

Appendix of Exploiting disagreement between high-dimensional variable selectors for uncertainty visualization

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A Appendix

A.1 Behavior of CSUV-m

Proposition 1. *If the signs for the non-zero $\hat{\beta}_j^k$'s for all k for which $M_k \in \mathcal{M}$ are the same, i.e.*

$$\tau_j = \frac{\sum_{\{k|M_k \in \mathcal{M}\}} \mathbb{1}_{\hat{\beta}_j^k \neq 0}}{|\mathcal{M}|},$$

then selecting a covariate j when $\tau_j \geq 1/2$ is equivalent to minimizing the average Hamming distance between the final selected sets of covariates \hat{S} and all the fitted models $M_k \in \mathcal{M}$.

Proposition 2. *Let $\tau_j^+ = \frac{1}{|\mathcal{M}|} \sum_{\{k|M_k \in \mathcal{M}\}} \mathbb{1}_{\hat{\beta}_j^k > 0}$ and $\tau_j^- = \frac{1}{|\mathcal{M}|} \sum_{\{k|M_k \in \mathcal{M}\}} \mathbb{1}_{\hat{\beta}_j^k < 0}$ (note $\tau_j = \max(\tau_j^+, \tau_j^-)$). Consider the following distance function between a model M and all the fitted models $M_k \in \mathcal{M}$:*

$$\text{dist}(M, \mathcal{M}) = \sum_{j=1}^p \sum_{\{k|M_k \in \mathcal{M}\}} |s_j^M - \text{sign}(\hat{\beta}_j^k)|$$

where s_j^M is the sign of the coefficient of the covariate j in model M which can take the value -1 , 0 or 1 . Selecting a covariate j when $\tau_j \geq 1/2$ and setting $s_j^M = +1$ when $\tau_j^+ \geq 1/2$ and -1 when $\tau_j^- \geq 1/2$ minimizes $\text{dist}(M, \mathcal{M})$.

A.2 Proof of Proposition 1

Proof.

$$\begin{aligned}
& \arg \min_M \frac{1}{|\mathcal{M}|} \sum_{\{k|M_k \in \mathcal{M}\}} \text{Hamming}(M_k, M) \\
\iff & \arg \min_M \frac{1}{|\mathcal{M}|} \sum_{\{k|M_k \in \mathcal{M}\}} \sum_{j=1}^p (\mathbb{1}_{\beta_j^k=0} \mathbb{1}_{j \in M} + \mathbb{1}_{\beta_j^k \neq 0} \mathbb{1}_{j \notin M}) \\
\iff & \arg \min_M \frac{1}{|\mathcal{M}|} \sum_{j=1}^p \sum_{\{k|M_k \in \mathcal{M}\}} [(1 - \mathbb{1}_{\beta_j^k \neq 0}) \mathbb{1}_{j \in M} + \mathbb{1}_{\beta_j^k \neq 0} (1 - \mathbb{1}_{j \in M})] \\
\iff & \arg \min_M \frac{1}{|\mathcal{M}|} \sum_{j=1}^p \sum_{\{k|M_k \in \mathcal{M}\}} [\mathbb{1}_{j \in M} (1 - 2\mathbb{1}_{\beta_j^k \neq 0})] \\
\iff & \arg \min_M \sum_{j=1}^p \mathbb{1}_{j \in M} \left(1 - 2 \frac{\sum_{\{k|M_k \in \mathcal{M}\}} \mathbb{1}_{\beta_j^k \neq 0}}{|\mathcal{M}|}\right) \\
\iff & \arg \min_M \sum_{j=1}^p \mathbb{1}_{j \in M} (1 - 2\tau_j)
\end{aligned}$$

□

A.3 Proof of Proposition 2

Proof. Let the number of fitted models for covariance j to be estimated with positive sign to be n_j^+ and those estimated with negative sign to be n_j^- .

$$\begin{aligned}
& \arg \min_M \frac{1}{|\mathcal{M}|} \sum_{\{k|M_k \in \mathcal{M}\}} \text{dist}(M_k, M) \\
\iff & \frac{1}{|\mathcal{M}|} \arg \min_{\{s_j^M | j=1, \dots, p\}} \sum_{\{k|M_k \in \mathcal{M}\}} |s_j^M - \text{sign}(\beta_j^k)| \\
\iff & \frac{1}{|\mathcal{M}|} \arg \min_{\{s_j^M | j=1, \dots, p\}} \sum_{\{k|M_k \in \mathcal{M}\}} [(|\mathcal{M}| - n_j^+ + n_j^-) \mathbb{1}_{s_j^M=+1} + (n_j^+ + n_j^-) \mathbb{1}_{s_j^M=0} + (|\mathcal{M}| + n_j^+ - n_j^-) \mathbb{1}_{s_j^M=-1}] \\
\iff & \arg \min_{\{s_j^M | j=1, \dots, p\}} \sum_{\{k|M_k \in \mathcal{M}\}} [(1 - \tau_j^+ + \tau_j^-) \mathbb{1}_{s_j^M=+1} + (\tau_j^+ + \tau_j^-) \mathbb{1}_{s_j^M=0} + (1 - \tau_j^- + \tau_j^+) \mathbb{1}_{s_j^M=-1}]
\end{aligned}$$

which is equivalent to setting

$$s_j^M = \begin{cases} +1 & \text{if } \tau_j^+ \geq 1/2 \\ -1 & \text{if } \tau_j^- \geq 1/2 \\ 0 & \text{otherwise} \end{cases}$$

□

A.4 Illustration of selection disagreement via Jaccard distance heatmap

The heat maps in Figure 1-5 show the average Jaccard distance ($\text{dist}_{\text{Jaccard}}(A, B) = \frac{|A \Delta B|}{|A \cup B|}$, where $A \Delta B = (A \cup B) - (A \cap B)$) among selected sets from five different variable selection methods under simulation setting 1-5 (see Section 5 more details) parameter settings 1-8 (except for simulation setting 1 for which there are only 3 parameter settings). The Jaccard distance shows the relative size of selection disagreement. It ranges from 0 to 1 and larger distance means larger dissimilarity between two selected sets. The Jaccard distance among some selection methods can be quite large, showing that relatively large number of covariates are selected by one method but not by another. Even for methods that are relatively similar like the Lasso and elastic Lasso, the difference among them is still not negligible for most settings.



Figure 1: Average Jaccard distance among fitted models from different methods using simulated data from model 1

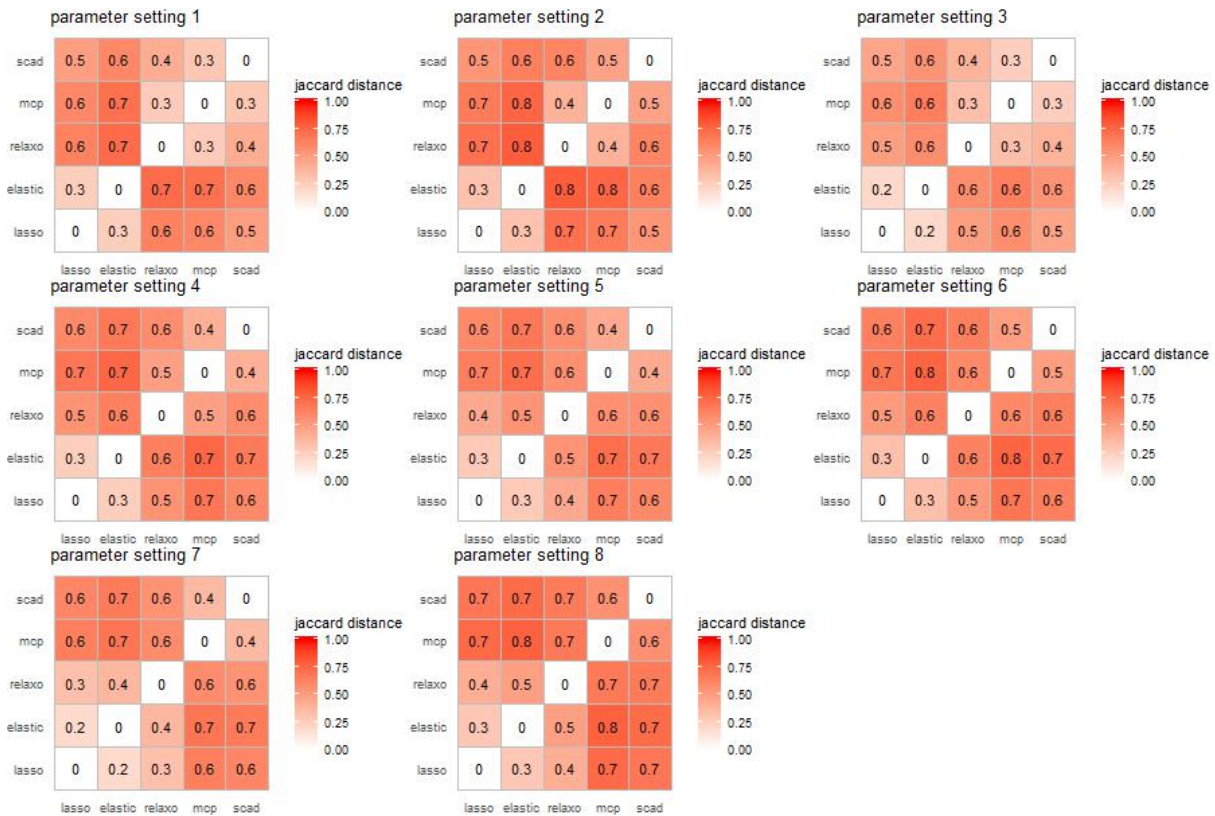


Figure 2: Average Jaccard distance among fitted models from different methods using simulated data from model 2

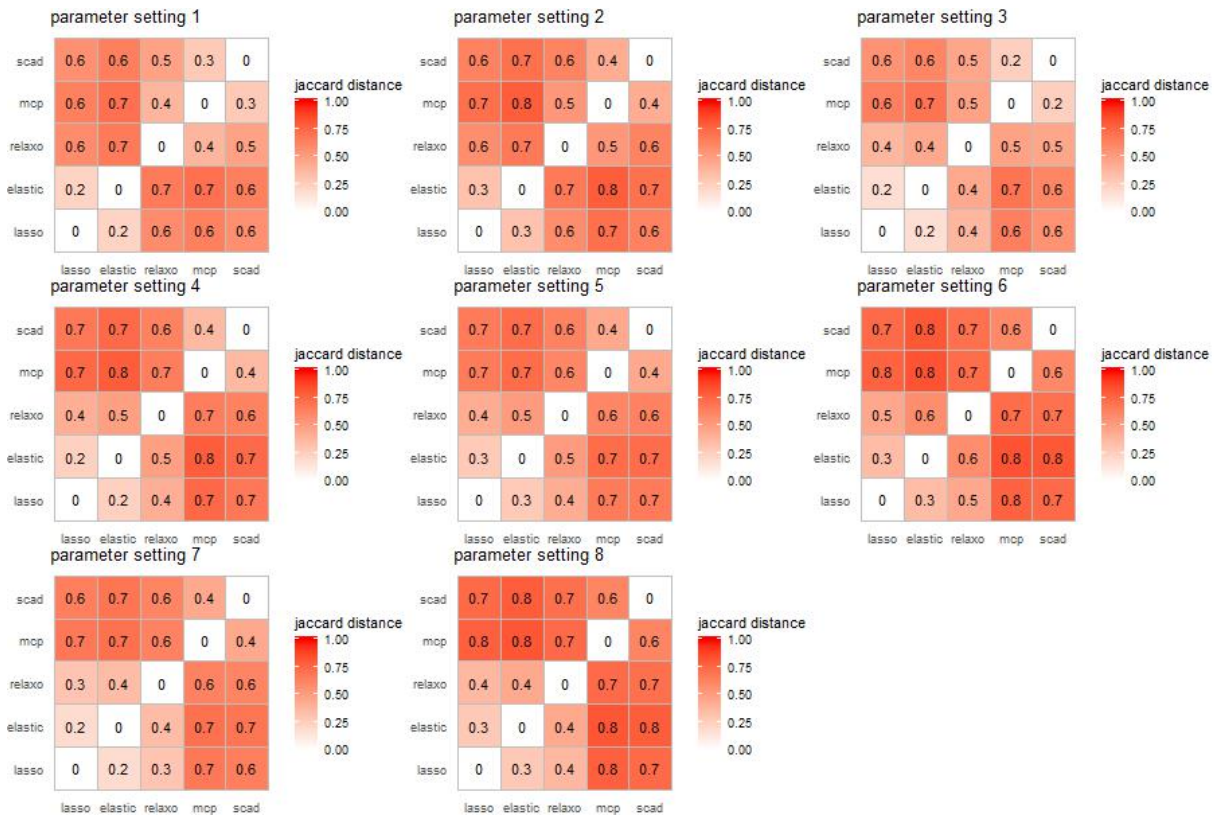


Figure 3: Average Jaccard distance among fitted models from different methods using simulated data from model 3

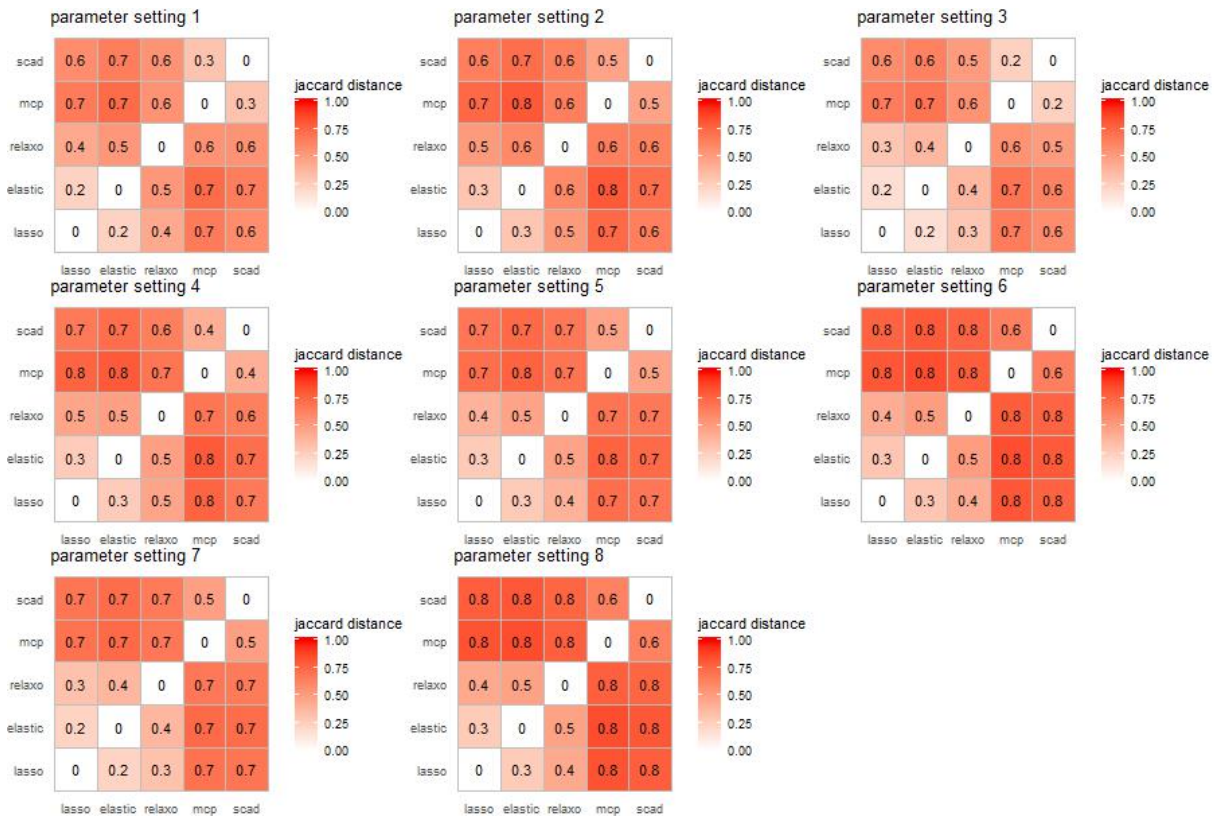


Figure 4: Average Jaccard distance among fitted models from different methods using simulated data from model 4

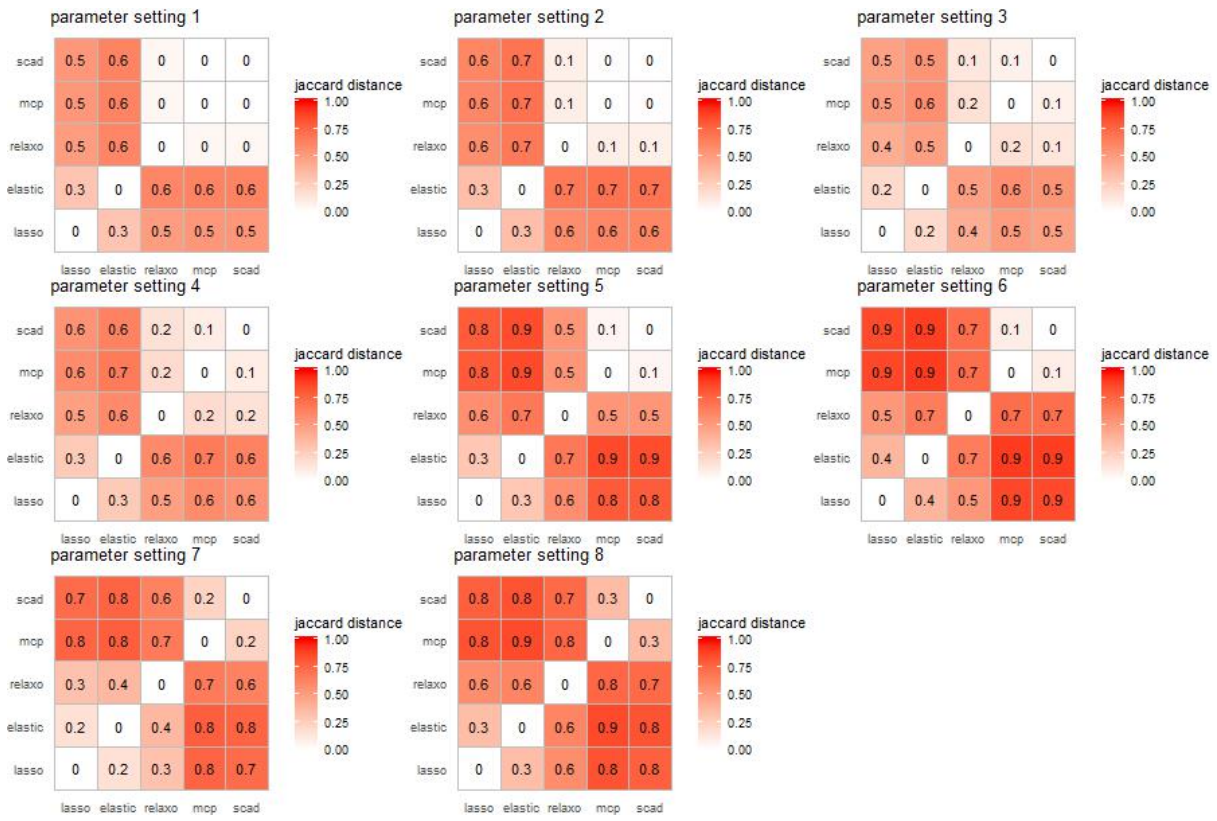


Figure 5: Average Jaccard distance among fitted models from different methods using simulated data from model 5

A.5 CSUV assessment of uncertainty

The CSUV plot provides a graphical tool to illustrate both the selection and the estimation uncertainty in the coefficients. The uncertainty illustrated by the CSUV plot should be interpreted to originate from the randomness of ϵ . This is similar to the classical confidence intervals in fixed- p , fixed-design regression.

In this section, our focus is on the uncertainty illustration by the default conditional boxes and whiskers, and on whether and how the information they carry can be used to assess the uncertainty in selection and estimation. Therefore our mentions of “boxes” or “whiskers” in this section refer to the conditional boxes and whiskers. Roughly speaking, the selection uncertainty is represented by the width of the boxes along the x-axis, and the estimation uncertainty is represented by the range of the boxes and whiskers along the y-axis. The plot provides a graphical aid to help users to decide whether to select a covariate by considering both dimensions of the corresponding box. The following similarities between the CSUV boxes and confidence intervals can be identified.

- Both provide intervals that are intended to cover the value of the true coefficient.
- Both aid the users in deciding if a covariate should be selected.

However, we also highlight the following differences between the two.

- *Information content.* Unlike the classical confidence interval, which is one-dimensional, the CSUV box is two-dimensional: both its width and its range should be used in deciding whether or not to include the corresponding covariate. This is because the ranges of CSUV boxes only contain information on non-zero estimated coefficients (i.e. any zero estimates for the coefficient are not reflected in the range of the box, but only in its width). For this reason, a covariate that is rarely chosen (and in particular, is not selected by CSUV-m) may have a box plot that does not cross 0. Therefore, the width of the box plot, which is directly proportional to the same-sign frequency with which the corresponding coefficient is selected, should also be considered in deciding whether or not to include the corresponding covariate in the model.
- *Covering percentiles.* The boxes in the CSUV plot represent the upper and the lower quartiles (i.e. 25% and 75% percentile) of the non-zero estimated coefficients. By contrast, classical confidence intervals are often considered in the context of much larger coverage; frequently,

90 or 95%. With this in mind, we set the whiskers in the box plots to describe the [5%, 95%] range (of the non-zero estimated coefficients) by default. This default range for the whiskers can be changed by users in the R package `CSUV`.

Moreover, the box plots are based on the individual empirical estimated coefficients, and do not take into account the effect of the selection uncertainty in other covariates. For example, if covariates X_1 and X_2 are highly correlated, whether X_2 is selected affects the estimated coefficients of X_1 . While the conditional approach considered by Loftus and Taylor (2014) and Tibshirani et al. (2016), and the debiased approach considered by Zhang and Zhang (2014) in principle can be used here, the generalization to `CSUV` is not straightforward and the conditional approach is computationally intensive.

The intertwining of the selection uncertainty and the estimation uncertainty makes it difficult to propose one simple interval that covers the true covariate with a given confidence level without a complicated adjustment e.g. as in Loftus and Taylor (2014) or Tibshirani et al. (2016). We instead restrict ourselves to investigating if the whiskers are useful in deciding if a covariate selected by `CSUV-m` should be chosen, without providing a confidence level guarantee.

Our investigation is as follows: using the simulated data from model settings 2-5, for covariates selected by `CSUV-m`, we want to find out if the covariates for which the whiskers cover zero are more likely to be the false covariates. For each realization of the simulated data, we separate the `CSUV-m` selected covariates into two sets: (1) whiskers covering zero, and (2) whiskers not covering zero. We then find out the frequency with which the covariates in the two sets are the true covariates.

The simulation results show that a covariate with whiskers crossing zero is much more likely to be a false covariate than a covariate with whiskers not crossing zero (Figure 6). This indicates that observing if the whiskers of a covariate cross zero does provide useful information in deciding if the covariate is a true one.

A.6 Simulation study – further details

A.6.1 Constituent methods – further details

See Table 1 for the list of the corresponding R packages, functions and parameter settings used in the `CSUV` package and also in this simulation. The concavity values of SCAD and MCP are set to the value recommended by the original papers from Fan and Li (2001) and Zhang (2010) respectively, which are also the default values in the `ncvreg` R package. For Elastic Net, we use $\alpha = 0.5$.

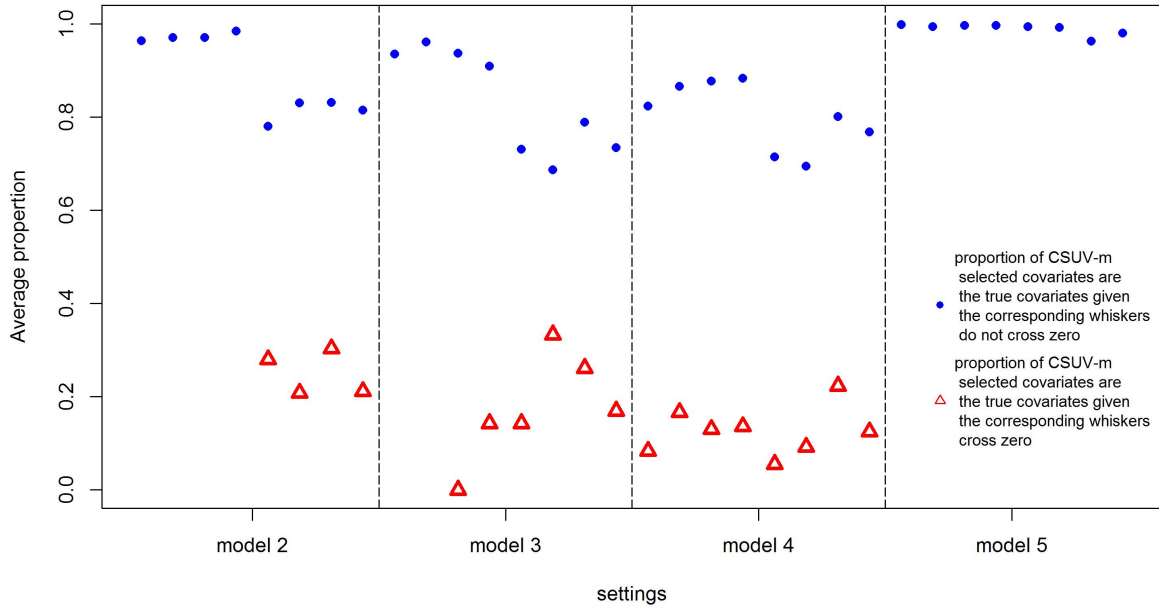


Figure 6: Average proportion of the CSUV-m selected covariates are the true covariates, using simulated data from simulation model 2-5 with eight different parameter settings under each model setting. Circles (blue in the color version) show the average proportions of the CSUV-m selected covariates are the true covariates given the corresponding whiskers do not cross zero whereas the triangles (red in the color version) show the average proportions of the CSUV-m selected covariates are the true covariates given the corresponding whiskers cross zero. If there is no triangle for a particular setting, it means that none of the CSUV-m selected covariates have whiskers crossing zero.

A.6.2 Competitors – further details

Both eBIC and delete- $n/2$ cross-validation uses the Lasso, MCP and SCAD (i.e. the methods used in the default case of CSUV) as the base methods. eBIC selects the fitted model that minimizes the corresponding information criterion value while delete- $n/2$ cross-validation selects the method that has the lowest estimated prediction error. The R packages and the parameter values used for the base methods are the same as what we use in CSUV for fair comparison. All the variable selection methods require tuning the regularization parameter λ . Default tuning in the R packages are used to simplify the analysis and the details of the tuning are shown in Table 1 of the main paper. eBIC and cross-validation have their own parameters and we set them as follow: For eBIC, we set $\gamma = 0.5$, which is one of the values considered in the simulations of the original paper (Chen and Chen, 2008) and the value used in Lim and Yu (2016). For the delete- $n/2$ cross-validation, we set the number of resampling $B = 100$, which is the same as the number of iterations we use in CSUV.

Method	R package	R function	Parameters	λ tuning
Lasso (Tibshirani, 1996)	glmnet	cv.glmnet	α : 0.5	default 10-fold cross-validation
Elastic Net (Zou and Hastie, 2005)	glmnet	cv.glmnet		default 10-fold cross-validation
Relaxed Lasso (Meinshausen, 2007)	relaxo	cvrelaxo	concavity: 3.7	default 5-fold cross-validation
SCAD (Fan and Li, 2001)	ncvreg	cv.ncvreg		default 10-fold cross-validation
MCP (Zhang, 2010)	ncvreg	cv.ncvreg	concavity: 3	default 10-fold cross-validation
Tree	tree	tree, prune.tree		

Table 1: Variable selection methods and the corresponding R packages and functions used in CSUV

For the VSD-minimizing method, we use the `glmvsd` R package to calculate the weight on each candidate model and then select the covariates that have aggregate weight greater than or equal to 0.5. Coefficients of the selected set from VSD is estimated using OLS. We use the default parameters in `glmvsd` (e.g. use the Lasso, MCP and SCAD to get the candidate models) except the weight which we use ARM instead. This is because using the default BIC to calculate the weight provides very poor results in some simulation settings.

A.6.3 Performance measures – further details

The F-measure is the harmonic mean of precision and recall:

$$F = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} = \frac{2}{\frac{TP+FP}{TP} + \frac{TP+FN}{TP}} = \frac{2TP}{2TP + FN + FP}$$

Note that comparing the above numbers individually can be misleading. For example, using only FN favors models that select a large number of covariates and using only FP favors models that select fewer number of covariates. Although the F-measure takes both precision and recall into account, assigning same weight to precision and recall is arbitrary. Nevertheless, we use the F-measure as our major measure when we compare the variable selection performance between different methods. Powers (2011) provide a detailed comparison of different evaluation methods.

A.6.4 Synthetic data – further details

Set $\mathbf{Y} = \tilde{\mathbf{X}}\boldsymbol{\beta} + \boldsymbol{\epsilon}$, $\epsilon_i \stackrel{i.i.d}{\sim} \mathcal{N}(0, \sigma^2)$. We generate observations with 100 realizations of \mathbf{X} using the model specifications below. We then normalize \mathbf{X} to get $\tilde{\mathbf{X}}$ so that all covariates have mean 0 and variance 1. Except from Model 1, the default number of observation is $n = 100$, the number of predictors $p = \{100, 300\}$, the number of true covariates $s = \{5, 10\}$ and $\sigma^2 = 1$. We also consider $p = 1000$ for Model 2 and 3 to see if CSUV perform well in high(er) dimensional settings, and $n = 1000$ for Model 2 to see how the performance of CSUV with three different splits ratios (25:75,

50:50 and 75:25) differs.

- **(Model 1) modified example 1 from the original Lasso paper (Tibshirani, 1996):** $\beta = \{3, 1.5, 0, 0, 2, 0, 0, 0\}$, $p = 8$ and $n = 50$. Predictors \mathbf{X} follow $\mathcal{N}(0, \Sigma)$, where $\Sigma_{k,m} = 0.5^{|k-m|}$ and $\sigma = \{1, 3, 6\}$. In the Lasso paper $n = 20$ but here we use $n = 50$ so that there are enough observations for subsampled fit. We include a more challenging SNR with $\sigma = 6$ ($\sigma = 3$ in the Lasso paper).
- **(Model 2) Toeplitz structure:** predictors \mathbf{X} follow $\mathcal{N}(0, \Sigma)$, where Σ is in Toeplitz structure with $\Sigma_{k,m} = \rho^{|k-m|}$ with $\rho = \{0, 0.9\}$.
- **(Model 3) block structure:** predictors \mathbf{X} follow $\mathcal{N}(0, \Sigma)$, where Σ is in block structure with $\Sigma_{k,m} = 1$ for $k = m$. For $k \neq m$, $\Sigma_{k,m} = 0$ except $\text{mod}_{10}(m) = \text{mod}_{10}(k)$ which $\Sigma_{k,m} = \{0.5, 0.9\}$.
- **(Model 4) factor model:** latent covariates $\phi_j, j = 1, \dots, J$ are i.i.d. and follow $\mathcal{N}(0, 1)$. Each covariate is generated by $X_k = \sum_{j=1}^J f_{k,j} \phi_j + \eta_k$, where $f_{k,j}, \eta_k$ are i.i.d. and follow $\mathcal{N}(0, 1)$. The number of factor $J = \{2, 10\}$.
- **(Model 5) modified example from Zhang and Yang (2015):** $\beta_j = 6/j$ for the true covariates $j = 1, \dots, s$ and $\beta_j = 0$ otherwise. Predictors \mathbf{X} follow $\mathcal{N}(0, \Sigma)$, where $\Sigma_{k,m} = \rho^{|k-m|}$, $\rho = \{0.5, -0.5\}$. The difference between Zhang and Yang (2015) and the model 5 here is that we use the same n and p as model 2-4.

For models 2-4, $\lfloor \frac{s}{2} \rfloor$ of the coefficient of the true s are chosen randomly from $U(0.5, 1.5)$ and $\lfloor \frac{s}{2} \rfloor$ of them are chosen uniformly from $U(-1.5, -0.5)$. The true β s are chosen randomly among the predictors, and once the β s are set, the same set of β s are used for all realizations.

A.6.5 Variable importance

CSUV is designed to provide more than a single measure of the importance of each variable, an output returned, for example, by the SOIL method of Ye et al. (2018). However, if desired, the output of CSUV can also be summarised into a single measure of variable importance. Perhaps the most intuitively, the relative same sign frequency τ_j measures the percentage of times that the j^{th} covariate is selected with the same sign in the retained fitted models. While τ_j is not

specifically designed as a variable importance measure, it can be used as such, as it provides a natural importance ranking of the covariates.

In this section, we compare the performance of τ_j as a single measure of variable importance yielded by CSUV with the measures of variable importance returned by SOIL and by the random forest. R packages `SOIL` and `randomForest` with default settings are used, with the variable importance for the random forest normalized to be in the range $[0, 1]$.

For each measure of variable importance, we use the following quantity to measure its performance: $\min(I_{j|\beta_j \neq 0}) - \max(I_{j|\beta_j = 0})$, where I is a variable importance measure that lies in the range $[0, 1]$. A large positive value indicates that the method of interest is capable of assigning high variable importance to the true covariates and at the same time giving low variable importance to the false covariates.

Table 2 summarises the performance under our simulation settings with parameter settings 1-3 for model 1 and 1-8 for model 2-5. Both CSUV and SOIL outperform the random forest. This is unsurprising as both CSUV and SOIL are designed for high-dimensional sparse linear models, whereas the random forest is not. SOIL and CSUV offer comparable performance, although we note that in the more difficult settings such as model 3 and 4 / parameter settings 6 and 8, CSUV tends to outperform SOIL.

A.6.6 Reasons for selected set to be small for CSUV-m

The number of covariates selected by CSUV-m is often small when comparing with other methods and the true size. Investigation into the collection of fitted models \mathcal{M} shows that for many simulation settings, the fitted models in \mathcal{M} can be very different in terms of variable selection. Sometimes all fitted models in \mathcal{M} select different sets of covariates. When the selection decision is so different among \mathcal{M} , it is very likely that only a few covariates will have $\tau_j \geq 1/2$. This causes the number of covariates chosen by CSUV-m to be small. Whether a small selected set is desirable depends on the purpose of variable selection. Selecting small(er) number of covariates by this selection rule may cause omission of some true covariates and possibly exclusion of some false covariates that are helpful for prediction. This may result in poor prediction in some situations. On the other hand, the set of covariates selected by CSUV-m often includes fewer false positives than other variable selection methods, as only covariates that are selected by the majority of the subsampled fits are included in CSUV-m.

A.7 Tables of the simulation results

References

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models	parameter settings	csuv	soil	random forest
1	1	0.66	0.83	0.06
	2	0.37	0.44	0.03
	3	-0.09	-0.09	-0.12
2	1	0.60	0.40	-0.05
	2	0.45	0.29	-0.12
	3	0.35	0.31	-0.18
	4	0.00	0.15	-0.25
	5	-0.28	-0.24	-0.73
	6	-0.21	-0.27	-0.75
	7	-0.52	-0.47	-0.76
	8	-0.52	-0.83	-0.84
3	1	0.19	0.24	-0.29
	2	0.19	0.20	-0.41
	3	-0.10	0.05	-0.38
	4	-0.26	-0.01	-0.63
	5	-0.54	-0.23	-0.78
	6	-0.64	-0.94	-0.86
	7	-0.67	-0.53	-0.79
	8	-0.65	-0.98	-0.96
4	1	-0.14	-0.08	-0.52
	2	-0.22	-0.08	-0.62
	3	-0.39	-0.22	-0.63
	4	-0.46	-0.44	-0.72
	5	-0.49	-0.49	-0.74
	6	-0.63	-0.80	-0.85
	7	-0.65	-0.64	-0.79
	8	-0.71	-0.96	-0.91
5	1	0.87	0.81	0.01
	2	0.86	0.83	-0.00
	3	0.63	0.63	-0.03
	4	0.48	0.61	-0.04
	5	0.80	0.61	-0.06
	6	0.72	0.76	-0.06
	7	-0.26	-0.03	-0.06
	8	-0.27	-0.05	-0.06

Table 2: Performance in terms of $\min(I_{j|\beta_j \neq 0}) - \max(I_{j|\beta_j = 0})$ of CSUV, SOIL and random forest in different simulation settings. See the Table 3-19 for the details of the parameters for each parameter setting.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 1 rho = 0.5 s = 3 p = 8	lasso	0.76 (0.01)	2.11 (0.14)	2.11	0	1.13 (0.02)	0.75 (0.04)	0.39 (0.02)	5.11 (0.14)
	elastic net	0.71 (0.01)	2.67 (0.14)	2.67	0	1.15 (0.03)	0.85 (0.04)	0.42 (0.02)	5.67 (0.14)
	relaxed lasso	0.91 (0.01)	0.7 (0.1)	0.7	0	1.11 (0.03)	0.6 (0.04)	0.34 (0.02)	3.7 (0.1)
	mcp	0.95 (0.01)	0.39 (0.09)	0.39	0	1.09 (0.02)	0.5 (0.04)	0.3 (0.02)	3.39 (0.09)
	scad	0.94 (0.01)	0.56 (0.12)	0.56	0	1.1 (0.02)	0.53 (0.04)	0.32 (0.02)	3.56 (0.12)
	vsd	0.98 (0)	0.14 (0.03)	0.14	0	1.08 (0.02)	0.44 (0.02)	0.29 (0.01)	3.14 (0.03)
	bic	0.96 (0.01)	0.36 (0.08)	0.36	0	1.09 (0.02)	0.5 (0.03)	0.31 (0.02)	3.36 (0.08)
	ebic	0.96 (0.01)	0.35 (0.08)	0.35	0	1.09 (0.02)	0.5 (0.03)	0.31 (0.02)	3.35 (0.08)
	cv	<u>0.93</u> (0.01)	<u>0.64</u> (0.12)	<u>0.64</u>	0	<u>1.1</u> (0.02)	0.55 (0.04)	0.32 (0.02)	3.64 (0.12)
	csuv.m	0.96 (0.01)	0.29 (0.05)	0.29	0	<u>1.1</u> (0.02)	0.51 (0.03)	0.32 (0.02)	3.29 (0.05)
	csuv.s	0.94 (0.01)	0.45 (0.06)	0.45	0	<u>1.1</u> (0.02)	<u>0.56</u> (0.03)	<u>0.34</u> (0.02)	3.45 (0.06)
	csuv.m.25	0.99 (0)	0.04 (0.02)	0.04	0	1.07 (0.02)	0.4 (0.02)	0.26 (0.01)	3.04 (0.02)
	csuv.m.75	0.9 (0.01)	0.75 (0.09)	0.75	0	1.12 (0.03)	0.65 (0.04)	0.38 (0.02)	3.75 (0.09)
	csuv.m.all	0.95 (0.01)	0.33 (0.05)	0.33	0	1.1 (0.02)	0.52 (0.03)	0.32 (0.02)	3.33 (0.05)
	csuv.m.mcp	0.98 (0.01)	0.17 (0.05)	0.17	0	1.08 (0.02)	0.45 (0.03)	0.29 (0.02)	3.17 (0.05)
	csuv.m.with.tree	0.95 (0.01)	0.33 (0.05)	0.33	0	1.1 (0.02)	0.52 (0.03)	0.32 (0.02)	3.33 (0.05)
setting 2 rho = 0.5 s = 3 p = 8	lasso	0.76 (0.01)	2.13 (0.14)	2.11	0.02	10.12 (0.21)	2.26 (0.11)	1.17 (0.05)	5.09 (0.14)
	elastic net	0.73 (0.01)	2.49 (0.14)	2.48	0.01	10.25 (0.23)	2.39 (0.11)	1.2 (0.04)	5.47 (0.14)
	relaxed lasso	0.87 (0.01)	1.01 (0.12)	0.96	0.05	10.11 (0.23)	1.99 (0.12)	1.12 (0.05)	3.91 (0.12)
	mcp	0.83 (0.01)	1.39 (0.14)	1.24	0.15	10.34 (0.24)	2.34 (0.14)	1.28 (0.07)	4.09 (0.16)
	scad	0.8 (0.01)	1.7 (0.14)	1.65	0.05	10.45 (0.24)	2.38 (0.13)	1.3 (0.06)	4.6 (0.15)
	vsd	0.86 (0.01)	0.71 (0.07)	0.08	0.63	11.06 (0.31)	2.3 (0.13)	1.49 (0.08)	2.45 (0.07)
	bic	0.85 (0.01)	1.11 (0.12)	0.96	0.15	10.23 (0.22)	2.13 (0.12)	1.22 (0.06)	3.81 (0.13)
	ebic	0.85 (0.01)	1.13 (0.12)	0.98	<u>0.15</u>	<u>10.2</u> (0.21)	2.13 (0.12)	<u>1.21</u> (0.06)	3.83 (0.13)
	cv	<u>0.76</u> (0.01)	<u>2.12</u> (0.14)	<u>2.1</u>	0.02	10.12 (0.21)	<u>2.26</u> (0.11)	1.17 (0.05)	5.08 (0.14)
	csuv.m	0.91 (0.01)	0.6 (0.09)	0.49	0.11	10.06 (0.21)	1.8 (0.11)	1.09 (0.06)	3.38 (0.08)
	csuv.s	0.9 (0.01)	0.72 (0.08)	0.62	0.1	10.08 (0.22)	1.87 (0.11)	1.11 (0.06)	3.52 (0.07)
	csuv.m.25	0.94 (0.01)	0.35 (0.06)	0.15	0.2	10.05 (0.22)	1.6 (0.1)	1.04 (0.06)	2.95 (0.06)
	csuv.m.75	0.9 (0.01)	0.75 (0.09)	0.69	0.06	10.13 (0.22)	1.93 (0.11)	1.13 (0.05)	3.63 (0.08)
	csuv.m.all	0.92 (0.01)	0.6 (0.09)	0.54	0.06	10.03 (0.22)	1.79 (0.11)	1.07 (0.05)	3.48 (0.08)
	csuv.m.mcp	0.9 (0.01)	0.7 (0.09)	0.51	0.19	10.26 (0.22)	1.98 (0.12)	1.19 (0.07)	3.32 (0.1)
	csuv.m.with.tree	0.92 (0.01)	0.56 (0.08)	0.5	0.06	9.99 (0.22)	1.73 (0.11)	1.04 (0.05)	3.44 (0.07)
setting 3 rho = 0.5 s = 3 p = 8	lasso	0.73 (0.02)	2.16 (0.14)	1.86	0.3	40.51 (0.85)	4.33 (0.21)	2.28 (0.09)	4.56 (0.16)
	elastic net	0.71 (0.01)	2.39 (0.14)	2.14	0.25	40.66 (0.9)	4.37 (0.2)	2.25 (0.08)	4.89 (0.16)
	relaxed lasso	0.73 (0.02)	1.78 (0.12)	1.13	0.65	41.41 (0.91)	4.52 (0.21)	2.51 (0.1)	3.48 (0.16)
	mcp	0.66 (0.02)	2.28 (0.13)	1.42	0.86	43.11 (0.98)	5.66 (0.23)	3.01 (0.1)	3.56 (0.22)
	scad	0.69 (0.02)	2.29 (0.14)	1.76	0.53	42.71 (0.97)	5.61 (0.22)	2.96 (0.1)	4.23 (0.17)
	vsd	0.55 (0.01)	2.21 (0.07)	0.01	2.2	48.44 (1.2)	5.89 (0.14)	3.51 (0.08)	0.81 (0.06)
	bic	0.67 (0.02)	2.03 (0.12)	1.1	0.93	42.27 (0.89)	5.04 (0.22)	2.76 (0.1)	3.17 (0.17)
	ebic	<u>0.67</u> (0.02)	2.03 (0.12)	1.1	0.93	42.27 (0.89)	<u>5.04</u> (0.22)	<u>2.76</u> (0.1)	3.17 (0.17)
	cv	0.73 (0.02)	<u>2.16</u> (0.14)	<u>1.86</u>	0.3	40.51 (0.85)	4.33 (0.21)	2.28 (0.09)	4.56 (0.16)
	csuv.m	0.73 (0.02)	1.46 (0.09)	0.44	<u>1.02</u>	<u>42.31</u> (0.93)	4.42 (0.19)	2.65 (0.1)	2.42 (0.12)
	csuv.s	0.74 (0.02)	1.48 (0.11)	0.59	0.89	41.94 (0.93)	4.46 (0.23)	2.62 (0.11)	2.7 (0.09)
	csuv.m.25	0.65 (0.02)	1.74 (0.09)	0.09	1.65	44.74 (1.1)	4.89 (0.17)	2.95 (0.09)	1.44 (0.09)
	csuv.m.75	0.72 (0.02)	1.62 (0.11)	0.72	0.9	41.81 (0.86)	4.7 (0.22)	2.72 (0.1)	2.82 (0.13)
	csuv.m.all	0.75 (0.02)	1.38 (0.09)	0.45	0.93	41.97 (0.92)	4.26 (0.2)	2.58 (0.1)	2.52 (0.12)
	csuv.m.mcp	0.69 (0.02)	1.58 (0.08)	0.36	1.22	42.99 (0.94)	4.72 (0.2)	2.84 (0.1)	2.14 (0.12)
	csuv.m.with.tree	0.73 (0.02)	1.42 (0.09)	0.39	1.03	42.39 (0.95)	4.36 (0.19)	2.64 (0.1)	2.36 (0.11)

Table 3: Model 1: performance of CSUV and methods it compares with. Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 1 rho = 0 s = 5 p = 100	lasso	0.43 (0.01)	15.7 (0.89)	15.7	0	1.28 (0.02)	1.76 (0.07)	0.53 (0.01)	20.7 (0.89)
	elastic net	0.35 (0.01)	21.17 (0.91)	21.17	0	1.36 (0.02)	2.22 (0.07)	0.6 (0.01)	26.17 (0.91)
	relaxed lasso	0.88 (0.02)	2.1 (0.47)	2.05	0.05	1.14 (0.02)	0.81 (0.07)	0.35 (0.02)	7 (0.47)
	mcp	0.84 (0.02)	2.6 (0.35)	2.6	0	1.1 (0.02)	0.7 (0.05)	0.3 (0.01)	7.6 (0.35)
	scad	0.66 (0.02)	6.11 (0.46)	6.11	0	1.09 (0.02)	0.76 (0.04)	0.3 (0.01)	11.11 (0.46)
	vsd	0.99 (0)	0.1 (0.03)	0.03	0.07	1.07 (0.02)	0.45 (0.02)	0.25 (0.01)	4.96 (0.03)
	bic	0.76 (0.02)	3.82 (0.35)	3.82	0	1.1 (0.02)	0.73 (0.05)	0.31 (0.01)	8.82 (0.35)
	ebic	0.84 (0.02)	2.51 (0.33)	2.51	0	<u>1.1</u> (0.02)	0.68 (0.04)	0.3 (0.01)	7.51 (0.33)
	cv	<u>0.76</u> (0.02)	<u>4.27</u> (0.5)	<u>4.27</u>	0	1.09 (0.02)	<u>0.71</u> (0.04)	0.3 (0.01)	9.27 (0.5)
	csuv.m	0.98 (0)	0.17 (0.04)	0.15	<u>0.02</u>	1.06 (0.02)	0.46 (0.02)	0.25 (0.01)	5.13 (0.04)
	csuv.s	0.94 (0.01)	0.75 (0.09)	0.74	0.01	<u>1.1</u> (0.02)	0.6 (0.03)	<u>0.31</u> (0.01)	5.73 (0.09)
	csuv.m.25	0.89 (0.01)	0.9 (0.08)	0	0.9	1.44 (0.04)	0.96 (0.05)	0.59 (0.03)	4.1 (0.08)
	csuv.m.75	0.95 (0.01)	0.65 (0.14)	0.64	0.01	1.09 (0.02)	0.58 (0.04)	0.29 (0.01)	5.63 (0.14)
	csuv.m.all	0.98 (0)	0.19 (0.04)	0.17	0.02	1.06 (0.02)	0.47 (0.02)	0.25 (0.01)	5.15 (0.04)
	csuv.m.mcp	0.99 (0)	0.08 (0.03)	0.03	0.05	1.06 (0.02)	0.43 (0.02)	0.24 (0.01)	4.98 (0.02)
csuv.m.with.tree	0.98 (0)	0.19 (0.04)	0.17	0.02	1.06 (0.02)	0.47 (0.02)	0.25 (0.01)	5.15 (0.04)	
setting 2 rho = 0 s = 5 p = 300	lasso	0.33 (0.01)	24.97 (1.53)	24.96	0.01	1.44 (0.03)	2.43 (0.11)	0.65 (0.02)	29.95 (1.53)
	elastic net	0.26 (0.01)	32.96 (1.51)	32.95	0.01	1.59 (0.03)	3.07 (0.1)	0.75 (0.02)	37.94 (1.51)
	relaxed lasso	0.78 (0.02)	4.25 (0.81)	4.12	0.13	1.28 (0.03)	1.3 (0.09)	0.49 (0.02)	8.99 (0.81)
	mcp	0.74 (0.02)	4.52 (0.43)	4.51	0.01	1.14 (0.02)	0.91 (0.05)	0.37 (0.01)	9.5 (0.43)
	scad	0.48 (0.02)	12.86 (0.69)	12.85	0.01	1.14 (0.02)	1.11 (0.04)	0.37 (0.01)	17.84 (0.69)
	vsd	0.93 (0.01)	0.55 (0.09)	0.01	0.54	1.31 (0.06)	0.79 (0.07)	0.44 (0.03)	4.47 (0.09)
	bic	0.52 (0.02)	13.67 (1.57)	13.66	0.01	1.2 (0.03)	1.43 (0.12)	0.43 (0.02)	18.65 (1.57)
	ebic	0.71 (0.02)	7.03 (1.45)	7.02	0.01	1.16 (0.02)	<u>1.07</u> (0.11)	0.38 (0.02)	12.01 (1.45)
	cv	<u>0.61</u> (0.02)	<u>8.88</u> (0.77)	<u>8.87</u>	0.01	1.13 (0.02)	1 (0.04)	0.36 (0.01)	13.86 (0.77)
	csuv.m	0.97 (0.01)	0.27 (0.06)	0.1	<u>0.17</u>	1.12 (0.02)	0.58 (0.03)	0.31 (0.02)	4.93 (0.05)
	csuv.s	0.86 (0.01)	1.74 (0.11)	1.69	0.05	<u>1.2</u> (0.02)	0.96 (0.03)	<u>0.45</u> (0.01)	6.64 (0.11)
	csuv.m.25	0.64 (0.02)	2.59 (0.1)	0	2.59	2.56 (0.09)	2.25 (0.08)	1.22 (0.03)	2.41 (0.1)
	csuv.m.75	0.93 (0.01)	0.87 (0.1)	0.83	0.04	1.14 (0.02)	0.76 (0.04)	0.38 (0.02)	5.79 (0.11)
	csuv.m.all	0.97 (0.01)	0.3 (0.06)	0.13	0.17	1.12 (0.02)	0.59 (0.03)	0.32 (0.02)	4.96 (0.05)
	csuv.m.mcp	0.97 (0.01)	0.29 (0.05)	0.02	0.27	1.15 (0.03)	0.62 (0.04)	0.35 (0.02)	4.75 (0.05)
csuv.m.with.tree	0.97 (0.01)	0.29 (0.06)	0.13	0.16	1.12 (0.02)	0.58 (0.03)	0.31 (0.02)	4.97 (0.05)	
setting 3 rho = 0 s = 10 p = 100	lasso	0.46 (0.01)	24.88 (0.93)	24.88	0	1.55 (0.03)	3.23 (0.1)	0.73 (0.01)	34.88 (0.93)
	elastic net	0.42 (0.01)	29.6 (0.89)	29.6	0	1.65 (0.03)	3.74 (0.1)	0.79 (0.01)	39.6 (0.89)
	relaxed lasso	0.8 (0.01)	5.53 (0.46)	5.49	0.04	1.36 (0.03)	1.95 (0.08)	0.58 (0.02)	15.45 (0.46)
	mcp	0.86 (0.01)	3.75 (0.32)	3.75	0	1.2 (0.02)	1.29 (0.05)	0.43 (0.01)	13.75 (0.32)
	scad	0.72 (0.01)	8.32 (0.4)	8.32	0	1.18 (0.02)	1.35 (0.04)	0.42 (0.01)	18.32 (0.4)
	vsd	0.98 (0)	0.43 (0.09)	0.11	0.32	1.26 (0.04)	1.08 (0.06)	0.44 (0.02)	9.79 (0.08)
	bic	0.81 (0.01)	5.65 (0.7)	5.65	0	1.22 (0.03)	1.42 (0.1)	0.44 (0.02)	15.65 (0.7)
	ebic	0.85 (0.01)	3.9 (0.34)	3.9	0	1.2 (0.02)	1.29 (0.05)	0.43 (0.01)	13.9 (0.34)
	cv	<u>0.64</u> (0.02)	<u>14.15</u> (1.13)	<u>14.15</u>	0	<u>1.35</u> (0.03)	<u>2.13</u> (0.12)	<u>0.55</u> (0.02)	24.15 (1.13)
	csuv.m	0.98 (0)	0.47 (0.07)	0.27	<u>0.2</u>	1.22 (0.03)	1.06 (0.05)	0.43 (0.02)	10.07 (0.08)
	csuv.s	0.86 (0.01)	3.26 (0.15)	3.24	0.02	1.32 (0.02)	1.67 (0.05)	<u>0.55</u> (0.01)	13.22 (0.16)
	csuv.m.25	0.61 (0.01)	5.52 (0.12)	0	5.52	4.29 (0.12)	4.77 (0.1)	1.79 (0.03)	4.48 (0.12)
	csuv.m.75	0.95 (0.01)	1.02 (0.13)	1.01	0.01	1.2 (0.02)	1.16 (0.05)	0.43 (0.01)	11 (0.14)
	csuv.m.all	0.98 (0)	0.45 (0.07)	0.3	0.15	1.2 (0.03)	1.04 (0.04)	0.41 (0.02)	10.15 (0.07)
	csuv.m.mcp	0.98 (0)	0.42 (0.08)	0.03	0.39	1.26 (0.04)	1.08 (0.06)	0.45 (0.02)	9.64 (0.08)
csuv.m.with.tree	0.98 (0)	0.45 (0.07)	0.3	0.15	1.2 (0.03)	1.04 (0.04)	0.41 (0.02)	10.15 (0.07)	

Table 4: Model 2: performance of CSUV and methods it compares with. Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 4 rho = 0 s = 10 p = 300	lasso	0.38 (0.01)	36.46 (1.52)	36.42	0.04	1.88 (0.05)	4.47 (0.14)	0.94 (0.02)	46.38 (1.52)
	elastic net	0.31 (0.01)	47.64 (1.59)	47.6	0.04	2.15 (0.05)	5.65 (0.15)	1.08 (0.02)	57.56 (1.6)
	relaxed lasso	0.66 (0.01)	11.84 (0.9)	11.61	0.23	1.7 (0.05)	3.2 (0.13)	0.81 (0.02)	21.38 (0.93)
	mcp	0.8 (0.01)	5.3 (0.35)	5.27	0.03	1.25 (0.03)	1.49 (0.06)	0.48 (0.02)	15.24 (0.34)
	scad	0.57 (0.01)	16.07 (0.53)	16.06	0.01	1.26 (0.03)	1.8 (0.07)	0.5 (0.02)	26.05 (0.52)
	vsd	0.88 (0.02)	2.04 (0.28)	0.03	2.01	2.27 (0.22)	2.28 (0.22)	0.89 (0.07)	8.02 (0.28)
	bic	0.61 (0.02)	18.22 (1.93)	18.19	0.03	1.4 (0.05)	2.44 (0.2)	0.59 (0.03)	28.16 (1.94)
	ebic	0.78 (0.02)	8.29 (1.43)	8.26	0.03	1.29 (0.04)	1.79 (0.15)	0.52 (0.02)	18.23 (1.43)
	cv	<u>0.42</u> (0.01)	<u>32.93</u> (1.69)	<u>32.9</u>	0.03	<u>1.8</u> (0.05)	<u>4.14</u> (0.17)	<u>0.88</u> (0.02)	42.87 (1.69)
	csuv.m	0.92 (0.01)	1.45 (0.14)	0.07	<u>1.38</u>	1.75 (0.08)	1.83 (0.11)	0.8 (0.04)	8.69 (0.13)
	csuv.s	0.76 (0.01)	6.51 (0.26)	6.27	0.24	1.51 (0.04)	2.35 (0.07)	0.7 (0.02)	16.03 (0.29)
	csuv.m.25	0.32 (0.01)	8.28 (0.1)	0	8.28	7.22 (0.19)	7.19 (0.11)	2.47 (0.03)	1.72 (0.1)
	csuv.m.75	0.95 (0.01)	1.17 (0.12)	1.02	0.15	1.26 (0.03)	1.31 (0.06)	0.5 (0.02)	10.87 (0.12)
	csuv.m.all	0.92 (0.01)	1.45 (0.15)	0.14	1.31	1.72 (0.08)	1.81 (0.11)	0.78 (0.04)	8.83 (0.12)
	csuv.m.mcp	0.8 (0.01)	3.18 (0.17)	0	3.18	2.73 (0.11)	3.04 (0.12)	1.26 (0.04)	6.82 (0.17)
csuv.m.with.tree	0.92 (0.01)	1.44 (0.14)	0.13	1.31	1.72 (0.08)	1.8 (0.1)	0.78 (0.04)	8.82 (0.12)	
setting 5 rho = 0.9 s = 5 p = 100	lasso	0.39 (0.01)	16.4 (0.67)	16.19	0.21	1.28 (0.02)	3.51 (0.11)	1.04 (0.03)	20.98 (0.68)
	elastic net	0.33 (0.01)	21.14 (0.69)	20.99	0.15	1.31 (0.02)	4.21 (0.11)	1.15 (0.02)	25.84 (0.69)
	relaxed lasso	0.49 (0.01)	10.58 (0.65)	10	0.58	1.31 (0.02)	3.31 (0.13)	1.07 (0.03)	14.42 (0.7)
	mcp	0.67 (0.02)	4.22 (0.32)	3.08	1.14	1.29 (0.03)	2.46 (0.18)	1.08 (0.06)	6.94 (0.24)
	scad	0.65 (0.02)	5.13 (0.35)	4.32	0.81	1.25 (0.03)	2.15 (0.16)	0.94 (0.06)	8.51 (0.3)
	vsd	0.75 (0.02)	2.13 (0.16)	0.53	1.6	1.37 (0.03)	1.93 (0.13)	1 (0.05)	3.93 (0.08)
	bic	0.69 (0.02)	4.23 (0.35)	3.4	0.83	1.25 (0.03)	2.19 (0.18)	0.95 (0.06)	7.57 (0.3)
	ebic	0.7 (0.02)	3.9 (0.33)	3	0.9	1.26 (0.03)	2.13 (0.17)	0.95 (0.06)	7.1 (0.28)
	cv	<u>0.45</u> (0.02)	<u>13.83</u> (0.75)	<u>13.55</u>	0.28	1.27 (0.02)	<u>3.25</u> (0.14)	<u>1.02</u> (0.03)	18.27 (0.77)
	csuv.m	0.78 (0.01)	2.15 (0.15)	0.92	<u>1.23</u>	<u>1.33</u> (0.03)	1.84 (0.1)	0.92 (0.04)	4.69 (0.11)
	csuv.s	0.67 (0.01)	4.28 (0.19)	3.53	0.75	1.26 (0.02)	2.36 (0.11)	0.96 (0.04)	7.78 (0.19)
	csuv.m.25	0.62 (0.02)	2.82 (0.11)	0.23	2.59	1.91 (0.06)	2.44 (0.1)	1.28 (0.04)	2.64 (0.08)
	csuv.m.75	0.76 (0.01)	2.71 (0.18)	1.88	0.83	1.24 (0.02)	1.93 (0.11)	0.88 (0.04)	6.05 (0.14)
	csuv.m.all	0.77 (0.01)	2.38 (0.16)	1.24	1.14	1.3 (0.03)	1.95 (0.11)	0.94 (0.04)	5.1 (0.12)
	csuv.m.mcp	0.69 (0.02)	2.52 (0.15)	0.41	2.11	1.79 (0.06)	2.33 (0.12)	1.21 (0.05)	3.3 (0.09)
csuv.m.with.tree	0.77 (0.01)	2.36 (0.16)	1.19	1.17	1.3 (0.03)	1.94 (0.11)	0.94 (0.04)	5.02 (0.12)	
setting 6 rho = 0.9 s = 5 p = 300	lasso	0.3 (0.01)	24.79 (1.08)	24.6	0.19	1.42 (0.03)	3.81 (0.15)	1.04 (0.03)	29.41 (1.09)
	elastic net	0.23 (0.01)	34.79 (1.22)	34.66	0.13	1.51 (0.03)	4.91 (0.14)	1.21 (0.02)	39.53 (1.21)
	relaxed lasso	0.51 (0.02)	10.84 (0.88)	10.37	0.47	1.35 (0.03)	3.13 (0.15)	0.99 (0.03)	14.9 (0.9)
	mcp	0.59 (0.02)	5.53 (0.34)	4.25	1.28	1.32 (0.03)	2.61 (0.16)	1.14 (0.06)	7.97 (0.25)
	scad	0.55 (0.02)	8.02 (0.43)	7.4	0.62	1.22 (0.02)	1.83 (0.13)	0.8 (0.05)	11.78 (0.39)
	vsd	0.76 (0.02)	2.5 (0.19)	0.58	1.92	1.9 (0.11)	2.31 (0.15)	1.14 (0.07)	3.66 (0.19)
	bic	0.59 (0.02)	8.37 (1.21)	7.56	0.81	1.28 (0.03)	2.36 (0.2)	0.93 (0.06)	11.75 (1.24)
	ebic	0.63 (0.02)	5.7 (0.73)	4.69	1.01	1.28 (0.03)	2.26 (0.17)	<u>0.98</u> (0.06)	8.68 (0.73)
	cv	<u>0.45</u> (0.02)	<u>16.02</u> (1.26)	<u>15.55</u>	0.47	1.32 (0.03)	<u>2.86</u> (0.18)	0.94 (0.05)	20.08 (1.28)
	csuv.m	0.8 (0.02)	1.91 (0.16)	0.84	<u>1.07</u>	<u>1.4</u> (0.04)	1.76 (0.12)	0.89 (0.05)	4.77 (0.09)
	csuv.s	0.64 (0.01)	5.42 (0.24)	5.05	0.37	1.25 (0.02)	2.37 (0.1)	0.89 (0.03)	9.68 (0.21)
	csuv.m.25	0.44 (0.01)	3.84 (0.08)	0.04	3.8	3.18 (0.07)	3.5 (0.07)	1.69 (0.03)	1.24 (0.08)
	csuv.m.75	0.76 (0.02)	2.9 (0.23)	2.22	0.68	1.25 (0.03)	1.9 (0.13)	0.83 (0.05)	6.54 (0.16)
	csuv.m.all	0.8 (0.02)	2 (0.16)	1.04	0.96	1.33 (0.03)	1.71 (0.12)	0.85 (0.05)	5.08 (0.1)
	csuv.m.mcp	0.68 (0.02)	2.51 (0.14)	0.39	2.12	2.06 (0.07)	2.41 (0.12)	1.23 (0.05)	3.27 (0.11)
csuv.m.with.tree	0.8 (0.02)	1.98 (0.16)	1	0.98	1.34 (0.04)	1.71 (0.12)	0.86 (0.05)	5.02 (0.1)	

Table 5: Model 2: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 7 rho = 0.9 s = 10 p = 100	lasso	0.47 (0.01)	22.41 (0.7)	21.75	0.66	1.49 (0.03)	6.3 (0.17)	1.49 (0.03)	31.09 (0.73)
	elastic net	0.42 (0.01)	27.11 (0.74)	26.68	0.43	1.54 (0.03)	7.11 (0.17)	1.57 (0.03)	36.25 (0.74)
	relaxed lasso	0.54 (0.01)	17.19 (0.83)	16.23	0.96	1.53 (0.03)	6.31 (0.22)	1.55 (0.03)	25.27 (0.91)
	mcp	0.64 (0.01)	8.05 (0.37)	4.87	3.18	1.67 (0.04)	6.29 (0.24)	2 (0.05)	11.69 (0.34)
	scad	0.66 (0.01)	8.01 (0.37)	5.49	2.52	1.5 (0.04)	5.05 (0.22)	1.72 (0.06)	12.97 (0.28)
	vsd	0.7 (0.02)	5.18 (0.24)	1.37	3.81	1.88 (0.08)	5.37 (0.21)	1.9 (0.06)	7.56 (0.15)
	bic	0.67 (0.01)	7.64 (0.39)	5.03	2.61	1.58 (0.04)	5.54 (0.25)	1.81 (0.06)	12.42 (0.34)
	ebic	0.68 (0.01)	7.07 (0.35)	4.35	<u>2.72</u>	1.57 (0.04)	5.38 (0.24)	<u>1.79</u> (0.06)	11.63 (0.31)
	cv	<u>0.47</u> (0.01)	<u>22.41</u> (0.7)	<u>21.75</u>	0.66	1.49 (0.03)	<u>6.3</u> (0.17)	1.49 (0.03)	31.09 (0.73)
	csuv.m	0.76 (0.01)	4.69 (0.2)	1.99	2.7	<u>1.67</u> (0.04)	4.42 (0.15)	1.54 (0.04)	9.29 (0.16)
	csuv.s	0.67 (0.01)	8.54 (0.24)	7.16	1.38	1.45 (0.03)	4.93 (0.12)	1.45 (0.03)	15.78 (0.23)
	csuv.m.25	0.49 (0.01)	6.92 (0.14)	0.42	6.5	3.98 (0.14)	6.83 (0.15)	2.37 (0.04)	3.92 (0.12)
	csuv.m.75	0.75 (0.01)	5.59 (0.26)	3.69	1.9	1.44 (0.03)	4.44 (0.15)	1.44 (0.04)	11.79 (0.23)
	csuv.m.all	0.76 (0.01)	4.88 (0.21)	2.39	2.49	1.63 (0.04)	4.41 (0.15)	1.51 (0.04)	9.9 (0.17)
	csuv.m.mcp	0.58 (0.02)	6.03 (0.19)	0.46	5.57	3.37 (0.14)	6.24 (0.2)	2.21 (0.06)	4.89 (0.14)
csuv.m.with.tree	0.76 (0.01)	4.87 (0.21)	2.38	2.49	1.63 (0.04)	4.41 (0.15)	1.51 (0.04)	9.89 (0.17)	
setting 8 rho = 0.9 s = 10 p = 300	lasso	0.39 (0.01)	32.19 (1.08)	31.64	0.55	1.72 (0.04)	6.9 (0.19)	1.5 (0.03)	41.09 (1.06)
	elastic net	0.32 (0.01)	41.56 (0.99)	41.14	0.42	1.83 (0.04)	8.36 (0.16)	1.68 (0.03)	50.72 (0.97)
	relaxed lasso	0.51 (0.01)	18.39 (0.75)	17.43	0.96	1.64 (0.04)	6.25 (0.18)	1.5 (0.03)	26.47 (0.79)
	mcp	0.53 (0.02)	11.72 (0.55)	7.87	3.85	2.07 (0.07)	7.38 (0.35)	2.2 (0.08)	14.02 (0.29)
	scad	0.54 (0.01)	13.88 (0.52)	11.65	2.23	1.72 (0.05)	5.3 (0.26)	1.71 (0.07)	19.42 (0.37)
	vsd	0.59 (0.02)	6.82 (0.33)	1.92	4.9	3.24 (0.22)	6.6 (0.31)	2.24 (0.08)	7.02 (0.25)
	bic	0.56 (0.02)	13.42 (1.07)	10.86	2.56	1.78 (0.06)	5.89 (0.32)	1.8 (0.07)	18.3 (1.08)
	ebic	0.57 (0.02)	11.01 (0.52)	7.92	3.09	1.85 (0.06)	6.13 (0.32)	<u>1.91</u> (0.08)	14.83 (0.38)
	cv	<u>0.39</u> (0.01)	<u>32.19</u> (1.08)	<u>31.64</u>	0.55	1.72 (0.04)	<u>6.9</u> (0.19)	1.5 (0.03)	41.09 (1.06)
	csuv.m	0.7 (0.01)	5.68 (0.21)	2.31	3.37	<u>2.34</u> (0.09)	5.05 (0.17)	1.74 (0.05)	8.94 (0.17)
	csuv.s	0.56 (0.01)	14.11 (0.37)	12.94	1.17	1.64 (0.04)	5.82 (0.16)	1.5 (0.03)	21.77 (0.38)
	csuv.m.25	0.26 (0.01)	8.81 (0.1)	0.1	8.71	8.77 (0.21)	8.02 (0.12)	2.7 (0.03)	1.39 (0.09)
	csuv.m.75	0.73 (0.01)	6.38 (0.28)	4.65	1.73	1.61 (0.05)	4.4 (0.17)	1.41 (0.05)	12.92 (0.26)
	csuv.m.all	0.71 (0.01)	5.7 (0.24)	2.62	3.08	2.18 (0.08)	4.91 (0.18)	1.68 (0.05)	9.54 (0.17)
	csuv.m.mcp	0.38 (0.02)	8.11 (0.16)	0.42	7.69	7.18 (0.22)	7.6 (0.17)	2.59 (0.05)	2.73 (0.15)
csuv.m.with.tree	0.71 (0.01)	5.7 (0.24)	2.62	3.08	2.18 (0.08)	4.91 (0.18)	1.68 (0.05)	9.54 (0.17)	
setting 9 rho = 0 s = 5 p = 1000	lasso	0.26 (0.01)	35.2 (2.05)	35.2	0	1.58 (0.03)	3.08 (0.12)	0.76 (0.01)	40.2 (2.05)
	elastic net	0.2 (0.01)	46.49 (2.06)	46.49	0	1.83 (0.04)	3.92 (0.12)	0.91 (0.02)	51.49 (2.06)
	relaxed lasso	0.74 (0.02)	5.38 (1)	5.18	0.2	1.4 (0.04)	1.6 (0.12)	0.59 (0.02)	9.98 (1.02)
	mcp	0.66 (0.02)	6.01 (0.42)	6.01	0	1.14 (0.02)	0.93 (0.04)	0.36 (0.01)	11.01 (0.42)
	scad	0.34 (0.01)	22.37 (0.95)	22.37	0	1.15 (0.02)	1.41 (0.05)	0.39 (0.01)	27.37 (0.95)
	vsd	0.83 (0.02)	1.26 (0.14)	0	1.26	1.73 (0.1)	1.29 (0.11)	0.71 (0.05)	3.74 (0.14)
	bic	0.34 (0.02)	29.06 (2.29)	29.06	0	1.29 (0.03)	2.1 (0.16)	0.49 (0.02)	34.06 (2.29)
	ebic	0.65 (0.02)	7.87 (1.35)	7.87	0	1.15 (0.02)	1.03 (0.08)	0.37 (0.02)	12.87 (1.35)
	cv	<u>0.49</u> (0.02)	<u>15.39</u> (1.27)	<u>15.39</u>	0	1.16 (0.03)	1.25 (0.08)	0.38 (0.02)	20.39 (1.27)
	csuv.m	0.96 (0.01)	0.37 (0.07)	0.07	<u>0.3</u>	1.18 (0.03)	0.63 (0.04)	0.36 (0.03)	4.77 (0.07)
	csuv.s	0.74 (0.01)	3.8 (0.24)	3.73	0.07	<u>1.34</u> (0.03)	<u>1.45</u> (0.06)	<u>0.56</u> (0.02)	8.66 (0.26)
	csuv.m.25	0.41 (0.01)	3.98 (0.07)	0	3.98	3.75 (0.09)	3.39 (0.07)	1.65 (0.03)	1.02 (0.07)
	csuv.m.75	0.94 (0.01)	0.75 (0.09)	0.73	0.02	1.13 (0.02)	0.7 (0.04)	0.35 (0.02)	5.71 (0.1)
	csuv.m.all	0.96 (0.01)	0.37 (0.07)	0.07	0.3	1.18 (0.03)	0.63 (0.04)	0.36 (0.03)	4.77 (0.07)
	csuv.m.mcp	0.92 (0.01)	0.63 (0.09)	0	0.63	1.36 (0.06)	0.83 (0.07)	0.48 (0.04)	4.37 (0.09)
csuv.m.with.tree	0.96 (0.01)	0.38 (0.07)	0.07	0.31	1.19 (0.03)	0.64 (0.04)	0.36 (0.03)	4.76 (0.07)	

Table 6: Model 2: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 10 rho = 0 s = 10 p = 1000	lasso	0.29 (0.01)	53.51 (2.09)	53.24	0.27	2.61 (0.08)	6.48 (0.17)	1.26 (0.03)	62.97 (2.13)
	elastic net	0.23 (0.01)	69.12 (2.17)	68.76	0.36	3.27 (0.1)	8.36 (0.18)	1.51 (0.03)	78.4 (2.22)
	relaxed lasso	0.5 (0.02)	22.46 (1.77)	21.26	1.2	2.7 (0.11)	5.56 (0.21)	1.26 (0.04)	30.06 (1.96)
	mcp	0.72 (0.01)	8.08 (0.33)	8.03	0.05	1.29 (0.03)	1.7 (0.06)	0.53 (0.02)	17.98 (0.34)
	scad	0.45 (0.01)	25.21 (0.68)	25.19	0.02	1.31 (0.03)	2.17 (0.06)	0.54 (0.02)	35.17 (0.69)
	vsd	0.31 (0.02)	9.01 (0.15)	0	9.01	8.34 (0.22)	8.1 (0.15)	2.72 (0.04)	0.99 (0.15)
	bic	0.4 (0.02)	40.2 (2.82)	40.11	0.09	1.85 (0.09)	4.17 (0.3)	0.83 (0.04)	50.02 (2.81)
	ebic	0.67 (0.02)	16.97 (2.61)	16.9	0.07	1.5 (0.06)	2.53 (0.24)	0.63 (0.03)	26.83 (2.6)
	cv	<u>0.36</u> (0.01)	<u>43.37</u> (2.31)	<u>43.23</u>	0.14	2.16 (0.09)	<u>5.04</u> (0.25)	1.02 (0.04)	53.09 (2.32)
	csuv.m	0.62 (0.02)	5.35 (0.17)	0.05	<u>5.3</u>	<u>4.15</u> (0.14)	4.64 (0.13)	<u>1.76</u> (0.04)	4.75 (0.16)
	csuv.s	0.68 (0.01)	7.49 (0.32)	5.29	2.2	2.69 (0.14)	3.86 (0.18)	1.22 (0.05)	13.09 (0.41)
	csuv.m.25	0.21 (0.01)	9.64 (0.06)	0	9.64	9.25 (0.16)	8.75 (0.06)	2.91 (0.02)	0.36 (0.06)
	csuv.m.75	0.93 (0.01)	1.51 (0.15)	1.15	0.36	1.36 (0.04)	1.52 (0.08)	0.58 (0.03)	10.79 (0.13)
	csuv.m.all	0.64 (0.02)	5.2 (0.17)	0.06	5.14	4.05 (0.14)	4.54 (0.13)	1.73 (0.04)	4.92 (0.16)
	csuv.m.mcp	0.44 (0.01)	7.18 (0.13)	0	7.18	5.65 (0.16)	6.14 (0.12)	2.17 (0.03)	2.82 (0.13)
csuv.m.with.tree	0.63 (0.02)	5.24 (0.17)	0.05	5.19	4.07 (0.14)	4.56 (0.13)	1.74 (0.04)	4.86 (0.16)	
setting 11 rho = 0.9 s = 5 p = 1000	lasso	0.28 (0.01)	29.64 (1.61)	29.39	0.25	1.52 (0.03)	3.89 (0.14)	1.06 (0.02)	34.14 (1.63)
	elastic net	0.2 (0.01)	44.62 (1.73)	44.5	0.12	1.65 (0.03)	5.26 (0.12)	1.29 (0.02)	49.38 (1.73)
	relaxed lasso	0.54 (0.01)	9.24 (0.83)	8.7	0.54	1.37 (0.02)	2.99 (0.13)	1.01 (0.03)	13.16 (0.85)
	mcp	0.54 (0.02)	7.16 (0.38)	5.95	1.21	1.35 (0.03)	2.67 (0.15)	1.18 (0.06)	9.74 (0.33)
	scad	0.4 (0.02)	15.29 (0.75)	14.66	0.63	1.27 (0.03)	2.12 (0.13)	0.81 (0.05)	19.03 (0.73)
	vsd	0.68 (0.02)	2.91 (0.18)	0.63	2.28	2.16 (0.12)	2.63 (0.15)	1.3 (0.06)	3.35 (0.15)
	bic	0.46 (0.02)	13.46 (1.4)	12.69	0.77	1.3 (0.03)	2.41 (0.17)	0.93 (0.06)	16.92 (1.42)
	ebic	0.55 (0.02)	7.85 (1.01)	6.75	1.1	1.35 (0.04)	2.54 (0.16)	<u>1.1</u> (0.06)	10.65 (1.01)
	cv	<u>0.36</u> (0.02)	<u>22.24</u> (1.71)	<u>21.74</u>	0.5	1.4 (0.03)	<u>3.03</u> (0.18)	0.97 (0.05)	26.24 (1.75)
	csuv.m	0.79 (0.01)	1.93 (0.13)	0.56	<u>1.37</u>	<u>1.62</u> (0.05)	1.74 (0.1)	0.95 (0.04)	4.19 (0.08)
	csuv.s	0.61 (0.01)	6.14 (0.25)	5.71	0.43	1.3 (0.03)	2.53 (0.1)	0.93 (0.03)	10.28 (0.25)
	csuv.m.25	0.38 (0.01)	4.29 (0.07)	0.04	4.25	4.19 (0.11)	3.73 (0.08)	1.78 (0.03)	0.79 (0.07)
	csuv.m.75	0.79 (0.02)	2.4 (0.18)	1.75	0.65	1.24 (0.03)	1.73 (0.11)	0.82 (0.05)	6.1 (0.14)
	csuv.m.all	0.79 (0.01)	2.01 (0.14)	0.7	1.31	1.58 (0.05)	1.75 (0.1)	0.93 (0.04)	4.39 (0.1)
	csuv.m.mcp	0.59 (0.02)	3.07 (0.13)	0.27	2.8	2.78 (0.11)	2.75 (0.12)	1.41 (0.04)	2.47 (0.11)
csuv.m.with.tree	0.78 (0.01)	2.02 (0.14)	0.69	1.33	1.59 (0.05)	1.76 (0.1)	0.94 (0.04)	4.36 (0.1)	
setting 12 rho = 0.9 s = 10 p = 1000	lasso	0.26 (0.01)	53.78 (1.77)	52.68	1.1	2.3 (0.05)	8.98 (0.21)	1.78 (0.03)	61.58 (1.79)
	elastic net	0.22 (0)	67.86 (1.67)	67.03	0.83	2.56 (0.05)	10.81 (0.17)	2 (0.02)	76.2 (1.65)
	relaxed lasso	0.39 (0.01)	28.39 (1.41)	26.57	1.82	2.27 (0.06)	8.46 (0.25)	1.83 (0.04)	34.75 (1.49)
	mcp	0.47 (0.01)	13.98 (0.47)	10.02	3.96	2.4 (0.08)	7.73 (0.28)	2.34 (0.06)	16.06 (0.32)
	scad	0.41 (0.01)	22.75 (0.66)	20.5	2.25	1.82 (0.07)	5.43 (0.29)	1.68 (0.08)	28.25 (0.54)
	vsd	0.28 (0.02)	9.36 (0.16)	0.11	9.25	8.84 (0.24)	8.58 (0.16)	2.86 (0.05)	0.86 (0.17)
	bic	0.39 (0.02)	32.81 (2.68)	30.62	2.19	2.02 (0.07)	6.94 (0.35)	1.8 (0.07)	38.43 (2.78)
	ebic	0.47 (0.01)	18.7 (1.9)	15.47	3.23	2.19 (0.07)	7.09 (0.29)	2.09 (0.07)	22.24 (2)
	cv	<u>0.26</u> (0.01)	<u>53.78</u> (1.77)	<u>52.68</u>	1.1	2.3 (0.05)	<u>8.98</u> (0.21)	1.78 (0.03)	61.58 (1.79)
	csuv.m	0.49 (0.01)	7.37 (0.18)	1.12	<u>6.25</u>	<u>4.57</u> (0.13)	6.53 (0.17)	<u>2.24</u> (0.04)	4.87 (0.15)
	csuv.s	0.46 (0.01)	17.19 (0.41)	14.36	2.83	2.46 (0.08)	7.81 (0.2)	1.94 (0.04)	21.53 (0.42)
	csuv.m.25	0.2 (0.01)	9.78 (0.05)	0.02	9.76	9.55 (0.18)	8.9 (0.06)	2.96 (0.02)	0.26 (0.05)
	csuv.m.75	0.69 (0.01)	6.38 (0.3)	3.46	2.92	2.25 (0.08)	5.03 (0.21)	1.7 (0.05)	10.54 (0.21)
	csuv.m.all	0.51 (0.01)	7.32 (0.2)	1.25	6.07	4.44 (0.12)	6.48 (0.19)	2.21 (0.05)	5.18 (0.16)
	csuv.m.mcp	0.27 (0.01)	9.01 (0.12)	0.27	8.74	7.72 (0.19)	8.15 (0.14)	2.75 (0.04)	1.53 (0.11)
csuv.m.with.tree	0.51 (0.02)	7.33 (0.2)	1.25	6.08	4.46 (0.13)	6.48 (0.19)	2.21 (0.05)	5.17 (0.16)	

Table 7: Model 2: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 13 rho = 0 s = 5 p = 100 n = 1000	lasso	0.45 (0.01)	14.2 (0.73)	14.2	0	1.02 (0)	0.47 (0.01)	0.14 (0)	19.2 (0.73)
	elastic net	0.35 (0.01)	20.9 (0.81)	20.9	0	1.03 (0)	0.62 (0.02)	0.17 (0)	25.9 (0.81)
	relaxed lasso	0.97 (0.01)	0.55 (0.22)	0.55	0	1.01 (0)	0.15 (0.01)	0.07 (0)	5.55 (0.22)
	mcp	0.93 (0.01)	1.12 (0.28)	1.12	0	1.01 (0)	0.15 (0.01)	0.07 (0)	6.12 (0.28)
	scad	0.88 (0.02)	2.22 (0.44)	2.22	0	1.01 (0)	0.16 (0.01)	0.07 (0)	7.22 (0.44)
	vsd	1 (0)	0.03 (0.02)	0.03	0	1.01 (0)	0.12 (0)	0.07 (0)	5.03 (0.02)
	bic	0.93 (0.01)	1.11 (0.27)	1.11	0	1.01 (0)	0.14 (0.01)	0.07 (0)	6.11 (0.27)
	ebic	0.94 (0.01)	1 (0.26)	1	0	1.01 (0)	0.14 (0.01)	<u>0.07</u> (0)	6 (0.26)
	cv	<u>0.89</u> (0.02)	<u>2.09</u> (0.44)	<u>2.09</u>	0	1.01 (0)	<u>0.15</u> (0.01)	<u>0.07</u> (0)	7.09 (0.44)
	csuv.m	1 (0)	0.01 (0.01)	0.01	0	1.01 (0)	0.12 (0)	0.06 (0)	5.01 (0.01)
	csuv.s	1 (0)	0.02 (0.01)	0.02	0	1.01 (0)	0.12 (0)	0.06 (0)	5.02 (0.01)
	csuv.m.25	1 (0)	0 (0)	0	0	1.01 (0)	0.11 (0)	0.06 (0)	5 (0)
	csuv.m.75	0.98 (0.01)	0.26 (0.06)	0.26	0	1.01 (0)	0.14 (0.01)	0.08 (0)	5.26 (0.06)
	csuv.m.all	1 (0)	0.02 (0.01)	0.02	0	1.01 (0)	0.12 (0)	0.06 (0)	5.02 (0.01)
	csuv.m.mcp	1 (0)	0.01 (0.01)	0.01	0	1.01 (0)	0.12 (0)	0.06 (0)	5.01 (0.01)
csuv.m.with.tree	1 (0)	0.01 (0.01)	0.01	0	1.01 (0)	0.12 (0)	0.06 (0)	5.01 (0.01)	
setting 14 rho = 0 s = 10 p = 100 n = 1000	lasso	0.49 (0.01)	22.22 (0.79)	22.22	0	1.04 (0)	0.8 (0.02)	0.19 (0)	32.22 (0.79)
	elastic net	0.42 (0.01)	28.41 (0.8)	28.41	0	1.05 (0)	0.95 (0.02)	0.2 (0)	38.41 (0.8)
	relaxed lasso	0.98 (0.01)	0.59 (0.27)	0.59	0	1.02 (0)	0.28 (0.01)	0.1 (0)	10.59 (0.27)
	mcp	0.96 (0.01)	1.03 (0.27)	1.03	0	1.01 (0)	0.27 (0.01)	0.1 (0)	11.03 (0.27)
	scad	0.92 (0.01)	2.4 (0.48)	2.4	0	1.01 (0)	0.28 (0.01)	0.1 (0)	12.4 (0.48)
	vsd	0.99 (0)	0.22 (0.04)	0.22	0	1.02 (0)	0.26 (0.01)	0.1 (0)	10.22 (0.04)
	bic	0.96 (0.01)	1.09 (0.27)	1.09	0	1.01 (0)	0.27 (0.01)	0.1 (0)	11.09 (0.27)
	ebic	0.96 (0.01)	0.99 (0.27)	0.99	0	1.01 (0)	0.27 (0.01)	<u>0.1</u> (0)	10.99 (0.27)
	cv	<u>0.92</u> (0.01)	<u>2.35</u> (0.48)	<u>2.35</u>	0	1.01 (0)	<u>0.28</u> (0.01)	<u>0.1</u> (0)	12.35 (0.48)
	csuv.m	1 (0)	0.03 (0.02)	0.03	0	1.01 (0)	0.24 (0.01)	0.09 (0)	10.03 (0.02)
	csuv.s	1 (0)	0.03 (0.02)	0.03	0	1.01 (0)	0.24 (0.01)	0.09 (0)	10.03 (0.02)
	csuv.m.25	1 (0)	0 (0)	0	0	1.01 (0)	0.24 (0.01)	0.09 (0)	10 (0)
	csuv.m.75	0.99 (0)	0.3 (0.06)	0.3	0	1.02 (0)	0.27 (0.01)	0.11 (0)	10.3 (0.06)
	csuv.m.all	1 (0)	0.03 (0.02)	0.03	0	1.01 (0)	0.24 (0.01)	0.09 (0)	10.03 (0.02)
	csuv.m.mcp	1 (0)	0 (0)	0	0	1.01 (0)	0.24 (0.01)	0.09 (0)	10 (0)
csuv.m.with.tree	1 (0)	0.03 (0.02)	0.03	0	1.01 (0)	0.24 (0.01)	0.09 (0)	10.03 (0.02)	
setting 15 rho = 0.9 s = 5 p = 100 n = 1000	lasso	0.42 (0.01)	14.7 (0.56)	14.7	0	1.02 (0)	0.9 (0.03)	0.27 (0.01)	19.7 (0.56)
	elastic net	0.31 (0.01)	23.23 (0.63)	23.23	0	1.03 (0)	1.4 (0.04)	0.37 (0.01)	28.23 (0.63)
	relaxed lasso	0.82 (0.01)	2.52 (0.28)	2.52	0	1.01 (0)	0.44 (0.03)	0.19 (0.01)	7.52 (0.28)
	mcp	0.96 (0.01)	0.51 (0.11)	0.51	0	1.01 (0)	0.16 (0.01)	0.08 (0)	5.51 (0.11)
	scad	0.96 (0.01)	0.58 (0.16)	0.58	0	1.01 (0)	0.15 (0.01)	0.07 (0)	5.58 (0.16)
	vsd	1 (0)	0 (0)	0	0	1.01 (0)	0.13 (0.01)	0.07 (0)	5 (0)
	bic	0.97 (0.01)	0.34 (0.08)	0.34	0	1.01 (0)	0.15 (0.01)	0.08 (0)	5.34 (0.08)
	ebic	0.98 (0.01)	0.25 (0.07)	0.25	0	1.01 (0)	0.15 (0.01)	0.08 (0)	5.25 (0.07)
	cv	<u>0.96</u> (0.01)	<u>0.52</u> (0.15)	<u>0.52</u>	0	1.01 (0)	0.15 (0.01)	0.07 (0)	5.52 (0.15)
	csuv.m	0.99 (0)	0.06 (0.02)	0.06	0	1.01 (0)	0.14 (0.01)	0.08 (0)	5.06 (0.02)
	csuv.s	0.98 (0)	0.21 (0.04)	0.21	0	1.01 (0)	<u>0.18</u> (0.01)	<u>0.1</u> (0.01)	5.21 (0.04)
	csuv.m.25	1 (0)	0.02 (0.01)	0.02	0	1.01 (0)	0.14 (0.01)	0.07 (0)	5.02 (0.01)
	csuv.m.75	0.95 (0.01)	0.55 (0.08)	0.55	0	1.01 (0)	0.23 (0.02)	0.12 (0.01)	5.55 (0.08)
	csuv.m.all	0.99 (0)	0.13 (0.04)	0.13	0	1.01 (0)	0.16 (0.01)	0.09 (0.01)	5.13 (0.04)
	csuv.m.mcp	1 (0)	0.02 (0.01)	0.02	0	1.01 (0)	0.13 (0.01)	0.07 (0)	5.02 (0.01)
csuv.m.with.tree	0.99 (0)	0.13 (0.04)	0.13	0	1.01 (0)	0.16 (0.01)	0.09 (0.01)	5.13 (0.04)	

Table 8: Model 2: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 16	lasso	0.5 (0.01)	21.05 (0.67)	21.05	0	1.04 (0)	1.62 (0.04)	0.39 (0.01)	31.05 (0.67)
	elastic net	0.42 (0.01)	28.49 (0.67)	28.49	0	1.04 (0)	2.11 (0.05)	0.46 (0.01)	38.49 (0.67)
rho = 0.9	relaxed lasso	0.71 (0.01)	8.86 (0.55)	8.86	0	1.03 (0)	1.13 (0.04)	0.32 (0.01)	18.86 (0.55)
	mcp	0.98 (0)	0.43 (0.1)	0.41	0.02	1.01 (0)	0.41 (0.02)	0.16 (0.01)	10.39 (0.09)
s = 10	scad	0.96 (0.01)	0.93 (0.17)	0.92	0.01	1.01 (0)	0.42 (0.02)	0.16 (0.01)	10.91 (0.17)
p = 100	vsd	1 (0)	0.09 (0.04)	0.07	0.02	1.01 (0)	0.38 (0.02)	0.15 (0.01)	10.05 (0.03)
	bic	0.98 (0)	0.41 (0.09)	0.4	0.01	1.01 (0)	0.4 (0.02)	0.16 (0.01)	10.39 (0.09)
n = 1000	ebic	0.98 (0)	0.38 (0.09)	0.37	<u>0.01</u>	1.01 (0)	0.4 (0.02)	0.16 (0.01)	10.36 (0.09)
	cv	<u>0.96</u> (0.01)	<u>0.92</u> (0.17)	<u>0.91</u>	<u>0.01</u>	1.01 (0)	0.42 (0.02)	0.16 (0.01)	10.9 (0.17)
	csuv.m	0.99 (0)	0.12 (0.03)	0.12	0	1.01 (0)	0.38 (0.01)	0.15 (0.01)	10.12 (0.03)
	csuv.s	0.97 (0)	0.63 (0.08)	0.63	0	<u>1.02</u> (0)	<u>0.48</u> (0.02)	<u>0.19</u> (0.01)	10.63 (0.08)
	csuv.m.25	1 (0)	0.05 (0.02)	0	0.05	1.01 (0)	0.39 (0.02)	0.17 (0.01)	9.95 (0.02)
	csuv.m.75	0.98 (0)	0.52 (0.09)	0.52	0	1.02 (0)	0.45 (0.02)	0.17 (0.01)	10.52 (0.09)
	csuv.m.all	0.99 (0)	0.13 (0.03)	0.13	0	1.01 (0)	0.38 (0.01)	0.15 (0.01)	10.13 (0.03)
	csuv.m.mcp	1 (0)	0.08 (0.03)	0.06	0.02	1.01 (0)	0.38 (0.02)	0.15 (0.01)	10.04 (0.02)
	csuv.m.with.tree	0.99 (0)	0.13 (0.03)	0.13	0	1.01 (0)	0.38 (0.01)	0.15 (0.01)	10.13 (0.03)

Table 9: Model 2: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 1 block.cor = 0.5 s = 5 p = 100	lasso	0.38 (0.01)	17.87 (0.75)	17.86	0.01	1.31 (0.02)	2.35 (0.07)	0.68 (0.01)	22.85 (0.75)
	elastic net	0.32 (0.01)	23.17 (0.81)	23.17	0	1.38 (0.02)	2.91 (0.08)	0.77 (0.01)	28.17 (0.81)
	relaxed lasso	0.62 (0.02)	7.16 (0.63)	6.79	0.37	1.3 (0.03)	1.76 (0.07)	0.63 (0.02)	11.42 (0.69)
	mcp	0.83 (0.01)	2.38 (0.27)	2.31	0.07	1.13 (0.03)	0.8 (0.07)	0.35 (0.02)	7.24 (0.28)
	scad	0.64 (0.01)	6.39 (0.39)	6.36	0.03	1.13 (0.03)	0.91 (0.07)	0.36 (0.02)	11.33 (0.39)
	vsd	0.92 (0.01)	0.65 (0.08)	0.04	0.61	1.2 (0.03)	0.85 (0.05)	0.49 (0.03)	4.43 (0.08)
	bic	0.8 (0.01)	2.95 (0.32)	2.9	0.05	1.13 (0.03)	0.85 (0.08)	0.36 (0.03)	7.85 (0.33)
	ebic	0.83 (0.01)	2.39 (0.27)	2.32	0.07	1.13 (0.03)	0.81 (0.07)	0.35 (0.02)	7.25 (0.28)
	cv	<u>0.69</u> (0.02)	<u>5.48</u> (0.53)	<u>5.43</u>	0.05	1.13 (0.03)	0.89 (0.08)	0.35 (0.02)	10.38 (0.54)
	csuv.m	0.92 (0.01)	0.76 (0.09)	0.21	<u>0.55</u>	<u>1.2</u> (0.03)	0.88 (0.06)	<u>0.48</u> (0.03)	4.66 (0.08)
	csuv.s	0.86 (0.01)	1.62 (0.13)	1.34	0.28	1.19 (0.03)	<u>1</u> (0.05)	<u>0.48</u> (0.02)	6.06 (0.15)
	csuv.m.25	0.76 (0.01)	1.9 (0.06)	0.01	1.89	1.54 (0.03)	1.6 (0.04)	0.96 (0.02)	3.12 (0.06)
	csuv.m.75	0.9 (0.01)	1.21 (0.13)	0.98	0.23	1.17 (0.03)	0.88 (0.06)	0.43 (0.03)	5.75 (0.14)
	csuv.m.all	0.92 (0.01)	0.78 (0.09)	0.24	0.54	1.2 (0.03)	0.88 (0.06)	0.48 (0.03)	4.7 (0.08)
	csuv.m.mcp	0.92 (0.01)	0.73 (0.08)	0.07	0.66	1.21 (0.03)	0.9 (0.05)	0.51 (0.03)	4.41 (0.07)
csuv.m.with.tree	0.92 (0.01)	0.76 (0.09)	0.23	0.53	1.2 (0.03)	0.87 (0.06)	0.48 (0.03)	4.7 (0.08)	
setting 2 block.cor = 0.5 s = 5 p = 300	lasso	0.29 (0.01)	26.36 (1.1)	26.31	0.05	1.49 (0.03)	3.18 (0.1)	0.85 (0.02)	31.26 (1.1)
	elastic net	0.23 (0.01)	35.15 (1.2)	35.09	0.06	1.62 (0.03)	3.94 (0.11)	0.98 (0.02)	40.03 (1.2)
	relaxed lasso	0.49 (0.01)	12.49 (0.9)	12.23	0.26	1.48 (0.03)	2.68 (0.12)	0.8 (0.03)	16.97 (0.94)
	mcp	0.78 (0.02)	3.29 (0.27)	3.2	0.09	1.15 (0.02)	0.96 (0.06)	0.42 (0.02)	8.11 (0.26)
	scad	0.55 (0.01)	9.52 (0.5)	9.49	0.03	1.15 (0.02)	1.1 (0.05)	0.41 (0.02)	14.46 (0.5)
	vsd	0.89 (0.02)	1.12 (0.15)	0.05	1.07	1.59 (0.09)	1.31 (0.12)	0.7 (0.06)	3.98 (0.15)
	bic	0.66 (0.02)	7.79 (1.18)	7.72	0.07	1.19 (0.03)	1.29 (0.12)	0.45 (0.03)	12.65 (1.18)
	ebic	0.77 (0.02)	3.99 (0.86)	3.9	0.09	1.16 (0.03)	1.03 (0.1)	0.43 (0.02)	8.81 (0.86)
	cv	<u>0.49</u> (0.02)	<u>14.8</u> (1.34)	<u>14.75</u>	0.05	1.29 (0.03)	<u>1.85</u> (0.15)	0.56 (0.03)	19.7 (1.35)
	csuv.m	0.92 (0.01)	0.74 (0.1)	0.21	<u>0.53</u>	<u>1.3</u> (0.05)	0.97 (0.08)	0.52 (0.04)	4.68 (0.08)
	csuv.s	0.72 (0.01)	4.12 (0.21)	3.98	0.14	1.28 (0.02)	1.61 (0.07)	<u>0.61</u> (0.02)	8.84 (0.21)
	csuv.m.25	0.56 (0.02)	3.18 (0.1)	0	3.18	2.84 (0.09)	2.94 (0.09)	1.47 (0.03)	1.82 (0.1)
	csuv.m.75	0.89 (0.01)	1.34 (0.14)	1.23	0.11	1.18 (0.02)	0.98 (0.06)	0.46 (0.02)	6.12 (0.13)
	csuv.m.all	0.92 (0.01)	0.76 (0.11)	0.26	0.5	1.28 (0.04)	0.97 (0.08)	0.52 (0.04)	4.76 (0.07)
	csuv.m.mcp	0.9 (0.01)	0.89 (0.1)	0.02	0.87	1.44 (0.05)	1.14 (0.08)	0.64 (0.04)	4.15 (0.09)
csuv.m.with.tree	0.92 (0.01)	0.77 (0.11)	0.26	0.51	1.29 (0.05)	0.97 (0.08)	0.52 (0.04)	4.75 (0.08)	
setting 3 block.cor = 0.5 s = 10 p = 100	lasso	0.48 (0.01)	22.55 (0.82)	22.53	0.02	1.52 (0.03)	3.77 (0.1)	0.88 (0.01)	32.51 (0.83)
	elastic net	0.44 (0.01)	26.42 (0.83)	26.4	0.02	1.58 (0.03)	4.22 (0.1)	0.94 (0.01)	36.38 (0.83)
	relaxed lasso	0.66 (0.01)	11.12 (0.69)	10.68	0.44	1.49 (0.02)	3.17 (0.1)	0.87 (0.02)	20.24 (0.75)
	mcp	0.89 (0.01)	2.61 (0.2)	2.43	0.18	1.22 (0.02)	1.49 (0.07)	0.53 (0.02)	12.25 (0.21)
	scad	0.75 (0.01)	6.74 (0.28)	6.63	0.11	1.23 (0.02)	1.6 (0.07)	0.54 (0.02)	16.52 (0.28)
	vsd	0.94 (0.01)	1.14 (0.11)	0.13	1.01	1.38 (0.03)	1.74 (0.08)	0.73 (0.03)	9.12 (0.1)
	bic	0.87 (0.01)	3.22 (0.28)	3.05	0.17	1.22 (0.02)	1.53 (0.07)	0.54 (0.02)	12.88 (0.29)
	ebic	0.89 (0.01)	2.61 (0.2)	2.43	0.18	1.22 (0.02)	1.49 (0.07)	0.53 (0.02)	12.25 (0.21)
	cv	<u>0.5</u> (0.01)	<u>21.53</u> (0.91)	<u>21.48</u>	0.05	<u>1.51</u> (0.03)	<u>3.68</u> (0.11)	<u>0.88</u> (0.02)	31.43 (0.92)
	csuv.m	0.92 (0.01)	1.5 (0.12)	0.57	<u>0.93</u>	1.39 (0.03)	1.87 (0.07)	0.76 (0.03)	9.64 (0.11)
	csuv.s	0.82 (0.01)	4.45 (0.16)	4.09	0.36	1.37 (0.03)	2.23 (0.07)	0.73 (0.02)	13.73 (0.18)
	csuv.m.25	0.69 (0.01)	4.68 (0.14)	0.06	4.62	3.21 (0.1)	4.31 (0.11)	1.66 (0.03)	5.44 (0.14)
	csuv.m.75	0.93 (0.01)	1.57 (0.16)	1.25	0.32	1.28 (0.03)	1.64 (0.07)	0.61 (0.02)	10.93 (0.17)
	csuv.m.all	0.92 (0.01)	1.55 (0.13)	0.72	0.83	1.37 (0.03)	1.84 (0.07)	0.74 (0.03)	9.89 (0.12)
	csuv.m.mcp	0.89 (0.01)	1.91 (0.11)	0.04	1.87	1.64 (0.05)	2.39 (0.09)	0.99 (0.03)	8.17 (0.11)
csuv.m.with.tree	0.92 (0.01)	1.55 (0.13)	0.72	0.83	1.37 (0.03)	1.84 (0.07)	0.74 (0.03)	9.89 (0.12)	

Table 10: Model 3: performance of CSUV and methods it compares with. Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 4 block.cor = 0.5 s = 10 p = 300	lasso	0.37 (0.01)	35.11 (1.13)	34.99	0.12	1.77 (0.04)	5.29 (0.13)	1.11 (0.02)	44.87 (1.13)
	elastic net	0.31 (0.01)	45.69 (1.37)	45.54	0.15	1.97 (0.05)	6.57 (0.17)	1.27 (0.02)	55.39 (1.37)
	relaxed lasso	0.51 (0.01)	20.03 (0.83)	19.75	0.28	1.73 (0.04)	4.62 (0.15)	1.04 (0.03)	29.47 (0.86)
	mcp	0.85 (0.01)	3.59 (0.27)	3.18	0.41	1.38 (0.06)	1.94 (0.13)	0.67 (0.04)	12.77 (0.21)
	scad	0.68 (0.01)	9.89 (0.43)	9.76	0.13	1.29 (0.03)	1.92 (0.09)	0.61 (0.03)	19.63 (0.42)
	vsd	0.9 (0.01)	1.93 (0.2)	0.21	1.72	1.91 (0.17)	2.38 (0.17)	0.94 (0.06)	8.49 (0.18)
	bic	0.73 (0.02)	10.53 (1.61)	10.33	0.2	1.36 (0.04)	2.34 (0.18)	0.68 (0.03)	20.13 (1.61)
	ebic	0.85 (0.01)	4.25 (0.81)	3.92	0.33	1.33 (0.04)	1.89 (0.12)	0.64 (0.03)	13.59 (0.81)
	cv	<u>0.37</u> (0.01)	<u>35.11</u> (1.13)	<u>34.99</u>	0.12	1.77 (0.04)	<u>5.29</u> (0.13)	<u>1.11</u> (0.02)	44.87 (1.13)
	csuv.m	0.86 (0.01)	2.64 (0.16)	0.88	<u>1.76</u>	<u>1.9</u> (0.07)	2.6 (0.12)	1.03 (0.04)	9.12 (0.14)
	csuv.s	0.6 (0.01)	12.91 (0.38)	12.39	0.52	1.63 (0.04)	3.82 (0.12)	0.98 (0.03)	21.87 (0.39)
	csuv.m.25	0.35 (0.01)	7.97 (0.11)	0	7.97	7.69 (0.2)	7.18 (0.11)	2.47 (0.03)	2.03 (0.11)
	csuv.m.75	0.91 (0.01)	1.89 (0.17)	1.5	0.39	1.35 (0.03)	1.83 (0.09)	0.67 (0.03)	11.11 (0.14)
	csuv.m.all	0.85 (0.01)	2.83 (0.17)	1.13	1.7	1.87 (0.07)	2.64 (0.12)	1.03 (0.04)	9.43 (0.14)
	csuv.m.mcp	0.61 (0.01)	5.53 (0.15)	0.03	5.5	4.58 (0.18)	5.2 (0.12)	1.89 (0.04)	4.53 (0.14)
	csuv.m.with.tree	0.85 (0.01)	2.83 (0.17)	1.13	1.7	1.87 (0.07)	2.64 (0.12)	1.03 (0.04)	9.43 (0.14)
setting 5 block.cor = 0.9 s = 5 p = 100	lasso	0.38 (0.01)	14.34 (0.77)	13.22	1.12	1.27 (0.02)	4.03 (0.14)	1.28 (0.02)	17.1 (0.85)
	elastic net	0.31 (0.01)	19.43 (0.84)	18.45	0.98	1.3 (0.02)	4.77 (0.15)	1.38 (0.02)	22.47 (0.91)
	relaxed lasso	0.48 (0.01)	8.15 (0.5)	6.46	1.69	1.26 (0.02)	3.42 (0.11)	1.26 (0.03)	9.77 (0.6)
	mcp	0.57 (0.02)	5.22 (0.27)	3.54	1.68	1.29 (0.02)	3.08 (0.16)	1.33 (0.05)	6.86 (0.3)
	scad	0.6 (0.02)	4.77 (0.27)	3.15	1.62	1.25 (0.03)	2.65 (0.17)	1.24 (0.05)	6.53 (0.33)
	vsd	0.65 (0.02)	2.88 (0.15)	0.46	2.42	1.25 (0.03)	2.43 (0.13)	1.26 (0.05)	3.04 (0.03)
	bic	0.61 (0.02)	4.63 (0.27)	3.05	1.58	1.28 (0.03)	2.97 (0.19)	1.31 (0.06)	6.47 (0.35)
	ebic	0.62 (0.02)	4.3 (0.25)	2.64	1.66	<u>1.27</u> (0.03)	2.79 (0.18)	1.27 (0.05)	5.98 (0.32)
	cv	<u>0.46</u> (0.02)	<u>10.55</u> (0.74)	<u>9.12</u>	1.43	1.26 (0.02)	<u>3.57</u> (0.16)	<u>1.29</u> (0.03)	12.69 (0.83)
	csuv.m	0.65 (0.01)	3.1 (0.13)	0.91	<u>2.19</u>	1.26 (0.03)	2.48 (0.1)	1.21 (0.03)	3.72 (0.1)
	csuv.s	0.58 (0.01)	4.73 (0.14)	2.9	1.83	1.22 (0.02)	2.95 (0.09)	1.22 (0.02)	6.07 (0.13)
	csuv.m.25	0.54 (0.02)	3.32 (0.11)	0.15	3.17	2.08 (0.07)	2.8 (0.1)	1.43 (0.04)	1.98 (0.08)
	csuv.m.75	0.66 (0.01)	3.48 (0.17)	1.7	1.78	1.21 (0.02)	2.6 (0.1)	1.17 (0.03)	4.92 (0.15)
	csuv.m.all	0.64 (0.01)	3.42 (0.15)	1.31	2.11	1.21 (0.02)	2.59 (0.1)	1.22 (0.03)	4.2 (0.11)
	csuv.m.mcp	0.52 (0.02)	3.48 (0.11)	0.18	3.3	2.38 (0.1)	3.06 (0.11)	1.55 (0.04)	1.88 (0.09)
	csuv.m.with.tree	0.63 (0.01)	3.39 (0.14)	1.21	2.18	1.24 (0.02)	2.6 (0.1)	1.23 (0.03)	4.03 (0.1)
setting 6 block.cor = 0.9 s = 5 p = 300	lasso	0.28 (0.01)	21.2 (1.05)	19.8	1.4	1.4 (0.02)	5.37 (0.15)	1.6 (0.02)	23.4 (1.1)
	elastic net	0.21 (0.01)	30.55 (1.35)	29.32	1.23	1.41 (0.02)	6.18 (0.2)	1.66 (0.02)	33.09 (1.41)
	relaxed lasso	0.34 (0.01)	14.1 (0.77)	12.28	1.82	1.41 (0.03)	5.18 (0.17)	1.65 (0.03)	15.46 (0.83)
	mcp	0.41 (0.01)	7.57 (0.24)	4.86	2.71	1.47 (0.03)	4.91 (0.15)	1.88 (0.04)	7.15 (0.24)
	scad	0.4 (0.02)	8.76 (0.32)	6.44	2.32	1.42 (0.03)	4.37 (0.18)	1.73 (0.05)	9.12 (0.28)
	vsd	0.45 (0.02)	4.76 (0.14)	1.14	3.62	2 (0.06)	4.38 (0.11)	1.92 (0.03)	2.52 (0.12)
	bic	0.4 (0.02)	10.19 (0.96)	7.86	2.33	1.45 (0.03)	4.9 (0.2)	1.79 (0.05)	10.53 (1.01)
	ebic	0.43 (0.02)	7.27 (0.26)	4.8	2.47	1.45 (0.03)	4.64 (0.16)	<u>1.8</u> (0.05)	7.33 (0.27)
	cv	<u>0.29</u> (0.01)	<u>20.18</u> (1)	<u>18.7</u>	1.48	1.4 (0.02)	<u>5.33</u> (0.14)	1.62 (0.02)	22.22 (1.06)
	csuv.m	0.52 (0.02)	3.96 (0.13)	0.88	<u>3.08</u>	<u>2.02</u> (0.06)	3.8 (0.1)	1.71 (0.03)	2.8 (0.11)
	csuv.s	0.45 (0.01)	7.24 (0.19)	5.15	2.09	1.37 (0.03)	4.39 (0.1)	1.62 (0.03)	8.06 (0.14)
	csuv.m.25	0.36 (0.01)	4.58 (0.06)	0.02	4.56	3.16 (0.06)	4.14 (0.05)	1.94 (0.02)	0.46 (0.06)
	csuv.m.75	0.52 (0.02)	5.02 (0.22)	2.63	2.39	1.46 (0.04)	4.08 (0.12)	1.67 (0.03)	5.24 (0.14)
	csuv.m.all	0.52 (0.02)	4.03 (0.15)	1.12	2.91	1.88 (0.06)	3.82 (0.11)	1.7 (0.03)	3.21 (0.12)
	csuv.m.mcp	0.41 (0.01)	4.2 (0.09)	0.11	4.09	2.89 (0.06)	3.89 (0.07)	1.83 (0.02)	1.02 (0.09)
	csuv.m.with.tree	0.52 (0.02)	3.98 (0.14)	1.04	2.94	1.91 (0.06)	3.79 (0.11)	1.7 (0.03)	3.1 (0.12)

Table 11: Model 3: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 7 block.cor = 0.9 s = 10 p = 100	lasso	0.5 (0.01)	18.54 (0.66)	17.19	1.35	1.42 (0.02)	6.55 (0.16)	1.65 (0.03)	25.84 (0.69)
	elastic net	0.44 (0.01)	22.85 (0.63)	21.67	1.18	1.43 (0.02)	7.18 (0.15)	1.7 (0.02)	30.49 (0.67)
	relaxed lasso	0.56 (0.01)	13.74 (0.64)	11.91	1.83	1.42 (0.03)	6.37 (0.18)	1.68 (0.03)	20.08 (0.72)
	mcp	0.54 (0.01)	8.46 (0.29)	3.38	5.08	1.72 (0.04)	7.08 (0.24)	2.31 (0.06)	8.3 (0.13)
	scad	0.59 (0.01)	7.75 (0.27)	3.22	4.53	1.62 (0.04)	6.29 (0.21)	2.19 (0.06)	8.69 (0.16)
	vsd	0.61 (0.01)	6.47 (0.23)	1.52	4.95	1.77 (0.06)	6.54 (0.22)	2.29 (0.06)	6.57 (0.09)
	bic	0.59 (0.01)	7.5 (0.26)	2.96	4.54	1.61 (0.04)	6.26 (0.21)	2.16 (0.06)	8.42 (0.14)
	ebic	0.59 (0.01)	7.35 (0.26)	2.72	<u>4.63</u>	<u>1.64</u> (0.04)	6.34 (0.22)	<u>2.18</u> (0.06)	8.09 (0.12)
	cv	<u>0.5</u> (0.01)	<u>18.54</u> (0.66)	<u>17.19</u>	1.35	1.42 (0.02)	<u>6.55</u> (0.16)	1.65 (0.03)	25.84 (0.69)
	csuv.m	0.69 (0.01)	5.86 (0.23)	2.55	3.31	1.61 (0.05)	5.19 (0.17)	1.75 (0.04)	9.24 (0.18)
	csuv.s	0.62 (0.01)	9.5 (0.27)	7.26	2.24	1.38 (0.02)	5.65 (0.13)	1.64 (0.03)	15.02 (0.2)
	csuv.m.25	0.51 (0.01)	6.66 (0.11)	0.28	6.38	3.92 (0.12)	6.52 (0.11)	2.31 (0.03)	3.9 (0.11)
	csuv.m.75	0.68 (0.01)	6.95 (0.27)	4.24	2.71	1.4 (0.03)	5.35 (0.15)	1.67 (0.04)	11.53 (0.23)
	csuv.m.all	0.7 (0.01)	6.02 (0.23)	2.96	3.06	1.54 (0.04)	5.15 (0.16)	1.71 (0.04)	9.9 (0.19)
	csuv.m.mcp	0.4 (0.01)	7.64 (0.13)	0.34	7.3	5.23 (0.26)	7.76 (0.14)	2.7 (0.05)	3.04 (0.12)
	csuv.m.with.tree	0.7 (0.01)	6.02 (0.23)	2.96	3.06	1.54 (0.04)	5.15 (0.16)	1.71 (0.04)	9.9 (0.19)
setting 8 block.cor = 0.9 s = 10 p = 300	lasso	0.33 (0.01)	34.07 (0.92)	32.27	1.8	1.59 (0.03)	10.03 (0.23)	2.1 (0.03)	40.47 (0.9)
	elastic net	0.29 (0.01)	42.66 (0.86)	41.11	1.55	1.62 (0.03)	10.86 (0.21)	2.15 (0.03)	49.56 (0.84)
	relaxed lasso	0.35 (0.01)	28.37 (0.78)	25.88	2.49	1.63 (0.03)	10.14 (0.22)	2.19 (0.04)	33.39 (0.88)
	mcp	0.38 (0.02)	13 (0.35)	6.84	6.16	2.19 (0.06)	11.18 (0.32)	3.07 (0.06)	10.68 (0.2)
	scad	0.43 (0.02)	12.69 (0.4)	7.37	5.32	2 (0.05)	9.98 (0.32)	2.88 (0.07)	12.05 (0.22)
	vsd	0.44 (0.02)	9.98 (0.31)	3.74	6.24	2.77 (0.17)	9.76 (0.29)	2.97 (0.06)	7.5 (0.15)
	bic	0.42 (0.02)	14.42 (1.03)	9.27	5.15	2 (0.05)	10.35 (0.36)	2.87 (0.07)	14.12 (1.13)
	ebic	0.44 (0.02)	11.91 (0.35)	6.54	5.37	1.97 (0.05)	9.86 (0.29)	<u>2.85</u> (0.06)	11.17 (0.19)
	cv	<u>0.33</u> (0.01)	<u>34.07</u> (0.92)	<u>32.27</u>	1.8	1.59 (0.03)	<u>10.03</u> (0.23)	2.1 (0.03)	40.47 (0.9)
	csuv.m	0.53 (0.01)	7.83 (0.23)	2.26	<u>5.57</u>	<u>3.7</u> (0.15)	7.69 (0.21)	2.49 (0.05)	6.69 (0.17)
	csuv.s	0.41 (0.01)	20.57 (0.34)	17.62	2.95	1.65 (0.03)	9.39 (0.19)	2.19 (0.04)	24.67 (0.27)
	csuv.m.25	0.22 (0.01)	9.37 (0.07)	0.03	9.34	10.56 (0.21)	8.56 (0.08)	2.87 (0.02)	0.69 (0.07)
	csuv.m.75	0.52 (0.01)	11.16 (0.33)	7.25	3.91	1.85 (0.05)	8.26 (0.22)	2.3 (0.05)	13.34 (0.28)
	csuv.m.all	0.53 (0.01)	7.92 (0.23)	2.48	5.44	3.53 (0.15)	7.65 (0.21)	2.47 (0.05)	7.04 (0.17)
	csuv.m.mcp	0.22 (0.01)	9.62 (0.09)	0.21	9.41	10.58 (0.2)	8.94 (0.1)	2.97 (0.03)	0.8 (0.08)
	csuv.m.with.tree	0.53 (0.01)	7.92 (0.23)	2.48	5.44	3.53 (0.15)	7.65 (0.21)	2.47 (0.05)	7.04 (0.17)
setting 9 block.cor = 0.5 s = 5 p = 1000	lasso	0.27 (0.01)	31.74 (1.78)	31.73	0.01	1.52 (0.03)	3.49 (0.14)	0.9 (0.02)	36.72 (1.78)
	elastic net	0.19 (0.01)	47.9 (2.13)	47.87	0.03	1.69 (0.03)	4.72 (0.16)	1.07 (0.02)	52.84 (2.13)
	relaxed lasso	0.52 (0.02)	11.5 (0.96)	11.4	0.1	1.38 (0.03)	2.52 (0.13)	0.76 (0.02)	16.3 (0.96)
	mcp	0.76 (0.01)	3.51 (0.26)	3.44	0.07	1.16 (0.02)	1 (0.06)	0.44 (0.02)	8.37 (0.25)
	scad	0.47 (0.01)	12.59 (0.55)	12.56	0.03	1.17 (0.02)	1.26 (0.06)	0.45 (0.02)	17.53 (0.54)
	vsd	0.86 (0.02)	1.14 (0.12)	0.05	1.09	1.6 (0.08)	1.31 (0.1)	0.72 (0.05)	3.96 (0.1)
	bic	0.57 (0.02)	15.12 (2.23)	15.08	0.04	1.22 (0.03)	1.76 (0.19)	0.52 (0.03)	20.04 (2.24)
	ebic	0.75 (0.02)	5.3 (1.31)	5.23	0.07	1.16 (0.03)	1.13 (0.11)	0.45 (0.02)	10.16 (1.31)
	cv	<u>0.35</u> (0.02)	<u>25.33</u> (1.8)	<u>25.32</u>	0.01	<u>1.4</u> (0.04)	<u>2.81</u> (0.17)	<u>0.77</u> (0.03)	30.31 (1.8)
	csuv.m	0.9 (0.01)	0.89 (0.11)	0.26	<u>0.63</u>	1.36 (0.05)	1.05 (0.08)	0.57 (0.04)	4.63 (0.08)
	csuv.s	0.6 (0.01)	6.99 (0.31)	6.83	0.16	1.33 (0.03)	2.08 (0.08)	0.71 (0.02)	11.67 (0.32)
	csuv.m.25	0.43 (0.01)	3.94 (0.08)	0.01	3.93	4.12 (0.12)	3.42 (0.07)	1.66 (0.03)	1.08 (0.08)
	csuv.m.75	0.92 (0.01)	0.96 (0.13)	0.79	0.17	1.16 (0.03)	0.89 (0.07)	0.43 (0.03)	5.62 (0.11)
	csuv.m.all	0.9 (0.01)	0.98 (0.12)	0.35	0.63	1.37 (0.05)	1.08 (0.09)	0.58 (0.04)	4.72 (0.08)
	csuv.m.mcp	0.74 (0.02)	1.93 (0.12)	0.02	1.91	2.14 (0.09)	1.89 (0.1)	1.03 (0.04)	3.11 (0.11)
	csuv.m.with.tree	0.9 (0.01)	0.98 (0.12)	0.35	0.63	1.37 (0.05)	1.08 (0.09)	0.58 (0.04)	4.72 (0.08)

Table 12: Model 3: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 10 block.cor = 0.5 s = 10 p = 1000	lasso	0.27 (0.01)	50.99 (1.63)	50.04	0.95	2.71 (0.07)	8.5 (0.18)	1.71 (0.03)	59.09 (1.65)
	elastic net	0.22 (0)	69.2 (2)	68.23	0.97	3.1 (0.07)	10.42 (0.18)	1.91 (0.03)	77.26 (2.05)
	relaxed lasso	0.34 (0.01)	33.4 (1.57)	31.28	2.12	2.88 (0.08)	8.38 (0.2)	1.77 (0.04)	39.16 (1.76)
	mcp	0.74 (0.02)	6.2 (0.41)	4.68	1.52	1.93 (0.1)	3.35 (0.23)	1.1 (0.07)	13.16 (0.3)
	scad	0.54 (0.01)	16.65 (0.62)	15.77	0.88	1.87 (0.1)	3.48 (0.23)	1.04 (0.06)	24.89 (0.53)
	vsd	0.26 (0.01)	9.12 (0.1)	0.01	9.11	7.05 (0.2)	8.07 (0.12)	2.72 (0.03)	0.9 (0.09)
	bic	0.53 (0.02)	27.5 (2.83)	26.54	0.96	2.05 (0.09)	5.08 (0.36)	1.2 (0.06)	35.58 (2.86)
	ebic	0.71 (0.02)	10.32 (1.8)	8.91	1.41	1.95 (0.1)	3.7 (0.29)	1.11 (0.07)	17.5 (1.81)
	cv	<u>0.29</u> (0.01)	<u>48.74</u> (1.78)	<u>47.77</u>	0.97	2.68 (0.08)	<u>8.18</u> (0.23)	1.66 (0.04)	56.8 (1.79)
	csuv.m	0.5 (0.01)	6.89 (0.12)	0.39	<u>6.5</u>	<u>4.23</u> (0.11)	5.96 (0.11)	<u>2.09</u> (0.03)	3.89 (0.12)
	csuv.s	0.47 (0.01)	14.75 (0.42)	11.13	3.62	3.2 (0.09)	7.12 (0.18)	1.87 (0.03)	17.51 (0.41)
	csuv.m.25	0.2 (0.01)	9.39 (0.06)	0	9.39	7.64 (0.18)	8.4 (0.08)	2.82 (0.02)	0.61 (0.06)
	csuv.m.75	0.76 (0.02)	4.44 (0.28)	1.68	2.76	2.4 (0.11)	3.86 (0.2)	1.36 (0.06)	8.92 (0.18)
	csuv.m.all	0.51 (0.01)	6.84 (0.13)	0.44	6.4	4.18 (0.11)	5.92 (0.11)	2.07 (0.03)	4.04 (0.13)
	csuv.m.mcp	0.32 (0.01)	8.14 (0.09)	0.02	8.12	5.47 (0.15)	6.91 (0.1)	2.39 (0.03)	1.9 (0.08)
csuv.m.with.tree	0.51 (0.01)	6.84 (0.13)	0.44	6.4	4.18 (0.11)	5.92 (0.11)	2.07 (0.03)	4.04 (0.13)	
setting 11 block.cor = 0.9 s = 5 p = 1000	lasso	0.22 (0.01)	27.46 (1.05)	26.08	1.38	1.41 (0.02)	6.17 (0.17)	1.66 (0.03)	29.7 (1)
	elastic net	0.16 (0.01)	44.15 (1.56)	43.11	1.04	1.42 (0.02)	7.31 (0.21)	1.73 (0.02)	47.07 (1.51)
	relaxed lasso	0.26 (0.01)	19.61 (1.15)	17.66	1.95	1.43 (0.03)	6.4 (0.24)	1.77 (0.03)	20.71 (1.14)
	mcp	0.29 (0.01)	9.32 (0.25)	5.67	3.65	1.7 (0.04)	6.55 (0.17)	2.38 (0.04)	7.02 (0.19)
	scad	0.35 (0.02)	9.41 (0.37)	6.57	2.84	1.61 (0.04)	5.39 (0.2)	2.1 (0.06)	8.73 (0.32)
	vsd	0.46 (0.02)	5.75 (0.22)	2.17	3.58	1.9 (0.07)	5.6 (0.19)	2.26 (0.06)	3.59 (0.08)
	bic	0.33 (0.02)	11.44 (1.2)	8.5	2.94	1.6 (0.04)	5.98 (0.23)	2.16 (0.05)	10.56 (1.23)
	ebic	0.36 (0.01)	8.33 (0.29)	5.21	3.12	1.61 (0.04)	5.69 (0.19)	<u>2.18</u> (0.05)	7.09 (0.24)
	cv	<u>0.22</u> (0.01)	<u>27.46</u> (1.05)	<u>26.08</u>	1.38	1.41 (0.02)	<u>6.17</u> (0.17)	1.66 (0.03)	29.7 (1)
	csuv.m	0.44 (0.02)	4.48 (0.14)	0.87	3.61	<u>3.4</u> (0.14)	4.22 (0.13)	1.9 (0.04)	2.26 (0.11)
	csuv.s	0.33 (0.01)	12.1 (0.26)	10.02	2.08	1.4 (0.03)	5.57 (0.12)	1.73 (0.03)	12.94 (0.21)
	csuv.m.25	0.33 (0)	4.83 (0.04)	0	4.83	5.95 (0.1)	4.29 (0.04)	2 (0.01)	0.17 (0.04)
	csuv.m.75	0.46 (0.02)	6.07 (0.22)	3.52	2.55	1.67 (0.06)	4.75 (0.15)	1.81 (0.04)	5.97 (0.18)
	csuv.m.all	0.45 (0.02)	4.51 (0.14)	1.06	3.45	3.12 (0.13)	4.24 (0.13)	1.89 (0.04)	2.61 (0.12)
	csuv.m.mcp	0.34 (0.01)	4.88 (0.05)	0.08	4.8	5.87 (0.1)	4.39 (0.06)	2.03 (0.02)	0.28 (0.05)
csuv.m.with.tree	0.45 (0.02)	4.5 (0.14)	1.02	3.48	3.17 (0.14)	4.24 (0.13)	1.9 (0.04)	2.54 (0.12)	
setting 12 block.cor = 0.9 s = 10 p = 1000	lasso	0.2 (0.01)	43.52 (1.59)	38.71	4.81	1.86 (0.03)	12.28 (0.25)	2.58 (0.03)	43.9 (1.62)
	elastic net	0.17 (0.01)	56.55 (1.65)	52.13	4.42	1.87 (0.03)	13.23 (0.24)	2.64 (0.02)	57.71 (1.68)
	relaxed lasso	0.22 (0.01)	32.56 (1.02)	27.06	5.5	1.88 (0.03)	12.13 (0.23)	2.63 (0.03)	31.56 (1.11)
	mcp	0.21 (0.01)	15.37 (0.25)	7.17	8.2	2.28 (0.05)	12.18 (0.23)	3.26 (0.04)	8.97 (0.17)
	scad	0.26 (0.01)	15.96 (0.35)	8.62	7.34	2.13 (0.05)	11.01 (0.27)	3.06 (0.06)	11.28 (0.23)
	vsd	0.2 (0.01)	11.05 (0.12)	1.65	9.4	4.66 (0.15)	10.44 (0.15)	3.26 (0.04)	2.25 (0.16)
	bic	0.24 (0.01)	25.21 (2.21)	18.35	6.86	2.11 (0.05)	12.14 (0.34)	3.01 (0.05)	21.49 (2.44)
	ebic	0.26 (0.01)	15.46 (0.81)	7.89	7.57	2.15 (0.06)	11.27 (0.28)	<u>3.08</u> (0.05)	10.32 (0.83)
	cv	<u>0.2</u> (0.01)	<u>43.52</u> (1.59)	<u>38.71</u>	4.81	1.86 (0.03)	<u>12.28</u> (0.25)	2.58 (0.03)	43.9 (1.62)
	csuv.m	0.27 (0.01)	9.25 (0.11)	0.74	<u>8.51</u>	<u>4.77</u> (0.15)	8.24 (0.13)	2.71 (0.03)	2.23 (0.12)
	csuv.s	0.24 (0.01)	22.57 (0.39)	16.15	6.42	2.02 (0.04)	11.62 (0.14)	2.73 (0.03)	19.73 (0.34)
	csuv.m.25	0.18 (0)	9.9 (0.03)	0	9.9	7.5 (0.11)	9 (0.04)	2.99 (0.01)	0.1 (0.03)
	csuv.m.75	0.33 (0.01)	11.36 (0.23)	4.2	7.16	2.66 (0.07)	9.39 (0.18)	2.71 (0.04)	7.04 (0.19)
	csuv.m.all	0.28 (0.01)	9.22 (0.12)	0.84	8.38	4.53 (0.14)	8.18 (0.14)	2.68 (0.03)	2.46 (0.12)
	csuv.m.mcp	0.18 (0)	9.99 (0.04)	0.08	9.91	7.42 (0.12)	9.13 (0.05)	3.03 (0.01)	0.17 (0.04)
csuv.m.with.tree	0.28 (0.01)	9.21 (0.11)	0.81	8.4	4.6 (0.14)	8.18 (0.13)	2.68 (0.03)	2.41 (0.12)	

Table 13: Model 3: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 1 num.factor = 2 s = 5 p = 100	lasso	0.37 (0.01)	18.19 (0.89)	17.98	0.21	1.85 (0.09)	3.02 (0.13)	0.9 (0.03)	22.77 (0.89)
	elastic net	0.32 (0.01)	23.2 (0.97)	23.01	0.19	1.98 (0.08)	3.57 (0.13)	0.98 (0.03)	27.82 (0.98)
	relaxed lasso	0.5 (0.02)	11.16 (0.77)	10.68	0.48	1.89 (0.08)	2.77 (0.12)	0.91 (0.03)	15.2 (0.81)
	mcp	0.74 (0.02)	3.43 (0.3)	2.75	0.68	1.72 (0.1)	1.65 (0.11)	0.75 (0.04)	7.07 (0.28)
	scad	0.64 (0.02)	5.58 (0.36)	5.08	0.5	1.58 (0.08)	1.57 (0.09)	0.71 (0.04)	9.58 (0.35)
	vsd	0.81 (0.02)	1.71 (0.15)	0.18	1.53	2.27 (0.16)	1.9 (0.13)	0.98 (0.06)	3.65 (0.13)
	bic	0.71 (0.02)	4.02 (0.31)	3.42	0.6	1.71 (0.1)	1.67 (0.11)	0.74 (0.04)	7.82 (0.3)
	ebic	0.74 (0.02)	3.4 (0.29)	2.74	0.66	1.71 (0.1)	1.62 (0.11)	0.74 (0.04)	7.08 (0.28)
	cv	<u>0.5</u> (0.02)	<u>13.23</u> (1.09)	<u>12.92</u>	0.31	1.75 (0.09)	<u>2.51</u> (0.16)	0.82 (0.03)	17.61 (1.11)
	csuv.m	0.82 (0.02)	1.72 (0.16)	0.71	<u>1.01</u>	<u>1.95</u> (0.13)	1.72 (0.11)	<u>0.85</u> (0.05)	4.7 (0.13)
	csuv.s	0.7 (0.01)	4 (0.23)	3.32	0.68	1.8 (0.09)	2.04 (0.1)	<u>0.85</u> (0.04)	7.64 (0.24)
	csuv.m.25	0.65 (0.02)	2.61 (0.12)	0.11	2.5	3 (0.17)	2.7 (0.11)	1.37 (0.04)	2.61 (0.12)
	csuv.m.75	0.78 (0.02)	2.72 (0.23)	2.09	0.63	1.68 (0.09)	1.73 (0.1)	0.76 (0.04)	6.46 (0.21)
	csuv.m.all	0.81 (0.02)	1.85 (0.16)	0.89	0.96	1.89 (0.11)	1.73 (0.11)	0.84 (0.05)	4.93 (0.14)
	csuv.m.mcp	0.78 (0.02)	1.74 (0.12)	0.14	1.6	2.29 (0.13)	2.06 (0.11)	1.06 (0.05)	3.54 (0.1)
	csuv.m.with.tree	0.81 (0.02)	1.83 (0.16)	0.86	0.97	1.91 (0.12)	1.73 (0.11)	0.84 (0.05)	4.89 (0.14)
setting 2 num.factor = 2 s = 5 p = 300	lasso	0.3 (0.01)	26 (1.59)	25.52	0.48	2.19 (0.08)	3.84 (0.15)	1.09 (0.03)	30.04 (1.64)
	elastic net	0.24 (0.01)	32.76 (1.45)	32.35	0.41	2.41 (0.09)	4.46 (0.14)	1.19 (0.03)	36.94 (1.49)
	relaxed lasso	0.43 (0.01)	14.49 (1.11)	13.72	0.77	2.17 (0.09)	3.44 (0.13)	1.07 (0.03)	17.95 (1.18)
	mcp	0.7 (0.02)	3.65 (0.25)	2.64	1.01	2.07 (0.13)	1.96 (0.12)	0.92 (0.05)	6.63 (0.22)
	scad	0.53 (0.02)	8.79 (0.48)	8.18	0.61	1.83 (0.1)	1.89 (0.11)	0.81 (0.04)	12.57 (0.48)
	vsd	0.67 (0.02)	2.56 (0.15)	0.18	2.38	3.2 (0.22)	2.64 (0.14)	1.32 (0.06)	2.8 (0.14)
	bic	0.57 (0.02)	10.28 (1.62)	9.51	0.77	1.92 (0.11)	2.31 (0.19)	0.88 (0.05)	13.74 (1.65)
	ebic	0.69 (0.02)	5.19 (1.14)	4.23	0.96	2.05 (0.12)	2.06 (0.16)	0.91 (0.05)	8.27 (1.17)
	cv	<u>0.39</u> (0.02)	<u>19.86</u> (1.55)	<u>19.34</u>	0.52	2.11 (0.09)	<u>3.2</u> (0.16)	1.01 (0.04)	23.82 (1.6)
	csuv.m	0.73 (0.02)	2.19 (0.13)	0.51	<u>1.68</u>	<u>2.37</u> (0.13)	2.19 (0.1)	<u>1.1</u> (0.05)	3.83 (0.14)
	csuv.s	0.61 (0.01)	5.41 (0.27)	4.43	0.98	2.07 (0.08)	2.54 (0.1)	1.01 (0.04)	8.45 (0.32)
	csuv.m.25	0.52 (0.02)	3.36 (0.11)	0.01	3.35	3.66 (0.17)	3.23 (0.09)	1.58 (0.04)	1.66 (0.11)
	csuv.m.75	0.76 (0.01)	2.68 (0.18)	1.78	0.9	1.91 (0.08)	1.98 (0.1)	0.91 (0.04)	5.88 (0.19)
	csuv.m.all	0.73 (0.02)	2.28 (0.13)	0.67	1.61	2.33 (0.12)	2.18 (0.1)	1.09 (0.05)	4.06 (0.15)
	csuv.m.mcp	0.66 (0.02)	2.44 (0.12)	0.05	2.39	2.87 (0.14)	2.56 (0.1)	1.31 (0.04)	2.66 (0.12)
	csuv.m.with.tree	0.73 (0.02)	2.25 (0.13)	0.61	1.64	2.31 (0.11)	2.17 (0.1)	1.09 (0.05)	3.97 (0.15)
setting 3 num.factor = 2 s = 10 p = 100	lasso	0.45 (0.01)	25.15 (0.93)	24.76	0.39	2.6 (0.11)	5.16 (0.15)	1.23 (0.03)	34.37 (0.95)
	elastic net	0.41 (0.01)	29.57 (0.97)	29.24	0.33	2.73 (0.11)	5.84 (0.15)	1.3 (0.02)	38.91 (0.99)
	relaxed lasso	0.56 (0.01)	16.19 (0.9)	15.26	0.93	2.74 (0.12)	4.82 (0.14)	1.25 (0.03)	24.33 (1)
	mcp	0.79 (0.01)	4.55 (0.28)	2.93	1.62	2.52 (0.14)	3.09 (0.15)	1.14 (0.05)	11.31 (0.25)
	scad	0.74 (0.01)	6.25 (0.29)	5.09	1.16	2.43 (0.14)	2.92 (0.13)	1.08 (0.05)	13.93 (0.32)
	vsd	0.72 (0.02)	4.25 (0.25)	0.19	4.06	4.13 (0.29)	4.35 (0.2)	1.67 (0.06)	6.13 (0.25)
	bic	0.78 (0.01)	4.96 (0.27)	3.68	1.28	2.43 (0.14)	2.97 (0.14)	1.09 (0.05)	12.4 (0.28)
	ebic	0.79 (0.01)	4.53 (0.27)	3.05	1.48	2.5 (0.14)	3.01 (0.14)	1.11 (0.05)	11.57 (0.27)
	cv	<u>0.47</u> (0.01)	<u>24.05</u> (1.02)	<u>23.55</u>	0.5	2.64 (0.11)	<u>5.08</u> (0.16)	1.23 (0.03)	33.05 (1.09)
	csuv.m	0.79 (0.01)	3.77 (0.16)	1.05	<u>2.72</u>	<u>3.38</u> (0.19)	3.66 (0.14)	<u>1.4</u> (0.05)	8.33 (0.19)
	csuv.s	0.71 (0.01)	6.98 (0.27)	5.29	1.69	2.87 (0.13)	3.84 (0.11)	1.27 (0.04)	13.6 (0.33)
	csuv.m.25	0.5 (0.02)	6.64 (0.15)	0.06	6.58	6.54 (0.38)	6.44 (0.14)	2.29 (0.04)	3.48 (0.15)
	csuv.m.75	0.81 (0.01)	4.14 (0.24)	2.73	1.41	2.49 (0.12)	3.15 (0.12)	1.12 (0.04)	11.32 (0.24)
	csuv.m.all	0.8 (0.01)	3.83 (0.17)	1.38	2.45	3.13 (0.17)	3.52 (0.13)	1.34 (0.04)	8.93 (0.22)
	csuv.m.mcp	0.67 (0.01)	4.86 (0.16)	0.11	4.75	5.19 (0.33)	5.25 (0.17)	1.96 (0.05)	5.36 (0.17)
	csuv.m.with.tree	0.8 (0.01)	3.83 (0.17)	1.37	2.46	3.16 (0.17)	3.53 (0.13)	1.35 (0.04)	8.91 (0.22)

Table 14: Model 4: performance of CSUV and methods it compares with. Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 4 num.factor = 2 s = 10 p = 300	lasso	0.32 (0.01)	40.36 (1.63)	39.15	1.21	3.71 (0.18)	7.53 (0.21)	1.64 (0.03)	47.94 (1.69)
	elastic net	0.28 (0.01)	48.14 (1.65)	46.96	1.18	4.11 (0.19)	8.48 (0.2)	1.74 (0.03)	55.78 (1.71)
	relaxed lasso	0.43 (0.01)	23.75 (1.41)	21.6	2.15	3.87 (0.22)	6.88 (0.21)	1.67 (0.04)	29.45 (1.59)
	mcp	0.67 (0.02)	7.03 (0.39)	4.07	2.96	3.99 (0.27)	4.68 (0.22)	1.63 (0.06)	11.11 (0.37)
	scad	0.59 (0.01)	11.25 (0.44)	9.18	2.07	3.45 (0.22)	4.28 (0.18)	1.49 (0.05)	17.11 (0.42)
	vsd	0.5 (0.02)	7.08 (0.24)	0.25	6.83	6.96 (0.38)	6.86 (0.22)	2.4 (0.07)	3.42 (0.23)
	bic	0.54 (0.02)	22.38 (2.39)	20.55	1.83	3.38 (0.21)	5.61 (0.3)	1.51 (0.05)	28.72 (2.49)
	ebic	0.66 (0.02)	9.95 (1.44)	7.35	2.6	3.65 (0.24)	4.7 (0.23)	1.57 (0.06)	14.75 (1.52)
	cv	<u>0.35</u> (0.01)	<u>36.8</u> (1.75)	<u>35.39</u>	1.41	3.66 (0.17)	<u>7.19</u> (0.21)	1.64 (0.03)	43.98 (1.88)
	csuv.m	0.62 (0.02)	5.65 (0.18)	0.56	<u>5.09</u>	<u>5.36</u> (0.3)	5.54 (0.15)	<u>2.02</u> (0.05)	5.47 (0.2)
	csuv.s	0.57 (0.01)	10.01 (0.36)	6.57	3.44	4.25 (0.21)	5.71 (0.17)	1.77 (0.05)	13.13 (0.46)
	csuv.m.25	0.31 (0.01)	8.3 (0.09)	0.05	8.25	7.61 (0.37)	7.86 (0.1)	2.66 (0.03)	1.8 (0.11)
	csuv.m.75	0.72 (0.01)	5.56 (0.29)	2.61	2.95	3.57 (0.2)	4.47 (0.18)	1.55 (0.05)	9.66 (0.33)
	csuv.m.all	0.63 (0.01)	5.64 (0.18)	0.72	4.92	5.14 (0.28)	5.43 (0.16)	1.97 (0.05)	5.8 (0.2)
	csuv.m.mcp	0.46 (0.02)	7 (0.16)	0.04	6.96	7.22 (0.43)	6.98 (0.16)	2.45 (0.05)	3.08 (0.15)
csuv.m.with.tree	0.63 (0.02)	5.66 (0.19)	0.71	4.95	5.16 (0.28)	5.45 (0.16)	1.98 (0.05)	5.76 (0.21)	
setting 5 num.factor = 10 s = 5 p = 100	lasso	0.39 (0.01)	15.08 (0.68)	14.51	0.57	2.5 (0.09)	4 (0.16)	1.22 (0.03)	18.94 (0.71)
	elastic net	0.33 (0.01)	20.63 (0.96)	20.2	0.43	2.76 (0.1)	4.84 (0.21)	1.32 (0.03)	24.77 (0.97)
	relaxed lasso	0.42 (0.01)	12.22 (0.73)	11.21	1.01	2.83 (0.13)	4.3 (0.21)	1.32 (0.04)	15.2 (0.8)
	mcp	0.54 (0.02)	5.68 (0.3)	3.89	1.79	3.49 (0.23)	3.81 (0.21)	1.44 (0.07)	7.1 (0.22)
	scad	0.52 (0.02)	6.92 (0.32)	5.32	1.6	3.54 (0.25)	3.69 (0.2)	1.42 (0.07)	8.72 (0.25)
	vsd	0.56 (0.03)	3.85 (0.22)	1.01	2.84	3.99 (0.25)	3.65 (0.18)	1.59 (0.07)	3.17 (0.13)
	bic	0.56 (0.02)	5.61 (0.32)	3.97	1.64	3.4 (0.23)	3.72 (0.22)	1.4 (0.07)	7.33 (0.23)
	ebic	0.56 (0.02)	5.47 (0.32)	3.77	1.7	<u>3.4</u> (0.23)	3.69 (0.22)	<u>1.4</u> (0.07)	7.07 (0.22)
	cv	<u>0.4</u> (0.01)	<u>14.89</u> (0.71)	<u>14.29</u>	0.6	2.55 (0.1)	<u>4</u> (0.16)	1.22 (0.03)	18.69 (0.73)
	csuv.m	0.62 (0.02)	3.66 (0.21)	1.7	<u>1.96</u>	2.93 (0.15)	3.13 (0.15)	1.33 (0.05)	4.74 (0.14)
	csuv.s	0.53 (0.01)	6.51 (0.21)	5.22	1.29	2.57 (0.11)	3.41 (0.14)	1.25 (0.04)	8.93 (0.23)
	csuv.m.25	0.52 (0.02)	3.78 (0.15)	0.65	3.13	3.89 (0.2)	3.58 (0.12)	1.64 (0.04)	2.52 (0.11)
	csuv.m.75	0.64 (0.02)	4.12 (0.25)	2.73	1.39	2.6 (0.14)	2.98 (0.16)	1.2 (0.05)	6.34 (0.21)
	csuv.m.all	0.62 (0.02)	3.81 (0.21)	1.98	1.83	2.84 (0.14)	3.13 (0.15)	1.3 (0.05)	5.15 (0.15)
	csuv.m.mcp	0.54 (0.02)	3.63 (0.16)	0.55	3.08	3.86 (0.21)	3.56 (0.13)	1.64 (0.05)	2.47 (0.09)
csuv.m.with.tree	0.62 (0.02)	3.72 (0.21)	1.87	1.85	2.88 (0.15)	3.1 (0.15)	1.3 (0.05)	5.02 (0.15)	
setting 6 num.factor = 10 s = 5 p = 300	lasso	0.28 (0.01)	22.46 (1.13)	21.37	1.09	3.19 (0.15)	5.23 (0.2)	1.46 (0.03)	25.28 (1.15)
	elastic net	0.23 (0.01)	30.02 (1.38)	29.07	0.95	3.48 (0.15)	5.97 (0.21)	1.55 (0.03)	33.12 (1.39)
	relaxed lasso	0.32 (0.01)	15.45 (0.87)	13.71	1.74	3.55 (0.19)	5.2 (0.21)	1.56 (0.04)	16.97 (0.92)
	mcp	0.42 (0.02)	7.28 (0.29)	4.61	2.67	4.49 (0.24)	4.9 (0.2)	1.79 (0.06)	6.94 (0.21)
	scad	0.38 (0.02)	9.17 (0.34)	6.8	2.37	4.32 (0.29)	4.65 (0.22)	1.73 (0.07)	9.43 (0.26)
	vsd	0.49 (0.02)	4.77 (0.18)	1.06	3.71	5.28 (0.3)	4.61 (0.16)	1.98 (0.06)	2.35 (0.12)
	bic	0.42 (0.02)	10.24 (1.21)	7.94	2.3	4.36 (0.28)	5.12 (0.28)	1.73 (0.07)	10.64 (1.26)
	ebic	0.43 (0.02)	7.17 (0.31)	4.62	2.55	<u>4.52</u> (0.27)	4.81 (0.22)	<u>1.75</u> (0.07)	7.07 (0.23)
	cv	<u>0.28</u> (0.01)	<u>21.89</u> (1.17)	<u>20.73</u>	1.16	3.25 (0.16)	<u>5.2</u> (0.21)	1.48 (0.04)	24.57 (1.2)
	csuv.m	0.5 (0.02)	4.18 (0.16)	1.3	<u>2.88</u>	3.9 (0.21)	3.76 (0.13)	1.63 (0.04)	3.42 (0.14)
	csuv.s	0.39 (0.01)	9.14 (0.27)	7	2.14	3.64 (0.18)	4.53 (0.13)	1.57 (0.04)	9.86 (0.28)
	csuv.m.25	0.43 (0.01)	4.29 (0.11)	0.38	3.91	4.54 (0.23)	4.05 (0.11)	1.87 (0.04)	1.47 (0.11)
	csuv.m.75	0.52 (0.02)	4.94 (0.24)	2.62	2.32	3.68 (0.19)	3.88 (0.15)	1.55 (0.05)	5.3 (0.18)
	csuv.m.all	0.51 (0.02)	4.38 (0.17)	1.63	2.75	3.84 (0.2)	3.84 (0.12)	1.63 (0.04)	3.88 (0.14)
	csuv.m.mcp	0.43 (0.01)	4.34 (0.12)	0.34	4	4.92 (0.26)	4.22 (0.12)	1.93 (0.04)	1.34 (0.08)
csuv.m.with.tree	0.5 (0.02)	4.33 (0.16)	1.55	2.78	3.84 (0.2)	3.83 (0.12)	1.64 (0.04)	3.77 (0.14)	

Table 15: Model 4: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 7 num.factor = 10 s = 10 p = 100	lasso	0.44 (0.01)	21.75 (0.68)	19.99	1.76	4.57 (0.2)	7.63 (0.19)	1.84 (0.04)	28.23 (0.77)
	elastic net	0.4 (0.01)	27.39 (0.79)	26.07	1.32	4.83 (0.23)	8.52 (0.24)	1.89 (0.04)	34.75 (0.86)
	relaxed lasso	0.46 (0.01)	19.07 (0.88)	16.61	2.46	5.34 (0.26)	8.24 (0.27)	2 (0.04)	24.15 (1.05)
	mcp	0.52 (0.02)	9.24 (0.3)	4.22	5.02	7.6 (0.44)	8.17 (0.24)	2.47 (0.06)	9.2 (0.28)
	scad	0.52 (0.02)	9.71 (0.31)	5.01	4.7	7.42 (0.43)	8 (0.25)	2.45 (0.06)	10.31 (0.24)
	vsd	0.43 (0.02)	8.25 (0.22)	1.25	7	8.83 (0.5)	8.32 (0.22)	2.7 (0.06)	4.25 (0.18)
	bic	0.55 (0.02)	9.1 (0.4)	4.67	4.43	6.65 (0.38)	7.73 (0.25)	2.34 (0.06)	10.24 (0.39)
	ebic	0.54 (0.02)	8.71 (0.29)	4.06	4.65	<u>6.92</u> (0.41)	<u>7.81</u> (0.25)	<u>2.4</u> (0.06)	9.41 (0.27)
	cv	<u>0.44</u> (0.01)	<u>21.75</u> (0.68)	<u>19.99</u>	1.76	4.57 (0.2)	7.63 (0.19)	1.84 (0.04)	28.23 (0.77)
	csuv.m	0.58 (0.01)	7.08 (0.22)	2.15	<u>4.93</u>	6.24 (0.36)	6.82 (0.18)	2.19 (0.05)	7.22 (0.21)
	csuv.s	0.54 (0.01)	10.64 (0.23)	7.07	3.57	5.08 (0.24)	6.92 (0.16)	2 (0.04)	13.5 (0.33)
	csuv.m.25	0.4 (0.02)	8.16 (0.16)	0.91	7.25	8.22 (0.41)	8.02 (0.16)	2.64 (0.04)	3.66 (0.16)
	csuv.m.75	0.62 (0.01)	7.56 (0.23)	3.9	3.66	5.23 (0.27)	6.35 (0.18)	1.98 (0.05)	10.24 (0.26)
	csuv.m.all	0.58 (0.01)	7.33 (0.22)	2.61	4.72	5.91 (0.31)	6.74 (0.17)	2.16 (0.04)	7.89 (0.23)
	csuv.m.mcp	0.39 (0.01)	8.01 (0.16)	0.51	7.5	8.68 (0.45)	8.2 (0.16)	2.73 (0.05)	3.01 (0.11)
csuv.m.with.tree	0.58 (0.01)	7.32 (0.23)	2.59	4.73	5.94 (0.31)	6.75 (0.17)	2.16 (0.04)	7.86 (0.23)	
setting 8 num.factor = 10 s = 10 p = 300	lasso	0.31 (0.01)	32.71 (1.19)	29.58	3.13	6.43 (0.26)	10.07 (0.22)	2.25 (0.03)	36.45 (1.33)
	elastic net	0.28 (0.01)	38.49 (1.23)	35.72	2.77	6.7 (0.26)	10.7 (0.19)	2.29 (0.03)	42.95 (1.35)
	relaxed lasso	0.32 (0.01)	25.3 (1.17)	21.11	4.19	7.22 (0.31)	10.41 (0.25)	2.39 (0.04)	26.92 (1.43)
	mcp	0.37 (0.02)	12.09 (0.31)	5.4	6.69	9.07 (0.42)	10.08 (0.26)	2.87 (0.06)	8.71 (0.24)
	scad	0.34 (0.01)	13.92 (0.37)	7.37	6.55	9.77 (0.45)	9.91 (0.23)	2.89 (0.06)	10.82 (0.3)
	vsd	0.25 (0.01)	10.72 (0.14)	1.7	9.02	12.33 (0.6)	10.69 (0.17)	3.37 (0.05)	2.68 (0.14)
	bic	0.37 (0.01)	17.82 (1.38)	12.19	5.63	8.57 (0.39)	10.19 (0.28)	2.7 (0.06)	16.56 (1.65)
	ebic	0.39 (0.01)	11.69 (0.3)	5.23	6.46	<u>8.8</u> (0.39)	9.72 (0.24)	<u>2.79</u> (0.05)	8.77 (0.24)
	cv	<u>0.31</u> (0.01)	<u>32.71</u> (1.19)	<u>29.58</u>	3.13	6.43 (0.26)	<u>10.07</u> (0.22)	2.25 (0.03)	36.45 (1.33)
	csuv.m	0.41 (0.02)	9.03 (0.22)	2.19	<u>6.84</u>	8.26 (0.36)	8.37 (0.19)	2.64 (0.05)	5.35 (0.2)
	csuv.s	0.37 (0.01)	15.24 (0.26)	9.87	5.37	7.4 (0.29)	9.13 (0.15)	2.46 (0.04)	14.5 (0.34)
	csuv.m.25	0.25 (0.01)	9.51 (0.13)	0.61	8.9	10.82 (0.48)	9.22 (0.15)	3.04 (0.04)	1.71 (0.11)
	csuv.m.75	0.47 (0.01)	10 (0.25)	4.47	5.53	7.28 (0.33)	8.11 (0.18)	2.41 (0.04)	8.94 (0.32)
	csuv.m.all	0.42 (0.01)	9.36 (0.23)	2.64	6.72	8.14 (0.34)	8.41 (0.18)	2.62 (0.04)	5.92 (0.21)
	csuv.m.mcp	0.25 (0.01)	9.67 (0.14)	0.61	9.06	11.29 (0.51)	9.62 (0.17)	3.17 (0.05)	1.55 (0.09)
csuv.m.with.tree	0.42 (0.01)	9.32 (0.23)	2.59	6.73	8.16 (0.35)	8.4 (0.18)	2.62 (0.04)	5.86 (0.22)	

Table 16: Model 4: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 1 rho = 0.5 s = 5 p = 100	lasso	0.58 (0.02)	9.52 (0.71)	9.52	0	1.18 (0.02)	1.18 (0.05)	0.42 (0.01)	14.52 (0.71)
	elastic net	0.49 (0.02)	12.79 (0.77)	12.79	0	1.23 (0.02)	1.42 (0.06)	0.46 (0.01)	17.79 (0.77)
	relaxed lasso	0.95 (0.01)	0.84 (0.32)	0.84	0	1.08 (0.02)	0.67 (0.04)	0.32 (0.01)	5.84 (0.32)
	mcp	1 (0)	0 (0)	0	0	1.06 (0.02)	0.6 (0.03)	0.33 (0.01)	5 (0)
	scad	1 (0)	0.01 (0.01)	0.01	0	1.21 (0.03)	1.02 (0.05)	0.57 (0.03)	5.01 (0.01)
	vsd	1 (0)	0.03 (0.02)	0.03	0	1.04 (0.02)	0.54 (0.02)	0.29 (0.01)	5.03 (0.02)
	bic	0.92 (0.02)	1.4 (0.32)	1.4	0	1.09 (0.02)	0.73 (0.03)	0.36 (0.01)	6.4 (0.32)
	ebic	1 (0)	0.01 (0.01)	0.01	0	<u>1.07</u> (0.02)	<u>0.62</u> (0.03)	<u>0.33</u> (0.02)	5.01 (0.01)
	cv	<u>0.98</u> (0.01)	<u>0.51</u> (0.27)	<u>0.51</u>	0	<u>1.07</u> (0.02)	<u>0.62</u> (0.03)	0.32 (0.01)	5.51 (0.27)
	csuv.m	1 (0)	0.01 (0.01)	0.01	0	1.04 (0.02)	0.53 (0.02)	0.28 (0.01)	5.01 (0.01)
	csuv.s	1 (0)	0.02 (0.01)	0.02	0	1.05 (0.02)	0.53 (0.02)	0.28 (0.01)	5.02 (0.01)
	csuv.m.25	1 (0)	0 (0)	0	0	1.04 (0.02)	0.52 (0.02)	0.28 (0.01)	5 (0)
	csuv.m.75	0.98 (0.01)	0.27 (0.07)	0.27	0	1.07 (0.02)	0.62 (0.03)	0.32 (0.01)	5.27 (0.07)
	csuv.m.all	1 (0)	0.02 (0.01)	0.02	0	1.05 (0.02)	0.53 (0.02)	0.28 (0.01)	5.02 (0.01)
	csuv.m.mcp	1 (0)	0 (0)	0	0	1.04 (0.02)	0.52 (0.02)	0.28 (0.01)	5 (0)
csuv.m.with.tree	1 (0)	0.02 (0.01)	0.02	0	1.05 (0.02)	0.53 (0.02)	0.28 (0.01)	5.02 (0.01)	
setting 2 rho = 0.5 s = 5 p = 300	lasso	0.49 (0.02)	15.04 (1.19)	15.04	0	1.23 (0.02)	1.46 (0.07)	0.45 (0.01)	20.04 (1.19)
	elastic net	0.38 (0.01)	19.82 (1.13)	19.82	0	1.32 (0.02)	1.79 (0.07)	0.52 (0.01)	24.82 (1.13)
	relaxed lasso	0.95 (0.01)	0.99 (0.4)	0.99	0	1.08 (0.02)	0.65 (0.05)	0.31 (0.01)	5.99 (0.4)
	mcp	1 (0)	0.04 (0.02)	0.04	0	1.06 (0.02)	0.57 (0.03)	0.3 (0.01)	5.04 (0.02)
	scad	0.99 (0)	0.07 (0.03)	0.07	0	1.18 (0.02)	0.94 (0.05)	0.52 (0.03)	5.07 (0.03)
	vsd	1 (0)	0.01 (0.01)	0.01	0	1.05 (0.02)	0.49 (0.02)	0.26 (0.01)	5.01 (0.01)
	bic	0.6 (0.03)	11 (1.13)	11	0	1.21 (0.02)	1.28 (0.07)	0.43 (0.02)	16 (1.13)
	ebic	0.99 (0)	0.08 (0.03)	0.08	0	<u>1.07</u> (0.02)	<u>0.61</u> (0.04)	<u>0.32</u> (0.02)	5.08 (0.03)
	cv	<u>0.98</u> (0.01)	<u>0.48</u> (0.39)	<u>0.48</u>	0	1.06 (0.02)	0.59 (0.04)	0.3 (0.01)	5.48 (0.39)
	csuv.m	1 (0)	0.02 (0.01)	0.02	0	1.05 (0.02)	0.5 (0.02)	0.26 (0.01)	5.02 (0.01)
	csuv.s	0.99 (0)	0.07 (0.03)	0.07	0	1.06 (0.02)	0.52 (0.03)	0.27 (0.01)	5.07 (0.03)
	csuv.m.25	1 (0)	0 (0)	0	0	1.04 (0.02)	0.49 (0.02)	0.26 (0.01)	5 (0)
	csuv.m.75	0.97 (0.01)	0.32 (0.07)	0.32	0	1.08 (0.02)	0.6 (0.03)	0.31 (0.01)	5.32 (0.07)
	csuv.m.all	1 (0)	0.03 (0.02)	0.03	0	1.05 (0.02)	0.5 (0.02)	0.26 (0.01)	5.03 (0.02)
	csuv.m.mcp	1 (0)	0 (0)	0	0	1.04 (0.02)	0.49 (0.02)	0.26 (0.01)	5 (0)
csuv.m.with.tree	1 (0)	0.03 (0.02)	0.03	0	1.05 (0.02)	0.5 (0.02)	0.26 (0.01)	5.03 (0.02)	
setting 3 rho = 0.5 s = 10 p = 100	lasso	0.65 (0.01)	12.09 (0.64)	12.09	0	1.29 (0.02)	1.97 (0.06)	0.56 (0.01)	22.09 (0.64)
	elastic net	0.6 (0.01)	14.59 (0.7)	14.59	0	1.34 (0.02)	2.19 (0.06)	0.59 (0.01)	24.59 (0.7)
	relaxed lasso	0.97 (0.01)	0.89 (0.32)	0.85	0.04	1.15 (0.02)	1.27 (0.05)	0.46 (0.01)	10.81 (0.32)
	mcp	0.93 (0.01)	1.21 (0.09)	0.02	1.19	1.9 (0.05)	3.41 (0.1)	1.33 (0.04)	8.83 (0.09)
	scad	0.95 (0.01)	0.88 (0.09)	0.14	0.74	2.41 (0.06)	4.33 (0.09)	1.64 (0.03)	9.4 (0.1)
	vsd	0.99 (0)	0.21 (0.04)	0	0.21	1.15 (0.02)	1.24 (0.05)	0.49 (0.02)	9.79 (0.04)
	bic	0.83 (0.02)	5.52 (0.72)	5.44	0.08	1.66 (0.05)	2.74 (0.11)	0.95 (0.05)	15.36 (0.73)
	ebic	0.94 (0.01)	1.34 (0.21)	0.82	<u>0.52</u>	<u>1.94</u> (0.06)	<u>3.36</u> (0.12)	<u>1.28</u> (0.05)	10.3 (0.25)
	cv	<u>0.65</u> (0.01)	<u>12.09</u> (0.64)	<u>12.09</u>	0	1.29 (0.02)	1.97 (0.06)	0.56 (0.01)	22.09 (0.64)
	csuv.m	0.99 (0)	0.13 (0.04)	0.04	0.09	1.12 (0.02)	1.15 (0.04)	0.45 (0.02)	9.95 (0.04)
	csuv.s	0.99 (0)	0.27 (0.05)	0.25	0.02	1.12 (0.02)	1.16 (0.04)	0.44 (0.01)	10.23 (0.05)
	csuv.m.25	0.96 (0)	0.71 (0.06)	0	0.71	1.31 (0.03)	1.69 (0.07)	0.69 (0.03)	9.29 (0.06)
	csuv.m.75	0.98 (0)	0.35 (0.08)	0.33	0.02	1.14 (0.02)	1.2 (0.04)	0.45 (0.01)	10.31 (0.08)
	csuv.m.all	0.99 (0)	0.12 (0.04)	0.04	0.08	1.12 (0.02)	1.14 (0.04)	0.44 (0.02)	9.96 (0.04)
	csuv.m.mcp	0.91 (0.01)	1.54 (0.09)	0	1.54	1.71 (0.06)	2.77 (0.13)	1.12 (0.05)	8.46 (0.09)
csuv.m.with.tree	0.99 (0)	0.12 (0.04)	0.04	0.08	1.12 (0.02)	1.14 (0.04)	0.44 (0.02)	9.96 (0.04)	

Table 17: Model 5: performance of CSUV and methods it compares with. Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 4 rho = 0.5 s = 10 p = 300	lasso	0.55 (0.01)	19.4 (1.1)	19.4	0	1.4 (0.02)	2.39 (0.08)	0.62 (0.01)	29.4 (1.1)
	elastic net	0.48 (0.01)	24.26 (1.09)	24.26	0	1.5 (0.03)	2.77 (0.08)	0.67 (0.01)	34.26 (1.09)
	relaxed lasso	0.96 (0.01)	1.3 (0.44)	1.23	0.07	1.19 (0.02)	1.39 (0.06)	0.5 (0.02)	11.16 (0.44)
	mcp	0.92 (0.01)	1.5 (0.09)	0.15	1.35	1.9 (0.04)	3.4 (0.09)	1.33 (0.03)	8.8 (0.08)
	scad	0.93 (0.01)	1.32 (0.11)	0.51	0.81	2.42 (0.05)	4.29 (0.09)	1.62 (0.03)	9.7 (0.12)
	vsd	0.96 (0)	0.75 (0.07)	0.02	0.73	1.35 (0.03)	1.75 (0.08)	0.73 (0.03)	9.29 (0.07)
	bic	0.61 (0.02)	16.53 (1.21)	16.48	0.05	1.48 (0.04)	2.53 (0.08)	0.72 (0.03)	26.43 (1.22)
	ebic	0.93 (0.01)	1.43 (0.17)	0.75	<u>0.68</u>	<u>2.07</u> (0.06)	<u>3.52</u> (0.11)	<u>1.36</u> (0.04)	10.07 (0.21)
	cv	<u>0.55</u> (0.01)	<u>19.4</u> (1.1)	<u>19.4</u>	0	1.4 (0.02)	2.39 (0.08)	0.62 (0.01)	29.4 (1.1)
	csuv.m	0.99 (0)	0.23 (0.04)	0.02	0.21	1.18 (0.02)	1.26 (0.05)	0.5 (0.02)	9.81 (0.05)
	csuv.s	0.97 (0)	0.63 (0.07)	0.54	0.09	1.18 (0.02)	1.31 (0.05)	0.5 (0.02)	10.45 (0.07)
	csuv.m.25	0.85 (0.01)	2.54 (0.11)	0	2.54	2.71 (0.12)	3.55 (0.13)	1.4 (0.04)	7.46 (0.11)
	csuv.m.75	0.99 (0)	0.31 (0.06)	0.25	0.06	1.16 (0.02)	1.21 (0.04)	0.47 (0.02)	10.19 (0.06)
	csuv.m.all	0.99 (0)	0.22 (0.05)	0.03	0.19	1.17 (0.02)	1.25 (0.05)	0.5 (0.02)	9.84 (0.04)
	csuv.m.mcp	0.88 (0)	2.11 (0.07)	0	2.11	2.07 (0.07)	3.46 (0.12)	1.4 (0.04)	7.89 (0.07)
	csuv.m.with.tree	0.99 (0)	0.22 (0.05)	0.03	0.19	1.17 (0.02)	1.25 (0.05)	0.5 (0.02)	9.84 (0.04)
setting 5 rho = -0.5 s = 5 p = 100	lasso	0.3 (0.01)	25.34 (0.85)	25.34	0	1.46 (0.03)	3.36 (0.09)	0.92 (0.02)	30.34 (0.85)
	elastic net	0.23 (0)	34.04 (0.8)	34.04	0	1.69 (0.04)	4.51 (0.1)	1.1 (0.02)	39.04 (0.8)
	relaxed lasso	0.62 (0.01)	7.04 (0.48)	7.04	0	1.27 (0.03)	1.76 (0.09)	0.57 (0.02)	12.04 (0.48)
	mcp	0.97 (0.01)	0.38 (0.07)	0.38	0	1.05 (0.02)	0.56 (0.02)	0.28 (0.01)	5.38 (0.07)
	scad	0.95 (0.01)	0.6 (0.11)	0.6	0	1.05 (0.02)	0.55 (0.02)	0.28 (0.01)	5.6 (0.11)
	vsd	1 (0)	0.02 (0.01)	0.02	0	1.05 (0.02)	0.54 (0.02)	0.28 (0.01)	5.02 (0.01)
	bic	0.95 (0.01)	0.66 (0.11)	0.66	0	1.05 (0.02)	0.56 (0.02)	0.28 (0.01)	5.66 (0.11)
	ebic	<u>0.96</u> (0.01)	0.47 (0.09)	0.47	0	1.05 (0.02)	0.56 (0.02)	0.28 (0.01)	5.47 (0.09)
	cv	<u>0.96</u> (0.01)	<u>0.55</u> (0.11)	<u>0.55</u>	0	1.05 (0.02)	0.55 (0.02)	0.28 (0.01)	5.55 (0.11)
	csuv.m	1 (0)	0.04 (0.02)	0.04	0	1.05 (0.02)	0.54 (0.02)	0.28 (0.01)	5.04 (0.02)
	csuv.s	0.98 (0)	0.26 (0.05)	0.26	0	<u>1.07</u> (0.02)	<u>0.62</u> (0.03)	<u>0.32</u> (0.01)	5.26 (0.05)
	csuv.m.25	0.82 (0.01)	1.42 (0.09)	0	1.42	2.59 (0.11)	2.98 (0.15)	1.69 (0.08)	3.58 (0.09)
	csuv.m.75	0.98 (0)	0.26 (0.06)	0.26	0	1.08 (0.02)	0.63 (0.03)	0.31 (0.01)	5.26 (0.06)
	csuv.m.all	1 (0)	0.04 (0.02)	0.04	0	1.05 (0.02)	0.54 (0.02)	0.28 (0.01)	5.04 (0.02)
	csuv.m.mcp	1 (0)	0 (0)	0	0	1.04 (0.02)	0.53 (0.02)	0.27 (0.01)	5 (0)
	csuv.m.with.tree	1 (0)	0.04 (0.02)	0.04	0	1.05 (0.02)	0.54 (0.02)	0.28 (0.01)	5.04 (0.02)
setting 6 rho = -0.5 s = 5 p = 300	lasso	0.21 (0)	40.87 (1.15)	40.87	0	1.86 (0.05)	5.07 (0.14)	1.28 (0.03)	45.87 (1.15)
	elastic net	0.15 (0)	57.05 (1.19)	57.04	0.01	2.72 (0.08)	7.81 (0.19)	1.79 (0.04)	62.03 (1.2)
	relaxed lasso	0.41 (0.01)	17.7 (1.17)	17.64	0.06	1.74 (0.06)	3.86 (0.2)	0.98 (0.04)	22.58 (1.18)
	mcp	0.96 (0.01)	0.52 (0.13)	0.52	0	1.05 (0.02)	0.57 (0.03)	0.28 (0.01)	5.52 (0.13)
	scad	0.9 (0.01)	1.3 (0.19)	1.3	0	1.05 (0.02)	0.57 (0.02)	0.28 (0.01)	6.3 (0.19)
	vsd	1 (0)	0.03 (0.02)	0.03	0	1.05 (0.02)	0.53 (0.02)	0.28 (0.01)	5.03 (0.02)
	bic	0.82 (0.03)	7.58 (1.82)	7.58	0	1.18 (0.04)	1.27 (0.2)	0.41 (0.04)	12.58 (1.82)
	ebic	0.93 (0.01)	0.97 (0.16)	0.97	0	1.05 (0.02)	0.58 (0.03)	0.28 (0.01)	5.97 (0.16)
	cv	<u>0.91</u> (0.01)	<u>1.25</u> (0.19)	<u>1.25</u>	0	1.05 (0.02)	0.57 (0.02)	0.28 (0.01)	6.25 (0.19)
	csuv.m	0.99 (0)	0.07 (0.03)	0.05	<u>0.02</u>	1.08 (0.02)	0.59 (0.04)	0.31 (0.02)	5.03 (0.03)
	csuv.s	0.96 (0.01)	0.52 (0.09)	0.52	0	<u>1.1</u> (0.02)	<u>0.69</u> (0.04)	<u>0.35</u> (0.02)	5.52 (0.09)
	csuv.m.25	0.62 (0.01)	2.73 (0.06)	0	2.73	4.29 (0.16)	5.14 (0.15)	2.69 (0.06)	2.27 (0.06)
	csuv.m.75	0.98 (0)	0.23 (0.06)	0.23	0	1.08 (0.02)	0.6 (0.03)	0.31 (0.01)	5.23 (0.06)
	csuv.m.all	0.99 (0)	0.07 (0.03)	0.05	0.02	1.08 (0.02)	0.59 (0.04)	0.31 (0.02)	5.03 (0.03)
	csuv.m.mcp	0.99 (0)	0.05 (0.03)	0.02	0.03	1.08 (0.03)	0.58 (0.05)	0.31 (0.03)	4.99 (0.03)
	csuv.m.with.tree	0.99 (0)	0.07 (0.03)	0.05	0.02	1.08 (0.02)	0.59 (0.04)	0.31 (0.02)	5.03 (0.03)

Table 18: Model 5: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.

parameters	methods	f	FP+FN	FP	FN	pred.err	l1.diff	l2.diff	size
setting 7 rho = -0.5 s = 10 p = 100	lasso	0.37 (0)	34.06 (0.68)	33.96	0.1	1.86 (0.04)	5.83 (0.12)	1.24 (0.03)	43.86 (0.7)
	elastic net	0.35 (0)	38.35 (0.66)	38.27	0.08	2.09 (0.05)	6.83 (0.13)	1.4 (0.03)	48.19 (0.68)
	relaxed lasso	0.48 (0.01)	22.32 (1.04)	21.73	0.59	1.87 (0.04)	5.2 (0.14)	1.18 (0.03)	31.14 (1.15)
	mcp	0.85 (0.01)	3 (0.21)	1.48	1.52	1.56 (0.04)	2.69 (0.12)	1.06 (0.05)	9.96 (0.16)
	scad	0.77 (0.01)	4.98 (0.25)	3.13	1.85	1.87 (0.05)	3.8 (0.11)	1.45 (0.03)	11.28 (0.24)
	vsd	0.81 (0.01)	3.06 (0.19)	0.15	2.91	1.85 (0.06)	3.28 (0.15)	1.32 (0.05)	7.24 (0.18)
	bic	0.84 (0.01)	3.54 (0.46)	2.16	1.38	1.59 (0.04)	2.78 (0.13)	1.08 (0.04)	10.78 (0.46)
	ebic	0.85 (0.01)	3.04 (0.2)	1.53	1.51	1.58 (0.04)	2.73 (0.12)	1.07 (0.05)	10.02 (0.16)
	cv	0.78 (0.01)	<u>4.81</u> (0.25)	<u>2.98</u>	1.83	1.84 (0.05)	3.68 (0.12)	1.41 (0.04)	11.15 (0.24)
	csuv.m	<u>0.77</u> (0.01)	3.78 (0.13)	0.19	<u>3.59</u>	<u>2.03</u> (0.05)	<u>3.85</u> (0.11)	<u>1.53</u> (0.03)	6.6 (0.13)
	csuv.s	0.8 (0.01)	3.82 (0.17)	1.63	2.19	1.85 (0.05)	3.37 (0.12)	1.27 (0.04)	9.44 (0.18)
	csuv.m.25	0.4 (0.01)	7.45 (0.06)	0	7.45	4.61 (0.15)	8.4 (0.15)	3.03 (0.05)	2.55 (0.06)
	csuv.m.75	0.85 (0.01)	3.11 (0.23)	1.65	1.46	1.61 (0.05)	2.75 (0.13)	1.02 (0.04)	10.19 (0.24)
	csuv.m.all	0.77 (0.01)	3.72 (0.13)	0.22	3.5	2.02 (0.05)	3.81 (0.11)	1.52 (0.04)	6.72 (0.13)
	csuv.m.mcp	0.72 (0.01)	4.27 (0.12)	0.04	4.23	2.2 (0.06)	4.27 (0.12)	1.68 (0.04)	5.81 (0.12)
csuv.m.with.tree	0.77 (0.01)	3.72 (0.13)	0.22	3.5	2.02 (0.05)	3.81 (0.11)	1.52 (0.04)	6.72 (0.13)	
setting 8 rho = -0.5 s = 10 p = 300	lasso	0.26 (0)	50.51 (1.39)	48.9	1.61	3.4 (0.11)	10.41 (0.21)	2.23 (0.05)	57.29 (1.54)
	elastic net	0.22 (0)	59.31 (1.44)	57.4	1.91	4.64 (0.17)	13.28 (0.23)	2.75 (0.06)	65.49 (1.64)
	relaxed lasso	0.35 (0.01)	26.61 (1.59)	22.95	3.66	3.76 (0.14)	9.65 (0.24)	2.33 (0.06)	29.29 (1.96)
	mcp	0.76 (0.01)	5.26 (0.28)	3.27	1.99	1.73 (0.05)	3.2 (0.14)	1.21 (0.05)	11.28 (0.26)
	scad	0.63 (0.01)	9.41 (0.36)	7.23	2.18	1.98 (0.05)	4.22 (0.13)	1.51 (0.04)	15.05 (0.34)
	vsd	0.67 (0.01)	4.82 (0.17)	0.03	4.79	2.49 (0.07)	4.94 (0.16)	1.87 (0.05)	5.24 (0.16)
	bic	0.61 (0.02)	20.39 (2.55)	18.84	1.55	2.09 (0.09)	5.19 (0.37)	1.43 (0.05)	27.29 (2.63)
	ebic	0.75 (0.01)	5.31 (0.27)	3.31	2	1.74 (0.06)	3.21 (0.14)	1.22 (0.05)	11.31 (0.26)
	cv	0.66 (0.01)	<u>8.38</u> (0.42)	<u>6.21</u>	2.17	1.93 (0.06)	4 (0.14)	1.44 (0.04)	14.04 (0.36)
	csuv.m	<u>0.59</u> (0.01)	5.74 (0.11)	0.06	<u>5.68</u>	<u>2.94</u> (0.08)	<u>5.92</u> (0.14)	<u>2.19</u> (0.04)	4.38 (0.11)
	csuv.s	0.64 (0.01)	6.13 (0.18)	1.75	4.38	2.64 (0.08)	5.42 (0.15)	1.9 (0.05)	7.37 (0.25)
	csuv.m.25	0.31 (0.01)	8.12 (0.05)	0	8.12	6 (0.18)	9.96 (0.15)	3.56 (0.05)	1.88 (0.05)
	csuv.m.75	0.76 (0.01)	4.04 (0.19)	0.78	3.26	2.09 (0.07)	3.95 (0.15)	1.49 (0.05)	7.52 (0.17)
	csuv.m.all	0.59 (0.01)	5.74 (0.11)	0.06	5.68	2.94 (0.08)	5.92 (0.14)	2.19 (0.04)	4.38 (0.11)
	csuv.m.mcp	0.56 (0.01)	6.06 (0.1)	0.02	6.04	3.18 (0.1)	6.32 (0.14)	2.32 (0.04)	3.98 (0.11)
csuv.m.with.tree	0.59 (0.01)	5.75 (0.11)	0.06	5.69	2.94 (0.08)	5.93 (0.14)	2.19 (0.04)	4.37 (0.11)	

Table 19: Model 5: performance of CSUV and methods it compares with (continue). Variable selection performance in terms of F-measure (f), total error (FP+FN), false positives (FP) and false negatives (FN), prediction error in terms of mse (pred.err), estimation error in terms of l1 and l2 distance (l1.diff and l2.diff) and average model size (size) are shown. The numbers are based on 100 simulations. The last 7 rows are the performance of CSUV with different parameters (e.g. csuv.m.mcp corresponds to CSUV with MCP as constituent method, and csuv.m.25 corresponds to CSUV with splitting ratio 25:75). Bold numbers: best result among delete- $n/2$ cross validation, eBIC and CSUV using Lasso, MCP and SCAD; underlined numbers: worst among those. Standard errors are shown inside the parentheses.