PSC4375: Summarizing bivariate relationships: cross-tabs, scatterplots, and correlation

Week 4: Lecture 8

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Effect of assasination attempts

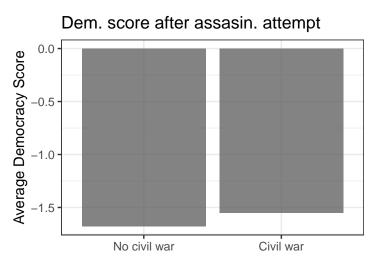
```
library(tidyverse)
data(leaders, package = "qss")
head(leaders[,1:7])
##
            country leadername age politybefore
    vear
## 1 1929 Afghanistan Habibullah Ghazi
                                    39
## 2 1933 Afghanistan Nadir Shah 53
                                                -6
## 3 1934 Afghanistan Hashim Khan 50
                                                -6
## 4 1924 Albania
                               Zogu 29
                               Zogu 36
## 5 1931 Albania
                                                -9
                        Boumedienne
                                    41
                                                -9
## 6 1968
        Algeria
    polityafter interwarbefore
##
## 1 -6.000000
## 2 -7.333333
## 3 -8.000000
## 4 -9.000000
## 5 -9.000000
## 6 -9.000000
```

Before we begin with lesson, Pset 2 help

```
PolityAfter <- leaders %>%
  group by(civilwarbefore) %>%
  summarize(polityafter_mean = mean(polityafter))
PolityAfterPlot <- PolityAfter %>%
  ggplot(aes(x=as.factor(civilwarbefore), y = polityafter_mean
  geom bar(stat = "identity", alpha=0.75) +
  scale x discrete(labels = c("No civil war", "Civil war")) +
  labs(title = "Dem. score after assasin. attempt",
       y = "Average Democracy Score", x = "") +
  theme bw()
```

Before we begin with lesson, Pset 2 help

PolityAfterPlot



More Pset 2 help!

Question 5 update:

- Given that the number of children might be a confounder for the relationship between number of girls and voting, let's estimate the effects using statistical control for the number of children using the following steps:
 - Create one subset of the data called girls_123 that restricts to judges with one, two or three children and have at least one girl.
 - Create another subset of the data called nogirls_123 that restricts to judges with one, two or three children and have no girls.
 - Calculate the mean of progressive_vote within levels of the numbers of kids (num_kids) for each of these subsets and save these vectors as girls_vote_by_nkids and nogirls_vote_by_nkids.
 - Use inner_join to combine the two data subsets then estimate the average treatment effect within levels, saving this vector as ate_nkids.

More Pset 2 help!

Use inner_join to combine the two data subsets...

```
PolityAfter <- leaders %>%
  group by(civilwarbefore) %>%
  summarize(polityafter mean = mean(polityafter))
PolityBefore <- leaders %>%
  group by(civilwarbefore) %>%
  summarize(politybefore mean = mean(politybefore))
PolityCombine <- inner_join(PolityAfter,PolityBefore)</pre>
PolityCombine
## # A tibble: 2 \times 3
     civilwarbefore polityafter_mean politybefore_mean
##
##
              <int>
                                <dbl>
                                                   <dbl>
                                                   -1.52
## 1
                                -1.68
## 2
                                -1.55
                                                   -1.53
```

Contingency tables

- With two categorical variables, we can create contingency tables
 - Also known as cross-tabs
 - Rows are the values of one variable, columns the other

```
leaders %>%
  group_by(civilwarbefore,civilwarafter) %>%
  count() %>%
  spread(civilwarafter, n)
```

• Quick summary how the two variables "go together"

Cross-tabs with proportions

```
leaders %>%
 group by(civilwarbefore,civilwarafter) %>%
  count() %>%
 ungroup() %>%
 mutate(prop = n/ sum(n)) %>%
 select(-n) %>%
 spread(civilwarafter, prop, drop = T)
## # A tibble: 2 x 3
    civilwarbefore '0' '1'
##
```

<int> <dbl> <dbl>

0 0.708 0.076

1 0.108 0.108

##

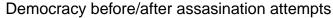
1

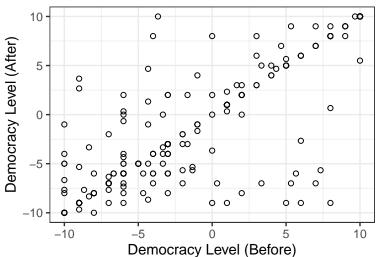
2

Cross-tabs with proportions (by row)

```
leaders %>%
  group by(civilwarbefore,civilwarafter) %>%
  count() %>%
  ungroup() %>%
  group_by(civilwarbefore) %>%
  mutate(prop = n/ sum(n)) %>%
  select(-n) %>%
  spread(civilwarafter, prop, drop = T)
## # A tibble: 2 x 3
```

```
## # Groups: civilwarbefore [2]
## civilwarbefore '0' '1'
             <int> <dbl> <dbl>
##
                 0 0.903 0.0969
## 1
## 2
                 1 0.5 0.5
```





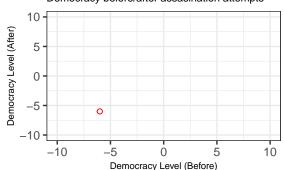
- Each point on the scatterplot (x_i, y_i)
- Use geom_point() function in ggplot

```
leaders %>%
  ggplot(aes(x = politybefore, y = polityafter)) +
  geom point(shape = 21) +
  labs(title = "Democracy before/after assasination attempts"
      x = "Democracy Level (Before)",
       y = "Democracy Level (After)") +
  theme bw() +
  theme(plot.title = element_text(size=12))
```

```
leaders[1, c("politybefore","polityafter")]
```

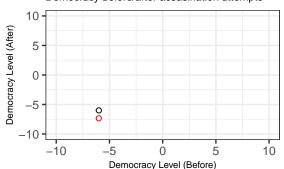
```
## politybefore polityafter
## 1     -6     -6
```

Democracy before/after assasination attempts



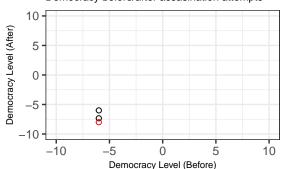
```
leaders[2, c("politybefore","polityafter")]
```

Democracy before/after assasination attempts



leaders[3, c("politybefore","polityafter")]

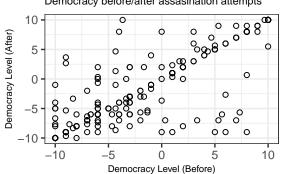
Democracy before/after assasination attempts



```
leaders[3, c("politybefore", "polityafter")]
```

```
##
     politybefore polityafter
                -6
                             -8
```

Democracy before/after assasination attempts



15/22

How big is big?

- Would be nice to have a standard summary of how similar variables are
 - Problem: variables on different scales!
 - Needs a way to put any variable on common units
 - z-score to the rescue!

z-score of
$$x_i = \frac{x_i - \text{mean of } x}{\text{standard deviation of } x}$$

Crucial property: z-scores don't depend on units

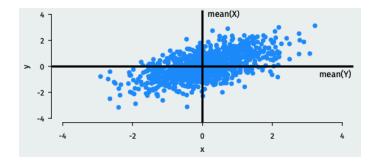
z-score of
$$(ax_i + b) = z$$
-score of x_i

Correlation

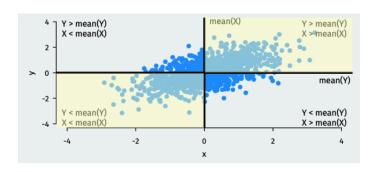
- How do variables move together on average?
- When x_i is big, what is y_i likely to be?
 - Positive correlation: when x_i is big, y_i is also big
 - Negative correlation: when x_i is big, y_i is small
 - High magnitude of correlation: data cluster tightly around a line
- The technical definition of the correlation coefficient:

$$\frac{1}{n-1}\sum_{i=1}^{n}\left[\left(\text{z-score for }x_{i}\right)\times\left(\text{z-score for }y_{i}\right)\right]$$

Correlation intuition:

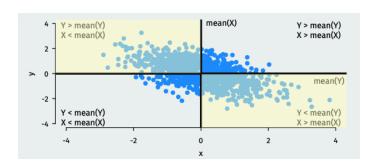


Correlation intuition:



- Large values of X tend to occur with large values of Y
 - (z-score for x_i) × (z-score for y_1) = (pos. num.) × (pos. num.) = +
- Small values of X tend to occur with small values of Y
 - (z-score for x_i) × (z-score for y_1) = (neg. num.) × (neg. num.) = +
- If these dominate → positive correlation

Correlation intuition:



- Large values of X tend to occur with small values of Y
 - (z-score for x_i) \times (z-score for y_1) = (pos. num.) \times (neg. num.) = -
- Small values of X tend to occur with large values of Y
 - (z-score for x_i) \times (z-score for y_1) = (neg. num.) \times (pos. num.) = -
- If these dominate → negative correlation

Properties of correlation coefficient

- Correlation measures linear association.
- Interpretation:
 - Correlation is between -1 and 1
 - Correlation of 0 means no linear association
 - Positive correlations → positive associations
 - Negative correlations → negative associations
 - Closer to -1 or 1 means stronger association
- Order doesn't matter: cor(x,y) = cor(y,x)
- Not affected by changes of scale:
 - cor(x,y) = cor(ax+b, cy+d)
 - Celsius vs. Fahrenheit; dollars vs. pesos; cm vs. in.

Correlation in R

• Use the cor() function

```
leaders %>%
  select(politybefore, polityafter) %>%
  cor()
```

```
## politybefore polityafter
## politybefore 1.0000000 0.8283237
## polityafter 0.8283237 1.0000000
```

-Very highly correlated!