

ETC5521: Exploratory Data Analysis

Working with a single variable, making transformations, detecting outliers, using robust statistics

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Week 5 - Session 2



Categorical variables

This lecture is based on Chapter 4 of

Unwin (2015) Graphical Data Analysis with R

There are two types of categorical variables

Nominal where there is no intrinsic ordering to the categories **E.g.** blue, grey, black, white.

Ordinal where there is a clear order to the categories. **E.g.** Strongly disagree, disagree, neutral, agree, strongly agree.

Categorical variables in R

In R, categorical variables may be encoded as factors.

```
data <- c(2, 2, 1, 1, 3, 3, 3, 1)
factor(data)</pre>
```

[1] 2 2 1 1 3 3 3 1 ## Levels: 1 2 3

• You can easily change the labels of the variables:

factor(data, labels = c("I", "II", "III"))
[1] II II I I III III III I
Levels: I II III

• Order of the factors are determined by the input:

```
# numerical input are ordered in increasing order
factor(c(1, 3, 10))
## [1] 1 3 10
## Levels: 1 3 10
# character input are ordered alphabetically
factor(c("1", "3", "10"))
## [1] 1 3 10
## Levels: 1 10 3
# you can specify order of levels explicitly
factor(c("1", "3", "10"),
  levels = c("1", "3", "10")
)
## [1] 1 3 10
## Levels: 1 3 10
                                               4/21
```

Numerical factors in R

```
x <- factor(c(10, 20, 30, 10, 20))
mean(x)</pre>
```

Warning in mean.default(x): argument is not numeric or logical: returning NA

[1] NA

A as.numeric function returns the internal integer values of the factor

```
mean(as.numeric(x))
```

```
## [1] 1.8
```

You probably want to use:

```
mean(as.numeric(levels(x)[x]))
```

[1] 18

mean(as.numeric(as.character(x)))

```
## [1] 18
```

Numerical summaries: counts, proportions, percentages and odds

## # A tibble: 22 × 7							
	country	iso3	year	count	р	pct	odds
	<chr></chr>	<chr></chr>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>
1	Australia	AUS	2000	982	0.0522	5.22	1
2	Australia	AUS	2001	953	0.0507	5.07	0.970
3	Australia	AUS	2002	1008	0.0536	5.36	1.03
4	Australia	AUS	2003	926	0.0493	4.93	0.943
5	Australia	AUS	2004	1036	0.0551	5.51	1.05
6	Australia	AUS	2005	1030	0.0548	5.48	1.05
7	Australia	AUS	2006	1127	0.0600	6.00	1.15
8	Australia	AUS	2007	1081	0.0575	5.75	1.10
9	Australia	AUS	2008	1182	0.0629	6.29	1.20
10	Australia	AUS	2009	1176	0.0626	6.26	1.20
11	Australia	AUS	2010	1146	0.0610	6.10	1.17
12	Australia	AUS	2011	1202	0.0640	6.40	1.22
13	Australia	AUS	2012	1259	0.0670	6.70	1.28
14	Australia	AUS	2013	512	0.0272	2.72	0.521
15	Australia	ALIC	2014		0 0050	0 50	0 100
	# # 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15	<pre># A tibble: 2 country <chr> 1 Australia 2 Australia 3 Australia 3 Australia 4 Australia 5 Australia 6 Australia 7 Australia 7 Australia 9 Australia 10 Australia 11 Australia 12 Australia 13 Australia 14 Australia </chr></pre>	<pre># A tibble: 22 × 7 country iso3 <chr></chr></pre>	<pre># A tibble: 22 × 7 country iso3 year <chr> <chr> <chr> <chr> <dbl> 1 Australia AUS 2000 2 Australia AUS 2001 3 Australia AUS 2002 4 Australia AUS 2003 5 Australia AUS 2004 6 Australia AUS 2004 6 Australia AUS 2005 7 Australia AUS 2006 8 Australia AUS 2007 9 Australia AUS 2008 10 Australia AUS 2008 10 Australia AUS 2010 12 Australia AUS 2010 12 Australia AUS 2011 13 Australia AUS 2012 14 Australia AUS 2013</dbl></chr></chr></chr></chr></pre>	<pre># A tibble: 22 × 7 country iso3 year count</pre>	<pre># A tibble: 22 × 7 country iso3 year count p</pre>	<pre># A tibble: 22 × 7 country iso3 year count p pct <chr> <chr></chr></chr></pre>

For qualitative data, compute

- count/frequency,
- proportion/percentage
- and sometimes, an odds ratio. Here we have used ratio relative to the count in year 2000.

Note: For exploration, no rounding of digits was done, but to report you would need to make the numbers pretty.

Revisiting Case study 1 2019 Australian Federal Election

🖬 data R





Sorting levels is (almost) always better when plotting

Order nominal variables meaningfully

Coding tip: use below functions to easily change the order of factor levels

```
stats::reorder(factor, value, mean)
forcats::fct_reorder(factor, value, median)
forcats::fct_reorder2(factor, value1, value2, func)
```

Case study 6 Aspirin use after heart attack

🖬 data R



- Meta-analysis is a statistical analysis that combines the results of multiple scientific studies.
- This data studies the use of aspirin for death prevention after myocardial infarction, or in plain terms, a heart attack.
- The ISIS-2 study has more patients than all other studies combined.
- You could consider lumping the categories with low frequencies together.

Fleiss JL (1993): The statistical basis of meta-analysis. *Statistical Methods in Medical Research* **2** 121–145 Balduzzi S, Rücker G, Schwarzer G (2019), How to perform a meta-analysis with R: a practical tutorial, Evidence-Based Mental Health.

Consider combining factor levels with low frequencies

</>
Coding tip: the following family of functions help to easily lump factor levels together:

```
forcats::fct_lump()
forcats::fct_lump_lowfreq()
forcats::fct_lump_min()
forcats::fct_lump_n()
forcats::fct_lump_prop()
# if conditioned on another variable
ifelse(cond, "Other", factor)
dplyr::case_when(
    cond1 ~ "level1",
    cond2 ~ "level2",
    TRUE ~ "Other"
)
```

Case study 🕖 Anorexia

data R



Table or Plot?

• Table for accuracy, plot for visual communication

Why not a point or line?



- This can be appropriate depending on what you want to communicate
- A barplot occupies more area compared to a point and the area does a better job of communicating size
- A line is suggestive of a trend

Hand, D. J., Daly, F., McConway, K., Lunn, D. and Ostrowski, E. eds (1993) A Handbook of Small Data Sets. Chapman & Hall, Data set 285 (p. 229) Venables, W. N. & Ripley, B. D. (2002) Modern Applied Statistics with S. Fourth Edition. Springer, New York. ISBN 0-387-95457-0

Case study Titanic

ы data R



Child Yes

What does the graphs for each categorical variable tell us?

- There were more crews than 1st to 3rd class passengers
- There were far more males on ship; possibly because majority of crew members were male. You can further explore this by constructing twoway tables or graphs that consider both variables.
- Most passengers were adults.
- More than two-thirds of passengers died.

Coloring bars



- Colour here doesn't add information as the x-axis already tells us about the categories, but colouring bars can make it more visually appealing, and provide subtle clues.
- If you have too many categories colour won't work well to differentiate the categories.

Case study 9 Opinion poll in Ireland Aug 2013

🖬 data R



- Pie chart is popular in mainstream media but are not generally recommended as people are generally poor at comparing angles.
- 3D pie charts should definitely be avoided!
- Here you can see that there are many people that are "Undecided" for which political party to support and failing to account for this paints a different picture.

Piechart is a stacked barplot just with a transformed coordinate system

```
df <- data.frame(var = c("A", "B", "C"), perc = c(40, 40, 20))
g <- ggplot(df, aes("", perc, fill = var)) +
   geom_col()
g</pre>
```

100 75 50 25 0 x

```
g + coord_polar("y")
```



Roseplot is a barplot just with a transformed coordinate system



g + coord_polar("x") + theme_void()



Visual inference

Typical plot description:

```
ggplot(data, aes(x=var1)) +
  geom_col()
```

```
ggplot(data, aes(x=var1)) +
  geom_bar()
```

Potential simulation method from binomial

```
# Only one option
null_dist("var1", "binom",
    list(size=n, p=phat))
```

Is the distribution consistent with a sample from a binomial distribution with a given p?

Lineup of tuberculosis count between sexes





Note: This is nothing more than you can learn from a conventional hypothesis test of

 $H_0: p = 0.5$

. Stay tuned for more interesting visual inference lineups in coming weeks!

Take away messages

- Again, be prepared to do multiple plots
- Changing bins or binwidth/bandwidth in histogram, violin or density plots can paint a different picture
- Consider different representations of categorical variables (reordering meaningfully, lumping low frequencies together, plot or table, pie or barplot, missing categories)

Resources and Acknowledgement

 Slides originally written by Emi Tanaka and constructed with xaringan, remark.js, knitr, and R Markdown.



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