IS5 in R: Relationships Between Categorical Variables–Contingency Tables (Chapter 3)

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Introduction and background

This document is intended to help describe how to undertake analyses introduced as examples in the Fifth Edition of *Intro Stats* (2018) by De Veaux, Velleman, and Bock. This file as well as the associated R Markdown reproducible analysis source file used to create it can be found at http://nhorton.people.amherst.edu/is5.

This work leverages initiatives undertaken by Project MOSAIC (http://www.mosaic-web.org), an NSF-funded effort to improve the teaching of statistics, calculus, science and computing in the undergraduate curriculum. In particular, we utilize the `mosaic` package, which was written to simplify the use of R for introductory statistics courses. A short summary of the R needed to teach introductory statistics can be found in the mosaic package vignettes (https://cran.r-project.org/web/packages/mosaic). A paper describing the mosaic approach was published in the *R Journal*: https://journal.r-project.org/archive/2017/RJ-2017-024.

Chapter 3: Relationships Between Categorical Variables–Contingency Tables

Section 3.1: Contingency Tables

```
library(mosaic)
library(readr)
library(janitor)
OKCupid <-
  read_csv("http://nhorton.people.amherst.edu/is5/data/OKCupid_CatsDogs.csv", skip = 1) %>%
  janitor::clean_names()
names(OKCupid)
```

```
## [1] "cats_dogs_both" "gender"         "drugs_y_n"      "smokes_y_n"
```

The `read_csv()` function lists the input variable names by default. These were suppressed using the `message = FALSE` code chunk option to save space. Here we use the `clean_names()` function from the `janitor` package to sanitize the names of the columns (which would otherwise contain special characters or whitespace). You can use the `names()` function to check the cleaned names. We use `skip = 1` because the first line in the original data set is a set of variable labels (e.g., `Col1`, `Col2`).

```
# Table 3.1, page 65
tally(~ cats_dogs_both + gender, margin = TRUE, useNA = "no", data = OKCupid)
```

```
##               gender
## cats_dogs_both    F    M Total
##       Has Both  897  577  1474
##       Has cats 3412 2388  5800
##       Has dogs 3431 3587  7018
##       Total    7740 6552 14292
```

```
# Table 3.2
tally(~ cats_dogs_both + gender,
  format = "percent", margin = TRUE, useNA = "no",
  data = OKCupid
)
```

```
##               gender
## cats_dogs_both          F          M      Total
##       Has Both   6.276238   4.037224  10.313462
##       Has cats  23.873496  16.708648  40.582144
##       Has dogs  24.006437  25.097957  49.104394
##       Total     54.156171  45.843829 100.000000
```

```
tally(cats_dogs_both ~ gender,
  format = "percent", margin = TRUE, useNA = "no",
  data = OKCupid
)
```

```
##               gender
## cats_dogs_both          F          M
##       Has Both  11.589147   8.806471
##       Has cats  44.082687  36.446886
##       Has dogs  44.328165  54.746642
##       Total    100.000000 100.000000
```

```
# Table 3.3
tally(gender ~ cats_dogs_both, format = "percent", margin = TRUE, data = OKCupid)
```

```
##        cats_dogs_both
## gender   Has Both  Has cats  Has dogs      <NA>
##   F      60.85482  58.82759  48.88857  35.87435
##   M      39.14518  41.17241  51.11143  64.12565
##   Total 100.00000 100.00000 100.00000 100.00000
```

Example 3.1: Exploring Marginal Distributions We begin by reading and tallying the data.

```
SuperBowl <-
  read_csv("http://nhorton.people.amherst.edu/is5/data/Watch_the_Super_bowl.csv",
    skip = 1
  )
tally(~ Plan + Sex, data = SuperBowl)
```

```
##              Sex
## Plan          Female Male
##   Commercials    156   81
##   Game           200  279
##   Wont Watch     160  132
```

Example 3.2: Exploring Percentages: Children and First-Class Ticket Holders First? We do the same for the Titanic data.

```
Titanic <- read_csv("http://nhorton.people.amherst.edu/is5/data/Titanic.csv")
tally(~ Class + Survived, format = "percent", margin = TRUE, data = Titanic)
```

```
##        Survived
## Class        Alive       Dead      Total
##   1       9.103261   5.570652  14.673913
```

```
##   2       5.389493   7.518116  12.907609
##   3       8.152174  24.003623  32.155797
##   Crew    9.601449  30.661232  40.262681
##   Total  32.246377  67.753623 100.000000
```

```
tally(Class ~ Survived, format = "percent", margin = TRUE, data = Titanic)
```

```
##        Survived
## Class         Alive       Dead
##   1       28.230337   8.221925
##   2       16.713483  11.096257
##   3       25.280899  35.427807
##   Crew    29.775281  45.254011
##   Total  100.000000 100.000000
```

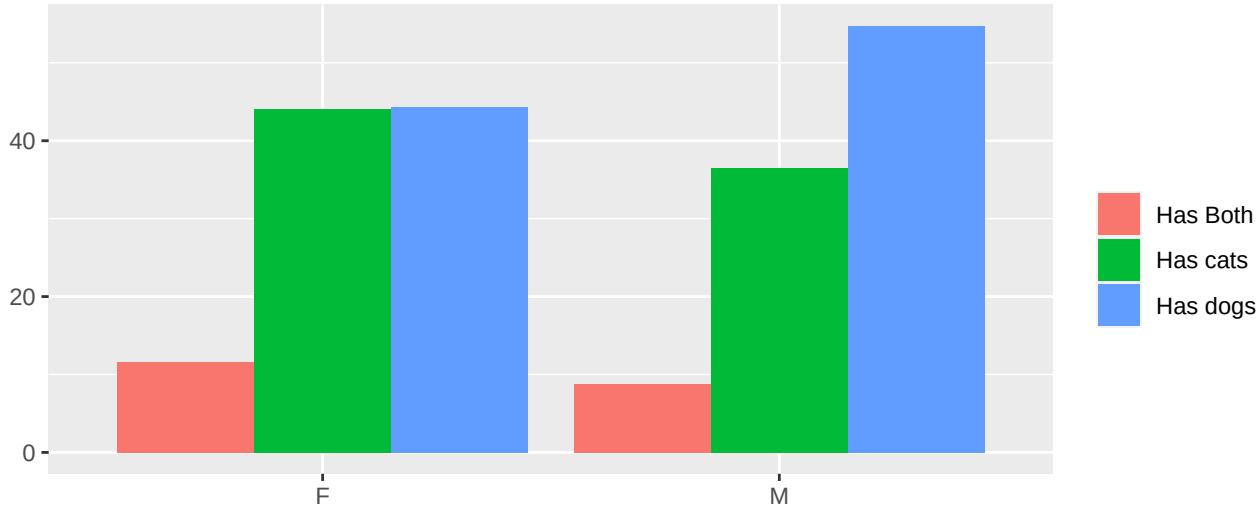
```
tally(Survived ~ Class, format = "percent", margin = TRUE, data = Titanic)
```

```
##          Class
## Survived         1         2         3      Crew
##    Alive  62.03704  41.75439  25.35211  23.84702
##    Dead   37.96296  58.24561  74.64789  76.15298
##    Total 100.00000 100.00000 100.00000 100.00000
```

Section 3.2: Conditional Distributions

See displays on 68-69.

```
OKdata <- tally(cats_dogs_both ~ gender,
  format = "percent", useNA = "no",
  data = OKCupid
) %>%
  data.frame()
# Figure 3.2, page 69
gf_col(Freq ~ gender, fill = ~cats_dogs_both, position = "dodge", data = OKdata) %>%
  gf_labs(x = "", y = "", fill = "")
```



Example 3.3: Finding Conditional Distributions: Watching the Super Bowl We can calculate conditional probabilities from tables using `mosaic::tally()`.

```
tally(~ Plan + Sex, margin = TRUE, data = SuperBowl)
```

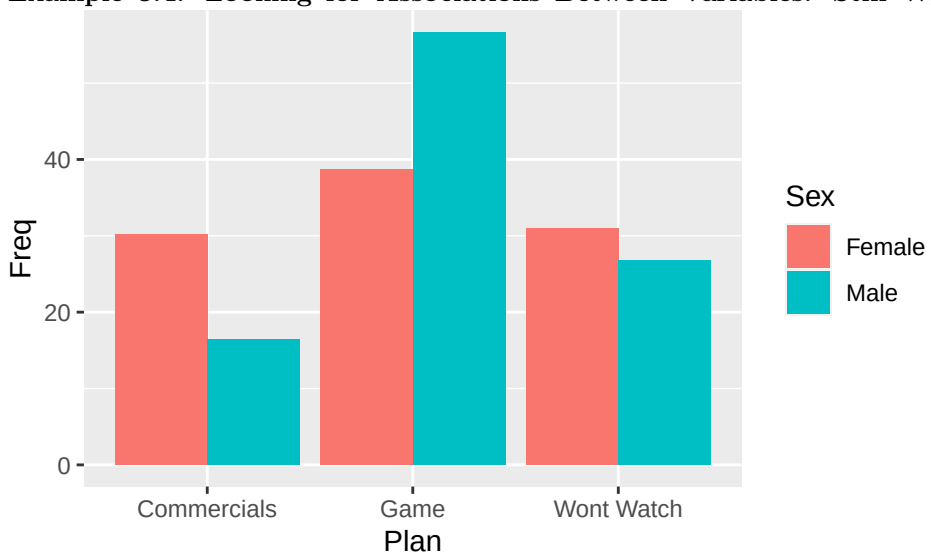
```
##              Sex
## Plan          Female Male Total
##   Commercials    156   81   237
##   Game           200  279   479
##   Wont Watch     160  132   292
##   Total          516  492  1008
```

```
tally(Plan ~ Sex, format = "percent", data = SuperBowl)
```

```
##              Sex
## Plan            Female     Male
##   Commercials 30.23256 16.46341
##   Game        38.75969 56.70732
##   Wont Watch  31.00775 26.82927
```

```
Superdata <- tally(Plan ~ Sex, format = "percent", data = SuperBowl) %>%
  data.frame()
gf_col(Freq ~ Plan, fill = ~Sex, position = "dodge", data = Superdata)
```

Example 3.4: Looking for Associations Between Variables: Still Watching the Super Bowl



Examining Contingency Tables See displays on page 72.

```
FishDiet <- read_csv("http://nhorton.people.amherst.edu/is5/data/Fish_diet.csv", skip = 1) %>%
  janitor::clean_names()
tally(~ diet_counts + cancer_counts, margins = TRUE, data = FishDiet)
```

```
##              cancer_counts
## diet_counts     No  Yes Total
##    Large       507   42   549
##    Moderate   2769  209  2978
##    Never       110   14   124
##    Small      2420  201  2621
##    Total      5806  466  6272
```

Random Matters See display on page 74.

```
Nightmares <- read_csv("http://nhorton.people.amherst.edu/is5/data/Nightmares.csv", skip = 1)
Nightmares <- Nightmares %>%
  mutate(Dream = ifelse(Dream == "N", "Nightmare", "SweetDreams"))
tally(~ Dream + Side, margins = TRUE, data = Nightmares)
```

```
##              Side
## Dream          L  R Total
##   Nightmare    9  6    15
##   SweetDreams 13 35    48
##   Total       22 41    63
```

Section 3.3: Displaying Contingency Tables

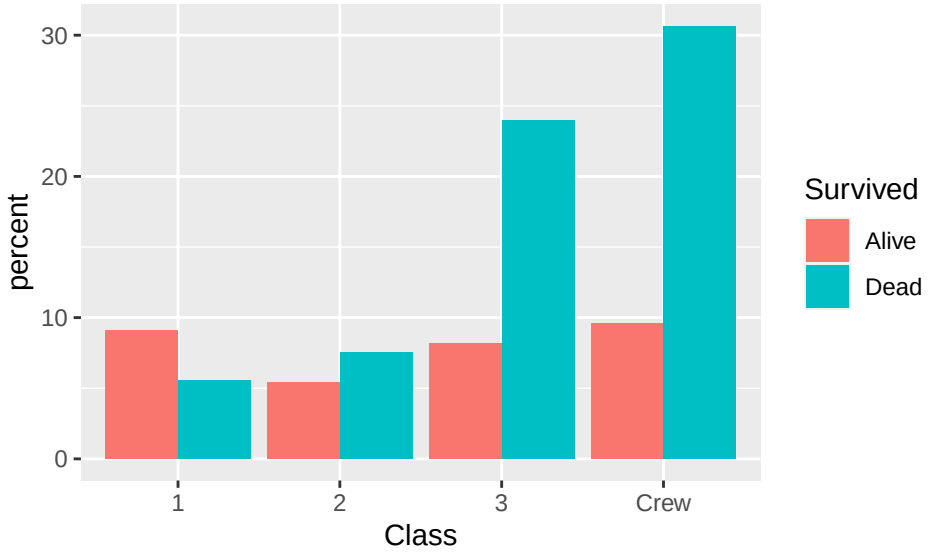
```
tally(~ Class + Survived, format = "count", data = Titanic)
```

```
##       Survived
## Class  Alive Dead
##   1      201  123
##   2      119  166
##   3      180  530
##   Crew   212  677
```

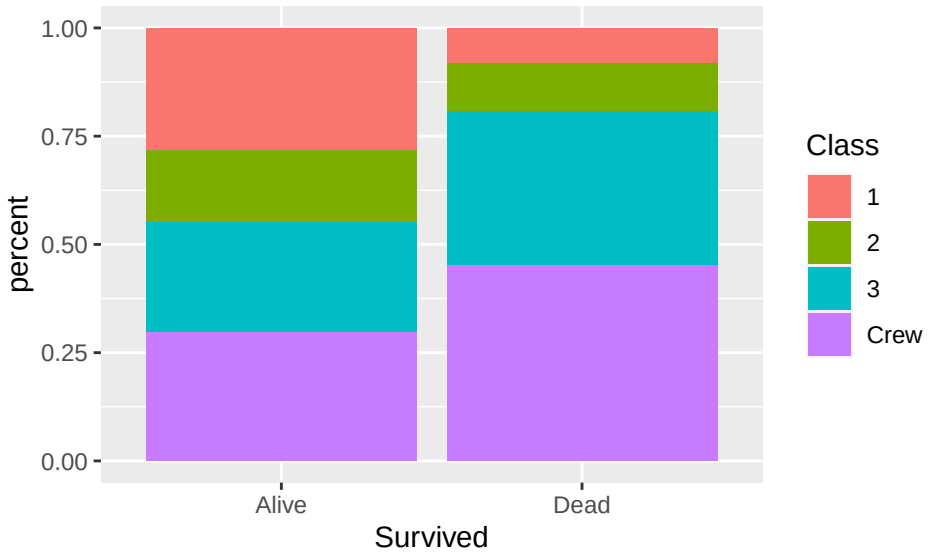
```
tally(~ Class + Survived, format = "percent", data = Titanic)
```

```
##       Survived
## Class      Alive      Dead
##   1     9.103261  5.570652
##   2     5.389493  7.518116
##   3     8.152174 24.003623
##   Crew  9.601449 30.661232
```

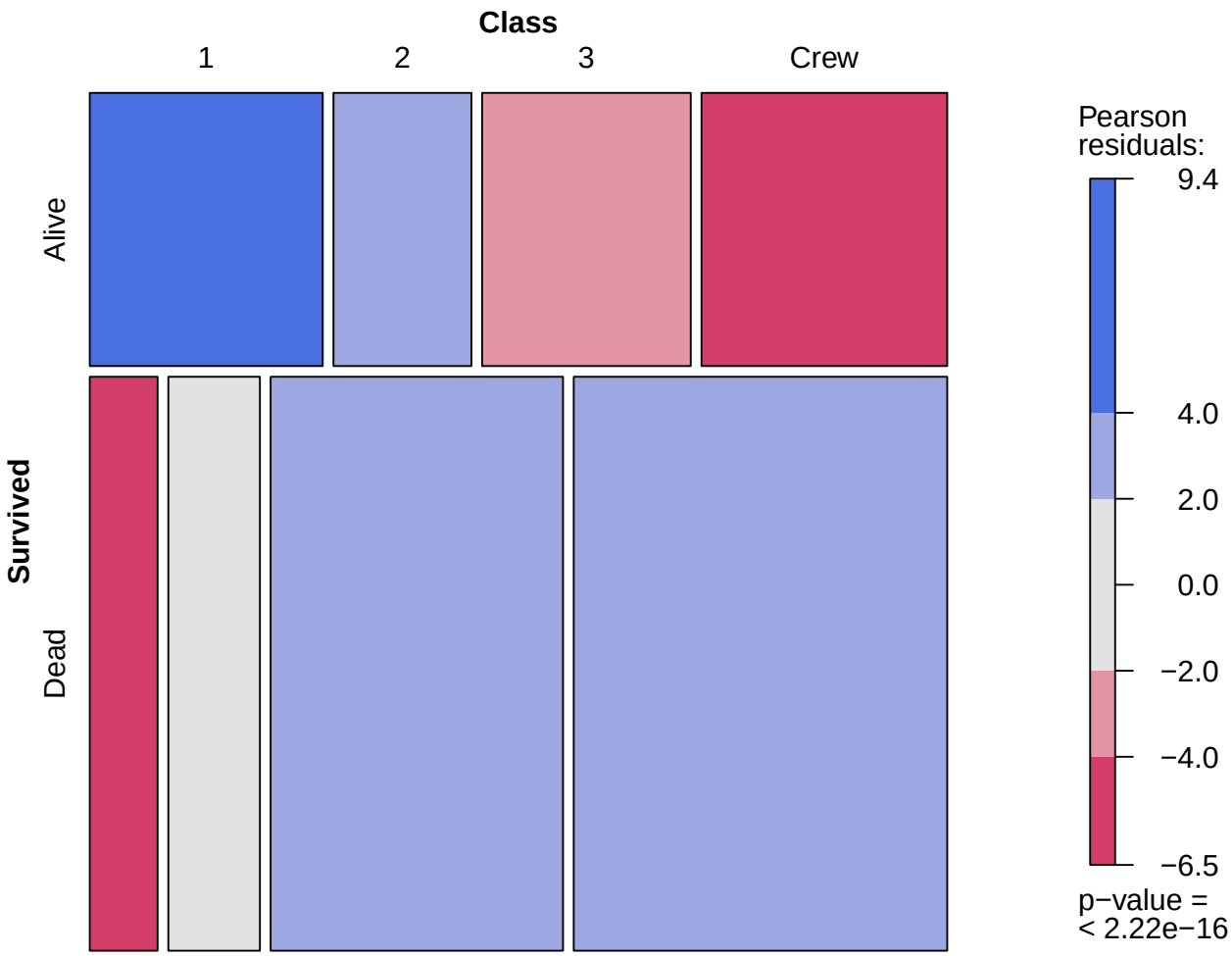
```
# Figure 3.4, page 75
gf_percents(~Class, fill = ~Survived, position = position_dodge(), data = Titanic)
```




```
# Figure 3.5
gf_percents(~Survived, fill = ~Class, position = "fill", data = Titanic)
```




```
# Figure 3.6, page 76
vcd::mosaic(tally(~ Survived + Class, data = Titanic),
  main = "Mosaic plot of Class by Survival",
  shade = TRUE
)
```



See the mosaic plots on page 77.

Section 3.4: Three Categorical Variables

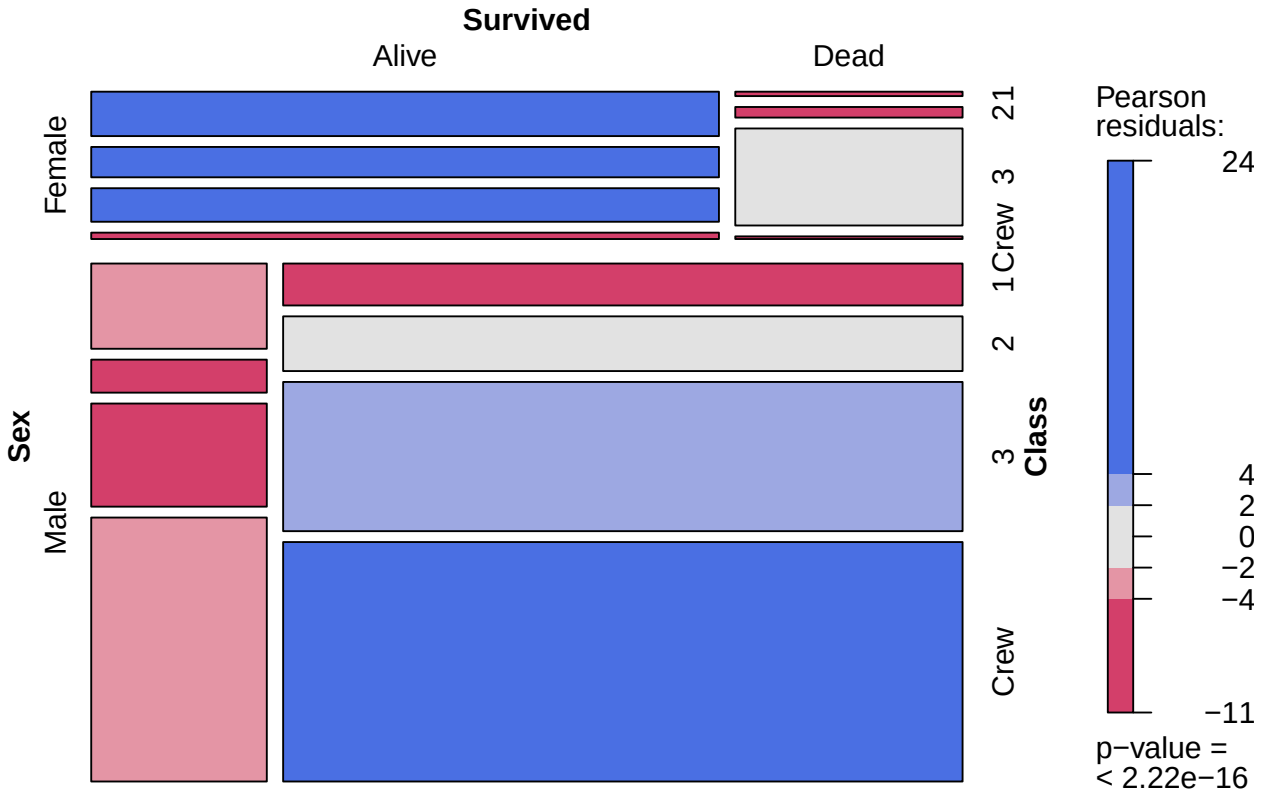
```
tally(~ gender + cats_dogs_both + drugs_y_n, format = "percent", data = OKCupid)
```

```
## , , drugs_y_n = No
##
##       cats_dogs_both
## gender   Has Both   Has cats   Has dogs       <NA>
##      F  1.0243064  3.4199156  3.9437466 18.0187845
##      M  0.5922293  2.0819779  3.7769214 30.0719016
##
## , , drugs_y_n = Yes
##
##       cats_dogs_both
## gender   Has Both   Has cats   Has dogs       <NA>
##      F  0.2085314  0.8941828  0.6272626  2.9794972
##      M  0.1901807  0.8658225  0.9041923  6.9132342
```

```
##
## , , drugs_y_n = NA
##
##       cats_dogs_both
## gender   Has Both   Has cats   Has dogs       <NA>
##      F  0.2635837  1.3779757  1.1527618  6.3226732
##      M  0.1801712  1.0359842  1.3029044 11.8512587
```

Example 3.7: Looking for Associations Among Three Variables at Once We can repeat the mosaic plot with three variables.

```
vcd::mosaic(tally(~ Sex + Survived + Class, data = Titanic), shade = TRUE)
```



Example 3.8: Simpson's Paradox: Gender Discrimination? Here we demonstrate how to generate one of the tables on page 80.

```
# Create a dataframe from the counts
# http://mathemathinking.blogspot.com/2012/06/simpsons-paradox.html
Berk <- rbind(
  do(512) * data.frame(admit = TRUE, sex = "M", school = "A"),
  do(825 - 512) * data.frame(admit = FALSE, sex = "M", school = "A"),
  do(89) * data.frame(admit = TRUE, sex = "F", school = "A"),
  do(19) * data.frame(admit = FALSE, sex = "F", school = "A")
)
```

In this case, `do(n)` creates `n` observations with the specified values in `data.frame()`. The `rbind()` function can then be used to combine the data frames into one.

```
tally(~ sex + admit, data = Berk)
```

```
##    admit
## sex TRUE FALSE
##   F   89    19
##   M  512   313
```

```
tally(admit ~ sex, format = "percent", data = Berk)
```

```
##        sex
## admit          F        M
##   TRUE  82.40741 62.06061
##   FALSE 17.59259 37.93939
```