Package ‘dfr’

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Title Dual Feature Reduction for SGL

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Description Implementation of the Dual Feature Reduction (DFR) approach for the Sparse Group Lasso (SGL) and the Adaptive Sparse Group Lasso (aSGL) (Feser and Evangelou (2024) <doi:10.48550/arXiv.2405.17094>). The DFR approach is a feature reduction approach that applies strong screening to reduce the feature space before optimisation, leading to speed-up improvements for fitting SGL (Simon et al. (2013) <doi:10.1080/10618600.2012.681250>) and aSGL (Mendez-Civieta et al. (2020) <doi:10.1007/s11634-020-00413-8> and Poignard (2020) <doi:10.1007/s10463-018-0692-7>) models. DFR is implemented using the Adaptive Three Operator Splitting (ATOS) (Pedregosa and Gidel (2018) <doi:10.48550/arXiv.1804.02339>) algorithm, with linear and logistic SGL models supported, both of which can be fit using k-fold cross-validation. Dense and sparse input matrices are supported.

Imports sgs, caret, methods, stats, grDevices, graphics, faux, Matrix

Suggests SGL, gglasso, glmnet, testthat

RoxygenNote 7.3.1

License GPL (>= 3)

Encoding UTF-8

URL https://github.com/ff1201/dfr

BugReports https://github.com/ff1201/dfr/issues

NeedsCompilation no

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`dfr_adap_sgl` *Fit a DFR-aSGL model.*

Description

Adaptive Sparse-group lasso (aSGL) with DFR main fitting function. Supports both linear and logistic regression, both with dense and sparse matrix implementations.

Usage

```
dfr_adap_sgl(
  X,
  y,
  groups,
  type = "linear",
  lambda = "path",
  alpha = 0.95,
  gamma_1 = 0.1,
  gamma_2 = 0.1,
  max_iter = 5000,
  backtracking = 0.7,
  max_iter_backtracking = 100,
  tol = 1e-05,
  standardise = "l2",
  intercept = TRUE,
  path_length = 20,
  min_frac = 0.05,
  screen = TRUE,
  verbose = FALSE,
  v_weights = NULL,
  w_weights = NULL
)
```

Arguments

X	Input matrix of dimensions $n \times p$. Can be a sparse matrix (using class `"sparseMatrix"` from the `Matrix` package).
y	Output vector of dimension n. For `type="linear"` should be continuous and for `type="logistic"` should be a binary variable.
groups	A grouping structure for the input data. Should take the form of a vector of group indices.
type	The type of regression to perform. Supported values are: `"linear"` and `"logistic"`.
lambda	The regularisation parameter. Defines the level of sparsity in the model. A higher value leads to sparser models: • `"path"` computes a path of regularisation parameters of length `"path_length"`. The path will begin just above the value at which the first predictor enters the model and will terminate at the value determined by `"min_frac"`. • User-specified single value or sequence. Internal scaling is applied based on the type of standardisation. The returned `"lambda"` value will be the original unscaled value(s).
alpha	The value of α, which defines the convex balance between the lasso and group lasso. Must be between 0 and 1. Recommended value is 0.95.
gamma_1	Hyperparameter which determines the shape of the variable penalties.
gamma_2	Hyperparameter which determines the shape of the group penalties.
max_iter	Maximum number of ATOS iterations to perform.
backtracking	The backtracking parameter, τ, as defined in Pedregosa and Gidel (2018).
max_iter_backtracking	Maximum number of backtracking line search iterations to perform per global iteration.
tol	Convergence tolerance for the stopping criteria.
standardise	Type of standardisation to perform on `X`: • `"l2"` standardises the input data to have ℓ_2 norms of one. When using this `"lambda"` is scaled internally by $1/\sqrt{n}$. • `"l1"` standardises the input data to have ℓ_1 norms of one. When using this `"lambda"` is scaled internally by $1/n$. • `"sd"` standardises the input data to have standard deviation of one. • `"none"` no standardisation applied.
intercept	Logical flag for whether to fit an intercept.
path_length	The number of λ values to fit the model for. If `"lambda"` is user-specified, this is ignored.
min_frac	Smallest value of λ as a fraction of the maximum value. That is, the final λ will be `"min_frac"` of the first λ value.
screen	Logical flag for whether to apply the DFR screening rules (see Feser and Evangelou (2024)).
verbose	Logical flag for whether to print fitting information.

`v_weights` Optional vector for the variable penalty weights. Overrides the adaptive SGL penalties if specified. When entering custom weights, these are multiplied internally by λ and α. To void this behaviour, set $\lambda = 2$ and $\alpha = 0.5$

`w_weights` Optional vector for the group penalty weights. Overrides the adaptive SGL penalties if specified. When entering custom weights, these are multiplied internally by λ and $1 - \alpha$. To void this behaviour, set $\lambda = 2$ and $\alpha = 0.5$

Details

`dfr_adap_sgl()` fits a DFR-aSGL model (Feser and Evangelou (2024)) using Adaptive Three Operator Splitting (ATOS) (Pedregosa and Gidel (2018)). It solves the convex optimisation problem given by (Poignard (2020) and Mendez-Civieta et al. (2020))

$$\frac{1}{2n} f(b; y, \mathbf{X}) + \lambda\alpha \sum_{i=1}^{p} v_i |b_i| + \lambda(1-\alpha) \sum_{g=1}^{m} w_g \sqrt{p_g} \|b^{(g)}\|_2,$$

where $f(\cdot)$ is the loss function, p_g are the group sizes, and (v, w) are adaptive weights. In the case of the linear model, the loss function is given by the mean-squared error loss:

$$f(b; y, \mathbf{X}) = \|y - \mathbf{X}b\|_2^2 .$$

In the logistic model, the loss function is given by

$$f(b; y, \mathbf{X}) = -1/n \log(\mathcal{L}(b; y, \mathbf{X})).$$

where the log-likelihood is given by

$$\mathcal{L}(b; y, \mathbf{X}) = \sum_{i=1}^{n} \left\{ y_i b^\intercal x_i - \log(1 + \exp(b^\intercal x_i)) \right\} .$$

The adaptive weights are chosen as, for a group g and variable i (Mendez-Civieta et al. (2020))

$$v_i = \frac{1}{|q_{1i}|^{\gamma_1}},\ w_g = \frac{1}{\|q_1^{(g)}\|_2^{\gamma_2}},$$

DFR uses the dual norm (the ϵ-norm) and the KKT conditions to discard features at λ_k that would have been inactive at λ_{k+1}. It applies two layers of screening, so that it first screens out any groups that satisfy

$$\|\nabla_g f(\hat{\beta}(\lambda_k))\|_{\epsilon'_g} \leq \gamma_g (2\lambda_{k+1} - \lambda_k)$$

and then screens out any variables that satisfy

$$|\nabla_i f(\hat{\beta}(\lambda_k))| \leq \alpha v_i (2\lambda_{k+1} - \lambda_k)$$

leading to effective input dimensionality reduction. See Feser and Evangelou (2024) for full details.

Value

A list containing:

beta	The fitted values from the regression. Taken to be the more stable fit between x and z, which is usually the former. A filter is applied to remove very small values, where ATOS has not been able to shrink exactly to zero. Check this against x and z.
x	The solution to the original problem (see Pedregosa and Gidel (2018)).
u	The solution to the dual problem (see Pedregosa and Gidel (2018)).
z	The updated values from applying the first proximal operator (see Pedregosa and Gidel (2018)).
type	Indicates which type of regression was performed.
lambda	Value(s) of λ used to fit the model.
success	Logical flag indicating whether ATOS converged, according to tol.
num_it	Number of iterations performed. If convergence is not reached, this will be max_iter.
certificate	Final value of convergence criteria.
intercept	Logical flag indicating whether an intercept was fit.

References

Feser, F., Evangelou, M. (2024). *Dual feature reduction for the sparse-group lasso and its adaptive variant*, https://arxiv.org/abs/2405.17094

Mendez-Civieta, A., Carmen Aguilera-Morillo, M., Lillo, R. (2020). *Adaptive sparse group LASSO in quantile regression*, https://link.springer.com/article/10.1007/s11634-020-00413-8

Pedregosa, F., Gidel, G. (2018). *Adaptive Three Operator Splitting*, https://proceedings.mlr.press/v80/pedregosa18a.html

Poignard, B. (2020). *Asymptotic theory of the adaptive Sparse Group Lasso*, https://link.springer.com/article/10.1007/s10463-018-0692-7

See Also

Other SGL-methods: dfr_adap_sgl.cv(), dfr_sgl(), dfr_sgl.cv(), plot.sgl(), predict.sgl(), print.sgl()

Examples

```
# specify a grouping structure
groups = c(1,1,1,2,2,3,3,3,4,4)
# generate data
data = sgs::gen_toy_data(p=10, n=5, groups = groups, seed_id=3,group_sparsity=1)
# run DFR-aSGL
model = dfr_adap_sgl(X = data$X, y = data$y, groups = groups, type="linear", path_length = 5,
alpha=0.95, standardise = "l2", intercept = TRUE, verbose=FALSE)
```

`dfr_adap_sgl.cv` *Fit a DFR-aSGL model using k-fold cross-validation.*

Description

Function to fit a pathwise solution of the adaptive sparse-group lasso (aSGL) applied with DFR using k-fold cross-validation. Supports both linear and logistic regression, both with dense and sparse matrix implementations.

Usage

```
dfr_adap_sgl.cv(
  X,
  y,
  groups,
  type = "linear",
  lambda = "path",
  path_length = 20,
  nfolds = 10,
  alpha = 0.95,
  gamma_1 = 0.1,
  gamma_2 = 0.1,
  backtracking = 0.7,
  max_iter = 5000,
  max_iter_backtracking = 100,
  tol = 1e-05,
  min_frac = 0.05,
  standardise = "l2",
  intercept = TRUE,
  error_criteria = "mse",
  screen = TRUE,
  verbose = FALSE,
  v_weights = NULL,
  w_weights = NULL
)
```

Arguments

`X`	Input matrix of dimensions $n \times p$. Can be a sparse matrix (using class `"sparseMatrix"` from the `Matrix` package).
`y`	Output vector of dimension n. For `type="linear"` should be continuous and for `type="logistic"` should be a binary variable.
`groups`	A grouping structure for the input data. Should take the form of a vector of group indices.
`type`	The type of regression to perform. Supported values are: `"linear"` and `"logistic"`.

`lambda` The regularisation parameter. Defines the level of sparsity in the model. A higher value leads to sparser models:

- `"path"` computes a path of regularisation parameters of length `"path_length"`. The path will begin just above the value at which the first predictor enters the model and will terminate at the value determined by `"min_frac"`.
- User-specified single value or sequence. Internal scaling is applied based on the type of standardisation. The returned `"lambda"` value will be the original unscaled value(s).

`path_length` The number of λ values to fit the model for. If `"lambda"` is user-specified, this is ignored.

`nfolds` The number of folds to use in cross-validation.

`alpha` The value of α, which defines the convex balance between the lasso and group lasso. Must be between 0 and 1. Recommended value is 0.95.

`gamma_1` Hyperparameter which determines the shape of the variable penalties.

`gamma_2` Hyperparameter which determines the shape of the group penalties.

`backtracking` The backtracking parameter, τ, as defined in Pedregosa and Gidel (2018).

`max_iter` Maximum number of ATOS iterations to perform.

`max_iter_backtracking`
Maximum number of backtracking line search iterations to perform per global iteration.

`tol` Convergence tolerance for the stopping criteria.

`min_frac` Smallest value of λ as a fraction of the maximum value. That is, the final λ will be `"min_frac"` of the first λ value.

`standardise` Type of standardisation to perform on `X`:

- `"l2"` standardises the input data to have ℓ_2 norms of one.
- `"l1"` standardises the input data to have ℓ_1 norms of one.
- `"sd"` standardises the input data to have standard deviation of one.
- `"none"` no standardisation applied.

`intercept` Logical flag for whether to fit an intercept.

`error_criteria` The criteria used to discriminate between models along the path. Supported values are: `"mse"` (mean squared error) and `"mae"` (mean absolute error).

`screen` Logical flag for whether to apply the DFR screening rules (see Feser and Evangelou (2024)).

`verbose` Logical flag for whether to print fitting information.

`v_weights` Optional vector for the variable penalty weights. Overrides the adaptive SGL penalties if specified. When entering custom weights, these are multiplied internally by λ and α. To void this behaviour, set $\lambda = 2$ and $\alpha = 0.5$

`w_weights` Optional vector for the group penalty weights. Overrides the adaptive SGL penalties if specified. When entering custom weights, these are multiplied internally by λ and $1-\alpha$. To void this behaviour, set $\lambda = 2$ and $\alpha = 0.5$

Details

Fits DFR-aSGL models under a pathwise solution using Adaptive Three Operator Splitting (ATOS) (Pedregosa and Gidel (2018)), picking the 1se model as optimum. Warm starts are implemented.

Value

A list containing:

`all_models`	A list of all the models fitted along the path.
`fit`	The 1se chosen model, which is a `"sgl"` object type.
`best_lambda`	The value of λ which generated the chosen model.
`best_lambda_id`	The path index for the chosen model.
`errors`	A table containing fitting information about the models on the path.
`type`	Indicates which type of regression was performed.

References

Feser, F., Evangelou, M. (2024). *Dual feature reduction for the sparse-group lasso and its adaptive variant*, https://arxiv.org/abs/2405.17094

Pedregosa, F., Gidel, G. (2018). *Adaptive Three Operator Splitting*, https://proceedings.mlr.press/v80/pedregosa18a.html

See Also

`dfr_adap_sgl()`

Other SGL-methods: `dfr_adap_sgl()`, `dfr_sgl()`, `dfr_sgl.cv()`, `plot.sgl()`, `predict.sgl()`, `print.sgl()`

Examples

```
# specify a grouping structure
groups = c(1,1,1,2,2,3,3,3,4,4)
# generate data
data = sgs::gen_toy_data(p=10, n=5, groups = groups, seed_id=3,group_sparsity=1)
# run DFR-SGL with cross-validation
cv_model = dfr_adap_sgl.cv(X = data$X, y = data$y, groups=groups, type = "linear",
path_length = 5, nfolds=5, alpha = 0.95, min_frac = 0.05,
standardise="l2",intercept=TRUE,verbose=TRUE)
```

`dfr_sgl` *Fit a DFR-SGL model.*

Description

Sparse-group lasso (SGL) with DFR main fitting function. Supports both linear and logistic regression, both with dense and sparse matrix implementations.

Usage

```
dfr_sgl(
  X,
  y,
  groups,
  type = "linear",
  lambda = "path",
  alpha = 0.95,
  max_iter = 5000,
  backtracking = 0.7,
  max_iter_backtracking = 100,
  tol = 1e-05,
  standardise = "l2",
  intercept = TRUE,
  path_length = 20,
  min_frac = 0.05,
  screen = TRUE,
  verbose = FALSE
)
```

Arguments

`X`	Input matrix of dimensions $n \times p$. Can be a sparse matrix (using class `"sparseMatrix"` from the `Matrix` package).
`y`	Output vector of dimension n. For `type="linear"` should be continuous and for `type="logistic"` should be a binary variable.
`groups`	A grouping structure for the input data. Should take the form of a vector of group indices.
`type`	The type of regression to perform. Supported values are: `"linear"` and `"logistic"`.
`lambda`	The regularisation parameter. Defines the level of sparsity in the model. A higher value leads to sparser models: • `"path"` computes a path of regularisation parameters of length `"path_length"`. The path will begin just above the value at which the first predictor enters the model and will terminate at the value determined by `"min_frac"`. • User-specified single value or sequence. Internal scaling is applied based on the type of standardisation. The returned `"lambda"` value will be the original unscaled value(s).

`alpha` The value of α, which defines the convex balance between the lasso and group lasso. Must be between 0 and 1. Recommended value is 0.95.

`max_iter` Maximum number of ATOS iterations to perform.

`backtracking` The backtracking parameter, τ, as defined in Pedregosa and Gidel (2018).

`max_iter_backtracking` Maximum number of backtracking line search iterations to perform per global iteration.

`tol` Convergence tolerance for the stopping criteria.

`standardise` Type of standardisation to perform on `X`:

- `"l2"` standardises the input data to have ℓ_2 norms of one. When using this `"lambda"` is scaled internally by $1/\sqrt{n}$.
- `"l1"` standardises the input data to have ℓ_1 norms of one. When using this `"lambda"` is scaled internally by $1/n$.
- `"sd"` standardises the input data to have standard deviation of one.
- `"none"` no standardisation applied.

`intercept` Logical flag for whether to fit an intercept.

`path_length` The number of λ values to fit the model for. If `"lambda"` is user-specified, this is ignored.

`min_frac` Smallest value of λ as a fraction of the maximum value. That is, the final λ will be `"min_frac"` of the first λ value.

`screen` Logical flag for whether to apply the DFR screening rules (see Feser and Evangelou (2024)).

`verbose` Logical flag for whether to print fitting information.

Details

`dfr_sgl()` fits a DFR-SGL model (Feser and Evangelou (2024)) using Adaptive Three Operator Splitting (ATOS) (Pedregosa and Gidel (2018)). It solves the convex optimisation problem given by (Simon et al. (2013))

$$\frac{1}{2n} f(b; y, \mathbf{X}) + \lambda\alpha \sum_{i=1}^{p} |b_i| + \lambda(1-\alpha) \sum_{g=1}^{m} \sqrt{p_g} \|b^{(g)}\|_2,$$

where $f(\cdot)$ is the loss function and p_g are the group sizes. In the case of the linear model, the loss function is given by the mean-squared error loss:

$$f(b; y, \mathbf{X}) = \|y - \mathbf{X}b\|_2^2.$$

In the logistic model, the loss function is given by

$$f(b; y, \mathbf{X}) = -1/n \log(\mathcal{L}(b; y, \mathbf{X})).$$

where the log-likelihood is given by

$$\mathcal{L}(b; y, \mathbf{X}) = \sum_{i=1}^{n} \left\{ y_i b^\intercal x_i - \log(1 + \exp(b^\intercal x_i)) \right\}.$$

SGL can be seen to be a convex combination of the lasso and group lasso, balanced through `alpha`, such that it reduces to the lasso for `alpha = 0` and to the group lasso for `alpha = 1`. By applying both the lasso and group lasso norms, SGL shrinks inactive groups to zero, as well as inactive variables in active groups. DFR uses the dual norm (the ϵ-norm) and the KKT conditions to discard features at λ_k that would have been inactive at λ_{k+1}. It applies two layers of screening, so that it first screens out any groups that satisfy

$$\|\nabla_g f(\hat{\beta}(\lambda_k))\|_{\epsilon_g} \leq \tau_g(2\lambda_{k+1} - \lambda_k)$$

and then screens out any variables that satisfy

$$|\nabla_i f(\hat{\beta}(\lambda_k))| \leq \alpha(2\lambda_{k+1} - \lambda_k)$$

leading to effective input dimensionality reduction. See Feser and Evangelou (2024) for full details.

Value

A list containing:

`beta`	The fitted values from the regression. Taken to be the more stable fit between `x` and `z`, which is usually the former. A filter is applied to remove very small values, where ATOS has not been able to shrink exactly to zero. Check this against `x` and `z`.
`x`	The solution to the original problem (see Pedregosa and Gidel (2018)).
`u`	The solution to the dual problem (see Pedregosa and Gidel (2018)).
`z`	The updated values from applying the first proximal operator (see Pedregosa and Gidel (2018)).
`type`	Indicates which type of regression was performed.
`lambda`	Value(s) of λ used to fit the model.
`success`	Logical flag indicating whether ATOS converged, according to `tol`.
`num_it`	Number of iterations performed. If convergence is not reached, this will be `max_iter`.
`certificate`	Final value of convergence criteria.
`intercept`	Logical flag indicating whether an intercept was fit.

References

Feser, F., Evangelou, M. (2024). *Dual feature reduction for the sparse-group lasso and its adaptive variant*, https://arxiv.org/abs/2405.17094

Pedregosa, F., Gidel, G. (2018). *Adaptive Three Operator Splitting*, https://proceedings.mlr.press/v80/pedregosa18a.html

Simon, N., Friedman, J., Hastie, T., Tibshirani, R. (2013). *A Sparse-Group Lasso*, https://www.tandfonline.com/doi/abs/10.1080/10618600.2012.681250

See Also

Other SGL-methods: `dfr_adap_sgl()`, `dfr_adap_sgl.cv()`, `dfr_sgl.cv()`, `plot.sgl()`, `predict.sgl()`, `print.sgl()`

Examples

```
# specify a grouping structure
groups = c(1,1,1,2,2,3,3,3,4,4)
# generate data
data = sgs::gen_toy_data(p=10, n=5, groups = groups, seed_id=3,group_sparsity=1)
# run DFR-SGL
model = dfr_sgl(X = data$X, y = data$y, groups = groups, type="linear", path_length = 5,
alpha=0.95, standardise = "l2", intercept = TRUE, verbose=FALSE)
```

`dfr_sgl.cv` *Fit a DFR-SGL model using k-fold cross-validation.*

Description

Function to fit a pathwise solution of the sparse-group lasso (SGL) applied with DFR using k-fold cross-validation. Supports both linear and logistic regression, both with dense and sparse matrix implementations.

Usage

```
dfr_sgl.cv(
  X,
  y,
  groups,
  type = "linear",
  lambda = "path",
  path_length = 20,
  nfolds = 10,
  alpha = 0.95,
  backtracking = 0.7,
  max_iter = 5000,
  max_iter_backtracking = 100,
  tol = 1e-05,
  min_frac = 0.05,
  standardise = "l2",
  intercept = TRUE,
  error_criteria = "mse",
  screen = TRUE,
  verbose = FALSE
)
```

Arguments

`X`	Input matrix of dimensions $n \times p$. Can be a sparse matrix (using class `"sparseMatrix"` from the `Matrix` package).
`y`	Output vector of dimension n. For `type="linear"` should be continuous and for `type="logistic"` should be a binary variable.

`groups`	A grouping structure for the input data. Should take the form of a vector of group indices.
`type`	The type of regression to perform. Supported values are: `"linear"` and `"logistic"`.
`lambda`	The regularisation parameter. Defines the level of sparsity in the model. A higher value leads to sparser models: • `"path"` computes a path of regularisation parameters of length `"path_length"`. The path will begin just above the value at which the first predictor enters the model and will terminate at the value determined by `"min_frac"`. • User-specified single value or sequence. Internal scaling is applied based on the type of standardisation. The returned `"lambda"` value will be the original unscaled value(s).
`path_length`	The number of λ values to fit the model for. If `"lambda"` is user-specified, this is ignored.
`nfolds`	The number of folds to use in cross-validation.
`alpha`	The value of α, which defines the convex balance between the lasso and group lasso. Must be between 0 and 1. Recommended value is 0.95.
`backtracking`	The backtracking parameter, τ, as defined in Pedregosa and Gidel (2018).
`max_iter`	Maximum number of ATOS iterations to perform.
`max_iter_backtracking`	Maximum number of backtracking line search iterations to perform per global iteration.
`tol`	Convergence tolerance for the stopping criteria.
`min_frac`	Smallest value of λ as a fraction of the maximum value. That is, the final λ will be `"min_frac"` of the first λ value.
`standardise`	Type of standardisation to perform on `X`: • `"l2"` standardises the input data to have ℓ_2 norms of one. • `"l1"` standardises the input data to have ℓ_1 norms of one. • `"sd"` standardises the input data to have standard deviation of one. • `"none"` no standardisation applied.
`intercept`	Logical flag for whether to fit an intercept.
`error_criteria`	The criteria used to discriminate between models along the path. Supported values are: `"mse"` (mean squared error) and `"mae"` (mean absolute error).
`screen`	Logical flag for whether to apply the DFR screening rules (see Feser and Evangelou (2024)).
`verbose`	Logical flag for whether to print fitting information.

Details

Fits DFR-SGL models under a pathwise solution using Adaptive Three Operator Splitting (ATOS) (Pedregosa and Gidel (2018)), picking the 1se model as optimum. Warm starts are implemented.

Value

A list containing:

`all_models`	A list of all the models fitted along the path.
`fit`	The 1se chosen model, which is a `"sgl"` object type.
`best_lambda`	The value of λ which generated the chosen model.
`best_lambda_id`	The path index for the chosen model.
`errors`	A table containing fitting information about the models on the path.
`type`	Indicates which type of regression was performed.

References

Feser, F., Evangelou, M. (2024). *Dual feature reduction for the sparse-group lasso and its adaptive variant*, https://arxiv.org/abs/2405.17094

Pedregosa, F., Gidel, G. (2018). *Adaptive Three Operator Splitting*, https://proceedings.mlr.press/v80/pedregosa18a.html

See Also

`dfr_sgl()`

Other SGL-methods: `dfr_adap_sgl()`, `dfr_adap_sgl.cv()`, `dfr_sgl()`, `plot.sgl()`, `predict.sgl()`, `print.sgl()`

Examples

```
# specify a grouping structure
groups = c(1,1,1,2,2,3,3,3,4,4)
# generate data
data = sgs::gen_toy_data(p=10, n=5, groups = groups, seed_id=3,group_sparsity=1)
# run DFR-SGL with cross-validation
cv_model = dfr_sgl.cv(X = data$X, y = data$y, groups=groups, type = "linear",
path_length = 5, nfolds=5, alpha = 0.95, min_frac = 0.05,
standardise="l2",intercept=TRUE,verbose=TRUE)
```

`plot.sgl` *Plot models of the following object types:* `"sgl"`, `"sgl_cv"`.

Description

Plots the pathwise solution of a cross-validation fit, from a call to one of the following: `dfr_sgl()`, `dfr_sgl.cv()`, `dfr_adap_sgl()`, `dfr_adap_sgl.cv()`.

Usage

```
## S3 method for class 'sgl'
plot(x, how_many = 10, ...)
```

Arguments

x	Object of one of the following classes: "sgl", "sgl_cv"..
how_many	Defines how many predictors to plot. Plots the predictors in decreasing order of largest absolute value.
...	further arguments passed to base function.

Value

A list containing:

response	The predicted response. In the logistic case, this represents the predicted class probabilities.
class	The predicted class assignments. Only returned if type = "logistic" in the model object.

See Also

dfr_sgl(), dfr_sgl.cv(), dfr_adap_sgl(), dfr_adap_sgl.cv()

Other SGL-methods: dfr_adap_sgl(), dfr_adap_sgl.cv(), dfr_sgl(), dfr_sgl.cv(), predict.sgl(), print.sgl()

Examples

```
# specify a grouping structure
groups = c(1,1,2,2,3)
# generate data
data = sgs::gen_toy_data(p=5, n=4, groups = groups, seed_id=3,signal_mean=20,group_sparsity=1)
# run DFR-SGL
model = dfr_sgl(X = data$X, y = data$y, groups=groups, type = "linear",
path_length = 20, alpha = 0.95,
min_frac = 0.05, standardise="l2",intercept=TRUE,verbose=FALSE)
plot(model, how_many = 10)
```

---

predict.sgl — *Predict using one of the following object types:* "sgl", "sgl_cv".

Description

Performs prediction from one of the following fits: dfr_sgl(), dfr_sgl.cv(), dfr_adap_sgl(), dfr_adap_sgl.cv(). The predictions are calculated for each "lambda" value in the path.

Usage

```
## S3 method for class 'sgl'
predict(object, x, ...)
```

Arguments

`object`	Object of one of the following classes: `"sgl"`, `"sgl_cv"`.
`x`	Input data to use for prediction.
`...`	further arguments passed to stats function.

Value

A list containing:

`response`	The predicted response. In the logistic case, this represents the predicted class probabilities.
`class`	The predicted class assignments. Only returned if type = "logistic" in the `"sgl"` or `"sgl_cv"` object.

See Also

`dfr_sgl()`, `dfr_sgl.cv()`, `dfr_adap_sgl()`, `dfr_adap_sgl.cv()`

Other SGL-methods: `dfr_adap_sgl()`, `dfr_adap_sgl.cv()`, `dfr_sgl()`, `dfr_sgl.cv()`, `plot.sgl()`, `print.sgl()`

Examples

```
# specify a grouping structure
groups = c(1,1,1,2,2,3,3,3,4,4)
# generate data
data = sgs::gen_toy_data(p=10, n=5, groups = groups, seed_id=3,group_sparsity=1)
# run DFR-SGL
model = dfr_sgl(X = data$X, y = data$y, groups = groups, type="linear", lambda = 1, alpha=0.95,
standardise = "l2", intercept = TRUE, verbose=FALSE)
# use predict function
model_predictions = predict(model, x = data$X)
```

`print.sgl` *Prints information for one of the following object types: `"sgl"`, `"sgl_cv"`.*

Description

Prints out useful metric from a model fit.

Usage

```
## S3 method for class 'sgl'
print(x, ...)
```

Arguments

x	Object of one of the following classes: "sgl", "sgl_cv".
...	further arguments passed to base function.

Value

A summary of the model fit(s).

See Also

dfr_sgl(), dfr_sgl.cv(), dfr_adap_sgl(), dfr_adap_sgl.cv()

Other SGL-methods: dfr_adap_sgl(), dfr_adap_sgl.cv(), dfr_sgl(), dfr_sgl.cv(), plot.sgl(), predict.sgl()

Examples

```
# specify a grouping structure
groups = c(rep(1:20, each=3),
          rep(21:40, each=4),
          rep(41:60, each=5),
          rep(61:80, each=6),
          rep(81:100, each=7))
# generate data
data = sgs::gen_toy_data(p=500, n=400, groups = groups, seed_id=3)
# run DFR-SGL
model = dfr_sgl(X = data$X, y = data$y, groups = groups, type="linear", lambda = 1, alpha=0.95,
standardise = "l2", intercept = TRUE, verbose=FALSE)
# print model
print(model)
```

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