### Week 4: Summarizing Data III and CLT

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Summarize Data (Advanced)

### Read Data

▶ A data frame is the most common way that we store and interact with data

```
## set working directory
setwd("~/Dropbox/Teaching/SOCUA-302/Week 2")

## read the file
gss <- read.csv("GSS_SOCUA_W2.csv")</pre>
```

### Combine data subsetting and summarizing (dplyr)

- We can also use dplyr to subset and summarize data
  - ▶ Remember filter() filters rows and select() select columns
- How do we calculate the mean value of sibs without negative sibs values?

```
library(dplyr)
gss %>% filter(sibs>0) %>% summarize(sibs_mean = mean(sibs))

## sibs_mean
## 1 4.066925
```

summarize() follows the format: summarize(your\_summarize\_name =
function(variable))

## Combine data subsetting and summarizing (dplyr)

- How do we calculate the mean value of sibs without negative sibs values?
- Why bothering using dplyr and summarize?
  - ▶ Because we can summarize data using different functions at the same time

```
## sibs_mean sibs_var
## 1 4.066925 9.620029
```

### Summarize data by group

- ► In many cases, we not only want data summaries for the total sample, but summaries for some sub-samples
- ► For example, we may want to summarize religious preference by gender (the column relig)
- ► In the relig column, 4 means no religious belief, and other non-zero numbers mean some religious belief
- ▶ It is a non-ordered categorical variable

```
unique(gss$relig)
```

## [1] 3 2 1 5 4 -99 -98 13 11 9 6 10 12 7 8 -97

### Summarize data by group

As there are many religious categories, we may only want two groups categorization for now: religious and non-religious individuals

```
gss[gss$relig!=4 & gss$relig>0,
    "relig"] <- 1
gss[gss$relig==4,
    "relig"] <- 0
unique(gss$relig)</pre>
```

```
## [1] 1 0 -99 -98 -97
```

### Summarize data by group

- ► We will use the group\_by() function in dplyr to summarize data by the group we specify
- ▶ It can be nested in a %>% pipeline

```
gss %>%
  filter(relig>=0&sex>0) %>%
  group_by(sex) %>%
  summarize(religious = mean(relig))
```

- ▶ The calculation above includes all individuals surveyed since 1972 until 2021
- ▶ How to get the same statistic, but only in 2021?

- ▶ The variable relig16 asks which religion was the respondent raised in
- ► How to get the proportion of religious people (at the time of being interviewed, the column relig) by whether they were raised in a religious family?
- Do not forget to drop missing values first!

```
gss[gss$relig16==4,"relig16"] <- 0
gss[gss$relig16!=4&gss$relig16>0,"relig16"] <- 1
gss %>%
  filter(relig>=0&sex>0&relig16>=0) %>%
  group by (relig16) %>%
  summarize(religious = mean(relig))
## # A tibble: 2 x 2
##
    relig16 religious
      <dbl> <dbl>
##
## 1
          0 0.450
## 2
                0.904
```

- The variable relig16 asks which religion was the respondent raised in
- ► How to get the proportion of religious people (at the time of being interviewed, the column relig) by whether they were raised in a religious family?
- ► How to add another column summarizing the proportion of non-religious people by whether they were raised in a religious family?

### Viasualizing the trend

- ▶ We have already calculated the proportion of religious men and women in all and one specific year(s)
- ► Another common exploration of such data is to analyze the temporal trend of the proportion of religious people by gender over the years

```
gss %>%
  filter(relig>=0&sex>0) %>%
  group_by(year, sex) %>%
  summarize(religious = mean(relig)) %>%
  head()
```

```
## # A tibble: 6 x 3
## # Groups: year [3]
     year sex religious
##
    <int> <int>
##
                    <dbl>
     1972
                    0.932
## 1
## 2
     1972
                    0.965
## 3
     1973
                    0.911
## 4
     1973
                    0.958
## 5
     1974
                    0.903
## 6
     1974
                    0.957
```

# Viasualizing the trend (ggplot2)

- ► While base R can handle such visualizations, we will introduce another powerful visualization package, ggplot2
- ▶ ggplot2 can also be nested in the %>% pipeline
- ▶ It is highly flexible in changing colors, setting fonts, customing legends, etc.

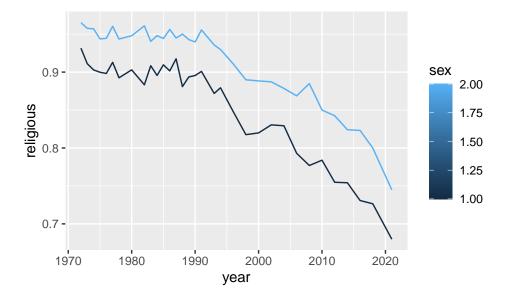
# Viasualizing the trend (ggplot2)

► The basic structure of ggplot2 is

- ► The basic **parameters** such as x-axis, y-axis, groups and colors, are controlled by aes() that stands for aesthetics
- To create a trend plot, we need a line plot controlled by geom\_line()
- ► There are many other options, including geom\_point() that creates scatter plot, geom\_histogram() that creates histograms, etc.
- Check this website for much more details of what ggplot2 can do!
- https://ggplot2.tidyverse.org/reference/

## Viasualizing the trend (ggplot2)

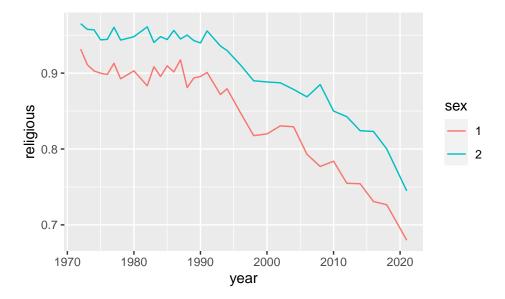
```
library(ggplot2)
gss %>%
  filter(relig>=0&sex>0) %>%
  group_by(year, sex) %>%
  summarize(religious = mean(relig)) %>%
  ggplot(aes(x=year,y=religious,group=sex,color=sex)) +
  geom_line()
```



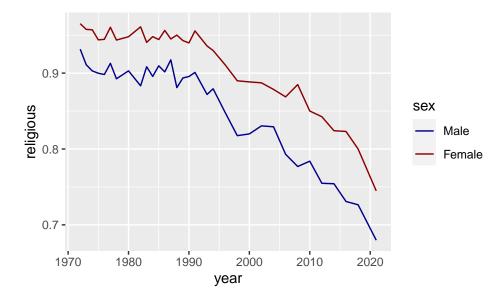
▶ It looks fine, but need some refinements!

- It looks fine, but need some refinements!
- ▶ R identifies the variable sex as a continuous variable, we need a categorical variable
  - We can change the data type of sex into characters
  - We use function mutate(new\_variable = ...) in dplyr to create new variable(s)
  - ► The new variable name can be the same as the original one (i.e., overwriting)

```
gss %>%
  filter(relig>=0 & sex>=0) %>%
  mutate(sex = as.character(sex)) %>%
  group_by(year, sex) %>%
  summarize(religious = mean(relig)) %>%
  ggplot(aes(x=year,y=religious,color=sex)) +
  geom_line()
```



- Readers do not know what 1 and 2 in sex means! We need male and female labels
- ▶ We may also want to change the line color



- The background looks a bit pale...
- ► And we need a title

```
gss %>%
  filter(relig>=0 & sex>=0) %>%
  mutate(sex = as.character(sex)) %>%
  group_by(year, sex) %>%
  summarize(religious = mean(relig)) %>%
  ggplot(aes(x=year,y=religious,color=sex)) +
  scale_color_manual(labels = c("Male", "Female"),
                     values = c("darkblue", "darkred")) +
  geom_line() +
  theme bw() +
  ggtitle("The Proportion of Religious People \n
          by Gender, 1972-2021, GSS")
```

**Female** 

0.7

1970

1980

1990



2000

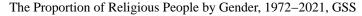
year

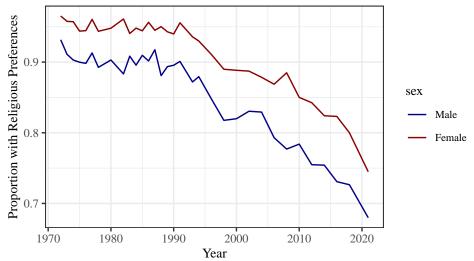
2010

2020

With more tweaks, we can make the figure publishable

```
gss %>%
  filter(relig>=0 & sex>=0) %>%
  mutate(sex = as.character(sex)) %>%
  group by (year, sex) %>%
  summarize(religious = mean(relig)) %>%
  ggplot(aes(x=year,y=religious,color=sex)) +
  geom line() +
  scale_color_manual(labels = c("Male", "Female"),
                     values = c("darkblue", "darkred")) +
  theme bw() +
  ggtitle("The Proportion of Religious People by Gender, 1972-2021, GSS") +
  xlab("Year") +
  ylab("Proportion with Religious Preferences") +
  theme(plot.title=element_text(size=10),
        text=element text(family="Times"),
        axis.title.x=element text(size=8),
        axis.title.y=element text(size=8),
        legend.title = element text(size=8),
        legend.text = element text(size=6))
```





### Central Limit Theorem

- ▶ The distribution of the sample means will be approximately normally distributed with sufficiently large sample sizes, regardless of the original distribution of the population.
  - ► Suppose we are interested in Americans' attitudes towards abortion (support v. oppose), e.g., the proportion of Americans supporting legal abortion
  - ► This proportion *p* is the **population parameter** we want to **estimate** using a random **sample**

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  - ► Suppose we are interested in Americans' attitudes towards abortion (support v. oppose), e.g., the proportion of Americans supporting legal abortion
  - ► This proportion *p* is the **population parameter** we want to **estimate** using a random **sample**
  - ▶ We take a random sample with sample size n = 1000 and find  $\bar{x} = 0.54$  ( $x_i \in (0, 1)$  where 1 means support and 0 oppose)
  - ► This estimate involves uncertainties! Why? \ha

- ► The distribution of the sample means will be approximately normally distributed with sufficiently large sample sizes, regardless of the original distribution of the population.
  - We also want to estimate the uncertainty of the estimation  $\bar{x} = 0.54$
  - ▶ We use the Central Limit Theorem to estimate the uncertainty

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  - We stack all these  $\bar{x}$  and make a histogram
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  - In each random sample, we calculate a  $\bar{x}$  (e.g.,  $\bar{x}=0.54$ ,  $\bar{x}=0.56$ ). This is where uncertainty comes from!
  - We stack all these  $\bar{x}$  and make a histogram
  - ▶ With sufficiently large n and K, the histogram of  $\bar{x}$  (K times) will look like a bell curve
  - ▶ The  $\bar{x}$  that corresponds to the peak of the histogram will be p
  - ▶ The standard deviation of the K  $\bar{x}$ s will be  $\sqrt{\frac{p(1-p)}{n}}$

### Simulation

▶ Suppose the true population **parameter** p = 0.52. Note that we never observe this population parameter.

```
## create population
population <- c(rep(0,4800000),rep(1,5200000))

## sample with n=1000
sample <- sample(population,1000)

## calculate sample mean
mean(sample)</pre>
```

## [1] 0.484

#### Simulation

▶ Now iterate this process for K = 2000 times

```
## empty vector to store means of sample (K times)
mean_of_sample <- c()

## iterate the process of 2000 times
for (i in 1:2000){
    ## sample with n=1000
    sample <- sample(population,1000)
    mean <- mean(sample)
    mean_of_sample <- c(mean_of_sample,mean)
}</pre>
```

### Simulation

```
## plot histogram
hist(mean_of_sample,breaks=20,
    main="Distribution of Sample Means",
    xlab="Sample Mean",
    cex.lab=0.5, cex.axis=0.5, cex.main=0.5, cex.sub=0.5)
```

#### **Distribution of Sample Means**

