Introduction to Statistical Inference (QTM 100 Lab)

Lecture 3: Data Cleaning and Manipulation

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Gameplan

Data Preliminaries

Creating New Variables

Numerical to Categorical

Categorical to Categorical

Data Preliminaries

Why clean data?

- Data we often recieve are often messy... ehem... more like garbage sometimes.
- Need a lot of preparation and care to data even before you begin the analysis
- Sadly, this is probably the *longest* step but also arguably the most crucial. It is what separates good analysis from trash!

American Community Survey (ACS)



- Detailed info on income, benefits, health insurance, education
- "Pretty big" Data (approx 3.5 million households surveyed annually)
- For class, we just take 1000 observations and 10 variables

Variables under Study

Variable	Description
Sex	gender
Age	age in years
MarStat	marital status
Income	annual income (in \$1,000s)
HoursWk	hours of work per week
Race	Asian, Black, White, or Other
US Citizen	citizen versus non-citizen
HealthInsurance	yes=have health insurance, no = no health insurance
Language	native English speaker versus other

Importing the Dataset (again)

• Like before, we can use point-and-click or the working directory

```
setwd("YourFilePath")
acs <- read.csv("acs.csv", header = TRUE)</pre>
```

Let's also examine the structure and give an overview of the dataset

```
str(acs)
summary(acs)
```

Creating New Variables

Looking at Age

Suppose you want to look at the distribution of Age. One way to do that is through a table

table(acs\$Age)

```
Console Terminal × Background Jobs ×

R 4.4.1 - / **

> table(acs$Age)

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 11 7 7 12 15 13 15 9 14 15 15 11 10 10 11 13 17 8 13 14 15 10 5 14 15 8 14 10 13 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 12 8 15 11 9 16 12 11 17 8 11 23 12 18 9 16 13 14 13 23 21 12 11 19 16 7 17 8 13 17 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 8 21 14 14 13 6 16 10 9 10 8 5 6 5 10 7 6 8 9 5 8 2 7 3 2 3 2 3 2 1 9 90 93 94 130

2 2 2 2 1
```

Look at the values? Do you see anything peculiar?

Looking at Age

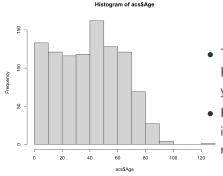
Suppose you want to look at the distribution of Age. One way to do that is through a table

table(acs\$Age)

Look at the values? Do you see anything peculiar?

```
Maybe 0, maybe 130?
```

Looking at Age



- There are 11 obs with a value of zero.
 But seems okay, there are a lot of young children in the ACS.
- However, the value of 130 is clearly impossible and needs to be re-coded to missing!

hist(acs\$Age)

Cleaning Age

Let's create a new variable which will be the cleaned version of Age, called Age2

We need to replace the value of Age2 of 130 with NA (missing). But maybe there are other implausible observations in age.

Any of these commands would show that the 157th entry contains a problematic age.

Indexing to Access

We can use square brackets to access (also called **indexing**) this observation and recode it to missing. I.O.W., brackets = where!

Recoding that entry of Age2 to NA

$$acs$Age2[157] <- NA$$

To verify that we recoded correctly, use the summary command

Maximum age is now 94 (previously 130), and there is now one NA (previously none)

More on Indexing

You could examine the rows of the dataset too using indexing. For example, print the entry in the 157th row and the second column

We could also see if all rows or columns satisfy a certain condition. For example, let us print all columns where Age2 is greater than 100

acs[acs\$Age2>100,]

Pesky NAs

When data entries take NA's, it may need an extra argument for some R commands to run. For example, consider taking the mean

It doesn't run properly because of the missing value. We need to specify an option to ${\tt R}$ to ignore the missing value

Numerical to Categorical

Having Age groups

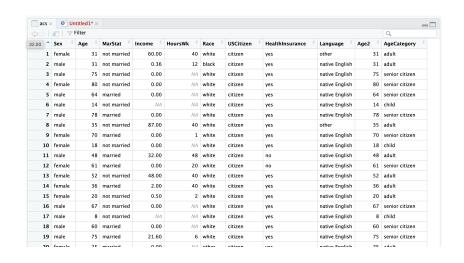
Consider classifying people by age in such a way that 0-18 are children, 19-55 are adults, and >55 are senior citizens. To do this, let us first create an AgeCategory variable which is a factor variable

```
acs$AgeCategory <- factor(NA,levels=c("child","adult","senior citizen"))</pre>
```

Then, we need to assign values of each age category

```
acs$AgeCategory[acs$Age2<=18] <- "child"
acs$AgeCategory[acs$Age2>18 & acs$Age2 <=55] <- "adult"
acs$AgeCategory[acs$Age2>55] <- "senior citizen"</pre>
```

Checking the Dataset Again



Categorical to Categorical

Recoding Race

As of now, Race has four categories. Suppose you want to classify individuals as "white" and "non-white" (to fit, say, a binomial distribution). We can do that by creating a new variable

```
acs$RaceNew <- factor(NA,levels=c("white","non-white"))</pre>
```

Then, we can re-assign the values of the new race variable

```
acs$RaceNew[acs$Race == "white"] <- "white"

acs$RaceNew[acs$Race == "asian" | acs$Race == "black"| acs$Race == "other"] <- "non-white"
```

Verify that you recoded it properly by using a table() command or just look at the dataset.