Lab 5 – MATH 243

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1

```r
#a
d <- d %>%
  mutate(MAPE = Price/Earnings_10MA_back)

summary(d[7])
```

```
##       MAPE
##  Min.   : 4.785
##  1st Qu.:11.708
##  Median :15.947
##  Mean   :16.554
##  3rd Qu.:19.959
##  Max.   :44.196
##  NA's   :120
```

```r
summary(d[4])
```

```
##  Earnings_10MA_back
##  Min.   : 8.51
##  1st Qu.:13.89
##  Median :17.48
##  Mean   :25.70
##  3rd Qu.:37.19
##  Max.   :77.00
##  NA's   :120
```

```r
d <- na.omit(d)

attach(d)
```

```
## The following objects are masked from d (pos = 3):
##
##     Date, Earnings, Earnings_10MA_back, Price, Return_10_fwd,
##     Return_cumul
```

Here Earnings_10MA_back had 120 NA values which caused the same number of NA's in MAPE.

```r
#b
lm_MAPE <- lm(Return_10_fwd ~ MAPE, data = d)

coef(summary(lm_MAPE))[2, -3]
```

```
##      Estimate     Std. Error       Pr(>|t|)
##  -4.588536e-03   1.727170e-04  1.641337e-127
```

MAPE is significant in this model.

```r
#c
z<- (length(Price) +1)/5
x <- rep(1, length(Price))
```

```r
x[z:(2*z)] <- 2
x[(2*z):(3*z)] <- 3
x[(3*z):(4*z)] <- 4
x[(4*z):(5*z - 1)] <- 5

d <- d %>%
  mutate(fold = x)
mse <- rep(0, 5)

for(i in 1:5){
  d_train <- d %>%
    filter(fold != i)

  d_test <- d %>%
    filter(fold == i)

  lm_cv5 <- lm(Return_10_fwd ~ MAPE, data = d_train)

  mse[i] <- mean((d_test$Return_10_fwd - predict(lm_cv5, newdata = d_test))^2)
}

cv_mse <- .2 * sum(mse)
cv_mse
```

```
## [1] 0.002508343
```

2

```r
#a
d <- d %>%
  mutate(inv_MAPE = 1/MAPE)
attach(d)
```

```
## The following objects are masked from d (pos = 3):
##
##     Date, Earnings, Earnings_10MA_back, MAPE, Price,
##     Return_10_fwd, Return_cumul

## The following objects are masked from d (pos = 4):
##
##     Date, Earnings, Earnings_10MA_back, Price, Return_10_fwd,
##     Return_cumul
```

```r
lm_invMAPE <- lm(Return_10_fwd ~ inv_MAPE, data = d)
summary(lm_invMAPE)
```

```
##
## Call:
## lm(formula = Return_10_fwd ~ inv_MAPE, data = d)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.106298 -0.030839  0.002955  0.028179  0.103866
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) -0.007659   0.002878  -2.661  0.00788 **
## inv_MAPE     0.995904   0.036513  27.275  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.04284 on 1482 degrees of freedom
## Multiple R-squared:  0.3342, Adjusted R-squared:  0.3338
## F-statistic: 743.9 on 1 and 1482 DF,  p-value: < 2.2e-16
```

```r
coef(summary(lm_invMAPE))[2, -3]
```

```
##      Estimate    Std. Error      Pr(>|t|)
##  9.959036e-01  3.651296e-02 4.408311e-133
```

Again, yes.

```r
#b
for(i in 1:5){
  d_train <- d %>%
    filter(fold != i)

  d_test <- d %>%
    filter(fold == i)

  lm_cv5 <- lm(Return_10_fwd ~ inv_MAPE, data = d_train)

  mse[i] <- mean((d_test$Return_10_fwd - predict(lm_cv5, newdata = d_test))^2)
}

cv_mse <- .2 * sum(mse)
cv_mse
```

```
## [1] 0.002260043
```

The MSE here is somewhat smaller than the MSE using the non-inverted model.

3

```r
#a
mse_3a <- mean((d$Return_10_fwd - d$inv_MAPE)^2)
mse_3a
```

```
## [1] 0.001896346
```

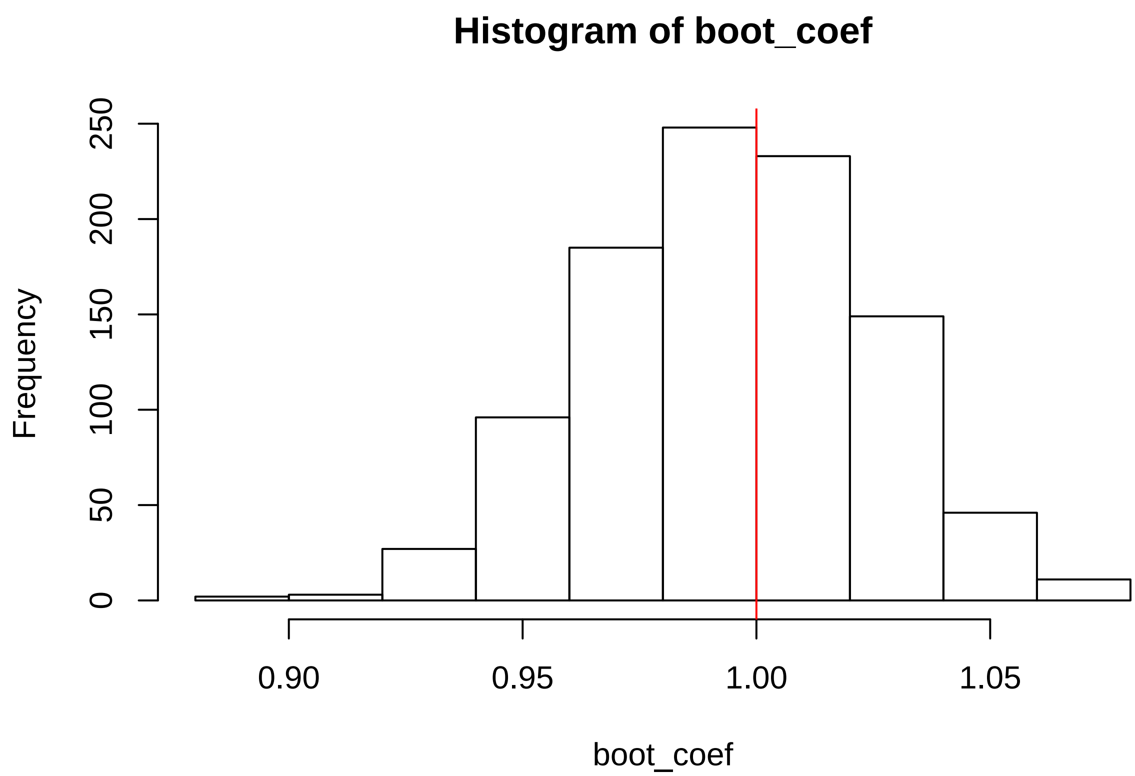
We are essentially not training the model, but just assuming its form. Therefore the training MSE is an estimate of the test MSE in the same way that we would have when cross validating.

4

```r
#a
boot.fn <- function(data, index){
  return(coef(lm(Return_10_fwd ~ inv_MAPE, data = data, subset = index)))
}

boot_coef <- rep(0, 1000)
for(i in 1:1000){
  boot_coef[i] <- boot.fn(d, sample(1484, 1484, replace = TRUE))[2]
}
```

```r
hist(boot_coef)
abline(v=1,col="red")
```




```r
confint(lm_invMAPE)[2, ]
```

```
##    2.5 %   97.5 %
## 0.924281 1.067526
```

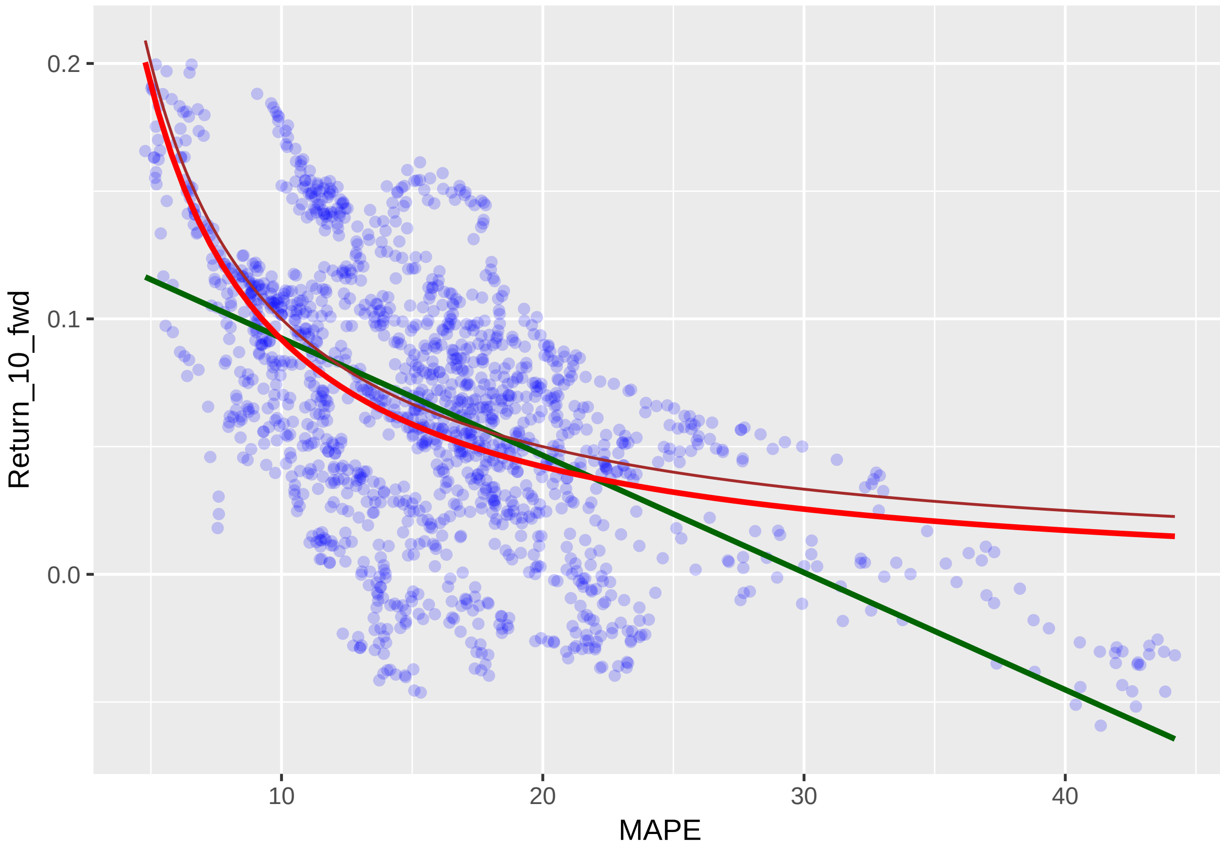
```r
error <- qt(0.975,df=length(boot_coef) - 1)*sd(boot_coef)/sqrt(length(boot_coef))
confint_pred <- c(mean(boot_coef) - error, mean(boot_coef) + error)
confint_pred
```

```
## [1] 0.9927336 0.9964354
```

The confidence interval for the booststraped slope is significantly smaller because it reflects the confidence interval of the mean of the boostraped distribution, while confint is the interval for the beta_1 itself.

5

```r
d %>% ggplot(aes(y = Return_10_fwd, x = MAPE)) +
  geom_point(aes(y = Return_10_fwd, x = MAPE), alpha = .2, color = "blue") +
  geom_smooth(method = lm, se = FALSE, color = "darkgreen", alpha = 3) +
  geom_smooth(method= lm ,formula= y ~ I(1/x), se = FALSE, color = "red") +
  geom_line(aes(y = inv_MAPE, x = MAPE), color = "brown")
```



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