

# ECONOMETRICS I: PROBLEM SET 3

## EXERCISE: MLE

- a) Show that, under  $e \sim N(0, \sigma^2)$  MLE estimators of  $\beta$  and  $\sigma^2$  are equivalent to OLS.
- b) Execute the following R code, which serves as an example to obtain robust standard errors for heteroscedasticity and the corresponding hypothesis t-tests.

Example:

```
#Environment:
library(AER)           # install.packages("AER")
data("CPSSWEducation")
attach(CPSSWEducation) # ?CPSSWEducation

# Model
reg <- lm(earnings ~ education)
summary(reg)

# Plot observations and add the regression line
plot(education, earnings, ylim = c(0, 150))
abline(labor_model, col = "steelblue", lwd = 2)

# Compute homoskedastic-robust standard errors.
t <- linearHypothesis(reg, "X = 0")$'Pr(>F)'[2] < 0.05

# Compute heteroskedasticity-robust (HC1) standard errors
t.rob <- linearHypothesis(reg,
                          "X = 0", white.adjust = "hc1")$'Pr(>F)'[2] < 0.05

# Show both t-tests, where 1="true" meaning Ho is "true" at the 95% level.
round(cbind(t = mean(t), t.rob = mean(t.rob)), 3)

# Same for the varcov matrix
(vcov <- vcovHC(labor_model, type = "HC1"))

# Compute the square root of the diagonal elements in vcov
(robust_se <- sqrt(diag(vcov)))
```

```
# We use `coefstest()` on our robust model and show the assumed-homoskedastic
# model:
coefstest(labor_model, vcov. = vcov)
summary(labor_model)
```

- Generate heteroscedastic data for two variables (X) and (Y) (as in 1.c), which satisfy the population equation  $Y = \alpha + \beta X + e$ , where  $\beta = 1$ .
  - Create a scatterplot of these variables with a fitted line showing their relationship.
  - Perform 10,000 regressions, each with new random samples drawn from the same distribution established in (1.c).
  - For each  $i = 1, \dots, 10,000$ , perform the “HC0” and “HC2” t-tests and store them in vectors `t` and `t.rob`.
  - Compute the percentage of rejections of the null hypothesis  $\beta = 1$ .
  - What is the conclusion of this result?
- c) MLE is the technique that helps us determine the parameters of the distribution that best describe the given data. Imagine that we have a sample that was drawn from a normal distribution with mean  $\mu = 5$  and variance  $\sigma^2 = 100$ . The objective is to estimate these parameters with MLE.

The normal log-likelihood function is given by:  $l = -\frac{1}{2}n\ln(2\pi) - \frac{1}{2}n\ln(\sigma^2) - \frac{1}{2\sigma^2} \sum (y_i - \mu)^2$

\*Note that minimizing a negative likelihood function is the same as maximizing the likelihood function.

```
# We define:
X <- rnorm(n = 1000, mean = 5, sd = 10)
df <- data.frame(X)

# We program the log-likelihood function in R:
normal.lik1 <- function(theta,y){
  mu<-theta[1]
  sigma2<-theta[2]
  n<-nrow(y)
  logl<- -.5*n*log(2*pi)-.5*n*log(sigma2)-(1/(2*sigma2))*sum((y-mu)^2)
  return(-logl)
}

# Here theta is a vector containing the two parameters of interest
# (i.e. theta[1] is equal to mu). The remainder sets n, and the log-likelihood function.

# we use optim(starting values, log-likelihood, data) with starting values 0 and 1.
optim(c(0,1), normal.lik1, y=df)

#We can ask for the method-of-moments-mean directly:
mean(X)
var(X)
```

- Now, estimate the MLE parameters  $\beta$  and  $\sigma^2$  with  $Y = 5 + 2X + e$ .

d) Show that plugging in the estimators  $\beta_{mle}^2$  and  $\hat{\sigma}_{mle}^2$  into:

$$l_n(\beta, \sigma^2) = -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (Y_i - X_i' \beta)^2$$

We get the maximized log likelihood function. How does it work as a measure of fit?

e) Let  $x_1, x_2, \dots, x_n$  be a random sample from each of the following probability density function (pdf):

(a) Bernoulli distribution

$$f(x; \theta) = \theta^x (1 - \theta)^{1-x}, \quad 0 \leq \theta \leq 1, \quad x = 0, 1$$

(b) Poisson distribution

$$f(x; \theta) = \frac{\theta^x e^{-\theta}}{x!}, \quad x = 0, 1, 2, \dots, \quad 0 \leq \theta < \infty$$

(c) Exponential distribution

$$f(x; \theta) = \theta e^{-\theta x}, \quad 0 < x < \infty, \quad 0 < \theta < \infty$$

Derive the maximum likelihood estimator (MLE) of  $\theta$  for a single case. Verify that the second derivative of the log-likelihood is negative, ensuring a maximum of the likelihood function.