

Rejoinder to ‘Post-selection shrinkage estimation for high-dimensional data analysis’

We sincerely thank all the discussants Kjell Doksum and Joan Fujimura (DF); Jianqing Fan (Fan); Peihua Qiu, Kai Yang, and Lu You (QYY); and Yanming Li, Hyokyung Grace Hong, and Yi Li (LHL) for the thought-provoking and insightful discussions on our paper. We would also like to thank the Editor Fabrizio Ruggeri for processing and organizing the discussion. Ahmed would like to specially thank him for his encouragement on this paper and patience.

1. Strong signal, weak signal, and noise

One fundamental ingredient of our work is to formally split the signals into strong and weak ones. The rationale is that the usual one-step method such as the least absolute shrinkage and selection operator (LASSO) may be very effective in detecting strong signals while failing to identify some weak ones, which in turn has a significant impact on the model fitting, as well as prediction. The discussions of both Fan and QYY contain very interesting comments on the separation of the three sets of variables. Regarding Assumption (A2) about the weak signal set S_2 , we admit that the original version was not as rigorous as it could have been, as it could have contained the variables in S_3 . We now propose the following Assumption (A2') that replaces (A2) in the original paper.

(A2'): The parameter vector β^* satisfies that $\|\beta_{S_2}^*\| \sim n^\tau$ for some $0 < \tau < 1$, where $\|\cdot\|$ is the ℓ_2 norm and $\beta_j^* \neq 0$ for any $j \in S_2$.

QYY mentioned that in practice, it is sometimes difficult to have a subjective separation of strong and weak signals. First of all, we would like to emphasize that the conditions imposed in the paper are from an asymptotic point of view, which demonstrate the great performance of the proposed estimators in the specified scalings and covariance structure. Second, we would like to argue that this separation is sometimes unnecessary in practice as the ultimate goal of high-dimensional regression is to provide accurate predictions for future data after variable selection and insightful interpretations on the importance of the predictors in terms of explaining the response. Third, the separation of strong and weak signals was mainly used to stimulate the post-selection shrinkage estimation (PSE) method, and the variables identified as ‘strong’ or ‘weak’ by PSE do not necessarily have a natural separation in terms of true regression coefficients, at least for a fixed sample size.

2. Conditions on designed matrix

We thank Fan for pointing out that the assumption on the design matrix could be strong. In fact, condition (B2) is mainly motivated from [1], and it requires the weak signals to be correlated to strong ones, in order for it to be detectable using the weighted ridge regression. On the other hand, condition (B4) requires that the eigenvalues of the design matrix corresponding to both strong and weak signals are bounded away from both 0 and infinity. Now, we describe one specific example. Consider an $n \times p$ design matrix $\mathbf{X} = [\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3]$. \mathbf{X}_1 and \mathbf{X}_2 correspond to strong and weak signals, and \mathbf{X}_3 includes noises. Suppose all signals in $\mathbf{Z} = [\mathbf{X}_1, \mathbf{X}_2]$ are correlated with constant correlation coefficient of r and uncorrelated with noises in \mathbf{X}_3 . Then, such a design matrix satisfies both conditions (B2) and (B4). We agree that some reasonably correlated design matrix for all variables could be excluded under those conditions.

3. MUJI variables

We thank LHL for bringing up the marginally unimportant but jointly informative (MUJI) variable set [2], namely, ‘marginally unimportant but jointly important’ variables. Indeed, the inclusion of MUJI variables could significantly improve the performance of the vanilla sure independence screening approach [3]. However, we would like to argue that

Table I. Simulated results for example 1

| Method | MUJI (Y/N) | | $p_n = 400$ | $p_n = 100,000$ |
|-----------|------------|---------------|-------------|-----------------|
| LASSO-PSE | No | $ \hat{S}_1 $ | 6 | 6 |
| | | MSE | 0.0015 | 0.0046 |
| | | MPE | 0.0501 | 0.1661 |
| | Yes | MSE | 0.0022 | 0.0129 |
| | | MPE | 0.0279 | 0.5374 |
| | | RMSE | 3.4907 | 1.0945 |
| MCP-PSE | No | $ \hat{S}_1 $ | 3 | 3 |
| | | MSE | 0.1284 | 0.0196 |
| | | MPE | 1.9041 | 0.2629 |
| | Yes | MSE | 0.0154 | 0.0049 |
| | | MPE | 0.2447 | 0.0755 |
| | | RMSE | 2.8821 | 2.6005 |
| CIS-PSE | No | $ \hat{S}_1 $ | 3 | 3 |
| | | MSE | 1.4339 | 0.1215 |
| | | MPE | 20.5638 | 1.6907 |
| | Yes | MSE | 0.0431 | 0.0151 |
| | | MPE | 0.5850 | 0.3049 |
| | | RMSE | 2.5070 | 1.9322 |

Larger RMSE, smaller MSE, and smaller MPE indicate better performance. CIS, Covariance Insured Screening; MPE, mean prediction error; MSE, mean squared error; PSE, post-selection shrinkage estimation; RMSE, relative mean squared error.

in our proposal, the estimation of S_1 could be done by any variable selection method that could identify the strong signals, for example, LASSO. As a result, S_1 could already contain the MUJI variables as it considers the joint regression on all predictors.

Motivated by the MUJI variables, LHL proposed a new shrinkage estimator called Covariance Insured Screening-based PSE (CIS-PSE), which uses two simulation examples to compare HD-PSE and CIS-PSE. They conclude that using MUJI can help to improve the risk performance of the shrinkage estimator. However, the comparison could be a little unfair because S_1 in CIS-PSE is generated by marginal correlation, while S_1 in HD-PSE is from LASSO. Thus, S_1 generated from two methods can be different. To ensure a fair comparison, we let S_1 in the first step from both CIS-PSE and HD-PSE be consistent. We consider different scenarios: (i) S_1 is selected by LASSO; (ii) S_1 is selected by the minimax concave penalty (MCP); (iii) S_1 is selected using the marginal strong set suggested by LHL in the first step while producing CIS-PSE. For each of those aforementioned three cases, we compute the MUJI set \hat{S}_{MUJI} as suggested by LHL and then shrinking $\hat{S}_1 \cup \hat{S}_{\text{MUJI}}$ in the direction of \hat{S}_1 . We define those three estimates as LASSO-PSE, MCP-PSE, and CIS-PSE, correspondingly. We then recheck those two examples, compare their performance, and report the results in Tables I and II [‡]. When $p_n = 100,000$, we apply ridge regression and keep the 500 variables with the largest absolute coefficients before applying our algorithm.

In the tables, we report mean squared error and relative mean squared error. We also report the mean prediction error based upon the selected subset, defined as

$$E(\mathbf{X}_{\hat{S}_1} \hat{\boldsymbol{\beta}}_{\hat{S}_1}^* - \mathbf{X}_{\hat{S}_1} \boldsymbol{\beta}_{\hat{S}_1}^*)^2.$$

In Example 1 in LHL, there is strong correlation among three covariates with weak signals and three covariates with strong signals. From the evaluation results reported in Table I, we observe that when using the MCP-PSE and CIS-PSE,

[‡]The results of LASSO-PSE and MCP-PSE are identical when $p_n = 400$ because they always select the same \hat{S}_1 .

Table II. Simulated results for example 2

| Method | MUJI(Y/N) | | $p_n = 400$ | $p_n = 100,000$ |
|-----------|-----------|---------------|-------------|-----------------|
| LASSO-PSE | | $ \hat{S}_1 $ | 3 | 3 |
| | No | MSE | 0.0018 | 0.0100 |
| | | MPE | 0.0225 | 0.1594 |
| | | RMSE | 8.4982 | 4.6249 |
| | Yes | MSE | 0.0067 | 0.0294 |
| | | MPE | 0.0917 | 0.4487 |
| RMSE | | 2.3025 | 1.5091 | |
| MCP-PSE | | $ \hat{S}_1 $ | 3 | 3 |
| | No | MSE | 0.0018 | 0.0100 |
| | | MPE | 0.0225 | 0.1594 |
| | | RMSE | 8.4982 | 4.6249 |
| | Yes | MSE | 0.0067 | 0.0294 |
| | | MPE | 0.0917 | 0.4487 |
| RMSE | | 2.2974 | 1.5091 | |
| CIS-PSE | | $ \hat{S}_1 $ | 3 | 3 |
| | No | MSE | 1.2953 | 0.0100 |
| | | MPE | 13.5683 | 0.1594 |
| | | RMSE | 0.0719 | 4.6249 |
| | Yes | MSE | 0.0262 | 0.0294 |
| | | MPE | 0.3166 | 0.4487 |
| RMSE | | 2.5238 | 1.5091 | |

Larger RMSE, smaller MSE, smaller MPE indicate better performance. CIS, Covariance Insured Screening; MPE, mean prediction error; MSE, mean squared error; PSE, post-selection shrinkage estimation; RMSE, relative mean squared error.

incorporating the MUJI variables improves the performance of the method as it can include additional signals from the MUJI set. However, when using LASSO-PSE, it is clear that using MUJI actually deteriorates the performance of the method by having larger mean squared errors and smaller relative mean squared errors. This is probably because LASSO already selects some weak signals in addition to the strong signals, which makes the MUJI detection step unnecessary. In Example 2 in LHL, there is strong correlation among three noise covariates and three covariates with strong signals. From the evaluation results reported in Table II, we observe that both Lasso and MCP only select strong signals with no weak signals. Incorporating MUJI variables deteriorates the performances of both MCP-PSE and LASSO-PSE in this case. This is because MUJI variables may pick up those noises in the second step. However, CIS-PSE with MUJI variables can help to improve the performance of the method.

From this preliminary numerical study, we can see that including MUJI variables may or may not improve the performance of the PSE, depending on the selected submodel.

The corresponding theoretical analysis regarding when the MUJI variables help the final estimation is an interesting open research question.

4. About the algorithm

DF suggested to use the partial least square method in the second step to select the weak signals, as opposed to the current weighted ridge regression. We appreciate the suggestion; however, one still needs to impose regularization on the estimates, which would lead to a different strategy and should be of interest for further research.

QYY posed the question about the selection of the tuning parameters a_n and r_n in the PSE strategy. We agree that the proposed cross-validation method, while effective in our limited numerical experience, may need further theoretical justification. Recently, [4, 5] conducted a systematic study on the cross-validation-based tuning parameter selection method for high-dimensional penalized regression problems. Some work along similar lines could be an interesting research project. In

addition, it is also important to develop a certain adaptive tuning parameter selection method and demonstrate its robustness against model misspecification.

5. Future directions

This paper introduced the post-shrinkage estimation framework and used specific methods to select the strong and weak signals. The shrinkage estimation received a lot of attention since its inception decades ago. It strikes a balance between post-selected submodels and high-dimensional weighted ridge estimators and is proved to be an effective strategy.

There are a number of alternatives to mimic the ideas of the PSE. For example, Fan suggested a great idea involving using the penalized least square with different penalty levels, closely related to the folded concave penalties including the smoothly clipped absolute deviations penalty (SCAD) and MCP.

The current methodology can be extended in a host of directions, including nonparametric models (suggested by QYY), spatially corrected data, among others. We would like to remark here that shrinkage estimation strategies have already been applied to some nonparametric models in low-dimensional cases such as [6–8], among others that can be extended to high-dimensional cases.

Another interesting direction would be to study the shrinkage method in robust high-dimensional data analysis, such as M-estimation. Recently, [9, 10] proposed penalized weighted least squares and penalized weighted least absolute deviation methods to study robust high-dimensional regression. The methods unify the M-estimation in a penalized weighted least squares and least absolute deviation framework. Such a connection will enable us to extend the post-selection shrinkage strategy to robust high-dimensional regression models.

The scope of research in PSE is expanding. How to develop a system of diagnostic tools for the high-dimensional post-shrinkage estimators is an important direction for future research, as suggested by QYY.

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