

# CorReg : Regression for correlated variables and application in steel industry

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**Abstract.** Linear regression generally suppose to have decorrelated covariates. This hypothesis is often irrealist with industrial datasets that contains many highly correlated covariates due to the process, physcial laws, *etc.* The proposed generative model consists in explicit modeling of the correlations with a family of linear regressions between the covariates permitting to obtain by marginalization a parsimonious correlation-free regression model, easily understandable and compatible with variable selection methods. The structure of correlations is found with an MCMC algorithm. An R package (CORREG) available on the CRAN implements this new method which will be illustrated on both simulated datasets and real-life datasets from steel industry.

**Keywords.** Regression, correlations, industry, variable selection, generative models

## 1 Introduction

When one wants to explain a phenomenon based on some covariates, the first statistical method tried frequently is the linear regression. It provides a predictive model with a good interpretability and is simple to learn for non-statistician. Therefore, linear regression is used in nearly all the fields where statistics are made, from industry (ballistic models to calibrate the process) to sociology (predicting some numerical properties of a population). Linear regression is a very classic situation that faces an also classical problem : the variance of the estimators. This variance increases based on two aspects :

- The dimension  $p$  (number of covariates) of the model : the more covariates you have the greater variance you get.
- The correlations within the covariates : strongly correlated covariates give bad-conditioning and increase variance of the estimators .

With the rise of informatic, datasets contains more and more covariates and thus more and more useless covariates. So dimension reduction becomes a necessity. Moreover, when you use more covariates, you increase the chance to have correlated ones. For example, this work takes place in an industrial (steel industry) context with a big set of covariates (many parameters of the whole process without any a priori) highly correlated (physical laws, process rules, etc). In such a context, variance of the estimators can lead to arbitrary results or even no results at all. Prediction and interpretation are both strongly needed, with a preference for interpretation in industrial context (better to improve the process when possible than to only predict defects).

When estimating the parameters of the regression we have to compute the inverse of a matrix[14] which will be ill-conditioned or even singular if some covariates depend linearly from each other. For a model defined by

$$Y = X\beta + \varepsilon \tag{1}$$

where  $X$  is the  $n \times p$  matrix of the explicative variables,  $Y$  the response vector and  $\varepsilon \sim \mathcal{N}(0, \sigma_Y^2)$  we have the following Ordinary Least Squares (OLS) estimators :

$$\hat{\beta} = (X'X)^{-1} X'Y \quad (2)$$

With variance

$$\text{Var}(\hat{\beta}) = \sigma_Y^2 (X'X)^{-1} \quad (3)$$

And when correlations between covariates are strong, the matrix to invert is ill-conditioned and the variance explodes.

Because it is the minimum-variance unbiased estimator, penalized methods try to reduce the variance introducing some bias to improve the bias-variance trade-off and get better prediction. Moreover, real datasets implies many irrelevant variables (datasets based on the whole process without any a priori) so we have to use variable selection methods.

In the following we note classical norms:  $\|\beta\|_2^2 = \sum_{i=1}^p (\beta_i)^2$  and  $\|\beta\|_1 = \sum_{i=1}^p |\beta_i|$

Ridge regression[12] proposes a biased estimator that can be written in terms of a parametric  $L_2$  penalty.:

$$\hat{\beta} = \text{argmin} \left\{ \|Y - X\beta\|_2^2 \right\} \text{ subject to } \|\beta\|_2^2 \leq k \quad (4)$$

But Ridge regression is not efficient to select covariates (it's an assumed choice) because coefficients tends to 0 but don't reach 0. So it gives difficult interpretations and is not adapted for our industrial context. We need to reduce the dimension of the model. Our goal is not just to predict but also to understand the response variable.

The Least Absolute Shrinkage and Selection Operator (LASSO)[15] consists in a shrinkage of the regression coefficients based on a  $\lambda$  parametric  $L_1$  penalty.

$$\hat{\beta} = \text{argmin} \left\{ \|Y - X\beta\|_2^2 \right\} \text{ subject to } \|\beta\|_1 \leq \lambda \quad (5)$$

The Least Angle Regression[4] (LAR) Algorithm offers a very efficient way to obtain the whole LASSO path and is very attractive. It requires only the same order of magnitude of computational effort as OLS applied to the full set of covariates. And it really selects covariates with coefficients set exactly to 0. But LASSO also faces consistency problems[21] when confronted with correlated covariates. This point will be developped further (see 4.3) with numerical results. Another limitation of the LASSO is that it preserves at most  $n$  predictors (troublesome when in high dimension). Some recent variants of the LASSO does exist for the choice of the penalization coefficient like the adaptative LASSO [22] or the random LASSO [17].

Elastic net[23] is a method developped to be a compromise between Ridge regression and the LASSO. Elastic net can be written:

$$\hat{\beta} = (1 + \lambda_2) \text{argmin} \left\{ \|Y - X\beta\|_2^2 \right\}, \text{ subject to } (1 - \alpha) \|\beta\|_1 + \alpha \|\beta\|_2^2 \leq t \text{ for some } t \quad (6)$$

where  $\alpha = \frac{\lambda_2}{(\lambda_1 + \lambda_2)}$  It seems to give good predictions. But it is based on the grouping effect and if the dataset contains two identical variables they will obtain the same coefficient whereas LASSO will choose between one of them and will then obtain same predictions with a more parsimonious model.

Another way of reducing the dimension is to consider clusters of variables with the same coefficients, like the Octogonal Shrinkage and Clustering Algorithm for Regression (OSCAR) [1]. The CLusterwise Effect REgression[18] (CLERE) describes the  $\beta_j$  no longer as fixed effect parameters but as unobserved independant random variables whith grouped  $\beta_j$  following a Gaussian Mixture distribution.

The idea is to hope that the model have a small number of groups of covariates and that the mixture will have few enough components to have a number of parameters to estimate significantly lower than  $p$ . In such a case, it improves interpretability and ability to yeld reliable prediction with a smaller variance on  $\hat{\beta}$ . But it requires to suppose having many covariates with the same level of effect on the response variable and seems to stay less efficient in prediction than elastic net. Spike and Slab variable selection [10] also relies on Gaussian mixture (the spike and the slab) hypothesis for the  $\beta_j$  and gives a subset of covariates (not grouped) on which to compute OLS but has no specific

protection against correlations issues.

When some try to reduce the dimension and then just hope to have small correlations in the remaining dimensions, we propose to focus on the correlations, giving a model with orthogonal covariates. In fact we search the greatest set of orthogonal covariates to keep the maximum but with an orthogonality constraint. This can be viewed as a pretreatment on the dataset allowing to use then dimension reduction tools without suffering from correlations. We only consider strong correlations (i.e. : problematic ones) thus we keep most of the information contained in the dataset.

Our work is based on the assumption that if we know that correlations are a problem and if we precisely know the correlations, we could use this knowledge to avoid the problem. The idea is to suppose explicitly a linear structure between the covariates. It gives a system of linear regression that can be viewed as a recursive Simultaneous Equation Model (SEM)[3]. Such a system is easy to interpret but estimation don't take advantage of the explicit structure [16] when the structure is straight forward (recursive SEM). Other method already rely on linear structure and start to take into account correlations but they only consider covariances between the residuals (SUR) [19] or covariances between the endogenous variables like SPRING (Structured selection of Primordial Relationships IN the General linear model) [2].

In this work, we decide to distinguish the response variable from the other endogenous variables (that are on the left of a regression). Thus we don't have a system of regressions but one regression on our response variable and a system of subregressions (without the response variable). And we consider correlations between the explicative covariates of the main regression, not between the residuals. The structure is supposed to be the source of the correlations and allows us to define a reduced set of independent covariates. Thus we reduce dimension and correlations in the same time. The structure justifies the eviction of the redundant covariates without significant information loss. It can be seen as a pretreatment on the dataset based on the hypothesis of a strong structure between the covariates (i.e. : small  $\varepsilon_X$ ).

We can use any variable selection method on the reduced dataset with improved efficiency (reduced variance) due to dimension reduction and correlation suppression. So we obtain two kinds of zeros in our first model : coerced zeros due to correlations (redundant information) and estimated ones with classical variable selection methods applied on remaining variables. This two kinds of zero won't be interpreted in the same way and thus consistency issues don't mean interpretation issues any more. So we dodge the drawbacks of both grouping effect and variable selection.

But to work, we need an explicit structure between the covariates. SEM are often used in social sciences and economy where a structure is supposed "by hand" but here we want to be able to find a structure without any a priori (possibility to include some known structure remains). Graphical LASSO [6] offers a method to obtain a structure based on the precision matrix (inverse of the variance-covariance matrix). It consists in a selection in the precision matrix, setting some covariances to zero. But the resulting matrix is symmetric and we need an oriented graph for our SEM. So we developed an MCMC algorithm to find it (R package CorReg on CRAN). However, Graphical LASSO can be used in the initialization step of our MCMC. This structure is based on gaussian mixture models to fit better real datasets and to allow identifiability of the structure in terms of complexity (number of parameters).

This paper will first present the reduced model and its properties before describing in Section 3 the algorithm used to find the structure. We will then look at some numerical results on simulated (Section 4) and real industrial datasets (Section 5) before concluding and giving some perspectives in the sixth part.

## 2 Model to decorrelate the covariates

### 2.1 The generative model

Let  $Y \in \mathcal{R}^n$  be a response variable we want to explain with a set  $X \in \mathcal{R}^{n \times p}$  of  $p$  correlated covariates. We propose to explicitly define a family of  $p_2$  internal regressions between covariates with  $I_2$  the set of indices of endogenous variables in  $X$  (explained ones) and  $I_1 = \{I_1^1, \dots, I_1^{p_1}\}$  the set of the sets of indices of exogenous covariates (explaining ones) with  $\forall j \notin I_2, I_1^j = \emptyset$ . Then we have an explicit structure  $S = (I_1, I_2, p_1, p_2)$  where  $p_1 = (p_1^1, \dots, p_1^{p_2})$  is the vector of the number of covariates in each internal regression. Thus we have  $p_2 = |I_2|$  and  $p_1^j = |I_1^j|$  where  $|\cdot|$  represents the cardinal of an ensemble.

In the following, we note  $X^j$  the  $j^{th}$  column of a matrix  $X$ . For lighter notation we define  $X_2 = X^{I_2}$  the matrix of the endogenous covariates and  $X_1 = X \setminus X_2$  the matrix of the remaining exogenous covariates.

We can now write the generative model:

- Main regression between  $Y$  and  $X$ :

$$Y_{|S} = XA + \varepsilon_Y = X_1A_1 + X_2A_2 + \varepsilon_Y \text{ with } \varepsilon_Y \sim \mathcal{N}(0, \sigma_Y^2 I_n); \quad (7)$$

where  $A = (A_1, A_2) \in \mathcal{R}^p$  is the vector of the regression coefficients and  $I_n$  the identity matrix,

- Family of  $p_2$  regressions within correlated covariates in  $X$ :

$$\forall j \in I_2 : X_{|X_1, S}^j = X_1 B_1^j + \varepsilon_j \text{ with } \varepsilon_j \sim (0, \sigma_j^2 I_n); \quad (8)$$

where  $B_1^j \in \mathcal{R}^{(p-p_2)}$  are the vectors of the regression coefficients between the covariates (containing some zeros according to  $I_1^j$ ).

- $p - p_2$  remaining independent exogenous Gaussian mixtures:

$$\forall j \notin I_2 : X_{|S}^j \sim f(\theta_j) = \mathcal{GM}(\pi_j; \mu_j; \sigma_j^2) \text{ with } \pi_j, \mu_j, \sigma_j^2 \text{ vectors of size } k_j; \quad (9)$$

We make the hypothesis of the uncrossing rule  $I_1 \cap I_2 = \emptyset$  *i.e.* endogenous variables don't explain other covariates, thus  $X = [X_1, X_2]$ .

This generative model is conditionnal to  $S$ , the discrete structure model that is identifiable because we can't permute some regressions in (8) and obtain the same joint distribution  $P(X, Y)$ , the residuals  $(\varepsilon_j)$  would not stay Gaussian. These residuals are in the following supposed independent but one can suppose dependencies between them and then use appropriate tools to estimate them and the  $B_1^j$  like SUR with Feasible Generalized Least Squares (FGLS) by Zellner [19] or SPRING as mentioned in the introduction.

If there are exact regressions in (8), the structure won't be identifiable. But it only means that several structure will have the same likelihood and they will have the same interpretation. So it's not really a problem. Moreover, when an exact subregression is found, we can delete one of the implied variables without any loss of information and the structure will define a list of variable from which to delete. CorReg (Our R package) prints a warning to point out exact regressions when found.

To better fit industrial variables (Figure 1), we suppose in (9) that variables in  $X_1$  follow Gaussian mixtures. The great flexibility [13] of such models makes our model more robust. But one can use other laws if needed. Gaussian case is just a special case ( $k_j = 1$ ) of Gaussian mixture so it is included in our hypothesis.

### 2.2 Estimator and properties

We note that (7) and (8) also give by simple integration on  $X_2$  a regression model on  $Y$  *depending only on uncorrelated covariates*  $X_1$ :

$$Y = X_1(A_1 + \sum_{j \in I_2} B_1^j A_j) + \sum_{j \in I_2} \varepsilon_j A_j + \varepsilon_Y = X_1 \alpha_1 + \varepsilon_\alpha \quad (10)$$

So we have the unbiased estimator:

$$\hat{\alpha}_1 = (X_1' X^1)^{-1} X_1' Y \text{ and } \hat{\alpha}_2 = 0 \quad (11)$$

with variance:

$$\text{Var}[\hat{\alpha}_1|X] = (\sigma_Y^2 + \sum_{j \in I_2} \sigma_j^2 A_j^2)(X_1' X^1)^{-1} \text{ and } \text{Var}[\hat{\alpha}_2|X] = 0 \quad (12)$$

We see that the variance is reduced (no correlations and smaller matrix give better conditioning) for small values of  $\sigma_j$  *i.e.* strong correlations. Moreover, the explicit structure is parsimonious and simply consists in linear regressions and thus is easily understood by non statistician, allowing them to have a better knowledge of the phenomenon inside the dataset. Expert knowledge can even be added to the structure. This new model is reduced even without variable selection and is just a linear regression so every method for variable selection in linear regression can be used. Hence we hope to obtain a parsimonious model with *two kinds of zeros*: those from decorrelating step and those from selection step, with different meanings.

The CORREG package proposes to make selection with both LASSO (with LAR), elasticnet, adaptative lasso, and others more classical methods. A last Ordinary Least Square step is added to improve estimation because penalisation is made to select variables but also shrinks remaining coefficients. This last step allows to keep the benefits of shrinkage (variable selection) without any impact on remaining coefficients (see [20]).

### 2.3 Why grouping effect is misleading

In industrial context, when a model explain why things go wrong, one will try to fix the problem. If  $X_1 = X_2 + e$  and we have the grouping effect, we will obtain a model like  $Y = aX_1 + aX_2$ . Then when one will try to modify Y he will modify one of the covariates and both will change so he won't get expected results. Nothing constrains us to give only one equation. It is clearly better to give the user another equation (or system for more complex models) describing the correlations. So you get the following model :  $Y = aX_1 + aX_2$  and  $X_1 = X_2 + e$ . So you have more information and are able to decide better actions. With such a model, grouping effect is no more useful because when saying  $Y = 2aX_2$  and  $X_1 = X_2 + e$  you clearly show that  $X_2$  is correlated with both  $Y$  and  $X_1$ . So it is possible to combine the advantages of grouping effect and selection just giving several equations. Each equation here is very simple so you don't really increase complexity of the model. Uncrossed model ( $I_1 \cap I_2 = \emptyset$ ) guarantee to keep a simple structure easily interpretable.

## 3 Estimating subregressions with Markov chain

### 3.1 Structure comparison

All our work is based on  $S$ , the linear structure between the covariates. Our generative model allows us to compare structures with criterions like the Bayesian Information Criterion ( $BIC$ ) which penalize the log-likelihood according to the complexity of the structure [11]. But  $BIC$  tends to give too complex structures because we test a great range of models. Thus CORREG allows to choose to penalise the complexity a bit more with a hierarchical uniform *a priori* law  $P(S) = P(I_1|p_1, I_2, p_2)P(p_1|I_2, p_2)P(I_2|p_2)P(p_2)$  instead of a simple uniform law on  $S$ . It increases penalty on complexity for  $p_2 < \frac{n}{2}$ . Hence this hypothesis is made and will become a constraint in the MCMC. But we can imagine to use other criterions, like the  $RIC$  (Risk Inflation Criterion [5]) that choose a penalty in  $\log p$  instead of  $\log n$  and thus gives more parsimonious models when  $p$  is larger than  $n$  (high dimension) or any other criterion [7] thought to be better in a given context.

Variables in  $X_1$  are supposed to be independent. Thus if one have some hypothesis on the distribution of some variables (exponentially distributed for example) he can compute corresponding  $BIC$  separately, give it as an input of CORREG and then improve the efficiency of the algorithm (it will find a structure only if it is really relevant). We will now use the following notation:  $\psi(S) = \psi(X|S)$  where  $\psi(X|S)$  is the chosen criterion that will be  $BIC$  in the following.

### 3.2 The neighbourhood

Let's define  $\mathcal{S}$  the ensemble of feasible structures (those with  $I_1 \cap I_2 = \emptyset$ ).

For each step, starting from  $S \in \mathcal{S}$  we define a neighbourhood:

$$\mathcal{V}_{S,j} = \{S\} \cup \{S^{(i,j)} | 1 \leq i \leq p, i \neq j\} \quad (13)$$

$$\text{where } j \sim \mathcal{U}(\{1, \dots, p\}) \quad (14)$$

With  $S^{(i,j)}$  defined by the following algorithm :

- if  $i \notin I_1^j$  (add):
  - $I_1^j = I_1^j \cup \{i\}$
  - $I_1^i = \emptyset$  (explicative variables can't depend on others : column-wise relaxation)
  - $I_1 = I_1 \setminus \{j\}$  (dependent variables can't explain others : row-wise relaxation)
- else (remove):  $I_1^j = I_1^j \setminus \{i\}$

At every moment, coherence between  $I_1$  and others parts of  $S$  can be done by  $\forall 1 \leq j \leq p : p_1^j = |I_1^j|$ ,  $I_2 = \{j | p_1^j > 0\}$ ,  $p_2 = |I_2|$ .

We have here at each step  $|\mathcal{V}_{S,j}| = p$  candidates but some other constraints can be added on the definition of  $\mathcal{S}$  and will consequently modify the size of the neighbourhood (for example a maximum complexity for the internal regressions or the whole structure, a maximum number of internal regressions, *etc.*). CORREG allows to modify this neighbourhood to better fit users constraints. Relaxation (column-wise and row-wise) is optional but gives more stability to the number of feasible candidates at each step and allows to modify several parts of  $I_1$  in only one step when needed. Hence it improves efficiency by a significant reinforcement of the irreducibility of the Markov chain.

#### 3.2.1 The walk

We first make the approximation

$$P(S|X) \approx \exp(\psi(S)). \quad (15)$$

The algorithm follows a time-homogeneous markov chain whose transition matrix  $\mathcal{P}$  has  $|\mathcal{S}|$  rows and columns (combinatory so we'll just compute the probabilities when we need them). At each step the markov chain moves with probabiliy:

$$\forall (S, \tilde{S}) \in \mathcal{S}^2 : \mathcal{P}(S, \tilde{S}) = \sum_{j=1}^p \mathbf{1}_{\{\tilde{S} \in \mathcal{V}_{S,j}\}} \frac{\exp(-\frac{1}{2}\psi(\tilde{S}))}{\sum_{S_l \in \mathcal{V}_{S,j}} \exp(-\frac{1}{2}\psi(S_l))} \quad (16)$$

$$(17)$$

And  $\mathcal{S}$  is a finite state space.

Because the walk follows a regular and thus ergodic markov chain with a finite state space, it has exactly one stationary distribution [9] and the output will be the best structure in terms of  $\psi$  which weights each candidate. Practically speaking, CORREG returns the best structure seen during the walk. Numerical results (Section 4) illustrates the efficiency of the walk when the true model really contains a linear structure (Table (??)) and when it does not (Tables (??) and (??)).

#### 3.2.2 Initialisation

If we have some knowledge about some sub-regressions (physical models for example) we can add them in the found and/or initial structure. So the model is really expert-friendly. The initial structure can be based on a first warming algorithm taking the correlations into account. coefficients are randomly placed into  $I_1$ , weighted by the absolute value of the correlations. Then this structure can be reduced by the hadamard product with the binary matrix obtained by Graphical Lasso[6].

Table 1: Results of the Markov chain.

### 3.2.3 Reduced neighbourhood

If the algorithm did not have time to converge, it can be finished with a few step for which the neighborhood would only contain smaller candidates (in terms of complexity). It is equivalent to ask for each element in  $I_1$  if the criterion  $\psi$  would be better without it. Thus it can be seen as a final cleaning step. But in fact, it's just continuing the MCMC with a reduced neighborhood.

### 3.2.4 Multiple try

One would rather test multiple short chains than lose time in initialisation or long chains [8]. It also helps to face local extrema.

## 4 Numerical results on simulated datasets

Now we have defined the model and the way to obtain it, we can have a look on some numerical results to see if CORREG keeps its promises. Each simulated dataset presented here had  $p = 40$  covariates to explain the response variable.

### 4.1 Finding the structure

#### 4.1.1 How to evaluate found structure ?

The first criterion is  $\psi$  which is minimised in the MCMC. We can compare this criterion for both the true Structure and the found one. But it won't show how far the found structure is from the true one in terms of  $S$ . So we define some indicators to compare the true model  $S$  and the found one  $\tilde{S}$ . Global indicators :

- $TL$  (True left) : the number of found dependent variables that really are dependent  $TL = |I_2 \cap \tilde{I}_2|$
- $WL$  (Wrong left) : the number of found dependent variables that are not dependent  $WL = |\tilde{I}_2| - TL$
- $ML$  (Missing left) : the number of really dependent variables not found  $ML = |I_2| - TL$
- $\Delta p_2$  : the gap between the number of sub-regression in both model :  $\Delta p_2 = |I_2| - |\tilde{I}_2|$ . The sign defines if  $\tilde{S}$  is too complex or too simple
- $\Delta compl$  : the difference in complexity between both model :  $\Delta compl = \sum_{j \in p_2} p_1^j - \sum_{j \in \tilde{p}_2} \tilde{p}_1^j$

#### 4.1.2 Results

These results on  $\tilde{S}$  are associated with the results of Table 2. True  $BIC(S)$  is the  $BIC$  of the True generative model  $S$ ,  $BIC(\emptyset)$  is the  $BIC$  of the trivial model (no regression,  $I_2 = \emptyset$ ) and  $BIC(\tilde{S})$  is the  $BIC$  of the found structure.

### 4.2 $Y$ depends only on some covariates in $X^{I_1}$

L'ensemble de la méthode à été programmé dans un package R dénommé CORREG. Pour les simulations présentées dans les tableaux 2 et 3, chacune des configurations à été simulée 100 fois. Les tableaux affichent le nombre de variables dépendantes trouvées ("bon gauche"), le nombre de variables jugées dépendantes à tort ("faux gauche") et les erreurs moyennes en prédiction (MSE) sur  $Y$  à partir d'échantillons de validation de 1 000 individus. Pour l'ensemble des simulations  $p = 40$ ,  $\sigma_Y = 10$ ,  $\sigma = 0.001$ , les  $X$  indépendants suivent des mélanges gaussiens à  $\lambda = 5$  classes de moyenne selon une loi de Poisson de paramètre  $\lambda$  et d'écart-type  $\lambda$ . Les  $B_1^j$  suivent la même loi de Poisson mais avec

$n$	$p_2$	Qualité de $\hat{S}$		Qualité de prédiction (MSE)		
		bon gauche	faux gauche	LAR	CORREG $\hat{S}$	CORREG vrai $S$
30	16	8.48	4.88	3 511 185.23	10 686.62	738.89
30	32	16.89	2.78	565.51	189.54	139.24
50	0	0	0	529.94	529.94	529.94
50	16	8.89	5.4	347.59	233.99	197.95
50	32	18.95	2.44	163.7	139.39	121.56
400	32	23.49	1.06	104.52	103.6	102.67

Table 2:  $Y$  dépend de  $X$  entier. CORREG gagne logiquement.

$n$	$p_2$	Qualité de $\hat{S}$		Qualité de prédiction (MSE)		
		bon gauche	faux gauche	LAR	CORREG $\hat{S}$	CORREG vrai $S$
30	16	8.29	5	5 851.45	559.58	340.29
30	32	17	2.59	893	196.01	135.78
50	16	8.98	5.19	201.56	164.58	162.49
50	32	19.05	2.32	172.93	136.77	121.19
400	32	23.51	1.09	104.49	103.02	102.26

Table 3:  $Y$  dépend de  $X_2$  uniquement (cas normalement défavorable à CORREG).

un signe aléatoire. On cherche ici à se comparer à la méthode LASSO dans les cas où celle-ci est en difficulté le vrai modèle est constitué de corrélations 2 à 2. CORREG a travaillé avec  $p_2$  et  $p_1$  libres et a utilisé Rmixmod pour estimer les densités dans  $X_1$ .

The CORREG package has been tested on simulated datasets. Each configuration has been tested 100 times and the Mean Squared Error (MSE) given were computed on a validation sample of 1000 individuals. Tables 2 et 3 show the results obtained using only CORREG, or CORREG combined with other methods.

Les tableaux 1 et 2 montrent que CORREG est équivalent au LASSO en l'absence de corrélations et le bat quand les corrélations sont fortes. On retrouve le phénomène attendu du LASSO moins impacté par les corrélations quand  $n$  grandit. On constate enfin la convergence asymptotique de CORREG vers le vrai modèle de régression.

On remarque que quand  $p_2$  augmente le LASSO commence à se ressaisir car il y a de plus en plus de faux modèles proches du vrai en termes de prédiction donc le LASSO trouve des modèles inconsistants en interprétation mais relativement corrects en prédiction.

### 4.3 Consistency Issues

Consistency issues of the LASSO are well known and Zhao [21] gives a very simple example to illustrate it. We have taken the same example to show how our method is more consistent. Here  $p = 3$  and  $n = 1000$ . We define  $X_1, X_2, \varepsilon_Y, \varepsilon_X i.i.d. \sim \mathcal{N}(0, 1)$  and then  $X_3 = \frac{2}{3}X_1 + \frac{2}{3}X_2 + \frac{1}{3}\varepsilon_X$  and  $Y = 2X_1 + 3X_2 + \varepsilon_Y$ . We compare consistencies of complete, explicative and predictive model with LASSO (and LAR) for selection. It happens that the algorithm don't find the true structure but a permuted one so we look at the results obtained with the true  $Z$  (but  $\hat{B}$  is used) and with the structure found by the Markov chain after a few seconds.

True  $Z$  is found 340 times on 1000 tries.

	Classical LASSO	Explicative	Predictive
True $Z$	1.006479	<b>1.005468</b>	<b>1.006093</b>
$\hat{Z}$	<b>1.006479</b>	1.884175	1.006517

Table 4: MSE observer on a validation sample (1000 individuals)

We observe as we hoped that explicative model is better when using true  $Z$  (coercing real zeros)



and that explicative with  $\hat{Z}$  is penalized (coercing wrong coefficients to be zeros). But the main point is that the predictive model stay better than the classical one with the true  $Z$  and corrects enough the explicative model to follow the classical LASSO closely when using  $\hat{Z}$ . And when we look at the consistency :

	Classical LASSO	Explicative	Predictive
True $Z$	0	1000	830
$\hat{Z}$	0	340	<b>621</b>

Table 5: number of consistent model found ( $Y$  depending on  $X_1, X_2$  and only them) on 1000 tries

299 times on 1000 tries, the predictive model using  $\hat{Z}$  is better than classical LASSO in terms of MSE and consistent (classical LASSO is never consistent).

We also made the same experiment but with  $X_1, X_2$  (and consequently  $X_3$ ) following gaussian mixtures (to improve identifiability) randomly generated by our R package. True  $Z$  is now found 714 times on 1000 tries . So it confirms that non-gaussian models are easier to identify.

	Classical LASSO	Explicative	Predictive
True $Z$	1.571029	<b>1.569559</b>	<b>1.570801</b>
$\hat{Z}$	1.005402	1.465768	<b>1.005066</b>

Table 6: MSE observed on a validation sample (1000 individuals)

And when we look at the consistency :

	Classical LASSO	Explicative	Predictive
True $Z$	0	1000	789
$\hat{Z}$	0	714	<b>608</b>

Table 7: number of consistent model found ( $Y$  depending on  $X_1, X_2$  and only them) on 1000 tries

299 times on 1000 tries, the predictive model using  $\hat{Z}$  is better than classical LASSO in terms of MSE and consistent (classical LASSO is never consistent).

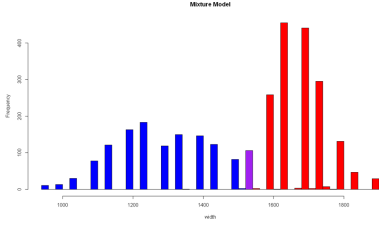


Figure 1: Exemple of non-Gaussian real variable easily modeled by a Gaussian mixture

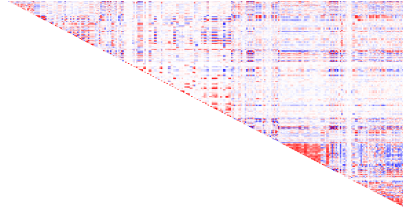
## 5 Numerical results on real datasets

This work takes place in steel industry context, with quality oriented objective : to understand and prevent quality problems on finished product, knowing the whole process. In particular, we focus on regression problems.

### 5.1 The dataset

- variables from the whole process
- The stakes : hundreds euros per ton (for information: Dunkerque site produces up to 7.5 millions tons a year)

Figure 2: Correlation matrix of the dataset ( $p = 293$ ,  $n = 3000$ )



Some observed correlations with physical meaning :

- Width and Weight : 0.905
- Temperature before and after a tool : 0.983
- Roughness of both faces : 0.919
- Mean & Max of a curve : 0.911

The method was tested on 205 variables without missing values.

### 5.2 Results

The algorithm gives a structure with 82 subregressions with a mean of 5 regressors. Some found subregressions with physical meaning :

- Mean.weight = f (Min.weight , Max.weight , Sigma.weight ) and other same-shaped subregressions.
- Width = f (Mean.flow , Mean.speed.CC)

True Physical model (not linear) :

- Width = flow / (speed \* thickness) (thickness is constant)

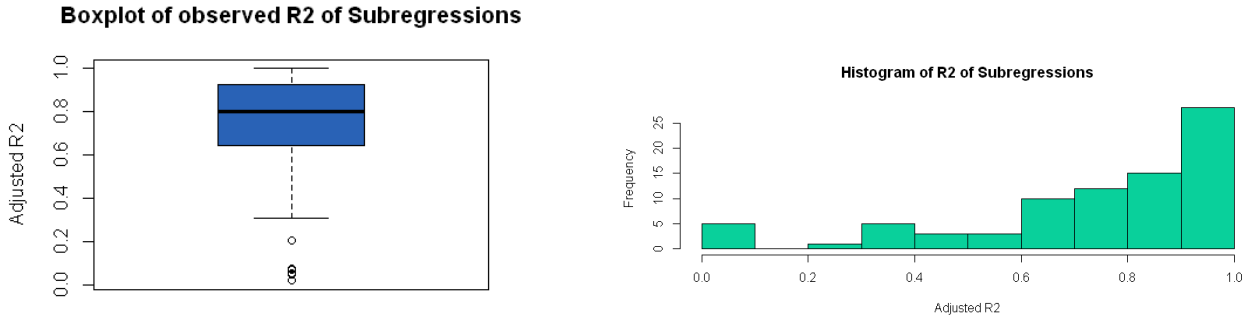


Figure 3: Adjusted R2 of found subregressions (industrial dataset)

Some of the other subregression represent physical models used to regulate the process and that were forgotten by the metallurgist we worked with. Found model has selected relevant variables (verified with metallurgist).

We used Elastic Net[23] on this dataset for selection (get better results than LASSO). Here are the observed MSE on a  $n = 847$  validation sample. Predictive model (sequential elastic net base on estimated structure and using all the variables) is 5,82% better (Figure 5.2) than elastic net computed on the whole dataset.

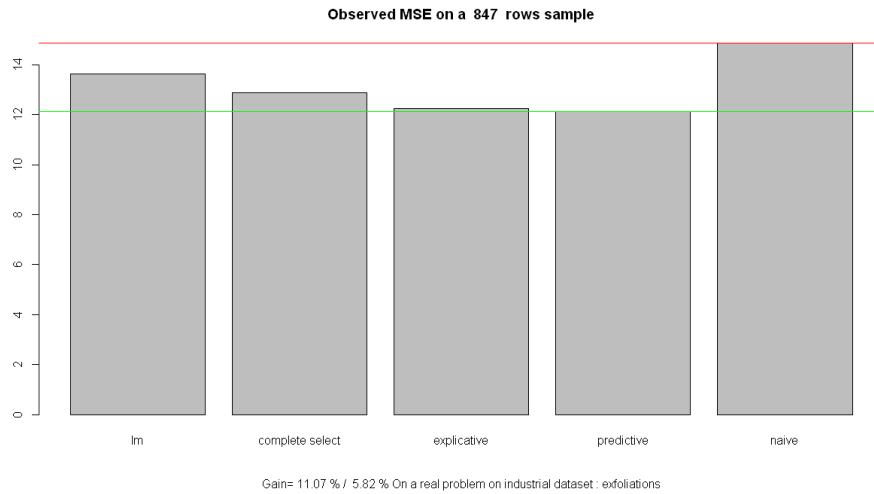


Figure 4: MSE comparison on industrial dataset

## 6 Conclusion

We have seen that correlations can lead to serious estimation and variable selection problems in linear regression and that in such a context, it can be useful to explicitly model the structure between the covariates and to use this structure (even sequentially) to avoid correlations issues. We also show that real industrial context faces this kind of situations so our model can help to interpret and predict physical phenomenon efficiently and to help to manage missing values. But for now we still need a full dataset to learn the structure between the covariates and even if correlations are strong, some information is lost. Further work is needed to face these two challenges.

CORREG is accessible on CRAN and has already proved its efficiency on real regression problematics in industry. CORREG's strength is its great interpretability of the model, composed of several short linear regression easily managed by non-statisticians while strongly reducing correlations issues that are everywhere in industry. Nevertheless, we need to enlarge its application field to missing values, also very commons in industry. The actual generative model allows such a fonctionnality without supplementary hypothesis and this also is a strength of CORREG.

Another perspective would be to take back lost information (the residual of each subregression) to improve predictive efficiency when needed. It would only consists in a second step of linear regression between the residuals and would thus still be able to use any selection method.

This paper only treats linear regression but such a pretreatment could be used for logistic regression, *etc.* So the subject is still wide opened.

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