Survey Data Analysis R Reference Guide

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Contents

1 Reading & Exploring Data

To read in your data:

```
# Comma delimited format
dat <- read.csv("~/your/file/path")
# Tab delimited format
dat <- read.table("~/your/file/path")
# Stata (.dta) format
library(haven)
dat <- read_dta("~/your/file/path")
```

To view observations or summaries of a variable:

```
# Print the top few observations of a variable
head(dataframe$vector)
# Print the bottom few observations of a variable
tail(dataframe$vector)
# Print all observations of a variable
print(dataframe$vector)
# Access a summary of a variable or model
summary(dataframe$vector)
summary(model)
```

To learn the structure or format of your data:

```
# Access the type / storage mode of the data
typeof(dataframe$vector)
# Access the structure of the data
str(dataframe)
str(dataframe$vector)
# Access the length of a vector (e.g. the number of observations)
length(dataframe$vector)
# Access the attributes and metadata of an object
attributes(dataframe)
attributes(dataframe$vector)
```

2 Manipulating Data

2.1 Recoding Data

To recode values in base R:

```
#Create a new vector to work with
cces16$ban_ar <- cces16$CC16_330d
#Attitudes toward gun control
#Call all values for "oppose" and replace with zero
cces16$ban_ar[cces16$ban_ar==2] <- 0
#Call all values for skipped / not asked and replace with missing
cces16$ban_ar[cces16$ban_ar==8] <- NA
cces16$ban_ar[cces16$ban_ar==9] <- NA
```

To collapse categories of an ordinal variable in base R:

```
#Create a new vector to work with
cces16$pid <- cces16$pid7
#Recode values to missing
cces16$pid[cces16$pid==98] <- NA
cces16$pid[cces16$pid==99] <- NA
cces16$pid[cces16$pid==8] <- NA
#Collapse the categories
cces16$pid[cces16$pid==2] <- 1
cces16$pid[cces16$pid==3] <- 1
cces16$pid[cces16$pid==4] <- 2
cces16$pid[cces16$pid==5] <- 3
cces16$pid[cces16$pid==6] <- 3
cces16$pid[cces16$pid==7] <- 3
```

To cut a continuous variable into an ordinal one in base R:

```
cces16$agecats <- cut(cces16$age,
                      breaks=c(-Inf, 35, 50, Inf),
                      labels=c("35 and Under","36 to 50","Over 50"))
```

To flip the direction of coding in base R:

```
#Flip the coding
cces16$pid_reverse <- 4 - cces16$pid
```

To apply labels to factor levels of a recoded variable:

```
cces16$pid_reverse <- factor(cces16$pid_reverse,
                             levels = c(1,2,3),
                             labels = c("Republican", "Independent",
                             "Democrat"))
```

2.2 Merging Data

To merge data that have one common vector with the same name:

```
library(haven)
cces16 <- read_dta("~/your/filepath/here")
cces16s <-  read.delim("~/your/filepath/here")
#Merge the primary and supplemental data by respondent state
cces16c <- merge(cces16, cces16s)
```

To merge data that have a common vector with different names:

```
#Merge by state with different column names
cces16c <- merge(cces16, cces16s,
                 by.x = "inputstate",
                 by.y = "inputstate")
```

3 Descriptive Statistics

3.1 Summary Statistics

To summarize a variable:

```
summary(cces16$age)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  18.00   33.00   49.00   47.88   61.00   99.00
```

To call specific summary statistics:

```
#Mean
mean(cces16$age)
#Standard deviation
sd(cces16$age)
#Minimum
min(cces16$age)
#Maximum
max(cces16$age)
#Range
range(cces16$age)
#Quantiles
quantile(cces16$age)
```

3.2 Tabulations & Cross Tabulations

To tabulate a variable:

```
# Tabulate PID
prop.table(table(cces16$pid_reverse))
 Republican Independent    Democrat
  0.3336641   0.1679444   0.4983915
```

To cross-tabulate two variables:

```
# Tabulate PID by age categories
pidxage <- table(cces16$pid_reverse, cces16$agecats)
pidxage
prop.table(pidxage,2)
              35 and Under  36 to 50   Over 50
  Republican     0.2613407 0.3150328 0.3868747
  Independent    0.1708327 0.1874692 0.1569152
  Democrat       0.5678266 0.4974981 0.4562101
```

3.3 Summary Statistics by Group

To summarize variables by group in base R:

```
#Create a dataframe of the variables of interest
subgroup_vars <- c("age","pid")
subgroup_matrix <- as.matrix(cces16[subgroup_vars])
subgroup_df <- as.data.frame(subgroup_matrix)
aggregate(subgroup_df$age, list(subgroup_df$pid), mean)

  Group.1        x
1       1 46.58152
2       2 46.97732
3       3 51.23725
```

To summarize variables by group with `dplyr`:

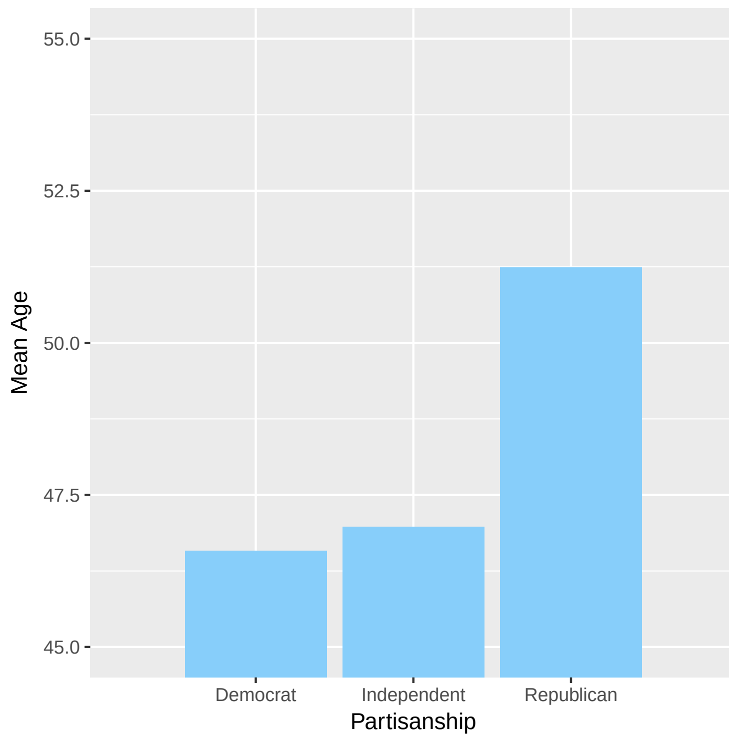
```
library(dplyr)
subgroup_means <- subgroup_df %>%
  group_by(pid) %>%
  summarise(mean = mean(age))
subgroup_means

# A tibble: 4 x 2
    pid  mean
  <dbl> <dbl>
1     1  46.6
2     2  47.0
3     3  51.2
4    NA  38.4
```

To visualize subgroup means with `ggplot`:

```
pid_labels <- c("Democrat", "Independent", "Republican")
sg_bp <- ggplot(subgroup_means, aes(y=mean, x=pid)) +
  geom_bar(fill="lightskyblue",stat="identity") +
  #xlab("Partisanship") +
  ylab("Mean␣Age") +
  scale_x_discrete(name = "Partisanship",
                   limits=pid_labels)
sg_bp + coord_cartesian(ylim=c(45,55))
```

Figure 1: *Bar Plot of Mean Age by Partisanship*

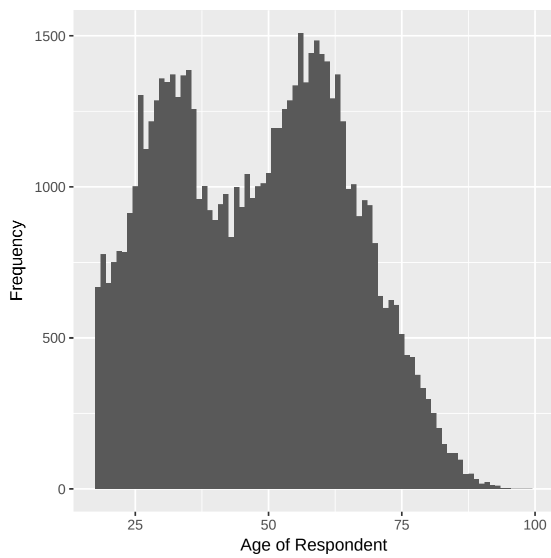


3.4 Distributions

To plot a histogram of a variable's distribution using `ggplot2`:

```
#Histogram for age
library(ggplot2)
age_matrix <- as.matrix(cces16$age)
age_df <- as.data.frame(age_matrix)
ggplot(data = age_df, aes(x=age_df)) +
  geom_histogram(binwidth = 1) +
  xlab("Age␣of␣Respondent") +
  ylab("Frequency")
#Density plot
ggplot(data = age_df, aes(x=age_df)) +
  geom_density(fill="lightblue") +
  xlab("Age␣of␣Respondent") +
  ylab("Density")
```

Figure 2: Plotting Variable Distributions



(a) Histogram

(b) Density Plot

4 Modeling

4.1 OLS Regression

```
## OLS Regression
# Prepare Obama approval as the DV
cces16$oa <- cces16$CC16_320a
cces16$oa[cces16$oa=="5"] <- NA
cces16$oa[cces16$oa=="8"] <- NA
cces16$oa <- 5 - cces16$oa
# Fit the OLS model
olsfit <- lm(oa ~ pid + ideology +
             gender + white + edu + age,
             data = cces16)
# Print the model summary
summary(olsfit)

Call:
lm(formula = oa ~ pid + ideology + gender + white + edu + age,
    data = cces16)

Residuals:
<Labelled double>
    Min      1Q  Median      3Q     Max
-2.9182 -0.4282 -0.0995  0.5670  3.4652

Coefficients:
              Estimate Std. Error  t value Pr(>|t|)
(Intercept)  3.5857187  0.0229650  156.139  < 2e-16 ***
pid         -0.8320592  0.0046920 -177.334  < 2e-16 ***
ideology     0.2180571  0.0038937   56.003  < 2e-16 ***
gender      -0.0514957  0.0067446   -7.635 2.29e-14 ***
white       -0.1420162  0.0062221  -22.824  < 2e-16 ***
edu          0.0450144  0.0023178   19.421  < 2e-16 ***
age         -0.0047770  0.0002035  -23.472  < 2e-16 ***
---
Signif. codes:  0 ‘***‘ 0.001 ‘**‘ 0.01 ‘*‘ 0.05 ‘.‘ 0.1 ‘ ‘ 1

Residual standard error: 0.7994 on 57165 degrees of freedom
  (7428 observations deleted due to missingness)
Multiple R-squared:  0.594,     Adjusted R-squared:  0.594
F-statistic: 1.394e+04 on 6 and 57165 DF,  p-value: < 2.2e-16
```

4.2 Logistic Regression

```
## Logistic Regression
# Prepare preference for AR ban as DV
cces16$ban_ar <- cces16$CC16_330d
cces16$ban_ar[cces16$ban_ar==2] <- 0
cces16$ban_ar[cces16$ban_ar==8] <- NA
cces16$ban_ar[cces16$ban_ar==9] <- NA
# Fit the logit model
lfit <- glm(ban_ar ~ pid + agecats + edu +
             gender + white + ideology,
           data=cces16, family = binomial())
# Print the model summary
summary(lfit)

Call:
glm(formula = ban_ar ~ pid + agecats + edu + gender + white +
    ideology, family = binomial(), data = cces16)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6730  -0.8953   0.4643   0.7626   2.1389

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.479470   0.062011   7.732 1.06e-14 ***
pid             -0.764097   0.013481 -56.678  < 2e-16 ***
agecats36 to 50  0.348234   0.028295  12.307  < 2e-16 ***
agecatsOver 50   0.787903   0.024658  31.953  < 2e-16 ***
edu              0.096402   0.007027  13.719  < 2e-16 ***
gender          -0.933141   0.020543 -45.423  < 2e-16 ***
white           -0.023337   0.018977  -1.230    0.219
ideology         0.492440   0.012057  40.842  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 74291  on 58396  degrees of freedom
Residual deviance: 59454  on 58389  degrees of freedom
  (6203 observations deleted due to missingness)
AIC: 59470

Number of Fisher Scoring iterations: 4
```

4.3 Ordinal Logistic Regression

```
## Ordinal Logistic Regression
# Convert Obama approval to a factor
cces16$oaf <- factor(cces16$oa)
library(MASS)
# Fit the ordinal logit model
olfit <- polr(oaf ~ pid + ideology +
                gender + white + edu + age,
              data = cces16, Hess = TRUE)
# Print the model summary
summary(olfit)

Call:
polr(formula = oaf ~ pid + ideology + gender + white + edu +
    age, data = cces16, Hess = TRUE)

Coefficients:
             Value Std. Error  t value
pid       -1.677610  0.0136729 -122.696
ideology   0.537569  0.0104278   51.552
gender    -0.156796  0.0175791   -8.919
white     -0.366697  0.0174166  -21.054
edu        0.106201  0.0060308   17.610
age       -0.009955  0.0005329  -18.681

Intercepts:
    Value    Std. Error t value
1|2   -3.0589    0.0613   -49.9253
2|3   -2.1221    0.0599   -35.4338
3|4   -0.3256    0.0587    -5.5420

Residual Deviance: 106440.27
AIC: 106458.27
(7428 observations deleted due to missingness)
```

4.4 Multinomial Logistic Regression

```
## Multinomial Logistic Regression
## Create a 2012 vote choice factor variable
cces16$vc <- cces16$CC16_326
cces16$vc[cces16$vc=="4"] <- NA
cces16$vc[cces16$vc=="5"] <- NA
cces16$vc <- factor(cces16$vc,
                    levels = c(1,2,3),
                    labels = c("Obama", "Romney","Other"))

library(nnet)
# Fit the multinomial logit model
mlfit <- multinom(vc ~ pid + agecats + edu +
                    gender + white + ideology,
                  data=cces16)
# weights:  27 (16 variable)
initial  value 50436.191560
iter  10 value 22736.899646
iter  20 value 17517.395617
iter  30 value 16746.999000
final  value 16746.972242
converged
# Print the model summary
summary(mlfit)
# Note: multinomial logit output omitted here for formatting
```

5 survey Package

All examples in this section require the `survey` package:

```
library(survey)
```

5.1 Weighted Tabulations

```
## WITHOUT WEIGHTING
# Tabulate PID
prop.table(table(cces16$pid_reverse))

# Tabulate PID by age categories
pidxage <- table(cces16$pid_reverse, cces16$agecats)
pidxage
prop.table(pidxage,2)

## WITH WEIGHTING
# Create a survey design dataframe
svy.cces16 <- svydesign(ids = ~1,
                        data = cces16,
                        weights = cces16$commonweight_vv)
# Weighted tabulation of PID
prop.table(svytable(~cces16$pid_reverse, design = svy.cces16))

# Weighted tabulation of PID by age categories
prop.table(svytable(~cces16$pid_reverse+cces16$agecats,
                    design = svy.cces16),2)
```

5.2 Weighted Models

```
## WITHOUT WEIGHTING
# Run a logit regression for attitudes toward gun control
fit <- glm(ban_ar ~ pid_reverse + agecats + edu +
             gender + white + ideology,
           data=cces16, family = binomial())
summary(fit)

## WITH WEIGHTING
wfit <- svyglm(ban_ar ~ pid_reverse + agecats + edu +
                 gender + white + ideology,
               design=svy.cces16, family = binomial())
summary(wfit)
```

5.3 Creating Post-Stratification Weights

For this example, we will mirror the process I used to generate post-stratification weights for the subsample from the 2016 CCES.