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# Semi-Lasso: a weighted Lasso designed for the integration of known regressors in linear model

Nicolas Champagnat, Anne Gégout-Petit, Anouk Rago

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Nicolas Champagnat Université de Lorraine, CNRS, Inria, IECL, UMR 7502  
Anne Gégout-Petit Université de Lorraine, CNRS, Inria, IECL, UMR 7502  
Anouk Rago<sup>1</sup> Université de Lorraine, CNRS, Inria, IECL, UMR 7502

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## Abstract

To encode prior information in a regression problem, statisticians may use a weighted LASSO, in which variables can have different weights in the penalization. In this paper, we propose an alternative method called semi-LASSO, which solves a specific case of weighted LASSO designed for the integration of known regressors in linear model. The optimization procedure is divided in two steps: the first one is an ordinary least squares method and the second one a classic LASSO procedure in lower dimension. Numerical experiments are performed on synthetic data to compare the performances of this new method with the usual weighted LASSO implemented in `glmnet`. The results show an improvement of the sensitivity, the variable selection and the prediction capability when using semi-LASSO.

*Keywords:* regression, LASSO, prior knowledge, R, gene network inference

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<sup>1</sup>Corresponding author: [anouk.rago@univ-lorraine.fr](mailto:anouk.rago@univ-lorraine.fr)

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## 21 **1 Introduction**

22 The LASSO (Tibshirani 1996) is a widely used technique when it comes to perform both estimation  
23 of parameters and variable selection for a linear model. The penalty on the  $l_1$  norm allows indeed  
24 to shrink some coefficients to 0. Moreover, it allows the user to handle cases where the number of  
25 variables  $p$  is greater than the number of observations  $n$  and thus is particularly convenient when  
26 one has to deal with large datasets like genomic data. This is why a lot of methods using LASSO  
27 and its derivative, like the adaptive LASSO (Zou 2006) or group LASSO (Yuan and Lin 2006) have  
28 been developed in particular to infer gene regulatory networks (Siahpirani, Chasman, and Roy 2019;  
29 Grzegorzczuk, Aderhold, and Husmeier 2019), which depict the relationships between genes. In these  
30 references, a regression model for each gene  $j \in [1, p]$  is built, giving for each gene a list of regressors  
31 linked to it in the network. But inferring this network using only transcriptomic data can be a  
32 delicate task due to the massive amount of genes ( $p \approx 20000$ ) present in the data compared to the  
33 small number of samples  $n$ : the LASSO is then a good tool to select the most relevant regressors  
34 among the genes.

35 In some cases, some prior biological information can be available and therefore be integrated in the  
36 model to improve the results. For example, protein-protein interactions are experimentally tested  
37 and the results are publicly available on the online databases of interacting proteins (Xenarios et al.  
38 2000). When using a LASSO, one way to perform prior information integration is to specify different  
39 penalty strengths for each gene/variable during the estimation of parameters, which is referred as  
40 the weighted LASSO and has been applied in various references. Bergersen, Glad, and Lyng (2011)  
41 use two different weights to add prior knowledge in their model : the first one is based on the  
42 correlation between gene expression and gene copy numbers, the second one relies on the association  
43 of gene copy number with survival. A weighted graphical LASSO is performed by Charbonnier,  
44 Chiquet, and Ambroise (2010) where prior information on the topology of the network is used.  
45 Greenfield, Hafemeister, and Bonneau (2013) rely on the elastic-net algorithm (Zou and Hastie 2005),  
46 and modifies the  $l_1$  norm to add prior knowledge on genes interactions. Moreover, it has been shown  
47 that optimizing the amount of prior knowledge included into the model gives significantly better  
48 results (Cassan et al. 2023). From a larger perspective, specifying different penalty weights can be  
49 useful in any regression problem where prior information on the potential regressors is available.  
50 The R package `glmnet` (Friedman, Hastie, and Tibshirani 2010) allows the user to do it, by tuning the  
51 `penalty.factor` parameter.

52 In this paper, we focus on a penalized linear regression model with prior information. We assume  
53 that this prior knowledge takes the form of a certainty that some potential regressors must belong to  
54 the model. In this particular case, their penalty strength is set to 0 as we want to be sure to include  
55 them in the model. Concerning the other potential regressors for which we have no information,  
56 we assume that their penalty strength is the same for all. The number of known regressors should  
57 not exceed the number of observations  $n$ , otherwise the method we propose would be inapplicable.  
58 As opposed to the procedure used in `glmnet`, which consists in optimizing the objective function  
59 directly with a cyclical coordinate descent method, we propose to first transform the problem to  
60 divide the optimization procedure in two steps, one which is an ordinary least squares method and  
61 the second one being a classic LASSO procedure in lower dimension. We will see that this procedure  
62 actually improves the parameters estimation, the true positive variables selection and reduces the

63 error of prediction.

64 The paper is organized as follows. In Section 2, we introduce the LASSO and weighted LASSO, and  
65 explain how to deal with the `glmnet` package. Section 3 presents our method called semi-LASSO.  
66 Finally, we compare the performance of `glmnet` and semi-LASSO on simulated datasets in Section 4  
67 and discuss the results in Section 5.

## 68 2 LASSO and weighted LASSO

69 We suppose that we have a set of  $p$  explicative variables  $(X_1, \dots, X_p) \in \mathbb{R}^p$  and a response variable  
70  $Y \in \mathbb{R}$  such that:

$$Y = \beta_0 + \sum_{j=1}^p \beta_j X_j + \epsilon, \quad (1)$$

71 with  $\epsilon \sim \mathcal{N}(0, \sigma^2)$  a centered noise and  $\boldsymbol{\beta} = (\beta_0, \beta_1, \dots, \beta_p) \in \mathbb{R}^{p+1}$  the coefficients of the model,  
72 potentially equal to zero. We also assume having  $n$  realizations of  $X_1, \dots, X_p$  and  $Y$ : we note  $\mathbf{x} = (x_{ij})$   
73 the  $n \times (p + 1)$  matrix of observations, the first column being filled with ones, and  $\mathbf{y} \in \mathbb{R}^n$  the  
74 observations of  $Y$ . Then the penalized LASSO regression is:

$$\min_{(\beta_0, \beta_1, \dots, \beta_p)} \frac{1}{2n} \|\mathbf{y} - \mathbf{x}\boldsymbol{\beta}\|_2^2 + \lambda P(\boldsymbol{\beta}), \quad (2)$$

75 with  $\lambda$  a positive regularization parameter and  $P(\boldsymbol{\beta})$  the LASSO penalty defined by:

$$P(\boldsymbol{\beta}) = \sum_{j=1}^p |\beta_j|. \quad (3)$$

76 The bigger  $\lambda$  is, the more the coefficients  $\boldsymbol{\beta}$  are penalized, which leads to more 0 coefficients and  
77 a sparser model. To solve Equation 2, two methods can be used. The first one, called the LARS  
78 algorithm (Efron et al. 2004) and implemented in the R package `lars`, relies on the correlation between  
79 the explicative variables and  $Y$ , and is not discussed here. The second one is a coordinate gradient  
80 descent directly applied on the objective function, as done in the R package `glmnet` (Friedman, Hastie,  
81 and Tibshirani 2010). In Equation 3, all  $\beta_j$  coefficients are treated the same way and are equally  
82 penalized, as the data is beforehand normalized before solving the optimization problem in `glmnet`.  
83 A possible extension for the LASSO is to add a different weight for each variable. The objective lying  
84 behind these weights can either be:

- 85 • to reduce the conflict between optimal prediction and consistent variable selection, thus  
86 achieving some theoretical properties. This is the adaptive LASSO, introduced by Zou (2006).  
87 In this case, the weights are first determined and linked to the data, then iteratively refined to  
88 reach some oracle properties.
- 89 • to add some prior information on the potential regressors of the model (Bergersen, Glad, and  
90 Lyng 2011; Charbonnier, Chiquet, and Ambroise 2010; Greenfield, Hafemeister, and Bonneau  
91 2013), as detailed in Section 1. This method is called the weighted LASSO. This variant of the  
92 LASSO can also resolve the issue raised by variables with similar profiles: only one of them  
93 is generally included into the model, not always the most relevant one. By including prior  
94 knowledge and so different weights in the objective function, the optimization step leads to a  
95 more relevant variables selection.

96 In these cases, the penalty function becomes:

$$P_{\mathbf{w}}(\boldsymbol{\beta}) = \sum_{j=1}^p w_j |\beta_j|. \quad (4)$$

97 where  $\mathbf{w} = (w_1, \dots, w_p) \in (\mathbb{R}^+)^p$  is the weights vector. A coefficient with a small weight will be  
 98 less penalized than a coefficient with a big one, and is more likely to be included into the final  
 99 model. This new problem can be solved with the same gradient descent method of `glmnet` used to  
 100 solve Equation 2. When using this R package, it is possible to specify particular weights with the  
 101 `penalty.factor` parameter.

## 102 3 Semi-LASSO, a specific weighted LASSO with a priori knowledge

### 103 3.1 Adding prior information into the model

104 Linear regression models with penalization are very used in the field of gene network inference  
 105 (Siahpirani, Chasman, and Roy 2019; Grzegorzczuk, Aderhold, and Husmeier 2019; Huynh-Thu and  
 106 Sanguinetti 2019). First because they can deal with big data especially when  $n \ll p$ , then because  
 107 they can select only a few interesting genes as regressors. Biologists are indeed aware that gene  
 108 regulatory networks are sparse (Leclerc 2008), which makes of the LASSO an interesting method as  
 109 it offers the possibility to perform variable selection among thousands of genes. But today, a lot of  
 110 biological information is available concerning the links existing between genes. This information can  
 111 be added in the model by using a weighted LASSO as described in Section 2, with carefully chosen  
 112 weights.

113 For this purpose, we focus in this paper on a specific case of weighted LASSO, where the weights  
 114 can be either 0, which means no penalization, or 1, as in the usual LASSO. Concretely, a weight  
 115 equals to 0 means that the variable associated to this weight will always be included in the model:  
 116 the associated regression coefficient  $\beta_j$  will generically be non-zero. It corresponds to the variable  
 117 for which we are certain that it has a relationship with  $Y$ , for example a known protein-protein  
 118 interaction.

119 The variables  $\mathbf{X}$  are then divided into two groups:

- 120 •  $G_K$  -K for Known-, the set of variables for which we are certain they are part of the model, as  
 121 we have prior knowledge on their relationship with  $Y$ . The method does not penalize these  
 122 variables and their weight will be set to 0.
- 123 •  $G_U$  -U for Unknown-, the set of variables for which we have no prior information on their  
 124 relationship with  $Y$ . Their weights will be set to 1, each of them being penalized the same way  
 125 by the parameter  $\lambda$ .

127 As it seems reasonable to assume the presence of an intercept in the majority of real data modeling,  
 128 the variable corresponding to the parameter  $\beta_0$  in Equation 1 is always set in  $G_K$ . The sum of cardinals  
 129 of the two groups is  $G_K$  and  $G_U$  is  $p + 1$  and we also assume in what follows that the number of  
 130 variables in  $G_K$  never exceeds  $n$ , otherwise the method we propose would be inapplicable.

### 131 3.2 Mathematical formulation

132 Using the notations above and those of Section 2, the problem we want to find the argmin in the  
 133 following minimization problem:

$$\min_{(\beta_0, \beta_1, \dots, \beta_p)} \frac{1}{2n} \|\mathbf{y} - \mathbf{x}\boldsymbol{\beta}\|_2^2 + \lambda P_1(\boldsymbol{\beta}), \quad (5)$$

134 with :

$$P_1(\boldsymbol{\beta}) = \sum_{j=1}^p \mathbb{1}_{X_j \in G_U} |\beta_j| = \sum_{j, X_j \in G_U} |\beta_j|.$$

135 We note  $\boldsymbol{\beta}_K$  (respectively  $\boldsymbol{\beta}_U$ ), the vector  $\boldsymbol{\beta}_K = (\beta_j, X_j \in G_K)$  (respectively  $\boldsymbol{\beta}_U = (\beta_j, X_j \in G_U)$ ). In  
 136 a similar way, we denote by  $\mathbf{x}_K$  (respectively  $\mathbf{x}_U$ ) the matrix containing the  $n$  observations of the  
 137 variables in  $G_K$  (respectively  $G_U$ ). Equation 5 can be rewritten as:

$$\min_{\boldsymbol{\beta}_U} \left( \min_{\boldsymbol{\beta}_K} \left( \frac{1}{2n} \|\mathbf{y} - \mathbf{x}\boldsymbol{\beta}\|_2^2 \right) + \lambda \sum_{j, X_j \in G_U} |\beta_j| \right).$$

138 The minimum in  $\boldsymbol{\beta}_K$  takes the form of :

$$\begin{aligned} \min_{\boldsymbol{\beta}_K} \frac{1}{2n} \|\mathbf{y} - \mathbf{x}\boldsymbol{\beta}\|_2^2 &= \min_{\boldsymbol{\beta}_K} \frac{1}{2n} \sum_{i=1}^n (y_i - \beta_0 - \sum_{j, X_j \in G_U} x_{ij}\beta_j - \sum_{j, X_j \in G_K} x_{ij}\beta_j)^2 \\ &= \min_{\boldsymbol{\beta}_K} \frac{1}{2n} \sum_{i=1}^n (z_i - \beta_0 - \sum_{j, X_j \in G_K} x_{ij}\beta_j)^2, \end{aligned} \quad (6)$$

139 with  $\mathbf{z} = (z_i)_{1 \leq i \leq n} = (y_i - \sum_{j \in G_U} x_{ij}\beta_j)_{1 \leq i \leq n} = \mathbf{y} - \mathbf{x}_U \boldsymbol{\beta}_U$ . The minimum above is reached when  $\boldsymbol{\beta}_K$  is  
 140 the ordinary least squares estimator, under the assumption that  $\mathbf{x}_K^t \mathbf{x}_K$  is invertible, which implies in  
 141 particular that the cardinal of  $G_K$  is lower than  $n$ . We have:

$$\widehat{\boldsymbol{\beta}}_K = \widehat{\boldsymbol{\beta}}_K(\boldsymbol{\beta}_U) = (\mathbf{x}_K^t \mathbf{x}_K)^{-1} \mathbf{x}_K^t \mathbf{z}. \quad (7)$$

142 Using this expression for  $\widehat{\boldsymbol{\beta}}_K$ , Equation 6 becomes:

$$\begin{aligned} \min_{\boldsymbol{\beta}_K} \frac{1}{2n} \|\mathbf{y} - \mathbf{x}\boldsymbol{\beta}\|_2^2 &= \frac{1}{2n} \|\mathbf{y} - \mathbf{x}_U \boldsymbol{\beta}_U - \mathbf{x}_K (\mathbf{x}_K^t \mathbf{x}_K)^{-1} \mathbf{x}_K^t (\mathbf{y} - \mathbf{x}_U \boldsymbol{\beta}_U)\|_2^2 \\ &= \frac{1}{2n} \|(I_n - \mathbf{x}_K (\mathbf{x}_K^t \mathbf{x}_K)^{-1} \mathbf{x}_K^t) \mathbf{y} - (\mathbf{x}_U - \mathbf{x}_K (\mathbf{x}_K^t \mathbf{x}_K)^{-1} \mathbf{x}_K^t \mathbf{x}_U) \boldsymbol{\beta}_U\|_2^2 \\ &= \frac{1}{2n} \|\mathbf{u} - \mathbf{v} \boldsymbol{\beta}_U\|_2^2, \end{aligned}$$

143 with  $\mathbf{u} = (I_n - \mathbf{x}_K (\mathbf{x}_K^t \mathbf{x}_K)^{-1} \mathbf{x}_K^t) \mathbf{y}$  and  $\mathbf{v} = \mathbf{x}_U - \mathbf{x}_K (\mathbf{x}_K^t \mathbf{x}_K)^{-1} \mathbf{x}_K^t \mathbf{x}_U$ . Equation 5 becomes :

$$\min_{\boldsymbol{\beta}_U} \left( \frac{1}{2n} \|\mathbf{u} - \mathbf{v} \boldsymbol{\beta}_U\|_2^2 + \lambda \sum_{j, X_j \in G_U} |\beta_j| \right). \quad (8)$$

144 Hence the minimization problem above corresponds to the classic objective function of the LASSO,  
 145 and only depends on  $\boldsymbol{\beta}_U$ . The solution of Equation 8 can thus be found numerically, using `glmnet` for  
 146 example. Once the solution  $\widehat{\boldsymbol{\beta}}_U$  is computed, we can obtain  $\widehat{\boldsymbol{\beta}}_K$  by injecting the obtained value for  $\widehat{\boldsymbol{\beta}}_U$   
 147 in Equation 7. The pseudocode corresponding to this procedure of estimation, called semi-LASSO, is  
 148 given below in Algorithm 1 .

149 An alternative solution would be to use `glmnet` directly, by specifying 0 and 1 weights in the  
 150 `penalty.factor` argument: this procedure will be referred as 0-1 weighted LASSO in what follows.

151 The semi-LASSO method can be more efficient than the 0-1 weighted LASSO for the following  
 152 reasons. By separating the variables in two distinct groups before numerically optimizing the  
 153 objective function Equation 5, we find ourselves solving two different minimization problems. The

154 first one is an ordinary least squares regression, which has a well-known analytical solution, and  
 155 the second one is a classic LASSO regression. This second problem will be solved numerically, but  
 156 in a space of smaller dimension (less variables) compared to the 0-1 weighted LASSO. We will see  
 157 in the next sections that our semi-LASSO method actually improves the parameter estimation, the  
 158 sensitivity and reduces the error of prediction.

---

### Algorithm 1 Semi-LASSO

---

```

1: Inputs:
2:    $G_K$  and  $G_U$  the groups of variables
3:    $\mathbf{x} \in \mathcal{M}_{n \times p}(\mathbb{R})$  the data matrix
4:    $\mathbf{y} \in \mathbb{R}^n$  the vector of observed values for  $Y$ 
5:
6: Output:
7:    $\boldsymbol{\beta}$  the vector of coefficients
8:
9: if  $G_K = \emptyset$  then                                     ▷ No prior information is known
10:    $\boldsymbol{\beta}$  obtained with classical LASSO
11:
12: else if  $G_U = \emptyset$  &  $|G_K| \leq n$  then                 ▷ All regressors are known
13:    $\boldsymbol{\beta}$  obtained with classical regression
14:
15: else
16:   compute  $\mathbf{x}_K$  and  $\mathbf{x}_U$  from  $\mathbf{x}$ 
17:   add a column of 1 in  $\mathbf{x}_K$  for the intercept estimation
18:   compute  $\mathbf{u} = (I_n - \mathbf{x}_K(\mathbf{x}_K^t \mathbf{x}_K)^{-1} \mathbf{x}_K^t) \mathbf{y}$  and  $\mathbf{v} = \mathbf{x}_U - \mathbf{x}_K(\mathbf{x}_K^T \mathbf{x}_K)^{-1} \mathbf{x}_K^t \mathbf{x}_U$ 
19:   solve  $\min_{\boldsymbol{\beta}_U} (\frac{1}{2n} \|\mathbf{u} - \boldsymbol{\beta}_U \mathbf{v}\|_2^2 + \lambda \sum_{j, X_j \in G_U} |\beta_j|)$  with glmnet to obtain  $\widehat{\boldsymbol{\beta}}_U$ 
20:   deduce  $\widehat{\boldsymbol{\beta}}_K$ 
21: end if

```

---

## 159 4 Numerical experiments

160 To compare our method of parameters estimation with the one of 0-1 weighted LASSO, we perform  
 161 numerical simulations. We focus on simulations where the number of observations  $n = 100$  and the  
 162 number of covariates  $p = 500$ . We also choose to run simulations where the explanatory variables  
 163  $(X_1, \dots, X_p)$  are correlated, to put our algorithm in a more challenging situation. Finally, only  $p_u = 40$   
 164 variables are actually used to build the model which means only 40 coordinates of  $\boldsymbol{\beta} \in \mathbb{R}^p$  are really  
 165 used to construct  $Y$ .

### 166 4.1 Data simulation

167 To simulate correlated data in a realistic way, we rely on the work by Friguet (2010). We first divide  
 168 the  $p$  variables in  $H$  independent groups. For each group  $h$ , a covariance matrix is computed using  
 169 gaussian latent variables to determine correlations between variables, and a dataset of size  $n \times \frac{p}{H}$  is  
 170 sampled from a multivariate normal distribution. The data generated for each group  $h \in [1, H]$  are  
 171 then merged together in a single dataset. The structure of the global covariance matrix of the data  
 172 is thus block diagonal. An excerpt of this matrix is presented Figure 1 as an example. The code to  
 173 generate the data, based on page 123 of Friguet (2010), is given below, the parameter  $H$  being set to 5.

```

library(mvtnorm)
library(corrplot, quietly = TRUE)

```

```

174 corrplot 0.92 loaded

p = 500
n = 100
H = 5
constant = 10 # intercept
q = rep(4,H) # number of latent variables in each group
strength = 7/10 # level of the correlation between variables of the same group
data = matrix(rep(0, n*p), ncol = p, nrow = n)
for (h in 1:H){
  B_k = strength*rmvnorm(p/H, mean = rep(0, q[h]), sigma = diag(q[h]))
  Sigma_k = apply(B_k^2, 1, sum) + rep(1, p/H)
  B_k = diag(1/sqrt(Sigma_k))%*%B_k
  Psi_k = diag(1/Sigma_k)
  # matrix of var-covar
  Var_k = B_k %*% t(B_k) + Psi_k
  # data generation
  X_k = rmvnorm (n, mean = rep(0,p/H), sigma = Var_k) # mean 0
  data[,((h-1)*p/H+1):(h*p/H)] = X_k
}
data = as.data.frame(data)

```

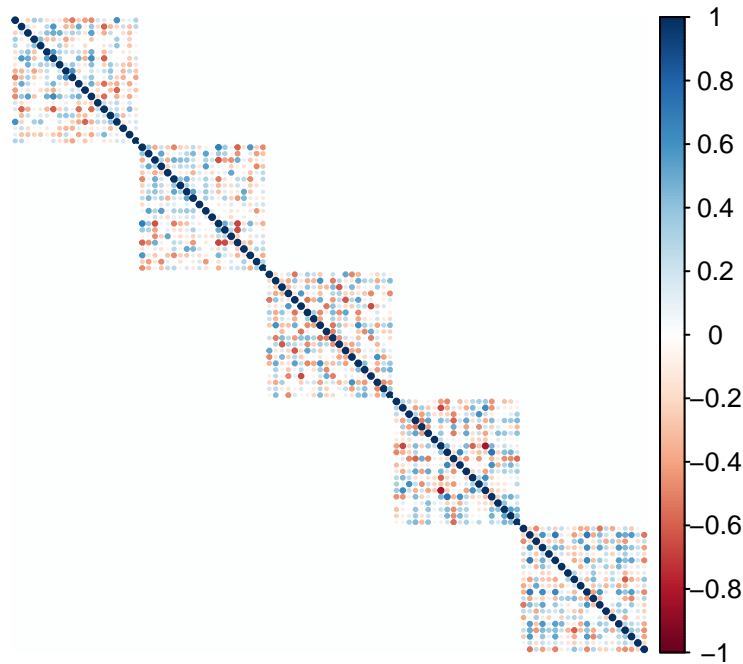


Figure 1: Correlation matrix of the variables of the model. Only the first 20 variables of each group are plotted.

175 Once we got the data matrix  $\mathbf{x}$ , we compute  $\mathbf{y}$  using the 8 first variables of each group. The coefficients  
 176  $\beta_j$  which are not 0 go from 1 to 8 in each group. Our final model for the numerical simulations is  
 177 thus:

$$y = \beta_0 + \sum_{j=1}^8 \beta_j x_j + \sum_{j=101}^{108} \beta_j x_j + \sum_{j=201}^{208} \beta_j x_j + \sum_{j=301}^{308} \beta_j x_j + \sum_{j=401}^{408} \beta_j x_j + \epsilon,$$

178 with  $\beta_1 = \beta_{101} = \dots = \beta_{401} = 1, \dots, \beta_8 = \beta_{108} = \dots = \beta_{408} = 8$  and  $\epsilon \sim \mathcal{N}(0, 4)$ .



```

library(expm,quietly = TRUE)
179
180 Attaching package: 'expm'
181 The following object is masked from 'package:Matrix':
182
183     expm
standard_d = 2
beta = rep(c(1:8,rep(0,92)),5)
Y = as.matrix(data)%*%beta + rnorm(n, mean = 0, sd = standard_d) + rep(constant, n)
colnames(Y) = "Y"
data = cbind(data,Y)

```

## 184 4.2 Introduction of a priori knowledge

185 To see how the semi-LASSO algorithm performs with different levels of prior knowledge, we pro-  
186 gressively add variables from the  $G_U$  group to the  $G_K$  group. 11 scenarii are tested, starting with  
187 with  $G_K = \emptyset$  where no regressor is known. We then add 4 variables (corresponding to 10% of true  
188 regressors) in  $G_K$  several times to finally reach  $G_K = (X_{j_1}, \dots, X_{j_{p_u}})$  where  $X_{j_1}, \dots, X_{j_{p_u}}$  are the  $p_u$   
189 variables used to build the model ( $j_1 = 1, \dots, j_8 = 8, j_9 = 101, \dots, j_{40} = 408$ ), as explained in Table 1.  
190 One variable of each group  $h \in [1, H - 1]$  is added in scenarii  $s_1$  to  $s_8$ , then four variables of the last  
191 group  $h = H$  are added in  $s_9$  and  $s_{10}$ . In scenario  $s_{10}$ , all  $p_u$  variables have been added to  $G_K$ .

Table 1: Description of each scenario to estimate the  $\beta$  coefficients

Scenario	% of prior knowledge	Variables in $G_K$	Variables in $G_U$
$s_0$	0	0	500
$s_1$	10	4	496
$s_2$	20	8	492
$s_3$	30	12	488
$s_4$	40	16	484
$s_5$	50	20	480
$s_6$	60	24	476
$s_7$	70	28	472
$s_8$	80	32	468
$s_9$	90	36	464
$s_{10}$	100	40	460

```

# Construction of the vector of prior knowledge used to progressively add variables in G_K
prior_know = c()
for (h in 1:(H-1)){
  # for the first 4 groups, the first 8 variables will be progressively added to G_K
  # (corresponding to scenarii s_1 to s_8)
  prior_know_h = c(1/10*1:8, rep("not used",92))
  # for the variables not used in the model, prior_know is set to `not used`.
  # It means they will never be included as prior knowledge in the model
  prior_know = c(prior_know, prior_know_h)
}
# Concerning the last group (h=5), the first 8 variables will be added in s_9 and s_10

```

```
prior_know = c(prior_know, rep(0.9,4),rep(1,4), rep("not used",92))
names(prior_know) = colnames(data[, -dim(data)[2]])
```

192 The vector of prior knowledge is then used to iteratively construct the groups  $G_K$  and  $G_U$  for each  
 193 scenario :

```
Groups_construction <- function (prior,partial_know){
  # prior : vector of the prior knowledge indicating when the variable enters into the G_K group
  # partial_know : proportion of partial knowledge to include (between 0 and 1)
  G_K = c()
  G_U = c()
  # G_K = group with a priori
  # G_U = group with no a priori
  for (j in 1:length(prior)){
    if((prior[j]<= partial_know)){
      G_K = c(G_K, names(prior)[j])
    }
    else{
      G_U = c(G_U, names(prior)[j])
    }
  }
  list(G_K, G_U)
}
```

### 194 4.3 Estimation of the parameters

195 To select an appropriate value for the parameter  $\lambda$ , we use, both in semi-LASSO and 0-1 weighted  
 196 LASSO methods, the `cv.glmnet` function which performs 10-fold cross-validation.  $K = 50$  datasets  
 197 are generated following the scheme of Section 4.1. A parameters estimation is performed for each  
 198 simulation in order to evaluate the variability coming both from the noise  $\epsilon$  in Equation 1 at the  
 199 step of data generation and the cross-validation in `cv.glmnet` . We use both semi-LASSO and 0-1  
 200 weighted LASSO to estimate  $\beta$  given a dataset and a scenario of Table 1. All the results presented  
 201 in Section 5 are shown as boxplots relative to these 50 replica. The code below shows how the  
 202 parameters estimation is performed for a particular dataset.

203 Loaded `glmnet` 4.1-8

```
load("data/Data.RData")
options( "digits"=5, "scipen"=0)
# loading of the list containing the K = 50 datasets
# We show how the estimation works using only the first dataset
data_K = Data[[1]]

# semi-LASSO
regressors_list_by_knowledge = list() # creation of the list of regressors
# each element of the list will correspond to a particular scenario
index = 1
for (l in seq(0, 1, by = 0.1)){ # levels of prior knowledge
  A_priori_group = Groups_construction(prior_know,l) # construction of G_K and G_U
  result = semi_LASSO(A_priori_group[[1]], A_priori_group[[2]], data_K,
                     colnames(data_K)[length(colnames(data_K))],
                     inter = TRUE)
```

```

regressors_list_by_knowledge[[index]] = result[[1]]
index = index + 1
}
names(regressors_list_by_knowledge) = seq(0, 1, by = 0.1)

# 0-1 weighted LASSO
regressors_list_by_knowledge_glmnet = list()
index = 1
for (l in seq(0,1, by = 0.1)){
  weights = as.numeric(prior_know>l) # transformation of prior_know into 0-1 weights
  # the p+1th variable in data_K is Y
  reg = cv.glmnet(x = as.matrix(data_K[,-(p+1)]), y = as.matrix(data_K[, (p+1)]), penalty.factor =
  result = coef(reg)[-1,] # reorder the position of the intercept estimation
  result = c(result, coef(reg)[1,])
  names(result)[p+1] = "Intercept"
  regressors_list_by_knowledge_glmnet[[index]] = result
  index = index + 1
}
names(regressors_list_by_knowledge_glmnet)<-seq(0, 1, by = 0.1)

```

```

# The first 8 estimated coefficients by semi-LASSO, for a prior knowledge of 20%
regressors_list_by_knowledge[[3]][1:8]

```

```

204      V1      V2      V3      V4      V5      V6      V7      V8
205 0.41737 2.45429 0.00000 0.00000 0.00000 6.75924 2.24398 3.21918

```

```

# The first 8 estimated coefficients by 0-1 weighted LASSO, for a prior knowledge of 20%
regressors_list_by_knowledge_glmnet[[3]][1:8]

```

```

206      V1      V2      V3      V4      V5      V6      V7      V8
207 0.18738 2.94932 0.00000 0.00000 0.00000 7.25378 0.39463 2.50380

```

#### 208 4.4 Criteria used to compare the methods

209 To compare the results from semi-LASSO and the 0-1 weighted LASSO, we use the following indica-  
210 tors:

- 211 • The sensitivity (true positive rate), defined as:

$$se = \frac{TP}{TP + FN} = \frac{|\{\beta_j \neq 0\} \cap \{\hat{\beta}_j \neq 0\}|}{|\{\beta_j \neq 0\}|},$$

212 with  $\hat{\beta}_j$  the estimated parameters of the model. TP is the number of true positives, i.e. the  
213 number of true regressors of the model that are correctly selected by the method, and FN is the  
214 number of false negatives, i.e the number of true regressors of the model that are not selected  
215 by the method. It measures the proportion of true regressors of the model correctly selected  
216 by the method among all the true regressors of the model .

- 217 • The specificity (true negative rate), defined as:

$$sp = \frac{TN}{TN + FP} = \frac{|\{\beta_j = 0\} \cap \{\hat{\beta}_j = 0\}|}{|\{\beta_j = 0\}|},$$

218 with TN the number of true negatives, i.e. the variables which are not regressors in the model  
 219 and not found as such by the method, and FP the false positives, i.e. the variables which are  
 220 not regressors in the model but found as such by the method. It measures the proportion of  
 221 variables which are not regressors in the model and that the method correctly identify as such.

- 222 • The Root Mean Square Error, defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2},$$

223 with  $\hat{y}_i = \sum_{j=1}^p \hat{\beta}_j x_{ij}$  the prediction of  $y_i$ . It measures the capacity of prediction of the fitted  
 224 model. It is calculated on a new dataset of size  $n$ , constructed with the procedure described in  
 225 Section 4.1. This dataset was not used to perform the parameters estimation.

- 226 • Individual coefficients estimation, defined as the gap between the estimated value  $\hat{\beta}_j$  and  
 227 the true one  $\beta_j$ , to identify which method performs better in finding the true value of the  
 228 coefficients, and the impact of the prior knowledge on the estimation.

229 The first two criteria concern the ability of the fitted model to select the true regressors whereas  
 230 the third one assesses the capacity to predict  $Y$ . As for the fourth one, it measures the quality of the  
 231 estimation of a particular  $\beta_j$ . We also want to see the impact of the prior knowledge level on these  
 232 indicators.

## 233 5 Results

234 We present here the results of the simulations introduced in Section 4.

```
library(ggplot2)
load("data/Data_final.RData") # load the RData containing
# - parameters estimations for semi-LASSO and 0-1 weighted LASSO
# - sensitivity
# - specificity
# - RMSE on the test dataset
```

### 235 5.1 Sensitivity and specificity

236 We first give the results about the performance of variables selection, which is emphasized by the  
 237 sensitivity and specificity described in Section 4.4.

238 Figure 2 and Figure 3 present respectively the sensibility and the specificity for the semi-LASSO and  
 239 0-1 weighted LASSO methods. Each boxplot corresponds to the 50 replica described in Section 4.1,  
 240 done for both methods (blue for 0-1 weighted LASSO, yellow for semi-LASSO) and a prior knowledge  
 241 given in abscissa (see Table 1).

242 We can first notice that in Figure 2 the sensitivity increases with prior knowledge for both methods,  
 243 which seems coherent with the fact that we force relevant variables to be included into the model.  
 244 With a level of prior knowledge lower than 80%, the semi-LASSO method seems to be more efficient  
 245 in finding true positive regressors. In the semi-LASSO method, we first remove the influence of the  
 246 variables of  $G_K$  before solving a LASSO problem on the remaining variables (see the expressions of  $\mathbf{u}$   
 247 and  $\mathbf{v}$  in Section 3). This suggests that this additional step allows the final LASSO procedure to be  
 248 more efficient in finding true regressors among the remaining variables. When the prior knowledge  
 249 level is high enough ( $> 90\%$ ), the given information is sufficient for both methods to perform equally  
 250 well in terms of sensitivity.

```

ggplot(Data_final, aes(x = PriorKnowledge, y = Sensitivity)) +
geom_boxplot(aes(fill = Method), position = position_dodge(0.9)) +
scale_fill_manual(values = c("#00AFBB", "#E7B800")) +
geom_hline(aes(yintercept = 1), color = "red") + expand_limits(y=c(0, 1)) +
labs(x = "% of prior knowledge", y = "Sensitivity")

```

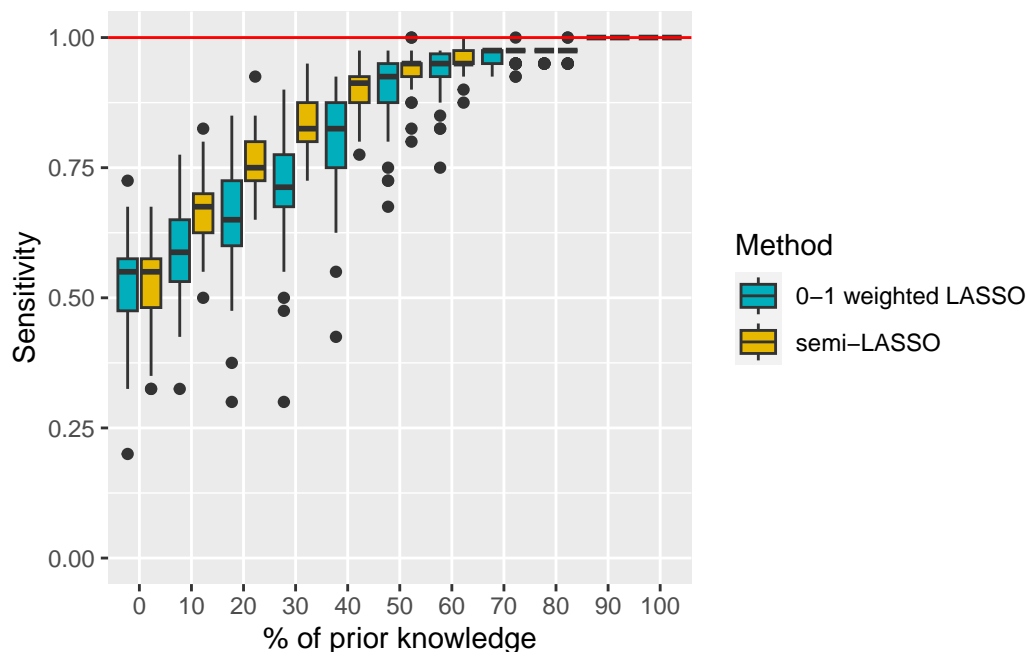


Figure 2: Boxplots of the sensitivity for each prior knowledge scenario and each method of parameters estimation.

251 Looking at the specificity in Figure 3, we see that it is high for both methods and prior knowledge levels.  
252 The 0-1 weighted LASSO method seems to perform better when the prior knowledge level increases,  
253 and to limit the number of false positive into the model. The step of LASSO in the semi-LASSO  
254 algorithm is performed in a smaller space, and tries to find non-zero values for some coefficients.  
255 When the prior knowledge information increases, there are less and less correct regressors to find,  
256 which means the LASSO will include more and more irrelevant variables in the model. It is particularly  
257 true when the prior knowledge is set to 1 and all correct regressors have been put in  $G_K$ . In the  
258 0-1 weighted LASSO, the optimization is done directly in  $\mathbb{R}^{p+1}$ , which restricts the number of false  
259 positives. In both cases, the global specificity never goes below 0.85, which is satisfying.

```

ggplot(Data_final, aes(x = PriorKnowledge, y = Specificity)) +
geom_boxplot(aes(fill = Method), position = position_dodge(0.9)) +
scale_fill_manual(values = c("#00AFBB", "#E7B800")) +
geom_hline(aes(yintercept = 1), color = "red") + expand_limits(y=c(0,1)) +
labs(x = "% of prior knowledge", y = "Specificity")

```

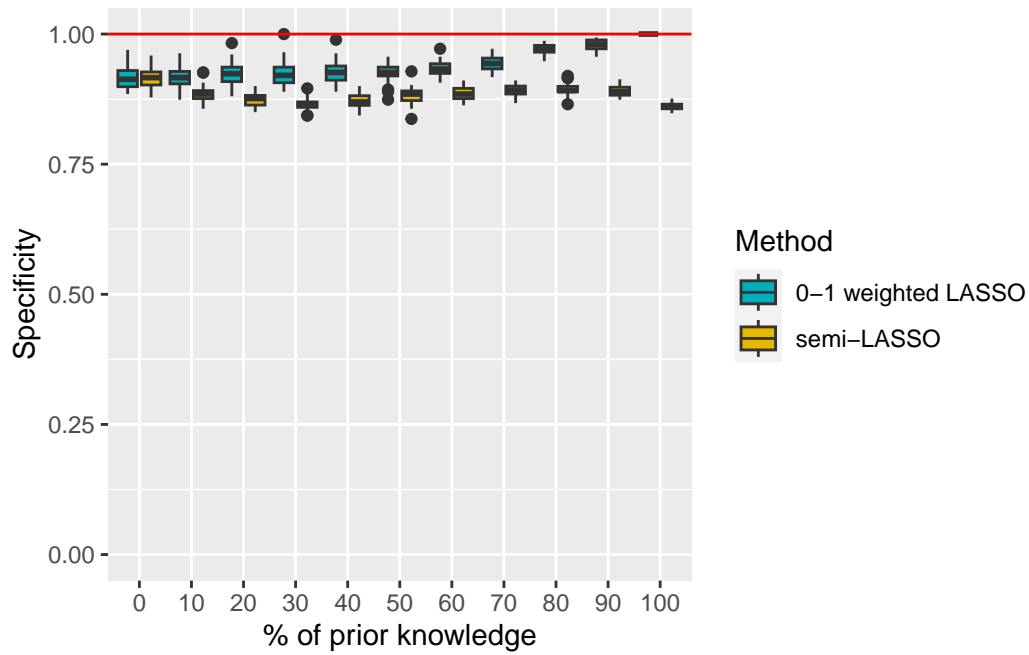


Figure 3: Boxplots of the specificity for each prior knowledge scenario and each method of parameters estimation.

## 260 5.2 RMSE

261 Regarding the RMSE values plotted in Figure 4, we can see that the semi-LASSO has a lower prediction  
 262 error than the 0-1 weighted LASSO for a prior knowledge level smaller than 80%. For higher values,  
 263 the 2 methods are similar, with a slight advantage for the 0-1 weighted LASSO. This can be explained  
 264 one more time by the irrelevant variables added into the model by the semi-LASSO method when  
 265 the prior knowledge level is high.

```
ggplot(Data_final, aes(x = PriorKnowledge, y = RMSEtest)) +
  geom_boxplot(aes(fill = Method), position = position_dodge(0.9)) +
  scale_fill_manual(values = c("#00AFBB", "#E7B800")) +
  labs(x = "% of prior knowledge", y = "RMSE")
```

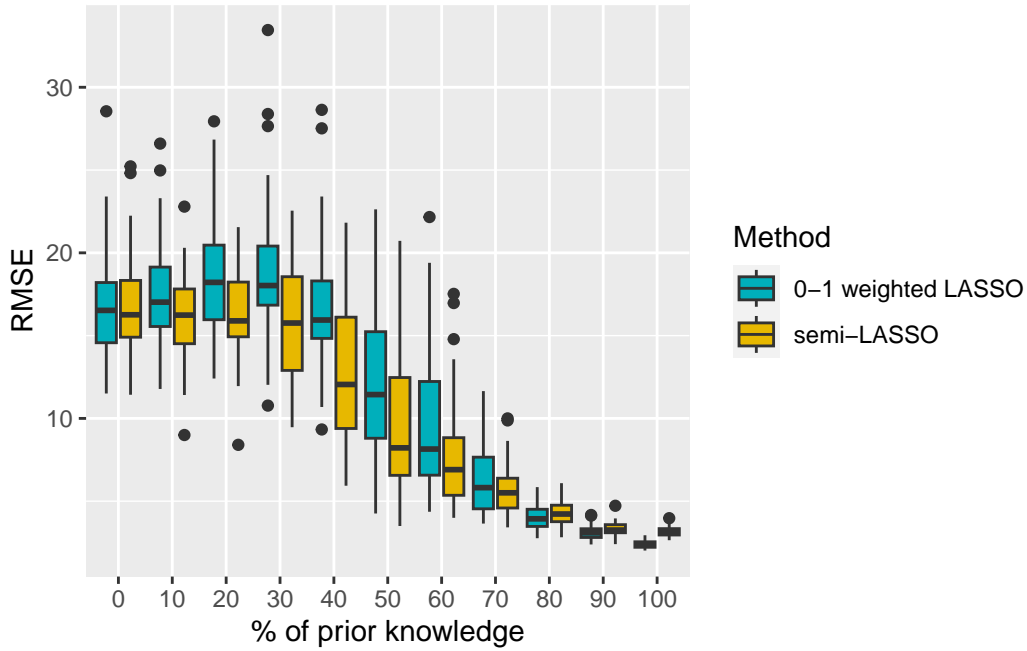


Figure 4: Boxplots of the RMSE calculated on a test dataset for each prior knowledge scenario and each method of parameters estimation.

### 266 5.3 Parameters estimation

267 To illustrate how the methods perform in estimating the parameters, we plot on Figure 5, the  
 268 estimation of the parameter  $\beta_7 = 7$ , associated to the variable  $X_7$ . The horizontal red line indicates  
 269 the true value of the coefficient, whereas the vertical one shows the first scenario where the variable  
 270  $X_7$  is added to  $G_K$  (see Table 1).

271 Until the prior knowledge level reaches 70%, the semi-LASSO estimates  $\beta_7$  using a classic LASSO, as  
 272  $X_7$  is in  $G_U$ . Nevertheless, other variables are progressively added to  $G_K$  when the prior knowledge  
 273 level increases. We can see that the estimation based on the semi-LASSO is better than the one made  
 274 with the 0-1 weighted LASSO. This difference certainly follows from the fact that the optimization  
 275 performed on a smaller space in the semi-LASSO than the one from the 0-1 weighted LASSO,  
 276 performed on  $R^{p+1}$ . After we reach 70% of prior knowledge,  $X_7$  belongs to  $G_K$ , which means it has  
 277 a 0 weight in the 0-1 weighted LASSO, and is estimated via ordinary least squares estimator in  
 278 semi-LASSO. At this point, both methods perform equally well for the estimation of  $\beta_7$ , since we  
 279 force the variable to be part of the model.

280 One can notice that for some levels of prior knowledge (20% to 40%), `glmnet` often does not include  
 281 the variable into the model, i.e. the estimated parameter  $\hat{\beta}_7$  is equal to zero, and thus generates some  
 282 false negatives which impacts the sensitivity on Figure 2. This is not the case for the semi-LASSO  
 283 method.

```
ggplot(Data_final, aes(x = PriorKnowledge, y = V7)) +
  geom_boxplot(aes(fill = Method), position = position_dodge(0.9)) +
  scale_fill_manual(values = c("#00AFBB", "#E7B800")) +
  geom_hline(aes(yintercept = 7), color = "red") +
  geom_vline(aes(xintercept = 8), color = "red") +
  labs(x = "% of prior knowledge", y = "X7")
```

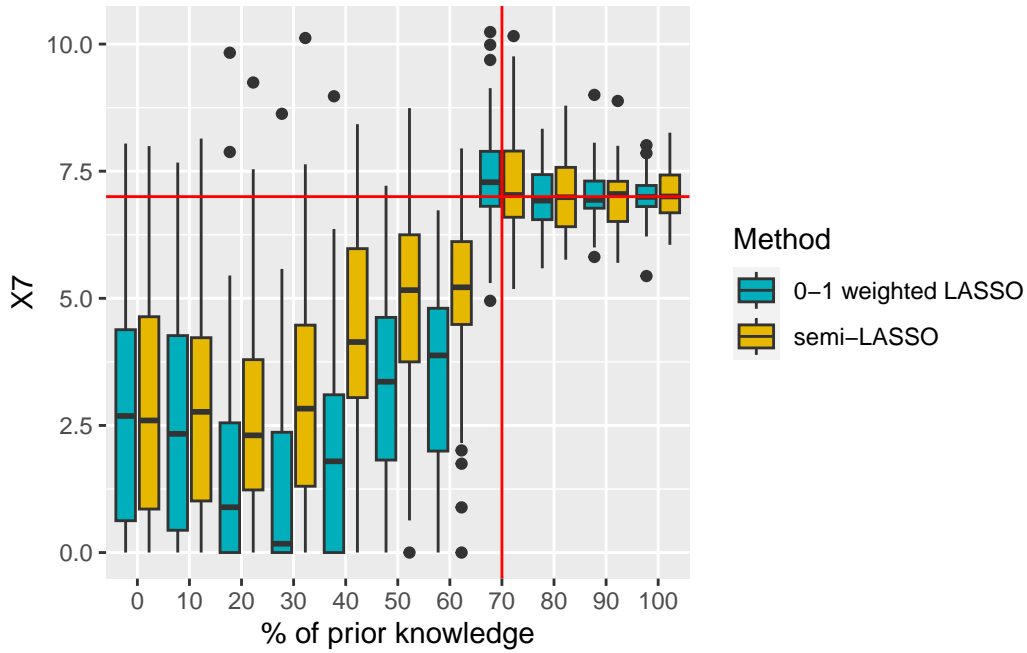


Figure 5: Boxplots of the estimated values for a coefficient of the model, for each prior knowledge scenario and each method of parameters estimation.

#### 5.4 Other tests and some possible extensions

Similar results as the ones presented in Section 5 were obtained with different settings including :

- The number of observations  $n$  being set to 1000 to have  $p < n$ .
- Independent variables ( $X_j, j \in [1, p]$ ) instead of correlated ones.
- A model without intercept<sup>2</sup>.
- Non-centered variables ( $X_j, j \in [1, p]$ ).
- Different values for  $\sigma$ .

In all cases, the obtained graphs show similar behaviors as the ones presented here and are thus not included in the paper.

Several extensions are possible using the framework of the semi-LASSO method. We can think at first of a weighted elasticnet method (Zou and Hastie 2005), with 0 and 1 weights. The mathematical formulation presented in Section 3 can indeed be generalized to this type of penalization.

Another possible extension would be a classic weighted LASSO with some 0 weights and other weights not all equal to 1. In this case, we could again use the decomposition of Section 3, but the classical LASSO in the semi-LASSO algorithm would be replaced by a weighted LASSO.

## 6 Conclusion

This paper introduces a new weighted LASSO method, called semi-LASSO, designed for the integration of prior knowledge into the model. It relies on the R package `glmnet`, but does not use the `penalty.factor` allowing to specify weights. Instead of that, it first transforms the problem to

<sup>2</sup>During the redaction of this paper, we tested several options in `glmnet`, in particular the `intercept` parameter that we set to `FALSE`. It seems that when the data given in entry of the function is not centered beforehand, `glmnet` does not produce convincing results. We then found ourselves with significantly better results using the semi-LASSO algorithm. It appears that this [issue](#) was raised years ago, but do not seem to be fixed.



303 divide the optimization procedure into two steps. The first one is an ordinary least square method,  
 304 which allows to reduce the space dimension for the second one: a classic LASSO procedure. The  
 305 reduction of dimension in the semi-LASSO procedure gives significantly better results than the use  
 306 of `penalty.factor` implemented in `glmnet` both on the proportion of true regressors detected by  
 307 the method and on the prediction error. We can also see a better coefficient estimation with the  
 308 semi-LASSO. These improvements come with a size restriction: our method can only be applied if  
 309  $|G_K| \leq n$  because the first step is an ordinary least squares problem.  
 310 Moreover, in terms of model selection, increasing the true positive rate using the semi-LASSO means  
 311 decreasing the true negative rate, compared to the 0-1 weighted LASSO. Depending on the problem  
 312 the user tries to solve, it is left to his discretion to use either semi-LASSO or `glmnet` to reduce the  
 313 most important rate at his eyes. The semi-LASSO procedure can also be applied in some extensions  
 314 like weighted LASSO with different weights, or an elastic-net penalization.

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 317 Rago.

## 318 Session information

```

319 sessionInfo()
320
321 R version 4.2.2 (2022-10-31)
322 Platform: x86_64-pc-linux-gnu (64-bit)
323 Running under: Ubuntu 22.04.4 LTS
324
325 Matrix products: default
326 BLAS: /usr/lib/x86_64-linux-gnu/openblas-pthread/libblas.so.3
327 LAPACK: /usr/lib/x86_64-linux-gnu/openblas-pthread/libopenblaspr0.3.20.so
328
329 locale:
330   [1] LC_CTYPE=C.UTF-8      LC_NUMERIC=C           LC_TIME=C.UTF-8
331   [4] LC_COLLATE=C.UTF-8    LC_MONETARY=C.UTF-8   LC_MESSAGES=C.UTF-8
332   [7] LC_PAPER=C.UTF-8     LC_NAME=C              LC_ADDRESS=C
333  [10] LC_TELEPHONE=C       LC_MEASUREMENT=C.UTF-8 LC_IDENTIFICATION=C
334
335 attached base packages:
336 [1] stats      graphics  grDevices datasets  utils      methods    base
337
338 other attached packages:
339 [1] ggplot2_3.4.4  glmnet_4.1-8  attempt_0.3.1  expm_0.999-8  Matrix_1.6-1.1
340 [6] corrplot_0.92  mvtnorm_1.2-4
341
342 loaded via a namespace (and not attached):
343 [1] Rcpp_1.0.11     compiler_4.2.2  pillar_1.9.0   iterators_1.0.14
344 [5] tools_4.2.2     digest_0.6.33  jsonlite_1.8.8 evaluate_0.23
345 [9] lifecycle_1.0.4 tibble_3.2.1   gtable_0.3.4   lattice_0.21-9
346 [13] pkgconfig_2.0.3 rlang_1.1.2    foreach_1.5.2  cli_3.6.2
347 [17] yaml_2.3.8      xfun_0.41       fastmap_1.1.1  withr_2.5.2
348 [21] knitr_1.45      vctrs_0.6.5    grid_4.2.2     glue_1.6.2
  
```

347 [25] R6\_2.5.1 fansi\_1.0.6 survival\_3.5-7 rmarkdown\_2.25  
 348 [29] farver\_2.1.1 magrittr\_2.0.3 scales\_1.3.0 codetools\_0.2-19  
 349 [33] htmltools\_0.5.7 splines\_4.2.2 shape\_1.4.6 colorspace\_2.1-0  
 350 [37] renv\_1.0.3 labeling\_0.4.3 utf8\_1.2.4 munsell\_0.5.0

## 351 Bibliography

- 352 Bergersen, Linn Cecilie, Ingrid K Glad, and Heidi Lyng. 2011. “Weighted Lasso with Data Integration.”  
 353 *Statistical Applications in Genetics and Molecular Biology* 10 (1).
- 354 Cassan, Océane, Charles Henri Lecellier, Antoine Martin, Laurent Brehelin, and Sophie Lèbre. 2023.  
 355 “Optimizing Data Integration Improves Gene Regulatory Network Inference in Arabidopsis  
 356 Thaliana.” *bioRxiv*, 2023–09.
- 357 Charbonnier, Camille, Julien Chiquet, and Christophe Ambroise. 2010. “Weighted-LASSO for  
 358 Structured Network Inference from Time Course Data.” *Statistical Applications in Genetics and  
 359 Molecular Biology* 9 (1).
- 360 Efron, Bradley, Trevor Hastie, Iain Johnstone, and Robert Tibshirani. 2004. “Least angle regression.”  
 361 *The Annals of Statistics* 32 (2): 407–99.
- 362 Friedman, Jerome, Trevor Hastie, and Rob Tibshirani. 2010. “Regularization Paths for Generalized  
 363 Linear Models via Coordinate Descent.” *Journal of Statistical Software* 33 (1): 1.
- 364 Friguet, Chloé. 2010. “Impact de La dépendance Dans Les Procédures de Tests Multiples En Grande  
 365 Dimension.” PhD thesis, Agrocampus-Ecole nationale supérieure d’agronomie de rennes.
- 366 Greenfield, Alex, Christoph Hafemeister, and Richard Bonneau. 2013. “Robust Data-Driven Incorporation of Prior Knowledge into the Inference of Dynamic Regulatory Networks.” *Bioinformatics* 29 (8): 1060–67.
- 369 Grzegorzczak, Marco, Andrej Aderhold, and Dirk Husmeier. 2019. “Overview and Evaluation of  
 370 Recent Methods for Statistical Inference of Gene Regulatory Networks from Time Series Data.”  
 371 *Gene Regulatory Networks: Methods and Protocols*, 49–94.
- 372 Huynh-Thu, Vân Anh, and Guido Sanguinetti. 2019. “Gene Regulatory Network Inference: An  
 373 Introductory Survey.” *Gene Regulatory Networks: Methods and Protocols*, 1–23.
- 374 Leclerc, Robert D. 2008. “Survival of the Sparsest: Robust Gene Networks Are Parsimonious.”  
 375 *Molecular Systems Biology* 4 (1): 213.
- 376 Siahpirani, Alireza Fotuhi, Deborah Chasman, and Sushmita Roy. 2019. “Integrative Approaches for  
 377 Inference of Genome-Scale Gene Regulatory Networks.” *Gene Regulatory Networks: Methods and  
 378 Protocols*, 161–94.
- 379 Tibshirani, Robert. 1996. “Regression Shrinkage and Selection via the Lasso.” *Journal of the Royal  
 380 Statistical Society Series B: Statistical Methodology* 58 (1): 267–88.
- 381 Xenarios, Ioannis, Danny W Rice, Lukasz Salwinski, Marisa K Baron, Edward M Marcotte, and David  
 382 Eisenberg. 2000. “DIP: The Database of Interacting Proteins.” *Nucleic Acids Research* 28 (1):  
 383 289–91.
- 384 Yuan, Ming, and Yi Lin. 2006. “Model Selection and Estimation in Regression with Grouped Variables.”  
 385 *Journal of the Royal Statistical Society Series B: Statistical Methodology* 68 (1): 49–67.
- 386 Zou, Hui. 2006. “The Adaptive Lasso and Its Oracle Properties.” *Journal of the American Statistical  
 387 Association*, 1418–29.
- 388 Zou, Hui, and Trevor Hastie. 2005. “Regularization and Variable Selection via the Elastic Net.” *Journal  
 389 of the Royal Statistical Society Series B: Statistical Methodology* 67 (2): 301–20.