# Problem Set 1

### Applied Stats II

Due: February 11, 2024

### Instructions

- Please show your work! You may lose points by simply writing in the answer. If the problem requires you to execute commands in R, please include the code you used to get your answers. Please also include the .R file that contains your code. If you are not sure if work needs to be shown for a particular problem, please ask.
- Your homework should be submitted electronically on GitHub in .pdf form.
- This problem set is due before 23:59 on Sunday February 11, 2024. No late assignments will be accepted.

## Question 1

The Kolmogorov-Smirnov test uses cumulative distribution statistics test the similarity of the empirical distribution of some observed data and a specified PDF, and serves as a goodness of fit test. The test statistic is created by:

$$D = \max_{i=1:n} \left\{ \frac{i}{n} - F_{(i)}, F_{(i)} - \frac{i-1}{n} \right\}$$

where F is the theoretical cumulative distribution of the distribution being tested and  $F_{(i)}$  is the *i*th ordered value. Intuitively, the statistic takes the largest absolute difference between the two distribution functions across all x values. Large values indicate dissimilarity and the rejection of the hypothesis that the empirical distribution matches the queried theoretical distribution. The p-value is calculated from the Kolmogorov- Smirnoff CDF:

$$p(D \le x) \frac{\sqrt{2\pi}}{x} \sum_{k=1}^{\infty} e^{-(2k-1)^2 \pi^2/(8x^2)}$$

which generally requires approximation methods (see Marsaglia, Tsang, and Wang 2003). This so-called non-parametric test (this label comes from the fact that the distribution of the test statistic does not depend on the distribution of the data being tested) performs

poorly in small samples, but works well in a simulation environment. Write an R function that implements this test where the reference distribution is normal. Using R generate 1,000 Cauchy random variables (rcauchy(1000, location = 0, scale = 1)) and perform the test (remember, use the same seed, something like set.seed(123), whenever you're generating your own data).

As a hint, you can create the empirical distribution and theoretical CDF using this code:

```
# create empirical distribution of observed data
ECDF <- ecdf(data)
empiricalCDF <- ECDF(data)
# generate test statistic
D <- max(abs(empiricalCDF - pnorm(data)))</pre>
```

#### Code for problem 1

```
# Kolmogorov-Smirnov test function
    set . seed (123)
    kol_smir_test <- function(sample_size = 1000, location = 0, scale = 1) {
3
      data <- reauchy (sample_size, location = location, scale = scale)
      ECDF <- ecdf (data)
5
      empiricalCDF <- ECDF(data)
      D <- max(abs(empiricalCDF - pnorm(data)))
7
      print(paste("Kolmogorov-Smirnov test statistic (D) : ", D))
      return (D)
9
    # Calling the function
    kol_smir_result <- kol_smir_test()
    print(kol_smir_result)
    # Calculating the p-value
14
    D \leftarrow 0.13472806160635
    pvalue_3 \leftarrow 1 - pnorm(sqrt(n) * D)
16
    pvalue_3 \leftarrow 1 - pnorm(sqrt(1000) * 0.13472806160635)
17
    print (pvalue_3)
18
    # doing the ks.test to compare results
19
    ks_result3 <- ks.test(data, "pnorm")
20
   print(ks_result3)
```

Output: The p-value from my function is pvalue-3 = 1.019963e-05 and the p-value from the ks.test is ks-result 3 = 2.22e-16. I know mine is still higher than the ks.test but is the closest to zero I got after changing the function a lot. Actual output from ks.test: Asymptotic one-sample Kolmogorov-Smirnov testdata: dataD = 0.13573, p-value = 2.22e-16 alternative hypothesis: two-sided

## Question 2

Estimate an OLS regression in R that uses the Newton-Raphson algorithm (specifically BFGS, which is a quasi-Newton method), and show that you get the equivalent results to using lm. Use the code below to create your data.

```
set.seed (123)
\frac{data}{data} \leftarrow \frac{data.frame}{data.frame} (x = runif(200, 1, 10))
\frac{data}{data} = 0 + 2.75 * \frac{data}{data} + \frac{data}{data} = 0 + 1.5
```

#### Code

```
1 # Generating the data
2 set . seed (123)
\frac{data}{data} \leftarrow \frac{data.frame}{data} \left( x = runif(200, 1, 10) \right)
\frac{data}{data} < 0 + 2.75 * \frac{data}{x} + \frac{rnorm}{200}, 0, 1.5
5 # defining the function
6 OLS_obj <- function(beta, x, y) {
     y_e esp \leftarrow beta[1] + beta[2] *x
     error \leftarrow y - y_esp
     return (sum (error ^2))
11 # Beta values at first
\frac{12}{12} \frac{\text{beta}}{\text{um}} \leftarrow c(0, 0)
13 # Optimising with BFGS
bfg_otimo \leftarrow optim(par = beta_um, fn = OLS_obj, x = data$x, y = data$y, method
        = "BFGS")
15 # getting the estimated coefficients
16 bfg_estcoef <- bfg_otimo$par
17 # Comparing the coefficients from BFGS with the lm
lm_{comp} \leftarrow lm(y x, data = data)
19 \operatorname{coef}_{-\operatorname{lm}} \leftarrow \operatorname{coef}(\operatorname{lm}_{-\operatorname{comp}})
20 #
print (bfg_estcoef)
22 print (coef_lm)
```

Output: bfg-estcoef = 0.1391778 , 2.7267000 and coef-lm = (Intercept) = 0.1391874 , x = 2.7266985