

# Variable Selection Methods Comparison

Hongjie Liu, Jiajun Tao, Shaohan Chen

2023-02-27

# Outline

- ▶ Background
- ▶ Statistical methods to be studied
- ▶ Objective
- ▶ Simulation
- ▶ Experiment Settings and Scenario

# Background

- ▶ Variable selection methods help to optimize models in high-dimensional settings where we need to select predictors that balance fitness and complexity.
- ▶ The presence of weak predictors is a problem that plagues traditional variable selection methods.

# Statistical Methods to be Studied

## Step-wise forward method

- ▶ Starts with the empty model, and iteratively adds the variables that best improve the model fit. That is often done by sequentially adding predictors with the largest reduction in AIC. For linear models,

$$AIC = n \log \left( \sum_{i=1}^n (y_i - \hat{y}_i)^2 / n \right) + 2p.$$

## Automated LASSO regression

- ▶ Estimates model parameters by optimizing a penalized loss function:

$$\min_{\beta} \frac{1}{2n} \sum_{i=1}^n (y_i - \mathbf{x}_i \beta)^2 + \lambda \sum_{k=1}^p |\beta_k|.$$

# Objectives

- (1) Evaluate the effectiveness of both methods in identifying weak and strong predictors.
- (2) Examine how the absence of “weak” predictors affects parameter estimations.

# Types of Signals

- ▶ Strong signals

$$S_{strong} = \{j : |\beta_j| > c\sqrt{\log(p)/n} \text{ for some } c > 0, 1 \leq j \leq p\}$$

- ▶ Weak-but-correlated (WBC) signals

$$S_{WBC} = \{j : 0 < |\beta_j| \leq c\sqrt{\log(p)/n} \text{ and } \text{corr}(X_j, X_{j'}) \neq 0 \\ \text{for some } j' \in S_1, 1 \leq j \leq p\}$$

- ▶ Weak-and-independent (WAI) signals

$$S_{WAI} = \{j : 0 < |\beta_j| \leq c\sqrt{\log(p)/n} \text{ and } \text{corr}(X_j, X_{j'}) = 0 \\ \text{for all } j' \in S_1, 1 \leq j \leq p\}$$

- ▶ Null signals:  $S_{null} = \{j : \beta_j = 0, 1 \leq j \leq p\}$

# Types of Signals

Thus,  $p$  predictors can be partitioned as

$$\{1, \dots, p\} = S_{strong} \cup S_{WBC} \cup S_{WAI} \cup S_{null}.$$

- ▶ We assume that  $|S_{strong}| = p_S$ ,  $|S_{WBC}| = p_{WBC}$ ,  $|S_{WAI}| = p_{WAI}$ .
- ▶ The number of true predictors  $p_S + p_{WBC} + p_{WAI}$  should be less than  $n$ .

# Data Generation

- ▶ Normality assumption

$$\mathbf{y} \sim N(\mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{I})$$

- ▶ For  $j \in S_{strong}$ ,  $\beta_j = 20$ ; For  $j \in S_{WBC} \cup S_{WAI}$ ,  $\beta_j = 0.5$ .
- ▶ We choose  $c = 20$  so that  $0.5 \leq c\sqrt{\log p/n} < 20$  for all scenarios to be investigated.
- ▶ For the error term, we set  $\sigma = 8$ .



# Data Generation - Design Matrix

- ▶ We assume

$$\mathbf{X} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

- ▶ All predictors are standardized. Then we have  $\boldsymbol{\mu} = \mathbf{0}$  and  $\Sigma_{i,i} = 1$  for all  $i$ .
- ▶ We set  $p_{WBC} \geq p_{strong}$ . For each strong predictor (except one of them), we set  $\lceil p_{WBC}/p_{strong} \rceil$  WBC predictors to be correlated with it. Each WBC predictor is set to be correlated with one and only one strong predictor.
- ▶ All other elements of  $\boldsymbol{\Sigma}$  are 0.

We use the `MASS::mvrnorm` function to generate data following a multivariate normal distribution.

## Data Generation - Simulation Code

```
corr_matrix = matrix(rep(0, len = p^2), nrow = p)
corr_num = pwbc %/% ps
for (i in 1:(ps - 1)) {
  for (j in (ps + 1 + (i - 1)*corr_num):(ps + i*corr_num)) {
    corr_matrix[i, j] = corr
    corr_matrix[j, i] = corr
  }
}
for (j in (ps + 1 + (ps - 1)*corr_num):(ps + pwbc)) {
  corr_matrix[ps, j] = corr
  corr_matrix[j, ps] = corr
}
diag(corr_matrix) = 1
X = MASS::mvrnorm(n, mu = rep(0, p), Sigma = corr_matrix)
beta = c(rep(20, ps), rep(0.5, pwbc + pwai),
          rep(0, p - ps - pwbc - pwai))
Y = X %*% beta + rnorm(n, mean = 0, sd = 8)
```

# Experiment Settings and Scenarios

- ▶ Number of parameters:  $p = 100$
- ▶ Number of observations:  
 $n = 100$  (high dimensional), 500, 2000
- ▶ Ratio of true and null signals: 2 : 3
- ▶ Ratio of strong, WBC, and WAI signals:  
 $p_{strong} : p_{WBC} : p_{WAI} = 1 : 4 : 5$  and  $3 : 3 : 4$
- ▶ Correlation between strong and WBC:  $corr = 0.4$

# Evaluation Metrics

Define true predictors as positive and null predictors as negative

## *Signal Identification*

▶ **Complexity:** Number of Selected Parameters

▶ **Sensitivity:**  $\frac{TP}{TP+FN}$

▶ **Specificity:**  $\frac{TN}{TN+FP}$

▶ **F1-score:**  $\frac{2 \cdot \text{sensitivity} \cdot \text{precision}}{\text{sensitivity} + \text{precision}}$

▶ **Accuracy:**  $\frac{TP+TN}{TP+TN+FP+FN}$

## *Parameter Estimation*

▶ **MSE:**  $\frac{1}{p} \sum_{i=1}^p (\hat{\beta}_i - \beta_i)^2$

# Signal Identification Performance - Complexity

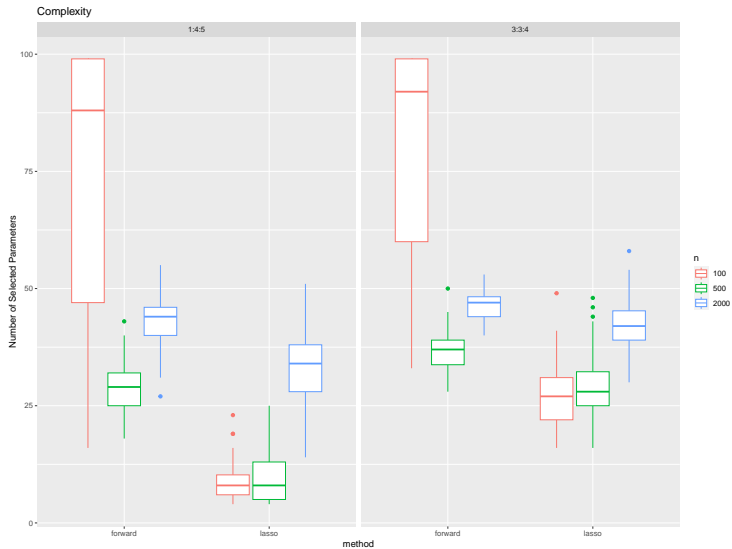


Figure 1: Model Complexity

# Signal Identification Performance - Complexity Exploration

- ▶ When in high dimensional scenario, forward selection tends to select nearly all of the predictors but Lasso does not
- ▶ Lasso tends to select much fewer predictors than forward selection, and the parameters it select will increase as  $n$  increases
- ▶ As  $n$  increases, the predictors that two models select are more precise (closer to true predictor number 40)

# Signal Identification Performance - Sensitivity

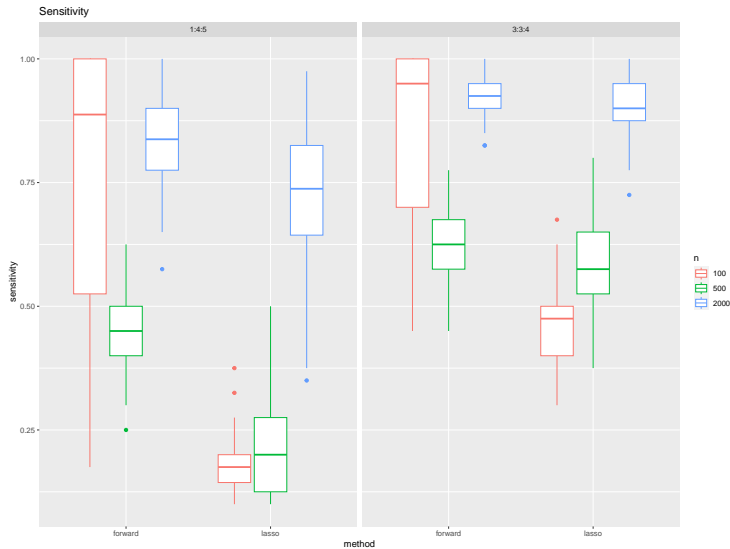


Figure 2: Sensitivity Performance

# Signal Identification Performance - Sensitivity

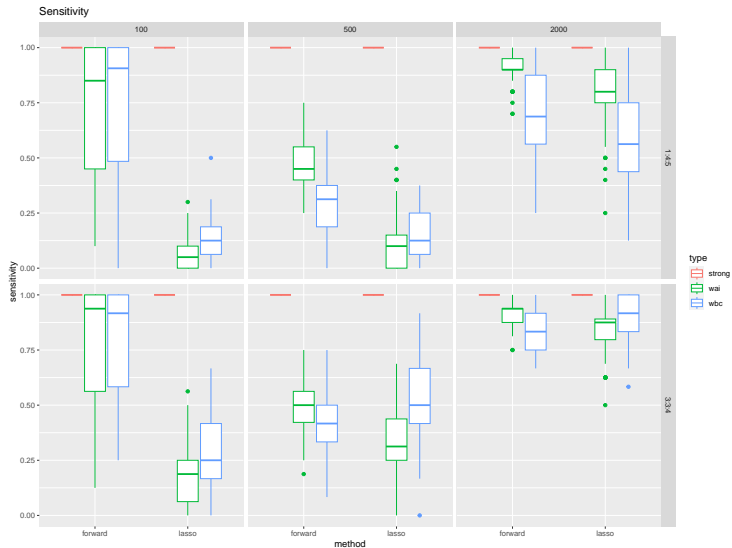


Figure 3: Sensitivity of True Signals



# Signal Identification Performance - Sensitivity Exploration

- ▶ Forward selection are highly sensitive in high dimensional case( $n=100$ ) while Lasso does not
- ▶ Overall, the sensitivity of two models increases as  $n$  increases
- ▶ Both models are sensitive in selecting strong signals. But when it comes to weak predictors, Lasso is much less sensitive in high dimensional scenario than forward selection.
- ▶ When  $n$  increases, the sensitivity discrepancy of selecting weak predictors between two models becomes smaller. But still, forward selection is overall more sensitive than Lasso
- ▶ The sensitivity discrepancy between two models are smaller when the ratio of strong predictors becomes larger

# Signal Identification Performance - Specificity

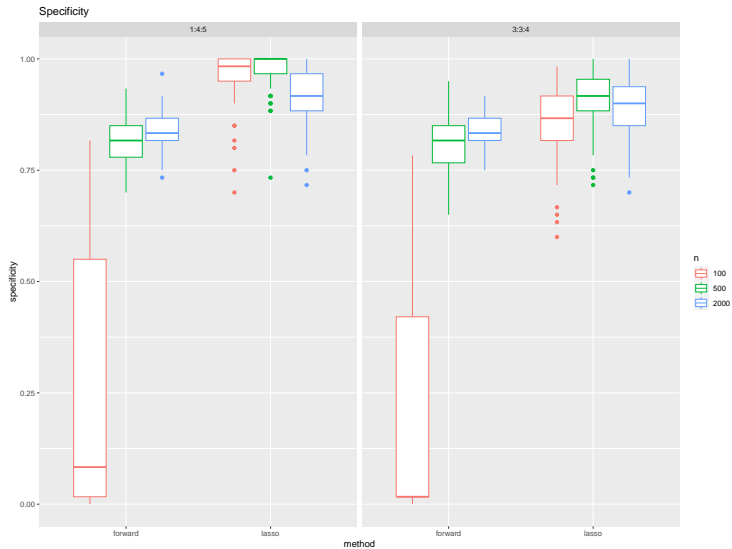


Figure 4: Specificity Performance

# Signal Identification Performance - Specificity Exploration

- ▶ In high dimensional scenario, the specificity of forward selection is near 0, which means it almost does not identify any null predictor, but Lasso in turn has high specificity
- ▶ In high dimensional scenario, forward selection is very assertive and tends to identify all 100 predictors as true, leading to extremely high sensitivity but low specificity
- ▶ In high dimensional scenario, Lasso is very conservative and tends to identify most 100 predictors as null, leading to low sensitivity but high specificity
- ▶ As  $n$  increases, forward selection has higher specificity. And overall, specificity are higher when the ratio of strong predictors are lower

# Signal Identification Performance - F1-Score

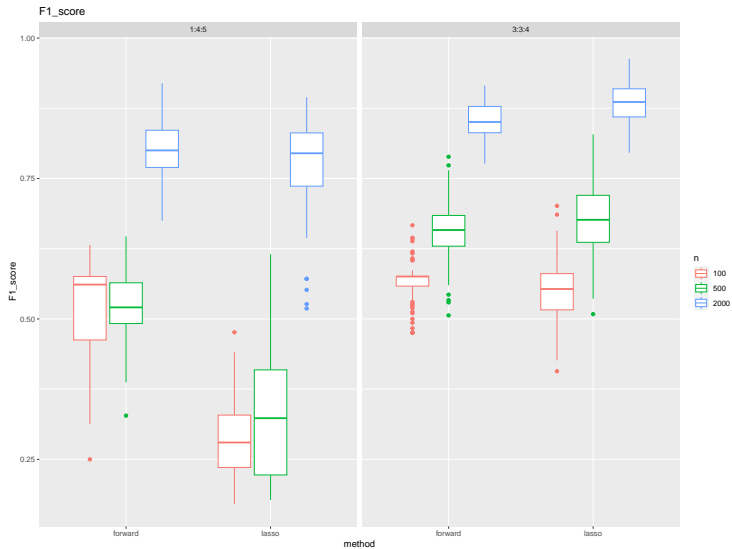


Figure 5: F1-Score Performance

# Signal Identification Performance - F1-Score

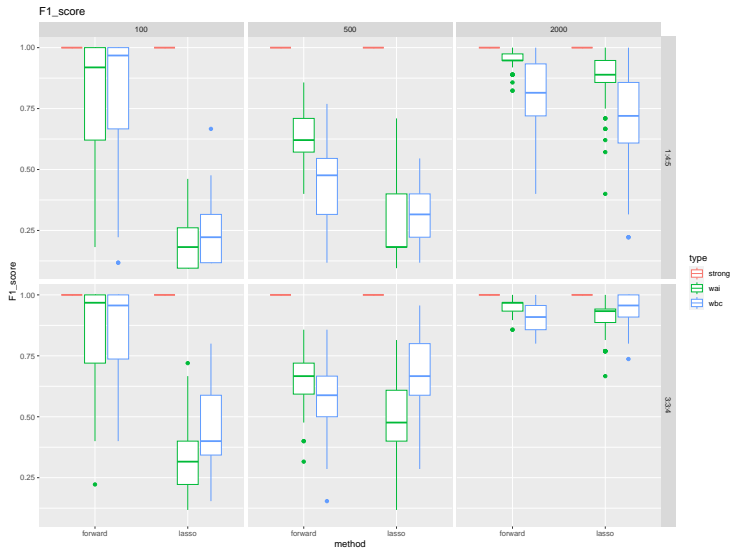


Figure 6: F1-Score of True Signals

# Signal Identification Performance - F1-score Exploration

- ▶ Lasso has lower F1-Score when  $n$  is not large. When  $n=2000$ , both models have similarly high F1-score
- ▶ F1-score will increase significantly for both models, when the ratio of strong predictors are larger. And F1-score is also higher when the ratio of strong predictors are larger
- ▶ Strong predictors have F1-Score=1 for each scenario, and weak predictors have higher F1-score when  $n$  increases for Lasso

# Signal Identification Performance - Accuracy

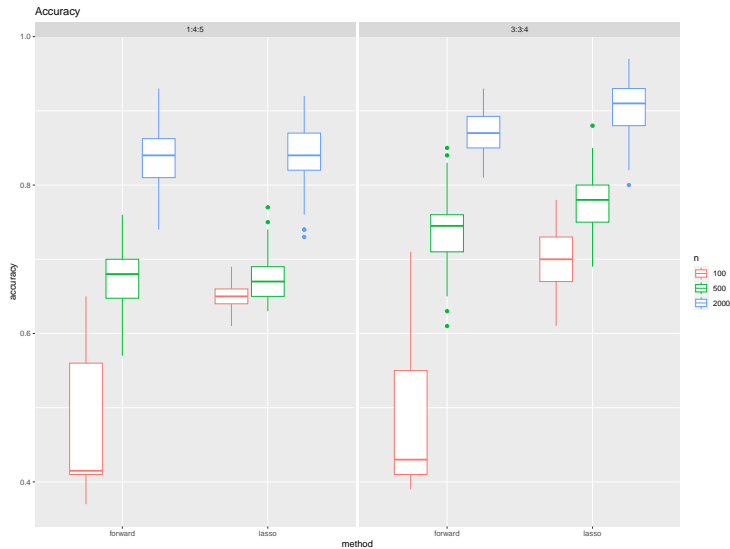


Figure 7: Accuracy Performance

# Signal Identification Performance - Accuracy

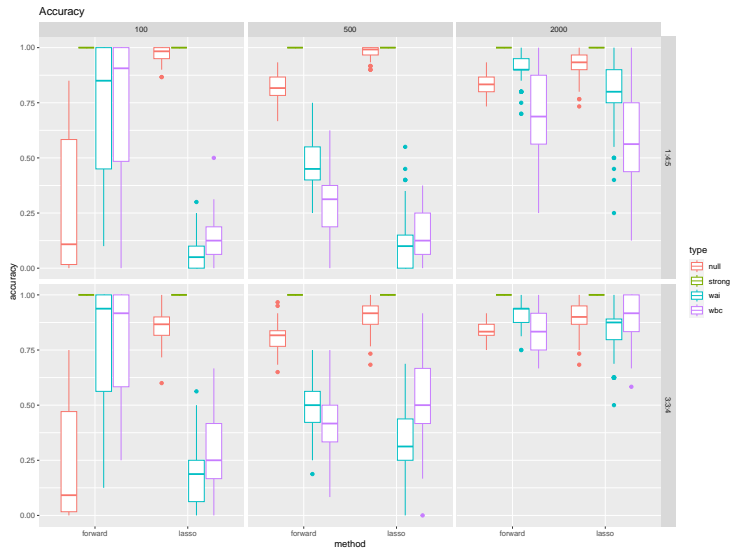


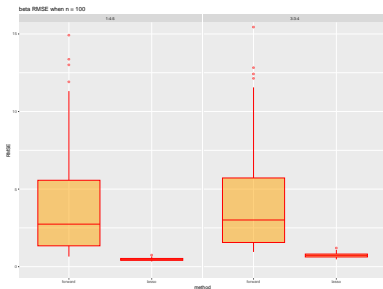
Figure 8: Accuracy of Different Signals



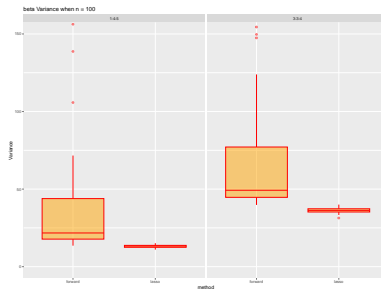
# Signal Identification Performance - Accuracy Exploration

- ▶ Accuracy is low in high dimensional scenario, especially forward selection
- ▶ Accuracy increases for both models when  $n$  increase
- ▶ Accuracy is higher when the ratio of strong predictors is higher, and Lasso has overall higher accuracy than forward
- ▶ In high dimensional, forward has higher accuracy for weak predictors than Lasso

# Parameter Estimation Performance: $n=100$



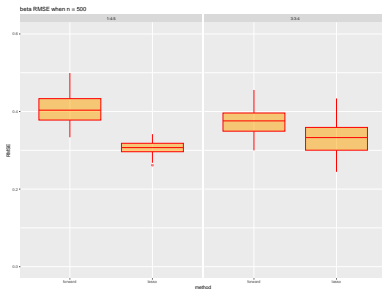
(a) Beta RMSE when  $n=100$



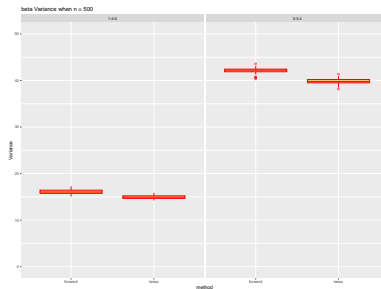
(b) Beta Variance when  $n=100$

Figure 9: Distribution of the datasets

# Parameter Estimation Performance: $n=500$



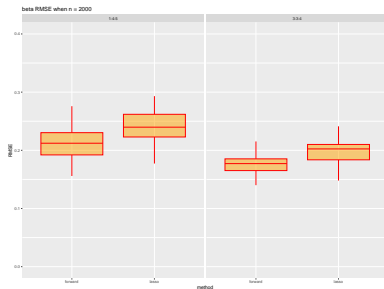
(a) Beta RMSE when  $n=500$



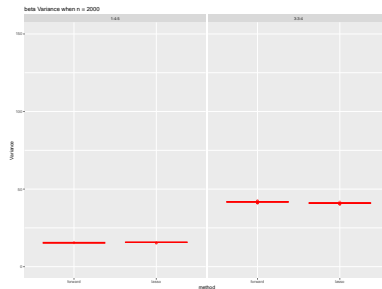
(b) Beta Variance when  $n=500$

Figure 10: Distribution of the datasets

# Parameter Estimation Performance: $n=2000$



(a) Beta RMSE when  $n=2000$



(b) Beta Variance when  $n=2000$

Figure 11: Distribution of the datasets

# Parameter Estimation Performance - Exploration

- ▶ In high-dimensional scenario, Lasso performs much better than forward
- ▶ Lasso performs better than forward when  $n=500$ , but worse than forward when  $n=2000$

# Predictors Identification Conclusions

## *High Dimensional Scenario( $n=100$ )*

- ▶ Forward selection tend to be assertive, with extremely high sensitivity and more selected predictors, better at identifying true signals
- ▶ Lasso tend to be conservative, with extremely high specificity and fewer selected predictors, better at identifying null signals
- ▶ Forward selection has an overall much higher F1-score but lower accuracy than Lasso
- ▶ Lasso performs smaller RMSE on parameter estimation than forward selection

# Predictors Identification Conclusions

## *Normal Scenario( $n=500, 2000$ )*

- ▶ Forward selection tends to overall select more predictors than Lasso, both methods select more predictors and more close to true predictor number(40) as  $n$  increases
- ▶ Both methods are sensitive for strong predictors. Forward selection is more sensitive than Lasso in identifying weak predictors than Lasso when there are fewer true strong predictors, else the discrepancy becomes smaller
- ▶ The sensitivity for identifying weak predictors are increasing as  $n$  increases for both models

# Predictors Identification Conclusions

*Normal Scenario( $n=500, 2000$ )*

- ▶ Lasso overall has higher specificity than forward, but the discrepancy becomes smaller as  $n$  increases
- ▶ The F1-score and accuracy increases as  $n$  increases for both models, overall Lasso has higher accuracy than forward
- ▶ Lasso performs better on parameter estimation than forward when  $n$  is small



# Missing Weak Predictors Analysis - Introduction

How missing “weak” predictors impacts the parameter estimations

Definition: missing weak predictors = true weak predictors but estimated as null

How to value parameter estimations: RMSE

# Missing Weak Predictors Analysis - Methods

How to value parameter estimations: RMSE

Most missing: simulations that have the least non-null estimations

Least missing: simulations that have the most non-null estimations

Middle: in between

# Missing Weak Predictors Analysis - Result: n=100

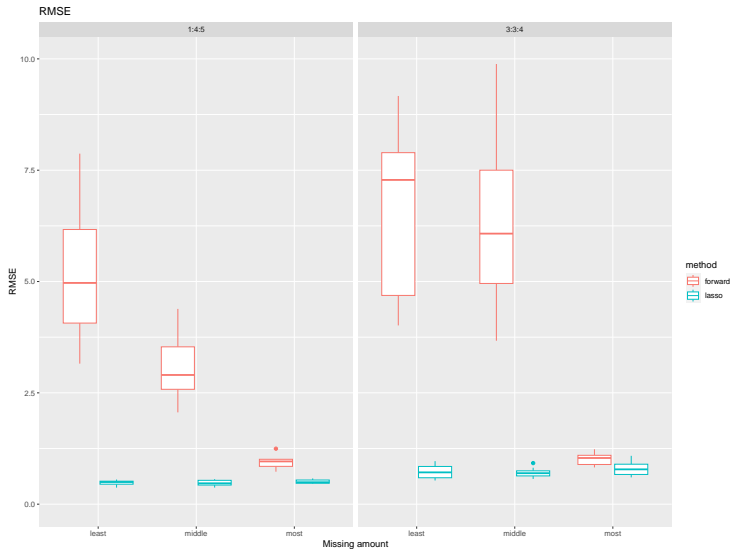


Figure 12: RMSE when n=100

# Missing Weak Predictors Analysis - Result: $n=500$

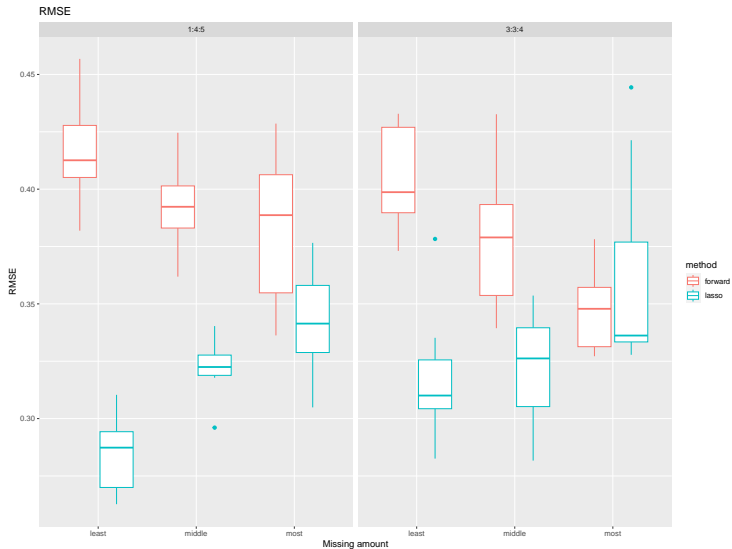


Figure 13: RMSE when  $n=500$

# Missing Weak Predictors Analysis - Result: $n=2000$

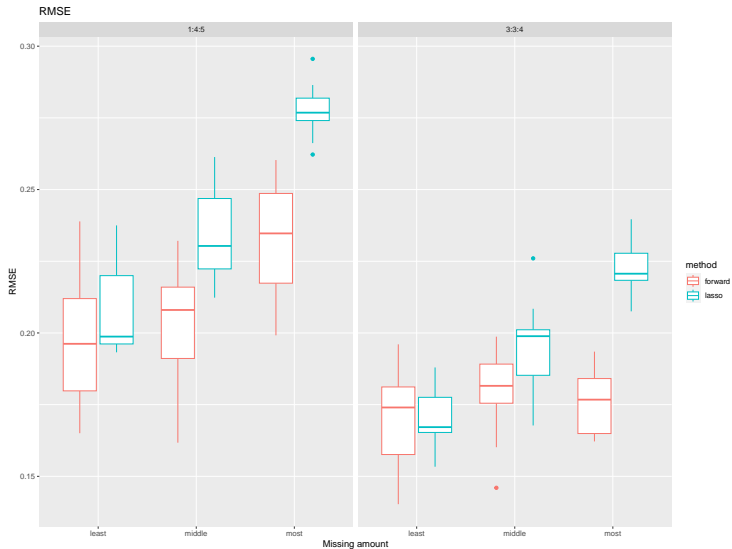


Figure 14: RMSE when  $n=2000$

# Missing Weak Predictors Analysis - Discussion

- ▶ No apparent patterns between different ratios
- ▶ In high-dimensional scenarios, Lasso performs much better than forward selection according to RMSE, no matter how much missing.
- ▶ When  $n$  is large enough, RMSE of both methods become small.
- ▶ When  $n = 500$ , Lasso is slightly better than forward selection, however, when  $n = 2000$ , just the reverse.
- ▶ In Lasso, RMSE seems to increase if the missing amount increases, but in forward selection, RMSE decreases when missing amount increases.

# Limitations

- ▶ Correlation matrix Pattern
- ▶ Number of observations  $n$  and number of parameters  $p$
- ▶ Ratio of Strong, Wbc, and Wai predictors

## Future Work

- ▶ Larger number of initial samples, narrower coverage window
- ▶ Increased sample size, changes in bootstrap performance?
- ▶ Changes in treatment propensity model
- ▶ Non-normal distributions of covariates