Contingency Table - Count Data Topics: Contingency table and mosaic plot Examples Passenger survival on Titanic • UC Berkeley admissions Simpson's paradox **Contingency Tables**  is a table of counts. Rows and columns are labelled with values of categorical variable (factor). • Value in each cell is the count of number of cases in that combination of categories Constructing a contingency table in R drugz <- data.frame(</pre> expand.grid(treatment=c("drugz", "placebo"), result=c("sicker", "better")), count=c(20,60,80,40)) drugz treatment result count ## ## 1 drugz sicker 20 ## 2 placebo sicker 60 ## 3 drugz better 80 ## 4 placebo better 40 drugztable <- xtabs(formula = count ~ treatment + result, data = drugz)</pre> drugztable ## result ## treatment sicker better drugz 20 placebo 60 40 Got it! drugztable is now a special data type representing a **contingency table**. 100 patients with some disease were treated with drug Z, and 100 patients were treated with a placebo. Nearly always, we are interested in interactions or correlations between the variables. The table above suggests that drug Z might cure people, not completely reliably. 3 ways to represent contingency tables in R 1. Case form: • Data frame (like a database table) with 2 factors Treatment and Result This needs to be counted! 2. Frequency form: • Data frame (like a database table) with factors Treatment, Result and one numeric column • Needs to be converted to table form using xtabs function 3. Table form: • A labelled multidimensional array. • This is the form we need in order to use the function mosaic For details on how to create and convert different forms, see: https://cran.r-project.org/web/packages/vcdExtra/vignettes/vcd-tutorial.pdf Shaded according to statistical significance A simple and effective visualization technique for contingency tables is the **mosaic plot**. #install.packages("vcd") #install.packages("vcdExtra") library(vcd) ## Warning: package 'vcd' was built under R version 4.0.5 ## Loading required package: grid library(vcdExtra) ## Loading required package: gnm library(gcookbook) library(datasets) mosaic(~treatment+result, drugztable, shade=TRUE, split\_vertical=c(FALSE, TRUE)) result sicker better Pearson residuals: 3.2 2.0 treatment 0.0 placebo -2.0 -3.2 p-value = 7.764e-09 The shade argument causes mosaic to shade the plot according to statistical significance of deviation from independence. **Constructing a Contingency Table in R** GSS <- data.frame( expand.grid(sex=c("female", "male"), party=c("dem", "indep", "rep")), count=c(279,165,73,47,22 5,191)) GSS ## sex party count ## 1 female dem ## 3 female indep ## 5 female rep 225 ## 6 male rep 191 gsstable <- xtabs( formula = count ~ sex + party, data = GSS)</pre> dimnames( gsstable ) ## \$sex ## [1] "female" "male" ## \$party ## [1] "dem" "indep" "rep" gsstable party ## sex dem indep rep ## female 279 73 225 47 191 Social survey data mosaic( ~party + sex, data=gsstable, highlighting=TRUE, highlighting\_fill=terrain.colors(3)) sex female male dem **party** indep **Assessing statistical significance** mosaic( ~party + sex, data=gsstable, shade=TRUE) sex female male Pearson residuals: 1.5 dem 0.0 rep -1.3 p-value = 0.030054 No individual box is significantly larger or smaller than expected, by itself. **Examples: Passenger survival on Titanic** Passenger survival: 4 dimensional contingency table giving 1. Class, 2. Age(adult/child), 3. Sex, and 4. whether Survived Titanic , , Age = Child, Survived = No ## Sex ## Class Male Female 2nd ## 3rd 35 17 ## Crew ## , , Age = Adult, Survived = No ## ## ## Sex ## Class Male Female 118 2nd 154 13 387 Crew 670 3 ## , , Age = Child, Survived = Yes ## ## Sex ## Class Male Female ## 2nd 11 13 3rd 13 14 ## Crew 0 0 ## , , Age = Adult, Survived = Yes ## ## Sex ## Class Male Female 57 14 80 ## 3rd 75 76 Crew 192 20 Titanic: overall survival  $mosaic (\verb|-Survived|, data=Titanic|, split_vertical=c(TRUE), highlighting\_fill=c("grey", "green"), highlighting=TRUE)$ Survived No Yes mosaic(~Survived + Class, data=Titanic, split\_vertical=c(TRUE, FALSE, FALSE), highlighting\_fill=rev(terrain.colors( 2, alpha=1)), highlighting=TRUE) Survived No Yes <u>1st</u> 2nd **Class** 3rd Crew Titanic: survival rates of men and women mosaic(~Survived + Sex, data=Titanic[,,"Adult",], split\_vertical=c(TRUE,FALSE), highlighting\_fill=rev(terrain.col ors(2)), highlighting=TRUE) Yes Male Female Titanic: survival by gender and class  $mosaic (\sim Survived + Class + Sex, data = Titanic, split\_vertical = c (TRUE, FALSE, FALSE), highlighting\_fill = rev (terrain.c) + rev (te$ olors(2, alpha=1)), highlighting=TRUE) Survived Yes No Female Male Fem**क्षीक्षरि**क्षान**िक्षा Sex** 1st 2nd **Class** 3rd Male Female With children separated from adults ... hard to read now for general display, but ok for exploration mosaic(~Survived + Class + Sex + Age, data=Titanic, split\_vertical=c(TRUE, FALSE, FALSE, FALSE), highlighting\_fill= rev(terrain.colors(2,alpha=1)),highlighting=TRUE) Survived Chink the Shd 1st Srd Chink the Shirt Shirt Chink the Shirt Shir Femal/tarFeemal/tale Female Male F Sex Crew Adult Male Selecting children only dimnames(Titanic) ## \$Class ## [1] "1st" "2nd" "3rd" "Crew" ## \$Sex ## [1] "Male" "Female" ## \$Age ## [1] "Child" "Adult" ## \$Survived ## [1] "No" "Yes" Titanic[ , , "Child", ] , , Survived = No Sex ## Class Male Female 17 3rd 35 ## Crew , , Survived = Yes ## ## Sex ## Class Male Female 11 13 3rd 14 Crew Titanic: survival of children  $\verb|mosaic(~Survived + Class + Sex, data=Titanic[,, "Child",]|, split\_vertical=c(TRUE, FALSE, FALSE)|, highlighting\_fill=relation of the context of the cont$ ev(terrain.colors(2)), highlighting=TRUE) Survived No Yes Female Manendale 1st Class Male **Sex** Felvhadee Female Crew Titanic: proportions of women among adults, by class mosaic(~Sex + Class, data=Titanic[,,"Adult",], split\_vertical=c(TRUE,FALSE), highlighting\_fill=rev(heat.colors(2)) )), highlighting=TRUE) Sex Female Male <u>1st</u> **Class** 3rd Crew Titanic: proportions of children, by class  $mosaic (\neg Age + Class, \ data = Titanic, \ split\_vertical = c (TRUE, FALSE), \ highlighting\_fill = rev (heat.colors(2)), \ highlighting\_fill = rev (heat$ ing=TRUE) Age Child Adult **1st Class** 3rd Crew Titanic: some qualitative conclusions • The legend is that the 1st class passengers were saved while the lower classes and the crew perished. • The visualisation shows a strong interaction of class and survival. • But there is also a strong interaction of survival with gender and age: a higher proportion of women and children of all classes survived than did even the men in 1st class. • Among men, the order of survival rates was 1st class, crew, 3rd class, 2nd class. • Among women, the order of survival rates was 1st class, 2nd class and crew, 3rd class. • The survival rate of female children was greater than for male children. • The apparent greater survival rate of 1st class passengers may be partly because a greater proportion of 1st class passengers were women. • Strikingly, the third-class children had much lower survival rates than first and second-class children. What happened? Were many of the third-class children younger, or was there some other reason? **Example: UC Berkeley Admissions** mosaic( ~Admit + Gender + Dept, data=UCBAdmissions, highlighting=TRUE, highlighting\_fill=terrain.colors(2)) Gender Male Female Reje**&tbraiRe**ge **%do**ni**r**Rege **%d**onitte**r**Rejecte**.**Adn**Riphilladd**d **Admit** ⋖ **Dept** C **UCB** admissions by Department ш

• When analysed by department, two out of six departments had slightly higher admissions rates for men than for women; in four

• Women mostly applied to departments with low admissions rates; on aggregate, therefore, the admission rate for women was lower than for

• Simpson's Paradox occurs when trends that appear when a dataset is separated into groups reverse when the data are aggregated. – This

• More statistically, it says that the apparent relationship between two variables can change in the light or absence of a third variable

departments, admissions rates for women were higher than for men.

result is often encountered in social science and medical science statistics.

• do we have enough observations to reliably identify an interaction?

men.

Simpson's Paradox

how can we see any interactions?2. Pattern or chance? Statistical significance

• what is the explanation of the interaction?

could the apparent interaction be just luck?

(cofounding variable).

3.Investigation: confounding factors

Three types of questions

1. Visualisation