Notes and Exercises Chapter 4 – Exploratory Data Analysis (EDA)
Math 217
Saidi

4.1 Contingency tables and bar plots

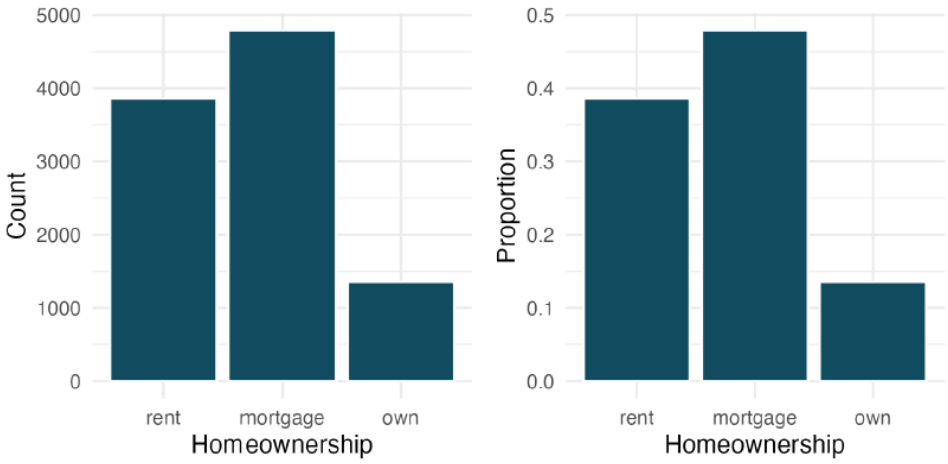
Single Categorical Variable

Table 4.1 below summarizes two variables: `application_type` and `homeownership`. A table that summarizes data for two categorical variables in this way is called a **contingency table.** Each value in the table represents the number of times a particular combination of variable outcomes occurred. For example, the value 3496 corresponds to the number of loans in the dataset where the borrower rents their home and the application type was by an individual.

Table 4.1: A contingency table for application type and homeownership.

	homeownership			
application_-type	rent	mortgage	own	Total
joint	362	950	183	1495
individual	3496	3839	1170	8505
Total	3858	4789	1353	10000

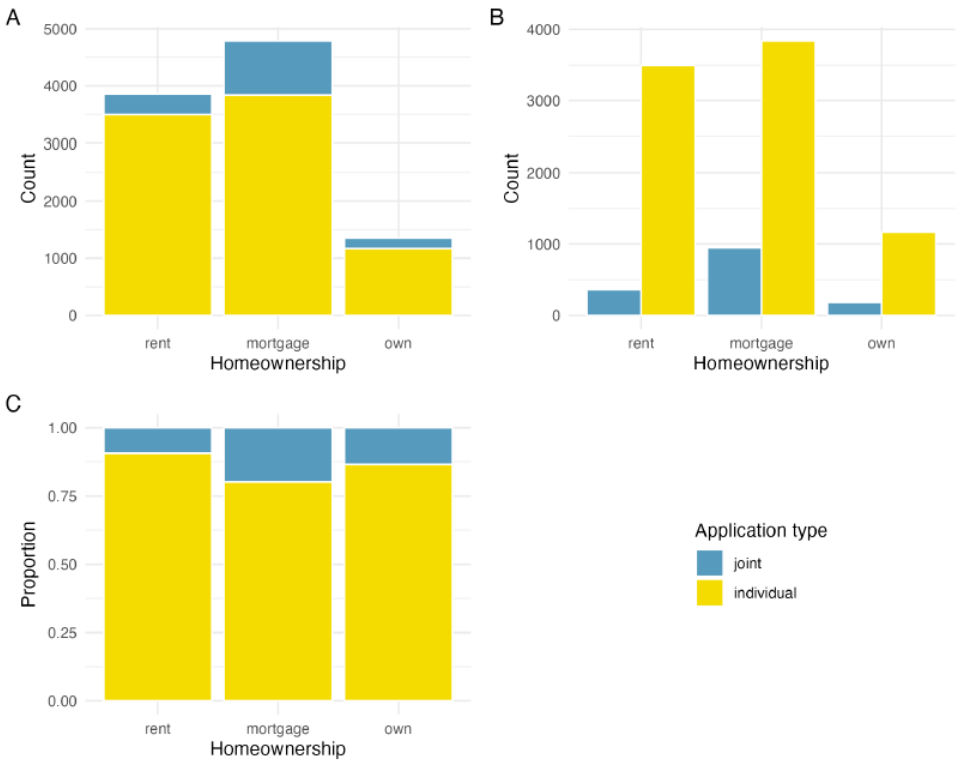
Bar charts for the frequencies and proportions for the single variable of homeownership by different types.



Two Categorical Variables

Now create bar charts using the two variables, homeownership and applicant type.

A. Shows a **"stacked"** bar graph of applicant type
B. Shows a **"dodge"** bar graph, where applicant type is shown as separate bars
C. Shows a **"fill"** bar graph, where applicant type fills each bar proportionally to add up to 1.00.



4.3 Row and column proportions

Table 4.3: A contingency table with row proportions for the application type and homeownership variables.

	homeownership			
application_-type	rent	mortgage	own	Total
joint	0.242	0.635	0.122	1
individual	0.411	0.451	0.138	1

Table 4.4: A contingency table with column proportions for the application type and homeownership variables.

	homeownership		
application_type	rent	mortgage	own
joint	0.094	0.198	0.135
individual	0.906	0.802	0.865
Total	1.000	1.000	1.000

Row and column proportions can also be thought of as **conditional proportions** as they tell about the proportion of observations in a given level of a categorical variable conditional on the level of another categorical variable.

Two-way Tables for Two Categorical Variables and Conditional Proportions

Often, we want to find a relationship, or an association between 2 categorical variables. We can use a two-way table to show all values and then compare proportions.

Example: Smoking and Pregnancy Rate

	Smoker	Non-smoker	Total
Pregnant	38	206	244
Not pregnant	97	337	434
Total	135	543	678

Be careful with what you designate as the denominator of the proportion.

a. What proportion **of this sample** were pregnant while smoking?

b. What proportion **of this sample** were pregnant while not smoking?

c. What proportion **of those who smoked** did NOT get pregnant?

d. What proportion **of those who did not get pregnant** were non-smokers?

Bar Charts and Waffle Charts (NEVER use pie charts if you want to show proportions)

Pie charts have entirely fallen out of favor in the data science world. People are not nearly as good at perceiving angle differences as they are at length differences:

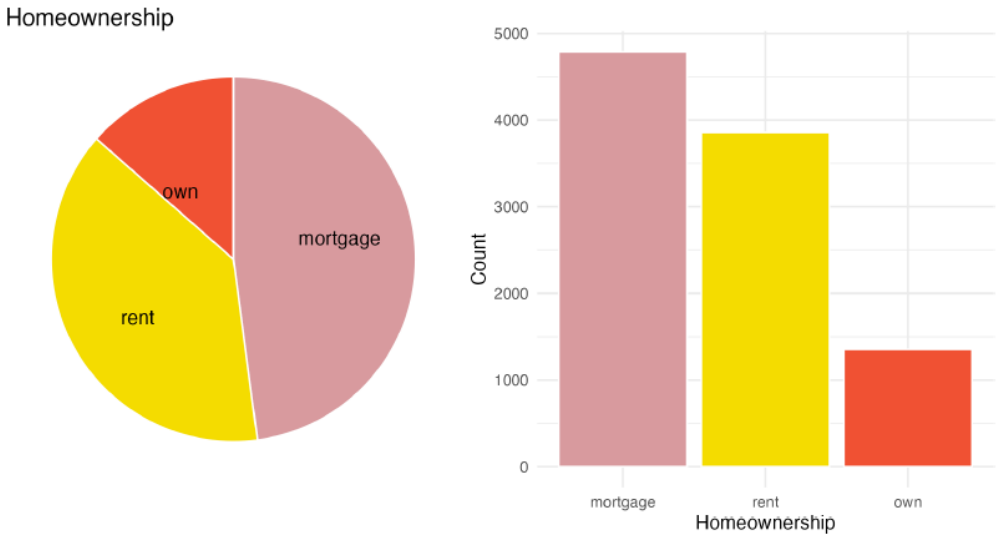


Figure 4.5: A pie chart and bar plot of homeownership.

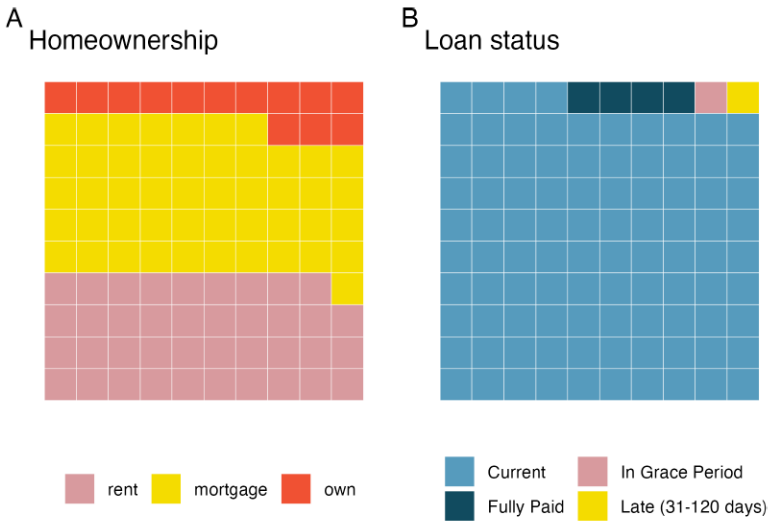


Figure 4.7: Plot A: Waffle chart of homeownership, with levels rent, morgage, and own. Plot B: Waffle chart of loan status, with levels current, fully paid, in grade period, and late.

4.6 Comparing numerical data across groups

Revisit the **`county`** dataset and compare the **median household income** for counties that gained population from 2010 to 2017 versus counties that had no gain. While we might like to make a causal connection between income and population growth, remember that these are observational data and so such an interpretation would be, at best, half-baked.

We have data on 3142 counties in the United States. We are missing 2017 population data from 3 of them, and of the remaining 3139 counties, in 1541 the population increased from 2010 to 2017 and in the remaining 1598 the population decreased. Table 4.6 shows a sample of 5 observations from each group.

Table 4.6: The median household income from a random sample of 5 counties with population gain between 2010 to 2017 and another random sample of 5 counties with no population gain.

State	County	Population change (%)	Gain / No gain	Median household income
Colorado	Custer County	14.28	gain	41330
Georgia	Murray County	1.35	gain	41617
Georgia	Pickens County	7.41	gain	61542
Texas	Wharton County	2.12	gain	50145
Washington	Grays Harbor County	2.30	gain	45483
Alabama	Conecuh County	-3.40	no gain	30434
Illinois	McDonough County	-4.32	no gain	42911
Iowa	Iowa County	-1.08	no gain	58077
Michigan	Genesee County	-1.95	no gain	45231
Wyoming	Campbell County	-3.76	no gain	80178

A. Show the **median household income** data as a **histogram,** filled by **change in population (gain or no gain).**
B. Show the **median household income** data as **side-by-side boxplots,** one is the **gain** and the other is **no gain.**
C. Show the **median household income** data as **ridge plots** one is the **gain** and the other is **no gain.**

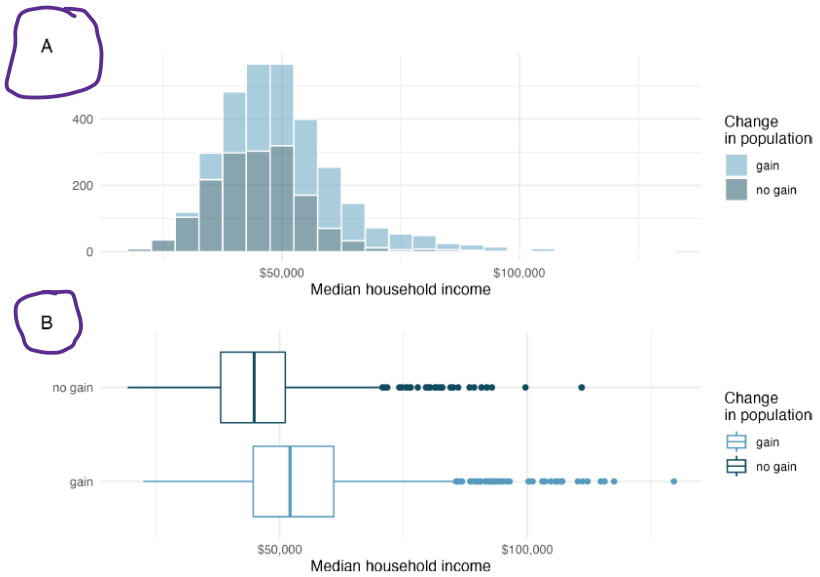


Figure 4.8: Histograms (Plot A) and side by-side box plots (Plot B) for median household income, where counties are split by whether there was a population gain or not.

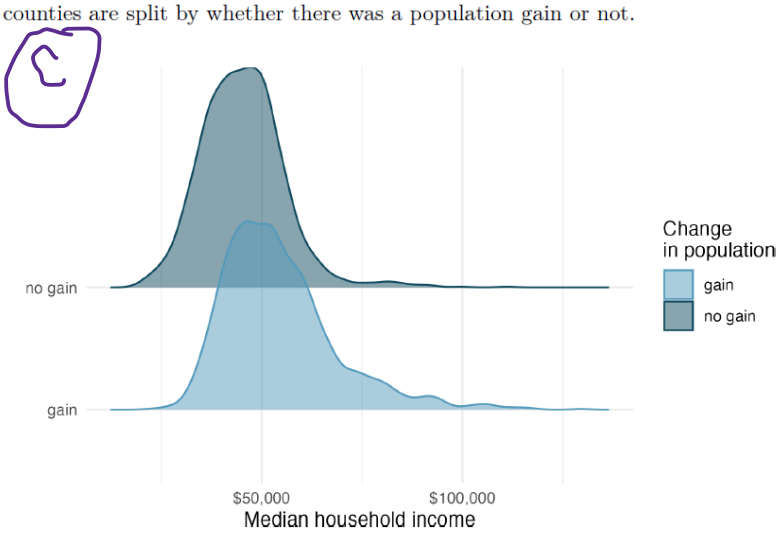
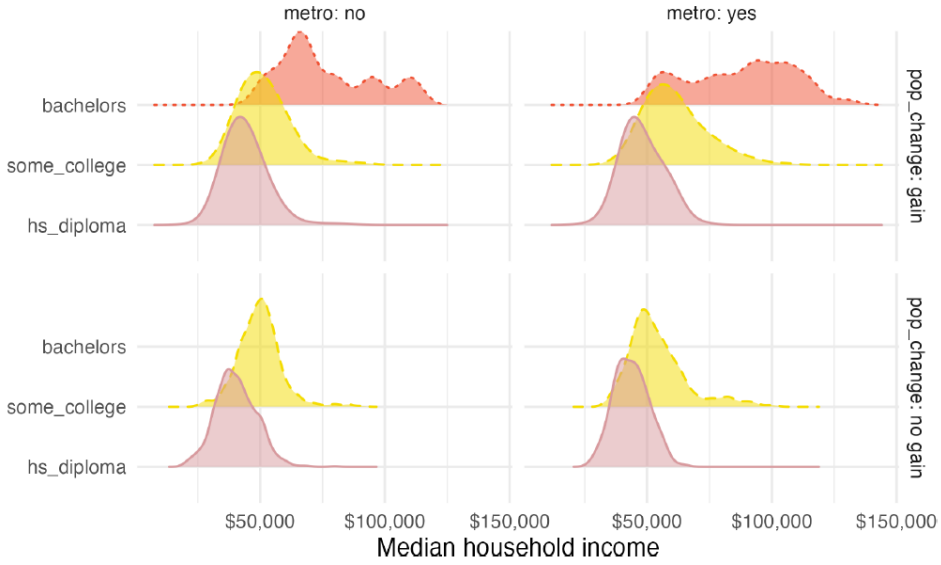


Figure 4.9: Ridge plot for median household income, where counties are split by whether there was a population gain or not.

Comparing data across more than 2 groups



Homework Chapter 4

1. Review section 4.7 (the chapter review)
2. Suggested problems from textbook section 4.8 exercises: 1, 3, and 5
3. Suggested tutorials to learn code: Tutorial 1 – Lessons 1, 2, and 3
    - **Visualizing categorical data**
    - **Visualizing numerical data**
    - **Summarizing with statistics**