

Package ‘MOFA2’

October 15, 2020

Type Package

Title Multi-Omics Factor Analysis v2

Version 0.99.8

Maintainer Britta Velten <britta.velten@gmail.com>

Date 2018-09-03

License GPL (>= 2)

Description

The MOFA2 package contains a collection of tools for running and analysing MOFA models.

Encoding UTF-8

Depends R (>= 4.0)

Imports rhdf5, dplyr, tidyr, reshape2, pheatmap, ggplot2, methods, GGally, RColorBrewer, cowplot, ggrepel, reticulate, HDF5Array, grDevices, stats, magrittr, forcats, utils, cor-plot, ggtrastr, DelayedArray, Rtsne, uwot

Suggests knitr, testthat, Seurat, ggpubr, doParallel, foreach, psych, MultiAssayExperiment

biocViews DimensionReduction, Bayesian, Visualization

URL <https://biofam.github.io/MOFA2/index.html>

BugReports <https://github.com/bioFAM/MOFA2>

VignetteBuilder knitr

LazyData false

NeedsCompilation yes

RoxygenNote 7.1.1

SystemRequirements Python (>=3), numpy, pandas, h5py, scipy, argparse, sklearn, mofapy2

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calculate_variance_explained	
	<i>Calculate variance explained by the model</i>

Description

This function takes a trained MOFA model as input and calculates the proportion of variance explained (i.e. the coefficient of determinations (R^2)) by the MOFA factors across the different views.

Usage

```
calculate_variance_explained(
  object,
  views = "all",
  groups = "all",
  factors = "all"
)
```

Arguments

object	a MOFA object.
views	character vector with the view names, or numeric vector with view indexes. Default is 'all'
groups	character vector with the group names, or numeric vector with group indexes. Default is 'all'
factors	character vector with the factor names, or numeric vector with the factor indexes. Default is 'all'

Value

a list with matrices with the amount of variation explained per factor and view.

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Calculate variance explained (R2)
r2 <- calculate_variance_explained(model)

# Plot variance explained values (view as x-axis, and factor as y-axis)
plot_variance_explained(model, x="view", y="factor")
```

```
# Plot variance explained values (view as x-axis, and group as y-axis)
plot_variance_explained(model, x="view", y="group")

# Plot variance explained values for factors 1 to 3
plot_variance_explained(model, x="view", y="group", factors=1:3)

# Scale R2 values
plot_variance_explained(model, max_r2 = 0.25)
```

cluster_samples

K-means clustering on samples based on latent factors

Description

MOFA factors are continuous in nature but they can be used to predict discrete clusters of samples. The clustering can be performed in a single factor, which is equivalent to setting a manual threshold. More interestingly, it can be done using multiple factors, where multiple sources of variation are aggregated.

Importantly, this type of clustering is not weighted and does not take into account the different importance of the latent factors.

Usage

```
cluster_samples(object, k, factors = "all", ...)
```

Arguments

object	a trained MOFA object.
k	number of clusters (integer).
factors	character vector with the factor name(s), or numeric vector with the index of the factor(s) to use. Default is 'all'
...	extra arguments passed to kmeans

Details

In some cases, due to model technicalities, samples can have missing values in the latent factor space. In such a case, these samples are currently ignored in the clustering procedure.

Value

output from [kmeans](#) function

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Cluster samples in the factor space using factors 1 to 3 and K=2 clusters
clusters <- cluster_samples(model, k=2, factors=1:3)
```

compare_elbo	<i>Compare different trained MOFA objects in terms of the final value of the ELBO statistics and number of inferred factors</i>
--------------	---

Description

Different objects of MOFA are compared in terms of the final value of the ELBO statistics. For model selection the model with the highest ELBO value is selected.

Usage

```
compare_elbo(models, log = FALSE, return_data = FALSE)
```

Arguments

models	a list containing MOFA objects.
log	logical indicating whether to plot the log of the ELBO.
return_data	logical indicating whether to return a data.frame with the ELBO values per model

Value

A ggplot object or the underlying data.frame if return_data is TRUE

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model1 <- load_model(file)
model2 <- load_model(file)

# Compare ELBO between models
## Not run: compare_elbo(list(model1,model2))
```

compare_factors	<i>Plot the correlation of factors between different models</i>
-----------------	---

Description

Different MOFA objects are compared in terms of correlation between their factors.

Usage

```
compare_factors(models, ...)
```

Arguments

models	a list with MOFA objects.
...	extra arguments passed to pheatmap

Details

If assessing model robustness across trials, the output should look like a block diagonal matrix, suggesting that all factors are robustly detected in all model instances.

Value

Plots a heatmap of the Pearson correlation between latent factors across all input models.

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model1 <- load_model(file)
model2 <- load_model(file)

# Compare factors between models
compare_factors(list(model1, model2))
```

correlate_factors_with_covariates

Plot correlation of factors with external covariates

Description

Function to correlate factor values with external covariates.

Usage

```
correlate_factors_with_covariates(
  object,
  covariates,
  factors = "all",
  groups = "all",
  abs = FALSE,
  plot = c("log_pval", "r"),
  alpha = 0.05,
  return_data = FALSE,
  transpose = FALSE,
  ...
)
```

Arguments

- | | |
|------------|---|
| object | a trained MOFA object. |
| covariates | <ul style="list-style-type: none"> • data.frame: a data.frame where the samples are stored in the rows and the covariates are stored in the columns. Use row names for sample names and column names for covariate names. Columns values must be numeric. • character vector: character vector with names of columns that are present in the sample metadata (<code>samples_metadata(model)</code>) |
| factors | character vector with the factor name(s), or numeric vector with the index of the factor(s) to use. Default is 'all'. |

groups	character vector with the groups names, or numeric vector with the indices of the groups of samples to use, or "all" to use samples from all groups.
abs	logical indicating whether to take the absolute value of the correlation coefficient (default is TRUE).
plot	character indicating whether to plot Pearson correlation coefficients (plot="r") or log10 adjusted p-values (plot="log_pval").
alpha	p-value threshold
return_data	logical indicating whether to return the correlation results instead of plotting
transpose	logical indicating whether to transpose the plot
...	extra arguments passed to corrplot (if plot=="r") or pheatmap (if plot=="log_pval").

Value

A [corrplot](#) (if plot=="r") or [pheatmap](#) (if plot=="log_pval") or the underlying data.frame if return_data is TRUE

create_mofa	<i>create a MOFA object</i>
-------------	-----------------------------

Description

Method to create a [MOFA](#) object. Depending on the input data format, this method calls one of the following functions:

- **long data.frame:** [create_mofa_from_df](#)
- **List of matrices:** [create_mofa_from_matrix](#)
- **MultiAssayExperiment:** [create_mofa_from_MultiAssayExperiment](#)
- **Seurat:** [create_mofa_from_Seurat](#)
- **SingleCellExperiment:** [create_mofa_from_SingleCellExperiment](#)

Please read the documentation of the corresponding function for more details on your specific data format.

Usage

```
create_mofa(data, groups = NULL, ...)
```

Arguments

data group information, only relevant when using the multi-group framework.

Value

Returns an untrained [MOFA](#) object

Examples

```
# Using an existing simulated data with two groups and two views
file <- system.file("extdata", "test_data.RData", package = "MOFA2")

# Load data (in long data.frame format)
load(file)
MOFAmodel <- create_mofa(dt)
```

create_mofa_from_df	<i>create a MOFA object from a data.frame object</i>
---------------------	--

Description

Method to create a [MOFA](#) object from a data.frame object

Usage

```
create_mofa_from_df(df)
```

Arguments

df	data.frame object with at most 5 columns: sample, group, feature, view, value. The group column (optional) indicates the group of each sample when using the multi-group framework. The view column (optional) indicates the view of each feature when having multi-view data.
----	--

Value

Returns an untrained [MOFA](#) object

create_mofa_from_matrix	<i>create a MOFA object from a a list of matrices</i>
-------------------------	---

Description

Method to create a [MOFA](#) object from a list of matrices

Usage

```
create_mofa_from_matrix(data, groups = NULL)
```

Arguments

data	A list of matrices, where each entry corresponds to one view. Samples are stored in columns and features in rows. Missing values must be filled in prior to creating the MOFA object (see for example the CLL tutorial)
groups	A character vector with group assignment for every sample. Default is NULL, no group structure.

Value

Returns an untrained [MOFA](#) object

```
create_mofa_from_MultiAssayExperiment
```

create a MOFA object from a MultiAssayExperiment object

Description

Method to create a [MOFA](#) object from a MultiAssayExperiment object

Usage

```
create_mofa_from_MultiAssayExperiment(  
  mae,  
  groups = NULL,  
  save_metadata = FALSE  
)
```

Arguments

mae	a MultiAssayExperiment object
groups	a string specifying column name of the colData to use it as a group variable. Alternatively, a character vector with group assignment for every sample. Default is NULL (no group structure).
save_metadata	logical indicating whether to incorporate the metadata from the MultiAssayExperiment object into the MOFA object

Value

Returns an untrained [MOFA](#) object

```
create_mofa_from_Seurat
```

create a MOFA object from a Seurat object

Description

Method to create a [MOFA](#) object from a Seurat object

Usage

```
create_mofa_from_Seurat(  
  seurat,  
  groups = NULL,  
  assays = NULL,  
  slot = "data",  
  features = NULL,  
  save_metadata = FALSE  
)
```

Arguments

seurat	Seurat object
groups	a string specifying column name of the samples metadata to use it as a group variable. Alternatively, a character vector with group assignment for every sample. Default is NULL (no group structure).
assays	assays to use, default is NULL, it fetched all assays available
slot	assay slot to be used such as scale.data or data (default).
features	a list with vectors, which are used to subset features, with names corresponding to assays; a vector can be provided when only one assay is used
save_metadata	logical indicating whether to incorporate the metadata from the Seurat object into the MOFA object

Value

Returns an untrained [MOFA](#) object

```
create_mofa_from_SingleCellExperiment
```

create a MOFA object from a SingleCellExperiment object

Description

Method to create a [MOFA](#) object from a SingleCellExperiment object

Usage

```
create_mofa_from_SingleCellExperiment(
  sce,
  groups = NULL,
  assay = "logcounts",
  save_metadata = FALSE
)
```

Arguments

sce	SingleCellExperiment object
groups	a string specifying column name of the colData to use it as a group variable. Alternatively, a character vector with group assignment for every sample. Default is NULL (no group structure).
assay	assay to use, default is logcounts.
save_metadata	logical indicating whether to incorporate the metadata from the SingleCellExperiment object into the MOFA object

Value

Returns an untrained [MOFA](#) object

factors_names	<i>factors_names: set and retrieve factor names</i>
---------------	---

Description

factors_names: set and retrieve factor names

Usage

```
factors_names(object)

factors_names(object) <- value

## S4 method for signature 'MOFA'
factors_names(object)

## S4 replacement method for signature 'MOFA,vector'
factors_names(object) <- value
```

Arguments

object	a MOFA object.
value	a character vector of factor names

Value

character vector with the factor names

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
factors_names(model)
```

features_metadata	<i>features_metadata: set and retrieve feature metadata</i>
-------------------	---

Description

features_metadata: set and retrieve feature metadata

Usage

```
features_metadata(object)

features_metadata(object) <- value

## S4 method for signature 'MOFA'
features_metadata(object)

## S4 replacement method for signature 'MOFA,data.frame'
features_metadata(object) <- value
```

Arguments

object	a MOFA object.
value	data frame with feature information, it at least must contain the columns feature and view

Value

a data frame with sample metadata

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
features_metadata(model)
```

features_names	<i>features_names: set and retrieve feature names</i>
----------------	---

Description

features_names: set and retrieve feature names

Usage

```
features_names(object)

features_names(object) <- value

## S4 method for signature 'MOFA'
features_names(object)

## S4 replacement method for signature 'MOFA,list'
features_names(object) <- value
```

Arguments

object	a MOFA object.
value	list of character vectors with the feature names for every view

Value

list of character vectors with the feature names for each view

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
features_names(model)
```

get_data	<i>Get data</i>
----------	-----------------

Description

Fetch the input data

Usage

```
get_data(
  object,
  views = "all",
  groups = "all",
  features = "all",
  as.data.frame = FALSE,
  add_intercept = TRUE,
  denoise = FALSE,
  na.rm = TRUE
)
```

Arguments

object	a MOFA object.
views	character vector with the view name(s), or numeric vector with the view index(es). Default is "all".
groups	character vector with the group name(s), or numeric vector with the group index(es). Default is "all".
features	a <i>*named*</i> list of character vectors. Example: list("view1"=c("feature_1","feature_2"), "view2"=c("feature_3","feature_4")) Default is "all".
as.data.frame	logical indicating whether to return a long data frame instead of a list of matrices. Default is FALSE.
add_intercept	logical indicating whether to add feature intercepts to the data. Default is TRUE.
denoise	logical indicating whether to return the denoised data (i.e. the model predictions). Default is FALSE.
na.rm	remove NAs from the data.frame (only if as.data.frame is TRUE).

Details

By default this function returns a list where each element is a data matrix with dimensionality (D,N) where D is the number of features and N is the number of samples.

Alternatively, if `as.data.frame` is `TRUE`, the function returns a long-formatted data frame with columns (view,feature,sample,value). Missing values are not included in the the long data.frame format by default. To include them use the argument `na.rm=FALSE`.

Value

A list of data matrices with dimensionality (D,N) or a data.frame (if `as.data.frame` is `TRUE`)

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Fetch data
data <- get_data(model)

# Fetch a specific view
data <- get_data(model, views = "view_0")

# Fetch data in data.frame format instead of matrix format
data <- get_data(model, as.data.frame = TRUE)

# Fetch centered data (do not add the feature intercepts)
data <- get_data(model, as.data.frame = FALSE)

# Fetch denoised data (do not add the feature intercepts)
data <- get_data(model, denoise = TRUE)
```

`get_default_data_options`*Get default data options*

Description

Function to obtain the default data options.

Usage

```
get_default_data_options(object)
```

Arguments

`object` an untrained [MOFA](#) object

Details

This function provides a default set of data options that can be modified and passed to the [MOFA](#) object in the [prepare_mofa](#) step (see example), i.e. after creating a [MOFA](#) object (using [create_mofa](#)) and before starting the training (using [run_mofa](#)) The data options are the following:

- **scale_views**: logical indicating whether to scale views to have the same unit variance. As long as the scale differences between the views is not too high, this is not required. Default is FALSE.
- **scale_groups**: logical indicating whether to scale groups to have the same unit variance. As long as the scale differences between the groups is not too high, this is not required. Default is FALSE.

Value

Returns a list with the default data options.

Examples

```
# Using an existing simulated data with two groups and two views
file <- system.file("extdata", "test_data.RData", package = "MOFA2")

# Load data dt (in data.frame format)
load(file)

# Create the MOFA object
MOFAmodel <- create_mofa(dt)

# Load default data options
data_opts <- get_default_data_options(MOFAmodel)

# Edit some of the data options
data_opts$scale_views <- TRUE

# Prepare the MOFA object
MOFAmodel <- prepare_mofa(MOFAmodel, data_options = data_opts)
```

get_default_model_options

Get default model options

Description

Function to obtain the default model options.

Usage

```
get_default_model_options(object)
```

Arguments

object an untrained [MOFA](#) object

Details

This function provides a default set of model options that can be modified and passed to the [MOFA](#) object in the [prepare_mofa](#) step (see example), i.e. after creating a [MOFA](#) object (using [create_mofa](#)) and before starting the training (using [run_mofa](#)) The model options are the following:

- **likelihoods**: character vector with data likelihoods per view: 'gaussian' for continuous data, 'bernoulli' for binary data and 'poisson' for count data. By default, they are guessed internally.
- **num_factors**: numeric value indicating the (initial) number of factors. Default is 15.
- **spikeslab_factors**: logical indicating whether to use spike and slab sparsity on the factors (Default is FALSE)
- **spikeslab_weights**: logical indicating whether to use spike and slab sparsity on the weights (Default is TRUE)
- **ard_factors**: logical indicating whether to use ARD sparsity on the factors (Default is TRUE only if using multiple groups)
- **ard_weights**: logical indicating whether to use ARD sparsity on the weights (Default is TRUE)

Value

Returns a list with the default model options.

Examples

```
# Using an existing simulated data with two groups and two views
file <- system.file("extdata", "test_data.RData", package = "MOFA2")

# Load data dt (in data.frame format)
load(file)

# Create the MOFA object
MOFAmodel <- create_mofa(dt)

# Load default model options
model_opts <- get_default_model_options(MOFAmodel)

# Edit some of the model options
model_opts$num_factors <- 10
model_opts$spikeslab_weights <- FALSE

# Prepare the MOFA object
MOFAmodel <- prepare_mofa(MOFAmodel, model_options = model_opts)
```

```
get_default_stochastic_options
```

```
Get default stochastic options
```

Description

Function to obtain the default options for stochastic variational inference.

Usage

```
get_default_stochastic_options(object)
```

Arguments

object an untrained [MOFA](#)

Details

This function provides a default set of stochastic inference options that can be modified and passed to the [MOFA](#) object in the [prepare_mofa](#) step), i.e. after creating a [MOFA](#) object (using [create_mofa](#)) and before starting the training (using [run_mofa](#)). These options are only relevant when activating stochastic inference in `training_options` (see example). The stochastic inference options are the following:

- **batch_size**: numeric value indicating the batch size (as a fraction). Default is 0.5 (half of the data set).
- **learning_rate**: numeric value indicating the learning rate. Default is 1.0
- **forgetting_rate**: numeric indicating the forgetting rate. Default is 0.5
- **start_stochastic**: integer indicating the first iteration to start stochastic inference Default is 1

Value

Returns a list with default options

Examples

```
# Using an existing simulated data with two groups and two views
file <- system.file("extdata", "test_data.RData", package = "MOFA2")

# Load data dt (in data.frame format)
load(file)

# Create the MOFA object
MOFAmodel <- create_mofa(dt)

# activate stochastic inference in training options
train_opts <- get_default_training_options(MOFAmodel)
train_opts$stochastic <- TRUE

# Load default stochastic options
stochastic_opts <- get_default_stochastic_options(MOFAmodel)

# Edit some of the stochastic options
stochastic_opts$learning_rate <- 0.75
stochastic_opts$batch_size <- 0.25

# Prepare the MOFA object
MOFAmodel <- prepare_mofa(MOFAmodel,
  training_options = train_opts,
  stochastic_options = stochastic_opts
)
```

`get_default_training_options`*Get default training options*

Description

Function to obtain the default training options.

Usage

```
get_default_training_options(object)
```

Arguments

`object` an untrained [MOFA](#)

Details

This function provides a default set of training options that can be modified and passed to the [MOFA](#) object in the [prepare_mofa](#) step (see example), i.e. after creating a [MOFA](#) object (using [create_mofa](#)) and before starting the training (using [run_mofa](#)) The training options are the following:

- **maxiter**: numeric value indicating the maximum number of iterations. Default is 1000. Convergence is assessed using the ELBO statistic.
- **drop_factor_threshold**: numeric indicating the threshold on fraction of variance explained to consider a factor inactive and drop it from the model. For example, a value of 0.01 implies that factors explaining less than 1% of variance (in each view) will be dropped. Default is -1 (no dropping of factors)
- **convergence_mode**: character indicating the convergence criteria, either "slow", "medium" or "fast", corresponding to 5e-7%, 5e-6% or 5e-5% deltaELBO change w.r.t. to the ELBO at the first iteration.
- **verbose**: logical indicating whether to generate a verbose output.
- **startELBO**: integer indicating the first iteration to compute the ELBO (default is 1).
- **freqELBO**: integer indicating the first iteration to compute the ELBO (default is 1).
- **stochastic**: logical indicating whether to use stochastic variational inference (only required for very big data sets, default is FALSE).
- **gpu_mode**: logical indicating whether to use GPUs (see details).
- **seed**: numeric indicating the seed for reproducibility (default is 42).

Value

Returns a list with default training options

Examples

```
# Using an existing simulated data with two groups and two views
file <- system.file("extdata", "test_data.RData", package = "MOFA2")

# Load data dt (in data.frame format)
load(file)

# Create the MOFA object
MOFAmodel <- create_mofa(dt)

# Load default training options
train_opts <- get_default_training_options(MOFAmodel)

# Edit some of the training options
train_opts$convergence_mode <- "medium"
train_opts$startELBO <- 100
train_opts$seed <- 42

# Prepare the MOFA object
MOFAmodel <- prepare_mofa(MOFAmodel, training_options = train_opts)
```

get_dimensions

*Get dimensions***Description**

Extract dimensionalities from the model.

Usage

```
get_dimensions(object)
```

Arguments

object a [MOFA](#) object.

Details

K indicates the number of factors, D indicates the number of features, N indicates the (total) number of samples and M indicates the number of views.

Value

list containing the dimensionalities of the model

Examples

```
# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
dims <- get_dimensions(model)
```

get_elbo

Get ELBO

Description

Extract the value of the ELBO statistics after model training. This can be useful for model selection.

Usage

```
get_elbo(object)
```

Arguments

object a [MOFA](#) object.

Details

This can be useful for model selection.

Value

Value of the ELBO

Examples

```
# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
elbo <- get_elbo(model)
```

get_expectations

Get expectations

Description

Function to extract the expectations from the (variational) posterior distributions of a trained [MOFA](#) object.

Usage

```
get_expectations(object, variable, as.data.frame = FALSE)
```

Arguments

object a trained [MOFA](#) object.
variable variable name: 'Z' for factors and 'W' for weights.
as.data.frame logical indicating whether to output the result as a long data frame, default is FALSE.

Details

Technical note: MOFA is a Bayesian model where each variable has a prior distribution and a posterior distribution. In particular, to achieve scalability we used the variational inference framework, thus true posterior distributions are replaced by approximated variational distributions. This function extracts the expectations of the variational distributions, which can be used as final point estimates to analyse the results of the model.

The priors and variational distributions of each variable are extensively described in the supplementary methods of the original paper.

Value

the output varies depending on the variable of interest:

- "Z" a matrix with dimensions (samples,factors). If `as.data.frame` is TRUE, a long-formatted data frame with columns (sample,factor,value)
- "W" a list of length (views) where each element is a matrix with dimensions (features,factors). If `as.data.frame` is TRUE, a long-formatted data frame with columns (view,feature,factor,value)

Examples

```
# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
factors <- get_expectations(model, "Z")
weights <- get_expectations(model, "W")
```

get_factors	<i>Get factors</i>
-------------	--------------------

Description

Extract the latent factors from the model.

Usage

```
get_factors(
  object,
  groups = "all",
  factors = "all",
  scale = FALSE,
  as.data.frame = FALSE
)
```

Arguments

object	a trained MOFA object.
groups	character vector with the group name(s), or numeric vector with the group index(es). Default is "all".
factors	character vector with the factor name(s), or numeric vector with the factor index(es). Default is "all".

scale	logical indicating whether to scale factor values.
as.data.frame	logical indicating whether to return a long data frame instead of a matrix. Default is FALSE.

Value

By default it returns the latent factor matrix of dimensionality (N,K), where N is number of samples and K is number of factors.

Alternatively, if as.data.frame is TRUE, returns a long-formatted data frame with columns (sample,factor,value).

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Fetch factors in matrix format (a list, one matrix per group)
factors <- get_factors(model)

# Concatenate groups
factors <- do.call("rbind",factors)

# Fetch factors in data.frame format instead of matrix format
factors <- get_factors(model, as.data.frame = TRUE)
```

get_imputed_data	<i>Get imputed data</i>
------------------	-------------------------

Description

Function to get the imputed data. It requires the previous use of the [impute](#) method.

Usage

```
get_imputed_data(
  object,
  views = "all",
  groups = "all",
  features = "all",
  as.data.frame = FALSE
)
```

Arguments

object	a trained MOFA object.
views	character vector with the view name(s), or numeric vector with the view index(es). Default is "all".
groups	character vector with the group name(s), or numeric vector with the group index(es). Default is "all".
features	list of character vectors with the feature names or list of numeric vectors with the feature indices. Default is "all".

`as.data.frame` logical indicating whether to return a long-formatted data frame instead of a list of matrices. Default is FALSE.

Details

Data is imputed from the generative model of MOFA.

Value

A list containing the imputed values or a data.frame if `as.data.frame` is TRUE

Examples

```
# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
model <- impute(model)
imputed <- get_imputed_data(model)
```

get_variance_explained

Get variance explained values

Description

Extract the latent factors from the model.

Usage

```
get_variance_explained(
  object,
  groups = "all",
  views = "all",
  factors = "all",
  as.data.frame = FALSE
)
```

Arguments

<code>object</code>	a trained MOFA object.
<code>groups</code>	character vector with the group name(s), or numeric vector with the group index(es). Default is "all".
<code>views</code>	character vector with the view name(s), or numeric vector with the view index(es). Default is "all".
<code>factors</code>	character vector with the factor name(s), or numeric vector with the factor index(es). Default is "all".
<code>as.data.frame</code>	logical indicating whether to return a long data frame instead of a matrix. Default is FALSE.

Value

A list of data matrices with variance explained per group or a data.frame (if as.data.frame is TRUE)

Examples

```
# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Fetch variance explained values (in matrix format)
r2 <- get_variance_explained(model)

# Fetch variance explained values (in data.frame format)
r2 <- get_variance_explained(model, as.data.frame = TRUE)
```

get_weights

Get weights

Description

Extract the weights from the model.

Usage

```
get_weights(
  object,
  views = "all",
  factors = "all",
  abs = FALSE,
  scale = FALSE,
  as.data.frame = FALSE
)
```

Arguments

object	a trained MOFA object.
views	character vector with the view name(s), or numeric vector with the view index(es). Default is "all".
factors	character vector with the factor name(s) or numeric vector with the factor index(es). Default is "all".
abs	logical indicating whether to take the absolute value of the weights.
scale	logical indicating whether to scale all weights from -1 to 1 (or from 0 to 1 if abs=TRUE).
as.data.frame	logical indicating whether to return a long data frame instead of a list of matrices. Default is FALSE.

Value

By default it returns a list where each element is a loading matrix with dimensionality (D,K), where D is the number of features and K is the number of factors.

Alternatively, if `as.data.frame` is TRUE, returns a long-formatted data frame with columns (view,feature,factor,value).

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Fetch weights in matrix format (a list, one matrix per view)
weights <- get_weights(model)

# Fetch weights for factor 1 and 2 and view 1
weights <- get_weights(model, views = 1, factors = c(1,2))

# Fetch weights in data.frame format
weights <- get_weights(model, as.data.frame = TRUE)
```

groups_names	<i>groups_names: set and retrieve group names</i>
--------------	---

Description

groups_names: set and retrieve group names

Usage

```
groups_names(object)

groups_names(object) <- value

## S4 method for signature 'MOFA'
groups_names(object)

## S4 replacement method for signature 'MOFA,character'
groups_names(object) <- value
```

Arguments

object	a MOFA object.
value	character vector with the names for each group

Value

character vector with the names for each sample group

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
groups_names(model)
groups_names(model) <- c("my_group")
```

impute

Impute missing values from a fitted MOFA

Description

This function uses the latent factors and the loadings to impute missing values.

Usage

```
impute(
  object,
  views = "all",
  groups = "all",
  factors = "all",
  add_intercept = TRUE
)
```

Arguments

object	a MOFA object.
views	character vector with the view name(s), or numeric vector with view index(es).
groups	character vector with the group name(s), or numeric vector with group index(es).
factors	character vector with the factor names, or numeric vector with the factor index(es). <ul style="list-style-type: none"> • response: gives mean for gaussian and poisson and probabilities for bernoulli. • link: gives the linear predictions. • inRange: rounds the fitted values from "terms" for integer-valued distributions to the next integer (default).
add_intercept	add feature intercepts to the imputation (default is TRUE).

Details

MOFA generates a denoised and condensed low-dimensional representation of the data that captures the main sources of heterogeneity of the data. This representation can be used to reconstruct the data, simply using the equation $Y = WX$. For more details read the supplementary methods of the manuscript.

Note that with [impute](#) you can only generate the point estimates (the means of the posterior distributions). If you want to add uncertainty estimates (the variance) you need to set `impute=TRUE` in the training options. See [get_default_training_options](#).

Value

This method fills the `imputed_data` slot by replacing the missing values in the input data with the model predictions.

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Impute missing values in all data modalities
imputed_data <- impute(model, views = "all")

# Impute missing values in all data modalities using factors 1:3
imputed_data <- impute(model, views = "all", factors = 1:3)
```

load_model	<i>Load a trained MOFA</i>
------------	----------------------------

Description

Method to load a trained MOFA

The training of mofa is done using a Python framework, and the model output is saved as an .hdf5 file, which has to be loaded in the R package.

Usage

```
load_model(
  file,
  sort_factors = TRUE,
  on_disk = FALSE,
  load_data = TRUE,
  remove_outliers = FALSE,
  remove_inactive_factors = TRUE,
  verbose = FALSE
)
```

Arguments

file	an hdf5 file saved by the mofa Python framework
sort_factors	logical indicating whether factors should be sorted by variance explained (default is TRUE)
on_disk	logical indicating whether to work from memory (FALSE) or disk (TRUE). This should be set to TRUE when the training data is so big that cannot fit into memory. On-disk operations are performed using the HDF5Array and DelayedArray framework.
load_data	logical indicating whether to load the training data (default is TRUE, it can be memory expensive)
remove_outliers	logical indicating whether to mask outlier values.
remove_inactive_factors	logical indicating whether to remove inactive factors from the model.
verbose	logical indicating whether to print verbose output (default is FALSE)

Value

a [MOFA](#) model

Examples

```
#' # Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
```

make_example_data	<i>Simulate a data set using the generative model of MOFA</i>
-------------------	---

Description

Function to simulate an example multi-view multi-group data set according to the generative model of MOFA2.

Usage

```
make_example_data(
  n_views = 3,
  n_features = 100,
  n_samples = 50,
  n_groups = 1,
  n_factors = 5,
  likelihood = "gaussian"
)
```

Arguments

n_views	number of views
n_features	number of features in each view
n_samples	number of samples in each group
n_groups	number of groups
n_factors	number of factors
likelihood	likelihood for each view, one of "gaussian" (default), "bernoulli", "poisson", or a character vector of length n_views

Value

Returns an untrained [MOFA](#) object containing simulated data as training data.

Examples

```
# Generate a simulated data set
MOFAexample <- make_example_data()
```

MOFA	<i>Class to store a mofa model</i>
------	------------------------------------

Description

The MOFA is an S4 class used to store all relevant data to analyse a MOFA model

Slots

data The input data
 intercepts Feature intercepts
 samples_metadata Samples metadata
 features_metadata Features metadata.
 imputed_data The imputed data.
 expectations expected values of the factors and the loadings.
 dim_red non-linear dimensionality reduction manifolds.
 training_stats model training statistics.
 data_options Data processing options.
 training_options Model training options.
 stochastic_options Stochastic variational inference options.
 model_options Model options.
 dimensions Dimensionalities of the model: M for the number of views, G for the number of groups, N for the number of samples (per group), D for the number of features (per view), K for the number of factors.
 on_disk Logical indicating whether data is loaded from disk.
 cache Cache.
 status Auxiliary variable indicating whether the model has been trained.

plot_ascii_data	<i>Visualize the structure of the data in the terminal</i>
-----------------	--

Description

A Fancy printing method

Usage

```
plot_ascii_data(object, nonzero = FALSE)
```

Arguments

object a [MOFA](#) object
 nonzero a logical value specifying whether to calculate the fraction of non-zero values (non-NA values by default)

Details

This function is helpful to get an overview of the structure of the data as a text output

Value

None

Examples

```
# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
plot_ascii_data(model)
```

plot_data_heatmap	<i>Plot heatmap of relevant features</i>
-------------------	--

Description

Function to plot a heatmap of the data for relevant features, typically the ones with high weights.

Usage

```
plot_data_heatmap(
  object,
  factor,
  view = 1,
  groups = "all",
  features = 50,
  annotation_features = NULL,
  annotation_samples = NULL,
  transpose = FALSE,
  imputed = FALSE,
  denoise = FALSE,
  max.value = NULL,
  min.value = NULL,
  ...
)
```

Arguments

object	a MOFA object.
factor	a string with the factor name, or an integer with the index of the factor.
view	a string with the view name, or an integer with the index of the view. Default is the first view.
groups	groups to plot. Default is "all".
features	if an integer (default), the total number of features to plot based on the absolute value of the weights. If a character vector, a set of manually defined features.

annotation_features	annotation metadata for features (rows). Either a character vector specifying columns in the feature metadata, or a data.frame that will be passed to pheatmap as annotation_col
annotation_samples	annotation metadata for samples (columns). Either a character vector specifying columns in the sample metadata, or a data.frame that will be passed to pheatmap as annotation_row
transpose	logical indicating whether to transpose the heatmap. Default corresponds to features as rows and samples as columns.
imputed	logical indicating whether to plot the imputed data instead of the original data. Default is FALSE.
denoise	logical indicating whether to plot a denoised version of the data reconstructed using the MOFA factors.
max.value	numeric indicating the maximum value to display in the heatmap (i.e. the matrix values will be capped at max.value).
min.value	numeric indicating the minimum value to display in the heatmap (i.e. the matrix values will be capped at min.value). See predict . Default is FALSE.
...	further arguments that can be passed to pheatmap

Details

One of the first steps for the annotation of a given factor is to visualise the corresponding weights, using for example [plot_weights](#) or [plot_top_weights](#).

However, one might also be interested in visualising the direct relationship between features and factors, rather than looking at "abstract" weights.

This function generates a heatmap for selected features, which should reveal the underlying pattern that is captured by the latent factor.

A similar function for doing scatterplots rather than heatmaps is [plot_data_scatter](#).

Value

A [pheatmap](#) object

Examples

```
# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
plot_data_heatmap(model, factor = 1, show_rownames = FALSE, show_colnames = FALSE)
```

plot_data_overview	<i>Overview of the input data</i>
--------------------	-----------------------------------

Description

Function to do a tile plot showing the missing value structure of the input data

Usage

```
plot_data_overview(object, colors = NULL, show_dimensions = TRUE)
```

Arguments

object a [MOFA](#) object.

colors a vector specifying the colors per view (see example for details).

show_dimensions logical indicating whether to plot the dimensions of the data (default is TRUE).

Details

This function is helpful to get an overview of the structure of the data. It shows the model dimensionalities (number of samples, groups, views and features) and it indicates which measurements are missing.

Value

A [ggplot](#) object

Examples

```
# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
plot_data_overview(model)
```

plot_data_scatter	<i>Scatterplots of feature values against latent factors</i>
-------------------	--

Description

Function to do a scatterplot of features against factor values.

Usage

```
plot_data_scatter(
  object,
  factor = 1,
  view = 1,
  groups = "all",
  features = 10,
  sign = "all",
  color_by = "group",
  legend = TRUE,
  alpha = 1,
  shape_by = NULL,
  stroke = NULL,
  dot_size = 2.5,
  text_size = NULL,
  add_lm = TRUE,
  lm_per_group = TRUE,
  imputed = FALSE
)
```


Arguments

object	a MOFA object.
factor	string with the factor name, or an integer with the index of the factor.
view	string with the view name, or an integer with the index of the view. Default is the first view.
groups	groups to plot. Default is "all".
features	if an integer (default), the total number of features to plot. If a character vector, a set of manually-defined features.
sign	can be 'positive', 'negative' or 'all' (default) to show only positive, negative or all weights, respectively.
color_by	specifies groups or values (either discrete or continuous) used to color the dots (samples). This can be either: <ul style="list-style-type: none"> the string "group": dots are coloured with respect to their predefined groups. a character giving the name of a feature that is present in the input data a character giving the same of a column in the sample metadata slot a vector of the same length as the number of samples specifying the value for each sample. a dataframe with two columns: "sample" and "color"
legend	logical indicating whether to add a legend
alpha	numeric indicating dot transparency (default is 1).
shape_by	specifies groups or values (only discrete) used to shape the dots (samples). This can be either: <ul style="list-style-type: none"> the string "group": dots are shaped with respect to their predefined groups. a character giving the name of a feature that is present in the input data a character giving the same of a column in the sample metadata slot a vector of the same length as the number of samples specifying the value for each sample. a dataframe with two columns: "sample" and "shape"
stroke	numeric indicating the stroke size (the black border around the dots, default is NULL, inferred automatically).
dot_size	numeric indicating dot size (default is 5).
text_size	numeric indicating text size (default is 5).
add_lm	logical indicating whether to add a linear regression line for each plot
lm_per_group	logical indicating whether to add a linear regression line separately for each group
imputed	logical indicating whether to include imputed measurements

Details

One of the first steps for the annotation of factors is to visualise the weights using [plot_weights](#) or [plot_top_weights](#). However, one might also be interested in visualising the direct relationship between features and factors, rather than looking at "abstract" weights. A similar function for doing heatmaps rather than scatterplots is [plot_data_heatmap](#).

Value

A [ggplot](#) object

Examples

```
# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
plot_data_scatter(model)
```

plot_dimred

Plot dimensionality reduction based on MOFA factors

Description

Plot dimensionality reduction based on MOFA factors

Usage

```
plot_dimred(
  object,
  method = c("UMAP", "TSNE"),
  groups = "all",
  show_missing = TRUE,
  color_by = NULL,
  shape_by = NULL,
  color_name = NULL,
  shape_name = NULL,
  label = FALSE,
  dot_size = 1.5,
  stroke = NULL,
  alpha_missing = 1,
  legend = TRUE,
  rasterize = FALSE,
  return_data = FALSE,
  ...
)
```

Arguments

object	a trained MOFA object.
method	string indicating which method has been used for non-linear dimensionality reduction (either 'umap' or 'tsne')
groups	character vector with the groups names, or numeric vector with the indices of the groups of samples to use, or "all" to use samples from all groups.
show_missing	logical indicating whether to include samples for which shape_by or color_by is missing
color_by	specifies groups or values used to color the samples. This can be either: (1) a character giving the name of a feature present in the training data. (2) a character giving the same of a column present in the sample metadata. (3) a vector of the same length as the number of samples specifying discrete groups or continuous numeric values.

shape_by	specifies groups or values used to shape the samples. This can be either: (1) a character giving the name of a feature present in the training data, (2) a character giving the name of a column present in the sample metadata. (3) a vector of the same length as the number of samples specifying discrete groups.
color_name	name for color legend.
shape_name	name for shape legend.
label	logical indicating whether to label the medians of the clusters. Only if color_by is specified
dot_size	numeric indicating dot size.
stroke	numeric indicating the stroke size (the black border around the dots, default is NULL, inferred automatically).
alpha_missing	numeric indicating dot transparency of missing data.
legend	logical indicating whether to add legend.
rasterize	logical indicating whether to rasterize plot
return_data	logical indicating whether to return the long data frame to plot instead of plotting
...	extra arguments passed to run_umap or run_tsne .

Details

This function plots dimensionality reduction projections that are stored in the dim_red slot. Typically this contains UMAP or t-SNE projections computed using [run_tsne](#) or [run_umap](#), respectively.

Value

Returns a ggplot2 object or a long data.frame (if return_data is TRUE)

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Run UMAP
model <- run_umap(model)

# Plot UMAP
plot_dimred(model, method = "UMAP")

# Plot UMAP, colour by Factor 1 values
plot_dimred(model, method = "UMAP", color_by = "Factor1")

# Plot UMAP, colour by the values of a specific feature
plot_dimred(model, method = "UMAP", color_by = "feature_0_view_0")
```

plot_enrichment	<i>Plot output of gene set Enrichment Analysis</i>
-----------------	--

Description

Method to plot the results of the gene set Enrichment Analysis

Usage

```
plot_enrichment(  
  enrichment.results,  
  factor,  
  alpha = 0.1,  
  max.pathways = 25,  
  text_size = 1,  
  dot_size = 5  
)
```

Arguments

enrichment.results	output of run_enrichment function
factor	a string with the factor name or an integer with the factor index
alpha	p.value threshold to filter out gene sets
max.pathways	maximum number of enriched pathways to display
text_size	text size
dot_size	dot size

Details

it requires [run_enrichment](#) to be run beforehand.

Value

a ggplot2 object

plot_enrichment_detailed	<i>Plot detailed output of the Feature Set Enrichment Analysis</i>
--------------------------	--

Description

Method to plot a detailed output of the Feature Set Enrichment Analysis (FSEA). Each row corresponds to a significant pathway, sorted by statistical significance, and each dot corresponds to a gene. For each pathway, we display the top genes of the pathway sorted by the corresponding feature statistic (by default, the absolute value of the weight) The top genes with the highest statistic (max.genes argument) are displayed and labeled in black. The remaining genes are colored in grey.

Usage

```
plot_enrichment_detailed(
  enrichment.results,
  factor,
  alpha = 0.1,
  max.genes = 5,
  max.pathways = 10,
  text_size = 3
)
```

Arguments

enrichment.results	output of run_enrichment function
factor	string with factor name or numeric with factor index
alpha	p.value threshold to filter out feature sets
max.genes	maximum number of genes to display, per pathway
max.pathways	maximum number of enriched pathways to display
text_size	size of the text to label the top genes

Value

a ggplot2 object

plot_enrichment_heatmap

Heatmap of Feature Set Enrichment Analysis results

Description

This method generates a heatmap with the adjusted p.values that result from the the feature set enrichment analysis. Rows are feature sets and columns are factors.

Usage

```
plot_enrichment_heatmap(
  enrichment.results,
  alpha = 0.1,
  cap = 1e-50,
  log_scale = TRUE,
  ...
)
```

Arguments

enrichment.results	output of run_enrichment function
alpha	FDR threshold to filter out insignificant feature sets which are not represented in the heatmap. Default is 0.10.

cap	cap p-values below this threshold
log_scale	logical indicating whether to plot the -log of the p.values.
...	extra arguments to be passed to the pheatmap function

Value

produces a heatmap

plot_factor	<i>Beeswarm plot of factor values</i>
-------------	---------------------------------------

Description

Beeswarm plot of the latent factor values.

Usage

```
plot_factor(
  object,
  factors = 1,
  groups = "all",
  group_by = "group",
  color_by = "group",
  shape_by = NULL,
  add_dots = TRUE,
  dot_size = 2,
  dot_alpha = 1,
  add_violin = FALSE,
  violin_alpha = 0.5,
  color_violin = TRUE,
  add_boxplot = FALSE,
  boxplot_alpha = 0.5,
  color_boxplot = TRUE,
  show_missing = TRUE,
  scale = FALSE,
  dodge = FALSE,
  color_name = "",
  shape_name = "",
  stroke = NULL,
  legend = TRUE,
  rasterize = FALSE
)
```

Arguments

object	a trained MOFA object.
factors	character vector with the factor names, or numeric vector with the indices of the factors to use, or "all" to plot all factors.
groups	character vector with the groups names, or numeric vector with the indices of the groups of samples to use, or "all" to use samples from all groups.

group_by	specifies grouping of samples: <ul style="list-style-type: none"> • (default) the string "group": in this case, the plot will color samples with respect to their predefined groups. • a character giving the name of a feature that is present in the input data • a character giving the name of a column in the sample metadata slot • a vector of the same length as the number of samples specifying the value for each sample.
color_by	specifies color of samples. This can be either: <ul style="list-style-type: none"> • (default) the string "group": in this case, the plot will color the dots with respect to their predefined groups. • a character giving the name of a feature that is present in the input data • a character giving the name of a column in the sample metadata slot • a vector of the same length as the number of samples specifying the value for each sample.
shape_by	specifies shape of samples. This can be either: <ul style="list-style-type: none"> • (default) the string "group": in this case, the plot will shape the dots with respect to their predefined groups. • a character giving the name of a feature that is present in the input data • a character giving the name of a column in the sample metadata slot • a vector of the same length as the number of samples specifying the value for each sample.
add_dots	logical indicating whether to add dots.
dot_size	numeric indicating dot size.
dot_alpha	numeric indicating dot transparency.
add_violin	logical indicating whether to add violin plots
violin_alpha	numeric indicating violin plot transparency.
color_violin	logical indicating whether to color violin plots.
add_boxplot	logical indicating whether to add box plots
boxplot_alpha	numeric indicating boxplot transparency.
color_boxplot	logical indicating whether to color box plots.
show_missing	logical indicating whether to remove samples for which shape_by or color_by is missing.
scale	logical indicating whether to scale factor values.
dodge	logical indicating whether to dodge the dots (default is FALSE).
color_name	name for color legend (usually only used if color_by is not a character itself).
shape_name	name for shape legend (usually only used if shape_by is not a character itself).
stroke	numeric indicating the stroke size (the black border around the dots).
legend	logical indicating whether to add a legend to the plot (default is TRUE).
rasterize	logical indicating whether to rasterize the plot (default is FALSE).

Details

One of the main steps for the annotation of factors is to visualise and color them using known covariates or phenotypic data.

This function generates a Beeswarm plot of the sample values in a given latent factor.

Similar functions are [plot_factors](#) for doing scatter plots.

Value

Returns a ggplot2

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Plot Factors 1 and 2 and colour by "group"
plot_factor(model, factors = c(1,2), color_by="group")

# Plot Factor 3 and colour by the value of a specific feature
plot_factor(model, factors = 3, color_by="feature_981_view_1")

# Add violin plots
plot_factor(model, factors = c(1,2), color_by="group", add_violin = TRUE)

# Scale factor values from -1 to 1
plot_factor(model, factors = c(1,2), scale = TRUE)
```

plot_factors

Scatterplots of two factor values

Description

Scatterplot of the values of two latent factors.

Usage

```
plot_factors(
  object,
  factors = c(1, 2),
  groups = "all",
  show_missing = TRUE,
  scale = FALSE,
  color_by = NULL,
  shape_by = NULL,
  color_name = NULL,
  shape_name = NULL,
  dot_size = 1.5,
  alpha = 1,
  legend = TRUE,
  stroke = NULL,
  return_data = FALSE
)
```

Arguments

object a trained [MOFA](#) object.

factors	a vector of length two with the factors to plot. Factors can be specified either as a characters
groups	character vector with the groups names, or numeric vector with the indices of the groups of samples to use, or "all" to use samples from all groups.
show_missing	logical indicating whether to include samples for which shape_by or color_by is missing
scale	logical indicating whether to scale factor values.
color_by	specifies groups or values used to color the samples. This can be either: (1) a character giving the name of a feature present in the training data. (2) a character giving the name of a column present in the sample metadata. (3) a vector of the name length as the number of samples specifying discrete groups or continuous numeric values.
shape_by	specifies groups or values used to shape the samples. This can be either: (1) a character giving the name of a feature present in the training data, (2) a character giving the name of a column present in the sample metadata. (3) a vector of the same length as the number of samples specifying discrete groups.
color_name	name for color legend.
shape_name	name for shape legend.
dot_size	numeric indicating dot size (default is 1.5).
alpha	numeric indicating dot transparency (default is 1).
legend	logical indicating whether to add legend.
stroke	numeric indicating the stroke size (the black border around the dots, default is NULL, inferred automatically).
return_data	logical indicating whether to return the data frame to plot instead of plotting

Details

One of the first steps for the annotation of factors is to visualise and group/color them using known covariates such as phenotypic or clinical data. This method generates a single scatterplot for the combination of two latent factors. TO-FINISH... [plot_factors](#) for doing Beeswarm plots for factors.

Value

Returns a ggplot2 object

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Scatterplot of factors 1 and 2
plot_factors(model, factors = c(1,2))

# Shape dots by a column in the metadata
plot_factors(model, factors = c(1,2), shape_by="group")

# Scale factor values from -1 to 1
plot_factors(model, factors = c(1,2), scale = TRUE)
```

plot_factor_cor	<i>Plot correlation matrix between latent factors</i>
-----------------	---

Description

Function to plot the correlation matrix between the latent factors.

Usage

```
plot_factor_cor(object, method = "pearson", ...)
```

Arguments

object	a trained MOFA object.
method	a character indicating the type of correlation coefficient to be computed: pearson (default), kendall, or spearman.
...	arguments passed to corrplot

Details

This method plots the correlation matrix between the latent factors.

The model encourages the factors to be uncorrelated, so this function usually yields a diagonal correlation matrix.

However, it is not a hard constraint such as in Principal Component Analysis and correlations between factors can occur, particularly with large number factors.

Generally, correlated factors are redundant and should be avoided, as they make interpretation harder. Therefore, if you have too many correlated factors we suggest you try reducing the number of factors.

Value

Returns a symmetric matrix with the correlation coefficient between every pair of factors.

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Plot correlation between all factors
plot_factor_cor(model)
```

plot_top_weights	<i>Plot top weights</i>
------------------	-------------------------

Description

Plot top weights for a given factor and view.

Usage

```
plot_top_weights(  
  object,  
  view = 1,  
  factors = 1,  
  nfeatures = 10,  
  abs = TRUE,  
  scale = TRUE,  
  sign = "all"  
)
```

Arguments

object	a trained MOFA object.
view	a string with the view name, or an integer with the index of the view.
factors	a character string with factors names, or an integer vector with factors indices.
nfeatures	number of top features to display. Default is 10
abs	logical indicating whether to use the absolute value of the weights (Default is FALSE).
scale	logical indicating whether to scale all weights from -1 to 1 (or from 0 to 1 if abs=TRUE). Default is TRUE.
sign	can be 'positive', 'negative' or 'all' to show only positive, negative or all weights, respectively. Default is 'all'.

Details

An important step to annotate factors is to visualise the corresponding feature weights. This function displays the top features with highest loading whereas the function [plot_top_weights](#) plots all weights for a given latent factor and view. Importantly, the weights of the features within a view have relative values and they should not be interpreted in an absolute scale. Therefore, for interpretability purposes we always recommend to scale the weights with scale=TRUE.

Value

Returns a ggplot2 object

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Plot top weights for Factors 1 and 2 and View 1
plot_top_weights(model, view = 1, factors = c(1,2))

# Do not take absolute value
plot_weights(model, abs = FALSE)
```

plot_variance_explained

Plot variance explained by the model

Description

plots the variance explained by the MOFA factors across different views and groups, as specified by the user. Consider using `cowplot::plot_grid(plotlist = ...)` to combine the multiple plots that this function generates.

Usage

```
plot_variance_explained(
  object,
  x = "view",
  y = "factor",
  split_by = NA,
  plot_total = FALSE,
  factors = "all",
  min_r2 = 0,
  max_r2 = NULL,
  legend = TRUE,
  use_cache = TRUE,
  ...
)
```

Arguments

<code>object</code>	a MOFA object
<code>x</code>	character specifying the dimension for the x-axis ("view", "factor", or "group").
<code>y</code>	character specifying the dimension for the y-axis ("view", "factor", or "group").
<code>split_by</code>	character specifying the dimension to be faceted ("view", "factor", or "group").
<code>plot_total</code>	logical value to indicate if to plot the total variance explained (for the variable in the x-axis)
<code>factors</code>	character vector with a factor name(s), or numeric vector with the index(es) of the factor(s). Default is "all".
<code>min_r2</code>	minimum variance explained for the color scheme (default is 0).

max_r2	maximum variance explained for the color scheme.
legend	logical indicating whether to add a legend to the plot (default is TRUE).
use_cache	logical indicating whether to use cache (default is TRUE)
...	extra arguments to be passed to calculate_variance_explained

Value

A list of [ggplot](#) objects (if plot_total is TRUE) or a single [ggplot](#) object

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Calculate variance explained (R2)
r2 <- calculate_variance_explained(model)

# Plot variance explained values (view as x-axis, and factor as y-axis)
plot_variance_explained(model, x="view", y="factor")

# Plot variance explained values (view as x-axis, and group as y-axis)
plot_variance_explained(model, x="view", y="group")

# Plot variance explained values for factors 1 to 3
plot_variance_explained(model, x="view", y="group", factors=1:3)

# Scale R2 values
plot_variance_explained(model, max_r2=0.25)
```

plot_variance_explained_per_feature

Plot variance explained by the model for a set of features Returns a tile plot with a group on the X axis and a feature along the Y axis

Description

Plot variance explained by the model for a set of features

Returns a tile plot with a group on the X axis and a feature along the Y axis

Usage

```
plot_variance_explained_per_feature(
  object,
  view,
  features = 10,
  split_by_factor = FALSE,
  group_features_by = NULL,
  groups = "all",
  factors = "all",
  min_r2 = 0,
```

```

    max_r2 = NULL,
    legend = TRUE,
    return_data = FALSE,
    ...
)

```

Arguments

object	a MOFA object.
view	a view name or index.
features	a vector with indices or names for features from the respective view, or number of top features to be fetched by their loadings across specified factors. "all" to plot all features.
split_by_factor	logical indicating whether to split R2 per factor or plot R2 jointly
group_features_by	column name of features metadata to group features by
groups	a vector with indices or names for sample groups (default is all)
factors	a vector with indices or names for factors (default is all)
min_r2	minimum variance explained for the color scheme (default is 0).
max_r2	maximum variance explained for the color scheme.
legend	logical indicating whether to add a legend to the plot (default is TRUE).
return_data	logical indicating whether to return the data frame to plot instead of plotting
...	extra arguments to be passed to calculate_variance_explained

Value

ggplot object

Examples

```

# Using an existing trained model
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
plot_variance_explained_per_feature(model, view = 1)

```

plot_weights

Plot distribution of feature weights (weights)

Description

An important step to annotate factors is to visualise the corresponding feature weights. This function plots all weights for a given latent factor and view, labeling the top ones. In contrast, the function [plot_top_weights](#) displays only the top features with highest loading.

Usage

```
plot_weights(
  object,
  view = 1,
  factors = 1,
  nfeatures = 10,
  color_by = NULL,
  shape_by = NULL,
  abs = FALSE,
  manual = NULL,
  color_manual = NULL,
  scale = TRUE,
  dot_size = 1,
  text_size = 5,
  legend = TRUE,
  return_data = FALSE
)
```

Arguments

object	a MOFA object.
view	a string with the view name, or an integer with the index of the view.
factors	character vector with the factor name(s), or numeric vector with the index of the factor(s).
nfeatures	number of top features to label.
color_by	specifies groups or values (either discrete or continuous) used to color the dots (features). This can be either: <ul style="list-style-type: none"> • (default) the string "group": in this case, the plot will color the dots with respect to their predefined groups. • a character giving the name of a feature that is present in the input data • a character giving the same of a column in the features metadata slot • a vector of the same length as the number of features specifying the value for each feature • a dataframe with two columns: "feature" and "color"
shape_by	specifies groups or values (only discrete) used to shape the dots (features). This can be either: <ul style="list-style-type: none"> • (default) the string "group": in this case, the plot will shape the dots with respect to their predefined groups. • a character giving the name of a feature that is present in the input data • a character giving the same of a column in the features metadata slot • a vector of the same length as the number of features specifying the value for each feature • a dataframe with two columns: "feature" and "shape"
abs	logical indicating whether to take the absolute value of the weights.
manual	A nested list of character vectors with features to be manually labelled (see the example for details).
color_manual	a character vector with colors, one for each element of 'manual'

scale	logical indicating whether to scale all weights from -1 to 1 (or from 0 to 1 if abs=TRUE).
dot_size	numeric indicating the dot size.
text_size	numeric indicating the text size.
legend	logical indicating whether to add legend.
return_data	logical indicating whether to return the data frame to plot instead of plotting

Value

A `ggplot` object or a `data.frame` if `return_data` is TRUE

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Plot distribution of weights for Factor 1 and View 1
plot_weights(model, view = 1, factors = 1)

# Plot distribution of weights for Factors 1 to 3 and View 1
plot_weights(model, view = 1, factors = 1:3)

# Take the absolute value and highlight the top 10 features
plot_weights(model, view = 1, factors = 1, nfeatures = 10, abs = TRUE)

# Change size of dots and text
plot_weights(model, view = 1, factors = 1, text_size = 5, dot_size = 1)
```

`plot_weights_heatmap` *Plot heatmap of the weights*

Description

Function to visualize the weights for a given set of factors in a given view.

This is useful to visualize the overall pattern of the weights but not to individually characterise the factors.

To inspect the weights of individual factors, use the functions `plot_weights` and `plot_top_weights`

Usage

```
plot_weights_heatmap(
  object,
  view = 1,
  features = "all",
  factors = "all",
  threshold = 0,
  ...
)
```


Arguments

object	a trained MOFA object.
view	character vector with the view name(s), or numeric vector with the index of the view(s) to use. Default is the first view.
features	character vector with the feature name(s), or numeric vector with the index of the feature(s) to use. Default is 'all'.
factors	character vector with the factor name(s), or numeric vector with the index of the factor(s) to use. Default is 'all'.
threshold	threshold on absolute weight values, so that weights with a magnitude below this threshold (in all factors) are removed
...	extra arguments passed to pheatmap .

Value

A [pheatmap](#) object

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
plot_weights_heatmap(model)
```

plot_weights_scatter *Scatterplots of weights*

Description

Scatterplot of the weights values for two factors

Usage

```
plot_weights_scatter(
  object,
  factors,
  view = 1,
  color_by = NULL,
  shape_by = NULL,
  dot_size = 1,
  name_color = "",
  name_shape = "",
  show_missing = TRUE,
  abs = FALSE,
  scale = TRUE,
  legend = TRUE
)
```

Arguments

object	a trained MOFA object.
factors	a vector of length two with the factors to plot. Factors can be specified either as a characters using the factor names, or as numeric with the index of the factors
view	character vector with the view name, or numeric vector with the index of the view to use. Default is the first view.
color_by	specifies groups or values used to color the features. This can be either <ul style="list-style-type: none"> • a character giving the name of a column in the feature metadata slot • a vector specifying the value for each feature. • a dataframe with two columns: "feature" and "color"
shape_by	specifies groups or values used to shape the features. This can be either <ul style="list-style-type: none"> • a character giving the name of a column in the feature metadata slot • a vector specifying the value for each feature. • a dataframe with two columns: "feature" and "shape"
dot_size	numeric indicating dot size.
name_color	name for color legend (usually only used if color_by is not a character itself)
name_shape	name for shape legend (usually only used if shape_by is not a character itself)
show_missing	logical indicating whether to include dots for which shape_by or color_by is missing
abs	logical indicating whether to take the absolute value of the weights.
scale	logical indicating whether to scale all weights from -1 to 1 (or from 0 to 1 if abs=TRUE).
legend	logical indicating whether to add a legend to the plot (default is TRUE).

Details

One of the first steps for the annotation of factors is to visualise and group/color them using known covariates such as phenotypic or clinical data. This method generates a single scatterplot for the combination of two latent factors.

Value

Returns a ggplot2 object

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
plot_weights_scatter(model, factors = 1:2)
```

predict

Do predictions using a fitted MOFA

Description

This function uses the latent factors and the weights to do data predictions.

Usage

```
predict(  
  object,  
  views = "all",  
  groups = "all",  
  factors = "all",  
  add_intercept = TRUE  
)
```

Arguments

object	a MOFA object.
views	character vector with the view name(s), or numeric vector with the view index(es). Default is "all".
groups	character vector with the group name(s), or numeric vector with the group index(es). Default is "all".
factors	character vector with the factor name(s) or numeric vector with the factor index(es). Default is "all".
add_intercept	add feature intercepts to the prediction (default is TRUE).

Details

MOFA generates a denoised and condensed low-dimensional representation of the data that captures the main sources of heterogeneity of the data. This representation can be used to reconstruct a denoised representation of the data, simply using the equation $Y = WX$. For more mathematical details read the supplementary methods of the manuscript.

Value

Returns a list with the data reconstructed by the model predictions.

Examples

```
# Using an existing trained model on simulated data  
file <- system.file("extdata", "model.hdf5", package = "MOFA2")  
model <- load_model(file)  
  
# Predict observations for all data modalities  
predictions <- predict(model)
```

prepare_mofa	<i>Prepare a MOFA for training</i>
--------------	------------------------------------

Description

Function to prepare a [MOFA](#) object for training. It requires defining data, model and training options.

Usage

```
prepare_mofa(
  object,
  data_options = NULL,
  model_options = NULL,
  training_options = NULL,
  stochastic_options = NULL
)
```

Arguments

object	an untrained MOFA
data_options	list of data_options (see get_default_data_options details). If NULL, default options are used.
model_options	list of model options (see get_default_model_options for details). If NULL, default options are used.
training_options	list of training options (see get_default_training_options for details). If NULL, default options are used.
stochastic_options	list of options for stochastic variational inference (see get_default_stochastic_options for details). If NULL, default options are used.

Details

This function is called after creating a [MOFA](#) object (using [create_mofa](#)) and before starting the training (using [run_mofa](#)). Here, we can specify different options for the data (`data_options`), the model (`model_options`) and the training (`training_options`, `stochastic_options`). Take a look at the individual default options for an overview using the `get_default_XXX_options` functions above.

Value

Returns an untrained [MOFA](#) with specified options filled in the corresponding slots

Examples

```
# Using an existing simulated data with two groups and two views
file <- system.file("extdata", "test_data.RData", package = "MOFA2")

# Load data dt (in data.frame format)
load(file)

# Create the MOFA object
```

```

MOFAModel <- create_mofa(dt)

# Prepare MOFA object using default options
MOFAModel <- prepare_mofa(MOFAModel)

# Prepare MOFA object changing some of the default model options values
model_opts <- get_default_model_options(MOFAModel)
model_opts$num_factors <- 10
MOFAModel <- prepare_mofa(MOFAModel, model_options = model_opts)

```

run_enrichment

Run feature set Enrichment Analysis

Description

Method to perform feature set enrichment analysis. Here we use a slightly modified version of the [pcgse](#) function.

Usage

```

run_enrichment(
  object,
  view,
  feature.sets,
  factors = "all",
  set.statistic = c("mean.diff", "rank.sum"),
  statistical.test = c("parametric", "cor.adj.parametric", "permutation"),
  sign = c("all", "positive", "negative"),
  min.size = 10,
  nperm = 1000,
  p.adj.method = "BH",
  alpha = 0.1,
  verbose = TRUE
)

```

Arguments

<code>object</code>	a MOFA object.
<code>view</code>	a character with the view name, or a numeric vector with the index of the view to use.
<code>feature.sets</code>	data structure that holds feature set membership information. Must be a binary membership matrix (rows are feature sets and columns are features). See details below for some pre-built gene set matrices.
<code>factors</code>	character vector with the factor names, or numeric vector with the index of the factors for which to perform the enrichment.
<code>set.statistic</code>	the set statistic computed from the feature statistics. Must be one of the following: "mean.diff" (default) or "rank.sum".
<code>statistical.test</code>	the statistical test used to compute the significance of the feature set statistics under a competitive null hypothesis. Must be one of the following: "parametric" (default), "cor.adj.parametric", "permutation".

sign	use only "positive" or "negative" weights. Default is "all".
min.size	Minimum size of a feature set (default is 10).
nperm	number of permutations. Only relevant if statistical.test is set to "permutation". Default is 1000
p.adj.method	Method to adjust p-values factor-wise for multiple testing. Can be any method in p.adjust.methods(). Default uses Benjamini-Hochberg procedure.
alpha	FDR threshold to generate lists of significant pathways. Default is 0.1
verbose	boolean indicating whether to print messages on progress

Details

The aim of this function is to relate each factor to pre-defined biological pathways by performing a gene set enrichment analysis on the feature weights.

This function is particularly useful when a factor is difficult to characterise based only on the genes with the highest weight.

We provide a few pre-built gene set matrices in the MOFAdat package. See <https://github.com/bioFAM/MOFAdat> for details.

The function we implemented is based on the [pcgse](#) function with some modifications. Please read this paper <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4543476> for details on the math.

Value

a list with five elements:

pval:	matrices with nominal p-values.
pval.adj:	matrices with FDR-adjusted p-values.
feature.statistics:	matrices with the local (feature-wise) statistics.
set.statistics:	matrices with the global (gene set-wise) statistics.
sigPathways	list with significant pathways per factor.

run_mofa	<i>Train a MOFA model</i>
----------	---------------------------

Description

Function to train an untrained [MOFA](#) object.

Usage

```
run_mofa(object, outfile = NULL, save_data = TRUE, save_expectations = NULL)
```

Arguments

object	an untrained MOFA object
outfile	output file for the model (.hdf5 format). If NULL, a temporary file is created.
save_data	logical indicating whether to save the training data in the hdf5 file. This is useful for some downstream analysis (mainly functions with the prefix plot_data), but it can take a lot of disk space.
save_expectations	vector with capitalized node names. If NA, only W and Z are saved by default.

Details

This function is called once a MOFA object has been created (using `create_mofa`) and possible options for training have been specified with `prepare_mofa`. In this step the R package is calling the mofapy2 Python package, where the model the training is performed.

The interface with Python is done with the `reticulate` package. If you have several versions of Python installed and R is not detecting the correct one, you can change it using `reticulate::use_python`.

Value

a trained MOFA object

Examples

```
# Using an existing simulated data with two groups and two views
file <- system.file("extdata", "test_data.RData", package = "MOFA2")

# Load data dt (in data.frame format)
load(file)

# Create the MOFA object
MOFAmodel <- create_mofa(dt)

# Prepare the MOFA object with default options
MOFAmodel <- prepare_mofa(MOFAmodel)

# Run the MOFA model
## Not run: MOFAmodel <- run_mofa(MOFAmodel, outfile = "~/model.hdf5")
```

run_tsne

Run t-SNE on the MOFA factors

Description

Run t-SNE on the MOFA factors

Usage

```
run_tsne(object, factors = "all", groups = "all", ...)
```

Arguments

<code>object</code>	a trained MOFA object.
<code>factors</code>	character vector with the factor names, or numeric vector with the indices of the factors to use, or "all" to plot all factors.
<code>groups</code>	character vector with the groups names, or numeric vector with the indices of the groups of samples to use, or "all" to use samples from all groups.
<code>...</code>	arguments passed to <code>Rtsne</code>

Details

use `set.seed` before the function call to get reproducible results.

Value

Returns a [MOFA](#) object with the dim_red slot filled with the t-SNE output

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Run t-SNE
## Not run: model <- run_tsne(model)

# Change hyperparameters passed to Rtsne
## Not run: model <- run_tsne(model, perplexity = 15)
```

run_umap

Run UMAP on the MOFA factors

Description

Run UMAP on the MOFA factors

Usage

```
run_umap(object, factors = "all", groups = "all", ...)
```

Arguments

object	a trained MOFA object.
factors	character vector with the factor names, or numeric vector with the indices of the factors to use, or "all" to plot all factors.
groups	character vector with the groups names, or numeric vector with the indices of the groups of samples to use, or "all" to use samples from all groups.
...	arguments passed to umap

Details

use set.seed before the function call to get reproducible results.

Value

Returns a [MOFA](#) object with the dim_red slot filled with the UMAP output

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Run UMAP
## Not run: model <- run_umap(model)

# Change hyperparameters passed to umap
## Not run: model <- run_umap(model, min_dist = 0.01, n_neighbors = 10)
```

samples_metadata	<i>samples_metadata: retrieve sample metadata</i>
------------------	---

Description

samples_metadata: retrieve sample metadata

Usage

```
samples_metadata(object)

samples_metadata(object) <- value

## S4 method for signature 'MOFA'
samples_metadata(object)

## S4 replacement method for signature 'MOFA,data.frame'
samples_metadata(object) <- value
```

Arguments

object	a MOFA object.
value	data frame with sample metadata, it must at least contain the columns sample and group. The order of the rows must match the order of samples_names(object)

Value

a data frame with sample metadata

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
samples_metadata(model)
```

samples_names	<i>samples_names: set and retrieve sample names</i>
---------------	---

Description

samples_names: set and retrieve sample names

Usage

```
samples_names(object)

samples_names(object) <- value

## S4 method for signature 'MOFA'
samples_names(object)

## S4 replacement method for signature 'MOFA,list'
samples_names(object) <- value
```

Arguments

object	a MOFA object.
value	list of character vectors with the sample names for every group

Value

list of character vectors with the sample names for each group

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
samples_names(model)
```

select_model	<i>Select a model from a list of trained MOFA objects based on the best ELBO value</i>
--------------	--

Description

Different objects of [MOFA](#) are compared in terms of the final value of the ELBO statistics and the model with the highest ELBO value is selected.

Usage

```
select_model(models, plot = FALSE)
```

Arguments

models	a list containing MOFA objects.
plot	boolean indicating whether to show a plot of the ELBO for each model instance

Value

A [MOFA](#) object

subset_factors	<i>Subset factors</i>
----------------	-----------------------

Description

Method to subset (or sort) factors

Usage

```
subset_factors(object, factors)
```

Arguments

object	a MOFA object.
factors	character vector with the factor names, or numeric vector with the index of the factors.

Value

A [MOFA](#) object

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Subset factors 1 to 3
model <- subset_factors(model, factors = 1:3)
```

subset_features	<i>Subset features</i>
-----------------	------------------------

Description

Method to subset (or sort) features

Usage

```
subset_features(object, view, features)
```

Arguments

object	a MOFA object.
view	character vector with the view name or integer with the view index
features	character vector with the sample names, numeric vector with the feature indices or logical vector with the samples to be kept as TRUE.

Value

A [MOFA](#) object

subset_groups	<i>Subset groups</i>
---------------	----------------------

Description

Method to subset (or sort) groups

Usage

```
subset_groups(object, groups)
```

Arguments

object	a MOFA object.
groups	character vector with the groups names, numeric vector with the groups indices or logical vector with the groups to be kept as TRUE.

Value

A [MOFA](#) object

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Subset the first group
model <- subset_groups(model, groups = 1)
```

subset_samples	<i>Subset samples</i>
----------------	-----------------------

Description

Method to subset (or sort) samples

Usage

```
subset_samples(object, samples)
```

Arguments

object	a MOFA object.
samples	character vector with the sample names or numeric vector with the sample indices.

Value

A [MOFA](#) object

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# (TO-DO) Remove a specific sample from the model (an outlier)
```

subset_views	<i>Subset views</i>
--------------	---------------------

Description

Method to subset (or sort) views

Usage

```
subset_views(object, views)
```

Arguments

object	a MOFA object.
views	character vector with the views names, numeric vector with the views indices, or logical vector with the views to be kept as TRUE.

Value

A [MOFA](#) object

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)

# Subset the first view
model <- subset_views(model, views = 1)
```

summarise_factors	<i>Summarise factor values using external groups</i>
-------------------	--

Description

Function to summarise factor values using a discrete grouping of samples.

Usage

```
summarise_factors(
  object,
  df,
  factors = "all",
  groups = "all",
  abs = FALSE,
  return_data = FALSE
)
```

Arguments

object	a trained MOFA object.
df	a data.frame with the columns "sample" and "level", where level is a factor with discrete group assignments for each sample.
factors	character vector with the factor name(s), or numeric vector with the index of the factor(s) to use. Default is 'all'.
groups	character vector with the groups names, or numeric vector with the indices of the groups of samples to use, or "all" to use samples from all groups.
abs	logical indicating whether to take the absolute value of the factors (default is FALSE).
return_data	logical indicating whether to return the fa instead of plotting

Value

A [ggplot](#) object or a data.frame if return_data is TRUE

views_names	<i>views_names: set and retrieve view names</i>
-------------	---

Description

views_names: set and retrieve view names

Usage

```
views_names(object)

views_names(object) <- value

## S4 method for signature 'MOFA'
views_names(object)

## S4 replacement method for signature 'MOFA,character'
views_names(object) <- value
```

Arguments

object	a MOFA object.
value	character vector with the names for each view

Value

character vector with the names for each view

Examples

```
# Using an existing trained model on simulated data
file <- system.file("extdata", "model.hdf5", package = "MOFA2")
model <- load_model(file)
views_names(model)
views_names(model) <- c("viewA", "viewB")
```

%>%	<i>Re-exporting the pipe operator See magrittr::Rpercent>Rpercent for details.</i>
-----	---

Description

Re-exporting the pipe operator See [magrittr::%>%](#) for details.

Usage

```
lhs %>% rhs
```

Arguments

lhs	see magrittr::%>%
rhs	see magrittr::%>%

Value

depending on lhs and rhs

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