Categorical Data Visualization

```
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```

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Reuters 2016 Polling Data

Data-Cleaning \& Preparation

R.na(): "If x = NA (is.na()), replace x with v, otherwise leave x alone."

Table 1: Summary information for 'party' data column *before* recoding NAs

M	0.42
SD	0.49
Min	0.00
Max	1.00
NAs	377.00

```
unique(dat$party)
```

```
o, 1 and NA
```

```
dat*party <- sapply(dat*party, R.na, v = 99)
```

Table 2: Summary information for 'party' data column after recoding NAs

24.59
42.42
0.00
99.00
0.00

o, 1 and 99

```
dat$response <- recode_factor(dat$response,</pre>
                                "other/no opinion" = NA_character_)
## see "recode_factor()" in the {dplyr} package ##
dat <- na.omit(dat)</pre>
sapply(dat, R.isna) ## bye-bye NAs! ... again ##
```

id	response	party	partmiss	ind
О	0	О	0	О

```
## but this time we only lost data for rows with NA
## in dat$response (but we did lose ALL of the data
## for those rows, as these were removed from the
## dataframe entirely, though the original datafile remains untouched).
```

Now the data are, in my opinion, ready for analysis & plotting.

BAR PLOT of polling data (using R's Base Graphics)

```
poll.t <- table(dat$response)</pre>
```

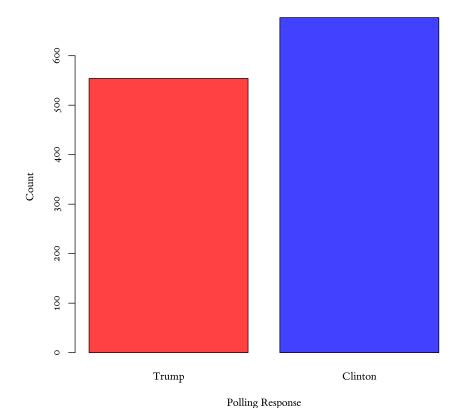
```
kable(as.data.frame(poll.t), caption = "Frequency Table of Polling Data",
      col.names = c("Response", "Frequency"))
```

Table 4: Frequency Table of Polling Data

Response	Frequency
Trump	554
Clinton	677

```
electpal <- c("red", "blue")</pre>
electpal <- sapply(electpal, adjustcolor, alpha = 0.75, USE.NAMES = FALSE)</pre>
palette(electpal)
barplot(poll.t, ylab = "Count",
        xlab = "Polling Response",
        family = "ETBembo",
        col = electpal, main = "Polling Responses")
```

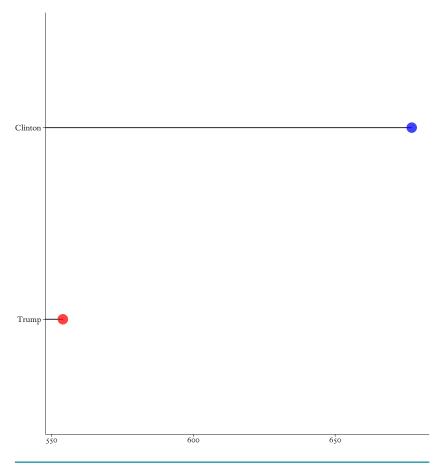
Polling Responses



Dot Plot of polling data using the ggplot2 package.

This would actually be interesting to do with repeated-measures data with the candidates on the Y-axis and time (in months/weeks) on the X-axis.

```
poll.df <- as.data.frame(poll.t)</pre>
names( poll.df) <- c("Response", "Frequency")</pre>
poll.df$N <- rep(x = nrow(dat), times = nrow(poll.df))
n <- poll.df[, 2]</pre>
bpoll <- ggplot( poll.df, aes(x = Frequency, y = Response)) +
    geom_segment(aes(yend = Response), xend = 0, colour = mypal[20]) +
    geom_point(size = 5, aes(colour = Response)) +
    scale_colour_manual(values = electpal, guide = FALSE) +
    labs(y = "", x = "") + thm_tft(xline = TRUE, yline = TRUE)
bpoll
```



Don't forget to set the x-and-y-limits! Otherwise, you could be presenting a potentially misleading visualization of the data. Since these are polling data, there is a true "zero" such that 0 would reflect 0 votes for a given candidate in a given poll. The data should thus be represented according to its appropriate scale limits.

¹ \textit{This has happened for one of the two current major party presidential candidates in the very recent past - I will not say who.}

```
bpoll + xlim(0, max( poll.df$Frequency)) +
    geom_text(vjust = -0.5, hjust = 0.5, stat = 'identity',
              position = 'identity', colour = mypal[19],
              size = rel(4), aes(family = "ETBembo", fontface = "italic",
                                  label = paste("n = ", n,
                                                 "\n", "(",
                                                 round(n/poll.df$N*100),
                                                 "%",")")))
                                                             n = 677
                                                              (55%)
  Clinton
                                                   n = 554
                                                    (45 %)
  Trump
```

Further, in plots like these, where discrete data with a relatively small number of categories² are juxtaposed with a continuous scale, setting the continuous axis' limits (in this case the x-axis) can help to further disambiguate the information.

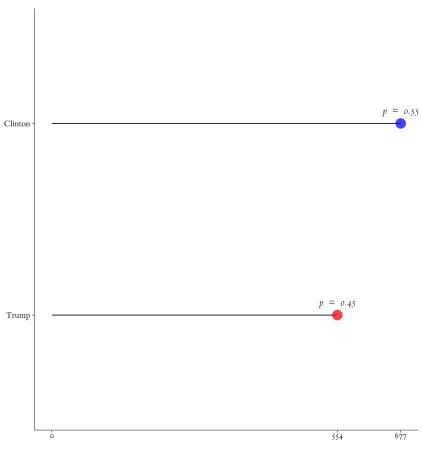
400

200

```
bpoll2 <- bpoll + scale_x_continuous(breaks = c(0, n),
                                     limits = c(0, max(n))
bpoll2 + geom_text(vjust = -1.5, hjust = 0.5, stat = 'identity',
```

² My persona rule of thumb for what constitutes a "relatively small category" is $N_{categories} \leq 5$

```
position = 'identity', colour = mypal[19],
size = rel(4), aes(family = "ETBembo",
                   fontface = "italic",
                   label = paste("p = ",
                                 round(n/ poll.df$N,
                                       digits = 2))))
```



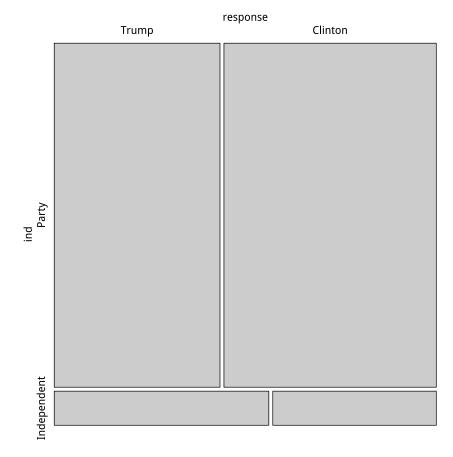
Mosaic Plots for polling data

```
dat <- within(dat, {</pre>
     resp.F <- factor(response)</pre>
     ind.F <- factor(ind)</pre>
})
tbl <- table(dat$ind.F, dat$resp.F)</pre>
tbl
```

	Trump	Clinton
0	491	629
1	63	48

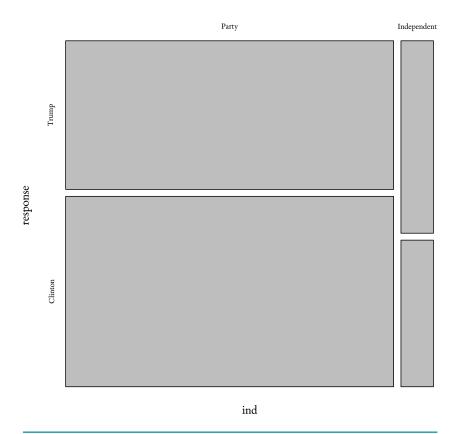
library(vcd)

```
dimnames(tbl) <- list(ind = c("Party", "Independent"),</pre>
                       response = c("Trump","Clinton"))
mosaic(tbl)
```



mosaicplot(tbl,main = "Reuters Poll Data")

Reuters Poll Data



Three-Way Mosaic Plot

```
dat <- R.rspss("data/cnnpoll.sav", vlabs = T)</pre>
ft <- with(dat, {</pre>
    ftable(dat, row.vars = 1:2, col.vars = 3)
})
ft
```

	"ind"	"party affiliate"	"independent"
"response"	"sex"		
"CLINTON	J " MALE"	100	106
	"FEMALE"	157	89
"TRUMP"	"MALE"	139	128
	"FEMALE"	140	77

```
ftc <- matrix(ft, nrow = 4, byrow = T)</pre>
```

ftc

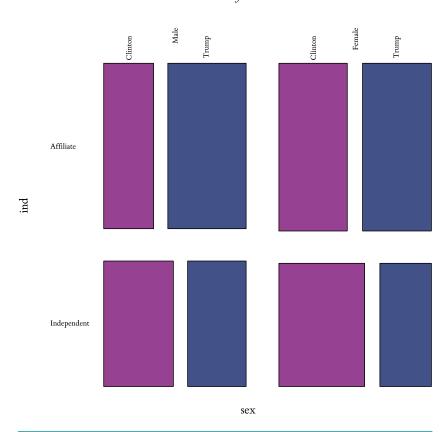
```
100
     157
139
     140
106
     89
128
     77
```

```
ftc.a <- array(ftc, dim = c(2, 2, 2), dimnames = list(</pre>
    sex = c("Male", "Female"),
    ind = c("Affiliate", "Independent"),
    response = c("Clinton", "Trump")))
ftc.a
```

100, 139, 106, 128, 157, 140, 89 and 77

mosaicplot(ftc.a, type = "deviance", las = 2, color = mypal.a75[c(5, 16)])

ftc.a



ioral and Social Sciences.

"See 'Chapter3, Figure4'"

³ Categorical Data Analysis for the Behav-

Azen and Walker3's (Chapter 3) Proficiency Data

"suppose that federal guidelines state that 80%\$ of students should demonstrate proficiency in mathematics, and in a randomly selected sample of 10 students only 70% of students were found to be proficient in mathematics. In such a case, we may wish to test whether the proportion of students who are proficient in mathematics in the population is significantly different than the federal guideline of 80%. In other words, we would like to know whether our obtained sample proportion of 0.7 is significantly lower than 0.8, so we would test the null hypothesis H_0 : $\pi=0.8$ against the (one-sided, in this case) alternative H_1 : $\pi<0.8$ " (p. 23).

"Two variables are entered: the proficiency level (prof) and the frequency (count)" (p. 32).

"Note that if raw data for 10 individuals (i.e., 10 rows of data) were analyzed, where the variable called prof consisted of 7yes responses and 3no responses, the counts would be computed by the program and would not be needed as input" (p. 32).

Azen and Walker, 4 (pp. 23 & 32)

⁴ Categorical Data Analysis for the Behavioral and Social Sciences.

The prof variable should be read by R as a string variable.

```
library(foreign) ## read.spss() ##
dat <- read.spss("data/proficient.sav", to.data.frame = TRUE)</pre>
```

Data Inspection & Cleaning

```
str(dat)
  'data.frame': 103978 obs. of 3 variables:
  $ id: num 1 2 3 4 5 6 7 8 9 10 ...
  $ response: num 1 1 1 1 1 1 1 1 1 1 . . .
  - attr(, "variable.labels")= Named chr
  ..- attr(, "names")= chr
  - attr(*, "codepage")= int 1252
   ## The proficient.sav dataset is HUGE!
dat <- tbl_df(dat)</pre>
   ## see the {dplyr} package - tbl_df's are just better
   ## (than dataframes), particularly when it comes to
   ## very large dataframes, such as these proficiency data.
glimpse(dat) ## {pkg:dplyr} ##
```

```
Observations: 103,978
  Variables: 3
  $ id 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 1...
  $ level advanced, advanced, advanced, advanced, advance...
Risna <- function(x) sum(is.na(x))
   ## Getting a count of NA values in the original dataframe ##
sapply(dat, Risna)
```

id	response	level
О	0	32269

It appears that there are several instances of NA in the level column. However, since I do not know these data too well just yet, I am apprehensive, to say the least, to just outright remove those rows containing NAs. Instead, I'm going to assign an arbitruary, but meaningful to me, value to all instances of NA throughout the dataset.

To ensure that I do not accidentally override an existing value for the level variable by assigning an arbitruary value to NA's, I first call unique(dat\$level) below to get a list of the numeric values currently assigned to the levels of dat\$level. Then, I create a quick function (R.na()) to replace NA values within a given R-object.

The output from sapply() above indicates that the level column is the only one with NAs. So, in the next set of analyses, we should only see changes to that column in the end.

```
unique(dat$level)
  advanced, proficient, basic, minimal and _NA_Levels: minimal basic
proficient advanced
levels(dat$level)
  minimal, basic, proficient and advanced
lv <- c(levels(dat$level), "Unknown")</pre>
    ## I'm going to have to re-assign the factor levels to dat$level, so
    ## I am saving the labels, with an added level for the NAs, to use later
R.na <- function(x, v = 0){
    ## x = object to be manipulated,
    ## v = value to assign to NAs ##
    x <- ifelse(is.na(x), v, x)</pre>
    return(x)
```

```
}
datlevel <- sapply(dat<math>level, R.na, v = 0)
    ## 0 does not currently mean anything else in this data, so I am going
    ## to use to represent it's acutal meaning, which is simply a NULL value
datslevel \leftarrow factor(datslevel, levels = c(4, 3, 2, 1, 0), labels = lv)
unique(dat$level)
  minimal, basic, proficient, advanced and _Unknown_Levels: minimal
basic proficient advanced Unknown
levels(dat$level)
  minimal, basic, proficient, advanced and Unknown
glimpse(dat)
  Observations: 103,978
  Variables: 3
  $ id 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 1...
  $ level minimal, minimal, minimal, minimal, minimal, mi...
sapply(dat, R.isna)
```

id	response	level
О	О	0

Setting up for binomial analysis

Based on their description (and the fact that the example pertains primarily to the Bernoulli Distribution), it appears that Azen and Walker⁵ used a dichotomized version of the level variable in their analysis example. However, I am curious about the level of extant intformation available from this variable's original 4-categories⁶, as well as the difference, if any, between the two categorical data structuring methods.

```
rec <- "c('proficient', 'advanced') = 1; c('Unknown', 'minimal', 'basic') = 0"
dat$lev.D <- car::recode(dat$level, rec)</pre>
    ## "D" = "Dichotomous" ##
```

⁵ Categorical Data Analysis for the Behavioral and Social Sciences.

⁶ i.e., minimal, basic, proficient, advanced, Unknown

summary(dat\$lev.D)

0	1
83182	20796

QUICK ASIDE: Instead of the above dichotomization, I could have done the following:

```
rec1 <- c("'minimal'=1; 'basic'=2; 'proficient'=3; 'advanced'=4; 'Unknown'=0")
dat$lev.D1 <- car:::recode(dat$level, rec1)</pre>
dat$lev.D1 <- as.integer(dat$lev.D1)</pre>
dat$lev.D1 <- cut(dat$lev.D1, breaks = 2, right = FALSE)</pre>
D1labs <- levels(dat$lev.D1)
levels(dat$lev.D1) <- c("0", "1")
summary(dat$lev.D1)
                          0
                                  1
                                  53065
                          50913
```

However, as you can see by the differences in the summary outputs above and the barplots below resulting from these different dichotomizing procedures, when I simply "cut()" the factor levels, I get a nicely split (i.e., "cut") factor. Unfortunately, the proportions of the newly dichotomized factor's levels do not necessarily reflect the actual proportions in the data.

```
dat$level <- relevel(dat$level, ref = "Unknown")</pre>
    ## re-ordering levels for presentation ##
```

Below are the exact same plots, except with a random sample of n = 10 cases from the proficiency data per the example in Azen and Walker⁷ (Chapter 3).

Moral of the story - be careful when cutting and never assume that R knows what you are trying to do (R's purpose is not to Harry Huidini your data by reading your mind (or your prof's/advisor's mind), but rather to provide you with a set (to put it mildly) of tools to help you do the work ... but you still have to do the actual thinking work).

⁷ Categorical Data Analysis for the Behavioral and Social Sciences.

References⁸

Allaire, JJ, Joe Cheng, Yihui Xie, Jonathan McPherson, Winston Chang, Jeff Allen, Hadley Wickham, Aron Atkins, and Rob Hyndman. rmarkdown: Dynamic Documents for R, 2016. https://CRAN. R-project.org/package=rmarkdown.

Arnold, Jeffrey B. Ggthemes: Extra Themes, Scales and Geoms for *Ggplot*2, 2016. https://CRAN.R-project.org/package=ggthemes.

Aust, Frederik, and Marius Barth. Papaja: Create APA Manuscripts with RMarkdown, 2015. https://github.com/crsh/papaja.

Azen, Razia, and Cindy M. Walker. Categorical Data Analysis for the Behavioral and Social Sciences. Kindle Edition. New York, NY, US: Routledge, 2011.

Boettiger, Carl. knitcitations: Citations for Knitr Markdown Files, 2015. https://CRAN.R-project.org/package=knitcitations.

Chang, Winston. Extrafont: Tools for Using Fonts, 2014. https: //CRAN.R-project.org/package=extrafont.

Daroczi, Gergely, and Roman Tsegelskyi. Pander: An R Pandoc Writer, 2015. https://CRAN.R-project.org/package=pander.

Fox, John, and Sanford Weisberg. An R Companion to Applied Regression. Second. Thousand Oaks CA: Sage, 2011. http://socserv. socsci.mcmaster.ca/jfox/Books/Companion.

François, Romain. Bibtex: Bibtex Parser, 2014. https://CRAN. R-project.org/package=bibtex.

Highlight: Syntax Highlighter, 2015. https://CRAN.R-project. org/package=highlight.

Meyer, David, Achim Zeileis, and Kurt Hornik. "Residual-Based Shadings for Visualizing (Conditional) Independence"." Journal of Statistical Software 17, no. 3 (2006): 1-48. http://www.jstatsoft.org/ v17/i03/.

Qiu, Yixuan. Showtext: Using Fonts More Easily in RGraphs, 2015. https://CRAN.R-project.org/package=showtext.

Qiu, Yixuan, and others. Sysfonts: Loading System Fonts into R, 2015. https://CRAN.R-project.org/package=sysfonts.

R Core Team. R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing, 2016. https://www.R-project.org/.

Wickham, Hadley. Ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, 2009. http://ggplot2.org.

—. Gtable: Arrange Grobs in Tables, 2016. https://CRAN. R-project.org/package=gtable.

——. Scales: Scale Functions for Visualization, 2016. https://CRAN. R-project.org/package=scales.

—. "The Split-Apply-Combine Strategy for Data Analysis."

⁸ Note: This document was created using R-v3.3.2 R Core Team, R, and the following R-packages: base-v3.3. R Core Team, R, bibtex-vo.4. Francois, Bibtex, car-v2.1. Fox and Weisberg, An R Companion to Applied Regression, dplyr-vo.5. Wickham and François, Dplyr, DT-vo.2. Xie, DT, extrafont-vo.17. Chang, Extrafont, ggplot2-v2.1. Wickham, Ggplot2, knitcitations-v1.o. Boettiger, knitcitations, knitr-v1.14. Xie, Dynamic Documents with R and Knitr, pander-vo.6. Daroczi and Tsegelskyi, Pander, papaja-vo.1. Aust and Barth, Papaja, plyr-v1.8. Wickham, "The Split-Apply-Combine Strategy for Data Analysis.", rmarkdown-v1.1. Allaire et al., rmarkdown, scales-vo.4. Wickham, Scales, tidyr-vo.6. Wickham, Tidyr, ggthemes-v3.2. Arnold, Ggthemes, gtable-vo.2. Wickham, Gtable, kableExtravo.o. Zhu, KableExtra, tufte-vo.2. Xie and Allaire, Tufte, vcd-v1.4. Meyer, Zeileis, and Hornik, "Residual-Based Shadings for Visualizing (Conditional) Independence".", devtools-v1.12. Wickham and Chang, Devtools, highlight-vo.4. Francois, Highlight, sysfonts-vo.5. Qiu and others, Sysfonts, and showtext-vo.4. Qiu, Showtext

Journal of Statistical Software 40, no. 1 (2011): 1-29. http://www. jstatsoft.org/v40/i01/.

———. Tidyr: Easily Tidy Data with Spread() and Gather() Functions, 2016. https://CRAN.R-project.org/package=tidyr.

Wickham, Hadley, and Winston Chang. Devtools: Tools to Make Developing RPackages Easier, 2016. https://CRAN.R-project.org/ package=devtools.

Wickham, Hadley, and Romain Francois. Dplyr: A Grammar of Data Manipulation, 2015. https://CRAN.R-project.org/package=dplyr.

Xie, Yihui. DT: A Wrapper of the Javascript Library Datatables, 2015. https://CRAN.R-project.org/package=DT.

——. Dynamic Documents with R and Knitr. 2nd ed. Boca Raton, Florida: Chapman; Hall/CRC, 2015. http://yihui.name/knitr/.

Xie, Yihui, and JJ Allaire. Tufte: Tufte's Styles for Rmarkdown Documents, 2016. https://CRAN.R-project.org/package=tufte.

Zhu, Hao. KableExtra: Decorate Kable Output Using Pipe Syntax, 2016. https://github.com/haozhu233/kableExtra.