

Problem Set 4

Applied Stats/Quant Methods 1

Due: December 3, 2023

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.
- This problem set is due before 23:59 on Sunday December 3, 2023. No late assignments will be accepted.

Question 1: Economics

In this question, use the **prestige** dataset in the **car** library. First, run the following commands:

```
install.packages(car)
library(car)
data(Prestige)
help(Prestige)
```

We would like to study whether individuals with higher levels of income have more prestigious jobs. Moreover, we would like to study whether professionals have more prestigious jobs than blue and white collar workers.

- (a) Create a new variable **professional** by recoding the variable **type** so that professionals are coded as 1, and blue and white collar workers are coded as 0 (Hint: **ifelse**).

```
1 Prestige$professional <- ifelse(Prestige$type == "professional", 1,
2 0)
```

This code creates a new variable **professional** in the **Prestige** dataset by recoding the variable **type**. Professionals are coded as 1, and blue and white collar workers are coded as 0.

- (b) Run a linear model with **prestige** as an outcome and **income**, **professional**, and the interaction of the two as predictors (Note: this is a continuous \times dummy interaction.)

```
1 model <- lm(prestige ~ income * professional, data = Prestige)
2
```

This code runs a linear model with **prestige** as the outcome variable and **income**, **professional**, and their interaction as predictors.

- (c) Write the prediction equation based on the result.

To write the prediction equation based on the result, you can use the following code in R:

```
1 summary(model)
2
```

This code provides a summary of the linear model, including the coefficients and the prediction equation.

Call:

```
lm(formula = prestige ~ income * professional, data = Prestige)
```

Residuals:

Min	1Q	Median	3Q	Max
-32.085	-8.648	-2.498	8.979	31.879

Coefficients: (2 not defined because of singularities)

Estimate Std. Error t value Pr(>|t|)

(Intercept)	2.760e+01	2.380e+00	11.594	< 2e-16 ***
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income	2.844e-03	2.933e-04	9.694	6.77e-16 ***
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professional	NA	NA	NA	NA
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income:professional	NA	NA	NA	NA
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---Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 12.22 on 96 degrees of freedom

(4 observations deleted due to missingness)

Multiple R-squared: 0.4946, Adjusted R-squared: 0.4894
 F-statistic: 93.97 on 1 and 96 DF, p-value: 6.773e-16

(d) Interpret the coefficient for `income`.

```
1 coefficients(summary(model))["income"]
2
```

[1] NA

(e) Interpret the coefficient for `professional`.

```
1 coefficients(summary(model))["professional"]
2
```

[1] NA

(f) What is the effect of a \$1,000 increase in income on prestige score for professional occupations? In other words, we are interested in the marginal effect of income when the variable `professional` takes the value of 1. Calculate the change in \hat{y} associated with a \$1,000 increase in income based on your answer for (c).

```
1 fitted_value <- fitted(model) new_income <- 1000 new_prestige <-
  predict(model, newdata = data.frame(income = new_income, professional
  = 1)) effect <- new_prestige - fitted_value effect
2
```

gov.administrators	general.managers	accountants
-32.277412	-70.745286	-23.519203
purchasing.officers	chemists	physicists
-22.364712	-21.050981	-28.521050
biologists	architects	civil.engineers
-20.638662	-37.429969	-29.507771
mining.engineers	surveyors	draughtsmen
-28.501145	-13.939201	-17.229217
computer.programers	economists	psychologists
social.workers	lawyers	librarians
-15.173313	-51.932198	-14.536352
vocational.counsellors	ministers	university.teachers
primary.school.teachers	secondary.school.teachers	physicians
veterinarians	osteopaths.chiropractors	nurses
-38.553181	-46.913289	-10.276678
nursing.aides	physio.therapsts	pharmacists
-7.066282	-11.635906	-26.820593
medical.technicians	commercial.artists	radio.tv.announcers
secretaries	typists	bookkeepers

-8.633092	-6.107998	-9.520287
tellers.cashiers	computer.operators	shipping.clerks
-4.117496	-9.469103	-10.694683
file.clerks	receptionsts	mail.carriers
-5.732646	-5.405635	-12.827364
postal.clerks	telephone.operators	collectors
-7.788550	-6.144964	-10.637812
claim.adjustors	travel.clerks	office.clerks
-11.522163	-14.954357	-8.743991
sales.supervisors	commercial.travellers	sales.clerks
-18.432049	-22.123008	-4.532657
service.station.attendant	insurance.agents	real.estate.salesme
buyers	firefighters	policemen
-19.779903	-22.450019	-22.438645
cooks	bartenders	funeral.directors
-6.017003	-8.331673	-19.532512
launderers	janitors	elevator.operators
-5.687149	-7.029316	-7.342109
farm.workers	rotary.well.drillers	bakers
-1.865385	-16.663346	-9.096594
slaughterers.1	slaughterers.2	canners
-11.755336	-11.755336	-2.530781
textile.weavers	textile.labourers	tool.die.makers
-9.790426	-7.066282	-20.027294
machinists	sheet.metal.workers	welders
-16.168564	-15.824491	-15.574257
auto.workers	aircraft.workers	electronic.workers
-13.680436	-15.847240	-8.365796
radio.tv.repairmen	sewing.mach.operators	auto.repairmen
aircraft.repairmen	railway.sectionmen	electrical.linemen
electricians	construction.foremen	carpenters
-17.479451	-22.407366	-12.224526
masons	house.painters	plumbers
-14.101285	-10.091845	-16.856709
construction.labourers	pilots	train.engineers
-8.274801	-37.057461	-22.307841
bus.drivers	taxi.drivers	longshoremen
-12.972386	-9.167684	-10.671934
typesetters	bookbinders	
-15.531603	-7.441634	

- (g) What is the effect of changing one's occupations from non-professional to professional when her income is \$6,000? We are interested in the marginal effect of professional

jobs when the variable `income` takes the value of 6,000. Calculate the change in \hat{y} based on your answer for (c).

```
1 new_income <- 6000new_prestige <- predict(model, newdata = data.frame
  (income = new_income, professional = 1))old_prestige <- predict(model,
  newdata = data.frame(income = new_income, professional = 0))effect <-
  new_prestige - old_prestige
2 effect
```

Question 2: Political Science

Researchers are interested in learning the effect of all of those yard signs on voting preferences.¹ Working with a campaign in Fairfax County, Virginia, 131 precincts were randomly divided into a treatment and control group. In 30 precincts, signs were posted around the precinct that read, “For Sale: Terry McAuliffe. Don’t Sellout Virginia on November 5.”

Below is the result of a regression with two variables and a constant. The dependent variable is the proportion of the vote that went to McAuliffe’s opponent Ken Cuccinelli. The first variable indicates whether a precinct was randomly assigned to have the sign against McAuliffe posted. The second variable indicates a precinct that was adjacent to a precinct in the treatment group (since people in those precincts might be exposed to the signs).

Impact of lawn signs on vote share	
Precinct assigned lawn signs (n=30)	0.042 (0.016)
Precinct adjacent to lawn signs (n=76)	0.042 (0.013)
Constant	0.302 (0.011)

Notes: $R^2=0.094$, $N=131$

- (a) Use the results from a linear regression to determine whether having these yard signs in a precinct affects vote share (e.g., conduct a hypothesis test with $\alpha = .05$).

¹Donald P. Green, Jonathan S. Krasno, Alexander Coppock, Benjamin D. Farrer, Brandon Lenoir, Joshua N. Zingher. 2016. “The effects of lawn signs on vote outcomes: Results from four randomized field experiments.” *Electoral Studies* 41: 143-150.

```

1 data <- data.frame( group = c(rep("treatment", 30), rep("control", 76)
   ), vote_share = c(0.042, 0.042, rep(NA, 104)), adjacent = c(rep(NA,
   30), rep(1, 76)))
2 # Run a linear regression
3 model <- lm(vote_share ~ group, data = data)
4 # Summary of the regression
5 summary(model)
6

```

Call:

```
lm(formula = prestige ~ income * professional, data = Prestige)
```

Residuals:

Min	1Q	Median	3Q	Max
-32.085	-8.648	-2.498	8.979	31.879

Coefficients: (2 not defined because of singularities)

Estimate Std. Error t value Pr(>|t|)

(Intercept) 2.760e+01 2.380e+00 11.594 < 2e-16 ***

income 2.844e-03 2.933e-04 9.694 6.77e-16 ***

professional NA NA NA NA

income:professional NA NA NA NA

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

Residual standard error: 12.22 on 96 degrees of freedom

(4 observations deleted due to missingness)

Multiple R-squared: 0.4946, Adjusted R-squared: 0.4894

F-statistic: 93.97 on 1 and 96 DF, p-value: 6.773e-16

- (b) Use the results to determine whether being next to precincts with these yard signs affects vote share (e.g., conduct a hypothesis test with $\alpha = .05$).

```

1 data <- data.frame( group = factor(c(rep("treatment", 30), rep("
   control", 76))), vote_share = c(0.042, 0.042, rep(NA, 104)),
   adjacent = c(rep(NA, 30), rep(1, 76)))
2 # Run a linear regression
3 model <- lm(vote_share ~ group + adjacent, data = data)
4 # Summary of the regression
5 summary(model)
6

```

- (c) Interpret the coefficient for the constant term substantively.

```
1 data <- data.frame( group = factor(c(rep("treatment", 30), rep("
  control", 76))), vote_share = c(0.042, 0.042, rep(NA, 104)),
  adjacent = c(rep(NA, 30), rep(1, 76)))
2 # Run a linear regression
3 model <- lm(vote_share ~ group + adjacent, data = data)
4 # Summary of the regression
5 summary(model)
6
```

- (d) Evaluate the model fit for this regression. What does this tell us about the importance of yard signs versus other factors that are not modeled?

```
1 # Load the data
2 data <- data.frame(
3   group = factor(c(rep("treatment", 30), rep("control", 76))),
4   vote_share = c(0.042, 0.042, rep(NA, 104)),
5   adjacent = c(rep(NA, 30), rep(1, 76))
6 )
7
8 # Run a linear regression
9 model <- lm(vote_share ~ group + adjacent, data = data)
10
11 # Evaluate the model fit
12 summary(model)
13
```

In the output of the `summary(model)` function, we can look at the R-squared value, which measures the proportion of the variance in the dependent variable that is predictable from the independent variables. A higher R-squared value indicates a better fit of the model to the data. Additionally, we can examine the p-values for the coefficients of the independent variables to assess their significance in explaining the variation in the dependent variable. This information will help us understand the importance of yard signs versus other factors that are not modeled in the regression.