

# Package: lessSEM (via r-universe)

September 19, 2024

**Type** Package

**Title** Non-Smooth Regularization for Structural Equation Models

**Version** 1.5.5

**Maintainer** Jannik H. Orzek <jannik.orzek@mailbox.org>

**Description** Provides regularized structural equation modeling (regularized SEM) with non-smooth penalty functions (e.g., lasso) building on 'lavaan'. The package is heavily inspired by the ['regsem'](<<https://github.com/Rjacobucci/regsem>>) and ['lslx'](<<https://github.com/psyphh/lslx>>) packages.

**License** GPL (>= 2)

**Encoding** UTF-8

**RoxygenNote** 7.2.3

**Depends** lavaan, methods

**Imports** Rcpp (>= 1.0.8), RcppArmadillo, RcppParallel, ggplot2, tidyr, stringr, numDeriv, utils, stats, graphics, rlang, mvtnorm

**Suggests** knitr, plotly, rmarkdown, Rsolnp

**LinkingTo** Rcpp, RcppArmadillo, RcppParallel

**VignetteBuilder** knitr

**SystemRequirements** GNU make, C++17

**URL** <https://github.com/jhorzek/lessSEM>

**BugReports** <https://github.com/jhorzek/lessSEM/issues>

**NeedsCompilation** yes

**Author** Jannik H. Orzek [aut, cre, cph]  
(<<https://orcid.org/0000-0002-3123-2248>>)

**Repository** CRAN

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---

.adaptBreakingForWls *.adaptBreakingForWls*

---

**Description**

wls needs smaller breaking points than ml

**Usage**

.adaptBreakingForWls(lavaanModel, currentBreaking, selectedDefault)

**Arguments**

- lavaanModel      single model or vector of models
- currentBreaking      current breaking condition value
- selectedDefault      was default breaking condition selected?

**Value**

updated breaking

---

`.checkPenalties`      *.checkPenalties*

---

**Description**

Internal function to check a `mixedPenalty` object

**Usage**

```
.checkPenalties(mixedPenalty)
```

**Arguments**

`mixedPenalty`      object of class `mixedPenalty`. This object can be created with the `mixedPenalty` function. Penalties can be added with the `addCappedL1`, `addLasso`, `addLsp`, `addMcp`, and `addScad` functions.

---

`.labelLavaanParameters`  
*.labelLavaanParameters*

---

**Description**

Adds labels to unlabeled parameters in the lavaan parameter table. Also removes fixed parameters.

**Usage**

```
.labelLavaanParameters(lavaanModel)
```

**Arguments**

`lavaanModel`      fitted lavaan model

**Value**

parameterTable with labeled parameters

---

*.updateLavaan*      *.updateLavaan*

---

### **Description**

updates a lavaan model. lavaan has an update function that does exactly that, but it seems to not work with testthat. This is an attempt to hack around the issue...

### **Usage**

```
.updateLavaan(lavaanModel, key, value)
```

### **Arguments**

lavaanModel	fitted lavaan model
key	label of the element that should be updated
value	new value for the updated element

### **Value**

lavaan model

---

*.useElasticNet*      *.useElasticNet*

---

### **Description**

Internal function checking if elastic net is used

### **Usage**

```
.useElasticNet(mixedPenalty)
```

### **Arguments**

mixedPenalty	object of class mixedPenalty. This object can be created with the mixedPenalty function. Penalties can be added with the addCappedL1, addLasso, addLsp, addMcp, and addScad functions.
--------------	--

### **Value**

TRUE if elastic net, FALSE otherwise

---

 adaptiveLasso

*adaptiveLasso*


---

### Description

Implements adaptive lasso regularization for structural equation models. The penalty function is given by:

$$p(x_j) = p(x_j) = \frac{1}{w_j} \lambda |x_j|$$

Adaptive lasso regularization will set parameters to zero if  $\lambda$  is large enough.

### Usage

```
adaptiveLasso(
  lavaanModel,
  regularized,
  weights = NULL,
  lambdas = NULL,
  nLambdas = NULL,
  reverse = TRUE,
  curve = 1,
  method = "glmnet",
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlGlmnet()
)
```

### Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
weights	labeled vector with weights for each of the parameters in the model. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object. If set to NULL, the default weights will be used: the inverse of the absolute values of the unregularized parameter estimates
lambdas	numeric vector: values for the tuning parameter lambda
nLambdas	alternative to lambda: If <code>alpha = 1</code> , lessSEM can automatically compute the first lambda value which sets all regularized parameters to zero. It will then generate nLambda values between 0 and the computed lambda.
reverse	if set to TRUE and nLambdas is used, lessSEM will start with the largest lambda and gradually decrease lambda. Otherwise, lessSEM will start with the smallest lambda and gradually increase it.



curve	Allows for unequally spaced lambda steps (e.g., .01,.02,.05,1,5,20). If curve is close to 1 all lambda values will be equally spaced, if curve is large lambda values will be more concentrated close to 0. See ?lessSEM::curveLambda for more information.
method	which optimizer should be used? Currently implemented are ista and glmnet. With ista, the control argument can be used to switch to related procedures (currently gist).
modifyModel	used to modify the lavaanModel. See ?modifyModel.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Adaptive lasso regularization:

- Zou, H. (2006). The adaptive lasso and its oracle properties. *Journal of the American Statistical Association*, 101(476), 1418–1429. <https://doi.org/10.1198/016214506000000735>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1198016>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

**Value**

Model of class regularizedSEM

**Examples**

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ l1*y1 + l2*y2 + l3*y3 + l4*y4 + l5*y5 +
      l6*y6 + l7*y7 + l8*y8 + l9*y9 + l10*y10 +
      l11*y11 + l12*y12 + l13*y13 + l14*y14 + l15*y15
f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- adaptiveLasso(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("l", 6:15),
  # in case of lasso and adaptive lasso, we can specify the number of lambda
  # values to use. lessSEM will automatically find lambda_max and fit
  # models for nLambda values between 0 and lambda_max. For the other
  # penalty functions, lambdas must be specified explicitly
  nLambdas = 50)

# use the plot-function to plot the regularized parameters:
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

# fit Measures:
```

```

fitIndices(lsem)

# The best parameters can also be extracted with:
coef(lsem, criterion = "AIC")
# or
estimates(lsem, criterion = "AIC")

#### Advanced ####
# Switching the optimizer #
# Use the "method" argument to switch the optimizer. The control argument
# must also be changed to the corresponding function:
lsemIsta <- adaptiveLasso(
  lavaanModel = lavaanModel,
  regularized = paste0("1", 6:15),
  nLambdas = 50,
  method = "ista",
  control = controlIsta())

# Note: The results are basically identical:
lsemIsta@parameters - lsem@parameters

```

---

addCappedL1

*addCappedL1*


---

## Description

Implements cappedL1 regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda \min(|x_j|, \theta)$$

where  $\theta > 0$ . The cappedL1 penalty is identical to the lasso for parameters which are below  $\theta$  and identical to a constant for parameters above  $\theta$ . As adding a constant to the fitting function will not change its minimum, larger parameters can stay unregularized while smaller ones are set to zero.

## Usage

```
addCappedL1(mixedPenalty, regularized, lambdas, thetas)
```

## Arguments

mixedPenalty	model of class mixedPenalty created with the mixedPenalty function (see ?mixed-Penalty)
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use getLavaanParameters(model) with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

CappedL1 regularization:

- Zhang, T. (2010). Analysis of Multi-stage Convex Relaxation for Sparse Regularization. *Journal of Machine Learning Research*, 11, 1081–1107.

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class `mixedPenalty`. Use the `fit()` - function to fit the model

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
```

```

                                data = dataset,
                                meanstructure = TRUE,
                                std.lv = TRUE)

# We can add mixed penalties as follows:

regularized <- lavaanModel |>
  # create template for regularized model with mixed penalty:
  mixedPenalty() |>
  # add penalty on loadings l6 - l10:
  addCappedL1(regularized = paste0("l", 11:15),
              lambdas = seq(0,1,.1),
              thetas = 2.3) |>
  # fit the model:
  fit()

```

---

addElasticNet

*addElasticNet*


---

## Description

Adds an elastic net penalty to specified parameters. The penalty function is given by:

$$p(x_j) = \alpha \lambda |x_j| + (1 - \alpha) \lambda x_j^2$$

Note that the elastic net combines ridge and lasso regularization. If  $\alpha = 0$ , the elastic net reduces to ridge regularization. If  $\alpha = 1$  it reduces to lasso regularization. In between, elastic net is a compromise between the shrinkage of the lasso and the ridge penalty.

## Usage

```
addElasticNet(mixedPenalty, regularized, alphas, lambdas, weights = 1)
```

## Arguments

mixedPenalty	model of class mixedPenalty created with the mixedPenalty function (see ?mixed-Penalty)
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use getLavaanParameters(model) with your lavaan model object
alphas	numeric vector: values for the tuning parameter alpha. Set to 1 for lasso and to zero for ridge. Anything in between is an elastic net penalty.
lambdas	numeric vector: values for the tuning parameter lambda
weights	can be used to give different weights to the different parameters

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Elastic net regularization:

- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B*, 67(2), 301–320. <https://doi.org/10.1111/j.1467-9868.2005.00503.x>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class `mixedPenalty`. Use the `fit()` - function to fit the model

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
```

```

# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# We can add mixed penalties as follows:

regularized <- lavaanModel |>
# create template for regularized model with mixed penalty:
mixedPenalty() |>
# add penalty on loadings 16 - 110:
addElasticNet(regularized = paste0("1", 11:15),
              lambdas = seq(0,1,.1),
              alphas = .4) |>
# fit the model:
fit()

```

---

addLasso

*addLasso*


---

## Description

Implements lasso regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda|x_j|$$

Lasso regularization will set parameters to zero if  $\lambda$  is large enough

## Usage

```
addLasso(mixedPenalty, regularized, weights = 1, lambdas)
```

## Arguments

<code>mixedPenalty</code>	model of class <code>mixedPenalty</code> created with the <code>mixedPenalty</code> function (see <code>?mixedPenalty</code> )
<code>regularized</code>	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object

weights	can be used to give different weights to the different parameters
lambdas	numeric vector: values for the tuning parameter lambda

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Lasso regularization:

- Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1), 267–288.

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class mixedPenalty. Use the `fit()` - function to fit the model



**Examples**

```

library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# We can add mixed penalties as follows:

regularized <- lavaanModel |>
  # create template for regularized model with mixed penalty:
  mixedPenalty() |>
  # add penalty on loadings 16 - 110:
  addLasso(regularized = paste0("1", 11:15),
           lambdas = seq(0,1,.1)) |>
  # fit the model:
  fit()

```

---

addLsp

*addLsp*


---

**Description**

Implements lsp regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda \log(1 + |x_j|/\theta)$$

where  $\theta > 0$ .

**Usage**

```
addLsp(mixedPenalty, regularized, lambdas, thetas)
```

## Arguments

<code>mixedPenalty</code>	model of class <code>mixedPenalty</code> created with the <code>mixedPenalty</code> function (see <code>?mixedPenalty</code> )
<code>regularized</code>	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
<code>lambdas</code>	numeric vector: values for the tuning parameter <code>lambda</code>
<code>thetas</code>	parameters whose absolute value is above this threshold will be penalized with a constant ( <code>theta</code> )

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

lsp regularization:

- Candès, E. J., Wakin, M. B., & Boyd, S. P. (2008). Enhancing Sparsity by Reweighted  $\ell_1$  Minimization. *Journal of Fourier Analysis and Applications*, 14(5–6), 877–905. <https://doi.org/10.1007/s00041-008-9045-x>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale  $L_1$ -regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for  $\ell_1$ -regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

**Value**

Model of class `mixedPenalty`. Use the `fit()` - function to fit the model

**Examples**

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# We can add mixed penalties as follows:

regularized <- lavaanModel |>
  # create template for regularized model with mixed penalty:
  mixedPenalty() |>
  # add penalty on loadings 16 - 110:
  addLsp(regularized = paste0("1", 11:15),
         lambdas = seq(0,1,.1),
         thetas = 2.3) |>
  # fit the model:
  fit()
```

---

 addMcp

---

*addMcp*


---

**Description**

Implements mcp regularization for structural equation models. The penalty function is given by:  
Equation Omitted in Pdf Documentation.

**Usage**

```
addMcp(mixedPenalty, regularized, lambdas, thetas)
```

## Arguments

<code>mixedPenalty</code>	model of class <code>mixedPenalty</code> created with the <code>mixedPenalty</code> function (see <code>?mixedPenalty</code> )
<code>regularized</code>	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
<code>lambdas</code>	numeric vector: values for the tuning parameter <code>lambda</code>
<code>thetas</code>	parameters whose absolute value is above this threshold will be penalized with a constant ( <code>theta</code> )

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

mcp regularization:

- Zhang, C.-H. (2010). Nearly unbiased variable selection under minimax concave penalty. *The Annals of Statistics*, 38(2), 894–942. <https://doi.org/10.1214/09-AOS729>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class `mixedPenalty`. Use the `fit()` - function to fit the model

**Examples**

```

library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# We can add mixed penalties as follows:

regularized <- lavaanModel |>
  # create template for regularized model with mixed penalty:
  mixedPenalty() |>
  # add penalty on loadings l6 - l10:
  addMcp(regularized = paste0("l", 11:15),
         lambdas = seq(0,1,.1),
         thetas = 2.3) |>
  # fit the model:
  fit()

```

---

addScad

*addScad*


---

**Description**

Implements scad regularization for structural equation models. The penalty function is given by:  
Equation Omitted in Pdf Documentation.

**Usage**

```
addScad(mixedPenalty, regularized, lambdas, thetas)
```

**Arguments**

`mixedPenalty` model of class `mixedPenalty` created with the `mixedPenalty` function (see `?mixedPenalty`)

regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

scad regularization:

- Fan, J., & Li, R. (2001). Variable selection via nonconcave penalized likelihood and its oracle properties. *Journal of the American Statistical Association*, 96(456), 1348–1360. <https://doi.org/10.1198/01621450175>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class `mixedPenalty`. Use the `fit()` - function to fit the model

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()
```

```

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# We can add mixed penalties as follows:

regularized <- lavaanModel |>
  # create template for regularized model with mixed penalty:
  mixedPenalty() |>
  # add penalty on loadings l6 - l10:
  addScad(regularized = paste0("l", 11:15),
          lambdas = seq(0,1,.1),
          thetas = 3.1) |>
  # fit the model:
  fit()

```

---

AIC, gpRegularized-method  
*AIC*

---

### Description

returns the AIC

### Usage

```
## S4 method for signature 'gpRegularized'
AIC(object, ..., k = 2)
```

### Arguments

object	object of class gpRegularized
...	not used
k	multiplier for number of parameters

### Value

data frame with fit values, appended with AIC

---

AIC,Rcpp\_mgSEM-method *AIC*

---

**Description**

AIC

**Usage**

```
## S4 method for signature 'Rcpp_mgSEM'
AIC(object, ..., k = 2)
```

**Arguments**

object	object of class Rcpp_mgSEM
...	not used
k	multiplier for number of parameters

**Value**

AIC values

---

AIC,Rcpp\_SEMCpp-method  
*AIC*

---

**Description**

AIC

**Usage**

```
## S4 method for signature 'Rcpp_SEMCpp'
AIC(object, ..., k = 2)
```

**Arguments**

object	object of class Rcpp_SEMCpp
...	not used
k	multiplier for number of parameters

**Value**

AIC values



---

AIC,regularizedSEM-method  
*AIC*

---

**Description**

returns the AIC

**Usage**

```
## S4 method for signature 'regularizedSEM'  
AIC(object, ..., k = 2)
```

**Arguments**

object	object of class regularizedSEM
...	not used
k	multiplier for number of parameters

**Value**

AIC values

---

AIC,regularizedSEMMixedPenalty-method  
*AIC*

---

**Description**

returns the AIC

**Usage**

```
## S4 method for signature 'regularizedSEMMixedPenalty'  
AIC(object, ..., k = 2)
```

**Arguments**

object	object of class regularizedSEMMixedPenalty
...	not used
k	multiplier for number of parameters

**Value**

AIC values

bfgs

*bfgs***Description**

This function allows for optimizing models built in lavaan using the BFGS optimizer implemented in lessSEM. Its elements can be accessed with the "@" operator (see examples). The main purpose is to make transformations of lavaan models more accessible.

**Usage**

```
bfgs(
  lavaanModel,
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlBFGS()
)
```

**Arguments**

lavaanModel      model of class lavaan  
 modifyModel      used to modify the lavaanModel. See ?modifyModel.  
 control            used to control the optimizer. See ?controlBFGS for more details.

**Value**

Model of class regularizedSEM

**Examples**

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)
```

```

lsem <- bfgs(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel)

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

```

---

bfgsEnet

*smoothly approximated elastic net*


---

### Description

Object for smoothly approximated elastic net optimization with bfgs optimizer

### Value

a list with fit results

### Fields

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a lambda and an alpha value.

---

bfgsEnetMgSEM

*smoothly approximated elastic net*


---

### Description

Object for smoothly approximated elastic net optimization with bfgs optimizer

### Value

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type `SEM_Cpp`, a lambda and an alpha value.

---

<code>bfgsEnetSEM</code>	<i>smoothly approximated elastic net</i>
--------------------------	--

---

**Description**

Object for smoothly approximated elastic net optimization with bfgs optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type `SEM_Cpp`, a lambda and an alpha value.

---

<code>BIC, gpRegularized-method</code>	<i>BIC</i>
--	------------

---

**Description**

returns the BIC

**Usage**

```
## S4 method for signature 'gpRegularized'
BIC(object, ...)
```

**Arguments**

<code>object</code>	object of class <code>gpRegularized</code>
<code>...</code>	not used

**Value**

data frame with fit values, appended with BIC

---

BIC,Rcpp\_mgSEM-method *BIC*

---

**Description**

BIC

**Usage**

```
## S4 method for signature 'Rcpp_mgSEM'  
BIC(object, ...)
```

**Arguments**

object	object of class Rcpp_mgSEM
...	not used

**Value**

BIC values

---

BIC,Rcpp\_SEMCpp-method  
*BIC*

---

**Description**

BIC

**Usage**

```
## S4 method for signature 'Rcpp_SEMCpp'  
BIC(object, ...)
```

**Arguments**

object	object of class Rcpp_SEMCpp
...	not used

**Value**

BIC values

BIC,regularizedSEM-method  
*BIC*

---

**Description**

returns the BIC

**Usage**

```
## S4 method for signature 'regularizedSEM'  
BIC(object, ...)
```

**Arguments**

object	object of class regularizedSEM
...	not used

**Value**

BIC values

---

BIC,regularizedSEMMixedPenalty-method  
*BIC*

---

**Description**

returns the BIC

**Usage**

```
## S4 method for signature 'regularizedSEMMixedPenalty'  
BIC(object, ...)
```

**Arguments**

object	object of class regularizedSEMMixedPenalty
...	not used

**Value**

BIC values

---

callFitFunction	<i>callFitFunction</i>
-----------------	------------------------

---

**Description**

wrapper to call user defined fit function

**Usage**

```
callFitFunction(fitFunctionSEXP, parameters, userSuppliedElements)
```

**Arguments**

fitFunctionSEXP	pointer to fit function
parameters	vector with parameter values
userSuppliedElements	list with additional elements

**Value**

fit value (double)

---

cappedL1	<i>cappedL1</i>
----------	-----------------

---

**Description**

Implements cappedL1 regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda \min(|x_j|, \theta)$$

where  $\theta > 0$ . The cappedL1 penalty is identical to the lasso for parameters which are below  $\theta$  and identical to a constant for parameters above  $\theta$ . As adding a constant to the fitting function will not change its minimum, larger parameters can stay unregularized while smaller ones are set to zero.

**Usage**

```
cappedL1(
  lavaanModel,
  regularized,
  lambdas,
  thetas,
  modifyModel = lessSEM::modifyModel(),
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

### Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the control argument can be used to switch to related procedures
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> (see <code>?controlIsta</code> )

### Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

CappedL1 regularization:

- Zhang, T. (2010). Analysis of Multi-stage Convex Relaxation for Sparse Regularization. *Journal of Machine Learning Research*, 11, 1081–1107.

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>



- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class regularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cappedL1(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 20),
  thetas = seq(0.01,2,length.out = 5))

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]
```

```

# fit Measures:
fitIndices(lsem)

# The best parameters can also be extracted with:
coef(lsem, criterion = "AIC")
# or
estimates(lsem, criterion = "AIC")

# optional: plotting the paths requires installation of plotly
# plot(lsem)

```

---

```

coef, cvRegularizedSEM-method
      coef

```

---

**Description**

Returns the parameter estimates of an `cvRegularizedSEM`

**Usage**

```

## S4 method for signature 'cvRegularizedSEM'
coef(object, ...)

```

**Arguments**

<code>object</code>	object of class <code>cvRegularizedSEM</code>
<code>...</code>	not used

**Value**

the parameter estimates of an `cvRegularizedSEM`

---

```

coef, gpRegularized-method
      coef

```

---

**Description**

Returns the parameter estimates of a `gpRegularized`

**Usage**

```

## S4 method for signature 'gpRegularized'
coef(object, ...)

```

**Arguments**

object            object of class gpRegularized  
 ...                criterion can be one of: "AIC", "BIC". If set to NULL, all parameters will be returned

**Value**

parameter estimates

---

coef,Rcpp\_mgSEM-method  
*coef*

---

**Description**

coef

**Usage**

```
## S4 method for signature 'Rcpp_mgSEM'
coef(object, ...)
```

**Arguments**

object            object of class Rcpp\_mgSEM  
 ...                not used

**Value**

all coefficients of the model in transformed form

---

coef,Rcpp\_SEMCpp-method  
*coef*

---

**Description**

coef

**Usage**

```
## S4 method for signature 'Rcpp_SEMCpp'
coef(object, ...)
```

**Arguments**

object	object of class Rcpp_SEMCpp
...	not used

**Value**

all coefficients of the model in transformed form

---

coef,regularizedSEM-method  
*coef*

---

**Description**

Returns the parameter estimates of a regularizedSEM

**Usage**

```
## S4 method for signature 'regularizedSEM'
coef(object, ...)
```

**Arguments**

object	object of class regularizedSEM
...	criterion can be one of the ones returned by fitIndices. If set to NULL, all parameters will be returned

**Value**

parameters of the model as data.frame

---

coef,regularizedSEMMixedPenalty-method  
*coef*

---

**Description**

Returns the parameter estimates of a regularizedSEMMixedPenalty

**Usage**

```
## S4 method for signature 'regularizedSEMMixedPenalty'
coef(object, ...)
```

**Arguments**

object            object of class regularizedSEMMixedPenalty  
 ...                criterion can be one of: "AIC", "BIC". If set to NULL, all parameters will be returned

**Value**

parameters of the model as data.frame

---

 controlBFGS

*controlBFGS*


---

**Description**

Control the BFGS optimizer.

**Usage**

```
controlBFGS(
  startingValues = "est",
  initialHessian = ifelse(all(startingValues == "est"), "lavaan", "compute"),
  saveDetails = FALSE,
  stepSize = 0.9,
  sigma = 1e-05,
  gamma = 0,
  maxIterOut = 1000,
  maxIterIn = 1000,
  maxIterLine = 500,
  breakOuter = 1e-08,
  breakInner = 1e-10,
  convergenceCriterion = 0,
  verbose = 0,
  nCores = 1
)
```

**Arguments**

**startingValues** option to provide initial starting values. Only used for the first lambda. Three options are supported. Setting to "est" will use the estimates from the lavaan model object. Setting to "start" will use the starting values of the lavaan model. Finally, a labeled vector with parameter values can be passed to the function which will then be used as starting values.

**initialHessian** option to provide an initial Hessian to the optimizer. Must have row and column names corresponding to the parameter labels. use `getLavaanParameters(lavaanModel)` to see those labels. If set to "gradNorm", the maximum of the gradients at the starting values times the stepSize will be used. This is adapted from `Optim.jl`

<https://github.com/JuliaNLSolvers/Optim.jl/blob/f43e6084aacf2dabb2b142952acd3fbb0e268439/src/mu>

If set to a single value, a diagonal matrix with the single value along the diagonal will be used. The default is "lavaan" which extracts the Hessian from the lavaanModel. This Hessian will typically deviate from that of the internal SEM representation of lessSEM (due to the transformation of the variances), but works quite well in practice.

saveDetails	when set to TRUE, additional details about the individual models are save. Currently, this are the Hessian and the implied means and covariances. Note: This may take a lot of memory!
stepSize	Initial stepSize of the outer iteration ( $\theta_{next} = \theta_{previous} + stepSize * Stepdirection$ )
sigma	only relevant when lineSearch = 'GLMNET'. Controls the sigma parameter in Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for 11-regularized logistic regression. The Journal of Machine Learning Research, 13, 1999–2030. <a href="https://doi.org/10.1145/2020408.2020421">https://doi.org/10.1145/2020408.2020421</a> .
gamma	Controls the gamma parameter in Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for 11-regularized logistic regression. The Journal of Machine Learning Research, 13, 1999–2030. <a href="https://doi.org/10.1145/2020408.2020421">https://doi.org/10.1145/2020408.2020421</a> . Defaults to 0.
maxIterOut	Maximal number of outer iterations
maxIterIn	Maximal number of inner iterations
maxIterLine	Maximal number of iterations for the line search procedure
breakOuter	Stopping criterion for outer iterations
breakInner	Stopping criterion for inner iterations
convergenceCriterion	which convergence criterion should be used for the outer iterations? possible are 0 = GLMNET, 1 = fitChange, 2 = gradients. Note that in case of gradients and GLMNET, we divide the gradients (and the Hessian) of the log-Likelihood by N as it would otherwise be considerably more difficult for larger sample sizes to reach the convergence criteria.
verbose	0 prints no additional information, > 0 prints GLMNET iterations
nCores	number of core to use. Multi-core support is provided by RcppParallel and only supported for SEM, not for general purpose optimization.

**Value**

object of class controlBFGS

**Examples**

```
control <- controlBFGS()
```

---

controlGlmnet	<i>controlGlmnet</i>
---------------	----------------------

---

## Description

Control the GLMNET optimizer.

## Usage

```
controlGlmnet(
  startingValues = "est",
  initialHessian = ifelse(all(startingValues == "est"), "lavaan", "compute"),
  saveDetails = FALSE,
  stepSize = 0.9,
  sigma = 1e-05,
  gamma = 0,
  maxIterOut = 1000,
  maxIterIn = 1000,
  maxIterLine = 500,
  breakOuter = 1e-08,
  breakInner = 1e-10,
  convergenceCriterion = 0,
  verbose = 0,
  nCores = 1
)
```

## Arguments

**startingValues** option to provide initial starting values. Only used for the first lambda. Three options are supported. Setting to "est" will use the estimates from the lavaan model object. Setting to "start" will use the starting values of the lavaan model. Finally, a labeled vector with parameter values can be passed to the function which will then be used as starting values.

**initialHessian** option to provide an initial Hessian to the optimizer. Must have row and column names corresponding to the parameter labels. use `getLavaanParameters(lavaanModel)` to see those labels. If set to "gradNorm", the maximum of the gradients at the starting values times the stepSize will be used. This is adapted from `Optim.jl` <https://github.com/JuliaNLSolvers/Optim.jl/blob/f43e6084aacf2dabb2b142952acd3fbb0e268439/src/mu>. If set to "compute", the initial hessian will be computed. If set to a single value, a diagonal matrix with the single value along the diagonal will be used. The default is "lavaan" which extracts the Hessian from the lavaanModel. This Hessian will typically deviate from that of the internal SEM representation of lessSEM (due to the transformation of the variances), but works quite well in practice.

**saveDetails** when set to TRUE, additional details about the individual models are save. Currently, this are the Hessian and the implied means and covariances. Note: This may take a lot of memory!

stepSize	Initial stepSize of the outer iteration ( $\theta_{next} = \theta_{previous} + stepSize * Stepdirection$ )
sigma	only relevant when lineSearch = 'GLMNET'. Controls the sigma parameter in Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. The Journal of Machine Learning Research, 13, 1999–2030. <a href="https://doi.org/10.1145/2020408.2020421">https://doi.org/10.1145/2020408.2020421</a> .
gamma	Controls the gamma parameter in Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. The Journal of Machine Learning Research, 13, 1999–2030. <a href="https://doi.org/10.1145/2020408.2020421">https://doi.org/10.1145/2020408.2020421</a> . Defaults to 0.
maxIterOut	Maximal number of outer iterations
maxIterIn	Maximal number of inner iterations
maxIterLine	Maximal number of iterations for the line search procedure
breakOuter	Stopping criterion for outer iterations
breakInner	Stopping criterion for inner iterations
convergenceCriterion	which convergence criterion should be used for the outer iterations? possible are 0 = GLMNET, 1 = fitChange, 2 = gradients. Note that in case of gradients and GLMNET, we divide the gradients (and the Hessian) of the log-Likelihood by N as it would otherwise be considerably more difficult for larger sample sizes to reach the convergence criteria.
verbose	0 prints no additional information, > 0 prints GLMNET iterations
nCores	number of core to use. Multi-core support is provided by RcppParallel and only supported for SEM, not for general purpose optimization.

**Value**

object of class controlGlmnet

**Examples**

```
control <- controlGlmnet()
```

---

controlIsta

*controlIsta*

---

**Description**

controlIsta



**Usage**

```
controlIsta(
  startingValues = "est",
  saveDetails = FALSE,
  L0 = 0.1,
  eta = 2,
  accelerate = TRUE,
  maxIterOut = 10000,
  maxIterIn = 1000,
  breakOuter = 1e-08,
  convCritInner = 1,
  sigma = 0.1,
  stepSizeInheritance = ifelse(accelerate, 1, 3),
  verbose = 0,
  nCores = 1
)
```

**Arguments**

<code>startingValues</code>	option to provide initial starting values. Only used for the first lambda. Three options are supported. Setting to "est" will use the estimates from the lavaan model object. Setting to "start" will use the starting values of the lavaan model. Finally, a labeled vector with parameter values can be passed to the function which will then be used as starting values.
<code>saveDetails</code>	when set to TRUE, additional details about the individual models are save. Currently, this are the implied means and covariances. Note: This may take a lot of memory!
<code>L0</code>	L0 controls the step size used in the first iteration
<code>eta</code>	eta controls by how much the step size changes in the inner iterations with $(\eta^i) * L$ , where i is the inner iteration
<code>accelerate</code>	boolean: Should the acceleration outlined in Parikh, N., & Boyd, S. (2013). Proximal Algorithms. Foundations and Trends in Optimization, 1(3), 123–231., p. 152 be used?
<code>maxIterOut</code>	maximal number of outer iterations
<code>maxIterIn</code>	maximal number of inner iterations
<code>breakOuter</code>	change in fit required to break the outer iteration. Note: The value will be multiplied internally with sample size N as the $-2\log$ -Likelihood depends directly on the sample size
<code>convCritInner</code>	this is related to the inner breaking condition. 0 = ista, as presented by Beck & Teboulle (2009); see Remark 3.1 on p. 191 (ISTA with backtracking) 1 = gist, as presented by Gong et al. (2013) (Equation 3)
<code>sigma</code>	sigma in (0,1) is used by the gist convergence criterion. larger sigma enforce larger improvement in fit
<code>stepSizeInheritance</code>	how should step sizes be carried forward from iteration to iteration? 0 = resets the step size to L0 in each iteration 1 = takes the previous step size as initial

	value for the next iteration 3 = Barzilai-Borwein procedure 4 = Barzilai-Borwein procedure, but sometimes resets the step size; this can help when the optimizer is caught in a bad spot.
verbose	if set to a value > 0, the fit every "verbose" iterations is printed.
nCores	number of core to use. Multi-core support is provided by RcppParallel and only supported for SEM, not for general purpose optimization.

**Value**

object of class `controlIsta`

**Examples**

```
control <- controlIsta()
```

---

covariances	<i>covariances</i>
-------------	--------------------

---

**Description**

Extract the labels of all covariances found in a lavaan model.

**Usage**

```
covariances(lavaanModel)
```

**Arguments**

lavaanModel      fitted lavaan model

**Value**

vector with parameter labels

**Examples**

```
# The following is adapted from ?lavaan::sem
library(lessSEM)
model <- '
  # latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + a*y2 + b*y3 + c*y4
  dem65 =~ y5 + a*y6 + b*y7 + c*y8

  # regressions
  dem60 ~ ind60
  dem65 ~ ind60 + dem60

  # residual correlations
```

```

y1 ~~ y5
y2 ~~ y4 + y6
y3 ~~ y7
y4 ~~ y8
y6 ~~ y8
,

fit <- sem(model, data = PoliticalDemocracy)

covariances(fit)

```

---

createSubsets	<i>createSubsets</i>
---------------	----------------------

---

**Description**

create subsets for cross-validation

**Usage**

```
createSubsets(N, k)
```

**Arguments**

N	number of samples in the data set
k	number of subsets to create

**Value**

matrix with subsets

**Examples**

```
createSubsets(N=100, k = 5)
```

---

curveLambda	<i>curveLambda</i>
-------------	--------------------

---

**Description**

generates lambda values between 0 and lambdaMax using the function described here: <https://math.stackexchange.com/question/function-with-values-between-0-and-1-for-x-values-between-0-and-1>. The function is identical to the one implemented in the regCtsem package.

**Usage**

```
curveLambda(maxLambda, lambdasAutoCurve, lambdasAutoLength)
```

**Arguments**

maxLambda        maximal lambda value  
 lambdasAutoCurve  
                   controls the curve. A value close to 1 will result in a linear increase, larger values in lambdas more concentrated around 0  
 lambdasAutoLength  
                   number of lambda values to generate

**Value**

numeric vector

**Examples**

```
library(lessSEM)
plot(curveLambda(maxLambda = 10, lambdasAutoCurve = 1, lambdasAutoLength = 100))
plot(curveLambda(maxLambda = 10, lambdasAutoCurve = 5, lambdasAutoLength = 100))
plot(curveLambda(maxLambda = 10, lambdasAutoCurve = 100, lambdasAutoLength = 100))
```

---

 cvAdaptiveLasso

*cvAdaptiveLasso*


---

**Description**

Implements cross-validated adaptive lasso regularization for structural equation models. The penalty function is given by:

$$p(x_j) = p(x_j) = \frac{1}{w_j} \lambda |x_j|$$

Adaptive lasso regularization will set parameters to zero if  $\lambda$  is large enough.

**Usage**

```
cvAdaptiveLasso(
  lavaanModel,
  regularized,
  weights = NULL,
  lambdas,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  method = "glmnet",
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
weights	labeled vector with weights for each of the parameters in the model. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object. If set to <code>NULL</code> , the default weights will be used: the inverse of the absolute values of the unregularized parameter estimates
lambdas	numeric vector: values for the tuning parameter lambda
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans ( <code>TRUE</code> , <code>FALSE</code> ) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to <code>TRUE</code> to return the parameters for each training set
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the <code>control</code> argument can be used to switch to related procedures (currently <code>gist</code> ).
modifyModel	used to modify the <code>lavaanModel</code> . See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> and <code>controlGlmnet</code> functions. See <code>?controlIsta</code> and <code>?controlGlmnet</code> for more details.

**Details**

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Adaptive lasso regularization:

- Zou, H. (2006). The adaptive lasso and its oracle properties. *Journal of the American Statistical Association*, 101(476), 1418–1429. <https://doi.org/10.1198/016214506000000735>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

model of class cvRegularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cvAdaptiveLasso(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
```

```

    lambdas = seq(0,1,.1))

# use the plot-function to plot the cross-validation fit
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

# The best parameters can also be extracted with:
estimates(lsem)

```

---

cvCappedL1

*cvCappedL1*


---

## Description

Implements cappedL1 regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda \min(|x_j|, \theta)$$

where  $\theta > 0$ . The cappedL1 penalty is identical to the lasso for parameters which are below  $\theta$  and identical to a constant for parameters above  $\theta$ . As adding a constant to the fitting function will not change its minimum, larger parameters can stay unregularized while smaller ones are set to zero.

## Usage

```

cvCappedL1(
  lavaanModel,
  regularized,
  lambdas,
  thetas,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  modifyModel = lessSEM::modifyModel(),
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)

```

**Arguments**

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the <code>control</code> argument can be used to switch to related procedures.
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> function. See <code>?controlIsta</code> for more details.

**Details**

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

CappedL1 regularization:

- Zhang, T. (2010). Analysis of Multi-stage Convex Relaxation for Sparse Regularization. *Journal of Machine Learning Research*, 11, 1081–1107.

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>



- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

model of class `cvRegularizedSEM`

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cvCappedL1(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 5),
  thetas = seq(0.01,2,length.out = 3))
```

```

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

# optional: plotting the cross-validation fit requires installation of plotly
# plot(lsem)

```

---

cvElasticNet

*cvElasticNet*


---

## Description

Implements elastic net regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \alpha\lambda|x_j| + (1 - \alpha)\lambda x_j^2$$

Note that the elastic net combines ridge and lasso regularization. If  $\alpha = 0$ , the elastic net reduces to ridge regularization. If  $\alpha = 1$  it reduces to lasso regularization. In between, elastic net is a compromise between the shrinkage of the lasso and the ridge penalty.

## Usage

```

cvElasticNet(
  lavaanModel,
  regularized,
  lambdas,
  alphas,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  method = "glmnet",
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlGlmnet()
)

```

## Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object

lambdas	numeric vector: values for the tuning parameter lambda
alphas	numeric vector with values of the tuning parameter alpha. Must be between 0 and 1. 0 = ridge, 1 = lasso.
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See ?lessSEM::createSubsets for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set standardize=TRUE to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
method	which optimizer should be used? Currently implemented are ista and glmnet. With ista, the control argument can be used to switch to related procedures.
modifyModel	used to modify the lavaanModel. See ?modifyModel.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Elastic net regularization:

- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B*, 67(2), 301–320. <https://doi.org/10.1111/j.1467-9868.2005.00503.x>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

model of class cvRegularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cvElasticNet(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 5),
  alphas = seq(0,1,length.out = 3))

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
```

```

lsem@parameters

# optional: plotting the cross-validation fit requires installation of plotly
# plot(lsem)

```

---

cvLasso

*cvLasso*


---

## Description

Implements cross-validated lasso regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda|x_j|$$

Lasso regularization will set parameters to zero if  $\lambda$  is large enough

## Usage

```

cvLasso(
  lavaanModel,
  regularized,
  lambdas,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  method = "glmnet",
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlGlmnet()
)

```

## Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the control argument can be used to switch to related procedures.

<code>modifyModel</code>	used to modify the <code>lavaanModel</code> . See <code>?modifyModel</code> .
<code>control</code>	used to control the optimizer. This element is generated with the <code>controlIsta</code> and <code>controlGlmnet</code> functions. See <code>?controlIsta</code> and <code>?controlGlmnet</code> for more details.

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Lasso regularization:

- Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1), 267–288.

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

model of class `cvRegularizedSEM`

**Examples**

```

library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cvLasso(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,.1),
  k = 5, # number of cross-validation folds
  standardize = TRUE) # automatic standardization

# use the plot-function to plot the cross-validation fit:
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

# The best parameters can also be extracted with:
estimates(lsem)

```

**Description**

Implements lsp regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda \log(1 + |x_j|/\theta)$$

where  $\theta > 0$ .

**Usage**

```
cvLsp(
  lavaanModel,
  regularized,
  lambdas,
  thetas,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  modifyModel = lessSEM::modifyModel(),
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the control argument can be used to switch to related procedures.
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> function. See <code>?controlIsta</code>



## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

lsp regularization:

- Candès, E. J., Wakin, M. B., & Boyd, S. P. (2008). Enhancing Sparsity by Reweighted  $l_1$  Minimization. *Journal of Fourier Analysis and Applications*, 14(5–6), 877–905. <https://doi.org/10.1007/s00041-008-9045-x>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale  $l_1$ -regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for  $l_1$ -regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

model of class `cvRegularizedSEM`

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
```

```

# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                          data = dataset,
                          meanstructure = TRUE,
                          std.lv = TRUE)

# Regularization:

lsem <- cvLsp(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 5),
  thetas = seq(0.01,2,length.out = 3))

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)$estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

# optional: plotting the cross-validation fit requires installation of plotly
# plot(lsem)

```

---

cvMcp

*cvMcp*


---

## Description

Implements mcp regularization for structural equation models. The penalty function is given by:  
Equation Omitted in Pdf Documentation.

## Usage

```
cvMcp(
```

```

lavaanModel,
regularized,
lambdas,
thetas,
k = 5,
standardize = FALSE,
returnSubsetParameters = FALSE,
modifyModel = lessSEM::modifyModel(),
method = "ista",
control = lessSEM::controlIsta()
)

```

### Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the <code>control</code> argument can be used to switch to related procedures.
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> function. See <code>?controlIsta</code>

### Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

mcp regularization:

- Zhang, C.-H. (2010). Nearly unbiased variable selection under minimax concave penalty. The Annals of Statistics, 38(2), 894–942. <https://doi.org/10.1214/09-AOS729>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

model of class `cvRegularizedSEM`

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
```

```

                                std.lv = TRUE)

# Regularization:

lsem <- cvMcp(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("l", 6:15),
  lambdas = seq(0,1,length.out = 5),
  thetas = seq(0.01,2,length.out = 3))

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

# optional: plotting the cross-validation fit requires installation of plotly
# plot(lsem)

```

---

cvRegularizedSEM-class

*Class for cross-validated regularized SEM*

---

## Description

Class for cross-validated regularized SEM

## Slots

parameters data.frame with parameter estimates for the best combination of the tuning parameters

transformations transformed parameters

cvfits data.frame with all combinations of the tuning parameters and the sum of the cross-validation fits

parameterLabels character vector with names of all parameters

regularized character vector with names of regularized parameters

cvfitsDetails data.frame with cross-validation fits for each subset

subsets matrix indicating which person is in which subset

subsetParameters optional: data.frame with parameter estimates for all combinations of the tuning parameters in all subsets

misc list with additional return elements

notes internal notes that have come up when fitting the model

cvRidge

*cvRidge***Description**

Implements ridge regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda x_j^2$$

Note that ridge regularization will not set any of the parameters to zero but result in a shrinkage towards zero.

**Usage**

```
cvRidge(
  lavaanModel,
  regularized,
  lambdas,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  method = "glmnet",
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the control argument can be used to switch to related procedures (currently <code>gist</code> ).
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> and <code>controlGlmnet</code> functions. See <code>?controlIsta</code> and <code>?controlGlmnet</code> for more details.

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Ridge regularization:

- Hoerl, A. E., & Kennard, R. W. (1970). Ridge Regression: Biased Estimation for Nonorthogonal Problems. *Technometrics*, 12(1), 55–67. <https://doi.org/10.1080/00401706.1970.10488634>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

model of class `cvRegularizedSEM`

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.
```

```

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cvRidge(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 20))

# use the plot-function to plot the cross-validation fit:
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

```

---

cvRidgeBfgs

*cvRidgeBfgs*


---

## Description

Implements cross-validated ridge regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda x_j^2$$

Note that ridge regularization will not set any of the parameters to zero but result in a shrinkage towards zero.



**Usage**

```

cvRidgeBfgs(
  lavaanModel,
  regularized,
  lambdas,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlBFGS()
)

```

**Arguments**

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>controlBFGS</code> function. See <code>?controlBFGS</code> for more details.

**Details**

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Ridge regularization:

- Hoerl, A. E., & Kennard, R. W. (1970). Ridge Regression: Biased Estimation for Nonorthogonal Problems. *Technometrics*, 12(1), 55–67. <https://doi.org/10.1080/00401706.1970.10488634>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>

- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1171111>

## Value

model of class cvRegularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cvRidgeBfgs(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 20))

# use the plot-function to plot the cross-validation fit:
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters
```

---

cvScad	<i>cvScad</i>
--------	---------------

---

### Description

Implements scad regularization for structural equation models. The penalty function is given by:  
Equation Omitted in Pdf Documentation.

### Usage

```
cvScad(
  lavaanModel,
  regularized,
  lambdas,
  thetas,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  modifyModel = lessSEM::modifyModel(),
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

### Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the control argument can be used to switch to related procedures.
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> function. See <code>?controlIsta</code>

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

scad regularization:

- Fan, J., & Li, R. (2001). Variable selection via nonconcave penalized likelihood and its oracle properties. *Journal of the American Statistical Association*, 96(456), 1348–1360. <https://doi.org/10.1198/016214501753>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

model of class `cvRegularizedSEM`

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.
```

```

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cvScad(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 3),
  thetas = seq(2.01,5,length.out = 3))

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

# optional: plotting the cross-validation fit requires installation of plotly
# plot(lsem)

```

---

cvScaler

*cvScaler*


---

### Description

uses the means and standard deviations of the training set to standardize the test set. See, e.g., [https://scikit-learn.org/stable/modules/cross\\_validation.html](https://scikit-learn.org/stable/modules/cross_validation.html).

### Usage

```
cvScaler(testSet, means, standardDeviations)
```

**Arguments**

testSet            test data set  
means              means of the training set  
standardDeviations  
                     standard deviations of the training set

**Value**

scaled test set

**Examples**

```
library(lessSEM)
data <- matrix(rnorm(50),10,5)

cvScaler(testSet = data,
          means = 1:5,
          standardDeviations = 1:5)
```

---

cvSmoothAdaptiveLasso *cvSmoothAdaptiveLasso*

---

**Description**

Implements cross-validated smooth adaptive lasso regularization for structural equation models. The penalty function is given by:

$$p(x_j) = p(x_j) = \frac{1}{w_j} \lambda \sqrt{(x_j + \epsilon)^2}$$

**Usage**

```
cvSmoothAdaptiveLasso(
  lavaanModel,
  regularized,
  weights = NULL,
  lambdas,
  epsilon,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlBFGS()
)
```

**Arguments**

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
weights	labeled vector with weights for each of the parameters in the model. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object. If set to NULL, the default weights will be used: the inverse of the absolute values of the unregularized parameter estimates
lambdas	numeric vector: values for the tuning parameter lambda
epsilon	epsilon > 0; controls the smoothness of the approximation. Larger values = smoother
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>controlBFGS</code> function. See <code>?controlBFGS</code> for more details.

**Details**

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Adaptive lasso regularization:

- Zou, H. (2006). The adaptive lasso and its oracle properties. *Journal of the American Statistical Association*, 101(476), 1418–1429. <https://doi.org/10.1198/016214506000000735>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

**Value**

model of class cvRegularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cvSmoothAdaptiveLasso(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,.1),
  epsilon = 1e-8)

# use the plot-function to plot the cross-validation fit
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

# The best parameters can also be extracted with:
coef(lsem)
```



## Description

Implements cross-validated smooth elastic net regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \alpha\lambda\sqrt{(x_j + \epsilon)^2} + (1 - \alpha)\lambda x_j^2$$

Note that the smooth elastic net combines ridge and smooth lasso regularization. If  $\alpha = 0$ , the elastic net reduces to ridge regularization. If  $\alpha = 1$  it reduces to smooth lasso regularization. In between, elastic net is a compromise between the shrinkage of the lasso and the ridge penalty.

## Usage

```
cvSmoothElasticNet(
  lavaanModel,
  regularized,
  lambdas,
  alphas,
  epsilon,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlBFGS()
)
```

## Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
alphas	numeric vector with values of the tuning parameter alpha. Must be between 0 and 1. 0 = ridge, 1 = lasso.
epsilon	epsilon > 0; controls the smoothness of the approximation. Larger values = smoother
k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See <code>?lessSEM::createSubsets</code> for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set <code>standardize=TRUE</code> to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>controlBFGS</code> function. See <code>?controlBFGS</code> for more details.

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Elastic net regularization:

- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B*, 67(2), 301–320. <https://doi.org/10.1111/j.1467-9868.2005.00503.x>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1181111>

## Value

model of class `cvRegularizedSEM`

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- cvSmoothElasticNet(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
```

```

regularized = paste0("1", 6:15),
epsilon = 1e-8,
lambdas = seq(0,1,length.out = 5),
alphas = .3)

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

# optional: plotting the cross-validation fit requires installation of plotly
# plot(lsem)

```

---

cvSmoothLasso

*cvSmoothLasso*


---

## Description

Implements cross-validated smooth lasso regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda \sqrt{(x_j + \epsilon)^2}$$

## Usage

```

cvSmoothLasso(
  lavaanModel,
  regularized,
  lambdas,
  epsilon,
  k = 5,
  standardize = FALSE,
  returnSubsetParameters = FALSE,
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlBFGS()
)

```

## Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
epsilon	epsilon > 0; controls the smoothness of the approximation. Larger values = smoother

k	the number of cross-validation folds. Alternatively, you can pass a matrix with booleans (TRUE, FALSE) which indicates for each person which subset it belongs to. See ?lessSEM::createSubsets for an example of how this matrix should look like.
standardize	Standardizing your data prior to the analysis can undermine the cross-validation. Set standardize=TRUE to automatically standardize the data.
returnSubsetParameters	set to TRUE to return the parameters for each training set
modifyModel	used to modify the lavaanModel. See ?modifyModel.
control	used to control the optimizer. This element is generated with the controlBFGS function. See ?controlBFGS for more details.

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Lasso regularization:

- Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1), 267–288.

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

## Value

model of class cvRegularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
     16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
     111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
```

```

f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                          data = dataset,
                          meanstructure = TRUE,
                          std.lv = TRUE)

# Regularization:

lsem <- cvSmoothLasso(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,.1),
  k = 5, # number of cross-validation folds
  epsilon = 1e-8,
  standardize = TRUE) # automatic standardization

# use the plot-function to plot the cross-validation fit:
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters

# The best parameters can also be extracted with:
coef(lsem)

```

---

 elasticNet

*elasticNet*


---

## Description

Implements elastic net regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \alpha\lambda|x_j| + (1 - \alpha)\lambda x_j^2$$

Note that the elastic net combines ridge and lasso regularization. If  $\alpha = 0$ , the elastic net reduces to ridge regularization. If  $\alpha = 1$  it reduces to lasso regularization. In between, elastic net is a compromise between the shrinkage of the lasso and the ridge penalty.

## Usage

```

elasticNet(
  lavaanModel,
  regularized,

```

```

  lambdas,
  alphas,
  method = "glmnet",
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlGlmnet()
)

```

### Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
alphas	numeric vector with values of the tuning parameter alpha. Must be between 0 and 1. 0 = ridge, 1 = lasso.
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the control argument can be used to switch to related procedures (currently <code>gist</code> ).
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>lessSEM::controlIsta()</code> and <code>controlGlmnet()</code> functions.

### Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Elastic net regularization:

- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B*, 67(2), 301–320. <https://doi.org/10.1111/j.1467-9868.2005.00503.x>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>

- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class regularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- elasticNet(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 5),
  alphas = seq(0,1,length.out = 3))
```

```

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

# optional: plotting the paths requires installation of plotly
# plot(lsem)

#### Advanced ####
# Switching the optimizer #
# Use the "method" argument to switch the optimizer. The control argument
# must also be changed to the corresponding function:
lsemIsta <- elasticNet(
  lavaanModel = lavaanModel,
  regularized = paste0("l", 6:15),
  lambdas = seq(0,1,length.out = 5),
  alphas = seq(0,1,length.out = 3),
  method = "ista",
  control = controlIsta())

# Note: The results are basically identical:
lsemIsta@parameters - lsem@parameters

```

---

estimates

*S4 method to extract the estimates of an object*


---

## Description

S4 method to extract the estimates of an object

## Usage

```
estimates(object, criterion = NULL, transformations = FALSE)
```

## Arguments

object	a model fitted with lessSEM
criterion	fitIndice used to select the parameters
transformations	boolean: Should transformations be returned?

## Value

returns a matrix with estimates



---

estimates,cvRegularizedSEM-method  
*estimates*

---

**Description**

estimates

**Usage**

```
## S4 method for signature 'cvRegularizedSEM'
estimates(object, criterion = NULL, transformations = FALSE)
```

**Arguments**

object	object of class cvRegularizedSEM
criterion	not used
transformations	boolean: Should transformations be returned?

**Value**

returns a matrix with estimates

---

estimates,regularizedSEM-method  
*estimates*

---

**Description**

estimates

**Usage**

```
## S4 method for signature 'regularizedSEM'
estimates(object, criterion = NULL, transformations = FALSE)
```

**Arguments**

object	object of class regularizedSEM
criterion	fit index (e.g., AIC) used to select the parameters
transformations	boolean: Should transformations be returned?

**Value**

returns a matrix with estimates

---

estimates,regularizedSEMMixedPenalty-method  
*estimates*

---

**Description**

estimates

**Usage**

```
## S4 method for signature 'regularizedSEMMixedPenalty'
estimates(object, criterion = NULL, transformations = FALSE)
```

**Arguments**

object	object of class regularizedSEMMixedPenalty
criterion	fit index (e.g., AIC) used to select the parameters
transformations	boolean: Should transformations be returned?

**Value**

returns a matrix with estimates

---

fit	<i>fit</i>
-----	------------

---

**Description**

Optimizes an object with mixed penalty. See ?mixedPenalty for more details.

**Usage**

```
fit(mixedPenalty)
```

**Arguments**

mixedPenalty	object of class mixedPenalty. This object can be created with the mixedPenalty function. Penalties can be added with the addCappedL1, addElastiNet, addLasso, addLsp, addMcp, and addScad functions.
--------------	--

**Value**

throws error in case of undefined penalty combinations.

**Examples**

```

library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# We can add mixed penalties as follows:

regularized <- lavaanModel |>
  # create template for regularized model with mixed penalty:
  mixedPenalty() |>
  # add penalty on loadings l6 - l10:
  addElasticNet(regularized = paste0("l", 11:15),
                lambdas = seq(0,1,.1),
                alphas = .4) |>
  # fit the model:
  fit()

```

---

fitIndices

*S4 method to compute fit indices (e.g., AIC, BIC, ...)*


---

**Description**

S4 method to compute fit indices (e.g., AIC, BIC, ...)

**Usage**

```
fitIndices(object)
```

**Arguments**

object            a model fitted with lessSEM

**Value**

returns a data.frame with fit indices

---

*fitIndices*,cvRegularizedSEM-method  
*fitIndices*

---

**Description**

*fitIndices*

**Usage**

```
## S4 method for signature 'cvRegularizedSEM'  
fitIndices(object)
```

**Arguments**

object            object of class cvRegularizedSEM

**Value**

returns a data.frame with fit indices

---

*fitIndices*,regularizedSEM-method  
*fitIndices*

---

**Description**

*fitIndices*

**Usage**

```
## S4 method for signature 'regularizedSEM'  
fitIndices(object)
```

**Arguments**

object            object of class regularizedSEM

**Value**

returns a data.frame with fit indices

---

fitIndices,regularizedSEMMixedPenalty-method  
*fitIndices*

---

**Description**

fitIndices

**Usage**

```
## S4 method for signature 'regularizedSEMMixedPenalty'  
fitIndices(object)
```

**Arguments**

object            object of class regularizedSEMMixedPenalty

**Value**

returns a data.frame with fit indices

---

getLavaanParameters    *getLavaanParameters*

---

**Description**

helper function: returns a labeled vector with parameters from lavaan

**Usage**

```
getLavaanParameters(lavaanModel, removeDuplicates = TRUE)
```

**Arguments**

lavaanModel    model of class lavaan  
removeDuplicates    should duplicated parameters be removed?

**Value**

returns a labeled vector with parameters from lavaan

**Examples**

```

library(lessSEM)

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)
getLavaanParameters(lavaanModel)

```

---

```

getTuningParameterConfiguration
      getTuningParameterConfiguration

```

---

**Description**

Returns the lambda, theta, and alpha values for the tuning parameters of a regularized SEM with mixed penalty.

**Usage**

```

getTuningParameterConfiguration(
  regularizedSEMMixedPenalty,
  tuningParameterConfiguration
)

```

**Arguments**

`regularizedSEMMixedPenalty`  
 object of type `regularizedSEMMixedPenalty` (see `?mixedPenalty`)

`tuningParameterConfiguration`  
 integer indicating which `tuningParameterConfiguration` should be extracted (e.g., 1). See the entry in the row `tuningParameterConfiguration` of `regularizedSEM-MixedPenalty@fits` and `regularizedSEMMixedPenalty@parameters`.

**Value**

data frame with penalty and tuning parameter settings

**Examples**

```

library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# We can add mixed penalties as follows:

regularized <- lavaanModel |>
  # create template for regularized model with mixed penalty:
  mixedPenalty() |>
  # add penalty on loadings 16 - 110:
  addLsp(regularized = paste0("1", 11:15),
         lambdas = seq(0,1,.1),
         thetas = 2.3) |>
  # fit the model:
  fit()

getTuningParameterConfiguration(regularizedSEMMixedPenalty = regularized,
                                tuningParameterConfiguration = 2)

```

---

glmnetCappedL1MgSEM    *CappedL1 optimization with glmnet optimizer*

---

**Description**

Object for cappedL1 optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (2) a list with control elements  
`setHessian` changes the Hessian of the model. Expects a matrix  
`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

`glmnetCappedL1SEM`      *CappedL1 optimization with glmnet optimizer*

---

**Description**

Object for cappedL1 optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires a list with control elements  
`setHessian` changes the Hessian of the model. Expects a matrix  
`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

`glmnetEnetGeneralPurpose`  
*elastic net optimization with glmnet optimizer*

---

**Description**

Object for elastic net optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements  
`setHessian` changes the Hessian of the model. Expects a matrix  
`optimize` optimize the model. Expects a vector with starting values, an R function to compute the fit, an R function to compute the gradients, a list with elements the fit and gradient function require, a lambda and an alpha value.



---

glmnetEnetGeneralPurposeCpp  
*elastic net optimization with glmnet optimizer*

---

**Description**

Object for elastic net optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEXP function pointer to compute the fit, a SEXP function pointer to compute the gradients, a list with elements the fit and gradient function require, a lambda and an alpha value.

---

glmnetEnetMgSEM      *elastic net optimization with glmnet optimizer*

---

**Description**

Object for elastic net optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a lambda and an alpha value.

---

glmnetEnetSEM      *elastic net optimization with glmnet optimizer*

---

**Description**

Object for elastic net optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a lambda and an alpha value.

---

glmnetLspMgSEM      *lsp optimization with glmnet optimizer*

---

**Description**

Object for lsp optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

glmnetLspSEM	<i>lsp optimization with glmnet optimizer</i>
--------------	---

---

**Description**

Object for lsp optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

glmnetMcpMgSEM	<i>mcp optimization with glmnet optimizer</i>
----------------	---

---

**Description**

Object for mcp optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

glmnetMcpSEM	<i>mcp optimization with glmnet optimizer</i>
--------------	---

---

**Description**

Object for mcp optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

glmnetMixedMgSEM	<i>mixed optimization with glmnet optimizer</i>
------------------	---

---

**Description**

Object for mixed optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

`glmnetMixedPenaltyGeneralPurpose`*mixed optimization with glmnet optimizer*

---

**Description**

Object for mixed optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

`glmnetMixedPenaltyGeneralPurposeCpp`*mixed optimization with glmnet optimizer*

---

**Description**

Object for mixed optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

glmnetMixedSEM	<i>mixed optimization with glmnet optimizer</i>
----------------	---

---

**Description**

Object for mixed optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

glmnetScadMgSEM	<i>scad optimization with glmnet optimizer</i>
-----------------	--

---

**Description**

Object for scad optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (2) a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

glmnetScadSEM	<i>scad optimization with glmnet optimizer</i>
---------------	--

---

**Description**

Object for scad optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires a list with control elements

`setHessian` changes the Hessian of the model. Expects a matrix

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

gpAdaptiveLasso	<i>gpAdaptiveLasso</i>
-----------------	------------------------

---

**Description**

Implements adaptive lasso regularization for general purpose optimization problems. The penalty function is given by:

$$p(x_j) = p(x_j) = \frac{1}{w_j} \lambda |x_j|$$

Adaptive lasso regularization will set parameters to zero if  $\lambda$  is large enough.

**Usage**

```
gpAdaptiveLasso(
  par,
  regularized,
  weights = NULL,
  fn,
  gr = NULL,
  lambdas = NULL,
  nLambdas = NULL,
  reverse = TRUE,
  curve = 1,
  ...,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

par	labeled vector with starting values
regularized	vector with names of parameters which are to be regularized.
weights	labeled vector with adaptive lasso weights. NULL will use 1/abs(par)
fn	R function which takes the parameters as input and returns the fit value (a single value)
gr	R function which takes the parameters as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
lambdas	numeric vector: values for the tuning parameter lambda
nLambdas	alternative to lambda: If alpha = 1, lessSEM can automatically compute the first lambda value which sets all regularized parameters to zero. It will then generate nLambda values between 0 and the computed lambda.
reverse	if set to TRUE and nLambdas is used, lessSEM will start with the largest lambda and gradually decrease lambda. Otherwise, lessSEM will start with the smallest lambda and gradually increase it.
curve	Allows for unequally spaced lambda steps (e.g., .01,.02,.05,1,5,20). If curve is close to 1 all lambda values will be equally spaced, if curve is large lambda values will be more concentrated close to 0. See ?lessSEM::curveLambda for more information.
...	additional arguments passed to fn and gr
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

**Details**

The interface is similar to that of `optim`. Users have to supply a vector with starting values (important: This vector *must* have labels) and a fitting function. This fitting functions *must* take a labeled vector with parameter values as first argument. The remaining arguments are passed with the ... argument. This is similar to `optim`.

The gradient function `gr` is optional. If set to NULL, the **numDeriv** package will be used to approximate the gradients. Supplying a gradient function can result in considerable speed improvements.

Adaptive lasso regularization:

- Zou, H. (2006). The adaptive lasso and its oracle properties. *Journal of the American Statistical Association*, 101(476), 1418–1429. <https://doi.org/10.1198/016214506000000735>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.



- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class gpRegularized

## Examples

```
# This example shows how to use the optimizers
# for other objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(lessSEM)
set.seed(123)

# first, we simulate data for our
# linear regression.
N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
       rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

# First, we must construct a fitting function
# which returns a single value. We will use
# the residual sum squared as fitting function.

# Let's start setting up the fitting function:
fittingFunction <- function(par, y, X, N){
  # par is the parameter vector
  # y is the observed dependent variable
  # X is the design matrix
  # N is the sample size
  pred <- X %% matrix(par, ncol = 1) #be explicit here:
  # we need par to be a column vector
  sse <- sum((y - pred)^2)
  # we scale with .5/N to get the same results as glmnet
```

```

    return((.5/N)*sse)
}

# let's define the starting values:
b <- c(solve(t(X)%*%X)%*%t(X)%*%y) # we will use the lm estimates
names(b) <- paste0("b", 1:length(b))
# names of regularized parameters
regularized <- paste0("b",1:p)

# define the weight for each of the parameters
weights <- 1/abs(b)
# we will re-scale the weights for equivalence to glmnet.
# see ?glmnet for more details
weights <- length(b)*weights/sum(weights)

# optimize
adaptiveLassoPen <- gpAdaptiveLasso(
  par = b,
  regularized = regularized,
  weights = weights,
  fn = fittingFunction,
  lambdas = seq(0,1,.01),
  X = X,
  y = y,
  N = N
)
plot(adaptiveLassoPen)
# You can access the fit results as follows:
adaptiveLassoPen@fits
# Note that we won't compute any fit measures automatically, as
# we cannot be sure how the AIC, BIC, etc are defined for your objective function

# for comparison:
# library(glmnet)
# coef(glmnet(x = X,
#             y = y,
#             penalty.factor = weights,
#             lambda = adaptiveLassoPen@fits$lambda[20],
#             intercept = FALSE,
#             standardize = FALSE))[,1]
# adaptiveLassoPen@parameters[20,]

```

---

gpAdaptiveLassoCpp

*gpAdaptiveLassoCpp*


---

## Description

Implements adaptive lasso regularization for general purpose optimization problems with C++ functions. The penalty function is given by:

$$p(x_j) = p(x_j) = \frac{1}{w_j} \lambda |x_j|$$

Adaptive lasso regularization will set parameters to zero if  $\lambda$  is large enough.

### Usage

```
gpAdaptiveLassoCpp(
  par,
  regularized,
  weights = NULL,
  fn,
  gr,
  lambdas = NULL,
  nLambdas = NULL,
  curve = 1,
  additionalArguments,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

### Arguments

par	labeled vector with starting values
regularized	vector with names of parameters which are to be regularized.
weights	labeled vector with adaptive lasso weights. NULL will use 1/abs(par)
fn	R function which takes the parameters as input and returns the fit value (a single value)
gr	R function which takes the parameters as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
lambdas	numeric vector: values for the tuning parameter lambda
nLambdas	alternative to lambda: If alpha = 1, lessSEM can automatically compute the first lambda value which sets all regularized parameters to zero. It will then generate nLambda values between 0 and the computed lambda.
curve	Allows for unequally spaced lambda steps (e.g., .01,.02,.05,1,5,20). If curve is close to 1 all lambda values will be equally spaced, if curve is large lambda values will be more concentrated close to 0. See ?lessSEM::curveLambda for more information.
additionalArguments	list with additional arguments passed to fn and gr
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

### Details

The interface is inspired by optim, but a bit more restrictive. Users have to supply a vector with starting values (important: This vector *must* have labels), a fitting function, and a gradient function.

These fitting functions *must* take an `const Rcpp::NumericVector&` with parameter values as first argument and an `Rcpp::List&` as second argument

Adaptive lasso regularization:

- Zou, H. (2006). The adaptive lasso and its oracle properties. *Journal of the American Statistical Association*, 101(476), 1418–1429. <https://doi.org/10.1198/016214506000000735>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class `gpRegularized`

## Examples

```
# This example shows how to use the optimizers
# for C++ objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(Rcpp)
library(lessSEM)

linreg <- '
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>

// [[Rcpp::export]]
double fitfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
```

```

arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

// compute the sum of squared errors:
arma::mat sse = arma::trans(y-X*b)*(y-X*b);

// other packages, such as glmnet, scale the sse with
// 1/(2*N), where N is the sample size. We will do that here as well

sse *= 1.0/(2.0 * y.n_elem);

// note: We must return a double, but the sse is a matrix
// To get a double, just return the single value that is in
// this matrix:
return(sse(0,0));
}

// [[Rcpp::export]]
arma::rowvec gradientfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // note: we want to return our gradients as row-vector; therefore,
  // we have to transpose the resulting column-vector:
  arma::rowvec gradients = arma::trans(-2.0*X.t() * y + 2.0*X.t()*X*b);

  // other packages, such as glmnet, scale the sse with
  // 1/(2*N), where N is the sample size. We will do that here as well

  gradients *= (.5/y.n_rows);

  return(gradients);
}

// Dirk Eddelbuettel at
// https://gallery.rcpp.org/articles/passing-cpp-function-pointers/
typedef double (*fitFunPtr)(const Rcpp::NumericVector&, //parameters
                          Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<fitFunPtr> fitFunPtr_t;

typedef arma::rowvec (*gradientFunPtr)(const Rcpp::NumericVector&, //parameters
                                       Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<gradientFunPtr> gradientFunPtr_t;

// [[Rcpp::export]]
fitFunPtr_t fitfunPtr() {
  return(fitFunPtr_t(new fitFunPtr(&fitfunction)));
}

```

```

// [[Rcpp::export]]
gradientFunPtr_t gradfunPtr() {
    return(gradientFunPtr_t(new gradientFunPtr(&gradientfunction)));
}

Rcpp::sourceCpp(code = linreg)

ffp <- fitfunPtr()
gfp <- gradfunPtr()

N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
       rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

data <- list("y" = y,
            "X" = cbind(1,X))
parameters <- rep(0, ncol(data$X))
names(parameters) <- paste0("b", 0:(length(parameters)-1))

a11 <- gpAdaptiveLassoCpp(par = parameters,
                        regularized = paste0("b", 1:(length(b)-1)),
                        fn = ffp,
                        gr = gfp,
                        lambdas = seq(0,1,.1),
                        additionalArguments = data)

a11@parameters

```

---

gpCappedL1

*gpCappedL1*


---

## Description

Implements cappedL1 regularization for general purpose optimization problems. The penalty function is given by:

$$p(x_j) = \lambda \min(|x_j|, \theta)$$

where  $\theta > 0$ . The cappedL1 penalty is identical to the lasso for parameters which are below  $\theta$  and identical to a constant for parameters above  $\theta$ . As adding a constant to the fitting function will not change its minimum, larger parameters can stay unregularized while smaller ones are set to zero.

## Usage

```
gpCappedL1(
  par,
```

```

    fn,
    gr = NULL,
    ...,
    regularized,
    lambdas,
    thetas,
    method = "glmnet",
    control = lessSEM::controlGlmnet()
)

```

### Arguments

par	labeled vector with starting values
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
...	additional arguments passed to fn and gr
regularized	vector with names of parameters which are to be regularized.
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

### Details

The interface is similar to that of `optim`. Users have to supply a vector with starting values (important: This vector *must* have labels) and a fitting function. This fitting functions *must* take a labeled vector with parameter values as first argument. The remaining arguments are passed with the ... argument. This is similar to `optim`.

The gradient function `gr` is optional. If set to NULL, the **numDeriv** package will be used to approximate the gradients. Supplying a gradient function can result in considerable speed improvements.

CappedL1 regularization:

- Zhang, T. (2010). Analysis of Multi-stage Convex Relaxation for Sparse Regularization. *Journal of Machine Learning Research*, 11, 1081–1107.

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.

- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class gpRegularized

## Examples

```
# This example shows how to use the optimizers
# for other objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

# This example shows how to use the optimizers
# for other objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(lessSEM)
set.seed(123)

# first, we simulate data for our
# linear regression.
N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
       rep(0,6)) # true regression weights
y <- X*%matrix(b,ncol = 1) + rnorm(N,0,.2)

# First, we must construct a fitting function
# which returns a single value. We will use
# the residual sum squared as fitting function.

# Let's start setting up the fitting function:
fittingFunction <- function(par, y, X, N){
  # par is the parameter vector
```



```

# y is the observed dependent variable
# X is the design matrix
# N is the sample size
pred <- X %>% matrix(par, ncol = 1) #be explicit here:
# we need par to be a column vector
sse <- sum((y - pred)^2)
# we scale with .5/N to get the same results as glmnet
return((.5/N)*sse)
}

# let's define the starting values:
b <- c(solve(t(X)%*%X)%*%t(X)%*%y) # we will use the lm estimates
names(b) <- paste0("b", 1:length(b))
# names of regularized parameters
regularized <- paste0("b",1:p)

# optimize
cL1 <- gpCappedL1(
  par = b,
  regularized = regularized,
  fn = fittingFunction,
  lambdas = seq(0,1,.1),
  thetas = c(0.001, .5, 1),
  X = X,
  y = y,
  N = N
)

# optional: plot requires plotly package
# plot(cL1)

# for comparison

fittingFunction <- function(par, y, X, N, lambda, theta){
  pred <- X %>% matrix(par, ncol = 1)
  sse <- sum((y - pred)^2)
  smoothAbs <- sqrt(par^2 + 1e-8)
  pen <- lambda * ifelse(smoothAbs < theta, smoothAbs, theta)
  return((.5/N)*sse + sum(pen))
}

round(
  optim(par = b,
    fn = fittingFunction,
    y = y,
    X = X,
    N = N,
    lambda = cL1@fits$lambda[15],
    theta = cL1@fits$theta[15],
    method = "BFGS")$par,
  4)
cL1@parameters[15,]

```

gpCappedL1Cpp

*gpCappedL1Cpp***Description**

Implements cappedL1 regularization for general purpose optimization problems with C++ functions. The penalty function is given by:

$$p(x_j) = \lambda \min(|x_j|, \theta)$$

where  $\theta > 0$ . The cappedL1 penalty is identical to the lasso for parameters which are below  $\theta$  and identical to a constant for parameters above  $\theta$ . As adding a constant to the fitting function will not change its minimum, larger parameters can stay unregularized while smaller ones are set to zero.

**Usage**

```
gpCappedL1Cpp(
  par,
  fn,
  gr,
  additionalArguments,
  regularized,
  lambdas,
  thetas,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

par	labeled vector with starting values
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
additionalArguments	list with additional arguments passed to fn and gr
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use getLavaanParameters(model) with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

## Details

The interface is inspired by `optim`, but a bit more restrictive. Users have to supply a vector with starting values (important: This vector *must* have labels), a fitting function, and a gradient function. These fitting functions *must* take an `const Rcpp::NumericVector&` with parameter values as first argument and an `Rcpp::List&` as second argument

CappedL1 regularization:

- Zhang, T. (2010). Analysis of Multi-stage Convex Relaxation for Sparse Regularization. *Journal of Machine Learning Research*, 11, 1081–1107.

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class `gpRegularized`

## Examples

```
# This example shows how to use the optimizers
# for C++ objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(Rcpp)
library(lessSEM)

linreg <- '
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>
```

```

// [[Rcpp::export]]
double fitfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // compute the sum of squared errors:
  arma::mat sse = arma::trans(y-X*b)*(y-X*b);

  // other packages, such as glmnet, scale the sse with
  // 1/(2*N), where N is the sample size. We will do that here as well

  sse *= 1.0/(2.0 * y.n_elem);

  // note: We must return a double, but the sse is a matrix
  // To get a double, just return the single value that is in
  // this matrix:
  return(sse(0,0));
}

// [[Rcpp::export]]
arma::rowvec gradientfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // note: we want to return our gradients as row-vector; therefore,
  // we have to transpose the resulting column-vector:
  arma::rowvec gradients = arma::trans(-2.0*X.t() * y + 2.0*X.t()*X*b);

  // other packages, such as glmnet, scale the sse with
  // 1/(2*N), where N is the sample size. We will do that here as well

  gradients *= (.5/y.n_rows);

  return(gradients);
}

// https://gallery.rcpp.org/articles/passing-cpp-function-pointers/
typedef double (*fitFunPtr)(const Rcpp::NumericVector&, //parameters
                           Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<fitFunPtr> fitFunPtr_t;

typedef arma::rowvec (*gradientFunPtr)(const Rcpp::NumericVector&, //parameters
                                       Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<gradientFunPtr> gradientFunPtr_t;

// [[Rcpp::export]]
fitFunPtr_t fitfunPtr() {

```

```

        return(fitFunPtr_t(new fitFunPtr(&fitfunction)));
    }

    // [[Rcpp::export]]
    gradientFunPtr_t gradfunPtr() {
        return(gradientFunPtr_t(new gradientFunPtr(&gradientfunction)));
    }
    ,

Rcpp::sourceCpp(code = linreg)

ffp <- fitfunPtr()
gfp <- gradfunPtr()

N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
       rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

data <- list("y" = y,
            "X" = cbind(1,X))
parameters <- rep(0, ncol(data$X))
names(parameters) <- paste0("b", 0:(length(parameters)-1))

cL1 <- gpCappedL1Cpp(par = parameters,
                   regularized = paste0("b", 1:(length(b)-1)),
                   fn = ffp,
                   gr = gfp,
                   lambdas = seq(0,1,.1),
                   thetas = seq(0.1,1,.1),
                   additionalArguments = data)

cL1@parameters

```

---

gpElasticNet

*gpElasticNet*


---

## Description

Implements elastic net regularization for general purpose optimization problems. The penalty function is given by:

$$p(x_j) = p(x_j) = \frac{1}{w_j} \lambda |x_j|$$

Note that the elastic net combines ridge and lasso regularization. If  $\alpha = 0$ , the elastic net reduces to ridge regularization. If  $\alpha = 1$  it reduces to lasso regularization. In between, elastic net is a compromise between the shrinkage of the lasso and the ridge penalty.

**Usage**

```
gpElasticNet(
  par,
  regularized,
  fn,
  gr = NULL,
  lambdas,
  alphas,
  ...,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

par	labeled vector with starting values
regularized	vector with names of parameters which are to be regularized.
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
lambdas	numeric vector: values for the tuning parameter lambda
alphas	numeric vector with values of the tuning parameter alpha. Must be between 0 and 1. 0 = ridge, 1 = lasso.
...	additional arguments passed to fn and gr
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

**Details**

The interface is similar to that of `optim`. Users have to supply a vector with starting values (important: This vector *must* have labels) and a fitting function. This fitting functions *must* take a labeled vector with parameter values as first argument. The remaining arguments are passed with the ... argument. This is similar to `optim`.

The gradient function `gr` is optional. If set to NULL, the **numDeriv** package will be used to approximate the gradients. Supplying a gradient function can result in considerable speed improvements.

Elastic net regularization:

- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B*, 67(2), 301–320. <https://doi.org/10.1111/j.1467-9868.2005.00503.x>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class gpRegularized

## Examples

```
# This example shows how to use the optimizers
# for other objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(lessSEM)
set.seed(123)

# first, we simulate data for our
# linear regression.
N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
       rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

# First, we must construct a fitting function
# which returns a single value. We will use
# the residual sum squared as fitting function.

# Let's start setting up the fitting function:
fittingFunction <- function(par, y, X, N){
  # par is the parameter vector
  # y is the observed dependent variable
```

```

# X is the design matrix
# N is the sample size
pred <- X %*% matrix(par, ncol = 1) #be explicit here:
# we need par to be a column vector
sse <- sum((y - pred)^2)
# we scale with .5/N to get the same results as glmnet
return((.5/N)*sse)
}

# let's define the starting values:
b <- c(solve(t(X)%*%X)%*%t(X)%*%y) # we will use the lm estimates
names(b) <- paste0("b", 1:length(b))
# names of regularized parameters
regularized <- paste0("b",1:p)

# optimize
elasticNetPen <- gpElasticNet(
  par = b,
  regularized = regularized,
  fn = fittingFunction,
  lambdas = seq(0,1,.1),
  alphas = c(0, .5, 1),
  X = X,
  y = y,
  N = N
)

# optional: plot requires plotly package
# plot(elasticNetPen)

# for comparison:
fittingFunction <- function(par, y, X, N, lambda, alpha){
  pred <- X %*% matrix(par, ncol = 1)
  sse <- sum((y - pred)^2)
  return((.5/N)*sse + (1-alpha)*lambda * sum(par^2) + alpha*lambda *sum(sqrt(par^2 + 1e-8)))
}

round(
  optim(par = b,
    fn = fittingFunction,
    y = y,
    X = X,
    N = N,
    lambda = elasticNetPen@fits$lambda[15],
    alpha = elasticNetPen@fits$alpha[15],
    method = "BFGS")$par,
  4)
elasticNetPen@parameters[15,]

```



**Description**

Implements elastic net regularization for general purpose optimization problems with C++ functions. The penalty function is given by:

$$p(x_j) = p(x_j) = \frac{1}{w_j} \lambda |x_j|$$

Note that the elastic net combines ridge and lasso regularization. If  $\alpha = 0$ , the elastic net reduces to ridge regularization. If  $\alpha = 1$  it reduces to lasso regularization. In between, elastic net is a compromise between the shrinkage of the lasso and the ridge penalty.

**Usage**

```
gpElasticNetCpp(
  par,
  regularized,
  fn,
  gr,
  lambdas,
  alphas,
  additionalArguments,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

par	labeled vector with starting values
regularized	vector with names of parameters which are to be regularized.
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
lambdas	numeric vector: values for the tuning parameter lambda
alphas	numeric vector with values of the tuning parameter alpha. Must be between 0 and 1. 0 = ridge, 1 = lasso.
additionalArguments	list with additional arguments passed to fn and gr
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

**Details**

The interface is inspired by optim, but a bit more restrictive. Users have to supply a vector with starting values (important: This vector *must* have labels), a fitting function, and a gradient function.

These fitting functions *must* take an `const Rcpp::NumericVector&` with parameter values as first argument and an `Rcpp::List&` as second argument

Elastic net regularization:

- Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B*, 67(2), 301–320. <https://doi.org/10.1111/j.1467-9868.2005.00503.x>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class `gpRegularized`

## Examples

```
# This example shows how to use the optimizers
# for C++ objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(Rcpp)
library(lessSEM)

linreg <- '
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>

// [[Rcpp::export]]
double fitfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
```

```

// extract all required elements:
arma::colvec b = Rcpp::as<arma::colvec>(parameters);
arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

// compute the sum of squared errors:
arma::mat sse = arma::trans(y-X*b)*(y-X*b);

// other packages, such as glmnet, scale the sse with
// 1/(2*N), where N is the sample size. We will do that here as well

sse *= 1.0/(2.0 * y.n_elem);

// note: We must return a double, but the sse is a matrix
// To get a double, just return the single value that is in
// this matrix:
return(sse(0,0));
}

// [[Rcpp::export]]
arma::rowvec gradientfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
// extract all required elements:
arma::colvec b = Rcpp::as<arma::colvec>(parameters);
arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

// note: we want to return our gradients as row-vector; therefore,
// we have to transpose the resulting column-vector:
arma::rowvec gradients = arma::trans(-2.0*X.t() * y + 2.0*X.t()*X*b);

// other packages, such as glmnet, scale the sse with
// 1/(2*N), where N is the sample size. We will do that here as well

gradients *= (.5/y.n_rows);

return(gradients);
}

// Dirk Eddelbuettel at
// https://gallery.rcpp.org/articles/passing-cpp-function-pointers/
typedef double (*fitFunPtr)(const Rcpp::NumericVector&, //parameters
                           Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<fitFunPtr> fitFunPtr_t;

typedef arma::rowvec (*gradientFunPtr)(const Rcpp::NumericVector&, //parameters
                                       Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<gradientFunPtr> gradientFunPtr_t;

// [[Rcpp::export]]
fitFunPtr_t fitfunPtr() {
return(fitFunPtr_t(new fitFunPtr(&fitfunction)));
}

```

```

}

// [[Rcpp::export]]
gradientFunPtr_t gradfunPtr() {
  return(gradientFunPtr_t(new gradientFunPtr(&gradientfunction)));
}
'

Rcpp::sourceCpp(code = linreg)

ffp <- fitfunPtr()
gfp <- gradfunPtr()

N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
      rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

data <- list("y" = y,
           "X" = cbind(1,X))
parameters <- rep(0, ncol(data$X))
names(parameters) <- paste0("b", 0:(length(parameters)-1))

en <- gpElasticNetCpp(par = parameters,
                    regularized = paste0("b", 1:(length(b)-1)),
                    fn = ffp,
                    gr = gfp,
                    lambdas = seq(0,1,.1),
                    alphas = c(0,.5,1),
                    additionalArguments = data)

en@parameters

```

---

gpLasso

*gpLasso*


---

### Description

Implements lasso regularization for general purpose optimization problems. The penalty function is given by:

$$p(x_j) = \lambda|x_j|$$

Lasso regularization will set parameters to zero if  $\lambda$  is large enough

### Usage

```
gpLasso(
```

```

    par,
    regularized,
    fn,
    gr = NULL,
    lambdas = NULL,
    nLambdas = NULL,
    reverse = TRUE,
    curve = 1,
    ...,
    method = "glmnet",
    control = lessSEM::controlGlmnet()
)

```

### Arguments

par	labeled vector with starting values
regularized	vector with names of parameters which are to be regularized.
fn	R function which takes the parameters as input and returns the fit value (a single value)
gr	R function which takes the parameters as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
lambdas	numeric vector: values for the tuning parameter lambda
nLambdas	alternative to lambda: If alpha = 1, lessSEM can automatically compute the first lambda value which sets all regularized parameters to zero. It will then generate nLambda values between 0 and the computed lambda.
reverse	if set to TRUE and nLambdas is used, lessSEM will start with the largest lambda and gradually decrease lambda. Otherwise, lessSEM will start with the smallest lambda and gradually increase it.
curve	Allows for unequally spaced lambda steps (e.g., .01,.02,.05,1,5,20). If curve is close to 1 all lambda values will be equally spaced, if curve is large lambda values will be more concentrated close to 0. See ?lessSEM::curveLambda for more information.
...	additional arguments passed to fn and gr
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

### Details

The interface is similar to that of `optim`. Users have to supply a vector with starting values (important: This vector *must* have labels) and a fitting function. This fitting functions *must* take a labeled vector with parameter values as first argument. The remaining arguments are passed with the ... argument. This is similar to `optim`.

The gradient function `gr` is optional. If set to NULL, the **numDeriv** package will be used to approximate the gradients. Supplying a gradient function can result in considerable speed improvements.

Lasso regularization:

- Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1), 267–288.

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class gpRegularized

## Examples

```
# This example shows how to use the optimizers
# for other objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(lessSEM)
set.seed(123)

# first, we simulate data for our
# linear regression.
N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
      rep(0,6)) # true regression weights
y <- X%*%matrix(b,ncol = 1) + rnorm(N,0,.2)

# First, we must construct a fitting function
```

```

# which returns a single value. We will use
# the residual sum squared as fitting function.

# Let's start setting up the fitting function:
fittingFunction <- function(par, y, X, N){
  # par is the parameter vector
  # y is the observed dependent variable
  # X is the design matrix
  # N is the sample size
  pred <- X %*% matrix(par, ncol = 1) #be explicit here:
  # we need par to be a column vector
  sse <- sum((y - pred)^2)
  # we scale with .5/N to get the same results as glmnet
  return((.5/N)*sse)
}

# let's define the starting values:
b <- rep(0,p)
names(b) <- paste0("b", 1:length(b))
# names of regularized parameters
regularized <- paste0("b",1:p)

# optimize
lassoPen <- gpLasso(
  par = b,
  regularized = regularized,
  fn = fittingFunction,
  nLambdas = 100,
  X = X,
  y = y,
  N = N
)
plot(lassoPen)

# You can access the fit results as follows:
lassoPen@fits
# Note that we won't compute any fit measures automatically, as
# we cannot be sure how the AIC, BIC, etc are defined for your objective function

```

---

gpLassoCpp

*gpLassoCpp*


---

## Description

Implements lasso regularization for general purpose optimization problems with C++ functions. The penalty function is given by:

$$p(x_j) = \lambda|x_j|$$

Lasso regularization will set parameters to zero if  $\lambda$  is large enough

**Usage**

```
gpLassoCpp(
  par,
  regularized,
  fn,
  gr,
  lambdas = NULL,
  nLambdas = NULL,
  curve = 1,
  additionalArguments,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

par	labeled vector with starting values
regularized	vector with names of parameters which are to be regularized.
fn	pointer to Rcpp function which takes the parameters as input and returns the fit value (a single value)
gr	pointer to Rcpp function which takes the parameters as input and returns the gradients of the objective function.
lambdas	numeric vector: values for the tuning parameter lambda
nLambdas	alternative to lambda: If alpha = 1, lessSEM can automatically compute the first lambda value which sets all regularized parameters to zero. It will then generate nLambda values between 0 and the computed lambda.
curve	Allows for unequally spaced lambda steps (e.g., .01,.02,.05,1,5,20). If curve is close to 1 all lambda values will be equally spaced, if curve is large lambda values will be more concentrated close to 0. See ?lessSEM::curveLambda for more information.
additionalArguments	list with additional arguments passed to fn and gr
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

**Details**

The interface is inspired by `optim`, but a bit more restrictive. Users have to supply a vector with starting values (important: This vector *must* have labels), a fitting function, and a gradient function. These fitting functions *must* take an `const Rcpp::NumericVector&` with parameter values as first argument and an `Rcpp::List&` as second argument

Lasso regularization:

- Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1), 267–288.



For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class gpRegularized

## Examples

```
# This example shows how to use the optimizers
# for C++ objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(Rcpp)
library(lessSEM)

linreg <- '
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>

// [[Rcpp::export]]
double fitfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // compute the sum of squared errors:
  arma::mat sse = arma::trans(y-X*b)*(y-X*b);

  // other packages, such as glmnet, scale the sse with
```

```

// 1/(2*N), where N is the sample size. We will do that here as well
sse *= 1.0/(2.0 * y.n_elem);

// note: We must return a double, but the sse is a matrix
// To get a double, just return the single value that is in
// this matrix:
return(sse(0,0));
}

// [[Rcpp::export]]
arma::rowvec gradientfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
// extract all required elements:
arma::colvec b = Rcpp::as<arma::colvec>(parameters);
arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

// note: we want to return our gradients as row-vector; therefore,
// we have to transpose the resulting column-vector:
arma::rowvec gradients = arma::trans(-2.0*X.t() * y + 2.0*X.t()*X*b);

// other packages, such as glmnet, scale the sse with
// 1/(2*N), where N is the sample size. We will do that here as well

gradients *= (.5/y.n_rows);

return(gradients);
}

// Dirk Eddelbuettel at
// https://gallery.rcpp.org/articles/passing-cpp-function-pointers/
typedef double (*fitFunPtr)(const Rcpp::NumericVector&, //parameters
                           Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<fitFunPtr> fitFunPtr_t;

typedef arma::rowvec (*gradientFunPtr)(const Rcpp::NumericVector&, //parameters
                                       Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<gradientFunPtr> gradientFunPtr_t;

// [[Rcpp::export]]
fitFunPtr_t fitfunPtr() {
return(fitFunPtr_t(new fitFunPtr(&fitfunction)));
}

// [[Rcpp::export]]
gradientFunPtr_t gradfunPtr() {
return(gradientFunPtr_t(new gradientFunPtr(&gradientfunction)));
}
,

Rcpp::sourceCpp(code = linreg)

```

```

ffp <- fitfunPtr()
gfp <- gradfunPtr()

N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
      rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

data <- list("y" = y,
            "X" = cbind(1,X))
parameters <- rep(0, ncol(data$X))
names(parameters) <- paste0("b", 0:(length(parameters)-1))

l1 <- gpLassoCpp(par = parameters,
                regularized = paste0("b", 1:(length(b)-1)),
                fn = ffp,
                gr = gfp,
                lambdas = seq(0,1,.1),
                additionalArguments = data)

l1@parameters

```

---

gpLsp

*gpLsp*


---

## Description

Implements lsp regularization for general purpose optimization problems. The penalty function is given by:

## Usage

```

gpLsp(
  par,
  fn,
  gr = NULL,
  ...,
  regularized,
  lambdas,
  thetas,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)

```

**Arguments**

par	labeled vector with starting values
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
...	additional arguments passed to fn and gr
regularized	vector with names of parameters which are to be regularized.
lambdas	numeric vector: values for the tuning parameter lambda
thetas	numeric vector: values for the tuning parameter theta
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

**Details**

The interface is similar to that of `optim`. Users have to supply a vector with starting values (important: This vector must have labels) and a fitting function. This fitting functions must take a labeled vector with parameter values as first argument. The remaining arguments are passed with the ... argument. This is similar to `optim`.

The gradient function `gr` is optional. If set to NULL, the **numDeriv** package will be used to approximate the gradients. Supplying a gradient function can result in considerable speed improvements.

lsp regularization:

- Candès, E. J., Wakin, M. B., & Boyd, S. P. (2008). Enhancing Sparsity by Reweighted  $\ell_1$  Minimization. *Journal of Fourier Analysis and Applications*, 14(5–6), 877–905. <https://doi.org/10.1007/s00041-008-9045-x>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale  $L_1$ -regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for  $\ell_1$ -regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

**Value**

Object of class gpRegularized

**Examples**

```

library(lessSEM)
set.seed(123)

# first, we simulate data for our
# linear regression.
N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
       rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

# First, we must construct a fitting function
# which returns a single value. We will use
# the residual sum squared as fitting function.

# Let's start setting up the fitting function:
fittingFunction <- function(par, y, X, N){
  # par is the parameter vector
  # y is the observed dependent variable
  # X is the design matrix
  # N is the sample size
  pred <- X %% matrix(par, ncol = 1) #be explicit here:
  # we need par to be a column vector
  sse <- sum((y - pred)^2)
  # we scale with .5/N to get the same results as glmnet
  return((.5/N)*sse)
}

# let's define the starting values:
b <- c(solve(t(X)%%X)%%t(X)%%y) # we will use the lm estimates
names(b) <- paste0("b", 1:length(b))
# names of regularized parameters
regularized <- paste0("b",1:p)

# optimize
lspPen <- gpLsp(
  par = b,
  regularized = regularized,
  fn = fittingFunction,
  lambdas = seq(0,1,.1),
  thetas = c(0.001, .5, 1),
  X = X,
  y = y,
  N = N
)

```

```

# optional: plot requires plotly package
# plot(lspPen)

# for comparison

fittingFunction <- function(par, y, X, N, lambda, theta){
  pred <- X %%% matrix(par, ncol = 1)
  sse <- sum((y - pred)^2)
  smoothAbs <- sqrt(par^2 + 1e-8)
  pen <- lambda * log(1.0 + smoothAbs / theta)
  return((.5/N)*sse + sum(pen))
}

round(
  optim(par = b,
        fn = fittingFunction,
        y = y,
        X = X,
        N = N,
        lambda = lspPen@fits$lambda[15],
        theta = lspPen@fits$theta[15],
        method = "BFGS")$par,
  4)
lspPen@parameters[15,]

```

---

gpLspCpp

*gpLspCpp*


---

## Description

Implements lsp regularization for general purpose optimization problems with C++ functions. The penalty function is given by:

$$p(x_j) = \lambda \log(1 + |x_j|/\theta)$$

where  $\theta > 0$ .

## Usage

```

gpLspCpp(
  par,
  fn,
  gr,
  additionalArguments,
  regularized,
  lambdas,
  thetas,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)

```

**Arguments**

par	labeled vector with starting values
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
additionalArguments	list with additional arguments passed to fn and gr
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	numeric vector: values for the tuning parameter theta
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> and <code>controlGlmnet</code> functions. See <code>?controlIsta</code> and <code>?controlGlmnet</code> for more details.

**Details**

The interface is inspired by `optim`, but a bit more restrictive. Users have to supply a vector with starting values (important: This vector must have labels), a fitting function, and a gradient function. These fitting functions must take an `const Rcpp::NumericVector&` with parameter values as first argument and an `Rcpp::List&` as second argument

lsp regularization:

- Candès, E. J., Wakin, M. B., & Boyd, S. P. (2008). Enhancing Sparsity by Reweighted  $\ell_1$  Minimization. *Journal of Fourier Analysis and Applications*, 14(5–6), 877–905. <https://doi.org/10.1007/s00041-008-9045-x>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale  $L_1$ -regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for  $\ell_1$ -regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.

- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class gpRegularized

## Examples

```
# This example shows how to use the optimizers
# for C++ objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(Rcpp)
library(lessSEM)

linreg <- '
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>

// [[Rcpp::export]]
double fitfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // compute the sum of squared errors:
  arma::mat sse = arma::trans(y-X*b)*(y-X*b);

  // other packages, such as glmnet, scale the sse with
  // 1/(2*N), where N is the sample size. We will do that here as well

  sse *= 1.0/(2.0 * y.n_elem);

  // note: We must return a double, but the sse is a matrix
  // To get a double, just return the single value that is in
  // this matrix:
  return(sse(0,0));
}

// [[Rcpp::export]]
arma::rowvec gradientfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // note: we want to return our gradients as row-vector; therefore,
  // we have to transpose the resulting column-vector:
```



```

    arma::rowvec gradients = arma::trans(-2.0*X.t() * y + 2.0*X.t()*X*b);

    // other packages, such as glmnet, scale the sse with
    // 1/(2*N), where N is the sample size. We will do that here as well

    gradients *= (.5/y.n_rows);

    return(gradients);
}

// Dirk Eddelbuettel at
// https://gallery.rcpp.org/articles/passing-cpp-function-pointers/
typedef double (*fitFunPtr)(const Rcpp::NumericVector&, //parameters
                          Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<fitFunPtr> fitFunPtr_t;

typedef arma::rowvec (*gradientFunPtr)(const Rcpp::NumericVector&, //parameters
                                       Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<gradientFunPtr> gradientFunPtr_t;

// [[Rcpp::export]]
fitFunPtr_t fitfunPtr() {
    return(fitFunPtr_t(new fitFunPtr(&fitfunction)));
}

// [[Rcpp::export]]
gradientFunPtr_t gradfunPtr() {
    return(gradientFunPtr_t(new gradientFunPtr(&gradientfunction)));
}

Rcpp::sourceCpp(code = linreg)

ffp <- fitfunPtr()
gfp <- gradfunPtr()

N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
      rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

data <- list("y" = y,
           "X" = cbind(1,X))
parameters <- rep(0, ncol(data$X))
names(parameters) <- paste0("b", 0:(length(parameters)-1))

l <- gpLspCpp(par = parameters,
            regularized = paste0("b", 1:(length(b)-1)),
            fn = ffp,

```

```

gr = gfp,
lambdas = seq(0,1,.1),
thetas = seq(0.1,1,.1),
additionalArguments = data)

```

```
l@parameters
```

---

gpMcp

*gpMcp*


---

### Description

Implements mcp regularization for general purpose optimization problems. The penalty function is given by:

Equation Omitted in Pdf Documentation.

### Usage

```

gpMcp(
  par,
  fn,
  gr = NULL,
  ...,
  regularized,
  lambdas,
  thetas,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)

```

### Arguments

par	labeled vector with starting values
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
...	additional arguments passed to fn and gr
regularized	vector with names of parameters which are to be regularized.
lambdas	numeric vector: values for the tuning parameter lambda
thetas	numeric vector: values for the tuning parameter theta
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

## Details

The interface is similar to that of `optim`. Users have to supply a vector with starting values (important: This vector *must* have labels) and a fitting function. This fitting functions *must* take a labeled vector with parameter values as first argument. The remaining arguments are passed with the ... argument. This is similar to `optim`.

The gradient function `gr` is optional. If set to `NULL`, the **numDeriv** package will be used to approximate the gradients. Supplying a gradient function can result in considerable speed improvements.

mcp regularization:

- Zhang, C.-H. (2010). Nearly unbiased variable selection under minimax concave penalty. *The Annals of Statistics*, 38(2), 894–942. <https://doi.org/10.1214/09-AOS729>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class `gpRegularized`

## Examples

```
# This example shows how to use the optimizers
# for other objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(lessSEM)
set.seed(123)

# first, we simulate data for our
```

```

# linear regression.
N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
       rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

# First, we must construct a fitting function
# which returns a single value. We will use
# the residual sum squared as fitting function.

# Let's start setting up the fitting function:
fittingFunction <- function(par, y, X, N){
  # par is the parameter vector
  # y is the observed dependent variable
  # X is the design matrix
  # N is the sample size
  pred <- X %% matrix(par, ncol = 1) #be explicit here:
  # we need par to be a column vector
  sse <- sum((y - pred)^2)
  # we scale with .5/N to get the same results as glmnet
  return((.5/N)*sse)
}

# let's define the starting values:
# first, let's add an intercept
X <- cbind(1, X)

b <- c(solve(t(X)%%X)%%t(X)%%y) # we will use the lm estimates
names(b) <- paste0("b", 0:(length(b)-1))
# names of regularized parameters
regularized <- paste0("b",1:p)

# optimize
mcpPen <- gpMcp(
  par = b,
  regularized = regularized,
  fn = fittingFunction,
  lambdas = seq(0,1,.1),
  thetas = c(1.001, 1.5, 2),
  X = X,
  y = y,
  N = N
)

# optional: plot requires plotly package
# plot(mcpPen)

```

**Description**

Implements mcp regularization for general purpose optimization problems with C++ functions. The penalty function is given by:

Equation Omitted in Pdf Documentation.

**Usage**

```
gpMcpCpp(
  par,
  fn,
  gr,
  additionalArguments,
  regularized,
  lambdas,
  thetas,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

par	labeled vector with starting values
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
additionalArguments	list with additional arguments passed to fn and gr
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use getLavaanParameters(model) with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	numeric vector: values for the tuning parameter theta
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

**Details**

The interface is inspired by optim, but a bit more restrictive. Users have to supply a vector with starting values (important: This vector *must* have labels), a fitting function, and a gradient function. These fitting functions *must* take an `const Rcpp::NumericVector&` with parameter values as first argument and an `Rcpp::List&` as second argument

mcp regularization:

- Zhang, C.-H. (2010). Nearly unbiased variable selection under minimax concave penalty. *The Annals of Statistics*, 38(2), 894–942. <https://doi.org/10.1214/09-AOS729>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class gpRegularized

## Examples

```
# This example shows how to use the optimizers
# for C++ objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(Rcpp)
library(lessSEM)

linreg <- '
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>

// [[Rcpp::export]]
double fitfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // compute the sum of squared errors:
```

```

    arma::mat sse = arma::trans(y-X*b)*(y-X*b);

    // other packages, such as glmnet, scale the sse with
    // 1/(2*N), where N is the sample size. We will do that here as well

    sse *= 1.0/(2.0 * y.n_elem);

    // note: We must return a double, but the sse is a matrix
    // To get a double, just return the single value that is in
    // this matrix:
    return(sse(0,0));
}

// [[Rcpp::export]]
arma::rowvec gradientfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
    // extract all required elements:
    arma::colvec b = Rcpp::as<arma::colvec>(parameters);
    arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
    arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

    // note: we want to return our gradients as row-vector; therefore,
    // we have to transpose the resulting column-vector:
    arma::rowvec gradients = arma::trans(-2.0*X.t() * y + 2.0*X.t()*X*b);

    // other packages, such as glmnet, scale the sse with
    // 1/(2*N), where N is the sample size. We will do that here as well

    gradients *= (.5/y.n_rows);

    return(gradients);
}

// Dirk Eddelbuettel at
// https://gallery.rcpp.org/articles/passing-cpp-function-pointers/
typedef double (*fitFunPtr)(const Rcpp::NumericVector&, //parameters
                          Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<fitFunPtr> fitFunPtr_t;

typedef arma::rowvec (*gradientFunPtr)(const Rcpp::NumericVector&, //parameters
                                       Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<gradientFunPtr> gradientFunPtr_t;

// [[Rcpp::export]]
fitFunPtr_t fitfunPtr() {
    return(fitFunPtr_t(new fitFunPtr(&fitfunction)));
}

// [[Rcpp::export]]
gradientFunPtr_t gradfunPtr() {
    return(gradientFunPtr_t(new gradientFunPtr(&gradientfunction)));
}

```

```

,

Rcpp::sourceCpp(code = linreg)

ffp <- fitfunPtr()
gfp <- gradfunPtr()

N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
      rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

data <- list("y" = y,
            "X" = cbind(1,X))
parameters <- rep(0, ncol(data$X))
names(parameters) <- paste0("b", 0:(length(parameters)-1))

m <- gpMcpCpp(par = parameters,
              regularized = paste0("b", 1:(length(b)-1)),
              fn = ffp,
              gr = gfp,
              lambdas = seq(0,1,.1),
              thetas = seq(.1,1,.1),
              additionalArguments = data)

m@parameters

```

---

gpRegularized-class    *Class for regularized model using general purpose optimization interface*

---

### Description

Class for regularized model using general purpose optimization interface

### Slots

penalty penalty used (e.g., "lasso")  
parameters data.frame with all parameter estimates  
fits data.frame with all fit results  
parameterLabels character vector with names of all parameters  
weights vector with weights given to each of the parameters in the penalty  
regularized character vector with names of regularized parameters  
internalOptimization list of elements used internally  
inputArguments list with elements passed by the user to the general purpose optimizer



gpRidge

*gpRidge***Description**

Implements ridge regularization for general purpose optimization problems. The penalty function is given by:

$$p(x_j) = \lambda x_j^2$$

Note that ridge regularization will not set any of the parameters to zero but result in a shrinkage towards zero.

**Usage**

```
gpRidge(
  par,
  regularized,
  fn,
  gr = NULL,
  lambdas,
  ...,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

par	labeled vector with starting values
regularized	vector with names of parameters which are to be regularized.
fn	R function which takes the parameters as input and returns the fit value (a single value)
gr	R function which takes the parameters as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
lambdas	numeric vector: values for the tuning parameter lambda
...	additional arguments passed to fn and gr
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

**Details**

The interface is similar to that of optim. Users have to supply a vector with starting values (important: This vector *must* have labels) and a fitting function. This fitting functions *must* take a labeled vector with parameter values as first argument. The remaining arguments are passed with the ... argument. This is similar to optim.

The gradient function `gr` is optional. If set to `NULL`, the **numDeriv** package will be used to approximate the gradients. Supplying a gradient function can result in considerable speed improvements.

Ridge regularization:

- Hoerl, A. E., & Kennard, R. W. (1970). Ridge Regression: Biased Estimation for Nonorthogonal Problems. *Technometrics*, 12(1), 55–67. <https://doi.org/10.1080/00401706.1970.10488634>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class `gpRegularized`

## Examples

```
# This example shows how to use the optimizers
# for other objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(lessSEM)
set.seed(123)

# first, we simulate data for our
# linear regression.
N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
       rep(0,6)) # true regression weights
y <- X%*%matrix(b,ncol = 1) + rnorm(N,0,.2)
```

```

# First, we must construct a fitting function
# which returns a single value. We will use
# the residual sum squared as fitting function.

# Let's start setting up the fitting function:
fittingFunction <- function(par, y, X, N){
  # par is the parameter vector
  # y is the observed dependent variable
  # X is the design matrix
  # N is the sample size
  pred <- X %>% matrix(par, ncol = 1) #be explicit here:
  # we need par to be a column vector
  sse <- sum((y - pred)^2)
  # we scale with .5/N to get the same results as glmnet
  return((.5/N)*sse)
}

# let's define the starting values:
b <- c(solve(t(X)%*%X)%*%t(X)%*%y) # we will use the lm estimates
names(b) <- paste0("b", 1:length(b))
# names of regularized parameters
regularized <- paste0("b",1:p)

# optimize
ridgePen <- gpRidge(
  par = b,
  regularized = regularized,
  fn = fittingFunction,
  lambdas = seq(0,1,.01),
  X = X,
  y = y,
  N = N
)
plot(ridgePen)

# for comparison:
# fittingFunction <- function(par, y, X, N, lambda){
#   pred <- X %>% matrix(par, ncol = 1)
#   sse <- sum((y - pred)^2)
#   return((.5/N)*sse + lambda * sum(par^2))
# }
#
# optim(par = b,
#       fn = fittingFunction,
#       y = y,
#       X = X,
#       N = N,
#       lambda = ridgePen@fits$lambda[20],
#       method = "BFGS")$par
# ridgePen@parameters[20,]

```

gpRidgeCpp

*gpRidgeCpp***Description**

Implements ridge regularization for general purpose optimization problems with C++ functions. The penalty function is given by:

$$p(x_j) = \lambda x_j^2$$

Note that ridge regularization will not set any of the parameters to zero but result in a shrinkage towards zero.

**Usage**

```
gpRidgeCpp(
  par,
  regularized,
  fn,
  gr,
  lambdas,
  additionalArguments,
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

par	labeled vector with starting values
regularized	vector with names of parameters which are to be regularized.
fn	R function which takes the parameters as input and returns the fit value (a single value)
gr	R function which takes the parameters as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
lambdas	numeric vector: values for the tuning parameter lambda
additionalArguments	list with additional arguments passed to fn and gr
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

## Details

The interface is inspired by `optim`, but a bit more restrictive. Users have to supply a vector with starting values (important: This vector *must* have labels), a fitting function, and a gradient function. These fitting functions *must* take an `const Rcpp::NumericVector&` with parameter values as first argument and an `Rcpp::List&` as second argument

Ridge regularization:

- Hoerl, A. E., & Kennard, R. W. (1970). Ridge Regression: Biased Estimation for Nonorthogonal Problems. *Technometrics*, 12(1), 55–67. <https://doi.org/10.1080/00401706.1970.10488634>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class `gpRegularized`

## Examples

```
# This example shows how to use the optimizers
# for C++ objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(Rcpp)
library(lessSEM)

linreg <- '
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>
```

```

// [[Rcpp::export]]
double fitfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // compute the sum of squared errors:
  arma::mat sse = arma::trans(y-X*b)*(y-X*b);

  // other packages, such as glmnet, scale the sse with
  // 1/(2*N), where N is the sample size. We will do that here as well

  sse *= 1.0/(2.0 * y.n_elem);

  // note: We must return a double, but the sse is a matrix
  // To get a double, just return the single value that is in
  // this matrix:
  return(sse(0,0));
}

// [[Rcpp::export]]
arma::rowvec gradientfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // note: we want to return our gradients as row-vector; therefore,
  // we have to transpose the resulting column-vector:
  arma::rowvec gradients = arma::trans(-2.0*X.t() * y + 2.0*X.t()*X*b);

  // other packages, such as glmnet, scale the sse with
  // 1/(2*N), where N is the sample size. We will do that here as well

  gradients *= (.5/y.n_rows);

  return(gradients);
}

// https://gallery.rcpp.org/articles/passing-cpp-function-pointers/
typedef double (*fitFunPtr)(const Rcpp::NumericVector&, //parameters
                             Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<fitFunPtr> fitFunPtr_t;

typedef arma::rowvec (*gradientFunPtr)(const Rcpp::NumericVector&, //parameters
                                       Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<gradientFunPtr> gradientFunPtr_t;

// [[Rcpp::export]]
fitFunPtr_t fitfunPtr() {

```

```

        return(fitFunPtr_t(new fitFunPtr(&fitfunction)));
    }

    // [[Rcpp::export]]
    gradientFunPtr_t gradfunPtr() {
        return(gradientFunPtr_t(new gradientFunPtr(&gradientfunction)));
    }
    ,

Rcpp::sourceCpp(code = linreg)

ffp <- fitfunPtr()
gfp <- gradfunPtr()

N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
       rep(0,6)) # true regression weights
y <- X%*%matrix(b,ncol = 1) + rnorm(N,0,.2)

data <- list("y" = y,
            "X" = cbind(1,X))
parameters <- rep(0, ncol(data$X))
names(parameters) <- paste0("b", 0:(length(parameters)-1))

r <- gpRidgeCpp(par = parameters,
               regularized = paste0("b", 1:(length(b)-1)),
               fn = ffp,
               gr = gfp,
               lambdas = seq(0,1,.1),
               additionalArguments = data)

r@parameters

```

---

gpScad

*gpScad*


---

### Description

Implements scad regularization for general purpose optimization problems. The penalty function is given by:

Equation Omitted in Pdf Documentation.

### Usage

```
gpScad(
  par,
```

```

fn,
gr = NULL,
...,
regularized,
lambdas,
thetas,
method = "glmnet",
control = lessSEM::controlGlmnet()
)

```

### Arguments

par	labeled vector with starting values
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
...	additional arguments passed to fn and gr
regularized	vector with names of parameters which are to be regularized.
lambdas	numeric vector: values for the tuning parameter lambda
thetas	numeric vector: values for the tuning parameter theta
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

### Details

The interface is similar to that of `optim`. Users have to supply a vector with starting values (important: This vector *must* have labels) and a fitting function. This fitting functions *must* take a labeled vector with parameter values as first argument. The remaining arguments are passed with the ... argument. This is similar to `optim`.

The gradient function `gr` is optional. If set to NULL, the **numDeriv** package will be used to approximate the gradients. Supplying a gradient function can result in considerable speed improvements.

scad regularization:

- Fan, J., & Li, R. (2001). Variable selection via nonconcave penalized likelihood and its oracle properties. *Journal of the American Statistical Association*, 96(456), 1348–1360. <https://doi.org/10.1198/016214501753>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.



- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class gpRegularized

## Examples

```
# This example shows how to use the optimizers
# for other objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(lessSEM)
set.seed(123)

# first, we simulate data for our
# linear regression.
N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),
      rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

# First, we must construct a fitting function
# which returns a single value. We will use
# the residual sum squared as fitting function.

# Let's start setting up the fitting function:
fittingFunction <- function(par, y, X, N){
  # par is the parameter vector
  # y is the observed dependent variable
  # X is the design matrix
  # N is the sample size
  pred <- X %% matrix(par, ncol = 1) #be explicit here:
  # we need par to be a column vector
  sse <- sum((y - pred)^2)
  # we scale with .5/N to get the same results as glmnet
```

```

    return((.5/N)*sse)
  }

# let's define the starting values:
# first, let's add an intercept
X <- cbind(1, X)

b <- c(solve(t(X)%*%X)%*%t(X)%*%y) # we will use the lm estimates
names(b) <- paste0("b", 0:(length(b)-1))
# names of regularized parameters
regularized <- paste0("b",1:p)

# optimize
scadPen <- gpScad(
  par = b,
  regularized = regularized,
  fn = fittingFunction,
  lambdas = seq(0,1,.1),
  thetas = c(2.001, 2.5, 5),
  X = X,
  y = y,
  N = N
)

# optional: plot requires plotly package
# plot(scadPen)

# for comparison
#library(ncvreg)
#scadFit <- ncvreg(X = X[,-1],
#                 y = y,
#                 penalty = "SCAD",
#                 lambda = scadPen@fits$lambda[15],
#                 gamma = scadPen@fits$theta[15])
#coef(scadFit)
#scadPen@parameters[15,]

```

---

gpScadCpp

*gpScadCpp*


---

### Description

Implements scad regularization for general purpose optimization problems with C++ functions. The penalty function is given by:

Equation Omitted in Pdf Documentation.

### Usage

```

gpScadCpp(
  par,

```

```

    fn,
    gr,
    additionalArguments,
    regularized,
    lambdas,
    thetas,
    method = "glmnet",
    control = lessSEM::controlGlmnet()
)

```

### Arguments

par	labeled vector with starting values
fn	R function which takes the parameters AND their labels as input and returns the fit value (a single value)
gr	R function which takes the parameters AND their labels as input and returns the gradients of the objective function. If set to NULL, numDeriv will be used to approximate the gradients
additionalArguments	list with additional arguments passed to fn and gr
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use getLavaanParameters(model) with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	numeric vector: values for the tuning parameter theta
method	which optimizer should be used? Currently implemented are ista and glmnet.
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

### Details

The interface is inspired by optim, but a bit more restrictive. Users have to supply a vector with starting values (important: This vector *must* have labels), a fitting function, and a gradient function. These fitting functions *must* take an `const Rcpp::NumericVector&` with parameter values as first argument and an `Rcpp::List&` as second argument

scad regularization:

- Fan, J., & Li, R. (2001). Variable selection via nonconcave penalized likelihood and its oracle properties. *Journal of the American Statistical Association*, 96(456), 1348–1360. <https://doi.org/10.1198/016214501753>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.

- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Object of class gpRegularized

## Examples

```
# This example shows how to use the optimizers
# for C++ objective functions. We will use
# a linear regression as an example. Note that
# this is not a useful application of the optimizers
# as there are specialized packages for linear regression
# (e.g., glmnet)

library(Rcpp)
library(lessSEM)

linreg <- '
// [[Rcpp::depends(RcppArmadillo)]]
#include <RcppArmadillo.h>

// [[Rcpp::export]]
double fitfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // compute the sum of squared errors:
  arma::mat sse = arma::trans(y-X*b)*(y-X*b);

  // other packages, such as glmnet, scale the sse with
  // 1/(2*N), where N is the sample size. We will do that here as well

  sse *= 1.0/(2.0 * y.n_elem);

  // note: We must return a double, but the sse is a matrix
  // To get a double, just return the single value that is in
  // this matrix:
  return(sse(0,0));
}
```

```

}

// [[Rcpp::export]]
arma::rowvec gradientfunction(const Rcpp::NumericVector& parameters, Rcpp::List& data){
  // extract all required elements:
  arma::colvec b = Rcpp::as<arma::colvec>(parameters);
  arma::colvec y = Rcpp::as<arma::colvec>(data["y"]); // the dependent variable
  arma::mat X = Rcpp::as<arma::mat>(data["X"]); // the design matrix

  // note: we want to return our gradients as row-vector; therefore,
  // we have to transpose the resulting column-vector:
  arma::rowvec gradients = arma::trans(-2.0*X.t() * y + 2.0*X.t()*X*b);

  // other packages, such as glmnet, scale the sse with
  // 1/(2*N), where N is the sample size. We will do that here as well

  gradients *= (.5/y.n_rows);

  return(gradients);
}

// Dirk Eddelbuettel at
// https://gallery.rcpp.org/articles/passing-cpp-function-pointers/
typedef double (*fitFunPtr)(const Rcpp::NumericVector&, //parameters
                          Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<fitFunPtr> fitFunPtr_t;

typedef arma::rowvec (*gradientFunPtr)(const Rcpp::NumericVector&, //parameters
                                       Rcpp::List& //additional elements
);
typedef Rcpp::XPtr<gradientFunPtr> gradientFunPtr_t;

// [[Rcpp::export]]
fitFunPtr_t fitfunPtr() {
  return(fitFunPtr_t(new fitFunPtr(&fitfunction)));
}

// [[Rcpp::export]]
gradientFunPtr_t gradfunPtr() {
  return(gradientFunPtr_t(new gradientFunPtr(&gradientfunction)));
}

Rcpp::sourceCpp(code = linreg)

ffp <- fitfunPtr()
gfp <- gradfunPtr()

N <- 100 # number of persons
p <- 10 # number of predictors
X <- matrix(rnorm(N*p), nrow = N, ncol = p) # design matrix
b <- c(rep(1,4),

```

```

      rep(0,6)) # true regression weights
y <- X%%matrix(b,ncol = 1) + rnorm(N,0,.2)

data <- list("y" = y,
            "X" = cbind(1,X))
parameters <- rep(0, ncol(data$X))
names(parameters) <- paste0("b", 0:(length(parameters)-1))

s <- gpScadCpp(par = parameters,
              regularized = paste0("b", 1:(length(b)-1)),
              fn = ffp,
              gr = gfp,
              lambdas = seq(0,1,.1),
              thetas = seq(2.1,3,.1),
              additionalArguments = data)

s@parameters

```

---

<code>istaCappedL1mgSEM</code>	<i>cappedL1 optimization with ista</i>
--------------------------------	--

---

**Description**

Object for elastic net optimization with ista optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta value, a lambda and an alpha value (alpha must be 1).

---

<code>istaCappedL1SEM</code>	<i>cappedL1 optimization with ista</i>
------------------------------	--

---

**Description**

Object for elastic net optimization with ista optimizer

**Value**

a list with fit results

**Fields**

- new creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements
- optimize optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta value, a lambda and an alpha value (alpha must be 1).

---

 istaEnetGeneralPurpose

*elastic net optimization with ista*


---

**Description**

Object for elastic net optimization with ista optimizer

**Value**

a list with fit results

**Fields**

- new creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements
- optimize optimize the model. Expects a vector with starting values, an R function to compute the fit, an R function to compute the gradients, a list with elements the fit and gradient function require, a lambda and an alpha value.

---

 istaEnetGeneralPurposeCpp

*elastic net optimization with ista*


---

**Description**

Object for elastic net optimization with ista optimizer

**Value**

a list with fit results

**Fields**

- new creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements
- optimize optimize the model. Expects a vector with starting values, a SEXP function pointer to compute the fit, a SEXP function pointer to compute the gradients, a list with elements the fit and gradient function require, a lambda and an alpha value.

---

istaEnetMgSEM      *elastic net optimization with ista optimizer*

---

**Description**

Object for elastic net optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a lambda and an alpha value.

---

istaEnetSEM      *elastic net optimization with ista optimizer*

---

**Description**

Object for elastic net optimization with glmnet optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a lambda and an alpha value.



---

`istaLSPMgSEM`*lsp optimization with ista*

---

**Description**

Object for lsp optimization with ista optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

`istaLSPSEM`*lsp optimization with ista*

---

**Description**

Object for lsp optimization with ista optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

istaMcpMgSEM	<i>mcp optimization with ista</i>
--------------	-----------------------------------

---

**Description**

Object for mcp optimization with ista optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

istaMcpSEM	<i>mcp optimization with ista</i>
------------	-----------------------------------

---

**Description**

Object for mcp optimization with ista optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

istaMixedPenaltyGeneralPurpose  
*mixed penalty optimization with ista*

---

**Description**

Object for elastic net optimization with ista optimizer

**Value**

a list with fit results

**Fields**

new creates a new object.

optimize optimize the model.

---

istaMixedPenaltyGeneralPurposeCpp  
*mixed penalty optimization with ista*

---

**Description**

Object for elastic net optimization with ista optimizer

**Value**

a list with fit results

**Fields**

new creates a new object. Requires (1) a vector with weights for each parameter, (2) a vector indicating which penalty is used, and (3) a list with control elements

optimize optimize the model.

istaMixedPenaltySEM *mixed penalty optimization with ista*

---

**Description**

Object for elastic net optimization with ista optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter, (2) a vector indicating which penalty is used, and (3) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta value, a lambda and an alpha value (alpha must be 1).

---

istaMixedPenaltySEM *mixed penalty optimization with ista*

---

**Description**

Object for elastic net optimization with ista optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter, (2) a vector indicating which penalty is used, and (3) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta value, a lambda and an alpha value (alpha must be 1).

---

istaScadMgSEM	<i>scad optimization with ista</i>
---------------	------------------------------------

---

**Description**

Object for scad optimization with ista optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

---

istaScadSEM	<i>scad optimization with ista</i>
-------------	------------------------------------

---

**Description**

Object for scad optimization with ista optimizer

**Value**

a list with fit results

**Fields**

`new` creates a new object. Requires (1) a vector with weights for each parameter and (2) a list with control elements

`optimize` optimize the model. Expects a vector with starting values, a SEM of type SEM\_Cpp, a theta and a lambda value.

lasso

*lasso***Description**

Implements lasso regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda|x_j|$$

Lasso regularization will set parameters to zero if  $\lambda$  is large enough

**Usage**

```
lasso(
  lavaanModel,
  regularized,
  lambdas = NULL,
  nLambdas = NULL,
  reverse = TRUE,
  curve = 1,
  method = "glmnet",
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
nLambdas	alternative to lambda: If <code>alpha = 1</code> , <code>lessSEM</code> can automatically compute the first lambda value which sets all regularized parameters to zero. It will then generate <code>nLambda</code> values between 0 and the computed lambda.
reverse	if set to <code>TRUE</code> and <code>nLambdas</code> is used, <code>lessSEM</code> will start with the largest lambda and gradually decrease lambda. Otherwise, <code>lessSEM</code> will start with the smallest lambda and gradually increase it.
curve	Allows for unequally spaced lambda steps (e.g., .01,.02,.05,1,5,20). If curve is close to 1 all lambda values will be equally spaced, if curve is large lambda values will be more concentrated close to 0. See <code>?lessSEM::curveLambda</code> for more information.
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the control argument can be used to switch to related procedures (currently <code>gist</code> ).
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> and <code>controlGlmnet</code> functions. See <code>?controlIsta</code> and <code>?controlGlmnet</code> for more details.

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Lasso regularization:

- Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1), 267–288.

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class `regularizedSEM`

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.
```

```

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- lasso(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  # in case of lasso and adaptive lasso, we can specify the number of lambda
  # values to use. lessSEM will automatically find lambda_max and fit
  # models for nLambda values between 0 and lambda_max. For the other
  # penalty functions, lambdas must be specified explicitly
  nLambdas = 50)

# use the plot-function to plot the regularized parameters:
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

# fit Measures:
fitIndices(lsem)

# The best parameters can also be extracted with:
coef(lsem, criterion = "AIC")
# or
estimates(lsem, criterion = "AIC")

#### Advanced ###
# Switching the optimizer #
# Use the "method" argument to switch the optimizer. The control argument
# must also be changed to the corresponding function:

```



```

lsemIsta <- lasso(
  lavaanModel = lavaanModel,
  regularized = paste0("l", 6:15),
  nLambdas = 50,
  method = "ista",
  control = controlIsta())

# Note: The results are basically identical:
lsemIsta@parameters - lsem@parameters

```

---

lavaan2lslxLabels	<i>lavaan2lslxLabels</i>
-------------------	--------------------------

---

## Description

helper function: lsx and lavaan use slightly different parameter labels. This function can be used to get both sets of labels.

## Usage

```
lavaan2lslxLabels(lavaanModel)
```

## Arguments

lavaanModel      model of class lavaan

## Value

list with lavaan labels and lsx labels

## Examples

```

library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,

```

```

                                std.lv = TRUE)

lavaan2ls1xLabels(lavaanModel)

```

---

lessSEM2Lavaan	<i>lessSEM2Lavaan</i>
----------------	-----------------------

---

### Description

Creates a lavaan model object from lessSEM (only if possible). Pass either a criterion or a combination of lambda, alpha, and theta.

### Usage

```

lessSEM2Lavaan(
  regularizedSEM,
  criterion = NULL,
  lambda = NULL,
  alpha = NULL,
  theta = NULL
)

```

### Arguments

regularizedSEM	object created with lessSEM
criterion	criterion used for model selection. Currently supported are "AIC" or "BIC"
lambda	value for tuning parameter lambda
alpha	value for tuning parameter alpha
theta	value for tuning parameter theta

### Value

lavaan model

### Examples

```

library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15

```

```

f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:
regularized <- lasso(lavaanModel,
                    regularized = paste0("1", 11:15),
                    lambdas = seq(0,1,.1))

# using criterion
lessSEM2Lavaan(regularizedSEM = regularized,
               criterion = "AIC")

# using tuning parameters (note: we only have to specify the tuning
# parameters that are actually used by the penalty function. In case
# of lasso, this is lambda):
lessSEM2Lavaan(regularizedSEM = regularized,
               lambda = 1)

```

---

lessSEMCoef-class	<i>Class for the coefficients estimated by lessSEM.</i>
-------------------	---

---

### Description

Class for the coefficients estimated by lessSEM.

### Slots

tuningParameters tuning parameters  
 estimates parameter estimates  
 transformations transformations of parameters

---

loadings	<i>loadings</i>
----------	-----------------

---

### Description

Extract the labels of all loadings found in a lavaan model.

### Usage

```
loadings(lavaanModel)
```

**Arguments**

lavaanModel      fitted lavaan model

**Value**

vector with parameter labels

**Examples**

```
# The following is adapted from ?lavaan::sem
library(lessSEM)
model <- '
  # latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + a*y2 + b*y3 + c*y4
  dem65 =~ y5 + a*y6 + b*y7 + c*y8

  # regressions
  dem60 ~ ind60
  dem65 ~ ind60 + dem60

  # residual correlations
  y1 ~~ y5
  y2 ~~ y4 + y6
  y3 ~~ y7
  y4 ~~ y8
  y6 ~~ y8
  '

fit <- sem(model, data = PoliticalDemocracy)

loadings(fit)
```

---

logicalMatch

*logicalMatch*

---

**Description**

Returns the rows for which all elements of a boolean matrix *X* are equal to the elements in boolean vector *x*

**Usage**

```
logicalMatch(X, x)
```

**Arguments**

*X*                      matrix with booleans  
*x*                        vector of booleans

**Value**

numerical vector with indices of matching rows

---

logLik,Rcpp\_mgSEM-method  
*logLik*

---

**Description**

logLik

**Usage**

```
## S4 method for signature 'Rcpp_mgSEM'
logLik(object, ...)
```

**Arguments**

object	object of class Rcpp_mgSEM
...	not used

**Value**

log-likelihood of the model

---

logLik,Rcpp\_SEMCpp-method  
*logLik*

---

**Description**

logLik

**Usage**

```
## S4 method for signature 'Rcpp_SEMCpp'
logLik(object, ...)
```

**Arguments**

object	object of class Rcpp_SEMCpp
...	not used

**Value**

log-likelihood of the model

---

logLikelihood-class	<i>Class for log-likelihood of regularized SEM. Note: we define a custom logLik - Function because the generic one is using df = number of parameters which might be confusing.</i>
---------------------	---

---

### Description

Class for log-likelihood of regularized SEM. Note: we define a custom logLik - Function because the generic one is using df = number of parameters which might be confusing.

### Slots

logLik log-Likelihood  
 nParameters number of parameters in the model  
 N number of persons in the data set

---

lsp	<i>lsp</i>
-----	------------

---

### Description

Implements lsp regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda \log(1 + |x_j|/\theta)$$

where  $\theta > 0$ .

### Usage

```
lsp(
  lavaanModel,
  regularized,
  lambdas,
  thetas,
  modifyModel = lessSEM::modifyModel(),
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

## Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the <code>control</code> argument can be used to switch to related procedures
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> (see <code>?controlIsta</code> )

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Isp regularization:

- Candès, E. J., Wakin, M. B., & Boyd, S. P. (2008). Enhancing Sparsity by Reweighted  $\ell_1$  Minimization. *Journal of Fourier Analysis and Applications*, 14(5–6), 877–905. <https://doi.org/10.1007/s00041-008-9045-x>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale  $L_1$ -regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for  $\ell_1$ -regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>

- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class `regularizedSEM`

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- lsp(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 20),
  thetas = seq(0.01,2,length.out = 5))

# the coefficients can be accessed with:
coef(lsem)
# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)$estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]
```



```
# fit Measures:
fitIndices(lsem)

# The best parameters can also be extracted with:
coef(lsem, criterion = "AIC")
# or
estimates(lsem, criterion = "AIC")

# optional: plotting the paths requires installation of plotly
# plot(lsem)
```

---

makePtrs

*makePtrs*

---

## Description

This function helps you create the pointers necessary to use the Cpp interface

## Usage

```
makePtrs(fitFunName, gradFunName)
```

## Arguments

fitFunName	name of your C++ fit function (IMPORTANT: This must be the name used in C++)
gradFunName	name of your C++ gradient function (IMPORTANT: This must be the name used in C++)

## Value

a string which can be copied in the C++ function to create the pointers.

## Examples

```
# see vignette("General-Purpose-Optimization", package = "lessSEM") for an example
```

mcp

*mcp***Description**

Implements mcp regularization for structural equation models. The penalty function is given by:  
Equation Omitted in Pdf Documentation.

**Usage**

```
mcp(
  lavaanModel,
  regularized,
  lambdas,
  thetas,
  modifyModel = lessSEM::modifyModel(),
  method = "ista",
  control = lessSEM::controlIsta()
)
```

**Arguments**

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the <code>control</code> argument can be used to switch to related procedures (currently <code>gist</code> ).
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> (see <code>?controlIsta</code> )

**Details**

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

In our experience, the `glmnet` optimizer can run in issues with the mcp penalty. Therefore, we default to using `ista`.

mcp regularization:

- Zhang, C.-H. (2010). Nearly unbiased variable selection under minimax concave penalty. *The Annals of Statistics*, 38(2), 894–942. <https://doi.org/10.1214/09-AOS729>

#### Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class regularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"
```

```

lavaanModel <- lavaan::sem(lavaanSyntax,
                          data = dataset,
                          meanstructure = TRUE,
                          std.lv = TRUE)

# Regularization:

lsem <- mcp(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 20),
  thetas = seq(0.01,2,length.out = 5))

# the coefficients can be accessed with:
coef(lsem)

# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

# fit Measures:
fitIndices(lsem)

# The best parameters can also be extracted with:
coef(lsem, criterion = "AIC")
# or
estimates(lsem, criterion = "AIC")

# optional: plotting the paths requires installation of plotly
# plot(lsem)

```

---

mcpPenalty\_C

*mcpPenalty\_C*


---

## Description

mcpPenalty\_C

## Usage

mcpPenalty\_C(par, lambda\_p, theta)

**Arguments**

par	single parameter value
lambda_p	lambda value for this parameter
theta	theta value for this parameter

**Value**

penalty value

---

mgSEM

*mgSEM class*

---

**Description**

internal mgSEM representation

**Fields**

`new` Creates a new mgSEM.

`addModel` add a model. Expects `Rcpp::List`

`addTransformation` adds transformations to a model

`implied` Computes implied means and covariance matrix

`fit` Fits the model. Returns objective value of the fitting function

`getParameters` Returns a data frame with model parameters.

`getParameterLabels` Returns a vector with unique parameter labels as used internally.

`getEstimator` Returns a vector with names of the estimators used in the submodels.

`getGradients` Returns a matrix with scores.

`getScores` Returns a matrix with scores. Not yet implemented

`getHessian` Returns the hessian of the model. Expects the labels of the parameters and the values of the parameters as well as a boolean indicating if these are raw. Finally, a double (eps) controls the precision of the approximation.

`computeTransformations` compute the transformations.

`setTransformationGradientStepSize` change the step size of the gradient computation for the transformations

mixedPenalty

*mixedPenalty***Description**

Provides possibility to impose different penalties on different parameters.

**Usage**

```
mixedPenalty(
  lavaanModel,
  modifyModel = lessSEM::modifyModel(),
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)
```

**Arguments**

lavaanModel	model of class lavaan
modifyModel	used to modify the lavaanModel. See ?modifyModel.
method	which optimizer should be used? Currently supported are "glmnet" and "ista".
control	used to control the optimizer. This element is generated with the controlIsta and controlGlmnet functions. See ?controlIsta and ?controlGlmnet for more details.

**Details**

The `mixedPenalty` function allows you to add multiple penalties to a single model. For instance, you may want to regularize both loadings and regressions in a SEM. In this case, using the same penalty (e.g., lasso) for both types of penalties may actually not be what you want to use because the penalty function is sensitive to the scales of the parameters. Instead, you may want to use two separate lasso penalties for loadings and regressions. Similarly, separate penalties for different parameters have, for instance, been proposed in multi-group models (Geminiani et al., 2021).

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well. Models are fitted with the `glmnet` or `ista` optimizer. Note that the optimizers differ in which penalties they support. The following table provides an overview:

Penalty	Function	glmnet	ista
lasso	addLasso	x	x
elastic net	addElasticNet	x*	-
cappedL1	addCappedL1	x	x
lsp	addLsp	x	x
scad	addScad	x	x
mcp	addMcp	x	x

By default, `glmnet` will be used. Note that the elastic net penalty can only be combined with other elastic net penalties.

Check vignette(topic = "Mixed-Penalties", package = "lessSEM") for more details.

#### Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Geminiani, E., Marra, G., & Moustaki, I. (2021). Single- and multiple-group penalized factor analysis: A trust-region algorithm approach with integrated automatic multiple tuning parameter selection. *Psychometrika*, 86(1), 65–95. <https://doi.org/10.1007/s11336-021-09751-8>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

## Value

Model of class `regularizedSEM`

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
```

```

meanstructure = TRUE,
std.lv = TRUE)

# Regularization:

# In this example, we want to regularize the loadings l6-l10
# independently of the loadings l11-15. This could, for instance,
# reflect that the items y6-y10 and y11-y15 may belong to different
# subscales.

regularized <- lavaanModel |>
  # create template for regularized model with mixed penalty:
  mixedPenalty() |>
  # add lasso penalty on loadings l6 - l10:
  addLasso(regularized = paste0("l", 6:10),
           lambdas = seq(0,1,length.out = 4)) |>
  # add scad penalty on loadings l11 - l15:
  addScad(regularized = paste0("l", 11:15),
          lambdas = seq(0,1,length.out = 3),
          thetas = 3.1) |>
  # fit the model:
  fit()

# elements of regularized can be accessed with the @ operator:
regularized@parameters[1,]

# AIC and BIC:
AIC(regularized)
BIC(regularized)

# The best parameters can also be extracted with:
coef(regularized, criterion = "AIC")
coef(regularized, criterion = "BIC")

# The tuningParameterConfiguration corresponds to the rows
# in the lambda, theta, and alpha matrices in regularized@tuningParameterConfigurations.
# Configuration 3, for example, is given by
regularized@tuningParameterConfigurations$lambda[3,]
regularized@tuningParameterConfigurations$theta[3,]
regularized@tuningParameterConfigurations$alpha[3,]
# Note that lambda, theta, and alpha may correspond to tuning parameters
# of different penalties for different parameters (e.g., lambda for l6 is the lambda
# of the lasso penalty, while lambda for l12 is the lambda of the scad penalty).

```

---

 modifyModel

*modifyModel*


---

## Description

Modify the model from lavaan to fit your needs



**Usage**

```

modifyModel(
  addMeans = FALSE,
  activeSet = NULL,
  dataSet = NULL,
  transformations = NULL,
  transformationList = list(),
  transformationGradientStepSize = 1e-06
)

```

**Arguments**

addMeans	If lavaanModel has meanstructure = FALSE, addMeans = TRUE will add a mean structure. FALSE will set the means of the observed variables to their observed means.
activeSet	Option to only use a subset of the individuals in the data set. Logical vector of length N indicating which subjects should remain in the sample.
dataSet	option to replace the data set in the lavaan model with a different data set. Can be useful for cross-validation
transformations	allows for transformations of parameters - useful for measurement invariance tests etc.
transformationList	optional list used within the transformations. NOTE: This must be used as an Rcpp::List.
transformationGradientStepSize	step size used to compute the gradients of the transformations

**Value**

Object of class modifyModel

**Examples**

```

modification <- modifyModel(addMeans = TRUE) # adds intercepts to a lavaan object
# that was fitted without explicit intercepts

```

---

newTau

*newTau*

---

**Description**

assign new value to parameter tau used by approximate optimization. Any regularized value below tau will be evaluated as zeroed which directly impacts the AIC, BIC, etc.

**Usage**

```
newTau(regularizedSEM, tau)
```

**Arguments**

```
regularizedSEM  object fitted with approximate optimization  
tau             new tau value
```

**Value**

regularizedSEM, but with new regularizedSEM@fits\$nonZeroParameters

**Examples**

```
library(lessSEM)  
  
# Identical to regsem, lessSEM builds on the lavaan  
# package for model specification. The first step  
# therefore is to implement the model in lavaan.  
  
dataset <- simulateExampleData()  
  
lavaanSyntax <- "  
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +  
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +  
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15  
f ~~ 1*f  
"  
  
lavaanModel <- lavaan::sem(lavaanSyntax,  
                           data = dataset,  
                           meanstructure = TRUE,  
                           std.lv = TRUE)  
  
# Regularization:  
  
lsem <- smoothLasso(  
  # pass the fitted lavaan model  
  lavaanModel = lavaanModel,  
  # names of the regularized parameters:  
  regularized = paste0("1", 6:15),  
  epsilon = 1e-10,  
  tau = 1e-4,  
  lambdas = seq(0,1,length.out = 50))  
newTau(regularizedSEM = lsem, tau = .1)
```

---

plot,cvRegularizedSEM,missing-method  
*plots the cross-validation fits*

---

**Description**

plots the cross-validation fits

**Usage**

```
## S4 method for signature 'cvRegularizedSEM,missing'  
plot(x, y, ...)
```

**Arguments**

x	object of class cvRegularizedSEM
y	not used
...	not used

**Value**

either an object of ggplot2 or of plotly

---

plot,gpRegularized,missing-method  
*plots the regularized and unregularized parameters for all levels of lambda*

---

**Description**

plots the regularized and unregularized parameters for all levels of lambda

**Usage**

```
## S4 method for signature 'gpRegularized,missing'  
plot(x, y, ...)
```

**Arguments**

x	object of class gpRegularized
y	not used
...	use regularizedOnly=FALSE to plot all parameters

**Value**

either an object of ggplot2 or of plotly

---

plot,regularizedSEM,missing-method

*plots the regularized and unregularized parameters for all levels of lambda*

---

### Description

plots the regularized and unregularized parameters for all levels of lambda

### Usage

```
## S4 method for signature 'regularizedSEM,missing'
plot(x, y, ...)
```

### Arguments

x	object of class gpRegularized
y	not used
...	use regularizedOnly=FALSE to plot all parameters

### Value

either an object of ggplot2 or of plotly

---

plot,stabSel,missing-method

*plots the regularized and unregularized parameters for all levels of the tuning parameters*

---

### Description

plots the regularized and unregularized parameters for all levels of the tuning parameters

### Usage

```
## S4 method for signature 'stabSel,missing'
plot(x, y, ...)
```

### Arguments

x	object of class stabSel
y	not used
...	use regularizedOnly=FALSE to plot all parameters

### Value

either an object of ggplot2 or of plotly

---

regressions	<i>regressions</i>
-------------	--------------------

---

**Description**

Extract the labels of all regressions found in a lavaan model.

**Usage**

```
regressions(lavaanModel)
```

**Arguments**

lavaanModel      fitted lavaan model

**Value**

vector with parameter labels

**Examples**

```
# The following is adapted from ?lavaan::sem
library(lessSEM)
model <- '
  # latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + a*y2 + b*y3 + c*y4
  dem65 =~ y5 + a*y6 + b*y7 + c*y8

  # regressions
  dem60 ~ ind60
  dem65 ~ ind60 + dem60

  # residual correlations
  y1 ~~ y5
  y2 ~~ y4 + y6
  y3 ~~ y7
  y4 ~~ y8
  y6 ~~ y8
  '

fit <- sem(model, data = PoliticalDemocracy)

regressions(fit)
```

---

 regsem2LavaanParameters

*regsem2LavaanParameters*


---

### Description

helper function: regsem and lavaan use slightly different parameter labels. This function can be used to translate the parameter labels of a cv\_regsem object to lavaan labels

### Usage

```
regsem2LavaanParameters(regsemModel, lavaanModel)
```

### Arguments

regsemModel	model of class regsem
lavaanModel	model of class lavaan

### Value

regsem parameters with lavaan labels

### Examples

```
## The following is adapted from ?regsem::regsem.
#library(lessSEM)
#library(regsem)
## put variables on same scale for regsem
#HS <- data.frame(scale(HolzingerSwineford1939[,7:15]))
#
#mod <- '
#f =~ 1*x1 + 11*x2 + 12*x3 + 13*x4 + 14*x5 + 15*x6 + 16*x7 + 17*x8 + 18*x9
#'
## Recommended to specify meanstructure in lavaan
#lavaanModel <- cfa(mod, HS, meanstructure=TRUE)
#
#regsemModel <- regsem(lavaanModel,
#                      lambda = 0.3,
#                      gradFun = "ram",
#                      type="lasso",
#                      pars_pen=c("l1", "l2", "l6", "l7", "l8"))
# regsem2LavaanParameters(regsemModel = regsemModel,
#                         lavaanModel = lavaanModel)
```

---

regularizedSEM-class *Class for regularized SEM*

---

**Description**

Class for regularized SEM

**Slots**

penalty penalty used (e.g., "lasso")  
 parameters data.frame with parameter estimates  
 fits data.frame with all fit results  
 parameterLabels character vector with names of all parameters  
 weights vector with weights given to each of the parameters in the penalty  
 regularized character vector with names of regularized parameters  
 transformations if the model has transformations, the transformed parameters are returned  
 internalOptimization list of elements used internally  
 inputArguments list with elements passed by the user to the general  
 notes internal notes that have come up when fitting the model

---

regularizedSEMMixedPenalty-class  
*Class for regularized SEM*

---

**Description**

Class for regularized SEM

**Slots**

penalty penalty used (e.g., "lasso")  
 tuningParameterConfigurations list with settings for the lambda, theta, and alpha tuning parameters.  
 parameters data.frame with parameter estimates  
 fits data.frame with all fit results  
 parameterLabels character vector with names of all parameters  
 weights vector with weights given to each of the parameters in the penalty  
 regularized character vector with names of regularized parameters  
 transformations if the model has transformations, the transformed parameters are returned  
 internalOptimization list of elements used internally  
 inputArguments list with elements passed by the user to the general  
 notes internal notes that have come up when fitting the model

---

 ridge
 

---



---

 ridge
 

---

### Description

Implements ridge regularization for structural equation models. The penalty function is given by:

$$p(x_j) = \lambda x_j^2$$

Note that ridge regularization will not set any of the parameters to zero but result in a shrinkage towards zero.

### Usage

```
ridge(
  lavaanModel,
  regularized,
  lambdas,
  method = "glmnet",
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlGlmnet()
)
```

### Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
method	which optimizer should be used? Currently implemented are <code>ista</code> and <code>glmnet</code> . With <code>ista</code> , the control argument can be used to switch to related procedures (currently <code>gist</code> ).
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>controlIsta</code> and <code>controlGlmnet</code> functions. See <code>?controlIsta</code> and <code>?controlGlmnet</code> for more details.

### Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

Ridge regularization:

- Hoerl, A. E., & Kennard, R. W. (1970). Ridge Regression: Biased Estimation for Nonorthogonal Problems. *Technometrics*, 12(1), 55–67. <https://doi.org/10.1080/00401706.1970.10488634>



### Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

### Value

Model of class regularizedSEM

### Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
```

```

meanstructure = TRUE,
std.lv = TRUE)

# Regularization:

lsem <- ridge(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 20))

# use the plot-function to plot the regularized parameters:
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

#### Advanced ###
# Switching the optimizer #
# Use the "method" argument to switch the optimizer. The control argument
# must also be changed to the corresponding function:
lsemIsta <- ridge(
  lavaanModel = lavaanModel,
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 20),
  method = "ista",
  control = controlIsta())

# Note: The results are basically identical:
lsemIsta@parameters - lsem@parameters

```

---

ridgeBfgs

*ridgeBfgs*


---

## Description

This function allows for regularization of models built in lavaan with the ridge penalty. Its elements can be accessed with the "@" operator (see examples).

## Usage

```

ridgeBfgs(
  lavaanModel,
  regularized,
  lambdas = NULL,

```

```

modifyModel = lessSEM::modifyModel(),
control = lessSEM::controlBFGS()
)

```

### Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>controlBFGS</code> function. See <code>?controlBFGS</code> for more details.

### Details

For more details, see:

1. Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>
2. Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>

### Value

Model of class `regularizedSEM`

### Examples

```

library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

```

```

# Regularization:

# names of the regularized parameters:
regularized = paste0("1", 6:15)

lsem <- ridgeBfgs(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  regularized = regularized,
  lambdas = seq(0,1,length.out = 50))

plot(lsem)

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

```

---

scad

*scad*


---

## Description

Implements scad regularization for structural equation models. The penalty function is given by:  
Equation Omitted in Pdf Documentation.

## Usage

```

scad(
  lavaanModel,
  regularized,
  lambdas,
  thetas,
  modifyModel = lessSEM::modifyModel(),
  method = "glmnet",
  control = lessSEM::controlGlmnet()
)

```

## Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda

thetas	parameters whose absolute value is above this threshold will be penalized with a constant (theta)
modifyModel	used to modify the lavaanModel. See ?modifyModel.
method	which optimizer should be used? Currently implemented are ista and glmnet. With ista, the control argument can be used to switch to related procedures (currently gist).
control	used to control the optimizer. This element is generated with the controlIsta (see ?controlIsta)

## Details

Identical to **regsem**, models are specified using **lavaan**. Currently, most standard SEM are supported. **lessSEM** also provides full information maximum likelihood for missing data. To use this functionality, fit your **lavaan** model with the argument `sem(..., missing = 'ml')`. **lessSEM** will then automatically switch to full information maximum likelihood as well.

scad regularization:

- Fan, J., & Li, R. (2001). Variable selection via nonconcave penalized likelihood and its oracle properties. *Journal of the American Statistical Association*, 96(456), 1348–1360. <https://doi.org/10.1198/01621450175>

Regularized SEM

- Huang, P.-H., Chen, H., & Weng, L.-J. (2017). A Penalized Likelihood Method for Structural Equation Modeling. *Psychometrika*, 82(2), 329–354. <https://doi.org/10.1007/s11336-017-9566-9>
- Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016>

For more details on GLMNET, see:

- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–20. <https://doi.org/10.18637/jss.v033.i01>
- Yuan, G.-X., Chang, K.-W., Hsieh, C.-J., & Lin, C.-J. (2010). A Comparison of Optimization Methods and Software for Large-scale L1-regularized Linear Classification. *Journal of Machine Learning Research*, 11, 3183–3234.
- Yuan, G.-X., Ho, C.-H., & Lin, C.-J. (2012). An improved GLMNET for l1-regularized logistic regression. *The Journal of Machine Learning Research*, 13, 1999–2030. <https://doi.org/10.1145/2020408.2020421>

For more details on ISTA, see:

- Beck, A., & Teboulle, M. (2009). A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *SIAM Journal on Imaging Sciences*, 2(1), 183–202. <https://doi.org/10.1137/080716542>
- Gong, P., Zhang, C., Lu, Z., Huang, J., & Ye, J. (2013). A General Iterative Shrinkage and Thresholding Algorithm for Non-convex Regularized Optimization Problems. *Proceedings of the 30th International Conference on Machine Learning*, 28(2)(2), 37–45.
- Parikh, N., & Boyd, S. (2013). Proximal Algorithms. *Foundations and Trends in Optimization*, 1(3), 123–231.

**Value**

Model of class `regularizedSEM`

**Examples**

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f ~~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- scad(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
  regularized = paste0("1", 6:15),
  lambdas = seq(0,1,length.out = 20),
  thetas = seq(2.01,5,length.out = 5))

# the coefficients can be accessed with:
coef(lsem)

# if you are only interested in the estimates and not the tuning parameters, use
coef(lsem)@estimates
# or
estimates(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

# fit Measures:
fitIndices(lsem)

# The best parameters can also be extracted with:
coef(lsem, criterion = "AIC")
# or
```

```

estimates(lsem, criterion = "AIC")

# optional: plotting the paths requires installation of plotly
# plot(lsem)

```

---

scadPenalty_C	<i>scadPenalty_C</i>
---------------	----------------------

---

### Description

scadPenalty\_C

### Usage

```
scadPenalty_C(par, lambda_p, theta)
```

### Arguments

par	single parameter value
lambda_p	lambda value for this parameter
theta	theta value for this parameter

### Value

penalty value

---

SEMCpp	<i>SEMCpp class</i>
--------	---------------------

---

### Description

internal SEM representation

### Fields

`new` Creates a new SEMCpp.

`fill` fills the SEM with the elements from an Rcpp::List

`addTransformation` adds transformations to a model

`implied` Computes implied means and covariance matrix

`fit` Fits the model. Returns objective value of the fitting function

`getParameters` Returns a data frame with model parameters.

`getEstimator` returns the estimator used in the model (e.g., fiml)

`getParameterLabels` Returns a vector with unique parameter labels as used internally.

getGradients Returns a matrix with scores.  
 getScores Returns a matrix with scores.  
 getHessian Returns the hessian of the model. Expects the labels of the parameters and the values of the parameters as well as a boolean indicating if these are raw. Finally, a double (eps) controls the precision of the approximation.  
 computeTransformations compute the transformations.  
 setTransformationGradientStepSize change the step size of the gradient computation for the transformations

---

show, cvRegularizedSEM-method

*Show method for objects of class cvRegularizedSEM.*

---

### Description

Show method for objects of class cvRegularizedSEM.

### Usage

```
## S4 method for signature 'cvRegularizedSEM'
show(object)
```

### Arguments

object            object of class cvRegularizedSEM

### Value

No return value, just prints estimates

---

show, gpRegularized-method

*show*

---

### Description

show

### Usage

```
## S4 method for signature 'gpRegularized'
show(object)
```

### Arguments

object            object of class gpRegularized



**Value**

No return value, just prints estimates

---

show,lessSEMCoef-method  
*show*

---

**Description**

show

**Usage**

```
## S4 method for signature 'lessSEMCoef'  
show(object)
```

**Arguments**

object            object of class lessSEMCoef

**Value**

No return value, just prints estimates

---

show,logLikelihood-method  
*show*

---

**Description**

show

**Usage**

```
## S4 method for signature 'logLikelihood'  
show(object)
```

**Arguments**

object            object of class logLikelihood

**Value**

No return value, just prints estimates

show,Rcpp\_mgSEM-method

*show*

---

**Description**

show

**Usage**

```
## S4 method for signature 'Rcpp_mgSEM'  
show(object)
```

**Arguments**

object            object of class Rcpp\_mgSEM

**Value**

No return value, just prints estimates

---

show,Rcpp\_SEMCpp-method

*show*

---

**Description**

show

**Usage**

```
## S4 method for signature 'Rcpp_SEMCpp'  
show(object)
```

**Arguments**

object            object of class Rcpp\_SEMCpp

**Value**

No return value, just prints estimates

---

show,regularizedSEM-method  
*show*

---

**Description**

show

**Usage**

```
## S4 method for signature 'regularizedSEM'  
show(object)
```

**Arguments**

object            object of class regularizedSEM

**Value**

No return value, just prints estimates

---

show,regularizedSEMMixedPenalty-method  
*show*

---

**Description**

show

**Usage**

```
## S4 method for signature 'regularizedSEMMixedPenalty'  
show(object)
```

**Arguments**

object            object of class regularizedSEM

**Value**

No return value, just prints estimates

---

```
show, stabSel-method  show
```

---

**Description**

show

**Usage**

```
## S4 method for signature 'stabSel'
show(object)
```

**Arguments**

object            object of class stabSel

**Value**

No return value, just prints estimates

---

```
simulateExampleData  simulateExampleData
```

---

**Description**

simulate data for a simple CFA model

**Usage**

```
simulateExampleData(
  N = 100,
  loadings = c(rep(1, 5), rep(0.4, 5), rep(0, 5)),
  percentMissing = 0
)
```

**Arguments**

N                    number of persons in the data set  
loadings            loadings of the latent variable on the manifest observations  
percentMissing    percentage of missing data

**Value**

data set for a single-factor CFA.

**Examples**

```
y <- lessSEM::simulateExampleData()
```

---

 smoothAdaptiveLasso    *smoothAdaptiveLasso*


---

### Description

This function allows for regularization of models built in lavaan with the smooth adaptive lasso penalty. The returned object is an S4 class; its elements can be accessed with the "@" operator (see examples).

### Usage

```
smoothAdaptiveLasso(
  lavaanModel,
  regularized,
  weights = NULL,
  lambdas,
  epsilon,
  tau,
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlBFGS()
)
```

### Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
weights	labeled vector with weights for each of the parameters in the model. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object. If set to NULL, the default weights will be used: the inverse of the absolute values of the unregularized parameter estimates
lambdas	numeric vector: values for the tuning parameter lambda
epsilon	epsilon > 0; controls the smoothness of the approximation. Larger values = smoother
tau	parameters below threshold tau will be seen as zeroed
modifyModel	used to modify the lavaanModel. See <code>?modifyModel</code> .
control	used to control the optimizer. This element is generated with the <code>controlBFGS</code> function. See <code>?controlBFGS</code> for more details.

### Details

For more details, see:

1. Zou, H. (2006). The Adaptive Lasso and Its Oracle Properties. *Journal of the American Statistical Association*, 101(476), 1418–1429. <https://doi.org/10.1198/016214506000000735>

2. Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>
3. Lee, S.-I., Lee, H., Abbeel, P., & Ng, A. Y. (2006). Efficient L1 Regularized Logistic Regression. *Proceedings of the Twenty-First National Conference on Artificial Intelligence (AAAI-06)*, 401–408.

## Value

Model of class regularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

# names of the regularized parameters:
regularized = paste0("1", 6:15)

# define adaptive lasso weights:
# We use the inverse of the absolute unregularized parameters
# (this is the default in adaptiveLasso and can also specified
# by setting weights = NULL)
weights <- 1/abs(getLavaanParameters(lavaanModel))
weights[!names(weights) %in% regularized] <- 0

lsem <- smoothAdaptiveLasso(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  regularized = regularized,
  weights = weights,
  epsilon = 1e-10,
  tau = 1e-4,
  lambdas = seq(0,1,length.out = 50))
```

```

# use the plot-function to plot the regularized parameters:
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

# AIC and BIC:
AIC(lsem)
BIC(lsem)

# The best parameters can also be extracted with:
coef(lsem, criterion = "AIC")
coef(lsem, criterion = "BIC")

```

---

smoothElasticNet	<i>smoothElasticNet</i>
------------------	-------------------------

---

## Description

This function allows for regularization of models built in lavaan with the smooth elastic net penalty. Its elements can be accessed with the "@" operator (see examples).

## Usage

```

smoothElasticNet(
  lavaanModel,
  regularized,
  lambdas = NULL,
  nLambdas = NULL,
  alphas,
  epsilon,
  tau,
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlBFGS()
)

```

## Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object
lambdas	numeric vector: values for the tuning parameter lambda

nLambdas	alternative to lambda: If alpha = 1, lessSEM can automatically compute the first lambda value which sets all regularized parameters to zero. It will then generate nLambda values between 0 and the computed lambda.
alphas	numeric vector with values of the tuning parameter alpha. Must be between 0 and 1. 0 = ridge, 1 = lasso.
epsilon	epsilon > 0; controls the smoothness of the approximation. Larger values = smoother
tau	parameters below threshold tau will be seen as zeroed
modifyModel	used to modify the lavaanModel. See ?modifyModel.
control	used to control the optimizer. This element is generated with the controlBFGS function. See ?controlBFGS for more details.

## Details

For more details, see:

1. Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B*, 67(2), 301–320. <https://doi.org/10.1111/j.1467-9868.2005.00503.x> for the details of this regularization technique.
2. Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>
3. Lee, S.-I., Lee, H., Abbeel, P., & Ng, A. Y. (2006). Efficient L1 Regularized Logistic Regression. *Proceedings of the Twenty-First National Conference on Artificial Intelligence (AAAI-06)*, 401–408.

## Value

Model of class regularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
```



```

                                std.lv = TRUE)

# Regularization:

# names of the regularized parameters:
regularized = paste0("1", 6:15)

lsem <- smoothElasticNet(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  regularized = regularized,
  epsilon = 1e-10,
  tau = 1e-4,
  lambdas = seq(0,1,length.out = 5),
  alphas = seq(0,1,length.out = 3))

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

```

---

smoothLasso

*smoothLasso*


---

## Description

This function allows for regularization of models built in lavaan with the smoothed lasso penalty. The returned object is an S4 class; its elements can be accessed with the "@" operator (see examples). We don't recommend using this function. Use `lasso()` instead.

## Usage

```

smoothLasso(
  lavaanModel,
  regularized,
  lambdas,
  epsilon,
  tau,
  modifyModel = lessSEM::modifyModel(),
  control = lessSEM::controlBFGS()
)

```

## Arguments

lavaanModel	model of class lavaan
regularized	vector with names of parameters which are to be regularized. If you are unsure what these parameters are called, use <code>getLavaanParameters(model)</code> with your lavaan model object

lambdas	numeric vector: values for the tuning parameter lambda
epsilon	epsilon > 0; controls the smoothness of the approximation. Larger values = smoother
tau	parameters below threshold tau will be seen as zeroed
modifyModel	used to modify the lavaanModel. See ?modifyModel.
control	used to control the optimizer. This element is generated with the controlBFGS function. See ?controlBFGS for more details.

## Details

For more details, see:

1. Lee, S.-I., Lee, H., Abbeel, P., & Ng, A. Y. (2006). Efficient L1 Regularized Logistic Regression. Proceedings of the Twenty-First National Conference on Artificial Intelligence (AAAI-06), 401–408.
2. Jacobucci, R., Grimm, K. J., & McArdle, J. J. (2016). Regularized Structural Equation Modeling. Structural Equation Modeling: A Multidisciplinary Journal, 23(4), 555–566. <https://doi.org/10.1080/10705511.2016.1191111>

## Value

Model of class regularizedSEM

## Examples

```
library(lessSEM)

# Identical to regsem, lessSEM builds on the lavaan
# package for model specification. The first step
# therefore is to implement the model in lavaan.

dataset <- simulateExampleData()

lavaanSyntax <- "
f =~ 11*y1 + 12*y2 + 13*y3 + 14*y4 + 15*y5 +
      16*y6 + 17*y7 + 18*y8 + 19*y9 + 110*y10 +
      111*y11 + 112*y12 + 113*y13 + 114*y14 + 115*y15
f =~ 1*f
"

lavaanModel <- lavaan::sem(lavaanSyntax,
                           data = dataset,
                           meanstructure = TRUE,
                           std.lv = TRUE)

# Regularization:

lsem <- smoothLasso(
  # pass the fitted lavaan model
  lavaanModel = lavaanModel,
  # names of the regularized parameters:
```

```
regularized = paste0("l", 6:15),
epsilon = 1e-10,
tau = 1e-4,
lambdas = seq(0,1,length.out = 50))

# use the plot-function to plot the regularized parameters:
plot(lsem)

# the coefficients can be accessed with:
coef(lsem)

# elements of lsem can be accessed with the @ operator:
lsem@parameters[1,]

# AIC and BIC:
AIC(lsem)
BIC(lsem)

# The best parameters can also be extracted with:
coef(lsem, criterion = "AIC")
coef(lsem, criterion = "BIC")
```

---

stabilitySelection      *stabilitySelection*

---

## Description

Provides rudimentary stability selection for regularized SEM. Stability selection has been proposed by Meinshausen & Bühlmann (2010) and was extended to SEM by Li & Jacobucci (2021). The problem that stability selection tries to solve is the instability of regularization procedures: Small changes in the data set may result in different parameters being selected. To address this issue, stability selection uses random subsamples from the initial data set and fits models in these subsamples. For each parameter, we can now check how often it is included in the model for a given set of tuning parameters. Plotting these probabilities can provide an overview over which of the parameters are often removed and which remain in the model most of the time. To get a final selection, a threshold  $t$  can be defined: If a parameter is in the model  $t\%$  of the time, it is retained.

## Usage

```
stabilitySelection(
  modelSpecification,
  subsampleSize,
  numberOfSubsamples = 100,
  threshold = 70,
  maxTries = 10 * numberOfSubsamples
)
```



```

stabSel <- stabilitySelection(
  # IMPORTANT: Wrap your call to the penalty function in an rlang::expr-Block:
  modelSpecification =
    rlang::expr(
      lasso(
        # pass the fitted lavaan model
        lavaanModel = lavaanModel,
        # names of the regularized parameters:
        regularized = paste0("1", 6:15),
        # in case of lasso and adaptive lasso, we can specify the number of lambda
        # values to use. lessSEM will automatically find lambda_max and fit
        # models for nLambda values between 0 and lambda_max. For the other
        # penalty functions, lambdas must be specified explicitly
        nLambdas = 50)
      ),
  subsampleSize = 80,
  numberOfSubsamples = 5, # should be set to a much higher number (e.g., 100)
  threshold = 70
)
stabSel
plot(stabSel)

```

---

stabSel-class

*Class for stability selection*


---

## Description

Class for stability selection

## Slots

regularized names of regularized parameters

tuningParameters data.frame with tuning parameter values

stabilityPaths matrix with percentage of parameters being non-zero averaged over all subsets for each setting of the tuning parameters

percentSelected percentage with which a parameter was selected over all tuning parameter settings

selectedParameters final selected parameters

settings internal

---

summary, cvRegularizedSEM-method

*summary method for objects of class cvRegularizedSEM.*

---

### Description

summary method for objects of class cvRegularizedSEM.

### Usage

```
## S4 method for signature 'cvRegularizedSEM'
summary(object, ...)
```

### Arguments

object	object of class cvRegularizedSEM
...	not used

### Value

No return value, just prints estimates

---

summary, gpRegularized-method

*summary*

---

### Description

summary

### Usage

```
## S4 method for signature 'gpRegularized'
summary(object, ...)
```

### Arguments

object	object of class gpRegularized
...	not used

### Value

No return value, just prints estimates

---

summary,regularizedSEM-method  
*summary*

---

**Description**

summary

**Usage**

```
## S4 method for signature 'regularizedSEM'  
summary(object, ...)
```

**Arguments**

object	object of class regularizedSEM
...	not used

**Value**

No return value, just prints estimates

---

summary,regularizedSEMMixedPenalty-method  
*summary*

---

**Description**

summary

**Usage**

```
## S4 method for signature 'regularizedSEMMixedPenalty'  
summary(object, ...)
```

**Arguments**

object	object of class regularizedSEMMixedPenalty
...	not used

**Value**

No return value, just prints estimates

---

`variances`*variances*

---

**Description**

Extract the labels of all variances found in a lavaan model.

**Usage**

```
variances(lavaanModel)
```

**Arguments**

```
lavaanModel    fitted lavaan model
```

**Value**

vector with parameter labels

**Examples**

```
# The following is adapted from ?lavaan::sem
library(lessSEM)
model <- '
  # latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + a*y2 + b*y3 + c*y4
  dem65 =~ y5 + a*y6 + b*y7 + c*y8

  # regressions
  dem60 ~ ind60
  dem65 ~ ind60 + dem60

  # residual correlations
  y1 ~~ y5
  y2 ~~ y4 + y6
  y3 ~~ y7
  y4 ~~ y8
  y6 ~~ y8
  '

fit <- sem(model, data = PoliticalDemocracy)

variances(fit)
```



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