

chapter\_template

DEE

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# Preface

An applied methods class for social scientists that uses real-world IPUMS data.  
This course is:

Open-source and customizable -  
All materials available on Github

Made with open-source tools -  
R, RStudio, bookdown

Driven by <sup>(nearly)</sup> open-source data -  
Harmonized across time and space: IPUMS

## What is IPUMS

IPUMS started as a project to digitize the historical records of the US census. It has expanded to include 9 data collections, which are united in their methods and principles of making social science research easier. IPUMS data consists of individual-level census and survey data from more than 100 countries around the world. Notably:

- IPUMS **harmonizes** these data, ensuring consistently coded values across time and space.
- IPUMS provides harmonized **GIS Shapefiles** for most census and survey data.
- IPUMS provides extensive **metadata**, including:
  - Original questionnaire text
  - Alerts about notable changes in variable definition, universe, or coding

IPUMS data is free to use for education and research purposes. Researchers just need to register with an **email address** and brief project description. Nothing

too formal - we're just trying to understand what kinds of questions researchers are interested in. For educators, we have additional resources to set up classroom accounts, making it easy to get your students registered and share IPUMS data with them.

## Why make this course

In a world where information and data are increasingly accessible, it is of utmost importance for individuals to understand data science and the interpretation of data. We believe that education should be easily accessible and teaching resources should be freely available to aid in this endeavor. While we (DEE) may be slightly biased, we think IPUMS is a fantastic resource for **Education** and **Research**. Real-world example datasets provide the bulk of the content for this course, providing an applied context we hope students (and instructors) will find engaging. We also know many instructors may be teaching across multiple disciplines, in large departments, or be the only “data person” at their institution. We think IPUMS data will be useful to virtually any social science field. We provide some example lessons, and encourage instructors to develop their own, using our **\*\*template\*\***, to tailor this course to their subject or interest.



# Course Description

This course is broken down into 3, 5-week units. Unit 1 focuses on familiarizing yourself with R and the IPUMS dataset. In Unit 2, each week will showcase a method/analysis using preselected variables. In class, students will walk through a given problem set and produce a lab report by the end of class. In Unit 3, students will work towards answering a research question that they pose, creating a research paper with literature review, data analysis, conclusion, and data outputs.

## Course Aims

Provide students with relevant, hands on, methodological training in data literacy and visualization.

## Learning Outcomes

After this course, students will be able to:

- Understand the depth of the IPUMS database and the variables it has to offer
- Compose R code to analyze the IPUMS data
- Produce visually pleasing data outputs in R
- Synthesize the information in a written report
- Present the analysis in a poster format for other students

## Guiding Principles

- Phenomenon-based learning
  - try to start the class with a **question** or **problem**

- *why* does the data look the way it does
  - structure class so students work towards solving the problem
- Relevant examples
  - Drawn from multiple disciplines (eg, economics, demography)
  - Can be added as modular examples/exercises

# Syllabus - Overview

This syllabus is initially envisioned as 3 5-week sections. However, compilation and content are intended to be modular with templates for instructors to include their own specialties.

The basic structure of this course is:

## **Unit 1 (Weeks 1-5):** Understanding and Testing Data

- Students use simple datasets bundled with the course or provided by the instructor.
- Simplified data to illustrate trends.
  - EG: plotting continuous variable (AGE); Table of categorical variable (SEX); Crosstabs

## **Unit 2 (Weeks 6-10):** Finding Data and Asking Questions

- Students begin to analyze real world, IPUMS, datasets, provided by course/instructor.
- Students begin to model real world phenomena
  - EG:  $SEX \sim EDUATTAIN$  ;  $SEX \sim EDATTAIN + EMPSTAT$
- Students learn to perform exploratory analysis, hypothesis testing, and statistical inference.
- Students learn to navigate IPUMS website, and find relevant data to their research interest.

## **Unit 3 (Weeks 11-15):** Discussing Data and Student Research

- Students develop a research question to be answered with IPUMS data.
  - Students are encouraged to fit it to their interests/major/discipline.
- Course time should be devoted to individual/small-group research.
- Instructor/class present on recent research.
  - Instructor models constructive / scholarly criticism.
  - Encourage students to critique published work - responsibly.

**Detailed Syllabus**

## Unit 1 Understanding and Testing Data

Students become gain familiarity and comfortability navigating RStudio, coding in R and performing simple data manipulation and visualization exercises. Datasets in this section consist of real-world (or synthetic) data, but the focus is on understanding data types (EG: using Age as a continuous variable; sex, education, employment as categorical; etc). Instructors should acknowledge these as **educational** datasets and make explicit trends found within these data are devoid of context, and must be taken with a (rather large) grain of salt, if at all.

By the end of Unit 1, students will be able to:

- Download R and RStudio
- Read data into R and
- Write (save) data out of R
- Summarize data visually
  - Using **base R**
  - Using **ggplot** (tidyverse)
- Summarize data in tables
  - Using base R
  - Using **gttable** / **tidyverse**
- Formally state and test assumptions of data
  - *EG*: t-test, anova, correlations, regression

By the end of Unit 1, students will understand

- Main types of data
  - *EG*: logical, numeric, character, etc
  - R specific vs general terms
- How to create and describe various data distributions
  - *EG*: normal, poisson, normal-skewed, etc
- Know which types statistical tests are appropriate for a given set of data.

**Week 1: Intro to R, data types, data structures**

**Week 2: Plotting Data, Distributions**

**Week 3: Statistcal testing of simple data sets**

**Week 4: Correlation and Relationships of simple data sets**

**Week 5: (TBD)**

## **Unit 2 Finding Data and Asking Questions (Using IPUMS Data)**

Here we demonstrate two **different** approaches to conducting research. Students become familiar writing up short lab reports detailing their findings. For Section 7.2, we/instructor provides students with simple datasets from IPUMS (or other real-world data). Students will learn exploratory data analysis techniques and how to create lab reports to summarize key findings.

For unit 7.3, students will learn to develop their own simple research questions or social-science hypotheses. They will seek out data to answer these questions, learning to navigate ipums.org, and create **data extracts**, as well as hypothesis-testing statistical methods. Again, lab reports to summarize findings.

### **0.0.0.1 Week 6: Intro to IPUMS**

#### **Week 7: Exploratory analysis**

If you've just collected a survey, or other raw data, you may not know what you're looking for. This is perfectly ok but goes against *the scientific method* most people learned in grade school.

This unit begins by presenting data/distributions and asking students to begin interpreting the data . visual exploration is encouraged and basic of data manipulation are taught \* *EG*: how to subset data, how to reshape data, how to re-code data, how to convert from one **data type** to another.

Example lab exercise:

Students given a data set (xls, csv, etc) \* load data, perform manipulations, basic summaries + cross tabs + group means by a covariate \* inspect data visually + *DESCRIBE* the distribution - is it normal? significant? \* *FIND* aquestion in the spread of the data + how can you test this (maybe small group work) \* write up/ present results + think on confounding factors / biases

**Week 8: Hypothesis Testing**

If, on the other hand you have an a pre-existing idea you want to test. We can follow the traditional *scientific method*. With a question in mind, the first question is: where to look. What better place than IPUMS!

Begin introducing navigation of web resources - mainly IPUMS international

Students should become comfortable working through lab exercises: \* Define a question (or be presented with one) \* Download variables from IPUMS (course downloads possible) \* Perform a basic analysis (discussed in Unit 1) \* Generate a **visual argument** for your analysis + Include explanation/interpretation/reflection on the question at hand, and the data used + Any obvious biases + Any obvious confounding factors

**Week 9: Statistical Inference****Week 10: (TBD)****Unit 3 Discussing Data and Student Research**

Students will select their own research question that can be answered with the IPUMS data set and will spend five weeks conducting a research project complete with data analysis, visualization, and interpretation.

In this section we encourage the instructor to provide ample time for independent student/small-group research. Some class time should be devoted to modeling healthy discussion and critique of methods. Students should learn to discuss not just *how* to answer a research question but *why* they are asking/answering it. What impact does the question/answers have. Is the question relevant/meaningful, and importantly, Is this research question perpetuating racist ideas.

We provide some examples here but encourage instructors (or students) to bring in recent journal/popular articles that do (or do not) apply data science methods well.

**Week 11: Students develop research Question****Week 12: Students find relevant variables from IPUMS****Week 13: Students test and evaluate results****Week 14: Students prepare presentations of results****Week 15: Students present work (slides, poster, podium, etc)**





# DEV NOTES

## TO DO

- Make chapter 1 chapter 2
- Anna Adds chapter con data science intro exclusive of R/IPUMS
- discuss style
  - key terms section for each chapter?
  - key terms in **bold**
  - italics for *emphasis*
  - are we pro-hyphens, or are they pedantic?

## MISC IDEAS

- Application forward
- Present research/ analysis/results FIRST, then explain the mathematical principals behind it
- daily/weekly “i’m stuck on...”
  - Students send in questions (night before class) and instructor spends 10-15 mins talking through (or collaboratively working through with class) solutions
  - Alternatively, once a month maybe a longer class covering “common problems asked this month” daily/weekly “recent research”
- pick out a recent article with good visualization (or bad) and spend 5-10 mins discussing what makes it good (or bad)
  - Encourage students to find articles for extra credit

**Documentation** This function grabs any packages in your project and adds them to a local list that can be referenced using `R-pacakgename * NOTE` in practice, that needs to be wrapped in markdown syntax, eg: `[@R-bookdown] *` See help files for more info - might be able to create/add a `citation` file



# Chapter 1

## Unit 1: The Basics

### 1.1 Week 1: Intro to R, data types, data structures

#### 1.1.1 Intro to R

#### 1.1.2 Data Types

**Data** is defined as “facts and statistics collected together for reference or analysis.” *This is from the internet and needs to be our words* As seen in Figure 1.1, there are two types of data: **quantitative** and **qualitative**. Quantitative data are able to be expressed in numerical format and are countable. These data are either **discrete** or **continuous**...

#### 1.1.3 Data Structures

### 1.2 Week 2: Plotting Data

#### 1.2.1 Normal Distributions

First we'll generate a normal distribution with the `rnorm()` function. This takes 3 arguments: `n`, `mean`, `sd`, which you can see filled in below. While we could print out a list of all these values, it's not easy to *understand* a list of numbers

```
normal_dist <- rnorm(n = 100, ## 100 samples
                     mean = 10, ## with a mean of 10
                     sd = 1 ## and a standard deviation of 1)
```

```
)

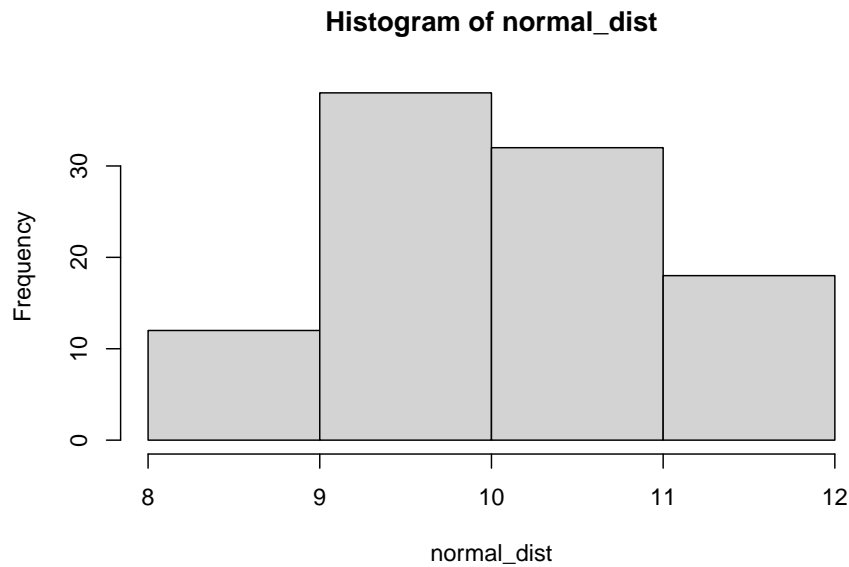
normal_dist
```

```
## [1] 11.214461 8.694534 9.332107 8.911323 11.054859 9.778740 8.993182
## [8] 10.761833 10.621199 8.467256 9.637717 9.545401 9.108842 9.414697
## [15] 10.719294 11.223581 10.519630 11.569280 9.971066 9.061314 9.319174
## [22] 9.952482 10.568586 10.124846 8.045733 8.616190 11.117656 9.436118
## [29] 9.085477 9.314522 10.479354 8.376964 9.609358 10.442525 11.419004
## [36] 9.801504 9.438599 9.239346 9.256506 9.267352 10.489208 10.123051
## [43] 10.685340 9.209459 9.662903 8.423936 10.624329 9.710164 8.998084
## [50] 9.607565 11.034620 10.507358 10.551401 9.854372 9.267117 10.654146
## [57] 9.282600 10.622289 10.317575 11.149847 11.597969 9.816142 9.525412
## [64] 11.654465 10.780633 10.516553 10.722217 10.725300 9.239157 9.730458
## [71] 10.517492 9.464276 11.352683 10.331018 9.666841 10.717898 10.900128
## [78] 11.745647 11.565378 11.387217 9.890903 8.986477 9.863902 10.213830
## [85] 9.842441 11.293145 10.296708 11.063484 11.296226 8.643745 10.287700
## [92] 10.182011 10.096620 9.354316 9.309954 10.301181 8.465279 11.020249
## [99] 10.094286 9.808483
```

Another better way to look at data would be to **visualize** or **plot** it. One way to do that is with a **histogram**, which groups **continuous values** into **bins**, then plots the **frequency** for each bin.

In R, we use the `hist()` function to plot a histogram of data. We can (try to) control the number of bins with the `breaks` argument, but note that it doesn't always match up. The `hist()` function will adjust based on the distribution of the data.

```
hist(normal_dist,breaks = 5)
```



Another way to visualize this would be with a d

## 1.2.2 What *is* normal?

### 1.2.2.1 Quantitative summaries

5num summary \* Min, 25th percentile, median, 75th percentile, Max

```
tab_normal_dist <- summary(normal_dist)
```

We can print the table in R by calling its name.

```
tab_normal_dist
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  8.046   9.329  10.033  10.046  10.693  11.746
```

Mean, standard deviation

### 1.2.2.2 Meaningful Comparisons

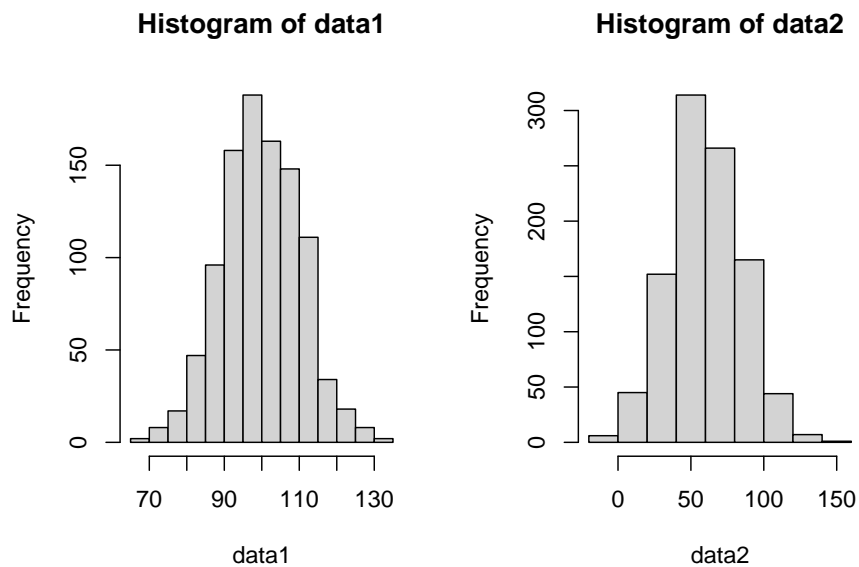
How to compare apples to oranges? Standardize the units / standardize the data

```
data1 <- rnorm(n=1000,  
              mean = 100,  
              sd = 10)  
  
data2 <- rnorm(n=1000,  
              mean = 60,  
              sd = 25)
```

Are these the same distribution?

Any issues??

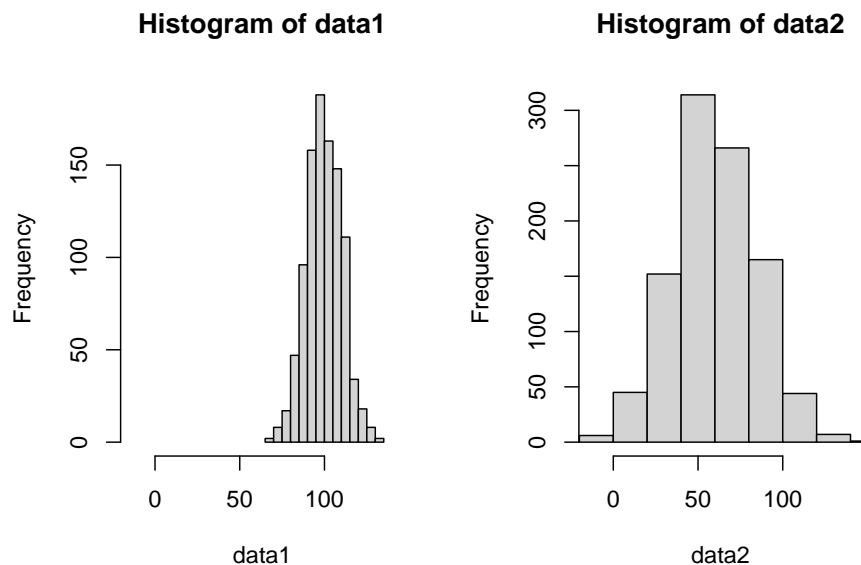
```
layout(matrix(1:2, ncol = 2))  
hist(data1)  
hist(data2)
```



```
total_range <- range(data1, data2)
```

Are they the same?

```
layout(matrix(1:2, ncol = 2))  
hist(data1, xlim = total_range)  
hist(data2, xlim = total_range)
```



Numerically / tabularly

Often times its important to tables of **summary statistics**

```
norm_comp_tab <- rbind(summary(data1),
                        summary(data2))

norm_comp_tab

##           Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## [1,]  68.20685 92.47337 99.62627 99.87993 107.07466 134.5889
## [2,] -14.10622 43.92996 59.10958 59.97304  77.27069 140.7663
```

Making the table a little nicer. Also an example of **conditional programming**.

```
rownames(norm_comp_tab) ## they're null
```

```
## NULL
```

```
if(is.null(rownames(norm_comp_tab))){
  rownames(norm_comp_tab) <- c("data1", "data2")
}
```

When working with **Rmarkdown** we can take advantage of **knitr** and **pandoc** to nice looking tables even easier.

```
knitr::kable(norm_comp_tab)
```

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
data1	68.20685	92.47337	99.62627	99.87993	107.07466	134.5889
data2	-14.10622	43.92996	59.10958	59.97304	77.27069	140.7663

**How** transform the data

Simple transformation (multiply all values by 100) \* to convert units \* other examples?

Complex transformations \* log-transformation (*DEE: not a fan*) \* z-scores (*DEE: a better option*)

**Why** transform the data? \* Real world applications? \* Is it always appropriate to transform data?

### 1.2.3 Skews

What to do if the data are **not** normal?

## 1.3 Week 3: Statisitcal testing of simple data sets

### 1.3.1 t-tests, ANOVA, chi2

## 1.4 Week 4: Relationships between variables in simple data sets

### 1.4.1 Correlation, Linear Regression

#### 1.4.1.1 Simple LM

#### 1.4.1.2 Complex LM

### 1.4.2 Genearlized Linear Model

## 1.5 Week 5:

For now, I have 3 main chapters for each of the main sections: \* Basics of data science / R 1 \* Applications/critiques using IPUMS data 7 \* Student-driven projects 8



Each of these **Chapters** contains multiple sections. We'll likely want to break these sections out into their own `.Rmd` files as they get fleshed out. For now, I'll try to keep the abundance of files limited.

**NOTE:** As these actually get filled out, we will probably want to insert different **parts** to the book (EG, the content of Unit 1 is covered in **Part I**). \* Declare parts with `# (PART) Part I {-}` immediately before the first chapter `#` it contains.

**Topics to include:** \* What is data? \* Everything can be data \* How do we interpret data \* Tables \* Plots \* Univariate distributions \* What can they tell us \* Multi-modality in distributions \* Categorical vs continuous data \* Don't need to get ahead of this yet \* Add in a grouping category - multi state/multi-national dataset \* Ttest / anova

**Type of Data:** Age distributions Specifically generate a dataset with old/young folks over-represented to highlight a bimodal distribution

Start with single state/country Add a second state/country to demo ttest Add more to demo anova

Alternatively, income by education level - may be more interesting/relevant to college students (or depressing)

## 1.6 Intro to R/RStudio

## 1.7 Reading Data / Distributions

### 1.7.1 What *is* a normal distribution

#### 1.7.1.1 How normal is it?

show increasingly unclear examples of normal vs not

introduce tests of normality

#### 1.7.1.2 Measuring normality - single sample

reinforce [concept of statistical] **normality**

is a value from a sample? - one way ttest something about tails

#### 1.7.1.3 comparing normality - two samples

standard / two-way t test

**1.7.1.4 comparing more than two - ANOVA**

#Glossary Data Quantitative Qualitative Discrete Continuous Nominal Ordinal

## Chapter 2

### Engage

Brief example of an engaging phenomenon. \* Poll students and discuss results + Does the *average* match up with individual experiences? \* Real-world research example \* Interrogating a commonly held assumption + the average height of humans is 5'5"



## Chapter 3

# Explore

Explore other examples of this phenomenon.

Build on the first one to show variation. \* Other ways to represent the phenomenon/data + tabular + visually \* can the example be grouped / broken into subgroups + does the same pattern/phenomenon apply? \* Is there a corollary / inverse phenomenon?



## Chapter 4

# Explain

Discuss/interrogate the pattern of the data \* does the shape imply anything \*  
try to have it student led / guided \* with time, students guess at what the data  
shows/doesn't show without labels





## Chapter 5

# Elaborate

Work through a new example, contextualizing the phenomenon using real-world data/examples.



## Chapter 6

# Evaluate/Exercises

short lab exercises for students to recreate / code in R

Build on past concepts reinforcing basic data manipulations, summaries, etc.



# Chapter 7

## IPUMS

### 7.1 Week 6 Introduction to IPUMS

### 7.2 Week 7 Exploratory analysis

If you've just collected a survey, or other raw data, you may not know what you're looking for. This is perfectly ok but goes against *the scientific method* most people learned in grade school (More on that to follow(*include\_link*)).

This unit begins by presenting data/distributions and asking students to begin interpreting the data . visual exploration is encouraged and basic of data manipulation are taught \* *EG*: how to subset data, how to reshape data, how to recode data, how to convert from one `data type` to another.

Example lab exercise:

Students given a data set (xls, csv, etc) \* load data, perform manipulations, basic summaries + cross tabs + group means by a covariate \* inspect data visually + *DESCRIBE* the distribution - is it normal? significant? \* *FIND* aquestion in the spread of the data + how can you test this (maybe small group work) \* write up/ present results + think on confounding factors / biases

#### 7.2.1 Advanced Exploration - Change Over Time

Here we demonstrate an approach to looking at how Family Structure (inferred from household relationships) has changed over time.

##### 7.2.1.1 Setup / Load Data

Install/update R packages

```
install.packages("ipumsr")
install.packages("tidyverse")
```

Data extract created online using the datacart system.

```
library(ipumsr)
library(dplyr)

ddi <- read_ipums_ddi("Data/ipumsi_00005.xml")
data <- read_ipums_micro(ddi)
```

**7.2.1.1.1 Inspect the Data** Using `haven` labeled values.

```
data$RELATE[1:100]
class(data$RELATE)

data %>% count(RELATE)
data %>% count(SEX)
```

What were those codes ??

```
## need to convert this to an image or something similar; kable table?
ipums_view(ddi)
```

**7.2.1.1.2 Visualize** A simple plot

```
plot(AGE ~ YEAR, data = data)
```

A fancier plot

```
plot(AGE~YEAR, data = data, type = "n", main = "Age by Sex, over Time, CO")
points(data$YEAR[data$SEX==1]-1, data$AGE[data$SEX==1], pch = 16, col = hsv(.6,.6,.8,.2))
points(data$YEAR[data$SEX==2]+1, data$AGE[data$SEX==2], pch = 16, col = hsv(1,.6,.8,.2))
abline(lm(AGE~YEAR, data = data), col = "green")
```

**7.2.1.1.3 Asking (logical) questions** Here we demonstrate how setting up logical questions can be used to easily filter/subset data.

```
age_test <- data$AGE > 18

class(age_test)

age_test
```

Logical vectors are stored as **TRUE** or **FALSE**, but can also be evaluated numerically as 1 or 0 respectively. We can therefore `sum()` the number of **TRUE** values and divide by total rows for a proportion.

```
sum(age_test)/nrow(data)
```

**7.2.1.1.4 HH vs persons** A unique characteristic of census and some survey data is the nested-structure with individuals being grouped into households. Often times it is necessary to choose to work at the hh or person level, and data must be appropriately manipulated to fit that case.

```
hh_total <- length(unique(data$SERIAL))
hh_total
ipums_view(ddi)
```

### 7.2.1.2 Nuclear Family

First we look at a nuclear family, comprising only parents and their immediate children.

```
library(ipumsr)
library(dplyr)

ddi <- read_ipums_ddi("/pkg/ipums/personal/ehrli097/AABA_2022/Data/ipumsi_00005.xml")
all_data <- read_ipums_micro(ddi)

census_years <- c(1860, 1870, 1880, 1900, 1910, 1960, 1970, 1980, 1990, 2000, 2010)

## subset census only
d2 <- all_data %>% filter(YEAR %in% census_years)

## make a household dataframe
hhs <- d2 %>% distinct(YEAR, SERIAL, .keep_all = TRUE) %>% select(YEAR, SERIAL, GEO1_US)

hhs %>% View()
```

```

hhs <- d2 %>% filter(RELATE ==4) %>%

distinct(YEAR, SERIAL) %>% mutate(extended_test=TRUE) %>% right_join(hhs, by = c("YEAR", "SERIAL"))

hhs <- d2 %>% filter(!RELATE %in% c(1, 2, 3) |
                     (RELATE == 3 &
                      MARST %in% c(2, 3, 4))
                     ) %>%

distinct(YEAR, SERIAL) %>% mutate(nuclear_test = FALSE) %>% right_join(hhs, by = c("YEAR", "SERIAL"))

table(hhs$extended_test, hhs$nuclear_test)

```

```

hhs <- d2 %>% filter(RELATED %in% c(4200, 4210, 4211, 4220, 4500, 4510, 4600)) %>% distinct(YEAR, SERIAL)

hhs <- d2 %>% filter(RELATED %in% c(4100, 4110, 4120, 4130, 4300, 4301, 4302)) %>% distinct(YEAR, SERIAL)

res_tabs <- list(
  "nuclear_test" = hhs %>% group_by(YEAR, nuclear_test, GEO1_US) %>% summarize(.groups = "drop"),
  "extended_test" = hhs %>% group_by(YEAR, extended_test, GEO1_US) %>% summarize(.groups = "drop"),
  "parent_test" = hhs %>% group_by(YEAR, parent_test, GEO1_US) %>% summarize(.groups = "drop"),
  "children_test" = hhs %>% group_by(YEAR, children_test, GEO1_US) %>% summarize(.groups = "drop")
)

```



```

collapsed_results <- res_tabs %>% purrr::map(function(x){
  x <- x %>% group_by(across(names(x)[1:3])) %>% summarize(.groups="drop", n = sum(n))
})

collapsed_results <- lapply(collapsed_results, function(x){
  colnames(x)[2] <- "test"
  colnames(x)[3] <- "state"
  return(x)
})

combined <- collapsed_results %>% purrr::reduce(full_join, by = c("YEAR", "test", "state"))

colnames(combined) <- c("YEAR", "test", "state", "n_nuclear", "n_extended", "n_parent", "n_childre
combined[is.na(combined)] <- 0

to_plot <- combined %>% group_by(YEAR, state) %>% mutate(n_tot = sum(n_nuclear)) %>% ungroup() %>

```

#### 7.2.1.2.1 Tabulate results

```

to_plot <- to_plot %>% filter(test==TRUE)

plot(to_plot$YEAR, to_plot$pct$n_nuclear, col = hsv(.4, .6, .8), pch = 16, ylim = c(0,1), xlab = "

```

#### 7.2.1.2.2 Visualize Nuclear Families

#### 7.2.1.3 Extended Family

Next we look at hhs with extended families present. IE, any that contain more relationships than just Parent/Child/Sibling (between children only)

```

to_plot <- to_plot %>% filter(test==TRUE)

glm_hist <- glm(pct$n_extended ~ YEAR, data = to_plot[to_plot$YEAR < 1950,], family = "quasibinomial")

glm_hist_x <- seq(from=1860, to = 1910, length.out = 100)
glm_hist_y <- predict(glm_hist, list(YEAR = glm_hist_x), type = "response")

glm_mod <- glm(pct$n_extended ~ YEAR, data = to_plot[to_plot$YEAR > 1950,], family = "quasibinomial")

glm_mod_x <- seq(from = 1960, to = 2010, length.out = 100)
glm_mod_y <- predict(glm_mod, list(YEAR = glm_mod_x), type = "response")

mods <- list("hist"=list(),
            "mod" = list()
            )
mods_plots <- list("hist"=list(),
                  "mod" =list()
                  )

for(i in names(to_plot$pct)){

  hist_x <- to_plot$YEAR[to_plot$YEAR < 1950]
  mod_x <- to_plot$YEAR[to_plot$YEAR > 1950]

  mods$hist[[i]] <- lm(pct[[i]] ~ YEAR, data = to_plot[to_plot$YEAR < 1950,])

  mods_plots$hist[[i]] <-
    data.frame("x" = hist_x,
              "y" = predict(mods$hist[[i]],
                            list(YEAR =hist_x),
                            type = "response")
              )

  mods$mod[[i]] <- lm(pct[[i]] ~ YEAR, data = to_plot[to_plot$YEAR > 1950,])

  mods_plots$mod[[i]] <-
    data.frame("x" = mod_x,
              "y" = predict(mods$mod[[i]],

```

```

    list(YEAR = mod_x),
    type = "response")
  )
}

```

#### 7.2.1.3.1 Generate models

```

plot(to_plot$YEAR, to_plot$pct$n_extended, col = hsv(.95, .6, .8), pch = 16, ylim = c(0, .25), bg =

lines(glm_hist_x, glm_hist_y, col = hsv(.95, .3, 1), lwd = 2)
lines(glm_mod_x, glm_mod_y, col = hsv(.95, .3, 1), lwd = 2, lty = 2)

points(to_plot$YEAR,
       to_plot$pct$n_extended,
       pch = 23,
       bg = hsv(.95, .6, .8))

```

#### 7.2.1.3.2 Visualize

#### 7.2.1.4 Even more DETAIL - maybe remove

```
ipums_view(ddi)
```

```

hhs <- d2 %>% filter(RELATED %in% c(4200, 4210, 4211, 4220, 4500, 4510, 4600)) %>%
distinct(YEAR, SERIAL) %>% mutate(parent_test=TRUE) %>% right_join(hhs, by = c("YEAR", "SERIAL")
hhs <- d2 %>% filter(RELATED %in% c(4100, 4110, 4120, 4130, 4300, 4301, 4302)) %>% distinct(YEA

```

```

plot(to_plot$YEAR, to_plot$pct$n_extended, col = hsv(.95, .6, .8), pch = 16, ylim = c(0, .25), bg =

```

```

lines(glm_hist_x,glm_hist_y, col = hsv(.95, .3, 1), lwd = 2)
lines(glm_mod_x, glm_mod_y, col = hsv(.95, .3, 1), lwd = 2, lty = 2)

lines(mods_plots$hist$n_parent,col = hsv(.8, .3,1), lwd = 2)

lines(mods_plots$mod$n_parent, col = hsv(.8, .3,1), lwd = 2, lty = 2)

points(to_plot$YEAR,
       to_plot$pct$n_parent,
       pch = 23,
       bg = hsv(.8, .6,.8))

points(to_plot$YEAR,
       to_plot$pct$n_extended,
       pch = 23,
       bg = hsv(.95,.6,.8))

```

#### 7.2.1.4.1 Parents Supporting Parents

```

plot(to_plot$YEAR, to_plot$pct$n_extended, col = hsv(.95, .6,.8), pch = 16, ylim =c(0,

lines(glm_hist_x,glm_hist_y, col = hsv(.95, .3, 1), lwd = 2)
lines(glm_mod_x, glm_mod_y, col = hsv(.95, .3, 1), lwd = 2, lty = 2)

lines(mods_plots$hist$n_children, col = hsv(.55,.3,1), lwd = 2)

lines(mods_plots$mod$n_children, col = hsv(.55,.3,1), lwd = 2, lty = 2)

points(to_plot$YEAR,
       to_plot$pct$n_children,
       pch = 23,
       bg = hsv(.55,.6,.8))

points(to_plot$YEAR,
       to_plot$pct$n_extended,

```

```
pch = 23,  
bg = hsv(.95, .6, .8))
```

#### 7.2.1.4.2 Parents Supporting (extended) children

## 7.3 Week 8 Hypothesis Testing

If, on the other hand you have an a pre-existing idea you want to test. We can follow the traditional *scientific method*. With a question in mind, the first question is: where to look. What better place than IPUMS!

Begin introducing navigation of web resources - mainly IPUMS international

Students should become comfortable working through lab exercises: \* Define a question (or be presented with one) \* Download variables from IPUMS (course downloads possible) \* Perform a basic analysis (discussed in Unit 1) \* Generate a **visual argument** for your analysis + Include explanation/interpretation/reflection on the question at hand, and the data used + Any obvious biases + Any obvious confounding factors

## 7.4 Week 9 Statistical Inference

## 7.5 Week 10 (TBD)

Some text to break up the sub-section headers

## 7.6 Intro to IPUMS website

### 7.6.1 background on ipums

### 7.6.2 navigating website

Find certain (very common) variables to answer (common) social science questions.

We describe our methods in this chapter.

Math can be added in body using usual syntax as follows. This may be useful, particularly for explaining the math side of things.

## 7.7 math example

$p$  is unknown but expected to be around  $1/3$ . Standard error will be approximated

$$SE = \sqrt{\left(\frac{p(1-p)}{n}\right)} \approx \sqrt{\frac{1/3(1-1/3)}{300}} = 0.027$$

You can also use math in footnotes like this<sup>1</sup>. Footnotes are helpful because they re-link to where you left off.

We will approximate standard error to  $0.027^2$

The `longnote` footnote seems particularly useful.

---

<sup>1</sup>where we mention  $p = \frac{a}{b}$

<sup>2</sup> $p$  is unknown but expected to be around  $1/3$ . Standard error will be approximated

$$SE = \sqrt{\left(\frac{p(1-p)}{n}\right)} \approx \sqrt{\frac{1/3(1-1/3)}{300}} = 0.027$$

## Chapter 8

# Unit 3: Independent Research

Students will select their own research question that can be answered with the IPUMS data set and will spend five weeks conducting a research project complete with data analysis, visualization, and interpretation.

In this section we encourage the instructor to provide ample time for independent student/small-group research. Some class time should be devoted to modeling healthy discussion and critique of methods. Students should learn to discuss not just *how* to answer a research question but *why* they are asking/answering it. What impact does the question/answers have. Is the question relevant/meaningful, and importantly, Is this research question perpetuating racist ideas.

We provide some examples here but encourage instructors (or students) to bring in recent journal/popular articles that do (or do not) apply data science methods well.

- 8.1 **Week 11: Students develop research Question**
- 8.2 **Week 12: Students find relevant variables from IPUMS**
- 8.3 **Week 13: Students test and evaluate results**
- 8.4 **Week 14: Students prepare presentations of results**
- 8.5 **Week 15: Students present work (slides, poster, podium, etc)**

By this point, students should be familiar with basic concepts from Chapter 1. These include:

- Basic Coding
  - read/write data in/out of R
  - basic manipulations
- Theoretical Basis
  - looking at data distributions
  - formal assessment of distributions

Students will also be familiar with how these concepts are applied from Chapter 7. Hopefully students will be able to:

- Come up with a social science question they are interested in
  - Critically think about target variable(s) of interest. Any *a priori* covariates? confounders?
  - Acquire relevant data from IPUMS
  - Analyze, Summarize, Visualize Data
    - \* scope and complexity at student/teach discretion
  - Present research to class
    - \* **potentially** critically discuss/evaluate each others work.



- \* **science is collaborative** everyone should be out to do their best work and represent the data as best we can. We all have conscious and unconscious biases, and the best way to confront them is share and receive (respectful) feedback.

During this Unit, we suggest giving ample class time for independent student research, peer-to-peer collaboration, and basic R/stats troubleshooting. This would also be a great time to model how to give respectful criticism by discussing recent research papers. \* We could maybe come up with 1-2 seed examples, with a few talking points

## 8.6 Example one

## 8.7 Example two



## Chapter 9

# Example RMD code

For now, this chapter is a bit of a placeholder. I'm not sure what/how the `references.Rmd` file actually fits in to the code/construction (it looks automatic) so I want to keep that in place and need a section to note that.

I also want a more centralized reference point to put any example code I find helpful while working in R/bookdown. This section could get really unruly really fast, but oh well.

### 9.1 Core

`index.Rmd` is required and treated as file 00. Chapters *should* be numbered for ease of sorting but custom orders are possible by specifying filenames somewhere **in this file**

Remember each Rmd file contains one and only one chapter, and a chapter is defined by the first-level heading `#`. + **IE** beyond the YAML header this file functions as a normal chapter since it starts with a top level header. + Note that `index.Rmd` has its own YMAL in addition to the various .yaml files...not sure exactly how these relate.

Reference a figure by its code chunk label with the `fig:` prefix, e.g., see Figure `@ref(fig:norm_dist_plot)`. Similarly, you can reference tables generated from `knitr::kable()`, e.g., see Table `@ref(tab:norm_summary_tab)`. \* Again, this prints an auto-generated numeral \* also leaving this in the context of the plots in Chapter 7

You can write citations, too. See `knitr::write_bib()` for more on this. Quick example from `demo/index` (may not work without `write_bib()` though): we are using the **bookdown** package (Xie, 2022) in this sample book, which was built

on top of R Markdown and **knitr** (Xie, 2015). \* If included, “Refernces” section gets added to each chapter. \* Not exactly sure where

Embed html renders (EG, fancy tables (IPUMS\_var\_desc), or any shiny app) with **webshot** R package and **phantomJS**.

```
install.packages("webshot")
webshot::install_phantomjs()
```

Embed figures from a folder.

For this, it’s usually best to use a code-chunk and **knitr**. There are a number of graphical paramerters you can set (or ignore) **out.width** will scale your image accordingly - irrespective of unit/display **fig.align** should be “left”, “right”, or “center” **fig.cap** allows you to provide “mouse over” captions for the image. **echo=FALSE** is important if you ONLY want the image (IE the result of the code). If you want the code itself to show, (IE, or echo) set **echo=TRUE**.



Figure 9.1: the ipums logo

## 9.2 Tips

\***Autonumber sections** Note the {-} used to indicate “do not number this section” eg: preface.

**LABEL EVERYTHING** you’ll likely want to reference it later \* code chunks that produce figures can be referenced via `@\ref{fig:[LABEL]}`

You can label chapter and section titles using `{#label}` after them, e.g., we can reference Chapter 1. If you do not manually label them, there will be automatic labels anyway, \* No idea how the automatic references work, so always be sure to declare them. \* **NOTE** these display as the relevant Chapter **numeral**.

## 9.3 Syntax

*italics* or *italics* (can handle spaces) **bold** code *equations*

### 9.3.1 Math

Randal Pruim features an extensive list of common math expression on their github page. Here are some quick notes:

In-line equations can be written within `$` and will be displayed right there:  $a^2 + b^2 = c^2$ . In contrast, you can also add equation chunks by using `$$`

This can be coded in-line,

$$\sum_{n=1}^{10} n^2$$

, but will result in a page break.

Alternatively, a more “classic” equation chunk:

`$$ Plain text doesnt get spaces`

`how`

`very`

`odd`

`$$`

To compile this example to PDF, you need XeLaTeX. You are recommended to install TinyTeX (which includes XeLaTeX): <https://yihui.name/tinytex/>.



## Chapter 10

### Engage

Brief example of an engaging phenomenon. \* Poll students and discuss results + Does the *average* match up with individual experiences? \* Real-world research example \* Interrogating a commonly held assumption + the average height of humans is 5'5"





## Chapter 11

# Explore

Explore other examples of this phenomenon.

Build on the first one to show variation. \* Other ways to represent the phenomenon/data + tabular + visually \* can the example be grouped / broken into subgroups + does the same pattern/phenomenon apply? \* Is there a corollary / inverse phenomenon?



## Chapter 12

### Explain

Discuss/interrogate the pattern of the data \* does the shape imply anything \*  
try to have it student led / guided \* with time, students guess at what the data  
shows/doesn't show without labels



## Chapter 13

### Elaborate

Work through a new example, contextualizing the phenomenon using real-world data/examples.



## Chapter 14

# Evaluate/Exercises

short lab exercises for students to recreate / code in R

Build on past concepts reinforcing basic data manipulations, summaries, etc.





# Bibliography

Xie, Y. (2015). *Dynamic Documents with R and knitr*. Chapman and Hall/CRC, Boca Raton, Florida, 2nd edition. ISBN 978-1498716963.

Xie, Y. (2022). *bookdown: Authoring Books and Technical Documents with R Markdown*. R package version 0.29.