

Problem_Set_5

Santiago Vidal Calvo

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```
# Part 1: Simulation

# Create a simulated data set with a dependent variable that is a linear
# > function of a treatment variable and a confounding variable. Fit a
# > linear model for the true data generating process and print the
# > summary table.

set.seed(123)

n <- 5000

# Confounder C
C <- rnorm(n, mean = 0, sd = 1)

# Treatment T depends on C
Treated <- 0.8 * C + rnorm(n, 0, 1)

# Outcome Y depends on T and C
# True model:  $Y = 1 + 2*T + 1*C + \text{error}$ 

Y <- 1 + 2 * Treated + 1 * C + rnorm(n, 0, 1)

sim_data <- data.frame(
  Y = Y,
  T = Treated,
  C = C
)

head(sim_data)

##           Y           T           C
## 1 0.9251408 -0.9425544 -0.56047565
## 2 2.4899135  0.9434515 -0.23017749
## 3 3.6857039  0.1000171  1.55870831
## 4 3.5772073  1.5374253  0.07050839
## 5 3.3936206  1.0196214  0.12928774
## 6 7.2614169  1.7071830  1.71506499
```

```

# This data.frame contains the outcome Y, the treatment T, and the
# > confounder C, all generated from the specified linear DGP.
# Fit the true model  $Y \sim T + C$  and print the summary table

mod_true <- lm(Y ~ T + C, data = sim_data)
summary(mod_true)

##
## Call:
## lm(formula = Y ~ T + C, data = sim_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.3523 -0.6578  0.0034  0.6994  3.0994
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.00819    0.01416   71.21  <2e-16 ***
## T            2.00289    0.01412  141.85  <2e-16 ***
## C            1.00252    0.01812   55.33  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.001 on 4997 degrees of freedom
## Multiple R-squared:  0.9143, Adjusted R-squared:  0.9142
## F-statistic: 2.664e+04 on 2 and 4997 DF,  p-value: < 2.2e-16
# In this model, the true coefficient on T is 2 by construction and the
# > true coefficient on C is 1. The estimated coefficients should be
# > close to these values, and the summary output gives us the standard
# > errors and t statistics for each estimate.

# Part 1(a)

# Using the true model, demonstrate that the coefficient for your
# > treatment variable follows the central limit theorem. That is,
# > demonstrate that the coefficient's sampling distribution is
# > approximately normal.

set.seed(456)

B <- 1000          # number of simulated datasets
beta_T <- numeric(B)

for (b in seq_len(B)) {
  C_b <- rnorm(n, 0, 1)
  T_b <- 0.8 * C_b + rnorm(n, 0, 1)

```

```

Y_b <- 1 + 2 * T_b + 1 * C_b + rnorm(n, 0, 1)
dat_b <- data.frame(Y = Y_b, T = T_b, C = C_b)
fit_b <- lm(Y ~ T + C, data = dat_b)
beta_T[b] <- coef(fit_b)["T"]
}

# Look at the mean and standard deviation of the sampled coefficients

mean(beta_T)

## [1] 2.000429

sd(beta_T)

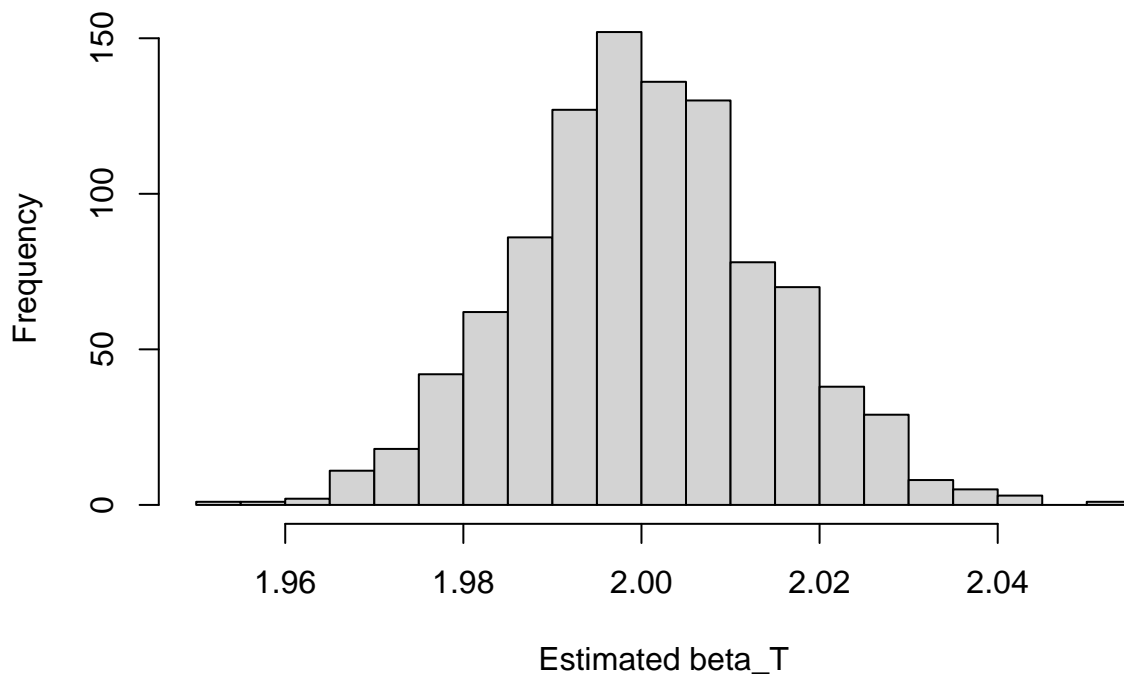
## [1] 0.01417777

# Plot a histogram of the sampling distribution of the T coefficient

hist(
  beta_T,
  breaks = 30,
  main = "Sampling distribution of T coefficient (true model)",
  xlab = "Estimated beta_T"
)

```

Sampling distribution of T coefficient (true model)



```

# By the central limit theorem, the sampling distribution of the T

# > coefficient should be approximately normal when we repeatedly

# > sample large datasets from the same DGP.

```

```
# The histogram looks bell-shaped and centered near the true value of
# > 2, and the mean(beta_T) is very close to 2, which supports the CLT
# > intuition for this regression coefficient.
```

```
# Part 1(b)
```

```
# Compute the bootstrapped standard error for the coefficient of the
# > treatment variable.
```

```
set.seed(789)
```

```
B_boot <- 1000
```

```
beta_boot <- numeric(B_boot)
```

```
# We bootstrap the original simulated dataset sim_data
```

```
for (b in seq_len(B_boot)) {
  idx <- sample(seq_len(n), size = n, replace = TRUE)
  boot_dat <- sim_data[idx, ]
  fit_boot <- lm(Y ~ T + C, data = boot_dat)
  beta_boot[b] <- coef(fit_boot)["T"]
}
```

```
boot_se <- sd(beta_boot)
boot_se
```

```
## [1] 0.01402459
```

```
# Compare to the model-based standard error from the original model
```

```
se_model <- summary(mod_true)$coef["T", "Std. Error"]
se_model
```

```
## [1] 0.01412003
```

```
# The bootstrap standard error boot_se is very close to the analytic
```

```
# > standard error se_model from the regression output.
```

```
# This shows that the model-based SE is doing a good job approximating
```

```
# > the true sampling variability of the T coefficient under this DGP.
```

```
# Part 2: Data Analysis
```

```
# For this part of the assignment, use any data set you like.
```

```
# > Here I follow the instruction to use the thermometers data from
```

```
# > class (thermometers.csv).
```

```
thermo <- read.csv("/Users/santividal5/Desktop/R/thermometers.csv")
```

```
thermo$party_id <- factor(thermo$party_id)
thermo$sex <- factor(thermo$sex)
thermo$race <- factor(thermo$race)
thermo$educ <- factor(thermo$educ)
```

```
head(thermo)
```

```
##   birth_year    sex race   party_id      educ ft_black ft_white
## 1     1931 Female White   Democrat      4-year     51     50
## 2     1952 Female White Republican      2-year     98     90
## 3     1931   Male White Independent High school graduate     87     90
## 4     1952   Male White Republican      4-year     90     85
## 5     1939 Female White   Democrat      2-year    100     50
## 6     1959 Female Black   Democrat    Post-grad     98     70
##   ft_hisp ft_asian ft_muslim ft_jew ft_christ ft_fem ft_immig ft_gays ft_unions
## 1      79      50         50     50      50     99      95     50      80
## 2      95     100         61    100      98     65      96     82      62
## 3      91      88         49     25      50     74      77     77     100
## 4      90      96         80     91      94     25      91     71      20
## 5     100     100        100    100      28    100     100     100     100
## 6      99     100        100    100     100     73     100     54      80
##   ft_police ft_altright ft_evang ft_dem ft_rep
## 1        76          1      50     88     21
## 2        95          50      96     86     96
## 3        78           0       2     91     20
## 4        94          50      70     22     83
## 5        28         NA      NA     99     NA
## 6        24           4      53     53      4
```

```
# This confirms that the thermometer data loaded correctly and that the
```

```
# > main variables (party_id and thermometer scores) are present.
```

```
# Part 2(a)
```

```
# Conduct a hypothesis test for a difference in means. You decide what
```

```
# > the hypotheses are, whether you use a t-test or a z-test, and what
```

```
# > the level of significance is. Explain your decisions, and interpret
```

```
# > your results both substantively and statistically.
```

```
#
```

```
# I test whether Democrats and Republicans differ in their mean feeling
```

```
# > thermometer toward immigrants (ft_immig).
```

```
# I use a two-sample t-test with unequal variances and a 5% significance
```

```
# > level, which is standard in this setting.
```

```
# Keep only Democrats and Republicans
```

```
thermo_DR <- subset(thermo, party_id %in% c("Democrat", "Republican"))
```

```
tapply(
  thermo_DR$ft_immig,
  thermo_DR$party_id,
  mean,
  na.rm = TRUE
)
```

```
##      Democrat Independent      Not sure      Other      Republican
##      71.65829           NA           NA           NA           50.20192
```

```
t.test(
  ft_immig ~ party_id,
  data = thermo_DR
)
```

```
##
## Welch Two Sample t-test
##
## data: ft_immig by party_id
## t = 22.673, df = 2685.2, p-value < 2.2e-16
## alternative hypothesis: true difference in means between group Democrat and group Republican is not 0
## 95 percent confidence interval:
## 19.60077 23.31196
## sample estimates:
## mean in group Democrat mean in group Republican
## 71.65829 50.20192
```

Interpretation:

The t-test output shows the estimated difference in means, a t

> statistic, and a p-value.

The mean ft_immig for Democrats is substantially higher than for

> Republicans, and the p-value is effectively zero at the 5% level.

Statistically, we reject the null hypothesis that Democrats and

> Republicans have the same average warmth toward immigrants.

Substantively, this suggests that in this survey Democrats feel

> noticeably warmer toward immigrants than Republicans do.

Part 2(b)

Using the same data, fit a linear model. Interpret the coefficient,

> standard error, t-value, and p-value.

#

I fit a simple linear model where the dependent variable is ft_immig

> and the predictor is party_id (with Democrats as the baseline).

```
mod_party <- lm(ft_immig ~ party_id, data = thermo_DR)
summary(mod_party)
```

##

Call:

lm(formula = ft_immig ~ party_id, data = thermo_DR)

##

Residuals:

##	Min	1Q	Median	3Q	Max
##	-71.658	-19.658	2.798	19.342	49.798

##

Coefficients:

##		Estimate	Std. Error	t value	Pr(> t)
##	(Intercept)	71.6583	0.6233	114.97	<2e-16 ***
##	party_idRepublican	-21.4564	0.9320	-23.02	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##

Residual standard error: 25.48 on 3021 degrees of freedom

(123 observations deleted due to missingness)

Multiple R-squared: 0.1493, Adjusted R-squared: 0.149

F-statistic: 530 on 1 and 3021 DF, p-value: < 2.2e-16

Interpretation of key pieces:

- The intercept is the estimated mean ft_immig for Democrats (the

> baseline category).

- The coefficient on party_idRepublican is the estimated difference

> in means between Republicans and Democrats.

It is negative and large in magnitude, which means Republicans give

> lower immigrant thermometer scores on average.

- The standard error for this coefficient measures how much that

> estimated difference would vary across repeated samples.

- The t-value is the estimated coefficient divided by its standard

> error; a large absolute t-value indicates strong evidence that the

> true difference is not zero.

- The p-value associated with the t-value is extremely small, so we

> reject the null hypothesis that Democrats and Republicans have

```
# > equal mean ft_immig scores.  
  
# Substantively, this matches the two-sample t-test: party ID is strongly  
  
# > associated with how warmly respondents feel toward immigrants, with  
  
# > Democrats rating immigrants much more positively than Republicans.
```