plot_trees_xgboost(model, train, file = "xgboost")
```

# **Arguments**

model object from xgboost::xgb.train

train Train dataset file output filename

plot\_ts 87

#### **Examples**

```
infert_formula<-formula(case~education+spontaneous+induced)</pre>
boston_formula<-formula(medv~crim+zn+indus+chas+nox+rm+age+dis+rad+tax+ptratio+black+lstat)
train_test_classification<-k_fold(df=infert,model_formula=infert_formula)</pre>
train_test_regression<-k_fold(df=MASS::Boston,model_formula=boston_formula)</pre>
xgb_classification<-xgboost::xgb.train(</pre>
                     data=train_test_classification$xgb$f1$train,
                     watchlist=train_test_classification$xgb$f1$watchlist,
                     nthread=8,
                     nround=20.
                     objective="binary:logistic")
xgb_regression<-xgboost::xgb.train(</pre>
                data=train_test_regression$xgb$f1$train,
                watchlist=train_test_regression$xgb$f1$watchlist,
                eta=.3,
                nthread=8,
                nround=20)
# xgboost::xgb.plot.multi.trees(model=xgb_classification,features_keep=2)
# plot_trees_xgboost(model=xgb_classification,
                      train=train_test_classification$xgb$f1,
#
                     file="Classification")
#
 plot_trees_xgboost(model=xgb_regression,
                      train=train_test_regression$xbg$f1,
                      file="Regression")
```

plot\_ts

Plot timeseries

## Description

Plot timeseries

## Usage

```
plot_ts(df, base_size = 10, ylab = "Count", title = "")
```

## **Arguments**

```
df ts object
base_size base font size
ylab y label
title plot title
```

#### Details

returns plot

88 proportion\_accurate

#### **Examples**

```
ts_data<-ts(UKDriverDeaths,start=1969,end=1984,frequency=12)
result<-plot_ts(ts_data,title="UK driver deaths")
for(i in 1969:1984)
    result<-result+geom_vline(xintercept=i,color="blue",size=1,alpha=.5)
result
autoplot(stl(ts_data,s.window='periodic'))+
    theme_bw(base_size=10)+
    labs(title="UK driver deaths")
forecast::gglagplot(data.frame(ts_data),do.lines=FALSE,lags=100)+
    theme_bw(base_size=10)+labs(title="UK driver deaths",y="count")</pre>
```

proper

Capitalize first character and lowercase the rest

## **Description**

Capitalize first character and lowercase the rest

#### Usage

proper(x)

#### **Arguments**

Х

Character

#### **Examples**

```
x<-generate_string(nchar=10,vector=LETTERS,vector_length=10)
proper(x)</pre>
```

proportion\_accurate

Proportion overall accuracy of a confusion matrix

## **Description**

Calculates the overall accuracy and Cohen's kappa statistics of a confusion matrix.

# Usage

```
proportion_accurate(observed, predicted)
```

## **Arguments**

observed Vector of observed variables. These are the true class labels.

predicted Vector of predicted variables. These are the predicted class labels.

questions\_by\_keys 89

#### **Details**

This function evaluates the performance of a confusion matrix by calculating the overall accuracy and Cohen's kappa statistics.

The function performs the following steps: 1. Computes the confusion matrix from the observed and predicted values. 2. Calculates the diagonal proportion (overall accuracy) and the off-diagonal proportion. 3. Computes Cohen's kappa statistics (unweighted,linear,and squared weights).

The output is a data.frame containing the following metrics: - 'cm\_diagonal': Proportion of correct classifications (diagonal elements). - 'cm\_off\_diagonal': Proportion of misclassified observations (off-diagonal elements). - 'kappa\_unweighted': Cohen's kappa statistic with no weights. - 'kappa\_linear': Cohen's kappa statistic with linear weights. - 'kappa\_squared': Cohen's kappa statistic with squared weights.

#### **Examples**

```
# Example with numeric observed and predicted values
proportion_accurate(observed=c(1,2,3,4,5,10),predicted=c(1,2,3,4,5,11))
```

questions\_by\_keys

Convert key to index list

## Description

Convert key to index list

#### Usage

```
questions_by_keys(key)
```

## **Arguments**

key

a vector indicating the dimension of each question. The order of the elements in the key represents the order of the questions, the numeric values represent the dimension the question belongs to

```
key < -c(1,2,3,4,5,1,2,3,4,5)
questions_by_keys(key)
```

90 rad2deg

```
{\it questions\_dimensions\_dataframe} \\ {\it Question~dimension~table}
```

## **Description**

Return a dataframe with the order of the questions, their respective dimensions, and the description of the dimensions

## Usage

```
questions_dimensions_dataframe(
  key,
  dimensions,
  elaborate_dimensions,
  questions
)
```

## **Arguments**

key

a vector indicating the dimension of each question. The order of the elements in the key represents the order of the questions, the numeric values represent the

dimension the question belongs to

dimensions

dimension names

elaborate\_dimensions

full dimension names

questions question names

## **Examples**

```
key<-c(1,2,3,4,5,1,2,3,4,5)
dimensions<-paste0("Dimension",1:10)
elaborate_dimensions<-paste0("Elaborated_Dimension",1:10)
questions<-paste0("Question",1:65)
questions_dimensions_dataframe(key,dimensions,elaborate_dimensions,questions)</pre>
```

rad2deg

Convert radians to degrees

## **Description**

Convert radians to degrees

```
rad2deg(radians)
```

rank3\_to\_triplets 91

#### **Arguments**

radians radians

## **Examples**

rad2deg(pi)

rank3\_to\_triplets

Convert thurstonian binary triplets to scale

## Description

Convert thurstonian binary triplets to scale

## Usage

```
rank3_to_triplets(mydata)
```

## **Arguments**

mydata

dataframe

## **Examples**

rank\_df\_to\_binary

Convert scale to thurstonian binary with n items per block and n blocks

## Description

Convert scale to thurstonian binary with n items per block and n blocks

```
rank_df_to_binary(mydata, items, reverse = TRUE)
```

92 rank\_to\_binary

## **Arguments**

mydata dataframe

items number of items in block

reverse if TRUE assumes that the highest value is first item in rank if FALSE the lowest

value is the first item in rank

## **Examples**

rank\_to\_binary

Convert scale to thurstonian binary with n items per ranking block

## **Description**

Convert scale to thurstonian binary with n items per ranking block

#### Usage

```
rank_to_binary(mydata, items, reverse = TRUE)
```

## Arguments

mydata dataframe

items number of items in block

reverse if TRUE assumes that the highest value is first item in rank if FALSE the lowest

value is the first item in rank

raw\_alpha 93

raw\_alpha

Raw alpha

#### **Description**

Raw alpha

#### Usage

```
raw_alpha(df)
```

## **Arguments**

df

dataframe with one dimension

## **Examples**

```
set.seed(12345)
df<-data.frame(matrix(.5,ncol=6,nrow=6))
correlation_martix<-as.matrix(df)
diag(correlation_martix)<-1
df<-round(generate_correlation_matrix(correlation_martix,nrows=1000),0)+5
psych::alpha(df)
raw_alpha(df=df)</pre>
```

rbind\_all

rbind dataframes or matrices with different lengths or collumn names

## Description

rbind dataframes or matrices with different lengths or collumn names

## Usage

```
rbind_all(df1, df2)
```

# Arguments

df1 dataframe or matrix df2 dataframe or matrix

```
df1<-generate_correlation_matrix(n=10)
df2<-generate_correlation_matrix(n=10)
names(df2)[4]<-"X11"
rbind_all(df1=df1,df2=df2)
row.names(df1)<-21:30
rbind_all(df1=df1,df2=df2)</pre>
```

recode\_scale\_dummy

recode\_scale\_dummy

Scale and dummy code

## **Description**

Scales numeric variables between 0 and 1 and creates dummy coding for character and factor variables.

#### Usage

```
recode_scale_dummy(df, categories = 10)
```

#### **Arguments**

df Dataframe containing the dataset to be scaled and dummy coded.

categories Numeric value representing the number of unique values a vector must have to

perform dummy coding. Defaults to 10.

#### **Details**

This function processes a dataframe by scaling numeric variables and creating dummy codes for character and factor variables. The numeric variables are scaled between 0 and 1, while the character and factor variables are converted to dummy variables if they have fewer unique values than the specified 'categories' parameter.

The function performs the following steps: 1. Identifies numeric variables in the dataframe and scales them. 2. Identifies character and factor variables and creates dummy variables if they meet the criteria. 3. Combines the scaled numeric variables and dummy variables into a single dataframe.

The output is a dataframe with scaled numeric variables and dummy-coded character/factor variables.

```
# Example with the 'infert' dataset
recode_scale_dummy(infert)

# Example with a custom dataframe
df<-data.frame(
   numeric_var = c(1,2,3,4,5),
   factor_var = factor(c('A','B','A','B','C'))
)
recode_scale_dummy(df)</pre>
```

remove\_nc 95

remove\_nc

Replace remove non computable values

#### Description

Replace remove non computable values

## Usage

```
remove_nc(
   df,
   value = NA,
   remove_rows = FALSE,
   aggressive = FALSE,
   remove_cols = FALSE,
   remove_zero_variance = FALSE)
```

# **Arguments**

```
dataframe

value replacement

remove_rows if TRUE it will remove rows with non computable values

aggressive if TRUE it will remove entire row if a single non computable value exists

if FALSE it will remove row if all values are non computable

remove_cols if TRUE it will remove collumns with non computable values

remove_zero_variance

if TRUE it will remove collumns with no variance
```

## Details

Non computable values are NA, NAN, inf and empty cells.

#### Note

This function internally replaces non computable values with the value choosen the default value is NA. Then it removes rows and collumns with NA values or zero variance

```
df<-mtcars
df[1,]<-as.numeric(NaN)
df[2,]<-as.numeric(Inf)
df[3,]<-as.numeric(-Inf)
df[4,]<-as.numeric(NA)
df[5,]<-""
remove_nc(df=df,value=NA)</pre>
```

```
cdf(remove_nc(df=df,value=NA))
df<-generate_missing(mtcars,missing=5)
remove_nc(df,remove_rows=TRUE,aggressive=FALSE)
remove_nc(df,remove_rows=TRUE,aggressive=TRUE)
df<-generate_missing(generate_correlation_matrix(nrows=5),missing=2)
df$X2<-NA
df$X3<-1
remove_nc(df,remove_cols=TRUE,remove_zero_variance=FALSE)
remove_nc(df,remove_cols=TRUE,remove_zero_variance=TRUE)</pre>
```

remove\_outliers

Remove outliers

## **Description**

Remove outliers

## Usage

```
remove_outliers(vector, probs = c(0.25, 0.75), na.rm = TRUE, ...)
```

## Arguments

vector numeric

probs numeric vector with lowest and highest quantiles

na.rm if TRUE removes NA values
... arguments passed to quantile

## **Examples**

```
vector<-generate_missing(rnorm(1000))
df<-generate_missing(mtcars[,1:2])
remove_outliers(vector)
data.frame(sapply(df,remove_outliers))</pre>
```

remove\_user\_packages Remove all user packages

## **Description**

Remove all user packages

```
remove_user_packages()
```

```
replace_na_with_previous
```

Replace NA with the previous element in a vector

## **Description**

Replace NA with the previous element in a vector

#### Usage

```
replace_na_with_previous(vector)
```

## **Arguments**

vector

Vector

## **Examples**

```
df1<-generate_missing(rnorm(10), missing=5)
df2<-generate_missing(rnorm(10), missing=5)
df3<-generate_missing(rnorm(10), missing=5)
df4<-generate_missing(rnorm(10), missing=5)
df5<-generate_missing(rnorm(10), missing=5)
df<-data.frame(df1, df2, df3, df4, df5)
row.names(df)<-paste0("A",row.names(df))
replace_na_with_previous(df1)
df[]<-lapply(df,replace_na_with_previous)</pre>
```

report\_alpha

Estimate alpha for several dimensions and export results to xlsx

# Description

Uses an arbitrary input

```
report_alpha(
  df,
  key = NULL,
  questions = NULL,
  reverse = NULL,
  mini = NULL,
  maxi = NULL,
  file = NULL,
  ...
)
```

98 report\_cfa

#### **Arguments**

df dataframe

key index of trait names and items constituting a trait

questions trait names and items constituting a trait reverse index of trait names and index for reversal

mini minimum rating in scale if NULL reversal will be performed using the empirical

minimum

maxi maximum rating in scale if NULL reversal will be performed using the empirical

maximum

file output filename

... arguments passed to psych::alpha

#### **Examples**

report\_cfa Report

# Description

Report

#### Usage

```
report_cfa(model, file = NULL, w = 10, h = 10)
```

# Arguments

model	lavaan object
file	output filename
W	width of pdf file
h	height of pdf file

report\_choric\_serial 99

#### **Examples**

report\_choric\_serial Report polychoric tetrachoric polyserial biserial correlation

## **Description**

Report polychoric tetrachoric polyserial biserial correlation

## Usage

```
report_choric_serial(
    x,
    y = NULL,
    file = NULL,
    w = 10,
    h = 10,
    type = "tetrachoric",
    ...
)
```

#### **Arguments**

У

The input may be in one of four forms:

a) a data frame or matrix of dichotmous data (e.g., the lsat6 from the bock data set) or discrete numerical (i.e., not too many levels, e.g., the big 5 data set, bfi) for polychoric, or continuous for the case of biserial and polyserial

b) a 2 x 2 table of cell counts or cell frequencies (for tetrachoric) or an n x m table of cell counts (for both tetrachoric and polychoric)

c) a vector with elements corresponding to the four cell frequencies (for tetrachoric)

d) a vector with elements of the two marginal frequencies (row and column) and the comorbidity (for tetrachoric)

matrix or dataframe of discrete scores. In the case of tetrachoric, these should be dichotomous, for polychoric not too many levels, for biserial they should be discrete (e.g., item responses) with not too many (<10?) categories

file output filename
w width of pdf file

100 report\_correlation

```
h height of pdf filetype "tetrachoric" "polychoric" "polyserial" "biserial"... arguments passed to psych::polychoric
```

## **Examples**

report\_correlation

Report correlation matrix

#### **Description**

Report correlation matrix

## Usage

```
report_correlation(
    x,
    y = NULL,
    use = "pairwise",
    method = "pearson",
    adjust = "holm",
    alpha = 0.05,
    ci = TRUE,
    file = NULL,
    w = 10,
    h = 10,
    base_size = 20,
    scatterplot = TRUE
)
```

## Arguments

```
x matrix or dataframe
y a second matrix or dataframe with the same number of rows as x
use "pairwise" is the default value and will do pairwise deletion of cases. "complete"
will select just complete cases
method "pearson" "spearman" "kendall"
```

report\_dataframe 101

```
"holm", "hochberg", "hommel", "bonferroni", "BH", "BY", "fdr", "none"
adjust
alpha
                   alpha level of confidence intervals
ci
                   By default, confidence intervals are found. However, this leads to a great slow-
                   down of speed. So, for just the rs, ts and ps, set ci=FALSE
file
                   output filename
                   width of pdf file
                  height of pdf file
h
                   base font size
base_size
                  if TRUE it will outpu scatterplots
scatterplot
```

## **Examples**

report\_dataframe

Write matrix or dataframe to excel sheet

## **Description**

Usefull for generic data where conditional formating of a spesific collumn is required

## Usage

```
report_dataframe(df, file = NULL, type = "critical_value", ...)
```

#### **Arguments**

df	dataframe or matrix
file	output filename of excel file
type	"critical_value" "matrix"
	arguments passed to excel_critical_value or to excel_matrix

102 report\_efa

```
gear="Number of forward gears",
              carb="Number of carburetors")
report_dataframe(mtcars, sheet="report", file="mtcars", comment=comment, numFmt="#0.00",
                  critical=list(am="<0.05"))</pre>
report_dataframe(mtcars, sheet="report", file=NULL, comment=comment, numFmt="#0.00",
                  critical=list(am="<0.05"))</pre>
```

report\_efa

Output EFA model

## **Description**

Output EFA model

# Usage

```
report_efa(
 model,
 df,
 file = NULL,
 w = 10,
 h = 5,
 cut = 0,
 base_size = 10,
  scores = FALSE
)
```

## **Arguments**

model psych EFA model df dataframe file output filename width of pdf file height of pdf file h cut point for loadings cut base font size base\_size

if TRUE it will output factor scores in excel file

Note

scores

Orthogonal=varimax, Oblique=oblimin

report\_factorial\_anova 103

#### **Examples**

```
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="minres",oblique.scores=TRUE)</pre>
report_efa(model=model,df=mtcars,file="efa")
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="uls",oblique.scores=TRUE)
report_efa(model=model,df=mtcars)
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="ols",oblique.scores=TRUE)</pre>
report_efa(model=model,df=mtcars)
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="wls",oblique.scores=TRUE)</pre>
report_efa(model=model,df=mtcars)
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="gls",oblique.scores=TRUE)</pre>
report_efa(model=model,df=mtcars)
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="pa",oblique.scores=TRUE)</pre>
report_efa(model=model,df=mtcars)
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="ml",oblique.scores=TRUE)</pre>
report_efa(model=model,df=mtcars)
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="minchi",oblique.scores=TRUE)
report_efa(model=model,df=mtcars)
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="minrank",oblique.scores=TRUE)</pre>
report_efa(model=model,df=mtcars)
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="old.min",oblique.scores=TRUE)</pre>
report_efa(model=model,df=mtcars)
model<-psych::fa(mtcars,nfactors=2,rotate="oblimin",fm="alpha",oblique.scores=TRUE)</pre>
#report_efa(model=model,df=mtcars)
```

report\_factorial\_anova

Plot means with standard error for every level in a dataframe

## **Description**

Plot means with standard error for every level in a dataframe

```
report_factorial_anova(
   df,
   dv,
   wid,
   within = NULL,
   within_full = NULL,
   between = NULL,
   within_covariates = NULL,
   between_covariates = NULL,
   observed = NULL,
   diff = NULL,
   reverse_diff = FALSE,
   type = 3,
   white.adjust = TRUE,
```

```
detailed = TRUE,
  return_aov = TRUE,
  file = NULL,
  post_hoc_test = TRUE,
  base_size = 15
)
```

#### **Arguments**

df dataframe

dv names of dependent variables

wid names of

within names of within factors

within\_full names of within factors after data are collapsed to means per condition

between names of between factors

within\_covariates

names of within covariates

between\_covariates

mames of between covariates

observed names in data that are already specified in either within or between that contain

predictor variables that are observed variables (not manipulated)

diff names of variables to collapse in a different score

reverse\_diff If TRUE, triggers reversal of the difference collapse requested by diff

type sum of squares 1 2 3

white.adjust if TRUE corrects for heteroscedasticity detailed if TRUE returns detailed information

return\_aov if TRUE returns aov object

file output filename

post\_hoc\_test if TRUE outputs post hoc in file

base\_size base font size

report\_hlr 105

```
df<-data.frame(df,cdf)</pre>
df$DV2<-df$DV2+10
df$DV3<-df$DV3+20
df$DV4<-df$DV4+30
df[df$IV1%in%"A",]$DV1<-df[df$IV1%in%"A",]$DV1+1</pre>
df[df$IV1%in%"B",]$DV1<-df[df$IV1%in%"B",]$DV1+2</pre>
df[df$IV1%in%"C",]$DV1<-df[df$IV1%in%"C",]$DV1+3
r1<-report_factorial_anova(df=df,wid="id",dv=c("DV1","DV2"),
                           within=c("IV1","IV2"),within_full=c("IV1","IV2"),
                           between=NULL,
                           within_covariates=NULL,between_covariates=NULL,
                           file="anova_within",
                           post_hoc=TRUE)
r2<-report_factorial_anova(df=df,wid="id",dv=c("DV1","DV2"),
                           within=NULL,within_full=NULL,
                           between=c("IV1","IV2"),
                           within_covariates=NULL, between_covariates=NULL,
                           file="anova_between",
                           post_hoc=TRUE)
r3<-report_factorial_anova(df=df,wid="id",dv=c("DV1","DV2"),
                           within=c("IV3","IV4"),within_full=c("IV3","IV4"),
                           between=c("IV1","IV2"),
                           within_covariates=NULL,between_covariates=NULL,
                           file="anova_mixed",
                           post_hoc=FALSE)
r4<-report_factorial_anova(df=df,wid="id",dv=c("DV1","DV2"),
                           within=c("IV1","IV2"),within_full=c("IV1","IV2"),
                           between=NULL,
                           within_covariates=c("DV3","DV4"),between_covariates=NULL,
                           file="anova_within_cov",
                           post_hoc=TRUE)
```

report\_hlr

Report HLR

# Description

Report HLR

```
report_hlr(
   df,
   corlist,
   factorlist,
   predictor,
   random_effect,
   file = NULL,
   sheet = "report"
)
```

report\_irt

## **Arguments**

df dataframe

factorlist Numeric outcome index
Numeric predictor index
Predictor Character predictor name

random\_effect Character random effect name

file Character file sheet Character sheet

## **Examples**

report\_irt

Output for irt model

#### **Description**

Output for irt model

#### Usage

```
report_irt(model, m2 = TRUE, file = NULL)
```

## **Arguments**

model object mirt

m2 if TRUE report m2 statistics

file output filename

```
set.seed(12345)
cormatrix<-psych::sim.rasch(nvar=5,n=50000,low=-4,high=4,d=NULL,a=1,mu=0,sd=1)$items
irt_onefactor<-mirt::mirt(cormatrix,1,empiricalhist=TRUE,calcNull=TRUE)
irt_twofactor<-mirt::mirt(cormatrix,2,empiricalhist=TRUE,calcNull=TRUE)
irt_threefactor<-mirt::mirt(cormatrix,3,empiricalhist=TRUE,calcNull=TRUE)
report_irt(model=irt_onefactor,file="one_factor")
report_irt(model=irt_twofactor,file="two_factors")
report_irt(model=irt_threefactor,file="three_factors")</pre>
```

report\_lda 107

report\_lda

Report for MASS::lda

## Description

Report for MASS::lda

## Usage

```
report_lda(model, file = NULL, w = 10, h = 10, base_size = 10, title = "")
```

## **Arguments**

```
model object from MASS::lda
file output filename
w width of pdf file
h height of pdf file
base_size base font size
title plot title
```

# **Examples**

```
model<-MASS::lda(case~.,data=infert)
result<-report_lda(model=model)
result<-report_lda(model=model,file="lda")
model<-MASS::lda(Species~.,data=iris)
result<-report_lda(model=model,file="lda")</pre>
```

report\_logistic

Report logistic regression

# Description

Report logistic regression

```
report_logistic(
  model,
  validation_data = NULL,
  file = NULL,
  title = "",
  w = 10,
  h = 10,
  base_size = 10,
  fast = FALSE
)
```

108 report\_logistic

#### **Arguments**

model object glm

validation\_data

validation data

file output filename

title plot title

w width of pdf file. Relevant only when file string is not empty
 h height of pdf file. Relevant only when file string is not empty

base\_size base font size

fast if TRUE it will not output individual scores and residuals

#### Note

(1) Problematic values for standardized residuals > +-1.96

Standardized residuals are residuals divided by an estimated standard deviation and they can be interpreted as z scores in that:

95 99 99.99 (2) Problematic values for dfBeta >=1

dfBeta estimates coefficients if the respective case is removed from the dataset

(3) Problematic values for Hat values (leverage) 2 or 3 times the average (k+1/n)

Hat values (leverage), gauge the influence of the observed value of the outcome variable over the predicted values

The average leverage value is defined as (k+1)/n, k=number of predictors, n=number of participants. Leverage values lie between 0 (no influence) and 1 (complete influence over prediction)

If no cases exert undue influence over the model then all leverage values should be close to (k+1)/n Hoaglin and Welsch (1978) recommends investigating cases with values greater than twice the average (2(k+1)/n)

Stevens (2002) recommends investigating cases with values greater than three times the average (3(k+1)/n)

(4) Problematic values for VIFs > 10

## **ASSUMPTIONS**

- (1) Linearity between continous predictors and the logit (test wether the interaction term between the predictor and its log transformation is significant)
- (2) Independence of errors
- (3) No multicolinearity

```
modelcategoricalpredictor0<-glm(case~education,data=infert,family=binomial)
modelcategoricalpredictor1<-glm(case~education,data=infert,family=gaussian)
#modelcategoricalpredictor2<-glm(case~education,data=infert,family=Gamma)
#modelcategoricalpredictor3<-glm(case~education,data=infert,family=inverse.gaussian)
modelcategoricalpredictor4<-glm(case~education,data=infert,family=poisson)
modelcategoricalpredictor5<-glm(case~education,data=infert,family=quasi)
modelcategoricalpredictor6<-glm(case~education,data=infert,family=quasibinomial)
modelcategoricalpredictor7<-glm(case~education,data=infert,family=quasipoisson)
modelcontinuouspredictor0<-glm(case~stratum,data=infert,family=binomial)</pre>
```

report\_manova 109

```
modeltwopredictors0<-glm(case~education+stratum,data=infert,family=binomial)
modeltwopredictors1<-glm(case~education+stratum,data=infert,family=gaussian)
#modeltwopredictors2<-glm(case~education+stratum,data=infert,family=Gamma)</pre>
#modeltwopredictors3<-glm(case~education+stratum,data=infert,family=inverse.gaussian)</pre>
modeltwopredictors4<-glm(case~education+stratum,data=infert,family=poisson)</pre>
modeltwopredictors5<-glm(case~education+stratum,data=infert,family=quasi)</pre>
modeltwopredictors6<-glm(case~education+stratum,data=infert,family=quasibinomial)
modeltwopredictors7<-glm(case~education+stratum,data=infert,family=quasipoisson)
report_logistic(model=modelcategoricalpredictor0)
report_logistic(model=modelcategoricalpredictor1)
#report_logistic(model=modelcategoricalpredictor2)
#report_logistic(model=modelcategoricalpredictor3)
report_logistic(model=modelcategoricalpredictor4)
report_logistic(model=modelcategoricalpredictor5)
report_logistic(model=modelcategoricalpredictor6)
report_logistic(model=modelcategoricalpredictor7)
report_logistic(model=modelcontinuouspredictor0)
report_logistic(model=modeltwopredictors0)
report_logistic(model=modelcategoricalpredictor0,
                file="logistic_categorical_predictor",
                validation_data=infert)
report_logistic(model=modelcontinuouspredictor0,
                file="logistic_continuous_predictor",
                validation_data=infert)
report_logistic(model=modeltwopredictors0,
                file="logistic_two_predictors",
                validation_data=infert[1:10,])
```

report\_manova

Manova result

#### **Description**

Manova result

#### Usage

```
report_manova(model, file = NULL)
```

#### **Arguments**

model object of manova model

file output filename

#### Note

Pillai-Bartlett trace (V): Represents the sum of the proportion of explained variance on the discriminant functions. As such, it is similar to the ratio of SS M /SS T, which is known as R 2.

Hotelling-s T 2: Represents the sum of the eigenvalues for each variate it compares directly to the

F-ratio in ANOVA

Wilks-s lambda (L): Represents the ratio of error variance to total variance (SS R /SS T ) for each variate.

Roy-s largest root: Represents the proportion of explained variance to unexplained variance (SS M /SS R) for the first discriminant function.

#### **ASSUMPTIONS**

Independence: Observations should be statistically independent.

Random sampling: Data should be randomly sampled from the population of interest and measured at an interval level.

Multivariate normality: In ANOVA,we assume that our dependent variable is normally distributed within each group. In the case of MANOVA,we assume that the dependent variables (collectively) have multivariate normality within groups.

Homogeneity of covariance matrices: In ANOVA, it is assumed that the variances in each group are roughly equal (homogeneity of variance). In MANOVA we must assume that this is true for each dependent variable, but also that the correlation between any two dependent variables is the same in all groups. This assumption is examined by testing whether the population variance-covariance matrices of the different groups in the analysis are equal.

# **Examples**

```
## Set orthogonal contrasts.
op<-options(contrasts=c("contr.helmert","contr.poly"))
model_mixed<-manova(cbind(yield,foo)~N*P*K,within(npk,foo<-rnorm(24)))
model_between<-manova(cbind(rnorm(24),rnorm(24))~round(rnorm(24),0)*round(rnorm(24),0))
report_manova(model=model_mixed)
report_manova(model=model_between)</pre>
```

report\_normality\_tests

Normality tests

## **Description**

Shapiro-Wilk Anderson-Darling Cramer-von-Mises Shapiro-Francia Jarque-Bera Kolmogorov-Smirnov Lilliefors Pearson X2

### Usage

```
report_normality_tests(df, file = NULL)
```

#### **Arguments**

df dataframe with continous or ordinal data

file output filename

#### Details

returns xlsx file

report\_oneway 111

## **Examples**

```
vector<-generate_missing(rnorm(1000))
df<-generate_missing(mtcars[,1:2])
report_normality_tests(df=df)
report_normality_tests(df=vector,file="normality_tests")</pre>
```

report\_oneway

One way

# Description

One way

# Usage

```
report_oneway(
   df,
   dv,
   iv,
   file = NULL,
   w = 10,
   h = 10,
   base_size = 10,
   note = "",
   title = "",
   type = "ci",
   plot_means = FALSE,
   plot_diagnostics = FALSE)
```

```
df
                  dataframe
dν
                  index of continous variables
                  index of factors
iν
file
                  output filename
                  width of pdf file
                  height of pdf file
h
                  base font size
base_size
                  text for footnote
note
                  plot title
title
                  type of bar to display "se" "ci" "sd" ""
type
                  if TRUE it will output mean plots and descriptives for plots
plot_means
plot_diagnostics
                  if TRUE it will output ANOVA diagnostics plots
```

report\_pdf

## Note

- (1) The Fisher procedure assumes heteroscedasticity
- (2) The Welch procedure does not assume heteroscedasticity
- (3) The Kruskal Wallis procedure does not assume normality but it is not an alternative for violations of heteroscedasticity
- (4) Posthoc Tuckey: not good for unequal sample sizes or heteroscedasticity
- (5) Posthoc Games Howell: good for unequal sample sizes and heteroscedasticity

#### **Examples**

report\_pdf

Report pdf

# Description

Report pdf

## Usage

```
report_pdf(
    ...,
    plotlist = NULL,
    file = NULL,
    title = NULL,
    w = 10,
    h = 10,
    print_plot = TRUE
)
```

```
plotlist list of plot objects

file output filename

title output filename

w width of pdf file

h height of pdf file

print_plot if TRUE it prints plot on graphics device
```

report\_regression 113

#### **Examples**

```
p1<-ggplot(ChickWeight,aes(x=Time,y=weight,colour=Diet,group=Chick))+</pre>
           geom_line()+
           ggtitle("Growth curve for individual chicks")+
           theme bw()
p2<-ggplot(ChickWeight,aes(x=Time,y=weight,colour=Diet))+</pre>
           geom_point(alpha=.3)+
           geom_smooth(alpha=.2,size=1,method="loess",formula="y~x")+
           ggtitle("Fitted growth curve per diet")+theme_bw()
cars_plot_multiplot<-plot_multiplot(plotlist=plot_histogram(mtcars[,1:4]),cols=2)</pre>
cars_plot_base<-plot_normality_diagnostics(mtcars)</pre>
report_pdf(p1,p2,print_plot=TRUE)
report_pdf(p1,p2,file="report",print_plot=FALSE)
report_pdf(plotlist=cars_plot_multiplot,print_plot=TRUE)
report_pdf(plotlist=cars_plot_multiplot,file="report",print_plot=FALSE)
report_pdf(plotlist=cars_plot_base,print_plot=TRUE)
report_pdf(plotlist=cars_plot_base,file="report",print_plot=FALSE)
```

report\_regression

Regression

#### **Description**

Regression

#### Usage

```
report_regression(
  model,
  base_size = 10,
  title = "",
  file = NULL,
  w = 10,
  h = 10,
  plot_diagnostics = TRUE
)
```

```
model object ml
base_size base font size
title plot title
file output filename
w width of pdf file. Relevant only when file string is not empty
h height of pdf file. Relevant only when file string is not empty
plot_diagnostics
    if TRUE it will output linear model diagnostics plots
```

114 report\_regression

#### Note

- (1) Problematic values for standardized residuals > +-1.96
- \*\*Standardized residuals\*\* are residuals divided by an estimated standard deviation and they can be interpreted as z scores in that:
- 95.00 99.00 99.99 (2) \*\*Studentized residuals\*\* indicate the ability of the model to predict that case. They follow a t distribution
- (3) \*\*DFFits\*\* indicate the difference between the adjusted predicted value and the original predicted value. Adjusted predicted value for a case refers to the predicted value of that case, when that case is excluded from model fit.
- (4) \*\*Cook's distance\*\* indicates leverage. Problematic values for cook's distance > 1 Cook and Weisberg (1982).
- (5) \*\*Hat values\*\* indicate leverage. Problematic values for Hat values 2 or 3 times the average (k+1/n)

The average leverage value is defined as (k+1)/n, k=number of predictors, n=number of participants. Leverage values lie between 0 (no influence) and 1 (complete influence over prediction)

- Hoaglin and Welsch (1978) recommends investigating cases with values greater than twice the average (2(k+1)/n)
- Stevens (2002) recommends investigating cases with values greater than three times the average (3(k+1)/n)
- \*\*T-tests\*\* test the hypothesis that b's are different from 0
- \*\*Multiple R^2\*\*: Variance Explained
- \*\*Adjusted R^2\*\*: Indicates how much variance in Y would be accounted for if the model is derived from the population from which the sample was taken. Idealy,  $R^2 = Adjusted R^2$
- \*\*F-Statistic\*\* tests the null hypothesis is that the overall model has no effect
- \*\*Covariance ratios\*\* critical values CVR>1+[3(k+1)/n] CRV<1-[3(k+1)/n]. In general we should obtain small values or we may have to remove cases \*\*ASSUMPTIONS\*\*
- (1) variable types: All predictors must be quantitative or categorical (with two levels), and the outcome variable must be quantitative (interval data), continuous and unbounded (no constraints on the variability of the outcome) (2) Non-zero variance
- (3) No perfect multicollinearity
- (4) Predictors are uncorrelated with -external variables-
- (5) Homoscedasticity: At each level of the predictor variable(s), the variance of the residual terms should be constant. Residuals at each level of the predictor(s) should have similar variance (homoscedasticity)
- (6) Independent errors: For any two observations the residual terms should be uncorrelated (or independent) This eventuality is sometimes described as a lack of autocorrelation. This assumption can be tested with the Durbin-Watson test, which tests for serial correlations between errors. Specifically, it tests whether adjacent residuals are correlated The size of the Durbin-Watson statistic depends upon the number of predictors in the model and the number of observations As a very conservative rule of thumb, values less than 1 or greater than 3 are definitely cause for concern; however, values closer to 2 may still be problematic depending on your sample and model R also provides a p-value of the autocorrelation. Be very careful with the Durbin-Watson test, though, as it depends on the order of the data: if you reorder your data, you-Il get a different value
- (7) Normally distributed errors: It is assumed that the residuals in the model are random, normally distributed variables with a mean of 0
- (8) Independence: It is assumed that all of the values of the outcome variable are independent (in other words, each value of the outcome variable comes from a separate entity)
- (9) Linearity: The mean values of the outcome variable for each increment of the predictor(s) lie

report\_ttests 115

```
along a straight line
```

#### **Examples**

```
form<-formula(mpg~qsec)
regressionmodel<-lm(form,data=mtcars)
multipleregressionmodel<-lm(mpg~qsec*hp*wt*drat,data=mtcars)
res<-report_regression(model=regressionmodel,plot_diagnostics=TRUE)
res<-report_regression(model=multipleregressionmodel)
res<-report_regression(model=regressionmodel,file="regression")
res<-report_regression(model=multipleregressionmodel,file="regression",plot_diagnostics=TRUE)</pre>
```

report\_ttests

T test

# Description

T test

## Usage

```
report_ttests(df, dv, iv, file = NULL, ...)
```

## **Arguments**

df	dataframe
dv	index of continous variables
iv	index of factors
file	output filename
	Arguments passed on to stats::t.test
	x a (non-empty) numeric vector of data values.

```
report_ttests(df=mtcars,dv=2,iv=9:10)
report_ttests(df=mtcars,dv=2:3,iv=9)
report_ttests(df=mtcars,dv=2:3,iv=9:10,alternative="two.sided")
report_ttests(df=mtcars,dv=2:7,iv=9:10,alternative="less")
report_ttests(df=mtcars,dv=2:7,iv=9:10,alternative="greater")
report_ttests(df=mtcars,dv=1:7,iv=8:10,var.equal=TRUE)
report_ttests(df=mtcars,dv=1:7,iv=8:10,var.equal=TRUE,file="ttest")
```

116 report\_xgboost

report\_wtests

Wilcoxon test

# Description

Wilcoxon test

# Usage

```
report_wtests(df, dv, iv, file = NULL, ...)
```

be omitted.

## Arguments

df	dataframe
dv	index of continous variables
iv	index of factors
file	output filename
	Arguments passed on to stats::wilcox.test
	x numeric vector of data values. Non-finite (e.g., infinite or missing) values will

# **Examples**

```
report_wtests(df=mtcars,dv=2,iv=9)
report_wtests(df=mtcars,dv=2;iv=9:10)
report_wtests(df=mtcars,dv=2:3,iv=9)
report_wtests(df=mtcars,dv=2:3,iv=9:10,alternative="two.sided")
report_wtests(df=mtcars,dv=2:7,iv=9:10,alternative="less")
report_wtests(df=mtcars,dv=2:7,iv=9:10,alternative="greater")
report_wtests(df=mtcars,dv=1:7,iv=8:10,var.equal=TRUE)
report_wtests(df=mtcars,dv=1:7,iv=8:10,var.equal=TRUE,file="wilcoxontest")
```

report\_xgboost

Report for xgboost::xgb.train

# Description

Report for xgboost::xgb.train

report\_xgboost 117

#### Usage

```
report_xgboost(
  model,
  validation_data = NULL,
  label = NULL,
  file = "xgboost",
  w = 10,
  h = 10,
  base_size = 10,
  title = "",
  fast = FALSE
)
```

# Arguments

model object from xgboost::xgb.train
validation\_data

label outcome variable name
file output filename
w width of pdf file
h height of pdf file
base\_size base font size
title plot title

fast if TRUE error values are not saved in output

```
infert_formula<-formula(case~education+spontaneous+induced)</pre>
boston_formula<-formula(medv~crim+zn+indus+chas+nox+rm+age+dis+rad+tax+ptratio+black+lstat)
                            rm+age+dis+rad+tax+ptratio+black+lstat)
train_test_classification<-k_fold(df=infert,model_formula=infert_formula)</pre>
train_test_regression<-k_fold(df=MASS::Boston,model_formula=boston_formula)</pre>
xgb_classification<-xgboost::xgb.train(</pre>
                     data=train_test_classification$xgb$f1$train,
                     watchlist=train_test_classification$xgb$f1$watchlist,
                     eta=.1,
                     nthread=8,
                     nround=20,
                     objective="binary:logistic")
xgb_regression<-xgboost::xgb.train(</pre>
                data=train_test_regression$xgb$f1$train,
                watchlist=train_test_regression$xgb$f1$watchlist,
                eta=.3,
                nthread=8,
                nround=20)
report_xgboost(model=xgb_classification,
               validation_data=train_test_classification$f$test$f1,
```

118 response\_frequency

```
label=train_test_classification$outcome,
    file="Classification")
report_xgboost(model=xgb_regression,
    validation_data=train_test_regression$f$test$f1,
    label=train_test_regression$outcome,
    file="Regression")
```

response\_dimension

index parameter and items relative to their dimensions

# Description

index parameter and items relative to their dimensions

# Usage

```
response_dimension(response, dimensions, items)
```

# **Arguments**

response vector one to number of items dimensions number of dimensions

items item comparisons

## **Examples**

```
response_dimension(c(1:18),3,c(1,2))
response_dimension(c(1:18),3,c(1,3))
response_dimension(c(1:18),3,c(2,3))
```

response\_frequency

Response frequencies

#### **Description**

returns count proportion percent

# Usage

```
response_frequency(
  df,
  max = 10,
  uniqueitems = NULL,
  type = "percent",
  file = NULL
)
```

# Arguments

```
df dataframe
max maximum score
uniqueitems number of unique items
type "frequency" "proportion" "percent" "all"
file output filename
```

#### **Details**

returns dataframe

#### **Examples**

result\_confusion\_performance

Plot performance of confusion matrix for different cut off points

## **Description**

This function generates a plot to visualize the performance of a confusion matrix at various cut-off points. It evaluates the proportion of correct classifications and identifies the optimal cut-off point.

## Usage

```
result_confusion_performance(
  observed,
  predicted,
  step = 0.1,
  base_size = 10,
  title = ""
)
```

observed	Vector of observed outcomes. This can be numeric or factor values representing
	the true class labels.
predicted	Vector of predicted outcome probabilities. This should have the same length as
	the observed vector and represent the predicted probabilities.
step	Numeric value representing the stepping for tested cut values. Defaults to 0.1.
base_size	Integer value representing the base font size for the plot. Defaults to 10.
title	String representing the title of the plot. Defaults to an empty string.

120 round\_dataframe

#### **Details**

This function evaluates the performance of a confusion matrix at different cut-off points. It iterates through a range of cut-off points, calculates the confusion matrix, and evaluates the proportion of correct classifications for each cut-off.

The function generates a plot that includes: - The proportion of correct classifications for different cut-off points. - Vertical lines indicating the optimal cut-off point. - A legend representing different performance metrics. - A caption showing the number of observations and the optimal cut-off point.

The function returns a list containing the plot, the data frame with cut-off performance, the optimal cut-off point, and the confusion matrix at the optimal cut-off.

#### **Examples**

round\_dataframe

Round dataframe

#### **Description**

It only processes numeric values in a dataframe

# Usage

```
round_dataframe(df, digits = 0, type = "round")
```

```
df dataframe
digits decimal points to return. It works only with "round" type
type "round" "ceiling" "floor" "tenth"
```

shrout 121

#### **Examples**

```
round_dataframe(df=change_data_type(df=mtcars,type="factor"),digits=0)
round_dataframe(df=change_data_type(df=mtcars,type="character"),digits=0)
round_dataframe(df=mtcars,digits=0)
round_dataframe(df=mtcars,digits=0,type="ceiling")
round_dataframe(df=mtcars,digits=0,type="floor")
round_dataframe(df=mtcars*100,digits=2,type="tenth")
```

shrout

Shrout reliability

# Description

Shrout reliability

## Usage

```
shrout(sperson, spersonitem, stime, spersontime, serror, m, k)
```

## **Arguments**

sperson variance component of participant

spersonitem variance component of participant by item interaction

stime variance component of time

spersontime variance component of participant by time interaction

serror variance component of error

m m item reportsk k time points

simulate\_cfa\_fit

simulate\_cfa\_fit

Simulate CFA from coefficients

#### Description

Simulates cfa from coefficients Simulates cfa from correlations of obeserved data Returns fit indices for predefined set of sample sizes

#### Usage

```
simulate_cfa_fit(
  model_sim = NULL,
  model = NULL,
  df = NULL,
  minnobs = 50,
  maxnobs = 1000,
  stepping = 10,
  file = NULL,
  w = 10,
  h = 10
)
```

## **Arguments**

```
model_sim
                  lavaan model spesification with defined coefficients
                  lavaan model spesification with free coefficients
model
df
                   dataframe
minnobs
                  start sample size
maxnobs
                  end sample size
                   stepping
stepping
file
                   output filename
                   width of pdf file
                  height of pdf file
h
```

```
simulate_correlation_from_sample
```

Generate a dataframe that produces the same correlation matrix as the input dataframe

# Description

Generate a dataframe that produces the same correlation matrix as the input dataframe

#### Usage

```
simulate_correlation_from_sample(cordata, nrows = 10)
```

#### **Arguments**

cordata dataframe

nrows number of rows to generate

## **Examples**

```
correlation_matrix<-generate_correlation_matrix()
stats::cor(correlation_matrix)
simulate_correlation_from_sample(correlation_matrix,nrows=1000)
stats::cor(simulate_correlation_from_sample(correlation_matrix,nrows=1000))</pre>
```

split\_str

Split string to dataframe

## **Description**

Split string to dataframe

# Usage

```
split_str(vector, split = "/", include_original = FALSE)
```

## **Arguments**

vector String

split Separation character

include\_original

if TRUE it will return the input on a separate collumn

split\_str\_df

# **Examples**

split\_str\_df

Split string in dataframe

# **Description**

Split string in dataframe

#### Usage

```
split_str_df(df, split = "/", type = "row", index, ...)
```

# **Arguments**

df	dataframe
split	Separation character
type	"row" "collumn" if "row" it will split the string of row names and it will display it on seperate collumns if "collumn" it will split the string of a spesified collumn and it will display it on separate collumns
index	Numeric index of collumn to split. This is only relevant if type="collumn"
	arguments passed to split_str

stat\_word\_char 125

stat\_word\_char

Text similarity measures

#### **Description**

Text similarity measures
Text similarity measures

## Usage

```
stat_word_char(text)
stat_word_char(text)
```

#### **Arguments**

text

character vector

# **Examples**

```
text<-"There are many variations of passages of Lorem Ipsum available, but the majority have suffered alteration in some form, by injected humour, or randomised words which don't look even slightly believable." stat_word_char(text) text<-"There are many variations of passages of Lorem Ipsum available, but the majority have suffered alteration in some form, by injected humour, or randomised words which don't look even slightly believable." stat_word_char(text)
```

string\_aes

Adjust string aesthetics

# Description

Treats spesific characters such as ".", as separating characters and separates strings with space. Trims leading and trailing spaces and capitalizes the first letter of the string and lowers the rest.

## Usage

```
string_aes(
  vector,
  characterlist = c(".", "_", "-", ",", "$", "", "", "<br/>", "<br/>", "<BR/>", "|", "/", "&nbsp"),
  proper = TRUE
)
```

sub\_str

# Arguments

vector Vector

characterlist List the list of characters to treat as separating characters

proper Logical TRUE capitalizes the first letter in sentense format

# **Examples**

```
vector<-c("TES.T","TES<p>T","TES&nbspT")
string_aes(vector=vector)
string_aes(vector=vector,proper=FALSE)
string_aes(vector=vector,proper=TRUE)
```

sub\_str

Return n characters from left or right

# Description

Return n characters from left or right

# Usage

```
sub_str(x, n = 2, type)
```

## **Arguments**

x Character

n Number of characters to return

type "right" "left"

```
sub_str("12345",n=2,type="right")
sub_str("12345",n=2,type="left")
```

swap 127

swap

Reverse a numeric vector

# Description

Reverse a numeric vector

## Usage

```
swap(vector)
```

## **Arguments**

vector

numeric

# **Examples**

```
swap(c(1:10,1,2,3))
```

symmetric\_matrix

Symmetric Matrix

## **Description**

Symmetric Matrix

# Usage

```
symmetric_matrix(matrix, duplicate = "lower", diagonal = NULL)
```

## **Arguments**

matrix matrix

duplicate "upper" duplicates upper triangle "lower" duplicates lower triangle

diagonal values

```
m_lower<-matrix_triangle(matrix(1:9,nrow=3,ncol=3),type="lower",diagonal=NA)
m_upper<-matrix_triangle(matrix(11:19,nrow=3,ncol=3),type="upper",diagonal=NA)
symmetric_matrix(matrix=m_lower,duplicate="lower",diagonal=NA)
symmetric_matrix(matrix=m_upper,duplicate="upper",diagonal=NA)</pre>
```

128 tag\_pos

tag\_pos

Part of speech tagging

## **Description**

Part of speech tagging

Part of speech tagging

## Usage

```
tag_pos(text)
tag_pos(text)
```

### **Arguments**

text

character vector

```
text1<-"word_one word_two word_three"</pre>
text2<-"word_three word_four word_six"</pre>
text3<-"All the Lorem Ipsum generators on the Internet tend to repeat predefined
chunks as necessary, making this the first true generator on the Internet."
text4<-"It uses a dictionary of over 200 Latin words, combined with a handful of
model sentence structures, to generate Lorem Ipsum which looks reasonable."
text5<-"The generated Lorem Ipsum is therefore always free from repetition,
injected humour, or non-characteristic words etc."
text<-c(text1,text2,text3,text4,text5)</pre>
tag_pos(text)
text1<-"word_one word_two word_three"</pre>
text2<-"word_three word_four word_six"
text3<-"All the Lorem Ipsum generators on the Internet tend to repeat predefined
chunks as necessary, making this the first true generator on the Internet."
text4<-"It uses a dictionary of over 200 Latin words, combined with a handful of
model sentence structures, to generate Lorem Ipsum which looks reasonable."
text5<-"The generated Lorem Ipsum is therefore always free from repetition,
injected humour, or non-characteristic words etc."
text<-c(text1,text2,text3,text4,text5)</pre>
tag_pos(text)
```

text\_similarity 129

text\_similarity

Text similarity measures

## **Description**

Text similarity measures
Text similarity measures

## Usage

```
text_similarity(text1, text2)
text_similarity(text1, text2)
```

## **Arguments**

text1 character vector text2 character vector

```
text1<-"word_one word_two word_three"
text2<-"word_three word_four word_six"
text3<-"All the Lorem Ipsum generators on the Internet tend to repeat predefined
chunks as necessary, making this the first true generator on the Internet."
text4<-"It uses a dictionary of over 200 Latin words, combined with a handful of
model sentence structures, to generate Lorem Ipsum which looks reasonable."
text5<-"The generated Lorem Ipsum is therefore always free from repetition,
injected humour, or non-characteristic words etc."
text<-c(text1,text2,text3,text4,text5)
text<-unlist(strsplit(text,split=" "))</pre>
text1<-unlist(strsplit(text1,split=" "))</pre>
text2<-unlist(strsplit(text2,split=" "))</pre>
text3<-unlist(strsplit(text3,split=" "))</pre>
text4<-unlist(strsplit(text4,split=" "))</pre>
text5<-unlist(strsplit(text5,split=" "))</pre>
text_similarity(text1,text1)
text_similarity(text1,text2)
text_similarity(text1,text3)
text_similarity(text1,text4)
text1<-"word_one word_two word_three"
text2<-"word_three word_four word_six"
text3<-"All the Lorem Ipsum generators on the Internet tend to repeat predefined
chunks as necessary, making this the first true generator on the Internet."
text4<-"It uses a dictionary of over 200 Latin words, combined with a handful of
model sentence structures, to generate Lorem Ipsum which looks reasonable."
text5<-"The generated Lorem Ipsum is therefore always free from repetition,
injected humour, or non-characteristic words etc."
text<-c(text1,text2,text3,text4,text5)</pre>
```

ts\_smoothing

```
text<-unlist(strsplit(text,split=" "))
text1<-unlist(strsplit(text1,split=" "))
text2<-unlist(strsplit(text2,split=" "))
text3<-unlist(strsplit(text3,split=" "))
text4<-unlist(strsplit(text4,split=" "))
text5<-unlist(strsplit(text5,split=" "))
text_similarity(text1,text1)
text_similarity(text1,text2)
text_similarity(text1,text3)
text_similarity(text1,text4)</pre>
```

trim\_df

Trim whitespace in dataframe

# Description

Trim whitespace in dataframe

#### Usage

```
trim_df(df)
```

#### **Arguments**

df

dataframe

# Examples

ts\_smoothing

Smoothing

## **Description**

smoothing for timeseries. uses base plot

wrapper 131

## Usage

```
ts_smoothing(
   df,
   start = 0.01,
   stop = 2,
   step = 0.001,
   title = "",
   type = "kernel"
)
```

# **Arguments**

```
df ts object
start start value
stop stop value
step step
title plot title
type "default" "kernel" "lowess" "friedman" "splines" "polynomial" "linear"
```

#### **Details**

returns plot

#### **Examples**

```
ts_data<-ts(UKDriverDeaths,start=1969,end=1984,frequency=12)
par(mfrow=c(2,2))
ts_smoothing(ts_data,start=.01,stop=2,step=.01,title="Driver Deaths in UK",type="default")
ts_smoothing(ts_data,start=.01,stop=2,step=.01,title="Driver Deaths in UK",type="polynomial")
ts_smoothing(ts_data,start=.01,stop=2,step=.01,title="Driver Deaths in UK",type="linear")
ts_smoothing(ts_data,start=.01,stop=2,step=.01,title="Driver Deaths in UK",type="kernel")
ts_smoothing(ts_data,start=.01,stop=2,step=.01,title="Driver Deaths in UK",type="lowess")
ts_smoothing(ts_data,start=.01,stop=2,step=.01,title="Driver Deaths in UK",type="friedman")
ts_smoothing(ts_data,start=.01,stop=2,step=.01,title="Driver Deaths in UK",type="splines")</pre>
```

wrapper

Wrap string

# Description

Wrap string

# Usage

```
wrapper(x, ...)
```

132 write\_txt

# Arguments

x title

... arguments passed to strwrap

## **Examples**

```
wrapper(rep("sting",50),30)
```

write\_txt

Log console in file

# Description

Logs console in file and then displays log in console

# Usage

```
write_txt(input, file = NULL)
```

# Arguments

input Script to log in log file file Filename of log

```
write_txt(mtcars)
write_txt(mtcars,file="mtcars")
```

# **Index**

* ANOVA	increase_index, 56
compute_aov_es, 12	plot_icc_thurstonian, 71
compute_kruskal_wallis_test, 19	plot_irt_onefactor, 73
compute_one_way_test, 22	rank3_to_triplets, 91
compute_posthoc, 22	rank_df_to_binary, 91
plot_interaction, 72	rank_to_binary, 92
plot_interaction, 72 plot_oneway, 79	report_irt, 106
plot_oneway_diagnostics, 80	response_dimension, 118
report_factorial_anova, 103	* ML
report_manova, 109	plot_trees_xgboost, 86
report_oneway, 111	report_lda, 107
· · · · · · · · · · · · · · · · · · ·	report_xgboost, 116
report_ttests, 115	* NLP
report_wtests, 116 * EFA	
<del></del>	<pre>clear_stopwords, 8 clear_text, 9</pre>
compute_residual_stats, 24	
model_loadings, 62	stat_word_char, 125
plot_loadings, 74	tag_pos, 128
plot_scree, 85	text_similarity, 129
report_efa, 102	* SEM
* IRT	plot_cfa, 67
cfa_icc_index, 7	report_cfa, 98
compute_ability, 10	simulate_cfa_fit, 122
compute_dummy_comparisons, 15	* Thurstonian
compute_icc_thurstonian, 17	cfa_icc_index,7
compute_info_1pl, 17	compute_ability, 10
compute_info_2pl, 18	compute_dummy_comparisons, 15
compute_info_3pl, 19	compute_icc_thurstonian, 17
compute_map, 21	compute_map, 21
compute_scores, 25	compute_scores, 25
compute_se_theta, 25	<pre>generate_comparisons_matrix, 49</pre>
compute_unidimensional_ability, 28	generate_matrix_A,52
compute_unidimensional_theta, 29	<pre>generate_matrix_lambda_hat, 52</pre>
generate_comparisons_matrix,49	<pre>generate_unique_comparisons_index,</pre>
generate_matrix_A,52	54
<pre>generate_matrix_lambda_hat, 52</pre>	<pre>get_mplus_thu_3t, 55</pre>
<pre>generate_unique_comparisons_index,</pre>	icc_cfa, 56
54	<pre>increase_index, 56</pre>
<pre>get_mplus_thu_3t, 55</pre>	plot_icc_thurstonian,71
icc_cfa, 56	rank3_to_triplets,91

rank_df_to_binary,91	plot_crosstable, 69
rank_to_binary, 92	plot_mosaic, 76
response_dimension, 118	plot_response_frequencies, 82
* assumptions	response_frequency, 118
outlier_summary,64	* dimensions
plot_boxplot, 67	questions_by_keys, 89
plot_histogram, 70	questions_dimensions_dataframe, 90
plot_normality_diagnostics, 78	* functions
plot_outlier, 81	c_bind, 33
plot_qq,81	<pre>call_to_string, 6</pre>
remove_outliers,96	cdf, 6
<pre>report_normality_tests, 110</pre>	change_data_type, 7
* check	comparison_combinations, 10
cdf, 6	<pre>compute_adjustment, 11</pre>
* correlation	<pre>compute_confidence_inteval, 13</pre>
<pre>compute_power_r, 23</pre>	<pre>compute_dissatenuation, 15</pre>
<pre>compute_power_r_matrix, 24</pre>	compute_kurtosis, 20
deg2rad, 35	compute_skewness, 26
plot_corrplot, 69	compute_standard, 26
rad2deg, 90	<pre>compute_standard_error, 27</pre>
report_choric_serial,99	confusion, 30
report_correlation, $100$	<pre>confusion_matrix_percent, 31</pre>
* dataframe	data_frame_index,33
cdf, 6	detach_package, 35
* datasets	<pre>display_upper_lower_triangle, 41</pre>
df_admission, 36	dotnames, 41
df_automotive_data,36	drop_levels, 42
df_blood_pressure, 37	dummy_arrange, 42
df_crop_yield,38	environment_options, 43
df_difficile,38	excel_confusion_matrix, 43
df_insurance, 39	excel_critical_value,44
df_responses_state, 39	<pre>excel_generic_format, 45</pre>
df_sexual_comp, 40	excel_matrix,47
* data	flatten_list, 49
generate_correlation_matrix, $50$	generate_correlation_matrix, $50$
generate_data, $50$	generate_data, 50
<pre>generate_factor, 51</pre>	<pre>generate_factor, 51</pre>
generate_missing, 53	generate_missing, 53
<pre>generate_multiple_responce_vector,</pre>	<pre>generate_multiple_responce_vector,</pre>
53	53
generate_string, 54	generate_string, 54
simulate_correlation_from_sample,	getfwp, 55
123	install_all_packages, 57
* descriptives	install_load, 57
compute_aggregate, 12	k_fold, 58
compute_crosstable, 14	k_sample, 59
compute_descriptives, 14	matrix_triangle, $60$
<pre>compute_frequencies, 16</pre>	mgsub, 61

min may inday 60	plot_logistic_model,75
<pre>min_max_index, 62 off_diagonal_index, 63</pre>	report_logistic, 107
output_separator, 65	* matrix
padNA, 66	display_upper_lower_triangle,41
plot_confusion, 68	matrix_triangle, 60
plot_confusion, 08 plot_multiplot, 77	off_diagonal_index, 63
<pre>plot_roc, 83 plot_separability, 85</pre>	symmetric_matrix, 127
	* plot
proper, 88	plot_multiplot, 77
proportion_accurate, 88	report_pdf, 112
questions_by_keys, 89	wrapper, 131
questions_dimensions_dataframe, 90	* regression
rbind_all, 93	compute_y_logistic, 30
recode_scale_dummy, 94	output_compare_model_logistic, 64
remove_nc, 95	plot_logistic_model, 75
remove_user_packages, 96	plot_scatterplot, 84
replace_na_with_previous,97	report_logistic, 107
report_dataframe, 101	report_regression, 113
report_pdf, 112	* reliability
result_confusion_performance, 119	alpha_diagnostics,5
round_dataframe, 120	extract_components, 48
<pre>simulate_correlation_from_sample,</pre>	key_to_cfa_model, 58
123	mean_sd_alpha, 61
split_str, 123	plot_mtmm, 76
split_str_df, 124	raw_alpha,93
string_aes, 125	report_alpha,97
sub_str, 126	shrout, 121
swap, 127	* series
symmetric_matrix, 127	<pre>compute_moving_average, 21</pre>
trim_df, 130	plot_acf, 66
wrapper, 131	plot_ts, 87
write_txt, 132	ts_smoothing, 130
* generate	* statistical
generate_correlation_matrix, $50$	compute_adjustment, 11
generate_data, 50	<pre>compute_confidence_inteval, 13</pre>
generate_factor, 51	compute_dissatenuation, 15
<pre>generate_missing, 53</pre>	compute_kurtosis, 20
<pre>generate_multiple_responce_vector,</pre>	compute_skewness, 26
53	compute_standard, 26
generate_string,54	compute_standard_error, 27
simulate_correlation_from_sample,	* strings
123	call_to_string, 6
* keys	mgsub, 61
questions_by_keys, 89	output_separator, 65
${\tt questions\_dimensions\_dataframe}, 90$	proper, 88
* logistic	split_str, 123
<pre>compute_y_logistic, 30</pre>	split_str_df, 124
output_compare_model_logistic,64	string_aes, 125

sub_str, 126	compute_power_r_matrix, 24
trim_df, 130	<pre>compute_residual_stats, 24</pre>
* timestamp	compute_scores, 25
<pre>convert_excel_unix_timestamp, 32</pre>	compute_se_theta, 25
<pre>decompose_datetime, 34</pre>	compute_skewness, 26
* time	compute_standard, 26
<pre>compute_moving_average, 21</pre>	compute_standard_error, 27
plot_acf, 66	compute_unidimensional_ability, 28
plot_ts, 87	compute_unidimensional_theta, 29
ts_smoothing, 130	compute_y_logistic, 30
* unidimensional	confusion, 30
compute_info_1pl, 17	confusion_matrix_percent, 31
compute_info_2pl, 18	<pre>convert_excel_unix_timestamp, 32</pre>
compute_info_3pl, 19	
compute_se_theta, 25	data_frame_index, 33
compute_unidimensional_ability, 28	decompose_datetime, 34
compute_unidimensional_theta, 29	deg2rad, 35
56pu65_u2161662662642	detach_package, 35
alpha_diagnostics, 5	df_admission, 36
,	df_automotive_data, 36
c_bind, 33	df_blood_pressure, 37
call_to_string, 6	df_crop_yield, 38
cdf, 6	df_difficile, 38
cfa_icc_index, 7	df_insurance, 39
change_data_type, 7	df_responses_state, 39
clear_stopwords, 8	df_sexual_comp, 40
clear_text, 9	display_upper_lower_triangle, 41
comparison_combinations, 10	dotnames, 41
compute_ability, 10	drop_levels, 42
<pre>compute_adjustment, 11</pre>	dummy_arrange, 42
compute_aggregate, 12	daming_arrange, 12
compute_aov_es, 12	<pre>environment_options, 43</pre>
compute_confidence_inteval, 13	excel_confusion_matrix, 43
compute_crosstable, 14	excel_critical_value,44
compute_descriptives, 14	excel_generic_format, 45
compute_dissatenuation, 15	excel_matrix, 47
compute_dummy_comparisons, 15	extract_components, 48
compute_frequencies, 16	,
compute_icc_thurstonian, 17	flatten_list, 49
compute_info_1pl, 17	
compute_info_2pl, 18	<pre>generate_comparisons_matrix, 49</pre>
compute_info_3pl, 19	generate_correlation_matrix, $50$
<pre>compute_kruskal_wallis_test, 19</pre>	generate_data, 50
compute_kurtosis, 20	generate_factor, 51
compute_map, 21	generate_matrix_A,52
<pre>compute_moving_average, 21</pre>	<pre>generate_matrix_lambda_hat,52</pre>
compute_one_way_test, 22	generate_missing, 53
compute_posthoc, 22	<pre>generate_multiple_responce_vector, 53</pre>
compute_power_r, 23	<pre>generate_string, 54</pre>

<pre>generate_unique_comparisons_index, 54</pre>	plot_separability,85
<pre>get_mplus_thu_3t, 55</pre>	plot_trees_xgboost,86
getfwp, 55	plot_ts,87
	proper, 88
icc_cfa, 56	proportion_accurate, 88
increase_index, 56	, ,
install_all_packages, 57	questions_by_keys, 89
install_load, 57	${\tt questions\_dimensions\_dataframe,} \ 90$
k_fold, 58	rad2deg, 90
k_sample, 59	rank3_to_triplets, 91
key_to_cfa_model, 58	rank_df_to_binary, 91
<b>,</b> – – ,	rank_to_binary,92
matrix_triangle, 60	raw_alpha, 93
mean_sd_alpha, 61	rbind_all, 93
mgsub, 61	recode_scale_dummy, 94
min_max_index, 62	remove_nc, 95
model_loadings, 62	remove_outliers,96
3.7	remove_user_packages, 96
off_diagonal_index, 63	replace_na_with_previous, 97
outlier_summary, 64	report_alpha, 97
output_compare_model_logistic, 64	report_cfa, 98
output_separator, 65	report_choric_serial, 99
	report_correlation, 100
padNA, 66	report_dataframe, 101
plot_acf, 66	report_efa, 102
plot_boxplot, 67	report_factorial_anova, 103
plot_cfa, 67	report_hlr, 105
plot_confusion, 68	report_irt, 106
plot_corrplot, 69	report_lda, 107
plot_crosstable, 69	report_logistic, 107
plot_histogram, 70	report_manova, 109
plot_icc_thurstonian, 71	report_normality_tests, 110
plot_interaction, 72	report_oneway, 111
plot_irt_onefactor, 73	report_pdf, 112
plot_loadings, 74	report_regression, 113
plot_logistic_model, 75	report_ttests, 115
plot_mosaic, 76	report_wtests, 116
plot_mtmm, 76	report_xgboost, 116
plot_multiplot, 77	response_dimension, 118
plot_normality_diagnostics, 78	response_frequency, 118
plot_oneway, 79	result_confusion_performance, 119
plot_oneway_diagnostics, 80	round_dataframe, 120
plot_outlier, 81	Touriu_uatarraille, 120
plot_qq, 81	shrout, 121
plot_response_frequencies, 82	simulate_cfa_fit, 122
plot_roc, 83	simulate_cra_fit, 122 simulate_correlation_from_sample, 123
plot_scatterplot, 84	split_str, 123
plot_scree, 85	split_str_df, 124
p=0-001 00, 00	

```
stat_word_char, 125
stats::t.test, 115
stats::wilcox.test, 116
string_aes, 125
sub_str, 126
swap, 127
symmetric_matrix, 127
tag_pos, 128
text_similarity, 129
trim_df, 130
ts_smoothing, 130
wrapper, 131
write_txt, 132
```