final_real

```
library(MASS)
library(ggplot2)
library(car)

Loading required package: carData

library(glmnet)

Loading required package: Matrix

Loaded glmnet 4.1-8

library(Matrix)
```

data generating

As you can see, 0.1 and 0.01 is different in the

```
set.seed(42)
generate_model_1_data <- function(n, att = 1) {
    x1 <- rnorm(n)
    x2 <- 0.9 * x1 + 0.01 * rnorm(n)
    x3 <- rnorm(n)
    X <- cbind(x1, x2, x3)
    y <- 0.2 * x1 + 0.3 * x2 + 0.4 * x3 + att * 0.1 * rnorm(n)
    return(list(X = X, y = y))
}
generate_model_2_data <- function(n, att = 1) {</pre>
```

```
# multi
x1 <- rnorm(n)
x3 <- rnorm(n)
x2 <- 0.45 * x1 + 0.45 * x3 + att * 0.01 * rnorm(n)
x4 <- rnorm(n)
X <- cbind(x1, x2, x3, x4)
y <- 0.2 * x1 + 0.3 * x2 + 0.1 * x3 + 0.39 * x4 + 0.01 * rnorm(n)
return(list(X = X, y = y))
}</pre>
```

VIF test

Show there is always a collinearity whether low or high

```
generate_model_1_data_vif <- function(n, att = 1) {</pre>
  x1 <- rnorm(n)
  x2 \leftarrow 0.9 * x1 + 0.01 * rnorm(n)
  x3 \leftarrow rnorm(n)
  X \leftarrow cbind(x1, x2, x3)
  y \leftarrow 0.2 * x1 + 0.3 * x2 + 0.4 * x3 + att * 0.1 * rnorm(n)
  return(list(x1 = x1, x2 = x2, x3 = x3, y = y))
generate_model_2_data_vif <- function(n, att = 1) {</pre>
 x1 <- rnorm(n)
  x3 <- rnorm(n)
  x2 \leftarrow 0.45 * x1 + 0.45 * x3 + att * 0.01 * rnorm(n)
  x4 \leftarrow rnorm(n)
  X \leftarrow cbind(x1, x2, x3, x4)
  y \leftarrow 0.2 * x1 + 0.3 * x2 + 0.1 * x3 + 0.39 * x4 + 0.01 * rnorm(n)
  return(list(x1 = x1, x2 = x2, x3 = x3, x4 = x4, y = y))
n < -300
data1 <- generate_model_1_data_vif(n)</pre>
data2 <- generate_model_2_data_vif(n)</pre>
model_original <- lm(y ~ ., data = data1)</pre>
vif(model_original)
```

```
x1 x2 x3
8123.723862 8124.553191 1.009242
```

```
model_original <- lm(y ~ ., data = data2)</pre>
vif(model_original)
                      x2
                                   xЗ
                                                x4
         x1
1895.803757 3990.943986 2216.141192
                                          1.004605
data1 <- generate_model_1_data_vif(n, 0.1)</pre>
data2 <- generate_model_2_data_vif(n, 0.1)</pre>
model_original <- lm(y ~ ., data = data1)</pre>
vif(model_original)
         x1
                      x2
                                   x3
9155.062520 9157.703829
                             1.030218
model_original <- lm(y ~ ., data = data2)</pre>
vif(model_original)
           x1
                         x2
                                       xЗ
                                                     x4
2.150360e+05 4.431463e+05 2.223649e+05 1.002214e+00
```

MC function definition

```
MC <- function(X, y, Xt, yt) {
    X_df <- data.frame(X)
    # train model
    lm_model <- lm(y ~ ., data = X_df) # Using all columns in X_df
    stepwise_model <- step(lm_model, direction = "both")
    pca_res <- prcomp(scale(X_df), center = TRUE, scale. = TRUE)
    pca_data <- as.data.frame(pca_res$x)
    pca_model <- lm(y ~ ., data = pca_data)
    ridge_model <- glmnet(X_df, y, alpha = 0)
    ridge_cv <- cv.glmnet(as.matrix(X_df), y, alpha = 0)
    ridge_lambda <- ridge_cv$lambda.min
    lasso_model <- glmnet(X_df, y, alpha = 1)
    lasso_cv <- cv.glmnet(as.matrix(X_df), y, alpha = 1)
    lasso_lambda <- lasso_cv$lambda.min</pre>
```

```
# predict
  X_df <- data.frame(Xt)</pre>
  lm_predictions <- predict(lm_model, newdata = X_df)</pre>
  stepwise_predictions <- predict(stepwise_model, newdata = X_df)</pre>
  pca_predictions <- predict(pca_model, newdata = data.frame(predict(pca_res, newdata = scale))</pre>
  ridge_predictions <- predict(ridge_model, newx = Xt, s = ridge_lambda)</pre>
  lasso_predictions <- predict(lasso_model, newx = Xt, s = lasso_lambda)</pre>
  # calculate mse
  lm_mse <- mean((yt - lm_predictions)^2)</pre>
  stepwise_mse <- mean((yt - stepwise_predictions)^2)</pre>
  pca_mse <- mean((yt - pca_predictions)^2)</pre>
  ridge_mse <- mean((yt - ridge_predictions)^2)</pre>
  lasso_mse <- mean((yt - lasso_predictions)^2)</pre>
  return(list(lm = lm_mse, stepwise = stepwise_mse, pca = pca_mse, ridge = ridge_mse, lasso :
MCn \leftarrow function(n = 20, t = 10, iterations = 100, at = 1) {
  lm_errors1 <- numeric(iterations)</pre>
  stepwise_errors1 <- numeric(iterations)</pre>
  pca_errors1 <- numeric(iterations)</pre>
  ridge_errors1 <- numeric(iterations)</pre>
  lasso_errors1 <- numeric(iterations)</pre>
  lm_errors2 <- numeric(iterations)</pre>
  stepwise_errors2 <- numeric(iterations)</pre>
  pca_errors2 <- numeric(iterations)</pre>
  ridge_errors2 <- numeric(iterations)</pre>
  lasso_errors2 <- numeric(iterations)</pre>
  for (i in 1:iterations) {
    # Generate datasets for both models
    data1 <- generate_model_1_data(n, att = at)</pre>
    data2 <- generate_model_2_data(n, att = at)</pre>
    data1t <- generate_model_1_data(t, att = at)</pre>
    data2t <- generate_model_2_data(t, att = at)</pre>
    # Run regression models for both datasets
    result1 <- MC(data1$X, data1$y, data1t$X, data1t$y)
    result2 <- MC(data2$X, data2$y, data2t$X, data2t$y)
```

```
# Store errors
lm_errors1[i] <- result1$lm
stepwise_errors1[i] <- result1$stepwise
pca_errors1[i] <- result1$pca
ridge_errors1[i] <- result1$ridge
lasso_errors1[i] <- result1$lasso
lm_errors2[i] <- result2$lm
stepwise_errors2[i] <- result2$stepwise
pca_errors2[i] <- result2$pca
ridge_errors2[i] <- result2$ridge
lasso_errors2[i] <- result2$ridge
lasso_errors2[i] <- result2$lasso
}

# Return the average errors across all iterations
return(list(model_co = list(lm_error = mean(lm_errors1), stepwise_error = mean(stepwise_errors)</pre>
```

Result return

simulation_results_10

\$model_co\$ridge_error

\$model_co\$lasso_error

[1] 0.01063807

[1] 0.006955523

final

```
$model_co
$model_co$lm_error
[1] 0.004951549

$model_co$stepwise_error
[1] 0.005301927

$model_co$pca_error
[1] 0.2118554
```

\$model_mulco
\$model_mulco\$lm_error
[1] 4.678484e-05

\$model_mulco\$stepwise_error
[1] 0.0001030844

\$model_mulco\$pca_error
[1] 0.1269923

\$model_mulco\$ridge_error
[1] 0.005175233

\$model_mulco\$lasso_error
[1] 0.0003404091

simulation_results_20

\$model_co
\$model_co\$lm_error
[1] 0.01561983

\$model_co\$stepwise_error
[1] 0.01536407

\$model_co\$pca_error
[1] 0.03457293

\$model_co\$ridge_error
[1] 0.01677616

\$model_co\$lasso_error
[1] 0.01547813

\$model_mulco
\$model_mulco\$lm_error
[1] 0.0001759014

\$model_mulco\$stepwise_error
[1] 0.0001842865

\$model_mulco\$pca_error
[1] 0.04048754

\$model_mulco\$ridge_error
[1] 0.003181603

\$model_mulco\$lasso_error
[1] 0.000615791

simulation_results_40

\$model_co
\$model_co\$lm_error
[1] 0.007585618

\$model_co\$stepwise_error
[1] 0.008286027

\$model_co\$pca_error
[1] 0.03752964

\$model_co\$ridge_error
[1] 0.01119759

\$model_co\$lasso_error
[1] 0.008431453

\$model_mulco
\$model_mulco\$lm_error
[1] 7.61861e-05

\$model_mulco\$stepwise_error
[1] 6.896133e-05

\$model_mulco\$pca_error
[1] 0.01966983

\$model_mulco\$ridge_error
[1] 0.001568552

\$model_mulco\$lasso_error

[1] 0.0004007357

simulation_results_80

\$model_co
\$model_co\$lm_error
[1] 0.005772981

\$model_co\$stepwise_error
[1] 0.00566902

\$model_co\$pca_error
[1] 0.04053034

\$model_co\$ridge_error
[1] 0.007139609

\$model_co\$lasso_error
[1] 0.005704319

\$model_mulco
\$model_mulco\$lm_error
[1] 0.0001359246

\$model_mulco\$stepwise_error
[1] 0.0001359246

\$model_mulco\$pca_error
[1] 0.01489648

\$model_mulco\$ridge_error
[1] 0.001408046

\$model_mulco\$lasso_error
[1] 0.0003926706

simulation_results_10_1

\$model_co
\$model_co\$lm_error

[1] 9.182781e-05

\$model_co\$stepwise_error

[1] 0.0001286884

\$model_co\$pca_error

[1] 0.030378

\$model_co\$ridge_error

[1] 0.001278453

\$model_co\$lasso_error

[1] 0.0004001677

\$model_mulco

\$model_mulco\$lm_error

[1] 0.0003857417

\$model_mulco\$stepwise_error

[1] 0.0004430776

\$model_mulco\$pca_error

[1] 1.591302

\$model_mulco\$ridge_error

[1] 0.002463018

\$model_mulco\$lasso_error

[1] 0.0005619589

simulation_results_20_1

\$model_co

\$model_co\$lm_error

[1] 0.0001345653

\$model_co\$stepwise_error

[1] 0.0001358162

\$model_co\$pca_error

[1] 0.08599611

\$model_co\$ridge_error
[1] 0.001497698

\$model_co\$lasso_error
[1] 0.0004302167

\$model_mulco
\$model_mulco\$lm_error
[1] 0.000129234

\$model_mulco\$stepwise_error
[1] 0.0001263228

\$model_mulco\$pca_error
[1] 0.3260658

\$model_mulco\$ridge_error
[1] 0.001483704

\$model_mulco\$lasso_error
[1] 0.0003638239

simulation_results_40_1

\$model_co
\$model_co\$lm_error
[1] 0.0001587497

\$model_co\$stepwise_error
[1] 0.0001587497

\$model_co\$pca_error
[1] 0.01925318

\$model_co\$ridge_error
[1] 0.00223085

\$model_co\$lasso_error
[1] 0.000447206

\$model_mulco
\$model_mulco\$lm_error
[1] 0.0001659282

\$model_mulco\$stepwise_error
[1] 0.0001659282

\$model_mulco\$pca_error
[1] 0.09030931

\$model_mulco\$ridge_error
[1] 0.001325038

\$model_mulco\$lasso_error
[1] 0.0004495081

simulation_results_80_1

\$model_co
\$model_co\$lm_error
[1] 8.652018e-05

\$model_co\$stepwise_error
[1] 8.652018e-05

\$model_co\$pca_error
[1] 0.06507261

\$model_co\$ridge_error
[1] 0.002382886

\$model_co\$lasso_error
[1] 0.0005170709

\$model_mulco
\$model_mulco\$lm_error
[1] 0.0001080691

\$model_mulco\$stepwise_error
[1] 0.0001080691

\$model_mulco\$pca_error
[1] 0.01093376

\$model_mulco\$ridge_error
[1] 0.001239442

\$model_mulco\$lasso_error
[1] 0.0003514962