Making Comparisons

POSC 3410 – Quantitative Methods in Political Science

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Goal for Today

Introduce students to basic making of comparisons between an independent variable and dependent variable.

Theories and Hypotheses

We previously discussed the importance of theory-writing.

- Theories are conceptual, representing your ideas and arguments.
    - It's the hardest part of political science, but the most important.

Some general things to consider:

- "Keep it Kosher"
- Speak conceptually. Test operationally.
- Don't fit theory to data.

We also discussed proper construction of hypotheses (i.e. testable statements).

Making Comparisons

This lecture will instruct on how to make comparisons among your independent variable and dependent variable.

- Consider this a kind of “first cut” of inferential statistics.
- A lot of peer-reviewed scholarship begins with the following tools.

We will begin to see if there is a preliminary association between our independent variable and dependent variable.

Cross-tabulation

A **cross-tabulation** has three rules in its presentation.

1. Independent variable is the column. Dependent variable is the row.
2. *Always* calculate percentages for the *independent* variable.
3. Interpret a cross-tab by comparing columns across the *same* value of the dependent variable.

Gun Control Opinions, by Partisanship

We'll start with the gun control question from the book.

- DV: "Would you favor or oppose a law which would require a person to obtain a police permit before he or she could buy a gun?"
- IV: Partisanship (7-point scale, condensed to Ds, Is, and Rs)

Data come from 2018 wave of GSS data.

R Code

```r
# require(tidyverse)
# require(stevemisc)
# require(qs)
# GSS <- qread("/home/steve/Dropbox/data/gss/GSS_spss-2018/gss7218.qs")

GSS %>% filter(year == 2018) %>% select(partyid, gunlaw) %>%
  mutate(pidcat = case_when(
    between(partyid, 0, 2) ~ "Democrat/Lean Democrat",
    partyid == 3 ~ "Independent",
    between(partyid, 4,6) ~ "Republican/Lean Republican"
  ),
  gunlaw = ifelse(gunlaw == 2, 0, 1)) -> gunlaw18

proptable <- with(gunlaw18, prop.table(table(gunlaw,pidcat), 2))
proptable <- rbind(proptable, c(1, 1, 1))
```

Table 1: A Crosstab on Support for Gun Control, by Partisanship (GSS, 2018)

	Democrat/Lean Democrat	**Independent**	**Republican/Lean Republican**
Oppose	17.91%	29.5%	40.78%
Favor	82.09%	70.5%	59.22%
TOTAL	*100%*	*100%*	*100%*

Intolerance Toward LGBTQIA+, by Age

Next example will explore social intolerance toward gay people as a function of age/generation.

- DV: "On this list are various groups of people. Could you please mention any that you would not like to have as neighbors?: (Homosexuals)"
  - Group was either mentioned or not mentioned.
- IV: Generation, as defined by Pew cutoffs

Data come from 7th wave (2017) of WVS data (United States).

R Code

```r
# USA7 <- haven::read_sav("/home/steve/Dropbox/data/wvs/F00010330-WVS_Wave_7__USA_Spss_v20200720.sav")

USA7 %>% rename_all(tolower) %>%
  mutate(age = q262,
         birthyr = q261,
         bornhere = q263,
         homelanguage = q272,
         raceethnic = q290,
         neighb_lgbt = ifelse(q22 == 1, 1, 0)) %>%
  select(age:ncol(.)) %>%
  mutate(agecat = carr(age, "18:29=1; 30:49=2; 50:100=3")) %>%
  filter(bornhere == 1 & raceethnic == 840001 & homelanguage == 1240) %>%
  haven::zap_labels() %>%
  mutate(generation = case_when(
    birthyr <= 1945 ~ "Greatest/Silent",
    between(birthyr, 1946, 1964) ~ "Boomers",
    between(birthyr, 1965, 1980) ~ "Gen X",
    between(birthyr, 1981, 1996) ~ "Millennials",
    birthyr >= 1997 ~ "Gen Z"
  )) %>%
  arrange(birthyr) %>%
  mutate(generation = forcats::fct_inorder(generation)) -> neighb17

proptable <- with(neighb17, prop.table(table(neighb_lgbt,generation), 2))
proptable <- rbind(proptable, c(1))
```

Table 2: Intolerance Toward LGBTQIA+ People, by Generation (WVS, 2017)

	Greatest/Silent	**Boomers**	**Gen X**	**Millennials**	**Gen Z**
Not Mentioned	75.24%	84.73%	90.23%	92.2%	95.74%
Mentioned	24.76%	15.27%	9.77%	7.8%	4.26%
TOTAL	*100%*	*100%*	*100%*	*100%*	*100%*

Mean Comparisons

When our dependent variable is interval, we can use a **mean comparison table**.

- It shows the mean of a dependent variable for different values of the independent variable.

Democratic Governance, by Ideology

Next example will explore attitudes about democracy in U.S. as a function of partisan identification

- DV: "And how democratically is this country being governed today? Again using a scale from 1 to 10, where 1 means that it is "not at all democratic" and 10 means that it is "completely democratic," what position would you choose?"
- IV: whether respondent is a Democrat, Republican, or something else.

Data again come from 7th wave (2017) of WVS data (United States).

R Code

```r
USA7 %>% rename_all(tolower) %>%
  haven::zap_labels() %>%
  mutate(howdem = q251) %>%
  mutate(partycat = dplyr::case_when(
           q223 == "5" ~ "Independent/Other",
           q223 == "840001" ~ "Republican",
           q223 == "840002" ~ "Democrat",
           q223 == "840004" ~ "Independent/Other",
           q223 == "840006" ~ "Independent/Other")) %>%
  select(howdem:ncol(.)) %>%
  arrange(partycat) %>%
  mutate(partycat = fct_inorder(partycat)) %>%
  filter(!is.na(partycat)) -> howdem17

howdem17 %>%
  group_by(partycat) %>%
  summarize(mean = mean(howdem, na.rm=T),
            n = n()) -> mct


howdem17 %>%
  summarize(mean = mean(howdem, na.rm=T),
            n = n())  %>%
  mutate(partycat = "TOTAL") %>%
  bind_rows(mct, .) -> mct
```

Table 3: How Democratically is the U.S. Governed, by Party ID (WVS, 2017)

	Mean	**Number of Observations**
Democrat	5.70	1126
Independent/Other	5.61	568
Republican	6.85	819
TOTAL	*6.05*	*2513*

Bar Charts and Line Charts

Graphically displaying data will help us make comparisons.

- Both communicate percentages or means of a dependent variable, for each value of an independent variable.
- Differ in representation (bars or markers connected by lines).

In each case, the independent variable is the x-axis. Dependent variable is the y-axis.

Types of Relationships

There are four types of relationships

1. Positive
2. Negative
3. Curvilinear
4. Zero

Types of Relationships

Note: curvilinear may also be a "normal-U"

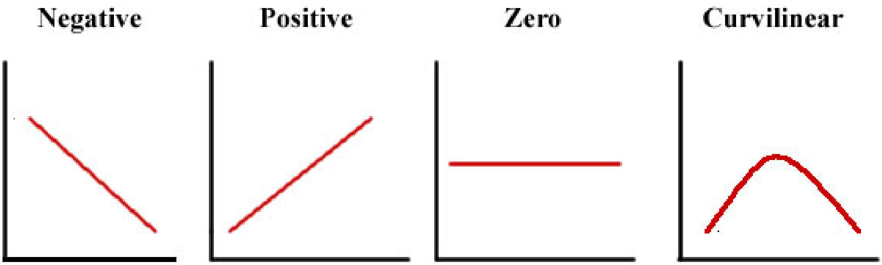


Figure 1: Types of Relationships

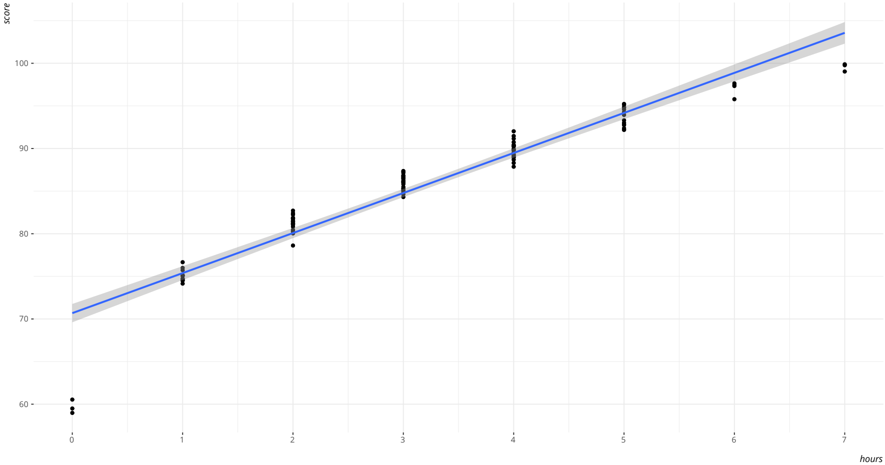
R Code

```r
set.seed(8675309)

tibble(b0 = 60,
       b1 = 15,
       n = 100,
       hours = rpois(n, 3),
       score = b0 + b1*(hours^(1/2)) + rnorm(n, 0, 1)) -> examscores
```

The Relationship Between Hours Studied and Exam Score (Linear Fit)

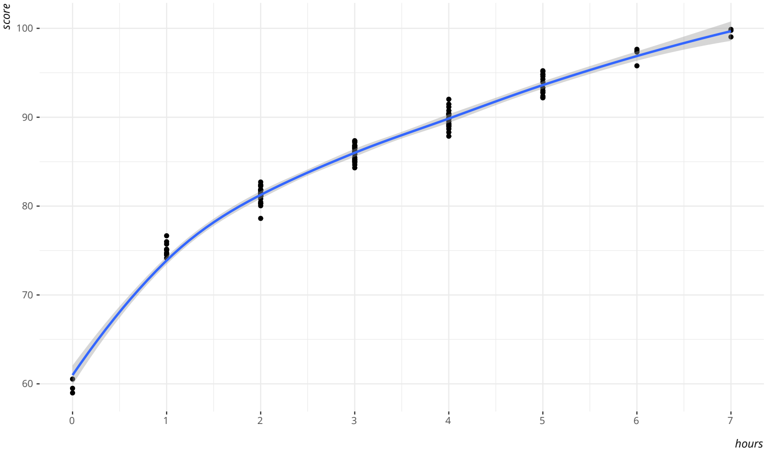
Notice a curvilinear relationship of a kind in the data, for which a straight line is not a good fit.



Data: Hypothetical, inspired by Pollock (2012).

The Relationship Between Hours Studied and Exam Score (Smooth Fit)

There are multiple relationships that cannot be meaningfully summarized by one straight line of best fit.



Data: Hypothetical, inspired by Pollock (2012).

Another Example

Your book has a peculiar example of social disconnectedness and age.

- DV: sum of ordinal measures of time spent with relatives, neighbors, and friends.
  - Ranges from 3 to 21.
  - Higher values = more “disconnectedness”
  - Basically: a 21 means respondent **never** spends any time whatsoever with relatives, neighbors or friends.
- IV: Age in years.

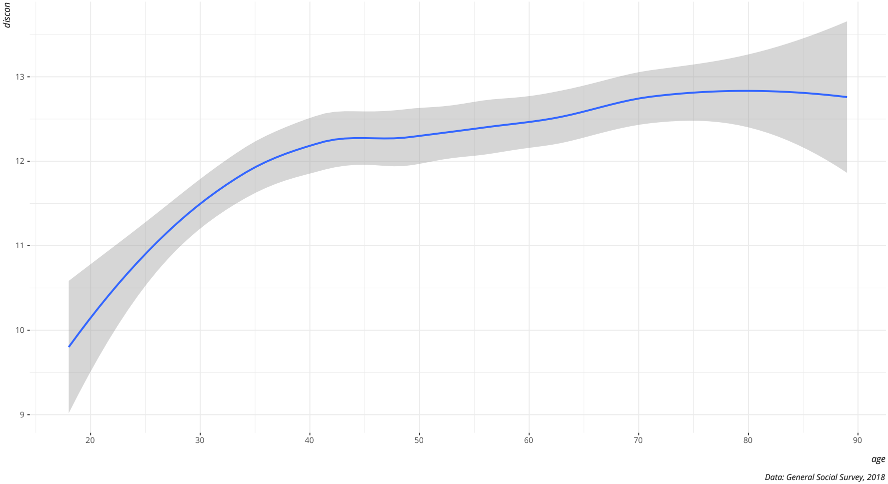
Data come from 2018 wave of GSS.

R Code

```r
GSS %>%
  filter(year == 2018) %>%
  select(year, age, socrel, socommun, socfrend) %>%
  mutate(discon = socrel + socommun + socfrend) %>%
  ggplot(.,aes(age, discon)) + geom_smooth(method = "loess")
```

The Relationship Between Age and Social Disconnectedness

Younger people are less likely to be socially disconnected. Plateaus emerge for the peak working age and declines for the elderly.



Another Example

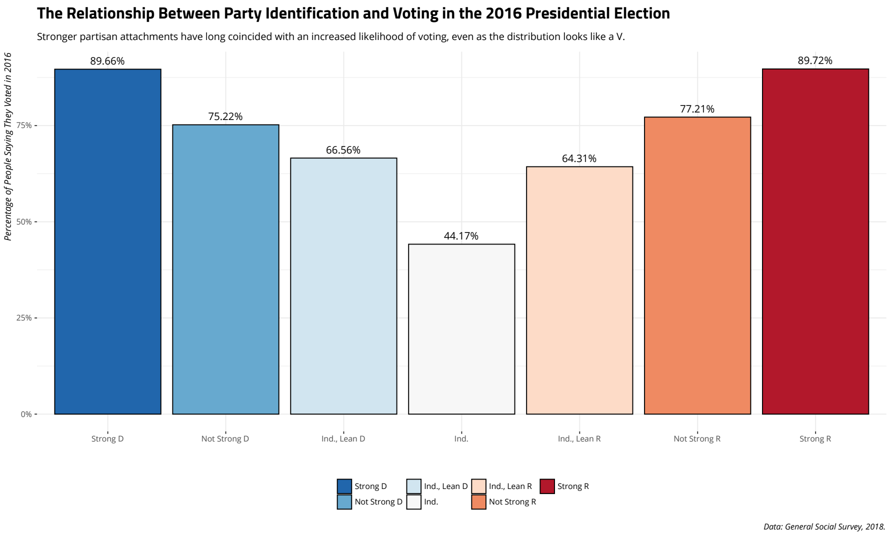
Voter turnout by partisanship

- DV: whether respondent voted in 2016 presidential election
- IV: partisanship on the familiar seven-point scale

Data come from 2018 wave of GSS.

R Code

```r
GSS %>% select(year, vote16, partyid) %>%
  filter(year == 2018 & partyid != 7) %>%
  mutate(partycat = case_when(
    partyid == 0 ~ "Strong D",
    partyid == 1 ~ "Not Strong D",
    partyid == 2 ~ "Ind., Lean D",
    partyid == 3 ~ "Ind.",
    partyid == 4 ~ "Ind., Lean R",
    partyid == 5 ~ "Not Strong R",
    partyid == 6 ~ "Strong R"
  ),
  vote16 = ifelse(vote16 == 2, 0, 1)) %>%
  haven::zap_labels() %>%
  arrange(partyid) %>%
  mutate(partycat = fct_inorder(partycat)) %>%
  group_by(partycat) %>%
  summarize(mean = mean(vote16, na.rm=T))
```



The Relationship Between Party Identification and Voting in the 2016 Presidential Election
Stronger partisan attachments have long coincided with an increased likelihood of voting, even as the distribution looks like a V.
Percentage of People Saying They Voted in 2016
0%
25%
50%
75%
89.66%
75.22%
66.56%
44.17%
64.31%
77.21%
89.72%
Strong D
Not Strong D
Ind., Lean D
Ind.
Ind., Lean R
Not Strong R
Strong R
Data: General Social Survey, 2018.

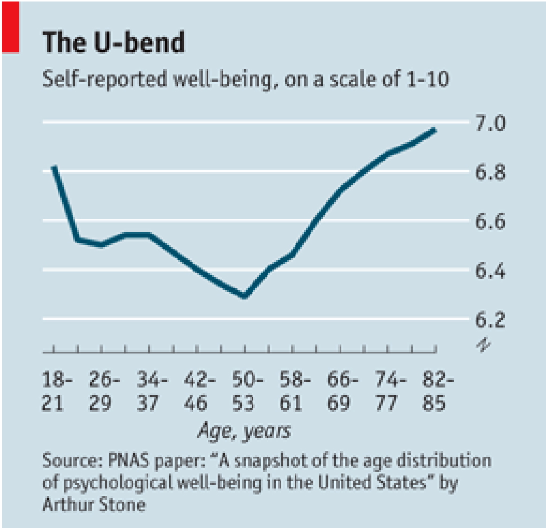


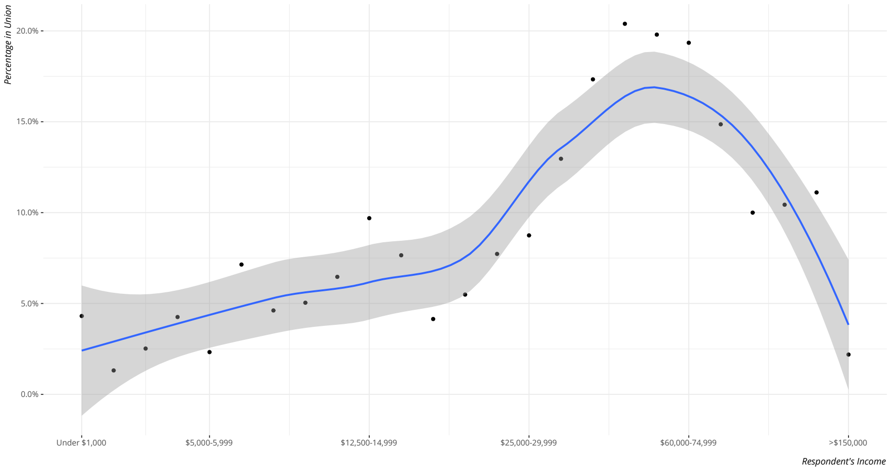
Figure 2: Age and Life Satisfaction

R Code

```r
GSS %>%
  select(year, union, rincom06) %>%
  filter(between(year, 2006, 2014)) %>%
  mutate(union = carr(union, "1=1;2:3=NA; 4=0")) %>%
  group_by(rincom06) %>%
  summarize(mean = mean(union, na.rm=T))
```

The Relationship Between Income and Union Membership, 2006-2014

Some relationships you'll encounter can't be neatly summarized by one or two lines at all.



Data: General Social Survey, 2006-2014.

Conclusion

We have several tools to make a preliminary association between dependent variable and independent variable.

- e.g. cross-tabs, mean comparison table, bar chart, line chart.

Use them!

- Our inferential statistical tools tend to assume linearity.
- Look carefully if there is a non-linear trend between your variables.

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