

RESEARCH ARTICLE

When to Impute? Imputation before and during cross-validation

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KEYWORDS:

Class file; \LaTeX ; Statist. Med.; Rmarkdown;

1 | INTRODUCTION

In evaluating the performance of complex predictive models, it is now well understood that so-called training error (the predictive error measured on observations used to fit the model) is a poor proxy for generalization error (the performance of the model on future, as-yet-unseen, observations). The training error of a model will often be overly optimistic for the generalization error. For more complex modeling procedures (or on high dimensional data) this over-optimism can be quite substantial. As such, it is now standard to use sample-splitting methods to estimate generalization error. These methods train and evaluate models on

separate data. Cross-validation (CV) is a common sample-splitting technique that repeatedly splits a single dataset into training and validation subsets to efficiently estimate generalization error.

For multi-step modeling procedures, it is recommended that the entire sequence of steps be carried out during each replicate of CV to mimic the application of the entire procedure to an independent test set. This is particularly important for supervised steps (those steps that use the outcome variable). It is thought that most unsupervised steps (*i.e.*, steps that do not access information about outcome variables) can be completed before conducting CV with only minimal bias. This has been empirically validated for PCA and variance-based dimension reduction, ??? (we need to fill in some stuff here)

Missing data (MD) occur frequently in applied settings, and several machine learning algorithms (e.g., regression) are incompatible with MD. Imputation is a technique that replaces MD with estimated values. Imputation of MD is often one of the most computationally expensive steps in modeling procedures. For example, the `missForest` imputation algorithm may fit one random forest model for each column that contains MD. Computational expense of applying `missForest` or other imputation strategies with similar complexity during each replicate of CV scales poorly to larger datasets and to higher numbers of replications. High computational cost may lead analysts to prefer more convenient but less effective strategies to handle MD. A more computationally efficient approach would be to implement ‘unsupervised imputation’ (*i.e.*, imputing MD without accessing outcome information) *before* conducting CV. However, there is a lack of evidence substantiating the claim that unsupervised imputation conducted before CV will provide reliable estimates of a multi-step modeling procedure’s generalization error. More importantly, there is a lack of evidence outlining scenarios when unsupervised imputation before CV can lead to biased estimates of model error.

In this manuscript, we identify scenarios when reliable model error estimates can (or cannot) be computed using unsupervised imputation *before* CV (a strategy we will refer to as $I \rightarrow CV$). We compare estimated model error according to $I \rightarrow CV$ with estimated model error when imputation is applied *during each replicate* of CV (a strategy hereafter referred to as $CV \cup I$). To objectively compare the accuracy of model error estimates using $I \rightarrow CV$ and $CV \cup I$, we compute ‘true’ model error using an external validation set with MD. Both simulated and real data are leveraged to draw these comparisons. Our analysis also introduces and applies the `ipa` R package (**i**mputation for **p**redictive **a**nalytics), which provides functions to create single or multiple imputed training and testing sets for prediction modeling.

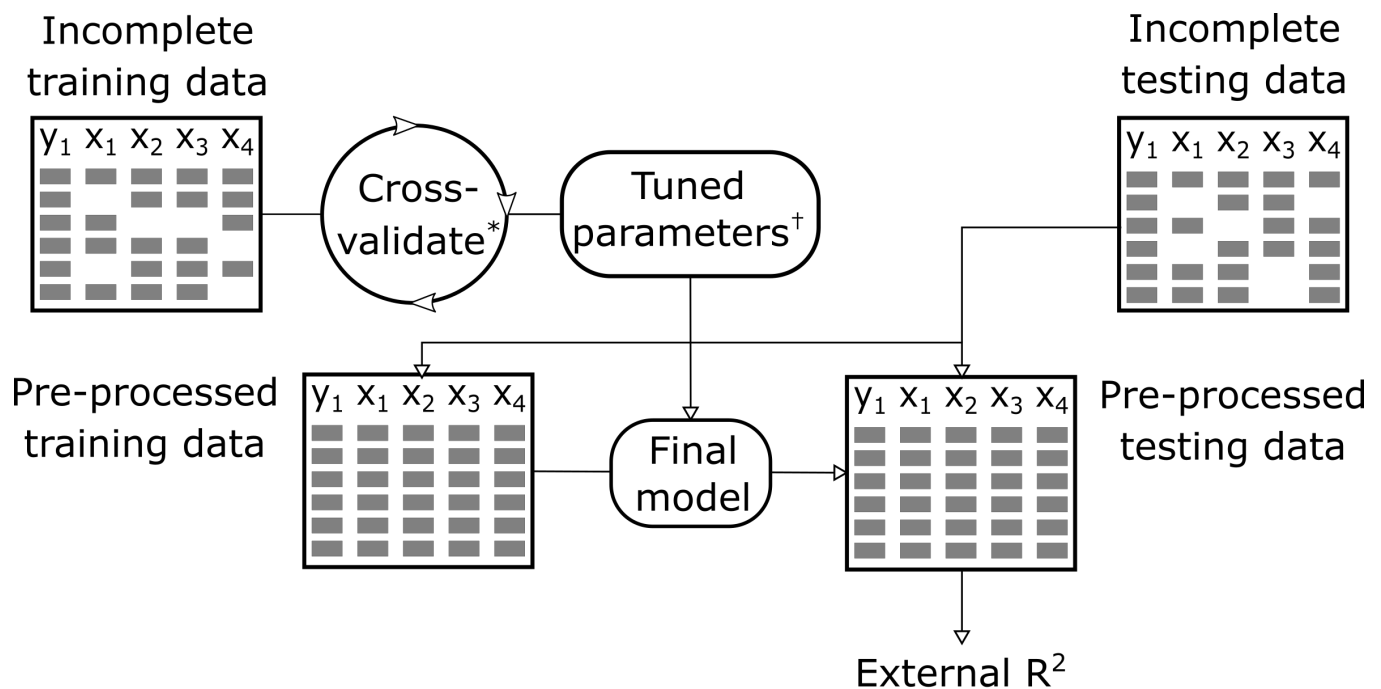
The rest of this manuscript is organized as follows. In Section 5, we summarize results from experiments using real data from public repositories. Results are summarized alongside our recommendations for applied practice in Section 6

2 | MISSING DATA AND CROSS-VALIDATION

MD mechanisms were first formalized by Rubin, who developed a framework to analyze MD that supposes each data point has some probability of being missing. If the probability of missingness is unrelated to the data (*i.e.*, all data are equally likely to be missing), then the data are missing completely at random (MCAR). When the probability of missingness is related to observed variables in the data (*i.e.*, all data within observed groups are equally likely to be missing), the data are missing at random (MAR). If the probability of missingness is determined by reasons that are unknown or unobserved, the data are missing not at random (MNAR). To illustrate, if a doctor did not run labs for a patient because the clinic was too crowded at the time, the patient's data are MCAR. If instead the doctor chose not to measure the patient's labs because the patient was too young, the patient's data are MAR. If the patient missed the appointment because the patient was too sick, the patient's data are MNAR. In the context of statistical learning, previous findings have shown that when data are MNAR, imputation alone is often less efficient than incorporating features that characterize missing patterns (*e.g.*, missingness incorporated as an attribute)^{1,2,3}. Since the primary aim of the current study is to assess the differences between two implementations of imputation (*i.e.*, $I \rightarrow CV$ and $CV \cup I$), we focus analyses on cases where data are MAR or MCAR.

The mechanisms of MD and methods to engage with MD have been studied thoroughly in the context of statistical inference. The primary focus in this setting is to obtain valid test statistics for statistical hypotheses in the presence of MD. Imputation to the mean and, more broadly, MD strategies that create a single imputed value, have been shown to increase type I errors for inferential statistics by artificially reducing the variance of observed data and ignoring the uncertainty attributed to MD, respectively. Multiple imputation, a widely recommended strategy to handle MD for statistical inference, is capable of producing valid test statistics when data are MCAR or MAR because it can simultaneously address the two shortcomings listed in the previous sentence. It is notable that the 'accuracy' of imputed values is not critical for the success of multiple imputation, given sufficient estimates of conditional distributions⁴. Instead, it is the consistency of the estimated covariance matrix for regression coefficients that makes this strategy ideal for statistical inference.

In the context of supervised statistical learning, data often include a training set and an external validation set. commonly ordered steps for model development are (1) data pre-processing, (2) tuning model hyper-parameters, (3) training the model(s) on the full training set, and (4) validating the model(s) using the validation set. Handling MD is a pre-processing task conducted in the training and validation sets, separately. In contrast to statistical inference, single imputation is often used in supervised learning workflows and strategies with greater imputation 'accuracy' are preferred. When k -fold CV is applied, the training data are split into k non-overlapping subsets (*i.e.*, folds). Each fold is then used as a testing set for the model(s) developed on the $k - 1$ other folds. Aggregating model errors over all k steps provides an estimate of the modeling procedure's generalization error, making k -fold CV an ideal resampling technique for tuning model hyper-parameters or comparing different modeling



* details on this analysis stage are provided in Figure 2

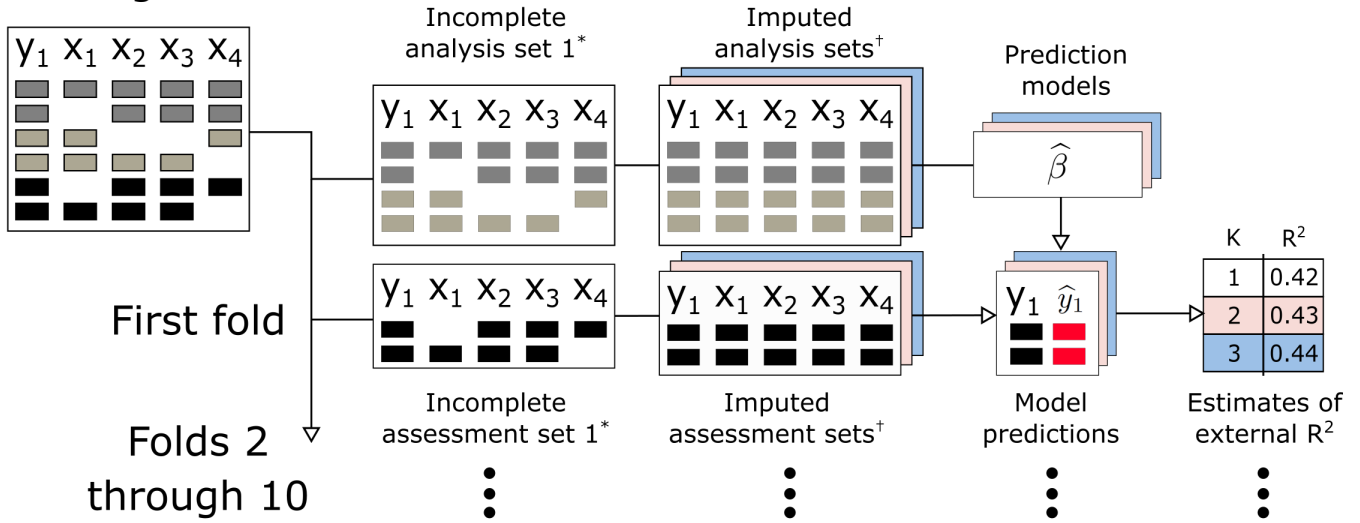
† tuning parameters are used for both pre-processing and model fitting

FIGURE 1 A standard workflow for machine learning analysis.

procedures. To mimic the application of the entire modeling procedure to an independent validation set, it is recommended that all data pre-processing steps be executed in each replicate of CV. Following CV, the generalization error of the modeling procedure(s) is measured by applying the ‘tuned’ modeling procedure to the entire training set and then evaluating the resulting prediction function’s accuracy in the external validation set.

There are at least two ways to evaluate the effectiveness of an imputation strategy. One approach is to evaluate how accurately the strategy imputes unobserved data. However, imputation accuracy can only be measured when the values of unobserved data are known, which limits its practical use. Another approach is to evaluate the generalization error of models fitted to the imputed data. This approach is applicable in any setting involving supervised learning. Evaluating imputation strategies in this manner also allows imputation parameters to be ‘tuned’ in the same manner as parameters in the prediction model. The current manuscript focusses exclusively on generalization error. <something about picking the right tuning parameters, and something else about estimating the error with as little bias as possible>

Incomplete training data



* Analysis and assessment sets play the roles of training and testing, respectively, during cross-validation

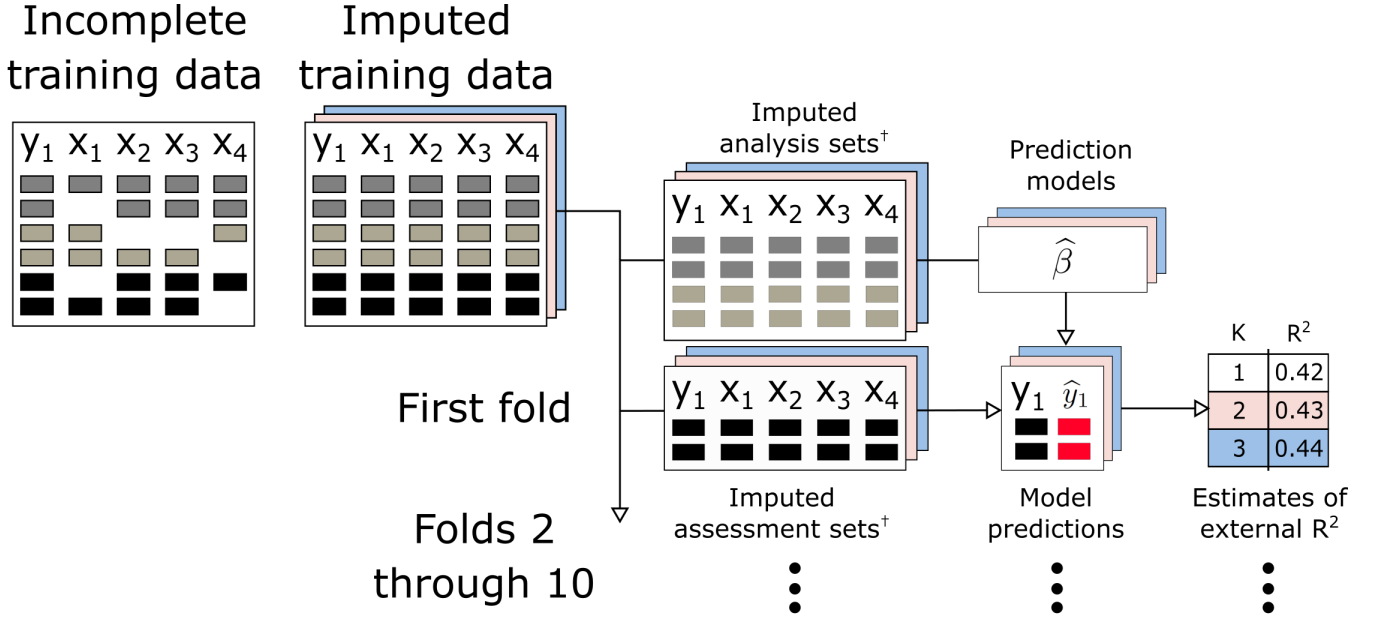
† Imputed datasets are created using 1, 2, and 3 nearest neighbors

FIGURE 2 A traditional workflow for cross-validation that applies imputation within each replicate (*i.e.*, $CV \cup I$).

3 | ORDER OF OPERATIONS

When employing supervised learning methods with split-sample-validation or cross-validation, it is critical that training data is separated from validation data before any “learning” is done: *The entire supervised pipeline must be run using only training data*. This applies both to the fitting procedure (eg. applying linear regression, or random forests, etc...), and to any supervised preprocessing steps. There are a number of examples in the literature where wildly optimistic estimates of validation error have been obtained because supervised variable selection was performed on the entire dataset, rather than just the training sample (CITE). In scenarios with a larger number of features, even simple methodologies, eg. selecting those features with high individual correlation with outcome, can induce substantial bias (CITE).

It is not unusual to separate training and validation data before performing even unsupervised preprocessing steps. For example, in many supervised learning frameworks, it is common to center and scale features, such that they are mean 0, variance 1 before engaging with the outcome. As this does not involve the outcome, it is entirely unsupervised. Nonetheless to most accurately replicate the “fitting process” in each replicate of CV, it is common to learn the centering and scaling parameters for each feature in each training subset, and apply those parameters to center/scale features in the corresponding validation subset (CITE).



* Analysis and assessment sets play the roles of training and testing, respectively, during cross-validation

† Imputed datasets are created using 1, 2, and 3 nearest neighbors

FIGURE 3 An experimental workflow for cross-validation that applies unsupervised imputation prior to data splitting (*i.e.*, $I \rightarrow CV$).

3.1 | Testing data

4 | SIMULATED EXPERIMENTS

Due in part to the plurality of methods used for prediction modeling and resampling, it is difficult to obtain meaningful theoretical results related to $I \rightarrow CV$ and $CV \cup I$. The goal of this section is to assess empirical findings comparing these two strategies. Our primary goal is to measure and compare how well each strategy approximates a model's generalization error. A secondary goal is to monitor the computation time of each approach and conduct relative comparisons. For these empirical experiments, we vary multiple parameters that may impact results, including the number of potential predictor variables, the number of training observations, and the missing mechanism (MCAR or MAR). As the difference between $I \rightarrow CV$ and $CV \cup I$ grows negligible when there are few missing data, we focus our comparisons to settings where 90% of observations contain at least 1 missing value and 30-50% of the data are missing. We apply nearest-neighbor imputation to handle MD and least absolute shrinkage and selection operator (LASSO) regression to develop prediction functions throughout the simulated experiments since these methods are widely recommended and used in applied settings. To generate data that matched the structure of our modeling procedure, we generated outcomes using linear effects without interaction. To be comprehensive, a separate appendix investigates the same simulation study where random forests

In addition to varying parameters in the data-generation process, we also consider three general data-generation scenarios. In scenario 1, the observed data are independent and identically distributed (iid). In scenario 2, the data are iid conditional on an observed grouping variable. A total of 11 groups are formed, one in the validation set and the remaining 10 in the training set. Each group is characterized by a unique mean value for predictor variables. During CV, the observed groups are separated into ten folds to mimic the prediction of outcomes in a population with different characteristics. Scenario 3 is identical to scenario 2 in all regards except that the grouping variable is latent. Consequently, CV does not break the observed groups into separate folds for scenario 3. Scenario 1 is an idealistic setting where $I \rightarrow CV$ and $CV \cup I$ should provide almost identical estimates of generalization error. Scenarios 2 and 3 are meant to test whether $I \rightarrow CV$ produces biased estimates of generalization error by omitting imputation from the CV process. In these scenarios, it is theoretically clear that $CV \cup I$ is more appropriate, but the degree to which $I \rightarrow CV$ is inappropriate has not yet been quantified and may be negligible in larger samples.

4.1 | Results

Overall, a total of 53,967 out of 54,000 (99.94%) simulation replicates were completed. Incomplete replicates were not analyzed, as these were replicates where at least one of the amputation, imputation, or prediction models did not converge. Across all scenarios, the mean external R^2 ranged from was 0.232 to 0.443 (**Table 1**). As one may expect, external R^2 values were positively correlated with training sample size and the ratio of predictors to junk variables. Notably, the mean external R^2 values in scenario 1 were uniformly greater than corresponding mean external R^2 values in scenarios 2 and 3, and the mean external R^2 values from scenario 2 were very similar to those from scenario 3 (max difference in mean external R^2 : 0.001). For scenario 1, the mean absolute difference for specific training sample sizes (*i.e.*, aggregating results over the 6 combinations of predictor to junk ratios and MD pattern) between $I \rightarrow CV$ and $CV \cup I$ in external R^2 estimates progressed from 0.01586 ($N = 100$) to 0.00092 ($N = 5000$; **Table 2**). Results followed a similar progression in scenario 3. In contrast, for scenario 2, the mean absolute difference between $I \rightarrow CV$ and $CV \cup I$ in external R^2 estimates remained high (0.01107) with $N = 5000$. These patterns were also apparent in visual depictions of the external R^2 estimates for each value of k neighbors that we evaluated (**Figure 4**).

For scenario 1, the overall bias (*i.e.*, aggregating over the 18 combinations of training sample size, predictor to junk ratios, and MD pattern) of R^2 estimates using $CV \cup I$ was 0.003, whereas the corresponding overall bias using $I \rightarrow CV$ was -0.001 (**Table 3**). In scenario 2, the bias of $CV \cup I$ was 0.004 and the bias of $I \rightarrow CV$ was -0.01. Similarly, in scenario 3, the biases of $CV \cup I$ and $I \rightarrow CV$ were -0.007 and -0.011, respectively. The overall standard deviation of R^2 estimates was higher for $CV \cup I$ versus $I \rightarrow CV$ in all three scenarios, but the difference was most pronounced in scenario 2 (0.045 versus 0.043; **Table 4**). A remarkable result is that, despite its bias, the lower variance of $I \rightarrow CV$ compared to $CV \cup I$ in scenario 2 leads to a lower overall root-mean-squared error of external R^2 estimates for $I \rightarrow CV$ versus $CV \cup I$ (0.055 versus 0.0562; **Table 5**).

TABLE 1 True external R^2 values for the modeling technique that is internally assessed using $CV \cup I$ and $I \rightarrow CV$.

N	Scenario 1		Scenario 2		Scenario 3	
	MAR	MCAR	MAR	MCAR	MAR	MCAR
10 predictors, 10 junk						
100	37.8 (3.44)	37.7 (3.42)	33.4 (6.43)	33.2 (6.62)	33.5 (6.45)	33.2 (6.60)
500	42.8 (2.92)	42.7 (2.94)	39.8 (5.51)	39.6 (5.56)	39.8 (5.54)	39.6 (5.57)
1000	43.5 (2.94)	43.5 (2.94)	40.9 (4.94)	40.7 (4.92)	40.9 (4.94)	40.7 (4.93)
5000	44.3 (3.00)	44.2 (3.01)	41.9 (4.53)	41.7 (4.65)	41.9 (4.53)	41.7 (4.66)
10 predictors, 40 junk						
100	34.5 (3.79)	34.5 (3.75)	30.3 (7.18)	30.3 (6.95)	30.3 (7.28)	30.3 (7.01)
500	40.6 (2.76)	40.6 (2.78)	38.2 (4.78)	38.1 (4.96)	38.2 (4.80)	38.1 (4.97)
1000	41.5 (2.73)	41.5 (2.74)	39.2 (4.72)	39.1 (4.79)	39.2 (4.71)	39.1 (4.78)
5000	42.6 (2.75)	42.6 (2.74)	40.4 (4.50)	40.3 (4.54)	40.4 (4.50)	40.3 (4.55)
10 predictors, 490 junk						
100	27.7 (5.09)	27.8 (4.99)	23.3 (6.92)	23.2 (6.69)	23.3 (6.73)	23.2 (6.70)
500	37.5 (2.94)	37.6 (2.93)	35.7 (4.30)	35.8 (4.31)	35.8 (4.28)	35.8 (4.31)
1000	38.8 (2.83)	38.7 (2.83)	37.2 (4.55)	37.1 (4.55)	37.1 (4.57)	37.1 (4.56)
5000	39.8 (2.78)	39.8 (2.79)	38.5 (4.41)	38.5 (4.30)	38.5 (4.37)	38.5 (4.30)

All values are scaled by 100 for convenience

5 | REAL DATA EXPERIMENTS

6 | DISCUSSION AND RECOMMENDATIONS

TABLE 2 Mean absolute differences in estimates of external R^2 between $CV \cup I$ and $I \rightarrow CV$.

N	Scenario 1		Scenario 2		Scenario 3	
	MAR	MCAR	MAR	MCAR	MAR	MCAR
10 predictors, 10 junk						
100	1.21 (1.05)	1.20 (0.99)	2.40 (1.73)	2.42 (1.74)	1.44 (1.21)	1.45 (1.15)
500	0.32 (0.29)	0.32 (0.29)	1.31 (1.09)	1.39 (1.18)	0.35 (0.30)	0.35 (0.30)
1000	0.21 (0.20)	0.21 (0.19)	1.17 (1.09)	1.24 (1.17)	0.22 (0.20)	0.23 (0.20)
5000	0.09 (0.08)	0.09 (0.09)	1.01 (0.86)	1.07 (0.97)	0.09 (0.09)	0.09 (0.09)
10 predictors, 40 junk						
100	1.48 (1.26)	1.47 (1.28)	2.64 (1.89)	2.67 (1.92)	1.74 (1.43)	1.79 (1.44)
500	0.34 (0.29)	0.34 (0.29)	1.38 (1.22)	1.42 (1.27)	0.36 (0.30)	0.35 (0.30)
1000	0.22 (0.20)	0.23 (0.20)	1.23 (1.08)	1.29 (1.16)	0.23 (0.20)	0.23 (0.20)
5000	0.09 (0.09)	0.10 (0.09)	1.11 (1.01)	1.20 (1.13)	0.10 (0.09)	0.10 (0.09)
10 predictors, 490 junk						
100	2.16 (1.72)	1.98 (1.60)	3.04 (2.24)	3.02 (2.15)	2.38 (1.82)	2.47 (1.89)
500	0.35 (0.30)	0.34 (0.29)	1.20 (1.08)	1.18 (1.06)	0.33 (0.28)	0.33 (0.29)
1000	0.22 (0.19)	0.22 (0.19)	1.12 (1.16)	1.12 (1.14)	0.21 (0.18)	0.20 (0.18)
5000	0.09 (0.08)	0.09 (0.08)	1.09 (1.06)	1.16 (1.13)	0.09 (0.08)	0.09 (0.08)

All values are scaled by 100 for convenience

TABLE 3 Bias of external R^2 estimates using $CV \cup I$ and $I \rightarrow CV$

N	Missing completely at random						Missing at random					
	Scenario 1		Scenario 2		Scenario 3		Scenario 1		Scenario 2		Scenario 3	
	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$
10 predictors, 10 junk												
100	0.45	-0.36	0.89	-1.29	-0.42	-1.49	0.64	-0.20	1.09	-1.06	-0.25	-1.33
500	0.05	-0.06	-0.02	-1.34	-1.28	-1.42	0.06	-0.03	0.12	-1.12	-1.09	-1.23
1000	0.11	0.06	0.18	-1.03	-1.04	-1.11	0.10	0.06	0.26	-0.88	-0.90	-0.97
5000	-0.05	-0.05	0.01	-1.06	-1.09	-1.11	-0.04	-0.05	0.14	-0.86	-0.91	-0.92
10 predictors, 40 junk												
100	0.97	-0.19	0.87	-1.59	-0.38	-1.92	1.11	-0.07	1.24	-1.20	-0.12	-1.57
500	0.14	0.00	0.49	-0.85	-0.77	-0.94	0.15	0.01	0.63	-0.68	-0.62	-0.78
1000	0.08	0.00	0.14	-1.11	-1.09	-1.17	0.09	0.02	0.18	-1.02	-1.00	-1.09
5000	0.07	0.04	-0.06	-1.25	-1.24	-1.28	0.06	0.04	-0.02	-1.13	-1.13	-1.17
10 predictors, 490 junk												
100	0.87	-0.91	1.74	-1.15	1.07	-1.26	0.86	-1.12	1.55	-1.36	0.88	-1.34
500	0.23	0.08	0.23	-0.80	-0.70	-0.84	0.38	0.22	0.39	-0.65	-0.56	-0.70
1000	0.15	0.08	0.08	-0.96	-0.95	-1.02	0.35	0.27	0.26	-0.77	-0.78	-0.85
5000	0.01	-0.01	0.18	-0.96	-0.97	-0.99	0.06	0.04	0.17	-0.90	-0.92	-0.93

All values are scaled by 100 for convenience

TABLE 4 Standard deviation of external R^2 estimates using $CV \cup I$ and $I \rightarrow CV$.

N	Missing completely at random						Missing at random					
	Scenario 1		Scenario 2		Scenario 3		Scenario 1		Scenario 2		Scenario 3	
	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$
10 predictors, 10 junk												
100	6.45	6.40	7.45	7.05	7.10	6.92	6.47	6.38	7.45	7.14	7.18	6.98
500	3.58	3.62	4.05	3.94	3.87	3.92	3.57	3.62	4.03	3.93	3.87	3.92
1000	3.32	3.35	3.78	3.63	3.57	3.60	3.32	3.36	3.76	3.63	3.58	3.61
5000	3.08	3.10	3.35	3.26	3.24	3.25	3.06	3.08	3.32	3.25	3.23	3.24
10 predictors, 40 junk												
100	6.82	6.66	7.38	6.95	7.07	6.87	6.68	6.56	7.22	6.84	6.97	6.73
500	3.54	3.58	3.79	3.65	3.60	3.65	3.56	3.61	3.73	3.62	3.61	3.65
1000	3.13	3.16	3.25	3.20	3.16	3.20	3.13	3.16	3.21	3.18	3.16	3.19
5000	2.83	2.84	3.01	2.87	2.85	2.87	2.82	2.84	2.97	2.87	2.86	2.88
10 predictors, 490 junk												
100	7.62	7.40	8.07	7.67	7.95	7.61	7.59	7.40	8.09	7.75	7.95	7.62
500	3.70	3.74	3.81	3.77	3.74	3.77	3.70	3.73	3.76	3.73	3.72	3.75
1000	3.25	3.27	3.28	3.22	3.20	3.22	3.24	3.27	3.29	3.24	3.21	3.24
5000	2.86	2.87	2.95	2.87	2.86	2.87	2.86	2.87	2.93	2.88	2.87	2.88

All values are scaled by 100 for convenience

TABLE 5 Root-mean-squared error of external R^2 estimates using $CV \cup I$ and $I \rightarrow CV$

N	Missing completely at random						Missing at random					
	Scenario 1		Scenario 2		Scenario 3		Scenario 1		Scenario 2		Scenario 3	
	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$
10 predictors, 10 junk												
100	5.90	5.81	9.12	8.86	8.76	8.75	5.94	5.75	8.95	8.69	8.64	8.62
500	2.18	2.17	5.55	5.51	5.50	5.54	2.17	2.17	5.49	5.43	5.43	5.48
1000	1.66	1.65	4.56	4.41	4.41	4.43	1.67	1.67	4.61	4.45	4.45	4.47
5000	0.82	0.83	3.75	3.73	3.74	3.75	0.82	0.82	3.62	3.57	3.57	3.58
10 predictors, 40 junk												
100	6.49	6.26	9.45	9.19	9.24	9.27	6.47	6.26	9.57	9.30	9.44	9.40
500	2.35	2.34	5.11	4.94	4.91	4.94	2.35	2.35	4.95	4.74	4.75	4.77
1000	1.67	1.66	4.57	4.54	4.51	4.54	1.66	1.67	4.49	4.45	4.43	4.45
5000	0.84	0.84	4.07	4.02	4.03	4.03	0.81	0.81	3.95	3.92	3.92	3.94
10 predictors, 490 junk												
100	7.29	7.25	9.13	8.92	8.99	8.98	7.46	7.50	9.30	9.18	8.89	8.89
500	2.45	2.44	4.41	4.35	4.32	4.35	2.41	2.38	4.30	4.20	4.17	4.19
1000	1.73	1.72	4.24	4.14	4.16	4.17	1.73	1.72	4.20	4.05	4.09	4.11
5000	0.85	0.85	3.69	3.59	3.59	3.60	0.87	0.87	3.81	3.72	3.68	3.68

All values are scaled by 100 for convenience

TABLE 6 The ratio (standard deviation) of computational time required to make imputed datasets and fit imputed models to each dataset using $CV \curvearrowright I$ (numerator) and $I \rightarrow CV$ (denominator).

N	Scenario 1		Scenario 2		Scenario 3	
	Make	Model	Make	Model	Make	Model
10 predictors, 10 junk						
100	21.1 (1.55)	9.95 (0.24)	21.1 (1.56)	10.1 (0.23)	21.0 (1.56)	10.0 (0.19)
500	12.4 (0.41)	9.76 (0.34)	12.4 (0.44)	9.83 (0.27)	12.4 (0.37)	9.75 (0.29)
1000	10.5 (0.28)	9.74 (0.27)	10.4 (0.28)	9.89 (0.26)	10.4 (0.34)	9.76 (0.26)
5000	9.14 (0.15)	9.61 (0.22)	9.16 (0.14)	9.96 (0.26)	9.15 (0.15)	9.61 (0.23)
10 predictors, 40 junk						
100	23.9 (1.69)	10.4 (0.23)	23.5 (1.83)	10.7 (0.32)	23.6 (1.99)	10.7 (0.33)
500	12.4 (0.54)	9.84 (0.17)	12.3 (0.53)	9.88 (0.26)	12.3 (0.53)	9.82 (0.26)
1000	10.4 (0.27)	9.74 (0.22)	10.5 (0.26)	9.87 (0.19)	10.5 (0.27)	9.79 (0.16)
5000	9.18 (0.20)	9.36 (0.17)	9.15 (0.14)	9.63 (0.17)	9.15 (0.15)	9.37 (0.19)
10 predictors, 490 junk						
100	37.0 (2.11)	8.95 (0.20)	36.5 (2.37)	8.78 (0.19)	36.2 (2.56)	8.78 (0.20)
500	12.5 (0.42)	5.99 (0.28)	12.5 (0.33)	6.24 (0.28)	12.4 (0.32)	6.25 (0.29)
1000	10.2 (0.22)	10.3 (0.26)	10.2 (0.23)	10.4 (0.32)	10.2 (0.20)	10.4 (0.34)
5000	9.10 (0.26)	9.72 (1.20)	9.09 (0.26)	9.75 (0.99)	9.12 (0.25)	9.70 (0.76)

All values are scaled by 100 for convenience

TABLE 7 Mean external R^2 when $\text{CV} \cup \text{I}$ and $\text{I} \rightarrow \text{CV}$ were applied to tune the number of neighbors used for imputation.

N	Missing completely at random						Missing at random					
	Scenario 1		Scenario 2		Scenario 3		Scenario 1		Scenario 2		Scenario 3	
	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$	$CV \cup I$	$I \rightarrow CV$
10 predictors, 10 junk												
100	38.1	38.0	33.9	33.9	34.0	34.0	38.2	38.2	34.0	34.1	34.0	34.0
500	43.8	43.8	40.5	40.6	40.6	40.6	43.9	43.9	40.8	40.8	40.8	40.8
1000	44.8	44.8	41.9	41.9	41.9	41.9	44.8	44.9	42.0	42.1	42.1	42.1
5000	45.7	45.7	43.2	43.2	43.2	43.2	45.8	45.8	43.4	43.4	43.4	43.4
10 predictors, 40 junk												
100	35.0	34.9	30.9	30.8	30.9	30.9	35.1	35.0	30.9	30.6	30.9	30.7
500	41.8	41.8	39.1	39.1	39.1	39.1	41.8	41.8	39.2	39.2	39.2	39.2
1000	42.8	42.8	40.2	40.3	40.2	40.3	42.8	42.8	40.3	40.3	40.4	40.3
5000	44.0	44.0	41.6	41.7	41.7	41.7	44.0	44.0	41.7	41.7	41.7	41.7
10 predictors, 490 junk												
100	29.0	28.7	24.1	23.8	24.0	23.7	28.7	28.5	23.9	23.7	24.2	23.9
500	39.1	39.1	37.1	37.2	37.1	37.2	39.1	39.1	37.1	37.2	37.1	37.2
1000	40.4	40.4	38.6	38.6	38.6	38.6	40.4	40.4	38.6	38.6	38.6	38.6
5000	41.5	41.5	40.1	40.1	40.1	40.1	41.5	41.5	40.0	40.0	40.1	40.1

All values are scaled by 100 for convenience

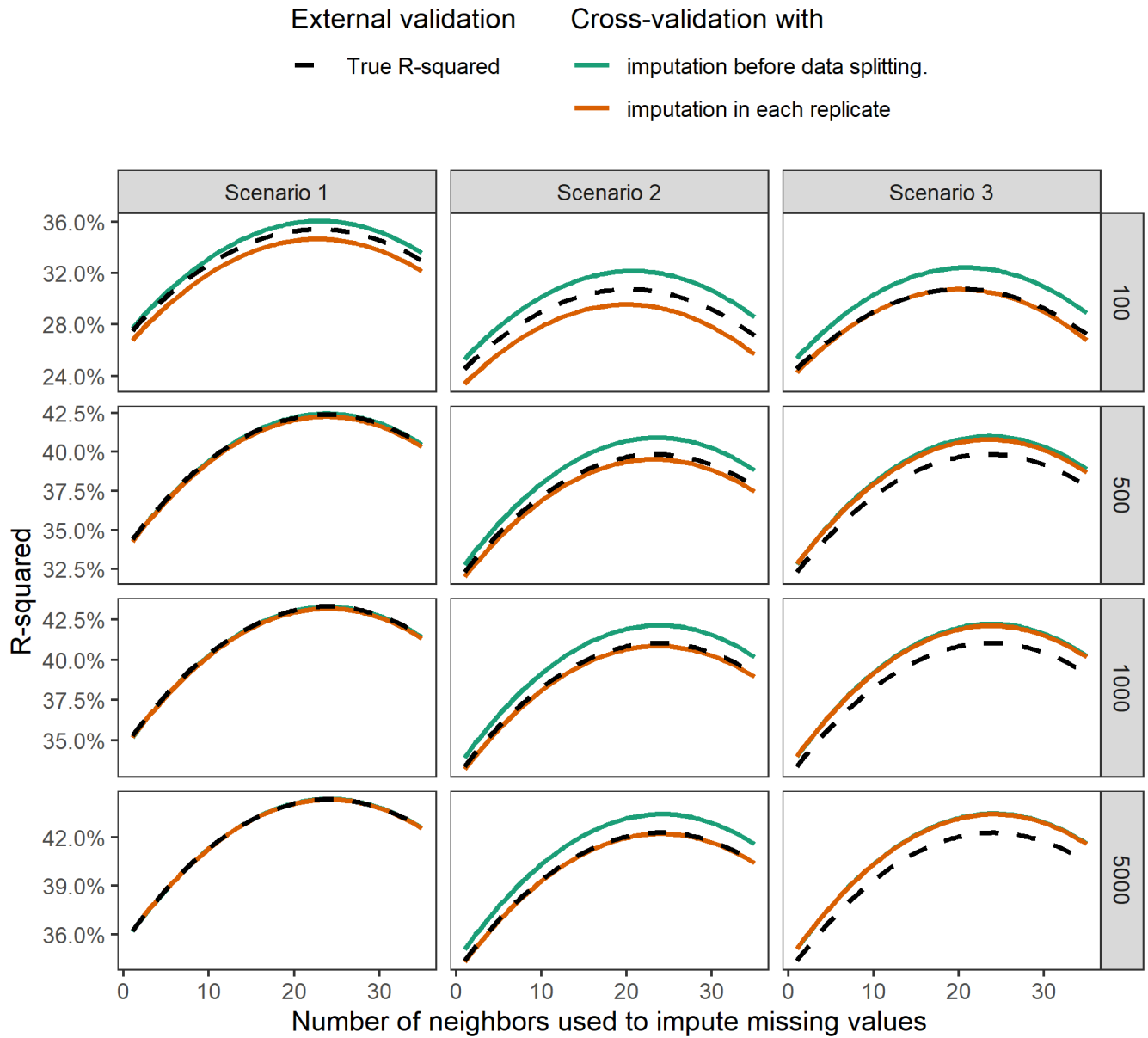


FIGURE 4 External generalization error and internal estimates of generalization error using $I \rightarrow CV$ and $CV \cup I$

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