HW3

Peiran Chen

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1.

a.

```
y <- rnorm(100)
y_test <- rnorm(100)
x <- matrix(rnorm(10000*100), ncol=10000)

lm_1a <- lm(y ~ x)
```

In matrix form, we could rewrite our expression as:

$$
\begin{aligned}
&Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_{10000} X_{10000} + \varepsilon, \text{ where } \varepsilon \sim N(0,1) \\
&Y = \beta X + \varepsilon
\end{aligned}
$$

And Least Squares will give us

$$
\hat{Y} = \beta X + \varepsilon
$$

Hence, it's MSE is

$$
\begin{aligned}
MSE &= E[Y - \hat{Y}]^2 \\
&= Var[\varepsilon] + Bias^2[\hat{f}(x_0)] + Var[\hat{f}(x_0)]
\end{aligned}
$$

As we can see, that $Var[\varepsilon]$ is irreducible, because it exists in nature, and we know that the least squares method derives by setting

```
(MSE <- mean(lm_1a$residuals^2))
```

```
## [1] 0
```

Since both

b.

```r
fc <- rep(0, 100)

bias_sq <- sum((fc - y)^2)
(bias <- sqrt(bias_sq))
```

```
## [1] 8.758788
```

Thus, we have the bias is equal to 8.758788.

c.

```r
(variance <- (sd(fc))^2)
```

```
## [1] 0
```

Thus, the variance for this procedure is 0.

d.

2.

3.

4.

a.